



A STUDY ON LEVERAGING ARTIFICIAL INTELLIGENCE TO PREDICT STOCK MARKET TRENDS OF INFORMATION TECHNOLOGY & AUTOMOBILE COMPANIES –A COMPREHENSIVE ANALYSIS

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ABSTRACT

This study examines how well traditional statistical methods and modern techniques perform in predicting stock prices in the IT and automobile sectors. With stock markets becoming more complex and unpredictable, there is a need for better forecasting methods. The main objective of this study is to compare the effectiveness of the Long Short-Term Memory (LSTM) model with the traditional ARIMA model in predicting stock price movements. Traditional forecasting methods often struggle to capture sudden changes and complex patterns in stock prices. Because of this, their predictions may not always be accurate in real market conditions. This study attempts to overcome these limitations by using more flexible and adaptive approaches that can better reflect actual market behavior. This study uses two different approaches for comparison: The ARIMA model, implemented using EViews The LSTM model, developed using Python and visualized with Matplotlib The analysis is based on monthly stock price data from 2020 to 2025 for ten companies: **IT Sector:** TCS, Infosys, Oracle Financial Services, L&T, Persistent Systems **Automobile Sector:** Bajaj Auto, Maruti Suzuki, Hero MotoCorp, Ashok Leyland, Mahindra & Mahindra A simple random sampling method was used to select: 5 companies from the IT sector 5 companies from the automobile sector The results show that the LSTM model generally provides better predictions than the ARIMA model, especially when the market is unstable. In the IT sector, companies such as Oracle Financial Services and Persistent Systems showed results closer to actual trends when using LSTM. In the automobile sector, Mahindra & Mahindra and Bajaj Auto also showed more accurate predictions with the LSTM model. The findings suggest that using modern forecasting techniques can help investors and managers make better decisions. These methods can improve risk management, provide clearer insights into market trends, and support better financial planning. Companies that adopt such approaches may gain an advantage in competitive and changing markets. The study concludes that the LSTM model performs better than the ARIMA model in predicting stock prices, particularly in uncertain market conditions. More advanced forecasting methods can offer improved accuracy and help in making better investment and financial decisions in both IT and automobile sectors.

KEYWORDS: Stock Market Prediction, LSTM, ARIMA, Time Series Forecasting, Stock Prices, Financial Analysis, Investment Decisions, Risk Management, Market Trends, SEBI.

1. INTRODUCTION

The stock market plays an important role in the global financial system, where shares of companies are bought and sold. It helps companies raise funds for growth and expansion, while also giving investors opportunities to earn returns through price changes and dividends. The stock market is often seen as an indicator of a country's economic condition. However, it is influenced by many factors such as company performance, economic conditions, political events, and investor behavior. Because of these factors, the market is highly unpredictable and involves both risk and reward, requiring careful decision-making. With advancements in technology and data analysis, stock markets have become more accessible and efficient. Today, a wide range of participants—from large institutional investors to individual traders—actively take part in the market, shaping its movements. This project, titled “**Stock Market Trend Analysis of Information Technology and Automobile Companies,**” focuses on studying and predicting stock price movements in two major sectors of the Indian economy: Information Technology (IT) and Automobiles. The companies selected for this study include TCS, Infosys, Oracle Financial Services Software, Persistent Systems, and Larsen & Toubro from the IT sector, and Bajaj Auto, Maruti Suzuki, Mahindra & Mahindra, Hero MotoCorp, and Ashok Leyland from the automobile sector. These companies were chosen based on their importance in the market, availability of data, and their role in their respective industries. Stock markets are known for their fluctuations, which are influenced by factors such as economic trends, sector performance, investor sentiment, and global events. Traditional forecasting methods like ARIMA are useful but often struggle to capture sudden changes and complex patterns in stock price movements. To address this, the study also considers more flexible approaches that can better analyze past trends and identify patterns for improved prediction. The methodology involves analyzing historical stock price data from 2020 to 2025. The data is organized and processed, and different forecasting methods are applied to estimate future price movements. The performance of these methods is then compared based on accuracy and reliability. The



main objective of this study is not only to compare different forecasting approaches but also to understand how modern tools and techniques can support better investment decisions. The analysis also considers additional factors such as financial performance and market trends to provide a more complete understanding of stock behavior. This approach reflects how investors combine data analysis with practical judgment in real-life situations. Furthermore, the study explores how these methods can be useful in areas such as trading strategies and portfolio management, helping investors manage risks and improve returns. The research is based on the assumption that modern, flexible methods provide better results than traditional models, especially in sectors like IT and automobiles, which are highly dynamic and sensitive to market changes. Overall, this project aims to provide useful insights for students, investors, analysts, and financial planners. It highlights the growing importance of advanced analytical techniques in understanding stock market behavior and supports better, more informed investment decisions in today's fast-changing financial environment.

2. OBJECTIVES OF THE STUDY

The researcher has made these objectives based on the topic of the research.

1. To examine how Artificial Intelligence enhances stock price prediction from 2025 – 28 and evaluate the effectiveness of various AI models in financial forecasting.
2. To analyse historical stock performance and integrate diverse data sources including financial reports and market sentiment for AI-driven trend analysis.
3. To improve the accuracy and efficiency of AI-based stock prediction models through comparative analysis with traditional methods.
4. To explore the application of AI models in algorithmic trading and portfolio management for informed, data-driven investment strategies.
5. To develop actionable recommendations for optimizing AI-based forecasting models to support better investment decisions and maximize returns.

3. RESEARCH METHODOLOGY

The research methodology used in this study is mainly based on secondary data collected from reliable financial and stock market sources. Historical monthly stock price data from 2020 to 2025 was gathered from sources such as NSE, BSE, Yahoo Finance, Moneycontrol, and Investing.com. Additional information was also collected from company annual reports, financial statements, journals, and published research papers. For the purpose of analysis, simple random sampling was used to select five companies from the Information Technology (IT) sector and five companies from the Automobile sector. The selected IT companies include Tata Consultancy Services, Infosys, Oracle Financial Services, Persistent Systems, and Larsen & Toubro. The Automobile companies selected for the study are Bajaj Auto, Maruti Suzuki, Mahindra & Mahindra, Hero MotoCorp, and Ashok Leyland. The study compares two different forecasting methods: ARIMA and LSTM. The ARIMA model was applied using EViews software, where the stock price data was first organized and adjusted to make it suitable for analysis. The LSTM model was developed using Python, and necessary steps such as data preparation and sequence formation were carried out before using the model. Finally, the results from both methods were compared based on their ability to predict stock price trends and overall accuracy. This comparison helped in understanding which method performs better under different market conditions.

3.2 Variables

Dependent Variables

The main outcomes of the study are stock prices and stock market volatility. These represent how stock values change over time and how stable or unstable the market

Independent Variables

The factors that influence stock prices include foreign investments, political situations, and other external conditions. These external factors may include natural disasters, global conflicts such as wars, and public health issues like the COVID-19 pandemic.

3.3 Statistical Tools

ARIMA Model (EViews)

The ARIMA (Auto-Regressive Integrated Moving Average) model was applied using EViews, a commonly used software for statistical and economic analysis. For this model, the stock price data was first organized and adjusted to make it suitable for analysis. Tests such as the Augmented Dickey-Fuller and Phillips-Perron were used to check the stability of the data.

LSTM Model (Python & Matplotlib)

The LSTM model was developed using Python. Various tools were used to prepare and organize the data before analysis. The stock price data was first scaled and arranged into a suitable format for the model. The model was then trained using past data to identify patterns and make future predictions.

3.4 Hypotheses

(H₀): There is no significant difference in the accuracy of stock price predictions between modern forecasting methods and traditional statistical methods in the IT and automobile sectors.

(H₁): There is a significant difference in the accuracy of stock price predictions between modern forecasting methods and traditional statistical methods in the IT and automobile sectors, with modern methods providing better results.

4. RESULTS

ARIMA Model

Null Hypothesis: D(BAJAJ_AUTO) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-6.667032	0.0000
Test critical values:		
1% level	-4.124265	
5% level	-3.489228	
10% level	-3.173114	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(BAJAJ_AUTO,2)
Method: Least Squares
Date: 04/15/25 Time: 15:07
Sample (adjusted): 2020M06 2025M03
Included observations: 58 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(BAJAJ_AUTO(-1))	-0.894346	0.134144	-6.667032	0.0000
C	74.50215	152.6926	0.487922	0.6275
@TREND("2020M04")	0.163603	4.378650	0.037364	0.9703
R-squared	0.446967	Mean dependent var	-1.918103	
Adjusted R-squared	0.426857	S.D. dependent var	737.3270	
S.E. of regression	558.2024	Akaike info criterion	15.53766	
Sum squared resid	17137445	Schwarz criterion	15.64423	
Log likelihood	-447.5921	Hannan-Quinn criter.	15.57917	
F-statistic	22.22580	Durbin-Watson stat	1.983419	
Prob(F-statistic)	0.000000			

Data is converted to stationarity by doing unit root test is a statistical procedure used to determine if a time series variable is stationary or non-stationary. A stationary time series has constant statistical properties (mean, variance, and autocorrelation) over time, while a non-stationary series exhibits trends or patterns that change over time.

Date: 04/15/25 Time: 15:08
Sample: 2020M04 2028M03
Included observations: 60

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
		1 0.957	0.957	57.724	0.000
		2 0.908	-0.091	110.58	0.000
		3 0.854	-0.075	158.21	0.000
		4 0.797	-0.062	200.46	0.000
		5 0.731	-0.143	236.59	0.000
		6 0.657	-0.112	266.33	0.000
		7 0.557	-0.352	288.13	0.000
		8 0.474	0.186	304.23	0.000
		9 0.398	0.033	315.78	0.000
		10 0.327	0.034	323.74	0.000
		11 0.259	0.030	328.81	0.000
		12 0.196	0.014	331.80	0.000
		13 0.136	0.026	333.27	0.000
		14 0.095	0.014	334.01	0.000
		15 0.053	-0.118	334.24	0.000
		16 0.016	0.001	334.26	0.000
		17 -0.016	-0.017	334.28	0.000
		18 -0.041	-0.003	334.43	0.000
		19 -0.062	0.013	334.78	0.000
		20 -0.081	-0.095	335.38	0.000
		21 -0.102	0.017	336.39	0.000
		22 -0.118	0.006	337.75	0.000
		23 -0.134	-0.055	339.54	0.000
		24 -0.146	0.011	341.74	0.000
		25 -0.152	0.060	344.20	0.000
		26 -0.159	-0.003	346.96	0.000
		27 -0.169	-0.054	350.18	0.000
		28 -0.173	-0.017	353.67	0.000

Here we check the p value for AR, and D values for MA, Significant autocorrelations (those outside the blue bars in the accompanying correlogram, which are approximately $\pm 1.96/\sqrt{T}$, where T is the sample size) indicate that past values of the series are useful for predicting current values.

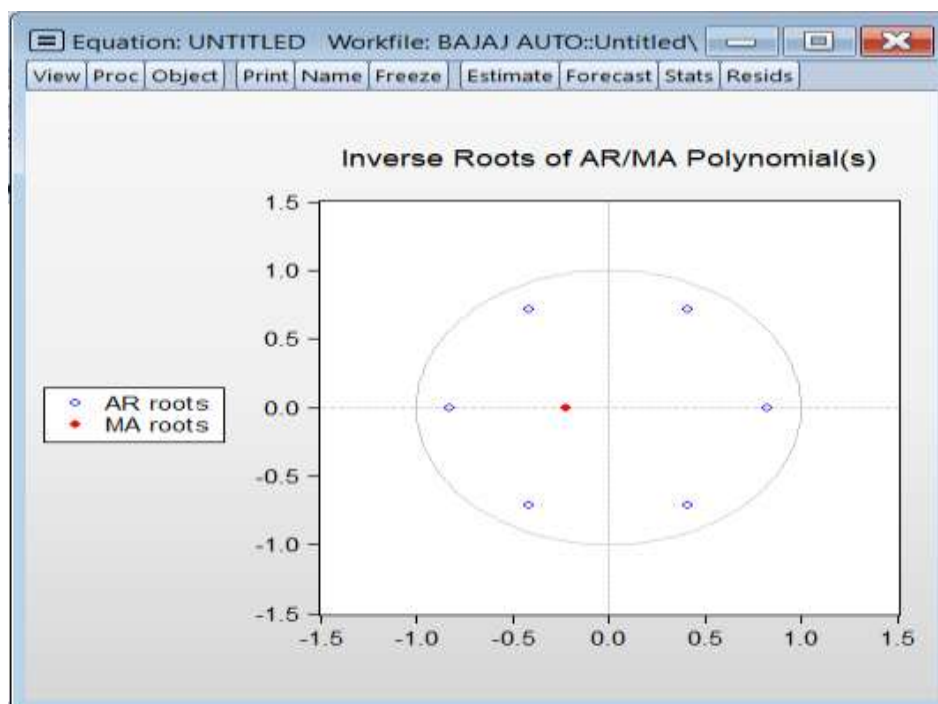
Dependent Variable: D(BAJAJ_AUTO)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 04/15/25 Time: 15:39
Sample: 2020M05 2025M03
Included observations: 59
Convergence achieved after 23 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(6)	0.309293	0.127401	2.427710	0.0184
MA(1)	0.216291	0.170351	1.269677	0.2095
SIGMASQ	277143.8	31649.88	8.756552	0.0000

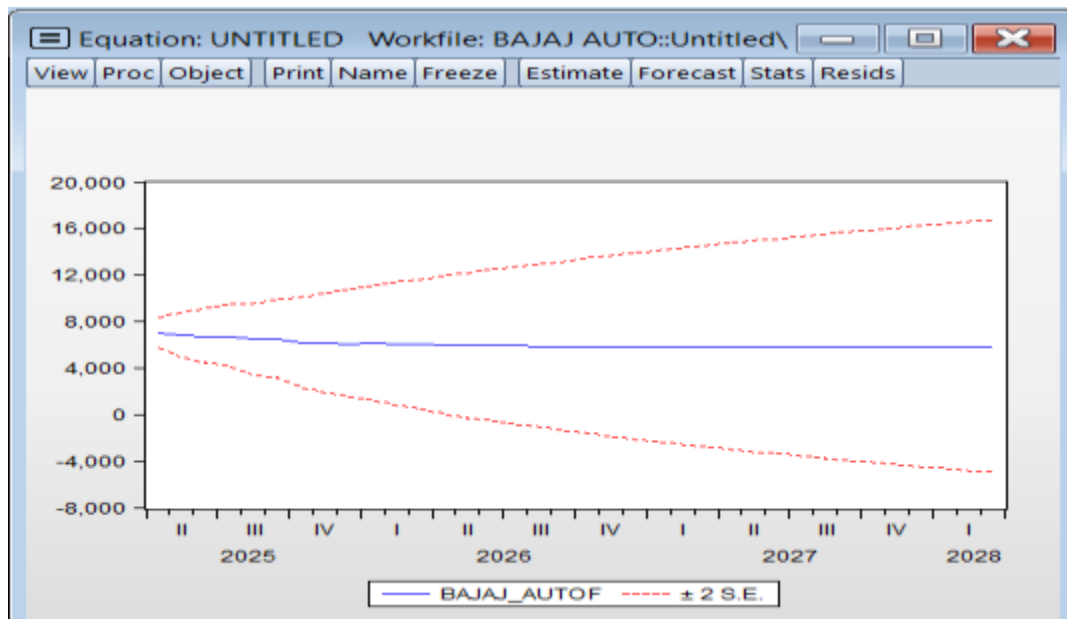
R-squared	0.056542	Mean dependent var	89.07712
Adjusted R-squared	0.022847	S.D. dependent var	546.6424
S.E. of regression	540.3617	Akaike info criterion	15.48290
Sum squared resid	16351483	Schwarz criterion	15.58854
Log likelihood	-453.7456	Hannan-Quinn criter.	15.52414
Durbin-Watson stat	2.022478		

Inverted AR Roots	.82	.41-.71i	.41+.71i	-.41-.71i
	-.41+.71i	-.82		
Inverted MA Roots	-.22			

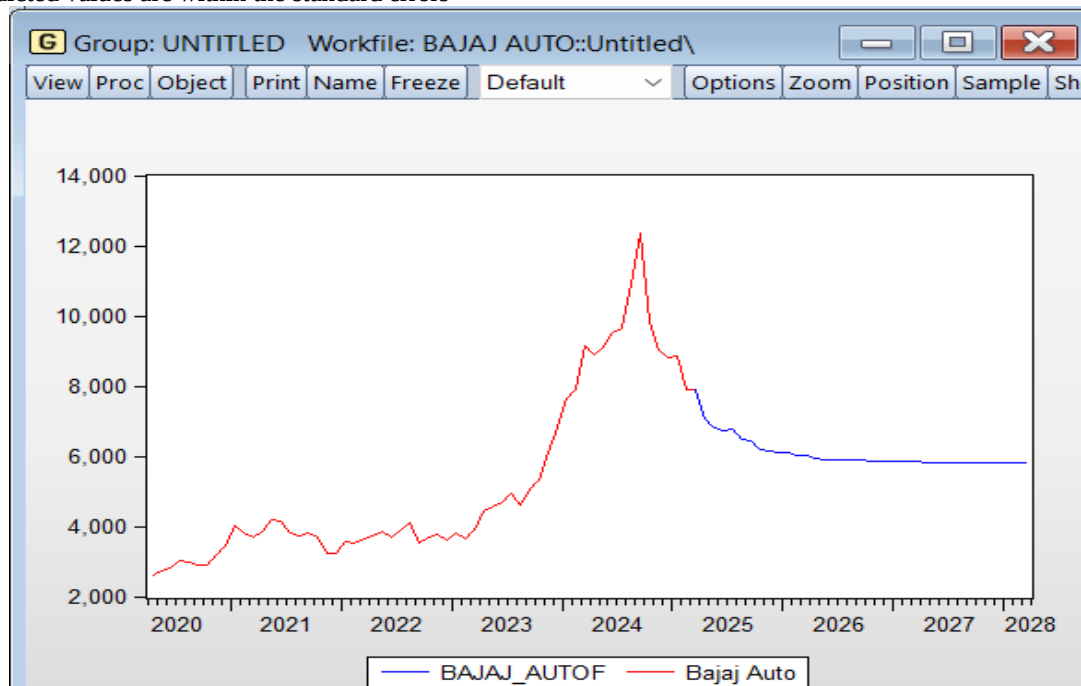
Here, 6th model is selected out of 11 models.



Here, the dots are inside the circle, so the selected ARIMA Model is suitable for predicting future stock prices .



The predicted values are within the standard errors



The graph displays the historical and forecasted stock prices of the company, where the red line represents actual data from 2020 to early 2025, and the blue line shows future projections using

the ARIMA model. The historical data indicates a steady upward trend beginning from 2020, followed by a sharp spike in prices around 2023, peaking near 14,000. This surge was likely driven by strong market momentum or company-specific developments. However, after reaching the peak, the stock experienced a rapid decline, suggesting a market correction or a reversal of prior gains. The ARIMA-based forecast predicts that the stock price will continue to decrease slightly in the short term and then stabilize around 6,000 in the coming years. This suggests that the stock may enter a period of relative stability with no significant upward or downward movement expected, indicating a mature or steady phase following the earlier volatility.

LSTM Model

```
import pandas as pd
import matplotlib.pyplot as plt
```

```
from sklearn.preprocessing import MinMaxScaler
from keras.models import Sequential
from keras.layers import LSTM, Dense
import date

df = pd.read_excel('/content/Bajaj Auto.xlsx', sheet_name='Sheet1')
df['Date'] = pd.to_datetime(df['Date'], dayfirst=True)
df.set_index('Date', inplace=True)
df = df[['Bajaj Auto']].dropna()
scaler = MinMaxScaler()

scaled_data = scaler.fit_transform(df)

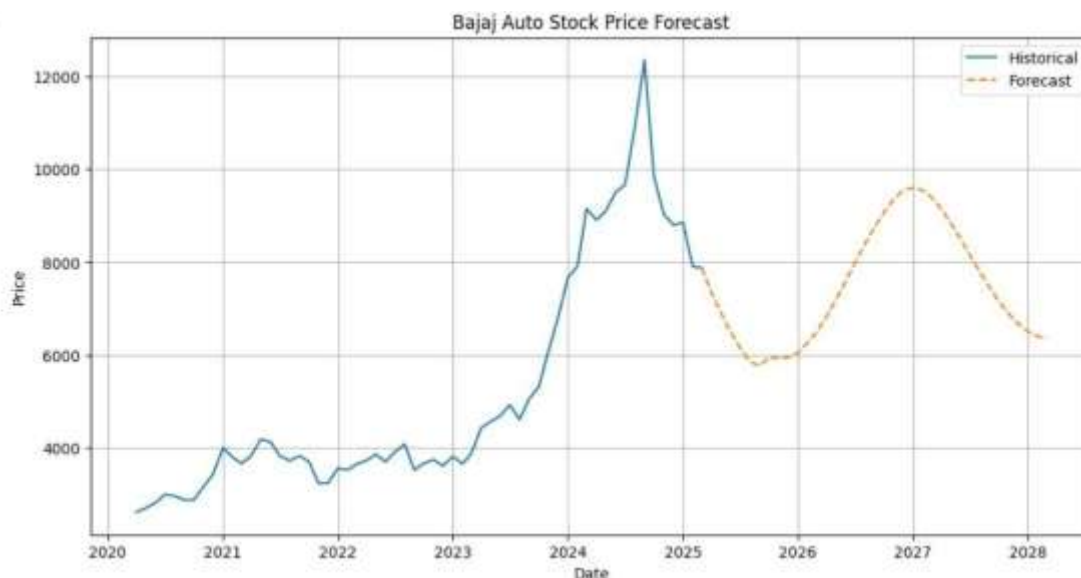
def create_dataset(data, time_step=12):
    X, y = [], []
    for i in range(len(data)-time_step):
        X.append(data[i:(i+time_step), 0])
        y.append(data[i + time_step, 0])
    return np.array(X), np.array(y)

time_step = 12
X, y = create_dataset(scaled_data, time_step)
X = X.reshape((X.shape[0], X.shape[1], 1))
model = Sequential()
model.add(LSTM(50, return_sequences=True, shape=(time_step, 1)))
model.add(LSTM(50))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mean_squared_error')
model.fit(X, y, epochs=200, verbose=0)

input_seq = scaled_data[-time_step:].reshape(1, time_step, 1)
future_preds = []
for _ in range(36):
    pred = model.predict(input_seq)[0][0]
    future_preds.append(pred)
    input_seq = np.append(input_seq[:, 1:], [[pred]], axis=1)

future_prices = scaler.inverse_transform(np.array(future_preds).reshape(-1, 1))
forecast_dates = pd.date_range(start=df.index[-1] + pd.DateOffset(months=1), periods=36, freq='MS')
forecast_df = pd.DataFrame(future_prices, index=forecast_dates, columns=['Forecast'])

plt.figure(figsize=(12, 6))
plt.plot(df, label='Historical')
plt.plot(forecast_df, label='Forecast', linestyle='dashed')
plt.title('Bajaj Auto Stock Price Forecast')
plt.xlabel('Date')
plt.ylabel('Price')
plt.legend()
plt.grid(True)
plt.show()
```



The chart titled " **Stock Price Forecast**" illustrates both historical and predicted stock prices using an LSTM model, a type of recurrent network commonly used for time series forecasting. From the graph, we observe that the stock experienced a steady rise from 2020 to early 2025, followed by a sharp peak around 2024, reaching prices above ₹12,000. This is succeeded by a rapid decline, indicating a correction or downturn post-peak. The orange dashed line represents the LSTM model's forecast from late 2025 onwards. The forecast suggests an initial dip, followed by a gradual upward trend peaking in 2027, and then the researcher noticed that there was a mild decline towards 2028. This cyclical pattern in the forecast implies that the model has detected seasonality or recurring trends in the historical data, projecting similar patterns into the future. Overall, the LSTM model anticipates moderate fluctuations with potential for growth over the next few years, albeit with some volatility. However, it's essential to remember that such forecasts are probabilistic, and real-world outcomes can be affected by numerous external factors not captured by the model.

5. SUGGESTIONS

1. Investors may consider Persistent Systems for long-term investment, as the analysis shows positive growth potential.
2. Maruti Suzuki appears suitable for medium- and long-term investment, as the forecasts indicate stable price levels in the coming years.



3. Investors in Mahindra & Mahindra should closely monitor price movements, as the stock is expected to show fluctuations during the forecast period.
4. Ashok Leyland can be considered a relatively low-risk investment, as the forecast shows gradual price growth with limited fluctuations.
5. Investors should be cautious while investing in Oracle Financial Services, as the analysis indicates a declining trend in stock prices.
6. Financial analysts are advised to use a combination of different forecasting methods, as this can improve prediction accuracy and reduce errors.

6. CONCLUSION

The study was carried out using both ARIMA and LSTM methods to analyze and forecast stock price movements. Based on the results, companies such as Oracle Financial Services, Persistent Systems, and Mahindra & Mahindra showed strong performance, making them attractive investment options due to their steady growth and positive trends. Among these, Oracle Financial Services experienced a significant increase in stock prices after 2023, indicating strong market confidence and growth potential. In the automobile sector, Mahindra & Mahindra and Bajaj Auto showed consistent recovery and stable performance, making them suitable for long-term investment. When comparing sectors, the IT sector showed more stable and consistent performance overall. On the other hand, the automobile sector experienced higher fluctuations, but it also offered better growth opportunities in certain stocks. In conclusion, the IT sector can be considered more stable and predictable, while the automobile sector provides selective opportunities for higher returns. Investors should make decisions carefully based on their risk preference and market conditions.

7. AREA FOR FURTHER RESEARCH

1. The study can be improved by looking at more companies from different industries
2. Using data over a longer period could help in understanding long-term trends better
3. Trying out different forecasting methods may give a clearer idea of which works best
4. It would be helpful to consider how economic conditions and government policies affect market
5. Events like wars, pandemics, and natural disasters can also be studied in more detail
6. Using updated or real-time data may make the results more practical

10. REFERENCES

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