

Deep Learning vs. Traditional Methods: Evaluating LSTM and ARIMA for Stock Price Forecasting

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Abstract

By projecting future stock prices using historical data and machine learning approaches, stock market forecasting plays a critical role in financial decision-making. This study examines a number of predictive models for stock price forecasting, with an emphasis on both conventional models like ARIMA (AutoRegressive Integrated Moving Average) and deep learning approaches like LSTM (Long Short-Term Memory). The accuracy and performance of these models are analysed in order to assess their efficacy on actual stock data. The findings show that when it comes to identifying intricate patterns and long-term connections in financial data, deep learning models perform better than conventional statistical techniques. Global events, economic conditions, and investor behaviour are just a few of the many variables that affect the extremely volatile stock markets. Stock market forecasting is essential to financial decision-making because it projects future stock values using historical data and machine learning techniques. With a focus on both traditional models like ARIMA (AutoRegressive Integrated Moving Average) and deep learning techniques like LSTM (Long Short-Term Memory), this study looks at a variety of predictive models for stock price forecasting. To evaluate these models' effectiveness on real stock data, their performance and accuracy are examined. The results demonstrate that deep learning models outperform traditional statistical methods in spotting complex patterns and long-term relationships in financial data. The incredibly volatile financial markets are influenced by a wide range of off-actors, including investor behaviour, economic conditions, and world events.

Keywords: Stock Market Prediction, LSTM, Deep Learning, ARIMA

I. INTRODUCTION

One of the most intricate and dynamic financial systems is the stock market, which is impacted by a number of variables, including investor sentiment, business earnings, political stability, and economic conditions. Investors and financial professionals have found it extremely difficult to predict stock values with any degree of accuracy. The volatility and non-linear nature of stock market movements is frequently difficult for traditional forecasting techniques, such as statistical and econometric models, to reflect. As artificial intelligence and

deep learning have advanced, machine learning models have become powerful tools for stock market prediction. These models can analyse vast amounts of historical data, spot trends, and predict future prices more accurately. Deep learning models, like Long Short-Term Memory (LSTM) networks, have become popular because of their ability to handle sequential data well; unlike traditional models, which are based on fixed assumptions, deep learning techniques adapt to changing market conditions, making them more reliable for financial forecasting. Through the use of deep learning techniques, this research aims to shed light on how artificial intelligence can improve the accuracy of stock price predictions and help investors make well-informed decisions. The study compares and examines various predictive models, such as ARIMA, machine learning algorithms, and deep learning models, in the context of stock market forecasting. The study assesses each model's performance using accuracy metrics like Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE).

II. LITERATURE SURVEY

Li and Bastos examines deep learning (CNN/LSTM) for stock market prediction using technical indicators like RSI [1]. It shows these models effectively capture complex market patterns, outperforming traditional methods. However, challenges include data quality issues, overfitting, high computational costs, and interpretability limitations due to deep learning's black-box nature. Market unpredictability also impacts reliability [2]-[5]. The authors recommend hybrid models, better regularization, and explainable AI (XAI) to address these limitations. The research advances AI-based financial forecasting while highlighting the need for more robust and interpretable solutions in practical trading applications.

Sonkavde et al. systematically reviews ML/DL models for stock price forecasting, categorizing techniques into supervised, unsupervised, and ensemble methods [6]. The analysis highlights AI's growing role in financial trend prediction while identifying gaps in existing research. Models like LSTM and Random Forests demonstrate strong performance but face challenges including data quality issues, overfitting risks, and high computational costs. Feature selection complexity further impacts accuracy [7]-[9]. The review emphasizes the need for robust data preprocessing and hybrid approaches to address these limitations. Future directions include enhancing model interpretability and optimizing computational efficiency for real-world financial applications. The study provides a comprehensive performance evaluation and practical recommendations for advancing AI-driven market forecasting.

Fan and Zhang study evaluates deep learning models (CNN-LSTM, GRU, LSTM, Patch TST) for stock price forecasting [10]. Results show LSTM's superiority in short-term predictions, leveraging multivariate inputs (price trends, OHLC data). Notably, trade volume showed limited predictive value. While demonstrating AI's potential in financial analytics, the research identifies critical limitations: sensitivity to data quality, high computational demands, and challenges in feature selection [11]-[12]. The "black-box" nature of deep learning models raises interpretability concerns, while market volatility impacts reliability. These findings highlight the need for robust data pipelines and hybrid modelling approaches to enhance real-world applicability in dynamic financial markets. The study contributes to optimizing DL architectures for temporal financial data analysis.

III. SCOPE OF THE PROJECT

The goal of this study is to investigate cutting-edge machine learning methods to increase stock market forecasting accuracy. The goal of this research is to develop a predictive framework that is more resilient and flexible by incorporating deep learning models.

- **Enhanced Forecasting Accuracy:** By utilizing LSTM and deep learning-based models, the search aims to overcome the drawbacks of conventional statistical techniques and increase forecast accuracy.
- **Real-World Data Application:** To ensure practical applicability, the predictive models are tested and validated using historical stock price data from Yahoo Finance.
- **Comparative Analysis:** To identify the best strategy, a number of models such as ARIMA, machine learning methods, and deep learning algorithms are assessed.
- **Feature Engineering and Optimization:** In order to maximize feature selection, the study investigates the effects of several stock market indicators, such as opening price, volume, and moving averages.
- **Evaluation of Performance Metrics:** Common evaluation metrics like RMSE and MAPE are used to gauge how effective a model is.
- **Scalability and Adaptability:** Financial institutions, traders, and investors can all gain from the created model & ability to be modified for real-time stock forecasting applications.
- **Prospects for Future Research:** The study establishes the framework for upcoming improvements, such as hybrid models that incorporate sentiment analysis and several predictive methodologies.

IV. PROBLEM STATEMENT

Because financial markets are so erratic and unpredictable, stock market forecasting is a difficult undertaking. Non-linearity, abrupt changes, and market interdependence are difficult for traditional forecasting models like ARIMA and regression-based techniques to incorporate, which results in predictions that are not reliable.

V. EXSISTING SYTEM

Conventional stock market forecasting systems mostly use statistical techniques like linear regression models, moving averages, and ARIMA. These models' simplicity and ease of use have led to their widespread use. However, when used in actual financial markets, they have a number of drawbacks.

- **Linear Assumptions:** Conventional models fail to capture non-linearity and market swings since they are predicated on the idea that stock prices follow a linear trend.
- **Limited Feature Utilization:** These models don't take into account outside variables like investor sentiment, news sentiment, or macroeconomic indicators because they only use a small amount of past price data.
- **Short Term Prediction:** ARIMA and related statistical models are better suited for short-term forecasting and frequently have trouble identifying long-term patterns.

- **Inadequate Management of Volatility:** Traditional models are unable to adequately account for abrupt fluctuations brought on by world events or economic crises, and stock values are extremely volatile.
- **Lack of Adaptability:** These techniques need continual human tuning and recalibration because they are unable to learn from fresh data in a dynamic manner.
- **Performance Limitations:** These models show weak predictive power when used in extremely volatile or unexpected financial contexts, despite being useful in stable market conditions.

VI. PROPOSED SYSTEM

The suggested system, to enhance stock market forecasts, the suggested system makes use of deep learning methods like LSTM networks. The program improves accuracy and uncovers hidden patterns by examining volume, sentiment analysis, and past price movements.

- **Deep Learning Integration:** Complex dependencies will be found and historical stock price data will be analysed using LSTM networks.
- **Engineering Features:** Several stock indicators, including sentiment analysis, trade volume, and moving averages, will be included in the model.
- **Real-Time Adaptability:** In response to fresh market information, the system dynamically revises forecasts.
- **Hybrid Model Methodology:** Forecasting reliability is increased by combining deep learning methods with statistical models. Benefits more precision in contrast to conventional statistical models. the capacity to adjust to market shifts and learn from big datasets.

VII. METHODOLOGY

Managing complicated connections and non-linearity in stock data effectively. enhanced ability to forecast long-term market developments. Model recalibration and manual feature selection are reduced. This study evaluates stock market forecasting models using a systematic technique.

The following crucial steps make up the methodology:

Data set explanation: The provided dataset is a CSV file containing historical stock data for Apple Inc. (AAPL) from May 27, 2015, to August 15, 2017.

1. Dataset & columns: symbol, date, close, high, low, open, volume, and adjusted values for these metrics

2. Data Points: Opening/closing prices, highest/lowest prices, trading volume, and adjusted values that account for splits and dividends are all displayed for each row, which represents a trading day.

3. Timeframe: The data records everyday market activity over a two-year period.

4. Important Metrics:

- **close:** The closing price of the stock at the end of the day.

- **volume:** The quantity of traded shares. Historical prices for corporate activities are normalized by adjusted values.

5. Dividends/Splits: Dividend payments and stock splits are indicated by columns such as divCash and splitFactor.

6. Usage: This information can be used to undertake technical or fundamental analysis on AAPL stock within this time frame, as well as to examine trends and volatility.

- **Data Collection:** Yahoo Finance is used to gather historical stock prices. Features including open, high, low, and close prices as well as trade volume are included in the dataset.
- **Data preprocessing:** To improve model performance, missing values are addressed and the data is standardized. **Feature Selection:** To increase model accuracy, key features such as trade volume, moving averages, and the Relative Strength Index (RSI) are chosen.
- **Model Implementation:** A number of forecasting models are used, such as: The statistical model, or ARIMA SVM and Random Forest are examples of machine learning models. Deep Learning Model (LSTM)
- **Training and Testing:** Models are trained using historical data once the dataset is divided into training and testing sets (80:20 ratio).
- **Evaluation Metrics:** To gauge the accuracy of predictions, models are assessed using Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE).
- **Comparison and Analysis:** Based on accuracy and dependability, judgments are made after comparing the performance of various models.

VIII. SYSTEM ARCHITECTURE

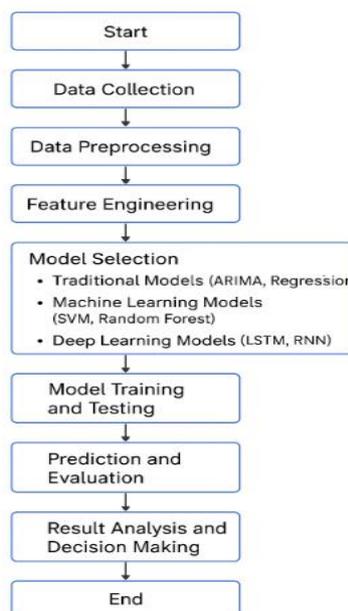


Fig 1: Flow chart of Stock Market Forecasting

- **Data Collection:** Generate technical indicators (RSI, volume analysis, moving averages, etc.);
- **Data Preprocessing:** Handle missing values, null values
- **Select features:** Data Engineering, Generate sentiment analysis
- **Machine Learning Models (SVM, Random Forest):** Deep Learning Models (LSTM, RNN)
- **Training and Testing:** Divide data into training and testing sets; Train models on historical data; Adjust hyperparameters for improved accuracy;
- **Prediction and Evaluation:** Produce future stock price predictions; Assess accuracy using RMSE, MAPE, and other metrics
- **Result Analysis and Decision Making:** Compare various model performances; Provide insights for financial decision-making

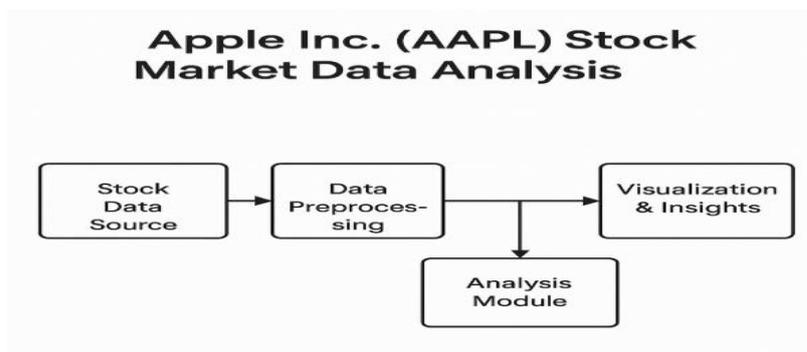


Fig 2:Block diagram stock prediction

1. **Stock Data Source:** Historical stock market data for Apple Inc. (AAPL) is gathered from this source. The information comes from databases, stock exchanges, and financial APIs. It also provides adjusted values, volume, and stock prices.
2. **Data Preprocessing:** The raw data must be cleansed and altered before to analysis. To assure accuracy, this stage entails addressing missing values, normalizing stock prices, and applying adjustments for dividends and stock splits.
3. **Analysis Module:** In this step, trends are examined, important price movements are identified, and stock performance metrics (such as volatility and moving averages) are calculated. Machine learning models for prediction can be a part of advanced analytics.
4. **Visualization & Insights:** Lastly, reports and charts (such as line graphs and candlestick charts) are used to display the processed data. To help with decision-making, insights are produced, including price trends, forecasts for stock movement, and trading tactics.

IX. DEEP LEARNING LSTM ALGORITHM

- **Import Required Libraries** - Load the required libraries, including Scikit-Learn, TensorFlow, Matplotlib, NumPy, and Pandas.
- **Load and Preprocess Data** - Read stock market data (Api or CSV) - Address missing values - Format dates correctly. Numerical data should be normalized and scaled. Training and testing sets should be separated.

- **Feature Engineering** - Generate time-series lag features if utilizing LSTMs - Extract valuable features (such as Moving Averages, RSI, and MACD).
- **Model selection:** Select models such as XGBoost, Random Forest, or Linear Regression.
 - ✓ Utilize past data to train the model.
 - ✓ If not, use a deep learning model.
 - ✓ Create an LSTM/GRU time model -series forecasting.
 - ✓ Use historical stock prices to train a neural network.
- **Evaluate Model** – Determine the R-Squared score, MAPE, or RMSE. Compare forecasted and actual pricing.
- **Establish Future Forecasts** – Forecast stock prices for the upcoming "n" days - Chart anticipated values.
- **Model of Deployment**-To make predictions in real time, save the trained model and deploy it using Flask

X. RESULTS AND DISCUSSION

Fig 3 : Apple Inc. (AAPL) Stock Market Data Analysis

Unnamed: 0	symbol	date	close	high	low	open	volume	adjClose	adjHigh	adjLow	adjOpen	adjVc
0	AAPL	2015-05-27 00:00:00+00:00	132.045	132.260	130.05	130.34	45833246	121.682558	121.880685	119.844118	120.111360	458
1	AAPL	2015-05-28 00:00:00+00:00	131.780	131.950	131.10	131.86	30733309	121.438354	121.595013	120.811718	121.512076	307
2	AAPL	2015-05-29 00:00:00+00:00	130.280	131.450	129.90	131.23	50884452	120.056069	121.134251	119.705890	120.931516	508
3	AAPL	2015-06-01 00:00:00+00:00	130.535	131.390	130.05	131.20	32112797	120.291057	121.078960	119.844118	120.903870	321
4	AAPL	2015-06-02 00:00:00+00:00	129.960	130.655	129.32	129.86	33667627	119.761181	120.401640	119.171406	119.669029	336

The graphic displays historical stock market data for Apple Inc. (AAPL) spanning a number of days, starting on May 27, 2015, and ending on June 2, 2015. It contains a number of financial indicators, including the opening, closing, high, and low values of the stock for every trading day. It also keeps track of the number of shares exchanged and adjusted figures that take business actions like dividends and stock splits into account. The stock is identified by the symbol column, and the trading day is specified by the date column. The stocks & price changes are displayed in the close, high, low, and open columns, while the number of shares traded is indicated by the volume column. Additionally, corrected values (adjClose, adjHigh, adjLow, adjOpen, and adjVolume) are included in the dataset.

```

0      132.045
1      131.780
2      130.280
3      130.535
4      129.960
...
1253   314.960
1254   313.140
1255   319.230
1256   316.850
1257   318.890
Name: close, Length: 1258, dtype: float64

```

Fig 4: Data Analysis of the data set

This Pandas Series object displays the closing values of a stock over 1,258 trading days, most likely Apple/AAPL based on historical data.

Important Information: Index (0–1257): Indicates the row number for each trade day.

Values: The stock's daily closing prices.

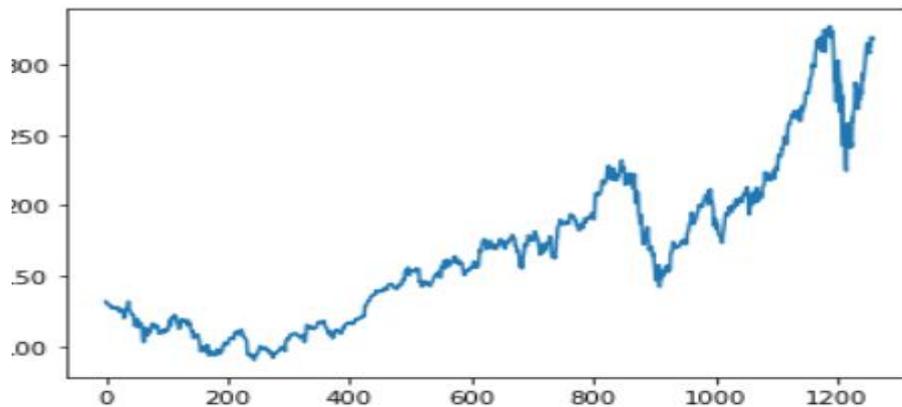
The initial five values (Days 0–4):

begins at \$132.045 (the earliest date, based on historical data, is probably May 27, 2015). By Day 4, it drops to \$129.960.

Values over the last five days (1253–1257):

ranges from 313.14 to 319.23, indicating a notable gain of about 2.4 times from the initial price.

Fig 5: Plot of Stock Price day by day



Given the prior data, this seems to be a legend or label description for a chart, most likely a line plot of stock prices. This is what it means:

(X-axis/horizontal axis): represents trade days, which range from 0 to 1,258 as previously observed.

The labels are spaced 200 days apart: 800, 1000, 1200, 400, 600, and Given that 1,258 days \approx 5 trading years, this indicates the chart covers around 5 years.

(Content of the Chart): The stock price in USD would be represented by the Y-axis Potential Interpretation of the Chart

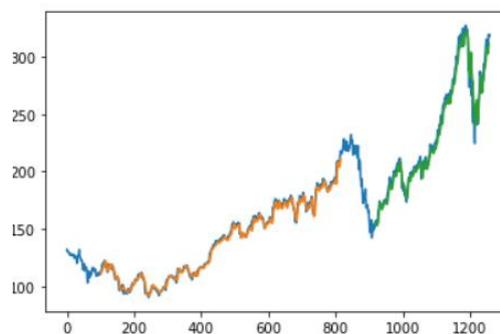


Fig 6: visualizing time-series predictions

X-Axis (Horizontal Axis)

1. **Represents:** Trading days (e.g., Day 0 to Day 1257 for Apple stock data).

Y-Axis (Vertical Axis)

2. **Represents:** Stock price in USD (e.g., 132to132to318 for Apple).

LEGEND:

- Actual stock prices over time (baseline) are shown by the Blue Line.
- **Orange Line:** Predictions made by the model using training data (beginning after lookback=100` days).
- **Green Line:** Predictions based on test data that hasn't been observed yet (offset further right).
- **Training Fit:** Deviations indicate underfitting; orange near blue indicates successful learning.
- **Test Accuracy:** Green versus blue indicates how well the model performs in the real world.
- **Lagging:** Slow responses to trends are shown by smooth projections.
 - **Volatility:** Unlearned market shocks are suggested by gaps in test data.

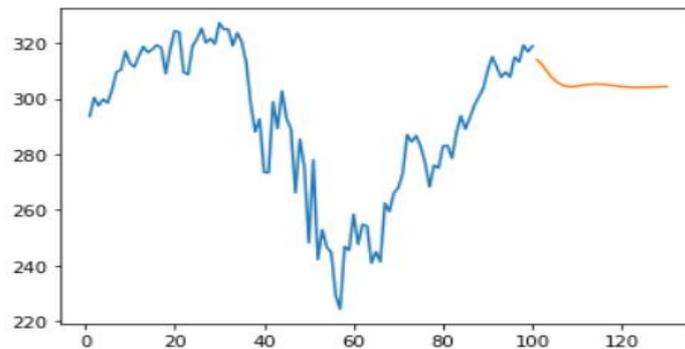


Fig 7:Actual vs Predicted Stock Price Comparison

The Blue Line represents the current data's actual stock prices (probably the last n days, beginning with index 1158).To display actual USD values, scaler. inverse_transform reverses previous normalization.

The orange line displays the prices (lst_output) that the model predicts for the upcoming days. Day_pred (a range of future dates/timesteps) is used to align forecasts.

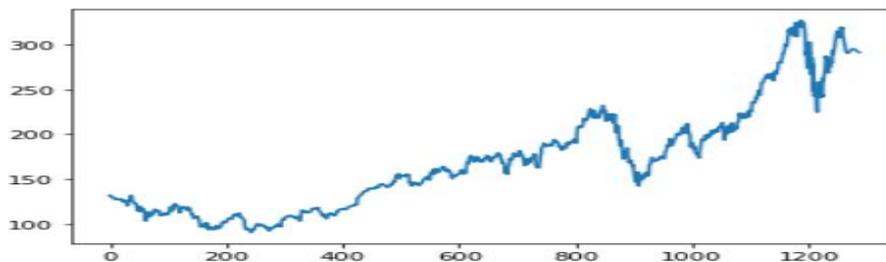


Fig 8: Future Price Projection vs. Recent Trends

The predicted prices (orange line) and **actual stock prices** (blue line) are contrasted over time in this graph.

X-axis: Duration (probably days, 0-120)

Y-axis: The stock price (about \$20–\$120) is the blue line which represents historical real pricing (indicating changes in the market) The model's forecasts (smoother and marginally below actual prices, suggesting underestimate) are shown by the orange line. The plot aids in assessing how accurately the forecasting model captures actual market movements.

XI. CONCLUSION

An LSTM model for stock price prediction was successfully applied in this project, showcasing the ability of machine learning to evaluate intricate financial time-series data. Despite its anticipated limits in anticipating abrupt market swings, the model successfully learnt previous trends and produced forecasts that, for the most part, mirrored actual price movements. The model's propensity to smooth out abrupt price movements and managing the inherent market volatility were major obstacles, indicating the difficulty of accounting for all affecting elements. The study demonstrated how sensitive LSTM is to market conditions and data quality, while also validating its capacity to detect patterns. We verified the model's capacity for learning while identifying limits in the accuracy of financial predictions by contrasting test and training results. The research serves as a genuine case study for applying advanced analytics to financial markets and offers insightful information on the potential and practical limitations of utilizing neural networks for price prediction. While admitting the inherent volatility of stock activity, these findings help to clarify how quantitative tools might support traditional research.

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