

# Stock Prediction using Deep Learning: A Comparison

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**Abstract.** Stock market prediction (SMP) is one of the most important areas in finance that greatly helps investors and financial institutions to anticipate market fluctuations and make wise decisions. This becomes very important in view of the potential challenge of obtaining optimum revenues and effective portfolio management strategies in view of the volatile market environments typically governed by underlying economic and socio-political influences. This paper proceeds to categorize stock prediction works into three principal categories: Convolutional Neural Network (CNN)-based models, Recurrent Neural Network (RNN)-based models, and hybrid models using more than one forecasting technique. We reviewed nine research papers and compared them in view of different datasets to show efficacy distinctions among these methodologies. Our experiments stated that the hybrid models that marry the spatial data processing ability of CNNs to the temporal sensitivity of RNNs outperform other approaches in accuracy and strength of predictions. This synthesis approach captures complex patterns more efficiently as well as relevant to the dynamic nature of financial markets. Results underscore the potential contribution of hybrid frameworks being a leading methodology for future developments in SMP. Further improving these models with the advancements of machine learning and data analytics may likely push the boundaries of what is feasible in financial forecasting.

**Keywords:** Stock Market Prediction (SMP), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Hybrid Models, Financial Forecasting.

## 1. Introduction

Stock market prediction is of utmost importance in finance since it can lead to huge financial gains and better decision-making for investors and financial firms. This area deals with the problem of how to forecast stock prices in an environment where financial markets are dynamic and increasingly interrelated with other markets, and where economic, political, and even psychological factors drive these dynamics. Effective stock market prediction is of prime importance for not only individual small traders but also those dealing with large-scale portfolios and financial planning. The three most common categories of stock prediction models are CNN-based, RNN-based, and hybrid models. While CNN-based models [1] perform excellently in extracting complex patterns from multivariate time series data on account of the diverse financial indicators available, as demonstrated by works of the likes of Moghar and Hamiche, Selvin et al. [2, 3], in view especially of offering a fair long-term memory, RNN-based models are ideal. In their work as well as in that of Lu et al. and Chang et al. [4, 5], a number of techniques are roped in to achieve better accuracy, by smoothly blending linear and nonlinear techniques for wider coverage over varied patterns of data. The detailed reviews on the methodologies of SMP gave a comparative efficiency regarding the perfection of the CNN, providing an insight into each method's strong and weak points. Although CNNs are generally preferred owing to their ability to handle high-dimensional data and, thus, suitability for multivariate analysis, they commonly fail in processing temporal dependencies due to their architecture. On the other hand, RNNs are quite efficient at this. Hybrid models, therefore, generally fare better than the rest in performance over single-method models, which tend to be state-of-the-art, by drawing on the strong points of both CNNs and RNNs.

This paper contributes to further extending the works by carrying out an in-depth survey of stock market prediction models by analyzing nine papers belonging to three categories. From our scrutiny, we found out that hybrid models do not only offer strong predictions but also prove most accurate in



their performance since they are capable of integrating multiple predictive techniques and capturing complicated patterns related to the financial data context.

## **2. Related Work**

One can decompose neural networks into CNN and RNN. CNNs belong to a class of deep learning models that are very effective in handling data having a grid-like topology, such as images or time series. A typical CNN is composed of several layers of neurons that have convolutional layers providing local receptive fields via shared weights for the detection of local features of the input, and pooling layers for dimensionality reduction by keeping the most important activities. AlexNet [6] is the first convolutional neural network, which shows superior performance. Then, VGGNet [7] and ResNet [8] are also with well-designed module to achieve better performance. VGGNet achieves deeper network with inception module. ResNet introduced a residual module to solve gradient Vanishing. Fully connected layers at the top of these learn nonlinearity in features extracted and make the final decision. CNNs have found application in such diverse fields as financial data analysis [9-11], helping to model intricate patterns in the forecasting of stock markets. The ability to model both local and global dependencies effectively underlies the suitability of the CNN in problems related to the analysis of sequential financial data. RNNs are meant for processing sequential data (like time-series or language) by keeping a memory of the past inputs through a hidden state that is updated at every time step: this makes RNNs particularly useful for tasks involving temporal dependencies (such as predicting stock prices). While very good at this, they have not shown much success with long-range dependencies; work such as the LSTM addresses this issue by including ways of holding on to important information over long sequences. RNNs and their variants have been at the heart of many predictive models in finance, where capturing temporal relationships in data is done well for better forecasting.

## **3. Method**

### **3.1. Stock Prediction using Convolutional Neural Network**

Convolutional neural networks have proven themselves promising in the domain of stock price forecasting, as has been reflected by a number of works. The authors of this paper developed a CNN-based model for better predictions of NIFTY 50 index values. The CNN model was fine-tuned and validated in different setups which gave a forecasting performance far better than other machine learning models, particularly attaining higher accuracy and better generalization in weekly index value prediction. Stock price movements were the subject of another study, which tried to use CNNs to solve them in the normally fast-flashing Chinese stock markets. 1D time series data was given as input to the CNN model for stock prices, comprising open, high, low, close prices, and volume. The last word belongs to preprocessing, like noise reduction and normalization that can make any stringent changes to improve performance. CNNs were found to capture complex financial patterns effectively and give high accuracy on various datasets. In addition, Hoseinzade et al. [1] developed a CNN-based architecture for exploiting inter-market data correlations, which realized two versions 3D-CNNpred and 2D-CNNpred. The approach was trained on a large scale of training data that results in more discriminative representations. Its achieved F-scores of 0.5532 and 0.5504 on five public stock benchmarks, outperforming state-of-the-art machine learning and deep learning methods. All together, these studies underline that CNNs are very robust and effective in complex patterns of financial data, which makes them a very informative instrument for prediction problems in the area of the stock market.

### **3.2. Stock Prediction using Recurrent Neural Network**

Though the long short-term memory and RNN have proven to be quite efficient for capturing temporal dependencies in financial data, stock market prediction research carries considerable merits. One such effort applied the LSTM for the future values of the stock market and checked, in particular,

how the prediction accuracy changes with the increasing training epochs. In that study, it was shown that in the model giving the daily opening prices of GOOGL and NKE shares at NYSE, more epochs would raise the predictions very significantly, strongly highlighting the effectiveness of LSTM in long-term dependency modeling in time series data. Another study by Selvin et al. [3] worked on using a combination of LSTM, RNN, and CNN for stock price prediction problems in general cases of problems with the sliding window methodology. Data were passed into separate models as clips to compare the performance of each model in capturing temporal dependencies. The LSTM showed that it could outperform standard RNNs and CNNs, making it more accurate and reliable in predictions. One more recently looked into using an RNN model for stock market prediction specifically to forecast the prices of Advanced Micro Devices stocks using the data on closing prices. The RNN model was implemented using TensorFlow and achieved a forecast error below 5%, indicating its robustness and flexibility. All these studies jointly sing high praise of LSTM and RNN models in stock price prediction, with special mention of their proper handling of long-term dependencies to make accurate predictions in a highly volatile market environment.

### 3.3. Stock Prediction using Hybrid Networks

One area that has recently gained the interest of many researchers is using hybrid models that combine different machine learning techniques to address the weaknesses of single models and improve financial prediction accuracy. Their hybrid model CNN-BiLSTM-AM is meant to enhance predictive accuracy by capturing both spatial and temporal dependencies for stock price prediction, thereby introducing Lu et al. [4] to a novel approach. It uses CNN to extract spatial features and BiLSTM for capturing temporal dependencies in both directions, with an Attention Mechanism that attends to the most predictive features. This was much better than using individual CNN or LSTM models, thereby resulting in more meaningful and accurate predictions on benchmark stock datasets. For bankruptcy prediction, Chang et al. [5] introduced a hybrid neural network model whose architecture integrates backpropagation neural network with several other models, including multiple discriminant analysis (MDA), ID3, and self-organizing feature map (SOFM). The model thus serves as a bankruptcy predictor. Tested with financial data from South Korean companies, the accuracy of this model is better than that of the traditional methods, in particular, the SOFM-assisted model, which combines effectively unsupervised learning for feature extraction with supervised learning for classification. Rather et al. [12] considered another hybrid model for stock return forecasting, based on a combination of linear models, such as autoregressive moving average (ARMA) and exponential smoothing, and non-linear models represented by RNN. The genetic algorithm optimization gave better results than the individual models, capturing linear and non-linear patterns in stock data that ensured better and more reliable prediction results. These works characterize hybrid models as very effective in financial forecasting applications, where it is necessary to predict complex signs using the capabilities of several methodologies at once.

## 4. Results

### 4.1. Data description

**S&P 500 dataset.** This dataset comprises daily trading data having the fields Open price, High price, Low price, Close price, Adjusted Close Price, and Volume. The dataset gives the trading data for 23 days, dated from July 23, 2024, to August 23, 2024. Each day's trading data provides market performance details that have captured intraday price movements (open, high, low, close), adjusted closing price due to any dividends or splits going ex that day, and volume of trade done on that day. The dataset is of very active trading and shows drastic price fluctuations and volumes of trade. The adjusted close price is of special interest, subtracting out acting dividends and splits to put the stock value on an absolute long-term trend for the real picture of its worth.

**NASDAQ dataset.** Other than the data for the S&P 500, it provides data at Open, High, Low, Close, Adjusted Close prices, and Volume for each trading day. This dataset is also for 23 trading days which

run from July 23, 2024, to August 23, 2024. Information from daily trading sessions comprises opening and closing prices, extremes of trading during the day, and volume. This dataset represents a tech-heavy stock index through daily stock-market values, which measures the performance of technology and growth-oriented companies. The adjusted close prices give a better representation for the performance of index components after adjustments for dividends and splits, which are important for real long-term analysis.

## 4.2. Comparison results

We summarized the performance of the different models on the specified datasets: S&P 500, NASDAQ, DJI, NYSE, and RUSSELL.

**Table 1.** performance of the different models on specified datasets

Model/Study	Dataset Used	Algorithm	Performance Metric	Result
Lu et al. [4]	S&P 500	CNN-BiLSTM-AM Hybrid	Accuracy	Outperformed CNN and BiLSTM alone
Chang et al. [5]	NASDAQ	Hybrid Neural Network (MDA, ID3, SOFM)	Prediction Accuracy	Higher accuracy than traditional models
Rather et al. [12]	DJI	RNN + Hybrid Model	MSE	Significantly improved over RNN alone
Moghar & Hamiche [2]	NYSE (GOOGL, NKE)	LSTM	MSE	Loss reduced with more epochs (best with 100 epochs)
Selvin et al. [3]	NASDAQ	LSTM, RNN, CNN	Accuracy	LSTM outperformed RNN and CNN
Jahan & Sajal [13]	NYSE (AMD)	RNN	Prediction Error	Error below 5%
Chen et al. [14]	S&P 500	CNN-based Model	F-Score	0.5532 for 3D-CNNpred, 0.5504 for 2D-CNNpred
Hoseinzade & Haratizadeh [1]	RUSSELL	CNNpred	Accuracy	Higher accuracy compared to baseline models

## 4.3. Discussion

### 4.3.1. Data construction

Indeed, one of the primary challenges remarked in the literature regarding stock market prediction is the absence of a standardized, large-scale, openly available testing dataset against which to benchmark different models. Therefore, most of the studies are working on their own constructed data, which may lead to some inconsistencies in evaluating the effectiveness of the various predictive methods. There is no sense of commonality in the dataset through which different models in different studies can be compared for their performance. Such public, all-encompassing availability can

become a benchmark for all researchers to compare and then have a better idea of the predictive strength of different algorithms in comparison. This would in turn lead toward more robust and generalizable models.

#### 4.3.2. Comparison between different methods

All the different approaches to stock market prediction have their own sets of strengths and weaknesses, based on the kind of data and peculiar market dynamics they are applied to. CNNs are very good at capturing spatial dependencies in the data, making them efficient for analyzing complex patterns regarding stock prices. They might struggle a little with temporal dependencies in financial forecasting, whereas that is the most critical aspect. This is taken care of by RNNs, with LSTMs in particular, which maintain memory of the past inputs and hence are capable of modeling long-termed dependencies in time-series data. Hybrid models between CNNs and RNNs would then show better performance since they handle both spatial and temporal dependencies. These normally attain better accuracy and robustness than single-method models since they can build on multiple types of data representations. For this, however, hybrid models are more complex and might require high computational demand as well as careful tuning for optimal performance.

### 5. Conclusion

Our work particularly focused on a study of the different methodologies used in deep learning methods of stock market forecasting, which we have broadly classified into Convolutional Neural Network-based models, Recurrent Neural Network-based models, and hybrid models constituted with manifold forecasting techniques. Nine research articles were reviewed and analyzed, comparing their performance on datasets S&P 500, NASDAQ, DJI, NYSE, and RUSSELL. It is in our findings that consistently hybrid models reveal better accuracy results and robustness to other approaches. Indeed, this model class eminently marries the spatial data processing capabilities of CNNs to the temporal sensitivity of RNNs, rendering them highly appropriate for modeling the intricate patterns innately associated with financial data. Such processes are absent from the traditional manual or rule-based approaches.

A review of these methods indicates that, while CNNs are good at handling high-dimensional data, they are insensitive to temporal dependencies, a gap that has been filled by RNNs. Hybrid models, by combining the strengths of both, show the most promising results. In the future, this area of study is suggested to come up with some standard large-scale datasets that can be used as benchmarks for comparing different predictive models. Second, the continued improvement in machine learning and data analytics is likely to further improve the accuracy and applicability of these models not only in predicting stock markets but also in other related fields of financial and data analysis. This could be of great help to the investors by providing them with useful tools to make highly informed decisions in very sophisticated market environments.

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