STOCK VISION – A REAL TIME STOCK VISUALIZER AND FORECASTER

COMMUNITY SERVICE PROJECT REPORT

Submitted by

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in partial fulfillment for the award of the degree of

BACHELOR OF TECHNOLOGY

IN

COMPUTER SCIENCE AND ENGINEERING

SCHOOL OF COMPUTING

COMPUTER SCIENCE AND ENGINEERING

KALASALINGAM ACADEMY OF RESEARCH AND EDUCATION

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DECLARATION

We affirm that the project work titled **"STOCK VISION – A REAL TIME STOCK VISUALIZER AND FORECASTER"** being submitted in partial fulfillment for the award of the degree of **Bachelor of Technology in Computer Science and Engineering** is the original work carried out by us. It has not formed part of any other project work submitted for the award of any degree or diploma, either in this or any other University.

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Under sec. 3 of UGC Act 1956. Accredited by NAAC with "A++" Grade

BONAFIDE CERTIFICATE

Certified that this project report **"STOCK VISION – A REAL TIME STOCK VISUALIZER AND FORECASTER"** is the bonafide work of "**HEEREHAL DHEERAJ KISHORE (99220040269), GIRAPPAGARI HEMANANDAN REDDY (99220040265), THEPIREDDY AKASH REDDY (99220040209), GEETHA VINAY KRISHNA (99220040267)"** who carried out the project work under my supervision.

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We would like to begin by expressing our heartfelt gratitude to the Supreme Power for the immense grace that enabled us to complete this project.

We are deeply grateful to the late **"Kalvivallal" Thiru T. Kalasalingam,** Chairman of the Kalasalingam Group of Institutions, and to "**Illayavallal" Dr. K. Sridharan**, Chancellor, as well as **Dr. S. Shasi Anand**, Vice President, who has been a guiding light in all our university's endeavours.

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PROJECT SUMMARY

Project Title	STOCK VISION – A REAL TIME STOCK VISUALIZER AND FORECASTER	
Project Team Members (Name with Register No)	Heerehal Dheeraj Kishore– 99220040269 Girappagari Hemanandan Reddy– 99220040265 Thepireddy Akash Reddy– 99220040209 Gogula Geetha Vinay Krishna– 99220040267	
Guide Name/Designation	Mrs. R. Durga Meena/ Assistant Professor	
Program Concentration Area	Financial Technologies	
Technical Requirements	Python, HTML, CSS, Dash	
Engineering standards and realistic constraints in these areas		
Area	**Codes & Standards / Realistic Constraints**	**Tick ✓**
Economic	Guarantees economic development and helps users by improving investment plans.	✓
Environmental		
Social	Encourages the community to make well-informed financial decisions.	✓
Ethical	Respects data privacy and integrity guidelines when managing financial data.	✓
Health and Safety		
Manufacturability	Utilizing modular code structures to facilitate web deployment and simple scalability.	✓
Sustainability	SDG 8: Decent Work and Economic Growth	✓

ABSTRACT

The project predicts stock market prices based on a hybrid approach, which involves some techniques of machine learning and deep learning. In this system, it uses Support Vector Regression (SVR), Random Forest, and Long Short-Term Memory (LSTM) algorithms to make correct predictions. The system fetches real-time information on stocks using yfinance, and its analysis of the historical trend is open, close, high, low prices, and trading volume, generating a number of predictions in various time horizons to enable traders and investors to make decisions from actual data. This model applies a two-stage approach: employing SVR in stage one as a basis for a preliminary forecast and then refining the outcome by integrating SVR with Random Forest in stage two. Key characteristics include technical indicators, stop-loss calculations determining when to close an automated trade, and false breakdown detection that identifies possible misleading price variation. Changing trading strategy as informed by up-to-date market data should also be helpful in the construction of the tool. The project shall align predictions with the trend of the market in order to improve the accuracy of the forecasts. It shall address the short-term analysis and help manage the risks properly. The program has easy interfaces for beginners and provides well-developed features to empower experienced traders in relation to making informed investment choices and dealing with dynamic market environments.

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LIST OF ABBREVIATION

SVR	Support Vector Regression
RF	Random Forest
EMA	Exponential Moving Average
LSTM	Long Short-Term Memory
ML	Machine Learning
DL	Deep Learning
RMSE	Root Mean Squared Error
MAPE	Mean Absolute Percentage Error
CNN	Convolutional Neural Networ
RNN	Recurrent Neural Network
Bi-GRU	Bidirectional Gated Recurrent Unit
SP-PDA	Stock Price Prediction with Political Data Analysis
GBMs	Gradient Boosting Machines
NSE	National Stock Exchange
MTRAN - TCN	Modified Transformer - Temporal Convolutional Network
UCB	upper confidence bound
CEEMDAN	Complete Ensemble Empirical Mode Decomposition with Adaptive Noise
SA	Simulated Annealing
CFFS	Comprehensive Fundamental Feature Set
AWFS	Advanced Wavelet Feature Set
FTFOFS	Fusion of Technical and Fundamental Feature Optimization Set
FOFFS	Fusion of Oscillator and Fundamental Feature Selection
CNX	Cricket News Exchange
BSE	S&P Bombay Stock Exchange
ANN	Artificial Neural Network
ARIMA	Auto Regressive Integrated Moving Average
AR	Auto Regressive
MA	Moving Average
API	Application Programming Interface
GUI	Graphical User Interface
GARCH	Generalized autoregressive conditional heteroskedasticity
HTML	HyperText Markup Language

CSS	Cascading Style Sheets
WSGI	Web Server Gateway Interface
HTTP	Hypertext transfer protocol
XML	eXtensible Markup Language
TBHAG	TextBlob Hybrid ARIMA-GARCH

CHAPTER –I

INTRODUCTION

One of the most important fields of financial study is still stock market price forecasting, which has a direct impact on trading decisions, risk management, and investing strategies. Because there are so many variables influencing the market, such as macroeconomic statistics, company news, investor sentiment, and economic events, it is difficult to predict stock prices. Traditional methods like statistical analysis and econometric models are less successful at capturing the complexities of financial data because of these dynamic and frequently unanticipated factors.

Deep Learning (DL) and Machine Learning (ML) approaches have recently demonstrated significant promise for more precise stock price forecasts. Among these, the Random Forest and Support Vector Regression (SVR) algorithms are notable for their superior accuracy over conventional techniques in modeling nonlinear connections in the data. These methods might, however, find it difficult to capture the time-dependent patterns and sequential dependencies present in stock market time series data.

Long Short-Term Memory (LSTM) networks, a kind of deep learning architecture, have shown great promise in overcoming this constraint. LSTM networks are perfect for financial time series forecasting because of their exceptional memory retention over lengthy sequences. A hybrid strategy that combines time-dependent pattern recognition and nonlinear modeling can be used to improve prediction accuracy when paired with machine learning approaches like SVR.

By forecasting stock prices and providing useful insights that might guide trading decisions, the suggested approach provides traders and investors with a potent tool. The model uses technical indicators and real-time market data to determine stop-loss limits, detect false breakouts, and increase the accuracy of short-term predictions. This strategy lowers the risks involved in stock market investing and improves stock price forecasting by fusing the advantages of both ML and DL models, offering significant chances for more informed decision-making.

CHAPTER-II

LITERATURE REVIEW

The literature survey is carried out to discuss existing research and advancements in stock market forecasting using machine learning and deep learning techniques. It is a very challenging problem that has been studied with respect to inherent volatility and complexity of financial markets and thus attracted much attention from researchers and practitioners. There have been many studies that looked at different approaches, from traditional statistical models to more recently developed machine learning algorithms and deep learning architectures.

These models are the Support Vector Regression (SVR) and Random Forest, which have gained immense popularity because of their capabilities to model non-linear relations in financial data. Techniques in deep learning have proved to be quite promising by capturing temporal dependencies and patterns in stock prices with Long Short-Term Memory (LSTM) networks. This is complemented by the increased use of hybrid and ensemble models that combine multiple algorithms to improve prediction performance, by leveraging the strengths of different techniques.

This section reviews key studies that have employed various predictive models and methodologies, highlighting their contributions, limitations, and areas for further improvement. Based on the survey of existing literature, a basis for developing a solid stock price forecasting framework using both machine learning and deep learning models is established and used to provide reliable and accurate predictions.

[1] Agrawal et al. developed a reinforced predictive model that combines sentiment analysis from social media with technical indicators to enhance stock market prediction. It uses a dataset of tweets from twenty companies to evaluate stock prices of Apple, General Electric, Ford Motors, and Amazon, aiming to improve accuracy and insights into market sentiment's influence on stock movements.

[2] Kothari et al. utilizes LSTM neural networks to predict NSE stock closing prices using nine selected predictors, including market fundamentals and technical indicators. It evaluates single-layer and multilayer models based on performance metrics like Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) to provide traders with accurate tools for stock market navigation.

[3] Ayyappa et al. predicted the stock price using ensemble of Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Bidirectional Gated Recurrent Unit (Bi-GRU), LSTM, and Deep Maxout classifiers. The study develops the SP-PDA (Stock Price Prediction with Political Data Analysis) model, which preprocesses stock, news, and political data using techniques like Z-score normalization and tokenization, employing a Map-Reduce architecture for feature extraction. It utilizes an ensemble of classifiers, including CNN, RNN, Bi-GRU, LSTM, and Deep Maxout, optimized with a Dwarf Mongoose Updated War Strategy-based algorithm to enhance prediction accuracy based on various error metrics.

[4] Upadhyay et al. introduced the TextBlob Hybrid ARIMA-GARCH (TBHAG) model, which integrates sentiment analysis from Twitter data to predict stock price movements in the National Stock Exchange of India (NIFTY 50). It captures investor and trader sentiment using the TextBlob model and applies a hybrid ARIMA-GARCH framework for prediction, demonstrating significant improvements in accuracy compared to baseline models while accounting for the influence of major events and market opinions.

[5] Jathe et al. predicted Stock Price using Linear Regression, Support Vector Regression (SVR), Random Forest Regression, or Gradient Boosting Machines (GBMs). The research presents a robust approach for predicting stock prices with risk analysis, integrating statistical and machine learning techniques. It utilizes granular daily stock price data from a credible company on India's National Stock Exchange (NSE), aggregating five-minute interval data to train forecasting models. The study emphasizes the importance of variable selection and model parameter fine-tuning to achieve high accuracy in predicting stock price fluctuations and short-term trends.

[6] Patra et al. demonstrated Stock Market Prediction Using Long Short-Term Memory (LSTM), Support Vector Machines (SVM) and Linear Regression. The chapter analyses the Indian stock market from 2000 to 2022, identifying Long Short-Term Memory (LSTM) as the most accurate machine learning technique for predicting market movements, while Support Vector Machines and linear regression demonstrate lower accuracy. It emphasizes the importance of robust predictive models for investors to identify return opportunities and mitigate risks in the emerging market.

[7] Wang and S. introduced the BiLSTM – MTRAN - TCN (Modified Transformer - Temporal Convolutional Network) method, combining BiLSTM with an enhanced transformer model (MTRAN-TCN) for stock price prediction that incorporates a Temporal Convolutional Network (TCN) for improved sequence dependency capture. It

validates the model's effectiveness on 5 index stocks and 14 Shanghai and Shenzhen stocks, demonstrating superior accuracy and generalization in stock price predictions compared to existing methods.

[8] Zhang et al. preferred a reinforcement learning-based dynamic parameter optimization algorithm to improve high-frequency trading frameworks for stock price trend prediction and trading strategies. It utilizes a rolling model training approach and a reward-enhanced upper confidence bound (UCB) algorithm for real-time optimization, showing competitive performance in the Chinese stock market.

[9] Zhang et al. demonstrated the study that focuses on decision fusion techniques rather than specific algorithms, reviewing various base learners (such as machine learning and deep learning models) used in stock market prediction. The study highlights the combination of forecasts from multiple models to improve prediction accuracy. Common base learners may include Random Forests, Support Vector Machines (SVMs), Neural Networks, and ensemble methods like Gradient Boosting. The fusion techniques could involve methods like weighted averaging, stacking, or voting. The study conducts a systematic literature review on decision fusion techniques for stock market prediction, highlighting the advantages of combining forecasts from multiple models. It discusses the characteristics of base learners, research trends over the past two decades, and proposes future directions for integrating various data types and sentiment analysis in decision fusion approaches.

[10] Sun et al. proposed a hybrid model that involves Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) for signal decomposition, Long Short-Term Memory (LSTM) for sequential learning, and Light GBM for boosting accuracy, optimized by the algorithm of Simulated Annealing (SA). It improves the prediction of variability, which is nonlinear and noisy in financial time series. The performance of the model was appraised using metrics of Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and accuracy compared with different baseline models.

[11] Das et al. introduced a feature fusion that involves momentum analysis, trend analysis, and volatility analysis in four strategies as Comprehensive Fundamental Feature Set (CFFS), Advanced Wavelet Feature Set (AWFS), Fusion of Technical and Fundamental Feature Optimization Set (FTFOFS), and Fusion of Oscillator and Fundamental Feature Selection (FOFFS) which optimized via the Aquila technique that enhances the feature weights of the chosen model. These feature sets through different forecasting models including decision tree, naive bayes, support vector regression, and multi-layer

perceptron over SBI and ICICI bank data from ten years. Short-term predictions of stock movements have been done using these models and the performance metrics in comparison with mean absolute error and correlation coefficient depict high significant improvement with the proposed method, FOFFS-Aquila.

[12] Bacco et al. investigated a multidimensional approach to the study, using the Recurrent Neural Networks and combining sentiment analysis by the LSTM and FinBERT models, for in-depth analysis of comprehensive financial metrics and Twitter sentiment data. The research has evaluated the condition of the US and EU markets, examined data aggregation by multiple banks, and also analysed the effect of a different span of historical data on model performance. The results have demonstrated that fresh data and public opinion do increase predictability by a significant margin and have unearthed separate market dynamics between US and European banks.

[13] Patel et al. demonstrated a approach that focuses on predicting a stock market index that is made up of Cricket News Exchange (CNX) Nifty and S&P Bombay Stock Exchange (BSE) Sensex with 10 years of history. In this approach, two-stage fusion is proposed for a combination of Support Vector Regression (SVR) followed by the second stage involving the use of SVR and Artificial Neural Network (ANN) along with Random Forest (RF) to construct the hybrid models: SVR–ANN, SVR–RF, and SVR–SVR. The single-stage models are compared against fusion models, namely ANN, RF, and SVR; ten technical indicators were adopted as inputs for the purpose of performance evaluation over prediction intervals of 1–10, 15, and 30 days.

[14] Siami-Namini et al. compared Auto Regressive Integrated Moving Average (ARIMA) and LSTM for time series forecasting. This analysis investigates the suitability of deep learning models like LSTM against traditional time series forecasting approaches such as ARIMA. Even though Auto Regressive (AR), Moving Average (MA), and ARIMA are very common models, they have given good results for short term predictions. However, as the computing power is very high now, it became possible to use deep learning techniques for forecasting. Based on this, the need to know whether LSTM will outperform ARIMA emerges. Empirical results show that LSTM tends to outperform ARIMA by 84-87% error rate reduction. Thus, it has superior prediction accuracy. Interestingly, the number of epochs in training does not have a consistent impact on model performance. On the contrary, it varies randomly.

[15] Mu et al. demonstrated a model based on investor sentiment and optimized deep learning. Gather and preprocess data, such as forum posts, which would be used to produce a

sentiment dictionary and calculate the sentiment index. Use Sparrow Search Algorithm to find out the best set of hyperparameters for the best LSTM model performance. Integration of sentiment index with the trading data and forecasting of stock prices with the optimized LSTM.

CHAPTER-III

PROBLEM DEFINITION AND PROJECT OBJECTIVES

Problem Definition:

Building a reliable system that can precisely forecast stock prices in the face of the complex and constantly shifting financial market dynamics is the difficult part. Current models frequently aren't able to adjust to quick changes and intricate patterns, which leads to poor forecasting that can result in large losses and missed investment possibilities. This shortcoming might jeopardize economic growth and resilience in addition to affecting individual trading. In order to provide accurate insights, it is imperative to develop an advanced forecasting strategy that makes use of machine learning and real-time data processing. More financial stability and economic growth would result from such a solution, which would improve investors' capacity to make prompt, well-informed decisions while successfully managing risk. This supports UN Sustainable Development Goal 8, which calls for better forecasting and strategic financial planning to promote resilience and sustainable economic growth.

Project Objectives:

Enables dynamic data visualization for interactive displays:

By enabling real-time user interaction with charts and graphs, dynamic data visualization helps make complex data easier to comprehend and use. Users can delve deeper into particular data points, spot trends, and learn more using interactive displays. By offering an immersive experience that makes data exploration easier, this feature improves user engagement. Enabling such capabilities allows consumers to make better judgments faster.

Provides accurate forecasting for reliable future trends:

To predict future price movements and market behaviours, accurate forecasting uses sophisticated machine learning algorithms. This talent aids traders and investors in foreseeing possible outcomes and formulating appropriate tactics. Accurate trend forecasting promotes improved risk management techniques and lowers uncertainty. Users consequently become more confident in their trading and investment choices, which improves their financial results.

Integrates predictive analytics to enhance data analysis:

By projecting future scenarios utilizing historical and real-time data, predictive analytics improves the overall analysis. This enables users to spot possible threats and possibilities before they become real. By revealing hidden patterns and insights in massive data sets, predictive analytics helps make data-driven decisions. This kind of integration helps with strategic planning and expedites the decision-making process.

Offers a user-friendly interface for easy navigation:

All users can effectively access and utilize the capabilities of the application thanks to an intuitive user interface. The system is easier to use and has a lower learning curve thanks to its clear menus, simple controls, and efficient workflows. Because of the decreased friction, users may concentrate on data analysis and decision-making instead of navigating with difficulty. Productivity and user happiness are increased overall with an accessible interface.

Ensures comprehensive data integration from various sources:

The system can extract information from various data sources thanks to thorough data integration, giving it a comprehensive picture of the market. This allows for in-depth examination by providing real-time price feeds, historical stock data, and financial news. Users can make better decisions and forecasts by combining data from several sources. A more precise and comprehensive understanding of market conditions is supported by such integration.

Supports performance evaluation to measure efficiency:

Tools for performance evaluation measure how well analytical techniques and predictive models work over time. This enables users to track important performance metrics and modify their strategy as necessary. Efficiency measurement aids in determining a model's advantages and disadvantages and improves accuracy. By continuously enhancing their forecasting skills based on actual feedback and metrics, users gain.

Delivers real-time updates for continuously refreshed insights:

Users can make fast judgments since real-time updates guarantee they have access to the most recent facts. This tool helps customers stay ahead of trends and steer clear of out-of-date

information by enabling prompt responses to changes in the market. Regular data refreshes increase the precision of analysis and forecasts while lowering the possibility of making judgments based on outdated information. It gives consumers the ability to take advantage of opportunities as they present themselves.

Assists in decision support for informed business choices:

By evaluating information and presenting the results, decision support systems help make strategic decisions by offering actionable insights. Users can compare results, assess different scenarios, and choose the best course of action with the aid of these tools. Businesses can use data-driven counsel to make better informed and self-assured decisions. In unpredictable markets, this ability helps reduce possible risks and promotes long-term growth.

CHAPTER-IV

PROPOSED METHODOLOGY

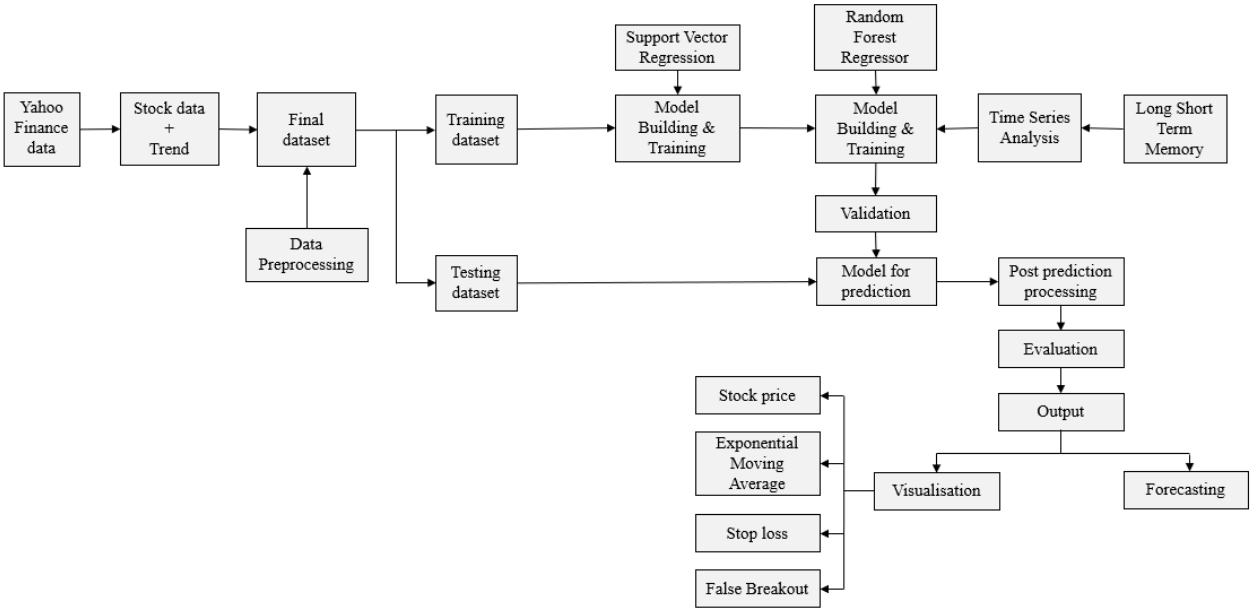

Fig. 1. Proposed Methodology of the Project

The proposed work is based on the development of a strong system for stock price forecasting by combining machine learning and deep learning models, namely Support Vector Regression (SVR), Random Forest, and an indirectly applied Long Short-Term Memory (LSTM) network. This hybrid approach will be taken to improve the accuracy of the forecast and to gain comprehensive insights into market trends.

Data Collected The data collected pertains to open, close, high, low prices, and trading volumes from the stock market. Data was fetched from Yahoo Finance through the yfinance API. In addition, the data encompasses financial news and external indicators, like currency and commodity prices, to incorporate more general influences from the market. The preprocessing step was undertaken in order to handle missing values, scale features, and structure the data for sequential modelling. Features: Added relevant technical indicators - moving averages and relative strength index to pick up market trends.

Models consist of main cores that use SVR and Random Forest. SVR works well with applications in regression, especially in good performance when strong linear interactions are captured, and the Random Forest applies an ensemble technique over decisions across multiple

trees for control of variance and stabilizing more predictions of response variables. Although indirect, an LSTM model supports learning on long dependencies in a time series; this makes for better control of pattern development in terms of controlling for temporal variability and associated volatility in markets.

The models are cross-validated to ensure that they have robust performance on various data segments. Accuracy measures include Mean Absolute Error and Root Mean Squared Error. The web interface, which has been built using Dash and Plotly, enables users to input stock codes, choose the date ranges, and see key insights, such as stop-loss levels and possible false breakouts from the predictions of the models. The user-friendly interface styled with custom CSS makes the forecasting tool accessible and actionable for investors and traders and enables them to make data-driven predictions for better-informed decisions.

CHAPTER-V

REQUIREMENTS AND MODULE DESCRIPTION

Hardware Requirements:

- RAM: 4 GB
- Storage: 500 GB
- CPU: 2 GHz or faster
- Architecture: 32-bit or 64-bit

Software Requirements:

- Python 3.5 and above in Visual Studio code or Pycharm
- Operating System: windows 7 and above or Linux based OS or MAC OS

Library Requirements:

- **NumPy:**

  The core Python library for numbers is called NumPy. Together with a large number of high-performance mathematical functions to work with these arrays, it supports enormous, N-dimensional arrays and matrices. Since array operations in NumPy are far faster than those in regular Python lists, they constitute a fundamental component of the majority of data science and machine learning applications.

- **Pandas:**

  An open-source Python package called Pandas offers sophisticated data analysis and manipulation capabilities. It has two main data structures: the one-dimensional labeled array called Series and the tabular structure called Data Frame. You can use it to work with structured data on a variety of computing platforms that support these packages. It is also ideal for data transformation, data exploration, and data cleaning. When working with tabular data, like stock market data, this is crucial.

- **Yfinance:**

  With the help of the Python package Yfinance, one may easily extract historical market data from Yahoo Finance, such as stock prices and trading volumes. Financial analysis and

research benefit from its easy-to-use query interface for historical data of individual stocks or market indices.

- **Gunicorn:**

  Gunicorn is a web server for Python applications that uses the WSGI HTTP interface. Python web apps are frequently hosted and run on it. This application is specifically used to host dash applications due to its strong performance and scalability, which makes it perfect for production servers.

- **Lxml:**

  XML and HTML documents can be processed using the Python package lxml. This is the quickest method for parsing and working with XML/HTML data, which makes it useful for data extraction, web scraping, and parsing XML-based APIs.

- **Scikit-learn:**

  Several supervised and unsupervised learning methods are implemented by this helpful Python machine learning library, which also includes tools for model selection, evaluation, and preprocessing. When creating machine learning models for tasks like classification, regression, clustering, and dimensionality reduction, Scikit-learn is frequently used.

Since they will include features for data processing, analysis, machine learning, and deployment, these libraries and technologies collectively serve as the foundation for the stock forecasting and visualization project. Developers can efficiently create and implement complex applications for stock market trend analysis and prediction by utilizing the strong tools provided by these libraries.

Module Description:

- **Develop the Main Website Structure**

  Use Dash's HTML and Core components to create an interactive web structure. The template will be a header, navigation bar menu, input forms, and graphical interfaces that will enable real-time interaction. The structure should appear intuitive in nature so that the client can easily locate the drop-downs, sliders, or buttons when navigating for stock information. The client will have the freedom to navigate and interact with the interface.

- **CSS Customization for a Better User Interface**

  Add custom CSS for making the web application visually more appealing. You will add different types of styles, such as font, colour, and spacing, so it would match the brand look. Implement responsive design so the application will perform well under different devices. Also, use hover effects and animations in an engaging manner so the user will interact smoothly while navigating through data visualization.

- **Fetching and Visualizing Data Using Plotly**

  Use yfinance library for fetching the real-time data regarding the stock market. Plotly is to be used for making interactive visualizations, such as line graphs, bar plots, and candlestick plots, showcasing how stocks are performing over time and also currently. Add some zooming/panning and hovering in it so detailed inspection of the data can be provided to the users as well for better analysis.

- **Implementation of Machine Learning Models**

  An interface and integration of machine learning models for prediction in the technical module developed using SVR, Random Forest, and LSTM. The above-mentioned models are then trained on historical data and optimized with key parameters to enhance the predictive performance. This allows users to input specific date ranges to obtain predictions tailored to their needs. This would allow end-users to make informed investment decisions by using these model-driven forecasts.

- **Post Prediction Analysis and Visualization**

  Fine-tune the output model to apply post-processing techniques. Calculate actionable insights, including potential stop-loss levels and false breakout points, to inform user decisions. Use Plotly for interactive graphs and charts for visualization of such insights to be better read and used for forecasted data.

- **Handling user input through interaction:**

  Design interactive components such as dropdowns, date pickers, and buttons that would take inputs related to stock codes and analysis parameters. Implement the same using the Dash framework so that one can input data with ease by interacting with them. The interaction flow of the user from input to visualization should always be smooth and responsive…

CHAPTER-VI

SYSTEM IMPLEMENTATION

Fig. 2. User Friendly Interface of Stock Vision Web Application

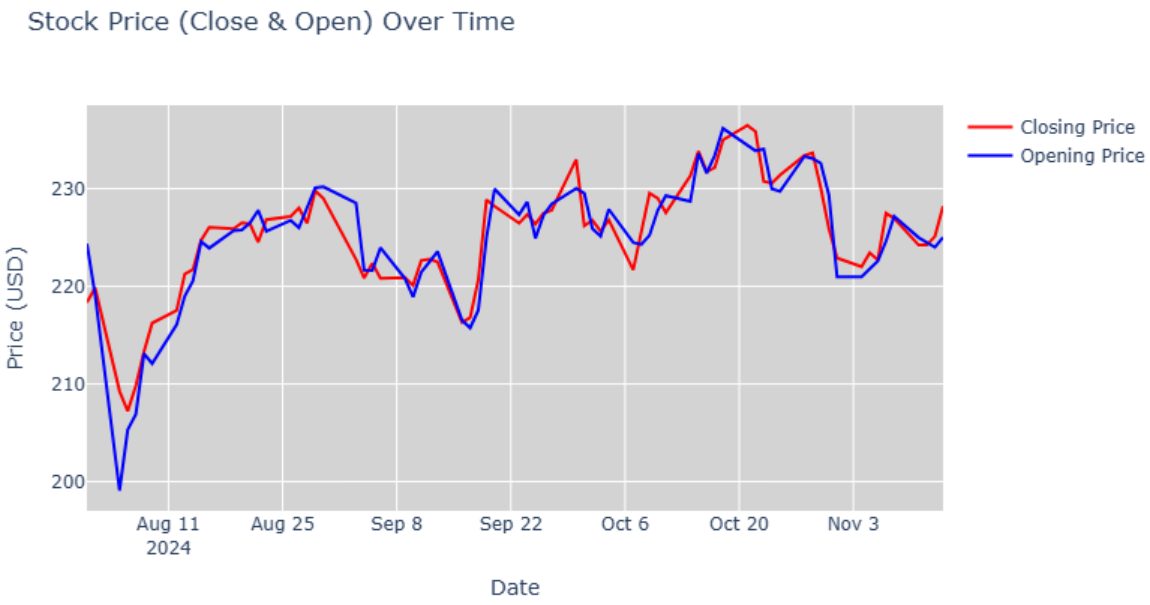

Fig. 3. Opening and Closing Price of Stock for Selected Time Period (AAPL)

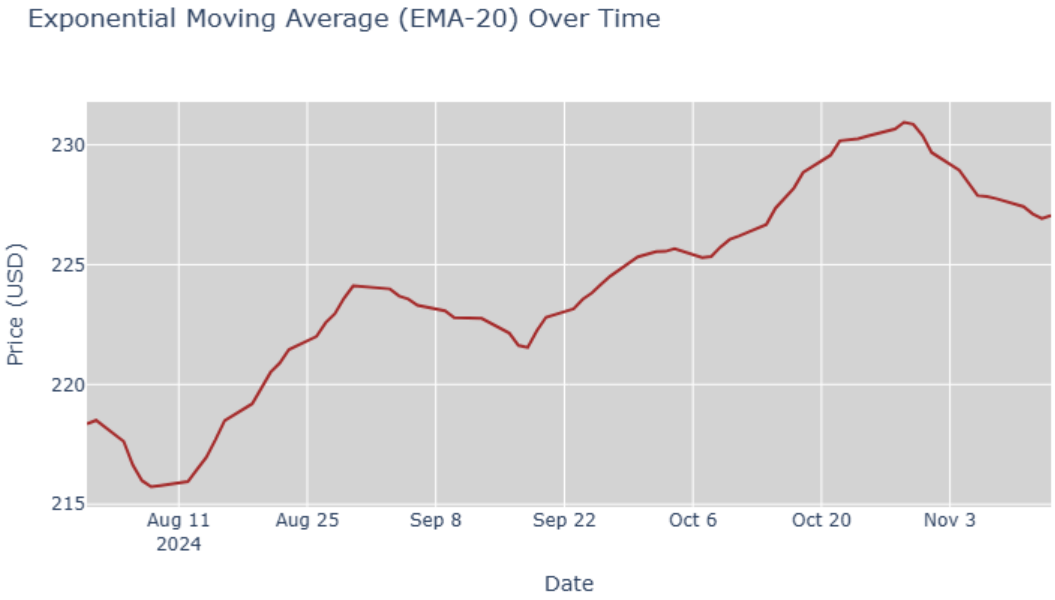

Fig. 4. Exponential Moving Average of Selected Stock and Time Period (AAPL)

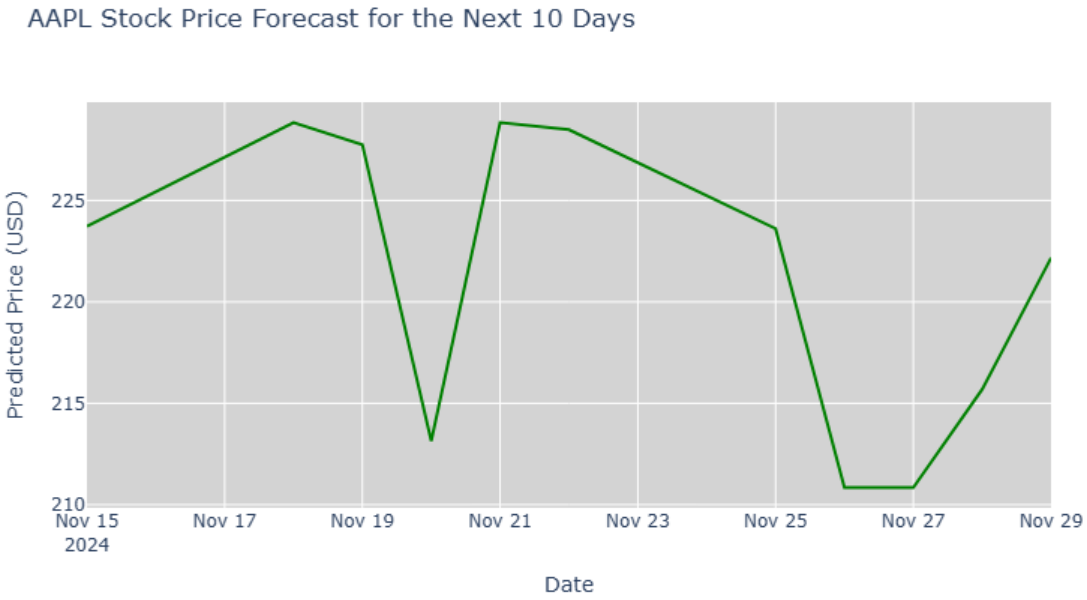

Fig. 5. Predicted Price of Stock for Next Selected No. of Days (10)

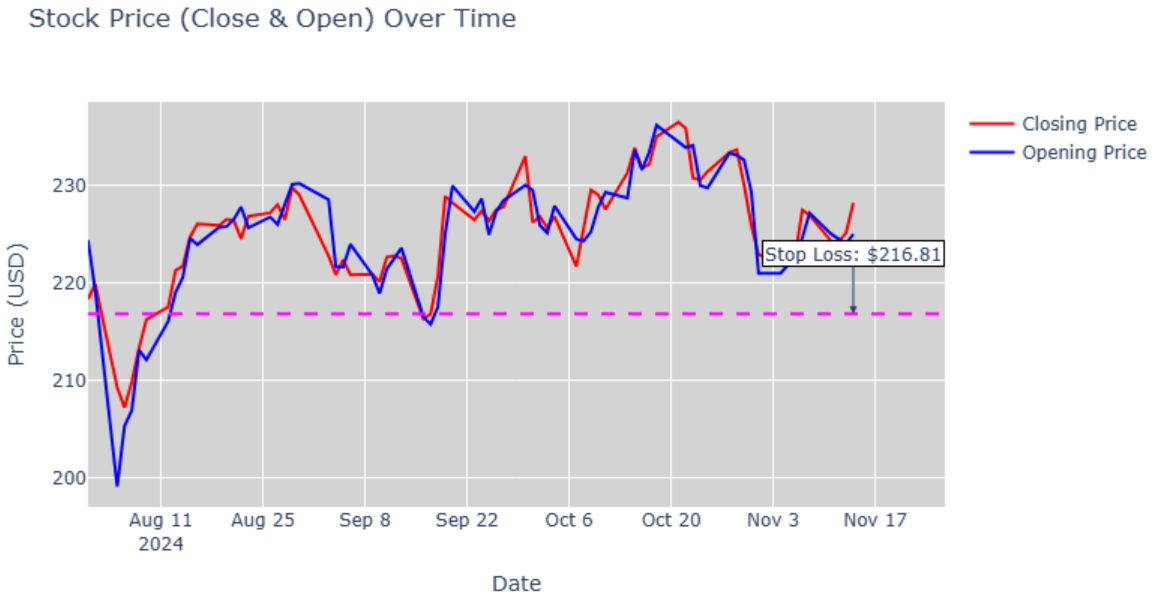

Fig. 6. Stop Loss Value for the Stock (AAPL)

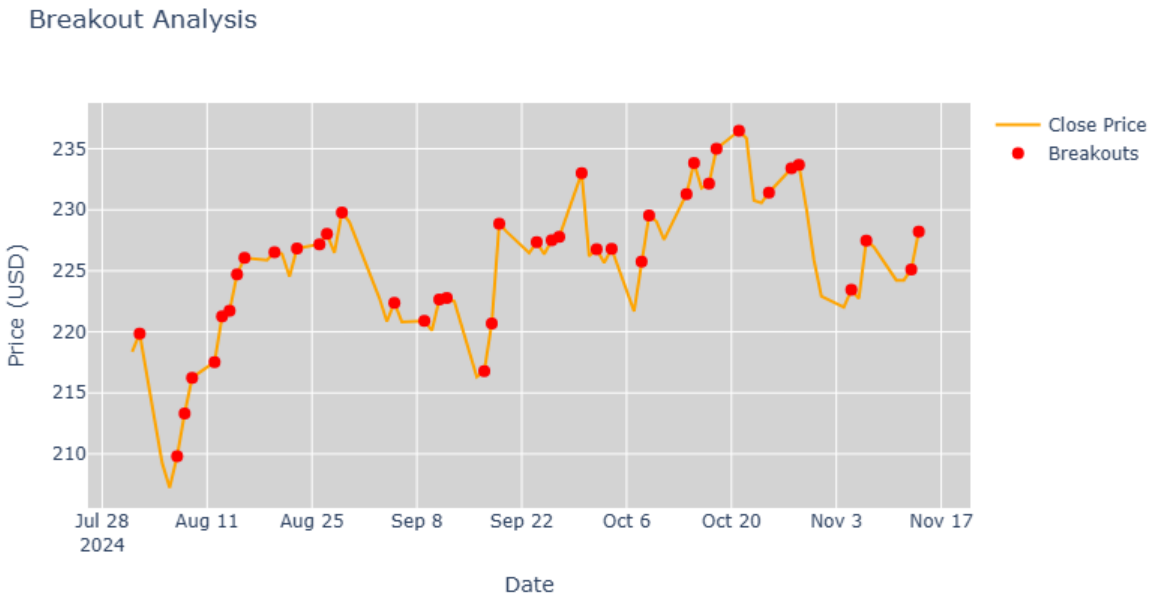

Fig. 7. False Breakout Point of the Stock (AAPL)

CHAPTER-VII

RESULTS AND DISCUSSION

The research proved the efficiency of machine learning and deep learning combined to predict stock prices and give actionable financial insights. With Support Vector Regression, Random Forest, and Long Short-Term Memory models, accurate and dynamic price prediction was made possible. Technical indicators included have been optimized for actual trading applications.

- **Model Performance and Evaluation**

  To evaluate the accuracy of models, some use Mean Absolute Error and Root Mean Square Error. It was noticed that with the Random Forest model, there were always the lowest error rates compared to SVR, which suggests higher predictive accuracy. This outcome suggests that the ensemble-based approach of Random Forest, aggregating results from multiple trees, benefits the picking of complex patterns in the stock data. This indirect application of the LSTM model has made it contribute to taking advantage of sequential patterns in time series data, hence making the model useful for trend prediction.

- **Financial Indicators Produced from Predictions**

  Post-prediction processing greatly improved the real use of price forecasts. Computing EMA, stop loss levels, and breakout detection took raw predictions and made them useful. These financial indicators can be used to trade better by setting stop-loss levels to reduce risks or recognizing trend reversals. The EMA provided more clarity in price trends. The stop loss and breakout indicators enhanced risk management techniques.

- **Visualization of Results**

  Visualization was important to make the output understandable and readable. Graphs that are interactive allow both short-term as well as long-term trends to be analyzed by showing forecasted stock prices, EMAs, stop loss, and false breakout points. Visualizations have been integrated into the dashboard on the website using Plotly, thus creating an interactive real-time interface, very helpful for a trader depending upon timely information. The GUI

was designed in such a way that complex data points were presented in an intuitive format, thus more user-friendly.

- **Observations Related to Volatility Impact**

  The results showed that there was variation in the performance of a model at different market circumstances. At stable market, the models produced reliable estimates, but during times when the market is volatile, the models had a failure in estimation. This therefore indicates that the models still need further fine-tuning or volatility-specific indicators would be included to help make estimations when there are radical changes in the market environment. This would mean carrying out research in future perhaps by adding models such as GARCH or incorporating finance news sentiment analysis for estimations to improve when a market is volatile.

CHAPTER-VIII

COMMUNITY IMPACT

- **Empowering Retail Investors:**

  The project offers real-time information and predictive analysis to ordinary investors, democratizing access to sophisticated stock market prediction tools. This makes it possible for those without formal trading experience to make better investing choices. Their capacity to handle market volatility and spot profitable chances is improved by utilizing machine learning and deep learning. More active involvement in the financial markets is encouraged by the availability of such tools.

- **Improving Trading Efficiency:**

  By providing short-term stock movement forecasts and highlighting important indicators such as false breakouts and stop-loss, the tool assists traders in taking prompt, effective action. By lowering the possibility of human error and the influence of emotional decision-making, this promotes trading techniques that are more methodical and data-driven. As a result, it promotes more strategic market approaches and increases trading efficiency overall. By using predictive analytics, users may maximize their transactions and increase profits.

- **Contributing to Financial Literacy:**

  Through the project's user-friendly interface, people can learn about technical indicators and stock market forecasts. Users learn more about stock trends, market dynamics, and investing strategies with the use of visualization and prediction tools. This encourages financial literacy, particularly for novices who might not have access to sophisticated trading resources or instruction. Having additional knowledge enables people to make more responsible and knowledgeable financial decisions.

- **Enhancing Risk Management:**

  Financial risk is reduced by identifying false breakouts and including stop-loss calculations. By establishing suitable limitations on possible losses, this enables traders and investors to

better manage their portfolios. Users can reduce their risk exposure by making decisions based on a better understanding of market volatility. This strategy improves users' overall financial stability by averting large losses due to unanticipated changes in the market.

- **Boosting Investor Confidence:**

  The technology gives investors, particularly those who are new to the stock market, more confidence by offering precise projections and predictive insights. Users can be confident that their decisions are more data-driven when they have access to real-time data and forecasts supported by machine learning algorithms. This self-assurance can encourage sustained involvement and more active stock market participation. It can therefore contribute to the development of a more active and knowledgeable investing community.

- **Supporting Economic Growth:**

  The technology helps improve market capital allocation as more people and organizations utilize it to make well-informed decisions. With resources going to high-performing businesses and industries, this improved investment efficiency results in stronger market growth. By encouraging more sustainable investments and a more dynamic stock market ecology, the tool's capacity to forecast and evaluate trends also benefits the economy as a whole**.**

CHAPTER-IX

CONCLUSION AND FUTURE SCOPE

The study is done so as to prove the possibility of a hybrid approach making use of the machine learning and deep learning models in particular, such as the support vector regression, the random forests, and long short-term memory models with respect to predicting stock price. The integrated model then yields actionable insights regarding the indicators such as the exponential moving averages, stop loss levels, and false breakout points. This gives the trader practical decision-making tools together with risk management skills.

This would be Random Forest, especially in its ensemble nature, that showed great predictive accuracy. The indirectly applied LSTM model captured temporal patterns, thus adding depth to trend analysis. Visualization through an interactive dashboard further enhanced the accessibility and interpretability of the results, allowing users to monitor trends and key indicators in real time.

Although the study highlighted some drawbacks, such as reduced predictability during high-volatility periods, the remedy to this challenge could include using volatility-specific indicators or even additional data sources such as macroeconomic factors and sentiment analysis for improving the resilience of predictions in a fluctuating market.

This work then creates a solid basis for even advanced stock forecasting models with an integration of varied methodologies. Future work might also advance this approach with possible architectures of deep learning, with broad datasets to allow it to be more flexible and exact in financial sectors in providing forecasting tools.

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PROJECT AUDIT REPORT

This is to certify that the project work entitled "**STOCK VISION – A REAL TIME STOCK VISUALIZER AND FORECASTER**" categorized as an internal project done by "**HEEREHAL DHEERAJ KISHORE (99220040269), GIRAPPAGARI HEMANANDAN REDDY (99220040265), THEPIREDDY AKASH REDDY (99220040209), GEETHA VINAY KRISHNA (99220040267)"** of the Department of Computer Science and Engineering, under the guidance of Mrs. R. DURGA MEENA during the Even semester of the academic year 2024 - 2025 are as per the quality guidelines specified by IQAC.

(Office use)

Quality Grade

Deputy Dean (IQAC)

Administrative Quality Assurance **Dean (IQAC)**