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Stock Price Prediction Using Machine Learning

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Abstract: This study evaluates the effectiveness of machine learning algorithms in predicting the stock market. Four models are used, with deep learning outperforming others. Support vector regression is ranked second in less error-prone techniques. The study aims to improve stock price prediction for retail investors using advanced machine learning algorithms like Keras Deep Neural Networks, LSTM, and linear regression. The ensemble model, which combines timeseries and deep learning models, offers substantial increases in prediction accuracy, making it a solid solution for retail investors.
Keywords: Artificial neural network, Support vector machine, Deep learning, LSTM

I. INTRODUCTION

In the global fiscal markets, stock price prediction is vital due to its role as a key metric in evaluating the performance of securities and the stock market. Stock price indicators, derived from fluctuations in stock prices across all or specific classes of companies, are essential for helping investors navigate the competitive financial landscape. With the availability of diverse global investment options, investors are increasingly informed and discerning, requiring sophisticated tools to make optimal portfolio choices. However, forecasting financial markets remains a formidable challenge due to the noisy, nonstationary, and irregular nature of financial time series data. Despite advancements in statistical and computational prediction techniques, the complexity of financial variables—particularly stock price indicators—poses significant hurdles. Research by Atsalakis and Valavanis underscores that predicting these variables is particularly difficult because financial markets exhibit nonlinear behavior,which limits the effectiveness of linear prediction models. This necessitates the exploration of more advanced approaches such as technical analysis, fundamental analysis, time series-based forecasting, and machine learning. Machine learning, in particular, has gained prominence for its ability to uncover patterns in historical data, identify nonlinear relationships, and model complex dependencies. Techniques such as support vector machines (SVM), artificial neural networks (ANN), and deep learning networks have demonstrated superior accuracy in predicting financial series compared to traditional methods.

II. LITERATURE SURVEY

The increasing complexity of machine learning methods in financial forecasting is highlighted by recent studies. According to a thorough literature analysis by Mintarya et al. (2023), neural networks—in particular, LSTMs and deep learning models—perform better than conventional techniques at identifying non-linear stock data trends. Similarly, Soni, Tewari, and Krishnan (2022) discovered that neural networks are excellent at handling complicated datasets, even while ensemble techniques like Random Forest and XGBoost show good prediction accuracy. Zhang, Sjarif, and Ibrahim (2023) went one step further and investigated deep learning models in financial time series forecasting, pointing out that Transformers and Graph Neural Networks (GNNs) were sometimes better than conventional LSTMs and CNNs. This pattern was supported by Gupta and Jaiswal (2024), who showed that deep learning models—like LSTMs and CNNs—perform noticeably better than statistics techniques such as SVM and ARIMA in terms of generalization and accuracy. When taken as a whole, these studies highlight the growing dependence on deep learning, hybrid models, and other data sources, such as text and social sentiment, for improved stock market prediction.

III. METHODOLOGY

A branch of artificial intelligence called machine learning was first proposed in the 1950s and uses computers to mimic human learning. It develops algorithms for data-driven learning and prediction. Artificial neural networks, SVMs, and deep learning are important algorithms. For stock market forecasting, nonlinear algorithms are advised; artificial neural networks operate especially well in financial markets. Techniques for regression are less successful.

A. Artificial Neural Network

Since its introduction by McCulloch and Pitts in 1943, artificial neural networks have been used extensively for simulating nonlinear systems.

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There are single-layer and multilayer versions of the perceptron, a kind of neural network. Using the back-propagation (BP) technique, McClelland, Rumelhart, and Hinton created the multilayer feedforward neural network (MLP) in 1986. Financial planning, decision-making, and bankruptcy prediction all make use of neural networks. In order to generate better output with fewer error values, the BP algorithm computes errors and modifies network parameters.

B. Support Vector Machine

The Support Vector Machine (SVM) is a nonlinear model used in financial markets to predict time series, especially when variables are nonstationary or complex. It has two types: SVM and SVR, with SVR being used for future price prediction. SVM is based on structural minimization of risk and linear classification of data. Quadratic programming techniques solve constraining problems, and a phi function transfers data to a larger space before linear classification.

C. Stock Market Prediction Based on Deep Learning (SMP-DL)

Advanced innovations have led to increased interest in stock market forecasting, which can help in making accurate predictions. Market information directly influences the trading and speculation of market trends. Stock market forecasting tools can be used for market observation, estimation, and control. These forecasts help financial professionals make informed decisions. Deep learning is used to train computers to learn specific procedures and explore the subject matter. Deep neural systems, including autoencoder CNNs, RNNs, and deep conviction systems, are used for forecasting. These systems handle consecutive signals and have a single memory for storing data. The proposed framework, Stock Market Forecast based on Deep Learning (SMP-DL), consists of two parts: data preprocessing (DP) and stock price expectation (SP2).

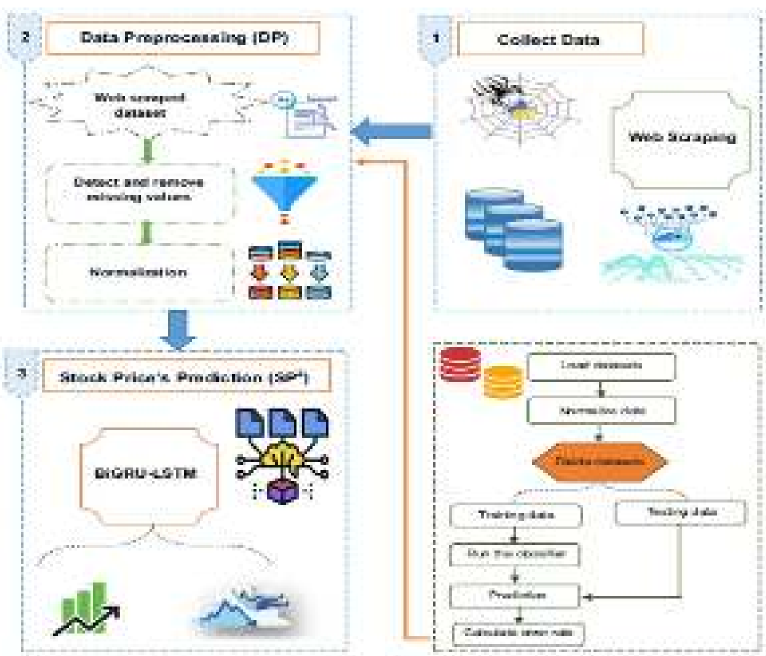

Fig. 1 The proposed SMP-DL

D. Long Short-Term Memory

Long Short-Term Memory (LSTM) is a framework for processing sequential data, evolving from Recurrent Neural Networks (RNNs) to address the vanishing gradient problem. LSTM consists of memory blocks designed by Hochreiter and Schmidhuber in 1997, enabling it to learn long-term dependencies. It is effective for long time series data, capturing information from 1000 time steps. Various types of LSTM exist, including stacked, encoder-decoder, bidirectional, CNN LSTMs, and generative LSTMs. Long Short-Term Memory (LSTM) is a framework for processing sequential data, evolving from Recurrent Neural Networks (RNNs) to address the vanishing gradient problem. LSTM consists of memory blocks designed by Hochreiter and Schmidhuber in 1997, enabling it to learn long-term dependencies. It is effective for long time series data, capturing information from 1000 time steps. Various types of LSTM exist, including stacked, encoder-decoder, bidirectional, CNN LSTMs, and generative LSTMs.

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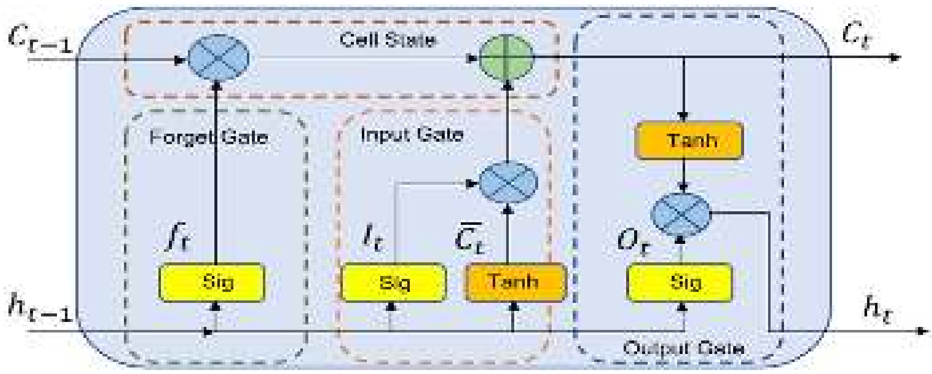

Fig. 3 LSTM architecture

The study presents a hybrid approach combining LSTM and BiGRU for time series prediction. The system uses a reset gate to remove state from the cell before a time step, and an update gate to determine the amount of state to use in the current time step. The BiGRU-LSTM hybrid model, which uses a range of input conditions, ensures precise forecasts by incorporating a temporal layer and reinforcing its temporal representation. The model uses previously processed 10- and 30-minute interval data from the original 1-minute interval data. The BiGRU layer gathers information from the BiGRU layer, while the LSTM layer gathers and produces a weighted value. The output neuron of the fourth hidden layer receives the data and produces the appropriate weight. The model includes a dropout between each layer for better accuracy.

IV. RESULT AND DISCUSSION

This section evaluates the proposed SMP-DL, consisting of two phases: DP and SP2. DP involves data collection, null removal, and normalization, while SP2 introduces a new prediction technique combining LSTM and BiGRU, aiming to improve stock market prediction accuracy.

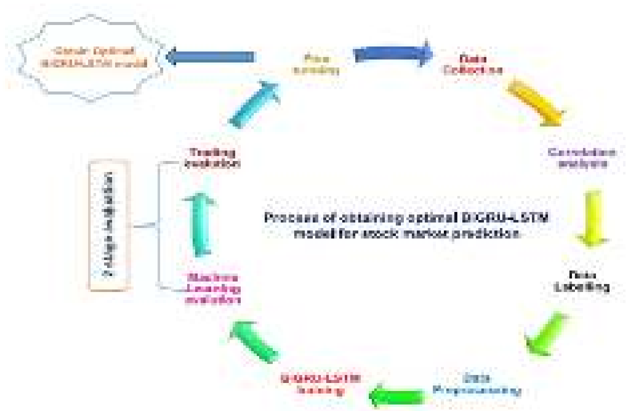

Fig. 5 Process of obtaining optimal BiGRU-LSTM model for stock market prediction

Fig. 6 The mechanism of dividing the used datasets

A. *Testing the Proposed SMP-DL*

The proposed framework uses an IBM dataset to assess its viability. The results show a low blunder rate, with an MAE of 0.2099 and an MSE of 0.0831. This is the lowest blunder rate, making it suitable for predicting IBM's stock closing cost. The MSE and MAE models are used for testing and preparing, with lower MSE scores indicating better prediction.

B. *Comparison of the Proposed BiGRU-LSTM*

The IBM dataset is used to test the proposed BiGRU-LSTM against various stock market prediction techniques. The results show that CNN-BiLSTM-AM has the highest degree of fitting, while MLP has the lowest. The prediction performance is ranked from low to high, with BiGRU-LSTM having the lowest RMSE and MAE. BiLSTM's R2 value is higher than PSO-LSTM's but lower than BiLSTM. CNN-BiLSTM-AM increases RMSE and MAE compared to BiLSTM. The predictive accuracy of LSTM increases with the introduction of BiGRU. The suggested BiGRU LSTM performs better in terms of epoch counts, with 40 out of 40 compared to other approaches.

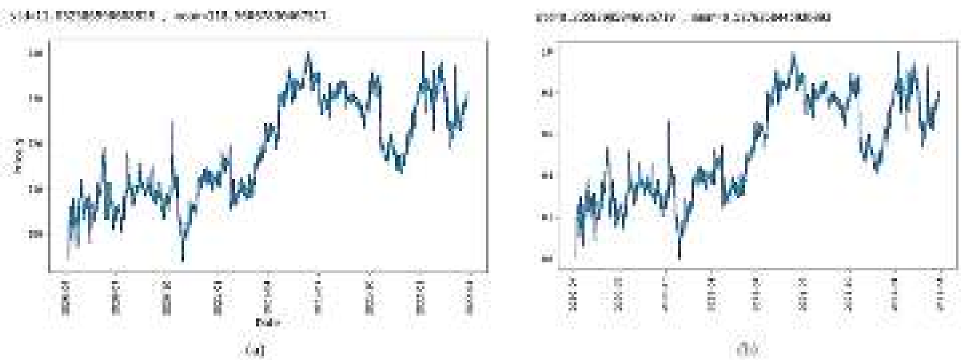

Fig. 7 IBM data, a before and b after normalization process

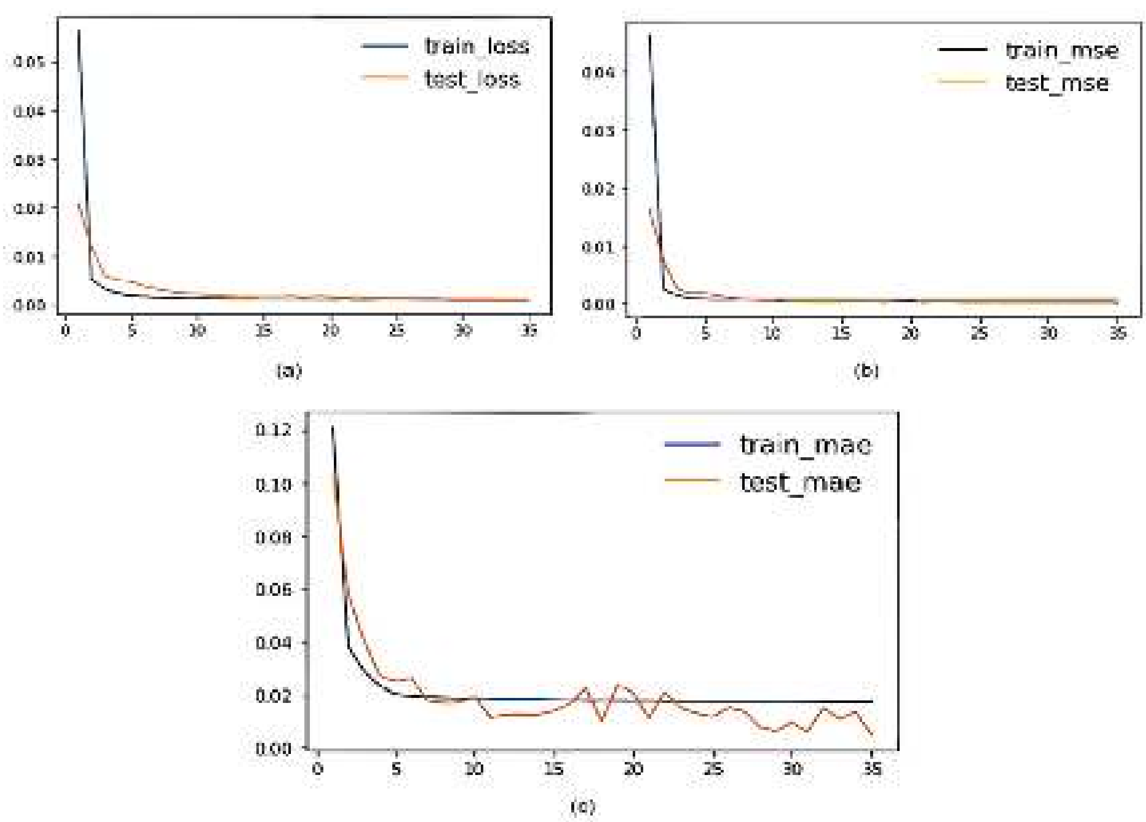

Fig. 8 The proposed model, a Training and testing loss b Training and testing MSE c Training and testing MAE

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Table 3 Comparison of our proposed model methods in terms of RMSE, MAE, R^2,computational time and the number of epochs

Prediction method	RMSE	MAE	R^2	Computational time (S)		Epochs
				Training	Testing	
ABC-ANFIS-SVM	0.3638	0.3652	0.9458	1730.5	6.5	140
DLSMP	0.3941	0.3785	0.9403	1124	7.5	120
CNN-BiLSTM-AM	0.3487	0.3591	0.9590	1650	8.6	150
PSO-LSTM	0.3987	0.3807	0.9400	1800	9	110
BiLSTM	0.3348	0.3564	0.9646	1250	4.5	100
CNN	0.3979	0.2755	0.9694	1500	6	130
CKELM	0.3169	0.2195	0.9804	1750	5	70
Proposed BiGRU-LSTM	0.2883	0.2099	0.9948	1500	2.5	40

V. CONCLUSION

Forecasting the stock market is crucial for financial traders, as accurate predictions can significantly influence their decisions. A smart trading platform (STP) has been developed to allow anyone to invest in stocks, futures, options, currencies, commodities, and bonds. The study demonstrated the efficacy of a hybrid model combining LSTM and BiGRU for stock market closing price forecasting. The BiGRU-LSTM hybrid model performed better than LSTM and GRU, two widely used time series analysts. The application can be used on any device with internet access, allowing investors to invest from anywhere.

VI. CHALLENGES AND FUTURE WORK

1) Data Noise: Stock prices are influenced by a multitude of random, non-deterministic factors, making it difficult to separate signal from noise.
2) Market Volatility: Sudden market events (e.g., economic crises, geopolitical events) can drastically impact stock prices, making predictions highly uncertain.
3) High Dimensionality: Large amounts of financial data (e.g., historical prices, volume, technical indicators, and macroeconomic factors) can lead to overfitting, making models overly complex.
4) Non-Stationarity of Data: Stock market data is non-stationary, meaning its statistical properties change over time, making it hard to model accurately.
5) Overfitting: Machine learning models, particularly deep learning models, can overfit to historical data, leading to poor performance on unseen data.
6) Advances in Deep Learning: Techniques like LSTMs (Long Short-Term Memory networks) and transformers may improve the accuracy of time-series predictions.
7) Integration of Alternative Data: Combining traditional financial data with alternative data sources (e.g., social media sentiment, satellite imagery, web scraping) could provide new insights.
8) Explainable AI: Increasing focus on explainable AI in finance to understand the reasoning behind model predictions and to build trust in AI-driven decision-making.
9) Ensemble Methods: Combining multiple models (e.g., boosting, bagging) could enhance prediction accuracy by reducing bias and variance.
10) Transfer Learning: Applying pre-trained models from similar domains (e.g., currency forecasting, commodity prices) could improve stock market predictions.

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