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| **Sr. no** | **Title** | **Published by** | **Technique** | **Result** |
| 1 | Stock Price Prediction using LSTM,RNN and CNN Sliding Window Model | Sreelekshmy Selvin, VinayaKumar R, GopalKrishnan E.A, Vijay Krishna Menon,Soman K.P | Time series analysis of stock data using LSTM, RNN and CNN for two different sectors(IT and Pharma sector) | CNN is proved to be the best in proposed method |
| 2 | Stock Market’s Price Movement Prediction With LSTM Neural Networks | David M. Q. Nelson, Adriano C. M. Pereira, Renato A. de Oliveira | Brazillian Stock Exchange data is used as a source to build a prediction system that predicts a particular stock will go up in next 15 minutes or not | The model has a p value less than 0.05. The model outperforms random forest model |
| 3 | A LSTM-based method for stock returns prediction : A case study of China stock market | Kai Chen ,Yi Jhou,  Fangyan Dai | A single input layer, multiple LSTM layers , a dense layer and Single output layer | Accuracy increased form 14.3% of existing systems to 27.2% of the proposed method |
| 4 | A Deep Learning based Stock Trading Model with 2-D CNN Trend Detection | M. Ugur Gudelek ,S. Arda Boluk, A. Murat Ozbayoglu | Uses Exchange Traded Fund(ETF) as a factor to eliminate volatility and hence increase accuracy.A virtual paper trading system is simulated where we buy and sell stocks to demonstrate that the method outperforms | Accuracy 70%  High precision, recall and accuracy and significantly outperforms Buy and Hold strategy |

Researches in the area of ﬁnancial time series analysis using Neural Network models used different input variables for predicting the stock return. In some works, data from a single time series were used as input. Certain works considered the inclusion of heterogeneous market information and macroeconomic variables. In other works a combination of ﬁnancial time series analysis and Natural Language Processing have been introduced.

Some researchers introduced the Efﬁcient Market hypothesis that deﬁnes that the current price of an asset always reﬂects all previous information available for it instantly. There is also the Random-walk hypothesis which claims that a stock price changes independently of its history, in other words, tomorrow’s price will only depend on tomorrow information regardless of today’s price. Those two hypothesis determine that there are no means to accurately predict a stock price. On top of that, some researchers has performed a series of experiments showing that a random strategy can outperform some of the most classic methods of technical trading, like Moving Average Convergence Divergence (MACD) and Relative Strength Index (RSI). On another hand, there are other authors who claim that, in fact, stock prices can be predicted at least to some degree. And a variety of methods for predicting and modeling stock behavior have been object of study of many different disciplines, such as economics, statistics, physics and computer science. It’s worth mentioning that in 2012, it was estimated that approximately 85% of trades within the United States’ stock markets were performed by algorithms.

In the case of stock market, the data generated is enormous and is highly non-linear. To model such kind of dynamical data we need models that can analyze the hidden patterns and underlying dynamics. A popular method of modeling and predicting the stock market is technical analysis, which is a method based on historic data from the market, mainly price and volume. It follows some assumptions: (1) prices are deﬁned exclusively by the supply-demand relation; (2) prices change following tendencies; (3) changes on supply and demand cause tendencies to reverse; (4) changes on supply and demand can be identiﬁed on charts; And (5) patterns on charts tend to repeat. In other words, technical analysis do not take into account any external factors like political, social or macro-economical.

In regards to computational intelligence there are plenty of studies assessing different methods in order to accomplish accurate predictions on the stock market. They go from evolutionary computation through genetic algorithms, statistical learning by using algorithms like Support Vector Machines (SVM) and a variety of others including neural networks, component modeling, textual analysis based on news data, which also proposed a new approach based on collective intelligence.

Taking a closer look into works related to deep learning in stock markets there are some examples like where a study is made on the usage of a Deep Belief Network (DBN), which is composed of stacked Restricted Boltzmann Machines, coupled to a Multi-level Perceptron (MLP) and using long range log returns from stock prices to predict above-median returns for each day.

On the other hand, some of the researchers have focused on sentimental factors like processing the market news and generating “Buy” and “Sell” signals. This wave was started by Ahmad et al. employing the Financial Information Grid (FinGrid). They proposed a distributed environment, using Globus and Java Commodity Grids, to offer services by working on both qualitative and quantitative market data, as they added text analysis to the market news, along with the standard technical analysis indicators. This way the market sentiments were determined using the text analysis.

Deep Learning has been shown to signiﬁcantly improve upon previous machine learning methods in tasks such as speech recognition , image captioning and question answering. Deep Learning models, such as Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs), have greatly contributed in the increase of performance on these ﬁelds, with ever deeper architectures producing even better results. A Restricted Boltzmann Machine (RBM) is trained to encode monthly closing prices of stocks and then it is ﬁne-tuned to predict whether each stock’s price will move above the median change or below it. This strategy is compared to a simple momentum strategy and it is established that the proposed method achieves signiﬁcant improvements in annualized returns. The daily data of the S&P 500 market fund prices and Google domestic trends of 25 terms like “bankruptcy” and “insurance” are used as the input to a recurrent neural network that it is trained to predict the volatility of the market fund’s price. This method greatly improves upon existing benchmarks, such as autoregressive GARCH and Lasso techniques. Then, a Support Vector Machine (SVM) is trained to predict whether the mid-price will move upwards or downward in the near future using these features.