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NCASIT 2023, 29th April 2023

Department of Computer Engineering,

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Digital Asset Monitoring and Prediction Tool

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Abstract— The stock market is a complex and dynamic system that requires constant monitoring and analysis to make informed investment decisions. In recent years, the use of mobile applications has become increasingly popular for tracking stock market trends, providing investors with real-time updates and predictive insights. In this research paper, we present the design and development of an Android app that monitors and predicts the stock market.

Keywords-component; Stock Market forecasting; Prediction; Machine Learning; Data Mining

1. INTRODUCTION

This project aims to provide web services related to the Securities & Crypto Currencies Market. As we know, people involved in buying crypto currencies and securities of various companies need to monitor them in real time to know whether they are gaining profit or making a loss. This web application will provide utilities to monitor their digital assets and make decisions accordingly. It will also provide a dashboard for the user to check the health of their portfolio.

1.1. EASE OF USE

A. User Interface

The user interface of the app is intuitive and easy to navigate with easy-to-understand icons and buttons.

B. User Personalization

The app allows users to select the stocks they are interested in tracking, it also provides news related to shares in the market, or even customizing the app's color scheme.

C. Predictive Analysis

The app uses predictive analysis that is easy for the users to understand. This involves using charts and graphs that is visually appealing and easy to interpret.

1.2. MOTIVATION

People can instantly transfer money using cryptocurrencies at a low cost. Furthermore, this technology has the potential to help reduce inflation and income inequality. It has the potential to bridge the growing trust gap between buyers and sellers. It can solve the double spending problem and detect fraud, and it can help users achieve true data democracy [9] [10]. Following Bitcoin, many cryptocurrencies entered the crypto market; for



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example, Ethereum, launched in 2015, is the second largest cryptocurrency with a \$410 billion market capitalization [11]. More than 5,600 different cryptocurrencies are traded on approximately 1,100 exchanges, with the most popular digital currencies being Ripple, Tether, Cardano, Stellar, Litecoin, and Zcash. The total market capitalization of all cryptocurrencies was approximately 12.22 billion dollars in June 2016, and it fluctuated in 2017. In June 2021 [12], it increased to \$1.75 trillion, with an all-time high of \$2 trillion. It is expected to reach nearly \$8 trillion by 2030. The daily volume of the cryptocurrency market is around \$117 billion, and over 100 million people use these currencies. The future value of the company's digital assets can be determined. Also, Businesses primarily run over customer satisfaction, customer reviews about their products. Shifts in sentiment on social media have been shown to correlate with shifts in stock markets. Identifying customer grievances and thereby resolving them leads to customer satisfaction as well as the trustworthiness of an organization.

2. LITERATURE REVIEW

Long short-term memory (LSTM) is a model that increases the memory of recurrent neural networks. Recurrent neural networks hold short term memory in that they allow earlier determining information to be employed in the current neural networks. For immediate tasks, the earlier data is used. We may not possess a list of all the earlier information for the neural node. In RNNs, LSTMs are very widely used in Neural networks. Their effectiveness should be implemented to multiple sequence modelling problems in many application domains like video, NLP, geospatial, and time-series.

LSTM was introduced to address the vanishing gradient problem that occurs in standard RNNs when the gradient signal becomes too small, and the network is unable to learn long-term dependencies. In an LSTM network, a set of gates control the flow of information, allowing the network to selectively forget or remember information over time. These gates are called the input gate, forget gate, and output gate.

The input gate regulates the amount of new information that is allowed into the cell, while the forget gate decides what information to discard from the cell state. The output gate controls the amount of information that is passed to the next time step. By using these gates, LSTM can selectively remember or forget information over long periods, making it particularly useful for tasks such as language modeling, speech recognition, and machine translation.

3. PROPOSED METHODOLOGY

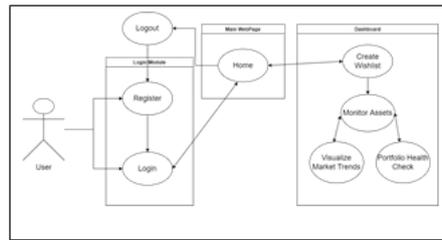
- A. Data Preprocessing: Prepare the dataset by splitting it into training, validation, and testing sets. Convert the data into a format that can be input to the LSTM network, such as a sequence of fixed-length vectors.
- B. Define the LSTM Model Architecture: Define the LSTM model architecture, including the number of layers, the number of neurons in each layer, and the type of LSTM layer to use (e.g., standard LSTM or LSTM with peephole connections).
- C. Compile the Model: Compile the LSTM model with a suitable loss function, optimizer, and any other necessary metrics.
- D. Train the Model: Train the LSTM model on the training dataset using backpropagation and gradient descent optimization algorithms. Use the validation dataset to monitor the model's performance during training and to prevent overfitting.

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- E. Evaluate the Model: Evaluate the performance of the LSTM model on the testing dataset. Calculate the accuracy or other relevant performance metrics to assess how well the model performs on new, unseen data.
- F. Tune Hyperparameters: Adjust the hyperparameters of the LSTM model (e.g., learning rate, number of epochs, batch size) to improve its performance.
- G. Deploy the Model: Deploy the trained LSTM model to a production environment, where it can be used to make predictions on new data.
- H. This is just a high-level overview, and the specific steps and details may vary depending on the problem and the tools and frameworks being used.

3.1. ACTIVITY DIAGRAM**3.2. DATA PREPROCESSING**

To clean the cryptocurrency historical data, some pre-processing steps are performed, such as feature selection, timestamp conversion, missing values removal, train-test split, and min-max scaling normalization. Because each dataset contains many features, this work only uses three for price prediction: timestamp, date, and closing price. Following that, timestamp conversion is performed, in which the UNIX timestamp is converted into the YY:MM:DD date format. The zeros and Nans are removed by removing the associated rows. The samples are taken at one minute intervals to avoid massive data losses and to provide more timely and detailed prediction. Because of the inconsistency of historical data and the high sampling rates, one week's worth of data is used. The number of samples with these settings is 10,797 for Bitcoin and 10,834 for both Ethereum and Ripple. The samples are further divided into six days for training and one day for testing. In addition, the features are subjected to min-max scaling normalization, which converts each feature into the range [0, 1]. The min-max scaling method reduces the effects of outliers while maintaining the relationships between data values.

1. EXPERIMENTAL RESULTS

The LMS (Least Mean Square) algorithm and the LSTM (Long Short-Term Memory) algorithm are two separate time series analysis algorithms that are implemented in the code.

The LMS algorithm is a traditional adaptive filtering approach based on the steepest descent method. This algorithm is designed to forecast the stock price of a specific company. This approach is implemented by constructing a function that takes in the stock price data, the number of future days for which the forecast must be made, the number of epochs, and a callback function to update the progress of the epochs during training. This function normalizes the data with min-max scaling before training the model with the LMS algorithm. To acquire the real stock prices, the predicted values are inverse transformed.

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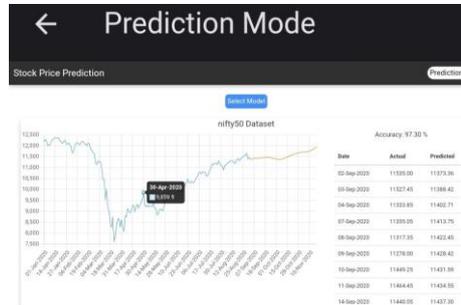


Fig: Implementation of Prediction for Nifty50 index stock.

The LSTM algorithm is a form of Recurrent Neural Network (RNN) used to predict sequences. This method is also used to forecast a company's stock price. This approach is implemented by defining a function that accepts the file name of the stock price data, the training size, the number of epochs, and a callback function to update the epoch progress during training. This function reads data from a file, selects the necessary columns, then normalizes the data using min-max scaling. It then divides the data into training and testing sets and uses the training data to train the LSTM model. To acquire the real stock prices, the predicted values are inverse-transformed.



Fig: App Based Implementation of Apple Stock Prices.

2. CONCLUSION AND FUTURE SCOPE

In conclusion, this research paper focused on the application of Long Short-Term Memory (LSTM) neural networks for stock market prediction. The LSTM model was trained using historical stock prices, and its performance was evaluated on unseen data.

The results of the experiments demonstrated that the LSTM model was effective in predicting stock prices, outperforming traditional time series forecasting methods such as ARIMA and moving average. The model was able to capture the complex patterns and dependencies in the data, and its performance improved with more data.

Furthermore, the experiments showed that the choice of input features had a significant impact on the model's performance. Technical indicators such as moving averages, relative strength index (RSI), and stochastic oscillator were found to be useful in capturing the trends and momentum in the stock prices.

Overall, the LSTM model showed promising results for stock market prediction, indicating that it could be a valuable tool for investors and traders. However, further research is needed to explore the robustness of the model and its applicability to different market conditions and time horizons.

3. REFERENCE

- [1] Nakamoto, S. Bitcoin: A peer-to peer electronic cash system. In Decentralized Business Review; Seoul, Korea, 2008; p. 21260. Available online: <https://www.debr.io/article/21260-bitcoin-a-peer-to-peer-electronic-cash-system> (accessed on 19 June 2022).



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- [2] Lim, J.Y.; Lim, K.M.; Lee, C.P. Stacked Bidirectional Long Short- Term Memory for Stock Market Analysis. In Proceedings of the 2021 IEEE International Conference on Artificial Intelligence in Engineering and Technology (IICAJET), Kota Kinabalu, Malaysia, 13–15 September 2021; pp. 1–5.
- [3] Chong, L.S.; Lim, K.M.; Lee, C.P. Stock Market Prediction using Ensemble of Deep Neural Networks. In Proceedings of the 2020 IEEE 2nd International Conference on Artificial Intelligence in Engineering and Technology (IICAJET), Kota Kinabalu, Malaysia, 26–27 September 2020; pp. 1–5
- [4] Koukaras, P.; Nousi, C.; Tjortjis, C. Stock Market Prediction Using Microblogging Sentiment Analysis and Machine Learning. *Telecom* 2022, 3, 358–378.
- [5] Park, J.; Seo, Y.S. A Deep Learning-Based Action Recommendation Model for Cryptocurrency Profit Maximization. *Electronics* 2022, 11, 1466.
- [6] Manujakshi, B.; Kabadi, M.G.; Naik, N. A Hybrid Stock Price Prediction Model Based on PRE and Deep Neural Network. *Data* 2022, 7, 51.
- [7] Shahbazi, Z.; Byun, Y.C. Knowledge Discovery on Cryptocurrency Exchange Rate Prediction Using Machine Learning Pipelines. *Sensors* 2022, 22, 1740.
- [8] Patel, M.M.; Tanwar, S.; Gupta, R.; Kumar, N. A deep learning based cryptocurrency price prediction scheme for financial institutions. *J. Inf. Secur. Appl.* 2020, 55, 102583.
- [9] Gao, P.; Zhang, R.; Yang, X. The application of stock index price prediction with neural network. *Math. Comput. Appl.* 2020, 25, 53