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Research Article

Deep Learning Techniques GAN and LSTM for Stock Market Closing Price Prediction

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ABSTRACT

Objective: The goal of this study is to enhance forecast accuracy by leveraging advanced deep learning (DL) methods, specifically Generative Adversarial Networks (GAN) and Long Short-Term Memory (LSTM) networks.

Methods: Using historical stock data and 32 influencing features, GANs and LSTMs are trained to predict the stock price using the RMSE, with 80% of the data being training and 20% testing.

Results: The GAN model achieved the lowest RMSE of 5.36 on the testing dataset, outperforming both LSTM and traditional ARIMA models. The LSTM model also showed robust performance with an RMSE of 6.6. These results indicate the effectiveness of GANs in capturing complex patterns in stock price data.

Conclusion: Despite computational challenges, the GAN model's superior accuracy underscores its potential for stock price prediction. This study highlights the value of integrating diverse features and DL models for financial forecasting, suggesting future research directions including sentiment analysis and hybrid model development for improved predictive performance.

Keywords: Stock Price Prediction, GAN, LSTM, Deep Learning.

1. INTRODUCTION

Predicting stock market prices is a complex and challenging task due to the highly dynamic and non-linear nature of financial markets. Accurate predictions can provide significant advantages for investors and traders. Recently, DL techniques have gained popularity for their ability to model complex patterns and dependencies in time-series data. This study focuses on leveraging advanced DL methods, LSTM networks and GANs, to predict stock prices, with a case study on Apple Inc.

Several researchers have explored various DL models for stock price prediction. Wu et al. (2022) introduced the S_I_LSTM model, which integrates traditional data with non-traditional data like stock posts and financial news, significantly improving prediction accuracy in the China Shanghai A-share market. Öztürk (2024) evaluated DL methods using Google's daily closing prices, finding that the GAN model performed best compared to LSTM and GRU models. Similarly, Vuletić et al. (2024) proposed a novel GAN approach with an economics-driven loss function, demonstrating superior performance in probabilistic forecasting of financial time series.

Shukla and Poornima (2023) utilized various DL models, including RNN, LSTM, GRU, and GAN, finding that the GRU network was the most efficient. They also addressed overfitting by generating artificial data with GANs. Ma (2023) combined empirical mode decomposition with LSTM networks and various GAN architectures, achieving significant improvements in prediction accuracy. Ghasemieh and Kashef (2023) introduced the GAF-EWGAN model, which combined enhanced WGANs with Gramian Angular Fields, outperforming traditional methods in key metrics.

Liu and Gu (2024) proposed the GAN-TrellisNet model, which improved accuracy and stability in stock price predictions by combining TrellisNet as the generator and CNN as the discriminator. Wu et al. (2023) developed a

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GAN-based framework with piecewise linear representation for predicting stock trading actions, effectively addressing overfitting and improving performance. Sonkiya et al. (2021) integrated sentiment analysis using BERT with a GAN framework, achieving superior prediction accuracy for Apple Inc.

He and Kita (2021) combined neural networks within a GAN framework for predicting S&P 500 stock prices, with the G-LSTM+D-LSTM model achieving the best accuracy. Xu et al. (2024) introduced TSGAN, which combines ACNN, LSTM, and ARIMA in the generator and CNN as the discriminator, showing superior accuracy in forecasting stock prices. Kumar et al. (2022) proposed a model combining Phase-space Reconstruction and GAN, significantly improving prediction accuracy and efficiency.

Kang (2024) proposed a novel method combining BiLSTM with WGAN to improve stock price predictions for newly listed companies with limited data. Vuong (2024) reviewed stock price forecasting methods, highlighting the strengths and limitations of various models, noting the rise of DL approaches from 2020 to 2023. Zhang et al. (2024) reviewed DL models for financial time series forecasting, emphasizing the shift from traditional methods to advanced models like Transformers, GANs, and GNNs.

The motivation behind this study is to leverage advanced DL techniques, specifically LSTM networks and GANs, to improve stock market predictions. Traditional methods often struggle with the complex, non-linear nature of financial data. This study is specifically motivated by the potential of these advanced methods to integrate various data sources—such as historical prices, technical indicators, and sentiment analysis from news—to create a more holistic and accurate predictive model. By focusing on Apple Inc., a highly influential and volatile stock, we aim to demonstrate the practical applications and benefits of these sophisticated modeling techniques.

In this study, we aim to enhance stock price prediction accuracy by leveraging the advanced architectures of LSTM and GAN. Our approach involves using various technical indicators, news sentiment analysis, and Fourier transforms to provide a robust model for predicting the closing prices of Apple stock. Through this study, we aim to contribute to the growing body of literature on the application of DL techniques in financial market analysis.

The following sections of this research work contains the materials and proposed work. The next section describes the result of the predictive model as well as discuss the strength and weakness of the approach by comparing the results with the existing studies. It will also explore the practical implications of our findings for traders as well as investors. The conclusion section will summarize the key findings of the study.

2. MATERIALS AND PROPOSED WORK

2.1. Materials

The initial step in building a model involves acquiring a dataset that includes the necessary features for training the model. In DL the dataset comprises target values that are utilized during the training process. In this particular scenario the dataset comprises continuous features extractions that are presented in a time series format. In this study the daily closing price of the APPLE stock data is used. The series covers 497 trade days from 2nd January, 2020 to 19th July, 2024. Overall, 1144 observations are present in the data set. Figure 1 provides a comprehensive analysis of AAPL stock performance showing the closing prices, moving averages, daily returns and their distribution.

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Figure 1: Analysis of AAPL Stock Performance

Long short-term memory (LSTM)

LSTM is a specific RNNf architecture proposed by Hochreiter and Schmidhuber in 1997. Unlike a traditional feed-forward neural network, LSTM includes feedback connections and can be used on sequences of data. The basic components of LSTM are an input gate, an output gate, and a forget gate. The LSTM network was developed to resolve the vanishing gradient problem while training traditional RNNs. It is a cell memory unit that can remove or add information to the cell state. LSTM has overcome the vanishing and exploding gradients problem that appeared in RNN through the specific internal structure of the units built in the model. Nowadays, LSTM is known as a powerful method capable of processing, classifying, and making predictions based on time series data.

Generative adversarial network

GAN is a minimax problem based on zero-sum non-cooperative games. GAN is composed of two components: a generator and a discriminator. The generator aims to create examples that look as real as possible, while the discriminator's goal is to distinguish between real and fake (generated) examples. The loss function for the discriminator is:

$$V_D = \frac{1}{m}\sum_{i=1}^{m} \log D\,(y^i) + \frac{1}{m}\sum_{i=1}^{m} (1 - \log D\,(G(x^i)))$$

The loss function for the generator is:

$$V_G = \frac{1}{m}\sum_{i=1}^{m} (1 - \log D\,(G(x^i)))$$

The GAN model uses cross-entropy loss to minimize the difference between two distributions, which is equivalent to minimizing the KL-JS divergence.

Feature Extraction from Data

Technical Indicators

This study calculated popular technical indicators for investors: 7-day and 21-day moving averages, exponential moving average, momentum, Bollinger bands, and MACD.

News Sentiment Analysis

News can indicate potential stock price movements. We scraped daily news about Apple Inc. and used FinBert to analyze the news, classifying it into positive, neutral, or negative sentiments with a score between -1 and 1.

Fourier Transforms

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This study created Fourier transforms to extract long-term and short-term trends in Apple stock. Fourier transforms decompose a function into sine waves, which, when combined, approximate the original function, helping the model pick prediction trends more accurately.

Data Structure

This study prepared the dataset for supervised learning by dividing it with a rolling window equal to 1. The original dataset is two-dimensional and reshaped the data to three dimensions according to the timesteps as shown in the figure 2.

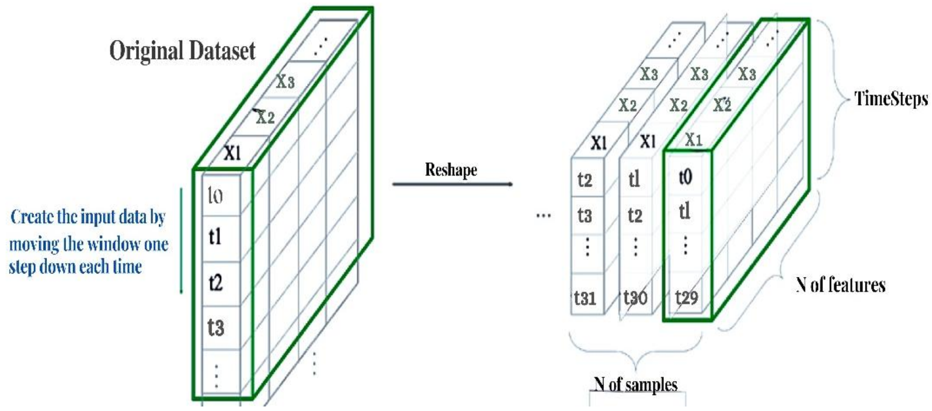

Figure 2: Reshaping the Original Dataset for Input Data Preparation

This study built a many-to-many model with a timestep of 30 and an output step of 3, using 30 days of historical prices to predict 3 days of stock prices which is visualized in figure 3.

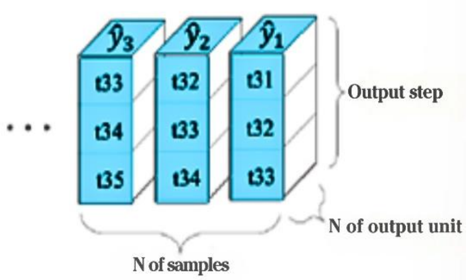

Figure 3: Many-to Many Models with Timestep of 30 and an Output Step of 3

METHODOLOGY

Generator

In this study of GAN model, the GRU is set as the generator due to its stability. Our dataset includes the past 10 years of stock price history and 32 features, including Open, High, Low, Close, Volume, NASDAQ, NYSE, S&P 500, FTSE100, NIKKI225, BSE SENSEX, Crude Oil, Gold, VIX, USD index, Reliance, MA7, MA21, MACD, 20SD, upper_band, lower_band, EMA, log momentum, absolute of 3 comp, angle of 3 comp, absolute of 6 comp, angle of 6 comp, absolute of 9 comp, angle of 9 comp, and News. We perform multi-step ahead prediction; the generator's input is three-dimensional data (batch size, input-step, and features) and the output is batch size and output-step. The generator uses three GRU layers with 1024, 512, and 256 neurons, and two Dense layers, with the latest layer's neuron number matching the output step to be predicted.

Discriminator

In this study of GAN model, the discriminator is a Convolutional Neural Network aimed at distinguishing real from fake data. The input for the discriminator can be either original data or generated data. The model includes three 1D Convolution layers with 32, 64, and 128 neurons, followed by three Dense layers with 220, 220, and 1 neuron. The

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Leaky Rectified Linear Unit (ReLU) is the activation function for all layers except the output layer, which uses Sigmoid activation for GAN and linear activation for WGAN-GP.

Architecture of GAN

Combining the generator and discriminator structures, we define our proposed GAN model. The model uses cross-entropy to calculate the loss for both the generator and discriminator. In the discriminator as shown in figure 4 this study combines the generated stock price with the historical stock price of input steps, enhancing data length and increasing accuracy in classification.

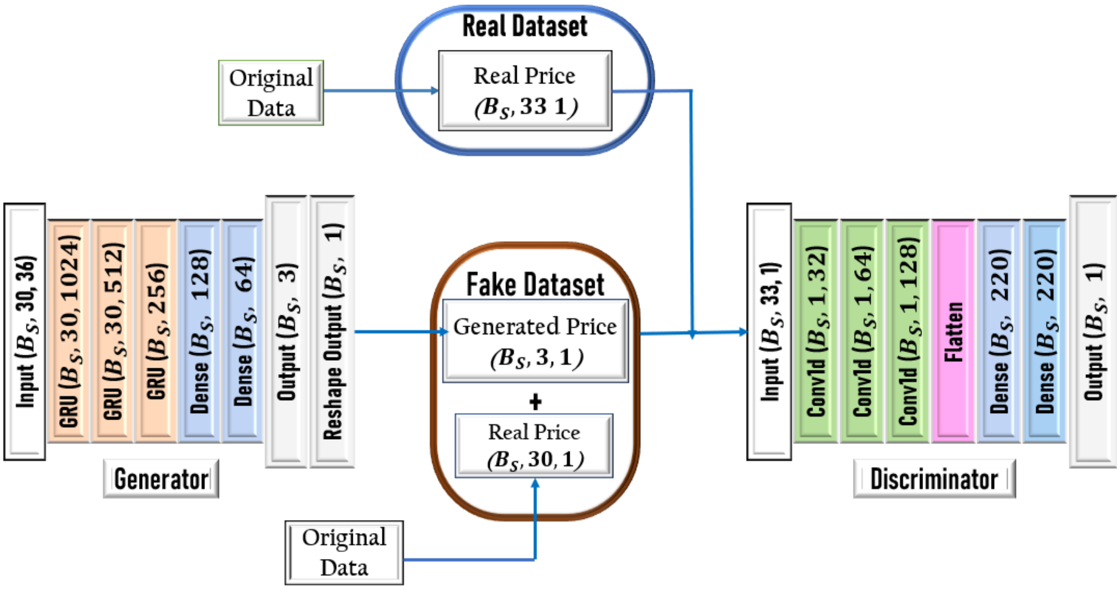

Figure 4: Architecture of GAN model

Proposed System

The proposed system leverages the advanced architectures of LSTM and GAN to predict stock prices using various technical indicators, news sentiment analysis, and Fourier transforms. This combination aims to provide a robust model for accurate stock price predictions.

3. DISCUSSION AND EXPERIMENTAL RESULTS

Training of our model

With the past 60 days of data this paper makes a prediction for the closing price of the stock in the next five days. This project will input not only the historical closing price but also 32 features that could influence the price when training the forecasting model. During the training process 80% of the data will go into a training set and 20% into a testing set.

Experimental Results

The research evaluated each model's performance using Root Mean Square Error (RMSE) which is defined as follows:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \widehat{x_1})^2}{N}}$$

In this project the research evaluated the models through comparing their RMSE on testing data for each of the N data points, x_i being the actual stock price, and $\widehat{x_1}$ being the predicted stock price.

Table 1: Calculations using the ARIMA model

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Dep. Variable	D.GS	No. Observations	1144
Model	ARIMA(2, 1, 0)	Log Likelihood	-4589.254
Method	css-mle	S.D. of innovations	3.789
Date	20.07.2024	AIC	998.245
Time	09.05.58	BIC	8956.785
Sample	1	HQIC	8936.458

Table 1 illustrates the ARIMA(2,1,0) model fit to the differenced GS series using 1144 observations. In order to evaluate the fit of the model information criteria (AIC, BIC, HQIC) can be used with lower values suggesting a better model. Additional insights into the performance of the model can be obtained from the standard deviation of innovations and the log likelihood. In order to ensure that the chosen model accurately captures the underlying patterns in the time series data the selection and evaluation process of models is crucial.

ARIMA

Figure 5: Forecasts based on ARIMA

Based on Figure 5 ARIMA approximates the real stock price very well. The predicted price will be used as an input feature into the LSTM because as this research mentioned previously the study want to capture as many features and patterns as possible about AAPLE.

LSTM

In this work Bidirectional LSTM was used in the first layer of LSTM model. Adam algorithm is used as the optimizer in this work with a learning rate of 0.001. A batch of 64 is trained on a stock price dataset followed by 50 epochs.

The GAN model in this baseline model uses historical data from the past 4.7 years along with 24 correlative features as input. Following the split of the data into the train set and the test set.

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Figure 6: Stock price prediction using an LSTM model

The figure 6 shows how an LSTM model performs in predicting stock prices with the x-axis representing the timeline from January 2020 to July 2024 and the y-axis representing closing prices in USD. In the blue line stock prices are shown in historical context showing a general upward trend but with fluctuations. In figure 2 the orange line represents the validation dataset which overlaps with the yellow prediction line to demonstrate the performance evaluation of the model. Based on the close alignment between the validation data and predictions it appears that the model has accurately captured the trend and continues to make accurate predictions. A model that forecasted stock prices well predicting a continued rise based on historical data trends indicates a model that performs well.

Basic GAN

It has been proposed that the GAN model in this paper will follow the structure suggested in the methodology section. This paper utilizes Adam algorithm with a learning rate of 0.00016 as the optimizer for our models. This dataset was trained for 165 epochs on 128 samples over 165 epochs.

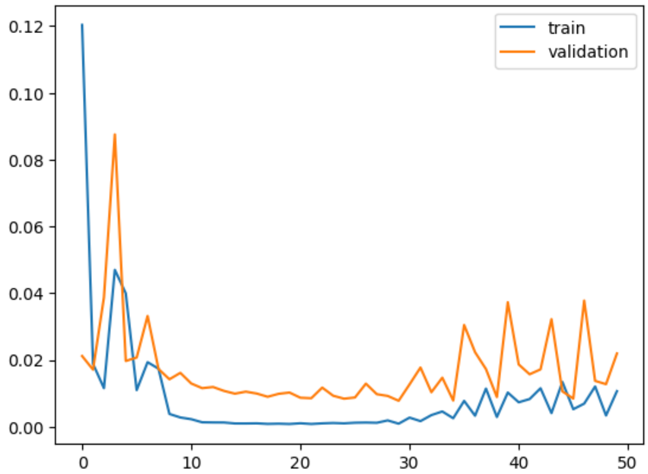

Figure 7: Basic GAN loss curves for training and validation

Based on 50 epochs of training and validation the figure 7 illustrates the loss curves of a Basic GAN (Generative Adversarial Network) model. Blue is the loss associated with training while orange is the loss associated with validation. In the first 10 epochs both training and validation losses are high. However they decrease significantly indicating rapid model learning. Following this initial phase the training loss gradually decreases, stabilizing and fluctuating around a lower value. The validation loss by contrast shows a greater degree of variability fluctuating between 0.02 and 0.04 suggesting that the model may have overfitted to the training data. Plotting the first 50 epochs reveals the model's learning dynamics as well as the balance between generator and discriminator improvements. Low and stable losses indicate that the model has been effectively trained and generalized.

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Figure 8: Forecasting GAN closing prices using ARIMA

A chart of GAN's historical and forecasted closing prices in USD is shown in figure 8. The plot is divided into three sections: training data (blue) from January 2020 to January 2023 validation data (red) from January 2023 to July 2024 and predictions (orange) for the same period. The training data shows initial growth, volatility and later stabilization of stock prices. Validation data shows an upward trend with volatility. A close alignment of the orange prediction line with the red validation data suggests that the ARIMA model has a high degree of robustness in forecasting future price trends. A visualization such as this illustrates the model's accuracy and its utility in predicting future trends and making informed investment decisions.

Table 2: Predictive Model Performance Based on RMSE

Model	**RMSE of Training Dataset**	**RMSE of Testing Dataset**
ARIMA	2	7.5
LSTM	1.52	6.6
GAN	1.64	5.36
RF[1]	1.8	6.4

The GAN model has the lowest RMSE indicating high predictive accuracy and effective generalization on the testing dataset as shown in table 2. LSTMs also perform well showing relatively low RMSE values. The ARIMA model performs moderately poorly with the highest RMSE on the testing dataset and the Random Forest model outperforms the GAN and LSTM models. GAN and LSTM models perform better in this particular prediction task.

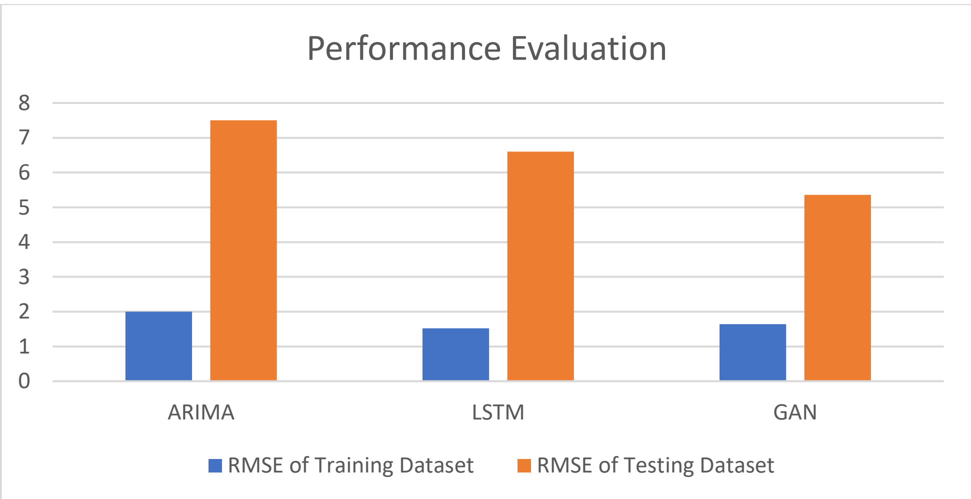

Figure 9: Comparison of model performance based on RMSE

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According to figure 9 the GAN model exhibits the highest predictive accuracy on the testing dataset with the lowest RMSE. A LSTM model that has a relatively low RMSE value also performs well suggesting that generalization is effective. A higher RMSE on the testing dataset indicates poor performance in predicting unseen data suggesting overfitting in the ARIMA model. According to these results the GAN model is superior at predicting future value generalization and accuracy.

Discussion

This work utilizes GAN as well as LSTM networks to predict the stock market closing prices, leveraging historical data as well as other influencing factors. This approach offers several advantages:

- *Enhanced Predictive Accuracy:* In this work the GAN model has achieved the lowest RMSE of 5.36 on the testing dataset showing its better predictive accuracy in comparison other models. These results are consistent with the findings by Öztürk (2024) noted that GAN model achieved the best with error rates in stock price prediction tasks which is distributed evenly.
- *Effective Feature Utilization:* 32 features were incorporated by this study that affect the stock prices of the current model which captures more complex patterns aligning with the method by Wu et al. (2022) integrated traditional as well as non-traditional data to improve prediction accuracy.
- *Robust Performance Across Different Data:* RMSE of 6.6 which is obtained by bidirectional LSTM model. This demonstrates the robustness in capturing temporal dependencies consistent with the research conducted by Ma (2023) shown that when combined with empirical mode decomposition LSTM models significantly enhance the prediction accuracy.
- *Addressing Overfitting:* The performance of GAN model showcases the capability to generalize well on the data which is not familiar. The advantage of traditional models like ARIMA exhibited greater RMSE values. The findings supports the research by Shukla as well as Poornima (2023) that overfitting can effectively mitigate by using GAN.
- *Economic Relevance:* The performance of current models in predicting the stock prices is consistent with the economic-driven GANs (Fin-GAN) approach which is proposed by Vuletić et al. (2024). This produced greater Sharpe Ratios showcasing the practical value of advanced DL models in financial markets.

In spite of the strengths there are flaws and areas for improvement in the current work:

- *High Computational Cost:* Training GANs along with LSTMs is computationally intensive which can be a limitation for real-time applications. Zhang et al. (2024) noted that DL models face difficulties as a result of their complexity as well as high computational requirements.

- *Need for Large Datasets:* To achieve high accuracy the current model uses large datasets. Such could be a drawback when there is the scarcity of data or when the data is not properly label. Vuong (2024) highlighted the significant increase in the use of DL models that require extensive datasets.

- *Potential Overfitting:* GAN model in the current research shown a good generalization. The validation loss fluctuated more compared to the training loss which indicates the potential overfitting. The current results are consistent with the study of Ghasemieh and Kashef (2023). They observed that while the enhanced WGAN model achieved well it was computationally expensive as well as susceptible to overfitting.

- *Limited Exploration of Prediction Cycles:* Scope of the current study was focused on short-term predictions. Further studies should be needed to examine different prediction cycles which is suggested by Wu et al. (2022). By Incorporating longer-term predictions as well as varying cycles could provide more thorough understanding.

- *Integration of Sentiment Analysis:* Even though the current study consists of 24 features which does not directly incorporate sentiment analysis from financial news as well as social media. This is demonstrated to enhance the prediction accuracy. Öztürk (2024) highlighted the importance of utilizing the sentiment analysis to enhance performance of the model.

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4. CONCLUSION

The current work explored the effectiveness of GAN as well as LSTM networks for predicting the stock market closing prices. It utilized historical data along with the comprehensive set of 32 significant factors. The GAN model achieved a low RMSE of 5.36 on the testing dataset which indicates the high accuracy in the prediction of stock price. By using a wide range of factors enabled current models to capture complex patterns in the stock market. The bidirectional LSTM model exhibited the robustness with an RMSE of 6.6 with the overfitting of GAN model and the outperforming of ARIMA model. The areas of improvement were identified as the Potential overfitting as well as the need for enhanced integration of sentiment analysis. This work highlights the potential of GANs along with the LSTMs in the prediction of stock market trends. It demonstrates their superior performance as well as the robustness. Future research must give importance in addressing the identified limits by optimizing computational efficiency, exploring hybrid models as well as integrating more diverse data sources which includes sentiment analysis. Accuracy of DL models as well as practical applicability in financial market analysis and stock price prediction can be enhanced.

Future Work

Future research should include sentiment analysis from financial news as well as social media data to build the accuracy. Investigating the hybrid models that use the strengths of several DL models like integrating GANs with GRU or Transformer networks could improve performance. Maximizing computational efficiency is essential which could be achieved by using more efficient training methods or leveraging hardware accelerators. Examining several prediction horizons like medium- as well as long-term forecasts will provide a more thorough understanding of market dynamics. Using GANs can mitigate overfitting as well as improve generalization. Incorporating more diverse features, such as economic indicators and sector-specific data, will help capture broader market trends. Creating the models which could forecast and manage large amount of streaming data will improve practical usefulness especially during financial crises.

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