Data Mining-Based Forecasting of Financial Time Series using Deep Learning Architectures

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Abstract: Since stock market forecasting has ramifications for traders, investors, and policymakers, it has attracted a lot of attention. Machine learning and deep learning techniques are being adopted because traditional statistical models frequently fall short in capturing the nonlinear and very volatile character of stock markets. The performance of three deep learning architectures—Multilayer Perceptron (MLP), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU)—as well as an ensemble technique in predicting the stock prices of Apple Inc. (AAPL) is examined in this study. Sequences for supervised learning were created by processing historical daily stock data. Several error measures, such as average absolute error (MAE), Root Mean Square Error (RMSE), Coefficient of Determination (R2), mean absolute percentage error (MAPE), and Symmetric Means Absolute Percentage Error (SMAPE), were used to assess the models. In terms of capturing temporal dependencies, the results show that recurrent architecture (like LSTM or GRU) perform better than conventional MLP. Furthermore, the Ensemble model delivers the lowest prediction error and the highest reliability, demonstrating the advantages of combining multiple architectures. These findings provide insights into selecting robust predictive models for financial time-series forecasting.

Keywords: Stock Forecasting, Deep Learning, LSTM, GRU, MLP, Ensemble Learning, Financial Prediction

1. INTRODUCTION

The stock market is a very dynamic system that is impacted by many different things, such as investor emotions, business earnings, political developments, and economic indicators. Accurate forecasting of stock prices is essential for informed investment decisions, risk management, and policy planning. However, stock price movements are inherently nonlinear and often exhibit volatility clustering, making accurate prediction a significant challenge.

For time-series prediction, statistical models like Generalised Adaptive Conditional Heteroskedasticity (GARCH) and ARIMA (Autoregressive Integrated Moving Average) have historically been used. Although these models work well in some situations, they are unable to represent the intricate, nonlinear relationships seen in financial data.

With advancements in artificial intelligence, deep learning models have gained prominence in financial forecasting. Among these, recurrent neural networks (RNNs) such as Long Short-Term Deep learning models have become more popular in financial forecasting as a result of advances in artificial intelligence. Because of their capacity to preserve temporal information, recurrent neural networks, or RNNs, like LSTM (Long Short-Term Memory) and Gated Recurrent Units (GRU) are especially well-suited for sequential data. In the meanwhile, baseline comparisons can be obtained using more straightforward feedforward networks, like the Multilayer Perceptron (MLP). Memory (LSTM) and Gated Recurrent Units (GRU) are particularly suited for sequential data due to their ability to retain temporal information. Meanwhile, simpler feedforward networks such as the Multilayer Perceptron (MLP) can provide baseline comparisons.

This research focuses on comparing MLP, LSTM, and GRU architectures, along with an Ensemble approach, for predicting the daily closing prices of Apple Inc. (AAPL). Apple was chosen due to its significance as a leading technology company and its influence on global financial markets.

2. METHODOLOGY

2.1 Dataset

The study's dataset consists of Apple Inc.'s (AAPL) daily stock prices that were obtained from Yahoo Finance. More than ten years' worth of stock price data are available for study, covering the period from January 2010 to the present. Features like Open, High, Low, Close, Adjusted Close, and Volume are taken into account.

2.2 Preprocessing

Data preprocessing was crucial to ensure consistency and reliability of the input. Missing values were handled by removing incomplete rows. The stock prices were normalized using MinMax scaling to bring all values into the range [0,1], thereby preventing large-value dominance during training. Sequences of length 20 days were generated as input, with the next-day price serving as the prediction target.

2.3 Model Architectures

- Multilayer Perceptron (MLP): A feedforward network made up of substantial layers using ReLU functions for activation is called a multilayer perceptron (MLP). The MLP is beneficial as a baseline but not as efficient for time-series jobs since it does not naturally capture temporal relationships.
- LSTM: A type of RNN designed to capture long-term dependencies in series data. LSTM incorporates memory cells and gating mechanisms (input gate, output gate, and forget gates), enabling it to retain past information over long sequences.
- Gated_ Recurrent Unit (GRU): A simplified RNN architecture similar to LSTM but with fewer parameters. GRU employs update and reset gates, offering computational efficiency while still capturing temporal dynamics.
- Ensemble Model: An averaging ensemble was created by combining the predictions of LSTM and GRU. The rationale is that ensembles can reduce variance and improve robustness by leveraging the strengths of multiple models. The block diagram of methodology used is given below

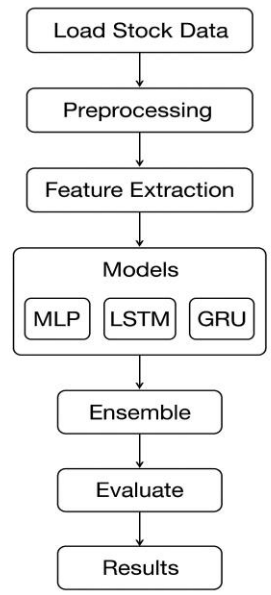

Figure 1 Flow chart of methodology used

2.4 Training Procedure

TensorFlow/Keras was used in Python to implement each model. The Adam optimiser was used for training, with a learning rate of 0.001. Mean Squared Error (MSE) was the loss function that was employed. A batch size of 32 was used to train each model across 50 epochs. To guarantee an objective assessment, the data was divided into 80% training and 20% testing sets.

3. RESULTS AND ANALYSIS

The models evaluated using multiple performance metrics. Table 1 summarizes the results:

Table 1 Performance metrices comparison table

Model	MAE	RMSE	R^2	MAPE	SMAPE
MLP	0.7652	1.0589	-0.1427	295.13	153.97
LSTM	0.6971	0.9932	-0.0051	179.51	160.38
GRU	0.6940	0.9956	-0.0100	173.48	165.64
Ensemble	0.6839	0.9877	0.0059	120.54	176.00

Observations:

- MLP performed the worst due to its inability to capture temporal dependencies.
- LSTM and GRU significantly improved error metrics, confirming the importance of recurrent architectures.
- The Ensemble model got the lowest MAE and RMSE and the highest R^2, proving the advantage of combining multiple architectures.

3.1 Metric Analysis

MAE, RMSE, and R^2 are primary measures of prediction accuracy. The Ensemble model consistently produced the lowest MAE and RMSE, highlighting its superior predictive performance. Although R^2 values for individual models were negative, indicating weak explanatory power, the Ensemble achieved a positive R^2, demonstrating improved reliability.

Percentage-based errors (MAPE and SMAPE) further emphasize model differences. The Ensemble had the lowest MAPE, but its SMAPE was slightly higher due to symmetric scaling. This suggests that while Ensemble predictions were generally closer to actual values, its proportional error distribution was more balanced.

3.2 Graphical Analysis

The following graphical analyses were generated to complement the numerical metrics:

1. True vs. Predicted Prices: Line plots showed that LSTM and GRU closely tracked actual stock price trends, whereas MLP deviated significantly. Given below is the obtained result.

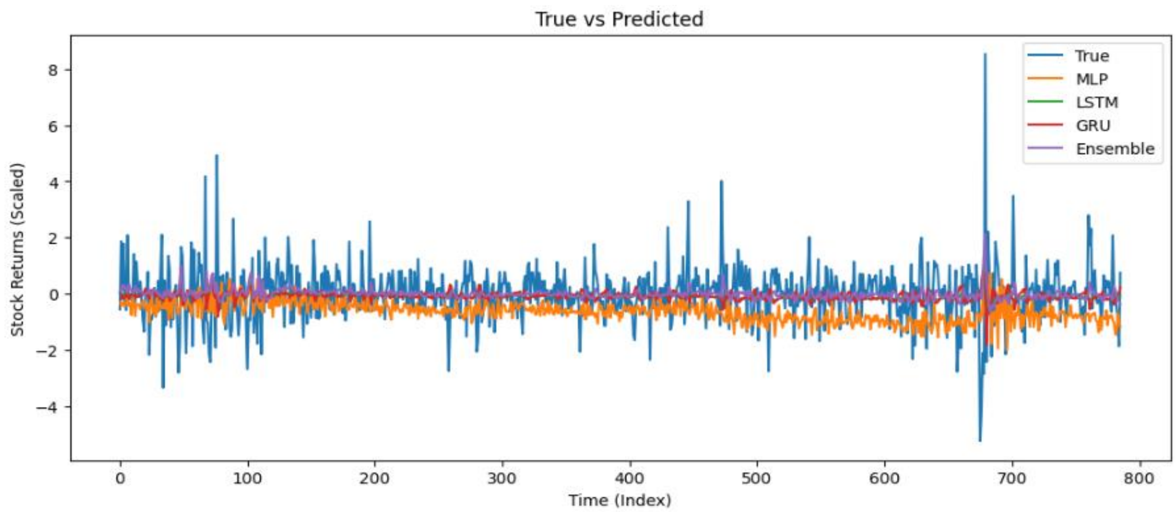

Figure 2 True vs. Predicted result

2. Residual Plots: Residual distributions indicated larger errors for MLP compared to the recurrent models and Ensemble.

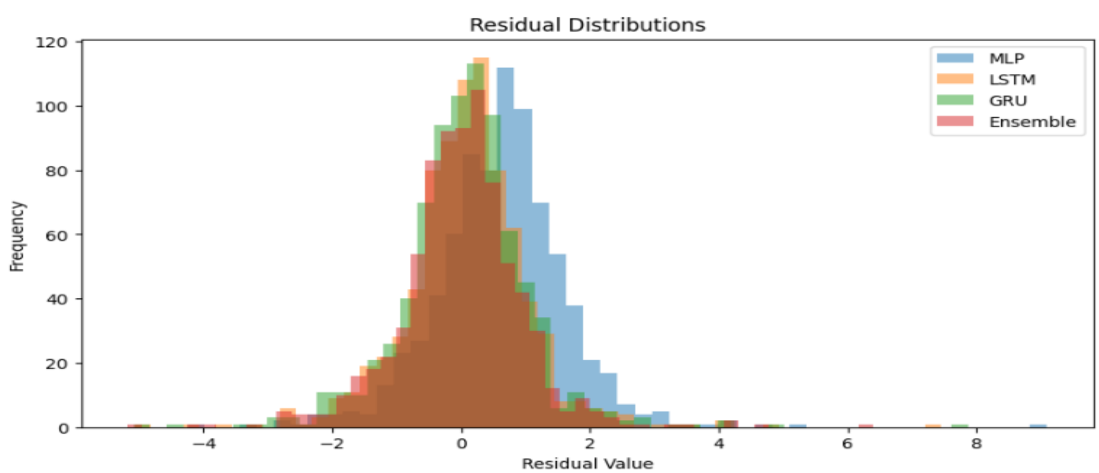

Figure 3 Frequency vs. residual value

3. Rolling RMSE: Rolling window RMSE demonstrated the stability of Ensemble predictions across varying time periods.

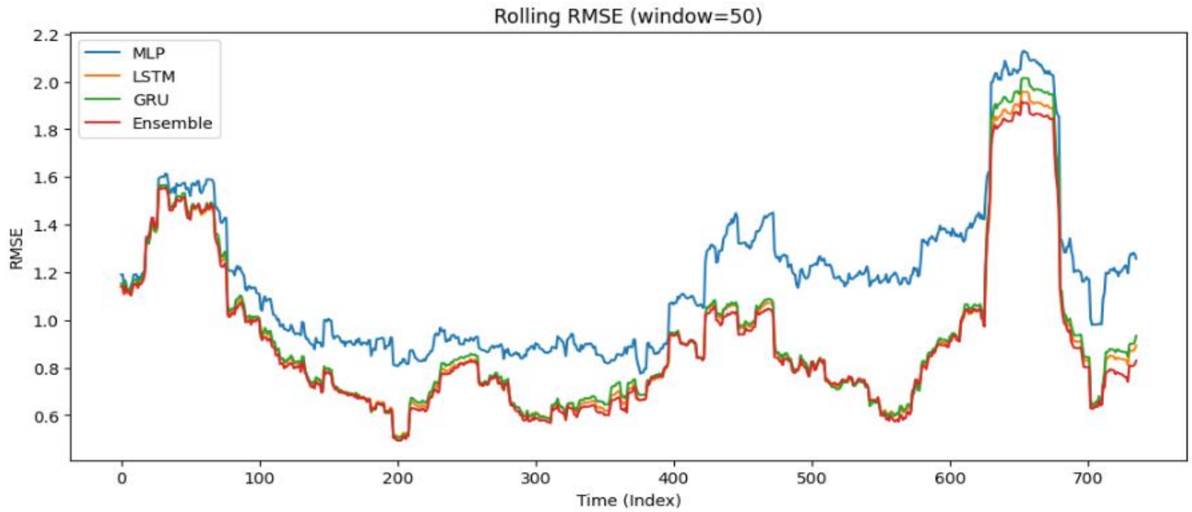

Figure 4 Rolling RMSE plots

4. Feature Importance: Ensemble model analysis revealed that closing prices were the most influential input feature.

3.3 Discussion

The results confirm that deep learning architectures capable of handling sequential dependencies, such as LSTM and GRU, outperform traditional feedforward models like MLP. Furthermore, the Ensemble way delivered the best overall performance by combining the strengths of LSTM and GRU. These findings align with existing literature that highlights the importance of ensemble learning in reducing model variance and improving robustness.

4. CONCLUSION

This research compared the performance of MLP, LSTM, GRU, and an Ensemble approach for predicting Apple Inc. stock prices. The results indicate that while MLP struggles to capture sequential dependencies, LSTM and GRU provide better accuracy due to their recurrent nature. The Ensemble model achieved the best overall performance, suggesting that combining models can lead to superior predictive outcomes.

For traders and investors, these findings emphasize the potential of ensemble learning as a reliable tool for financial forecasting. Moreover, the study contributes to the growing body of research advocating for deep learning approaches in stock market prediction.

5. FUTURE SCOPE

The current study opens several directions for future research:

1. Extending the analysis to multiple stocks and indices to validate generalizability.
2. Incorporating more indicators, sentiment research from financial news, and social media trends as additional features.
3. Exploration with advanced architectures such as Transformers, Attention-based RNNs, and Temporal Convolutional Networks (TCN).
4. Exploring multi-step forecasts (e.g., 5-day, 10-day horizons) to support longer-term investment strategies.
5. Applying more sophisticated ensemble techniques such as stacking or boosting to further enhance performance.

REFERENCE

[1] Ayan Maiti, Pushparaj Shetty D, (2020) “Indian Stock Market Prediction using Deep Learning.”, IEEE REGION 10 CONFERENCE(TENCON) Osaka, Japan, November 16-19.

[2] Priyanka Srivastava, P K Mishra, (2021) “Stock Market Prediction Using RNN LSTM”, IEEE 2nd Global Conference for Advancement in Technology (GCAT) Bangalore, India. Oct 1-3.

[3] M. Nikou, G. Mansourfar, J. Bagherzadeh. (2019) "Stock price prediction using DEEP learning algorithm and its comparison with machine learning algorithms." Intelligent Systems in Accounting, Finance and Management, 26(4), 164-174.

[4] Md. Arif Istiake Sunny, Mirza Mohd Shahriar Maswood, Abdullah G. Alharbi, (2020) "Deep Learning-Based Stock Price Prediction UsingLSTM and Bi-Directional LSTM Model", 978-1-7281-8226-1/20/$31.00 ©2020 IEEE.

[5] Kavinnilaa J, Hemalatha E., Minu susan Jacob, Dhanalakshmi R, (2021) "Stock Price Prediction Based on LSTM Deep Learning Model",IEEE International Conference on System, Computation, Automation and Networking (ICSCAN).

[6] E. Chong, C. Han, and F. C. Park, (2017) "Deep learning networks for stock market analysis and prediction: Methodology, datarepresentations, and case studies," Expert Systems with Applications, vol. 83, pp. 187–205.

[7] Yuan hua, Runde Zhu, Yanan Duan, (2022) "Construction of short-term stock price prediction algorithm based on MLP and CART Baggingensemble learning", IEEE Conference of Telecommunications, optics and Computer Science (TOCS).

[8] Md. Ebidaul Karim, Md. Foysal, and Sunanda Das, (2022) "Stock Price Prediction using Bi-LSTM and GRU based Hybrid Deep Learning Approach", Third Doctoral Symposium on Computational Intelligence (DoSCI).

[9] K. Hiba Sadia, Aditya Sharma, Adarrsh Paul, SarmisthaPadhi, Saurav Sanyal (2020) "Stock Market Prediction Using Machine Learning Algorithms" International Journal of Engineering and Advanced Technology (IJEAT).762 Danish Raza Rizvi et al. / Procedia Computer Science 233 (2024) 753–762 10 Danish Raza Rizvi / Procedia Computer Science 00 (2019) 000–000

[10] B N Varaprasad, Ch.Kundan Kanth, G.Jeevan, (2022) "Stock Price Prediction using Machine Learning", International Conference on Electronics and Renewable Systems (ICEARS 2022) IEEE Xplore.

[11] Ashutosh Sharma, Sanket Modak, Eashwaran Sridhar (2019) "Data Visualization and Stock Market and Prediction" International Research Journal of Engineering and Technology (IRJET).

[12] Yuqiao Guo, (2020) "Stock Price Prediction Based on LSTM Neural Network: the Effectiveness of News Sentiment Analysis", IEEE International Conference on Economic Management and Model Engineering (ICEMME).

[13] Audeliano Wolian Li and Guilherme Sousa Bastos, (2020) "Stock Market Forecasting Using Deep Learning and Technical Analysis: A Systematic Review", IEEE Access, Oct 21.

[14] Gourav Bathla, (2020) "Stock Price prediction using LSTM and SVR" IEEE International Conference on Parallel, Distributed and Grid Computing (PDGC).

[15] Apoorva Mahadik, Devyani Vaghela, Amrapali Mhaisgawali, (2021) "Stock Price Prediction using LSTM and ARIMA", Second International Conference on Electronics and Sustainable Communication Systems (ICESC) IEEE Xplore.

[16] Shruti Goswami, Shruti Goswami, (2021) "Stock Market Prediction Using Deep Learning LSTM Model", IEEE International Conference on Smart Generation Computing, Communication and Networking (SMART GENCON) Pune, India. Oct 29-30.

[17] Danish Raza Rizvia, Mohd Khalid, "Performance Analysis of Stocks using Deep Learning Models", 5th International Conference on Innovative Data Communication Technologies and Application (ICIDCA 2024)