A MAJOR PROJECT-II REPORT

ON

PREDICTIVE MODELING IN CRYPTOCURRENCY: A CASE STUDY OF BITCOIN USING RNN

SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF

MASTER OF TECHNOLOGY (M.TECH)

IN

COMPUTER SCIENCE & ENGINEERING

Submitted by

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CANDIDATE'S DECLARATION

I **Shashi Prakash Gupta, 2K22/CSE/21** students of M.Tech hereby declare that the project Dissertation titled "**Predictive Modeling in Cryptocurrency: A case Study of Bitcoin using RNN**" which is submitted by me to the **Department of Computer Science and Engineering, Delhi Technological University, Delhi** in partial fulfilment of the requirement for the award of degree of **Master of Technology**, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma Associateship, Fellowship or other similar title or recognition.

Place: **Delhi** **Shashi Prakash Gupta**
Date: **2K22/CSE/21**

CERTIFICATE

I hereby certify that the Project Dissertation titled "**Predictive Modeling in Cryptocurrency: A case Study of Bitcoin using RNN**" which is submitted by **Shashi Prakash Gupta, 2K22/CSE/21**, **Department of Computer Science and Engineering**, **Delhi Technological University, Delhi** in partial fulfilment of the requirement for the award of the degree of **Master of Technology**, is a record of the project work carried out by the student under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

Place: **Delhi** **Dr. Manoj Sethi**
Date: **Professor**

ABSTRACT

Predictive Modeling in Cryptocurrency: A case Study of Bitcoin using RNN is a research based project, which contains the prediction result of the bitcoin prices using the deep learning model trained using LSTM (Long Short Term Memory) model under the RNN(Recurrent Neural Network) system. The data-set used to train the RNN model was composed of a time-series based price of the bitcoin in minutes time frame. Collectively, the size of dataset are over 5,000,000 input points for the two year time-period.

The project also consists of a interactive implementation of LSTM model building using different optimizer function, loss Function to compare the result using different models. Additionally, the varying factor of Neurons number and Epochs iteration can also be altered using the interactive interface.

The problem among other systems was to predict the prices of the hyper volatile time varying component such as Bitcoin Prices using large data-sets. Comparison of accuracy difference using different optimizer function using r2 score.

We have simplified the LSTM implementation using various layer of abstraction to make it easy to change various components such as activation and loss function in the model building, training and final prediction result.

The outcome is an interactive, ready to use LSTM based RNN model where the type and size of the data sets along with activation and loss function can be easily altered to see varying prediction result.

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I wish to express my sincerest gratitude to **Dr. Manoj Sethi** for his continuous guidance and mentorship that he provided us during the project. His direction helped me understand and accomplish my objectives, emphasizing the significance and industrial relevance of this project. He was always available to assist and clarify any doubts we encountered. This project would not have been successful without his continuous support and encouragement.

I would like to extend my sincere thanks to **"Dr. Vinod Kumar"**, *Head of Department*, Department of Computer Engineering, Delhi Technological University, Delhi for his valuable suggestions and feedback on our project work.

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CHAPTER.1
INTRODUCTION

Predictive Modeling in Cryptocurrency: A case Study of Bitcoin using RNN is a project aimed at forecasting future Bitcoin prices through research and the use of the (A. M. Tripathi, 2024)[2] LSTM (Long Short-Term Memory) model. Cryptocurrencies are an emerging asset class that has garnered significant interest from the financial sector. These digital forms of currency and payment systems are secured using blockchain technology. The major cryptocurrencies dominating the market include Bitcoin, Ethereum, Ripple, and Litecoin, although this lineup is constantly evolving as investor interest shifts. Bitcoin, Ethereum, and Litecoin all operate on a unified network, maintaining identical transaction records across various computers, which enhances security and reduces the likelihood of discrepancies. Currently, Bitcoin leads the cryptocurrency market. It also forms the basis for the algorithms used in many other cryptocurrencies. Each cryptocurrency establishes its own regulations regarding aspects such as total currency supply, the creation of new units, privacy measures, transaction speeds for adding to the blockchain, and the competitive strategies miners use to gain rewards.

Technologies Used

Base Environment: Jupyter Notebook, Python 3.6.2 kernel

Libraries: Skit-Learn, Tenserflow, Pandas, Numpy, ipywidgets

1.1 Existing Systems

1.1.1 Binary Classification Model

Machine learning models designed for binary classification tasks predict one of two potential outcomes. Amazon ML employs logistic regression, a widely recognized learning algorithm, to train these models. Examples of binary classification scenarios include determining whether an email is spam or not (M. Sethi, 2023)[18], predicting if a customer will purchase a product, distinguishing whether an item is a book or a farm animal, and identifying if a review was authored by a human or generated by a robot.

1.1.2 Multiclass Classification Model

M.L models for multi class classification can predict multiple outcomes, allowing predictions from more than just two categories. To train these models, Amazon[14] ML utilizes a well-established learning algorithm called multinomial logistic regression. Examples of multiclass classification include identifying whether a product is a book, movie, or piece of clothing, determining the genre of a movie—whether it's a romantic comedy, documentary, or thriller—or figuring out which product category most appeals to a customer.

1.1.3 Regression Model

Machine learning models for regression tasks are designed to predict a numerical value. Amazon ML employs [1] linear regression, a standard algorithm in the industry, for training these models.

1.1.4 Types

(1) Artificial Neural Networks (ANN): ANNs function primarily as feed-forward networks, where information moves through the layers sequentially without revisiting any node. This architecture, inspired by the neural pathways in the human brain, allows ANNs to recognize patterns in unprocessed data, aiding in the resolution of intricate problems. Similar to how the human brain learns, ANNs improve incrementally with each new piece of data they process, continuously enhancing their performance independently.

(2) Convolution Neural Networks (CNN): Mainly, Convolution neural networks are added with image and video recognition, recommendation systems, and image analysis and classification. Before, the process of detecting objects in photographs required manual labour. However, CNN (M. Arjmand 2024)[17] has aided in scaling the procedure by recognising patterns in photos using the concepts of linear algebra.

(3) Recurrent Neural Networks (RNN): RNNs were created to see the shortcomings of feed-forward networks because they have the ability to process input and historical data, recall information, and process both simultaneously. Apple's Siri and Google's voice search are two useful examples. RNN uses training data to learn, just like ANN and CNN do. After then, it doesn't process data using just the data that was entered. Instead, it makes a choice by utilising information from earlier inputs as well.In other words, this architecture is made for 'having a memory.' The limitations are:

- It uses small number of data.
- It can only be used for small term predictions.
- Less variety of tools.

Since the RNN has an internal memory, it is able to give relatively accurate predictions. We have taken sequential time series data as input, which is implemented using an LSTM model under RNN. It is useful for the purpose of sequential data-based problem solving. Keeping that in mind, some applications in RNN are.

- Predictive problems.
- Machine translation.
- Less variety of tools.
- Stock price forecasting.
- Sentiment analysis.
- Text and language generation model.

1.2 Problem Statement

It is very crucial to have correct forecasts of the price of the cryptocurrencies since it is crucial to investors and other stakeholders in the cryptocurrency market especially with the ever popular and volatile Bitcoin. Due to the unpredictable and volatile nature of Bitcoin prices, there is a need to establish accurate predictive models that can capture the variability of Bitcoin prices and the relationship between price movements and other variables. This thesis aims at applying Recurrent Neural Networks (RNN) to overcome the problem of future Bitcoin prices prediction by employing deep learning methodologies. The idea is to develop a complex machine learning algorithm that would accurately and efficiently forecast the activity of Bitcoin prices.

The purpose of this research is to extend the knowledge in the field of financial forecasting and make a contribution to those who make decisions in the cryptocurrency market by evaluating the efficiency of an RNN-based LSTM Model. In the course of the study, different deep learning architectures will be compared with a view to recommending the best layout for interactive LSTM in the prediction of Bitcoin prices. In the end, it aims at expanding our knowledge of dynamic financial processes and providing investors with accurate information about projected Bitcoin values to make the right decision.

1.3 Our Contributions

To set our system apart from the other system giving predictive analysis, we have added a set of extra datasets, that will enhance the prediction and support the better results closer to the expected output. Unlike other systems, our system will have approx 2.5 lakhs data to analyse and predict the future.

Most of the systems give priority to only Adam Optimizer, while our system consists of various other tools for prediction. Some of them are:

- Adagrid
- Adamax
- Interactor
- Nadam

Due to the presence of various other tools, the prediction becomes more optimized and closer to what future value should be expected.

1.4 Conceptual Background

1. Software Development Life Cycle
2. Agile Model Phases
3. NADAM
4. Interactor
5. LSTM Model

CHAPTER.2
LITERATURE REVIEW

2.1 Overview

The emergence of Bitcoin in 2008 revolutionized the financial landscape, ushering in a decentralized digital currency with far-reaching implications across sectors. This review amalgamates insights from multiple pivotal research papers that have significantly shaped our comprehension of Bitcoin's multifaceted dimensions. Beginning with Nakamoto's ground-breaking work on the peer-to-peer electronic cash system, the exploration traces subsequent literature addressing in- efficiencies, modeling intricacies, and predictive capabilities of Bitcoin. Diverse methodologies, encompassing machine learning algorithms, Bayesian neural networks, and deep learning chaotic neural networks, underscore the interdisciplinary nature of this evolving field.

In conclusion, the combinations of result from the reviewed papers underscores the multidimensional nature of Bitcoin research. While market unpredictability persists as a challenge, advancements in predictive modeling present potential avenues for mitigating risks associated with Bitcoin investments. The interdisciplinary collaboration between financial experts, computer scientists, and statisticians becomes evident, emphasizing the need for a holistic understanding of the cryptocurrency landscape.

2.2 Related Work

The base of Bitcoin to appear was the fundamental work of Nakamoto et al. (2008) [24]. So great was this work that it set the framework for a decentralized system of digital currency, which has to do with the process of blockchain technology and peer-to-peer transactions. It is, therefore, all captured in the fine details that define the paper by Nakamoto et al., as it delves into the technical implications of bitcoin, explaining terms in use like proof-of-work, consensus mechanisms, and transaction validation. This seminal contribution has since become foundational in the fields of cryptocurrency and distributed ledger technology.

Urquhart (2016)[34] critically examines in his work the inefficiencies of Bitcoin as a currency and store of value. In presenting such an analysis, Urquhart draws the attention of one to the serious issues that are encountered by the Bitcoin network: discomforting scalability issues, prolonged transaction confirmation times, and the high energy consumption entailed in Bitcoin mining activities. This paper outlines some of the pertinent considerations with regard to the practicality and sustainability of Bitcoin as a medium of exchange widely adopted and an asset.

The authors Jang and Lee (2017) [13] further made a step towards predicting prices of Bitcoin through an empirical study. Their study examines whether Bayesian neural networks may be applied to forecasting Bitcoin prices using information found in this blockchain. More importantly, by focusing on modeling price trends, volatility, and the detection of determinants that influence the value of Bitcoin, Jang and Lee contributed to the emerging literature that aims to understand and predict cryptocurrency market dynamics.

The authors Dennys and Mallqui [6] have delved into the prediction of Bitcoin exchange rate using the methodologies of machine learning. They tested how effectively different methods of machine learning predict daily Bitcoin exchange rates, most likely based on historical price information, trade volumes, and sentiment analysis. That is, Dennys and Mallqui contribute to the current debate in the case that now advanced computational techniques are utilized for understanding and forecasting cryptocurrency market behavior.

Authors McNally, Roche, and Caton (2018) [22] write on the topic of forecasting cryptocurrencies by the use of deep learning models while applying chaoistic neuronet technology. Their work is in using such state-of-the-art neural network architectures to predict cryptocurrency trends, likely between time series analysis, market sentiment analysis, and developing new, innovative neural network architectures that fit idiosyncratic cryptocurrency data. McNally, Roche, and Caton will contribute to extending predictive techniques for understanding and foretelling the dynamics of cryptocurrency markets.

In the digital currency world, Atsalakis et al. (2019)[3] explored neuro-fuzzy concepts regarding Bitcoin price prediction with fuzzy logic and neural networks using a blending approach to model the dynamic character of value in Bitcoin. Goodfellow, Bengio, and Courville (2016) [12], though it was not directly focused on Bitcoin, gives foundational insights into deep learning methodologies that are quite key to understanding and operationalizing predictive models in the cryptocurrency domain. Madan, Saluja, and Zhao (2015) [19] also investigate machine learning algorithms devised toward automated Bitcoin trading, discussing likely feature engineering approaches at performance using different predictive models.

Along similar lines, Lahmiri and Bekiros 2019 [16] investigate the significant area of chaotic neural networks to predict cryptocurrencies, emphasizing time series prediction in general and the capture of the nonlinear dynamics driving cryptocurrency markets. Performance analysis and comparison results show that the Long Short-Term Memory (LSTM) and Bi-LSTM outperform the GRU in most binary classification and prediction tasks [10]. Paresh Kumar et al., 2019 [29] investigated the association between Bitcoin price growth and monetary policy in Indonesia, while Pant, Neupane, Poudel, Pokhrel, and Lama, 2018 [18] integrated recurrent neural networks and sentiment analysis of Twitter data for price prediction of Bitcoin.

The groundbreaking piece of work by Bachelier (1900)[4], "Théorie de la spéculation," laid the cornerstone for mathematical finance and stochastic processes. He introduced the idea of Brownian motion in his thesis and applied it to absolutely pioneering modeling of stock prices, which has been very influential in current financial theory.

The author, Christophe Schinckus [33], offers a thorough ex- amination of the evolutionary trajectory of econophysics over the preceding two decades. Employing Imre Lakatos' method- ology, the paper delves into the methodological progression of econophysics and identifies three concurrent approaches within the field: statistical econophysics, bottom-up agent- based econophysics, and topdown agent-based econophysics.

The focus of the paper is on highlighting the conceptual coherence inherent in econophysics as a distinctive research domain. It underscores the field's ability to evolve by embrac- ing methodological enrichments while steadfastly preserving its fundamental conceptual tenets. This valuable analysis con- tributes to our understanding of how econophysics has evolved over time, emphasizing the coexistence of diverse methodolo- gies within a framework of core conceptual principles. The paper is accessible under the Open Access license, promoting the widespread dissemination of knowledge in the realm of econophysics.

The author,Kutner et al. [15] deliver a brilliant view of the main accomplishments of interdisciplinary fields, such as econophysics and sociophysics, with their application of Quantitative Methodological Tools to studying socio-economic phenomena. In no small measure do these disciplines help delimit and develop research territories. Indeed the authors have summed up well the important roles played by the disciplines of econophysics and sociophysics, therefore outlining key milestones, nagging challenges, and an area of continued inquiry.

On the one hand, "The paper highlights the fundamental role that these disciplines play in modeling large social phenomena, including behavioral dissemination, opinion formation, cultural dynamics, crowd behavior, social contagion and rumors, conflicts and the evolution of language." However, the authors, while conveying achievements, discuss carefully issues and open problems that must be encountered by these fields. They span from the need for ever more accurate data in the development of new kinds of models to the synthesis of different paradigms. In short, the paper is a serious and profound reflection on the achievements and challenges faced in econophysics and sociophysics; in fact, the two nascent interdisciplinary fields are being outlined.

Mariana et al. [21] examined the safe-haven role of cryptos in their study during the COVID-19 pandemic. Some of the dependencies probably considered here to unravel the behavior of digital assets in times of economic uncertainty are the probability distribution and underlying Bitcoin price changes against volatility in the stock markets. Melki and Nefzi[21] studied the features of a safe haven in cryptos and how the market treated crises by using a smooth transition technique in the context of global economic shocks.

Phaladisailoed and Numnonda [30] conducted this research to make a systematic comparison among different machine learning methodologies applied to forecasting Bitcoin prices. The research uses Bitstamp Bitcoin exchange platform trading data at 1-minute resolution for the period from January 1, 2012 to January 8, 2018. This study investigates important predictive capabilities in a number of varied implementations of regression models using the scikit-learn and Keras libraries.The most promising results are shown in the extremely low values of MSE, down to 0.00002, and very high values of R^2, up to 99.2%. These results reflect the success of the applied machine learning models in capturing and predicting Bitcoin price dynamics. What follows is background discussion—a fairly extensive one—on scikit-learn, TensorFlow, and Keras, to give the reader a full understanding of the underlying frameworks and methodologies used in this paper.

It was Fernandes et al. (2021)[9] who initially reported an indicator for the economic performance in macroeconophysics, such as the "Macroeconophysics Indicator of Economic Efficiency," which will be capable of embedding, in economic analysis, properties related to the economy's behavior in reality. The works by them allude to, but not limit to, through papers like "COVID-19 Lethality in Brazilian States[8]," "Predictability of COVID-19 Worldwide Lethality," and "Brazilian Inflation Index Predictability[7]," have probably used information-theory quantifiers that would take into account patterns in deaths, forecast the course of the COVID-19 crisis, and analyze inflation[10] dynamics and forecasting accuracy.

These studies span a wide spectrum of research from Bachelier's pioneering work on finance, economics, and computational methods, to Mandelbrot's challenge of traditional financial models and Schinckus' review of econophysics,[20] all the way to Kutner et al.'s groundbreaking studies. All of this is indicative of how interdisciplinary the study of modern economics has become. Moreover, the analyses of behavior in a cryptocurrency during crises come from investigations such as that by Mariana et al. and by Melki and Nefzi[23]. Fernandes et al. elaborately enter multi-aspect studies from the indicators of economic efficiency to analyses of COVID-19 and predictability of inflation, enriching knowledge about finance markets and macro phenomena, enlightening not only theoretical frameworks but also practical applications.

CHAPTER.3
METHODOLOGY

The methodology presented in this paper encompasses the utilization of two distinct deep learning-based prediction models to anticipate the daily price fluctuations of Bitcoin. A key facet of this approach involves the models autonomously identifying and assessing pertinent features crucial for accurate forecasting. By subjecting Bitcoin price prediction to both models, a comparative analysis is undertaken to ascertain the superior accuracy of one model over the other. This comparison aids in the identification and selection of optimal parameters, thereby enhancing overall predictive performance.

The deep learning techniques suggested in this study, particularly the LSTM model[32], are recognized as modern and effective methods for predicting Bitcoin prices. Given Bitcoin's status as the most popular cryptocurrency, the need to tackle its price fluctuations quickly is crucial, highlighting the importance of using these sophisticated deep learning approaches[26].

In the business world, the Software Development Life Cycle (SDLC) is a widely adopted process for planning, building, and testing high-quality software. It aims to develop software that stays within budget, is delivered on time, and meets or surpasses customer expectations.

3.1 Stages of SDLC :

Stage 1 : Planning and Requirement Analysis

The first crucial step in the Software Development Life Cycle (SDLC) is requirement analysis, typically carried out by experienced team members with input from clients, sales teams, market studies, and industry experts[27]. This information helps project strategists develop a detailed plan and assess the feasibility of the product in terms of its operations, technology, and finances.

Another important part of the planning process involves setting quality assurance guidelines and identifying potential risks for the project. A technical feasibility study is performed to choose the best technological solutions for the project while minimizing risks.

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Stage 2 : Requirements Definition

Following the analysis phase, a Software Requirement Specification (SRS) document is drafted. This document clearly outlines all the requirements for the product and includes everything that needs to be developed for the project. It must be approved by either market analysts or the client before moving forward.

Stage 3 : Architecture Design

Product architects use the Software Requirement Specification (SRS) as a guide when creating the best possible architecture for new products. Based on the specifications listed in the SRS, a Design Document Specification (DDS) usually includes a number of architectural designs that are suggested and described in detail. After this DDS has been reviewed by all pertinent parties, the best architectural design is selected. Assessment of risk, product lustiness, design flexibility financial restrictions, and time limitations are some of the selection factors.

During the design phase, all of the modules product's architectural are identified, and the data flows and communication between the product and any external or third-party modules are described. The DDS should have an extensive and detailed documentation of these modules' internal designs.

Stage 4 : Development

Within the SDLC, this step signifies the start of real product development. Here, the DDS is used as a basis for writing programming code. Coding can go more easily if the design documentation is complete and structured.

Developers use a variety of programming tools, including as interpreters, debuggers, and compilers, to follow the coding standards set out by their organisation. The particular requirements of the software being produced determine whether programming language, such as C, C++, Pascal, Java, or PHP, is chosen.

Stage 5 : Testing the Product

This Testing is a critical phase that overlaps with all other stages in many contemporary SDLC models, reflecting ongoing testing activities. However, this specific stage focuses exclusively on testing the product to identify and address defects. Issues are identified, tracked, fixed, and retested, ensuring the product consistently meets the quality standards set out in the SRS until it is deemed satisfactory.

Stage 6 : Market Deployment and Maintenance

The product is introduced to the intended market after undergoing extensive testing and being deemed ready. The deployment is frequently phased in accordance with the business plan of the organisation. To measure performance in actual use, the product may first be introduced to a small market.

The product may be introduced with additional enhancements in the selected market categories or as is, depending on the feedback received. The product is still being maintained and supported for its current customer base after it was released.

Figure 3.1 shows the above mentioned SDLC process in a diagrammatic way.

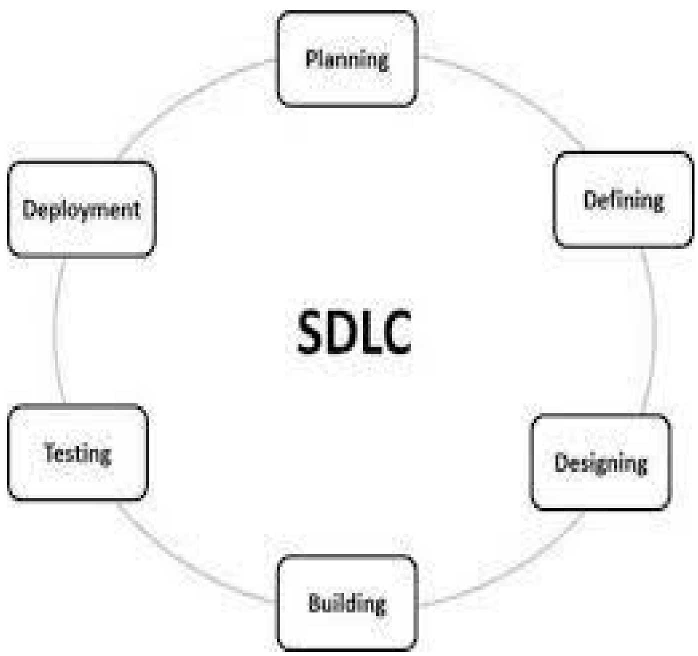


Figure 3.1: SDLC

3.2 Types of SDLC models

- WATERFALL MODEL:

  The Waterfall Model is endorse as the first Process Model to be used in software development. The Waterfall Model is well-known for having a linear, sequential life cycle and being easy to comprehend and implement. Each stage in this model needs to be finished completely before moving on to the next., with no overlapping of phases.

Historically, it represents the earliest method of structured software development, where the process is visualized as flowing steadily downwards (like a waterfall) through several non-overlapping phases.

- SPIRAL MODEL:

  The Spiral Model combines the iterative development process with the linear framework of the Waterfall Model, focusing heavily on risk analysis. This model supports iterative enhancement by allowing for incremental updates with each iteration or "spiral." In the Spiral Model, there are four distinct phases, with each spiral iteration allowing the project to pass through these phases repeatedly, enhancing and refining the product progressively.

3.3 SDLC Model used

Agile Model of software development is used for developing our project. REASONS:

- The main reason is that in Agile model software is divided into small components and is developed individually.
- Due to individual development, any faults or errors can be easily identified and corrected.
- If there are any changes required, it can be done easily without any complexity.

3.4 Description of Agile Model

The Agile model states that every project should be handled differently and that current approaches should be modified to best meet the project's particular requirements. In Agile, jobs are broken up into brief intervals called "time boxes" in order to produce one and only features for a release.

This method is iterative, and after each cycle, a working version of the programme is produced. Up until the last version has all of the features that the customer has requested, each version builds upon the previous one by gradually adding more features. .

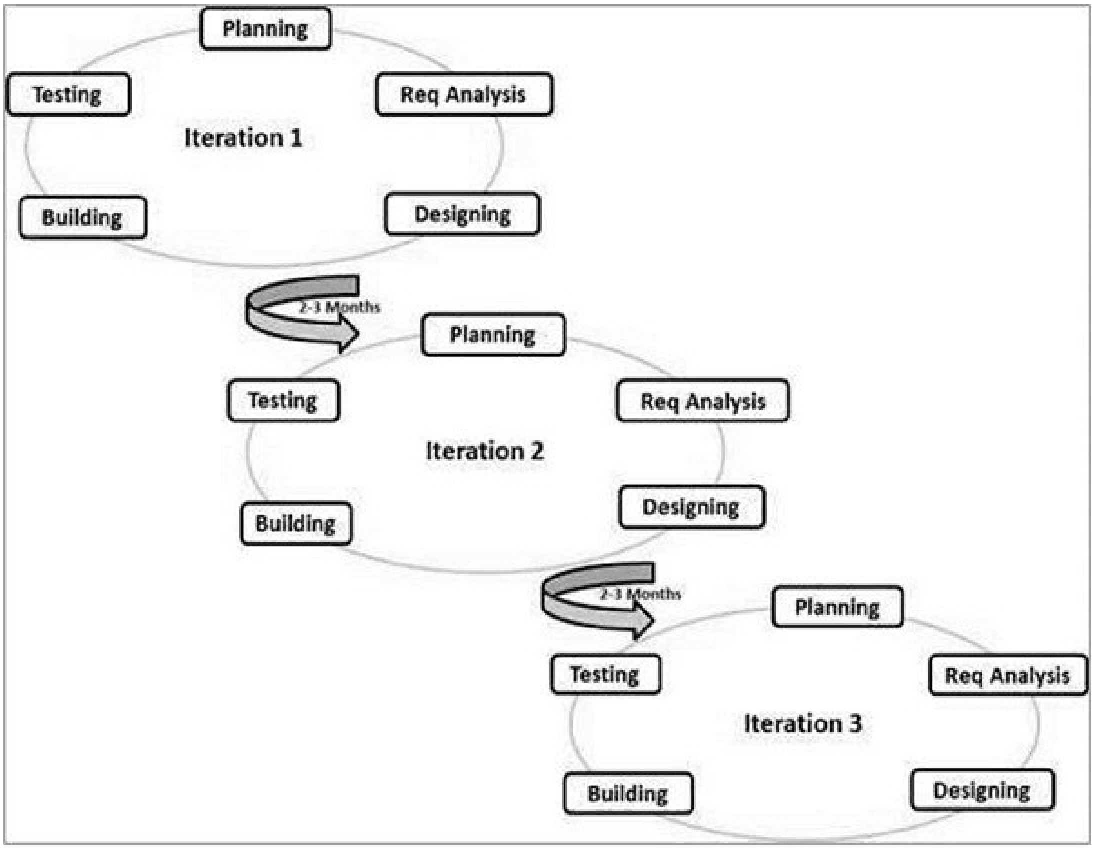


Figure 3.2: Agile phases

Figure 3.2 shows the various steps used in an agile development model.

Early on in the software development process, the Agile technique started to take shape. It gained popularity over time because it was adaptable and responsive.

The Rational Unified Process (released in 1994), Scrum (1995), Crystal Clear, Extreme Programming (1996), Adaptive Software Development, Feature Driven Development, and the Dynamic Systems Development Method (DSDM, 1995) are a few of the most well-known Agile techniques. Since the Agile Manifesto was published in 2001, these methods have been referred to as Agile Methodologies.

The principles outlined in the Agile Manifesto are as follows:

- **Individuals and interactions :** Agile development prioritizes self-organization and motivation, emphasizing the importance of team interactions, such as co-location and pair programming.
- **Working software :** Agile prefers demonstrating working software over extensive documentation as a means to better communicate with clients and clarify their requirements.
- **Customer collaboration :** Agile recognizes that customer needs cannot be completely understood at the project's onset due to various factors, making ongoing engagement with the customer essential for refining product requirements.
- **Responding to change :** Agile methodologies highlight the importance of responding quickly to change and fostering continuous improvement throughout the development process.

3.4.1 Requirements

Stakeholders assess the entire project to estimate the necessary time and resources for development. Concurrently, the project owner evaluates potential risks and prioritizes the functions according to their significance to the business.

3.4.2 Design

The program owner convenes with the software development team to discuss the requirements identified in the initial phase. The team deliberates on the sequence for introducing features and selects essential tools like the programming language, libraries, and foundational frameworks. At this stage, the team may also create prototypes of the user interface.

3.4.3 Development and Coding

Upon finalizing the plan with the customer, the development team proceeds to construct the product. The development is segmented into sprints, each aimed at enhancing the existing version of the product and potentially incorporating new functionalities.

Testing is conducted in each development cycle, and the final product undergoes a thorough inspection. During this phase, methodologies such as Scrum and the Kanban system, which organizes tasks, are employed.

3.4.4 Integration and Testing

Now that the product is accessible to the public, the team conducts extensive testing to ensure its full functionality. Any detected issues or defects are immediately rectified. User feedback is also collected at this stage to inform further improvements.

3.4.5 Implementation and Deployment

The software is now fully deployed and available to customers, transitioning into the maintenance phase. The development team continues to provide support to ensure the software operates smoothly and addresses any newly discovered issues. There is also the potential for further iterations to enhance the existing product or introduce additional features over time.

3.4.6 Review

This marks the conclusion of the Agile development cycle. The development team reports the outcomes achieved in meeting the project requirements to the owner. Following this review, the Agile process may either begin a new iteration or move to the next phase to expand the Agile implementation.

3.5 Design

The initial phase in a successful project is its design. Design of project involves maintaining ideas, materials, and work on processes to gain a specific objective. Project managers utilize strategic design to prevent errors and maintain alignment with critical project aspects, such as timelines and budgets.

3.6 Data Flow Diagram of proposed model:

Brief Working:

Talking about the working of our project model, it starts with our user providing the list of parameters namely Number of Neurons, Epochs, Optimizer Function and Loss Function to implement in our LSTM model. Using an interactive drop-down menu and slider, the parameters are selected and are fed into the system.

We fetch the data of the bitcoin prices using a API from the external server and store it in a local database in a CSV format.

The data are preprocessed and normalized , the data is then splitted and post processed using favorable window length and batch sizes.

The LSTM model builder receives the parameters detail as well as the post processed data and build a sequential model of LSTM units.

The model is then used to predict the test data-set and the compared with the actual prices and the accuracy is also calculated.

For the model that seems favourable in terms of accuracy, the user can use it to predict the future prices.

Figure 3.3 and 3.4 show DFD-level 0 and DFD-level 1 respectively.

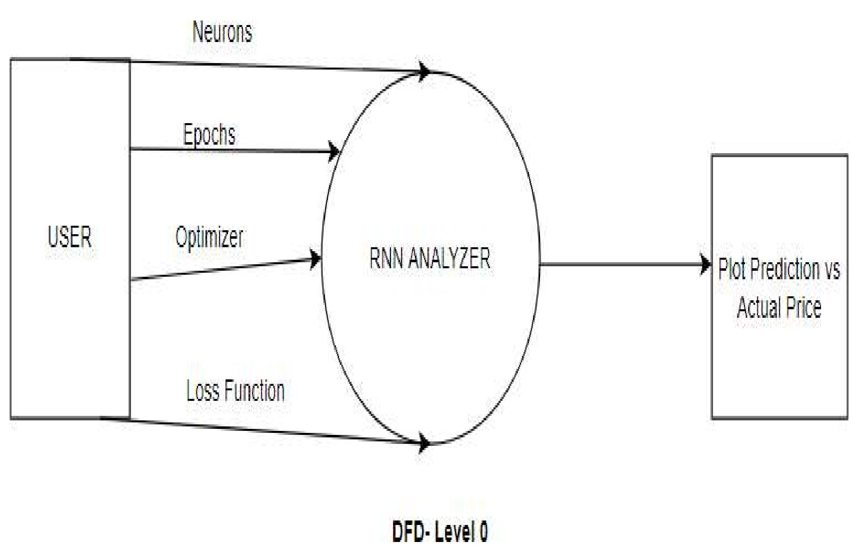


Figure 3.3: DFD-level 0

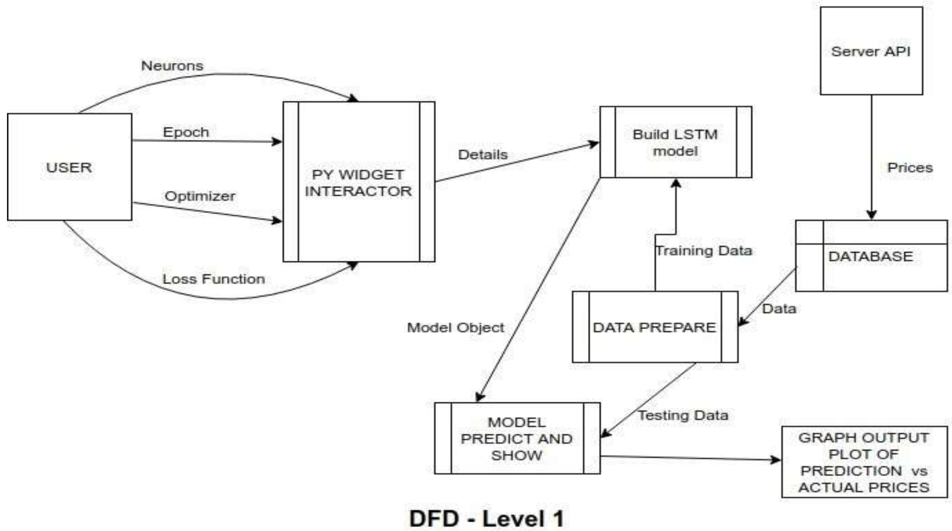


Figure 3.4: DFD-Level 1

3.7 Data Preprocessing:

The data-set used is imported from a external source from an API and is stored in a local machine in a CSV format. The file imported from the CSV is converted into a pandas DataFrame.

Initially, the DataFrame has 9 columns but is trimmed to only 2 columns, i.e. time and closing price of the bitcoin prices. The dataset is then splitted into a training and testing size in the ratio 4:1 respectively.

3.7.1 Initial Dataset:

The collection created for the customer as shown in figure 4.3 will be quite simple. It will contain the basic information of the customer like name, ID etc. the customers will also be provided the list to add items in it as soon as they login.
Customers can clean their item list or add according to their wish.

	unix	date	symbol	open	high	low	close	Volume BTC	Volume USD
0	1653610740	2022-05-27 00:19:00	BTC/USD	29241.41	29253.22	29241.41	29253.22	0.392701	11487.783081
1	1653610680	2022-05-27 00:18:00	BTC/USD	29252.98	29253.23	29228.16	29241.41	0.129137	3776.159075
2	1653610620	2022-05-27 00:17:00	BTC/USD	29281.81	29286.13	29257.71	29267.22	0.062760	1836.812776
3	1653610560	2022-05-27 00:16:00	BTC/USD	29224.36	29291.15	29222.86	29274.80	0.219500	6425.818893
4	1653610500	2022-05-27 00:15:00	BTC/USD	29226.61	29244.80	29200.85	29244.80	0.062912	1839.850027
...	...	...	...	...	...	...	...	...	...
205416	1640995500	2022-01-01 00:05:00	BTC/USD	46305.36	46431.25	46303.04	46431.25	2.556501	118701.524984
205417	1640995440	2022-01-01 00:04:00	BTC/USD	46326.81	46326.81	46289.56	46289.56	4.159950	192562.242161
205418	1640995380	2022-01-01 00:03:00	BTC/USD	46359.84	46386.33	46319.86	46342.63	0.098252	4553.263034
205419	1640995320	2022-01-01 00:02:00	BTC/USD	46310.02	46370.36	46276.28	46370.36	0.545551	25297.389313
205420	1640995260	2022-01-01 00:01:00	BTC/USD	46218.47	46278.36	46199.90	46278.36	0.193640	8961.351812

205421 rows × 9 columns

Figure 3.5: Dataset of Bitcoin Prices

3.7.2 Splitting Data:

The resulting pandas DataFrame is split into two distinct datasets: one for training and another for testing the LSTM model. The training dataset, which comprises 80% of the total data, is used to train and fit the model. The remaining 20% serves as the testing dataset, used to evaluate the model's accuracy in predicting Bitcoin prices.

A graph is created to visually differentiate these datasets: the training data is represented in blue, while the testing data is shown in red.

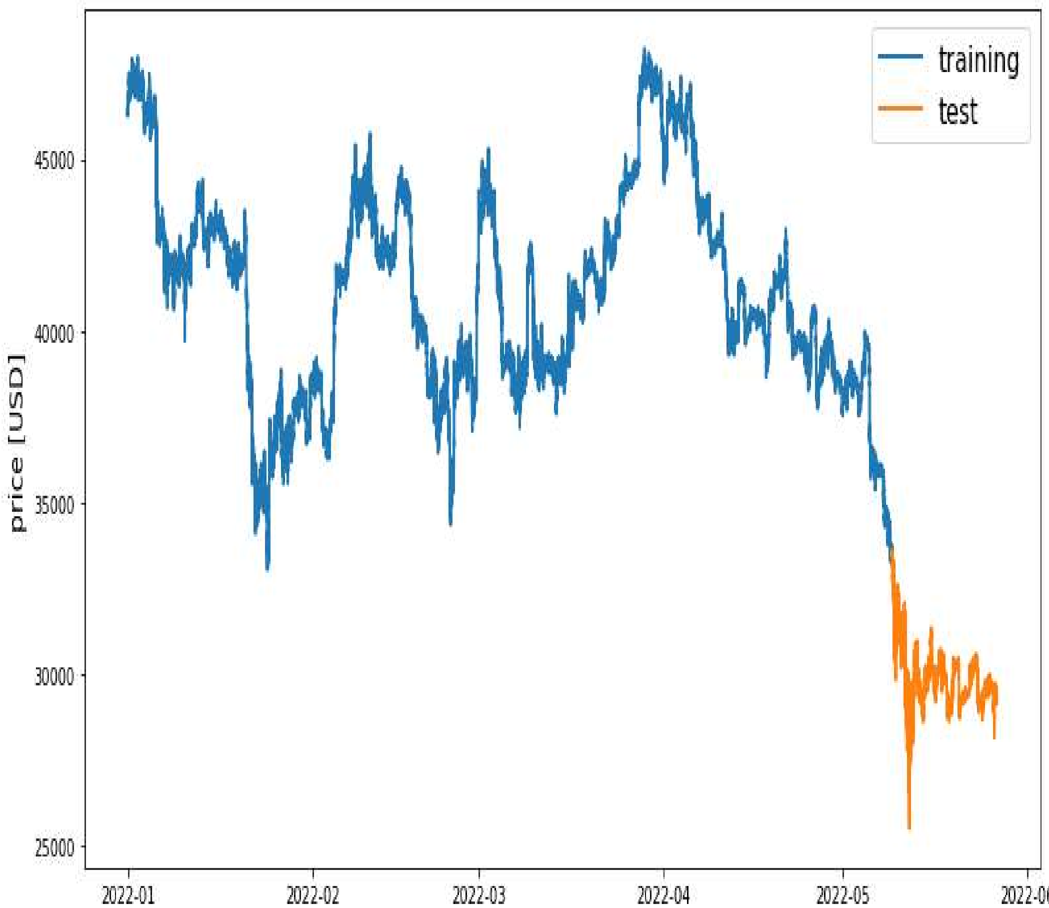


Figure 3.6: Training and Testing data

Figure 3.6 shows the graph representing the extent of training and testing data.

CHAPTER.4
RESULT AND OBSERVATION

4.1 Development And coding

Since, we are using Agile model it is necessary to stick to the development of different phases of project needs to be handled differently. Development of the model is majorly done in two phases.

- Structure of the interactive analyzer.
- Structure of Deep Learning Model

4.1.1 Interactive Analyzer development

We have used the library ipywidget to developed an interactive analyzer which gives the user an ease of selecting their favourable parameters to build and train the L.S.T.M. model according to their needs and wants.

The input box contains the combination of slider and dropdown menus, from which the user can select the input parameters to the model as shown in the figure below.

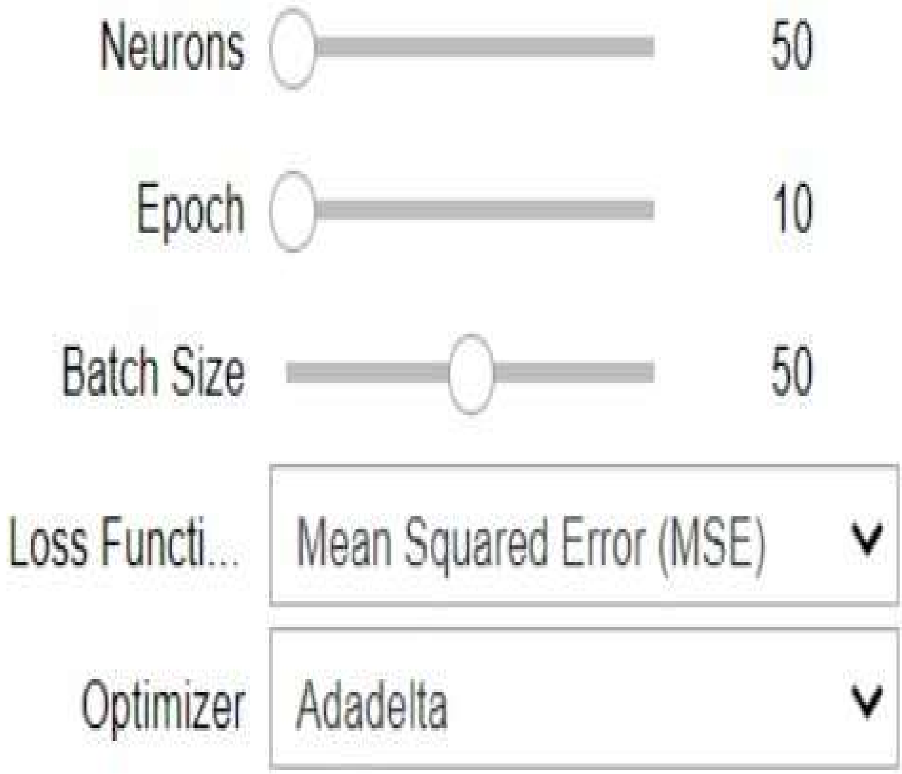


Figure 4.1: Interactive Input Box

Figure 4.1 shows Interactive Input Box. So in actuality, when the user selects one of the options, an array of parameters whose value is mapped to inbuilt-functions in the keras library used to create the model to the input parameters is created. The input parameters is then passed to the LSTM model builder to be considered for building and training the model.

4.1.2 Deep Learning Model

Our Deep Learning Model primarily works on supervised neural network layer. It uses the L.S.T.M. implementation of a RNN Model to construct and train the neural network on the time-series normalized input 3D dataset. The shape of the dataset is (batchsize, timesteps, units per timesteps).

RNN: Recurrent Neural Networks (RNNs) is class of ANN designed to handle sequential data by repeatedly applying the same task to a sequence of inputs. Unlike Convolutional Neural Networks (CNNs), RNNs incorporate an internal memory that helps them maintain context by remembering previous inputs. This capability makes them particularly suitable for processing time series data or sequence, as they can establish relationships between consecutive inputs[35].

LSTM: Long Short Term Memory Networks [1] fig 4.2 popularly known as LSTMs are extended versions of Recurrent Neural Networks which are capable of handling long term dependencies in a sequence of data. -They tackle the exploding or vanishing gradient issue that is associated with traditional RNNs and which poses some challenges in deep learning networks. LSTMs have the feature of memory, keeping information for longer durations, allowing for the functionality in complex structures of DNNs when information storage is vital.

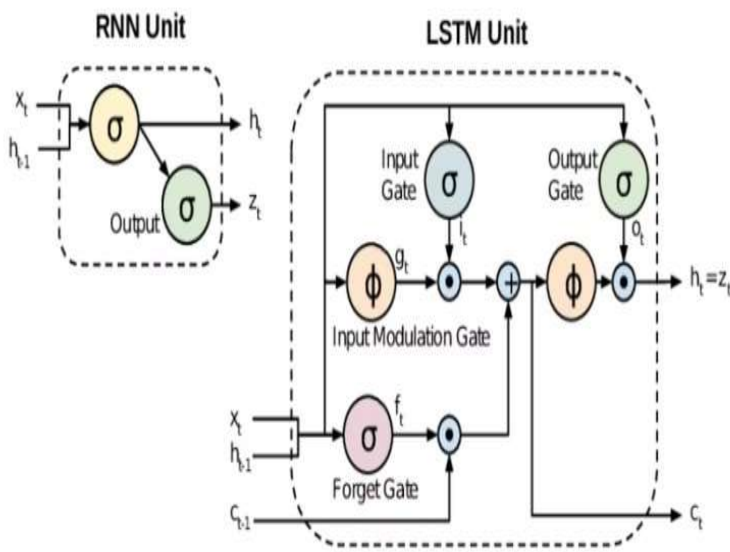
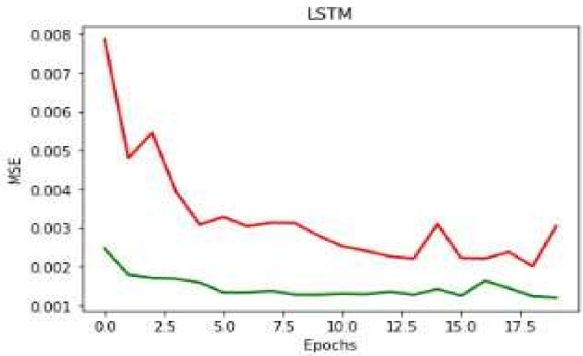


Figure 4.2: RNN and LSTM units.

4.1.3 Optimizer Functions

ADAM: Adam is an optimization algorithm used as an alternative to traditional stochastic gradient descent for updating network weights during training. Its name, derived from "adaptive moment estimation," highlights its method of adjusting the learning rate for each network weight by estimating the first and second moments of the gradients. This helps in achieving more efficient and effective network training.




```
7/7 [==============================] - 0s 3ms/step
Accuracy -> 95.43066962829748
```

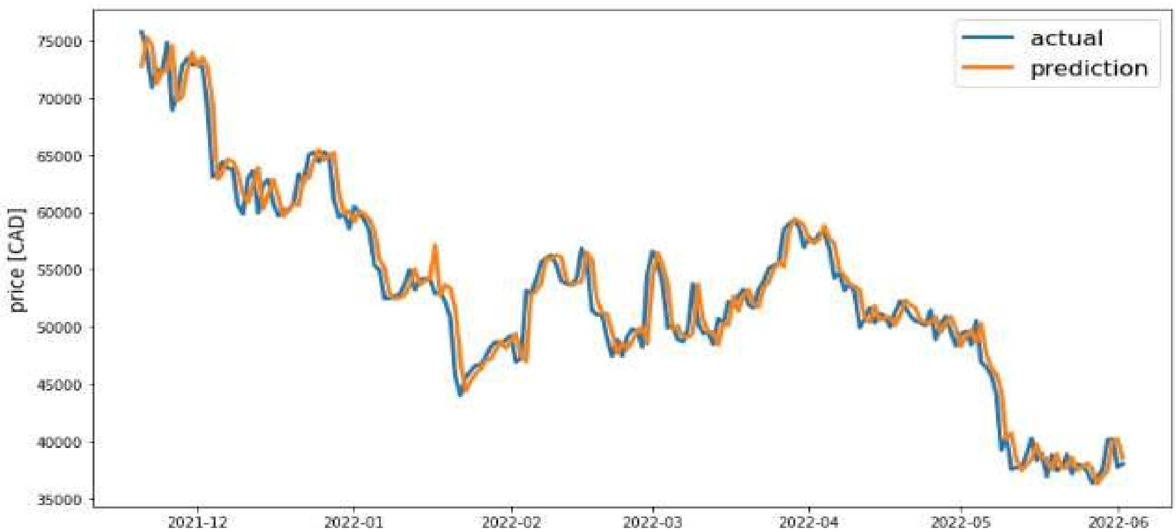


Figure 4.3: Prediction Output using Adam Optimizer

ADAMAX: The Gradient Descent Optimisation technique is a variation that the AdaMax algorithm relies upon, namely the Adaptive Movement Estimation (Adam) optimisation algorithm. Adam updates weights in an inversely proportionate manner to the scaled L2 norm (squared) of previous gradients, a concept first presented in Diederik Kingma and Jimmy Lei Ba's 2014 paper "Adam: A Method for Stochastic Optimisation". By using the infinite norm (maximum) of previous gradients, AdaMax expands on this concept by changing the weight update rule so that it is inversely proportional to the maximum norm of the weights' gradients.

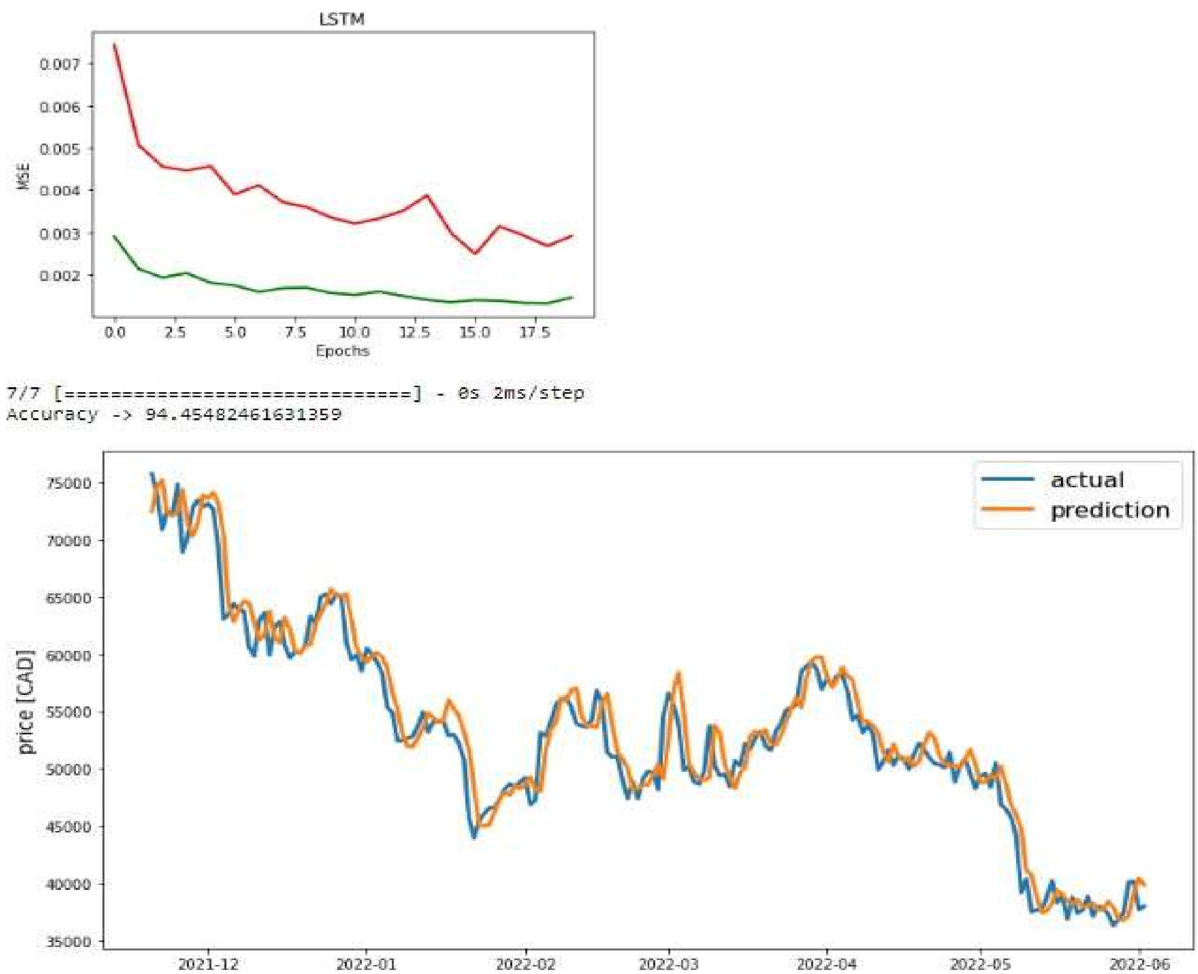
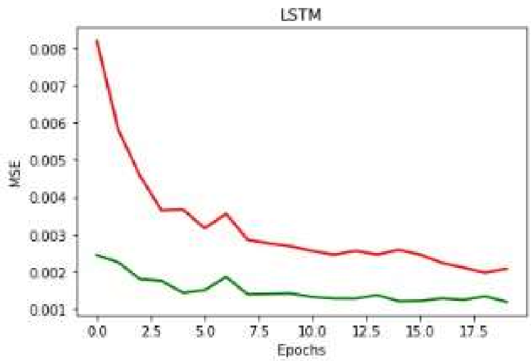


Figure 4.4: Prediction Output using Adamax Optimizer

NADAM: NAdam, short for Nesterov-accelerated Adam, combines the Nesterov momentum with the Adam optimizer. Unlike the standard momentum used by Adam, Nesterov momentum updates gradients more effectively by incorporating foresight into gradient adjustments.




```
7/7 [==============================] - 0s 3ms/step
Accuracy -> 95.50532557081627
```

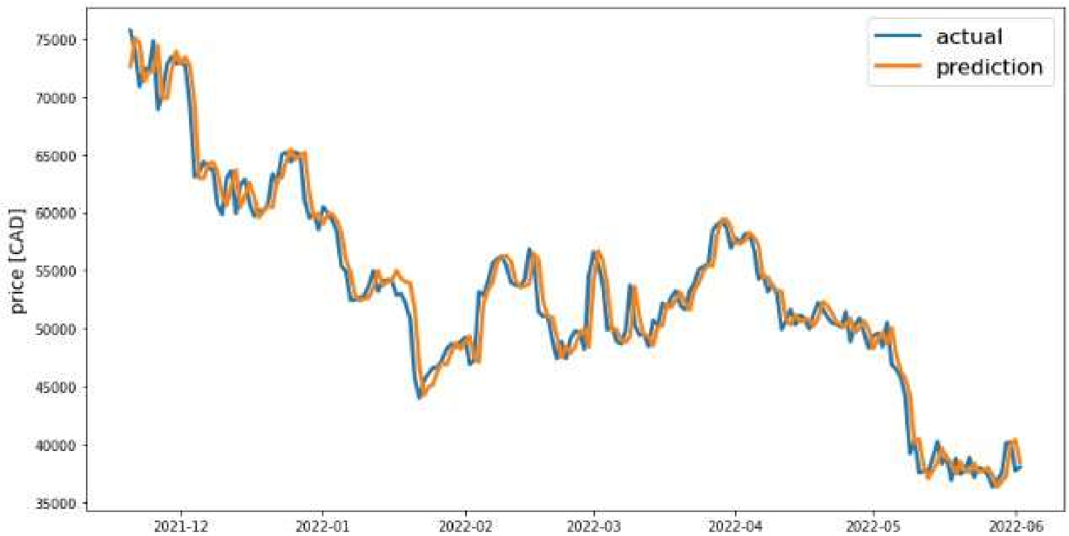


Figure 4.5: Prediction Output using Nadam Optimizer

Adadelta: AdaDelta is another optimization technique within the stochastic gradient descent framework that modifies the per-dimension learning rate. It improves upon Adagrad's method, which diminishes the learning rate too aggressively over time. AdaDelta addresses this by limiting the window of assembled past gradients to a definite size, using a recursive formula to calculate a decaying average of past squared gradients, thus avoiding the need to store them.

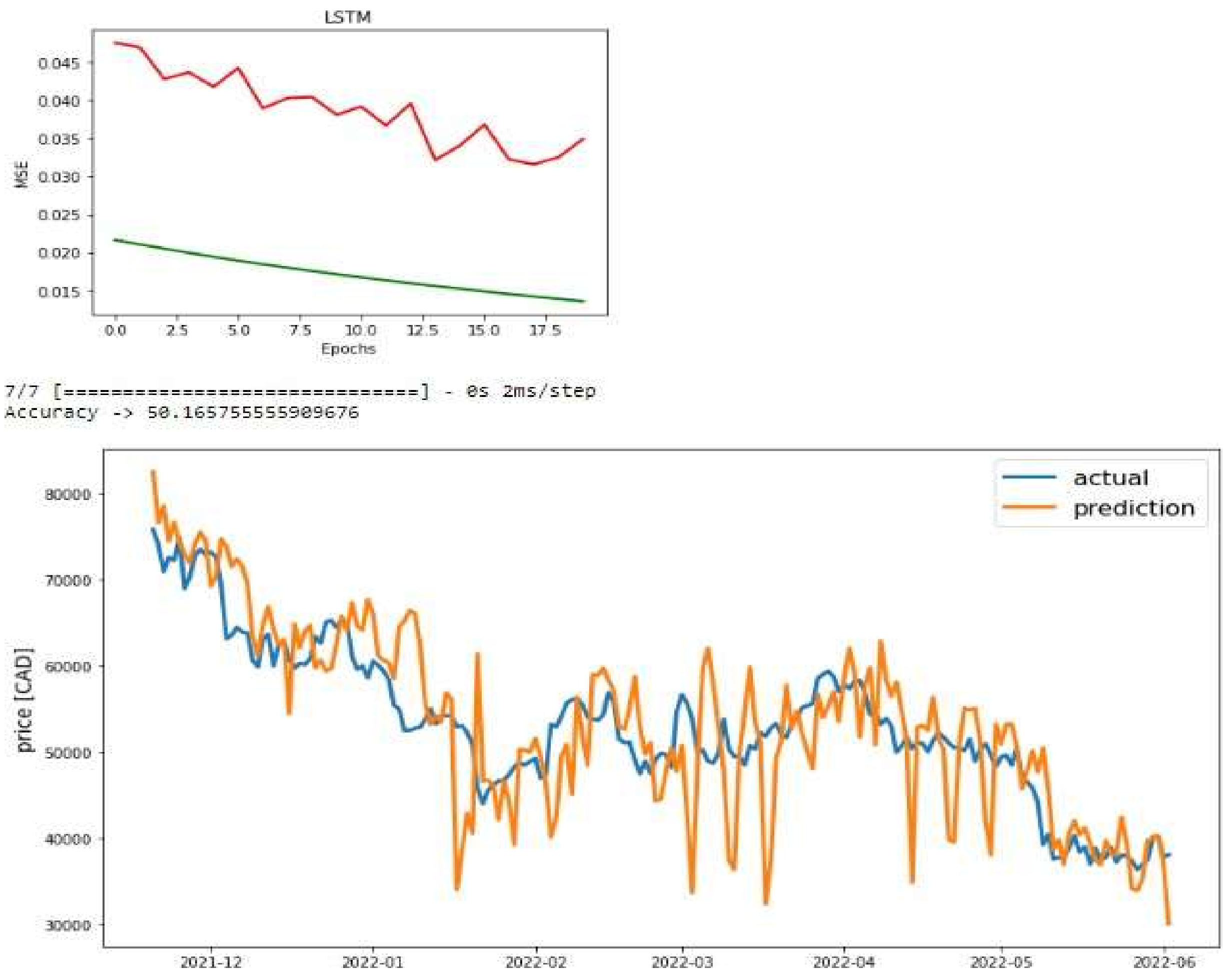


Figure 4.6: Prediction Output using AdaDelta Optimizer

AdaGrid: In the context of machine learning, the effectiveness of a model heavily depends on a well-defined training objective. This is particularly true for training objectives in graph neural networks for link prediction, an area that remains under-explored. These objectives often include techniques like negative sampling and a variety of hyperparameters such as the edge message ratio, which dictates the utilization of training edges. Typically, these hyperparameters are optimized through exhaustive grid searches, which are both time-intensive and model-specific. To solve these challenges, the proposed Adaptive Grid Search (AdaGrid) method allows attuning its variables such as the edge message ratio during the training of the model without invasions of the model's architecture thus offering a future model-agnostic and highly scalable solution that showed potential to improve model performance greatly in tests.

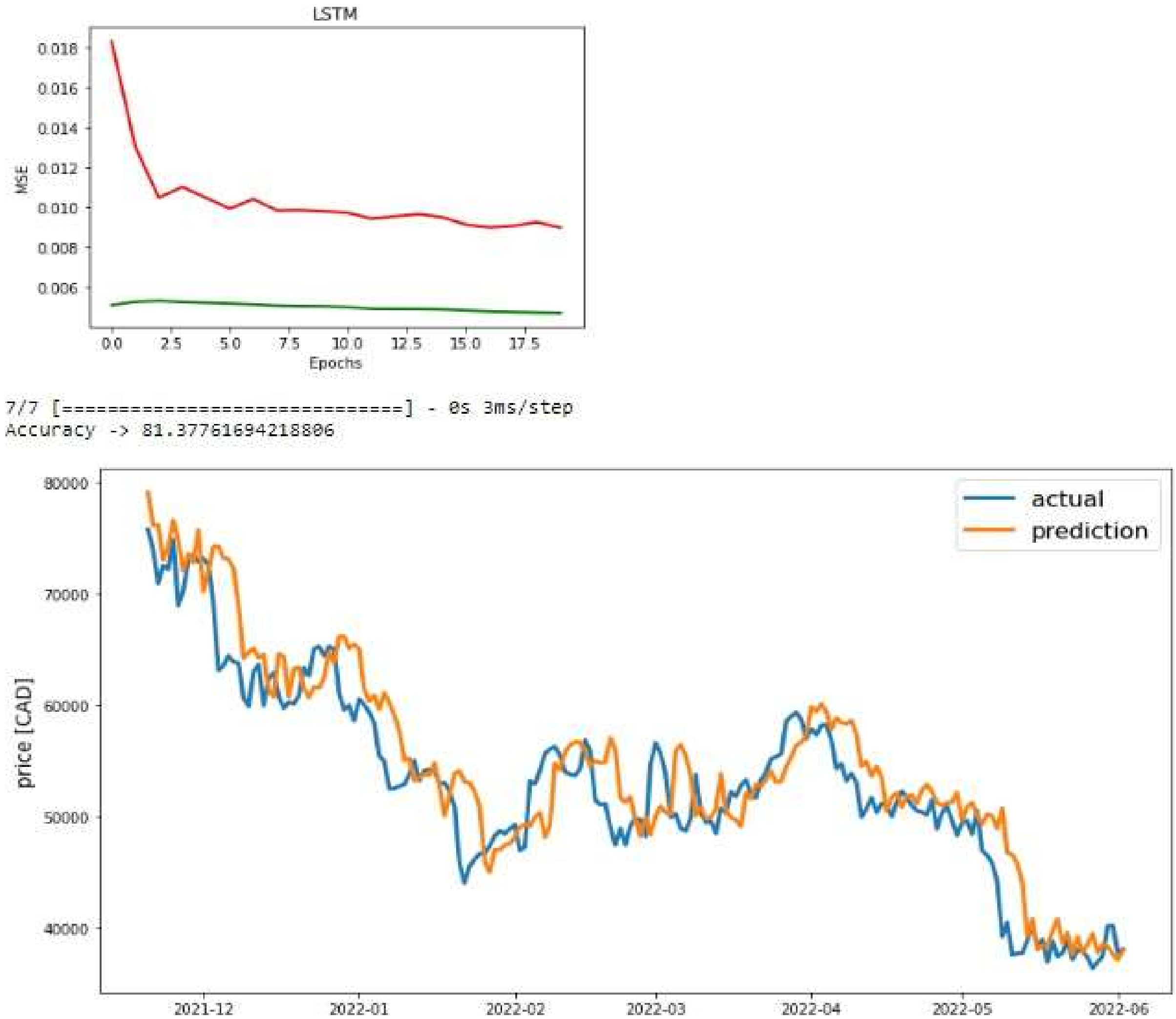


Figure 4.7: Prediction Output using AdaGrid Optimizer

Ftrl Optimizer: The "Follow The Regularized Leader" (FTRL) optimization algorithm was developed at Google in the early 2010s designed to improve click through rate predictions. It fares better in simple models that seek to work with big data having many features while containing limited instances. This algorithm was presented in a paper by McMahan and others in 2013.

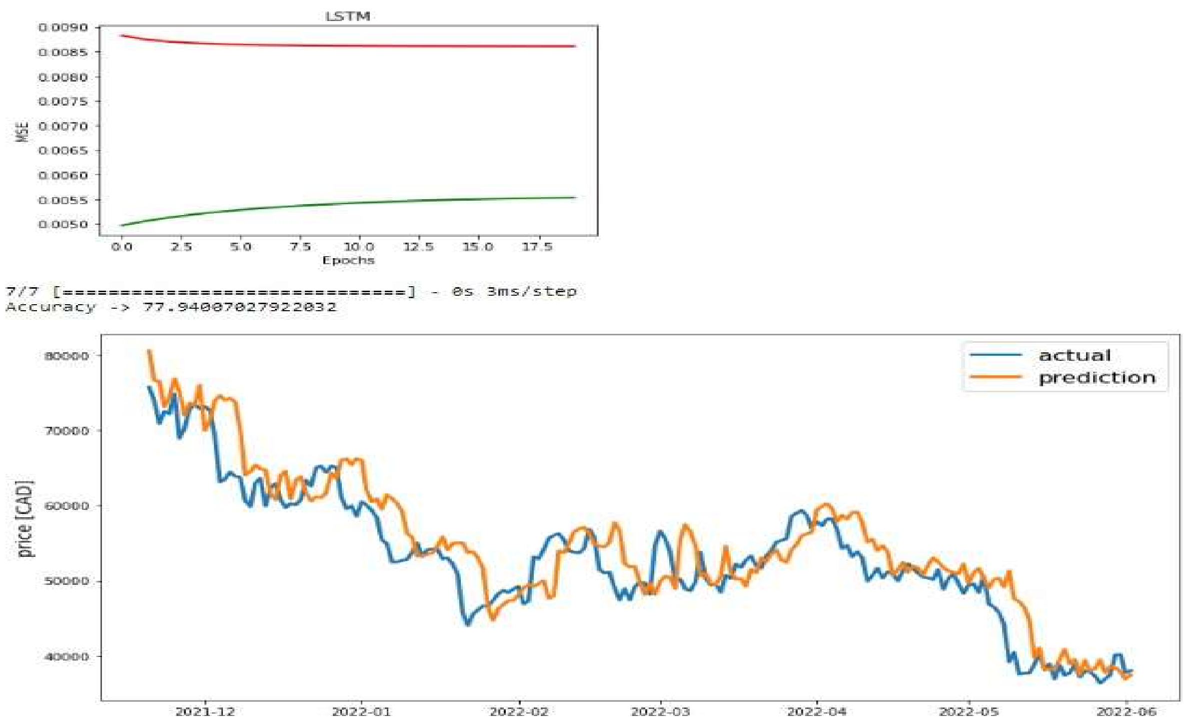


Figure 4.8: Prediction Output using Ftrl Optimizer

4.1.4 Loss Functions

MSE Loss: Mean Squared Error (MSE) is one of the most common measures used in the solutions of regression issues which computes the mean of squares of the distances shown by the difference between the presently predicted and actual values.

Hinge Loss: It is a cost function for classification strategy because it seeks to maximize the margin between the decision boundary and the samples. Others indicate that even if some observation is classified correctly, it will be penalized if it lies in a close proximity to the boundary where the margin is low and gets a greater penalty as the margin reduces.

MAE Loss: It measures how the distance between the midpoint and the paired observations in two variables, across the set of observations, is on the average. It stands for the arithmetic average of the UPS and is easier to interpret than the square root of the mean squared deviations of the points in the primal scatterplot from the Y=X line because it measures the distance between two points without using sophisticated means.

Forecasting prices of cryptocurrencies, or any currency, is always risky, and that is present in this case as well.This section explores the various determinants of cryptocurrency prices and reviews existing methodologies used to identify trends in their price movements.

4.2 The Volatility of Cryptocurrency:

A Focus on Bitcoin, the prices of cryptocurrency can be extremely unstable. For example, data taken from from CoinDesk on April 12 2018, shows that in the space of one hour (11:00- 12:00 GMT) the price of Bitcoin spiked from just under $7000 to just under $8000. There are countless of occurrences of this happening throughout the lifetime of Bitcoin. Another example of this volatility is when the currency reached its highest price on December 16 2017 of over $19,300, before plummeting to $13,800 a mere five days later a drop of almost 30%. It is the sheer instability of cryptocurrency prices and the rate at which they change that determines there will never be a dependable method of predicting prices.

However, one can take into account a variety of things when considering buying or selling cryptocurrency to determine if the time is right. It is important to clarify that the price is solely governed by demand, but there are indeed a great number of factors which may indirectly influence the price of cryptocurrency.

4.2.1 Influencing Factors in Cryptocurrency Prices

Traditional currencies are influenced by many things, such as warfare, political instability, and national debt. In contrast, there is only one direct cause for a change in the price of any cryptocurrency, and that is demand. Since demand is a single thing that directly affects cryptocurrencies, various things affect the present level of need.

Price of Bitcoin

The price of Bitcoin frequently influences the prices of other cryptocurrencies due to its dominant position in the market. It's reasonable to suggest that when Bitcoin's price changes due to certain events, the prices of other cryptocurrencies might also shift similarly. Bitcoin's significant size and popularity often make it a reference point for those looking to trade in the cryptocurrency market.

For example, consider a sudden increase in negative media content related to Blockchain[5] tech- nology. If the majority agree with the negative content, the majority of the market could decide to sell their investments. Bitcoin, with an estimated market dominance of 40-45% , also the majority, would subsequently decline in price. If most of the majority sold their Bitcoin, owners of other cryptocurrencies would be likely to sell due to the majority of the market declining.

By comparing graphed data of the prices of a given cryptocurrency against those of Bitcoin, it becomes clear that Bitcoin activity does in fact have a bearing on other cryptocurrency prices. Although it might seem coincidental, the correlation observed over a week may not be sufficient to establish a clear relationship. However, similar patterns can also be observed over a longer duration, such as three months, suggesting a more persistent connection.

In both instances, the money of both Bitcoin and Ether follow roughly the same path. Bit- coin prices can be seen to be much more volatile, rising and falling more severely and in shorter spaces of time than Ethereum prices. For example, one should consider the sharp rise in price of Bitcoin shortly after April 12, 2018 against the slightly more dulled rise of Ethereum. This can also be observed in the rise and fall of the prices from Febrary to March 2018; the price of Bitcoin is seen to be more erratic, detailing many sudden increases and decreases. Ethereum follows the same general path with less sharp changes, implying that Bitcoin does lead to increased buying or selling of Ethereum.

4.2.2 Deciphering Trends in Prices

With this understanding, we move forward to the practical phase of this project. As noted earlier, it is impossible to predict cryptocurrency prices with absolute accuracy, but it is feasible to analyze and potentially forecast trends using advanced technologies. Building upon the discussions from this and earlier chapters, we will explore the practical application of this project through a web application that displays and predicts Bitcoin prices relative to the Euro.

It is important to mention that while the web application is designed for user-friendliness, it is recommended that users have some familiarity with the content discussed in the previous chapters of this dissertation to fully grasp its functionality.

CHAPTER. 5
CONCLUSION AND FUTURE WORK

5.1 Conclusion

The evaluation of Long Short-Term Memory (LSTM) models for this prediction model reveals their strong potential in capturing temporal patterns in cryptocurrency data. LSTM shows promising performance in forecasting Bitcoin prices accurately compared to other models. Metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and r2 demonstrate the dependability of LSTM in making price predictions. Its capacity to remember information over long periods makes it ideal for forecasting time-series data. In its standard form, LSTM effectively understands the trends in cryptocurrency markets, providing useful predictions. Future studies could enhance LSTM by experimenting with different designs to improve Bitcoin price predictions.

Using interactive layouts, like the analyzer built with the ipywidget library, offers a straightforward way for users to choose settings for configuring and training the LSTM model. These interactive features improve the user experience by letting individuals tailor and select input options based on their needs and preferences. The interactive analyzer aids in a clearer comprehension and management of the model development process, helping users to make knowledgeable decisions about model setups. Adding interactive features to the project increases its flexibility and user-friendliness, making the model more approachable and focused on user needs.

Following conclusions have been drawn so far from the work done on the project:

- Choice of optimizer has a significant impact on the final prediction result.
- Over all Loss (MSE) Decreased proportionally to number of epochs except for Ftrl optimizer.
- Nadam and Adam Optimizers gave the best prediction accuracy according to r2 score.
- Adadelta optimizer gave the worst prediction accuracy according to r2 score.

5.2 Future Scope

- The time-series which is input to the LSTM model is currently a univariate time-series predicting prices only on the closing prices of the bitcoin. With advanced integration of sentiment analysis of a data scrapped and indexed with time from a social site like twitter, the prices can be predicted on a multi-variate input system.
- Use of a front-end framework like react, the prediction result can be made available on a website along with implementation of a real-time prediction using a back-end framework such as node.
- Ideally, the application would incorporate and provide forecasts for major cryptocurrencies like Ethereum, Litecoin, Ripple, and the newer Bitcoin Cash. However, due to limitations in time and the memory capacity on Heroku, it was decided to concentrate on the cryptocurrency with the largest market capitalization.
- Natural language processing (NLP) has been utilized to track price fluctuations in cryptocurrencies. Integrating an NLP component that scans selected websites for negative or positive discussions about cryptocurrencies could enhance this project. This feature could help predict potential price changes or simply track the daily popularity shifts of various cryptocurrencies.

  • Beyond natural language processing, implementing a neural network model capable of long-term predictions would enhance the application's utility, especially for those interested in long-term investments in cryptocurrencies. Currently, the application is only equipped to provide short-term price estimates, but adding a long-term prediction feature that combines machine learning and NLP could make it more appealing to potential users.
- Docker was initially considered for its containerisation capabilities. The technology was not crucial and due to time constraints was not implemented to facilitate more crucial work being completed. However, the use of Docker in the system would add an extra layer of robustness, allowing for easy local deployment should the Heroku deployment ever be unavailable.

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Congratulations....!!!!!

On behalf of the ICAC2N-2024 organising Committee, we are delighted to inform you that the submission of “Paper ID- 601 “ titled “ From Past to Present: A Historical Review of Recurrent Neural Networks in Bitcoin Price Prediction “ has been accepted for presentation and further publication with IEEE at the ICAC2N- 24. All accepted papers will be submitted for inclusion into IEEE Xplore subject to meeting IEEE Xplore’s scope and quality requirements.

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Acceptance Notification 1st IEEE ICAC2N-2024 & Registration: Paper ID 673 @ ITS Engineering College, Greater Noida

1 message

Microsoft CMT <email@msr-cmt.org>   Mon, May 13, 2024 at 12:15 AM
Reply-To: "Dr. Vishnu Sharma" <vishnu.sharma@its.edu.in>
To: Shashi Prakash Gupta <shashi17999@gmail.com>

Dear Shashi Prakash Gupta,
Delhi Technological University

Greetings from ICAC2N-2024 ...!!!

Congratulations....!!!!!

On behalf of the ICAC2N-2024 organising Committee, we are delighted to inform you that the submission of "Paper ID- 673 " titled " Predictive Modeling in Cryptocurrency: A case Study of Bitcoin using RNN " has been accepted for presentation and further publication with IEEE at the ICAC2N- 24. All accepted papers will be submitted for inclusion into IEEE Xplore subject to meeting IEEE Xplore's scope and quality requirements.

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Registration Confirmation 1st IEEE ICAC2N-2024 : Paper ID 673 @ ITS Engineering College, Greater Noida

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Microsoft CMT <email@msr-cmt.org>   Wed, May 22, 2024 at 12:16 AM
Reply-To: "Dr. Vishnu Sharma" <vishnu.sharma@its.edu.in>
To: Shashi Prakash Gupta <shashi17999@gmail.com>

Dear Shashi Prakash Gupta,
Delhi Technological University

Greetings from ICAC2N-2024 ...!!! Thanks for Completing your registration...!!

Paper ID- "673 “
Paper Title- “ Predictive Modeling in Cryptocurrency: A case Study of Bitcoin using RNN “

This email is to confirm that you have successfully completed your registration for your accepted paper at ICAC2N-2024. We have received your registration and payment details. Further, your submitted documents will be checked minutely and if any action will be required at your end you will be informed separately via email.

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