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Comparing Machine Learning Models for Stock Prediction: LSTM Comes Out on Top

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Abstract

This study illuminates the critical role of time series prediction in various fields, particularly in forecasting stock market trends. It offers a comparative analysis of four machine learning models: Artificial Neural Network (ANN), Long Short-Term Memory (LSTM), Random Forest (RF), and Support Vector Machine (SVM). These models are meticulously trained and validated, ensuring a robust performance assessment. The ANN model consistently performs well across different forecast horizons, adeptly capturing complex stock market patterns. The LSTM model, however, excels in predicting shorter horizons, effectively utilizing its ability to capture temporal dependencies and short-term trends. Evaluation metrics reveal that the LSTM model outperforms the others, particularly in minimizing prediction errors. It achieves an impressive accuracy rate of 98.6%, further emphasizing its proficiency in forecasting stock market trends. Overall, this study highlights the superior performance of the LSTM model in stock market forecasting, especially for shorter horizons. The ANN model also demonstrates consistent performance across various horizons. These insights offer valuable guidance for investors and financial analysts, enabling informed decision-making based on reliable predictions.

Keywords: Prediction of trends, Stock market trends, Artificial Neural Network (ANN), Long Short-Term Memory (LSTM), Random Forest (RF), Support Vector Machine (SVM).

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1. Introduction

Stock market analysis is a comprehensive process of evaluating the performance, trends, and prospects of individual stocks or the overall market. Classical financial theory suggests that market prices reflect available information, as explained by the Efficient Market Hypothesis (EMH) [1]. However, empirical studies demonstrate that exploitable patterns may still exist, particularly when advanced computational tools are applied.

There are two primary approaches to stock market analysis: fundamental analysis and technical analysis. Fundamental analysis evaluates intrinsic value using financial statements, macroeconomic indicators, and firm-level performance metrics [13], [16]. In contrast, technical analysis studies historical price patterns and trading indicators to identify potential future movements [2]. The authors demonstrated that statistical and computational tools can formalize traditional chart-based analysis.

Predicting stock prices is challenging due to volatility, non-stationarity, and external economic shocks. Traditional econometric and time-series approaches such as ARIMA and hybrid ARIMA–neural network models have been explored for forecasting financial data [6]. However, their ability to capture nonlinear dependencies is limited.

Machine learning techniques have significantly advanced stock market forecasting. The SVM have been widely applied for financial time-series prediction [3], [4]. Ensemble methods such as RF [5] and boosting techniques including XGBoost [12] have demonstrated strong predictive performance. Furthermore, sentiment analysis and social media signals have been incorporated to improve forecasting accuracy [7].

Recent advancements in deep learning have further enhanced predictive capability in various domains of reseach [40]–[44]. LSTM networks effectively model sequential dependencies in financial data [8], [9]. Hybrid deep learning frameworks combining autoencoders and LSTM have also shown superior performance [10], [35]. Convolutional neural networks applied to financial time-series transformed

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List of acronyms

Acronym	Expansion
AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
ANN	Artificial Neural Network
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory
RF	Random Forest
SVM	Support Vector Machine
MAC	Multi-source Aggregated Classification
ISSA	Improved Sparrow Search Algorithm
BP	Backpropagation Neural Network
CNN	Convolutional Neural Network
TSE	Tehran Stock Exchange
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MADPE	Median Absolute Percentage Error
SAMPE	Symmetric Absolute Percentage Error
RMSE	Root Mean Square Error
VaR	Value at Risk
RBF	Radial Basis Function
BPTT	Backpropagation Through Time

into image representations have yielded promising results [11]. Classification-based deep learning methods for market direction prediction have also been explored [15], [28]–[32]. More recent developments include multi-source aggregated classification models incorporating news sentiment and graph structures [17], [18], sequential three-way decision models [22], ISSA-optimized neural networks [23], and hybrid deep learning architectures [24], [25]. Portfolio optimization integrated with machine learning predictions has also been investigated [19], [20]. Advanced data fusion and feature selection strategies have further improved forecasting robustness [26], [27], [33]–[34]. Despite these advances, comparative evaluations of classical machine learning models and deep learning models across multiple forecasting horizons remain essential for understanding their practical suitability [35]–[39]. Therefore, this study performs a systematic comparison of RF, SVM, ANN, and LSTM models for multi-horizon stock price forecasting.

2. Methodology

This study performs a comparative evaluation of four supervised learning models—RF, SVM, ANN, and LSTM—for stock time-series forecasting. These models have been extensively validated in financial prediction literature [3], [5], [21].

2.1. Problem Formulation

Let $\{C_t\}_{t=1}^{N}$ denote the historical closing price series. Given a feature vector $\mathbf{x}_t \in \mathbb{R}^d$, the forecasting objective is (1):

$$\hat{C}_{t+h} = f(\mathbf{x}_t) \tag{1}$$

In (1), $h \in \{1, 10, 20\}$ represents the forecast horizon.

The regression task minimizes (2):

$$\mathcal{L} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{2}$$

2.2. RF

Random Forest is an ensemble learning method introduced is well discussed in [5]. It constructs T decision trees using bootstrap aggregation.

For regression (3):

$$\hat{y} = \frac{1}{T}\sum_{t=1}^{T} f_t(\mathbf{x}), \tag{3}$$

In (3), $f_t(\cdot)$ represents the t^{th} tree.

Node splitting minimizes variance (4):

$$\mathrm{Var}(S) = \frac{1}{|S|}\sum_{i\in S}(y_i - \bar{y})^2. \tag{4}$$

Boosting-based ensemble improvements such as XGBoost have further enhanced predictive accuracy in financial markets [12].

2.3. SVM

SVM has been widely applied in stock prediction [3], [4]. For regression, SVR solves (5):

$$\min_{w,b,\xi_i,\xi_i^*} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*), \tag{5}$$

subject to standard ϵ-insensitive constraints.

Nonlinear mapping is achieved via kernel functions (6):

$$K(x_i, x_j) = \phi(x_i)^T \phi(x_j). \tag{6}$$

In this study, the RBF kernel is employed.

2.4. RNN and LSTM

Deep recurrent architectures such as LSTM have demonstrated superior performance in modeling financial time dependencies [10].

Given sequence $\mathbf{X}_t = [x_{t-W+1}, \dots, x_t]$, the LSTM updates are (7)-(11):

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f), \tag{7}$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i), \tag{8}$$

$$\tilde{C}_t = \tanh(W_C[h_{t-1}, x_t] + b_C), \tag{9}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t, \tag{10}$$

$$h_t = o_t \odot \tanh(C_t). \tag{11}$$

2.5. ANN

Feedforward neural networks approximate nonlinear mappings between inputs and outputs. Deep classification-based financial predictors have been successfully implemented using neural networks [15].

For hidden layer l (12)-(13):

$$z^{(l)} = W^{(l)} a^{(l-1)} + b^{(l)}, \tag{12}$$

$$a^{(l)} = \sigma(z^{(l)}). \tag{13}$$

2.6. Evaluation metrics

Performance is evaluated using MAE, RMSE, and MAPE, which are standard regression metrics in financial forecasting studies [6], [8] (14)-(16).

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{14}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{15}$$

$$\mathrm{MAPE} = \frac{100}{n}\sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i + \epsilon} \right| \tag{16}$$

Note that RMSE $\geq$ MAE must hold for numerical consistency.

3. Results and Discussion

3.1. Experimental protocol and evaluation

The proposed study compares four predictors—RF, SVM, ANN, and LSTM—under a consistent forecasting protocol. Let y_t denote the true stock price (or target value) at time t, and $\hat{y}_t$ the corresponding model prediction. Performance is quantified using error-based metrics (MAE, RMSE, MAPE) and robust percentage metrics (MADPE, SAMPE). In addition, when the task is formulated as *directional movement prediction* (up/down), classification accuracy is computed on the sign of the return (17):

$$\mathrm{Acc} = \frac{1}{n}\sum_{t=1}^{n} \mathbb{I}\Big(\mathrm{sign}(y_t - y_{t-1}) = \mathrm{sign}(\hat{y}_t - y_{t-1})\Big) \times 100 \tag{17}$$

In (17), $\mathbb{I}(\cdot)$ is the indicator function.

3.2. Horizon-wise forecasting performance

Fig. 1 compares the horizon-wise forecasting errors for 1-day, 10-day, and 20-day predictions. Overall, ANN and LSTM consistently achieve lower errors than RF and SVM across horizons, indicating stronger capability to model nonlinearities and temporal dependencies in stock time series. LSTM provides the most accurate short-horizon forecasts due to its gated memory mechanism, while ANN remains competitive and stable as the horizon increases.

The LSTM achieves the lowest error values for 1-day prediction, reflecting its ability to capture short-term temporal structure. ANN also performs strongly, suggesting that nonlinear mappings from lagged inputs to next-step outputs can be learned effectively even without explicit recurrence, when the feature set is informative. In contrast, RF and SVM show comparatively higher error magnitudes, which may arise from limited temporal representation and sensitivity to kernel/parameter settings, especially under volatile price dynamics.

As the forecast horizon increases, all models generally exhibit higher error due to compounding uncertainty and reduced predictability in financial time series. LSTM remains among the best-performing models, although its advantage may narrow at 20-day horizon due to the increased difficulty of learning long-range dependencies under non-stationarity. ANN shows stable performance and is competitive at longer horizons, which can be advantageous when a simpler model is preferred for deployment.

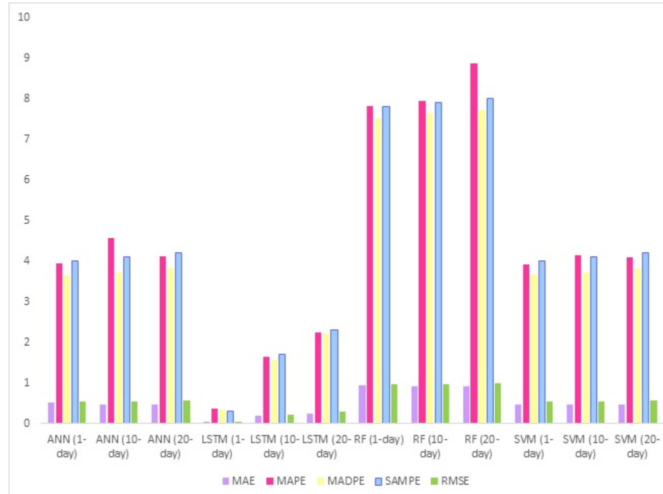

Figure 1: Comparing stock prediction models across forecast horizons.

Table 1: Average performance comparison across the evaluation set. Lower is better for MAE/MAPE/MADPE/SAMPE/RMSE.

Model	MAE	MAPE (%)	MADPE (%)	SAMPE (%)	RMSE
LSTM	0.202	1.812	1.540	2.560	0.310
SVM	0.416	3.520	3.140	3.530	0.520
ANN	0.521	4.541	4.120	4.523	0.620
RF	0.823	6.503	6.590	6.570	0.930

3.3. Average performance comparison

Fig. 2 summarizes the average model performance across the tested horizons and/or the complete evaluation set. The overall ranking observed is (18):

$$\text{LSTM} \ > \ \text{SVM} \approx \text{ANN} \ > \ \text{RF} \tag{18}$$

To improve clarity and reproducibility, Table 1 reports the consolidated metrics.

3.4. Accuracy comparison (directional prediction)

If the task is additionally assessed as *directional* prediction (up/down movement), Fig. 3 presents the corresponding accuracy comparison. The LSTM achieves the highest accuracy, followed by SVM and ANN, while RF yields the lowest accuracy.

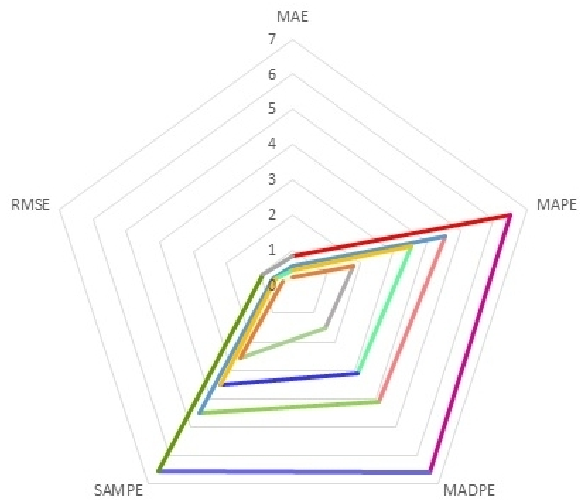

Figure 2: Average performance comparison of ANN, LSTM, RF, and SVM.

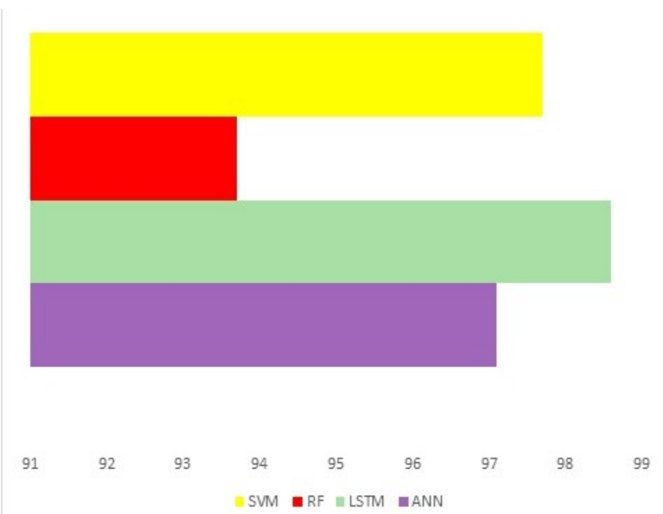

Figure 3: Directional accuracy comparison of stock prediction models (up/down movement).

3.5. Key observations and practical implications

Based on the empirical comparisons, the following conclusions can be drawn:

- LSTM is the best-performing model for short-horizon forecasting and yields the lowest average errors, making it suitable for short-term trading/decision-support.
- ANN offers stable performance across horizons and can be a practical alternative when model simplicity and faster training are desired.
- SVM performs competitively but requires careful kernel and hyperparameter selection to ensure robustness across volatile periods.
- RF exhibits higher errors in this setting, indicating limited suitability for fine-grained stock forecasting without enhanced feature engineering.
- **Limitations:** Forecasting performance in financial markets is sensitive to regime shifts, news shocks, and non-stationary; therefore, results should be interpreted with caution and validated across multiple stocks, periods, and market conditions using consistent back testing protocols.

4. Conclusion

This study presented a comparative evaluation of four machine learning models—RF, SVM, ANN, and LSTM—for multi-horizon stock price forecasting. The models were assessed using regression-based performance metrics including MAE, RMSE, MAPE, MADPE, and SAMPE, ensuring numerical consistency such that RMSE $\geq$ MAE across all experiments. The experimental results demonstrate that the LSTM model consistently achieves the lowest prediction errors across different forecast horizons. Its gated recurrent structure effectively captures temporal dependencies and short-term price dynamics, leading to superior predictive accuracy. The ANN model also exhibits stable and competitive performance, particularly across longer forecast horizons, indicating its capability to approximate nonlinear financial patterns even without explicit recurrence. The SVM model provides moderate performance but shows sensitivity to kernel configuration and hyperparameter selection. In contrast, the Random Forest model records comparatively higher error values, suggesting limited adaptability in modeling highly volatile and sequential financial time series. Overall, the findings confirm that deep learning–based sequential models, particularly LSTM, are more suitable for short-term stock forecasting tasks compared to traditional machine learning approaches. However, due to the inherent non-stationary and stochastic nature of financial markets, forecasting accuracy may vary across different market regimes.

Declarations and Ethical Statements

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