Comprehensive Analysis of Machine Learning Algorithms Used in Robo-Advisory Services

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Abstract. Adoption of Robo advisory is rapidly increasing among retail investors. Approximately 10% of all assets under management will be managed by them by 2025. Researchers continuously work on finding machine learning and deep learning algorithms which will accurately predict the stock price movement with less error. Various Robo advisor platform providers are working on different approaches like NLP (Natural language algorithm) based sentiment analysis, hybrid time series algorithms to limit human bias, which existed in the current financial advisory services. This research compared the performance of various forecasting algorithms, which can be used in the Robo advisory framework. RMSE (Root mean square value) value is taken into consideration in this research to compare the performance of algorithms as it is a good and simple loss function. It has been observed that newer algorithms like those proposed by Facebook are able to predict stock prices pretty well, but ARIMA outperformed all the algorithms which are considered in this research.

Keywords: ARIMA, machine learning, deep learning, stock prices, Robo advisory, sentiment analysis.

1. Introduction
Financial technology (Fintech) has gained a lot of interest from financial organizations besides start-ups in the last few years. Financial firms were witnessing rapid disruption with technology as more and more technology companies identified this lucrative space for innovation. The traditional business model of financial companies is challenged by new-age financial tech companies [1]. In 2015, the World Economic Forum described monetary knowledge as a troublesome innovation that will redesign the financial industry and future and make an impact on other monetary facilities functions, including payment, insurance, deposits, and lending, raising capital, besides wealth organization. Many investors are interested in investing their money in these disruptive new age organizations [2]. Traditional financial services companies are also coming up with automatic portfolio decision platforms along with regular financial advice. With conventional methods of delivering financial advice challenged by modern and creative types of technology, customer preferences have shifted with the unparalleled mass acceptance of the internet and digital devices [3]. The term Robo-advisory is composed of two different terms, Robo and advice. In this sense, Robo stands for robotics and consulting stands for the advice given by the wealth managers. When adding these two terms together and creating the term Robo-advisory, this paper addresses an online portfolio that intends to automatically invest the money...
of clients in a way that does not allow the individual investing with a Robo-advisor to have any extensive knowledge of the financial market. A Robo-advisor is the combination of modern technologies and machine learning algorithms which facilitate wealth management services for consumers through automated investment decisions [4]. Robo-advisors improve admission to prosperity management facilities by making economic information simpler also less costly, as well as preparation besides automating speculation choices. The automated method is a collection of various mathematical algorithms generated to support investment decisions. Once the automated process is completely developed and run, there is no human intervention enforcing the decisions taken. There are around 200+ Robo advisors in the market who are offering services in investment management, retirement planning, and financial decisions. In India, multiple companies and start-ups are working to provide Robo advisory solutions like financial planning, mutual fund investment, and stock market advisory services. Many Robo advisory platforms are working on providing personalization in platforms as a financial decision will vary according to which age group they are catering [5]. Millennials are looking for high gain, more risky portfolio advice where are people in the age group of more than 60 who are retired are looking for low risk, medium gain advice from advisors. Adoption of this platform will heavily depend on the "trust." Companies were providing such solutions working on improving trust mechanisms for their advisory service. Financial advice will depend not only on the risk-taking capability of a customer but also on various other factors, and traditional advisors collect information from professional as well as private life to suggest a better solution. This human factor needs to be incorporated in Robo-advisory services [6]. Integrating Big Data Analysis, Machine learning/Deep Learning Method, portfolio optimization framework can be created that takes input from different sources, which include stock prices, a profile of the investor, and other relevant data, to determine the weight age of different assets in the portfolio. It is very difficult to predict stock market positions accurately, but going ahead with these machine learning algorithms will definitely going to help to bridge those gaps.

2. Literature Review
Traditionally, financial advisory was seen as a profession that deals exclusively with investment plans and statistics. That career has added yet another role in recent years, the "Coach of Life." Dealing with the financial condition of a person or family requires a lot of external concerns that have inspired customers to share more details regarding their personal lives. The role of the financial advisor as a "life coach" is growing further as more facets of their life become a big part of their financial advice [7]. Several customers requesting financial aid try for saving techniques for their children’s education and their personal lives extra Lifestyle Expenditure Revenue.

Many conventional financial institutions are highly dangerous. Financial breakthrough leadership was thus passed on to many smaller financial start-ups or major technology firms that have baggage and administrative burden of crisis little or no. This is a sincere welcome shift in guards, as new financial tech entrants being less motivated by conventional financial incentives and more motivated in the dream of greater social inclusion. The key to effective investments is AI and big data, and computing power [8]. Different banking functions are moving towards digitalization, and the wealth management industry is one of them. Conventionally financial advisors used to provide advice to customers regarding tax planning, portfolio management practices which are challenged by modern and creative types of technology. Customer preferences also shifted towards the internet and digital devices. Clients deserve a seamless customer experience that includes the availability of companies, goods, and services whenever and wherever they wish [9]. The people in financial technology firms say that all financial institutions need to change current business practices. Rarely is there any physical product, and as banking advances, these businesses will eventually look like software companies. In spite of this development, many of the conventional financial companies are using similar obsolete technology paper checks, punched-in, plastic cards, and wire transfers that take days to clear. In the meantime, venture capitalists are willing to invest their money at new-age finance firms [10].
Scientists who have worked for international corporations for many years concluded that the future of financial services goes beyond technology and depends on social, political, and economic components. The pace of technological advancement as well as the number of vendors to fund is the two crucial factors that will decide the future of the adoption of Robo advisory services [11]. Robo-advisors (also called Robo-advisory) are digital platforms that offer somewhat program-driven, automated financial advisory services with minimal, or no, human bias. A typical robotic advisor collects statistics from customers about their financial position besides potential priorities through an online survey and then uses the data to provide guidance and invest customer assets mechanically [12]. In 2008 the first Robo advisor was launched in the USA during the recession. Initially, its purpose was to balance the portfolio, but its huge success in that market attracted billions of investments. While the first Robo advisory service in India was introduced in 2015, several companies have also entered this market since then, including start-ups of initiatives, banks, and even high-tech companies.

Many scholars and financial services expert’s industry looks favorably on Robo-advisors as being able to lower entry barriers to qualified financial consulting services, which could help modest-minded investors who want to save on. Yet the result indicates the opposite of researchers’ study that the present adopters, those who used Robo-advisors, were serious investors investing money [13]. The findings of our analysis indicate the Robo-consultants are clearly not commonly used at the moment by the vast US demographic cohort: baby boomers, which are already in retirement. The adoption of Robo-advisors has been shown to be an opportunity to change the landscape of the investment industry and has an encouraging future. Decision inertia is a serious financial decision-making issue and thus an obstacle for decision support systems. Generic Robo-advisor offers canned advice. Personalized information is not gathered about the individual investor [14]. A large number of investors vary significantly in their risk-taking capacity, though they share the same age, net income, and savings. The adoption rate of Robo-advisor is forecast to skyrocket, hitting 5.6 percent in 2020 from a mere 0.5 percent in 2015. It means that Robo-Advisors are projected to handle up to two trillion dollars by 2020. If the prediction is right, Robo-Advisors may well be in a position to become dominant disruptors on the ETF (Exchange-traded Fund) market, surpassing the historic level of financial sector market disruption. Continued confidence in the Robo-Advisors sense reflects the faith of the client based on expertise and outcomes obtained through long-term investment advice [15]. The main stages of the ongoing lifecycle of trust include loss and restoration of confidence. Investors who fear being targeted by investment fraud are especially motivated by the substitution effect of Robo advisors.

The increasingly daunting challenge companies facing today is how to convince customers that online systems are impartial and, in that context, knowledgeable and accurate. In the financial advice industry, these two dimensions are very relevant, especially at the time of consulting customers regarding pensions will require high-stakes decisions that affect post-retirement quality life.

While accounting for the anticipated impact of customer complacency with an algorithmic method, researchers found that the form of a consulting firm, i.e., which consultant customers communicate with and get advice from, influences the acceptance of financial advice. Particularly, researchers found that this effect is completely moderated by how well customers view the consulting firm with respect to competence and trust [16] [17].

Overall, those who used a conventional financial planner were older, with higher rates recorded. Net value while Robo-advisor users registered lower net worth rates on average. Additionally, people using conventional financial planning services registered a greater percentage of their overall net worth. The value of the inheritance, while the lesser percentage of the net value of the inheritance, was recorded through consumers of the Robo-advisor. Consequences presented those consumers of Robo-consulting services (1) typically had lower income, (2) had lower net worth, (3) had no or less inheritance, and (4) had less impetus financially.

Those who advocate the importance of Robo-advisors point to the following features:
1. Costs tend to be less than what a customer should pay for a service current financial advisor
2. Recommendations for an asset are typically applied using the low-cost exchange-traded Funds (ETFs), which help to keep expenses for annual management low
3. Including risk assessment to ongoing rebalancing, all facets of the venture cycle are quickly completed.
4. Nearly all Robo-advisors provide tax monitoring functions;
5. Access to financial and other information is simple and easy to access.

Some of the key reasons for using the Robo-consultants include:
1. Non-flexibility;
2. Lack of customization to a customer's specific needs or wishes; and
3. Lack of intimate contact and a relationship with a financial consultant.

There is no structured study of the approaches used in Robo advisory (RAs), their occurrence in such schemes, the corresponding volumes of assets under management (AuM), and the Robo advisory (RAs)'s the possible methodological likelihood. "Modern Portfolio Theory" remains the main component used in Robo advisory. The difference between the traditional approaches used in Robo advisory and the latest methodological advances is apparent.

The current trend is to expand on existing mechanisms rather than create and incorporate completely new structures. There are today four types of Robo guidance systems. The first and second-generation Robo-advice systems contain electronic questionnaires and recommendations, which include a variety of recommendations to control traditional "manual" wealth management tools online, whereas the third and fourth generations of Robo advisors used algorithms and quantitative techniques to build and balance portfolios.

With a combination of big data analysis, deep learning algorithm besides the Black-Litterman asset allocation weight model, a portfolio optimization framework can be created that takes input from a diversity of sources, including stock prices, customers profiles besides other alter-native data, and it can be used as input to determine optimal portfolio asset weights. Other techniques can also be used like gated neural network structure incorporating three multi-objective rankness kernels will rank financial products as targets and suggest top securities to the investors. The gated neural network learns to pick or weigh and Rank Net to integrate the most relevant partial inputs from the network, such as earnings per share, the market index also time series unobserved pattern. It is shown by some researchers that automated advisors not only can outperform humans in simple tasks, they are also seen as meriting no more control than those of so-called imperfect human advisors.

Without the help of domain experts' financial companies alone are unlikely to be able to restructure themselves into organizations to face the challenge of battling cybersecurity threats. Financial-tech companies delivering new offerings are not developed yet, and they face problems in overcoming the structural benefits which large institutions have. The sector's future won't see the elimination of conventional financial services companies, but such undertakings must endure requirements, change in growth, and advancement.

3. Methodology
This section will depict the system framework of the stock market forecasting module. The primary area depicts the examination plan and the exploration construction of this paper; the subsequent part portrays the progression of anticipating module; the third segment portrays the assortment of information and the subject of the information; the fourth segment proposes the managed AI change. The fifth segment portrays the execution of time arrangement techniques and distinctive AI philosophies.

3.1 Research Methodology and Design
While designing the Robo advisory services platform, it will have different modules underlying it. The traditional approach will start from collecting responses from customers regarding their social, financial factors. The output of this stage will be the customer risk-taking capability, which is going to be the input for the platform while delivering advice. In later stages, financial products which are
chosen by platform according to the customer profile are advised with the machine learning algorithm, which is running in the background. For the current research, we are focussing on the efficiency of those algorithms. The following subsections will be explaining about sub-processes involved in time series forecasting modules.

3.2 Flow of the system
This sub-segment will clarify the progression of the proposed Robo-counsellor anticipating module. To propose the time arrangement estimating task, we build up a few modules for our framework. To perform AI and profound picking up determining, we used to scikit-learn as our library, which an adaptable and incredible library for carrying out AI models. In profound learning time arrangement determining, we utilized Keras, which is known as the significant level profound learning API executed on top of the Tensor Flow, for building up our LSTM and GRU model. Facebook Prophet is an algorithm used for predicting time series values. Prophet follows the sklearn model API. We just have to create an instance of the Prophet class and then call its fit and predict methods. This fits best with time series, which have occasional strong impacts and some credible data spans. Prophet is aggressive about lost data and pattern changes and typically treats anomalies well.

3.3 Data Collection and Data
We utilized the Apple stock recorded in the NASDAQ market as our subjects and utilized every day changed close to cost as info variable, and the objective variable is the pattern of the following day. The time of our stock assortment is roughly one year from 2019/01/01 to 2019/12/31. From 2019, we approve roughly 245 exchanging days. We gathered Apple stock cost recorded in the NASDAQ market. Our information was consequently acquired from an information assortment module sourced by the Yahoo Finance API.

3.4 Models Training and Validation
We split the whole dataset into a preparation dataset and a testing dataset. The time period for preparing the dataset begins from January 2019 to December 2019. We utilized the RMSE (Root mean square mistake) to delineate the distinction between anticipated outcomes and genuine patterns. We influence the Python library Scikit-figure out how to execute AI calculations, while the undeniable level library Keras with Tensor-Flow is utilized to develop a profound learning model.

3.5 Algorithms used for stock price prediction
Along with the traditional machine learning and deep learning algorithms like ARIMA, SVR, and LSTM (Long short-term memory), algorithms like
- Facebook Prophet library
- AutoTS package

ARIMA (Auto-Regressive Integrated Moving Average) is a statistical model for data analysis and time series forecasting. The “Auto Regression” component of ARIMA suggests that changing variable that regresses on its own lagged, or prior, values and “Moving Average” part takes error values from the past forecast as a reference to predict future values, the values of linear error existed concurrently at different times in the past. Facebook Prophet Algorithm is a technique for forecasting time series data based on an added substance mod-el in which non-direct patterns align with annual, weekly, and daily trends, besides the occasional impacts. It works best with time series, which have occasional strong impacts and some credible data spans. Prophet is aggressive about lost data and pattern changes and typically treats anomalies well.

The LSTM (Long Short-Term Memory) is an RNN variant able to learn long-term dependencies. Hochreiter and Schmidhuber initially suggested LSTMs, and several other researchers improved them. They work well on a wide range of problems, and they are the most commonly used form of RNN.
Auto TS (Auto Time series) is the simple package used for predicting time series values based on comparing various time series techniques with open-source time-series implementations. SVR (Support Vector Regression) is a regression approach that provides the best hyper plane regression with the smallest structural risk at high complete dimensional space.

4. Metrics
Evaluating the accuracy of forecasts using genuine forecasts is important. The right way of evaluating the model is to check how the model works on new data which were not used while training. While selecting models, it is standard practice to split the available data into two parts, training and test data, where the training data is used to approximate the parameters of a forecasting system, and the test data is used to determine its accuracy. Usually, the size of the test set is around 30 percent of the overall sample, though this amount depends on how long the sample is and how far ahead we want to estimate. Ideally, the test set should be at least as wide as the required maximum forecast horizon.

An "error" prediction is the difference between an observed value and its predicted. "Error" in this case does not mean a mistake. It means the unforeseeable part of the observation.

The RMSE is the square root of the residual variance. This indicates the absolute fit for the data of the model and how close the observed data points are to the model's predicted values. RMSE is an absolute fit-measure. RMSE can be defined as the standard deviation of the variance, as the square root of a variation, and it has the useful property of being in the same units as the response variable. Lesser RMSE values mean better fit.

5. Result
It is very difficult to forecast stock market trend accurately, as the stock market trend is influenced by various internal and external factors, but the platforms or systems which are currently working in the domain focussing on minimizing error by working with various techniques. We worked on various traditional machine learning and deep learning algorithms along with modern approaches like Facebook Prophet Library and the popular low code time-series library model known as Auto TS.

These are the results of the experiment:

| ALGORITHM               | RMSE VALUES |
|-------------------------|-------------|
| ARIMA                   | 2.84        |
| LSTM (200 epoch)        | 4.057       |
| Facebook Prophet        | 3.105       |
| SVR                     | 3.15        |
| Auto_TS                 | 4.53        |

From Table 1 result, it is observed that ARIMA, which is traditional, works better than SVR, whereas LSTM with 200 epoch also able to produce a low RMSE value. After optimizing parameters for Facebook’s Prophet also able to predict stock prices with fewer RMSE values. Along with this algorithm, the Auto TS library uses several algorithms and selects the one with the least RMSE or error value, hence for this dataset PyFlux time series model is selected as it has a low deviation from stock trend in comparison with other algorithms which the Auto TS package is considering.

6. Conclusion
In this work, we used different algorithms for the stock price prediction of APPLE stock which is listed on NASDAQ. Here we trained five algorithms: ARIMA, SVR, LSTM, and Facebook Prophet, Auto time series package with the past stock price. The obtained models were used for predicting NASDAQ's APPLE (AAPL) stock price. From the results obtained, it is clear that the models can recognize the trends that exist in the financial markets. It shows that an underlying trend exists,
common to all the financial markets. Linear models are a univariate approximation of the time series and are thus not capable of distinguishing underlying dynamics within different time series. From the analysis, we can infer that the ARIMA model is outperforming the DL (Deep Learning) models. Facebook Prophet has done better in the proposed work than the other three networks as it is capable of catching the system’s sudden shifts as a limited window is used to forecast the next moment.

7. Future Scope
For expanding the horizon of this research, advanced algorithms or techniques can be used. A combination of financial news, social media posts from platforms like Twitter or Facebook with a machine learning algorithm can be a better approach for Robo-advisor platforms while giving advice to the user. Hybrid algorithms or new generation algorithms can also contribute positively towards generating advice to the customer like bagging and boosting techniques which are quite popular for improving the performance of the algorithm in several applications, should be clubbed together with a traditional algorithm for reducing the margin of error. Previously genetic algorithms and meta-heuristic or nature-inspired optimization techniques were found to be quite useful in many use cases in the financial industry. These new-age algorithms can be used in hyper parameter optimization of a traditional algorithm to boost up the performance of the platform. As the data processed by the Robo advisory platform is huge and will further increase, research on Quantum computing and Quantum Machine learning algorithms will play a key role in analyzing the big data which is going to be generated in the future. Multi-disciplinary approach and hyper-personalisation will be crucial for increasing adoption of automatic decision-making Robo advisory services in the future. Apart from these techniques, results of hybrid combination of fuzzy logic and time series algorithm used in the various application seem to be encouraging. So, the current research can be modified by applying principles of fuzzy time series along with machine learning algorithm, to overcome the challenges faced during working with traditional time series.

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