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Improving Stock Price Prediction Accuracy Through Deep Learning Models and Hidden Markov Models: A Comparative Analysis

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Abstract: Stock price prediction is a crucial research area, especially in the financial market, which plays a critical role in the global economy. This research compares the forecasting performance of several deep learning models on the BSE dataset. The models used are Long Short-Term Memory (LSTM), CNN-LSTM, Recurrent Neural Network (RNN), and a hybrid model of CNN-LSTM and Hidden Markov Models (HMM). Standard performance measures, such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2), are used to compare the models. The experimental results showed that the hybrid LSTM-HMM model achieved the best predictive performance among the approaches tested. The RNN model performed well in forecasting, while the CNN-LSTM and RNN-HMM models showed relatively weak performance. The results indicate that deep learning can be combined with probabilistic models like Hidden Markov Models to enhance the prediction accuracy and reliability of the stock price. Future research may focus on incorporating advanced optimization algorithms with these hybrid models to further enhance forecasting performance.

Keywords: Stock Price Prediction, Deep Learning, LSTM, CNN-LSTM, RNN, Hidden Markov Models.

1. Introduction

The typical marketplace is inherently unstable and unpredictable, and complex, with ordinary price prediction being a challenging task influenced by factors such as administrative events, worldwide monetary circumstances, commercial economic intelligence, and company presentation. This has, consequently, resulted in proving such methods invaluable while predicting stock prices based on past trends in an effort to maximize profits and limit losses and contribute to better market movement-related decision-making, according to sources [1] and [2]. Traditionally, binary classification methods are used in forecasting common values. The first is a practical investigation into the ancient information of standard remain, which may include primary prices, final prices, interchange capacity, and altered near prices used to forecast approaching tendencies. This is followed by the qualitative study, which gives consideration to various external factors from company performance and marketplace dynamics to political and economic conditions, supported by textual sources from financial news articles on social media forums and expert bloggers [3]. In recent times, advanced intelligent methods that integrate both quantitative and qualitative analyses have been widely used for stock price prediction. Stock market data is generally large and displays complex, nonlinear patterns. Therefore, to deal with such complexity, robust models are needed that can unveil the hidden relationships and latent patterns within large datasets. Researchers have shown that machine learning-based approaches enhance the accuracy of predictions significantly, which has improved efficiency by 60-86% over traditional methods [4].

2. Literature Review

The increasing volatility of the stock market in recent years has triggered interest in applying artificial intelligence to predict stock trends. Among various AI techniques, Long Short-Term Memory, a sophisticated variant of Recurrent Neural Networks, has been demonstrated to be especially effective in addressing the problem of vanishing gradients and maintaining long-term dependencies. Therefore, LSTM is a good tool for stock trend forecasting [5]. AI and machine learning have emerged as transformative tools in financial analysis, with LSTM models achieving notable success in accurately predicting NSE stock prices. The single-layer LSTM has demonstrated exceptional performance, underscoring the powerful intersection of advanced machine-learning techniques and financial applications [6].

This study investigates the integration of LSTM models with advanced analytics, which has shown potential for enhancing traditional trading strategies. These methods, by their nature as LSTM-based techniques, have surpassed conventional approaches in their capacity to use varying strategies of adjustment to respond appropriately to dynamic conditions in making the best decision during turbulent periods of financial dealings [7]. In addition, the TRNN model, when processing time series, includes features like trading volumes and sliding windows. It beats conventional RNN and LSTM approaches, thus gaining applicability at broader dimensions [8]. Other models like GA-LSTM and RNN-LSTM have been used to deal with the non-linear and dynamic nature of stock markets. Comparative studies reveal their importance in the forecast of trends and as a direction for future research [9].

The research further explores the development and challenges of cryptocurrency markets, where the CNN-LSTM deep learning model has been identified as a powerful tool for predicting Bitcoin prices, offering insights for further advancements in this domain [10]. By employing approaches such as CNN, LSTM, and hybrid CNN-LSTM models, this study demonstrates the effectiveness of these techniques in enhancing stock market prediction accuracy for NSE-listed companies. The sliding window method is adopted to accommodate dynamic market conditions, and RMSE is used as a key performance metric [11]. A method based on the Hidden Markov Model (HMM) was proposed to predict the closing prices for the following day of trading. The data considered belonged to four different companies, namely TATA Steel, Apple Inc., IBM Corporation, and Dell Inc. Input features comprised Open, Close, High, and Low prices. The individual stocks were modeled independently with seven months as a training period. Testing used Mean Absolute Percentage Error, MAPE, for evaluating the model [12]. A feed-forward neural network-based approach predicted the stock prices of the 2011 data for Microsoft Corporation. The key features, which include Open, High, Low, Adjusted Close, and Volume, were utilized in predicting the closing price for the next day. A multilayer feed-forward architecture with a backpropagation training methodology revealed accuracy as judged by Mean Squared Error. The existing literature on the use of neural networks in the context of stock market prediction was also studied to establish further validation of the methodology [13].

A new approach to predict the SSE index time series was proposed based on the SVR-CM, which is a hybrid linear and nonlinear regression model combined with SVR. Linear regression extracted the linear features of the data, while neural network algorithms captured the complex nonlinear patterns of the data. The outputs were combined using SVM regression, and the performance was measured using metrics such as MAPE, RMSE, and Trend Accuracy. The SVR-CM model revealed superior learning and prediction capabilities, showing its efficacy in stock market prediction [14].

3. Methods

A. Description of Data

In using the BSE stock prices for this stock price forecasting analysis, the dataset had a date range from 01-Oct-20 to 24-Oct-24. These Indices, BSE Financial Services, were obtained directly from BSE. The structured data was processed in a Pandas DataFrame in order to carry out efficient manipulation, streamlined process handling, and smooth analytical processing. It is an open-access resource from the publicly accessible source repository, mainly from the BSE India website [15].

B. LSTM

LSTM is an advanced variant of RNN, which was specifically designed to overcome the limitations of short-term memory in standard RNNs, becoming prominent as the depth of the network and the duration of training increase. By introducing gating mechanisms for managing memory, LSTM effectively overcomes issues such as vanishing and exploding gradients during the training of long sequences [16][17]. Experimental results indicate that LSTM has better performance in dealing with multivariable or multi-input problems, and therefore it is more appropriate for time series prediction tasks due to its structural advantages.

C. CNN-LSTM

The CNN-LSTM model combines the capabilities of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, making it particularly effective for applications involving both spatial and temporal data. CNNs are adept at extracting key features by identifying local patterns in inputs such as time-series stock prices, while LSTMs excel at capturing long-term dependencies across sequences. This integration helps a CNN-LSTM model to bring very accurate predictions in complex tasks such as forecasting the price of stocks, where one needs to be able to understand short-term fluctuations and long-term trends. With spatial as well as temporal insights, CNN-LSTM surpasses standalone models in domains such as financial forecasting or video classification, and much more.

D. RNN

Market trends, global economic conditions, and public sentiment are a few factors that make the stock market inherently unpredictable. To counter this, we created an RNN-based model that leverages data mining and machine learning techniques to analyze time-series stock data for accurate closing price predictions and shows its applicability to other volatile financial instruments [18]. Experimental results reveal that RNNs perform extremely well in complicated multivariable or multi-input scenarios, making it highly suitable for the issues related to time series forecasting.

E. HMM

Neural Networks, SVM, and Hidden Markov Models for stock market prediction suggest that HMM would be a great approach to more accurate results in comparison with conventional methods [19]. This work aims to employ HMMs in the process of forecasting stock prices of airline companies, focusing on the use of their effectiveness in modeling dynamic systems and pattern recognition for promising performance in stock market prediction [20].

4. Experimental and Parameter Setting

Alongside establishing the capacity of the prediction model, there was an LSTM-HMM model in a comparison against four other deep models, including RNN, CNN-LSTM, LSTM, and RNN-HMM.

A. LSTM

This uses an LSTM model to predict stock prices from BSE Financial Services index data. After preprocessing the "Close" prices with MinMaxScaler, a 60-day window is used to create training and testing datasets. The LSTM, comprising two layers with 50 units and dropout to reduce overfitting, is trained over 100 epochs. Predictions are evaluated using MAE, MSE, RMSE, and R^2 metrics. Fig. 1 Comparative plot highlights the match between predictions and actual values; it shows how accurately the model can capture the stock price trend.

B. CNN-LSTM

Using the historical data of the stock price, this study uses a CNN-LSTM to predict the closing price. Creating sequences of 60 time steps to capture dependencies of time, scaled "Close" prices are put through MinMaxScaler. Local patterns are found using a 1D convolutional layer while max-pooling is performed for dimension reduction. Two layers of LSTM is taken to capture dependencies of long duration in time, coupled with dropout. MAE, MSE, RMSE, R^2 measure model performance to express how accurately the system makes its forecasts. Fig. 2 compares Predicted Price v/s Actual Price, comparing how effective a model could plot stock prices.

C. RNN

The work presents a Simple Recurrent Neural Network-based model for the task of forecasting stock prices by using financial time-series data. It scales historical closing prices between 0 and 1 with MinMaxScaler, structures the sequence into 60-time-step sequences for trend learning, and employs an RNN architecture of two SimpleRNN layers of size 50 units each with dropout layers for prevention of overfitting, along with a dense output layer to predict prices. The model's performance is measured using metrics like MAE, MSE, RMSE, and R^2, trained on 70% of the data. Fig. 3, a visualization of predicted vs. actual prices, depicts the efficiency of the model and the application of deep learning in predicting volatile financial trends.

D. RNN-HMM

The developed research integrates a Simple Recurrent Neural Network (RNN) with Hidden Markov Models (HMM) for forecasting stock prices and analyzing market state. The MinMaxScaler has been used for the scaling of the closing prices, while sequences of 60-time steps have been prepared to capture temporal dependencies. It used two SimpleRNN layers in the architecture and dropout to prevent overfitting, followed by a dense output layer. For evaluation, the MAE, MSE, RMSE, and R^2 metrics were used. The predictions from the RNN are fed to a Gaussian HMM with three hidden states to reveal hidden regimes in the market. Fig. 4 visualization overlays predicted prices with hidden states, reflecting how effectively RNNs and HMMs combine to perfectly forecast and interpret underlying market patterns.

E. LSTM-HMM

This is a combination of LSTM networks and Hidden Markov Models (HMM) in the application to predict stock price using the BSE Financial Services index. The "Close" prices are scaled, and sequences are made to train an LSTM with two layers of 50 units with dropout to avoid overfitting. Predictions are fed into an HMM with three hidden states to discern latent market conditions. Metrics used for the model are MAE, MSE, RMSE, and R^2. Refer to equations 1 to 8 that we used in this algorithm. Fig. 5 outcomes are visualized by overlaying predictions and actual values using HMM state classifications, providing a robust framework for financial time series analysis.

Hidden State Set $S = \{S_1, S_2, \dots S_N\}$ (1)

Observation Sequence $O = \{O_1, O_2, \dots O_N\}$ (2)

Initial State Probability $\pi_i = p(q_1 - S_i)$ (3)

State Transition Probability $a_{ij} = p(q_{t+1} = S_j \backslash q_t = S_i)$ (4)

Observation (Emission) Probability

$$b_j(O_t) = \frac{1}{\sqrt{2\pi\sigma_j^2}} \exp\left(-\frac{(O_t - \mu_j)^2}{2\sigma_j^2}\right) \quad (5)$$

Complete HMM $\lambda = (A, B, \pi)$ (6)

where

A = transition probability matrix

B = Gaussian emission probabilities

π = initial state probabilities

Likelihood of the Observation Sequence

$$P(O\backslash\lambda) = \sum_Q P(O, Q\backslash\lambda) \quad (7)$$

Hidden State Prediction $Q^* = \operatorname{argmax} P(Q\backslash O, \lambda)$ (8)

5. Results and Discussion

From the analysis of Table 1 and Fig. 1-6, the following conclusions can be drawn. Comparative analysis of the stock price forecasting models reveals great insight into how they perform along different metrics. In comparison with the individual models, the RNN had better performance in the given set, achieving a Mean Absolute Error of 121.5372, Mean Squared Error of 28502.15, and Root Mean Squared Error of 168.8258. In addition, the model produced an R-squared (R^2) of 0.949. This suggests its superiority in grasping temporal relationships between stock prices. The CNN-LSTM model did better than LSTM, with the MAE obtained being 214.5572 and R^2 being 0.8887, which showcases the benefit that can be harnessed while combining convolution layers to extract the local patterns, while LSTM can build sequential dependencies.

The HMM was also further added to improve the predictive nature of both models, namely RNN and LSTM. The best overall performance was achieved by the LSTM-HMM model, with an MAE of 117.9528, MSE of 27916.9, RMSE of 167.0835, and the highest R^2 value of 0.95. This means that the integration of HMMs enables the identification of latent market states, which enhances the accuracy of the forecast. Similarly, the RNN-HMM model maintained competitive results with an MAE of 123.4863 and an R^2 of 0.9459 while providing additional interpretability by uncovering underlying market conditions.

Overall, the results indicate that hybrid approaches such as LSTM-HMM and RNN-HMM are indeed effective, capitalizing on deep learning and probabilistic modeling strengths. These models yield higher accuracy and deeper insights into market dynamics, making them robust tools for financial forecasting.

Table 1. Performance Evaluation of Various Models on the BSE Dataset

MODEL	MAE	MSE	RMSE	R-SQUARED
LSTM	236.7834	71258.53	266.9429	0.8725
CNN-LSTM	214.5572	62214.09	249.4275	0.8887
RNN	121.5372	28502.15	168.8258	0.949
LSTM-HMM	**117.9528**	**27916.9**	**167.0835**	**0.95**
RNN-HMM	123.4863	30229.17	173.8654	0.9459

Fig. 1. Analysis of the Actual vs. Predicted Stock Prices on Test Data Using LSTM

Fig. 2. Comparison of Actual and Predicted Stock Prices on Test Data using CNN-LSTM

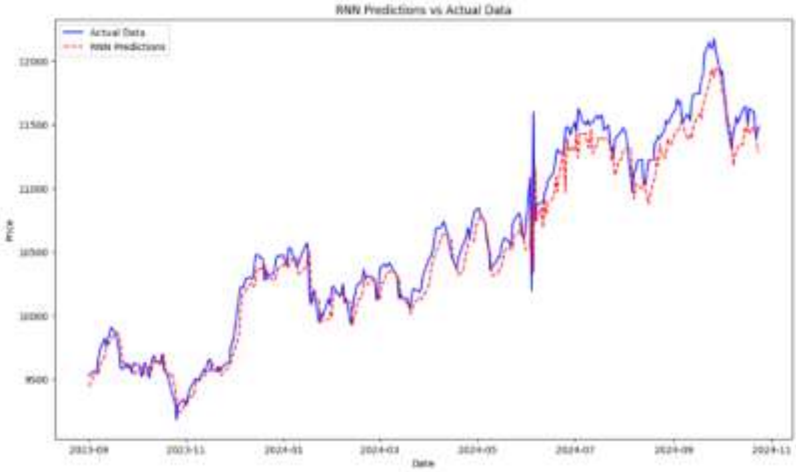

Fig. 3. Analysis of the Actual vs. Predicted Stock Prices on Test Data Using RNN

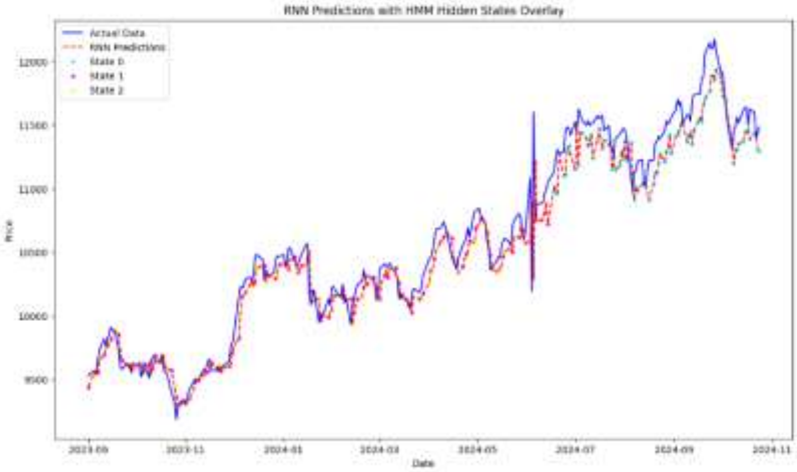

Fig. 4. Analysis of the Actual vs. Predicted Stock Prices on Test Data Using RNN and HMM

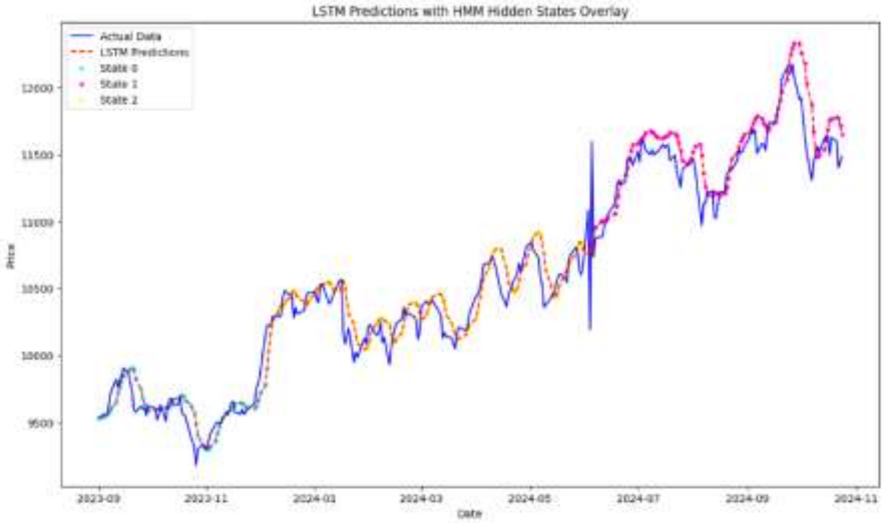

Fig. 5. Analysis of the Actual vs. Predicted Stock Prices on Test Data Using LSTM and HMM

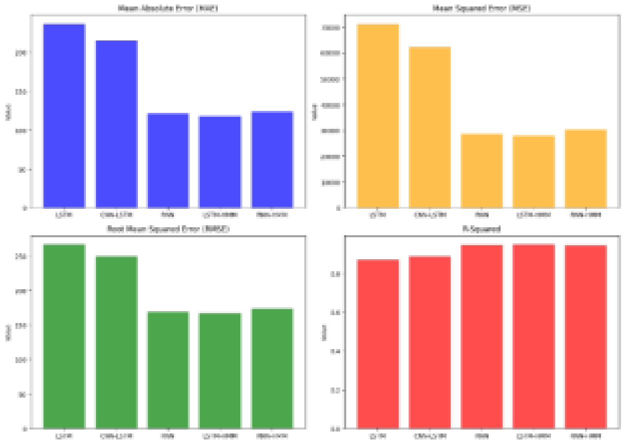

Fig. 6. Model Performance Comparison Across Metrics (MAE, MSE, RMSE, R-Squared)

6. Conclusion

This work shows that deep learning and hybrid models, specifically the LSTM-HMM, can be effectively applied to the problem of stock price forecasting. The LSTM-HMM model has shown the lowest error metrics and highest R-squared compared with other models and has successfully captured both temporal dependencies and latent market states. RNNs have also shown excellent performance in financial forecasting, highlighting the importance of recurrent architectures. Hybrid models, such as LSTM-HMM and RNN-HMM, merge the predictive power of deep learning with the HMM's ability to model market dynamics, yielding highly accurate and informative predictions in volatile markets. Potential future research can focus on integration with optimization algorithms such as PSO or GWO, macroeconomic and sentiment data, and extensions to multi-asset predictions using Graph Neural Networks (GNNs). Real-time deployment and enhanced interpretability would be very important for practical applications in live trading environments.

Author Contributions

M. Poornima wrote the main manuscript text, prepared figures, and tables. N. Nithyapriya reviewed the manuscript. All authors have read and agreed to the published version of the manuscript.

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Conflict of Interest Statement

There is no conflict of interest.

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