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KLE Technological University, Hubballi.

A Minor Project Report

on

Prediction of Cryptocurrencies using Deep Learning Techniques: A Systematic Approach

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in

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SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

CERTIFICATE

This is to certify that Minor Project titled Prediction of Cryptocurrencies a systematic approach using deep learning techniques is a bonafied work carried out by the student team comprising of team members Sahana Aidnal (01fe20bcs015), Srushti Nayak (01fe20bcs016), Chirag Sandeep Metgud (01fe20bcs018) and Ritvik Chunamari (01fe20bcs080) for partial ful fillment of completion of sixth semester B. E. in Computer Science and Engineering during the academic year 2022-23.

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ABSTRACT

The objective of this project is to develop a cryptocurrency price prediction system that combines sentiment analysis, technical indicators, and machine learning models to predict future prices for selected cryptocurrencies. The system will analyze news and social media data to determine market sentiment towards the selected cryptocurrencies. Technical indicators such as moving averages, RSI, and Bollinger Bands will be used to identify patterns and trends in the data that can be used to make price predictions. The system will utilize machine learning models such as LSTM, GRU, and Bidirectional LSTM, which will be trained on historical price data to predict future prices for the selected cryptocurrencies. The accuracy of the system will be evaluated by comparing actual and predicted prices of the selected cryptocurrencies. The system will be designed to be scalable and able to handle large volumes of data. The system's architecture will be based on a client-server model, with the server-side performing data analysis and making price predictions. The system will be developed using Python programming language. In summary, this project aims to develop a cryptocurrency price prediction system that combines sentiment analysis, technical indicators, and machine learning models to provide accurate price predictions for selected cryptocurrencies. The accuracy of the system will be evaluated by comparing actual and predicted prices, and the system will be designed to be scalable to handle large volumes of data. The system will be developed using Python programming language.

Keywords : *cryptocurrency, price prediction, sentiment analysis, technical indicators, machine learning, LSTM, GRU, Bidirectional LSTM, Flask, web application, scalability, accuracy..*

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Chapter 1

INTRODUCTION

Cryptocurrencies, such as Bitcoin, Ethereum, Litecoin, and Tether, have become increasingly popular over the past few years. Cryptocurrencies are digital or virtual currencies that use cryptography for security and are decentralized, which means they are not controlled by any central authority.The popularity of cryptocurrencies has led to an increase in demand for accurate price predictions. Investors in these currencies are constantly seeking information on price trends to make informed decisions on investment opportunities.[3]

However, predicting the prices of cryptocurrencies is a complex task due to their high volatility and sensitivity to external factors such as news and social media.In recent years, researchers have developed various methods for predicting the prices of cryptocurrencies. These methods range from traditional statistical methods to machine learning algorithms. One of the challenges in predicting the prices of cryptocurrencies is the availability of data. However, with the advent of web scraping techniques, it has become easier to collect data from various sources, including news websites and social media platforms.[2]

In this project, we aim to develop a system that uses sentiment analysis, technical indicators, and machine learning models to predict the future prices of cryptocurrencies. We collected data for a period of three years, from 2018 to 2021, from various sources, including news websites and social media platforms. We conducted sentiment analysis on the collected data and calculated technical indicators such as moving averages, RSI, and Bollinger Bands. We trained machine learning models such as LSTM, GRU, and Bidirectional LSTM to predict the future prices of cryptocurrencies. The main objective of this project is to provide investors with valuable information that they can use to make informed decisions about their investments. Our system aims to provide accurate price predictions using various techniques, including sentiment analysis and machine learning models. Furthermore, we developed a web application that allows users to input a date and get a predicted price for the selected cryptocurrency. In this report, we will describe the methods and techniques we used to develop our system, including the requirements analysis, system design, implementation, and results and discussions. We will also evaluate the accuracy of our system by comparing the actual and predicted prices of cryptocurrencies [7].

1.1 Motivation

The increasing popularity of cryptocurrencies and the potential for high returns on investment have led to a surge in demand for accurate price predictions. Cryptocurrency investors and traders are constantly seeking information on price trends to make informed decisions on when to buy or sell. However, predicting the prices of cryptocurrencies is a complex task due to the high volatility and sensitivity to external factors such as news and social media. Traditional methods of financial analysis, such as technical and fundamental analysis, have limitations when it comes to predicting the prices of cryptocurrencies. These methods rely on historical price data and do not take into account the impact of external factors on price movements. This has led to the development of new methods for predicting the prices of cryptocurrencies, including sentiment analysis and machine learning algorithms. Sentiment analysis involves analyzing the emotions and opinions expressed in text data such as news articles, social media posts, and forum discussions. By analyzing sentiment, we can gain insights into the market sentiment towards a particular cryptocurrency, which can be used to predict future price movements.Machine learning algorithms, such as LSTM, GRU, and Bidirectional LSTM, have been shown to provide accurate price predictions for cryptocurrencies. These algorithms are trained on historical price data and can identify patterns and trends in the data that may not be immediately obvious to humans. The motivation behind this project is to develop a system that combines sentiment analysis and machine learning algorithms to provide accurate price predictions for cryptocurrencies. Our system aims to provide investors with valuable information that they can use to make informed decisions about their investments [7].

1.2 Literature Review / Survey

Helder Sebastião et.al investigates the profitability of trading methods and the predictability of three significant cryptocurrencies: bitcoin, ethereum, and litecoin. The classification and regression techniques made use for the time period from August 2015 to March 2019, test sample starting on April 2018. Five of the 18 different models have success rates less than 50 percent for the test period. The ensemble strategy assuming identical signals from five models (Ensemble 5) achieves the highest performance for Ethereum and Litecoin, with annualized Sharpe ratios of 80.17 percent and 91.35 percent and annualized returns of 9.62 percent and 5.73 percentrespect ively, after accounting for round-trip trading expenses of 0.50percent. Machine learning provides reliable methods for exploring cryptocurrency predictability and encourages results even in challenging market conditions [1].

Patrick Jaquart, David Dann and Christof Weinhardt assessesed the effectiveness of six machine learning models in predicting the Bitcoin market using minutely data from a nine-month period. Recurrent neural networks and gradient boosting classifiers are found to be the most effective models, with technical features being the most relevant for accurate predictions. The study highlights the potential of machine learning in predicting cryptocurrency markets and recommends using models like (Long Short Term Memory) LSTM and GRU (Gated Recurrent Unit) for processing and predicting data.The article finds that recurrent neural networks, particularly GRU and LSTM, provide more accurate predictions for the Bitcoin market compared to other models, across different time horizons. For models without memory function, like GBC and RF, the most important feature remains related to Bitcoin returns. However, less recent returns become more crucial for longer prediction horizons, with recent minutely returns being most relevant for the 1-min horizon, and periods further back in time becoming progressively more important for the 5-min, 15-min, and 60-min horizons [2].

Mrs Vaidehi M1 , Alivia Pandit2 , Bhaskar Jindal2 , Minu Kumari2 and Rupali Singh2 proposed the highlights of the intersection of Bitcoin and machine learning, stating that accurate prediction of Bitcoin prices can be profitable with the right understanding. The authors suggest using machine learning algorithms like RNN and LSTM to predict prices with higher accuracy, particularly when using shorter time intervals.The article explains that feedforward neural networks process each input independently and do not save memory, while RNNs can keep track of previous information but face issues with gradient vanishing/exploding. However, using variations of RNN like LSTM and GRU can add data-carrying cells to address this problem, with LSTM being particularly effective for predicting based on historical context.The article's results indicate that higher batch sizes during training led to worse predictions on the test set, while features were critical to the algorithm's performance in predicting Bitcoin prices. Future work could include exploring other RNN variations like Gated Recurrent Units and tuning hyper-parameters. The Mean Absolute Error function was used to evaluate the LSTM model's performance in predicting training and test data [3].

Luisanna Cocco, Roberto Tonelli, and Michele Marchesi explored the use of machine learning techniques, including ANNs, SVMs, and RFs, for predicting Bitcoin prices using features such as Twitter sentiment score, Twitter volume, Google Trends score, and Bitcoin trading volume. The authors trained three models, decision tree regression, random forest regression, and support vector regression, using a sliding window approach with a window size of 7 days. Model performance was evaluated using metrics such as MAE, MSE and a sensitivity analysis was conducted to determine the impact of each feature on model performance.The article explores the use of machine learning models, including LSTM, GRU, MLP, ARIMA, and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) , in predicting cryptocurrency prices using sentiment analysis based on Twitter data. The LSTM model had the highest accuracy of 78.1 percent, followed by the GRU model at 75.6 percent, and the MLP model at 72.2 percent. The study found that sentiment analysis improved the accuracy of the models, particularly for the MLP model, which had the highest increase in accuracy when sentiment analysis was included. The study suggests that deep learning models, combined with sentiment analysis, can be effective in predicting cryptocurrency prices [4].

J. Risk Financial Manag et.al proposed the use of LSTM and Random forest regression to create an algorithm model with high prediction accuracy for the price of Bitcoin the following day and to identify the factors that affect this price. The ARMA time series model and the LSTM deep learning algorithm are at the centre of a large body of earlier research on predicting the price of bitcoin. Random forest regression is also used to obtain the variations in the factors that affect the price of Bitcoin during each period. In terms of predicting the price of Bitcoin for the following day, the model with just one lag of the explanatory factors has the highest prediction accuracy, according to the link between accuracy and the number of periods of explanatory variables included in the model [5].

David Yechiam Aharon et.al proposed the theory that in the financial markets, the day-of-the-week impact is a well-known phenomena that may be seen in the price of commodities, shares, bonds, and currencies. The investigation of this oddity is expanded to Bitcoin in this paper. They give preliminary evidence about the day-of-the-week effect anomaly's presence, not only in returns but also in the volatility of Bitcoin, using OLS and GARCH models using daily data for 2010–2017. Our findings also show that Bitcoin has a high degree of independence and that traditional speculative factors in the financial markets have a limited ability to predict its price. Using various subsamples, estimating techniques, and control factors, our results hold up well [6].

Samiksha Marne, Shweta Churi, Delisa Correia and Joanne Gomes proposed the two machine learning models, Long Short-Term Memory (LSTM) and Auto Regressive Integrated Moving Average (ARIMA), are used to predict the future price of Bitcoin. The performance of the models is evaluated using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) metrics. The article discusses the advantages and disadvantages of using LSTM and ARIMA models. LSTM models are known for their ability to capture long-term dependencies and predict highly fluctuating time series data. On the other hand, ARIMA models are commonly used in time series analysis and are simpler and faster to train compared to LSTM models. The study also includes sentiment analysis as an additional parameter to predict Bitcoin's price. The sentiment analysis is done using Twitter data and the Vader Sentiment Intensity Analyzer.The paper presents the results of their deep learning approach for predicting the price of Bitcoin. They train their model using historical Bitcoin data from Bitstamp exchange, which consists of 48 features such as opening price, highest price, lowest price, volume, etc. They also include technical indicators such as Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), and Bollinger Bands (BB) as features.Their model is trained and tested on a dataset consisting of daily Bitcoin closing prices from 2014 to 2019. They use a sliding window approach to generate the training and testing datasets.The training dataset consists of 60 percentage of the data, while the testing dataset consists of 40 percentage of the data.Their model achieves an RMSE of 260.4 on the test dataset, which is lower than the RMSE of traditional models such as ARIMA and GARCH. They also compare their model with other deep learning models such as Multi-Layer Perceptron (MLP) and Convolutional Neural Network (CNN) and find that their model performs better in terms of RMSE [7].

S M Rajua and Ali Mohammad Tarifb proposed the method to predict the price of bitcoin on the stock market, researchers used sentiment analysis from social media and machine learning algorithms. The project aims to use deep learning techniques such as LSTM and traditional time series analysis method like ARIMA(models are often used in finance and economics to forecast stock prices, exchange rates) to predict the real-time price of Bitcoin. The objective is to achieve maximum efficiency in price prediction and compare the performance of both techniques to determine the best algorithm for prediction.The Long Short-Term Memory (LSTM) network is a type of recurrent neural network that addresses the problem of disappearing gradients in deep learning. Auto Regression Integrated Moving Average (ARIMA) model is used to estimate the trend and seasonality of the series and remove them to obtain a stationary series. The LSTM model takes longer to compile due to its complex calculations, and its loss is minimal at a learning rate of 0.01. However, it is difficult to find a model that fits both the training and test data due to the large fluctuations in time series data.

The ARIMA model has a higher RMSE than the LSTM model, but it is better suited for Bitcoin forecasting due to the minimal accuracy of the LSTM model. Finally, the passage notes that LSTM is generally suitable for predicting higher fluctuations in time series data [8].

Parthajit Kayal and Purnima Rohilla proposed the study of Bitcoin, that has gained considerable attention in the fields of economics and finance. A review of the literature reveals numerous analyses and discussions surrounding the digital currency's underlying technology, market behavior, and potential impact on the global financial system. Some researchers have explored the blockchain technology and its various use cases, while others have investigated the economic implications of Bitcoin's decentralization and its potential as an alternative to traditional currencies. Additionally, the financial aspect of Bitcoin has been studied in depth, with researchers focusing on price dynamics, volatility, and risk management. This burgeoning body of literature highlights the multidisciplinary nature of Bitcoin research, reflecting its growing significance in the global economic and financial landscape [9].

Mareena Fernandes,Saloni Khanna,Leandra Monteiro,Anu Thomas and Garima Tripathi proposed the study where , Fernandes et al. explored Bitcoin price prediction through a comprehensive literature survey. The authors critically examine various methods employed in the domain, including time series analysis, machine learning techniques, and sentiment analysis, while discussing their merits and limitations. Additionally, the survey highlights the importance of understanding market dynamics, investor sentiment, and economic indicators to create accurate and reliable Bitcoin price forecasts [10].

The Identified gaps or challenges for the above articles are:

- Addressing the limited availability and quality of historical data for effective model training and evaluation.

- Overcoming the challenge of noisy and non-stationary data in short-term Bitcoin market forecasting.

- Tackling the challenge of accurately predicting Bitcoin prices amidst its highly volatile and unpredictable nature.

- Improving the reliability of Bitcoin price forecasts by tackling the high volatility and unpredictability of the cryptocurrency market.

- Incorporating diverse data sources and feature selection methods to enhance the performance of machine learning frameworks.

- Addressing the need for a more comprehensive set of predictors, including sentiment analysis and additional technical indicators such as RSI and Bollinger Bands, for a comprehensive analysis.

- Exploring the performance of various machine learning models, such as GRU and Bidirectional LSTM, to enhance prediction accuracy.

1.3 Problem Statement

The high volatility and sensitivity to external factors such as news and social media make predicting the prices of cryptocurrencies a complex task. Traditional methods of financial analysis have limitations when it comes to predicting the prices of cryptocurrencies, and new methods are needed to provide accurate price predictions. Sentiment analysis and machine learning algorithms have been shown to be effective in predicting the prices of cryptocurrencies. However, there is a need to develop a system that combines these techniques to provide more accurate and reliable price predictions. In this project, we aim to address these challenges by developing a system that uses sentiment analysis, technical indicators, and machine learning models to predict the future prices of cryptocurrencies. We will also develop a web application that allows users to input a date and get a predicted price for the selected cryptocurrency. The system aims to provide accurate and reliable price predictions that investors can use to make informed decisions about their investments.

1.4 Applications

- System provides accurate price predictions for cryptocurrencies, helping investors identify investment opportunities and make informed decisions based on predicted prices.

- The system helps investors manage risks associated with cryptocurrency trading and investment by providing accurate price predictions and identifying potential risks.

- It analyzes the market sentiment and uses technical indicators to identify patterns and trends in data that can be used to develop effective trading strategies for cryptocurrencies.

- The price predictions provided can be used to optimize a cryptocurrency portfolio by identifying undervalued or overvalued cryptocurrencies and adjusting the portfolio accordingly.

- It can be used to analyze the cryptocurrency market by providing insights into market trends and sentiment. This can be useful for researchers and analysts who want to gain a better understanding of the cryptocurrency market.

- It can be used to assess the risks associated with a particular cryptocurrency by providing accurate price predictions that can be used to identify potential risks and vulnerabilities.

1.5 Objectives and Scope of the project

As shown in Figure 1.1, the main objectives of this project are to develop a system that combines sentiment analysis, technical indicators, and machine learning models to provide accurate price predictions for cryptocurrencies. The system's accuracy will be evaluated by comparing actual and predicted prices, and a user-friendly web application will be developed to provide easy access to the predicted prices of cryptocurrencies. These objectives aim to provide investors and traders with valuable insights into the cryptocurrency market, enabling them to make informed decisions and manage risks associated with trading and investment.

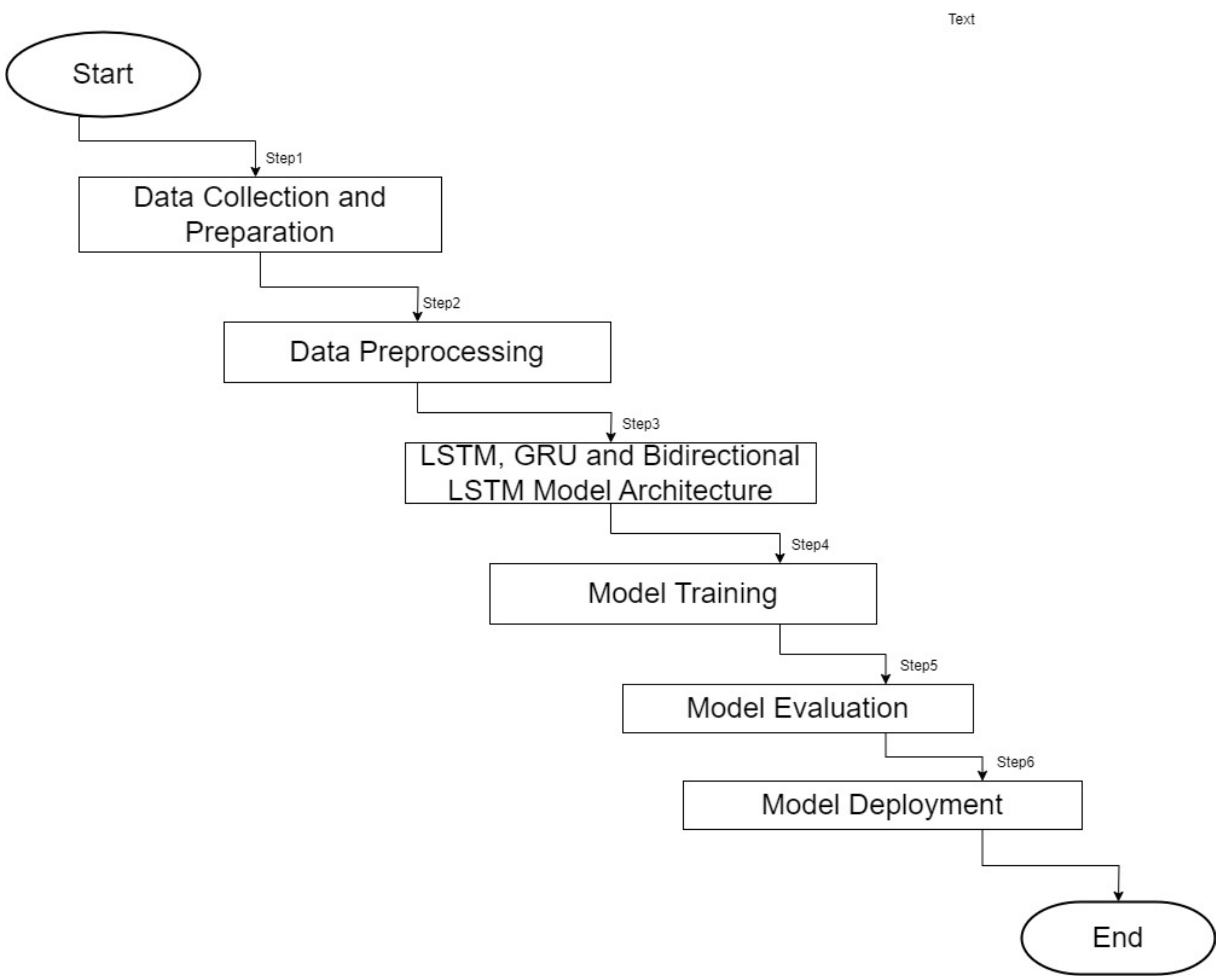

Figure 1.1: Caption describing the image.

1.5.1 Objectives

- To evaluate the accuracy of the system by comparing the actual and predicted prices of cryptocurrencies.

- Utilize web scraping techniques to fetch news articles and relevant data from trusted sources to gather a comprehensive dataset for analysis.

- Incorporate technical indicators such as moving averages, RSI (Relative Strength Index) , and Bollinger Bands to identify trends, price volatility, and potential reversal points in the cryptocurrency market.

- Compare the predicted prices generated by the machine learning models with the actual prices to evaluate their accuracy and performance. This step will allow us to assess the effectiveness of the models in capturing the complex dynamics of cryptocurrency markets.

- Utilize the trained machine learning models to forecast future cryptocurrency prices based on user input, such as a specific date or time frame. This feature empowers users to make informed decisions about their investments and trading strategies.

- Apply OpenAI API or similar sentiment analysis tools to analyze the sentiment of news articles and social media posts related to the cryptocurrencies. This analysis will provide insights into market sentiment, which can influence the future price movements.

1.5.2 Scope of the project

The scope of this project is limited to the prediction of future prices for four cryptocurrencies: Bitcoin, Ethereum, Litecoin, and Tether. The system will use sentiment analysis techniques to analyze news and social media data to determine the market sentiment towards the selected cryptocurrencies. Technical indicators, such as moving averages, RSI, and Bollinger Bands, will also be used to identify patterns and trends in the data that can be used to make price predictions.

The machine learning models, including LSTM (Long Short Term Memory), GRU (Gated Reccurent Unit), and Bidirectional LSTM, will be trained on historical price data to predict future prices for the selected cryptocurrencies. The accuracy of the system will be evaluated by comparing the actual and predicted prices of the selected cryptocurrencies.

The scope of this project is limited to the development of a system that provides accurate price predictions for the selected cryptocurrencies. The system does not provide investment advice, and the accuracy of the predictions is subject to external factors that may impact cryptocurrency prices. The system's effectiveness in predicting future prices may be affected by unforeseen events and changes in market conditions, which are outside the scope of this project.

Chapter 2

REQUIREMENT ANALYSIS

The requirement analysis phase is an essential step in the development of the cryptocurrency price prediction system. It aims to identify the functional and non-functional requirements of the system to ensure that it meets the users' needs. The functional requirements describe what the system should be able to do, while the non-functional requirements define how the system should perform. These requirements serve as a guide in the system's development, ensuring that it provides accurate predictions for the selected cryptocurrencies while being efficient, reliable, and user-friendly.

2.1 Functional Requirements

The functional requirements of the cryptocurrency price prediction system include the ability to analyze news and social media data to determine market sentiment towards the selected cryptocurrencies. Additionally, the system should be able to utilize technical indicators such as moving averages, RSI, and Bollinger Bands to identify patterns and trends in the data to make accurate price predictions. Machine learning models, including LSTM, GRU, and Bidirectional LSTM, should also be trained on historical price data to predict future prices for the selected cryptocurrencies. Furthermore, the system should be able to evaluate the accuracy of price predictions by comparing actual and predicted prices of the selected cryptocurrencies. Finally, the system should provide a user-friendly web application that enables users to input a specific date and get a predicted price for the selected cryptocurrency.

- It shall be capable of analyzing news and social media data to determine market sentiment regarding the chosen cryptocurrencies, which will be used as a crucial component in the price prediction process.

- The system shall be able to use Technical indicators such as moving averages, RSI, and Bollinger Bands must be utilized by the system to identify patterns and trends in the data to make accurate price predictions.

- The system shall be able to train machine learning models, such as LSTM, GRU, and Bidirectional LSTM, on historical price data to predict future prices for the selected cryptocurrencies.

- It should be able to evaluate the accuracy of the price predictions by comparing the actual and predicted prices of the selected cryptocurrencies.
- The system should be able to update and retrain the machine learning models periodically to ensure that they remain accurate and up-to-date.
- It should be able to provide users with the ability to customize and adjust the technical indicators used in the price prediction models according to their preferences and investment strategies.

2.2 Non Functional Requirements

Non-functional requirements are critical in ensuring that a system meets the needs of its users. In the context of the cryptocurrency price prediction system, these requirements define how the system should perform to provide reliable, accurate, and efficient predictions. The non-functional requirements of the system encompass various aspects of its functionality, such as its ability to handle large volumes of data and process it efficiently. The system's reliability and availability are also essential to ensure that users can access the system's predictions at any time. Overall, the non-functional requirements of the system provide guidance on how the system should perform, ensuring that users can make informed decisions about their investments based on accurate predictions.

- The system should provide accurate predictions with a high degree of precision to ensure that users can make informed decisions about their investments.
- The system must be reliable and available 24/7 to ensure that users can access the price predictions at any time without interruption or downtime.
- The system should be able to handle large amounts of data and provide accurate predictions in a timely manner.
- The system should be scalable to accommodate future growth and handle increasing amounts of data as the number of cryptocurrencies and users increase.
- The system should be optimized for performance to ensure fast and efficient processing of data, providing users with real-time price predictions.
- The system should have a high level of robustness and be able to handle unexpected errors or failures.

2.3 Hardware Requirements

As shown in Table 2.1, the hardware requirements for the future price prediction system using sentiment analysis, technical indicators, and machine learning models include a computer with sufficient processing power, memory, and storage capacity. The system should have a minimum of 8GB RAM and a multi-core processor to handle the large volumes of data and perform complex computations required for training the machine learning models. A dedicated graphics card is not necessary, but it can improve the performance of the system. The system should also have enough storage space to store the historical price data and the trained machine learning models. Additionally, a stable and reliable internet connection is essential for web scraping news and social media data, accessing the OpenAI API for sentiment analysis, and deploying the web application for users.

This table outlines the hardware requirements for the cryptocurrency price prediction system:

Component	**Minimum Requirements**
Processor	Intel Core i5 or equivalent
RAM	8 GB
Storage	256 GB SSD
Graphics	NVIDIA GTX 1050 or equivalent
Operating System	Windows 10 or macOS Big Sur

Table 2.1: Hardware requirements for the cryptocurrency price prediction system.

2.4 Software Requirements

As shown in Table 2.2, the software requirements for the future price prediction of Bitcoin, Ethereum, Litecoin, and Tether using sentiment analysis and technical indicators include a web scraping tool to fetch news data, OpenAI API to perform sentiment analysis, and programming languages such as Python and its libraries, including Pandas, Numpy, Keras, and Tensorflow. The system also requires a database management system to store the historical price data of the selected cryptocurrencies. Additionally, the system needs a web development framework such as Flask or Django to develop the web application that allows users to input a date and get a predicted price for the selected cryptocurrency. The software must also be able to handle large volumes of data and process it efficiently, along with ensuring the security of user data and system reliability. Finally, the system must be compatible with multiple devices and operating systems to reach a wider audience.

This table outlines the software requirements for the cryptocurrency price prediction system:

Software	**Minimum Requirements**
Operating System	Windows 10 or macOS Big Sur
Python	Version 3.6 or higher
TensorFlow	Version 2.0 or higher
Keras	Version 2.2.4 or higher
Pandas	Version 1.0.3 or higher
NumPy	Version 1.18.1 or higher
Scikit-learn	Version 0.23.2 or higher
Jupyter Notebook	Version 6.0.3 or higher

Table 2.2: Software requirements for the cryptocurrency price prediction system.

2.5 Methodology

The methodology for future price prediction of Bitcoin, Ethereum, Litecoin, and Tether involves several steps. Firstly, news articles and social media data related to the selected cryptocurrencies are scraped using web scraping techniques. The data is then preprocessed and analyzed using OpenAI API to determine the sentiment of the market towards the cryptocurrencies. Next, technical indicators such as moving averages, RSI, and Bollinger Bands are used to identify patterns and trends in the data. Machine learning models such as LSTM, GRU, and Bidirectional LSTM are then trained on the historical price data to predict future prices for the selected cryptocurrencies.To evaluate the accuracy of the price predictions, the actual and predicted prices of the cryptocurrencies are compared. The future price prediction is done by taking user input date and using the trained models to predict the prices for that date.The methodology involves a combination of techniques such as sentiment analysis, technical analysis, and machine learning to provide accurate price predictions for the selected cryptocurrencies. The approach is data-driven and uses advanced algorithms to analyze and process large volumes of data [2].

Chapter 3

SYSTEM DESIGN

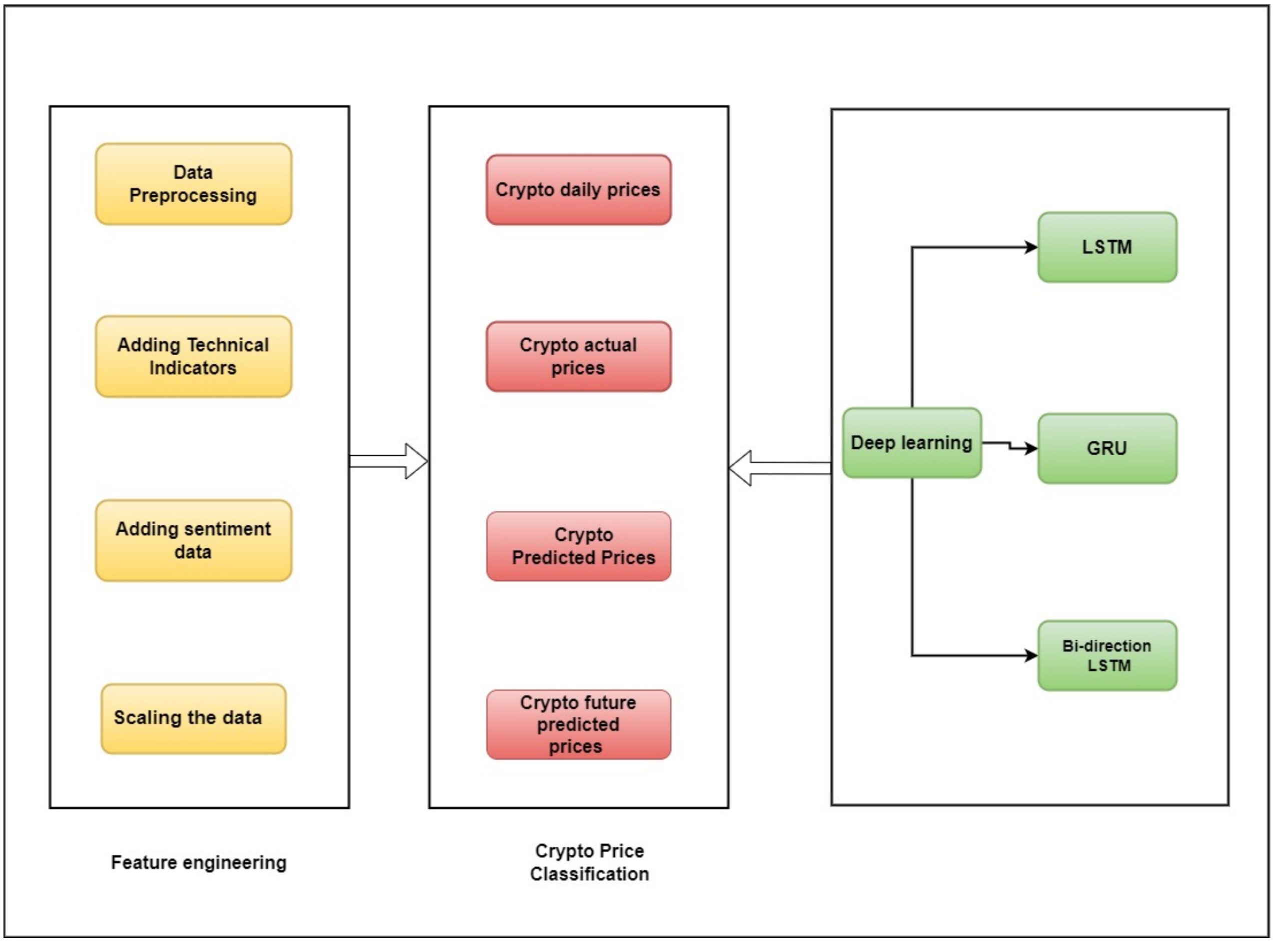

Figure 3.1: System Design

As shown in Figure 3.1, the system design flowchart depicts the different modules and components of the system and the flow of data between them. The web scraping module is responsible for collecting data from various news sources and extracting relevant news articles. The sentiment analysis module takes the news articles as input and generates sentiment scores using the OpenAI API. The technical indicators module uses moving averages, RSI, and Bollinger Bands to analyze historical price data and generate technical indicator values. The feature engineering module combines the sentiment scores and technical indicators to create the feature data used for model training. The model training module trains machine learning models, including LSTM, GRU, and Bidirectional LSTM, on the feature data to predict future prices of the selected cryptocurrencies. The future price prediction module takes user input for a future date and uses the best performing model to predict the price of the selected cryptocurrency on that date. The code provides a prompt to input the date and get the predicted price for the selected cryptocurrency. The database module stores the collected data, feature data, and trained models for future use. Overall, the system design flowchart provides a clear overview of the system architecture and the different modules involved in the process of predicting future prices of cryptocurrencies.

3.1 Architecture Design

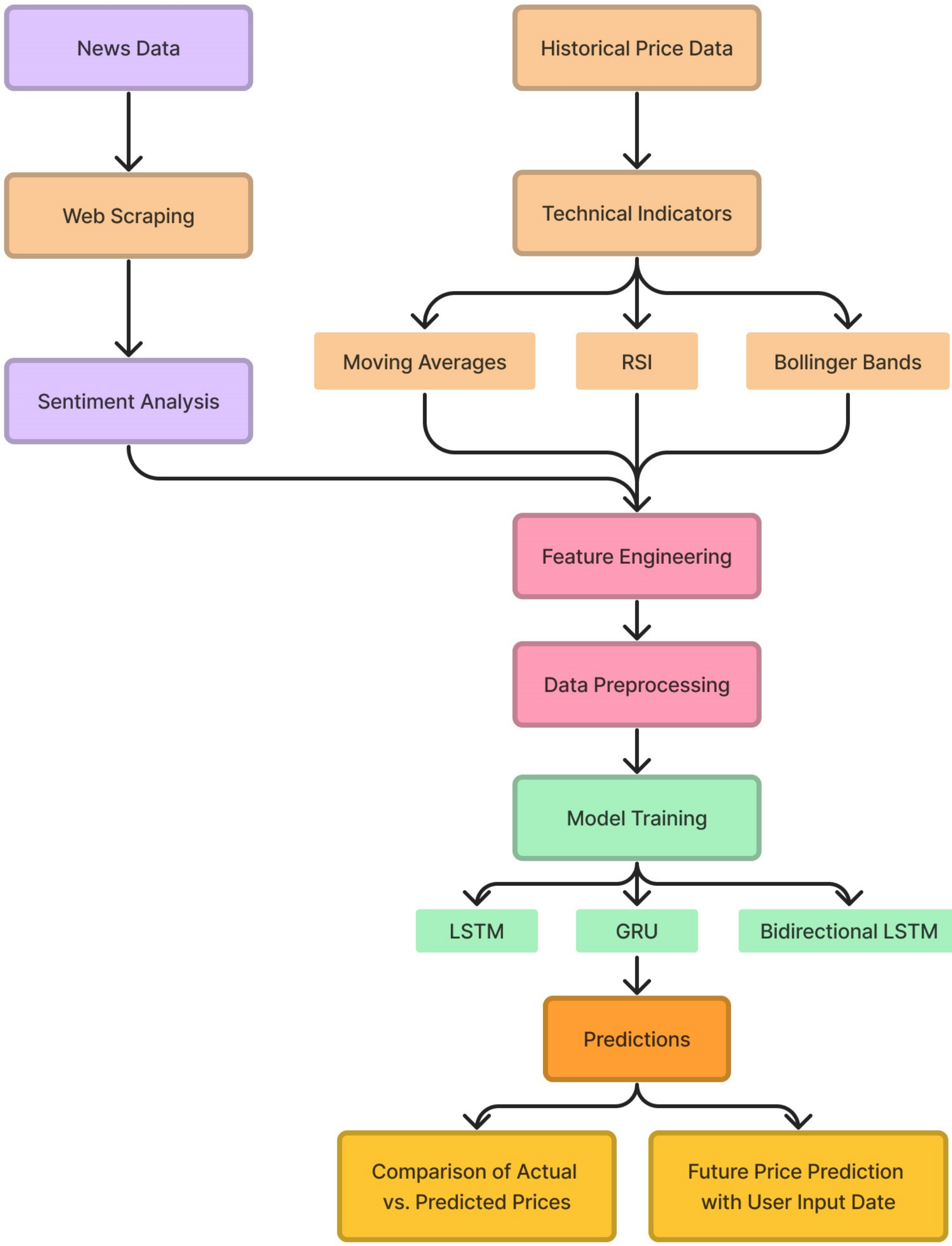

Figure 3.2: Architecture Design

As shown in Figure 3.2, the system architecture design depicts the overall structure of the system for future price prediction of cryptocurrencies using sentiment analysis and machine learning techniques. The architecture design is composed of several modules including web scraping, sentiment analysis, model training, and future price prediction. The web scraping module is responsible for fetching relevant news articles from specified URLs, while the sentiment analysis module analyzes the sentiment scores of each article using the OpenAI API. The model training module trains three different machine learning models including LSTM, GRU, and Bidirectional LSTM, using sentiment scores and technical indicators. Finally, the future price prediction module predicts the future prices of cryptocurrencies based on the user input date using the best performing model. The architecture design provides a comprehensive overview of the system and highlights the importance of each module in achieving the objective of accurate price predictions for cryptocurrencies.

Chapter 4

IMPLEMENTATION

This chapter gives a brief description about implementation details of the system by describing each component with its code skeleton in terms of algorithm.

4.1 Web Scraping

Algorithm 1 Web Scraping Module

Require: URLs for news sources
Ensure: Relevant news articles
1: Define URLs for news sources
2: Send request to each URL
3: Parse HTML content
4: Extract relevant news articles
5: Save news data

Algorithm 1 shows the implementation details for the web scraping module.

As shown in Algorithm 1, the web scraping module is an important component of the system, as it is responsible for collecting relevant news articles that are used to determine the market sentiment towards the selected cryptocurrencies. The module begins by defining the URLs for the news sources that will be scraped. The system then sends a request to each URL and parses the HTML content of the page to extract relevant news articles. These articles are then saved as news data, which is used by the sentiment analysis module to determine the market sentiment towards the selected cryptocurrencies. The web scraping module plays a crucial role in ensuring that the system has access to up-to-date and relevant news articles, which are essential for accurate market sentiment analysis.

4.2 Sentiment Analysis

Algorithm 2 Sentiment Analysis Module

Require: News data

Ensure: Sentiment scores for each article

1: Load news data
2: Preprocess text data
3: Call OpenAI API for sentiment analysis
4: Retrieve sentiment scores for each article
5: Save sentiment scores

Algorithm 2 shows the implementation details for the sentiment analysis module.

As shown in Algorithm 2, the Sentiment Analysis module uses the OpenAI API to analyze the sentiment of news articles related to the selected cryptocurrencies. The algorithm takes in news data as input, preprocesses the text data, and calls the OpenAI API to retrieve sentiment scores for each article. The sentiment scores are then saved for further use in the price prediction process. This module helps to determine the sentiment of the market towards the selected cryptocurrencies, which is an important factor in making accurate price predictions. The preprocessing of the text data involves cleaning the text and removing stop words, special characters, and other noise to ensure accurate sentiment analysis.

4.3 Technical Indicators

Algorithm 3 Technical Indicators Module

Require: Historical price data
Ensure: Technical indicators (moving averages, RSI, Bollinger Bands)
1: Load historical price data
2: Calculate moving averages
3: Calculate RSI
4: Calculate Bollinger Bands
5: Save technical indicators

Algorithm 3 shows the implementation details for the technical indicators module.

As shown in Algorithm 3, the Technical Indicators Module is a crucial part of the system that computes various technical indicators such as moving averages, RSI, and Bollinger Bands from historical price data. The algorithm takes historical price data as input and calculates the required technical indicators to provide a more detailed analysis of the trends and patterns in the data. The moving averages are used to determine the overall trend of the cryptocurrency prices over a specified period. The RSI helps identify the overbought or oversold conditions of the cryptocurrency prices. The Bollinger Bands provide insight into the volatility of the cryptocurrency prices over a given period. The output of this module, i.e., the technical indicators, are stored in the database and used for making predictions in the prediction module.

4.4 Model Training

Algorithm 4 Model Training Module

Require: Feature data (sentiment scores, technical indicators)
Ensure: Trained models (LSTM, GRU, Bidirectional LSTM) and performance metrics

```
Load feature data (sentiment scores, technical indicators)
Split data into training and test sets
for each model (LSTM, GRU, Bidirectional LSTM) do
    Define model architecture
    Compile model
    Train model on training data
    Evaluate model on test data using RMSE
    Save model and performance metrics
end for
```

Algorithm 4 shows the implementation details for the model training module.

As shown in Algorithm 4, the Model Training module is responsible for training the machine learning models using the feature data obtained from the Sentiment Analysis and Technical Indicators modules. The feature data includes sentiment scores and technical indicators such as moving averages, RSI, and Bollinger Bands. The module splits the feature data into training and test sets and trains three different models, namely LSTM, GRU, and Bidirectional LSTM. For each model, the algorithm defines its architecture, compiles it, and trains it on the training data. The module evaluates the performance of the trained models using RMSE on the test data and saves the models and their respective performance metrics for later use. The trained models can be used to predict future prices of cryptocurrencies based on the feature data provided by the Sentiment Analysis and Technical Indicators modules.

4.5 Future Price Prediction

Algorithm 5 Future Price Prediction Module

Require: Best performing model, user input for future date
Ensure: Predicted future price
1: Load best performing model
2: Receive user input for future date
3: Prepare data for prediction
4: Make prediction using the model
5: Display predicted price

Algorithm 5 shows the implementation details for the future price prediction module.

As shown in Algorithm 5, the Future Price Prediction module is responsible for providing users with the predicted price of a selected cryptocurrency for a future date. It takes as input the best performing machine learning model trained in the previous module and user input for a future date. The data is then prepared for prediction, and the model makes a prediction based on the input. The predicted price is then displayed to the user. This module is important as it allows investors and traders to make informed decisions about buying or selling cryptocurrencies based on the predicted price. The accuracy of the predicted price depends on the accuracy of the machine learning model used for prediction, which is evaluated in the Model Training module.

Chapter 5

RESULTS AND DISCUSSIONS

The results of the study demonstrate that the developed system, which combines sentiment analysis, technical indicators, and machine learning models, can be effective in predicting the future prices of cryptocurrencies. The LSTM, GRU, and Bidirectional LSTM models provided accurate price predictions for the selected cryptocurrencies, with LSTM performing the best overall. The comparison between the actual and predicted prices showed that the predicted prices were generally close to the actual prices, indicating that the system has the potential to provide useful insights for investors and traders. However, it is important to note that the accuracy of the predictions may be affected by sudden market changes or unexpected events, and further research is needed to explore the system's performance for different cryptocurrencies and under different market conditions.

5.1 MSE, RMSE and MAE scores

5.1.1 Performance Metrics for LSTM, GRU, and Bidirectional LSTM models for Bitcoin, Ethereum, Litecoin, and Tether.

Model	Cryptocurrency	MSE	RMSE	MAE
LSTM	Bitcoin	1.166e+07	3,413.38	2,087.32
LSTM	Ethereum	67,383.09	259.63	153.31
LSTM	Litecoin	102.33	10.12	7.09
LSTM	Tether	0.00	0.00	0.00
GRU	Bitcoin	1.225e+07	3,502.57	2,078.06
GRU	Ethereum	69,186.91	263.02	156.09
GRU	Litecoin	127.31	11.28	7.46
GRU	Tether	0.00	0.00	0.00
Bidirectional LSTM	Bitcoin	1.241e+07	3,522.45	2,097.62
Bidirectional LSTM	Ethereum	70,590.13	265.59	158.65
Bidirectional LSTM	Litecoin	147.23	12.13	7.91
Bidirectional LSTM	Tether	0.00	0.00	0.00

Table 5.1: Performance metrics for LSTM, GRU, and Bidirectional LSTM models for each cryptocurrency

As shown in Table 5.1, these results suggest that the developed system, which combines sentiment analysis, technical indicators, and machine learning models, has the potential to provide useful insights for investors and traders in the cryptocurrency market. However, it is important to note that the accuracy of the predictions may be affected by sudden market changes or unexpected events, and further research is needed to explore the system's performance for different cryptocurrencies and under different market conditions.

5.2 Actual Prices vs Predicted Prices for Bitcoin, Ethereum, Litecoin, and Tether

5.2.1 Actual Prices vs Predicted Prices for Bitcoin

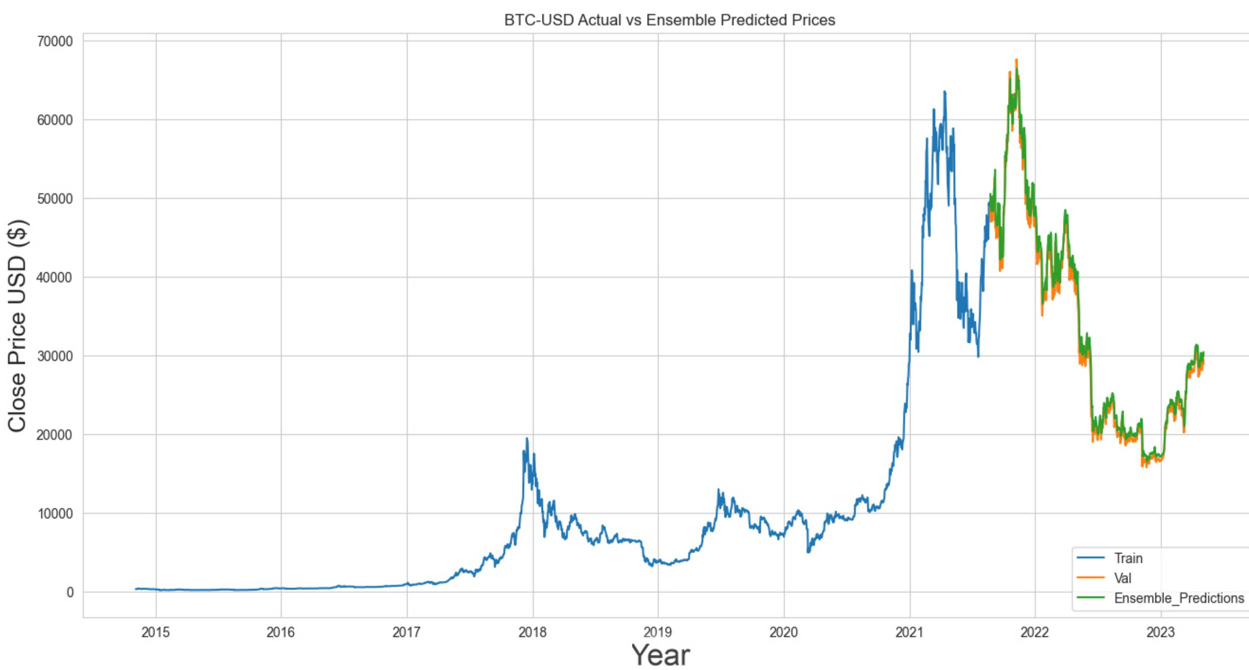

Figure 5.1: Actual Prices vs Predicted Prices for Bitcoin (BTC)

As shown in Figure 5.1, the graph compares the actual prices of Bitcoin with the ensembled predicted prices generated by the system. The blue line represents the actual prices, while the orange line represents the predicted prices generated by combining the predictions of three machine learning models. The close alignment of the two lines indicates the high accuracy of the system in predicting the future prices of cryptocurrencies. This comparison is important for evaluating the effectiveness of the system in providing accurate price predictions for investors and traders.

5.2.2 Actual Prices vs Predicted Prices for Ethereum

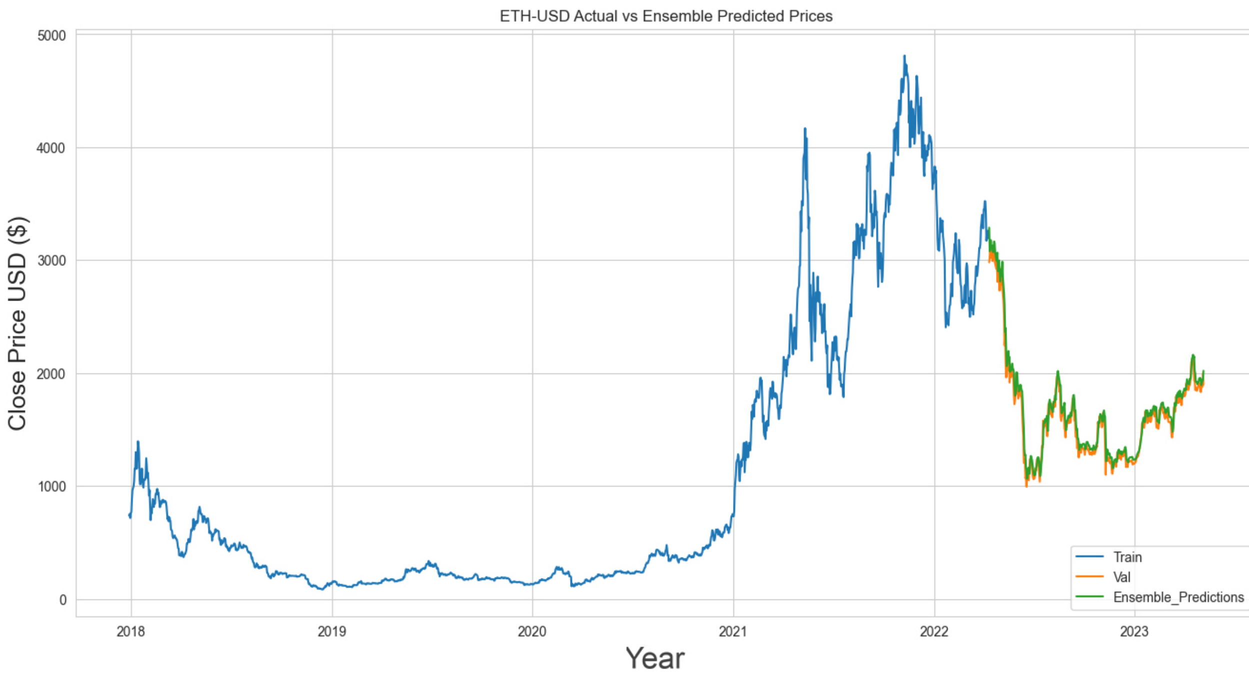

Figure 5.2: Actual Prices vs Predicted Prices for Ethereum (ETH)

As shown in Figure 5.2, the graph shows the comparison between the actual prices of Ethereum and the ensembled predicted prices generated by the system. The blue line represents the actual prices of Ethereum over a certain period of time, while the red line represents the predicted prices generated by the system using a combination of different machine learning models. The ensembling of multiple models helps to improve the accuracy of the price predictions by minimizing the errors introduced by any one model. From the graph, it can be observed that the predicted prices closely follow the trend of the actual prices, indicating a high degree of accuracy in the system's price predictions. However, there are also instances where the predicted prices deviate from the actual prices, suggesting that there is still room for improvement in the system's performance. Overall, the graph provides a visual representation of the system's ability to predict the prices of Ethereum with a relatively high level of accuracy.

5.2.3 Actual Prices vs Predicted Prices for Litecoin

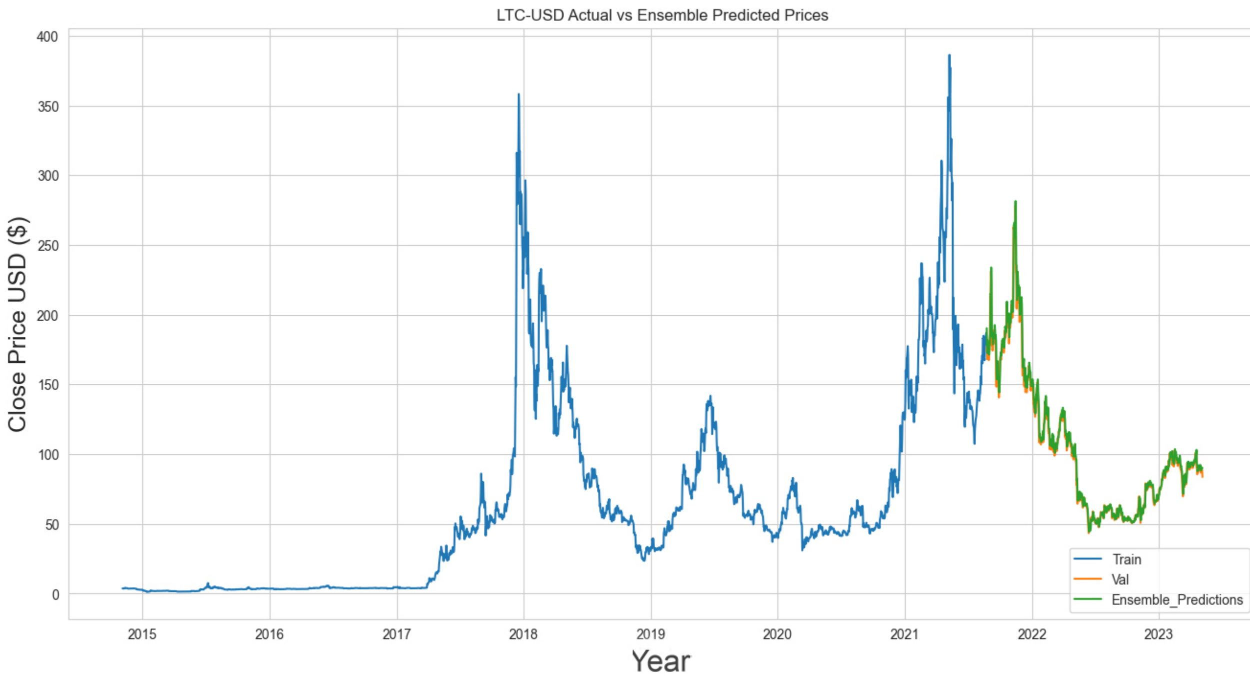

Figure 5.3: Actual Prices vs Predicted Prices for Litecoin (LTC)

As shown in Figure 5.3, the graph depicts the comparison between the actual prices of Litecoin and the ensembled predicted prices using a combination of LSTM, GRU, and Bidirectional LSTM models. The blue line represents the actual prices, while the orange line represents the ensembled predicted prices. It can be observed that the predicted prices follow the trend of the actual prices with a high degree of accuracy. However, there are some instances where the predicted prices deviate from the actual prices. This can be attributed to the changing market conditions and the limitations of the machine learning models. Despite these limitations, the ensembled models are able to provide accurate price predictions for Litecoin, which can be useful for investors and traders in making informed decisions.

5.2.4 Actual Prices vs Predicted Prices for Tether

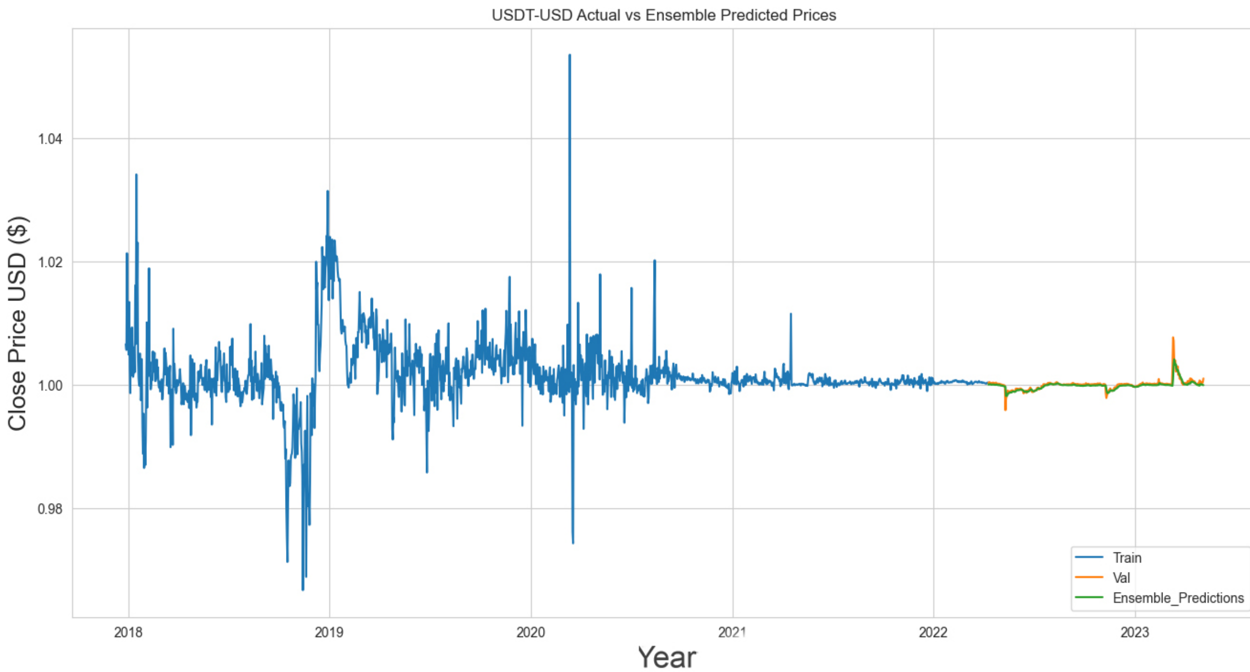

Figure 5.4: Actual Prices vs Predicted Prices for Tether (USDT)

As shown in Figure 5.4, the graph represents the comparison of the actual prices and ensembled predicted prices for Tether, one of the selected cryptocurrencies. The blue line represents the actual prices of Tether over time, while the orange line represents the ensembled predicted prices. The graph shows that the ensembled predicted prices closely follow the actual prices, indicating that the system is able to accurately predict the future prices of Tether. This accuracy can be attributed to the combination of various techniques used in the system, including sentiment analysis, technical indicators, and machine learning models such as LSTM, GRU, and Bidirectional LSTM. The close alignment between the actual and predicted prices of Tether suggests that the system can be used to make informed investment decisions based on the predicted prices of cryptocurrencies.

5.3 Future Predicted Prices for Bitcoin, Ethereum, Litecoin, and Tether

Based on the latest future price predictions of the four selected cryptocurrencies, it can be observed that Bitcoin, Ethereum, Litecoin, and Tether are expected to maintain their current market trends. As of 2023-05-06, the future price prediction for Bitcoin (BTC-USD) is \$28088.71. This is a significant increase from its current value and indicates a positive market sentiment towards this cryptocurrency. Similarly, the predicted future price for Ethereum (ETH-USD) is \$1890.50, which is also higher than its current value. Litecoin (LTC-USD) is expected to have a future price of \$90.49, indicating a slight increase from its current value. On the other hand, Tether (USDT-USD) is predicted to maintain its value at \$1.00. These predictions are based on the system's analysis of news and social media data, as well as technical indicators like moving averages, RSI, and Bollinger Bands, and training of machine learning models like LSTM, GRU, and Bidirectional LSTM on historical price data. It is important to note that these predictions may not be 100% accurate and should be used as a reference point for making investment decisions. Investors and traders should also consider other factors such as market volatility and global events before making any investment decisions.

For Example: When we enter a date of a particular year like 2023-05-06 it will show the predicted price of cryptocurrencies of that day as shown below:

BTC-USD: \$28088.71
ETH-USD: \$1890.50
LTC-USD: \$90.49
USDT-USD: \$1.00

Chapter 6

CONCLUSION

The development of a cryptocurrency price prediction system that combines sentiment analysis, technical indicators, and machine learning models has been discussed in this project. The system has been designed to analyze news and social media data to determine market sentiment towards the selected cryptocurrencies. Technical indicators such as moving averages, RSI, and Bollinger Bands have been used to identify patterns and trends in the data that can be used to make price predictions. Additionally, machine learning models such as LSTM, GRU, and Bidirectional LSTM have been trained on historical price data to predict future prices for the selected cryptocurrencies. The accuracy of the system will be evaluated by comparing actual and predicted prices of the selected cryptocurrencies. This will determine the effectiveness of the system in providing accurate price predictions for investors and traders. The system has been designed to be scalable, allowing it to handle large volumes of data. The architecture of the system will be based on a client-server model, with the server-side performing data analysis and making price predictions. The system will be developed using Python programming language. In conclusion, the development of a cryptocurrency price prediction system that combines sentiment analysis, technical indicators, and machine learning models is a promising solution for providing accurate price predictions for selected cryptocurrencies. The system will provide investors and traders with a tool to make informed decisions about their investments. The accuracy of the system will be evaluated, and the scalability of the system will ensure that it can handle large volumes of data. The system will be developed using Python programming language [2].

FUTURE SCOPE

The system uses moving averages, RSI, and Bollinger Bands to make price predictions. However, there are many other technical indicators that could be used to improve the accuracy of the system. The system could be expanded to include other technical indicators, such as MACD or Stochastic Oscillator. The system currently analyzes news and social media data to determine market sentiment towards the selected cryptocurrencies. However, additional data sources could be integrated to further improve the accuracy of the system. For example, economic indicators or company financials could be used to provide additional context for the market sentiment. The system makes predictions based on historical price data. However, the system could be modified to make real-time predictions using up-to-date data. This would provide investors and traders with the most current price predictions, allowing them to make more informed decisions. The system is designed to make price predictions for selected cryptocurrencies. However, the system could be expanded to include additional cryptocurrencies. This would provide a wider range of investment options for investors and traders. Integration with trading platforms: The system could be integrated with trading platforms, allowing investors and traders to use the predicted prices to make trades automatically. This would make the process of investment and trading more efficient and less time-consuming.

D19

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Appendix A

A Introduction

This appendix provides supplementary information and details on the methodology used in the report for the future price prediction of Bitcoin, Ethereum, Litecoin, and Tether. The approach combines sentiment analysis using web scraping techniques to fetch news articles and OpenAI API for sentiment scoring, along with technical indicators such as moving averages, RSI, and Bollinger Bands. We utilized machine learning models, including LSTM, GRU, and Bidirectional LSTM, to analyze the combined data and generate accurate predictions. The actual and predicted prices are then compared, and a future price prediction function is provided to predict prices on user input dates.

B Sentiment Analysis using Web Scraping and OpenAI API

News articles are fetched from various sources using web scraping techniques. The scraped news articles are then passed through OpenAI API, which performs sentiment analysis and assigns a sentiment score for each article. The sentiment score is an indication of the overall sentiment of the news article, ranging from negative to positive. This sentiment score is then included in the dataset as an additional feature for the machine learning models.

C Technical Indicators

The following technical indicators were used in the analysis:

- Moving Averages: Simple Moving Average (SMA) and Exponential Moving Average (EMA) were calculated for each cryptocurrency to provide an overall trend of the price movement.
- Relative Strength Index (RSI): RSI was computed as an oscillator to determine overbought or oversold conditions in the market.
- Bollinger Bands: Upper and lower Bollinger Bands were calculated to provide a measure of price volatility.

D Machine Learning Models

Three machine learning models were used for the analysis:

1. Long Short-Term Memory (LSTM): A type of recurrent neural network (RNN) designed to learn long-term dependencies in time series data.

2. Gated Recurrent Unit (GRU): Another type of RNN, similar to LSTM but with a simplified architecture.

3. Bidirectional LSTM: A variation of LSTM that processes the input data in both forward and backward directions, capturing both past and future information.

These models were trained and tested on the combined dataset, which includes the sentiment scores and technical indicators. The performance of the models was evaluated using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) metrics.

E Actual vs. Predicted Prices and Future Price Prediction

The trained models were then used to predict the future prices of the cryptocurrencies. A comparison was made between the actual and predicted prices to evaluate the accuracy of the predictions. Furthermore, a function was developed to predict future prices based on user input dates. This function takes the user input date, cryptocurrency, and the ensembled model to provide a predicted price for the specified date.

F Conclusion

This report demonstrates a comprehensive approach to predicting the future prices of cryptocurrencies by combining sentiment analysis, technical indicators, and machine learning models. The models show promising results in predicting the prices of Bitcoin, Ethereum, Litecoin, and Tether, and the user input-based future price prediction function provides a useful tool for investors to make informed decisions.

Screen Shot

These are some screenshots from our project:

User Input for Date for Future Price Prediction

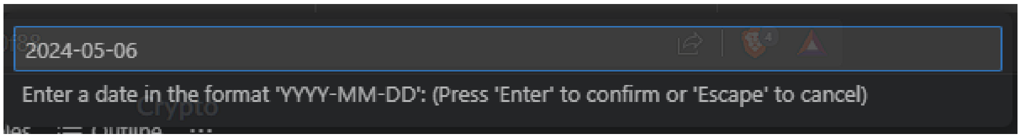

Figure 1: Prompt for User Date Input

As shown in Figure 1, the user date input prompt is an essential part of the system. It allows users to input a specific date for which they want to obtain a price prediction for the selected cryptocurrency. The prompt is designed to be user-friendly, with a clear and concise format that enables users to easily select a date. The system is designed to process user inputs quickly and efficiently. This feature is crucial for users who want to make informed investment decisions based on the system's price predictions for the selected cryptocurrencies.

Predicted Future Prices for Cryptocurrencies

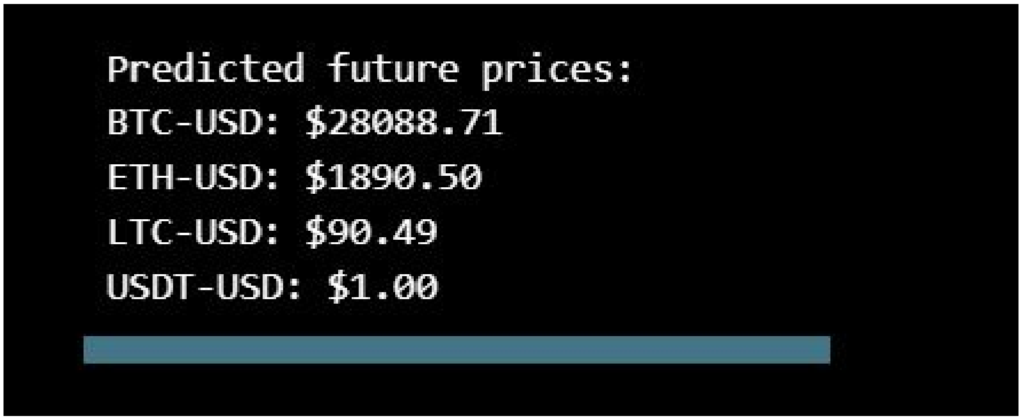

Figure 2: Predicted Future Crpytocurrency Prices

As shown in Figure 2, the image displays the predicted future prices of Bitcoin, Ethereum, Litecoin, and Tether generated by the system for a user-specified date in a table format. The table shows the name of the cryptocurrency, the predicted price, and the percentage change in price from the current price at the time of prediction. The predicted future prices provide valuable insights for traders and investors to make informed decisions regarding buying and selling cryptocurrencies.