Integrating Clustering and Regularization for Robust LSTM-Based Stock Price Prediction

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Abstract

Stock price forecasting has oftentimes interested several researchers around the world. Making predictions for the future largely depends on the data that will be used to train the model. In general, historical data are used to train models, which contain a features of different types, out of which, not all are necessarily helpful in making predictions. It is, hence, crucial to select the features that can be most useful to make precise predictions. This article proposes a feature selection approach based on the K-means clustering algorithm and elastic net regularization. We have used the K-means algorithm to cluster all the correlated features together and apply elastic net regularization to select the most predictive features within each cluster. We use the selected features to train an LSTM model which predicts the future closing price of a stock for the upcoming trading day. We evaluate the performance of our proposed approach in comparison to the existing approach and observe performance improvement.

Keywords: Stock price prediction; Feature selection scheme; Long short-term memory; Deep learning

1 Introduction

A large number of people invest their money in the financial markets, especially in share markets, looking for higher profits and better returns on their investments. Despite the complex and highly fluctuating nature of the stock market, the potential returns that can be made, attract many investors and researchers to study the volatile nature of the market. The vivid patterns of the market can be analyzed to draw meaningful insights and forecast future price movements. Hence, forecasting movements in the market using historical data and past fluctuations interests a lot of researchers. Figure 1 shows the price movements and volatility of the index NIFTY 50 in the National Stock Exchange (NSE), India, indicating the complex and non-linear nature of the stock markets.

The share market can be influenced by a large number of different types of events, including new policies, government changes, macroeconomic issues, etc., that affect the prices directly or indirectly. All these data combines to create the market data which can be used to make prediction of future prices. Market data comprises of various features that can be though of as individual measurable properties within a recorded dataset.

DOI: https://doi.org/10.54216/FPA.180218

Received: August 06, 2024 Revised: November 15, 2024 Accepted: January 20, 2025

Figure 1: Historical price data of NIFTY 50 Index

A collection of such features can be used to make better predictions of the stock price. Initially this set of features may contain different type of features that may not contribute equally to making quality predictions of future prices. Some features may be redundant and not relevant in making the predictions. Hence, feature selection becomes vital to obtain relevant and important features from the original set of features.

The process of analyzing the initial set of features to get rid of the redundant and irrelevant features, selecting only the important features is known as feature selection. It is very important because the features which are not relevant can mislead the model training process and can lead to a model that is trained on unnecessary data. Feature selection can be used to analyze data, get rid of unnecessary features, handle large-sized data, optimize computational cost, and increase predictive performance. The algorithm used to derive the set of selected features can strongly influence them. And not all features may contribute equally in making the predictions. This article proposes a deep neural network system integrated with a hybrid k-means and elastic net regularization-based feature selection approach for predicting stock price.

1.1 Motivation

Coefficient of variation-based k-means clustering can be used to group similar features in the same cluster. Then the largest cluster of features can be selected to train the model because that cluster will have features with high CV value. However, selecting only the largest cluster, can miss out on potential features which can have a huge impact on making precise predictions. Hence, we integrated the elastic net regularization to select the top relevant and crucial features within each cluster made using the CV-based K-means algorithm. By doing this we ensured that all the relevant features, which might be present in different clusters and can be impactful in making predictions, are selected and used to train the model. Elastic net regularization is composed of both lasso (L1) and ridge (L2) regression techniques to create a better regularization technique. The following points are the major contributions of the proposed approach:

• Hybrid K-means and elastic net regularization-based feature selection approach is proposed to select the most relevant features from each cluster made using the K-means clustering algorithm.

• An LSTM model is trained with the selected features in order to make efficient predictions of future stock prices.

• Comparative analysis between the existing approach and proposed approach is carried out to determine the feasibility of the proposed approach.

The upcoming article is formatted as follows: Section 2 comprises the related work; a detailed walk-through of the suggested approach is presented in Section 3; the results of the experimental analysis are given in Section 4; and the comparison of the existing and proposed approach along with the conclusions and potential future work is discussed in Section 5.

DOI: https://doi.org/10.54216/FPA.180218

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2 Related Work

Stock markets are known for their high volatility, unpredictable nature, and huge potential returns, which attracts a huge number of researchers and investors to study the nature of the market. There has been an enormous amount of research to study the behaviour of the stock market which aims to understand and predict future stock prices. Here is an overview of related work where researchers attempted to predict future stock prices.

Various different studies and researches have been conducted, proposing different approaches for predicting future stock prices. Yepeng Liu et. al proposed an variational mode decomposition based stock price prediction model along with dual channel attention network.[9] Manali Patel et. al came up with a hybrid relational approach for predicting future stock prices in different markets including American, Indian and Korean markets.[11] Dongbo et. al conducted a research to introduce VGC-GAN which is a multi graph convolutional framework in order to predict future stock prices.[10] An approach to predict stock price using LSTM, CNN deep learning models and frequency decomposition to decompose the time series to different spectra of frequency, was conducted by Hadi et. al.[12] Chaojie et. al developed an approach using deep transformer model to predict future of stock market index.[16]

It is not necessary to solely rely on the past price data of the particular stock to predict the future prices as various other indicators and data points can be used along with historical price data to aid the future price predictions. Qing Li et. al proposed an stock prediction approach by taking into account online news related to the stock market which can help in predicting the future prices.[7] Shangkun Deng et. al conducted a research proposing an approach for predicting stock index using ensemble learning models and investor sentiments.[3]

Predicting future stock prices can largely depend on the type of model being used to make the predictions and the hyper-parameters of the employed model. So, studying about how to effectively tune the model to make precise predictions becomes important. Burak et. al[4] developed an artificial rabbits optimization algorithm to optimize the hyperparameters of the LSTM model to make better stock price predictions. LSTM models are widely used for making stock price predictions because it can handle time series data effectively. However, building an appropriate LSTM model becomes challenging, considering the number of hyperparameters, layers, and attributes that can be configured. Hence the Burak Gülmez[4] paper helps optimize the LSTM model to make better predictions.

Making the performance of the prediction model better, is generally focus of the researchers in order to make better predictions. However, analyzing the data used to train the model is very important. Yechan et. al[5] proposed an N-Period Min-Max (NPMM) labeling technique that labels the input data at particular time points to avoid frequent and minute changes in price.

The are multiple parameters influencing the stock market, consisting of external factors like political issues, market, economy etc. and internal factors like structure of the organisations, ability of the management, innovation capabilities etc. which is then combined to create stock market data, used for making future predictions. The available historical data on the stock market comprises various features that may or may not affect the precise predictions of future stock prices. Irrelevant and redundant features do not only result in higher computational costs but also can mislead the model and cause an inadequately trained model. Hence, analyzing and selecting the most relevant and useful features becomes necessary. Guanzhi et al.[6] proposed a method to select particular features to predict future stock prices which is based on the Pearson correlation coefficient (PCC) and the Broad Learning System (BLS).

Kinjal et. al[2] proposed a feature selection approach to predict stock prices based on the coefficient of variation (CV). The CV for each feature is calculated and it is then integrated with the k-means algorithm, median range, and top M. The set of features selected using k-means has features which are part of the biggest cluster, the median range having features of a defined range and, the top M having the features with the highest CV values.

Wentao Li et. al did research and came up with an approach for selecting features based on fuzzy c-means clustering algorithm along with the principle of refined justifiable granularity.[8] Kyung et. al integrated feature selection with the interpretable stock price prediction model based on genetic algorithm and machine learning regressions.[17]

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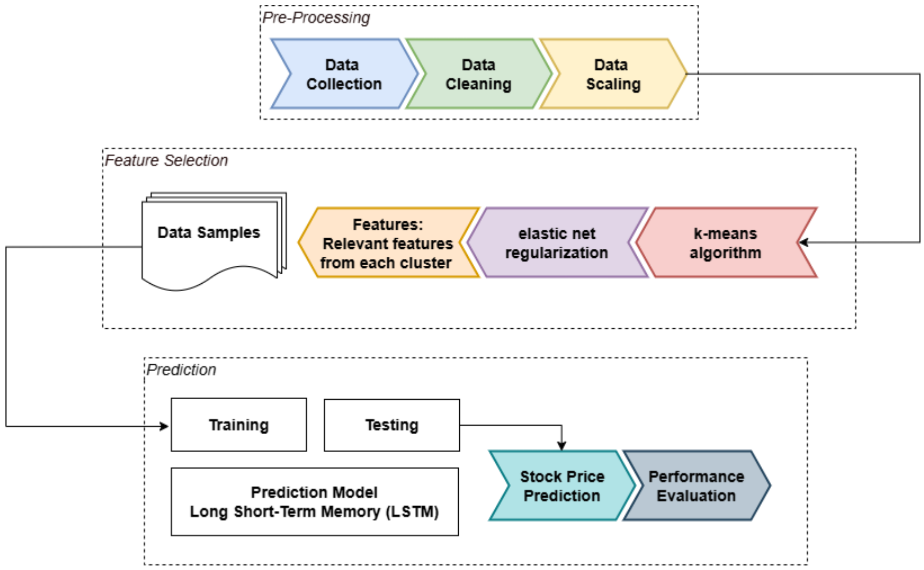

Figure 2: An architectural overview of the suggested approach for feature selection

The importance of feature selection can be observed in various other domains as well. Fatih Abut et. al conducted study to predict the real estate prices by combining detection of outliers, selecting relevant and important features using feature selection and clustering.[1] The study highlighted the usefulness of this hybrid approach and addressed the challenges that arises for realistic price prediction. A research to predict the intentions to use social media of students along with identifying the underlying reason for the intent, was conducted by Shrawan et. al, using a hybrid feature selection and a stacked SVM model.[15]

3 Proposed Approach

Feature selection plays a crucial role when building any predictive model. In this article, we have incorporated a hybrid approach for feature selection that leverages both clustering and regularization to identify the most useful and important features for making predictions. This approach uses K-means clustering to combine similar features based on their characteristics and clusters them together, with Elastic net regularization to select the most relevant features within each cluster. An architectural overview of the proposed approach is shown in Figure 2. The detailed methodology is discussed below:

3.1 Data Collection

At first, the time series data in the form of historical stock price data of different stocks listed on the Indian Stock Exchange, is collected. We have downloaded the Kaggle dataset which consisted of data of the top 50 companies listed on the Indian Stock Exchange. We used the stock price data of Tata Motors Co. for this research. For a given trading day, Table 1, shows all the features initially present in the dataset.

3.2 Data Cleaning

At first, we will set the "Date" column of the dataset as the index of the entire pandas dataframe. The collected data may have missing/incomplete values and to make precise predictions we should first handle the discrepancies in the data. After analyzing we observed that there were a few missing values only, hence we decided to drop all the rows containing any missing values. Then we created a "Target" column that contains the data of the closing price of the next trading day, which we would like to predict. Then we split the entire dataframe in two parts, one for all the features and another for the "Target" column, which we will be predicting. The dataframe containing the features is further modified by dropping the "Symbol" and "Series" columns because they remain constant throughout the entire data.

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Table 1: Initial features

Sr. No.	Feature Name	Description
1.	Date	Date of the trading day
2.	Symbol	Market symbol of the stock
3.	Series	It denotes the series of the stock (EQ: Equity, in this case)
4.	Prev Close	Indicates the closing price of the previous trading day
5.	Open	Indicates the opening price
6.	High	Indicates the highest price
7.	Low	Indicates the lowest price
8.	Last	Indicates the last traded price
9.	Close	Indicates the closing price
10.	VWAP	It is the volume-weighted average price
11.	Volume	It is the total amount bought and sold
12.	Turnover	It is the turnover of the stock
13.	Trades	It is the number of the trades
14.	Deliverable Volume	It is the volume of deliverable trades
15.	%Deliverable	It is the percentage of the deliverable trades in the day

3.3 Data Scaling

The collected and processed data may contain different features which may contain values of different numeric ranges. For example, the stock data on the trading day 23-04-2021 had a volume of 58,158,986 while it closing price was INR 294.0. Variations like these in the range of data can lead to biased models which can affect the predictions for the future closing prices. Hence, we did data normalization to bring all data to similar ranges. We used min-max normalization using (1)

$$X' = \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}} \tag{1}$$

Where, X is the feature value, X' is the normalized value of X, X_{min} is the minimum value for X and X_{max} is the maximum value of X.

3.4 Feature Selection

The collected and derived data can now be further considered for the selection of features. To obtain the desired set of features that will be relevant for making precise predictions of future closing prices we have developed a hybrid k means regularization approach. Details of the process are as follows. The proposed approach for feature selection based on k-means clustering and elastic net regularization is presented in Algorithm 1.

3.4.1 k-means algorithm

We employed K-means clustering algorithm in this study to club data points into clusters based on their similarity. The algorithm makes clusters making sure that the variance within a cluster is minimized and variance between different clusters is maximized, which ensures that data points within the same cluster are closely related, while those in different clusters are distinct from each other. In our approach, the algorithm was applied to the transposed data, where each feature is treated as a data point. This helped us to capture correlations and patterns between features based on their properties. After clustering, elastic-net regularization was applied on each cluster to select the most relevant features within each cluster.

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Algorithm 1 Hybrid K-Means and Regularization-Based Feature Selection

Input: Dataset with features $F = [F_1, F_2, \ldots, F_N]$, Number of clusters, Regularization parameters $alpha$, $l1\_ratio$ for ElasticNet
Output: Selected features $M \subseteq F$

```
Transpose the dataset to cluster features instead of samples
Apply K-Means clustering on the transposed data
Assign each feature F_i to a cluster C_k
Create an empty list to store selected features
for all clusters C_k do:
    Retrieve all features belonging to C_k as F_cluster
    Extract the data corresponding to F_cluster
    Initialize an Elastic Net model with alpha and l1_ratio
    Fit the model on F_cluster using the target variable
    Identify features with non-zero coefficients
    Add these features to selected features list
end for
Remove duplicates from selected features list
```

3.4.2 Elastic-Net Regularization

Elastic net regularization is a linear regression technique that uses the penalties from the Lasso (L1) and Ridge (L2) techniques. It effectively combines both methods by learning their shortcomings to do better regularization. Elastic Net is used for regularization because it selects a subset of the most relevant features and handles multicollinearity effectively which is common in financial datasets. Loss in elastic net regularization can be calculated using (2)

$$L(\beta) = \sum_{i=1}^{n}(y_i - \sum_{j=1}^{m}(X_{ij}\beta_j))^2 + \lambda \left(\alpha \sum_{j=1}^{m} |\beta_j| + \frac{1-\alpha}{2} \sum_{j=1}^{m} |\beta_j^2| \right) \tag{2}$$

where:

- $L(\beta)$:Loss function for elastic net
- y: Vector of observed values.
- X: Matrix of input features.
- β: Vector of coefficients (parameters to be estimated).
- λ: Regularization parameter controlling the overall strength of regularization.
- α: Mixing parameter for elastic net, where $0 \leq \alpha \leq 1$.
  - $\alpha = 1$: Lasso (ℓ_1 regularization).
  - $\alpha = 0$: Ridge (ℓ_2 regularization).

In this research, Elastic Net is applied on the clusters formed using the k-means algorithm. For each feature within the cluster, if its coefficient from the elastic net regularization model is non-zero, it is considered important and is selected.

3.4.3 Features

This hybrid approach ensures that feature selection is informed by both:

• Global Structure, achieved by using K-means algorithm as it groups all the similar features into the same cluster.

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• Local Structure, achieved by using elastic net regularization which only selects the most predictive features within each cluster.

This methodology combines the strengths of clustering and regularization. Clustering ensures features with similar patterns are grouped. Elastic net ensures that only the most important and non-redundant features from each group are retained. The features obtained are then divided into training and testing sets, with a train-test ratio of 80:20.

3.5 Prediction Model

In this research, an LSTM (Long Short-Term Memory) model was employed to make predictions of the closing price of the next day. The dataframe created after selecting the most appropriate features using the hybrid-means-regularization approach, is used to train the LSTM model. LSTM model is used for making predictions because it is a special type of recurrent neural network (RNN), which is capable of capturing temporal dependencies present in data and can remember long-term dependencies which is crucial for modelling complex relationships inherent in stock price data.

LSTM uses a memory cell to manage information over time. The flow of information through the LSTM cell is made up of three gates, namely, input gate, forget gate and output gate. The gates in the memory cell works as discussed ahead:

- **Forget Gate:** Responsible for determining how much information received from the earlier cell state is to be retained. Equation (3) is the equation for the forget gate.

$$f_t = \sigma(w_f \cdot [h_{t-1}, x_t] + b_f) \tag{3}$$

- **Input Gate:** Responsible for deciding which new information has to be kept in the cell state. the equation of the input gate is:

$$i_t = \sigma(w_i \cdot [h_{t-1}, x_t] + b_i) \tag{4}$$

$$\tilde{c}_t = \tanh(w_c \cdot [h_{t-1}, x_t] + b_c) \tag{5}$$

- **Updating Cell State:** Updates the cell state using the forget gate and input gate as shown in (6)

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \tilde{c}_t \tag{6}$$

- **Output Gate:** Controls the output of the cell and the hidden state. The equation for the output gate is:

$$o_t = \sigma(w_o \cdot [h_{t-1}, x_t] + b_o) \tag{7}$$

$$h_t = o_t \cdot \tanh(c_t) \tag{8}$$

where:

- x_t: Input vector at time t.
- h_t: Hidden state (output) at time t.
- c_t: Cell state at time t.
- σ: Sigmoid activation function, defined as $\sigma(z) = \frac{1}{1+e^{-z}}$.
- $\tanh$: Hyperbolic tangent activation function, defined as $\tanh(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$.
- W: Trainable weight matrices for the gates.
- b: Trainable bias vectors for the gates.

However, LSTM models tend to have black box nature, which makes it difficult to trace how the actual predictions are made. Not knowing how the output is exactly generated by the model, makes it less reliable and difficult to trust. Hence, multiple explainable AI techniques can be used to interpret the predictions made by the model[13].[14]

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3.6 Performance Evaluation

In this research, we aim to predict the closing price of a particular stock for the next trading day, where it becomes crucial to evaluate whether the predictions made by the model are accurate and close enough to the actual closing price or not. Hence, we have used various metrics including mean squared error (MSE), mean absolute error (MAE), and R2 score to evaluate the predictions made by the model.

3.6.1 Mean squared error(MSE)

It is measured as the difference in values of the actual and predicted values, which is then squared and averaged. The lower value of MSE indicates lesser error in predicting the actual values and hence the lower value of MSE is better. It can be calculated using (9)

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{9}$$

where:

- n: total length of data rows
- y_i: original value of the ith data row
- $\hat{y}_i$: obtained value for the ith data row

3.6.2 Mean absolute error(MAE)

It is measured as the difference in values of the actual and predicted values, and taking average of it for all the values. The lower value of MAE indicates a lesser error in predicting the actual values and hence lower value of MAE is desirable. It can be calculated using (10).

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{10}$$

where:

- n: total length of data rows
- y_i: original value of the ith data row
- $\hat{y}_i$: obtained value for the ith data row

3.6.3 R squared score

It is the proportion of the variance in the target variable that is predicted using the features. The value of R^2 shows whether the model can make good predictions and whether it is a good fit for the given data set. The value of R^2 ranges between 0 to 1 where 0 means the target variable can't be predicted using the features. And 1 shows that the target variable can be predicted from the features without any error. Hence higher value of R^2 is desirable. It can be calculated using (11).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{11}$$

where:

- n: total length of data rows
- y_i: original value of the ith data row
- $\hat{y}_i$: obtained value for the ith data row
- $\bar{y}$: average of the original values

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4 Experimental Results

In this study, existing and suggested approaches were integrated for selecting useful features namely, the k-means algorithm and elastic net regularization to sort out the most predictive and relevant features for making predictions. The model is trained using the selected features and predict the closing price of a stock for the next trading day. A simple lstm model was employed to imply more focus on the feature selection approach. The parameters used to train the model and make prediction is specified in Table 2.

Table 2: Model Trained

Sr. No.	Parameter	Value
1.	LSTM	10
2.	Dense	1
3.	Loss	Mean squared error
4.	Optimizer	Adam

The performance of our proposed K-means-elastic-net feature selection approach is evaluated and compared with the existing approach.[2]

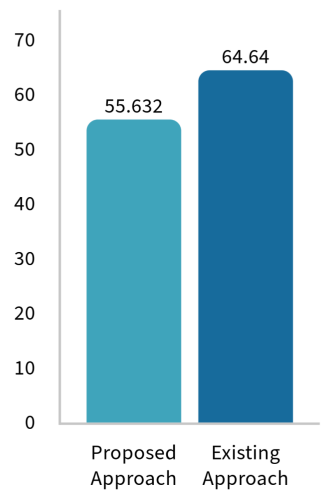

Figure 3: Mean Squared Error (MSE) for proposed and existing approach

As observed in figure 3, MSE of 55.632 and 64.64 was achieved for the proposed and existing approach, respectively. The proposed approach showed an enhancement of about 13.93% than the existing approach in MSE.

The MAE achieved for proposed and existing approaches was 5.1 and 5.74, respectively, as presented in figure 4. The proposed approach resulted in 11.15% better predictions than the existing approach.

The R2 score observed for the proposed and existing approaches is 0.9878 and 0.9859, respectively, as observed in figure 4. The proposed approach did 0. 192% better than the existing approach in terms of the R2 score. The analysis shows that the proposed approach can help make better predictions of future closing prices of a stock when compared to the existing approach.[2]

5 Conclusion and Discussion

This study discussed the importance of feature selection to effectively train the model and make better predictions. K-means and elastic net regularization based feature selection approach was proposed to address the problems in using a simple K-means algorithm and selecting the largest cluster. The K-means and elastic net regularization approach select the most relevant and important features from each formed cluster. An analysis

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Received: August 06, 2024 Revised: November 15, 2024 Accepted: January 20, 2025

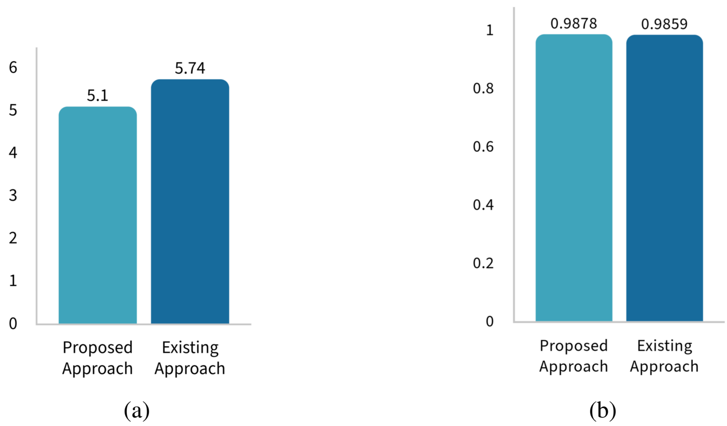

Figure 4: (a) Mean Absolute Error (MAE) for proposed and existing approach; (b) R squared score for proposed and existing approach

was conducted with the existing approach which indicates the enhancement in predictions when the proposed method was used.

The challenges of this study are as follows: (1) The number of clusters to be made using the K-means clustering algorithm can impact the overall feature selection process. Hence, it is necessary to select the number adequately by analyzing the performance of the entire system with different values for the number of clusters; (2) The number of features selected after feature selection can vary based on the data and parameters of the algorithm. Hence, choosing and building an appropriate machine learning model, while keeping the attributes of data and features in mind, becomes necessary.

Furthermore, even though the proposed feature selection approach performs better than the existing approach, the applicability of the proposed approach to other time series-based forecasting problems remains yet to be explored.

Credits and contribution of authors
Dhruvin and Rutvij were involved in the conception and design Dhruvin and Ashish were involved in results and analysis. All the authors were involved in drafting, reviewing, editing and proofreading of the paper.

Disclosure statement
The authors report there are no competing interests to declare.

Data availability statement
The data that support the findings of this study are openly available in kaggle at dataset link.

Disclosure of interest
There are no relevant financial or non-financial competing interests to report.

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DOI: https://doi.org/10.54216/FPA.180218
Received: August 06, 2024 Revised: November 15, 2024 Accepted: January 20, 2025