CryptoProphet: Building a Cryptocurrency Portfolio App with Integrated Market Predictive Models

Yared Shewarade
shewaradeyared1@cityuniversity.edu

Sherin Aly
alysherin@cityu.edu

Hee Jung Yoon
yoonhee@cityu.edu

Sam Chung
chungsam@cityu.edu

School of Technology & Computing (STC)
City University of Seattle (CityU)

Abstract

The volatility and unpredictability of cryptocurrency lead to financial losses for investors. We develop a predictive portfolio mobile app called CryptoProphet that leverages deep learning models to predict future prices and help crypto traders make informed decisions. A unique approach called the Individualized Model Selection (IMS) Strategy is adopted instead of relying on an ensemble or single model type across all cryptocurrencies. The IMS Strategy involves training each of the 30 cryptocurrencies using Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Bidirectional LSRM (Bi-LSTM) models. Then, the best-performing model for each cryptocurrency is selected for next-day price predictions using performance metrics of Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R2). This research addresses the highly volatile nature of cryptocurrencies for ensuring accurate predictions. This approach includes collecting historical data, preprocessing it, and training the models on sequences of price data. The evaluation of the models using the aforementioned metrics confirms their effectiveness. The app seamlessly integrates these predictions, providing users real-time price forecasts and essential market insights. The findings showed that the CryptoProphet portfolio app predicts prices accurately, reducing risks and maximizing profits in the volatile cryptocurrency market. Future work will focus on improving prediction accuracy by incorporating sentiment analysis and additional features such as market capitalization and volume to further improve prediction accuracy.

Keywords: Cryptocurrency, Predictive Model, Deep Learning, Portfolio Management, Real-time Data, Artificial Neural Network

1. INTRODUCTION

Cryptocurrency is a decentralized, secured, and transparent virtual currency that has revolutionized the traditional financial system through blockchain technology (Białkowski, 2020). Nakamoto (2008) stated that Bitcoin, the first cryptocurrency, introduced the concept of digital assets that operate independently of central authorities, opening new avenues for the

ISSN: 2473-4901
v10 n6133

financial system. Thousands of cryptocurrencies have been developed since the first introduction of cryptocurrency.

According to Nakamoto (2008), the cryptocurrency ecosystem enables users to exchange digital assets directly per peer without the need for intermediaries between transactions. These platforms allow individuals to exchange cryptocurrencies securely between buyers and sellers. As explained by Nakamoto (2008) peer-to-peer exchanges empower users to participate in the cryptocurrency market on their own terms as it offers greater accessibility and flexibility compared to traditional financial system.

The cryptocurrency market has high volatility and unpredictability, which leads to financial losses for investors. The lack of reliable predictive tools increases the risk of financial losses, particularly during periods of extreme market movements. Chaudhary et al. (2020) explained that the unique characteristics of cryptocurrency, such as market liquidity, trading volume, and news, further complicate the prediction task in addition to high volatility.

Several studies have been conducted on the volatile nature of cryptocurrencies and their impact on investment. Almeida and Gonçalves (2022) reported in their research that there is a need for predictive models to manage the volatility and risks associated with cryptocurrencies. Similarly, Kim et al. (2021) suggested the importance of advanced modeling techniques for accurate predictions, and they reported that models like Bayesian Stochastic Volatility (SV) outperform traditional models in forecasting cryptocurrency.

The CryptoProphet project aims to develop a predictive portfolio application that leverages deep learning models to forecast cryptocurrency prices and help make informed decisions. In this project, a unique approach called the Individualized Model Selection (IMS) strategy was adopted instead of applying a uniform ensemble model or a single model for each cryptocurrency. IMS is a unique approach in which each cryptocurrency selects its own best model based on the performance metrics after each of the 30 cryptocurrencies trained using Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Bidirectional LSTM (Bi-LSTM) models. The best-performing model for each cryptocurrency is selected for next-day price predictions by evaluating performance metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R2). This strategy ensures smart and accurate predictions and effectively addresses the volatility and unpredictability of the cryptocurrency market.

This research aims to build a crypto portfolio management application with integrated price prediction to help users make informed decisions, reduce risks, and maximize profits. The CryptoProphet portfolio app aims to enhance investment awareness and confidence in the volatile cryptocurrency market by providing real-time price forecasts and essential market insights through a user-friendly mobile application.

2. RELATED WORK

Cryptocurrency is a virtual currency built on blockchain technology and has transformed the financial system rapidly since the first introduction of cryptocurrency, Bitcoin, in 2009. It offers a decentralized, peer-to-peer system for transactions without intermediate traditional banking systems. This innovation has attracted significant interest from different prominent investors, speculators, and institutions, leading to the emergence of a vast ecosystem of digital assets. Sabry et al. (2020) mentioned in their report that investors face unique challenges due to high volatility, unpredictable price fluctuations, and a lack of centralized regulation besides the growth of the cryptocurrency ecosystem.

Nair et al. (2023) explored how LSTM networks can effectively model the temporal dependencies in cryptocurrency price movements. Similarly, Irfan (2022) focused on time series prediction of Bitcoin returns using machine learning models, demonstrating their ability to capture the dynamic of cryptocurrency prices. Jin and Li (2023) introduced a novel approach by combining frequency decomposition with deep learning techniques, highlighting the benefits of decomposing time series data to improve prediction accuracy.

Rather (2023) adopted a new ensemble learning method for cryptocurrency price prediction that combines multiple models to improve accuracy. Patel et al. (2020) illustrated the potential of ensemble and hybrid approaches in capturing patterns in cryptocurrency historical data, and they emphasized the robustness of stochastic neural networks for cryptocurrency price prediction in handling the stochastic nature of cryptocurrency markets.

One of the primary challenges of cryptocurrency trading is the difficulty of portfolio management

 ISSN: 2473-4901
v10 n6133

across various exchange platforms. Unlike traditional financial markets, cryptocurrencies are decentralized, which results in investors holding assets in different wallets or on multiple trading platforms. Holding crypto assets on different platforms makes it challenging to track and manage portfolios effectively, resulting in inefficient management and missed opportunities. Sahu et al. (2024) stated in their report that a centralized tool to view the holding assets is crucial in making informed trading decisions because of the fast-paced nature of the cryptocurrency market.

Furthermore, the crypto price fluctuates significantly within a short period of time because of the volatile nature of cryptocurrencies, which makes it less effective in predicting future trends using traditional financial methods. Sahun et al. (2024) stressed this volatility and the need for advanced predictive models and tools that can provide insights into market trends and guide investment decisions.

The CryptoProphet portfolio app aims to address these challenges by offering a comprehensive cryptocurrency portfolio app that centralizes portfolio management and integrates market predictive models. It intends to help investors by providing real-time data and predictive insights to facilitate better decision-making.

3. APPROACH

Our work is built on a reliable solution for investors to fill the critical gap in cryptocurrency trading by providing future price predictions for making informed decisions to reduce risk and maximize profit. CryptoProphet portfolio app leverages a neural network model of deep learning to predict future prices of cryptocurrency based on the pre-trained model of 30 cryptocurrencies. The project followed valuable approaches to give the portfolio app live, from collecting historical crypto data from genuine resources, understanding and cleaning data, training models, and building the portfolio app with price prediction integration.

Design

The CryptoProphet project combines advanced deep learning techniques with a user-friendly mobile app to provide a comprehensive tool for cryptocurrency investors. It is designed to predict and provide real-time cryptocurrency prices for investors to manage portfolios, reduce loss, optimize returns, and make informed decisions. As shown in Figure 1 (Appendix), the design of the project follows structured and systematic approaches to provide price prediction and portfolio management app for investors, starting from data collection, preprocessing, model training, model selection, mobile app development using React Native, model integration with Flask Application Programming Interface (API), and real-time data extraction from CoinGecko API. The design structure ensures that each component works together smoothly to provide accurate predictions and real-time data.

Data Preprocessing

Historical price data was collected for the selected 30 cryptocurrencies using the CmcScraper library from CoinMarketCap. The collected data is preprocessed and normalized using MinMaxScaler from the scikit-learn library to ensure uniform scaling of input features, which is crucial for the performance of neural network models. The data is split into training and test sets in which the last 365 days are reserved for testing to evaluate the model's performance on recent data. The normalized price data is then transformed into sequences of fixed length (lookback= 30 days) to capture temporal dependencies and then used to predict the next day's step. This sequence ensures that the models can learn from historical patterns to make future predictions.

Individualized Model Selection (IMS)

In the CryptoProphet project, a unique approach named the IMS strategy was proposed to select the best predictive models among many trained models for predicting the final price of each cryptocurrency. Each of the 30 cryptocurrencies was trained using three different models: LSTM, GRU, and Bi-LSTM, and then the IMS strategy was implemented instead of an ensemble model or a single model type across all cryptocurrencies. The models are evaluated to select the best-performing one for each cryptocurrency after the compilation of the training phase. Validation loss is the primary evaluation metric for selecting the final best model with the minimum validation loss.

The IMS approach's rationale is that existing ensemble techniques were inadequate due to the highly volatile nature of cryptocurrencies. Since cryptocurrencies are dynamic, their response to different predictive models can vary significantly. What works well for one cryptocurrency might not yield the same results for another. Additionally, experiments revealed that model performance could fluctuate significantly upon rerunning the training processes. For instance, while the GRU model initially performed well for cryptocurrencies like Solana and Bitcoin, its

©2024 ISCAP (Information Systems and Computing Academic Professionals)

 ISSN: 2473-4901
v10 n6133

performance was inconsistent in subsequent runs. This unpredictability leads to the proposal for a more adaptable and resilient approach, leading to the development of the IMS strategy. This approach ensures that each cryptocurrency is paired with its best predictive model, thereby enhancing the overall accuracy and reliability of the predictions. This method recognizes and accommodates the unique characteristics and behaviors of different cryptocurrencies, offering a more robust solution compared to traditional ensemble methods. By leveraging the IMS strategy, CryptoProphet provides more accurate and dynamic predictions, effectively addressing the complexities of the cryptocurrency market.

Model Training

The model was trained on a MacBook Pro M1 chip, 10-core CPU, 16-core GPU, 16GB unified memory, and 1TB SSD, and it involves building and training three types of deep learning models: LSTM, GRU, and Bi-LSTM. Each model is trained on the sequences of 30 cryptocurrencies' historical preprocessed price data. The training process begins by defining the single architecture layer of each model, followed by compiling them with Adam optimizer and using MSE as the loss function. The models are then trained using training data with a 10% validation set to monitor performance. The possibility of overfitting was prevented using early stopping, which stops the training process when the validation loss no longer improves. The models are trained using the following settings: 1) Adam optimizer is used for efficient learning, 2) MSE is used as the loss function to minimize the prediction error, and 3) Early stopping is used to prevent overfitting and monitor the validation loss with patience of 10 epochs.

Mobile App Development

The mobile application development phase focuses on creating a user-friendly interface using React Native, which supports cross-platform functionality for both iOS and Android devices. The core functionality of the app is integrating real-time data retrieval, user input handling, and predictive modeling. The CryptoProphet portfolio app is composed of several key components designed to provide comprehensive functionality. As illustrated in Figure 2 in the Appendix, the AssetInput component allows users to input the cryptocurrency they have invested in, while the PurchasedPriceInput and QuantityInput components capture the purchase price and quantity of the cryptocurrency, respectively. CurrentPriceDisplay, TotalValueDisplay, ProfitLossDisplay, and ForecastDisplay are used to show the current price, total value of holdings, profit or loss, and predicted future prices of the cryptocurrencies.

Flask API

The Flask API is developed to handle requests from the mobile app and provide predictions based on user input. When a user interacts with the app and inputs their crypto name and the purchased quantity, the app sends this information to the Flask API.

The API processes the input data using the pre-trained models stored on the server. Specifically, the API normalizes the user input data, feeds it into the model to generate a prediction, and then inversely transforms the prediction back to the original price before sending it back to the mobile app. This interaction allows the app to display real-time price predictions to the user based on their input and the latest available data. The integration ensures that the models are used effectively to enhance the user experience by offering accurate and timely predictions.

Implementation

CryptoProphet implementation involves several key steps, from data collection and preprocessing to model training and user interface development. The app is built with a combination of backend and frontend using Flask API and React Native, respectively. Data preprocessing, model training, and API development were implemented with Python 3 using libraries and modules, such as Pandas, NumPy, and Matplotlib, for data processing and analysis, numerical computing, and data visualization.

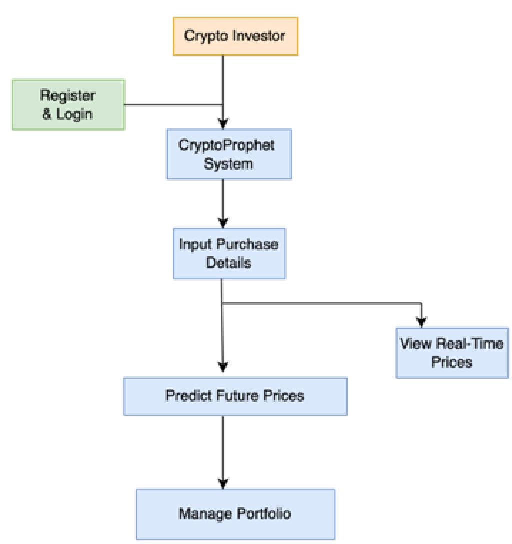

Figure 3: User Interaction Flowchart

©2024 ISCAP (Information Systems and Computing Academic Professionals)

Figure 3 shows how the users interact with the CryptoProphet portfolio app to manage their cryptocurrency investments, make informed decisions, and optimize their portfolios for maximum profitability by leveraging real-time data and predictive analytics. Users input details of their cryptocurrency investments, including the assets, purchase price, and quantity. The app then fetches real-time price data from the CoinGecko API and displays it alongside the user's input data. Additionally, the app provides future price predictions based on the trained models, giving users insights into the potential future values of their investments. This functionality enables users to make informed decisions about their cryptocurrency portfolio based on both real-time data and predictive analytics.

4. DATA COLLECTION

The list of 30 cryptocurrencies was selected aimed at representing the diverse and dynamic nature of the crypto market, data availability, and predictive relevance. This extensive list served as the foundation for subsequent evaluation and selection based on specific criteria such as market capitalization, trading volume, historical performance, and diversity in use cases and technology. Table 1 in the Appendix shows the list of selected cryptos, which includes high-market capitalization cryptos like Bitcoin (BTC) and Ethereum (ETH) due to their market dominance and rich historical data. The selection also included cryptos with significant market activities and exchanges (e.g., Binance Coin (BNB), Cardano (ADA), and Solana (SOL):), Memes (e.g., Dogecoin (DOGE), Shiba Inu (SHIB)), Metaverse and Gaming (e.g. Decentraland (MANA)), privacy coins (e.g., Monero (XMR)), Decentralized Finance (e.g., Maker (MKR), Avalanche (AVAX), ChainLink (LINK), and Fantom (FTM)), and other categories. The exclusion criteria for the selection of 30 cryptos were 1) small market and volume size, 2) recent launch without sufficient historical data, 3) lack of enough market value, and 4) low market capitalization. This careful selection of 30 cryptocurrencies allows CryptoProphet to deliver valuable predictions that can help users make informed investment decisions in the rapidly evolving cryptocurrency market.

After selecting the 30 cryptocurrencies, historical price data was meticulously collected from the beginning of each cryptocurrency's launch year up to the end of May 2024 using the CmcScraper tool from CoinMarketCap. This process ensured a comprehensive dataset that covers the entire trading history of each cryptocurrency, providing a robust foundation for analysis and prediction. As shown in Table 2 (Appendix), the collected data includes daily "Open," "High," "Low," and "Close" prices, as well as "Volume" and "Market Cap" values, ensuring a thorough understanding of each cryptocurrency's market performance over time.

Table 2 shows the data collection start date, market dominance, and the number of observations for each selected cryptocurrency. For example, BTC, with a market cap of $1.33 trillion and a dominance of 62.77%, had data collected since July 13, 2010, resulting in 5060 observations. ETH, with a market cap of $454.93 billion and a dominance of 21.44%, had data collected since August 7, 2015, totaling 3209 observations. Other notable cryptocurrencies include BNB, ADA, and SOL, each with substantial market caps and significant numbers of observations.

5. DATA ANALYSIS

In the CryptoProphet project, data analysis is crucial for transforming raw historical data into actionable insights and accurate predictions. The analysis involves the examination of the selected 30 cryptocurrencies to understand their market dynamics, identify trends, and evaluate relationships. Analytical techniques such as descriptive statistics, temporal analysis, comparative analysis, and correlation analysis are used to uncover the key patterns and behaviors in the cryptocurrency market, which is essential for making informed investment decisions and developing effective forecasting models.

Descriptive Analysis

As we learned from Table 1 in the Appendix, the predictive model in CryptoProphet can leverage the rich data to provide highly accurate predictions for major cryptocurrencies like BTC, ETH, BNB, and SOL. Their vast market cap and dominance indicate that they are less volatile compared to similar cryptocurrencies, making them reliable for long-term investment strategies. This stability can be reflected in the app's user interface by emphasizing these assets as potentially lower-risk options for users. On the other hand, cryptocurrencies with smaller market caps and lower dominance, like FTM, Quant (QNT), and NEO, often referred to as" Ethereum of China," introduce more volatility and higher risk but also potentially higher rewards. The app can incorporate these insights by offering different risk profiles for users based on these metrics. Furthermore, the number of observations for each cryptocurrency can directly

ISSN: 2473-4901
v10 n6133

impact the accuracy of the machine-learning models employed in the CryptoProphet app. Cryptocurrencies with a higher number of observations, like BTC, ETH, and LTC, allow for more robust and reliable predictive models. In contrast, new cryptos with fewer observations might need more sophisticated algorithms or hybrid models to achieve comparable predictive performance.

Lag Analysis

Comprehensive lag analysis at different time intervals was conducted to understand the influence of past prices on future prices, which is crucial for accurate price prediction. As shown in the lag plots in Figure 4 (Appendix), there is a relationship between the value of a cryptocurrency at a given time point $y(t)$ and its value at a specific lag period (1 day, 1 week, and 1 month). These plots help identify the autocorrelation in the cryptocurrency data. As we can learn from the lag plot, the 1-Day lag plot shows a strong linear relationship between a given time point $y(t)$ and the next time point $y(t+1)$. This indicates a high degree of autocorrelation at a 1-day interval, suggesting that the price of the cryptocurrency on any given day is highly predictive of its price the next day. In the CryptoProphet project, these lag plots provide critical insights for model development and feature selection. The strong autocorrelation at the 1-day lag suggests that the collected historical Close price data should be organized in a daily format. Therefore, the collected historical data from CoinMarketCap is formatted daily based on the lag analysis for the Close price. The lag plot analysis supports the design of CryptoProphet by informing the choice of input features (Close price), providing reliable short-term forecasts and well-informed long-term predictions, and making informed decisions in their cryptocurrency investments.

Correlation Matrix Analysis

Figure 5 in the Appendix shows the pairwise correlations between various cryptocurrencies for their daily Close price. A correlation value close to 1 indicates a strong positive correlation, which means the cryptocurrencies tend to move in the same direction. While a value close to -1 indicates a strong negative correlation in which the cryptocurrencies tend to move in opposite directions. Values near 0 suggest little or no linear relationship between the cryptocurrencies.

As we can learn from the correlation matrix plot, many cryptocurrencies exhibit moderate to high positive correlations with each other. For example, Cardano (ADA) with Cosmos (ATOM), Decred (DCR), and VeChain (VET) have a strong positive correlation. As a result, these assets move together in the market. Cryptocurrencies like BTC, ETH, and BNB also show high correlations with several other cryptos, reflecting their influential roles in the market. However, there are instances of weaker or even negative correlations like Render Token (RNDR) with some other assets. Understanding these correlations is crucial for the CryptoProphet project as it can significantly enhance the app’s predictive modeling and portfolio management features. For example, knowing that certain cryptocurrencies are highly correlated can help improve the accuracy of selected models by leveraging the combined predictive power of these assets. This correlation insight ensures that the CryptoProphet app not only provides accurate predictions but also helps users make more informed and balanced investment decisions.

Selection of Lookback Period

In the CryptoProphet project, the lookback period is a critical parameter that defines how much historical data the model considers when making predictions. Selecting an appropriate lookback period is essential for capturing relevant patterns and trends in the cryptocurrency market, which can significantly influence the model’s performance. The lookback period refers to the number of previous time steps used as input features for the predictive model. As shown in Figure 6 (Appendix), the performance metrics, including MSE, MAE, RMSE, and the R2 value, were evaluated for different lag intervals. We can learn from the plot that a lookback period of 30 days provided the lowest MSE, MAE, and RMSE while achieving the highest R2 value. This indicates that the 30-day lookback period optimally balances between capturing significant market trends and maintaining model responsiveness to recent changes. By incorporating this longer historical data span, the models can more accurately forecast future cryptocurrency prices, providing users with valuable insights for their investment decisions.

6. FINDINGS

The CryptoProphet project aims to develop a portfolio application that can predict cryptocurrency prices using advanced deep learning techniques. Rapid volatility and high stakes in the cryptocurrency market compel us to build robust and accurate forecasting models to assist traders and investors in making informed decisions. This CryptoProphet project leverages three neural network architectures, LSTM, GRU, and Bi-LSTM, to capture the complex temporal

©2024 ISCAP (Information Systems and Computing Academic Professionals)

 ISSN: 2473-4901
v10 n6133

dependencies and patterns in cryptocurrency price data.

Predictive vs. Actual Plot

The CryptoProphet project has shown insightful results in predicting the prices of various cryptocurrencies. Figure 7 illustrates the predictive performance for a sample of four different cryptocurrencies: BTC, ETH, FTM, and NEO. These findings serve as examples that reveal the ability of our models to closely track the actual market prices, indicating the robustness and effectiveness of the implemented LSTN, GRU, and Bi-LSTM architectures. These four examples are representative samples out of the 30 cryptocurrencies analyzed in the CryptoProphet project. The close alignment between the actual (blue lines) and the predicted prices (red lines) indicates a high level of accuracy in the predictions.

For BTC in Figure 7, the GRU model shows a remarkable performance, with the predicted prices closely tracking the actual prices throughout the year. This is evident from the minimal divergence between the two lines, particularly during periods of both gradual and rapid price changes. This alignment suggests that the GRU model is capable of accurately capturing the complex patterns and volatility in the BTC market.

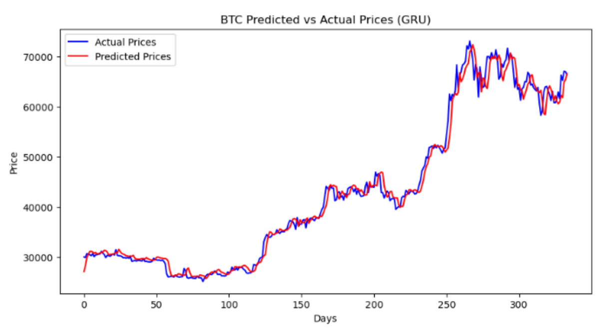

Figure 7: BTC Predictive vs. Actual Prices

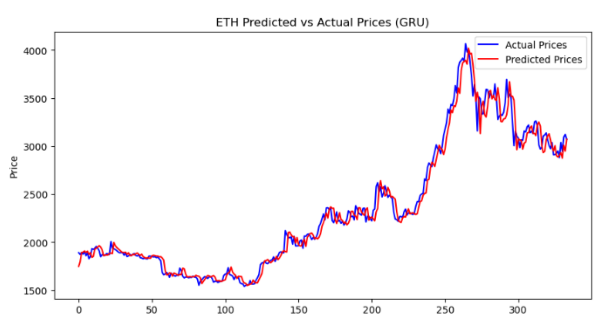

Figure 8: ETH Predictive vs. Actual Prices

For ETH, in Figure 8, the GRU model displays strong predictive accuracy similar to that of Bitcoin. The model successfully follows the sharp rise in prices around mid-year and the subsequent fluctuations. The close match between the actual and predicted prices highlights the model's ability to adapt to significant market movements and maintain its accuracy.

For FTM in Figure 9, the LSTM model shows a good fit between the actual and predicted prices. Although there are slight deviations during some of the more volatile periods, the overall trend is well captured. This indicates that the LSTM model can effectively handle the price dynamics of FTM, albeit with minor inaccuracies during high volatility.

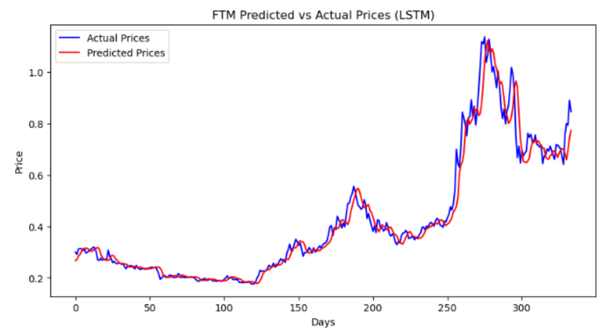

Figure 9: FTM Predictive vs. Actual Prices

For NEO in Figure 10, the Bi-LSTM model demonstrates a strong predictive capability, with the predicted prices closely mirroring the actual prices. The model performs well in tracking the general upward trend and the various peaks and troughs of the year. This close correlation suggests that the Bi-LSTM model is well-suited for forecasting NEO prices.

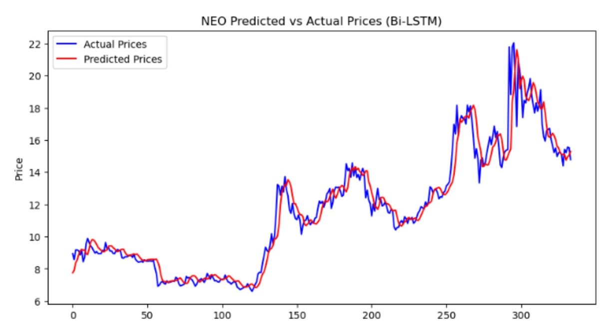

Figure 10: NEO Predictive vs. Actual Prices

The CryptoProphet project successfully integrates advanced machine learning models to provide accurate price predictions for multiple cryptocurrencies. The examples of BTC, ETH,

©2024 ISCAP (Information Systems and Computing Academic Professionals)

 ISSN: 2473-4901
v10 n6133

FTM, and NEO show that the GRU, LSTM, and Bi-LSTM models can closely align with actual prices, confirming the robustness and reliability of the predictions. These consistent results across various cryptocurrencies demonstrate the app's potential as a valuable tool for investors and traders in the cryptocurrency market. The app's precise forecasts can enhance decision-making and potentially improve investment outcomes.

3D Scatter Plot
The 3D scatter plot in Figure 11 (Appendix) shows the relationship between trading volume, market capitalization, and prices for sample cryptocurrencies, BTC and ETH. Each dot represents a specific data point in time for the crypto, with the color indicating the price. The x-axis, y-axis, and z-axis represent trading volume, market capitalization, and price, respectively. As we can learn from the 3D plot, there is a clear positive correlation between the three parameters, as higher volumes and market caps are associated with higher prices. This indicates that incorporating additional features like market cap and volume can further improve prediction accuracy.

Performance Metrix
As shown in Table 3 (Appendix), the performance metrics for the CryptoProphet project confirm the effectiveness and accuracy of various deep learning models in predicting cryptocurrency prices. The metrics used to evaluate the models include MAE, MSE, RMSE, MAPE, and the R2 value.

For BTC and ETH, the GRU model achieves high accuracy with MAE values of 1146.023 and 66.780, RMSE values of 1707.753 and 98.711, and R2 values of 0.9869 and 0.9782, respectively. Similarly, for BNB and ADA, the GRU model records MAE values of 11.057 and 0.0179, RMSE values of 18.226 and 0.0275, and R2 values of 0.9829 and 0.9667. The performance is also strong for SOL, with a GRU model achieving an R2 value of 0.9812, although XRP predictions show room for improvement with an R2 of o.7785. The CryptoProphet project demonstrates the capability of advanced machine learning models, particularly GRU, LSTM, and Bi-LSTM, to provide accurate price predictions for various cryptocurrencies. The GRU model shows high accuracy across multiple cryptocurrencies, which makes it a reliable choice for forecasting. The app's robust performance metrics, such as low MAE, MSE, and RMSE values, combined with high R2 values, underscore its potential as a valuable tool for crypto investors. The consistent results across different cryptocurrencies validate the efficiency of the predictive models used in the CryptoProphet project.

7. CONCLUSIONS AND FUTURE WORK

The CryptoProphet project successfully addresses the volatility and unpredictability of the cryptocurrency market by providing accurate price prediction using deep learning models. The portfolio app integrates LSTM, GRU, and Bi-LSTM models, which conforms to excellent performance in predicting next-day prices for various cryptocurrencies. Each cryptocurrency is paired with the most suitable predictive model based on specific performance metrics by employing IMS strategies. This smart approach confirms that the unique characteristics and behaviors of different cryptos are effectively captured and improve the overall accuracy and reliability of the predictions. The portfolio app provides a user-friendly interface that presents real-time forecasts, current prices, and profit/loss calculations, which makes it an invaluable tool for investors. The findings highlight the app's capability to mitigate risks and maximize profits, thereby contributing significantly to informed decision-making in the cryptocurrency market.

The CryptoProphet portfolio app has demonstrated significant potential in assisting cryptocurrency investors with price predictions and effective portfolio management. However, there are some areas where the app can be further improved to improve its functionality and user experience. One of the key areas for future work is to incorporate additional features such as market capitalization and trading volume. These features can offer a more detailed analysis of the market conditions and help improve the accuracy of the price predictions. The second future work will incorporate sentiment analysis into the prediction models, which can enhance the accuracy of the prediction. The app would allow users to understand the market mood and anticipate price movements based on public sentiment.

8. ACKNOWLEDGMENT

Special thanks to Dr. Ho-Kyeong Ra for providing the technical guidance necessary to conduct this research.

8. REFERENCES

Almeida, J., & Gonçalves, T. C. (2023). A systematic literature review of investor behavior in the cryptocurrency markets. *Journal of Behavioral and*

Experimental Finance, *37*, 100785. https://doi.org/10.1016/j.jbef.2022.100785

Almeida, J.; Gonçalves, T.C. (2022) A Systematic Literature Review of Volatility and Risk Management on Cryptocurrency Investment: A Methodological Point of View. *Risks*, *10(5)*, 107. https://doi.org/10.3390/risks10050107

Cocco, L., Tonelli, R., & Marchesi, M. (2021). Predictions of bitcoin prices through machine learning based frameworks. *PeerJ Computer Science,* https://doi.org/10.7717/peerj-cs.413

Erdinc, A., Ahmet, G., & Ahmet, S. (2021). Prediction of cryptocurrency returns using machine learning. *Annals of Operations Research, 297*(1-2), 3-36. https://doi.org/10.1007/s10479-020-03575-y

Gupta, H., & Chaudhary, R. (2022). An Empirical Study of Volatility in Cryptocurrency Market. *Journal of Risk and Financial Management*, *15*(11), 513. https://doi.org/10.3390/jrfm15110513

Hamayel, M. J., & Amani, Y. O. (2021). A Novel Cryptocurrency Price Prediction Model Using GRU, LSTM and bi-LSTM Machine Learning Algorithms. *Ai, 2*(4), 477. https://doi.org/10.3390/ai2040030

Helder, S., & Godinho, P. (2021). Forecasting and trading cryptocurrencies with machine learning under changing market conditions. *Financial Innovation, 7*(1)https://doi.org/10.1186/s40854-020-00217-x

Irfan, H. S. (2022). Time series prediction using machine learning: a case of Bitcoin returns. *Studies in Economics and Finance, 39*(3), 458-470. https://doi.org/10.1108/SEF-06-2021-0217

Jin, C., & Li, Y. (2023). Cryptocurrency Price Prediction Using Frequency Decomposition and Deep Learning. *Fractal and Fractional, 7*(10), 708. https://doi.org/10.3390/fractalfract7100708

Kang, C. Y., Lee, C. P., & Lim, K. M. (2022).Cryptocurrency Price Prediction with Convolutional Neural Network and Stacked Gated Recurrent Unit. *Data*, *7*(11), 149. https://doi.org/10.3390/data7110149

Kim, Jong-Min, Chulhee Jun, and Junyoup Lee. (2021). "Forecasting the Volatility of the Cryptocurrency Market by GARCH and Stochastic Volatility" *Mathematics* 9(14) 1614. https://doi.org/10.3390/math9141614

Miller, D., & Jong-Min, K. (2021). Univariate and Multivariate Machine Learning Forecasting Models on the Price Returns of Cryptocurrencies. *Journal of Risk and Financial Management, 14*(10), 486. https://doi.org/10.3390/jrfm14100486

Mohammed, A. A., & Theyazn, H. H. A. (2022). Deep Learning Algorithm to Predict Cryptocurrency Fluctuation Prices: Increasing Investment Awareness. *Electronics, 11*(15), 2349. https://doi.org/10.3390/electronics11152349

Nair, M., Marie, M. I., & Abd-Elmegid, L. (2023). Prediction of Cryptocurrency Price using Time Series Data and Deep Learning Algorithms. *International Journal of Advanced Computer Science and Applications, 14*(8) https://doi.org/10.14569/IJACSA.2023.0140837

Patel, J., Kalariya, V., Parmar, P., Tanwar, S., Kumar, N., & Alazab, M. (2020). Stochastic neural networks for cryptocurrency price prediction. *IEEE Access*, *8*, 82804–82818. https://doi.org/10.1109/access.2020.2990659

Phumudzo, L. S., Claude Rodrigue, B. M., & Pindza, E. (2023). Forecasting Cryptocurrency Prices Using LSTM, GRU, and Bi-Directional LSTM: A Deep Learning Approach. *Fractal and Fractional, 7*(2), 203. https://doi.org/10.3390/fractalfract7020203

Rather, A. M. (2023). A new method of ensemble learning: case of cryptocurrency price prediction. *Knowledge and Information Systems, 65*(3), 1179-1197. https://doi.org/10.1007/s10115-022-01796-0

Sabry, F., Labda, W., Erbad, A., & Malluhi, Q. (2020). Cryptocurrencies and Artificial Intelligence: Challenges and opportunities. *IEEE Access, 8*, 175840-175858. https://doi.org/10.1109/ACCESS.2020.3025211

Sahu, S., Ochoa Vázquez, J. H., Alejandro Fonseca Ramírez, & Jong-Min, K. (2024). Analyzing Portfolio Optimization in Cryptocurrency Markets: A Comparative Study of Short-Term Investment Strategies Using Hourly Data Approach. *Journal of Risk*

ISSN: 2473-4901
v10 n6133

and Financial Management, 17(3), 125. https://doi.org/10.3390/jrfm17030125

©2024 ISCAP (Information Systems and Computing Academic Professionals)
https://iscap.us/proceedings/

ISSN: 2473-4901
v10 n6133

Appendix

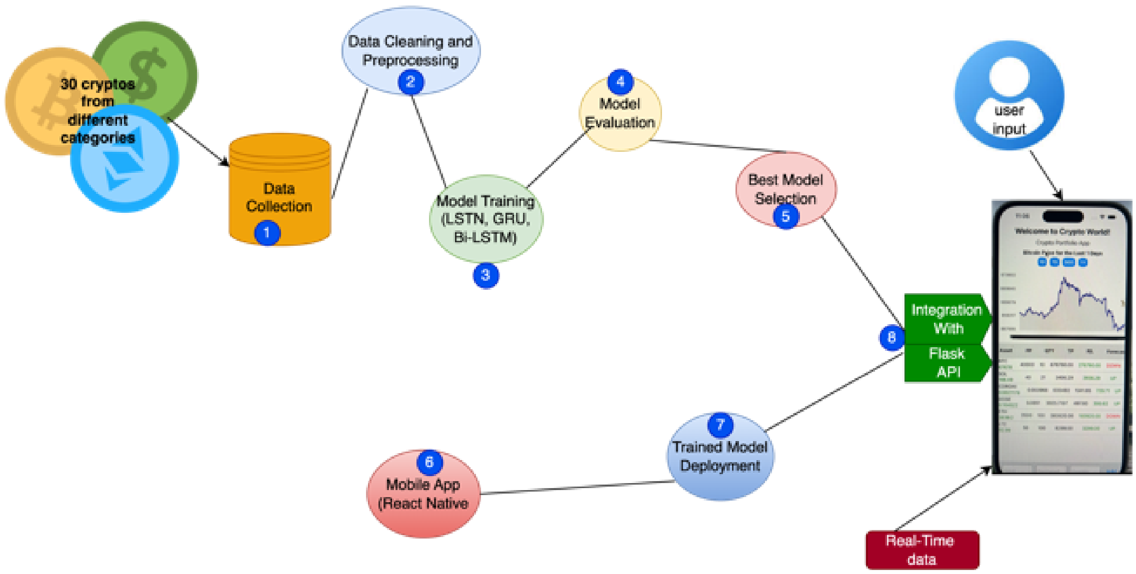

Figure 1: Design of the CryptoProphet Portfolio Mobile App

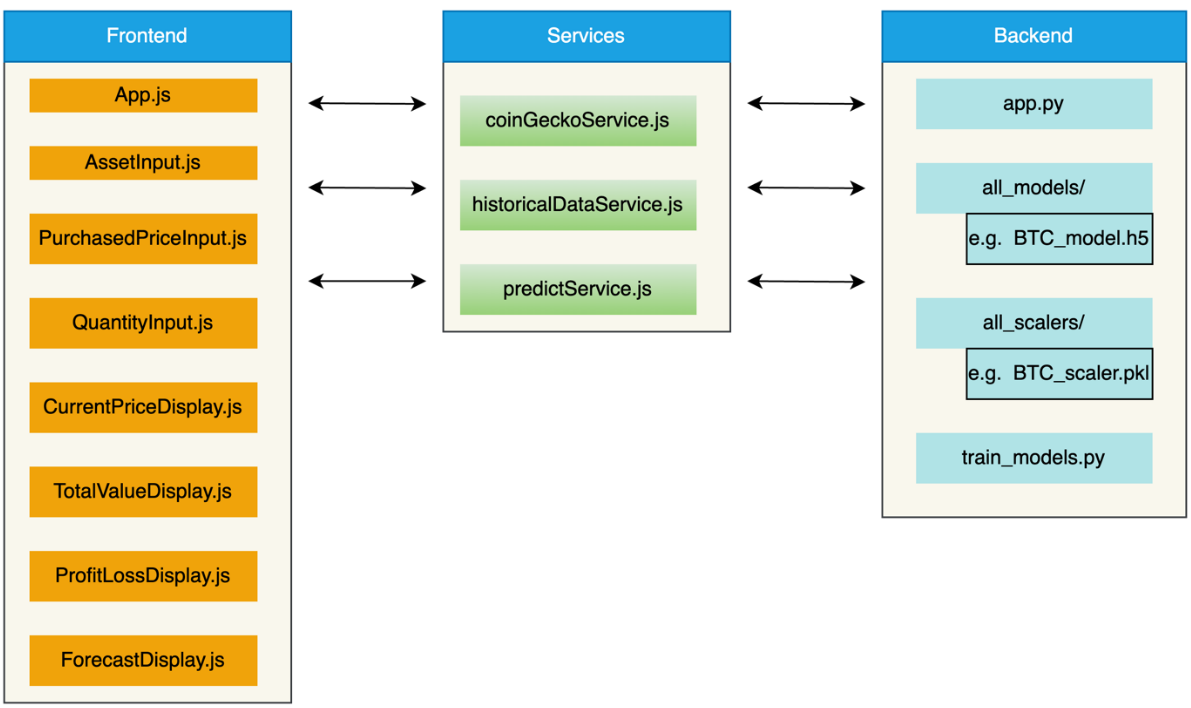

Figure 2: Interaction Flow Between Components

©2024 ISCAP (Information Systems and Computing Academic Professionals)
https://iscap.us/proceedings/

ISSN: 2473-4901
v10 n6133

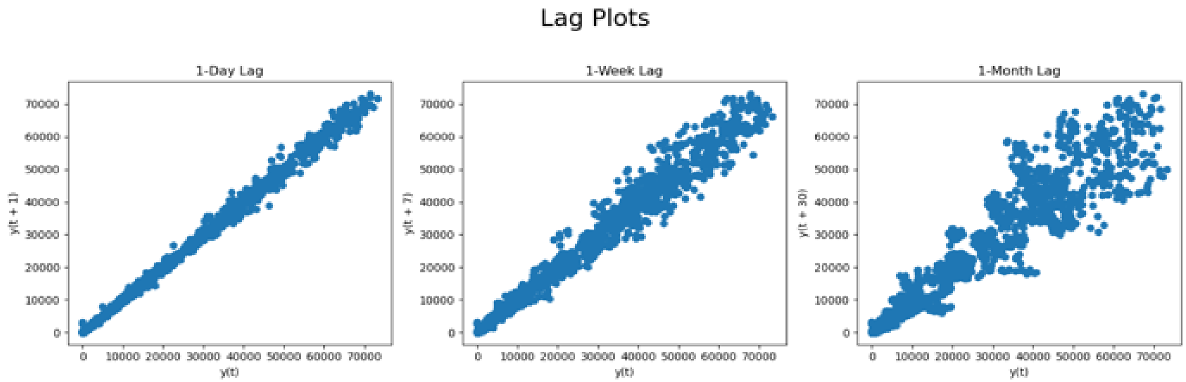

Figure 4: Lag Plots at Different Time Interval

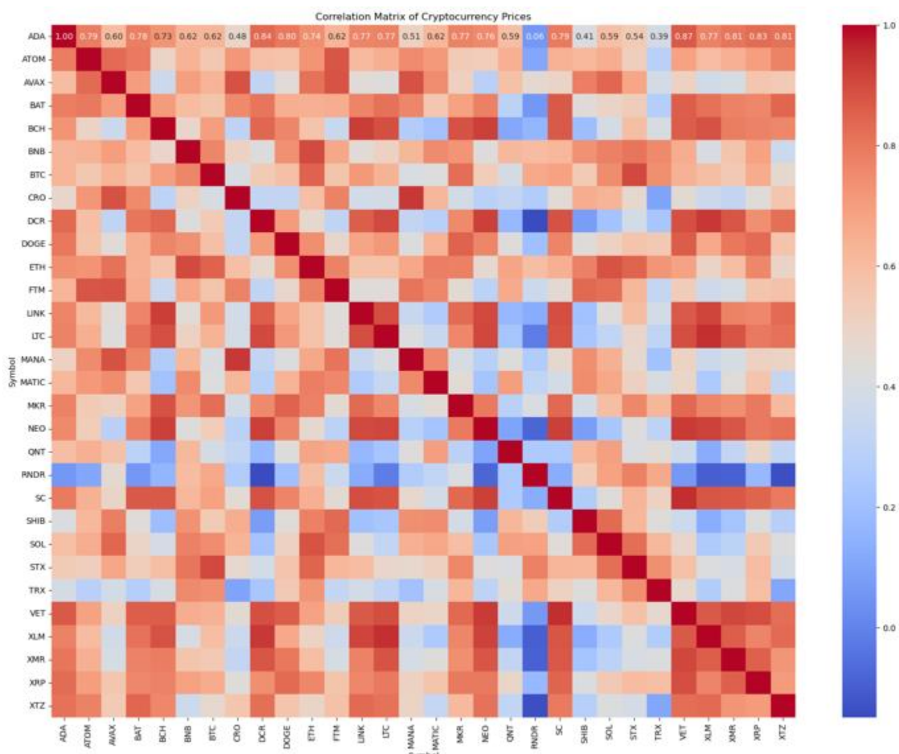

Figure 5: Correlation Matrix Plot

ISSN: 2473-4901
v10 n6133

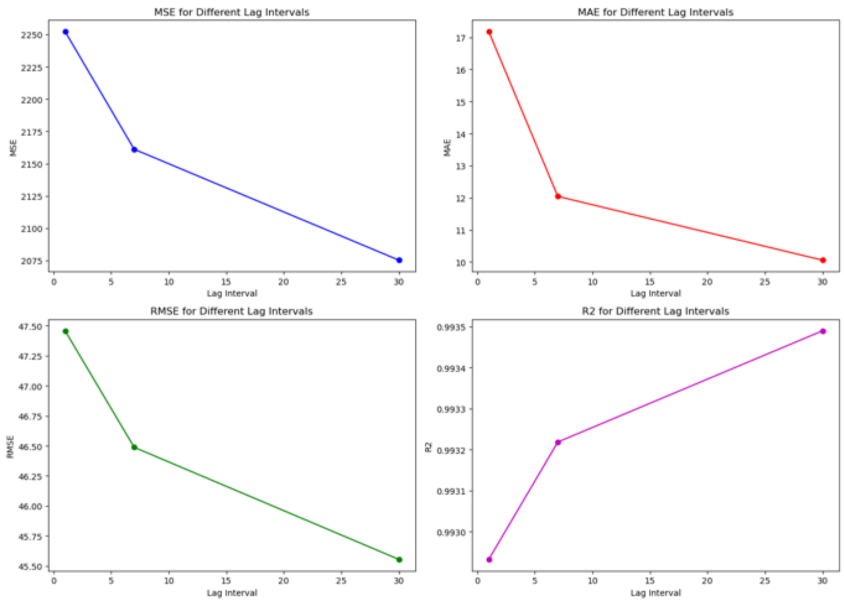

Figure 6: Lag Interval for the Lookback Period

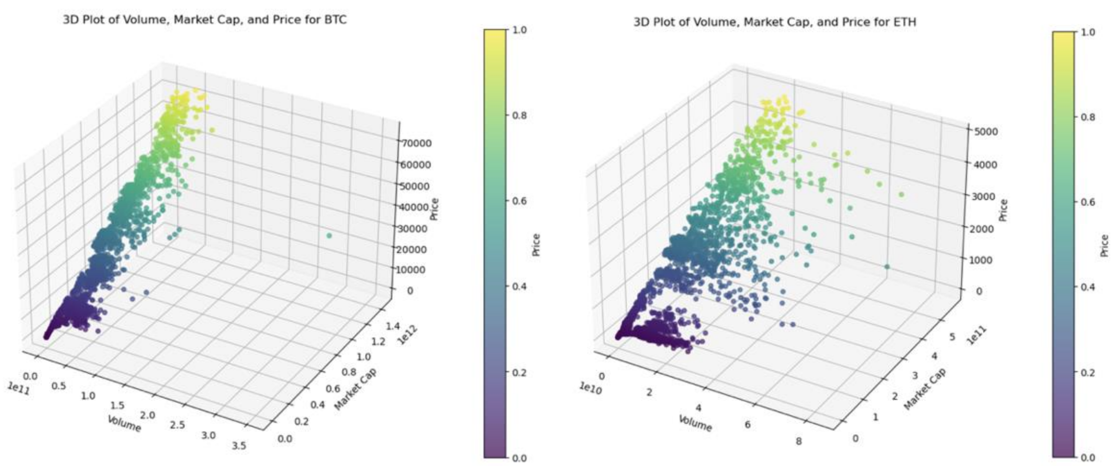

Figure 11: Additional Feature Plots

 ISSN: 2473-4901
v10 n6133

	Crypto	Symbol	Market Cap	Dominance (%)	Date Since	Number of Observations
1	Bitcoin	BTC	$1.33 Trillion	62.77%	7/13/10	5060
2	Tezos	XTZ	$944.60 Million	0.04%	7/1/18	2150
3	Decentraland	MANA	$848.82 Million	0.04%	9/17/17	2437
4	Ethereum	ETH	$454.93 Billion	21.44%	8/7/15	3209
5	Siacoin	SC	$391.06 Million	0.02%	8/26/15	3189
6	Basic Attention Token	BAT	$362.93 Million	0.02%	6/1/17	2545
7	Decred	DCR	$332.54 Million	0.02%	2/10/16	3022
8	BNB	BNB	$87.73 Billion	4.13%	7/25/17	2491
9	Solana	SOL	$76.45 Billion	3.60%	4/10/20	1501
10	XRP	XRP	$28.68 Billion	1.35%	8/4/13	3942
11	Dogecoin	DOGE	$23.06 Billion	1.09%	12/15/13	3809
12	Cardano	ADA	$16.04 Billion	0.76%	10/1/17	2423
13	Shiba Inu	SHIB	$15.07 Billion	0.71%	8/1/20	1388
14	Avalanche	AVAX	$14.25 Billion	0.67%	7/13/20	1338
15	Chainlink	LINK	$10.85 Billion	0.51%	9/20/17	2430
16	TRON	TRX	$9.80 Billion	0.46%	9/13/17	2441
17	Bitcoin Cash	BCH	$9.01 Billion	0.42%	7/23/17	2493
18	Polygon	MATIC	$6.90 Billion	0.33%	4/28/19	1849
19	Litecoin	LTC	$6.22 Billion	0.29%	4/28/13	4040
20	Render	RNDR	$3.92 Billion	0.18%	6/11/20	1439
21	Cosmos	ATOM	$3.27 Billion	0.15%	3/14/19	1894
22	Stellar	XLM	$3.08 Billion	0.15%	8/5/14	3576
23	Cronos	CRO	$3.01 Billion	0.14%	12/14/18	1984
24	Monero	XMR	$2.74 Billion	0.13%	5/21/14	3651
25	Stacks	STX	$2.68 Billion	0.13%	10/28/19	1666
26	Maker	MKR	$2.56 Billion	0.12%	1/29/17	2390
27	VeChain	VET	$2.47 Billion	0.12%	8/3/18	2117
28	Fantom	FTM	$2.23 Billion	0.11%	10/30/18	2029
29	Quant	QNT	$1.09 Billion	0.05%	8/10/18	2110
30	Neo	NEO	$1.03 Billion	0.05%	9/9/16	2810

Table 1: Number of Collected Data for each Cryptocurrency

©2024 ISCAP (Information Systems and Computing Academic Professionals)
https://iscap.us/proceedings/

ISSN: 2473-4901
v10 n6133

	Date	Open	High	Low	Close	Volume	Market Cap	Symbol
0	2024-05-19	66937.930074	67694.298780	65937.177806	66278.370082	1.924909e+10	1.305732e+12	BTC
1	2024-05-18	67066.211043	67387.330366	66663.496521	66940.804410	1.671228e+10	1.318742e+12	BTC
2	2024-05-17	65231.298680	67459.459502	65119.314977	67051.874913	2.803128e+10	1.321187e+12	BTC
3	2024-05-16	66256.111817	66712.429379	64613.056046	65231.580313	3.157308e+10	1.285008e+12	BTC
4	2024-05-15	61553.989847	66454.449965	61330.408780	66267.491467	3.981517e+10	1.305167e+12	BTC
...	...	...	...	...	...	...	...	...
77418	2016-09-13	0.374469	0.375092	0.301766	0.309509	3.336910e+03	0.000000e+00	NEO
77419	2016-09-12	0.376312	0.376671	0.360443	0.374598	1.115840e+03	0.000000e+00	NEO
77420	2016-09-11	0.390948	0.398459	0.372790	0.376150	8.787000e+02	0.000000e+00	NEO
77421	2016-09-10	0.558536	0.559143	0.370960	0.391001	8.108000e+02	0.000000e+00	NEO
77422	2016-09-09	0.181483	0.558951	0.181357	0.558478	1.348860e+03	0.000000e+00	NEO

77423 rows × 8 columns

Table 2: Cryptocurrency Historical Data

crypto	model_type	MAE	MSE	RMSE	MAPE (%)	R2
BTC	GRU	1146.0229321972000	2916420.6418867500	1707.75309746074	2.526062224546220	0.9869227677820090
ETH	GRU	66.78026471892760	9743.943418532300	98.71141483401150	2.655017971449970	0.9781979175542160
BNB	GRU	11.057782877637000	332.1959967684940	18.226244724805300	2.8557689672004600	0.9828556751790460
ADA	GRU	0.017889472364757700	0.000758691206405504	0.027544349809089800	3.8602479463543400	0.9666757555366180
SOL	GRU	4.854035250080750	58.67239108778780	7.659790538114460	5.864999796478180	0.9812088934695300
XRP	GRU	0.018729255525508200	0.001134329845508730	0.033679813620457200	3.1595227463612000	0.7785169654025020
LTC	Bi-LSTM	2.923520203379290	19.37832613392660	4.402082022625950	3.6754623549424100	0.863105585084624
LINK	GRU	0.6012970016320770	0.7197413603101720	0.8483757188358070	4.7272386802480700	0.9692517604859360
DOGE	GRU	0.004610810178388240	6.83605849443954E-05	0.008268046017312400	4.024969471139600	0.9581056503990430
SHIB	GRU	7.19919392859641E-07	2.92902939802795E-12	1.7114407375156E-06	4.381922087552310	0.9542085456060000
MANA	GRU	0.023106293994709400	0.0010679181385870700	0.032679016793457400	5.0594217310575700	0.913702047802004
VET	GRU	0.0012468831566193800	3.7655912806984E-06	0.0019405131488084300	4.1377853096424000	0.967659690083565
XMR	GRU	3.6116782307255500	33.98404643104450	5.829583727080730	2.525304546294720	0.8732362591629850
BCH	GRU	18.171766180874800	1023.9637527871900	31.999433632287800	5.493657568017290	0.9271112351005340
AVAX	GRU	1.49466274076195	5.50489677241659	2.3462516430290700	5.070813859164450	0.9751543555680090
TRX	GRU	0.00454479766252581	3.05800892760126E-05	0.0055299266971644900	4.1691896982153700	0.9197688011755720
MATIC	GRU	0.03302981351632030	0.0020522104373780300	0.045301329311379200	4.2246037889708000	0.9268865155650640
CRO	GRU	0.0034410429478797300	3.31033284283272E-05	0.005753549202738010	3.516257135728380	0.9704685576649470
RNDR	GRU	0.33958221439565800	0.35661467712877600	0.5971722340571240	6.00182941944931	0.9662588770692870
XTZ	GRU	0.037505869275487300	0.0028733952662834600	0.05360406016603090	3.8557211895831400	0.9351222550756140
BAT	LSTM	0.009542970976180780	0.00018828176915124700	0.013721580417402600	4.0168782335176900	0.9123285366684590
SC	GRU	0.0004354427850027760	8.9422452394013E-07	0.0009456344557703730	5.83763196472438	0.9122506107237390
FTM	LSTM	0.02795194253367830	0.002380025628127990	0.04878550633259830	5.628912505142950	0.9591150057339260
DCR	GRU	0.9146203903271100	1.7346623507345100	1.317065811087100	5.095647665838270	0.9068616632997060
MKR	GRU	91.49046257125120	19907.86463745810	141.0952325114430	4.762330713780950	0.9662447712515940
ATOM	GRU	0.39836987342936500	0.28695069220600900	0.5356777876727850	4.322235201654790	0.9012193019140290
STX	GRU	0.09799387577272990	0.02801945174424010	0.16739011841874100	5.788644870104680	0.9702536203679250
XLM	LSTM	0.0043210773701783	4.73242277575921E-05	0.006879260698475680	3.472503977705360	0.7462423785002910
QNT	GRU	4.0850830704828800	31.903498917999600	5.64831823802445	3.7309829481302600	0.7953354456345730
NEO	Bi-LSTM	0.5653299034222750	0.8393385753969280	0.9161542312279790	4.547300440034160	0.9370619607352130

Table 3: Performance Metrics for Cryptocurrency

©2024 ISCAP (Information Systems and Computing Academic Professionals)

https://iscap.us/proceedings/