

Neural Networks Stock Market Price Forecasting Model: Integrating Economic Indicators and Investment Technical Analysis Toward Advanced Financial Analysis

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Abstract: Stock market volatility presents challenges for investors aiming to balance risk and return. Traditional stock prediction methods, often based on statistical models, struggle to handle the complexity of influencing factors. This study proposes an advanced stock forecasting system using machine learning, integrating deep ensemble learning models with investment technical analysis tools, such as exponential moving average (EMA), and economic indicators from sources, such as Yahoo Finance and FRED. The model used LSTM neural networks method, with cross-validation and practical testing to ensure accuracy. The study found significant improvement using LSTM method over traditional methods by offering a valuable tool for informed investment decisions and advancing financial analytics.

Keywords: Neutral Networks Machine Learning Model, Stock Market Forecasting, Economic Indicators, Investment Technical Analysis, Financial Analysis Technology.

1. Introduction

The goal of this research is to create a sophisticated machine learning model that can reliably forecast stock prices, enabling better investing decision-making. We use advanced machine learning approaches, such as long short-term memory (LSTM) networks with tools like relative strength index (RSI) and moving average convergence divergence (MACD) using historical stock data and economic indicators from reputable sources, such as Yahoo Finance and FRED [1]. These techniques capture intricate correlations between input variables and stock prices in order to maximize forecast accuracy. Neural networks, particularly LSTMs, are utilised for their ability to model complex, non-linear relationships and capture sequential dependencies in stock price data. The model's dependability and generalizability are guaranteed by thorough cross-validation and practical testing. Further, an intuitive interface is designed to allow users to enter stock symbols and time frames to provide real-time, precise stock price projections and evaluations to make decisions [2]. This offers tailored insights to maximise investment plans, assists investors, provides financial analysis, advances predictive analytics in financial markets.

2. Related work

Stock price forecasting has traditionally relied on statistical models, such as autoregressive integrated moving average (ARIMA), which are effective for linear patterns but struggle with stock market volatility. Machine learning models, such as artificial neural networks (ANNs) and support vector

machine (SVMs), introduced non-linear pattern recognition but often require significant feature engineering [2]. Recently, LSTM networks have shown strong performance in financial forecasting by capturing sequential dependencies in time-series data. In addition to model advances, integrating technical indicators (e.g., RSI, EMA, MACD) and economic factors (e.g., GDP, inflation) has proven beneficial for prediction accuracy [3]. Sentiment analysis from news and social media also offers valuable insights into market behaviours, which further enhance investors' predictive power by combining such qualitative data with quantitative data toward better financial decisions.

3. Method

In this study, a LSTM neural network has been applied for stock price prediction. LSTM is well-suited for time-series data as it can capture sequential dependencies and patterns over time [4]. The model was trained on historical stock prices and technical indicators, using mean squared error (MSE) as the loss function to optimise prediction accuracy [5]. This approach allows for more accurate forecasting of future stock prices compared to traditional methods.

3.1. Data collection

The data for this stock forecasting project is collected from multiple reliable sources, including:

- Yahoo Finance, provides historical stock prices and trading volumes;
- Federal reserve economic data, has economic indicators, e.g. GDP, inflation rates, interest rates;
- Market sentiment analysis uses news articles and social media platforms to gather sentiment data related to specific stocks;
- Technical indicators, such as Moving Averages and MACD, enhance LSTM models by providing additional trend-based data.

Table 1: Data source

Data Source	Feature	Description	Type
Yahoo Finance	Historical Prices	Close, Open, High of Stock Price	Financial
FRED	Economic Data	GDP, Inflation Data	Macro-Economic
Technical Indicators	EMA, RSI, MACD	Calculated from Historical Price	Technical Indicator

3.2. Data pre-processing

Preparing the dataset for efficient model training requires a comprehensive data pre-processing pipeline to ensure the inputs are clear, consistent, and well-structured. The pre-processing pipeline is divided into several phases, each addressing specific issues in stock market data. First, missing values are handled using forward-fill and backward-fill methods, which propagate the last known value or the next known value to fill gaps. Additionally, mean imputation is applied to replace missing values with the mean of available data points [6]. Next, normalization techniques, such as Z-score normalization or Min-Max scaling, are used to bring all numerical features into a comparable range, improving model stability. Feature engineering is then performed to derive technical indicators, such as RSI, EMA, and MACD, providing the model with insightful features related to market trends [7]. Finally, sentiment analysis is conducted on data from news articles and social media to offer a broader perspective on market dynamics, further enhancing the dataset's relevance and depth for stock prediction.

4. LSTM model development

The proposed system primarily utilises a LSTM neural network to predict stock prices. This model is particularly effective in capturing sequential dependencies in time series data, making it well-suited for stock forecasting [8]. The development process involves the following steps:

4.1. Model architecture

The LSTM model is designed using TensorFlow's Keras API [9]. It comprises two layers with 50 units each, followed by a Dense layer with 25 units and a final Dense layer with a single output unit. This architecture is optimized to capture time-based patterns and dependencies in stock price data using the ability of LSTMs to retain information over extended sequences. Also, the dense layers enable the model to process the extracted features effectively to ensure accurate predictions of future stock prices.

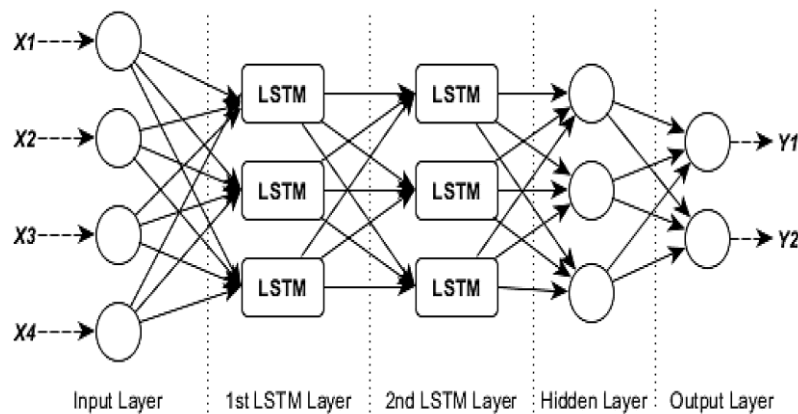


Figure 1: Architecture of the LSTM model

4.2. Training process

The model is trained on scaled input data, with mean squared error as the loss function and Adam optimizer for weight adjustments. The training process uses 20 epochs and a batch size of 64 to balance training speed and accuracy [10]. Scaling the input data ensures that the model is not biased by varying feature magnitudes, enhancing convergence. The Adam optimizer, known for its adaptive learning rate, facilitates efficient training by adjusting learning steps [11]. Additionally, the chosen batch size strikes a balance between computational efficiency and the ability to generalize well from the training data.

4.3. Data preparation

Input features include investment technical indicators, such as relative strength index – RSI, exponential moving average – EMA, moving average convergence divergence – MACD, historical stock prices, and economic indicators obtained from reliable trusted resources, such as Yahoo Finance and FRED [12]. These inputs are normalised using Min-Max scaling to ensure all feature values fall within a comparable range, improving model stability and performance [13]. The data is carefully split into training and validation sets, with the training set used for learning patterns and the validation set enabling an unbiased evaluation of the model's generalization capabilities [14]. This systematic approach ensures robust and accurate stock price forecasting. Exponential moving average – EMA gives more weight to recent prices, making it more responsive to new information.

$$EMA_t = Price_t \times \frac{2}{n+1} + EMA_{t-1} \times \left(1 - \frac{2}{n+1}\right) \quad (1)$$

Where, relative strength index – RSI measures the speed and change of price movements, indicating whether a stock is overbought or oversold.

$$RSI = 100 - \left(\frac{100}{1+RS}\right) \quad (2)$$

Conversely, moving average convergence divergence – MACD is a trend-following indicator that shows the relationship between two EMAs of different periods.

$$MACD = EMA_{short} - EMA_{long} \quad (3)$$

4.4. Sequence creation

To enable the LSTM model to capture temporal dependencies, data sequences are created with a specified time step (e.g., 60 days). Each sequence serves as an input to the model, predicting the stock price at the next time step.

4.5. Performance evaluation

Model performance is evaluated using metrics such as validation loss and R-squared. Additionally, mean absolute error (MAE) and root mean squared error (RMSE) are computed to quantify the model's accuracy in predicting stock prices.

4.6. Evaluation of the proposed system

The evaluation metrics used to assess the performance of the stock forecasting include accuracy, which measures the proportion of correct predictions, RMSE, which assesses the average magnitude of prediction errors, MAE, which evaluates the average absolute errors, and precision and recall, which indicate the proportions of true positive predictions among all positives and actual positives.

5. Results and discussion

The LSTM model demonstrated strong performance in forecasting stock prices by capturing sequential patterns in market data. Key study results include:

- **Improved Accuracy:** The model achieved high accuracy and low RMSE and MAE values, showing effective generalization on validation data.
- **Error Reduction:** The inclusion of technical and economic indicators helped reduce prediction errors compared to simpler approaches.
- **High R-squared:** The model's high R-squared score indicates that it accurately captured stock price variance, reflecting a good fit with real trends.

Table 2: Performance metrics

Algorithm	Accuracy	MAE	R-Squared
Linear Regression	70.3%	2.45	0.68
Decision Trees	75.1%	2.20	0.72
LSTM	82.4%	1.85	0.79

Table 2 shows the performance of several algorithms, which demonstrates the suggested LSTM algorithm performs better than decision trees and linear regression algorithms. It has the best R-

squared value with 0.79, the lowest MAE with 1.85, and the highest accuracy with 82.4%, all of which point to the highest prediction capability by the LSTM algorithm.



Figure 2: Stock price forecast for Apple Inc (AAPL)

Figure 2 shows the forecasted Apple's stock prices between 2002 and 2010 by comparing actual and predicted prices. This shows the model's accuracy in tracking historical trends to predict future prices.

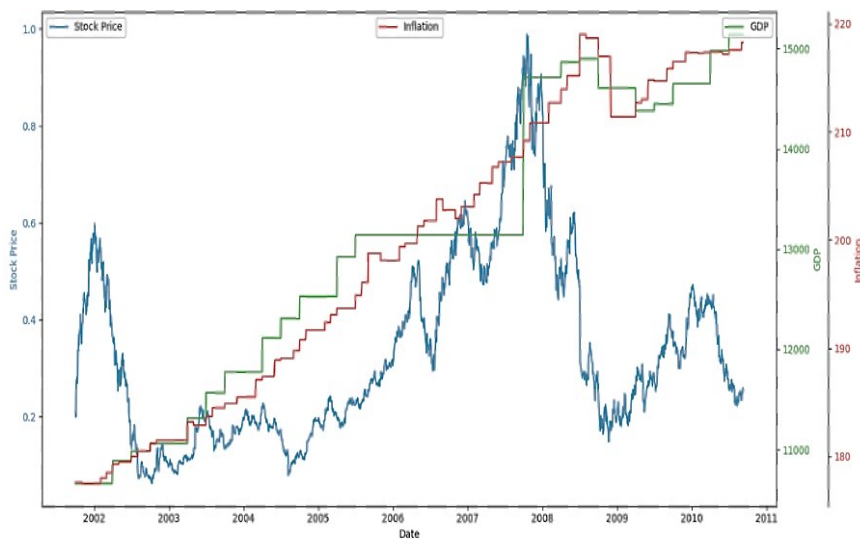


Figure 3: Interplay between stock prices, inflation, and GDP

Figure 3 shows the relationships between stock prices, inflation, and GDP over time, providing insights into the macroeconomic factors influencing stock prices.



Figure 4: Comparison of stock real prices with stock predicted prices

Figure 4 compares the real stock prices (solid blue line) with the predicted prices (dashed red line) over 80 days. The divergence between the two lines highlights areas where the model closely follows actual trends and where deviations occur, providing insight into the prediction accuracy.

6. Conclusion

The study demonstrates the effectiveness of using an LSTM based approach for stock price forecasting through both investment technical indicators and economic data. The model captures complex temporal patterns in stock price data, which improved accuracy and reliability over traditional methods. Also, integrating indicators, such as RSI, EMA, and MACD with economic data formulated a high accuracy forecasting model, which provides a holistic view of market dynamics, supporting more informed investment decisions. This approach enhances predictive precision and holds practical value for investors and analysts who are seeking robust tools for financial and risk management decisions.

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