Machine Learning Based Model to Predict Stock Prices: A Survey

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Abstract. In this survey paper, we provide the findings obtained from extensive reading of 35 research papers that span the financial domain (specifically the Stock Market) as well as explore various Machine Learning algorithms and offer a comparative analysis of the same. Through this, we observed that there is a general preference towards Technical Indicators and how a new trend of using Hybridized Indicators is emerging. We also show that Support Vector Machines have been constantly preferred due to their ability to handle complexity but new alternatives like Auto Regressive Integrated Moving Average and Long-Short Term Memory models are on the rise.

Keywords: Machine learning, Support Vector Machines, stock market, technical analysis, technical indicators, feature selection, forecasting, stock prices, sentiment analysis, auto regressive integrated moving average, Long-Short Term Memory.

1 Introduction

Stock markets are public markets where people can buy or sell shares on the stock exchange. Since their inception, they have existed to serve the wider economy. They are indicative of the state of the economy, help companies raise capital and increase personal wealth. For this reason, there has been an increasing interest in being able to predict trends in the stock markets[1].

Machine learning, which is considered a subset of Artificial Intelligence, has the capability to learn and improve autonomously. The ability to learn from past trends and make sense of large chunks of data has made Machine Learning advances extremely relevant to the financial domain. Machine Learning has the capability to make the process of analyzing years of data to spot patterns and generate an output easier which can then guide traders towards a particular decision [4].

While approaching the stock market and trying to make predictions about how a stock may behave in the future, there can be 2 approaches taken – fundamental analysis and technical analysis. Fundamental analysis evaluates stocks by trying and measuring its intrinsic value, i.e., a variety of factors such as overall economy, financial strength, management of companies, etc., are considered along with assets and liabilities. On the other hand, Technical analysis observes the statistical trends of the stock such as its opening and closing price, high price and low price, volume traded to make assumptions about it. It assumes that all fundamental factors are already accounted for in the price of the stock.
Predictive Machine Learning models can help refine and improve the process of understanding a stock and where its headed [9], [17]. The above problem is treated as a classification problem since the price can either move up or down. Various classification algorithms such as Support Vector Machines, Naïve-Bayes, Regression models, Decision trees, and Neural Networks can be used and improved with the help of feature selection methods to solve this problem.

In the following survey, we read and reviewed 35 research papers pertaining to the above topics. This was done with the purpose of understanding the domains involved in creating a project that incorporates the financial domain with machine learning.

2 Survey of Literature

The following survey includes findings from 35 different research papers which belong to either the financial domain, machine learning domain or a culmination of both. Through this, not only did we attempt to obtain a better understanding of the nuances of these fields, we also list their findings in order to provide a comprehensive analysis comparing these findings and highlighting some underlying trends.

A comparative study on various Machine Learning algorithms used to detect patterns and use that to diagnose diseases [1]. The authors explored the accuracy, advantages and disadvantages of SVM, Naïve-Bayes and Forest Trees. They realized that although SVM is a good classifier it fails to perform finer classifications. On the other hand, Naïve-Bayes can combat this issue but requires a much larger data set. However, they observed that there was direct correlation between any algorithm’s efficiency and the input features fed.

The effect of multi-class sentiment on prediction is researched by [2]. They focused on 2 main aspects – selecting features and training a multi-class sentiment classifier. They worked with Decision Trees, Naïve-Bayes, SVM, K-Nearest Neighbors and Neural Networks and explored different feature selection techniques. Their research proved advantageous since they explored multiple sentiments apart from the regular positive and negative sentiment which helped prevent over-simplification. However, there was a lack of information about what input sentiments they had considered. Their observations show that SVMs outperform other algorithms due to their ability to handle complexity however KNNs are desired for faster execution.

ML algorithms to solve a classification problem of sorting different ecosystems using remotely sensed data that covered a wide area [3]. They used SVM, Naïve-Bayes, Random Forest, Regression and KNN. Although their study doesn’t provide a very clear answer as to which algorithm is best suited for classification problems, they were able to show that SVMs have the best adaptability and that the SVMs accuracy decreases much less compared to the other algorithms when given more complex inputs.

A comparative analysis between existing ML algorithms and used preprocessing techniques along with feature selection by [4]. They mainly focused on SVMs, NNs and KNNs. They cleaned and normalized their data, ran the algorithms and applied feature selection to observe the effect it would have on the working of the algorithms. Although their paper does not offer any new groundbreaking trend, it does reinforce that SVMs are superior when it comes to handling complexity.

Three popular ML algorithms – Artificial NN, KNN and Auto-Regressive Integrated Moving Averages (ARIMA) were looked into by [5]. Through their work, they observed that artificial NN model works best when it comes to timeseries data, KNN is the most resistant to external noise but that ARIMA is the best model amongst the three as it gives the most accurate results especially in terms of short-term estimations. They display the potential of ARIMA in predictive analysis models.

Deep learning model were implemented by [6] to analyze what impact COVID-19 had on the commodities market. The authors used the Granger Causality Method was used which checks for both, correlation and causality. They made use of Long-Short Term Memory (LSTM) models for this purpose and found that by using LSTM, the long-term dependence on problems can be avoided and that this method is suited for performing time-series predictions. Through this, they were able to show a that a negative correlation exists between the market and COVID-19, i.e., the pandemic negatively impacted the commodities market. They were also able to show through the Granger method that investors should focus more on resilient commodities when such a negative correlation is observed.

An in-depth analysis of technical indicators used in the stock market for technical analysis and how they’re better than fundamental indicators was performed by [7]. The author considered 3 indicators – Simple Moving Averages (SMA), Exponential Moving Averages (EMA) and MACD. The research highlights the usefulness of technical indicators but does not prove how they are superior to fundamental indicators. He does manage to give detailed information about the technical indicators and shows that a new trend of using them is emerging.
To understand which indicators – technical or fundamental, is more important in the context of performing predictive analysis [8]. They followed a simple approach of implementing the same models with different indicators to see which performed better. Their observations showed that fundamental indicators in fact outperform technical indicators. They’re research offers solid proof that simply following the trend of technical indicators in not enough and that fundamental indicators must be incorporated in some way to boost predictive ability of ML algorithms when it comes to analyzing stocks.

The disadvantages of relying heavily on traditional approaches in performing stock market prediction and attempt to show the benefits of performing sentiment analysis [9]. They used 2 types of inputs – Qualitative (news that affects the price) and Quantitative (Historical data). Through their work, they showed that sentiment analysis by itself provides erroneous results but when it is incorporated with technical indicators, it gives promising results. They also show that by using fuzzy logic, the model can be further improved and that by working on the training data scale and timeframe will yield better results.

The analysis of Stock Market trends, finding algorithms to evaluate for long term was focused [10]. They approached the problem by collecting historical data of Stock Markets and observing various trends and taking feedback from users. They were able to get insights for technical analysis and a picture where one has scope to predict the movements of the market for a longer time period. The authors explored various algorithms and evaluated how powerful they are in performing long-term predictions. They did this because they envisioned markets as being weighing machines which, after a while of its usage, has less noise and more predictability in its behaviour. Through their research, they found that a hybrid model which incorporates statistical as well as machine learning techniques will be more useful for the purpose of prediction.

To use Technical indicators and where to use Fundamental indicators were focused [11]. The author approached this problem by collecting data of professional portfolio managers and amateur investors. This helped in gaining some insight on different approaches used in different areas. However, no statistically significant difference has been found with respect to how often professional or non-professional investors in the market use certain investment tools (either fundamental or technical). The authors claim that one possible reason for this is that professional investors have access to tools that are non-conventional and generally more sophisticated than those that are available to the non-professional investors. Through their study, they show that the common hypothesis that says that technical and fundamental analysis-based tools cannot be mixed together is broken by the indication that all investors use some tools such as resistance lines, financial statements, etc. as a primary means to judge the behaviour of the market.

Higher-order information of time series to predict values of stocks [12]. Time series is a sequence of the price of a given share. Financial time series is generally recognized as chaotic time series. In this paper, the authors explored a new method to perform prediction of the time series trend by using reconstructed time series via motifs. Compared to different time series, these series hold some special features which greatly influences the microstructure of the financial market. A convolution neural network (CNN) was implemented. It was observed that this technique had a positive impact on prediction accuracy. The method implemented by these authors boasts of 6% higher accuracy than traditional models.

The detection of stock chart patterns using CNN and LSTM in order to construct a deep learning-based recognizer model [13]. They incorporated different parameters in order to pull the patterns characteristics. However, there is not much information about what these parameters are. As expected, there was a correlation between the rise and falls in the chart and the patterns pulled which means it could help in future predictions. Although the CNN and LSTM models were fed the same input parameters and both had errors, CNN performed significantly worse as compared to LSTM. The LSTM model can be improved by feeding it more inputs.

The prediction of stock prices using the ARIMA model [14] performed auto regressive model states the current value of output variable as a linear combination of its own past values and present values of the input variables. If the output variable depends linearly on its previous values, then it an auto regression model which is a regression equation. The auto regressive model is very prevalent and predicts the stock prices accurately. From the results obtained by the authors, it is observed that the predicted price almost coincides with the actual price Their method of predicting the return of an investment has the potential to help the financial organizations and stock brokers to predict the future price in any uncertain conditions.

The data mining to perform the analysis of stocks and utilise that to try and predict the trends observed in the stocks [15]. Their approach was divided into 3 main areas – partitioning, analysis, and
prediction. In the area of financial analysis, K-means and Fuzzy c-means have found increasing use. Their results show that this methodology showed significant improvement as compared to some other models that are currently in place and being used regularly. Although this model is able to predict trends of stocks in few countries, it is unable to make the same generalization for some other countries. Upon improvement, this method has a lot of potential.

The main approach mainly on the risks and returns involved quantitative analysis and observed the statistics [16]. The stats tell us about the variance, portfolio risk, and the difference between large cap, mid cap and small cap firms in terms of market capitalization. Risk of holding a stock is the standard deviation of returns from the stock during the period. Variance is a yearly concept, and hence the risk of the holding period has to be adjusted to make it per annum. Clearly, if the returns from the two stocks are positively correlated, then the portfolio risk will be more than the sum of holding the two stocks and hence it is not rational to hold these two stocks in the portfolio.

Multi-Layer Perceptron (MLP) and Discounted Cash Flow model (DCF) to compute the present value of a company as the total amount of its discounted future cash flows [18]. The Machine learning model was introduced by the authors to try and evaluate a function between the input data and perks and to minimize the cost function thereby optimizing the performance. The methods enlisted in their paper can be only be applied to options pricing. According to this method, any implied instability must be same for all prices of the options but in reality, this is not found to be true.

A twitter sentiment analysis model superior to the traditional models and provided a comparison of the same developed by [19]. They implemented Closed-End Fund Discount Method and Twitter Sentiment Analysis. Keywords were used to identify positive and negative sentiments. A positive score of 1 was assigned for every positive sentiment and negative 1 for every negative sentiment and this process helped the authors to quantify the sentiments expressed. The real-time twitter sentiment score (TSS) was implemented by the authors with baseline correlation that dissociates the historical TSS data trend which improves the efficiency of the model. With the help of TSS, prediction of market in advance by 15-time samples had an accuracy of 67.22% and hence this model is better for an upward market than a downward market to mitigate losses.

The stock price prediction using Hybrid ARIMA and Gated Recurrent Unit (GRU) models attempted by [20]. The authors picked these models to see if they had the ability to overcome the uncertainty that lies in such a prediction problem. Like any pattern recognition algorithm, the models identify patterns/trends in the data, analyze what data is best suited for prediction and attempts to provide an answer. When the authors compared their work to that of other papers, they observed that although the Hybrid ARIMA and GRU models work efficiently only when there is no limitation on time complexity and a very large input data set is given, they can easily outperform standard RNN-ML algorithms and have a lot of potential.

A hybrid model to a data set from NIFTY 50 index [21]. Data from the previous 3 years was collected by the authors and on the data obtained, LSTM, SOFNN, ANN, and Random Forest model was applied. Their paper deviated from the classical approach of trying to perform long-term predictions and instead focused on short-term movement from intraday traders. What they observed was that LSTM reduces the problem of vanishing gradients and ANN has the best specificity (however, it had poor sensitivity). They also found that incorporating sentiment analysis with SOFNN amplified its results and allowed it to outperform LSTM networks.

A strategy to forecast the directional movement of stocks for intraday trading using LSTM and Random Forest models [22]. The trading strategy focused upon in this paper is that on a trading day, that 10 highest priority stocks are bought and the ones with the lowest priority are sold to outperform the market in standings to the daily returns. The highlight of their research was their use of multi-feature method that not only focuses on the closing price of stocks rather also on the daily opening prices to find patterns that might otherwise be missed. Despite this, both the models performed in the 50-60% range with LSTM performing slightly better than Random Forest models.

A deep learning technique for the purpose of performing predictive analysis on stocks developed by [23]. The authors chose stocks from 3 different sectors – financial banking, information and technology, and medical sector. This was done with the purpose of observing how well the models generalize on seemingly unrelated stocks/companies. Random Forest models, ANN, SVM, Bagging, Mean Absolute Percentage Error (MAPE), and LSTM techniques were utilized. Although many time constraints were not met, the paper produced results with accuracies in the range of 90% by converging the losses. In predicting the closing price, LSTM performed very well and was highlighted in the paper.

To compare and contrast the LSTM and SVM Machine Learning algorithms with regards to stock price prediction [24]. The output accuracy or the performance is measured in terms of their Root Mean Squared Error (RMSE), Mean Squared Error (MSE), Mean Absolute Error (MAPE) and R squared (R2)
score values. Without including moving averages as an input indicator, both the models using base stock price dataset perform well. With moving averages, LSTM applied over the entire combined dataset was evaluated to be the more efficient model for predictive analysis.

A univariate time series forecasting methods for the stock market index and SP 500 with emphasis on Box-Jenkins ARIMA modelling [25]. The methodology in the paper also includes four forecasting methods that were used as a benchmark for other forecasting methods – Average Method, Naïve Method, Exponential Smoothing, Random Walk Model, Engle-Granger method. These methods worked well for many economic and financial time series. In the end, however, ARIMA for forecasting based on scale-dependent errors.

The focused on building a system that incorporates mathematical function, sentiments, machine learning techniques to detect patterns and other such factors to get a model that can perform exceptionally well future stock prediction [26]. Their set up steps included – collecting data sources (news sentiment and historical prices) from Reuters platforms (10 years data) for 4 companies, data pre-processing, aligning news with tick data, performing feature selection and testing the model. A large quantity of data was required to make their work but this was their only drawback. The model they created operated with an efficiency of 82.91% and proved effective.

The aim to forecast how the stock prices of a company might turn out the next day using ML algorithms incorporated with news sentiments gathered from New York Times [27]. The authors implemented a model such that it recommends investing on stock that have the potential to maximize the user’s profits or whether to buy or sell a stock based on some simulated prices. Their work demonstrates a systemic method of performing stock value prediction by starting with an ML algorithm, checking accuracy of the simulated prices and even including a stop loss order to represent a safe limit of investment.

The future value of a stock using past trends in data with SVMs and Long Short-Term Memory (LSTM) model [28]. The author took the traditional approach of training and validating the models with simple input features. The problem was treated as a rudimentary classification problem where an output 0 meant closing price of current day was lesser than previous day and output 1 meant otherwise. Although both the algorithms had accuracies in the 70% range, LSTM actually outperformed SVM by a small margin.

Themultiple ML algorithms – ARIMA, MLP, Independently Recurrent Neural Network (IndRNN), GRU and LSTM models to demonstrate their potential in making predictions with respect to stock prices [29]. Their study placed emphasis on the IndRNN model which was insightful as it is not a model that is implemented often. After running the models, they focused on fine-tuning the IndRNN algorithms by changing the activation function from Parametric Rectified Linear Unit to a Rectified Linear function. They measured the accuracy of the model by means of MSE and found that the fine-tuned model worked better than by giving a lower MSE as compared to any of the other models examined. By this, the authors concluded that IndRNN with fine tuning has immense potential in the predictive analysis field.

An Efficient-Market Hypothesis (EMH) [30] in their work concluded the efficient Market Hypothesis means that that stock prices reflect all available information, so that there is no guesswork done on the stock prices. EMH is an application of Rational Expectations Theory which states that any random phenomena can happen in the stock market and the past trends of stock cannot be used to determine how it will behave in the future. The authors used Particle Swarm Organization (PSO) to update their network parameters and they incorporated this with deep-learning models. What they observed was that all their models perform numerous cycles to customize patterns and improve predictions with each cycle. Based on their results, using PSO worked extremely well and has a scope for improvement in the future.

A linear and non-linear approaches to forecast stock prices [31] used 4 ML algorithms – MLP, RNN, LSTM and CNN and a linear model like ARIMA. They trained the networks with 5 different companies from NSE and NYSE. The companies were chosen such that they were highly traded stocks. From their result, they found that all the models were capable in identifying patterns but that CNNs worked better than ARIMA (linear model) which was unable to identify the underlying dynamics amongst various timeseries.

The technical indicators with NNs to perform stock market prediction [32] used common technical indicators and applied sensitivity analysis to accept or reject some indicators. The findings of their papers remained consistent with multiple others in showing that technical indicators are a good means to make predictions and when used with NNs, the problem of overfitting can also be solved. They observed that the network had low mean squared error and high correlation coefficient and generalized well on data and also reinforced the fact that the algorithm itself doesn’t matter so much as long as appropriate input features are chosen.
To discover the relationship between technical indicators and trend of a security by means of Decision Trees [33], they used 22 technical indicators and analyzed them using 3 algorithms – ID3, C5.0 and CART decision trees. By doing so, they showed that non-conventional algorithms provide good results as well instead of just using SVMs. Among the algorithms used, C5.0 performed the best in establishing a relationship between the indicators and trend of stock in consideration and shows potential in predictive analysis.

An unconventional indicator called “risk tendencies” was incorporated and used fuzzy logic to perform predictions on how a stock would perform [34]. They described risk tendency as being a subjective indicator which varies from trader to trader and attempted to quantify it in order to run the model. They showed that by implementing risk tendencies, they were able to tailor the model to the trader’s preference and observed that traders who used this model got significantly better results (more profit) than those who didn’t. They showed that models that are not based on purely mathematical indicators can also make close to accurate predictions.

The aim of seeing how a mix of technical and fundamental indicators, also known as hybridized indicators, impact the prediction accuracy using neural networks [35]. Through their research, they showed that hybridized indicators are an overlooked aspect as their model had high correlation between the indicators they used and their prediction accuracy. They argue that hybridized indicators are an avenue that should be explored more instead of just using one type of indicator since it gives better results.

3 Comparative Analysis

In recent years, a variety of research has been done to analyze what factors affect a stock most and which Machine Learning models work best to perform predictive analysis. Below is a brief review of the most significant findings we have encountered.

When it comes to analyzing a stock, the most frequently asked question was whether Technical Analysis was better than Fundamental Analysis [7], [8], [11]. Most researchers argue that Technical Analysis (and use of Technical Indicators) are a better technique as they hold data and patterns that most closely represent the behavior of the stock. These indicators were broadly divided into 4 main categories – trend, momentum, volume, and volatility and technical indicators were chosen from each category. When implemented with Machine Learning algorithms, these indicators proved to be worthy input features (and better than fundamental indicators) and a trend of relying on these indicators is emerging [7], [32-34]. Some studies used just fundamental indicators from which it was apparent that they often work well only while performing long-term predictions. However, research conducted using Hybrid indicators [35], i.e., a mix of technical and fundamental indicators shows that by combining these 2 types of indicators, better output results can be obtained. A high correlation between network accuracy and hybridized indicators was established. This hybridized approach has the potential to enhance the quality of future stock predictions as compared to an only-technical indicator approach.

Multiple ML classification models were tested (on their ability to perform regular classification as well as on stock price prediction). Among all the research done, the one model that consistently stood out was Support Vector Machines. SVMs work incredibly well due to their ability to work with complex data but on the flipside, they don’t do well to make finer classifications and require more time to deliver the output. It was observed that KNNs work much better in a shorter time frame and are being preferred for problems that need faster execution. Many other models such as ARIMA, LSTM, GRU, C5.0, and Decision trees were also tested. Hybrid ARIMA and GRU were able to perform regular NNs in multiple scenarios and are gaining traction due to their ability to produce values that very closely mimic real values. Although a new trend of using ARIMAs is approaching and it produces promising outputs, a major drawback is that a very large input data set is required and since it is a linear model, which was unable to identify the underlying dynamics among multiple time series, LSTM doesn’t not show any significant advantage over the other models and C5.0 (based on limited research available) seems to have the capability to perform well [1], [3-4], [6], [9-10], [13], [20-30].

An upcoming trend in the field of stock price prediction is sentiment analysis. Combining qualitative analysis (sentiment) with quantitative analysis (stock characteristics/indicators) is enabling predictions to be made with higher accuracy. Particularly, multi-sentiment classification, which deviates from the standard practice of using just positive/negative sentiment, is showing a clear correlation between popular sentiments and the performance of a stock. Even though there is not much information about what constitutes the “multiple sentiments”, the results shown were promising. This comparative analysis highlights the best results we have come across from the financial as well as Artificial Intelligence domain. We believe that by incorporating these results, i.e., attempting to develop a SVM model that
uses hybrid indicators as input features supplemented with sentiment analysis has the potential to give rise to a system that can produce results with very high accuracy. [2], [9], [19].

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4. Conclusion
From our survey, a very clear trend of using SVMs is evident. SVMs have an immense capability to handle ambiguous data but also require more time. In situations where fast execution time is vital, KNNs are gaining popularity. Models like ARIMA and C5.0 are slowly proving themselves to be worthy competitors of SVMs showing that there can be other alternatives. When it comes to integrating Machine Learning algorithms with the world of the Stock Market, it was proven time and again that using Hybridized indicators as opposed to the conventional practice of using just Technical Indicators provides better results and integrating sentiment analysis is becoming popular practice.

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