IJFANS INTERNATIONAL JOURNAL OF FOOD AND NUTRITIONAL SCIENCES
ISSN PRINT 2319 1775 Online 2320 7876
Research Paper , UGC CARE Listed (Group -I) Journal Volume 11, Iss 1, 2022

Stock Price Pridiction Model Using LSTM

Dr. M. P. Sardey[1], Alkesh Bhagat[2], Shantanu Sable[3] and Shreyas Zope[4]

Department of Electronics and Telecommunication Engineering, AISSMS Institute of Information Technology, Pune 411001, India

Corresponding Author: mohini.sardey@aissmsioit.org, bhagatalkesh738@gmail.com, shreyaszope15@gmail.com, shantanusablecr7@gmail.com

Abstract— Stock price prediction is an essential task for investors, traders to make informed decision and earn high return. In this study, we will look at the topic of stock price prediction. The price prediction will help the traders and investors to make a idea of the stocks price. Artificial intelligence (AI) in the sense of machine learning and deep learning algorithms can help solve problems. machine learning algorithm has an ability to capture complex pattern and relationship in stock market data. the model is train on the stock price data over the year and is capable of predicting the future stock price. The input data is preprocessed using various technique such as normalization and generalization. The model is evaluated using various performance metrics including mean square error and mean absolute error.

Keywords— Stock Price Prediction, Machine learning, Prediction, LSTM Model, Deep Learning, Price Prediction.

I. INTRODUCTION

Today, one of the first businesses to invest with high return and with very less chance of failing is in stocks. In the todays industries, Artificial intelligence (AI) based on machine learning and deep learning can assist with challenges including data analysis and processing, stock price prediction and trend analysis. Stock price prediction model can help the investors and traders to identify the trends and patterns in the market and can make decisions based on the insights. Machine learning algorithms can take large amount of data with different source of information to find trends that can be relevant to stock price.

The algorithm can identify relevant features which can affect the stock prices. It can reduce the risk of overfitting. The algorithm can analyze the time series data to identify patterns which can help to capture the dynamic nature of stock market. The data collected and processed a variety of financial. the accuracy of such existing models depends on the data fields can various machine leaning models for example the linear regression model shows less accuracy on stock price data because the stock market data is volatile, random and the linear regression model can't train such data with very entropy. the LSTM model shows greater accuracy and reliability as found in the study. The quality of the data which used is one of the important factor the more relevant and high quality of the data can result in more accurate the model likely to be. The data preprocessing technique such as normalization and generalization will help improve the quality of the data. By predicting the future stock price, the investors can make more relevant decision and earn higher returns. The stock market is inherently volatile and accurate prediction is a challenging factor. We apply information theory to continuous stock time series to describe the quantitative probability distributions and their non-linear relationship between different stocks, which facilitate the RNN modeling of price dynamics.

II. LITERATURE SURVEY

Prior research [1] This study investigates the use of LSTM and regression-based machine learning approaches to estimate stock prices. Measured variables include open, closed, low, and high volume. According to a study by Ishita Parmar, Ridam Arora, and Lokesh Chauhan [2], the main objective of the proposed work is to build a connection between stock prices and two current time series algorithms, ARIMA and Holt Winter. Some of its limitations include the work that is never taken into account in this experiment and other circumstances like news about any new marketing tactics or media releases relevant to any companies. [3] The stock price is one of the most important components of the financial system. LSTM machine learning is used to predict the prices of Amazon, Facebook, Apple, and Google. In order to model the dynamics of stock prices, this paper proposes a time series analysis method based on information theory and LSTM. Despite a little divergence in their mean absolute errors (MAE) and root mean square errors (RMSE), the projected outcome and real stock price have a significant association. [4]The stock price is one of the most important components of the financial system. In this study, the LSTM machine learning model is used to predict the prices of Amazon, Facebook, Apple, and Google. In order to model the dynamics of stock prices, this paper proposes a time series analysis method based on information theory and LSTM.

Although their mean absolute error and root mean square error are barely different, the projected outcome and actual stock price exhibit a good association. [6] This paper presents a comprehensive investigation into the application of various data mining techniques in the domain of finance. Delving into the complexities of financial datasets, the study aims to discern patterns, relationships, and insights to aid decision-making processes. It leverages the power of parallel processing to enhance the efficiency of data mining operations, ensuring faster computation and scalability when dealing with vast amounts of financial data. By conducting an in-depth comparative analysis, the research highlights the strengths and weaknesses of different data mining algorithms, thus facilitating the identification of the most suitable approaches for financial data analysis. Furthermore, the study underscores the importance of parallel processing in this context, as it enables quicker and more effective analysis, thereby empowering financial institutions to make timely and informed decisions. While the paper offers valuable contributions to the field, it would benefit from incorporating more recent developments in data mining and parallel processing techniques to ensure its continued relevance in the rapidly evolving landscape of financial technology.

ISSN PRINT 2319 1775 Online 2320 7876
 UGC CARE Listed (Group -I) Journal Volume 11, Iss 1, 2022

III. METHODOLOGY

A. LSTM Architechure

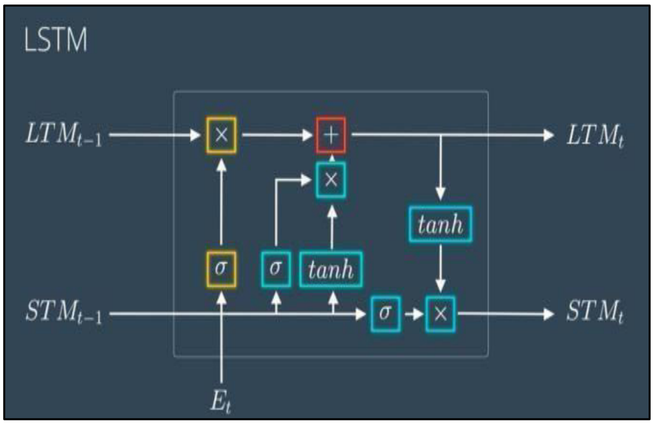

Fig1: -LSTM architecture

a) Forget Gate(f):- A forget gate determines the extent to which the network should forget the previous data.

b) Input Gate(i):- An input gate determines the extent of information be written onto the Internal Cell State.

c) Input Modulation Gate (g):- It is the sub-part of the input gate which is not even mentioned in the LSTM architecture. It is used to modulate the information that the input gate will write onto the Internal State Cell by adding non-linearity to the information and making the information Zero- Mean.

d) Output Gate (o):- It determines what output to generate from the current Internal Cell State.

B. Working of the LSTM recurrent unit

To implement a Long Short-Term Memory (LSTM) neural network, the model takes inputs of the current input, the previous hidden state, and the previous internal cell state. From there, the values of the four different gates are calculated through a series of steps. Firstly, for each gate, the parameterized vectors are computed by element-wise multiplication of the input and previous hidden state with the respective weights for each gate. Secondly, the activation function for each gate is applied element-wise on the parameterized vectors. The list of gates with the corresponding activation function to be applied is as follows:

1) Input gate : Sigmoid activation function
2) Forget gate : Sigmoid activation function
3) Output gate : Sigmoid activation function
4) Input modulation gate : Sigmoid activation function

Finally, the current internal cell state is computed by first multiplying the input gate and the input modulation gate element-wise, followed by multiplying the forget gate and the Previous internal cell state element-wise, and then adding the two vectors. This process enables the

LSTM network to selectively remember or forget information over time, making it well-suited for tasks involving sequential data.

C. Specifications of the System.

1) Hardware Requirements

a) RAM: 4 GB

b) Storage: 500 GB

c) CPU: 2.4 GHz or faster

d) Architure:32-bit or 64- bit

2) Hardware Requirements: - Python 3.5 in Google Colaboratary Operating System: Windows 7 and above or Linux based OS

D. Yahoo Finance Export: Excel

Export Stock Data from Yahoo Finance in the form of Excel sheet -

1) Go to finance.yahoo.com and search for the required stock

2) Click on the Historical Data tab, select the appropriate time period and frequency for the historical prices, and click on Apply.

3) Now, right-click on the Download option available in the top-right corner of the table, and click on Copy link address.

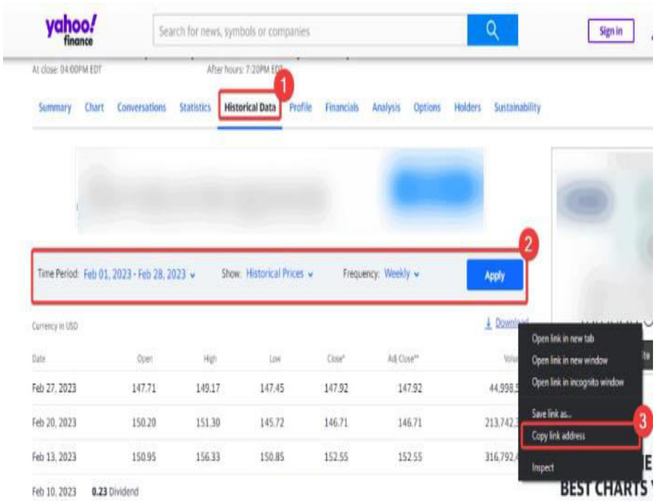

Fig 2: -Yahoo finance historic data

4) Now, we usedthe copied link as a web source to get the required table from Yahoo Finance to Excel.

5) Open the Excel file, and select the cell where you want to import the table

6) Go to Data > Get & Transform Data > From Web.

7) Now, paste the copied URL into the respective field and click on OK.

8) Now, the popup will show a preview of the table. Review it and click the Load button to run the Yahoo Finance export to Excel.

IV. METHODS TO ANALYSE THE STOCK MARKET

A. Fundamental Analysis

Fundamental analysts focus on buying and selling the stock. They evaluate a company's performance history and the reliability of its funds. Create different products to help market professionals calculate product quality, such as price-earnings ratios. Warren Buffett is probably the most famous analyst of all.

What fundamental analysis in the stock market tries to accomplish is to plot the true value of the stock and then match that with the true value of the stock. It is known whether there is a product whose price is below its name and therefore its value in the market. Finding the right price can be done through many strategies, often with similar content. The principle is that organizations value all future benefits. These future benefits must be discounted to their present value. The theoretical basis of this principle is that in business everything is for profit and nothing else. Unlike scientific analysis, statistical analysis is considered a long-term method.

The analysis is based on the belief that people naturally need capital to be successful, and if the company is doing well, it should generate more profits through capital growth and cause business prices to rise. Analysis is often used by financial managers because it is the most informative, objective and is prepared based on publicly available information, such as financial analysis.

Another point of analysis is at the bottom - it comes to business analysis, discussing top-down analysis starting with first world economy analysis, then country analysis and sectoral analysis and finally company analysis.

B. Technicall Analysis

The long-term price of a stock, usually based solely on past trends. The values they set (a form of time series analysis). head and shoulders or cup and Plates are varied and come in numerous patterns. Techniques and patterns are also used. Like oscillators, exponential moving averages (EMA), support lines, momentum, Volume indicator. The candlestick pattern is believed to have originally been developed by the Japanese. Rice trading is now widely used by technical analysts. As for the short-term approach, Technical analysis is used for the long term. Therefore, in the product market and foreign exchange market, It is more prevalent where traders focus on short-term price movements. There are basics This analysis uses the following rules: Firstly, everything important about the company is already reflected in the stock price, secondly, the value changes according to trends, and finally, the history (of the price) Again, this is primarily due to market science.

V. SUPPORT VECTOR MACHINES

SVM not only provides linear boundaries, but also models nonlinear hyperplanes. A nonkernel function used to model nonlinear boundaries. stock volatility Profitability, stock return dynamics and index returns used as characteristics in the study. The study is performed by varying the parameter “N” (N days elapsed). Volatility and momentum trends can be used to predict future price changes. A kernel of radial basis to transform the input space into a higher dimensional space. Features used. The advantage of the radial kernel function is that it can output: Nonlinear boundary function. We also match the test data points to the training data. Display points using the minimum Euclidean distance. Gives weight to closer training data points. Outputs strongly predicted labels.

A. Input Features used in SVM

four functions are used to predict the direction of stock prices. The four factors are index volatility, index momentum, stock price volatility and Stock market momentum. Volatility gives investors the experience of market returns. The higher the probability of market growth/decline, the lower/higher the volatility. If the volatility index is high or low, the market will continue to rise or fall. Performance tends to increase/decrease and thus risk and profitability also increase. /Decreases. Once volatility is predicted, investors can understand it. Adjust your portfolio to your expected returns. So we took Our study used stock price volatility and index volatility as input data. stock Volatility shows the average percentage change in a stock over the last N days. price per day. Index volatility displays the average value over the last N days. This is the percentage change in the daily index price. Momentum is the average rate of change in a stock's price movement. this Measures the rate of change in price. Momentum is used to define trend lines. Investors/traders often buy or sell stocks with expectations. The momentum will continue in either an upward or downward direction. inside However, impulse investing is a purely technical indicator. Therefore we rely Technical signs of momentum in our research measuring speed and price changes Sympathy. The stock momentum indicator shows the average value of stock momentum. The exponential momentum over the last N days is the average of the exponential momentum. For the past N days

VI. SINGLE LAYERED PERCEPTRON

In a single layered perceptron, the weight of each input node is randomly assigned because there is no prior information about them.

Additionally, the threshold has been compiled. Now the SLP includes the weight of all devices and if the number is higher than the threshold, turn on the network.

If the value contains the expected value, the model is complete. If it does not match, there must be an error as there is no reversal in this process. Add the formula below and the required weight.

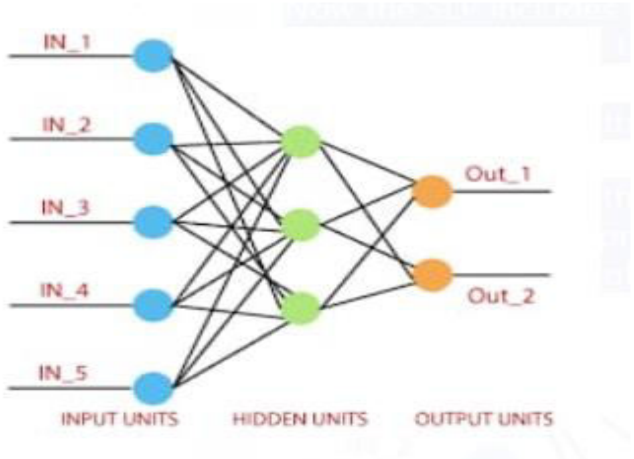

Fig 3: - Single layered perceptron

VII. MULTILAYER PERCEPTRON

MLP consists of a network. Neurons densely connected between adjacent layers. one The characteristics of a feedforward neural network are as follows. The output from one layer is not passed back to the previous layer. The input to each neuron is a weighted sum. All outputs from previous layers of the neural network. Converting this input to output is done using: Continuous and differentiable activation function. exit One pass is made after the input signal has been propagated. To the output layer. The error per pass is calculated as: Regression is usually mean squared error or mean. Square error. Learning algorithms are usually of some kind Gradient descent algorithm, adjusting neuron weights Errors must be reduced. Data is passed to the model. The weights must be adjusted several times to reduce errors. The specified number of epochs has been reached

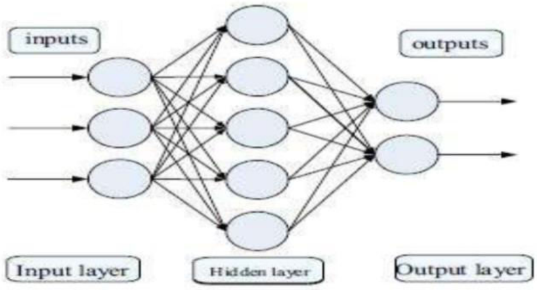

Fig 4: - Multilayered perceptron

VIII. WORKFLOW OF THE SYSTEM AND ITS EXPLANATION

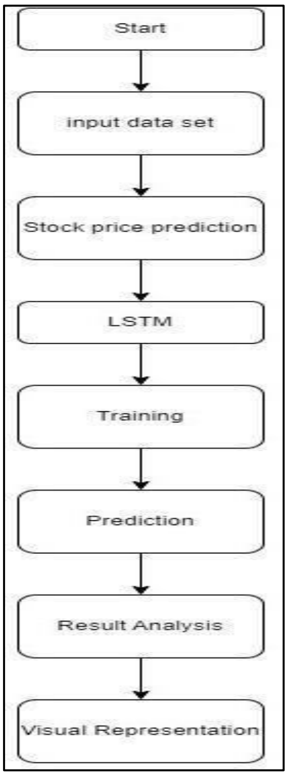

Fig 5: - Work flow of the system

A. Explanation

The input of the model is the dataset we retrieved from the websites of the various Stock Exchanges in .csv or .xls format. The data is preprocessed using various libraries python provides. We clean the data to make it ready for the Machine Learning models. The next stage is to apply various Machine Learning models (here, LSTM) to compute the results.
We check the accuracy of the result using many parameters like Mean Square Error (MSE), Root Mean Square Error (RMSE), etc. For this stage we use the testing dataset. This is the ultimate stage of the project where we choose the most suitable model and predict the result for the interested stock.

IX. SOFTWARE DESIGN.

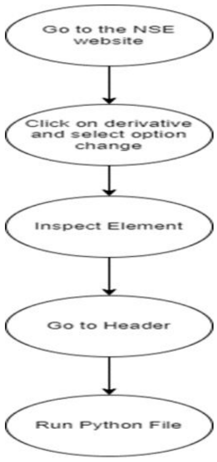

Fig 6: - Work flow of the system

A. Explanation

The beginning of the ML project starts with the extraction of the dataset. This project needs dataset related to the price action movement of the stock. The dataset can be extracted from the NSE website using the above-mentioned steps. The dataset will be produced after following the steps. The file will be in .csv format with various fields which depicts the price action.

X. PRE-PROCESSING OF THE DATA.

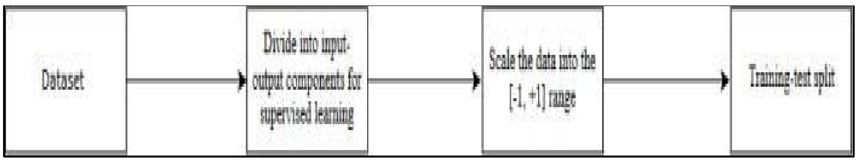

Fig 7: -processing of the data

A. Explanation

The implementation of the ML models requires a clean dataset, free from anomaly, outliers and null-free. We use various python libraries like Sci-kit learn, Pandas and NumPy to clean the data. To define the accuracy of the model, we need training dataset. In this stage, we also split our dataset into 2 parts –

training, testing datasets. The dataset consists of parameters which have different scales. To implement the model there is the need of a common scale. Thus, we normalize the dataset using Min- Max Scaler from Sci-kit Learn library.

XI. AN ARCHITECTURE OF THE PROJECT

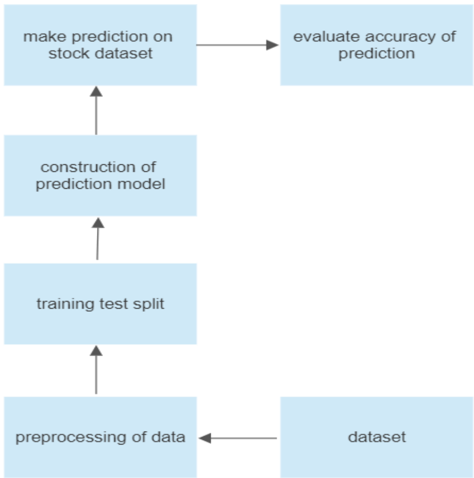

Fig 8:-Project Architecture

A. Explanation

After the pre-processing stage, we construct a predictive model of the dataset by implementing various ML models. The LSTM model uses the Keras library and we repeat the construction of the model until we achieve the maximum achievable accuracy from the dataset. After this, the evaluation of the result is carried out using the testing dataset. We check if the model is underfitted or overfitted.

XII. ACTIVITY DIAGRAM

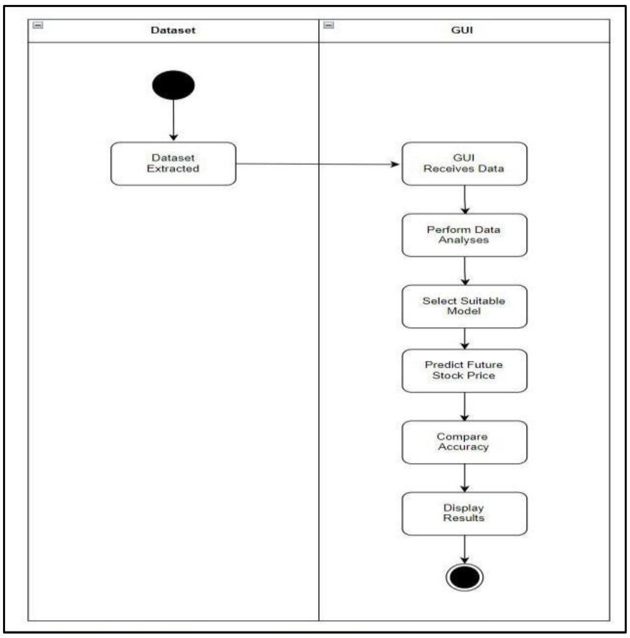

Fig 9:- Control flow of the model

The following activity diagram depicts the behavior of the system. It shows the control flow from a start point to a finish point showing the various decision paths that exist while the activity is being executed

XIII. VARIATION IN TRENDS

When it comes to stock prices, their behavior can be quite intriguing. Typically, at the onset of the year, we witness a rise in stock prices, only to see them fall as August and September roll in. Now, this phenomenon may seem random, but it is far from accidental. In fact, it is attributed to the seasonality of stock prices. You see, there are several factors that contribute to this seasonal pattern. One of the reasons behind the rise in stock prices towards the end of the year is an attempt to improve capital. It's like a collective effort by investors to boost the value of their stocks. Additionally, part of the year-end bond coupon payment finds its way into the stock market, owing to the December interest payment. This influx of funds further influences the prices. Furthermore, the tastes of buyers also tend to vary depending on the holiday season. It's like the festive spirit fuels their sentiment towards investments, resulting in a generally positive outlook. Interestingly, different markets have their own unique set of reasons for stock price seasonality. Pinpointing exact criteria becomes

challenging, but some factors come into play, such as specific payouts during certain seasons, the emotional intelligence of investors during holidays, deviations in financial reports, and so on. Now, let's shift gears and talk about traders. These individuals employ various forms of technical analysis to identify trends in the stock market. They rely on tools like trend lines, price action, and technical indicators to gain insights. One of the key trends they look out for is an uptrend. An uptrend refers to an overall increase in prices. Of course, there will always be fluctuations along the way, but the overarching direction needs to be higher for it to be considered an uptrend. To confirm this trend, traders observe the swing lows. The most recent swing low must be higher than the previous one, just like the swing highs. However, as with everything, nothing can go right indefinitely. Eventually, the structure of an uptrend may begin to crumble, leading to its exhaustion or even a reversal into a downtrend. A downtrend, on the other hand, is characterized by lower lows and lower highs. When a trend is on the rise, traders assume it will continue until evidence to the contrary emerges. This evidence could include lower lows or lower highs, price breaking below a trend line, or technical indicators signaling a bearish shift. During an uptrend, traders focus on buying and aim to profit from the continuous upward movement of prices. Conversely, when the trend starts to turn, traders shift their focus towards selling or shorting. Their goal is to minimize losses or potentially profit from the declining prices. It's worth noting that most downtrends eventually reverse at some point. As the price continues to fall, more and more traders begin to view it as a bargain and step in to buy. This influx of buyers can potentially lead to the emergence of a new uptrend.

It's important to highlight that trends are not limited to technical analysis; they are also relevant to investors who focus on fundamental analysis. This approach involves examining changes in revenue, profit, or other business and economic indicators. For instance, a fundamental analyst may closely observe trends in earnings per share and revenue growth. If earnings have been on the rise over the past four quarters, it indicates a positive trend. Conversely, a decline in earnings during the same period would signal a negative trend. Now, what happens when there is an absence of trend? Such a period, characterized by little overall upward or downward progress, is referred to as a continuous or trendless period. During these times, the market lacks a clear direction, making it challenging for traders and investors to make decisive moves.

In conclusion, the world of stock prices is a fascinating one, influenced by seasonality, human sentiment, technical analysis, and fundamental factors. Understanding the perplexity and burstiness of content in this domain can help convey these complex ideas and insights more effectively.

XIV. RESULTS

A. ASIAN PAINTS.

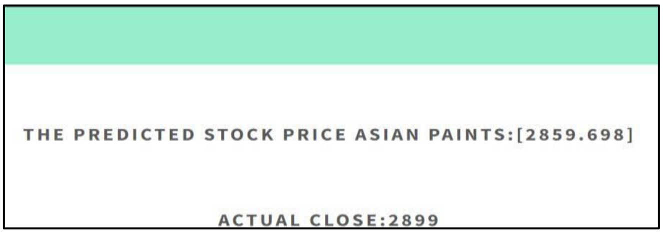

Fig 10:- Predicted Price of ASIAN PAINTS

In this study, we developed a stock price prediction model using a Long Short-Term Memory (LSTM) neural network to forecast the daily closing prices of ASIAN PAINTS. The model was trained on historical stock price data, technical indicators. Our evaluation metrics revealed promising results, with a Loss Percentage of 1.3 , indicating that the model's predictions were 40₹ less of the actual closing prices. Further analysis and model refinement are recommended to enhance its reliability for real-world applications.

B. CDSL

Fig 11:- Predicted Price of CDSL

Our endeavor focused on constructing a robust stock price prediction model for CDSL using cutting- edge Long Short-Term Memory (LSTM) neural network architecture. The model's training involved a comprehensive dataset comprising historical stock prices, carefully engineered financial indicators. The outcome of our assessment displayed promising performance, evidenced by a reasonable Loss Percentage of 4.2 , signifying the 42.2 ₹ less price than actual closing prices. Our model showcases potential predictive capability, continual scrutiny, refinement, and real-world validation are imperative to bolster its practicality and effectiveness in live trading scenarios.

C. COAL INDIA

Fig 12:- Predicted Price of COAL INDIA

Our quest involved the development of an adept stock price prediction model tailored for COAL INDIA utilizing the advanced Long Short-Term Memory (LSTM) neural network architecture. Rigorously trained on an extensive dataset encompassing historical stock prices, thoughtfully engineered financial indicators from a diverse range of financial news sources. By far our model is showing 4.3 ₹ greater than the predicted price.

Above images shows the predicted price of the model which is trained till the date 25th April 2023.The model predicts the price of 26 April 2023 of stocks viz., Asian Paints, CDSL & Coal India. The model shows different results for different stock prices by inferring the pattern of these stocks. This is the reason the Loss percentage of each stock is different. Thus, in this way, we applied the model on the different stocks of NSE to predict the future prices of the stocks. Below table shows our predictions for each stock and the loss percentage calculated using it. The Loss percentage we used has the formula:

$$\%\ \text{Loss} = \frac{(\text{Actual Price} - \text{Predicted Price}) \times 100}{\text{Actual Price}} \quad ----------- (1)$$

XV. CONCLUSION

The model proposed here employs, a machine learning-based model for stock price prediction The suggested model of stock price prediction of the stock is generic after testing, and can also better adapt to the diverse parameters of the stock's price action. Even though the model was trained on considerably very small database because the stock market data is huge, good results were achieved. Data extension can be done in the future to raise the dataset's size. Also, the model can be further enhanced to predict the stock price with a higher accuracy in a form of a range between the open and close price of a particular stock. There have been enhancements in the methods used for stock price prediction, accurately predicting stock prices remains a challenging task. Further research is needed to improve the accuracy and reliability of predictions, and factors beyond stock data should be taken into account when making predictions.

The growth of economic activity encourages researchers and financial analysts to explore new methods that use new ideas from existing statistical methods. The art of forecasting is

useful not only for academics but also for investors, brokers and anyone interested in the stock market. To provide a tool for predicting product, a predictive model with good accuracy is needed. The aim here is to predict market indices. The aim of this study is to increase the performance of the short-term memory network in stock market prediction. The purpose of this article is to create a trading model that can record market movements and provide traders with an overview. The ability to predict stock prices using LSTM was investigated.
LSTM is used because it focuses on important variables and is more accurate than other methods. Availability of information is important to estimate the value of the product because needs and reality depend on it. Facts vary from company to company because each organization has different information.

XVI. LIMITATION AND FUTURE WORK

A. Limitations

a) Market unpredictability:-Stock prices can be affected by a variety of factors, such as economic news, political events, and investor sentiment, which can be difficult to predict.

b) Rapid market changes:-The stock market can change quickly, and models that are not updated regularly may become outdated and inaccurate.

c) Black Swan events:- These are rare and unexpected events that can have a significant impact on the stock market, such as the COVID-19 pandemic, and are difficult to predict using traditional models

d) Human behavior:- Stock prices can be influenced by the behavior of individual investors, and models that do not take into account human emotions and irrationality may not accurately predict stock prices.

B. Future Scope

a) Predictable Artificial Intelligence:- Build models that not only accurately predict stock prices, but also provide insight into the principles underlying the predictions. This can help traders understand the rationale behind the forecast and make more informed decisions.

b) Integration with other financial models:- Integrating cost estimation models with other financial models such as risk management or optimization can provide more insight into the financial market.

c) Develop long-term investment models:- Developing long- term investment models that can predict not only short-term markets but also market prices can provide good insight for investors seeking long-term investment in the stock market

ACKNOWLEDGMENTS

It is my great pleasure in expressing sincere and deep gratitude towards my guide DR M P Sardey, Assistant Professor Electronics & Telecommunication Engineering Department for her valuable guidance and constant support throughout this work and help to peruse additional studies in Machine learning and Data Mining.

We take this opportunity to thank Head of the Department Dr. M. P. Sardey and Project coordinator Dr. M. P. Sardey and all staff members of department of Electronics & Telecommunication Engineering AISSMS IOIT, Pune, for cooperation provided by them in many ways.

The motivation factor for this work was the inspiration given by our honorable principal Dr. P. B. Mane.

Lastly, I am thankful to those who have directly or indirectly supported for our work.

REFERENCES

[1] Mulani, A. O., & Shinde, G. N. (2021). An approach for robust digital image watermarking using DWTPCA. Journal of Science & Technology (JST), 6(Special Issue 1), 59-62.

[2] Deshpande, H. S., Karande, K. J., & Mulani, A. O. (2015, April). Area optimized implementation of AES algorithm on FPGA. In 2015 International Conference on Communications and Signal Processing (ICCSP) (pp. 0010-0014). IEEE.

[3] Ghodake, M. R. G., & Mulani, M. A. (2016). Sensor based automatic drip irrigation system. Journal for Research, 2(02).

[4] Mulani, A. O., & Mane, P. B. (2016). Area efficient high speed FPGA based invisible watermarking for image authentication. Indian journal of Science and Technology, 9(39), 1-6.

[5] Stock Price Forecasting Using Data from Yahoo Finance and Analysing Seasonal and Nonseasonal Trend. Publication Year: 2018 IEEE.

[6] Stock Market Prediction using Machine Learning - Ishita Parmar, Ridam Arora, Lokesh Chauhan, Navanshu Agarwal

[7] Stock Market Prediction Using Machine Learning Techniques. Publication Year: 2016 - Author:Mehak Usmani, Syed Hasan Adil, Kamran Raza, Syed Saad Azhar Ali

[8] Stock Price Prediction Based on Information Entropy and Artificial Neural Network.Publication Year: 2019 -Zang Yeze, Wang Yiying.

[9] Takale, S., & Mulani, D. A. Video Watermarking System. International Journal for Research in Applied Science & Engineering Technology (IJRASET), 10.

[10] Manh Ha Duong Boriss Siliverstovs June 2006 - The Stock Market and Investment.

[11] S. Qamar, & S. H. Adil, "Comparative analysis of data mining techniques for financial data using parallel processing," In Proceedings of the 7th International Conference on Frontiers of Information Technology, 2009.

[12] S. H. Adil, & S. Qamar. "Implementation of association rule mining using CUDA," International Conference on Emerging Technologies (ICET), 2009.

[13] S. S. A. Ali, M. Moinuddin, K. Raza, & S. H. Adil, "An adaptive learning rate for RBFNN using time-domain feedback analysis," The Scientific World Journal, 2014

[14] Kolekar, S. D., Walekar, V. B., Patil, P. S., Mulani, A. O., & Harale, A. D. (2022). Password Based Door Lock System. Int. J. of Aquatic Science, 13(1), 494-501.

[15] A. W. Lo, & A. C. MacKinlay, "Stock market prices do not follow random walks: Evidence from a simple specification test," Review of financial studies, vol. 1, no. 1, pp. 41-66, 1988.

[16] C. D. R. Aurangzeb, "Factors Affecting Performance of Stock Market: Evidence from South Asian Countries," International journal of academic research in business and social sciences, vol. 2, no. 9, 2012.

[17] S. Fatima, & G. Hussain, "Statistical models of KSE100 index using hybrid financial systems," Neurocomputing, vol. 71, no. 13, pp. 2742-2746, 2008.

[18] I. Ali, K. U. Rehman, A. K. Yilmaz, M. A. Khan, & H. Afzal, "Causal relationship between macro-economic indicators and stock exchange prices in Pakistan," African Journal of Business Management, vol. 4. No. 3, pp. 312, 2010.

[19] Shinde, R., & Mulani, A. O. (2015). Biomedical Image fusion using Wavelet transform. In International Conference On Current Advances in Electronics, Electrical and Computer science (ICEECS), August.

[20] Mulani, A. O., & Mane, P. (2018). Secure and area efficient implementation of digital image watermarking on reconfigurable platform. International Journal of Innovative Technology and Exploring Engineering, 8(2), 56-61.

[21] J. Bollen, H. Mao, & X. Zeng, "Twitter mood predicts the stock market.Journal of Computational Science," vol. 2, no. 1, pp. 1-8, 2011.

[22] S. Shen, H. Jiang, & T. Zhang, "Stock market forecasting using machine learning algorithms, 2012.

[23] S. Asur, & B. A. Huberman, "Predicting the future with social media," International Conference on Web Intelligence and Intelligent Agent Technology (WI-IAT), 2010.

[24] N. H. Hung, & Y. Zhaojun, "Profitability of Applying Simple Moving Average Trading Rules for the Vietnamese Stock Market," Journal of Business Management, vol. 2, no. 3, pp. 22-31, 2013.

[25] T. Wilson, P. Hoffmann, S. Somasundaran, J. Kessler, J. Wiebe, Y. Choi, & S. Patwardhan, "OpinionFinder: A system for subjectivity analysis," In Proceedings of emnlp on interactive demonstrations, pp. 34-35, 2005.

[26] Mulani, A. O., & Mane, P. B. (2017). Watermarking and cryptography based image authentication on reconfigurable platform. Bulletin of Electrical Engineering and Informatics, 6(2), 181-187.

[27] Korake, D. M., & Mulani, A. O. (2016). Design of Computer/Laptop Independent Data transfer system from one USB flash drive to another using ARM11 processor. International Journal of Science, Engineering and Technology Research.

[28] Abhangaro, R. (2017). Design And Implementation Of 8-bit Vedic Multiplier. International Journal of Research Publications in Engineering and Technology (ISSN No: 2454-7875).

[29] Mulani, A. O., & Mane, P. B. (2014, October). Area optimization of cryptographic algorithm on less dense reconfigurable platform. In 2014 International Conference on Smart Structures and Systems (ICSSS) (pp. 86-89). IEEE.

[30] Mulani, A. O., & Mane, P. B. (2019). High-Speed area-efficient implementation of AES algorithm on reconfigurable platform. Computer and Network Security, 119.

[31] Mane, P. B., & Mulani, A. O. (2018). High speed area efficient FPGA implementation of AES algorithm. International Journal of Reconfigurable and Embedded Systems, 7(3), 157-165.