Mining Oncology Data: Knowledge Discovery in Clinical Performance of Cancer Patients

by

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Abstract

Our goal in this research is twofold: to develop clinical performance databases of cancer patients, and to conduct data mining and machine learning studies on collected patient records. We use these studies to develop models for predicting cancer patient medical outcomes. The clinical database is developed in conjunction with surgeons and oncologists at UMass Memorial Hospital. Aspects of the database design and representation of patient narrative are discussed here. Current predictive model design in medical literature is dominated by linear and logistic regression techniques. We seek to show that novel machine learning methods can perform as well or better than these traditional techniques.

Our machine learning focus for this thesis is on pancreatic cancer patients. Classification and regression prediction targets include patient survival, wellbeing scores, and disease characteristics. Information research in oncology is often constrained by type variation, missing attributes, high dimensionality, skewed class distribution, and small data sets. We compensate for these difficulties using preprocessing, meta-learning, and other algorithmic methods during data analysis. The predictive accuracy and regression error of various machine learning models are presented as results, as are t-tests comparing these to the accuracy of traditional regression methods. In most cases, it is shown that the novel machine learning prediction methods offer comparable or superior performance. We conclude with an analysis of results and discussion of future research possibilities.

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1 Introduction

The pursuit of cancer research has become one of the most important scientific endeavors of the 21st century. The Cancer Genome Project defines cancer research as *"the intense scientific effort to understand the development of cancer and identify potential therapies"* [Ins]. In 2004, the American Cancer Society announced that cancer had officially replaced heart disease as the highest disease-related cause of death for Americans under the age of 85. Over 1.3 million new cancer cases occurred in the United States in 2005, and it is estimated that one out of every three Americans will be affected by some form of cancer in their lifetime [Soc].

Most major life science fields are already involved extensively in the field of cancer research. Biology and medical science have been an integral part of cancer study since the time of the Ancient Greeks. However, as technologies and therapies evolve in the modern era, there is an increasing demand for specialized advances from the field of computer science. Just a few of computer science's contributions to cancer research include diagnostic tools, predictive modeling, imaging and data analysis, bioinformatics, medical training applications, and collaborative research databases. Discoveries from computer science are already implemented in a wide variety of cancer therapies, including surgery, radiotherapy, chemotherapy, diagnostic imaging, immunotherapy, and genetic therapy.

Study of clinical performance is one of cancer research's most important research subjects, as it directly concerns the patient's wellbeing. Clinical performance refers to a patient's response to applied medical therapy. Response factors may include changes in health, progression of illness, disease pathology, and systemic behaviors of the body. More refined analysis of clinical performance is always needed, given the frequent complexity and difficulty of cancer treatment. These analyses may include building predictive models for clinical performance generated using the data mining and machine learning techniques from the field of computer science.

Our goal in this research is twofold: to develop clinical performance databases of cancer patients, and to conduct data mining and machine learning studies on the collected patient

records. We present a novel database designed by UMass Memorial Medical School oncologists for representing highly-detailed clinical performance of breast and gastrointestinal cancer patients. Machine learning techniques will be applied to the patient contents of this database to generate a variety of predictive models. The tools and techniques of data mining and machine learning are ideal for this type of analysis. We present and evaluate models based on pancreatic cancer patient data for predicting disease characteristics and prognosis of survival and wellbeing.

This research is a joint effort between the WPI Computer Science Department and UMass Memorial Medical School. The clinical database is composed of data from patients seen at the UMass Memorial Department of Surgical Oncology. This project is advised by Prof. Carolina Ruiz, whose research focus is machine learning and data mining. Prof. George Heineman of WPI and Prof. Sergio Alvarez of Boston College provided additional computer science advising. Medical advising is provided by the Surgical Oncology staff at UMass Memorial, particularly Dr. Giles Whalen and Mary Sullivan NP for the gastrointestinal module, and Dr. Robert Quinlan for the breast module. A grant provided by UMass Memorial in August 2005 funded this research.

2 Medical Background

Cancer refers to diseases resulting from uncontrolled cell growth in regions known as *neoplasms* or *tumors*. A tumor may refer to any distinct mass in a tissue or organ, and its growth may either be *benign* or *malignant*. Malignant tumors are characterized by their ability to spread to surrounding local tissue (*invasion*) or distant sites in the body (*metastasis*). The malignant tumors discussed in this research are a form of cancer known as *carcinoma*, or cancers arising from *epithelial* cells. Tumor growth may be caused by damage or mutations to cell DNA from different factors, including hereditary conditions, environmental exposure, and infectious disease. Chemical or physical agents which trigger cancer-causing DNA mutations are referred to as *carcinogens*. Symptoms of cancer depend on the site of the body affected, the nature of the tumor, and metastatic spread of the disease.

Oncology is the branch of medicine which deals with the diagnosis and treatment of malignant tumors. Various methods exist to treat cancer. *Resection* is the surgical excision of tumor growth from bodily tissue. *Chemotherapy* is the systemic or localized application of antineoplastic drugs to destroy or retard the development of tumor growth. *Radiotherapy* refers to treatments which use irradiation to destroy cancerous cells. *Palliation* collectively refers to the methods intended to relieve cancer symptoms rather than effect cure. Palliative measures may include *stenting*, *anastomosis*, feeding tubes, nerve blocks, and various forms of surgery, chemotherapy, and radiotherapy, as well as other medications for symptom management. The intention of a resection may be either curative or palliative. Tumor *immunotherapy* is a biological protocol which uses methods such as vaccination to trigger an immune system response which destroys cancerous cells. *Gene counseling* is a series of DNA tests which establish susceptibility of a patient or their family to certain forms of cancer.

An important aspect of patient clinical performance research is quantification of a patient's wellbeing. Measurements of wellbeing are important in evaluating treatment response and qualifications for different forms of care. Throughout the course of their treatment, patient overall health and performance status may be rated by quality-of-life (QoL) scores

Score	Status
100%	Normal, No Complaints, No Signs of Disease
90%	Capable of Normal Activity, Few Symptoms or Signs of Disease
80%	Normal Activity with Some Difficulty, Some Symptoms or Signs
70%	Caring for Self, Not Capable of Normal Activity or Work
60%	Requiring Some Help, Can Take Care of Most Personal Requirements
50%	Requires Help Often, Requires Frequent Medical Care
40%	Disabled, Requires Special Care and Help
30%	Severely Disabled, Hospital Admission Indicated but No Risk of Death
20%	Very Ill, Urgently Requiring Admission, Requires Treatment
10%	Moribund, Rapidly Progressive Fatal Disease Processes
0%	Death

Table 1: QoL/Karnofsky Scores

Score	Status
0	Asymptomatic
1	Symptomatic but Completely Ambulant
2	Symptomatic, <50% in Bed During the Day
3	Symptomatic, >50% in Bed, but Not Bedbound
4	Bedbound
5	Death

Table 2: ECOG Scores

(also known as Karnofsky scores), which ranges 0-100%, or Eastern Cooperative Oncology Group (ECOG) scores, which ranges 0-5. Tables 1 and 2 detail the criteria for these scores [KB49, OC82]. For the purpose of this thesis, patient wellbeing will be measured using the ECOG system.

Different factors may be used to describe the nature of tumors. *Histology* refers to the microscopic structure of tumor tissue. The behavior and severity of a cancer may vary depending on its histologic composition. *Adenocarcinoma* is carcinoma which develops within glandular epithelium which typically behaves in a very malignant fashion. *Neuroendocrine* tumors grow in nervous or endocrine tissue. For some cancers, including malignancies of the pancreas, these neuroendocrine tumors tend to behave in a more indolent fashion than adenocarcinomas. *Cysts* refer to closed cavities of glandular epithelium where retained se-

cretions are accumulated, and may behave in a benign or malignant fashion. Two common histologic forms of breast cancer are *lobular* and *ductal* types. The study of cells at a microscopic level is referred to as *cytology*. At the microscopic level, the symptoms of cancer are often influenced by the growth and penetration of tumors into bodily structures. *Lymph nodes* are small bodies along lymphatic vessels which filter bacteria and foreign bodies. The presence of tumorous tissue within regional lymph nodes is an important prognostic factor for many types of cancer. The penetration of tumors into *vasculature*, or blood vessels, can be an important factor in determining the spread and resectability of the disease.

The American Joint Committee on Cancer (AJCC) maintains a staging system to provide a unified methodology for describing cancer. Malignant tumors are classified by TNM staging, which refers to Tumor, Node, and Metastasis. Each parameter is paired with a number from a discrete range to indicate disease stage. The meaning of these parameters differs by cancer etiology. T refers to primary tumor size and ranges from 0 to 4 or 'is' for *in situ* growth. N refers to regional lymph node involvement and ranges from 0 to 3. M refers to metastatis to distant organs and is denoted 0 if absent and 1 if present. Other parameters may be used to describe cancer. R is used to denote tumor growth on margins of surgically excised tissue: 0 for clean margins, 1 for microscopic tumor growth, and 2 for gross tumor growth. L and V (0-1) denote the absence or presence of tumor invasion into lymphatic vessels and veins. G (1-4) stands for the grade or differentiation between tumor cells and surrounding normal cells. The criteria for staging depends on the tumor location and histology. Most tumor forms use TNM staging, but not all use the full range. In all staging systems, a parameter paired with X stands for an unknown or unevaluated quantity [oC04].

A variety of tools are used to diagnose cancer. *Serum studies* refer to blood tests, which may include nutritional levels, liver functions, and molecular *tumor markers*. *Biopsy* refers to a small sample of tumor tissue taken to evaluate its histologic composition and malignancy. Biopsies may be taken in a variety of ways, including fine-needle aspiration (FNA), core-cutting needle, incisional biopsy, and excisional biopsy. Cancer is frequently diagnosed using

imaging studies. Quantifying the accuracy and reliability of imaging studies is a crucial research topic. *X-rays* are the process of visualizing an internal body image by catching high-energy photons on photographic film. A *computed axial tomography* (CT or CAT) creates a three-dimensional internal view of a patient using a series of sectional x-rays across a common axis. *Ultrasound* uses ultrasonic waves to create a sonographic visualization a body's internal structure. *Endoscopic ultrasound* (EUS) is an ultrasound study generated by a thin, flexible ultrasound probe passed through the gastrointestinal tract. *Magnetic resonance imaging* (MRI) uses the magnetic resonance of photons to create a high-contrast density image. Biopsies are often taken using guidance by imaging studies. Different diagnoses are used depending on the type and location of cancer [VD93].

2.1 Pancreatic Cancer Background

Pancreatic cancer remains a challenging disease for physicians, oncologists, and surgeons, and is the machine learning analytic focus of this thesis. Here, pancreatic cancer is a general term for cancer of the pancreas and periampullary region. The *pancreas* is a long gland which sits behind the stomach and secretes digestive juices into the small intestine and bloodstream. The *periampullary region* refers to the area containing the duodenum, distal common bile duct, and ampulla of Vater. The *duodenum* refers to the upper part of the small intestine, which starts from the lower end of the stomach and extends to the *jejunum* (middle small intestine). The *distal common bile duct* is the portion of the excretory passage close to the duodenum which carries bile from the liver. The ampulla of Vater is a dilation in the duodenal wall through which the common bile duct and pancreatic duct empty into the small intestine. Please refer to Figures 1 and 2 [Gra95, Cen].

Tumors of the pancreatic and periampullary region are known for a high degree of mortality and morbidity. This disease stands as the fourth largest cancer killer in the country, even though it only accounts for 2% of total cancer diagnoses. Approximately 25,000 new patients are diagnosed with this disease in the United States each year; median survival from time of diagnosis is six months, with five-year survival rates at 3% [Bre04]. The severity and treatment of these cancers depend largely on their locations and histologic types. The most frequently occurring types are adenocarcinomas, which are the most aggressive and have the highest associated mortality rates. A less common and more indolent form of the disease are neuroendocrine or *islet cell* tumors. *Intraductal papillary mucinous neoplasms* (IPMNs or IPMT's) are cystic pancreatic tumors which can progress to cancers.

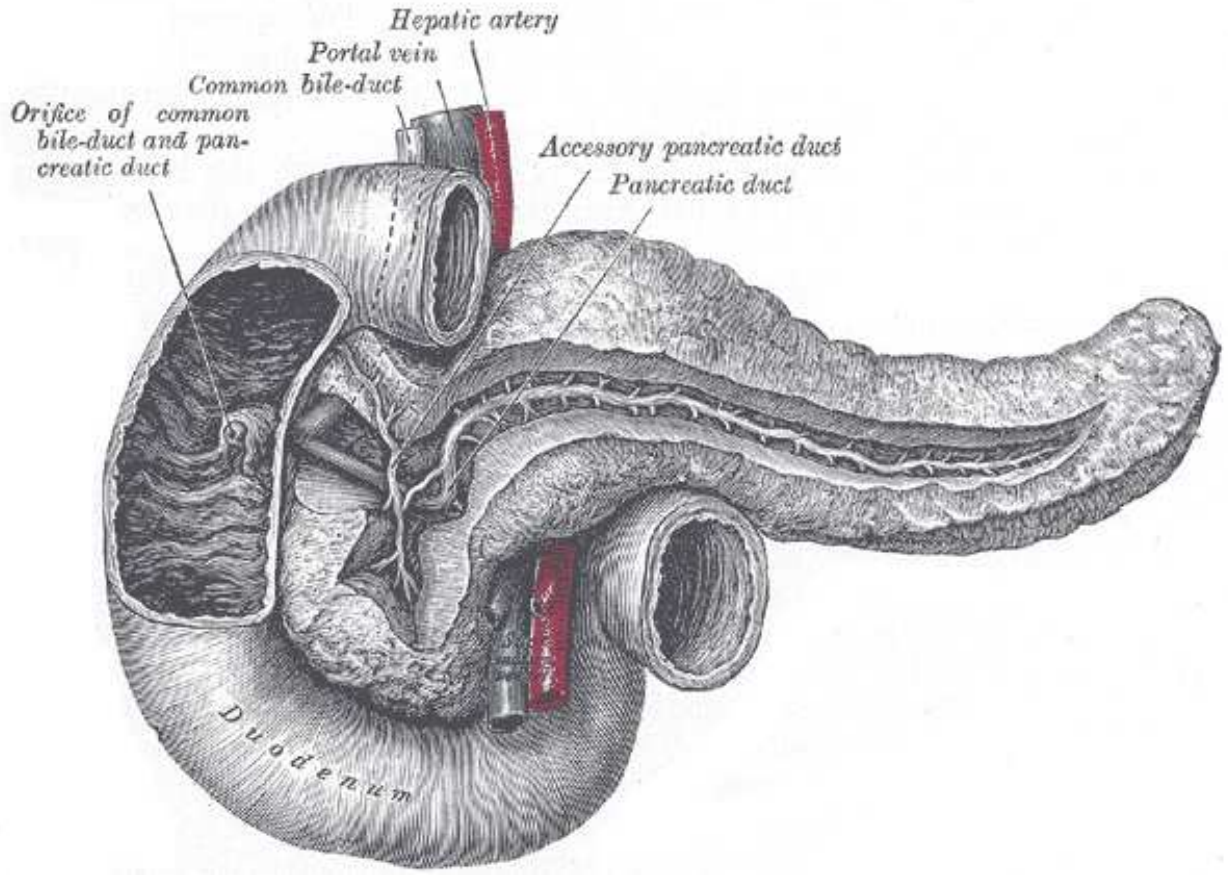


Figure 1: Gray's Anatomy - Pancreas and Periampullary Region [Gra95]

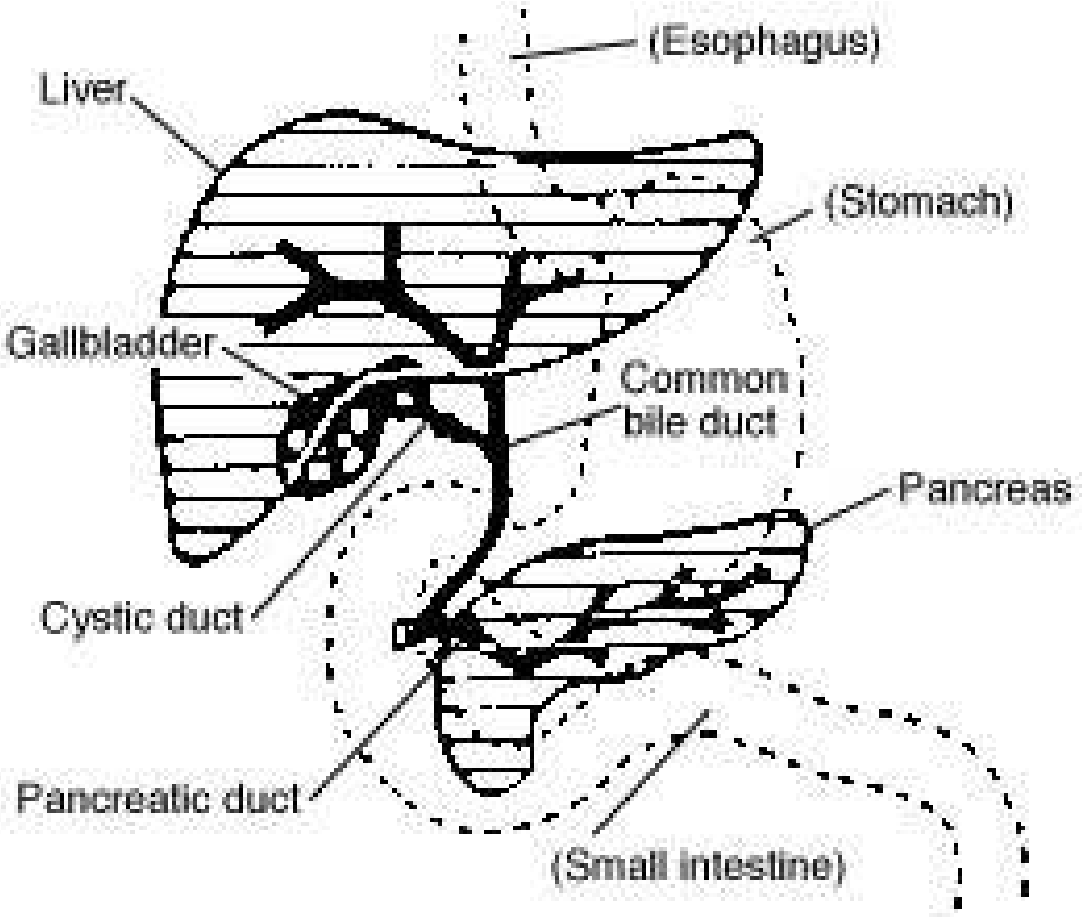


Figure 2: Digestive System with Common Bile Duct Illustrated [Cen]

Pancreatic cancer typically presents itself through non-specific symptoms, abdominal pain and painless jaundice being the most frequent. Risk factors include age, smoking, obesity, diabetes, diets high in meat, chronic pancreatitis, and genetic family history. Diagnosis is typically performed using chest x-rays, serum studies, abdominal CT scans, and endoscopic ultrasound. Imaging studies be used to determine tumor size, regional lymph note involvement, and distant metastatic spread. Biopsies taken by *fine needle aspiration* (FNA) during endoscopic ultrasound can be used to predict tumor histology and malignancy. Nuclear tumor markers such as CEA and CA19-9, as well as nutritional and liver function serum levels, can confirm the systemic presence of pancreatic cancer or evaluate its effects. In preliminary evaluation, approximately 15% of patients are deemed as potentially resectable, 40% as locally advanced/unresectable, and 45% as metastatic or equivocal.

TNM staging for pancreatic cancer determines the treatment course and prognosis of disease. The T-stage in pancreatic cancer refers to the tumor's size and penetration into surrounding gastrointestinal anatomy. A simplified version of the AJCC staging criteria [oC04] is presented in Table 3. Regional lymph node involvement as denoted by N-stage and presence of metastatis as denoted by M-stage is presented in Tables 4 and 5. Tumor spread in pancreatic cancer may involve vascular structures, which impacts disease spread and difficulty of resection. Vascular structures which may be invaded include the *celiac axis*, *hepatic artery*, *superior mesenteric artery*, *superior mesenteric vein*, *inferior vena cava*, *portal vein*, and *splenic vein*. If a tumor penetrates a venous structure, then sections of the vein may be resected. However, arterial penetrations cannot be resected given current medical technology, although studies are being done. The microscopic penetration of tumor into a vascular structure is denoted by V-staging as described above.

The most common surgical procedure to treat pancreatic cancer is a *Whipple procedure*, or *pancreaticoduodenectomy*. The procedure involves removal of the distal half of stomach, gall bladder, distal common bile duct, head of the pancreas, duodenum, proximal jejunum, and regional lymph nodes. The remaining anatomy is anastomosed together to reconstruct

T-Stage	Criteria
TX	Primary tumor cannot be assessed
T0	No evidence of primary tumor
Tis	Carcinoma in situ
T1	Tumor limited to pancreas and measures 2 cm or less in greatest dimension, without blood vessel involvement
T2	Tumor greater than 2 cm in greatest dimension, still limited to the pancreas, without involve any blood vessels
T3	Any tumor that extends beyond the pancreas, does not involve the celiac axis or superior mesenteric artery.
T4	Any tumor that invades the superior mesenteric artery or the celiac axis (unresectable cancer)

Table 3: Pancreatic Cancer T-Staging

N-Stage	Criteria
NX	Regional lymph node involvement cannot be assessed
N0	No evidence of regional lymph node involvement
N1	Presence of regional lymph node involvement

Table 4: Pancreatic Cancer N-Staging

M-Stage	Criteria
MX	Distant metastasis cannot be assessed
M0	No evidence of distant metastasis
M1	Presence of distant metastasis

Table 5: Pancreatic Cancer M-Staging

a working digestive tract. The pre and post-surgical anatomy of a Whipple procedure are shown in Figures 3 and 4 [Cli]. The surgical mortality rate of a Whipple procedure is approximately 5%, 3% in high-volume centers. Resective surgery is usually performed in most circumstances where possible, as it represents the highest likelihood of complete cure. Reasons not to resect include local tumor spread, involvement of vasculature, distant metastatis, and patient unwillingness or inability to endure surgery.

Chemotherapy and radiotherapy are frequently applied as pancreatic cancer treatments. The most common regimens of chemotherapy applied at UMass Memorial are 5-Flurouracil and Gemcitabine. Cancer therapies may be either *adjuvant* (applied post-surgery) or *neoadjuvant* (applied pre-surgery, frequently in an effort to reduce tumor size). Palliative measures intended to alleviate but not cure disease include feeding tubes, stenting, gastric bypasses, nerve blocks, and palliative chemo or radiotherapy. After initial treatment, patients are followed at three-month intervals for the first two years, and six-month intervals for two to five years, and yearly intervals afterwards. Factors monitored during follow-up include disease status, recurrent symptoms, weight, serum markers, and general wellbeing scores.

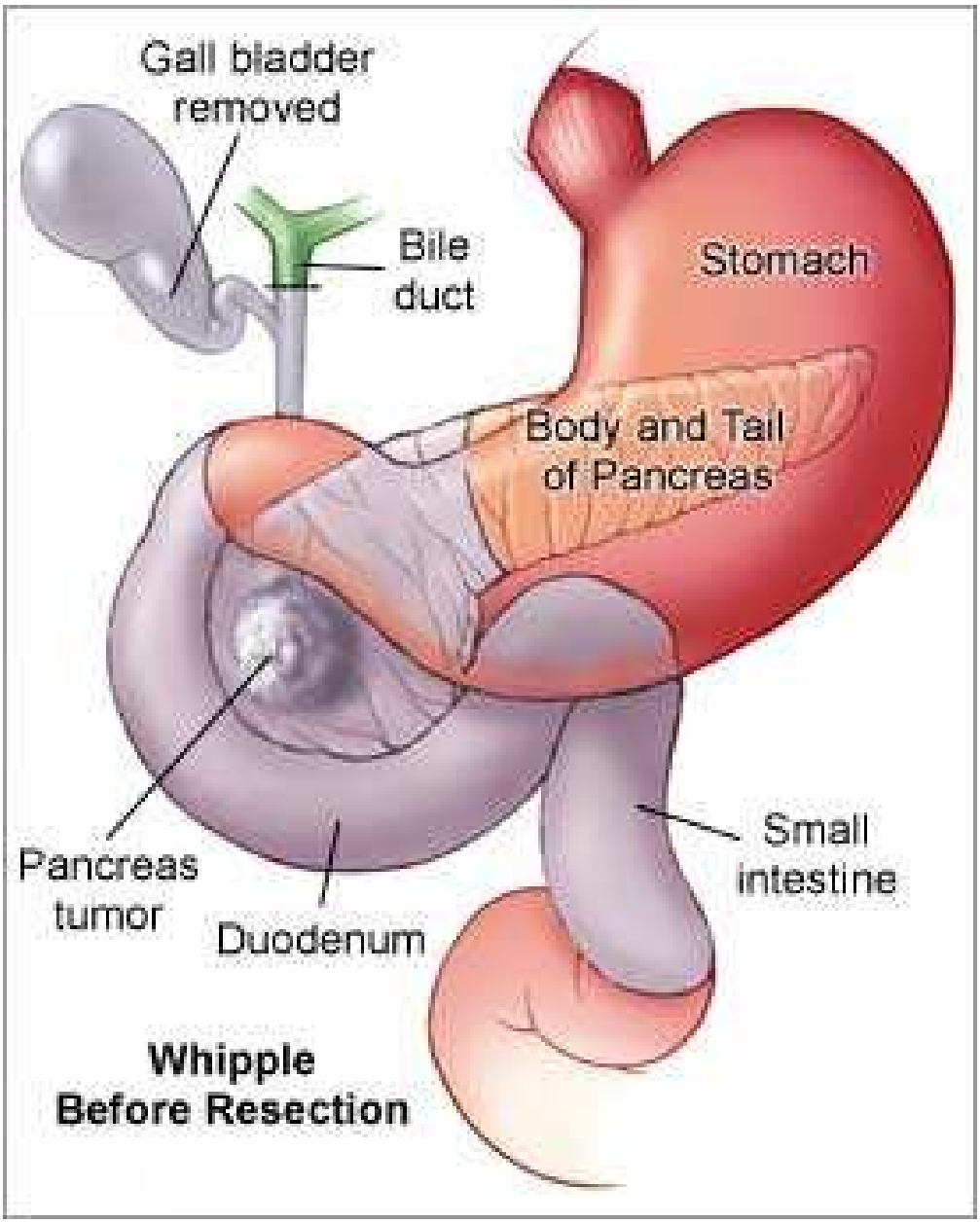


Figure 3: Whipple Procedure - Pre-Surgical Anatomy [Cli]

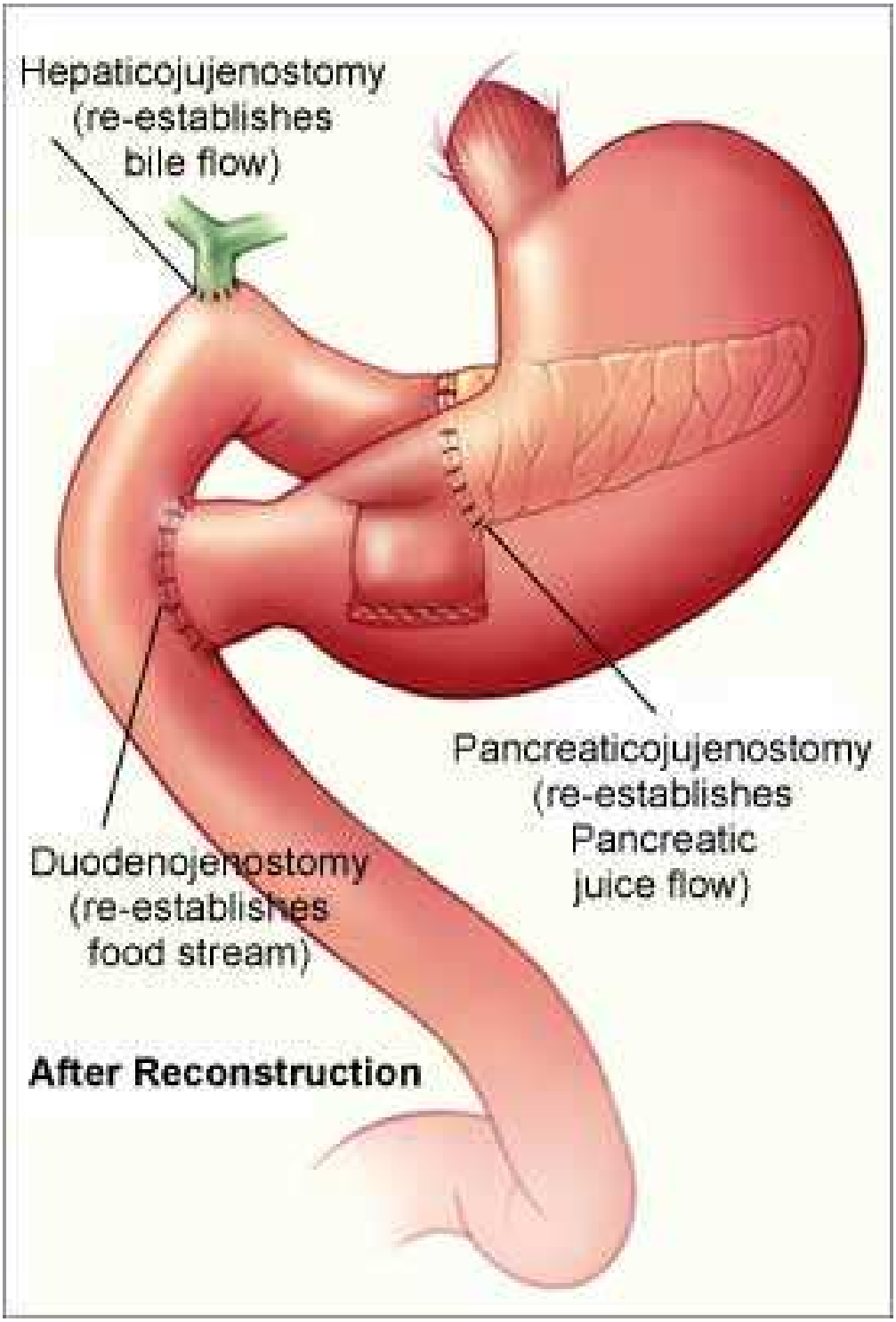


Figure 4: Whipple Procedure - Post-Surgical Anatomy [Cli]

3 Clinical Database Construction

The clinical database is where our patient information is collected. Our database was developed using Microsoft Access 2003 with Visual Basic scripting and SQL Server for data storage. It is hoped that these additional cancer modules will be used in future analytic work. Prof. George Heineman of WPI and [Szo82] provided many useful suggestions in representing the patient treatment narrative within a software application.

Specific details pertaining to the patient medical factors are too complex to be discussed here; for those interested, [VD93] provides an accessible discussion of clinical oncology for both medical and non-medical audiences alike.

3.1 Gastrointestinal Cancer Database

For this project, database modules were developed for six major forms of gastrointestinal cancer (pancreatic, biliary, esophageal, gastric, colorectal, and hepatocellular). Specific design of the gastrointestinal cancer modules were based on Dr. Whalen algorithms for patient treatment. Portions of the table schema and interface were based on earlier work by Tiffany Wei of UMass Memorial.

In this database, the major elements of patient treatment were decomposed into eight categories:

- Presentation
- Medical History
- Diagnostic Tests
- Preliminary Outlook
- Treatment
- Surgical Resection Details/Reasons for Not Pursuing Resection

- Pathology Reports
- Follow-Up

Each of these categories is represented by a table schema within the database. They are related to a core patient record by a zero-to-many cardinality; this allows for a flexible, efficient representation of what can often be a very complex clinical narrative.

3.1.1 Pancreatic Cancer

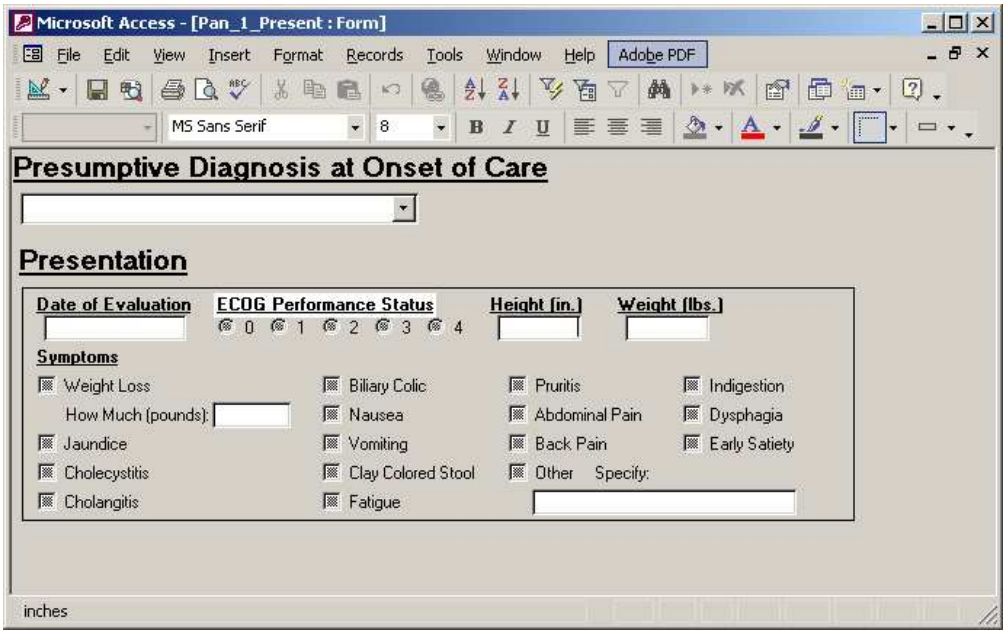


Figure 5: Pancreatic Cancer Presentation Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
PresumptiveDx	Number	Presumptive Diagnosis (Pancreatic tumor, periampullary tumor, etc...)
DemEvalDate	Date/Time	Demographics - Date Evaluated by Surgical Oncology
DemECOG	Number	Demographics - ECOG Score (0-4)
DemHeight	Number	Demographics - Height in Inches of Patient
DemWeight	Number	Demographics - Weight in Pounds of Patient at Admission
SxWtloss	Yes/No	Initial Symptoms - Weight Loss
SxWtlossP	Number	Initial Symptoms - Weight Loss - Pounds
SxJaun	Yes/No	Initial Symptoms - Juandice
SxChole	Yes/No	Initial Symptoms - Cholecystitis
SxChola	Yes/No	Initial Symptoms - Cholangitis
SxBC	Yes/No	Initial Symptoms - Biliary Colic
SxNau	Yes/No	Initial Symptoms - Nausea
SxVom	Yes/No	Initial Symptoms - Vomiting
SxCCS	Yes/No	Initial Symptoms - Clay Colored Stool
SxFati	Yes/No	Initial Symptoms - Fatigue
SxPru	Yes/No	Initial Symptoms - Pruritis
SxInd	Yes/No	Initial Symptoms - Indigestion
SxAbd	Yes/No	Initial Symptoms - Abdominal Pain
SxBack	Yes/No	Initial Symptoms - Back Pain
SxDyspha	Yes/No	Initial Symptoms - Dysphagia
SxSatiety	Yes/No	Initial Symptoms - Early Satiety
SxOT	Yes/No	Initial Symptoms - Other
SxOTSpe	Text	Initial Symptoms - Other - Specify

Figure 6: Pancreatic Cancer Presentation Schema

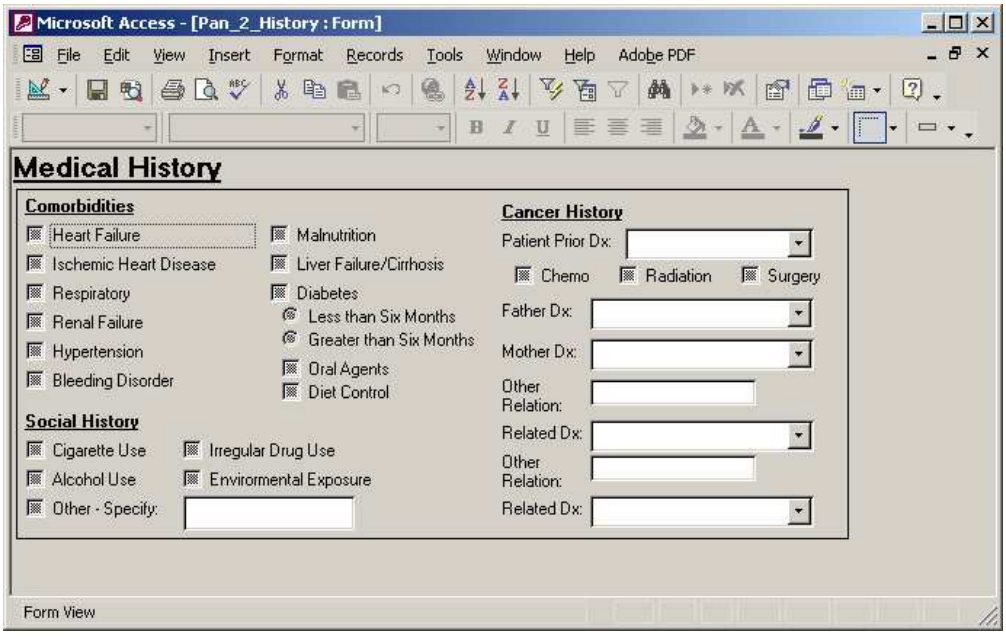


Figure 7: Pancreatic Cancer Medical History Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
CxHF	Yes/No	Comorbidities - Heart Failure
CxIHD	Yes/No	Comorbidities - Ischemic Heart Disease
CxResp	Yes/No	Comorbidities - Respiratory
CxDiab	Yes/No	Comorbidities - Diabetes
CxDiabOral	Yes/No	Comorbidities - Diabetes - Insulin - Oral
CxDiabDiet	Yes/No	Comorbidities - Diabetes - Insulin - Diet Control
CxDiabOnset	Number	Comorbidities - Diabetes - Onset (1=Less than six months, 2 =Greater than six months)
CxRF	Yes/No	Comorbidities - Renal Failure
CxHyper	Yes/No	Comorbidities - Hypertension
CxBleed	Yes/No	Comorbidities - Bleeding Disorder
CxLiver	Yes/No	Comorbidities - Liver Failure
CxMal	Yes/No	Comorbidities - Malnutrition
CxPriorCancer	Number	Comorbidities - Prior Cancer Dx
CxPriorCancerChemo	Yes/No	Comorbidities - Prior Cancer Dx - Chemo
CxPriorCancerRadiation	Yes/No	Comorbidities - Prior Cancer Dx - Radiation
CxPriorCancerSurgery	Yes/No	Comorbidities - Prior Cancer Dx - Surgery
SHCigarette	Yes/No	Social History - Cigarettes (significant use)
SHAlcohol	Yes/No	Social History - Alcohol (significant use)
SHDrugUse	Yes/No	Social History - Drug Use
SHExposure	Yes/No	Social History - Environmental Exposure
SHOther	Yes/No	Social History - Other
SHOtherS	Text	Social History - Other - Specify
FamilyFatherDx	Number	Family History - Father Dx
FamilyMotherDx	Number	Family History - Mother Dx
FamilyOther1	Text	Family History - Other1
FamilyOther1Dx	Number	Family History - Other1 Dx
FamilyOther2	Text	Family History - Other2
FamilyOther2Dx	Number	Family History - Other2 Dx

Figure 8: Pancreatic Cancer Medical History Table Schema

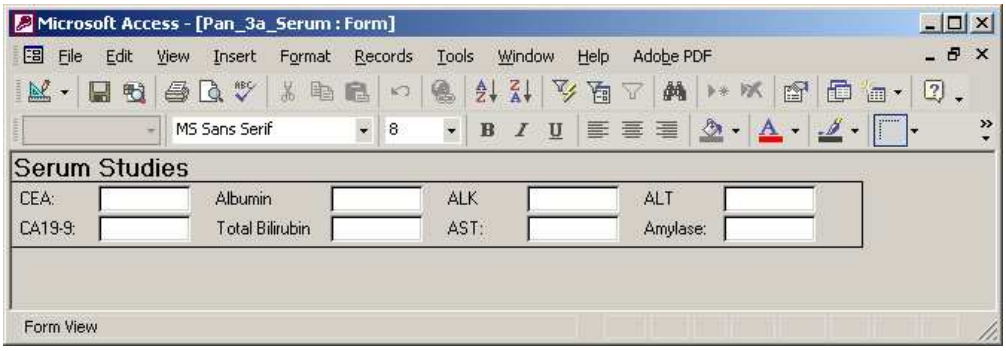


Figure 9: Pancreatic Cancer Serums Studies Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
LabCEA	Number	Laboratory - CEA
LabCA19-9	Number	Laboratory - CA19-9
LabAlb	Number	Laboratory - Albumin
LabBili	Number	Laboratory - Bilirubin
LabAlka	Number	Laboratory - Alkaline phosphotase
LabALT	Number	Laboratory - ALT
LabAST	Number	Laboratory - AST
LabAmylase	Number	Laboratory - Amylase

Figure 10: Pancreatic Cancer Serums Studies Table Schema

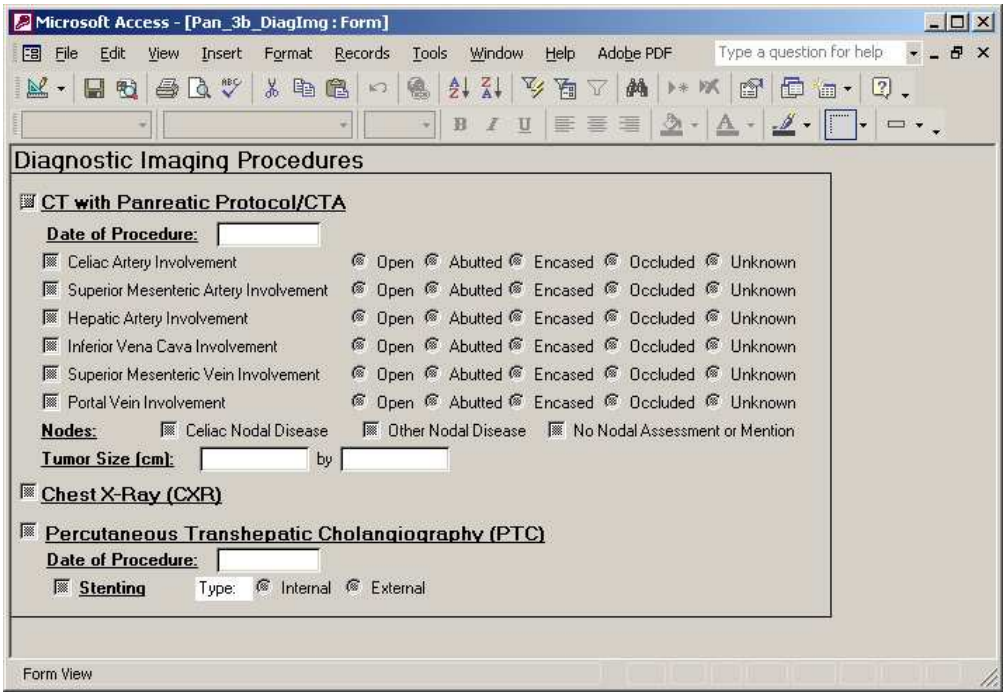


Figure 11: Pancreatic Cancer Diagnostic Imaging Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
CXRDx	Yes/No	CXR - Diagnosis
CTDx	Yes/No	CT - Diagnosis
CTEvalDate	Date/Time	CT - Date Evaluated
CTVascOmit	Yes/No	CT - Vascular Omission
CTCeliac	Yes/No	CT - Celiac Involvement
CTCeliacClass	Number	CT - Celiac Involvement Class
CTSMA	Yes/No	CT - SMA Involvement
CTSMAClass	Number	CT - SMA Involvement Class
CTHepatic	Yes/No	CT - Hepatic Involvement
CTHepaticClass	Number	CT - Hepatic Involvement
CTInferior	Yes/No	CT - Inferior Vena Cava Involvement
CTInferiorClass	Number	CT - Inferior Vena Cava Involvement Class
CTSMV	Yes/No	CT - SMV Involvement
CTSMVClass	Number	CT - SMV Involvement Class
CTPortal	Yes/No	CT - Portal Vein Involvement
CTPortalClass	Number	CT - Portal Vein Involvement Class
CTCeliacNode	Yes/No	CT - Celiac Nodal Disease
CTOtherNode	Yes/No	CT - Other Nodal Disease
CTNodeOmit	Yes/No	CT - Node Omission
CTTumorSizeX	Number	CT - Tumor Size (cm) - Width
CTTumorSizeY	Number	CT - Tumor Size (cm) - Height
PTCDx	Yes/No	PTC - Diagnosis
PTCEvalDate	Date/Time	PTC - Date Evaluated
PTCStent	Yes/No	PTC - Stent
PTCStentType	Number	PTC - Stent Type

Figure 12: Pancreatic Cancer Diagnostic Imaging Table Schema

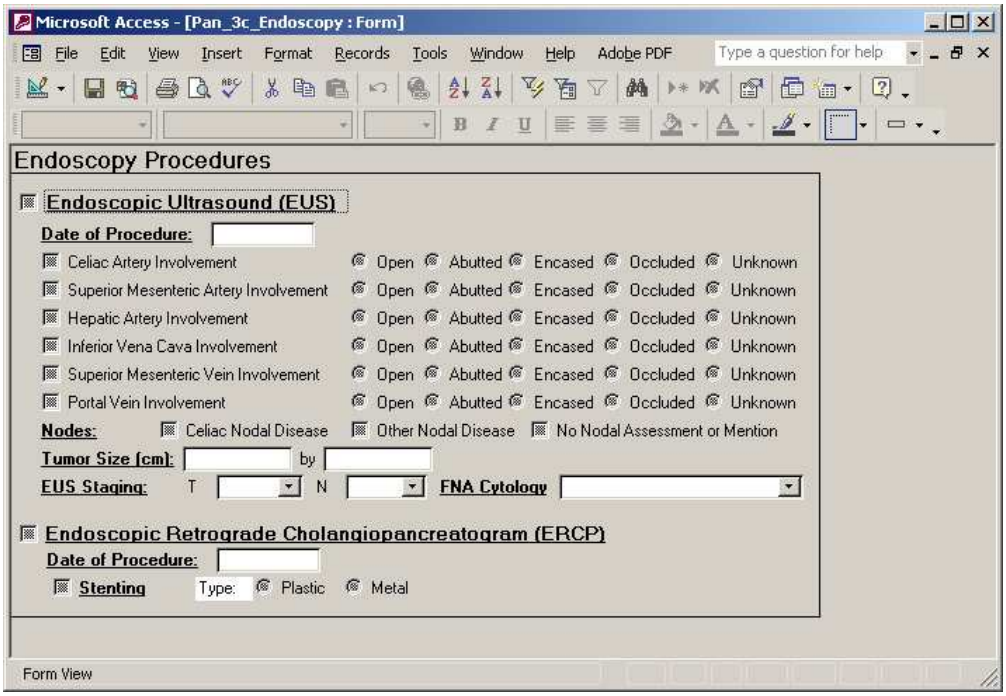


Figure 13: Pancreatic Cancer Endoscopy Studies Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
EUSDx	Yes/No	EUS - Diagnosis
EUSEvalDate	Date/Time	EUS - Date Evaluated
EUSVascOmit	Yes/No	EUS - Omission
EUSCeliac	Yes/No	EUS - Celiac Involvement
EUSCeliacClass	Number	EUS - Celiac Involvement Class
EUSSMA	Yes/No	EUS - SMA Involvement
EUSSMAClass	Number	EUS - SMA Involvement Class
EUSHepatic	Yes/No	EUS - Hepatic Involvement
EUSHepaticClass	Number	EUS - Hepatic Involvement Class
EUSInferior	Yes/No	EUS - Inferior Vena Cava Involvement
EUSInferiorClass	Number	EUS - Inferior Vena Cava Involvement Class
EUSSMV	Yes/No	EUS - SMV Involvement
EUSSMVClass	Number	EUS - SMV Involvement Class
EUSPortal	Yes/No	EUS - Portal Vein Involvement
EUSPortalClass	Number	EUS - Portal Vein Involvement Class
EUSCeliacNode	Yes/No	EUS - Celiac Node Disease
EUSOtherNode	Yes/No	EUS - Other Nodal Disease
EUSNoNode	Yes/No	EUS - No Nodes Mentioned
EUSTumorSizeX	Number	EUS - Tumor Size (cm) - Width
EUSTumorSizeY	Number	EUS - Tumor Size (cm) - Height
EUSStagingT	Number	EUS - Staging - T
EUSStagingN	Number	EUS - Staging - N
EUSCyto	Number	EUS - FNA Cytology
ERCPDx	Yes/No	ERCP - Diagnosis
ERCPEvalDate	Date/Time	ERCP - Date Evaluated
ERCPStent	Yes/No	ERCP - Stent
ERCPStentType	Number	ERCP - Stent Type

Figure 14: Pancreatic Cancer Endoscopy Studies Table Schema

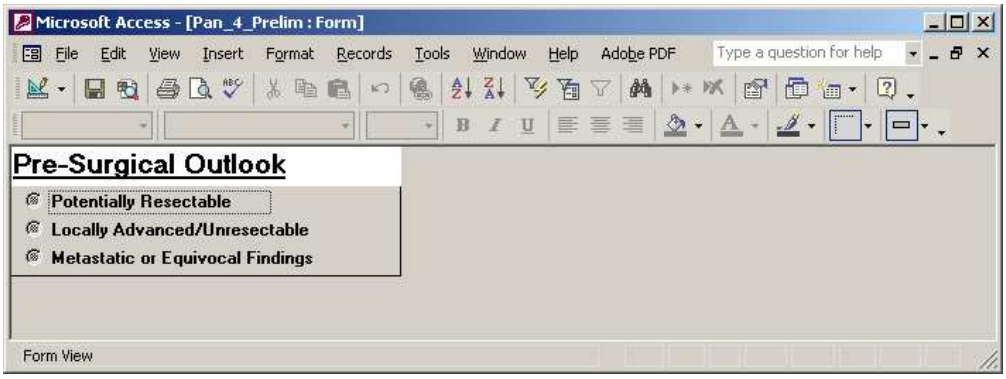


Figure 15: Pancreatic Cancer Preliminary Outlook Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
PreOutlook	Number	Pre-Surgical Tumor Outlook (Potentially Resectable, Locally Advanced/Unresectable, Metastatic or Equivocal Findings)

Figure 16: Pancreatic Cancer Preliminary Outlook Table Schema

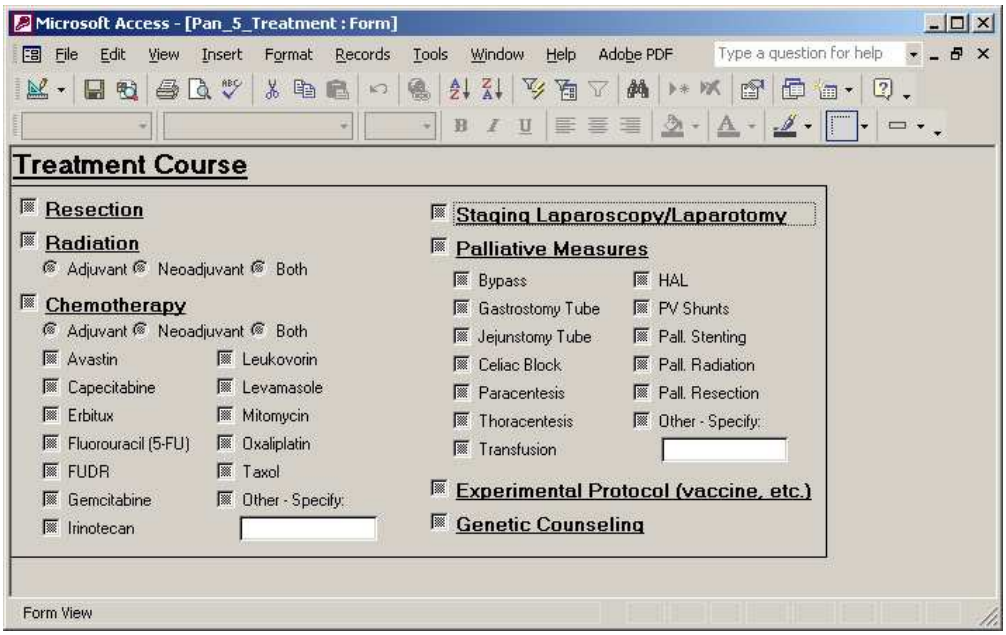


Figure 17: Pancreatic Cancer Treatment Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
TxResect	Yes/No	Treatment - Resection
TxLap	Yes/No	Treatment - Laparoscopy
TxRadia	Yes/No	Treatment - Radiation
TXRadiaAdju	Number	Treatment - Radiation - Adjuvancy
TxChemo	Yes/No	Treatment - Chemo
TXChemoAdju	Number	Treatment - Chemo - Adjuvancy
TxChemoAVA	Yes/No	Treatment - Chemo - Avastin
TxChemoCap	Yes/No	Treatment - Chemo - Capecitabine
TxChemoErb	Yes/No	Treatment - Chemo - Erbitux
TxChemoFlu	Yes/No	Treatment - Chemo - Fluorouracil (5-FU)
TxChemoFUDR	Yes/No	Treatment - Chemo - FUDR
TxChemoGem	Yes/No	Treatment - Chemo - Gemcitabine
TxChemoIri	Yes/No	Treatment - Chemo - Irinotecan
TxChemoLeu	Yes/No	Treatment - Chemo - Leukovorin
TxChemoLev	Yes/No	Treatment - Chemo - Levamasole
TxChemoMit	Yes/No	Treatment - Chemo - Mitomycin
TxChemoOxa	Yes/No	Treatment - Chemo - Oxaliplatin
TxChemoTax	Yes/No	Treatment - Chemo - Taxol
TxChemoOth	Yes/No	Treatment - Chemo - Other
TxChemoOS	Text	Treatment - Chemo - Other - Specify
TxPal	Yes/No	Treatment - Palliation
TxPalRes	Yes/No	Treatment - Palliation - Pall. Resection
TxPalBypass	Yes/No	Treatment - Palliation - Bypass
TxPalCeliac	Yes/No	Treatment - Palliation - Celiac Block
TxPalPara	Yes/No	Treatment - Palliation - Paracentesis
TxPalTho	Yes/No	Treatment - Palliation - Thoracentesis
TxPalRad	Yes/No	Treatment - Palliation - Pall. Radiation
TxPalTrans	Yes/No	Treatment - Palliation - Transfusion
TxPalStens	Yes/No	Treatment - Palliation - Pall. Stenting
TxPalPV	Yes/No	Treatment - Palliation - PV Shunts
TxPalHAL	Yes/No	Treatment - Palliation - HAL
TxPalGasTube	Yes/No	Treatment - Palliation - Gastrostomy Tube
TxPalJejTube	Yes/No	Treatment - Palliation - Jejunstomy Tube
TxPalOth	Yes/No	Treatment - Palliation - Other
TxPalOS	Text	Treatment - Palliation - Other - Specify
TxExp	Yes/No	Treatment - Experimental protocol (ie. vaccine)
TxGene	Yes/No	Treatment - Gene Counseling

Figure 18: Pancreatic Cancer Treatment Table Schema

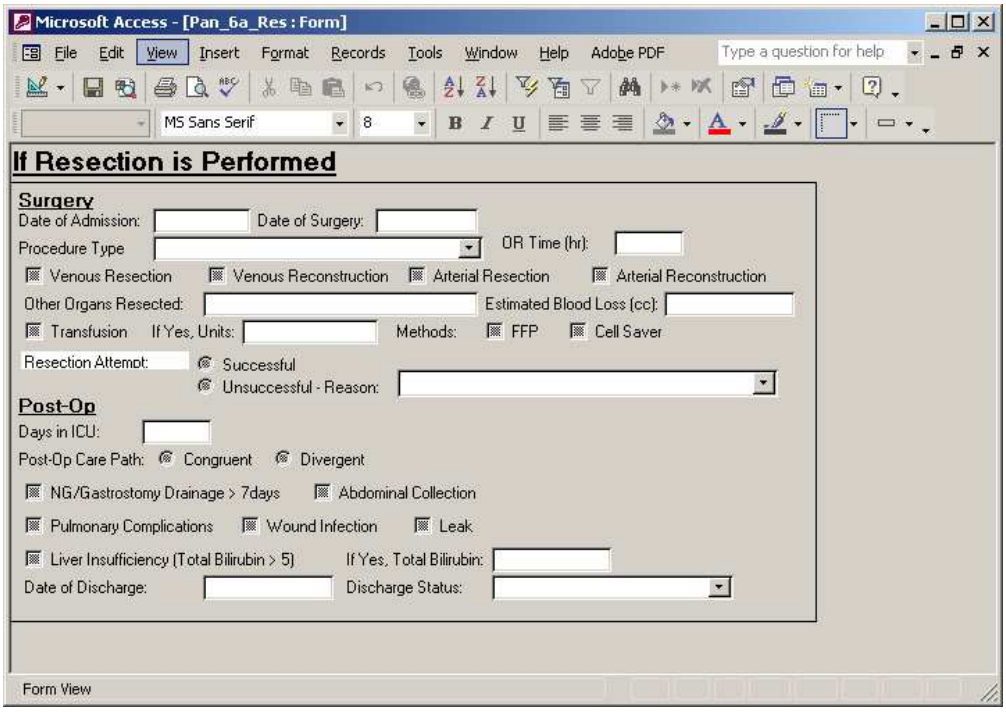


Figure 19: Pancreatic Cancer Resection Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
ResDAdm	Date/Time	Resection - Date of Admission
ResDSurg	Date/Time	Resection - Date of Surgery
ResPxType	Number	Resection - Procedure Type (Whipple, total pancreatectomy, distal pancreatectomy, etc…)
ResORTime	Number	Resection - OR Time (hr.)
ResVenRes	Yes/No	Resection - Venous Resection
ResVenRec	Yes/No	Resection - Venous Reconstruction
ResArtRes	Yes/No	Resection - Arterial Resection
ResArtRec	Yes/No	Resection - Arterial Reconstruction
ResOrgans	Text	Resection - Other Organs Resection
ResBloodLoss	Number	Resection - Estimated Blood Loss (cc)
ResTransfusion	Yes/No	Resection - Tranfusion
ResTUnits	Number	Resection - Transfusion Units
ResTFFP	Yes/No	Resection - Transfusion - FFP
ResTCell	Yes/No	Resection - Transfusion - Cell
ResAttempt	Number	Resection - Resection Attempt
ResAttemptUn	Number	Resection - Resection Unsuccessful Reason (Tumor involvement, Operative mishap, etc…)
ResPOCourse	Number	Resection - PO - Post-Op Care Path
ResPODays	Number	Resection - PO - Time in ICU (days)
ResPOInfection	Yes/No	Resection - PO - Wound infection
ResPOLeak	Yes/No	Resection - PO - Leak
ResPONG	Yes/No	Resection - PO - NG/gastrotomy drainage
ResPOAbdominal	Yes/No	Resection - PO - Abdominal Collection
ResPOPulmComp	Yes/No	Resection - PO - Pulminary Complications
ResPOLiverInsuf	Yes/No	Resection - PO - Liver Insufficiency
ResPOLiverTB	Number	Resection - PO - Liver Insufficiency - Total Bilirubin
ResPODDischarge	Date/Time	Resection - Date of Discharge
ResPODischStatus	Number	Resection - Discharge Status

Figure 20: Pancreatic Cancer Resection Table Schema

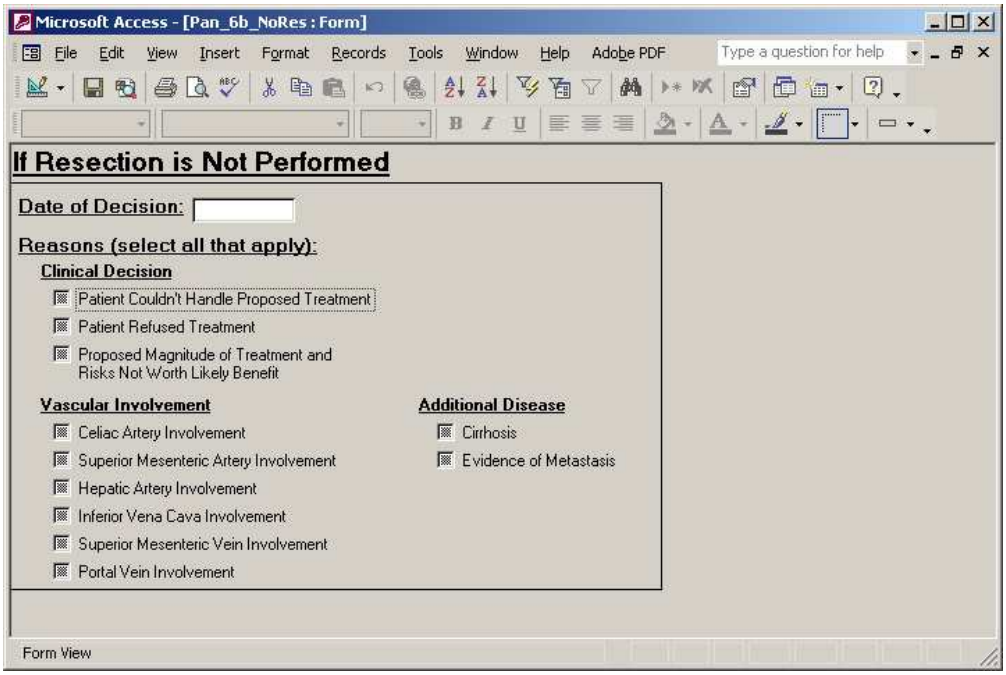


Figure 21: Pancreatic Cancer No Resection Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
NoResEvalDate	Date/Time	No Resection - Decision Date
NoResNoHandle	Yes/No	No Resection - Couldn't Handle Proposed Treatment
NoResRefused	Yes/No	No Resection - Refused Treatment
NoResMagnitude	Yes/No	No Resection - Magnitude Not Worth Benefits
NoResCeliacInvolve	Yes/No	No Resection - Celiac Trunk Involvement
NoResSMAInvolve	Yes/No	No Resection - SMA Involvement
NoResHepaticInvolve	Yes/No	No Resection - Hepatic Involvement
NoResIVCInvolve	Yes/No	No Resection - Inferior Vena Cava Involvement
NoResSMVInvolve	Yes/No	No Resection - SMV Involvement
NoResPVInvolve	Yes/No	No Resection - Portal Vein Involvement
NoResCirrhosis	Yes/No	No Resection - Cirrhosis
NoResMetastatic	Yes/No	No Resection - Metastatic

Figure 22: Pancreatic Cancer No Resection Table Schema

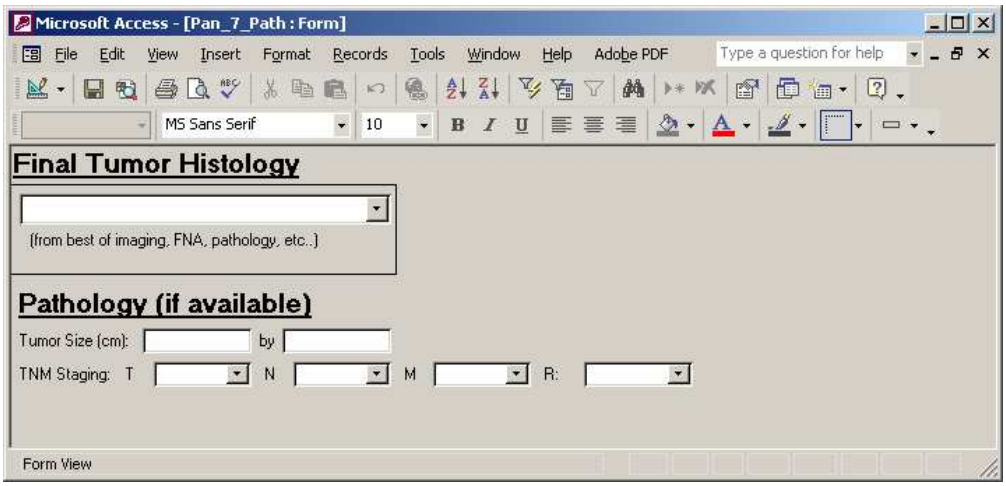


Figure 23: Pancreatic Cancer Pathology Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
Histology	Number	Histology
ResPathT	Number	Resection - Pathology Staging - T
ResPathN	Number	Resection - Pathology Staging - N
ResPathM	Number	Resection - Pathology Staging - M
ResPathR	Number	Resection - Pathology Staging - R
ResPathV	Number	Resection - Pathology Staging - R
ResPathSizeX	Number	Resection - Pathology Tumor Size (cm) - Width
ResPathSizeY	Number	Resection - Pathology Tumor Size (cm) - Height

Figure 24: Pancreatic Cancer Pathology Table Schema

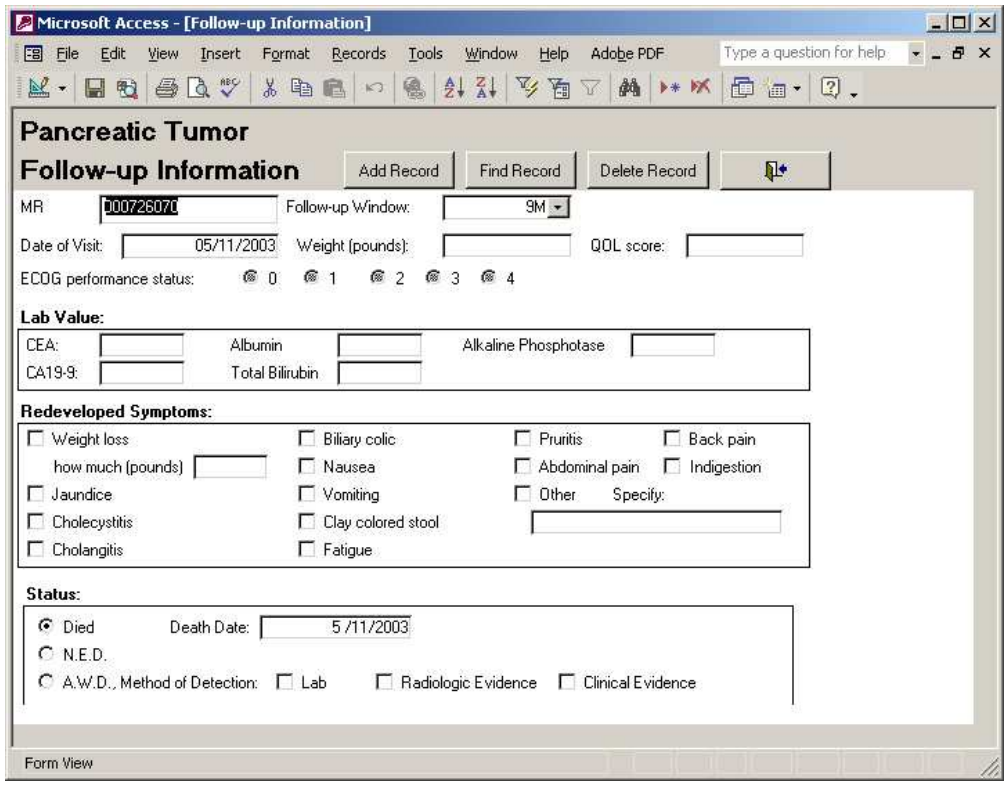


Figure 25: Pancreatic Cancer Follow-Up Form

Field Name	Data Type	Description
ID	AutoNumber	
MR	Text	Meditech Medical Record Number for Patient
FUWin	Number	Follow-Up Windows
VisitDate	Date/Time	Visit Date
Weight	Number	Weight (lbs.)
QOLscore	Number	QoL Score (0-100)
ECOG	Number	ECOG Score (0-4)
LabCEA	Number	Laboratory - CEA
LabCA19-9	Number	Laboratory - CA19-9
LabAlb	Number	Laboratory - Albumin
LabBili	Number	Laboratory - Bilirubin
LabAlka	Number	Laboratory - Alkaline phosphotase
SxWtloss	Yes/No	Symptoms - Weight Loss
SxWtlossP	Number	Symptoms - Weight Loss (lbs.)
SxJaun	Yes/No	Symptoms - Jaundice
SxChole	Yes/No	Symptoms - Cholecystitis
SxChola	Yes/No	Symptoms - Cholangitis
SxBC	Yes/No	Symptoms - Biliary Colic
SxNau	Yes/No	Symptoms - Nausea
SxVom	Yes/No	Symptoms - Vomiting
SxCCS	Yes/No	Symptoms - Clay Colored Stool
SxFati	Yes/No	Symptoms - Fatigue
SxPru	Yes/No	Symptoms - Pruritis
SxInd	Yes/No	Symptoms - Indigestion
SxAbd	Yes/No	Symptoms - Abdominal Pain
SxBack	Yes/No	Symptoms - Back Pain
SxOT	Yes/No	Symptoms - Other
SxOTSpe	Text	Symptoms - Other - Specify
Status	Number	Status (NED, AWD, Died)
DeathDate	Date/Time	Death Date
StatusAWDLab	Yes/No	AWD - Lab Evidence
StatusAWDRad	Yes/No	AWD - Radiology Evidence
StatusAWDCli	Yes/No	AWD - Clinical Evidence

Figure 26: Pancreatic Cancer Follow-Up Table Schema

3.1.2 Hepatocellular Cancer

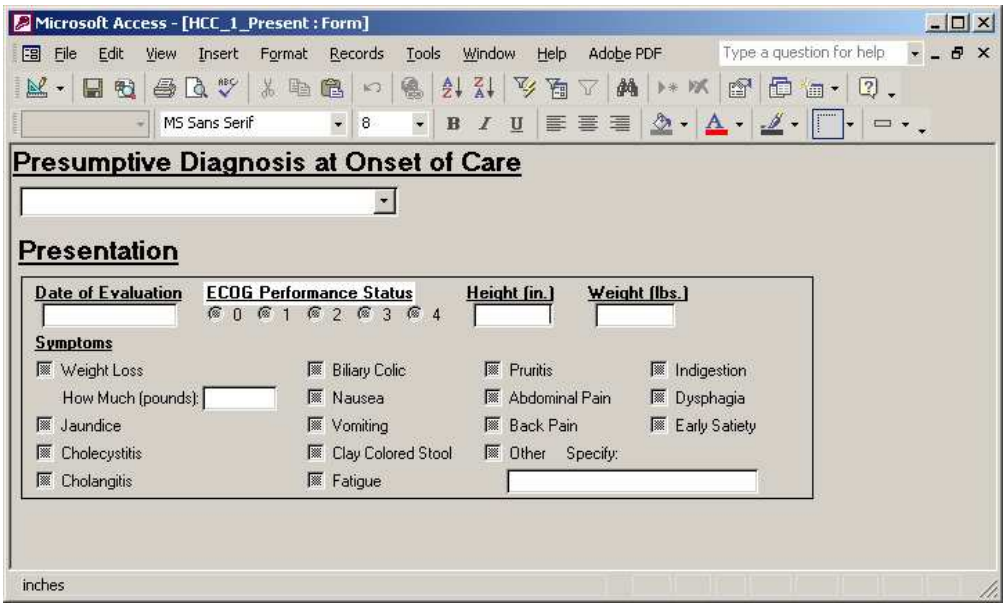


Figure 27: Hepatocellular Cancer Presentation Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
PresumptiveDx	Number	Presumptive Diagnosis (Pancreatic tumor, periampullary tumor, etc...)
DemEvalDate	Date/Time	Demographics - Date Evaluated by Surgical Oncology
DemECOG	Number	Demographics - ECOG Score (0-4)
DemHeight	Number	Demographics - Height in Inches of Patient
DemWeight	Number	Demographics - Weight in Pounds of Patient at Admission
SxWtloss	Yes/No	Initial Symptoms - Weight Loss
SxWtlossP	Number	Initial Symptoms - Weight Loss - Pounds
SxJaun	Yes/No	Initial Symptoms - Juandice
SxChole	Yes/No	Initial Symptoms - Cholecystitis
SxChola	Yes/No	Initial Symptoms - Cholangitis
SxBC	Yes/No	Initial Symptoms - Biliary Colic
SxNau	Yes/No	Initial Symptoms - Nausea
SxVom	Yes/No	Initial Symptoms - Vomiting
SxCCS	Yes/No	Initial Symptoms - Clay Colored Stool
SxFati	Yes/No	Initial Symptoms - Fatigue
SxPru	Yes/No	Initial Symptoms - Pruritis
SxInd	Yes/No	Initial Symptoms - Indigestion
SxAbd	Yes/No	Initial Symptoms - Abdominal Pain
SxBack	Yes/No	Initial Symptoms - Back Pain
SxDyspha	Yes/No	Initial Symptoms - Dysphagia
SxSatiety	Yes/No	Initial Symptoms - Early Satiety
SxOT	Yes/No	Initial Symptoms - Other
SxOTSpe	Text	Initial Symptoms - Other - Specify

Figure 28: Hepatocellular Cancer Presentation Table Schema

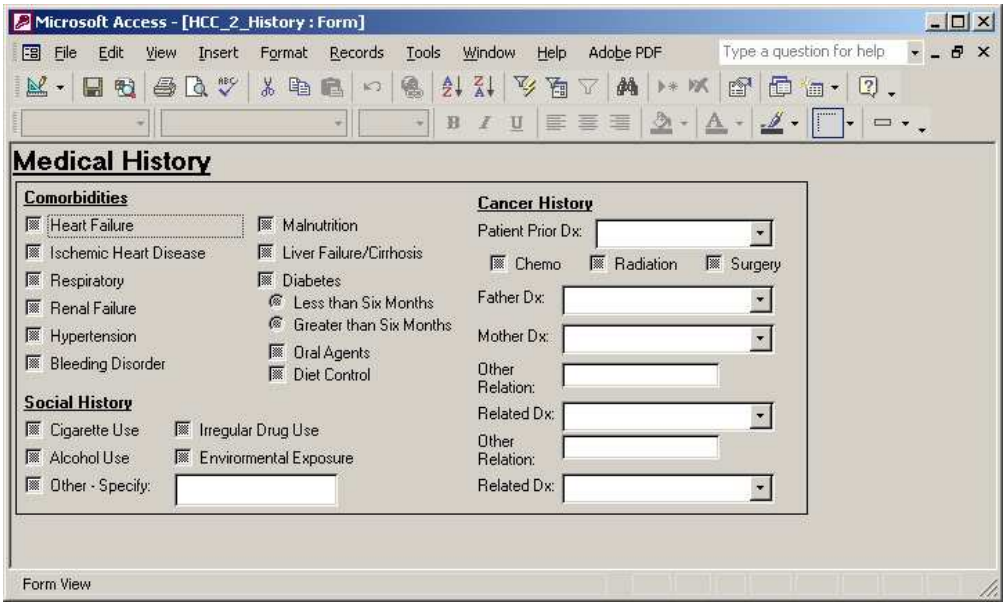


Figure 29: Hepatocellular Cancer Medical History Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
CxHF	Yes/No	Comorbidities - Heart Failure
CxIHD	Yes/No	Comorbidities - Ischemic Heart Disease
CxResp	Yes/No	Comorbidities - Respiratory
CxDiab	Yes/No	Comorbidities - Diabetes
CxDiabOral	Yes/No	Comorbidities - Diabetes - Insulin - Oral
CxDiabDiet	Yes/No	Comorbidities - Diabetes - Insulin - Diet Control
CxDiabOnset	Number	Comorbidities - Diabetes - Onset (1=Less than six months, 2 =Greater than six months)
CxRF	Yes/No	Comorbidities - Renal Failure
CxHyper	Yes/No	Comorbidities - Hypertension
CxBleed	Yes/No	Comorbidities - Bleeding Disorder
CxLiver	Yes/No	Comorbidities - Liver Failure
CxMal	Yes/No	Comorbidities - Malnutrition
CxPriorCancer	Number	Comorbidities - Prior Cancer Dx
CxPriorCancerChemo	Yes/No	Comorbidities - Prior Cancer Dx - Chemo
CxPriorCancerRadiation	Yes/No	Comorbidities - Prior Cancer Dx - Radiation
CxPriorCancerSurgery	Yes/No	Comorbidities - Prior Cancer Dx - Surgery
SHCigarette	Yes/No	Social History - Cigarettes (significant use)
SHAlcohol	Yes/No	Social History - Alcohol (significant use)
SHDrugUse	Yes/No	Social History - Drug Use
SHExposure	Yes/No	Social History - Environmental Exposure
SHOther	Yes/No	Social History - Other
SHOtherS	Text	Social History - Other - Specify
FamilyFatherDx	Number	Family History - Father Dx
FamilyMotherDx	Number	Family History - Mother Dx
FamilyOther1	Text	Family History - Other1
FamilyOther1Dx	Number	Family History - Other1 Dx
FamilyOther2	Text	Family History - Other2
FamilyOther2Dx	Number	Family History - Other2 Dx

Figure 30: Hepatocellular Cancer Medical History Table Schema

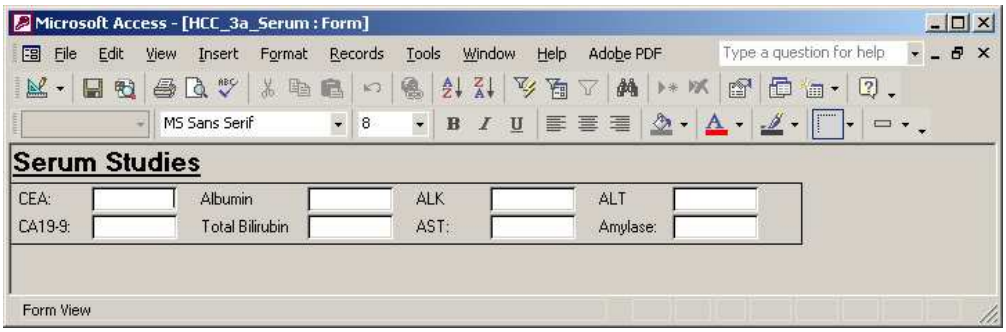


Figure 31: Hepatocellular Cancer Serum Studies Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
LabCEA	Number	Laboratory - CEA
LabCA19-9	Number	Laboratory - CA19-9
LabAlb	Number	Laboratory - Albumin
LabBili	Number	Laboratory - Bilirubin
LabAlka	Number	Laboratory - Alkaline phosphotase
LabALT	Number	Laboratory - ALT
LabAST	Number	Laboratory - AST
LabAmylase	Number	Laboratory - Amylase

Figure 32: Hepatocellular Cancer Serum Studies Table Schema

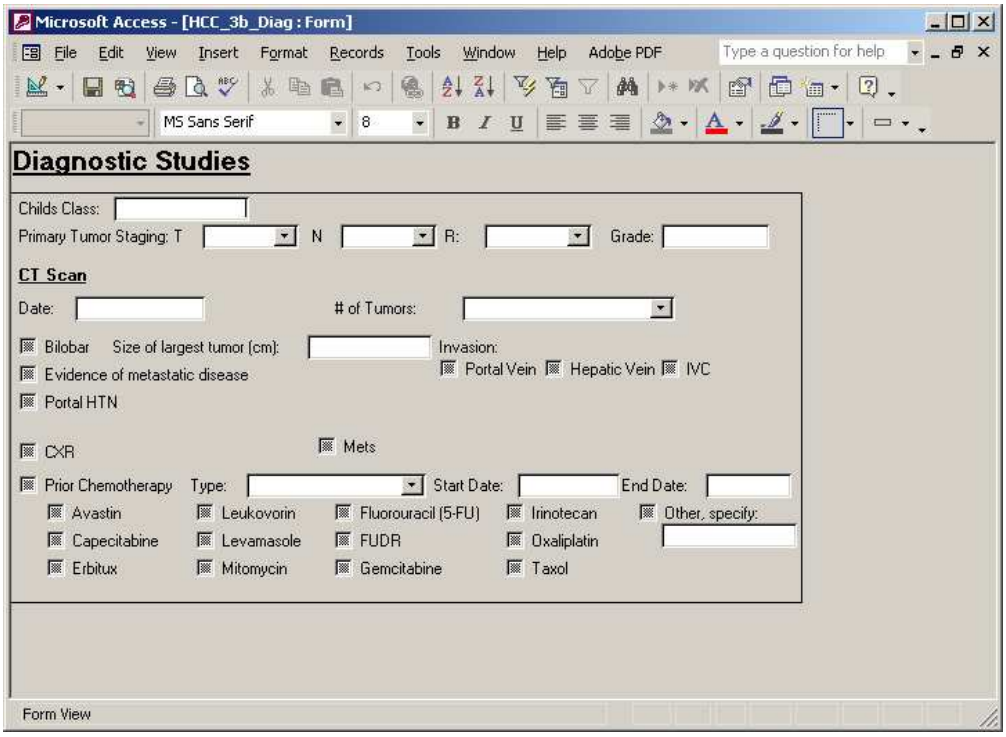


Figure 33: Hepatocellular Cancer Diagnostic Imaging Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
ChildsC	Number	Childs Class
TStage	Number	Imaging T-Stage
NStage	Number	Imaging N-Stage
RStage	Number	Imaging R-Stage
CTDate	Date/Time	CT Date
CTCount	Number	CT Tumor Count
Bilobar	Yes/No	Bilobar
TumorSize	Number	Size of Largest Tumor
Invasion_PV	Yes/No	Invasion - Portal Vein
Invasion_HV	Yes/No	Invasion - Hepatic Vein
Invasion_IVC	Yes/No	Invasion - Inferior Vena Cava
Metastatic	Yes/No	Metastatic Evidence
Portal	Yes/No	Portal HTN
CXR	Yes/No	Chest X-Ray
CXRMets	Yes/No	Chest X-Ray - Metastatic Evidence
PChemo	Yes/No	Prior Chemo
PChemoType	Number	Prior Chemo - Type
PChemoStartD	Date/Time	Prior Chemo - Start Date
PChemoEndD	Date/Time	Prior Chemo - End Date
PChemo_AVA	Yes/No	Prior Chemo - Avastin
PChemo_Cap	Yes/No	Prior Chemo - Capecitabine
PChemo_Erb	Yes/No	Prior Chemo - Erbitux
PChemo_Flu	Yes/No	Prior Chemo - Fluorouracil (5-FU)
PChemo_FUDR	Yes/No	Prior Chemo - FUDR
PChemo_Gem	Yes/No	Prior Chemo - Gemcitabine
PChemo_Iri	Yes/No	Prior Chemo - Irinotecan
PChemo_Leu	Yes/No	Prior Chemo - Leukovorin
PChemo_Lev	Yes/No	Prior Chemo - Levamasole
PChemo_Mit	Yes/No	Prior Chemo - Mitomycin
PChemo_Oxa	Yes/No	Prior Chemo - Oxaliplatin
PChemo_Tax	Yes/No	Prior Chemo - Taxol
PChemo_Oth	Yes/No	Prior Chemo - Other
PChemo_OS	Text	Prior Chemo - Other - Specify

Figure 34: Hepatocellular Cancer Diagnostic Imaging Table Schema

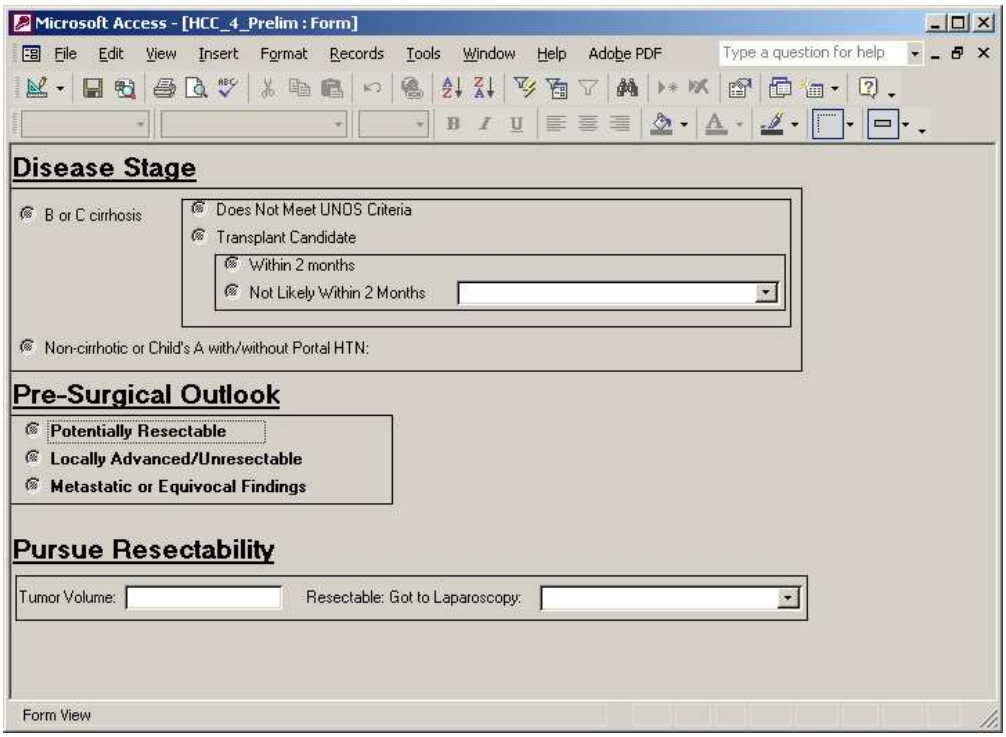


Figure 35: Hepatocellular Cancer Preliminary Outlook Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
Cirr	Number	Cirrhosis Type
CirrBC	Number	Cirrhosis BC Type
TranTime	Number	Transplant Time
TranTime2	Number	Transplant Time > 2 Months
PreOutlook	Number	Pre-Surgical Tumor Outlook (Potentially Resectable, Locally Advanced/Unresectable, Metastatic or Equivocal Findings)
TumorVol	Number	Tumor Volume
SurgTreat	Number	Initial Surgical Decision (Resect, Ablate, Resect/Ablate)

Figure 36: Hepatocellular Cancer Preliminary Outlook Table Schema

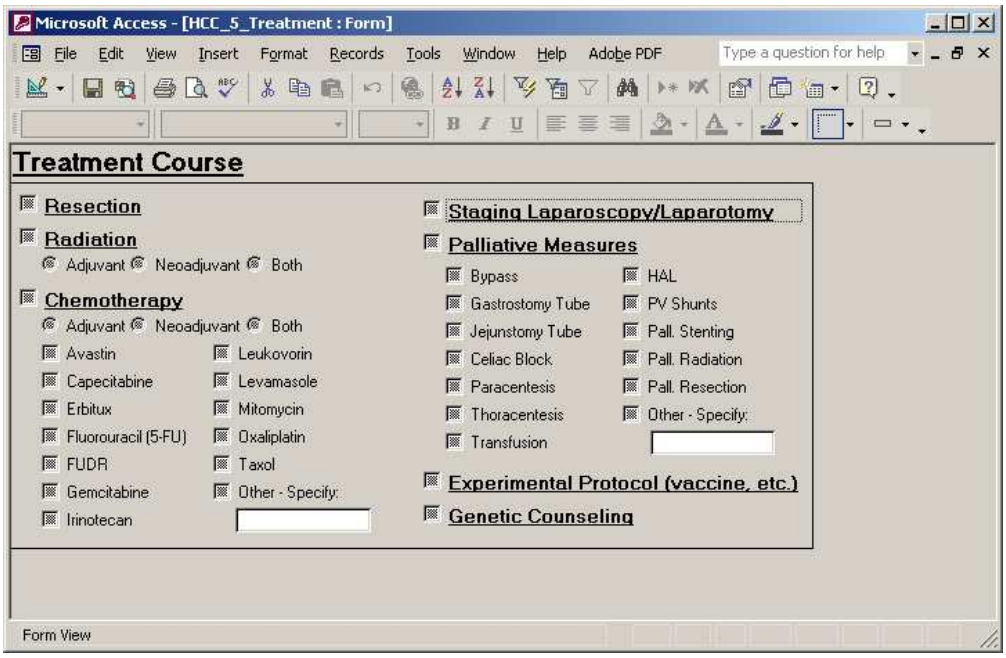


Figure 37: Hepatocellular Cancer Treatment Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
TxResect	Yes/No	Treatment - Resection
TxLap	Yes/No	Treatment - Laparoscopy
TxRadia	Yes/No	Treatment - Radiation
TXRadiaAdju	Number	Treatment - Radiation - Adjuvancy
TxChemo	Yes/No	Treatment - Chemo
TXChemoAdju	Number	Treatment - Chemo - Adjuvancy
TxChemoAVA	Yes/No	Treatment - Chemo - Avastin
TxChemoCap	Yes/No	Treatment - Chemo - Capecitabine
TxChemoErb	Yes/No	Treatment - Chemo - Erbitux
TxChemoFlu	Yes/No	Treatment - Chemo - Fluorouracil (5-FU)
TxChemoFUDR	Yes/No	Treatment - Chemo - FUDR
TxChemoGem	Yes/No	Treatment - Chemo - Gemcitabine
TxChemoIri	Yes/No	Treatment - Chemo - Irinotecan
TxChemoLeu	Yes/No	Treatment - Chemo - Leukovorin
TxChemoLev	Yes/No	Treatment - Chemo - Levamasole
TxChemoMit	Yes/No	Treatment - Chemo - Mitomycin
TxChemoOxa	Yes/No	Treatment - Chemo - Oxaliplatin
TxChemoTax	Yes/No	Treatment - Chemo - Taxol
TxChemoOth	Yes/No	Treatment - Chemo - Other
TxChemoOS	Text	Treatment - Chemo - Other - Specify
TxPal	Yes/No	Treatment - Palliation
TxPalRes	Yes/No	Treatment - Palliation - Pall. Resection
TxPalBypass	Yes/No	Treatment - Palliation - Bypass
TxPalCeliac	Yes/No	Treatment - Palliation - Celiac Block
TxPalPara	Yes/No	Treatment - Palliation - Paracentesis
TxPalTho	Yes/No	Treatment - Palliation - Thoracentesis
TxPalRad	Yes/No	Treatment - Palliation - Pall. Radiation
TxPalTrans	Yes/No	Treatment - Palliation - Transfusion
TxPalStens	Yes/No	Treatment - Palliation - Pall. Stenting
TxPalPV	Yes/No	Treatment - Palliation - PV Shunts
TxPalHAL	Yes/No	Treatment - Palliation - HAL
TxPalGasTube	Yes/No	Treatment - Palliation - Gastrostomy Tube
TxPalJejTube	Yes/No	Treatment - Palliation - Jejunstomy Tube
TxPalOth	Yes/No	Treatment - Palliation - Other
TxPalOS	Text	Treatment - Palliation - Other - Specify
TxExp	Yes/No	Treatment - Experimental protocol (ie. vaccine)
TxGene	Yes/No	Treatment - Gene Counseling

Figure 38: Hepatocellular Cancer Treatment Table Schema

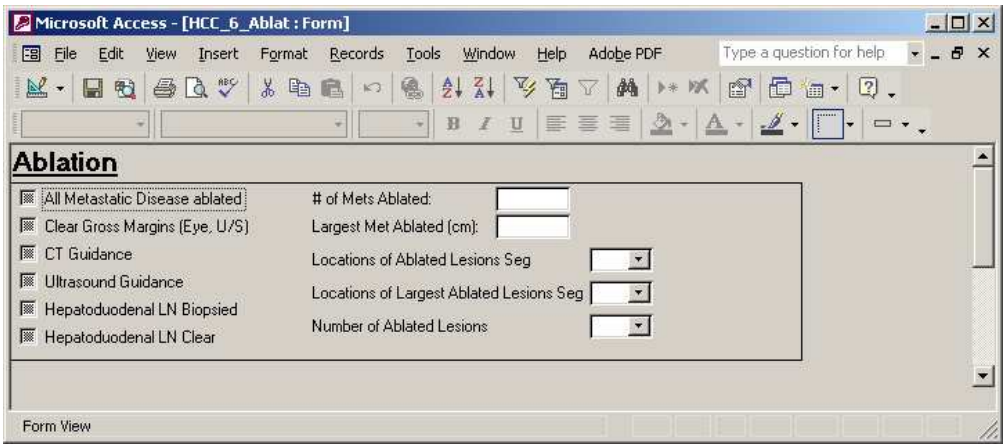


Figure 39: Hepatocellular Cancer Ablation Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
Abl_MetsAll	Yes/No	Ablation - All Mets Ablated
Abl_MetsClear	Yes/No	Ablation - Clear Gross Margins
Abl_MetsCount	Number	Ablation - Number of Mets
Abl_MetsLargest	Number	Ablation - Largest Met Ablated (cm)
Abl_CT	Yes/No	Ablation - CT Guidance
Abl_US	Yes/No	Ablation - US Guidance
Abl_LNBio	Yes/No	Ablation - Hepatoduodenal LN Biopsed
Abl_LNClear	Yes/No	Ablation - Hepatoduodenal LN Clear
Abl_LesionSeg	Number	Ablation - Locations of Ablated Lesions
Abl_LesionCount	Number	Ablation - Number of Ablated Lesions
Abl_LesionLargest	Number	Ablation - Locations of Largest Ablated Lesions

Figure 40: Hepatocellular Cancer Ablation Table Schema

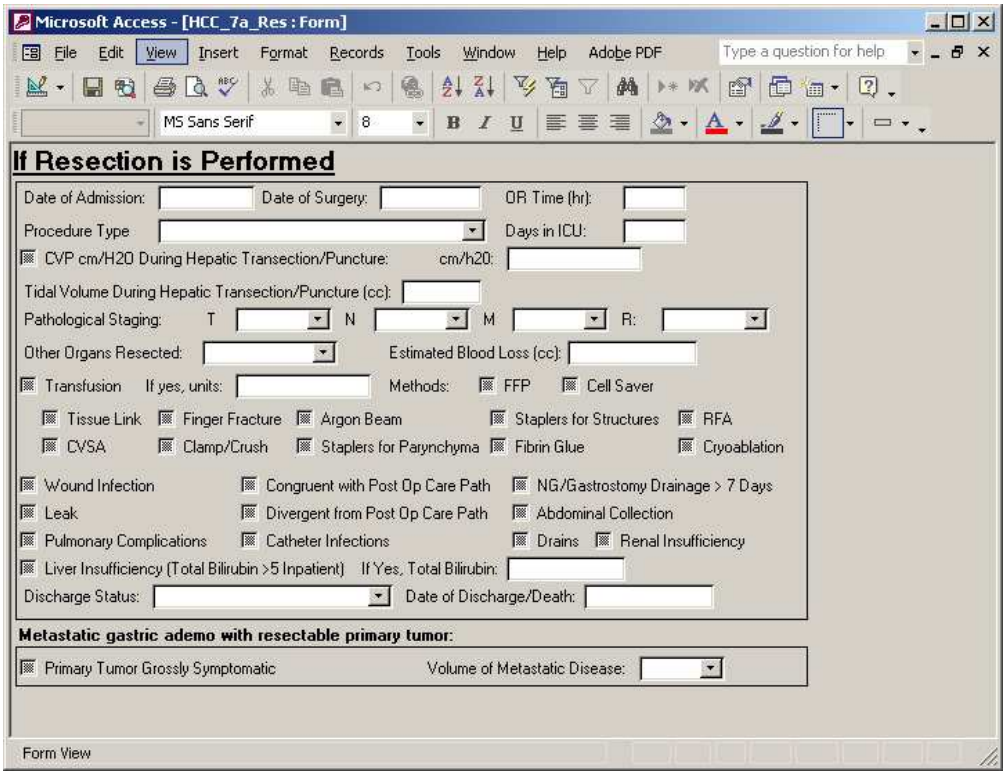


Figure 41: Hepatocellular Cancer Resection Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
DAdm	Date/Time	Date of Admission
DSurg	Date/Time	Date of Surgery
ORTime	Number	OR Time
PxType	Number	Procedure Type
Organs	Text	Other Organs Resected
BloodLoss	Number	Blood Loss (cc)
CVP	Yes/No	CVP cm/H20 During Hepatic Transection/Puncture
CVPcm	Number	CVP cm/H20
Tidalcc	Number	Tidal Volume During Hepatic Transection/Puncture (cc)
Transfusion	Yes/No	Transfusion - Needed?
T_Units	Number	Transfusion - Units
T_FFP	Yes/No	Transfusion - Fresh Frozen Plasma
T_Cell	Yes/No	Transfusion - Cell Saver
T_Tissue	Yes/No	Transfusion - Tissue Link
T_CVSA	Yes/No	Transfusion - CVSA
T_Finger	Yes/No	Transfusion - Finger Fracture
T_Clamp	Yes/No	Transfusion - Clamp/Crush
T_Argon	Yes/No	Transfusion - Argon Beam
T_Pary	Yes/No	Transfusion - Staplers for Parynchyma
T_Struct	Yes/No	Transfusion - Staplers for Structures
T_Glue	Yes/No	Transfusion - Fibrin Glue
T_RFA	Yes/No	Transfusion - RFA
T_Cry	Yes/No	Transfusion - Cryoablation
ICUdays	Number	Days in ICU
Infection	Yes/No	PO - Wound Infection
Leak	Yes/No	PO - Leak
Congruent	Yes/No	PO - Congruent Post-Op Path
Divergent	Yes/No	PO - Divergent Post-Op Path
NG	Yes/No	PO - NG/Gastrostomy Drainage > 7 Days
Abdominal	Yes/No	PO - Abdominal Collection
PulmCx	Yes/No	PO - Pulmonary Complications
Catheter	Yes/No	PO - Catheter Infections
Drains	Yes/No	PO - Drains
RenalInsuf	Yes/No	PO - Renal Insufficiency
LiverInsuf	Yes/No	PO - Liver Insufficiency
LI_TB	Number	PO - Liver Insufficiency - Total Bilirubin
DDischarge	Date/Time	Date of Discharge
DischStatus	Number	Discharge Status
DDeath	Date/Time	Date of Death

Figure 42: Hepatocellular Cancer Resection Table Schema

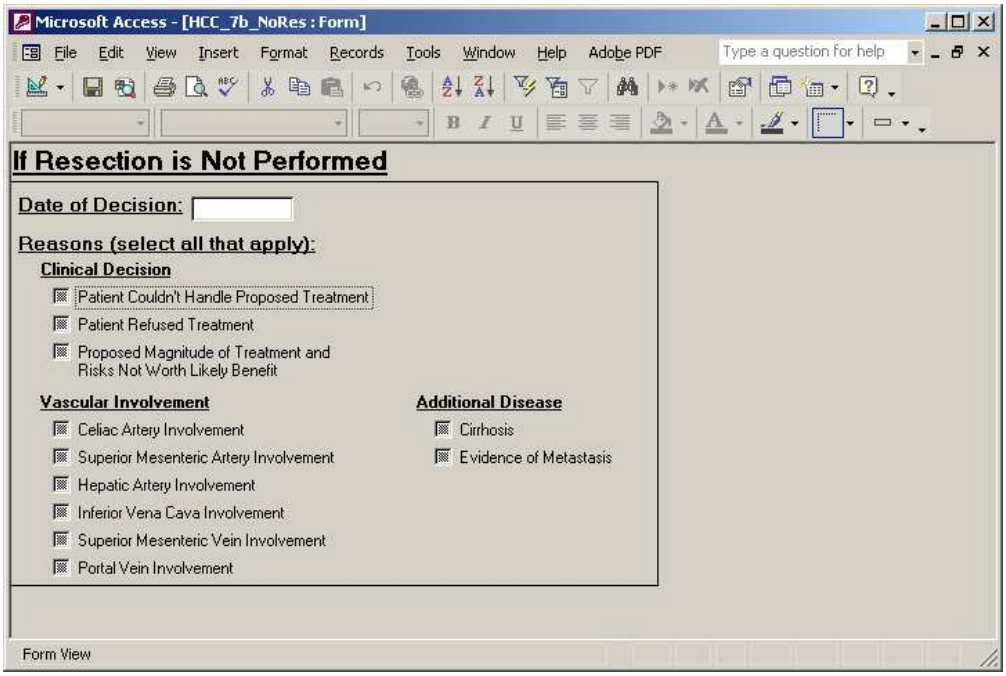


Figure 43: Hepatocellular Cancer No Resection Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
NoResEvalDate	Date/Time	No Resection - Decision Date
NoResNoHandle	Yes/No	No Resection - Couldn't Handle Proposed Treatment
NoResRefused	Yes/No	No Resection - Refused Treatment
NoResMagnitude	Yes/No	No Resection - Magnitude Not Worth Benefits
NoResCeliacInvolve	Yes/No	No Resection - Celiac Trunk Involvement
NoResSMAInvolve	Yes/No	No Resection - SMA Involvement
NoResHepaticInvolve	Yes/No	No Resection - Hepatic Involvement
NoResIVCInvolve	Yes/No	No Resection - Inferior Vena Cava Involvement
NoResSMVInvolve	Yes/No	No Resection - SMV Involvement
NoResPVInvolve	Yes/No	No Resection - Portal Vein Involvement
NoResCirrhosis	Yes/No	No Resection - Cirrhosis
NoResMetastatic	Yes/No	No Resection - Metastatic

Figure 44: Hepatocellular Cancer No Resection Table Schema

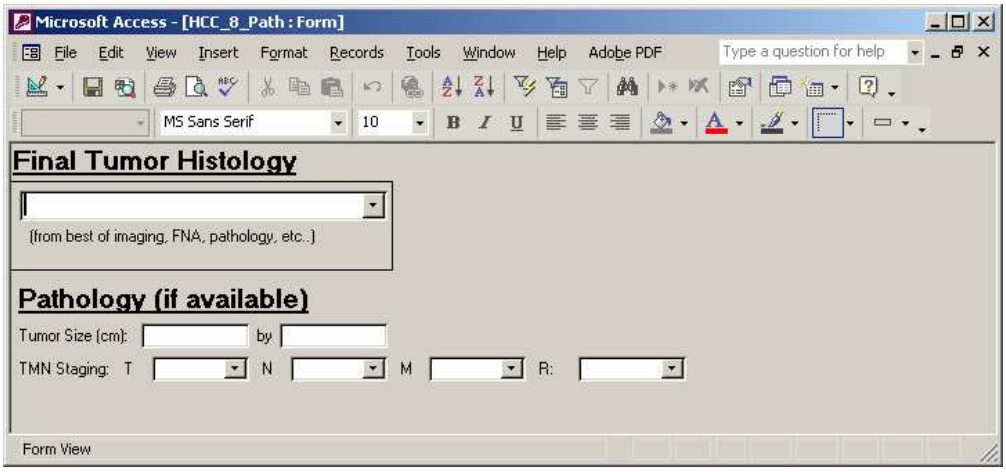


Figure 45: Hepatocellular Cancer Pathology Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
Histology	Number	Histology
ResPathT	Number	Resection - Pathology Staging - T
ResPathN	Number	Resection - Pathology Staging - N
ResPathM	Number	Resection - Pathology Staging - M
ResPathR	Number	Resection - Pathology Staging - R
ResPathV	Number	Resection - Pathology Staging - R
ResPathSizeX	Number	Resection - Pathology Tumor Size (cm) - Width
ResPathSizeY	Number	Resection - Pathology Tumor Size (cm) - Height

Figure 46: Hepatocellular Cancer Pathology Table Schema

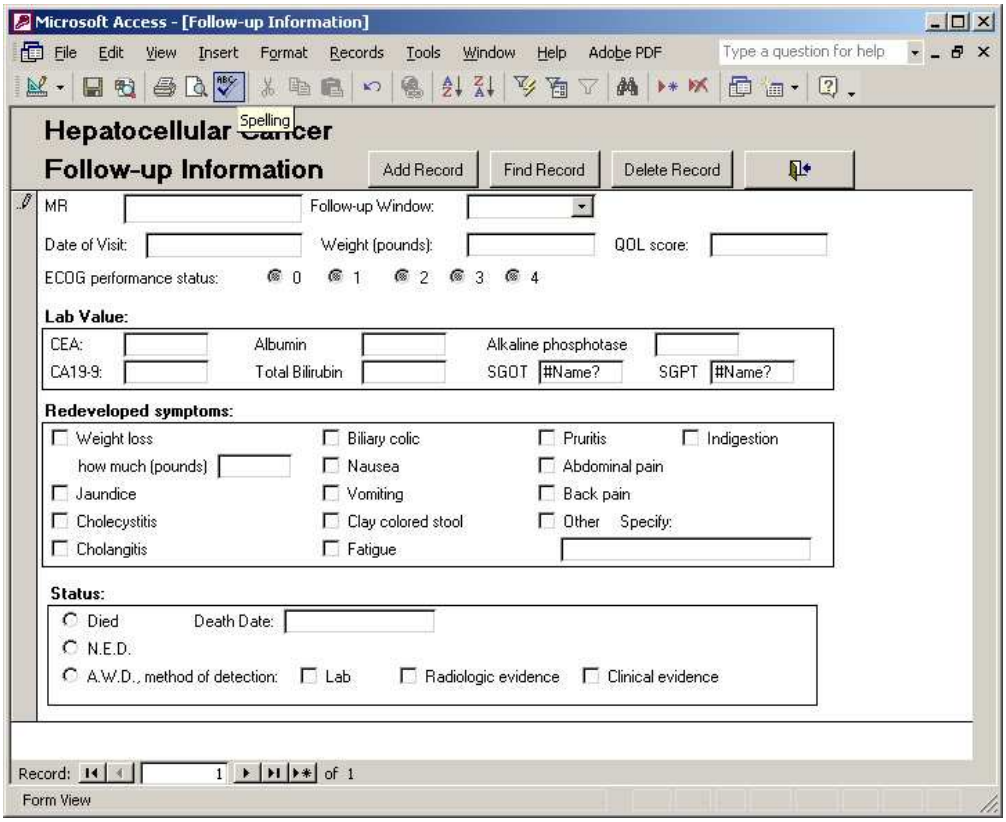


Figure 47: Hepatocellular Cancer Follow-Up Form

Field Name	Data Type	Description
ID	AutoNumber	
MR	Text	Meditech Medical Record Number for Patient
FUWin	Number	Follow-Up Windows
VisitDate	Date/Time	Visit Date
Weight	Number	Weight (lbs.)
QOLscore	Number	QoL Score (0-100)
ECOG	Number	ECOG Score (0-4)
LabCEA	Number	Laboratory - CEA
LabCA19-9	Number	Laboratory - CA19-9
LabAlb	Number	Laboratory - Albumin
LabBili	Number	Laboratory - Bilirubin
LabAlka	Number	Laboratory - Alkaline phosphotase
SxWtloss	Yes/No	Symptoms - Weight Loss
SxWtlossP	Number	Symptoms - Weight Loss (lbs.)
SxJaun	Yes/No	Symptoms - Jaundice
SxChole	Yes/No	Symptoms - Cholecystitis
SxChola	Yes/No	Symptoms - Cholangitis
SxBC	Yes/No	Symptoms - Biliary Colic
SxNau	Yes/No	Symptoms - Nausea
SxVom	Yes/No	Symptoms - Vomiting
SxCCS	Yes/No	Symptoms - Clay Colored Stool
SxFati	Yes/No	Symptoms - Fatigue
SxPru	Yes/No	Symptoms - Pruritis
SxInd	Yes/No	Symptoms - Indigestion
SxAbd	Yes/No	Symptoms - Abdominal Pain
SxBack	Yes/No	Symptoms - Back Pain
SxOT	Yes/No	Symptoms - Other
SxOTSpe	Text	Symptoms - Other - Specify
Status	Number	Status (NED, AWD, Died)
DeathDate	Date/Time	Death Date
StatusAWDLab	Yes/No	AWD - Lab Evidence
StatusAWDRad	Yes/No	AWD - Radiology Evidence
StatusAWDCli	Yes/No	AWD - Clinical Evidence

Figure 48: Hepatocellular Cancer Follow-Up Table Schema

3.1.3 Gall Bladder/Biliary Cancer

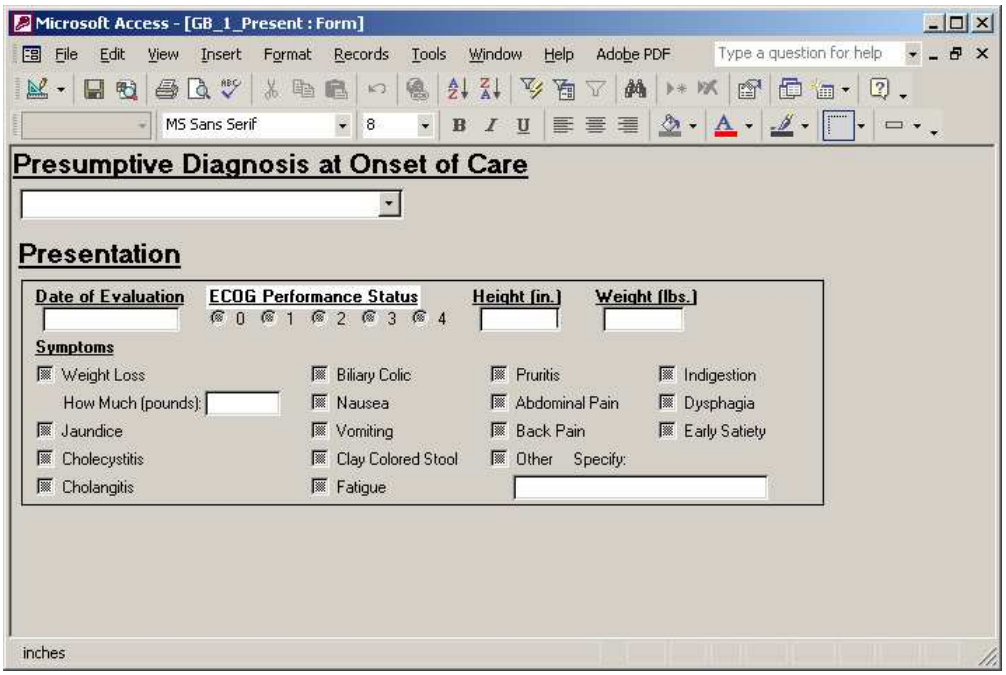


Figure 49: Gall Bladder/Biliary Cancer Presentation Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
PresumptiveDx	Number	Presumptive Diagnosis (Pancreatic tumor, periampullary tumor, etc...)
DemEvalDate	Date/Time	Demographics - Date Evaluated by Surgical Oncology
DemECOG	Number	Demographics - ECOG Score (0-4)
DemHeight	Number	Demographics - Height in Inches of Patient
DemWeight	Number	Demographics - Weight in Pounds of Patient at Admission
SxWtloss	Yes/No	Initial Symptoms - Weight Loss
SxWtlossP	Number	Initial Symptoms - Weight Loss - Pounds
SxJaun	Yes/No	Initial Symptoms - Juandice
SxChole	Yes/No	Initial Symptoms - Cholecystitis
SxChola	Yes/No	Initial Symptoms - Cholangitis
SxBC	Yes/No	Initial Symptoms - Biliary Colic
SxNau	Yes/No	Initial Symptoms - Nausea
SxVom	Yes/No	Initial Symptoms - Vomiting
SxCCS	Yes/No	Initial Symptoms - Clay Colored Stool
SxFati	Yes/No	Initial Symptoms - Fatigue
SxPru	Yes/No	Initial Symptoms - Pruritis
SxInd	Yes/No	Initial Symptoms - Indigestion
SxAbd	Yes/No	Initial Symptoms - Abdominal Pain
SxBack	Yes/No	Initial Symptoms - Back Pain
SxDyspha	Yes/No	Initial Symptoms - Dysphagia
SxSatiety	Yes/No	Initial Symptoms - Early Satiety
SxOT	Yes/No	Initial Symptoms - Other
SxOTSpe	Text	Initial Symptoms - Other - Specify

Figure 50: Gall Bladder/Biliary Cancer Presentation Table Schema

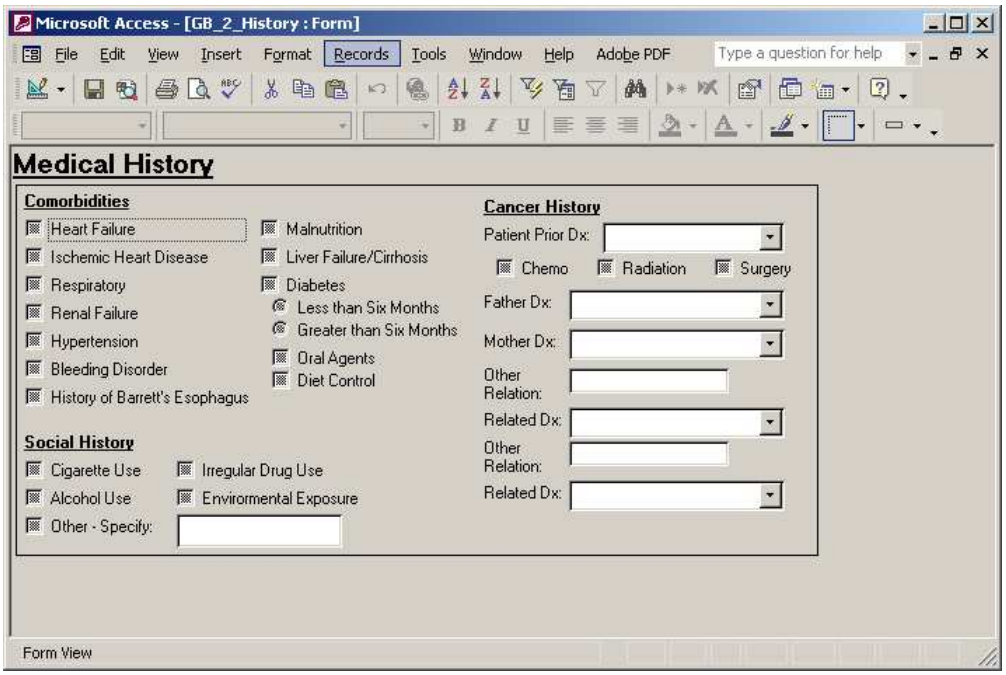


Figure 51: Gall Bladder/Biliary Cancer Medical History Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
CxHF	Yes/No	Comorbidities - Heart Failure
CxIHD	Yes/No	Comorbidities - Ischemic Heart Disease
CxResp	Yes/No	Comorbidities - Respiratory
CxDiab	Yes/No	Comorbidities - Diabetes
CxDiabOral	Yes/No	Comorbidities - Diabetes - Insulin - Oral
CxDiabDiet	Yes/No	Comorbidities - Diabetes - Insulin - Diet Control
CxDiabOnset	Number	Comorbidities - Diabetes - Onset (1=Less than six months, 2 =Greater than six months)
CxRF	Yes/No	Comorbidities - Renal Failure
CxHyper	Yes/No	Comorbidities - Hypertension
CxBleed	Yes/No	Comorbidities - Bleeding Disorder
CxLiver	Yes/No	Comorbidities - Liver Failure
CxMal	Yes/No	Comorbidities - Malnutrition
CxPriorCancer	Number	Comorbidities - Prior Cancer Dx
CxPriorCancerChemo	Yes/No	Comorbidities - Prior Cancer Dx - Chemo
CxPriorCancerRadiation	Yes/No	Comorbidities - Prior Cancer Dx - Radiation
CxPriorCancerSurgery	Yes/No	Comorbidities - Prior Cancer Dx - Surgery
SHCigarette	Yes/No	Social History - Cigarettes (significant use)
SHAlcohol	Yes/No	Social History - Alcohol (significant use)
SHDrugUse	Yes/No	Social History - Drug Use
SHExposure	Yes/No	Social History - Environmental Exposure
SHOther	Yes/No	Social History - Other
SHOtherS	Text	Social History - Other - Specify
FamilyFatherDx	Number	Family History - Father Dx
FamilyMotherDx	Number	Family History - Mother Dx
FamilyOther1	Text	Family History - Other1
FamilyOther1Dx	Number	Family History - Other1 Dx
FamilyOther2	Text	Family History - Other2
FamilyOther2Dx	Number	Family History - Other2 Dx

Figure 52: Gall Bladder/Biliary Cancer Medical History Table Schema

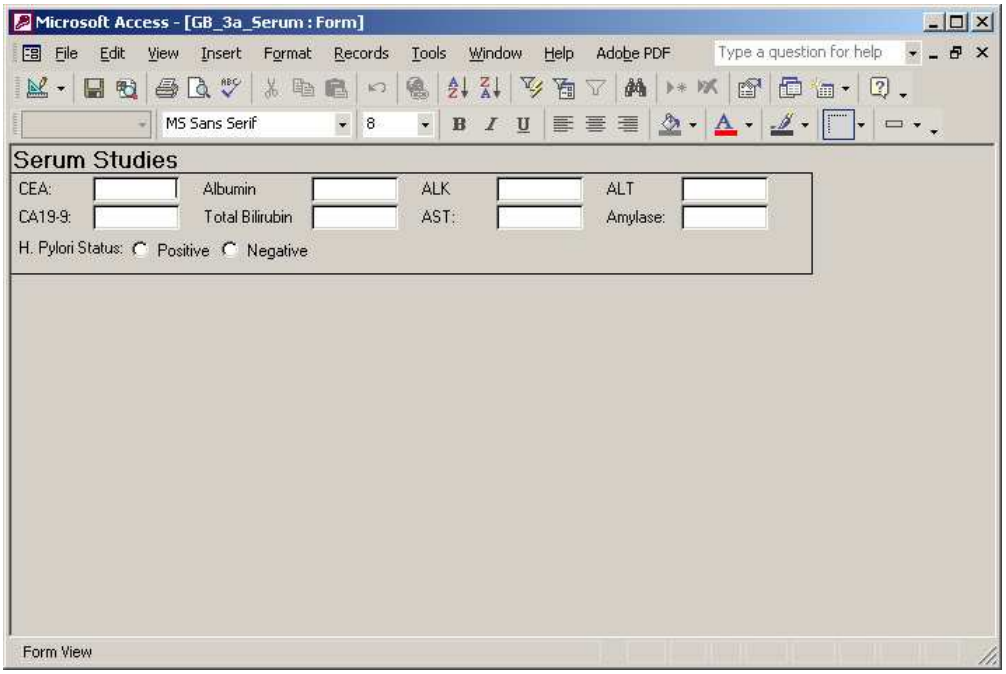


Figure 53: Gall Bladder/Biliary Cancer Serum Studies Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
LabCEA	Number	Laboratory - CEA
LabCA19-9	Number	Laboratory - CA19-9
LabAlb	Number	Laboratory - Albumin
LabBili	Number	Laboratory - Bilirubin
LabAlka	Number	Laboratory - Alkaline phosphotase
LabALT	Number	Laboratory - ALT
LabAST	Number	Laboratory - AST
LabAmylase	Number	Laboratory - Amylase

Figure 54: Gall Bladder/Biliary Cancer Serum Studies Table Schema

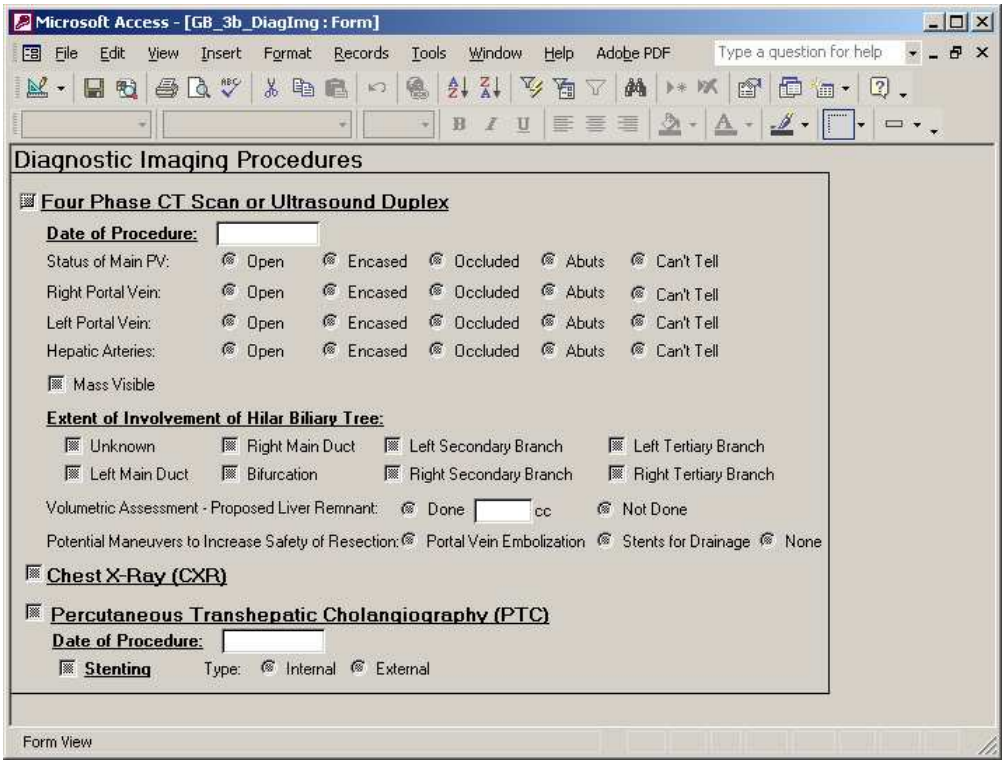


Figure 55: Gall Bladder/Biliary Cancer Diagnostic Imaging Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
CXRDx	Yes/No	CXR - Diagnosis
CTDx	Yes/No	CT - Diagnosis
CTEvalDate	Date/Time	CT - Date Evaluated
CTMainPVClass	Number	CT - Main Portal Vein Involvement Class
CTRightPVClass	Number	CT - Right Portal Vein Involvement Class
CTLeftPVClass	Number	CT - Left Portal Vein Involvement Class
CTHepaticClass	Number	CT - Hepatic Arteries Involvement
CTMassVisible	Yes/No	CT - Mass Visible
CTHBUnknown	Yes/No	CT - Hilar Biliary Tree Involvement - Unknown
CTHBLeft	Yes/No	CT - Hilar Biliary Tree Involvement - Left Main Duct
CTHBRight	Yes/No	CT - Hilar Biliary Tree Involvement - Right Main Duct
CTHBBifurcation	Yes/No	CT - Hilar Biliary Tree Involvement - Bifurcation
CTHBLeft2nd	Yes/No	CT - Hilar Biliary Tree Involvement - Left Secondary Duct
CTHBRight2nd	Yes/No	CT - Hilar Biliary Tree Involvement - Right Secondary Duct
CTHBLeft3rd	Yes/No	CT - Hilar Biliary Tree Involvement - Left Tertiary Duct
CTHBRight3rd	Yes/No	CT - Hilar Biliary Tree Involvement - Right Tertiary Duct
CTVolLiverDone	Number	CT - Volumetric Assessment - Done
CTVolLiverCC	Number	CT - Volumetric Assessment - CCs
CTSafetyMan	Number	CT - Potential Manuevers
PTCDx	Yes/No	PTC - Diagnosis
PTCEvalDate	Date/Time	PTC - Date Evaluated
PTCStent	Yes/No	PTC - Stent
PTCStentType	Number	PTC - Stent Type

Figure 56: Gall Bladder/Biliary Cancer Diagnostic Imaging Table Schema

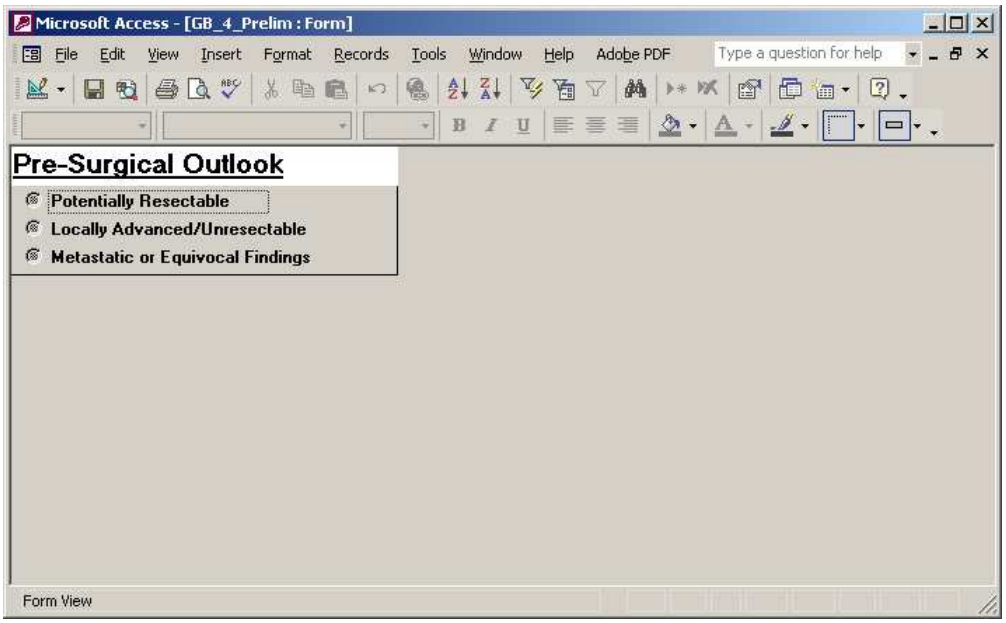


Figure 57: Gall Bladder/Biliary Cancer Preliminary Outlook Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
PreOutlook	Number	Pre-Surgical Tumor Outlook (Potentially Resectable, Locally Advanced/Unresectable, Metastatic or Equivocal Findings)

Figure 58: Gall Bladder/Biliary Cancer Preliminary Outlook Table Schema

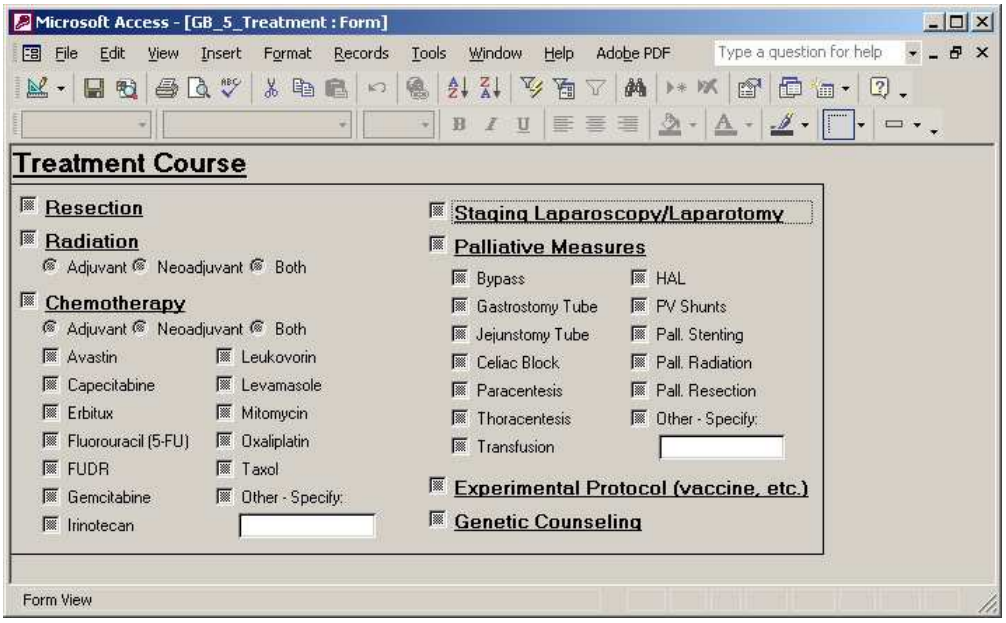


Figure 59: Gall Bladder/Biliary Cancer Treatment Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
TxResect	Yes/No	Treatment - Resection
TxLap	Yes/No	Treatment - Laparoscopy
TxRadia	Yes/No	Treatment - Radiation
TXRadiaAdju	Number	Treatment - Radiation - Adjuvancy
TxChemo	Yes/No	Treatment - Chemo
TXChemoAdju	Number	Treatment - Chemo - Adjuvancy
TxChemoAVA	Yes/No	Treatment - Chemo - Avastin
TxChemoCap	Yes/No	Treatment - Chemo - Capecitabine
TxChemoErb	Yes/No	Treatment - Chemo - Erbitux
TxChemoFlu	Yes/No	Treatment - Chemo - Fluorouracil (5-FU)
TxChemoFUDR	Yes/No	Treatment - Chemo - FUDR
TxChemoGem	Yes/No	Treatment - Chemo - Gemcitabine
TxChemoIri	Yes/No	Treatment - Chemo - Irinotecan
TxChemoLeu	Yes/No	Treatment - Chemo - Leukovorin
TxChemoLev	Yes/No	Treatment - Chemo - Levamasole
TxChemoMit	Yes/No	Treatment - Chemo - Mitomycin
TxChemoOxa	Yes/No	Treatment - Chemo - Oxaliplatin
TxChemoTax	Yes/No	Treatment - Chemo - Taxol
TxChemoOth	Yes/No	Treatment - Chemo - Other
TxChemoOS	Text	Treatment - Chemo - Other - Specify
TxPal	Yes/No	Treatment - Palliation
TxPalRes	Yes/No	Treatment - Palliation - Pall. Resection
TxPalBypass	Yes/No	Treatment - Palliation - Bypass
TxPalCeliac	Yes/No	Treatment - Palliation - Celiac Block
TxPalPara	Yes/No	Treatment - Palliation - Paracentesis
TxPalTho	Yes/No	Treatment - Palliation - Thoracentesis
TxPalRad	Yes/No	Treatment - Palliation - Pall. Radiation
TxPalTrans	Yes/No	Treatment - Palliation - Transfusion
TxPalStens	Yes/No	Treatment - Palliation - Pall. Stenting
TxPalPV	Yes/No	Treatment - Palliation - PV Shunts
TxPalHAL	Yes/No	Treatment - Palliation - HAL
TxPalGasTube	Yes/No	Treatment - Palliation - Gastrostomy Tube
TxPalJejTube	Yes/No	Treatment - Palliation - Jejunstomy Tube
TxPalOth	Yes/No	Treatment - Palliation - Other
TxPalOS	Text	Treatment - Palliation - Other - Specify
TxExp	Yes/No	Treatment - Experimental protocol (ie. vaccine)
TxGene	Yes/No	Treatment - Gene Counseling

Figure 60: Gall Bladder/Biliary Cancer Treatment Table Schema

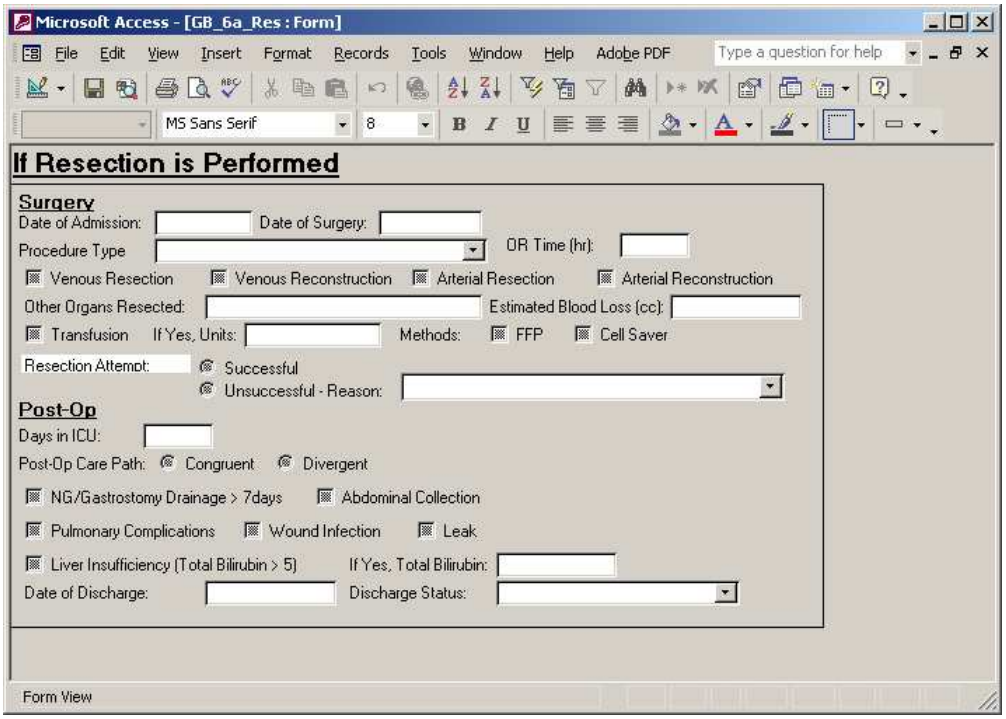


Figure 61: Gall Bladder/Biliary Cancer Resection Form

	Field Name	Data Type	Description
🔑	ID	AutoNumber	ID
	MR	Text	Meditech Medical Record Number for Patient
	ResDAdm	Date/Time	Resection - Date of Admission
	ResDSurg	Date/Time	Resection - Date of Surgery
	ResPxType	Number	Resection - Procedure Type (Whipple, total pancreatectomy, distal pancreatectomy, etc...)
	ResORTime	Number	Resection - OR Time (hr.)
	ResVenRes	Yes/No	Resection - Venous Resection
	ResVenRec	Yes/No	Resection - Venous Reconstruction
	ResArtRes	Yes/No	Resection - Arterial Resection
	ResArtRec	Yes/No	Resection - Arterial Reconstruction
	ResOrgans	Text	Resection - Other Organs Resection
	ResBloodLoss	Number	Resection - Estimated Blood Loss (cc)
	ResTransfusion	Yes/No	Resection - Tranfusion
	ResTUnits	Number	Resection - Transfusion Units
	ResTFFP	Yes/No	Resection - Transfusion - FFP
	ResTCell	Yes/No	Resection - Transfusion - Cell
	ResAttempt	Number	Resection - Resection Attempt
	ResAttemptUn	Number	Resection - Resection Unsuccessful Reason (Tumor involvement, Operative mishap, etc...)
	ResPOCourse	Number	Resection - PO - Post-Op Care Path
	ResPODays	Number	Resection - PO - Time in ICU (days)
	ResPOInfection	Yes/No	Resection - PO - Wound infection
	ResPOLeak	Yes/No	Resection - PO - Leak
	ResPONG	Yes/No	Resection - PO - NG/gastrotomy drainage
	ResPOAbdominal	Yes/No	Resection - PO - Abdominal Collection
	ResPOPulmComp	Yes/No	Resection - PO - Pulminary Complications
	ResPOLiverInsuf	Yes/No	Resection - PO - Liver Insufficiency
	ResPOLiverTB	Number	Resection - PO - Liver Insufficiency - Total Bilirubin
	ResPODDischarge	Date/Time	Resection - Date of Discharge
	ResPODischStatus	Number	Resection - Discharge Status

Figure 62: Gall Bladder/Biliary Cancer Resection Table Schema

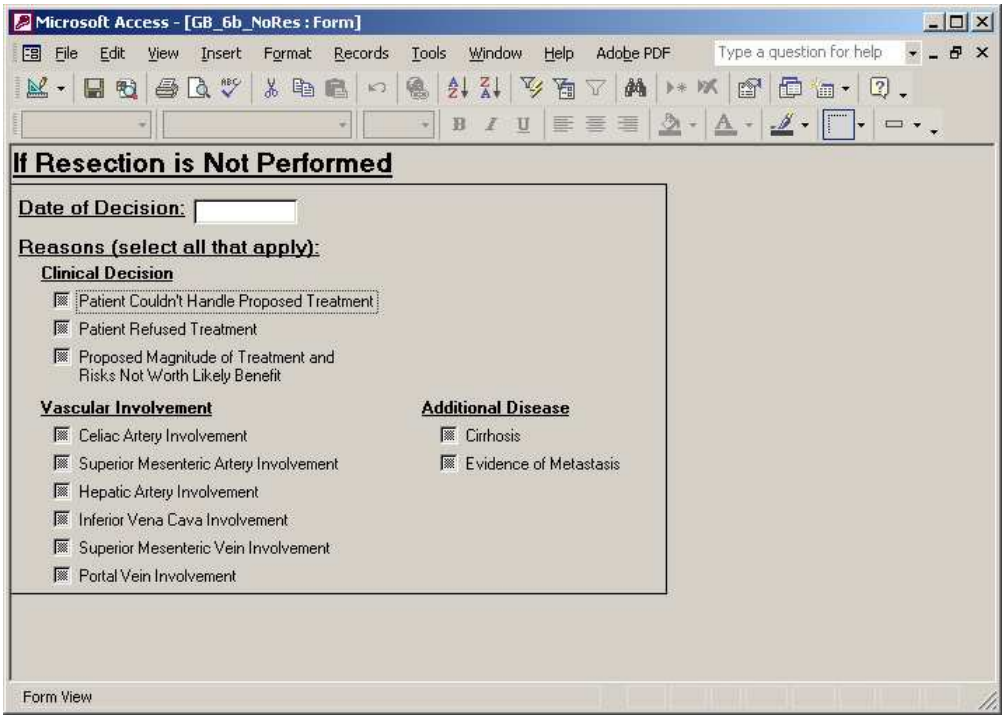


Figure 63: Gall Bladder/Biliary Cancer No Resection Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
NoResEvalDate	Date/Time	No Resection - Decision Date
NoResNoHandle	Yes/No	No Resection - Couldn't Handle Proposed Treatment
NoResRefused	Yes/No	No Resection - Refused Treatment
NoResMagnitude	Yes/No	No Resection - Magnitude Not Worth Benefits
NoResCeliacInvolve	Yes/No	No Resection - Celiac Trunk Involvement
NoResSMAInvolve	Yes/No	No Resection - SMA Involvement
NoResHepaticInvolve	Yes/No	No Resection - Hepatic Involvement
NoResIVCInvolve	Yes/No	No Resection - Inferior Vena Cava Involvement
NoResSMVInvolve	Yes/No	No Resection - SMV Involvement
NoResPVInvolve	Yes/No	No Resection - Portal Vein Involvement
NoResCirrhosis	Yes/No	No Resection - Cirrhosis
NoResMetastatic	Yes/No	No Resection - Metastatic

Figure 64: Gall Bladder/Biliary Cancer No Resection Table Schema

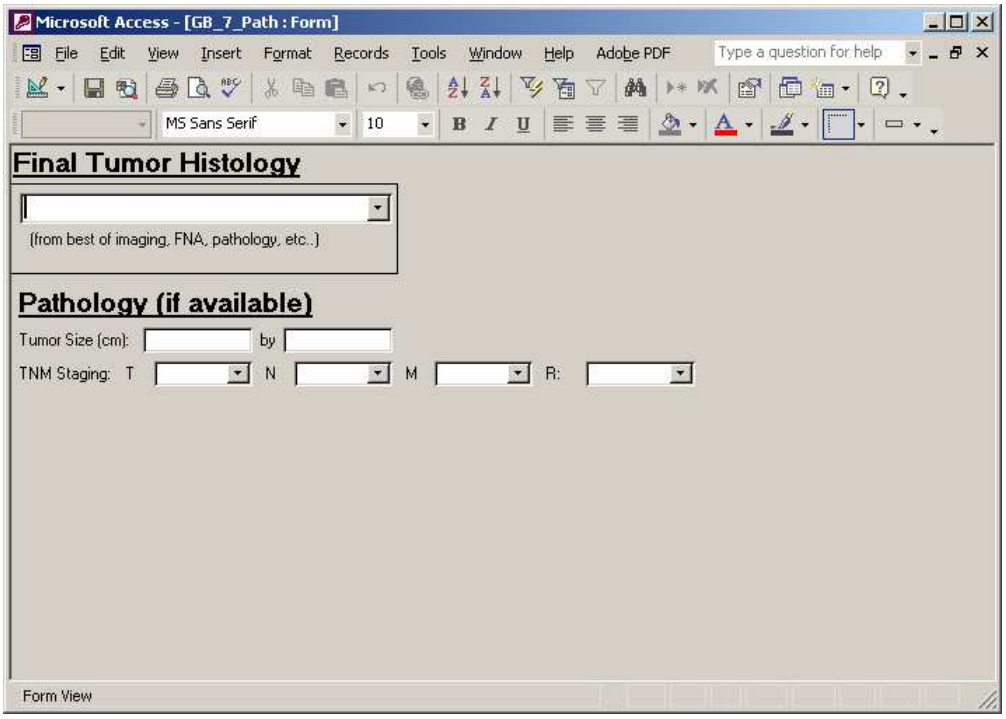


Figure 65: Gall Bladder/Biliary Cancer Pathology Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
Histology	Number	Histology
ResPathT	Number	Resection - Pathology Staging - T
ResPathN	Number	Resection - Pathology Staging - N
ResPathM	Number	Resection - Pathology Staging - M
ResPathR	Number	Resection - Pathology Staging - R
ResPathV	Number	Resection - Pathology Staging - R
ResPathSizeX	Number	Resection - Pathology Tumor Size (cm) - Width
ResPathSizeY	Number	Resection - Pathology Tumor Size (cm) - Height

Figure 66: Gall Bladder/Biliary Cancer Pathology Table Schema

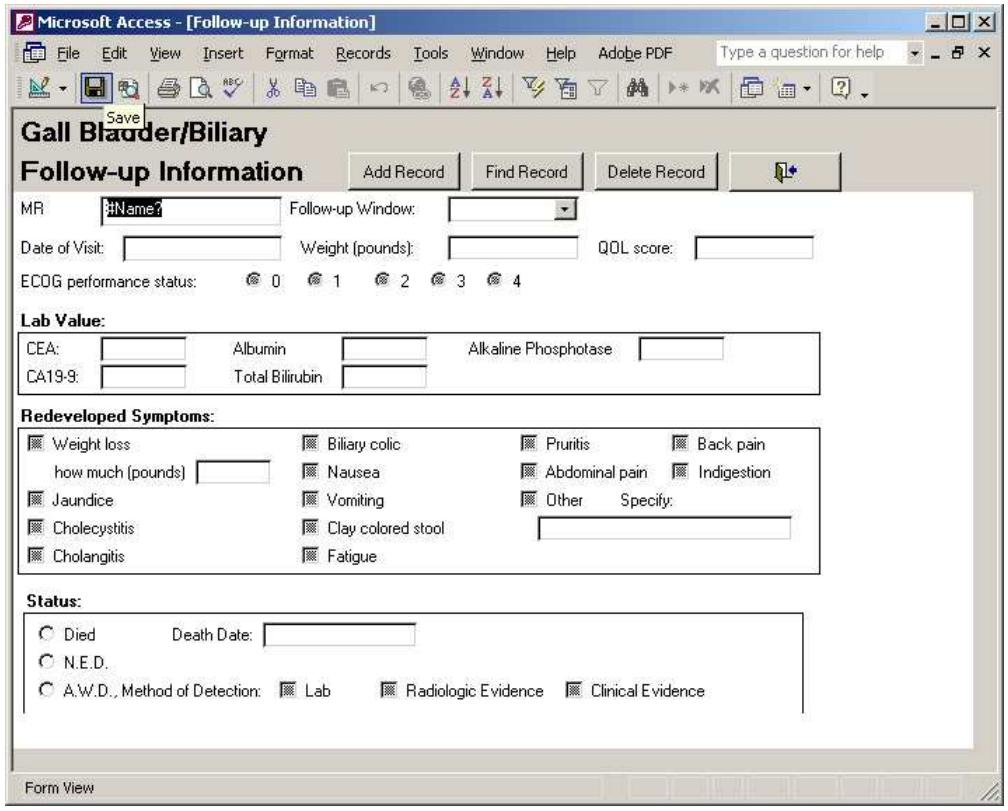


Figure 67: Gall Bladder/Biliary Cancer Follow-Up Form

Field Name	Data Type	Description
ID	AutoNumber	
MR	Text	Meditech Medical Record Number for Patient
FUWin	Number	Follow-Up Windows
VisitDate	Date/Time	Visit Date
Weight	Number	Weight (lbs.)
QOLscore	Number	QoL Score (0-100)
ECOG	Number	ECOG Score (0-4)
LabCEA	Number	Laboratory - CEA
LabCA19-9	Number	Laboratory - CA19-9
LabAlb	Number	Laboratory - Albumin
LabBili	Number	Laboratory - Bilirubin
LabAlka	Number	Laboratory - Alkaline phosphotase
SxWtloss	Yes/No	Symptoms - Weight Loss
SxWtlossP	Number	Symptoms - Weight Loss (lbs.)
SxJaun	Yes/No	Symptoms - Jaundice
SxChole	Yes/No	Symptoms - Cholecystitis
SxChola	Yes/No	Symptoms - Cholangitis
SxBC	Yes/No	Symptoms - Biliary Colic
SxNau	Yes/No	Symptoms - Nausea
SxVom	Yes/No	Symptoms - Vomiting
SxCCS	Yes/No	Symptoms - Clay Colored Stool
SxFati	Yes/No	Symptoms - Fatigue
SxPru	Yes/No	Symptoms - Pruritis
SxInd	Yes/No	Symptoms - Indigestion
SxAbd	Yes/No	Symptoms - Abdominal Pain
SxBack	Yes/No	Symptoms - Back Pain
SxOT	Yes/No	Symptoms - Other
SxOTSpe	Text	Symptoms - Other - Specify
Status	Number	Status (NED, AWD, Died)
DeathDate	Date/Time	Death Date
StatusAWDLab	Yes/No	AWD - Lab Evidence
StatusAWDRad	Yes/No	AWD - Radiology Evidence
StatusAWDCli	Yes/No	AWD - Clinical Evidence

Figure 68: Gall Bladder/Biliary Cancer Follow-Up Table Schema

3.1.4 Gastric Cancer

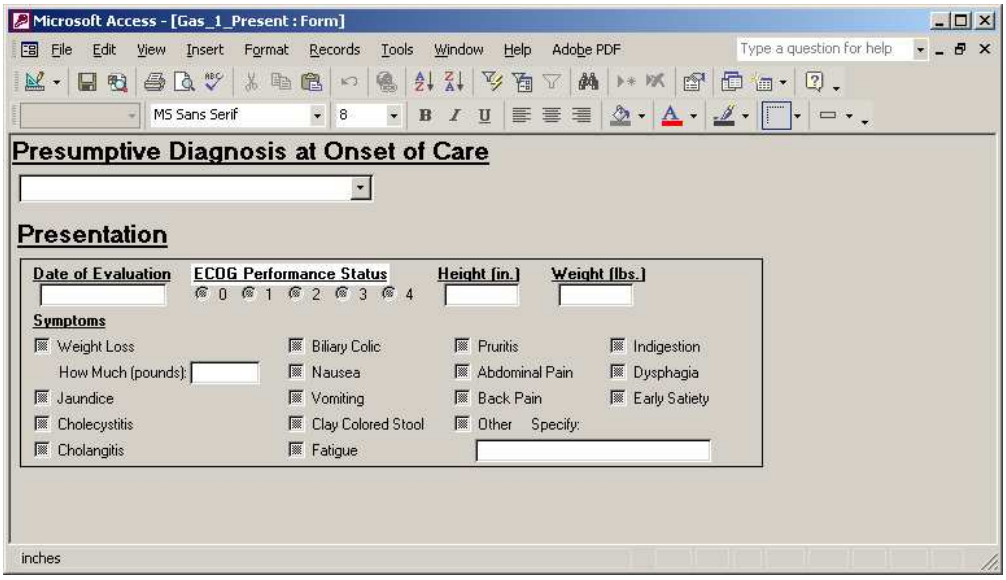


Figure 69: Gastric Cancer Presentation Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
PresumptiveDx	Number	Presumptive Diagnosis (Pancreatic tumor, periampullary tumor, etc...)
DemEvalDate	Date/Time	Demographics - Date Evaluated by Surgical Oncology
DemECOG	Number	Demographics - ECOG Score (0-4)
DemHeight	Number	Demographics - Height in Inches of Patient
DemWeight	Number	Demographics - Weight in Pounds of Patient at Admission
SxWtloss	Yes/No	Initial Symptoms - Weight Loss
SxWtlossP	Number	Initial Symptoms - Weight Loss - Pounds
SxJaun	Yes/No	Initial Symptoms - Juandice
SxChole	Yes/No	Initial Symptoms - Cholecystitis
SxChola	Yes/No	Initial Symptoms - Cholangitis
SxBC	Yes/No	Initial Symptoms - Biliary Colic
SxNau	Yes/No	Initial Symptoms - Nausea
SxVom	Yes/No	Initial Symptoms - Vomiting
SxCCS	Yes/No	Initial Symptoms - Clay Colored Stool
SxFati	Yes/No	Initial Symptoms - Fatigue
SxPru	Yes/No	Initial Symptoms - Pruritis
SxInd	Yes/No	Initial Symptoms - Indigestion
SxAbd	Yes/No	Initial Symptoms - Abdominal Pain
SxBack	Yes/No	Initial Symptoms - Back Pain
SxDyspha	Yes/No	Initial Symptoms - Dysphagia
SxSatiety	Yes/No	Initial Symptoms - Early Satiety
SxOT	Yes/No	Initial Symptoms - Other
SxOTSpe	Text	Initial Symptoms - Other - Specify

Figure 70: Gastric Cancer Presentation Table Schema

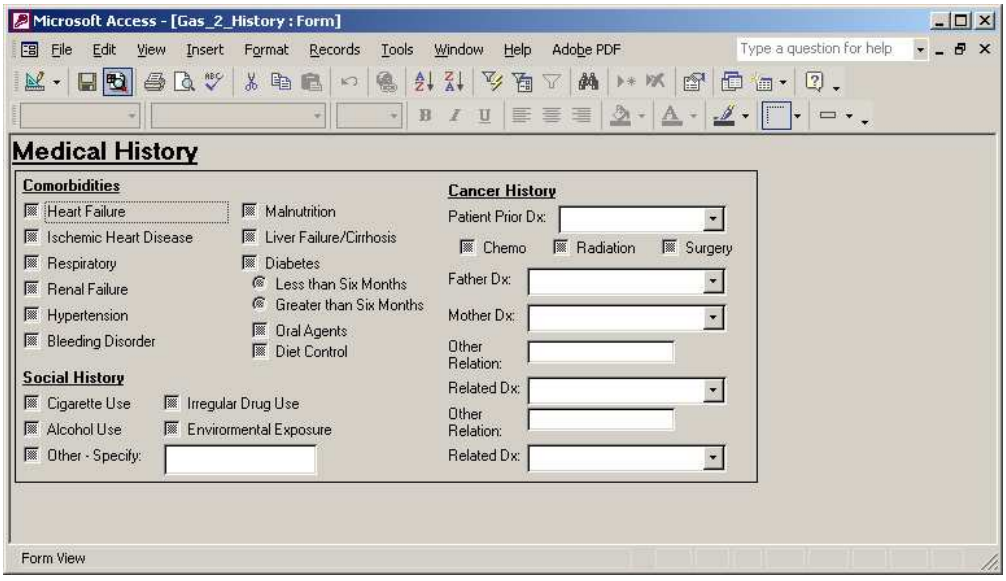


Figure 71: Gastric Cancer Medical History Form

	Field Name	Data Type	Description
🔑	ID	AutoNumber	ID
	MR	Text	Meditech Medical Record Number for Patient
	CxHF	Yes/No	Comorbidities - Heart Failure
	CxIHD	Yes/No	Comorbidities - Ischemic Heart Disease
	CxResp	Yes/No	Comorbidities - Respiratory
	CxDiab	Yes/No	Comorbidities - Diabetes
	CxDiabOral	Yes/No	Comorbidities - Diabetes - Insulin - Oral
	CxDiabDiet	Yes/No	Comorbidities - Diabetes - Insulin - Diet Control
	CxDiabOnset	Number	Comorbidities - Diabetes - Onset (1=Less than six months, 2 =Greater than six months)
	CxRF	Yes/No	Comorbidities - Renal Failure
	CxHyper	Yes/No	Comorbidities - Hypertension
	CxBleed	Yes/No	Comorbidities - Bleeding Disorder
	CxLiver	Yes/No	Comorbidities - Liver Failure
	CxMal	Yes/No	Comorbidities - Malnutrition
	CxPriorCancer	Number	Comorbidities - Prior Cancer Dx
	CxPriorCancerChemo	Yes/No	Comorbidities - Prior Cancer Dx - Chemo
	CxPriorCancerRadiation	Yes/No	Comorbidities - Prior Cancer Dx - Radiation
	CxPriorCancerSurgery	Yes/No	Comorbidities - Prior Cancer Dx - Surgery
	SHCigarette	Yes/No	Social History - Cigarettes (significant use)
	SHAlcohol	Yes/No	Social History - Alcohol (significant use)
	SHDrugUse	Yes/No	Social History - Drug Use
	SHExposure	Yes/No	Social History - Environmental Exposure
	SHOther	Yes/No	Social History - Other
	SHOtherS	Text	Social History - Other - Specify
	FamilyFatherDx	Number	Family History - Father Dx
	FamilyMotherDx	Number	Family History - Mother Dx
	FamilyOther1	Text	Family History - Other1
	FamilyOther1Dx	Number	Family History - Other1 Dx
	FamilyOther2	Text	Family History - Other2
	FamilyOther2Dx	Number	Family History - Other2 Dx

Figure 72: Gastric Cancer Medical History Table Schema

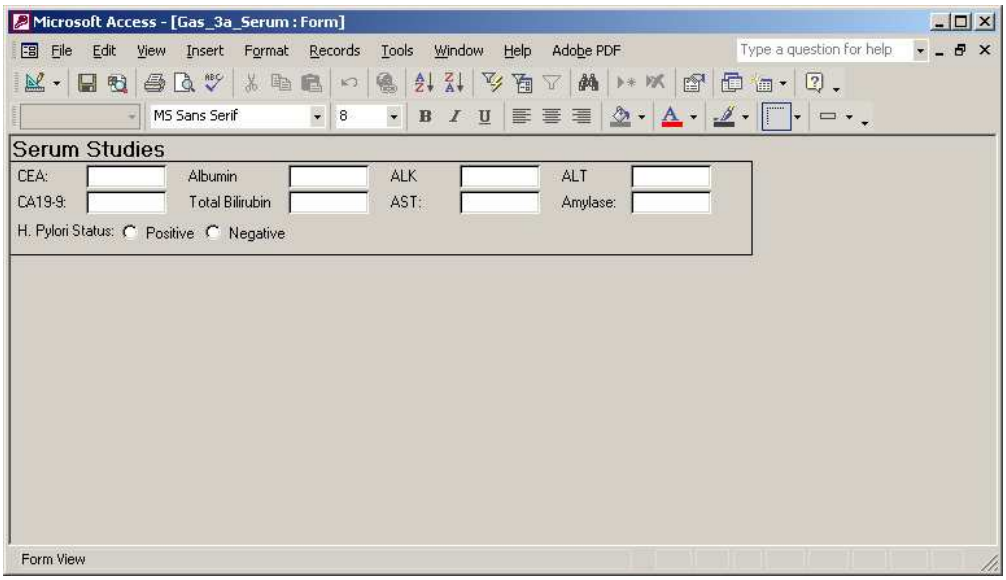


Figure 73: Gastric Cancer Serum Studies Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
LabCEA	Number	Laboratory - CEA
LabCA19-9	Number	Laboratory - CA19-9
LabAlb	Number	Laboratory - Albumin
LabBili	Number	Laboratory - Bilirubin
LabAlka	Number	Laboratory - Alkaline phosphotase
LabALT	Number	Laboratory - ALT
LabAST	Number	Laboratory - AST
LabAmylase	Number	Laboratory - Amylase
LabHPylori	Number	Laboratory - H. Pylori Status

Figure 74: Gastric Cancer Serum Studies Table Schema

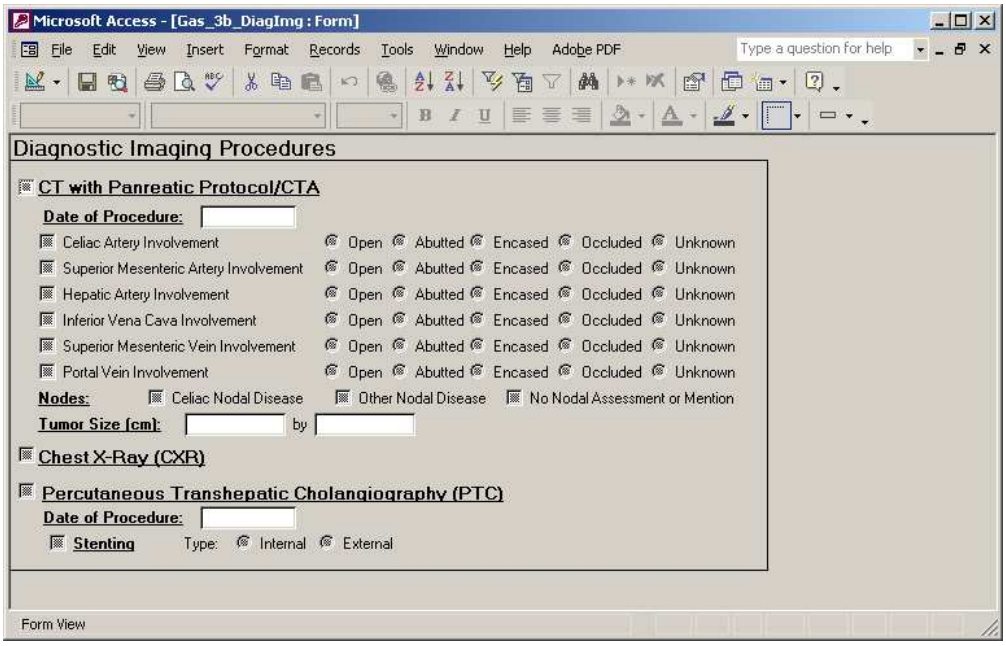


Figure 75: Gastric Cancer Diagnostic Imaging Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
CXRDx	Yes/No	CXR - Diagnosis
CTDx	Yes/No	CT - Diagnosis
CTEvalDate	Date/Time	CT - Date Evaluated
CTVascOmit	Yes/No	CT - Vascular Omission
CTCeliac	Yes/No	CT - Celiac Involvement
CTCeliacClass	Number	CT - Celiac Involvement Class
CTSMA	Yes/No	CT - SMA Involvement
CTSMAClass	Number	CT - SMA Involvement Class
CTHepatic	Yes/No	CT - Hepatic Involvement
CTHepaticClass	Number	CT - Hepatic Involvement
CTInferior	Yes/No	CT - Inferior Vena Cava Involvement
CTInferiorClass	Number	CT - Inferior Vena Cava Involvement Class
CTSMV	Yes/No	CT - SMV Involvement
CTSMVClass	Number	CT - SMV Involvement Class
CTPortal	Yes/No	CT - Portal Vein Involvement
CTPortalClass	Number	CT - Portal Vein Involvement Class
CTCeliacNode	Yes/No	CT - Celiac Nodal Disease
CTOtherNode	Yes/No	CT - Other Nodal Disease
CTNodeOmit	Yes/No	CT - Node Omission
CTTumorSizeX	Number	CT - Tumor Size (cm) - Width
CTTumorSizeY	Number	CT - Tumor Size (cm) - Height
PTCDx	Yes/No	PTC - Diagnosis
PTCEvalDate	Date/Time	PTC - Date Evaluated
PTCStent	Yes/No	PTC - Stent
PTCStentType	Number	PTC - Stent Type

Figure 76: Gastric Cancer Diagnostic Imaging Table Schema

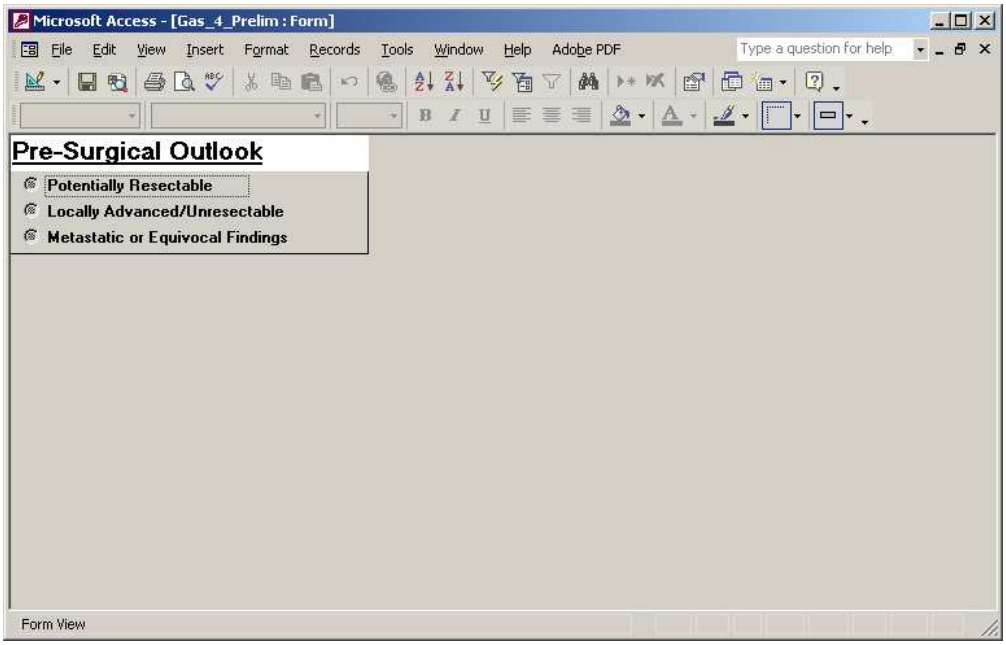


Figure 77: Gastric Cancer Preliminary Outlook Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
PreOutlook	Number	Pre-Surgical Tumor Outlook (Potentially Resectable, Locally Advanced/Unresectable, Metastatic or Equivocal Findi

Figure 78: Gastric Cancer Preliminary Outlook Table Schema

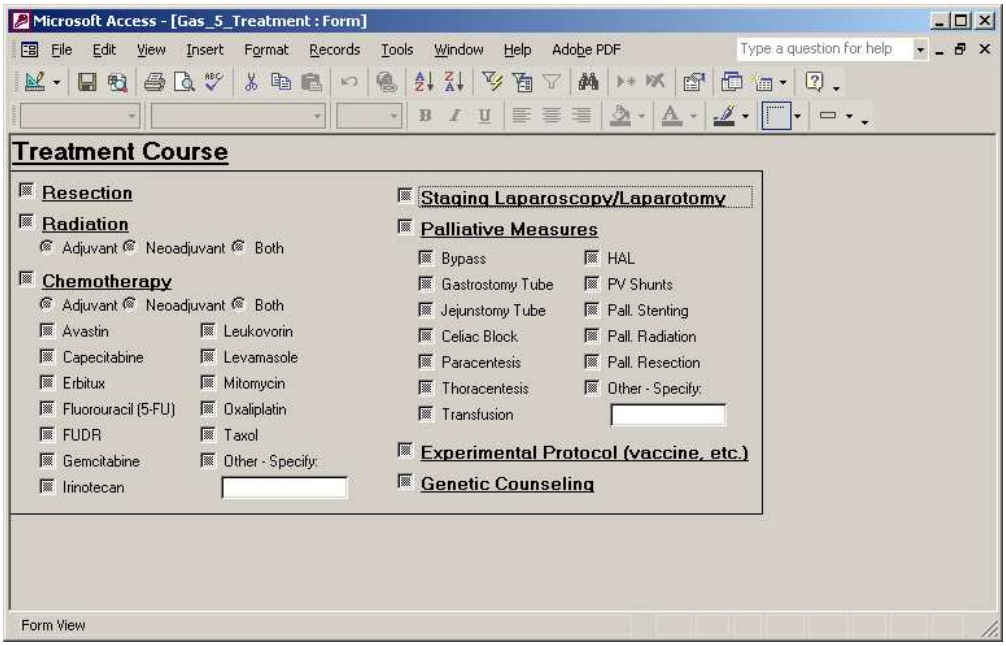


Figure 79: Gastric Cancer Treatment Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
TxResect	Yes/No	Treatment - Resection
TxLap	Yes/No	Treatment - Laparoscopy
TxRadia	Yes/No	Treatment - Radiation
TXRadiaAdju	Number	Treatment - Radiation - Adjuvancy
TxChemo	Yes/No	Treatment - Chemo
TXChemoAdju	Number	Treatment - Chemo - Adjuvancy
TxChemoAVA	Yes/No	Treatment - Chemo - Avastin
TxChemoCap	Yes/No	Treatment - Chemo - Capecitabine
TxChemoErb	Yes/No	Treatment - Chemo - Erbitux
TxChemoFlu	Yes/No	Treatment - Chemo - Fluorouracil (5-FU)
TxChemoFUDR	Yes/No	Treatment - Chemo - FUDR
TxChemoGem	Yes/No	Treatment - Chemo - Gemcitabine
TxChemoIri	Yes/No	Treatment - Chemo - Irinotecan
TxChemoLeu	Yes/No	Treatment - Chemo - Leukovorin
TxChemoLev	Yes/No	Treatment - Chemo - Levamasole
TxChemoMit	Yes/No	Treatment - Chemo - Mitomycin
TxChemoOxa	Yes/No	Treatment - Chemo - Oxaliplatin
TxChemoTax	Yes/No	Treatment - Chemo - Taxol
TxChemoOth	Yes/No	Treatment - Chemo - Other
TxChemoOS	Text	Treatment - Chemo - Other - Specify
TxPal	Yes/No	Treatment - Palliation
TxPalRes	Yes/No	Treatment - Palliation - Pall. Resection
TxPalBypass	Yes/No	Treatment - Palliation - Bypass
TxPalCeliac	Yes/No	Treatment - Palliation - Celiac Block
TxPalPara	Yes/No	Treatment - Palliation - Paracentesis
TxPalTho	Yes/No	Treatment - Palliation - Thoracentesis
TxPalRad	Yes/No	Treatment - Palliation - Pall. Radiation
TxPalTrans	Yes/No	Treatment - Palliation - Transfusion
TxPalStens	Yes/No	Treatment - Palliation - Pall. Stenting
TxPalPV	Yes/No	Treatment - Palliation - PV Shunts
TxPalHAL	Yes/No	Treatment - Palliation - HAL
TxPalGasTube	Yes/No	Treatment - Palliation - Gastrostomy Tube
TxPalJejTube	Yes/No	Treatment - Palliation - Jejunstomy Tube
TxPalOth	Yes/No	Treatment - Palliation - Other
TxPalOS	Text	Treatment - Palliation - Other - Specify
TxExp	Yes/No	Treatment - Experimental protocol (ie. vaccine)
TxGene	Yes/No	Treatment - Gene Counseling

Figure 80: Gastric Cancer Treatment Table Schema

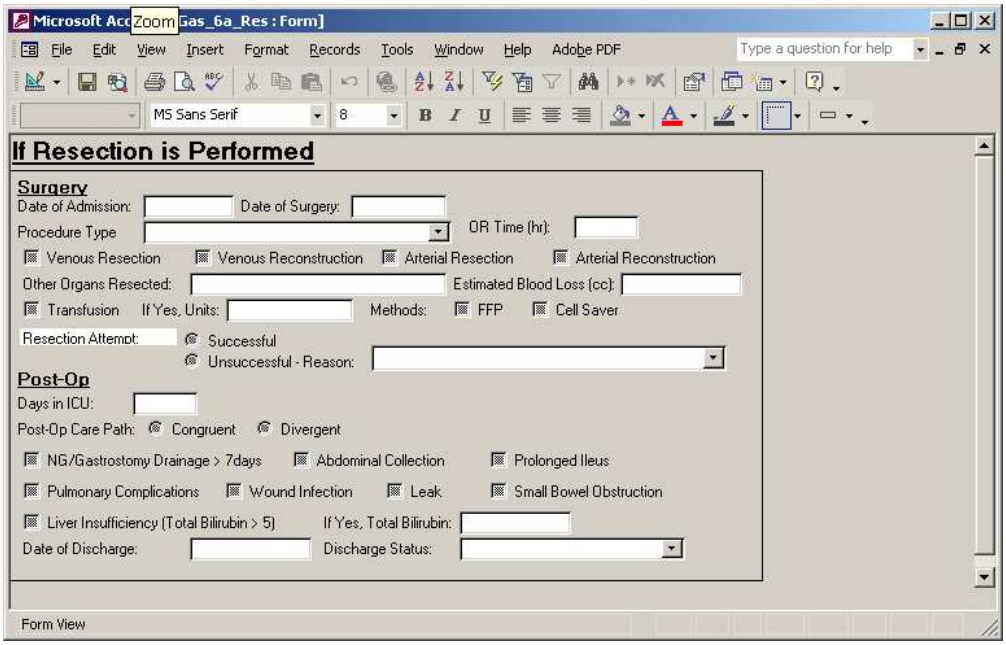


Figure 81: Gastric Cancer Resection Form

	Field Name	Data Type	Description
🔑	ID	AutoNumber	ID
	MR	Text	Meditech Medical Record Number for Patient
	ResDAdm	Date/Time	Resection - Date of Admission
	ResDSurg	Date/Time	Resection - Date of Surgery
	ResPxType	Number	Resection - Procedure Type (Whipple, total pancreatectomy, distal pancreatectomy, etc...)
	ResORTime	Number	Resection - OR Time (hr.)
	ResVenRes	Yes/No	Resection - Venous Resection
	ResVenRec	Yes/No	Resection - Venous Reconstruction
	ResArtRes	Yes/No	Resection - Arterial Resection
	ResArtRec	Yes/No	Resection - Arterial Reconstruction
	ResOrgans	Text	Resection - Other Organs Resection
	ResBloodLoss	Number	Resection - Estimated Blood Loss (cc)
	ResTransfusion	Yes/No	Resection - Tranfusion
	ResTUnits	Number	Resection - Transfusion Units
	ResTFFP	Yes/No	Resection - Transfusion - FFP
	ResTCell	Yes/No	Resection - Transfusion - Cell
	ResAttempt	Number	Resection - Resection Attempt
	ResAttemptUn	Number	Resection - Resection Unsuccessful Reason (Tumor involvement, Operative mishap, etc...)
	ResPOCourse	Number	Resection - PO - Post-Op Care Path
	ResPODays	Number	Resection - PO - Time in ICU (days)
	ResPOInfection	Yes/No	Resection - PO - Wound infection
	ResPOLeak	Yes/No	Resection - PO - Leak
	ResPONG	Yes/No	Resection - PO - NG/gastrotomy drainage
	ResPOAbdominal	Yes/No	Resection - PO - Abdominal Collection
	ResPOPulmComp	Yes/No	Resection - PO - Pulminary Complications
	ResPOLiverInsuf	Yes/No	Resection - PO - Liver Insufficiency
	ResPOLiverTB	Number	Resection - PO - Liver Insufficiency - Total Bilirubin
	ResPODDischarge	Date/Time	Resection - Date of Discharge
	ResPODischStatus	Number	Resection - Discharge Status

Figure 82: Gastric Cancer Resection Table Schema

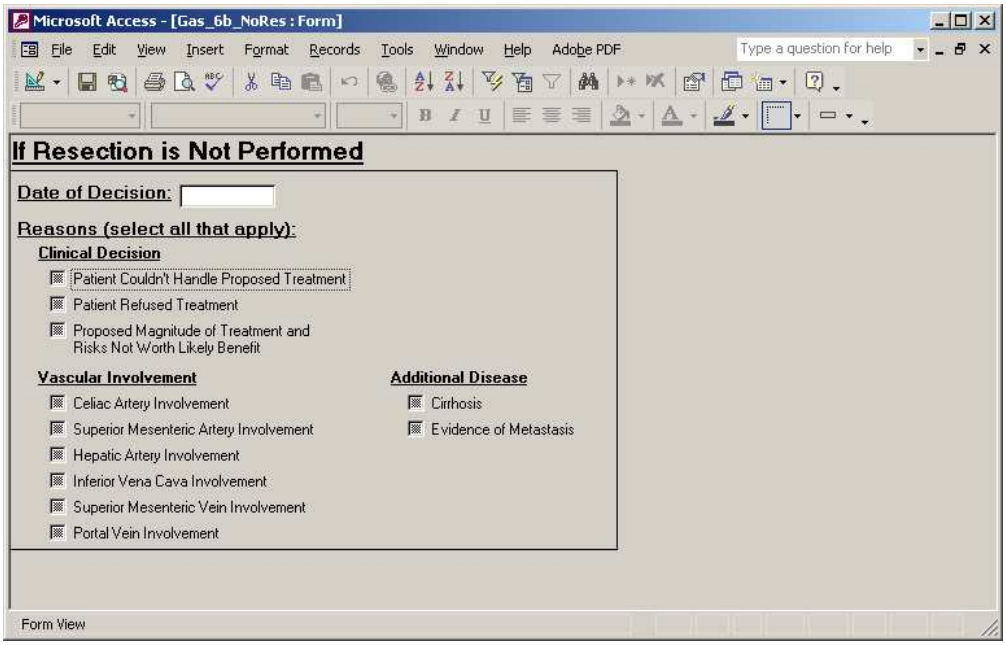


Figure 83: Gastric Cancer No Resection Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
NoResEvalDate	Date/Time	No Resection - Decision Date
NoResNoHandle	Yes/No	No Resection - Couldn't Handle Proposed Treatment
NoResRefused	Yes/No	No Resection - Refused Treatment
NoResMagnitude	Yes/No	No Resection - Magnitude Not Worth Benefits
NoResCeliacInvolve	Yes/No	No Resection - Celiac Trunk Involvement
NoResSMAInvolve	Yes/No	No Resection - SMA Involvement
NoResHepaticInvolve	Yes/No	No Resection - Hepatic Involvement
NoResIVCInvolve	Yes/No	No Resection - Inferior Vena Cava Involvement
NoResSMVInvolve	Yes/No	No Resection - SMV Involvement
NoResPVInvolve	Yes/No	No Resection - Portal Vein Involvement
NoResCirrhosis	Yes/No	No Resection - Cirrhosis
NoResMetastatic	Yes/No	No Resection - Metastatic

Figure 84: Gastric Cancer No Resection Table Schema

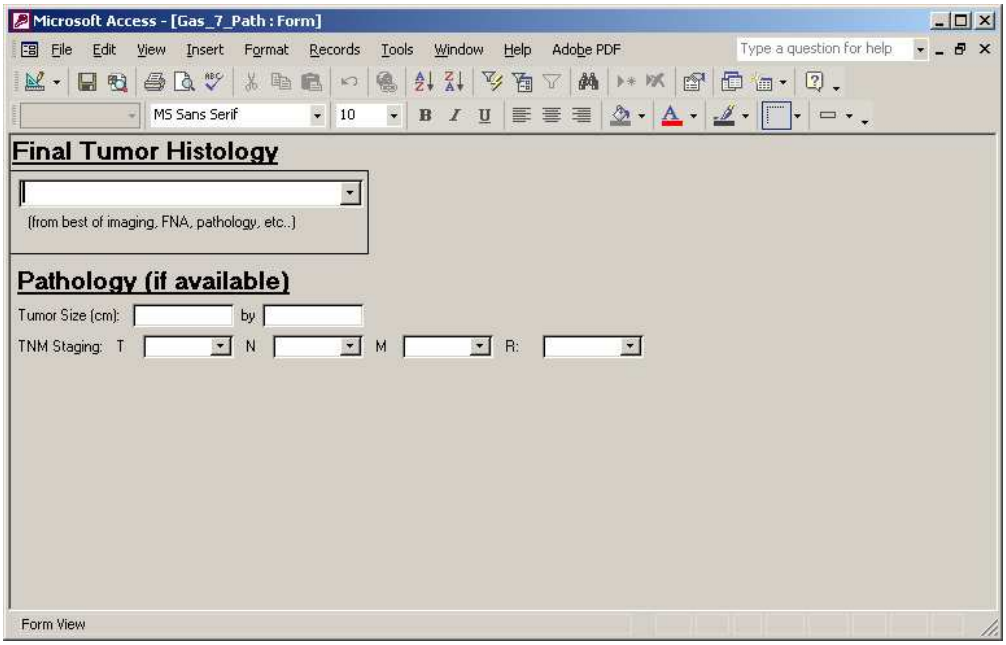


Figure 85: Gastric Cancer Pathology Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
Histology	Number	Histology
ResPathT	Number	Resection - Pathology Staging - T
ResPathN	Number	Resection - Pathology Staging - N
ResPathM	Number	Resection - Pathology Staging - M
ResPathR	Number	Resection - Pathology Staging - R
ResPathV	Number	Resection - Pathology Staging - R
ResPathSizeX	Number	Resection - Pathology Tumor Size (cm) - Width
ResPathSizeY	Number	Resection - Pathology Tumor Size (cm) - Height

Figure 86: Gastric Cancer Pathology Table Schema

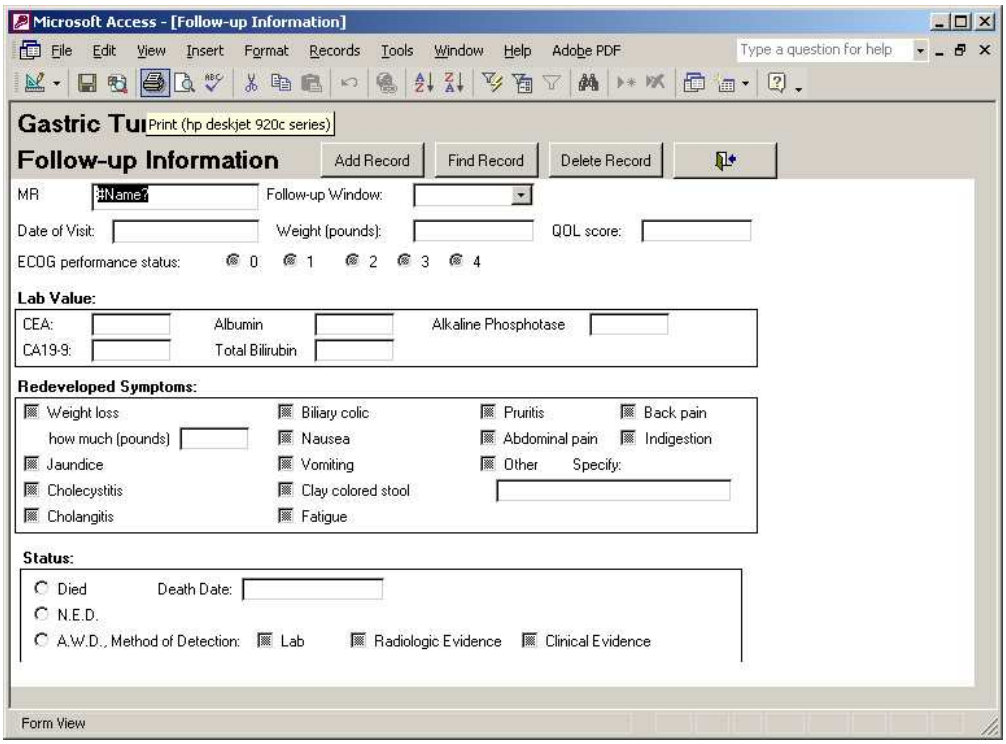


Figure 87: Gastric Cancer Follow-Up Form

	Field Name	Data Type	Description
🔑	ID	AutoNumber	
	MR	Text	Meditech Medical Record Number for Patient
	FUWin	Number	Follow-Up Windows
	VisitDate	Date/Time	Visit Date
	Weight	Number	Weight (lbs.)
	QOLscore	Number	QoL Score (0-100)
	ECOG	Number	ECOG Score (0-4)
	LabCEA	Number	Laboratory - CEA
	LabCA19-9	Number	Laboratory - CA19-9
	LabAlb	Number	Laboratory - Albumin
	LabBili	Number	Laboratory - Bilirubin
	LabAlka	Number	Laboratory - Alkaline phosphotase
	SxWtloss	Yes/No	Symptoms - Weight Loss
	SxWtlossP	Number	Symptoms - Weight Loss (lbs.)
	SxJaun	Yes/No	Symptoms - Jaundice
	SxChole	Yes/No	Symptoms - Cholecystitis
	SxChola	Yes/No	Symptoms - Cholangitis
	SxBC	Yes/No	Symptoms - Biliary Colic
	SxNau	Yes/No	Symptoms - Nausea
	SxVom	Yes/No	Symptoms - Vomiting
	SxCCS	Yes/No	Symptoms - Clay Colored Stool
	SxFati	Yes/No	Symptoms - Fatigue
	SxPru	Yes/No	Symptoms - Pruritis
	SxInd	Yes/No	Symptoms - Indigestion
	SxAbd	Yes/No	Symptoms - Abdominal Pain
	SxBack	Yes/No	Symptoms - Back Pain
	SxOT	Yes/No	Symptoms - Other
	SxOTSpe	Text	Symptoms - Other - Specify
	Status	Number	Status (NED, AWD, Died)
	DeathDate	Date/Time	Death Date
	StatusAWDLab	Yes/No	AWD - Lab Evidence
	StatusAWDRad	Yes/No	AWD - Radiology Evidence
▶	StatusAWDCli	Yes/No	AWD - Clinical Evidence

Figure 88: Gastric Cancer Follow-Up Table Schema

3.1.5 Esophageal Cancer

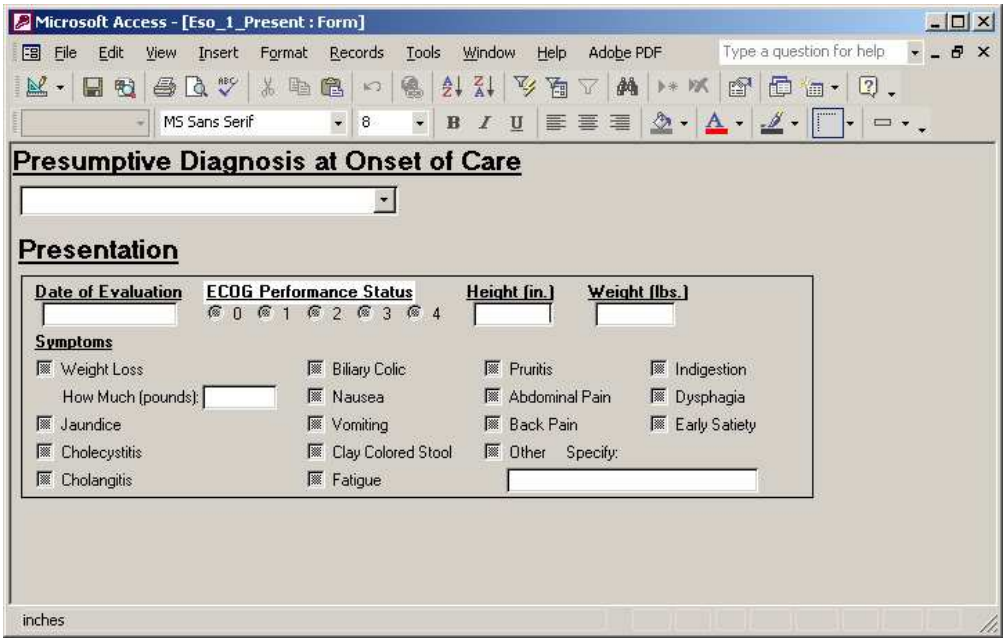


Figure 89: Esophageal Cancer Presentation Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
PresumptiveDx	Number	Presumptive Diagnosis (Pancreatic tumor, periampullary tumor, etc...)
DemEvalDate	Date/Time	Demographics - Date Evaluated by Surgical Oncology
DemECOG	Number	Demographics - ECOG Score (0-4)
DemHeight	Number	Demographics - Height in Inches of Patient
DemWeight	Number	Demographics - Weight in Pounds of Patient at Admission
SxWtloss	Yes/No	Initial Symptoms - Weight Loss
SxWtlossP	Number	Initial Symptoms - Weight Loss - Pounds
SxJaun	Yes/No	Initial Symptoms - Juandice
SxChole	Yes/No	Initial Symptoms - Cholecystitis
SxChola	Yes/No	Initial Symptoms - Cholangitis
SxBC	Yes/No	Initial Symptoms - Biliary Colic
SxNau	Yes/No	Initial Symptoms - Nausea
SxVom	Yes/No	Initial Symptoms - Vomiting
SxCCS	Yes/No	Initial Symptoms - Clay Colored Stool
SxFati	Yes/No	Initial Symptoms - Fatigue
SxPru	Yes/No	Initial Symptoms - Pruritis
SxInd	Yes/No	Initial Symptoms - Indigestion
SxAbd	Yes/No	Initial Symptoms - Abdominal Pain
SxBack	Yes/No	Initial Symptoms - Back Pain
SxDyspha	Yes/No	Initial Symptoms - Dysphagia
SxSatiety	Yes/No	Initial Symptoms - Early Satiety
SxOT	Yes/No	Initial Symptoms - Other
SxOTSpe	Text	Initial Symptoms - Other - Specify

Figure 90: Esophageal Cancer Presentation Table Schema

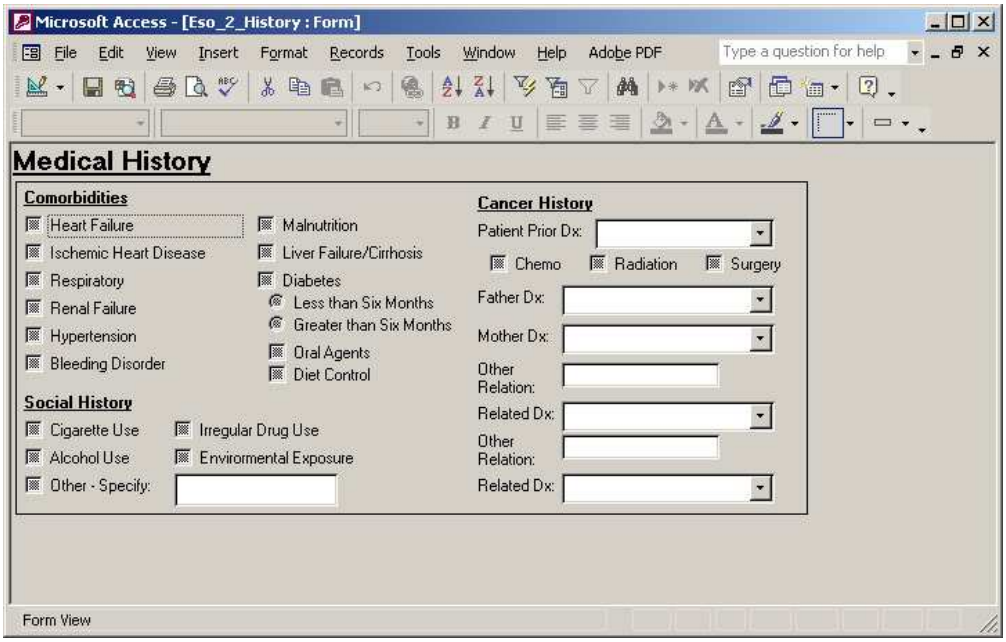


Figure 91: Esophageal Cancer Medical History Form

	Field Name	Data Type	Description
🔑	ID	AutoNumber	ID
	MR	Text	Meditech Medical Record Number for Patient
	CxHF	Yes/No	Comorbidities - Heart Failure
	CxIHD	Yes/No	Comorbidities - Ischemic Heart Disease
	CxResp	Yes/No	Comorbidities - Respiratory
	CxDiab	Yes/No	Comorbidities - Diabetes
	CxDiabOral	Yes/No	Comorbidities - Diabetes - Insulin - Oral
	CxDiabDiet	Yes/No	Comorbidities - Diabetes - Insulin - Diet Control
	CxDiabOnset	Number	Comorbidities - Diabetes - Onset (1=Less than six months, 2 =Greater than six months)
	CxRF	Yes/No	Comorbidities - Renal Failure
	CxHyper	Yes/No	Comorbidities - Hypertension
	CxBleed	Yes/No	Comorbidities - Bleeding Disorder
	CxLiver	Yes/No	Comorbidities - Liver Failure
	CxMal	Yes/No	Comorbidities - Malnutrition
	CxPriorCancer	Number	Comorbidities - Prior Cancer Dx
	CxPriorCancerChemo	Yes/No	Comorbidities - Prior Cancer Dx - Chemo
	CxPriorCancerRadiation	Yes/No	Comorbidities - Prior Cancer Dx - Radiation
	CxPriorCancerSurgery	Yes/No	Comorbidities - Prior Cancer Dx - Surgery
	SHCigarette	Yes/No	Social History - Cigarettes (significant use)
	SHAlcohol	Yes/No	Social History - Alcohol (significant use)
	SHDrugUse	Yes/No	Social History - Drug Use
	SHExposure	Yes/No	Social History - Environmental Exposure
	SHOther	Yes/No	Social History - Other
	SHOtherS	Text	Social History - Other - Specify
	FamilyFatherDx	Number	Family History - Father Dx
	FamilyMotherDx	Number	Family History - Mother Dx
	FamilyOther1	Text	Family History - Other1
	FamilyOther1Dx	Number	Family History - Other1 Dx
	FamilyOther2	Text	Family History - Other2
	FamilyOther2Dx	Number	Family History - Other2 Dx

Figure 92: Esophageal Cancer Medical History Table Schema

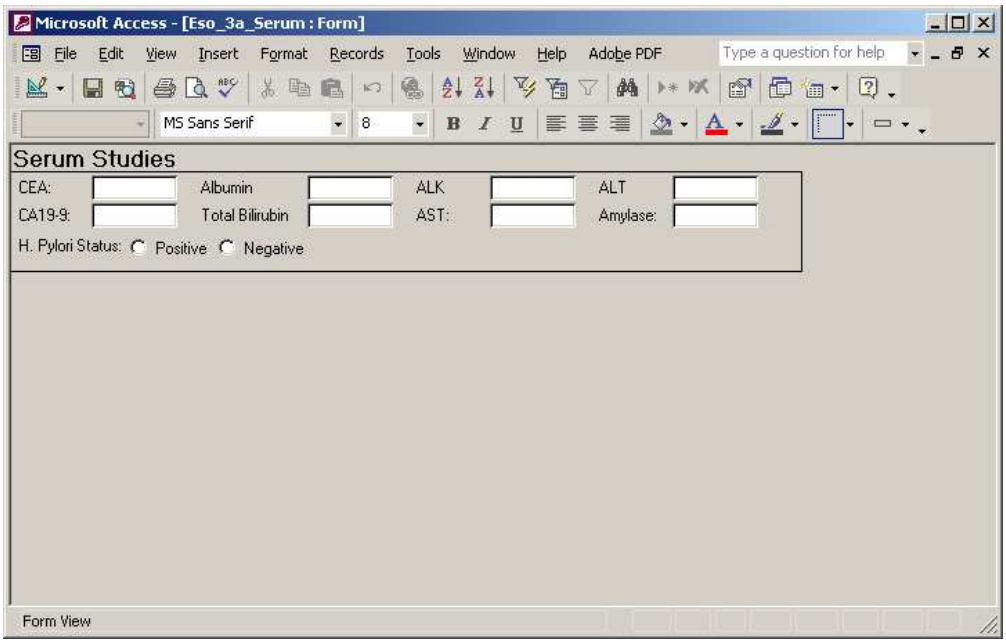


Figure 93: Esophageal Cancer Serum Studies Form

	Field Name	Data Type	Description
▶	ID	AutoNumber	ID
	MR	Text	Meditech Medical Record Number for Patient
	LabCEA	Number	Laboratory - CEA
	LabCA19-9	Number	Laboratory - CA19-9
	LabAlb	Number	Laboratory - Albumin
	LabBili	Number	Laboratory - Bilirubin
	LabAlka	Number	Laboratory - Alkaline phosphotase
	LabALT	Number	Laboratory - ALT
	LabAST	Number	Laboratory - AST
	LabAmylase	Number	Laboratory - Amylase
	LabHPylori	Number	Laboratory - H. Pylori Status

Figure 94: Esophageal Cancer Serum Studies Table Schema

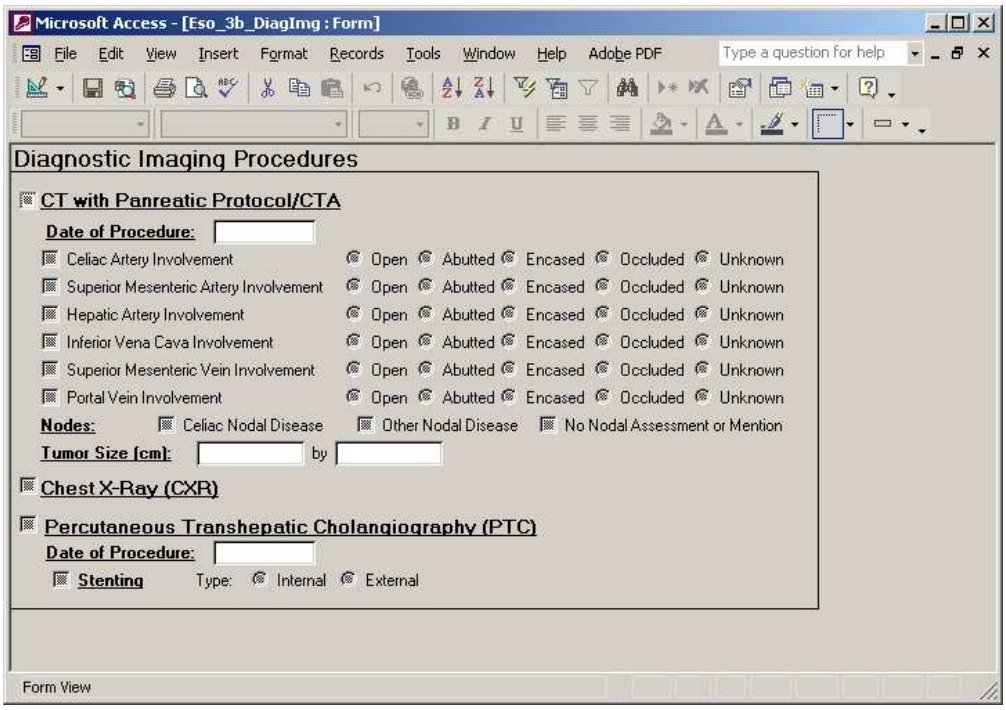


Figure 95: Esophageal Cancer Diagnostic Imaging Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
CXRDx	Yes/No	CXR - Diagnosis
CTDx	Yes/No	CT - Diagnosis
CTEvalDate	Date/Time	CT - Date Evaluated
CTVascOmit	Yes/No	CT - Vascular Omission
CTCeliac	Yes/No	CT - Celiac Involvement
CTCeliacClass	Number	CT - Celiac Involvement Class
CTSMA	Yes/No	CT - SMA Involvement
CTSMAClass	Number	CT - SMA Involvement Class
CTHepatic	Yes/No	CT - Hepatic Involvement
CTHepaticClass	Number	CT - Hepatic Involvement
CTInferior	Yes/No	CT - Inferior Vena Cava Involvement
CTInferiorClass	Number	CT - Inferior Vena Cava Involvement Class
CTSMV	Yes/No	CT - SMV Involvement
CTSMVClass	Number	CT - SMV Involvement Class
CTPortal	Yes/No	CT - Portal Vein Involvement
CTPortalClass	Number	CT - Portal Vein Involvement Class
CTCeliacNode	Yes/No	CT - Celiac Nodal Disease
CTOtherNode	Yes/No	CT - Other Nodal Disease
CTNodeOmit	Yes/No	CT - Node Omission
CTTumorSizeX	Number	CT - Tumor Size (cm) - Width
CTTumorSizeY	Number	CT - Tumor Size (cm) - Height
PTCDx	Yes/No	PTC - Diagnosis
PTCEvalDate	Date/Time	PTC - Date Evaluated
PTCStent	Yes/No	PTC - Stent
PTCStentType	Number	PTC - Stent Type

Figure 96: Esophageal Cancer Diagnostic Imaging Table Schema

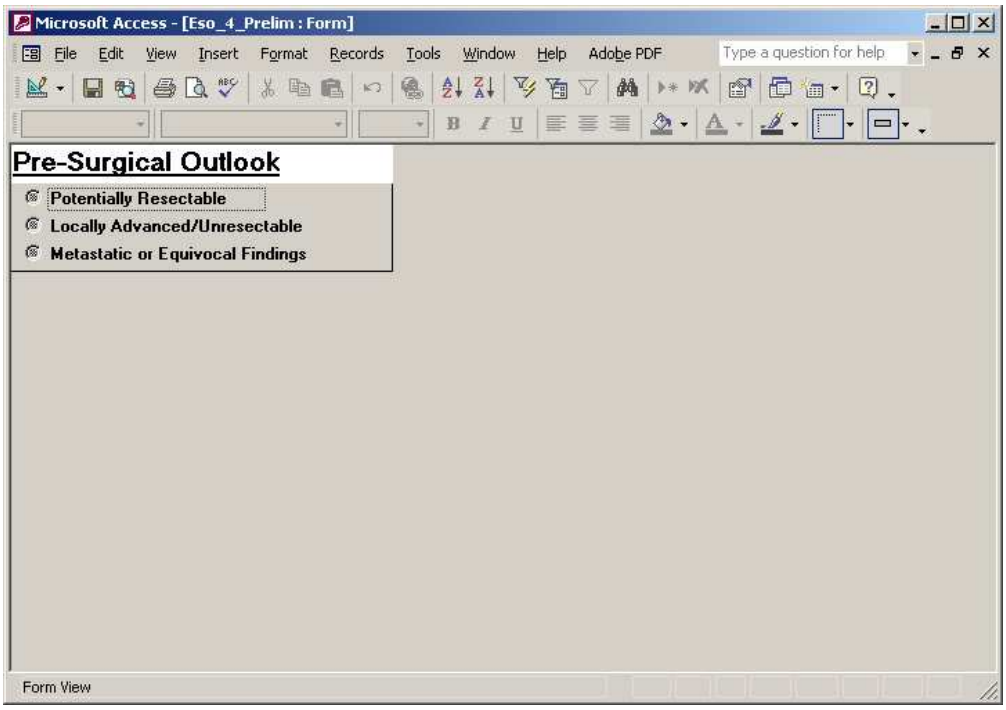


Figure 97: Esophageal Cancer Preliminary Outlook Form

	Field Name	Data Type	Description
🔑	ID	AutoNumber	ID
	MR	Text	Meditech Medical Record Number for Patient
	PreOutlook	Number	Pre-Surgical Tumor Outlook (Potentially Resectable, Locally Advanced/Unresectable, Metastatic or Equivocal Findi

Figure 98: Esophageal Cancer Preliminary Outlook Table Schema

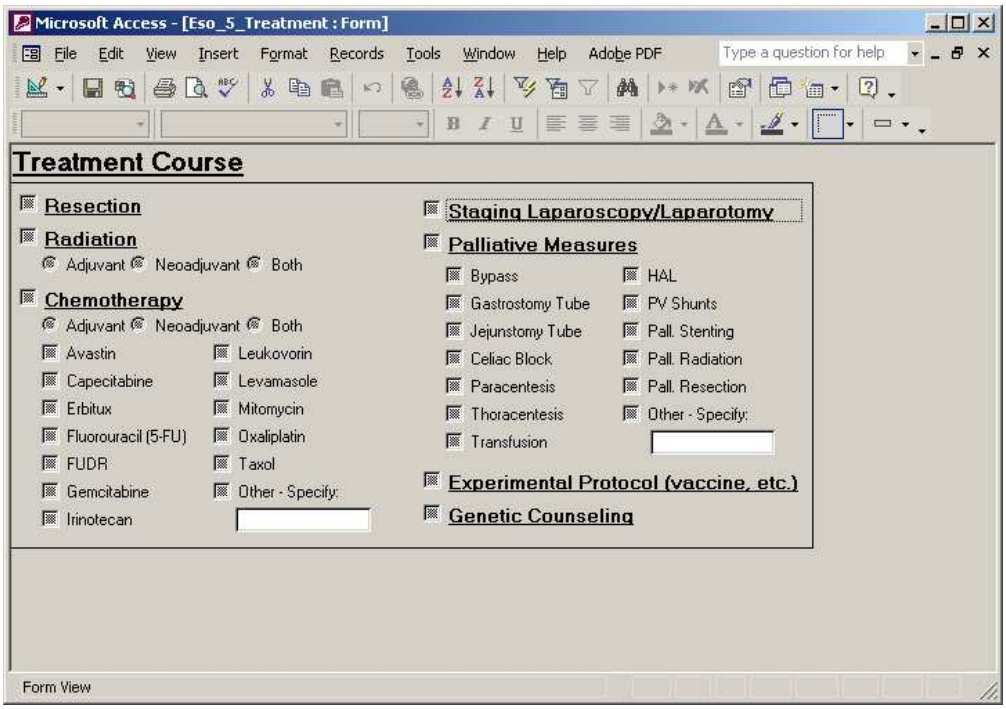


Figure 99: Esophageal Cancer Treatment Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
TxResect	Yes/No	Treatment - Resection
TxLap	Yes/No	Treatment - Laparoscopy
TxRadia	Yes/No	Treatment - Radiation
TXRadiaAdju	Number	Treatment - Radiation - Adjuvancy
TxChemo	Yes/No	Treatment - Chemo
TXChemoAdju	Number	Treatment - Chemo - Adjuvancy
TxChemoAVA	Yes/No	Treatment - Chemo - Avastin
TxChemoCap	Yes/No	Treatment - Chemo - Capecitabine
TxChemoErb	Yes/No	Treatment - Chemo - Erbitux
TxChemoFlu	Yes/No	Treatment - Chemo - Fluorouracil (5-FU)
TxChemoFUDR	Yes/No	Treatment - Chemo - FUDR
TxChemoGem	Yes/No	Treatment - Chemo - Gemcitabine
TxChemoIri	Yes/No	Treatment - Chemo - Irinotecan
TxChemoLeu	Yes/No	Treatment - Chemo - Leukovorin
TxChemoLev	Yes/No	Treatment - Chemo - Levamasole
TxChemoMit	Yes/No	Treatment - Chemo - Mitomycin
TxChemoOxa	Yes/No	Treatment - Chemo - Oxaliplatin
TxChemoTax	Yes/No	Treatment - Chemo - Taxol
TxChemoOth	Yes/No	Treatment - Chemo - Other
TxChemoOS	Text	Treatment - Chemo - Other - Specify
TxPal	Yes/No	Treatment - Palliation
TxPalRes	Yes/No	Treatment - Palliation - Pall. Resection
TxPalBypass	Yes/No	Treatment - Palliation - Bypass
TxPalCeliac	Yes/No	Treatment - Palliation - Celiac Block
TxPalPara	Yes/No	Treatment - Palliation - Paracentesis
TxPalTho	Yes/No	Treatment - Palliation - Thoracentesis
TxPalRad	Yes/No	Treatment - Palliation - Pall. Radiation
TxPalTrans	Yes/No	Treatment - Palliation - Transfusion
TxPalStens	Yes/No	Treatment - Palliation - Pall. Stenting
TxPalPV	Yes/No	Treatment - Palliation - PV Shunts
TxPalHAL	Yes/No	Treatment - Palliation - HAL
TxPalGasTube	Yes/No	Treatment - Palliation - Gastrostomy Tube
TxPalJejTube	Yes/No	Treatment - Palliation - Jejunstomy Tube
TxPalOth	Yes/No	Treatment - Palliation - Other
TxPalOS	Text	Treatment - Palliation - Other - Specify
TxExp	Yes/No	Treatment - Experimental protocol (ie. vaccine)
TxGene	Yes/No	Treatment - Gene Counseling

Figure 100: Esophageal Cancer Treatment Table Schema

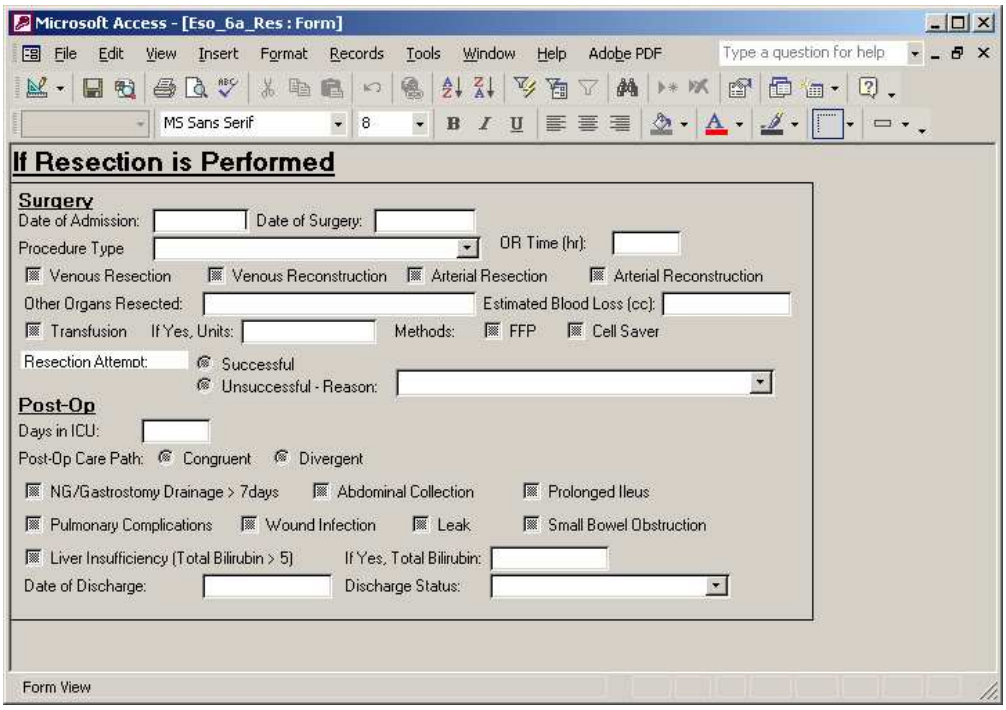


Figure 101: Esophageal Cancer Resection Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
ResDAdm	Date/Time	Resection - Date of Admission
ResDSurg	Date/Time	Resection - Date of Surgery
ResPxType	Number	Resection - Procedure Type (Whipple, total pancreatectomy, distal pancreatectomy, etc...)
ResORTime	Number	Resection - OR Time (hr.)
ResVenRes	Yes/No	Resection - Venous Resection
ResVenRec	Yes/No	Resection - Venous Reconstruction
ResArtRes	Yes/No	Resection - Arterial Resection
ResArtRec	Yes/No	Resection - Arterial Reconstruction
ResOrgans	Text	Resection - Other Organs Resection
ResBloodLoss	Number	Resection - Estimated Blood Loss (cc)
ResTransfusion	Yes/No	Resection - Tranfusion
ResTUnits	Number	Resection - Transfusion Units
ResTFFP	Yes/No	Resection - Transfusion - FFP
ResTCell	Yes/No	Resection - Transfusion - Cell
ResAttempt	Number	Resection - Resection Attempt
ResAttemptUn	Number	Resection - Resection Unsuccessful Reason (Tumor involvement, Operative mishap, etc...)
ResPOCourse	Number	Resection - PO - Post-Op Care Path
ResPODays	Number	Resection - PO - Time in ICU (days)
ResPOInfection	Yes/No	Resection - PO - Wound infection
ResPOLeak	Yes/No	Resection - PO - Leak
ResPONG	Yes/No	Resection - PO - NG/gastrotomy drainage
ResPOAbdominal	Yes/No	Resection - PO - Abdominal Collection
ResPOPulmComp	Yes/No	Resection - PO - Pulminary Complications
ResPOLiverInsuf	Yes/No	Resection - PO - Liver Insufficiency
ResPOLiverTB	Number	Resection - PO - Liver Insufficiency - Total Bilirubin
ResPODDischarge	Date/Time	Resection - Date of Discharge
ResPODischStatus	Number	Resection - Discharge Status

Figure 102: Esophageal Cancer Resection Table Schema

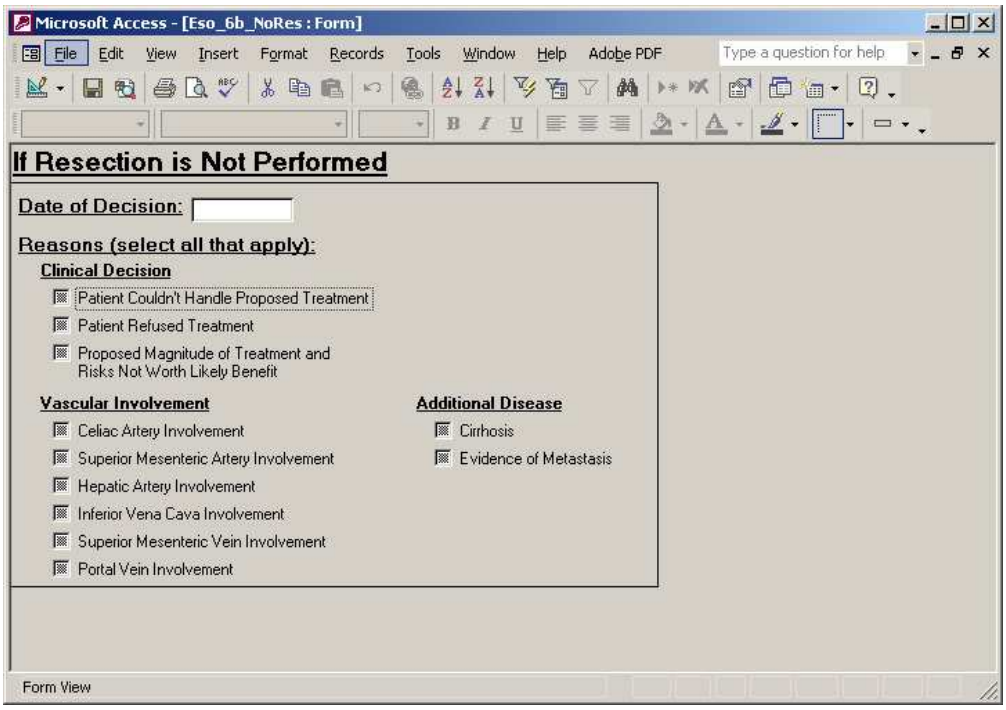


Figure 103: Esophageal Cancer No Resection Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
NoResEvalDate	Date/Time	No Resection - Decision Date
NoResNoHandle	Yes/No	No Resection - Couldn't Handle Proposed Treatment
NoResRefused	Yes/No	No Resection - Refused Treatment
NoResMagnitude	Yes/No	No Resection - Magnitude Not Worth Benefits
NoResCeliacInvolve	Yes/No	No Resection - Celiac Trunk Involvement
NoResSMAInvolve	Yes/No	No Resection - SMA Involvement
NoResHepaticInvolve	Yes/No	No Resection - Hepatic Involvement
NoResIVCInvolve	Yes/No	No Resection - Inferior Vena Cava Involvement
NoResSMVInvolve	Yes/No	No Resection - SMV Involvement
NoResPVInvolve	Yes/No	No Resection - Portal Vein Involvement
NoResCirrhosis	Yes/No	No Resection - Cirrhosis
NoResMetastatic	Yes/No	No Resection - Metastatic

Figure 104: Esophageal Cancer No Resection Table Schema

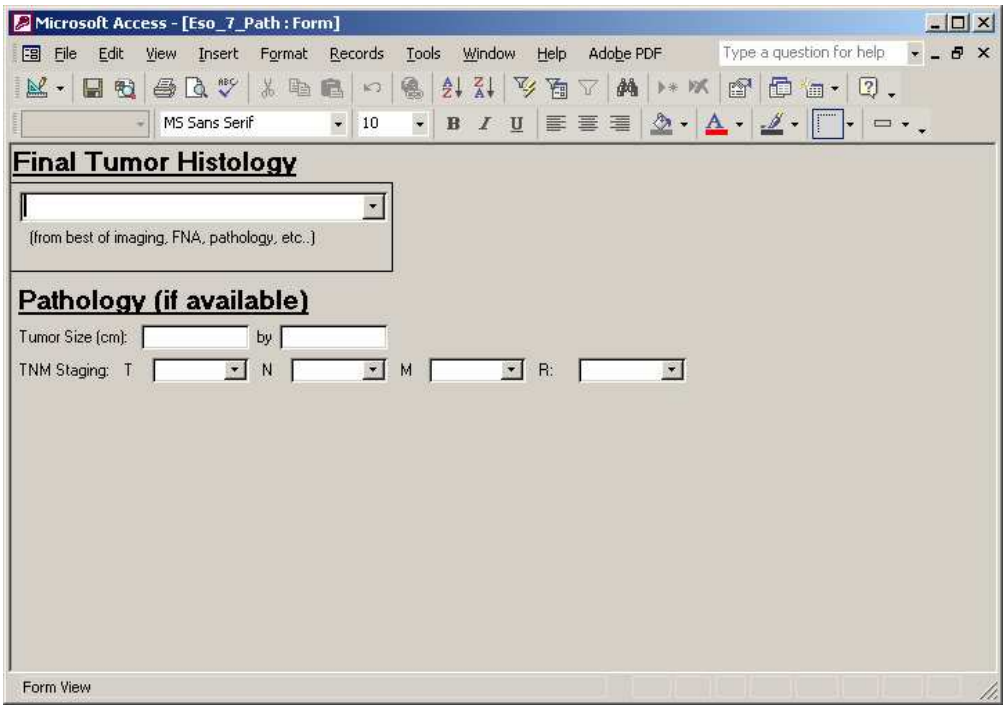


Figure 105: Esophageal Cancer Pathology Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
Histology	Number	Histology
ResPathT	Number	Resection - Pathology Staging - T
ResPathN	Number	Resection - Pathology Staging - N
ResPathM	Number	Resection - Pathology Staging - M
ResPathR	Number	Resection - Pathology Staging - R
ResPathV	Number	Resection - Pathology Staging - R
ResPathSizeX	Number	Resection - Pathology Tumor Size (cm) - Width
ResPathSizeY	Number	Resection - Pathology Tumor Size (cm) - Height

Figure 106: Esophageal Cancer Pathology Table Schema

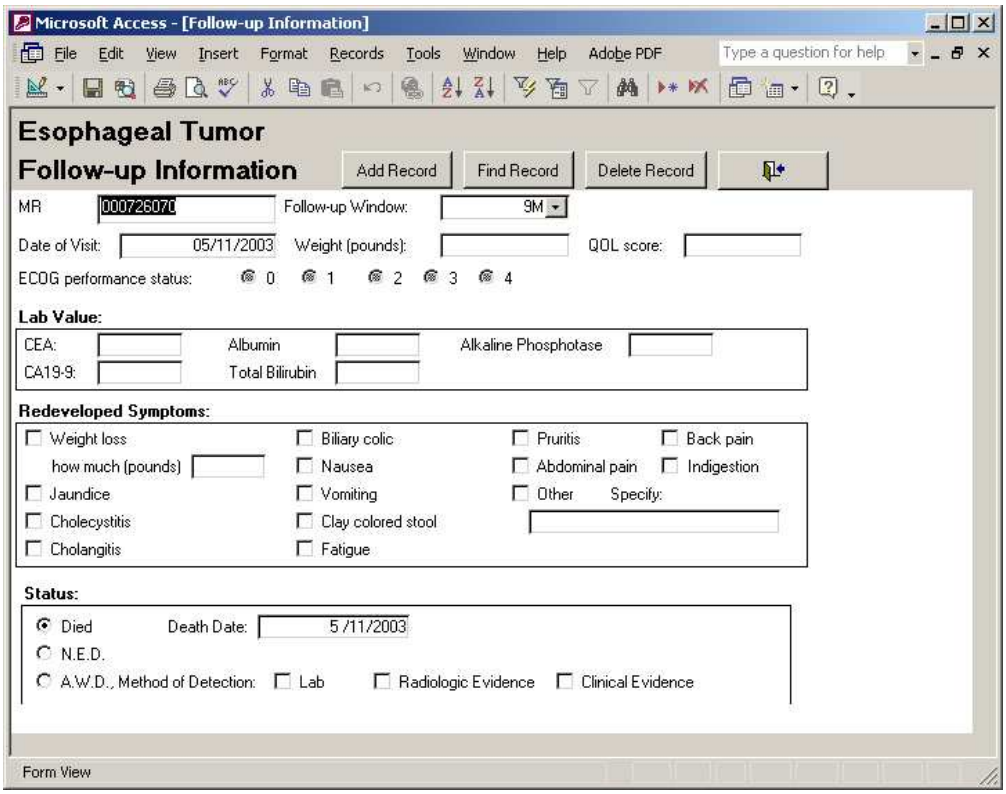


Figure 107: Esophageal Cancer Follow-Up Form

Field Name	Data Type	Description
ID	AutoNumber	
MR	Text	Meditech Medical Record Number for Patient
FUWin	Number	Follow-Up Windows
VisitDate	Date/Time	Visit Date
Weight	Number	Weight (lbs.)
QOLscore	Number	QoL Score (0-100)
ECOG	Number	ECOG Score (0-4)
LabCEA	Number	Laboratory - CEA
LabCA19-9	Number	Laboratory - CA19-9
LabAlb	Number	Laboratory - Albumin
LabBili	Number	Laboratory - Bilirubin
LabAlka	Number	Laboratory - Alkaline phosphotase
SxWtloss	Yes/No	Symptoms - Weight Loss
SxWtlossP	Number	Symptoms - Weight Loss (lbs.)
SxJaun	Yes/No	Symptoms - Jaundice
SxChole	Yes/No	Symptoms - Cholecystitis
SxChola	Yes/No	Symptoms - Cholangitis
SxBC	Yes/No	Symptoms - Biliary Colic
SxNau	Yes/No	Symptoms - Nausea
SxVom	Yes/No	Symptoms - Vomiting
SxCCS	Yes/No	Symptoms - Clay Colored Stool
SxFati	Yes/No	Symptoms - Fatigue
SxPru	Yes/No	Symptoms - Pruritis
SxInd	Yes/No	Symptoms - Indigestion
SxAbd	Yes/No	Symptoms - Abdominal Pain
SxBack	Yes/No	Symptoms - Back Pain
SxOT	Yes/No	Symptoms - Other
SxOTSpe	Text	Symptoms - Other - Specify
Status	Number	Status (NED, AWD, Died)
DeathDate	Date/Time	Death Date
StatusAWDLab	Yes/No	AWD - Lab Evidence
StatusAWDRad	Yes/No	AWD - Radiology Evidence
StatusAWDCli	Yes/No	AWD - Clinical Evidence

Figure 108: Esophageal Cancer Follow-Up Table Schema

3.1.6 Colorectal Cancer

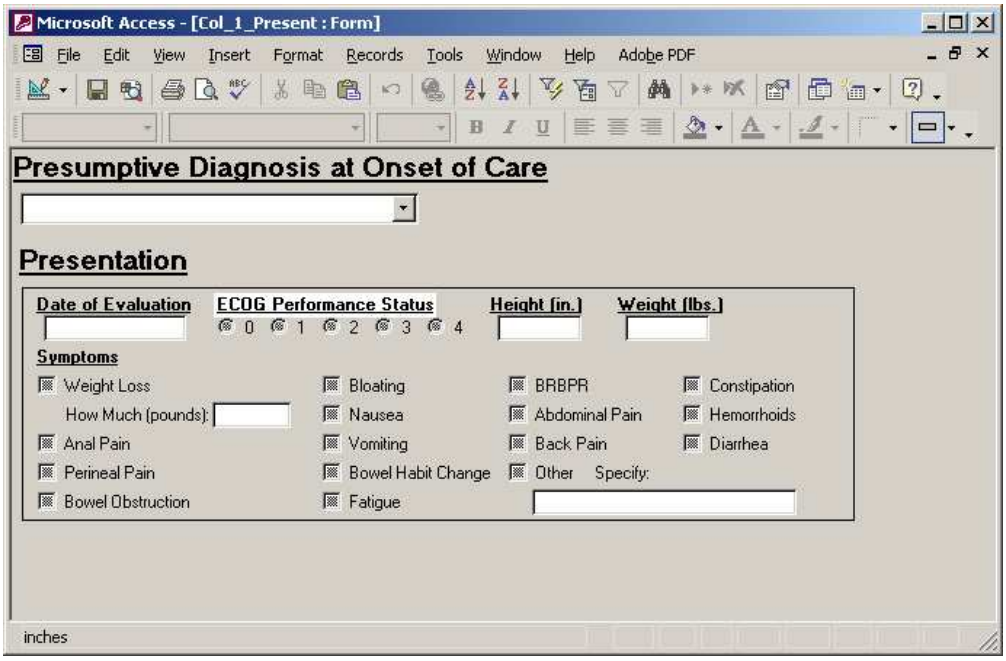


Figure 109: Colorectal Cancer Presentation Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
PresumptiveDx	Number	Presumptive Diagnosis (Pancreatic tumor, periampullary tumor, etc...)
DemEvalDate	Date/Time	Demographics - Date Evaluated by Surgical Oncology
DemECOG	Number	Demographics - ECOG Score (0-4)
DemHeight	Number	Demographics - Height in Inches of Patient
DemWeight	Number	Demographics - Weight in Pounds of Patient at Admission
SxWtloss	Yes/No	Initial Symptoms - Weight Loss
SxWtlossP	Number	Initial Symptoms - Weight Loss - Pounds
SxAnalPain	Yes/No	Initial Symptoms - Anal Pain
SxPerPain	Yes/No	Initial Symptoms - Perineal Pain
SxBObs	Yes/No	Initial Symptoms - Bowel Obstruction
SxBloat	Yes/No	Initial Symptoms - Bloating
SxNau	Yes/No	Initial Symptoms - Nausea
SxVom	Yes/No	Initial Symptoms - Vomiting
SxBHabit	Yes/No	Initial Symptoms - Bowel Habit Change
SxFati	Yes/No	Initial Symptoms - Fatigue
SxBRBPR	Yes/No	Initial Symptoms - BRBPR
SxAbd	Yes/No	Initial Symptoms - Abdominal Pain
SxBack	Yes/No	Initial Symptoms - Back Pain
SxConst	Yes/No	Initial Symptoms - Constipation
SxHemorr	Yes/No	Initial Symptoms - Hemorrhoids
SxDiar	Yes/No	Initial Symptoms - Diarrhea
SxOT	Yes/No	Initial Symptoms - Other
SxOTSpe	Text	Initial Symptoms - Other - Specify

Figure 110: Colorectal Cancer Presentation Table Schema

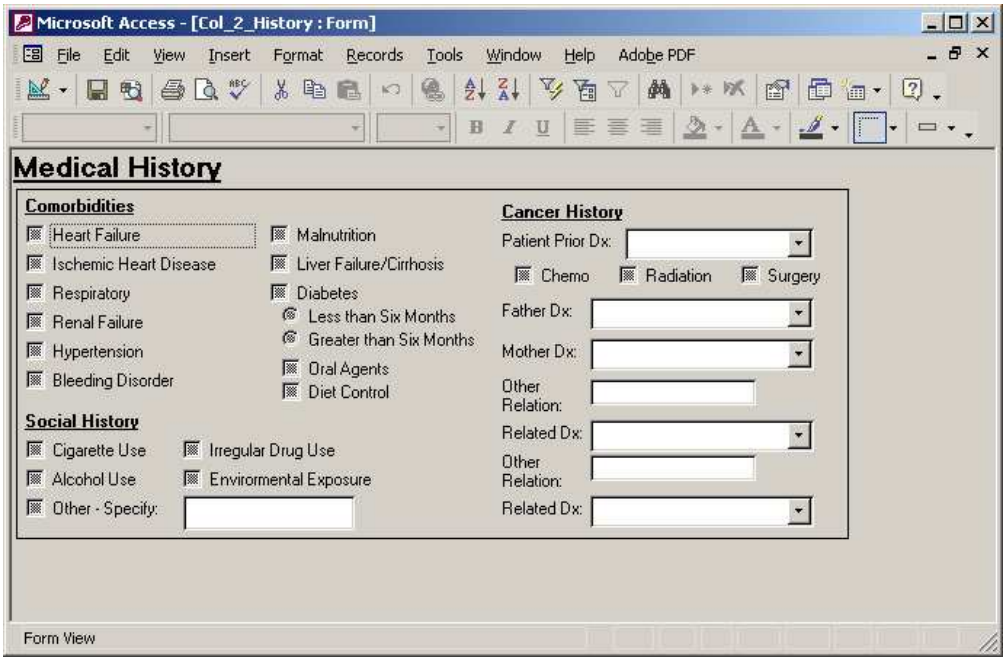


Figure 111: Colorectal Cancer Medical History Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
CxHF	Yes/No	Comorbidities - Heart Failure
CxIHD	Yes/No	Comorbidities - Ischemic Heart Disease
CxResp	Yes/No	Comorbidities - Respiratory
CxDiab	Yes/No	Comorbidities - Diabetes
CxDiabOral	Yes/No	Comorbidities - Diabetes - Insulin - Oral
CxDiabDiet	Yes/No	Comorbidities - Diabetes - Insulin - Diet Control
CxDiabOnset	Number	Comorbidities - Diabetes - Onset (1=Less than six months, 2 =Greater than six months)
CxRF	Yes/No	Comorbidities - Renal Failure
CxHyper	Yes/No	Comorbidities - Hypertension
CxBleed	Yes/No	Comorbidities - Bleeding Disorder
CxLiver	Yes/No	Comorbidities - Liver Failure
CxMal	Yes/No	Comorbidities - Malnutrition
CxPriorCancer	Number	Comorbidities - Prior Cancer Dx
CxPriorCancerChemo	Yes/No	Comorbidities - Prior Cancer Dx - Chemo
CxPriorCancerRadiation	Yes/No	Comorbidities - Prior Cancer Dx - Radiation
CxPriorCancerSurgery	Yes/No	Comorbidities - Prior Cancer Dx - Surgery
SHCigarette	Yes/No	Social History - Cigarettes (significant use)
SHAlcohol	Yes/No	Social History - Alcohol (significant use)
SHDrugUse	Yes/No	Social History - Drug Use
SHExposure	Yes/No	Social History - Environmental Exposure
SHOther	Yes/No	Social History - Other
SHOtherS	Text	Social History - Other - Specify
FamilyFatherDx	Number	Family History - Father Dx
FamilyMotherDx	Number	Family History - Mother Dx
FamilyOther1	Text	Family History - Other1
FamilyOther1Dx	Number	Family History - Other1 Dx
FamilyOther2	Text	Family History - Other2
FamilyOther2Dx	Number	Family History - Other2 Dx

Figure 112: Colorectal Cancer Medical History Table Schema

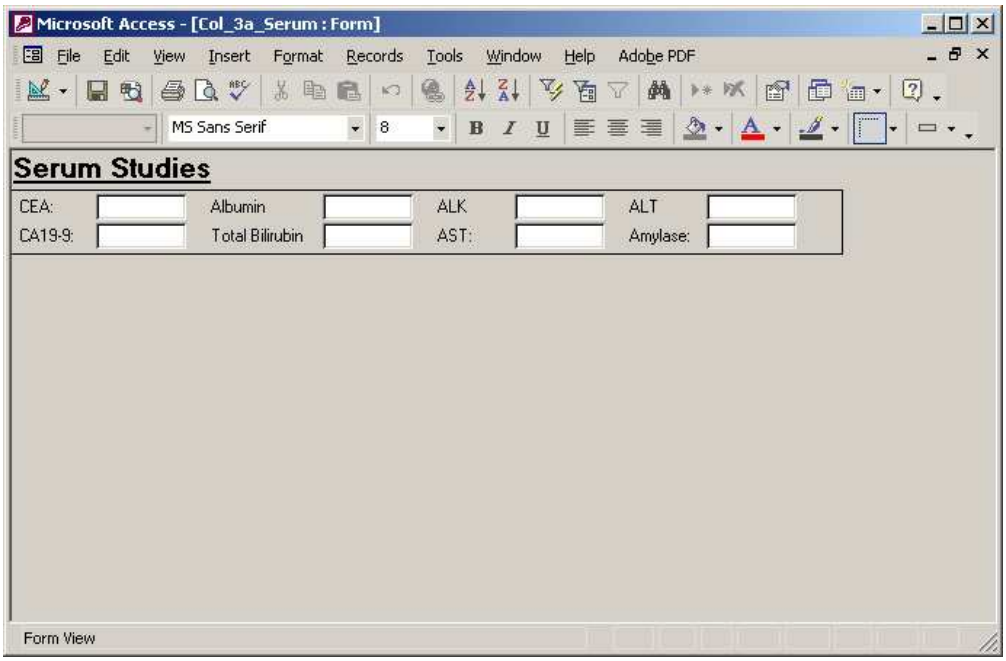


Figure 113: Colorectal Cancer Serum Studies Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
LabCEA	Number	Laboratory - CEA
LabCA19-9	Number	Laboratory - CA19-9
LabAlb	Number	Laboratory - Albumin
LabBili	Number	Laboratory - Bilirubin
LabAlka	Number	Laboratory - Alkaline phosphotase
LabALT	Number	Laboratory - ALT
LabAST	Number	Laboratory - AST
LabAmylase	Number	Laboratory - Amylase
LabHPylori	Number	Laboratory - H. Pylori Status

Figure 114: Colorectal Cancer Serum Studies Table Schema

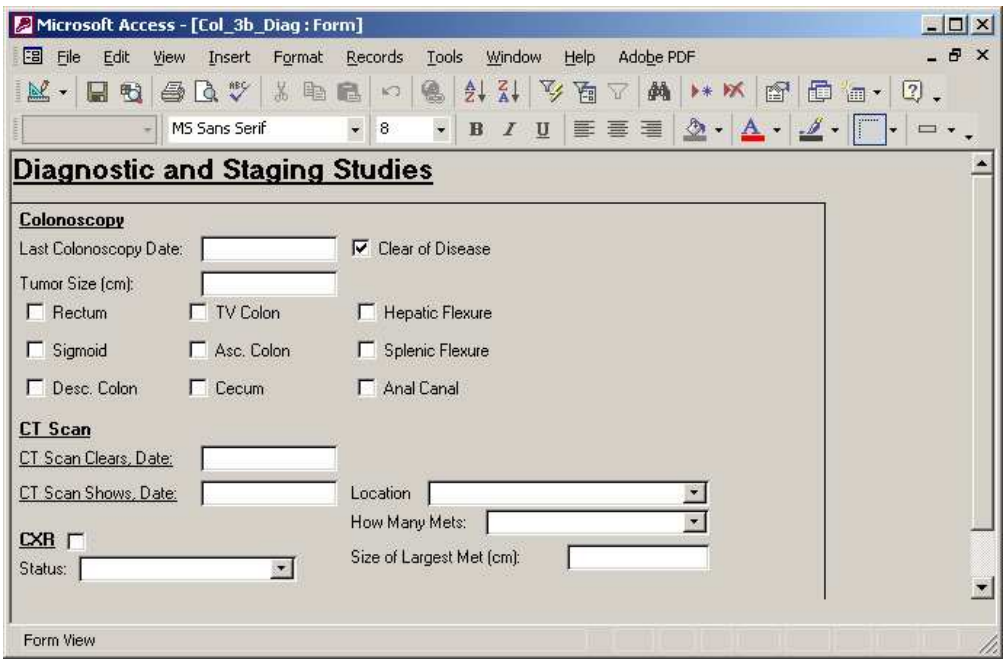


Figure 115: Colorectal Cancer Diagnostic Imaging Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
ColLastD	Date/Time	Colonoscopy - Last Date
ColClear	Yes/No	Colonoscopy - Clear
ColSize	Number	Colonoscopy - Size (cm)
ColRectum	Yes/No	Colonoscopy - Rectum
ColSigmoid	Yes/No	Colonoscopy - Sigmoid
ColDesc	Yes/No	Colonoscopy - Descending Colon
ColTV	Yes/No	Colonoscopy - T.V. Colon
ColAsc	Yes/No	Colonoscopy - Ascending Colon
ColCecum	Yes/No	Colonoscopy - Cecum
ColHep	Yes/No	Colonoscopy - Hepatic Flexure
ColSplen	Yes/No	Colonoscopy - Splenic Flexure
ColAnal	Yes/No	Colonoscopy - Anal Canal
CTClearD	Date/Time	CT Scan Clears - Date
CTShowD	Date/Time	CT Scan Shows - Date
CTLocation	Number	CT Scan Location
CTMetCount	Number	CT Met Count
CTMetSize	Number	CT Met Size
CXR	Yes/No	CXR
CXRStatus	Number	CXR

Figure 116: Colorectal Cancer Diagnostic Imaging Table Schema

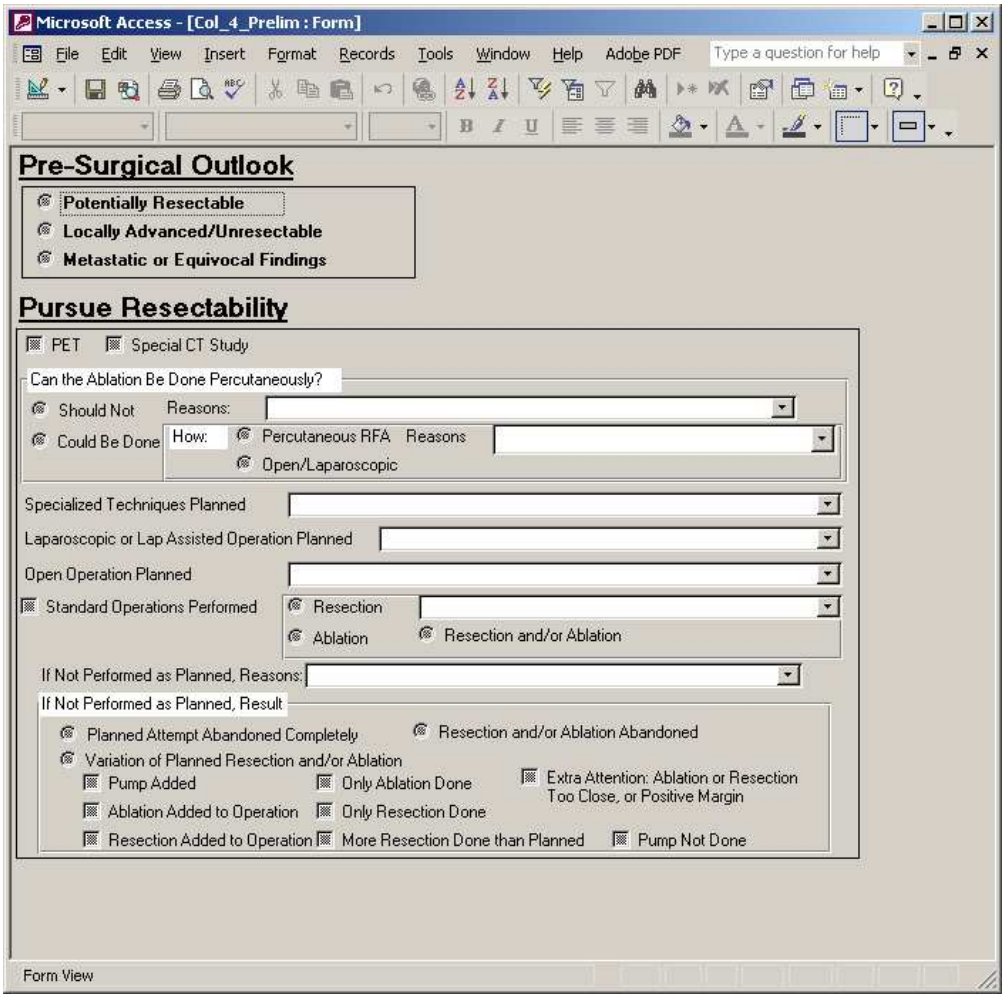


Figure 117: Colorectal Cancer Preliminary Outlook Form

Save	Name	Data Type	Description
	ID	AutoNumber	ID
	MR	Text	Meditech Medical Record Number for Patient
	PreOutlook	Number	Pre-Surgical Tumor Outlook (Potentially Resectable, Locally Advanced/Unresectable, Metastatic
	PET	Yes/No	PET Scan
	SpecialCT	Yes/No	Special CT
	Percut	Number	Percutaneous Ablation -
	PercutN	Number	Percutaneous Ablation - Should Not - Reasons
	PercutY	Number	Percutaneous Ablation - Could Be - How
	PercutYRFA	Number	Percutaneous Ablation - Could Be - RFA
	Techniq	Number	Specialized Techniques
	Lap	Number	Laparoscopic Operation Planned
	Operation	Number	Other Operation Planned
	Plan	Yes/No	Standard Operations Performed
	PlanY	Number	Standard Operations Performed - Types
	PlanYR	Number	Standard Operations Performed - Resection
	PlanNRes	Number	Standard Operations Not Performed - Reason
	PlanNType	Number	Standard Operations Not Performed - Result
	PlanNType_PA	Yes/No	Standard Operations Not Performed - Result - Pump Added
	PlanNType_AAO	Yes/No	Standard Operations Not Performed - Result - Ablation Added to Operation
	PlanNType_RAO	Yes/No	Standard Operations Not Performed - Result - Resection Added to Operation
	PlanNType_OAD	Yes/No	Standard Operations Not Performed - Result - Only Ablation Done
	PlanNType_ORD	Yes/No	Standard Operations Not Performed - Result - Only Resection Done
	PlanNType_MR	Yes/No	Standard Operations Not Performed - Result - More Resection Done than Planned
	PlanNType_EA	Yes/No	Standard Operations Not Performed - Result - Extra Attention: Ablation or Resection Too Close
	PlanNType_PND	Yes/No	Standard Operations Not Performed - Result - Pump Not Done

Figure 118: Colorectal Cancer Preliminary Outlook Table Schema

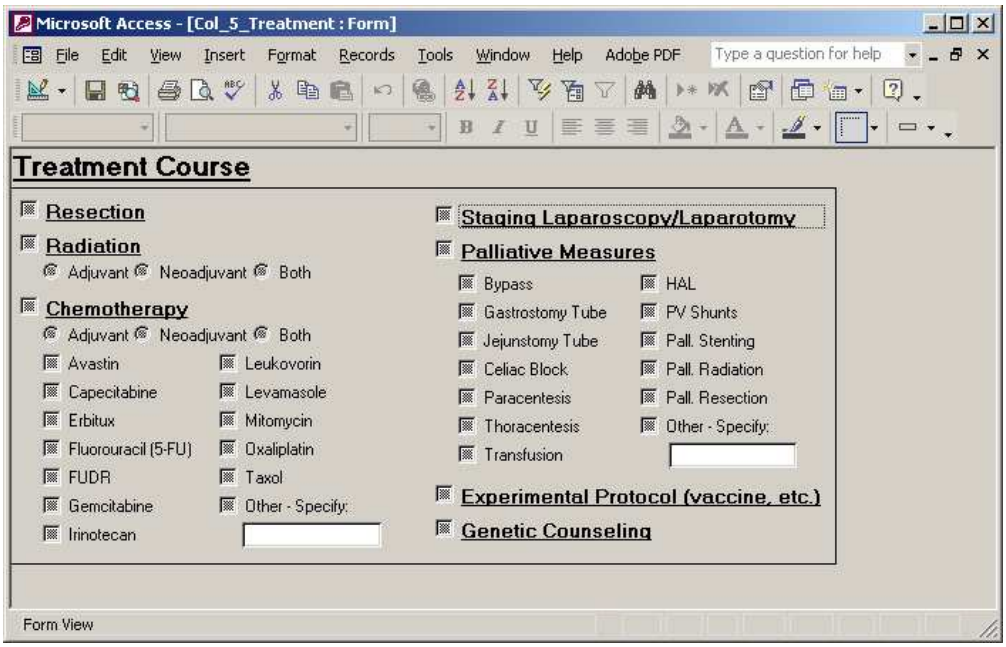


Figure 119: Colorectal Cancer Treatment Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
TxResect	Yes/No	Treatment - Resection
TxLap	Yes/No	Treatment - Laparoscopy
TxRadia	Yes/No	Treatment - Radiation
TXRadiaAdju	Number	Treatment - Radiation - Adjuvancy
TxChemo	Yes/No	Treatment - Chemo
TXChemoAdju	Number	Treatment - Chemo - Adjuvancy
TxChemoAVA	Yes/No	Treatment - Chemo - Avastin
TxChemoCap	Yes/No	Treatment - Chemo - Capecitabine
TxChemoErb	Yes/No	Treatment - Chemo - Erbitux
TxChemoFlu	Yes/No	Treatment - Chemo - Fluorouracil (5-FU)
TxChemoFUDR	Yes/No	Treatment - Chemo - FUDR
TxChemoGem	Yes/No	Treatment - Chemo - Gemcitabine
TxChemoIri	Yes/No	Treatment - Chemo - Irinotecan
TxChemoLeu	Yes/No	Treatment - Chemo - Leukovorin
TxChemoLev	Yes/No	Treatment - Chemo - Levamasole
TxChemoMit	Yes/No	Treatment - Chemo - Mitomycin
TxChemoOxa	Yes/No	Treatment - Chemo - Oxaliplatin
TxChemoTax	Yes/No	Treatment - Chemo - Taxol
TxChemoOth	Yes/No	Treatment - Chemo - Other
TxChemoOS	Text	Treatment - Chemo - Other - Specify
TxPal	Yes/No	Treatment - Palliation
TxPalRes	Yes/No	Treatment - Palliation - Pall. Resection
TxPalBypass	Yes/No	Treatment - Palliation - Bypass
TxPalCeliac	Yes/No	Treatment - Palliation - Celiac Block
TxPalPara	Yes/No	Treatment - Palliation - Paracentesis
TxPalTho	Yes/No	Treatment - Palliation - Thoracentesis
TxPalRad	Yes/No	Treatment - Palliation - Pall. Radiation
TxPalTrans	Yes/No	Treatment - Palliation - Transfusion
TxPalStens	Yes/No	Treatment - Palliation - Pall. Stenting
TxPalPV	Yes/No	Treatment - Palliation - PV Shunts
TxPalHAL	Yes/No	Treatment - Palliation - HAL
TxPalGasTube	Yes/No	Treatment - Palliation - Gastrostomy Tube
TxPalJejTube	Yes/No	Treatment - Palliation - Jejunstomy Tube
TxPalOth	Yes/No	Treatment - Palliation - Other
TxPalOS	Text	Treatment - Palliation - Other - Specify
TxExp	Yes/No	Treatment - Experimental protocol (ie. vaccine)
TxGene	Yes/No	Treatment - Gene Counseling

Figure 120: Colorectal Cancer Treatment Table Schema

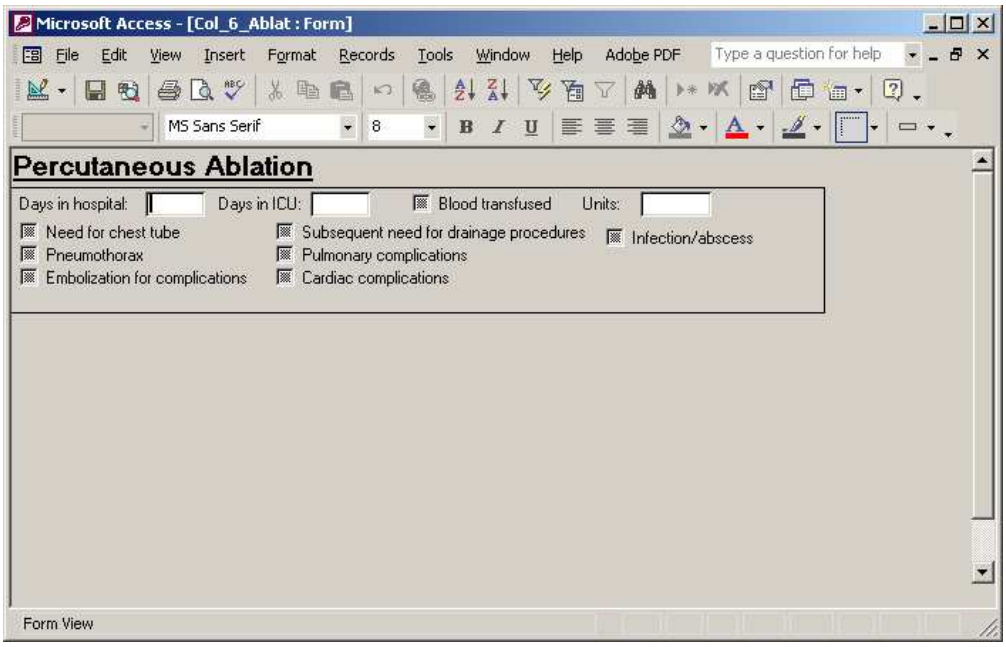


Figure 121: Colorectal Cancer Ablation Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
Per_DIH	Number	Days in Hospital
Per_ICU	Number	Days in ICU
Per_Trans	Yes/No	Blood Transfusion
Per_Trans_Units	Number	Units
Per_chest	Yes/No	Chest Tube
Per_pneu	Yes/No	Pneumothorax
Per_emb	Yes/No	Embolization
Per_sub	Yes/No	Subsequent Drainage
Per_pul	Yes/No	Pulmonary Complications
Per_car	Yes/No	Cardiac Complications
Per_inf	Yes/No	Infection/Abscess

Figure 122: Colorectal Cancer Ablation Table Schema

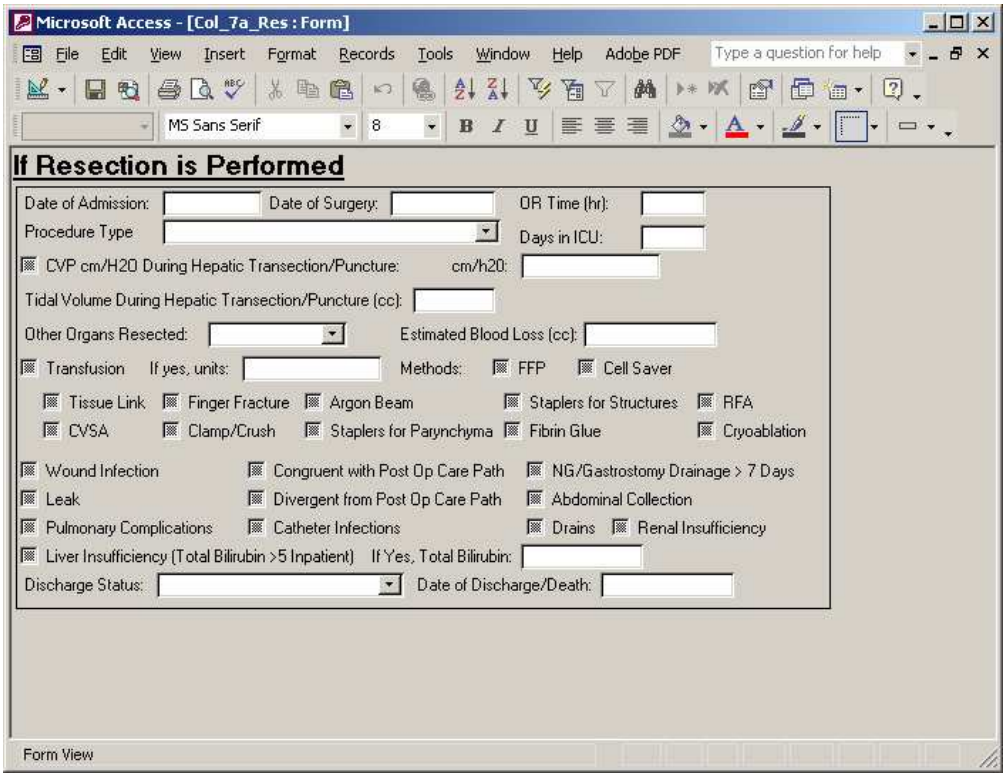


Figure 123: Colorectal Cancer Resection Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
DAdm	Date/Time	Date of Admission
DSurg	Date/Time	Date of Surgery
ORTime	Number	OR Time
PxType	Number	Procedure Type
Organs	Text	Other Organs Resected
BloodLoss	Number	Blood Loss (cc)
CVP	Yes/No	CVP cm/H20 During Hepatic Transection/Puncture
CVPcm	Number	CVP cm/H20
Tidalcc	Number	Tidal Volume During Hepatic Transection/Puncture (cc)
Transfusion	Yes/No	Transfusion - Needed?
T_Units	Number	Transfusion - Units
T_FFP	Yes/No	Transfusion - Fresh Frozen Plasma
T_Cell	Yes/No	Transfusion - Cell Saver
T_Tissue	Yes/No	Transfusion - Tissue Link
T_CVSA	Yes/No	Transfusion - CVSA
T_Finger	Yes/No	Transfusion - Finger Fracture
T_Clamp	Yes/No	Transfusion - Clamp/Crush
T_Argon	Yes/No	Transfusion - Argon Beam
T_Pary	Yes/No	Transfusion - Staplers for Parynchyma
T_Struct	Yes/No	Transfusion - Staplers for Structures
T_Glue	Yes/No	Transfusion - Fibrin Glue
T_RFA	Yes/No	Transfusion - RFA
T_Cry	Yes/No	Transfusion - Cryoablation
ICUdays	Number	Days in ICU
Infection	Yes/No	PO - Wound Infection
Leak	Yes/No	PO - Leak

Figure 124: Colorectal Cancer Resection Table Schema

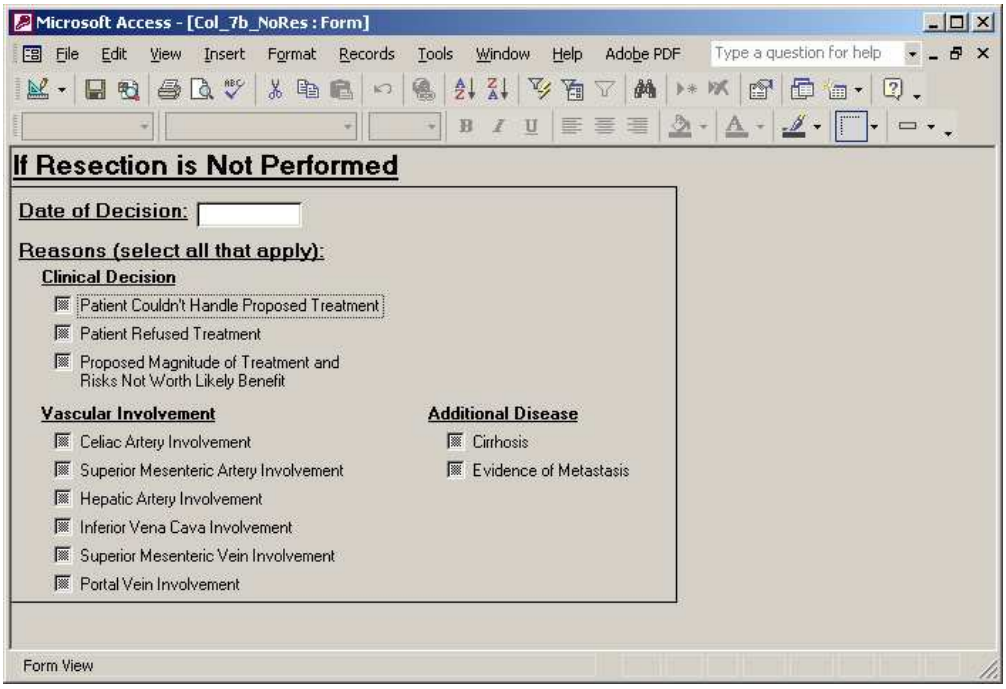


Figure 125: Colorectal Cancer No Resection Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
NoResEvalDate	Date/Time	No Resection - Decision Date
NoResNoHandle	Yes/No	No Resection - Couldn't Handle Proposed Treatment
NoResRefused	Yes/No	No Resection - Refused Treatment
NoResMagnitude	Yes/No	No Resection - Magnitude Not Worth Benefits
NoResCeliacInvolve	Yes/No	No Resection - Celiac Trunk Involvement
NoResSMAInvolve	Yes/No	No Resection - SMA Involvement
NoResHepaticInvolve	Yes/No	No Resection - Hepatic Involvement
NoResIVCInvolve	Yes/No	No Resection - Inferior Vena Cava Involvement
NoResSMVInvolve	Yes/No	No Resection - SMV Involvement
NoResPVInvolve	Yes/No	No Resection - Portal Vein Involvement
NoResCirrhosis	Yes/No	No Resection - Cirrhosis
NoResMetastatic	Yes/No	No Resection - Metastatic

Figure 126: Colorectal Cancer No Resection Table Schema

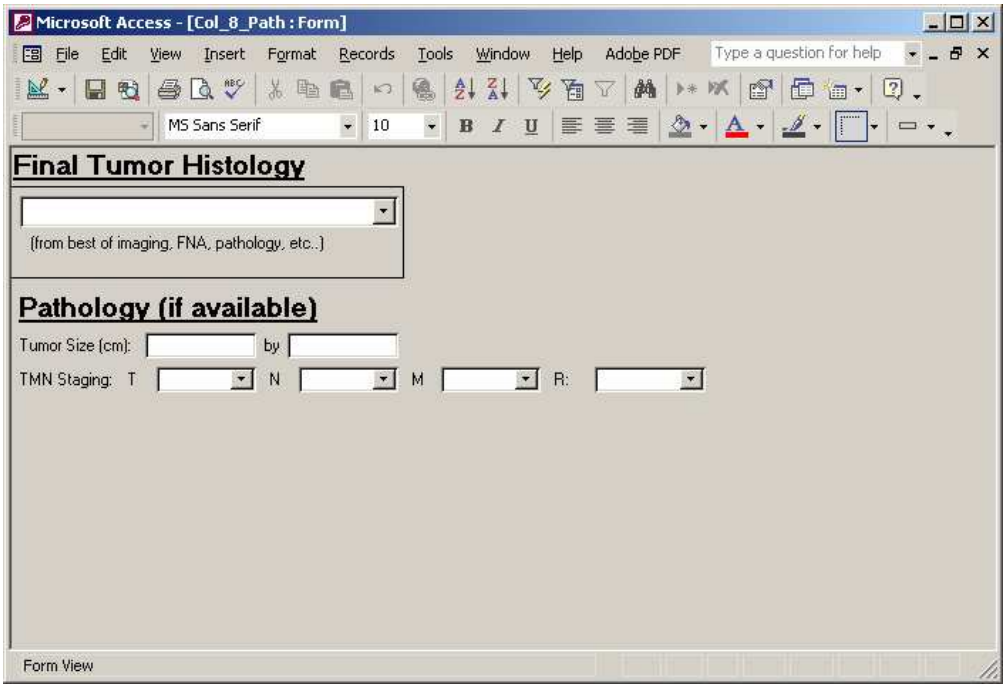


Figure 127: Colorectal Cancer Pathology Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	Meditech Medical Record Number for Patient
Histology	Number	Histology
ResPathT	Number	Resection - Pathology Staging - T
ResPathN	Number	Resection - Pathology Staging - N
ResPathM	Number	Resection - Pathology Staging - M
ResPathR	Number	Resection - Pathology Staging - R
ResPathV	Number	Resection - Pathology Staging - R
ResPathSizeX	Number	Resection - Pathology Tumor Size (cm) - Width
ResPathSizeY	Number	Resection - Pathology Tumor Size (cm) - Height

Figure 128: Colorectal Cancer Pathology Table Schema

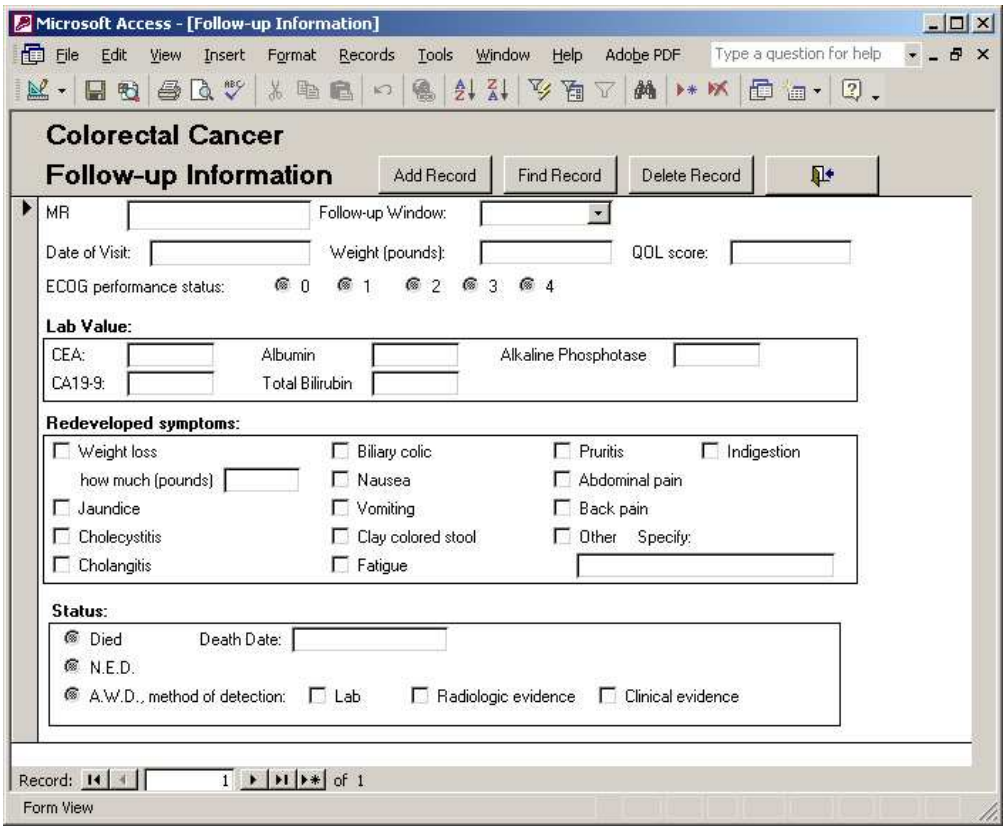


Figure 129: Colorectal Cancer Follow-Up Form

Field Name	Data Type	Description
ID	AutoNumber	
MR	Text	Meditech Medical Record Number for Patient
FUWin	Number	Follow-Up Windows
VisitDate	Date/Time	Visit Date
Weight	Number	Weight (lbs.)
QOLscore	Number	QoL Score (0-100)
ECOG	Number	ECOG Score (0-4)
LabCEA	Number	Laboratory - CEA
LabCA19-9	Number	Laboratory - CA19-9
LabAlb	Number	Laboratory - Albumin
LabBili	Number	Laboratory - Bilirubin
LabAlka	Number	Laboratory - Alkaline phosphotase
SxWtloss	Yes/No	Symptoms - Weight Loss
SxWtlossP	Number	Symptoms - Weight Loss (lbs.)
SxJaun	Yes/No	Symptoms - Jaundice
SxChole	Yes/No	Symptoms - Cholecystitis
SxChola	Yes/No	Symptoms - Cholangitis
SxBC	Yes/No	Symptoms - Biliary Colic
SxNau	Yes/No	Symptoms - Nausea
SxVom	Yes/No	Symptoms - Vomiting
SxCCS	Yes/No	Symptoms - Clay Colored Stool
SxFati	Yes/No	Symptoms - Fatigue
SxPru	Yes/No	Symptoms - Pruritis
SxInd	Yes/No	Symptoms - Indigestion
SxAbd	Yes/No	Symptoms - Abdominal Pain
SxBack	Yes/No	Symptoms - Back Pain
SxOT	Yes/No	Symptoms - Other
SxOTSpe	Text	Symptoms - Other - Specify
Status	Number	Status (NED, AWD, Died)
DeathDate	Date/Time	Death Date
StatusAWDLab	Yes/No	AWD - Lab Evidence
StatusAWDRad	Yes/No	AWD - Radiology Evidence
StatusAWDCli	Yes/No	AWD - Clinical Evidence

Figure 130: Colorectal Cancer Follow-Up Table Schema

3.2 Breast Cancer Database

The table schema and interface layout was designed with the help of UMass Medical School oncologists through one-on-one work and efforts of a database committee headed by Dr. Robert Quinlan.

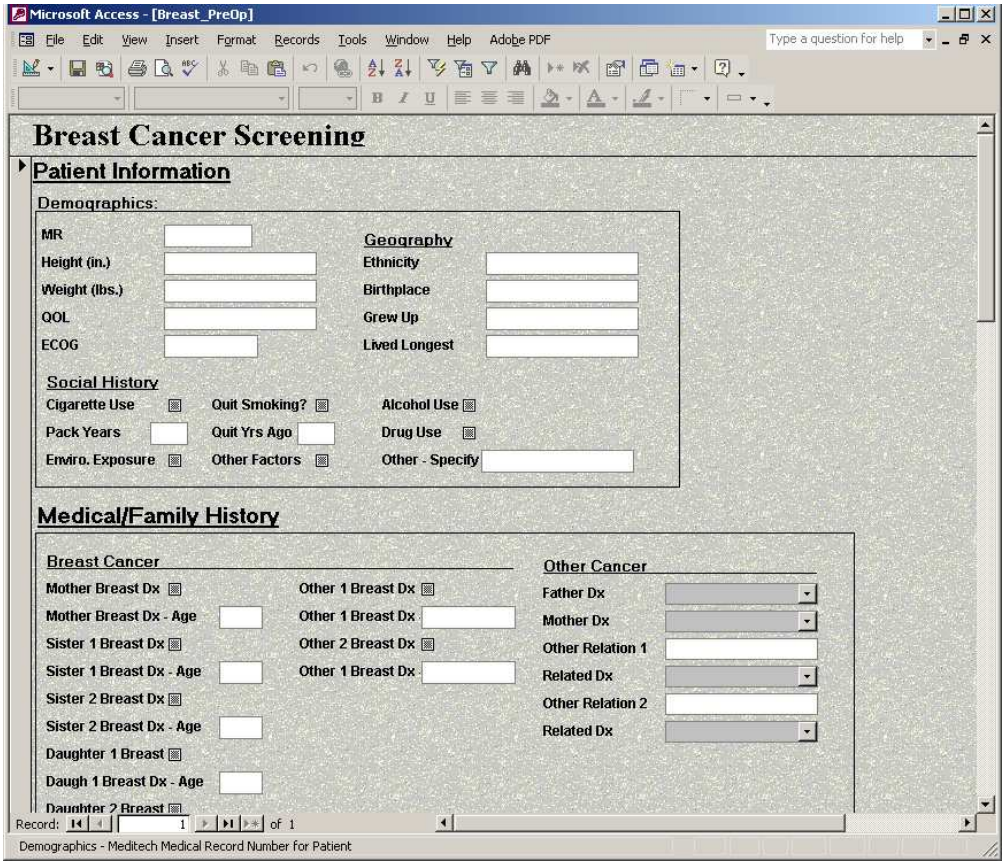


Figure 131: Breast Cancer Screening Form

Field Name	Data Type	Description
ID	AutoNumber	ID
MR	Text	MR
DemMR	Text	Demographics - Meditech Medical Record Number for Patient
DemHeight	Number	Demographics - Height in Inches of Patient
DemWeight	Number	Demographics - Weight in Pounds of Patient at Admission
DemQOL	Number	Demographics - QOL Score (0-100)
DemECOG	Number	Demographics - ECOG Score (0-4)
DemSHCigarette	Yes/No	Demographics - Social History - Cigarettes (significant use)
DemSHCigarettePYrs	Number	Demographics - Social History - Cigarettes - Pack Years
DemSHCigaretteQuit	Yes/No	Demographics - Social History - Cigarettes - Quit?
DemSHCigaretteQuitYrs	Text	Demographics - Social History - Cigarettes - Quit? - Years
DemSHAlcohol	Yes/No	Demographics - Social History - Alcohol (significant use)
DemSHDrugUse	Yes/No	Demographics - Social History - Drug Use
DemSHExposure	Yes/No	Demographics - Social History - Environmental Exposure
DemSHOther	Yes/No	Demographics - Social History - Other
DemSHOtherS	Text	Demographics - Social History - Other - Specify
DemEthnicity	Text	Demographics - Ethnicity
DemGeographyBP	Text	Demographics - Geography - Birthplace
DemGeographyGU	Text	Demographics - Geography - Grew Up
DemGeographLL	Text	Demographics - Geography - Lived Longest
FamilyBreastMother	Yes/No	Family History - Mother Breast Dx
FamilyBreastMotherAge	Number	Family History - Mother Breast Dx Age
FamilyBreastSister1	Yes/No	Family History - Sister1 Breast Dx
FamilyBreastSister1Age	Number	Family History - Sister1 Breast Dx Age
FamilyBreastSister2	Yes/No	Family History - Sister2 Breast Dx
FamilyBreastSister2Age	Number	Family History - Sister2 Breast Dx Age
FamilyBreastDaughter1	Yes/No	Family History - Daughter1 Breast Dx
FamilyBreastDaughter1Age	Number	Family History - Daughter1 Breast Dx Age
FamilyBreastDaughter2	Yes/No	Family History - Daughter2 Breast Dx
FamilyBreastDaughter2Age	Number	Family History - Daughter2 Breast Dx Age
FamilyBreastOther1	Yes/No	Family History - Other1 Breast Dx
FamilyBreastOther1Age	Number	Family History - Other1 Breast Dx Age
FamilyBreastOther2	Yes/No	Family History - Other2 Breast Dx
FamilyBreastOther2Age	Number	Family History - Other2 Breast Dx Age
FamilyFatherDx	Number	Family History - Father Dx
FamilyMotherDx	Number	Family History - Mother Dx
FamilyOther1	Text	Family History - Other1
FamilyOther1Dx	Number	Family History - Other1 Dx
FamilyOther2	Text	Family History - Other2
FamilyOther2Dx	Number	Family History - Other2 Dx
PriorBiopDate1	Date/Time	Prior Breast Biopsy - Date1
PriorBiopPlace1	Text	Prior Breast Biopsy - Place1
PriorBiopType1	Text	Prior Breast Biopsy - Type1
PriorBiopFindings1	Text	Prior Breast Biopsy - Findings1
PriorBiopDate2	Date/Time	Prior Breast Biopsy - Date2
PriorBiopPlace2	Text	Prior Breast Biopsy - Place2
PriorBiopType2	Text	Prior Breast Biopsy - Type2
PriorBiopFindings2	Text	Prior Breast Biopsy - Findings2
ReproMenses	Number	Repro History - Menses Onset
ReproLastMenstrual	Date/Time	Repro History - Last Menstrual Date
ReproMenoType	Number	Repro History - Menopause Type
ReproPregnancies	Number	Repro History - Pregnancies
ReproChildren	Number	Repro History - Children
ReproAbortions	Number	Repro History - Abortions
ReproAgeFirstBirth	Number	Repro History - Age of First Birth
ReproAgeMenopause	Number	Repro History - Age of Menopause
ReproBreastFeeding	Number	Repro History - Breast Feeding
ReproHormoneOral	Number	Repro History - Hormone - Oral Contraceptives
ReproHormoneFertility	Number	Repro History - Hormone - Fertility Treatments
ReproHormoneHRT	Number	Repro History - Hormone - Hormone Replacement Therapy
ReproHormoneHolistic	Number	Repro History - Hormone - Holistic/Homeopathic
ReproGeneticCounseling	Memo	Repro History - Genetic Counseling Notes
SxSympPrimary	Number	Initial Symptoms - Primary Symptom
SxSympSecondary1	Number	Initial Symptoms - Secondary Symptom
SxSympSecondary2	Number	Initial Symptoms - Secondary Symptom
SxSympSecondary3	Number	Initial Symptoms - Secondary Symptom
SxBreastMassDiscovery	Text	Initial Symptoms - Breast Mass - Discovery
SxMastalgia	Yes/No	Initial Symptoms - Mastalgia
SxMastalgiaType	Number	Initial Symptoms - Mastalgia - Type
SxNDischarge	Yes/No	Initial Symptoms - Nipple Discharge
SxNDischargeType	Text	Initial Symptoms - Nipple Discharge - Type
SxAxillaryMass	Yes/No	Initial Symptoms - Axillary Mass
SxRetraction	Yes/No	Initial Symptoms - Nipple/Skin Retraction
SxSystemicPain	Yes/No	Initial Symptoms - Systemic - Pain
SxSystemicWeightLoss	Yes/No	Initial Symptoms - Systemic - Weight Loss
SxSystemicWeightLossLbs	Number	Initial Symptoms - Systemic - Weight Loss Lbs.
SxSystemicDyspnea	Yes/No	Initial Symptoms - Systemic - Dyspnea
SxSystemicNausea	Yes/No	Initial Symptoms - Systemic - Pain
SxSystemicOTSpe	Memo	Initial Symptoms - Systemic - Other
WorkUpScreening	Yes/No	Workup - Screening
WorkUpScreeningType	Number	Workup - Screening - Type
WorkUpBreastMass	Yes/No	Workup - Breast Mass
WorkUpBreastMassSizeX	Number	Workup - Breast Mass - Size - Width (cm)
WorkUpBreastMassSizeY	Number	Workup - Breast Mass - Size - Height (cm)
WorkUpMammo	Number	Workup - Mammogram
WorkUpBiRad	Number	Workup - BIRAD
WorkUpUltra	Number	Workup - Ultrasound
WorkUpMRI	Number	Workup - MRI
BiopPalFNA	Yes/No	Biopsy - Palpable - Fine Needle Aspiration
BiopPalFNAImg	Yes/No	Biopsy - Palpable - Fine Needle Aspiration - Imaging
BiopPalCNB	Yes/No	Biopsy - Palpable - Core-cutting Needle Biopsy
BiopPalCNBImg	Yes/No	Biopsy - Palpable - Core-cutting Needle Biopsy - Imaging
BiopPalIncB	Yes/No	Biopsy - Palpable - Incisional Biopsy
BiopPalIncBImg	Yes/No	Biopsy - Palpable - Incisional Biopsy - Imaging
BiopPalExcB	Yes/No	Biopsy - Palpable - Excisional Biopsy
BiopPalExcBImg	Yes/No	Biopsy - Palpable - Excisional Biopsy - Imaging
BiopNonPalMammo	Yes/No	Biopsy - Non-palpable - Mammography
BiopNonPalUltra	Yes/No	Biopsy - Non-palpable - Ultrasound
BiopDisp	Text	Biopsy - Disposition
CBiopPalFNA	Yes/No	Contra Biopsy - Palpable - Fine Needle Aspiration
CBiopPalFNAImg	Yes/No	Contra Biopsy - Palpable - Fine Needle Aspiration - Imaging
CBiopPalCNB	Yes/No	Contra Biopsy - Palpable - Core-cutting Needle Biopsy
CBiopPalCNBImg	Yes/No	Contra Biopsy - Palpable - Core-cutting Needle Biopsy - Imaging
CBiopPalIncB	Yes/No	Contra Biopsy - Palpable - Incisional Biopsy
CBiopPalIncBImg	Yes/No	Contra Biopsy - Palpable - Incisional Biopsy - Imaging
CBiopPalExcB	Yes/No	Contra Biopsy - Palpable - Excisional Biopsy
CBiopPalExcBImg	Yes/No	Contra Biopsy - Palpable - Excisional Biopsy - Imaging
CBiopNonPalMammo	Yes/No	Contra Biopsy - Non-palpable - Mammography
CBiopNonPalUltra	Yes/No	Contra Biopsy - Non-palpable - Ultrasound
CBiopDisp	Text	Contra Biopsy - Disposition

Figure 132: Breast Cancer Screening Table Schema

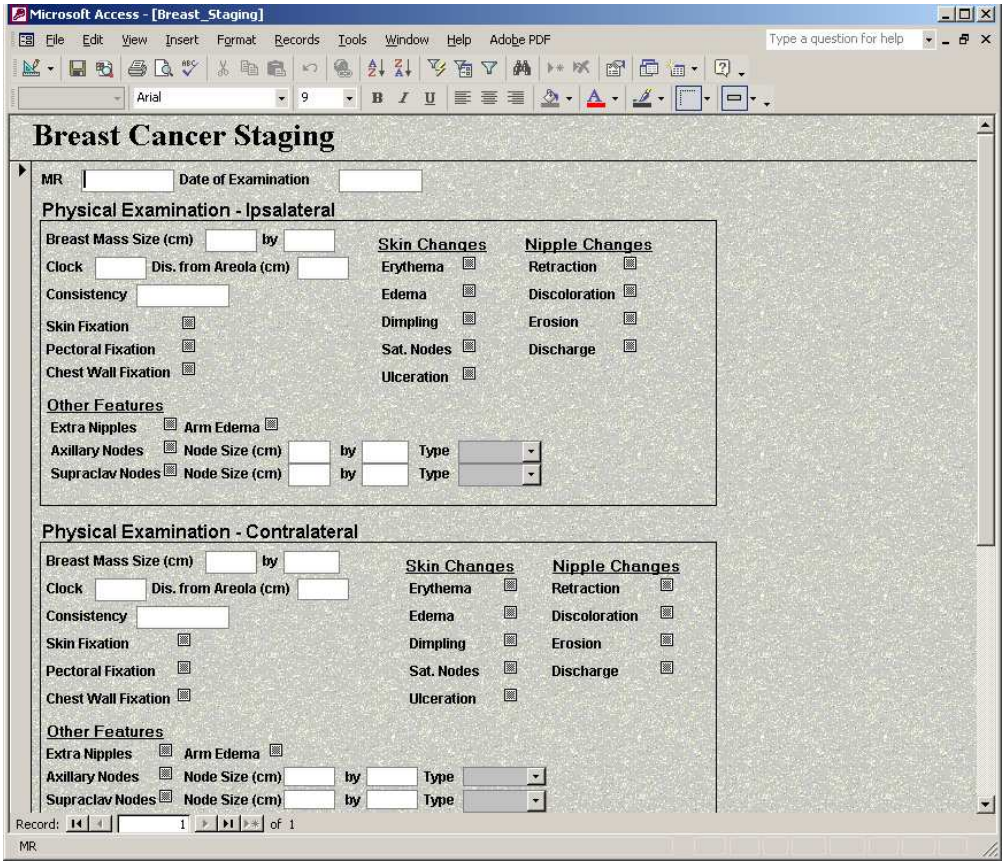


Figure 133: Breast Cancer Staging Form

Field Name	Data Type	Description
ID	AutoNumber	
MR	Text	MR
Date	Date/Time	Date of Examination
Ipsa_Mass_SizeX	Number	Physical Exam - Ipsa - Breast Mass - SizeX
Ipsa_Mass_SizeY	Number	Physical Exam - Ipsa - Breast Mass - SizeY
Ipsa_Mass_Clock	Number	Physical Exam - Ipsa - Breast Mass - Clock
Ipsa_Mass_AreolaD	Number	Physical Exam - Ipsa - Breast Mass - Areola Distance
Ipsa_Mass_Consistency	Text	Physical Exam - Ipsa - Breast Mass - Consistency
Ipsa_Mass_FixSkin	Yes/No	Physical Exam - Ipsa - Breast Mass - Skin Fixation
Ipsa_Mass_FixPect	Yes/No	Physical Exam - Ipsa - Breast Mass - Pectoral Fixation
Ipsa_Mass_FixChest	Yes/No	Physical Exam - Ipsa - Breast Mass - Chest Wall Fixation
Ipsa_Skin_Erythema	Yes/No	Physical Exam - Ipsa - Skin Changes - Erythema
Ipsa_Skin_Edema	Yes/No	Physical Exam - Ipsa - Skin Changes - Edema
Ipsa_Skin_Dimpling	Yes/No	Physical Exam - Ipsa - Skin Changes - Dimpling
Ipsa_Skin_Satellite	Yes/No	Physical Exam - Ipsa - Skin Changes - Satellite Nodes
Ipsa_Skin_Ulceration	Yes/No	Physical Exam - Ipsa - Skin Changes - Ulceration
Ipsa_Nipple_Retraction	Yes/No	Physical Exam - Ipsa - Nipple Changes - Retraction
Ipsa_Nipple_Discolor	Yes/No	Physical Exam - Ipsa - Nipple Changes - Discoloration
Ipsa_Nipple_Erosion	Yes/No	Physical Exam - Ipsa - Nipple Changes - Erosion
Ipsa_Nipple_Discharge	Yes/No	Physical Exam - Ipsa - Nipple Changes - Discharge
Ipsa_Extra_Nipples	Yes/No	Physical Exam - Ipsa - Extra Nipples
Ipsa_Nodes_Axil	Yes/No	Physical Exam - Ipsa - Axillary Nodes
Ipsa_Nodes_Axil_SizeX	Number	Physical Exam - Ipsa - Axillary Nodes - SizeX
Ipsa_Nodes_Axil_SizeY	Number	Physical Exam - Ipsa - Axillary Nodes - SizeY
Ipsa_Nodes_Axil_Type	Number	Physical Exam - Ipsa - Axillary Nodes - Type
Ipsa_Nodes_Clav	Yes/No	Physical Exam - Ipsa - Supraclavicular Nodes
Ipsa_Nodes_Clav_SizeX	Number	Physical Exam - Ipsa - Supraclavicular Nodes - SizeX
Ipsa_Nodes_Clav_SizeY	Number	Physical Exam - Ipsa - Supraclavicular Nodes - SizeY
Ipsa_Nodes_Clav_Type	Number	Physical Exam - Ipsa - Supraclavicular Nodes - Type
Ipsa_Arm_Edema	Yes/No	Physical Exam - Ipsa - Arm Edema
Contra_Mass_SizeX	Number	Physical Exam - Contra - Breast Mass - SizeX
Contra_Mass_SizeY	Number	Physical Exam - Contra - Breast Mass - SizeY
Contra_Mass_Clock	Number	Physical Exam - Contra - Breast Mass - Clock
Contra_Mass_AreolaD	Number	Physical Exam - Contra - Breast Mass - Areola Distance
Contra_Mass_Consistency	Text	Physical Exam - Contra - Breast Mass - Consistency
Contra_Mass_FixSkin	Yes/No	Physical Exam - Contra - Breast Mass - Skin Fixation
Contra_Mass_FixPect	Yes/No	Physical Exam - Contra - Breast Mass - Pectoral Fixation
Contra_Mass_FixChest	Yes/No	Physical Exam - Contra - Breast Mass - Chest Wall Fixation
Contra_Skin_Erythema	Yes/No	Physical Exam - Contra - Skin Changes - Erythema
Contra_Skin_Edema	Yes/No	Physical Exam - Contra - Skin Changes - Edema
Contra_Skin_Dimpling	Yes/No	Physical Exam - Contra - Skin Changes - Dimpling
Contra_Skin_Satellite	Yes/No	Physical Exam - Contra - Skin Changes - Satellite Nodes
Contra_Skin_Ulceration	Yes/No	Physical Exam - Contra - Skin Changes - Ulceration
Contra_Nipple_Retraction	Yes/No	Physical Exam - Contra - Nipple Changes - Retraction
Contra_Nipple_Discolor	Yes/No	Physical Exam - Contra - Nipple Changes - Discoloration
Contra_Nipple_Erosion	Yes/No	Physical Exam - Contra - Nipple Changes - Erosion
Contra_Nipple_Discharge	Yes/No	Physical Exam - Contra - Nipple Changes - Discharge
Contra_Extra_Nipples	Yes/No	Physical Exam - Contra - Extra Nipples
Contra_Nodes_Axil	Yes/No	Physical Exam - Contra - Axillary Nodes
Contra_Nodes_Axil_SizeX	Number	Physical Exam - Contra - Axillary Nodes - SizeX
Contra_Nodes_Axil_SizeY	Number	Physical Exam - Contra - Axillary Nodes - SizeY
Contra_Nodes_Axil_Type	Number	Physical Exam - Contra - Axillary Nodes - Type
Contra_Nodes_Clav	Yes/No	Physical Exam - Contra - Supraclavicular Nodes
Contra_Nodes_Clav_SizeX	Number	Physical Exam - Contra - Supraclavicular Nodes - SizeX
Contra_Nodes_Clav_SizeY	Number	Physical Exam - Contra - Supraclavicular Nodes - SizeY
Contra_Nodes_Clav_Type	Number	Physical Exam - Contra - Supraclavicular Nodes - Type
Contra_Arm_Edema	Yes/No	Physical Exam - Contra - Arm Edema
Imaging_Study_1	Number	Imaging - Study - 1
Imaging_Study_1_SizeX	Number	Imaging - Study - 1 - SizeX
Imaging_Study_1_SizeY	Number	Imaging - Study - 1 - SizeY
Imaging_Study_2	Number	Imaging - Study - 2
Imaging_Study_2_SizeX	Number	Imaging - Study - 2 - SizeX
Imaging_Study_2_SizeY	Number	Imaging - Study - 2 - SizeY
Imaging_Study_3	Number	Imaging - Study - 3
Imaging_Study_3_SizeX	Number	Imaging - Study - 3 - SizeX
Imaging_Study_3_SizeY	Number	Imaging - Study - 3 - SizeY
Imaging_Study_4	Number	Imaging - Study - 4
Imaging_Study_4_SizeX	Number	Imaging - Study - 4 - SizeX
Imaging_Study_4_SizeY	Number	Imaging - Study - 4 - SizeY
Imaging_Study_5	Number	Imaging - Study - 5
Imaging_Study_5_SizeX	Number	Imaging - Study - 5 - SizeX
Imaging_Study_5_SizeY	Number	Imaging - Study - 5 - SizeY
Primary_Stage	Number	Staging - Primary Tumor Stage
Node_Stage	Number	Staging - Lymph Node Stage
Mets_Stage	Number	Staging - Metastatic Stage
Prelim_Outlook	Number	Preliminary Outlook

Figure 134: Breast Cancer Staging Table Schema

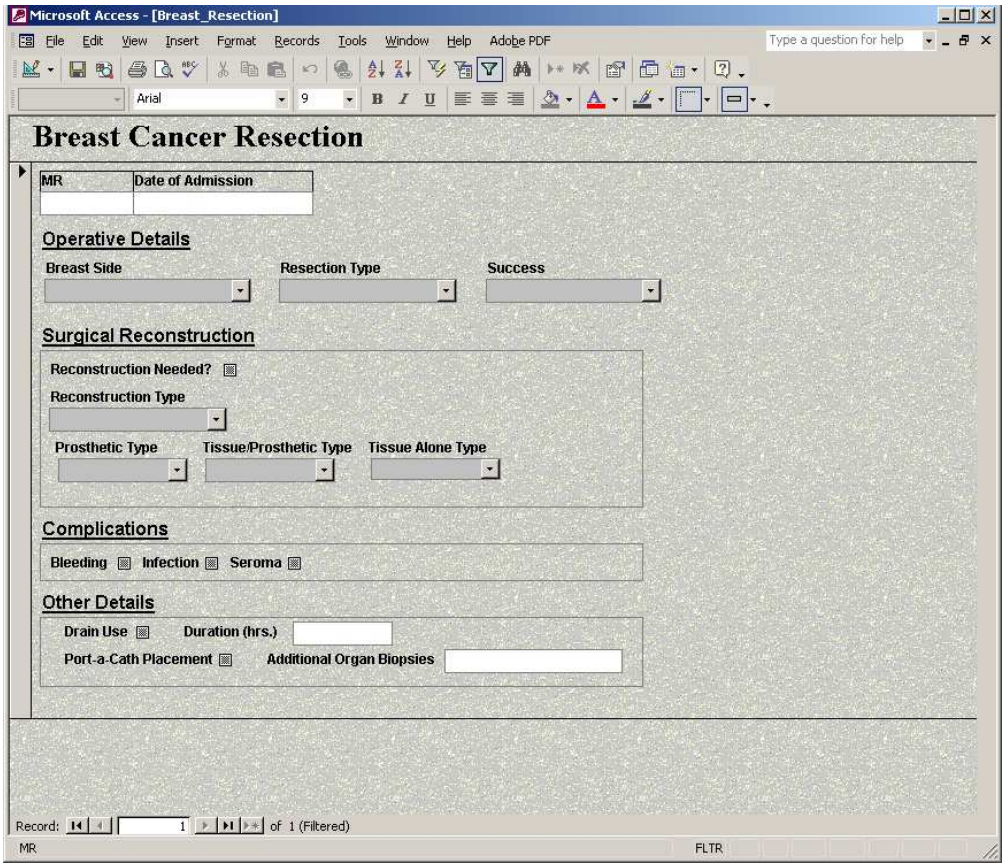


Figure 135: Breast Cancer Resection Form

Field Name	Data Type	Description
ID	AutoNumber	
MR	Text	MR
Date	Date/Time	Date of Admission/Surgery
Breast_Side	Number	Breast Side
Resection_Type	Number	Resection Type
Reconstruction	Yes/No	Reconstruction
Reconstruction_Type	Number	Reconstruction - Type
Pros_Type	Number	Reconstruction - Prosthetic Type
Tiss_Pros_Type	Number	Reconstruction - Tissue/Prosthetic Type
Tiss_Alone_Type	Number	Reconstruction - Tissue Alone Type
Drain_Use	Yes/No	Drain Use
Drain_Use_Duration	Number	Drain Use - Duration
Comp_Bleed	Yes/No	Complications - Bleeding
Comp_Infection	Yes/No	Complications - Infection
Comp_Seroma	Yes/No	Complications - Seroma
Other_Catheter	Yes/No	Other - Port-a-Cath
Other_Biopsies	Text	Other - Additional Organ Biopsies
Success	Number	Resection Success

Figure 136: Breast Cancer Resection Table Schema

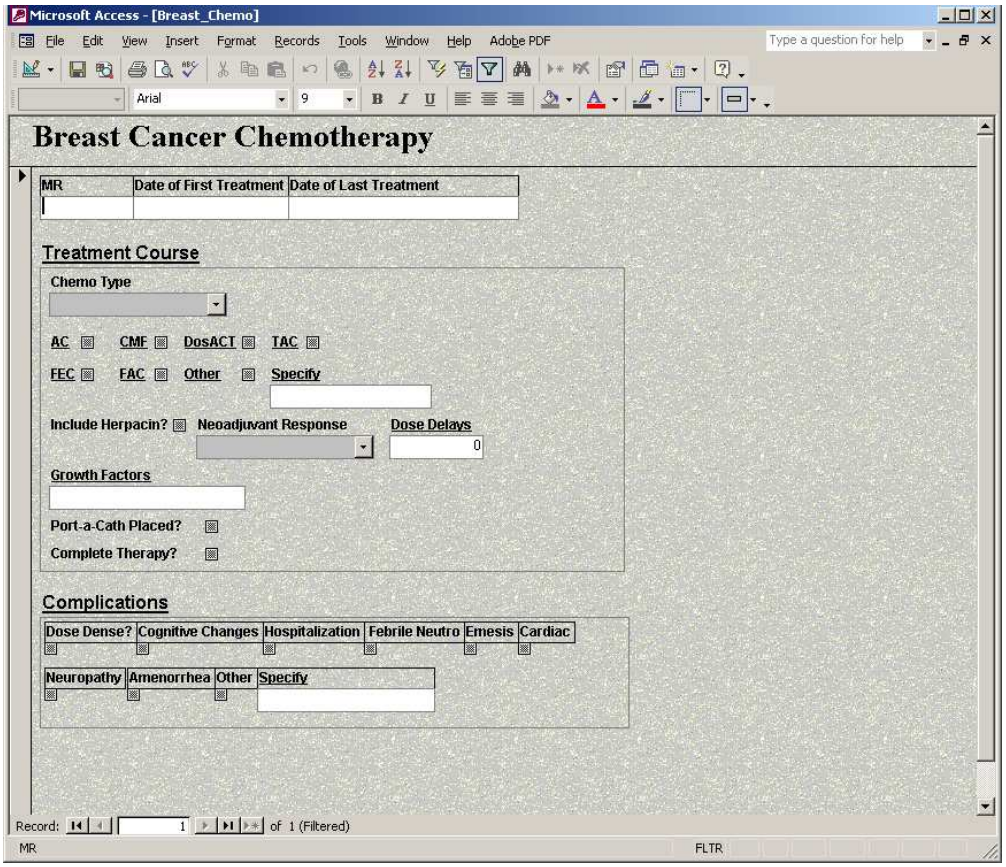


Figure 137: Breast Cancer Chemotherapy Form

Field Name	Data Type	Description
ID	AutoNumber	
MR	Text	MR
Date_First	Date/Time	Date of First Treatment
Date_Last	Date/Time	Date of Last Treatment
Chemo_Type	Number	Chemo - Type
Chemo_AC	Yes/No	Chemo - AC
Chemo_CMF	Yes/No	Chemo - CMF
Chemo_DosACT	Yes/No	Chemo - DosACT
Chemo_TAC	Yes/No	Chemo - TAC
Chemo_FEC	Yes/No	Chemo - FEC
Chemo_FAC	Yes/No	Chemo - FAC
Chemo_Other	Yes/No	Chemo - Other
Chemo_OtherS	Text	Chemo - Other - Specify
Chemo_Herpacin	Yes/No	Chemo - Herpacin
Neo_Response	Number	Neoadjuvant Response
Dose_Delays	Number	Dose Delays
Growth_Factors	Text	Growth Factors
Dose_Dense	Yes/No	Dose Dense
Comp_Cog	Yes/No	Complications - Cognitive Changes
Comp_Hosp	Yes/No	Complications - Hospitalization
Comp_Feb	Yes/No	Complications - Febrile Neutro
Comp_Eme	Yes/No	Complications - Emesis
Comp_Car	Yes/No	Complications - Cardiac
Comp_Neu	Yes/No	Complications - Neuropathy
Comp_Ame	Yes/No	Complications - Amenorrhea
Comp_Other	Yes/No	Complications - Other
Comp_OtherS	Text	Complications - Other - Specify
Other_Catheter	Yes/No	Other - Port-a-Cath
Complete	Yes/No	Complete Therapy?

Figure 138: Breast Cancer Chemotherapy Table Schema

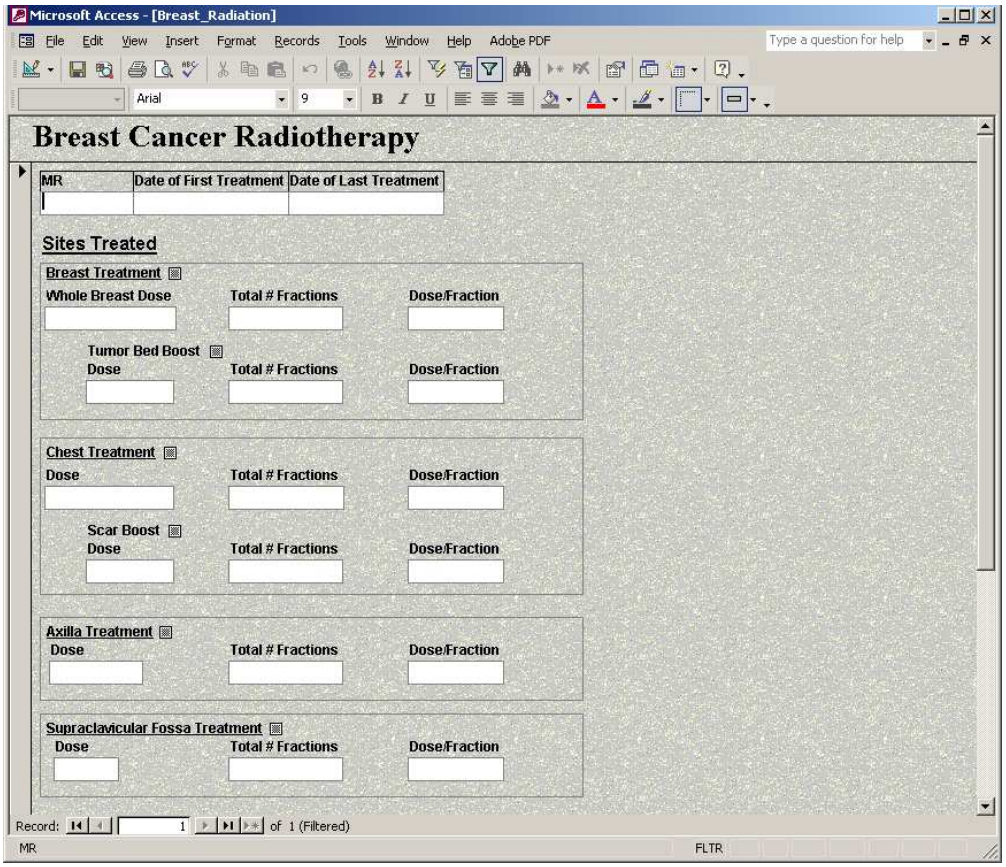


Figure 139: Breast Cancer Radiotherapy Form

Field Name	Data Type	Description
ID	AutoNumber	
MR	Text	MR
Date_First	Date/Time	Date of First Treatment
Date_Last	Date/Time	Date of Last Treatment
Breast_Treatment	Yes/No	Breast - Treatment
Breast_Dose	Number	Breast - Whole Breast Dose
Breast_Fractions	Number	Breast - Total # Fractions
Breast_FracDose	Number	Breast - Dose/Fraction
Breast_Boost	Yes/No	Breast - Tumor Bed Boost
Breast_Boost_Dose	Number	Breast - Tumor Bed Boost - Dose
Breast_Boost_Fractions	Number	Breast - Tumor Bed Boost - Total # Fractions
Breast_Boost_FracDose	Number	Breast - Tumor Bed Boost - Dose/Fraction
Chest_Treatment	Yes/No	Chest - Treatment
Chest_Dose	Number	Chest - Whole Breast Dose
Chest_Fractions	Number	Chest - Total # Fractions
Chest_FracDose	Number	Chest - Dose/Fraction
Chest_Boost	Yes/No	Chest - Scar Boost
Chest_Boost_Dose	Number	Chest - Scar Boost - Dose
Chest_Boost_Fractions	Number	Chest - Scar Boost - Total # Fractions
Chest_Boost_FracDose	Number	Chest - Scar Boost - Dose/Fraction
Axilla_Treatment	Yes/No	Axilla - Treatment
Axilla_Dose	Number	Axilla - Whole Breast Dose
Axilla_Fractions	Number	Axilla - Total # Fractions
Axilla_FracDose	Number	Axilla - Dose/Fraction
Supra_Treatment	Yes/No	Supraclavicular Fossa - Treatment
Supra_Dose	Number	Supraclavicular Fossa - Whole Breast Dose
Supra_Fractions	Number	Supraclavicular Fossa - Total # Fractions
Supra_FracDose	Number	Supraclavicular Fossa - Dose/Fraction
IntNodes_Treatment	Yes/No	Internal Mammary Nodes - Treatment
IntNodes_Dose	Number	Internal Mammary Nodes - Whole Breast Dose
IntNodes_Fractions	Number	Internal Mammary Nodes - Total # Fractions
IntNodes_FracDose	Number	Internal Mammary Nodes - Dose/Fraction
Unsched_Interrupt	Yes/No	Unscheduled Treatment Interruption
Unsched_Interrupt_Days	Number	Unscheduled Treatment Interruption - Days
Unsched_Interrupt_Why	Text	Unscheduled Treatment Interruption - Why?
Complete	Yes/No	Patient Completion
Complete_IfNoWhy	Number	Patient Completion - If No Why
Concur_Chemo_TAM	Yes/No	Concurrent TAM or Chemo?
Toxic_RT	Yes/No	Toxicity of RT
Toxic_RT_Grade	Number	Toxicity of RT - Grade

Figure 140: Breast Cancer Radiotherapy Table Schema

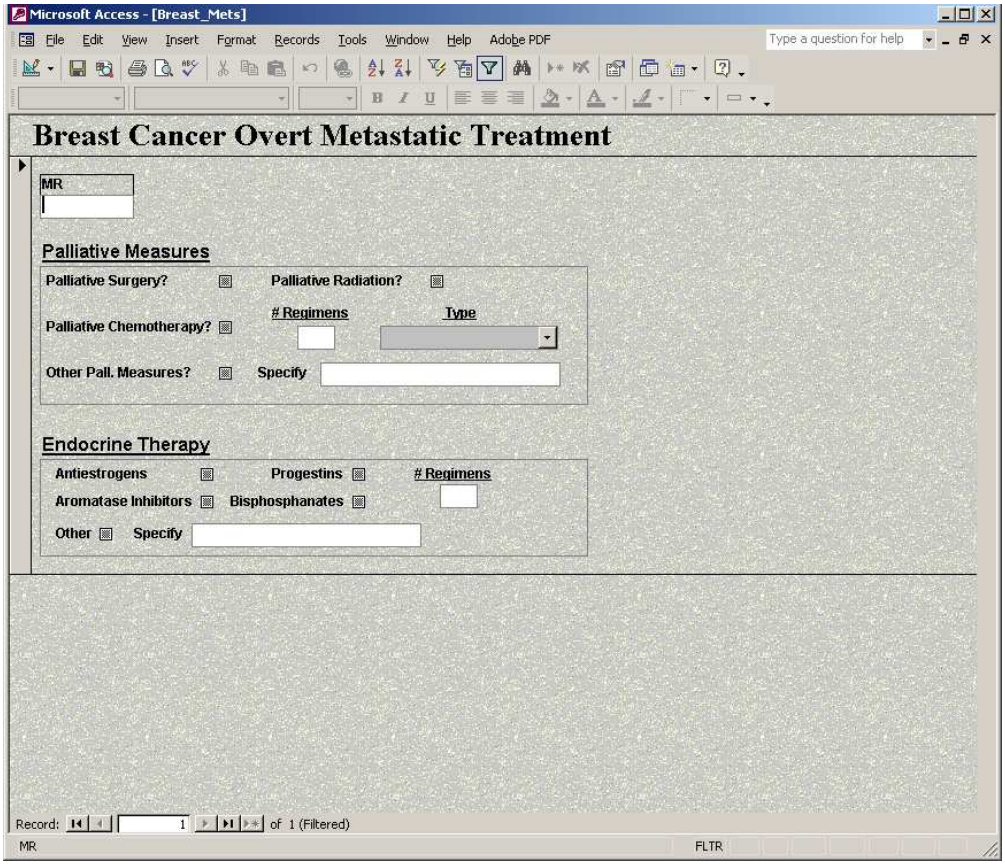


Figure 141: Breast Cancer Metastatic Treatment Form

Field Name	Data Type	Description
ID	AutoNumber	
MR	Text	MR
Palliative_Surgery	Yes/No	Palliative Surgery?
Palliative_Radiation	Yes/No	Palliative Radiation?
Palliative_Chemo	Yes/No	Palliative Chemotherapy?
Palliative_Chemo_Type	Number	Palliative Chemotherapy? - Type
Palliative_Chemo_Regimens	Number	Palliative Chemotherapy? - # Regimens
Palliative_Other	Yes/No	Palliative Other?
Palliative_OtherS	Text	Palliative Other? - Specify
Endoc_Anti	Yes/No	Endocrine Therapy - Antiestrogens
Endoc_Prog	Yes/No	Endocrine Therapy - Progestins
Endoc_Arom	Yes/No	Endocrine Therapy - Aromatase Inhibitors
Endoc_Other	Yes/No	Endocrine Therapy - Other
Endoc_OtherS	Text	Endocrine Therapy - Other - Specify
Endoc_Regimens	Number	Endocrine Therapy - # Regimens
Bisphos	Yes/No	Bisphosphanates

Figure 142: Breast Cancer Metastatic Treatment Table Schema

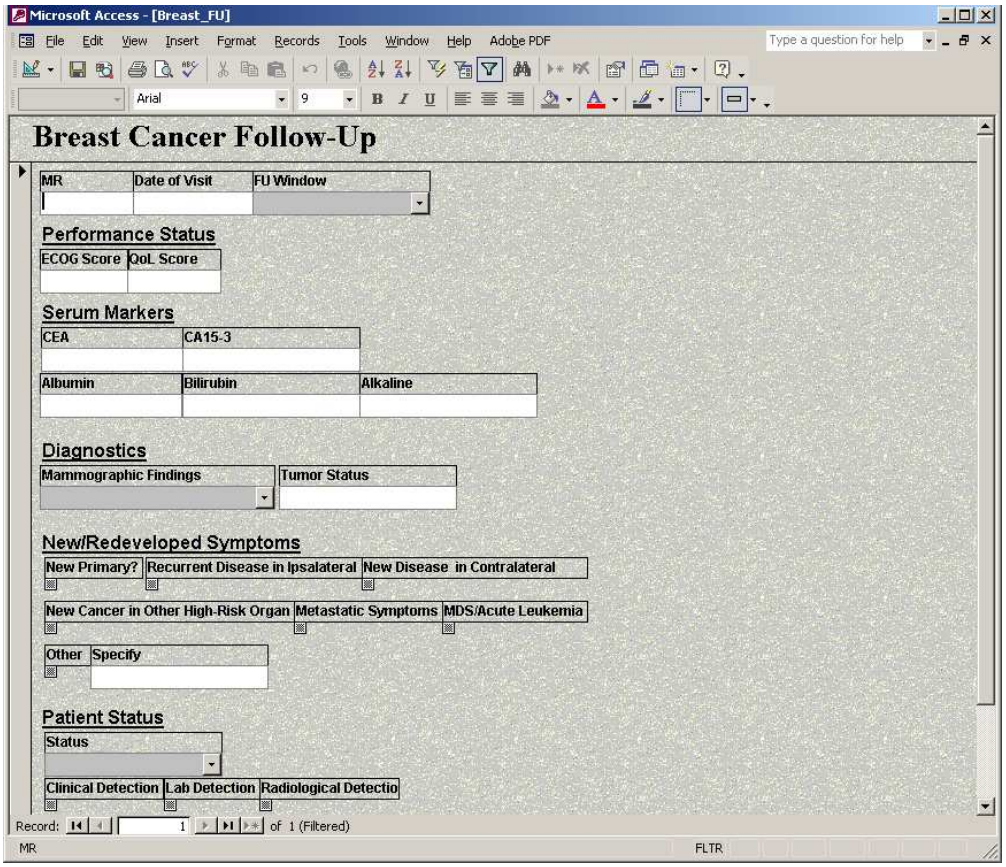


Figure 143: Breast Cancer Follow-Up Form

Field Name	Data Type	Description
ID	AutoNumber	
MR	Text	MR
Date	Date/Time	Date of Visit
FU_Window	Number	FU Window
ECOG	Number	ECOG Score
QoL	Number	QoL Score
LabCEA	Number	CEA
LabCA15-3	Number	CA15-3
LabAlb	Number	Albumin
LabBili	Number	Bilirubin
LabAlka	Number	Alkaline
Mammo_Find	Number	Mammographic Findings
Tumor_Status	Text	Tumor Status
Tumor_Status_Prim	Yes/No	Tumor Status - New Primary?
Redev_Rec	Yes/No	Redeveloped Symptoms - Recurrent Disease in Ipsalateral Breast
Redev_Contra	Yes/No	Redeveloped Symptoms - New Cancer in Contralateral Breast
Redev_Organ	Yes/No	Redeveloped Symptoms - New Cancer in Other High-Risk Organ
Redev_Mets	Yes/No	Redeveloped Symptoms - Metastatic Symptoms
Redev_Leu	Yes/No	Redeveloped Symptoms - MDS/Acute Leukemia
Redev_Other	Yes/No	Redeveloped Symptoms - Other
Redev_OtherS	Text	Redeveloped Symptoms - Other - Specify
Status	Number	Status
Status_AWD_Lab	Yes/No	Status - AWD - Lab Detection
Status_AWD_Rad	Yes/No	Status - AWD - Radiological Detection
Status_AWD_Cli	Yes/No	Status - AWD - Clinical Detection
Status_Died_Date	Date/Time	Status - Died - Date of Death
Status_Died_Cause	Text	Status - Died - Cause of Death

Figure 144: Breast Cancer Follow-Up Table Schema

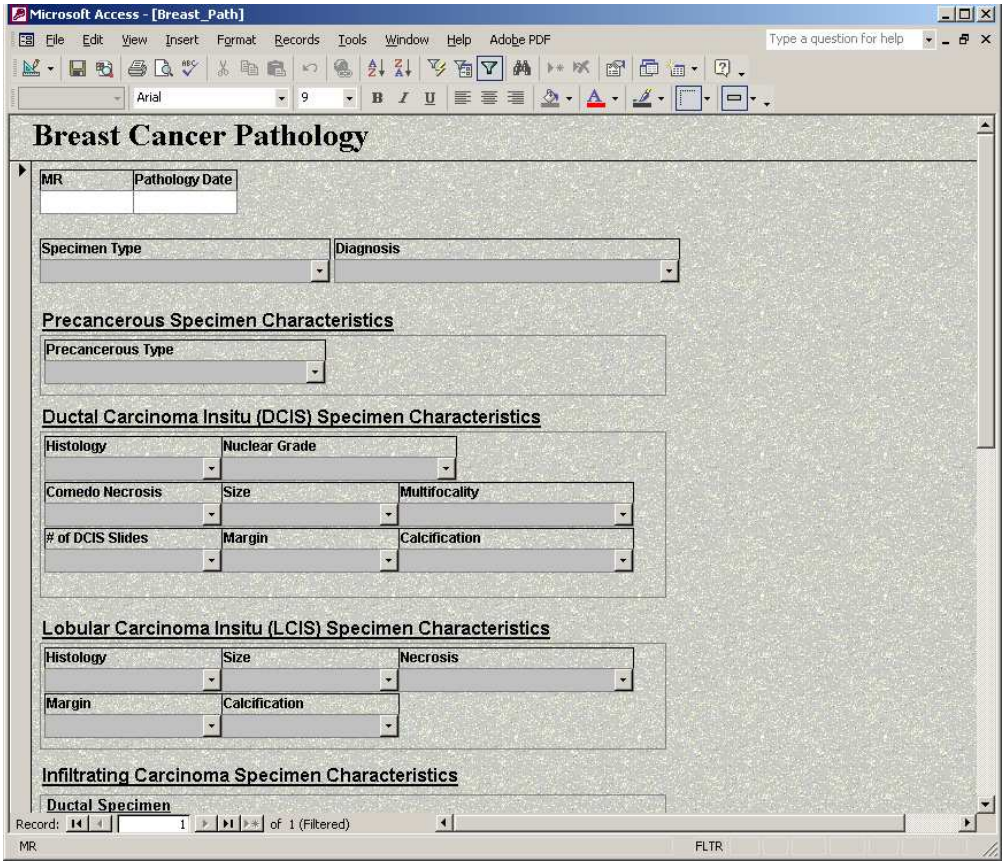


Figure 145: Breast Cancer Pathology Form

Field Name	Data Type	Description
ID	AutoNumber	
MR	Text	MR
Date	Date/Time	Pathology Date
Specimen_Type	Number	Specimen Type
Diag_Type	Number	Diagnosis Type
Precan_Type	Number	Precancerous Type
DCIS_Hist	Number	DCIS Histology
DCIS_Grade	Number	DCIS Grade
DCIS_Comedo	Number	DCIS Comedo Necrosis
DCIS_Size	Number	DCIS Size
DCIS_Multifoc	Number	DCIS Multifocality
DCIS_Slides	Number	DCIS Slides
DCIS_Margin	Number	DCIS Margin
DCIS_Calc	Number	DCIS Calcification
LCIS_Hist	Number	LCIS Histology
LCIS_Size	Number	LCIS Size
LCIS_Necrosis	Number	LCIS Necrosis
LCIS_Margin	Number	LCIS Margin
LCIS_Calc	Number	LCIS Calcification
DIC_Type	Number	DIC Type
LIC_Type	Number	LIC Type
LIC_Grade	Number	LIC Grade
LIC_Size	Number	LIC Size
LIC_LVI	Number	LIC Lymphovascular Invasion
LIC_Necrosis	Number	LIC Necrosis
LIC_Margin	Number	LIC Margin
LIC_Skin	Number	LIC Skin Involvement
LIC_Nipple	Number	LIC Nipple Involvement
LIC_IS_Presense	Number	LIC IS Presense
LIC_IS_Type	Number	LIC IS Type
LIC_IS_Grade	Number	LIC IS Grade
LIC_IS_Invasion	Number	LIC IS Invasion
LIC_IS_EIC	Number	LIC IS EIC
LIC_Node_Type	Number	LIC Node Type
LIC_Node_Pos	Number	LIC Node Positivity
LIC_Node_Extracap	Number	LIC Node Extracapsular Invasion
LIC_Micro	Number	LIC Microcalcification
LIC_Rec_Estro	Number	LIC Estrogen Receptor
LIC_Rec_Prog	Number	LIC Progesterone Receptor
LIC_Rec_IHC	Number	LIC IHC Receptor
LIC_Rec_FISH	Number	LIC FISH Receptor
LIC_Stage	Number	LIC Pathology Stage

Figure 146: Breast Cancer Pathology Table Schema

4 Clinical Performance Machine Learning - Procedure & Design

4.1 Objectives of Analysis

As the pancreatic cancer module was the most developed and populated module within our database, it was chosen to be the focus of our machine learning analysis. Given the aggressive nature of these tumors, treatment decisions may often be a complex and ambiguous task, particularly in regard to resective surgery. Physicians seek *prediction models* to aid in the application of pancreatic cancer therapies in a clinical setting. Prediction models for pancreatic cancer clinical factors, particularly survival rates, have been suggested based on such factors as TNM staging, age, gender, presentation symptoms, medical comorbidities, tumor histology, and relation of disease to vasculature. The majority of these predictive models in modern oncology literature are generated by *regression algorithms* (e.g. linear regression, logistic regression, and Cox's proportional hazard model) [Tse04, FS03, SR02].

We have chosen a set of *prediction targets* for which to develop prediction models. We use linear and logistic regression algorithms, as well as machine learning *classification algorithms* (Bayesian methods, decision trees, k-nearest-neighbor, multi-layer perceptrons, etc.), to generate prediction models which are novel to pancreatic cancer research. Our hope is that these novel prediction models may enlightened and improve upon current treatment methods. For the preparation and analysis of our data, *pre-processing algorithms* will be used, including supervised discretization and correlation-based feature selection. *Meta-learning algorithms*, such as Bagging and AdaBoostM1, will be used to boost prediction model effectiveness. The accuracy of these novel prediction models will be statistically compared to models generated by traditional regression methods. The prediction targets studied will include tumor size, T-staging, N-staging, vasculature involvement, tumor histology, malignancy, survival rates, and ECOG scores at 6-month, 9-month, and 12-month follow-up intervals.

4.2 Patient Data Set

Our study population is composed of pancreatic cancer patients seen over the past three years at UMass Memorial hospital in Worcester, Massachusetts. Complete screening, treatment, and follow-up records were retrospectively compiled from the hospital's Meditech electronic record system into our clinical database. Supervision by the medical staff was provided for the interpretation of ambiguous or incomplete records. A total of 91 evaluations for pancreatic cancer treatment were done between April 2003 and May 2006, representing 87 unique patients.

During these evaluations, all patients were screened for tumor resection using diagnostic imaging and clinical evaluation. A total of 74 (81%) resections were subsequently performed with a surgical success rate (complete excision of tumor) of 96%. Radiotherapy was assigned in 37 (41%) evaluations, chemotherapy in 39 (43%) evaluations, and palliative measures in 11 (12%) evaluations. Among the tumors evaluated, 75 (82%) were deemed potentially resectable, 7 (8%) locally advanced/unresectable, and 9 (10%) metastatic or equivocal. Patient age at time of enrollment ranged from 28.5 to 85.1, with an average age of 63.9. Among the patients, 49 (56%) were female. Distribution and availability of this study's prediction targets are detailed in Tables 6 through 15.

Our objective of effective data mining was challenged by various aspects of this data set. Only a relatively small number of patient instances were available for the study, which is a frequent concern in oncology research. Studies are often constrained by the number of patients seen at an institution, or the rarity of certain disease etiologies [KBK+97]. However, the number of patients available here has proved sufficient in other pancreatic cancer studies [DD04, SR02]. The limited number of patients is made more difficult by the inconsistent availability of certain prediction targets. Factors such as T-stage, N-stage, tumor size, and follow-up ECOG scores are not provided for all patients. Unavailability of clinical factors also extends to many patient attributes.

In an effort to create a detailed clinical database, patient representations in table schemata

are highly dimensional. After serializing attributes are removed, approximately 190 columns of data are processed for each patient instance. Although this creates a very detailed clinical representation of the patient, the attributes vary greatly in importance, accuracy, and availability, which in turn impacts predictive model accuracy. Data typing also varies–both nominal and numeric attributes are captured in a patient instance. As many aspects of the clinical narrative are tracked, from presentation to treatment to follow-up, there are even some theoretical questions as to whether a collaborative interpretation of these factors may be the correct approach.

Finally, there is the issue of skewed class distribution in data sets. In pancreatic cancer, certain values may frequently dominate various clinical factors. For example, in our patient data set, a large majority of the histologic types are ductal adenocarcinoma, T3 value accounts for 76% of all T-stagings, 82% tumors behave in a malignant fashion, and the majority of patients do not require a vascular resection. These data patterns lend themselves to predictive models which underemphasize the importance of correctly predicting non-majority class values.

In our experimental design, various data mining methods are incorporated to compensate for these issues. Use of meta-learning algorithms helps compensate for small data sets and reduces the effect of over-fitting. Supervised discretization creates a uniformly typed set of attributes. Feature selection algorithms pare highly dimensional groups of attributes to smaller sets of independently behaving features which are highly correlated to the target class. Future research will incorporate over-sampling techniques to improve models based on skewed data sets. These techniques will be discussed more thoroughly in the following section.

Value	Count
0.0 - 2.0 cm	19
2.0 - 3.2 cm	20
3.2 - 4.8 cm	18
4.8 cm - inf	17
N = 74	

Table 6: Tumor Size Distribution

Value	Count
T0	1
T1	2
T2	3
T3	39
T4	6
N = 51	

Table 7: T-Stage Distribution

Value	Count
N0	16
N1	34
N2	1
N = 51	

Table 8: N-Stage Distribution

Value	Count
True	13
False	61
N = 74	

Table 9: Vasculature Involvement Distribution

Value	Count
Adenocarcinoma of Pancreas - NOS	24
Ampullary Adenocarcinoma	9
Benign Cyst	1
Cystadenoma	4
Distal Cholangiocarcinoma	1
Duodenal Adenocarcinoma	2
Ductal Adenocarcinoma of Pancreas	27
IPMN - Benign or CiS	11
MEN-I	1
Mucinous Cystic Neoplasm	1
Neuroendocrine	5
Pseudopapillary Tumor	1
Renal Mets	3
Von Hippel-Lindau Syndrome	1
N = 91	

Table 10: Histology Distribution

Value	Count
Benign	16
Malignant	75
N = 91	

Table 11: Malignancy Distribution

Value	Count
0	37
1	27
2	8
N = 68	

Table 12: ECOG 6-Month Distribution

Value	Count
0	33
1	13
2	7
3	4
N = 57	

Table 13: ECOG 9-Month Distribution

Value	Count
0	23
1	12
2	7
3	2
N = 34	

Table 14: ECOG 12-Month Distribution

Value	Count
0 - 6 mo.	20
6 - 12 mo.	20
12 - inf mo.	20
N = 60	

Table 15: Survival Distribution

4.3 Data Mining and Machine Learning Algorithms Used

The following machine learning algorithms are used in our experiments to generate prediction models. In creating prediction models, a target may be interpreted as a *nominal* (categorical) or *numeric* class. The interpretation of the prediction target influence what machine learning algorithms may be applied. Brief descriptions and research citations are provided. All algorithm executions are run using the Weka machine learning workbench [IW05]. The debug parameter is set to False for all algorithm executions.

4.3.1 Benchmark Algorithms

These algorithms generate prediction models which are used as performance benchmarks for our remaining experiments.

- ZeroR - Rudimentary zero-knowledge algorithm used to predict entity classification. ZeroR models in nominal prediction choose the most frequently occurring target classification across all available instances. ZeroR models in numeric prediction choose the average target value of available instances [Mit97].

- Linear Regression - Algorithm which expresses a numeric class as a linear combination of weighted attributes. The weights of each attribute are calculated based on the training data. Weights are chosen during model generation such that sum of squares of differences between the training and prediction instances is minimized. Weka's implementation of linear regression uses Akaike criterion for model selection. Weka parameters used are attributeSelectionMethod = M5 method, eliminateColinearAttributes = True, ridge = 1.0E-8 [Aka74, Dev95].

- Logistic Regression - Works in a similar fashion to linear regression in combining a weighted set of attributes. Used for nominal targets. For dual-class targets, the linear model is based on a logit transformation of the target class. Multiple classes ar generated using pairwise classification. Attribute weights are assigned by maximizing

log-likelihood of the predictive model. Weka parameters used are maxIts = -1, ridge = 1.0E-8 [lCvH92].

4.3.2 Classification Algorithms

Classification algorithms are used to generate prediction models for nominal targets and binned ranges of numeric targets.

- OneR - Rudimentary algorithm which uses single-attribute models to predict entity classification. Also known as 1R or Learn-One-Rule. OneR is known for reasonable accuracy in characterizing experimental data in spite of its relative simplicity. Weka parameters used are minBucketSize = 6 [Mit97].

- J48 - A Java implementation of the C4.5 decision tree learning algorithm. C4.5 is an evolution of the basic ID3 decision tree algorithm which accounts for missing values, continuous attributes, pruning of decision trees, and rule derivation. Weka parameters used are binarySplits = False, confidenceFactor = 0.25, minNumObj = 2, numFolds = 3, reducedErrorPruning = False, saveInstanceData = False, seed = 1, subtreeRaising = True, unpruned = False, useLaplace = False [IW05, Qui93].

- Locally Weighted Learning - Instance-based prediction model which weights training instances in relation to their distance to the test instance. Closer instances are assigned higher weight and more relevance to the prediction. Can be combined with most classifier algorithms. Locally weighted learning plus Naive Bayes is known to be very effective on small data sets and can outperform independent executions of Naive Bayes and k-nearest-neighbor. Weka parameters used are KNN = -1, classifier = NaiveBayes, dontNormalize = False, weightingKernel = 0 [FHP03, AMS97].

- K-Nearest-Neighbor - An instance-based model which produces a classification by calculating the k-closest known members in instance space. Assumes attributes are equally important and normalized. Space between attribute values is calculated using

Euclidean distance. Value of k is determined by cross-validation. Weka parameters used are KNN = varies by experiment, crossValidate = False, distanceWeighting = No distance weighting, meanSquared = False, noNormalization = False, windowSize = 0 [AKA91].

- Naive Bayes - The NaiveBayes algorithm is a predictive classifier based on probability models rooted in Bayes Theorem. It assumes statistical independence amongst the attributes in predicting a target classification. NaiveBayes offers surprising accuracy in characterizing data from a variety of domains despite its statistical simplicity. Weka parameters used are useKernelEstimator = False, useSupervisedDiscretization = False [Mit97].

- Bayes Net - Bayesian networks are directed acyclic graphs which represent complex statistical relationships for attributes of an entity. Bayesian net predictors construct a graph probability model for classification using a specified network evaluator and network-space search function. Weka parameters used are BIFFile = null, estimator = SimpleEstimator -A 0.5, searchAlgorithm = K2 -P [varies by experiment], useADTree = False [IW05].

4.3.3 Regression Algorithms

Regression algorithms are used to generate prediction models for numeric classes.

- M5P - A Java implementation of the M5 algorithm. M5 is a decision tree predictor which builds model trees based on information gain measures. These model trees split the data into test outcomes, which are used to produce a set of multivariate linear regression models. Weka allows both regression trees and model trees to be produced as output. Weka parameters used are buildRegressionTree = False, minNumInstances = 4.0, saveInstances = False, unpruned = False, useUnsmoothed = False [IW05, Qui92].

- Multi-layer Perceptron - A neural network which uses backpropagation to train network connection weights. The number of layers for each model are determined during the experiment. Attributes and numeric classes are normalized during execution. Weka parameters used are GUI = false, autoBuild = False, decay = False, hiddenLayers = varies by experiment, learningRate = 0.3, momentum = 0.2, nominalToBinaryFilter = True, normalizeAttributes = True, normalizeNumericClass = True, randomSeed = 0, reset = True, trainingTime = 500, validationSetSize = 0, validationThreshold = 20 [IW05].

- Radial Basis Function Network - A variation on the multi-layer perceptron which is implemented by a feedforward network. Computation at each hidden node is performed using k-means computation of distance space. The output, or activation, of the node depends on its distance from the input instance–closer distance generates stronger activation. Similarity measures are calculated using a Gaussian activation function. Network output is a linear combination of hidden node outputs. Weka parameters used are clusteringSeed = 1, maxIts = -1, minStdDev = 0.1, numClusters = 2, ridge = 1.0E-8 [MD89].

4.3.4 Data Preprocessing Algorithms

Data preprocessing methods allow us to achieve various representations of the clinical patient data when conducting experiments. These can potentially improve accuracy of the prediction models generated.

- Discretization - Numeric attribute data may be discretized to form nominal attributes. Discretization is either a *supervised* or *unsupervised* process. Unsupervised discretization proceeds by simply binning data into specified ranges. Supervised discretization bins attributes relative to changes in the target classification. Here, we measure changes in target classification using the Minimum Descriptive Length (MDL) principle. Weka

parameters used for supervised discretization are attributeIndices = first-last, invertSelection = False, makeBinary = False, useBetterEncoding = False, useKononenko = False [FI93].

- Feature Selection - Correlation-based Feature Selection (CFS) is an attribute-selection algorithm used for eliminating noisy and redundant features in data sets. Attributes are selected using heuristic search of correlation measurements. Optimal attribute sets exhibit high correlation to their target class and low correlation to other attributes. Feature selection is useful for paring down high-dimensional data. Weka parameters used are evaluator = CfsSubsetEval, search = BestFirst -D 1 -N 5 [Hal98].

4.3.5 Meta-Learning Algorithm

Meta-learning algorithms are used to improve the accuracy of our machine learning tests. Meta-learning refines models to be more robust against noisy data and less susceptible to over-fitting, particularly when dealing with small data sets.

- AdaBoostM1 - AdaBoostM1 works by incrementally running classifiers on samples of test data and combining them into an aggregate model. Each individual or *weak* classifier contributes to the aggregate model in proportion to its accuracy. After each iteration, test data is reweighted based on incorrect aggregate classifications. This boosts the emphasis of misclassified instances, which refines future weak classifier executions. Weka parameters used are classifier = varies by experiment, numIterations = 10, seed = 1, useResampling = False, weightThreshold = 100 [FS96].

- Bagging - Bagging (or Bootstrap Aggregating) works similarly to Boosting by combining the results of multiple classifiers into an aggregate model. Multiple prediction models are trained and aggregated using equal-sized resamples from the training data. Bagging is known to be particularly useful when small changes in data can imply large

changes in classification. Weka parameters used are bagSizePercent = 100, calcOutOf-Bag = False, classifier = varies by experiment, numIterations = 10, seed = 1 [Bre96].

- Stacking - The Stacking algorithm is a meta-learner which reduces individual bias by combining multiple classifier types. First, a series of general classifiers generate *level-0* prediction models from a given test set. Data assembled from the output of these models is combined by another classifier to generate a *level-1* prediction model. Weka parameters used are classifiers = varies by experiment, metaClassifier = DecisionStump, numFolds = 10, seed = 1 [Wol90].

4.4 Experimental Design

Clinical prediction models are generated using classification for nominal targets and regression for numeric targets. The experiment names of nominal targets (which also include binned numeric ranges) are listed in Table 16. The experiment names of numeric targets are listed in Table 17.

Each experiment is performed using 10-fold cross-validation. As some of these experiments are probabilistic in nature, they are repeated over 10 iterations with random seeding. Performance of classification models are evaluated by calculating the average *accuracy* (percentage correct) classifications across these iterations. Regression models are evaluated by calculating *r-squared* values (Equation 1), which define percentage of response variability accounted for by the prediction model [Dev95].

$$r^2 = \frac{ESS}{TSS} \tag{1}$$

ESS stands for *Explained Sum of Squares* (Equation 2). It stands for the sum of squares of the differences of the predicted independent variable ($\hat{y}_i$) within the regression model and the overall average of actual independent variables, or grand mean ($\bar{y}$). TSS stands for *Total Sum of Squares* (Equation 3). It stands for the sum of squares of the differences of the actual independent variable (y_i) and the grand mean.

$$ESS = \sum_{i=1}^{n} (\hat{y}_i - \bar{y})^2 \tag{2}$$

$$TSS = \sum_{i=1}^{n} (y_i - \bar{y})^2 \tag{3}$$

Experiment	Prediction Target
C1	Tumor Size (binned)
C2	T-Stage
C3	N-Stage
C4	Vasculature Involvement
C5	Histology
C6	Malignancy
C7	ECOG 6-Month
C8	ECOG 9-Month
C9	ECOG 12-Month
C10	Survival (binned)

Table 16: Classification Experiments

Experiment	Prediction Target
R1	Tumor Size
R2	ECOG 6-Month
R3	ECOG 9-Month
R4	ECOG 12-Month
R5	Survival

Table 17: Regression Experiments

Category	Symbol	Algorithm
Rule-based	ZR	ZeroR
	1R	OneR
Decision Trees	J48	C4.5 Decision Trees
Lazy Evaluators	IB1	K-Nearest-Neighbor k=1
	IB2	K-Nearest-Neighbor k=2
	IB3	K-Nearest-Neighbor k=3
	LWL	Locally Weighted Learning w/ Naive Bayes
Bayesian Methods	BN1	Bayes Net p=1
	BN2	Bayes Net p=2
	BN3	Bayes Net p=3
	NVB	Naive Bayes
Regression	LGR	Logistic Regression

Table 18: Classification Algorithms

4.4.1 Classification Tests

The classification algorithms used and their associated parameters are described in Table 18. Each classification algorithm was repeated using AdaBoostM1 (AB1) and Bagging (BG) meta-learners.

Four data sets (A-D) based on each prediction target (C1-C10) were created from the clinical database. Each data set was first anonymized and stripped of serializing attributes (date of admission, medical record number, etc.). Numeric targets (tumor size, survival, etc.) were binned into equal frequency numeric ranges so to be compatible with nominal classification. Classification target ranges, including numeric bins, are described in Table 19. Preprocessing methods were applied to each data set as described in Table 20. Supervised discretization was used to create uniform nominal attributes, which occasionally produces more accurate experimental results [IW05]. Attribute selection was used to pare down the high dimensionality of the original data sets. Frequently, attribute selection produces more accurate prediction models. It was also useful in generating a medically novel set of highly-correlated, independently behaving attributes for the clinical factor in question.

Clinical Factors - Nominal Categories	
Tumor Size	0 - 2.0 cm, 2.0 - 3.2 cm, 3.2 - 4.8 cm, 4.8 cm - inf
T-Stage	TX - T4
N-Stage	NX - N2
Vasculature Involvement	Yes, No
Histology	Adenocarcinoma of Pancreas - NOS, Ampullary Adenocarcinoma, Ductal Adeno of Pancreas, Neuroendocrine, Duodenal Adenocarcinoma, Distal Cholangiocarcinoma, Renal Mets, Cystadenoma, IPMN - Benign or CiS, Benign Cyst
Malignancy	Malignant, Benign
ECOG 6-Month	0 - 4 (Ref. Table 2)
ECOG 9-Month	0 - 4 (Ref. Table 2)
ECOG 12-Month	0 - 4 (Ref. Table 2)
Survival Rate	0 - 7.0 mo., 7.0 - 16.8 mo., 16.8 - inf

Table 19: Classification Target Values

Data Set	**Pre-processing Filters (ref. Section 4.3.4)**
A	*Class Discretization*: Discrete target classes are required for classification algorithms. Nominal target classes are naturally discrete. Numeric target are discretized via unsupervised equal-frequency binning.
B	*Supervised Attributes Discretization*: Instance attributes are discretized via MDL method. Derived from Data Set A.
C	*Correlation-based Feature Selection*: Attribute subsets are chosen based on the CFS method. Derived from Data Set A.
D	*Correlation-based Feature Selection and Supervised Discretization*: Uses both MDL discretization and CFS attribute selection. Derived from Data Set B.

Table 20: Classification Data Sets

Category	Symbol	Algorithm
Rule-based	ZR	ZeroR
Decision Trees	M5M	M5P w/ Model Trees
	M5R	M5P w/ Regression Trees
Neural Network	MLP	Multi-layer Perceptron
	RBF	Radial Basis Function
Regression	LNG	Linear Regression

Table 21: Regression Algorithms

Clinical Factors - Numeric Ranges	
Tumor Size	0.0 - 11.0 cm
ECOG 6-Month	0 - 2
ECOG 9-Month	0 - 3
ECOG 12-Month	0 - 3
Survival Rate	1.4 - 44.2 mo.

Table 22: Regression Experiments

4.4.2 Regression Tests

The regression algorithms used and their associated parameters are described in Table 21. Regression target numeric ranges are described in Table 22. Each regression run is repeated using Bagging (BG) meta-learners (AdaBoostM1 is unable to handle numeric targets). Additionally, the Stacking (STK) meta-learner is used to combine the M5P decision trees, RBF networks and linear regression models.

Two data sets (E-F) based on each prediction target (R1-R5) were created from the clinical database. Data sets were anonymized and serializing attributes removed as with classification tests. Attribute selection preprocessing methods were applied as described in Table 23. Supervised discretization filtering was not applied as it requires a nominal target class [FI93].

Data Set	**Pre-processing Filters (ref. Section 4.3.4)**
E	*Unaltered Data Set*: Uses original instance data with numeric target classes.
F	*Correlation-based Feature Selection*: Attribute subsets are chosen based on the CFS method. Derived from Data Set E.

Table 23: Regression Data Sets

5 Clinical Performance Machine Learning - Results & Analysis

For each experiment, we present result sets and graphs for basic algorithm executions and executions using meta-learners. For classification tests, we conduct t-tests of performance of algorithms versus logistic regression. For regression tests, t-tests are performed of algorithm performance versus linear regression. All t-tests are performed with significance $\alpha = .05$ [Dev95]. T-test results are denoted with '=' for statistically equivalent performance, '+' for superior performance, and '−' for inferior performance.

5.1 C1 - Tumor Size

For the tumor size tests among N=74 patients, we predict tumor size of 4 numeric bins which contain roughly equal numbers of patients. Distribute of target values is shown in Table 6. Classification accuracy for tumor size prediction generally ranges from 40% to 55%. The majority of algorithms performed comparably to logistic regression via t-testing. Data sets with supervised discretization and attribute selection generally produced more accurate results. No statistically significant change was seen when meta-learning was introduced.

Classification - Tumor Size												
Data Set	LGR	ZR	1R	J48	IB1	IB2	IB3	LWL	NVB	BN1	BN2	BN3
A	44.96	25.71	46.54	27.23	32.36	33.52	34.48	36.50	36.88	39.25	37.43	34.36
B	39.89	25.71	38.54	29.11	36.43	39.91	42.82	48.45	48.02	42.63	41.52	39.77
C	49.66	25.71	48.36	35.54	50.89	44.80	44.30	54.52	54.61	54.77	50.62	48.21
D	48.77	25.71	38.29	40.59	48.73	45.07	46.16	49.50	54.12	56.32	53.61	52.02

Figure 147: Tumor Size - Accuracy Results (Percentage)

Classification - Tumor Size - AdaBoostM1											
Data Set	LGR	1R.AB1	J48.AB1	IB1.AB1	IB2.AB1	IB3.AB1	LWL.AB1	NVB.AB1	BN1.AB1	BN2.AB1	BN3.AB1
A	44.96	35.64	28.73	32.36	31.32	34.63	36.16	35.59	39.29	38.36	38.27
B	39.89	34.54	28.68	36.43	38.20	42.64	48.66	38.71	42.57	40.39	40.00
C	49.66	39.70	39.61	50.89	49.95	45.29	50.66	54.32	50.18	46.45	46.52
D	48.77	33.68	43.05	50.38	46.23	45.54	46.64	50.21	54.20	51.55	50.79

Figure 148: Tumor Size - Accuracy Results (Percentage) - AdaBoostM1

Classification - Tumor Size - Bagging											
Data Set	LGR	1R.BG	J48.BG	IB1.BG	IB2.BG	IB3.BG	LWL.BG	NVB.BG	BN1.BG	BN2.BG	BN3.BG
A	44.96	42.25	30.71	32.50	31.79	33.55	36.86	38.38	42.30	38.96	37.27
B	39.89	33.46	31.84	35.16	38.41	37.73	46.43	45.39	42.20	40.73	38.27
C	49.66	43.25	40.79	49.82	46.82	46.54	54.73	51.91	54.61	49.55	50.16
D	48.77	37.21	40.93	48.27	47.07	46.77	50.50	53.52	54.95	48.54	47.80

Figure 149: Tumor Size - Accuracy Results (Percentage) - Bagging

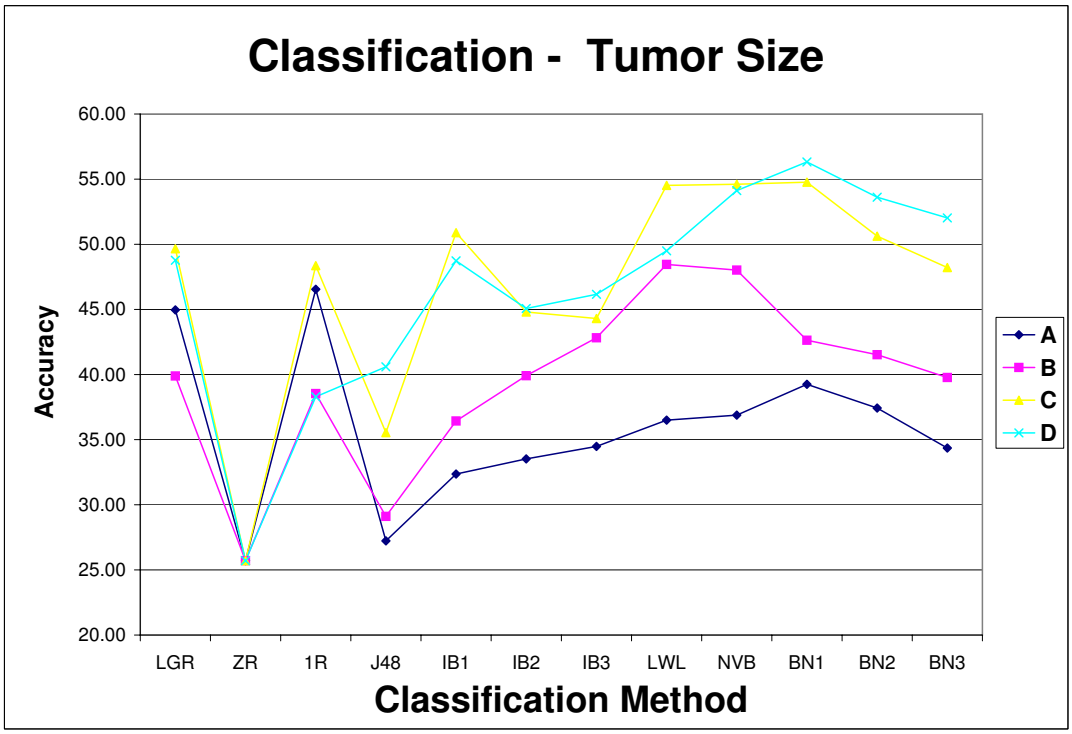


Figure 150: Tumor Size - Results Graph

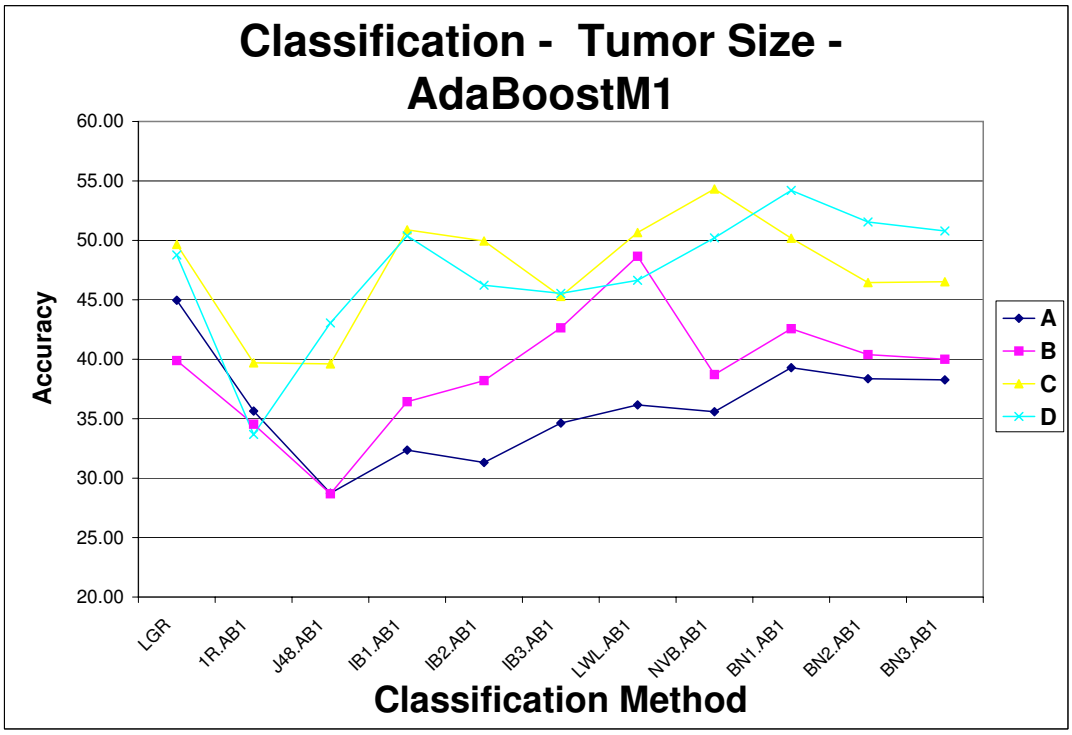


Figure 151: Tumor Size - Results Graph - AdaBoostM1

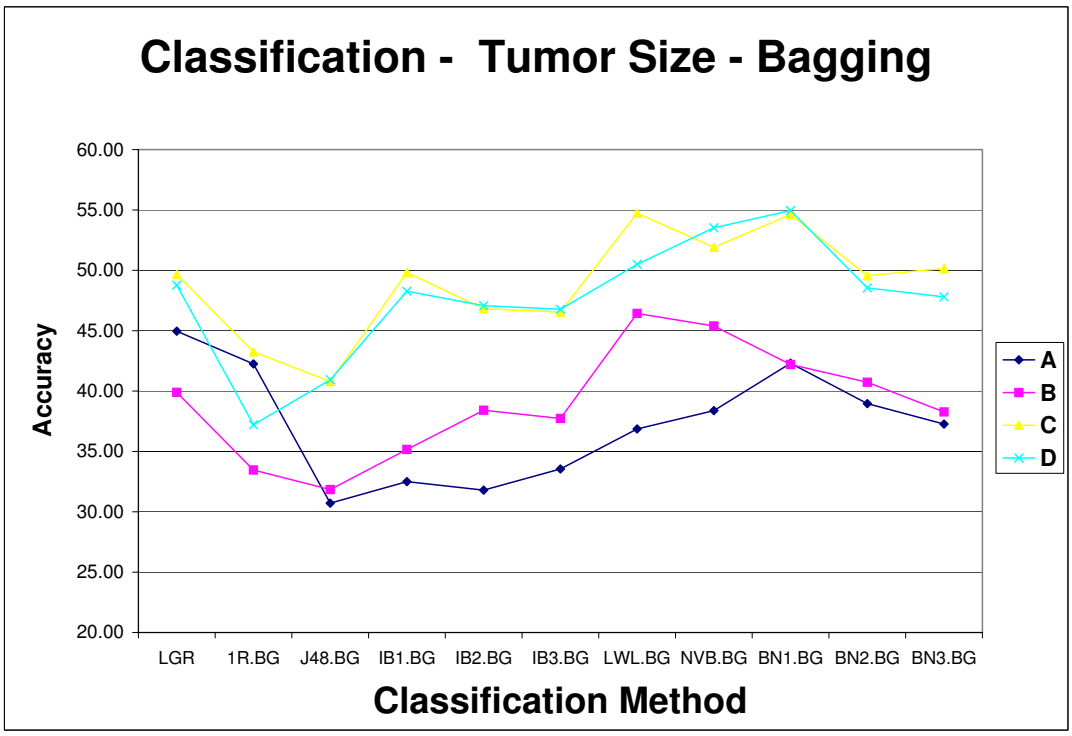


Figure 152: Tumor Size - Results Graph - Bagging

Tumor Size T-Test - ML Algorithms vs. Logistic Regression											
Data Set	ZR	1R	J48	IB1	IB2	IB3	LWL	NVB	BN1	BN2	BN3
A	-	=	-	-	=	=	=	=	=	=	=
B	-	=	=	=	=	=	=	=	=	=	=
C	-	=	=	=	=	=	=	=	=	=	=
D	-	=	=	=	=	=	=	=	=	=	=
+ : Superior to LGR = : Equivalent to LGR - : Inferior to LGR											

Figure 153: Tumor Size - T-Test vs. Logistic Regression

Tumor Size T-Test - ML Algs. w/ AdaBoostM1 vs. Logistic Regression										
Data Set	1R.AB1	J48.AB1	IB1.AB1	IB2.AB1	IB3.AB1	LWL.AB1	NVB.AB1	BN1.AB1	BN2.AB1	BN3.AB1
A	=	-	-	-	=	=	=	=	=	=
B	=	=	=	=	=	=	=	=	=	=
C	=	=	=	=	=	=	=	=	=	=
D	=	=	=	=	=	=	=	=	=	=
+ : Superior to LGR = : Equivalent to LGR - : Inferior to LGR										

Figure 154: Tumor Size - T-Test vs. Logistic Regression - AdaBoostM1

Tumor Size T-Test - ML Algs. w/ Bagging vs. Logistic Regression										
Data Set	1R.BG	J48.BG	IB1.BG	IB2.BG	IB3.BG	LWL.BG	NVB.BG	BN1.BG	BN2.BG	BN3.BG
A	=	-	-	-	=	=	=	=	=	=
B	=	=	=	=	=	=	=	=	=	=
C	=	=	=	=	=	=	=	=	=	=
D	=	=	=	=	=	=	=	=	=	=
+ : Superior to LGR = : Equivalent to LGR - : Inferior to LGR										

Figure 155: Tumor Size - T-Test vs. Logistic Regression - Bagging

5.2 C2 - T-Stage

For the t-staging tests among N=51 patients, we predict t-stage of 5 classes which are dominated by value T3 (approx. 75% of patients). Distribute of target values is shown in Table 7. Classification accuracy for t-size prediction generally ranges from 70% to 80%. Unfortunately, analysis of the associated confusion matrices show that prediction dominates for the majority T3 class and under-predicts the remaining values. The majority of algorithms in A and B data sets performed better than logistic regression via t-testing–this seems due more to logistic regression's unusually poor performance for these sets. Data sets with supervised discretization and attribute selection generally produced results of comparable accuracy. No statistically significant change was seen when meta-learning was introduced.

Classification - T-Stage												
Data Set	LGR	ZR	1R	J48	IB1	IB2	IB3	LWL	NVB	BN1	BN2	BN3
A	49.40	76.67	73.70	72.40	67.27	76.27	75.47	78.27	76.90	74.57	75.97	74.30
B	51.67	76.67	75.20	73.40	71.43	74.90	76.67	76.67	76.67	74.57	75.97	74.30
C	69.57	76.67	76.67	76.67	69.93	73.93	74.13	77.40	76.67	78.23	73.50	74.70
D	69.57	76.67	76.67	76.67	69.93	73.93	74.13	77.40	76.67	78.23	73.50	74.70

Figure 156: T-Stage - Accuracy Results (Percentage)

Classification - T-Stage - AdaBoostM1											
Data Set	LGR	1R.AB1	J48.AB	IB1.AB1	IB2.AB1	IB3.AB1	LWL.AB1	NVB.AB1	BN1.AB1	BN2.AB1	BN3.AB1
A	49.40	74.77	67.10	67.27	59.30	51.57	78.27	75.53	74.87	74.47	75.07
B	51.67	74.13	66.50	71.43	62.13	63.47	76.67	71.97	71.03	73.90	74.37
C	69.57	75.40	70.80	69.93	65.83	65.73	75.83	75.90	76.10	74.53	75.27
D	69.57	75.40	70.80	69.93	65.83	65.73	75.83	75.90	76.10	74.53	75.27

Figure 157: T-Stage - Accuracy Results (Percentage) - AdaBoostM1

Classification - T-Stage - Bagging											
Data Set	LGR	1R.BG	J48.BG	IB1.BG	IB2.BG	IB3.BG	LWL.BG	NVB.BG	BN1.BG	BN2.BG	BN3.BG
A	49.40	76.50	75.47	67.80	70.53	74.07	76.67	76.67	75.37	74.77	74.17
B	51.67	76.67	76.27	71.40	73.77	75.67	76.67	76.67	75.37	74.77	73.97
C	69.57	76.67	76.27	68.57	73.33	75.90	77.63	76.47	78.60	76.27	77.47
D	69.57	76.67	76.27	68.57	73.33	75.90	77.63	76.47	78.60	76.27	77.47

Figure 158: T-Stage - Accuracy Results (Percentage) - Bagging

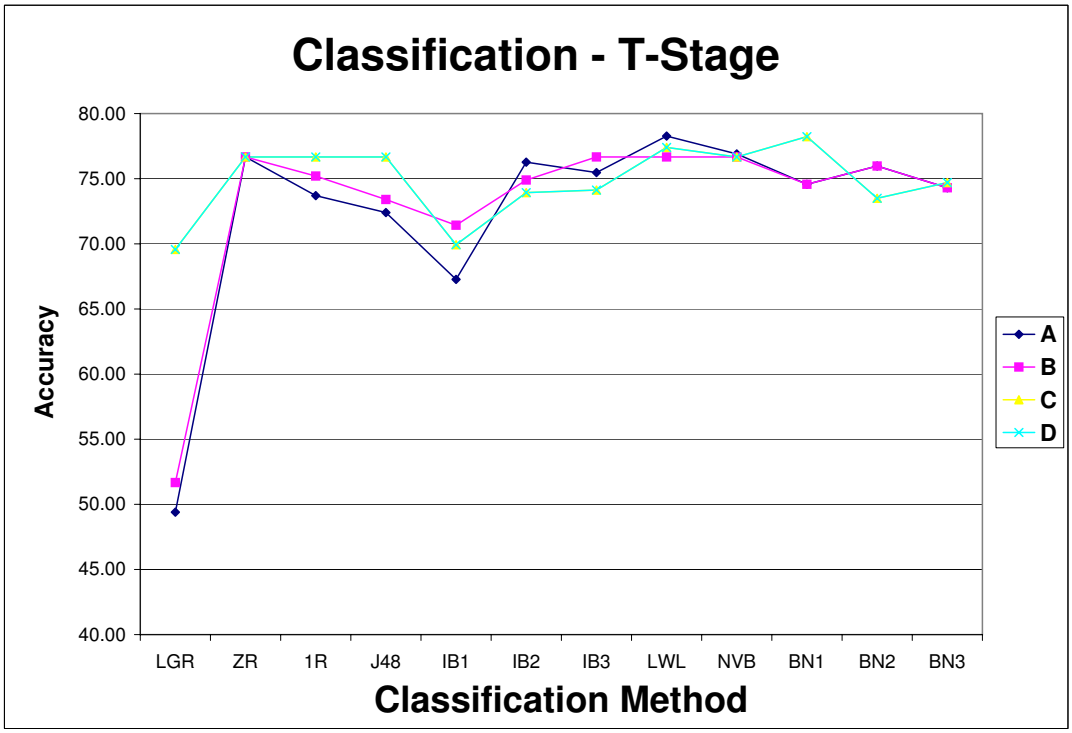


Figure 159: T-Stage - Results Graph

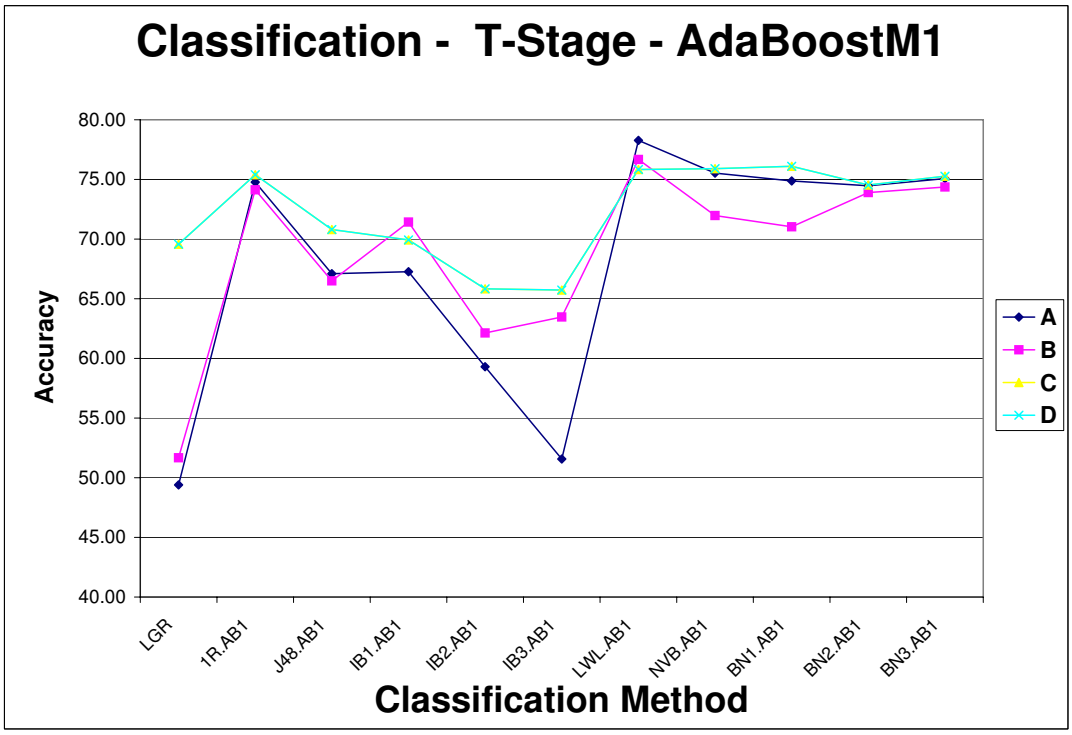


Figure 160: T-Stage - Results Graph - AdaBoostM1

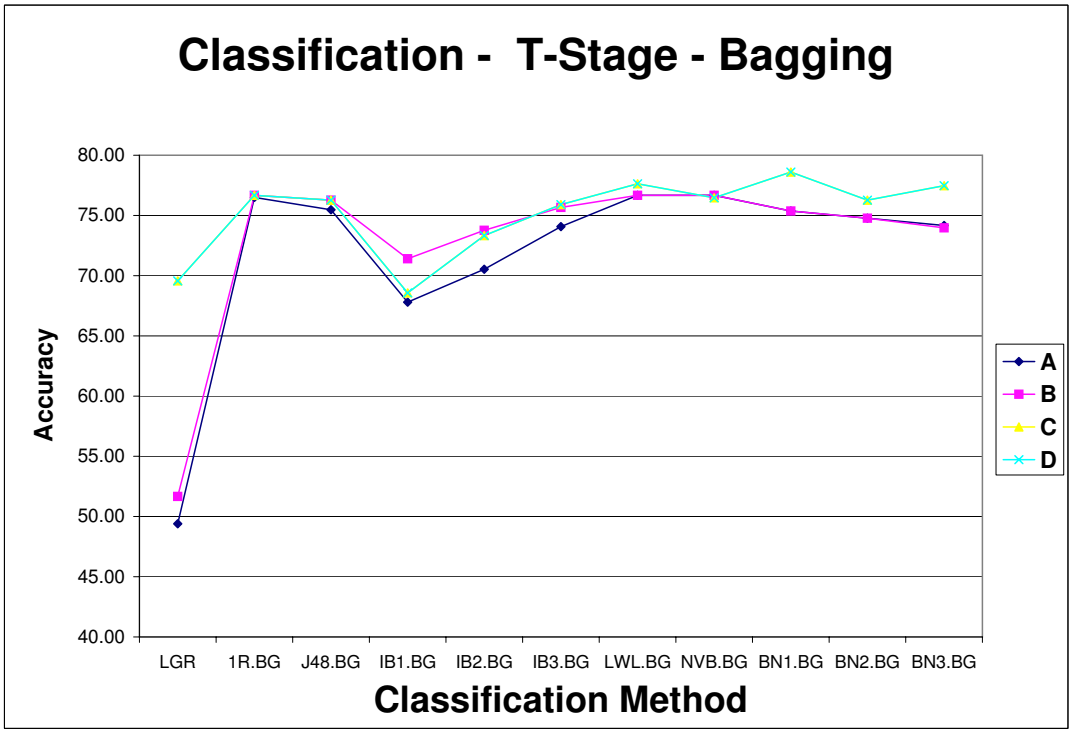


Figure 161: T-Stage - Results Graph - Bagging

T-Stage T-Test - ML Algorithms vs. Logistic Regression											
Data Set	ZR	1R	J48	IB1	IB2	IB3	LWL	NVB	BN1	BN2	BN3
A	+	+	+	+	+	+	+	+	+	+	+
B	+	+	+	+	+	+	+	+	+	+	+
C	=	=	=	=	=	=	=	=	=	=	=
D	=	=	=	=	=	=	=	=	=	=	=
+ : Superior to LGR = : Equivalent to LGR - : Inferior to LGR											

Figure 162: T-Stage - T-Test vs. Logistic Regression

T-Stage T-Test - ML Algs. w/ AdaBoostM1 vs. Logistic Regression										
Data Set	1R.AB1	J48.AB1	IB1.AB1	IB2.AB1	IB3.AB1	LWL.AB1	NVB.AB1	BN1.AB1	BN2.AB1	BN3.AB1
A	+	+	+	=	=	+	+	+	+	+
B	+	+	+	=	=	+	+	+	+	+
C	=	=	=	=	=	=	=	=	=	=
D	=	=	=	=	=	=	=	=	=	=
+ : Superior to LGR = : Equivalent to LGR - : Inferior to LGR										

Figure 163: T-Stage - T-Test vs. Logistic Regression - AdaBoostM1

T-Stage T-Test - ML Algs. w/ Bagging vs. Logistic Regression										
Data Set	1R.BG	J48.BG	IB1.BG	IB2.BG	IB3.BG	LWL.BG	NVB.BG	BN1.BG	BN2.BG	BN3.BG
A	+	+	+	+	+	+	+	+	+	+
B	+	+	+	+	+	+	+	+	+	+
C	=	=	=	=	=	=	=	=	=	=
D	=	=	=	=	=	=	=	=	=	=
+ : Superior to LGR = : Equivalent to LGR - : Inferior to LGR										

Figure 164: T-Stage - T-Test vs. Logistic Regression - Bagging

5.3 C3 - N-Stage

For the n-staging tests among N=51 patients, we predict n-stage of 3 classes which are dominated by value N1 (approx. 2:1 ratio to remaining values). Distribute of target values is shown in Table 8. Classification accuracy for n-size prediction generally ranges from 55% to 85%. The majority of algorithms in the original A data sets performed better than logistic regression via t-testing–particulary k-nearest-neighbor, locally-weighted-learning, and Bayesian nets. For the remaining data sets, algorithms generally performed equally. Data sets with supervised discretization and attribute selection generally produced results with higher accuracy. No statistically significant change was seen when meta-learning was introduced.

Classification - N-Stage												
Data Set	LGR	ZR	1R	J48	IB1	IB2	IB3	LWL	NVB	BN1	BN2	BN3
A	54.97	66.80	62.10	54.10	70.53	70.57	67.87	67.57	66.60	63.73	68.60	64.87
B	58.60	66.80	67.93	55.27	69.90	66.23	66.43	66.47	64.70	63.73	68.60	64.87
C	73.83	66.70	70.00	60.67	70.80	74.30	72.73	78.57	80.10	82.87	82.30	83.30
D	73.83	66.70	70.00	60.67	70.80	74.30	72.73	78.57	80.10	82.87	82.30	83.30

Figure 165: N-Stage - Accuracy Results (Percentage)

Classification - N-Stage - AdaBoostM1											
Data Set	LGR	1R.AB1	J48.AB1	IB1.AB1	IB2.AB1	IB3.AB1	LWL.AB1	NVB.AB1	BN1.AB1	BN2.AB1	BN3.AB1
A	54.97	62.27	57.43	70.53	67.50	62.07	67.57	62.83	63.10	66.70	60.13
B	58.60	66.07	55.77	69.90	62.07	65.70	66.47	64.70	63.47	67.90	59.33
C	73.83	70.30	71.03	70.80	72.00	77.47	73.03	79.50	81.17	78.73	79.17
D	73.83	70.30	71.03	70.80	72.00	77.47	73.03	79.50	81.17	78.73	79.17

Figure 166: N-Stage - Accuracy Results (Percentage) - AdaBoostM1

Classification - N-Stage - Bagging											
Data Set	LGR	1R.BG	J48.BG	IB1.BG	IB2.BG	IB3.BG	LWL.BG	NVB.BG	BN1.BG	BN2.BG	BN3.BG
A	54.97	64.83	64.03	70.73	70.57	68.83	69.20	66.77	62.63	69.73	69.00
B	58.60	67.43	64.60	68.27	66.27	66.23	67.43	64.53	62.80	70.27	68.53
C	73.83	70.57	67.47	70.23	71.97	73.13	76.80	79.87	83.10	80.20	79.87
D	73.83	70.57	67.47	70.23	71.97	73.13	76.80	79.87	83.10	80.20	79.87

Figure 167: N-Stage - Accuracy Results (Percentage) - Bagging

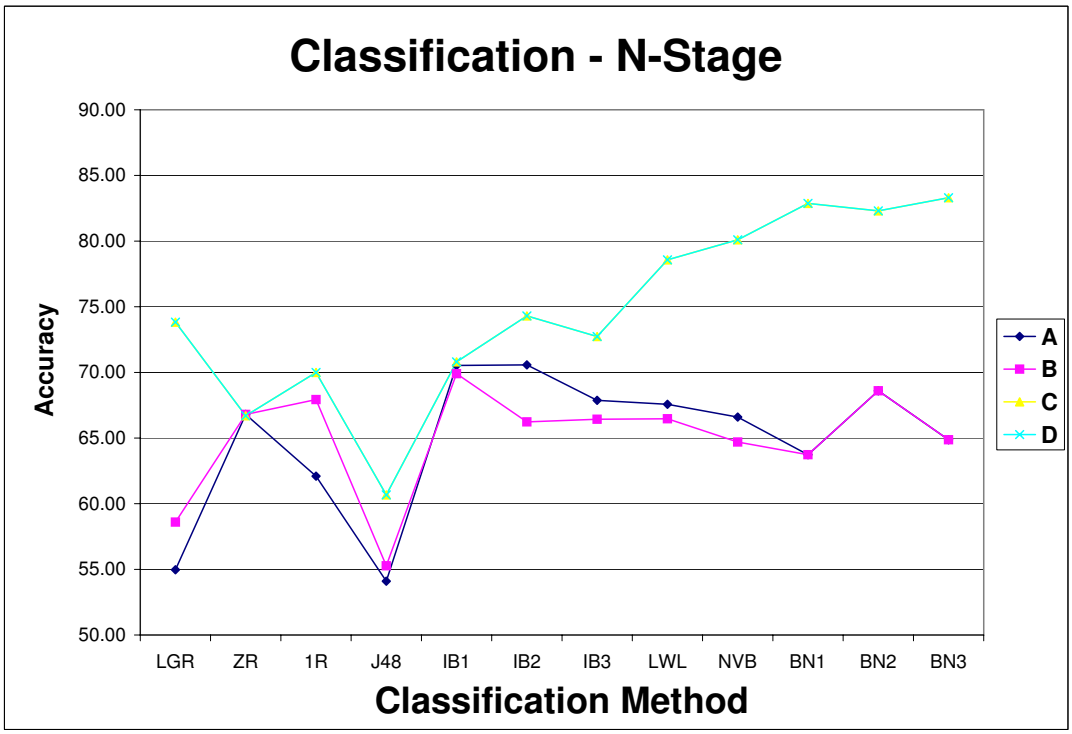


Figure 168: N-Stage - Results Graph

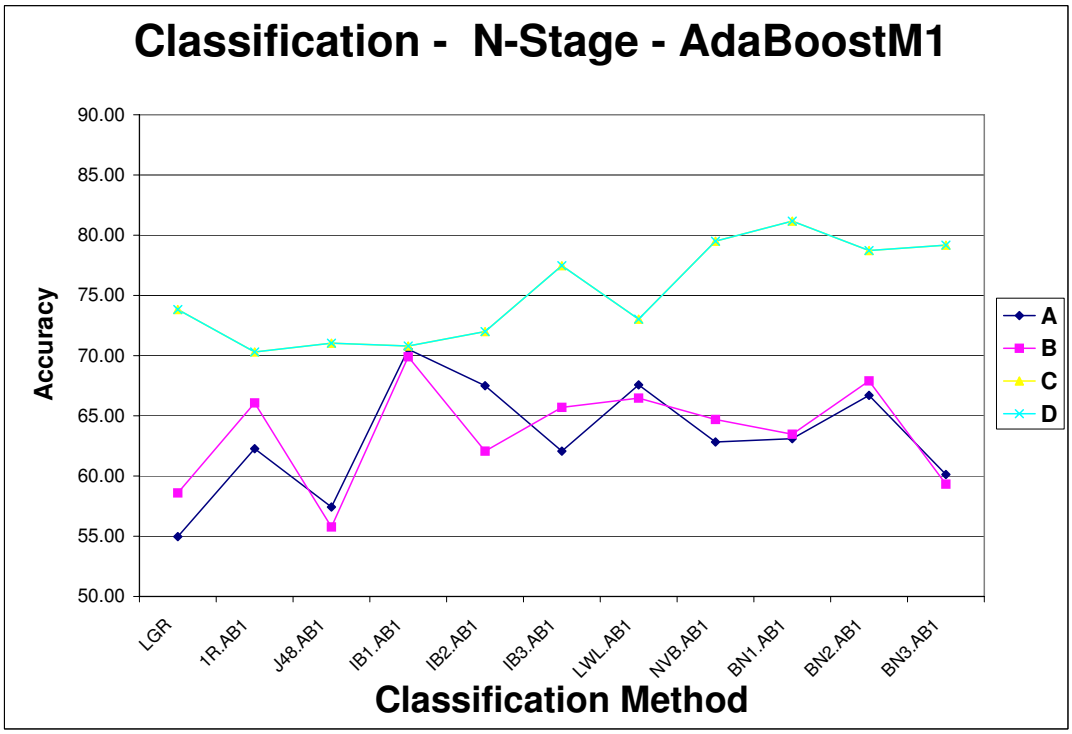


Figure 169: N-Stage - Results Graph - AdaBoostM1

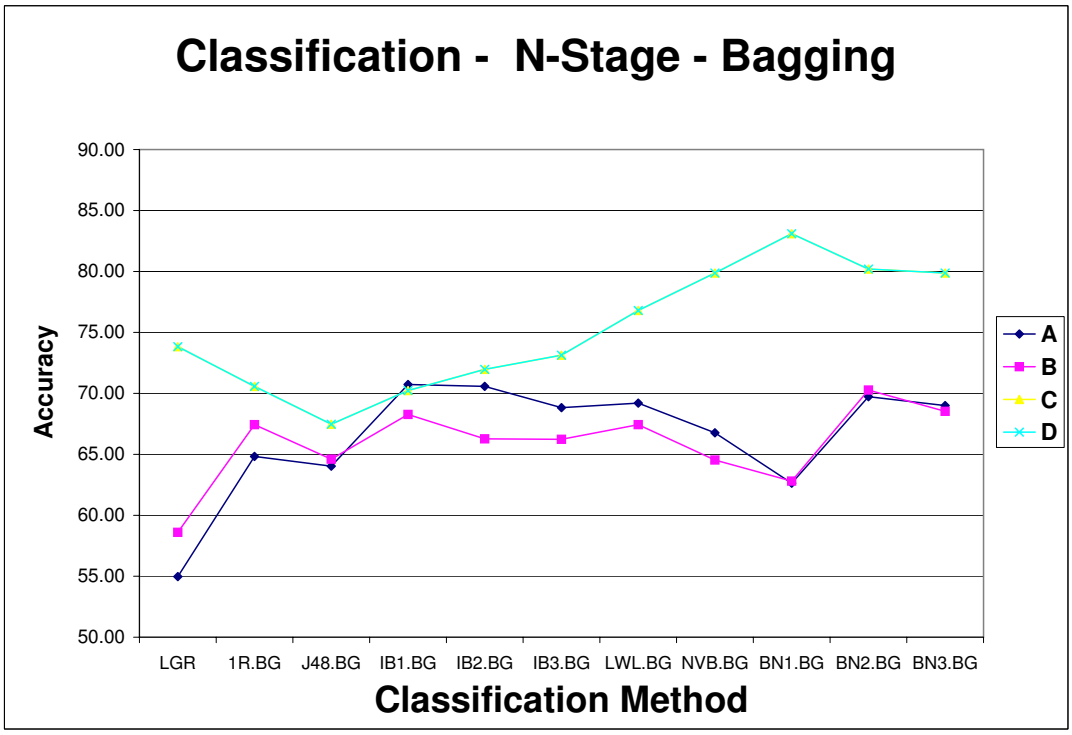


Figure 170: N-Stage - Results Graph - Bagging

N-Stage T-Test - ML Algorithms vs. Logistic Regression											
Data Set	ZR	1R	J48	IB1	IB2	IB3	LWL	NVB	BN1	BN2	BN3
A	+	=	=	+	+	+	+	+	=	+	=
B	=	=	=	=	=	=	=	=	=	=	=
C	=	=	=	=	=	=	=	=	=	=	=
D	=	=	=	=	=	=	=	=	=	=	=
+ : Superior to LGR = : Equivalent to LGR - : Inferior to LGR											

Figure 171: N-Stage - T-Test vs. Logistic Regression

N-Stage T-Test - ML Algs. w/ AdaBoostM1 vs. Logistic Regression										
Data Set	1R.AB1	J48.AB1	IB1.AB1	IB2.AB1	IB3.AB1	LWL.AB1	NVB.AB1	BN1.AB1	BN2.AB1	BN3.AB1
A	=	=	+	+	=	+	=	=	=	=
B	=	=	=	=	=	=	=	=	=	=
C	=	=	=	=	=	=	=	=	=	=
D	=	=	=	=	=	=	=	=	=	=
+ : Superior to LGR = : Equivalent to LGR - : Inferior to LGR										

Figure 172: N-Stage - T-Test vs. Logistic Regression - AdaBoostM1

N-Stage T-Test - ML Algs. w/ Bagging vs. Logistic Regression										
Data Set	1R.BG	J48.BG	IB1.BG	IB2.BG	IB3.BG	LWL.BG	NVB.BG	BN1.BG	BN2.BG	BN3.BG
A	=	=	+	+	+	+	+	=	+	+
B	=	=	=	=	=	=	=	=	+	=
C	=	=	=	=	=	=	=	=	=	=
D	=	=	=	=	=	=	=	=	=	=
+ : Superior to LGR = : Equivalent to LGR - : Inferior to LGR										

Figure 173: N-Stage - T-Test vs. Logistic Regression - Bagging

5.4 C4 - Vascular Involvement

For the vascular involvement tests among N=74 patients, we predict the values of 2 classes which are dominated by 'false' values (approx. 80% of patients). Distribute of target values is shown in Table 9. Classification accuracy for vascular involvement prediction generally ranges from 75% to 85%. Analysis of the associated confusion matrices show that prediction dominates for the majority 'false' class and under-predicts the remaining values. Data sets with supervised discretization and attribute selection generally produced results with higher accuracy. No statistically significant change was seen when meta-learning was introduced.

Classification - Vasculature												
Data Set	LGR	ZR	1R	J48	IB1	IB2	IB3	LWL	NVB	BN1	BN2	BN3
A	75.51	85.78	80.56	79.72	77.32	84.23	79.28	83.80	78.48	77.17	79.93	78.82
B	77.24	85.78	82.26	79.82	81.82	85.33	83.91	79.73	77.87	76.83	79.81	79.13
C	84.39	85.78	83.91	84.78	82.90	83.89	84.00	85.74	86.96	86.60	84.52	84.53
D	84.39	85.78	83.91	84.78	82.90	83.89	84.00	85.74	86.96	86.60	84.52	84.53

Figure 174: Vascular Involvement - Accuracy Results (Percentage)

Classification - Vasculature - AdaBoostM1											
Data Set	LGR	1R.AB1	J48.AB1	IB1.AB1	IB2.AB1	IB3.AB1	LWL.AB1	NVB.AB1	BN1.AB1	BN2.AB1	BN3.AB1
A	75.51	86.33	84.56	77.32	74.67	74.00	82.37	82.97	82.46	80.40	80.38
B	77.24	81.27	80.12	81.82	74.94	73.72	79.98	78.18	77.83	76.94	79.56
C	84.39	85.19	78.94	80.69	78.48	80.38	82.77	85.39	85.93	83.00	82.12
D	84.39	85.19	78.94	80.69	78.48	80.38	82.77	85.39	85.93	83.00	82.12

Figure 175: Vascular Involvement - Accuracy Results (Percentage) - AdaBoostM1

Classification - Vasculature - Bagging											
Data Set	LGR	1R.BG	J48.BG	IB1.BG	IB2.BG	IB3.BG	LWL.BG	NVB.BG	BN1.BG	BN2.BG	BN3.BG
A	75.51	85.22	84.13	78.09	79.50	82.06	85.99	82.78	81.60	82.71	81.14
B	77.24	85.23	84.12	81.73	81.93	82.82	81.38	79.29	78.94	80.92	79.68
C	84.39	85.22	84.57	83.44	84.32	84.33	85.19	87.39	86.82	85.86	85.63
D	84.39	85.22	84.57	83.44	84.32	84.33	85.19	87.39	86.82	85.86	85.63

Figure 176: Vascular Involvement - Accuracy Results (Percentage) - Bagging

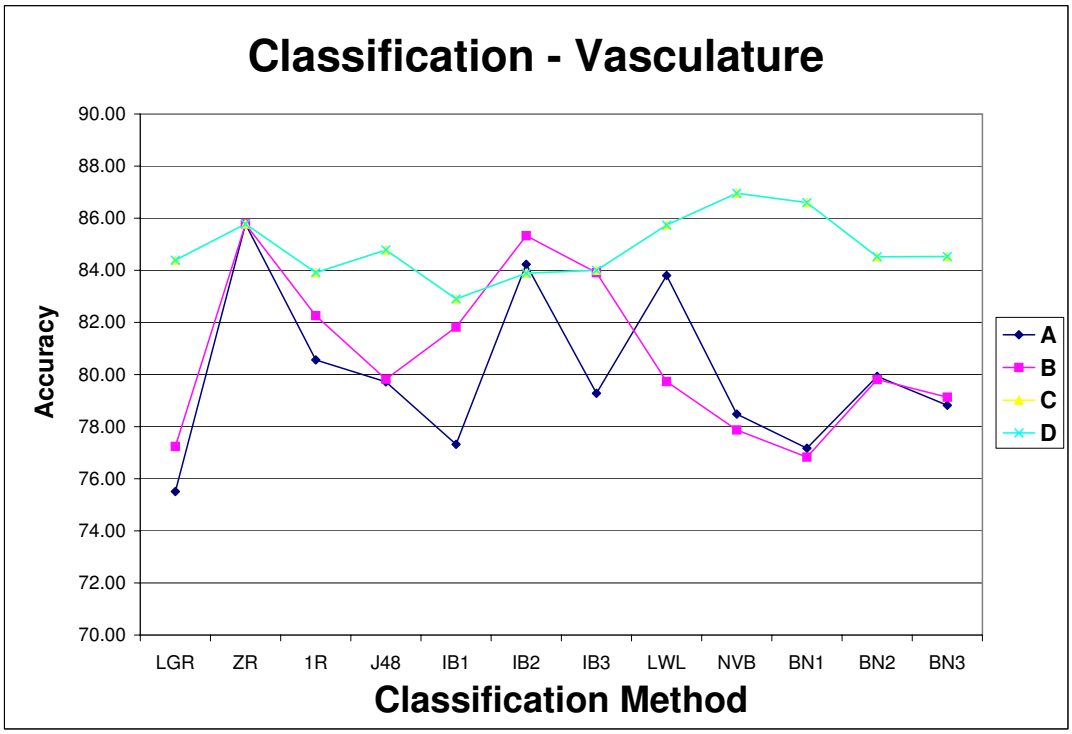


Figure 177: Vascular Involvement - Results Graph

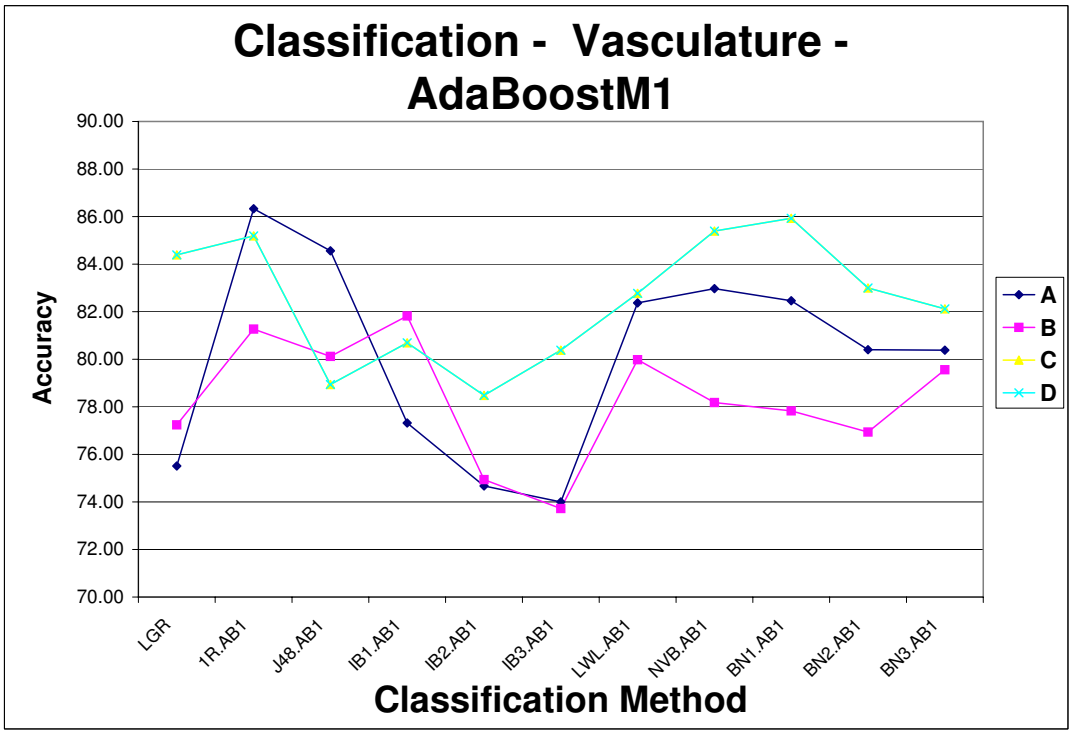


Figure 178: Vascular Involvement - Results Graph - AdaBoostM1

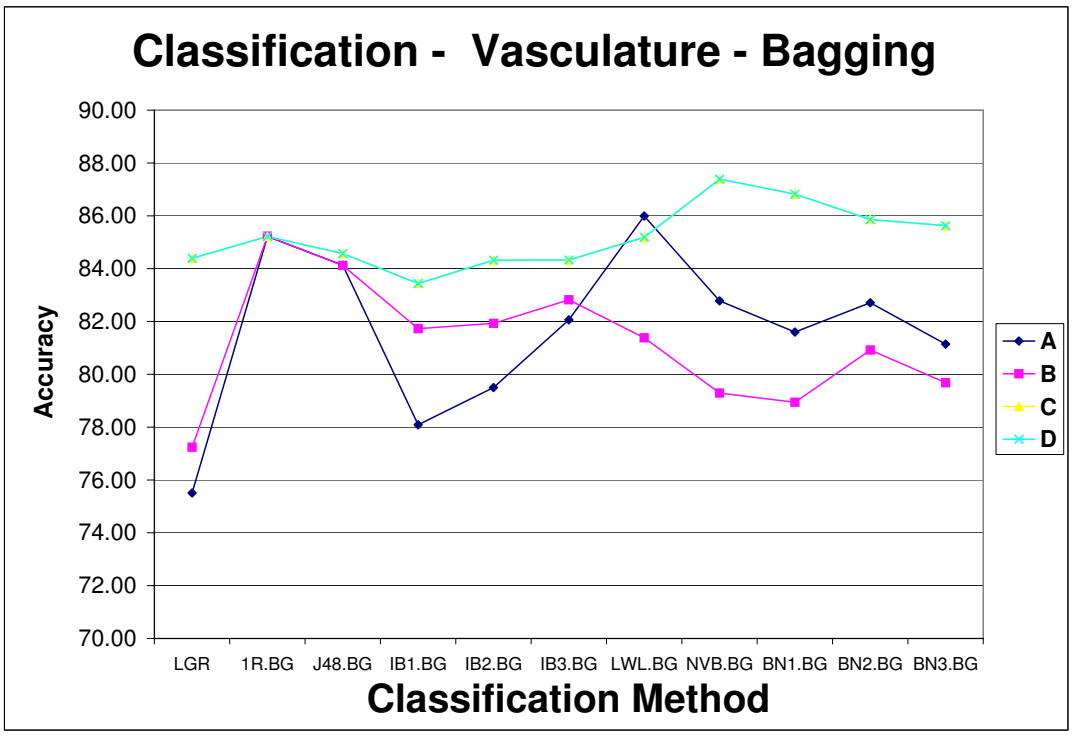


Figure 179: Vascular Involvement - Results Graph - Bagging

Vasculature T-Test - ML Algorithms vs. Logistic Regression											
Data Set	ZR	1R	J48	IB1	IB2	IB3	LWL	NVB	BN1	BN2	BN3
A	+	=	=	=	=	=	=	=	=	=	=
B	+	=	=	=	=	=	=	=	=	=	=
C	=	=	=	=	=	=	=	=	=	=	=
D	=	=	=	=	=	=	=	=	=	=	=
+ : Superior to LGR = : Equivalent to LGR - : Inferior to LGR											

Figure 180: Vascular Involvement - T-Test vs. Logistic Regression

Vasculature T-Test - ML Algs. w/ AdaBoostM1 vs. Logistic Regression										
Data Set	1R.AB1	J48.AB1	IB1.AB1	IB2.AB1	IB3.AB1	LWL.AB1	NVB.AB1	BN1.AB1	BN2.AB1	BN3.AB1
A	+	=	=	=	=	=	=	=	=	=
B	=	=	=	=	=	=	=	=	=	=
C	=	=	=	=	=	=	=	=	=	=
D	=	=	=	=	=	=	=	=	=	=
+ : Superior to LGR = : Equivalent to LGR - : Inferior to LGR										

Figure 181: Vascular Involvement - T-Test vs. Logistic Regression - AdaBoostM1

Vasculature T-Test - ML Algs. w/ Bagging vs. Logistic Regression										
Data Set	1R.BG	J48.BG	IB1.BG	IB2.BG	IB3.BG	LWL.BG	NVB.BG	BN1.BG	BN2.BG	BN3.BG
A	=	=	=	=	=	=	=	=	=	=
B	=	=	=	=	=	=	=	=	=	=
C	=	=	=	=	=	=	=	=	=	=
D	=	=	=	=	=	=	=	=	=	=
+ : Superior to LGR = : Equivalent to LGR - : Inferior to LGR										

Figure 182: Vascular Involvement - T-Test vs. Logistic Regression - Bagging

5.5 C5 - Histology

For the histology tests among N=91 patients, we predict value of 14 target class values which are dominated by 'Adenocarcinoma of Pancreas - NOS' and 'Ductal Adenocarcinoma of Pancreas' (these histology values dominate approximately 55% of instances). Distribute of target values is shown in Table 10. Classification accuracy for histology prediction models generally range from 35% to 55%. Analysis of the associated confusion matrices show that prediction dominates for the majority classes and 'IPMN - Benign or CiS' while under-predicting the remaining values. Data sets with supervised discretization and attribute selection combined with Bayesian net predictions generally produced results with higher accuracy than logistic regression via t-tests. Remaining machine learning algorithms were comparable to logistic regression accuracy in most cases. No statistically significant change was seen when meta-learning was introduced. High-performance models based on histology classification are presented in Section 6.1.

Classification - Histology

Data Set	LGR	ZR	1R	J48	IB1	IB2	IB3	LWL	NVB	BN1	BN2	BN3
A	45.69	29.73	35.12	39.41	37.71	36.69	40.52	45.34	42.91	51.52	52.89	51.18
B	43.79	29.73	35.78	40.07	43.81	41.67	48.59	50.00	51.52	51.41	52.89	51.07
C	41.59	29.73	35.78	42.93	47.57	47.91	49.96	53.52	56.07	54.39	50.36	49.46
D	41.59	29.73	35.78	42.93	47.57	47.91	49.96	53.52	56.07	54.39	50.36	49.46

Figure 183: Histology - Accuracy Results (Percentage)

Classification - Histology - AdaBoostM1

Data Set	LGR	1R.AB1	J48.AB1	IB1.AB1	IB2.AB1	IB3.AB1	LWL.AB1	NVB.AB1	BN1.AB1	BN2.AB1	BN3.AB1
A	45.69	35.68	43.41	37.71	41.29	40.66	45.34	40.92	52.22	54.30	53.36
B	43.79	38.07	45.44	43.81	44.13	48.70	50.56	48.56	51.32	54.21	53.01
C	41.59	37.73	48.32	47.57	43.44	49.84	51.82	48.74	50.19	47.13	47.59
D	41.59	37.73	48.32	47.57	43.44	49.84	51.82	48.74	50.19	47.13	47.59

Figure 184: Histology - Accuracy Results (Percentage) - AdaBoostM1

Classification - Histology - Bagging											
Data Set	LGR	1R.BG	J48.BG	IB1.BG	IB2.BG	IB3.BG	LWL.BG	NVB.BG	BN1.BG	BN2.BG	BN3.BG
A	45.69	43.89	46.87	36.49	38.77	43.44	44.36	41.39	51.66	51.54	50.69
B	43.79	43.54	47.07	42.37	43.81	44.88	51.89	52.77	51.98	52.77	51.21
C	41.59	43.43	48.83	46.13	49.77	52.18	53.77	54.57	53.40	51.23	50.48
D	41.59	43.43	48.83	46.13	49.77	52.18	53.77	54.57	53.40	51.23	50.48

Figure 185: Histology - Accuracy Results (Percentage) - Bagging

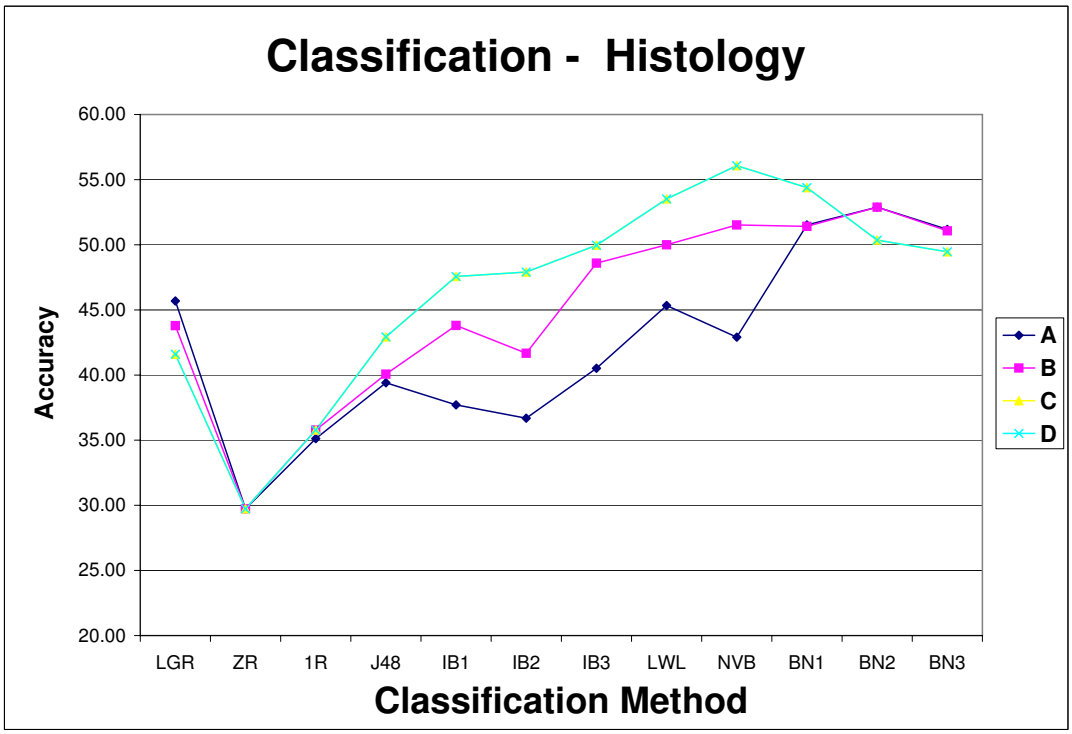


Figure 186: Histology - Results Graph

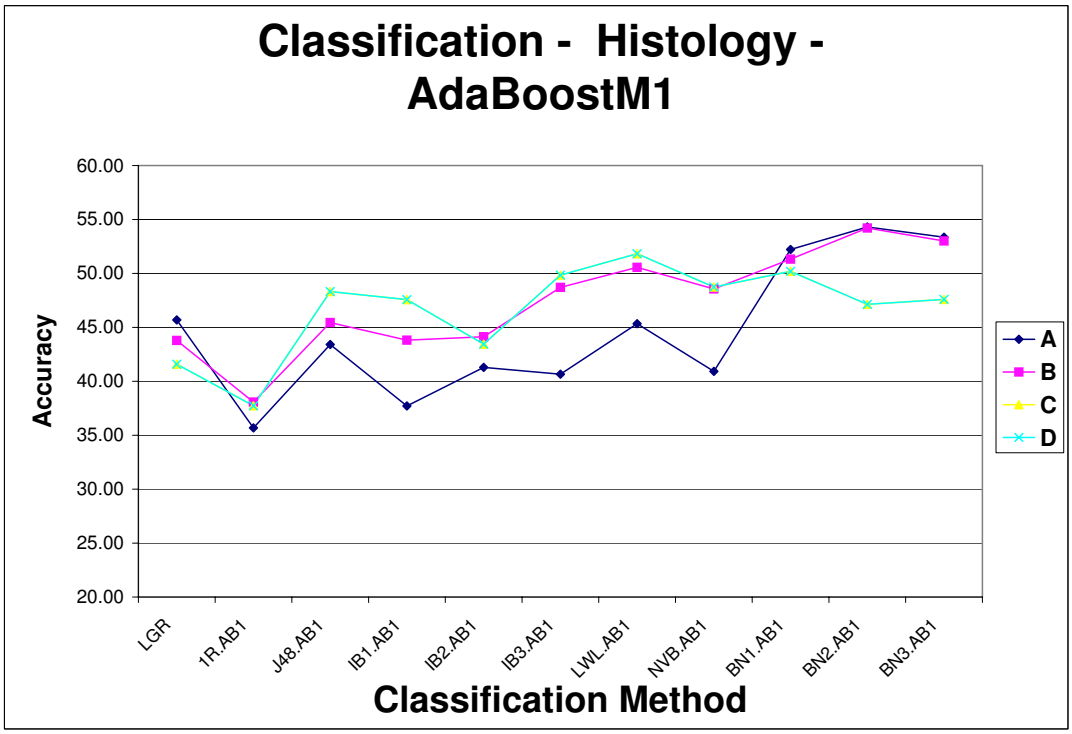


Figure 187: Histology - Results Graph - AdaBoostM1

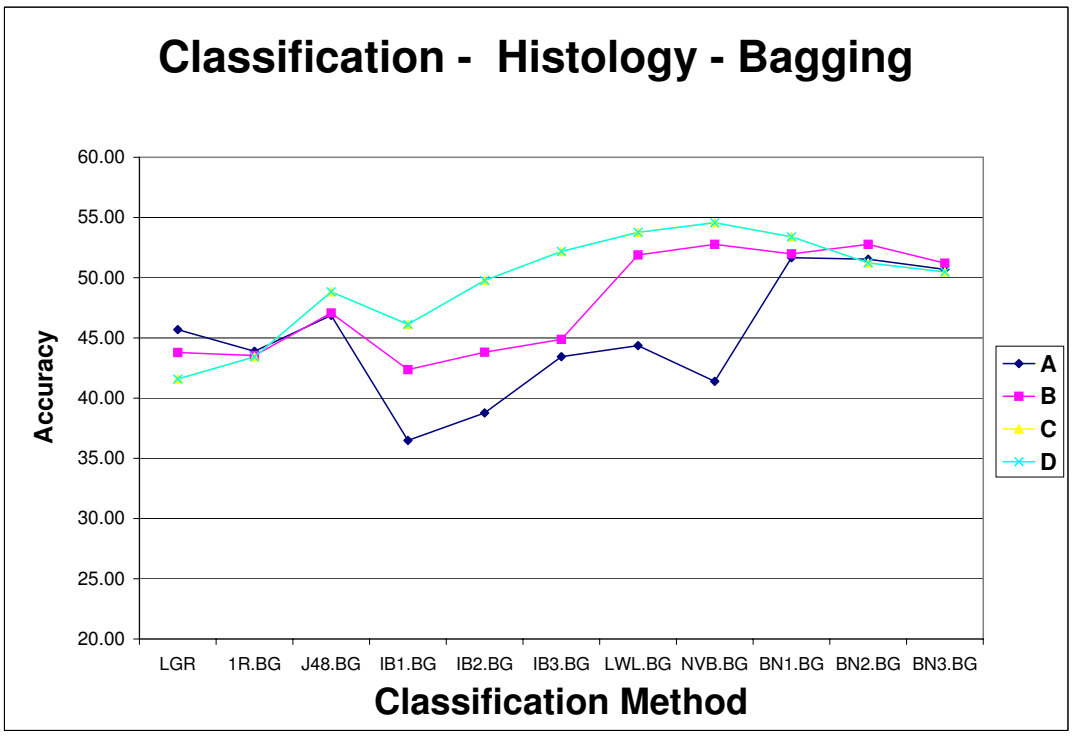


Figure 188: Histology - Results Graph - Bagging

Histology T-Test - ML Algorithms vs. Logistic Regression											
Data Set	ZR	1R	J48	IB1	IB2	IB3	LWL	NVB	BN1	BN2	BN3
A	-	=	=	=	=	=	=	=	=	=	=
B	-	=	=	=	=	=	=	=	=	=	=
C	-	=	=	=	=	=	=	+	+	=	=
D	-	=	=	=	=	=	=	+	+	=	=
+ : Superior to LGR = : Equivalent to LGR - : Inferior to LGR											

Figure 189: Histology - T-Test vs. Logistic Regression

Histology T-Test - ML Algs. w/ AdaBoostM1 vs. Logistic Regression										
Data Set	1R.AB1	J48.AB1	IB1.AB1	IB2.AB1	IB3.AB1	LWL.AB1	NVB.AB1	BN1.AB1	BN2.AB1	BN3.AB1
A	=	=	=	=	=	=	=	=	=	=
B	=	=	=	=	=	=	=	=	=	=
C	=	=	=	=	=	=	=	=	=	=
D	=	=	=	=	=	=	=	=	=	=
+ : Superior to LGR = : Equivalent to LGR - : Inferior to LGR										

Figure 190: Histology - T-Test vs. Logistic Regression - AdaBoostM1

Histology T-Test - ML Algs. w/ Bagging vs. Logistic Regression										
Data Set	1R.BG	J48.BG	IB1.BG	IB2.BG	IB3.BG	LWL.BG	NVB.BG	BN1.BG	BN2.BG	BN3.BG
A	=	=	=	=	=	=	=	=	=	=
B	=	=	=	=	=	=	=	=	=	=
C	=	=	=	=	=	+	+	=	=	=
D	=	=	=	=	=	+	+	=	=	=
+ : Superior to LGR = : Equivalent to LGR - : Inferior to LGR										

Figure 191: Histology - T-Test vs. Logistic Regression - Bagging

5.6 C6 - Malignancy

For the malignancy tests among N=91 patients, we predict value of 2 classes which are dominated by 'Malignant' values (approx. 80% of cases). Distribute of target values is shown in Table 11. Classification accuracy for malignancy prediction generally ranges from 70% to 85%. Analysis of the associated confusion matrices show a reasonable spread between the majority classes and minority values. Data sets with supervised discretization and attribute selection generally produced results with higher accuracy. Classification algorithms were t-test comparable to logistic regression accuracy in most cases. No statistically significant change was seen when meta-learning was introduced.

Classification - Malignancy

Data Set	LGR	ZR	1R	J48	IB1	IB2	IB3	LWL	NVB	BN1	BN2	BN3
A	76.90	82.44	84.64	84.44	70.56	79.14	77.38	64.39	57.97	75.42	74.10	74.63
B	75.38	82.44	79.68	79.07	72.51	78.82	77.40	80.31	76.18	72.12	71.56	72.84
C	83.18	82.44	80.44	82.44	82.87	84.61	84.61	85.63	81.56	83.54	83.84	83.51
D	83.18	82.44	80.44	82.44	82.87	84.61	84.61	85.63	81.56	83.54	83.84	83.51

Figure 192: Malignancy - Accuracy Results (Percentage)

Classification - Malignancy - AdaBoostM1

Data Set	LGR	1R.AB1	J48.AB1	IB1.AB1	IB2.AB1	IB3.AB1	LWL.AB1	NVB.AB1	BN1.AB1	BN2.AB1	BN3.AB1
A	76.90	76.48	80.54	70.56	63.38	75.93	72.36	69.38	81.13	78.12	75.93
B	75.38	75.20	74.52	72.51	73.62	69.54	77.80	76.70	77.93	74.36	73.73
C	83.18	81.57	80.30	80.33	77.79	81.68	82.74	84.84	85.08	83.87	83.22
D	83.18	81.57	80.30	80.33	77.79	81.68	82.74	84.84	85.08	83.87	83.22

Figure 193: Malignancy - Accuracy Results (Percentage) - AdaBoostM1

Classification - Malignancy - Bagging

Data Set	LGR	1R.BG	J48.BG	IB1.BG	IB2.BG	IB3.BG	LWL.BG	NVB.BG	BN1.BG	BN2.BG	BN3.BG
A	76.90	82.33	85.54	70.54	74.50	76.17	70.41	66.88	75.66	77.73	76.44
B	75.38	81.22	80.27	71.40	74.41	76.17	79.64	76.63	72.49	75.96	74.79
C	83.18	81.67	81.57	82.53	83.62	84.83	84.74	81.46	82.88	85.94	85.07
D	83.18	81.67	81.57	82.53	83.62	84.83	84.74	81.46	82.88	85.94	85.07

Figure 194: Malignancy - Accuracy Results (Percentage) - Bagging

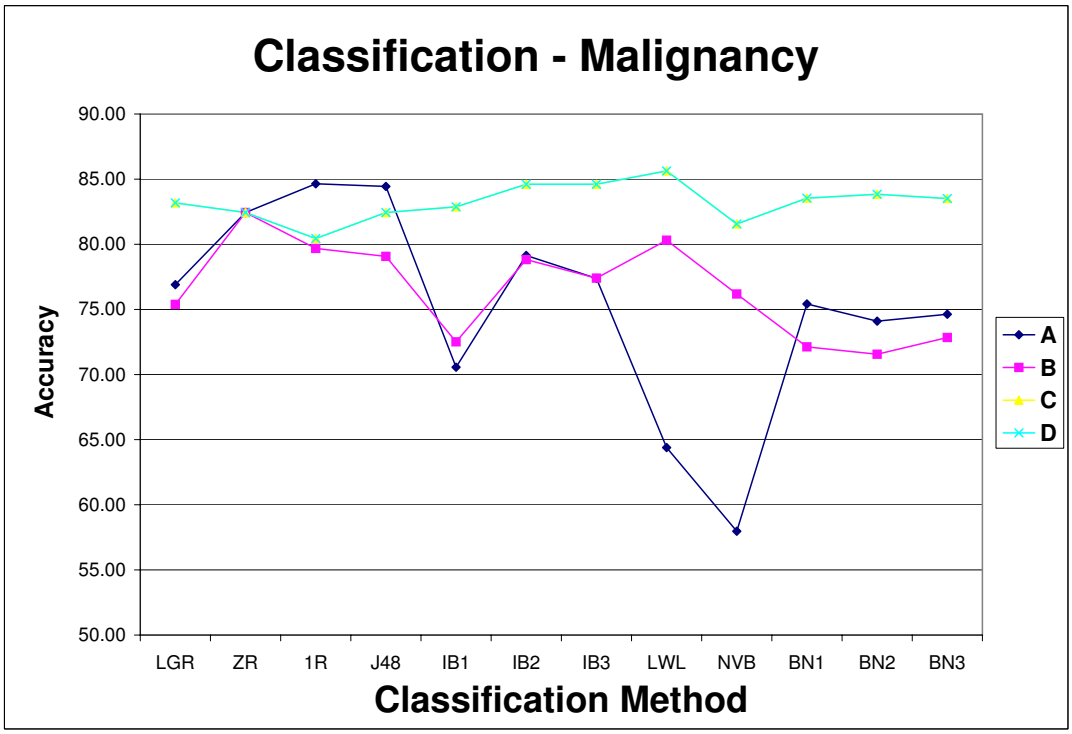


Figure 195: Malignancy - Results Graph

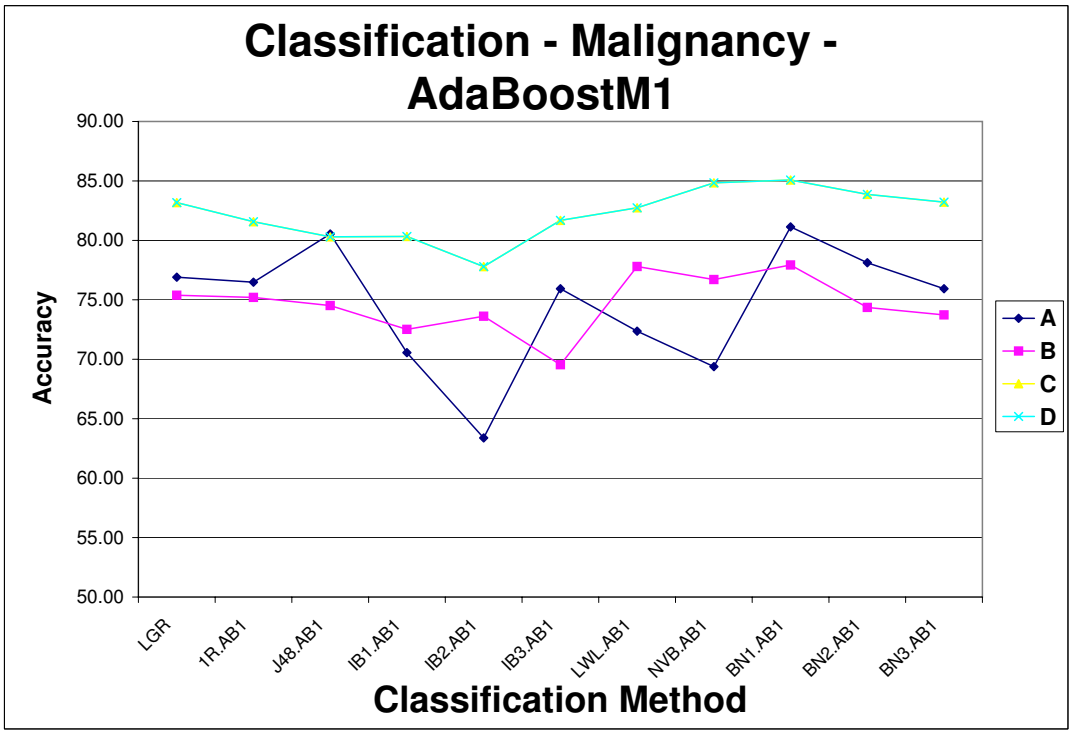


Figure 196: Malignancy - Results Graph - AdaBoostM1

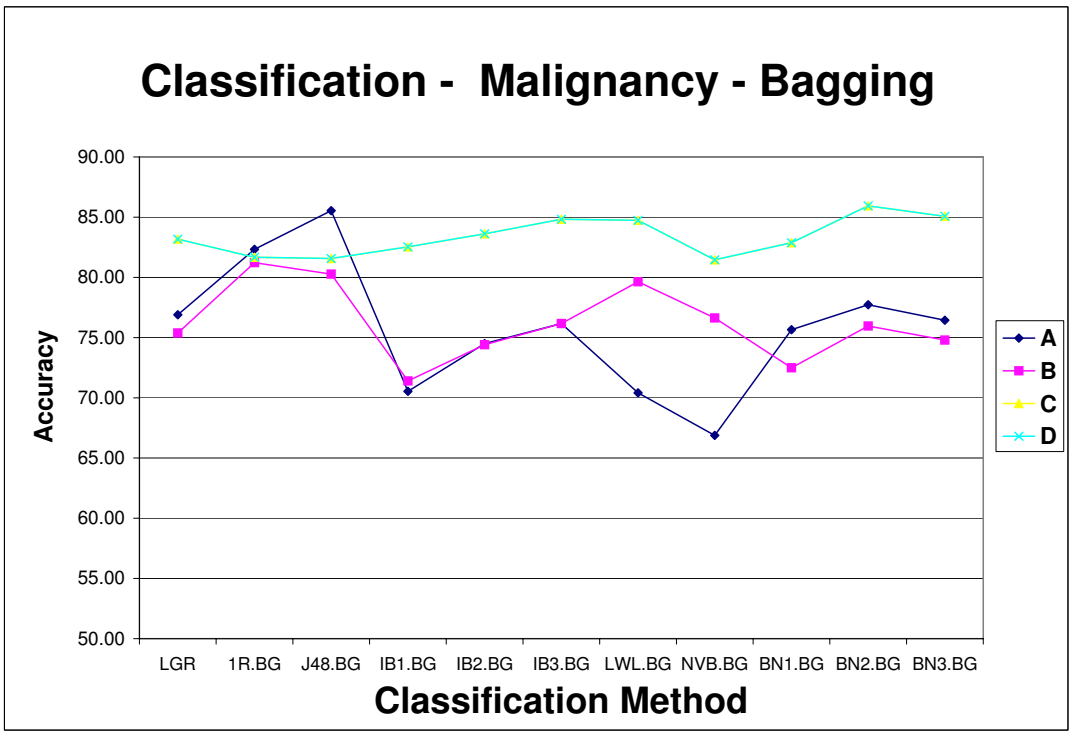


Figure 197: Malignancy - Results Graph - Bagging

Malignancy T-Test - ML Algorithms vs. Logistic Regression											
Data Set	ZR	1R	J48	IB1	IB2	IB3	LWL	NVB	BN1	BN2	BN3
A	=	=	=	=	=	=	-	-	=	=	=
B	=	=	=	=	=	=	=	=	=	=	=
C	=	=	=	=	=	=	=	=	=	=	=
D	=	=	=	=	=	=	=	=	=	=	=
+ : Superior to LGR = : Equivalent to LGR - : Inferior to LGR											

Figure 198: Malignancy - T-Test vs. Logistic Regression

Malignancy T-Test - ML Algs. w/ AdaBoostM1 vs. Logistic Regression										
Data Set	1R.AB1	J48.AB1	IB1.AB1	IB2.AB1	IB3.AB1	LWL.AB1	NVB.AB1	BN1.AB1	BN2.AB1	BN3.AB1
A	=	=	=	=	=	=	=	=	=	=
B	=	=	=	=	=	=	=	=	=	=
C	=	=	=	=	=	=	=	=	=	=
D	=	=	=	=	=	=	=	=	=	=
+ : Superior to LGR = : Equivalent to LGR - : Inferior to LGR										

Figure 199: Malignancy - T-Test vs. Logistic Regression - AdaBoostM1

Malignancy T-Test - ML Algs. w/ Bagging vs. Logistic Regression										
Data Set	1R.BG	J48.BG	IB1.BG	IB2.BG	IB3.BG	LWL.BG	NVB.BG	BN1.BG	BN2.BG	BN3.BG
A	=	+	=	=	=	=	=	=	=	=
B	=	=	=	=	=	=	=	=	=	=
C	=	=	=	=	=	=	=	=	=	=
D	=	=	=	=	=	=	=	=	=	=
+ : Superior to LGR = : Equivalent to LGR - : Inferior to LGR										

Figure 200: Malignancy - T-Test vs. Logistic Regression - Bagging

5.7 C7 - ECOG 6-Month

For ECOG 6-Month tests among N=72 patients, we predict value of 3 classes which are reasonably well-distributed (ECOG values represented are those available among instances.). Distribution of target values is shown in Table 12. Classification accuracy for ECOG prediction generally ranges from 55% to 75%. Data sets with supervised discretization and attribute selection generally produced results with higher accuracy. Classification algorithms were t-test comparable to logistic regression accuracy in most cases. No statistically significant change was seen when meta-learning was introduced.

Classification - ECOG 6-Month

Data Set	LGR	ZR	1R	J48	IB1	IB2	IB3	LWL	NVB	BN1	BN2	BN3
A	49.20	51.43	48.21	49.68	55.16	57.34	54.95	51.55	54.09	63.54	55.43	54.30
B	53.21	51.43	54.84	52.34	53.12	56.71	56.86	66.16	65.23	63.37	55.43	54.73
C	64.93	51.43	55.37	59.43	68.27	69.80	68.80	72.29	69.64	70.89	70.30	68.21
D	64.93	51.43	55.37	59.43	68.27	69.80	68.80	72.29	69.64	70.89	70.30	68.21

Figure 201: ECOG 6-Month - Accuracy Results (Percentage)

Classification - ECOG 6-Month - AdaBoostM1

Data Set	LGR	1R.AB1	J48.AB1	IB1.AB1	IB2.AB1	IB3.AB1	LWL.AB1	NVB.AB1	BN1.AB1	BN2.AB1	BN3.AB1
A	49.20	53.89	50.82	55.16	54.68	55.75	50.59	45.82	58.21	50.34	56.86
B	53.21	55.20	49.77	53.12	55.96	55.09	57.32	54.96	58.82	51.00	51.77
C	64.93	57.91	57.86	59.84	70.07	72.21	62.32	66.25	66.29	64.79	61.05
D	64.93	57.91	57.86	59.84	70.07	72.21	62.32	66.25	66.29	64.79	61.05

Figure 202: ECOG 6-Month - Accuracy Results (Percentage) - AdaBoostM1

Classification - ECOG 6-Month - Bagging

Data Set	LGR	1R.BG	J48.BG	IB1.BG	IB2.BG	IB3.BG	LWL.BG	NVB.BG	BN1.BG	BN2.BG	BN3.BG
A	49.20	53.18	54.00	55.37	54.86	57.02	53.14	55.21	63.12	58.14	54.05
B	53.21	56.70	55.93	55.89	57.80	57.95	66.57	66.23	63.77	58.71	55.36
C	64.93	58.75	61.45	68.79	69.23	69.68	72.14	69.96	70.21	69.43	69.91
D	64.93	58.75	61.45	68.79	69.23	69.68	72.14	69.96	70.21	69.43	69.91

Figure 203: ECOG 6-Month - Accuracy Results (Percentage) - Bagging

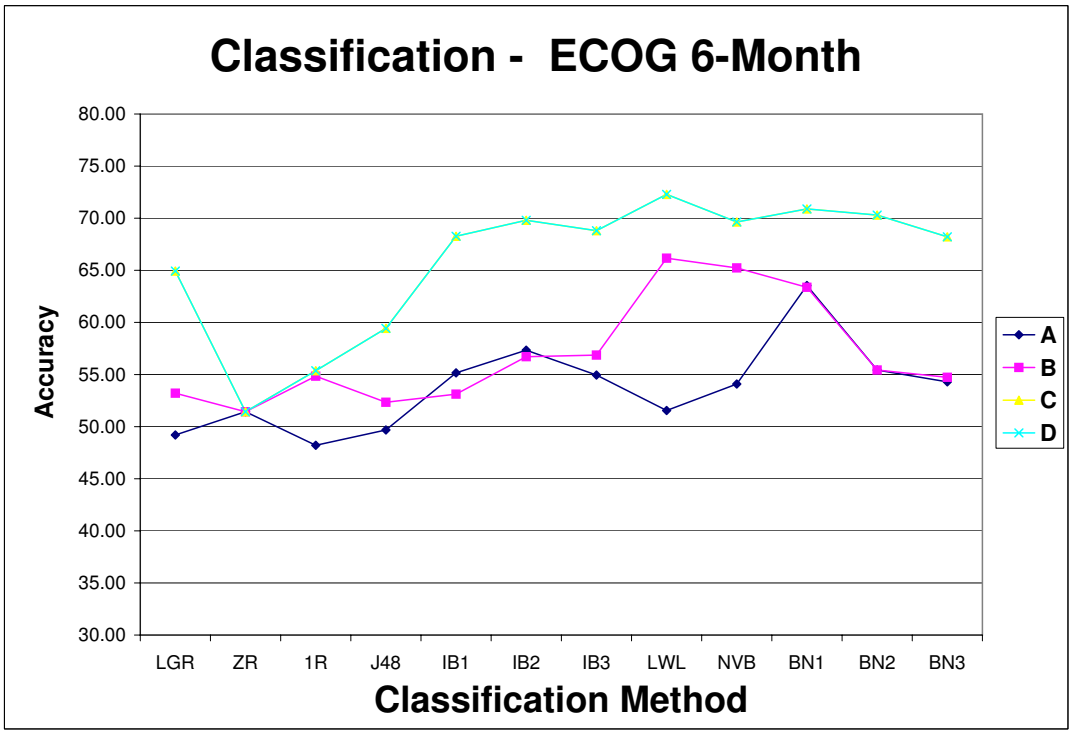


Figure 204: ECOG 6-Month - Results Graph

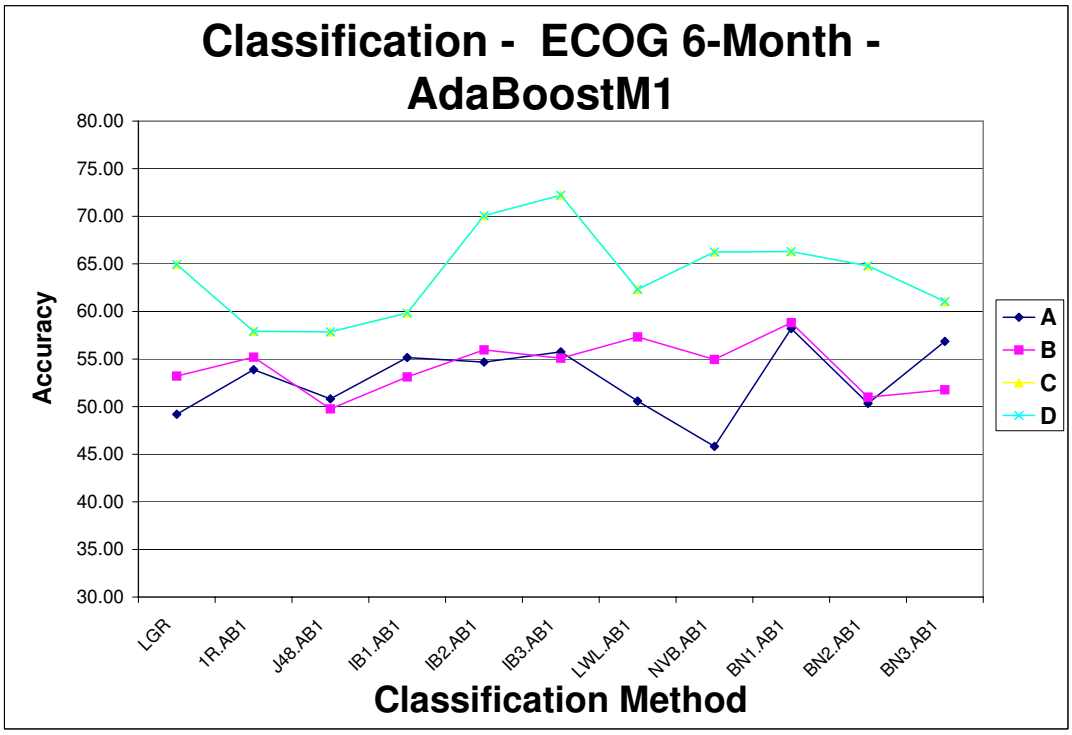


Figure 205: ECOG 6-Month - Results Graph - AdaBoostM1

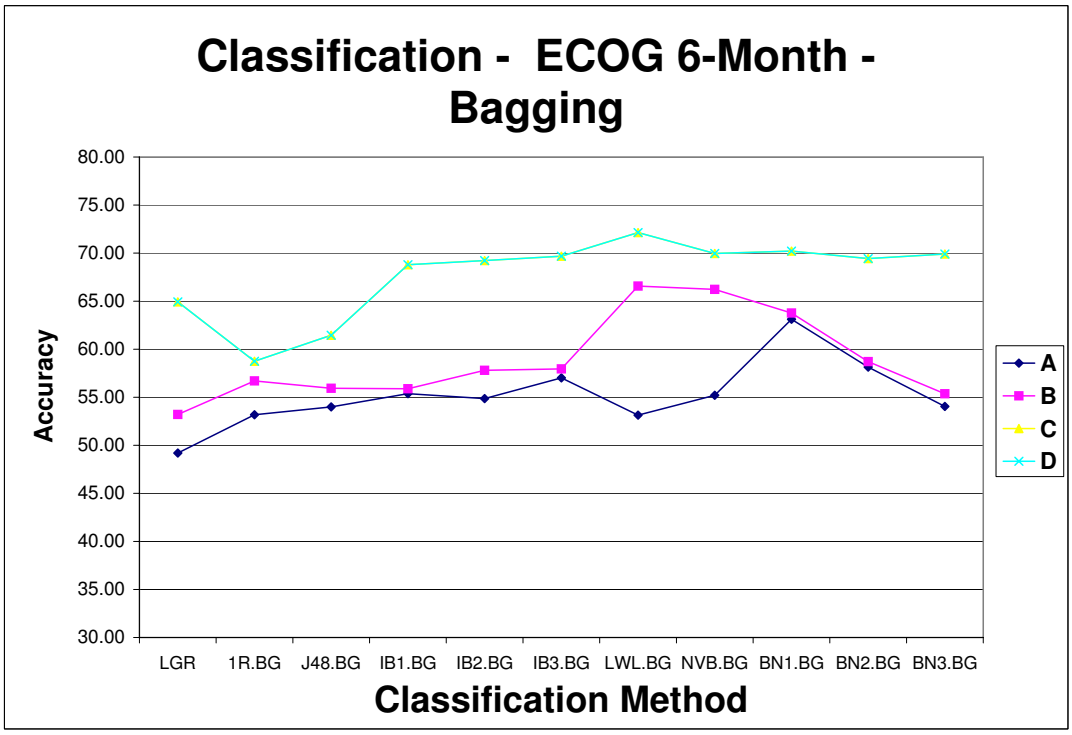


Figure 206: ECOG 6-Month - Results Graph - Bagging

ECOG 6-Month T-Test - ML Algorithms vs. Logistic Regression											
Data Set	ZR	1R	J48	IB1	IB2	IB3	LWL	NVB	BN1	BN2	BN3
A	=	=	=	=	=	=	=	=	=	=	=
B	=	=	=	=	=	=	=	=	=	=	=
C	=	=	=	=	=	=	=	=	=	=	=
D	=	=	=	=	=	=	=	=	=	=	=
+ : Superior to LGR = : Equivalent to LGR - : Inferior to LGR											

Figure 207: ECOG 6-Month - T-Test vs. Logistic Regression

ECOG 6-Month T-Test - ML Algs. w/ AdaBoostM1 vs. Logistic Regression										
Data Set	1R.AB1	J48.AB1	IB1.AB1	IB2.AB1	IB3.AB1	LWL.AB1	NVB.AB1	BN1.AB1	BN2.AB1	BN3.AB1
A	=	=	=	=	=	=	=	=	=	=
B	=	=	=	=	=	=	=	=	=	=
C	=	=	=	=	=	=	=	=	=	=
D	=	=	=	=	=	=	=	=	=	=
+ : Superior to LGR = : Equivalent to LGR - : Inferior to LGR										

Figure 208: ECOG 6-Month - T-Test vs. Logistic Regression - AdaBoostM1

ECOG 6-Month T-Test - ML Algs. w/ Bagging vs. Logistic Regression										
Data Set	1R.BG	J48.BG	IB1.BG	IB2.BG	IB3.BG	LWL.BG	BN1.BG	BN2.BG	BN3.BG	NVB.BG
A	=	=	=	=	=	=	=	=	=	=
B	=	=	=	=	=	=	=	=	=	=
C	=	=	=	=	=	=	=	=	=	=
D	=	=	=	=	=	=	=	=	=	=
+ : Superior to LGR = : Equivalent to LGR - : Inferior to LGR										

Figure 209: ECOG 6-Month - T-Test vs. Logistic Regression - Bagging

5.8 C8 - ECOG 9-Month

For ECOG 9-Month tests among N=57 patients, we predict value of 4 classes which are reasonably well-distributed (ECOG values represented are those available among instances.). Distribute of target values is shown in Table 13. Classification accuracy for ECOG prediction generally ranges from 45% to 70%. Data sets with supervised discretization and attribute selection generally produced results with higher accuracy. Classification algorithms were t-test comparable to logistic regression accuracy in most cases. No statistically significant change was seen when meta-learning was introduced.

Classification - ECOG 9-Month												
Data Set	LGR	ZR	1R	J48	IB1	IB2	IB3	LWL	NVB	BN1	BN2	BN3
A	45.57	58.10	46.90	47.47	44.07	56.33	52.43	59.53	60.07	49.67	53.57	51.87
B	42.63	58.10	49.80	50.57	43.47	53.70	51.37	54.97	54.53	49.50	53.57	51.87
C	62.20	58.10	50.97	52.67	58.80	54.47	55.53	64.80	70.33	70.20	63.87	64.00
D	62.20	58.10	50.97	52.67	58.80	54.47	55.53	64.80	70.33	70.20	63.87	64.00

Figure 210: ECOG 9-Month - Accuracy Results (Percentage)

Classification - ECOG 9-Month - AdaBoostM1											
Data Set	LGR	1R.AB1	J48.AB	IB1.AB1	IB2.AB1	IB3.AB1	LWL.AB1	NVB.AB1	BN1.AB1	BN2.AB1	BN3.AB1
A	45.57	48.20	42.80	44.07	37.60	49.07	59.53	59.10	50.30	45.67	47.57
B	42.63	51.77	43.00	43.47	32.60	51.17	52.70	45.53	49.17	44.13	48.13
C	62.20	51.90	50.40	58.80	52.43	58.23	53.10	57.03	53.87	59.00	57.90
D	62.20	51.90	50.40	58.80	52.43	58.23	53.10	57.03	53.87	59.00	57.90

Figure 211: ECOG 9-Month - Accuracy Results (Percentage) - AdaBoostM1

Classification - ECOG 9-Month - Bagging											
Data Set	LGR	1R.BG	J48.BG	IB1.BG	IB2.BG	IB3.BG	LWL.BG	NVB.BG	BN1.BG	BN2.BG	BN3.BG
A	45.57	55.20	53.80	42.57	45.57	50.03	60.80	61.17	49.73	51.77	49.13
B	42.63	53.87	54.60	38.53	44.13	51.30	55.37	54.53	49.70	52.47	49.27
C	62.20	54.67	57.20	54.27	57.17	55.70	64.70	70.03	70.63	62.53	61.40
D	62.20	54.67	57.20	54.27	57.17	55.70	64.70	70.03	70.63	62.53	61.40

Figure 212: ECOG 9-Month - Accuracy Results (Percentage) - Bagging

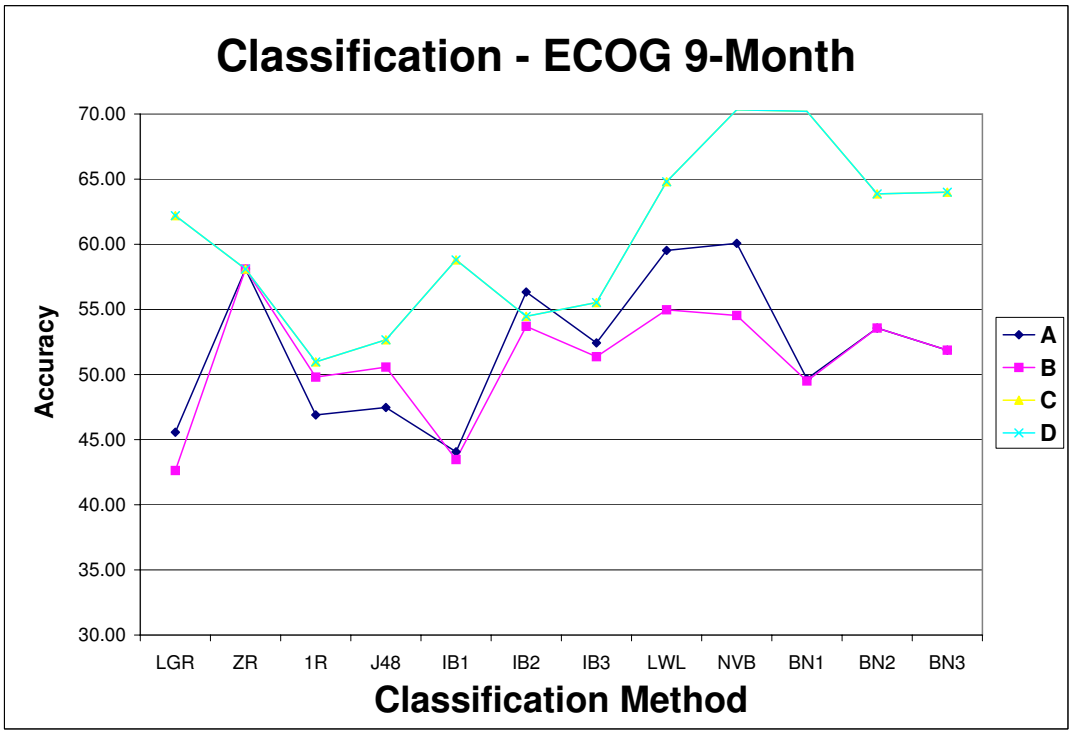


Figure 213: ECOG 9-Month - Results Graph

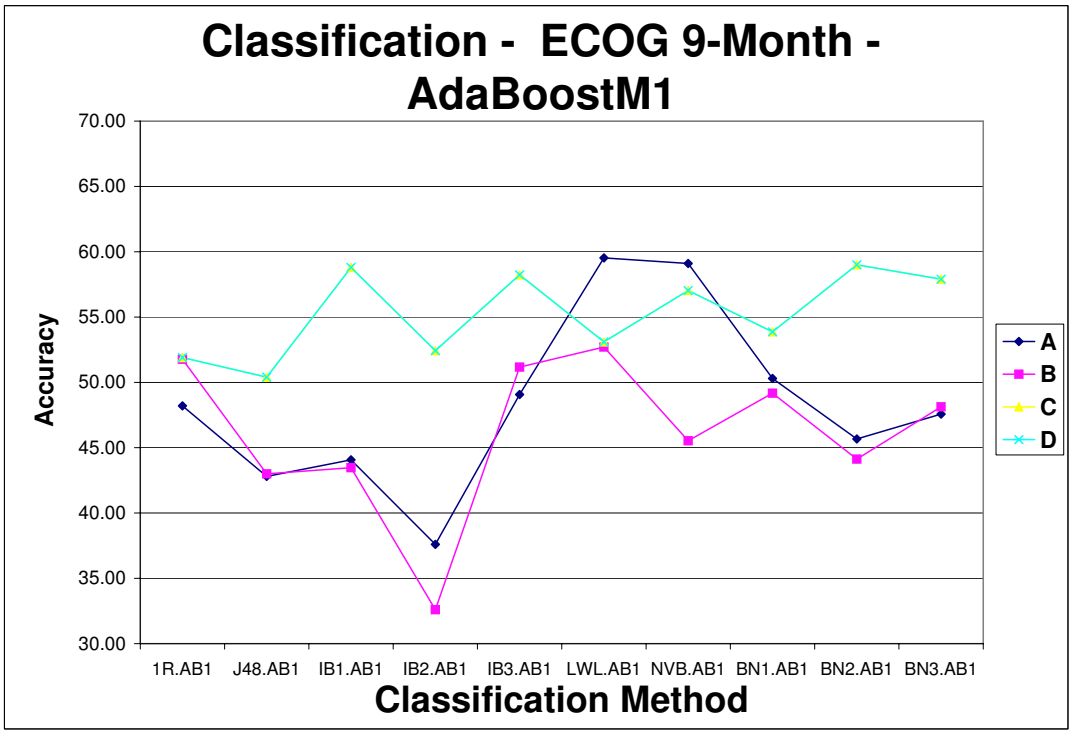


Figure 214: ECOG 9-Month - Results Graph - AdaBoostM1

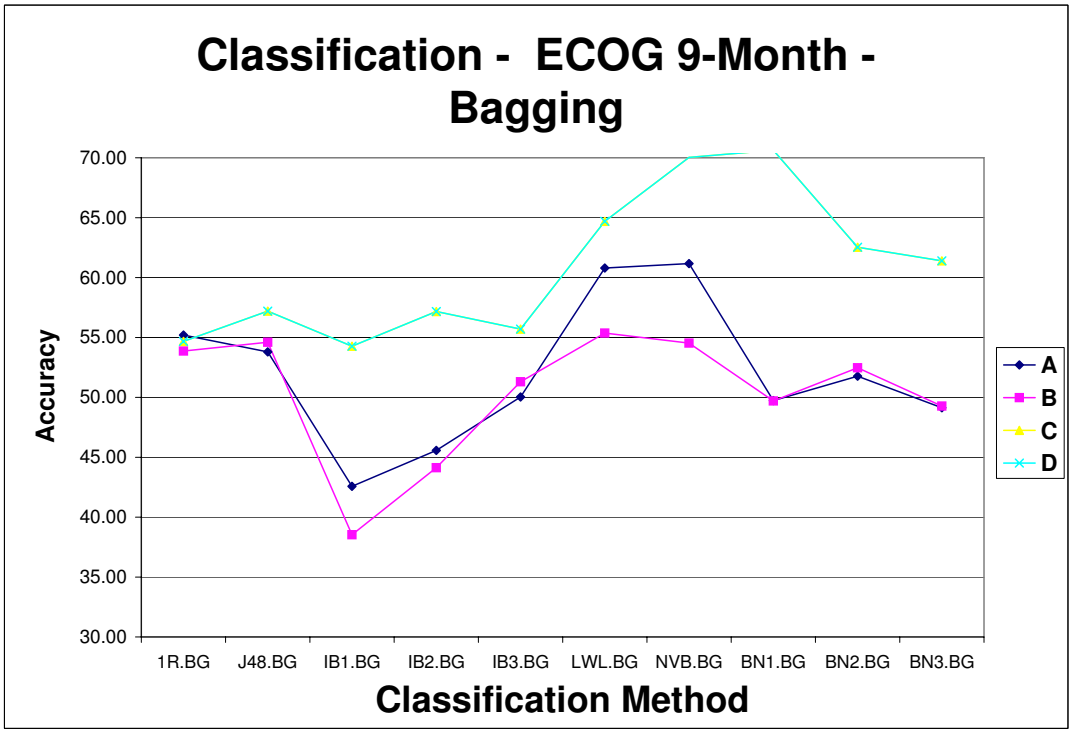


Figure 215: ECOG 9-Month - Results Graph - Bagging

ECOG 9-Month T-Test - ML Algorithms vs. Logistic Regression											
Data Set	ZR	1R	J48	IB1	IB2	IB3	LWL	NVB	BN1	BN2	BN3
A	=	=	=	=	=	=	+	+	=	=	=
B	+	=	=	=	=	=	=	=	=	=	=
C	=	=	=	=	=	=	=	=	=	=	=
D	=	=	=	=	=	=	=	=	=	=	=
+ : Superior to LGR = : Equivalent to LGR - : Inferior to LGR											

Figure 216: ECOG 9-Month - T-Test vs. Logistic Regression

ECOG 9-Month T-Test - ML Algs. w/ AdaBoostM1 vs. Logistic Regression										
Data Set	1R.AB1	J48.AB1	IB1.AB1	IB2.AB1	IB3.AB1	LWL.AB1	NVB.AB1	BN1.AB1	BN2.AB1	BN3.AB1
A	=	=	=	=	=	+	+	=	=	=
B	=	=	=	=	=	=	=	=	=	=
C	=	=	=	=	=	=	=	=	=	=
D	=	=	=	=	=	=	=	=	=	=
+ : Superior to LGR = : Equivalent to LGR - : Inferior to LGR										

Figure 217: ECOG 9-Month - T-Test vs. Logistic Regression - AdaBoostM1

ECOG 9-Month T-Test - ML Algs. w/ Bagging vs. Logistic Regression										
Data Set	1R.BG	J48.BG	IB1.BG	IB2.BG	IB3.BG	LWL.BG	NVB.BG	BN1.BG	BN2.BG	BN3.BG
A	=	=	=	=	=	+	+	=	=	=
B	=	=	=	=	=	=	=	=	=	=
C	=	=	=	=	=	=	=	=	=	=
D	=	=	=	=	=	=	=	=	=	=
+ : Superior to LGR = : Equivalent to LGR - : Inferior to LGR										

Figure 218: ECOG 9-Month - T-Test vs. Logistic Regression - Bagging

5.9 C9 - ECOG 12-Month

For ECOG 12-Month tests among N=44 patients, we predict value of 4 classes which are reasonable well distributed (ECOG values represented are those available among instances.). Distribute of target values is shown in Table 14. Classification accuracy for ECOG prediction generally ranges from 35% to 55%. The majority of algorithms in A and B data sets performed better than logistic regression via t-testing; again, this seems due more to logistic regression's poor performance on these sets. Data sets with supervised discretization and attribute selection generally produced results with equivalent accuracy. Classification algorithms in C and D sets were t-test comparable to logistic regression accuracy in most cases. No statistically significant change was seen when meta-learning was introduced.

Classification - ECOG 12-Month												
Data Set	LGR	ZR	1R	J48	IB1	IB2	IB3	LWL	NVB	BN1	BN2	BN3
A	37.90	52.20	47.05	41.25	42.45	48.45	48.35	48.15	41.35	46.85	39.50	38.70
B	40.70	52.20	48.00	45.05	42.40	49.55	43.05	48.70	50.60	47.25	39.50	38.90
C	43.60	52.20	39.40	54.45	48.15	45.50	46.15	50.55	53.95	51.80	49.30	48.70
D	43.60	52.20	39.40	54.45	48.15	45.50	46.15	50.55	53.95	51.80	49.30	48.70

Figure 219: ECOG 12-Month - Accuracy Results (Percentage)

Classification - ECOG 12-Month - AdaBoostM1											
Data Set	LGR	1R.AB1	J48.AB	IB1.AB1	IB2.AB1	IB3.AB1	LWL.AB1	NVB.AB1	BN1.AB1	BN2.AB1	BN3.AB1
A	37.90	43.25	41.95	40.70	42.80	43.25	46.00	43.30	46.25	42.50	42.45
B	40.70	43.50	38.55	38.70	35.95	38.60	46.95	47.60	45.25	42.40	40.00
C	43.60	41.10	51.10	43.80	45.00	45.75	49.55	51.05	50.90	47.55	46.90
D	43.60	41.10	51.10	43.80	45.00	45.75	49.55	51.05	50.90	47.55	46.90

Figure 220: ECOG 12-Month - Accuracy Results (Percentage) - AdaBoostM1

Classification - ECOG 12-Month - Bagging											
Data Set	LGR	1R.BG	J48.BG	IB1.BG	IB2.BG	IB3.BG	LWL.BG	NVB.BG	BN1.BG	BN2.BG	BN3.BG
A	37.90	48.40	45.10	43.20	43.35	45.50	44.50	39.85	46.05	39.45	38.00
B	40.70	47.65	47.40	38.80	40.30	43.80	50.25	49.70	46.55	40.95	38.15
C	43.60	43.25	57.00	48.45	46.90	44.30	50.20	55.45	51.70	46.60	47.40
D	43.60	43.25	57.00	48.45	46.90	44.30	50.20	55.45	51.70	46.60	47.40

Figure 221: ECOG 12-Month - Accuracy Results (Percentage) - Bagging

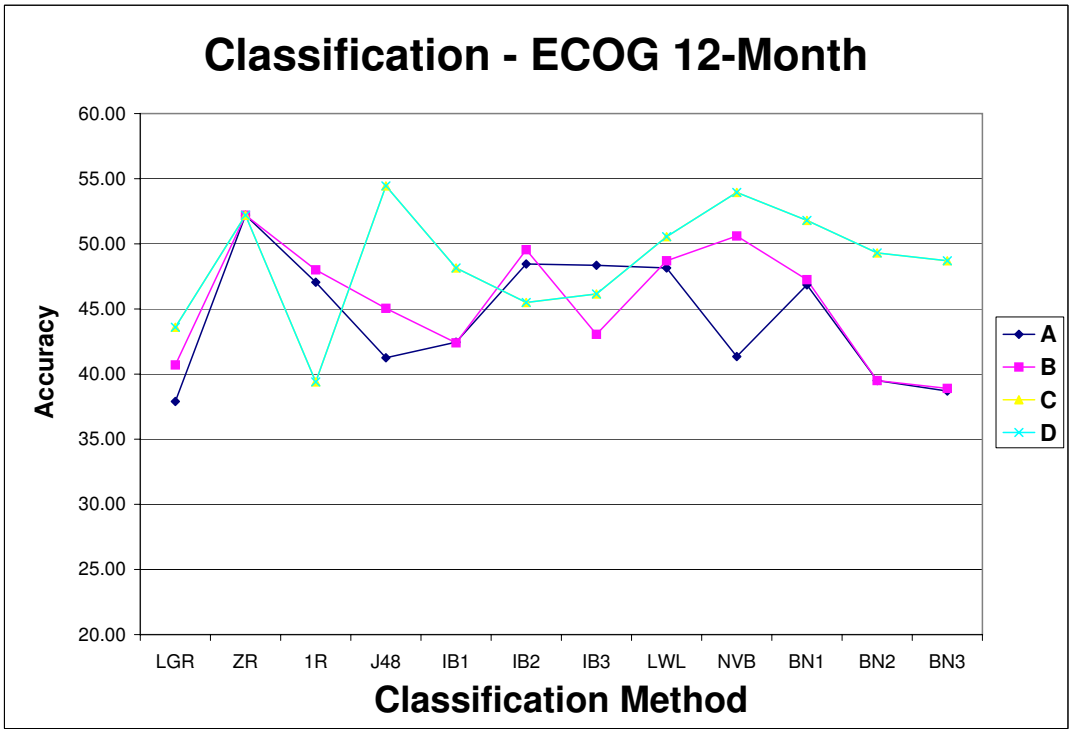


Figure 222: ECOG 12-Month - Results Graph

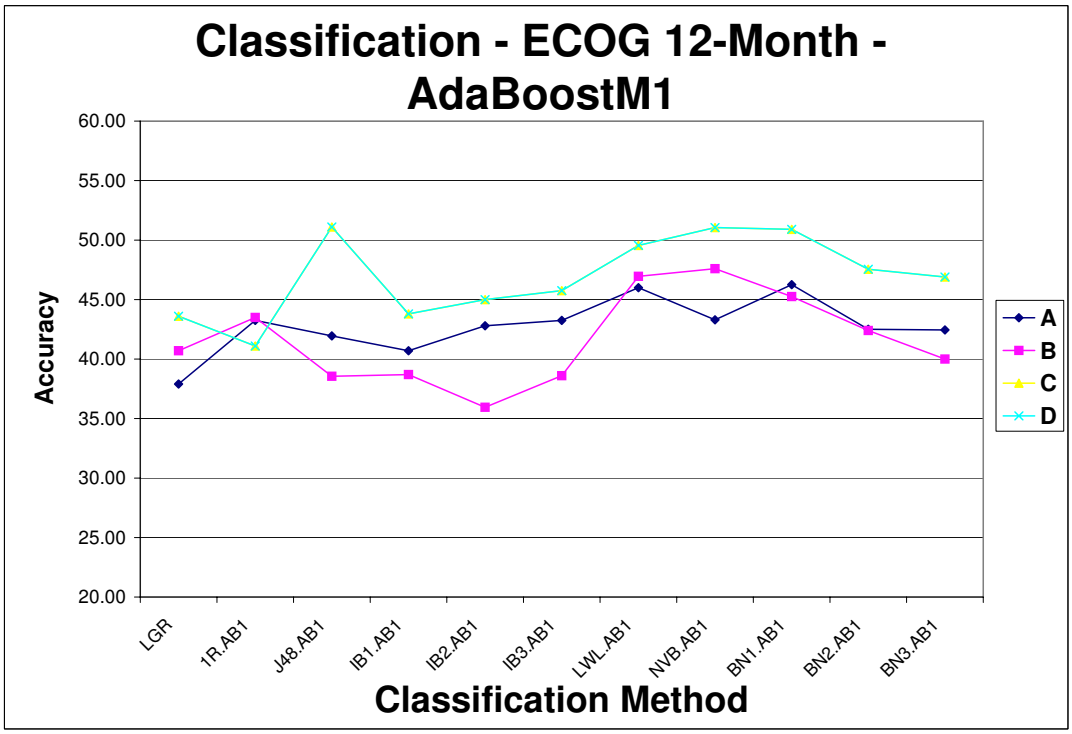


Figure 223: ECOG 12-Month - Results Graph - AdaBoostM1

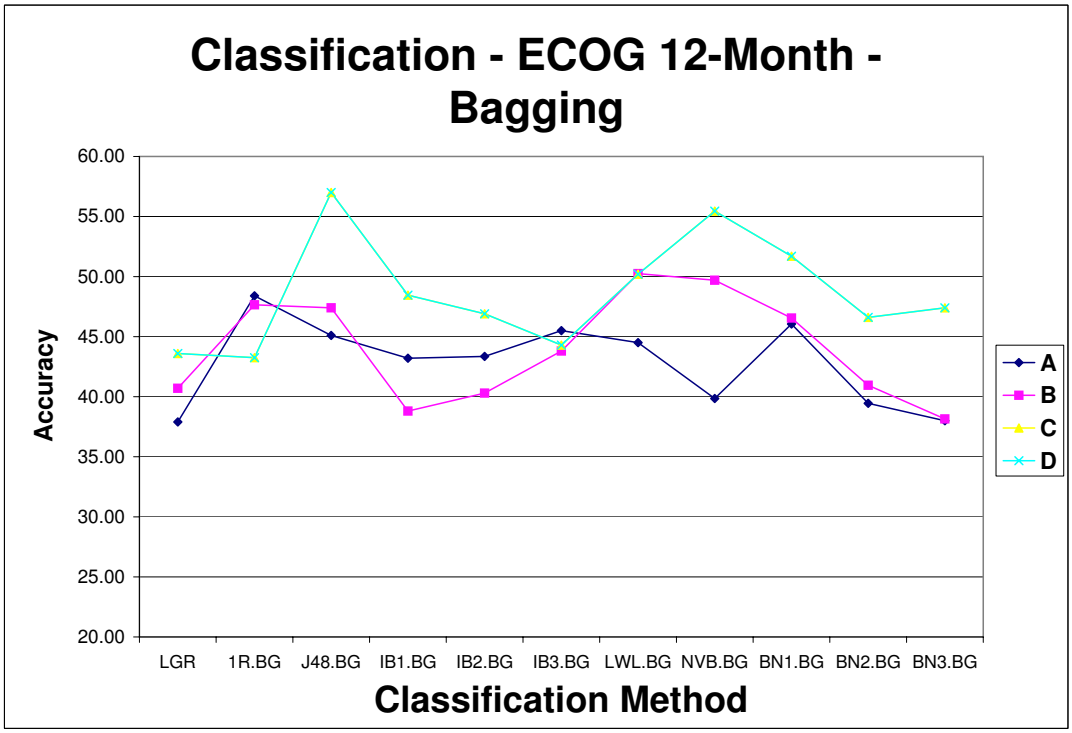


Figure 224: ECOG 12-Month - Results Graph - Bagging

ECOG 12-Month T-Test - ML Algorithms vs. Logistic Regression											
Data Set	ZR	1R	J48	IB1	IB2	IB3	LWL	NVB	BN1	BN2	BN3
A	=	=	=	=	=	=	=	=	=	=	=
B	=	=	=	=	=	=	=	=	=	=	=
C	=	=	=	=	=	=	=	=	=	=	=
D	=	=	=	=	=	=	=	=	=	=	=
+ : Superior to LGR = : Equivalent to LGR - : Inferior to LGR											

Figure 225: ECOG 12-Month - T-Test vs. Logistic Regression

ECOG 12-Month T-Test - ML Algs. w/ AdaBoostM1 vs. Logistic Regression										
Data Set	1R.AB1	J48.AB1	IB1.AB1	IB2.AB1	IB3.AB1	LWL.AB1	NVB.AB1	BN1.AB1	BN2.AB1	BN3.AB1
A	=	=	=	=	=	=	=	=	=	=
B	=	=	=	=	=	=	=	=	=	=
C	=	=	=	=	=	=	=	=	=	=
D	=	=	=	=	=	=	=	=	=	=
+ : Superior to LGR = : Equivalent to LGR - : Inferior to LGR										

Figure 226: ECOG 12-Month - T-Test vs. Logistic Regression - AdaBoostM1

ECOG 12-Month T-Test - ML Algs. w/ Bagging vs. Logistic Regression										
Data Set	1R.BG	J48.BG	IB1.BG	IB2.BG	IB3.BG	LWL.BG	NVB.BG	BN1.BG	BN2.BG	BN3.BG
A	=	=	=	=	=	=	=	=	=	=
B	=	=	=	=	=	=	=	=	=	=
C	=	=	=	=	=	=	=	=	=	=
D	=	=	=	=	=	=	=	=	=	=
+ : Superior to LGR = : Equivalent to LGR - : Inferior to LGR										

Figure 227: ECOG 12-Month - T-Test vs. Logistic Regression - Bagging

5.10 C10 - Survival

For survival tests among N=60 patients, we predict value of 4 numeric ranges which are evenly distributed between bins. Distribute of target values is shown in Table 15. Classification accuracy for survival prediction generally ranges from 40% to 60%. Naive Bayes and Bayesian nets in A and B data sets performed better than logistic regression via t-testing–a notable result. Data sets with supervised discretization and attribute selection generally produced results with higher accuracy. Remaining machine learning algorithms were t-test comparable to logistic regression accuracy in most cases. No statistically significant change was seen when meta-learning was introduced.

Classification - Survival

Data Set	LGR	ZR	1R	J48	IB1	IB2	IB3	LWL	NVB	BN1	BN2	BN3
A	41.67	33.33	26.17	46.00	50.33	46.17	33.67	45.83	40.83	43.33	47.50	47.50
B	39.33	33.33	31.83	45.00	47.67	39.50	34.50	47.00	41.17	43.33	48.50	48.00
C	42.50	33.33	34.17	43.50	55.67	54.83	56.00	52.67	57.17	56.67	55.67	52.00
D	42.50	33.33	34.17	43.50	55.67	54.83	56.00	52.67	57.17	56.67	55.67	52.00

Figure 228: Survival - Accuracy Results (Percentage)

Classification - Survival - AdaBoostM1

Data Set	LGR	1R.AB1	J48.AB	IB1.AB1	IB2.AB1	IB3.AB1	LWL.AB1	NVB.AB1	BN1.AB1	BN2.AB1	BN3.AB1
A	41.67	32.33	43.17	50.33	41.33	33.67	45.83	42.50	45.00	46.83	47.33
B	39.33	32.83	42.00	47.67	39.33	33.83	47.00	38.83	43.17	47.83	48.50
C	42.50	34.00	44.50	54.33	52.50	55.50	53.17	54.67	53.83	53.17	49.00
D	42.50	34.00	44.50	54.33	52.50	55.50	53.17	54.67	53.83	53.17	49.00

Figure 229: Survival - Accuracy Results (Percentage) - AdaBoostM1

Classification - Survival - Bagging

Data Set	LGR	1R.BG	J48.BG	IB1.BG	IB2.BG	IB3.BG	LWL.BG	NVB.BG	BN1.BG	BN2.BG	BN3.BG
A	41.67	34.33	43.50	47.83	40.50	38.17	42.17	40.17	42.00	46.33	46.33
B	39.33	34.17	44.67	44.50	43.17	40.67	46.33	40.00	40.50	47.50	46.83
C	42.50	35.50	45.67	51.50	54.00	53.50	52.83	55.83	55.00	53.00	53.00
D	42.50	35.50	45.67	51.50	54.00	53.50	52.83	55.83	55.00	53.00	53.00

Figure 230: Survival - Accuracy Results (Percentage) - Bagging

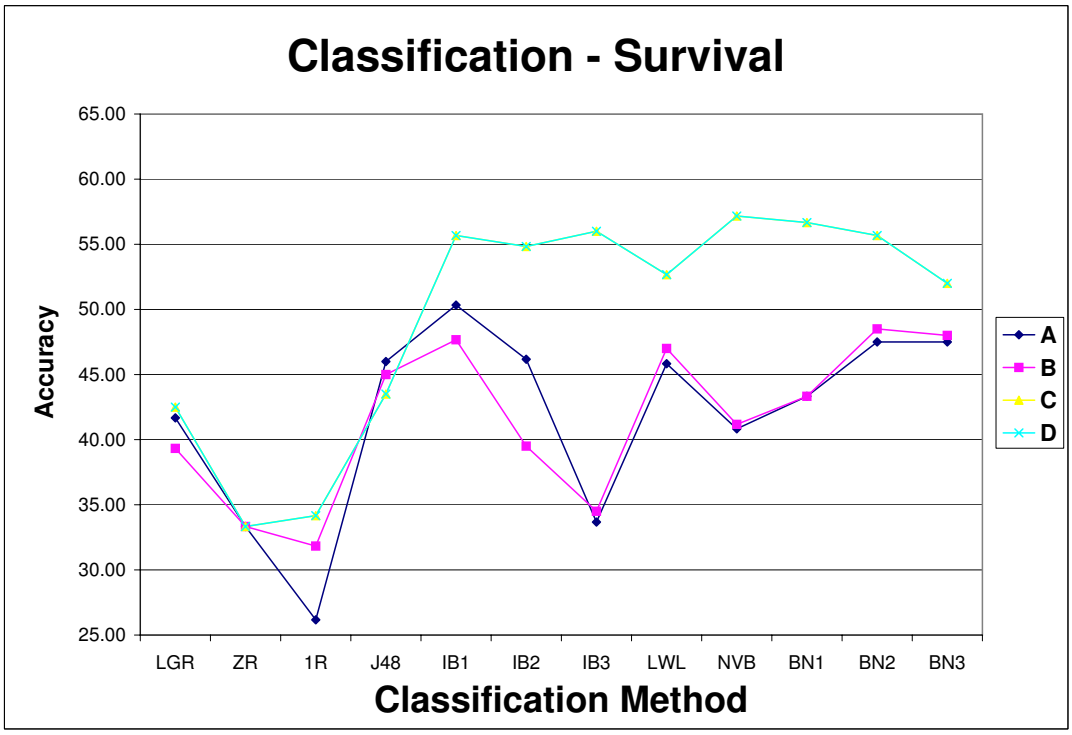


Figure 231: Survival - Results Graph

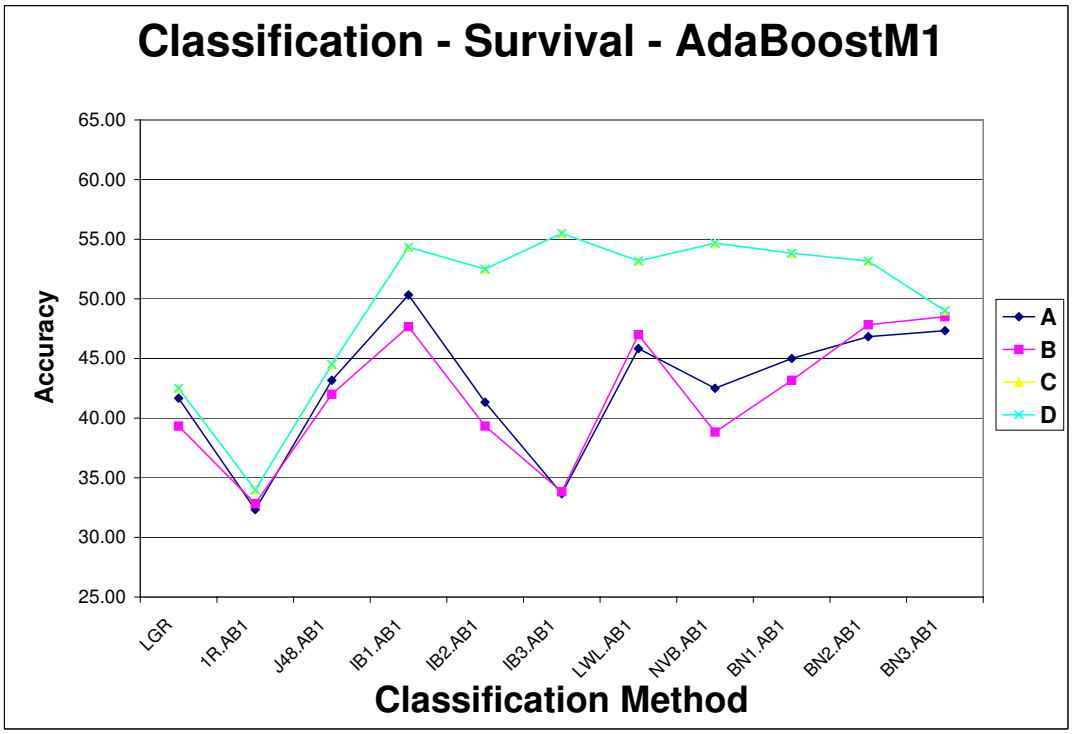


Figure 232: Survival - Results Graph - AdaBoostM1

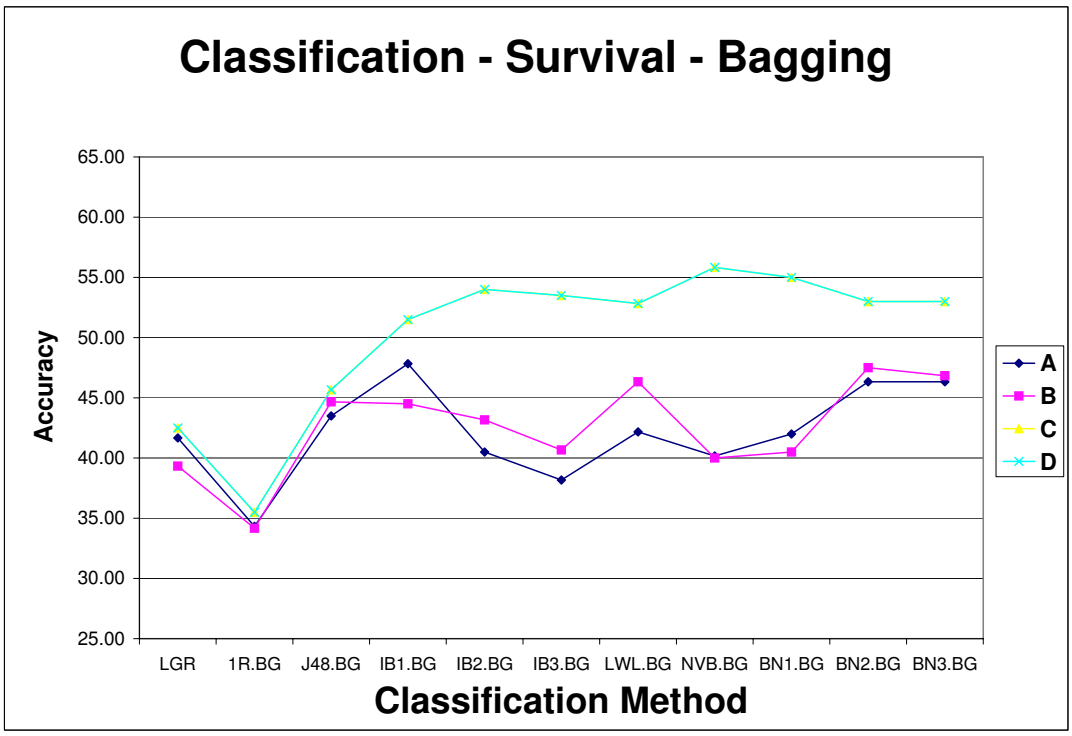


Figure 233: Survival - Results Graph - Bagging

Survival T-Test - ML Algorithms vs. Logistic Regression											
Data Set	ZR	1R	J48	IB1	IB2	IB3	LWL	NVB	BN1	BN2	BN3
A	=	-	=	=	=	=	=	=	=	=	=
B	=	=	=	=	=	=	=	=	=	=	=
C	=	=	=	=	=	=	=	+	=	=	=
D	=	=	=	=	=	=	=	+	=	=	=
+ : Superior to LGR = : Equivalent to LGR - : Inferior to LGR											

Figure 234: Survival - T-Test vs. Logistic Regression

Survival T-Test - ML Algs. w/ AdaBoostM1 vs. Logistic Regression										
Data Set	1R.AB1	J48.AB1	IB1.AB1	IB2.AB1	IB3.AB1	LWL.AB1	NVB.AB1	BN1.AB1	BN2.AB1	BN3.AB1
A	=	=	=	=	=	=	=	=	=	=
B	=	=	=	=	=	=	=	=	=	=
C	=	=	=	=	=	=	=	=	=	=
D	=	=	=	=	=	=	=	=	=	=
+ : Superior to LGR = : Equivalent to LGR - : Inferior to LGR										

Figure 235: Survival - T-Test vs. Logistic Regression - AdaBoostM1

Survival T-Test - ML Algs. w/ Bagging vs. Logistic Regression										
Data Set	1R.BG	J48.BG	IB1.BG	IB2.BG	IB3.BG	LWL.BG	NVB.BG	BN1.BG	BN2.BG	BN3.BG
A	=	=	=	=	=	=	=	=	=	=
B	=	=	=	=	=	=	=	=	=	=
C	=	=	=	=	=	=	=	=	=	=
D	=	=	=	=	=	=	=	=	=	=
+ : Superior to LGR = : Equivalent to LGR - : Inferior to LGR										

Figure 236: Survival - T-Test vs. Logistic Regression - Bagging

5.11 R1 - Tumor Size

For tumor-size regression tests among N=74 patients, we predict numeric values ranging from 0 to 11 cm. Distribute of target values is shown in Table 6. Regression r-squared values for survival prediction range from .00 to .45. Linear regression and M5 model trees performed best. Data sets with attribute selection generally produced results with comparable r-squared values. Remaining machine learning algorithms were t-test inferior to linear regression accuracy in most cases. Meta-learning introduced statistically superior performance in multi-layer perceptrons when compared to linear regression performance.

Regression - Tumor Size

Data Set	LNR	ZR	M5M	M5R	RBF	MLP2	MLP3
E	0.27	0.00	0.28	0.29	0.03	0.17	0.17
F	0.41	0.00	0.37	0.28	0.07	0.32	0.32

Figure 237: Tumor Size - R-Squared Results

Regression - Tumor Size - Bagging and Stacking

Data Set	LNR	M5M.BG	M5R.BG	LNR.BG	RBF.BG	MLP2.BG	MLP3.BG	STK
E	0.27	0.29	0.36	0.28	0.03	0.26	0.24	0.15
F	0.41	0.45	0.30	0.42	0.17	0.41	0.38	0.20

Figure 238: Tumor Size - R-Squared Results - AdaBoostM1

Figure 239: Tumor Size - Regression Results Graph

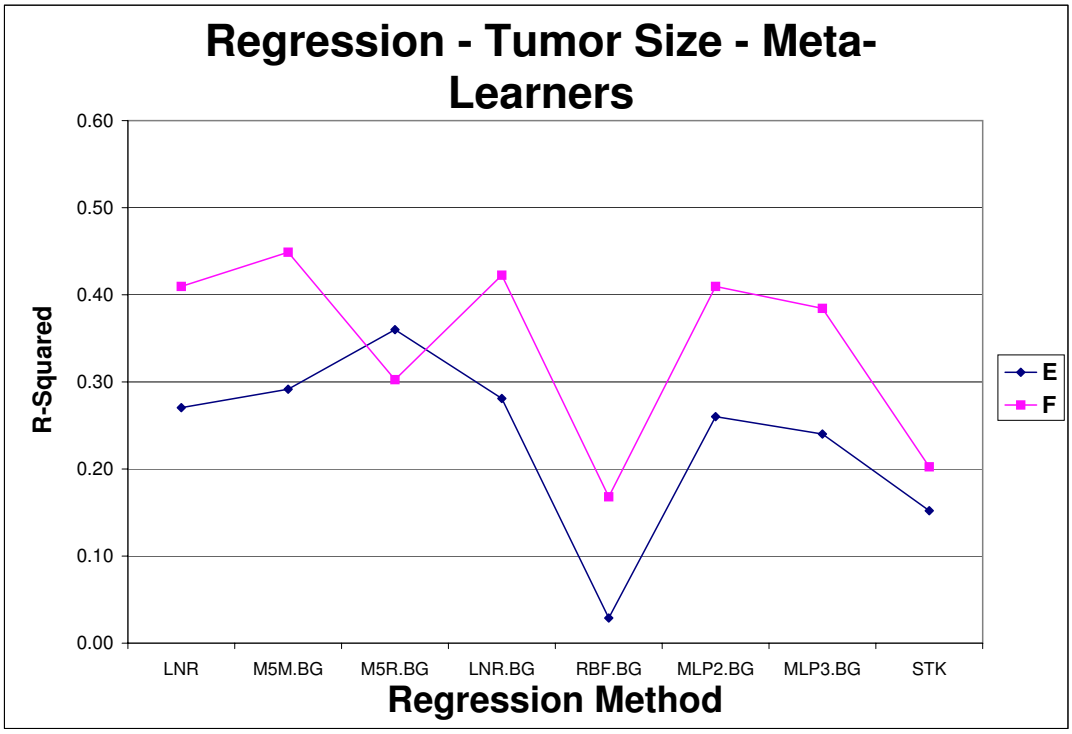


Figure 240: Tumor Size - Regression Results Graph - Bagging and Stacking

Tumor Size T-Test - ML Algorithms vs. Linear Regression

Data Set	ZR	M5M	M5R	RBF	MLP2	MLP3
E	-	=	=	-	-	-
F	-	=	-	-	-	-

+ : Superior to LNR = : Equivalent to LNR - : Inferior to LNR

Figure 241: Tumor Size - T-Test vs. Linear Regression

Tumor Size T-Test - ML Algorithms w/ Meta-Learners vs. Linear Regression							
Data Set	M5M.BG	M5R.BG	LNR.BG	RBF.BG	MLP2.BG	MLP3.BG	STK
E	=	=	=	-	=	=	-
F	=	-	=	-	=	=	-
+ : Superior to LNR = : Equivalent to LNR - : Inferior to LNR							

Figure 242: Tumor Size - T-Test vs. Linear Regression - Meta-learners

5.12 R2 - ECOG 6-Month

For ECOG 6-Month regression tests among N=72 patients, we predict numeric values ranging from 0 to 2 (ECOG values represented are those available among instances.). Distribute of target values is shown in Table 12. Regression r-squared values for ECOG prediction range from .00 to .27. Multi-layer perceptrons and RFB networks perform best, particularly with meta-learning on set F. Data sets with attribute selection generally produced results with higher r-squared values. Remaining machine learning algorithms were t-test inferior to linear regression accuracy in most cases. Meta-learning introduced statistically superior performance in multi-layer perceptrons, M5 model trees, and linear regression with bagging when compared to standard linear regression performance. High-performance models based on ECOG 6-Month regression are presented in Section 6.3.

Regression - ECOG 6-Month

Data Set	LNR	ZR	M5M	M5R	RBF	MLP2	MLP3
E	0.03	0.00	0.16	0.01	0.06	0.07	0.09
F	0.26	0.00	0.23	0.23	0.14	0.17	0.27

Figure 243: ECOG 6-Month - R-Squared Results

Regression - ECOG 6-Month - Bagging and Stacking

Data Set	LNR	M5M.BG	M5R.BG	LNR.BG	RBF.BG	MLP2.BG	MLP3.BG	STK
E	0.03	0.13	0.12	0.04	0.08	0.12	0.11	0.03
F	0.26	0.25	0.23	0.32	0.24	0.31	0.32	0.18

Figure 244: ECOG 6-Month - R-Squared Results - AdaBoostM1

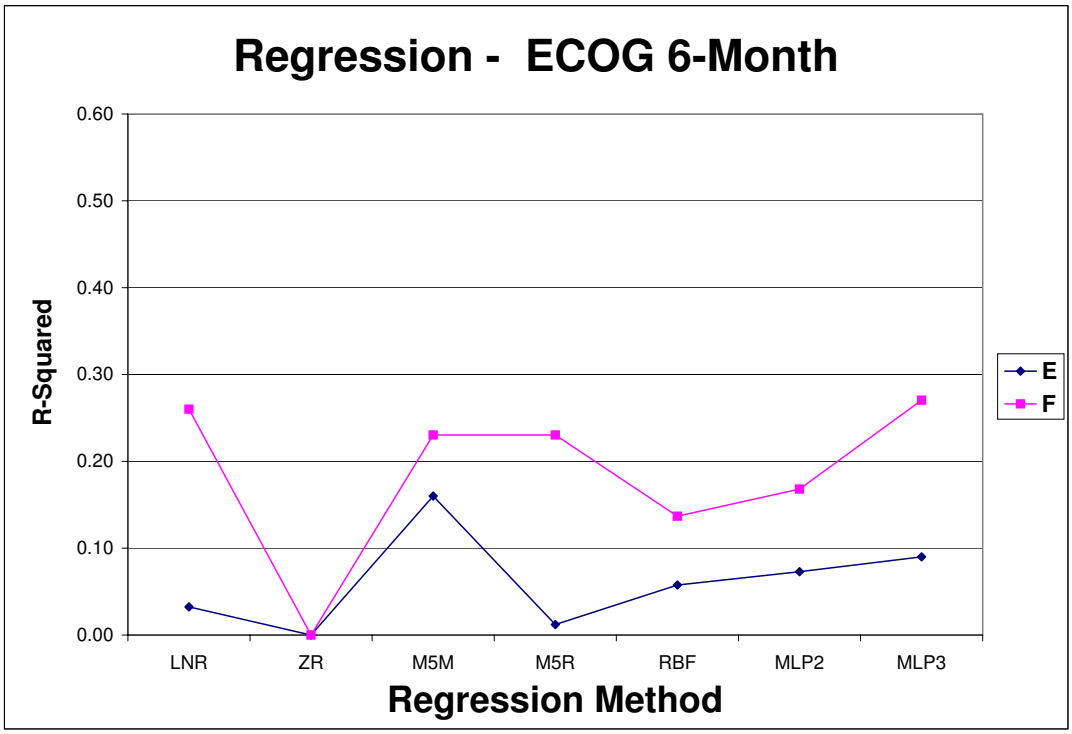


Figure 245: ECOG 6-Month - Regression Results Graph

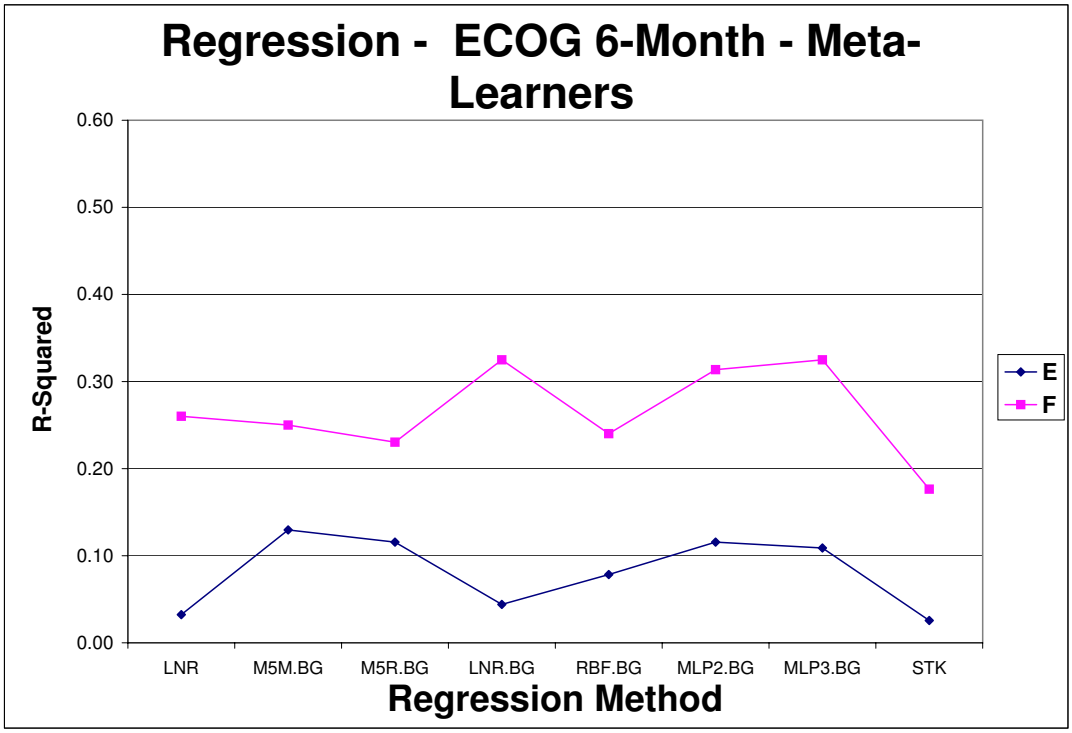


Figure 246: ECOG 6-Month - Regression Results Graph - Bagging and Stacking

ECOG 6-Month T-Test - ML Algorithms vs. Linear Regression

Data Set	ZR	M5M	M5R	RBF	MLP2	MLP3
E	-	+	=	=	+	+
F	-	=	=	-	-	=

+ : Superior to LNR = : Equivalent to LNR - : Inferior to LNR

Figure 247: ECOG 6-Month - T-Test vs. Linear Regression

ECOG 6-Month T-Test - ML Algorithms w/ Meta-Learners vs. Linear Regression							
Data Set	M5M.BG	M5R.BG	LNR.BG	RBF.BG	MLP2.BG	MLP3.BG	STK
E	+	+	+	=	+	+	=
F	=	=	+	=	=	+	-
+ : Superior to LNR = : Equivalent to LNR - : Inferior to LNR							

Figure 248: ECOG 6-Month - T-Test vs. Linear Regression - Meta-learners

5.13 R3 - ECOG 9-Month

For ECOG 9-Month regression tests among N=57 patients, we predict numeric values ranging from 0 to 3 (ECOG values represented are those available among instances.). Distribute of target values is shown in Table 13. Regression r-squared values for ECOG prediction range from .00 to .25. Multi-layer perceptrons and RFB networks perform best, particularly on set E. Data sets with attribute selection generally produced results with higher r-squared values. Remaining machine learning algorithms were t-test comparable or inferior to linear regression accuracy in most cases. Meta-learning introduced statistically superior performance in most tested models when compared to standard linear regression performance. High-performance models based on ECOG 9-Month regression are presented in Section 6.4.

Regression - ECOG 9-Month							
Data Set	LNR	ZR	M5M	M5R	RBF	MLP2	MLP3
E	0.00	0.00	0.07	0.03	0.00	0.00	0.00
F	0.04	0.00	0.10	0.00	0.12	0.08	0.10

Figure 249: ECOG 9-Month - R-Squared Results

Regression - ECOG 9-Month - Bagging and Stacking								
Data Set	LNR	M5M.BG	M5R.BG	LNR.BG	RBF.BG	MLP2.BG	MLP3.BG	STK
E	0.00	0.07	0.08	0.00	0.03	0.01	0.01	0.00
F	0.04	0.13	0.14	0.08	0.25	0.16	0.13	0.06

Figure 250: ECOG 9-Month - R-Squared Results - AdaBoostM1

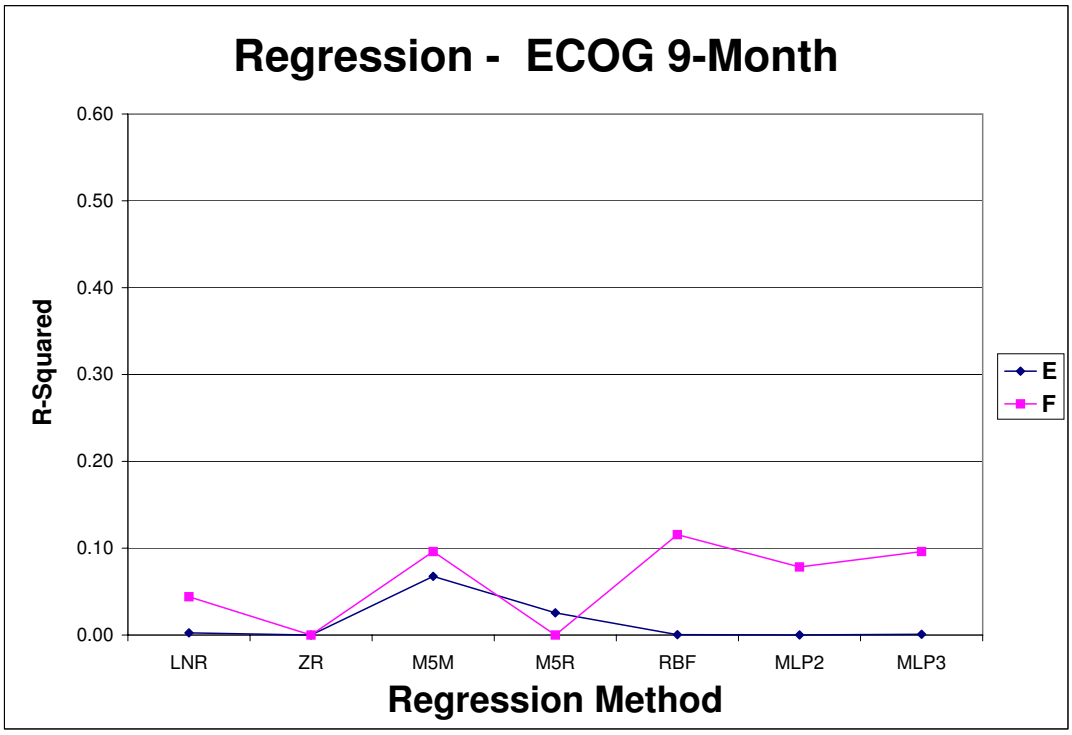


Figure 251: ECOG 9-Month - Regression Results Graph

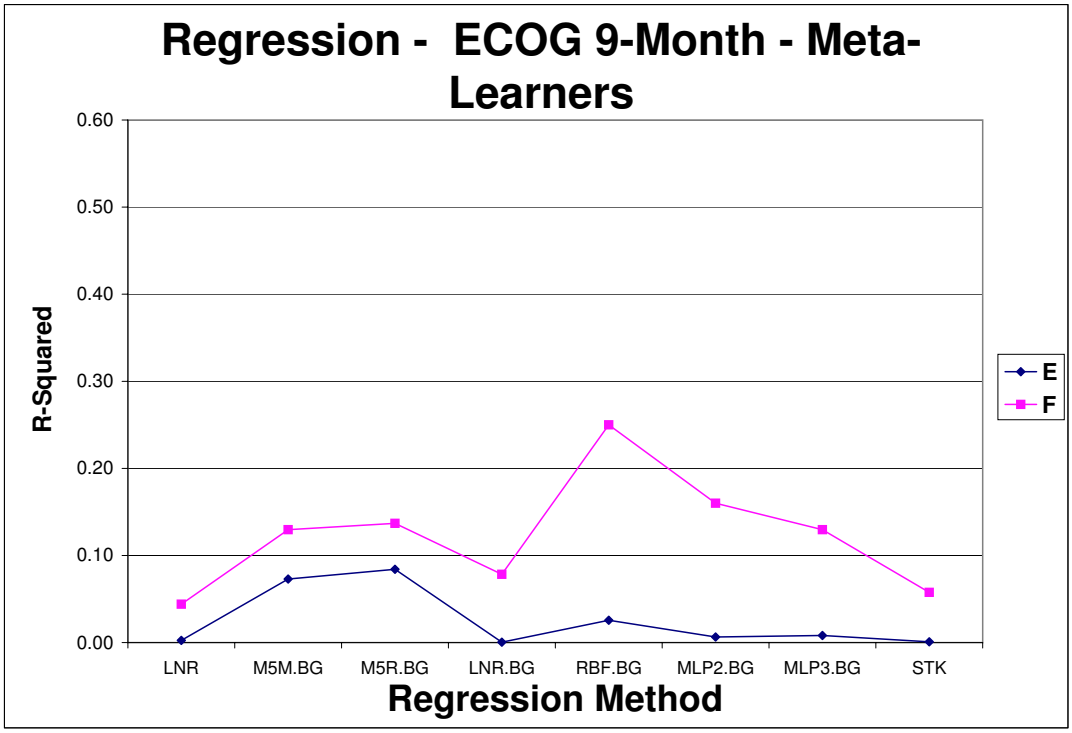


Figure 252: ECOG 9-Month - Regression Results Graph - Bagging and Stacking

ECOG 9-Month T-Test - ML Algorithms vs. Linear Regression						
Data Set	ZR	M5M	M5R	RBF	MLP2	MLP3
E	=	+	+	=	=	=
F	-	=	-	=	=	=
+ : Superior to LNR = : Equivalent to LNR - : Inferior to LNR						

Figure 253: ECOG 9-Month - T-Test vs. Linear Regression

ECOG 9-Month T-Test - ML Algorithms w/ Meta-Learners vs. Linear Regression							
Data Set	M5M.BG	M5R.BG	LNR.BG	RBF.BG	MLP2.BG	MLP3.BG	STK
E	+	+	+	+	+	+	=
F	+	+	=	+	+	+	=
+ : Superior to LNR = : Equivalent to LNR - : Inferior to LNR							

Figure 254: ECOG 9-Month - T-Test vs. Linear Regression - Meta-learners

5.14 R4 - ECOG 12-Month

For ECOG 12-Month regression tests among N=44 patients, we predict numeric values ranging from 0 to 3 (ECOG values represented are those available among instances.). Distribute of target values is shown in Table 14. Regression r-squared values for ECOG prediction range from .00 to .28. Data sets with attribute selection generally produced results with higher r-squared values. Remaining machine learning algorithms were t-test comparable or inferior to linear regression accuracy in most cases. Meta-learning introduced statistically superior performance in multi-layer perceptrons on the data set E when compared to standard linear regression performance.

Regression - ECOG 12-Month							
Data Set	LNR	ZR	M5M	M5R	RBF	MLP2	MLP3
E	0.00	0.00	0.03	0.00	0.01	0.07	0.05
F	0.22	0.00	0.14	0.00	0.10	0.25	0.20

Figure 255: ECOG 12-Month - R-Squared Results

Regression - ECOG 12-Month - Bagging and Stacking								
Data Set	LNR	M5M.BG	M5R.BG	LNR.BG	RBF.BG	MLP2.BG	MLP3.BG	STK
E	0.00	0.01	0.00	0.01	0.01	0.07	0.05	0.00
F	0.22	0.23	0.05	0.28	0.21	0.27	0.24	0.08

Figure 256: ECOG 12-Month - R-Squared Results - AdaBoostM1

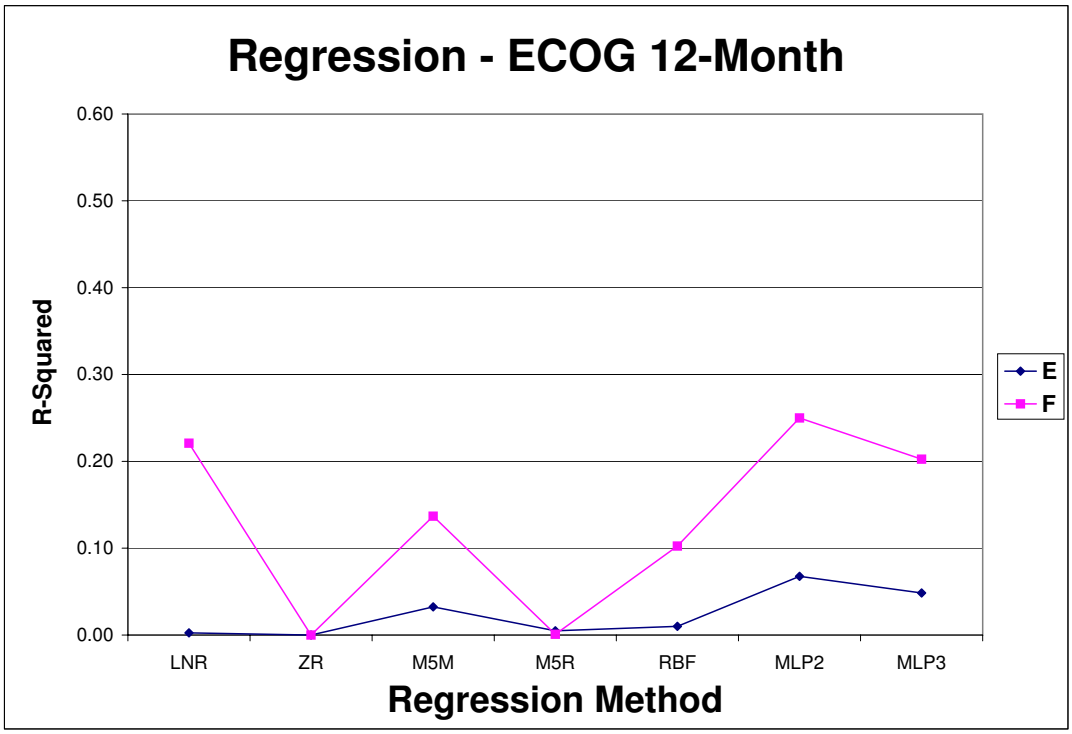


Figure 257: ECOG 12-Month - Regression Results Graph

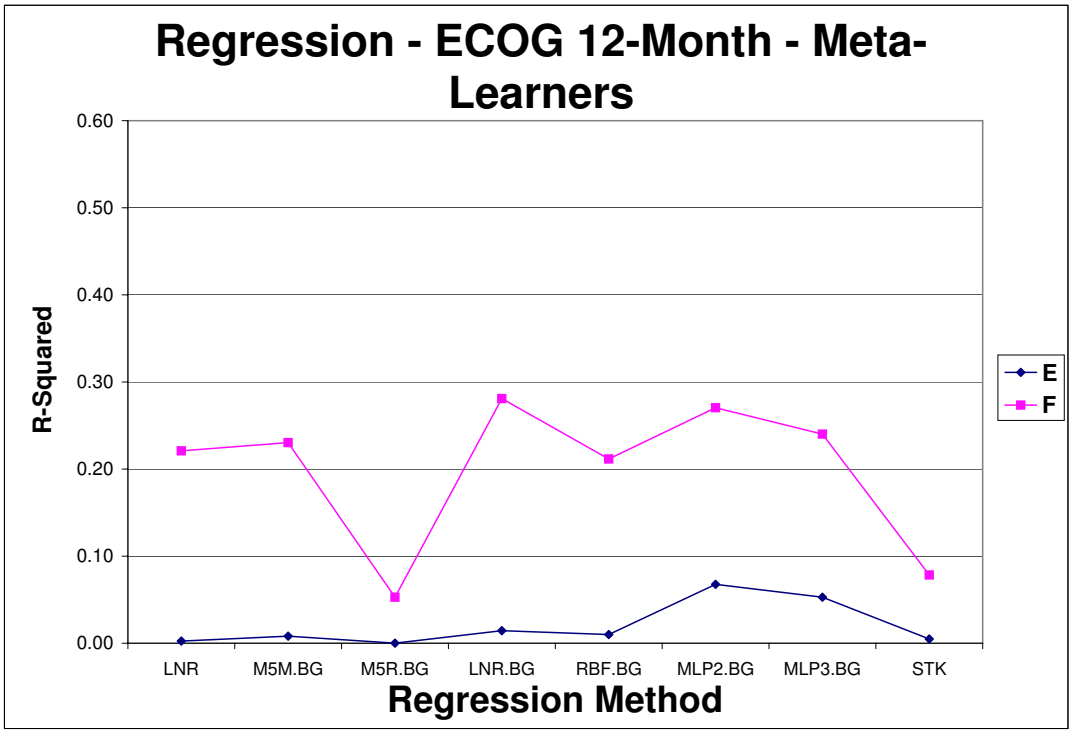


Figure 258: ECOG 12-Month - Regression Results Graph - Bagging and Stacking

ECOG 12-Month T-Test - ML Algorithms vs. Linear Regression

Data Set	ZR	M5M	M5R	RBF	MLP2	MLP3
E	-	-	-	-	+	+
F	-	-	-	-	=	=

+ : Superior to LNR = : Equivalent to LNR - : Inferior to LNR

Figure 259: ECOG 12-Month - T-Test vs. Linear Regression

ECOG 12-Month T-Test - ML Algorithms w/ Meta-Learners vs. Linear Regression

Data Set	M5M.BG	M5R.BG	LNR.BG	RBF.BG	MLP2.BG	MLP3.BG	STK
E	-	=	=	=	+	+	=
F	=	-	+	=	=	=	-

+ : Superior to LNR = : Equivalent to LNR - : Inferior to LNR

Figure 260: ECOG 12-Month - T-Test vs. Linear Regression - Meta-learners

5.15 R5 - Survival

For survival regression tests among N=60 patients, we predict numeric values ranging from 0.9 to 29.3 months. Distributions of target values is shown in Table 15. Regression r-squared values for survival prediction range from .00 to .28. Multi-layer perceptrons and linear regression with bagging performed generally better than linear regression, particularly on set E. Data sets with attribute selection generally produced results with higher r-squared values for meta-learning tests. Remaining machine learning algorithms had varied t-test accuracies when compared to linear regression. Meta-learning introduced instances of statistically inferior performance on both data sets.

Regression - Survival							
Data Set	LNR	ZR	M5M	M5R	RBF	MLP2	MLP3
E	0.01	0.00	0.00	0.00	0.01	0.08	0.05
F	0.25	0.00	0.00	0.00	0.02	0.26	0.25

Figure 261: Survival - R-Squared Results

Regression - Survival - Bagging and Stacking								
Data Set	LNR	M5M.BG	M5R.BG	LNR.BG	RBF.BG	MLP2.BG	MLP3.BG	STK
E	0.01	0.01	0.00	0.02	0.00	0.07	0.07	0.00
F	0.25	0.03	0.00	0.27	0.06	0.28	0.27	0.04

Figure 262: Survival - R-Squared Results - AdaBoostM1

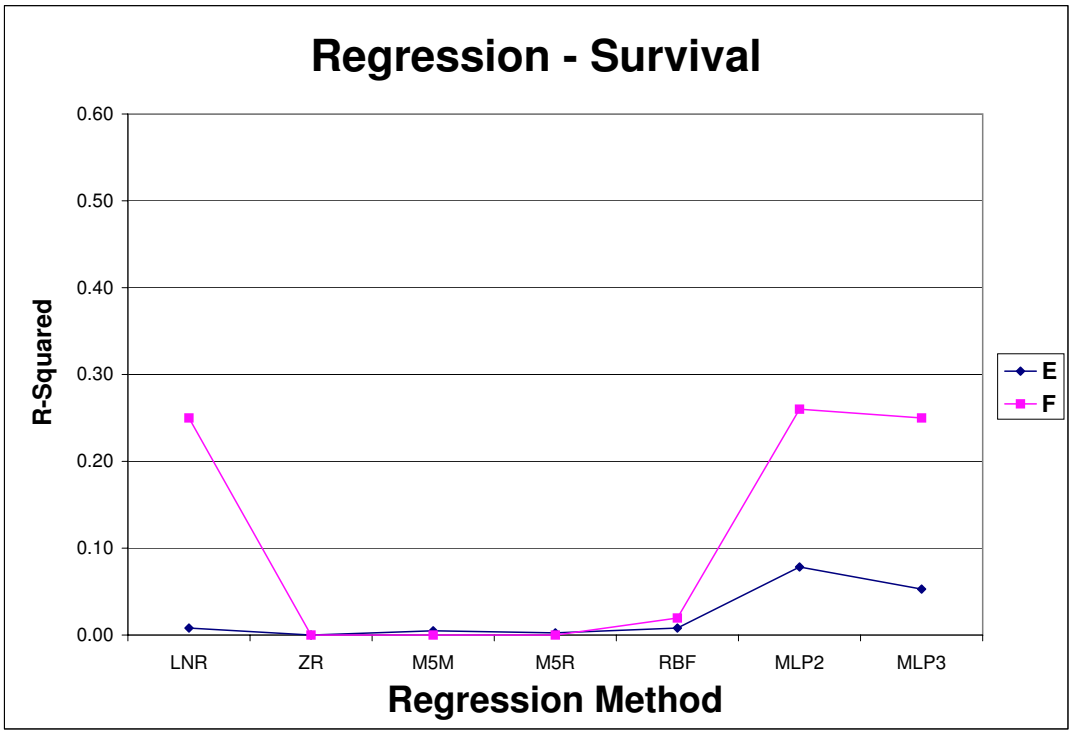


Figure 263: Survival - Regression Results Graph

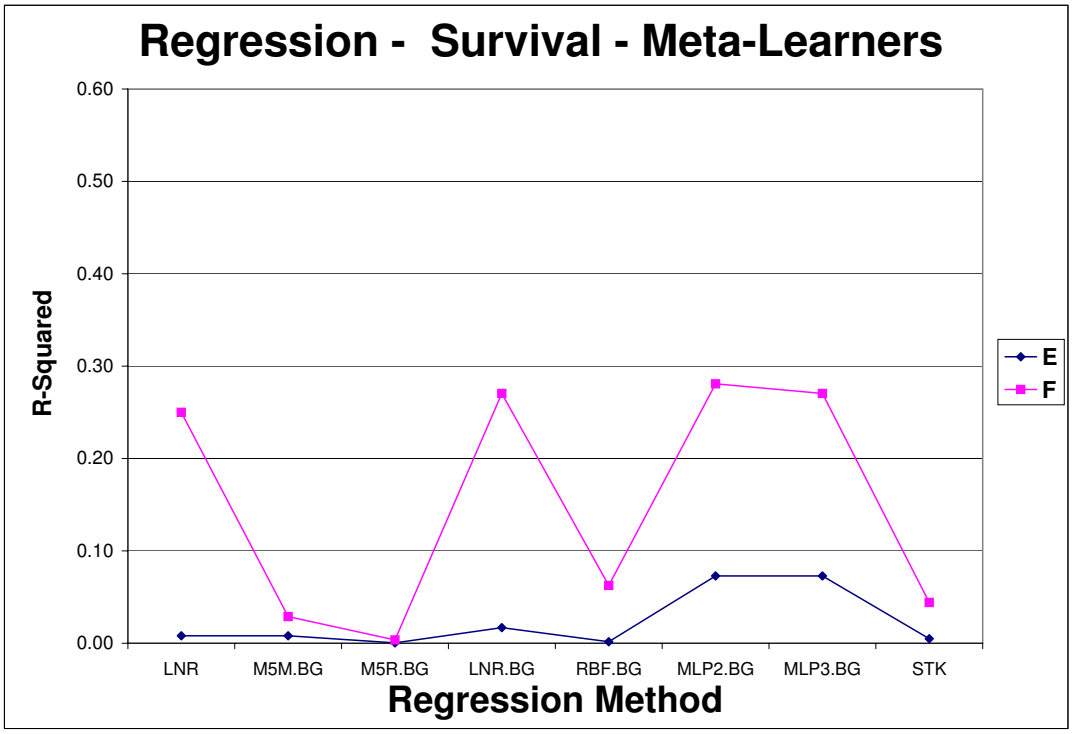


Figure 264: Survival - Regression Results Graph - Bagging and Stacking

Survival T-Test - ML Algorithms vs. Linear Regression

Data Set	ZR	M5M	M5R	RBF	MLP2	MLP3
E	-	=	-	=	+	+
F	-	-	-	-	=	=

+ : Superior to LNR = : Equivalent to LNR - : Inferior to LNR

Figure 265: Survival - T-Test vs. Linear Regression

Survival T-Test - ML Algorithms w/ Meta-Learners vs. Linear Regression							
Data Set	M5M.BG	M5R.BG	LNR.BG	RBF.BG	MLP2.BG	MLP3.BG	STK
E	=	=	+	=	+	+	=
F	-	-	=	-	=	=	-
+ : Superior to LNR = : Equivalent to LNR - : Inferior to LNR							

Figure 266: Survival - T-Test vs. Linear Regression - Meta-learners

6 High-Performance Predictive Models

Several of the high-performance machine learning models are described in this section. Two models from the classification experiments and two from the regression experiments are demonstrated. Each of these models outperform traditional regression methods via statistical tests. Each model also exhibits interesting structural characteristics, both in their internal design and the feature-selected attribute sets used to generate them. Verbatim Weka output of these models follows each section.

6.1 Classification - Histology - Data Set C - Bayesian Net 2-Parent

Shown here is a Bayesian Net 2-Parent classifier with high predictive accuracy for majority target class values. This model is taken from the C5 experiments in Section 5.5. Histology prediction is difficult given the wide variety of categorical possibilities (14 types are represented here). Additionally, certain histology types are only rarely represented in the clinical setting (MEN-I, pseudopapillary tumors, renal mets). As accurate prediction across all types is difficult, we seek instead to demonstrate models which can predict some of the more frequently occurring histologic values, including adenocarcinomas, neuroendocrine tumors, and IMPNs.

A graphical representation of this Bayes Net model is demonstrated in Figures 267 and 268. Classification accuracy for this particular Bayes Net model is 50.55%. For the three most frequently occurring histologic types, 'Adenocarcinoma of Pancreas - NOS', 'Ductal Adenocarcinoma of Pancreas', and 'IPMN - Benign or CiS', the predictive accuracy of this model is 79.03%. The Confusion matrix illustrated in Figure 269 illustrates the model's predictive accuracy for different histologic values, with the three majority histologic values shown boxed.

Experimental iterations of this data set with other Bayesian methods show that the accuracy can be pushed even higher. Naive Bayes classification retains the highest experiment

accuracy at 56.07% (ref. Figure 183), although the Bayesian Net shown here exhibits a much more interesting probability structure. Each node on the Bayesian Net reflects the joint probability distribution for its related attribute as determined by the attribute values of its parent nodes. These probability distributions are determined by the comparative frequencies of attribute values within the data sets. Examples of these distributions are shown in Figure 270.

Feature-selection generated a 24 attribute subset for data sets C and D in these experiments. The field names and their explanations are listed in Table 24. Generally, experimental accuracy was much higher for feature-selected data sets. As this entire subset consists of categorical attributes, supervised discretization induces no change to the result set. Therefore, no experimental variation exists on models generated from data set C or D.

Field	Description
PresumptiveDx	Presumptive Diagnosis
SxWtloss	Presentation - Weight Loss
SxJaun	Presentation - Jaundice
SxNau	Presentation - Nausea
SxFati	Presentation - Fatigue
SxPru	Presentation - Pruritis
SxOT	Presentation - Other
CxDiab	Comorbidities - Diabetes
CTNodeOmit	CT - Nodal Omission
EUSVascOmit	EUS - Vascular Omission
EUSPortal	EUS - Portal Vein Involvement
EUSNoNode	EUS - No Nodal Involvement
EUSStagingT	EUS - T Staging
EUSCyto	EUS - Cytology
TxLap	Treatment - Laparoscopy
TxRadia	Treatment - Radiotherapy
TxChemo	Treatment - Chemotherapy
TxChemoGem	Treatment - Chemotherapy - Gemcitabine
ResPxType	Resection - Procedure Type
ResTransfusion	Resection - Transfusion
ResPOCourse	Resection - Postoperative Course
ResPathN	Resection - Pathology N-Stage
SurOncName	Surgical Oncologist
RadOncName	Radiation Oncologist

Table 24: Histology Feature-Selected Attribute Subset

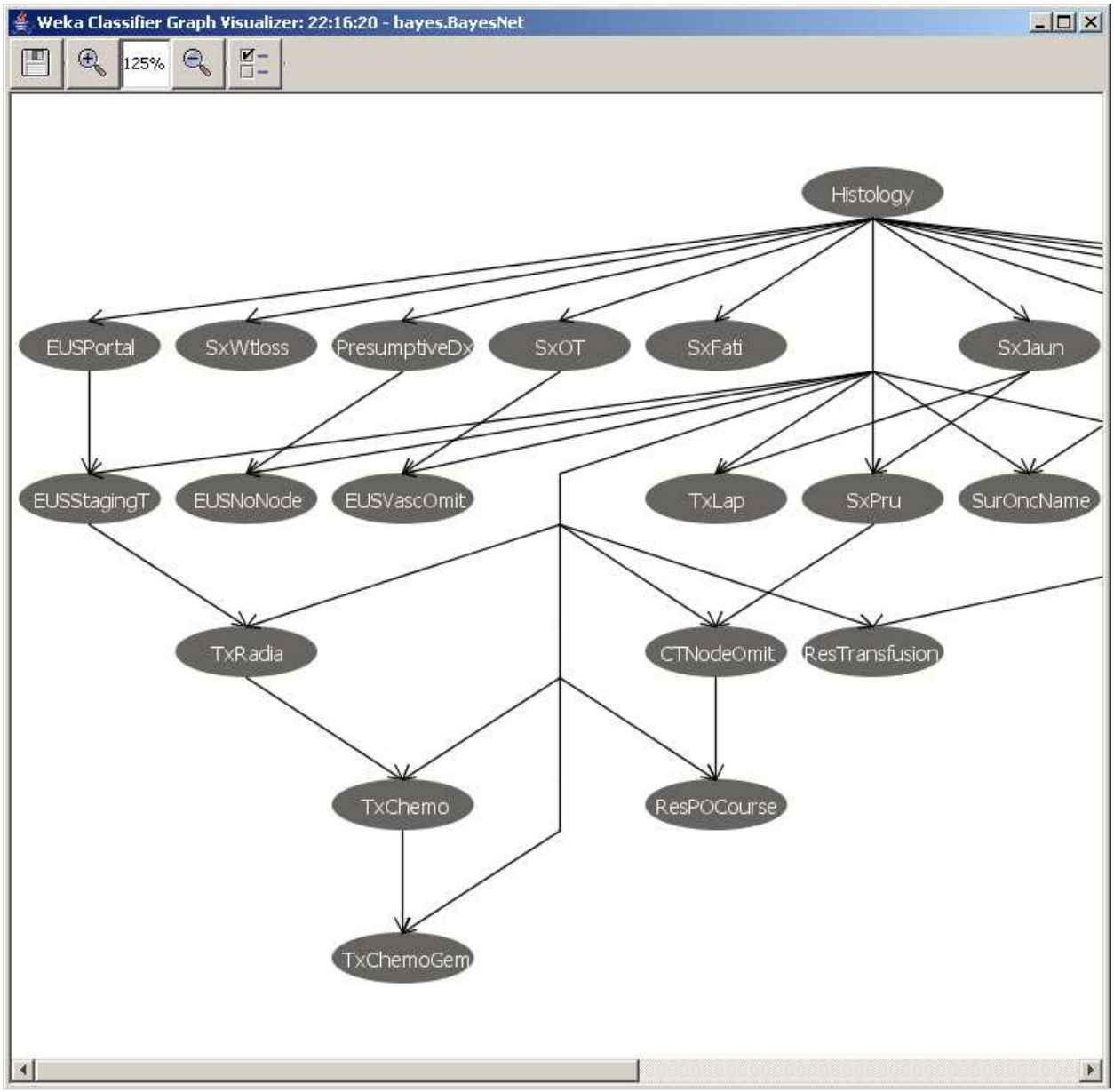


Figure 267: Classification - Histology - Data Set C - Bayesian Net 2-Parent

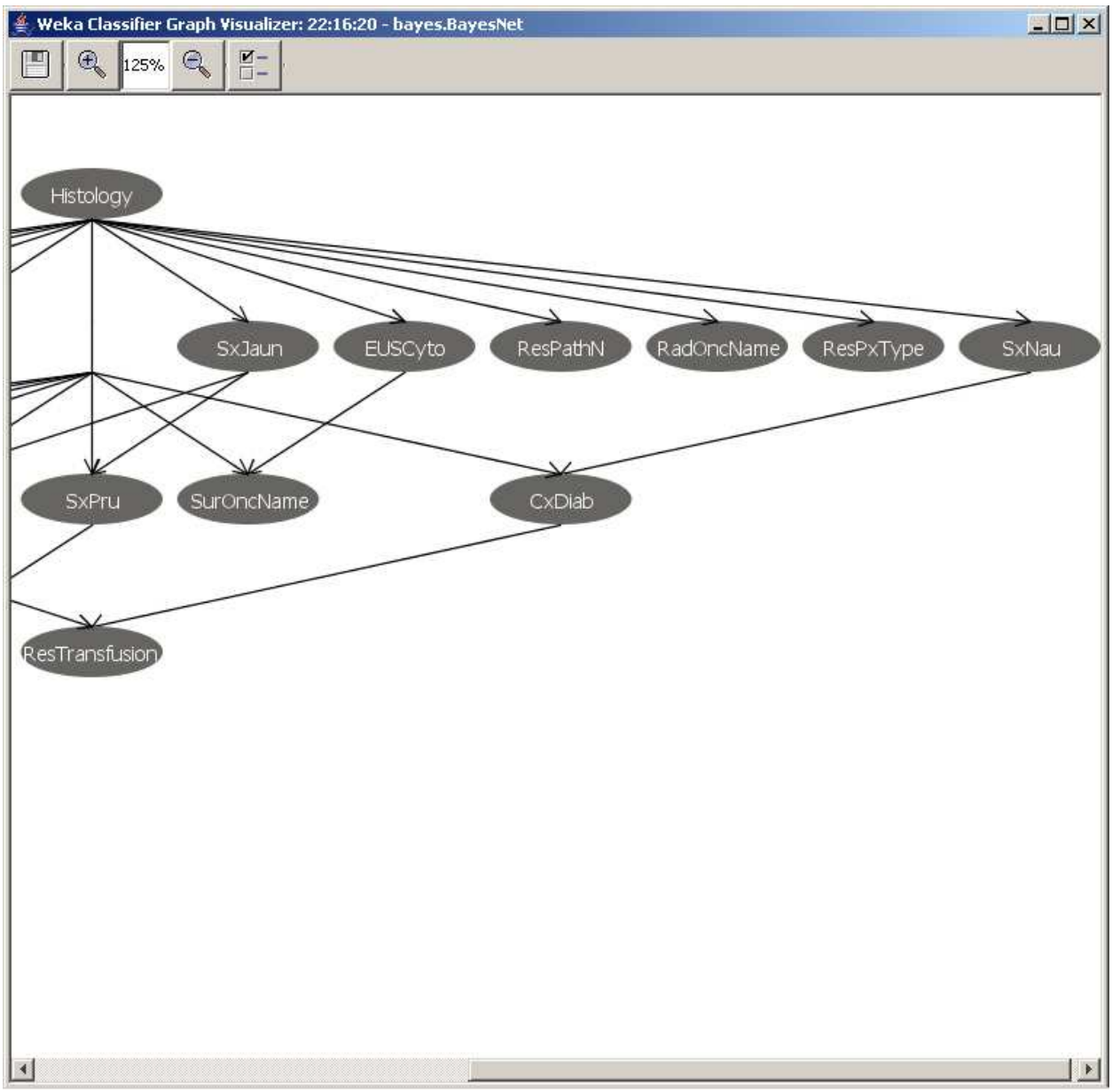
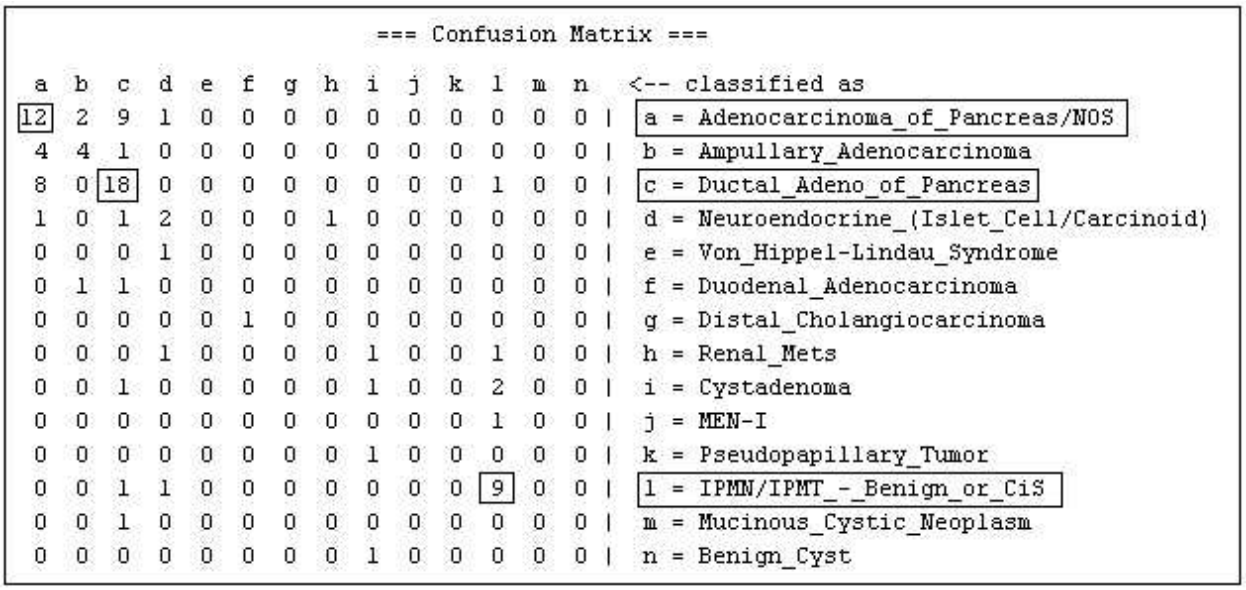


Figure 268: Classification - Histology - Data Set C - Bayesian Net 2-Parent (continued)



=== Confusion Matrix ===

a	b	c	d	e	f	g	h	i	j	k	l	m	n	<-- classified as
12	2	9	1	0	0	0	0	0	0	0	0	0	0	a = Adenocarcinoma_of_Pancreas/NOS
4	4	1	0	0	0	0	0	0	0	0	0	0	0	b = Ampullary_Adenocarcinoma
8	0	18	0	0	0	0	0	0	0	0	1	0	0	c = Ductal_Adeno_of_Pancreas
1	0	1	2	0	0	0	1	0	0	0	0	0	0	d = Neuroendocrine_(Islet_Cell/Carcinoid)
0	0	0	1	0	0	0	0	0	0	0	0	0	0	e = Von_Hippel-Lindau_Syndrome
0	1	1	0	0	0	0	0	0	0	0	0	0	0	f = Duodenal_Adenocarcinoma
0	0	0	0	0	1	0	0	0	0	0	0	0	0	g = Distal_Cholangiocarcinoma
0	0	0	1	0	0	0	0	1	0	0	1	0	0	h = Renal_Mets
0	0	1	0	0	0	0	0	1	0	0	2	0	0	i = Cystadenoma
0	0	0	0	0	0	0	0	0	0	0	1	0	0	j = MEN-I
0	0	0	0	0	0	0	0	1	0	0	0	0	0	k = Pseudopapillary_Tumor
0	0	1	1	0	0	0	0	0	0	0	9	0	0	l = IPMN/IPMT_-_Benign_or_CiS
0	0	1	0	0	0	0	0	0	0	0	0	0	0	m = Mucinous_Cystic_Neoplasm
0	0	0	0	0	0	0	0	1	0	0	0	0	0	n = Benign_Cyst

Figure 269: Classification - Histology - Data Set C - Confusion Matrix

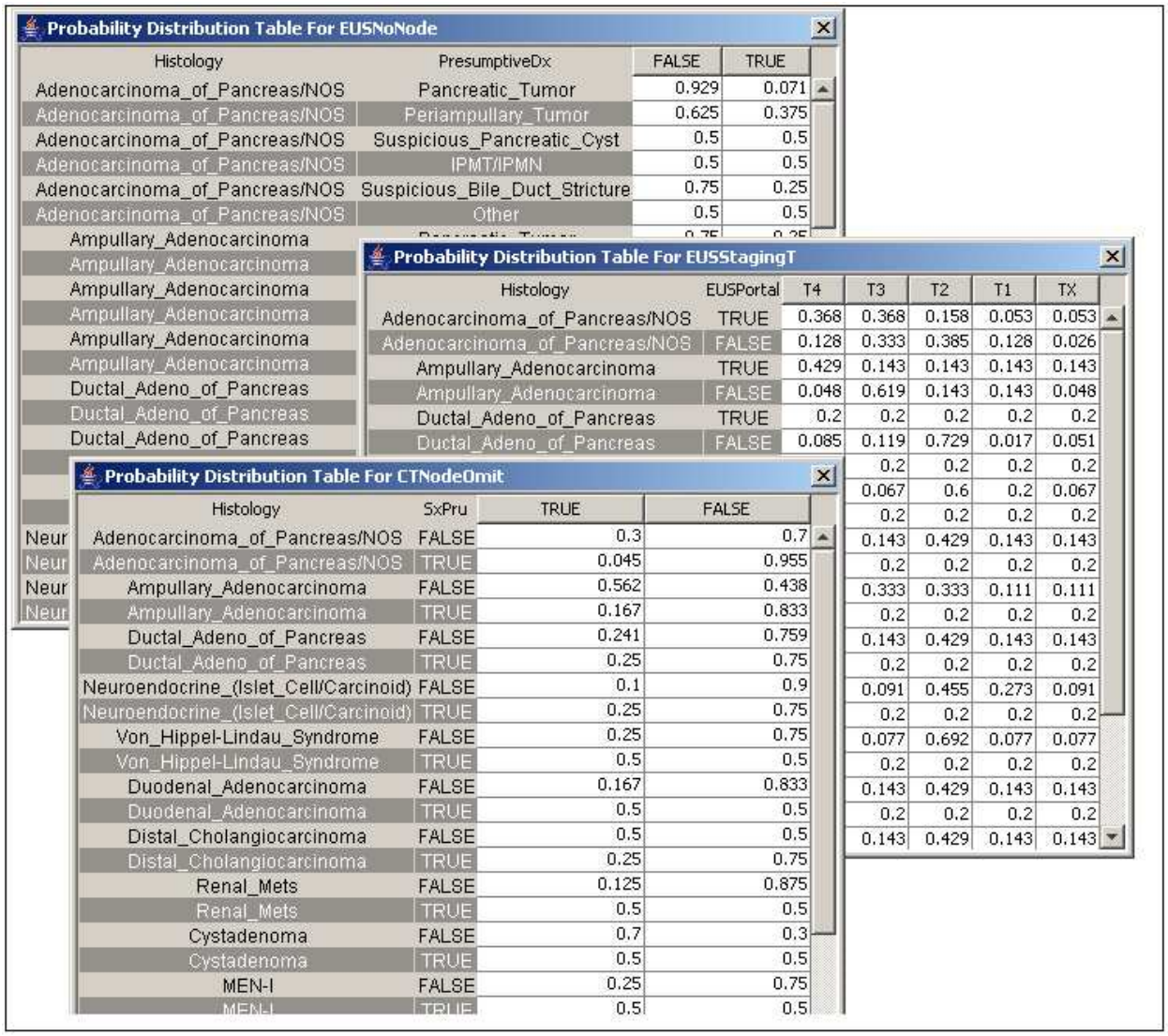


Figure 270: Classification - Histology - Data Set C - Joint Probability Distribution Examples

Weka Output:

```
=== Run information ===

Scheme:       weka.classifiers.bayes.BayesNet -D -Q weka.classifiers.bayes.
                net.search.local.K2 -- -P 2 -E weka.classifiers.bayes.net.
                estimate.SimpleEstimator -- -A 0.5
Relation:     Book1-weka.filters.supervised.attribute.AttributeSelection-
                Eweka.attributeSelection.CfsSubsetEval-Sweka
                .attributeSelection.BestFirst -D 1 -N 5
Instances:    91
Attributes:   25
              PresumptiveDx
              SxWtloss
              SxJaun
              SxNau
              SxFati
              SxPru
              SxOT
              CxDiab
              CTNodeOmit
              EUSVascOmit
              EUSPortal
              EUSNoNode
              EUSStagingT
              EUSCyto
              TxLap
              TxRadia
```

```
                TxChemo
                TxChemoGem
                ResPxType
                ResTransfusion
                ResPOCourse
                ResPathN
                SurOncName
                RadOncName
                Histology
Test mode:    10-fold cross-validation

=== Classifier model (full training set) ===

Bayes Network Classifier
not using ADTree
#attributes=25 #classindex=24
Network structure (nodes followed by parents)
PresumptiveDx(6): Histology
SxWtloss(2): Histology
SxJaun(2): Histology
SxNau(2): Histology
SxFati(2): Histology
SxPru(2): Histology SxJaun
SxOT(2): Histology
CxDiab(2): Histology SxNau
CTNodeOmit(2): Histology SxPru
EUSVascOmit(2): Histology SxOT
```

```
EUSPortal(2): Histology

EUSNoNode(2): Histology PresumptiveDx

EUSStagingT(5): Histology EUSPortal

EUSCyto(7): Histology

TxLap(2): Histology SxJaun

TxRadia(2): Histology EUSStagingT

TxChemo(2): Histology TxRadia

TxChemoGem(2): Histology TxChemo

ResPxType(7): Histology

ResTransfusion(2): Histology CxDiab

ResPOCourse(2): Histology CTNodeOmit

ResPathN(3): Histology

SurOncName(3): Histology EUSCyto

RadOncName(6): Histology

Histology(14):

LogScore Bayes: -1735.470575102397

LogScore BDeu: -232.372454610241

LogScore MDL: -5005.723116036344

LogScore ENTROPY: -2418.745189048893

LogScore AIC: -3565.745189048918



Time taken to build model: 0.08 seconds


=== Stratified cross-validation ===

=== Summary ===
```

```
Correctly Classified Instances          46               50.5495 %
Incorrectly Classified Instances        45               49.4505 %
Kappa statistic                          0.3721
Mean absolute error                      0.0767
Root mean squared error                  0.2312
Relative absolute error                 64.7016 %
Root relative squared error             95.6473 %
Total Number of Instances               91

=== Detailed Accuracy By Class ===

TP Rate   FP Rate   Precision   Recall  F-Measure   Class
  0.5       0.194      0.48      0.5       0.49
                                                   Adenocarcinoma_of_Pancreas/NOS
  0.444     0.037      0.571     0.444     0.5
                                                   Ampullary_Adenocarcinoma
  0.667     0.234      0.545     0.667     0.6
                                                   Ductal_Adeno_of_Pancreas
  0.4       0.047      0.333     0.4       0.364
                                                   Neuroendocrine_(Islet_Cell)
  0         0          0         0         0
                                                   Von_Hippel-Lindau_Syndrome
  0         0.011      0         0         0
                                                   Duodenal_Adenocarcinoma
  0         0          0         0         0
                                                   Distal_Cholangiocarcinoma
  0         0.011      0         0         0
```

```
                                                  Renal_Mets
  0.25       0.034       0.25       0.25       0.25
                                                  Cystadenoma
  0          0           0          0          0
                                                  MEN-I
  0          0           0          0          0
                                                  Pseudopapillary_Tumor
  0.818      0.063       0.643      0.818      0.72
                                                  IPMN/IPMT_-_Benign_or_CiS
  0          0           0          0          0
                                                  Mucinous_Cystic_Neoplasm
  0          0           0          0          0
                                                  Benign_Cyst

=== Confusion Matrix ===

   a  b  c  d  e  f  g  h  i  j  k  l  m  n   <-- classified as
  12  2  9  1  0  0  0  0  0  0  0  0  0  0 |  a = Adenocarcinoma_of_Pan
   4  4  1  0  0  0  0  0  0  0  0  0  0  0 |  b = Ampullary_Adenocarcinoma
   8  0 18  0  0  0  0  0  0  0  0  1  0  0 |  c = Ductal_Adeno_of_Pancreas
   1  0  1  2  0  0  0  1  0  0  0  0  0  0 |  d = Neuroendocrine_(Islet)
   0  0  0  1  0  0  0  0  0  0  0  0  0  0 |  e = Von_Hippel-Lindau_Syn
   0  1  1  0  0  0  0  0  0  0  0  0  0  0 |  f = Duodenal_Adenocarcinoma
   0  0  0  0  0  1  0  0  0  0  0  0  0  0 |  g = Distal_Cholangiocarcinoma
   0  0  0  1  0  0  0  0  1  0  0  1  0  0 |  h = Renal_Mets
   0  0  1  0  0  0  0  0  1  0  0  2  0  0 |  i = Cystadenoma
   0  0  0  0  0  0  0  0  0  0  0  1  0  0 |  j = MEN-I
```

```
0  0  0  0  0  0  0  0  1  0  0  0  0  0 |  k = Pseudopapillary_Tumor
0  0  1  1  0  0  0  0  0  0  0  9  0  0 |  l = IPMN/IPMT_-_Benign_or_CiS
0  0  1  0  0  0  0  0  0  0  0  0  0  0 |  m = Mucinous_Cystic_Neoplasm
0  0  0  0  0  0  0  0  1  0  0  0  0  0 |  n = Benign_Cyst
```

6.2 Classification - Survival - Data Set C - Bayesian Net 2-Parent

Here we have a highly accurate Bayesian Net 2-Parent classifier for survival. This model is taken from the C10 experiments in Section 5.10. Survival prediction is one of the most important topics in oncology research, and is subject of many other research papers (ref. Section 7). As many of these papers use traditional regression methods for survival prediction, it is particularly important here to demonstrate higher performance of novel methods.

A graphical representation of this Bayes Net model is illustrated in Figures 271 and 272. Overall accuracy for this model is rated 60.00%, as compared to average logistic regression performance 42.50% (ref. Figure 228). The accuracy of 60.00% for this single generation of the model exceeds the average iterated performance of the models in C10, which means it outperforms logistic regression via t-testing. There is fairly even coverage across predictions of different survival categories, as shown via the Confusion Matrix in Figure 273.

An interesting feature of this model is the 19 attribute subset chosen via feature-selection. The attributes chosen by feature-selection here contain many elements (diabetes, smoking history, prior chemotherapy treatments, need for palliative measures, etc.) which are known to be highly important in traditional medical assessment of pancreatic cancer survival rates [VD93]. The descriptions of these attribute fields are shown in Table 25. This selection of biologically-correlated attributes makes a strong argument for the medical applicability of this model.

Field	Description
PresumptiveDx	Presumptive Diagnosis
SxSatiety	Presentation - Early Satiety
SxOT	Presentation - Other
CxDiabDiet	Comorbidities - Diabetes Diet Controlled
CxPriorCancerChemo	Comorbidities - Prior Chemo Treatment
SHCigarette	Social History - Cigarettes
PTCDx	PTC Diagnosis
EUSDx	EUS Diagnosis
EUSSMV	EUS - SMV Involvement
EUSNoNode	EUS - No Nodal Involvement
Histology	Histology
PreOutlook	Preliminary Outlook
TxChemoIri	Treatment - Chemotherapy - Irinotecan
TxChemoTax	Treatment - Chemotherapy - Taxol
TxPal	Treatment - Palliation
TxPalStens	Treatment - Palliation - Stenting
ResPOPulmComp	Resection - Postoperative Course - Pulmonary Complications
NoResNoHandle	No Resection - Patient Can't Handle
SurOncName	Surgical Oncologist

Table 25: Survival Feature-Selected Attribute Subset

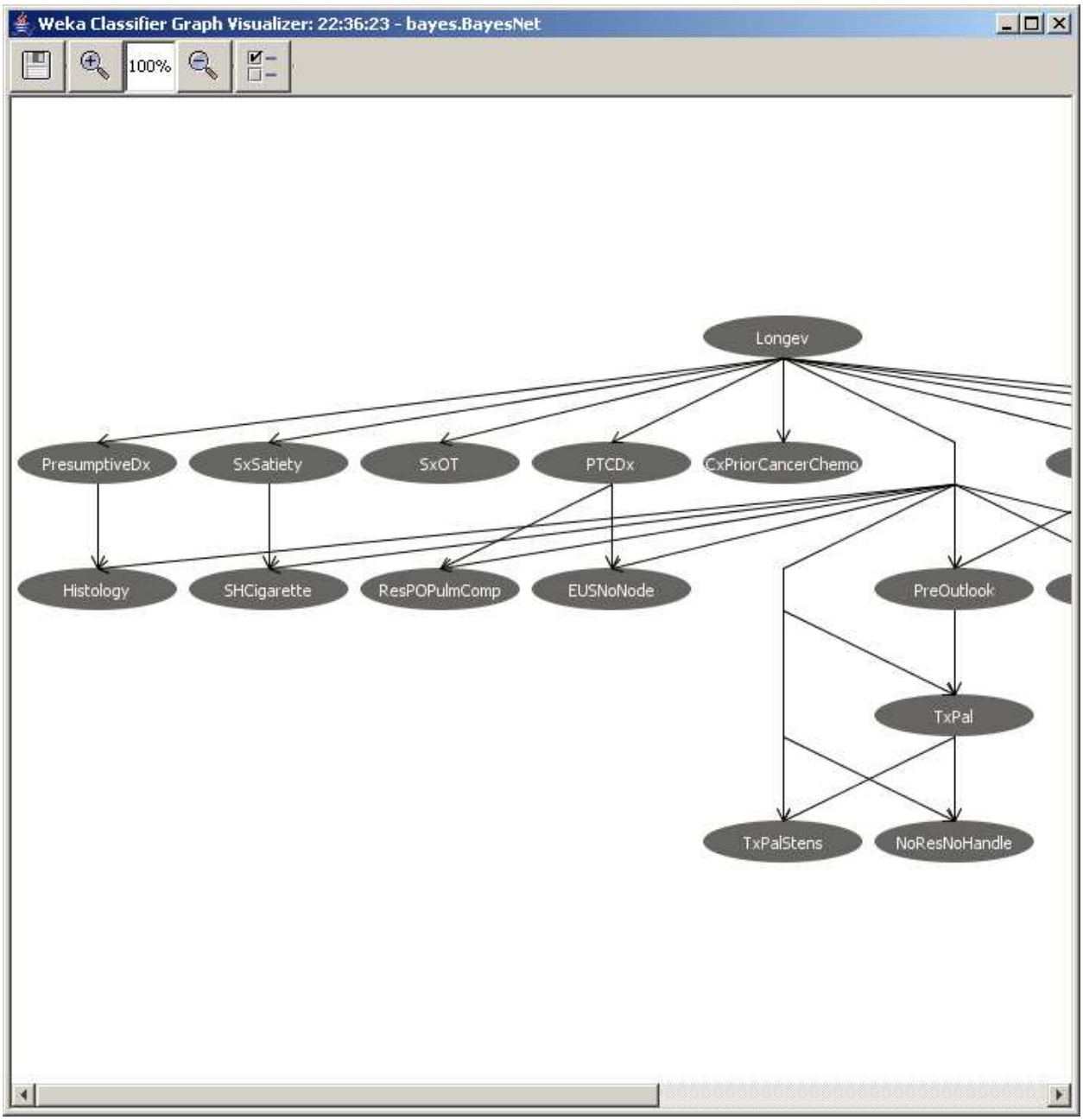


Figure 271: Classification - Survival - Data Set C - Bayesian Net 2-Parent

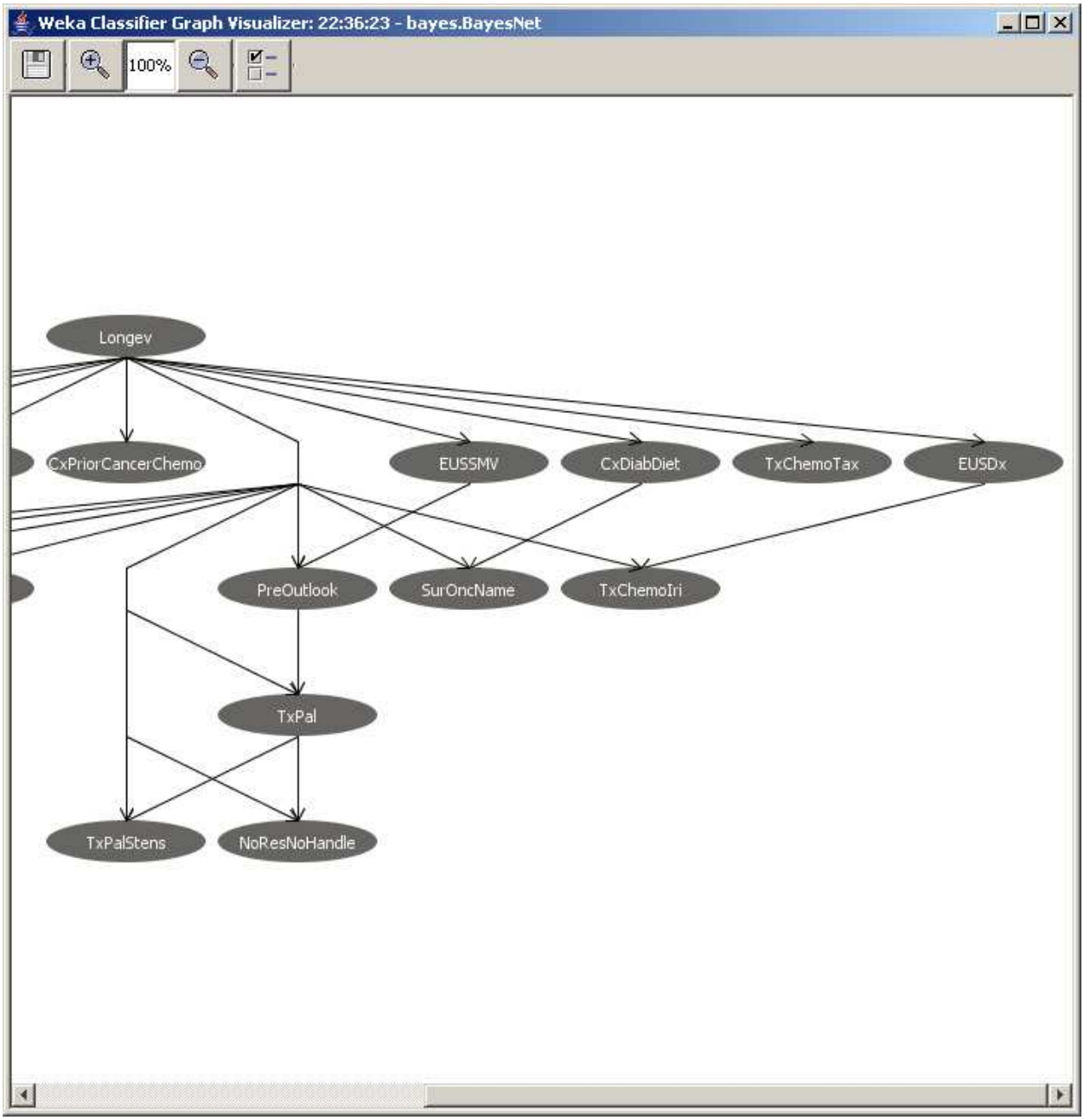


Figure 272: Classification - Survival - Data Set C - Bayesian Net 2-Parent (continued)

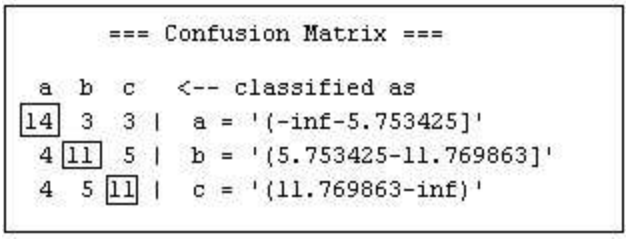


Figure 273: Classification - Survival - Data Set C - Confusion Matrix

Weka Output:

```
=== Run information ===

Scheme:       weka.classifiers.bayes.BayesNet -D -Q weka.classifiers
                .bayes.net.search.local.K2 -- -P 2 -E weka.classifiers
                .bayes.net.estimate.SimpleEstimator -- -A 0.5
Relation:     Book1-weka.filters.unsupervised.attribute.Discretize-
                F-B3-M-1.0-R191-weka.filters.unsupervised.attribute.
                Remove-R184-weka.filters.supervised.attribute.
                AttributeSelection-Eweka.attributeSelection
                .CfsSubsetEval-Sweka.attributeSelection.BestFirst -D 1 -N 5
Instances:    60
Attributes:   20
              PresumptiveDx
              SxSatiety
              SxOT
              CxDiabDiet
              CxPriorCancerChemo
              SHCigarette
              PTCDx
              EUSDx
              EUSSMV
              EUSNoNode
              Histology
              PreOutlook
              TxChemoIri
              TxChemoTax
```

```
                TxPal
                TxPalStens
                ResPOPulmComp
                NoResNoHandle
                SurOncName
                Longev
Test mode:    10-fold cross-validation

=== Classifier model (full training set) ===

Bayes Network Classifier
not using ADTree
#attributes=20 #classindex=19
Network structure (nodes followed by parents)
PresumptiveDx(6): Longev
SxSatiety(2): Longev
SxOT(2): Longev
CxDiabDiet(2): Longev
CxPriorCancerChemo(2): Longev
SHCigarette(2): Longev SxSatiety
PTCDx(2): Longev
EUSDx(2): Longev
EUSSMV(2): Longev
EUSNoNode(2): Longev PTCDx
Histology(11): Longev PresumptiveDx
PreOutlook(3): Longev EUSSMV
TxChemoIri(2): Longev EUSDx
```

```
TxChemoTax(2): Longev

TxPal(2): Longev PreOutlook

TxPalStens(2): Longev TxPal

ResPOPulmComp(2): Longev PTCDx

NoResNoHandle(2): Longev TxPal

SurOncName(3): Longev CxDiabDiet

Longev(3):

LogScore Bayes: -648.3033238760419

LogScore BDeu: -199.86101028520844

LogScore MDL: -1466.702725061748

LogScore ENTROPY: -873.0227635395436

LogScore AIC: -1163.0227635395436



Time taken to build model: 0 seconds


=== Stratified cross-validation ===

=== Summary ===


Correctly Classified Instances          36               60      %

Incorrectly Classified Instances        24               40      %

Kappa statistic                          0.4

Mean absolute error                      0.3055

Root mean squared error                  0.4237

Relative absolute error                 68.7481 %

Root relative squared error             89.8773 %

Total Number of Instances               60
```

```
=== Detailed Accuracy By Class ===

TP Rate   FP Rate   Precision   Recall  F-Measure   Class
  0.7       0.2        0.636     0.7       0.667    '(-inf-5.753425]'
  0.55      0.2        0.579     0.55      0.564    '(5.753425-11.769863]'
  0.55      0.2        0.579     0.55      0.564    '(11.769863-inf)'

=== Confusion Matrix ===

  a  b  c   <-- classified as
 14  3  3 |  a = '(-inf-5.753425]'
  4 11  5 |  b = '(5.753425-11.769863]'
  4  5 11 |  c = '(11.769863-inf)'
```

6.3 Regression - ECOG 6-Month - Data Set F - Linear Regression w/ Bagging

Here we have a highly accurate Linear Regression w/ Bagging regressor for 6-Month ECOG scores. This model is taken from the R2 experiments in Section 5.12. This is one of the first experiments where meta-learning affects a statistical improvement to a model. The r-squared value for this model is 0.32, as opposed to 0.26 for standard linear regression, a statistically significant improvement via t-testing. This is also one of the first experiments where machine learning successfully amplifies a traditional predictive regression.

Figure 274 illustrates the Bagging 'committee' which constitutes this model. Each committee member is trained on an N/10 resample of the data set. Training on the resample produces a unique linear regression equation for each member. Each equation uses different coefficients and combinations of attributes from the feature-selected data set. When evaluating a new instance, each member in the committee evaluates and 'votes' on a possible value for 6-Month ECOG. The votes are weighted equally by the model, and an aggregate ECOG prediction is produced. Refer to Section 4.3.5 or [Bre96] for further details on Bagging.

As with most experiments, feature-selected data sets in 6-Month ECOG generally produced more accurate results. Feature-selection generated a 17 attribute subset for data sets F in these experiments. The field names and their explanations are listed in Table 26. Interesting, the majority of these fields involve of chemo regimen and details pertaining to whether a patient underwent resection. These are interesting results, considering that many of these treatment decisions are made directly regarding a patient's potential wellbeing performance.

Field	Description
SxChola	Presentation - Cholangitis
SxBC	Presentation - Biliary Colic
CxDiab	Comorbidities - Diabetes
CxPriorCancerChemo	Comorbidities - Prior Chemo Treatment
EUSDx	EUS Diagnosis
EUSSMVClass	EUS - SMV Involvement Class
EUSCeliacNode	EUS - Celiac Nodal Involvement
ERCPStentType	ERCP Stent Type
TxChemoAva	Treatment - Chemotherapy - Avastin
TxChemoCap	Treatment - Chemotherapy - Capecitabine
TxChemoTax	Treatment - Chemotherapy - Taxol
ResOrgans	Resection - Additional Organs
ResPOAbdominal	Resection - Postoperative Course - Abdominal Collection
ResPOPulmComp	Resection - Postoperative Course - Pulmonary Complications
NoResNoHandle	No Resection - Patient Can't Handle
NoResRefused	No Resection - Patient Refused Treatment
NoResPVInvolve	No Resection - Portal Vein Involvement

Table 26: ECOG 6-Month Feature-Selected Attribute Subset

Figure 274: Regression - ECOG 6-Month - Data Set F - Linear Regression w/ Bagging

Weka Output:

```
=== Run information ===

Scheme:       weka.classifiers.meta.Bagging -P 100 -S 1 -I 10 -W
                weka.classifiers
                .functions.LinearRegression -- -S 0 -R 1.0E-8
Relation:     Book1-weka.filters.supervised.attribute.AttributeSelection
                -Eweka.attributeSelection.CfsSubsetEval-Sweka.attribute
                Selection.BestFirst -D 1 -N 5
Instances:    72
Attributes:   18
              SxChola
              SxBC
              CxDiab
              CxPriorCancerChemo
              EUSDx
              EUSSMVClass
              EUSCeliacNode
              ERCPStentType
              TxChemoAVA
              TxChemoCap
              TxChemoTax
              ResOrgans
              ResPOAbdominal
              ResPOPulmComp
              NoResNoHandle
              NoResRefused
```

```
               NoResPVInvolve
               ECOG
Test mode:     10-fold cross-validation

=== Classifier model (full training set) ===

All the base classifiers:


Linear Regression Model

ECOG =

      1.0084 * CxDiab=TRUE +
      0.6853 * EUSDx=FALSE +
      0.9238 * EUSSMVClass=Encased +
      1.6886 * EUSCeliacNode=TRUE +
      0.5635 * ResPOPulmComp=FALSE +
      0.7205 * NoResPVInvolve=TRUE +
     -0.4369


Linear Regression Model

ECOG =

      0.8263 * CxDiab=TRUE +
```

```
       0.8083 * EUSDx=FALSE +
       1.7504 * EUSCeliacNode=TRUE +
       0.8035 * ERCPStentType=Metal +
       0.6628 * ResPOPulmComp=FALSE +
       0.6595 * NoResPVInvolve=TRUE +
      -0.5322


Linear Regression Model

ECOG =

       0.7708 * CxDiab=TRUE +
       0.7257 * EUSDx=FALSE +
       1.4554 * EUSSMVClass=Encased +
       1.0454 * ResPOPulmComp=FALSE +
      -0.7265 * NoResNoHandle=TRUE +
       0.9548 * NoResRefused=TRUE +
       1.6817 * NoResPVInvolve=TRUE +
      -1.4986


Linear Regression Model

ECOG =

       0.6748 * CxDiab=TRUE +
```

```
       0.7406 * EUSDx=FALSE +
       0.4859 * ResPOPulmComp=FALSE +
       0.8273 * NoResPVInvolve=TRUE +
      -0.0964


Linear Regression Model

ECOG =

       1.2688 * SxChola=TRUE +
       0.6268 * CxDiab=TRUE +
       0.514  * EUSDx=FALSE +
       1.3384 * EUSSMVClass=Encased +
       1.561  * EUSCeliacNode=TRUE +
       0.4906 * NoResRefused=TRUE +
       0.1044


Linear Regression Model

ECOG =

       0.6175 * CxDiab=TRUE +
       0.6021 * EUSDx=FALSE +
       1.3825 * EUSSMVClass=Encased +
       1.556  * EUSCeliacNode=TRUE +
```

```
       0.5224 * ResOrgans=spleen +
       0.7066 * ResPOPulmComp=FALSE +
       1.0307 * NoResRefused=TRUE +
      -1.2459


Linear Regression Model

ECOG =

       0.8249 * SxChola=TRUE +
       0.7269 * CxDiab=TRUE +
       0.6689 * EUSDx=FALSE +
       1.3587 * EUSSMVClass=Encased +
       1.7183 * EUSCeliacNode=TRUE +
       0.6451 * ResPOPulmComp=FALSE +
       0.471  * NoResRefused=TRUE +
       0.6194 * NoResPVInvolve=TRUE +
      -0.8164


Linear Regression Model

ECOG =

       0.9979 * SxChola=TRUE +
       0.683  * CxDiab=TRUE +
```

```
       0.7269 * EUSDx=FALSE +
       1.4165 * EUSSMVClass=Encased +
       0.6263 * NoResRefused=TRUE +
       0.5182 * NoResPVInvolve=TRUE +
      -0.1991


Linear Regression Model

ECOG =

       0.6933 * CxDiab=TRUE +
       0.6812 * EUSDx=FALSE +
       1.6045 * EUSCeliacNode=TRUE +
       0.7885 * NoResPVInvolve=TRUE +
       0.3955


Linear Regression Model

ECOG =

       0.7232 * CxDiab=TRUE +
       0.7302 * EUSDx=FALSE +
       1.5916 * EUSCeliacNode=TRUE +
       0.8539 * ERCPStentType=Metal +
       0.5216 * ResOrgans=spleen +
```

```
      0.6263 * ResPOPulmComp=FALSE +
      0.9463 * NoResPVInvolve=TRUE +
     -0.8171


Time taken to build model: 0.11 seconds

=== Cross-validation ===
=== Summary ===

Correlation coefficient                  0.5706
Mean absolute error                      0.4522
Root mean squared error                  0.5616
Relative absolute error                 72.7155 %
Root relative squared error             81.3339 %
Total Number of Instances               72
```

6.4 Regression - ECOG 9-Month - Data Set F - Multi-layer Perceptron w/ 2 Hidden Layers

Here we have a highly accurate Multi-layer Perceptron regressor for 9-Month ECOG scores. This model is taken from the R3 experiments in Section 5.13. The r-squared value for this model is 0.16, as opposed to 0.04 for standard linear regression, a statistically significant improvement via t-testing. Multi-layer perceptrons exhibited high r-squared values for many of the regression experiments. They are generally known in medical data mining for high accuracy, but it is difficult to discern from their internal structure how their decisions are produced [KK95].

Figure 275 shows the network layout of this particular regressor. Weights are conditioned via backpropagation on the training sets. Two hidden layers are used, with a learning weight of 0.3 and momentum of 0.2. For new instances, input nodes pass attribute values through the two trained hidden layers, which are aggregated down to produce a ECOG 9-Month prediction. Following the MLP figure is Weka output showing the trained weights on each network connection.

Feature-selected data sets in 9-Month ECOG generally produced more accurate results. Feature-selection generated a 19 attribute subset for data sets F in these experiments. The field names and their explanations are listed in Table 27. As with 6-Month ECOG, the majority of these fields involve chemo regimen and details pertaining the patient's resection. It may be interesting future work to examine whether there is research precedence that these factors significantly affect wellbeing performance.

Field	Description
SxChola	Presentation - Cholangitis
SxBack	Presentation - Back Pain
SxDyspha	Presentation - Dysphasia
CxDiabDiet	Comorbidities - Diabetes Diet Control
CxHyper	Comorbidities - Hypertension
CxPriorCancerChemo	Comorbidities - Prior Chemo Treatment
CXRDx	Chest X-Ray Diagnosis
EUSSMVClass	EUS - SMV Involvement Class
EUSPortal	EUS - Portal Vein Involvement
EUSPortalClass	EUS - Portal Vein Involvement Class
TxChemoAva	Treatment - Chemotherapy - Avastin
TxChemoIri	Treatment - Chemotherapy - Irinotecan
TxChemoLeu	Treatment - Chemotherapy - Leukovorin
TxChemoTax	Treatment - Chemotherapy - Taxol
ResTFFP	Resection - Transfusion - Fresh Frozen Plasma
ResPOLeak	Resection - Postoperative Course - Leak
ResPOAbdominal	Resection - Postoperative Course - Abdominal Collection
ResPOPulmComp	Resection - Postoperative Course - Pulmonary Complications
ResPathR	Resection - Pathology R-Stage

Table 27: ECOG 9-Month Feature-Selected Attribute Subset

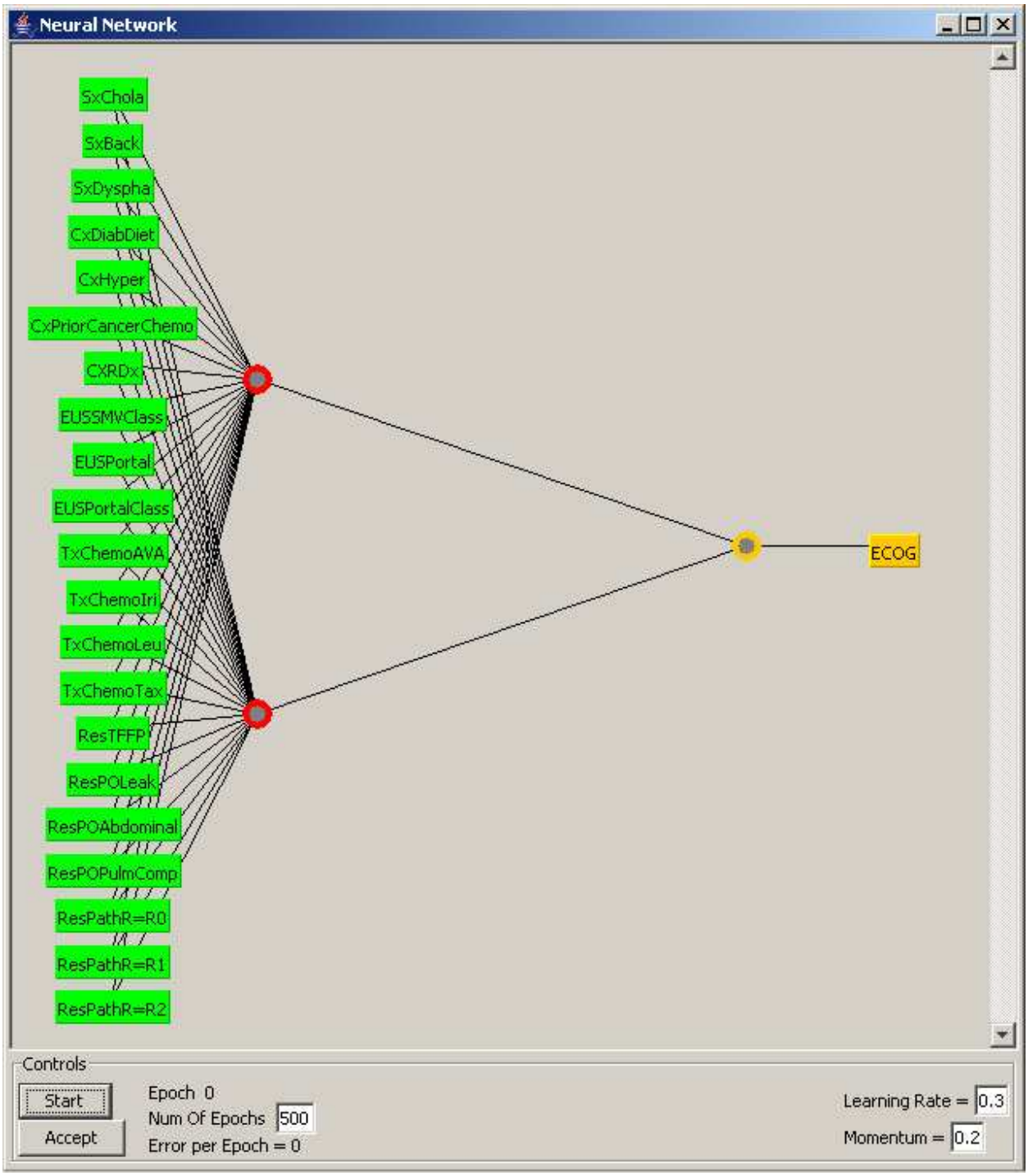


Figure 275: Regression - ECOG 9-Month - Data Set F - Multi-layer Perceptron w/ 2 Hidden Layers

Weka Output:

```
=== Run information ===


Scheme:       weka.classifiers.functions.MultilayerPerceptron -L 0.3 -M 0.2
                -N 500 -V 0 -S 0 -E 20 -H 2
Relation:     Book1-weka.filters.supervised.attribute.AttributeSelection-
                Eweka.attributeSelection.CfsSubsetEval-Sweka.
                attributeSelection.BestFirst -D 1 -N 5
Instances:    72
Attributes:   18
              SxChola
              SxBC
              CxDiab
              CxPriorCancerChemo
              EUSDx
              EUSSMVClass
              EUSCeliacNode
              ERCPStentType
              TxChemoAVA
              TxChemoCap
              TxChemoTax
              ResOrgans
              ResPOAbdominal
              ResPOPulmComp
              NoResNoHandle
              NoResRefused
              NoResPVInvolve
```

```
               ECOG
Test mode:    10-fold cross-validation


=== Classifier model (full training set) ===


Linear Node 0
    Inputs    Weights
    Threshold    -0.27907681180500077
    Node 1    -0.6689299459785472
    Node 2    2.0634974138324895
Sigmoid Node 1
    Inputs    Weights
    Threshold    0.2161565560886697
    Attrib SxChola    -0.8240512834848186
    Attrib SxBC    0.9719889319602957
    Attrib CxDiab    2.4018587825692728
    Attrib CxPriorCancerChemo    1.5612434307033178
    Attrib EUSDx    -1.7402535693664936
    Attrib EUSSMVClass    -2.380758092011916
    Attrib EUSCeliacNode    -2.2846632584637074
    Attrib ERCPStentType    0.27077130269695104
    Attrib TxChemoAVA    1.6004461214131707
    Attrib TxChemoCap    1.0846704053365328
    Attrib TxChemoTax    1.3085182989378599
    Attrib ResOrgans=spleen    -3.775846082844799
    Attrib ResOrgans=duodenum_preserving    -2.308761590318322
    Attrib ResOrgans=pylorus-sparing    -1.0989356680294642
```

```
    Attrib ResPOAbdominal    1.7485222222375152
    Attrib ResPOPulmComp    4.995927948745733
    Attrib NoResNoHandle    -0.8438995490964636
    Attrib NoResRefused    -1.1648150708131346
    Attrib NoResPVInvolve    -1.9970562590263103
Sigmoid Node 2
    Inputs    Weights
    Threshold    0.01931248644125251
    Attrib SxChola    1.3618203056809814
    Attrib SxBC    -9.480039587078225E-4
    Attrib CxDiab    -2.3505528703455143
    Attrib CxPriorCancerChemo    -0.8645973811683567
    Attrib EUSDx    2.3745261715454515
    Attrib EUSSMVClass    3.5097969956607966
    Attrib EUSCeliacNode    2.617837343077885
    Attrib ERCPStentType    0.8113622216035797
    Attrib TxChemoAVA    -0.5206862062795482
    Attrib TxChemoCap    0.12298147304095629
    Attrib TxChemoTax    -0.40371463564664195
    Attrib ResOrgans=spleen    0.8047396124851516
    Attrib ResOrgans=duodenum_preserving    -0.27889286068420516
    Attrib ResOrgans=pylorus-sparing    -0.20715130545850244
    Attrib ResPOAbdominal    -0.16035164493704002
    Attrib ResPOPulmComp    -2.2285130411821803
    Attrib NoResNoHandle    -0.29341318666906574
    Attrib NoResRefused    0.5048077573826775
    Attrib NoResPVInvolve    2.006560027984653
```

```
Class
    Input
    Node 0


Time taken to build model: 0.27 seconds

=== Cross-validation ===
=== Summary ===

Correlation coefficient                  0.4798
Mean absolute error                      0.5168
Root mean squared error                  0.655
Relative absolute error                 83.1096 %
Root relative squared error             94.8561 %
Total Number of Instances               72
```

7 Related Work

A significant amount of work in medical diagnosis using machine learning has come from the University of Ljubljana, Slovenia, under Prof. Igor Kononenko. [KK95] provides an excellent overview of the medical applicability of machine learning techniques, and presents the advantages and disadvantages of different algorithmic approaches. [Kon93] covers similar ground and presents inductive and Bayesian learning technical for medical analysis in more detail. The techniques discussed in his works have been applied in many medical fields, including pathology, urology, cardiology, and neuropsychology. Work done in [KBK+97] applies specifically to oncology, using machine learning to predict the survival time of patients with thyroid carcinoma. The algorithmic focus of this work deals primarily with regression, Assistant decision trees, and Bayesian techniques. We present a broader variety of predictive algorithms in our oncological analysis, and examine different ways to improve algorithmic accuracy, including feature selection and meta-learning.

Machine learning techniques, particularly regression methods, are used commonly in medical literature. [FS03] uses multivariate logistic regression and Cox's proportional hazard model to show that liver metastatis and peritoneal implants are major predictive factors in pancreatic cancer survival. [SR02] contends, using Kaplan-Meier survival analysis, that tumor grading, angioinvasion and perineural invasion are not sufficient pancreatic cancer survival factors. Dr. Murray Brennan makes prolific use of machine learning techniques in his research, and presents in [Bre04] a predictive nomogram for pancreatic cancer survival. Dr. Jennifer Tseng in [Tse04] uses multivariate regression to study survival rates of pancreatic cancer who undergo superior mesenteric or portal vein resections. Our research differs in our broader variety of predictive techniques, and that we look additionally at patient wellbeing and tumor pathology characteristics.

8 Conclusions and Future Work

This thesis set out with two goals–to develop detailed clinical databases of cancer patients, and to conduct machine learning studies on the patient data. With the help of medical professionals at UMass Memorial Hospital, we were able to successfully build clinical databases of seven different cancer forms which can represent the broad narrative of patient treatment. This database was tested by accumulating about a hundred detailed pancreatic cancer patient records. Using this data, we tested a variety of novel machine learning techniques to form predictive models for clinical patient outlook. The accuracy of these novel techniques were statistically tested against linear and logistic regression, the standard medical prediction methods.

We found that most novel machine learning techniques that we tested were able to deliver comparable performance. Both classification and regression algorithms were considered. Generally, Multi-Layer Perceptrons, Bayesian methods, and Locally Weighted Learning with Naive Bayes performed best. In most cases, the novel models performed as well as traditional regression; in some instances they performed even better. Novel regression techniques delivered better performance more frequently than classification techniques. Models based on data sets which used feature selection and supervised discretization generally delivered higher accuracy. In most cases, meta-learning did not improve the accuracy of predictive models. This is a somewhat surprising result, since meta-learning is designed to overcome data mining limitations of smaller data sets.

Future work will expand upon the research basis presented here, and should consider some of the limitations we encountered. First and foremost is attaining a larger patient data set–whether through accumulating additional UMass patients, or expanding the study to include additional institutions or research databases like the HCUP National Inpatient Sample. Continuing to add detail and functionality to the clinical databases will allow for more thorough studies. New knowledge may be gained in testing a populated database module for other gastrointestinal cancers or breast cancer. Studies may be conducted on

the individual modules, and clinical performance may even be tested across different disease forms.

There are a broad variety of machine learning predictive algorithms which we did not cover, as well as potential parameter variation for those algorithms we used. There is also algorithm evaluation to consider. In most cases, our novel classifiers had much higher accuracy than logistic regression. However, very often the classifiers performed only as well as a ZeroR guess. The way that single target class values dominate these medical data sets lends itself to predictions for most common class type. This shows simple measurements of accuracy may not always be the best metric of predictive model quality. Other means of evaluation may be necessary and should be explored. Furthermore, the algorithms covered here were based on target class prediction; machine learning to mine association rules and instance clustering has not yet been considered.

The next step in this research should be to continue adding pancreatic patients to the clinical database and generating new predictive models. An informal goal set by Dr. Whalen was to eventually attain classification accuracies of 70% and r-squared values of .50, which makes it clear that more data and further model refinements are still needed. It is important to see whether our experimental results hold up or improve across a broader study population. From the clinical database side, the remaining modules will need further testing and developing. Accumulating clinical data is a critical part of illuminating the design of these modules; much of the functionality of the pancreatic module was decided upon as patient data was being entered and research needs became clearer. Further experiments with neural network based algorithms (MLP, RFB) should be explored in both classification and regression settings, given their initial accuracy and the broad variety of possible algorithm parameters. In experiments where majority classes dominate (t-stage, malignancy, etc.), over-sampling techniques should be explored to emphasize the importance of correctly representing minority classes. Finally, for the more promising predictive models that we've presented here, their performance should be verified against broader pancreatic cancer pa-

tient sets, or distinct patient sets from other institutions. This will allow us to conclude the potential of these models for future medical research publication.

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Glossary

Adenocarcinoma: carcinoma which develops within glandular epithelium which typically behaves in a very malignant fashion, 5

Adjuvant: therapy applied post-surgery, 12

Ampulla of Vater: dilation in the duodenal wall through which the common bile duct and pancreatic duct empty into the small intestine, 7

Anastomosis: surgically connecting anatomically separate organs to form a continual channel, 3

Benign: cell growth characterized as not spreading to surrounding tissue, 3

Biopsy: a small sample of tumor tissue taken to evaluate its histologic composition and malignancy, 6

Cancer: Diseases resulting from uncontrolled cell growth in regions known as neoplasms or tumors, 3

Carcinogen: Chemical or physical agents which trigger cancer-causing DNA mutations, 3

Carcinoma: cancers arising from epithelial tissue, 3

Celiac axis: artery which originates in the abdominal aorta below the diaphragm, 10

Chemotherapy: systemic or localized application of antineoplastic drugs to destroy or retard the development of tumor growth, 3

Computed axial tomography (CT or CAT): a three-dimensional internal view of a patient using a series of sectional x-rays across a common axis, 6

Cyst: closed cavities of glandular epithelium where retained secretions are accumulated, and may behave in a benign or malignant fashion, 5

Cytology: study of cells at a microscopic level, 5

Distal common bile duct: portion of the excretory passage closest to the duodenum which carries bile from the liver, 7

Duodenum: upper part of the small intestine, which extends from the lower end of the stomach, 7

ECOG: Eastern Cooperative Oncology Group (ECOG) score for wellbeing, ranges 0-5, consult Table 2, 4

Endoscopic ultrasound (EUS): ultrasound study generated by a thin, flexible camera passed through the gastrointestinal tract, 6

Epithelial: related to the epithelium, a membrane of tissue which lines most internal and external surfaces of the body and organs, 3

Fine needle aspiration (FNA): a biopsy procedure where a sample of cells is obtained applying suction through a fine needle, 10

G-Stage: refers to grade or differentiation between tumor cells and surrounding normal cells, ranges from 1 to 4, 5

Gene counseling: series of DNA tests which establish susceptibility of a patient or their family to certain forms of cancer, 3

Hepatic artery: artery which originates in the celiac artery and supplies the liver with blood, 10

Histology: the microscopic structure of tumor tissue, 5

Immunotherapy: for tumors, experimental protocol which uses vaccination to trigger an immune system response which destroys cancerous cells, 3

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