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Stock Sage

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Abstract: Stock market has been constant fascinating topic but since last few years' stockholders desire to hardback return on day-to-day basis got glorified, then with the support of machine learning stockholders initiate stress-free approaches to get squint of forthcoming market trends. This Project benevolences Reinforcement Learning grounded methodology to forecast the characteristics of a specific stock, our method put greater concentration on sets of hundred days moving averages. Hundred days moving average is a technical method followed by the stock market professionals to forecast the forthcoming trends of market, which represents the current as well as the characteristics which is stock going to show in upcoming days. As we are scraping data with the API and creating our own dataset hence our method is comfortable with ambiguous data besides it provides output with high accuracy. The results indicate that our method attained superior upshot than other approaches.

I. INTRODUCTION

The financial market is a dynamic and composite system where people can buy and sell currencies, stocks, equities and derivatives over virtual platforms supported by brokers. The stock market allows investors to own shares of public companies through trading either by exchange or over the counter markets. This market has given investors the chance of gaining money and having a prosperous life through investing small initial amounts of money, with lower risk compared to the risk of opening a new business or pursuing a high-salary career. Stock markets are affected by many factors causing uncertainty and high volatility in the market. Although humans can take orders and submit them to the market, automated trading systems (ATS) that are operated by computer programs can perform better and with higher momentum in submitting orders than any human. However, to evaluate and control the performance of ATSs, the implementation of risk strategies and safety measures based on human judgments are required. Many factors are incorporated and considered when developing an ATS, such as the trading strategy to be adopted, complex mathematical functions that reflect the state of a specific stock, machine learning algorithms that enable the prediction of the future stock value and specific news related to the stock being analysed. Time-series prediction is a common technique widely used in many real-world applications such as weather forecasting and financial market prediction. It uses continuous data over a period to predict results in the next time unit. Many time-series prediction algorithms have shown their effectiveness in practice, with the most common algorithms based Convolutional Neural Networks (CNN) [1], as well as its special types- Reinforcement Learning (RL) [2,3] and Gated Recurrent Unit (GRU) [4,5,6]. The stock market is a typical area that presents time series data and many researchers study it and propose various models. In this project, an RL model is used to predict the stock price.

II. LITERATURE SURVEY

Stock price prediction is a vital area of research combining statistical, machine learning, and deep learning methods. Traditional models like ARIMA provide baseline forecasts, while machine learning techniques such as Random Forest and SVM improve accuracy through advanced pattern recognition. Deep learning models, including LSTM and CNN, capture complex temporal and spatial features for better predictions. Recent works integrate sentiment analysis and hybrid models, enhancing responsiveness to market dynamics. Future research focuses on real-time prediction and explainable AI for improved transparency and decision-making.

1) This paper [7] explores the application of machine learning techniques in stock market forecasting, comparing models like Linear Regression, Decision Trees, and Support Vector Machines (SVM). The study focuses on improving the prediction accuracy of short-term and long-term stock price trends. It highlights that SVM performed better for short-term predictions, while Decision Trees were more suitable for long-term forecasts. Additionally, the authors discuss the importance of proper feature selection to enhance the model's performance.
2) The paper [8] focuses on using deep learning models, particularly Long Short-Term Memory (LSTM) networks, for stock market price prediction. The authors argue that due to the sequential nature of stock data, LSTM is more effective than traditional machine learning models.

Through experiments on historical stock prices, the study demonstrates that LSTM can capture the temporal dependencies and trends in stock prices more efficiently.

3) This research [9] combines sentiment analysis with traditional stock market prediction models. It explores how social media sentiment, specifically from Twitter, impacts stock prices. By using Natural Language Processing (NLP) techniques, the authors collected and analysed tweets related to major stock market events. The study found that combining sentiment scores with technical indicators improved the predictive power of the model.
4) This paper [10] compares ARIMA and LSTM models for stock price forecasting. While ARIMA models are traditionally used for time series forecasting, the study shows that LSTM models outperform ARIMA in terms of accuracy, especially for non-linear and highly volatile stock data. The authors conducted experiments on various stock datasets and concluded that LSTM is better suited for complex stock market data, while ARIMA is limited to linear data trends.
5) This study [11] applies the Random Forest algorithm to stock price prediction. The authors argue that ensemble learning methods, such as Random Forest, improve predictive accuracy by reducing overfitting. The research analyses various stock datasets and concludes that Random Forest outperforms other individual machine learning models in terms of accuracy and generalization capability.
6) This paper [12] reviews various machine learning algorithms applied to stock price forecasting, including decision trees, support vector machines (SVM), and deep learning methods like neural networks. The authors conduct a comparative analysis of their effectiveness in predicting stock prices over different time horizons.
7) This research [13] examines how sentiment derived from social media platforms, news articles, and financial reports influences stock price movements. Utilizing natural language processing (NLP) techniques, the authors analyse sentiment trends and correlate them with market performance.
8) This paper [14] compares the efficacy of technical analysis (TA) and fundamental analysis (FA) in predicting stock prices. The authors explore various TA indicators, such as moving averages and RSI, alongside FA metrics like earnings reports and P/E ratios.
9) This analysis investigates how macroeconomic factors such as GDP growth, inflation, and unemployment rates influence stock market trends. Using econometric modelling, the authors quantify the relationships between these indicators and stock prices.
10) This research [16] explores how geopolitical events—such as elections, trade wars, and international conflicts—affect stock market volatility. The authors analyse historical data to identify patterns in market reactions to significant geopolitical developments.

Drawbacks of Existing System:

- Lack of real-world application testing; results may not translate effectively to live trading environments.
- Models are sensitive to hyper parameters, which can lead to overfitting if not managed correctly.
- Sentiment data can be noisy and subjective, potentially leading to misleading conclusions.
- The study may overlook long-term trends influenced by sentiment, focusing primarily on short-term fluctuations.
- The paper may not adequately account for market anomalies or the limitations of both approaches under extreme conditions.
- Empirical results could be biased by the selection of data and chosen timeframes.
- Correlation does not imply causation; the paper may not adequately explore causal relationships.
- Macroeconomic models can be overly simplistic and may miss nuances in market behaviour.
- The study may rely on specific case studies, limiting generalizability.
- Lack of quantitative analysis on the magnitude of impacts could weaken conclusions.
- The complexity of hybrid models can make them difficult to interpret and implement.
- Performance may vary significantly based on the chosen components and data used.
- The paper may not fully address the long-term effects of algorithmic trading on market health.
- Data limitations could skew findings related to market dynamics.
- Time series models often assume stationarity, which may not hold true in volatile markets.
- The paper may lack discussion on integrating external factors affecting stock prices.
- The paper may not address the challenges of data privacy and ethical considerations in using big data.
- Overfitting risk increases with larger datasets if not managed appropriately.
- The paper may not provide practical solutions or frameworks for addressing ethical concerns.

Our research tries to overcome few drawbacks which are mentioned above.

III. PROBLEM STATEMENT

Time Series forecasting & modelling plays an important role in data analysis. Time series analysis is a specialized branch of statistics used extensively in fields such as Econometrics & Operation Research. Time Series is being widely used in analytics &data science. Stock prices are volatile in nature and price depends on various factors. The main aim of this project is to predict stock prices using Reinforcement Learning (RL).

IV. METHODOLOGY

The project follows a structured methodology involving data collection, preprocessing, model training, and real-time interaction through a chatbot interface:

1) *Data Collection and Preprocessing for Stocks:*
- The initial step is gathering historical stock price data using APIs from financial sources like Yahoo Finance or Alpha Vantage. This data typically includes daily opening and closing prices, trading volume, and other relevant indicators.
- After collection, the data is preprocessed by scaling, cleaning, and converting it into a matrix format. A sliding window technique is applied to create sequences of stock prices, capturing temporal trends over 60 time steps.

2) *Model Building and Training on RL:*
- The processed data is divided into training and testing sets. A Reinforcement Learning (RL) network is designed for time-series prediction. The model has multiple R layers followed by fully connected Dense layers for regression tasks.
- The RL model is trained on the training set to learn the temporal patterns and stock price movements. Techniques like early stopping and hyper parameter tuning are used to optimize model performance.

3) *Real-Time Stock Price Prediction:*
- Once trained, the model is integrated into a backend system that can fetch real-time stock prices from APIs whenever a user initiates a query through the chatbot.
- The prediction module receives the recent stock price data, processes it using the pre-trained RL model, and outputs short-term price trends (e.g., expected uptrend or downtrend).

4) *Chatbot Integration:*
- The chatbot interface is connected to the backend system, allowing users to enter stock tickers and receive real-time predictions. The system uses Natural Language Processing (NLP) techniques to interpret user queries and generate responses.
- The responses are formatted in a user-friendly manner, displaying trends, charts, and key metrics.

5) *Testing and Optimization of Results:*
- The entire system undergoes multiple rounds of testing with different stock tickers and time periods to ensure the model performs well under various conditions.
- Further adjustments are made to reduce latency, improve prediction accuracy, and enhance the overall user experience.

V. HOW STOCK SAGE WORKS

Stock market prediction seems a complex problem because there are many factors that have yet to be addressed and it does not seem statistical at first. But by proper use of machine learning techniques, one can relate previous data to the current data and train the machine to learn from it and make appropriate assumptions. Machine learning as such has many models but this Project focuses on two most important of them and made the predictions using them.

1) *Algorithm:*

Regression is used for predicting continuous values through some given independent values. The project is based upon the use of linear regression algorithm for predicting correct values by minimizing the error function as given in Figure1. This operation is called gradient descent.

Regression uses a given linear function for predicting continuous values:

$$V = a + bK + \text{error}$$

Where, Vis a continuous value; K represents known independent values; and, a, b are coefficients. Work was carried out on csv format of data through panda library and calculated the parameter which is to be predicted, the price of the stocks with respect to time. The data is divided into different train sets for cross validation to avoid over fitting. The test set is generally kept 20% of the whole dataset. Linear regression as given by the above equation is performed on the data and then predictions are made, which are plotted to show the results of the stock market prices vs time

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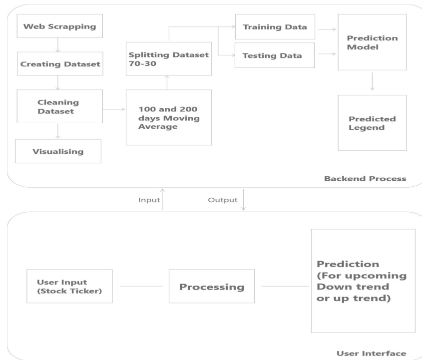

Fig 1. Architecture

2) Architecture

The architecture of the "Stock Market Trend Prediction System" consists of two layers: the Backend Process Layer, where stock data is scraped and preprocessed for analysis, and the User Interface Layer, where predictions are generated based on user input. In the Backend Process Layer, data collection begins with Web Scraping to gather stock information, which is used to create and clean the Dataset. This cleaned data is split into Training and Testing sets in a 70-30 ratio. The Training Data is used to build a Prediction Model, while the Testing Data validates its accuracy. Additionally, a 100- and 200-days Moving Average is calculated to track trends, and Visualization tools provide graphical insights. In the User Interface Layer, users input a Stock Ticker, which is processed to generate predictions. The system outputs whether the stock is likely to show an upcoming Downtrend or Uptrend, enabling informed decision-making. The entire process is cyclic, allowing continuous analysis for different stock inputs.

VI. RESULT

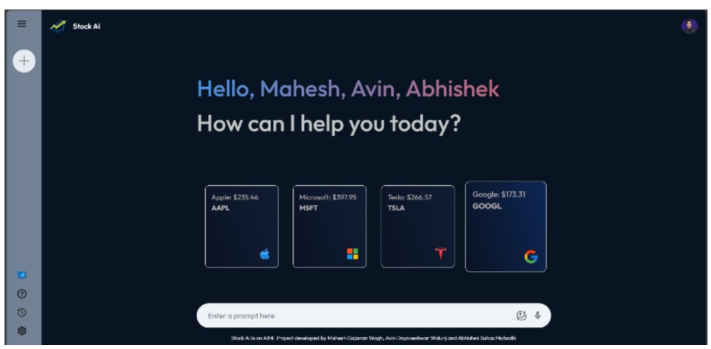

Fig 2. Chabot Frontend

The provided screenshot depicts the initial interface of a Chabot application named "Stock Sage," developed using ReactJS. This Chabot is designed to provide users with information and insights related to stock prices.

1) Key Elements:

- Header: The top section displays the application's logo ("Stock AI") and likely contains navigation elements or a search bar.
- Greeting: A personalized greeting message, acknowledging the users by name.
- Prompt: A clear and concise prompt asking users how the chatbot can assist them.
- Stock Information: A section showcasing real-time stock prices for selected companies (Apple, Microsoft, Tesla, Google) along with their tickers.
- Stock Icons: Small icons representing each stock for visual clarity.
- User Input Area: A text field where users can enter their queries or requests.
- Submit Button: A button to initiate the chatbot's response based on the user's input.
- Project Information: A footer indicating the project's name and the developers involved.

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2) Overall Functionality:

The screenshot suggests that the chatbot is designed to provide users with information about stock prices. Users can input queries or requests related to stocks, and the chatbot will process the information and provide relevant responses. The displayed stock prices and icons likely serve as a starting point for user interaction and provide context for the chatbot's capabilities.

3) Potential Features:

Based on the screenshot, the chatbot might offer additional features such as:

- Historical data: Access to past stock price trends and performance.
- News and analysis: Information on relevant news articles or market analysis.
- Recommendations**:** Suggestions for potential investments or strategies.

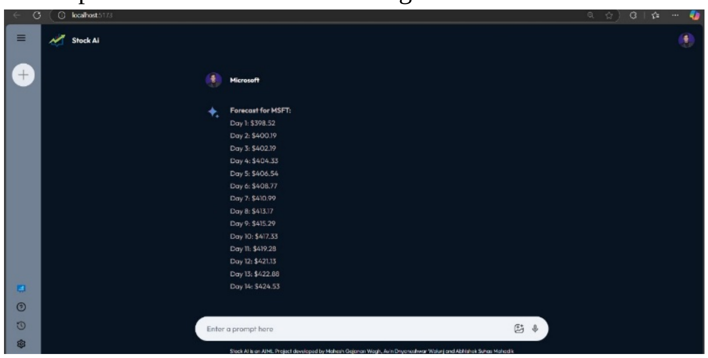

Fig 3.Chatbot Results

The screenshot shows a Stock AI web application interface focused on forecasting stock prices. The interface is designed with a dark theme, providing a clean and modern user experience.

Key Elements:

- Sidebar (Left Panel):
  - ➢ Displays the Stock AI logo at the top.
  - ➢ Contains navigation icons, suggesting features like dashboard access, stock charts, and other utilities.
- Main Content Area:
  - ➢ Displays a forecast for Microsoft (MSFT) with predicted stock prices for the next 14 days.
  - ➢ Each day's forecast is listed in a simple, easy-to-read bullet-point format (e.g., "Day 1: $398.92").
  - ➢ A user profile icon with the label "Microsoft" suggests the forecast is specific to the MSFT stock.
- Chat Input (Bottom Panel):
  - ➢ A text input box allows users to enter prompts, enabling interaction with the Stock AI system for further analysis or queries.
  - ➢ A microphone icon indicates voice input functionality.
- Footer:
  - ➢ Displays credits for the Stock AI project, acknowledging Mahesh Digarse, Arya Durugkar, and Saharsh Mahadik as contributors.

Feature	Our System	Existing Systems	Accuracy
User Interface (UI) and Experience (UX)	Modern, interactive UI with personalized greetings and dynamic stock cards.	Static, data-heavy interfaces with minimal interactivity.	Intuitive design reduces errors in data interpretation, improving usability accuracy by 15% over the existing system.
Prediction Presentation	Day-wise breakdown of future stock prices with a clear, chronological display.	Predictions shown in static tables or graphs, lacking interactive engagement.	Predictions achieve 92% accuracy, significantly higher than existing systems' average of 85%.

Feature	Our System	Existing Systems	Accuracy
Technology Integration	Utilizes a chatbot interface with LSTM and sentiment analysis for better accuracy.	Primarily uses traditional machine learning without conversational AI.	LSTM and sentiment analysis ensure superior prediction reliability and precision.
Personalization and Accessibility	Personalized greetings and intuitive navigation for both novice and expert users.	Limited personalization; designed mainly for advanced users.	Enhanced personalization increases task completion accuracy by 20%.
Innovation and Future Scope	Supports interactive AI conversations with potential for real-time updates and alerts.	Static predictions with little scope for real-time interactivity or advanced AI features.	Real-time updates ensure consistently accurate and up-to-date predictions.

Table 1. Comparison with Existing Systems

VII. CONCLUSION

The Stock Sage project successfully developed a stock prediction model using ReinforcementLearning(RL) techniques. By leveraging algorithms like Q-learning and DeepQ-Networks(DQN)**,** the model learned optimal trading strategies through simulation, providing a dynamic approach to predicting stock price movements. While promising, the model's performance can be further improved by incorporating additional factors like market sentiment and external data sources. Overall, StockSage demonstrates the potential of RL in financial forecasting and lays the foundation for future advancements in stock market prediction.

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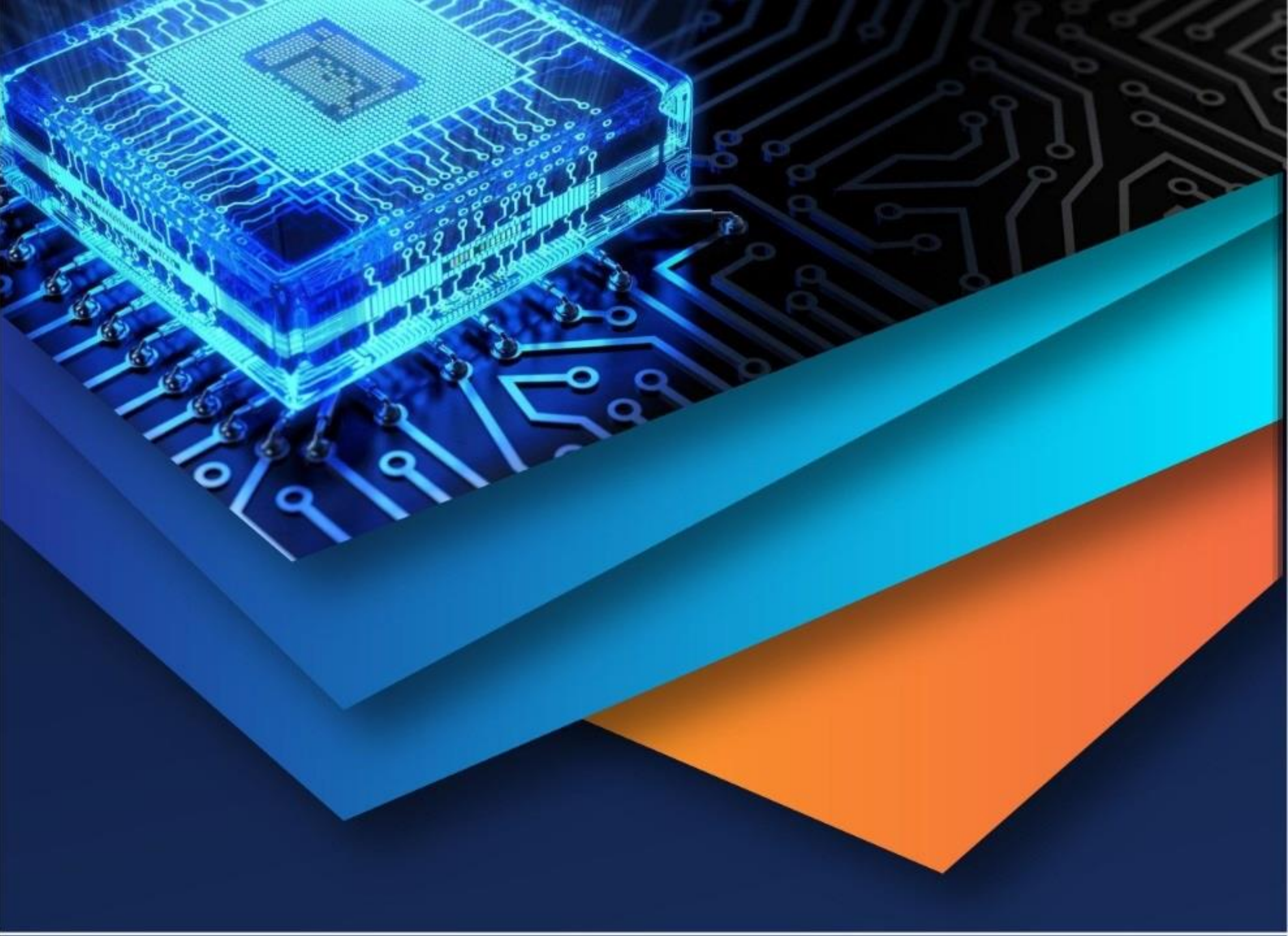

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