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Auto-ML Stock Prediction: A Rule based Model Approach to Forecast the Bull and Bearish Markets in Different Sectors

Subhasis Patra[1*] Snehadhanya Dutta[2]

[1*]Dean's Associate, Teaching Fellow, Information Management & Analytics SP Jain Institute of Management & Research Mumbai - 400 058, India
[2]Lecturer, Dept. of Computer Science, Srikrishna College, Bagula, Nadia, West Bengal – 741502, India

***Corresponding author**: Subhasis Patra
Dean's Associate, Teaching Fellow, Information Management & Analytics SP Jain Institute of Management & Research Mumbai - 400 058, India

ABSTRACT
In Stock Market Prediction, the main aim to predict the Sector Wise Model Selection to Forecast Based on Bullish & Bearish Condition of Share Market explores the development and implementation of a comprehensive framework for stock price prediction using ARIMA, SARIMA, and LSTM models. Multiple process of attempts to forecast future stock market behaviour, but due to its complexity, accurate predictions remain challenging. Machine learning techniques which have proven effective in this domain.
The primary aim is to forecast stock prices by analysing historical data, identifying trends, and evaluating model performance using various statistical and machine learning approaches. The study incorporates data from selected stocks over different time periods, applying logarithmic transformations and splitting data into training and validation sets to enhance model accuracy. Additionally, the project examines bullish and bearish trends separately to provide more granular insights. Performance metrics such as RMSE, MAPE, and MSLE are used to evaluate and compare model predictions. The results demonstrate the potential of these models in capturing stock price movements and highlight areas for further refinement and integration of more advanced techniques.

Keywords: Ensemble, Bagging, forecasting, Stock market, Auto ML, Bull market, Bear market

1. INTRODUCTION

Predicting the trends in stock market expenses is a completely difficult task due to many uncertainties involved and lots of variables that affect the marketplace value on a particular day including economic conditions, investors' sentiments towards a specific company, political activities, etc. Because of this, inventory markets are at risk of brief changes, inflicting random fluctuations inside the stock rate. Stock market collections are commonly dynamic, nonparametric, chaotic, and noisy. Hence, the stock market rate motion is a random method. Among the different principal methodologies used to predict stock market prices are: 1) Technical Analysis, 2) Time-Series Forecasting, 3) Machine Learning and Data Mining and 4) Modelling and Predicting Volatility of stocks.
The methodology that is discussed in this paper is Sector Wise Model Selection to Forecast Based on Bullish & Bearish Condition of Share Market. This paper aims at proposing a comparison of the prediction different values by utilizing different models. The analysis can be done based on different frameworks. The framework is again consisting of two modules:

- **Weekday Selection**: An algorithmic trading strategy determines the best weekdays for bullish or bearish conditions.
- **Ensemble Model**: Combining an ensemble-based classification module (using the Extra Tree classifier) and an ensemble-based regression module (using the SGD regressor), the framework predicts market trends.

Evaluation results using Nifty-50 indices show an average RMSE value of 0.2091 for the regression model and an accuracy range between 95.65% and 99.59% for the classification model. With this framework, even investors with limited knowledge can minimize losses and maximize profits. Despite the voluminous empirical research on the potential predictability of stock returns, much less attention has been paid to the predictability of bear and bull stock markets.
Based on the analysis of the data set, bear and bull markets are predictable in and out of sample. In particular, substantial additional predictive power can be obtained by allowing for a dynamic structure in the binary response model. Probability forecasts of the state of the stock market can also be utilized to obtain optimal asset allocation decisions between stocks and bonds. It turns out that the dynamic probit models yield much higher portfolio returns than the buy-and-hold trading strategy in a small-scale market timing experiment. A bull market is characterized by rising stock prices and optimistic investor sentiment. Here are some key points about bull markets. A bull market is a period when stock prices consistently rise, indicating a strong economy. The market signifies a sustained period of rising stock prices, reflecting a robust economy. During these phases, investor confidence soars, fueled by the expectation that the upward trend will persist.

Strong economic indicators—such as healthy GDP growth, low unemployment rates, and robust consumer spending—often align with bull markets. These favourable conditions can endure for months or even years, prompting investors to strategically seek opportunities for long-term asset accumulation.
A bear market**,** on the other hand, is characterized by falling stock prices and pessimistic investor sentiment. A bear market is a period of widespread pessimism and declining stock prices, reflecting investors' fears and concerns about the future. During such times, investor sentiment is dominated by apprehension, leading many to sell off assets in an attempt to protect their portfolios from further losses. Bear markets often coincide with economic challenges, such as economic slowdowns, rising unemployment rates, and corporate struggles, which fuel the negative sentiment. These periods can vary in duration, with some being relatively brief while others persist for an extended period. Regardless of their length, bear markets tend to be characterized by heightened volatility, with stock prices exhibiting significant swings. In the face of such conditions, some investors adopt a defensive stance, shifting their investments into cash or more conservative assets like bonds, patiently awaiting signs of recovery and improved market conditions before re-entering riskier investments.
Stock price prediction is a critical task in financial markets, aiming to forecast future price movements based on historical data and various predictive models. Accurate predictions can significantly aid investors in making informed decisions, thereby maximizing profits and minimizing risks. The challenge lies in the inherently volatile and complex nature of financial markets, influenced by numerous factors including economic indicators, market sentiment, and geopolitical events.
This paper implements a framework leveraging ARIMA, SARIMA, and LSTM models to predict stock prices, analyse trends, and evaluate performance. By combining traditional statistical methods with modern machine learning techniques, the framework aims to provide accurate and reliable forecasts.

The framework's significance is highlighted through several key aspects:
1. Enhanced Predictive Accuracy:
- Combination of ARIMA, SARIMA, and LSTM models.
- Aims to improve accuracy by leveraging strengths of both traditional and modern methods.

2. Comprehensive Performance Evaluation:
- Evaluates model performance using RMSE, MAPE, and MSLE metrics.
- Identifies the most effective model for different market conditions.

3. Adaptive Market Analysis:
- Distinguishes between bullish and bearish trends.
- Adapts predictions to varying market conditions, providing nuanced insights.

4. Interactive and User-Friendly Interface:
- Includes widgets for sector, stock, and time range selection.
- Real-time plotting of technical indicators enhances user experience.

5. Data-Driven Decision Making:
- Empowers users with analytical tools for informed investment decisions.
- Reduces reliance on intuition and speculation.

6. Versatility and Scalability:
- Modular design allows for easy updates and scalability.
- Framework can be extended to incorporate additional models or indicators.

In summary, the framework's ability to provide accurate, adaptive, and user-friendly stock price predictions significantly enhances financial analysis and investment decision-making through advanced modelling techniques. By exploring the strengths and limitations of each model, the project aims to identify the most reliable approach for stock price prediction, contributing to financial forecasting and offering practical tools for investors and analysts.

2. LITERATURE REVIEW

Sector analysis plays a crucial role in navigating the complexities of bullish markets, where stock prices are generally rising, and investor sentiment is positive. Understanding the importance of sector analysis in bullish conditions is essential for making informed investment decisions and optimizing forecasting models. Sector rotation analysis is a valuable approach that links the current strengths and weaknesses in the stock market with the general business cycle, allowing investors to identify sectors that are likely to outperform during bullish phases. By focusing on sector-specific factors, investors can gain insights into the dynamics of different industries and select appropriate statistical models for forecasting based on the unique characteristics of each sector.

In bullish market conditions, selecting the most suitable statistical models for forecasting requires a deep evaluation of sector-specific factors and trends. Various statistical models, such as machine learning algorithms, deep learning solutions like Relational Stock Ranking (RSR), and traditional trend analysis techniques, can be employed to predict stock price movements in different sectors. While traditional models heavily rely on indicator selection and trend data analysis, newer approaches like RSR aim to address the limitations of mainstream solutions by offering innovative strategies for stock prediction. Additionally, utilizing the Bry-Boschan algorithm to determine market conditions and predict trends can provide valuable insights for model selection and forecasting in bullish markets.

To enhance the accuracy and effectiveness of forecasting models in bullish market conditions, investors can leverage a combination of historical data, expert insights, and advanced analytical tools. By integrating sector-specific analysis with data-driven models, investors can make more informed decisions regarding stock selection, portfolio optimization, and risk management. Utilizing oscillating indicators to measure stock momentum and provide bullish and bearish signals can further refine forecasting strategies and improve decision-making processes in bullish market environments. By incorporating a multidimensional approach that considers both sector-specific dynamics and statistical model selection, investors can enhance their forecasting capabilities and capitalize on opportunities in bullish market conditions.

Selection of models based on sector analysis in a bearish market

Sector analysis plays a crucial role in navigating bearish markets, providing investors with valuable insights into the performance and trends of specific industries. In a bear market, characterized by declining stock prices and negative investor sentiment, understanding sector dynamics becomes essential for making informed investment decisions. Sector rotation analysis, which evaluates the strengths and weaknesses of different sectors based on the business cycle, can help investors identify opportunities and risks within specific industries. By leveraging sector analysis, investors can strategically position their portfolios to mitigate losses and capitalize on potential upturns in select sectors.

When it comes to selecting forecasting models for bearish market conditions, it is essential to consider the unique characteristics and challenges presented by a downturn in the market. Traditional forecasting models may not perform optimally during periods of market pessimism and heightened volatility. Therefore, incorporating sector-specific variables into forecasting models can enhance accuracy and reliability in predicting stock price movements during bearish phases. For instance, models that utilize sector-specific stock information to forecast economic activity can provide a more nuanced understanding of how different industries may be affected by market downturns, enabling investors to adjust their strategies accordingly.

In the quest for improved forecasting accuracy in bearish market conditions, it is crucial to explore innovative modelling techniques that can adapt to the dynamic nature of the stock market. Leveraging advanced algorithms like long short-term memory (LSTM) neural networks or logistic regression models tailored to predict stock performance can offer valuable insights into market trends and price movements. By incorporating these sophisticated modelling approaches alongside sector-specific variables, investors can gain a comprehensive understanding of the market landscape and make data-driven decisions to navigate the complexities of a bearish market environment effectively.

Comparative analysis of model selection in different sectors during market fluctuations

Performance evaluation of forecasting models in both bullish and bearish market conditions is crucial for effective investment decision-making. In a bullish market, characterized by rising stock prices and positive investor sentiment, forecasting models need to capture the upward trends accurately. Conversely, in a bearish market, where stock prices are falling, models must be able to predict the downward movements to protect investments. The quality of these models is often assessed using metrics such as Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and R-squared value to determine their accuracy and reliability. Researchers have explored various methodologies, including traditional statistical models and newer deep learning approaches like Relational Stock Ranking (RSR) to enhance forecasting capabilities. By comparing the performance of these models in different market conditions, investors can make informed decisions to optimize their portfolio management strategies.

Sector-wise comparison of forecasting accuracy is essential to understand how different industries respond to market fluctuations. Each sector may exhibit unique characteristics and sensitivities to bullish and bearish trends, influencing the effectiveness of forecasting models. For example, a study analysing the stock prices of nine selected companies found that the Long Short-Term Memory (LSTM) model demonstrated superior prediction accuracy in comparison to other models. By tailoring forecasting techniques to specific sectors, researchers can gain insights into the factors driving stock price movements within industries and adjust their models accordingly for more precise predictions. This sector-specific approach enables investors to make sector-weighted investment decisions based on the forecasted market conditions, enhancing portfolio diversification and risk management strategies.

Adjusting forecasting models based on market conditions can lead to enhanced predictions and more accurate investment strategies. By utilizing methods like the Bry-Boschan algorithm to determine market conditions and predict stock price movements, researchers can adapt their models dynamically to changing market sentiments. Additionally, incorporating advanced computational frameworks such as the Long Short-Term Memory (LSTM) model can improve the accuracy of stock index price predictions, especially during volatile market conditions. Trend analysis techniques, including novel deep learning models like Peephole LSTM with TAL (PLSTM-TAL), offer innovative approaches to forecasting future stock price trends based on historical data patterns. By integrating rule-based trading frameworks that consider both market forecasts and optimal trading days, investors can make data-driven decisions to capitalize on bullish trends and mitigate risks during bearish market phases.

3. OBJECTIVE OF THE STUDY

The primary objective of this the proposed model is to develop a robust and versatile tool for predicting stock prices and comparing the performance of different forecasting models. Specifically, the script aims to:

1. Implement Advanced Predictive Models: Utilize three sophisticated forecasting models—ARIMA, SARIMA, and LSTM—to predict stock prices based on historical data.
2. Evaluate Model Performance: Assess the accuracy and reliability of each model using key performance metrics such as RMSE, MAPE, and MSLE.
3. Trend Analysis: Distinguish between bullish and bearish market conditions and evaluate model performance under these different scenarios.
4. Interactive Analysis: Provide an interactive interface for users to select sectors, stocks, and time ranges, and visualize technical indicators to aid in decision-making.
5. Comprehensive Comparison: Compare the results of ARIMA, SARIMA, and LSTM models to identify the most effective model for various market conditions.

5. SIGNIFICANCE OF TECHNICAL INDICATORS

Technical indicators are essential tools used by traders and analysts to interpret stock price movements and predict future trends. They are based on mathematical calculations derived from historical price, volume, and sometimes open interest data. In this framework, several key technical indicators are utilized to provide a comprehensive analysis of stock trends:

Simple Moving Average (SMA):

• **Definition**: The SMA is an arithmetic moving average calculated by adding recent closing prices and then dividing the total by the number of time periods.

The formula for SMA is:

$$\text{SMA} = \frac{A_1 + A_2 + \ldots + A_n}{n}$$

where:

A_n = the price of an asset at period n

n = the number of total periods

• **Usage**: It helps to smooth out price data over a specified period, making it easier to identify the direction of the trend. Short-term SMAs (e.g., 20-day) react faster to price changes than long-term SMAs (e.g., 200-day).

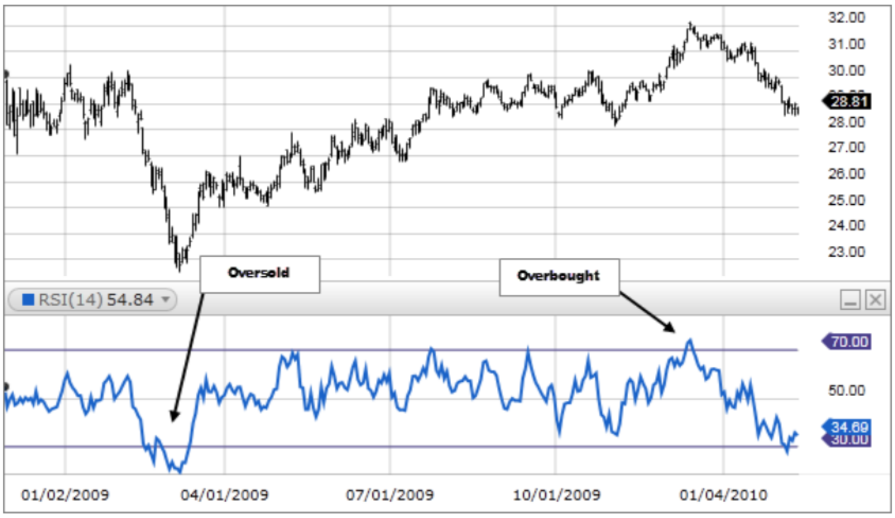
Example

Relative Strength Index (RSI):

- **Definition:** RSI is a momentum oscillator that measures the speed and change of price movements. It ranges from 0 to 100.
- **Usage:** RSI is used to identify overbought or oversold conditions. An RSI above 70 typically indicates that a stock is overbought, while an RSI below 30 suggests that it is oversold.

The RSI uses a two-part calculation that starts with the following formula:

$$RSI_{\text{step one}} = 100 - \left[\frac{100}{1+\frac{\text{Average gain}}{\text{Average loss}}} \right]$$



Example

Fibonacci Retracement:

- **Definition:** Fibonacci Retracement levels are horizontal lines that indicate where support and resistance are likely to occur.

- **Usage:** These levels are based on Fibonacci numbers and are typically used to predict the potential retracement levels of the stock's price movement.

- **Key Levels:** 23.6%, 38.2%, 50%, 61.8%, and 100%

How this indicator works
- The percentage retracements identify possible support or resistance areas, 23.6%, 38.2%, 50%, 61.8%, 100%. Applying these percentages to the difference between the high and low price for the period selected creates a set of price objectives.
- Depending on the direction of the market, up or down, prices will often retrace a significant portion of the previous trend before resuming the move in the original direction.
- These countertrend moves tend to fall into certain parameters, which are often the Fibonacci Retracement levels.

6. FORECASTING MODELS AND METHODS

In this framework, we utilize a combination of traditional statistical methods and modern machine learning techniques to forecast stock prices. Each model has unique strengths, making it suitable for different aspects of time series forecasting:

1. ARIMA (Autoregressive Integrated Moving Average):

- **Definition**: ARIMA is a popular time series forecasting method that combines autoregressive (AR) terms, differencing (I) to make the series stationary, and moving average (MA) terms.
- **Usage**: Suitable for univariate time series data where the data points are dependent on previous values.
- **Components**:
- p: Number of lag observations (autoregressive part)
- d: Number of times the raw observations are differenced (integrated part)
- q: Size of the moving average window

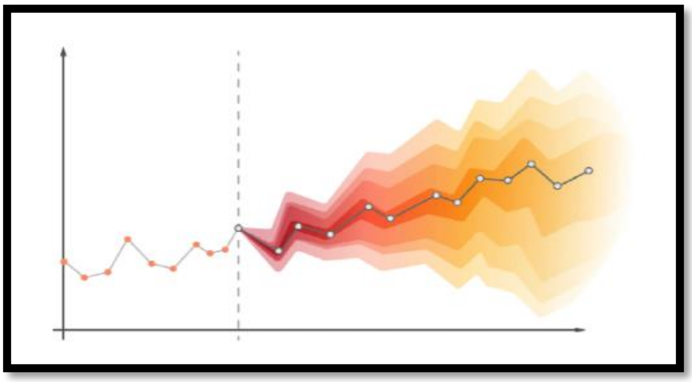


Diagram: ARIMA

ARIMA model is a class of linear models that utilizes historical values to forecast future values. ARIMA stands for Autoregressive Integrated Moving Average, each of which technique contributes to the final forecast.

Autoregressive (AR)

In an autoregression model, we forecast the variable of interest using a linear combination of past values of that variable. The term autoregression indicates that it is a regression of the variable against itself. That is, we use lagged values of the target variable as our input variables to forecast values for the future. An autoregression model of order p will look like:
$m_t = 0 + 1m_t\text{-}1 + 2m_t\text{-}2 + 3m_t\text{-}3 + \ldots + {}_{p}m_{t-p}$
In the above equation, the currently observed value of m is a linear function of its past p values. [0, p] are the regression coefficients that are determined after training. There are some standard methods to determine optimal values of p one of which is, analyzing Autocorrelation and Partial Autocorrelation function plots.
The autocorrelation function (ACF) is the correlation between the current and the past values of the same variable. It also considers the translative effect that values carry over with time apart from a direct effect. For example, prices of oil 2 days ago will affect prices 1 day ago and eventually, today. But the prices of oil 2 days ago might also have an effect on today which ACF measures.
Partial Autocorrelation (PACF) on the other hand measures only the direct correlation between past values and current values. For example, PACF will only measure the effect of prices of oil 2 days ago on today with no translative effect.
ACF and PACF plots help us determine past value dependency which in turn helps us deduce p in AR. Head over here to understand how to deduce values for p (AR), and q(MA) in depth.

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Integrated (I)
Integrated represents any differencing that has to be applied in order to make the data stationary. A dickey-fuller test (code below) can be run on the data to check for stationarity and then experiment with different differencing factors. A differencing factor, d=1 means a lag of i.e.
m_t-m_{t-1}.

Sample Code Example

```
def check_stationarity(ts):
    dftest = adfuller(ts)
    adf = dftest[0]
    pvalue = dftest[1]
    critical_value = dftest[4]['5%']
    if (pvalue < 0.05) and (adf < critical_value):
        print('The series is stationary')
    else:
        print('The series is NOT stationary')
```

Moving Average (MA):
Moving average models uses past forecast errors rather than past values in a regression-like model to forecast future values. A moving average model can be denoted by the following equation:
$m_t = 0 + {}_1e_{t-1} + {}_2e_{t-2} + {}_3e_{t-3} + \ldots + {}_qe_{t-q}$
This is referred as MA(q) model. In the above equation, e is called an error and it represents the random residual deviations between the model and the target variable. Since e can only be determined after fitting the model and since it's a parameter too so in this case e is an unobservable parameter. Hence, to solve the MA equation, iterative techniques like Maximum Likelihood Estimation are used instead of OLS.

2. SARIMA (Seasonal AutoRegressive Integrated Moving Average):
- **Definition**: SARIMA extends ARIMA to support seasonal data by including seasonal autoregressive and moving average terms, along with seasonal differencing.
- **Usage**: Effective for data with seasonal patterns, incorporating both seasonal and non-seasonal elements.
- Components:
- Seasonal p, d, q: Similar to ARIMA but for seasonal component
- Seasonal period s: Number of observations per cycle (e.g., 12 for monthly data)

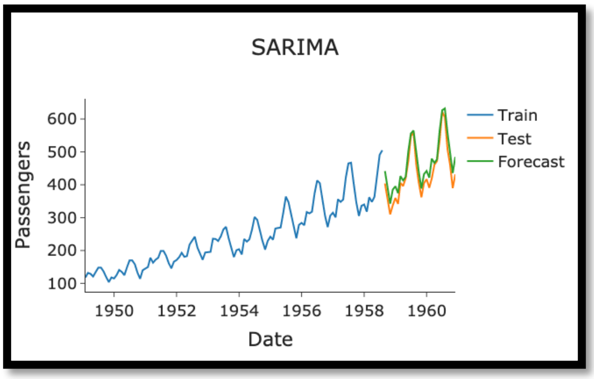

Diagram: SARIMA

3. LSTM (Long Short-Term Memory):
- **Definition**: LSTM is a type of recurrent neural network (RNN) that is capable of learning long-term dependencies, particularly useful for sequential data.
- **Usage**: Effective for capturing complex patterns in time series data, suitable for long-term predictions due to its memory cell structure.
- **Architecture**:
- **Input Gate:** Controls the input to the memory cell.
- **Forget Gate:** Controls the extent to which a value remains in the cell.
- **Output Gate:** Controls the output from the cell to the next hidden state.

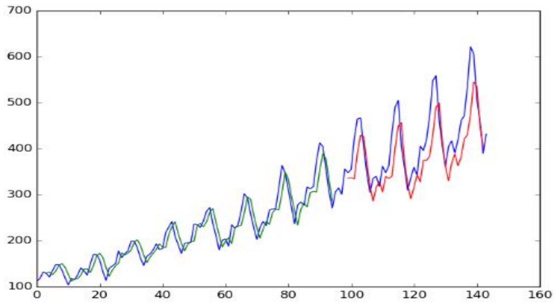

Diagram: LSTM

By integrating these forecasting models, the framework can provide a robust and comprehensive approach to stock price prediction, adapting to various market conditions and ensuring reliable performance for investors and analysts.

7.FLOW OF WORK OF THE PROPOSED SYSTEMS

This structured workflow ensures that the stock price prediction system is comprehensive, accurate, a nd user-friendly, providing valuable insights and predictions for stock market analysis.

1. **Data Fetching and Pre-processing**:
- Fetch historical stock price data for selected stocks and periods from a JSON API.
- Apply data transformations, such as logarithmic scaling, to prepare the data for model training and evaluation.

2. **Technical Indicator Analysis**:
- Calculate and plot key technical indicators, including Simple Moving Averages (SMA), Relative Strength Index (RSI), and Fibonacci retracement levels, to provide additional context for the stock price predictions.

3. Model Implementation:
- **ARIMA Model**: Implement ARIMA for time series forecasting, focusing on non-seasonal data.
- **SARIMA Model**: Extend ARIMA to SARIMA to account for seasonality in stock price data.
- **LSTM Model**: Implement LSTM neural networks to capture complex patterns and dependencies in the data.

4. Performance Evaluation:
- Split data into training and validation sets.
- Train each model on the training set and make predictions on the validation set.
- Calculate RMSE, MAPE, and MSLE to evaluate model performance.

5. Bullish and Bearish Analysis:
- Perform trend analysis to segment data into bullish and bearish periods.
- Apply ARIMA, SARIMA, and LSTM models to these segmented datasets to assess model performance under different market conditions.

6. Comparison and Visualization:
- Compare the performance of ARIMA, SARIMA, and LSTM models across total, bullish, and bearish data.
- Visualize the actual vs. predicted stock prices and the performance metrics to aid in model comparison and selection.

By encompassing these areas, the script provides a comprehensive framework for stock price prediction and model comparison, enabling users to make data-driven investment decisions and gain deeper insights into market behaviour.

CODE AND DATASET

The pseudo code & dataset for performing the analysis for this research is attached to the mentioned link.
Code Link and Data fetch Link
Library function for fetching the data from Yahoo Finance

```
import yfinance as yf
import requests
from tabulate import tabulate
import ipywidgets as widgets
import math
from math import ceil, floor
from tensorflow.keras.models import Sequential
```

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```
from tensorflow.keras.layers import Dense, LSTM
from statsmodels.tools.sm_exceptions import ConvergenceWarning
from statsmodels.tools.sm_exceptions import ValueWarning
from tqdm import tqdm
```

DATASET

This study employs different stock market data to be tested by different classifiers, in order to find the best machine learning algorithm for stock market forecasting based on some specific models. Further, our study focuses on comparing four datasets from different stock market indices, which are as given as per the below mentioned table (Table 1). All stock data were fetched from Yahoo Finance for a specific time span whereas Yahoo Finance is a media that provides stock prices of different companies.

TABLE 1

BFS Sector	**IT Sector**	**Consumer Goods Sector**	**Automobiles Sector**
HDFC Bank Limited	TCS Service Limited	HUL Limited	Maruti Suzuki India Limited
ICICI Bank Limited	Infosys Limited	ITC Limited	Tata Motors Limited
State Bank of India	Wipro Limited	Nestle India Limited	Mahindra & Mahindra Limited
Bajaj Finance Limited	HCL technology Limited	Britannia Industries Limited	Hero MotoCorp Limited
Telecommunications Sector	**Healthcare and Pharmaceuticals Sector**	**Energy Sector**	**Real Estate Sector**
Bharti Airtel Limited	Sun Pharmaceutical Industries Limited	Reliance Industries Limited	DLF Limited
Vodaphone Idea Limited	Dr. Reddy's Laboratories Limited	ONGC Limited	Godrej Properties Limited
Reliance Communication Limited	Cipla Limited	IOCL Corps Limited	Oberoi Reality Limited
Tata Communications Limited	Lupin Limited	GAIL India Limited	Prestige Estates Projects Limited

7.ANALYTICAL FINDINGS (RESULTS)

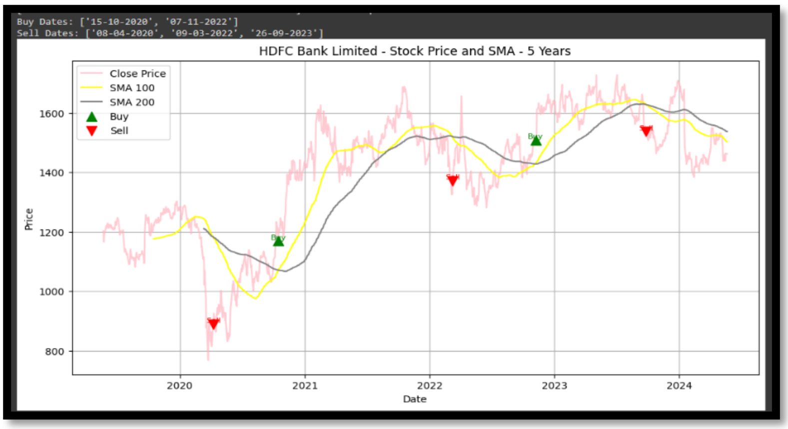
Date	Open	High	Low	Close	Adj Close	Volume
10-05-2024	1439.000000	1451.949951	1426.800049	1437.900024	1437.900024	13638304
13-05-2024	1432.000000	1459.800049	1430.300049	1455.250000	1455.250000	13523601
14-05-2024	1452.250000	1465.500000	1450.300049	1460.949951	1460.949951	12832571
15-05-2024	1459.699951	1459.699951	1435.800049	1438.500000	1438.500000	19465998
16-05-2024	1446.050049	1462.550049	1435.500000	1460.250000	1460.250000	17472618
17-05-2024	1446.199951	1468.000000	1446.199951	1464.099976	1464.099976	10460095
21-05-2024	1450.099976	1469.699951	1450.099976	1462.050049	1462.050049	12536286

OUTPUT 1

Explanation of Output 1

This output provides a detailed view of the historical stock prices of HDFC Bank Limited over a few trading days in May 2024. The interface allows users to select different sectors, stocks, and time ranges, providing flexibility for comprehensive analysis. The presented data includes essential trading metrics such as opening and closing prices, highest and lowest prices of the day, adjusted closing prices, and trading volume, which are crucial for financial analysis and investment decision-making.

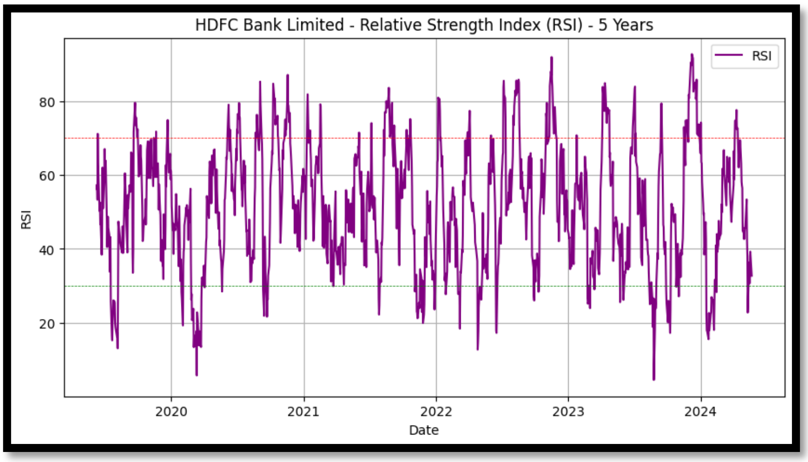
OUTPUT 2



Explanation of OUTPUT 2

The output consists of two main parts: a tabular display and a graphical representation. The tabular data shows historical stock data for HDFC Bank Limited from 10-05-2024 to 21-05-2024, including Open, High, Low, Close, Adjusted Close, and Volume values. The graphical representation is a chart plotting the closing prices over the past five years, augmented with 100-day (yellow) and 200-day (gray) Simple Moving Averages (SMA). The chart includes buy signals on 15-10-2020 and 07-11-2022, and sell signals on 08-04-2020, 09-03-2022, and 26-09-2023. These signals are derived from SMA crossovers, indicating optimal trading times for maximizing investment returns.

OUTPUT 3

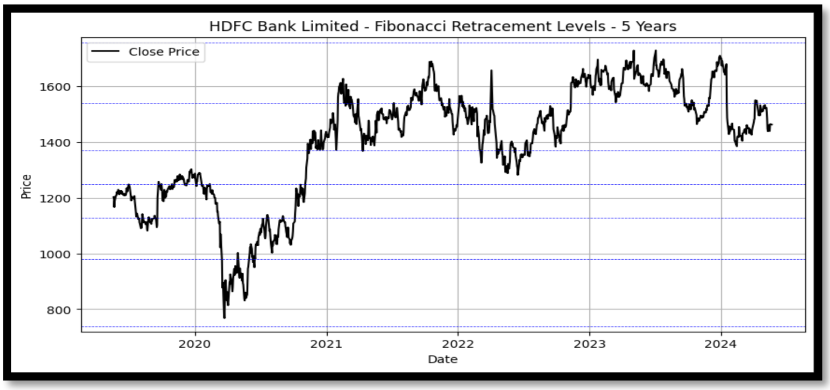


Explanation of OUTPUT 3

The Relative Strength Index (RSI) is a momentum oscillator used in technical analysis to assess the speed and change of price movements. RSI values range from 0 to 100, calculated using average gains and losses over a specified time frame, often 14 days. Higher RSI suggests overbought conditions, indicating potential for price correction, while lower RSI indicates oversold conditions, possibly signalling buying opportunities. Traders use RSI to identify trend reversals, confirm trends, or generate buy/sell signals. Plotting RSI involves looking for divergences, overbought/oversold conditions, and crossovers with key levels like 30 and 70. This summary aids traders in gauging price momentum and formulating trading strategies.

```
Overbought conditions (RSI > 70) identified on the following dates:
['13-06-2019', '20-09-2019', '23-09-2019', '24-09-2019', '25-09-2019', '26-09-2019', '27-09-2019',

Oversold conditions (RSI < 30) identified on the following dates:
['19-07-2019', '22-07-2019', '23-07-2019', '24-07-2019', '25-07-2019', '26-07-2019', '29-07-2019',

Key Fibonacci retracement levels:
Level 1: 738.75
Level 2: 979.175
Level 3: 1127.9125
Level 4: 1248.125
Level 5: 1368.3375
Level 6: 1539.4875000000002
Level 7: 1757.5
```

OUTPUT 4



Explanation of Output 4

Fibonacci retracement is a tool in technical analysis for identifying potential support and resistance levels based on key Fibonacci ratios like 23.6%, 38.2%, 50%, 61.8%, and 100%. Traders use it by selecting significant high and low points in a price movement and drawing horizontal lines at these Fibonacci levels. These lines indicate where price may reverse or consolidate. The 50% level is not a Fibonacci number but is included for its psychological importance. Traders often look for confluence with other indicators or patterns to confirm potential reversal zones. Overall, Fibonacci retracement visually highlights areas of support and resistance in a price trend.

OUTPUT 5

```
-----------------------------------------------------------
---------IMPLEMENTING ARIMA BASED ON TOTAL DATA---------
-----------------------------------------------------------



Shape of Training Set: (1113, 1)
Shape of Validation Set: (123, 1)
Performing stepwise search to minimize aic
 ARIMA(2,1,2)(1,0,1)[12] intercept   : AIC=-5827.432, Time=7.33 sec
 ARIMA(0,1,0)(0,0,0)[12] intercept   : AIC=-5828.779, Time=0.14 sec
 ARIMA(1,1,0)(1,0,0)[12] intercept   : AIC=-5826.535, Time=0.86 sec
 ARIMA(0,1,1)(0,0,1)[12] intercept   : AIC=-5826.753, Time=1.11 sec
 ARIMA(0,1,0)(0,0,0)[12]             : AIC=-5830.632, Time=0.07 sec
 ARIMA(0,1,0)(1,0,0)[12] intercept   : AIC=-5827.265, Time=0.66 sec
 ARIMA(0,1,0)(0,0,1)[12] intercept   : AIC=-5826.887, Time=0.54 sec
 ARIMA(0,1,0)(1,0,1)[12] intercept   : AIC=-5825.197, Time=1.05 sec
 ARIMA(1,1,0)(0,0,0)[12] intercept   : AIC=-5828.001, Time=0.20 sec
 ARIMA(0,1,1)(0,0,0)[12] intercept   : AIC=-5828.194, Time=0.62 sec
 ARIMA(1,1,1)(0,0,0)[12] intercept   : AIC=-5826.264, Time=0.15 sec

Best model:  ARIMA(0,1,0)(0,0,0)[12]
Total fit time: 12.777 seconds
[*********************100%%**********************]  1 of 1 completed
[*********************100%%**********************]  1 of 1 completed
RMSE value on validation set: 0.06070656
MAPE value on validation set: 0.00675201
MSLE value on validation set: 0.00005292
-----------------------------------------------------------
```

Explanation of Output 5

Implementing ARIMA on stock market data to predict future prices involves several steps. First, historical stock price data is collected, typically daily or hourly prices over a specified time period. Next, the data is pre-processed, which may involve cleaning, transforming, and ensuring stationarity through techniques like differencing.

Once the data is prepared, an ARIMA model is fitted to the dataset. This involves selecting appropriate values for the ARIMA parameters: p (autoregressive order), d (degree of differencing), and q (moving average order). This selection can be done using methods such as grid search, AIC, or BIC.

After fitting the ARIMA model, it is validated using techniques such as train-test split or cross-validation to assess its performance on unseen data. Evaluation metrics like RMSE, MAPE, and MLSE are computed to quantify the accuracy of the model's predictions.

Finally, the model is used to forecast future stock prices based on the fitted ARIMA parameters. These forecasts can provide valuable insights for traders and investors in making informed decisions.

However, it's important to note that stock prices are influenced by a multitude of factors beyond historical price data alone, such as market sentiment, economic indicators, and news events. Therefore, while ARIMA can be a useful tool for stock price prediction, it should be used in conjunction with other analysis techniques and considered alongside fundamental and qualitative factors.

```
-------------------------------------------------------------
-----------IMPLEMENTING ARIMA BASED ON BULLISH AND BEARISH DATA-----------
-------------------------------------------------------------

Performing stepwise search to minimize aic
 ARIMA(2,1,2)(0,0,0)[0] intercept   : AIC=6560.913, Time=1.13 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=6575.082, Time=0.06 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=6572.398, Time=0.07 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=6571.515, Time=0.37 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=6573.437, Time=0.06 sec
 ARIMA(1,1,2)(0,0,0)[0] intercept   : AIC=6571.917, Time=0.89 sec
 ARIMA(2,1,1)(0,0,0)[0] intercept   : AIC=6571.218, Time=0.50 sec
 ARIMA(3,1,2)(0,0,0)[0] intercept   : AIC=6562.870, Time=2.15 sec
 ARIMA(2,1,3)(0,0,0)[0] intercept   : AIC=6567.161, Time=1.48 sec
 ARIMA(1,1,1)(0,0,0)[0] intercept   : AIC=6572.049, Time=0.31 sec
 ARIMA(1,1,3)(0,0,0)[0] intercept   : AIC=6570.976, Time=0.74 sec
 ARIMA(3,1,1)(0,0,0)[0] intercept   : AIC=6571.916, Time=0.85 sec
 ARIMA(3,1,3)(0,0,0)[0] intercept   : AIC=6569.687, Time=1.81 sec
 ARIMA(2,1,2)(0,0,0)[0]             : AIC=6564.046, Time=0.41 sec

Best model:  ARIMA(2,1,2)(0,0,0)[0] intercept
Total fit time: 10.853 seconds
```

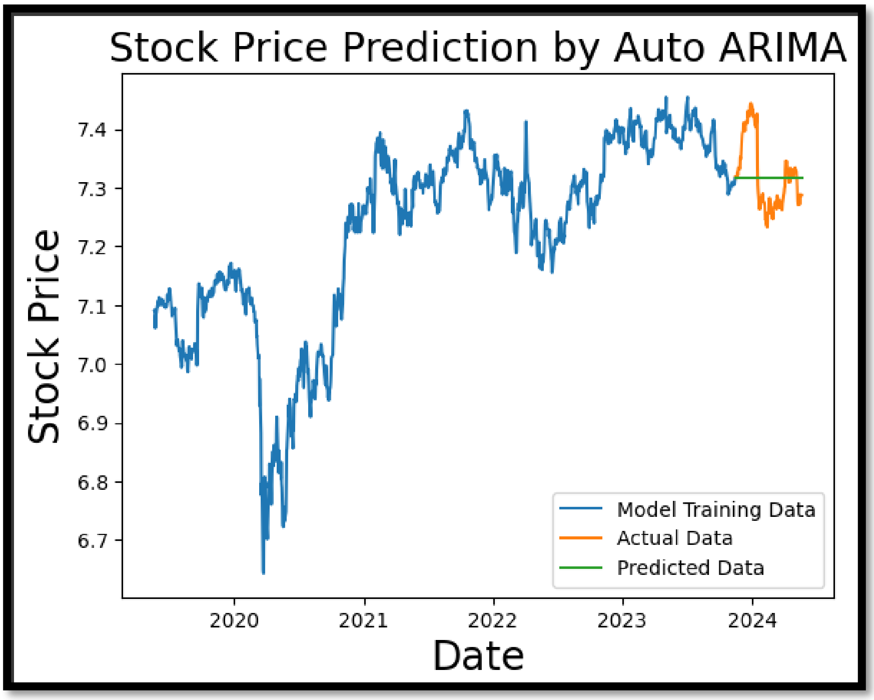
Implementation of ARIMA based on Bullish Data, collected from the SMA

```
Performing stepwise search to minimize aic
 ARIMA(2,1,2)(0,0,0)[0] intercept   : AIC=3729.319, Time=0.58 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=3731.264, Time=0.02 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=3729.177, Time=0.11 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=3728.673, Time=0.19 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=3730.521, Time=0.02 sec
 ARIMA(1,1,1)(0,0,0)[0] intercept   : AIC=3726.134, Time=0.19 sec
 ARIMA(2,1,1)(0,0,0)[0] intercept   : AIC=3727.545, Time=0.47 sec
 ARIMA(1,1,2)(0,0,0)[0] intercept   : AIC=3727.531, Time=0.43 sec
 ARIMA(0,1,2)(0,0,0)[0] intercept   : AIC=3729.519, Time=0.21 sec
 ARIMA(2,1,0)(0,0,0)[0] intercept   : AIC=3729.963, Time=0.14 sec
 ARIMA(1,1,1)(0,0,0)[0]             : AIC=3725.294, Time=0.11 sec
 ARIMA(0,1,1)(0,0,0)[0]             : AIC=3727.704, Time=0.05 sec
 ARIMA(1,1,0)(0,0,0)[0]             : AIC=3728.209, Time=0.05 sec
 ARIMA(2,1,1)(0,0,0)[0]             : AIC=3726.620, Time=0.20 sec
 ARIMA(1,1,2)(0,0,0)[0]             : AIC=3726.610, Time=0.19 sec
 ARIMA(0,1,2)(0,0,0)[0]             : AIC=3728.659, Time=0.08 sec
 ARIMA(2,1,0)(0,0,0)[0]             : AIC=3729.113, Time=0.07 sec
 ARIMA(2,1,2)(0,0,0)[0]             : AIC=3728.226, Time=0.28 sec

Best model:  ARIMA(1,1,1)(0,0,0)[0]
Total fit time: 3.389 seconds
```

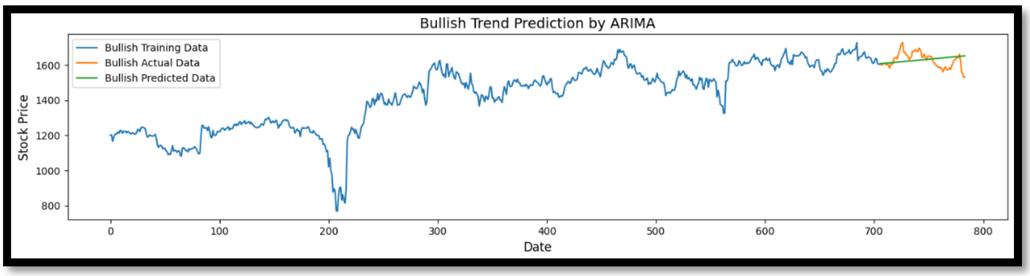
Implementation of ARIMA based on Bearish Data, collected from the SMA

```
----------------------------------------------------------
-------------------------BULLISH DATA-------------------------
----------------------------------------------------------
Shape of Bullish Training Set: (706, 1)
Shape of Bullish Validation Set: (78, 1)

RMSE value on bullish validation set: 48.71497503
MAPE value on bullish validation set: 0.02382078
MSLE value on bullish validation set: 0.00089679
-----------------------------------------------------------
----------------------------------------------------------
-------------------------BEARISH DATA-------------------------
----------------------------------------------------------
Shape of Bearish Training Set: (407, 1)
Shape of Bearish Validation Set: (45, 1)
RMSE value on bearish validation set: 69.89113815
MAPE value on bearish validation set: 0.03951313
MSLE value on bearish validation set: 0.00225144
-----------------------------------------------------------
```

Calculation of Training Set and Validation set of both Bullish and Bearish trend data. It also calculates RMSE, MAPE, MLSE of both Bullish and Bearish data.



Plotting of stock data after calculating ARIMA on overall Data. In this graph, green line is depicting predicted data.



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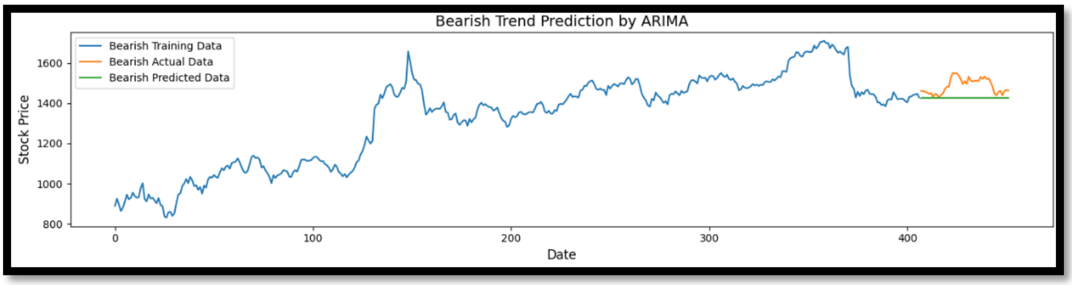
Plotting of stock data after calculating ARIMA on Bullish Trend Data. In this graph, green line is depicting predicted data, where as blue is Training Data and Orange is Actual data.



Plotting of stock data after calculating ARIMA on Bearish Trend Data. In this graph, green line is depicting predicted data.

OUTPUT 6

```
-------------------LSTM MODEL IMPLEMENTATION-----------------
----------------------------------------------------------
----------------------------------------------------------
-----------STOCK PRICE PREDICTION BY LSTM----------------
----------------------------------------------------------
Shape of Training Set: (1113, 1)
Shape of Validation Set: (123, 1)

Epoch 1/5
1053/1053 - 11s - loss: 0.0049 - 11s/epoch - 10ms/step
Epoch 2/5
1053/1053 - 7s - loss: 0.0018 - 7s/epoch - 7ms/step
Epoch 3/5
1053/1053 - 7s - loss: 0.0013 - 7s/epoch - 7ms/step
Epoch 4/5
1053/1053 - 7s - loss: 0.0011 - 7s/epoch - 6ms/step
Epoch 5/5
1053/1053 - 7s - loss: 9.5107e-04 - 7s/epoch - 7ms/step
4/4 [==============================] - 1s 5ms/step
-----------------------------------------------------------
------------------PERFORMANCE METRICS---------------------
-----------------------------------------------------------
RMSE value on validation set: 0.01727710
MAPE value on validation set: 0.00183623
MSLE value on validation set: 0.00000428
```

Explanation of Output 6
Implementing an LSTM model for stock price prediction involves data preparation, model training, and evaluation. Historical stock price data is partitioned into training and validation sets. The LSTM model is trained for 5 epochs on the training data while monitoring its performance on the validation set to prevent overfitting. Predictions are then made on the validation set, and evaluation metrics such as RMSE, MAPE, and MLSE are computed to assess the model's accuracy. Based on these metrics, adjustments can be made to improve the model's predictive capabilities.

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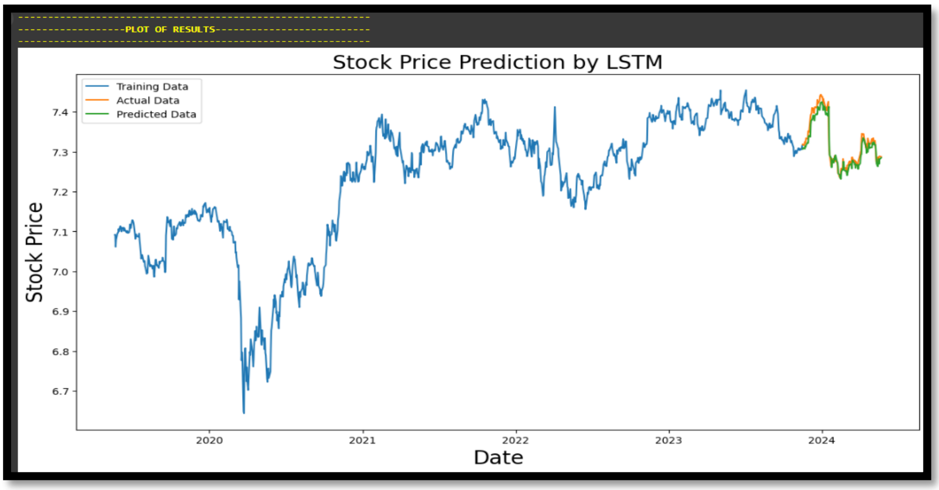


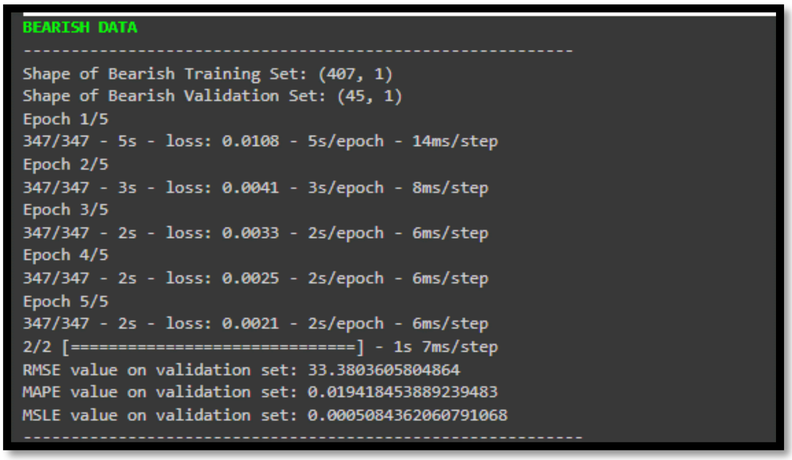
Plotting the results of an LSTM model involves visualizing both the actual and predicted stock prices to assess the model's performance visually. Initially, the actual stock prices from the validation set are plotted to establish a baseline for comparison. Then, the predicted stock prices generated by the LSTM model are plotted, typically overlaid on the same plot as the actual prices, facilitating direct comparison. Additionally, you can visualize the errors or residuals between the actual and predicted prices to analyze the model's performance at different points in time. Through trend analysis of the plotted data, you can identify patterns and discrepancies, providing insights into the model's strengths and weaknesses. This visual assessment allows for a comprehensive evaluation of the LSTM model's predictive accuracy and effectiveness in forecasting future stock prices.

```
-----------IMPLEMENTING LSTM BASED ON BULLISH AND BEARISH DATA-----------
--------------------------------------------------------------

BULLISH DATA
--------------------------------------------------------------
Shape of Bullish Training Set: (706, 1)
Shape of Bullish Validation Set: (78, 1)
Epoch 1/5
646/646 - 8s - loss: 0.0094 - 8s/epoch - 12ms/step
Epoch 2/5
646/646 - 4s - loss: 0.0032 - 4s/epoch - 6ms/step
Epoch 3/5
646/646 - 4s - loss: 0.0025 - 4s/epoch - 6ms/step
Epoch 4/5
646/646 - 5s - loss: 0.0018 - 5s/epoch - 8ms/step
Epoch 5/5
646/646 - 4s - loss: 0.0017 - 4s/epoch - 6ms/step
3/3 [==============================] - 1s 19ms/step
RMSE value on validation set: 34.51987119323897
MAPE value on validation set: 0.018872011959305747
MSLE value on validation set: 0.0004508383012731318
--------------------------------------------------------------
```

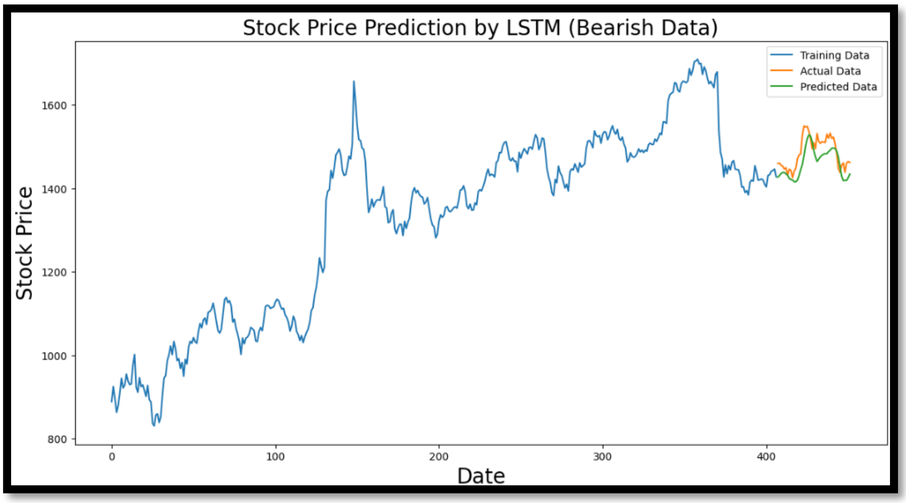
Now, similar steps to be followed for Bullish trend data.

Plotting LSTM on Bullish Trend data.

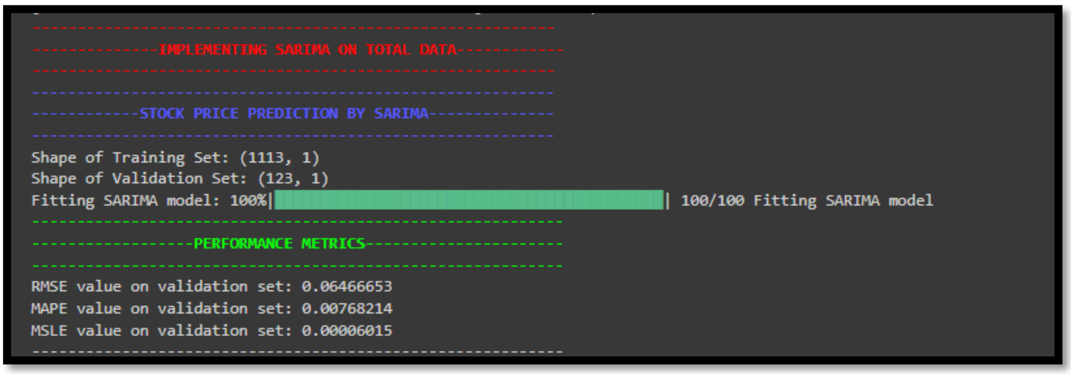


```
BEARISH DATA
----------------------------------------------------------
Shape of Bearish Training Set: (407, 1)
Shape of Bearish Validation Set: (45, 1)
Epoch 1/5
347/347 - 5s - loss: 0.0108 - 5s/epoch - 14ms/step
Epoch 2/5
347/347 - 3s - loss: 0.0041 - 3s/epoch - 8ms/step
Epoch 3/5
347/347 - 2s - loss: 0.0033 - 2s/epoch - 6ms/step
Epoch 4/5
347/347 - 2s - loss: 0.0025 - 2s/epoch - 6ms/step
Epoch 5/5
347/347 - 2s - loss: 0.0021 - 2s/epoch - 6ms/step
2/2 [==============================] - 1s 7ms/step
RMSE value on validation set: 33.3803605804864
MAPE value on validation set: 0.019418453889239483
MSLE value on validation set: 0.0005084362060791068
-----------------------------------------------------------
```

Calculating LSTM on bearish data.



Plotting the LSTM based on Bearish Trend Data.
OUTPUT 7



```
-------------------------------------------------------
--------------IMPLEMENTING SARIMA ON TOTAL DATA------------
-------------------------------------------------------
-------------------------------------------------------
------------STOCK PRICE PREDICTION BY SARIMA-------------
-------------------------------------------------------
Shape of Training Set: (1113, 1)
Shape of Validation Set: (123, 1)
Fitting SARIMA model: 100%|████████████████████| 100/100 Fitting SARIMA model
--------------------------------------------------------
-----------------PERFORMANCE METRICS---------------------
--------------------------------------------------------
RMSE value on validation set: 0.06466653
MAPE value on validation set: 0.00768214
MSLE value on validation set: 0.00006015
--------------------------------------------------------
```

Explanation of Output 7

Implementing SARIMA on stock market data involves several steps aimed at time series forecasting. Initially, historical stock market data is collected and preprocessed, which includes dealing with missing values, scaling, and partitioning the data into training and validation sets. SARIMA modeling begins by identifying the appropriate parameters (p, d, q, P, D,

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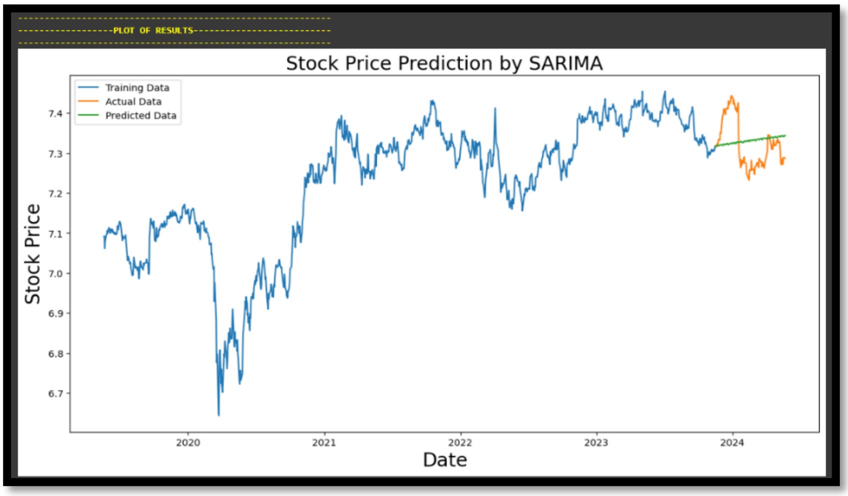
Q, s) through techniques like grid search or analyzing autocorrelation and partial autocorrelation plots. The SARIMA model is then fitted to the training data, incorporating seasonality and trends.
After training, predictions are made on the validation set, and evaluation metrics such as RMSE, MAPE, MLSE are calculated to assess the model's accuracy.



Finally, the results can be visualized by plotting the actual and predicted stock prices on a graph, allowing for a visual comparison of the model's performance over time. Through this process, SARIMA provides insights into future stock price movements, aiding investors and analysts in decision-making processes.

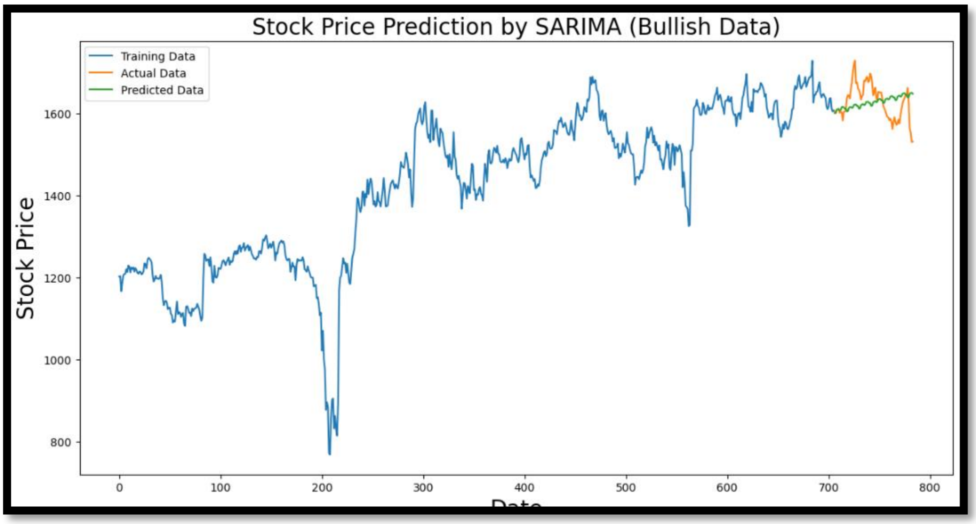
\

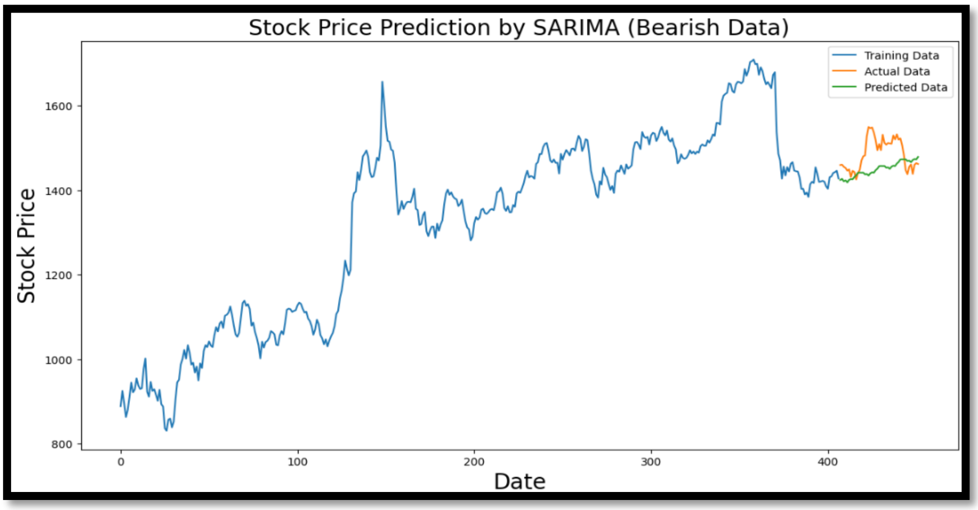
```
-------------IMPLEMENTING SARIMA BASED ON BULLISH AND BEARISH DATA-------------
----------------------------------------------------------

BULLISH DATA
----------------------------------------------------------
Shape of Bullish Training Set: (706, 1)
Shape of Bullish Validation Set: (78, 1)
RMSE value on validation set: 48.59034574
MAPE value on validation set: 0.02378855
MSLE value on validation set: 0.00089178
-----------------------------------------------------------
```

The similar things is followed in the case of Bullish and Bearish Data

```
BEARISH DATA
----------------------------------------------------------
Shape of Bearish Training Set: (407, 1)
Shape of Bearish Validation Set: (45, 1)
RMSE value on validation set: 51.62288413
MAPE value on validation set: 0.02831311
MSLE value on validation set: 0.00120836
-----------------------------------------------------------
```





Plotting of SARIMA Graph based on Bullish and Bearish Trend data.
OUTPUT 8

```
----------------------------------------------------------
-------------Comparisons based on all the trends-------------
----------------------------------------------------------
Best model based on RMSE (Total): SARIMA
Best model based on MAPE (Total): LSTM
Best model based on MSLE (Total): LSTM
Best model based on RMSE (Bullish): ARIMA
Best model based on MAPE (Bullish): LSTM
Best model based on MSLE (Bullish): LSTM
Best model based on RMSE (Bearish): ARIMA
Best model based on MAPE (Bearish): LSTM
Best model based on MSLE (Bearish): LSTM
```

Explanation of Output 8
In the final stage of analysis, the RMSE, MAPE, and MLSE metrics are compared across different subsets of the data—total, bullish, and bearish—across three models: ARIMA, LSTM, and SARIMA. This comprehensive comparison allows for a nuanced understanding of each model's performance under varying market conditions. By evaluating these metrics across different subsets of data, such as during bullish and bearish market phases, insights can be gained into the robustness and adaptability of each model.

10. CONCLUSION

This research demonstrates a comprehensive approach to stock price prediction using three different models: ARIMA, SARIMA, and LSTM. Each model was applied to historical stock data, and their performance was evaluated using key metrics such as RMSE, MAPE, and MSLE. The interactive interface allowed users to dynamically select sectors, stocks, and time ranges for analysis, enhancing the user experience and making the analysis more accessible.

11. KEY FINDINGS

1. **Model Performance**:

- The ARIMA model was straightforward to implement and provided reasonable predictions, especially for non-seasonal data.
- The SARIMA model extended ARIMA's capabilities by accounting for seasonality, resulting in improved accuracy for seasonal data.
- The LSTM model leveraged deep learning to capture complex patterns and long-term dependencies in the stock data, showing robust performance.

The following tables (Table 2) defines the different results based on executing different models for a specific company data

TABLE 2

Stock Market Forecasting									
Company Name : HDFC BANK Limited									
10 Years Data									
Model Name	RMSE			MAPE			MLSE		
	Overall	Bullish	Bearish	Overall	Bullish	Bearish	Overall	Bullish	Bearish
ARIMA	0.14054	101.12541	52.84169	0.01567	0.05266	0.02843	0.00028	0.00367	0.00124
LSTM	0.01462	23.93580	30.83669	0.00142	0.01212	0.01711	0.00000	0.00022	0.00043
SARIMA	0.13954	108.73422	42.27727	0.01554	0.05657	0.02187	0.00028	0.00421	0.00080

2. **Metrics and Comparisons**:

Each model's performance varied across different metrics and data segments (total, bullish, and bearish). For instance, LSTM performed exceptionally well in capturing long-term trends, while SARIMA excelled in seasonal data prediction. The comprehensive evaluation highlighted that no single model is universally best; the choice of model depends on the specific characteristics of the data and the forecasting horizon.

3. Visualization and User Interaction:

- Visualizations played a crucial role in interpreting the results, providing clear insights into the models' predictions versus actual stock prices.
- The interactive widgets and dynamic plotting made the tool user-friendly, allowing for real-time updates and tailored analysis based on user input.

4. Implications:

The research underscores the importance of using multiple models to address the complexities of stock price prediction. By comparing different models and using interactive visual tools, investors and analysts can gain deeper insights into market trends and make more informed decisions. This approach can be extended to other financial instruments and adapted for various forecasting needs, reinforcing its versatility and practical value in financial analytics.

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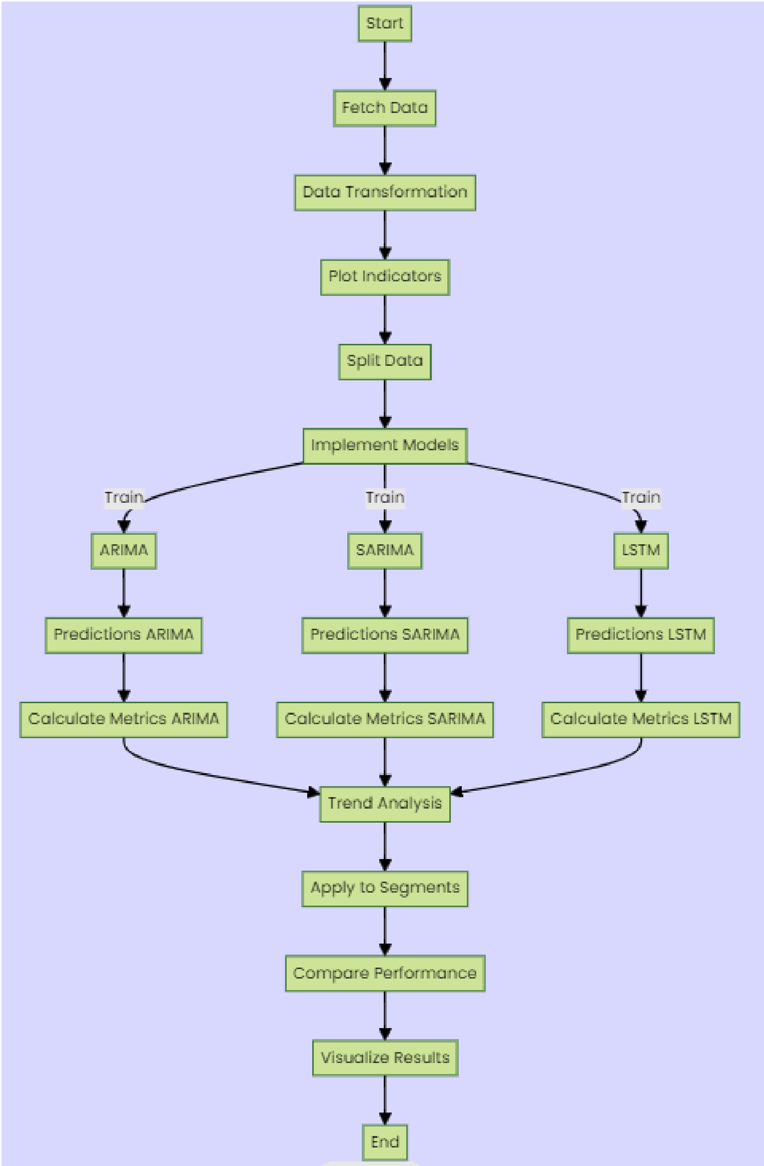
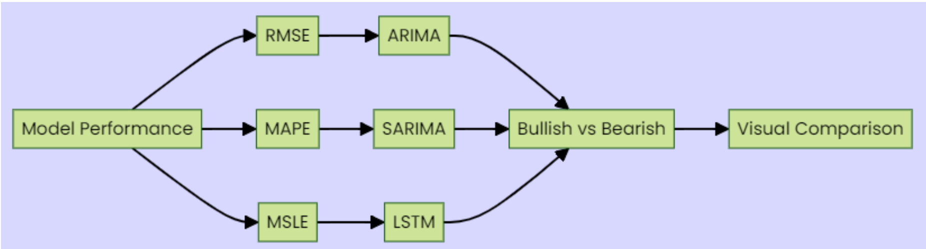
12. FLOWCHART IMPLEMENTATION



Visualization
The flowchart visually represents the sequence of steps in the stock price prediction analysis. It helps to clarify the process and ensure that all necessary actions are taken in the correct order.
Performance Metrics Visualization



Footnote Used
- **SMA**: Simple Moving Average
- **RSI**: Relative Strength Index

- **ARIMA**: Autoregressive Integrated Moving Average
- **SARIMA**: Seasonal ARIMA
- **LSTM**: Long Short-Term Memory
- **RMSE**: Root Mean Square Error
- **MAPE**: Mean Absolute Percentage Error
- **MSLE**: Mean Squared Logarithmic Error

13. FUTURE SCOPE OF THE RESEARCH WORK

Future enhancements could include:

- Incorporating more advanced models and hybrid approaches to further improve prediction accuracy.
- Extending the analysis to other financial indicators and incorporating external factors such as economic indicators and news sentiment analysis.
- Developing a more comprehensive user interface with additional features for in-depth analysis and customization.

In summarization, this proposed framework demonstrates a robust methodology for stock price prediction, combining statistical and machine learning techniques with interactive data visualization. It offers valuable insights and a practical tool for financial forecasting, paving the way for more advanced and user-friendly predictive analytics in finance.

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