



A Comprehensive Comparative Study of Artificial Neural Network (ANN) and Support Vector Machines (SVM) on Stock Forecasting

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Abstract

From exchanging budgetary instruments to tracking individual spending plans to detail a business's profit, money-related organisations utilise computational innovation day by day. Here in this paper, we focus on the significance of innovation in accounts such as financial risk management and stock prediction. We discuss two significant algorithms that have a notable role in stock forecasting. Artificial Neural Networks (ANN), as absenteeism of some data points, does not hamper the network functioning. Secondly, Support Vector Machines (SVM) has several features, and due to simple decision boundaries, it avoids over-fitting. The paper first looks at the different technologies applied in stock market prediction. It examines how sentimental analysis, decision trees, moving average algorithm, and data mining is applied in various stock prediction scenarios. The paper covers the recent past studies to explore the concepts and methodologies through which ANN's and SVM's have been used. Additionally, the paper incorporates significant aspects of novel methods and technologies in which ANN as a hybrid model like ANN-MLP, GARCH-MLP, a combination of the Backpropagation algorithm and Multilayer Feed-forward network, yields better results. Simultaneously, SVM's have been successfully applied in stock prediction, giving an accuracy of about 60%–70% for simple SVM, which is further improved by combining methods like Random Forest, Genetic Algorithm more accurate outcomes. Further, we present our thoughts on where SVM's and ANN's stand as prediction algorithms and challenges like the time constraint, current scenarios, data limitation, and cold start problems were raised. Conclusively SVM and ANN played prominent roles in tackling these issue to an extent and can further be enhanced with their integration with other novel techniques resulting in hybrid methodologies. It will lead students, researchers and financial enthusiasts to more potent approaches for Stock forecasting.

Keywords Machine learning · ANN · SVM

1 Introduction

In the society of finance, the stock market has a crucial role. The stock exchange is the place individual and institutional financial specialists meet up to purchase and sell partakes. Stock trades additionally give offices to the issue (posting), reclamation (delisting) of protections, and other capital occasions, including the instalment of salary and profits). The stock exchange forecast has consistently been a fascinating and testing issue for finance and measurement specialists [1]. Meanwhile, it has become an example of scepticism in recent past years that stocks can be predicted through a hunch, information, or technology. If we only predict stocks through the current business scenario, then the recommendation system has a huge success. Recommender frameworks involved a crucial job in settling on expectations in the data and choice overpowered world. It has not just changed the point of view of dynamic by presenting bunch insight but also helped users amplify the monetary benefit by applying and considering such social suggestions into internet business and money [2]. A generous segment of the computational knowledge for finance research is given to financial time series forecasting [3]. One of the methodologies, like Extraordinary Gradient Boosting (XGBoost), has ended up being an efficient calculation with over 87% of precision for multi-day and multi-day time frames and it has ended up being vastly improved when contrasted with customary non-gathering learning techniques. The proposed model beats all current gauging models in writing and can gauge on long haul premises [4]. Stock predictions in computation technology in the major time use the machine learning technique, and it is related to the algorithm which has been their part earlier. Analysts have utilized an assortment of calculations in most cases, for example, SVM [5], Neural Network [6], Naive Bayesian Classifier [7], and so on [8].

Data science is gathering data sets and boiling them down to extract the essence of the inconsequential. Data science depends extensively on data modeling, specifically the time series model for stock forecasting, i.e. change of value over a period. Data science employs an approach that uses math to extrapolate future outcomes. It can be inculcated to predict the outcomes of a cricket match, cancer detection, healthcare industry, waste management analysis, oil price analysis [9] and stock market forecasting.

The stock market has always been a tremendous challenge for analysts due to its uncertain nature. The introduction of Artificial Intelligence (AI) has significantly helped due to its fantastic ability to find hidden patterns in the humongous chunk of data [10]. In recent years the term AI has become a household name, and it comes with no surprise that AI has a vast majority of uses in real-world applications. The world of finance has embraced AI with open arms and has seen tremendous functionality in multiple domains. Many government sectors are now investing in AI technologies [11] to improve financial predictions, thereby enhancing their economy. Since AI's basic fundamental is to automate processes, the labour cost significantly decreases and increases efficiency [12]. This makes AI an essential factor in the financial world.

AI finds excellent uses in the stock market. It can be used to predict the prices of stocks priorly; it can be used to distinguish “Good” stocks from the “Bad” stocks, which in turn can help make educated decisions in investing [13]. Portfolio Management [14, 15] is another important aspect of smart investing to minimize risk for the financial sector people, Machine Learning (ML) algorithms such as K-means based clustering can be implemented for asset management [16]. Different Machine Learning algorithms have their fair share of pros and cons and are generally used together or individually to necessary abstract information and gain the most out of it [17].

Stock Market prediction involves data analysis. For predicting, various Algorithms are used amongst which Support Vector Machines (SVM), and Artificial Neural Network (ANN) are one of the best-suited Algorithms that predicts the stock market tendency by using the Data [18]. The benefit of using SVM is that it takes out a load of comparing present price pattern with the historical ones. By using SVM, we implement data classification and plot each data as a point in an n-dimensional plane where n would be unique datasets available. Classification is done by searching out the hyperplane, which differentiates two classes explicitly [19]. Hereby SVM classifies the plane and divides so that most of the points of a particular category fall on one side of the boundary while most of the different categories fall on the other side of the boundary [20]. Artificial Neural Network (ANN) has also gained importance in predicting Stock Market volatility. It provides interesting Techniques that replicate the Nervous system and the human brain methodologies [17]. The core benefit of ANN lies in the fact that it can discover Non-Linear relationships in an input dataset without prior knowledge of the dependency between input and output [21].

Many authors and researchers have suggested highly efficacious approaches like ANN and SVM for developing a predictive model. However, the ANN and SVM-based algorithms are continuously evolving to solve the existing state-of-art techniques. This paper targets to provide the implementation of other technology in the field of the financial sector, followed by a detailed analysis and study of recent past studies to gain the essence of ANN and SVM technology in the field of the financial sector to analyse the improvements, challenges and further work suggested by the researchers.

2 Applications of Other Technologies in the Stock Market

Machine learning and Artificial Intelligence technologies have excelled in the highly volatile and random stock market. Algorithms implementing sentimental analysis utilize numerical or sentimental data derived from newspapers and articles, and more recently, from microblogging services such as Twitter [22]. Sentimental analysis, even though it has a good generalization ability, can fall short. It yet faces difficulty while recognizing sarcasm and irony, which may lead to faulty predictions. Similarly, Decision trees are great candidates for predicting future stock prices since they excel at categorization problems where features are analysed to determine the final category but decision tree algorithms faces the obstacle of over-fitting [8]. This greatly reduces the generalization capability despite

the high accuracy scores on the training set. Random forests can help reduce the problem up to a certain amount, but they still may persist.

One of the most used ML and AI algorithms in Stock market predictions are SVM's and ANN's. These algorithms generally use Stock Technical Indicators (STI) calculated from historical data and past prices to analyse profit margin [23]. Since SVM's can map a given set of data points into a higher dimensional feature space, the challenges caused by a low-dimensional space can be stripped down to a linearly separable problem by converting it into a higher dimension. An SVM also accounts for errors and thus has great generalization ability [24]. ANN's are based on the Biological Neural Network (BNN). The ANN learns boundaries and predictions in a similar way a biological system would. One of the most used supervised ANN is the multi-layered perceptron (MLP). ANN model [25] showed an accuracy of 96.22% (R2 score) on the NASDAQ exchange rate. Whereas An ANN with MLP trained model [26] demonstrated greater predictability comparatively.

Stock price prediction using any computational technique needs specific data related to it undeniably. When it comes to whole data of any stock its gives us many things like its volume, 52-week high price, 52-week low price, Opening price, and the closing price of any day, major shareholders, turnover, face-value, market capital, sales, quarterly reports, and many such things when a combined bulk number of stocks and their all specifications is said as big data. Large information is utilized to find valuable concealed examples and other data like client decisions, advertise patterns that can assist associations with making increasingly educated and client situated business choices. Large information or bog data is a term that portrays the information described by 3Vs: the outrageous volume of information, the variety of information types, and the velocity at which the information must be prepared.

Large information can be broken down for bits of knowledge that lead to better choices and key business moves. Predicting a stock number keeping all the factors into consideration is a very flummoxing task so there are appropriate methods and tricks through which price is being predicted. There is a method of stock prediction of big data with pattern graph analysis to propose an intricate system that finds the ideal chronicled dataset with comparative examples as indicated by different calculations for each stock thing and gives an increasingly precise forecast of the day by day stock cost [27, 28]. In the [29] framework, the hereditary calculation is utilized to discover anticipating capacity which when given year of expectation it will create the determined outcomes.

Forecasting the stock market, currency exchange rate, bank bankruptcies, understanding and managing financial risk, trading futures, credit rating, loan management, bank customer profiling, and money laundering analysis have always been vital financial tasks of Data Mining [30]. By Mining Techniques, one can predict stock, generate effective patterns of past data for future analysis, optimally utilize the capital of shareholders, bring new Investors in the stock market who are lacking in analysis, increase transparency in the market. In the moving average algorithm, the dataset of recent ones is considered, and it keeps adding a new dataset while removing the old ones. The main benefit of using this algorithm is looking out for recent trends and predicting the stock market [31]. But over the period SVM and ANN have

been developed to tackle the shortcomings of typical machine learning algorithms such developments make the use of ANN and SVM significant even in current time.

3 Artificial Neural Network in Stock Market Prediction

Artificial Neural Network is one of the most widely used methodologies in Stock Market Prediction. A neural network is a bio-inspired system with several single processing elements, called neurons. The neurons are connected by joint mechanisms consisting of assigned weights (Fig. 1.). Various ML algorithms found ANN comes out to be one of the best algorithms for predicting stocks taking up a practical approach. ANN doesn't contain standard formulas and can easily adapt to the changing environment of the market. ANN is also found to be a bit accurate with noisy data, unlike any other methods. The advancement of technology and datasets, ANN comes out to be useful for this purpose. Many researchers have developed novels models in neural networking and some of them have compared the methodologies.

4 Novel Artificial Neural Network methodologies

Dhenuvakonda et al. [32] Applied ANN by taking an example of a company called INFRATEL based on their data of 60 days including required parameters like stock closing, opening, high, low, etc. This paper's point was proving ANN is supercilious than the other three different methodologies LSTM (Long Short-Term Memory), RNN (Recurrent Neural Networks), Deep Learning. The whole dataset consisted of previous closing, opening, high, low, and volume of that company's stocks. Using the previous history dataset, they predicted the 61st

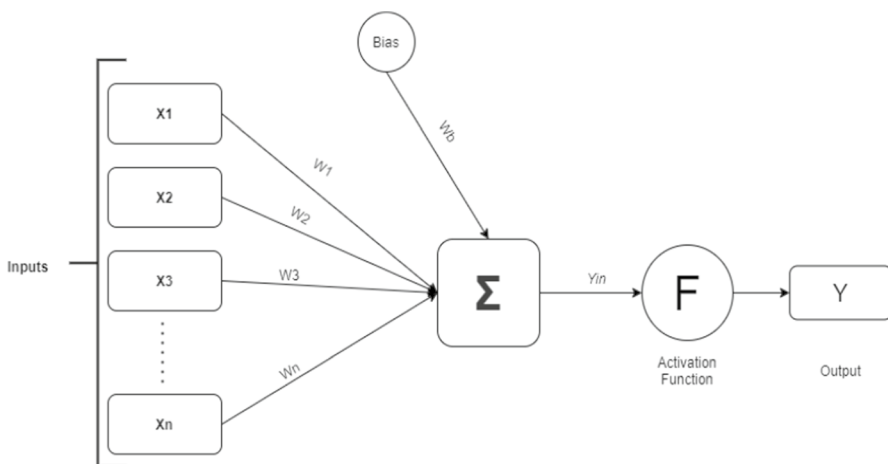


Fig. 1 The internal structure of ANN with interconnected neurons and assigned weights (w_i), aggregate (Y_{in}) to pass to an activation function

day and were shown with closing day price, which worked as advantageous for intraday users. This resulted in how these models are sensibly proficient in perceiving the examples in the space of financial exchange. In this manner, we infer that from results how these neural frameworks beat existing direct models.

Chopra et al. [33] Investigated the effects on Indian stock market prices before and after demonetization using an ANN. They focused on forecasting the stock prices of stocks before and after demonetization in India. They trained a back-propagation model using the Marquardt Levenberg algorithm with min–max normalization on the input data. MSE and regression value is used to test model performance. The neural network contains 2 hidden layers with transfer function as tangent sigmoid function and pure linear function between the hidden and output layer. The optimal number of neurons is found to be 10 and is further used to make all predictions. Regression values obtained, i.e. 0.999, show that the models have increased efficiency when predicting stock prices, with MSE as low as 10^{-6} . The proposed model predicts closing prices with high efficiency. Hence, as the model is fed with more past data, its accuracy and robustness increase to predict the stock market's volatile nature accurately.

Amit et al. [34] Studied the different effects of ANN algorithms on stock prediction. These included ANN's Feed-forward Backpropagation algorithm, the Resilient Backpropagation method, Conjugate gradient methods, Marquardt Lavenberg (ML) method, One step secant, Quasi-Newton methods, Bayesian learning, etc. with various activation functions (Sigmoid, Tanh, etc.). To train and test these ANN's data of Larsen and Toubro and ICICI Bank were considered with the goal to forecast the one month price. The ANN used consisted of 5–15 neurons in the hidden layer. The data from 5 months was used to train the model to predict the opening price of the 6th month. Using trial and error the optimal result for ICICI Bank forecasted prices were achieved by the ML method consisting of 5 neurons in the hidden layer giving an accuracy of about 92%. The result for L&T was also achieved by the ML (Marquardt Lavenberg) method with 7 neurons in the hidden layer with an accuracy of about 85%. Moreover with the inclusion of increased data size, in accordance with its correlation with the current data, the pattern can be more fine-tuned to provide more accuracy.

Shah et al. [35] Assessed ANN to anticipate the stock costs of a couple of chosen organizations from the National Stock Index. The target of the paper was to feature the endeavours to anticipate the financial exchange utilizing Artificial Neural Networks. With the sheer number of neural nets available and the endless possibilities of internal configurations, it is tough to find the optimal network. But ANN has the best accuracy of about 98%. Dataset consisted of 300 to 700 tuples ranging from 3 to 5 years which they got from the website Quandl. The ANN inputs consisted of Opening Price, High Price, Low Price, Last Price, Closing Price, Total Trade, and Turnover. In the wake of normalizing the information utilizing the z score capacity of MATLAB, they were able to foretell stock prices with 98% accuracy. Subsequently from this, we have presumed that utilizing ANN, stock costs can be anticipated up to some degree with specific measures of information. (Table 1)

5 Recent Past Artificial Neural Network Methodologies

Chauhan et al. [36] Analysed ANN with the back-propagation method on many different companies. This task's point is the execution of neural systems with back engendering calculation for financial exchange with data mining concepts [37]. Their historical information in the market was shown using data mining techniques [38]. The algorithmic process was divided into 5 steps: Take all input, perform its weighted summation, apply it input layer neurons, process all input by transfer function and get individual outputs and thereby passing this output to the hidden layer. The results which were shown in the form of the actual price and the predicted price showed the accuracy was pretty remarkable. Subsequently, we presumed that the back multiplication count is the best estimation to be used in the feed-forward neural framework since it reduces a slip-up between the genuine yield and needed yield in a tendency to drop way.

Yetis et al. [39] Trained and used an Artificial Neural Network (ANN) to predict the stock market prices. The trained ANN with the assistance of MLP, MLP that consisted of ten input neurons and one output neuron with Backpropagation which utilized the MSE as the loss function. The NASDAQ historical data used is split into three parts. 70% for training, 15% for validation, and the remaining 15% for testing purposes to test generalization ability. The data is normalized before using as input to improve model performance. Regression was used to validate the network's performance and R score was used as the scoring metric. The result shows that the R scores for each training, validation, and training set is about 0.99 or above. Considering the sheer amount of instances used in training the error comes down to smaller than 2%. To conclude, the ANN could predict stock prices with great precision and accuracy, which can be beneficial for investors looking to invest. Further, this model can be tested for different data sets to check its adaptability for different scenarios and environment.

Korade [40] Gauged an ANN using back-propagation in predicting prices of shares in the stock exchange market. The Dataset of any stock should be in a linear format and unwanted data should be removed and should be normalized between -1 to 1 . Resulting subsets are Set of training data, a set of validating data, and a set of testing data. In the suggested model they implemented feed-forward MLP neural network, the predicted values differ from the original one with a very less delta value. After completing the whole back-propagation process it showed how accurate their results are to buy or sell the share on the next day.

Simon et al. [41] Surveyed advance ANN models that were used in stock market prediction. The authors studied various vastly used models to compare the generalization capability of each. They saw that the accuracy of the models could be improved by using a task-relevant ANN model, by implementing statistical techniques with ANN models and using special algorithms (Hybrid algorithms) [42–44] that can denoise, select, and optimize parameters. The authors present further strategies that could be used to improve model accuracy. These include hybrid analysis which combines the best of both technical analysis and fundamental analysis and carefully selecting input features which could also drastically

increase accuracy. Another major factor that affects accuracy is ANN component optimization. It is crucial to find the optimal ANN model (mostly by trial-and-error) to understand the underlying relation. It is observed that ANN models outperform traditional models and MLP with back-propagation is found to be the most widely used ANN model for stock market prediction.

Haider Khan et al. [1] Appraised ANN on the past historical data of the ACI pharmaceutical company of Bangladesh stock exchange market predicting with proper accuracy. The paper's main aim was to show how a combination of the Back-propagation algorithm and Multilayer Feed-forward network in ANN is very advantageous. The historical data of the pharmaceutical company was used. In this ANN featured 2 input dataset in the first example and the second example, there was 5 dataset. Thence it was seen that sum squared error was high for the 5 input dataset than the 2 input data sets but the error of prediction was the lowest at all, it was noted that when the data is in from continuous date the prediction is more accurate then discontinued date. Taking everything into account we can say that if we train our framework with more info informational index it creates a more blunder-free forecast cost. Further, this discussed model can be implemented in current time with proper data scrapping or live data yielding on daily basis to produce more accurate predictions.

Gurusen et al. [45] Worked upon stock market prediction techniques using artificial neural networks. The study's main objective was to compare various ANN models in forecasting time series used in market values. The authors used a Multilayer perceptron (MLP) for forecasting stocks. MLP comparatively tends to achieve good accuracy for approximating arbitrary functions. Due to its 2-peculiarity, which includes nonlinear processing elements (PEs), which have a nonlinearity that must be smooth and massive interconnectivity. It stated various steps that can be used to improve forecasting efficiency, which included normalizing of data, using Tanh function instead of a logarithmic scale, setting the step size more towards input, use of more sophisticated learning methods, etc. DAN2 EGARCH—MLP and GARCH—MLP models are also being explained in it. Mean absolute deviate (MAD) for the following models were noted in ANN and Hybrid models for testing, MLP 2.5%, GARCH-MLP 2.77%, DAN2 2.76% and GARCH-DAN2 6.48%. They further suggested to compare the GARCH or E-GARCH has a better correcting effect on the financial forecasts.

Majumder [21], in their paper, worked upon forecasting of Indian stock market index using an artificial neural network. They stated that data pre-processing helps predict the stocks better as the algorithm efficiency works upon the data set. So to improve the accuracy, they adapted a nonlinear scaling method. After scaling the database, they worked on it using Neural Network and stated that the prediction of the stock market trend is more important than the value of the index. After necessary amends, the model could predict stock markets with a minimum accuracy of 69.72% and Maximum accuracy of 89.64%. They stated that there is a wide range of future scope of Stock market prediction using ANN. It is in the developing phase and there is a great possibility of forecasting the stock market at an evolutionary stage and there are future possibilities of improvement in the prediction accuracy and reliability on it. They concluded that in this highly volatile market like the Indian Stock

Market, the performance levels of the neural network models reported in their paper will be very useful. Especially, the prediction of the direction of the market with fairly high accuracy will guide the investors and the regulators.

Zekic [46] Explained neural network applications in stock market predictions. He stated that with uncertain, fuzzy, or insufficient data that fluctuates rapidly, Neural Networks had become a vital technique in stock market prediction. Paper targets the comparative analysis of Neural Network (NN) methodology of; (1) problem domain of application, (2) data model used in the application, and (3) results obtained by NN in stock markets. The author stated that almost all stock market applications with NN are based on different data models. The author plotted various data sets and found that no data model was predominant compared to others. The results concluded that NN outperformed, and 68% to 90% accuracy was observed. He concluded that NN was efficient in stock market prediction, but there was no solution to certain problems; the stock market prediction was made even after stock modelling being a prominent problem.

In this section, the paper discussed the recent or novel and recent past ANN methodologies implemented in the field of the financial sector to yield the best outcome in terms of model functioning. Many researchers studied and implemented various methodologies like simple ANN, ANN-MLP, GARCH-MLP, a combination of the Backpropagation algorithm and Multilayer Feed-forward network in ANN, etc. to predict the best result. Anatomizing various research works helped surmise that ANN is and will play a crucial role in financial forecasting.

6 Support Vector Machine in Stock Market Prediction

SVM is one of the most used Supervised Learning calculations, which is utilized for classification just as regression issues. Nonetheless, it is utilized for Classification issues in Machine Learning. The SVM calculation objective is to make the best line or choice limit that can isolate n-dimensional space into classes so we can without much of a stretch put the new information point in the right classification later on. This best choice limit is known as a hyperplane. SVM picks the outrageous focuses/vectors that help make the hyperplane (Fig. 2). These outrageous cases are called Support vectors, and consequently, the calculation is named Support Vector Machine.

There are two types of SVM—linear and non-linear. Linear SVM is utilized for linearly distinguishable information, which implies if a dataset can be arranged into two classes by utilizing a solitary straight line, at that point such information is named linearly separable data, and the classifier is utilized as Linear SVM classifier (Fig. 3). Non-Linear SVM is utilized for non-directly isolated information, which implies on the off chance that a dataset can't be ordered by utilizing a straight line, at that point such information is named as non-direct information, and the classifier utilized is called as Non-straight SVM classifier. SVM Algorithms are commonly utilized for Face identification, picture arrangement, text categorization, stock forecast, and so forth. (Table 2)

Fig. 2 Graphical description of SVM margin, demonstrating support vectors, and the optimized hyperplane for given data set

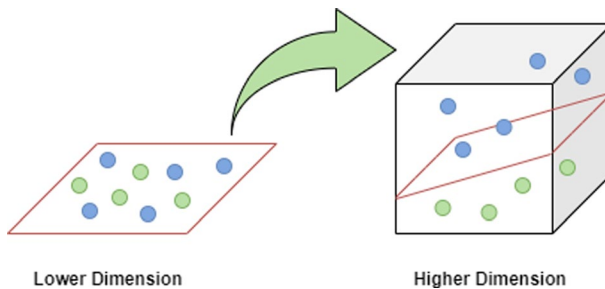
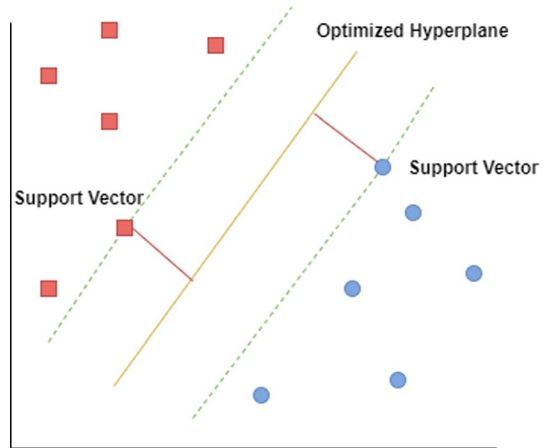


Fig. 3 Translation of lower-dimensional data into higher dimensional data to classify Non-linear data

7 Novel Support Vector Machine Methodologies

Gururaj et al. [47] Compared linear progression and SVM, in the prediction of stock prices with matching prerequisites. The target of the paper was to feature the advantages and disadvantages of SVM contrasted with direct relapse by anticipating costs and looking at calculations. The dataset comprised of Coca Cola Company stock details from 2017 to 2018 downloaded from Quandl. These files were utilized to gauge the anticipated precision near the real worth, root mean square error (RMSE) of 3.22, the mean absolute error (MAE) of 2.53, the mean square error (MSE) of 10.37 and correlation coefficient (R) of 0.73 was observed for Linear Regression whereas for SMV following values were observed 1.58 for RMSE, 1.33 for MAE, 2.51 for MSE and 0.93 for R-Squared. Thereby proving that SVM performs better than the Linear Regression model.

Hiba Sadia et al. [19] Discussed the best model to predict the stock market using various techniques and figuring out the best out of it. The main aim of their paper was to select the correct database. They worked upon it making use of 11 different parameters. By making use of SVM and RFs (Random forest classifier)

Table 1 Tabularized summaries of literature reviewed for stock market forecasting using artificial neural networks (ANN)

Dataset Used	Machine Learning Technique	Application	Method	Accuracy	Limitation	Reference
Fiat (FCAU)	Multi Layer Perceptron with back propagation and moving simulation.	To predict opening prices for the next day.	MLP-BP trained with moving simulation to reduce inaccuracy in prediction. Sigmoid activation function applied on a 4-6-1 architecture.	Relative prediction error 2.2%	The size of the "moving window" considered may not be optimal for other similar datasets.	Turchenko et al. (2011)
Infosys	Artificial neural network and svm	To predict stock prices	Support Vector Machine along with RBF kernel algorithm	Seeing all the features results and graph it was seen 89% accuracy	The results are only predicted on the next week, next day and next minute stock values but the investors ,brokers	Deepak et al.(2017)
Tata Steel ONGC M&M					demand for more too.	
S&P500 FOREX EUR/USD	Artificial Neural Network (ANN) and Neural Networks architectures, namely the Multi-layer Perceptron (MLP), the Convolutional Neural Networks (CNN), and the Long Short-Term Memory (LSTM) recurrent neural networks technique	To predict stock indices	MLP, CNN, and RNN and combination of novelWavelet+CNNalgorithm	S&P500 62 % FORE X EUR/ USD 83%	Low data of forex shows less effective learning patterns and so are results.	Persio and Honchar (2016)
NASDAQ	artificial neural network	Stock market index	Backpropagation algorithm with several	Dataset which were taken were	Without this input	Moghaddam et
		prediction	feedforward ANN's to train them.	validated	dataset it's not possible.	al.(2016)
TESLA	artificial neural network	to predict stock market price	Backpropagation algorithm with Multilayer feed forward perceptron	94% accuracy	Without the historical data its not possible	Barapatre et al.(2018)

Table 1 (continued)

Korea composite stock price index (KOSPI)	Hybrid of Artificial neural network and genetic algorithm.	Predict the future direction of change in stock price.	Uses a ANN with genetic algorithms for optimal feature transformation.	<table border="1" data-bbox="636 225 733 414"> <tr> <th colspan="2">Hit Ratio (%)</th> </tr> <tr> <td>LTM</td> <td>50.00</td> </tr> <tr> <td>FTM</td> <td>58.15</td> </tr> <tr> <td>GTM</td> <td>64.16</td> </tr> </table>	Hit Ratio (%)		LTM	50.00	FTM	58.15	GTM	64.16	The number of categories for the discretization is limited to three. This number is varied with the nature of each feature.	Kim and Lee (2004)																																																												
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Turkish stock market	ANN with Harmony Search (HS) and Genetic	Evaluating the effectiveness of	ANN hybridised with HS and GA to find the		Due to the lack of computational power	Gökçen et al. (2016)																																																																				
	Algorithm (GA)	using technical indicators on stock market prediction.	optimal technical indicators to increase generalization ability.	<table border="1" data-bbox="636 534 789 1040"> <thead> <tr> <th></th> <th>HS-ANN</th> <th>GA-ANN</th> <th>regular ANN</th> </tr> </thead> <tbody> <tr> <td>M</td> <td>2597.</td> <td>2950.2</td> <td>2951.55</td> </tr> <tr> <td>A</td> <td>321</td> <td>51</td> <td>4</td> </tr> <tr> <td>E</td> <td></td> <td></td> <td></td> </tr> <tr> <td>M</td> <td>11236</td> <td>12202</td> <td>145166</td> </tr> <tr> <td>S</td> <td>305</td> <td>954</td> <td>50</td> </tr> <tr> <td>E</td> <td></td> <td></td> <td></td> </tr> <tr> <td>R</td> <td>3352.</td> <td>3493.2</td> <td>3810.07</td> </tr> <tr> <td>M</td> <td>06</td> <td>73</td> <td>2</td> </tr> <tr> <td>S</td> <td></td> <td></td> <td></td> </tr> <tr> <td>E</td> <td></td> <td></td> <td></td> </tr> <tr> <td>M</td> <td>0.033</td> <td>0.0386</td> <td>0.03819</td> </tr> <tr> <td>A</td> <td>814</td> <td>28</td> <td>1</td> </tr> <tr> <td>R</td> <td></td> <td></td> <td></td> </tr> <tr> <td>E</td> <td></td> <td></td> <td></td> </tr> </tbody> </table>		HS-ANN	GA-ANN	regular ANN	M	2597.	2950.2	2951.55	A	321	51	4	E				M	11236	12202	145166	S	305	954	50	E				R	3352.	3493.2	3810.07	M	06	73	2	S				E				M	0.033	0.0386	0.03819	A	814	28	1	R				E				only 1 hidden layer was implemented. The ANN uses predetermined transfer and training functions.									
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				<table border="1" data-bbox="636 1058 789 1555"> <tbody> <tr> <td>M</td> <td>0.001</td> <td>0.0019</td> <td>0.00225</td> </tr> <tr> <td>S</td> <td>81</td> <td>95</td> <td>6</td> </tr> <tr> <td>R</td> <td></td> <td></td> <td></td> </tr> <tr> <td>E</td> <td></td> <td></td> <td></td> </tr> <tr> <td>R</td> <td>0.042</td> <td>0.0446</td> <td>0.04749</td> </tr> <tr> <td>M</td> <td>541</td> <td>71</td> <td>3</td> </tr> <tr> <td>S</td> <td></td> <td></td> <td></td> </tr> <tr> <td>R</td> <td></td> <td></td> <td></td> </tr> <tr> <td>E</td> <td></td> <td></td> <td></td> </tr> <tr> <td>M</td> <td>3.381</td> <td>3.8628</td> <td>3.81905</td> </tr> <tr> <td>A</td> <td>416</td> <td>37</td> <td>6</td> </tr> <tr> <td>P</td> <td></td> <td></td> <td></td> </tr> <tr> <td>E</td> <td></td> <td></td> <td></td> </tr> <tr> <td>M</td> <td>18.09</td> <td>19.954</td> <td>22.5560</td> </tr> <tr> <td>S</td> <td>704</td> <td>54</td> <td>2</td> </tr> <tr> <td>P</td> <td></td> <td></td> <td></td> </tr> <tr> <td>E</td> <td></td> <td></td> <td></td> </tr> </tbody> </table>	M	0.001	0.0019	0.00225	S	81	95	6	R				E				R	0.042	0.0446	0.04749	M	541	71	3	S				R				E				M	3.381	3.8628	3.81905	A	416	37	6	P				E				M	18.09	19.954	22.5560	S	704	54	2	P				E					
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Nestle Nigerian Plc.																																								
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<table border="1"> <tr> <td>market indexes (S&P, Dow Jones, etc.)</td> </tr> <tr> <td>Fortune 500 and Business Week Top 1000</td> </tr> <tr> <td>Swales and Yoon</td> </tr> </table>	market indexes (S&P, Dow Jones, etc.)	Fortune 500 and Business Week Top 1000	Swales and Yoon	NN	Stock Market Prediction	Back Propagation Various Methodology Analysis	70-80%	For more complex dataset, accuracy decrease. Specific method from NN to predict stocks most efficiently is yet unknown. Without Previous dataset, prediction is yet	Zekic,(1998)																															
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on the dataset (Kaggle dataset) and concluded that by utilizing SVC (Support Vector Classifier) resulted in 78.7% accuracy, while with RFS they achieved 80.8% accuracy. Based on these databases they concluded that these are one of the best algorithms to predict stocks and they can be an asset for brokers and Investors. For further work, the inclusion of more parameters can result in removing many boundaries to achieve more accuracy.

Table 1 (continued)

					difficult	
Reliance Private Limited	ANN	Predicting Stocks Of Tick Data and 15-min dataset	Levenberg-Marquardt, Scaled Conjugate Gradient and Bayesian Regularization	99.9% on tick data Poor accuracy With 15-min dataset	More Dataset can be used Recurrent NN can be used	Selvamuthu et al.(2019)
NSE RELIANCE	NN	Stock Market Prediction	Back Propagation	Close enough	Exact Percentage of accuracy cannot be predicted. It worked on a small dataset.	Gurjar et al.(2018)

Hargreaves [17] Assessed Support Vector Machine to anticipate stock costs for the huge and little capitalizations and in the three distinct markets, utilizing costs with both every day and regularly updated frequencies. In this paper, the principal objective was enormous dataset esteem which is gathered from various worldwide budgetary markets resulting in their day-by-day slants with higher efficiency. In this paper, they have shown it can be predicted of any stock. In this task, we utilize four highlights to foresee stock value heading – value instability, value force, segment unpredictability, and area energy. After applying the suggested model, they assisted it with a graph of the actual price vs. stock predicted price. The graphical results depict that mathematical outcomes propose high productivity in contrast with other models.

Zheng et al. [48] Evaluated the effect of using various AI algorithms on time series data and to find the optimal one. They implemented Logistic Regression, Bayesian Network, Simple Neural Network, and SVM with RBF kernel to assess near future prices of one specific stock named “MSFT” (Microsoft). Preliminary Experiments conducted using past prices only revealed that it’s not sufficient enough to correctly predict trends in practice regardless of SVM with RBF (Radial Base Function) kernel performed the best. An in-depth evaluation with past prices and technical indicators shows that a Linear Regressor performs fairly well. Due to a lack of computational power, the SVR was trained on 5% of the dataset and still performed better than the Linear Regressor (accuracy as high as 69.5%). This proves that SVM’s can be used in real-world for stock forecasting because of its capability of avoiding the problem of cold start.

Patil et al. [49] Stated that the traditional prediction system faces many challenges. According to the study, SVM, a relatively new algorithm, has required characteristics for the decision family’s control. Authors have stated an empirical and theoretical framework to support SVM. The process consisted of basic steps,

Table 2 Tabularized summaries of literature reviewed for stock market forecasting using support vector machines (SVM)

Dataset Used	Machine Learning Technique	Application	Method	Accuracy	Limitation	Reference											
<table border="1"> <tr><td>Brazilian Stocks</td></tr> <tr><td>American Stocks</td></tr> <tr><td>Chinese Stocks</td></tr> </table> <p>Three Blue Chip and Three Small cap stocks of each were chosen.</p>	Brazilian Stocks	American Stocks	Chinese Stocks	SVR with linear, radial and polynomial kernels.	Predict Closing stock prices	They used an SVR to predict closing price and referred to random walk model for comparison	<table border="1"> <tr><td>RMSE</td><td>MAPE</td></tr> <tr><td>0.03869</td><td>0.22941</td></tr> <tr><td>0.02817</td><td>0.14257</td></tr> <tr><td>0.03088</td><td>0.16923</td></tr> </table>	RMSE	MAPE	0.03869	0.22941	0.02817	0.14257	0.03088	0.16923	The lack of data quality assurance methods and length of period of historical data.	Henrique et al. (2018)
Brazilian Stocks																	
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<table border="1"> <tr><td>Hon Hai Company (HHC)</td></tr> <tr><td>Taiwan Semiconductor Company (TSC)</td></tr> <tr><td>Evergreen Company (EC)</td></tr> <tr><td>Taiwan 50 Index (TW50)</td></tr> </table>	Hon Hai Company (HHC)	Taiwan Semiconductor Company (TSC)	Evergreen Company (EC)	Taiwan 50 Index (TW50)	SVM with a quasi-linear kernel.	Stock market trend prediction.	Hybridized SVM with correlation-based SVM filter method and a quasi-linear SVM.	<table border="1"> <tr><td>Hit Ratio</td></tr> <tr><td>70.45%</td></tr> <tr><td>65.91%</td></tr> <tr><td>70.45%</td></tr> <tr><td>65.91%</td></tr> </table>	Hit Ratio	70.45%	65.91%	70.45%	65.91%	The chosen indicators are not sufficient and may be inconsistent depending on their settings.	LIN et al. (2013)		
Hon Hai Company (HHC)																	
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downloading and pre-processing the dataset, which included starting and ending value to stocks. Then in GUI, the stocks are being used by implementing SVM on them. The results then show the graphs of the datasets. Then they applied a logarithmic function to increase efficiency. Followed by in the final step, it displayed the original value and predicted value of that stock. According to their results, SVM showed up 100% accuracy in their training phase and more than 90% accuracy in

Table 2 (continued)

<p>Information Technology (Adobe, Hp, and Oracle); Financials (American Express and Bank of New York); Health Care (Life Technologies, and Hospira); Energy (Exxon-Mobile and Duck energy); Communications (AT&T); Materials (FMC Corporation); Industrials (Honey Well)</p>	<p>Particle swarm optimization (PSO) and least square support vector machine (LS-SVM).</p>	<p>to predict the daily stock prices and showed how particle swarm optimization (PSO) algorithm and LS-SVM is better than ANN-BP</p>	<p>Combination of particle swarm optimization (PSO) algorithm and LS-SVM with historical data and technician indicators.</p>	<p>—</p>	<p>Without the help of indicators there accuracy is not seen.</p>	<p>Hegazy et al.(2013)</p>								
<p>Tokyo Stock exchange (TSE)</p>	<p>Many techniques of Neural Networks , SVM's and unique</p>	<p>Quantitative trending ,stock prediction and forecasting the</p>	<p>Neural networks and svm with their supervised and</p>		<p>Predicting through a neural network turns out to be very expensive.</p>	<p>Vats and Samdani (2019)</p>								
	<p>bifurcations in Genetic Algorithms and Back Propagations along with the Time-Series Wavelet</p>	<p>probable moment of the market.</p>	<p>unsupervised techniques accordingly</p>	<table border="1"> <tr> <td data-bbox="600 772 665 975">Neural Networks</td> <td data-bbox="665 772 747 975">20% initially but modern day accuracy close to 60%</td> </tr> <tr> <td data-bbox="600 975 665 1098">Support Vector Machines</td> <td data-bbox="665 975 747 1098">Close to 89%</td> </tr> <tr> <td data-bbox="600 1098 665 1204">Multiple Kernel Learning</td> <td data-bbox="665 1098 747 1204">Between 55 to 58%</td> </tr> <tr> <td data-bbox="600 1204 665 1323">Random Forest Learning Method</td> <td data-bbox="665 1204 747 1323">Around 95%</td> </tr> </table>	Neural Networks	20% initially but modern day accuracy close to 60%	Support Vector Machines	Close to 89%	Multiple Kernel Learning	Between 55 to 58%	Random Forest Learning Method	Around 95%		
Neural Networks	20% initially but modern day accuracy close to 60%													
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their testing phase. They concluded that SVM works on large datasets and doesn't come up with an over-fitting problem. There are various techniques proposed and used for prediction but the designed model generates higher profit compared to selected benchmarks.

Pan [50] Worked upon Data Normalization on a stock market prediction by using SVM and Technical Indicators. SVM implements a Structural risk minimization

Table 2 (continued)

				<table border="1"> <tr> <td></td> <td></td> </tr> <tr> <td>K-Means Clustering Technique</td> <td>Best case 79.1%</td> </tr> </table>			K-Means Clustering Technique	Best case 79.1%						
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<table border="1"> <tr> <td>Google Inc. (GOOG)</td> </tr> <tr> <td>Yahoo Inc. (YHOO)</td> </tr> </table>	Google Inc. (GOOG)	Yahoo Inc. (YHOO)	Multiple machine learning techniques are applied such as linear regression, SVM, Boosting etc.	Evaluate different machine learning techniques for stock predictions.	Used different ML algorithms on a dataset to predict closing prices.	<p>SVM</p> <table border="1"> <tr> <td>RMSE</td> <td>Accuracy</td> </tr> <tr> <td>0.485 +/-</td> <td>60.20 +/-</td> </tr> <tr> <td>0.012</td> <td>0.49%</td> </tr> </table>	RMSE	Accuracy	0.485 +/-	60.20 +/-	0.012	0.49%	The author assumes that the dataset includes effects of "Unknown Factors" such elections etc.	Shah (2007)
Google Inc. (GOOG)														
Yahoo Inc. (YHOO)														
RMSE	Accuracy													
0.485 +/-	60.20 +/-													
0.012	0.49%													
S&P 500 Index	three-layered	Predict stock	three-layered	Results showed in this order	Only with the help of	Chia-Cheng Chen et								
	feedforward ANN, maximum margin classifier of SVM and decision tree learning of random forest	value of S&P 500 index	feedforward ANN, maximum margin classifier of svm and decision tree learning.	Random forest >SVM>ANN	Sharpe ratio, Treynor ratio, Information ratio, and Modigliani ratio is possible without this it is not possible	al.(2020)								
<table border="1"> <tr> <td>AAPL</td> </tr> <tr> <td>google</td> </tr> <tr> <td>fb</td> </tr> <tr> <td>amazon</td> </tr> </table>	AAPL	google	fb	amazon	recurrent neural network (RNN), feed forward neural network (FFNN), support vector machines (SVM) and support vector regression (SVR)	Predicting the stock price with including factor news about the stock and perfect time to but also predicting the closed value on that day.	They used four methods mainly RNN,FFNN,SVM and SVR	Comparing all the four methods it showed SVM with the highest accuracy 82.91%.	Without the historical data and news it's not possible for them to predict stock prices and svm cannot perform well on a linear set of problems.	Mariam Moukalled et al.(2019)				
AAPL														
google														
fb														
amazon														

principle compared to the empirical risk minimization principle implemented by various other algorithms, including ANN. By structural risk minimization principle, they work upon minimizing the upper bound of generalization error compared to minimizing empirical error. The authors also stated that SVM could be used globally due to its unlikely nature to over-fitting. Hence, before working upon datasets, data Normalization is being carried out, which scales down the transformation of attributes, decreasing the value magnitude to shallow values. Various Normalization techniques are being used, which includes Min–Max Normalization, which scales down

Table 2 (continued)

Allegiant Travel Company(ALGT), Alliance Fiber Optic Products(AFOP), AT & T Inc. (T), Bank of New York Mellon Corpora(BK), eBay, Inc(EBAY), EXCO TECH(XTC.TO), Facebook, Inc(FB), FORD, Inc(FORD), IBM, Inc(IBM), Kofax Limited(KFX), Old Second Bancorp, Inc(OSBC), SLM Corporation(SLM), Xilinx, Inc(XLNX).	SVM	To predict Stock Market	Collecting datasets of particular company and using it to predict stocks by using SVM and getting the training and testing efficiency m	91.13%	100% efficiency can't be obtained	Patil et al. (2016)						
DJI, S&P 500 and Nasdaq-100	SVM	To forecast the	Improved hybrid IPSOS	64% Hit Ratio	More Accuracy can	Karazmodch et al. (2013)						
and www.marketwatch. com.			optimization of technical indicators, and the SVM module was used to produce trading signals (Buy/Sale/Hold/Ne utral)	<table border="1" data-bbox="656 763 850 853"> <tr> <td>RMSE</td> <td>0.0096</td> </tr> <tr> <td>MAE</td> <td>0.0088</td> </tr> <tr> <td>MAPE (%)</td> <td>0.7283</td> </tr> </table>	RMSE	0.0096	MAE	0.0088	MAPE (%)	0.7283	0.0096 improved.	
RMSE	0.0096											
MAE	0.0088											
MAPE (%)	0.7283											
CME-SP, CBOT-US, CBOT-BO, EUREX- BUND MATIF-CAC40	Support Vector machine	Financial Time Series	Support Vector Machine and it's risk management techniques kernel function	Good Performance.	Training requires experience and care	Tay et al. (2001)						
S&P500	Support Vector Machine	Mining Stock Market Tendency	Genetic Algorithm based Support Vector Machine	The prediction performance comparison of various models	Higher Accuracy can't be achieved	Yu et al.(1970)						
				<table border="1" data-bbox="656 1136 773 1312"> <tr> <td>Mining Models</td> <td>Hit Ratio (%)</td> </tr> <tr> <td>RW</td> <td>51.06</td> </tr> <tr> <td>ARIMA</td> <td>56.13</td> </tr> </table>	Mining Models	Hit Ratio (%)	RW	51.06	ARIMA	56.13		
Mining Models	Hit Ratio (%)											
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ARIMA	56.13											

the values between $[0, 1]$ or $[-1, 1]$, Z-Score Normalization, which scales down the values by using Mean and Standard Deviation, Decimal Scaling Normalisation which scales down the values by moving the decimal point of that value and Median and Median Absolute Deviation (MMAD) Normalization which is a bit similar to Z Normalisation but this uses median and median absolute deviation for rescaling. They used a radial basis function kernel to construct SVM models. They concluded that by using SVM, it came out to be the best optimal results by SVM compared to

Table 2 (continued)

and www.marketwatch.com.			optimization of technical indicators, and the SVM module was used to produce trading signals (Buy/Sale/Hold/Neutral)	<table border="1"> <tr> <td>RMSE</td> <td>0.009</td> </tr> <tr> <td>MAE</td> <td>0.0088</td> </tr> <tr> <td>MAPE (%)</td> <td>0.7283</td> </tr> </table>	RMSE	0.009	MAE	0.0088	MAPE (%)	0.7283	0.009 is improved.	
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CME-SP, CBOT-US, CBOT-BO, EUREX-BUND MATIF-CAC40	Support Vector machine	Financial Time Series	Support Vector Machine and it's risk management techniques kernel function	Good Performance.	Training requires experience and care	Tay et al. (2001)						
S&P500	Support Vector Machine	Mining Stock Market Tendency	Genetic Algorithm based Support Vector Machine	The prediction performance comparison of various models <table border="1"> <tr> <td>Mining Models</td> <td>Hit Ratio (%)</td> </tr> <tr> <td>RW</td> <td>51.06</td> </tr> <tr> <td>ARIMA</td> <td>56.13</td> </tr> </table>	Mining Models	Hit Ratio (%)	RW	51.06	ARIMA	56.13	Higher Accuracy can't be achieved	Yu et al.(1970)
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				<table border="1"> <tr> <td>BPNN</td> <td>69.78</td> </tr> <tr> <td>SVM</td> <td>78.65</td> </tr> <tr> <td>GASVM</td> <td>84.57</td> </tr> </table>	BPNN	69.78	SVM	78.65	GASVM	84.57		
BPNN	69.78											
SVM	78.65											
GASVM	84.57											

2970 other technics. With data Normalization, they achieved a bit increase in accuracy compared to other optimal technics without Normalization.

8 Recent Past Support Vector Machine Methodologies

Di et al. [51] trained an SVM model to predict short term stock prices (1–10 days). The author used APPL, AMZN, and MSFT stocks historical data to predict the immediate future’s closing prices. The model was trained on technical indicators as features extracted from the data. The results show that APPL stocks were robust and had an accurate prediction of 70% and above. AMZN stocks were prone to fluctuations in the short term but could be predicted in the long term. MSFT was in the middle, the most accurate predictions were in between 5-days to 10-days in the future. On average, the SVM model accurately predicts stock prices for 1-day in the future with 56% accuracy and an accuracy of 70% for the next couple of days, showing the model’s capacity to precisely forecast the trend.

Karazmodeh et al. [52] States about Particle Swarm Optimization (PSO) Improved via Genetic Algorithm (IPSO) based on Support Vector Machines

(SVM) for efficient prediction of various stock indices. They explained that the risk minimization was done by SVM as its structural in nature whereas other traditional algorithms which were empirical principles. They explained that there exists a certain correlation between the prices of certain stocks, prices of one stock is correlated and assists in predicting the prices of other stocks. They presented that IPSO SVM (Improved Particle swarm optimization) with an average hit ratio of 64.012% (For three stocks: DJI, S&P 500 and NASDAQ) performed better compared to PSO SVM with an average hit ratio of 61.617% for the same stocks. The mutation in the particles led them to better results and accuracy. Moreover, this model can be enhanced by including political and economic aspects accuracy of it can be improved.

Hu et al. [53] Evaluated an SVM on the data of various companies like the Federal Reserve Bank of St Louis, Big Charts Historical Stock Quotes, and each company's annual report. The objective of the paper was to highlight the superiority of SVM compared to previous traditional predictive regression models and highlight the predictive capability of SVM on previously unseen data. The data was divided into a training set and a test set of 78 sample entries and 10 sample entries respectively. The SVM input features consisted of four company-specific variables (i.e. net revenue, net income, Price per earnings ratio of stock etc.) and six macroeconomic variables (i.e. consumer investment, consumer spending, etc.). Since such a problem is not linearly separable, regression models failed at giving accurate predictions whereas SVM showed an accuracy of 97.43% on training sets and 70% on test sets. Accordingly, inferring that SVM's beat other customary procedures in financial exchange expectation. Further, the authors suggest that multivariate statistics can be used to analyse the relationship between the company's performance and the stock market trend.

Shan et al. [54] Tried to determine the closing prices of the global stock market before opening the United States market. The global stock market plays a significant role in the value of a particular stock market (here being the US stock market), experiments on single feature predictions reveal a strong correlation on features such DAX and Australian Dollars (AUD). Similarly, long term predictions also show a trend in prediction accuracy. Using Multi-feature prediction illuminates that the SVM has prediction accuracy as high as 74%. The SVM model excels here too, with an RMSE of 21.6. All in all, the paper shows that from the various models utilized, SVM gives an extraordinary speculation capacity and effectively decides the hidden connection between worldwide stock costs and the US securities exchange.

In this section, the paper discussed the recent or novel and recent past SVM methodologies implemented in the field of the financial sector to yield the best outcome in terms of model functioning. Many researchers studied and implemented various methodologies like SVM, SVM with Random Forest, Hybrid models like Particle Swarm Optimization (PSO) Improved via Genetic Algorithm (IPSO) based on Support Vector Machines (SVM) and more to yield the best result. Many observations were made with the above-detailed studies, like, SVM aides in avoiding the problem of over-fitting and also start giving accurate results with a small amount of data thereby assisting preventing the problem of cold start.

9 Our Opinion

With the use of a support vector machine or a support vector Regressor a general trend is observed. SVM's / SVR's are an excellent tool for forecasting stock predictions overall and short on data or when real-time analysis is required. The most esteemed tool that gives SVM's an edge over other similar networks is its ability to work in an infinite-dimensional space. Real-world data is often "messy" and unorganized. Thus it makes it cumbersome to find an underlying pattern that generalizes the data well. Previously proposed algorithms, such as Linear Regression, were not ideal in predicting stock prices when put head-to-head against an SVM despite yielding satisfactory results. The different SVM models evaluated in this paper shows an average accuracy of prediction between 60%–70%; SVM's could also be used with different algorithms, such as IPOS, resulting in further improved accuracy. However, SVM's fall short when dealing with large datasets. Usually, they require high computational power to run and can thus be time-consuming. SVM's are also very sensitive to the type of data provided. It can produce incorrect results if the data spans a wide range. Thus it is essential to normalize the data before training it on a Support Vector Machine.

With Artificial Neural Networks employed for stock prediction, it is observed that the most frequently used network is a multilayer perceptron (MLP) with back-propagation. With various scoring, matrices can be concluded that an ANN generally performs better than other similar neural networks. The key, in our anatomized study, which gives an ANN an edge over other networks, is its ability to be customized. Since finding the optimal hyperplane that generalizes the data points well is a trial and error method, it becomes essential to try a variety of available options. It is observed that different types of problems require different forms of ANN's. Suppose an ANN that might work well with one kind of dataset may not work well with some other dataset. Here the ability of the network to adapt becomes a powerful tool. An ANN can be further combined with other technologies such as statistical analysis and other algorithms to increase accuracy. The accuracy varied vastly with disparate models, ranging from 60% to as high as 95%. Even though its ability to fit a dataset well is a great advantage, it can often hinder it. Since it is a trial and error game, finding the optimal network becomes tedious and periodically time-consuming. Furthermore, unlike SVM, ANN's also tend to overfit models and thus reduce their generalization ability.

10 Challenges

It has been seen that ANN has given some great results in stock market prediction. It is one of the best methods used in stock market prediction. However, it is also found that when using it in prediction, taking up different datasets, it varied in its efficiency and accuracy. Hence cannot consider it as a reliable technique in stock market prediction. There is a lot more to research and develop an accurate

method for Stock market prediction, which can be used to predict stocks with perfect accuracy when working upon different datasets. Also, Considering different time zones and coming up with the same accuracy in each scenario comes out to be a cumbersome task for ANN. So there is yet more possibility of progress in this methodology. Delivering complex algorithm methods in real-time usage is also vital in the roles that need to be done. We may find accuracy and efficiency when worked on it on paper. Development of a system or methodology is needed that gets a quick response as getting up results in a given time as is crucial in stock market prediction.

It has been seen that SVM has given some extraordinary outcomes in financial exchange expectations. It is probably the best strategy utilized in financial exchange expectations. Be that as it may, it is likewise discovered that when utilizing it in expectation, taking up various datasets, it shifted from normal in its effectiveness and precision of the model. Therefore cannot consider it as a dependable method in financial exchange expectations. There is more to investigate upon it and think of a precise technique for a Stock market forecast that can be utilized to anticipate stocks with immaculateness when working upon various datasets. Moreover, taking up an enormous dataset and thinking of the same exactness in every situation comes out to be an extreme errand for SVM. So it should be created and thought of a calculation that can work for a large dataset and get the best precise outcomes. Also, SVM does not perform well overall when the informational collection has more clamoured; for example, target classes overlap. This needs to perform in a like manner. We may discover precision and effectiveness when worked upon it on paper, yet making it up in huge information and getting up the same exactness is likewise significant. Development of a framework that gets a quick reaction as getting up brings about a significant in the financial exchange forecast is much needed.

11 Future Scope

Different kinds of algorithms can be used to test their efficiency. Stock market prediction is more efficient when more dataset is being used. Hence more dataset should be included to train, test and yield better results. Moreover, stock market trends vary based on time. So methods should be developed and tested to predict stocks on a varied time basis. Since ANN is an efficient technique, it can be used and combined with other techniques to get better output. An optimized dataset and trained dataset can be used in each algorithm to get better output. Support vector machines are viewed as generally reasonable for time arrangement forecasts. It may be utilized both for grouping and relapse tasks, useful in future forthcoming expectations for stocks. The SVM depends on the basic structure minimization principle. This standard forestalls the over-fitting issue by fusing the idea of limit control. Mathematical programming and Kernel Functions are the two critical components in the execution of SVM. It additionally decreases the computational expense because the built model has reliance just on help vectors. The SVM is considered a fantastic prescient instrument for securities exchange forecasts in the budgetary market.

Despite the numerous advantages of each algorithm, real-world applications require further processing to get better prediction accuracy. Conventional methods such as determining technical indicators (Technical analysis) and machine learning methods provide a good generalization ability. Normalization also plays a vital role in prediction capability, as normalized data as input has shown to improve accuracy significantly. The most common limitation of most studies proved to be the lack of computational power or data inaccuracy, i.e. many factors that may affect stock prices (public sentiment, Politics, calamities, etc.) were ignored. Future studies should include these factors with trying hybrid models for a better forecasting model.

12 Conclusion

Nowadays, from trading to calculating to keeping up personal records everywhere, technology plays a vital role in the financial market. Also, a stock market prediction is in trend for ages and is about to stay for a long time, so involving technology will play a vital role. Several models and methods produce an output of stocks' prediction, but the prediction accuracy varies in each method. The research found SVM and ANN to be some of the most feasible techniques that can be used to produce greater accuracy in predicting stocks.

This paper elucidated how ANN showed promising results on various calculation methods, including MSE, RMSE, MAE, SSE, MARE, MSRE, RMSRE, MAPE, MSPE, RMSPE, hit ratios with LTM, FTM, GTM, etc. Moreover, we also emphasized hybrid models of ANN like ANN-MLP, GARCH-MLP, a combination of the Backpropagation algorithm and Multilayer Feed-forward network in ANN to yield the best possible results.

Furthermore, SVM was also found as virtuoso methods to predict stocks. These can be used in stock prediction as an extensive database, with the help of normalization, can be accommodated by this algorithm, and better results can be achieved with more datasets. Various techniques were used to predict stocks using SVM and got a sound output, including RMSE, MAPE, hit ratios using PNN, Clustering, RFM, etc. On average, about 60–70% accuracy can be obtained using SVM. Further accuracy can be increased by combining it with other methods like Random Forest, Genetic Algorithm, POS-SVM, etc.

Although there have been several worth mentioning advancements in this field, there is still scope of improvement for a better approach which can tackle challenges like predicting in consideration with different time zones, preventing cold start problem (i.e. give better result compared to the less available data) and simultaneously provide the accurate forecast to the user.

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