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Stock Sense Analytics: A Web-Based Stock Prediction and Analysis System Using Machine Learning

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***Abstract*—This study presents a comprehensive approach to stock market analysis and prediction through the development of Stock Sense Analytics, a web-based system that leverages machine learning techniques. The primary objective of this research is to design a predictive framework capable of forecasting stock price movements and trends using historical financial data. The system utilises time series modelling, particularly the ARIMA (Autoregressive Integrated Moving Average) model, along with other machine learning algorithms to identify patterns, trends, and seasonality in stock market data. Data is collected from reliable financial sources and processed to generate accurate predictions of stock prices and market behaviour. The proposed system highlights the effectiveness of data-driven approaches in enhancing stock market transparency, improving investment strategies, and supporting financial analysis.**

***Index Terms*—IMA, Stock Market Prediction, Machine Learning, Time Series Forecasting, Financial Analytics, Web- Based Application, Predictive Modelling, Data Visualization, Real-Time Stock Analysis.**

I. INTRODUCTION

In the modern financial landscape, stock market forecasting plays a crucial role in enabling informed decision-making for investors, financial analysts, and policymakers. With the rapid evolution of digital trading platforms and globalization of financial markets, analysing stock trends has become increasingly complex. Various dynamic factors, such as stock price volatility, market sentiment, economic indicators, and global events, significantly influence market behaviour. The stock market is inherently dynamic and highly sensitive to both internal and external factors, making accurate prediction a challenging task.

1.1 Background and Motivation

The rapid evolution of stock markets and the increasing availability of financial data have created new opportunities for data-driven forecasting and analysis. Traditional forecasting techniques, such as moving averages and exponential smoothing, although widely used, often struggle to handle the highly volatile and non-stationary nature of stock price movements. These limitations reduce their effectiveness in capturing complex patterns present in modern financial markets. To overcome these challenges, machine learning and time series forecasting techniques have gained significant importance. These approaches enable the analysis of large volumes of historical stock data and provide more accurate predictions of future trends. Among these techniques, the Autoregressive Integrated Moving Average (ARIMA) model has emerged as a reliable and interpretable method for time series forecasting. moving average components along with differencing to transform non-stationary data into a stationary form. This makes it particularly suitable for modelling stock price data, which often exhibits trends, seasonality, and random fluctuations. Motivated by these advantages, this research focuses on leveraging ARIMA within a web-based system to enhance stock market prediction and analysis, enabling users to make informed financial decisions.

1.2 Problem Statement

Stock market prediction is inherently challenging due to the dynamic, nonlinear, and volatile nature of financial data. Traditional statistical methods often fail to capture temporal dependencies and sudden fluctuations, leading to inaccurate forecasts. Developing a model that can effectively analyse historical data and predict future stock trends remains a significant challenge. Additionally, there exists a gap between advanced predictive models and their practical usability. Most sophisticated forecasting tools require technical

1.3 Objectives

The primary objectives of this research are as follows:

- To design and develop a web-based system for stock
- market prediction and analysis using machine
- learning techniques.
- To implement a predictive framework based on time
- series models such as ARIMA for forecasting
- stock prices using historical data.
- To provide real-time visualization and analysis of
- stock trends through an interactive and user-friendly
- interface.
- To enable users to evaluate prediction accuracy and
- derive actionable insights for better investment
- decisions.
- To enhance financial awareness and decision-
- making through data-driven insights.

II. LITERATURE SURVEY

Sr. No	Article Title, Author, and Publication Year	Study focus, design, goals, methodology, and sample size	The study's findings and conclusion ns	The Scholar's Remarks
1	"ARIMA Based Stock Price Forecasting in Financial Markets – Lee et al. (2023)	Focus: Stock price prediction using ARIMA; Dataset: Historical stock data (2000–2022)	ARIMA (1,1,1) effectively captured stock price trends and short-term movements	Shows ARIMA i s reliable for stock market time series forecasting
2	Stock Market Prediction Using ARIMA and LSTM Hybrid Models – Mehta & Ramesh (2023)	Focus: Comparison of ARIMA and LSTM using stock datasets (S&P 500)	Hybrid ARIMA–LSTM reduced prediction error by 12%	Combining ML and statistical models improves prediction accuracy
3	Time Series Analysis of Stock Market Data Using ARIMA – Das & Al- Khatib (2024)	Focus: Forecasting stock prices using the ARIMA model	ARIMA Outperformed traditional methods like the moving average	Confirms ARIMA's effectiveness s for stock trend prediction
4	Stock Price Prediction Using ARIAX with External Factors – Nguyen et al. (2024)	Focus: ARIMAX model with external variables like interest rates and news sentiment	ARIMAX improved forecasting accuracy compared to ARIMA	Highlights the importance of external features in stock prediction
5	Hybrid ARIMA–GARH Model for Stock Market Volatility – Oliveia & Costa (2025)	Focus: ARIMA (trend) + GARCH (volatility) for stock markets	Hybrid model reduced forecasting error significantly	Useful for capturing both price Trends and market volatility
6	Web- Based Stock Analysis and Visualisation System – Khan & Iyer (2025)	Focus: Development of a web dashboard for stock prediction and visualisation	Interactive dashboards improved user understanding and decision- making	Supports integration of ML models with web applications

2.1 Foundations of Time Series Forecasting

Before the adoption of advanced statistical and machine learning techniques, stock market forecasting primarily relied on traditional methods such as moving averages and exponential smoothing. These approaches are effective for identifying basic trends and smoothing short-term fluctuations in stock price data. However, they often fail to capture the complex, non-stationary, and highly volatile nature of modern stock markets.

2.2 The ARIMA Model in Stock Market Forecasting

The Autoregressive Integrated Moving Average (ARIMA) model is widely used in stock market prediction due to its effectiveness in analysing time-dependent data. It combines autoregressive (AR), differencing (I), and moving average (MA) components to transform non-stationary stock data into a stationary form suitable for forecasting.

2.3 Advanced and Hybrid Forecasting Models

Although ARIMA is effective for linear time series modelling, its limitations in capturing nonlinear patterns have led to the development of advanced and hybrid models.

Hybrid Models:

Combining ARIMA with machine learning techniques has significantly improved forecasting accuracy. Mehta and Ramesh (2023) developed a hybrid ARIMA–LSTM model for stock price prediction, achieving a 12% reduction in Root Mean Squared Error (RMSE)compared to standalone

III. METHODOLOGY

The methodology for this project follows a systematic pipeline designed to ensure robust data analysis, accurate forecasting, and an intuitive user experience. This section outlines the system architecture, data sources, preprocessing steps, the ARIMA model, evaluation metrics, and the web application's technical stack.

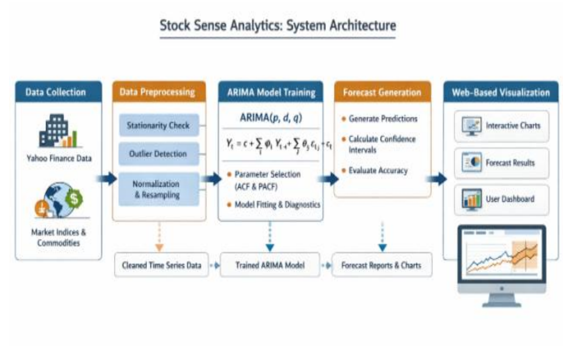

Figure 1: Flowchart of the ARIMA-Based Global Finance Forecasting System

3.1 System Architecture

The proposed system, Stock Sense Analytics, is designed as an end-to-end pipeline for stock market analysis and prediction. The workflow begins with data collection from reliable financial sources such as stock market APIs and publicly available datasets. The collected raw time series data is then processed through a preprocessing module to ensure data quality and stationarity. After preprocessing. The trained model generates future predictions based on historical trends. Finally, both historical data and predicted results are presented to the user through an interactive web-based interface, enabling efficient analysis and decision-making.

3.2 Data Collection and Description

This study utilises publicly available financial datasets to ensure reliability and real-time applicability:

- Yahoo Finance Dataset:

primary dataset includes daily stock prices such as opening price, closing price, high, low, and trading volume for multiple companies across different sectors.

- Supplementary Financial Data:

Additional data, such as market indices and commodity prices (e.g., gold, oil), are incorporated to provide broader market insights.

To ensure consistency:

- All date-time values are standardised to YYYY-MM-DD format
- Missing values are handled using interpolation techniques

Data from different sources is aligned based on timestamps.

3.3 Data Preprocessing Pipeline

The following steps are implemented:

1) Stationarity Check:

Stock price data is often non-stationary. The Augmented Dickey-Fuller (ADF) test is applied to verify stationarity. If the p-value exceeds 0.05, differencing is performed until the data becomes stationary.

2) Outlier Detection and Removal:

Extreme values are identified using the Interquartile Range (IQR) method and removed to prevent distortion in model predictions.

3) Data Resampling and Normalisation:

Daily stock data is resampled into weekly averages for smoother trend analysis. Additionally, Min-Max normalisation is applied to scale the data for better visualisation and model performance.

3.4 ARIMA Model Formulation

The Autoregressive Integrated Moving Average (ARIMA) model is used for time series forecasting and is denoted as ARIMA (p, d, q), where:

- p (Autoregressive term): Number of lag observations
- d (Differencing term): Number of times data is differenced
- q (Moving Average term): Size of the moving average window
-

Mathematical Representation $Y_t = c + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t$

Where:

- Y_t= Actual value at time t
- ϕ_i= Autoregressive coefficients
- θ_j= Moving average coefficients
- ϵ_t= Error term

The model parameters are selected using:

- ACF (Autocorrelation Function)
- PACF (Partial Autocorrelation Function)

The model is trained using the Box-Jenkins methodology, and residual diagnostics are performed to ensure the error terms behave like white noise.

3.5 Model Evaluation Metrics

To evaluate the performance of the ARIMA model, the following metrics are used:

- Root Mean Squared Error (RMSE):

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

$$Y_t = c + \sum_{i=1}^{p} \phi_i Y_{t-i} + \epsilon_t$$

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Mean Absolute Error (MAE):

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

Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{100}{n}\sum_{i=1}^{n} | \frac{y_i - \hat{y}_i}{y_i} |$$

These metrics help in assessing prediction accuracy and model reliability.

IV. RESULTS

The proposed system, Stock Sense Analytics, was successfully implemented and tested using real-time stock data. The ARIMA model was applied to TCS.NS is using historical data from January 2022 to April 2026. The system generated the following key results

Live Market Price (LTP): ₹2,539.80

Forecast Window: 30 days

Predicted Price Range: ₹1,976.17 to ₹2,929.18

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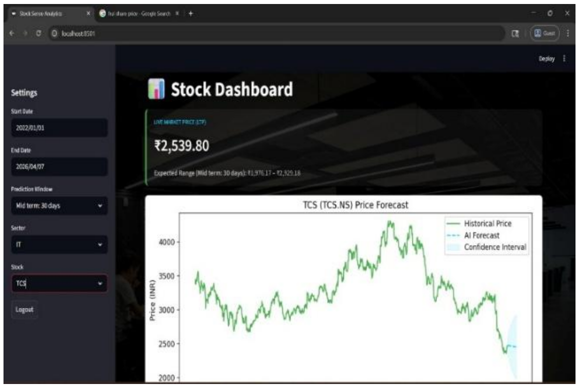

The output graph displayed

Historical stock price trends showing market volatility Forecasted values for the selected period Confidence interval indicating prediction uncertainty The ARIMA model successfully captured the trend and produced a stable mid-term forecast, demonstrating its effectiveness for stock price prediction in a web-based environment.

V. CONCLUSION

In conclusion, this research successfully demonstrates that the integration of ARIMA-based time series modelling within a web-based stock analysis system provides a powerful, transparent, and user-friendly solution for stock market forecasting. The proposed system, Stock Sense Analytics, effectively combines statistical modelling with interactive visualisation to deliver meaningful insights from historical stock data. By automating essential processes such as data pre-processing, stationary testing, model training, and visualisation, the application enables users to generate reliable short-term stock price predictions without requiring deep technical expertise.

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