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Stock Price Prediction Using Artificial Intelligence : A Survey

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***Abstract*—The stock market and the investments into it are two aspects which have gained quite some popularity in the previous decade. Although a lot of people are involved in trading and analysis of the stock market yet stock price prediction remains an exigent task . Scientists and researchers have tried their hands on different methodologies performing the same. A variety of techniques ranging from basic statistical models to stat of the art Deep Learning models have been used in performing stock price prediction .The beginning of the previous decade began with people using trivial machine learning regression models to determine stock prices , then some tried incurring sentiment analysis along with the stock regression. And finally toward the end of the decade a bunch of authors have shown very promising results using advanced Neural Networks like Generative Adversarial Networks.The aim and the purpose of this paper is to summarise the recent progress in the stock price prediction domain, comparing the recent works in the same domain. Comparison has been done on parameters like data set used , sentiments , models / algorithms, evaluation metrics and the conclusion laid down by different authors.**

***Index Terms*—Stock Market, Stock Price Prediction, Machine Learning, Deep Learning and Survey.**

I. Introduction

The heart of stock price prediction lies between technical analysis and fundamental analysis of the listed companies in the market. Technical analysis refers to finding patterns in the stock prices with the help of some technical indicators that further revolve around some mathematical formulas. Some example of the technical indicators include Relative Strength Index (RSI) , Bollinger Bands (BB) and Simple Moving Average (SMA) . Based on certain threshold and ranges of these technical indicators, stock prices are predicted.
Another aspect of the stock price prediction is the fundamental analysis. As the word says this analysis revolves around the core of the organisation, the past performance , the board of directors , market value and the sentiments also.

With the medium of this paper we have tried to summarise how differently researchers and authors have predicted stock prices. In different types of markets like New York Stock Exchange (NYSE) , Shanghai Stock Exchange , National Stock Exchange (NSE) India etc. researchers have applied algorithms ranging from Naive Bayes , Support Vector Machine (SVM), Auto Regressive Integrated Moving Average (ARIMA) and all the way to Neural Networks like Convolution Neural Networks (CNN) and Generative Adversarial Network (GAN). For evaluation metrics our findings show the use of different metrics like accuracy , mean squared error , precision etc.
The rest of the paper is organised as follows: Section 2 depicts the other survey papers that have been in existence and cover different papers revolving around stock price prediction. Section 3 talks about the findings that we were able to dig from surveying different research papers. Section 3 is further divided into sub-sections based in the parameter of differentiation between different research papers. Section 4 is the conclusion that closes our survey for stock prices prediction and contains our concluding remarks. Section 5 depicts what all can be performed in future on the basis of conclusion laid in section 4.

II. RELATED WORK

Stock market prediction has always been a topic of interest for investors and concerned masses.Numerous efforts have been made using deep learning to predict the market. A bunch of researchers have surveyed these techniques along with the traditional regression based algorithms . Atsalakis et al. [6] in 2009 surveyed more than 110 published research papers . These papers circulated around neural networks and fuzzy logic applied to stock markets . The parameters they used were the algorithm used, evaluation metrics and the data set used. Another remarkable survey evolving around neural network , Artificial Neural Networks (ANN) to be precise was done by Li and Ma in 2010 [40] . They included futures , options , exchange rates and risks involved in the trading process. Nikfarjam et al. [54] in 2010 surveyed few papers that performed fundamental analysis on the textual data concluding how the company performs , their ideology and the approach to do business and on basis of that predict the market prices. in 2015 Anguilar et al. [1] surveed research papers that involved genetic programming and sequencing. Through these techniques they gave a distribution of the prediction. In 2016 Cavalcante et al. [14] gave a brief of all the popular research done between 2008 - 2016 , they categorised on the basis of market movements , data used and financial textual information. In 2016 itself Verner et al. [73] laid down research papers based on how neural networks have been applied in day to day activities and revenue generating processes, they took a huge time gap and surveyed articles from late 1990's to 2015. They concluded that most of the application of neural networks have been done in spam/ham classification of transactions , stock marker prediction and further some typical classification tasks . They also concluded that in addition to the naive perceptron models that people use with stochastic gradient descent , a new era of hybrid deep learning models is seen where scientists and researcher's have successfully been able to increase the efficiency by making a hybrid of neural networks.

In 2018 Xing et al. [79] summarised some published research papers on market prediction based on Natural Language Processing. The data they used to collect the papers was revolving around how twitter financial news can be used for stock market prediction using sentiment analysis. Rundo et al. [60] in 2018 published a survey of papers that performed portfolio management and its optimization using machine and deep learning. Shah et al. [65] laid out the application of deep learning in algorithmic systems of trade , sentiment analysis and market prediction. Nti et al. [56] focused on papers having both fundamental analysis and technical analysis which have been discussed in the introduction. They also concluded that Artificial Neural Networks and support vector machines are two techniques which have been used the most by researchers and scientists.

Apart from the traditional survey papers revolving around studying different research papers on stock market prediction Reschenhofer et al. [59] have summarised articles via the science citation index in the business and finance category. They concluded with pointing out the mishaps in the trading environment ranging from short calling to old unconventional trading strategies. The most recent survey papers on the topic of stock market prediction have been focusing on a broader aspect of market for example Shah et al. [65] focused on predicting the stock market prices with the help of machine learning whereas Sezer et al. [64] have used the same to predict the movements of other financial instruments. Shofiqul et al. [32] have done a wonderful job by surveying close to 50 recent research papers all using Deep Learning to predict the stock market. The data that they used as a parameter to group the research papers was textual data. Further the research papers performed sentiment analysis on different types of data belonging to different markets. The sentiment analysis was also performed using Deep Learning. Algorithms like Long Short Term Memory(LSTM), Bi-Directional Gated Recurrent Units (GRU), Convolutional Neural Network and Capsule Based Networks were used as a parameter to survey different published research papers. In the due period of doing the literature survey of this paper we also figured out that close to 75 percentage of the research papers on stock market prediction are done on daily basis. These predict the close price or the open price of the concerned stock. The other 25 percentage of the research papers use intraday prediction i.e on a single day predicting the stock prices at certain pre-defined intervals. Whatever the case may be equal proportions further are done into the regression and classification tasks. The regression tasks predict the numerical value of the concerned stock whereas the classification deals with movement of the stock whether it will go up or down.

The aim of this survey paper is to spread awareness regarding the even recent techniques and algorithms that have successfully overpowered the naive and conventional algorithms. As an instance Ballings et al. [8] concluded that Random Forest algorithms is the most preferred over all other naive and vanilla alogrithms whereas Ersan et al [23] have concluded that Artificial Neural Networks are proved to give better results than every other algorithm. The main focus of this paper will be to survey papers mostly using deep learning just like Sezer et al. [64] . Most importantly the recent progress highlighting the unique and nontraditional methods for example Priyank and Vikas et al. [70] have shown how ensembling a Generative Adversarial Network with sentiment analysis output done via Bi-Directional Encoder Representation of Transformers (BERT) can lead to promising and efficient results which are better than all the most popular algorithms.

III. OBSERVATIONS

The main purpose surveying the recent progress in stock price prediction ,the research papers shortlisted are from 2017 to early 2021. Various research papers are further differentiated on the basis of data used i.e which stock market or index the researcher/scientist is referring to and what the time horizon used. Next research papers are also differentiated on the basis of data preprocessing techniques used involving feature engineering , train test splits and data augmentation. The next parameter is the prediction model that is the algorithm/technique that have been used to determine the stock prices. Finally the last parameter of differentiation is the model evaluation . Different scientists and researchers use different evaluation metrics like Root Mean Square Error (RMSE), Mean Absolute Error (MAE) etc.

A. DATA SETS

The data for stock market prediction can be the past prices or the textual news data of various stock indexes. The graph of number of research papers per country is shown below. Clearly evident USA being the most powerful economy most of the research papers were published on the USA markets and indexes. Different indexes like SandP 500 , Dow Jones Industrial Average , NASDAQ , NYSE and Russel were used to fetch historical and textual data. Further the Chinese market

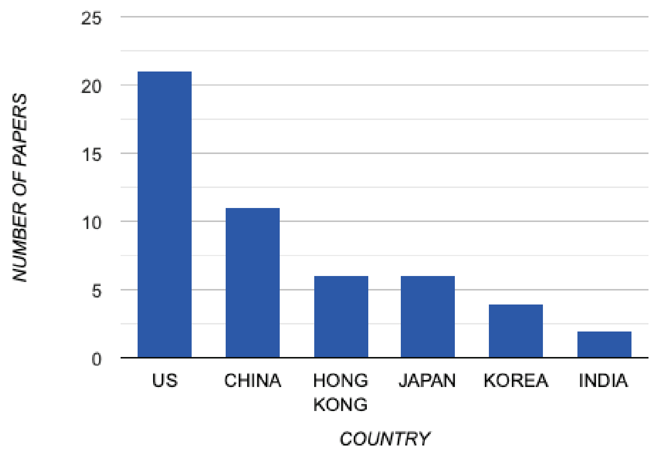

Fig. 1. Market of Countries v/s Count of Research Papers Written

too has has 2 major division in SSE composite concerned with the Shanghai Stock Exchange and the CSI 300 which also incorporates the Shenzhen stock exchange. Research papers using stock data of emerging stock markets of Hong Kong (HSI) , Japan (Nikkei 225) , Korea (KC) and India (NSE) are also considered in small numbers.

1) DIFFERENT TYPES OF DATASETS: The unprocessed data can be of various types depending on what technique or algorithm is being used like -

- Stock market past data : This refers to the past days data of a particular company or an index. The prices like open,high,low,close and the volume of shares traded in the past are the components of this type of data. The price data can help in calculating the technical indicators which have been discussed in the Introduction section. These indicators have the capability of predicting the pattern of the market.
- Textual Data : This refers to the social media and news related data. The textual data can reveal the hidden sentiments of the people in a particular stock. The sentiments can thence be used to predict the market.
- Economical Data : The economic data contains the instruments of the economy like Gross Domestic Product (GDP), Repo Rate (RR) , Reverse Repo Rate and inflation rate. These instruments are capable of showing the overall economy of a particular country and the overall economy is capable of driving the index prices as well.
- Fundamental Reports : This includes the basic metrics of a company / market. Every quarter in a year companies release there quarterly reports showing their performances , there goal and there future aspirations. Analysing these reports and the other fundamentals of the company can help in the prediction task.
- 2-Dimensional Image Data: In recent years the Convolutional Neural Networks (CNN) have gained much popularity and scholars have experimented in solving various problem statements with CNN's. One such idea is to use the daily candlestick charts of the stock market data and treat it like a 2 dimensional. Proven that CNN's work excellent with image data the prediction task remains no longer a challenge .
- Financial Reports : Many financial and consulting organisation publish reports on listed companies ,their performance and advance analytics. These reports help scholars in taking a summary of the market and visualising the price movement of the stocks. A brief of the data used by various scholars is mentioned in the below table.

TABLE I
DIFFERENT RESEARCH PAPERS AND DATASET USED.

Type Of Data	Research Papers
Stock Market - Past Prices Data	Chen et al. (2019) [16]; Nguyen et al.(2018) [51]; Li and Tam (2017) [41]; Nikou et al. (2017) [55]; Liu and Chen (2019) [44]; Siami-Namini et al. (2019) [67]; Zhao et al. (2018) [87]; Althelaya et al. (2019) [3]; Baek and Kim (2019) [7]; Tran et al. (2019) [74]; Zhang et al. (2018) [85]; Cao and Wang (2019) [13]; Arajao et al. (2020) [4]; Long et al. (2019) [47]; Eapen et al. (2018) [22]; Siami et al. (2018) [66].
Technical Indicators + Past Prices Data	Assis et al. (2019) [5]; Gunduz et al.(2018) [27]; Sanboon et al. (2019) [62]; Thelaya et al. (2019) [2]; Yan et al. (2019) [80]; Sethia et al. (2020) [63]; Tsiamas et al. (2018) [10]; Yang et al. (2018) [81]; Merello et al.(2019) [49].
Textual Data+ Past Prices Data	Jin et al (2019) [33]; Wang et al. (2019) [43]; Chen and Tang(2019) [72]; Kumar et al.(2019) [35]; Hu et al.(2018) [31].
Economical Data+ Past Prices Data	Fournier et al.(2018) [21]; Bao et al. (2018) [9]; Hoseinzade et al.(2019) [28].
2-d Image Data	Sezer et al.(2018) [64]; Sim et al.(2019) [68].
Fundamental Reports +Past Prices Data .	Ballings et al.(2015) [8]; Niaki et al.(2018) [53]

2) DATA LENGTH: The length of data to be considered is quite a subjective parameter. The problem being if the training is data is considered to be of short duration then the model can tend to overfit and produce vague results on the test set. In large duration data sets the main problem can be recognising and giving importance to false patterns which may not be actually driving the market.
From our detailed survey we saw that for daily past data - 60% of the researcher use 4-10 years of data , 30% use more than 10 years of data and the remaining use less than 1 year of data. For intraday prediction only 10% researchers use data more than 1 year which is quite fair because intraday data has nothing to do with long term patterns and prices. Hence majority i.e 90% use data of less than 1 year.

B. DATA PREPROCESSING

Any task related to data science includes this very basic step of data preprocessing at the elementary stage. Data preprocessing further has the below mentioned parts .

1) Handling Missing Data: One problem at the most basic stage of doing data modelling is handling the missing data. Missing data is important to handle so as to avoid data leakage. Since the traditional method of using mean and medians does not make sense, majority of the scholars either tend to remove the data point or just repeat the neighbourhood value in the missing value.

2) Handling Noisy Data: The next step in data preprocessing is removing the noise in the stock market data. Based on our survey we found that most of the scholars have sourced the data from giants like Yahoo Finance , hence the noise has already been taken care of . In other cases and sources for example one such unique method to remove the noise from the stock market data was used by Bao et al. [9]. They used the wavelet transformation algorithm which is mostly used with signal processing data to remove the noise. Another unique technique is used by Sun et al. [71] by using the K-Nearest Neighbour classification to eliminate the noise by taking two training sets with different classes for preparing the data.

3) Pattern Recognition and Extraction: For the machine learning and deep learning models to perform efficiently , recognising the features and the patterns in data is an essential tasks. As mentioned in the dataset used section most scholars prefer to use the technical indicators like moving averages and relative strength index (RSI). These indicators when used as a attribute are themselves capable to reveal the pattern of the data and its distribution. However the main task is to extract the features from the textual data. At the root level Liu et al. [45] used the word to vector (W2V) model which is a multi layer neural network used to embed words into a vector of numbers. One more word embedding technique used by Tang et al. [72] is the Global Vectors For Word Representation (GloVe) in which the dimension is fixed on the basis of certain pre-defined features.
More advanced methods like Convolutional Neural Networks have been used by Wang et al. [78] and Jin et al. [33] to perform sentiment analysis by firstly using a lexicon based approach. There are also instances of scholars like Priyank and Vikas et al. [70] who have used state of the art techniques like BERT for performing the sentiment analysis and extracting the features from the textual data.

4) Dimensionality Reduction: The historical price data along with the technical indicators may sometimes tend to reveal the same pattern and tell the same story. Also components of daily data like open price , close price, high price ,low price may reveal the same pattern individually. In such cases it is important to reduce the dimensions which is the number of attributes to reduce the complexity of the model and to give importance to the most important attribute. Majority of the scholars have ignored performing the dimensionality reduction step , the attributes being less in number. Scolars like Gao et al. [25],Zhong et al. [88], Singh and Srivastava. [69] and Chong et al. [18] have used the Principal Component Analysis (PCA) algorithm to find the most attributes. PCA reduces the dimension with the help of Singular Value Decomposition i.e reducing multiple dimensions into one or more dimensions.
Others like Zhao et al. [87] have used the Boltzmann machine and Sethia et. al. [63] have used the Independent Component Analysis (ICA). There has also been evidence of usage of advanced dimensionality reduction techniques like Auto Correlation Function (ACF) by Lei [37].

5) Standardization and Normalization: The historical prices data can attain huge values even in thousand of US dollars. Such a scenario requires the attributes to be either scaled or to be normalized. When scaled the data ensures that a feature does not get more importance just because its scale was more. This step also helps in speeding the model performance as the values reduce according to the technique used. Our findings regarding this step were that more tha 80% of scholars have used standardization and Normalization in there research papers. To list, few scholars like Gunduz et al. [27],Singh and Srivastava [69],Baek et al. [7],Gao et al. [25],Zhan et al. [82], Cao et al. [12],Lee et al. [36] and Sethia et al. [63] have used the normalization technique which scales down the feature between -1 and 1. Whereas scholars like Zhang et al. [86] and Li et al. [38] have used the standardization technique to calculate the z value by subtracting the mean and dividing by the standard deviation.

6) Training and Testing Data: The last step before creating the prediction model is to divide the processed data into training and testing sets. The model gets trained on the training dataset and then the evaluation is done on the testing data set. For time series sequential data often a rolling or a sliding window of data is used. This time step based look back data helps in recognising the short term dependencies efficiently. This time step based data split was used by Bao et al. [9],Fischer et al. [24],Nelson et al. [50],Zhao et al. [87],Yoon et al. [52] and Wang et al. [77].
One variation of considering the rolling window can be to consider the previous rolling window data in the next time step value. This can ensure long term as well as short term dependencies of the data.

C. PREDICTION MODEL

The stock prediction task is often performed on either the close price or the open price of the particular stock. This being the case majority of the scholars have chosen to apply the supervised models of machine learning and deep learning to complete the prediction task. The further division of the prediction models can be done into - Basic Linear Regressions Models, Traditional Machine Learning Models, Deep Learning Models and Hybrid and Advanced Models.

1) Basic Linear Regressions Models:

- Linear Regression: In simple words the Linear Regression technique finds the best fit line that passes through the training points. Further the regression can be advanced to L1 and L2 regularization that adds a penalty parameter to avoid over fitting.

- Generalized Auto regressive Conditional Heteroskedasticity(GARCH): This model is a type of an adaptive learning one. Here the variance in error is proven to be sequentially correlated. It incorporates the lagged conditional variances unlike the unconventional Auto Regressive Conditional Heteroskedasticity (ARCH) model.
- Autoregressive Integrated Moving Average: This is a three parameter model with capability to perform well with sequential time series data. The three parameter correspond to the no of lags ,degree of differencing used to make the stationary and the size of the moving average window. This model breaks down the task in Auto Regressive and Moving Average parts , hence the name.

2) Traditional Machine Learning Models:

- Logistic Regression(LOGIT): Having some similarity with the linear regression model the logistic regression model classifies the data in a binary fashion by creating a best fit line that maximises the distance between the training points .The best fit line differentiates the training points that went on a higher price from those which went on a lower price. Hence performing the classification task efficiently.
- K-Nearest Neighbour (KNN): K refers to the number of data points to consider to take the average of either the regression or the classification values. For a given test point k nearest neighbours are calculated either on the basis of euclidean distance or Manhattan distance according to the problem statement. Then if its a regression task then mean/median is taken and the majority class vote if the task is classification.
- Support Vector Machine(SVM): Just like linear regression and logistic regression the best fit line is more refined in Support Vector Machine model .SVM's have proven capability in classification by creating a hyper plane that differentiated data points belonging to different classes . With Support Vectors both classification and regression tasks are possible. SVM's have different kernel functions which can be chosen according to the problem and are efficient enough in dealing with non-linear data.

3) Deep Learning Models:

- Artificial Neural Networks: This type of neural network stands primarily for the feed-forward neural networks. Designed to perfectly mimic the human brain these type of neural networks are the most basic networks. Multilayer Perceptron (MLP) model , Deep Neural Neural Network (DNN) and the Autoencoder network models are also part of this category.
- Convolutional Neural Networks (CNN): The need to work on image based 2-dimensional data gave rise to CNN's .They have predefined filters of various dimensions according to different features and on basis of the filters multiple features are extracted from the image data. This process to extract the feature by applying different filters is called convolution. This similar model can be applied on 1-dimensional time series data by performing appropriate convolutions on the data. Some instances have also been found where scholars have used candlestick data as 2-dimensional image and directly fed to the CNN (Deng et al. [19]).
- Recurrent Neural Networks (RNN): Recurrent Neural Networks are just like the basic back-propagation models just having extra capabilities to subset the information to be propagated in the activation function. This type of network has same type of cells coiled one after the another for maximum pattern recognition from the temporal or the time series data. This capability proves in speed and better performance of the model. But the basic RNN's have been reported to be affected majorly by vanishing and exploding gradient problems. Hence Long Short Term Memory (LSTM) and Gated Recurrent Units (GRU) come to the rescue. These both have advance implementation in the logic gates that allow them to skip undesired information and solve the problem of vanishing and exploding gradients. Among LSTM and GRU the latter has better performance both in terms of time complexity and efficiency. LSTM have further been developed into bi-directional LSTM for the propagation to happen both in the forward and the backward direction.
- Sequence-to-Sequence Model: This type of encoder decoder neural network is primarily used with textual data. Both the encoder and the decoder are some neural networks (RNN's). This model is efficient in extracting the pragmatic meaning hidden in news and articles used for sentiment analysis for example Liu et al. [45].

The focus and scope of this paper is to survey the recent and most popular models used by scholars. Hence we ignore the traditional Machine Learning and the linear models as they literally make no sense in presence of highly advanced deep learning models. The table shows the list of the research work along with the models used and also the comparison made.

4) Hybrid and Advanced Models:

- Hybrid Models: These are some unique combination of different machine learning or deep learning models used together. One type can be to use traditional model with a neural network or another type can be to use two neural networks parallel to each other. The examples of former type can to ensemble Bagging and a simple ANN. Further an instance of the latter can be to use a CNN with a LSTM i.e textual data along with numerical data.
- Recent Advanced Models: The advanced new age state of the art models contains the Generative Adversarial Networks (GAN) put forward by Goodfellow et al. [26]. A GAN contains two neural networks which compete against each other finally replicating the original time series distribution by playing a min-max game. This type of network has been used by Zhou et al. [87] , Priyank and Vikas et al. [70]. The latter has show better results than former in terms of Root Mean Square Error Values. Another type of advanced model is the Capsule based

TABLE II
DEEP LEARNING MODELS AND RESEARCH WORK

Deep Learning Model	Research Paper	Baseline Comparison
ANN (Deep)	Hoseinzade et al.(2013) [53]	Logistic Regression
	Ding et al.(2015) [20]	SVM & Bag of Words
	Chen et al.(2017) [15]	ARIMA & GARCH
	Singh et al.(2018) [69]	RNN
	Sun et al.(2018) [9]	SVM & Logit
	Hu et al.(2018) [31]	Backprogoation
	Arajao et al.(2109) [4]	ARIMA,SVM & MLP
	Song et al.(2019) [42]	DNN
CNN	Fournier et al.(2018) [21]	Logit & SVM
	Gunduz et al.(2017) [27]	RNN,LSTM &RNN
	Sezer et al.(2019) [64]	LSTM & MLP
	Hoseinzade et al.(2019) [28]	ANN,CNN & PCA
	Deng et al.(2019) [19]	ARIMA,LSTM,CNN
	Sim et al.(2020) [9]	ANN & SVM
RNN	Li and Tam(2017) [41]-(LSTM+PCA)	LSTM
	Li et al.(2017) [39] (LSTM)	SVM
	Tsantekidis et al.(2017) [75] (LSTM)	SVM & MLP
	Zhang et al(2018) [83](GRU)	SVM
	Zhao et al.(2018) [87](LSTM)	RNN,SVM,ANN
	Cheng et al.(2018) [17](LSTM)	N/A
	Fischer et al.(2018) [24](LSTM)	DNN & Logit
	Gao et al.(2018) [25](LSTM)	ARIMA,GARCH&SVM
	Liu et al.(2018) [46](LSTM)	BoW
	Siami et al.(2018) [66](LSTM)	ARIMA
	Yan et al.(2018) [80](LSTM)	MLP,KNN,SVM
	Cao et al.(2019) [13](LSTM)	LSTM,SVM,MLP
	Liu et al.(2019) [46](GRU)	N/A
	Nguyen et al.(2019) [52](D-LSTM)	LSTM
	Sachdeva et al.(2019) [61](LSTM)	N/A
	Siami et al.(2019) [66](Bi-LSTM)	LSTM,ARIMA
	Tan et al.(2019) [72](LSTM)	SVM,ANNN,LSTM

TABLE III
HYBRID NETWORK MODELS AND RESEARCH WORK

Hybrid Model Type	Research Paper	Baseline Comparison
Wavelet+LSTM	Bao et al.(2017) [9]	LSTM,RNN
RNN+Attention	Qin et al.(2017) [58]	ARIMA,RNN
CNN+LSTM	Vargas et al.(2017) [76]	DNN.CNN
LSTM+GRU	Hossain et al.(2018) [29]	MLP,RNN,CNN
AE+LSTM	Pang et al.(2019) [57]	MLP
CNN+LSTM	Zhan et al.(2019) [82]	LSTM,GRU
CNN+biLSTM	Eapen et al.(2019) [22]	SVM
CNN+RNN	Long et al.(2019) [47]	RNN,LSTM,CNN
LSTM+S2S	Wang et al.(2019) [77]	CNN,LSTM,S2S
CNN+LSTM	Zhang et al.(2020) [85]	SVM,MLP,CNN

TABLE IV
ADVANCED STATE OF THE ART MODELS AND RESEARCH WORK

Model Type	Research Paper	Baseline Comparison
GAN	Zhao et al.(2018) [87]	ARIMA,ANN,SVM
GAN	Zhang et al.(2019) [84]	LSTM,SVM
GAN+BERT	Priyank and Vikas et al.(2021) [70]	LSTM,GRU,ARIMA,GAN
H-GAN	Kim et al.(2019) [34]	MLP,CNN,LSTM
GAN	Matsunaga et al.(2019) [48]	LSTM
Capsule Nets	Liu et al.(2019) [45]	RNN,GAN
Q-Learning	Lee et al.(2019) [36]	LSTM,CNN

Neural Network. Similar to a CNN , capsule based networks differ just in displacement of the pooling and the convolution operation performed in regular CNN. This network was firstly used by Liu et al. [45].
The most unique and different technique is to use the Reinforcement Learning. This award based technique learns by maximising the agent profit in place of some reward. This technique can be applied to longer intervals to avoid time stepping and the same has proven in efficient results as laid out by Lee et al. [36] and Deng et al. [53].

D. MODEL EVALUATION

The entire domain of stock price prediction can be either classification or regression task. On the basis of the same, according metrics are used for model evaluation. Now because each scholar works on a different data set for different time intervals, hence only the type of evaluation metric used has been surveyed, ignoring the numerical value of the corresponding metric. Hence the two different categories of evaluation in detail are:

- Evaluation of Classification Models: Classification is performed to track the movement of the particular stock price, whether it goes up or down. A detailed review of these metrics is given by Hossin et al. [30].Based on these two categories classification can be evaluated by using metrics like - accuracy, precision, recall, F1-score, AUC-ROC score and the entire confusion matrix containing all the positives and negatives.Table 5 shows the detailed use of classification based evaluation metrics.
- Evaluation of Regression Models: Regression Metrics are used to asses the performance of models that actually pre-

TABLE V
CLASSIFICATION EVALUATION METRICS AND RESEARCH WORK.

Evaluation Metric	Research Papers
Precision	Zhang et al.(2020) [85]; Sezer et al.(2019) [64]; Tasntekidis et al.(2017) [75]; Nelson et al.(2017) [50]; Gunduz et al.(2017) [27]
Recall	Zhang et al.(2020) [85]; Sezer et al.(2018) [64]; Tsantekidis et al.(2017) [75];Nelson et al. (2017) [50]; Gunduz et al.(2017) [27].
Accuracy	Wang et al.(2019) [78]; Sanboon et al.(2019) [62]; Nguyen and Yoon (2019) [52]; Long et al.(2019) [47]; Tran et al.(2018) [74]; Sezer et al. (2018) [64]; Pang et al.(2018) [57]; Gao and Chao(2018) [25]; Fischer et al.(2018) [24]; Zhang et al.(2017) [83]; Sun et al.(2018) [9]; Singh et al.(2017) [69]; Li et al.(2017) [41]; Ding et al.(2016) [20]; Niaki et al.(2013) [53];
F1-Score	Zhang et al.(2019) [85]; Tran et al.(2018) [74]; Sezer et al.(2018) [64]; Tsantekidis et al.(2017) [75]; Nelson et al.(2017) [50]; Gunduz et al.(2017) [27].
AUC Score	Zhang et al. (2019) [74]; Borovkova et al.(2019) [10]; Ballings et al.(2015) [8];

TABLE VI
REGRESSION EVALUATION METRICS AND RESEARCH WORK.

Evaluation Metric	Research Papers
Mean Squared Error (MSE)	Sachdeva et al.(2019) [61] ; Nguyen et al.(2019) [51]; Eapen et al.(2019) [22]; Arajo et al.(2019) [4]; Pang et al.(2018) [57]; Hossain et al.(2018) [29]; Baek et al.(2018) citer28; Zhang et al.(2017) [85]; Li et al.(2017) [40].
Mean Absolute Error (MAE)	Zhang et al.(2019) [13]; Nguyen et al. (2109) [51]; Nikou et al.(2019) [55]; Al-Thelaya et al.(2019) [2]; Hossain et al.(2018) [29]; Gao et al.(2018) [25]; Baek et al.(2018) [7]; Zhao et al. (2017) [87]; Li et al.(2017) [40]; Chong et al.(2017) [18].
Root Mean Square Error (RMSE)	Priyank and Vikas et al.(2021) [70]; Zhao et al.(2017) [87]; Zhang et al.(2019) [84]; Sun et al.(2019) [9]; Siami et al.(2019) [66]; Sethia et al.(2019) [63]; Lei(2018) [37]; Gao et al.(2018) [25]; Singh et al.(2017) [69]; Li et al.(2017) [40].
Normalized RMSE	Kumar et al.(2019) [35].
R-square Error	Sethia et al.(2019) [63]; Althelaya et al.(2018) [3]; Bao et al. (2017) [9].

dicted the numerical price.A detailed review of regression metrics is given by Alexei [11]. Some of the common regression metrics used by scholars are - Root Mean Square Error(RMSE), Mean Absolute Error(MAE), Mean Squared Error(MSE), R-square error and Normalised Root Mean Square Error (N-RMSE). Table 6 shows the detailed use of regression based evaluation metrics.

IV. FUTURE WORK

Based on the detailed journey of our survey, we list some insights for the upcoming scholars and new age scientist to refer to. Some type of neural networks for example Generative Adversarial and Capsule based networks are yet to be explored immensely. These have not been saturated just like LSTM ,CNN and regular RNN's. Hence there lies a scope in exploring the advanced and hybrid neural networks.

For sentiment analysis despite a lot of work done on attention models and encoder - decoder based sequence to sequence models there lies lack of research performed in state of the art attention and NLP mechanism like BERT. BERT pre-trained NLP model by google as used by Priyank and Vikas et al. [70] works best till date with textual data yet not many scholars have explored the same.

One important insight regarding the data is the collection of data from the affecting factors as well. Majority of the researchers have only considered either the historical price data or the textual data for analysis. A possibility to explore in future can be to incorporate the commodities data and the data of subsidiary stock indexes as well. For example using the crude oil, world gold, stock index of various countries like USA, Korea ,Japan and Hong-Kong altogether proved to be. very efficient for Priyank and Vikas et al. [70].

The last scope of future work can be to explore reinforcement learning. The most recent and top of hierarchy in artificial intelligence , this technique is yet to be explored by majority of the scholars and has been proven efficient in other domains of data science. A direct product of reinforcement learning is algorithmic trading where in buying orders and selling ordered are placed automatically on the basis of reward to the agent.

V. CONCLUSION

Influenced highly by social media, new investing trends and rise of stock market literacy we performed a detailed survey of more than 60 published research papers on stock price prediction. Each of the step in a data science tasks' life cycle ranging from data collection to model evaluation was surveyed. Extra focus of this survey was to consider modern era research papers published from late 2016 to late 2020's involving Deep Learning. Since the traditional Machine Learning regression/classification models are not in direct use in current era hence they were only used for comparison and data gathering. With the above listed opportunities and domains which can be focused in the future, we give insights to upcoming scientists and researchers to work on.

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