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Stock Price Prediction in the Banking Sector of Bangladesh: an Ensemble LSTM Framework

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Abstract

Predicting the values of stock prices remains one of the most challenging problems due to the complex, nonlinear, and volatile nature of financial markets. Many influencing factors dictate the nature of stock prices. Not only macro-economic factors like inflation rate and exchange rate, but also socio-political issues exert influence on the overall stock market behaviour of the banks in Bangladesh. This study proposes a data-driven framework for predicting the closing stock prices of banks in the Dhaka Stock Exchange (DSE). An exhaustive dataset of stock market data and relevant factors was also prepared for this study. The framework proposed consists of a two-stage ensemble learning technique. Separate Long Short-Term Memory (LSTM) sub-models are trained on historical data of individual banks, and the outputs are then integrated to develop a meta-level dataset. A meta-model was trained on the meta-level dataset. Model evaluation is performed through a pipeline of trained submodels and a metamodel on a merged test dataset. The training and testing processes have been performed on different dataset combinations to capture the relevance of the factors to the predictions.

Keywords: Stock Price Prediction, Banking Sector of Bangladesh, Political Unrest, Macroeconomic Factors, Long Short-Term Memory, Dhaka Stock Exchange (DSE).

1 Introduction

As Bangladesh is transitioning towards a more diverse economy [1], the performance of the stock market is serving more and more as a key indicator of economic soundness [2], as it directly reflects public confidence in the economy and illustrates sector-wise performance and the overall stability of financial systems [3]. Thus, understanding market behavior is a key to improving investor confidence [4] and to ensuring sustainable economic development.

Among all the sectors of the stock market, the banking sector, specifically, plays a crucial role in the financial system [5], as it is the primary channel for credit distribution, savings, and monetary transactions. Consequently, the performance of banking institutions in the stock market holds considerable importance. Stability or upward trends in the stock prices of banking institutes are often viewed as indicators of financial system stability, whereas significant fluctuations in their prices indicate underlying issues related to governance, liquidity, or compliance. The above reasons make the banking sector a critical point for investors, policymakers, and researchers.

Macroeconomic variables such as inflation and exchange rates have significant influence in determining the stock market performance of a business entity [6] [7] [8]. With increasing inflation, purchasing power decreases, which influences interest rates, resulting in alterations in bank profitability and investor expectations. Similarly, fluctuations in the exchange rate impact import costs and foreign trade. As the stock market as a whole is deeply influenced by both the domestic and the international financial environment, shifts in inflation and exchange rates are directly translated into stock prices of banks. It is therefore very essential to take into consideration these macroeconomic factors that influence market behavior.

Political conditions also exert significant influence on the dynamics of the stock market in Bangladesh. Political unrest, elections, strikes, and governance disruptions affect investor confidence and market stability. From historical evidence it is apparent that political instability causes abrupt market downturns by increasing risk perceptions among investors. In countries like Bangladesh, where political volatility is very common, social and political events can cause steep and unexpected fluctuations in the stock prices. So while developing a model for the prediction of stock prices, considering these factors plays a significant role.

The combined influence of macroeconomic and socio-political factors on the stock prices of banking institutes poses a challenge in effective investment planning and risk management [9]. Being able to predict the closing prices of the stocks enables investors to anticipate market movements and to make data-driven decisions. We are introducing a novel ensemble deep learning model that integrates multiple LSTM-based architectures to predict temporal patterns more effectively in this study called EnsemLSTM. In this model we incorporate opening prices of the stocks, trading volume, inflation, exchange rate variations, and political indicators to deliver more robust and reliable predictions of closing stock prices in Bangladesh's banking sector.

2 Literature Review

Stock price prediction has attracted researchers from many different methodological backgrounds, including classical machine learning, deep learning, and modern big data analytics. One common observation has emerged across these studies that financial markets are nonlinear, noisy, and highly volatile. This pushes researchers to move beyond simple statistical tools. It motivates the use of advanced machine learning models that can capture temporal characteristics. They can be utilized to analyze the effect of influencing factors too.

2.1 Stock Prediction Models

Over the years, many studies have investigated the efficiency of stock price prediction using a variety of modeling techniques, ranging from simple regression models to advanced deep learning architectures. The following works illustrate key methodological developments and their applications in the Dhaka Stock Exchange. Das et al (2020). [10]. experimented with Support Vector Regression (SVR) and Linear Regression to predict the stock prices of Grameenphone. Their results showed that Linear Regression performed the best when evaluated using SSE. It outperforms SVR with both linear and RBF kernels. Their findings indicate that when the feature set is small and does not reflect broader market conditions, simple regression models can sometimes work better than more complex nonlinear methods.

Muhammad et al. (2022) [11] proposed a transformer-based model enhanced with time2vec encoding. The goal was forecasting daily and weekly price movements for eight stocks listed on the Dhaka Stock Exchange (DSE). Their approach depicted the transformer's strength in capturing long-range dependencies through multi-head self-attention. This leads to low RMSE scores across multiple companies. The study shows incorporating richer temporal encodings and contextual embeddings can improve financial time-series forecasting when models are trained individually for each stock. This is highly related to our work because we have worked on the stocks of 36 different banks of Bangladesh.

Miah et al. (2015) [12] developed a fuzzy-neural model for stock prediction. The fuzzy component produced rule-based estimates of target prices. The neural network component learned the nonlinear patterns in the data. Their system used inputs such as market capitalization, earnings indicators, and trading volume. It produced stable predictions of the stock prices of a local business conglomerate. This hybrid approach shows that combining human-interpretable rules with learning models can help manage uncertainty in volatile markets.

Islam et al. (2023) [13] worked with a large feature set, including technical indicators, macroeconomic factors, sentiment from news and social media, etc. They trained several machine learning models, for example, Random Forest, SVM, LSTM, and SVR. Their results showed that mixing structured financial data with sentiment features leads to better predictions. So this work highlights the value of external factors like political events, economic shocks, and investor mood. As these factors matter even more in emerging markets such as Bangladesh, we have considered macro-economic and socio-political factors in our research work.

2.2 Influencing Factors

While many studies have been conducted based on price-based indicators, recent literature highlights the crucial role of macroeconomic, social, and political factors in determining stock market behavior. Macroeconomic variables such as GDP, inflation rates, money supply, and interest rate adjustments have repeatedly been shown to influence investor decision-making and market trends. The rise of digital and social media has encouraged researchers to study more unstructured factors—such as news sentiment, social media discussions, and political climate—that influence the behavior of investors towards particular establishments. These sources help to capture the psychological dimension of the market, which traditional financial metrics may often overlook.

In the Bangladesh stock market, this multidimensional approach has only recently begun to gain attention. Fabiha et al. (2025) [14] incorporated macroeconomic and firm-specific indicators using regression and ensemble models, shedding light on the factors that influence price variability within the Dhaka Stock Exchange. However, a noticeable gap still remains, as many studies based on Bangladesh focus heavily on historical prices, with limited exploration of how macroeconomic and socio-political parameters and media sentiment affect them.

Our work aims to bridge this gap. By systematically integrating macroeconomic indicators (such as inflation and exchange rates) with socio-political factors (such as major national events and public sentiment), we developed a unified machine learning framework specifically for the Bangladeshi banking sector. This approach not only improves predictive performance but also helps to interpret how different real-world activities, such as economic conditions, political shifts, and market psychology, collectively shape stock price movements.

3 Dataset

A comprehensive dataset of stock prices and relevant influencing factors was developed from multiple sources for this study. Stock market-related data and data for the macroeconomic factors like inflation rate and exchange rate were collected from reliable sources. A dataset indicating political effects on stock prices was also prepared manually. The dataset covers the time span of almost eight years from January 2017 to September 2024.

3.1 Data Availability

The dataset used in this study is publicly available at the [EnsemLSTM-Dataset] repository [https://github.com/tahmid013/EnsemLSTM-Dataset] [15].

3.2 Stock Market Data

Daily stock data for the following 36 Bangladeshi banks were collected from a financial information service platform named AmarStock [16]:

AB Bank Limited, Al-Arafah Islami Bank Limited, Bank Asia Limited, BRAC Bank Limited, The City Bank Limited, Dhaka Bank Limited, Dutch-Bangla Bank Limited, Eastern Bank Limited, Export Import Bank of Bangladesh Limited, First Security Islami Bank Limited, Global Islami Bank Limited, ICB Islamic Bank Limited, IFIC Bank Limited, Islami Bank Bangladesh Limited, Jamuna Bank Limited, Mercantile Bank Limited, Midland Bank Limited, Mutual Trust Bank Limited, National Bank Limited, NCC Bank Limited, NRB Bank Limited, NRB Commercial Bank Limited, One Bank PLC, Premier Bank Limited, Prime Bank Limited, Pubali Bank Limited, Rupali Bank Limited, South Bangla Agriculture & Commerce Bank Limited, Shahjalal Islami Bank Limited, Social Islami Bank Limited, Southeast Bank Limited, Standard Bank Limited, Trust Bank Limited, United Commercial Bank Limited, Union Bank Limited, Uttara Bank PLC.

For each bank, the following daily trading parameters were collected:

- **Trading Date**: The specific calendar day on which trading activity occurred was considered one of the parameters, as it serves as the temporal index for the dataset. This parameter allows time-series analysis of stock price movements and trading behavior.
- **Open Price**: It refers to the first recorded trading price of a stock at the beginning of a trading session. It is an important parameter to understand the gap between the initial valuation of the stocks and the final valuation.
- **High Price**: This variable captures the peak valuation reached within the trading timeline and is useful for understanding the upper bound of the price of stocks.
- **Low Price**: The low price indicates the lowest valuation of a stock reached within a trading session. Together with the high price, it helps measure volatility and price dispersion.
- **Close**: The close price is the final trading price of the stock at the end of the trading session. It is often considered the most reliable parameter because it reflects the outcome of all trading decisions made during the day.
- **Volume**: Volume refers to the total number of shares traded during a fixed trading session. It is an important parameter indicator of market liquidity and investor participation.

3.3 Exchange Rate Data

The daily USD to BDT exchange rate data were collected from the website of Bangladesh Bank (the central bank of Bangladesh). Exchange rate changes play a key role in determining the performance of the stock market because they impact foreign trade and the management of currency reserves. Sudden shifts in the currency rates create chaos and uncertainty in the market. In our study, two parameters regarding the exchange rates were collected:

- **Buying Rate**: The buying rate represents the price at which commercial banks purchase USD from customers or the market. This represents the demand for foreign currency in the domestic economy.
- **Sell Rate**: The selling rate indicates the price at which banks sell USD. This particularly impacts the cost of foreign transactions and imports.

3.4 Inflation Data

Inflation directly influences the purchasing power of the customers in a market and also the interest rates. It affects overall economic stability. Including inflation provides important macroeconomic context for the forecasting model. Monthly inflation data were also collected from the website of Bangladesh Bank: The inflation data was recorded on a monthly basis. In this model we have considered inflation rates to be constant throughout the respective months. This is justified as inflation rates usually do not change significantly on a day-to-day basis.

3.5 Political Event Data

Political instability can trigger market disruptions in emerging economies. In the context of predicting the performances of a particular bank in the stock market, political events are important. Investor sentiment, operational uncertainty, and risk perception all play a role. Banking stocks in Bangladesh are highly sensitive to political events. By incorporating this variable into the model, a more robust framework able to capture sudden stock movements is designed.

A manually prepared political event dataset was constructed with a binary indicator (0 or 1) marking days affected by significant political disruptions (e.g., strikes, blockades, election activities, or major announcements).

3.6 Dataset Variants and Their Significance

As mentioned earlier, eight different datasets were created to examine the financial, economic, and political impacts of stock market performances of banking institutes. We first collected and organized both the stock data and the additional external factors to create these datasets. The trading-related dataset contained only the basic stock information: opening price, closing price, high, low, and trading volume. Other datasets combine these stock features with external indicators, such as inflation, exchange rates, or political events. The most extensive dataset includes all the features: stock, inflation, exchange rate, and political factors. These datasets allow us to analyze how each factor, individually or in combination, influences prediction accuracy.

Table 1 Dataset Configurations Based on Feature Combinations

Combination	Datasets Included
C1	Stock
C2	Stock + Inflation rate
C3	Stock + Exchange rate
C4	Stock + Inflation rate + Exchange rate
C5	Stock + Political influence
C6	Stock + Inflation rate+ Political influence
C7	Stock + Political influence + Exchange rate
C8	Stock + Inflation rate+ Political influence + Exchange rate

3.7 Dataset Analysis

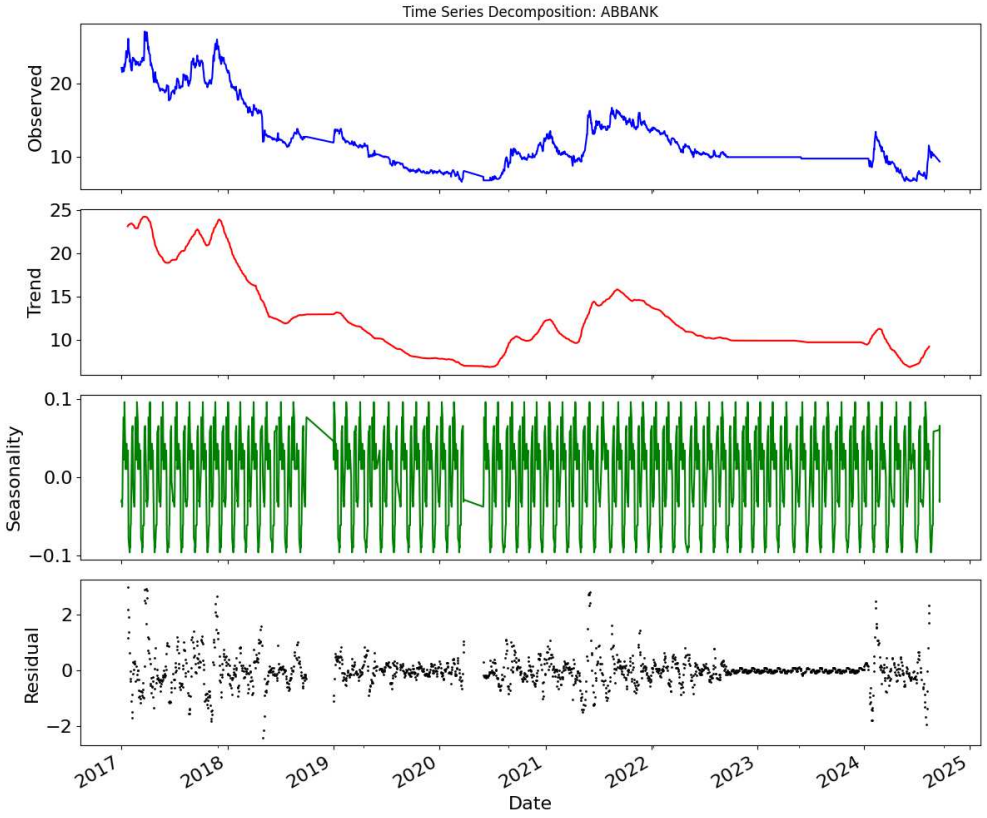


Fig. 1 AB Bank Time Series Statistics

We examined the decomposed time-series components of two representative banks (AB Bank and Al-Arafah Islami Bank) to understand the underlying market behavior.

The decomposition results from 2017 to 2024 show clear differences between the two banks. From the time series analysis, it is visible in Fig. 1 that AB Bank experienced a strong downward shift from 2018 to 2020. The trend then recovered slightly and stabilized at a lower price level. In the later years, the trend remained mostly stable. This pattern shows weak long-term growth. The stock prices of Al-Arafah Islami Bank also declined around 2020, as illustrated in Fig. 2. However, for Al-Arafah Bank, the recovery is stronger. Both banks show clear seasonal cycles with frequent oscillations of similar size. This pattern reflects recurring trading behavior over time. The residual components show clearer differences. In the comparison, AB Bank shows wider dispersion, with several sharp spikes visible. Al-Arafah Bank shows tighter residual

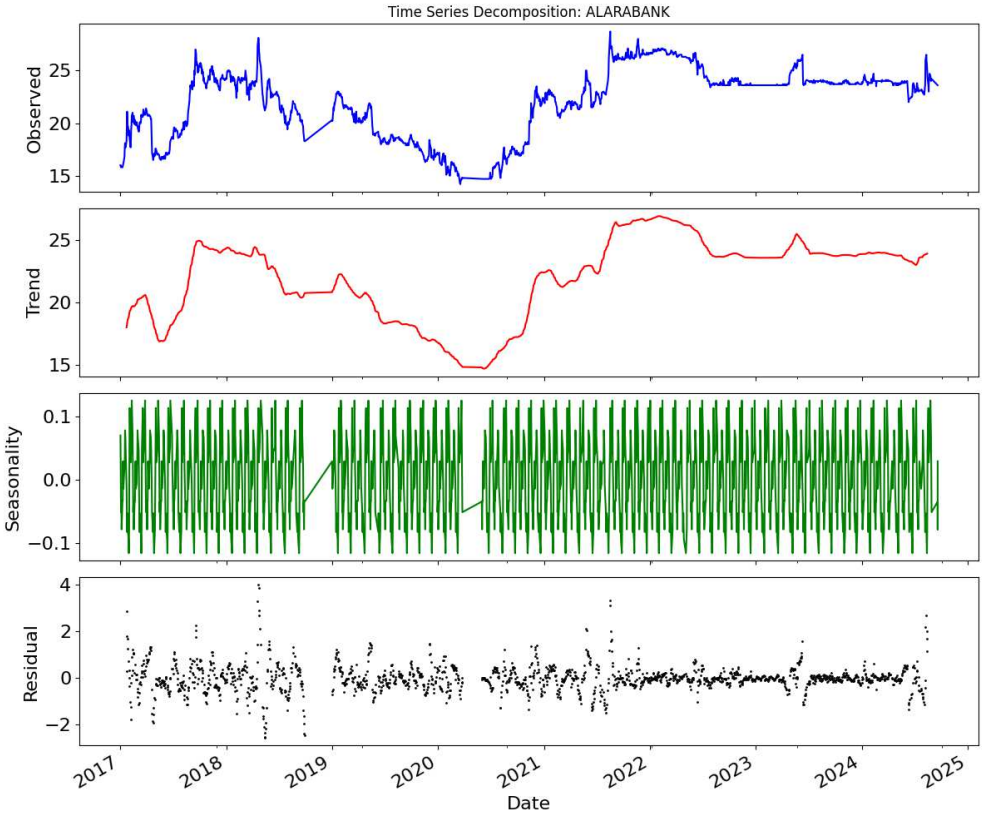


Fig. 2 Al Arafah Bank Time Series Statistics

movement with few extreme deviations. The graphs indicate stronger trend recovery and lower irregular variation for Al-Arafah compared to AB Bank.

Figure 3 and 4 depict the comparison between AB Bank and Al-Arafah Islami Bank using return distributions and normalized price growth with base 100 for 2022 and 2023. The graphs show clear differences in volatility and performance.

For AB Bank, volatility dropped from 2022 to 2023. In 2022, return distribution showed a wider spread with heavier tails. In 2023, the distribution becomes narrow and centered near zero. Price movement becomes limited.

Al-Arafah Islami Bank shows a different pattern. The return distributions for 2022 and 2023 showed a similar pattern, while the 2022 curve had slightly heavier tails. Overall spread remained moderate in both years. For Al Arafah Islami Bank, no sharp decline in volatility was observed.

The growth curves of the two banks showed a stronger contrast. AB Bank faced constant decline throughout 2022, with the base value of 100 falling to around 70. However, in 2023, the price remained almost constant.

Al-Arafah Islami Bank also faced a decline in 2022, but the drop was not as significant as AB Bank. In 2023, the price rose above 110 and settled slightly above the base level. This pattern shows improved performance compared to AB Bank.

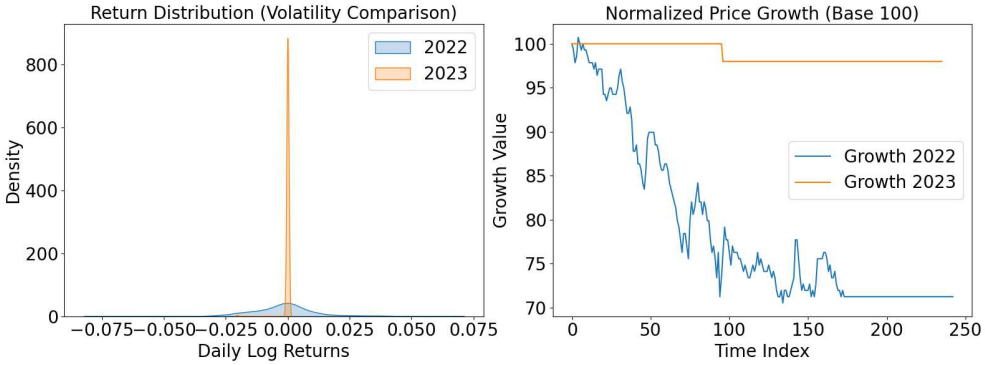


Fig. 3 Return Distribution and Growth rate of AB Bank

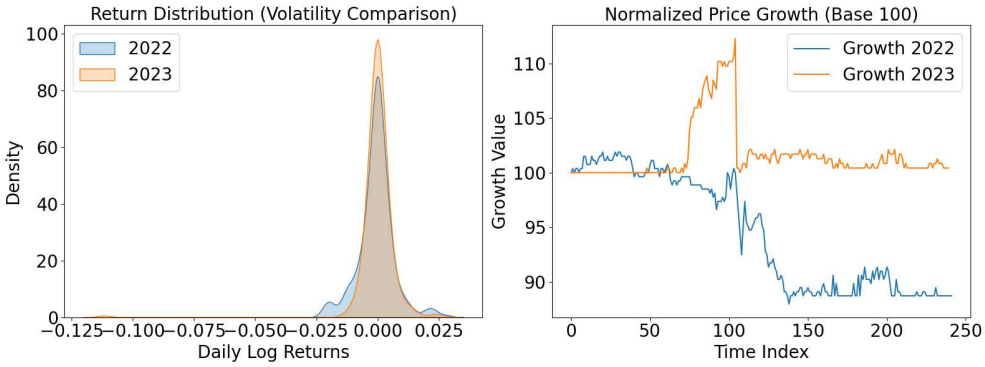


Fig. 4 Return Distribution and Growth rate of Al Arafah Bank

The graphs show clear differences between the two banks. AB Bank moves from a high-volatility decline in 2022 to a low-volatility stagnant phase in 2023. Price movement becomes narrow, and growth remains weak. Al-Arafah Islami Bank shows moderate volatility in both years. The bank records a stronger recovery in 2023. Price growth turns positive, and momentum improves compared to AB Bank.

4 Methodology

This study employs a two-stage modeling approach that integrates bank-specific submodels with a higher-level meta-model. The methodology is organized into four main

phases: data preparation, submodel training, meta-model training, and testing with evaluation.

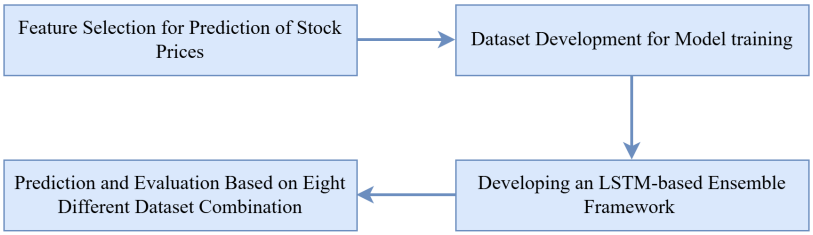


Fig. 5 Workflow

4.1 Problem Formulation

The problem addressed in this study is the prediction of stock prices in the banking sector. Let the historical dataset for n banks be represented as

$$D = \{D_1, D_2, \ldots, D_n\},$$

where each

$$D_i = \{(x_{i1}, y_{i1}), (x_{i2}, y_{i2}), \ldots, (x_{im_i}, y_{im_i})\}$$

contains m_i time-ordered instances, with x_{ij} denoting the feature vector (e.g., stock indicators, market variables) and y_{ij} denoting the corresponding target value (e.g., closing price).

For each bank i, the objective is to learn a predictive function

$$f_i : X_i \to Y_i$$

that maps its historical features to future stock prices. Relying only on individual bank models can miss shared market patterns. These patterns often affect multiple banks at the same time. To overcome this, we use a meta-learning framework. In this setup, a meta-model F learns to combine the outputs from all the individual submodels. $\{f_1, f_2, \ldots, f_n\}$.

Formally, given the predictions of the submodels on a combined dataset, represented as:

$$\hat{Y}_{val} = [f_1(X_{val}), f_2(X_{val}), \ldots, f_n(X_{val})],$$

and the corresponding ground truth values Y_{val}, the objective of the meta-model is to learn a function that minimizes the prediction error.

$$F : \hat{Y}_{val} \to Y$$

The final optimization goal can be expressed as:

$$\min_{f_1,\ldots,f_n,F} \mathcal{L}(Y_{test}, F([f_1(X_{test}), \ldots, f_n(X_{test})])),$$

where $\mathcal{L}$ is a loss function defined using standard error metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE).

4.2 Dataset Partitioning and Aggregation:

In the first phase, shown in Fig. 6, we collected and processed stock data along with economic factors from n banks. Each bank's dataset was split into three parts: 70% for training, 15% for validation, and 15% for testing. The validation sets from all banks were combined into a single mega-validation set. The test sets were also merged into a mega-test set, which is shown in Fig. 7. The purpose behind this is to support cross-bank generalization.

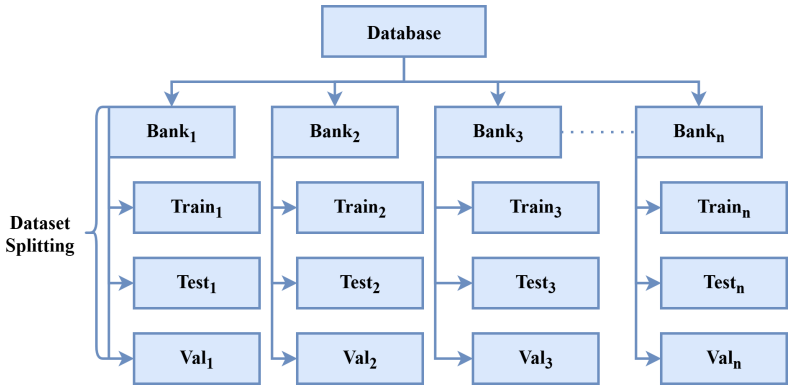


Fig. 6 Dataset Partitioning Across Multiple Banks

4.3 Sub-Model Training Framework:

The second phase, illustrated in Fig. 8, focused on training the submodels. Each bank had a submodel trained on its own data. So the training set for each bank was split again for this purpose. Ninety percent formed a sub-training set and the remaining 10% formed a sub-validation set. Each submodel was an LSTM model. LSTM models are better at capturing time-series characteristics. SO we have used that. Once trained, the submodels made predictions on the mega-validation set. Predictions from all submodels were combined. They were paired with the actual stock values. This created a new dataset. It was used to train the meta-model.

4.4 Meta-Model Training

To enhance predictive performance, a meta-model is constructed by aggregating the outputs of previously trained sub-models. As illustrated in Fig. 9, the input

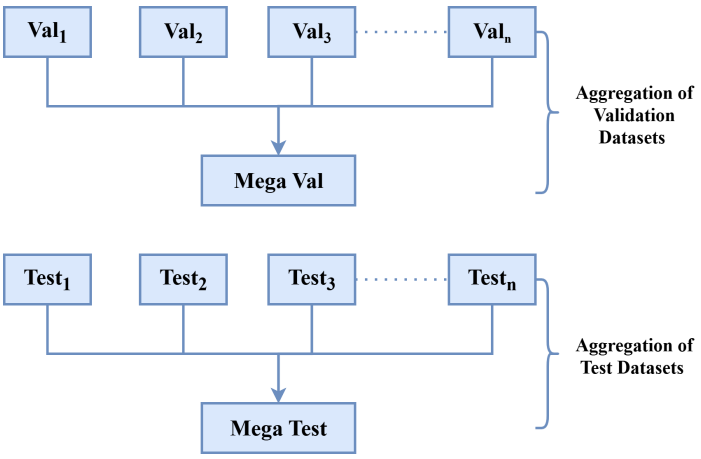


Fig. 7 Formation of Mega Val and Mega Test Datasets

features are first taken from the mega validation dataset. Each trained sub-model $(M_1, M_2, \ldots, M_n)$ generates corresponding predictions $(P_1, P_2, \ldots, P_n)$ using these input features.

These prediction outputs are then combined to form a new feature space, where each P_i represents a meta-feature. Alongside these features, the target variable is obtained from the mega validation target column. This process results in a new dataset specifically designed for meta-model training, effectively capturing the collective knowledge of all sub-models.

Subsequently, as shown in 10, the constructed dataset is used to train the final meta-model. This model learns to optimally combine the predictions of the sub-models, thereby improving overall generalization and predictive accuracy.

4.5 Prediction and Evaluation:

The final phase focused on testing and evaluation. Each trained submodel and meta model was saved. So we made a pipeline to test and predict on the testing data. First, we applied trained submodels to the mega test set to generate predictions. The outputs were combined to build an intermediate dataset for the meta-model, as shown in Fig. 11. Then the dataset was fed into the meta model. The meta-model then produced the final predictions, shown in Fig. 12.

4.6 Evaluation Metrics:

Performance was measured using four error metrics. Mean Absolute Error (MAE) shows the average of the prediction errors. Mean Squared Error (MSE) squares the differences between actual and predicted values. This gives more weight to larger differences. Root Mean Squared Error (RMSE) is the root of MSE. It makes the error value on the same scale as the data. The Coefficient of Determination (R^2) shows how well the predictions capture the variation in the actual values.

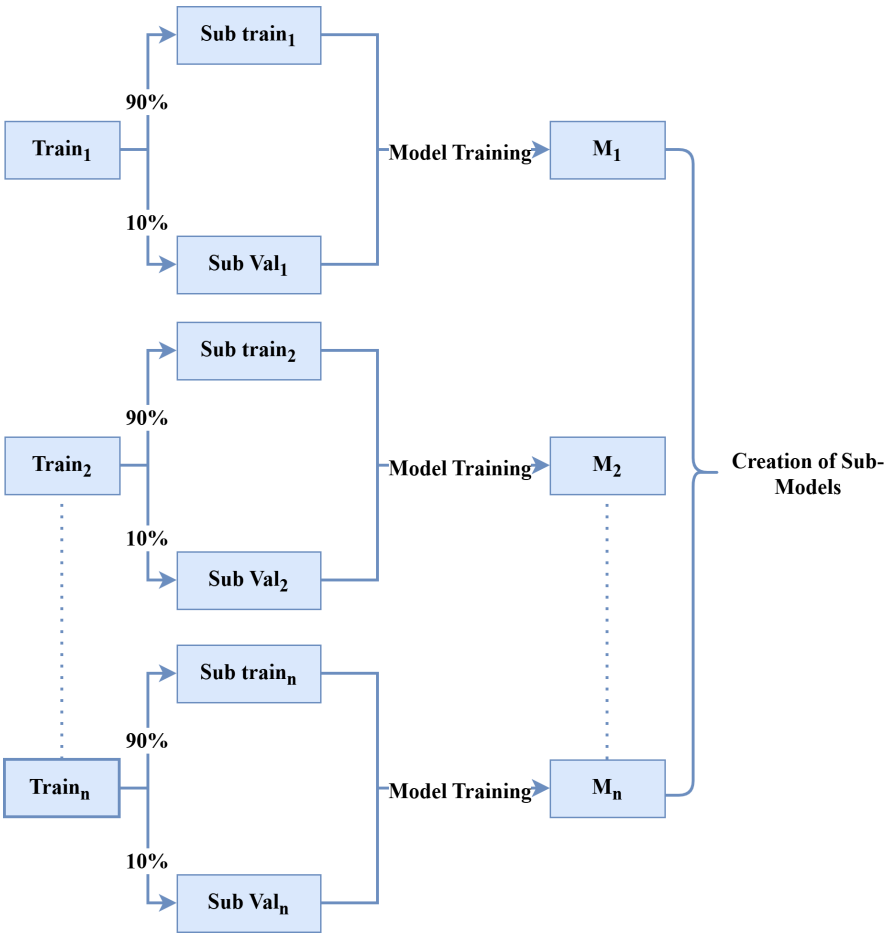


Fig. 8 Sub-Model Training Framework with Train–Validation Splitting

Table 2 Performance Metrics

Metric	Formula
Mean Absolute Error (MAE)	$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\lvert y_i - \hat{y}_i\rvert$
Mean Squared Error (MSE)	$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$
Root Mean Squared Error (RMSE)	$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$
Coefficient of Determination (R^2)	$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$

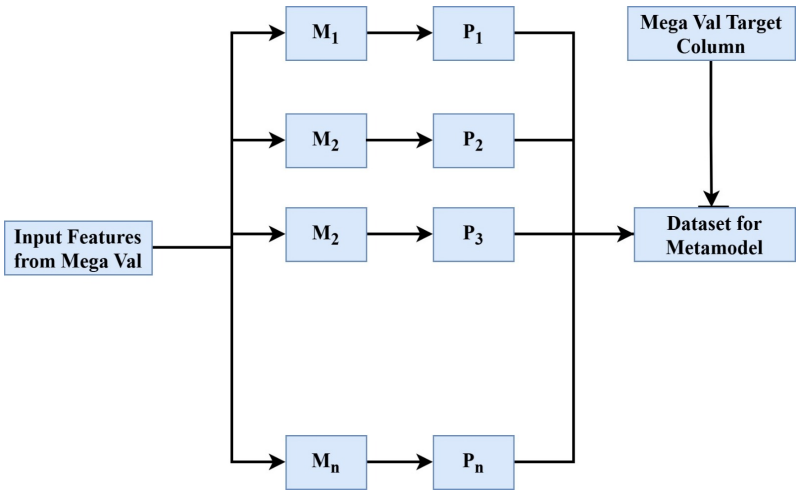


Fig. 9 Dataset Formation for Meta-model Training



Fig. 10 Meta-Model Training

5 Results

The meta-model was tested on datasets of the individual banks. The setups used for evaluation are described in Section IV. Performance metrics of the model evaluated using MAE, MSE, RMSE, R^2, and MAPE are shown in Figure 13.

Among the eight variants of dataset combinations, the baseline model used only stock-related features, which performed well. Although MAE and RMSE were low in the baseline model, R^2 was high. Performance improved when we added a single external feature, such as the exchange rate or a political indicator. These features added useful context without adding noise. However, performance dropped when we combined several but not all variables due to overlapping. An increase in MAE, RMSE, and MAPE and a decrease in.R^2 suggest overfitting.

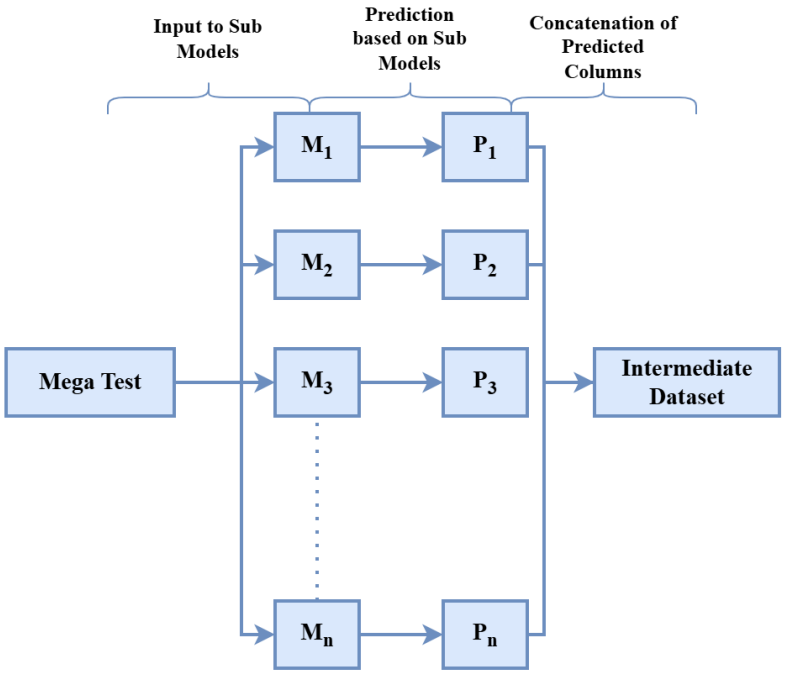


Fig. 11 Intermediate Dataset Formation for Prediction

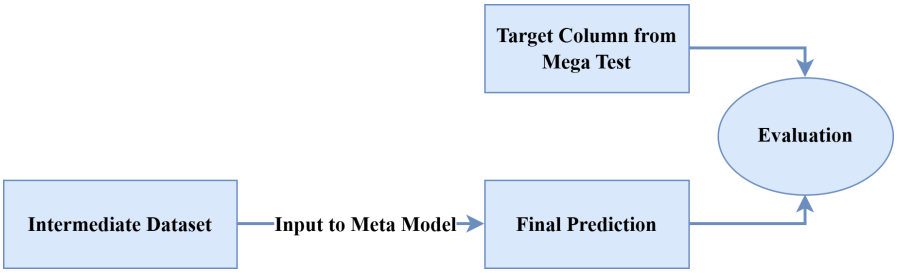


Fig. 12 Prediction and Evaluation

In this study, it was apparent that using a meta-model reduced prediction fluctuations successfully by combining its submodels. It performed very well in stable market periods with R^2 above 0.99 and MAPE below 5%. During volatile market periods. R^2 fell to around 0.87–0.89, and MAPE rose above 20% which is also justifiable.

The configurations that gave the best results are stock-related features combined with inflation **(C2)** and the combination of stock, political, inflation, and exchange rate features **(C8**. Both were strong across tests.

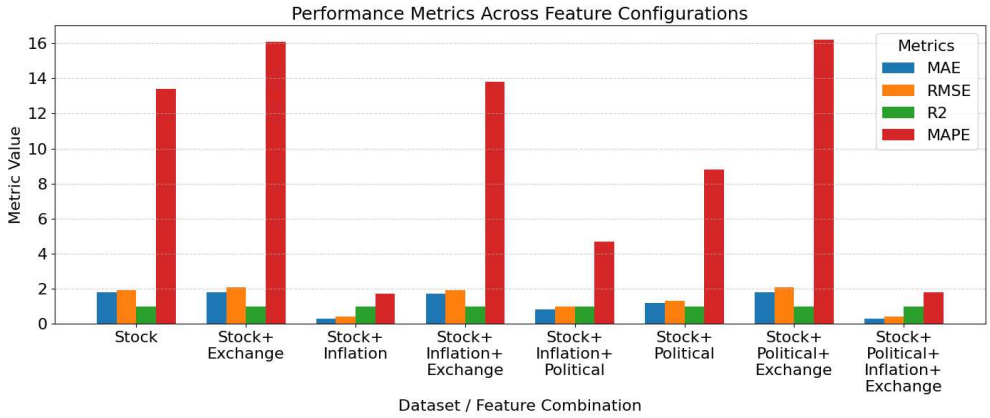


Fig. 13 Performance Metrics

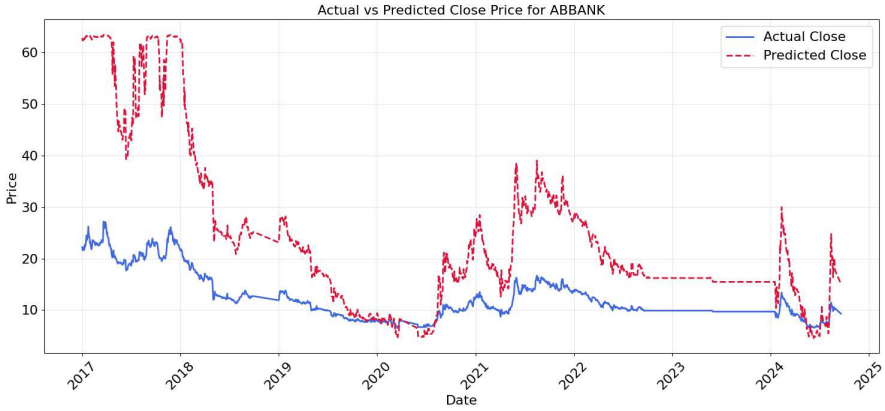


Fig. 14 Actual vs Predicted Close Price for AB Bank

The performance of the proposed EnsemLSTM framework was further evaluated across two representative banks: AB Bank and BRAC Bank. Figures 14 and 15 illustrate the comparison between actual and predicted closing prices for these institutions.

For AB Bank, the model captures the overall direction of price movements from after 2019. The trend in predictions follows the actual pattern during periods of moderate fluctuation. There is a visible issue in earlier years, especially during 2017–2018. Throughout the period that has been studied The predicted values stayed much higher than the actual prices, which shows an upward bias. In 2021 and 2024, the model successfully detects the rise but pushes the peak too high. The same situation arises when estimating the drops of stock prices within the same timeline. However, after some sharp drops, the predicted line does not show sudden falls and predicts the pattern more accurately. From the pattern of the actual vs. predicted prices of AB Bank, we

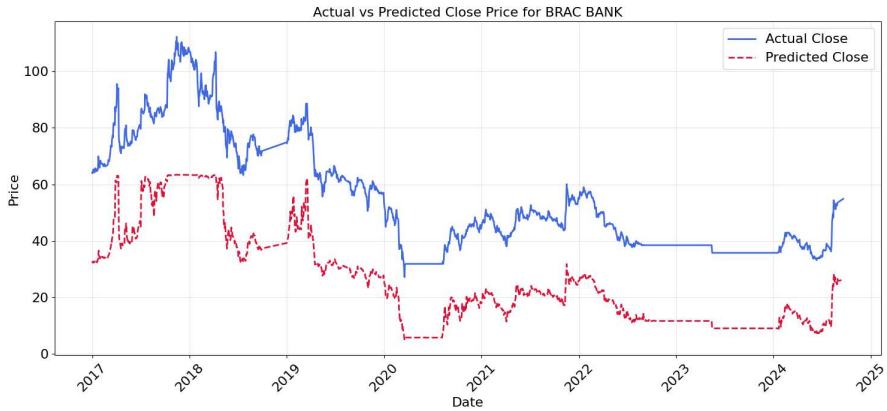


Fig. 15 Actual vs Predicted Close Price for BRAC Bank

can conclude that the model reacts strongly to rising signals. It keeps that momentum longer than the real market.

For BRAC Bank, the model captures the overall trend of the price movement. The direction of change is consistent with the actual data. It is also apparent that the predicted values remain lower than the actual prices for most of the period. This shows a clear underestimation pattern. From the comparison of the actual vs. prediction, it is also visible that the model sometimes misses the strength of upward movements, which can be attributed to some other external factor not considered in this study.

From the two representative banks, a key strength of the EnsemLSTM framework is found to be its ability to consistently capture trend dynamics. The model successfully learns temporal relationships and generates predictions that reflect the underlying structure of stock price movements. This demonstrates the effectiveness of the ensemble approach in leveraging both bank-specific patterns and shared market information.

While the overall performance is strong, minor deviations can be observed during periods of abrupt market fluctuations, where the predicted values occasionally diverge from the exact magnitude of the actual prices. Such behavior is expected in highly volatile financial environments and also can be attributed to much more complex market drivers. The discrepancies offer opportunities for future enhancement in more extensive feature incorporation.

6 Conclusion

This study proves that prediction accuracy increases when macroeconomic and political factors are incorporated in the prediction process. After implementing the model on eight different dataset configurations, it was apparent that accuracy improved when selective external variables were taken into consideration. The proposed model can be used as an efficient aid in informed decision-making for investors in Bangladesh. The extensive dataset created for this study can also be a source for further economic studies and model trainings.

Future work can include sentiment data or attention-based models to better handle times of high market volatility. Additionally, integrating attention mechanisms within the LSTM architecture could enhance the model's ability to capture long-range dependencies and dynamically focus on the most relevant temporal patterns. This may further improve predictive accuracy, especially in complex and rapidly changing market conditions. Finally, incorporating real-time data streams and developing adaptive or online learning variants of the model could make the framework more suitable for practical deployment in live financial forecasting systems.

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