Radar and AI-based Soil Moisture Monitoring for Efficient Farm Irrigation

A Major Qualifying Project (MQP) Report Submitted to the Faculty of

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Abstract

This study presents a novel approach using Stepped Frequency Continuous Wave (SFCW) radar technology and machine learning models to develop a non-invasive, cost-effective method for soil moisture estimation. Using the Akela AVMU radar system, we collected and processed radar data, which was then combined with ground truth data moisture data collected using the PR2-Probe by Delta- T Devices. Various machine learning models were applied to data the, with Gradient Boosting Regressor achieving the best overall model performance with a test RMSE of 0.408 when predicting soil moisture at the depth of 20 cm and XGBoost Regressor achieving a test RMSE of 0.814 which is the best overall for the depths of 0 to 40 cm combined. Despite challenges like extended model run times, complex data handling, and limited data size, our study achieved significant improvements in non-invasive soil moisture prediction methods. This research helps open avenues for broader applications in agriculture such as ground water level assessment and drought prediction, contributing to sustainable agricultural practices.

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Introduction

Accurate soil moisture estimation and measurement is important for optimal irrigation, crop yields, and soil health. Soil moisture estimation not only allows for efficient usage of water, but also supports sustainable practices [1]. Recently, ground-penetrating radar (GPR) has shown promise for soil moisture and characteristics measurements due to its non-invasive methods to collect data over a large area [2]. However, the setup, radar configuration, and the environment introduce noise and interference to the GPR data. Therefore, it is important to take account of them in the GPR data analysis process.

Figure 1: Image depicting an SFCW radar over a mega farm creating soil moisture maps.

Project Objectives

This study aims to develop and implement a machine learning-based model to analyze soil moisture data collected using a Stepped Frequency Continuous Wave (SFCW) radar called AKELA AVMU. Through the combination of radar technology and machine learning models, we aim to provide a cost-friendly, non-invasive, and high-resolution method to estimate soil moisture to enable more sustainable water resource usage.

Task 1: Data Collection

To develop a method for collecting soil moisture radar data using the AKELA AVMU radar system and ground truth soil moisture data using the Delta-T Devices PR2 Profile Probe while also maintaining accurate and efficient data collection.

Task 2: Probe Data Analysis

Analyze the collected ground truth soil moisture data.

Task 3: Understand SFCW and Extract Information

Gain an understanding of the SFCW radar technology and extract relevant information from the soil moisture radar data, such as raw/complex values, magnitude, and phase.

Task 4: Dataset Creation

Create a dataset that contains the processed radar data and ground truth soil moisture data while making sure it is organized and ready for machine learning applications.

Task: 5 Machine Learning

Run and evaluate different machine learning models (Linear Regression, Random Forest, Gradient Boost Regression, Support Vector Regressor, Multi-layer Perceptron, etc) to identify the most efficient and accurate model for estimating soil moisture at different depths, different datasets, and different radar data subsets.

Background

The one key element in agriculture, environmental monitoring, geology, and many others is soil moisture and being able to monitor it allows stakeholders like farmers to make well informed irrigation decisions to improve water management. Some methods of measuring soil moisture range from satellite imagery to soil sampling and for many reasons, they are limited. Examples include, low-resolution imaging, lack of depth penetration, invasive, and cost [3]. This study aims to overcome these challenges.

As humans increase agricultural productivity, water tends to become scarce and comes the need for efficient and accurate estimation of soil moisture. As stated before, many of the current methodologies have drawbacks: satellite imagery lacks resolution and does not reach the root zone, probing the soil is invasive, expensive, and does not scale well [4]. Advances in the field of subsurface sensing demonstrate the power of GPR. The SFCW radar stands out due to its high resolution and ability to penetrate many subsurface materials [5].

There are still many challenges when estimating soil moisture using a SFCW even if radar technology has become more advanced. The data received is usually in-phase and quadrature elements and needs to be processed. In addition, data handling and analysis is more complex due to manual collection of data and data being disorganized. We evaluate several machine learning models using RMSE and through the transformation of radar values into different attributes (raw/complex (real and imaginary), magnitude, and phase) to set new benchmarks in the field of soil moisture estimation and GPR data analysis.

Collaborating with the Michigan Tech Research Institute (MTRI) and Worcester Polytechnic Institute (WPI), we capture data from realistic agricultural settings to improve the accuracy of soil moisture estimation.

Data Collection and Experimental Setup

Site Setup

To conduct our experiments, we chose a plot of land at 87 Prescott St in Worcester, Massachusetts. Since the native soil in the area contained large, hard rocks, we excavated the site so that these rocks would not present themselves as an interference in our measurements. The soil was replaced with a uniformly compacted layer of loam to mimic long-term farmland soil conditions. This site was then left to settle naturally for several days after the compaction process to stabilize the structure, thereby minimizing any potential discrepancies in data due to soil instability.

Radar System Configuration

Our study utilized the Akela AVMU radar which is a version of the Stepped Frequency Continuous Wave (SFCW) radar system renowned for its precise and dependable data collection capabilities. The radar was set to operate over a frequency range of 400 MHz to 2 GHz, a common spectrum in GPR applications due to its optimal balance between depth penetration and resolution. The frequency response of the site was measured by stepping the transmitter through each frequency incrementally, allowing the radar to capture echoes from the scene and mix them with the transmitted signal to compute complex values indicative of the subsurface characteristics. This configuration provided an estimated penetration depth of up to 400 meters in a vacuum and was optimal for our setup.

Antenna Setup

Two types of antennas were employed: the Log Periodic (LP) Antenna [6] and the Vivaldi Antenna [7] as seen in *Figure 2A* and *Figure 2B*. The LP antenna is known for its broad frequency bandwidth and consistent radiation pattern. The Vivaldi antenna is characterized by its planar look with a tapered slot and offers ultra-wide band frequency coverage and high gain. This structure makes it suitable for multiple operational frequencies with minimal signal loss.

Figure 2: Log periodic antenna (co-pole) and ladder structure (Fig. A), Vivaldi antenna (cross-pole) wooden structure(Fig. B), Customized wooden structure with three heights h1,h2,h3(Fig. C)

Moisture Probe

For ground truth data collection, the Probe-PR2 and HH2 moisture meter from Delta-T Devices were used. These instruments were used to measure soil moisture at 10 cm, 20 cm, 30 cm, and 40 cm below ground, allowing for a comprehensive profile of the soil's moisture content across different layers. Data from these probes were collected at six positions namely A1, A2, B1, B2, C1, and C2. The measurements of these were then averaged to come up with one reading for each position A, B, and C.

Data Collection Methodology

To ensure comprehensive soil analysis, radar data was collected at various heights of 35 in, 54 in, and 79 in above ground as seen in *Figure 2C*. All measurements were conducted every 2 hours to ensure that any changes in soil moisture were accounted for. For each measurement round, radar data was collected above point A, point B, and point C and to simulate drone movements, radar data was collected in a sweeping motion moving from point A to C as seen in *Figure 3*. This series of collections was done of each of the heights and each of the antenna types as well. Each measurement point was sampled 100 times to ensure data reliability. After radar data was collected, moisture data, along with external temperature, soil temperature and UV index was also recorded.

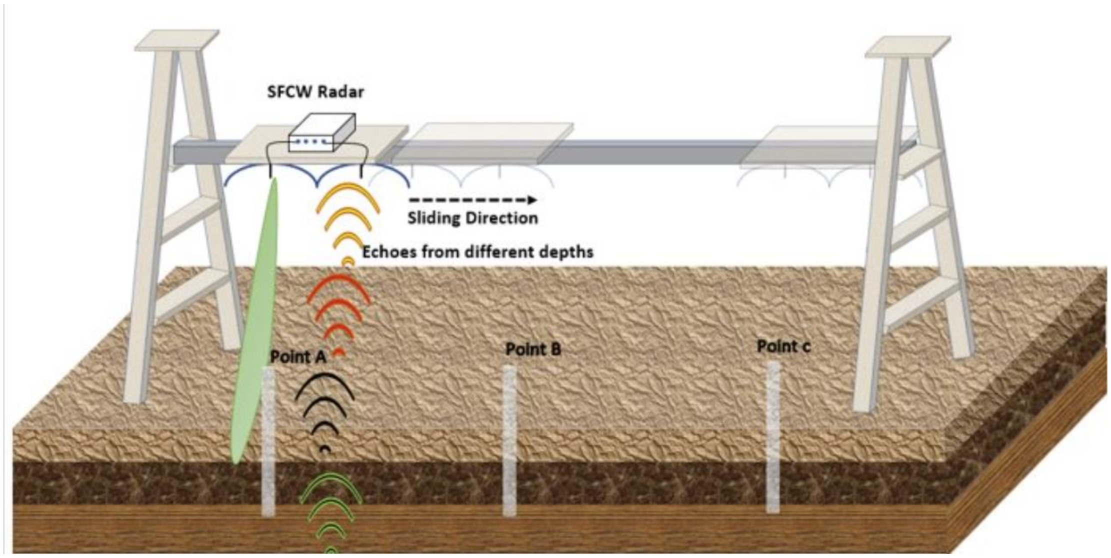

Figure 3: Experimental setup demonstrating each probe and the different positions of the radar

Data Processing and Analysis

The data recorded by the radar system in a .imb format contained amplitude, phase, and complex value information processed using AKELA APRD software and MATLAB. This analysis included the generation of range and delay profiles and an evaluation of signal attenuation across different frequencies, providing insights into the subsurface conditions.

Probe Data Analysis

In this section, we present the analysis of the data gathered from moisture probes inserted at depths of 10 cm, 20 cm, 30 cm, and 40 cm, across various points and times within our test site. The aim is to understand the statistical characteristics of soil moisture, examining the correlation, distribution, and variability across different depths to better understand the soil moisture dynamics.

Descriptive Statistics Overview

Our dataset comprises 153 measurements of each depth, reflecting a robust set of data points that show a detailed examination of soil moisture trends. The average moisture content shows a gradual increase with depth, with values starting at 25.05% at 10cm and rising to 40.24% at 40cm as seen in *Table 1*. This increment suggests a trend of moisture accumulation at deeper soil layers. The standard deviation indicates variability in measurements, which is relatively high at 30 cm, suggesting fluctuating moisture levels possibly influenced by external environmental factors or soil heterogeneity. The range of measurements, marked by the minimum and maximum values, highlight the moisture extremes with particularly notable fluctuations observed at the deepest layer of 40 cm. These fluctuations could be attributed to underlying water tables or distinct soil properties that affect moisture retention. A visualization of these statistics can be seen in *Figure 4*.

	10 cm	20 cm	30 cm	40 cm
Count	153.00	153.00	153.00	153.00
Mean	25.01667	30.25000	34.44902	49.23824
STD	3.72124	4.25835	5.66221	1.79976
Min	19.90000	22.95000	24.35000	46.3000
25%	21.80000	25.25000	27.40000	47.400000
50%	24.00000	31.500000	38.100000	49.050000
75%	27.750000	34.300000	38.450000	50.700000
Max	32.350000	35.400000	39.350000	53.900000

Table 1: Descriptive statistics table for probe data

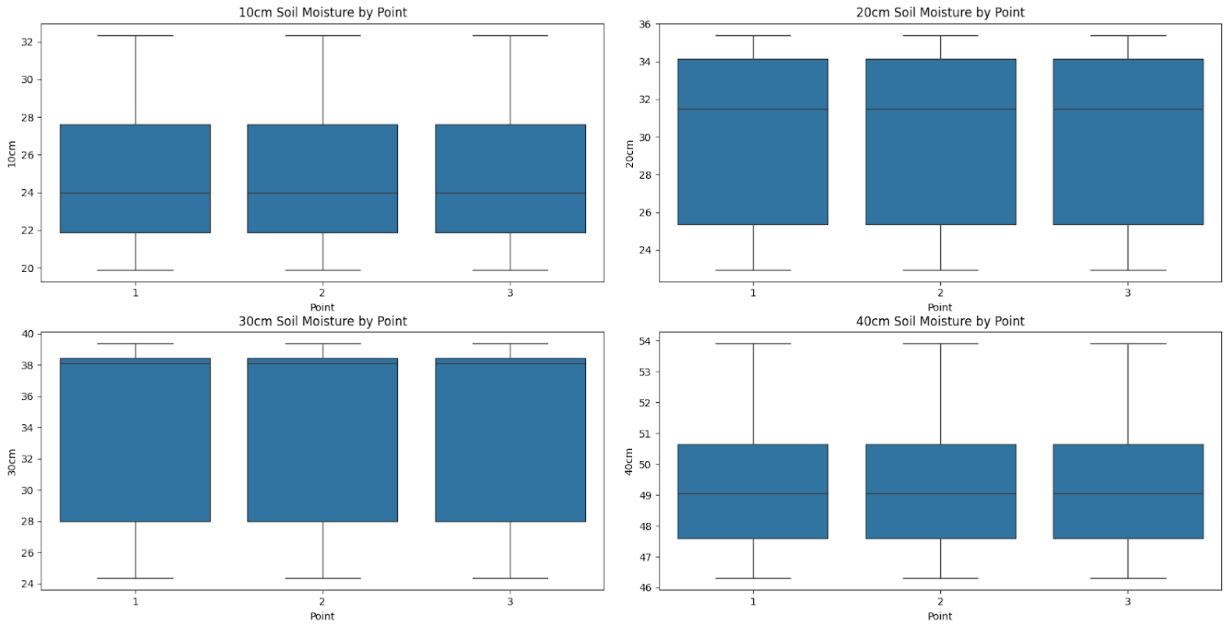

Figure 4: Box plots for probe data by depth

Correlation Analysis

The correlation matrix reveals significant relationships between moisture content at various soil depths. As seen in the heatmap below, a high correlation coefficient of 0.93 between the 20 cm and 30 cm depths indicates similar moisture retention behaviors, likely due to comparable soil textures of capillary movements within these layers as seen in *Figure 5*. Conversely, the correlation between the shallowest (10 cm) and the deepest (40 cm) depths is relatively low at 0.25, suggesting differing moisture dynamics. This disparity may be driven by factors such as surface evaporation affecting the shallower depths and more stable hydrological influences at deeper levels.

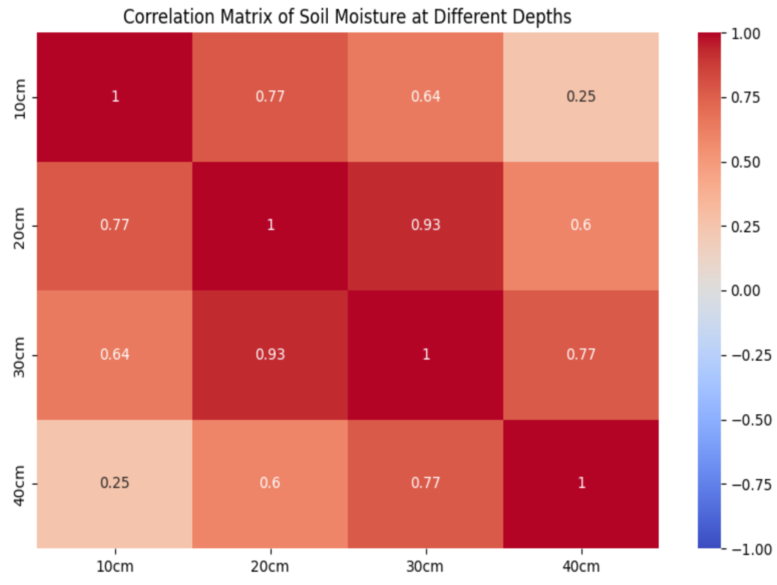

Figure 5: Correlation matrix of soil moisture at different depths

Moisture Distribution Analysis

Figure 5 shows the distribution of moisture content at each depth and further provides insights into the soil's moisture dynamics. Histograms and their corresponding fitted curves for the 10 cm depth suggest a nearly normal distribution with slight skewness towards lower moisture levels. This could show the impact of surface hydration and can possibly be linked to recent precipitation events. In contrast, the distribution at especially 30 cm displays a greater variability and a broader range of moisture content. This coupled with the higher moisture levels found at the 40 cm depth could indicate the presence of subsurface water flows or variations in soil composition that affect moisture distribution.

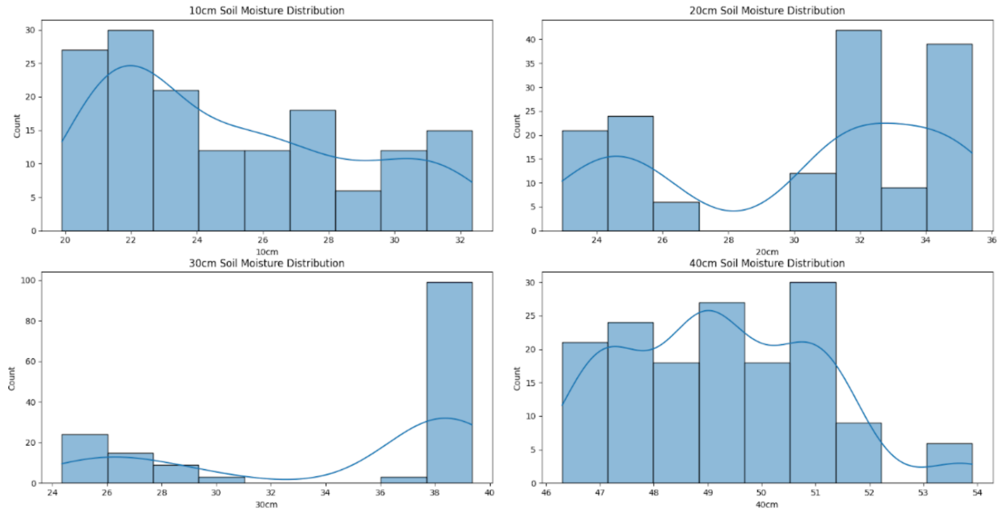

Figure 6: Distribution graph of probe data by depth

Understanding the SFCW Radar

The SFCW radar, like the AKELA AVMU, is a humble yet powerful tool for soil moisture estimation and measurement. By emitting several electromagnetic waves over a series of frequencies in a specified range, it can provide high-resolution data by stepping through frequencies and capturing important information about different materials/layers.

The data collected by the AKELA AVMU consists of data in the frequency domain. Normally, SFCW radars output data in the time domain by applying the Fast Fourier Transform (FFT) onto the vector of N (N = Number of frequency steps) complex numbers for each timestep in the frequency domain resulting in a 1xM (M = number of time steps) matrix. The AKELA AVMU applies the Inverse Fast Fourier Transform (IFFT) onto the timesteps for each frequency step resulting in a 1xN matrix [8] as seen in *Figure 7*. This is essential to understand because due to the use of the AKELA AVMU radar system, important information about depth is lost. However, the frequency domain can still be transformed into the time domain using the IFFT, but information is still lost.

The frequency domain enables detailed analysis of subsurface properties and the converted values of time domain result range bin samples. These samples provide a comprehensive view of the subsurface conditions, which is crucial for accurate soil moisture estimation.

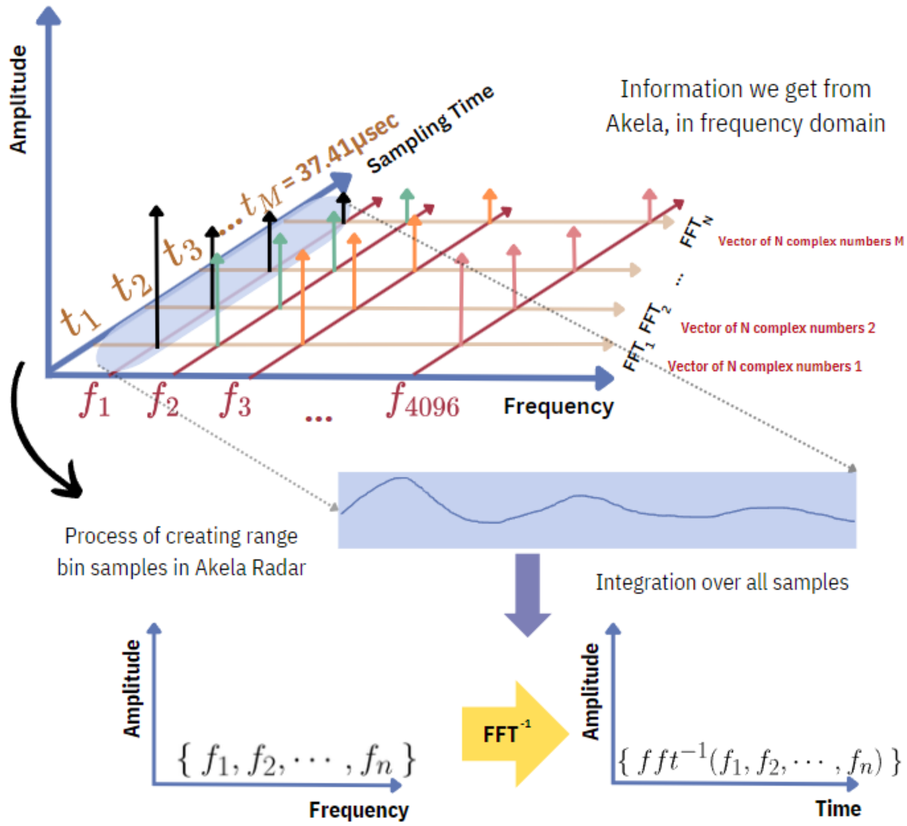

Figure 7: Image depicting how the Akela Radar creates bin samples. This is information that is received in the frequency domain which is then integrated over and an IFFT is performed to extract information in the time domain.

Dataset description

A dataset was created combining the radar data and the actual moisture values provided by the probe data. 4 steps were utilized to create this dataset. Loading radar files, running MATLAB code, reading moisture data from excel files, and combining data.

1. **Loading Radar Files**: The radar files from the Akela radar are saved in a .imb format and are stored into a folder containing all of the measurements and the excel files containing the moisture data.
2. **Running MATLAB Code**: The raw radar data in the .imb format were processed using the python MATLAB API to run a custom MATLAB script provided by our partners at MTRI. This script performs data extraction and FFT to process the data into readable complex numbers for the time and frequency domains.
3. **Reading Moisture Data**: Moisture data is read from the excel files and saved in a separate data frame. This moisture data includes measurements taken at different depths (10cm, 20cm, 30cm, 40cm) and is associated with specific days, hours, and locations (A, B, or C)
4. **Combining Data**: The processed radar data and the moisture data are then combined by matching the day, hour, and location. This process is applied to both the time and frequency domains and results in two datasets with 4104 columns and 153 rows each. Four columns of file identification, 4096 columns of complex values, and four columns of moisture data labels.

A comprehensive dataset that can be applied to machine learning models to predict soil moisture accurately is completed by processing and combining the radar and moisture data. The enables the evaluation and comparison of different models to determine the best for soil moisture estimation using SFCW radar technology.

Machine Learning

What or how many features are important to contribute to soil moisture? Utilizing the dataset created values from 10 to 4096 both sequentially and randomly were tested to reduce the dimensionality of the data.

A variety of machine learning models were utilized and evaluated by their Root Mean Square Error (RMSE) scores. The models included: Linear Regression, Random Forest, Gradient Boost Regression, Support Vector Regressor, Multi-layer Perceptron, Extra Trees, AdaBoost, SVM with a linear kernel, Lasso and Ridge Regression, ElasticNet, and XGBoost. Each model was configured with specific parameters. For example, lasso and elastic net has 2000 iterations to ensure convergence and stability. Hyper parameter tuning was also conducted using grid search to find the best parameters for each model.

50% of the data was utilized to train the data, 20% to validate, and then 30% to test the data. Being able to easily interpret and compare performances was important and as a result, RMSE was utilized to evaluate the model performances. Test accuracy was also utilized to have a more comprehensive understanding of how accurate our models were.

Statistical analysis, mainly standard deviation, was utilized to visualize the significance of the results and the models' performances were analyzed and compared to identify best-performing models based on RMSE. Test-predictions from each model were also compared to each model and the actual values to visualize what models performed the best.

The most effective models and feature sets for accurate soil moisture estimation were able to be identified and it not only enhanced our understanding of the data but also supported the development of data- driven solutions for sustainable agriculture.

Experimental Results

This section presents the tested performance of the machine learning models in our study, where each model's effectiveness was seen using the RMSE score. After running the machine learning models a few times, a general trend can be seen.

Model	**Dataset**	**Depth**	**Columns**	**Train RMSE**	**Test RMSE**
XGBR	Frequency (Raw)	10 cm	50	0.0005370271564425	0.5493709537998298
XGBR	Range (Raw)	10 cm	4096	0.0002578200069026	0.8823480925267241
Gradient Boosting	Range (Raw)	20 cm	1000	3.673483290261e-05	0.4087374982253327
AdaBoost	Frequency (Raw)	20 cm	10	0.1821391096985867	0.4107473052442718
Ridge	Frequency (Magnitude)	30 cm	1000	0.0002178966045078	0.4764156459610246
Linear Regression	Frequency (Magnitude)	30 cm	1000	6.59355753730e-15	0.4766433965577863

Random Forest	Frequency (Phase)	40 cm	10	0.5250401770340998	0.5625346378224247
Linear Regression	Frequency (Magnitude)	40 cm	10	0.5805386950519528	0.5669129392924247
XGBR	Frequency (Raw)	All depths	50	0.0005279905866127	0.8141779276009659

Table 2: Best RMSEs per depth and their associated parameters

Appendix A includes graphs of the performance of each model over different numbers of columns used. Where we see the RMSE changes due to the number of columns. We can see that most models perform best with around 1000-1500 columns. Appendix B contains the best test RMSE for each model and depths.

Table 2 shows the best RMSEs per depth and their associated parameters and the lowest test RMSE score was 0.408 performed by the Gradient Boosting model at 20 cm into the ground and only using 1000 out of the 4096 range bins/columns. Other models like AdaBoost at 20 cm into the ground and Ridge Regression at 30 cm into the ground also performed well with a test RMSE score near the 0.41 range. When looking at the entire soil or at the combined 0 to 40cm range, XGBR or XGBoost Regressor performed the best utilizing the complex numbers in the frequency domain and only 50 columns.

The analysis of our models also identifies the most important features in predicting soil moisture. Models that were unable to provide these features included: Support Vector Regressor (SVR), Multi-layer Perceptron (MLP), and SVM with a non-linear kernel. Finding that the first half of the data set contained the most important features. Unfortunately, at this time, a graph covering all the features was unable to be completed. An interesting finding was that even when the subset of columns was randomized, the first fourth of the dataset still contained the most important features. This applies to both the frequency and time domains and may not make sense since with lower frequency bandwidths, there is lower resolution.

However, from a machine learning point of view, cutting down on the number of parameters from 4096 helps each model significantly due to reduced computational complexity, leading to faster training times and less risk of overfitting. With fewer, more relevant features, each model can generalize better to the new data and improve overall performance.

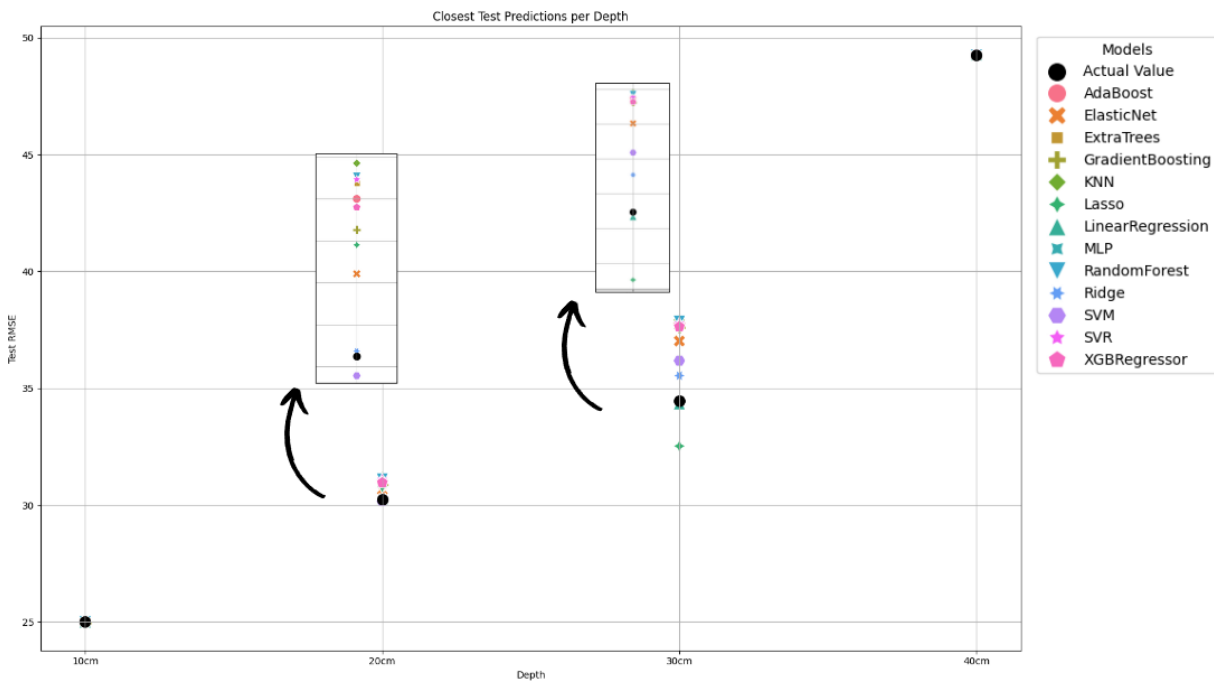

Figure 8: Graph of closest test predictions per depth for each model. Results for 20 cm and 30 cm are zoomed into.

Figure 8 shows a graph of the closest test predictions per depth for each model. As can be seen that for 10 cm and 40 cm, the models generalize and perform relatively well. However, for depths of 20 cm and 30 cm, every time the models were run, there was a small change in which model performed the best. As the standard deviation of the actual values in 20 cm and 30 cm is larger, it is understood that the models will fluctuate as it is harder to estimate and predict.

When compared with previous studies, the results of this study perform as well or even better than previous methods. This study really highlights the dimension reduction of our data and how in previous studies the number of parameters may have affected the result.

We achieved significant improvements in model performance to estimate soil moisture by focusing on the most relevant features and reducing the dimensionality of our data. Through the integration of these techniques into agricultural management systems, globally better resource utilization, higher crop yields, and more sustainable farming practices can be achieved.

Conclusion and Future Work

With a test RMSE of 0.8141779276009659, the best performing model overall for soil moisture is XGBoost Regressor. An understanding that these transformation techniques applied to different radar signals each have their own benefits. However, when the data is converted into the time domain, using the raw complex values, and when a model is attempting to predict soil moisture for a specific depth, we see a lower RMSE and predictions that are closer to the actual value.

The findings from this study offer many practical applications in the agricultural field. By estimating soil moisture accurately using radar data and machine learning models, optimization of watering crops, reduction of water wastage, and crops receiving the ideal amount of moisture can be done. The scalability of this study is the most valuable point as the integration of radar technology and machine learning in agriculture shows the potential to be utilized in larger agricultural areas and possibly locations with various environmental conditions. This ensures that this enhances soil moisture estimation can be used by small family farmers to large mega farms. The practicality of this technology makes it an indispensable tool to farmer's arsenal.

This study contributes to the development of non-invasive, soil moisture estimation techniques and by advancing in SFCW radar combined with machine learning algorithms, we push the boundaries of what is possible in agricultural engineering. These steps are important to developing sustainable farming practices to make informed decisions. This approach not only shows the effectiveness of soil moisture estimation but also is a model for future research where environmental and technological challenges require unique solutions.

While this model provides a robust framework for estimating soil moisture, there is a large room for improvement. Future research should focus on refining these models by integrating additional datasets, collecting more data, applying different transformations of the data for the models to make more refined choices. Experimenting with more complex neural networks like CNNs or GNNs could also possibly increase the accuracy of these predictions.

We experienced several challenges during this study, including combating the extended run times for our models as they were iterating over our data multiple times. Some models took up to two days to run on a Turing High Power Computer. This challenge posed significant hurdles in iterating through the data and refining our models. Additionally, the data collection process has been long and not as smooth as anticipated. There are chances of some collections being botched due to simple human error. Despite these obstacles, we were able to address the issue of handling complex data through our Python script, which streamlined the data preprocessing and transformation phases. Another major challenge was the limited size of our dataset. However, we were able to manage these shortcomings and achieved notable results.

The techniques in this study also have different applications beyond soil moisture estimation. They can be adapted for other estimation tasks like assessing groundwater levels, predicting drought conditions, or even estimating moisture on extraterrestrial landscapes. Expanding the applications could help address a wide range of agricultural challenges, making it more relevant on a global scale.

As we continue to push the boundary, it is important that research and development continues to focus on innovations that address agricultural challenges. This study is one example of how targeted research results in lots of benefits, and it is important we continue to support research that leads to sustainable practices.

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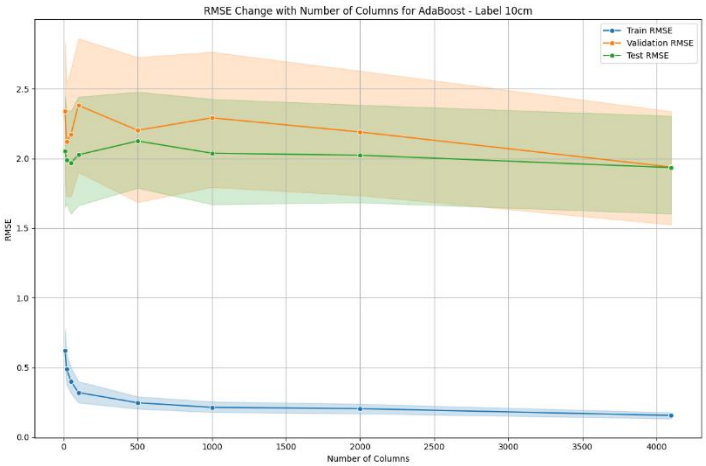
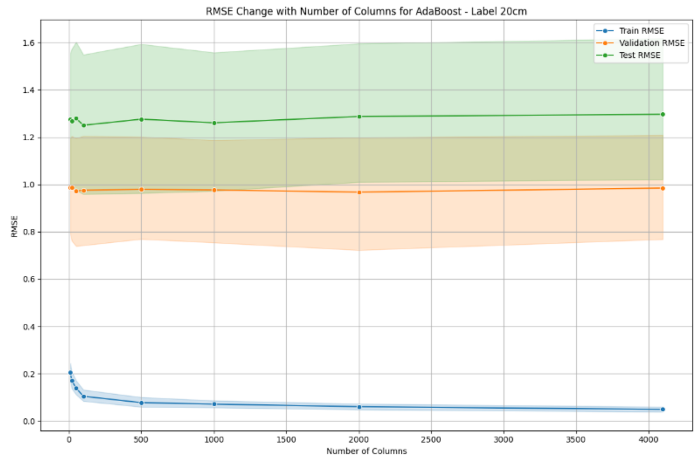
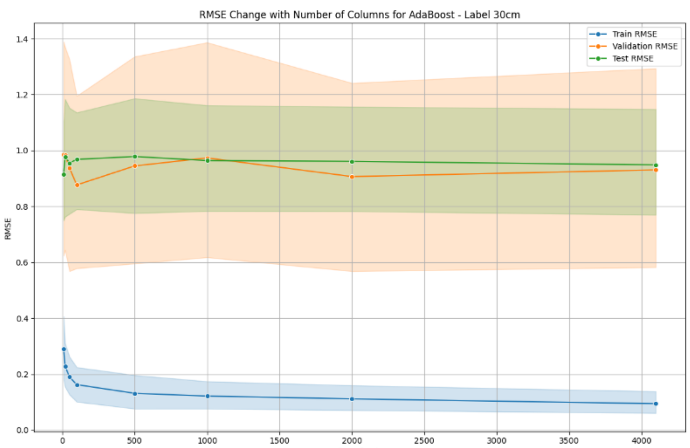
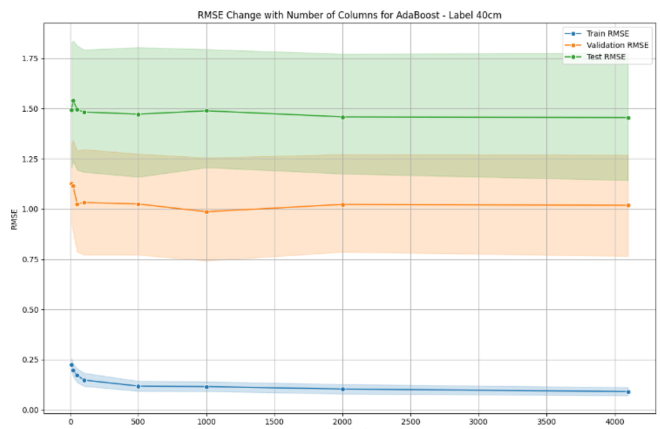
Appendix A

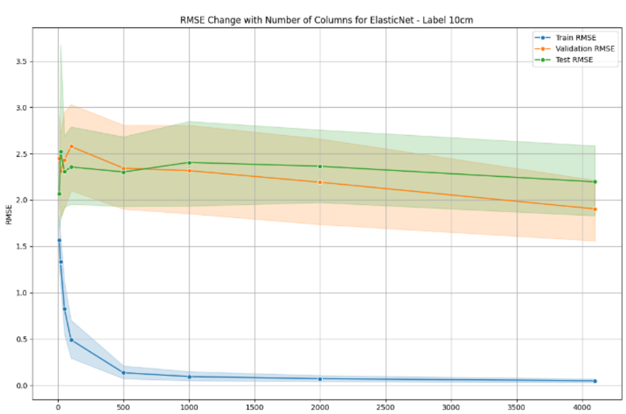
RMSE Change with different number of columns for each model.

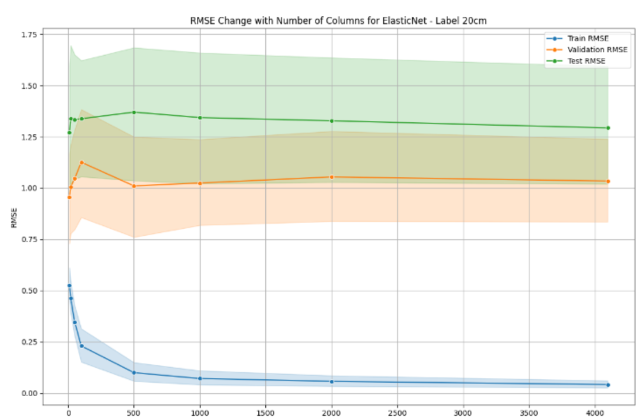


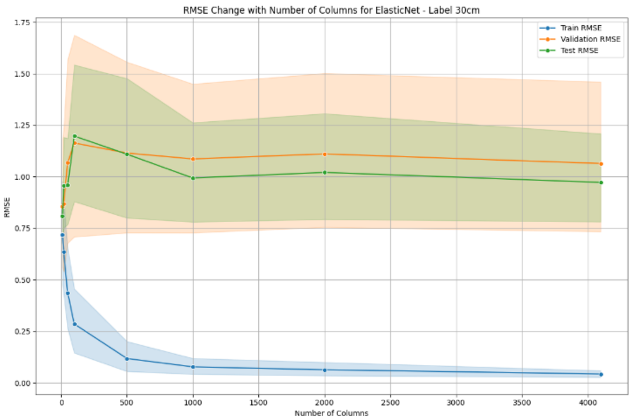


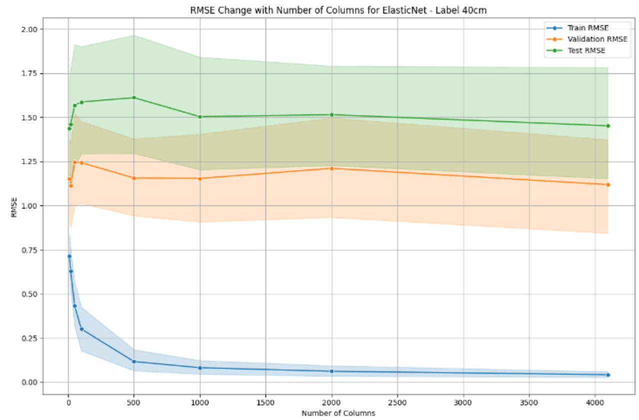


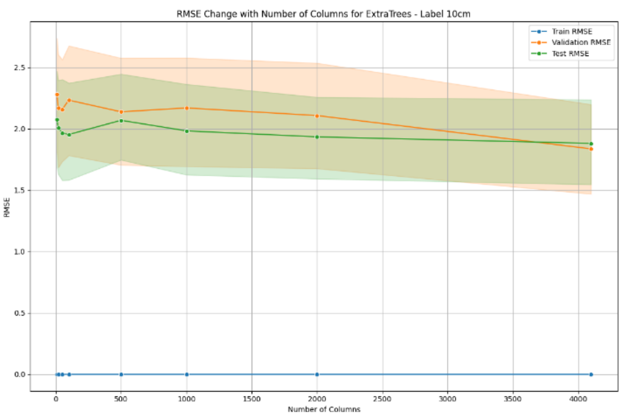


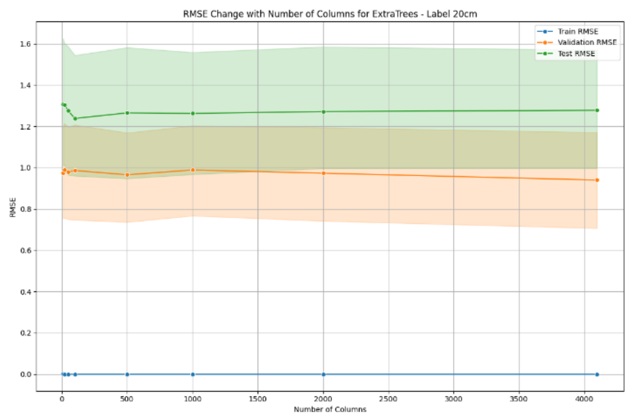





RMSE Change with Number of Columns for ElasticNet - Label 30cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns


RMSE Change with Number of Columns for ElasticNet - Label 40cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns


RMSE Change with Number of Columns for ExtraTrees - Label 10cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns


RMSE Change with Number of Columns for ExtraTrees - Label 20cm
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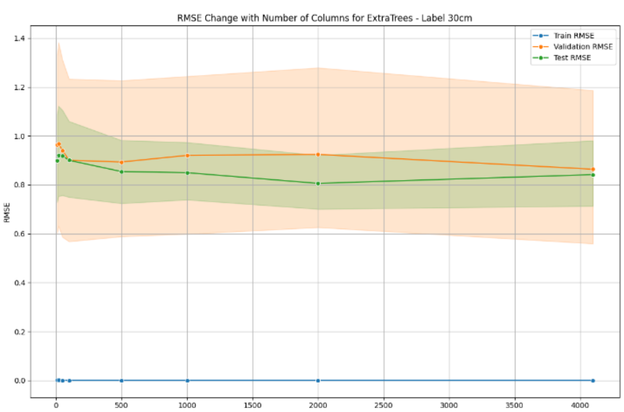
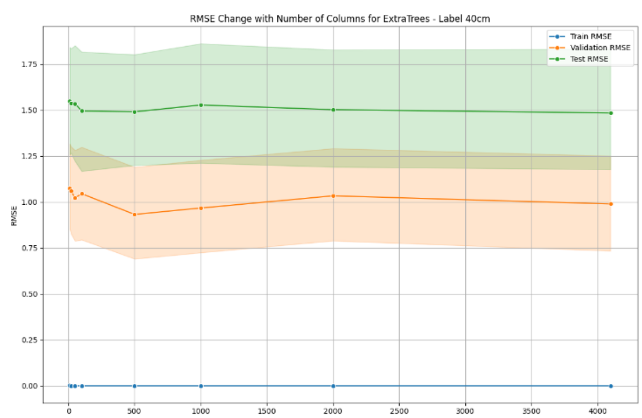
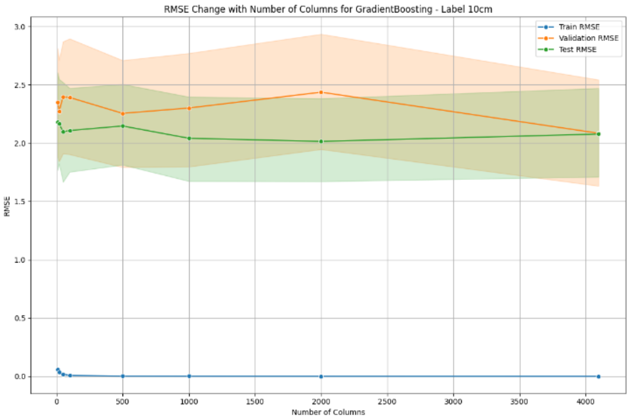
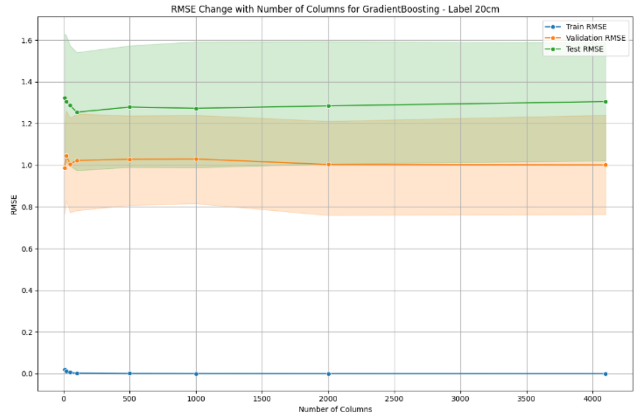
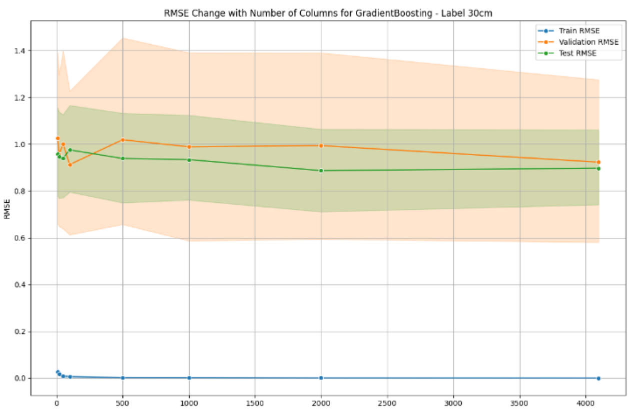
Validation RMSE
Test RMSE
RMSE
Number of Columns

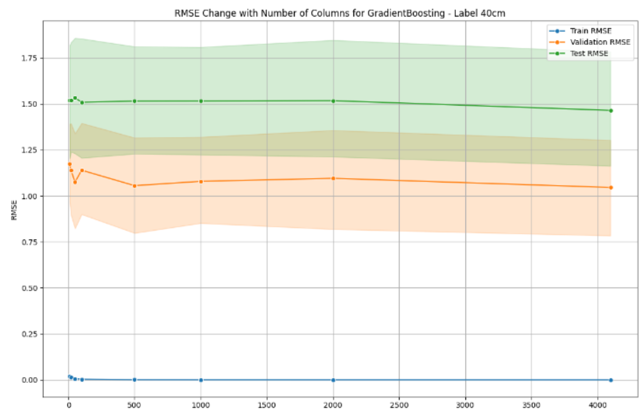

RMSE Change with Number of Columns for ExtraTrees - Label 30cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns


RMSE Change with Number of Columns for ExtraTrees - Label 40cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns


RMSE Change with Number of Columns for GradientBoosting - Label 10cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns


RMSE Change with Number of Columns for GradientBoosting - Label 20cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns


RMSE Change with Number of Columns for GradientBoosting - Label 30cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns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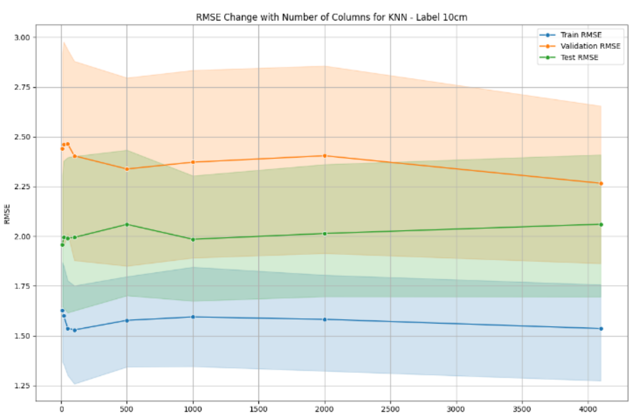
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns


RMSE Change with Number of Columns for KNN - Label 10cm
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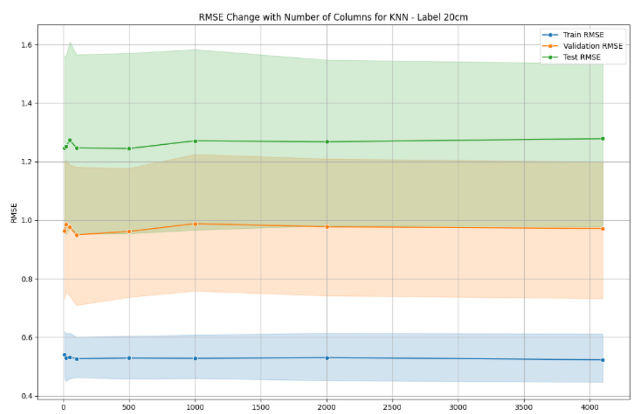
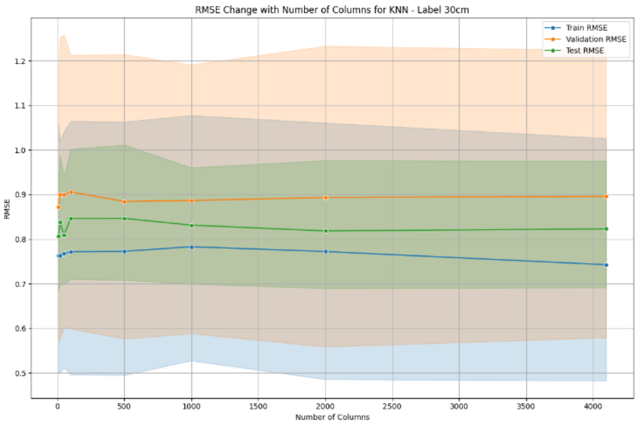
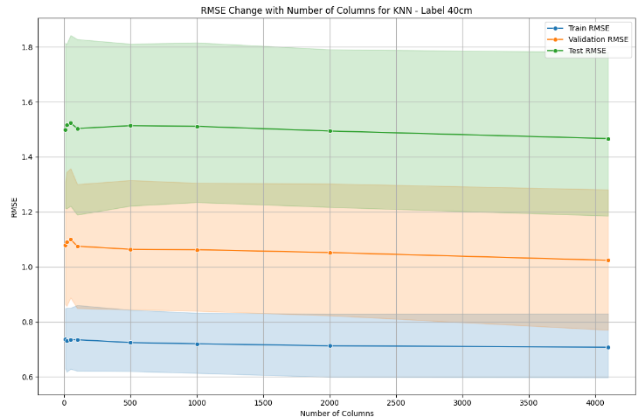
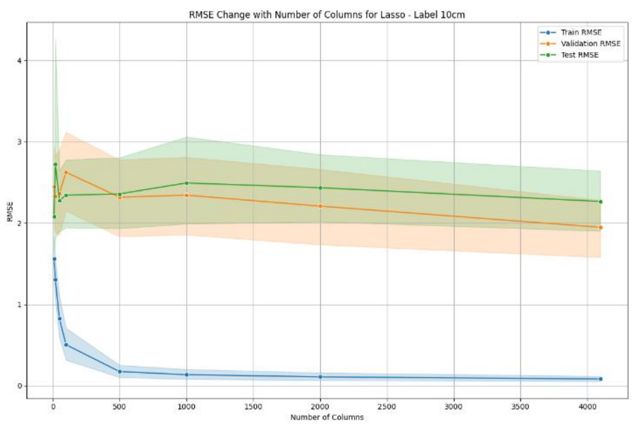
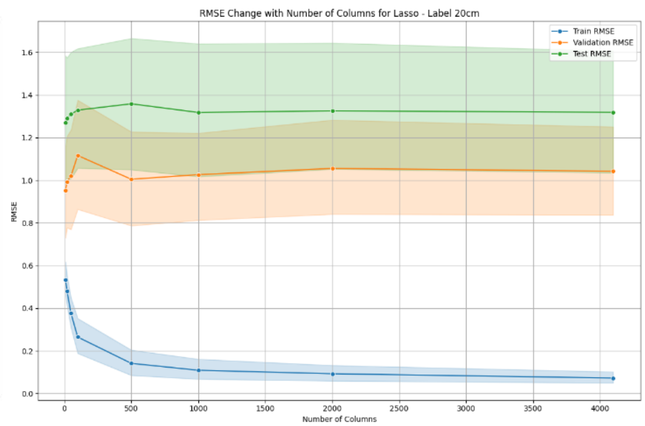
Validation RMSE
Test RMSE
RMSE
Number of Columns

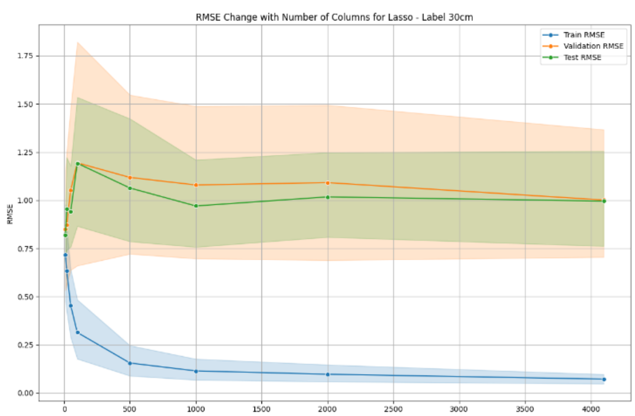

RMSE Change with Number of Columns for KNN - Label 20cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns

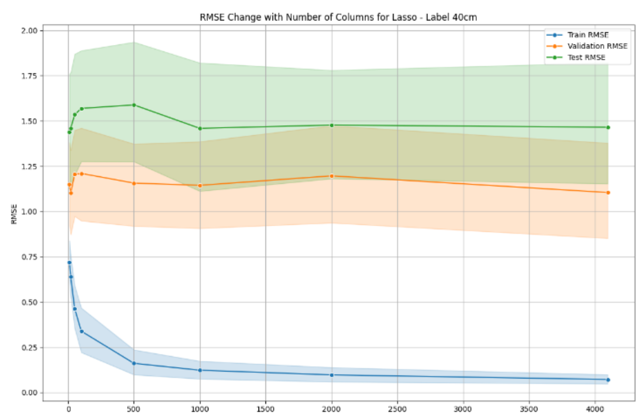

RMSE Change with Number of Columns for KNN - Label 30cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns

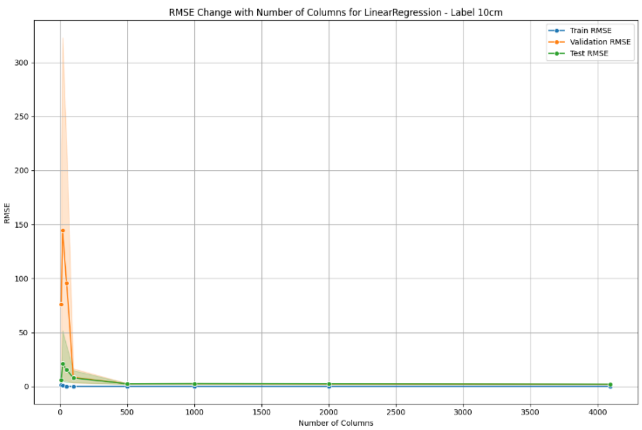

RMSE Change with Number of Columns for KNN - Label 40cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns

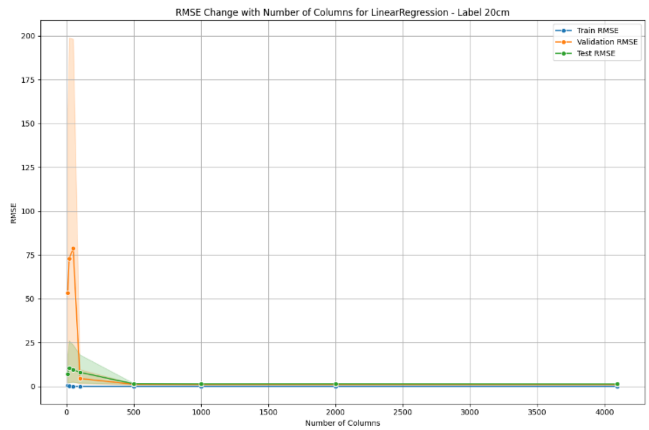

RMSE Change with Number of Columns for Lasso - Label 10cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns

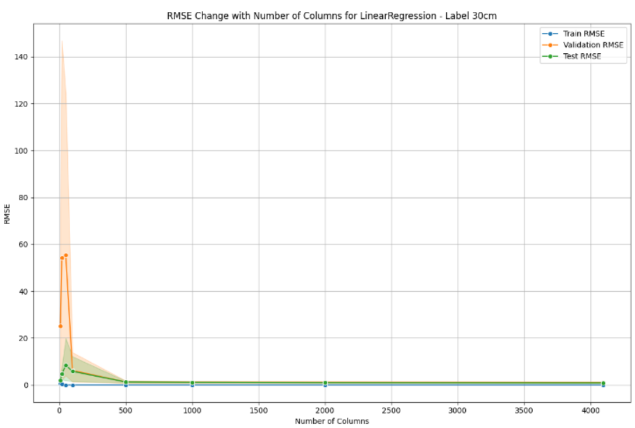

RMSE Change with Number of Columns for Lasso - Label 20cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns

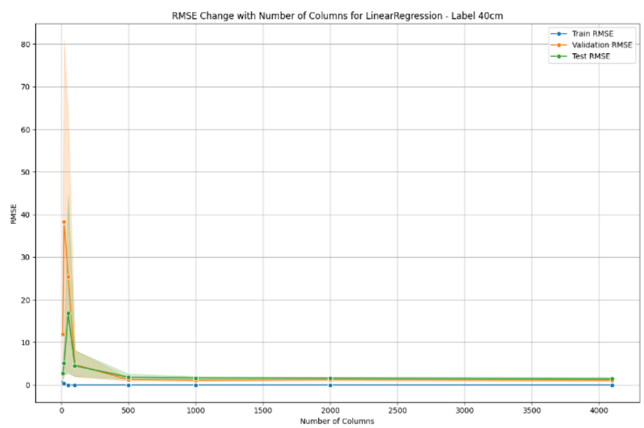

RMSE Change with Number of Columns for Lasso - Label 30cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns

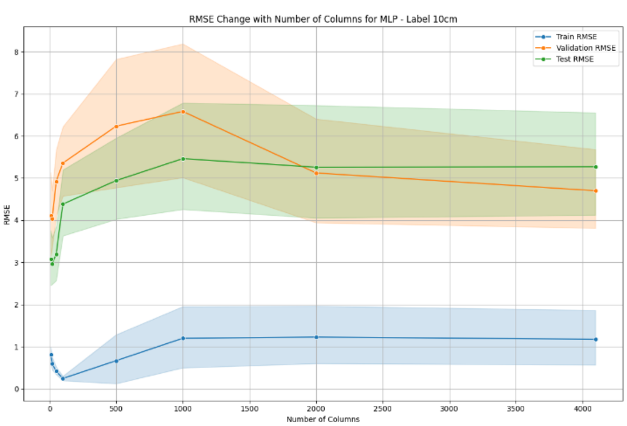

RMSE Change with Number of Columns for Lasso - Label 40cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns

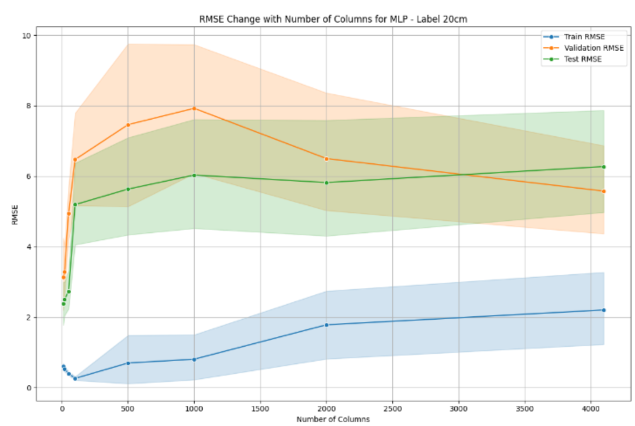

RMSE Change with Number of Columns for LinearRegression - Label 10cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns

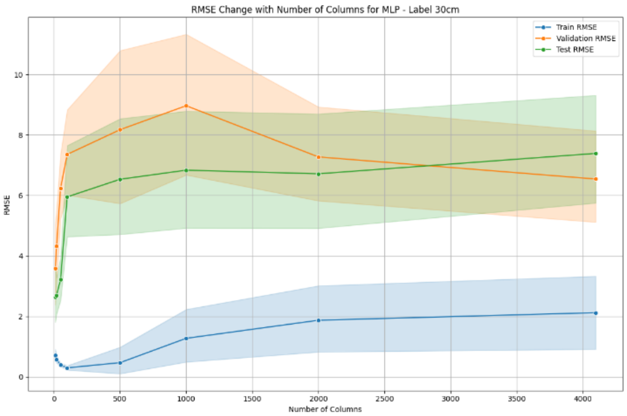

RMSE Change with Number of Columns for LinearRegression - Label 20cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns

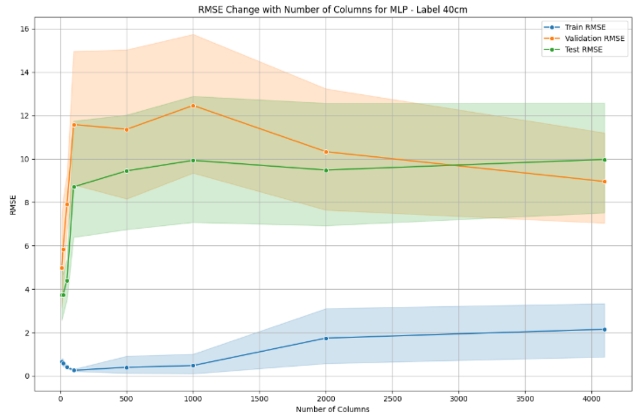

RMSE Change with Number of Columns for LinearRegression - Label 30cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns

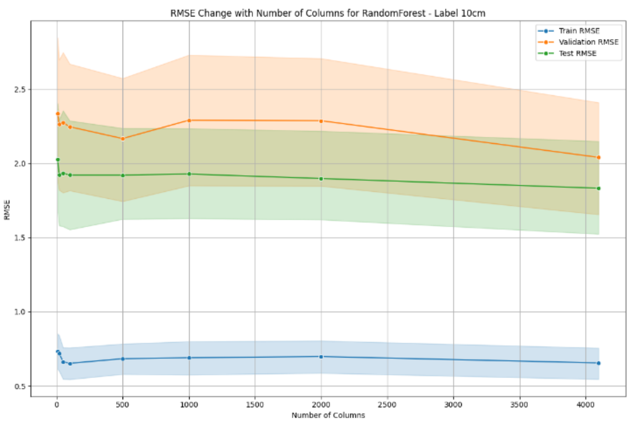

RMSE Change with Number of Columns for LinearRegression - Label 40cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns

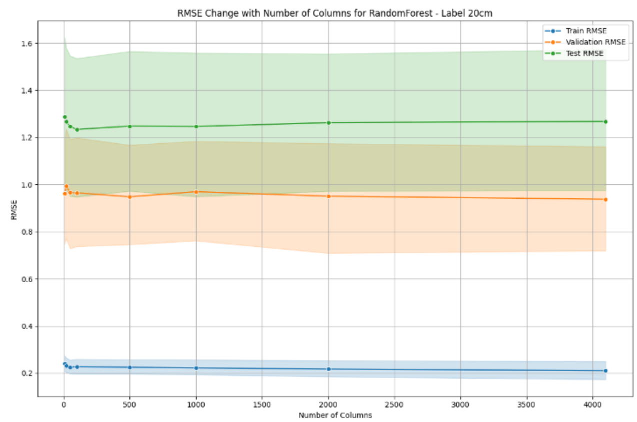

RMSE Change with Number of Columns for MLP - Label 10cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns

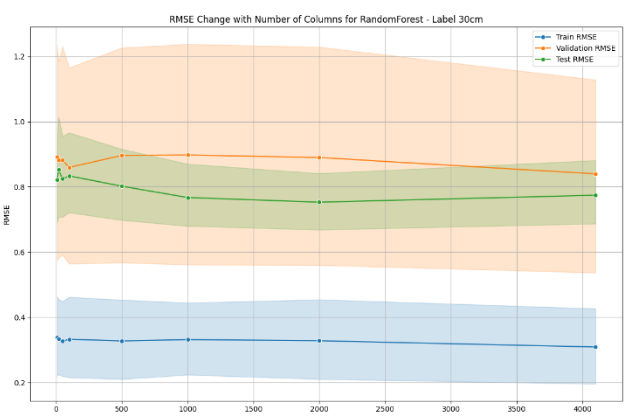

RMSE Change with Number of Columns for MLP - Label 20cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns

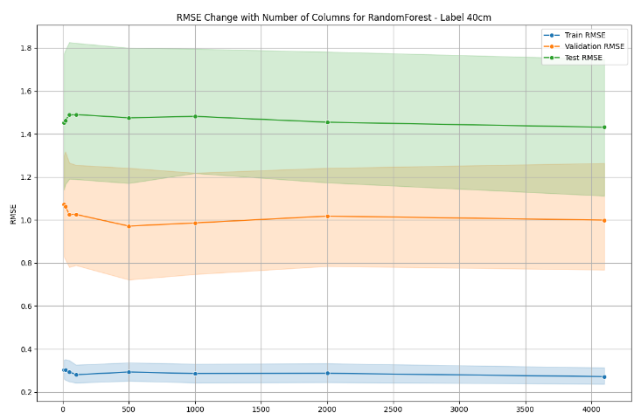

RMSE Change with Number of Columns for MLP - Label 30cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns

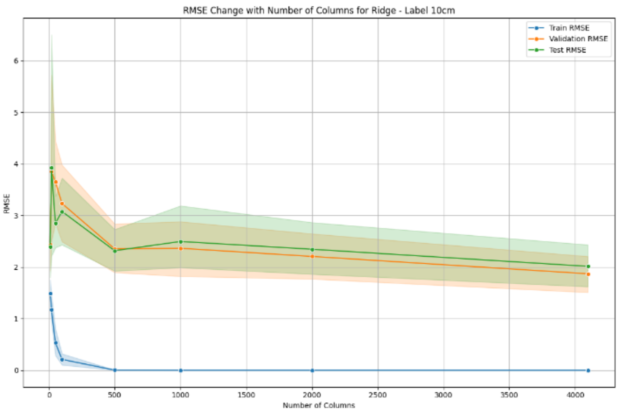

RMSE Change with Number of Columns for MLP - Label 40cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns

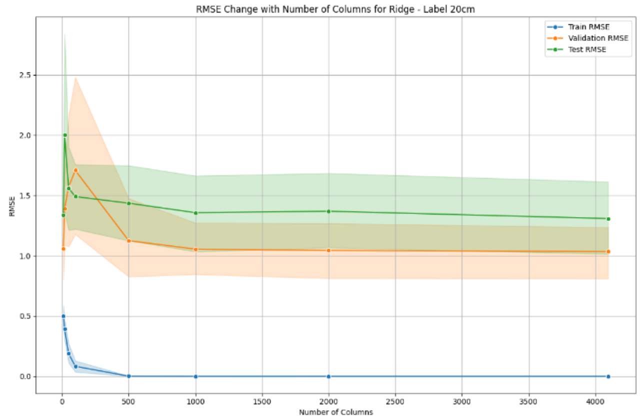

RMSE Change with Number of Columns for RandomForest - Label 10cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns

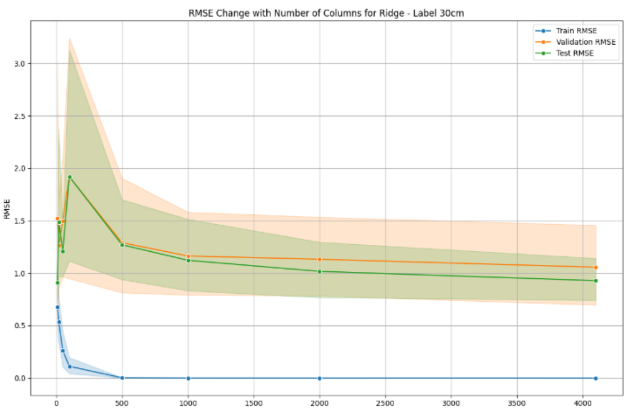

RMSE Change with Number of Columns for RandomForest - Label 20cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns

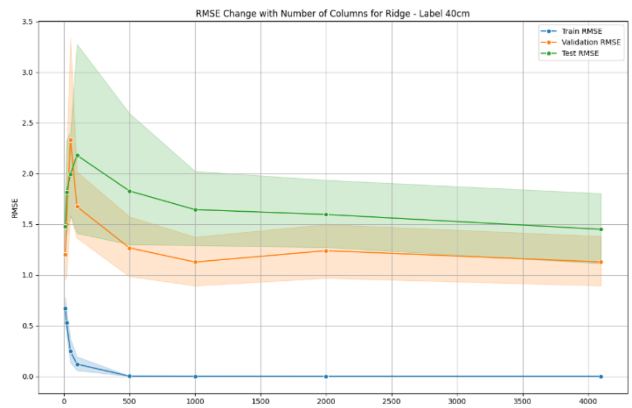

RMSE Change with Number of Columns for RandomForest - Label 30cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns

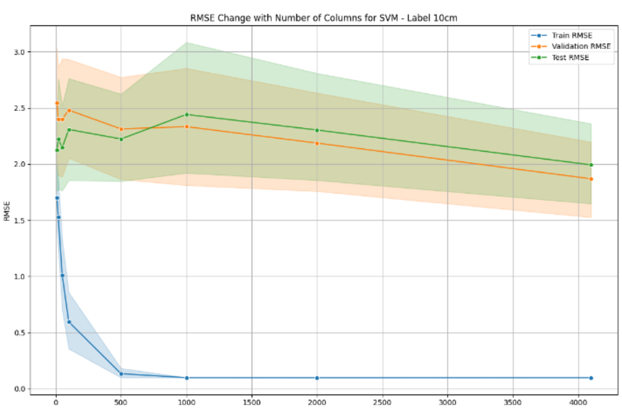

RMSE Change with Number of Columns for RandomForest - Label 40cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns

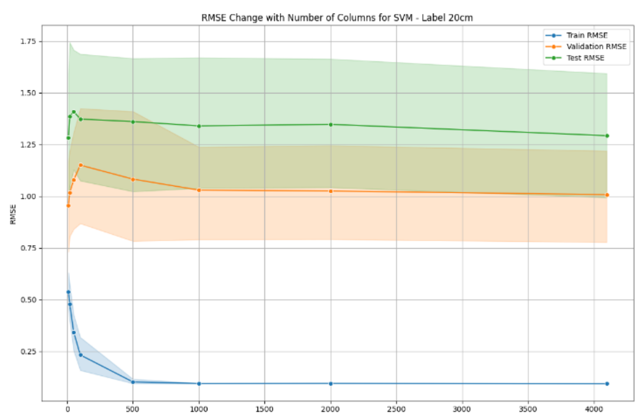

RMSE Change with Number of Columns for Ridge - Label 10cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns

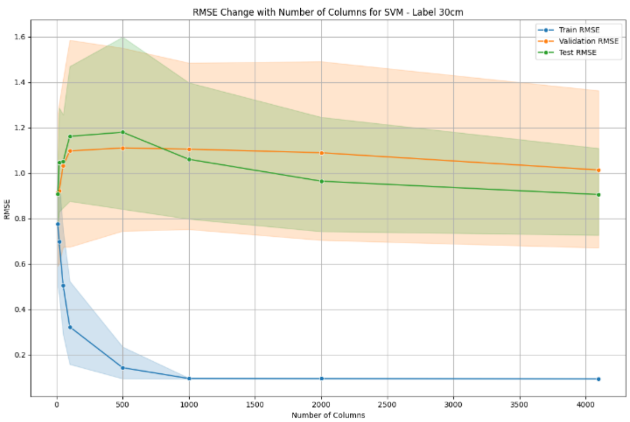

RMSE Change with Number of Columns for Ridge - Label 20cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns

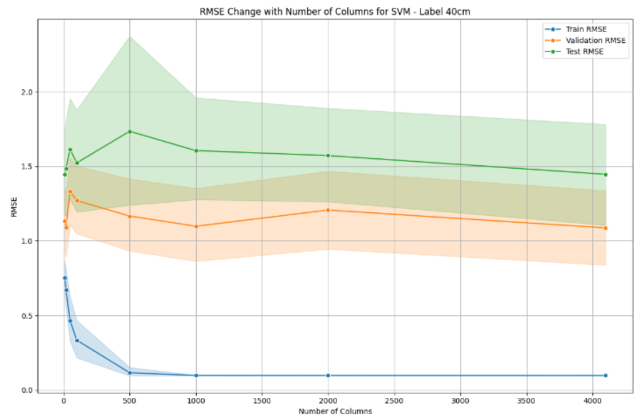

RMSE Change with Number of Columns for Ridge - Label 30cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns

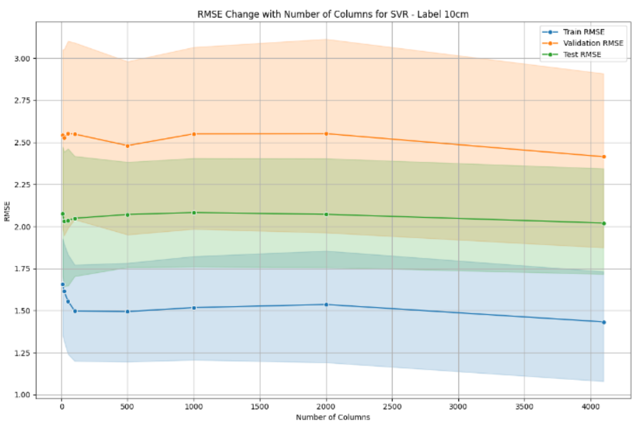

RMSE Change with Number of Columns for Ridge - Label 40cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns

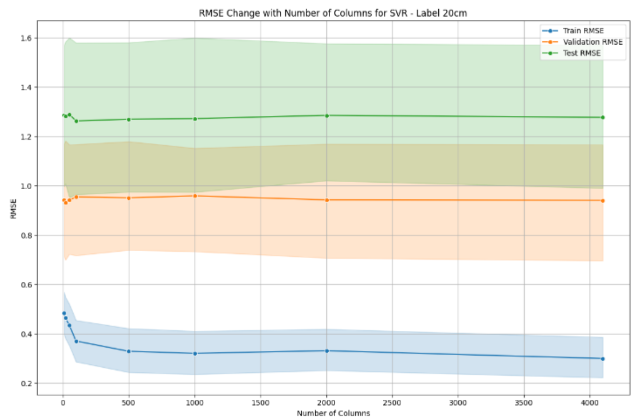

RMSE Change with Number of Columns for SVM - Label 10cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns

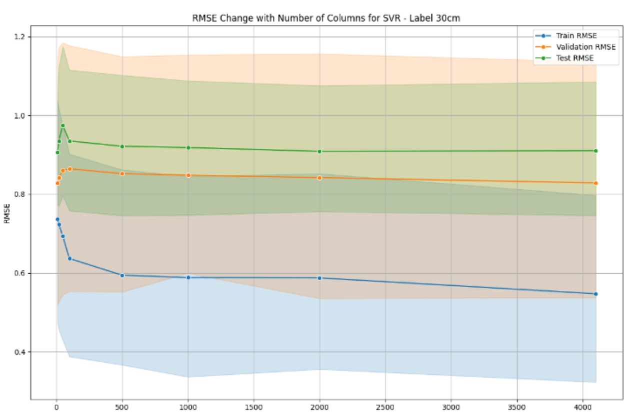

RMSE Change with Number of Columns for SVM - Label 20cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns

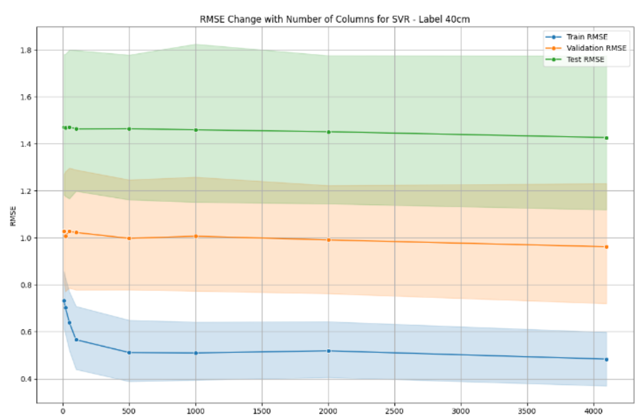

RMSE Change with Number of Columns for SVM - Label 30cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns

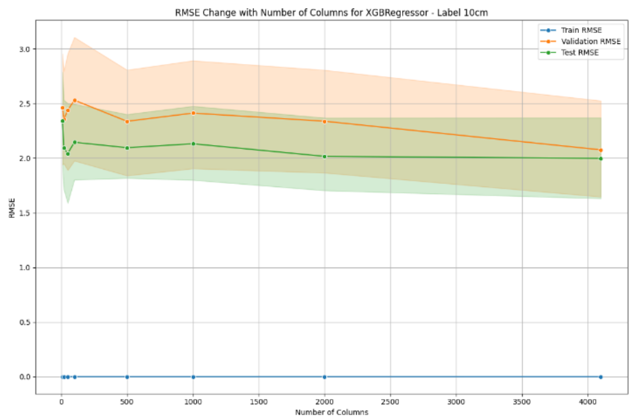

RMSE Change with Number of Columns for SVM - Label 40cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns

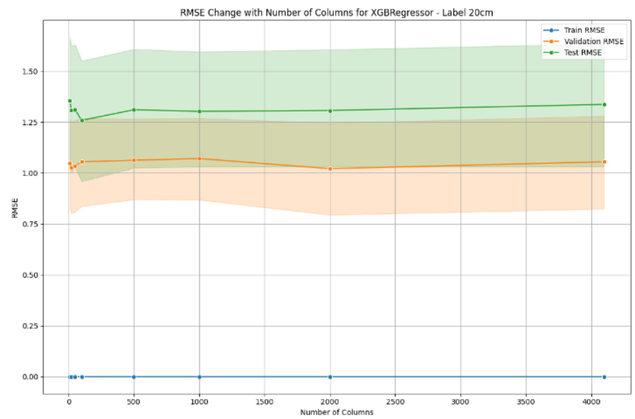

RMSE Change with Number of Columns for SVR - Label 10cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns

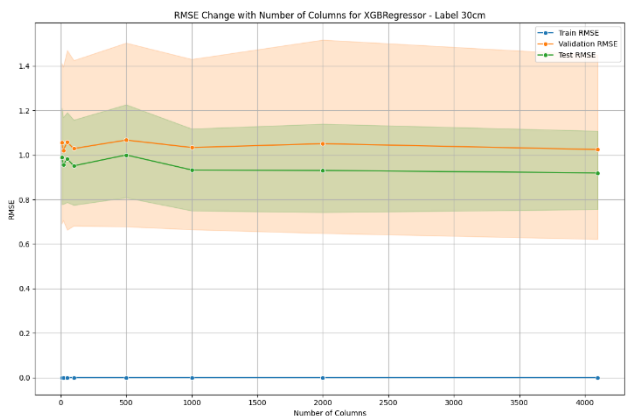

RMSE Change with Number of Columns for SVR - Label 20cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns

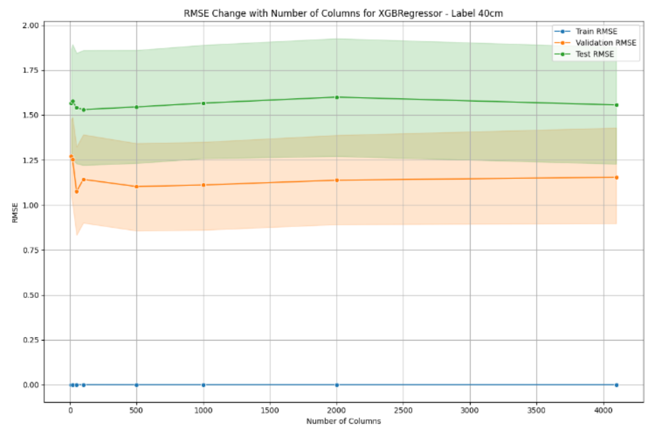

RMSE Change with Number of Columns for SVR - Label 30cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns


RMSE Change with Number of Columns for SVR - Label 40cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns


RMSE Change with Number of Columns for XGBRegressor - Label 10cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns


RMSE Change with Number of Columns for XGBRegressor - Label 20cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns


RMSE Change with Number of Columns for XGBRegressor - Label 30cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns


RMSE Change with Number of Columns for XGBRegressor - Label 40cm
Train RMSE
Validation RMSE
Test RMSE
RMSE
Number of Columns

Appendix B

Best test RMSE for each model and depths.

Model	Dataset	DataType	Depth	Columns	Identifier	Train RMSE	Validation RMSE	Test RMSE
LinearRegression	Range	Magnitude	10cm	10	A	2.1078643080287165	3.441858661426946	2.2187693427696384
RandomForest	Range	Magnitude	10cm	2000	A	0.70722	3.215343867691284	2.0132304264539465
GradientBoosting	Range	Raw	10cm	500	A	0.000243	3.780833146912608	2.263799567459756
SVR	Frequency	Magnitude	10cm	20	A	2.186436039309501	3.586060257619171	2.394785195795823
MLP	Frequency	Raw	10cm	20	A	0.4559925185053935	4.481021937877176	2.867784631156147
KNN	Frequency	Magnitude	10cm	2000	A	2.128653069170477	3.2537574433260983	2.188401242916848
ExtraTrees	Range	Magnitude	10cm	4096	A	3.8273059059653544e-14	2.2449664877788256	2.1041301572740005

AdaBoost	Frequency	Magnitude	10cm	20	A	0.7609578241066074	3.893827124480495	2.3398627858890664
SVM	Range	Magnitude	10cm	50	A	0.2907541723005564	3.291274039215712	2.5022630711197023
Lasso	Range	Raw	10cm	100	A	0.091196	3.607167277704664	2.336407584690817
Ridge	Range	Magnitude	10cm	10	A	2.1079806474688096	3.446557642469464	2.2265197406748527
ElasticNet	Range	Raw	10cm	100	A	0.066719	3.2611486441363837	2.403911302631122
XGBRegressor	Range	Magnitude	10cm	1000	A	0.000305	2.539453563178802	2.208729856373171
LinearRegression	Frequency	Magnitude	10cm	4096	B	1.101404907291834e-14	2.231673967999076	1.393509165354765
RandomForest	Frequency	Phase	10cm	100	B	0.8538231789037715	2.0537061239987504	1.0937914420720312
GradientBoosting	Frequency	Phase	10cm	100	B	0.026424	2.191213394986426	1.0920239762946728

SVR	Frequency	Raw	10cm	50	B	2.146749626961861	2.912752515096115	1.4374244350530974
MLP	Range	Raw	10cm	50	B	0.2056182763292285	3.0772530147593606	1.259860926267239
KNN	Frequency	Phase	10cm	20	B	1.9565388941813668	2.123013777628397	1.142830914877612
ExtraTrees	Frequency	Raw	10cm	50	B	2.8624526666646523e-14	2.0675995441574275	1.0849030918704263
AdaBoost	Range	Raw	10cm	4096	B	0.1426431456227262	2.5013051369312285	1.0955789229732804
SVM	Frequency	Phase	10cm	100	B	1.1349637166908189	2.5667382756013084	1.0159690161348651
Lasso	Range	Raw	10cm	10	B	1.7297685174770534	3.2652949056454417	1.0718339697264014
Ridge	Range	Raw	10cm	10	B	1.454802662934575	3.130651236223943	1.3486097171445373
ElasticNet	Frequency	Phase	10cm	100	B	0.989849	2.6928984064899195	1.1983305682358183

XGBRegressor	Frequency	Raw	10cm	50	B	0.000537	2.2797672299171974	0.5493709537998298
LinearRegression	Range	Raw	10cm	4096	C	8.477853123686641e-15	0.9094086104647998	1.132406801439504
RandomForest	Frequency	Raw	10cm	50	C	0.3383669728760948	0.9621086542069898	1.043835879700446
GradientBoosting	Frequency	Raw	10cm	50	C	0.008145	0.9876426309928892	0.9425378681205606
SVR	Frequency	Phase	10cm	20	C	0.7757526273554938	0.8856996251891943	1.1993752687462953
MLP	Frequency	Phase	10cm	10	C	1.127653846967728	4.244800019895871	1.0976635894100266
KNN	Range	Phase	10cm	4096	C	0.8332116577837022	0.9905238513029356	1.1115585904485643
ExtraTrees	Frequency	Raw	10cm	50	C	2.7589184879705765e-14	1.083314503041465	0.9802668004171136
AdaBoost	Frequency	Magnitude	10cm	10	C	0.4502637044880713	1.0178664355455174	0.9623521535739888

SVM	Frequency	Raw	10cm	50	C	0.717729	0.9178254395706492	1.0643738254804758
Lasso	Range	Phase	10cm	1000	C	0.031039	1.060281897330974	0.944694
Ridge	Frequency	Raw	10cm	20	C	0.672548	0.5926987176535463	0.9417407443341296
ElasticNet	Range	Phase	10cm	1000	C	0.017253	0.9994817846587952	1.0019510239197642
XGBRegressor	Range	Raw	10cm	4096	C	0.000258	0.6090940622905886	0.8823480925267241
LinearRegression	Frequency	Magnitude	20cm	20	A	0.3783710932659033	1.5405740739824096	1.5934191022348685
RandomForest	Range	Phase	20cm	500	A	0.158757	1.5170167064010829	2.027207091974077
GradientBoosting	Range	Phase	20cm	500	A	8.98194371340478e-05	1.5568455065610771	1.970862342997658
SVR	Range	Phase	20cm	2000	A	0.093536	1.4994077796344585	2.0467193608753083

MLP	Frequency	Raw	20cm	10	A	0.5242588442330631	1.318027265987384	1.8311088950933323
KNN	Range	Phase	20cm	1000	A	0.3858468320172901	1.517329067803028	2.0001656181426597
ExtraTrees	Range	Phase	20cm	4096	A	5.920005108327088e-14	1.5165463848824428	2.0461700045450724
AdaBoost	Range	Magnitude	20cm	4096	A	0.034938	1.5996122445536245	2.068162026343467
SVM	Frequency	Magnitude	20cm	500	A	0.096891	1.3733393231955953	1.665266939313675
Lasso	Range	Raw	20cm	2000	A	0.037933	1.3645973059452383	1.9995243831321208
Ridge	Frequency	Magnitude	20cm	1000	A	0.000365	1.3387653540668374	1.821033649856512
ElasticNet	Frequency	Magnitude	20cm	500	A	0.1845629923480055	1.473515674439232	1.8855771080728296
XGBRegressor	Range	Phase	20cm	500	A	0.000341	1.4711971288684276	1.859218802450384

LinearRegression	Frequency	Magnitude	20cm	1000	B	3.552713678800501e-15	0.6063750739340434	0.4137805462133156
RandomForest	Range	Magnitude	20cm	1000	B	0.1609848811051725	0.3017467895438098	0.4680583897869951
GradientBoosting	Range	Raw	20cm	1000	B	3.673483294400261e-05	0.5471007716569551	0.4087374982253327
SVR	Frequency	Magnitude	20cm	500	B	0.2485903702048383	0.4300154243634931	0.47496
MLP	Frequency	Magnitude	20cm	10	B	0.5639062983708821	1.1656002218740815	0.6782477644406166
KNN	Range	Phase	20cm	20	B	0.3753109821645687	0.4000624951179497	0.4440157654858675
ExtraTrees	Frequency	Magnitude	20cm	500	B	4.3200342583474175e-14	0.4073512765415126	0.4561559149567178
AdaBoost	Frequency	Raw	20cm	10	B	0.1821391096985867	0.4262162822228393	0.4107473052442718
SVM	Frequency	Magnitude	20cm	1000	B	0.094353	0.4735992237644599	0.4191596693917491

Lasso	Frequency	Magnitude	20cm	500	B	0.1833093729342521	0.4812369110451418	0.4194453470325814
Ridge	Frequency	Magnitude	20cm	1000	B	0.00017	0.6057222255046774	0.4137424478925561
ElasticNet	Frequency	Magnitude	20cm	100	B	0.3422691467492753	0.5876849730204745	0.4523625078240348
XGBRegressor	Range	Magnitude	20cm	1000	B	0.000311	0.3639090712822854	0.424885
LinearRegression	Range	Raw	20cm	1000	C	4.470400011810908e-15	0.9054148026354868	0.9464130835201794
RandomForest	Frequency	Phase	20cm	50	C	0.3010665647143287	0.9081289659238916	0.886293
GradientBoosting	Frequency	Phase	20cm	50	C	0.009744	0.9964299258955368	0.9023560676393608
SVR	Frequency	Raw	20cm	20	C	0.7198270619770601	0.8353774413231788	0.9605347390276726
MLP	Frequency	Phase	20cm	10	C	0.8292089719225334	2.308313633299861	0.9028492382493593

KNN	Range	Phase	20cm	100	C	0.7394329659347837	0.8993052874302481	0.8854659790189573
ExtraTrees	Frequency	Raw	20cm	100	C	2.9900541119693475e-14	1.0646558863078763	0.8681535722439843
AdaBoost	Frequency	Raw	20cm	50	C	0.1687829217076333	0.8248653381324111	0.8845611125248036
SVM	Range	Phase	20cm	20	C	0.7040732233747752	1.2664922844333446	0.948785
Lasso	Range	Raw	20cm	2000	C	0.057897	0.8993133961171178	0.8924628964521848
Ridge	Range	Raw	20cm	1000	C	2.5396058741584068e-05	0.904029	0.9474041438541256
ElasticNet	Frequency	Phase	20cm	4096	C	0.030193	0.9549358339013084	0.8892403355287002
XGBRegressor	Frequency	Phase	20cm	100	C	0.000554	1.405622262579146	0.6842740953867348
LinearRegression	Frequency	Magnitude	30cm	1000	A	6.593557537388058e-15	0.5692489155272705	0.4766433965577863

RandomForest	Frequency	Magnitude	30cm	20	A	0.1123958777417378	0.3969358417930813	0.5354948354092638
GradientBoosting	Frequency	Magnitude	30cm	20	A	0.009132	0.4344222356240266	0.5141495470322257
SVR	Range	Raw	30cm	20	A	0.1057026261819739	0.4486742712258195	0.5789526049252334
MLP	Frequency	Magnitude	30cm	10	A	0.4718781718822956	0.5507388286498257	0.7177365545727873
KNN	Range	Magnitude	30cm	1000	A	0.2263048582971402	0.4318130382468781	0.5770940131382424
ExtraTrees	Frequency	Magnitude	30cm	20	A	6.62750142985318e-14	0.3799843335586166	0.5078684007693289
AdaBoost	Frequency	Magnitude	30cm	20	A	0.1029157033876908	0.3811090059874371	0.5274399435796767
SVM	Frequency	Magnitude	30cm	1000	A	0.094661	0.5845557103011868	0.5245588139664117
Lasso	Range	Raw	30cm	2000	A	0.037313	0.4836834935217516	0.546532

Ridge	Frequency	Magnitude	30cm	1000	A	0.000218	0.5692095867616451	0.4764156459610246
ElasticNet	Range	Raw	30cm	2000	A	0.020368	0.4839581836577643	0.535805
XGBRegressor	Frequency	Magnitude	30cm	20	A	0.000868	0.4100836459413463	0.532556
LinearRegression	Frequency	Raw	30cm	10	B	0.3846401063371706	0.5853728182240548	0.5717571925728611
RandomForest	Frequency	Phase	30cm	2000	B	0.2067829310062887	0.3649116759573672	0.5580017641101109
GradientBoosting	Frequency	Phase	30cm	2000	B	0.000761	0.271407	0.5317666348760874
SVR	Range	Phase	30cm	4096	B	0.1264976605664468	0.3805133322261724	0.6460073671669917
MLP	Frequency	Magnitude	30cm	20	B	0.52471	1.0579724322999302	0.6598017472732697
KNN	Range	Phase	30cm	20	B	0.4551709080725121	0.4156771583813571	0.5419063572241967

ExtraTrees	Range	Raw	30cm	10	B	5.6732287925851606e-14	0.4837153088336462	0.5839369882530152
AdaBoost	Frequency	Phase	30cm	50	B	0.1616703274746446	0.3067906714976357	0.6532215861299303
SVM	Frequency	Phase	30cm	500	B	0.093246	0.3457147434424899	0.6044971769069736
Lasso	Range	Raw	30cm	4096	B	0.044439	0.6061055014911682	0.5599118015432273
Ridge	Frequency	Raw	30cm	10	B	0.4470575213863823	0.3204220194549028	0.5747665778030551
ElasticNet	Range	Raw	30cm	4096	B	0.025427	0.5562340728340477	0.5643571550503665
XGBRegressor	Frequency	Phase	30cm	2000	B	0.000378	0.2622525769149622	0.5167246353474992
LinearRegression	Frequency	Phase	30cm	10	C	1.4151960465205755	438.1423509575957	0.9433811813896982
RandomForest	Frequency	Magnitude	30cm	1000	C	0.7145968511840893	2.0093547082956755	0.7925407126766391

GradientBoosting	Frequency	Phase	30cm	2000	C	0.003682	2.564081	0.987787
SVR	Range	Raw	30cm	10	C	1.499690615500126	1.8059658874717115	1.2479464762552577
MLP	Frequency	Magnitude	30cm	10	C	1.6816275345432912	1.7029918258846923	0.9407042886618988
KNN	Frequency	Phase	30cm	10	C	1.5806389355081831	1.7526123359145898	0.8722241684337814
ExtraTrees	Frequency	Raw	30cm	2000	C	3.6012321893809396e-14	2.1463321475251744	0.8927056835822188
AdaBoost	Range	Magnitude	30cm	4096	C	0.1341110050051103	2.1253662070240384	1.1805582557158676
SVM	Frequency	Phase	30cm	2000	C	0.098828	2.582912104156752	1.0041084849491515
Lasso	Range	Raw	30cm	10	C	1.1710011090383643	1.8415286670540156	0.9788193997207092
Ridge	Frequency	Magnitude	30cm	50	C	1.2995161371307324	1.953421721179948	0.8223911515386395

ElasticNet	Range	Raw	30cm	10	C	1.199438832158085	1.827279559386671	0.9594317455904602
XGBRegressor	Range	Magnitude	30cm	4096	C	0.000261	1.9084690626921876	0.9605293925563978
LinearRegression	Range	Magnitude	40cm	10	A	0.4457152242033577	1.9193091485563336	1.8824218656951663
RandomForest	Frequency	Magnitude	40cm	10	A	0.2336699803616845	1.631202365204878	2.203867537988612
GradientBoosting	Frequency	Raw	40cm	10	A	0.019908	1.841201851379633	2.294456
SVR	Frequency	Magnitude	40cm	10	A	0.642013	1.594972343138777	2.2422134936036464
MLP	Frequency	Magnitude	40cm	20	A	0.683902	2.029566844674328	1.948633289693175
KNN	Frequency	Magnitude	40cm	10	A	0.6014311635128695	1.6328732345163852	2.101651136606643
ExtraTrees	Frequency	Magnitude	40cm	10	A	6.177364447876705e-14	1.5787390340078369	2.299055594151643

AdaBoost	Frequency	Raw	40cm	20	A	0.174504	1.7320871529171804	2.2735917666997607
SVM	Range	Magnitude	40cm	10	A	0.5091727584531212	1.744855946507765	2.189025485789448
Lasso	Frequency	Phase	40cm	10	A	0.6043343432044491	1.5709330551228462	2.205906
Ridge	Range	Magnitude	40cm	10	A	0.4458403877643065	1.9144218750643331	1.9004197371660103
ElasticNet	Range	Magnitude	40cm	10	A	0.4793771356208341	1.8117658491092103	2.1997208604475973
XGBRegressor	Frequency	Magnitude	40cm	1000	A	0.000369	1.7333716509510413	2.1561364684849904
LinearRegression	Frequency	Raw	40cm	4096	B	1.6323592850267968e-14	1.5945455055677131	0.6264250262540167
RandomForest	Frequency	Phase	40cm	10	B	0.5250401770340998	0.7759514723872939	0.5625346378224247
GradientBoosting	Frequency	Phase	40cm	20	B	0.05938	0.8282920726352428	0.5894044243176602

SVR	Range	Raw	40cm	100	B	0.8283993159775306	0.7986810313677444	1.0598536257903295
MLP	Frequency	Phase	40cm	10	B	1.262579634668867	1.438167659888509	0.81376
KNN	Range	Raw	40cm	100	B	1.0425196507607035	0.8070393422875971	0.8683245361038703
ExtraTrees	Range	Phase	40cm	100	B	5.3840513305986836e-14	0.7683651068990552	0.9936745097113018
AdaBoost	Range	Phase	40cm	100	B	0.1877585126791617	0.5163796813741183	1.018948803737354
SVM	Frequency	Raw	40cm	4096	B	0.097979	1.4646246603175772	0.6830892540768214
Lasso	Frequency	Raw	40cm	4096	B	0.1846388713949585	1.317421069226213	0.6826827341480048
Ridge	Frequency	Raw	40cm	4096	B	6.383118119147653e-05	1.5944531648221385	0.6264536164969675
ElasticNet	Frequency	Raw	40cm	4096	B	0.1100638026756353	1.4898253469663705	0.6471072181601092

XGBRegressor	Frequency	Phase	40cm	100	B	0.000562	1.0736176410252318	1.0550880574283052
LinearRegression	Frequency	Magnitude	40cm	10	C	0.5805386950519528	0.5986757229586451	0.5669129392924247
RandomForest	Range	Phase	40cm	10	C	0.2919933051934369	0.5399204802561152	0.7019946358413245
GradientBoosting	Range	Phase	40cm	10	C	0.014683	0.6426745416430137	0.6369075800351799
SVR	Frequency	Magnitude	40cm	4096	C	0.3664815582387216	0.3910601464390477	0.7411426055306967
MLP	Frequency	Phase	40cm	10	C	1.1477356822983458	5.519907094243267	0.9679600639560508
KNN	Range	Magnitude	40cm	2000	C	0.6029165226906085	0.5522340989109621	0.7904745410195102
ExtraTrees	Frequency	Magnitude	40cm	4096	C	6.766756459892375e-14	0.4504387097597289	0.6323061956045962
AdaBoost	Range	Phase	40cm	10	C	0.2138575876770671	0.5542788275500713	0.6346066534973941

SVM	Frequency	Phase	40cm	1000	C	0.0989	0.5064859723575672	0.6520845719682261
Lasso	Frequency	Phase	40cm	1000	C	0.071252	0.7517213494132432	0.6075337245457948
Ridge	Range	Magnitude	40cm	100	C	0.000637	0.816214	0.6003910440111043
ElasticNet	Range	Raw	40cm	20	C	0.3162187258558846	0.2548491036490274	0.6222191323272201
XGBRegressor	Range	Phase	40cm	100	C	0.000381	0.3820890018373016	0.5805622696748597
LinearRegression	Range	Magnitude	All Depths	10	A	1.0966418969789136	2.1169169083021546	1.9019685286727608
RandomForest	Range	Magnitude	All Depths	500	A	0.4005972819324575	1.6099595928547323	1.9016837584591857
GradientBoosting	Range	Magnitude	All Depths	2000	A	0.000116	2.192063155483339	1.988972519845402

SVR	Frequency	Magnitude	All Depths	20	A	1.1519719648834206	2.1114364621721635	1.996620765059247
MLP	Frequency	Magnitude	All Depths	10	A	1.095905854187924	2.172650766221704	2.341719499358615
KNN	Frequency	Magnitude	All Depths	2000	A	1.121327338469905	2.0083007431657243	1.9306273268033896
ExtraTrees	Range	Magnitude	All Depths	1000	A	5.739737313350087e-14	1.5573790206826577	1.960560414938789
AdaBoost	Range	Magnitude	All Depths	2000	A	0.1097421124542717	1.7334435187238233	1.9972548685839056
SVM	Range	Magnitude	All Depths	50	A	0.166834	2.0222187909579774	2.0789561140906416

Lasso	Frequency	Phase	All Depths	10	A	1.047965109806155	1.8622805083457084	1.9877568312181528
Ridge	Range	Magnitude	All Depths	10	A	1.096712549689246	2.117717330144321	1.9075996395494863
ElasticNet	Frequency	Phase	All Depths	10	A	1.0469540010821945	1.8653513741296268	1.987495
XGBRegressor	Range	Magnitude	All Depths	1000	A	0.000299	1.7950929894490508	1.9911127542788016
LinearRegression	Frequency	Magnitude	All Depths	4096	B	7.799355160121197e-15	1.4673340228997305	0.9071936259224798
RandomForest	Frequency	Phase	All Depths	50	B	0.5285279675665243	1.1220600439314743	0.8633417224294822

GradientBoosting	Frequency	Phase	All Depths	100	B	0.016143	1.2256022830569413	0.8491659539570483
SVR	Frequency	Raw	All Depths	50	B	1.2531846512599332	1.541455732673341	1.0284842729670478
MLP	Frequency	Magnitude	All Depths	10	B	0.961276	2.183085456319924	1.3092208441515976
KNN	Frequency	Phase	All Depths	20	B	1.1746831724152498	1.269427774629183	0.8450351324057479
ExtraTrees	Frequency	Phase	All Depths	100	B	0.001532	0.9802812614563704	0.8933794773918865
AdaBoost	Frequency	Phase	All Depths	4096	B	0.1433369050372465	1.1215368274893007	0.8919541934649378

SVM	Frequency	Magnitude	All Depths	4096	B	0.096824	1.389090502015466	0.9122533613398404
Lasso	Frequency	Raw	All Depths	10	B	1.2128362716991623	1.320393496695868	0.947461
Ridge	Frequency	Magnitude	All Depths	4096	B	4.794470820201292e-05	1.4672880973245186	0.9071685774954706
ElasticNet	Frequency	Raw	All Depths	10	B	1.2107725893222607	1.325434470368175	0.9403866720350724
XGBRegressor	Frequency	Raw	All Depths	50	B	0.000528	1.2777459253123535	0.8141779276009659
LinearRegression	Frequency	Phase	All Depths	1000	C	6.045705523364516e-15	1.440697708486255	1.0494761447791523

RandomForest	Frequency	Magnitude	All Depths	2000	C	0.4551839982053648	1.203557380097643	0.999281
GradientBoosting	Frequency	Magnitude	All Depths	4096	C	0.000913	1.1381820604991737	1.0263604012717662
SVR	Frequency	Phase	All Depths	20	C	0.9818631550494034	1.1191751828498022	1.1095534139397634
MLP	Frequency	Phase	All Depths	10	C	1.0787459223363216	1.809992585717141	1.0912745507838817
KNN	Frequency	Phase	All Depths	10	C	1.0374822622312363	1.1858422639626227	0.9726606551105074
ExtraTrees	Frequency	Phase	All Depths	2000	C	4.3390644465454556e-14	1.373971919632095	1.0508474184556875

AdaBoost	Frequency	Phase	All Depths	10	C	0.5323850729572529	1.460340102100942	1.0940807456154686
SVM	Frequency	Phase	All Depths	1000	C	0.099514	1.4268032443735466	1.0429471713856593
Lasso	Frequency	Phase	All Depths	20	C	0.894852	1.2575963803847243	1.0015995603771926
Ridge	Frequency	Phase	All Depths	20	C	0.8405291557038305	4.076037807313566	0.9960738703352212
ElasticNet	Frequency	Phase	All Depths	20	C	0.891541	1.3590309369221352	1.0003051019616456
XGBRegressor	Range	Magnitude	All Depths	4096	C	0.000282	1.2326822572673526	1.0592983926121602