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Technical Analysis Based Prediction of Stock Market Trading Strategies Using Deep Learning and Machine Learning Algorithms

Nitin Nandkumar Sakhare[1], Dr. S. Sagar Imambi [2]

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Abstract: Stock market movement follows the random walk nature. The technical analysis incorporates the use of various technical indicators. Technical analysis is well suited for short term predictions. In this research work, Machine learning algorithms - Decision Tree, Support Vector Machine, Naïve Bayes and Deep Learning algorithms- Convolutional Neural Networks and Generative Adversarial Networks are used for the stock market prediction problem. Datasets of three companies- Maruti Suzuki, HDFC and Infosys belonging to Automobile, Banking and IT sector listed on National Stock Exchange (NSE) - Indian stock market over the period of 6 years (June 2014-June 2020) are considered. Performance of the above algorithms is measured in terms of how accurately they predict the stock movements. For the construction of learning models cross validation as well as training-testing percentage split are used. From the results, it is clear that deep learning algorithms show better prediction accuracy as compared to machine learning models.

Keywords: *Stock Market; Technical Analysis; Machine Learning; Deep Learning; Prediction*

1. Introduction

95% of all intraday traders fail. But no research paper exists that proves this number right. 80% of all intra-day investors quit inside the initial two years. Among all intra-day traders, about 40% intraday trade for just a single month. Inside three years, just 13% keep on and following five years, just 7% remain. Intraday trading is a type of trading in which stocks are bought and sold on the same day. In India, losses suffered by individual intra-day traders are around 2% of GDP. Stocks are bought and sold in large numbers strategically with the intention of booking profits in a day. Short term trading can be rewarding, yet it can likewise be dangerous. A momentary exchange can keep going for as insufficient as a couple of minutes to up to a few days. To prevail in this technique as a trader, you should comprehend the dangers and rewards of each exchange. You should not just realize how to spot great transient chances yet additionally how to secure yourself. According to World Bank 2019 statistics, the size of the world securities exchange (all-out market capitalization) is about US $79.225 trillion. By nation, the biggest market is the United States (about 34%), trailed by China (about 20%), Japan (about 6%) and the United Kingdom (about 6%). As per 2019 statistics, India contributes to $2.73 trillion in August 2019 with the aim of $5 trillion by 2024. Stock exchange implies the exchange (in return for cash) of a stock or security from a buyer to a seller. This requires buyers and sellers to concur on a price. The stock market trend can also be identified using the number of buyers and sellers. When there are more buyers than sellers' stock market trend is up and when there are more sellers than buyers' stock market trend is down. Organizations offer stocks so as to generate revenue for further horizontal as well as vertical development their organizations. Organization is said to be traded in an open stock market when it offers a part of ownership to public through shares. Stock prices of the company rise when it is performing nicely. But when company is not performing well stock prices fall. Stocks can be purchased and sold instantly and this exchange also impacts the price of the stock. When buying volume is greater than selling volume, stock price increases however when selling volume is greater than buying volume stock prices fall. Intraday trading is quite different from that of long term investments. Intraday trading requires different skills, understanding of technical analysis, personality as well. Swing trading is a type of trading which is mean of intraday trading and long term investments. In swing trading trades last for few days to few months. This paper tends to provide intraday trading strategies using machine learning and deep learning based technical analysis. The rest of the paper is organized as: section 2 contains details of literature review along with summary including methodology and gaps identified. Section 3 contains details of the datasets used for experimentation. Section 4 gives the brief overview of the approaches for developing the trading strategies. Section 5 briefs about the various machine learning and deep learning approaches to be used for technical analysis. Section 6 gives the detail description of experimental work and results. Section 7 contains conclusion of the experimental work along with future scope.

2. Literature Review

Since many years, various machine learning algorithms have been applied for the prediction of stock market trends. Popular machine learning algorithms used for the stock trend prediction problem are Decision Tree, Support Vector Machine, and Artificial Neural Network (Patel, Shah, Thakkar, & Kotecha, 2014a; Aldin, Dehnavi, & Entezari, 2012). Since stock price data is time-series

[1] *Research Scholar, Computer Science, and Engineering Department, Koneru Lakshmaiah Education Foundation*
Vaddeswaram, AP, India
ORCID ID: 0000-0002-1748-799X
[2] *Associate Professor, Computer Science, and Engineering Department Koneru Lakshmaiah Education Foundation*
Vaddeswaram, AP, India
ORCID ID: 0000-0003-0600-6959
** Corresponding Author Email: nitinsakhare4@gmail.com*

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data, many regression-based techniques like linear regression, polynomial regression also have been widely used (Sakhare & Shaik, 2019). Patel, Shah, Thakkar, & Kotecha, (2014a) used four prediction models, Artificial Neural Network, Support Vector Machine, Random Forest and Naïve Bayes. They had considered ten technical indicators for determining the trend of the stock movement. The evaluation was carried out on 10 years of historical data for two stocks namely Reliance industries, and Infosys Ltd. J. Patel, Shah, Thakkar, & Kotecha, (2015b) developed 2-stage fusion approach for prediction of stock movement for 1-10, 15 and 30 days in advance. They had used (t+n)th day's technical parameters to predict (t+n)th day closing price. Zhang, Cui, Xu, Li, & Li (2018) proposed a novel stock market prediction system using technical analysis with the machine learning approach. Wu & Diao (2015) performed the technical analysis using three oscillators based indicators- MACD, RSI and KDJ Rules in Shanghai and Shenzhen Stock Exchange. Sakhare & Shaik (2019) studied the prediction of stock movement using regression-based machine learning algorithms considering the time-series nature of the stock market data. They compared the performance of Linear Regression, Polynomial Regression, and Support Vector Regression in prediction. Shynkevich, McGinnity, Coleman, Belatreche, & Li (2017) used 10 technical indicators and set input window length as a time frame parameter to determine the prediction horizon. They concluded the highest prediction performance is observed when the input window length is approximately equal to the prediction horizon. Qiu, Song, & Akagi (2016) used Artificial Neural Network for the prediction of stock market returns. Instead of technical indicators, they had used fundamental parameters and verified prediction ability of these new parameters. In the second phase, they employed a genetic algorithm and simulated annealing to improve the prediction accuracy of ANN. R. Dash & Dash (2016) used 6 technical indicators for a computational efficient functional link artificial neural network to generate buy, hold, and sell signal. Romero, Torres & Etcheverry (2016) developed a recommender system to increase the investor's gain. They worked on the prediction of daily return price time series by learning redundant dictionaries. Tsinaslanidis (2017) worked on the pattern-based classification of stocks into bullish and bearish classes. Zhang, Cui, Xu, Li, & Li (2018) developed a stock price trend prediction system along with interval of growth/decline. They had classified the trend into four classes- up, down, flat, and unknown for a precise understanding of movement. Najafi & Pourahmadi (2016) developed an efficient heuristic method based on grid optimization method for dynamic portfolio selection. Tayali & Tolun (2018) used the mean-variance model and non-negative reduction methods for portfolio optimization with a goal of minimizing risk with expected returns. Lean, Huanhuan, Wang, & Lai (2009) used for support vector machine for mining stock trends. They had opted genetic algorithm for input feature selection for least squares support vector machines (LSSVM). Rubio, Bermudez & Vercher (2016) proposed a weighted fuzzy time series methods for prediction of portfolio returns. They modelled uncertain parameters of fuzzy portfolio selection of models and approximate the uncertain future return by trapezoidal fuzzy members. Tripathi & Seth (2014) performed the study of Indian Equity Market in the context of market performance and macroeconomic factors. Technical analysis of stocks is often performed using various statistical measures known as Technical indicators. Table 1 illustrates the most widely used technical indicators for technical analysis.

Table 1: Technical Indicators

Sr. No.	Technical Indicator	Type
1	Moving averages, Stop and Reverse, Oscillators based on Moving Averages	Trend
2	Stochastic, Commodity Channel Index, Chande's momentum Oscillator, Relative Strength Index	Momentum
3	Average True Range, Bollinger Bands, Cboe Volatility Index	Volatility
4	On Balance Volume, Chaikin Money flow, Klinger Oscillator	Volume

3. Research Data

For the research work, we have used the dataset of three major industries- Maruti Suzuki, HDFC and Infosys available at Kaggle- a well-known repository of datasets for machine learning and deep learning algorithms. Maruti Suzuki (Automobile), HDFC (Banking) and Infosys (IT) are listed on both NSE and BSE. The time period considered for the dataset is 6 years (June 2014 – June 2020) as technical analysis is always performed over past time-frame (https://www.kaggle.com/hk7797/stock-market-india). This dataset has stock prices in terms on open, high, low and closing prices of the corresponding stock. Open price and close price refers to the opening and closing price of the stock for the particular day. High and low price is the highest and lowest price respectively that stock has got for the day. Technical indicators can be calculated by applying statistical formulae applied on open, high, low and close prices of the stock. Many indicators exhibit similar significance towards technical analysis. For example, a simple moving average and simple moving median are just the same except prior one calculates the average and later one calculates the median. In this

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paper, we have not considered such indicators. Emphasis is given on indicators with different types and different significance

4. Significance of Technical Indicators to Develop Trading Strategies

A trading strategy is a collection of objectives, goals, supreme guidelines characterizing when a trader will make a move to buy or sell stocks (Wang, 2015 a). Ordinarily, trading strategy incorporate both exchange channels and triggers, the two of which are regularly founded on indicators. More precisely, a strategy is not as simple as "Buy when price crosses above the moving average." This statement is ambiguous and gives no affirmative details for taking any decision (Prasetijo, Saputro, Windasari & Windarto 2017). Consider the following set of questions

1. Which moving average (Simple Moving Average, Exponential Moving Average, Double Exponential Moving Average, etc.) will be used, including time frame/period and price opinion to be used in the calculation?
2. Length of period (9 days, 15 days, 20 days, 50 days) over the moving average and price need to be considered?
3. Should the trade be entered/exited as soon as indicator triggers the action?
4. What type of order to be placed for a trade? Intraday? Limit? Market?
5. How many stocks or shares (volume of shares) will be traded?
6. What are the money flow rules? (Long term capital gain Taxes and rates)
7. What are the exit rules?

All and many other relevant such questions must be carefully thought and answered to formulate a strategy based on well-structured rules. An indicator cannot be defined as a trading strategy. An indicator only supports traders to recognize market conditions; a strategy is how trader uses indicators to buy or sell stocks and thereby achieves profit. The way indicators are interpreted, understood, and practically in order to make sophisticated predictions about future market activity. Technical indicators are typically classified into 4 categories: Momentum, Volume, Volatility, and trend-based indicators (Chen, 2014; Dash & Dash, 2016). Traders preferably use multiple indicators to formulate a strategy, but indicators of various types are recommended while creating a strategy. There could be problems when using three different indicators of the same type – trend, for example – results in the duplicate information for trading decision. In statistics, this is referred to as multi-collinearity. Multi-collinearity should be avoided by taking combinations of various types of indicators as it is responsible for ambiguous results and can mark other indicators less significant. As an alternative, traders should choose indicators from different categories, such as one volume indicator and one volatility indicator. One simple strategy is to generate a trading signal using one type of indicator and use another type to confirm the same. A moving average based indicator may be associated with the use of a momentum indicator for better affirmation of the trading decision (Wu, & Diao, 2015). For example, consider Relative Strength Index (RSI) –a momentum-based technical indicator which calculates the average price change of progressing periods with the average price change of decaying periods. Thus it will identify the overbought and oversold conditions. In this way, RSI can confirm any trading signals generated by moving average, says Simple Moving Average. Contradictory, other indicators may indicate that the signal is less accurate and that the trade should be evaded. Each indicator and combination of different types of indicators requires critical exploration to determine which combination is the most suitable in accordance to the trader's smartness and risk-taking ability. Statistics based technical analysis using such indicators allows traders to develop a strategy to assess historical data with a backtracking process. However, traders should be aware that this analysis only helps in forming profitable trading strategies and cannot guarantee exact results. Irrespective of which technical indicators are used, a strategy must expose precisely how the indicators will be explored and exactly what action will be taken. Indicators are mathematical tools that traders use to develop strategies; Traders must also remember that indicators do not create any trading signals on their own (Wang, 2015a). Any ambiguity can mislead them. The type of technical indicator a trader utilizes to form a strategy depends on the type of strategy he is developing and also on the period of investments. Traders who look for long term investments with large profits may use on a trend-deterministic strategy, and, therefore, exploit a trend-based indicator such as a moving average A trader interested in short term investments say intraday trader may go for a strategy based on volatility. Again, different types of indicators may be used for validation. There are many "black box" trading systems available commercially. Traders can purchase and utilize trademarked strategies for investments. The benefit of purchasing such black box systems is that all of the research, exploration and backtracking of historical data has already been done by analysts and traders can directly start trading without worrying of statistical calculations of technical indicators. However trader has no idea about the methodology incorporated as it is not usually revealed, and traders won't be able to change their trading styles, strategies easily (Qiu, Song & Akagi, 2016 ; Nuij, Milea, Hogenboom, Frasincar & Kaymak, 2014). Technical Analysis is the investigation of past market information to conjecture the heading of future value developments (Patel, Shah, Thakkar, & Kotecha, 2014a). Apart from how much amount you have to buy stocks there are still number of factors that decide how many stocks to buy.

1. Observe the current price of the stock you are looking to buy. It is important to look at the live quote and not the delayed one.
2. Divide the amount of money you have by the current price of the stock.
3. If fractional quantity is allowed to buy then you can buy or make the number of stocks to a rounded off digit and then buy

You should not just buy from only one stock if you are ready for doing investments in stock market. Diversification is very important and you should invest your amount in multiple stocks of different sectors. It is more sensible to spread your amount across many different stocks. One should hold at least 10 different stocks in the portfolio. You should have at least 10 stocks in your portfolio for better diversification of your investments. Well maintained portfolio is always helpful for investors which can give good returns by minimizing the risk of losing the money. While building the portfolio an individual investor must always look at the short term as well as long term personal goals and own risk taking ability instead of copying someone else's portfolio. Portfolio structuring refers to the allocation of your investments among different asset

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classes (Najafi, Pourahmadi, 2016). Important parameters while structuring your portfolio is your age and how much time you have to so that your investment grows. Longer the time you invest more is profit you can earn. For example 22 years old college graduate person have different investment needs than a 55 years old person. Another parameter to consider is risk taking ability. Can you tolerate the loss of your money for greater returns in future? Every other person look for better returns in short amount of time but are you willing to suffer the short term losses is an important question to handle. Portfolio structure depends on current financial situation, short term and long term goals, and risk taking ability. As per the principle for risk/return tradeoff greater the risk taking ability greater can be the profit made.

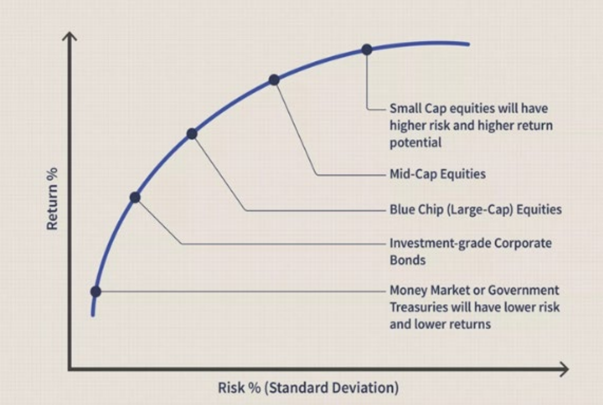

Fig 1: Risk vs. Return Graph

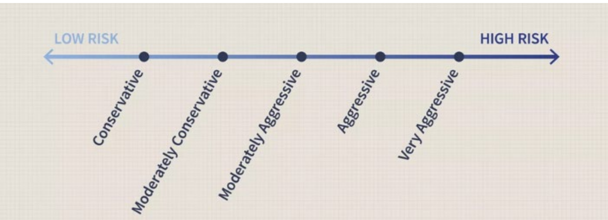

Fig 2: Portfolio Type- Based on Level of Risk

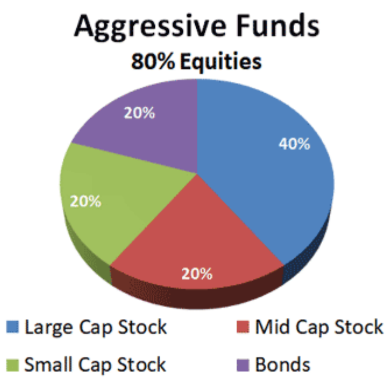

Fig 3: Aggressive Portfolio Structure

More risk takers have aggressive portfolio where these investors invest maximum amount into equities and less amount to fixed income assets like bonds, debt funds or liquid funds. Portfolio will be more conservative of you have less risk taking ability.

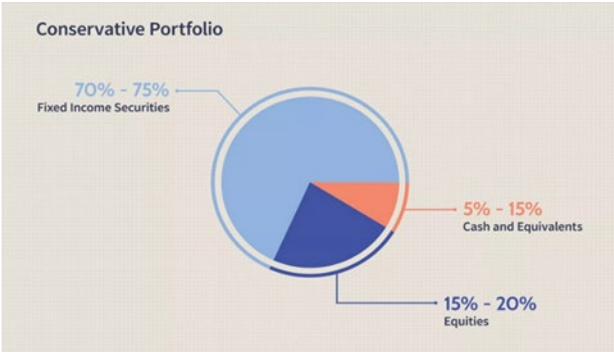

Fig 4: Conservative Portfolio Structure

Protecting the value is the main goal of conservative portfolio. Conservative portfolio is based on maximum (80%) investment in fixed income and minimum (20%) investment into equity. So better portfolio can be structured by picking good stocks which requires you to continuously monitor the prices of the stocks and look at the news impacting the stocks. Bond picking requires you to look at the bond type, maturity period, interest rates and credit ratings. Mutual funds and Exchange Traded Funds (ETFs) can also help to structure the portfolio in a better way. It is also important to monitor and rebalance your portfolio as the price changes over the period of time. As the financial situation, future goals and risk taking ability changes you may need to restructure your portfolio accordingly (Tayali & Tolun, 2018). For example with the drop in risk taking ability you may reduce the investments in equity. Even when you have made a good profit over the years from stocks, while selling the stocks you may incur a long term capital gain tax. In this case instead of contributing to the equity more you may want to invest in some other assets. You need to take care of your portfolio by rebalancing it from time to time.

Technical analysis of the stock prices helps investor to decide when to buy and when to sell the stocks (Prasetijo, Saputro, Windasari & Windarto 2017). Oversold stocks always provide a good buying opportunity as the prices are more likely to rise in future. Establishing a buying price range is more important. Technical analysis combined with fundamental analysis can provide much better picture of when to buy and sell the stocks. You also need to hold undervalued stocks more patiently. It might take some time for the stock prices to meet its true value. Three-five years of holding time is always considered as the better holding period. Investors must also keep update about changes in trading rules. Investors must always plan their trading strategy by following the day’s trend. For better profits, timing the market is very important thing to do (Shynkevich, McGinnity, Coleman, Belatreche, & Li, 2017). As the market opens in the morning, volume traded and stock prices may behave abnormally and there

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could be more volatility observed with previous day's closing prices and the current news. A skilled trader may be able to identify the buying or selling opportunities during this volatile time making quick profits with the experience whereas a novice trader may avoid trading during this time. As the Indian stock market opens at 9.15 AM biggest moves can happen in the shortest time. So as a trader if you can quickly recognise these moves it's always a good opportunity to trade in the morning. Many professional traders stop trading around 11.30 AM and further movements become slow. Middle of the day is quite a silent and stable period where a novice trader can trade and grab small profits as the returns are predictable. At this point of time traders wait for the news to decide the further movement of the market. Quick and sharp reversals tend to happen in the last hour of trading, especially in the last minutes of the trading as the volume and volatility increases. Intraday traders try to square-off their positions during 3 PM to 4 PM and join the movement late in a hope that same momentum will be observed in next trading day

5. Machine Learning and Deep Learning Techniques for Technical Analysis

5.1. Decision Tree

The following list outlines the different types of graphics published in IEEE journals. They are categorized based on their construction, and use of color / shades of gray:

$$Entropy = \sum_{i=1}^{c} -P_i \log_2 P_i \quad (1)$$

Decision tree uses the lowest entropy for splitting.

Information Gain = 1-Entropy (2)

More details about decision tree can be seen in (Sakhare & Joshi, 2014)

5.2. Support Vector Machine

Support Vector Machine (SVM) is a supervised machine learning algorithm which is commonly used for prediction, classification, or regression analysis. SVM represents data points in n-dimensional space and separate into groups that are divided by a clear gap. New data points are then mapped into the same space and prediction is made to identify to which group they belong, on the basis of to which side of the gap they fall (Kantavat & Kijsirikul, 2008). SVM is widely used for linear classification or prediction problems. But they can also be used for nonlinear classification using kernel function. Kernel function maps input from one-dimensional space to higher-dimensional space. They are based on the idea of finding a maximum margin hyperplane (Lean, Huanhuan, Wang, & Lai, 2009 ; Patel, Shah, Thakkar, & Kotecha, 2014a). Margin is the distance between the hyperplane and the nearest data points. There could be multiple hyperplanes possible but a hyperplane with greatest distance between nearest data point and the hyperplane is selected always, giving a greater chance of new data being classified correctly. Optimal hyperplane best divides the given dataset into given categories. SVM views the data points as n-dimensional vectors so that it is possible to divide the data points with (n-1) dimension hyperplane. The simplest form of SVM is linear classification. In SVM, if we have data points that are not linearly separable, we need to view data points in higher dimensions making separation easy to interpret. This transformation is normally done by kernel function k(x, y).

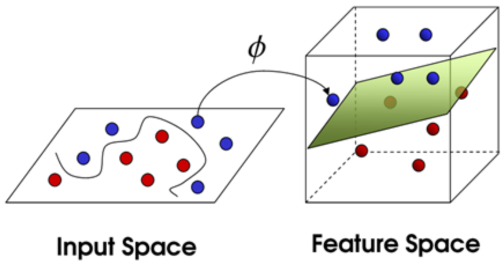

Fig 5: Transformation of input space to feature space

Hyperplane in higher dimensional space are represented by the set of points whose dot product with an input data vector is constant. Hyperplane is defined as:

$$\Sigma_i \propto_i k(x_i , x) = constant \quad (3)$$

Where each x_i represents feature vectors and k indicates kernel function. Summation of kernel function indicates the relative proximity of data points (Patel, Shah, Thakkar, & Kotecha, 2014a).

5.2.1 Linear SVM

Consider a training dataset of n data points such that,

$$\{ (\overrightarrow{x_1}, y_1), \ldots\ldots, (\overrightarrow{x_n}, \ y_n) \}$$

$\overrightarrow{x_i}$ is an n-dimensional feature vector and $y_i$represents classes where each $\overrightarrow{x_i}$ belongs.

y_i is either +1 or -1. In our stock market trend prediction problem, +1 indicates uptrend, and -1 indicates a downtrend.

The goal with SVM is to find the "maximum-margin hyperplane" that best divides each $\overrightarrow{x_i}y_i$ to = +1 or -1 such that margin between the hyperplane and nearest $\overrightarrow{x_i}y_i$ to is maximized. Hyperplane can be defined as,

$$\overrightarrow{W} . \vec{X} - b = 0 \quad (4)$$

$\overrightarrow{W}$ represents a normal vector to the hyperplane. The above equation represents Hesse Normal Form.

5.2.2 Non-Linear SVM

Vladimir N. Vapnik developed non-linear classifier using kernel functions to maximize the margin for hyperplanes. This is same as that for linear SVM, but the in non-linear SVM dot product is replaced by a non-linear kernel function. Non-linear kernel functions represent maximum-margin hyperplane in n-dimensional feature space. However, there could be a great chance of generalization error in SVM with higher dimensional feature space. Some well-known kernel functions for non-linear SVM are given in the table 2.

Table 2: Kernel Functions

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Polynomial Kernel	k $(\vec{x_i}, \vec{x_j}) = (\vec{x_i} . \vec{x_j})^d$
Gaussian Radial Basis	k$(\vec{x_i}, \vec{x_j})$=$exp(-_\gamma \|\|(\vec{x_i} - \vec{x_j}\|\|)^2$
Hyperbolic Tangent	k$(\vec{x_i}, \vec{x_j}) = tanh\ (k(\vec{x_i} . \vec{x_j} + c)$ for k>0 and c<0

5.3. Naïve Bayes

Naïve Bayes is probability-based machine learning models that follow Bayes theorem with naïve (strong) independency between attributes (Patel, Shah, Thakkar, & Kotecha, 2014a; Joshi & Sakhare, 2015). A conditional probabilistic model for Naïve Bayes for our stock market trend prediction problem is given as:
Where k=2 which represent possible outcomes of prediction: uptrend and downtrend. If there are too many features, and also of these features take many values; it becomes very complex to assign probabilities. So Naïve Bayes algorithm decides on Bayes' theorem, using which conditional probability is calculated as:

$$P(X) = \frac{P(C_k)\ P(X|C_k)}{P(X)} \quad (5)$$

Above equation is simplified as

$$posterior\ probability = \frac{prior_{proabibility}\ X\ likelihood}{Experiment} \quad (6)$$

Consider an input dataset

X = $(x_1, x_2, \ldots\ldots.., x_n)$ where x is instances of daily stock transaction dataset and n indicates features which are technical indicators which are independent of each other, Naïve Bayes assigns a probability for each indicator using the equation:

P $(C_k |\ x_1, x_2, \ldots\ldots.., x_n)$

Since the number of experiments is a constant number, hence the numerator is very important, and it is considered as a joint probability model:

P$(C_k |\ x_1, x_2, \ldots\ldots.., x_n)$

The same equation can be interpreted using chain rule as:

P $(x_1 |\ x_2, \ldots\ldots.., x_n, C_k)$ P $(x_n|C_k)$ x P (C_k)

$$= \text{P } (C_k)\sum_{i=1}^{n} * P(x_i|C_k) \quad (7)$$

Naïve Bayes considers strong conditional independence as all features X= (x_1,x_2,……..,x_n) are independent of each other (Joshi & Sakhare, 2015).

5.4. Convolutional Neural Network (CNN)

Convolutional Neural Network is a type of neural network having three layers: A convolution layer, a pooling layer and a fully connected layer.

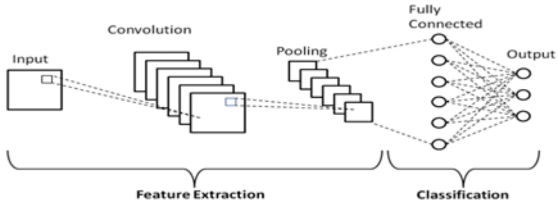

Fig 6: Architecture of Convolutional Neural Network

A convolutional layer performs matrix multiplication. Matrix contains all input parameters. Dot product of the vectors establishes the relationship between input and output.

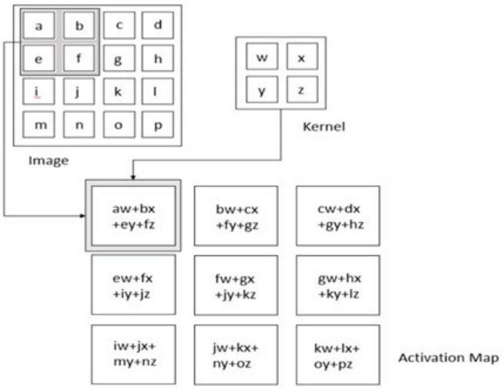

Fig 7: Function performed by convolution layer

A convolutional layer performs matrix multiplication. Matrix contains all input parameters. Dot product of the vectors establishes the relationship between input and output.
CNN does sparse interaction between input and output by reducing the size of kernel smaller than that of input. This makes memory management of the model to be smaller as we need to store only few parameters. This also significantly improves the statistical efficiency of the model. Pooling layer is responsible to achieve optimization of the output as it replaces the output at few locations in the network by summarizing the statistics of outputs in the nearby area. This reduces the number of computations required to calculate all output values. Max pooling is the popular pooling function which gives maximum output from the neighbourhood.

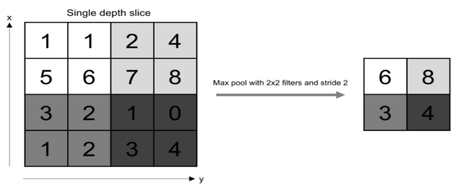

Fig 8: Max Pooling Function

Fully connected layer is responsible to connect all neurons in the CNN and provides the mapped representation between input and output. More details about CNN can be seen in (Hiransha Gopalakrishnan, Menon, & Soman , 2018).

5.5. Generative Adversarial Networks(GANs)

GANs are based on generative modelling approach and are one of the most popular deep learning methods. Generative modelling is

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based on unsupervised learning approach that automatically identifies and learns the new patterns and the trained model then can be used to generate new examples. The entire GAN model consists of two sub models- the generator model and the discriminator model. The generator model is trained to generate the new instances similar to that of original instances. Discriminator model takes the input as real instances as well as generated instances (output of the generator model) and tries to classify the instances as real or fake. Discriminator model is a simple classification model. Once the training process is completed the discriminator model is discarded and only generator model is used.

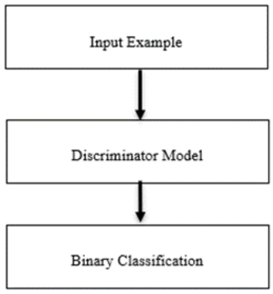

Fig 9: Discriminator Model

More details about Generative Adversarial Networks are available with (Zhang, Zhong, Dong, Wang, & Wang, 2019).

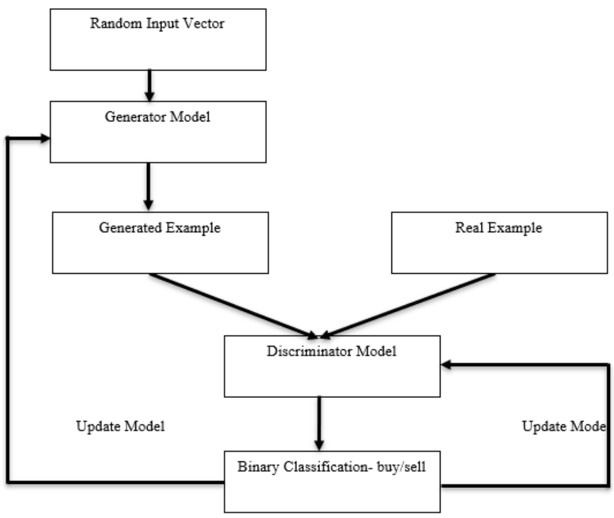

Fig 10: Generative Adversarial Networks

6. Experimental Work

To measure the performance accuracy of machine learning and deep learning models we have used two approaches- cross validation and training and testing data split.

6.1. Cross validation

Cross-Validation is often known as k-fold cross validation. Parameter k indicates the number of partitions into which given data is partitioned into. Cross validation takes the following approach.

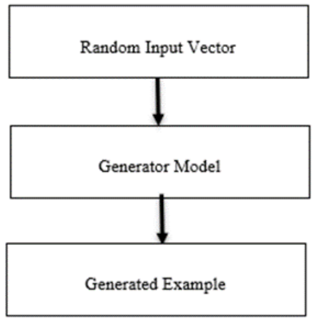

Fig 10: Generator Model

Step 1: Shuffle the dataset randomly.
Step 2: Split the dataset into k groups
Step 3: For each unique group:
Take the group as a holdout or test data set
-Take the remaining groups as a training data set
-Fit a model on the training set and evaluate it on the test set
-Retain the evaluation score and discard the model
-Summarize the skill of the model using the sample of model evaluation scores

6.2. Training and Testing Percentage Data Split

In training and testing percentage data split, entire dataset is divided as training set—a subset to train a model and a test set—a subset to test the trained model. In our experimental work we have divided entire dataset with 66% for training dataset and 34% for testing purpose. Training data is used to teach (train) the model whereas testing data is used to depict how appropriately model predicts based on learning using the training data. We have performed the experiment using both-Cross validation and training-testing percentage data split to understand the appropriateness of both approaches. To measure the performance of Decision Tree, Support Vector Machine and Naïve Bayes we use the various evaluators like true positive rate, precision, recall, f-measure which can be statistically calculated based on confusion matrix (Sakhare & Joshi, 2014).

Table 3: Confusion Matrix for Decision Tree (10-fold cross validation)-Dataset- Maruti Suzuki

a	b	
536	204	a = sell
256	480	b = buy

Table 4: Confusion Matrix for Decision Tree (Training-Testing Percentage Split) - Dataset- Maruti Suzuki

a	b	
159	96	a = sell
82	165	b = buy

Table 5: Confusion Matrix for Decision Tree (10-fold cross validation) - Dataset- HDFC

a	b	
159	96	a = sell
82	165	b = buy

Table 6: Confusion Matrix for Decision Tree (Training-Testing Percentage Split)- Dataset- HDFC

a	b	
139	103	a = sell
49	211	b = buy

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Table 7: Confusion Matrix for Decision Tree (10-fold cross validation) - Dataset- Infosys

a	b	
513	196	a = sell
253	514	b = buy

Table 8: Confusion Matrix for Decision Tree (Training-Testing Percentage Split)- Dataset- Infosys

a	b	
144	102	a = sell
69	187	b = buy

Table 9: Confusion Matrix for Support Vector Machine (10-fold cross validation)- Dataset- Maruti Suzuki

a	b	
480	260	a = sell
217	519	b = buy

Table 10: Confusion Matrix for Support Vector Machine (Training-Testing Percentage Split) - Dataset- Maruti Suzuki

a		
158	97	a = sell
62	185	b = buy

Table 11: Confusion Matrix for Support Vector Machine (10-fold cross validation) - Dataset- HDFC

a	b	
472	247	a = sell
209	548	b = buy

Table 12: Confusion Matrix for Support Vector Machine (Training-Testing Percentage Split)- Dataset- HDFC

a	b	
146	96	a = sell
69	191	b = buy

Table 13: Confusion Matrix for Support Vector Machine (10-fold cross validation) - Dataset- Infosys

a	b	
468	241	a = sell
210	557	b = buy

Table 14: Confusion Matrix for Support Vector Machine (Training-Testing Percentage Split)- Dataset- Infosys

a	b	
165	81	a = sell
68	188	b = buy

Table 15: Confusion Matrix for Naïve Bayes (10-fold cross validation)- Dataset- Maruti Suzuki

a	b	
326	414	a = sell
177	559	b = buy

Table 16: Confusion Matrix for Naïve Bayes (Training-Testing Percentage Split) - Dataset- Maruti Suzuki

a	b	
112	143	a = sell
64	183	b = buy

Table 17: Confusion Matrix for Naïve Bayes (10-fold cross validation) - Dataset- HDFC

a	b	
413	306	a = sell
257	500	b = buy

Table 18: Confusion Matrix for Naïve Bayes (Training-Testing Percentage Split)- Dataset- HDFC

a	b	
137	105	a = sell
85	175	b = buy

Table 19: Confusion Matrix for Naïve Bayes (10-fold cross validation) - Dataset- Infosys

a	b	
378	331	a = sell
247	520	b = buy

Table 20: Confusion Matrix for Naïve Bayes (Training-Testing Percentage Split)- Dataset- Infosys

a	b	
148	98	a = sell
93	163	b = buy

Table 21: Confusion Matrix for Convolutional Neural Networks (10-fold cross validation)- Dataset- Maruti Suzuki

a	b	
711	145	a = sell
66	554	b = buy

Table 22: Confusion Matrix for Convolutional Neural Networks (Training-Testing Percentage Split) - Dataset- Maruti Suzuki

a	b	
204	40	a = sell
37	221	b = buy

Table 23: Confusion Matrix for Convolutional Neural Networks (10-fold cross validation) - Dataset- HDFC

a	b	
702	125	a = sell
75	574	b = buy

Table 24: Confusion Matrix for Convolutional Neural Networks (Training-Testing Percentage Split)- Dataset- HDFC

a	b	
191	37	a = sell
50	224	b = buy

Table 25: Confusion Matrix for Convolutional Neural Networks (10-fold cross validation) - Dataset- Infosys

a	b	
706	130	a = sell
71	569	b = buy

Table 26: Confusion Matrix for Convolutional Neural Networks (Training-Testing Percentage Split)- Dataset- Infosys

a	b	
197	44	a = sell
44	217	b = buy

Table 27: Confusion Matrix for Generative Adversarial Networks (10-fold cross validation)- Dataset- Maruti Suzuki

a	b	
718	110	a = sell
59	589	b = buy

Table 28: Confusion Matrix for Generative Adversarial Networks (Training-Testing Percentage Split) - Dataset- Maruti Suzuki

a	b	
209	32	a = sell
32	229	b = buy

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Table 29: Confusion Matrix for Generative Adversarial Networks (10-fold cross validation) - Dataset- HDFC

a	b	
708	144	a = sell
70	554	b = buy

Table 30: Confusion Matrix for Generative Adversarial Networks (Training-Testing Percentage Split)- Dataset- HDFC

a	b	
203	67	a = sell
38	194	b = buy

Table 31: Confusion Matrix for Generative Adversarial Networks (10-fold cross validation) - Dataset- Infosys

a	b	
722	92	a = sell
55	607	b = buy

Table 32: Confusion Matrix for Generative Adversarial Networks (Training-Testing Percentage Split)- Dataset- Infosys

a	B	
213	27	a = sell
28	234	b = buy

Table 33: Performance evaluation parameters (10 fold cross validation) – Dataset- Maruti Suzuki

		TPR	FPR	Precision	Recall	F1-Score	MCC
Decision Tree	sell	0.724	0.348	0.677	0.724	0.700	0.378
	buy	0.652	0.276	0.702	0.652	0.676	
Support Vector Machine	sell	0.649	0.295	0.689	0.649	0.668	0.354
	buy	0.705	0.351	0.666	0.705	0.685	
Naïve Bayes	sell	0.441	0.240	0.648	0.441	0.525	0.211
	buy	0.760	0.559	0.575	0.760	0.654	
Convolutional Neural Network	sell	0.923	0.202	0.941	0.923	0.901	0.402
	buy	0.798	0.077	0.823	0.798	0.775	
Generative Adversarial Networks	sell	0.931	0.150	0.955	0.931	0.905	0.415
	buy	0.850	0.069	0.885	0.850	0.882	

Table 34: Performance evaluation parameters (Training-Testing Percentage Split) – Dataset- Maruti Suzuki

		TPR	FPR	Precision	Recall	F1-Score	MCC
Decision Tree	sell	0.624	0.332	0.660	0.624	0.641	0.292
	buy	0.668	0.376	0.632	0.668	0.650	
Support Vector Machine	sell	0.620	0.251	0.718	0.620	0.665	0.371
	buy	0.749	0.380	0.656	0.749	0.699	
Naïve Bayes	sell	0.439	0.259	0.636	0.439	0.520	0.189
	buy	0.741	0.561	0.561	0.741	0.639	
Convolutional Neural Network	sell	0.846	0.154	0.880	0.846	0.862	0.420
	buy	0.846	0.154	0.820	0.846	0.865	
Generative Adversarial Networks	sell	0.867	0.223	0.905	0.867	0.890	0.432
	buy	0.877	0.233	0.893	0.877	8.898	

Table 35: Performance evaluation parameters (10-fold cross validation) – Dataset- HDFC

		TPR	FPR	Precision	Recall	F1-Score	MCC
Decision Tree	sell	0.637	0.251	0.707	0.637	0.670	0.389
	buy	0.749	0.363	0.685	0.749	0.715	
Support Vector Machine	sell	0.656	0.276	0.693	0.656	0.674	0.381
	buy	0.724	0.344	0.689	0.724	0.706	
Naïve Bayes	sell	0.574	0.339	0.616	0.574	0.595	0.231
	buy	0.661	0.426	0.620	0.661	0.640	
Convolutional Neural Network	sell	0.912	0.172	0.880	0.912	0.894	0.430
	buy	0.828	0.088	0.853	0.828	0.804	
Generative Adversarial Networks	sell	0.918	0.199	0.878	0.918	0.861	0.437
	buy	0.801	0.082	0.825	0.801	0.842	

Table 36: Performance evaluation parameters (Training-Testing Percentage Split) – Dataset – HDFC

		TPR	FPR	Precision	Recall	F1-Score	MCC
Decision Tree	sell	0.574	0.188	0.739	0.574	0.647	0.398
	buy	0.812	0.426	0.672	0.812	0.735	
Support Vector Machine	sell	0.603	0.265	0.679	0.603	0.639	0.341
	buy	0.735	0.397	0.666	0.735	0.698	
Naïve Bayes	sell	0.566	0.327	0.617	0.566	0.591	0.241

	buy	0.673	0.434	0.625	0.673	0.648	
Convolutional Neural Network	sell	0.792	0.142	0.816	0.792	0.813	0.398
	buy	0.858	0.208	0.843	0.858	0.834	
Generative Adversarial Networks	sell	0.842	0.257	0.867	0.842	0.870	0.401
	buy	0.743	0.158	0.727	0.743	0.719	

Table 37: Performance evaluation parameters (10 fold cross validation) – Dataset – Infosys

		TPR	FPR	Precision	Recall	F1-Score	MCC
Decision Tree	sell	0.724	0.330	0.670	0.724	0.696	0.394
	buy	0.670	0.276	0.724	0.670	0.696	
Support Vector Machine	sell	0.660	0.274	0.690	0.660	0.675	0.387
	buy	0.726	0.340	0.698	0.726	0.712	
Naïve Bayes	sell	0.533	0.322	0.605	0.533	0.567	0.213
	buy	0.678	0.467	0.611	0.678	0.643	
Convolutional Neural Network	sell	0.917	0.179	0.896	0.917	0.920	0.423
	buy	0.821	0.083	0.801	0.821	0.842	
Generative Adversarial Networks	sell	0.937	0.125	0.901	0.937	0.954	0.451
	buy	0.875	0.063	0.896	0.875	0.844	

Table 38: Performance evaluation parameters (Training-Testing Percentage Split) – Dataset – Infosys

		TPR	FPR	Precision	Recall	F1-Score	MCC
Decision Tree	sell	0.585	0.270	0.676	0.585	0.627	0.319
	buy	0.730	0.415	0.647	0.730	0.686	
Support Vector Machine	sell	0.671	0.266	0.708	0.671	0.689	0.406
	buy	0.734	0.329	0.699	0.734	0.716	
Naïve Bayes	sell	0.602	0.363	0.614	0.602	0.608	0.238
	buy	0.637	0.398	0.625	0.637	0.631	
Convolutional Neural Network	sell	0.817	0.169	0.847	0.817	0.844	0.417
	buy	0.831	0.183	0.803	0.831	0.808	
Generative Adversarial Networks	sell	0.883	0.104	0.907	0.883	0.901	0.421
	buy	0.896	0.117	0.870	0.896	0.883	

Table 39: Overall accuracy of each model (10 fold Cross Validation)

Algorithm	Dataset- Maruti Suzuki	Dataset- HDFC	Dataset- Infosys
Decision Tree	68.83%	69.44%	69.58%
Support Vector Machine	67.68%	69.10%	69.44%
Naïve Bayes	59.95%	61.85%	60.84%
Convolutional Neural Network	85.70%	86.44%	86.38%
Generative Adversarial Networks	88.55%	85.50%	90%

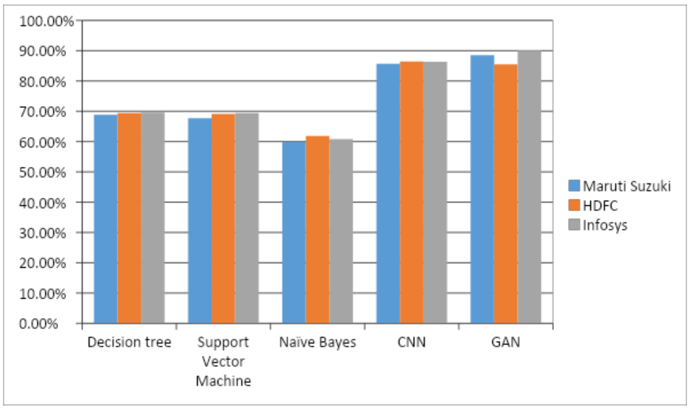

Fig 11: Performance Comparison of Machine Learning and Deep Learning Models for 10 fold cross validation

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Table 40: Overall accuracy of each model (Training-Testing Percentage Split)

Algorithm	Dataset- Maruti Suzuki	Dataset- HDFC	Dataset- Infosys
Decision Tree	64.54%	69.72%	65.93%
Support Vector Machine	68.32%	67.13%	70.31%
Naïve Bayes	58.76%	62.15%	61.95%
Convolutional Neural Network	84.66%	82.66%	82.47%
Generative Adversarial Network	87.25%	79.08%	89.04%

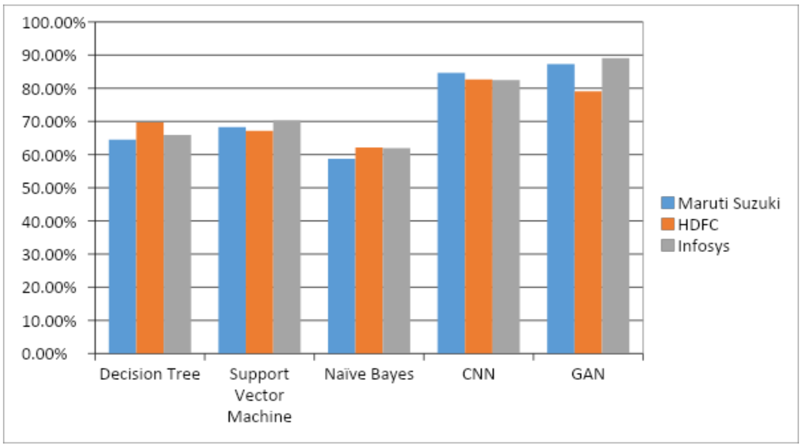

Fig 12: Performance Comparison of Machine Learning and Deep Learning Models for training-testing percentage split

6 Conclusion

Prediction of the stock market is a challenging problem. Analysts try to predict the future value of stocks by using various technical indicators like moving averages, oscillators, trend, and volume flow. Positive prediction of stock market movement can yield a significant profit to investors. Machine learning and deep learning techniques can effectively identify and predict stock market trend given the historical data of the stock market. In our research work, we have considered Decision Tree, Support Vector Machine, and Naïve Bayes machine learning algorithms and Convolutional Neural Network and Generative Adversarial Networks deep learning algorithms for prediction. From the results, it is clear that deep learning techniques predict stock market trend more accurately as compared to machine learning algorithms. We have used two approaches cross validation and training-testing percentage split to avoid any confusion between selection of dataset to evaluate the performance of learning models and understanding the suitability of approaches for training and testing the models. Both the approaches have their own advantages and disadvantages. However cross validation is more handy and better to use as it filters out any noise or randomness occurred in the results due to the equal split on your training dataset to create the cross validation dataset. By rotating through the partitions of data for training v/s testing, it helps ensure that the resulting model rounded properly and not biased based on how the training data was split into training and testing datasets. It is worth to experiment with other machine learning and deep learning algorithms. We also discussed how the prediction of market movement could help investors to formulate trading strategies. In-depth analysis of technical indicators can help analysts to take a direct decision for buying or selling of stocks instead of predicting only trend movement. Significant work can also be performed to transform the output of technical indicators to buy/sell strategies. For better trading signals this work could be extended two multiclass prediction problem with five classes – strong buy, buy, hold, sell, strong sell. For better results, technical analysis can also be paired with a fundamental analysis of the stock market. The fundamental analysis determines the overall health of a company. The combined approach of technical and fundamental analysis will help investors to understand the short term as well as long term investments.

References

[1] Patel, J., Shah, S., Thakkar, P., & Kotecha, K. (2014 a). Predicting stock and stock price index movement using trend deterministic data preparation and machine learning techniques. Expert Systems with Applications. Volume 42, Issue 1, January 2015, Pages 259-268. https://doi.org/10.1016/j.eswa.2014.07.040

[2] Patel, J., Shah, S., Thakkar, P., & Kotecha, K. (2015 b). Predicting stock market index using fusion of machine learning techniques. Expert Systems with Applications. Volume 42, Issue 4, Pages 2162-2172. https://doi.org/10.1016/j.eswa.2014.10.031

[3] Aldin, M., M., Dehnavi, H., D., & Entezari, S. (2012) Evaluating the employment of technical indicators in predicting stock price index variations using artificial neural networks (case study: Tehran stock exchange). International Journal of Business & Management, Vol. 7, No. 15. 10.5539/ijbm.v7n15p25

[4] Sakhare, N., & Shaik I. (2019). Performance Analysis of Regression-Based Machine Learning Techniques for Prediction of Stock Market Movement. International Journal of Recent Technology and Engineering (IJRTE) ISSN: 2277-3878, Volume-7, Issue-6S4, April 2019.

[5] Wu, M., and Diao, X. (2015). Technical Analysis of Three Stock Oscillators- Testing MACD, RSI and KDJ Rules in SH and SZ stock markets. INSPEC Accession Number: 16090318, 2015 4th International Conference on Computer Science and Network Technology (ICCSNT), 10.1109/ICCSNT.2015.7490760

International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

[6] Zhang, J., Cui, S., Xu, Y., Li, Q., & Li, T, (2018). A novel data-driven stock price trend prediction system. Expert Systems with Applications. Volume 97, 1 May 2018, Pages 60-69. https://doi.org/10.1016/j.eswa.2017.12.026

[7] Romero R., Torres A., & Etcheverry, G.(2016). Forecasting of Stock Return Prices with Sparse Representation of Financial Time Series Over Redundant Dictionaries. Expert Systems with Applications. Volume 57, 15 September 2016, Pages 37-48. https://doi.org/10.1016/j.eswa.2016.03.021

[8] Shynkevich, Y., McGinnity, T.M., Coleman, S.A., Belatreche, A., Li, Y., (2017). Forecasting price movements using technical indicators: Investing the impact of varying input window length. Neurocomputing Volume 264, 15 November 2017, Pages 71-88. https://doi.org/10.1016/j.neucom.2016.11.095

[9] Najafi, A., Pourahmadi,Z. (2016) An efficient heuristic method for dynamic portfolio selection problem under transaction costs and uncertain conditions, Physica A: Statistical Mechanics and its Applications, Volume 448, 2016, Pages 154-162, ISSN 0378-4371, https://doi.org/10.1016/j.physa.2015.12.048.

[10] Dhar, V., (2011) Prediction in financial markets: The case for small disjuncts. ACM Transactions on Intelligent Systems and Technology. May 2011 Article No.: 19 https://doi.org/10.1145/1961189.1961191

[11] Tripathi V, Seth R. Stock Market Performance and Macroeconomic Factors: The Study of Indian Equity Market. Global Business Review. 2014;15(2):291-316. doi:10.1177/0972150914523599

[12] Kantavat, P., & Kijsirikul, B., (2008). Combining Technical Analysis and Support Vector Machine for Stock Trading. 2008 Eighth International Conference on Hybrid Intelligent Systems. INSPEC Accession Number: 10234656 DOI: 10.1109/HIS.2008.76

[13] Wang, L.,X., (2015 a). Dynamic Models of Stock Prices Based On Technical Trading Rules Part-I: The Models., INSPEC Accession Number: 15328525, IEEE Transactions on Fuzzy Systems, Volume: 23, Issue: 4, pp. 787 – 801. DOI: 10.1109/TFUZZ.2014.2327994

[14] Wang, L., X., (2015 b). Dynamic Models of Stock Prices Based On Technical Trading Rules Part-II: The Models, INSPEC Accession Number: 15328516, IEEE Transactions on Fuzzy Systems, Volume: 23, Issue: 4, pp. 1127 – 1141.

[15] Lean, Y., Huanhuan, C., Wang, S., & Lai, K., (2009). Evolving Least Squares Support Vector Machines for Stock Market Trend Mining. IEEE Transaction on Evolutionary Computation, vol. 13, issue 1, pp.87-102. INSPEC Accession Number: 10417124 DOI: 10.1109/TEVC.2008.928176

[16] Tayali,H.A.,& Tolun, S. (2018). Dimension reduction in mean-variance portfolio optimization. Expert Systems with Applications

[17] Volume 92, February 2018, Pages 161-169. https://doi.org/10.1016/j.eswa.2017.09.009

[18] Sharma, A., Bhuniya, D., & Singh, U. (2017). Survey of Stock Market Prediction Using Machine Learning Approach. IEEE, International Conference of Electronics, Communication and Aerospace Technology, INSPEC Accession Number: 17433061 DOI: 10.1109/ICECA.2017.8212715

[19] Rubio, A., Bermudez, J., & Vercher, E. (2016). Forecasting portfolio returns using weighted fuzzy time series methods. International Journal of Approximate Reasoning. Volume 75, August 2016, Pages 1-12. https://doi.org/10.1016/j.ijar.2016.03.007

[20] Nuij, W., Milea, V., Hogenboom, F., Frasincar, F., & Kaymak, U. (2014). An Automated Framework for Incorporating News into Stock Trading Strategies," IEEE Transactions on Knowledge and Data Engineering, Volume: 26, Issue: 4, April 2014, pp: 823 – 835 INSPEC Accession Number: 14181444, DOI: 10.1109/TKDE.2013.133

[21] Huang, W., Nakamori, Y., & Wang, S. (2005) Forecasting stock market movement direction with support vector machine Computers & Operations Research. Vol. 32 pp. 2513 – 2522. DOI:10.1016/j.cor.2004.03.016

[22] Cervello-Royo, R., Guijarro, F., & Michniuk, K., (2015) Stock market trading rule based on pattern recognition and technical analysis: Forecasting the DJIA index with intraday data. Expert Systems with Applications Volume 42, Issue 14, 15 August 2015, Pages 5963-5975 https://doi.org/10.1016/j.eswa.2015.03.017

[23] Tsinaslandis, P., E., (2018). Subsequence dynamic time wrapping for charting: Bullish and bearish class predictions for NYSE stocks. Expert Systems with Applications. Volume 94, 15 March 2018, Pages 193-204. https://doi.org/10.1016/j.eswa.2017.10.055

[24] Chen, Y., (2014) Enhancement of Stock Market Forecasting Using a Technical Analysis Based Approach. 2014 IEEE 5th International Conference on Software Engineering and Service Science, INSPEC Accession Number: 14698833 DOI: 10.1109/ICSESS.2014.6933664

[25] Qiu, M., Song, Y., & Akagi, F. (2016). Application of artificial neural network for the prediction of stock market returns: The case of Japanese Stock Market. Chaos, Solitons & Fractals. Volume 85, April 2016, Pages 1-7. https://doi.org/10.1016/j.chaos.2016.01.004

[26] Dash, R., & Dash, P. (2016). A hybrid stock trading framework integrating technical analysis with machine learning techniques. The Journal of Finance and Data Science. Volume 2, Issue 1, March 2016, Pages 42-57. https://doi.org/10.1016/j.jfds.2016.03.002

[27] Joshi, S., & Sakhare, N. (2015). History Bits based novel algorithm for classification of structured data. IEEE International Advance Computing Conference (IACC), Banglore, pp. 609-612. DOI: 10.1109/IADCC.2015.7154779.

[28] Zhang, K., Zhong, G., Dong, J., Wang, S., & Wang, Y. (2019). Stock Market Prediction Based on Generative Adversarial Network. Procedia Computer Science Volume 147, Pages 400-406. https://doi.org/10.1016/j.procs.2019.01.256

[29] Hiransha M, Gopalakrishnan E.A., Menon, V., K., Soman K.P., (2018) NSE Stock Market Prediction Using Deep-Learning Models, Procedia Computer Science, Volume 132, Pages 1351-1362, ISSN 1877-0509, https://doi.org/10.1016/j.procs.2018.05.050.

[30] Sakhare, N. & Joshi, S. (2014). Classification of Criminal Data Using J48 Algorithm, International Journal of Data warehousing and Mining. Vol. 4.pp. 167-171.

[31] Prasetijo, A., Saputro, T., Windasari, I., & Windarto, Y., (2017) Buy/sell signal detection in stock trading with Bollinger bands and parabolic SAR: With web application for proofing trading strategy 2017 4th International Conference on Information Technology, Computer, and Electrical Engineering (ICITACEE). INSPEC Accession Number: 17503416 DOI: 10.1109/ICITACEE.2017.8257672

[32] Sakhare, N., Shaik, S., Kagad, S., Kapadwanjwala, T., Malekar, H., & Dalal, M. (2020) Stock Market Prediction Using Sentiment Analysis. International Journal of Advanced Science and Technology. 29, 4s 1126 - 1133.

[33] Aitken, M., Cumming, D., & Zhan, F., (2015). High frequency trading and end-of-day price dislocation, Journal of Banking & Finance,

[34] Volume 59, Pages 330-349, ISSN 0378-4266, https://doi.org/10.1016/j.jbankfin.2015.06.011.

[35] https://www.investopedia.com/terms/t/technical-analysis-of-stocks-and-trends.asp