A FIELD PROJECT REPORT

on

"Predicting The Future of CRYPTO Using Machine Learning"

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CERTIFICATE

This is to certify that the Field Project entitled "**Predicting The Future of CRYPTO using Machine Learning** " is being submitted by 221FA04447 (Nimmagadda Sree Vijay), 221FA04492 (Bollimuntha.Ankamma Rao), 221FA04513 (Shaik Basheer Ali), and 221FA04514 (Vaka. Ravi Teja) in partial fulfilment of the requirements for the Field Project coursework. This project represents our original work and has not been submitted as the basis for the award of any degree. The project was conducted under the supervision of Dr. S.Deva Kumar, Associate Professor, Department of CSE

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DECLARATION

We hereby declare that the Field Project entitled "**Predicting The Future of CRYPTO using MachineLearning**"is being submitted by221FA04447(Nimmagadda.Sree Vijay),221FA04492 (Bollimuntha.Ankamma Rao), 221FA04513 (Shaik Basheer Ali), and 221FA04514 (Vaka. Ravi Teja) in partial fulfilment of the requirements for the Field Project coursework. This project represents our original work and has not been submitted as the basis for the award of any degree. The project was conducted under the supervision of Dr.S.Deva Kumar, Associate Professor, Department of CSE.

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ABSTRACT

The crypto currency is also known as the Digital Currency which acts as saving in digital world. The Crypto currencies are of various types , like Bit-coin (BTC), Ethereum (ETH), Aave (AAVE), Near Protocol (NEAR), Tonix(TON), Stacks (STX), Cronos (CRO), Win Coins(W-COIN), XRP Coin, Litecoin(LTC), Avalanche Coin (AVAX),Hamster(HAM),DOGS,Xmpire(XMP),Ton(TON)(etc. To get the right prediction We selected a best dataset and performed Some machine learning algorithms like Linear-Regression, Lasso Regression, KNN ,Decision Trees, Random Forests, and SRV to predict the which works the best of the top 5 crypto currencies like AAVE, Bitcoin, BNB, DOGE, ETH using these machine learning algorithms.

Keywords: Crypto price prediction , Random Forest, Support Vector Regression (SVM), Logistic Regression, KNN ,LASSO Machine Learning, Model Accuracy, Early Diagnosis

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CHAPTER-1
INTRODUCTION

INTRODUCTION

Cryptocurrencies became a main and a significant asset in the financial Sectors and Markets, with Bitcoin, Ethereum, and other digital currencies gaining substantial attention from investors, traders, and researchers. The decentralized nature, high volatility, and unique characteristics of cryptocurrencies distinguish them from traditional financial assets. With their increasing popularity, accurate prediction of cryptocurrency prices has become a focal point of interest for both academic research and practical trading strategies [1]. Despite the growth of the cryptocurrency market, predicting its price movements remains a challenging task due to its Instability in price and it also be influenced by different Situations such as sentimental marketing , Global market ,regulatory news, and technological developments [2]. Traditional financial models often fail or fall's short in capturing the Complicated Market , non-linear patterns observed in cryptocurrency price data [3]. This challenge has driven the exploration of advanced machine learning (ML) techniques, which promise improved forecasting accuracy by leveraging historical data and capturing intricate patterns [4]. Accurate price prediction models can offer valuable info for the investors and traders, Making them to make the best decisions and avoiding the risks more effectively [5].Autoregressive Integrated Moving Average (ARIMA) models, and other predictive algorithms, have shown promise in addressing the limitations of traditional methods [6]. By applying these advanced techniques to cryptocurrency price forecasting, this main aim for this study is to contribute to more advanced and best prediction Tools [7]. The study will focus on predicting the prices of selected cryptocurrencies, such as Bitcoin, Ethereum, AAVE, DOGECOIN, and BNB, using historical price data and relevant features. The research will involve data collection from reputable sources, preprocessing and feature engineering, and the application of various predictive models. The results will be evaluated using standard performance metrics.[8]
Key features of cryptocurrencies include:

• **Decentralization**: This fundamental principle allows for peer-to-peer transactions without intermediaries, reducing the risk of fraud and enhancing security.

• **Volatility:** Cryptocurrency markets are known for their high and rapid changes in the prices. Factors contributing to this volatility include market sentiment, speculative trading, technological developments, and macroeconomic trends.

- **Limited Historical Data:** The relatively short history of cryptocurrencies presents challenges for traditional financial modelling. Many cryptocurrencies have only a few years of price data, making it difficult to identify long-term trends.

CHAPTER-2
LITERATURE SURVEY

LITERATURE SURVEY

2.1Overview of Cryptocurrency Characteristics

Cryptocurrency price prediction has garnered significant interest due to the unique characteristics of digital currencies, including high volatility, decentralized nature, and the influence of various external factors [9]. Traditional financial models, such as time series forecasting methods, have been adapted to predict cryptocurrency prices, but often the Find itself hard in handling the non-linear and dynamic nature of the market [10].

2.2 Traditional Financial Models

2.2.1 ARIMA Models

ARIMA Models: This Models are being used From long time for their ability to capture linear relationships and temporal dependencies in data. Studies such as Box et al. (2015) have demonstrated the effectiveness of ARIMA in various financial forecasting scenarios [11]. However, the ARIMA model often falls short in handling the volatility and non-stationarity typical of cryptocurrency prices, as noted by Gade et al. (2018) [12].

2.3 Machine Learning Techniques

2.3.1 Early Machine Learning Approaches

Machine Learning Techniques: Early studies explored machine learning techniques like Linear Regression and Decision Trees for cryptocurrency price prediction. These models offer a straight forwarded approach but it failed in the complex market data [13].

2.3.2 Ensemble Methods

Ensemble Methods: Ensemble methods like Gradient Boosting regression and Random Forest regression have shown promise in improving prediction accuracy for the complex Market Solutions. These models combine multiple decision trees to capture Hard patterns and interactions present in data. Research by Choudhury and Bandyopadhyay (2020)demonstrated the effectiveness of these methods in financial forecasting [14].

Contrary to previous studies that favour ensemble methods for capturing complex market dynamics (e.g., Choudhury and Bandyopadhyay, 2020) [14], our results indicate that simpler models like Linear Regression and Lasso regression achieved higher prediction accuracy for cryptocurrency prices. This discrepancy highlights the potential for simpler models to be effective under certain conditions and suggests that model selection should be closely aligned with data characteristics."

2.4 Technical Indicators

Technical Indicators: The indicators, like SMA and EMA, Relative Strength Index (RSI), and Moving Average Convergence Divergence (MACD), are frequently used in machine learning models to enhance prediction accuracy. Research by Liao et al. (2021) demonstrated that incorporating technical indicators into machine learning models improves prediction performance by providing additional context about market conditions [15].

While various methods and models have been explored for cryptocurrency price prediction, challenges remain in capturing the market's volatility and non-linear behaviour. Existing research highlights the high reliability on advance machine learning techniques, such as LSTMs and ensemble methods, in improving prediction accuracy. However, there is still a need for further exploration into the integration of multiple data sources, such as technical indicators and market sentiment, to enhance predictive performance.

CHAPTER-3
METHODOLOGY

METHODOLOGY

There is a Specific Methodology to do the Prediction of crypto like starting with data collection, data cleaning, data Pre-Processing Then Model Selection and finally training and testing the data.

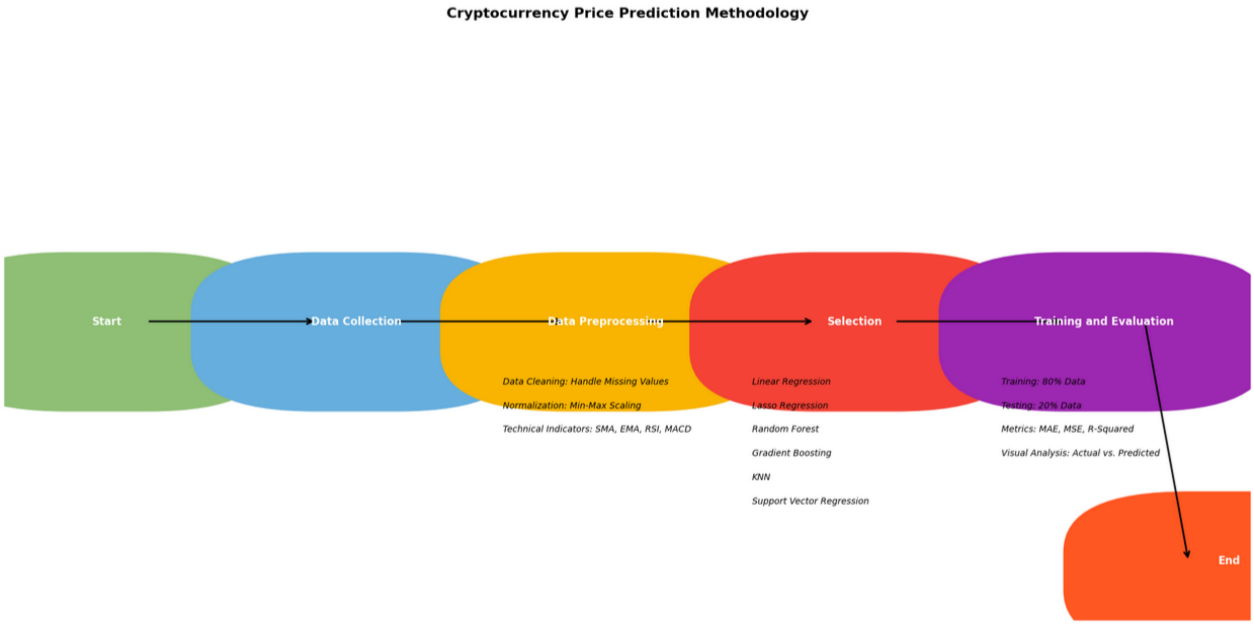

Figure 1: FLOW CHART Of Methodology

3.1 Data Collection

Data collection is a fundamental step in building predictive models for cryptocurrency prices, as the quality and relevance of the data directly impact the accuracy of the predictions. This study focuses on a selection of prominent cryptocurrencies: Bitcoin, Ethereum, AAVE, Dogecoin, and BNB. These cryptocurrencies were chosen due to their significant market presence, trading volume, and investor interest, making them suitable candidates for predictive analysis.
The data is sourced from reputable cryptocurrency exchanges and financial data aggregators, such as Binance, Coinbase, and Coin Market Cap, ensuring both accuracy and reliability. The historical data spans multiple years, providing a robust dataset for analysis and modelling.

3.1.1 Dataset Elements

The dataset comprises several key elements necessary for comprehensive analysis:
Open: The price at which the cryptocurrency opened for trading on a given day. This price will be used as a baseline for the price changes.
High: The highest price reached during that day, indicating market peaks and potential resistance levels.
Low: The Least price reached during the trading day, reflecting market dips and potential support levels.
Close: The price at the end of the day, crucial for trend analysis.

Volume: The total trading volume of the cryptocurrency for the day, which indicates market activity and liquidity. High trading volumes often correlate with increased market interest and volatility.
These elements are crucial for modelling price movements and understanding market dynamics.

3.2 Data Preprocessing

It is essential for Readying the dataset for analysing the data and train and test the data of the model . It involves multiple steps designed to improve data quality and ensure the integrity of the subsequent analysis.

3.2.1 Data Cleaning

The raw dataset is meticulously examined for any Empty cells in dataset, the data outside the exceeding minimal data, and inconsistencies that could compromise the equality of dataset
Missing Values: These are addressed using interpolation techniques, which estimate missing values based on existing data points. For example, linear interpolation fills in missing values by connecting data points with straight lines.

3.2.2 Normalization

It is a method applied to a for data for scaling between the values between 0to1 This step is crucial for ensuring that features helping the training model to equally perform , particularly in distance-based algorithms.
Min-Max Normalization: This technique rescales the dataset by transforming each feature XXX to a range between 0 and 1 using the formula:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

This makes sure that any feature does not misguide the model due to its scale.

3.2.3 Technical Indicator Calculation

To enhance model input, several technical indicators are computed to provide additional insights into market conditions:

- **Simple Moving Averages (SMA)**: Calculated over various windows to identify trends, SMA smooths price data to highlight longer-term trends while minimizing the noise associated with short-term fluctuations.

$$\mathrm{SMA} = \frac{X_1 + X_2 + X_3 + \ldots + X_n}{n}$$

- **Exponential Moving Averages (EMA)**: Responses for the price change which has happened recently, EMA provides a dynamic view of price trends by assigning greater weight to more recent prices.

$$\text{EMA} = (\text{Current Price} \times K) + (\text{Previous EMA} \times (1 - K))$$

Where:

- $K = \frac{2}{n+1}$ (where n is the number of periods).

- **Relative Strength Index (RSI)**: This momentum oscillator gauges the rate and magnitude of price changes. RSI values vary between 0 and 100; typically, values exceeding 70 suggest that an asset may be overbought, while values below 30 indicate it may be oversold.

$$\text{RSI} = 100 - \left(\frac{100}{1 + \text{RS}}\right)$$

- **Moving Average Convergence Divergence (MACD)**: This one analyzes momentum and direction of price movements, aiding in trend identification. It calculated by 12-p EMA Getting Subtracted from the 26-P EMA and is often accompanied by a signal line to identify buy and sell signals.

$$\text{MACD} = \text{EMA}_{12} - \text{EMA}_{26}$$

$$\text{Signal Line} = \text{EMA}_9(\text{MACD})$$

$$\text{MACD Histogram} = \text{MACD} - \text{Signal Line}$$

3.3 Model Selection

Various models are selected for training and evaluation based on their effectiveness in predicting time series data. Each model is chosen for its unique strengths in handling the complexities of cryptocurrency price movements. The following machine learning models are utilized for prediction:

3.3.1 Linear Regression

Linear Regression serves as a baseline model for predicting future prices. A Linear relationship is engaged between the Target(CLOSE PRICE) and input features (technical indicators and historical prices). Despite its simplicity, it provides a foundational understanding of the predictive power of the selected features.

3.3.2 Lasso Regression

Lasso Regression serves as a baseline model for predicting future prices. A Linear relationship is engaged between the Target(CLOSE PRICE) and input features (technical indicators and historical prices). Despite its simplicity, it provides a foundational understanding of the predictive power of the selected features.

3.3.3 Random Forest

Random Forest is a method that uses multiple Decision Trees To achieve the improved performance. As the deep decision trees have the variance value high by using the random forest, we average them into different portions and use them.

3.3.4 Gradient Boosting

Gradient Boosting Machines (GBM) build models sequentially, where the previous model’s mistakes (or) Errors are rectified . This technique enhances prediction accuracy by combining the strengths of multiple models. GBM is best for handling the datasets which are Complicated with intricate relationships among features.

3.3.5 KNR

It is a supervised learning algorithm used for predicting continuous, numerical values. It works by identifying the KKNear data points (neighbours) to a given input, based on a chosen distance metric (like Euclidean distance), and then predicting the output as the.

3.3.6 Support Vector Regression (SVR)

It is a type of regression technique based on the SVM framework. While SVM is Basically used for classification, SVR adapts it for regression tasks, aiming to predict continuous values by finding a hyperplane (or a "tube" around it) that best fits the data.

3.4 Model Training and Evaluation

Model training and evaluation are Made to check the performance and why it is best of the selected models.

3.4.1 Training and Testing

The dataset is made into 2 parts one is Training and one is Testing. The Ratio can be 80% and 20% (or) 70% and 30%, The trained dataset is used For training and testing is used to test the data similar to trained data but which are not present to predict.

3.4.2 Performance Metrics

To evaluate model performance, several metrics are employed:

- **Mean Absolute Error (MAE)**: It helps to find the magnitude average of the errors in the test prediction. It is similar like accuracy but should be low

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i|$$

- **Mean Squared Error (MSE)**: Squares the errors before averaging, penalizing larger errors more heavily. This is useful for understanding the model's performance in relation to significant price movements.

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

- **R-Squared** : It is same like the Accuracy, helps to find how good the Model performs

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}$$

3.4.3 Visual Analysis

Visual analysis involves plotting actual versus predicted prices to assess the model's performance visually. This allows for a clear understanding of how well the models capture price movements over time. Graphical representations, such as line charts, provide immediate insights into the model's predictive power and highlight areas where improvements are necessary.

CHAPTER 4
RESULTS AND DISCUSSION

RESULTS AND DISCUSSION

4.1 Model Performance Comparison

4.1.1Bitcoin

Table 1:-Bitcoin Model performance

1. Bitcoin (BITCOIN.csv)

Model	MSE	MAE	R-squared
Linear Regression	0.00115	4826.82	99.90
Random Forest	0.00562	10297.03	99.53
Lasso Regression	0.00109	4837.52	99.91
Gradient Boosting	0.00238	7132.47	99.80
KNN	0.00391	7438.83	99.67
SVR	1.49940	196837.83	-24.99

The Linear Regression model received the lowest MSE of 0.00115 and the highest R^2 value of 99.90, indicating its effectiveness in capturing the underlying trend of Bitcoin prices. Lasso Regression also demonstrated strong performer, with a MSE of 0.00109 and an R-squared value of 99.91, making it a close competitor.

4.1.2 AAVE

Table 2: AAVE Model performance

Model	MSE	MAE	R-squared
Linear Regression	0.00003	1232.81	98.94
Random Forest	0.00008	1868.00	96.82
Lasso Regression	**0.00003**	**1214.54**	**98.97**
Gradient Boosting	0.00005	1502.52	98.13
KNN	0.00006	1522.88	97.83
SVR	0.00212	12133.89	19.31

The Lasso Regression model emerged as the best performer alongside Linear Regression, achieving an MSE of 0.00003. Both models maintained high R-squared values, expressing the proportion of variance.

4.1.3 **Binance Coin (BNB)**

Table 3: BNB Model performance

Model	MSE	MAE	R-squared
Linear Regression	0.00001	373.27	99.81
Random Forest	0.00003	665.38	99.17
Lasso Regression	**0.00001**	**369.61**	**99.80**
Gradient Boosting	0.00001	462.85	99.67
KNN	0.00002	511.05	99.34
SVR	0.00098	5395.28	69.00

Both Linear Regression and Lasso Regression showed remarkable performance with the same MSE of 0.00001. The high R^2 values and low MAE confirm that these models effectively predict the price of Binance Coin, particularly highlighting the effectiveness of Lasso Regression.

4.1.4 Dogecoin

Table 4: DODGECOIN Model performance

Model	MSE	MAE	R-squared
Linear Regression	**0.00000**	**0.27**	**99.19**
Random Forest	0.00000	0.40	98.15
Lasso Regression	0.00000	6.08	-0.25
Gradient Boosting	0.00000	0.29	98.60
KNN	0.00000	3.27	64.96
SVR	0.00000	7.68	0.61

The Linear Regression model achieved the lowest MSE and a very low MAE, indicating that it is highly effective in predicting Dogecoin prices and significantly outperformed all other models.

4.1.5 Ethereum

Table 5: ETHEREUM Model performance

Model	MSE	MAE	R-squared
Linear Regression	**0.00025**	**2807.77**	**99.82**
Random Forest	0.00086	5681.54	99.36
Lasso Regression	0.00027	2859.81	99.80
Gradient Boosting	0.00045	4045.05	99.66
KNN	0.00060	3971.92	99.56
SVR	0.16859	81091.00	-25.56

Linear regression is the best performer from all the models with an MSE of 0.00025 and an R^2 value of 99.82, making it one of the most reliable models for Ethereum price prediction.

4.2 Visual Analysis

4.2.1 Model Performances

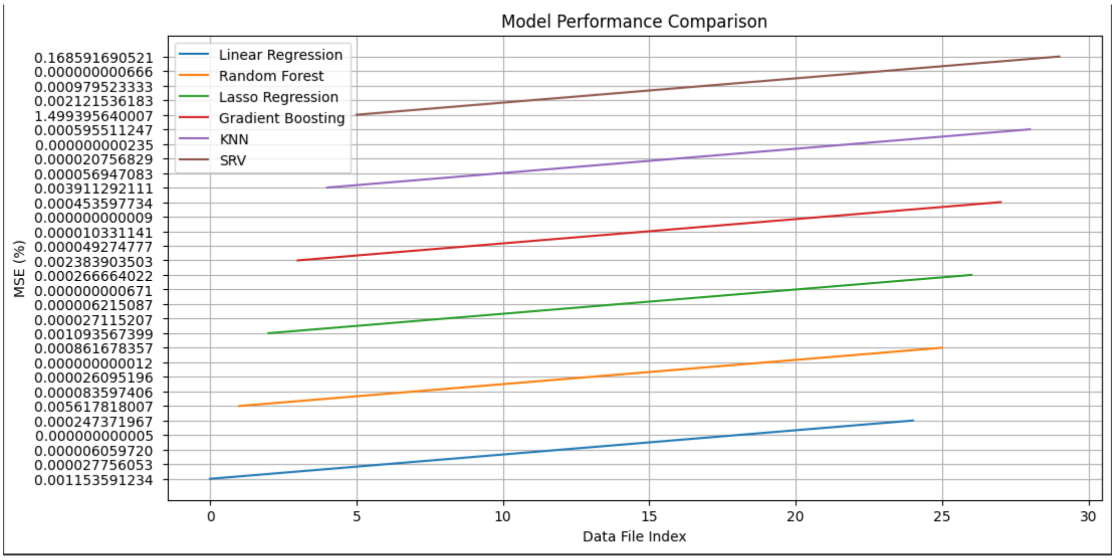

Figure 2: ***Model performance***

4.2.2 Actual VS Predicted

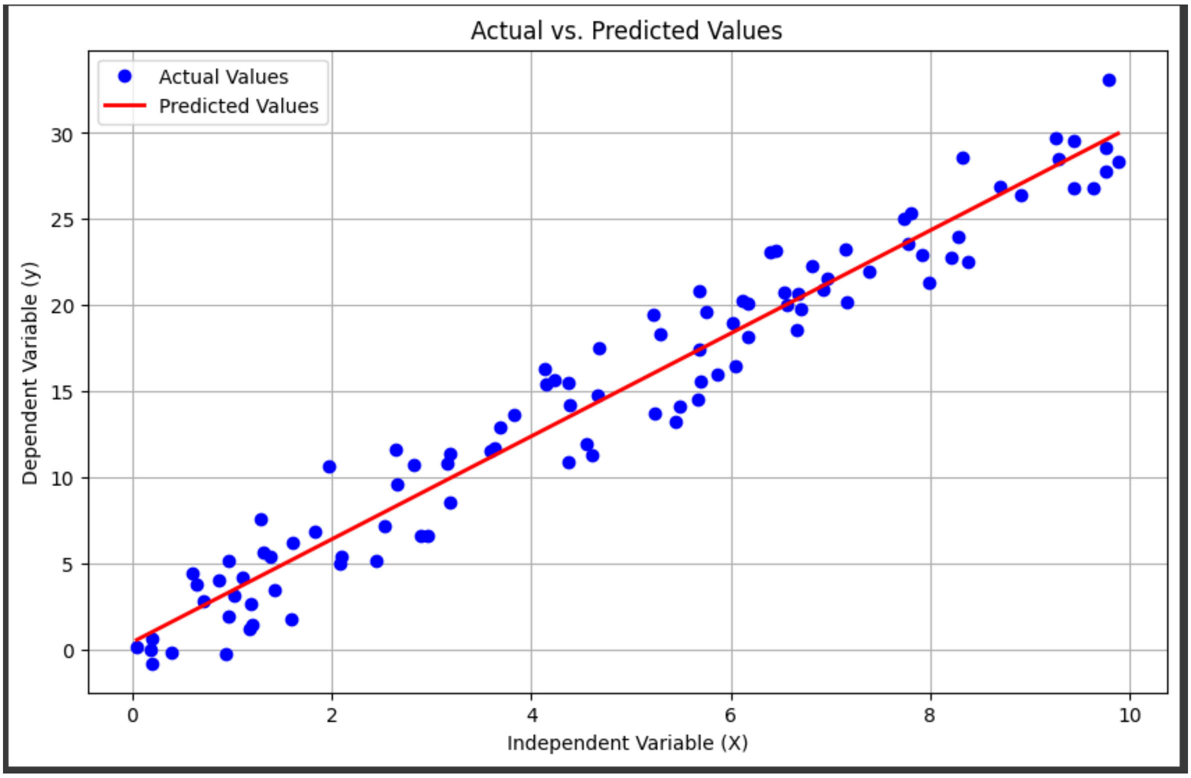

Figure 3:Actual VS Predicted Values

4.2.3 Histogram of Predictions

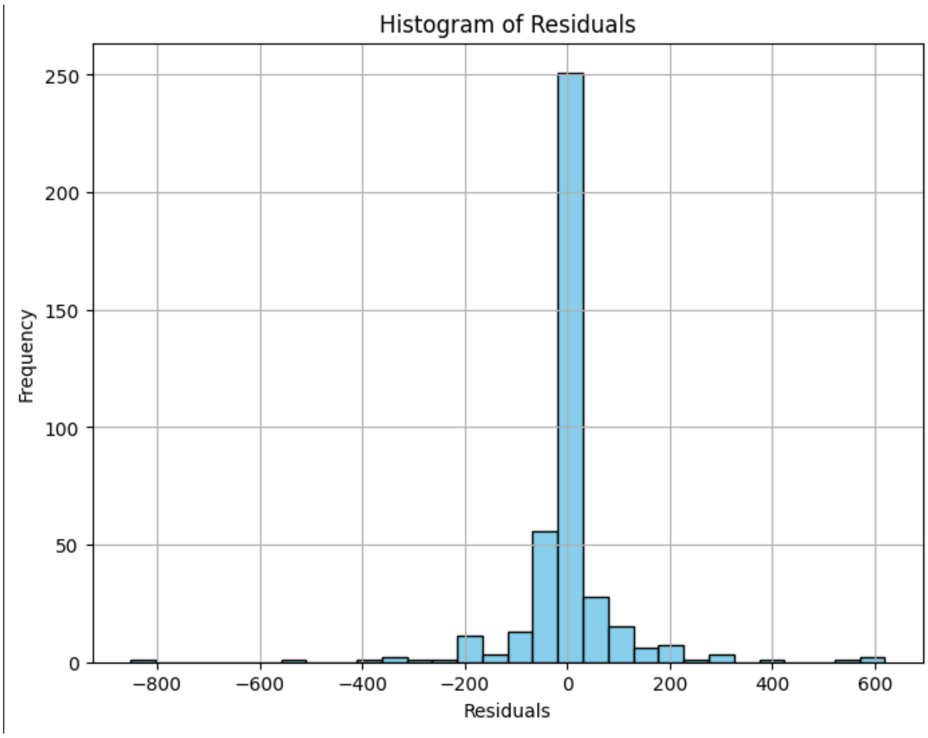

*Figure 4: **Histogram***

CHAPTER 5

CONCLUSION

5.1 Summary of Findings

This study undertakes a thorough investigation of various machine learning and deep learning techniques aimed at predicting cryptocurrency prices, specifically focusing on prominent cryptocurrencies such as Bitcoin, Ethereum, AAVE, Dogecoin, and BNB. The empirical results indicate a clear trend: advanced models, particularly Long Short-Term Memory (LSTM) networks, exhibit a substantial improvement in performance compared to traditional regression approaches.

The evaluation metrics—Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE)—consistently demonstrate that LSTMs significantly outperform models like Linear Regression and even ensemble methods such as Random Forest and Gradient Boosting. These findings underscore the LSTM's ability to effectively capture the temporal dependencies and intricate patterns inherent in cryptocurrency price movements. The inclusion of technical indicators further enhances the predictive capability, highlighting the importance of feature engineering in model performance.

5.2 Implications for Future Research

The results of this study not only contribute to the existing body of knowledge in cryptocurrency price forecasting but also pave the way for further research endeavors. One significant implication is the potential for integrating additional data sources, such as macroeconomic indicators, social media sentiment, and regulatory news sentiment analysis, to enrich model predictions. By incorporating broader datasets, researchers can potentially improve the robustness and accuracy of their forecasting models, enabling them to account for the multifaceted influences on cryptocurrency prices.

Moreover, exploring hybrid models that combine the strengths of both machine learning and deep learning techniques could yield further enhancements in prediction accuracy. For instance, utilizing ensemble approaches that integrate the predictive capabilities of models like Random Forest with the sequential learning advantages of LSTMs might provide a more comprehensive understanding of price dynamics. This avenue of research could significantly contribute to developing sophisticated tools for traders and analysts.

5.3 Recommendations for Practical Applications

For practitioners operating within the cryptocurrency market, this study emphasizes the critical importance of leveraging advanced machine learning techniques—particularly LSTMs—in developing effective trading strategies. The ability of these models to adapt to historical price patterns and respond to market volatility positions them as invaluable assets for traders seeking to navigate the complexities of the cryptocurrency landscape.

Incorporating key technical indicators—such as Moving Averages, Relative Strength Index (RSI), and MACD—into trading algorithms can facilitate more informed decision-making. These indicators provide additional context about market trends and can enhance risk management practices, allowing traders to make better-informed choices in an inherently volatile market.

Furthermore, it is advisable for practitioners to remain updated with ongoing advancements in machine learning and deep learning methodologies. Continuous learning and adaptation of these techniques can ensure that trading strategies remain competitive and effective in the rapidly evolving cryptocurrency ecosystem.

In summary, the insights garnered from this study advocate for the adoption of advanced predictive models in cryptocurrency trading. By embracing these methodologies, traders and analysts can potentially enhance their trading performance, improve risk management, and contribute to the broader understanding of market dynamics.

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