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Predictive Analytics for Stock Market Investment Using Advanced Large Language Models (LLMS) in Finance

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Abstract: *The goal of investors seeking buy and sell guidance from brokers and specialists is to increase their earnings. Mistakes are common when trying to predict the share price by brokers or software. This paper focuses on stock market prediction based on the historical stock data of Apple Inc., which consists of Open, High, Low, Adjusted Close, and Volume. Extensive preprocessing such as missing values, non-trading day removal, normalization and feature selection. The best results were obtained by BERT (R 2 = 99.73, RMSE =0.00756), and RoBERTa (R 2 = 99.25, RMSE = 0.01246). Findings reveal that the model that is based on transformer models has much higher performance than classic deep learning strategies, including LSTM, GRU, and PSO-LSTM, used to make reliable stock market predictions.*

Keywords: Stock Market Prediction, Time-Series Forecasting, Transformer Models, Feature Selection, Financial Data Analysis

I. INTRODUCTION

Stock market predictions are notoriously difficult since the market is both complex and dynamic, subject to influence from a wide range of sources. Despite their widespread use, classical models fail miserably when faced with the complicated, non-linear, and time-varying dynamics of stock market activity [1]. More sophisticated and precise forecasting models are now within reach, thanks to the rise of deep learning [2][3]. For emerging countries' financial systems, capital generation, resource allocation, and crucial investment opportunities to take the next step forward, robust stock markets must be established. There has long been a correlation between rising stock prices and expanding economies in the empirical research [4][5]. The government has embarked on several programs to change the investment behavior of the people. University students are an important group of future employees and possible investors. Knowing their intentions regarding investments is thus a crucial factor in informing the policies on the way forward to enhance financial inclusion and economic development in general [6].

AI methods have recently gained popularity in stock market prediction because they are better than their traditional competitors. AI models are transforming the finance industry with the use of financial data and machine learning capabilities [7]. The finance industry is being disrupted by AI models that have access to a lot of financial data and machine learning. The rapid advancement of deep learning and machine learning in recent years has piqued many people's interest in the field of stock market prediction [8][9]. Many domains have shown great promise for deep learning models, such as language modelling, machine translation, picture and speech recognition, and many more [10][11]. Predicting stock prices using deep learning methods is a topic that has attracted a lot of attention from researchers. One use of machine learning is the prediction of stock prices through the identification of patterns in data [12]. Typically, stock markets produce tremendous volumes of structured and unstructured heterogeneous data [13][14]. Utilizing machine learning algorithms, it can analyse heterogeneous data significantly more quickly and with greater precision. Plus, there's been a flurry of activity researching the potential applications of LLMs in a wide range of domains, thanks to the widespread interest in their integration [15][16]. Still uncharted territory is their potential stock

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market use, particularly in the realm of zero-shot learning target-level financial investment research.

A. Motivation and Contributions of the Study

The complexity of the stock market with its dynamic, non-linear and time-varying factors makes accurate prediction a difficult task. The conventional models are usually not dependable when it comes to investment decision-making since they do not capture these complex patterns. Due to the increasingly high role that strong stock markets play in promoting economic growth, especially in developing nations, there is an urgent need to have more sophisticated and precise forecasting techniques. A chance to overcome these limitations and uncover hidden patterns in massive amounts of financial data has arisen because of recent advancements in DL and LLMs. This paper is driven by the fact that transformer-based architectures, including BERT and RoBERTa, have the potential to deliver a better predictive performance in stock market investment analysis, which in turn can make economic activities more inclusive, enable informed choice-making, and contribute to the overall growth of the economy. Some of the most important contributions made by the study are as discussed below:

- Utilized the Apple Inc. stock market dataset from Kaggle as a benchmark financial dataset for model development and evaluation.
- Addressed missing values, removed non-trading days, and applied Min-Max normalization to ensure data consistency and comparability.
- Used the Select Best method to get the best features, which made the model work better and reduced the number of dimensions.
- The application of advanced transformer-based models (BERT and RoBERTa) to forecast stock market movements highlights the practicality of NLP frameworks in financial data.
- Conducted a comprehensive performance assessment using R^2, RMSE, and MSE, enabling robust comparison of predictive accuracy.

B. Significance of the Study

Investment decisions in stocks could be enhanced with the use of better natural language processing models, which is why this research is crucial. This work demonstrates how deep learning may be applied to uncover complex correlations and patterns in financial data and improve their prediction power using transformer-based models, such as BERT and RoBERTa. This is especially relevant in highly volatile stock market where even minor advances in prediction can lead to huge financial benefits and minimized risks in investment. The study also provides a scalable method applicable across diverse financial datasets and market settings, and it offers a paradigm encompassing rigorous pre-processing, feature selection, and robust evaluation metrics. In the end, the findings can help financial institutions, analysts, and investors make smarter investment choices.

C. Organization of the Study

The paper is organized as follows Reviewing the relevant literature on stock market investment is covered in Section II. Section III further discussed the methodology, including the dataset, pre-processing, and the LLM models implementation. Section IV outlines the results and discussion. Section V concludes the study and discusses its future directions.

II. LITERATURE REVIEW

This study is built upon a thorough review and critical evaluation of prior research on stock market investment, which served to refine its scope and guide the overall direction of the work.

Govindasamy, Radhakrishnan and Shankar (2025) proposed RRE-DLBSP framework develops an LSTM (long short-term memory) paradigm for RRE assessment. The research results demonstrated the RRE-DLBSP method's superiority over the cutting-edge approaches based on a variety of performance metrics. The suggested RRE-DLBSP has an MSE

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of 0.0436 and 0.0656, while the mean for the evaluated techniques in training and evaluation is 0.725 and 0.6124, respectively [17].

E et al. (2025) behavioral trends with a simulation model including historical market data and investor sentiment tracking with machine learning, and thus featuring psychological aspects demonstrated by Results of a thousand trading day simulation with a 15.2% improvement in expected accuracy compared with traditional models. This result also demonstrated some visible connections between sentiment-based trading and price changes. One instance of this would be the measurement of loss aversion, which showed a twenty percent drop in risk tolerance after a negative market shock [18].

Sekhar Dash and Mishra (2024) show a novel approach to forecasting stock market movements by integrating neural networks with sentiment analysis data derived from publicly accessible financial reports. The accuracy rate of the deep learning-based trend prediction model employing sentiment analysis data exceeds 96%. The result of research benefit in the field of financial investment and risk management in the Indian stock market [19].

Yadav et al. (2024) the framework utilizes GNNs to construct a graph representation of financial market data, capturing structural dependencies and latent patterns. Evaluation of the proposed framework against existing methods to demonstrate its effectiveness. The proposed framework achieves a high precision rate of 85.6%, indicating a significant proportion of accurately identified anomalies[20]. Albaooth, (2023) offers a model that can assist investors in making more informed decisions by predicting stock market behaviours using deep learning. According to the findings, the suggested model outperformed the understudied dataset in terms of prediction accuracy, reaching over 99.98%. This can significantly enhance the decisions of individual investors for better future predictions of stock markets [21]. Fetrina, Utami and Arizki, (2023). This study's overarching goal is to identify the most accurate time series analysis method by comparing three different approaches to the stock price index data of Bank Central Asia from 2020 to 2022: Linear Trend Regression, Exponential Smoothing, and ARIMA. Out of the three methods tested, the ARIMA (1,1,0) method had the highest accuracy level and the lowest root-mean-squared error (RMSE) number (162.9544), according to the study's results [22].

Research gap

Predictions of stock prices made using time-series forecasting, sentiment analysis, graph-based models, and deep learning have yielded encouraging results in previous research. While these approaches demonstrate high accuracy and effectiveness, several research gaps remain. Most models are often tested on specific datasets or limited time periods, raising concerns about their generalizability across different markets and conditions. Many methods also focus on accuracy without addressing real-world deployment challenges such as scalability, computational complexity, and adaptability to dynamic market fluctuations. Furthermore, extreme accuracy values suggest risks of overfitting, highlighting the need for robust validation across diverse datasets. Additionally, psychological and behavioral factors influencing investor decisions are not comprehensively integrated into prediction frameworks, leaving room for more holistic models that combine financial, sentiment, and macroeconomic indicators. Finally, hybrid and transformer-based architectures remain underexplored, offering opportunities for future research to build more reliable, interpretable, and scalable stock market prediction systems.

III. RESEARCH METHODOLOGY

Testing sets. To make predictions and analyze data, two deep learning models based on transformers are used: BERT and RoBERTa. Lastly, the models' performance is assessed using important statistical measures, including the R^2 coefficient, RMSE, and MSE. The findings are then summarized for future comparisons. The proposed methodology's flow is depicted in Figure 1.

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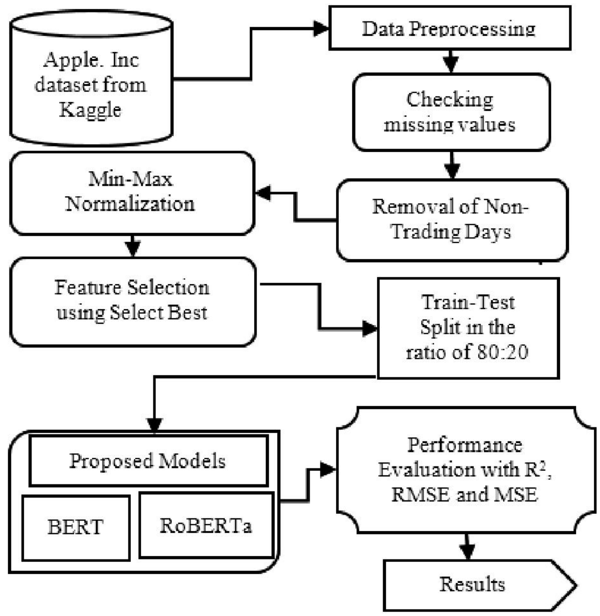

Fig. 1. Proposed Flowchart for Stock Market Investment

The subsequent section details the process depicted in the proposed flowchart for stock market investment.

A. Data Gathering and Visualization

Apple Inc. The dataset, sourced from Kaggle, is utilised in this investigation. From the beginning of time until June 22, 2021, this dataset contains stock market data for Apple Inc. (AAPL). For a comprehensive analysis of Apple's stock performance over the years, data such as Date, Open, High, Low, Close, Adjusted Close, and Volume are disclosed daily. Spanning several decades, the dataset captures key trends, including long-term growth, market volatility, and significant price movements, making it useful for financial analysis, time-series forecasting, and stock market prediction studies. Some EDA of the dataset is shown below in Figure 2.

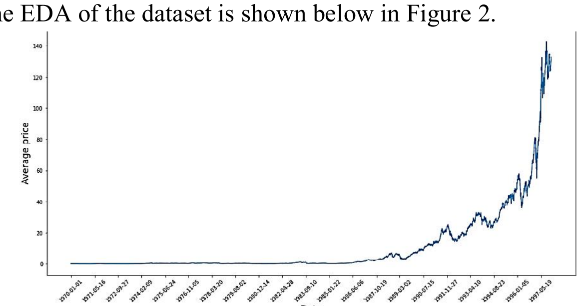

Fig. 2. Apple Prices of Apple's Shares

Figure 2 presents a line graph of the historical average asset price from 1970 to mid-1997. Prices remained low and stable (below 10) through the 1970s and 1980s, followed by a gradual rise in the late 1980s to early 1990s. From the mid-1990s, the trend shifted sharply, with prices surging exponentially from around 40 to over 120 by the end of the period.

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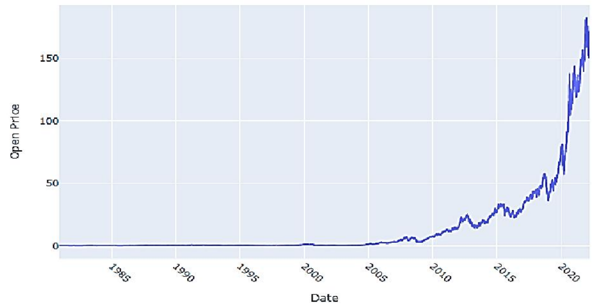

Fig. 3. Apple Open Price

Figure 3 depicts a line graph of the asset's Open Price from the early 1980s to mid-2020. Prices stayed near zero until around 2000, then rose gradually through the 2000s. From 2015 onward, the increase accelerated sharply, with the price soaring past 150 by the end of the period.

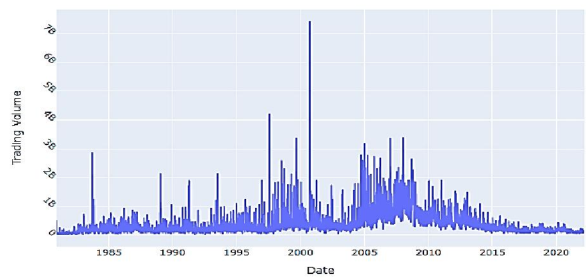

Fig. 4. Apple Shares Trading Volume

Figure 4 shows a line graph of the asset's Trading Volume from the early 1980s to mid-2020. Volume was low and stable through the 1980s–early 1990s, with occasional spikes. It surged in the late 1990s, peaking above 70 around 2000, and remained elevated with frequent spikes through the mid-to-late 2000s. From 2010 onward, trading volume steadily declined with reduced volatility, returning to lower levels by the end of the period.

B. Data Pre-processing

Data preparation (DP) is an essential system step since it influences the subsequent stage. Because of this, it is a crucial step in making better predictions. So, it's a multi-step procedure that includes things like finding missing information, eliminating trade days, normalizing using min-max, and selecting features with Select Best.

- **Check the missing values:** The first thing to do is deal with missing values. Used the pandas functions "sum" and ".isnull()" to check for missing values, and checked and saw that dataset does not have any.
- **Removing the Non-Trading Days:** No opening, closing, maximum, or minimum price data exist for days when trading did not occur since these records were erased.

C. Min-Max Normalization

Using this strategy, even when dealing with massive amounts of data, you can scale it to fit within a particular timeframe. Optimizing gradient descent with normalization enhances its accuracy and speed [23]. One typical method for data scaling between specified ranges is min-max normalization, which involves applying a linear modification to the starting data. Equation (1) shows the formula:

$$z_n = \frac{x - x_{min}}{x_{max} - x_{min}} \left(New_{max_x} - New_{min_x}\right) + New_{min_x} \quad (1)$$

The variables x_{max}&x_{min} stand for the maximum and minimum values that can be found, respectively. The notation New_{min_x} is used to represent the lowest number, whereas New_{max_x} is used to represent the greatest number.

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Feature Selection using Select Best

Machine learning feature selection is accomplished using the Select Best method in scikit-learn [24]. When it comes to picking the best K features from a dataset, though, they apply different statistical techniques. The feature selection using Select KBest ranked the input variables based on their importance scores, highlighting the most significant predictors for the model.

D. Models Classification

The present section introduces the proposed transformer-based models, BERT and RoBERTa, which are employed in stock market investment.

BERT

The BERT Transformer model, which gained popularity for NLP tasks, is now also useful for sequence-to-sequence modelling; this has important consequences for cloud computing resource allocation prediction. Understanding the temporal relationships in resource allocation is a strong suit of the Transformer due to its self-attention mechanism and its skill in processing sequence data. Additionally [25], the capability of the model to process multi-tasking and adapt well to various lengths of sequences in historical resource data ensures that it is very adaptable and efficient [26]. These characteristics render the Transformer model an attractive choice when it comes to resource allocation prediction because it takes into account the sequence of the past resource use information and the characteristics related to it. Another operation that is employed to map queries, trace key-value pairings, and generate data as vectors is called attention. In Equation (2) the attention equation is evident:

$$attention(Q,K,V) = \text{SoftMax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \qquad (2)$$

In which, Q is the query building matrix (a vector of each word), K the key, V itself, d_k the dimension of key vector K, $\frac{QK^T}{\sqrt{d_k}}$ is the step to compute the attention weight, the outcome of the dot product of Q and K, divided by the square root of d_k. $SoftMax$ is a deep learning activation that may be applied to attention weights that result in a probability value between 0 and 1.

RoBERTa

The ROBERTa model is an NLP system that was created in 2019 by Facebook AI Research (FAIR). The BERT model, from which RoBERTa is derived, has shown success in a number of language processing tasks. prior knowledge. Though structurally comparable to BERT, RoBERTa outperforms it on NLP tasks including sentiment analysis, coarse language detection, and natural language comprehension by making use of more advanced training methods and larger data sets [27][28]. Although not an algorithm in and of itself, RoBERTa was constructed using the aforementioned training algorithm and is now among the most prominent NLP models in use. It processes data and generates specific outputs as a result.

E. Evaluation Metrics

R2, MSE, and RMSE: are among the assessment measures used to measure the models' performance following data preparation. The improved dataset is then applied to the training dataset using BERT and RoBERTa models [29]. Here are the evaluation metrics

Coefficient of Determination (R2): The coefficient of determination illustrates the extent to which the independent factors may predict the dependent variable's variance. In Equation (3), this is shown:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \qquad (3)$$

Mean Squared Error (MSE): The mean squared error (MSE) is calculated by averaging the squared difference between the actual and projected numbers. As demonstrated by Equation (4), by applying mathematical:

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$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2 \quad (4)$$

Root Mean Squared Error (RMSE): The square root of the mean squared error (MSE) is identical to the root-mean-squared error (RMSE), which is a unit-wise error metric for the target variable. For its expression, they use Equation (5):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2} \quad (5)$$

IV. RESULTS AND DISCUSSION

The Nvidia GeForce RTX 3070 Ti Laptop, which boasts a 16 GB GPU and 32 GB RAM, was utilized to evaluate these models. Using important assessment measures, Table I summarizes the performance of the proposed BERT and RoBERTa models for stock market investment prediction. A high R^2 score of 99.73% was achieved by BERT, while RoBERTa achieved 99.25%. Both models show good predictive accuracy. In comparison to RoBERTa, which has a slightly higher MSE of 0.01246, BERT has a slightly lower Mean Squared Error (MSE) of 5.7258 and a Root Mean Squared Error (RMSE) of 0.00756 when examining error metrics. It is clear from these outcomes that both transformer-based models are strong contenders; BERT stands out for its excellent variance explanation and general accuracy, while RoBERTa shows remarkable accuracy in reducing prediction error.

Table 1: Performance Results of the Proposed Models for Stock Market Investment

Performance Matrix	**BERT**	**RoBERTa**
R2	99.73	99.25
MSE	5.7258	0.01246
RMSE	0.00756	0.000155

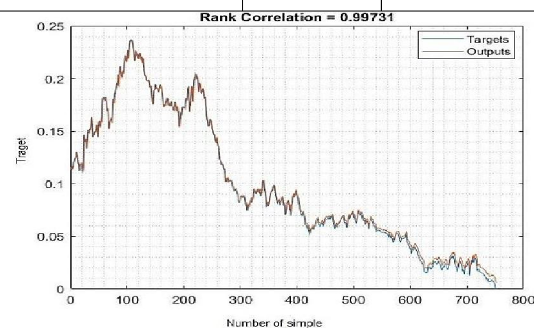

Fig. 5. Rank Correlation of the BERT Model

Figure 5 displays a time-series figure that compares Outputs and Targets. You can see the number of samples on the x-axis and the goal values on the y-axis. Predicted and actual values are highly congruent, as seen by the tight overlap of the two curves. A near-perfect positive relationship is supported by the high Rank Correlation (0.99731), meaning that the Outputs can be used as a great approximation of the Targets.

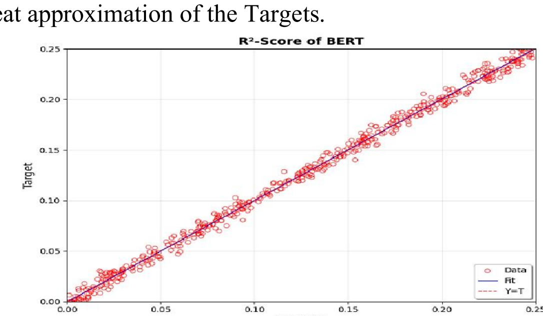

Fig. 6. Squared Regression Plot of the BERT Model

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Figure 6 demonstrates the behaviour of a BERT model on a regression task with the help of a scatter diagram of the predicted values (x-axis) against the actual targets (y-axis) in a scatter diagram. Red circles denote individual data points, while the dashed red line (Y=T) indicates perfect prediction. The solid blue line (Fit) closely aligns with this reference, showing a strong linear relationship and high correlation. The high R^2 score further confirms the model's accuracy and reliable predictive performance.

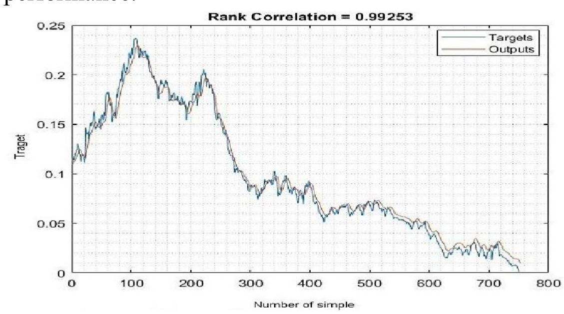

Fig. 7. Rank Correlation of the RoBERTa Model

Figure 7 displays a time-series plot of Targets and Outputs, with the two curves closely overlapping across samples. The high Rank Correlation (0.99253) indicates a near-perfect positive relationship, confirming that the Outputs provide an excellent approximation of the Targets.

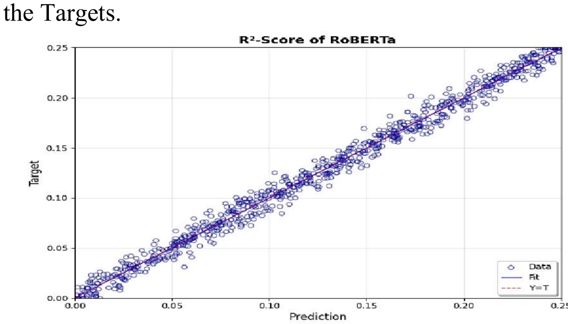

Fig. 8. Squared Regression plot of the RoBERTa Model

Figure 8 presents the performance of a RoBERTa model on a regression task, plotting predictions (x-axis) against actual targets (y-axis). Blue circles mark the data points, with the solid blue Fit line closely following the dashed red Y=T line, which represents perfect prediction. The strong alignment indicates a very high R^2 score, confirming that RoBERTa achieves highly accurate predictions and explains most of the variance in the target values.

Comparative Analysis

The several models used to forecast investments in the stock market are compared in Table II. With R^3 scores of 71.0% and 81.65%, respectively, and relatively high RMSE values of 8.13 and 10.58, standard deep learning models such as LSTM and GRU perform middling. The PSO-LSTM model significantly improves prediction accuracy, reaching an R^2 of 94.0% with a reduced RMSE of 0.3987. In contrast, transformer-based models deliver superior results: BERT achieves the highest R^2 of 99.73% with the lowest RMSE (0.00756) and MSE (5.7258), while RoBERTa follows closely with an R^2 of 99.25% and RMSE of 0.01246. These results confirm that BERT and RoBertA are significantly better than traditional models, which provide very accurate and reliable returns in predicting the stock market investment.

Table 2: Performance Comparison of Different Models for Stock Market Investment

Models	R2	RMSE	MSE
LSTM [30]	71.0	8.13	66.07
GRU [31]	81.65	10.58	112.10
PSO-LSTM [32]	94.00	0.3987	-

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BERT	99.73	0.00756	5.7258
RoBERTa	99.25	0.01246	0.00756

BERT and RoBERTa have substantial benefits in terms of stock market investment prediction because they are based on transformer-based architectures that are outstanding at learning intricate patterns and contextual interactions in sequential information. They are able to handle long-term dependencies and finer interactions effectively unlike traditional models, and can therefore give a more accurate forecast of trends. Their strength also enables them to generalize effectively in different market environments, whereas their capability of reducing errors when predicting provides a higher degree of stability in making decisions. Generally, both of these models have offered a strong and effective framework for working with the complexity of financial time series data.

V. CONCLUSION AND FUTURE STUDY

The stock market is infamous for its instability, dynamism and non-linearity. Precise forecasting of stock prices is highly challenging because of various influences such as politics, the prevailing situation in the global economy, unpredictable events, and financial performance of a firm among others. This however does not mean that there is an abundance of data to cut through to extract patterns. In conclusion, this research shows that, utilizing Apple Inc.'s historical data, transformer-based models may accurately forecast stock market investment. BERT and RoBERTa models, the proposed models, demonstrated impressive predictive accuracy of 99.73 and 99.25, respectively, and significantly exceeded the traditional deep learning models. They can specifically learn complicated patterns and long-term dependencies from unconstrained financial time-series data because of their transformer-based topologies with self-attention. This is what enables them to be very useful when it comes to predicting market trends and helping in the decision-making on investments. In general, the results show that transformer models are strong, precise, and effective frameworks for contemporary stock market prediction.

Although the findings demonstrate the strength of these models, it might be possible to continue this study with more financial indicators, macroeconomic variables, and multi-stock data to further increase generalization. Furthermore, it is possible to consider the exploitation of hybrid forms of architecture based on transformers and optimization methods or reinforcement learning to open new opportunities to enhance predictive capabilities and facilitate more adaptable trading policies.

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