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An Intelligent Stock Price Prediction System Using Large Language Models in Financial News Understanding

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***Abstract*—The stock market is always fluctuating due to factors Numerous variables, including investor mood, economic statistics, and financial news, impact the ever-changing stock market. Natural Language Processing (NLP) has emerged as an effective approach for analyzing financial news headlines and identifying market sentiment to improve stock price forecasting. This study proposes an intelligent stock price prediction system using a Financial Generative Pre-Trained Transformer (FinGPT), which integrates financial news understanding with historical S&P 500 market data to predict stock closing prices more accurately. The data was cleaned, labelled, and normalized using Z-scores before model training, and the train-test split was 70:30. R^3, RMSE, and MAPE evaluation measures were used to evaluate the performance of the proposed FinGPT model with ARIMA, LSTM, and GRU. As shown by the experimental findings, the suggested FinGPT outperformed the previous models in terms of prediction accuracy, with an R^2 of 99.9%, an RMSE of 39.9628, and a MAPE of 0.8267. The outcomes demonstrate that the suggested framework is an effective and trustworthy system for intelligent financial forecasting by combining the strength of transformer-based financial language understanding with historical market data. This integration significantly improves the accuracy of stock price prediction.**

***Keywords*—Financial Sentiment Analysis, Stock Price Prediction, Natural Language Processing, Word Embedding, Deep Learning; Transformer.**

I. .INTRODUCTION

Investor confidence and economic performance are reflected in the stock market, which is a critical element of the global financial system. All parties involved in making investment decisions, optimizing portfolios, and managing risk rely on accurate stock price predictions [1][2]. This includes traders, investors, financial institutions, and lawmakers. Corporate profits, economic policies, geopolitical events, market trends, investor behaviour, and overall are some of the many factors that impact stock prices, which are in a constant state of flux [3]. Because of their heavy dependence on numerical data from the past, traditional methods of financial market forecasting—including technical and fundamental analysis, statistical models, and econometric techniques—often fail to adequately account for the markets' complex and nonlinear behaviour [4][5].

Recent developments in AI, ML, and DL have made it possible to intelligently analyze massive amounts of financial data, which has greatly enhanced stock market predictions [6]. Machine learning (ML) algorithms automatically identify hidden patterns from historical market data, while deep learning (DL) techniques effectively capture nonlinear relationships and temporal dependencies to improve prediction accuracy[7]. These intelligent approaches have demonstrated superior performance over conventional statistical methods by utilizing historical stock prices, technical indicators, and structured financial information for reliable forecasting [8] [9][10]. Despite these advancements, relying solely on historical market data is often insufficient because stock prices are also strongly influenced by unstructured financial information[11]. Financial news, including corporate announcements, earnings reports, government policies, and global economic events, significantly affects investor sentiment and market behaviour [12][13]. Conventional sentiment analysis techniques generally require extensive feature engineering and are limited in capturing contextual semantics and long-range dependencies in financial text[14][15]. Consequently, integrating financial news with numerical market data remains an important challenge for developing intelligent and reliable stock price prediction systems[16].

The ability to comprehend financial news in its entirety via contextual reasoning and semantic representation has been made possible by recent advancements in Large Language Models (LLMs), which have revolutionized financial natural language processing [17][18] [19]. Unlike conventional ML and DL methods, LLMs automatically extract meaningful information from unstructured financial text with minimal feature engineering while effectively modelling long-range contextual relationships[20]. Their capability to combine qualitative financial news with quantitative market information provides a promising direction for improving stock price forecasting accuracy and supporting more reliable financial decision-making in intelligent prediction systems[21].

A. *Motivation and Contribution of this study*

The motivation behind this study is to improve the accuracy and reliability of stock price prediction by integrating financial news understanding with historical market data. Financial news contains contextual information that traditional forecasting methods rely on numerical data to miss. Consequently, this study makes use of a FinGPT to enhance investment and financial decision-making by combining market trends with relevant financial insights for smarter forecasting. This research offers several key contributions as listed below:

- Developed an intelligent stock price prediction system using the proposed Financial Generative Pre-Trained Transformer (FinGPT) model.
- Integrated financial news understanding with historical S&P 500 stock market data to improve prediction performance.
- Leveraged transformer-based self-attention to capture contextual information and sentiment from financial news articles.
- Verified the accuracy of the performance evaluation by assessing the suggested model with industry-standard regression metrics such as R^2, RMSE, and MAPE.
- Demonstrated the effectiveness of LLMs for financial news understanding and intelligent market forecasting.

B. *Justification and Novelty*

The justification of this study is the increasing demand for intelligent stock price prediction systems that can effectively utilize both historical market data and financial news information. Financial language context is difficult to grasp using traditional ML, DL, and statistical methods. The novelty of this work lies in the proposed FinGPT, which integrates transformer-based financial news understanding with historical stock market data to improve prediction accuracy and provide a more robust and reliable forecasting framework.

C. *Organization of the Paper*

This paper is organized as follows for the rest of it. Section II begins with a listing of relevant works. Section III goes on to detail the methodology. Results from the experiments are detailed in Section IV, and finally, Section V. As a last point, the paper.

II. LITERATURE REVIEW

The development of this study is informed and enhanced by a thorough review and analysis of key research studies on Stock Price Prediction System for Financial News Understanding.

C. Ozdes and G. K. Koru (2026) introduced FinAI, an AI-powered platform for stock price prediction that is accessible via mobile devices and online. To improve the accuracy of predictions, FinAI uses an ensemble model that incorporates numerous machine learning models. These models include Linear Regression, Random Forest, XGBoost, CatBoost, and MLP. While ReactJS powers the front end, Python's Flask handles backend development and integrates with third-party APIs like Yahoo Finance and Alpha Vantage. On average, experimental evaluations of BIST100 stock data show a prediction accuracy of about 80% [22].

W. Dwiyanti et al. (2025) explore the role of news emotion in predicting the Jakarta Composite Index (JCI) using the SVR approach. Using both historical JCI stock data and financial news articles from Kompas.com, a dual dataset approach was used. As part of the study, the prediction model is enhanced with sentiment analysis characteristics derived from ChatGPT LLMs. Based on the results, Scenario 4 is the most accurate predictor across all metrics. In the log metric evaluation, the RMSE and MAE values are 0.009555 and 0.007298, respectively. In the absolute metric evaluation, the values are 47.616867 and 36.52605, and in the stock closing price evaluation, they are 85.146387 and 70.34775 [23].

K. H. Ali Almarzoog et al. (2025) developed a worldwide stock market news-specific sentiment analysis approach that combines event-aware and temporal contextual characteristics with financial natural language processing models based on transformers. Financial event classes including earnings calls, regulatory disclosures, and macroeconomic briefings were used to evaluate the system, together with FinBERT, RoBERTa-fin, and annotated financial corpora. Impressive sentiment classification accuracies (>96.8%), F1-scores (>0.94), and peak sentiment-price alignment correlations (>0.71) were routinely achieved [24].

Y. K. Jakhar et al. (2024) include many different algorithms, such as Multilayer Perceptron (MLP2, 2), XGBOOST, Linear Kernel, Poly Kernel, and SVM. MAE and RMSE have also been calculated to test how well various models perform. When it came to predicting daily high prices, the MLR model outperformed the competition. With a MAE of 11.57 and an RMSE of 14.69, MLR had the best results of all the algorithms tested [25].

S. M et al., (2024) This is accomplished by utilizing a novel regression strategy in a Bi-LSTM–DNN. A projected portfolio, which incorporates the previously made predictions, is used to construct a group of investments. Many experiments have been carried out utilizing NIFTY-50 stock data obtained from the Indian National Stock Exchange. With Bi-LSTM-DNN, the suggested DL network for stock prediction has an RMSE of 0.81 [26].

M. Lavanya and P. Gnanasskaran (2023) the goal is to draw a conclusion about the future by analyzing the past and finding patterns in the data. Stock open, high, low, and close rates are some of the financial data that are fed into the model. This document makes use of a linear regression model, one of many available, to forecast the commodity stock price by calculating the expected closing price of the stock five days from now. Opposed to the current model, the suggested LR achieves the best results, outperforming it by 92% [27].

L. Mathanprasad and M. Gunasekaran (2022) The use of a focus ML classification algorithm has allowed for the prediction of stock market prices and movements, as well as the evaluation of performance and the suggestion of work to the user, allowing them to easily determine which stocks remain in the market for a longer period of time. Examining and improving upon the stock exchange's prediction accuracy to 94.17% with the use of ML algorithms [28].

M. Sariyer et al., (2022) prediction algorithm gauges the volume and price movements of individual firm stocks featured in BIST30 by integrating sentiment on Twitter with disclosures from these companies. To further improve the model's prediction accuracy, financial data pertaining to market conditions is also included, including daily price changes of BIST30, DJI, USD, and Gold per Ounce. For companies with a high number of public disclosures and social media presence, algorithm can reach an accuracy of up to 80% when predicting individual stock prices. Also, across all BIST30 firms, manage a mean volume prediction accuracy of 74.7% [29].

The proposed models, datasets, major findings, and challenges encountered in the recent research on Stock Price Prediction System for Financial News Understanding are detailed in Table I.

TABLE I. RECENT STUDIES ON STOCK PRICE PREDICTION FOR FINANCIAL NEWS USING MACHINE LEARNING TECHNQIUES

Author	Proposed Work	Dataset	Results	Limitations & Future Work
Ozdes and Koru (2026)	Developed FinAI, an AI-based web platform integrating financial news, technical indicators, and ensemble ML models (LR, RF, XGBoost, CatBoost, MLP) for stock prediction.	BIST100 stock data, Yahoo Finance, Alpha Vantage APIs	Average prediction accuracy of 80%.	Uses traditional ML instead of LLMs; future work can incorporate transformer-based LLMs for better financial news understanding.
Dwiyanti, Aquarini and Gunawan (2025)	Proposed stock prediction using SVR combined with ChatGPT-based sentiment analysis from financial news.	Jakarta Composite Index (JCI) historical data and Kompas.com financial news	Best scenario achieved RMSE = 0.009555 and MAE = 0.007298.	Limited to sentiment integration with SVR; future work should explore end-to-end LLM-based forecasting models.
Ali Almarzoog et al. (2025)	Introduced a transformer-based financial sentiment framework using FinBERT and RoBERTa-fin with event-aware contextual analysis.	Financial news corpus with annotated financial events	96.8% sentiment accuracy and F1-score = 0.94.	Focuses on sentiment classification rather than stock price prediction; future work may integrate forecasting models.
Jakhar, Sharma and Ahmed (2024)	Compared MLR, SVM, MLP, and XGBoost for stock price prediction using historical data.	Historical stock market data (2009–2023)	MLR achieved MAE = 11.57 and RMSE = 14.69.	Does not utilize financial news or LLMs; future work can integrate textual market information.
M et al. (2024)	Proposed Bi-LSTM-DNN with regression for stock prediction and portfolio optimization.	NIFTY-50 stock dataset	RMSE = 0.81.	Relies only on historical numerical data; future work can incorporate news sentiment using LLMs.
Lavanya and Gnanasskaran (2023)	Implemented Linear Regression with feature engineering for forecasting future stock closing prices.	Yahoo Stock Market dataset	92% prediction accuracy.	Uses a simple regression model without financial news analysis; future work may adopt deep learning and LLMs.
Mathanprasad and Gunasekaran (2022)	Proposed a machine learning classification approach for stock market prediction.	Real-time historical stock market dataset	94.17% prediction accuracy.	Limited to traditional ML techniques; future research should explore transformer-based financial language models.
Sariyer et al. (2022)	Combined Twitter sentiment, public disclosures, and market indicators for stock price and volume prediction.	BIST30, Twitter, Public Disclosure Platform (KAP), DJI, USD, Gold datasets	80% stock price accuracy and 74.7% volume prediction accuracy.	Uses conventional sentiment analysis instead of LLMs; future work can leverage advanced financial LLMs

Research gaps: A number of limitations persist, despite the fact that ML, DL, and transformer-based approaches have been shown to be effective in predicting stock prices in recent studies. Many existing methods primarily rely on historical stock prices, technical indicators, or sentiment extracted from financial news without fully integrating contextual financial language understanding with numerical market data. Several studies also focus on conventional models such as ARIMA, SVM, LSTM, GRU, XGBoost, and ensemble learning, which have limited capability to capture long-range semantic dependencies in financial text. Furthermore, the performance of sentiment-based prediction models is highly dependent on feature engineering, scenario selection, and hyperparameter tuning, reducing their generalization ability across different market conditions. Therefore, there is a need for an intelligent framework that effectively combines transformer-based financial language understanding with historical stock market information to achieve more accurate and reliable stock price prediction.

III. RESEARCH METHODOLOGY

Data cleaning, label encoding, Z-score normalization, and a 70:30 train-test split are used to preprocess the S&P 500 Stock Market dataset in this study. This ensures that the input for model building is of good quality. To enhance stock closing price prediction, the suggested FinGPT model combined financial news knowledge with historical stock market data using transformer-based self-attention. To conclude, R^3, RMSE, and MAPE were used to measure the model's performance in terms of accuracy, error, and overall forecasting efficacy in terms of predictions. The suggested stock price prediction system for financial news utilizing LLM is shown in Figure. 1, which is a flow diagram.

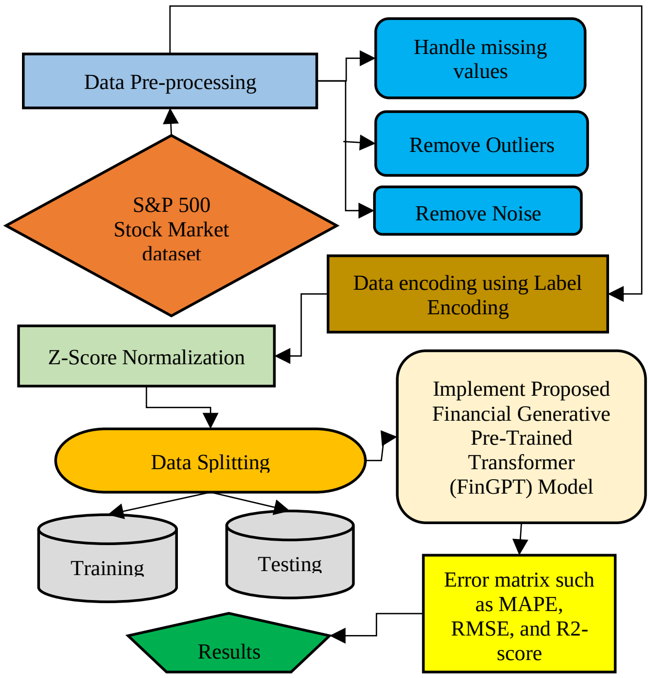

Fig. 1. Proposed flowchart for Stock Price Prediction

The following section presents a detailed explanation of each step in the proposed methodology:

A. *Data Gathering and Analysis*

In this study, the S&P 500 Stock Market dataset consisting of 1,000 records and 7 attributes is utilized to develop the proposed stock price prediction model. Data visualizations, including heatmaps and line charts, are used to analyze price movement distributions, examine feature correlations, and understand the underlying patterns in the dataset.

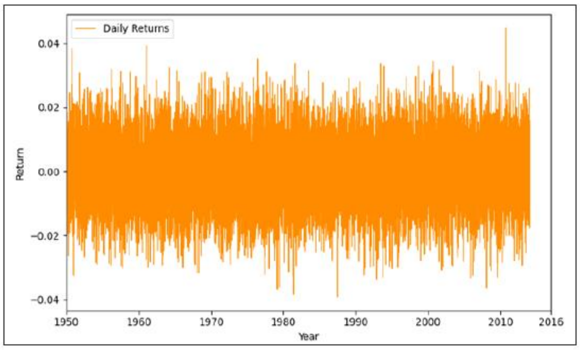

Fig. 2. S&P 500 Daily Returns

Figure 2 illustrates the daily returns of the S&P 500 index over the observation period, showing continuous fluctuations around zero with periods of both positive and negative returns. The differences in returns reflect how volatile the stock market can be and demonstrate the fluctuation of daily price changes.

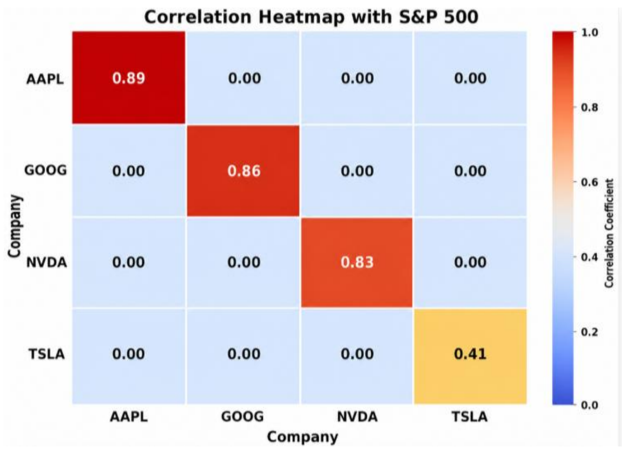

Fig. 3. Correlation Matrix Heatmap

Figure 3 illustrates the relationships among the selected financial variables, where the diagonal values indicate the strongest self-correlation, while the off-diagonal values are close to zero, showing very weak correlations between different variables. Feature correlation analysis and the identification of useful factors to improve the accuracy of the stock price prediction model are both aided by this display.

B. *Data Pre-processing*

The dataset is prepared through a systematic preprocessing pipeline that includes data cleaning, and normalization. The preprocessing steps involved handling missing values, removing duplicate and irrelevant records, reducing noise, performing data encoding, and applying normalization to improve data quality and enhance the performance of the proposed prediction model:

C. *Data cleaning*

Cleaning the data makes the financial time series better and more reliable before training the model. To ensure temporal continuity, missing values caused by non-trading days or data inconsistencies were handled using forward-fill or backwards-fill techniques. Statistical approaches including the Z-score and the Interquartile Range (IQR) were used to identify outliers. To reduce their impact, they were either removed, smoothed, or capped. By reducing noise and ensuring a consistent dataset, these preprocessing techniques strengthened the suggested prediction model.

D. *Data encoding using Label Encoding*

ML models can better process and analyze data that is encoded, which consists of transforming textual or categorical data into numerical values. To train ML models, it is necessary to convert categorical variables to numerical values, and Label Encoding is used for this purpose. Maintaining data consistency and minimizing computing complexity are achieved by assigning a unique integer label to each unique category. Because of this encoding method, the suggested models could effectively handle category data without raising the dataset's dimensionality.

E. *Z-Score Normalization*

Z-Score normalization, often called standardization, is a data preprocessing step that normalizes numerical data to a predetermined scale. The data has been rescaled such that it has a standard deviation of one and an average of zero. It creates a consistent scale across features or variables, which avoids one characteristic from dominating others during model training. For each given data point x, the Z-score normalisation can be expressed as (1):

$$z = \frac{x-\mu}{\sigma} \qquad (1)$$

where:

z stands for the transformed value, x for the initial value, μ for the data's average, and σ for its standard deviation.

F. *Data Splitting*

The whole dataset is split into 70% training data and 30% testing data. The training set is used to teach the suggested models what to do, and the testing set is used to see how well they can predict the future and how well they can generalize.

G. *Proposed Financial Generative Pre-trained Transformer (FinGPT) Model*

In this study, the proposed FinGPT model was implemented to develop an intelligent stock price prediction system by integrating historical S&P 500 market data with financial news understanding for accurate stock closing price forecasting. FinGPT is a domain-specific LLM designed for financial natural language processing tasks, including financial news understanding, sentiment analysis, market trend analysis, and stock price prediction. It processes financial news articles and extracts contextual and sentiment information, which is combined with historical stock market data to improve forecasting accuracy. The Multi-Head Self-Attention shown in Equation (2) allows FinGPT to capture long-range dependencies and semantic linkages in financial text by utilizing transformer-based architectures and attention processes:

$$Attention(Q,K,V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)v \qquad (2)$$

where d_k stands for the key dimension and Q, K, and V are the query, key, and value matrices, respectively.

The self-attention mechanism enables FinGPT to identify important financial terms and contextual relationships within news articles by assigning higher attention weights to influential words. This mechanism enhances semantic understanding and improves the extraction of meaningful information for stock market prediction, as shown in Equation (3):

$$\hat{y} = Softmax(Wh + b) \quad (3)$$

where h is the contextual representation generated by FinGPT, W is the weight matrix, b is the bias vector, and $\hat{y}$ denotes the predicted sentiment probability. The predicted sentiment scores are integrated with historical stock market features to generate informative representations for the prediction model. This fusion of textual sentiment and numerical financial data enables more accurate stock price forecasting by capturing both market behaviour and the influence of financial news.

The AdamW optimiser, a learning rate of 2×10^{-5}, a batch size of 16, training epochs of 10, maximum sequence length of 512, a dropout rate of 0.1, and weight decay of 0.01 were the parameters that were set up for the suggested FinGPT model. In order to train the model to learn financial news contextual representations effectively, a hidden size of 768, 12 attention heads, and 12 transformer layers. Stable convergence and better stock price prediction performance were achieved by integrating textual and historical market information efficiently using these hyperparameter settings.

H. Evaluation Metrics

Model evaluation is an important aspect of building ML models as it helps understand the model performance and makes it easier to explain the results of the models. However, it can be difficult to predict the exact value of a regression model thus, the goal becomes to show how close the predicted values are to the actual values. In this research, the models were evaluated using three performance evaluation metrics: R2, RMSE and MAPE

1) R-Squared

A regression model's goodness-of-fit can be evaluated using R^2, which shows how much of the observed data variance can be explained by the predicted values. Closer values of R^2 to 1 show stronger agreement between the actual and predicted values and better predictive performance, which can take on values between 0 and 1. Equivalent to R^2 in mathematics is given by Equation (4):

$$R^2 = \frac{\sum_{i=1}^{n}(y_i - y_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \quad (4)$$

2) RMSE (Root Mean Squared Error)

A model's RMSE measures the extent to which its predictions differ from the actual values. Model performance is improved when the RMSE value is lower. The root-mean-squared error (RMSE) formula is (5):

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

3) MAPE (Mean Absolute Percentage Error)

MAPE figures out mistakes as a percentage. More specifically, it is the average percentage difference between predictions and the dataset values that they were meant to hit. As a percentage, MAPE is also equal to the MAE that was returned (6).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} / \left(\frac{(y_i - y_i^{\dot{P}})^2}{y_i}\right) / 100 \quad (6)$$

These metrics, when taken as a whole, show how well the model predicts the target variable.

IV. RESULTS AND DISCUSSION

The experiments were carried out on a laptop running Windows 10, with hardware specifications including an Intel® Xeon® E3-1230 v6 @ 3.50 GHz CPU, NVIDIA Quadro M2000 GPU, 16 GB RAM, and the suggested FinGPT model applied using the Jupyter Notebook environment and the Keras DL framework. In Table II proposed model achieved an R^2 of 99.9%, MAPE of 0.8267, and RMSE of 39.9628, indicating excellent predictive performance with minimal forecasting error.

TABLE II. PERFORMANCE OF THE PROPOSED MODEL FOR STOCK PRICE PREDICTION SYSTEM

Performance matrix	FinGPT
R2	99.9
MAPE	0.8267
RMSE	39.9628

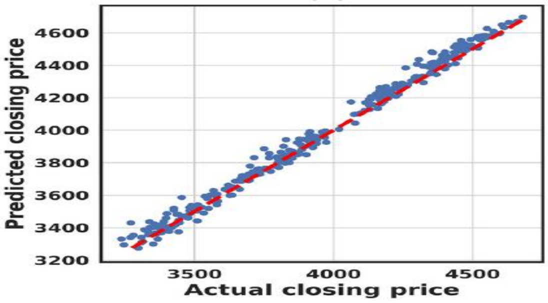

Fig. 4. Scatter Plot of Actual vs Predicted Closing Prices

The blue data points are tightly clustered around the red dashed regression line in Figure. 4, which shows the link between the actual and forecasted closing prices. With little prediction error, the prediction model successfully captures the underlying trend of the stock prices, as shown by the strong linear alignment. The tight clustering of the points around the reference line shows how well and accurately the model predicts.

Fig. 5. Actual vs. Predicted Closing Price Comparison

The actual and forecasted closing prices for the testing period are compared in Figure. 5, proving the model's efficacy in capturing market patterns and swings, the predicted closing price tracks the actual closing price quite closely. Both curves closely overlap, which means the suggested stock price prediction model has a low prediction error and does a great job of predicting stock prices.

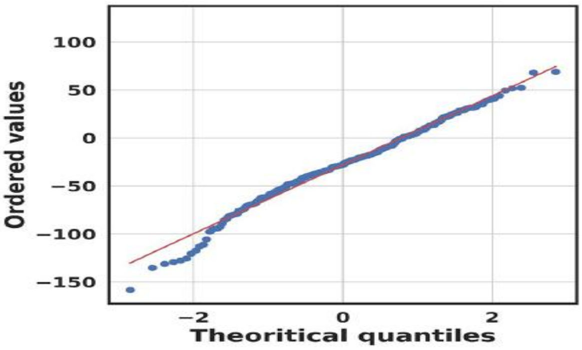

Fig. 6. Comparison of Actual and Predicted Closing Prices

Figure 6 shows a comparison between the test period's actual and forecasted closing prices. Over the course of the timeline, the actual values and anticipated values nearly match, suggesting that the suggested model adequately captures both the long-term trend of the market and the short-term variations in price. The model's excellent generalizability and great prediction accuracy are shown by the small variation between the two curves.

A. *Comparative analysis*

The comparison between the models to predict stock price movement, as presented in Table III, highlights the differences in predictive performance among the evaluated approaches. The ARIMA model achieved an R^2 of 78%, while LSTM and GRU improved the prediction accuracy to 88.2% and 97.4%, respectively. The proposed FinGPT outperformed all existing models with the highest R^2 of 99.9%, demonstrating superior forecasting capability. Although the error metrics vary across models, the proposed FinGPT model consistently delivers highly reliable stock price predictions by effectively leveraging financial news understanding and historical market data.

TABLE III. COMPARISON OF EXISTING AND PROPOSED MODELS FOR STOCK PRICE PREDICTION SYSTEM

Model	R-squared
ARIMA[30]	78
LSTM[31]	88.2
GRU[32]	97.4
FinGPT	**99.9**

The proposed FinGPT offers superior stock price prediction by effectively integrating historical market data with financial news understanding. Its advanced language modelling capability captures contextual and semantic information from financial news, leading to more accurate market trend analysis. The model achieved a High R^2 value demonstrating excellent predictive performance with strong generalization ability. Furthermore, FinGPT provides robust forecasting with minimal prediction error, making it highly suitable for intelligent stock market prediction systems.

V. CONCLUSION AND FUTURE STUDY

The convergence of NLP and financial analysis has garnered a lot of interest in this age of rapidly developing AI because of the useful insights it may bring into the behaviour of financial markets. Since market movements are heavily impacted by contextual information and investor mood, financial news sentiment is an essential factor in predicting stock prices. The intricate semantic relationships found in financial text are frequently too difficult for traditional ML and DL models to grasp. The testing results showed that the suggested FinGPT outperformed ARIMA (78%), LSTM (88.2%), and GRU (97.4%), achieving the maximum prediction performance with an R-squared value of 99.9%. These findings demonstrate that integrating financial news understanding with historical market data significantly enhances forecasting accuracy, making the proposed FinGPT model an effective and reliable solution for intelligent stock price prediction.

This research might not be generalizable to other stock markets or economic situations because it relies on data from just the S&P 500 and financial news. We will validate the proposed FinGPT framework on a variety of stock markets around the world to enhance its robustness and generalization ability. Future research will also involve integrating multimodal data sources like social media, macroeconomic indicators, and company financial reports.

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