Predicting TBI by using Smartphone-sensed mobility patterns, gait and balance

By

Bhoomi Patel

A Thesis

Submitted to the Faculty

Of the

Worcester Polytechnic Institute

In Partial fulfillment of the requirements for the

Degree of Master of Science

In Computer Science

Approved:

____

Prof. Emmanuel O. Agu, Thesis Advisor

____

Prof. Michael A. Gennert, Thesis Reader

____

Prof. Craig E. Wills, Head of Department

Abstract

In the United States, Traumatic Brain Injury (TBI) has become a major cause of death and disability. 56,800 deaths were reported due to TBI in the year 2014. Violent blow, sudden jerk to the head or the body are some causes of TBI. Methods to detect TBI at an early stage can help reduce emergency visits and even create life-saving experiences. Imaging tests such as Computerized Tomography (CT), Magnetic resonance imaging (MRI) and Glasgow Coma Scale (GCS) have been widely utilized by doctors and physicians to detect TBI. However, these tests often mis-diagnose the injury and are costly as well. Moreover, these tests require active user involvement and frequent clinic visits. Smartphones are now ubiquitously owned with powerful in-built sensors, making them useful for continuous health monitoring.

This thesis focuses of using smartphone sensors for detecting TBI at the onset of injury. A lot of previous work has focused on understanding TBI by extracting the patterns obtained from smartphone sensors. In this thesis, three approaches to understand how the patterns of TBI differ from that of Non-TBI users are compared, namely; i) computing hand-crafted features on raw sensor data; ii) computing hand-crafted features on pre-processed sensor data; iii) using auto-encoder based approach using location, gait and balance. The location patterns extracted have been taken from the work of *Mirco Musolesi*. 6 location features, 9 gait and 4 balance statistical features were extracted from the location and accelerometer sensor data using different segmentation methods. These features were then normalized and classified using machine learning algorithms. Hand-crafted feature extraction on raw-sensor data gave the best results on 3rd day - 24 hours window size with XGBoost having Sensitivity as 0.889 and Specificity of 1. For the second approach, the best results were obtained using 50% overlap with Random Forest having Sensitivity as 0.667 and Specificity of 1. For the auto-encoder based approach, Random Forest performed the best on 2nd day with 12 hours of window-size having Sensitivity as 0.778 and Specificity of 0.959.

Keywords: Mobile Health, Machine learning, Traumatic Brain Injury (TBI)

Acknowledgements

I would like to express my special thanks and gratitude towards Professor Emmanuel Agu, who gave me the golden opportunity to undertake this wonderful thesis project on the topic Predicting TBI by using Smartphone-sensed mobility patterns, gait and balance, which also helped me develop a Research-based approach and think analytically. I came across a variety of new things, which is a great learning experience before kick-starting a career in a similar field.

I would like to thank Professor Michael Gennert for being my thesis reader and providing invaluable feedback that helped me improve this thesis.

I am also grateful to my teammates Srinarayan Srikanthan and Florina Asani who were immensely supportive and with whom this thesis has been a great learning experience.

Last but not the least, I would also like to appreciate my parents and friends who pushed me to get through the tough time during this thesis. Without their tremendous understanding and encouragement in the past few years, it would be impossible for me to complete my study.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

From 2006 – 2014, the number of hospitalizations and deaths caused due to Traumatic Brain Injury (TBI) have increased by 53%. In 2013, United States faced approximately 2.87 million TBI Emergency Department Visits, Hospitalization and Deaths [1]. Based on these numbers, every American has more than 1:160 chance of experiencing a Traumatic Brain Injury each year [2]. Of the various principal mechanisms of injury, falls, being struck by or against an object and motor vehicle crashes, are accounted as the majority causes for TBI among all age groups. Approximately 47% of the injuries were caused due to a fall and it was observed to be the major cause for young children and adults over the age of 65. 21% of the injuries were caused due to sports while 15% were caused due to blunt force trauma, 14% accounted for car accidents while 9% due to violent physical assaults [2].

1.1 Effects of TBI

Traumatic Brain Injury (TBI) - is caused due to a sudden jerk to the head which eventually causes damage to parts of the brain [1]. Based on the impact, there are three levels of TBI injury: Mild, Moderate and Severe. Concussion is a form of mild TBI and constitutes 75% of TBIs that occur each year. Symptoms of mild TBI include headache, confusion, blurred visions, and behavioral changes; while that of moderate and severe TBI include vomiting, nausea, slurred speech, weakness in legs and arms followed by problems with cognitive abilities [3]. Further, Table *1* [4] depicts how Healthcare providers rank TBI based on a person's level of consciousness and memory level.

Falls being the major cause of brain injury, 81% of TBI related emergency visits were made by persons with age 65 or above [5]. This could be because the senior citizens have limited motor ability and poor physical balance. Further, some adults live unaccompanied which leads to the inability of seeking immediate medical care. Continuous monitoring of movement for such adults can help to provide care instantly while also creating life-saving experiences.

Table 1: Classification into Mild, Moderate and Sever TBI

Mild TBI	Moderate TBI	Sever TBI
Conscious or unconscious for less than 30 mins	Unconscious for more than 30 mins but less than 24 hours	Unconscious for more than 2 hours
Memory loss for less than 24 hours	Memory loss from 24 hours to 7 days	Memory loss for more than 7 days

1.2 Diagnosing TBI

Healthcare providers use different tests and measures to diagnose TBI. There is no singular significant test that detects TBI and hence several tests are performed and used together to diagnose TBI. Apart from the tests, healthcare workers also ask a series of questions that help them assess TBI patient's brain and body function. Below are few of the tests performed by doctors and physicians to diagnose TBI:

1.2.1 Imaging Tests:

Computed Axial Tomography (CAT or CT): This scan produces cross-sectional pictures of the 3-D brain images. This method shows the brain's density and abnormalities such as swelling, bleeds and skull fractures [6].

Magnetic Resonance Imaging (MRI): This test uses radio waves which makes it more sensitive to provide in-depth details. This test in usually performed in Emergency Department during the initial treatment after a brain injury [6]. Figure *1* shows the MRI of a 66-year-old male after a motor vehicle accident.

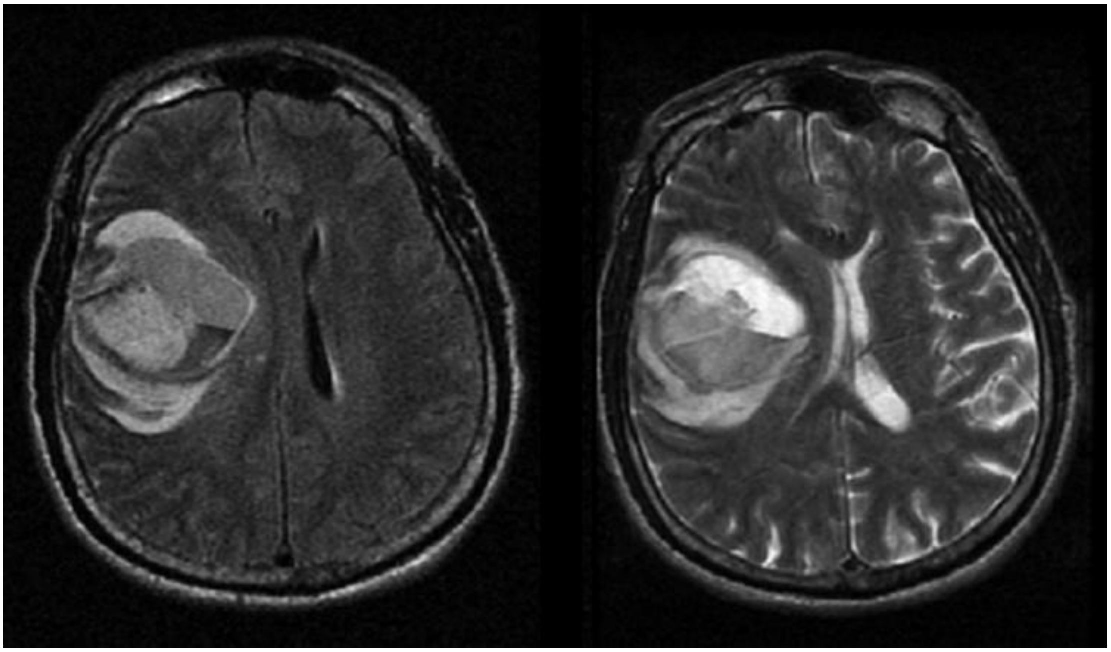


Figure 1: MRI image of 66-year male after accident showing diffusion on the left-side of the brain [7]

Computed Tomography Angiography (CTA): This process provides images of blood vessels in the brain and the body to show abnormalities and blockages [6].

X-ray: This imaging test allows to locate skull fractures [6].

Electroencephalogram (EEG): This test measures the electrical activity in a person's brain to determine brain activity and detect any suspected seizer of brain activities. Figure *2* shows the EEG of the 67-year-old man with epileptic seizures who did not remember his occurrence of head trauma.

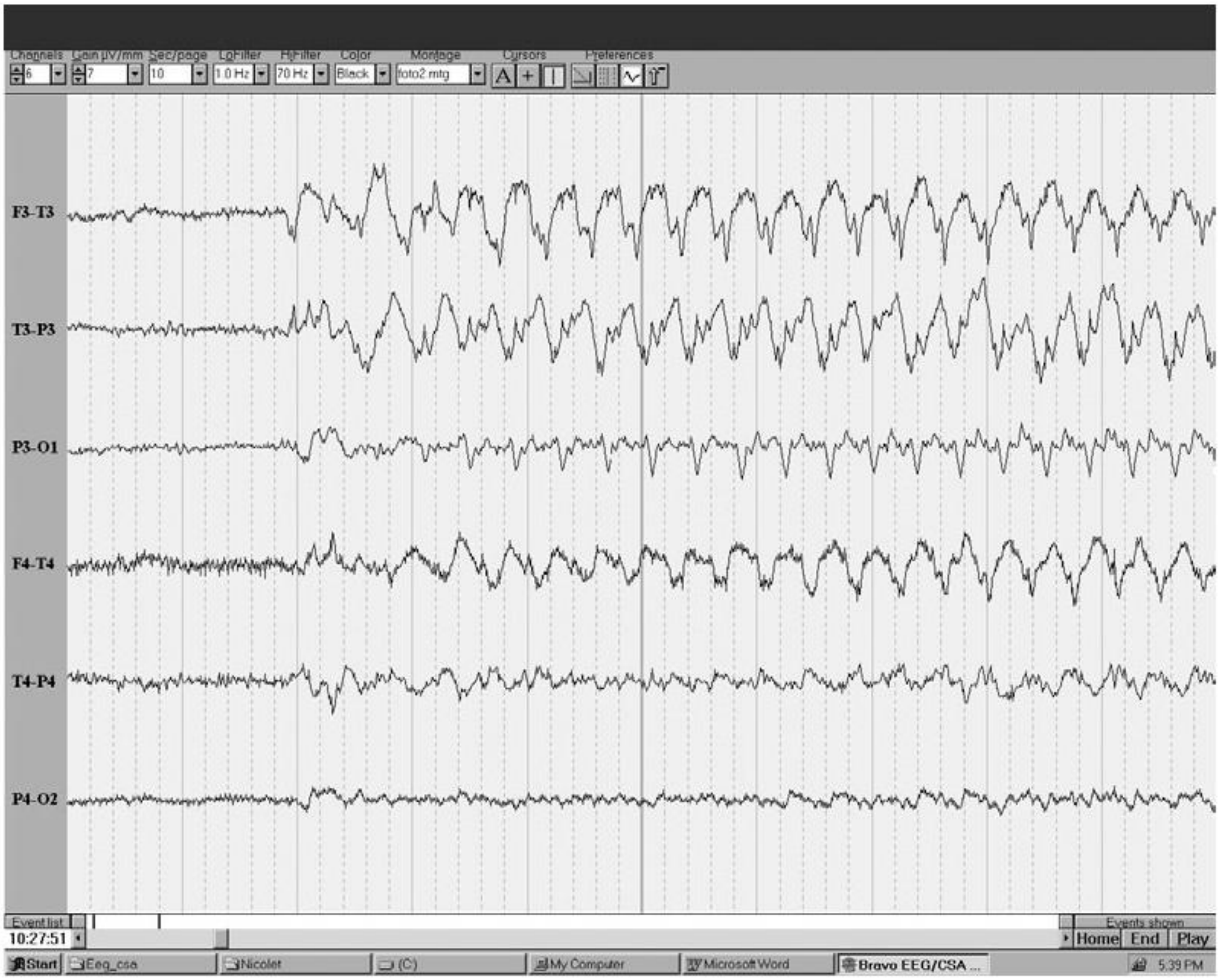


Figure 2: EEG of a 67-year man with seizures [8]

1.2.2 Glasgow Coma Scale (GCS):

This is a brief assessment that helps in determining the next steps to be taken in the individual's care [9]. It provides a way to measure a person's functioning in three areas:

Ability to speak (V): It measures the ability of the person to speak in terms of speaking normally, speaking in a way that does not make sense or cannot speak at all.

Ability to open eyes (E): This measures if a person is able to open his/her eyes or not.

Ability to move (M): This measures the ability of the person to move his/her arm normally or in response to pain.

Table *2* shows the GCS questions that are used collectively to make decision and monitor a patient's progress and Table *3* shows the GCS score range as a measure to predict the level of brain injury.

Table 2: GCS questions used for evaluating TBI

(V) Verbal Response	**(E) Eye Opening**	**(M) Motor Response**
(5) Oriented & converses	(4) Natural	(6) Follows commands
(4) Disoriented & converses	(3) To voice	(5) Localizes to pain
(3) Inappropriate words	(2) To pain	(4) Withdrawal to pain
(2) Incomprehensible sounds	(1) No response	(3) Decorticate
(1) No response		(2) Decerebrate
		(1) No response

Table 3: GCS Score to determine level of injury

GCS Score	Level of Injury
13 to 15	Mild TBI
9 to 12	Moderate TBI
Less than 8	Severe TBI

1.3 Problems with Manual Assessment

Cognitive, emotional, behavioral, and physical impairments are common in TBI patients, however in the case of mild TBI, these symptoms are more subtle and less often recognized [10]. Studies have shown that only 10% of patients having mild TBI have positive finding on CT [11]. Further, these tests are so expensive that even reduction by 10% may yield more than $10 million savings each year [12]. Though MRI perform 10 – 20% better than CT [13], there is no evidence of the test performing better than CT in terms of mild injury. As majority of the ED visits of TBI cases represent mild level i.e. concussion, it is important to assess them accurately to identify cases at major risk of complications versus those that can be safely discharged.

1.4 Opportunity: Smartphone to Assess TBI

Smartphones being ubiquitous, their computing power has paved way to perform various operations such as monitoring health and fitness. Modern smartphones have sensors such as GPS, accelerometer, gyroscope, location, etc. These sensors provide continuous and real-time based human activity identification and assessment which can help categorize simple and complex activities. Further, these sensors have low power consumption and higher throughput. The data collected from these smartphones when processed, tend to accurately project the behavior of an individual which can help the machine learning model learn patterns and draw conclusions. For example, using microphone and recording the conversations, an individual's stress level or emotional state can be deduced [14]. Additionally, accelerometer can provide information related to a person's physical activity and movement during sleep. GPS can provide information about the location which gives context into variety of activities. Another study captures the accelerometer data and facial images to develop a smartphone-based posture monitoring application [15].

The symptoms exhibited by a TBI patient are quite different and can be easily distinguished with those of Non-TBI patients. For example, a TBI patient has sensitivity to light and trouble concentrating which draws the probabilities of reduced screen usage. A patient's cognitive abilities like thinking, reasoning also get affected due to brain injury [16]. Depression being a common problem after TBI, nearly two-thirds are affected by it within seven years of injury [17]. The symptoms of depression include moving slowly, feeling restless or agitated. Enough evidence exists to prove that location sensors can predict depression symptom severity [18, 19, 20]. This is because the features extracted from the location sensor provide behavioral markers that are strongly related to the depression symptom severity.

Gait Problems caused by TBI: People with TBI have problems with walking, and they walk slower than Non-TBI patients. Walking requires multi-level coordination between the system and due to the brain injury, the co-ordination system of the body is affected. For instance, using GAITRite [27], the authors were successfully able to identify abnormalities and proved that TBI patients moved slower than healthy ones. Since gait has an ability to assess the way humans walk, the features extracted using gait analysis can help understand conditions affecting their ability to walk. Smartphone accelerometers having a strong ability to detect motion, features extracted from this sensor helps in identifying TBI patterns.

Balance Problems caused by TBI: TBI patients have problems with balance due to dizziness and lightheadedness. The modified Clinical Test of Sensory Integration and Balance (mCTSIB) [30] was able to justify that TBI patients have more sway than healthy ones. Smartphone sensors being well capable of identifying falls, one can exploit various smartphone sensors to identify patterns of TBI which differ from Non-TBI.

Depression caused by TBI: Depression is a common problem caused by TBI [21]. Location sensors have the ability to capture the GPS positions which can be used to detect the person's location traces and the amount of time spend at different locations. Mood-Traces [21] has been correctly able to distinguish depression patterns and has also depicted the potential to identify future possibilities of depression. Since, a TBI person shows symptoms of depression like spending more time at home and avoiding crowded places, computing features from location data can help understand the patterns of depression which is directly linked to TBI.

Figure 3 shows the general smartphone-based solution that couples smartphone sensors with survey-based human participation. The solution consists of passive sensor data collection along with in-app questionnaires where the participants submit their symptoms along with the date of head injury. This data is then stored into a secure cloud storage from which the features are computed and fed to the machine learning pipeline.

Such a solution can be deployed at various medical centers, sports academies to get more insights into the behavioral changes and symptoms faced by a TBI patient. For example, with this solution, nurses can monitor a large team of soldiers or civilian patients. As mild TBI is difficult to diagnose, there is a possibility of athletes' first brain injury getting unnoticed. If no proper treatment is received and the athlete gets involved in another head injury, complexity of the case increases leading to extremes such as death. In such cases, this mobile solution will help in proper monitoring and eventually assist in getting the right aid.

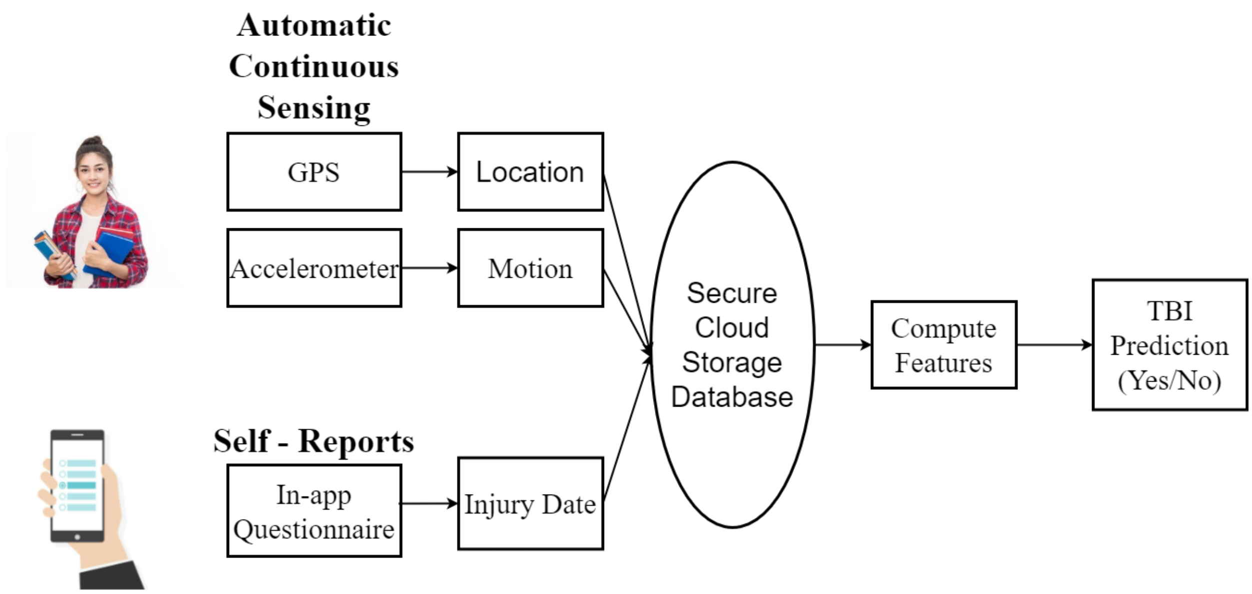


Figure 3: General Smartphone-based Solution for TBI detection

1.5 Thesis Goal

The objective of this thesis is to compare various approaches by extracting location and balance patterns along with performing gait analysis. The main contributions of the research are as follows:

- *Explore location features* – to examine functional mobility levels and outdoor activity of TBI population with the Non-TBI group.

- *Explore Gait and Balance features* – to examine the motion and balance of TBI population with the Non-TBI group.

- *Finding correlation between TBI and depression* – Prior work focuses on location, gait and balance patterns to identify depression. Also, since the symptoms depicted by TBI population is like those in depression, extend the same set of features to detect TBI patterns.

- *Comparing various feature extraction approaches* – Compare three feature extraction approaches, namely, raw sensor data, pre-processed sensor data and autoencoder based approach to identify pattern of TBI.

- *Running Models* – Synthesize Machine Learning and Deep Learning based classification to help distinguish smartphone users with TBI.

1.6 Thesis Approach

The approach consists of using two datasets with total of 23 TBI instances, who have responded to various survey questions on daily and weekly basis. Moreover, these responses consist of injury date along with sensor data for several days. Here, TBI instances are those who have been in an accident or reported an injury to their head and have been diagnosed with TBI by a professional during the length of the study.

Further, to perform accurate classification and identification of patterns, 179 Non-TBI users are chosen. Here, Non-TBI users are those who have not reported to be in an accident or had a head injury during the length of the study.

The technique comprises of assessing different feature extraction methods to predict TBI as soon as possible from the date of injury. Prediction is achieved by comparing the patterns of Non-TBI users and how they differ from those of TBI users. Here, the comparison is mainly based on the below three approaches:

i. Performing manual feature extraction on raw sensor data

ii. Performing manual feature extraction with pre-processing on the sensor data

iii. Creating a representation of the sensor data

1.7 Summary of Prior Work & Novelty of Thesis Approach

As of today, TBI is a clinical testing and hence no single definitive test can confirm its diagnosis [21]. CT Scans and MRI are the most common tests to diagnose it. However, the results of these tests highly depend on the gap between the injury occurred and test performed. Further, these tests are quite unsuccessful in case of mild TBI wherein a patient is diagnosed to be normal. Additionally, these tests take longer to predict and are not affordable to everyone. To address these issues, sensors can be used to detect TBI at an early stage.

As cognitive abilities of patients get affected post brain injury, various studies have employed the use of smartphones to assess these abilities of TBI patients by quantifying the results [22]. Few such techniques include measuring Pupillary Light Reflex (PLR) [23] and using smartphone with calendar to inspect effectiveness of a prospective memory aid [24]. However, the results obtained are not promising and do not provide enough guidance to the clinical decisions. Further, such work also does not take into consideration the inbuilt sensors of the smartphones.

Another set of studies focuses on using the smartphone sensors such as location with an aim to extract patterns such as distance travelled and radius of gyration [18, 26] to identify relationship between location sensor data and other illnesses. Nonetheless, they focus on applying these patterns to flu or depression as opposed to identifying the patterns of TBI.

As TBI patients have difficulty with walking and problem maintaining their balance, gait and balance patterns have previously been used to understand the variations in TBI patients from those of Non-TBI users. Few of those instances include GAITRite; which examines dynamic stability by measuring spatial and temporal variability of foot placement [26], 3GDA; that evaluates gait disorder by accurately measuring the joint moment [27]. However, they are done in a proctored manner rather than from periodic capturing of sensor data.

1.8 Main Contributions

Since, the approach consists of using the inbuilt smartphone sensors such as location and accelerometer, the idea is to extract features from these sensors and feed it to a machine learning model with an aim to detect TBI at the earliest from the date of injury. Thus, the main contributions of this thesis are as follows:

- *Approach I* – Creating hand-crafted features from raw sensor data, extract location, balance, and gait patterns.

- *Approach II* – Creating hand-crafted features by performing different types of pre-processing to extract location, balance, and gait patterns.

- *Approach III* – Using autoencoders for automatically extracting location patterns from the raw input data. To this representation, merge the statistical features of balance and gait patterns.

- For each of the above feature extraction approaches, create Machine Learning and Deep Learning models that help distinguish TBI patterns from those of Non-TBI.

- Compare the above three approaches; Approach I, Approach II and Approach III, to find a solution which is optimal.

1.9 Roadmap

The following section of this thesis consists of: (1) Related work that discusses specific techniques of other work along with the main results/findings. (2) Methodology that presents the hypotheses along with experimental conditions and tools used. (3) Evaluation and Results that describe the evaluation of the solution coupled with the metrics. (4) Discussion that will talk about learning and main take-aways. (5) Conclusion and Future Work that will summarize the main work and achievements along with future scope.

Chapter 2

Related Work

Prior research on detecting TBI using traditional approaches and smartphones is reviewed here with their corresponding findings.

2.1 mHealth

Shannon B. Juengst and Tessa Hart [28] describe mHealth as the use of mobile communications to analyze and treat health conditions. As smartphones are ubiquitous and have wide availability of applications, they are used by majority of the individuals. The current healthcare services for TBI are limited to emergency visits whereas there is a need for interventions even during the post TBI stage. Since, the maintenance of positive health behaviors and managing chronic symptoms is critically important post TBI, the author examines the use of mHealth in TBI population to identify its use in intervention.

The author covered 12 distinct mHealth interventions in 15 distinct studies. Articles were identified from multiple sources like PubMed and PsychInfo. Further, all the articles were published after 2012 considering the various advances in the smartphone technology. Articles included in the review went through two-stage review process. Articles included had the following criteria: i) included participants with TBI; ii) involved use of smartphone device as an intervention. 9 studies had individuals with moderate and severe TBI while 2 had individuals with mild TBI. 11 studies included adults and 4 had adolescents with TBI.

The interventions in the various articles included alerts through text, emails or calendar apps followed by reminders to improve goal attainment and alerts for symptom reporting. Extensive reviews provided foundation for effectiveness of using mHealth as: i) an alternate method for memory impairment, organization, and planning difficulties along with problem-solving; ii) a tool that supports social and community participation and goal attainment; iii) an aid for symptom monitoring and reduction.

While the findings have been promising, it was observed that none of the studies specifically investigated the degree of cognitive improvement. Moreover, the study focused on using smartphone apps rather than smartphone sensors to assist TBI patients. Also, all the articles in the study focused on aiding patients post TBI, rather than trying to predict TBI using the smartphones.

2.2 PupilScreen

Alex Mariakakis, Jacob Baudin [23] proposed PupilScreen, that measures pupillary light reflex (PLR) in quantitative measures to predict the outcome of a person's traumatic brain injury. PupilScreen is a smartphone app accompanied with 3D-printed box that mimics the penlight test used by clinicians in emergency situations. Figure *4* shows the VR headset like box that controls the position of the box and the lightning that reaches the light. In a penlight test, a clinician directs a penlight towards each of the patient's eye and observes the pupil's response. It is observed that PLR of patients suffering from TBI is lower or not pronounced.

This study had a dataset of 42 volunteers: 16 males and 26 females. Further, there was a balanced mix of iris colors: 17 blue, 20 brown, and 5 with a noticeable gradient between different colors. The data was collected using an iPhone SE. The phone is then placed into a slot in the back of the PupilScreen box. The PupilScreen app records 8 second video of a person's eyes as the response of pupil to the smartphone's flash. Later, this video is fed to two different Convolutional Neural Networks (CNN). The first architecture estimates the location of the pupil and second estimates the diameter of the pupil given cropped images by performing pixelwise segmentation.

The errors across all users of the first network had a median of 0.43 mm in the Euclidean distribution and a 90^{th} of 0.87mm. For the second network, the distribution of absolute errors had a median of 0.36mm and 90^{th} percentile of 1.09 mm. Though this error was better than manual examination, it was worse than that of a clinical pupillometer. Further, there was a distinguishable difference between different iris colors wherein images of brown eyes led to worse results.

Figure 4: PupilScreen system that measures PLR and lightning that reaches the eye [23]

Upon clinical feedback, it was observed that most of the clinicians felt that the existence of the box is bulkier. Further, this kind of app is difficult to use on people who went unconscious after a TBI. In case of unconscious patient, manipulating the patient's face could lead to more light to pass to the app leading to inaccurate results.

This methodology only makes use of camera sensor of the Smartphone. Using other powerful sensors such as accelerometer and gyroscope to compute gait and balance patterns can help understand dynamic posture and coordination during movement as opposed to using the PupilScreen which depends on just one factor i.e. PLR to detect TBI.

2.3 Mood-Traces

Mirco Musolesi [25] tries to discover whether mobile phone sensors can be used to monitor individuals suffering through depression by analyzing the mobility patterns from the GPS traces. This is done using an android application named Mood-Traces, that periodically collects the location of the users. The author tries to devise mechanisms and propose a solution that forecasts depressive mood changes from the mobility data.

The study is based on general population instead of just few individuals that suffer from severe depression. The data is collected from 28 users by obtaining the location. Further, Mood Traces collects answers to 8 daily questions from the "PHQ-8" depression test which is used a ground truth. On average, each user was monitored for 71 days. Upon the data collection, a set of mobility metrics is extracted from the mobility traces of the users and a personalized general machine learning model is used to predict PHQ scores. Personalized models are achieved upon training on the history data of the user and finding the prediction for the next possible hour. Figure *5* shows the approach of training personalized models where T_{HIST} is the duration over which mobility metrics are computed whereas T_{HOR} represents how much in advance the metrics are computed.

It was observed that the model performed well when 14 history days were taken into consideration. Personalized models performed better than the general models however, general models could be used when a user installs the app for the first time. Further, upon fixing the number of history days, it was observed that there is scope for an early detection of the depressive moods. Due to the promising results obtained, it was concluded that there is significant correlation between mobility patterns and depressive moods.

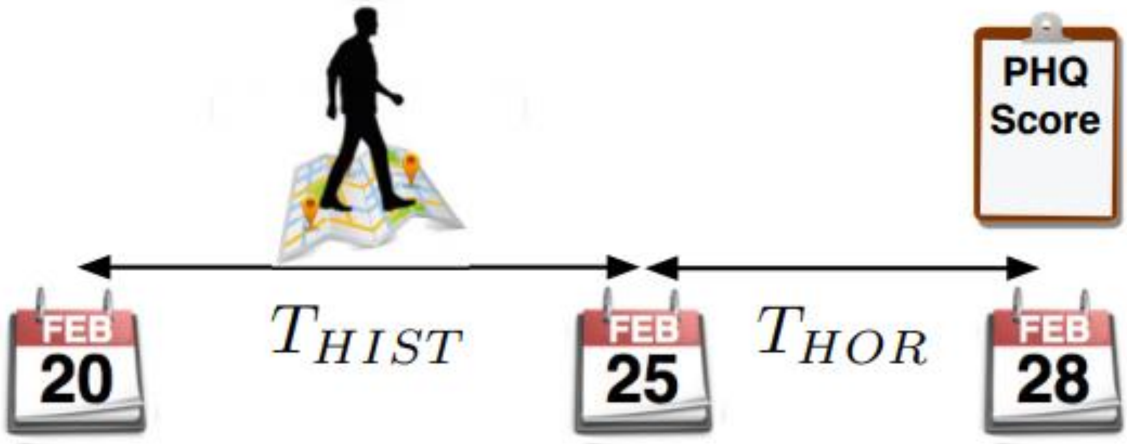


Figure 5: Approach for building personalized models using Mood-Traces [25]

Another approach used by this author consists of using autoencoders for automatically extracting features from the raw input [29]. This method proposed different input representation of autoencoders while quantifying the effectiveness in predicting user's depressive mood. The technique consists of using output of the encoder that consists of compressed input representations from the raw input data. The GPS data points are normalized to allow for common pattern extraction and then fed to the autoencoder for training. The output of the encoder i.e., the mobility metrics is fed to the machine learning model.

This approach achieved better results as compared to the pervious one, wherein statistical features were used to train the machine learning model. To be specific, using mobility metrics such as Displacement Representation (DR) and Significant Place Representation (SPR) with activation function as ReLU and SVM as machine learning model achieved the best results. This implies that the mobility features extracted by using autoencoder are way more effective and can learn the representation in much detail.

Depression is a common problem caused by TBI and therefore, the behavior observed in TBI patients is similar to depression. The results obtained in this study seem promising and hence we can extract similar location patterns by using statistical as well as encoder-based approach with ground truth as TBI patient and Non TBI patient.

2.4 GAITRite

Patients with TBI exhibit problems with balance which can clearly be reflected upon their mobility assessment. E.Niechwiej-Szwedo [27] proposed a study that examines the dynamic stability during gait in patients with TBI. Even patients with high level of recovery tend to have great variability in gait values implying that mobility problems stick with a TBI patient long after the injury.

In this study, 20 participants were appointed who had TBI and 20 healthy participants were selected. GAITRite model was used to measure the spatiotemporal gait parameters. Each participant was asked to perform three walking tasks: i) walk at preferred pace; ii) walk as fast as possible; iii) walk with eyes closed at preferred pace.

It was observed that TBI patients exhibited greater variability in step time and step length for the third task, i.e. walking with eyes closed. Further, step time variability increased when the patients were asked to improve their velocity. Thus, it could be concluded that temporal and spatial variability of foot placement is significant in TBI patients, particularly when the task became more complex.

The study indicated gait measurement as a strong indication to distinguish TBI patterns. However, the study here was done in a proctored manner instead of continuous passive monitoring using the smartphone sensors. The various metrics used in this study could be incorporated in the thesis to obtain gait variability using the smartphone sensors.

2.5 mCTSIB

TBI patients tend to experience balance-related symptoms such as dizziness, unsteadiness, and imbalance post injury. Geetanjali Gera [30] proposes the modified Clinical Test of Sensory Integration and Balance (mCTSIB) as a tool to observe quality of sway in individuals using wearable inertial sensors.

The study included athletes who were above the age of 18 years and have sustained a mild TBI or have no TBI in the past 6 months. 38 mTBI patients were appointed along with 81 healthy subjects. These participants were asked to perform four quiet stance for 30 s with feet close together and arms across the chest: i) Eyes Open (EO) firm surface, ii) Eyes Closed (EC) firm surface, iii) Eyes Open (EO) foam surface, iv) Eyes Closed (EC) foam surface. Postural sway was computed using the wearable inertial sensor which consisted of a tri-axial accelerometer, a tri-axial gyroscope, and a tri-axial magnetometer.

The results obtained after the study had three important findings: i) at approx. 2 – 3 days after the injury, TBI patients had increased postural sway; ii) Eyes closed compared with eyes opened had more impairment under foam conditions; iii) Dizziness severity was related to the postural sway deficits in TBI. Further, it was observed that the TBI patients were more dependent on the vision and thus had difficulty performing tasks which involved closing the eyes.

The results of this study show promising results in comparing balance of TBI patients vs Healthy ones. Postural sway was an important feature to identify the balance patterns. However, this study was also done in a proctored manner rather than using continuous passive monitoring. Computing postural sway with various other balance features using smartphone sensors can help distinguish and identify patterns of TBI from those of healthy ones.

Chapter 3

Methodology

3.1 Overview

This section describes the approach followed to prove the hypothesis. To create a smartphone application that could passively detect TBI, classifiers are required that takes input as the location and the accelerometer sensors from the user's smartphone. To build the classifiers, smartphone sensor data is required along with their date of head injury. Figure *6* represents the steps involved in building the machine learning pipeline for TBI detection.

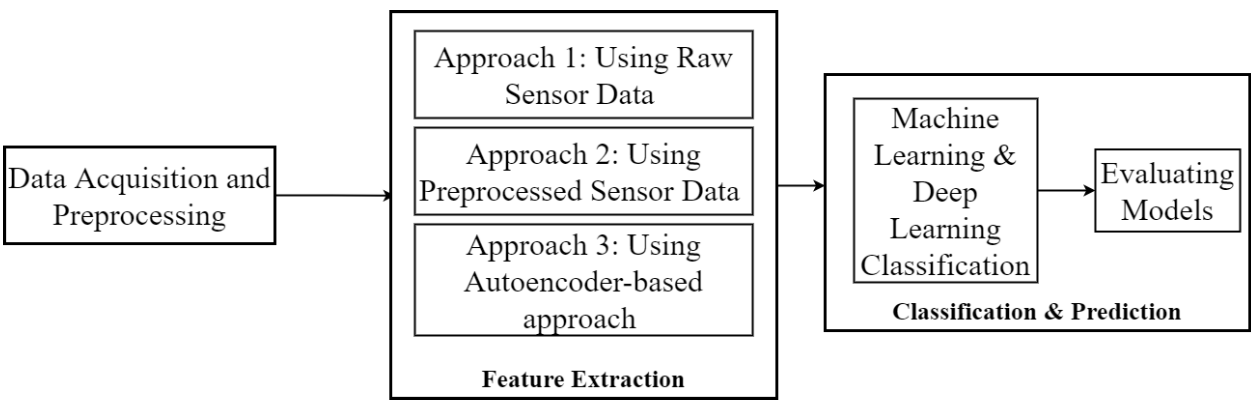


Figure 6: Machine Learning Pipeline for TBI detection

To gather sensor data and survey data of users, Charles River Analytics Dataset and Lockheed Martin Dataset were used. The details of the Data Gathering are mentioned in Section 3.2. The rest of the section is divided as follows: Section 3.3 explains the Machine Learning Analysis. Section 3.4 talks about data pre-processing step; Upon acquiring the data, three different approaches were applied; i) Hand-crafted features on raw sensor data; ii) Hand-crafted feature extraction with overlapping window sizes; iii) Auto-encoder based representation to extract location, gait and balance patterns. This process in explained in Section 3.5; The normalization performed on the data is discussed in Section 3.6 and machine learning classifiers along with evaluation metrics are discussed in Section 3.7.

3.2 Data Gathering

To gather the data required for training the machine learning algorithms, Charles River Analytics' and Lockheed Martin dataset was used. This dataset consists of daily and weekly survey responses followed by smartphone sensor data of various users.

The data gathering was done by the Charles River Analytics company. Initially subjects were recruited using Google Ads and Facebook and the inclusion criteria for the participants recruited using these platforms were as follows: Individuals over 19 years of age, English speaker and owns a smartphone (Android or iOS) with a data plan and Wi-Fi or 3G/4G capabilities and be the primary user of the phone. The exclusion criteria were as follows: Individuals under the age of 19, Non-English speaker, does not own a smartphone with Wi-Fi or 3G/4G capabilities, unable to provide informed consent, Employee of the University of Washington, Unwilling to provide access to accelerometer and gyroscope sensors, Use of a VPN (virtual private network), Bad actors/fraudulent enrollees. Figure *7* shows the distribution of all the participants based on gender.

After a participant self-identifies as willing to participate, they need to review an information consent that contains all the necessary elements of the consent. After reviewing the consent, participants need to fill their demographic information such Sex, Birth Date, Height, Weight. Based on the demographic and taking into the consideration the inclusion and exclusion criteria, it is determined whether the participant is eligible to continue to the survey. Upon recruitment, participants receive a link to download the mobile application. Further, the participants provide consent for passive data collection through sensors. Upon downloading the application, the participant is prompted to complete a baseline questionnaire regarding the participant's health, mood, physical activity, and smart phone usage.

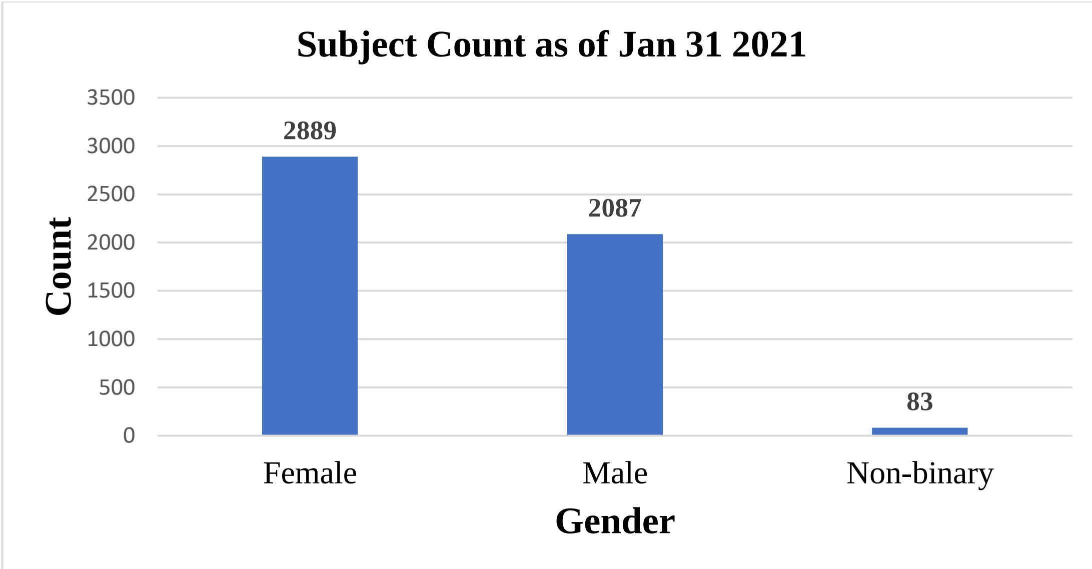


Figure 7: Distribution of participants based on Gender as of Jan 31, 2021

The recruited participants then use the application for a period of 12 weeks wherein they answer to survey responses in the morning (Noon) and in the evening (6:00 PM). These questions ask about the participant's health, mood, employment status, active duty/veteran status, physical activity, and smart phone usage. Consent is also requested for voice recordings, still images, and videos at various points throughout the study. Figure *8* represents the different types of survey questions asked during the study period. This was done using an android/ iOS application "*mSense*". Figure *9* represents the screen of the application with a survey question. Along with this, the app was also responsible for passively collecting the sensor data.

Participants received amazon gift cards based on the number of surveys completed and continued uploads of passive data from accelerometer and gyroscope. Table *5* and Table *6* represents and various iOS and Android sensors collected by the mobile application, respectively. The mobile application keeps track of the number of assessments completed and the provided information is deidentified before it uploads to the server. Once uploaded, each participant receives a unique User ID and Device ID. Later this data is also encrypted using FIPS 140-2 approved AES cryptographic implementations with 256-bit keys.

	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7	Week 8	Week 9	Week 10	Week 11	Week 12
Day 1	SID1	SID8	SID15	SID22	SID29	SID36	SID43	SID50	SID57	SID64	SID71	SID78
Day 2	SID2	SID9	SID16	SID23	SID30	SID37	SID44	SID51	SID58	SID65	SID72	SID79
Day 3	SID3	SID10	SID17	SID24	SID31	SID38	SID45	SID52	SID59	SID66	SID73	SID80
Day 4	SID4	SID11	SID18	SID25	SID32	SID39	SID46	SID53	SID60	SID67	SID74	SID81
Day 5	SID5	SID12	SID19	SID26	SID33	SID40	SID47	SID54	SID61	SID68	SID75	SID82
Day 6	SID6	SID13	SID20	SID27	SID34	SID41	SID48	SID55	SID62	SID69	SID76	SID83
Day 7	SID7	SID14	SID21	SID28	SID35	SID42	SID49	SID56	SID63	SID70	SID77	SID84

Color Scheme
Baseline
Survey A
Survey B
Survey C
Survey D
Survey E
Survey F
Survey G
End of Study Survey

Figure 8: Daily and weekly surveys asked during the period of 12-week study

The baseline survey includes the demographic questions such as chronic illness, allergies, alcohol use, drug use. Surveys consisting of questions related to TBI and Flu included asking about flu shot, been in contact with anyone sick, getting tested for flu/COVID-19. The survey also asked questions related to sleep patterns, body temperatures, interaction with other people, symptoms related to flu, etc. Finally, there was another survey, Static by Day, which was asked on every Saturday of the 12-week period. Table *4* shows TBI specific questions asked in the Static by Day Survey. Figure *10* shows the symptoms experienced by the TBI participants during the length of their study

Table 4: TBI specific Survey Questions

TBI-related Survey Questions
Were you in any accidents this week?
Did you hit your head at all this week?
What day did it happen?
Did you become unconscious due to the injury?
Did you see a doctor for your head injury?
Did the doctor say you have a concussion?

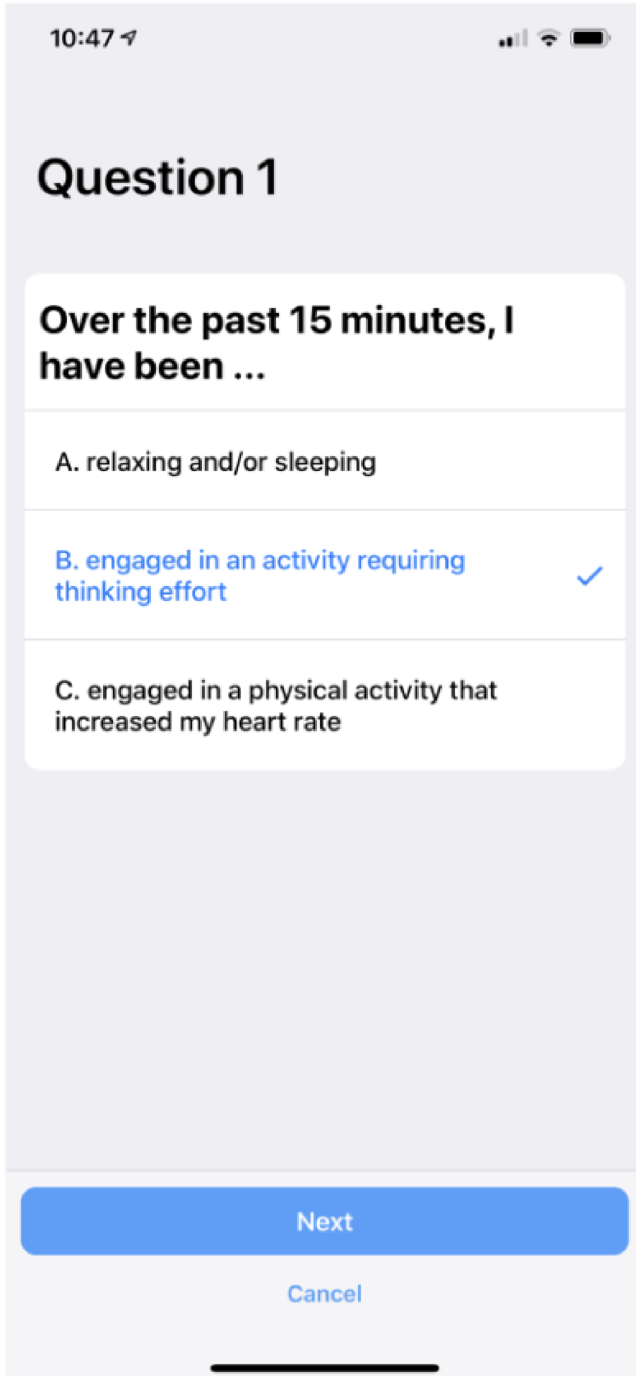


Figure 9: Example Question from one of the surveys asked by *mSense*

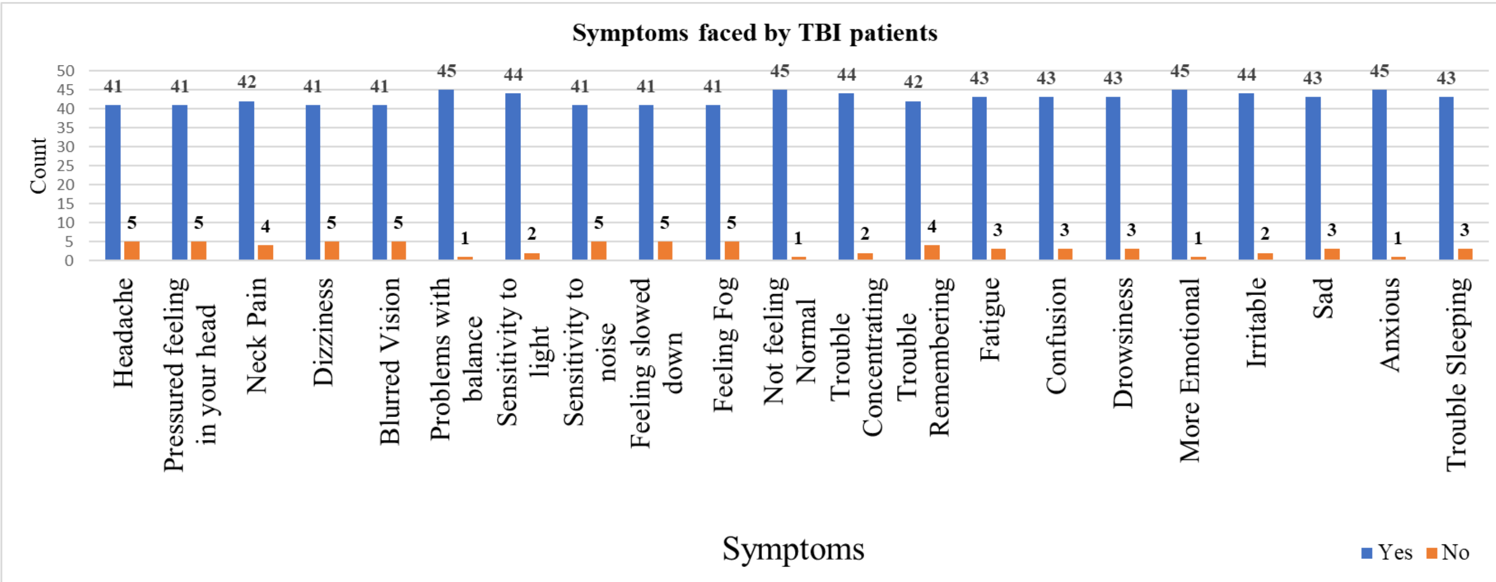


Figure 10: Various symptoms experienced by the TBI participants

Table 5: iOS Sensors

Operating System	Sensor	Description
iOS	Accelerometer	Acceleration of the device in 3-dimensional space
	Gyroscope	Instantaneous rotation around the spatial axis
	Magnetometer	Device's orientation relative to the Earth's magnetic field
	Pedometer	Calculates step-counting, distance travelled
	Altitude	Measures altitude data
	Barometer	Measures air pressure
	GPS	Device's geographic location

	Compass	Reports device's orientation
	Accessibility	Accessibility features enabled on the device such as the following: Assistive Touch, Voice Over, Switch Control, Shake to Undo

Table 6: Android Sensors

Operating System	Sensor	Description
Android	Accelerometer	Measures acceleration force across the 3-axis
	Gyroscope	Measures device's rate of rotation across the 3-axis
	Magnetic Field	Measures geomagnetic field across x, y and z axis
	GPS	Determines user's physical location using latitude and longitude
	Pressure	Measure the ambient pressure
	Step Counter	Counts the number of steps taken by the user
	SMS	The messages sent and received by the user
	Bluetooth	Determine if Bluetooth is active or not and get its current state

3.3 Machine Learning Analysis

Figure *6* shows the machine learning pipeline used for this thesis. Upon data acquisition, it is pre-processed to obtain the date of injuries. This raw data is then segmented into different timeframe and window-sizes and passed to feature extraction step for generating features from this sensor data. The feature extraction step uses three approaches to generate features out of the sensor data. The extracted features are normalized and then fed to the machine learning models after which the results obtained are evaluated.

3.4 Data Pre-processing

Figure *11* shows the pre-processing steps used to acquire the data for TBI and Non-TBI users.

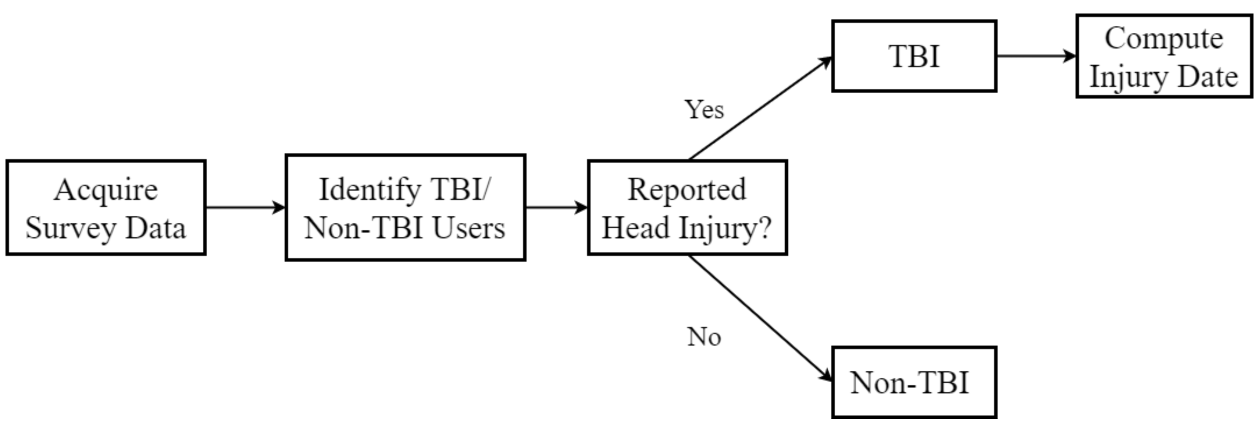


Figure 11: Data Pre-processing to acquire data for TBI and Non-TBI

Acquiring Survey Data: Survey data is pulled from the Secured Cloud Database Storage where all the sensor and survey data of the users are uploaded.

Identifying TBI & Non-TBI Users: Upon acquiring all the survey and sensor data from the server, TBI and Non-TBI users are identified. Here, TBI users are those who have reported a head injury or were in an accident and have been diagnosed with TBI during the length of their survey i.e. users who have answered *yes* to questions like "*Were you in any accidents this week?*" or "*Did you hit your head at all this week?*" whereas Non-TBI users are those who never reported to be in an accident or had an injury during their survey period i.e. users who answered *no* or *NA* to questions like “*Were you in any accidents this week?*” or “*Did you hit your head at all this week?*”

Head Injury Reporting & Computing of Injury Date: On every Saturday, users respond to survey question "*Were you in any accidents this week?*" and "*Did you hit your head at all this week?*". If they answer “*Yes*” to any of these, they are asked to report the day on which the injury occurred. This weekly based survey is used to infer the injury date of each of the user who have been diagnosed with TBI. So, for example, if a user answered *yes* to the injury question on 25^{th} July 2020 and mentioned his day of injury as Tuesday, then the injury date is 21^{st} July 2020, which is Tuesday in the week of 25^{th} July. Upon performing this analysis, 18 TBI instances were identified who were diagnosed with concussion during their 12-week study period.

Pre-processing for Lockheed Martin Dataset:

Another dataset used for this thesis was Lockheed Martin Dataset. This dataset also consisted of TBI users along with users who were diagnosed with various other disease such as Flu, Bronchitis. This dataset had 17 TBI users who had responded to the survey question “*When did the injury occur? (Provide date in MM/DD/YY format OR I don't recall)*”. Of the 18 users, 10 reported I don’t recall or garbage values while only 7 had the injury date. Of the 7, only 4 had good sensor data while 3 had missing accelerometer and location sensor data. Figure *12* shows the response of TBI users in the Lockheed Martin Dataset.

Thus, in total, by combing both the datasets, 179 Non-TBI users were chosen along with 23 TBI instances.

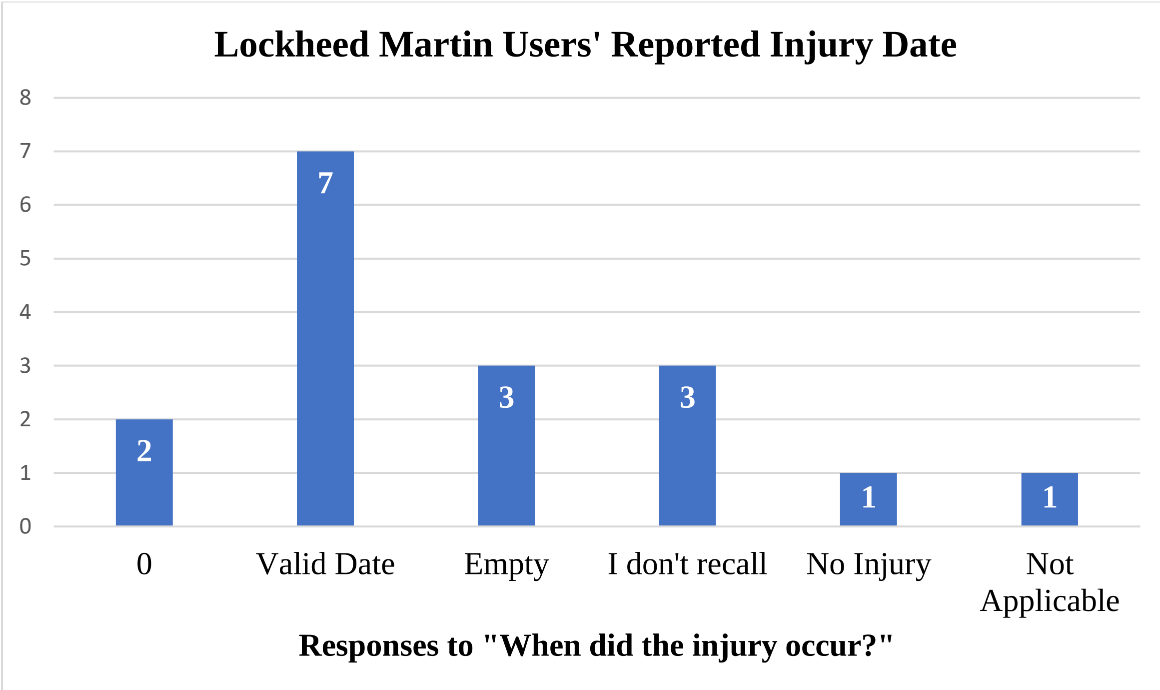


Figure 12: Response to the date of injury in the Lockheed Martin Dataset

3.5 Feature Extraction

This thesis focuses on extracting features from location sensor data while also extracting gait and balance patterns from accelerometer sensor data. Thus, the focus of this work in mainly based upon two sensors i.e. location and accelerometer. For each of the approaches, different pre-processing techniques were used, which will be described below.

3.5.1 Approach I - Extracting features from Raw Sensor Data

Pre-Processing:

The pre-processing steps consists of segmentation on the raw sensor data and then applying hand-crafted features on the sensor data. Table *7* shows the various segmentation length with their corresponding window-sizes applied on the raw sensor data.

Table 7: Segmentation of Time Series data with corresponding Window sizes

Time Frame	Window Sizes
24 hours	3 hours
	6 hours
48 hours	6 hours
	12 hours
72 hours	12 hours
	24 hours

Extracting Location Patterns:

GPS sensor aggregates information about user data. The location patterns obtained from this sensor data reflects behavioral patterns associated with TBI along with movements to various locations. The location metrics used in this have been effectively able to capture the depression patterns [25] and since TBI patients tend to depict behavior, which is like depression, these patterns can be used to identify TBI patterns at the earliest possibility. Table *8* shows the location patterns extracted from the GPS data using different time frame and window sizes.

Table 8: Hand-crafted features extracted from location sensor data

Feature	Formulae	Description	REF
Total Distance Covered	$D_T(t_1, t_2) = \sum_{i=1}^{N(t_1,t_2)-1} d(C_i, C_{i+1})$	Here, $d(C_i, C_{i+1})$ is the Haversine distance between two latitude-longitude pairs	[25]
Maximum Distance between two locations	$D_M(t_1, t_2) = \max_{i,j \in \{1,\ldots\ldots,N(t_1,t_2)\}} d(C_i, C_{i+1})$	$D_M(t_1, t_2)$ represents the maximum span of the area covered	

Radius of Gyration	$G(t_1,t_2) = \sqrt{\frac{1}{T}\sum_{i=1}^{N(t_1,t_2)} T_i \cdot d(C_i,C_{cen})^2}$	This feature measures the coverage area and computes deviation from the centroid in the time interval [t1, t2]	
Standard Deviation of the displacements	$\sigma_{dis} = \sqrt{\frac{1}{N(t_1,t_2)-1}\sum_{i=1}^{N(t_1,t_2)-1} (d(C_i,C_{i+1}) - D_{dis}}$	Here, $D_{dis} = \frac{1}{N(t_1,t_2)}\sum_{i=1}^{N(t_1,t_2)-1} d(C_i,C_i$ is the average displacement	
The number of different places visited	$N_{diff}(t_1,t_2) = \sum_{j=1}^{N(t_1,t_2)} max\left\{1-\sum_{j\neq i} I_{ij}, 0\right\}$	Here, I_{ij} is the indicator function, which is 1 if, $ID_i = ID_j$	
Number of stops	$d_j = (\mathrm{I}_j, \Delta l_j^{dest})$	Here, L = {I_j} is the set of locations and D = {d_j} is all destinations at a particular geographic scale.	[31, 28]

Extracting Gait & Balance Patterns:

A lot of medications prescribed by the professionals after brain injury can cause dizziness, lightheadedness, and imbalance. About 30% of the individuals have complained about impaired balance and altered coordination. This is because walking and balance involves a complex interaction of sensory, motor programming and musculoskeletal systems [33]. An extensive evaluation of Gait and Balance will help in detecting TBI as early as possible.

Further, the two important goals involved in understanding mTBI are: i) how brain activity patterns change after injury; ii) how these changes may reflect true injury severity and clinical outcome [34]. And these goals become difficult to achieve due to cost and logistic challenges involved in constantly monitoring brain activities. When gait and Balance patterns are extracted from the accelerometer sensor data, they reduce the cost and enable effective monitoring of the patient's brain patterns. Table *9* shows the various gait features and Table *10* shows the various balance features extracted from accelerometer sensor data.

Table 9: Hand-crafted gait features extracted from accelerometer data

Feature	Formulae/Method	Description	REF
Peak Frequency	Peak frequency f_p is computed by smoothing the accelerometer using low-pass filter. Then the accelerometer data is converted by FFT from which highest peak of power spectrum is computed. Finally, f_p is detected in the frequency space to where power spectrum had the highest peak.	This value indicates the gait cycle, i.e. time taken for one step	[35]
Root Mean Square	$RMS = \sqrt{\frac{\int_{t_1}^{t_2} a(t)^2 dt}{t_n - t_1}}$	This value indicates the degree of gait instability	
Autocorrelation Peak	$R_{xx}(k) = \frac{1}{n-k}\sum_{i=1}^{n-k} x_{t_i} x_{t_{i+k}}$	This indicates the degree of gait balance and $x(t) = \frac{a(t) - a_{mean}}{a_{SD}}$	
Coefficient of Variance	$CV = \frac{t_{SD}}{t_{mean}}$	This value indicates the degree of gait variability	
Step Count	$steps = n_{peaks}$	The number of steps walked during the period t	[36]
Cadence	$c = 60\, f/n$	c is defined as steps per minute	[37]
Step Regularity	$step\ regularity = R_{xx}(A, A_{d1})$	This feature shows consistency in step-to-step pattern. Here, A_{d1} is first dominant phase shift of one step	

Stride Regularity	$step\ regularity = R_{xx}(A, A_{d2})$	This feature shows consistency in stride-to-stride pattern. Here, A_{d2} is the second dominant phase shift of one step	
Step Symmetry	$step\ symmetry = \frac{step\ regularity}{stride\ regularity}$	This value indicates the symmetry between two steps of both legs.	

Table 10: Hand-crafted balance features extracted from accelerometer data

Feature	**Formulae**	**Description**	**REF**
Trajectory Length	$TL = \sum_{n=1}^{N} dist(P_n, P_{n-1}) = \sqrt{(a_{xn} - a_{xn-1})^2 + (a_{yn} - a_{yn-1})^2 + (a_{zn} - a_{zn-1})^2}$	Total accelerometer trajectory length measured in m/s^2	[38]
Sway Area	$SA = ConvexHull(x, y, z)$	Area spanned from the acceleration signals with respect to the duration of the measurement	[38, 39]
Jerk Index	$j(t) = \frac{d\|a(t)\|}{dt}$	This feature measures the amplitude, smoothness, and frequency.	[38, 40]
Entropy	$entropy = \sum_{i=1}^{n} -a_i\ log_2 a_i$	This feature describes the nature of point-to-point fluctuations in a physiological signal.	[38, 41]

3.5.2 Approach II - Extracting features with pre-processing

Pre-Processing:

The pre-processing steps consists of passing the accelerometer data through the low-pass 3rd order Butterworth filter. Further, the normal cut-off frequency was computed using cut-off frequency and Nyquist frequency. This helped to reconstruct a signal from a sequence of samples to capture peaks and troughs of the original waveform. Figure *13* shows the preprocessed accelerometer 1 day data of healthy user and Figure *14* shows the preprocessed accelerometer data of a TBI user post injury. Comparing both the figures, we can clearly see the difference in movements across the three axes: x, y and z. For example, the pre-processing helped identify the peak movements for both the users.

The pre-processed accelerometer data was then segmented into different timeframes with windows-sizes and overlapping percent. Finally, to this segmented data, hand-crafted features were computed. Table *11* shows the various segmentation length with their corresponding window-sizes and overlapping sizes applied on the pre-processed sensor data.

Table 11: Segmentation of Time Series data using Overlapping Window sizes

Time Frame	Window Sizes	Overlapping Window Size
24 hours	3 hours	33%
	6 hours	33% and 50%
48 hours	6 hours	33% and 50%
	12 hours	33% and 50%
72 hours	12 hours	33% and 50%
	24 hours	50%

Extracting Location Patterns:

The features mentioned in Table *8* were used to compute location patterns from the Location Sensor data. These features were computed over the various segmentation mention in Table *11*.

<u>Extracting Gait & Balance Patterns:</u>

The features mentioned in Table *9* and Table *10* were used to calculate Gait and Balance patterns from the pre-processed accelerometer data. These features were computed over the various segmentation mention in Table *11*.

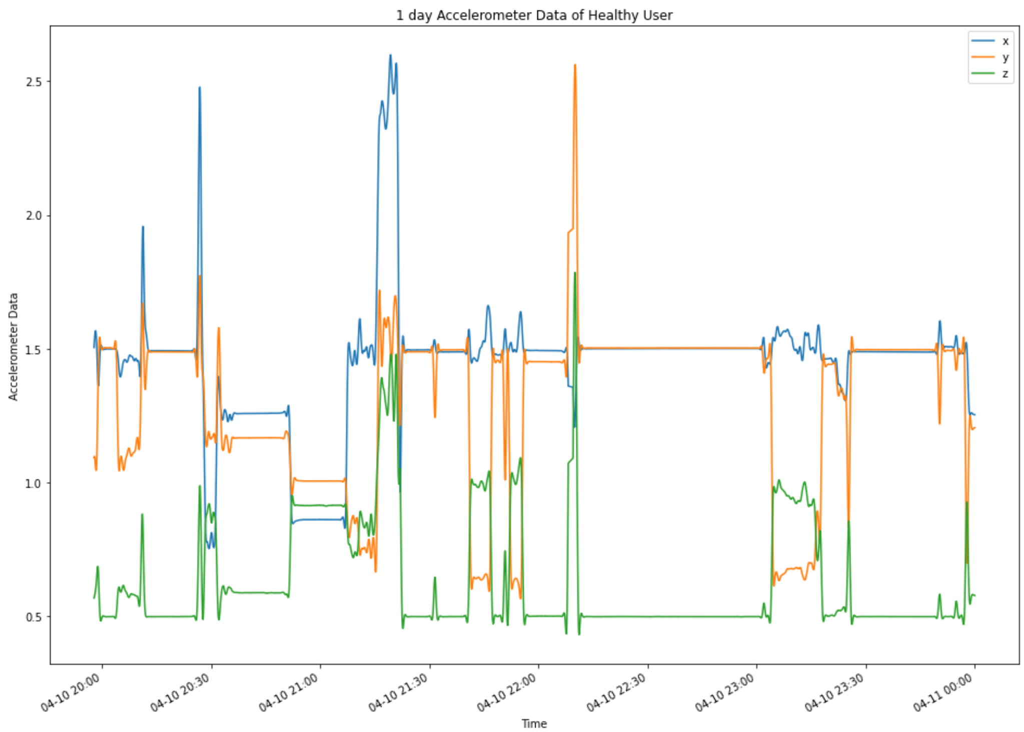


Figure 13: Accelerometer Data of Healthy User

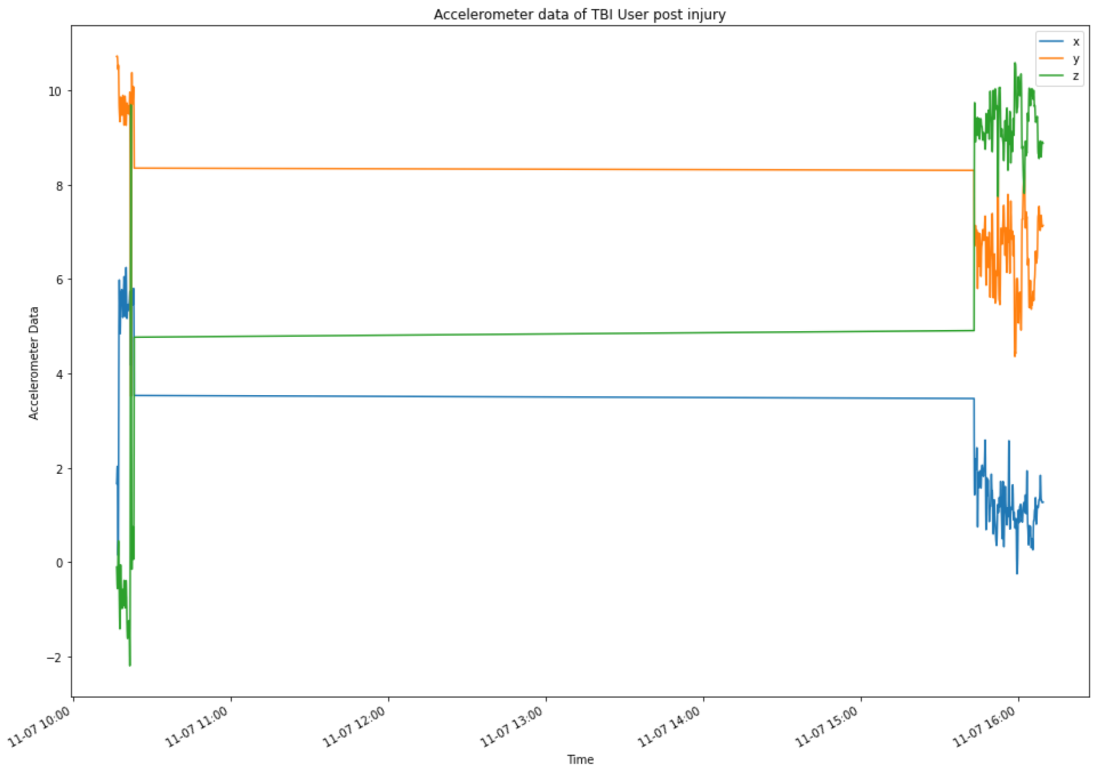


Figure 14: Accelerometer Data of TBI User Post Injury

3.5.3 Approach III – Using Autoencoder-based approach

Mirco Musolesi [29] proposed a novel technique to extract location patterns using input representations to predict depression. The research shows that using autoencoder-based features for predicting depression was more effective than the hand-crafted features. Since, TBI patients depict depression symptoms, the goal of this approach is extract mobility patterns from raw data using autoencoder and combine them with statistical gait and balance patterns. Later, compare this approach with the previous two approaches to find an optimal method to predict TBI.

Pre-Processing:

The pre-processing steps consists of segmentation on the raw sensor data and then using autoencoder based approach for location sensor data along with hand-crafted features for gait and balance for accelerometer sensor data. Table *12* shows the various segmentation length with their corresponding window-sizes applied on the raw sensor data.

Table 12: Segmentation of location time series data with gait and balance window sizes

Time Frame	Window Sizes	Location + Statistical time window frame
24 hours	3 hours	24 hours + 3 hours
	6 hours	24 hours + 6 hours
48 hours	6 hours	48 hours + 6 hours
	12 hours	48 hours + 12 hours
72 hours	12 hours	72 hours + 12 hours
	24 hours	72 hours + 24 hours

Extracting Location Patterns:

Since mobility patterns differ for each person, the first step involves normalizing the location sensor data to make them comparable. From the raw sensor data, it gets impossible for an autoencoder to learn common compressed representations. Hence, the GPS data is transformed into three different representations as follows [29]:

- *Displacement Representation (DR)*: A vector of distances between all adjacent pairs of location is computed which is followed by implementing a normalization function.

  Given (P_1, P_2, P_3, ….. ,P_N) with N GPS points, displacement vector is defined as:

  $$D = \{d_1, d_2, \ldots\ldots, d_i, \ldots, d_{N-1}\}$$

  with

  $$d_i = dist(p_i, p_{i+1})$$

  where *dist()* is the Haversine distance between two points.

  Finally, the displacement vector is normalized as follows:

  $$D_{MinMax} = MinMax\ (D)$$

  where *MinMax()* is the minmax scaling function applied to D

- *Change in Displacement Representation (CDR)*: This is a vector that contains ratios of distances for all pairs of adjacent points with the distance of the previous points.

  Given (P_1, P_2, P_3, ….. ,P_N) with N GPS points, change in displacement vector is defined as:

$$C = \{c_1, c_2, \ldots\ldots, c_i, \ldots, c_{N-2}\}$$

with

$$c_i = 1 - d_{i+1}/d_i$$

where

d_i is the distance between two points p_i and p_{i+1}

- *Significant Place Representation (SPR)*: In order to obtain this representation, time spent at the most significant place is computed.

  More specifically, given a set of GPS points **P**, stop location is computed using the approach presented in [32]. Upon computing the stop location, the time spent by the user at these locations is calculated.

  Therefore, given a set of significant places

$$S = \{s_1, s_2, \ldots\ldots, s_k\}$$

  Time spent by the user at all places is computed as follows:

$$T = \{t_{s_1}, t_{s_2}, \ldots\ldots, t_{s_k}\}$$

<u>Extracting gait & Balance Patterns:</u>

The features mentioned in Table *9* and Table *10* were used to calculate gait and Balance patterns from the accelerometer data. These features were computed over the various segmentation mention in Table *12*.

Figure *15* presents the architecture of the autoencoder-based approach. The process consists of 7 steps:

Step 1: train three generic autoencoders using the three input representations from the training data of all the users.

Step 2: extract the three trained encoders from these autoencoders.

Step 3: compute mobility features for the training data by using input representations as input to all trained encoders.

Step 4: Compute statistical gait and balance features using the various window-sizes mentioned in Table *12*.

Step 5 & 6: Combine the mobility features with the statistical gait and balance with training labels.

Step 7: Upon combining the features, train the Machine Learning model to obtain trained model.

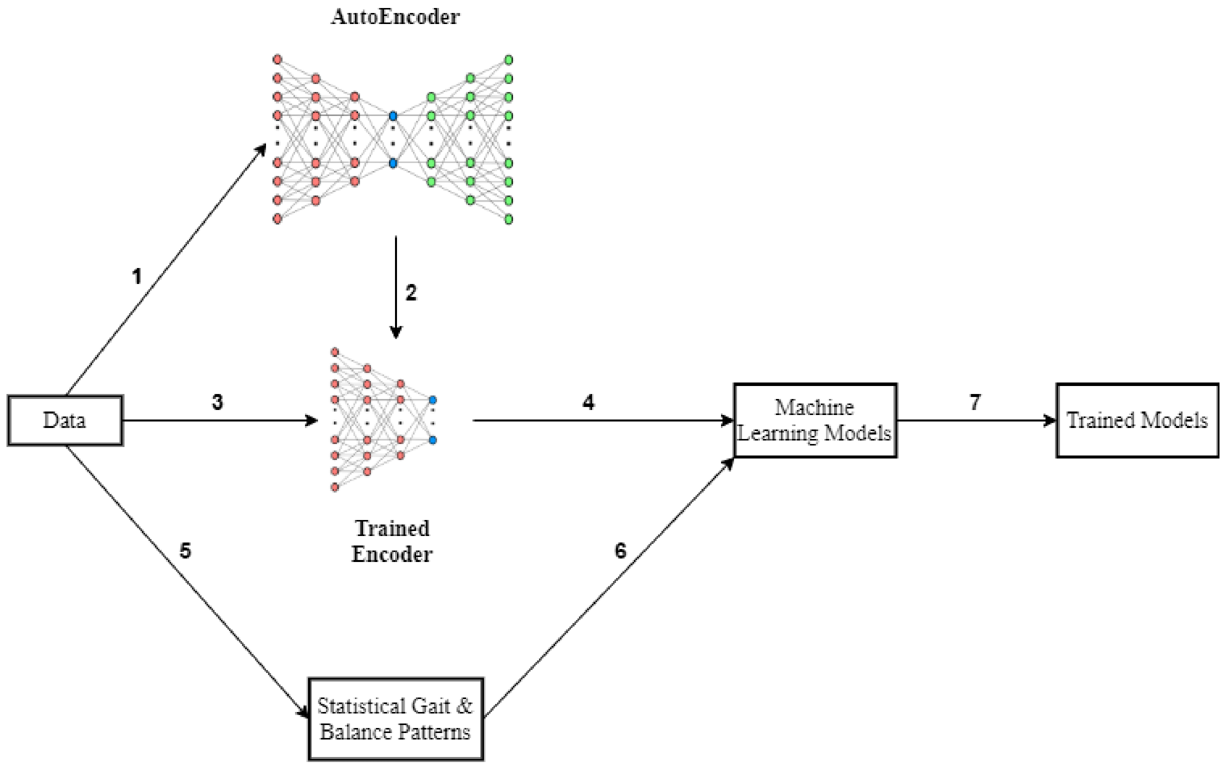


Figure 15: Approach 3 – Using Autoencoder-based approach

3.6 Normalization

After calculating features using the methods discussed in 3.5, normalization was applied to take into account the different variations in walking style of different people. Further, normalization helps to get an accurate result. The normalization was done using sklearn's normalize function, with norm = 'l2', which computes the distance of the vector coordinate from the origin of the vector space.

Given x, a vector with i components, we define $||x||_2$, L2 norm as follows:

$$||x||_2 = \sqrt{\sum_i x_i^2} = \sqrt{x_1^2 + x_2^2 + \ldots + x_i^2}$$

3.7 Classification

3.7.1 Machine Learning Classifiers

In machine learning, classification is the process of predicting the class (target/label) of given data points [42]. Classification belongs to the supervised learning category where the targets are provided with the input data. Classifier is an algorithm of classification that maps a function from input variables to discrete output variables which are the targets.

In this thesis, upon performing feature extraction and normalizing the features, 4 classifiers namely; XGBoost, Random Forest, Multi-Layer Perceptron and Stochastic Gradient Descent, performance is evaluated and compared to obtain the best results for the classification. These classifiers are briefly introduced below:

XGBoost: XGBoost stands for eXtreme Gradient Boosting and is an implementation of gradient boosted decision trees which are designed for performance and speed [43]. Gradient Boosting is an ensemble technique that provides better models through a combination of reweighting and aggregation. In this method the weights of the instances that were incorrectly predicted are increased and weights of the correct predictions decreased accordingly. This process is done on different samples with modified weights and finally an aggregated classifier is formed.

Random Forest: Random Forest models are kind of non-parametric used for regression and classification [44]. It is an ensemble method that uses a group of weak learners to obtain a strong and aggregated model. The output of the model is the model of the classes or the mean prediction of the individual trees.

Multi-layer Perceptron (MLP): Multi-layer Perceptron is a feedforward artificial neural network model that maps set of input data to a set of appropriate outputs [45]. The model consists of fully connected layers and each layer consists of neurons that are activated using a non-linear activation function. This makes neural networks capable of classifying unknown (noisy or incomplete input) pattern with a known (pure and complete) one by analyzing the features shared between the two patterns.

Stochastic Gradient Boosting: Stochastic Gradient Boosting is based upon gradient boosting, which is one of the powerful techniques for building predictive models [46]. Gradient boosting consists of three elements; a loss function, weak learners that make predictions and an additive model to that adds weak learns for minimizing the loss function.

Since, Gradient boosting is a greedy algorithm and has high probability of overfitting, regularization methods are adopted. One of them is Stochastic Gradient Boosting that performs bagging and boosting greedily from subsamples of the training dataset and helps to reduce the correlation.

3.7.2 Evaluation Metrics

To evaluate the results of the machine learning model, performance metrics such as Specificity, Sensitivity and F-beta measure were computed. SHAP was used to understand the feature importance and output of tree-based models.

Confusion Matrix:

Confusion matrix helps measure the effectiveness which in turn help evaluates the performance of the model. Thus, confusion matrix is a performance measurement for the classification-based machine learning algorithms where the output can be two or more classes. Table *13* shows the structure of the confusion matrix.

Table 13: Structure of Confusion Matrix

	Positive (1)	Negative (0)
Positive (1)	TP	FP
Negative (0)	FN	TN

where,

TP (True Positive): Predicted values correctly identified as actual positive

FP (False Positive): Predicted values incorrectly identified as actual positive i.e. negative values predicted as positive

FN (False Negative): Positive values identified as negative

TN (True Negative): Predicted values corrected identified as an actual negative

Upon, computing the confusion matrix, we can compute other metrics as follows:

Sensitivity: This metric measures the proportion of positives that are correctly classified i.e., it evaluates the model's ability to predict true positive for each category.

$$Sensitivity = \frac{TP}{TP + FN}$$

Specificity: This metric quantifies the proportion of negatives that are correctly classified i.e., it evaluates the model's ability to predict true negative for each category.

$$Specificity = \frac{TP}{TP + FN}$$

F-beta: This metric evaluates a binary classification model based on the predictions made for the positive class. This measure is calculated using Precision and Recall. It is a generalization of F-Measure which uses a configuration parameter beta in order to give more weight to precision or recall. For this thesis, the beta value used is 0.6 which gives higher weight to precision.

F-beta measure is computed as follows:

$$F - Measure = \frac{(1 + \beta^2) * Recall * Precision}{\beta^2 * Precision + Recall}$$

SHAP (SHapley Additive exPlanations):

SHAP is a game theoretic approach that explains the output of any tree-based machine learning model [47]. It is a high-speed exact algorithm that shows each feature's contribution either positively or negatively and how it pushes the model output. Each observation has its own set of SHAP values that increases the model's transparency. This helps in providing insights into how a model can be improved.

Chapter 4

Results

4.1 Effect of Normalization

Figure *16* represents the box plots of normalized vs unnormalized for autocorrelation feature on Day 1 between TBI and Non-TBI participants whereas Figure *17* represents the box plots of normalized vs not normalized for Step Regularity on Day 1. We can see the bad distribution of raw data and how normalization helps brings them to a common scale without distorting the differences in the range of values or losing information.

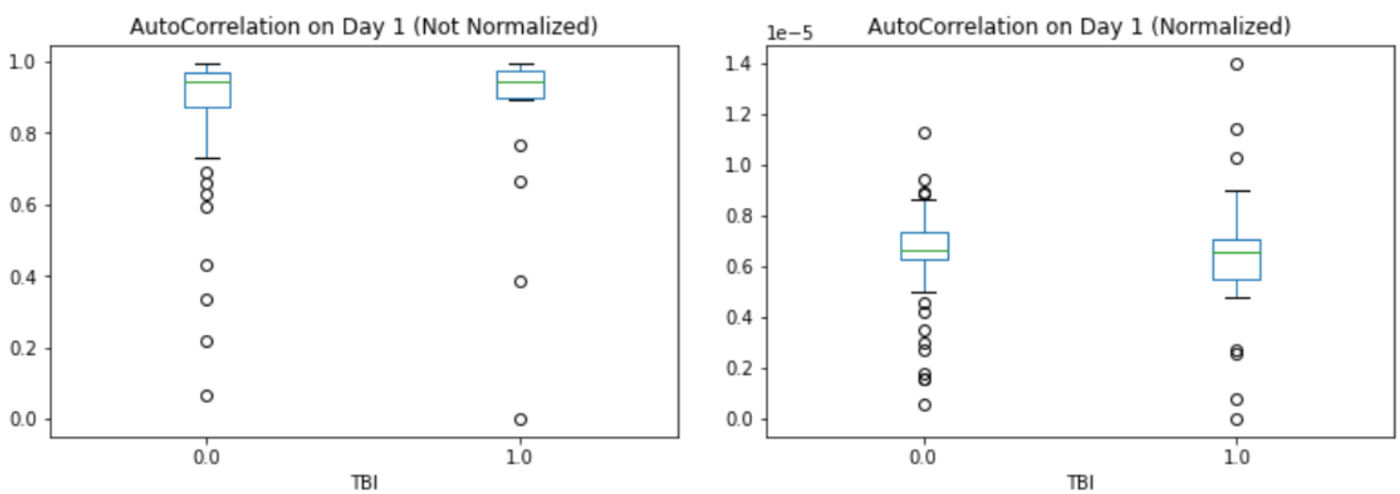


Figure 16: Data Distribution of Autocorrelation Feature (Not Normalized vs Normalized)

Figure *18* shows the data distribution of few features before normalization and Figure *19* shows the data distribution of same features normalized. From the two different figures, we can see how normalization makes data comparable and allows for extraction of common patterns.

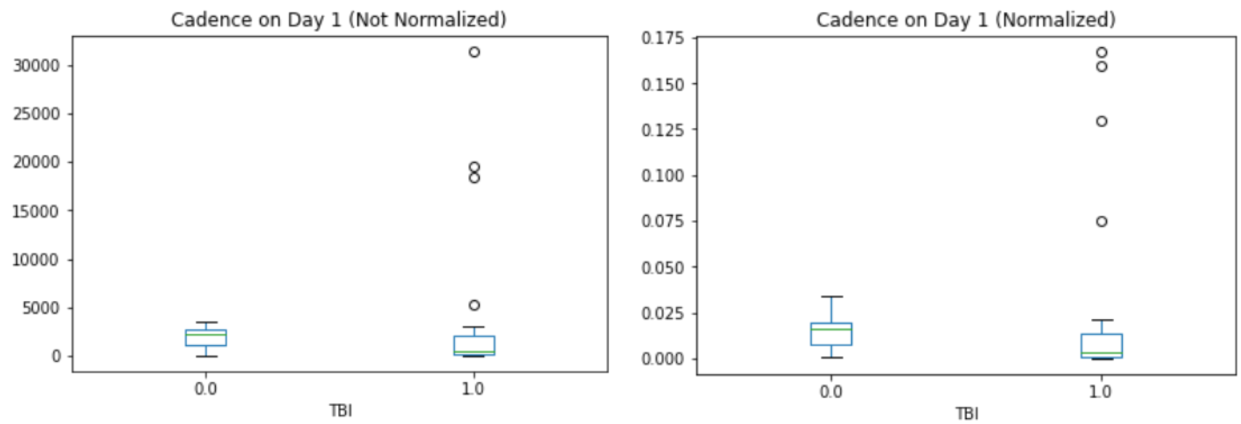


Figure 17: Data Distribution of Cadence Feature (Not Normalized vs Normalized)

4.2 Classification Results

This section summarizes the results obtained by following the approach mentioned in Section 3. This section is further divided into 3 parts, where results of each of the approaches i.e. i) hand-crafted features on raw sensor data; ii) hand-crafted features with pre-processing (filtering and overlapping) and iii) auto-encoder based approach; are discussed that detect TBI patterns from Non-TBI. Table *14* shows results of the best models from each of the approaches with their corresponding metrics.

Table 14: Best Results obtained across each approach with their corresponding metrics

Approach	Segmentation	Model	Sensitivity	Specificity	F_beta Score
Approach I	**3 days; 24 hours window-size**	**XGBoost**	**0.889**	**1**	**0.968**
Approach II	2 days; 12 hours window-size and 50% overlap	XGBoost	0.778	1	0.93
Approach III	2 days; 12 hours window-size	Random Forest	0.778	0.959	0.778

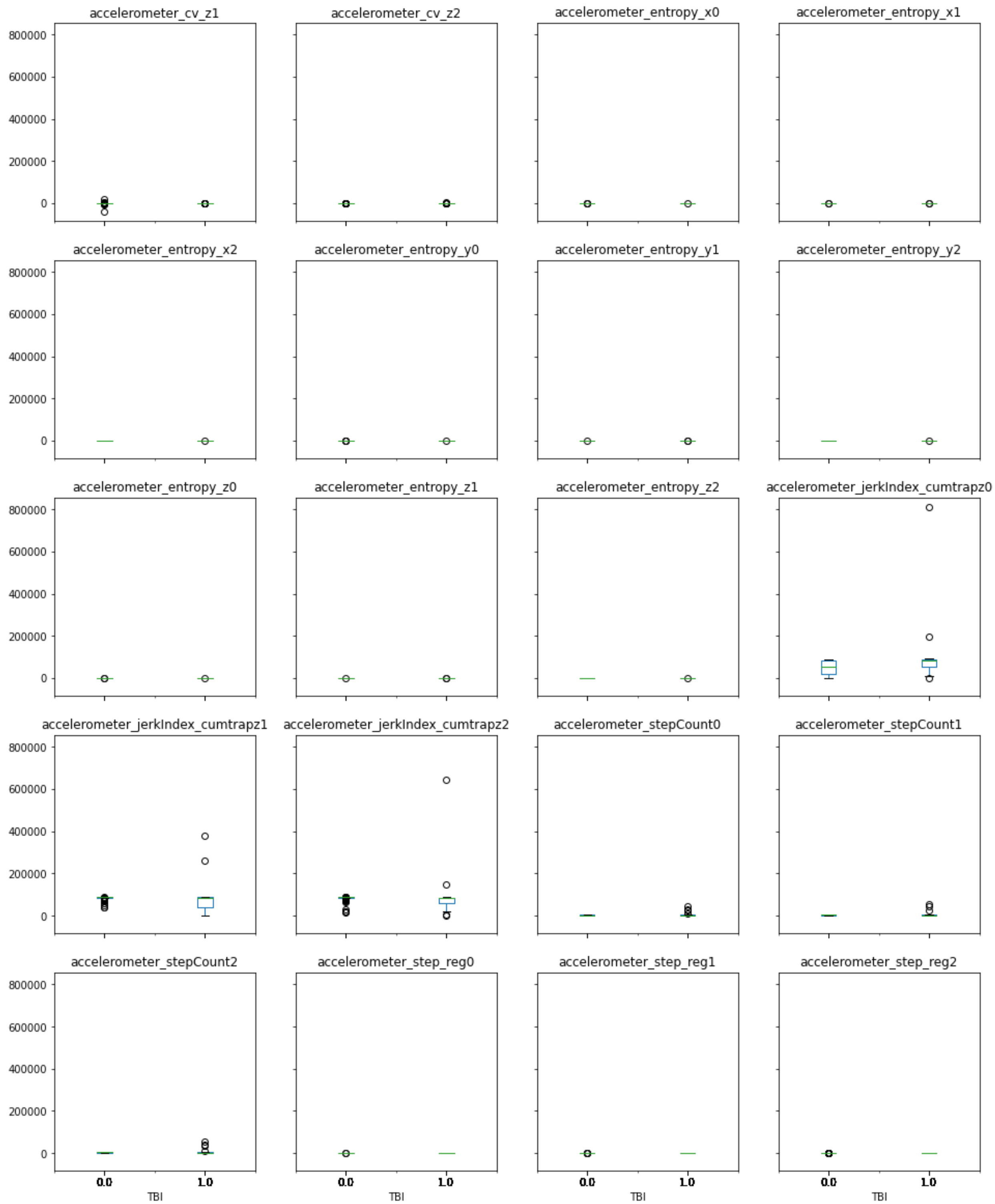


Figure 18: Data Distribution of features on 3rd day before normalization

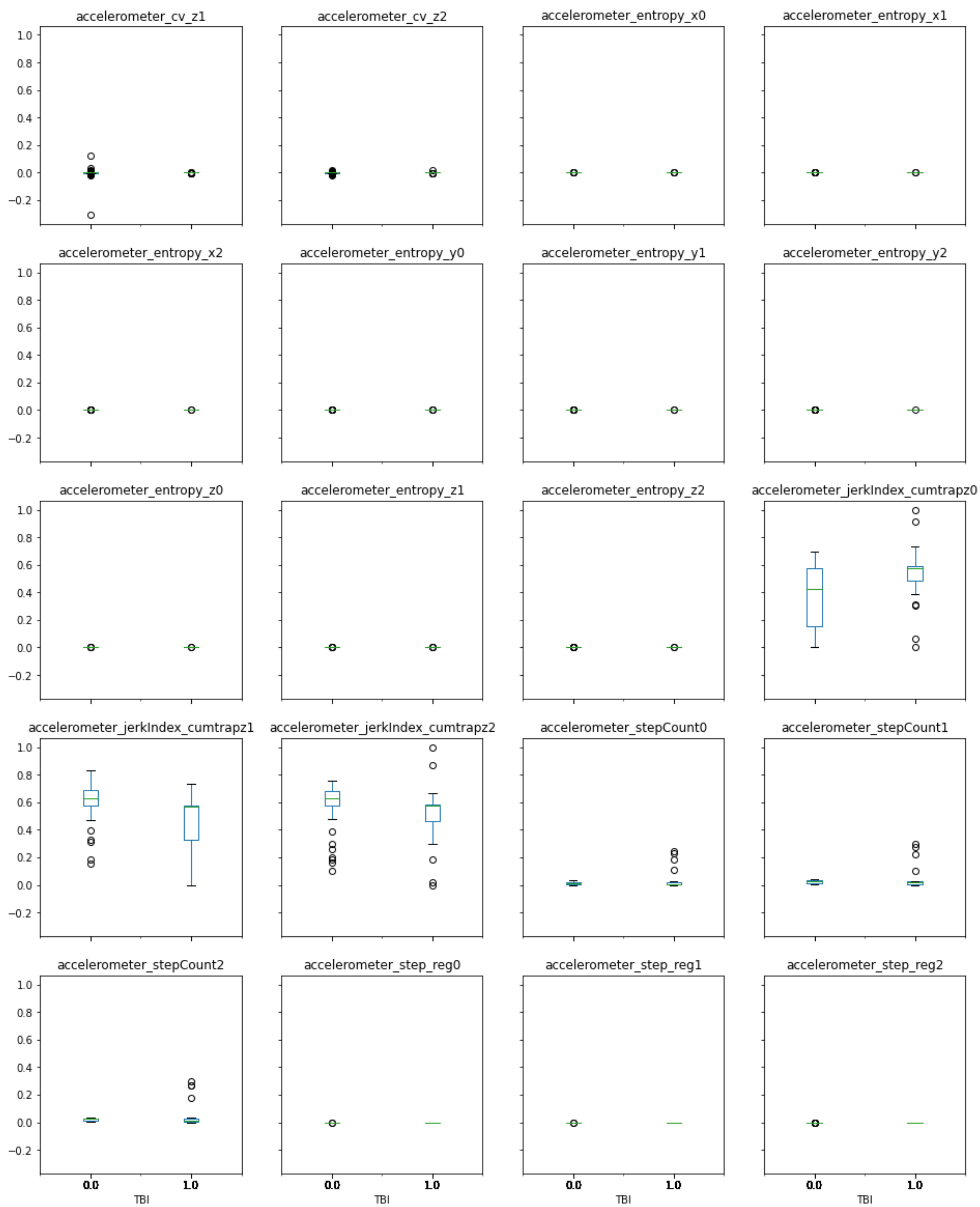


Figure 19: Data Distribution of features on 3rd day after normalization

Since, each of the feature computed in all the approaches are significantly important, p-values of the features are computed along with data distribution performed day-wise i.e., 1st, 2nd, and 3rd day after injury to understand how the features co-relate with the target variable. Upon presenting the feature analysis, 4 classifiers discussed in Section 3.5 are trained using the different combination of timeframe and window-size as shown in table Table *7*, Table *11* and Table *12*. With each of the best results obtained, feature importance of the model is shown that reflects insights into data and model to understand which input features are useful at predicting the target variable which in this case is TBI or Non-TBI.

4.2.1 Approach I - Extracting features from Raw Sensor Data

The goal of this approach is to distinguish TBI patterns from Non-TBI using the raw sensor data and further compare it with the other two approaches to observe how well the raw sensor data approach performs.

This approach uses the different segment sizes mentioned in Table *7* and performs feature extraction by creating hand-crafted location, gait and balance features mentioned in Table *8*, Table *9* and Table *10*, respectively. These features were then fed to four different machine learning models by splitting the data in the ratio of 3:1 as train as test.

Figure *20* and Figure *21* shows the data distribution of few features on Day 1, 2 with 6 hours and 12 hours of window-size, respectively. From Figure *20*, we can observe that autocorrelation across z follows a normal distribution whereas that of entropy across z is skewed towards right. From Figure *21*, we can see how coefficient of variance (cv) across x is normally distributed for both TBI and Non-TBI users.

Figure *22* and Figure *23* shows the Pearson correlation between all the different features with the same combination of time frame and window-sizes. From both the figures, we can observe that the features are not correlated with each other and thus do not share linear relationships among themselves. This helps model to learn thoroughly and generate effective results.

Using all the features computed by the method mentioned in approach 3, 4 different classifiers were evaluated namely XGBoost, Multi-layer Perceptron, Random Forest, and Stochastic Gradient Descent. Figure 24 – 27 shows the performance of each model over a period using different segmentation as mentioned in Table *7*.

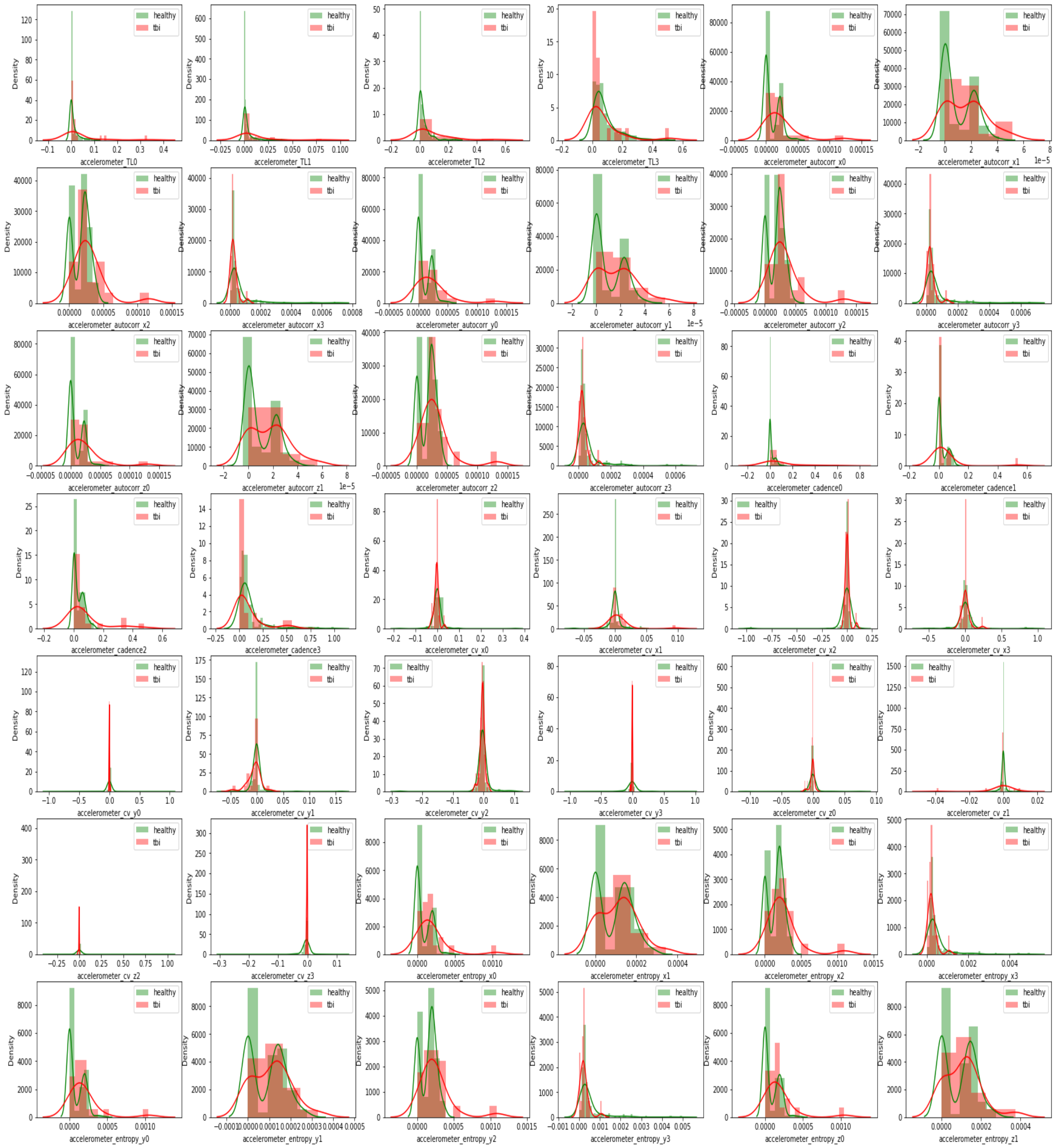


Figure 20: Data Distribution of features on Day 1 with 6 hours of window-size

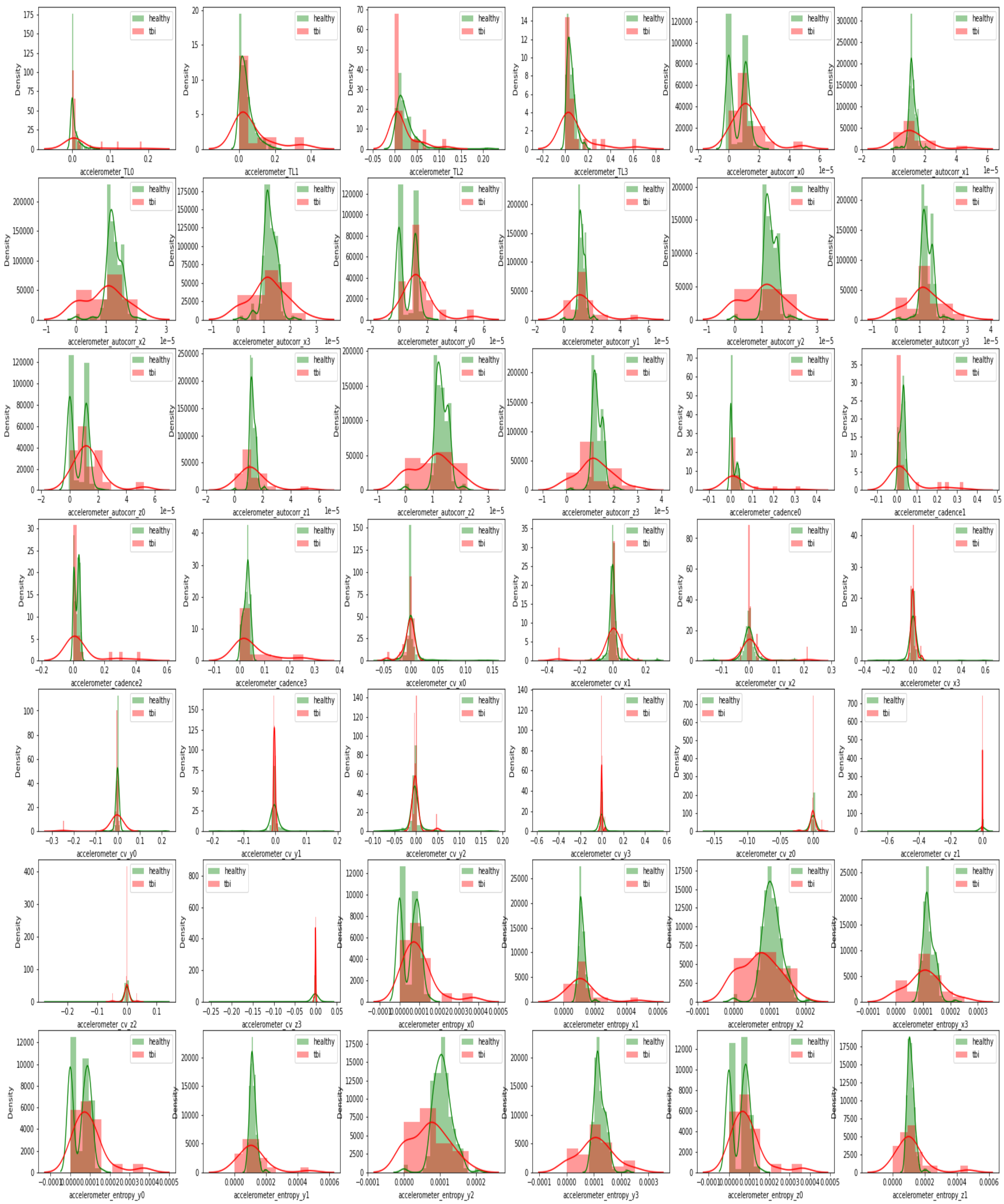


Figure 21: Data Distribution of features on Day 2 with 12 hours of window-size

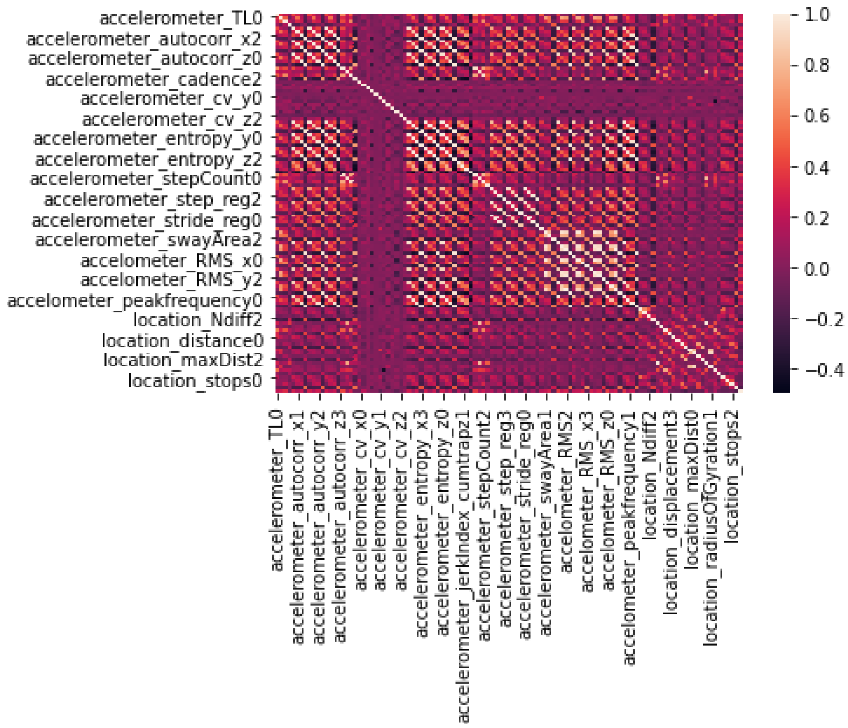


Figure 22: Pairwise correlation of features on day 1 with 6 hours window

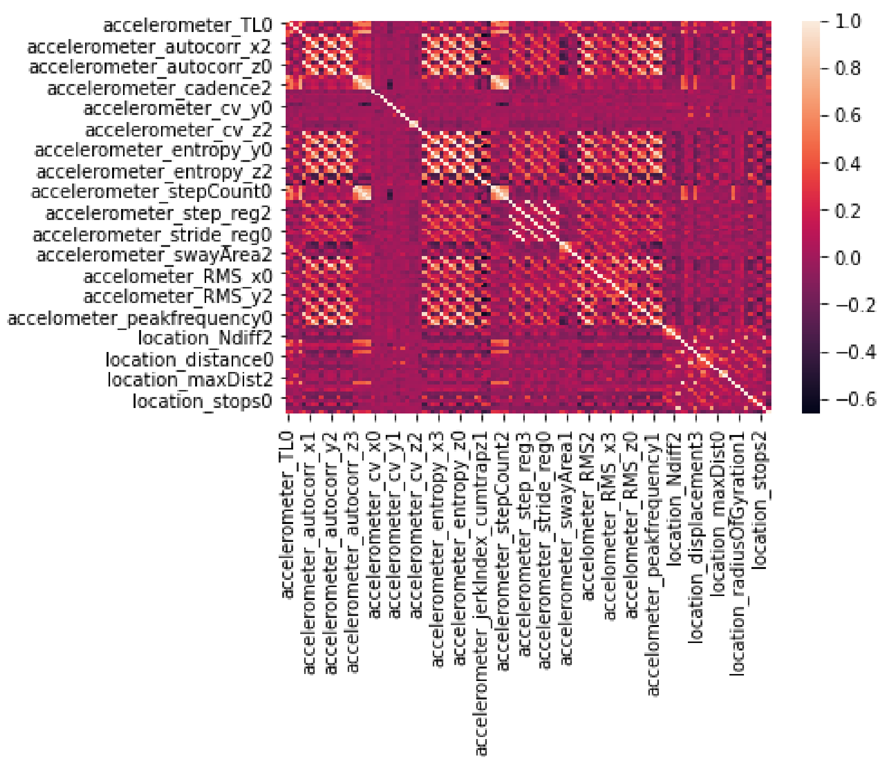
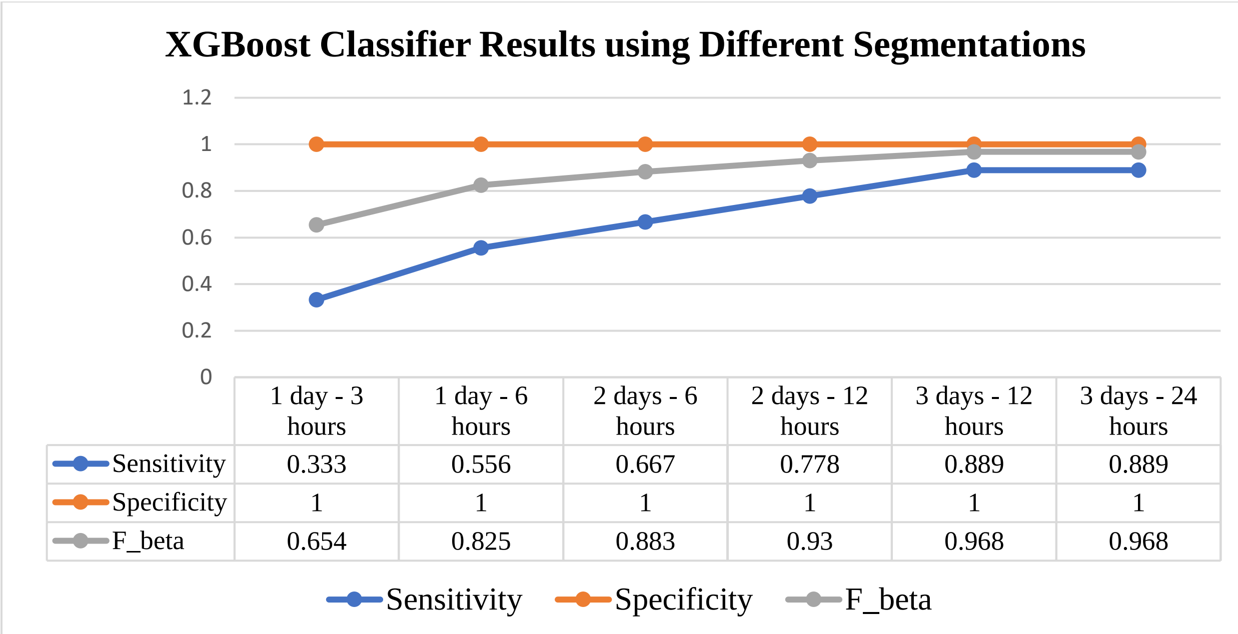
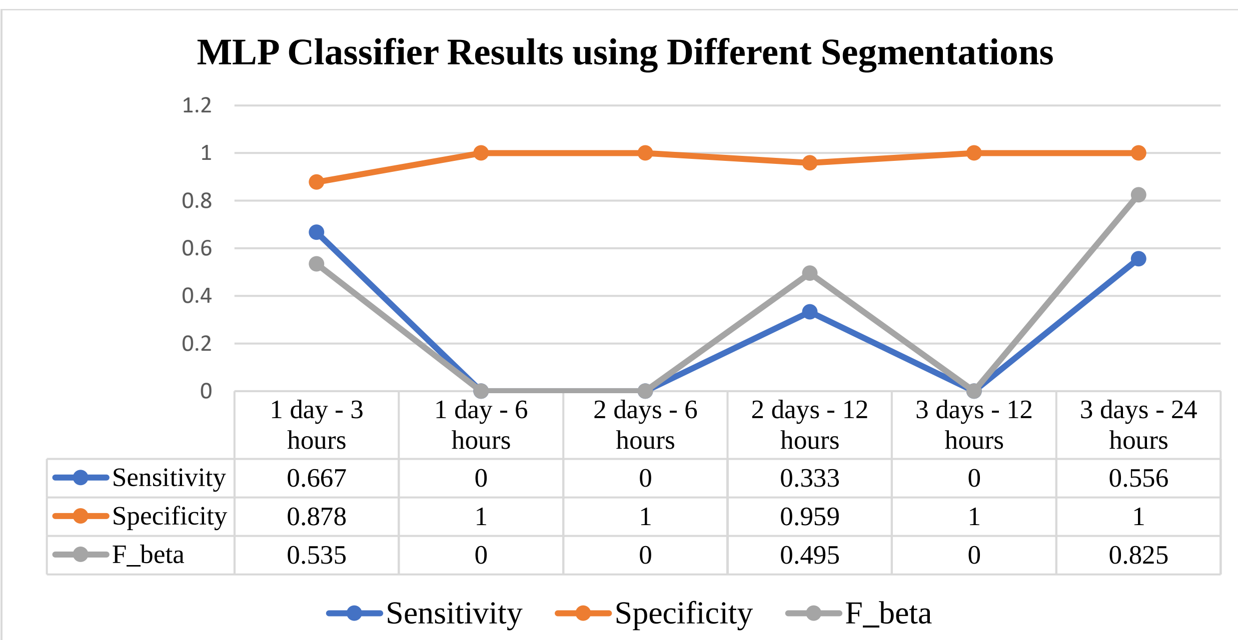


Figure 23: Pairwise correlation of features on day 2 with 12 hours window



	1 day - 3 hours	1 day - 6 hours	2 days - 6 hours	2 days - 12 hours	3 days - 12 hours	3 days - 24 hours
Sensitivity	0.333	0.556	0.667	0.778	0.889	0.889
Specificity	1	1	1	1	1	1
F_beta	0.654	0.825	0.883	0.93	0.968	0.968

Figure 24: XGBoost Classifier Results using Approach I (hand-crafted features on raw sensor data)



	1 day - 3 hours	1 day - 6 hours	2 days - 6 hours	2 days - 12 hours	3 days - 12 hours	3 days - 24 hours
Sensitivity	0.667	0	0	0.333	0	0.556
Specificity	0.878	1	1	0.959	1	1
F_beta	0.535	0	0	0.495	0	0.825

Figure 25: Multi-layer Perceptron Classifier Results using Approach I (hand-crafted features on raw sensor data)

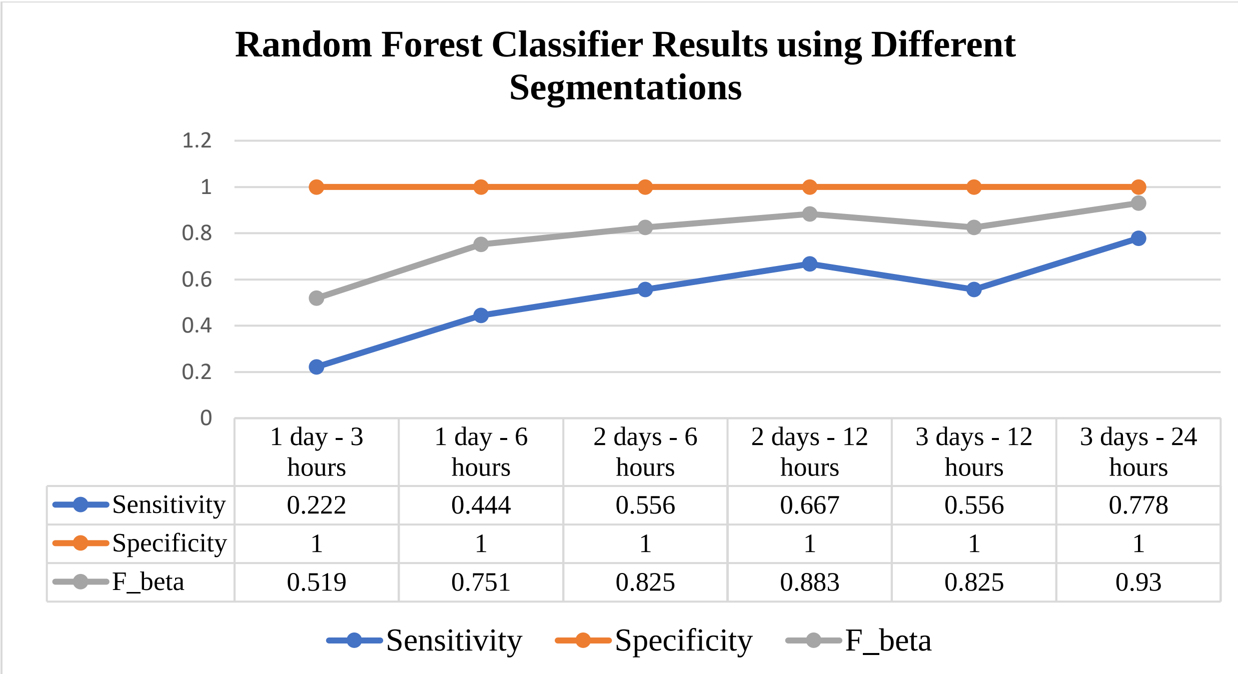


Figure 26: Random Forest Classifier Results using Approach I (hand-crafted features on raw sensor data)

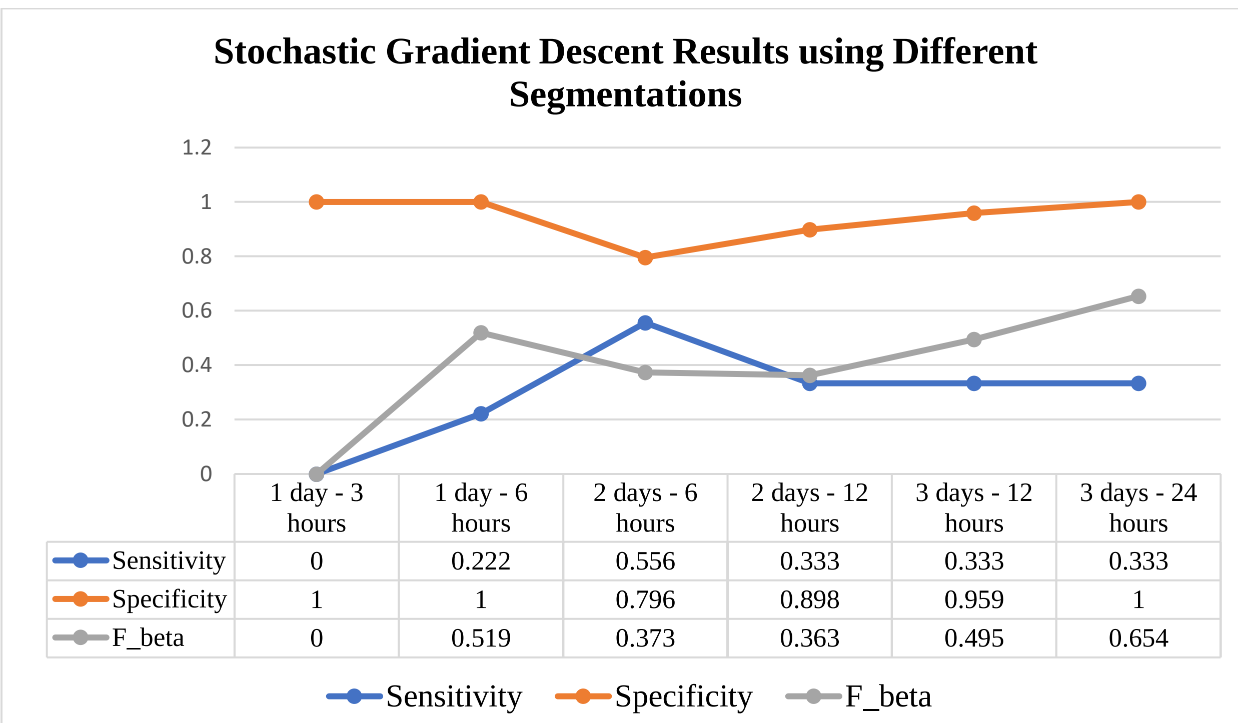


Figure 27: Stochastic Gradient Descent Classifier Results using Approach I (hand-crafted features on raw sensor data)

From the 4 different figures, we can see how the XGBoost model improved over the period with more data and the best results were obtained from 3 days with 12 hours and 24 hours window-size. Figure *28* shows the feature importance of 3 days with 24 hours window-size for XGBoost along with their impact on the model.

For Random Forest, the best result was obtained on 3 days with 24 hours of window. It can be observed that Random Forest learnt well over time and Figure *29* shows the feature importance for 3 days with 24 hours window-size along with the distribution of impact these features have on the Random Forest Model.

From Figure *28*, we can see the SHAP measurement for the XGBoost model. The y-axis indicates the variable name in order of feature importance from top to bottom. The x-axis shows the SHAP values which indicates the change in log-odds. Each point in the graph represents a row from the original dataset.

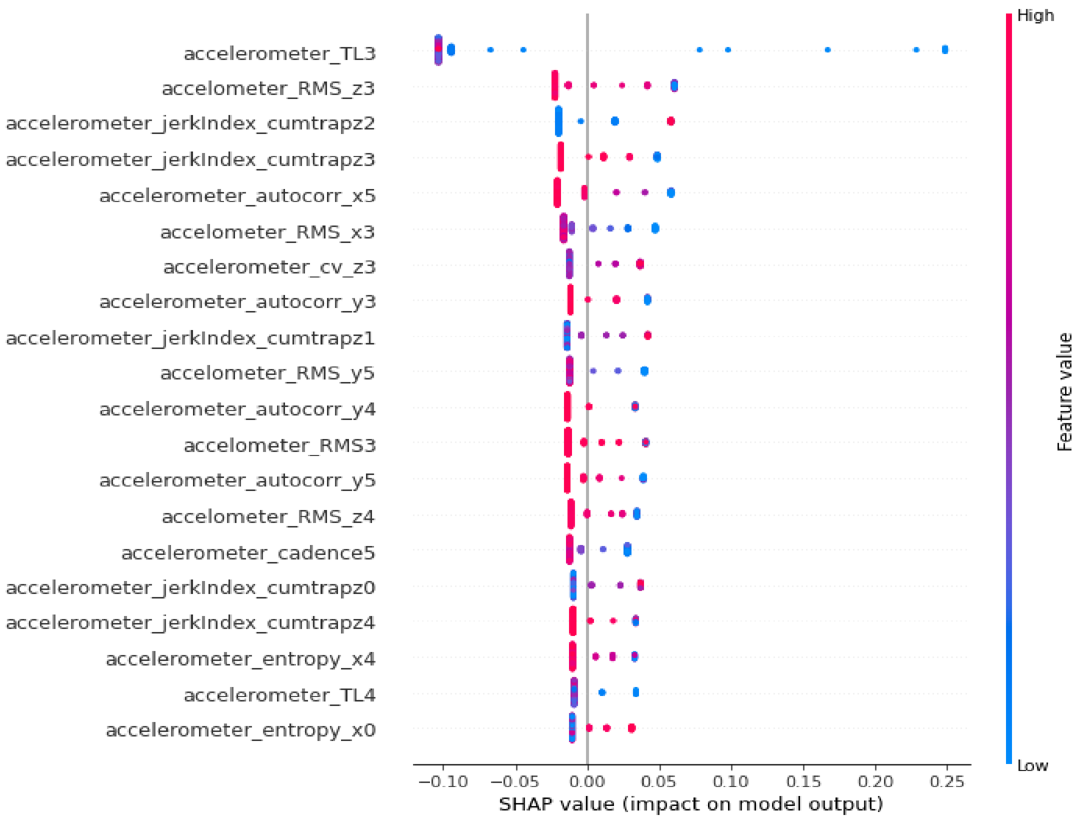


Figure 28: SHAP measurement for XGBoost Model with 3 days, 24 hours of window-size

For the XGBoost model, we can clearly see that a high value for RMS, i.e degree of gait instability, implies that participants have patterns related to TBI. Similarly, Figure *29* indicates SHAP measurement for the Random Forest model. Looking at the figure, we can induce that low location values for maxDist indicates that participant has patterns related to TBI.

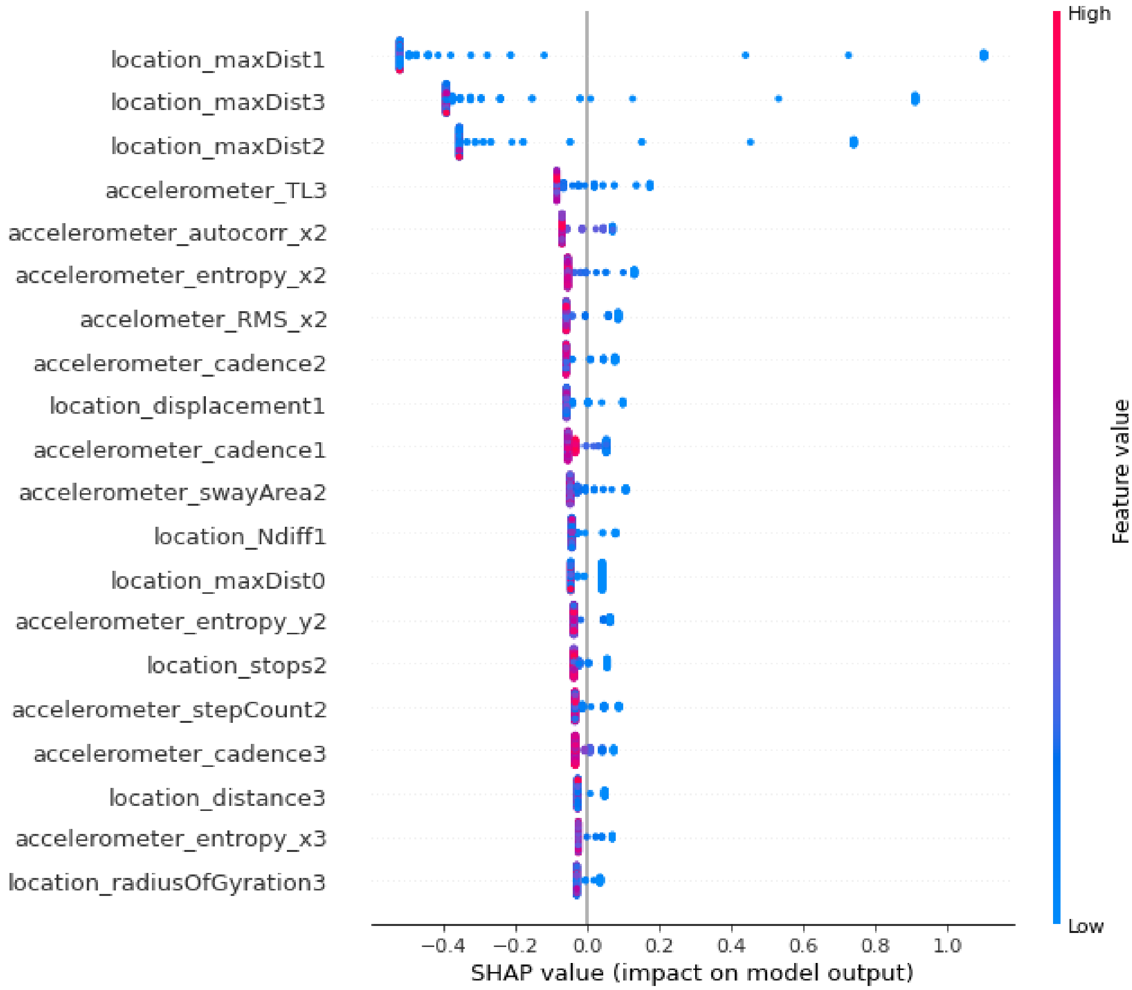


Figure 29: SHAP measurement for Random Forest Model with 3 days, 24 hours of window-size

4.2.2 Approach II - Extracting features using Pre-processing

The goal of this approach is to distinguish TBI patterns from Non-TBI using the pre-processed sensor data with different overlapping percent and further compare it with the other two approaches to observe how well the pre-processed sensor data approach performs.

This approach consists of filtering the accelerometer data using a Butterworth filter and then performing two different types of overlapping (33% and 50%) with segmentation timeframe and window-size mentioned in Table *11*. Upon generating the segmented data, location, gait and balance features mentioned in Table *8*, Table *9* and Table *10* respectively. This data is then fed to the machine learning model using train and test data in the ratio of 3:1.

Figure *30* shows the correlation between different features for the same segment. We can deduce that again the features are not highly correlated. Figure *31* shows the data distribution of 3 days with 24 hours of window-size and 50% overlap and we can clearly observe the varied distribution in each of the features for TBI and Non-TBI users.

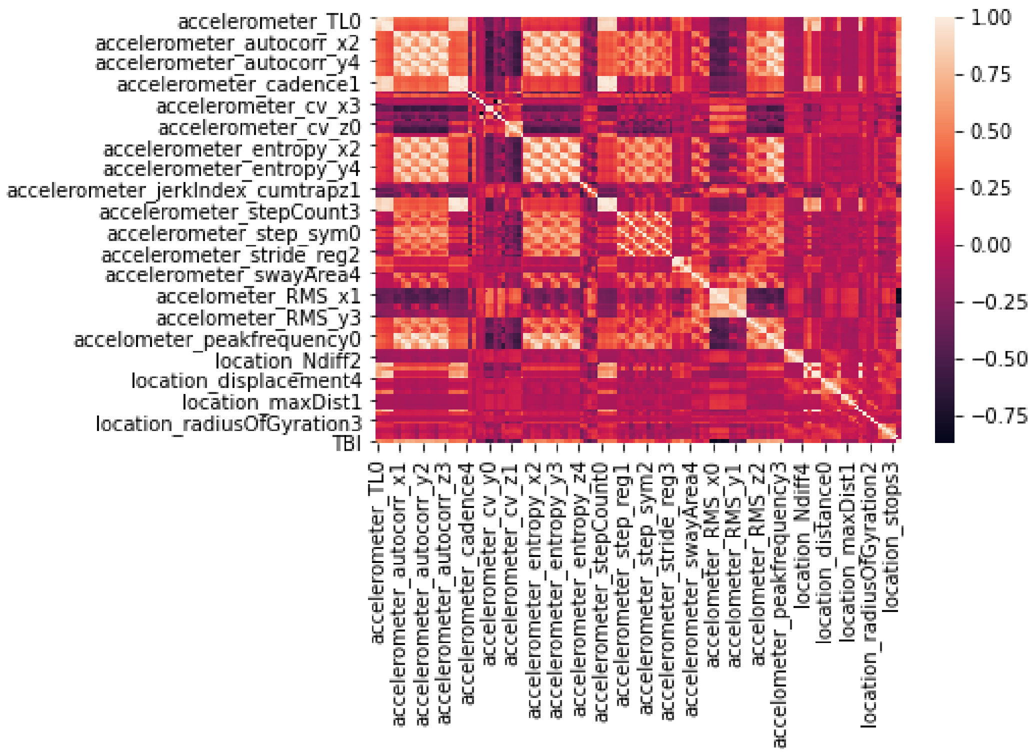


Figure 30: Pairwise correlation of features on day 3 with 24 hours window and 50% overlap

Figure 32 – 39 shows the results of all the 4 models with different overlapping percent; 33% and 50%. These overlapping percent were applied to the different segments mentioned in Table *11*. From the results, we can observe that XGBoost performed the best. The best results were obtained on Day 2 with 12 hours of window size and 50% overlap. Figure *41* shows the feature importance of the model along with SHAP values.

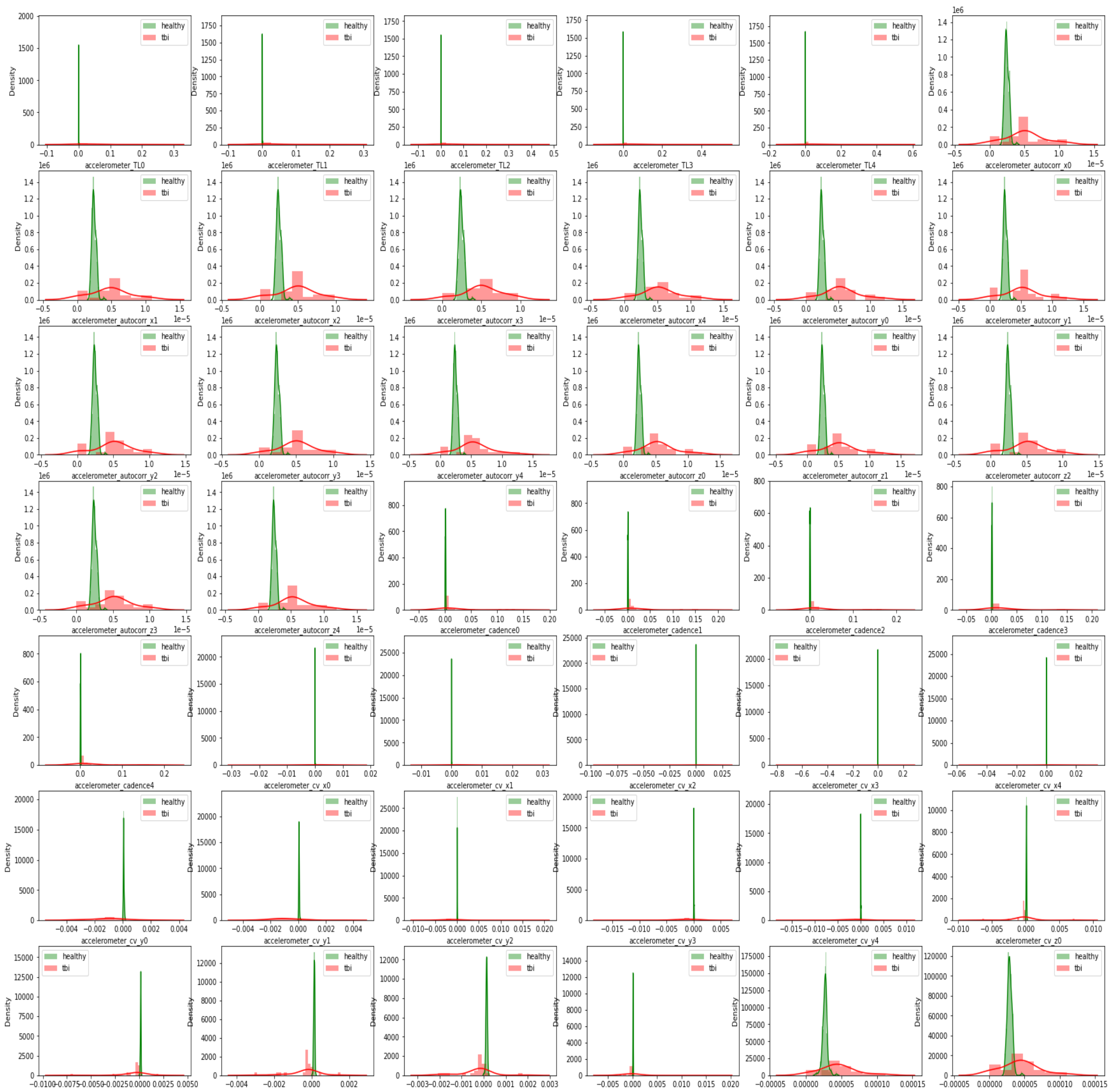


Figure 31: Data Distribution of features on Day 3 with 24 hours window-size and 50% overlap

Random Forest learnt the patterns with more data and over time. The best results for this model were obtained on Day 2 with 12 hours of window-size and 50% overlap. Thus, in short, both the model gave best results on the same day. Figure *41* shows the feature importance of Random Forest model on Day 2 with 12 hours with window-size and 50% overlap with their corresponding SHAP values.

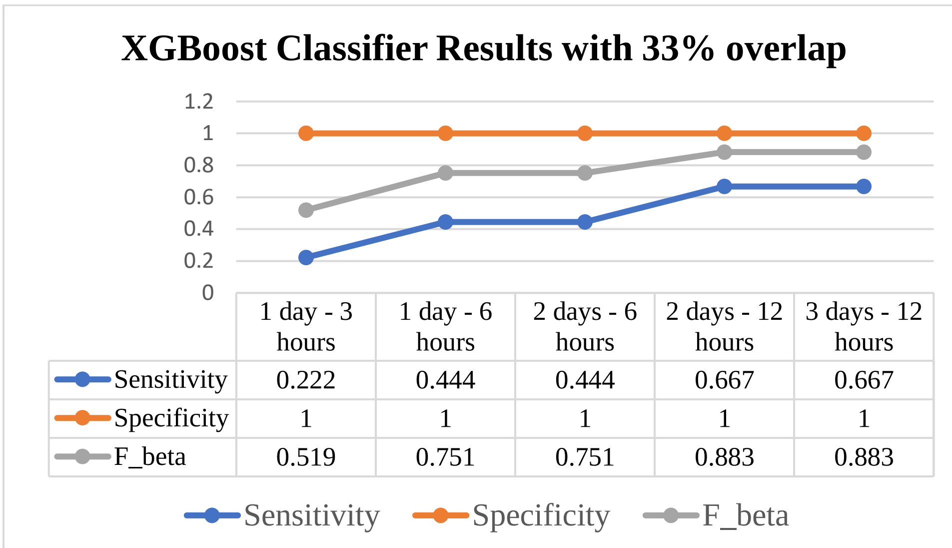


Figure 32: XGBoost Classifier Results using Approach II with 33% overlap

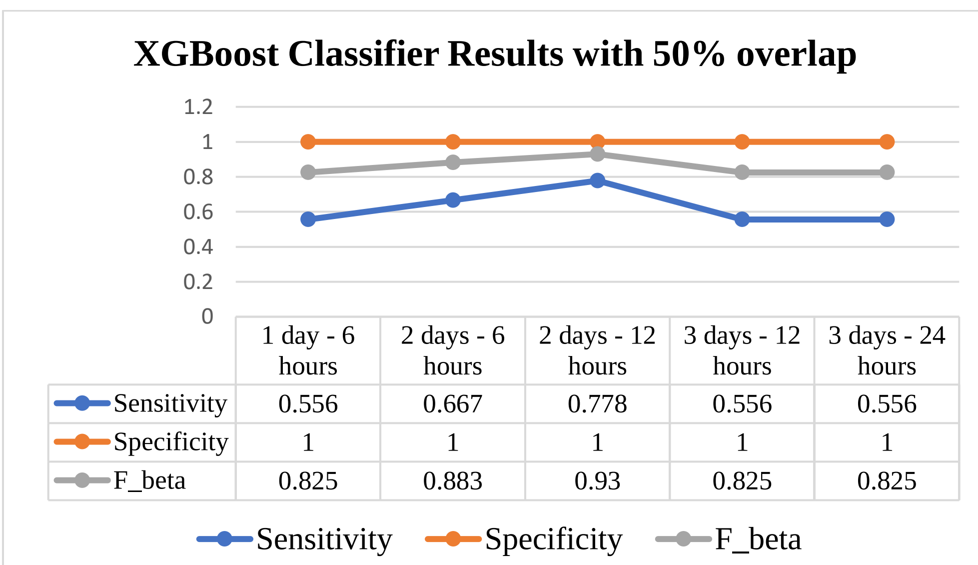


Figure 33: XGBoost Classifier Results using Approach II with 50% overlap

Figure *40* shows the distribution of the data with their corresponding SHAP values for the XGBoost model. We can observe that a low trajectory length implies that not much area was covered and indicates patterns related to TBI.

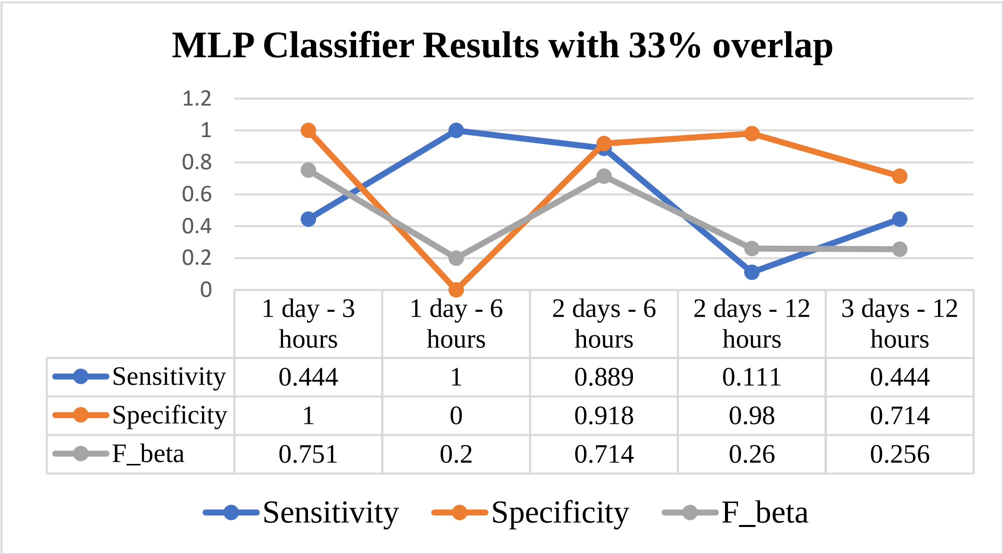


Figure 34: MLP Classifier Results using Approach II with 33% overlap

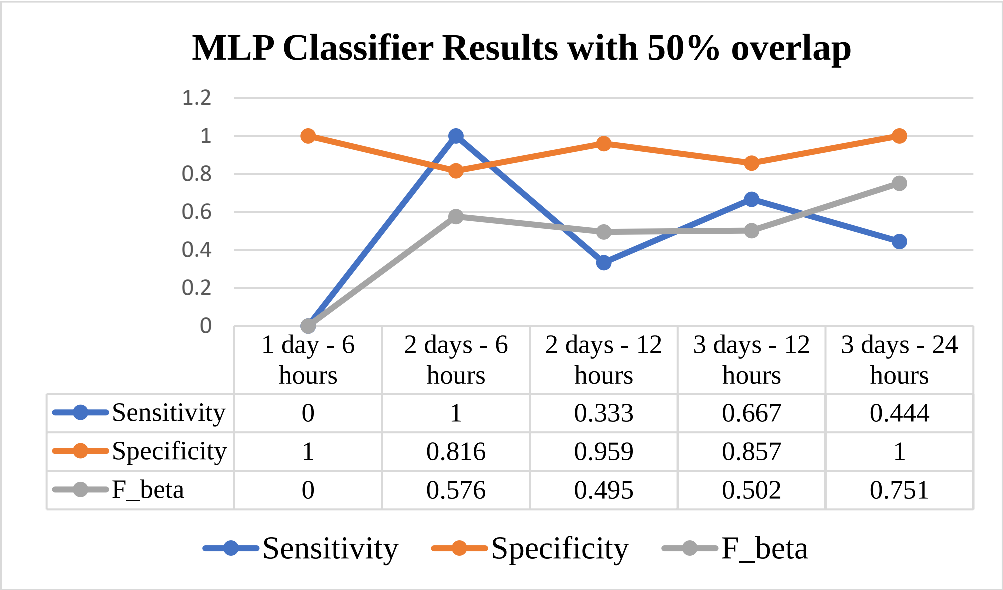


Figure 35: MLP Classifier Results using Approach II with 50% overlap

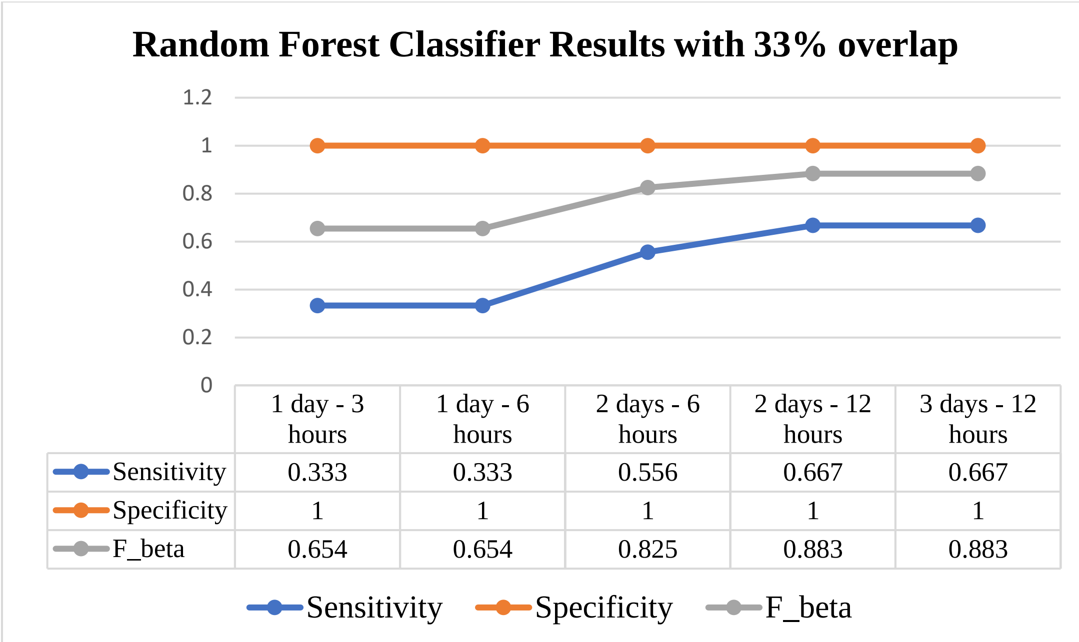


Figure 36: Random Forest Classifier Results using Approach II with 33% overlap

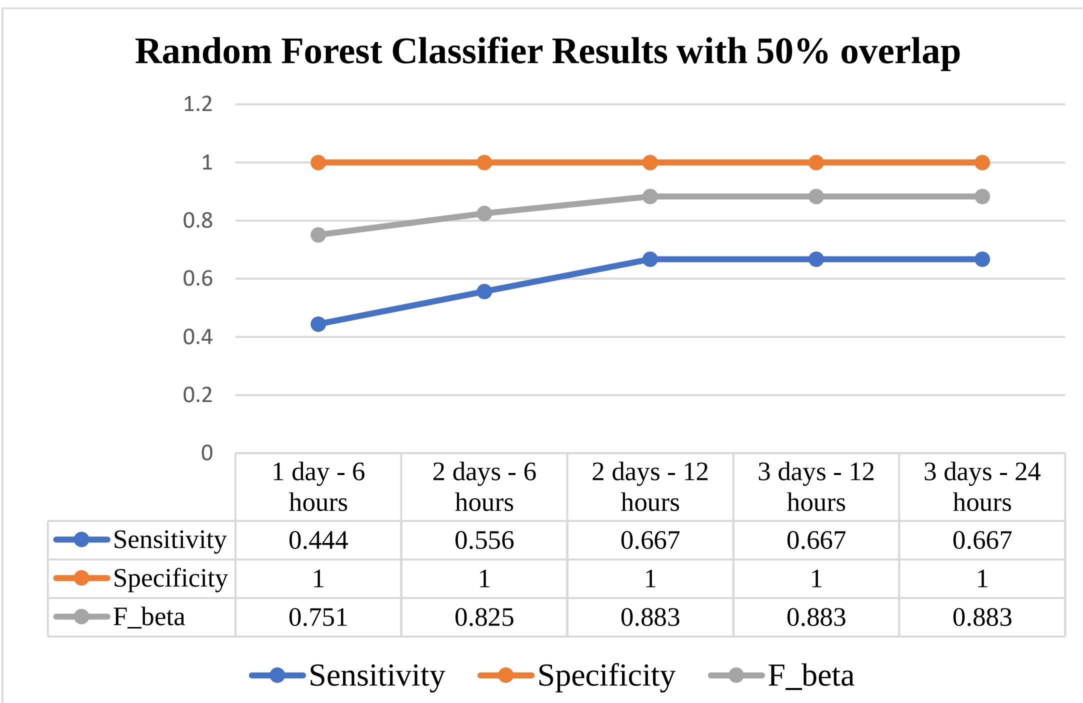
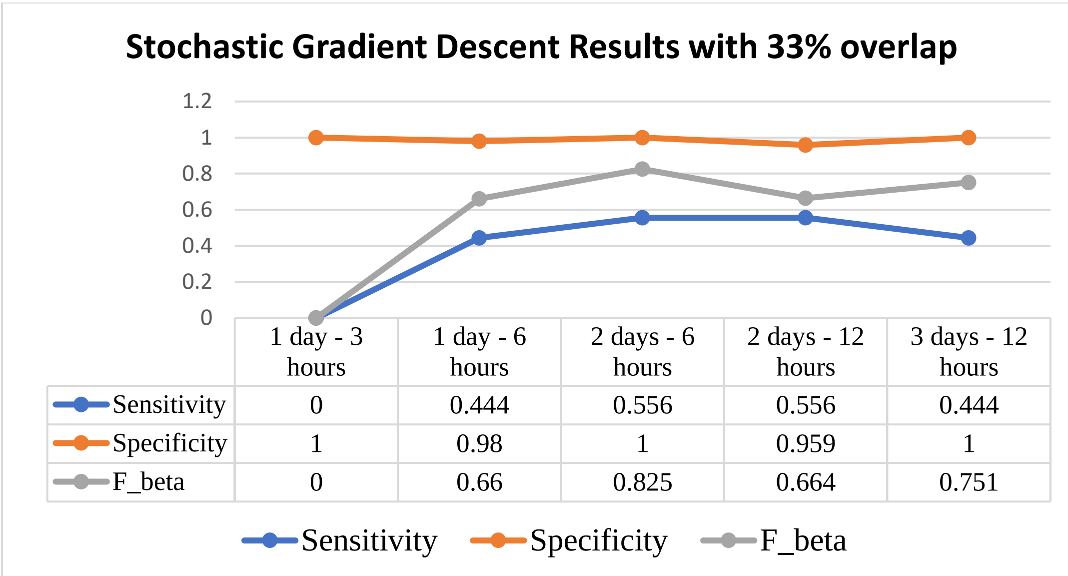
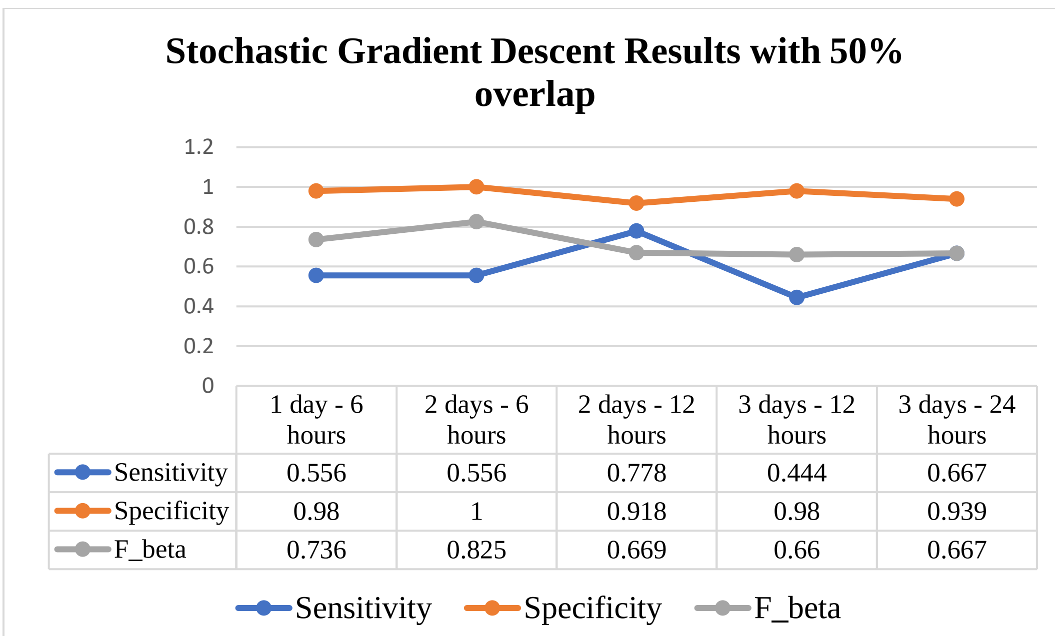


Figure 37: Random Forest Classifier Results using Approach II with 50% overlap



	1 day - 3 hours	1 day - 6 hours	2 days - 6 hours	2 days - 12 hours	3 days - 12 hours
Sensitivity	0	0.444	0.556	0.556	0.444
Specificity	1	0.98	1	0.959	1
F_beta	0	0.66	0.825	0.664	0.751

Figure 38: SGD Classifier Results using Approach II with 33% overlap



	1 day - 6 hours	2 days - 6 hours	2 days - 12 hours	3 days - 12 hours	3 days - 24 hours
Sensitivity	0.556	0.556	0.778	0.444	0.667
Specificity	0.98	1	0.918	0.98	0.939
F_beta	0.736	0.825	0.669	0.66	0.667

Figure 39: SGD Classifier Results using Approach II with 50% overlap

Figure *41* shows the SHAP values for the Random Forest model. The model shows the important features along with their distribution. From the figure, we can see that a high value of sway area and cadence indicates the person has patterns related to healthy.

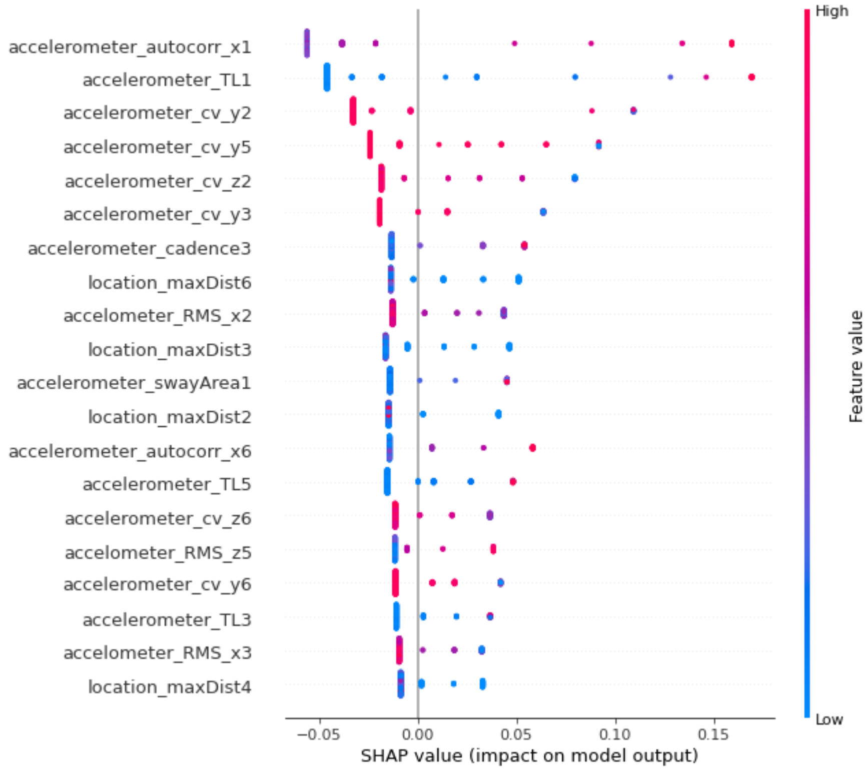


Figure 40: SHAP values for XGBoost Model with 2 days, 12 hrs window-size and 50% overlap

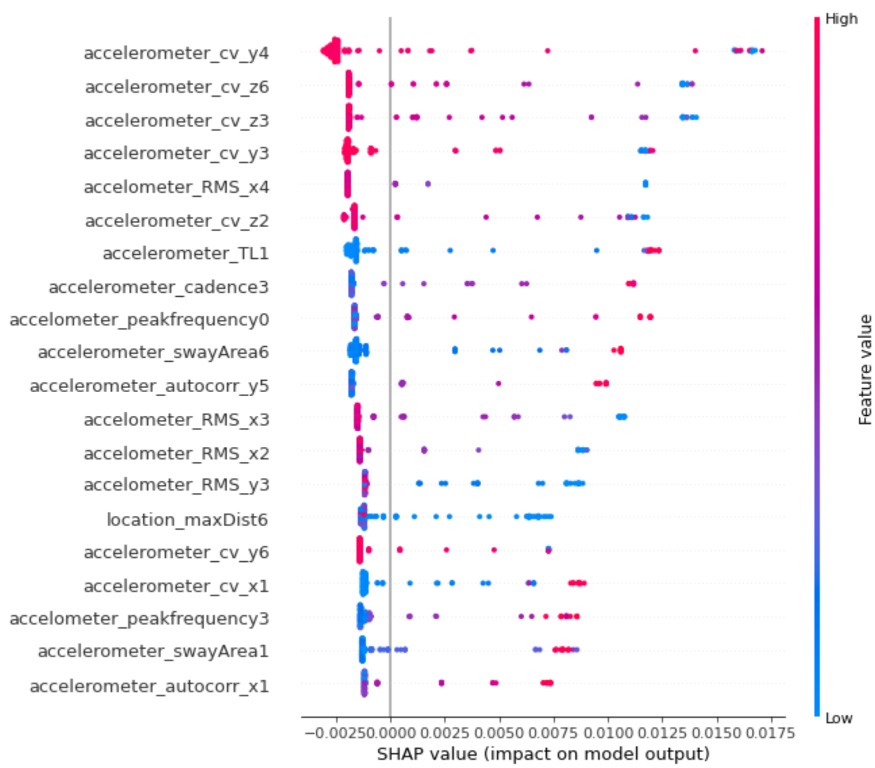


Figure 41: SHAP for Random Forest Model with 2 days, 12 hrs window-size and 50% overlap

4.2.3 Approach III – Using Autoencoder-based approach

In this approach, we transform the raw data into three different input representations mentioned in Section 3.5.3 and then combine the representations with statistical gait and balance features using different segmentation mentioned in Table *12*.

Figure *42* shows the original distribution of the raw input representation and Figure *43* shows distribution obtained after training the autoencoder and generating the latent space for the Displacement Representation.

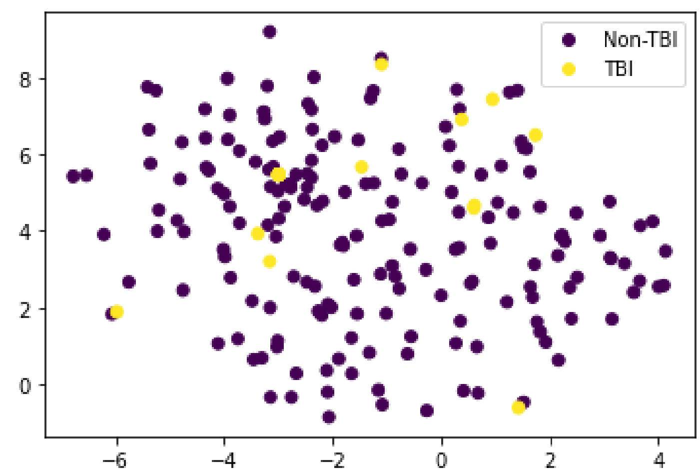


Figure 42: Raw input representation of Displacement vector

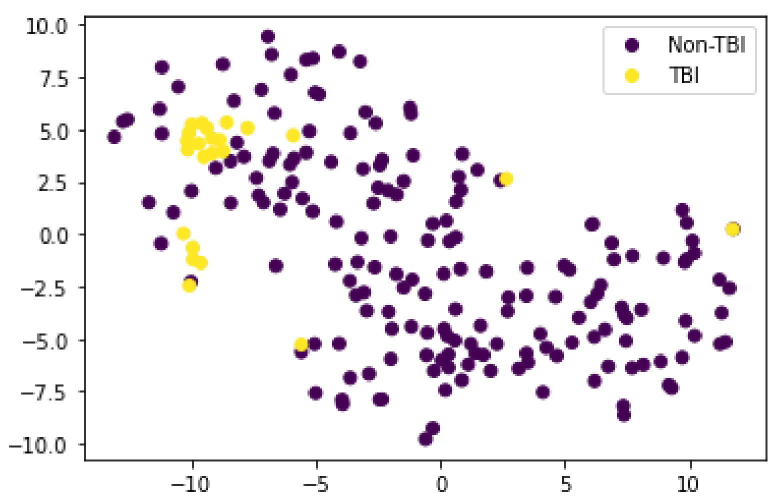


Figure 43: Latent space representation of the Displacement vector

Figure *44* shows the result of the 4 models of latent space representation combined with the statistical gait and balance features. From the figure, we can see that the best results for XGBoost were obtained on 3rd day with 24 hours of window-size. Figure *45* shows the feature importance along with their corresponding SHAP values.

For Random Forest, the best results were obtained on 2nd day with 12 hours of window-size. Figure *46* shows the feature importance along with their corresponding SHAP values.

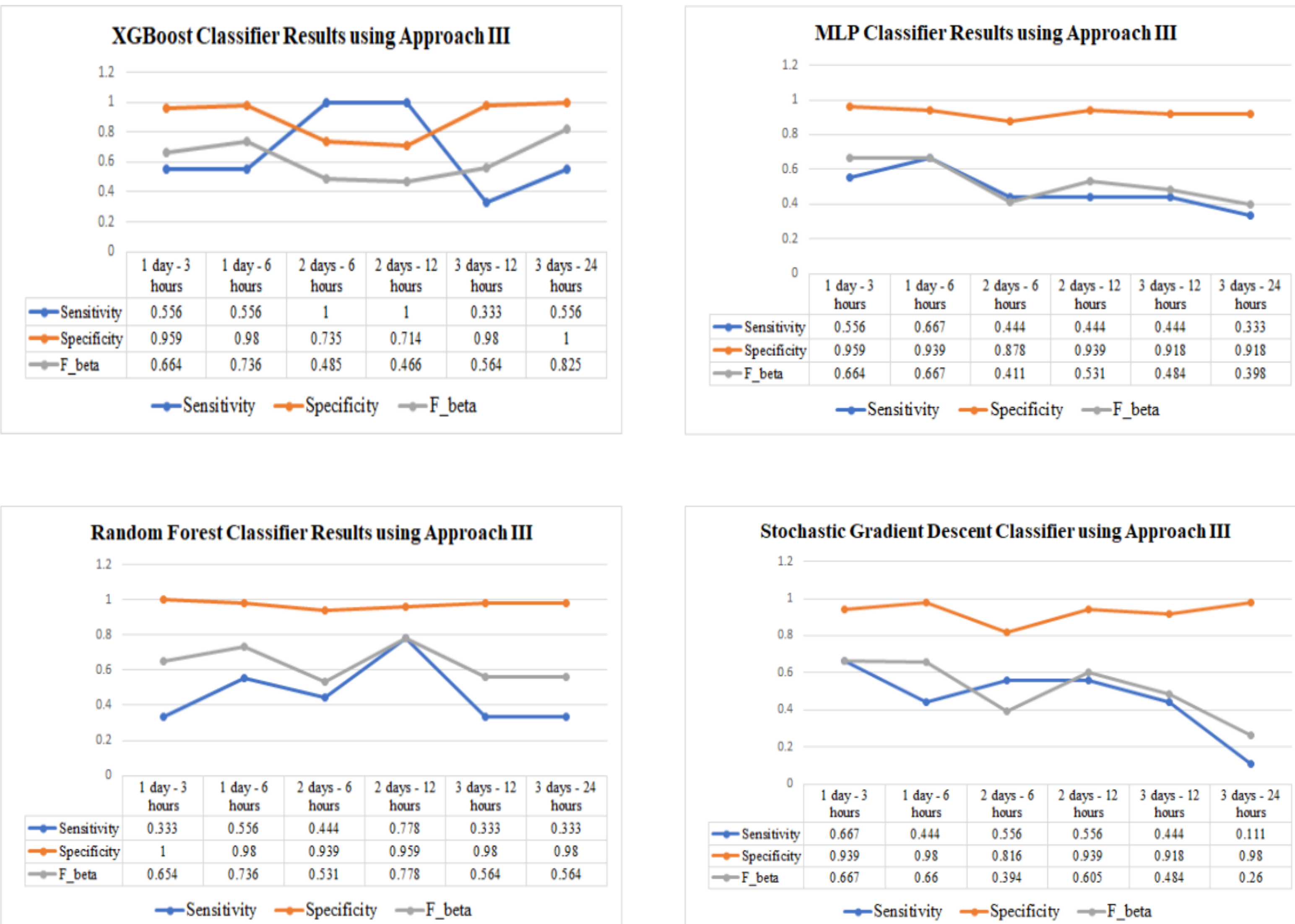


Figure 44: Results of 4 models using approach III (Using autoencoder-based approach)

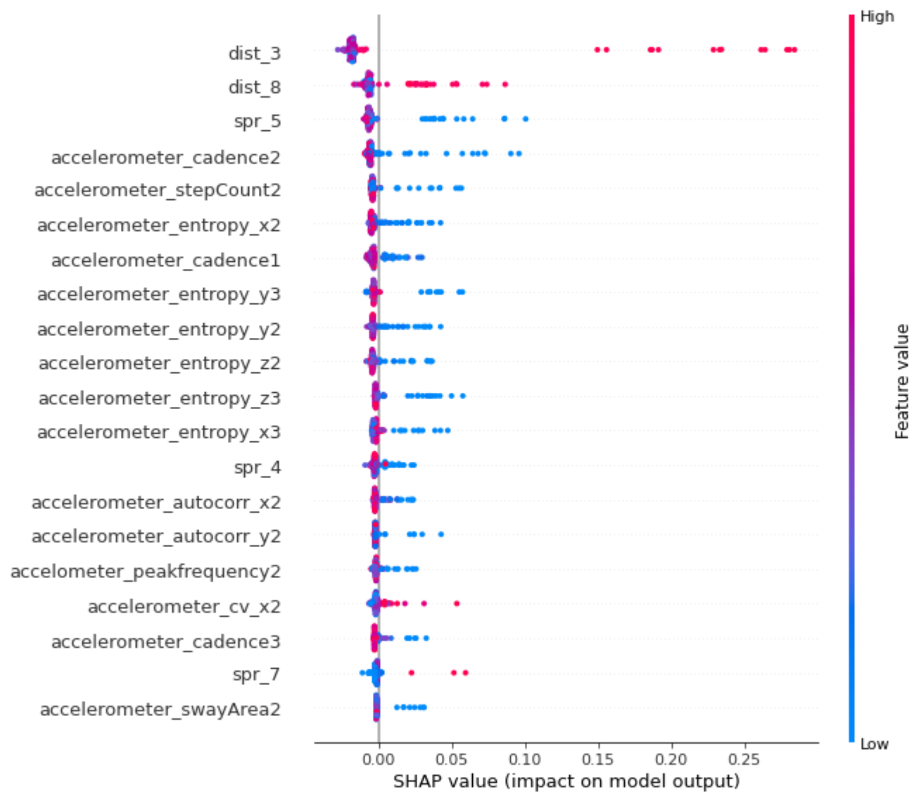


Figure 45: SHAP values for Random Forest Model with 2 days, 12 hrs window-size

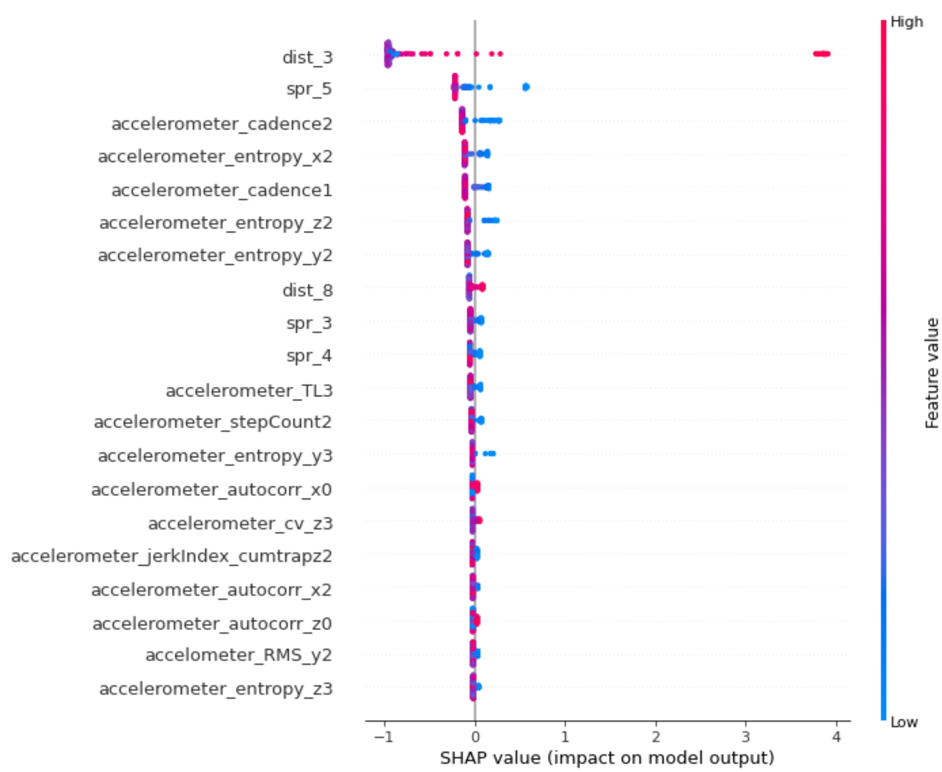


Figure 46: SHAP values for XGBoost Model with 3 days, 24 hrs window-size

Chapter 5

Discussions

This section discusses the results and learning along with few shortcomings faced while working towards this thesis.

1) *Autoencoder & pre-processed Sensor Data Approach helped in earlier prediction:* Figure 24 – 27, 32 – 39 and 44 show results of Approach I, Approach II and Approach III, respectively. The hand-crafted features extracted from the raw sensor data performed the best on 3 days with 24 hours of data with XGBoost model i.e after 3 days of the injury having specificity as 1 and sensitivity as 0.899. This was probably because with more sensor data, the model was better able to distinguish the patterns between TBI and Non-TBI. The hand-crafted features extracted from the pre-processed sensor data performed the best with 50% overlap and was able to give best results on Day 2 with 12 hours of window-size with XGBoost model. The specificity obtained was 1 and the sensitivity obtained was 0.778. This was probably because with 50% of overlap, the number of data points increased and important events that help understand the TBI patterns were not missed. Using auto-encoder for the location-based sensors performed the best on Day 2 with 12 hours of window-size and Random Forest as the best model. The specificity rate obtained was 0.959 and the sensitivity was 0.778. Random Forest on the other hand for Raw and Pre-processed sensor did not give such good results in terms of detecting the false positives. Improved results in this case could be accounted for the latent space representation that helped the model understand the location patterns and structural similarities/dissimilarities between the two classes. Thus, in line with the hypothesis, it could be concluded that location, gait and balance patterns can be used to detect instances of Traumatic Brain Injury.

2) *Difficulty with model interpretability*: Across, all the three approaches it was observed that neural networks did not perform well. This result build on the existing evidence that neural networks require larger datasets to work with. Further, since neural networks are like a black-box, it was difficult to interpret their internal workings to identify this behavior.

Moreover, the progressive splitting of the feature to optimize the information gain would have outperformed the neural network's ability to take probabilistic view towards piece-by-piece model fitting. Further, 33% overlap did not give good results and did not even perform better than the raw sensor data approach. This could be because of the sparseness in the data which further led to not capturing important information.

3) *Issues with Survey & Sensor Data*: The major limitation of this thesis was issues with the data. The data selection widely depended on the surveys filled by the user and the sensor data collection. Though 2 datasets were taken into consideration, each of them had their own limitations. For Lockheed Martin dataset, 18 TBI users were identified, however, only 4 were taken into consideration. This was because only 7 users had reported a valid injury date. Of the 7 users, only 4 had sensor data after the injury date. Thus, only 4 TBI users were taken into consideration. For the Charles River Dataset, 45 users had reported a head injury or an accident which had led to concussion. Of the 45, a lot of users had reported injury twice which led to duplicate counting. Further, a lot of user did not have sensor data. This was because, the mobile app used for data gathering had a toggle button that allowed the user to stop passive data collection. Due to all this, only 18 users from this dataset were taken into consideration.

4) *Possible Future Work*: Due to ample issues with data, an important aspect of the future work would be to have a cleaner dataset. Taking more features into consideration and weighing the false positive and true positive correctly would ensure the right customization to build the mobile application.

Chapter 6

Conclusion & Future Work

TBI has led to numerous deaths in the United States. Having a reliable smartphone-based system can help minimize the impact and can assist in getting appropriate aid at an early stage. This thesis compares three different approaches namely, raw sensor data, pre-processed sensor data and auto-encoder based approach, using location sensor data along with gait and balance features. Using 179 Non-TBI users and 23 TBI users, and three approaches with their corresponding results, it can be concluded that location sensors can be useful in predicting TBI as their behavior is similar to those in depression. Further, gait and balance patterns clearly depict the symptoms of TBI and hence can be used effectively for prediction. Tree-based models interestingly learnt the location, gait and balance patterns and produced good results for classification. Of the three approaches, using raw sensor data best results were obtained. However, if early detection is taken into consideration, then Auto-encoder based approach using Random Forest suits the best.

Below is the detailed description of the future work associated with this thesis.

Developing a mobile application:

For future work, the researcher could develop a mobile application by integrating the classifiers. Further, the same application that has the survey and passive sensor data collection can integrate these classifiers to procure a fully functional mobile application.

Collecting more, high quality data:

More data is one of the very crucial part of this thesis and hence, the researcher could work along with data gathering party to focus on getting the correct data as that helps in including more participants for the study. Errors associated with the injury date and missing sensor data could be addressed which would help avoid dropping of TBI users. Moreover, the surveys could be verified before they are uploaded to the server. Further, more location, gait and balance features can be exploited to extract TBI-related patterns from the user.

Explore alternative Segmentation Method:

Apart from the segmentation methods mentioned in this thesis, one can experiment with sampling at different times of the day. For example, creating features and training models using segments as 12 AM to 6 AM, 6 AM to 12 PM noon, 12 PM to 6 PM and 6 PM to 12 AM. Since for some users, the health situation deteriorates during specific period of the time, this method can help is clearly distinguishing TBI patterns thus leading to better prediction.

Using cost sensitive learning:

Developing a mobile application for such would require one to focus on the accuracy build using false positives or false negatives. Using cost sensitive learning, one can customize the app for healthcare workers where more false positive is taken into consideration whereas the app customized for patients should not take into consideration false positives at the cost of false negatives.

Bibliography

[1] TBI: Get the Facts. https://www.cdc.gov/traumaticbraininjury/get_the_facts.html, accessed on 03/22/2021

[2] 9 1/2 Need-to-Know Facts About Traumatic Brain Injury. https://www.brainline.org/article/9-12-need-know-facts-about-traumatic-brain-injury, accessed on 03/22/2021

[3] Traumatic Brain Injury: What to Know Office Commissioner - https://www.fda.gov/consumers/consumer-updates/traumatic-brain-injury-what-know-about-symptoms-diagnosis-and-treatment, accessed on 03/25/2021

[4] How do healthcare providers diagnose traumatic brain injury (TBI)? https://www.nichd.nih.gov/health/topics/tbi/conditioninfo/diagnose, accessed on 03/25/2021

[5] Traumatic Brain Injury in Adults https://www.asha.org/Practice-Portal/Clinical-Topics/Traumatic-Brain-Injury-in-Adults/, accessed on 03/25/2021

[6] Neuroimaging https://www.biausa.org/brain-injury/about-brain-injury/diagnosis/neuroimaging, accessed on 04/30/2021

[7] Lee, Bruce, and Andrew Newberg. “Neuroimaging in traumatic brain imaging.” NeuroRx : the journal of the American Society for Experimental NeuroTherapeutics vol. 2,2 (2005): 372-83. doi:10.1602/neurorx.2.2.372

[8] Ronne-Engstrom, E., and T. Winkler. "Continuous EEG monitoring in patients with traumatic brain injury reveals a high incidence of epileptiform activity." Acta Neurologica Scandinavica 114.1 (2006): 47-53.

[9] Gabbe BJ, Cameron PA, Finch CF. The status of the Glasgow Coma Scale. Emerg

Med (Fremantle). 2003 Aug;15(4):353-60. doi: 10.1046/j.1442-2026.2003.00474.x. PMID: 14631703.

[10] Williams DH, Levin HS, Eisenberg HM. Mild head injury classification. Neurosurgery. 1990 Sep;27(3):422-8. doi: 10.1097/00006123-199009000-00014. PMID: 2234336.

[11] Joseph S. Jeret, M.D., Menachem Mandell, M.D., Brian Anziska, M.D., Mark Lipitz, D.O., Antenor P. Vilceus, M.D., James A. Ware, M.D., Theresa A. Zesiewicz, M.D., Clinical Predictors of Abnormality Disclosed by Computed Tomography after Mild Head Trauma, Neurosurgery, Volume 32, Issue 1, January 1993, Pages 9–16, https://doi.org/10.1227/00006123-199301000-00002

[12] Miller EC, Holmes JF, Derlet RW. Utilizing clinical factors to reduce head CT scan ordering for minor head trauma patients. J Emerg Med. 1997 Jul-Aug;15(4):453-7. doi: 10.1016/s0736-4679(97)00071-1. PMID: 9279694.

[13] Lee, Bruce, and Andrew Newberg. “Neuroimaging in traumatic brain imaging.” NeuroRx : the journal of the American Society for Experimental NeuroTherapeutics vol. 2,2 (2005): 372-83. doi:10.1602/neurorx.2.2.372

[14] Lu, Hong, et al. "Stresssense: Detecting stress in unconstrained acoustic environments using smartphones." Proceedings of the 2012 ACM conference on ubiquitous computing. 2012.

[15] Lee, Hosub, et al. "A new posture monitoring system for preventing physical illness of smartphone users." 2013 IEEE 10th Consumer Communications and Networking Conference (CCNC). IEEE, 2013.

[16] Cognitive Problems after Traumatic Brain Injury https://msktc.org/tbi/factsheets/Cognitive-Problems-After-Traumatic-Brain-Injury, accessed on 04/28/2021

[17] Depression After Traumatic Brain Injury https://msktc.org/tbi/factsheets/depression-after-traumatic-brain-injury, accessed on 04/30/2021

[18] Saeb, Sohrab et al. "The relationship between mobile phone location sensor data and depressive symptom severity." PeerJ vol. 4 e2537. 29 Sep. 2016, doi:10.7717/peerj.2537

[19] Grünerbl, Agnes et al. "Smartphone-based recognition of states and state changes in bipolar disorder patients." IEEE journal of biomedical and health informatics vol. 19,1 (2015): 140-8. doi:10.1109/JBHI.2014.2343154

[20] Saeb, Sohrab et al. "Mobile Phone Sensor Correlates of Depressive Symptom Severity in Daily-Life Behavior: An Exploratory Study." Journal of medical Internet research vol. 17,7 e175. 15 Jul. 2015, doi:10.2196/jmir.4273

[21] Traumatic Brain Injury (TBI) and Concussion https://www.asnr.org/patientinfo/conditions/tbi.shtml, accessed on 03/25/2021

[22] "Smartphones as Assistive Technology Following Traumatic Brain Injury: A Preliminary Study of What Helps and What Hinders | Request PDF." ResearchGate, https://www.researchgate.net/publication/309227024_Smartphones_as_assistive_technology_following_traumatic_brain_injury_a_preliminary_study_of_what_helps_and_what_hinders

[23] Alex Mariakakis, Jacob Baudin, Eric Whitmire, Vardhman Mehta, Megan A. Banks, Anthony Law, Lynn McGrath, and Shwetak N. Patel. (2017). PupilScreen: Using Smartphones to Assess Traumatic Brain Injury. Proceedings of the ACM on

Interactive, Mobile, Wearable and Ubiquitous Technologies, 1(3), 81. DOI: https://doi.org/10.1145/3131896

[24] Evald, Lars. "Prospective memory rehabilitation using smartphones in patients with TBI." Disability and rehabilitation vol. 40,19 (2018): 2250-2259. doi:10.1080/09638288.2017.1333633

[25] Canzian, Luca, and Mirco Musolesi. "Trajectories of Depression: Unobtrusive Monitoring of Depressive States by Means of Smartphone Mobility Traces Analysis." Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing, Association for Computing Machinery, 2015, pp. 1293–1304. ACM Digital Library, doi:10.1145/2750858.2805845.

[26] et, E., et al. "Changes in Gait Variability during Different Challenges to Mobility in Patients with Traumatic Brain Injury." Gait & Posture, vol. 25, no. 1, Jan. 2007, pp. 70–77. ScienceDirect, doi:10.1016/j.gaitpost.2006.01.002.

[27] Williams, Gavin et al. "Incidence of gait abnormalities after traumatic brain injury." Archives of physical medicine and rehabilitation vol. 90,4 (2009): 587-93. doi:10.1016/j.apmr.2008.10.013

[28] Juengst, S.B., Hart, T., Sander, A.M. et al. Mobile Health Interventions for Traumatic Brain Injuries. Curr Phys Med Rehabil Rep 7, 341–356 (2019). https://doi.org/10.1007/s40141-019-00240-9

[29] Abhinav Mehrotra and Mirco Musolesi. 2018. Using Autoencoders to Automatically Extract Mobility Features for Predicting Depressive States. Proc. ACM Interact. Mob. Wearable Ubiquitous Technol. 2, 3, Article 127 (September 2018), 20 pages. DOI:https://doi.org/10.1145/3264937

[30] Geetanjali Gera, PT, PhD, Jim Chesnutt, MD, Martina Mancini, PhD, Fay B Horak, PT, PhD, Laurie A King, PT, PhD, Inertial Sensor-Based Assessment of Central Sensory Integration for Balance After Mild Traumatic Brain Injury , Military Medicine, Volume 183, Issue suppl_1, March-April 2018, Pages 327–332, https://doi.org/10.1093/milmed/usx162

[31] Pappalardo, Luca & Barlacchi, Gianni & Simini, Filippo & Pellungrini, Roberto. (2019). scikit-mobility: a Python library for the analysis, generation and risk assessment of mobility data.

[32] HMIHARAN, Ramaswamy, and Kentaro TOYAMA. “Project Lachesis: Parsing and Modeling Location Histories.” Lecture Notes in Computer Science. Berlin: Springer, 2004. 106–124.

[33] Basford JR, Chou LS, Kaufman KR, Brey RH, Walker A, Malec JF, Moessner AM, Brown AW. An assessment of gait and balance deficits after traumatic brain injury. Arch Phys Med Rehabil. 2003 Mar;84(3):343-9. doi: 10.1053/apmr.2003.50034. PMID: 12638101.

[34] Irimia, Andrei et al. “Mobile Monitoring of Traumatic Brain Injury in Older Adults: Challenges and Opportunities.” Neuroinformatics vol. 15,3 (2017): 227-230. doi:10.1007/s12021-017-9335-z

[35] Nishiguchi, Shu et al. “Reliability and validity of gait analysis by android-based smartphone.” Telemedicine journal and e-health : the official journal of the American Telemedicine Association vol. 18,4 (2012): 292-6. doi:10.1089/tmj.2011.0132

[36] Kang X, Huang B, Qi G. A Novel Walking Detection and Step Counting Algorithm Using Unconstrained Smartphones. Sensors. 2018; 18(1):297. https://doi.org/10.3390/s18010297

[37] Moe-Nilssen, Rolf, and Jorunn L Helbostad. "Estimation of gait cycle characteristics by trunk accelerometry." Journal of biomechanics vol. 37,1 (2004): 121-6. doi:10.1016/s0021-9290(03)00233-1

[38] Kutilek, Patrik & Adamová, Barbora & Cakrt, Ondrej & Svoboda, Zdenek & Viteckova, Slavka & Smrcka, Pavel. (2018). Quantifying postural stability of patients with cerebellar disorder during quiet stance using three-axis accelerometer. Biomedical Signal Processing and Control. 40. 378–384. 10.1016/j.bspc.2017.09.025.

[39] Wollseifen, Thomas. (2011). Different methods of calculating body sway area. Pharmaceutical Programming. 4. 91-106. 10.1179/175709311X13166801334271.

[40] G. Castignani, T. Derrmann, R. Frank and T. Engel, "Driver Behavior Profiling Using Smartphones: A Low-Cost Platform for Driver Monitoring," in IEEE Intelligent Transportation Systems Magazine, vol. 7, no. 1, pp. 91-102, Spring 2015, doi: 10.1109/MITS.2014.2328673.

[41] Nguyen N, Phan D, Pathirana PN, Horne M, Power L, Szmulewicz D. Quantification of Axial Abnormality Due to Cerebellar Ataxia with Inertial Measurements. Sensors. 2018; 18(9):2791. https://doi.org/10.3390/s18092791

[42] Machine Learning Classifiers Sidath Asiri - http://towardsdatascience.com/machine-learning-classifiers-a5cc4e1b0623, accessed on 04/18/2021

[43] Tianqi Chen and Carlos Guestrin. 2016. XGBoost: A Scalable Tree Boosting System. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. Association for Computing Machinery, New York, NY, USA, 785–794. DOI:https://doi.org/10.1145/2939672.2939785

[44] Breiman, L. Random Forests. Machine Learning 45, 5–32 (2001). https://doi.org/10.1023/A:1010933404324

[45] E. Wilson and D. W. Tufts, "Multilayer perceptron design algorithm," Proceedings of IEEE Workshop on Neural Networks for Signal Processing, 1994, pp. 61-68, doi: 10.1109/NNSP.1994.366063.

[46] Amari, Shun-ichi. "Backpropagation and stochastic gradient descent method." Neurocomputing 5.4-5 (1993): 185-196

[47] Lundberg, Scott, and Su-In Lee. "A unified approach to interpreting model predictions." arXiv preprint arXiv:1705.07874 (2017).