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The applications of artificial neural networks, support vector machines, and long–short term memory for stock market prediction

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ABSTRACT

The future is unknown and uncertain, but there are ways to predict future events and reap the rewards safely. One such opportunity is the application of machine learning and artificial intelligence for stock market prediction. The stock market is turbulent, yet using artificial intelligence to make calculated predictions is possible and advisable before investing. This study presents an overview of artificial intelligence and machine learning as predictive analytics tools in the stock market. We discuss the strengths and weaknesses of machine learning for stock market prediction and provide some insight into the opportunities and threats in applying advanced technologies for stock market prediction. We further study the applications of three machine learning technologies in the stock market prediction, including artificial neural networks, support vector machines, and long–short term memory.

1. Introduction

The stock market or equity market comprises several stock exchanges worldwide. Investors and the general public buy and sell shares that constantly switch their prices due to the law of demand and supply. A share or stock is ownership in the firm or corporation. Buyers try to buy a share at the lowest possible price, while sellers try to sell it at the highest possible price [1]. The largest stock exchange in the world is the New York Stock Exchange (NYSE), with as of February 2018, it had market capitalization worth US$30.1 trillion. The stock market is one of the most important platforms to raise money, along with debt markets which are more imposing but do not trade publicly. The stock exchange is highly liquid, making it easy for the interested parties to sell or buy securities easily. A key feature in any upcoming economy is the increased involvement of the people in the stock market and its upward movement, too [2].

Stock markets movements can have a substantial impact on the economy and individuals. A collapse in share prices can highly dysfunctional the economy. For instance, the stock market crash of 1929 was the principal reason triggering the Great Depression of the 1930s [3]. When the stock prices are high, more companies are likely to issue an Initial Public Offering (IPO) to raise capital through transfer ownership. Mergers and acquisitions are also prevalent during BULL MARKET. This increased investment leads to more remarkable economic growth [4]. Currently, an advanced model known as Prescriptive Analytics is much in discussion. They are considered as one of the upcoming solutions to indicate a profitable mode of action. The model is a blessing in disguise for investors and the general public as a whole [5].

What if investors started to know when a stock price was going to increase or decrease? They would put all their money in that stock and avail themselves of the maximum profit possible. However, this is not possible; what is possible is to make estimated guesses and informed forecasts based on the past and present information available on certain shares. The practice of estimated guessing and informed forecasting to predict the future is known as Technical Analysis or Machine Learning [6]. [7] Machine learning is a subsidiary of A.I. that deals with creating and testing algorithms with the help of data [8]. Automation is taking over many industries; computers make high-speed decisions on online trading using mathematical models. It creates markets where the long-term outlook shifts to short-term movements and sell-offs [9]. ANN and SVM are the most commonly used algorithms to predict and analyze the stock market and future movements. These algorithms provide up to 99.9% accuracy using tick data [10]. Financial forecasting can be tagged as data-intensive, noisy, non-stationary, and unstructured and hidden relations [11,12]. Here in this paper, three algorithms have been discussed — ANN, SVM, and LSTM.

ANN or Artificial Neural Network is an algorithm designed to understand complicated issues that cannot be undertaken by basic machine learning algorithms or accessible neural networks. ANNs are built in a more complex and complicated web of interconnectivity than the human brain. The method is based on algebraic equations aiming

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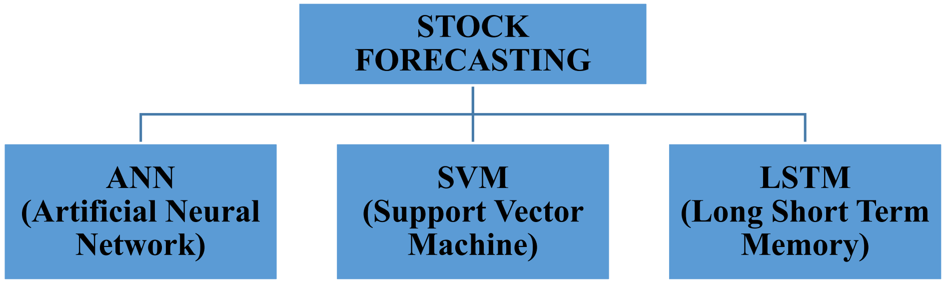

Fig. 1. Stock forecasting using ANN, SVM and LSTM.

to channel information to a model or time-series line [13]. SVM or Support Vector Machines is a superintended machine learning model which can either be used for classification or regression challenges. Being most extensively used for classification problems, the SVM algorithm works best in spaces of high dimension or in situations where several dimensions exceed the number of samples [14]. This algorithm provides abnormal returns on investments to investors and serves as a risk management tool [15]. The last machine learning algorithm discussed in this paper is LSTM or Long Short Term Memory Networks. LSTM, a popular recurrent neural network, can learn order dependence for solving sequence prediction problems [16]. The LSTM algorithm comprises the cell, input, output, and forgets gate. The gates look after the inflow of data in and out of the cell. The cell is the primary unit of the model, which remembers values over various time intervals [17].

The article is a detailed description and walkthrough of machine learning techniques. The authors contributed to the article by conducting definitive analyses on the three models discussed in the article: ANN, SVM, and LSTM. The article answers various misconceptions about the algorithms and explores diversified fields where Machine Learning has been put to work. The outcome is identifying the world's problems and providing a trustworthy solution to such problems.

The paper aims to introduce to the readers how the evolution of machine learning has benefited society by showing its utility in the stock market. It indicates that machine learning can widen the scope and extent to which various activities occur with such a broad application base. The paper tries to prove how effective machine learning can reduce human effort and provide optimum results. All the researches done in the paper involve segregation, understanding, and bifurcation of loads of data. However, with the help of machine learning and other filters, the most relevant results were available with the smallest of details.

The paper is distinct from other research articles on a similar topic because of its extensive focus on three algorithms: ANN, SVM, and LSTM, as shown in Fig. 1. The paper focuses on the conducted studies done on each of the models. The tables meticulously summarized the studies for quick and efficient understanding by discussing LSTM, SVM, and ANN techniques used in the stock market and anatomized the facts that can further help researchers, trainers, banks, finance firms, enthusiasts, and practitioners. We also discuss the evolution of technology in methods and how the advanced technology aided in the finance sector followed by multiple applications of the suggested models in finance like result prediction, trend pattern, etc. It has been observed that ANN, SVM, and LSTM models are fairly effective in recognizing trends in the stock market environment [18,19], as shown in Tables 2–4. It demonstrates the existence of an underlying dynamic that is highly similar to all stock markets. Hence we selected these algorithms for stock forecasting.

2. Classification of advanced tech in stock market prediction and analysis

In the present world, it is almost impossible for any industrial activity to happen without machine learning. Machine learning is beneficial as it can easily recognize and provide solutions to complex problems. Machine learning is applied in daily life by using recommendation engines from Facebook, Netflix, and Amazon. Siri, Alexa, and Google Assistant are examples of virtual assistants that use machine learning as their prime. Another stunning example of machine learning is the face recognition mechanism in mobile phones. The entire process seems to be quite complicated but is a simple use of Machine Learning. Not everyone notices this, but there is an algorithm that blocks spam emails from the mailboxes. Online fraud detection, Chabot, Search engine result refining, and millions of other applications involve machine learning [20]. Before the advent of machine learning, statistical methods were used like ARIMA, ESN (Echo State Networks), and Regression. These methods were used both linearly and singularly [21].

There are two ways of machine learning, supervised and unsupervised. In supervised learning, the training data is presented in a series of labeled examples; each is a collection set consisting of features (labeled with the correct output corresponding to the feature set). Unsupervised learning comprises samples in which the feature set is unlabeled. The Data is generally clustered into distinct groups by the algorithm [22].

ANN proves to be the best modeling technique for datasets. These have a non-linear relationship like data fitting and prediction for which it is applied. It is a Multi-layer perceptron (MLP) and a self-organizing map; the MLP uses supervised learning, while the Kohonen network uses unsupervised learning [23].

The best binary classifiers are none other than Support Vector Machines; it creates a boundary so that the points are segregated as their category and divided by the boundary. SVM model's results are one-tenth of a point better than just guessing during prediction. The machine learning model's accuracy is most impacted by Feature Selection [22].

LSTMs are a critical part of machine learning; most RNN cannot overcome short-term memory. Hence, it becomes tough to carry information from past steps to steps taken in the future. For example, if processing a dataset or some numbers is predicted, Recurring Neural Networks could leave some data from the past.

The stock market crash of 1987 set the market into motion, a trend and need of digitization. In 2005, the U.S. government forced stock exchanges like NASDAQ (National Association of Securities Dealers Automated Quotations) and the NYSE to become publicly traded companies. As a result, many new exchanges like BATS (Better Alternative Trading System) and direct edge opened up. Due to the presence of so many exchanges, competition increased, and profit margins started sinking. The commission schedule in force in 1973 is summarized in Table 1.

The one thing that changed the whole stock market were start-ups; it enabled expensive stocks to be bought by mass markets consumers. Companies such as Robinhood, eToro, and Freetrade, etc., rose with the concept of investing small amounts of money in multimillion-dollar companies. It was made possible by reducing fees, making fractional shares available, and providing interfaces. It gradually democratized the stock exchanges and grabbed quick revenue by making space for improved consumer polls. Due to the lower prices offered by these start-ups, older digital trading platforms like E*TRADE, T.D. Ameritrade and

Table 1
Commissions were charged per 100 shares for the year 2020 [24].

Principal ranges	% of principal value	Fixed dollar amount	Cents per share ($0.10 - subject to a cap of)
Under $1999	5.00%	$0.00	$100.00
$2000 – $9999	2.00%	$60.00	$380.00
$10,000 – $24,999	1.75%	$85.00	$905.00
$25,000 – $49,999	1.20%	$225.00	$1655.00
$50,000 – $99,999	1.00%	$325.00	$3155.00
$100,000– $249,999	0.90%	$425.00	$6905.00
$250,000 or more	0.70%	$925.00	2.50% of principal plus $655.0

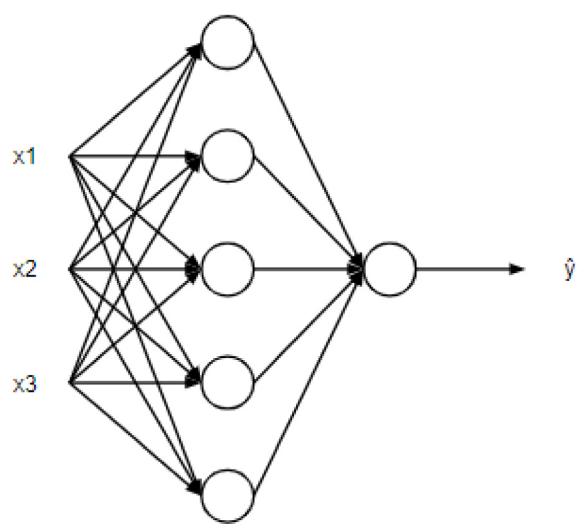

Fig. 2. Generic structure of ANN.

banking giants JP Morgan Chase started competing by eliminating fees and switching to apps. Five hundred billion euros in 2017, from 250 billion euros in 2013, was the number of assets managed on online platforms. The period saw the opening of 2.2 million new accounts. Self-directed investors have increased more in the U.S. than advised traders; this group (self-directed investors) is growing at 4.9%, while the advised traders are growing at just 1.4% [25].

3. ANN in stock market

In the simplest of words, Artificial Neural Networks are a mesh of numerical equations. One or more input variables are taken and then processed by a sequence of equations resulting in one or multiple outputs. Any network generally has three layers — An input layer, Hidden layer, and Output layer. The layer containing all the feature variables shown as x1, x2, x3 up to xn is the input layer. The hidden layer comprises one or more nodes (hidden units). The circles in the diagrams below represent a node. Then comes the output, which can be one or more than one. The more nodes and layers, the more complex calculations can be solved through the network [26].

An artificial neural network structure containing four neurons in the first layer and a single neuron in the second layer is an example of a generic structure shown in Fig. 2. The hidden layer is considered the most crucial layer of the algorithm; it acts as a distillation layer that only forwards important data and patterns from the input to the next layer. It makes the network significantly faster and efficient [27]. Fig. 3 represents the neural network layers of three types of layers: input layer, hidden layer, and output layer. The key to getting a good model is the accurate prediction of the Weights. The Back Propagation Algorithm achieves this task; this algorithm is what makes ANN a learning model. It learns from the mistakes and adjusts itself accordingly. ANN can model better data with high volatility and non-constant variance. ANN has also come out as the most efficient in predicting financial time series as the Data is also highly volatile [28,29].

Shahvaroughi Farahani and Razavi Hajiagha [30] Today, the stock market serves an essential purpose and may be used to indicate economic strength. To forecast stock price index values using an artificial neural network (ANN) that has been trained utilizing many novel metaheuristic algorithms like social spider optimization (SSO) as well as the bat algorithm (B.A.) is described. As input variables, some technical indicators were used. They then utilized genetic algorithms (G.A.) as a heuristic method for feature selection and indication selection. But in the other hand, specific time series forecasting models, such as ARMA and ARIMA, are also used to forecast stock prices. It finds that via the use of G.A., the set of input variables was substantially decreased. As a result, the computation speed and accuracy of the network and the coefficient of determination improved. Also, the Hybrid models achieve a higher level of accurately explaining the model. As a result, the primary suggestion is to train the network using various novel metaheuristic methods.

Jamous et al. [31] As mentioned before, artificial neural networks (ANNs) have already been used to forecast stock market closing prices. However, standalone ANNs have several constraints, which result in reduced prediction accuracy. This constraint is overcome via the use of hybrid models. As a result, the literature reported on a mixture of artificial intelligence networks & particle swarm optimization for effective stock market prediction [32]. To accomplish high-accuracy prediction in a short time, this article proposes a new enhanced technique dubbed PSOCoG. Hence ANN-PSOCoG beat ANN-SPSO in prediction accuracy by about 13%, SPSOCOG by about 17%, SPSO by nearly 20%, and ANN by nearly 25% using the S&P 500 dataset. When the DJIA dataset was used, ANN-PSOCoG beat ANN-SPSO by about 18%, SPSOCOG by approximately 24 percent, SPSO by approximately 33 percent, and ANN by approximately 42 percent in terms of prediction accuracy. Additionally, the suggested model is tested in the presence of COVID-19. The findings demonstrated the suggested model's ability to accurately forecast the closing price when MAPE, MAE, and RE values were extremely tiny for the S&P 500, GOLD, NASDAQ-100, & CANUSD datasets.

Selvamuthu et al. [10] conducted a study to remove the barrier of time series data by using the ANN algorithm. The algorithm incorporates analyzing and hence predicting stock exchanges' price movements. The aim was to find if the algorithm would forecast stock prices despite its dynamic nature and liable to quick changes. The abundance of data and technological enhancement makes it possible to form algorithms that can work and how one wishes. The study employs three algorithms: Levenberg–Marquardt (L.M.), Scaled Conjugate Gradient (SCG), and Bayesian Regularization. The results showed that SCG gave the best validation in 103 (54) iterations and L.M. in 10 (13) tick datasets. However, referring to the time barrier again, SCG was quicker than L.M. Bayesian Regularization gave the least squared error over all datasets.

Nevertheless, performance-wise Scaled Conjugate Gradient was the most promising. The study used three Neural Network learning algorithms. The three algorithms provided 99.9% accuracy when using tick data.

Moghaddam et al. [33] experimented with the ability of ANN to predict the NASDAQ. Two networks for the NASDAQ index prediction were developed and validated. The methods used in the study took into context both short-term and historical stock prices along with daily data. ANN has performed better in bankruptcy prediction, discriminant analysis, and logistic regression. ANN can predict better than statistical methods as it is related complexly among input variable data and financial data. The model used input parameters as previous four to nine days (working). The model output displayed nothing to do with the number of days as inputs in the prediction process.

Trifonov et al. [34] examined the ANN algorithm under the contract with National Science Fund in Bulgaria. The research included

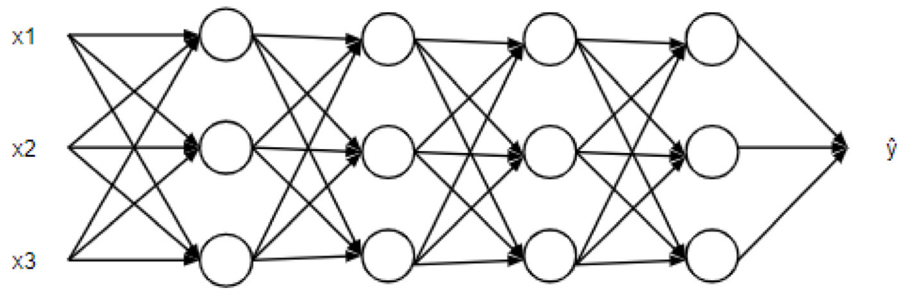

Fig. 3. Layers of a neural network.

extensive experimenting with the network parameters. They could confidently state that choice of input, pre-processing of data, variables, and the network's structure had a significant impact on the working of the algorithm. After running the test multiple times, the researchers concluded that the Neural Network Algorithm is considerably accurate in predicting the movement of the prices a day before the actual price change. Systems designed with Neural Networks are universal and can be applied to any number of financial devices using the most basic technical indicators as input data.

Shahvaroughi Farahani and Razavi Hajiagha [30] tested ANN on the NSE (National Stock Exchange, India). A prediction model was built using Multilayer Perceptron (MLP) Neural Network technique. The years 2015, 2016, and 2017 were used to train and test the MLP prediction model. The results were in contrast with the studies and researches done above. The MLP neural network showed promising results and had just a Median Normalized Error of 0.05995, a Median Standard Deviation of 6.39825. MLP neural network is considered to predict the companies listed under the LIX15 index of the NSE (National Stock Exchange, India), and the results were satisfactory.

Dhenuvakonda et al. [13] defined the capabilities of the ANN network to be so versatile that it could even identify the latest sample test data, even if it were not used to boost up the model. They used the stock data of Infratel. Information like the high, low volume of stocks and even previous opening and closing were considered input data. The set of data was extracted for about two months to train the algorithm. And then, on the 61st day, the network was ready to predict the company's stock price. The algorithm proved to be reasonably efficient and was at par with the A.R. (Auto Regression) and ARIMA models. A.R. and ARIMA are univariate time-series bases predicting algorithms. These types of models are impotent in recognizing the underlaid dynamics. However, ANN can tackle this problem and is superior to the first choice for stock market prediction.

Chopra et al. [35] ran the experiment in 2016 after demonetization in India. They developed such a Neural Network which could predict the Indian stock market even after demonetization. Generally, the stock market is volatile after a significant change because short-term investors tend to withdraw their capital. Their network predicted the closing price of any day very efficiently. The model proved to be well structured to predict the stock prices for various stocks and NIFTY50 (a benchmark Indian stock that comprises the most significant 50 companies on the NSE) Index. It can be predicted that the larger the data for training, testing, etc., the more accurate the values predicted.

Wamkaya and Muchemi [23] research proved that the 5:21:21:1 model of configuration achieved the best accuracy in prediction. The study concluded that at least 1000 records were trained over 130000 cycles to gain such results. The records were around 80% of the training data. Sixty future values were predicted using this model. After being trained, the ANN was very precise in predictions. The model was then put to work to predict three stocks on the NYSE. The model accurately predicted the prices with errors ranging from 0.71% to 2.77% (validation done using Encog and Neuroph).

Inthachot et al. [36] used ANN and Genetic Algorithm (G.A.) and tested it on Thailand's SET50 index trend. The imported data constituted of 4 inputs variables based on four different lengths: 3-, 5-, 10-, including 15 days before the prediction. It helped in creating a pool of diversified inputs. G.A. then segregated the data to a more manageable number. Data of the SET50 from 2009 to 2014 was used for the evaluation. The results were more accurate when using a single input variable for one fixed length of period. G.A. proved to be 12.4011% more accurate than ANN. Its average accuracy is 63.30%. If ANN is combined with other machine learning models, higher prediction accuracy can be obtained.

DiPersio and Honchar [37] Used SVM, CNN (Convolution Neural Network), MLP, RNN (Recurrent Neural Network) to predict the S and P 500 Index stock prices. The Data was taken from 1950 to 2016 for the training and testing of the algorithms. CNN, MLP, and RNN are types of ANN networks and can compare results to other types of networks. All the Neural Networks were trained using Keras. Results showed that CNN was the best algorithm that predicted the price movement accurately amongst all the networks. CNN showed the least Mean Square Error and highest prediction accuracy. A Wavelet-CNN network was prepared for improving the performance, and it showed even better results than a standard CNN network. Every algorithm has a different method for identifying patterns and afterward predicting them. Moreover, we have summarized several studies based upon their novelty of work in a concise tabular format for ease of understanding in Table 2.

4. SVM in the stock market

SVM or Support Vector Machines is a superior form of machine learning. It uses classification algorithms for two-group classification problems. When given any set of labeled training data for separate categories, SVM can categorize new texts. It can perform to its optimum capacity when provided with limited data. Linearly separable Data is SVM's primary function, as it can easily classify it. SVM also tends to be faster and efficient when compared with ANN (when samples amount to thousands) [46]. SVM models aim to form the best line to differentiate n-dimensional spaces into groups so that new data can be easily divided into the correct category in the coming times. The best hyperplane is the one that maximizes the training data's margin is shown in Fig. 4.

SVM can broadly be subdivided into:

- **Linear SVM** is the linearly separable Data (statistics divisible in two groups by a single straight line). Linear Data is classified with Linear SVM classifier.
- **Non-Linear SVM** operates on no linearly separable data (statistics that cannot be divided into groups using a single line). It is classified using a Non-Linear SVM classifier.

Some advantages of SVM are –

- It is most productive with a clear margin of separation.
- Highly powerful in spaces with high dimensions.
- It works well when the number of samples exceeds the number of dimensions.

Table 2
Summarized studies of ANN for stock market prediction.

Models	Dataset	Method	Conclusion	Reference
Decision Tree, Bagging, Random Forest, Adaboost, Gradient Boosting, XGBoost (Tree-Based models). ANN, RNN, LSTM (Neural Networks).	Diversified financials, petroleum, non-metallic minerals, and basic metals from the Tehran Stock Exchange.	Creating Decision Tree models, Bagging model (a regressor model), Random Forest models using various Decision Trees. ANN and RNN (RNN and LSTM) algorithms were created and trained.	LSTM was the top performer with the lowest amount of error and best fitting ability. But specifically for Tree-Based models, Adaboost Regressor stood out the most with accuracy, fit, and runtime.	Nabipour et al. [38]
Deep neural networks (DNNs) and traditional artificial neural networks	S&P 500 2003–2013	By controlling the overfitting, a pattern for the classification accuracy of the DNNs was detected and observed as the number of the hidden layers increased gradually from 12 to 1000	The trading strategies guided by the DNN classification process based on PCA-represented data perform slightly better than the baseline model	Zhong and Enke [39]
MLP and LSTM (RNN).	Past ten days of stock price data were obtained from Yahoo Finance. Keras (a software library, open-sourced). It also helped with the Python Interfaces for the networks.	The entire Data is divided by 200, which helps by making the weights in the neural network not too large. AdaGrad and RMSProp are used to maintain the performance.	The LSTM model proved quite satisfactory but could do better with further working on the algorithm. The stock prices of Apple were forecasted and almost matched.	Vivek Palaniappan [40]
Moving Averages, Stochastic Oscillator, Standard, Deviation, On-Balance-Volume.	The stock prices of NSE like NIFTY 50, CNX, and S&P.	Exchange rates, moving averages, etc., are taken into consideration for comparison.	The model can predict prices maximum for the coming five days. The model proved able to handle more than 50 stocks.	Gurjar et al. [41]
ANN algorithm. Two types of input variables were chosen so that the results could be comparable.	Predicting Nikkei 225 Index of the Japanese stock market with the help of ANN.	The model was tweaked with the help of G.A. to make it less convergent and more precise.	The model proved to have an 81.27% accuracy rate. This model was further compared with other models and proved to be the best for prediction.	Qiu and Song [42]
ANN + Decision trees (D.T.) to forecast stock price movements.	The stock prices of the electron industry in Taiwan. All the indexes (fundamental, technical, and macroeconomic) were collected from TEJ.	One hidden layer was used in the ANN. 1 and 0 could be the answers to the decision model (1 being prices rise, 0 being prices fall). Then ANN and D.T. are combined. Also, a DT+DT model is created for comparison.	The ANN + Decision Tree model had a total prediction accuracy of 77%. Only DT gave 65% accuracy, and only ANN gave 59% accuracy. DT+DT gave an average of 67%.	Tsai and Chen [43]
Eight ANN models were prepared for seven different Prediction Systems (P.S.).	Istanbul Stock Exchange (ISE-30). Daily closing prices of each stock were collected and employed to calculate indicators of P.S. algorithms.	Stock prices- - Decrease when output is greater than or equal to 0 and less than 0.5 - Stay same when output is equal to 0.5 - Increase when output is greater than 0.5 and equal to or less than 0 -Stopping criteria = 10 000 -Activation Function = Linear Sigmoid -Learning Rate = 0.2.	78.47% was the success rate averaged out, 50% was the minimum success rate for each stock, showing high predicting capability. The best ANN topology was ANNM3.11.1 (with three inputs, 11 hidden neurons, and one output).	Senol and Ozturan [44]
	Mobarakeh-Steel Co. tries from the Tehran Stock exchange. Data was used from Mar 15, 2007, to Feb 14, 2011.	The model had three layers, trained to use fast backpropagation algorithm. Ten neurons are comprised of the hidden layer.	The results were that the algorithm formed was 97% accurate. But overall, the algorithm was marked to be 83% correct during any new news released regarding the particular company.	Aghababaeyan and Tamannasiddiqui [45]

- SVM is also great at remembering data; it uses a subset of training points called Support Vectors.

SVM has one downside. It is slower when large amounts of data are processed due to more training periods [14].

The general structure of Artificial Neural Network & the Support Vector Machine (SVM) (Fig. 5) is a learning method that may be used to solve problems like pattern recognition and prediction and analyze and map both linear and non-linear functions. A high-dimensional space creates a hyperplane or group of hyperplanes (classes) that may subsequently be utilized for classification. SVM can be used to learn Polynomial, Radial Basis Function (RBF), and MLP classifiers. SVM works on the principle of Risk Minimization and goes hand in hand with the Regularization theory. SVM functions mainly on techniques of mathematical programming and Kernel Function. SVM is used for regression and classification of data [2].

Panwar et al. [47] The initial objective of this study is to gather datasets from stock data via web scraping. Then put the Data on a graph and see if stock prices are rising or falling. Following that, they use SVM and linear regression to forecast stock prices. After evaluating the SVR and Linear Regression prediction findings, it was determined that the Amazon stock data Linear Regression had an accuracy of 98.76 percent, and the SVR had an accuracy of 94.32 percent. As a result, it can be concluded that Linear regression is superior to State Vector Regression for stock market prediction.

Kurani et al. [48] The article discusses significant features of new techniques and technologies in which ANN is a hybrid model, such

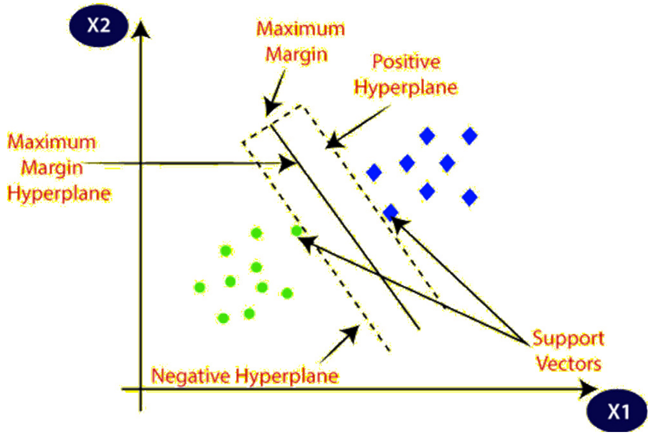

Fig. 4. SVM Hyperplane [46].

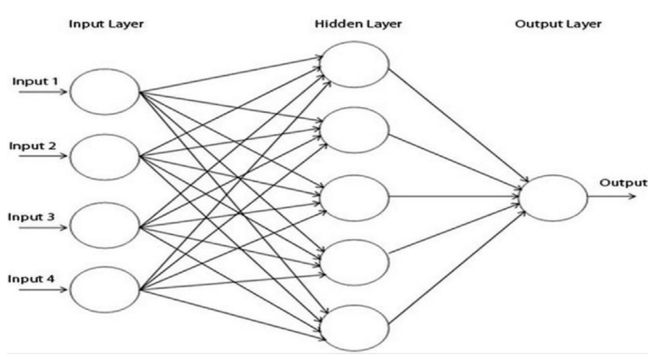

Fig. 5. Structural similarity of SVM and ANN [46].

as ANN-MLP, GARCH-MLP, or a mixture of Backpropagation and Multilayer Feed-forward networks, produces superior outcomes. Simultaneously, SVMs have been successfully used to stock prediction, with an accuracy of about 60%–70% for basic SVMs, further enhanced by integrating techniques such as Random Forest and Genetic Algorithms to provide more accurate results. Although there have been numerous notable advancements in this field, there is still scope for further improvement in terms of development. A more robust approach can address issues such as predicting across time zones, avoiding cold start problems (i.e., producing a better result with less available Data), and simultaneously providing the user with an accurate forecast.

Drew Scatterday [49] conducted a very detailed analysis of the SVM algorithm. He predicted the stocks of Tesla by using an SVM model known as Support Vector Regression with sci-kit-learn. In addition to this, he used an LSTM using Keras. Linear regression was employed to obtain a line of best fit relating to two variables. The neural network was provided with stock prices of the previous 36 days to eventually calculate the closing price of the next day. The results were almost identical to the actual prices. The test data frame gave the predictions to be transformed into values lying between 0 and 1. LSTM and SVM predicted the price for a whole year, and the results matched perfectly.

Gururaj et al. [50] took the dataset from the Quandl website (historical daily prices). The experiment was done to define whether SVM was accurate than Linear Regression (L.R.). The R API package of Quandl is highly active and can collect stock prices of companies for any time range in just a single code line. So a step of mining data is eliminated. The stock of Coca-Cola Company was tested from 2017 to 2018. Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Square Error (MSE), and Correlation Regression (R) and non-linear multiple correlation factor were used as the evaluation metrics. After carrying out the experiment and precisely calculating the results using the earlier models, it was concluded that SVM was more accurate than L.R.

Patil et al. [2] tested SVM's predicting ability on various stocks: Allegiant Travel Company, Alliance Fiber Optic Products, AT & *T* Inc, Bank of New York Mellon Corpora, eBay Inc, EXCO TECH, Facebook Inc, Ford Inc, IBM Inc, Kofax Limited, Old Second Bancorp Inc, SLM Corporations, Xilink Inc. SVM model accurately predicted 10 out of the 13 companies The error rate was around 23%. For a more detailed analysis, IBM Inc's share prices were predicted from 2014 to 2015. Seventy-nine datasets are tested, out of which seven turned out to be in error, while the other 72 were predicted correctly. It provided an Efficiency Rate of 91.13%.

Yang [51] used gold as a medium to calculate the prediction accuracy of the SVM model. ESMD multi-combination model is used; this model is used to inflate the prediction accuracy of any network. This model was prepared to help the gold investors in decision-making regarding buying or selling the commodity. Ultimately it will help in improving market risk prevention and reduce loss of value of gold. Three SVM models were used to predict separately. A combined model known as ESMD is proposed, which is based on pole symmetry mode decomposition. ESMD was chosen over EMD to save the prices from being influenced by inherent defects in the EMD model. For research purposes, the closing prices of the Shanghai Gold Exchange Au9995 prices were taken to get the most up-to-date prices of gold and then convert them to price sequences. The results proved that the predicted prices were not exactly the original prices but were almost undifferentiated.

Agustini et al. [52] predicted the stock prices of the Jakarta Composite Index with the help of Brownian motion. Closing prices were taken from January 2014 to December 2014. This Data would then be used to train the algorithm and then predict the stock prices of January 2015. The process was divided into many stages: Calculating return prices, evaluating parameters, collecting the price results after stock forecasting, and finally calculating the MAPE value. Geometric Brownian motion was used to obtain four forecasts, and the MAPE value was less than equal to 20%. The verdict was that short-term forecasts were more accurate and efficient than long-term forecasts.

Rahul Bhatia [53] used TA-Lib and Pandas (a data cleaning and analysis tool). Mathematical instruments like simple moving averages, moving standard deviation, exponentially weighted moving average, relative strength index, Williams R%, parabolic SAR, and average directional index. The stock prices of Reliance were used as input data (from 2009 to 2019). The results were: Linear SVM accuracy 51.43%, Polynomial Kernel-based SVM accuracy 53.15%, RBF Kernel-based SVM accuracy 52%. With just seven mathematical instruments, this result proved to be satisfactory. Some things that could be improved to get better results are Sentiment Analysis and News on Reliance. Use more technical indicators as SVM works well with high-dimensional data; try other classifiers like KNN, etc.

Rustam et al. [54] predicted the Indonesian Stock Market's share movement: PT. Bank Rakyat Indonesia, Tbk (BBRI). Data from January 2016 to December 2016 was collected for the study; SVM and Fuzzy Kernel C-Means were used for preparing the model. Mathematical instruments that help in using historical stock price movement data were used for comparisons. It was observed that models using SVM are more accurate with input data. With 90% training data, FKCM proved to be the most accurate with 92% accuracy. The best model with continuous data achieved a prediction accuracy of 70.72%, while that with discrete data had an average accuracy of 81.65%.

Fanita and Rustam [55] evaluated the Indonesian Stock Exchange's stock: the Jakarta Composite Index (JKSE). It is a standard to calculate an investor's portfolio. ANFIS (Adaptive Neuro-Fuzzy Inference System) is used to calculate the index. ANFIS is a system that has yielded more accurate prediction results than ANN, Fuzzy Logic, and G.A. The stock prices are adjusted to the values from 2013 to 2016. MATLAB Program is also used to yield two outputs. A maximum of 98.90% accuracy

Table 3
Summarized studies of SVM for stock market prediction.

Models	Dataset	Method	Conclusion	Reference
SVM and K Nearest Neighbor (KNN).	Indonesian Stock Prices from the company P.T. Waskita Karyaa (Persero) Tbk. Data used was from January, 2013 to December, 2016.	First, the class labels were predicted. Then, with the help of SVM, indicators were chosen to help anticipate stock price movement and predict the future trend of the stock.	The research ends with three indicators representing results that show the good capacity to predict prices.	Puspitasari and Rustam [56]
A homogeneous ensemble classifier known as GASVM, which is based on the G.A. This helps select and optimize SVM and its factors.	In the study, 10-day price movements were predicted from the Ghana Stock Exchange (GSE). Data was used from Jun 25, 2007, to Aug 27, 2019.	Other models like RMSE, MAE, AUC, Accuracy, Recall were used to compare their efficiency.	In the end, GASVM showed the most promising results and predicted the prices of stocks from the GSE more accurately. The model developed provided an accuracy of 93.7%.	Nti et al. [57]
SVM model is implemented in Python Programming Language.	Dataset is obtained from Web Scrapping to train the algorithm Data has been scrapped from Yahoo Finance. Apple. Inc's data has been used from Jan 1, 2013, to Dec 30, 2019.	Pandas_Datareader is imported to the header of Python Code to train the dataset. Pandas for Data manipulation and analysis, NumPy for core scientific computations, sklearn to import SVM and Matpltlib for 2-D plots f array.	SVM proved to be the best choice to carry out the experiment as it can handle a large pool of data and trains faster than many other algorithms. SVM also improves results with more training.	John et al. [58]
Multiple Linear regression (MLR), SVM with RBF Kernel.	SVM model predicts the S and P 500 stock Index. The Data contains 27 features and 1192 days from Dec 7, 2009, to Sept 2, 2014.	The Data was sampled weekly. The samples were divided into 100 Samples as training sets and 43 as testing sets.	SVM outperforms MLP and MLR models in training as well as testing. SVM also has the advantage of using multiple kernels, which makes the model flexible.	Sheta et al. [59]
SVM and Support Vector Classifier (SVC).	Twenty stocks were selected from the Chinese Stocks as testing data. Stocks were chosen based on trade volumes, stock sectors, publishing date, and price.	Text mining Technology was used on SVM. The same was done with SVC so that both models can be compared on a common basis. News heavily affected the results as the articles were also taken into consideration.	The SVM method showed excellent results especially when predicting one single stock. SVC did not even portray satisfactory results.	Xie and Jiang [60]
SVM and Back Progression (B.P.) are used to compare the results simultaneously.	The S and P 500 Daily Index in the Chicago Mercantile is used. Training data is taken from Apr 1, 1993, till the end of December 1994. And test data is taken from Mar 1, 1995, till the end of December 1995.	Performance is evaluated based on Normalized Mean Squared Error (NMSE), MAE, Directional Symmetry (D.S.), Correct Up Trend (C.P.), and Correct Down Trend (CD).	SVM's forecasting proved to be superior to B.P. due to reduced NMSE and MAE and increased D.S., CP, and CD than B.P. SVM even trains faster than B.P.	Cao and Tay [61]
SVM model was used to see if the Efficient Markets Hypothesis (EMH) proves true. It says that the stocks should be impossible to be predicted as they move on randomly.	NASDAQ-100 Technology Sector Index (NDXT). It consists of 34 to 39 stocks. The statistics are taken from 2007 to 2014.	70% of the Data was used for training and the remaining 30% for testing. Radial Kernel was used for the model. Price Volatility and Momentum were employed along with Sector Volatility and Momentum for prediction.	The results proved EMH true. Also proved was that short-term and long-term trends were the best ways to predict future prices. Some stocks showed accuracy up to 80%, but some could only reach 30%.	Madge and Bhatt [22]

was obtained with 40% training data and relative error below 3% and maximum accuracy of 83.72% with the relative error below 1% for 90% training data. The kernel that provides the most precise outcomes is the polynomial with parameter 2.

Henrique et al. [15] tested the SVM model on three blue-chip and three small-cap stocks from Brazil, America and China's stock exchanges. The total number of assets summed up to 18. Ten years of data were extracted from sources like Yahoo Finance, Reuters, and BM&F Bovespa. The Data was divided as 70% for training and 30% for testing and comparisons. To calculate the accuracy, RMSE and MAPE were determined from the results. Testing proved that SVM or SVR had improved outcomes when used with a linear kernel. The final results were compared with a random walk-based model. This test indicated that the SVM model improved without periodic updates and showed better results by giving precise prediction values. It proves that SVM is far superior to any random walk model. Moreover, we have abstracted several studies based upon their novelty of work in a concise tabular format in Table 3 for ease of understanding.

5. LSTM in the stock market

LSTM or Long Short-Term Memory networks are recurrent neural networks that can learn order dependence in sequence prediction problems. LSTM is used in machine translation, speech recognition, etc., due to its favorable features for solving such complex problems [16]. LSTM can store past information, too; this helps in stock price prediction as past prices play a significant role in predicting future prices of stocks [62].

The structure of an LSTM model consists of the cell, input gate, an output gate, and forget gate [17]

The long short-term memory (LSTM) architecture (Fig. 6) is a kind of recurrent neural network (RNN) utilized in the area of deep learning. In contrast to conventional feed-forward neural networks, LSTMs have feedback connections [64,65]. A typical LSTM unit comprises four components: a cell, an input gate, an output gate, and a forget gate. The cell stores all values over time; the input & output of data from the cell is controlled by the gates. The Input gate regulates all the new information that goes in as input data; forget gate takes care of

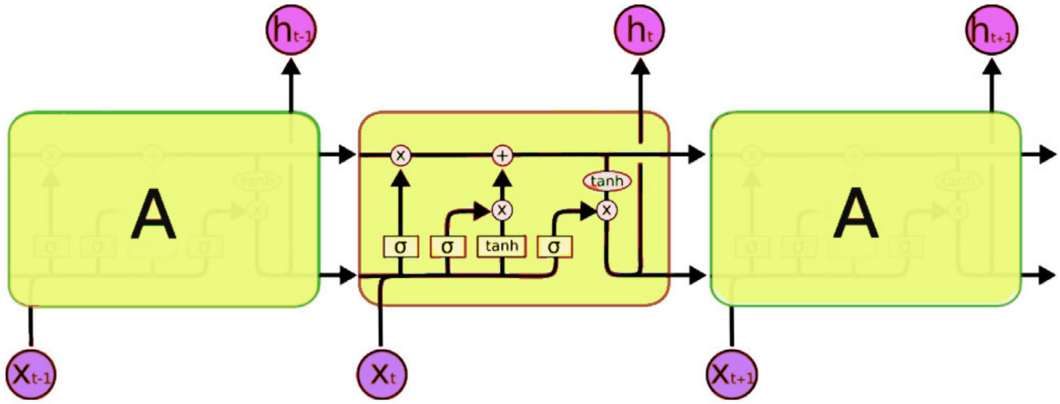

Fig. 6. LSTM architecture [63].

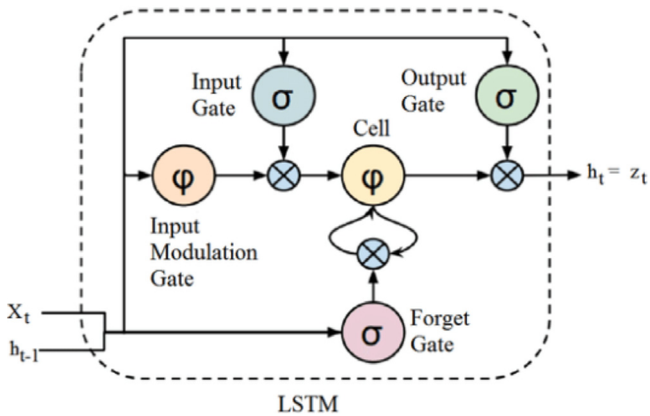

Fig. 7. LSTM network structure [63].

what remains inside the cell. The output gate looks after the limit to which the cell uses the Data fed and calculates output activation of the algorithm [17]. The below diagram depicts the interior structure of an LSTM network. Input Modulation Gate is a part of the input gate and is used for further segregation of data.

A typical LSTM unit (Fig. 7) comprises four components: a cell, an input gate, an output gate, and a forget gate. The cell retains data across arbitrary periods and the three gates to control the inflow and outflow of information. LSTM model has a wide variety of applications; it can model languages or generate texts. Image processing is another promising field to use LSTM, but the model needs extensive training and refinement for this to happen. LSTM can predict musical notes just like text generation by analyzing given notes as input. LSTM is also a very reliable model to develop Language Translation software. The encoder–decoder LSTM model is used in such soft wares; it converts inputs to vector representations and outputs to its translated version.

Moghar and Hamiche [66] The purpose of this article is to develop a model for forecasting future stock market values using Recurrent Neural Networks (RNN) and, more specifically, the Long–Short Term Memory (LSTM) model. The primary goal is to determine the accuracy with which a machine learning algorithm can forecast and the extent to which epochs may enhance our model. For various datasets, it is observed that training with much fewer data and far more epochs improve our testing result while also allowing us to get superior forecast and prediction values. A future study will attempt to identify the optimal sets in terms of data length and training epochs that best fit our assets and optimize our prediction accuracy.

Yan and Yang [67] In this article, they use an encoder–decoder paradigm of attention to include attention mechanisms from both features and time. LSTM neural networks are used in both the encoder and decoder. This technique addresses two issues associated with time series prediction. The first issue is that various input characteristics affect the target sequence in varying degrees. To address this issue, the feature attention method is employed. The second issue would be that the data before and following the sequence are highly correlated in time. To address this issue, the temporal attention method is utilized, and weights at various time points may be acquired to improve resilience and timing dependencies. The simulation experiments demonstrate that by including the attention mechanism, prediction errors may be reduced, demonstrating the model's efficacy in addressing stock forecasting issues.

Moghar and Hamiche [68] used LSTM RNN to forecast closing prices of two stocks from the NYSE, Google, and Nike. Data was taken from August 2004 to December 2019 and January 2010 to December 2019 to predict Google and Nike's stock prices, respectively. 80% of the Data was used for training and the other 20% for testing. The mean squared model was used to refine the model. For a different dataset, if the model is trained with fewer data and more Epochs (one complete pass of training dataset through the algorithm) improved the results. The testing results were not precisely the original movements but followed the trends quite well and could trace both stocks' opening prices.

Alexandre Xavier [69] predicted the stock price movements of four companies. He referred to them as Companies A, B, C, and D. The data had been collected from Yahoo Finance from August 2010 to July 2019. Pandas had been used to segregate the data. Moving Averages was the main algorithm used to carry out the study. Prices were predicted individually and all four together, but the results did not prove to be up to the mark. Only Company C's results were satisfactory and that to when done individually. Although the best model was selected for the experiment, it did not yield desirable results. It proved very clearly that relying only on historical data of closing prices is not enough to predict stock movements.

Lu et al. [70] created a CNN-LSTM model to predict the stock market. Networks like MLP, CNN, RNN, LSTM, and CNN–RNN were employed for comparative analysis to make the CNN-LSTM algorithm more efficient and accurate. Price movements of The Shanghai Composite Index were taken as experimental data. The stock data used was taken from July 1991 to August 2020, including 7127 trading days. For historical Data, opening and closing prices, highest and lowest prices, turnover ups and downs, volume, and change were considered. Experiments show that the CNN-LSTM model has the most accurate depiction of stock price movements than MLP, CNN, RNN, LSTM, and CNN–RNN. CNN-LSTM model improved by 2.2%, 0.6%, 0.5% and 0.2% respectively.

Serafeim Loukas [71] used the closing stock prices of Tesla. Inc to put the LSTM model to the test. The Data was taken from the year 2015 till 2020 (source of data Yahoo Finance). A multi-layered LSTM neural network was to be prepared, which could predict the stock price movements. The model has 50 neurons and four hidden layers, which would act as a sieve for the output data. One neuron was assigned to calculate the prices. The neuron assigned was placed in the output layer. Due to the Covid-19 Lockdown, the stock prices showed abnormal movements in the end that the algorithm could not predict, but it did systematically predict the earlier price movements. All the jumps and drops were followed precisely, and it can safely be concluded that the model was not far from being precise.

Asutosh Nayak [72] predicted the stock prices of General Electric (G.E.) using the LSTM algorithm. There were 14 060 items, each representing some stock related feature of the company on a particular day. Time steps were taken to be 60, so two months of data were looked into to predict the next day's price. Time steps are incremental changes in time for which the governing equations are being solved (for example, when working on a character prediction problem, for instance, a network is to be fed with six characters at a time, then the time step becomes 6). LSTM provided astonishing results. The author chose LSTM over 100 other combinations as it worked the best out of all the others and fulfilled the purpose of the study.

Zou and Qu [73] used the daily prices and volumes of the top 10 S and P 500 stocks. The statistics were from the year 2004 to 2013. The Data was split in the ratio of 70:15:15 for training, development and testing data, respectively. To obtain the best model, four models: ARIMA, LSTM, Stacked-LSTM, and Attention-LSTM. MSE was considered for model assessment. Out of the four models, Attention-LSTM proved to be superior amongst all; the model can predict the financial time series much better due to the long-term dependence of time series.

Qiu et al. [74] created an Attention-based LSTM model to predict future stock prices, the S and P 500 Index, Dow Jones Industrial Average (DJIA), and the Hang Seng Index (HSI). Three other models were used to compare the results: the LSTM model, the LSTM model with wavelet denoising, and the Gated Recurrent Unit (GRU) neural network. S and P 500 Index and DJIA data were taken from January 2000 to July 2019. Moreover, the HSI data was taken from January 2002 to July 2019. The Data contains a total of 6 variables. MSE evaluated prediction results, RMSE, MAE, and Coefficient of Determination (Rˆ2); the smaller the MSE, RMSE, MAE, the closer the actual value and prediction are. The more the Rˆ2 tends toward 1, the model shows better the fit). The model proved to be highly competitive to the existing market-leading models and was way ahead of the three models selected for comparison.

Pramod and Mallikarjuna Shastry Pm [75] Developed a stock data predictor using the LSTM technique. The model considers a company's historical equity share prices and applies the LSTM model to predict price movements. The historical Data consists of opening, closing price, day low, day high, trading date, turnover, and total quantity traded. The model was used to predict price movements of the TATAMOTORS share price. It efficiently achieved an accuracy of 96, LSTM units were employed, and an epoch batch size of 50. The results were clear cut. The model showed an astonishing 0.0024 minimum loss rate and moved just along the actual value of the share price. ON the 300th day, the actual opening price was 172 INR, while the predicted price of the model amounted to 166 INR.

Ghosh et al. [76] proposed an LSTM model to predict the stock prices of various Indian banks; State Bank of India (SBI), HDFC Bank and ICICI Bank. The Data was collected from the official BSE website. 2 months of data was taken as training data. The model predicted future values for three months, six months, 1, and 3 years intervals. The model was included with 3 LSTM layers and a dense layer with a linear activation function for the model to be the finest. The error values over the period kept on decreasing significantly. The average error for one month was around 232.6, and that of 3 years was 0.89. The experiment proved that LSTM thrived on prediction on a much more extensive range of data. Moreover, we have abstracted several studies based upon their novelty of work in a succinct Table 4. It describes different dataset and methods used by different models to predict the stock prices. Among all the models we have described LSTM is proved to be better than others.

6. Challenges and future scope

The stock market has been one of the most important avenues for investing money and growing it over time. Machine Learning Models have proved to provide more precise results about future price movements. However, there are several obstacles faced in between to get the optimum results from these algorithms. Stock market prediction is highly avoided due to the chaotic data presentation. Finding the desirable data suitable for the algorithm in use [84]. Predicting the stock market requires forming a model that requires high knowledge in Coding and Software. This type of knowledge is not available in abundance to people and also needs specialized training. So there is no large pool of people who can create an algorithm with their preferences and filters to predict the stock market prices and create a fully functional model to predict the stock market; it is necessary to train it accordingly, and this period is generally long. So a person whose principal occupation is not investing would careless to do so. A professional investor could only assess a machine learning model that helps predict future price movements' worth as it is the main job. He will have no issues directing his time in developing something that works in his best interests. Creating an ML predicting model is a costly affair. Dedicated and trained personnel are required along with expensive technology to maximize the output. People are unaware of A.I. prediction; they do not know what sites provide reliable data or which sources top investors trust for their investments.

Major mass is just investing in stock without the necessary expertise, whereas a stock should be analyzed first and then bought. The world needs to start smart investing. This leads to the next obstacle, which is the mentality. In third-world countries like India, Myanmar, Indonesia, etc., people are not comfortable with a machine guiding them to invest their money. The citizens think in the typical old-fashioned way. There is no trust in intricate machinery that can solve complex equations; the mass follows advice from small brokers/investors from personal yet unreliable sources. Broader application base and awareness are the need of the hour to promote machine learning and its benefits to the users.

The use of machine learning in almost every field in the future is inevitable. It is going to be embraced and pushed to the boundaries by us humans. However, to create such a situation, there is an urgent need to spread awareness and lead focused developments in this sector to obtain what it offers. At the rate at which the number of computer engineers is increasing, machine learning will soon be a popular sector within technology. By running active campaigns and familiarizing the people with the benefits and diversity of A.I., a domino effect will be created to promote machine learning, prediction, and other related activities.

Anything related to technology is bound to grow in the future; there will be advancements and new inventions in every field. That is the case with machine learning too. The machine learning market is highly expected to touch US$ 8.81 Billion by 2022. The industry has shown a growth rate of 44.1% annually. Machine learning has become a vital element to companies like Google, IBM, Microsoft, etc. Progress in the field of Improved Unsupervised Algorithms. An algorithm can learn independently and finds hidden patterns or groupings amongst the data to provide on-the-point prediction results. With inventions like BrainBox A.I. and Quantum Computers, it is clear that machine learning will become essential in the lives of many people in the years to come. Machine learning is getting flexible and flexible as the days pass. It can be tweaked according to the need and preferences of a person. This perk is why 82% of marketing leaders use A.I. and Machine Learning to determine investment avenues and take decisions accordingly [85]. By integrating advanced sentiment analysis methods with features engineering or deep learning models, there is also a strong possibility of developing a complete prediction system trained on various kinds of data, including tweets, News, and other text-based data. We may include data forecasts relating to stock-related News and basic information, thus enhancing the model's stability and accuracy in the event of a significant occurrence.

Table 4
Summarized studies of LSTM for stock market prediction.

Models	Dataset	Method	Conclusion	Reference
LSTM, MLP, SVM.	Eleven stocks were selected from the Brazilian stock series of 2016 with total data of 250 days. The majority of these stocks were part of the main Brazilian Index (BOVA11) in 2016.	The figures were divided into 166 days of training data and 84 days of test data. The LSTM model contained four layers with 8, 4, and 2 LSTM units, respectively. The last layer was the output layer.	LSTM stood out of all the models, although the gap was not very large due to the limited data. If the data had been more like 2000 days, LSTM would have been the winner with a huge margin.	Mesquita et al. [77]
LSTM, other models like SVM, CNN, NFNN, and Multiple Pipeline models were used to compare results.	S and P 500 stock prices were taken as prediction data. Data was taken for 20 years, from Jan 30, 1999, to Jan 30, 2019.	Multiple LSTMs were taken to learn the time dependencies of features of different time scales. All the information was combined to predict the closing price in the future.	The LSTM model proved to be better than other models due to its impressive capability of efficiently processing the data. The model had an accuracy of 74.55% over one month.	Hao and Gao [78]
MLP, LSTM, CNN and Uncertainty-Aware Attention (U.A.).	CSI300 from China, S and P 500, Nikkei225 of Tokyo. All the stock data is selected from July, 2008 to September 2016. 90% of the Data was used as training data, while 10% was used as test data.	The LSTM model had 140 hidden layers. Each model was predicted using MAPE, RMSE, and R.	LSTM model performed well in predicting CSI300 but overall had a higher MAPE, RMSE, R. U.A. performed better than all the others, MLP performed the worst.	Gao et al. [79]
LSTM, LSTM-based deep recurrent neural network (DRNN), Associated Neural Network (Associated Net).	Shanghai Composite Index, PetroChina, ZTE with 6112, 2688, and 4930 historical Data, respectively.	MSE and MAE are used for comparison.	LSTM model did not perform well, and it had too many deviations from the actual data. DRNN and Associated Net provided almost identical results with very little to no deviation.	Ding and Qin [80]
LSTM, CNN, Stock Sequence Array Convolution LSTM (SACLSTM).	AAPL, IBM, MSFT, F.B., AMZN from American stock exchange and CDA, CFO, DJO, DVO, IJO from Taiwan stock exchange. Data is from October 2018 to October 2019.	60% of data was employed to train the model, 20% was used to test the model, and the other 20% was for verification purposes. TensorFlow was the model which gave effect to CNN and LSTM.	SACLSTM performed the best with minimum error and definitive price movement graphs. CNN and LSTM did not show good results.	Wu et al. [81]
R language-based LSTM model.	P.T. Bank Central Asia Tbk and P.T. Bank Mandiri. 80% of data was used for training and the remaining 20% for testing.	Results of the model were calculated based on different periods and varying numbers of epochs.	The most promising results were obtained using a period of 1 year and a total of 100 epochs. The accuracy summed up to 94.59%.	Budiharto [82]
Comparison between ANN and LSTM. To compare results, RMSE was used.	Dixon Hughes, Cooper Tire and Rubber, PNC financial, CitiGroup, Alcoa Corp.	The LSTM model had 1 Input layer having five neurons, 'n' hidden layers, and one output layer.	LSTM had a much better prediction accuracy. For every company, RMSE was lower when predicted through LSTM and slightly higher through ANN.	Nandakumar et al. [83]

7. Conclusion

The stock market is highly volatile. However, it gives investors tremendous opportunities to appreciate their money. They can do so by referring to charts, graphs, balance sheets of companies, etc. Alternatively, they could make a Machine Learning Algorithm do it for them. The model can process historical Data, trend lines, charts, etc., quickly and advise with the right course of action for the future. Technology like Machine Learning is revolutionary, and so has it proven for thousands of investors. The paper proves the point by critically analyzing three Machine Learning models and proving the best in their fields. Sections 1 and 2 introduce the stock market, its benefits, drawbacks and set the stage by introducing the concept of machine learning to the readers. The three neural networks focused on this paper-ANN, SVM, LSTM-are presented with their features and application. The following three sections talk about neural networks in greater depth.

Additionally, in each section, summaries of practical experiments done by enthusiasts, doctors, professionals with each network are tabulated. Each of these three sections contains sixteen experiments summarizing and portraying the capability of machine learning can be. Collectively the paper shows why Machine Learning needs to be embraced and how it can change the dynamic of investing.

CRediT authorship contribution statement

Parshv Chhajer: Participated in drafting the manuscript, Wrote the main manuscript, Discussed the results and implication on the manuscript at all stages. **Manan Shah:** Participated in drafting the manuscript, Discussed the results and implication on the manuscript at all stages. **Ameya Kshirsagar:** Participated in drafting the manuscript, Wrote the main manuscript, Discussed the results and implication on the manuscript at all stages.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Availability of data and material

All relevant data and material are presented in the main paper.

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