Predicting Stock Price Movements in Volatile Markets: A Multi-Model Fusion Approach

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***Abstract*—The dynamic financial markets where forecasting stock prices poses a persistent challenge, many recent researches in finance have focused on deep learning-based stock price prediction. Our model proposes an innovative Multi-Model Fusion Deep Learning approach that intricately integrates stock and news data to enhance predictive accuracy. Recognizing the intricate interplay of various variables in stock market dynamics, the method underscores the importance of considering market volatility for precise predictions. Capitalizing on the rapid assimilation of information into stock prices, a ground breaking fusion technique is introduced, seamlessly combining features extracted from both stock price data using a customized architecture inspired by LSTM and textual news data through a specialized NLP. The key to this approach lies in a sophisticated fusion layer, where distinct yet complementary features converge, enabling the model to synthesize a comprehensive understanding of market behavior. This hybrid architecture, finely tuned through joint training, demonstrates its effectiveness through comprehensive experimentation, assessing its performance in predicting stock price movements. The findings of our model are its higher accuracy which is 93.84%, 90.9% precision, 93.02% F1 score, 95.23% Recall and 0.006 Mean squared Error (MSE) which is lower in prediction of stock movements. By seamlessly blending insights from diverse data sources, this innovative approach charts a promising path toward refining stock price predictions in the volatile landscape of financial markets, offering potential improvements in forecasting accuracy and decision making.**

Keywords— Stock Price Movement, Multi-Model Fusion Deep Learning approach, Textual News Data, LSTM, NLP, Mean Squared Error

I. INTRODUCTION

Stock market is relatively a major aggressive economic business sector where the dealers are required and process the economic workloads with lower latency alongside higher throughput. Accurately predicting stock price is still a constant difficulty in the dynamic world of financial markets. Due to these markets dynamic character, which is impacted by a wide range of elements including geopolitical events and economic data, creative solutions that can efficiently utilize a variety of information sources are required. Formerly, economists were utilizing the customary store and cycle technique to figure out the weighty economic workload productively. However, to accomplish low idleness and high throughput, server farms had to be genuinely found near the information sources, rather than other all the more financially gainful areas. The primary explanation, the information is that streaming model has been created and it. can handle enormous measures of information more proficiently. Anyway as opposed to utilizing those customary strategies, we moved toward the issues utilizing AI procedures [1]. We attempted to redefine the manner in which individuals address information preparing issues in financial exchange by foreseeing the conduct of the stocks. People who are hoping to put resources into financial exchanges are regularly unconscious of the conduct of financial exchanges. Therefore, they do not realize what offers to buy and which to offer to augment their benefits. These financial investors realize that stock exchange development relies upon related news. In this manner, they need precise and opportune data about stock trade postings, so their exchanging choices can be made with convenient and exact data[2-3]. Complex models especially deep learning algorithms, are prone to overfitting when trained on historical data but fail to generalize to new data and these models can be computationally expensive and require substantial computing resources and time for training the models [4].

An accurate expectation of stock exchange is exceptionally difficult, and this research addresses this difficulty by introducing a revolutionary Multi-Model Fusion Deep Learning technique that integrates stock and news data to improve the accuracy of stock price predictions. The acquired estimate and detail coefficients after weakening of the first run through arrangement information are utilized as information factors of back propagation neural organization to future stock costs [5]. A number of fields, including financial research and stock market trading, now depend heavily on computational intelligence and machine learning techniques. To help traders make well informed judgements [6] seeks to improve labelling efficacy. It is difficult to estimate stock prices because of the interconnectedness of stocks, which poses a huge difficulty. Time-series prediction in domains with hidden spatial dependencies might be improved using clustering and dimensionality reduction. Complex Neural organizations are prepared by Liebenberg-Marquardt calculation, covered up layer move work is digression sigmoid, and yield layer move work is unadulterated straight. A few organizations are made by shifting the quantity of neurons to accomplish least Mean Squared Error for an ideal exactness [7-9].

In any case, financial investors' assumptions dependent on monetary news alone as an exchanging procedure may not be sufficient. In existing prescient frameworks, specialists utilized web-based media posts or news information alongside financial exchange information for the stock forecasts.

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Apparently, no prescient framework has utilized the two kinds of information for stock expectation [10]. These components should be considered for exact stock exchange forecast, whereas interest in the stock exchange is hazardous, yet when drawn nearer in a restrained way. However, it perhaps the most effective approach to appreciate significant benefits. Financial investors assess the performance evaluation of an organization prior to choosing to buy its stock to try not to purchase dangerous stocks. Substantially, this assessment remembers the investigation of the organization's metric or merits for the web-based media and economic news sites. Be that as it may, a particularly immense measure of web-based media and economic news information cannot be totally evaluated by financial investors. Accordingly, a mechanized choice emotionally supportive network is important for financial investors, as this framework will assess stock patterns consequently utilizing such a lot of information [11].

The motivation behind this research is driven by several factors such as Financial Market Complexity which is characterized by intricate dynamics, and accurate stock price predictions have significant implications for investors, traders, and financial professionals. In the digital age, an abundance of data, including stock prices and news articles, is readily available, providing an opportunity to harness this information for improved predictions. Advances in deep learning and model fusion techniques have created the potential to develop more sophisticated and accurate prediction models and real word impact which involves enhanced stock price predictions can assist investors in making informed decisions, potentially mitigating financial risks and improving financial outcomes.

The main objective of this research is addressing all these difficulties by introducing a revolutionary Multi-Model Fusion Deep Learning technique that involves creation of a particular Natural Language Processing (NLP) model for textual news analysis and a unique architecture for processing stock price data that draws inspiration from Long Short-Term Memory (LSTM) networks. Through a complex fusion layer connecting these elements, different but complimentary traits converge, allowing the model to synthesize a comprehensive picture of market behaviour. This method's primary contribution is its capacity to combine knowledge from several data sources and smoothly incorporate it into a single predictive framework. The hybrid architecture takes into consideration the intricate relationships between market variables and it is fine-tuned through joint training to maximize prediction performance. The efficacy of the multi-model fusion paradigm is demonstrated by the use of evaluation metrics including accuracy, F1 score, Mean squared error (MSE).

Our creative method shows a promising direction toward improving stock price forecasts in the unstable world of financial markets by combining insights from news and stock data in a seamless manner. The purpose of this study is to promote the use of predictive approaches in financial market analysis by offering a thorough explanation of our methodology, experiments, and conclusions with results and discussions.

The main contribution of this article can be summarized as:

- Introduces a novel Multi-Model Fusion Deep Learning approach, seamlessly integrating stock and news data for enhanced stock price prediction accuracy.
- Highlights the significance of accounting for market volatility, utilizing a ground-breaking fusion technique with a sophisticated layer for comprehensive market behaviour understanding.
- Demonstrates the effectiveness through meticulously calibrated joint training, supported by evaluation metrics such as accuracy, Precision, Recall, F1 score, Mean Square error promising refined stock price predictions.

In this paper we focus on the performance of our novel Multi-Model Fusion Deep Learning approach, which integrates stock and news data for enhanced stock price prediction. The rest of the paper is organized as follows. Section II presents related work about research on fundamental and technical analysis. Section III presents proposed method and section IV presents results and discussions. The final section V presents conclusion and future work.

II. RELATED WORK

Y. Zhao et al., [12], the stock markets are considered to build money-making opportunities; the prospective returns of investments within a comparatively shorter period of time have been an attractive aspect of these financial markets. An enormous number of individuals carry out different strategies to trade through stock markets. While the companies can decide to get listed in one or more stock exchanges for their eventual growth, individuals may choose to support these firms by purchasing a part of their ownership and hence, providing financial assistance also, such investments are expected to open the scope of receiving higher profits. However, one of the unavoidable factors associated with financial market investments is the economic risk. Human psychology may have different preferences which, in turn, can represent the individuals' behaviours to take a risk. The risk-averse investors may settle to a lower return rate in order to preserve the invested amount; in contrast to that, the risk-seeking investors may wish to receive a higher return of their investment even by possibly endangering their invested money.

Z. H. Kilimci and R. Duvar [13], A portfolio is a collection of financial investments (); such investments can belong to various assets of the stock market. The primary motivation to have a portfolio is to invest in such a way that would reduce the overall risk and the investors could get a profit from the overall portfolio; in other words, instead of relying on a single asset of a specific firm of a sector, a portfolio can be designed to distribute the given amount among various assets which may belong to different firms of the same or diverse sectors. As compared to single-asset investment, this can be a more useful approach such that even if a loss of valuables would be encountered for one asset, the other assets of the portfolio would bring an opportunity to give expected or higher returns to maintain an overall profit; financial literacy plays a vital role in such concept of portfolio diversification.

H. Tian, et.al [14], the stock market has been a subject of interest for a large number of investors, industrialists, as well as researchers. Based on the market characteristics, various beliefs and opinions are provided and their feasibilities are evaluated. This study aims to develop a generic method, GERU, to effectively model the dynamic evolutions of learned stock dependencies and stock time series. The system consists of two components: the ADGL module, which learns stock dependencies from raw data, and the Gated Graph Recurrent Unit, which uses Graph Neural Networks to encode stock representations. This study conducted several analyses, including ablation, robustness, scalability, and dynamic temporal stock graph analysis. Results showed GERU's superiority over static or heuristically dynamic stock graphs, and sparse dynamic stock graphs were promising for predictive accuracy. The traditional efficient market hypothesis (EMH) assumes a frictionless market without imperfections such that the available market information is expected to be incorporated within the stock prices. However, due to the controversial validation proofs on EMH, several alternate opinions are being demonstrated.

E. Koo and G. Kim, [15], It has also been observed that for region-specific stock markets, several events can play important roles in transforming such relationship polarity; for example, the annual industrial production growth rate indicated a positive impact on Tunisian mutual funds returns before the revolution, however, it transformed into having a negative relationship after the revolution. Several studies have been conducted on different national economies to establish a relationship between macroeconomic factors and stock performance. Apart from these variables, there are various domains that can have a likely impact on the stock market performance.

K. R. Reddy, et.al [16], another possible way to invest in such markets is with the help of agents, market experts, or other individuals' trustworthiness of the advice. In support to analyse the financial movements, various discussion forums are available online where experts evaluate different factors and try to predict the potential market trend. Similarly, various news channels offer programs to explore the public sentiments that affect the stock markets; such public opinions through social media can also be a deciding factor. In certain cases, the falsified information broadcast or news reports can mislead the crowd for a large fluctuation in stock markets.

R. Jindal, et.al [17], another critical integration of technologies for the financial market forecasting is based on artificial intelligence. Financial investments process may encounter momentary irrationality or emotion-driven decisions, however, adaptation of a computational intelligence can potentially eliminate such driving forces. The methodology used in this paper enhances stock market prediction by incorporating COVID-19 factors involves data collection, feature engineering, and training of prediction models. Historical data, including price movements and trading volumes, is collected for indices like the S&P 500 Index, Nifty50 Index, and RTS Index. Feature selection techniques are applied to identify relevant features for prediction. Results show improved performance when COVID-19 features are incorporated, emphasizing the importance of pandemic-related factors in stock market prediction models.

A. B. Gumelar et al., [18], This study conducted an experiment of predicting the close stock price for 25 companies. The two Machine Learning algorithms used are Long Short-Term Memory (LSTM) and Extreme Gradient Boosting (XG Boost), both known for its high accuracy of prediction from various representative data. Stock price prediction is challenging task because of fluctuations of the data and different patterns of stock price and its natural dynamic and real-time movement.

M. A. Nadif, [19], In order to solve the problem of stock market prediction, several research works have been carried out for correct prediction. Due to their inability to handle the complexity of stock market data, traditional linear algorithms perform poorly in prediction tasks. The experiment shows well the LSTM-based model which is excellent at processing sequential data predicts stock prices using data from Beximco collected over an 11-year period. It provides a reliable way to deal with the volatility of the stock market.

X. Zhang, [20], In this research, the deep learning model LSTM's influencing aspects for stock market prediction are studied. The historical Shanghai A-share index, the historical US NASDAQ index, and the frequency of increased and decreased positions on Weibo are the three types of influential factors that have been chosen. Mean absolute percentage error (MAPE), root mean square error (RMSE), and mean absolute error (MAE) are metrics used to measure prediction results. It was discussed that some of the limitations of being stuck in local optima can be addressed using evolutionary algorithms. The selection of models requires identification of potential challenges such as long-term dependencies, number of parameters, architectural complexities etc.

R. Patel, [21], the stock market is influenced by a myriad of factors, including historical stock market data and social media and financial information like news data, and accurately forecasting price trends is crucial for investors and financial professionals. This paper proposes a NLP for feature extraction and LSTM for training the dataset. This proposes a unique method which finds strong correlation between historical stock market data and social media news emotions. This outperforms the current approaches through simulated tests, obtaining excellence prediction accuracy and drastically lowering mean square error. Apart from this, stock market behaviour can be influenced by various unpredictable factors beyond news sentiment, such as geopolitical events or economic events.

J. Choi, [22], This paper proposes a new fusion mix by integrating stock and news data features and propose a hybrid information mixing module, which consists of a feature mixing MLP and interaction mixing MLP to learn the mixed feature created by integrating the time-series feature of the price data and the semantic feature of the text data. This tackles the problem of stock price prediction while taking into account the market's dynamic character that is impacted by a number of factors. To evaluate the efficacy of the suggested method, performance assessment measures including accuracy, F1 score, and Mean Squared Error (MSE) are applied.

Hutto, C., [23], This study introduces VADER, a rule-based model for sentiment analysis in social media content. It compares VADER's performance with eleven benchmarks and machine learning algorithms. VADER uses a gold-standard list of lexical features and sentiment intensity measures for microblog like contexts. Results show VADER outperforms human raters in classification accuracy and generalizes better across different contexts. It also acknowledges some limitations such as reliance on predefined rules, limited benchmarks, potential performance variations based on dataset and domain, and limited diversity.

III. PROPOSED METHOD

The multi-model fusion method for stock price prediction is put out in this research. [Fig. 1] depicts the general methodology of this model, which is broken down into several parts such text embedding, and price embedding which is also known as feature embedding is fed to a multi-layer perceptron to forecast accuracy. The binary classifier predicts whether the movement of the stock price will be upward or downward.

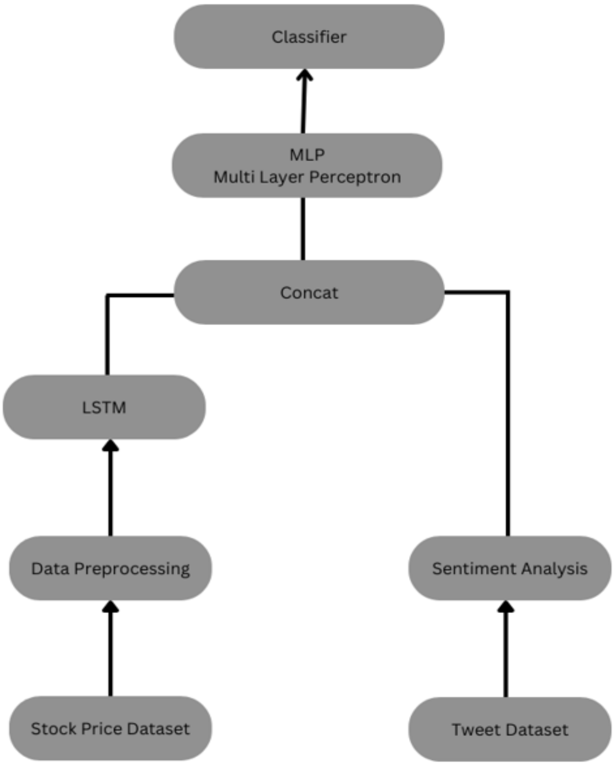

Figure 1: A novel Multi model fusion Approach for Stock Price Prediction

A. Dataset:

The stock price [Fig. 2] and news datasets [Fig. 3], which are derived from open sources, are the datasets utilized in this strategy. The Twitter news concerning the particular company and the publication date are included in the stock news dataset. This study makes use of 253 trading days for 85 businesses in the Stock dataset, spanning the period from September 30, 2022, to September 20, 2016.Opening, high, low, close, adjacent close and trading volume prices are among the five market variables for which price data are available. The opening price is the price at which a stock trades first when the exchange opens on the trading day, closing price is the last level at which an asset was traded, low value is lowest price which the scrip has traded, high value is highest value where the scrip, volume is the total number of stocks that are bought and sold in that day. The factors of the current market, sentiment analysis of news data, and features gathered the day before are used to predict stocks.

A	B	C	D	E	F	G
Date	Open	High	Low	Close	Adj Close	Volume
########	260.3333	263.0433	258.3333	258.4933	258.4933	53868000
########	259.4667	260.26	254.53	258.4067	258.4067	51094200
########	265.5	268.99	258.7067	260.51	260.51	91449900
########	261.6	265.77	258.0667	260.1967	260.1967	55297800
########	258.7333	262.22	257.74	260.9167	260.9167	43898400

Figure 2: Stock Price dataset

Date	Tweet
2022-09-29 :	Mainstream media has done an amazing job
2022-09-29 :	Tesla delivery estimates are at around 364k fı
2022-09-29 :	3/ Even if I include 63.0M unvested RSUs as o
2022-09-29 :	@RealDanODowd @WholeMarsBlog @Tesla
2022-09-29 :	@RealDanODowd @Tesla Stop trying to kill k
2022-09-29 :	@RealDanODowd @Tesla This is you https://
2022-09-29 :	For years @WholeMarsBlog viciously silencec
2022-09-29 :	$NIO just because I'm down money doesn't n

Figure 3: Stock Tweets dataset

B. Data Preprocessing:

Raw stock price data is often noisy and irregular, which can adversely affect model performance The dataset is carefully pre-processed when it is collected to make sure deep learning models can use it. In this stage, class imbalance, normalizing numerical characteristics, and managing missing or incorrect data are addressed and help to reduce the irregularity. An index that can represent the stock market's fluctuation pattern is created using price data.

C. Price Embedding:

This study extracted time-series features using each company's historical price data. Using the LSTM to analyse and capture stock market fluctuation signals from the price dataset, timeseries features are derived in the price embedding process. RNN methods provide calculated outputs that depend on the networks' memory because the hidden state, acting as the networks' memory, records the prior temporal information history. Compared to current RNNs, the LSTM approach is more suited for learning long-term dependencies and is effective at processing time-series data. To extract the time series feature in this technique, we used the following market variables: open, low, high, close, and volume. The market variables are fed into the day's LSTM model by creating sequences of five, and the result is a feature that represents the latest output's hidden state. This feature is added to the dataset in a manner similar to how tomorrow's variables are merged with today's hidden state.

$W_i^O, W_i^H, W_i^L, W_i^C, W_i^V$ represent open, high, low, close, volume, h denotes the hidden state value.

$$W_i = \{W_i^O, W_i^H, W_i^L, W_i^C, W_i^V\} \quad (1)$$

$$Y_i = LSTM_W\left(W_{i,}, h_{i-1}\right), \mathrm{t} - \mathrm{T} \leq \mathrm{i} \leq \mathrm{t} - 1 \quad (2)$$

D. Text Embedding:

The stock tweets played an important role in predicting the close price of the particular day. There will be lot of tweets on a company every day, and every text has different sentiment value. Text data derived from tweets represents user attitude toward stocks and provides factual information. Daily tweets and historical prices have differing effects on stock price fluctuations. Sentiment analysis with VADER, a vocabulary and rule-based sentiment analysis tool called VADER (Valence Aware Dictionary and Sentiment Reasoner) is particularly geared to the sentiments expressed in social media, although it also performs well on texts from other domains. Using VADER Lexicon, the tweets released on the day of the transaction are analysed and appraised (Natural Language Processing). Numerous tweets will be sent, and the and the average of those numbers will be used as parameters predict the movement of the stock.

$$k_i = VADER_m(U_i), i \in [1, N] \quad (3)$$

$$m_i = \frac{1}{N}(\sum_{i=1}^{N} k_i) \quad (4)$$

E. Feature Mixing:

The forecast of stock movement is primarily influenced by several time-series factors. Using the attributes of our price and tweet datasets, we will enhance the prediction of the transaction day closing price in this study. The LSTM model is used to extract features(Y_i), and sentiment analysis using the VADER lexicon(k_i) is then combined with the market variables found in the pricing data to create a dataset. The key to combining the features is to add the hidden state from the previous day to the current transaction day. This will enable us to analyse the specifics of the previous day. These attributes provide strength to our dataset and enable us to decrease mean squared error and increase accuracy.

F. Multi-Layer Perceptron:

This study use Multi-Layer Perceptron (MLP) regressor model for predicting stock prices. The aggregated dataset is prepared which has all the market variables: open, low, high, LSTM _feature and sentiment score. First step is data preparation where we select specific columns to create a feature matrix which consists of open, low, high, volume, LSTM feature (Y_i), sentiment_score (k_i) and other data frame which has close values. Now we split the datasets into training and testing datasets in the ratio of 80:20. Next we standardizes the features according to the training set's mean and standard deviation by applying the scaler to the training data. Then create a new MLP Regressor model with two hidden layers that have 50 and 100 neurons in each. Rectified Linear Unit, or RELU, , is the activation function that is employed. Use the scaled test data and the trained model to predict the target variable. Determines the Mean Squared Error (MSE) resulting from the comparison of the predicted values and the actual target values. Prints the mean squared error (MSE), a measurement of the discrepancy between the expected and actual data.

G. Classification:

Better model performance is indicated by lower MSE values. For the real motions in the test set, we create binary labels in this study. If the closing price today is higher than or equal to the closing price yesterday, suggesting a positive movement, it assigns a value of 0. Our model determines the MLP Regressor model's accuracy score by contrasting the predicted and actual binary labels. The ratio of accurately anticipated movements to the total number of motions is the accuracy score.

IV. RESULTS AND DISCUSSION

Table1: Comparative analysis of Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
LSTM [22]	68.53	63.21	94.42	75.73
GRU [22]	69.20	63.49	95.19	76.17
LSTM+VADER lexicon	93.84	90.9	95.23	93.02

Price data is analysed using LSTM and GRU models. The performance gap between these algorithms varies based on the job. We gave a performance. A comparison of LSTM and GRU algorithms for price embedding was conducted, with the latter outperforming the former in predicting stock price movements. The experiment results in enhanced accuracy, precision, recall and f1-score as 93.84, 90.9, 95.23, 93.02[Table 1]. It proves that this multi-model increases the chances of predicting the close price than the single model. In Table 1 only LSTM results in accuracy, precision, recall and f1-score as 68.53, 63.21, 94.42, 75.73 and GRU results in accuracy, precision, recall and f1-score as 69.20, 63.49, 95.19, 76.17.

LSTM to make the same forecast before, the accuracy was 78 and the mean squared error was 0.022. When the two datasets together to make the same prediction, the accuracy was 93.6 and the mean squared error was 0.006. In comparison to earlier models, the mean squared error is lower for this model. Here these results are shown in bar graph as a performance analysis [Figure 4].

In the fields of regression analysis and machine learning, the Mean Square Error (MSE) is a crucial metric for evaluating the performance of predictive models. It measures the average squared difference between the predicted and the actual target values within a dataset.

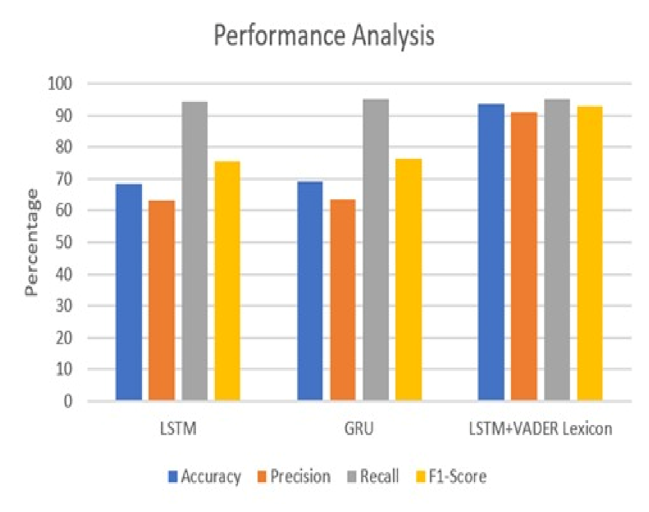

Figure 4: performance Analysis

V. CONCLUSION

In conclusion, this article a pioneering Multi-Model Fusion Deep Learning approach that addresses the persistent challenge of forecasting stock prices in dynamic financial markets. By intricately integrating stock and news data, the method recognizes the complex interplay of variables in stock market dynamics, emphasizing the crucial role of considering market volatility for precise predictions. The innovative fusion technique, combining features from stock price data and textual news data through a tailored architecture, proves ground-breaking. The sophisticated fusion layer facilitates the synthesis of a comprehensive understanding of market behaviour. Finely tuned through joint training, the hybrid architecture demonstrates its effectiveness in predicting stock price movements, as evidenced by evaluation metrics like accuracy, Mean squared error (MSE), and F1 score. This multi-model fusion paradigm, seamlessly blending insights from diverse data sources, holds promise for refining stock price predictions within the volatile landscape of financial markets, contributing valuable advancements to the field.

This study has some limitations, such as the fact that LSTM networks are effective in capturing language dependencies but have some limitations, like computational complexity. NLP VADER Lexicon, while useful for sentiment analysis, may struggle with domain-specific trends and complex sentence structures. Here in this paper, we used stock news and stock price datasets. If we have taken additional company relationship information, we may get better accuracy than this study.

Future work could refine the Multi-Model Fusion Deep Learning approach by incorporating additional data Sources like social media sentiments and macroeconomic indicators. Exploring real-time adaptability and scalability for dynamic market conditions would enhance the model's practical utility. Furthermore, efforts to improve interpretability and incorporate explainability features could bolster stakeholders' confidence in the model's decision-making process, contributing to its reliability in the intricate realm of stock price forecasting.

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