REVIEW PAPER ON:

ALGORITHMIC TRADING USING ARTIFICIAL INTELLEGENCE

Sachin Jadhav[1], Vrushal Chaudhari[2], Pratik Barhate[3], Kunal Deshmukh[4], Tarun Agrawal[5]

[1]*Professor, Dept. of Information Technology, PCCOE, Pune, Maharashtra, India*
[2-5]*Engineering Student, Dept. of Information Technology, PCCOE, Pune, Maharashtra, India*

***Abstract** - Stock markets plays major role in economic growth of the country in today's world. And as these markets are most liquid markets in the world lots of studies proved that traditional way of trading has to face many problems. Hence in this paper we present a observed framework to apply different trading strategies to predict stock market in this artificial intelligence are regularly used for reducing risk factor and try to get the maximum net return profit by means of diverse algorithms for trading. Different techniques are used for algorithmic trading for detecting stock price in next time period such as using Neural Network, XGBoost, SVM. In this paper how the dataset is taken, the analysis of data and stocks and brief about this techniques is given along with some test cases. The result is important which shows the best technique used for AT using some machine learning algorithms to get maximum return*.

***Keywords:** Artificial Intelligence, Stock Trading, SVM – support verctor machine, Machine Learning*

1. INTRODUCTION

Customarily Models of stock value expectation have commonly utilized specialized pointers alone to produce stock exchanging signals for creating benefit. In this paper, we have contemplated exchanging methodologies by applying AI procedures to both specialized investigation markers and live value information.

The subsequent expectation ML-models should be utilized as a automated-trader to exchange on some stock market.

Artificial Intelligence has increased in a lot of significance in foreseeing stock patterns. Strategies in Artificial insight, for example, neural system are utilized to detect co-relation, connections, and market changes dependent on recorded information and decide future patterns of a stock.

One of the extreme issues glanced in demonstrating monetary market developments is gigantic amount of sources from which the information move in. From various ML-models made in this area, we made a decision to receive a technique with help of tremendous information and data accessible. The test is to identify a ML-model having decent presentation with top of the line exactness. Using fewer measure of information preparing and examination, the last objective is to trace the finest design of the ML-model to get greater performance than other models. This review paper will be focused on solving these problem and exploring various techniques to carry the specified trading task. We are focusing on finding algorithm which will consume less resources but will be able to give most accurate result as possible.

Various techniques are used in past to predict, the stock price but we will be focusing on method based on artificial intelligence. The key contributions made here are proposing XGBoost method for stock trading rather than more conventional machine learning methods.

2. LITERATURE SURVEY

There are various techniques that are used for forecasting the future price of the stocks in a certain time period. Here, we are using three different techniques such as Neural Network, Support Vector Machine and XG Boost. And afterwards we are comparing all these techniques to get the most efficient technique which gives maximum net return profit.

2.1 Neural Network

Neural Networks is much of the time applied to lessen the different dangers and boost the net returns in different sorts of algorithmic trading techniques. Straightforward neural systems models are equipped for giving predictions of future financial exchange value development [3].

Definitions regarding stock trading in Neural Network:

Log-return :-

Let cp be the current closing price and let cp−1 the previous closing price.

$R = \log_e(cp/cp-1)*100$ %

$= (\log_e (cp) - \log_e (cp-1))*100$ %

Pseudo log-return :-

Pseudo log return is a logarithmic difference between average costs for back to back minutes.

Assume cp be the current minute average price and cp−1 the previous minute average price.

$R = \log_e(cp/cp-1)*100\ \%$

$= (\log_e (cp) - \log_e (cp-1))*100\ \%$

One-minute Trend Indicator :-

It is one of the measurable marker registered as per direct model's incline (cost = at+b) fitted on to the exchange cost for a specific moment, where t is milliseconds time inside the specific moment [4].

Minor slope in the next minute indicates that price will remain stable.

If the result get is positive then it indicates that price will rise in next minute.

If the result get is negative then it indicates that price will fall in next minute.

Change is proportional to distance, according to distance price will rice or fall.

Spread :-

Spread = Ask price – Bid Price

Neural Network predictions are used for building trading strategy. At the starting of every minute it will check whether next minute predicted average price is greater than last minute closing price, if so then it will buy stock. In that particular minute if price reach to predicted average price then it will sell stock, and if the price doesn’t reach to the predicted price then it will sell stock at the end of minute. This is the strategy for buy and sell of stock using neural network [4].

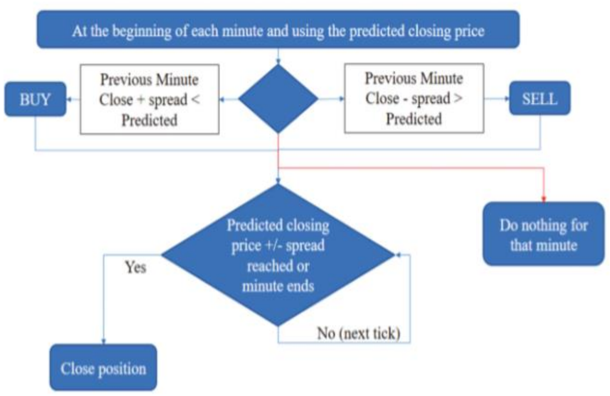

Fig1. Strategy Flowchart for neural network based model to buy, sell or hold the stocks depending on prediction of stock price [4].

From Fig1, We can see how neural network method works for stock trading. If previous minute close + spread < Predicated, we buy the stock and sell if previous minute close + spread > Predicted.

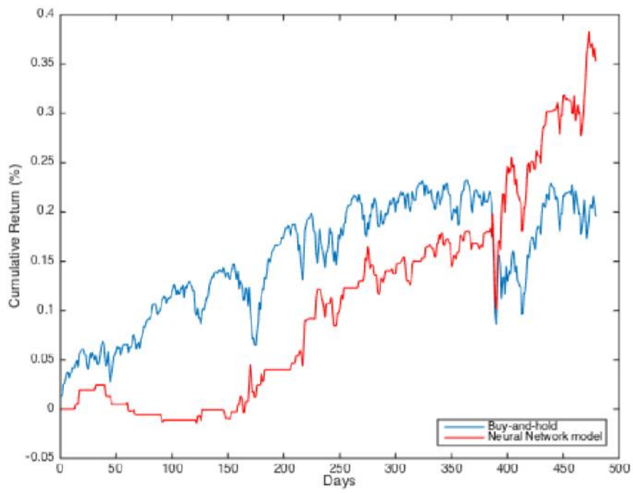

Fig2. Above gives the collective stock performance of neural network based model against buy and hold strategy [5].

From Fig2. , It is evidently clear that Neural Network gives higher return than buy-and-hold strategy as mentioned in reference paper

Advantages:-

- Capacity to work with fragmented information : After NN preparing, the information may deliver yield even with inadequate data. The loss of execution here relies upon the significance of the missing data.
- Having adaptation to internal failure: Corruption of at least one cells of ANN doesn't keep it from producing yield. This element makes the systems shortcoming lenient.
- Equal preparing ability: Artificial neural systems have numerical quality that can perform more than one employment simultaneously.

Disadvantages:-

- Equipment reliance: Artificial neural systems require processors with equal preparing power, as per their structure. Therefore, the acknowledgment of the gear is reliant.
- Assurance of legitimate system structure: There is no particular standard for deciding the structure of counterfeit neural systems. Suitable system structure is accomplished through understanding and experimentation.

2.2 Support Vector Machine

Support Vector Machines (SVM) is one of the finest binary classifiers. They make a choice limit ,with the end goal in which maximum focuses in single classification goes in the the solitary facet of edge even as greater focuses in different classification goes in the alternate part of the edge. After that components within a single classification shall be to an extent that the whole is more noteworthy than zero, even as components in the other classification will consider aggregate to be under zero. With marked models Consider a n-dimensional component vector x = (X1,... ... ..,Xn) [14].

We can characterize a straight limit (hyperplane) as

$$y = \beta_0 + \sum \alpha_i y_i K(x(i), x)$$

Where, $\beta o + \Sigma(i=1 \text{ to } n) \beta i\, Xi = y$

and $y \in (-1,1)$.

The stock price prediction will depend on y. if y is 1 then value increased otherwise decreased. The ideal hyperplane is with the end intention such as if we amplify the gap from that flat surface to anypoint. That is known as the margin. The most margin hyperplane satisfactory parts the statistics. Be that as it may, since it may not be an ideal separation, we can add blunder variable e1 to en and keep their aggregate underneath some spending B. The most significant component is that solitary the focuses close to the edge that only essential for hyperplane choice, and rest is insignificant. The particular focuses are characterized as support vectors and the hyperplane is characterized as Support Vector Classifier (SVC) as it puts every support vector in unit explicit type [18].

SVM MODEL :

The kernel feature we're utilizing here which mostly used mean to be radial kernel. The feature is among the foremost mainstream accessible kernel function [13].

$$K(x_i, x_k) = exp\left(-\frac{1}{\delta^2}\sum_{j=1}^{n}(x_{ij} - x_{kj})^2\right)$$

Which is shown above ,in which δ is considered to be band width of the kernel function .The favorable condition is that it can deal with various different taking in dataset, because there are some restrictions on the information obtained through inputs..

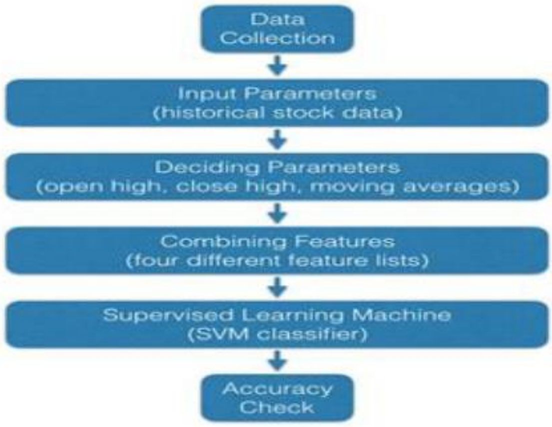

Fig3. Architecture of the support vector machine based model with step-by-step procedure for stock prediction [17].

In above Fig3 figure we can see how the actual process from data collection to training models to checking accuracy check takes place

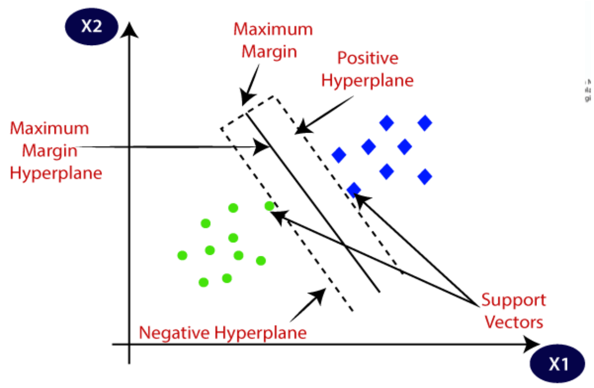

Fig4. SVM Classifiers which classify in two different categories using decision boundary (Hyperplane).

From Fig4, we get sense about how exactly classifier makes two different choices i.e buy and sell

FEATURES FOR MODEL :

Here we utilize four highlights for forecasting stock value heading – price volatility, price momentum, sector volatility, and sector momentum. Further info about these will be clearly mentioned in table [13].

As we look into Table we portray how every feature is determined by mean some amount for the last n days. Our model can be verified by changing the variable n to spectate precisely the change in features occurred also in case of index as well as stock, which will help us to determine the future price change in stocks.

PERFORMANCE :

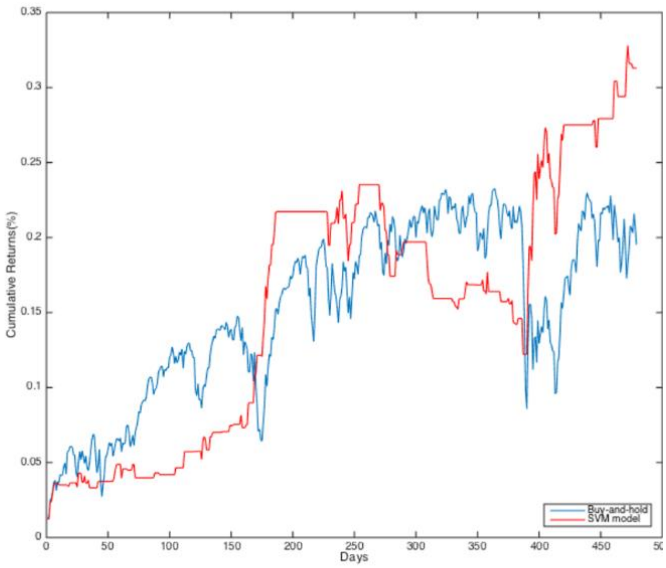

Fig5. Collective stock performance of SVM based model against buy and hold strategy [5].

From Fig5. , It is evidently clear that SVM method gives higher return than buy-and-hold strategy as mentioned in reference paper

Advantages:-

- SVM generally operates well when there is boundary of separation between classes.
- SVM can efficiently handle non-aligned information with the help of kernel trick hence it is genuine powerhouse of SVM. With a suitable kernel function, we can take care of any complicated issues.
- Not at all like in neural systems, SVM isn't explained for localoptima, but it solved for global optima. Hence it is defined by convex optimization problem.
- A little change to the information doesn't incredibly influence the hyperplane and thus the SVM. So the SVM model is steady. And hence it gives better results than other models.

Disadvantages:-

- As kernel trick is powerhouse of SVM, but selection of that kernel function is extremely difficult.
- SVM or Support vector machine is certifiably not a probabilistic model so we cannot clarify the characterization possibly, as the support vector classifier operates by concentrating information, exceeding and beneath the categorized boundary.
- It is hard to comprehend and decipher the SVM model contrasted with Decision tree as SVM is progressively perplexing.

From literature survey , we can conclude that following are the limitations of existing methods
1) Relatively unstable return and high fluctuations
2) Higher Training Time , resulting in late trades

3. PROPOSED METHOD

Xtreme Gradient Boosting

3.1 Preprocessing

Data preprocessing is an important step to achieve required accurate results.

We will be taking stock market price data from our source.

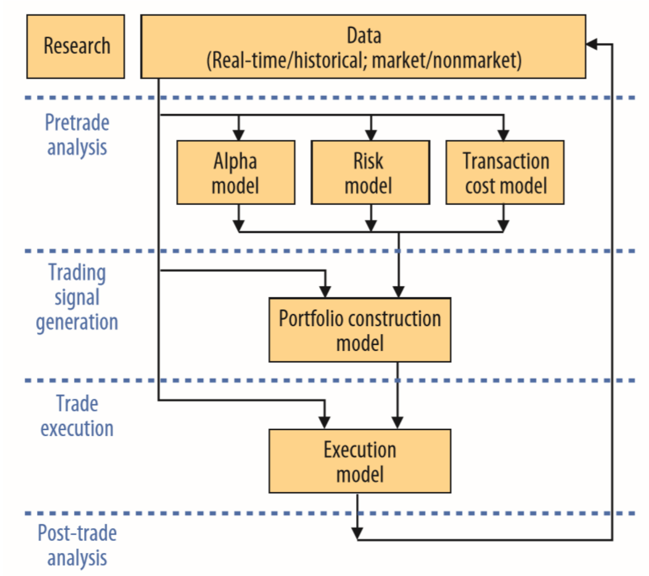

Fig6 .preprocessing model [1].

From Fig6, We can see how data travels through the entire model and how it reaches the execution model to make trade we will be removing the outliers in the data as they can give unstable reults.

Then we need to label the data features accordingly. Later need to check if the returns are independent and identically distributed.

If some labels are highly dependent on each other, we need to remove the unnecessary data.

3.2 Methodology

3.2.1 Decision Tree

Tree boosting uses Decision tree as a classifier. CART also known as output function of eXtreme gradient boosting is regression tress linear superposition.

This Decision trees are building blocks of XGBoost Algorithm. XGBoost iterates over this trees and improve the performance.

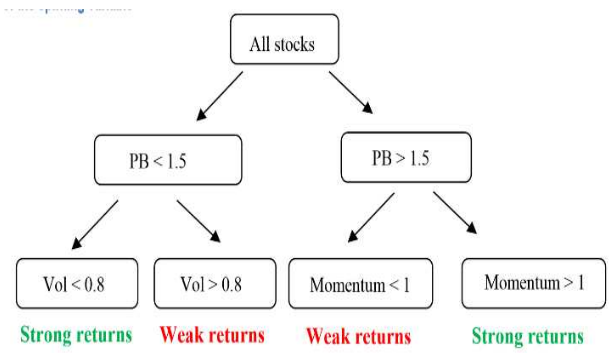

Fig 7. example of decision tree

Above figure7, explains how decision tree works. If P.B. < 1.5 and vol < 0.8 then strong returns are expected. Likewise other combinations are described

3.2.2 Tree Boosting

In the tree boosting phase, we actually take into consideration various decision tress which will be improved upon based on previous trees.

Tree boosting enables us to make multi factor decision as decision trees are used as weak learners.

Tree ensemble model is used by ensemble technique. Tree ensemble model is set of regression trees and classification trees (CART). Multiple tree prediction sum is considered by using CART [10].

By improving upon previous methods and combining together the previous results, new models are created to get the end prediction. This process is Gradient Boosting.

eXtreme Gradient Boost model objective function:

Objective = Loss_func + regular_comp

Loss_func denotes the controller over the predictive strength, and regular_comp controls straightforwardness and overfitting which is regularization component [12].

In the beginning, we have to process through a bunch of processing of data and tuning of model. The algorithm for grid search is used for tuning various values for eXtreme gradient boosting.

Reciver operating characteristics curve is a plot of FPR vs TPR that explains binary classifier model diagnostic ability as variation of discrimination threshold occurs.

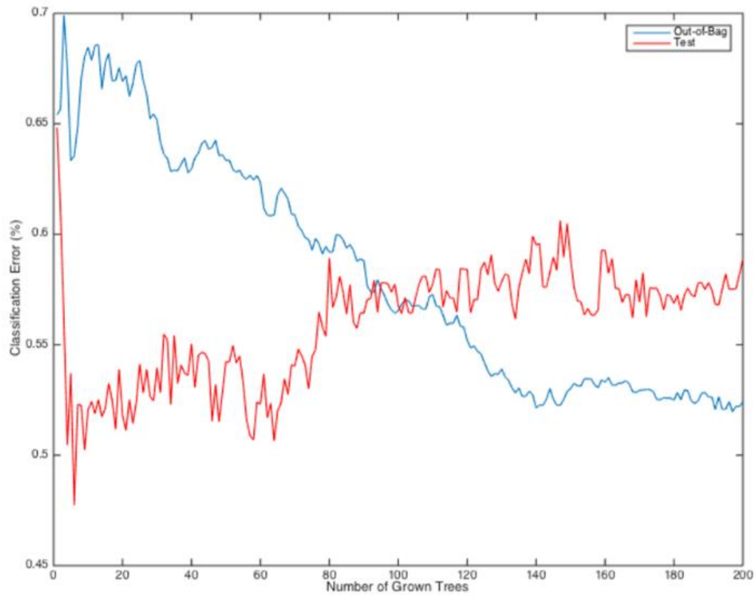

Fig 8. trading performance of decision tree [5].

Fig8, helps us to get clear idea about how decision trees perform therefore giving hints about XGBoost and we are using multiple decision trees in that technique

As we can see that it gave a steep loss in the beginning hence It is not much suitable for our use because of its low performance.

Now we will apply XGBoost algorithms on this decision trees and will look at the performance.

After applying the XGBoost we can see great performance of the algorithm. It is making profit more predictively and as market takes downturn till its making profit which is required.

It is more optimized and take less resources to run the program. This gives it edge in faster computing and less requirement of resources.

ADVANTAGES OF XGBOOST:

- Faster parallel learning using Block structure :
- For scalable and quick calculations, eXtreme gradient Boost uses multiple cores available in the processor. It can be achieved because of specific system design structure of XGBoost known as block structure. Information is arranged and kept in the various units in memory known as blocks. In difference to different algorithm and methods, layout of data can be used again by iterations in future and processes, rather than recomputing.
- Cache awareness: For eXtremeGradient Boost, gradient statistics by row index is achieved using non-continuous memory. Hence, XGBoost makes

ideal utilization of given Hardware. This is accomplished by distributing internal parts of memory to individual thread, where storage of gradient statistics is possible in the memory.

- Out-of-core computing: It maximizes memory usageand optimizes the available disk space when dealing with huge datasets that can notbestored into memory at same time

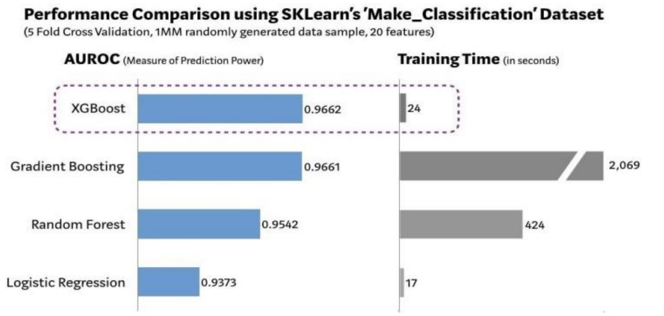

Fig 9. trading performance of decision tree [5].

Fig9, givens clear comparison between various machine learning algorithms and clearly denotes that XGBoost outperforms other algorithms in both predictive power and training time.

4. CONCLUSION

We investigated three broadly utilized AI techniques applied to stock price data and other available information to make suitable trading systems. We analyzed the exhibition of these models available data sets and our exact outcomes demonstrated that, in spite of poor forecasting precision, the subsequent trading techniques out-played out the market over this period. XGBoost algorithm gave the highest return and uses less training resources resulting in faster processing time. By taking into consideration of the results and other advantages, 1) We conclude that we found XGBoost to be the best artificial intelligence model for stock selection. 2) XGBoost will be the most suitable method for implementation.

REFERENCES

1. Mrs.S.Mahalakshmi and Mr.Vignesh P,"OPENING RANGE BREAKOUT STOCK TRADING ALGORITHMIC MODEL",International Journal on Cybernetics & Informatics (IJCI) Vol. 5, No. 1, February 2016.
2. Giuseppe Nuti, MahnooshMirghaemi, Philip Treleaven, and ChaiyakornYingsaeree,"Algorithmic Trading", UK Centre in Financial Computing, London.
3. Everton Silva∗ Douglas Castilho, Adriano Pereira and HumbertoBrandao, "A Neural Network based approach to support the Market Making strategies in High-Frequency Trading", 978-1-4799-1484-5/14 ©2014 IEEE
4. "Algorithmic Trading Using Deep Neural Networks on High Frequency Data", Springer Internal Publicaion AG 2017
5. Application of Machine Learning: Automated Trading Informed by Event
Driven Data by Jason W. Leung, page no 24,25,39-42
6. An Algorithmic Trading Agent based on a Neural Network Ensemble:a Case of Study in North American and Brazilian Stock Markets, 2015,IEEE.
7. "Predicting Stock Market Price Using Support Vector Regression", Dept of Computer Science & Engineering University of Chittagong, Bangladesh, IEEE 2013.
8. FORECASTING PROFITABILITY IN EQUITY TRADES USING RANDOM FOREST, SUPPORT VECTOR MACHINE AND XGBOOST Ritesh Ghosh1, PriyankaPurkayastha2 1Engineer, Cisco Video Technologies India Pvt Ltd, (India) 2Lead Consultant, BT e-Serv India Pvt Ltd, (India)
9. Forecasting to Classification: Predicting the direction ofstock market price using Xtreme Gradient Boosting ShubharthiDeyYash Kumar.
10. Zhang, X., & Chen, W. (2019). Stock Selection Based on Extreme Gradient Boosting, IEEE.
11. http://www.statsoft.com/textbook/XGBoost-for-trading
12. https://blog.quantinsti.com/forecasting-markets-using-extreme-gradient-boosting-xgboost
13. K. jae Kim, "Financial time series forecasting using support vector machines," Neurocomputing, vol. 55, 2003
14. M. Halls-Moore, "Support vector machines: A guide for beginners," September 2014.[Online].
15. Application of Support Vector Machine on AlgorithmicTrading,Szklarz J1., Rosillo R2., Alvarez N2., Fernández I2., and Garcia N2.Programmer, Izertis S.L, Gijón, Asturias, SpainBusiness Management Dept., University of Oviedo, Gijón, Asturias, Spain.
16. D. d. l. F. Rafael Rosillo, Javier Giner, "Stock market simulation using support vector machines," Journal of Forecasting, vol. 33, pp. 488–500, July 2014.
17. Machine Learning Approach in Stock Market Prediction, Raut Sushrut Deepak, Shinde Isha Uday, Dr. D. Malathi, International Journal of Pure and Applied Mathematics, Volume 115 , No. 8, 2017, 71-77.
18. Predicting Stock Price direction using support vector machines, Saahil Madge, Independent Work Report Spring 2015.