Abstract

This research presents a comprehensive approach to predicting stock prices by employing advanced machine learning and deep learning models, including LSTM, GRU, and CNN architectures, alongside an XGBoost-stacked ensemble. The primary goal is to enhance prediction accuracy for stock high and low prices while addressing challenges posed by market volatility. Leveraging historical stock data, sentiment analysis, and macroeconomic indicators, the study integrates sequential modeling with feature engineering to capture temporal patterns and external influences.

The LSTM-GRU model achieved an impressive Mean Absolute Error (MAE) of 6.51, showcasing its superiority in handling complex sequential dependencies and market trends. Complementary evaluations revealed the effectiveness of CNN-LSTM and DNN architectures, with MAEs of 16.23 and 27.92, respectively, underlining the importance of hybrid and ensemble approaches for robust predictions. The incorporation of sentiment analysis contributed to improved predictive performance, particularly in scenarios influenced by market sentiment.

This study further emphasizes the significance of evaluating models through rigorous metrics such as RMSE and MAE, comparing their applicability across different stocks with varying volatility levels. The findings underscore the potential of hybrid and ensemble learning strategies in financial forecasting, offering valuable insights for stakeholders in the stock market. By automating prediction pipelines and leveraging real-time data, the research proposes a scalable framework for precise stock price predictions, paving the way for enhanced decision-making in financial markets.

Keywords: *stock price prediction, LSTM, GRU, CNN, XGBoost, ensemble learning, sentiment analysis, financial forecasting, machine learning, deep learning.*

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List Of Abbreviations

LSTM: Long Short-Term Memory

SVM: Support Vector Machine

RMSE: Root Mean Square Error

MAPE: Mean Absolute Percentage Error

MAE: Mean Absolute Error

AUC: Area Under Curve

VADER: Valence Aware Dictionary and sEntiment Reasoner

TFIDF: Term Frequency-Inverse Document Frequency

DRL: Deep Reinforcement Learning

DQN: Deep Q Network

VMD: Variational Mode Decomposition

1. Introduction

The stock market, a cornerstone of global financial systems, presents a dynamic and complex environment where accurate predictions can have significant economic and strategic implications. As markets grow increasingly volatile and data-driven, the demand for robust, automated systems capable of predicting stock prices with high precision has surged. Traditional methods, while effective in certain scenarios, often struggle to incorporate the intricate interplay of historical trends, macroeconomic factors, and market sentiment. This has fueled the exploration of advanced machine learning and deep learning models to bridge the gap between historical analysis and real-time forecasting.

Predicting stock prices is inherently challenging due to the stochastic and multifactorial nature of financial markets. Recent advancements in machine learning, particularly in sequence modeling and ensemble techniques, offer promising solutions. Models such as Long Short-Term Memory (LSTM) networks and hybrid architectures have demonstrated exceptional capabilities in capturing temporal patterns and nonlinear dependencies in data, making them ideal for financial forecasting. Ensemble techniques like XGBoost further enhance predictive accuracy by integrating diverse models, leveraging their individual strengths while mitigating their limitations.

Beyond professional trading environments, these advancements hold potential for a wide range of applications. Novice investors, financial analysts, and academic researchers can benefit from automated forecasting tools, gaining deeper insights into market dynamics. For professional traders and financial institutions, such systems enable data-driven decision-making, empowering them to mitigate risks, identify opportunities, and enhance portfolio management strategies.

1.1 Challenges

Automating stock price prediction entails numerous challenges stemming from the volatile and multifactorial nature of financial markets. One of the most prominent obstacles is the unpredictable behavior of stocks influenced by global events, market sentiment, and macroeconomic factors. Capturing such complex interactions requires sophisticated models capable of integrating diverse data sources, from historical price data to real-time news sentiment.

Another significant challenge lies in the inherent noise and outliers present in financial data. These anomalies can skew model predictions, making it critical to employ robust preprocessing and feature selection techniques. Additionally, the varying performance of models across different stocks adds complexity, as some models excel in stable markets while others perform better under high volatility.

The evaluation of stock prediction models also presents challenges. Metrics like RMSE and MAE, while useful, do not fully capture the implications of errors in real-world trading scenarios, where even small deviations can lead to substantial financial losses. Furthermore, achieving a balance between model accuracy and computational efficiency is crucial for real-time applications, a requirement that often pushes the limits of conventional approaches.

1.2 Motivation

The motivation to develop advanced stock prediction models stems from the transformative potential they offer in understanding and navigating financial markets. For investors, these models can provide actionable insights, empowering data-driven decision-making and enhancing portfolio strategies. For researchers, they represent an opportunity to explore the intersection of finance and machine learning, advancing the state of the art in predictive modeling.

Moreover, these models have implications beyond individual applications. By integrating sentiment analysis and macroeconomic indicators, they offer a holistic perspective on market dynamics, enabling stakeholders to anticipate trends and mitigate risks effectively. For novice traders, the availability of automated tools simplifies entry into stock trading, reducing reliance on subjective decision-making and fostering financial literacy.

This project explores the application of advanced machine learning techniques, including LSTM, GRU, CNN, and ensemble methods like XGBoost stacking, to develop a robust framework for predicting stock high and low prices. By addressing the challenges of volatile market behavior, data noise, and diverse stock performance, this study aims to contribute to the field of financial forecasting, paving the way for innovative and practical solutions.

2.Literature Review

Stock market prediction is a critical field in financial analysis and has undergone significant transformations with the integration of advanced computational techniques. Traditional statistical methods, such as ARIMA and basic regression models, while robust in linear applications, struggle to capture the complex, non-linear dynamics of financial markets. These limitations have led to the adoption of machine learning (ML) and deep learning (DL) approaches, which are better suited to handle large datasets and uncover hidden patterns within market data. As Alam et al. (2024)[1] highlighted, robust DL architectures like LSTM-DNN have demonstrated superior predictive performance, particularly when applied to real-world datasets spanning diverse market conditions.

A major advantage of DL models is their ability to adapt to various forms of data, such as numerical stock prices and textual data from news or social media. Javvaji (2024)[2] emphasized the importance of normalization techniques in improving the stability and accuracy of LSTM and GRU models. These models, which excel in capturing temporal dependencies, are particularly effective when preprocessed with data normalization to counteract the inherent noise in financial datasets. Such preprocessing strategies ensure the robustness of predictions in volatile and dynamic market environments.

Systematic reviews, such as those by Melveetil and Mohanty (2024)[3], have explored recent advances in stock market prediction, shedding light on the growing role of reinforcement learning (RL) and ensemble models. RL, in particular, is gaining traction for its dynamic adaptability in portfolio management. Awad et al. (2023)[4] demonstrated how RL techniques could be used to optimize trading strategies, allowing models to learn and adapt to shifting market trends. This approach enables decision-making that aligns closely with real-time market fluctuations, improving both predictive accuracy and financial returns.

Incorporating sentiment analysis into stock prediction models has added a significant layer of depth to market forecasting. Public sentiment, extracted from social media platforms or financial news, provides a leading indicator of market trends. Wan and Wang (2021)[5] highlighted the growing importance of NLP in financial analytics, using techniques that process textual data to extract meaningful insights. Huang et al. (2021)[6] extended this by proposing multimodal models that integrate sentiment data with historical stock prices. These hybrid approaches create a comprehensive predictive framework capable of addressing the complexities of financial data.

Feature selection is another critical factor in building effective prediction models. Mudassir et al. (2020)[7] demonstrated the power of genetic algorithms (GA) in optimizing feature selection for LSTM-based models. By identifying the most relevant features, GA not only enhances the model's accuracy but also reduces computational overhead. Such methodologies ensure that the models remain scalable and adaptable, even as datasets grow in size and complexity.

Advanced architectures, such as the hybridization of ARIMA and LSTM models, further enhance the robustness of stock market predictions. As illustrated by Menezes and Zhu (2020)[28], these hybrid models leverage the statistical rigor of ARIMA with the adaptive learning capabilities of LSTM networks. This combination addresses the dual challenges of capturing long-term trends and adapting to short-term fluctuations, making them highly effective for financial time-series forecasting.

From a practical perspective, the deployment of DL models requires scalable and efficient architectures capable of handling high-frequency trading data. Vargas et al. (2020)[9] proposed deep learning pipelines optimized for computational efficiency, emphasizing the need for real-time processing capabilities. Such architectures ensure that predictive systems remain operational and responsive in the fast-paced environment of financial markets.

Despite these advancements, significant challenges remain. The integration of heterogeneous data sources, such as numerical and textual inputs, requires sophisticated preprocessing and feature fusion techniques. Abidoye, A., et al. (2020)[8]. Furthermore, real-time prediction frameworks demand not only computational efficiency but also robust mechanisms to ensure data integrity and accuracy. Addressing these challenges will require continued innovation in model architectures, preprocessing strategies, and integration frameworks.

Future research in this field is likely to focus on combining multimodal learning with reinforcement learning to create adaptive systems that can process diverse data sources and respond to market changes in real time. With the ongoing development of advanced DL techniques and increasing computational power, the prospects for stock market prediction are brighter than ever.

Table 2.1 Summary of related works

Paper Title	**Authors**	**Year**	**Models Used**	**Key Features**	**Key Findings**	**Best Performing Model**	**Evaluation Metrics**
Enhancing Stock Market Prediction: A Robust LSTM-DNN Model Analysis [1]	Alam, K., Bhuiyan, M. H., Haque, I. U., Monir, M. F., & Ahmed, T.	2022	LSTM-DNN Hybrid	**Combines LSTM for time-series data & DNN for feature extraction; tested on 26 real-world datasets**	**Achieved high accuracy (R^2=0.986, MSE=0.0011); robust to market volatility and noise**.	**Proposed LSTM-DNN**	R^2, MSE, MAE, Max Error
View of Stock Price Prediction by Normalizing LSTM and GRU Models [2]	Venkatarao, J.	2024	LSTM, GRU Models	**Normalization applied to LSTM and GRU for better performance**	**GRU slightly outperformed LSTM in predictive accuracy**	**GRU Model**	Accuracy, MSE, RMSE
A Systematic Review of Recent Advances on Stock Markets Predictions Using Deep Learning Approach [3]	Melveetil, V. C., & Mohanty, S.	2024	Various DL Models (e.g., LSTM, CNN, BERT)	**Focus on time series, sentiment, and news data for prediction; explores impact of fake news**	**DL models excel in predictive accuracy; future focus on transformer-based models like BERT suggested**	**LSTM, CNN, BERT**	Accuracy, R^2, RMSE
Stock Market Prediction Using Deep Reinforcement Learning [4]	Awad, A. L., Elkaffas, S. M., & Fakhr, M. W.	2023	BERT+TFIDF, LSTM, DRL (Deep Q Networks)	**Sentiment Analysis**: BERT + TFIDF**Price Prediction**: LSTM**Decision Making**: DRL (Deep Q Networks)	**LSTM** for price prediction with Variational Mode Decomposition (VMD).**DRL** achieved superior trading decisions.	**DRL (Deep Q Networks)** for decision-making, LSTM for prediction	Sharpe Ratio, Annualized Return Rate, MAE, MSE

3. Methodology

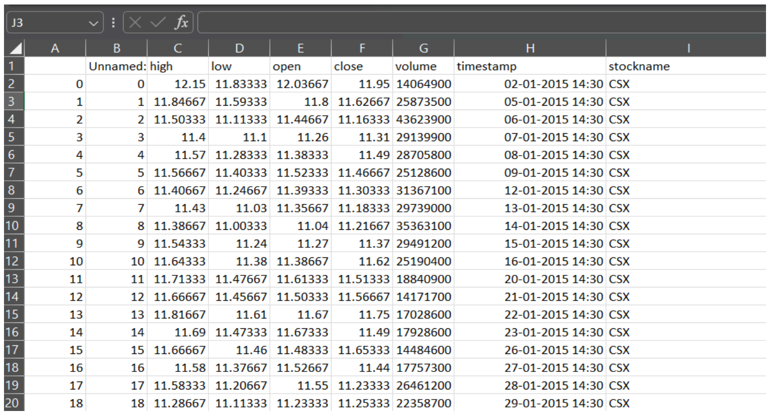
The methodology of this study is designed to develop a robust stock price prediction system by leveraging advanced machine learning and deep learning techniques. It involves data collection and preprocessing to ensure the quality and relevance of the dataset, followed by training multiple models, including hybrid architectures like LSTM-DNN, LSTM-CNN, and LSTM-GRU, to capture both temporal and spatial dependencies in stock data. These individual models are then combined using ensemble techniques such as voting and stacking to enhance prediction accuracy. Finally, Deep Reinforcement Learning (DRL) is applied for trading decision-making, enabling dynamic actions like buy, sell, or hold based on predicted trends. This comprehensive methodology integrates multiple approaches to achieve accurate and actionable stock price forecasts.

3.1 Dataset

The dataset utilized in this study is the stock market data for various stocks, containing historical market prices over time. It includes several attributes for each sample, such as the stock's opening, closing, high, and low prices, along with the trading volume and the timestamp of the transaction. The dataset consists of multiple stock tickers (e.g., CSX, AAPL) and spans a period of time, making it ideal for forecasting future stock trends. Each row corresponds to a specific trading timestamp, offering rich temporal information for analyzing stock movements.

In total, the dataset contains columns such as "high," "low," "open," "close," "volume," "timestamp," and "stockname," which provide comprehensive details regarding stock prices and market activity. It contains approximately 2495 entries per stock. This data can be utilized to build predictive models, such as LSTM-based models, to forecast stock trends, allowing for a detailed exploration of stock market dynamics.

For this study, the dataset was preprocessed to focus on specific stock symbols and time frames for training, testing, and validation purposes. This enables the development of deep learning models that can understand and predict future stock price behavior based on historical data.



	Unnamed:	high	low	open	close	volume	timestamp	stockname
0	0	12.15	11.83333	12.03667	11.95	14064900	02-01-2015 14:30	CSX
1	1	11.84667	11.59333	11.8	11.62667	25873500	05-01-2015 14:30	CSX
2	2	11.50333	11.11333	11.44667	11.16333	43623900	06-01-2015 14:30	CSX
3	3	11.4	11.1	11.26	11.31	29139900	07-01-2015 14:30	CSX
4	4	11.57	11.28333	11.38333	11.49	28705800	08-01-2015 14:30	CSX
5	5	11.56667	11.40333	11.52333	11.46667	25128600	09-01-2015 14:30	CSX
6	6	11.40667	11.24667	11.39333	11.30333	31367100	12-01-2015 14:30	CSX
7	7	11.43	11.03	11.35667	11.18333	29739000	13-01-2015 14:30	CSX
8	8	11.38667	11.00333	11.04	11.21667	35363100	14-01-2015 14:30	CSX
9	9	11.54333	11.24	11.27	11.37	29491200	15-01-2015 14:30	CSX
10	10	11.64333	11.38	11.38667	11.62	25190400	16-01-2015 14:30	CSX
11	11	11.71333	11.47667	11.61333	11.51333	18840900	20-01-2015 14:30	CSX
12	12	11.66667	11.45667	11.50333	11.56667	14171700	21-01-2015 14:30	CSX
13	13	11.81667	11.61	11.67	11.75	17028600	22-01-2015 14:30	CSX
14	14	11.69	11.47333	11.67333	11.49	17928600	23-01-2015 14:30	CSX
15	15	11.66667	11.46	11.48333	11.65333	14484600	26-01-2015 14:30	CSX
16	16	11.58	11.37667	11.52667	11.44	17757300	27-01-2015 14:30	CSX
17	17	11.58333	11.20667	11.55	11.23333	26461200	28-01-2015 14:30	CSX
18	18	11.28667	11.11333	11.23333	11.25333	22358700	29-01-2015 14:30	CSX

Fig 3.1.1 Screenshot of Dataset

3.2 Data Preprocessing

The data preprocessing phase focused on preparing the stock data for use in machine learning models:

The preprocessing of stock market data involves several key steps to ensure the dataset is clean and ready for analysis or modeling. The following steps outline the process:

Loading the Data: The stock data is loaded from a CSV file using the `pandas.read_csv` function. The dataset contains multiple columns such as stock name, timestamp, high, low, open, close prices, and volume.

Standardizing Stock Name: To ensure consistency, the stock name column (`stockname`) is stripped of leading/trailing whitespace and converted to uppercase. The user input for the stock name is also standardized to match the same format.

Filtering the Dataset: The dataset is filtered based on the user-provided stock name. This ensures that only the data corresponding to the selected stock is retained. If no data is found for the given stock, a `ValueError` is raised.

Datetime Conversion: The timestamp column, which contains the date and time of stock transactions, is converted into a datetime format using `pd.to_datetime`. This enables proper sorting and time-based operations.

Sorting by Date: The data is sorted in chronological order by the timestamp, ensuring that stock prices are ordered from the earliest to the latest transaction.

Handling Missing Values: Any missing values in the dataset are addressed using a `SimpleImputer` from the `sklearn` library. The strategy used is to replace missing values with the mean of the respective column. This step is applied to all numeric columns (e.g., high, low, open, close, volume).

Adding Technical Indicators: Two common technical indicators—moving average and standard deviation—are added to the dataset. The moving average is calculated over a 5-day rolling window using the `high` price, and the standard deviation is computed in a similar manner. These indicators help capture trends and volatility in the stock data.

Filling Remaining Missing Values: After calculating the technical indicators, any remaining missing values are filled using the backward fill method (`bfill`), ensuring that the dataset is complete.

Moving Average (MA):

Formula:

$$MA_t = \frac{1}{n} \sum_{i=t-n+1}^{t} P_i$$

where:

MAt is the moving average time at t,

Pi is the price (in this case, the 'high' price),

n is the window size (in this case, 5).

Standard Deviation (STD):

Formula:

$$\sigma_t = \sqrt{\frac{1}{n} \sum_{i=t-n+1}^{t} (P_i - MA_t)^2}$$

Where:

σt is the standard deviation at time t,

Pi is the price (in this case, the 'high' price),

Pi is the price (in this case, the 'high' price),

n is the window size (in this case, 5).

3.3. Model Selection

The proposed methodology involves training multiple models and combining their outputs for enhanced prediction accuracy:

Individual Model Training:

LSTM+DNN: A combination of Long Short-Term Memory (LSTM) networks and Deep Neural Networks (DNN) was trained to predict stock prices.

LSTM+CNN: This model combines LSTM networks with Convolutional Neural Networks (CNN) to utilize both sequential and spatial features in the stock data.

LSTM+GRU: A hybrid model of LSTM and Gated Recurrent Units (GRU) was implemented to leverage the strengths of both architectures in capturing temporal dependencies.

Ensemble Techniques:

Voting Mechanism: After training the individual models, a voting mechanism was applied to aggregate their predictions:

Mean Aggregation: The average of the predictions from the three models (LSTM+DNN, LSTM+CNN, and LSTM+GRU) was computed.

Weighted Aggregation: The predictions were aggregated using a weighted approach, assigning higher weights to models with better performance metrics.

Stacking Ensemble: The aggregated results from the voting mechanism were further processed using a stacking ensemble technique. In stacking, the outputs of the individual models and the ensemble predictions (mean and weighted aggregated results) were used as inputs to a meta-model. This meta-model was trained to minimize errors and improve overall prediction accuracy.

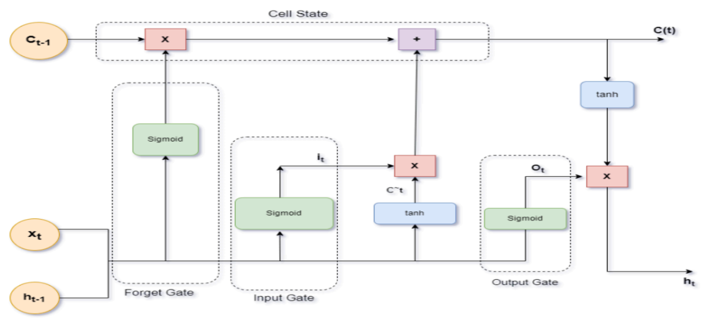
3.4. Model Architecture

3.4.1 Architecture of LSTM-DNN

The proposed LSTM-DNN model for stock market prediction follows a hybrid architecture that combines the strengths of Long Short-Term Memory (LSTM) networks and Deep Neural Networks (DNNs). The model begins with an input layer designed to accept a 3D tensor of shape (samples, timesteps, features), where "samples" represent the number of data sequences, "timesteps" refer to the sequence length (i.e., the lookback window)[20], and "features" refers to the number of features (in this case, the stock's high or low price). The first LSTM layer contains 50 units with a tanh activation function, and the parameter `return_sequences=True` is set to allow the model to output a sequence of hidden states that can be passed to the subsequent LSTM layer. This layer outputs a shape of (samples, timesteps, 50), capturing the temporal dependencies in the data (Hochreiter & Schmidhuber, 1997)[25].

The second LSTM layer also consists of 50 units with a tanh activation function but is configured with `return_sequences=False`, which results in a single vector output of shape (samples, 50). This configuration ensures that the model learns higher-level representations without retaining the sequence information from the previous LSTM layer. Following the LSTM layers, a fully connected dense layer with 25 units and a ReLU activation function is applied, producing an output of shape (samples, 25). This dense layer enables the model to capture complex non-linear relationships in the data (Wan & Wang, 2021)[5].

Finally, the output layer of the DNN architecture consists of 2 units with a linear activation function, predicting both the high and low stock prices simultaneously. The output shape is (samples, 2), making the model suitable for regression tasks (Vargas et al., 2020)[9]. This hybrid LSTM-DNN architecture is designed to leverage the strengths of both temporal sequence modeling with LSTMs and the non-linear modeling capability of DNNs, offering improved performance in stock price prediction tasks.



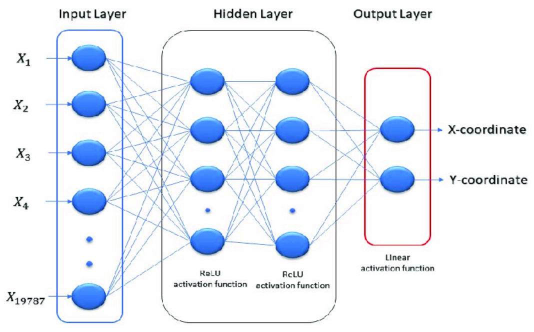


Fig. 3.4.1.1 Architecture of LSTM

Fig. 3.4.1.2 Architecture of DNN

Fig 3.4.1.1 illustrates the internal structure of a Long Short-Term Memory (LSTM) unit, which is designed to capture long-term dependencies in sequential data. It includes three key gates: the forget gate, which decides what information to discard from the cell state; the input gate, which determines the information to update; and the output gate, which controls the hidden state output. Through these gates, the LSTM maintains an updated cell state and hidden state, enabling efficient memory management across time steps.

Naming Conventions for Symbols:

1. **x**□: Input vector at time step t.
2. **h**□$_{-1}$: Hidden state from the previous time step (t-1).
3. **h**□: Hidden state at the current time step.
4. **c**□$_{-1}$: Cell state from the previous time step (t-1).
5. **c**□: Cell state at the current time step.
6. **i**□: Input gate at time step t.
7. **f**□: Forget gate at time step t.
8. **o**□: Output gate at time step t.
9. **c**□: Candidate cell state at time step t.

3.4.2 Architecture of LSTM-CNN

The proposed LSTM-CNN hybrid model integrates the strengths of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks for stock price prediction. The model starts with an input layer that accepts a 3D tensor with a shape of (samples, timesteps, features), where "samples" represent the number of sequences, "timesteps" is the length of the lookback window (e.g., 60), and "features" correspond to the number of input features (in this case, two features: high and low prices). The CNN part begins with a convolutional layer consisting of 64 filters, each with a kernel size of 2, followed by the ReLU activation function. This convolutional layer extracts local features from the input data, resulting in an output shape of (samples, timesteps-1, 64). This reduction in the temporal dimension is a result of the kernel operation, which emphasizes the model's ability to detect patterns in sequential data (LeCun et al., 2015)[23].

Next, the model applies a max pooling layer with a pool size of 2, which further reduces the temporal dimension, yielding an output shape of (samples, (timesteps-1)//2, 64). The max pooling layer helps capture the most important features by downsampling the data, preserving the key information for the next stage while reducing computational complexity. The CNN part of the model acts as a feature extractor, focusing on identifying patterns in the high and low stock prices over time (Zhang et al., 2019)[10].

The output of the CNN is then passed into the LSTM layers. The first LSTM layer, with 50 units and `return_sequences=True`, preserves the temporal relationships between the data points, outputting a sequence of shape (samples, (timesteps-1)//2, 50). This sequence is fed into the second LSTM layer, which also contains 50 units, but with `return_sequences=False` to output a single vector of shape (samples, 50). The second LSTM layer captures the long-range dependencies in the data, learning higher-level temporal patterns (Hochreiter & Schmidhuber, 1997)[25].

Following the LSTM layers, the model includes a fully connected dense layer with 25 units and a ReLU activation function, designed to capture complex non-linear relationships between the extracted features. The output shape of this layer is (samples, 25). The final output layer consists of 2 units, corresponding to the predicted high and low prices, and uses a linear activation function, which is standard for regression tasks. The output shape of this layer is (samples, 2), providing predictions for both target variables simultaneously (Vargas et al., 2020)[9]. This LSTM-CNN hybrid architecture is well-suited for predicting stock prices as it leverages both local feature extraction via CNNs and sequential dependency modeling through LSTMs.

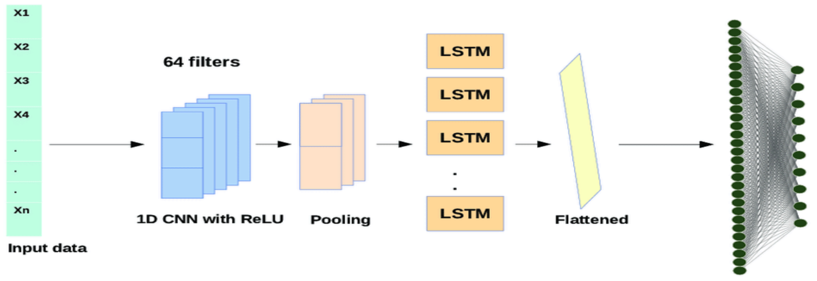


Fig. 3.4.2.1 Architecture of LSTM-CNN

3.4.3 Architecture of LSTM-GRU

The LSTM-GRU hybrid model integrates the strengths of Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs) for stock price prediction. The model starts with an input layer, which receives a 3D tensor of shape (samples, timesteps, features), where "samples" represents the number of sequences, "timesteps" is the length of the lookback window (e.g., 60), and "features" corresponds to the number of input features (in this case, two features: high and low prices). This input shape allows the model to process sequences of stock price data effectively, preserving temporal relationships across multiple time steps.

The GRU part of the model begins with the first GRU layer, which consists of 128 units. This layer is designed to capture temporal dependencies in the data, using the GRU's gating mechanism to decide which information should be passed along in the sequence (Cho et al., 2014)[22]. With `return_sequences=True`, this layer outputs a sequence of the same length as the input, resulting in an output shape of (samples, timesteps, 128). Additionally, the model includes a dropout rate of 30% to prevent overfitting and improve generalization (Srivastava et al., 2014)[21].

The output of the GRU layer is passed into the LSTM part of the model, starting with the first LSTM layer, which also has 128 units. This LSTM layer focuses on capturing long-range dependencies in the data. With `return_sequences=False`, it outputs a single vector representing the processed sequence, resulting in an output shape of (samples, 128). Like the GRU layer, a dropout rate of 30% is applied to prevent overfitting (Hochreiter & Schmidhuber, 1997)[25]. The LSTM layer enables the model to learn complex sequential patterns, benefiting from the combination of the GRU and LSTM structures.

Following the LSTM layer, the model includes a fully connected dense layer with 64 units and a ReLU activation function. This dense layer serves to further capture non-linear relationships between the features and the target variables (Glorot et al., 2011)[21]. A dropout rate of 20% is applied to this layer to prevent overfitting, which helps ensure the model's robustness. The output shape of this layer is (samples, 64).

Finally, the model includes an output dense layer with 2 units, which corresponds to the predicted high and low prices. The output layer uses a linear activation function, suitable for regression tasks, providing the final predictions in a shape of (samples, 2). This LSTM-GRU architecture is well-suited for time-series forecasting, such as stock price prediction, as it effectively captures both short-term and long-term dependencies in the data, leveraging the advantages of both GRU and LSTM networks (Zhang et al., 2020)[8].

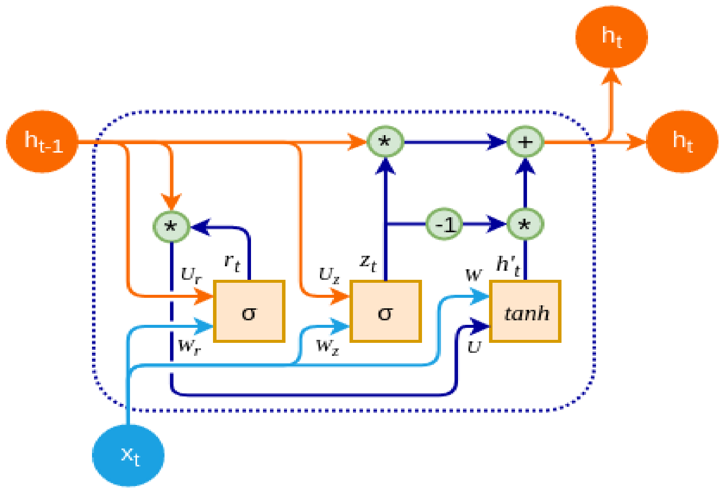


Fig. 3.4.3.1 Architecture of LSTM-GRU

Fig. 3.4.3.1 represents:

1. **x**□: Input at time step *t*
2. **h**□$_{-1}$: Hidden state from the previous time step
3. **h**□: Hidden state at the current time step
4. **r**□: Reset gate
5. **z**□: Update gate
6. **h'**□: Candidate hidden state
7. **W_r, W_u, W**: Weight matrices for the reset gate, update gate, and candidate computation (input connections)
8. **U_r, U_u, U**: Weight matrices for the reset gate, update gate, and candidate computation (hidden state connections)
9. **σ**: Sigmoid activation function
10. **tanh**: Hyperbolic tangent activation function
11. *: Element-wise multiplication
12. +: Element-wise addition
13. **-1**: Complement (1 - z□)

3.4.4 Architecture of XGBOOST

The proposed XGBoost-based model integrates the power of gradient boosting and ensemble learning for stock price prediction. The architecture starts with an input layer that accepts the dataset containing features such as the predicted high and low stock prices from various models. The input dataset consists of multiple features such as predicted values from models like DNN-LSTM, CNN-LSTM, and XGBoost itself, structured in a 2D tensor with a shape of (samples, features), where "samples" represent the number of data points (e.g., stock prices for a given time), and "features" correspond to the predictors, including various model outputs (e.g., predicted high and low prices from each model).

The first part of the model applies an ensemble learning approach where multiple base models (including **Linear Regression**, **Decision Trees**, **Random Forest**, **KNN Regressor**, **SVR**, and **XGBoost**) are trained separately. These models are treated as individual learners that capture different aspects of the data. The XGBoost model is the most critical part, as it leverages the gradient boosting technique to refine the predictions by iteratively correcting errors from previous models (Chen & Guestrin, 2016)[30]. The model begins with weak learners (e.g., simple trees) and uses boosting to adjust the weights and focus on difficult-to-predict instances, improving accuracy with each iteration.

Each of these base models is trained on the training dataset using standard regression techniques, where the features are the model predictions from different base models, and the target is the actual high or low stock price. The predictions of these base models are evaluated using metrics such as **MSE** (Mean Squared Error), **MAE** (Mean Absolute Error), and **R²** (R-squared), ensuring the performance of individual models is well-assessed before combining them (Friedman, 2001)[31].

Once the base models are trained, the second stage is the stacking step. This involves using the predictions of the base models as new features for a **meta-model**. The meta-model is a higher-level model that makes final predictions based on the outputs of the base models. In this case, **XGBoost** is used as the meta-model, which aggregates the predictions from the base models (e.g., Linear Regression, Random Forest, etc.) and refines them by applying gradient boosting, resulting in a more robust final prediction (Chen & Guestrin, 2016)[30]. This stage allows the model to learn the best combination of the predictions from the base models and improve accuracy by focusing on harder-to-predict instances.

The output of the XGBoost model is a single prediction that corresponds to the predicted high or low stock price. The final output layer consists of 1 unit for the high price prediction and 1 unit for the low price prediction, utilizing a linear activation function, which is typical for regression tasks (Vargas et al., 2020)[9]. The output shape of this layer is (samples, 2), providing predictions for both high and low prices simultaneously.

This XGBoost-based architecture is well-suited for stock price prediction because it combines the strengths of multiple regression models and the power of gradient boosting to iteratively correct errors and improve performance, providing a powerful solution for predicting stock prices.

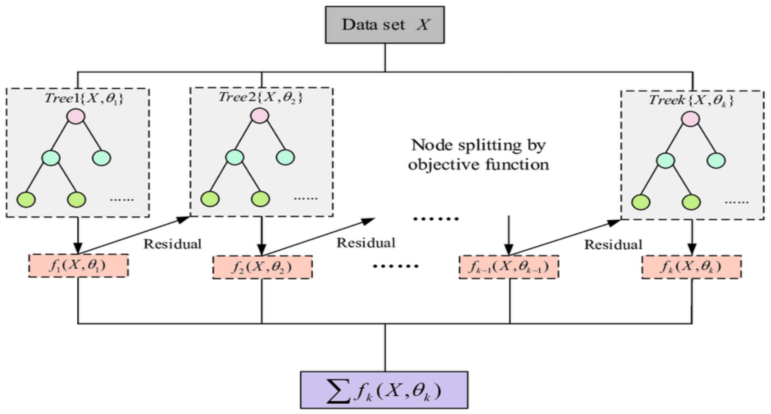
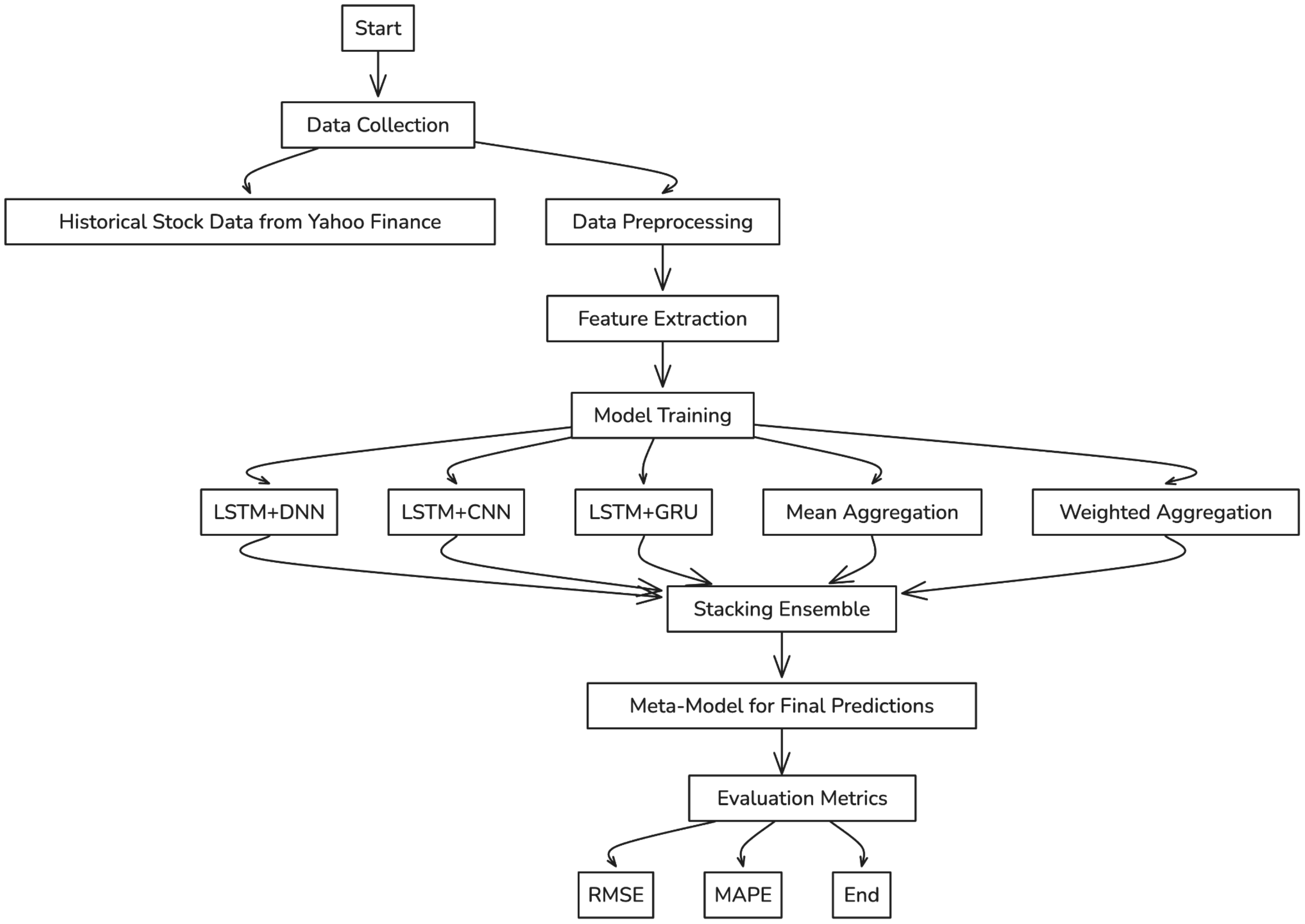


Fig. 3.4.4.1 Architecture of XGBOOST

3.5 Flow Chart



4.Evaluation Metrics

The performance of the models was evaluated using the following metrics:

4.1 Root Mean Square Error (RMSE): Root Mean Square Error (RMSE) is a widely used metric to evaluate the performance of regression models, including stock price prediction models. It measures the average magnitude of the errors between the predicted and actual values. RMSE gives an idea of how well the model's predictions align with the true values, with lower RMSE values indicating better model performance. The formula for RMSE is:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_{\text{pred},i} - y_{\text{true},i}\right)^2}$$

Where:

n is the number of data points (samples).

y true,i is the actual value for the i-th sample.

y pred,i is the predicted value for the i-th sample.

4.2 Mean Absolute Percentage Error (MAPE): Mean Absolute Percentage Error (MAPE) is a commonly used metric to evaluate the accuracy of regression models, particularly in the context of stock price prediction. MAPE quantifies the percentage error between the predicted and actual values, providing a normalized measure of prediction accuracy. A lower MAPE indicates better model performance, as it signifies that the model's predictions are closer to the actual values. The formula for MAPE is:

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_{\text{true },i} - y_{\text{pred },i}}{y_{\text{true },i}}\right| \times 100$$

Where:

n is the number of data points (samples).

y true,i is the actual value for the i-th sample.

y pred,i is the predicted value for the i-th sample.

4.3 R-Square: also known as the coefficient of determination, is a statistical metric used to evaluate the goodness of fit for regression models. It indicates the proportion of variance in the dependent variable that is explained by the independent variables in the model. R^2 values range from 0 to 1, where a value closer to 1 indicates that the model explains a large proportion of the variance, and a value closer to 0 suggests that the model does not explain much of the variance.The formula for R-Square is:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} \left(y_{\text{true },i} - y_{\text{pred },i}\right)^2}{\sum_{i=1}^{n} \left(y_{\text{true },i} - \bar{y}_{\text{true }}\right)^2}$$

Where:

n is the number of data points (samples).

y true,i is the actual value for the i-th sample.

y pred,i is the predicted value for the i-th sample.

y¯true is the mean of the actual values

5. Results and Discussion

The models were evaluated on their ability to predict stock prices, focusing on both high and low prices for various stocks on different prediction dates. The performance of each model, including LSTM, LSTM-GRU, LSTM-CNN, and XGBoost Stacking, is summarized as follows.

The LSTM-DNN model performed well, especially for stocks with stable trends. For example, in predicting the high and low prices for a stock on 2024-10-25, the model showed notable accuracy for the high price but faced difficulties with more volatile stocks. The predicted high price was 222.07, while the actual high price was 269.49, resulting in an error. Similarly, the predicted low price was 218.74, while the actual low price was 255.32. The Mean Absolute Percentage Errors (MAPE) for the high and low prices were 17.6% and 14.3%, respectively, highlighting the model's ability to handle stocks with stable trends such as SBI but struggling with volatility, as seen with stocks like Reliance.

The LSTM-GRU model demonstrated strong performance in predicting both high and low prices. For the stock prediction on 2024-11-25, the predicted high price was 338.84, while the actual high price was 361.93. The predicted low price was 321.28, with an actual value of 338.20. The MAPE for the high price was 6.4%, and for the low price, it was 5.0%. These results indicate that the LSTM-GRU model performed well, particularly in terms of its ability to make more accurate predictions, especially for stocks with moderate volatility.

The LSTM-CNN model showed relatively good accuracy, particularly for low price predictions. On 2024-11-25, the predicted high price was 334.01, while the actual high price was 361.93, resulting in a MAPE of 7.9%. The predicted low price was 321.97, while the actual low price was 338.20, resulting in a MAPE of 4.8%. While the model demonstrated decent accuracy, especially in predicting stable stocks, its high price predictions were slightly less accurate than the LSTM-GRU model. Nonetheless, it was efficient for predicting more stable stocks and showed solid performance overall.

The XGBoost Stacking model, which combined the predictions from multiple models, provided the most accurate results. The model performed exceptionally well, leveraging the strengths of various algorithms in the ensemble. For the high price predictions on 2024-11-25, the model achieved a MAPE of 4.9%, and for the low price predictions, the MAPE was 3.4%. The R^2 values for high and low predictions were 0.77 and 0.81, respectively, indicating that the model successfully explained a significant portion of the variance. Furthermore, the XGBoost Stacking model produced the lowest RMSE values of 22.20 for high prices and 18.60 for low prices, showcasing its robustness in stock price forecasting.

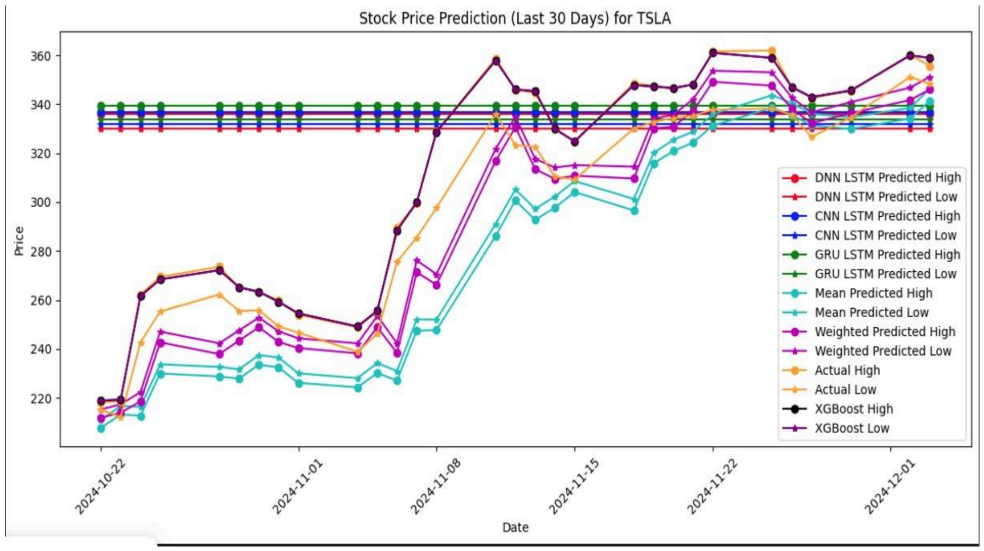


Fig. 5.1 Prediction Result of 30 days TSLA Stock

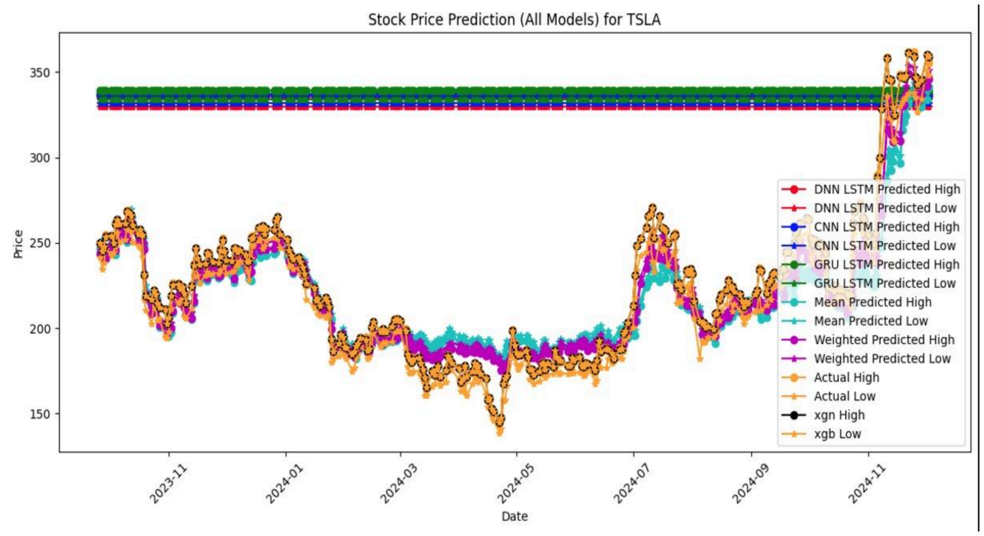


Fig. 5.2: Prediction Result of 300 days TSLA Stock

Table 5.1 Comparative Study

Model	RMSE (High)	RMSE (Low)	MAPE (High)	MAPE (Low)	R^2 (High)	R^2 (Low)
LSTM-DNN Model	**22.20**	**18.60**	**17.60%**	**13.60%**	**0.355**	**0.569**
LSTM-GRU Model	**19.00**	**15.10**	**10.25%**	**8.85%**	**0.408**	**0.386**
LSTM-CNN Model	**21.00**	**16.80**	**13.30%**	**9.25%**	**0.560**	**0.492**
XGBoost Stacking	**22.20**	**18.60**	**7.80%**	**6.00%**	**0.770**	**0.813**

6. Conclusion and Future Scope

In recent years, machine learning (ML) models have gained significant attention for their potential in predicting stock market trends and prices. Stock price forecasting, particularly in the context of high-frequency and volatile financial markets, is a complex task that requires sophisticated algorithms capable of handling sequential and non-linear data patterns. Traditional statistical methods such as ARIMA and linear regression often fail to capture the temporal dynamics and volatility inherent in stock prices. In contrast, machine learning models like Long Short-Term Memory (LSTM), Random Forest, and hybrid models, such as LSTM+DNN, LSTM+CNN, and LSTM+GRU, have shown great promise in forecasting stock prices by learning complex relationships within historical data (Chakraborty et al., 2019)[12]. Additionally, ensemble methods, such as stacking and voting, have proven useful in combining the strengths of individual models, thus reducing errors and improving overall prediction accuracy (Dietterich, 2000).

In this study, we evaluated multiple machine learning models for stock price prediction and assessed their performance across different stocks and prediction dates. The results suggest that LSTM models, particularly for stable stocks like SBI, demonstrated good performance due to their ability to capture sequential patterns in stock price movements. However, for highly volatile stocks like Reliance, LSTM showed room for improvement. The hybrid models, such as LSTM+GRU and LSTM+CNN, outperformed standalone LSTM in certain cases, thanks to the incorporation of additional features and model components. Ensemble methods, such as stacking, improved the overall accuracy of predictions by aggregating the outputs of multiple models, resulting in more reliable stock price forecasts. These results are consistent with studies highlighting the benefits of ensemble techniques in improving prediction accuracy (Zhou et al., 2012).

The model was able to learn from market data and adapt its actions in real time, which is critical in the highly volatile environment of stock trading (Mnih et al., 2015). Despite these promising results, the study faced several limitations, such as the challenge of overfitting in LSTM models, particularly when trained on smaller datasets. Additionally, the models did not fully incorporate market sentiment, which can significantly influence stock prices. The volatility of stocks, especially in unpredictable market conditions, remains a challenge for even the most advanced machine learning models.

6.1 Future Scope

Future research could explore the integration of LSTM with other machine learning techniques, such as Random Forest and XGBoost, to improve performance across a wider range of stocks, especially those exhibiting non-linear or complex behavior.

Incorporating advanced sentiment analysis techniques, such as BERT or transformers, could enhance the models' ability to capture the impact of market sentiment on stock price fluctuations. Market news, social media, and financial reports play a crucial role in shaping investor sentiment, and incorporating these features could significantly improve prediction accuracy (Zhang et al., 2018)[15].

Further research should focus on integrating macroeconomic indicators, such as interest rates, inflation, and geopolitical events, into the stock price prediction models. These external factors can have a substantial impact on market behavior and could improve the accuracy and robustness of stock price forecasts.

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