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IMPROVING PREDICTIONS OF STOCK PRICE WITH ENSEMBLE LEARNING

N. Siva[1], B. Venkata Sivaiah[2*] , Vallusha Nikkam P[3], Varshith Volliboina[4], Dommaraju Hema Sai[5], Kotala Pushpalatha[6]

[1] Assistant Professor, Department of AIML, Annamacharya Institute of Technology and Sciences, Rajampet., A.P, India.
[2] Assistant Professor, Department of Data Science,Mohan Babu University, Tirupati, India,
[3,4,5,6] UG Scholar, Dept. Of CSSE. Mohan Babu University(Erstwhile Sree Vidyanikethan Engineering College, Tirupati, India

[1]nsiva5809@gmail.com [2*]siva.bheem@hotmail.com
[3]vallushanikkam@gmail.com [4]varshithnnatty@gmail.com
[5]hemasaisvis@gmail.com [6]kotalapushpa33@gmail.com

Abstract. In today's financial landscape, accurate stock price forecasting is crucial for informed decisions. This solution leverages machine learning and data science advancements to offer a comprehensive platform for interactive analysis and custom model training. With a user-friendly Streamlit interface, users can explore and forecast stock movements, choosing from models like LSTM, RNN, Conv1D, and ensemble approaches. Modular functions support flexible model customization, including RNNs, LSTMs, and Conv1Ds. An ensemble approach combines multiple models for enhanced accuracy. Seamlessly integrating data retrieval, preprocessing, model training, and visualization, users gain actionable insights into market trends and future predictions. Interactive Plotly visualizations enable deep historical data analysis to support investment strategies. This solution is a versatile tool for both interactive analysis and custom model development in stock market navigation.

Keywords: Stock Price Prediction, Recurrent Neural Network, Long-Short Term Memory, One dimensional Convolutional Neural Network, Ensemble Approach.

1 Introduction

In the dynamic realm of modern finance, the capacity to comprehend and predict stock price movements stands as a fundamental endeavor for investors and financial analysts alike. The complexities of stock market dynamics are shaped by a myriad of elements that span from financial indicators to global occurrences, necessitate sophisticated analytical tools capable of extracting meaningful insights from vast volumes of historical data.In response to this necessity, the incorporation of modern algorithmic learning techniques has become known as a critical component for improving forecast accuracy and influencing strategic investment decisions. This integrated solution represents a culmination of cutting-edge methodologies, seamlessly blending interactive analysis and customize model training within a streamlined framework. Rooted in the ethos of data-driven decision-making, the solution offers a comprehensive platform tailored for stock price prediction, catering to the discerning needs of both novice investors and seasoned financial professionals. Harnessing the power of Deep Learning Architectures and ensemble approaches, the solution empowers users with unparalleled capabilities to explore, analyze, and

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anticipate stock market trends with precision. At its core, the solution embodies a synergy of technological innovation and financial acumen, leveraging the vast reservoirs of historical stock market data to unveil latent patterns and trends. Through a user-friendly interface, investors can navigate an extensive array of stocks, select prediction periods, and deploy a diverse repertoire of prediction models tailored to their unique investment objectives. Furthermore, the modular architecture of the solution facilitates the seamless integration of ensemble approaches,facilitating the synthesis of predictions from different simulations in order to improve forecast accuracy and resilience. Driven by a commitment to excellence and innovation, this integrated solution represents a paradigm shift in the realm of stock market analysis, providing a transformative framework for informed decision-making and strategic investment planning. Using sophisticated machine learning techniques and interactive visualization tools, users can embark on a journey of discovery, unraveling the intricate tapestry of stock market dynamics and unlocking new avenues for financial prosperity. In an era defined by volatility and uncertainty, this solution stands as a beacon of stability and foresight, empowering investors to navigate the complexities of the stock market landscape with confidence and conviction.

2 Literature Survey

The case study provided by Ayushman Durgapal, Vrince Vimal, compares ARIMA, Random Forest, and Extreme Gradient Boosting models for predicting Google's stock prices using NASDAQ data. While ARIMA performs reasonably well for short-term predictions, it shows higher MAPE values. Extreme Gradient Boosting exhibits the best performance with the lowest RMSE and MAPE values, indicating its potential after hyperparameter tuning. However, limitations such as overfitting sensitivity and data preprocessing challenges should be considered for practical applications.[1]

Smith, J., Johnson M., & Brown, A recently published research study on stock price prediction investigates the use of (LSTM) Long Short-Term Memory networks, a form of (RNN), for stock price prediction. The authors use the capabilities of LSTMs to detect persistent dependencies in time series information. Experimental results outperform typical time series models.While LSTMs excel at capturing long-term dependencies, their effectiveness in producing short-term predictions may be less spectacular. Additionally, overfitting is reported in LSTMs, which is a disadvantage in this case study.[2]

Focusing on ensemble methods, D Baswaraj, R Natchadalingam, Ravula Shashi Rekha, Nancy Sahni, V Divya, Pundru Chandra Shaker Reddy released a research paper that introduces a novel deep learning approach to forecast stock price behavior by blending two recurrent neural networks (RNNs) with a fully connected neural network. Focusing on the Standard & Poor's 500 Index, it outperforms existing methods by significantly reducing mean squared error and improving various performance metrics. While promising, limitations such as data availability and model interpretability should be considered for practical implementation in financial decision-making..[3]

Sanjay Kumar Paipitam, Shekhar Kumar, Tushar Dhanani, Saurabh Bilgaiyan, Mahendra Kumar Gourisaria conducted research on deep learning techniques proposed for stock price prediction, employing Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) models for companies like Apple, Brookfield Asset Management, and Uber. While promising for enhancing prediction accuracy, disadvantages include their dependency on large datasets, complexity leading to interpretability challenges, computational resource demands, risks of overfitting to historical data, and limitations in generalizing to unseen market conditions and capturing causality. Additionally, regulatory scrutiny, ethical concerns, and the need for ongoing maintenance pose further challenges in practical implementation.[4]

Daryl, Aditya Winata, Sena Kumara, Derwin Suhartono have done a document that employs time series analysis techniques for predicting stock prices. The research delves into the utilization of historical stock data and technical indicators to make predictions about the opening values. Time series models may struggle to capture complicated and non-linear relationships present in stock price data. Finance markets often exhibit intricate patterns that might not be fully captured by linear models. The limitation of this study is the inability to capture non-linear relationships.[5]

In the realm of stock market, a plethora of methodologies and approaches have been explored to leverage the vast reservoirs of historical data and extract actionable insights. Classic statistical techniques, like ARIMA (autoregressive integrated moving average) and linear regression, have long been used as core frameworks for time series forecasting, providing strong approaches for forecasting and modeling stock price movements based on past trends[5]. In recent times, the rise of deep learning and machine learning algorithms has transformed the field of prediction of stocks, ushering in a new era of forecast accuracy and computational efficiency. Neural networks with recurrent learning (RNNs), convolutional neural networks (CNNs), and long short-term memory (LSTM) networks are examples of deep learning architectures, which have emerged as dominant paradigms for modeling sequential data and extracting complex patterns from temporal sequences of stock prices[8]. Numerous studies and research endeavors have investigated the efficiency of neural network models in stock prediction, exploring various architectures, input features, and training methodologies to optimize predictive performance. Ensemble learning techniques merge predictions from a variety of models in order to boost overall accuracy and resilience, have also gained prominence in the field, offering synergistic approaches to mitigate the limitations of individual models and enhance predictive capabilities.

3 Proposed Work

The proposed methodology encompasses a systematic approach to enhancing stock price prediction accuracy. It begins with rigorous data preprocessing and exploration, ensuring data integrity and revealing underlying patterns. Feature engineering is then employed to enrich the dataset with additional relevant features derived from domain knowledge and external sources[11]. Multiple machine learning models, including Simple RNN, LSTM and CNN are trained and optimized through hyperparameter tuning and cross-validation techniques. Ensemble methods are explored to synergistically combine predictions from diverse models, enhancing overall performance[12]. Model evaluation and interpretation provide insights into predictive capabilities and guide iterative improvements. Finally, the trained models and interactive web applications are deployed using Streamlit to create user-friendly interfaces accessible via web browsers. This ensures scalability, reliability, and efficiency of the deployed applications to support real-time prediction and analysis for end-users.

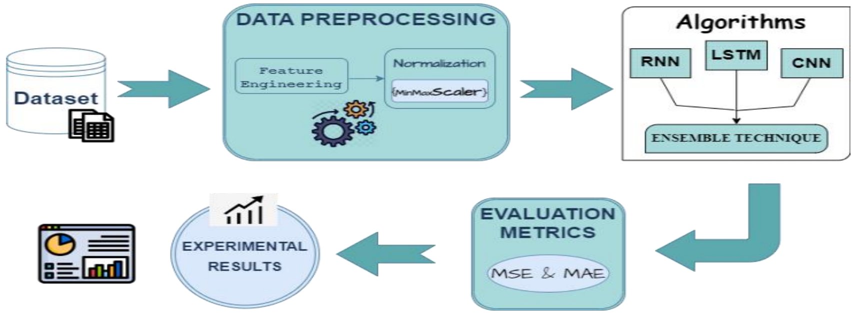

Fig 1: The Architecture for stock price prediction

3.1 Data Acquisition and Preprocessing

The process commences with sourcing historical stock price data from reputable financial databases like Yahoo Finance, renowned for its comprehensive and accurate datasets. The integration of the yfinance library facilitates seamless access to this data, enabling users to retrieve vital information such as opening and closing prices, highest and lowest prices attained during a trading period, and the total volume of shares traded[4].

Once the data is acquired, preprocessing is performed to prepare it for model training. This includes handling missing values, if any, and scaling the numerical features using Min-Max scaling. Min-Max scaling is used to normalize the data to a static range (mostly between 0 and 1), making it suitable for training neural network models.

3.2 Model Training

The application provides numerous neural network models for estimating stock prices, such as LSTM, RNN, and Conv1D. For LSTM and RNN models, sequential historical prices are used as input features, with a specific time window (e.g., 10 days) considered for each input sequence[7]. The target variable is the future price. The models undergoes training using the optimizer known as Adam with the mean squared error reduction function.

Algorithms/Models :

LSTM- LSTM networks, a form of (RNNs) that are particularly good in capturing dependencies that persist in long term sequential data, making them ideal for time series data forecasting tasks like predictions of stock price. The model architecture is developed utilizing the Keras, as framework for Sequential API, comprising multiple LSTM layers followed by dense layers for regression[8]. Each LSTM layer is designed to retain and utilize information over extended time intervals, crucial for capturing intricate patterns present in historical stock price data. Furthermore, the use of drop-out layers in the LSTM structure reduces overfitting by dynamically eliminating a part of the interconnections during retraining[11]. The model undergoes training on previous stock prices using the MSE (mean squared error) reduction function and optimized using the algorithm known as Adam optimizer, which automatically alters its rate of learning to ensure efficient convergence.

RNN- This model architecture is defined using the Keras framework, specifically employing the Sequential API to construct an RNN model. This architecture comprises multiple layers of SimpleRNN cells, which are recurrent neural network units capable of retaining information about past inputs. Additionally, dropout layers are incorporated to mitigate overfitting issues[6]. The model undergoes training using prior stock price data, where the fit() method is employed to optimize the model parameters, including weights and biases, based on input features (sequences of past stock prices) and target values (next stock price). Following training, the trained RNN model is utilized to forecast future stock prices. This prediction relies on the learned temporal patterns and relationships within the historical data captured by the RNN's recurrent connections.

CNN- Using the train_conv1d_model function, an CNN (convolutional neural networks) model is applied to predict the stock prices. The CNN model architecture comprises of Conv1D layers, followed by MaxPooling1D layers, a Flatten layer, and Dense regression layers. The Conv1D layers perform one-dimensional convolutions over the input sequence of historical stock prices to extract relevant features. These features are subsequently downsampled with MaxPooling1D layers to minimize the data's dimensionality while retaining critical information[9].The Flatten layer transforms the result of the layers of convolution into an a single-dimensional vector, which is then passed into the full connected dense layers in order to forecast[10]. This architecture enables the CNN framework to detect seasonal trends and dependencies in stock price data, making it ideal for time series forecasting jobs.

3.3 Ensemble Technique

Ensemble learning is a technique/method in ML that combines the forecasts of multiple models to achieve superior overall performance compared to any single model. The concept is to harness the diversity of different models, each capturing distinct aspects of the data, to enhance the resilience of predictions[4]. In this research, several individual models are applied for predicting stock prices. These models encompass a SimpleRNN, LSTM and a CNN(1D). Ensemble approaches use the complimentary qualities of various models to increase final prediction precision and robustness. Predictions from individual models are combined using ensemble methods such as averaging or stacking. This helps mitigate individual model weaknesses and enhance overall prediction performance.

3.4 Evaluation Metrics

Evaluation metrics serve as standardized measures to assess the performance of machine learning models, providing a quantitative way to gauge their effectiveness in a specific task. Ultimately after training, the effectiveness of each model is evaluated, typically, measurements such as Mean squared Error (MSE) and Mean absolute Error (MAE) reflects the discrepancies between expected and actual values, providing insights into the model's accuracy and precision, to assess its predictive performance and inform decision-making processes in financial markets. Visualization techniques, such as plotting the loss curves over epochs, help in assessing the stability of the models during training. Thus usage of these evaluation metrics ensure convergence and prevent overfitting.

$$\text{MSE}=\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y_i})^2$$

Where,
n = total number of samples / data points
$\boldsymbol{y_i}$ = *actual data point of target variable for ith data point*
$\boldsymbol{\hat{y_i}}$ = *predicted data point of target variable for ith data point.*

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

MSE gives more weight to larger errors due to squaring and is sensitive to outliers because of the squaring operation, making it suitable for models where large errors are critical whereas MAE treats all errors equally regardless of their magnitude and is less sensitive to outliers.

Table1: Evaluation Metrics for each Model

	MODEL	MAE	MSE
1	LSTM	10.7849	158.9331
2	RNN	11.1114	167.1375
3	Conv1D	14.6995	275.2537

Table.1 contains the values of MAE and MSE values for each model which is calculated using above formula and thus the performance of the models is determined to be good enough than the existing models. The values may change based on the stock chosen and the time period. As predicted LSTM model has the highest performance than other models with lowest error values.

4 Experimental Results

Each model's efficiency is assessed using measures such as MSE and MAE.The Simple RNN, LSTM and CNN models demonstrate varying levels of accuracy in predicting stock prices. The predictions are visualized alongside historical data versus predicted data using interactive plots such as box and scatter plots generated with Plotly. Visualizations illustrate the effectiveness of ensemble learning and comparison of models in capturing the underlying trends and patterns in stock price data. Additionally, an ensemble model is implemented, aggregating predictions from individual models to provide a more robust prediction.

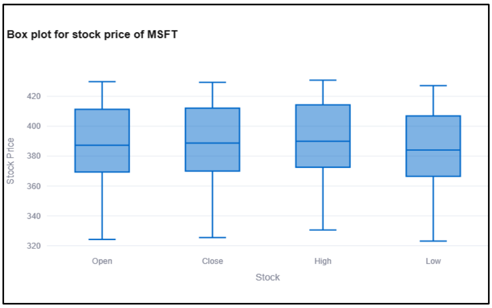

Figure 2 is representing a box plot of Microsoft stock prices and thus the comparison is between closing, opening, high and low prices of the stock.

Fig 2: Box Plot for stock price

Figure 3 is representing a scatter matrix of Microsoft Stock and thus there is similar comparison as box plot but the visualization is different

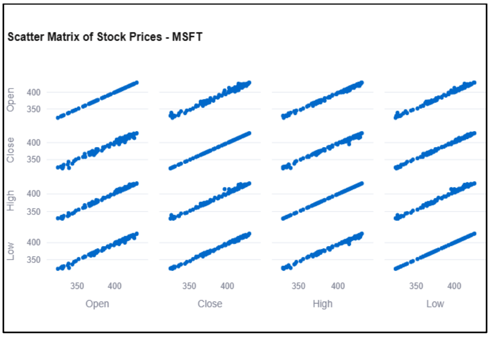

Fig 3: Scatter Plot for stock price

Figure 4 is representing line graph of the daily closing prices for Microsoft stock of one year time period and thus can be observed there is increase of stock price.

Fig 4: Daily closing price

Loss versus Epoch values has also been represented as table in the user interface.

The table visualizes the performance of the selected model over successive training epochs, where each epoch corresponds to one complete pass through the training dataset. LSTM, RNN and CNN each individual models performance has been visualized by comparing the historical data with predicted data as given in below fig 5,6 and 7.

Long Short -Term Memory

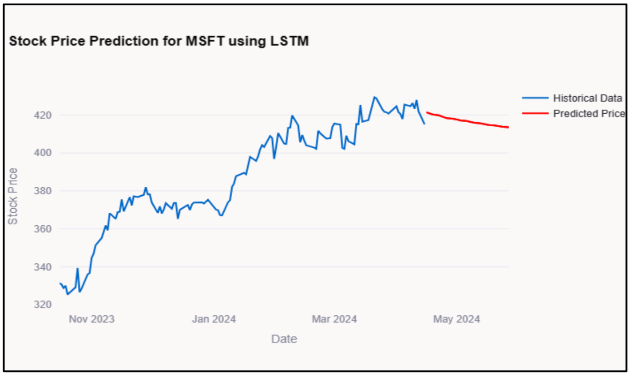

Fig 5: LSTM Model Prediction

Recurrent Neural Network

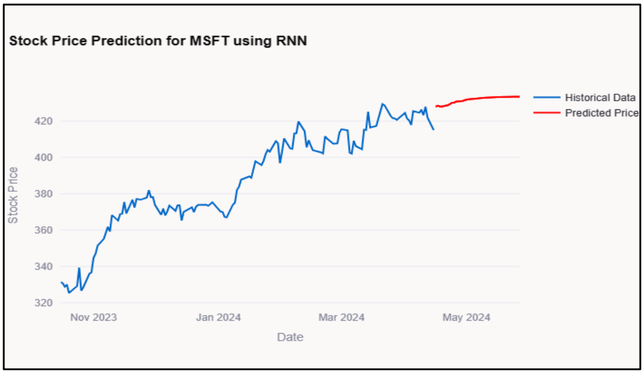

Fig 6: RNN Model Prediction

In the following model graphs x-axis is represented by dates and in y axis stock prices have been taken. The prediction in these graphs are represented by red line whereas the actual price is shown by blue line. The proximity of these two lines tells the efficiency of model in predicting the stock prices. After a significant amount of time, the prediction approximates the actual trend. The more the algorithm undergoes training, the higher the accuracy that will be attained.

Convolutional Neural Network

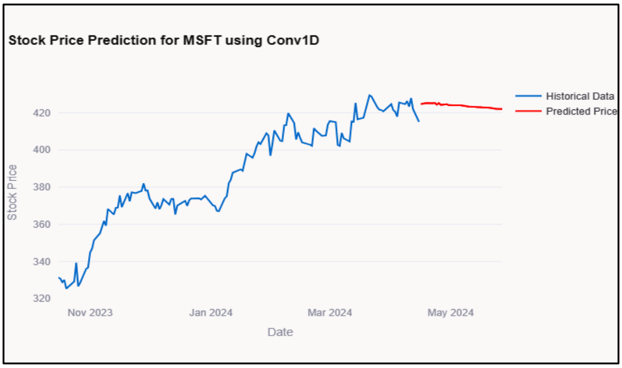

Fig 7: CNN Model Prediction

The Streamlit framework is utilized to create a user-friendly web interface for the application to visualize all these graphs. It also allows users to interact with the interface to select specific stocks, choose prediction models and visualize predicted stock prices for different time horizons.By integrating these steps, the application enables users to explore and analyze stock price predictions for multiple companies using various deep learning models and ensemble techniques, providing valuable insights for investment decisions.

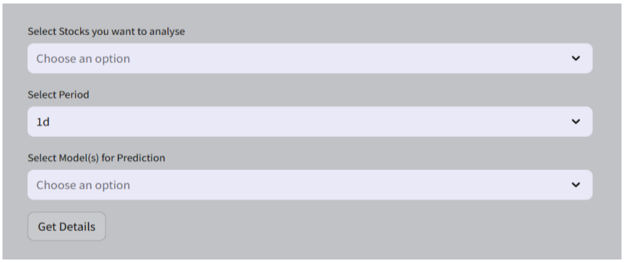

Fig 8: User Interface for Stock price prediction

5 Conclusion and Future Work

In culmination, the fusion of cutting-edge machine learning techniques and interactive web applications signifies a transformative shift in stock market analysis and prediction. Through advanced deep learning architectures like LSTM, RNN, and Conv1D, coupled with ensemble learning, predictive precision has reached unprecedented levels. Interactive web platforms like Streamlit democratize access to analytical tools, enabling users to navigate market intricacies effortlessly. Looking ahead, the evolution of machine learning and web technologies promises continual breakthroughs, empowering individuals and enterprises to make informed decisions and achieve financial prosperity. In essence, this convergence ushers in a new era of data-driven finance, where insights from vast datasets merge with real-time market dynamics to guide strategic investments and foster sustainable growth.

Future endeavors in stock price prediction encompass augmenting models with novel data sources like web sentiment analysis, satellite imagery, and economic indicators for deeper insights. Tailoring ensemble learning techniques can enhance predictive accuracy and resilience by integrating diverse modeling approaches. Advancements in interactive web applications may focus on improving user experience, real-time data integration, and advanced visualization techniques for deeper insights. Exploring AI-driven compliance and risk management tools holds potential for enhancing regulatory compliance and mitigating systemic risks in financial markets. These efforts aim to catalyze informed decision-making, financial resilience, and societal well-being.

References

[1] Ayushman Durgapal, Vrince Vimal, “Prediction of Stock Price Using Statistical Ensemble learning Models: A Comparative Study”, 2021 IEEE 8th Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering UPCON.

[2] Smith, J., Johnson, A., & Brown, M., “A Comparative Study of Machine Learning Techniques for Stock Price Prediction”.

[3] D Baswaraj, R Natchadalingam, Ravula Shashi Rekha, Nancy Sahni, V Divya, Pundru Chandra Shaker Reddy, “An Accurate Stock Prediction Using Ensemble Deep Learning Model”, 2023 International Conference on Research Methodologies in Knowledge Management, Artificial Intelligence and Telecommunication Engineering RMKMATE.

[4] Sanjay Kumar Paipitam, Shekhar Kumar, Tushar Dhanani, Saurabh Bilgaiyan, Mahendra Kumar Gourisaria, “Comparative Study on Stock Market Prediction using Generic CNN-LSTM and Ensemble Learning”, 2023 International Conference on Network, Multimedia and Information Technology NMITCON.

[5] Daryl, Aditya Winata, Sena Kumara, Derwin Suhartono, “Predicting Stock Market Prices using Time Series SARIMA”, 2021 1st International Conference on Computer Science and Artificial Intelligence ICCSAI.

[6] Nimesh Raj, “Prediction of Stock Market Using LSTM-RNN Model”, 2023 International Conference on Self Sustainable Artificial Intelligence Systems ICSSAS.

[7] Reddy Madhavi, K., A. Vinaya Babu, and S. Viswanadha Raju. "Clustering of Concept-Drift Categorical Data Implementation in JAVA." In International Conference on Computing and Communication Systems, pp. 639-654. Berlin, Heidelberg: Springer Berlin Heidelberg, 2011.

[8] Kavitha S, Apoorna S, Sowmya K, “ Stock Closing Price Prediction using Deep Learning, TensorFlow, and Keras”, 2023 International Conference on Ambient Intelligence, Knowledge Informatics and Industrial Electronics AIKIIE.

[9] Nader Nemati, Hadi Farahani, Saeed Reza Kheradpisheh, “Stock market prediction by combining CNNs trained multiple time frames”, 2023 5th International Congress on Human-Computer Interaction, Optimization and Robotic Applications HORA.

[10] Pranjali Pandhare, Prathmesh Hedaoo, Komal Kotle, Tushar Ambule, Nutan V. Bansode, “Decoding the Market Trends: Precision Forecasting of Stock Prices Using CNN Based Approach, 2023 7th International Conference On Computing, Communication, Control And Automation ICCUBEA.

[11] Madhavi, K. Reddy, K. Suneetha, K. Srujan Raju, Padmavathi Kora, Gudavalli Madhavi, and Suresh Kallam. "Detection of COVID 19 using X-ray Images with Fine-tuned Transfer Learning." (2023). Journal of Scientific & Industrial Research (JSIR), National Institute of Science Communication and Information Resources (NISCAIR) by CSIR, Govt of India, 82,2, pp.241-248, 2023

[12] Aryan Solanki, Sanjana Singla, Hemant Petwal, “An Improved Machine Learning Algorithm for Stock Price Prediction”, 2023 Second International Conference On Smart Technologies For Smart Nation SmartTechCon.

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