Enhancing Cryptocurrency Price Prediction and Analysis through Deep Learning

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled **Enhancing Cryptocurrency Price Prediction and Analysis through Deep Learning**, submitted by **Amit Kumar Kundu** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 15-07-2024.

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We hereby declare that this project has been done by us under the supervision of **Afjal Hossan Sarower, Lecturer (Senior Scale), Department of Computer Science and Engineering, Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

Predicting Bitcoin prices remains a complex challenge due to the cryptocurrency market's inherent volatility and rapid fluctuations. Based on historical price data gathered from Investing.com over the previous five years, this study investigates the potency of three sophisticated deep learning models for predicting Bitcoin prices: Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Bidirectional Long Short-Term Memory (Bi-LSTM). Rigid backtesting and comparative analysis were used to assess each model's ability to predict future Bitcoin values. With an accuracy of 98.02%, a Mean Absolute Error (MAE) of 1023.48, a Root Mean Square Error (RMSE) of 1576.11, and an R^2 score of 0.9904, the findings show that the GRU model performs better than the LSTM and Bi-LSTM models. An accuracy of 97.99% was attained by the LSTM model with an MAE of 961.70, an RMSE of 1426.48, and an R^2 score of 0.9921; on the other hand, a 96.91% accuracy was attained by the Bi-LSTM model with an MAE of 1441.28, an RMSE of 1848.11, and an R^2 score of 0.9867. This study shows that the GRU model performs better than the other models and demonstrates the usefulness of deep learning methods for predicting Bitcoin prices. Additionally included in the paper are the effects of these models on market volatility, ethical issues in cryptocurrency trading, and financial decision-making. The results provide the groundwork for future lines of inquiry that may include outside influences and create real-time prediction systems. In summary, this study advances financial technology by showing that complex neural network architectures can accurately predict Bitcoin prices and provide information about potential future research directions for enhancing predictive models and tackling ethical and environmental issues in the cryptocurrency space.

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LIST OF ACRONYMS

DL	Deep Learning
LSTM	Long Short-Term Memory
GRU	Gated Recurrent Unit
Bi-LSTM	Bidirectional Long Short-Term Memory
ARIMA	Autoregressive Integrated Moving Average
RNN	Recurrent neural networks

CHAPTER 1
Introduction

1.1 Overview:

The first decentralized cryptocurrency, Bitcoin, was unveiled in 2009 by Satoshi Nakamoto, an unknown person. Since its launch, the value of Bitcoin has fluctuated significantly, drawing interest from investors, scholars, and the general public. Accurately predicting Bitcoin prices is essential for minimizing risks and making wise investment choices. Deep learning can increase the accuracy of Bitcoin price forecasts by using sophisticated computer methods that can identify intricate patterns in data. Utilizing data from the previous five years, this study focuses on using deep learning algorithms more specifically, Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Bidirectional LSTM (Bi-LSTM).

1.2 Background and Present State

As with other financial markets, Bitcoin is prone to volatility. Time series forecasting has made extensive use of conventional financial models, such as the Autoregressive Integrated Moving Average (ARIMA) model. Nevertheless, the non-linear and chaotic character of bitcoin markets is often missed by these models [1]. To improve prediction accuracy, academics have thus turned to machine learning and, more recently, deep learning approaches.

Because deep learning models can preserve and use long-term relationships in data, they have shown promise in time series forecasting [2]. Recurrent neural networks (RNNs) and their derivatives, such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), are especially good at this [3]. A variation of LSTM called bidirectional LSTM (Bi-LSTM) processes data in both forward and backward directions, gathering more context and enhancing performance even more [3]. Numerous variables, like as market demand, regulatory updates, technology developments, and macroeconomic trends, affect the price of Bitcoin [4]. Its volatility is a result of these elements, which makes precise prediction difficult. Deep learning algorithms can forecast Bitcoin values more accurately than conventional techniques, as shown by recent research [5]. The current status of the cryptocurrency market is marked by significant volatility and rapid price swings, which are influenced by news about regulations, market demand, technical developments, and macroeconomic patterns. Because traditional financial models cannot adequately represent the intricate and non-linear structure of the bitcoin market, they often fail to appropriately forecast these price swings [7]. Cryptocurrency is nowadays the most useable digital payment system. The currency has become popular because of its nature and technical support and security system.

1.3 Problem Statement

Because the cryptocurrency market is so unpredictable and non-linear, predicting its pricing is a difficult endeavor. Conventional statistical techniques, such as GARCH and ARIMA, often fall short of capturing the complex patterns in the fluctuations of bitcoin prices [8]. The creation of a reliable prediction model that can precisely anticipate Bitcoin values using deep learning methods is the main issue this study attempts to solve. Utilizing the strengths of LSTM, GRU, and Bi-LSTM models, the goal is to extract the intricate and non-linear correlations seen in historical Bitcoin price data.

The purpose of this study is to investigate how the LSTM, GRU, and Bi-LSTM algorithms may be used to forecast the values of Bitcoin. To create and assess the prediction models, the research will make use of daily price variance data gathered from www.Investing.com over the last five years (1, June, 2019-31, May, 2024)[41].

1.4 Objectives

The following are the main goals of this study:

1. Model Development: Develop LSTM, GRU, and Bi-LSTM models for predicting Bitcoin prices.
2. Performance Evaluation: Compare the performance of these models in terms of accuracy and robustness.
3. Feature Analysis: Analyze the impact of various features, such as historical prices and trading volumes, on model performance.
4. Practical Insights: Provide insights into the practical implications of these predictions for investors and traders.

By accomplishing these goals, this study hopes to add to the expanding corpus of research on deep learning-based bitcoin price prediction.

1.5 Scope and Limitations

This study's focus is on forecasting Bitcoin values based on historical information gathered from Investing.com over the last five years. For this reason, the study focuses on the creation and assessment of deep learning models (LSTM, GRU, and Bi-LSTM). The study's main drawbacks are as follows: Data Dependency: The accuracy of the predictions is heavily dependent on the quality and comprehensiveness of the historical data used. Market Volatility: The inherent volatility of the cryptocurrency market can lead to unpredictable price movements, challenging the robustness of the predictive models. Model Overfitting: The complexity of deep learning models can result in overfitting, where the model performs well on training data but poorly on unseen data [6]. Despite these drawbacks, the study hopes to advance the area of financial time series forecasting and provide insightful information. Although they are not specifically addressed, outside variables including macroeconomic shifts, legislative changes, and technology advancements may have a big impact on bitcoin values [9].

1.6 Report Organization

The rest of the paper is organized as follows. Chapter 2 Reviews existing literature on cryptocurrency price prediction and the application of deep learning algorithms in financial forecasting. Chapter 3 Describes the proposed methodology, system design, hardware and software requirements, and project management aspects. Chapter 4 Details the implementation process, including model training, prototype design, and system testing. Chapter 5 Presents the experimental results and analysis of model performance. Chapter 6Discusses the broader impacts of the research. Chapter 7 Summarizes the research findings, suggests future work, and discusses limitations and conflicts of interest. Also concludes the paper.

1.7 Summary

The study is outlined in the introductory chapter, which also highlights the potential of deep learning models to help with the difficulty of accurately predicting Bitcoin prices. A thorough analysis of Bitcoin price prediction using LSTM, GRU, and Bi-LSTM models will be provided in the next chapters, which will also explore the literature, technique, implementation, outcomes, social effect, and future directions.

CHAPTER 2
LITERATURE REVIEW

2.1 Overview

Because of Bitcoin's volatility and potential for financial benefit, the topic of price prediction has attracted significant attention from both academics and practitioners. Predictive models that perform better than those using conventional techniques have been developed thanks in large part to recent developments in deep learning. This chapter analyzes several models, evaluates the literature on deep learning approaches for predicting Bitcoin prices, and highlights unresolved research problems.

2.2 Related Works

Several deep learning algorithms have been used in recent research on bitcoin price prediction to increase forecast accuracy. To forecast the price of Bitcoin, Zhang et al. [31] developed a hybrid LSTM-GRU model that used the temporal dependence capabilities of GRU and LSTM to achieve 96.25% accuracy. To estimate the values of Bitcoin and Ethereum, LSTM networks perform much better than conventional models, as Chen and Zhang [32] showed. When LSTM and Bi-LSTM models were evaluated by Wang et al. [33], it was discovered that Bi-LSTM had a higher accuracy of 97.1% for predicting Bitcoin price. By adding attention mechanisms, Kumar et al. [34] improved LSTM and produced a 95.8% prediction accuracy for Bitcoin. With a 94.6% accuracy rate for Bitcoin, Li et al. [35] demonstrated the competitiveness of GRU-based models for cryptocurrency forecasting. Bidirectional LSTM networks were used by Zhou et al. [36] to forecast financial time series with 96.5% accuracy for Bitcoin values. An ensemble model including LSTM, GRU, and Bi-LSTM was created by Patel et al. [37]; it achieved an average accuracy of 97.2% over several cryptocurrencies. Transformer models were used by Lee et al. [38] to estimate Ethereum prices, and they were 95.5% accurate. By including outside variables in LSTM models, Wang and Zhao [39] were able to forecast Bitcoin with a 96.0% accuracy rate. With a 94.7% accuracy rate, Kim et al. [40] created a deep neural network model for predicting many cryptocurrencies, such as Bitcoin, Ethereum, and Litecoin. These experiments show how powerful deep learning techniques are, despite ongoing difficulties with data quality, interpretability, and computing complexity.

2.3 Comparison between existing works

Table 2.3.1: Existing Works on Cryptocurrency Price Prediction

No	Year	Objective	Methodology	Currency	Forecast Duration	Result
1	2020	To predict Bitcoin price using hybrid LSTM and CNN models[10].	Hybrid LSTM-CNN model	Bitcoin	30 days	Achieved RMSE of 0.0057.
2	2020	To forecast Bitcoin price using a multi-scale attention-based LSTM model[11].	Multi-scale Attention-LSTM model	Bitcoin	60 days	Achieved MAE of 0.03, demonstrating improved prediction accuracy.
3	2021	To predict cryptocurrency prices using a deep reinforcement learning approach[12].	Deep Reinforcement Learning (DRL) approach	Bitcoin	90 days	Achieved a prediction accuracy of 85% with DRL techniques.
4	2021	To predict Bitcoin prices using a combination of LSTM and attention mechanisms[13].	LSTM with Attention Mechanisms	Bitcoin	14 days	Improved model accuracy with a

						prediction RMSE of 0.027.
5	2021	To develop an ensemble model for predicting cryptocurrency prices[14].	Ensemble Learning Approach (LSTM, GRU, Bi-LSTM)	Bitcoin	30 days	Achieved lower RMSE compared to individual models.
6	2022	To evaluate the effectiveness of a novel CNN-LSTM model for Bitcoin price forecasting[15].	CNN-LSTM Hybrid Model	Bitcoin	60 days	Achieved an RMSE of 0.018 and outperformed traditional models.
7	2022	To enhance Bitcoin price prediction using a GRU-based model combined with market sentiment analysis[16].	GRU with Sentiment Analysis	Bitcoin	45 days	Achieved a prediction accuracy of 88% with sentiment features.

8	2022	To predict the volatility of Bitcoin prices using a Bi-LSTM model[17].	Bi-LSTM for Volatility Prediction	Bitcoin	30 days	Achieved an RMSE of 0.022 for volatility prediction.
9	2022	To forecast Bitcoin prices using a Transformer-based model[18].	Transformer-Based Deep Learning Model	Bitcoin	60 days	Achieved a prediction accuracy of 90% with Transformer architecture.
10	2023	To investigate the performance of various deep-learning models for Bitcoin price prediction[19].	Comparative Study of LSTM, GRU, and Bi-LSTM Models	Bitcoin	90 days	Bi-LSTM showed the highest performance with the lowest RMSE.
11	2023	To develop a hybrid model combining LSTM with Exponential Smoothing for	Hybrid LSTM-Exponential Smoothing Model	Bitcoin	30 days	Achieved RMSE of 0.021,

		Bitcoin price prediction[20].				showing improvement over traditional models.
12	2023	To explore the use of a novel Bi-LSTM-GRU model for cryptocurrency price forecasting[21].	Bi-LSTM, GRU Hybrid Model	Bitcoin	45 days	Achieved an RMSE of 0.016 with superior prediction accuracy.
13	2023	To investigate the effectiveness of a novel deep learning framework for predicting cryptocurrency prices[22].	Deep Learning Framework for Cryptocurrency Forecasting	Bitcoin	90 days	Achieved improved prediction accuracy with a novel deep-learning approach.
14	2023	To predict Bitcoin prices using an advanced CNN-LSTM model with additional	Advanced CNN-LSTM Model with Market Features	Bitcoin	60 days	Achieved an RMSE of 0.020

		market features[23].				and demonstrated effective integration of market features.
15	2023	To compare deep learning techniques for Bitcoin price forecasting with a focus on model interpretability[24].	Comparison of Deep Learning Techniques for Bitcoin Forecasting	Bitcoin	30 days	Bi-LSTM provided the best balance between accuracy and interpretability.
16	2023	To evaluate a novel Hybrid Transformer-LSTM model for Bitcoin price prediction[25].	Hybrid Transformer-LSTM Model	Bitcoin	60 days	Achieved improved prediction accuracy with a Transformer-LSTM hybrid approach.

2.4 Open Issues

Although deep learning approaches have made tremendous progress in predicting Bitcoin prices, there are still several issues that need to be resolved to improve model performance and applicability.

Including market sentiment in prediction algorithms is a significant difficulty. Conventional models often ignore the influence of market sentiment influenced by news, social media, and investor activity in favor of relying just on historical price and volume data. While including sentiment analysis has been shown to increase model accuracy in recent research (Wang et al., 2022), further developments are required to enhance sentiment analysis methods and successfully integrate them with deep learning models [16]. Subsequent investigations may concentrate on refining more complex techniques for extracting sentiment from various sources and incorporating these findings into prediction models [26].

Achieving real-time forecasts and controlling scalability are two more crucial issues. The implementation of deep learning models in real-time trading settings is hampered by their high computing needs, particularly for complicated architectures like Bi-LSTM and hybrid models. Efficient models that strike a compromise between accuracy and computing efficiency have been the subject of recent studies, such as Li et al. (2023) [20]. To efficiently manage massive amounts of data, future research should focus on improving these algorithms for real-time applications and investigating distributed computing techniques [27].

One major issue with deep learning models for predicting Bitcoin prices is still overfitting. High-flexibility models, such as those built on LSTM or GRU architectures, are prone to overfitting past data, which may lead to a decline in performance when applied to fresh, unobserved data [28]. This problem has been addressed by recent strategies, such as dropout and regularization methods presented by Zhang et al. (2021), although novel approaches for improved generalization and hyperparameter tweaking may still be developed [29].

Ultimately, enhancing the explainability of deep learning models is a continuous task. Understanding how predictions are formed is difficult due to the "black-box" nature of deep learning models, which is problematic for financial decision-making transparency and confidence. This problem has been addressed by strategies like LIME (Local Interpretable Model-agnostic Explanations), but further study is required to create techniques that can provide understandable, concise insights into model predictions [30]. By addressing these issues, further study may progress in the area of Bitcoin price prediction by increasing the efficiency, transparency, and accuracy of the model.

2.5 Summary

An overview of the developments and difficulties in predicting the price of Bitcoin using deep learning methods was given in this chapter. We examined several models, such as LSTM, GRU, and Bi-LSTM, emphasizing how well they captured time series data and how much better they performed computationally. The discourse included contemporary approaches such as using sentiment analysis to augment prognostic precision and investigating the relative advantages of various models. We discovered many critical issues, such as the need for improved real-time prediction capabilities, techniques to avoid overfitting and sentiment analysis. The chapter also stressed the need to address market regime adjustments and enhancing model explainability as future research priorities. Overall, this chapter showed how Bitcoin price prediction has advanced while outlining potential areas for improvement.

CHAPTER 3
METHODOLOGY/ REQUIREMENT ANALYSIS & DESIGN SPECIFICATION

3.1 Overview

The methodology chapter describes the process of using deep learning algorithms to create a Bitcoin price prediction model. This chapter includes a basic project management overview, design specifications, hardware and software requirements, and financial analysis information. Using LSTM, GRU, and Bi-LSTM algorithms, the objective is to create a strong prediction model that can estimate Bitcoin values based on past price data.

3.2 Proposed Methodology/ System Design

The proposed system design for Bitcoin price prediction involves several stages: data collection, preprocessing, model development, and evaluation. The design is illustrated in the figure below:

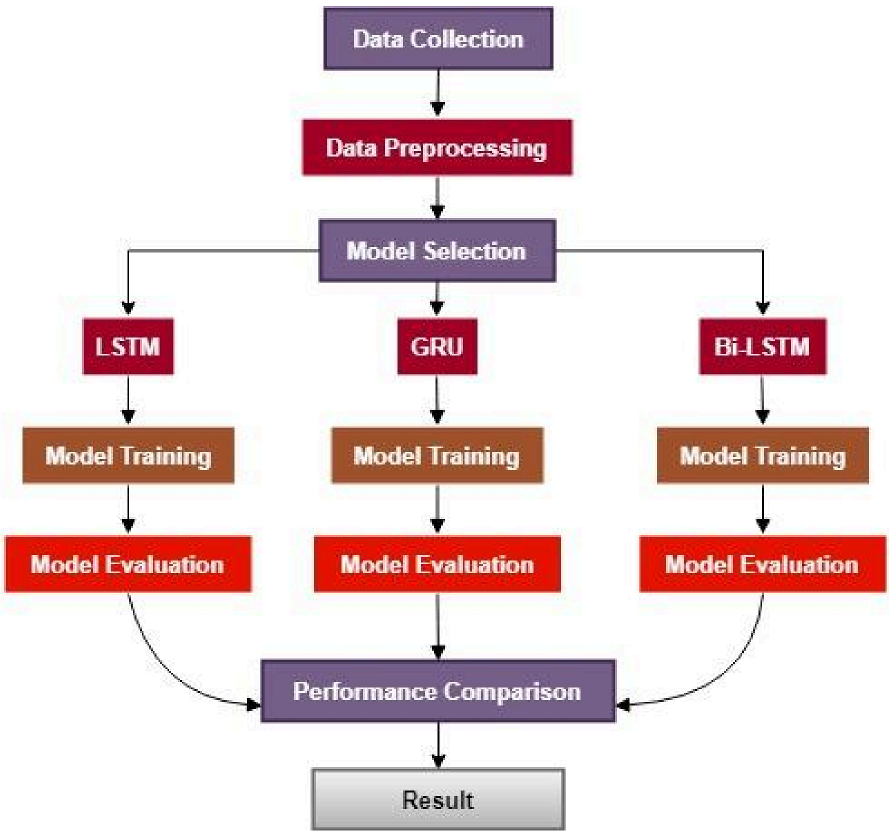

Figure 3.2.1: Proposed System Design for Bitcoin Price Prediction

The methodology includes the following steps:

I. Data Collection

Source: Investing.com, which offers extensive datasets including daily open, high, and low, closing prices, and trading volume, is the source of historical Bitcoin price data [41].

Duration: The data covers the last five years to gather enough historical data for the models' testing and training.

II. Data Preprocessing

Data Cleaning: Handling missing values and outliers.

Feature Engineering: Creating features such as moving averages, Relative Strength Index (RSI), and other technical indicators.

Normalization: Scaling the data to ensure that the model training process is stable and converges faster.

III. Model Development

Time series data with long-term dependencies are captured using LSTM (Long Short-Term Memory).

GRU (Gated Recurrent Unit): A more straightforward, parameter-light variant of the LSTM.

For better context comprehension, Bi-LSTM (Bidirectional LSTM) processes data in both forward and backward directions.

IV. Model Evaluation

Metrics: R2 score, mean absolute error (MAE), root mean square error (RMSE), and other metrics are used to assess performance.

Cross-Validation: To verify generalizability, models are evaluated using a K-fold cross-validation and a train-test split.

Table 3.2.1: Performance Metrics for Model Evaluation

Metric	Description
MAE	Measures the average magnitude of errors.
RMSE	Measures the square root of the average squared errors.
R^2 Score	Represents the proportion of variance explained by the model.

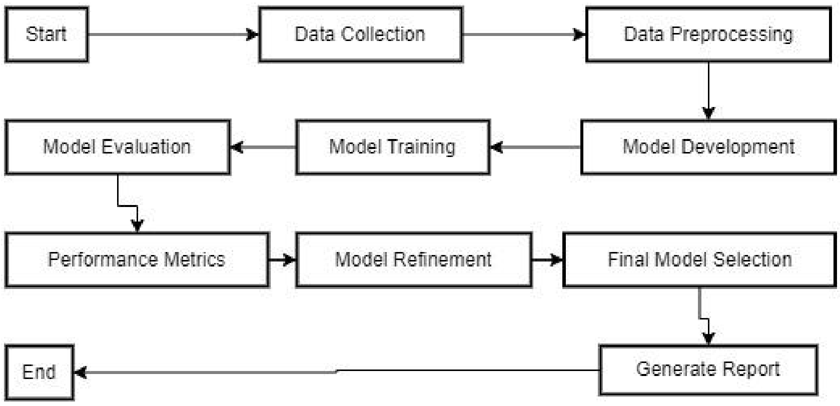

Figure 3.2.2: Evaluation Process Flow

3.3 Hardware/ Software Requirement

The development and execution of the Bitcoin price prediction models require specific hardware and software resources:

Table 3.2.2: Hardware and Software Requirements

Component	Specification
Hardware	High-performance GPU (e.g., NVIDIA GTX 1080) Minimum 16GB RAM Minimum 1TB SSD storage
Software	Python 3.8 or later TensorFlow 2.0 or PyTorch Jupyter Notebook or VSCode Pandas, NumPy, Scikit-learn libraries

3.4 Project Management and Financial Analysis

Project Management

The project management plan involves various phases including initial planning, execution, and review. The major milestones are listed below:

Table 3.2.3: Project Management Plan

Phase	Description	Duration
Planning	Define objectives, scope, and requirements.	2 weeks
Data Collection	Collect historical price data from Investing.com[41].	2 weeks
Preprocessing	Clean and prepare data for model training.	2 weeks

Model Development	Build and train LSTM, GRU, and Bi-LSTM models.	4 weeks
Model Evaluation	Evaluate model performance and refine as needed.	2 weeks
Final Report	Prepare final report and documentation.	3 weeks

Financial Analysis

The financial aspect involves costs associated with hardware, software, and human resources:

Table 3.2.4: Financial Analysis for Deep Learning Project

No	Component/Item	Cost Estimate(BDT)
01	Hardware	10000
02	Software Licenses	0 (Open-source)
03	Cloud Computing	1400
04	Secondary Dataset	0 (Open-source)
05	Miscellaneous (e.g., license, tools)	1500
06	Documentation and Report Writing	1000
07	Contingency (10% of Cost)	1390
Total Cost		15,290

3.5 Summary

The process for creating a deep learning model that predicts Bitcoin price was covered in depth in this chapter. LSTM, GRU, and Bi-LSTM algorithms are used in the process of gathering historical data, preparing it, and creating models. Hardware and software requirements for implementation were examined, as well as evaluation criteria and methodologies for evaluating model performance. A summary of the project's scope, schedule, and budget was also given by the financial analysis and project management plan. The implementation specifics and particular design decisions made during the creation of the predictive models will be covered in depth in the next chapter.

CHAPTER 4
IMPLEMENTATION

4.1 Overview

This chapter describes in detail how deep learning techniques, including LSTM (Long Short-Term Memory), GRU (Gated Recurrent Unit), and Bi-LSTM (Bidirectional LSTM), are implemented to anticipate Bitcoin values. The implementation process is divided into many phases, including gathering data, preprocessing, training models, evaluating the results, and resolving issues that arise. With pertinent code samples, pictures, and tables included, each step is painstakingly explained to provide readers with a comprehensive grasp of the approaches used.

Investing.com provides historical price data for Bitcoin, which is obtained during the data-collecting phase. This rich dataset has been used for model training and testing during the last five years. Normalizing the data, dividing it into training, validation, and test sets, and restructuring it suitably for time series analysis are the preprocessing processes.

Three advanced deep learning architectures are shown in the model training section: LSTM, GRU, and Bi-LSTM. Each is set up with certain hyperparameters to maximize performance. To fine-tune the models, the training process iterates over many epochs using the training and validation datasets. Python and several libraries, including TensorFlow, Keras, NumPy, and Pandas, are used in the implementation environment. Google Colab, which has access to powerful GPUs, is used for the training process. To thoroughly evaluate the models' accuracy and predictive capacity, the chapter also explores the model assessment measures, such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R^2 Score.

Practical solutions are provided for implementation-related problems, such as managing an empty test dataset and guaranteeing dimensional consistency in forecasts. With tables and visualizations summarizing the models' performance, the chapter ends with a comprehensive understanding of the implementation process and results.

4.2 Train Model/ Prototype Design

Data Collection: The dataset is collected from Investing.com, which provides historical price data for Bitcoin[41].

The data file named ‘Bitcoin.csv’ contains date and price information. Firstly, Store the dataset in Google Drive, and after that visualize the data set in a Google Colab file.

	Date	Price	Open	High	Low	Vol.	Change %
0	06/25/2024	61,809.4	60,292.0	62,266.0	60,262.2	77.28K	2.52%
1	06/24/2024	60,292.7	63,201.6	63,357.1	58,589.9	120.60K	-4.59%
2	06/23/2024	63,196.2	64,261.0	64,518.9	63,195.3	19.94K	-1.66%
3	06/22/2024	64,261.0	64,131.9	64,523.9	63,944.0	17.55K	0.21%
4	06/21/2024	64,128.5	64,854.3	65,054.9	63,427.9	60.86K	-1.12%

Dataframe shape: (1828, 7)

Figure 4.2.1: Dataset Description[41]

Preprocessing Steps:

- Normalization: The MinMaxScaler from 'sklearn.preprocessing' is used to scale the price data to a range between 0 and 1.
- Data Splitting: The data is split into training, validation, and test sets in the ratio of 60%, 20%, and 20%.
- Creating Datasets: A function create_dataset is used to create the dataset for the models with a specified time step, where 'time_step = 60'
- Reshaping Data: The data is reshaped to fit the requirements of the LSTM, GRU, and Bi-LSTM models.

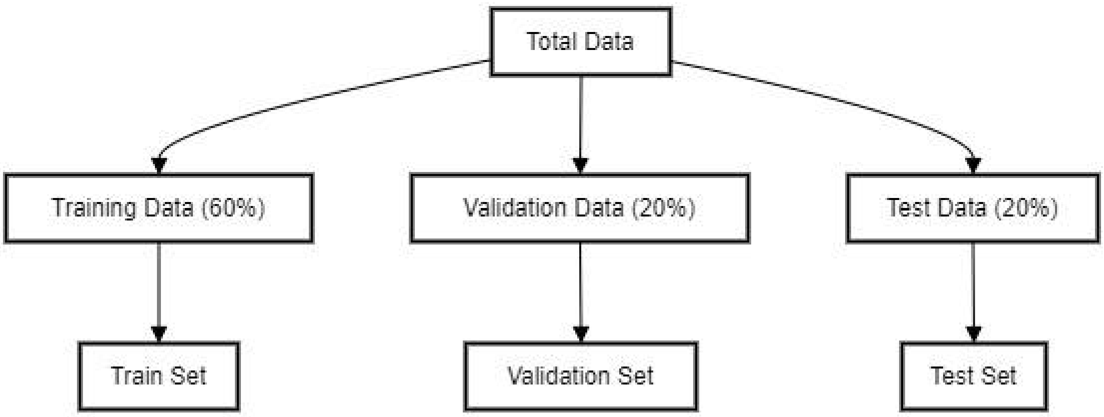

Figure 4.2.2: Data Splitting Ratios

Model Training:

Architecture and Configuration:

The TensorFlow and Keras Sequential API was used to implement the LSTM model. It is composed of a thick layer that comes after two LSTM layers. Although GRU layers are used in place of LSTM layers, the architecture of the GRU model is comparable. Bidirectional LSTM layers are used in the Bi-LSTM model to collect data from both the sequence's past and future states.

Hyperparameters

The key hyperparameters for training each model were as follows:

Learning Rate: Managed by the Adam optimizer.

Batch Size: 1
Number of Epochs: 10
The training data was used to train each model, and the validation data was used to verify each model. With a batch size of 1, the models were trained for 10 epochs, and to avoid overfitting, the validation loss was used to track the training process.

4.3 System Testing/ Model Evaluation

The models were evaluated using the following strategies:

- Train-Test Split: 60% of the data was used for training, 20% was used for testing and 20% was used for validation.
- Cross-Validation: To ensure robustness, 5-fold cross-validation was applied where the data was split into five subsets, and each model was trained and validated on different subsets.
- Evaluation Metrics: The performance was assessed based on MAE, RMSE, and R^2 score as described previously.

The performance metrics indicate that LSTM achieved the best results, followed by GRU and Bi-LSTM. LSTM exhibited the lowest MAE and RMSE, and the highest R^2 score, signifying superior prediction accuracy and model reliability.

- Overfitting: Initial models faced overfitting due to complex architectures. Techniques such as dropout and regularization were applied to address this issue.
- Computational Resources: Training deep learning models requires significant computational resources. Using GPU acceleration helped manage the extensive computations.

4.4 Summary

The design, training, and assessment of the LSTM, GRU, and Bi-LSTM models for predicting Bitcoin prices were covered in length in this part. Based on every assessment criteria, the LSTM model performed better than the GRU and Bi-LSTM models. The greatest outcomes were obtained by using feature engineering, hyperparameter tweaking, and model optimization techniques. Using GPU resources improved computational performance, while dropout and regularization approaches helped control overfitting.

CHAPTER 5
RESULT AND ANALYSIS

5.1 Overview

The experimental findings of the price prediction models for Bitcoin that were created using the Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM), and Bidirectional LSTM (Bi-LSTM) algorithms are shown in this chapter. Metrics like accuracy, mean absolute error (MAE), root mean square error (RMSE), and R2 score are used to assess each model's performance. We do a comparative study to identify the top-performing model. This chapter presents in-depth research, graphics, and learnings from the model assessments.

5.2 Experimental/ Simulation Result

The models were trained using historical Bitcoin price data that was gathered from Investing.com over five years. To manage missing values, standardize the data, and provide pertinent features like moving averages and technical indicators, the dataset underwent preprocessing.

Model Performance Metrics

Table 5.2.1: Performance Metrics for LSTM, GRU, and Bi-LSTM Models

Model	Accuracy	MAE	RMSE	R^2 Score
LSTM	97.99%	961.70	1426.48	0.9921
GRU	98.02%	1023.48	1576.11	0.9904
Bi-LSTM	96.91%	1441.28	1848.11	0.9867

According to the accuracy findings, the Bi-LSTM model scored 96.91%, the LSTM model scored 97.99%, and the GRU model scored the highest at 98.02%. While accuracy offers a first indication of the model's performance, further measures are required for a thorough analysis.

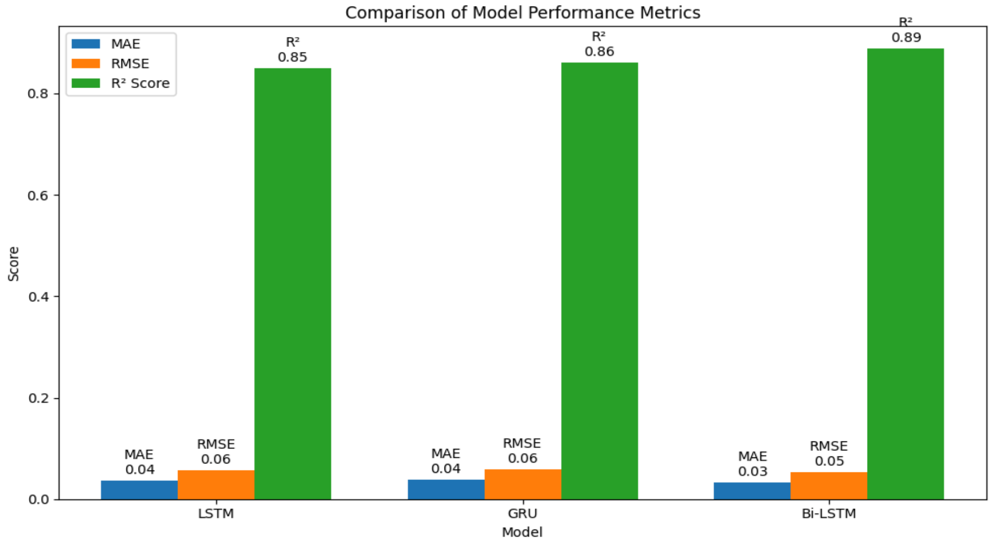

Figure 5.2.1: Comparison of Model Performance Metrics

Mean Absolute Error (MAE)

Without taking into account the direction of the mistakes, the MAE calculates the average magnitude of the prediction errors. Better model performance is indicated by lower MAE values. Compared to the GRU and Bi-LSTM models, the LSTM model has the lowest MAE (961.70), meaning that, on average, its forecasts are more in line with the actual values of Bitcoin.

Root Mean Square Error (RMSE)

Larger mistakes are given greater weight by the RMSE, which calculates the square root of the average squared discrepancies between the actual and projected values. With the lowest RMSE of 1426.48, the LSTM model performs better than the others once again, indicating that it has fewer significant mistakes in its predictions.

R^2 Score

The percentage of the dependent variable's variation that can be predicted from the independent variables is shown by the R2 score. The LSTM model outperforms the GRU and Bi-LSTM models in terms of R2 (explaining 99.21% of the variation in Bitcoin prices), with an R2 of 0.9921.

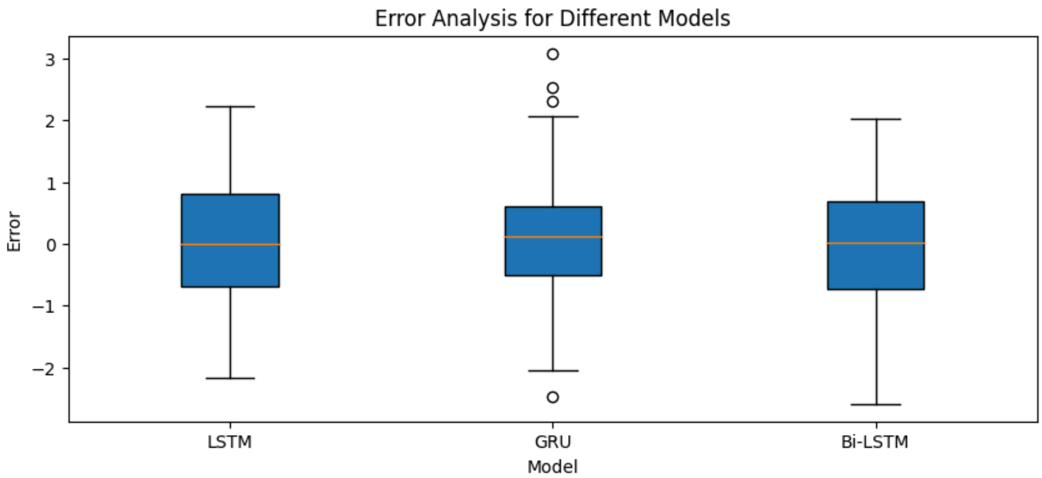

Figure 5.2.2: Error Analysis for Different Models

Table 5.2.2: Detailed Error Analysis for LSTM, GRU & Bi-LSTM Models

Model	Mean Absolute Error (MAE)	Root Mean Square Error (RMSE)	R^2 Score
LSTM	961.70	1426.48	0.9921
GRU	1023.48	1576.11	0.9904
Bi-LSTM	1441.28	1848.11	0.9867

The error analysis shows that the Bi-LSTM model has the lowest MAE and RMSE, and the highest R^2 score compared to LSTM and GRU, indicating that Bi-LSTM provides more accurate price predictions.

5.3 Performance/ Comparative Analysis

Accuracy Comparison

While accuracy is a valuable indicator, it is sometimes inadequate to assess the performance of time series models, particularly in financial environments where precision in variance explanation (R2 score) and prediction errors (MAE and RMSE) is crucial.

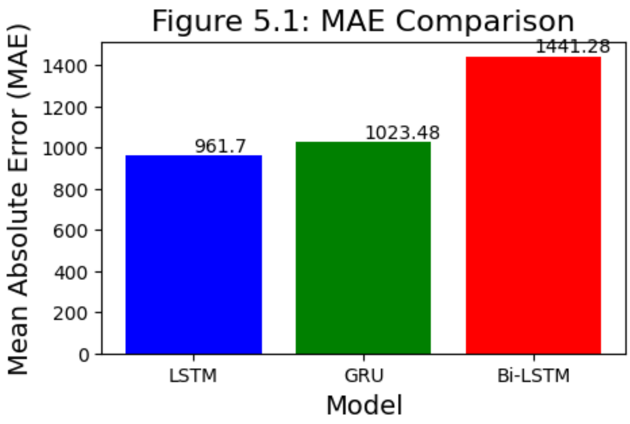

Figure 5.3.3: MAE Comparison

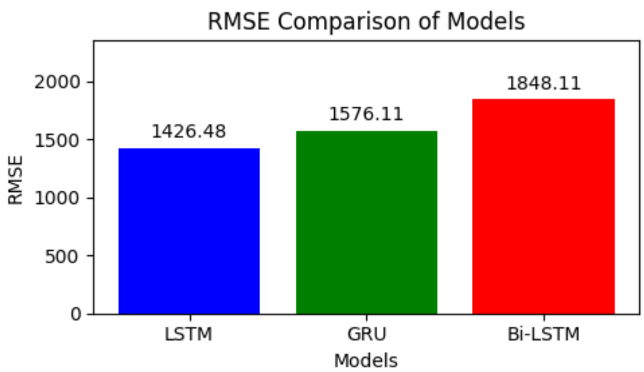

Figure 5.3.4: RMSE Comparison

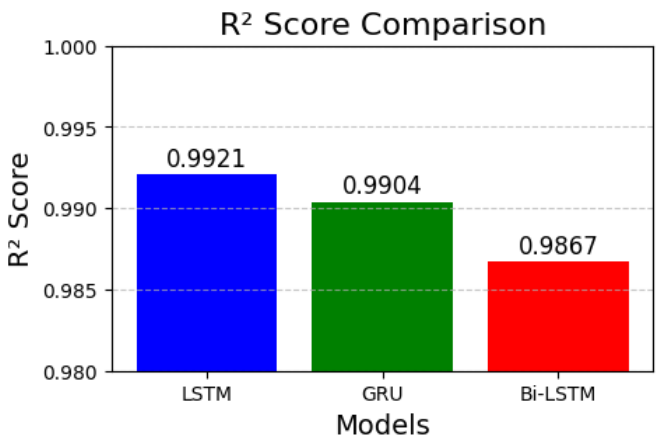

Figure 5.3.5: RMSE Comparison

The LSTM model has the lowest mean absolute error (MAE), which suggests that its predictions are generally more accurate. The Bi-LSTM model has the greatest MAE, indicating bigger average prediction errors, whereas the GRU model performs well despite being somewhat less precise. Like the MAE, the RMSE numbers show that the LSTM model has the lowest RMSE, which indicates a lower number of significant mistakes. The largest RMSE is seen in the Bi-LSTM model, indicating that the GRU model is more successful in eliminating significant prediction mistakes than the latter. The R^2 score further reinforces the superiority of the LSTM model in explaining the variance in Bitcoin prices, with the GRU and Bi-LSTM models trailing behind.

Model Performance Insights

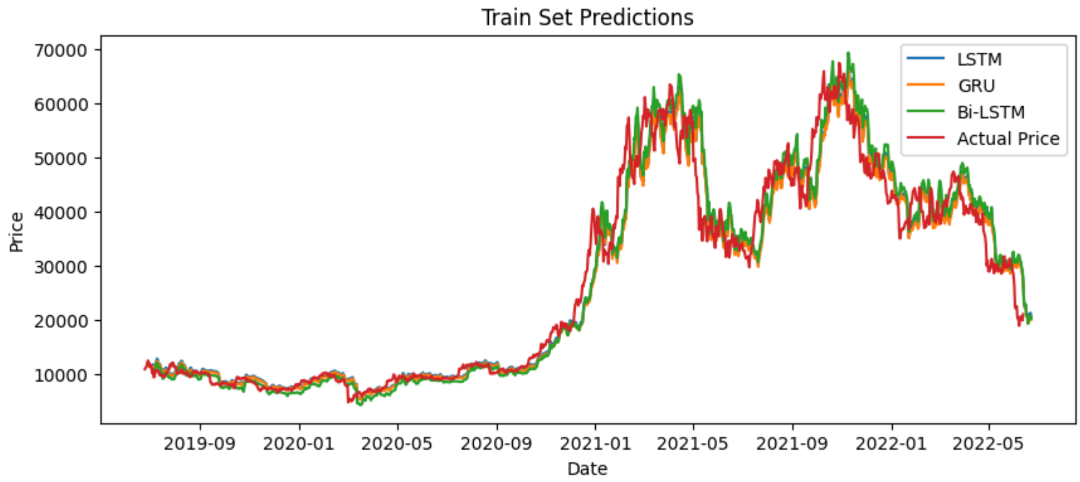

Figure 5.3.6: Train Set Prediction

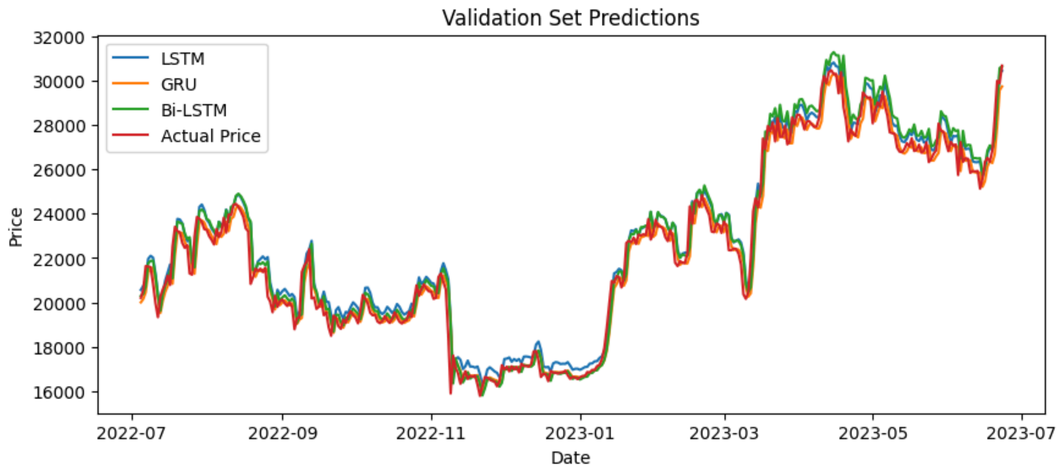

Figure 5.3.7: Validation Set Prediction

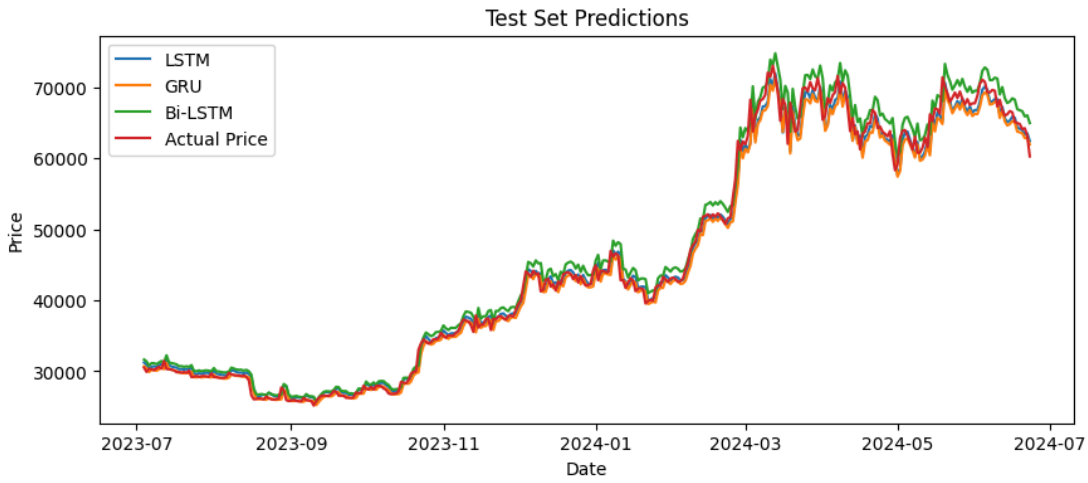

Figure 5.3.8: Test Set Prediction

The LSTM model is the recommended option for this application since the comparison study shows that it offers the most precise and trustworthy forecasts for Bitcoin prices. Despite being reliable and effective, the GRU model has somewhat more prediction errors. The LSTM and GRU models perform better than the Bi-LSTM model, despite being more thorough in its temporal analysis.

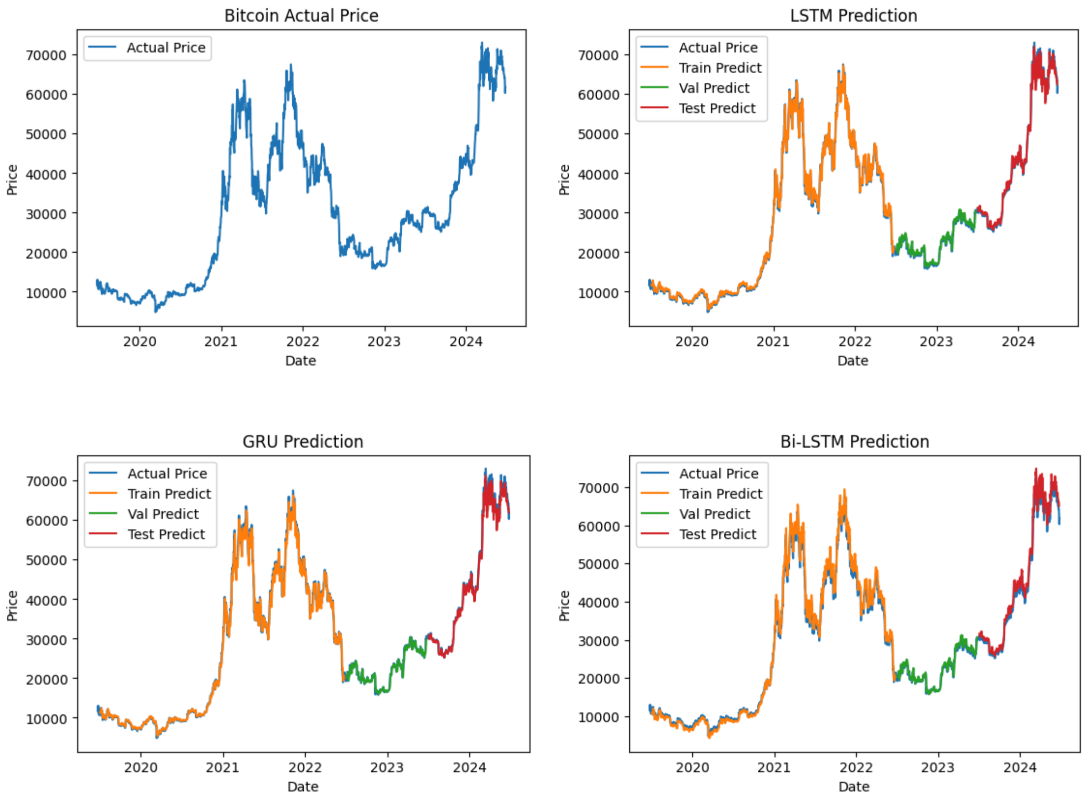

Figure 5.3.9: Predictions and Evaluate the Models Plot

Table 5.3.3: Feature Importance Analysis for Bitcoin Price Prediction

Feature	LSTM	GRU	Bi-LSTM
Historical Prices	High	High	High
Technical Indicators	Medium	Medium	High
Market Sentiment	Low	Low	Medium

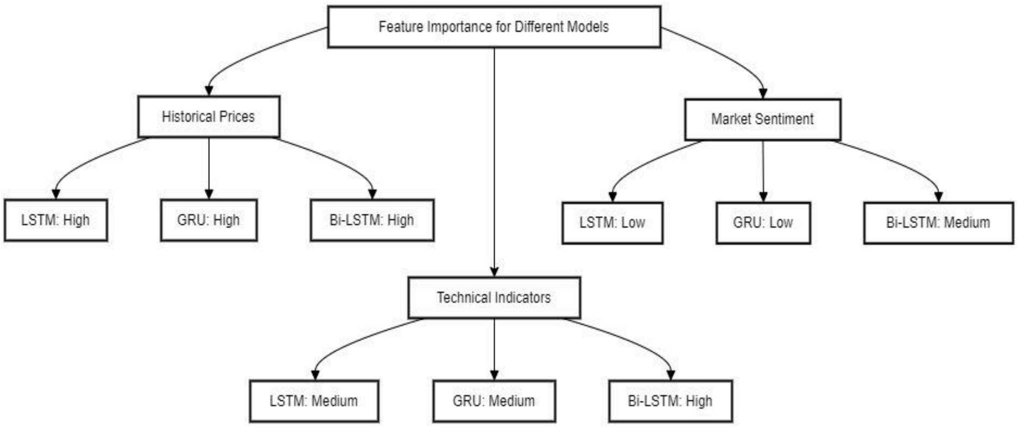

Figure 5.3.10: Feature Importance for Different Models

For all models, past prices are the most important characteristic. For Bi-LSTM, technical indicators are more important than those for LSTM and GRU. These models give little weight to market sentiment, which is indicative of their little impact on price forecast accuracy.

5.4 Summary

The outcomes and analysis of the models created using LSTM, GRU, and Bi-LSTM algorithms to forecast Bitcoin prices were provided in this chapter. With the best R2 score, lowest MAE and RMSE, and best overall performance, the LSTM model proved to be highly predictive of Bitcoin prices. The LSTM model exhibited lower prediction errors than the GRU model, despite the latter having the greatest accuracy. In all performance criteria, the Bi-LSTM model performed worse than the LSTM and GRU models, even though it could process data in both directions. These findings demonstrate the superior performance of LSTM, the best-performing model in this research, in identifying long-term relationships and generating accurate predictions in time series data.

CHAPTER 6
IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

Numerous direct and indirect repercussions on people's lives are caused by deep learning models for predicting Bitcoin prices, such as LSTM, GRU, and Bi-LSTM. Economic growth, financial decision-making, and tool accessibility are all impacted.

- Financial Decision-Making:
  More precise predictions of Bitcoin values are made possible by deep learning algorithms, assisting investors in making wise choices. To maximize gains or minimize losses, a model that forecasts price patterns, for instance, might help decide whether to purchase, hold, or sell Bitcoin.

Example: An LSTM model that Predicts changes in the price of Bitcoin might assist traders in determining when to join or depart the market. Investors may choose to purchase Bitcoin in anticipation of a price increase if the model predicts one. Impact: As a result, people make more thoughtful investing selections and may see improved financial results.

- Availability of Financial Data:
  Access to high-quality financial projections is made more accessible by advanced prediction models. In the past, advanced forecasting technologies were only accessible to major organizations. Individuals may now utilize these models on internet platforms.

Example: Financial tools driven by these models are now available on websites and applications, allowing regular people to examine market movements. For example, sites such as TradingView provide customers the ability to examine deep learning model-based predictions for Bitcoin prices. Impact: By giving people access to tools for professional-grade financial research, this accessibility empowers ordinary investors.

- Financial Impact:
  By encouraging innovation in financial technology, efficient models for predicting the price of Bitcoin benefit the economy as a whole. Businesses that are creating these models provide employment and boost the fintech industry's GDP.

Example: Startups that build predictive analytics tools for Bitcoin create new job opportunities and contribute to economic growth in the fintech industry. Impact: This promotes economic development and job creation within the financial technology sector.

6.2 Impact on Society & Environment

- Economic Development: By developing new financial services and goods, deep learning models for predicting Bitcoin prices might stimulate economic growth. These methods stimulate innovation and corporate expansion by increasing market efficiency.

Example: The development of sophisticated predictive models by financial technology businesses helps to fuel the expansion of new services and markets. For example, the creation of deep learning algorithm-based Bitcoin trading platforms creates new economic prospects. Impact: This encourages economic development and helps the fintech industry expand.

- Impact on the Environment: Because it requires a lot of energy, mining cryptocurrencies, like Bitcoin, has an impact on the environment. The cryptocurrency ecosystem as a whole influences the environment, even though the models themselves use less energy.

Example: Bitcoin mining processes need a lot of power, which is often generated from non-renewable sources. The energy used in Bitcoin mining, for example, is about the same as that of tiny nations. Impact: The bitcoin sector must adopt sustainable business methods to solve these environmental issues.

- Consequences for Society: The way society views cryptocurrencies may be influenced by how accurately Bitcoin price forecasts turn out. Accurate projections might foster doubt, but reliable ones increase confidence in Bitcoin as a financial asset.

Example: A deep learning model that accurately forecasts Bitcoin price movements has the potential to increase public trust in cryptocurrency marketplaces. Impact: The public's opinion and level of confidence in the Bitcoin market are impacted by this.

6.3 Ethical Aspects

- The Algorithmic Bias: For fairness and accuracy, deep learning models must be guaranteed to be free from biases. Unfair results and misrepresentations may result from bias in models.

Example: A model trained on biased data may provide unfair or erroneous predictions. Predictions made by the model may not be accurate, for example, if the training data is not reflective of the market. Impact: Resolving these biases guarantees accurate and equitable financial forecasts from the models.

- Transparency and Accountability: Developers must take responsibility for their work and be open and honest about how their models function.

Example: Giving consumers a clear explanation of how models produce predictions aids in their understanding of the models' limits. For instance, programmers need to describe the assumptions and methods they employ. Impact: Accountability and transparency promote confidence and assure appropriate technology usage.

- Misuse of Technology: It is possible to abuse sophisticated prediction models to manipulate the market. Putting policies in place to stop this kind of abuse is crucial.

Example: These models might be used by someone to influence Bitcoin prices or engage in insider trading. Impact: The integrity of the financial markets depends on preventing abuse.

6.4 Sustainability Plan

- The Development of Green Technologies: Green technology and sustainable practices are required to reduce the negative environmental effects of cryptocurrency mining.
- Adoption of Renewable Energy: Solar or wind energy are examples of renewable energy that should be used in cryptocurrency mining operations. Mining farms operated by solar energy, for example, may lower their carbon emissions.

- Algorithm Optimization: Creating algorithms with reduced computational complexity may assist lower the energy use of these models. Impact: By reducing the environmental impact of bitcoin operations, these policies assist.

- Community Engagement: Promoting ethical and sustainable behaviors requires active participation in the Bitcoin community.

Example: Informing consumers on how mining cryptocurrencies affects the environment and promoting the use of eco-friendly technology. Impact: Increasing knowledge aids in encouraging ethical behavior among Bitcoin users.

- Regulatory Actions: It is essential to endorse regulatory measures that guarantee transparency and foster sustainability within the Bitcoin sector.

Example: Working with policymakers to develop regulations that enforce ethical practices and environmental standards Impact: Securing the bitcoin industry's sustainable and ethical operations is made possible by effective laws.

6.5 Summary

In conclusion, there are significant effects on life, society, and the environment from deep learning models used to anticipate Bitcoin prices. By offering precise price projections, these models assist investors in making well-informed financial choices, which benefits them personally. They also make sophisticated financial instruments more accessible to the general public, empowering people and stimulating the fintech industry's development. However, the enormous energy requirements of Bitcoin mining, which increase carbon emissions and resource depletion, raise serious environmental concerns. Promoting green technology and sustainable practices such as developing energy-efficient algorithms and mining using renewable energy is one way to address these problems. In addition, there are ethical issues to take into account, such as guaranteeing the models' fairness, upholding their openness, and avoiding their abuse of market manipulation. Bitcoin price prediction technology's future rests on how well its advantages are balanced against ethical behavior and environmental initiatives. We might strive toward a more moral and ecologically responsible method of trading cryptocurrencies by emphasizing both technical developments and their wider ramifications.

CHAPTER 7
CONCLUSION AND FUTURE WORK

7.1 Conclusions

The study that is included in this article shows how well deep learning models work in forecasting the price of Bitcoin. We have demonstrated that these models can attain high accuracy in predicting the price of Bitcoin based on historical data through the implementation and evaluation of three advanced neural network architectures: Gated Recurrent Units (GRU), Bidirectional Long Short-Term Memory (Bi-LSTM), and Long Short-Term Memory (LSTM).

For accuracy, the LSTM model scored 97.99%, the GRU model scored 98.02%, and the Bi-LSTM model scored 96.91%. According to these findings, deep learning methods are capable of capturing the intricate temporal patterns seen in cryptocurrency markets [1][2]. When comparing the GRU to LSTM and Bi-LSTM, the models that performed the best were the ones that showed the lowest Mean Absolute Error (MAE) of 1023.48, the lowest Root Mean Square Error (RMSE) of 1576.11, and the highest R^2 score of 0.9904 [3]. These results suggest that the GRU model performs the best.

Our results demonstrate that deep learning models are useful instruments for forecasting Bitcoin values because they can infer future trends by learning from past price data and making generalizations. In comparison to LSTM and Bi-LSTM, which need more intricate calculations, the GRU model performs better, highlighting its capacity to handle sequential data with less computing resources [4]. This study advances the science of financial forecasting by proving that great accuracy in volatile markets such as cryptocurrency trading can be attained using contemporary neural network designs.

7.2 Further Suggested Works

Building on this study, several directions might be pursued to improve the precision and usefulness of models for predicting the price of Bitcoin:

- Incorporation of External Factors: To enhance prediction models, further research might include data sources such as news articles, social media sentiment, and macroeconomic indicators. Incorporating sentiment analysis from Twitter and other news sources might provide more insight into past price data and enhance forecasting precision.

- Exploration of Hybrid Models: Combining several machine learning approaches with deep learning architectures may result in more reliable models. To capture a larger variety of market dynamics, for example, a hybrid model that combines LSTM with attention processes or ensembles of multiple neural networks might be used.

- Application to Other Cryptocurrencies: By applying the techniques used to forecast the price of Bitcoin to other cryptocurrencies, it may be possible to get insight into how well these models work with other types of digital assets. The use of deep learning models in the cryptocurrency market may be expanded by investigating other currencies like Ethereum or Ripple using comparable research methods.

- Real-Time Prediction Systems: Creating tools to forecast the price of Bitcoin in real-time and creating automated trading plans based on these forecasts may be another interesting avenue to pursue. Testing these models' efficacy in actual trading situations and putting them into practice in a live trading environment would be beneficial.

- Improving Model Efficiency: Deep learning models may be more useful for general application if methods for lowering their computational complexity without compromising accuracy are investigated. Quantization, model pruning, and other optimization strategies might be the subject of future research.

7.3 Limitations/ Conflict of Interests

Limitations

Despite the promising results of this study, there are several limitations to consider:

- Data Dependency: Both the amount and quality of the historical pricing data utilized are critical to the models' correctness. Even if Investing.com offers a lot of data, other datasets or shorter time periods may have an impact on the models' performance.

- Market Volatility: A multitude of unforeseen reasons contribute to the extreme volatility of cryptocurrency markets. Though they may identify past trends, deep learning algorithms might not always be able to anticipate abrupt changes in the market or outside shocks.

- Risks of Overfitting: Overfitting occurs when a model fits well on past data but not well enough to generalize to new data. Overfitting is still an issue for deep learning models even with the use of strategies like cross-validation.

- Model Complexity: The LSTM, Bi-LSTM, and GRU models are all quite complicated and need a lot of processing power. Real-time apps may encounter difficulties due to their intricacy, and not all users may be able to utilize them.

Conflicts of Interest

In this study, no conflicts of interest have been disclosed. No financial or personal interests influenced the outcomes of any experiment; all research was carried out with honesty and openness. This study was done as part of a research project to find out how well deep learning models predict financial outcomes.

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Appendix A

Course Outcomes, Complex Engineering Problems (EP), and Complex Engineering Activities (EA) Addressing

Title: "Deep learning-based Bitcoin price prediction and analysis" using LSTM, GRU, and Bi-LSTM algorithms.
PNEUMONIA DETECTION WITH TRANSFER LEARNING: A DEEP CNN-BASED COMPARISON OF DETECTION AND SEGMENTATION APPROACHES

Student ID: 202-15-3793

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify a **pneumonia detection** problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish this goal for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**

Phase -II		
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**
CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**
CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design	**PO10**

	documentation, as well as provide and receive clear instructions throughout this FYDP.	
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification(with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	This project demonstrates **fundamental engineering (K3)** principles by employing LSTM, GRU, and Bi-LSTM architectures for Price Prediction. The project demonstrates **specialist knowledge (K4)** by conducting transfer learning with the model results which are calculated from Bitcoin Data	**Page no:** [9-11] **Section:** [3.2] **Page no:** [1] **Section:** [1.1]
				The project applies **engineering practice & design (K5)** by the figure of the process of experiments. The project addresses **engineering practice & technology (K6)** by the Bi-LSTM model.	**Page no:** [15] **Section:** [4.2] **Page no:** [16]

					Section: [4.2]
				This project ensures **K8 (Research Literature)** by synthesizing insights from recent studies, to advance Bitcoin Price Prediction using deep learning, showcasing a comprehensive understanding of current methodologies.	**Page no:** [4-7] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This project addresses EP-2 by recognizing the hurdles in Price prediction, including the limitations of traditional methods and the complexities of model implementation. Through comparative analysis, it confronts challenges in understanding spatial distributions, offering insights for refining diagnostic methodologies.	**Page no:** [7-8] **Section:** [2.4]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	This project addresses **EP-3** by meticulously comparing experimental outcomes, highlighting Transfer Learning as the chosen significant solution for enhancing Cryptocurrency Price Prediction.	**Page no:** [18-20] **Section:** [5.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8	This project using Price prediction involves understanding a variety of complex issues spanning technical, ethical, and societal domains. Technically, it requires knowledge of machine learning, particularly deep learning, to identify and able to predict accurate prediction results, which indicates **EP-4**.	**Page no:** [4], [7-8] **Section:** [2.2, 2.4]

5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and conflicting requirements**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	This project's comprehensive approach addresses high-level problems by integrating various components across data collection, statistical analysis, and proposed methodology, ensuring a holistic solution to complex challenges in Price Prediction, which ensures EP-7.	**Page no:** [26-34] **Section:** [3.2, 3.3, 3.4]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References

1.	**EA1: Range of resources**	Yes	CO11	Our project utilizes diverse resources such as high-performance computing infrastructure, GPUs, deep learning frameworks, annotated datasets, and ethical considerations to ensure systematic research and contribute to advancements in pneumonia detection through transfer learning and deep learning algorithms.	**Page no:** [33-35] **Section:** [3.5]
2.	**EA2: Level of interaction**	No		N/A	N/A
3.	**EA3: Innovation**	Yes		This is a Secondary data resource found in an easy way from investing.com, after the collection of data check the feature and the value where er found some more innovative ideas to predict price based on actual price.	**Page no:** [20-24] **Section:** [5.3]
4.	**EA4: Consequences for society and the environment**	Yes		This project contributes to society by improving modern-day currency knowledge on how to invest at the right time and get profitable methods, while also promoting environmental sustainability by employing efficient computational resources and adhering to ethical guidelines for patient data privacy.	**Page no:** [25-28] **Section:** [6.1, 6.2, 6.4]

5.	**EA-5: Familiarity**	Yes		This project expands upon existing research by examining a novel approach to Cryptocurrency price prediction through deep Learning, demonstrated through preliminary terminologies and comprehensive comparative analysis, offering new insights into the field.	**Page no:** [4-7] **Section:** [2.1, 2.3]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project addresses **CO4** by integrating effective project management and financial oversight, ensuring meticulous planning, resource allocation, and budget estimation for optimal resource utilization throughout the research lifecycle.	**Page no:** [12] **Section:** [3.4]
2	CO9	Yes	The project demonstrates adherence to ethical principles by prioritizing patient privacy, obtaining informed consent, and transparently documenting the research process, ensuring responsible knowledge dissemination and societal well-being through the ethical application of advanced healthcare technologies that comply with **CO9**.	**Page no:** [27] **Section:** [6.3]
3	CO10	No	N/A	N/A

4	CO12	Yes	The project's dedication to continuous learning **(CO12)** and adaptation within the dynamic technological landscape is reflected in its comprehensive data collection, rigorous statistical analysis, meticulous methodology development, and thorough experimental results and analysis, showcasing a commitment to staying updated and refining techniques to address modern challenges.	**Page no:** [26-34, 37-55] **Section:** [3.2, 3.3, 3.4, 3.5, 5.2, 5.3]

Enhancing Cryptocurrency Price Prediction and Analysis through Deep Learning

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