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Financial Market Prediction using News and Financial Data by Sentimental Analysis

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Abstract: There was a period when economists and other scientists were deeply captivated by the anticipation of speculative exchange costs. Political factors, economic factors, leadership changes, investor perception, and a host of other attributes all made stock prices extremely volatile and difficult to predict. It has been proven to be inadequate to attempt to predict stock prices based on either historical information or published data. Existed studies on opinion analysis show that good amount of correlation has been found between stock price movements and news story publications. A number of estimation studies have been conducted at various stages using algorithms including support vector machines, naive Bayes regression, and deep learning. The accuracy of deep learning algorithms depends on the amount of training data provided. However, the amount of text data collected and analyzed in previous studies was insufficient, resulting in low accuracy in predictions. In this paper, we demonstrate that stock price prediction accuracy can be improved through the collection and analysis of time series data in conjunction with related news using deep learning models. The assembled datasets include daily stock prices for S&P500 companies for a decade, along with more than 265,000 financial news articles related to these companies. Due to the large size of the datasets, we utilize cloud computing as a primary resource for training forecast model and performing predictions for a particular stock in real time. Keywords: stock market prediction, cloud, big data, machine learning, regression.

Keywords: Companies, models, Data ,Feature extraction, Facebook, Recurrent neural networks, Stock markets.

I. INTRODUCTION

Even while it's often believed that investing in the stock market will increase your profits over time, that isn't always true. The choice of stock ultimately dictates the amount of profit that may be achieved. I can think of nothing easier than putting money into a publicly traded company's stock in the expectation that it would increase in value over time. An investor's due diligence is essential for making sound investments. A comprehensive investigation is a necessary step before committing to a certain stock before making any investment. A large loss is probable from investments based on random selection.

When it comes to the future of a certain company, the majority of inexperienced investors today know very little. To them, it's as simple as buying any stock; if the price goes up, that's fantastic; if it goes down, they'll just have to try again later. To put it plainly, that is not how it works. Predicting how a stock's value will rise or fall in the future is a complex and hotly contested topic that has spanned disciplines as varied as computer science, economics, finance, and technology. The ability to foretell when a stock's price will rise or fall is crucial for making profitable investment decisions. Several market-related variables, such as the equilibrium between supply and demand, decide the price of stock. When there is more demand than supply for a certain stock, its price goes up, and vice versa when supply goes down. Belief is also a popular choice with many stock market participants. There are investors who think it's difficult to anticipate stock values, and there are others who think it's easy as pie with a little bit of math and some graphs. The second set of investors has valid points, but the reality is quite different.

Predicting the stock price is made much easier by taking into account the public's and investors' expectations, attitudes, and societal perceptions. Technical predictors have access to a plethora of

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resources that allow them to do thorough assessments in very short time frames. Recently, news stories published on the internet have a significant impact on how the stock market moves. The impact of internet news items on the future stock price of certain firms is statistically significant. With money on the line, even something seemingly little like this might have serious consequences. Therefore, it is possible to forecast the future stock price of a financial institution by keeping an eye on news stories about that firm that are published online.

Another reason manual monitoring is next to impossible is the enormous volume of news pieces that need to be digested in short periods of time. Here, the world's most impressive computer sciences come to the rescue. Stock price prediction is a process that may be accomplished with the help of certain techniques, such Sentiment Analysis. In a flash, you may get the general feeling based on a compilation of news stories and commentary. The stock market patterns are made glaringly obvious and easy to grasp with little effort thanks to these strategies, which are quite popular. Incredible volatility characterises the stock market. So, it is critical to accurately predict how stock bids will continue to move.

A stock's price movement in response to a series of events, financial indicators of the firm, and news stories about the business all play a role in influencing investment decisions. The three main goals of this work are to establish a system that calculates a company's overall financial status, to build an advanced model that evaluates and predicts stock price movements over time based on past events, and to provide evidence supporting the relationship between stock values and news articles. First, let's look at some statistics.

Mumbai, India is home to the Bombay Stock Exchange (BSE), which has been in operation since 1875. With a market valuation of $1.7 trillion as of January 23, 2015, BSE was ranked by Wikipedia as the tenth biggest stock exchange globally. Indian Internet users have grown exponentially since the early 1990s, when the technology first began to spread throughout the country. There are more than 243,198,922 Internet users in the nation, putting it in third place globally as of 2014. In February 2002, internet trading was initially permitted by stock exchanges [Source: Wikipedia]. Given the foregoing, it is safe to say that stock market participants who are actively seeking information on the market and companies rely heavily on the internet.

II. RELATED WORKS

A model for estimating drifts in a stock selection's daily returns was developed by Zhong and Eake in 2019. The full dataset, together with two datasets that have been modified using PCA (Principle Component Analysis), is used to train Deep Neural Networks (DNNs) and conventional ANNs to forecast the daily change in index value. Overfitting is somewhat controlled, and as the number of hidden layers increases from 12 to 1000, the so-called "tuning phenomenon" in the classification accuracy of the DNNs is noticed and shown. The findings of the simulation show that compared to other hybrid machine learning techniques and DNNs utilising the whole untransformed dataset, DNNs using two PCA-represented datasets perform better. No other trading strategy, not even two industry standards, could match the performance of the DNN-based methods using PCA-decompressed datasets.

In 2018, Pierdzioch and Risse use boosted regression trees (BRT), a machine learning method, to conduct an orthogonality test on the rationality of aggregate stock market predictions. For accurate burnout forecasts, the BRT algorithm will automatically choose prediction variables that reflect the forecasters' data sets. Additionally, the BRT method accounts for the interdependencies between predictor variables and the non-linear potential impact of the prediction error on those variables. The rational expectations hypothesis (REH) is shown to be reasonable and cannot be dismissed for short term predictions using the set of predictor variables in this research, which is their key discovery.

Opponents use it for long-term predictions, while supporters use evidence in its favour. Three other sets of forecasters' findings corroborate the main conclusion.

Chong, Han, and Park (2017) investigate how deep learning networks may be used for stock market research and prediction. The capacity of deep learning networks to automatically extract features from enormous volumes of raw data is a clear benefit for the high-frequency financial market. They provide fair assessments of the benefits and drawbacks of using deep learning methods for stock market research and prediction. Using high-frequency intra-day stock returns as input data, they explore the influence on prediction accuracy of three unsupervised feature extraction methods: principal component analysis, autoencoder, and the constrained Boltzmann machine.

A trading signal mining tool that uses an extreme learning machine (ELM) to forecast stock prices from two data streams at once was detailed in 2016 by Li et al. They used intraday data from the H-share market and real-time news data to compare ELM with BPNNs and support vector machines. According to the results, RBF ELM and RBF SVM both beat BPNN in terms of accuracy and prediction speed, but RBF ELM is even more accurate than RBF SVM. Moreover, RBF ELM is faster than RBF SVM.

Dash and Dash created a novel decision-support system in 2016 using a rule set for better trading choices and a computationally efficient functional link artificial neural network (CEFLANN). Buying, holding, or selling are the three potential outcomes of the stock trading choice issue, which they see as a categorisation problem. The decision-support system's CEFLANN network evaluates the nonlinear correlations between several widely-used technical indicators in order to provide ongoing trading signals. Additionally, established trading rules are applied to the output trade signals in order to observe trends and make trading choices based on such trends. This innovative method combines technical analysis with a CEFLANN neural network to automate effective stock trading. We compare the model against a number of different machine learning techniques, including support vector machines, decision trees, K-nearest neighbour, and naïve Bayesian models.

Four Indian stock market predictors—ANN, SVM, random forest, and naive-Bayes—with two input methods were studied by Patel, Shah, Thakkar, and Kotecha in 2015. Two methods are considered here: one uses stock trading data (open, high, low, and closing prices) to compute 10 technical metrics, while the other uses trend deterministic data to represent these same parameters. Using both input methods, they assess the precision of each prediction model. The results show that random forest outperforms the other three prediction models when it comes to the initial approach to input data. When these technical factors are trend deterministic data, they also find that all of the prediction models perform better.

By examining the model input parameters from nine studies in 2013, Chavan and Patil improve our understanding of ANN stock market prediction. They look for the input parameters that have the greatest impact on the accuracy of the model. Their research showed that when it comes to predicting the value of stock market indices, microeconomic data was more important than technical data attributable to macroeconomic variables affecting stock price predictions. In contrast, most ML algorithms used technical data. In addition, as compared to using just one kind of input variable, the results obtained using hybridised parameters were superior.

A time series forecasting model for Asian stock markets was created in 2012 by Dai, Wu, and Lu. It combines neural networks with nonlinear independent component analysis (NLICA). In the absence of a mixing mechanism or relevant data mechanism, NLICA is a novel feature extraction approach for separating independent sources from nonlinear mixed data. The suggested approach begins with using NLICA to convert the raw time series data into a feature space, from which they can then extract independent components that stand in for the underlying information. Next, the

In order to build the prediction model, the neural network is fed independent components using regression as input variables.

Guresen, Kavakutlu, and Daim (2011) assessed the efficacy of DAN2, an artificial neural network with many layers of perceptrons, and hybrid neural networks that include GARCH for the purpose of generating new input variables. While several hybrid and neural network models have been developed to outperform linear and nonlinear models in stock market prediction, the majority of these ANN models still exhibit performance gaps.

Concerning the hyperparameters of the kernel function, Yeh, Huang, and Lee examine problems with using Support Vector Regression to predict the stock market. In this scenario, the value of the hyperparameter is predetermined before the model begins its learning phase, as is typical. Their method improves the system's overall performance by allowing one to reap the advantages of different hyperparameter setups. Their two-stage multiple-kernel learning methodology combines the gradient projection method with sequential minimum optimisation. The results showed that the improved strategy beat all of the competitors in the experimental research that used datasets from the

Taiwan Capitalisation Weighted Stock Index.

This study's overarching goal is to survey the existing literature on the topic and to outline the parameters within which future research on machine learning stock market prediction may operate. It is feasible to get some conclusions about our knowledge in this field of study by considering the taxonomy categories mentioned above, in addition to the ML-systems, issue domains, and outcomes in each selected paper. To start, the prediction issues and the ML algorithms used are highly correlated. The logic here is similar to that of task-technology fit, which states that optimal system performance is dependent on a harmony between various technological components. Predicting the exact values of stock market indexes, for instance, is where artificial neural networks really shine. Whether the stock market index is going to go up or down is an example of a classification issue that support vector machines excel at. By optimising the projected return on investment via the solution of an evolutionary issue, a genetic algorithm can forecast which stocks should be included in a portfolio. Although the studies showed that the strategies work, the limits of the single-method applications were obvious. Applying hybrid ML approaches may alleviate some of these limitations.

The problem arises when having a system becomes too complex. In terms of theory and application this is an issue which can be solved by future research.

III. STRATEGY FOR THE PROPOSED FRAMEWORK

Stock movement prediction frameworks often include several steps, such as data collection, data cleansing, and feature selection. Certain programming activities are required for the thorough research. The languages that will be used include R, Python, and Java. The algorithms that were proposed were executed using the libraries of these tools.

There are two main categories of information needed to solve the current challenge. Two sources are needed to determine the sentiments: first, stock prices from historical datasets; and second, news items. Our system uses streaming datasets in addition to static ones, which makes it apart from others that depend just on static databases. The stock forecasting process begins with the setup of a crawler to monitor a certain website in search of news items about the firm in question. Acquiring news items with timestamps is necessary for synchronising stock prices with them. Following this, the sentiment analysis module receives these news stories together with their timestamps.

Researchers in the area of sentiment analysis have been exploring several directions for a while now. These algorithms integrate different aspects of sentiment analysis and are designed for sentiment categorisation. These algorithms all provide different answers, and they all have their own set of pros and cons. Considerations such as domain, dataset availability, and expert knowledge play a significant role in choosing a particular method for sentiment analysis. A decision between lexicon-based, machine learning, and linguistic approaches is required. Picking a particular algorithm from inside a given strategy is the next step.

In the first module, "Neural Network Predictor," I trained an artificial neural network to forecast future stock values by feeding it data on past prices and a sentiment score assigned to news stories.

.The following Figure 4.1 shows work flow in the module neural network predictor.

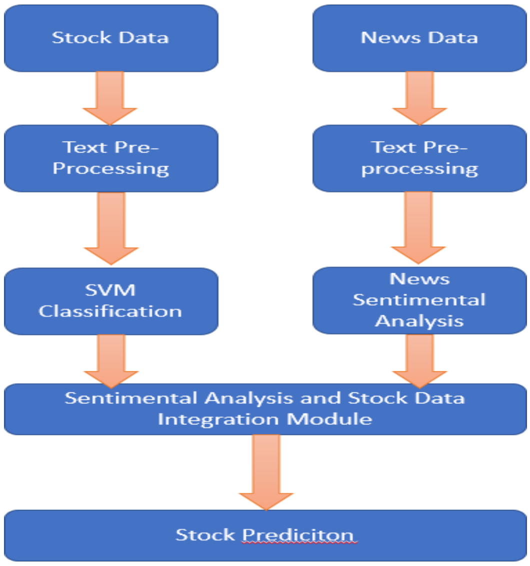

Figure 4.1: Work flow of Stock Price Predictor module

Using a combination of technical and sentiment analysis, this module gives a bird's-eye view of how well a business is doing. As a result, the potential investor may decide with confidence whether or not to put their money into the business. The diagram in Figure shows how the module that combined technical and emotional analysis worked.

TEXT PREPROCESSING

Using an ideal data prepossessing strategy may improve the accuracy of sentiment analysis. This fact illustrates the significance of the data pre-processing stage. Because of user-generated information, such as Twitter snippets, for instance, certain news stories need additional processing beyond that of ordinary pre-processing. " Data pre-processing may drastically cut down on word space, but it also increases the risk of information loss.

Data preprocessing involves the following steps:

- "Tokenization: A possible preliminary approach would be to cut up news articles into elements based on any non-alphanumeric characters. There may be information loss, which is why better methods are required for performing text tokenization. This step would be domain dependent."

- The dropping of common words: Ellipsis (the leaving out of words that are common) happens when you have a word which has no or little information value. In this example, be, an, is, and in, are identified as common words. There is great text space savings and cleaner data for sentiment identification sinks.

- Normalization: This is a process of constructing an equivalence class for the term. Its simplest form would be INFOSYS and INFY.

- Lemmatization and Stemming: Different forms of a given news headline may exist.

SENTIMENT ANALYSIS ALGORITHM

The subsequent task is to ascertain the tone of the retrieved news articles. A general impression of the article's positivity, negativity, or neutrality will be derived. Finding out how a news piece feels about a financial firm is the goal of sentiment analysis algorithms. There are three processes to emotional analysis, and we addressed them before. Pay close attention to the graphic above:

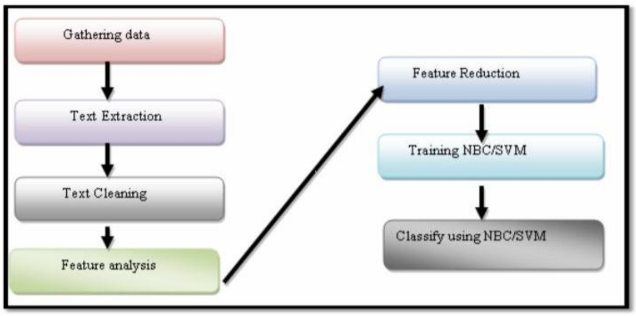

Figure 4.2: Steps in sentiment analysis

It is the steps in sentiment analysis, so keep that in mind. In this case, let's imagine. First Step: Gathering information from the nominator is the initial stage in data collecting; in this instance, the SOR is ICICI Bank. Internet reconnaissance, also known as web mining, is using a segment of code called a crawler to gather all the information found online on sites that mention SOR.

As for the second step, data and text mining include both simple and complex approaches, including "neural networks" and "DOM structure mining" (a.k.a. "keyword matching"). Web pages are notoriously unstructured, which is a major obstacle in this field. Furthermore, there is no silver bullet that will ensure flawless text extraction from any given document.

Third Step: Most text cleaning algorithms are based on heuristics and are often inaccurate. In order to find the parts of the extracted contents from Step 2 that aren't wanted, one needs to take into consideration the various kinds of web documents (e.g., news articles, blogs, reviews, microblogs, etc.), create learning algorithms that include detection of these parts, and then run simple clean-up algorithms that successfully remove these parts with a high accuracy rate.

Fourth, we use a number of knowledge processing engines to examine the corpus that has been cleaned up by our document cleaning procedures. Customisation of the analysed data is possible to meet many requirements, including but not limited to market research, sentiment analysis, consumer buzz trends, and feature or business analytics. Because of the diversity of uses, different approaches are developed for certain tasks. The Inverse Document Frequency (TF-IDF) method may be used to soar a pool of features; for instance, ICICI Bank can soar a pool of features such as customer service, credit card, recovery agent, customer satisfaction, etc. The term for this procedure is feature analysis. From this pool, one may ascertain the frequency with which customers express happiness with their credit card or the word "recovery agent" while discussing their credit card.

Because they don't match the necessary detailed description of the analysis, the characteristics that are given here will, as anticipated, produce a lot of undesirable features in Step 4.1. Feature mapping from pools containing keywords denoting features recognised for such verifiability allows for adjustments to analysis. It is also possible for the SOR to predefine features to delete.

In Step 5, the document is categorised as either good, negative, or neutral using the Sentiment Analysis. Either a human rater or an automated system may finish the sentiment analysis for processed online content. When dealing with a huge number of online papers, manual grading becomes slow, even if it is the most accurate way. However, since it is using machine learning to deduce human attitudes, the automated system would be less accurate without user-generated information, although being far quicker. The problem of language is another obstacle to computerised sentiment analysis. Still, these issues have been the focus of much Natural Language Processing research, which has led to state-of-the-art machine learning tools that can analyse the sentiment of documents hosted on the web. Maximum Entropy Support Vector Machines (SVMs) and the Naive Bayesian Classifier (NBC) are the most effective methods for this. Therefore, lexicon-based methods may also be useful for other things.

In order to learn how to infer feelings from online content, these algorithms first analyse a predefined collection of texts, or corpus.

Phase 5.1: NBC/SVM Training The training method using NBC and SVM is well-established and easy to understand. The process begins with the creation of a corpus of thousands of online papers. Each SOR is then given a rating, which may be good, neutral, or negative. After that, the NBC/SVM submits them to the engines along with the criteria that determine the range for each document and sort them into one of three categories: neutral, positive, or negative.

Fifthly, with the help of outside consultants, assess the history and development of the project. They are also capable of classifying other online content according to their own criteria. There will be several iterations of training and adjustment that can bring the accuracy closer to 100% while simultaneously improving the precision. Predictions about the stock market are based on the direction of these values, which are derived from sentiment analysis, when paired with past data. Predictions are made using methods such as Artificial Neural Networks and NBC, as previously stated. Two hidden layers, five input neurones, and a single output neurone make up an artificial neural network. The system takes sentiment score and historical pricing data as inputs, and the network adapts itself using that data. The algorithm takes the supplied sentiment score and past stock prices to determine the following day's price. Here at NBC, we train our classifier to identify good, negative, and neutral news pieces by looking at the likelihood of certain attributes.

III. RESULT

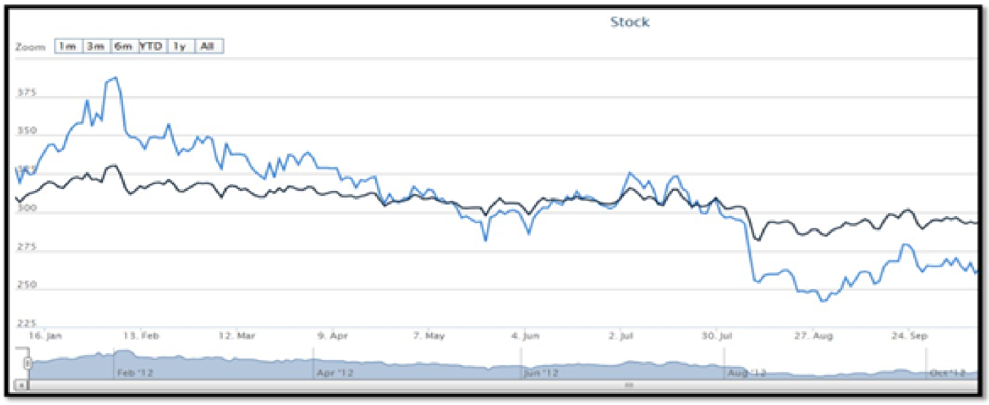

Figure 5.2: Plotting of Stock values for AIRTEL

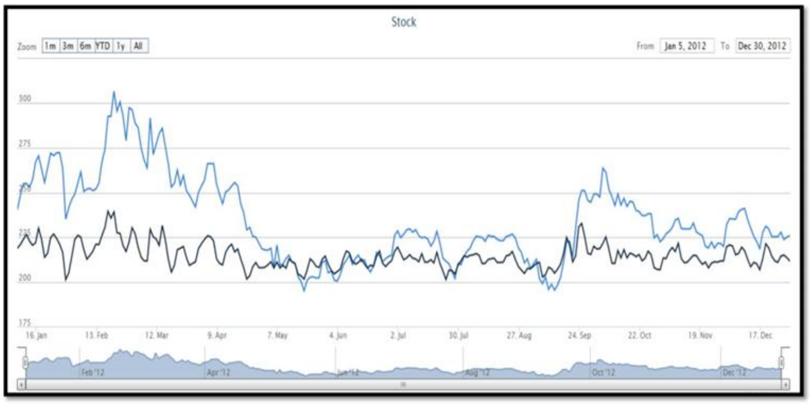

Figure 5.3: Plotting of Stock values for BHEL

Experiment Analysis

$$Precision = \frac{Number\ of\ correct\ positive\ predictions}{Number\ of\ positive\ predictions}$$

$$F1\ Score = \frac{2 * Recall * Precision}{Recall + Precision}$$

$$Recall = \frac{Number\ of\ correct\ positive\ predictions}{Number\ of\ positive\ examples}$$

Table-5.4: Comparison of classifiers

	Precision	Recall	F1 Sore	Accuracy
SVM	71.34%	72.11%	71.23%	74.3%
Auto Regressive Model	86.5%	85.3%	85.11%	87.6%
boosted regression trees	89.3%	88.8%	89.4%	90.34%
hybrid machine learning algorithms (ANN/DNN)	91.8%	90.3%	91.2%	92.5%
Proposed Model	95.5%	94.2%	95.3%	96.9%

IV. CONCLUSION

In the study conducted to meet the third goal, only firms with adverse publicity were selected, and their results confirmed that there is a decline in the company's stock price shortly after negative news is publicized. It indicates that there is an increase in tendency after some event has occurred. The empirical research conducted for this thesis would assist an investor in making a decision, so that he could invest without risk in a firm and retrieve a hefty profit. The new methods of sentiment analysis applied in this work have effectively accomplished all three objectives, and they are useful in practical situations.

V. REFERENCES

[1] Zhong, X., & Enke, D. (2019). Predicting the daily return direction of the stock market using hybrid machine learning algorithms. Financial Innovation, 5(1), 4

[2] Pierdzioch, C., & Risse, M. (2018). A machine-learning analysis of the rationality of aggregate stock market forecasts. International Journal of Finance & Economics, Cabitza, F., Locoro, A., & Banfi, G. (2018). Machine learning in orthopedics: a literature review. Frontiers in Bioengineering and Biotechnology, 6, 75.

[3] Chong, E., Han, C., & Park, F. C. (2017). Deep learning networks for stock market analysis and prediction: Methodology, data

representations, and case studies. Expert Systems with Applications, 83, 187-205.

[4] Li, X., Xie, H., Wang, R., Cai, Y., Cao, J., Wang, F., ... & Deng, X. (2016). Empirical analysis: stock market prediction via extreme learning machine. Neural Computing and Applications, 27(1), 67-78.

[5] Dash, R., & Dash, P. K. (2016). A hybrid stock trading framework integrating technical analysis with machine learning techniques. The Journal of Finance and Data Science, 2(1), 42-57.

[6] Patel, J., Shah, S., Thakkar, P., & Kotecha, K. (2015). Predicting stock and stock price index movement using trend deterministic data preparation and machine learning techniques. Expert Systems with Applications, 42(1), 259-268.

[7] Chavan, P. S., & Patil, S. T. (2013). Parameters for stock market prediction. International Journal of Computer Technology and Applications, 4(2), 337.

[8] Dai, W., Wu, J. Y., & Lu, C. J. (2012). Combining nonlinear independent component analysis and neural network for the prediction of Asian stock market indexes. Expert systems with applications, 39(4), 4444-4452.

[9] Chiu, D. Y., & Chen, P. J. (2009). Dynamically exploring internal mechanism of stock market by fuzzy-based support vector machines with high dimension input space and genetic algorithm. Expert Systems with Applications, 36(2), 1240-1248.

[10] Das, S. P., & Padhy, S. (2012). Support vector machines for prediction of futures prices in Indian stock market. International Journal of Computer Applications, 41(3).

[11] Guresen, E., Kayakutlu, G., & Daim, T. U. (2011). Using artificial neural network models in stock market index prediction. Expert Systems with Enke,

[12] D., & Thawornwong, S. (2005). The use of data mining and neural networks for forecasting stock market returns. Expert Systems with applications, 29(4), 927-940.

[13] Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. MIS quarterly, 213-236. Applications, 38(8), 10389-10397.

[14] Holland, J. H. (1992). Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control, and artificial intelligence.

[15] MIT press.Jasic, T., & Wood, D. (2004). The profitability of daily stock market indices trades based on neural network predictions: Case study for the S&P 500, the DAX, the TOPIX and the FTSE in the period 1965–1999. Applied Financial Economics, 14(4), 285-297.

[16] Kim, H. J., & Shin, K. S. (2007). A hybrid approach based on neural networks and genetic algorithms for detecting temporal patterns in stock markets. Applied Soft Computing, 7(2), 569-576.

[17] Kim, K. J., & Han, I. (2000). Genetic algorithms approach to feature discretization in artificial neural networks for the prediction of stock price index. Expert systems with Applications, 19(2), 125-132.

[18] Kim, K. J., & Lee, W. B. (2004). Stock market prediction using artificial neural networks with optimal feature transformation. Neural computing & applications, 13(3), 255-260.

[19] Kim, M. J., Min, S. H., & Han, I. (2006). An evolutionary approach to the combination of multiple classifiers to predict a stock price index. Expert Systems with Applications, 31(2), 241- 247.

[20] Kumar, L., Pandey, A., Srivastava, S., & Darbari, M. (2011). A hybrid machine learning system for stock market forecasting. Journal of International Technology and Information Management, 20(1), 3.

[21] Lee, K. H., & Jo, G. S. (1999). Expert system for predicting stock market timing using a candlestick chart. Expert systems with applications, 16(4), 357-364.

[22] Lee, M. C. (2009). Using support vector machine with a hybrid feature selection method to the stock trend prediction. Expert Systems with Applications, 36(8), 10896-10904.

[23] Liao, Z., & Wang, J. (2010). Forecasting model of global stock index by stochastic time effective neural network. Expert Systems with Applications, 37(1), 834-841.

[24] Malhotra, R. (2015). A systematic review of machine learning techniques for software fault prediction. Applied Soft Computing, 27, 504-518.

[25] Mosavi, A., Ozturk, P., & Chau, K. W. (2018). Flood prediction using machine learning models: Literature review. Water, 10(11), 1536.

[26] O, J., Lee, J., Lee, J. W., & Zhang, B-T. (2006). Adaptive stock trading with dynamic asset allocation using reinforcement learning. Information Sciences, 176(15), 2121-2147.

[27] Ou, P., & Wang, H. (2009). Prediction of stock market index movement by ten data mining techniques. Modern Applied Science, 3(12), 28-42.

[28] Pound, J. (2019, December 24). Global stock markets gained $17 trillion in value in 2019. Retrieved from https://www.cnbc.com/2019/12/24/global-stock-markets-gained-17-trillion-in-value-in-2019.html.

[29] Qian, B., & Rasheed, K. (2007). Stock market prediction with multiple classifiers. Applied Intelligence, 26(1), 25-33.

[30] Schumaker, R. P., & Chen, H. (2009). Textual analysis of stock market prediction using breaking financial news: The AZFin text system. ACM Transactions on Information Systems (TOIS), 27(2), 12.

[31] Schumaker, R. P., & Chen, H. (2010). A discrete stock price prediction engine based on financial news. Computer, 43(1), 51-56.

[32] Wen, J., Li, S., Lin, Z., Hu, Y., & Huang, C. (2012). Systematic literature review of machine learning based software development effort estimation models. Information and Software Technology, 54(1), 41-59.

[33] Yu, L., Chen, H., Wang, S., & Lai, K. K. (2008). Evolving least squares support vector machines for stock market trend mining. IEEE Transactions on evolutionary computation, 13(1), 87- 102.Innovation, 5(1), 4