

# Artificial Intelligence in Investment Industry

Bhagwat Nagargoje<sup>1</sup>, Suraj More<sup>2</sup>, Prajwal Zurunge<sup>3</sup>  
Dr. Badrinarayan Mohapatra<sup>4</sup>

*#Instrumentation Department, Savitribai Phule Pune University AISSMS Institute of Information  
Technology, Pune-411001, Maharashtra, India.*

**Abstract:** In recent years, due to the rapid development of artificial intelligence and machine learning, its application has been widely used in many aspects of financial area, as well as significantly impacts financial market, institutions and regulations. The artificial intelligence technology brings huge change to the entire financial industry, which creates a series of innovative financial services such as intelligent consultant, lending, monitoring and warning, and intelligent customer service as times required. In this paper, it aims to summarize the development and application of artificial intelligence and machine learning in financial system, as well as its impacts on macroeconomics and microeconomics. In the meantime, it is realized that a series of problems and risks were conducted by artificial intelligence during its use. Lastly, some suggestions and strategies are provided for reasonable usage of artificial intelligence in financial risk management (FRM), based on the financial risk management raised by artificial intelligence.

**Keywords—** share market, artificial intelligence, technical, fundamental, ML, algo trading.

## I. INTRODUCTION

As the booming development of Internet and information technology (IT), as well as in the context of Internet-Finance, method of financial data wrangling is not only limited to traditional statistical approach, but also adopt and combine with various information processing technology such as machine learning, which has obtained significant achievements. In the stock investment of financial market, public always wish to grasp the rule behind the transaction, which could be used for right analysis and prediction. Investment analysts from all around world are also trying to apply different methods of investment analysis and data mining in the amount of stock data, in order to find out potential operating rules and stock trading rule behind the share market, and to predict the stock market trend, aiming to maximize the profit and risk reward ratio. Since the stock market is affected by various market and non-market factors, which interact with each other, it is difficult to establish an accurate model to describe the mechanism of internal interaction. With the increasing of computer computing power, more sophisticated artificial intelligence algorithm can satisfy the need of new power in financial field. More specifically, AI is widely used in investment management, algorithm trading, fraud detection. Besides, artificial intelligence has profound impacts on financial regulation institution, evolve from past experience based on supervise transaction with algorithm and analysis of massive amount of data, while new required skills and knowledge for regulators will be presented. Therefore, this paper aims to summarize the development of artificial intelligence and machine learning in financial field, and the impacts on macroeconomics and microeconomics, as well as providing suggestions for enhancement of financial regulation by using artificial intelligence and machine learning. (rise, drop or sideways).

### Studies Using Genetic Algorithms with Other Techniques to Analyze Stock Markets

As illustrated in the first two study categories, systems primarily based on ANNs or SVMs have had some success improving stock market value prediction but, over time, there appears to be an increasing interest in trying to further improve results using multi-technique approaches. One alternative machine learning method that has potential to do this is incorporating genetic algorithms with either ANNs or SVMs to reduce single technique restrictions. A genetic algorithm is a form of evolutionary algorithm. The evolutionary process begins with a set of randomly generated problem solutions. In each iterative generation, the fitness of each solution is measured by an objective function. The solutions with higher fitness are retained (survival of the fittest) and combined with other high fitness solutions to create a new generation of solutions. Parent solutions combine to create a new child solution that retains some characteristics from both original solutions. This process continues until a certain number of generations has been created or the population of solutions reaches a satisfactory fitness level. The following studies develop systems that integrate GAs with ANNs and SVMs.

## II. RESEARCH METHODOLOGY

1. Algorithmic trading is mostly deployed in high-frequency trading (HFT). The concept of trading is buying a potential share at a low price and selling it while it touches the peak growth in the market. This involves a lot of statistical verification and stock analysis process to find out the potentiality of the stock.
2. It depends on variables like time, price, volume, and technical indicators to implement this trading activity. Over the process, the trading decision should also clash the human error.
3. In the case of algorithmic trading, these activities are curatively programmed to achieve the highest profit in each trading activity with no error.
4. As the algorithm could process in the timely cycle, it could do more number of trades in a given time that results in the accumulation of huge profits. This is referred to as HFT, which allows more liquidity in the market.
5. This algorithmic trading reduces the error and processes more trading activities to attain maximum profit.

**Basic and advance Technical Trading Signals** There are critical technical tools of the trade to gauge the market activity which helps us to determine and predict future market behaviour.

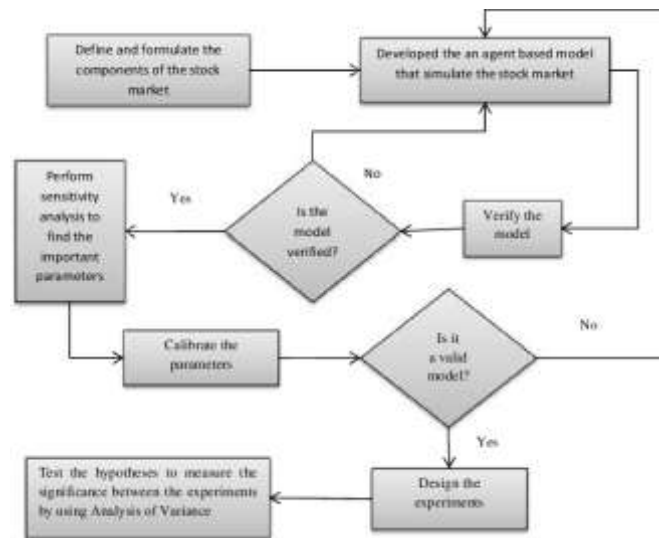
**Moving average (SMA/EMA):** trend following and lagging indicator

**Moving Average Convergence Divergence (MACD):** momentum oscillator primarily used to trade trends.

**Accumulation or Distribution Line (A/D):** these measures future price changes using the relation between the asset's price and volume.

**On Balance Volume (OBV):** measures positive and negative volume flows.

**Relative Strength Index (RSI):** measures strength and weakness.



### Summary of Literature Survey

The objective for this study is to identify directions for future machine learning stock market prediction research based upon a review of current literature. Given the ML-related systems, problem contexts, and findings described in each selected article, and the taxonomy categories presented earlier, several conclusions can be made about our current knowledge in this research area. First, there is a strong link between ML methods and the prediction problems they are associated with. This is analogous to task-technology fit (Goodhue and Thompson, 1995) where system performance is determined by the appropriate match between tasks and technologies. Artificial neural networks are best used for predicting numerical stock market index values. Support vector machines best fit classification problems such as determining whether the overall stock market index is forecast to rise or fall. Genetic algorithms use an evolutionary problem-solving approach to identify.

Higher quality system inputs, or predict which stocks to include in a portfolio, to produce the best returns. While each study did illustrate that the methods can be effectively applied, the single method applications do have limitations. Hybrid machine learning techniques are one solution that can mitigate some of these limitations. The problem is that, at some point, the systems become so complex that they are not useful in practice. This is a theoretical and practical problem that can be addressed in future studies. The second conclusion from this review of past studies is that generalizability of findings needs to be improved. Most studies evaluate their ML system using one market and/or one time period without considering whether the system will be effective in other situations. Three enhancements can be made for the experimental system assessment. First, many of the studies are based on results from Asian stock market. These systems could also be tested in the same time period for US or European markets. Second, the systems could be evaluated using data from times where markets are rising or when markets are declining to assess how they perform in different market conditions. For example, would an approach accurately predict market values in the US during the financial crisis of 2008-2009 and also during the recent market growth period from 2018-2019? If systems are able to predict market growth, are they also able to predict market contraction? Finally, proposed methods could be used to evaluate predictive performance for stock market indices that include only small firms vs. only large firms. Are systems effective under different risk and volatility environments? Any of these experimental method enhancements will provide a stronger research and practice contribution. The final set of conclusions was also apparent after reflection. Financial investment theory needs to be a stronger driver underlying the ML systems' inputs, algorithms, and performance measures. If this is not the case then results may just be random and this not have any practical use. Too many studies use techniques without consideration of the vast amount of financial theory that has been developed over the past centuries. Reporting failures where techniques do not improve predictive performance would also be informative. At this point this rarely occurs so it is impossible to find patterns where there is a mismatch between a particular stock market prediction problem and a machine learning technique. Finally, the irony in this research area is that it is a zero-sum game for investors. If the best machine learning stock market prediction technique is found, and all investors adopt this system, the result is that no one is better off. Large investment firms researching the best machine learning methods have no incentive to share this information with others.

### III. RESULTS AND DISCUSSION

1. As per the money management rule 78% trades are in Profit
2. Risk to reward ratio was 1:3. (1% risk and 3% profit)
3. Total sample size = 100 trades
4. Expected error in price change = 0.5%
5. 78 right trade =  $78 \times 3 = 234\%$  and  $22 \times 1 = 22\%$
6. =  $234 - 22 = 212\%$  reward

Every time we have to follow risk management and our AI system.  
WE majorly using this in midcap or largcap means blue chip companies.  
If we change our risk to reward ratio then output may change.

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