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STOCK MARKET PREDICTION AND ALGO-TRADING

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***Abstract**:* The purpose of this study is to discuss how to improve stock market forecasting precision via the use of ML models to algorithmic trading. The following are methodological techniques: Quantitative archival research, historical stock price data and strong count economic indicators from reliable databases, LSTM networks and Ensemble techniques. The feature engineering, gradient boosting models, and backtesting were performed to measure the obligation models and trading strategies. Here main results point the superiority of the ML approach, primarily LSTM model to the traditional models in predicting short-term stock prices and its ability to generate positive excess returns net of risk in actual trading applications. High volatility, however, causes the model's efficiency to drop, highlighting the need for efficient methods. Hence the study recommends that for machine learning to be effective in stock markets, there is need to combine external data with the data generated from the stock market, periodically update the model, employ both single and concurrent models, and employ better risk management strategies given the changing and volatile nature of the stock markets.

Index Terms – Stock Market, Algo-Trading, Machine Learning (ML), LSTM, Backtesting, Earnings per Share (EPS), Price-to-Earnings (P/E) Ratio, Price-to-Book (P/B) Ratio, Technical analysis, Moving Average (EMA), Bollinger Bands, Fibonacci Retracement, Alpha Vantage, Quandl (Nasdaq Data Link), Kaggle Datasets, Stock Price Prediction, Stock Movement Prediction, Portfolio Management, Trading Strategies.

1 INTRODUCTION

1.1 Background

The unpredictable, intricate, and ever-evolving nature of the stock market has long piqued the curiosity of investors and researchers alike, making reliable forecasts a formidable challenge. The goal of stock market prediction is to project how much a company's shares or other financial instruments traded on an exchange will be worth in the future. Making a correct forecast about the price of a stock in the future may be very profitable. The efficient-market hypothesis asserts that stock prices reflect all accessible information at the present time and that price fluctuations that do not stem from newly disclosed information are inherently unexpected. Others disagree, and those who hold this position claim to have several methods and technologies for obtaining future pricing knowledge.

Making accurate stock market forecasts is one of the most tough undertakings. Forecasting is challenging due to the inherent volatility of global financial markets. Factors such as physical variables (rather than technological ones), rational and irrational behaviour, and other similar factors are all included in the prediction. All of these things combine to make share values very volatile and unpredictable. Through the analysis of data such as a company's quarterly sales reports and most recent announcements, ML algorithms may uncover patterns and insights that have not been observed before, enabling the development of highly accurate forecasts [1].

1.1.1 Methods of Stock Market Analysis

Stock market analysis can be done in two ways: Fundamental Analysis and Technical Analysis [2]. All of these approaches fall under the general heading of equity analysis (Figure 1), which aids the analyst in analysing, assessing, and comprehending market and economic situations.

Fundamental Analysis: While making financial investment choices, fundamental analysis is a vital tool for assessing a company's performance.

[3] Finding discrepancies between the stock's true worth and its current market price is the job of the fundamental analyst. To achieve this goal, we consider macroeconomic variables in addition to the company's financial reports. The basic premise is that the factors influencing stock prices perform this [2]. The Efficient Market Hypothesis asserts that all information is returned at stock prices. However, it makes little sense to benefit from this, even if it violates the hypothesis [4]. The focus on cause and effect is central to basic analysis. Inventory levels, weather, trade balance, economic indicators, government policies, and the responses of traders to specific occurrences are all crucial factors to take into account. The following are some of the instruments used in the fundamental analysis: a model for price elasticity, a balance table, several methods (tabular and graphical), a model for regression analysis using econometrics, and a model for seasonal price analysis[5]. Important parts of basic analysis include learning about the state of the economy as a whole, examining the future of a certain sector, and evaluating the performance of individual companies. This is also known as EIC frameworks, which stand for ”Economy, Industry, and Company Analysis.”[6] Aside from assisting in valuing a company's shares, financial ratios are helpful for comparing companies within the same sector or with comparable time horizons.

1. Fundamental Analysis Tools:

Fundamental analysis tools used in stock price movement is for evaluating the intrinsic value of securities by studying the economic, financial condition, and growth prospects of a company. Below are some tools and measures that are found useful in fundamental analysis in predicting stock prices[7][8]

- **Earnings per Share (EPS)**

It is one of the key measures of financial performance reflecting company's operating profitability and soundness of its financials and is computed as Net Income divided by total number of shares of stock. EPS helps investors determine the company's earnings per share, or what share of company's profit belongs to shareholders, which is crucial for evaluating profitability of equity shares. The EPS is also preferred by investors because a high or increasing EPS means future growth of the company. There are many techniques applied by analysts where the history of EPS growth is used to forecast future, and often for increased stock price in case of constant improvement of the company's profitability.

- **Price-to-Earnings (P/E) Ratio**

It is one of the most often used estimates that reflect relations between the price of one share and company earnings per share. ME is defined as the extent that the owners are willing to invest for each dollar of earnings given by P/E of the stock divided by EPS. If the P/E ratio is high, this may be because the share is expensive because of high growth expectations, or the P/E ratio may be low to attract value investors because of undervalued shares. When using P/E ratio, an investor can compare the current ratio with the industry average to see how the company's stock is valued or compare it with its historical ratio to determine the future performance.

- **Price-to-Book (P/B) Ratio**

It is rate compares a firm's current stock price with its book value arrived through the division of the former by the latter, namely book value per share. Determining which stock is over or under priced is a great factor that is assisted by the P/B ratio since it compares the company's market value to its net asset. Value investors seek an indication that stock prices are low vis a vis tangible commodities and hence a P/B ratio that is low will suggest this fact. Of course this ratio must be appreciated in context of given industry since some industries are going to have higher or lower P/B by virtue of asset intensity and growth possibilities.

- **Discounted Cash Flow (DCF) Analysis**

It is a simple approach to value estimation which derives a firm's value based on a cash flow model. In DCF process, the future revenue and operating cost and capital expenditure are forecasted and then reduced by dividing the result by the cost of capital. If the DCF value gives a figure higher than the current price then the stock might be opportunities for an upside. However using DCF is more useful for long-term investment holders seeking to know the real value of a firm but suffers from inherent wrong assumption about growth and risk.

- **Debt-to-Equity (D/E) Ratio**

It is the ratio shows the degree of employ of financial leverage by a business entity and calculated through the use of the formula Total Liabilities/Shareholders' Equity. To what extent is the company exposed to financial risks and has to depend on borrowed funds, is clearly seen from this ratio. A ratio above this denotes high risk in cases of economic adversity because the firm depends on debts while a ratio below this one means the firm has a conservative capital structure. The D/E ratio is used to evaluate how well the organization is equipped to handle its debt because high leverage makes earnings more sensitive to fluctuations affecting the company's stock prices.

- **Dividend Yield**

Divide the yearly dividend per share by the price per share to get the dividend yield, a financial ratio that measures the proportion of dividend paid per share to the current price. It is important for investors interested in high-income yield as opposed to growth in the value of their investment. The following are common overly mechanical interpretations of basic financial ratios – Dividend yields where high yields may be attractive for investors seeking stable and sustainable income may alternatively be interpreted as signs of poor performance Equally, low or no dividends could be interpreted as evidence of poor performance other than the reality that the company is likely directing earnings for growth. Concerning dividends, this study incorporates dividend yield in an effort to help investors make decisions based on the company's endeavour of dividends that result in stock price stability as well as investors' confidence.

- **Return on Equity (ROE)**

It refers to the ratio of net incomes to equities as an indication of the efficiency of the company in utilising shareholders' funds. ROE gives an idea of how well a company can generate returns given the investors' money, the higher the ROE the better the company's financial position. The formula for ROE is used to compares firms within industries since it identifies competitive strengths and managerial efficiencies of a firm. The high ROE values are normally related to the firms that have stable profit margins and may lead to stock appreciation in future period.

Free Cash Flow (FCF)

FCF is calculated as Cash generated from operating activities less capital expenditure needed for a company to maintain or increase its base of fixed assets. This measure is very important for evaluating the company's solvency and its capability to provide funds for expansion, dividend payments or investments into fixed assets. FCF ¿ 0 and FCF increasing is normally seen as a positive sign because it means a business will always have enough cash to reinvest or buy back stock. FCF is, therefore, a positively coded variable with investors perceiving high FCF as a positive sign indicative of sound financial health or future capacity to enhance stock value particularly if the firm has a history of good FCF performance.

Economic Indicators and Market Trends

Fundamental analysis places a heavy emphasis on economic indicators like GDP growth, inflation, and interest rates because of their impact on market conditions and firm success.

For example, rising interest rates can increase borrowing costs, potentially slowing business expansion and affecting stock valuations. By considering macroeconomic data, investors can assess broader economic trends and their potential impact on specific sectors or individual stocks. Keeping track of these indicators helps investors align their stock predictions with the economic environment, enabling better decisions regarding the timing and selection of investments.

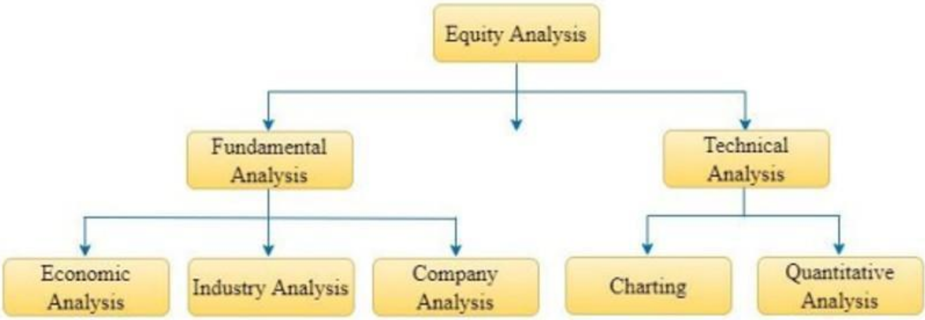

Figure 1: Equity (stock market) analysis approaches

2. Technical analysis

Financial market investors use technical analysis, a methodology for analysing market prices using a supply and demand approach, to direct their investment management calls. Technical analysts seek to mitigate the impact of human biases and emotions on investing outcomes by the use of a systematic and disciplined methodology. Technical analysis may be used to predict how securities prices will move in the future if patterns in stock prices and volumes have been appropriately identified. Technical analysis sometimes involves making price charts and then searching for patterns in order to get highly accurate future forecasts. From the various geometric regularities in prices, traders may learn about what's to come, according to the primary principle. Technical analysis uses a variety of techniques, including as the relative strength index, exponential moving average, charts, Dow Theory, and wave theory, to construct models and trading rules that are based on transaction volume and price[9].

Technical research evaluates equity shares by analysing historical stock prices and volume as a result of market performance. The goal of technical analysis is not to determine a stock's true value, but rather to find trading patterns through the use of charts and other tools. Exactly, since there are many investment strategies based on different kinds of technical projections. The exclusive use of historical price and volume data by technical analysts distinguishes them from fundamental analysts. The three assumptions that underpin technical analysis are:

1. **Market Discounts Everything:** According to technical analysis, any piece of data can affect the value of a security's stock price. Market prices reflect all information available about a stock and its prospects for the future. The market as a mechanism is extremely effective at discounting something that has the potential to influence prices. And unanticipated developments, such as new competition, legal or financial challenges, a business merger, a founder's death, and so on, are easily priced into the stock.

2. **Price Moves in trend:** Price movements are assumed to follow a price trend in technical analysis. Future price movements are more likely to follow a pattern than to deviate from it after it has been established. Future pricing behaviour may be predicted by analysing historical market data.

3. **History Repeat itself:** The foundational premise of technical analysis is the idea that patterns tend to repeat themselves, most obviously in relation to price fluctuations[10].

- **Tools of technical analysis Exponential Moving Average (EMA)**

An exponential moving average (EMA) uses a much larger volume of weights than a simple moving average (SMA), making it more sensitive to new price data. The EMA put more weight on the latest data hence the EMA responds faster to shifts in price direction helping traders to determine the current trend and signals for change of trend. Often for the shorter terms, 9 or 12 days EMAs are used to identify the short-term movements and the 26 or 50 days to measure trends. These over-simplified strategies include crossover systems, through which the crossing of shorter EMA over a longer EMA suggests potential buying or selling signs[11].

Support and Resistance

A support and a resistance level is a price level on a chart where price action tends to change its direction. Seek is the price point at which one expects demand to rise due to accumulation while offer is the price point that one expects supply to rise due to selling. These levels are used to Look for entry and exit signals in trades; the price tends to fail in breaking the support or resistance without changes in circumstances. These levels are opinion based, which incorporates psychological factors & market sentiment, thus makes it easy to predict the behavior of the market[12].

Bollinger Bands

Bollinger Bands, identified as a technical indicator on the basis of volatility, include a SMA and two bands which lie at standard deviations above and below the line of SMA. These bands adjust to market value movements and act as indicators of a buy or sell signal when the price status falls within or goes beyond these band levels. The mid-point amongst these two boundaries usually provides a reasonable indication of fair value and when prices go beyond these boundaries then it may be suggestive of over extension and a return to central tendencies is usually expected. There are few indicators as useful in giving signal of possible breakout or, in the same wavelength, signals of possible continuation or reversal as the Bollinger Bands [13].

Fibonacci Retracement

The Fibonacci Retracement tool uses key Fibonacci levels (0.236, 0.382, 0.5, 0.618, and 0.786) to predict possible levels of support and resistance based on previous price moves. This tool is based on the Fibonacci sequence, a mathematical principle observed in natural patterns. In technical analysis, traders use these retracement levels to identify potential reversal points, assuming that prices often retrace to these levels before continuing in the direction of the original trend. Fibonacci retracement is popular for establishing entry and exit points and setting price targets within ongoing trends[14].

Gap Down and Gap Up Theory

Gap Up and Gap Down: it is the distance from the starting price of the day to the previous day's close on a chart. A gap up market situation is one in which the price at which the market opens is higher than the highest price recorded in the previous day; while a gap down is one where the opening price is lower than the lowest recorded price in the previous day. These gaps can indicate a very definite trend and momentum in that direction although often the price will need to be examined further to ascertain whether it will continue the trend and go through the gap or it will reverse and gap in the opposite direction. It tends to emerge in the vicinity of earning announcements, news items or changes in large markets' characteristics [15].

Efficient Market Hypothesis (EMH)

It consists of two parts Efficient Market Hypothesis (EMH). The EMH postulates that all existing information regarding a particular stock is already factored into the stock price; hence, there are no genuine opportunities to earn superior returns through market forecasting. According to economist Eugene Fama's hypothesis, there are three tiers of market efficiency: weak, semi-strong, and strong. These tiers reflect the varying degrees to which public and private knowledge impact stock prices. In fact, according to EMH, technical and fundamental analysis are useless in forecasting the movements in the stock prices because the new information is immediately reflected in the prices. However, critics continue to argue that there are areas of the market that are inefficient and can be arbitraged by great traders [16].

1. Various dataset used in stock market prediction

To develop "stock market prediction and algorithmic trading models" using machine learning, here are some well-known datasets it could use to gather historical stock prices, trading volumes, and economic indicators:

1. Yahoo Finance

Yahoo Finance is an online sever to find historical data on stock prices, volume, other financial statistics associated with a specific security or index such as stocks and indexes, etc. It is also important, for modelling and analysis purposes that users can readily obtain this data using the finance Python library. This library allows for downloading historical data, including high, low, close prices, trading volumes and daily open, and making it a valuable resource for stock market prediction projects..https://pypi.org/project/yfinance/

2. **Alpha Vantage**

Alpha Vantage is an active service provider that offers free Equity Price Data service which include scurrent and historical data on equities in global stock markets, forex and cryptocurrency markets. This dataset is easy to access if only the users go to the API for a free API key. The available endpoints within the API pertain to time-series data, comprehensive technical indicators and fundamental data necessary for creating accurate predictive models and detailed evaluations of market and stock fluctuations. https://www.alphavantage.co/

3. **Quandl (Nasdaq Data Link)**

Quandl, which is now a product of Nasdaq Data Link, has hundreds of thousands of datasets in the areas of stocks, bonds, and commodities, among other macroeconomic data such as historical prices. While some datasets can be accessed with free downloads, others, which offer additional and more recent data, are available for paid subscriptions. By utilizing Quandl's extensive collection of data, users can enhance their machine-learning models with rich historical context and economic factors that may influence stock market behaviour.https://data.nasdaq.com/institutional-investors

4. **Kaggle Datasets**

Kaggle contests is one of the most popular resources for data scientists and machine learning enthusiasts which contains a number of datasets among them there are some related to stock market data. For example, users can get data like S&P 500 stock price level, trading data within a day, or the sentiment of the financial news. Kaggle consists of a friendly platform for data search, as well as tools for dataset sharing, which makes Kaggle of great interest to researchers and developers who need the environment for data analysis with the purpose of predictive algorithms' building and testing.

5. **Google Dataset Search**

Google Dataset Search serves as a powerful tool for discovering datasets from various sources across the internet. By using keywords like "stock market data" or "financial datasets," users can find relevant datasets hosted by different organisations and academic institutions. Financial analysts and stock market forecasters can benefit from this search engine's ability to make it easier to explore a variety of datasets.

6. **Financial News and Sentiment Datasets**

Financial news and sentiment datasets provide text-based data that can be utilised for sentiment analysis in stock prediction models. These datasets often include financial head- lines, articles, and user-generated content from platforms like Reddit, particularly the Wall Street Bets community. By analysing the sentiment of news articles and social media discussions, users can gain insights into market trends and public sentiment, which can be crucial for developing effective trading strategies.

1.1.2 Method

Before delving into the mechanics of the deep learning model, we will first define four important stock market prediction tasks and provide a synopsis of the concepts associated with each work. Some of these tasks include predicting stock prices and fluctuations, trading strategies, and portfolio management. The majority of modern stock market prediction employment fall into one of these categories.

- **Stock Price Prediction.** Research into the future worth of stocks and other financial assets traded on stock exchanges is the goal of time-series data used in stock price prediction. Achieving large gains is the end game of this projection. Psychological elements and both rational and irrational conduct are among the many other components that impact the prediction process. Together, these elements contribute to the dynamic and volatile nature of share prices.
- **Stock Movement Prediction.** Three categories are often used in the work of stock movement prediction: sideways, downtrend, and uptrend. By examining the variation in a stock's adjusted closing prices throughout a certain trading day, this process is formalised.
- **Portfolio Management.** The deliberate selection and supervision of a group of in- vestments with the goal of reaching financial goals is known as portfolio management. Assigning resources in a manner that optimises returns while lowering risks is the aim of portfolio management.
- **Trading Strategies.** A trading strategy is a systematic technique to purchasing and selling stocks that is based on pre-established rules and criteria. An investor's risk tolerance, market capitalisation, fundamental research, degree of portfolio diversification, investing style (growth vs. value), technical

indicators, and leverage are some of the many variables that could impact the complexity of a trader's strategy. Common trading tactics in DL-based stock market prediction challenges include policy optimisation, event-driven, and data-driven.

The method of predicting the stock market is at the centre of the aforementioned responsibilities. With the goal of elucidating all methods based on deep learning[17].

1.2 Problem statement

A stock market is a complex and dynamic environment characterised by high volatility and unpredictability. Investors and traders continuously seek effective methods to forecast stock prices and optimise trading strategies. Traditional analysis methods, including fundamental and technical analysis, often struggle to account for the multitude of factors that influence market behaviour, leading to suboptimal investment decisions. The emergence of machine learning techniques presents a promising opportunity to improve stock market predictions and develop algorithmic trading strategies. However, the challenge remains to assess the effectiveness of various machine learning models in real-world trading scenarios and to understand their ability to adapt to changing market conditions.

1.3 Project Objective

This research aims to address these challenges by exploring machine learning methodologies for stock market prediction and algorithmic trading using Python. By systematically reviewing existing literature and employing advanced algorithms, this project seeks to contribute valuable insights into an application of ML in finance.

The objectives of this research are as follows:

1. **Literature Review:** Review all of the published scholarly works and business reports on ML-based algorithmic trading and stock market prediction. This will provide a basic knowledge of the status of the research at the moment and point out any gaps that this study can fill.
2. **Evaluate Different Machine Learning Techniques:** Analyse various ML algorithms, including regression models, DT, RF, SVM, and NN, to determine their effectiveness in predicting stock prices.
3. **Feature Selection and Engineering:** Identify and engineer relevant features from historical stock market data, like price trends, trading volumes, and economic indicators, to enhance the predictive accuracy of the models.
4. **Develop a Predictive Model:** Utilising the chosen ML methods, develop a strong predictive model that forecasts future changes in stock prices based on previous data.
5. **Implement an Algorithmic Trading Strategy:** Design and develop an algorithmic trading system that uses the predictive model to execute trades automatically, aiming to optimise returns while minimising risks.
6. **Backtesting and Performance Evaluation:** To evaluate the trading strategy's performance, thoroughly backtest it using historical data. To determine how successful it is in actual trading situations, consider criteria like accuracy, ROI, Sharpe ratio, and maximum drawdown.
7. **Contribute to the Field:** Contribute to the expanding corpus of knowledge in the domain of financial technology (FinTech) and the use of ML in stock trading by offering your thoughts and suggestions in light of the results.

2 LITERATURE REVIEW

2.1 Review of relevant literature

In this work, Chihab et al., (2019) provide a method for intraweek foreign exchange trading that combines a number of technical indicators for currency markets. This two-level decision- making system is based on RF rule discovery and the Probit regression model. A trading strategy must meet two minimum requirements: a rule for entering and exiting the market. Our proposed technique for entering the currency market must meet two prerequisites. The first should go at the next week's access rules in RF, while the second should utilise Probit to predict a positive result for the next day. A single bad prediction from Random Forest or Probit is enough to pull out of the currency market. The development of dynamic portfolio trading systems made use of this method. For USD/(EUR, JYN, BRP) fluctuations between 2014 and 2016, the model's profitability was examined. Improved forecast accuracy is possible using the suggested method. This suggests a high level of market behaviour prediction and aids in determining the optimal times to join or exit the market[18].

Mathur et al., (2021) The goal of the project is to further this revolution in future markets by creating an Algorithmic Trading Bot that, depending on user approach and different market situations, would automatically trade user strategies in addition to its own algorithms for daily trading. In order to guarantee the optimal trading turnover for the day and reduce transaction costs, the bot will also trade and invest constantly throughout the day, allowing for significant returns for all users—individuals or organisations[19].

Liu, Fu and Yilmaz, (2019) study is to employ the stacked LSTMs model to predict high frequency trading time series financial data for algorithmic trading investment strategies. The intention is to present a DL method that may be advantageous for algorithmic trading's intricate investment methods. This study does not provide a comprehensive profit and loss curve (PNL)-generating investment technique. Instead, it demonstrates how time series financial data may be predicted using deep neural networks based on LSTM. It has the ability to forecast asset returns or prices, and the forecasts it generates can be used to decide whether to exit a short position or establish a long one[20].

The, Aloud, (2020) offer a straightforward data-driven trading decision assistance system for the stock market that makes use of genetic algorithms (GAs), decision trees, and multiple technical indicators. It generates classes for buy, hold, and sell that correlate to trading choices using a decision tree built from technical indicators and stock trading rules. The implementation of GAs based on a two-step classification procedure is the main contribution of this work. In this way, the relevant inputs may be selected and modified according to the market's characteristics. Both the weight selection and the data input selection stages involve the employment of GAs. In the first phase, classifiers of various technical indicators are trained, and in the second step, these classifiers are merged into trading rules. In the first step, methods for selecting data input and random sampling were employed to provide the necessary diversity of technical indicators. The suggested algorithm increased forecasting accuracy from 73.6% to 81.78%[21].

Makwana et al., (2024) abstract discusses the integration of three key elements in algorithmic trading: Algorithmic Trading, Price Prediction Models, and News Web Scraping.

Algorithmic Trading uses mathematical algorithms to execute high-frequency, data-driven trading strategies, while Price Prediction Models use historical and real-time data to fore- cast asset prices. News Web Scraping aggregates data from news sources and social media platforms, providing traders with real-time insights. This holistic approach to trading allows algorithms to adapt rapidly to changing market conditions and refine trading strategies and risk management[22].

In this study, Sakhare et al., (2021) The LSTM model, a neural network approach, is used as the algorithm to forecast stock values. Preexisting models are less reliable since they ignore technological considerations. Overcoming this constraint and taking temporal factors into account, the LSTM model achieves an error of just 0.00036%[23].

In this work, Chihab et al., (2019) suggest a monetary market intra-week foreign exchange speculative strategy using a mix of technical indicators. This system uses the Probit regression model and RF to develop rules; it includes two levels of decision-making. A trading strategy must include both a rule to join the market and a rule to leave it. Two requirements must be met for our suggested system to join the currency market. In the first one, RF access rules should be validated throughout the course of the next week, and in the second, Probit should forecast a positive result for the next day. A single negative warning from RF or Probit is sufficient to abandon the currency market. Dynamic portfolio trading systems were created using this technique. From January 2014 to January 2016, the model's profitability was investigated for variations in the USD/(EUR, JYN, and BRP) exchange rate. The suggested approach makes it possible to increase forecast accuracy. This suggests a sound forecast of market behaviour and aids in determining when it is best to join or exit the market[18].

In this paper, Moedjahedy et al., (2020) five telecoms firms' stock prices: Bakrie Telecom Tbk (BTEL), PT. XL Axiata Tbk (EXCL), PT. Smartfren Telecom Tbk (FREN), PT. Two algorithms, the Gaussian Process and SMOreg, are used to forecast stock prices for Teleko - munikasi Indonesia Tbl (TLKM) and PT. Indosat Tbk (ISAT), with the training dataset spanning from January 1, 2017, to December 31, 2019. Compared to the Gaussian Process, SMOreg outperforms it in terms of RMSE (0.00005), MAPE (1.88%), and MBE (0.00025)[24].

This paper, Liu and Song, (2018) presents a model for prediction utilising a deep residual network (ResNet) that takes the stock price graph as input. In comparison to the stochastic indicator's 0.33 accuracy, the ResNet model achieved an average accuracy of 0.40[25] .

In this study, Kalra and Prasad, (2019) a model is suggested for daily stock market prediction in India that makes use of news items and historical data. The news text is categorised as having a negative or positive sentiment using the Naive Bayes classifier. Use historical data, the number of positive and negative sentiments expressed in news items each day, and the variance of the closing prices of the days immediately following to make predictions with an accuracy range from 65.30 to 91.2% using a variety of machine learning algorithms[26].

This study, Mathanprasad and Gunasekaran, (2022) perform a computational automated methodology has been developed to predict stock market data values using historical data. The method uses machine learning classification to identify variations in stock market trends. The performance of the new method is evaluated through comparative analysis, ensuring accurate predictions. The machine learning classification algorithm predicts stock market price and movement changes, with an accuracy of 94.17%. This improved prediction helps investors assess current and future stock market values, enhancing their decision-making process. The proposed work is recommended for users to make informed decisions[27].

This study, Chang, Luo and Hsiao, (2022) examine if there is a methodical approach to identifying equities that are buyable and, more crucially, when to purchase and sell them. These days, AI has emerged as a viable solution to several problems due to advancements in hardware. Two popular approaches in AI are ML and DL. This research demonstrates the use of machine learning in stock recommendation and prediction. Following testing, they discovered that LightGBM had the ability to forecast and suggest stocks. They validated the strategy using Taiwan stock market data. The prognosis and suggestion were contrasted with the well-known Taiwan ETFs 0050 and 0056. The findings demonstrate that the approach is workable, efficient, and performs better than Taiwan ETFs 0050 and 0056[28] .

The comparative study, Reddy and Jaisharma, (2022) of increased accuracy when predicting stock market price values utilising SNLSTM in conjunction with Back Propagation (BP). Accuracy is functioning for both the SNLSTM (N=1000) and Back Propagation (N=1000) algorithms, which are computed using two groups and 2000 samples total with g-power of 0.8. The accuracy rate of SNLSTM (63.10%) is higher than that of Back Propagation (61.03%). Differences between the SNLSTM Algorithm and Backpropagation are regarded as statistically significant when they are (p¡0.05), or p=.000. This demonstrates that SNL- STM outperforms Back Propagation in stock market price prediction and increases accuracy level %[29].

This study, Selvin et al., (2017) provide a formalisation for stock price prediction based on DL. It is evident that DNN topologies can both make predictions and capture hidden dynamics. They were able to forecast the stock prices of Infosys, TCS, and Cipla after training the algorithm on Infosys data. The suggested system can find certain interrelationships in the data, as shown here. Additionally, the findings show that CNN architecture can detect trend changes. We found that CNN is the optimal model to use with our suggested technique. It makes predictions based on the data available at a given time[30].

In this study, Patil et al., (2020) new method based on graph theory is suggested. This method models the stock market as a complex network and uses information about the spatial and temporal relationships between stocks to make investment decisions. In order to construct two hybrid models, this graph-based method is combined with two other approaches. A correlational graph is generated using the stock's historical price data, and a causality-based graph is generated from the stock's financial news mentions during a certain time period. A more conventional ML strategy is used by the second model, whereas the first hybrid model makes use of deep learning CNNs. Along with other statistical models, these models are evaluated and the pros and cons of graph-based models are addressed. Both graph-based methods outperform the conventional ones, according to their tests, since they use structural information to construct the prediction model Collapse[31].

Vedapradha et al., (2023) the study's overarching goal is to ascertain how knowledgeable brokers are in relation to the use of technology in trading. Using the Systematic Sampling approach, 235 stock brokers from the Bangalore area who are active on the NSE and BSE were surveyed using 350 structured questions that they were asked to complete on their own time. Critical factors detected to verify the hypothesis using Simple Percentage Analysis and Chi-Square Analysis utilising Statistical Analysis Software (SAS) were awareness, auto- mated trading, elimination of human mistake, portfolio management, tracking orders, and order placement. Stock brokers from both the NSE and BSE in Bangalore showed a strong correlation between their familiarity with the aforementioned technology and its potential uses. One of the most common uses of algorithmic trading in the stock broking industry is portfolio management, which is closely related to automated trading[32].

Shah and Patil, (2023) Developed a unique approach for predicting stock market performance that combines fuzzy categorisation with genetic optimisation and ML for prediction. They have thus begun an experimental approach to solve the limits of current tactics by using fuzzy-genetic ML for a small number of stocks' average prices. Machine learning techniques based on fuzzy genetics will be used for making predictions and identifying patterns. They want to train the suggested evolutionary model in future work using the outcomes of the rela- tive strength index approach and the moving average convergence/divergence technique(Shah and Patil, 2023)[33].

Patra, Patra and Gupta, (2022) an optimal research approach will optimise an exponential moving average (EMA), relative strength index (RSI), and average true range (ATR) to construct a position. The suggested method not only alerts you when to buy and sell, but it also sends signals to set a stop-loss order and a target price for your position. Moreover, the profits and losses for a certain time are shown[34].

Fikri et al., (2022) neural network-based automated trading method that predicts market movements utilising triple exponential weighted moving averages (EMA), Bollinger bands, and stochastic RSI is proposed in this research. To avoid misleading signals and guarantee effective trading in volatile markets, the method employs a market-adaptive and distributed MLP known as channelled multi-layer perceptron (CMLP). The CMLP has shown its efficacy when compared to Multi-Modal GARCH-ARIMA[35].

Rupali Atul Mahajan, Arup Kadia, Monika Singh, Rajesh Dey, Salina Kassim, (2024) study's goal is to determine how AI has influenced the impact of open interest and option volumes on monthly futures prices. The share prices of 30 businesses, 10 from each of the small, mid, and large-cap categories on the National Stock Exchange, were evaluated. The research was conducted between 2017 and 2021. Two independent variables—open interest and options volume—were regressed against monthly future prices using the statistical method of ordinary least square regression. The findings aligned with previous research. During the research period, it was discovered that the open interest predictor coefficients were statistically significant. Recent research indicates that algorithmic trading has enhanced the visibility of the connection between option volumes, open interest, and future prices[36].

Iyer and Iyer, (2024) objective of this essay is to delve into the perspectives of investors about manual and algo trading tactics. Eighty investors from the Bangalore East IT industry are selected for this reason. Investor demographics, trading history, trading strategy choice (manual vs. algo), and technical knowledge are some of the factors that inform the data analysis. Investor mood at the ever-changing crossroads of algorithmic and human trading is better understood according to this study[37].

2.2 Key theories, concepts, and findings

This study explores different approaches in algorithmic trading and prediction models by assessing the methods of improving the entry and exit points of the market, refining the accuracy of the predictions, and optimizing trading to achieve maximum profits. One is the two-stage decision system that uses regression and rule-based decision-making criteria in the identification of entry/exit points for currencies markets based on positive/negative signals. Another approach involves the use of an automatic trading robot that involves readjustment of trading techniques during the day, lowers costs of transactions, and enhances size of turnovers. Big data numerical computations are used in machine learning, including stacked LSTMs, to forecast high-frequency trading data, from which traders can gain an understanding of the prices and make decisions. However, DL like CNN, and a new level of hybrid models using genetic algorithms, decision trees, and a fuzzy logic system has strengthened the forecast's precision. AI has brought remarkably advanced techniques like sentiment analysis of article related to trading, data-driven decision trees, and even network models based on graph theory in the trading sector, which enables the systems to learn complex pattern of trading and make intelligent prognosis. By means of such innovative solutions, overwhelming algorithmic trading is gradually evolving into a more flexible, adaptive and accurate method, capable of providing the fastest response possible to certain market shifts.

2.3 Identification of gaps

The current trends in algorithmic trading and prediction models demonstrate that the technical approach as well as AI-based strategies are highly effective; however, there are some gaps in the literature. Firstly, many of the studies focus on model predictive capability over a fixed set of conditions in the financial market, with very few experiments conducted to assess how these models would perform in different and often unstable conditions in a financial market. A large number of studies mainly focuses on evaluating models on backtesting data and does not consider such factors as shocks in macroeconomics or abnormally high stock price volatility, which may affect the effectiveness of the developed forecasts in real-life conditions. Furthermore, although some of the investigations use sentiment analysis derived from the news, fewer examine the impact of various, high influence news kinds or how certain geopolitical or economic phenomena affect trading algorithms. Similarities and differences are also found in regard to research results related to a performance of DL-based models, like LSTM and CNNs while comparing them with the hybrid models comprising technical indicators and fuzzy logic; further studies are required to discover the context and configuration that best suits each model. As such, filling these research gaps forms the rationale for this study – to assess algorithmic trading models under a more realistic, real-time, and multi-faceted environment and towards proposing a framework for enhancing the adaptability of such models to inherently volatile and uncertain markets. The research questions that therefore inform this study are therefore centred on identifying how it is possible to maintain high levels of predictive accuracy while trading during very volatile times, the degree to which high-impact news events affect trading results and a comparison of hybrid models to standalone deep learning models. These questions seek to foster a healthier and more sustainable trend in algorithmic trading, contributing to the advancement of the field with inputs that enhance the robustness of the developing automation systems within an ever-shifting market environment.

3 METHODOLOGY

3.1 Research methods Used

The study on stock market prediction and machine learning based algorithmic trading work use both qualitative and quantitative data. This mixed-method approach enables an assessment of the research questions using both quantitative model implementation and qualitative review of literature. Each research method is then used in relation to various objectives in literature review, data collection, model selection, algorithm design and performance assessment respectively.

1. Literature Review

- **Purpose:** The literature review also provides knowledge of the various methodologies, methods, algorithms, and assessment indicators currently employed in foreign stock market evaluation and algorithmic trading.

- **Process:** An extensive literature review was done in the databases including IEEE Xplore, ScienceDirect and Google Scholar using the keywords "Machine learning stock market prediction", "Algorithmic trading" and "Python Machine learning". Performing this search resulted in a number of effective findings on approaches to stock prediction and trading with results that are better or worse than others.
- **Findings:** The literature search provided evidence that algorithms such as SVM, LSTM networks or Random Forest algorithms are more popular and are accuracy-high in stock prediction. Further, the literature review establishes the need for feature extraction, especially concerning the selection of indicators such as historical prices, moving averages, trading volume and other macro-economic variables with an aim of creating predictive models with higher accuracy.

2. Quantitative Approach for Model Development and Evaluation

- **Data Collection:** The data for the analysis consists of historical stock market data from databases including Yahoo Finance, Alpha Vantage and Quandl. Fundamental data encompasses some of the closing prices, the high and low prices, volume of trading, and any other related financial values in any given period.
- **Feature Engineering and Selection:** The raw data is then cleaned, and key features affecting stock prices are extracted and later engineered. They include indicators like; the moving average, the RSI, gross Domestic product and interest rates.
- **Model Selection:** Concretely, the following techniques are used Regression and DT, RF, and LSTM networks. Models are selected with reference to learning obtained from the literature analysis and their capacity to capture temporal variations.
- **Model Training and Testing:** The models use data in the division of 70:30 for training and testing respectively. To improve the model's stability and lessen the impact of overemphasised outcomes, a technique known as cross validation is used.
- **Performance Metrics:** As measures of accuracy of prediction, the MAE, RMSE, and R-square are used. Such measures make it possible to numerically assess the model in terms of its ability to make predictions.

3. Quantitative Approach for Algorithmic Trading Strategy Development

- **Algorithmic Trading Rules:** From the obtained predictive model, algorithms for algorithmic trading are derived. These rules are based on market entry and exit points which is shown by the predicted prices.
- **Backtesting:** This trading strategy is back tested using historical data to assess how certain trades would have gone if they were real. The performance of the strategy and the risk that it has associated to is measured using Sharpe Ratio, ROI, Maximum Drawdown.
- **Sensitivity Analysis:** In addition, the sensitivity analysis of different key factors (time windows of indicators) is performed to improve its fit to trading results by testing the sensitivity of the trading microstructure to changes in indicators.

4. Qualitative Approach for Interpreting Model and Strategy Findings

- **Evaluation of Algorithmic Trading Outcomes:** An interpretation of model and algorithmic trading results benefits from the qualitative approach focusing on the model in the context of outcomes. This is done by reviewing back testing performances and deconstructing or reconstructing a system in order to determine causes of deviations.
- **Discussion of Limitations and Future Directions:** Based on the findings of the literature review and empirical work, this section enlightens the discussion on the existing limitations such as the effect of market irregularities or external factors, before pointing out potential research directions.

3.2 Data Collection

The quantitative data of this research is collected using archival research techniques with historical stocks data (daily open, close, high, and low price and trade volume) from financial revised databases including Yahoo finance, Alpha Vantage and Quandl databases for the period of 5-20 Years. Besides, firm-specific characteristics and variables such as stock returns and trading volumes of an individual stock are obtained from the World Wide Wrap by Fact- Set while other broad based economic factors like interest rates, inflation rates, GDP growth and unemployment rates are obtained from reliable databases such as the FRED hosted by the Federal Reserve and the World Bank. Such data sets underpin the exercise of time series analysis and forecasting. In addition to the model development, to contextualise the results of the study, a literature review was conducted Featuring information from recent studies and industry reports, the known methodologies were determined, as well as the understanding of ML in stock market prediction and algorithmic trading was deepened.

3.3 *Analytical Techniques or Flowchart*

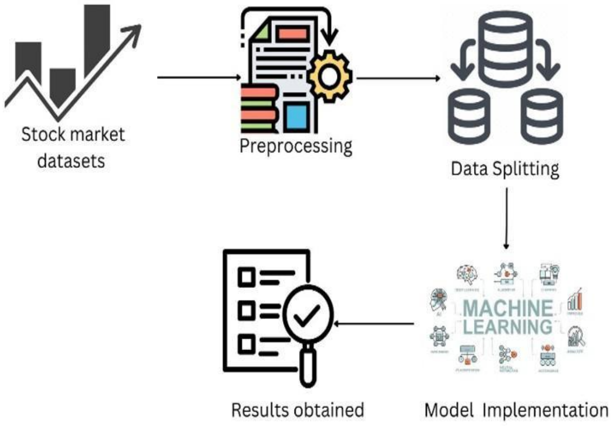

Figure 2: Analytical flowchart

4 DISCUSSIONS

4.1 Presentation of findings

The results obtained in this study for the stock market prediction and for the algorithmic trading are organized in a tabular and graphical form along with the explanatory text so that these results are more comprehensible. Different content tools such as tables can be used to show every ML model's performance metrics like RMSE, MAE, R-sq values in a comparative manner that can determine the level of accuracy in predictive models. Such presentation facilitates comparison of models to identify the method that best forecasted the changes in stock prices. Also, line graphs and bar charts are used for observing the forecasted price data in comparison to the corresponding actual stock price data as it provides a perfect view of every built model that exemplifies the capability of capturing the daily or weekly price movement. The backtesting results of the algorithmic trading strategy are shown in tables that contain columns explaining the overall profitability measured by the return on investment (ROI), risk estimator, the Sharpe ratio, and the maximum drawdown. These figures will allow to provide a clear vision of the performance of the strategy in different conditions and periods of its activity, as well as to make a preliminary assessment of the degree of risk to which the rates were subjected. The text that follows the charts detailing the observations and visualizations provides a qualitative summary of the submitted work that contributed to the identification of the main conclusions, patterns and deviations, as well as the qualitative and quantitative characteristics of the applicability of each model.

4.2 Analysis and interpretation

The analysis of the findings provides key information about the success rates of applying machine learning models for stock market prediction that would be relevant to algorithmic trading. For example, more complex models such as LSTM and Random Forests models expressed a remarkable capability of identifying short-term stock price movements owing to the capacity of those models to model temporal data commodity and intricate patterns of data, and hence the low MAE and RMSE when compared with simple regression models. Spearheaded by these predictive models, the algorithmic trading strategy revealed its ability to deliver post risk-adjusted returns greater than market averages since the Sharpe ratio was positive. However, high levels of performance can only be achieved from the backtesting results during the low volatility environment, and dependence on the model seems to predict slow performance during the high volatility period. Hence, the result highlights the necessity of model modification or incorporation of other factors that might eliminate market activity volatility and, thus, decrease market risk exposure. In conclusion, there is evidence that machine learning models are able to give future direction of the stock prices, which will be of help to the traders in the market. However, it also shed light on constraints that affect reliability especially in situations of fluctuations in the market price which may be alleviated by the use of more robust models or other economic externalities.

4.3 Comparison with Literature

The results of this study are in general agreement with the large body of literature that has shown that machine learning techniques, such as ensemble methods and deep learning, may significantly enhance the accuracy of stock market predictions. In parallel with previous studies, it has also been observed that, in particular, LSTM structures can work well for the time series characteristic of financial data and thus increase short-time accurate predictability. The results for this study support the common perception that machine learning algorithms are superior to conventional approaches because of their ability to capture subtle patterns and relationships in financial data. This research also shows that model performance is lower during volatile period, contrary to some studies which indicates that deep learning models can independently address all intricate features of stock prices. The decline in performance observed during these periods can be rectified through the integration of additional data feeds, including sentiment or economic, together with machine learning algorithms. Furthermore, the backtesting results discussed in this paper suggest rounds of days must be respected with elevated ROI numbers because they are sensitive to model assumptions and market circumstances, a criticism often mentioned in the literature review of backtested trading strategies. These results extend the relevant literature by providing support for the efficacy of ML in the context of stock prediction, and by highlighting the need for model flexibility, as well as the integration of multiple data sources for producing accurate and profitable predictions and trades in real-world conditions.

5 Conclusion

Summarised findings,

It also shows that using the Long Short-Termed Memory networks and Random Forest are half the way to improving the accuracy of short-term stock price prediction. These models proved to be superior to conventional approaches in terms of error statistics and the quality of fit to the target financial time-varying series data. Further, the algorithmic trading strategy employing these predicted models yields reasonable profitability in excess of benchmark index returns and is associated with the positive Sharpe ratios suggesting good risk-adjusted returns. However, according to the findings of the research, its efficiency is lower during periods of high fluctuations and therefore requires the use of more effective, adaptive or the addition of extra data to the model.

Discuss Implications,

Based on these observations, it is possible to state that the automation of data mining technologies holds latent strength in the stock market analysis and trading systems. In other words, for investors and trading firms, machine learning represents means to improve the decision-making process and reach better outcomes. However, the drawbacks mentioned during uproarious conditions indicate the fact that although the machine learning models prove useful for improving trading proficiency, they are not absolute solutions during unstable conditions. This suggests the need to integrate these models with other adaptive scenarios and additional market information about abnormal situations and external macroeconomic conditions.

Recommendations Based on the Research

To further enhance predictive accuracy, growing external data sources like macroeconomic fundamental data, global news summary sentiment score and geopolitical risk index into the training dataset can be useful in capturing other systematic shocks influencing stock price fluctuations, especially during the periods of abrupt volatility. The other a worked-out model needs before being implemented is constant adjustment and preventive checks to determine how it performs in different situations with fairly frequent retraining to accommodate shifts in trends. Using of probabilistic models combining machine learning with more classical financial forecasting might make applied models more stable in case of sudden shifts in market trends. Further, the application of strong risk management policies as a part of algorithmic exploration can prevent severe losses resulting from wrong predictions during low volatility zones.

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