International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
***Article Received:** 25 April 2023 **Revised:** 12 June 2023 **Accepted:** 30 July 2023*

Technical Analysis-Based Data Mining Strategies for Stock Market Trend Observation

Bhagyashree Pathak
Research Scholar
Department of Computer Science
SAGE University, Indore, (M.P.), India
Bhagyashreepthk@gmail.com

Dr. Snehlata Barade
Research Supervisor,
Professor and Head of CSE/IT, SAGE University, Indore, (M.P.), India
snehlata.barade@sageuniversity.in

Abstract— This study introduces a comprehensive approach that utilizes technical analysis-based data mining strategies to observe and predict stock market trends, by leveraging historical trading data, technical indicators such as moving averages, RSI, and MACD, to systematically analyze and interpret market behavior, thereby providing investors and traders with actionable insights for making informed decisions in the volatile environment of stock trading. By integrating quantitative analysis with predictive modeling, the methodology aims to enhance the accuracy of trend forecasts and identify profitable trading opportunities. Through the application of cross-validation and backtesting techniques, the effectiveness of these strategies is rigorously evaluated against actual market movements, offering a robust framework for risk management and portfolio optimization. This interdisciplinary approach not only demystifies the complexities of the stock market but also opens new avenues for research and development in financial technology, promising a significant contribution to the field of economic forecasting and investment strategy.

Keywords- Technical Analysis , Technical Indicators , Stock Market Trend , Data Mining , Neural Network.

I. Introduction

1.1 Overview

This is my first research as a student so I decided to pick a topic which is center of attraction for many people and is of wide use also. In this process, I came across many topics but as I have to use data mining techniques on my related domain, I chose stock market as a co-domain because of increasing amount of financial data available on internet. Also it is widely discussed among people and everybody is somehow affected and concerned about stock market's direction as they are linked with it directly or indirectly.

As I liked the topic, I tried to find out more advantages of this selection. I came across with the following benefits.

1. It can be good source of secondary income.
2. It is very randomly traded by common man.
3. 85 % of people lose money in stock market in long run by trading in different instruments.
4. It is a big center of attraction for the people especially who are the earning members of their family.
5. Stock market is seen as quick money generator.

This thesis focuses on generation of trading signals with the help of technical analysis. The main feature of any algorithm based trading system is that it eliminates the weaknesses and improper interference of a trader, and guides it through the tough times which he may not stand. Any pattern is well backtested and thus to be followed as it is.

1.2 Introduction of Data Mining

In this thesis we are using Neural Network as the application of Data Mining concept for predicting the trend in stock market. Data mining is a process of discovering various models, summaries, and derived values from a given collection of data. It is one of the fastest growing fields in the computer industry and provides a wide range of methodologies and techniques that can be applied to a host of problem sets [5][6]. Many data mining techniques have been applied to stock data to achieve better financial solutions [1,2,3,4]

Data mining refers to the finding of relevant and useful information from databases. Data mining and knowledge discovery is a new interdisciplinary field, merging ideas from statistics, machine learning, data bases and parallel computing. Researchers have defined the term 'data mining' in many ways: [39][39]

Data mining or knowledge discovery in data bases, as it is also known, is the non trivial extraction of implicit, previously unknown and potentially useful information from the data. [7] [30]

The amount of data continues to grow at an enormous rate even though the data stores are already vast. [31] The primary challenge is how to make the database a competitive business advantage by converting seemingly meaningless data into useful information. [32] How this challenge is met is critical because companies are increasingly relying on effective analysis of the information simply to remain competitive. A mixture of new techniques and technology is emerging to help sort through the data and find useful competitive data.[8][9][29] By knowledge discovery in databases, interesting knowledge, regularities, or high-level information can be extracted from the relevant sets of data in databases and be investigated from different angles, [40] and large databases thereby serve as rich and reliable sources for knowledge generation and verification.

1.3 Basics

Two main parts of financial analysis are:
1. Fundamental analysis
2. Technical analysis

1.3.1 Fundamental Analysis:

This is done specially by professional analysts who have taken degree in commerce field such as CA, CS, MBA in finance etc. This analysis based on financial data provided by company every quarter, which includes financial attributes such as growth forecast, PE ratio, dividend yield, upper and lower base line estimations, balance sheets etc. It also depends on the quality of management running the company. It needs updating very frequently and detailed analysis is required. [10][11] [28]

1.3.2 Technical analysis:

It is focused on past history of share performance, analyzed statistically through various formulas and indicators such as moving averages (MA). It emphasize on predicting the trend of stock and make use of competitive trading among institutes.

II. LITERATURE REVIEW

In previous chapter we discussed the basic concept of data mining. It is a general definition of data mining. Now a day's data mining has been extensively used in many fields, Such as banking and financial markets. In banking industry it is heavily used to model and predict credit fraud, to evaluate risk, to perform trend analysis, and to analyze profitability, as well as to help with direct marketing campaigns. [12]

In the financial markets, neural networks have been used in stock markets to analyze the trend, stock price forecasting, in option trading, in bond rating, in portfolio management, in commodity price prediction, in mergers and acquisitions, as well as in forecasting financial disasters. [12]

In this chapter we present small introduction on data mining and few research papers discussion on our subject. Most papers are based on application of neural network in stock market.

2.1 Definitions of Data mining by different Authors

Richard et al. [33] says that, Data mining is the process of employing one or more computer learning techniques to automatically analyze and extract data.

Edelstein et al. [34], states that data mining involves the use of sophisticated data analysis tools to discover previously unknown, valid patterns and relationships in large data sets.

Nitchi et al. [35] gives a simple definition considers the data mining as the process of extracting predictive information hidden in large datasets.

Mining information and knowledge from large database has been recognized by many researchers as a key research topic in database systems and machine learning. Companies in Many industries also take knowledge discovering as an important area with an opportunity of major revenue (Fayyad et al., 1996. Piatetsky-Shapiro et al. 1991, Silberschatz ET al.1995). The discovered knowledge can be applied to information management, query processing, decision making, process control, and many other applications.

2.2 Neural Network

It's a relatively new process of data mining in computing which is based on development of a system through the ability to learn and recognize patterns in a given set of data, which is very complex for any computer techniques to find and establish. Several elements are interconnected like neurons of brain which then provide a pattern which is useful in some sense.

Berry et al. [36], according to neural networks are the most widely used known and the least understood of the major data mining techniques. He says training a neural network is a process that involves setting weights on inputs to best approximate a target variable. This is important for optimizing the neural network. Three steps are involved in training. Training instance variables, calculating outputs using existing weights and calculating errors and accordingly adjusting weights.

Pyle et al. [37], describes neural networks as network construction network system of interconnected interacting weights at each node acting as input and output stations. Each input to the network gets its own node which consists of a transformation of input variables fed in. The input unit is connected to the output unit with a weighting and the input is combined in the output unit with a combination function. The activation function is the passed transfer function.

Singh et al., 2022, This study aims to advance and introduce a more rigorous neural network approach for predicting stock market trends. The present study presents a comprehensive examination of stock market forecasting using neural networks. The analysis of stock market forecast may be conducted using a wide range of machine learning techniques. This study investigates the buying and selling prices of stocks on the Bombay Stock Exchange (BSE) and analyses the provided data. To predict stock market trends, I used a comprehensive Long-Short-Term Memory Neural Network (LSTM) with an embedded layer and LSTM Neural Network. Applying deep LSTM with layers improves the experimental layout. The prediction technology demonstrates precise outcomes that provide exceptional financial gains. [41]

Liu et al., 2022, Forecasting stock market indices is an alluring subject. Conducting a thorough examination of this subject matter will provide significant insights for investors, traders, and policymakers involved in the attractive stock markets. This paper presents a novel sparrow search technique that aims to enhance the initial weight and threshold estimation of BPNN. The algorithm is specifically designed for the purpose of predicting stock market indices. This article primarily focuses on the following aspects: (1) The sine chaos model is used for population initialization. (2) The position update formula of the discoverer incorporates the global optimum solution from the preceding generation, together with adaptive weights to optimise the coordination between local mining and global exploration capabilities. In order to develop novel solutions, the Gaussian mutation operator and the reverse learning technique are used to perform perturbation mutation at the ideal point. In order to optimise the initial weight and threshold of the BP neural network, the improved sparrow algorithm (ISSA) is used. The suggested model's performance is assessed on four datasets, namely SSE, SZSE, SP500, and DJI. The suggested mode is contrasted with two kinds of models. One approach involves using swarm intelligence optimisation algorithms, such as GA-BP, PSO-BP, ACO-BP, GWO-BP, CS-BP, and SSA-BP, to optimise BPNN. The remaining models are classified as deep learning models. The empirical findings demonstrate that the three solutions put forward in this study significantly enhance the optimisation efficacy of the sparrow search algorithm. The ISSA-BP model has shown significant efficacy in the realm of short-term stock price prediction, therefore enabling investors to forecast market trends and identify optimal trading opportunities. Furthermore, policymakers may evaluate the rationale of policies by analysing market patterns, so enhancing the advancement of the stock market. [42]

Napitupulu et al., 2022, The worldwide COVID-19 outbreak has elicited widespread anxiety. Furthermore, it caused significant disruptions to global life and economic operations. Forecasting the stock market throughout the COVID-19 epidemic was a significant obstacle because to the non-stationary, unpredictable, and intricate nonlinear nature of the data. Therefore, it is essential to conduct a comprehensive examination of the aforementioned patterns in order to construct a suitable prognostic framework for forecasting the stock market within the pandemic. The objective of this project is to develop a stock market prediction model for the Indonesia Stock Exchange during the COVID-19 epidemic. The model uses a deep learning method that relies on artificial neural networks. This study focuses on the pharmaceutical business within the health sector that is publicly traded on the IDX. The factors being considered in this study include the suggested model for forecasting stock prices, which incorporates daily stock price fluctuations, as well as COVID-19 trend indicators and the government's reaction tightness index to COVID-19 in Indonesia. The research findings indicate that all suggested model systems have exceptional accuracy in predicting stock market prices, with a Mean Absolute Percentage Error (MAPE) of at least 10%. Among all the investigated models, Model 6-20-20-1 stands out as the most superior, with an MSE of 0.00055, RMSE of 0.007418, and MAPE of 1.17%. [43]

Sharma et al., 2022, Stock market forecasting often use both traditional statistical methods and artificial intelligence tools. The presence of nonlinearity in stock data might lead to inaccurate forecasting results when employing a conventional or single intelligent approach. Hence, it is essential to cultivate a fusion of intelligent methodologies in order to construct a proficient prediction model. This article presents a novel approach to forecasting by combining an Artificial Neural Network (ANN) with a Genetic Algorithm (GA). The proposed technique utilises two prominent US stock market indices, namely DOW30 and NASDAQ100, for the purpose of forecasting. The datasets were divided into three subsets: training, testing, and validation. The validation of the model was conducted using the stock data during the COVID-19 period. The experimental results obtained using the DOW30 and NASDAQ100 datasets demonstrate that the GA and ANN hybrid model outperforms the single ANN (BPANN) method in terms of accuracy for both the DOW30 and NASDAQ100, both in the short and long term. [44]

Srivinay et al., 2022, The volatility of stock prices may be attributed to several elements inherent in the stock market, including geopolitical tensions, corporate profits, and commodity prices, all of which have an influence on stock prices. Certain factors, such as reserve bank policy, government policy, inflation, and global market uncertainty, might influence stock prices. Estimating the volatility of stocks is a significant challenge for traders. A precise forecast of stock prices aids investors in mitigating the risk associated with their portfolios or investments. Equity prices exhibit nonlinearity. We suggest using a hybrid stock prediction model that combines the prediction rule ensembles (PRE) approach with deep neural network (DNN) to address the issue of nonlinearity in the data. The identification of an upward trend in stock prices is facilitated by the use of stock technical indicators. The moving average technical indicators that were taken into consideration are the moving average of 20 days, the moving average of 50 days, and the moving average of 200 days. Furthermore, the PRE approach was used to calculate many rules for stock prediction. Subsequently, the rules exhibiting the lowest root mean square error (RMSE) score were chosen. Furthermore, the three-layer deep neural network (DNN) is being used for stock prediction. The hyperparameters of the deep neural network (DNN) have been optimised, including the number of layers, learning rate, number of neurons, and number of epochs in the model. Furthermore, the PRE and DNN prediction models are aggregated to get the average results. The outcomes of the hybrid stock prediction model are calculated using the mean absolute error (MAE) and root mean square error (RMSE) metrics. The hybrid stock prediction model has superior performance compared to the individual prediction models, namely the DNN and ANN, exhibiting a 5% to 7% enhancement in the root mean square error (RMSE) score. The study takes into account the Indian stock price data. [45]

Manujakshi et al., 2022, The volatility of stock prices may be attributed to several elements inherent in the stock market, including geopolitical tensions, corporate profits, and commodity prices, all of which have an influence on stock prices. Certain factors, such as reserve bank policy, government policy, inflation, and global market uncertainty, might influence stock prices. Estimating the volatility of stocks is a significant challenge for traders. A precise forecast of stock prices aids investors in mitigating the risk associated with their portfolios or investments. Equity prices exhibit nonlinearity. We suggest using a hybrid stock prediction model that combines the prediction rule ensembles (PRE) approach with deep neural network (DNN) to address the issue of nonlinearity in the data. The identification of an upward trend in stock prices is facilitated by the use of stock technical indicators. The moving average technical indicators that were taken into consideration are the moving average of 20 days, the moving average of 50 days, and the moving average of 200 days. Furthermore, the PRE approach was used to calculate many rules for stock prediction. Subsequently, the rules exhibiting the lowest root mean square error (RMSE) score were chosen. Furthermore, the three-layer deep neural network (DNN) is being used for stock prediction. The hyperparameters of the deep neural network (DNN) have been optimised, including the number of layers, learning rate, number of neurons, and number of epochs in the model. Furthermore, the PRE and DNN prediction models are aggregated to get the average results. The outcomes of the hybrid stock prediction model are calculated using the mean absolute error (MAE) and root mean square error (RMSE) metrics. The hybrid stock prediction model has superior performance compared to the individual prediction models, namely the DNN and ANN, exhibiting a 5% to 7% enhancement in the root mean square error (RMSE) score. The study takes into account the Indian stock price data. [46]

Sako et al., 2022, The forecasting of financial and economic time series has historically posed challenges because to its susceptibility to political, economic, and social influences. Due to this rationale, individuals engaged in financial market investments and currency exchange often seek resilient models that can effectively optimise their portfolio and mitigate potential losses. Recent research have shown that Recurrent Neural Networks (RNNs), a specific form of Artificial Neural Networks (ANNs), might enhance the prediction accuracy of financial data over time. The objective of this study is to predict the closing prices of eight stock market indexes and six foreign exchange rates associated with the USD. This will be achieved by using the Recurrent Neural Networks (RNNs) model, namely the Long Short-Term Memory (LSTM) and the Gated Recurrent Unit (GRU) variations. The findings indicate that the GRU model yields superior outcomes, particularly in the context of univariate out-of-sample forecasting for currency exchange rates and multivariate out-of-sample forecasting for stock market indexes. [47]

Li et al., 2022, The examination of forecasting stock market volatility has considerable importance in effectively managing financial market risks and maximising investment returns. This subject has garnered substantial interest from both academic and business spheres. Nevertheless, due to its dynamic and intricate nature, the stock market is subject to the influence of many causes and has a complete capacity to incorporate intricate financial information. The analysis and processing of multi-source heterogeneous data in the stock market pose significant constraints for present intelligent algorithms due to the various, heterogeneous, and complicated nature of the explanatory variables of influencing factors. Hence, this research employs the edge weight and information transmission mechanism that is well-suited for subgraph data in order to thoroughly screen nodes. Additionally, the gate recurrent unit (GRU) and long short-term memory (LSTM) are used to combine subgraph nodes. The collected data includes the metapaths of three categories of index data, and the incorporation of the association relationship attention dimension efficiently extracts the underlying meanings of diverse data from several sources. The integration of the metapath attention mechanism with a graph neural network enables the comprehensive categorization of diverse graph data from several sources. This integration facilitates the prediction of stock market volatility. The findings indicate that the aforementioned approach is viable for integrating diverse stock market data and extracting implicit semantic information related to association relationships. The suggested technique in this research demonstrates a 16.64% increase in accuracy compared to the dimensional reduction index and a 14.48% increase compared to other methods used for fusion and prediction of heterogeneous data using the same model. [48]

Li and Qian, 2022, Forecasting stock prices is essential but also difficult in any stock market trading strategy. Presently, the use of recurrent neural networks (RNNs) has become prevalent in the field of stock prediction, yielding several notable achievements. Nevertheless, challenges persist in enhancing the efficacy of RNNs in a complex stock market. RNNs are insufficient in extracting distinctive characteristics from a multitude of signals in the flow of stock information. Furthermore, while using RNN, a solitary long time cell from the market is often combined into a solitary feature, resulting in the loss of crucial temporal information necessary for accurate stock prediction. In this study, we propose a new hybrid neural network called the frequency decomposition induced gate recurrent unit (GRU) transformer, also known as FDGRU-transformer or FDG-trans, to address these two problems. In FDG-transformer, we use empirical model decomposition to break down the whole ensemble of cluttered data into a trend component and many informative and independent mode components, drawing inspiration from the success of frequency decomposition. With the use of decomposition, the FDG-transformer has the capability to extract distinctive insights from signals that are crowded. The FDG-transformer employs a hybrid neural network consisting of GRU, long short term memory (LSTM), and multi-head attention (MHA) transformers to preserve the temporal information in the observed jumbled data. The integrated

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
***Article Received:** 25 April 2023 **Revised:** 12 June 2023 **Accepted:** 30 July 2023*

transformer network may encode the influence of various weights from previous time steps to the present one, leading to the creation of a higher-level time series model. We use the created FDG-transformer model to analyse Limit Order Book data and conduct a comparative analysis with the outcomes acquired from other contemporary methodologies. The comparative analysis demonstrates that our algorithm efficiently provides accurate price forecasts. Furthermore, a comprehensive ablation investigation is undertaken to substantiate the significance and indispensability of every constituent inside the suggested model. [49]

2.3 Previous Work in the field

Nhamo Mdzingw et al, [30] focused on data or turning data into information by a process requiring a unique combination of tools for each application. He tries to adhoc methodology nearly used data mining in the commercial world mainly focusing and the data mining process and data mining algorithms used. It will also include a brief description of the Oracle data mining tool.

Boris kovalerchuck et al, [31] describes data mining in finance by discussing financial tasks, specifies methods and techniques in data mining field. in the first part of thesis they includes time dependence, data selection ,forecast horizon, measures of success, quality of patterns hypothesis evaluation, problem id, method profile, attribute based and relational methodologies. In the second part of the thesis discusses data mining modals and practice in finance. It covers use of neural networks in use of portfolio management, design of interpretable trading and discovering money laundering schema using decision rules and relational data mining methods.

Selv Nhamo Mdzingw et al, an Simon et al [20], suggested an ANN (artificial neural network) model for the prediction in stock market. They have used the basic 3 steps of neural network viz input layer, middle or hidden layer and final or output layer. [14] The middle layer consists of many statistical methods and formulas. It's hidden because it processes the information passed from the 1st layer in many steps and result is shown to user. Authors also compared many different techniques for stock market prediction like RNN, MLP,BNPP etc and emphasized that better results can be obtained when these techniques are used with association with their ANN model for prediction of stock market.

Monica Tirea et al, [21] proposed a Multi-Agent Stock Trading Algorithm Model which uses both fundamental and technical analysis simultaneously. It basically works for investors and not trades who trade frequently.

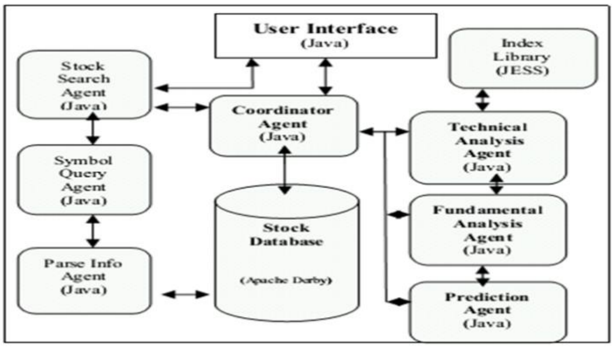

Figure 1. Multi-Agent System Architecture

It also consists of a future signal prediction for X % change in a stock price so to make predictions easy. Many efforts are made to combine fundamental and technical analysis and this MASA provides a good model which enhances all stock related data and information at one go for an investor to outperform stock market through choosing active and directional stocks with proper exits.

K. Senthamarai Kannan et al [22], on the other hand only took technical analysis as the base of their BSRCTB algorithm and connected all different statistical indicators to outperform the stock and simple individual indicator returns. In BSRCTB algorithm, they combined Typical Price (TP), Bollinger Bands, Relative Strength Index (RSI), CMI and Moving Average (MA). TP is calculated by averaging the previous day's open, high and low. [19] This algorithm beats the markets n absolute terms and according to authors, it can be used for trading analysis and is good for swing traders.

Savinderjit Kaur et al [23], in their article on application of data mining conclude that there is a need to more automation of systems and new hybrid systems should be worked on. They also states that Data mining has been used in stock market to make predictions regarding trends and prices to gain maximum profits. A lot of research has been carried out on its various aspects. [15] There is still room for improving accuracy of these prediction methods by developing new hybrid methods and by improving the existing algorithms. More research can be done in detecting trends in the stock market like studying the abnormal stock returns, trends preceding and following executive stock options awards, book-to-market effect, bubble diagnosis, inter industry patterns etc.

Author, focused on effectiveness of technical analysis and Dow's theory, for this they use the daily data of three stock market: DJIA, HIS, Taiwan stock market for the technical analysis. In this paper mostly they are using buy and hold trading strategy. [16] In this paper he proposed a DBN model to predict Taiwan stock market. [24]

Robert P. Schumacher et al [25], experimented using several linguistic textual representations, including Bag of Words, Noun Phrases, and Named Entities approaches. He believe that using textual representations other than the de facto standard Bag of Words will yield improved predictability results. [17] They also used many Stock Market prediction taxonomy of the various machine learning techniques such as

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
***Article Received:** 25 April 2023 **Revised:** 12 June 2023 **Accepted:** 30 July 2023*

genetic algorithm, Naïve Bayesian technique, SVM (support vector machine).
S. Abdulsalam Suleiman et al, [26] presented regression analysis as a data mining technique and developed tool for exploiting especially time series data in financial institution. A prediction system has been built that uses data mining technique to produce periodically forecasts about stock market prices his technique complement proven numeric forecasting method using regression analysis with technology taking as input the financial information.
Ayo Charles K. et al [27], identifies that stock market prediction is one of the most important issue now a days. so In this paper, author present a hybridized approach which combines the use of the variables of technical and fundamental analysis of stock market indicators for prediction of future price of stock in order to improve on the existing approaches with the help of Ann technique. The hybridized approach was tested with published stock data and the results obtained showed remarkable improvement over the use of only technical analysis variables. [18] Also, the prediction from hybridized approach was found satisfactorily adequate as a guide for traders and investors in making qualitative decisions.

III. TECHNICAL PARAMETER STUDIED

Our system is totally based on analysis of technical parameters and there are vast numbers of technical parameters available with different properties. We checked following technical indicators with both preceding and lagging properties and oscillators but considered only those which gave proper results with less number of whipsaws and stoploss limits and got in tune with swing trading system. Here, we are giving record of those technical parameters which e studied but not used.
The most widely used technical indicators are as follows.

3.1 Bollinger Band

A band plotted two standard deviations away from a simple moving average, developed by famous technical trader John Bollinger.

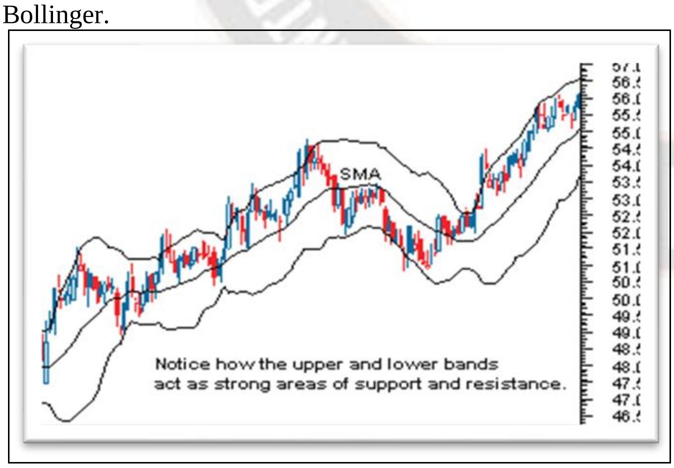

Figure 2. Bollinger Bands

In this example of Bollinger Bands, the price of the stock is banded by an upper and lower band along with a 21-day simple moving average. Because standard deviation is a measure of volatility, Bollinger Bands adjust themselves to the market conditions. When the markets become more volatile, the bands widen (move further away from the average), and during less volatile periods, the bands contract (move closer to the average). The tightening of the bands is often used by technical traders as an early indication that the volatility is about to increase sharply. The closer the prices move to the upper band, the more overbought the market, and the closer the prices move to the lower band, the more oversold the market.

3.2 Stochastic

A technical momentum indicator that compares a security's closing price to its price range over a given time period. The oscillator's sensitivity to market movements can be reduced by adjusting the time period or by taking a moving average of the result. This indicator is calculated with the following formula:
%K = 100[(C - L14)/(H14 - L14)]

C = the most recent closing price
L14 = the low of the 14 previous trading sessions
H14 = the highest price traded during the same 14-day period.

%D = 3-period moving average of %K

Figure 3. Stochastic

The theory behind this indicator is that in an upward-trending market, prices tend to close near their high, and during a downward-trending market, prices tend to close near their low. Transaction signals occur when the %K crosses through a three-period moving average called the"%D".

1) 3.3 RSI (Relative strength index)

A technical momentum indicator that compares the magnitude of recent gains to recent losses in an attempt to determine overbought and oversold conditions of an asset. It is calculated using the following formula:

RSI = 100 - 100/ (1 + RS*)

*Where RS = Average of x days' up closes / Average of x days' down closes.

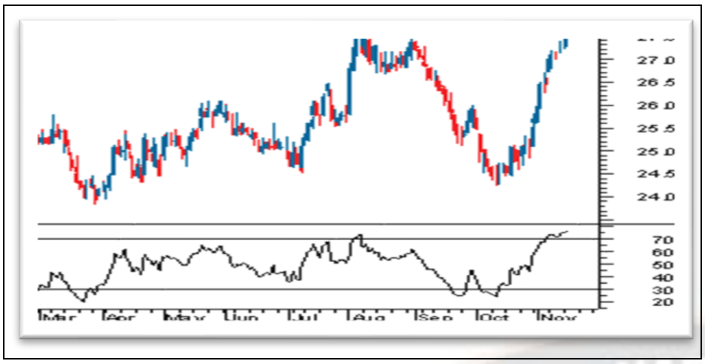

Figure 4 . RSI (Relative strength index)

As shown in the chart, the RSI ranges from 0 to 100. An asset is deemed to be overbought once the RSI approaches the 70 level, meaning that it may be getting overvalued and is a good candidate for a pullback. Likewise, if the RSI approaches 30, it is an indication that the asset may be getting oversold and therefore likely to become undervalued.

A trader using RSI should be aware that large surges and drops in the price of an asset will affect the RSI by creating false buy or sell signals. The RSI is best used as a valuable complement to other stock-picking tools.

3.4 ADX (Average Directional Index)

An indicator used in technical analysis as an objective value for the strength of trend. ADX is non-directional so it will quantify a trend's strength regardless of whether it is up or down. ADX is usually plotted in a chart window along with two lines known as the DMI (Directional Movement Indicators). ADX is derived from the relationship of the DMI lines. Analysis of ADX is a method of evaluating trend and can help traders to choose the strongest trends and also how to let profits run when the trend is strong.

Figure 5. ADX

3.5. SAR (Stop-and-Reverse)

A technical analysis strategy that uses a trailing stop and reverse method called "SAR," or stop-and-reversal, to determine good exit and entry points.

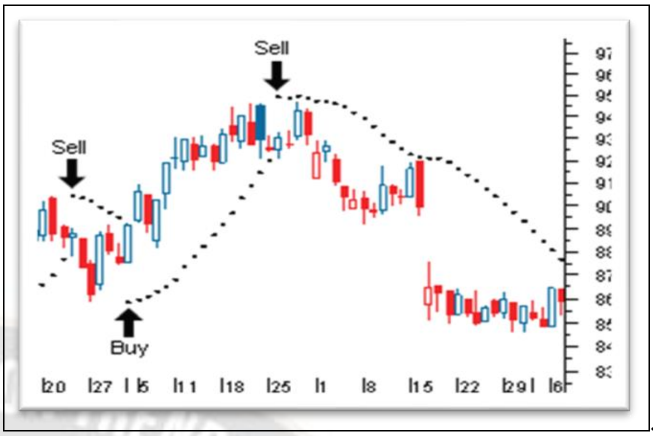

Figure 6. Parabolic SAR (Stop and Reverse)

This method was developed by J. Wells Wilder. Basically, if the stock is trading below the parabolic SAR (PSAR) you should sell. If the stock price is above the SAR then you should buy (or stay long).

3.6 William's %R

In technical analysis, this is a momentum indicator measuring overbought and oversold levels, similar to a stochastic oscillator. It was developed by Larry Williams and compares a stock's close to the high-low range over a certain period of time, usually 14 days.

Figure 7. William's %R

It is used to determine market entry and exit points. The Williams %R produces values from 0 to -100, a reading over 80 usually indicates a stock is oversold, while readings below 20 suggests a stock is overbought.

3.7 Candle Stick

The Japanese began using technical analysis to trade rice in the 17th century. While this early version of technical analysis was different from the US version initiated by Charles Dow around 1900, many of the guiding principles were very similar:

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
***Article Received:** 25 April 2023 **Revised:** 12 June 2023 **Accepted:** 30 July 2023*

1. The "what" (price action) is more important than the "why" (news, earnings, and so on).
2. All known information is reflected in the price.
3. Buyers and sellers move markets based on expectations and emotions (fear and greed).
4. Markets fluctuate.
5. The actual price may not reflect the underlying value.

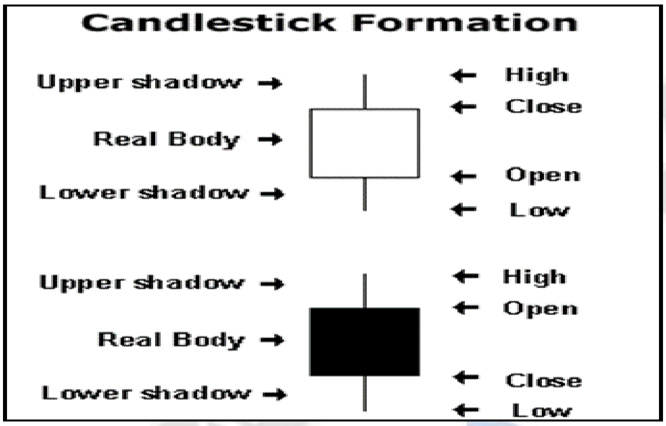

Figure 8. Candlestick Formation

Candlestick charting first appeared sometime after 1850. Much of the credit for candlestick development and charting goes to a legendary rice trader named Homma from the town of Sakata. It is likely that his original ideas were modified and refined over many years of trading eventually resulting in the system of candlestick charting that we use today.

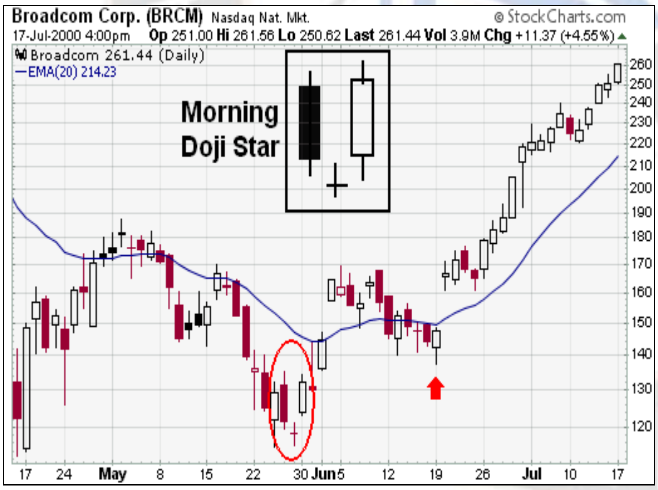

Figure 9. Candlestick Pattern - Morning Doji Star

Here given an example of a famous bullish pattern called as Morning Doji Star, which consists of 3 candles. This pattern is an indication of a trend reversal from bearish to bullish. The opposite of this pattern is called as Evening Doji Star which acts as a trend reversal from bullish to bearish.

Here are some examples of famous patterns of candlesticks: Bullish Engulfing, Bearish Engulfing, Bullish Harami, Bearish Harami, Hammer, Hanging Man, Inverted Hammer, Shooting Star, Morning Star, Piercing Pattern, Dark Cloud Cover, Three White Soldiers, Three Black Crows etc.

3.8 Trend Lines

Technical analysis is built on the assumption that prices trend. Trend Lines are an important tool in technical analysis for both trend identification and confirmation. A trend line is a straight line that connects two or more price points and then extends into the future to act as a line of support or resistance. Many of the principles applicable to support and resistance levels can be applied to trend lines as well.

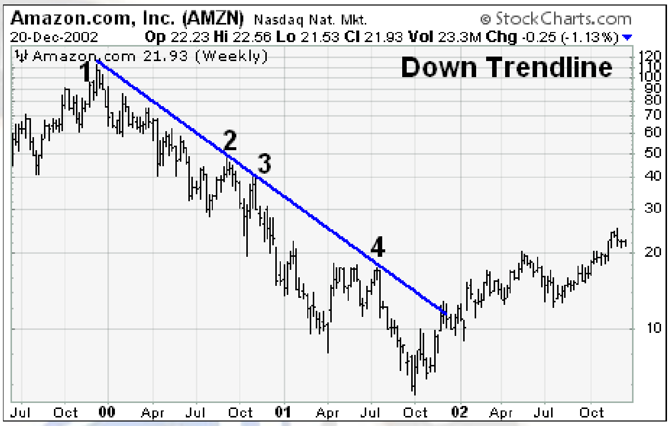

Figure 10. Trend Line

Trend lines can offer great insight, but if used improperly, they can also produce false signals. Other items - such as horizontal support and resistance levels or peak-and-trough analysis - should be employed to validate trend line breaks. While trend lines have become a very popular aspect of technical analysis, they are merely one tool for establishing, analyzing, and confirming a trend. Trend lines should not be the final arbiter, but should serve merely as a warning that a change in trend may be imminent. By using trend line breaks for warnings, investors and traders can pay closer attention to other confirming signals for a potential change in trend.

IV. QUANTITATIVE TRADING

Quantitative trading is methodology employing advanced statistical techniques to make trading decision which can be traded either manually or electronically. With advancement in computing power, it is advantageous to implement such back-tested strategies as algorithmic trading which removes chances of human error significantly. The frequency of trade can be high or low as per the strategy.

Quantitative investing represents an investing technique typically employed by the most sophisticated, technically advanced hedge funds. These quant shops employ fast computers to find predictable patterns within financial data.

4.1 Overview on Algorithmic Trading

Automated or Algorithmic trading is using computers to generate trading signals, sending orders and managing portfolio using algorithms with or without human initiation. Sophisticated electronic markets/platforms are used by the algorithms to trade in the similar fashion as done in electronic trading. The difference is that in algorithmic trading decisions about volume or size, timing and price are determined by the algorithm. Furthermore, algorithmic trading efficiently increases the universe being traded by an individual trader which is limited in electronic trading environment.

Automated or algorithmic trading is a system for trading through programmed software that can make around 800 transactions per second. The software-helped trading was allowed by Bombay Stock Exchange (BSE) and National Stock Exchange (NSE) in 2005.
A third of all European Union and United States stock trades in 2006 were driven by automatic programs, or algorithms, according to Boston-based financial services industry research and consulting firm Aite Group. As of 2009, HFT firms account for 73% of all US equity trading volume.

High-Frequency Trading (HFT):
It is a special category of algorithmic trading characterized by unusually brief position-holding periods, low-latency response times, and high trading volumes in a day. Algorithms are written so as to exploit trading opportunities which appear in very brief time periods as short as milli- or micro- seconds. The margin of each trade is small, which is compensated by fast speed and large volumes.

4.2 Stock Market History

A Brief History of Indian Stock Market (BSE and NSE) :

In 1957, it became the first stock exchange to be recognized by the Indian Government under the Securities Contracts Regulation Act.
It is the oldest stock exchange in Asia (established in 1875) and is currently located on Dalal Street, Mumbai.

- It is the 6th largest stock exchange in Asia and the 14th largest in the world with equity market capitalization of US$1 trillion as of December 2011.
- It has also introduced the world's first centralized exchange-based internet trading system, BSEWEBx.co.in to enable investors anywhere in the world to trade on the BSE platform.
- There are over 5,112 listed Indian companies and over 8,196 scripts on this exchange as of December 2011.

Bombay Stock Exchange (BSE) - Introduction, Facts & Major Evolutions :

- BSE launched **SENSEX** (**BSE 30**), a free-float market Capitalization-weighted stock market index on January 2, 1986, with a base value 100 and base year 1978-1979.
- The SENSEX consists of 30 well-established and financially sound companies listed on BSE Limited. These Companies represents various industrial sectors of the Indian economy.
- The market capitalization of the SENSEX was about Rs. 29,275 billion while its free-float market capitalization was Rs.14,660 billion as of April,2012.
- In January 1989, BSE National Index was introduced, which was renamed as BSE-100 Index from October 14, 1996 and launched its dollar-linked version on May 22, 2006.
- On July 25, 1990, the SENSEX touched the four-digit figure for the first time and closed at 1,001.
- SEBI was formed officially by the Government of India in 1992 with SEBI Act 1992 being passed by the Parliament of India.
- On 27 May 1994, BSE launched two new index series: The 'BSE-200' and the 'DOLLEX-200'.
- In 1995, the BSE switched to an automated, screen-based trading platform called BSE On-line trading (BOLT), which at present has a capacity of 8 million orders per day. In 1997, the BOLT system expanded nation-wide.
- BSE-500 Index and 5 sectorial indices were launched in 1999.
- In 2001, BSE launched BSE-PSU Index, DOLLEX-30 and the country's first free-float based index - the BSE TECk Index.
- The index calculation for the SENSEX was shifted from the ‘full market capitalization’ method to the ‘free float method’ on Sep 1, 2003. Over the years, BSE shifted all its indices to the free-float methodology (except BSE-PSU index).
- On June 20, 2005, the news of the settlement between the Ambani Brothers helped the SENSEX crossed 7,000 points for the first time.
- On 17th May 2004, second biggest fall of all time, Circuit filters used twice in a day (564.71 points, 11.14%).
- In 2005, the BSE (Corporatization and Demutualization) Scheme, 2005 was introduced by SEBI and the exchange turned into a corporate entity renamed as Bombay Stock Exchange Limited from Bombay Stock Exchange.
- On February 7, 2006, the SENSEX closed above the 10,000-mark.
- On March 7, 2007, Singapore Exchange Limited entered into an agreement to invest in a 5% stake in BSE Limited.
- Due to effects of the Subprime crisis in the U.S and heavy selling in the international markets, the BSE SENSEX fell by 615 points in a single day on Wednesday August 1, 2007.
- On Jan 08, 2008, The SENSEX touched all time peak of 21078 before closing at 20873.
- The World Council of Corporate Governance has awarded the Golden Peacock Global CSR Award for BSE's initiatives in Corporate Social Responsibility (CSR).
- On May 18, 2009, the SENSEX surged 2110.79 points from the previous closing. This event created history in Dalal Street, by being the first ever time that trade had been suspended for an increase in value. This rally is primarily due to the victory of the UPA in the 15th General elections.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
***Article Received:** 25 April 2023 **Revised:** 12 June 2023 **Accepted:** 30 July 2023*

National Stock Exchange Limited (NSE) - Introduction, Facts & Major Evolutions :

- It was incorporated in November 1992 as a tax-paying company and in April 1993, it was recognized as a stock exchange under the Securities Contracts Regulation Act, 1956.
- *It is the 16th largest stock exchange in the world and largest in India by daily turnover and number of trades, for both equities and derivative trading.*
- As of December 2011, it has a market capitalization of around US$985 billion.
- It is the second fastest growing stock exchange in the world with a recorded growth of 16.6% and over 1,640 listings as of December 2011.
- It is the third largest Stock Exchange in the world in terms of the number of trades in equities.
- In 1994, Wholesale Debt Market segment Capital Market (Equities) segment goes live.
- In 1995, the NSE established Investor Grievance Cell, NSCCL (the first Clearing Corporation), and Investor Protection Fund.
- In 1996, the NSE launched **S**&P CNX Nifty (Nifty 50), a stock market index owned and managed by India Index Services and Products Nifty 50 is the largest single financial product in India, with an ecosystem comprising: exchange traded funds (onshore and offshore), exchange-traded futures and options, other index funds and OTC derivatives (mostly offshore).
- From June 26, 2009, the computation for calculating Nifty Index was changed to free float methodology from full market capitalization methodology.
- The base period for the S&P CNX Nifty index is November 3, 1995. The base value of the index has been set at 1000, and a base capital of Rs 2.06 trillion.
- In December 1996, CNX Nifty Junior was launched. It consists of 50 companies representing approximately 10% of the traded value of all stocks on the NSE. The CNX Nifty Junior is owned and operated by India Index Services and Products Ltd.
- In June 2005, Futures & options in BANK Nifty Index were launched on National Stock Exchange.
- In 2007, the NSE launched derivatives on Nifty Junior & CNX 100 and derivatives on Nifty Midcap 50.
- In August 2009, Interest Rate Futures was launched on this Exchange.
- *The NSE controls more than 90 percent of India's $28 billion equity derivatives market and handles 75 percent of the stock trades.*

4.3 Introduction to Swing Trading

Swing Trading takes advantage of brief price swings in strongly trending stocks to ride the momentum in the direction of the trend. [37]

1 Swing trading combines the best of two worlds -- the slower pace of investing and the increased potential gains of day trading.

2 Swing traders hold stocks for days or weeks playing the general upward or downward trends.

3 Swing Trading is not high-speed day trading. Some people call it momentum investing, because you only hold positions that are making major moves.

4 By rolling your money over rapidly through short term gains you can quickly build up your equity.

4.5 Proposed Methodology

As said above, this system tries to be simple as well as effective, so common and simple technical indicators are used here from a wide variety. We studied EMA, their crossovers, RSI, MACD, ADX, SAR, Candlestick Patterns, Trend Lines etc. After working on various combinations we tried to find out the main link which provides maximum coverage of conditions occurring in stock market. The few main aspects, we found necessary for a trading strategy are as follows:

1. Selection of Time Frame.
2. Indicator Spotting Right Market Direction.
3. Strength in Signal.
4. Using the Signals to their Full Capacity.
5. Removing Low Probability Trades.

4.5.1 Selection of Time Frame

We tried different time frames in our analysis which were, hourly, 3 hourly, daily and weekly. Hourly were too volatile and weekly was untradeable in our selected indicators. So after selecting daily close as time interval for our trades, we optimized other indicators in accordance to it.

4.5.2 Indicator Spotting Right Market Direction

On daily basis the use of ADX indicator helped in a lot to decide market direction in near term. It also showed the maturity of trade position and also kept the whipsaws to minimum ADX have 3 lines viz positive green line, negative red line and calculate ADX third line.
When green line is above red and ADX is above 20, it's an indication of start of a positive trade. If red is above green line and ADX is above 20 it's a short trade and markets/stocks are weak. Below ADX less than 20, there is no direction present in market and hence they should be avoided. ADX considers 14 days as it defaults value.
In our trading system, we optimized it and changed it from 14 to 8 days and it enhanced the results. As we reduced the default time frame, and the traded instrument is index futures and not stock, we also made changed in the base line of ADX (8) and changed it to 16. Below 16 we considered not to trade and above 40, the trade is considered fully matured and caution is exercised.

4.5.3 Strength in Signal

Generation of signal only after the trend is properly set by buying or shorting by bigger player in market. For e.g. FII, DII, FDI, LIC, Insurance companies, Mutual funds etc.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
***Article Received:** 25 April 2023 **Revised:** 12 June 2023 **Accepted:** 30 July 2023*

Any trend is followed by a consolidation phase which consists of profit booking and/or shorting activities. When a signal is generated it should be ensured that it is backed by the positions of bigger institutes like mentioned above. When there is a break point in the price and market comes out of consolidation phase, that breakout should be volume based, else there is a high probability that the breakout will result in a whipsaw. So until markets direction is set by position taken by bigger players, our system should not generate a buy or sell signal. We took proper note of this and EMAs in our system are selected accordingly.

4.5.4 Using the Signals to their Full Capacity

As we backtested our system in the range of April 2005 to march 2012, where we came across all the moods of nifty, we observed that there were 57% of successful trades and 43% of loss making trades. As this ratio is close so it was necessary to use a trailing stoploss instead of fixed price target or to step by step booking of profit by playing in multiple numbers. After different research methods we came across the idea to put stoploss of a trailing EMA for all trades. Benefit of a trailing stoploss is that, it triggers by itself and there is no need to pre-assume the price targets which involve human emotional interference. There are times when a trade goes long enough beyond the imagination of anyone. It can only be ridded by not fixing any target profit. Least the decision making of individual better will be the system. It's a market saying that 80% of profits come from only 20% of trades.

4.5.5 Removing Low Probability Trades

Like MACD we have also used crossover of EMAs. But not getting into complex calculation. We only took 2 EMAs, one for shorter period and second for bigger trend. We tried to use SAR (stop and reverse) strategy in market but found that buying in negative trend and shorting in positive trend does not give satisfactory result in long run. So we decided to trade only long trades by combinations of bigger EMA, Macd and ADX and to short only when trend is negative. This boosted our results.

4.6 Explanation of Technical Parameters Used

4.6.1 EMA (EXPONENTIAL MOVING AVERAGE)

A type of moving average that is similar to a simple moving average, except that more weight is given to the latest data. The exponential moving average is also known as "exponentially weighted moving average". Here's a chart with both an SMA and an EMA on it.

Figure 11. Chart for Exponential moving average

SMA: 10 period sum / 10
Multiplier: (2 / (Time periods + 1)) = (2 / (10 + 1)) = 0.1818 (18.18%)
EMA: {Close - EMA (previous day)} x multiplier + EMA (previous day).

A 10-period exponential moving average applies an 18.18% weighting to the most recent price. A 10-period EMA can also be called an 18.18% EMA. A 20-period EMA applies a 9.52% weighing to the most recent price (2/(20+1) = .0952). Notice that the weighting for the shorter time period is more than the weighting for the longer time period. In fact, the weighting drops by half every time the moving average period doubles.
The first parameter we selected is the most popular and commonly used in high grade trading strategies, EMA. [32] The Exponential Moving Average (EMA) weighs current prices more heavily than past prices. This gives the Exponential Moving Average the advantage of being **quicker to respond to price fluctuations** than a Simple Moving Average; however, they are **more prone to whipsaws too**. This was the main reason to select EMA before MA.

Formula:
EMA = Price (t) * k + EMA (y) * (1 – k)
Where t = today, y = yesterday, N = number of days in EMA, k = 2/(N+1)

4.6.2 EMA Combination

Two different EMA's were taken as a combination. They are the shorter -EMA (8), and the longer EMA (34).
Reason for choosing 8 and 34 ema is that 8 ema covers approx 1.5 weeks trading days and 34 ema covers 1.5 month. So it's a combination of weekly and monthly emas. They are specially optimized for trading the swing for index futures. These two parameters are widely used by day-traders and acts as strong support and resistance to price movements in index.
The strategy includes the exemption of trades which lies between these two ema lines. The shorter ema reacts to faster movements in index while the bigger decides the upward or downward bias of index. All trades going against the trend are skipped. Emas are combined because they give a slow entry

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
***Article Received:** 25 April 2023 **Revised:** 12 June 2023 **Accepted:** 30 July 2023*

and hence useful in avoiding the volatile times and also it waits for a trend to ripe.

4.6.3 ADX (Average directional index)

An indicator used in technical analysis as an objective value for the strength of trend. ADX is non-directional so it will quantify a trend's strength regardless of whether it is up or down. ADX is usually plotted in a chart window along with two lines known as the DMI (Directional Movement Indicators). ADX is derived from the relationship of the DMI lines. Analysis of ADX is a method of evaluating trend and can help traders to choose the strongest trends and also how to let profits run when the trend is strong.

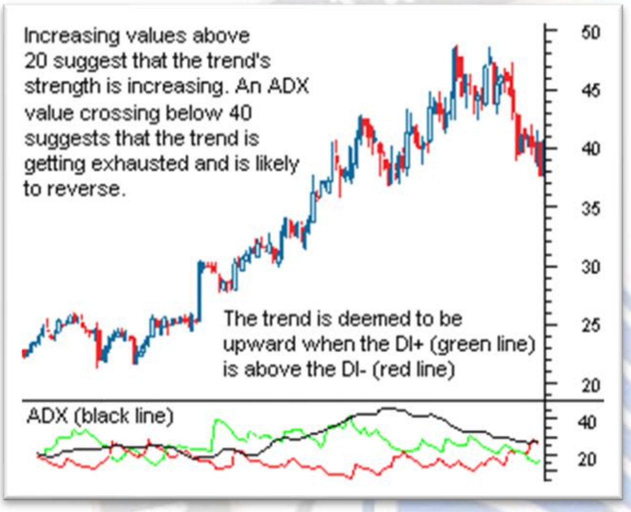

Figure 12. ADX

Reason for using beside other indicator is that there are times in market they are directionless. The combination of Emas used above fails in those conditions and put a series of whipsaws (false signals) which cannot be traded through them. For this, we needed an indicator which gives the information of direction of market. ADX does this well and the use of it kept the strategy back on track by keeping out the trader from entering into market.
We optimized ADX from its default parameter of 14 to 8 as per the need of the system.
ADX = modify moving average of DX

DX = 100 x [(+DI – (-DI)) / (+DI + (-DI))]

and

+DI = +DMn / TRn , -DI = -DM / TRn
+DM = Ht - Ht-1 , -DM = Lt - Lt-1
CL = Ct - Ct-1
TR = largest of +DM,-DM ,and CL.
Where

+DI	= current positive directional index	+DMn	= current modified moving average of +DM
-DI	= current negative directional index	+DM	= current positive directional movement value
Ht	= current high	Ht-1	= previous high
Lt	= current low	Lt-1	= previous low
-DMn	= current modified moving average of -DM	-DM	= current negative directional movement value
TRn	= current modified moving average of the true range	TRANSACTION	= true range
N	= number of periods	DX	= current DX

4.6.4 MACD (Moving average convergence and divergence)

A trend-following momentum indicator that shows the relationship between two moving averages of prices. The MACD is calculated by subtracting the 26-day exponential moving average (EMA) from the 12-day EMA. A nine-day EMA of the MACD, called the "signal line", is then plotted on top of the MACD, functioning as a trigger for buy and sell signals.
The default settings for the MACD indicator are (26,12 and 9)
Ema:

- Slow moving average - 26 days
- Fast moving average - 12 days
- MACD = 12 Day exponential moving average - 26 Day exponential moving average
- Signal line - 9 day moving average of the difference between fast and slow.
- All moving averages are exponential.

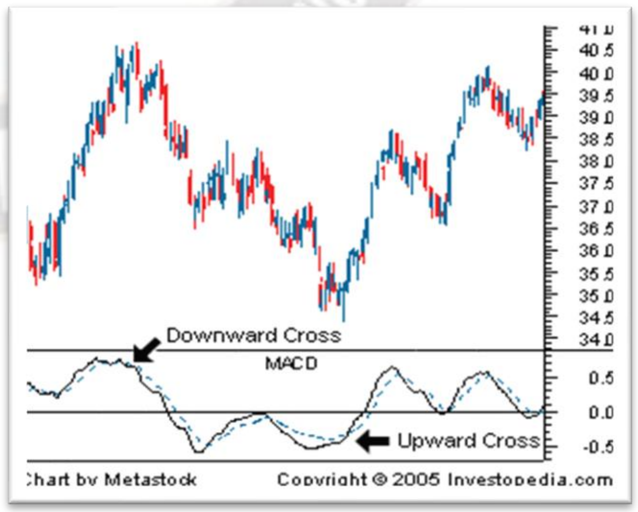

Figure 13. MACD

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
***Article Received:** 25 April 2023 **Revised:** 12 June 2023 **Accepted:** 30 July 2023*

4.7 Combining Trading Signals Using Neural Network

An Artificial Neural Network, often just called a neural network, is a mathematical model inspired by biological neural networks. A

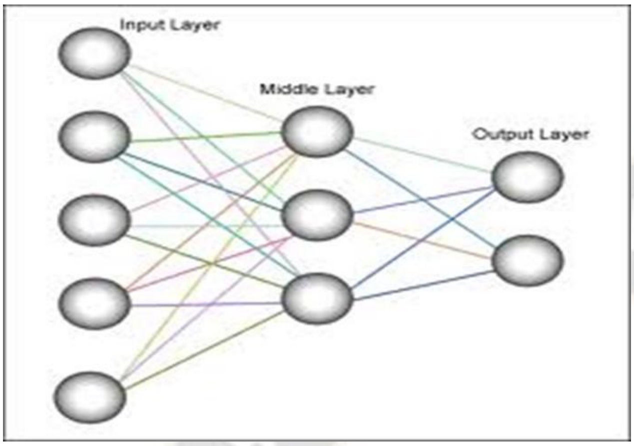

Figure 14. Neural Network

Neural network consists of an interconnected group of artificial neurons, and it processes information using a connectionist approach to computation. In most cases a neural network is an adaptive system that changes its structure during a learning phase. Neural networks are used to model complex relationships between inputs and outputs or to find patterns in data.

A trading strategy can consists of one or more signals. Individual results of technical parameters don't outperform a stock, and they have a unique way to give some indication about the stock. E.g. RSI (Relative strength index) gives a overbought indication when it's above 70, and oversold when below 30. But this doesn't mean that we won't need any other indicator and only RSI is sufficient. Individual results in backtesting RSI gave bad results, but it a well known and popular indicator. So combining different signals and trying to overcome one's weakness by other, led to the concept of automated trading strategy system.

$$\text{Signal} = \begin{cases} 1 = \text{if all signals return } 1 \\ 0 = \text{ if all signals return } 0 \\ 0.5 \text{ else} \end{cases}$$

4.8 Procedure and Algorithm of Proposed Methodology

1. Data of Index Future are collected from NSE Server 15 min before stock market closing and are taken as close of that day.
2. Data is updated into the trading signal generating software.(E.g. Amibroker, Ninja Trader etc.)
3. Positions are taken in last 5 min of market closing, if any signal/stoploss is generated.
4. All the stoplosses are considered as triggered only on the closing basis.
5. No positions are taken in between, if a trade is missed.

Algorithm:
Begin
Buy Signal :
If index close is above the bigger EMA, and
ADX is not showing consolidation phase, and
Macd is Positive.
Stoploss :

This buy trade will be kept open till the index close is above the shorter EMA, which acts as a trailing stop loss.

Triggering the stoploss, if index rises above the shorter EMA, again a buy is created.
Shorting Signal :
If index close is below bigger EMA, and
ADX not showing consolidation, and
Macd is Negative.
Stoploss :
This trade will be kept open till index closes above shorter EMA, which acts as a trailing stop loss
Triggering the stoploss, if index return below the shorter EMA, again a short is created.
Every positions stoploss is the shorter EMA.
If ADX value in any occurrence is showing a directionless value, the buy/short trade will be skipped.
If at any time, Macd or Adx is not supporting the signal, they will be waited for the attunement and then only a signal will be generated.
End.

V. RESULTS AND OBSERVATIONS

Figure 15 . A snapshot of our trading system with signals and technical parameters.

Explanation of our System's snapshot: The given chart is subdivided into 3 parts. The 1st part shows the Nifty movement with add-ons of 8 and 34 Emas. It also shows where the signals are generated and where their stoploss triggered. Signals are shown by arrows, green and red, and stoplosses are shown by green and red stars. The 2nd segment contains the Adx signal and 3rd shows the Macd indicator.

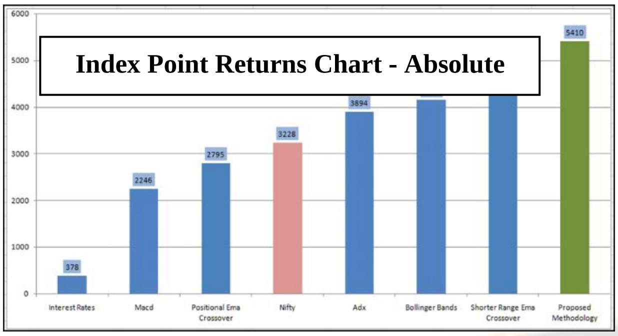

Figure 16. Index Point Returns Chart - Absolute

Observation: The following chart shows that our Proposed Methodology has outperformed all signals and indicators including Nifty. Nifty futures have a lot size of 50 shares, which can be taken as absolute return of any system trading on index futures. Absolute return of Nifty is 3228 points which is handsomely outperformed by our Proposed Methodology of 5410 points. ADX and Bollinger bands individually outperform Nifty with generating 3894 and 4151 points.

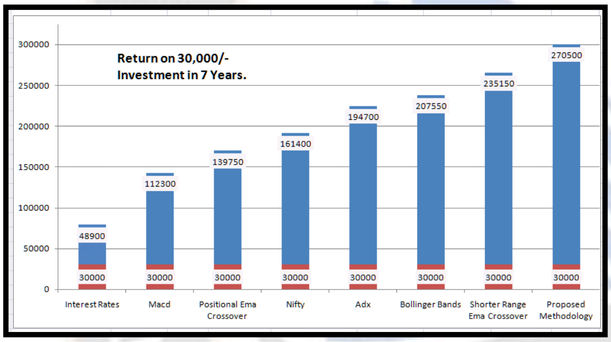

Figure 17. Return on Investment

Observation: Trading with Proposed Methodology generates a handsome returns of Rs 270500/- in 7 years on investment of Rs 30000/-. A maximum brokerage of Rs 15000/- can be considered. Short term capital tax implications are not considered. All technical parameters outperform FD (fixed deposit) interest rates with quite a margin.

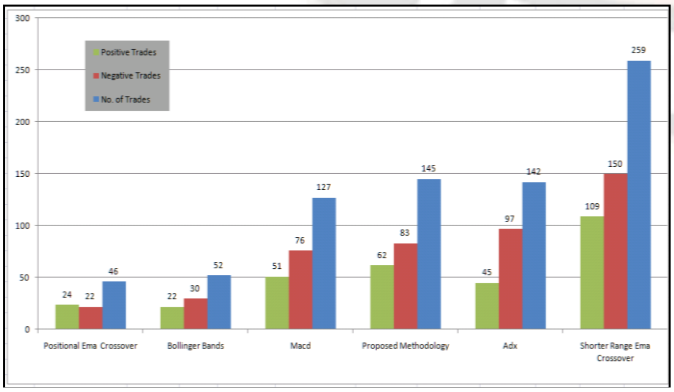

Figure 18. No. of Positive and Negative Trades

Observation: This chart explains about the number of positive and negative trade occurring in any strategy. A common observation is that, in most strategies, the negative trades are more than positive trades, which shows that all these strategies, works on the principle of taking small losses to generate big profits. They chose the higher probability trades through technical analysis.

Serial	File Name	Profit in Points	Total Trades	Negative Trades	Positive Trades	% Return	% Return per year	Return on 30000 Investment
1	**Interest Rates**					63.00%	9.00%	48900
2	**Macd**	2246	127	76	51	62.12%	8.87%	112300
3	**Positional Ema Crossover**	2795	46	22	24	65.98%	9.43%	139750
4	**Nifty**	3228	84			146.28%	20.90%	161400
5	**Adx**	3894	142	97	45	121.25%	17.32%	194700
6	**Bollinger Bands**	4151	52	30	22	113.62%	16.23%	207550
7	**Shorter Range Ema Crossover**	4703	259	150	109	115.96%	16.57%	235150
8	**Proposed Methodology**	5410	145	83	62	138.10%	19.73%	270500

Figure 19. Strategies and their performance

Observation and clarification:

This table gives all details of the schemes compared. The "% Return" column gives the absolute return from the schemes but they can't be compared because their bases are different. For example, the starting position of nifty index was near 2000 and at end it reached 5000, so for calculations, 2000 was taken as base for a single trade. As far as our Proposed Methodology is concerned, there are 145 trades of different bases. So "Profit in Points" column gives a better idea of the performance, where our methodology generated 5410 points as compared to 3228 generated by Nifty. So we conclude that our Proposed Methodology outperforms Base Index - Nifty.

VI. CONCLUSION & FUTURE SCOPE

The simulation result and observations in chapter 4 can be summarized as follows: Note that these observations are restricted to the scope of the project which is using Index Futures as trading instrument during the period of April 2005 to March 2012.

1. From all technical signals, Bollinger bands signal exhibited the highest annual return on investments.
2. Adx and Bollinger bands both outperformed the Nifty index but Macd could not. Proposed Methodology gave highest returns on the absolute index point return basis.
3. Number of negative trades mostly exceeds the positives trades in all strategies.
4. Automated trading shows better performance in long term as compared to hit and trail methods.
5. Volume of trading has increased significantly when SEBI permitted automated trading in India in 2005.
6. Combination of indicators results in better performance than individual indicators which are unidirectional in their approach.

Future Scope: This Proposed Methodology does not include the hedging strategies, and also it is not tested in "Nifty Options" which can reduce the loss generated in more than half of total trades. Future work could involve both these left aspects. The third main addition can be the inclusion of candlestick patterns. All these ideas are left for later versions of this Proposed Methodology.

REFERENCE

[1] M. C. Chan, H. C. Leung, and W. D. Luo, " Association mining system for financial ratios and stock prices in China and Hong Kong stock exchange" In A. Abraham, Y. Dote, T. Furuhashi, M. K¨oppen, A. Ohuchi, and Y. Ohsawa, editors, Soft Computing as Tran disciplinary Science and Technology, pages1151–1160. Springer Verlag Berlin Heidelberg, 2005.

[2] E. Fink and K. B. Pratt. Indexing of compressed time series. In M. Last, A. Kandel, and H. Bunke, editors, Data Mining in Time Series Databases, volume 57 of Machine Perception and Artificial Intelligence, pages 43–65. World Scientific, 2004.

[3] L. Lin, L. Cao, J.Wang, and C. Zhang. The applications of genetic algorithms in stock market data mining optimization. In Proceedings of Fifth International Conference on Data Mining, Text Mining and their Business Applications, pages 273–280, 2004

[4] L. Lin, D. Luo, and L. Liu. Mining domain-driven correlations in stock markets. In S. Zhang and R. Jarvis, editors, AI 2005: Advances in Artificial Intelligence: 18th Australian Joint Conference on Artificial Intelligence, pages 979–982,2005

[5] E. Fink and K. B. Pratt. Indexing of compressed time series. InM. Last, A. Kandel, and H. Bunke, editors, Data Mining in Time Series Databases, volume 57 of Machine Perception and Artificial Intelligence, pages 43–65. World Scientific, 2004[6] M. Kantardzic. Data Mining – Concepts, Models, Methods, and Algorithms. IEEE Press, Piscataway, NJ, USA, 2003.

[6] M. Kantardzic. Data Mining – Concepts, Models, Methods, and Algorithms. IEEE Press, Piscataway, NJ, USA, 2003.

[7] http://www.investopedia.com/active-trading/technical-indicators/#axzz25hOUjQ00

[8] John L. Person " A complete guide to technical trading tactics "

[9] Richard Dennis and William Eckhardt , " The original Turtle Trading Rules "

[10] http://en.wikipedia.org

[11] http://www.ino.com, "17 Money making candlestick patterns"

[12] http://thebestbusinessintheworld.blogspot.in/search?q=34+ema

[13] Nikhil Bakshi ETH Zurich Aug 2008, " Stock market prediction using online data : fundamental and technical approaches"

[14] Suhasini Subramanian Batch 2011, MSc Student of Economics and Finance Durham Business School, Ustinov College Durham University United Kingdom (UK), "The Impact of the Introduction of Index Futures on Volatility and Noise Trading "

[15] Http://www.informedtrades.com/f400/

[16] Darie Moldovan , Babes-Bolyal university of Cluj-Napoca Dec 2011 ,"Business intelligence – data mining in finance"

[17] Http://www.swing-trade-stocks.com/swing-trading-strategy.html

[18] Richi Nayak and Paul te Braak, Faculty of Information technology, Queensland university of technology, Brisbane, " Temporal Pattern matching for the prediction of stock prices "

[19] Http://stockcharts.com

[20] "Accuracy Driven Artificial Neural Networks in Stock market Prediction" Selvan Simon and Arun Raoot Asst. Professor, P. G. Dept. of Computer Sci., SNDT Women's University, Mumbai selvansimon@gmail.com Professor, National Institute of Industrial Engineering, Vihar Lake, Mumbai.

[21] Monica Tirea Computer Science Department West University of Timisoara Timisoara, Romania tirea.monica@info.uvt.ro, "Multi-Agent Stock Trading Algorithm Model". Loan Tandau Green Mountain Analytics Cary, North Carolina USA tandauioan@gmail.com and Viorel Negru Computer Science Department West University of Timisoara Timisoara, Romania vnegru@info.uvt.ro

[22] K. Senthamarai Kannan, P. Sailapathi Sekar, M. Mohamed Sathikand P. Arumugam, "Financial Stock Market Forecast using Data Mining Techniques"

[23] Savinderjit Kaur - Department of Information Technology, UIET,PU, Chandigarh, India and Veenu Mangat -Assistant Professor, department of Information Technology, UIET, PU, Chandigarh, India. "Applications of data mining in stock market "

[24] The empirical study of applying technical analysis on DJI , HSI and Taiwan stock market

[25] Robert P. Schumaker and Hsinchun Chen Artificial Intelligence Lab, Department of Management Information Systems The University of Arizona, Tucson, Arizona 85721, USA{rschumak, hchen}@eller.arizona.edu

[26] " Stock Trend Prediction Using Regression Analysis – A Data Mining Approach " S Abdulsalam Sulaiman Olaniyi, 2Adewole, Kayode S. , 3Jimoh, R. G 1Al-Hikmah University,Ilorin, Nigeria,2Kwara State University, Malete, Nigeria,3University of Ilorin,Ilorin, Nigeria.1sulepy@yahoo.com, 2Keystonetech09@yahoo.co.uk, 3Jimoh_rasheed@yahoo.com

[27] Ayo Charles K., 1Adebiyi Marion O., and 2Otokiti Sunday O. Stock Price Prediction using Neural Network with Hybridized Market Indicators 1 Adebiyi Ayodele A.,1Department of Computer and Information sciences, Covenant University, Ota, 2 Department of Business Studies, Covenant University, Ota, Nigeria Author: VOL. 3, NO. 1, January 2012 ISSN 2079-8407 Journal of Emerging Trends in Computing and Information Sciences.

[28] http://www.icharts.in/charts.html

[29] Arun K. Pujari, " Data Mining Techniques "

[30] Nhamo Mdzingwa Supervisor :John Ebden " Data Mining with Oracle 10g using Clustering and Classification Algorithms : 30 May2005 : Rhodes University COMPUTER SCIENCE HONOURS PROJECT

[31] Boris kovalerchuck central Washington University USA Evgenni Vityaev institute of mathematics, Russian academy of sciences, Russia : "Data mining for financial application"

[32] http://www.onlinetradingconcepts.com/TechnicalAnalysis/MAExponential.html

[33] Tutorial PPT by Richard J.Roiger, Michael Geatz. Data Mining: A Tutorial Based Primer

[34] Discovery of Patterns and evaluation of Clustering Algorithms in Social Network Data (Face book 100Universities) through Data Mining Techniques and Methods Edelstein, 1999) Nan cy.P1, Dr.R. Geetha Ramani2 1Ph.D Research

[35] Nitchi & Avram-Nitchi, 1997

[36] [Berry et al, 2000]

[37] [Pyle, 2000]

[38] http://www.tradersedgeindia.com/swing_trading.htm

[39] http://kalyan-city.blogspot.in/2010/11/what-is-stock-exchange-its-definitions.html

[40] Fayyad et al., 1996. Piatetsky-Shapiro et al. 1991, Silberschatz et al.1995

[41] Singh, A., Bhardwaj, G., Srivastava, A.P., Bindra, A. and Chaudhary, P., 2022, April. Application of neural network to technical analysis of stock market prediction. In 2022 3rd International Conference on Intelligent Engineering and Management (ICIEM) (pp. 302-306). IEEE.

[42] Liu, X., Guo, J., Wang, H. and Zhang, F., 2022. Prediction of stock market index based on ISSA-BP neural network. *Expert Systems with Applications*, *204*, p.117604.

[43] Napitupulu, H., Sambas, A., Murniati, A. and Kusumaningtyas, V.A., 2022. Artificial Neural Network-Based Machine Learning Approach to Stock Market Prediction Model on the Indonesia Stock Exchange During the COVID-19. *Engineering Letters*, *30*(3).

[44] Sharma, D.K., Hota, H.S., Brown, K. and Handa, R., 2022. Integration of genetic algorithm with artificial neural network for stock market forecasting. *International Journal of System Assurance Engineering and Management*, *13*(Suppl 2), pp.828-841.

[45] Srivinay, Manujakshi, B.C., Kabadi, M.G. and Naik, N., 2022. A hybrid stock price prediction model based on PRE and deep neural network. *Data*, *7*(5), p.51.

[46] Manujakshi, B.C., Kabadi, M.G. and Naik, N., 2022. A hybrid stock price prediction model based on pre and deep neural network. *Data*, *7*(5), p.51.

[47] Sako, K., Mpinda, B.N. and Rodrigues, P.C., 2022. Neural networks for financial time series forecasting. *Entropy*, *24*(5), p.657.

[48] Li, X., Wang, J., Tan, J., Ji, S. and Jia, H., 2022. A graph neural network-based stock forecasting method utilizing multi-source heterogeneous data fusion. *Multimedia tools and applications*, *81*(30), pp.43753-43775.

[49] Li, C. and Qian, G., 2022. Stock Price Prediction Using a Frequency Decomposition Based GRU Transformer Neural Network. *Applied Sciences*, *13*(1), p.222.