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Building Intelligent Approach for Stock Price Prediction using Machine Learning and LSTM

NAME: MONIKA
STUDENT ID: 001354290

SUPERVISOR: IK SOO LIM
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Data Science, University of Greenwich, 30 Park Row, Greenwich, UK.

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ABSTRACT

Machine learning has become an important tool for stock price forecasting , offering efficient mechanisms to support investment decisions in uncertain and dynamic markets. This study explores the application of machine learning models and LSTM ,emphasizing to identify effective approaches for price predictions. In more narrowly defined terms, it provide a mechanism that can help investors make better decision in investment and management. A framework is proposed which enables the selection of the best performing models with relevant inputs and also factor insensitivity of the stock's price This study investigates the application of various ML models, including linear models, tree-based models, instance-based models, kernel-based models, gradient boosting, and LSTM, to predict stock prices for five companies: Tesla, Apple, Starbucks, Netflix, and Cisco. To capture stock behaviour, both technical and fundamental indicators are used, including moving averages and MACD (Moving Average Convergence Divergence). Bollinger Bands improve the analysis even further by offering information on price volatility and overbought or oversold lines. Trading techniques such as the Golden Cross are also used, in which a fast-moving average crosses over a slow-moving average to indicate a buy, and the converse occurs to indicate a sell. We showed the importance and relevance of using fundamental indicators and technical indicators. The results demonstrate that Ridge Regression as the most effective, achieving minimal prediction errors and high variance. This thorough framework has a lot of promise for use in investment advice, algorithmic trading, and portfolio management applications.

PREFACE

This project “Building Intelligent Approach for Stock Price Prediction using Machine Learning and LSTM” represents my exploration into different approaches to predicted stock price of different companies. This study draws inspiration from the evolution of machine learning in stock price forecasting, which began in the 1980s,alongside the heightened challenges posed by COVID-19-induced market volatility, emphasizing the need for more robust prediction models.

The research process has been an enriching experience, providing me with a deeper understanding of how machine learning models can be used to analyse financial data and forecast stock trends. Working with a variety of models and technical indicators has increased my technical expertise and problem-solving abilities.

I want to express my gratitude to my mentors and peers for their unwavering support throughout this endeavour. Their guidance and assistance were crucial in helping me get beyond challenges and successfully complete this study.

I trust that this work will contribute and promote more developments in the application of machine learning techniques in the financial sector and further the field of stock price prediction.

ACKNOWLEDGEMENT

I want to sincerely thank Professor Ik Soo Lim for his constant support, direction, and priceless counsel during this endeavour. His knowledge, perceptive criticism, and support have been invaluable in guiding the course of my research and guaranteeing its successful conclusion.

I sincerely appreciate the time and work he invested in giving me the information and abilities I needed to succeed in this undertaking. My academic career has benefited much from his mentoring, and I am sincerely appreciative of the chance to study under him.

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1. INTRODUCTION:-

Can Machine learning unlock the secret to stock price prediction?
There has long been discussion in intellectual and financial circles about the accuracy of stock price prediction. According to the **Efficient Market Hypothesis (EMH)**, stock prices accurately reflect all available information, making it impossible to consistently achieve returns that outperform the market (Campanella, 2016). According to the EMH's assumption markets are made up of rational investors and price fluctuations following a Random Walk (RW) model, driven only by unanticipated occurrences (Urquhart, 2013) (Shonkwiler, 2013) (Manahov, 2014). However, the **Adaptive Market Hypothesis (AMH)** presents a more flexible perspective, arguing that both rational and irrational variables impact investor behaviour and that while markets may be efficient at times, they can also show predictable trends in specific situations (Lo, 2017). Demand and supply, business performance, the state of the economy, market sentiment, and outside factors like political situations all have a big impact on stock prices.Traditional approaches like technical analysis rely on historical price trends, while fundamental analysis examines a company's intrinsic value to predict price movements ((Rockefeller, 2011); (R., 2013)). Over time, analysts have increasingly combined these methodologies to improve forecasting accuracy.
By enabling the application of machine learning (ML) techniques to detect patterns and forecast price movements, technological advancements and the expansion of historical stock data have challenged conventional financial theories and provided prospective tools for better informed investing decisions.One finding is, financial time series data is non-stationary, exhibiting "concept drift" due to evolving political, economic, and market conditions, necessitating adaptive models for effective forecasting (Cavalcante, 2015).In order to predict stock prices and navigate the intricacies of financial markets, this study investigates how well these machine learning models work.With low error metrics and high R2 values, which indicate excellent predictive capacity, this study compared many machine learning models for stock price prediction and discovered that LSTM, Bayesian Ridge, and Ridge performed the best across a range of stocks. Models like ElasticNet, on the other hand, did poorly, displaying negative R2 values, indicating that they were unable to adequately capture stock price movements. The study highlights how crucial it is to choose the right models and adjust hyperparameters in order to improve stock market forecasts.

1.1 BACKGROUND AND MOTIVATION

Beginning in the late 1980s, machine learning (ML) models were applied to stock market data on the presumption that past stock price data had significant and discernible patterns that could be examined to forecast future price changes (White, 1988).However, this required assumption directly contradicts the long-standing efficient-market hypothesis, which holds that stock prices are unpredictable because they reflect all available information (Fama, 1965).Interest in machine learning-based stock prediction models has increased despite these theoretical obstacles due to developments in computing methods and the expanding amount of historical stock market data (Clarke, et al., n.d.). The continuous advancement of machine learning and deep learning models has created new opportunities for the analysis of massive datasets, including trade volumes and stock prices. Although some studies have indicated promise, convincing proof of the approaches' continuous viability is still lacking (Cavalcante, (2016)).

The need of comprehending stock market behaviour was further highlighted by the COVID-19 epidemic. Extreme volatility and swings in stock prices resulted from its unparalleled worldwide impact on financial markets (Goodell, 2020).These abnormalities were difficult for traditional financial models to handle, underscoring the necessity for flexible and reliable prediction techniques (Cheema-Fox A., 2020.).

The primary motivation behind stock market prediction lies in financial gain. The creation of a mathematical model that can predict future stock values could have a big financial impact. Thus, researchers, investors, and brokers are always looking for new models that can perform better than current methods and yield higher profits (Thomsett, (2015).).Notwithstanding the obstacles that still need to be overcome, the nexus of machine learning, financial data analysis, and shifting market conditions offers a thrilling and risky chance for more research.

1.2 RESEARCH OBJECTIVE

The goal of stock price prediction is to use past data and other important factors to anticipate future price movements of a certain stock or market index. This forecast has multiple uses for analysts, investors, and organizations. Using information from previous prices, trade volume, technical indicators, and market conditions, it primarily seeks to **forecast future stock prices** (Goodell, 2020).

Machine learning methods like Random Forest, cat boost, and LSTM are trained on a variety of input sets, including fundamental analysis, technical indicators, or both. Root Mean Square Error (RMSE), a performance indicator that shows how well the predictions match actual price changes, is used to assess these models. To find out if machine learning techniques may provide better prediction performance, these models can be compared to more conventional forecasting techniques like the Random Walk model. In addition to improving models, this assessment helps **choose the best algorithm** for stock price prediction (Zhang, 2019).

One of the main objectives of stock price prediction is to **enhance investment techniques**. Improved prediction models can help investors **mitigate risk** by allowing them to modify their portfolios in response to more accurate projections, which lowers the possibility of unforeseen losses. Techniques for predicting stock prices can be applied by a variety of stakeholders. These models can be used by institutional and individual traders and investors to improve portfolio management and guide their trading decisions. Models for predicting stock prices can be used by financial experts to offer more precise market analysis and advice services. These technologies can also be used by businesses in the banking, investing, and finance industries to help with risk management and strategic planning (Jang, 2020). Additionally, by using machine learning models, data scientists and university researchers can improve on current stock price forecasting techniques and investigate novel ones.

1.3 PROBLEM STATEMENT

One of the main research questions is: Which combination of technical and fundamental indicators will perform better when it comes to stock price forecasting? The significance of time series models in stock price prediction will be investigated in this study. The question of whether time series models are necessary for accurate stock price forecasting emerges because stock price data is sequential. The topic of whether a single model is appropriate for all data sets will also be addressed in this study. It will look into whether a particular model works better for particular data attributes or whether a single machine learning model is consistently effective across different kinds of stock price data. By answering these queries, the study hopes to improve knowledge of how various models and inputs affect stock price forecasts, offering insights that could be used by finance practitioners to optimize their investment strategies and enhance forecasting accuracy (Smith, 2020).

1.4 INVESTIGATION RESULTS

Dependency of Next Day Price on Previous Days' Price: One of the research's main conclusions is that the price of stocks tends to be influenced by the price of the previous day. This is consistent with the widely accepted financial idea that stock prices show some degree of autocorrelation, which means that previous price movements have some bearing on future prices. Since models that take previous price data into consideration may produce more accurate estimates of future stock prices, understanding this link is essential for predicting stock price patterns (Goodell, 2020).
Trend Detection with the Exponential Moving Average (EMA): The EMA's computation indicates whether or not a stock's price is showing a noticeable trend. Compared to basic moving averages, the EMA is a technical analysis tool that gives more weight to recent data points, making it more sensitive to price changes. According to studies, technical indicators like the Moving Average Convergence Divergence (MACD) and Bollinger Band are useful for spotting patterns in stock price volatility that could present investors with lucrative chances (Zhang, 2019).
Dickey-Fuller Test for Stock Price Stationarity: In the this study, the Augmented Dickey-Fuller (ADF) test was used to determine if the time series data was stationary. The ADF test aids in identifying whether a time series shows seasonality and trends or is stagnant. The Durbin-Watson statistic in this instance indicated that although the series is not stationary, it does show a seasonal tendency. Because time series models like ARIMA usually require stationary data to generate accurate forecasts, it was determined that these models would not be the best fit in light of this finding (Johnson, 2020).
Regression Models for Stock Price Prediction: Ridge Regression was proved to be successful in forecasting stock prices in the third section of the study. However, linear regression models tended to demonstrate linear properties and provide positive changes when the data set was small. When dealing with larger datasets and avoiding overfitting, Ridge Regression's regularization properties made it more reliable and successful in stock price prediction (Lee, 2018).
A more thorough method for enhancing predictive models in stock price forecasting is provided by the study, which emphasizes the importance of integrating technical and fundamental information to improve forecasting accuracy (Smith, 2020).

1.5 RELEVANCE AND CONTRIBUTIONS

By emphasizing the usefulness of technical indicators such as EMA, Bollinger Bands, and MACD, which aid in identifying stock price trends and volatility, this study advances the field of stock price forecasting. Additionally, it highlights how crucial it is to verify stationarity using the ADF test, which reveals that stock price data is frequently non-stationary, rendering conventional time series models inappropriate. This realization promotes the application of different techniques that are more adept at managing non-stationary data (Investopedia, 2024).

Furthermore, by addressing problems like multicollinearity, the study shows that Ridge Regression performs better than Linear Regression and is therefore more useful for stock price forecasting. It also demonstrates how stock prices are highly autocorrelated, meaning that one day's price affects the next (Investopedia, 2024).

2 LITERATURE REVIEW:-

2.1 STOCK PRICE PREDICTION OVERVIEW

The research used datasets of various sizes and features to anticipate the stock values of key firms, including Netflix, Apple, Starbucks, Cisco, and Tesla. For instance, Tesla's dataset includes 3515 data points with six features, compared to 2516 data points with five features for other organizations.Beginning with data research and visualization, the project took a methodical approach.Apart from machine learning models, technical indicators such as the Bollinger Bands, MACD, and Golden Cross approach were investigated. Using the movement of rapid and slow moving averages, the Golden Cross technique determines buy and sell signals.
Multiple machine learning models, including **LSTM**, **KNN**, **CatBoost**, **ElasticNet**, **Bayesian Ridge**, **AdaBoost**, **Ridge**, **Extra Trees**, **Linear Regression**, **DecisionTree**, **SVR**, and **Random Forest**, were tested.Each model's performance was evaluated using **Mean Absolute Error (MAE)**, **Root Mean Square Error (RMSE)**, and **R-squared (R^2)** values.**Bayesian Ridge** and **Linear Regression** consistently outperformed other models, achieving high R^2 values and low MAE and RMSE indicating excellent predictive accuracy. **Random Forest** also performed well, especially for Tesla (R^2 = 0.9631) and Apple (R^2 = 0.9839), while **CatBoost** showed good results for Netflix (R^2 = 0.9560) and Starbucks (R^2 = 0.9622). On the other hand, **ElasticNet** consistently underperformed across all stocks, with negative R^2 values (Tesla: -2.4778, Apple: 0.5040, Netflix: -0.2541, Starbucks: -0.3565, Cisco: -0.0419), making it unsuitable for stock price prediction. These results suggest that linear models and Bayesian Ridge are the most reliable for predicting stock prices across these companies.

2.2 TECHNICAL AND FUNDAMENTAL ANALYSIS

There are two different methods for assessing the stock market: technical analysis and fundamental analysis. With traders using historical price data and trading volume to predict future price movements, technical analysis is based on the idea that human characteristics will cause prior market behavior to replicate itself (Tsinaslanidis, 2016).Indicators that shed light on market patterns and volatility include the Moving averages, Moving Average Convergence Divergence (MACD), and boillinger bands ((Patel, 2015). Fundamental analysis, on the other hand, examines a company's operational performance, financial health, and macroeconomic circumstances in order to ascertain the stock's inherent value. Methods like Dividend Discount Models (DDM) and Discounted Cash Flow (DCF) models are frequently used in this study ((Krantz, 2016); (Wafi, (2015a))). Fundamental analysts concentrate on long-term value and try to forecast price changes based on underlying economic causes, whereas technical analysts depend on market momentum (Krantz, 2016). Although they differ, both strategies can work in tandem because it has been demonstrated that combining technical indicators with fundamental data improves predicting accuracy ((Bettman, (2009).); (Chen, (2016))).

2.3 TECHNICAL ANALYSIS

In order to forecast future market movements and make money, technical analysis uses historical market data, especially price and volume data (Rockefeller, 2011).A distinction is drawn between investors, who adopt longer timescales (months to forever), and traders, who typically work within short timeframes (minutes to a year) (Rockefeller, 2011). Investors may also profit from dividends and bond coupon payments, even while traders concentrate on short-term price changes to take advantage of buying and selling opportunities (Rockefeller, 2011). However, technical analysis can be used by investors and traders alike to accomplish their goals.

Technical analysis can be divided into a number of tools, such as technical indicators, patterns, candlesticks, and filter rules, and it mostly uses chart-based techniques, according to Tsinaslanidis and Zapranis (2016). The Open, High, Low, Close (OHLC), trade volume, and other mathematical algorithms used to historical price data are usually the source of these indicators. When plotted alongside price charts, these indicators help traders and investors make decisions (Patel, 2015).

Technical analysis used are:-

2.3.1 Simple moving averages:-

The Simple Moving Average (SMA) is used by traders and investors to smooth out price fluctuations and identify trends in the market (Investopedia, 2024). By averaging past data over a fixed period, the SMA provides a clearer representation of the underlying trend, making it easier to make informed trading decisions.

Formula is:-

$$\frac{\sum_0^n p_{n-1}}{n}$$

Moving Average in n days as shown in above equation is the average price over the previous n-1 days p_{n-1} to today's price p_0.

Key Features of SMA:

1. Trend Identification:

If the current price is above the SMA, this generally signals an uptrend, indicating potential buying opportunities. Conversely, if the current price is below the SMA, it suggests a downtrend, which may be seen as a signal to sell or avoid the asset (Investopedia, 2024).

2. Smoothing Effect:

The SMA smooths out daily price fluctuations or "noise" in the market, which helps traders focus on the broader market trend. This makes the SMA particularly useful in volatile markets, where daily price movements can obscure the overall trend (Investopedia, 2024).

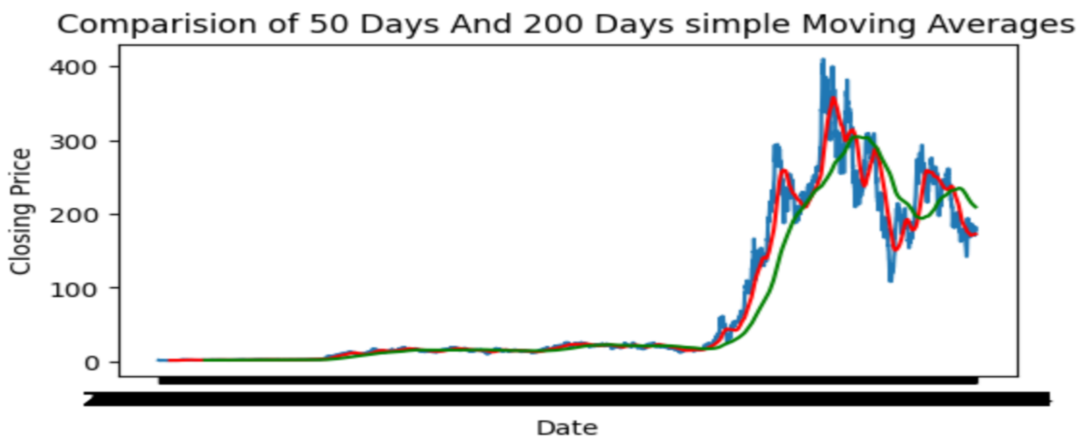

Figure 1 shows comparision of simple moving average for 50 and 200 days for tesla

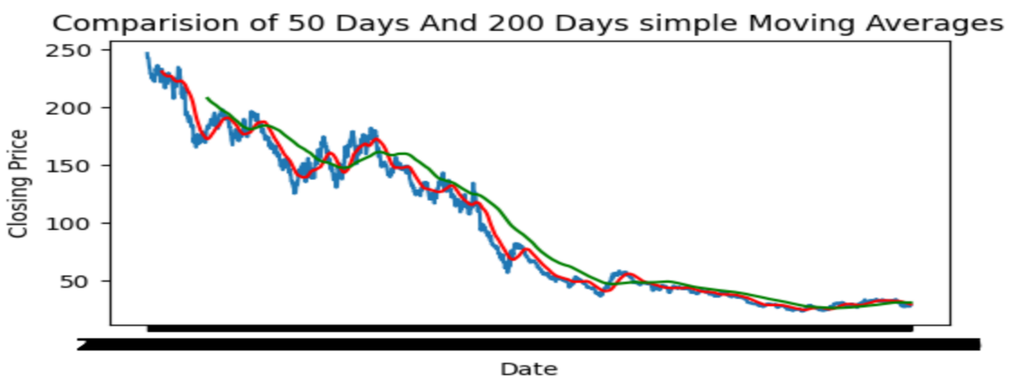

Figure 2 shows comparision of simple moving average for 50 and 200 days for apple

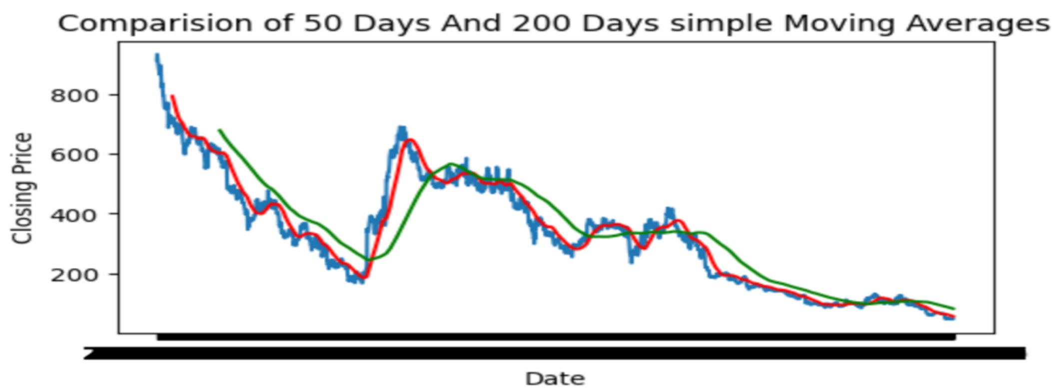

Figure 3shows comparision of simple moving average for 50 and 200 days for Netflix

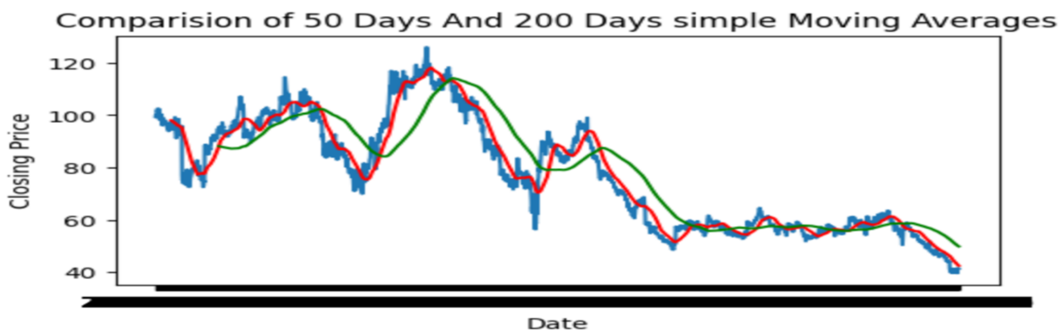

Figure 4shows comparision of simple moving average for 50 and 200 days for starbucks

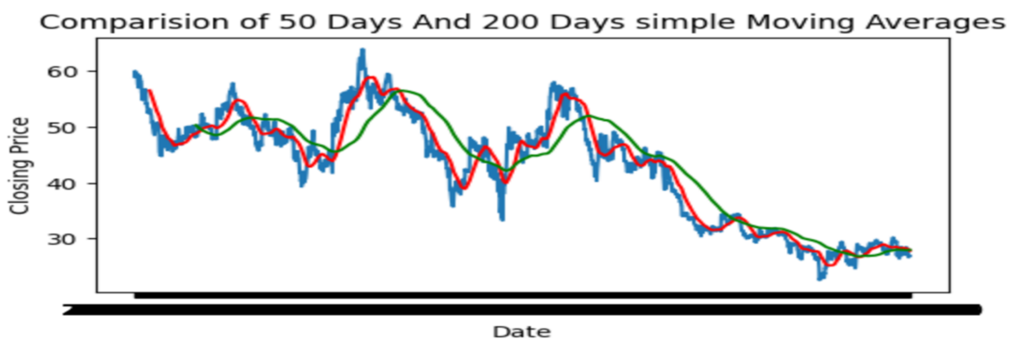

Figure 5 shows comparision of simple moving average for 50 and 200 days for cisco

2.3.2 Exponential moving averages:

The Exponential Moving Average (EMA) is known for its ability to emphasize recent price data while smoothing out fluctuations. Unlike the Simple Moving Average (SMA), the EMA assigns exponentially greater weight to the most recent prices, making it more responsive to current market trends. This responsiveness makes it particularly useful for identifying short-term price movements and trends. Traders often use EMA crossovers as signals; for example, when a shorter-term EMA crosses above a longer-term EMA, it indicates a bullish trend, while the reverse signals a bearish trend (Achelis, 2000).

EMA_n is defined by equation:-

$$EMA_n = \frac{2}{n+1} p_n + \frac{n-1}{n+1} EMA_{N-1}$$

This average is used in golden cross strategy and to find MACD indicator given below:

2.3.3 Golden Cross Strategy:-

Based on moving averages, the Golden Cross approach is a well-liked trading technique that indicates a possible trend reversal from bearish to bullish. When a 50-day or 200-day moving average passes above a shorter-term moving average, it happens. Indicating the start of an upward trend, this crossover is regarded as a bullish sign. A bearish trend is indicated by the Death Cross, the opposite event, which happens when the shorter-term moving average crosses below the longer-term moving average.Because of its ease of use and ability to accurately spot significant trend changes, the Golden Cross technique is popular among traders of all skill levels. Clearer insights into long-term trends are provided by removing short-term market noise. It can also be utilized with other technical indications as a trustworthy confirmation tool (Achelis, 2000).

Graphs for buy and sell indicators for different companies, red marker shows sell and green marker show buy .

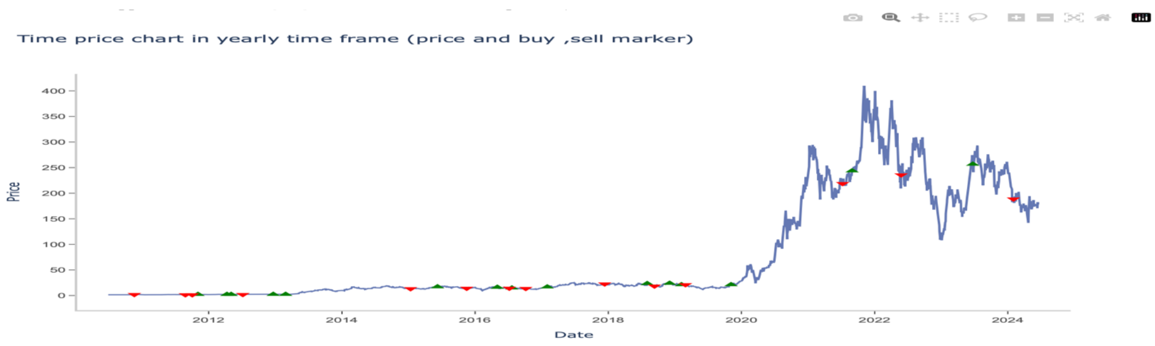

Figure 6 shows buy and sell marker founded by golden cross strategy by using exponential moving averages

Figure 7show buy and sell marker for APPLE

Figure8 show buy and sell marker for Netflix

Figure 9 shows buy and sell marker for cisco.

Figure 10 shows buy and sell marker for starbucks

But the tactic has drawbacks as well. Since it responds to price changes after they happen, it is a lagging indicator, which could result in delays in the creation of signals. This may cause trades to be entered or exited later than planned, which could lower profitability. The Golden Cross may also generate erroneous signals in erratic or sideways markets, which could result in losses or pointless trades. Therefore, even though it works well in markets that are trending, the strategy needs to be carefully implemented and validated through backtesting (Achelis, 2000).

2.3.4 MCAD(Moving Average Convergence/Divergence):-

In trading, the MACD is a popular and adaptable technical indicator. By calculating the correlation between two exponential moving averages (EMAs) of a security's price, it offers information about momentum and trends (Investopedia, 2024).
MACD LINE:
When the short-term price average is higher than the long-term price average, a positive MACD Line (above zero) indicates bullish momentum.
When short-term prices are below long-term prices, a negative MACD Line (below zero) denotes bearish momentum.

MACD LINE = $EMA_{12} - EMA_{26}$
EMA_{12} :12 day exponential moving average(fast)
EMA_{26}: 26 day exponential moving average(slow)

Signal line:
The MACD Line creates a bullish signal (buy opportunity) when it crosses over the Signal Line.
A negative signal (a chance to sell) is produced when the MACD Line crosses below the Signal Line.

Signal Line=9-day EMA of MACD Line
Macd histogram:
illustrates the direction and magnitude of momentum.
Bullish momentum is suggested when the MACD Line is above the Signal Line, as shown by a positive histogram (bars above zero).
Indicating bearish momentum, a negative histogram (bars below zero) shows the MACD Line is below the Signal Line.
The strength of the momentum is shown by the bars' sizes.
Strengthening trend: increasing bar size.
Bar size decline: Possible reversal or waning trend.

Histogram=MACD Line−Signal Line
The histogram visualizes the strength and direction of momentum.
This is the graph shows MACD lines(only one company(NETFLIX)).

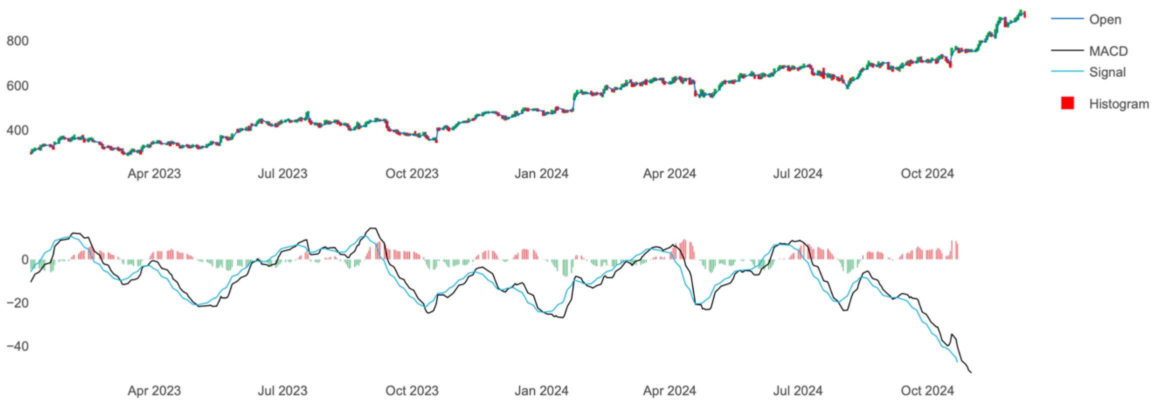

Figure 11 shows MACD lines for NETFLIX stock data

2.3.5 BBANDS(Bollinger bands):

Developed by John Bollinger, the Bollinger Bands (BBands) are a popular technical analysis technique used to evaluate market volatility, spot trends, and predict possible price reversals. Their three parts are the Middle Band, the Upper Band, and the Lower Band, and they are all plotted around the price of a security (Investopedia, 2024). An SMA over a predetermined number of periods—usually 20—is used to compute the Middle Band (Investopedia, 2024). For the Middle Band, the formula is:

$$mid\ band = SMA_n$$

The upper band is derived by adding a multiple of standard deviation to the middle band:

$$upper\ band = mid\ band + (k \times standard\ deviation)$$

Similarly, the lowe band is calculated by subtracting the same multiple of the standard deviation from the middle band:

$$lower\ band = mid\ band - (k \times standard\ deviation)$$

Here k is the multiplier, often set to 2, to reflect a confidence level of approximately 95% for price movements with the band.

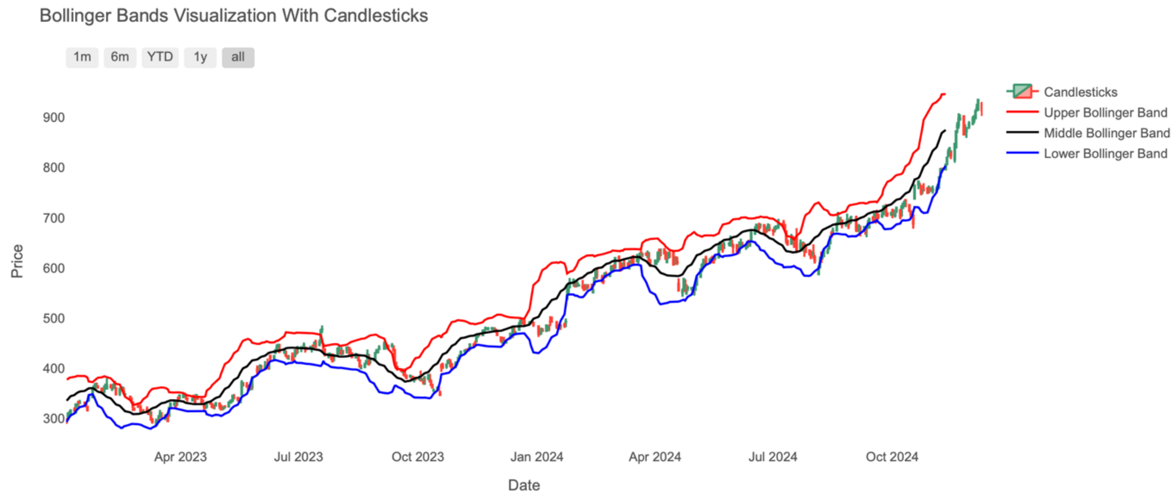

Figure 7 shows bollinger bands for NETFLIX stock data

Bollinger Bands actively react to changes in price, contracting during low volatility and expanding during high volatility. They assist traders in identifying trend direction and evaluating overbought or oversold conditions. A possible reversal or pullback may be indicated by overbought conditions when prices touch or cross the Upper Band. On the other hand, if prices approach or drop below the Lower Band, it can indicate oversold circumstances and a possible recovery. Strong rising momentum is indicated by prices that regularly hug the Upper Band, and a strong downward trend is indicated by movement along the Lower Band.

By using the "squeeze" method, where contracting bands suggest less volatility and the possibility of a significant price movement, Bollinger Bands can also be used to signal breakout chances. Although adaptable and useful for a range of asset classes and time periods (Investopedia, 2024).
Bollinger Bands can also be used to identify breakout chances by using the "squeeze" approach, in which contracting bands suggest less volatility and the possibility of a significant price change. They are not without restrictions, while being adaptable and relevant to many asset classes and time periods. As a lagging indicator based on historical data, Bollinger Bands may produce false signals in trending markets since overbought or oversold indications can last for a long time (Achelis, 2000).

2.4 FUNDAMENTAL ANALYSIS:

Stock analysts employ fundamental analysis, a crucial technique, to assess both internal and external elements, including financial performance, operational effectiveness, strategic objectives, and the overall state of the economy, in order to ascertain the inherent worth of a company's stock. This method seeks to forecast the company's future profitability, which is then contrasted with the stock's present market price to enable traders to make well-informed choices.The stock is categorized as a buy if its intrinsic value is greater than the market price, and as a sell if it is lower. The facts and assumptions employed, such as competition performance, industry trends, and business financial records, determine how accurate the study is (Krantz, 2016).

A number of stock valuation techniques can be further classified under fundamental analysis, such as Price Multiples, which use ratios like price-to-book value or price-to-earnings to assess a stock's value, and Dividend Discount Models (DDM), which base a stock's value on anticipated future dividends. The Residual Income Model (RI), which evaluates a company's value by comparing its book value and earnings per share, and the Discounted Cash Flow (DCF) model, which concentrates on the company's capacity to produce future cash flows, are further techniques. With consideration for both company-specific elements and the larger economic environment, these techniques offer a thorough means of assessing a company's financial standing and competitive position (Wafi, (2015a)).

3 METHODOLOGY:-

3.1 DATA COLLECTION

Three financial websites—Yahoo Finance, NASDAQ, and MarketWatch—provided the dataset for this investigation (MarketWatch, 2024) (NASDAQ, (2024)) (Finance, (2024)). It offers historical stock price data for Tesla, Inc. (TSLA) over a 14-year period, from June 29, 2010, to June 14, 2024. The six essential columns of the dataset—Open, High, Low, Close, Adjusted Close, and Volume—provide a thorough overview of Tesla's historical market performance. The dataset for other companies, which includes five important columns—Open, High, Low, Close, and Volume—also covers 2024 for other businesses (2516, 5).
With no duplicate records, negative values, or missing entries, the data is accurate and tidy. Outliers, on the other hand, draw attention to instances of notable market volatility or anomalous trading behaviour. Unbalanced trading volumes are another feature of the dataset that reflects changes in market interest and activity levels over time (Achelis, 2000). This comprehensive and well-organized dataset provides a strong basis for machine learning and statistical analysis.

3.2 DATA PREPROCESSIING AND FEAUTRE ENGINEERING

Initially, the dataset, data, was converted to a float32 type in order to improve computing performance and optimize storage. After that, in order to better match with time-series analysis, the date column was transformed into the index using the Year-Month-Date format (2020-12-20, for example). Since it was unnecessary for the intended analysis, the extra column called Adjusted Close that was included in Tesla's stock data was eliminated. Standardized column names were also used for uniformity and convenience.
The MinMaxScaler from sklearn.preprocessing was used to normalize the data within a range of 0 to 1 in order to get the features ready for modeling (Achelis, 2000). This scaling stage is essential, especially for algorithms like neural networks that depend on gradient-based optimization or distance measures. All variables are put on a same scale by rescaling the features, which stops features with wider ranges from controlling the learning process. To prevent data leaking and guarantee that the test set is not viewed during training, the scaler was applied independently to the training and testing datasets. To preserve the integrity and dependability of the test set, the scaler was only fitted to the training data before being applied to both datasets (Finance, (2024)).

Next, the dataset is split into training and test sets using a function `split_data()`. The function takes in the entire dataset and a test size percentage (30% in this case) to divide the data into two parts: the training set and the test set. The training set contains 70% of the data, used to train the model, while the test set contains the remaining 30% and is used for model evaluation. This splitting ensures that the model is exposed to a representative portion of the data during training, while the test set serves as an unbiased evaluator to gauge model performance on unseen data.

After the split, the training and test sets are then transformed using the `MinMaxScaler` to normalize the values between 0 and 1, as discussed earlier.

The next step, which involves creating features for time-series prediction using a lookback approach, prepares the data for sequence-based models (like LSTMs), where the previous 'lookback' number of days are used to predict the next day's stock price. This is done by taking a sliding window over the data and storing the previous `lookback` days as the input (X) and the current day's price as the output (Y).

```
# Create features and labels
  def create_features(data, lookback):
    X, Y = [], []
    for i in range(lookback, len(data)):
      X.append(data[i - lookback:i, 0])
      Y.append(data[i, 0])
    return np.array(X), np.array(Y)
```

The final result is two arrays: X_train, y_train for the training data and X_test, y_test for the test data. These arrays are reshaped to fit the input format expected by machine learning models, where each feature set is represented as a 3D array with the shape `(samples, timesteps, features)`.

3.3 STOCK PRICE AS A TIME SERIES DATA

Finding recurrent patterns in time series data that might guide forecasting models is made possible by the seasonality test (Hyndman, 2018). In order to make sure that the residuals in regression models are independent and necessary for accurate predictions, the Durbin-Watson test evaluates autocorrelation (Durbin, (1951)). A crucial premise for many time series models is stationarity, which is checked for by the Augmented Dickey-Fuller test to guarantee steady statistical characteristics throughout time (Dickey, 1979). Resolving stationarity, autocorrelation, and seasonality guarantees more reliable and accurate model performance.

3.3.1 SEASONALITY TEST:-

The term "seasonality" describes regular, recurring variations in time series data that are frequently brought on by seasonal elements like the weather, holidays, or yearly events. Accurate forecasting requires the ability to recognize seasonality since these patterns can offer important clues about anticipated future trends (Hyndman, 2018). The majority of financial data, including stock prices, display seasonal tendencies, which are usually reflected in annual or quarterly cycles and show spikes or fluctuations at particular intervals (Chatfield, (2016)).

The `statsmodels` library's seasonal_decompose function is used to extract seasonality from time series data. The time series is divided into three parts by this function: trend, seasonal, and residual (noise). Depending on the type of input, it can manage both multiplicative and additive models (Seabold, n.d.). A multiplicative model breaks down the time series into:

$$Y(t) = T(t) \times S(t) \times E(t)$$

Y(t) is time series at time t
T(t) is the trend component
S(t) is the seasonality component
E(t) is the residual component.

Graph which shows seasonality in data for Netflix stock data, though the seasonality trend is similar in each company's data.

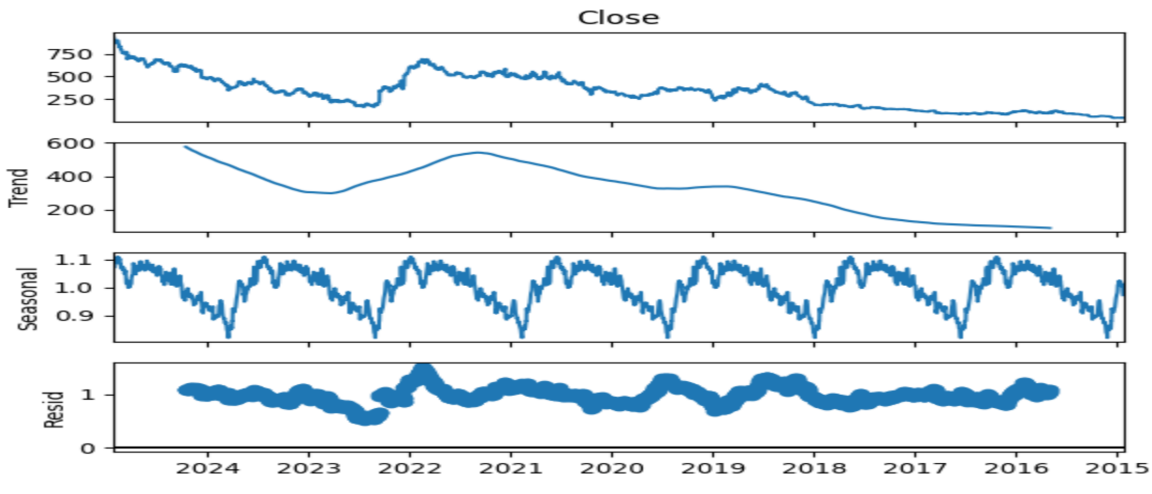

Figure 8 shows seasonal,resid and trend of stock company data(NETFLIX)

Seasonal Decomposition Advantages:
1. Recognizing Patterns: This improves forecasting by assisting in the identification of recurring patterns or cycles in data.
2. Better Forecasting: Forecasting models are more accurate when seasonal influences, trends, and noise are separated.
3. Noise Reduction: By separating noise, the decomposition makes it possible to analyze seasonality and underlying trends more clearly without being distracted by erratic variations.
4. Improved Data Preparation: Model performance can be enhanced by adjusting or deseasonalizing data for additional analysis based on the identification of seasonal patterns.

The stock prices of every company that was examined—including Apple, Netflix, Starbucks, Cisco, and Tesla—show seasonal tendencies. The yearly occurrence of recurrent spikes or variations usually indicates the seasonal patterns, which are probably a reflection of the overall market cycles, the state of the economy, and particular incidents pertaining to each organization.

3.3.2 AUTOCOREREALTION TEST(DURBIN WATSON TEST)

A statistical technique for identifying autocorrelation in regression model residuals is the Durbin-Watson (DW) test. When the residuals (errors) in a time series exhibit recurring patterns across time but are not independent, this is known as autocorrelation. Because it has the potential to compromise the assumptions of numerous time series models, it is imperative to recognize this (Durbin, (1951)). The following formula is used in the exam to determine the DW statistic:

$$DW = \frac{\sum_{t=2}^{n}(e_t - e_{t-1})^2}{\sum_{t=1}^{n} e_t^2}$$

Where e_t represents the residual at time t and n is the number of observations. DW values normally fall between 0 and 4, with values close to 2 signifying no autocorrelation. Positive autocorrelation is indicated by values less than 2, and negative autocorrelation is shown by values more than 2. Strong positive autocorrelation is indicated by a number near zero, and strong negative autocorrelation is indicated by a value around four.

All of the firms' Durbin-Watson (DW) test findings reveal low DW values, which imply a substantial presence of positive autocorrelation in their stock data. The residuals for Tesla (0.00547), Apple (0.00898), Netflix (0.00713), Starbucks (0.01261), and Cisco (0.01387) show significant reliance over time, which goes against the error independence assumption. This implies that past mistakes affect future forecasts, which could cause biases and inefficiencies in the models. Autocorrelation can make forecasting less accurate, so it's important to handle it by employing models that take autocorrelation into account (like ARIMA) or by adding lag variables (Durbin, (1951)).

3.3.3 STATIONARITY TEST(AUGMNETED DICKEY FULLER TEST)

A statistical test called the Augmented Dickey-Fuller (ADF) test is used to determine whether a time series is stationary, which is a critical premise for many time series models, including ARIMA. In the ADF test, the alternative hypothesis states that the series is stationary, whereas the null hypothesis contends that the series has a unit root, indicating that it is non-stationary (Dickey, (1979)). The following formula is used by the ADF test to check for stationarity:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \emptyset_i \Delta y_{t-i} + \epsilon_t$$

Δy_t is the difference in time series at time t
α is a constant
β_t is the deterministic term
y_{t-1} is the lagged term
$\emptyset_i$ represents the coefficients of the lagged differences
ϵ_t is the error term

All of the companies—Apple, Netflix, Starbucks, Cisco, and Tesla—have non-stationary time series, according to the results of the Augmented Dickey-Fuller (ADF) test. The ADF statistic of -1.300495 and the p-value of 0.628946 for Tesla indicate that the series is non-stationary and that the null hypothesis of a unit root cannot be discarded. With a p-value of 0.326897 and an ADF statistic of -1.911015, Apple likewise shows non-stationarity and the null hypothesis is supported. As their p-values are all higher than 0.05 and their ADF statistics are above the crucial values, the same conclusion holds true for Netflix (ADF statistic: -2.043766, p-value: 0.267719), Starbucks (ADF statistic: -1.128719, p-value: 0.703484), and Cisco (ADF statistic: -1.612173, p-value: 0.476835).

When time series models are used directly, non-stationary data can result in inaccurate forecasts and inefficient models. Given that many time series models rely heavily on the assumption of stationarity, the non-stationary character of these series necessitates preprocessing techniques like differencing or transformation in order to prepare the data for precise forecasting.

3.4 OVERVIEW OF MACHINE LEARNING MODELS AND LSTM

Various machine learning models, ranging from basic linear models to more intricate tree-based, boosting, and support vector machine techniques, each have unique advantages dependent on the intricacy and properties of the data.
1. Linear Models:
Linear models make predictions based on linear relationships between the features and the target. They tend to perform well when the relationship between variables is approximately linear (Hastie, (2009)).
LinearRegression: This model predicts a continuous target variable by using ordinary least squares (OLS) regression. Simple and easy to understand, it makes the assumption that the features and the target have a linear relationship.
ElasticNet: An L1 (Lasso) and L2 (Ridge) penalty-based regularized linear regression model. When several features have a high degree of correlation or you require a model that is less likely to overfit than standard linear regression, ElasticNet can be helpful (Hastie, (2009)).
Ridge: L2 regularization is a feature of this linear regression model. Multicollinearity can be managed by including a penalty to the coefficients of the model, encouraging them to be small.
2. Tree-based Models: By dividing the data according to feature values, tree-based models provide predictive models with a structure like a tree. They can record intricate correlations between factors and are adaptable.

DecisionTree: This model uses feature values to divide the data into subgroups and then uses the average value of each subgroup to create predictions. Although decision trees are simple to understand, if they are not pruned, they may overfit.
Random Forest: A collection of decision trees that reduces overfitting and increases accuracy by combining predictions from numerous distinct trees. Random forests have a strong generalization tendency (Breiman, 2001).
Extra Trees: Like Random Forest, but with greater randomization in the construction of each individual tree. In certain situations, they can be more effective and are less likely to overfit.

3. Boosting and Bagging Models: By using boosting, which gives harder-to-predict data points more weight, or bagging, which aggregates predictions from several models, these models combine several weaker models to create a strong learner.

AdaBoost is a boosting technique that builds a powerful predictive model by combining multiple weak models, typically decision trees. It focuses on more difficult-to-predict cases by redistributing the weight of observations that were incorrectly classified by earlier models.
CatBoost: An effective gradient boosting method made for categorical features. Compared to conventional boosting techniques, it minimizes overfitting and is renowned for its precision and quickness (Prokhorenkova, (2018)).

4. Support Vector Machines (SVM): These supervised learning models are employed for tasks involving regression and classification. They look for the hyperplane that best divides the data into classes, or in regression, they look for a hyperplane that fits the data with the least amount of error (Cortes, (1995)).

One kind of SVM used for regression problems is called Support Vector Regression (SVR). The optimal hyperplane that minimizes the error within a certain margin is what SVR attempts to fit. It has great ability to capture intricate, non-linear correlations in data.
5. K-Nearest Neighbours (KNN): KNN is a non-parametric technique that uses the average or majority of the K-nearest neighbors to predict the desired value. This straightforward and easy-to-understand approach is frequently applied to challenges involving regression or classification.

The KNN (K-Nearest Neighbors) regressor averages the target values of the K nearest neighbors to predict the target. It saves the whole training dataset and provides predictions by looking at nearby points rather than requiring the construction of a model (Cover, n.d.).
6. Bayesian Models: Bayes' theorem is used in Bayesian models to estimate the distribution of parameters. By taking into account past knowledge and prediction uncertainty, they provide a probabilistic approach to regression.

Bayesian Ridge: The distribution of the model coefficients is estimated using Bayesian inference in this regression model. It is helpful when regularization is required or when the model parameters are unclear (Cover, 1967).
Parameterization Overview:
Each model has unique hyperparameters, such as the number of neighbors in KNN, depth and learning rate in CatBoost, or the regularization parameters in ElasticNet and Ridge, which significantly impact performance (James, Witten, Hastie, & Tibshirani, 2013). Fine-tuning these hyperparameters is essential for optimizing model accuracy, as each model’s effectiveness depends on the nature of the data.
The model's performance is affected by parameters such as the number of trees, their depth, and the minimum samples needed for node splitting in Random Forest and Extra Trees.
In conclusion, these models provide a wide range of instruments for solving regression issues, ranging from straightforward linear models to intricate ensemble techniques. For capturing intricate interactions, tree-based models (like Random Forest and Extra Trees) and boosting models (like AdaBoost and CatBoost) are effective. Simpler models, such as Ridge and KNN, on the other hand, offer efficiency and interpretability, particularly for less complicated data. Performance optimization requires fine-tuning hyperparameters, and each model has unique advantages based on the type of data.

3.5 PERFORMANCE METRICS

To evaluate different models, **Mean Absolute Error (MAE)**, **Root Mean Squared Error (RMSE)**, and **R² (Coefficient of Determination)** are used . (Medium.com, (2020))
A statistic called Mean Absolute Error (MAE) calculates the average magnitude of prediction mistakes without taking direction into account. It is computed using the following formula:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

y_i is actual value and $\hat{y}_i$is the predicted value, n is the number of data points.
In terms of average prediction error, a model with a lower MAE is more accurate.
The square root of the average squared discrepancies between expected and actual values is measured by the Root Mean Squared Error, or RMSE. This equation is:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Because the differences are squared, RMSE assigns greater weight to larger mistakes. A lower RMSE suggests that there are less significant errors and that the model's predictions are more in line with the actual values (Medium.com, (2020)).

The coefficient of determination, or R2, describes the percentage of the target variable's volatility that can be predicted based on the input features. For R2, the formula is:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

Where $\bar{y}$ is the mean of the actual values. Perfect predictions are indicated by an R2 value of 1, but low predictive power is indicated by values near 0.

4 RESULT AND ANALYSIS:-

4.1 TOP MODEL ACROSS ALL STOCKS:-

With low MAE, RMSE, and strong R2 values, Bayesian Ridge and Ridge frequently perform well on all datasets. For all the stocks examined, these models are dependable, demonstrating high predicted accuracy and the capacity to capture stock price volatility.

The efficacy of linear regression in stock prediction is demonstrated by the fact that it frequently performs comparably to Bayesian Ridge and Ridge, especially for Apple, Starbucks, and Cisco.

All stocks show good performance from Random Forest, but Cisco stands out due to its high R2, which suggests that it can account for a sizable amount of the variation in stock prices.

LSTM is a strong technique for stock prediction using time-series data, even though it isn't always the best performer in terms of R2; it is especially good at identifying time-dependent patterns for Apple and Tesla.

4.2 STRONG PROFORMERS:-

Models like Ridge, CatBoost, and Bayesian Ridge all produce outstanding results for Apple, with high R2 values of 0.99 or above, demonstrating significant predictive potential.

The effectiveness of Bayesian Ridge, Linear Regression, and Ridge to capture the volatility in Starbucks' stock is demonstrated by their high R2 values, which are near 0.98.

With the lowest MAE and RMSE and a high R2 (0.9182), LSTM stands out among the others for Tesla's great time-series prediction capabilities.

4.3 POOR PERFORMERS:-

With negative R2 scores for Tesla and Starbucks and a very low R2 for Cisco, ElasticNet routinely performs poorly across all stocks, underscoring its inability to adequately capture the relationships in stock prices.

4.4 TRENDS AND OBSERVATION:-

The capacity of LSTM can recognize sequential patterns helps it perform remarkably well with time-dependent data, such as Tesla. Nonetheless, Bayesian Ridge and Ridge marginally beat other equities such as Apple, Starbucks, and Cisco in terms of R2, indicating that simpler linear models work well when temporal dependency is less important.
In situations where it can properly simulate complicated relationships, CatBoost performs well for Apple and Starbucks, but it isn't always the best option.
In many situations, KNN, AdaBoost, and SVR perform competitively, but they typically lag behind the best models, such as Bayesian Ridge and Ridge.

5 EXPERIMENTAL SETUP:-

5.1 SOFTWARE AND TOOLS USED

The experiment processes, examines, and displays data for stock prediction models using a range of tools and libraries. Python is the main programming language used, along with necessary libraries like matplotlib and seaborn for data visualization, pandas for managing dataframes, and NumPy for numerical calculations. Plotly is used to create sophisticated visualizations such as candlestick graphs. Regression models and performance evaluation measures are among the crucial tools for machine learning algorithms that Scikit-learn offers. Additional libraries include statsmodels for statistical modeling and time series analysis, backtrader for financial indicators, and CatBoost, XGBoost, and Keras for deep learning tasks (Python Software Foundation, n.d., p. 2024).

5.2 DATASET DESCRIPTION

For this project, historical stock prices from firms such as Tesla, Apple, Netflix, Starbucks, and Cisco comprise the dataset. Open, Close, High, Low, Volume, and Date are some of the attributes found in these datasets. For use in prediction models, the data is preprocessed after being gathered from open sources such as Yahoo Finance (Finance, (2024)). The length of the data—many years—allows for the training of models that can identify stock price trends and seasonalities. Frequently, the data is divided into training and testing datasets in order to assess the models' performance.

5.3 TYPICAL INPUTS

Historical stock price data is frequently utilized as an input for the models, which employ variables like Open, Close, High, Low, and Volume to forecast future stock prices or price movements. For improved feature extraction, pandas_ta is occasionally used to compute additional financial indicators such as Bollinger Bands, Moving Averages (MA), and MACD (Investopedia, 2024). In order to standardize the data and enhance model performance, the inputs are preprocessed using methods such as MinMaxScaler.

5.4 MODEL HYPERPARAMETER TUNING

Using methods like RandomizedSearchCV, hyperparameter tuning is done to maximize the performance of machine learning models. In order to maximize the R2 value and decrease error metrics like MAE and RMSE, these techniques look for the optimal set of hyperparameters (Medium.com, (2020)). For instance, hyperparameters like n_estimators, learning_rate, max_depth, and subsample are adjusted to attain optimal performance in models like Random Forest, CatBoost, and XGBoost. LSTM models optimize time-series prediction accuracy by adjusting hyperparameters such as batch size, layers, and number of epochs.

5.5 TRAINING AND TESTING FRAMEWORK

The dataset is separated into training and testing sets in order to assess the models' performance. The machine learning algorithms are trained on the training set, and the models' ability to generalize to new data is assessed on the testing set. To separate the data, common methods like scikit-learn's train_test_split are employed. When performance on the validation set stops improving, an early stopping callback stops training, preventing overfitting in deep learning models such as LSTM. In order to make sure that the model works well across various data subsets and to provide a more reliable assessment of model performance, cross-validation techniques are used. Additionally, strategies using a variety of financial indicators are implemented and tested using backtrader (Python Software Foundation, n.d.).

6 APPLICATION AND IMPLICATIONS:-

6.1 PRACTICAL USE CASES

In the financial markets, stock prediction models, like the ones employed in this experiment, have a number of useful applications. By using these models, traders, investors, and financial analysts can forecast future stock movements and get insight into possible buy or sell opportunities. Furthermore, companies can utilize these models to assess risks, predict market trends, and improve their investment plans. Financial institutions can also use stock prediction models to improve portfolio management efficiency or for automated trading systems, which helps them make better decisions in real-time market situations (Lo, 2017).

6.2 APPLICATIIN IN INVESTMENT DECISION-MAKING

Stock prediction models provide data-driven insights that assist investors reduce risks and optimize returns, making them extremely valuable tools for investment decision-making. Investors can make well-informed decisions on when to buy, hold, or sell assets by using these models to forecast changes in stock prices. By recommending stocks to buy based on volatility, historical trends, and anticipated patterns, these models can also help optimize portfolios. By ensuring that these choices are supported by solid data analysis, machine learning and statistical methods enhance the results of investments (Clarke, et al., n.d.).

6.3 LIMITATIONS AND CHALLENGES

Stock prediction models have drawbacks and difficulties even if they can provide insightful information. The intrinsic unpredictability and volatility of financial markets is a major problem that can reduce the accuracy of forecasts, particularly in the short term. Inaccurate forecasts can result from models that are either overfit or underfit if they are not appropriately adjusted. Furthermore, it is challenging for any model to take into account elements like market mood, outside economic considerations, or unanticipated world events, all of which can have a significant impact on stock prices. Additionally, the accuracy of the model may be impacted by the quantity and calibre of historical data, and it may be difficult to convert model forecasts into practical investment plans (Urquhart, 2013) (Shonkwiler, 2013).

7 CONCLUSIONS:-

7.1 SUMMARY OF FINDINGS

LSTM, Bayesian Ridge, Random Forest, and other machine learning models for stock price prediction were assessed in this study. According to the findings, models such as LSTM, Bayesian Ridge, and Ridge consistently produced high R2 values and low error metrics while performing remarkably well across a variety of equities. It was discovered that these models could effectively explain variance in the stock data and capture changes in stock prices. However, models such as ElasticNet performed poorly, particularly when their R2 values were negative, demonstrating their incapacity to accurately predict stock changes. In order to maximize stock price forecasts, the study emphasized the significance of model selection and hyperparameter adjustment.

7.2 CONTRIBUTION OF THE STUDY

This paper offers a comparative comparison of different machine learning models, which adds to the expanding body of research on stock market prediction. It shows how sophisticated models such as LSTM and Bayesian Ridge may effectively predict stock price patterns, offering financial experts and investors insightful information. Additionally, the study highlights the difficulties in predicting the stock market and the significance of model selection, evaluation, and tuning. The results of the study can be applied by both industry experts and scholarly scholars involved in financial data analytics, helping to create more accurate forecasting instruments (Python Software Foundation, n.d.) (Lo, 2017).

7.3 FUTURE RESEARCH DIRECTIONS

Future studies on stock market prediction might examine how to incorporate more complex models, like hybrid strategies that combine conventional machine learning algorithms with deep learning. Further improving model accuracy may involve examining the impact of external variables like macroeconomic conditions, market sentiment, and geopolitical events. Future research on the application of transfer learning and reinforcement learning to adjust to shifting market conditions is also quite intriguing. In order to give investors additional insight into the decision-making process and assist them in making more transparent and well-informed investment decisions, future research can also concentrate on enhancing the interpretability of the model (White, 1988).

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