SPATIAL-TEMPORAL DEEP LEARNING MODEL FOR PREDICTING PARTICULATE MATTER 2.5 (PM2.5) IN SRI LANKAN URBAN CITIES

Project Report - Group 11

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ABSTRACT

Air pollution, particularly from fine particulate matter (PM2.5), presents a critical challenge in urban areas worldwide, including Sri Lanka. This research project endeavors to develop a spatial-temporal deep learning model specifically tailored for predicting PM2.5 concentrations in Sri Lankan urban environments. Given the severe health and environmental ramifications associated with PM2.5 pollution, accurate forecasting and understanding of its distribution are imperative. Our objectives encompass the development of a robust predictive model employing advanced deep learning techniques. Additionally, we aim to extend the model's applicability to regions lacking sensor networks by leveraging satellite imagery data. The overarching goal is to provide actionable insights crucial for public health interventions and urban planning initiatives. Through our research, we seek to contribute significantly to efforts aimed at enhancing public health, guiding sustainable urban development practices, and fostering environmental stewardship in Sri Lanka.

This study entails a comprehensive exploration of PM2.5 concentrations across urban areas in Sri Lanka. We conduct extensive experiments involving various statistical and deep learning models to ascertain the most effective predictive approach. Our methodology involves evaluating the performance of traditional statistical models such as Autoregressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA) in conjunction with state-of-the-art deep learning architectures including Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU). Through rigorous analysis and comparative assessment, we aim to identify the model that offers superior predictive accuracy and generalizability.

The outcomes of our research are anticipated to yield significant benefits for Sri Lanka's urban communities and environmental management initiatives. By harnessing cutting-edge machine learning methodologies and satellite-based technologies, we aim to deliver actionable insights that empower decision-makers to enact targeted interventions aimed at mitigating PM2.5 pollution and fostering sustainable urban development. Through collaborative efforts with stakeholders, our research endeavors to drive positive change, promote public health, and safeguard the environment for current and future generations in Sri Lanka.

ACKNOWLEDGEMENTS

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER ONE

INTRODUCTION

1.1 Background Information

Air pollution is a significant environmental issue with significant implications for human health and the well-being of the ecosystem worldwide. Among the various pollutants of concern, Particulate Matter 2.5 (PM2.5) stands out as a particularly harmful component due to its ability to penetrate deep into the respiratory system and cause a range of health problems, including respiratory and cardiovascular diseases. Particulate Matter 2.5 (PM2.5), a type of fine particulate matter with a diameter of 2.5 micrometers or less, is a complex mixture of solid and liquid particles suspended in the air, with sources including vehicle emissions, industrial processes, construction activities, and biomass burning. In urban areas, where population density and economic activities are high, PM2.5 pollution levels often exceed regulatory standards, posing a significant threat to public health.

Sri Lanka, like many other countries, faces the challenge of air pollution in its urban centers. Rapid urbanization, industrialization, and increased vehicular traffic have led to an increase in air pollution in cities across the country. The adverse health effects of PM2.5 pollution are well affected in these urban areas, where populations are densely concentrated.

The methodology of this study began with the collection of data from a sensor network that consists of 18 stations positioned throughout Sri Lanka. After the data collecting phase, data analysis and preprocessing were done to ensure data quality and get a basic understanding of the dataset. We were able to find some correlation among the data in between some stations. Both traditional machine learning techniques such as ARIMA and SARIMA, as well as advanced deep learning methodologies including LSTM and GRU are used to build a predictive model. After evaluating various approaches, we selected the most effective method to forecast future data trends. Furthermore, we are willing to use satellite imagery to supplement ground-based sensor data, providing a more comprehensive understanding of spatial-temporal variations in PM2.5 concentrations.

1.2 Significance of the project

This research project aims to address the need for improved prediction and understanding of PM2.5 concentrations in Sri Lankan urban cities. By using advanced techniques like spatial-temporal deep learning, along with satellite images and sensor readings, to create a system that can predict PM2.5 levels and find where pollution might be coming from. This study is significance because it could help improve public health, urban planning, and environmental protection in Sri Lanka.

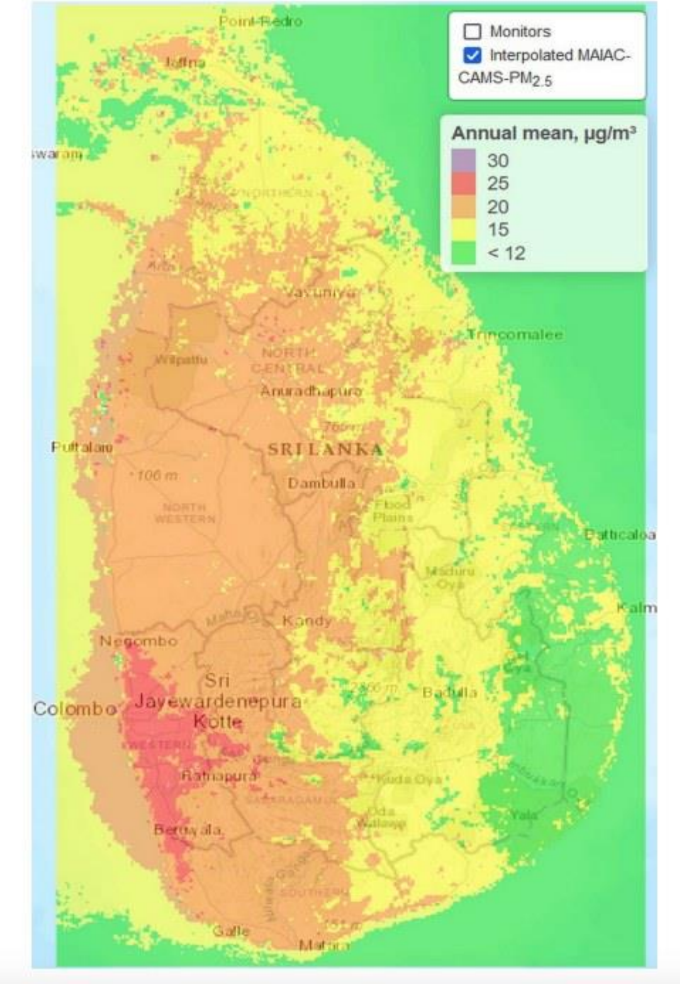


Figure 1.1: $PM_{2.5}$ concentrations at 1 km intervals over Sri Lanka.[1]

1.3 Aim

The aim of this project is to predict and understand the distribution of Particulate Matter 2.5 (PM2.5) in Sri Lankan urban cities, providing actionable insights to protect public health, guide urban planning, and pave the way for cleaner, more sustainable urban environments.

1.4 Objectives

- To develop a powerful predictive model using deep learning techniques for accurate insights into PM2.5 concentrations in Sri Lankan urban cities, helping us identify trends, patterns, and potential sources of air pollution.
- To extend our model's predictive capabilities to areas without sensor networks using satellite imagery and advanced deep learning techniques. This will enable us to provide air quality information even in locations where traditional sensor networks are not available.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

A literature review allows us to gain a comprehensive understanding of the current state of knowledge in the field, encompassing previous studies, methodologies, and findings related to PM2.5 prediction and spatial-temporal modeling. Furthermore, reviewing literature allows us to identify best practices, challenges, and lessons learned from previous studies and analytical approaches that are informed by the experiences of others.

2.2 Existing models

2.2.1 Introduction

Recently, deep learning has become increasingly widely used in the fields of artificial intelligence and big data. The reason is that it can learn effective feature representations from a large amount of input data and excavate the profound features of the data. Hence, the study of urban air quality concentration prediction based on deep learning has been popularized in research. At present, the PM2.5 prediction model is primarily divided into the classic model of time series estimation and the combined model of the spatiotemporal forecast. Existing time-series models, like the auto-regressive integrated moving average model (ARIMA), seasonal ARIMA can capture the temporal dependencies very well. Recurrent neural networks (RNNs) have been used successfully for sequence learning tasks. The incorporation of long short-term memory (LSTM), or gated recurrent unit (GRU), enables RNNs to learn long-term temporal dependency. For capturing the spatial variations of the PM2.5 concentration models such as CNNs are widely used. CNNs can be combined with other types of RNN architectures, to create hybrid models that capture both spatial and temporal dependencies in the PM2.5 data.

2.2.2 LSTM-CNN models

LSTM networks are a specialized type of recurrent neural network (RNN) architecture that excels at modeling sequential data, making them well-suited for time series forecasting tasks such as predicting PM2.5 concentrations. By leveraging the memory capabilities of LSTM units, the model can effectively capture complex temporal patterns and dependencies in the PM2.5 data. According to the study, the most common and widely used model for capturing the spatial and temporal variations in the PM2.5 data is the LSTM-CNN model.

The LSTM-CNN model is used most of the time with different improvements to the LSTM-CNN model. Some models have used batch normalization, Scaled Exponential Linear Units (SELU), and early stopping techniques to improve the training efficiency and accuracy.[1]

Another research used mutual information (MI) estimator to select the spatiotemporal feature vector(STFV) that reflects both linear and nonlinear correlations between the target PM2.5 concentration. These improvements to the model have improved the stability and prediction performance of the model.[2]

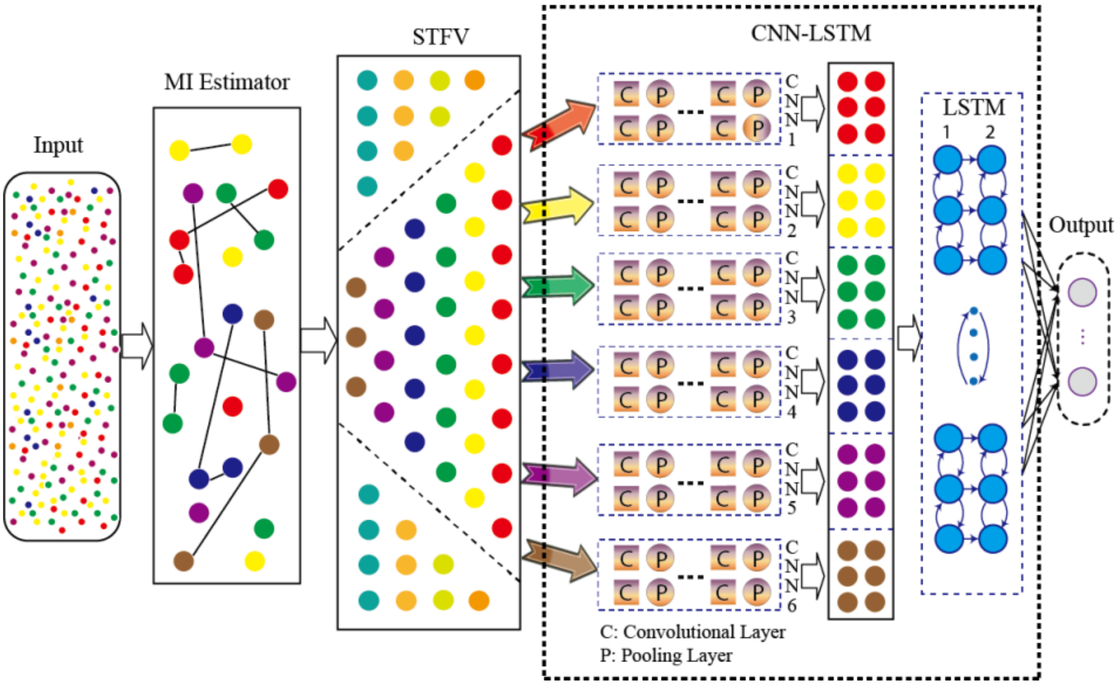


Figure 2.1: CNN-LSTM model

2.2.3 GRU-CNN model

GRUs are a type of recurrent neural network (RNN) architecture, similar to Long Short-Term Memory (LSTM) units, designed to address the vanishing gradient problem commonly encountered in traditional RNNs. GRUs are particularly well-suited for modeling sequential data with long-range dependencies, making them ideal for tasks such as time series forecasting. The combined GRU-CNN model is also a common method used in the spatial-temporal PM2.5 forecasting models.

A PM2.5 prediction research based on the GRU-CNN model used air pollution and meteorological data from several stations in Tehran, Iran, and learned the spatial and temporal patterns of PM2.5 using 3D CNN and GRU layers. The model also uses dynamic time warping (DTW) to find the most similar stations and process them together. Also, this model has achieved good results compared to LSTM-CNN models.[3]

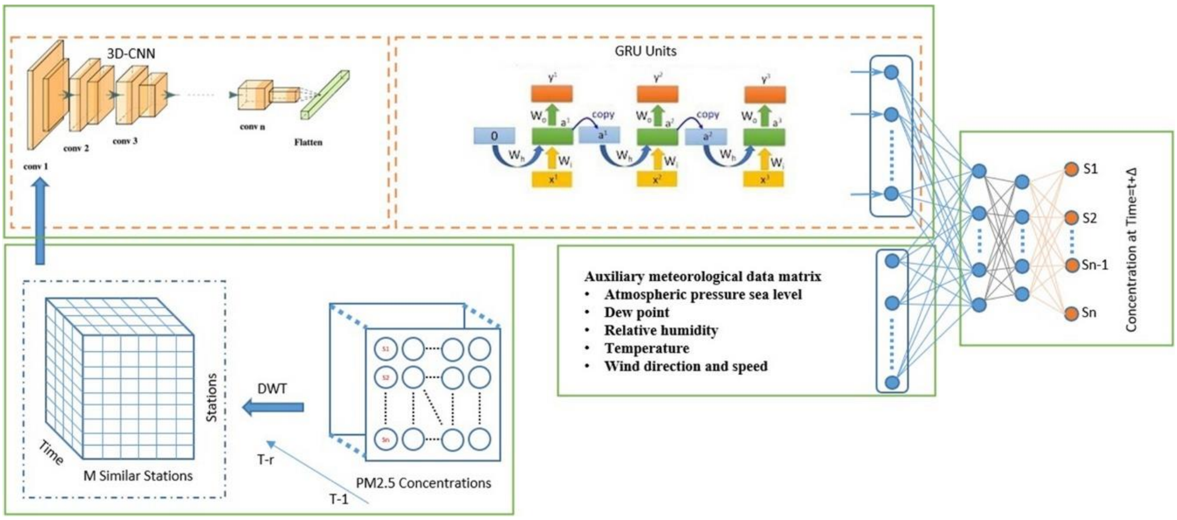


Figure 2.2: 3D CNN-GRU model

2.2.4 RF-CNN model

Random forest is a strong ensemble learning algorithm which, well-known for its adaptability and durability when working with complex datasets. The RF combined with CNN can be used for spatial-temporal PM2.5 forecasting models.

Some researchers have tried the RF-CNN models for forecasting PM2.5 concentrations, The RF part uses temperature, relative humidity and sea-level pressure to predict a PM2.5 baseline map, while the CNN part uses high-resolution satellite images to predict the PM2.5 residuals at a 300 m resolution. The final PM2.5 map is obtained by adding the RF-predicted baseline and the CNN-predicted residual.[4]

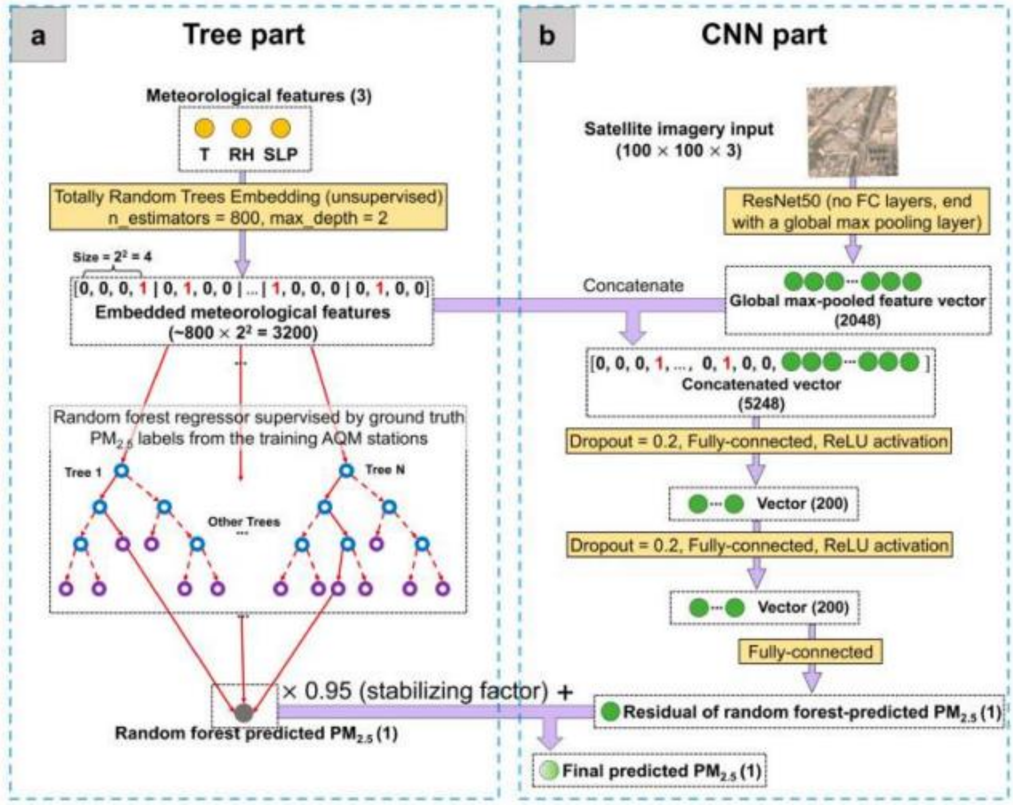

a
Tree part
Meteorological features (3)
T RH SLP
Totally Random Trees Embedding (unsupervised) n_estimators = 800, max_depth = 2
Size = 2² = 4
[0, 0, 0, 1 | 0, 1, 0, 0 | ... | 1, 0, 0, 0 | 0, 1, 0, 0]
Embedded meteorological features (~800 × 2² = 3200)
Random forest regressor supervised by ground truth PM2.5 labels from the training AQM stations
Tree 1
Other Trees
Tree N
× 0.95 (stabilizing factor) +
Random forest predicted PM2.5 (1)
b
CNN part
Satellite imagery input (100 × 100 × 3)
ResNet50 (no FC layers, end with a global max pooling layer)
Concatenate
Global max-pooled feature vector (2048)
[0, 0, 0, 1, ..., 0, 1, 0, 0, ...]
Concatenated vector (5248)
Dropout = 0.2, Fully-connected, ReLU activation
Vector (200)
Dropout = 0.2, Fully-connected, ReLU activation
Vector (200)
Fully-connected
Residual of random forest-predicted PM2.5 (1)
Final predicted PM2.5 (1)

Figure 2.3: The RF–CNN joint model

2.3 Validation Methods

2.3.1 Mean Absolute Error (MAE)

Mean Absolute Error (MAE) is a metric used to evaluate the accuracy of a predictive model. It measures the average absolute difference between the predicted values and the actual values. The formula for Mean Absolute Error is:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}(y_i - ý)$$

where n is the number of observations or data points, y_i is the actual or observed value for the i-th data point and ý is the predicted value for the i-th data point.

MAE provides a simple and intuitive measure of how well a model is performing in terms of absolute errors. It is expressed in the same units as the original data, making it easy to interpret. A lower MAE indicates better accuracy, as it means the model's predictions are closer to the actual values on average.

2.3.2 Root Mean Square Error (RMSE)

Root Mean Squared Error (RMSE) is another metric used to evaluate the accuracy of a predictive model. It is similar to Mean Absolute Error (MAE) but gives more weight to larger errors by taking the square root of the average of squared differences between the predicted values and the actual values. The formula for RMSE is:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - ý)^2}$$

Where n is the number of observations or data points, y_i is the actual or observed value for the i-th data point and ý is the predicted value for the i-th data point.

The main difference between MAE and RMSE lies in the squaring of the errors in RMSE. Squaring the errors penalizes larger errors more heavily than smaller errors. RMSE is useful when you want to give more importance to outliers or significant deviations between predicted and actual values.

CHAPTER THREE

METHODOLOGY

3.1 Introduction

This chapter describes the main steps of the methodology of this research and the overall flowchart of the methodology is given in Figure 3.1.

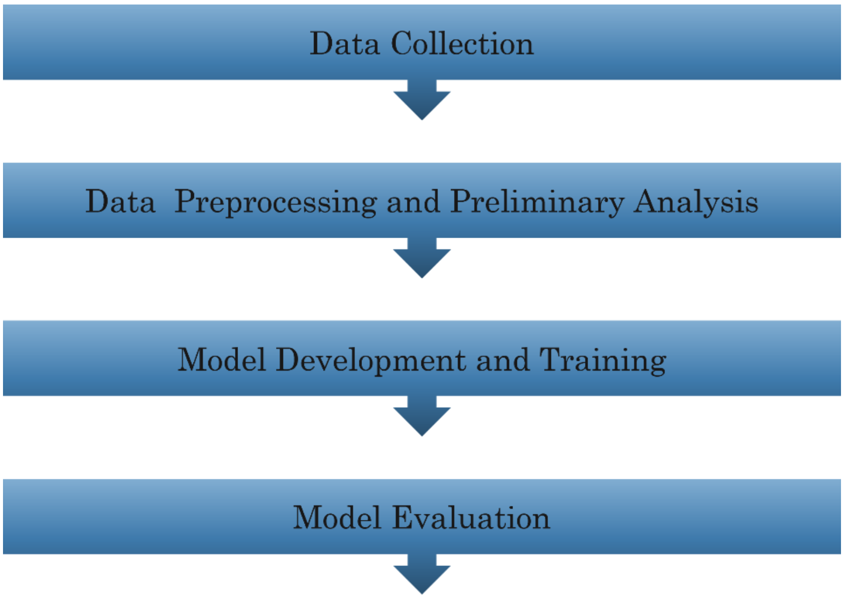

Data Collection
Data Preprocessing and Preliminary Analysis
Model Development and Training
Model Evaluation

Figure 3.1: Overall flowchart of the methodology

3.2 Data collection

Data collection is the first step of the methodology. Data used for this project are collected our data using a network of 18 stations located throughout Sri Lanka. These stations are situated in various cities including Ampara, Batticaloa, Colombo Fort, Battaramulla, Katubedda, Galle, Hambantota, Matara, Jaffna, Mannar, Kandy, Kilinochchi, Kanthale, Polonnaruwa, Anuradhapura, Mulativu, and Pointpedro. Hourly data on PM2.5 levels was collected using Bluesky Air quality monitors installed at these stations.

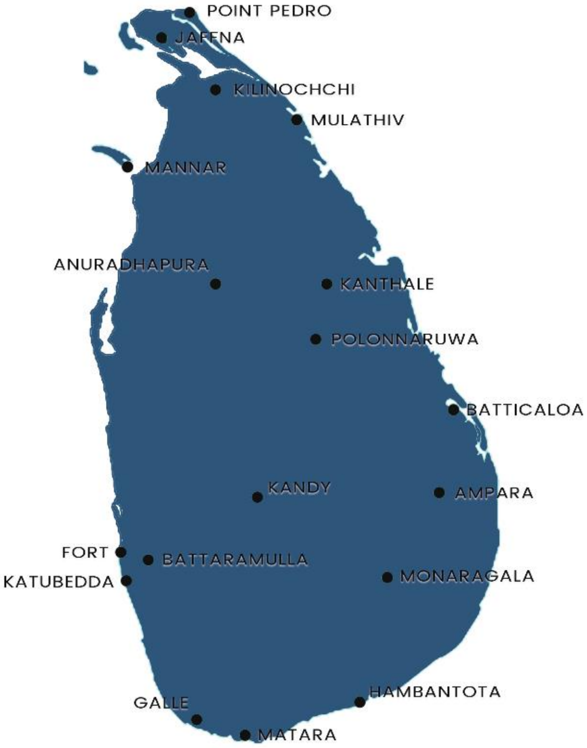


Figure 3.2: Locations of the Stations of the Sensor Network

3.3 Data Preprocessing and Preliminary Analysis

3.3.1 Introduction

After collecting data, it is essential to perform preprocessing and preliminary analysis on the collected data to ensure that the data is clean, consistent, and appropriately formatted, laying a solid foundation for accurate modeling and analysis. By detecting and handling missing values, and outliers, preprocessing mitigates the risk of biased or misleading results, thereby enhancing the reliability and validity of the data. preliminary analysis, including correlation analysis, clustering, and seasonal, trend pattern identification, offers valuable insights into the spatial and temporal dynamics of PM2.5 pollution. Also, preprocessing s allows us to normalize the data, ensuring that features are on a comparable scale and optimizing the performance of the model.

3.3.2 Preprocessing

3.3.2.1 Outlier detection and treatment

There are different techniques to remove outliers. As the first step, the data points which deviate significantly from the majority of the data can be removed from the visual inspection. In advance, statistical methods such as the z-score method and inter-quartile range (IQR) method can be used to remove outliers. Also, there are machine learning algorithms like K-Nearest neighbor and isolation forest.

The Z-score method is a statistical approach employed for detecting and eliminating outliers within a dataset. This technique involves calculating the mean and standard deviation of the dataset, and then determining the Z-score for each data point by measuring its deviation from the mean in terms of standard deviations. By setting a predefined threshold, often at Z-scores beyond 3 or -3, data points that fall significantly outside the expected range are identified as outliers. Because most of the peak events were considered as the outliers. this method was not suitable for the PM2.5 data set. In the following figure, marked red points are the outliers identified using the Z-score method.

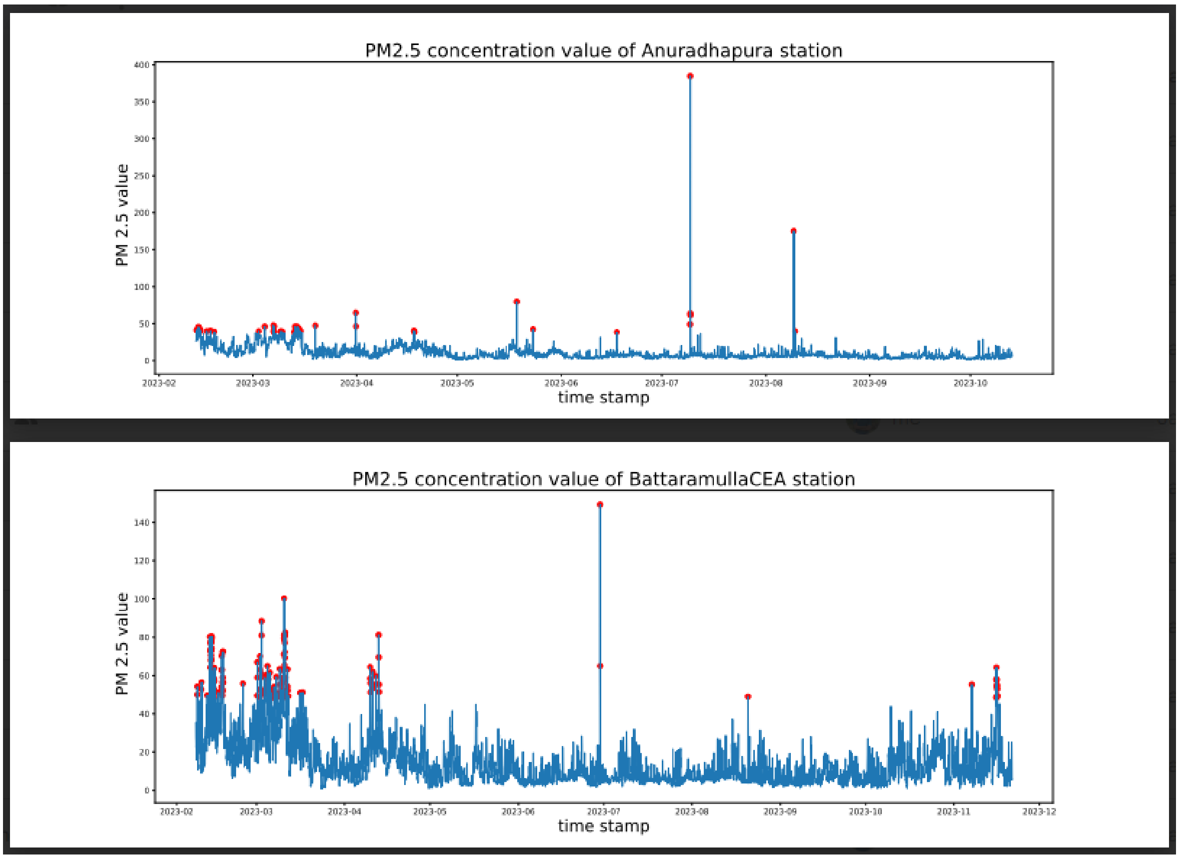


Figure 3.3: Detected outliers using the Z-score method in Anuradhapura and Battaramulla

Then K-Nearest neighbor method was considered. In this method, it identifies the outliers by measuring the distance between each data point and its K nearest neighbors. By setting a predefined threshold, if the distance is greater than the defined threshold data point is treated as an outlier. This method showed comparatively better results, it only detected very high erroneous values as outliers. In the following figure, marked red points are the outliers identified using the KNN method.

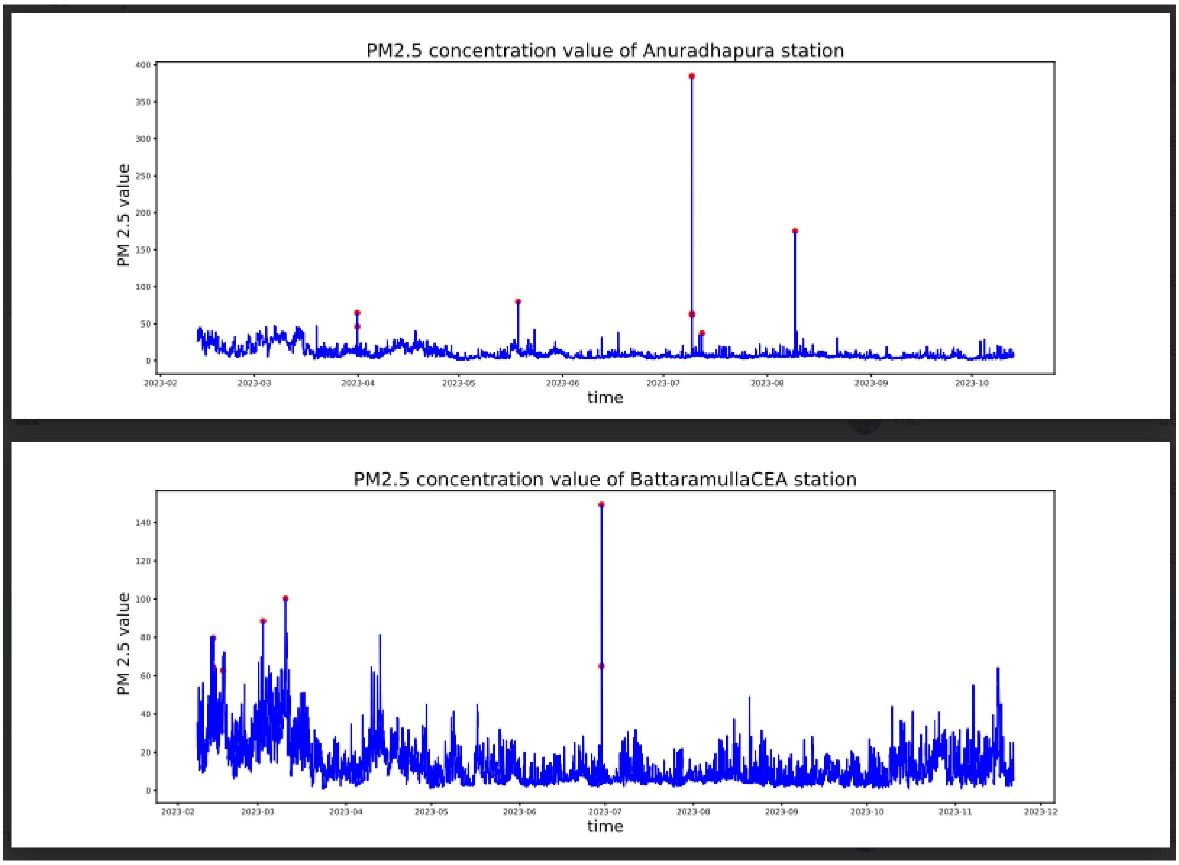
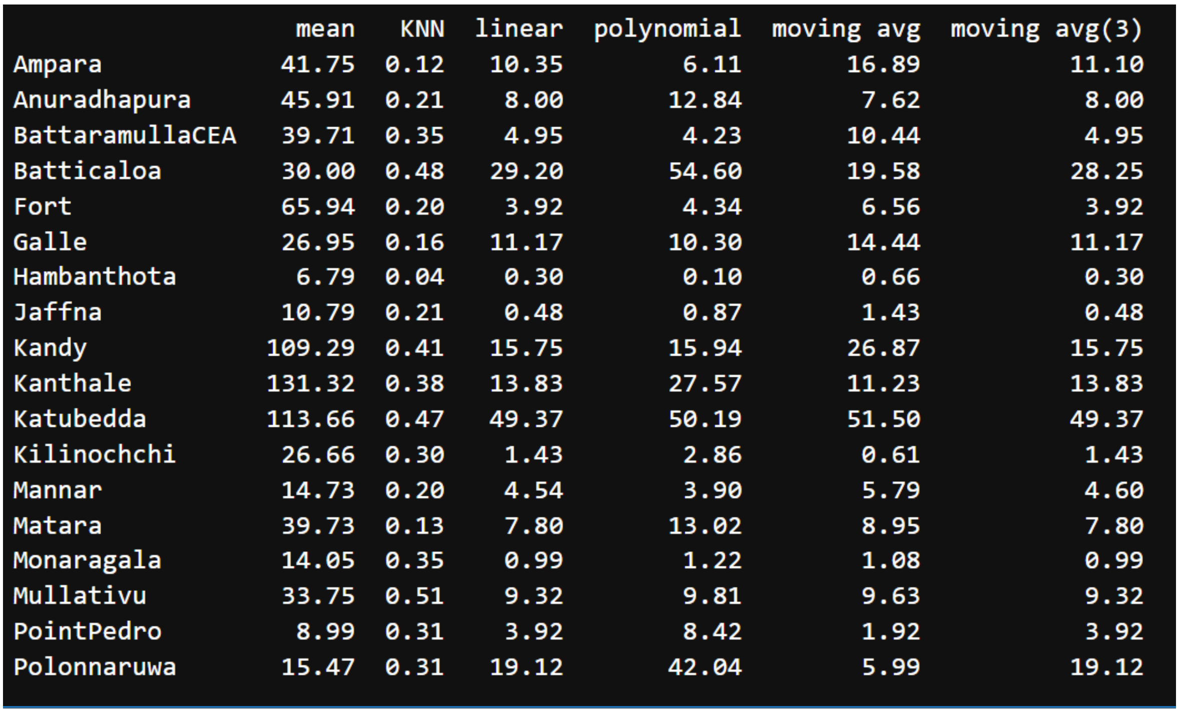


Figure 3.4: Detected outliers using the KNN method in Anuradhapura and Battaramulla

After identifying outliers next step is to choose a method to impute those outliers. For that several methods have been used,

1. filling the outliers using the mean of the PM2.5
2. KNN imputation
3. linear interpolation
4. polynomial interpolation
5. Moving average method

To assess the efficacy of these methods, a randomly selected dataset is chosen, and outliers are imputed using each of the mentioned techniques. Subsequently, the Mean Square Error (MSE) is calculated for each method as a metric for evaluating imputation accuracy. The method yielding the lowest MSE is identified as the optimal approach for outlier imputation in our dataset.



```
                   mean   KNN  linear  polynomial  moving avg  moving avg(3)
Ampara            41.75  0.12   10.35        6.11       16.89          11.10
Anuradhapura      45.91  0.21    8.00       12.84        7.62           8.00
BattaramullaCEA   39.71  0.35    4.95        4.23       10.44           4.95
Batticaloa        30.00  0.48   29.20       54.60       19.58          28.25
Fort              65.94  0.20    3.92        4.34        6.56           3.92
Galle             26.95  0.16   11.17       10.30       14.44          11.17
Hambanthota        6.79  0.04    0.30        0.10        0.66           0.30
Jaffna            10.79  0.21    0.48        0.87        1.43           0.48
Kandy            109.29  0.41   15.75       15.94       26.87          15.75
Kanthale         131.32  0.38   13.83       27.57       11.23          13.83
Katubedda        113.66  0.47   49.37       50.19       51.50          49.37
Kilinochchi       26.66  0.30    1.43        2.86        0.61           1.43
Mannar            14.73  0.20    4.54        3.90        5.79           4.60
Matara            39.73  0.13    7.80       13.02        8.95           7.80
Monaragala        14.05  0.35    0.99        1.22        1.08           0.99
Mullativu         33.75  0.51    9.32        9.81        9.63           9.32
PointPedro         8.99  0.31    3.92        8.42        1.92           3.92
Polonnaruwa       15.47  0.31   19.12       42.04        5.99          19.12
```

Figure 3.5: Data acquired using the KNN method in all stations

According to the figure above KNN imputation consistently shows superior results in terms of imputation accuracy. As a result, KNN imputation was used as the preferred approach for handling outliers in our PM2.5 dataset.

3.3.3 Preliminary analysis

3.3.3.1 Correlation between stations

Identifying correlations between stations allows us to understand the spatial relationships and dependencies among different monitoring locations. By quantifying the degree of correlation between PM2.5 concentrations measured at various stations, we can discern spatial patterns of pollution distribution. This knowledge is invaluable for clustering the stations.

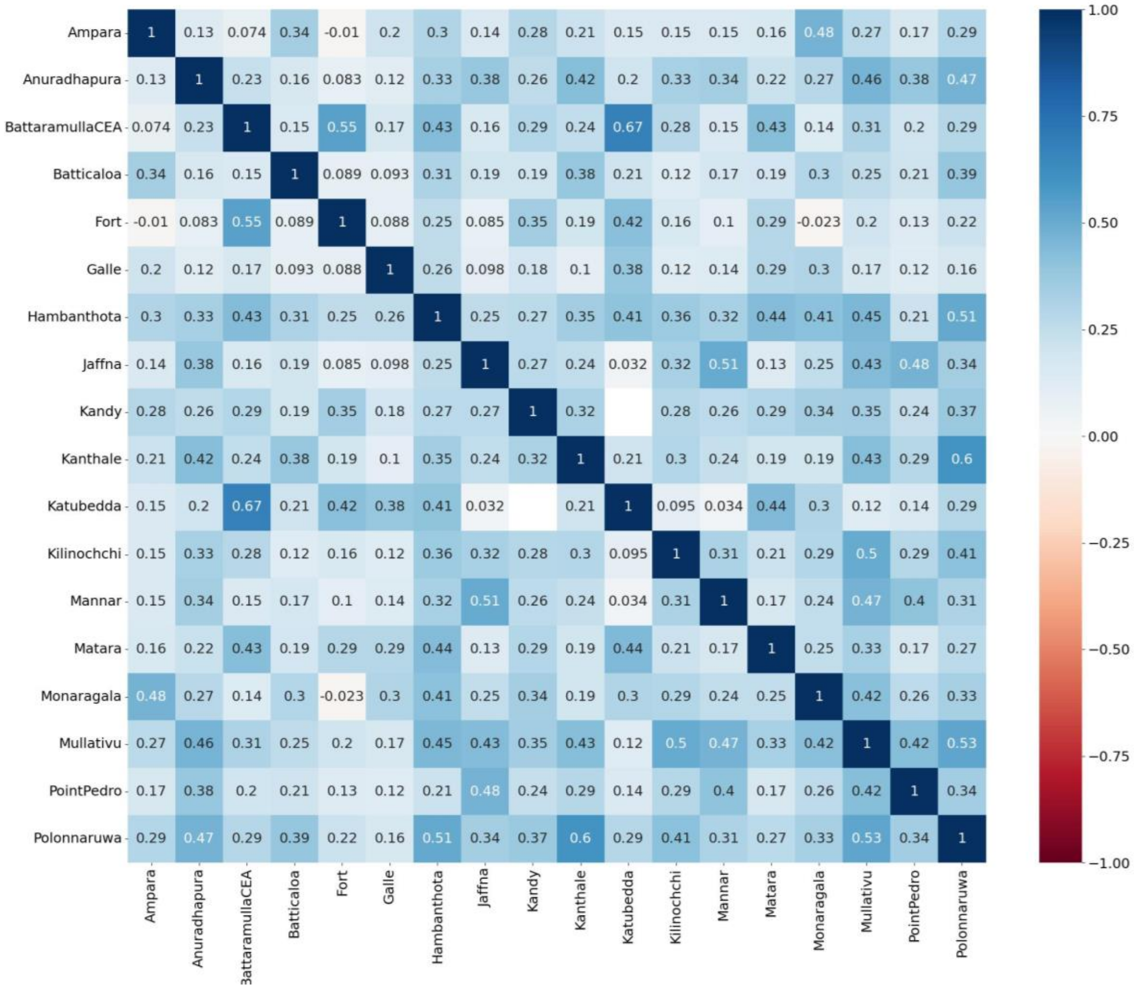


Figure 3.6: Correlation coefficients between the stations

The figure above shows the correlation coefficient values between different stations according to the above figure ‘Battaramulla’ and ‘Katubedda’ stations show the highest correlation coefficient value of 0.67. When analyzing the correlation coefficient values it can be observed that stations located closer to each other tend to have higher correlation coefficients. This can be due to the reason, stations that are close to each other often share similar environmental characteristics, such as local weather patterns, and topographical features.

3.3.3.2 Clustering the stations for modeling

Clustering the stations serves several important purposes in our research project on predicting PM2.5 concentrations. Since the lack of data in certain stations clustering the stations can used to increase the number of data points and it helps in mitigating overfitting, a common challenge in DL models.

By providing a larger and more diverse training dataset, clustering helps in regularizing the model and improving its ability to generalize to unseen data. This leads to DL models that are more robust and reliable in making predictions.

For clustering of the stations dendrogram chart was used.it is a hierarchical tree-like diagram commonly used in clustering analysis to visualize the arrangement of clusters and their relationships. In these algorithms correlation coefficient between stations is used for clustering the stations.

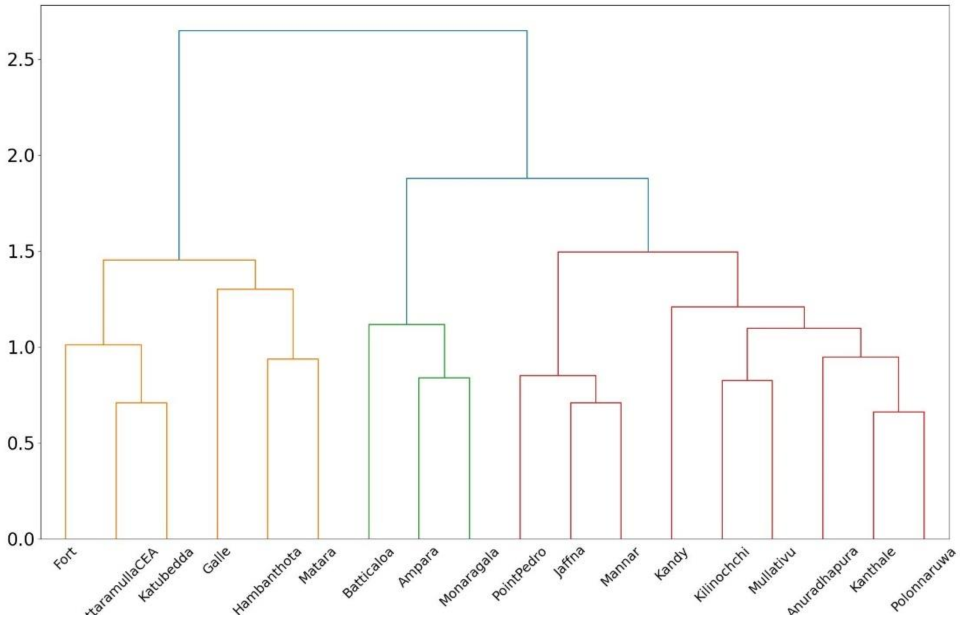


Figure 3.7: Dendrogram chart

In the above figure, each vertical line segment represents a cluster, and the height of the line indicates the distance at which clusters were merged. So the clusters having low distance values have a high correlation. By defining the threshold values all stations can be divided into clusters. According to the above chart, all stations can be divided into 3 main clusters.

1. cluster 1 - Ampara , Batticaloa , Ampara
2. cluster 2 - Colombo Fort, Battaramulla , Katubedda , Galle , Hambanthota , Matara
3. cluster 3 - Jaffna , Mannar , Kandy , Kilinochchi ,Kanthale, Polonnaruwa, Anuradhapura, Mulativu, Pointpedro

3.4 Model development

We used a wide range of forecasting techniques during the model selection phase to determine the best method for predicting PM2.5 levels. In particular, we trained and implemented six different models: the Gated Recurrent Unit (GRU), the Long Short-Term Memory (LSTM), Random Forest and the Seasonal Autoregressive Integrated Moving Average (SARIMA), Exponential Smoothing (ETS) and the Autoregressive Integrated Moving Average (ARIMA). Because each of these models has distinct qualities and abilities, we are able to thoroughly assess how well they handle the intricate temporal dependencies present in PM2.5 data.

Exploring statistical and deep learning methods for PM2.5 prediction provides a more comprehensive approach. Statistical methods provide interpretability, robustness to noise, and computational efficiency, making them appropriate for understanding linear relationships in data and dealing with irregular real-world datasets. However, they may struggle with nonlinear dynamics, necessitating manual feature engineering. Deep learning methods excel at automatically capturing complex nonlinear relationships and long-term dependencies, but they are difficult to interpret, require significant computational resources, and may necessitate a large amount of training data. By combining the strengths of both approaches, we hope to improve the accuracy and robustness of PM2.5 prediction models while addressing their respective limitations.

Choosing the best model for PM2.5 prediction requires a thorough evaluation process. We start by defining relevant evaluation metrics and categorizing the dataset as training, validation, and test sets. Each candidate model is then trained and validated on the relevant datasets, with hyperparameters fine-tuned as necessary. The model with the best overall performance is chosen, taking into account predictive accuracy, interpretability, computational efficiency, and generalization to previously unseen data. Sensitivity analysis ensures that the chosen model is robust, while thorough documentation and reporting provide transparency and reproducibility. This systematic approach ensures that the selected model effectively addresses the challenges of PM2.5 prediction while also meeting the project's objectives.

3.4.1 Statistical Models

3.4.1.1 ARIMA Model

The Autoregressive Integrated Moving Average (ARIMA) model is a popular statistical method for forecasting time series data. It combines three main components to capture the temporal structure of the data.

- Autoregression (AR): This component represents the relationship between an observation and a series of lagged observations (its own past values). The AR component of ARIMA represents the linear relationship between the current observation and its lag values. The 'p' parameter specifies the order of the autoregressive component, which determines how many lagged observations are included in the model.

- Integration (I): This component entails differencing the time series data to achieve stationarity. Stationarity indicates that the statistical properties of the series (such as mean and variance) remain constant over time. The 'd' parameter in ARIMA represents the amount of differencing needed to make the series stationary.

- Moving Average (MA): This component represents the relationship between an observation and a residual error obtained from a moving average model applied to lagged observations. The MA component of ARIMA captures short-term effects in the data, which helps to smooth out any random fluctuations. The 'q' parameter indicates the order of the moving average component, which determines how many lagged forecast errors are included in the model.

Finding the parameters (p, d, and q) for an ARIMA model usually starts with a visual inspection of the time series data to identify patterns and trends, followed by an examination of autocorrelation and partial autocorrelation plots to determine the values of p and q. The order of differencing (d) required to achieve stationarity is determined by examining the data's trend and seasonality. While this process can be manual and iterative, built-in Python libraries like pmdarima provide automated methods for determining the optimal parameters.

These libraries use advanced algorithms and statistical techniques to efficiently search through various parameter combinations and select the most appropriate.

3.4.1.2 SARIMA Model

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model is an extension of the ARIMA model that incorporates seasonality into the forecasting process. In addition to the autoregressive (AR), differencing (I), and moving average (MA) components present in ARIMA, SARIMA also includes seasonal AR, seasonal differencing, and seasonal MA terms.

- Seasonal Autoregression (SAR): SAR terms capture the relationship between an observation and its lagged values at seasonal intervals. This accounts for the seasonal patterns and cyclicality present in the data.

- Seasonal Integration (SI): Similar to the non-seasonal differencing in ARIMA, seasonal differencing (SI) is applied to the time series data to remove any seasonal trends and achieve stationarity.

- Seasonal Moving Average (SMA): SMA terms model the relationship between an observation and the residual errors from the seasonal moving average model applied to lagged observations. This helps capture the short-term fluctuations and noise in the seasonal component of the data.

The seasonal components (P, D, Q) of SARIMA mirror the non-seasonal components (p, d, q) but apply to the seasonal variations in the data. Finding the optimal parameters for SARIMA involves a similar process of data analysis, visualization, and model evaluation as with ARIMA. However, SARIMA requires additional consideration of seasonal patterns and trends, making it particularly suitable for time series data with clear seasonal variations

3.4.1.3 ETS Model

Exponential Smoothing is a widely used method for time series forecasting that assigns exponentially decreasing weights to past observations. Unlike ARIMA or SARIMA models, Exponential Smoothing does not require the data to be stationary or possess explicit seasonality.

The basic idea of Exponential Smoothing is to generate forecasts by combining the weighted sum of past observations with a smoothing parameter (alpha) that controls the rate at which the weights decrease exponentially. The most common form of Exponential Smoothing is Simple Exponential Smoothing, which is suitable for time series data without any trend or seasonality.

In Simple Exponential Smoothing, forecasts are generated by updating the exponentially weighted average of past observations using the formula:

$$\hat{Y}_{t+1} = \alpha \, Y_t + (1-\alpha) \, \hat{Y}_t$$

$\hat{Y}_{t+1}$ is the forecast for the next time period.

Y_t is the actual observation at time period

$\hat{Y}_t$ is the forecast for time period

α is the smoothing parameter, also known as the smoothing factor or smoothing constant. It controls the rate at which the weights decrease, typically ranging from 0 to 1. One of the advantages of Exponential Smoothing is its simplicity and ease of implementation. It is computationally efficient and can handle time series data with irregular patterns or short-term fluctuations. However, it may not perform well for data with complex trends or seasonality.

3.4.2 DEEP LEARNING MODELS

3.4.2.1 LSTM Model

Long Short-Term Memory (LSTM) is a recurrent neural network (RNN) architecture that can effectively model and predict sequential data, making it ideal for time series forecasting tasks. Unlike traditional feedforward neural networks, which process input data in a single pass, LSTM networks use feedback connections to retain and process information over time, allowing them to detect long-term dependencies in sequential data.

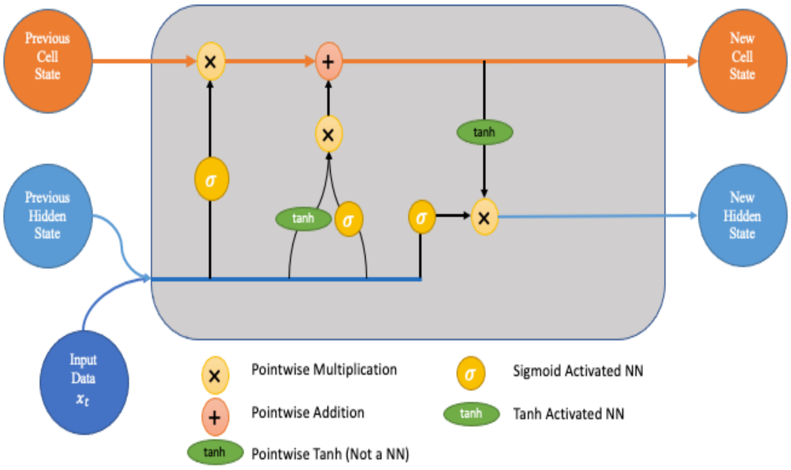


Figure 3.8 : Long Short Memory Model Architecture

The key components of an LSTM network include:

Memory Cells: LSTM networks contain memory cells that can store information over long periods of time. These memory cells are equipped with gating mechanisms that control the flow of information into and out of the cell, allowing the network to learn which information to remember or forget.

Gates: LSTM networks have three types of gates: input gates, forget gates, and output gates.

Input gates regulate the flow of new information into the memory cell.
Forget gates control the retention or removal of information from the memory cell.
Output gates determine the output of the memory cell.
Hidden States: LSTM networks maintain hidden states, which are updated based on the input data and the current state of the memory cells. These hidden states capture the network's learned representation of the input sequence and are used to make predictions.

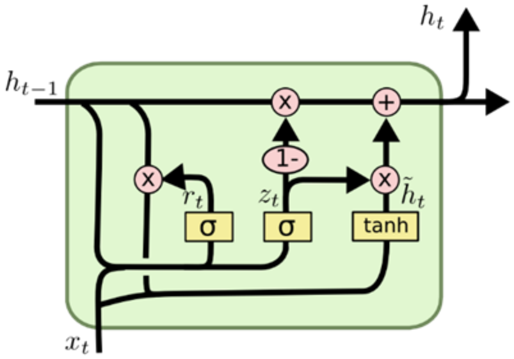
In the context of time series prediction, LSTM networks are trained using historical time series data to learn the underlying patterns and relationships. During training, the network adjusts its parameters to minimize the difference between the predicted values and the actual values in the training data. Once trained, the LSTM network can be used to generate forecasts by feeding it with historical data and predicting future values based on the learned patterns.

LSTM networks offer several advantages for time series prediction:

Ability to Capture Long-Term Dependencies: LSTM networks can effectively capture complex temporal relationships and dependencies in the data, making them suitable for forecasting tasks with long-term patterns.
Flexibility: LSTM networks can handle various types of time series data, including those with irregular patterns, trends, and seasonality.
Automatic Feature Learning: LSTM networks can automatically learn relevant features from the input data, reducing the need for manual feature engineering.

3.4.2.2 Gated Recurrent Unit (GRU)

Gated Recurrent Unit (GRU) is a type of recurrent neural network (RNN) architecture, similar to LSTM, that is designed to effectively model sequential data, making it suitable for time series forecasting. GRU was proposed as a simpler alternative to LSTM, requiring. fewer parameters and computational complexity while still capturing long-term dependencies in sequential data.



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Figure 3.9 : GRU Architecture

Update Gate: The update gate in GRU controls the flow of information from the previous hidden state to the current hidden state. It determines how much of the previous hidden state should be retained and how much of the new information should be incorporated.

Reset Gate: The reset gate in GRU controls the extent to which the previous hidden state should be ignored when computing the new hidden state. It allows the network to selectively reset or update the information stored in the memory cells based on the current input.

Hidden States: GRU networks maintain hidden states that represent the network's learned representation of the input sequence. These hidden states are updated based on the input data, the current hidden state, and the gates' activations.

In the context of time series prediction, GRU networks are trained using historical time series data to learn the underlying patterns and relationships. During training, the network adjusts its parameters to minimize the difference between the predicted values and the actual values in the training data. Once trained, the GRU network can be used to generate forecasts by feeding it with historical data and predicting future values based on the learned patterns.

GRU networks offer several advantages for time series prediction:

Simplicity: GRU networks have a simpler architecture compared to LSTM, making them easier to train and interpret.
Efficiency: GRU networks have fewer parameters and computational complexity, making them more computationally efficient, especially for smaller datasets.
Flexibility: GRU networks can handle various types of time series data, including those with irregular patterns, trends, and seasonality.

3.4.2.3 RANDOM FOREST MODEL

Random Forest is a versatile and powerful machine learning algorithm that can be applied to various types of predictive tasks, including time series prediction. Here are some reasons why Random Forest is often used for time series prediction

Random Forest is an ensemble learning technique that generates predictions by combining several decision trees. Random Forest produces predictions that are more reliable and accurate by combining the predictions of several trees, which helps to lessen the variance and overfitting that are frequently associated with individual decision trees.

Nonlinearity: Random Forest is an effective method for capturing the nonlinear relationships between variables that are frequently seen in time series data. Random Forest's ensemble of decision trees is useful for capturing the nonlinear dynamics found in many time series because it can simulate intricate interactions and patterns in the data.

Feature Importance: Each input variable's contribution to the prediction is indicated by the feature importance metric that Random Forest offers. Time series prediction tasks can benefit from this as it helps determine which features are most important for predicting future values.

Random Forest is inherently resistant to overfitting due to its ensemble approach and use of bootstrapping and feature bagging during training. This helps the model avoid learning noise or irrelevant patterns in the data, resulting in more generalizable predictions.

Handling Missing Values and Outliers: Random Forest can handle missing values and outliers in data without the need for imputation or preprocessing, making it ideal for real-world time series datasets with irregularities or measurement errors.

Scalability: Random Forest is relatively scalable and can handle large datasets effectively. It is easily parallelizable, resulting in faster training on multi-core processors or distributed computing environments.

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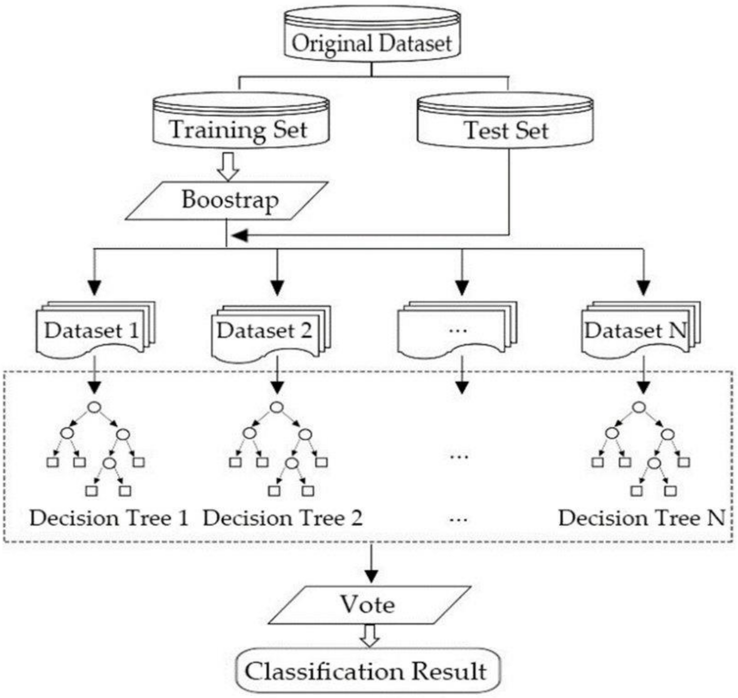

Figure 3.10 : Random Forest Architecture

CHAPTER FOUR

RESULTS

4.1 Introduction

In this chapter, the results of the analysis, which include the performance evaluation of predictive models, and the accuracy of PM2.5 predictions, are included. As described in the previous chapter we used six predictive models which include three deep learning models and three statistical models. The results of each method were validated with the plotting graphs of test data and predicted values together in the same plot, and some validation methods like MAE, RMSE, and MSE have been used to validate the method. Through this brief analysis, we seek to understand air pollution dynamics in Sri Lankan urban cities.

4.2 Data Visualization

The data we used in this analysis contains an Hourly PM2.5 concentration of 18 stations which spans over nearly 7 months. Here we clustered these 18 stations into 3 clusters according to their geographic locations and correlation of their data. Following are the preprocessed data variations against the time of these 3 clusters. According to these three graphs, we can see that PM2.5 concentrations in cluster 1 vary between 3-25 ($\mu g/m^3$) in normal days. But some peak events have changed this concentration to around 30 ($\mu g/m^3$). According to the other 2 clusters, we can see that average values have been changed in some months. This may be monsoonal winds that occurred between December to May.

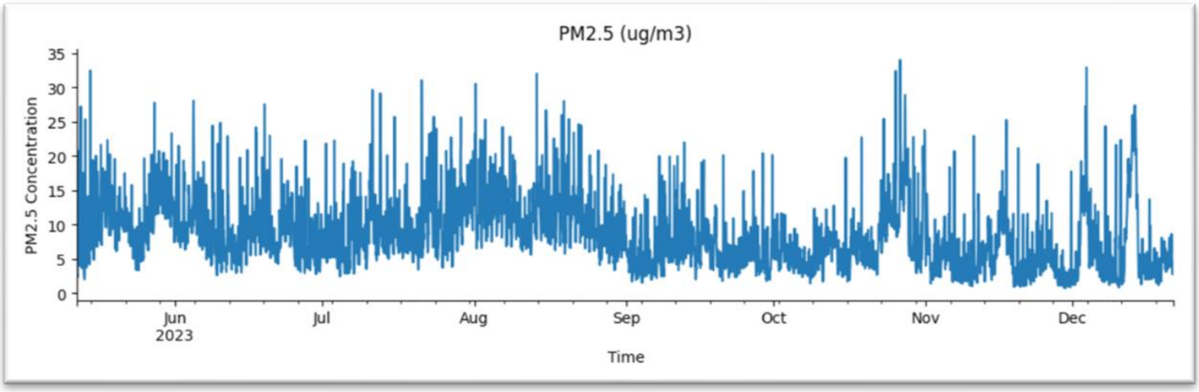

Figure 4.1: Hourly Concentration of PM2.5 ($\mu g/m^3$) in cluster 1.

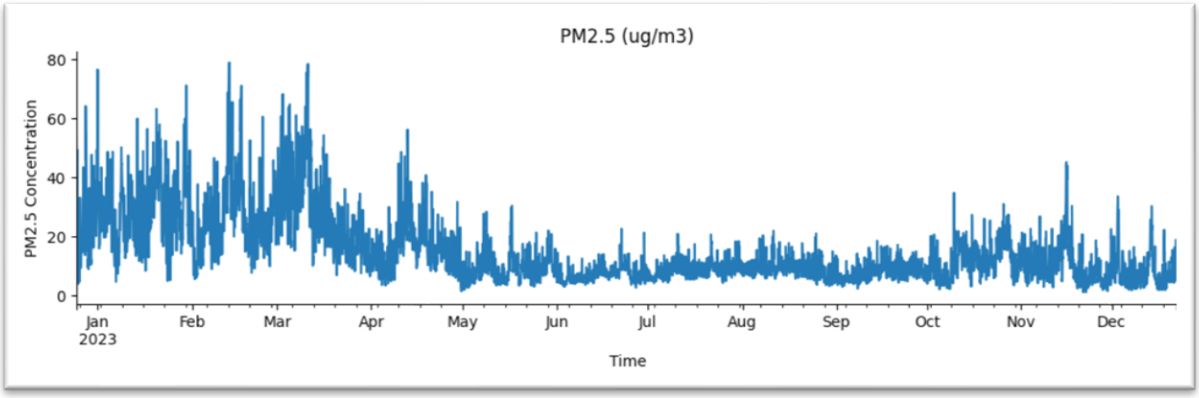

Figure 4.2: Hourly Concentration of PM2.5 ($\mu g/m^3$) in cluster 2

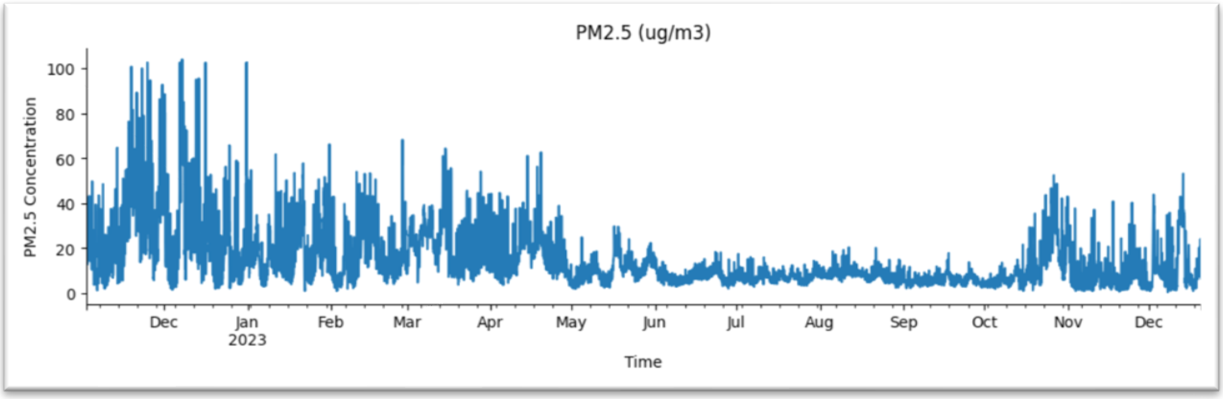

Figure 4.3: Hourly Concentration of PM2.5 ($\mu g/m^3$) in cluster 3.

4.3 Autocorrelation and Partial autocorrelation in the data

In this analysis, Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots are used to understand the autocorrelation structure of the data. The ACF plot shows the correlation between a series of data and its lagged values. Each point on the ACF plot represents the correlation between the series and its lagged values at different lags (time intervals). On the other hand, the PACF plot represents the correlation between the series and its lagged values after removing the linear dependence of the earlier lags. Similar to the ACF plot, each point on the PACF plot represents the correlation at different lags. These two plots help to identify the order of the ARIMA model by the p parameter can be identified using ACF plot while the q parameter can be identified using PACF plot. Following are the ACF and PACF plots of the 3 clusters.

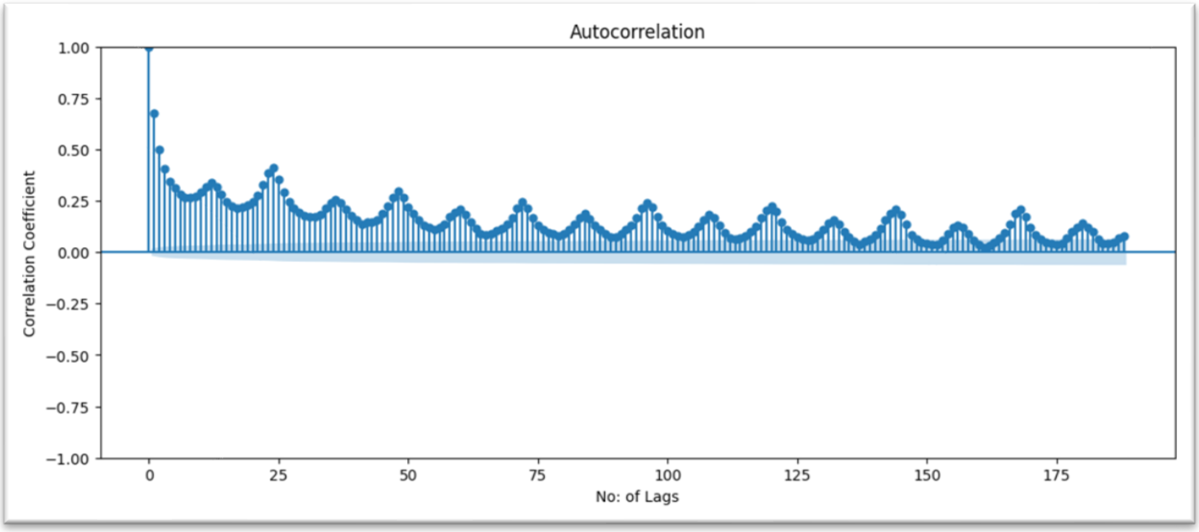

Figure 4.4: Autocorrelation of PM2.5 data in cluster 1.

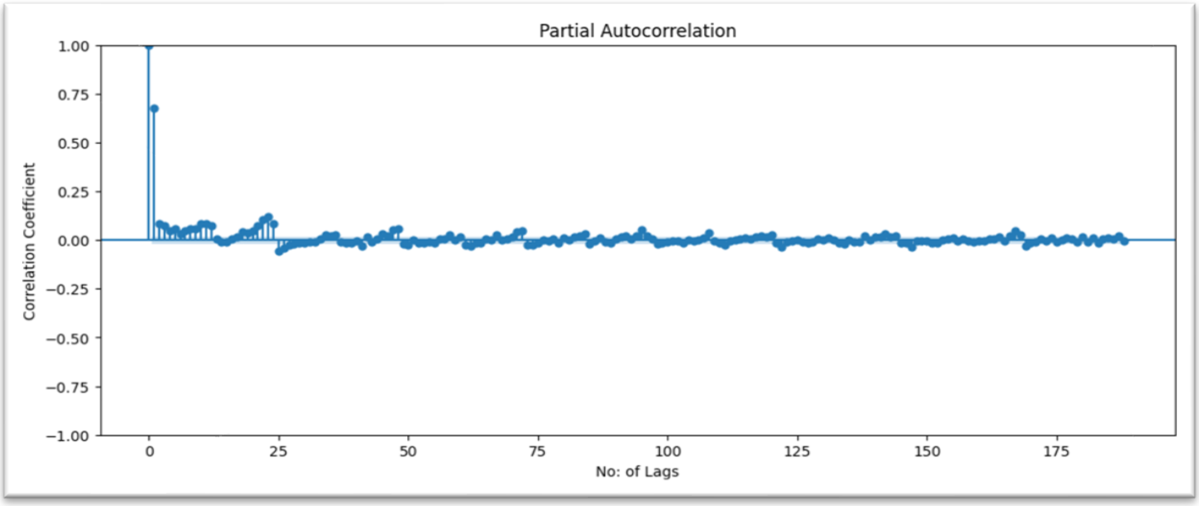

Figure 4.5: Partial autocorrelation of PM2.5 data in cluster 1

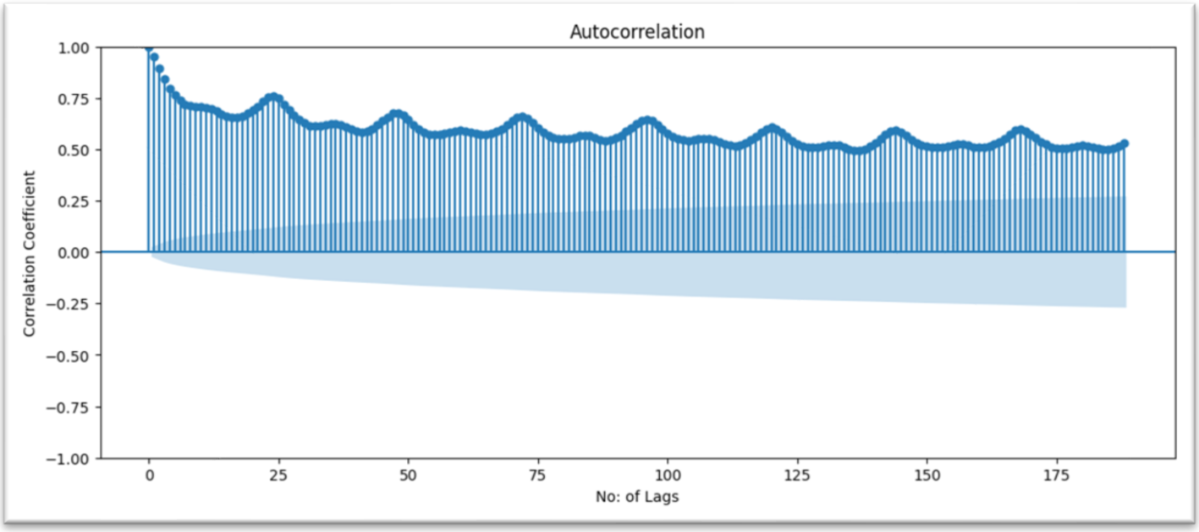

Figure 4.6: Autocorrelation of PM2.5 data in cluster 2

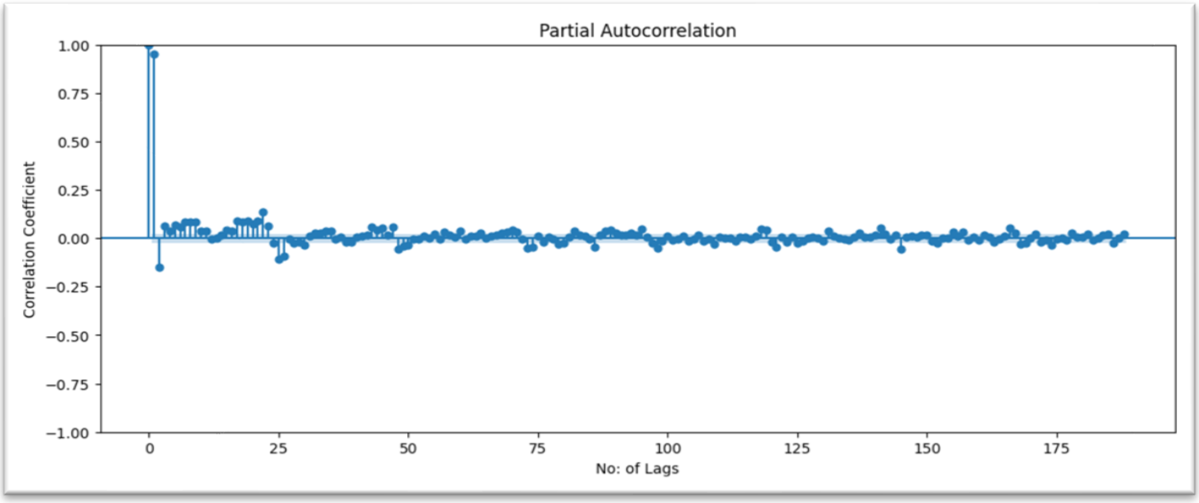

Figure 4.7: Partial autocorrelation of PM2.5 data in cluster 2

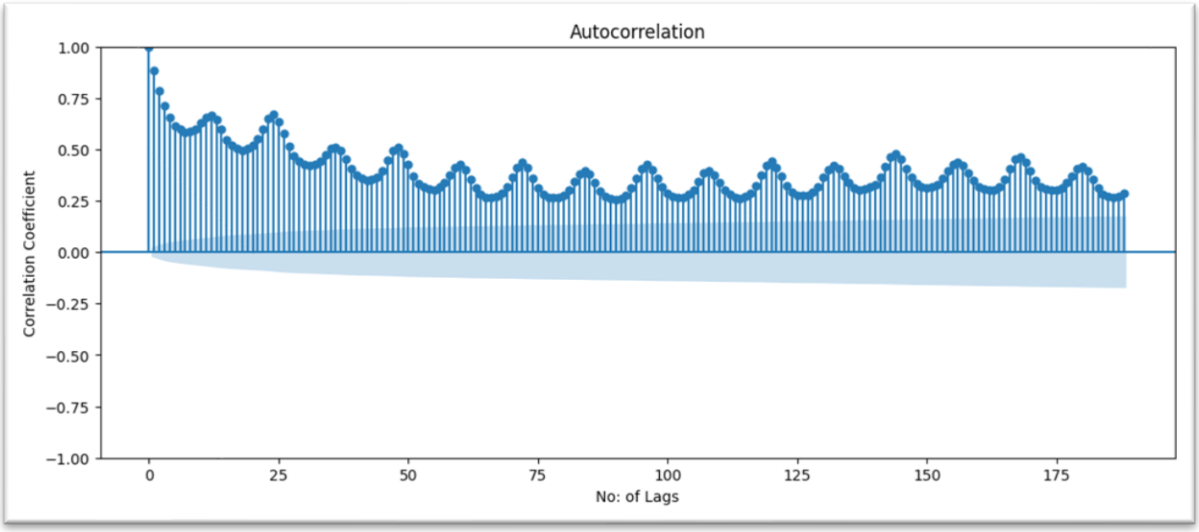

Figure 4.8: Autocorrelation of PM2.5 data in cluster 3

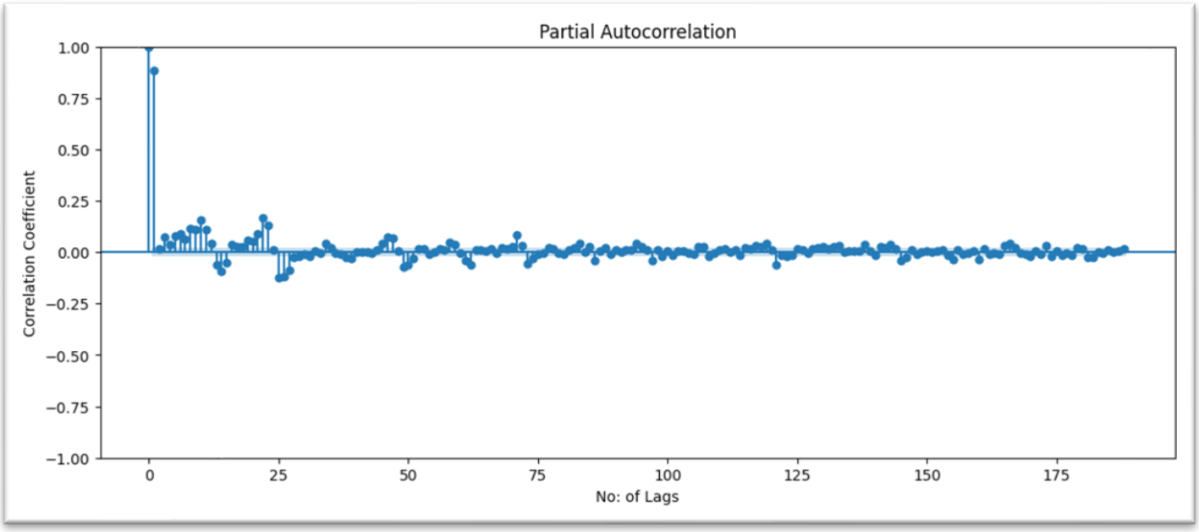

Figure 4.9: Partial autocorrelation of PM2.5 data in cluster 3

4.4 Model Performance Evaluation

In this section, we evaluate the performance of our predictive models by comparing the predicted values generated by the models with the actual test values obtained from the dataset. The accuracy of our models is compared through visual representations to check how well our models capture the temporal trends and variations in PM2.5 levels.

4.4.1 ARIMA Model

ARIMA Model is a simple linear model used in time series predictions. Following are the results obtained through that model.

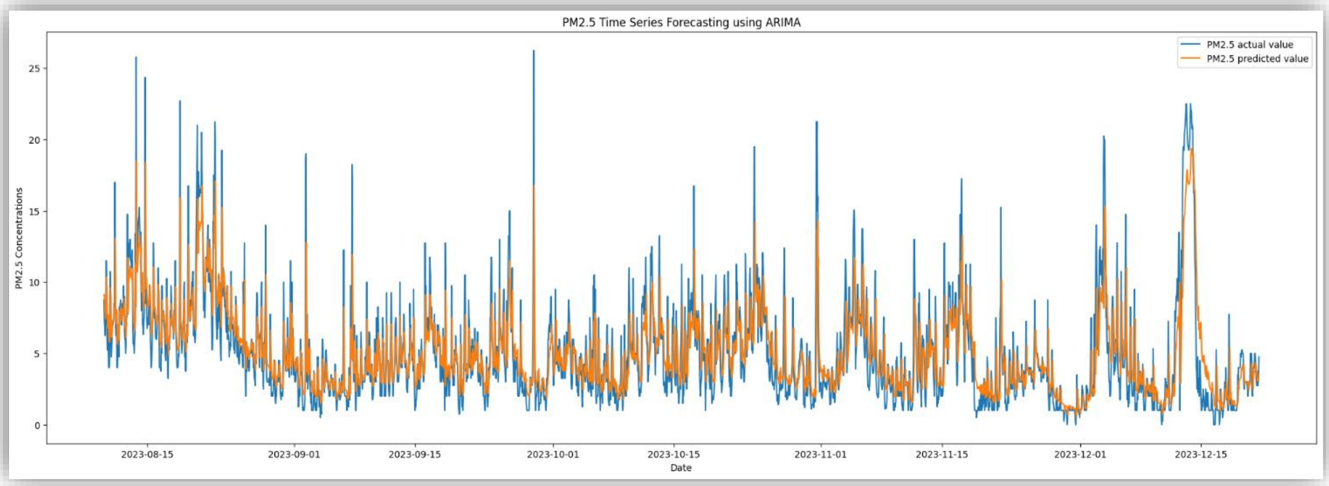

Figure 4.10: Predicted values of ARIMA Model vs Test data values of cluster 1

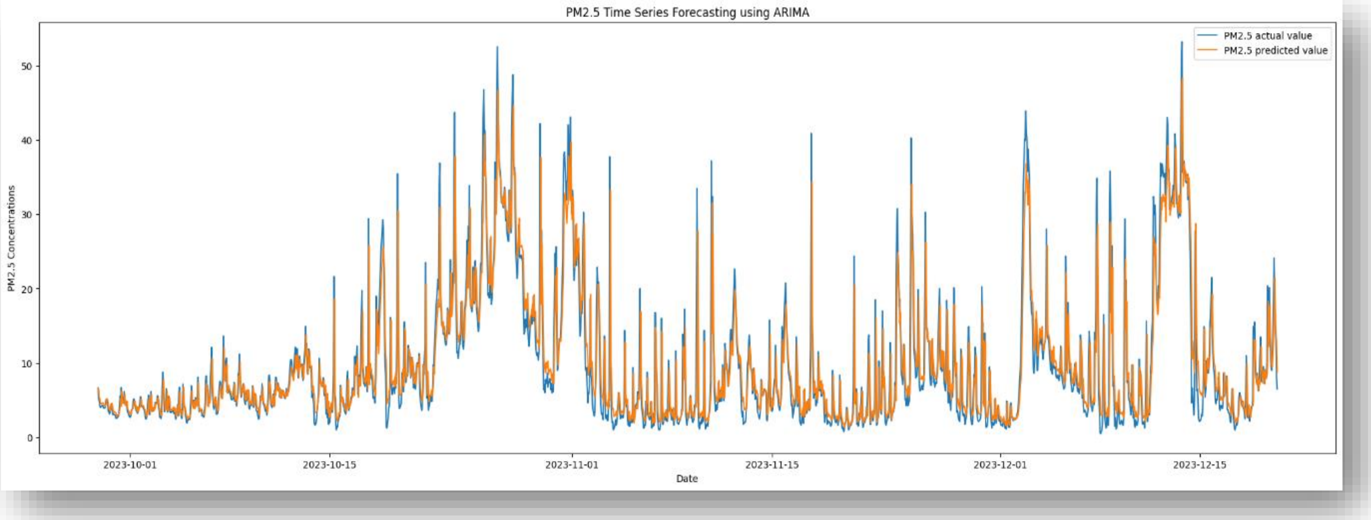

Figure 4.11: Predicted values of ARIMA Model vs Test data values of cluster 1

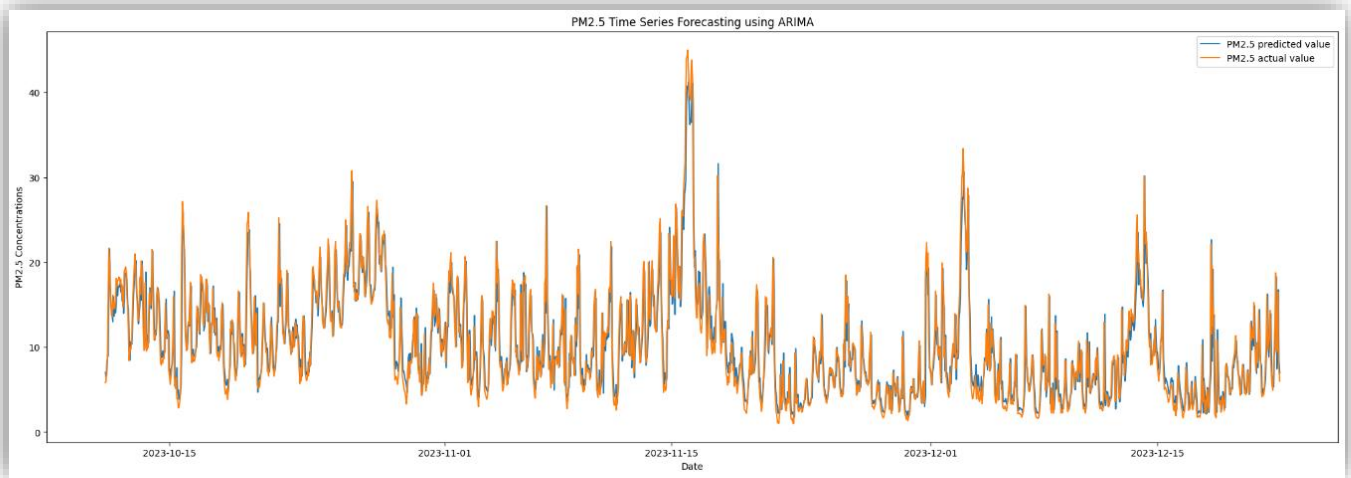

Figure 4.12: Predicted values of ARIMA Model vs Test data values of cluster 3

The graphs illustrate the comparison between the predicted PM2.5 values generated by the ARIMA model and the actual observed values from the test dataset. Overall, the ARIMA model demonstrates a close alignment between the predicted and actual PM2.5 concentrations, indicating its ability to capture the underlying patterns and fluctuations in the data. However, there are instances such as peak events where the predicted values deviate slightly from the observed values. We should try deep learning methods to get rid of those deviations.

4.4.2 SARIMA Model

The SARIMA Model is an extension of the ARIMA model while this model has an additional component related to the seasonality of the data.

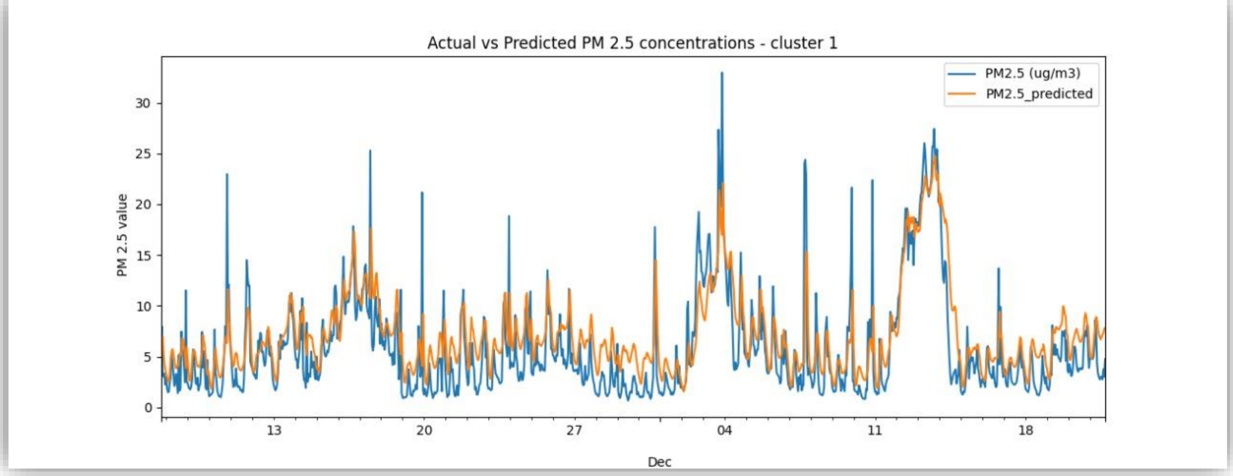

Figure 4.13: Predicted values of SARIMA Model vs Test data values of cluster 1

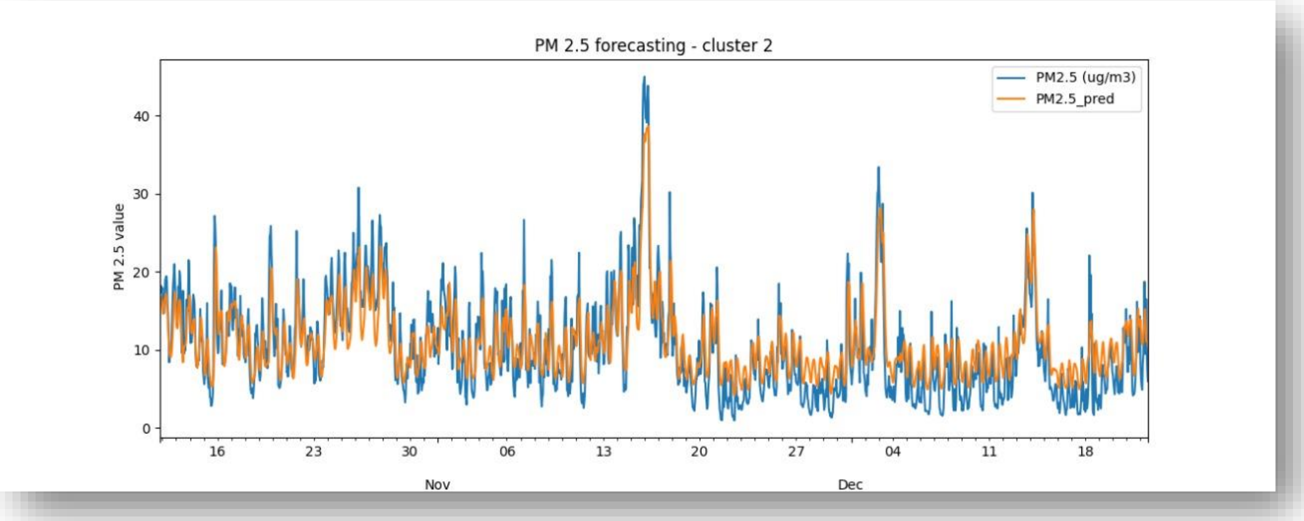

Figure 4.14: Predicted values of SARIMA Model vs Test data values of cluster 2

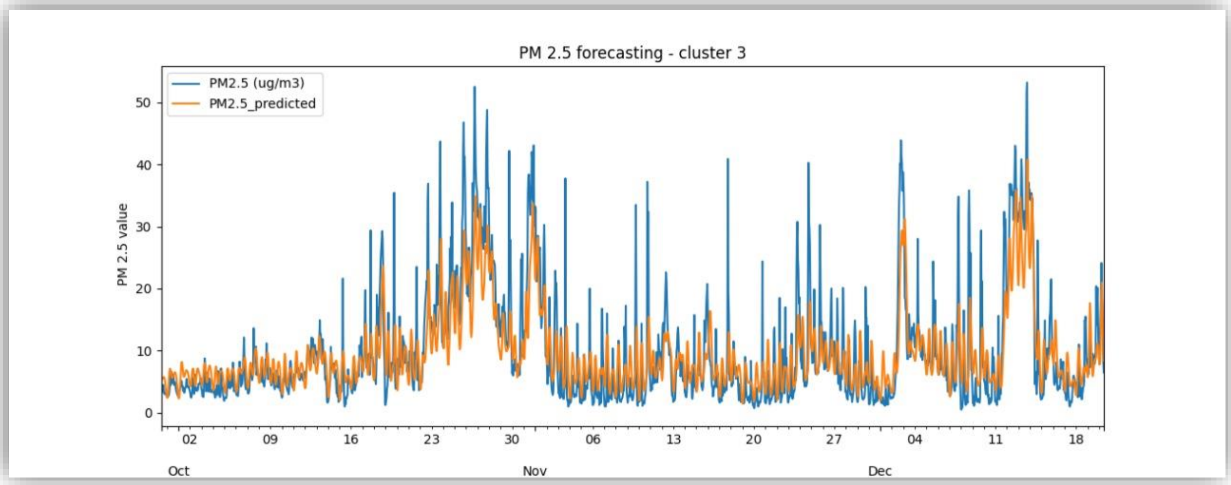

Figure 4.15: Predicted values of SARIMA Model vs Test data values of cluster 3

The graphs illustrate the comparison between the predicted PM2.5 values generated by the SARIMA model and the actual observed values from the test dataset. Here in this data, we could not find the seasonality in our data set. Because we haven’t enough data to calculate the yearly seasonality of the dataset. So this Model doesn't give much accuracy than the ARIMA model as we expected. So this model doesn’t fit our data well.

4.4.3 ETS Model

The Exponential Smoothing State-Space (ETS) model, a time series forecasting technique, uses exponential smoothing to capture underlying patterns and trends in sequential data, this helps to identify seasonality variations in time series data. However, we found that our data doesn't have any monthly seasonal variations. So this model also doesn't give a good prediction as we expected. As we can see in the graphs this model doesn't understand the data patterns in our data. So predicted values have big deviations from the test data values. So we would use a deep learning model instead of these models.

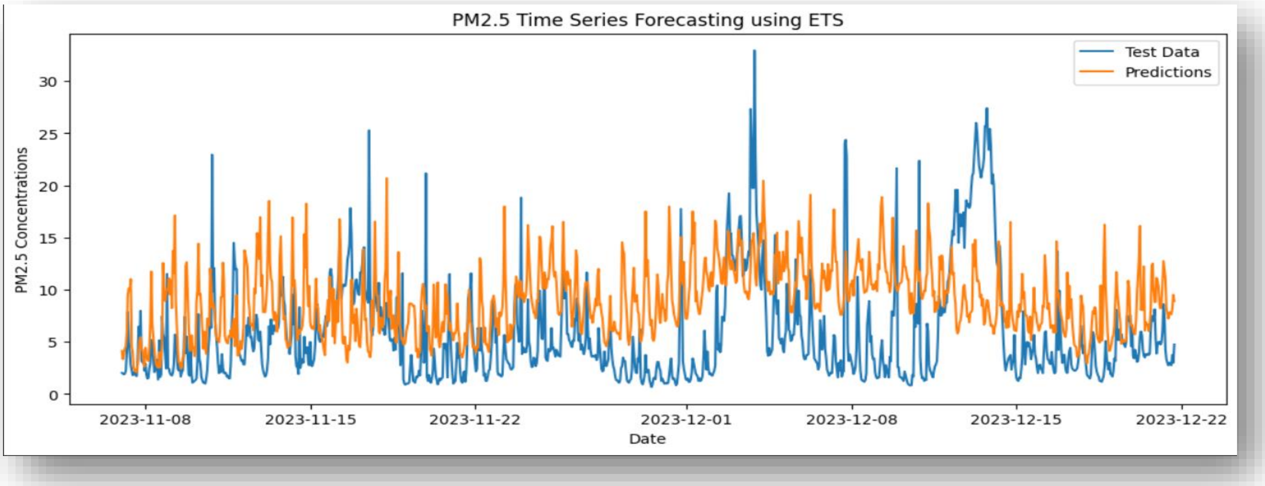

Figure 4.16: Predicted values of ETS Model vs Test data values of cluster 1

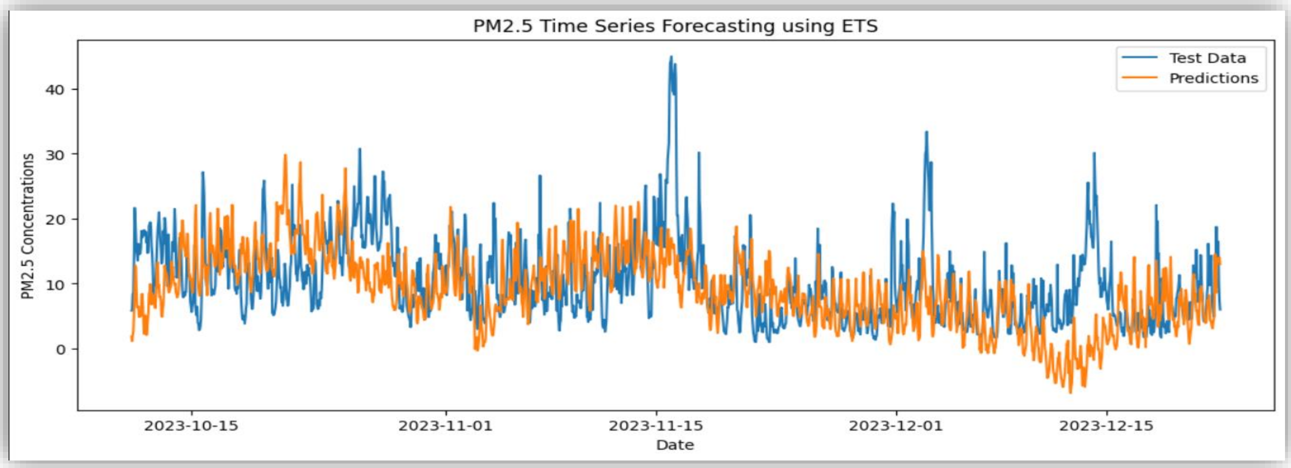

Figure 4.17: Predicted values of ETS Model vs Test data values of cluster 2

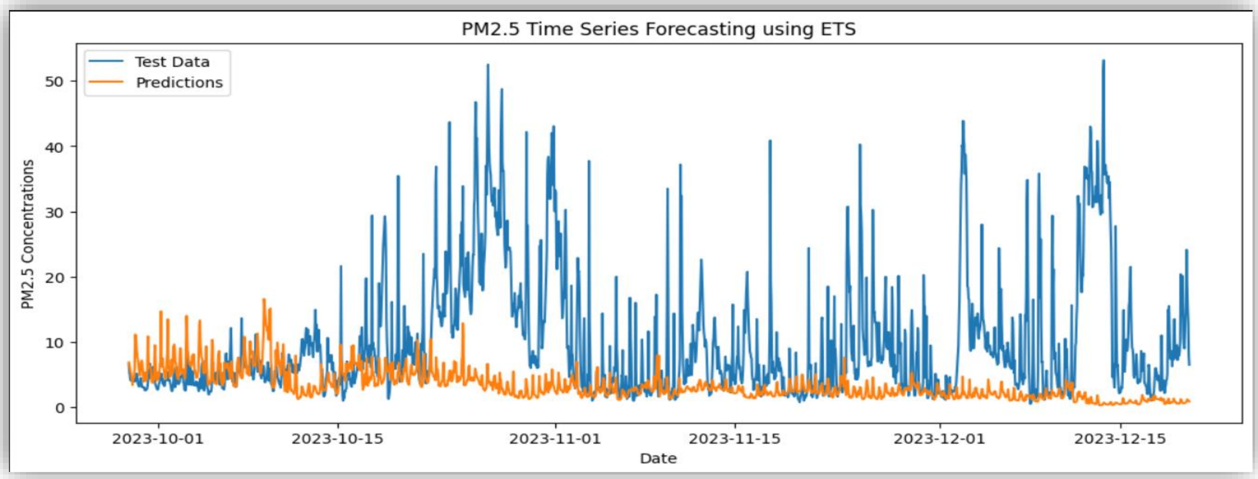

Figure 4.18: Predicted values of ETS Model vs Test data values of cluster 3

4.4.4 LSTM Model

The Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) architecture. LSTMs are capable of learning and remembering information over long sequences, making them well-suited for time series forecasting. As looking at the graphs this method is very good in predicting the future values. Both the test values and predicted values are same in most of the cases.

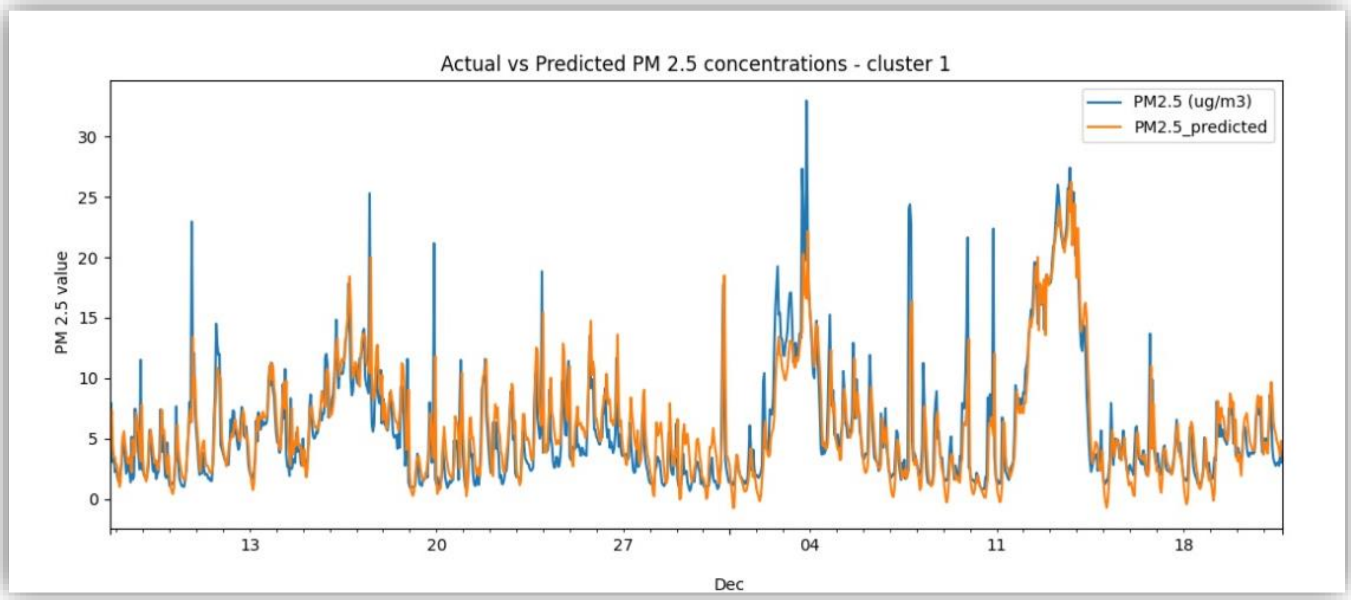

Figure 4.19: Predicted values of LSTM Model vs Test data values of cluster 1

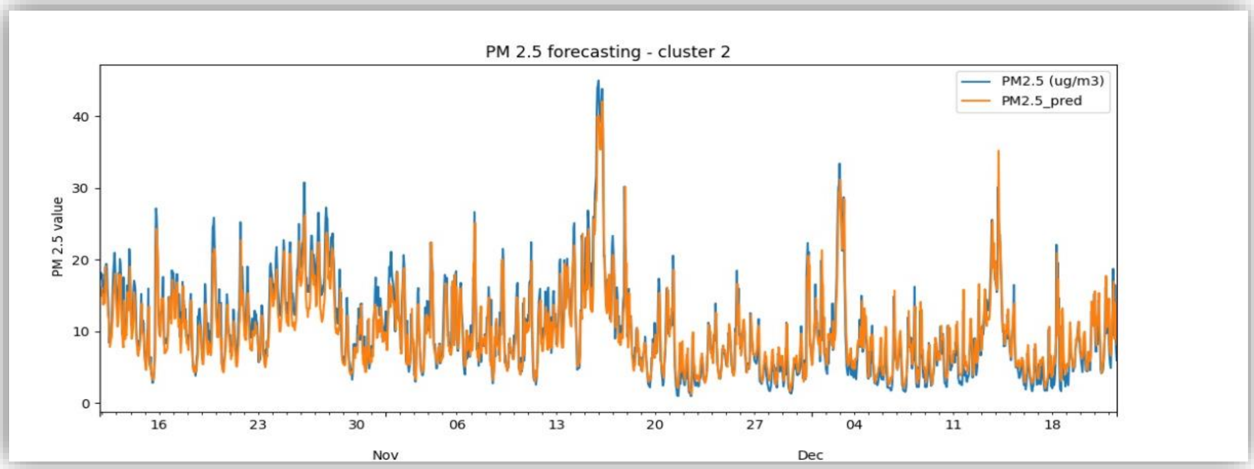

Figure 4.20: Predicted values of LSTM Model vs Test data values of cluster 2

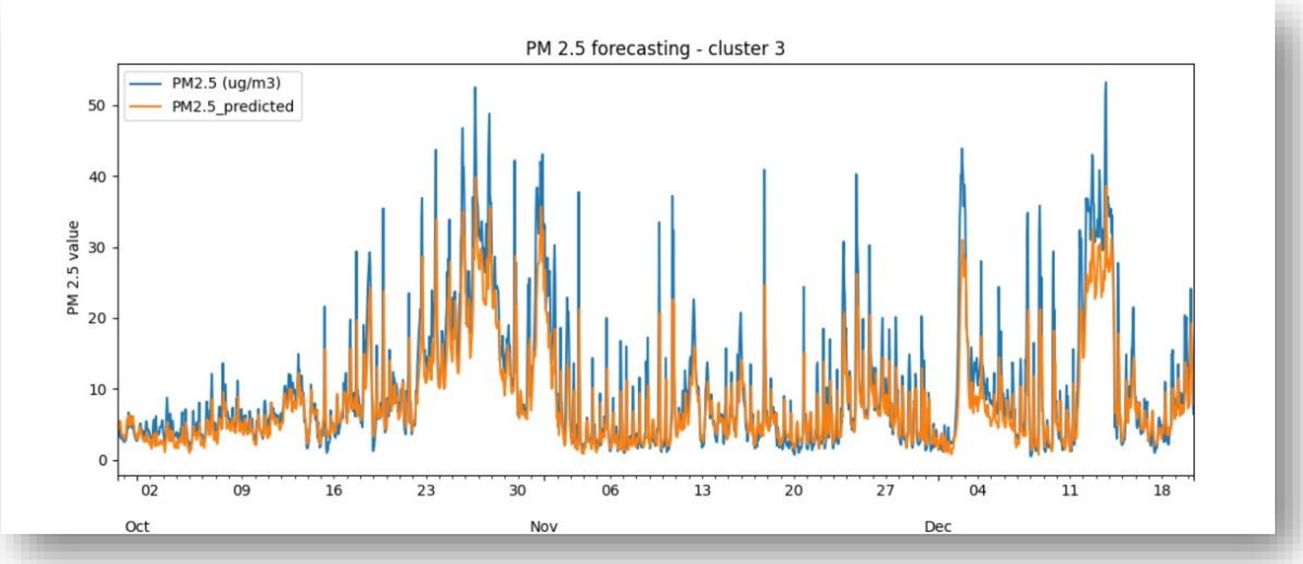

Figure 4.21: Predicted values of LSTM Model vs Test data values of cluster 3

4.4.5 GRU Model

TheGated Recurrent Units (GRUs) are a type of recurrent neural network (RNN) architecture similar to Long Short-Term Memory (LSTM) networks. They are designed to capture and model sequential data, such as time series, by efficiently learning long-term dependencies.. However, GRUs have a simpler architecture compared to LSTMs, with fewer parameters and computational requirements. However, as our data set is small this have been effective than the LSTM model. But looking at the graphs of LSTM and GRU we can see like same accuracy has been in the both methods.

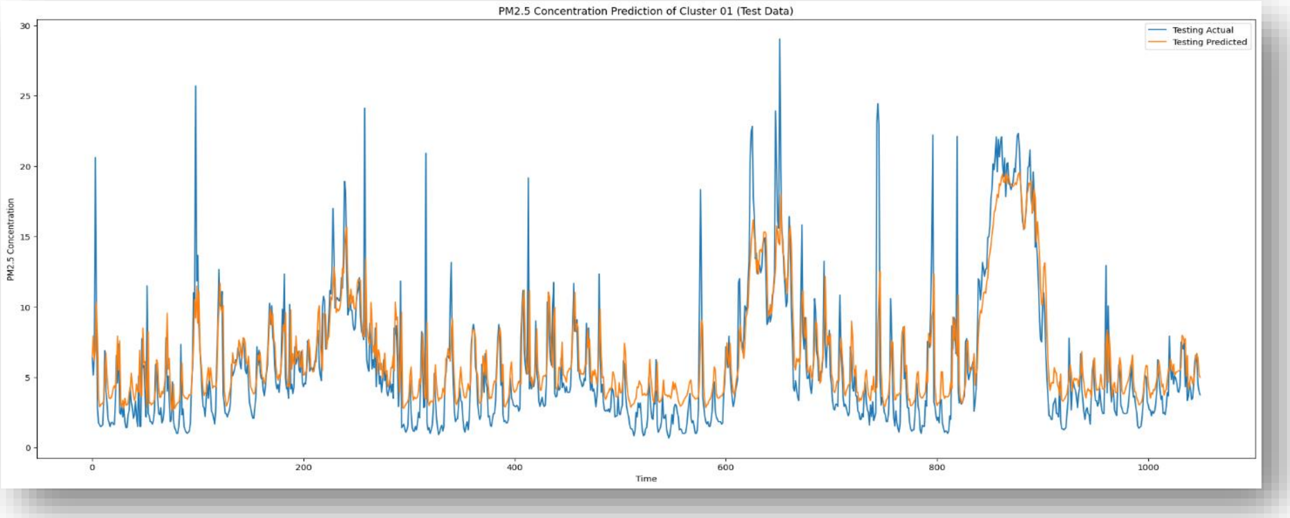

Figure 4.22: Predicted values of GRU Model vs Test data values of cluster 1

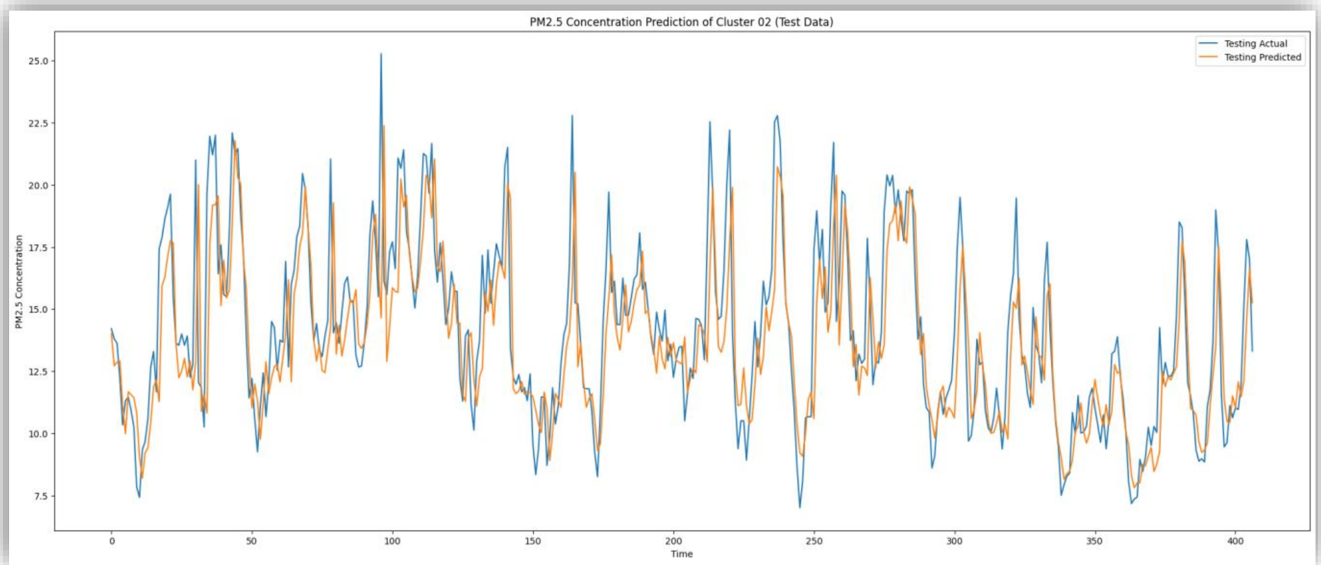

Figure 4.23: Predicted values of GRU Model vs Test data values of cluster 2

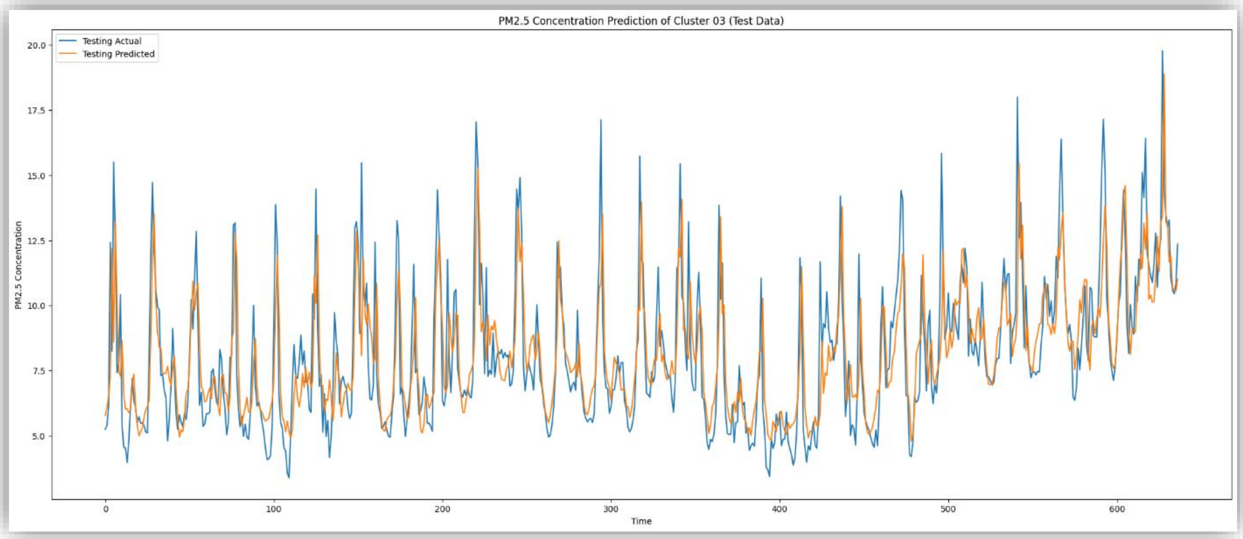

Figure 4.24: Predicted values of GRU Model vs Test data values of cluster 3

4.4.6 Random Forest Model

The Random Forest is a popular machine learning algorithm used for both classification and regression tasks. It is works like a forest with lot of trees and branches. Branch with the higher probability is taken as the predicted value. But for our dataset this was not much accurate than the previous methods like LSTM and GRU. As seen in the graph this model couldn’t fit the our test data well. But it was somehow nearly catcth the pattern of our dataset.

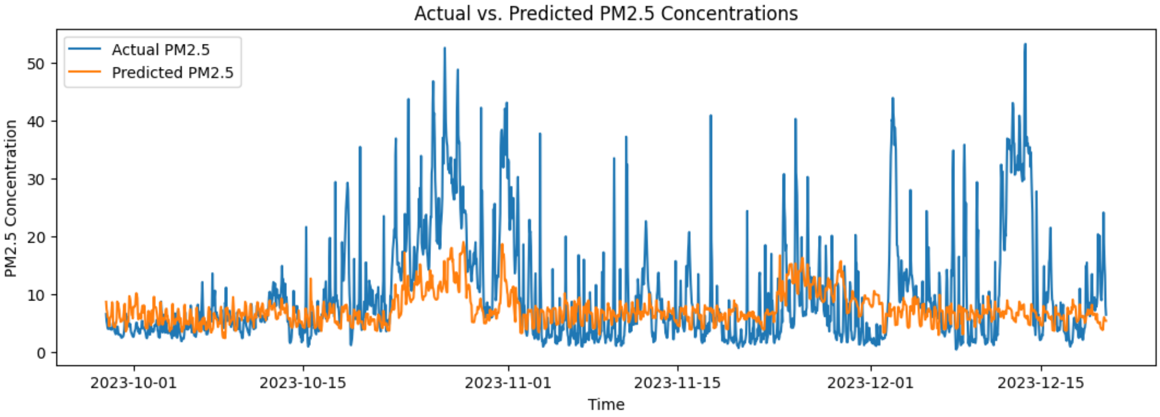

Figure 4.25: Predicted values of Random Forest Model vs Test data values of cluster 1

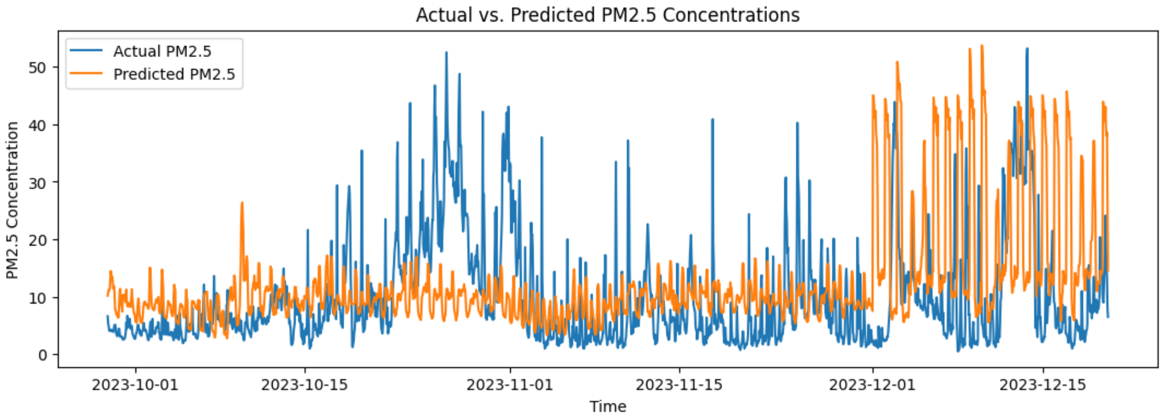

Figure 4.26: Predicted values of Random Forest Model vs Test data values of cluster 2

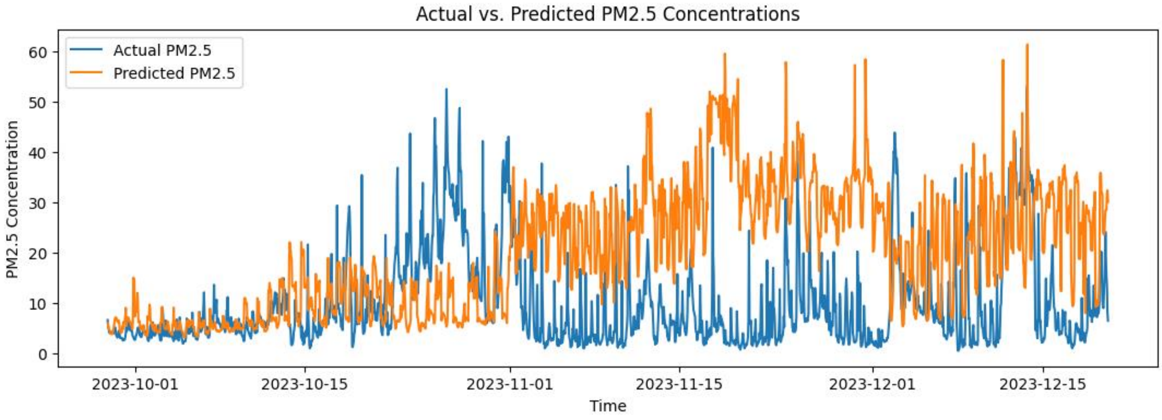

Figure 4.27: Predicted values of Random Forest Model vs Test data values of cluster 3

4.5 Model Validation

Table 4.1: Model Validation

Model	Cluster 1		Cluster 2		Cluster 3	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
ARIMA	1.74	2.72	1.87	2.69	2.37	3.96
SARIMA	2.32	3.07	2.75	3.36	3.65	5.43
ETS	5.04	6.12	5.12	6.94	7.58	8.02
LSTM	1.60	2.60	2.08	2.25	1.29	2.60
GRU	1.81	2.65	2.59	2.86	1.45	2.98
RF	8.17	13.64	14.42	18.47	5.71	9.08

CHAPTER FIVE

CONCLUSION AND FUTURE WORK

5.1 Conclusion

In this study, different methods for forecasting PM2.5 concentration in 3 clustered were compared. The 4.1 table shows MAE and RMSE values for each model. we have identified LSTM as the most accurate and reliable model for PM2.5 prediction for our dataset. Our results show the significance of using deep learning methods for temporal PM2.5 concentration forecasting, particularly LSTM networks. The LSTM model is ideally suited to handle the dynamic and complex nature of air pollution dynamics in urban locations because of its ability to accurately model long-term dependencies and nonlinear interactions in the data.

5.2 Future work

In future work, our focus will be on further enhancing the performance of our machine learning and deep learning models. This will involve fine-tuning the existing models by optimizing hyperparameters, exploring different architectures, and incorporating new techniques to achieve even higher prediction accuracy. Additionally, we plan to develop a hybrid model that combines satellite imagery and advanced deep-learning techniques to predict PM2.5 levels in areas without sensor networks. This innovative approach will expand the predictive capabilities of our model, allowing us to provide air quality information in locations where traditional sensor networks are not available. Furthermore, we recognize the importance of ongoing evaluation of model performance using real-time data. By continuously monitoring and analyzing air quality patterns, we can identify any changes or trends and ensure that our predictive models remain effective and reliable over time. Through these efforts, we aim to contribute to the ongoing efforts to address air pollution challenges and promote environmental sustainability in Sri Lanka and beyond.

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