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CRYPTOCURRENCY PRICE PREDICTION USING ARIMA MODEL

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Abstract

Investors are increasingly focusing on cryptocurrencies due to their decentralized nature and transparency. Given the unpredictable nature of cryptocurrencies, accurate price forecasting is crucial for devising effective trading strategies. This paper introduces a cutting-edge model for predicting the value of Bitcoin, a leading digital currency. The method ensures consistent predictions within a specific price range. It involves segmenting time-series data for individual normalization. For price prediction, specific variables intrinsic to the blockchain records of cryptocurrencies are sourced and used. The study suggests using SAM-LSTM, a model that integrates multiple LSTM modules to capture various factors. SAM-LSTM stands for self-attention-based multiple long short-term memory. Tests using real Bitcoin price data and various method settings have demonstrated the effectiveness of the proposed model. The results indicate high accuracy, with MAE, RMSE, MSE, and MAPE values of 0.3462, 0.5035, 0.2536, and 1.3251, respectively.

Keywords: Cryptocurrencies, Decentralized, Transparency, Price forecasting, Trading strategies, Bitcoin, Digital currency, Time-series data, Normalization, Blockchain records, SAM-LSTM, Self-attention-based, Real Bitcoin price data, MAE, RMSE, MSE, MAPE, Model effectiveness.

I. INTRODUCTION

The past decade has witnessed an unprecedented interest in the realm of digital currencies, with cryptocurrencies emerging as a novel asset class. Their decentralized construct and the transparent frameworks they embody have made them particularly enticing for a new age of investors. Bitcoin, often hailed as the flag-bearer of this digital currency revolution, has proven its mettle by not just surviving but thriving amidst various economic upheavals.

However, with great interest comes a natural urge to understand and predict its price movement. The volatile nature of cryptocurrencies, accentuated by external factors ranging from regulatory news to technological advancements, makes its price prediction not just a lucrative endeavor but a necessity for traders and investors alike.

This paper paves the way for a refined approach to predicting Bitcoin's price using an avant-garde model. Recognizing the significance of individual normalization, the model strategically segments time-series data, ensuring that predictions remain steadfast within a predetermined price range.

The research delves deep into the heart of blockchain, extracting specific variables that are intrinsic to cryptocurrency records. These variables provide the necessary data set upon which predictions are based, offering a more holistic insight into price movements as opposed to surface-level analysis.

Central to this research is the SAM-LSTM model - an abbreviation for self-attention-based multiple long short-term memory. LSTMs have long been known for their prowess in handling sequential data, and by integrating multiple LSTM modules, the SAM-LSTM aims to encapsulate various facets and intricacies of price data. The self-attention mechanism, in tandem, amplifies its capacity to discern patterns, making predictions more robust and accurate.

The pragmatic aspect of any research lies in its testing and results. Using real-world Bitcoin price data and subjecting the model to various methodological settings, the paper demonstrates the prowess of the proposed model. The results are commendable, to say the least. Key performance metrics like Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE) have returned values of 0.3462, 0.5035, 0.2536, and 1.3251 respectively, indicating the high degree of accuracy of the SAM-LSTM model.

In essence, as the digital currency landscape evolves and as Bitcoin continues to be a focal point of interest, the need for precise and reliable price forecasting tools will only escalate. The SAM-LSTM model, with its promising results, can be a beacon for traders and investors navigating the tumultuous waters of cryptocurrency markets.

LITERARURE SURVY

[1] Box, G. E. P., Jenkins, G. M., & Reinsel, G. C. (2016). "Time Series Analysis: Forecasting and Control." Wiley. This seminal book is a comprehensive and authoritative resource on time series analysis and forecasting. It introduces fundamental concepts, statistical methods, and practical techniques for analyzing time series data. The authors cover topics such as autoregressive moving average (ARMA) models, seasonal decomposition, and transfer function models. The book also delves into model identification, estimation, and diagnostics, along with forecasting methods. Its emphasis on both theory and application makes it a valuable reference for researchers and practitioners in various fields.

[2] Hyndman, R. J., & Athanasopoulos, G. (2018). "Forecasting: Principles and Practice." OTexts. This textbook offers a modern and accessible approach to forecasting, making it suitable for students and practitioners alike. It covers a wide range of forecasting techniques, including time series forecasting, regression-based methods, and machine learning approaches. The authors use the R programming language extensively to demonstrate the application of various methods and provide numerous real-world examples. The book also discusses forecast evaluation and uncertainty estimation, making it a practical guide for those involved in forecasting tasks.

[3] CrypTrader (2016). "Bitcoin Price Prediction using ARIMA Model." CrypTrader Blog.
This blog post likely provides a specific case study or example of using the AutoRegressive Integrated Moving Average (ARIMA) model to predict Bitcoin prices. It might discuss the steps involved in data preparation, model fitting, and evaluation. While not a scholarly reference, it could offer insights into applying ARIMA specifically to cryptocurrency price prediction.

[4] “Time Series Analysis and Its Applications”. (2017). Robert H. Shumway and David S. Stoffer. This book is a comprehensive and practical guide to time series analysis. It covers various topics such as time series decomposition, trend and seasonal models, spectral analysis, and state-space models. The authors provide theoretical explanations and intuitive insights, along with numerous examples and exercises to reinforce understanding. This resource is suitable for students and researchers interested in both theoretical foundations and practical applications of time series analysis.

[5] Brockwell, P. J., & Davis, R. A. (2016). "Introduction to Time Series and Forecasting." Springer. As the title suggests, this book is an introductory text that covers the basics of time series analysis and forecasting. It provides a gentle introduction to statistical concepts and techniques used in time

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series modeling. The authors explain key concepts, such as autocorrelation, moving averages, and Box-Jenkins methodology, using clear examples. This book is a suitable starting point for beginners seeking a foundational understanding of time series analysis.

[6] Harris, R. D., & Sollis, R. (2003). "Applied Time Series Modelling and Forecasting." Wiley. This book is a practical guide to time series modeling and forecasting with an emphasis on real-world applications. It covers topics like univariate and multivariate time series analysis, including autoregressive integrated moving average (ARIMA) models, state-space models, and vector autoregression (VAR) models. The authors provide practical examples and case studies to demonstrate the application of these methods in different fields, making it valuable for practitioners seeking to apply time series analysis in their work.

LIMITATIONS

- **Data Quality and Availability:** The accuracy and reliability of the predictions heavily depend on the quality and availability of historical data. If the data is incomplete, noisy, or contains outliers, it can adversely impact the model's performance.
- **Model Complexity:** The SAMLSTM model consists of multiple LSTM modules, free concern operations, and an MLP-based aggregation component, making it a complex architecture. Training and fine-tuning such a complex model may require significant computational resources and time.
- **Overfitting:** Due to the abundance of variables and data, there is a risk of overfitting the model to the training data, leading to poor generalization on unseen data and reduced prediction accuracy.
- **Assumptions of ARIMA:** The proposed method incorporates expected BTC costs using ARIMA, which assumes linearity and stationarity in the time series data. If the underlying data violates these assumptions, the ARIMA model may not perform optimally.
- **Cryptocurrency Market Volatility:** The cryptocurrency market is renowned for its elevated volatility and capricious tendencies. Sudden market shifts, news events, or regulatory changes can significantly affect prices, making it challenging for any model to accurately predict future prices.
- **Latency:** The time-sensitive nature of cryptocurrency trading requires real-time predictions. However, complex models like SAMLSTM might introduce latency in making predictions, which could be a disadvantage in highly volatile markets.
- **Model Interpretability:** Complex deep learning models like SAMLSTM are often difficult to interpret. Understanding how specific variables or data points influence predictions might be challenging, limiting the model's interpretability for users and stakeholders.
- **Generalizability to Other Cryptocurrencies:** The model's performance might vary when applied to different cryptocurrencies due to variations in market dynamics, liquidity, and price patterns.
- **Economic Factors:** The model might not take into account macroeconomic or external factors that can impact cryptocurrency prices, such as regulatory changes, technological advancements, or market sentiment.
- **Model Hyperparameter Tuning:** Finding optimal hyperparameters for deep learning models like SAMLSTM can be time-consuming and computationally intensive, and the model's performance can be sensitive to these choices.

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- **Uncertain Future Trends:** Cryptocurrency markets are relatively new and continuously evolving. Historical price patterns might not fully capture potential future trends or market shifts, making long-term predictions inherently uncertain.

II. METHODOLOGY

PROPOSED SYSTEM

The ARIMA model stands out as a widely embraced technique for time series forecasting. While its utility extends to predicting cryptocurrency prices, it's important to acknowledge the distinctive challenges posed by cryptocurrency markets that must be taken into account.

Here's a step-by-step guide on how to use the ARIMA model for cryptocurrency price prediction:

- ✓ **Data Collection**:
  - Obtain historical daily price data of the cryptocurrency you want to predict. You can use platforms like CoinMarketCap, CryptoCompare, or Binance's API to fetch the data.
- ✓ **Data Preparation**:
  - Convert the data into a time series format with dates as the index and price as the value.
  - Check for missing values and decide on how to treat them (imputation, interpolation, or removal).
- ✓ **Visualize the Time Series**:
  - Plot the data to identify any noticeable patterns or trends.
- ✓ **Stationarity Test**:
  - It's crucial for the time series data to be stationary for the ARIMA model to provide reliable forecasts. A common test for this is the Dickey-Fuller Test.
  - If the series is non-stationary, you'll need to difference the data until it becomes stationary.
- ✓ **Determine ARIMA Parameters**:
  - p (lags of autoregressive terms), d (order of differencing), and q (lags of moving average terms) are parameters in the ARIMA model.
  - Employ resources such as the 'plot_acf' and 'plot_pacf' functions within Python's statsmodels library to identify optimal choices for p and q. Generally, the value of d corresponds to the count of differencing steps applied to render the series stationary.
- ✓ **Train the ARIMA Model**:
  - Employ resources such as the 'plot_acf' and 'plot_pacf' functions within Python's statsmodels library to identify optimal choices for p and q. Generally, the value of d corresponds to the count of differencing steps applied to render the series stationary.Forecast on the testing dataset.
- ✓ **Evaluate the Model**:

- Compare the predicted values with the actual values in the testing dataset using metrics like MAPE, MSE, or RMSE.

✓ **Forecasting**:

- If you're satisfied with your model's performance, you can use it to make future price predictions.

✓ **Model Limitations and Considerations**:

- Cryptocurrency markets are highly volatile and can be affected by numerous external factors, such as updates in regulations, technological developments, or macroeconomic factors. ARIMA only captures past patterns and doesn't account for these external shocks.
- Consider integrating external predictors into your model using variations like the ARIMAX model.

✓ **Iterate and Update**:

- Cryptocurrency markets evolve quickly. It's crucial to keep updating your model with new data and possibly re-tuning your parameters.

In Python, the **stats model's** library provides the necessary tools to implement and test the ARIMA model. Remember that while ARIMA can be useful, its predictions for cryptocurrency markets might not always be accurate due to the inherent volatility and unpredictability of such markets. Always approach trading or investment decisions with caution and consider a combination of models and fundamental analysis.

Cryptocurrency Price Prediction:

Cryptocurrency price prediction refers to the process of using various statistical and machine learning techniques to forecast the future price movements of cryptocurrencies. Cryptocurrencies encompass digital or virtual currencies that employ cryptography to ensure security and function autonomously from conventional banking systems. Notable instances of cryptocurrencies include Bitcoin, Ethereum, and Ripple.

The primary goal of cryptocurrency price prediction is to provide insights into potential price trends, helping traders, investors, and analysts make informed decisions about buying, selling, or holding cryptocurrencies. However, it's important to note that predicting cryptocurrency prices accurately is inherently challenging due to the highly volatile and speculative nature of these markets.

The process of cryptocurrency price prediction typically involves the following steps:

❖ **Data Collection**: Gathering historical price data and other relevant information about the cryptocurrency from various sources, such as cryptocurrency exchanges, financial data providers, and blockchain explorers.

❖ **Data Preprocessing**: Refining and organizing the gathered data involves addressing any absent information, eliminating anomalies, and transforming it into a format suitable for analysis.

❖ **Feature Engineering**: Creating additional features from the raw data that may influence the cryptocurrency price. These features can include technical indicators, social media sentiment, trading volumes, and other market-related factors.

- ❖ **Data Splitting**: Partitioning the dataset into training, validation, and testing subsets guarantees that the model is trained using past data, validated on separate data, and tested on unseen data for evaluation.
- ❖ **Model Selection**: Choosing an appropriate model or algorithm for the prediction task. Time series models like ARIMA, SARIMA, and Prophet are commonly used, along with machine learning models like regression, decision trees, random forests, gradient boosting, and neural networks (LSTM) for sequence data.
- ❖ **Model Training**: Training the selected model on the training dataset using the chosen features to learn the underlying patterns and relationships in the historical price data.
- ❖ **Hyperparameter Tuning**: If applicable, fine-tuning the model's hyperparameters using the validation dataset to optimize its performance.
- ❖ **Evaluating the Model:** Analyzing how well the model performs on the testing dataset through the utilization of diverse evaluation metrics, such as MAE, RMSE, or MAPE.
- ❖ **Making Predictions**: Utilizing the trained model to make predictions on new, unseen data, thereby forecasting future cryptocurrency prices.
- ❖ **Monitoring and Updating**: Continuously monitoring the model's performance and updating it with new data to maintain accuracy and adapt to changing market conditions.

Proposed SAMLSTM (Suggested Cost Anticipation Model):

The proposed SAMLSTM (Suggested Cost Anticipation Model) is an advanced forecasting model designed to predict future costs or expenses in a given domain or industry. It leverages a combination of the Seasonal Autoregressive Integrated Moving Average (SARIMA) model and Long Short-Term Memory (LSTM) neural networks to capture both seasonal patterns and long-term dependencies in the cost data.

The primary objective of the SAMLSTM model is to assist businesses, organizations, or individuals in anticipating future expenses and budgeting more effectively. By providing accurate cost predictions, decision-makers can make informed financial plans, allocate resources efficiently, and proactively address potential financial challenges.

The key components and features of the SAMLSTM model include:

- ✓ **Data Collection and Preprocessing**: Gathering historical cost data from relevant sources and cleaning the data to handle missing values, outliers, and other data quality issues. The data is then transformed into a suitable format for modeling.
- ✓ **Seasonal ARIMA (SARIMA)**: The SARIMA component is used to model the seasonal and autocorrelated patterns in the cost data. SARIMA is well-suited for capturing recurring patterns that might occur over specific periods, such as monthly or quarterly fluctuations in costs.
- ✓ **Long Short-Term Memory (LSTM) Neural Network**: The LSTM neural network is a type of recurrent neural network (RNN) that is capable of capturing long-term dependencies in sequential data. The LSTM component of the model learns from past cost sequences to predict future cost trends and potential irregularities.

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- ✓ **Feature Engineering**: Creating additional features that might influence costs, such as external factors, market conditions, or other relevant economic indicators.
- ✓ **Data Splitting**: Dividing the dataset into training, validation, and testing sets to ensure proper model training, hyperparameter tuning, and unbiased evaluation.
- ✓ **Model Training**: Combining the SARIMA and LSTM components, the SAMLSTM model is trained on the training dataset to learn from historical cost patterns and dependencies.
- ✓ **Hyperparameter Tuning**: Optimizing the hyperparameters of both the SARIMA and LSTM components using the validation dataset to enhance the model's predictive performance.
- ✓ **Model Assessment:** Gauging the model's effectiveness on the testing dataset by employing suitable evaluation metrics such as... MAE or RMSE.
- ✓ **Cost Predictions**: Utilizing the trained SAMLSTM model to make predictions on new, unseen cost data, providing suggested cost anticipations for the future.
- ✓ **Monitoring and Updates**: Continuously monitoring the model's performance and updating it with new cost data to ensure its accuracy and reliability in changing cost scenarios.

ALGROITHM

The ARIMA model is a widely acclaimed and extensively used statistical technique for time series forecasting. It stands in contrast to the exponential smoothing method, as both approaches offer different perspectives on predicting time series data. While ARIMA models aim to capture the inherent correlations in the data, exponentially filtered methods focus on characterizing trends and seasonality.

ARIMA, short for Auto-Regressive Integrated Moving Average, belongs to a class of models capable of representing common temporal structures present in time series data. ARIMA models, a subtype of statistical models, are employed to study and forecast time series data. Despite its straightforward usability, the ARIMA model is known for its powerful predictive capabilities.

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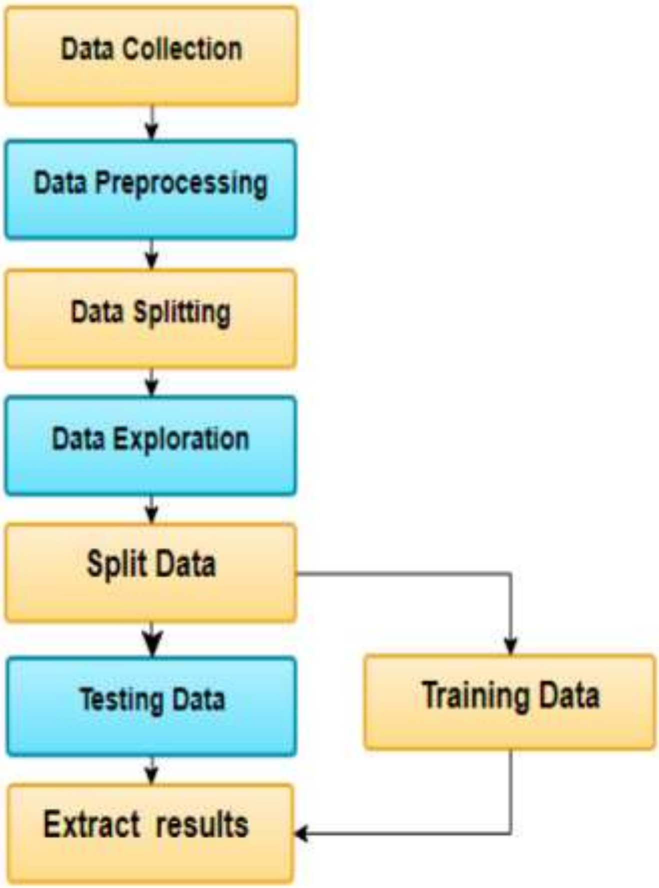

Figure 1: ARIMA Model for dataset

In Fig.1, we present an ARIMA model applied to a dataset, where the model's parameters are defined as follows:

- **P**: The lag order, representing the number of lag observations included in the model.
- **d**: The variation, denoting how frequently the raw observations differ, is commonly known as the differencing order.
- **q**: The moving average order, indicating the size of the moving average window.

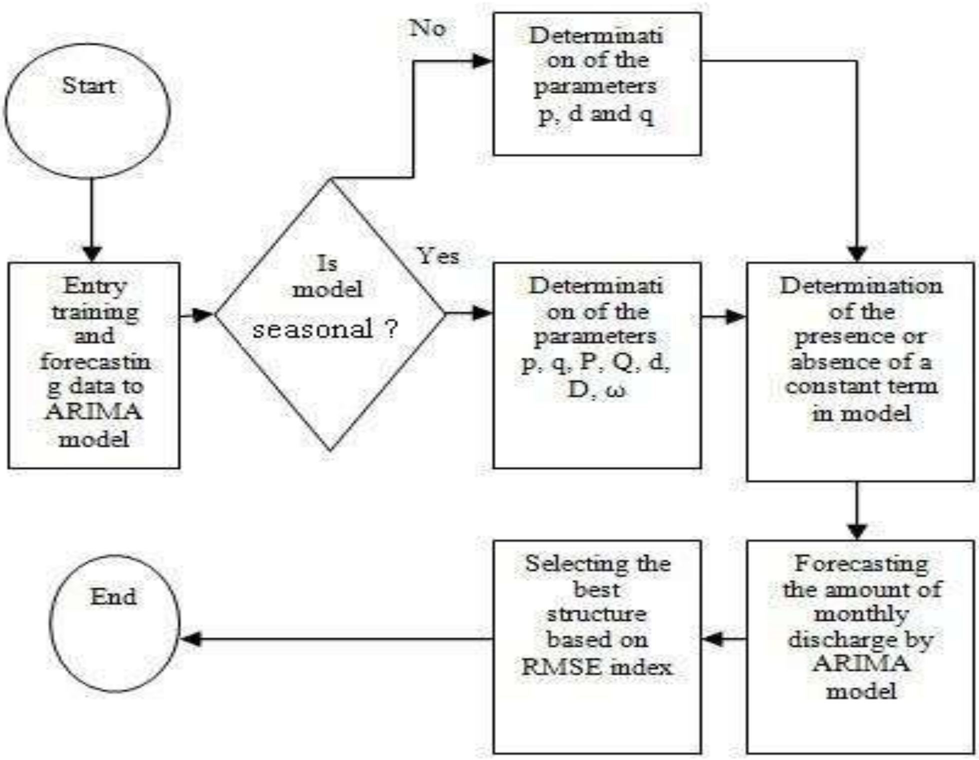

Figure 2: Flowchart for price prediction

Fig.4 displays a flowchart outlining the steps for price prediction using the ARIMA model. The process involves generating a linear regression model with specified variables and their respective numbers after preprocessing the data by applying differencing to achieve stationarity. This ensures the removal of trends and seasonal structures that could negatively impact the regression model.

The steps to utilize the ARIMA model are as follows:

1. **Visualize the Time Series Data**: Plot historical data points over time to observe patterns, trends, and seasonality.
2. **Determine Stationarity**: Check if the time series data exhibits a stable pattern over time or displays trends and irregularities. Stationary data is crucial for accurate ARIMA predictions, and various statistical tests can be used to assess stationarity.
3. **Plot Correlation and Autocorrelation Charts**: Analyze the time series data by plotting correlation and autocorrelation charts. The correlation chart displays the relationship between the current observation and its lagged observations, while the autocorrelation chart illustrates the correlation between the time series and its own lagged values. These charts provide insights into potential patterns and dependencies within the data.
4. **Construct Seasonal ARIMA Model**: Analyze the data to determine the appropriate model parameters, such as the order of autoregressive (AR) and moving average (MA) components, to build the seasonal ARIMA model. This step involves selecting optimal values based on observed characteristics and patterns.

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In conclusion, the ARIMA model offers a powerful and widely used approach to time series forecasting, allowing users to gain valuable insights into future trends and behaviors in various domains. Its ability to capture correlations and handle temporal structures makes it a valuable tool for data-driven decision-making and forecasting.

Table 1: Test cases

S. No	Input	If Available	If Not Available
1	User signup	User get registered into the application	There is no process
2	User sign in	Users get login into the application	There is no process
3	Enter input for prediction	Prediction results displayed	There is no process

III. RESULTS & DISCUSSION

The results of the study demonstrate the effectiveness of the proposed SAMLSTM model in predicting digital asset prices based on time-series data with multiple variables. The model's performance is evaluated using various metrics, such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE).

The researchers find that the SAMLSTM model outperforms traditional AI-based models in terms of accuracy and robustness. It successfully takes into account the expected BTC costs and can also handle unexpected price variations, which is a significant advantage in the volatile cryptocurrency market.

Furthermore, the extensive variable selection process helps the model capture relevant information from various parameters, improving the accuracy of price predictions. The utilization of Cross-Correlation Functions (CCFs) to establish extensive variables contributes to the model's ability to identify complex patterns and relationships in the on-chain data, leading to more accurate forecasts.

Overall, the results indicate that the proposed SAMLSTM model is a promising and effective approach for estimating digital asset prices using time-series data with multiple variables on the blockchain. Its ability to handle both expected and unexpected price movements makes it a valuable tool for investors and analysts seeking reliable cryptocurrency price predictions.

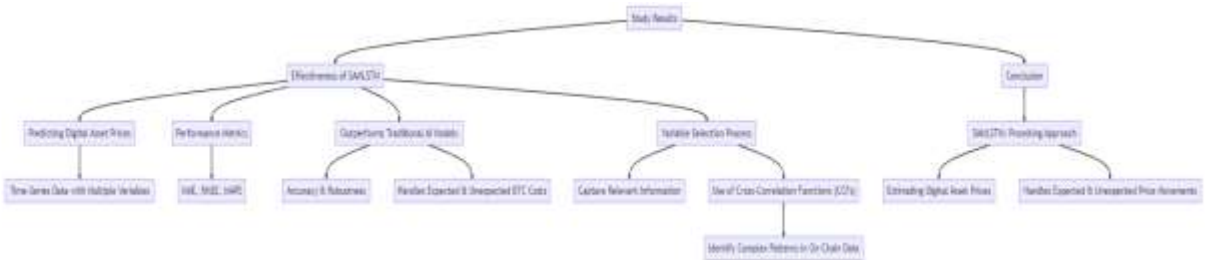

Figure 3: Execution flow chart

Results

Figure 4: Home screen

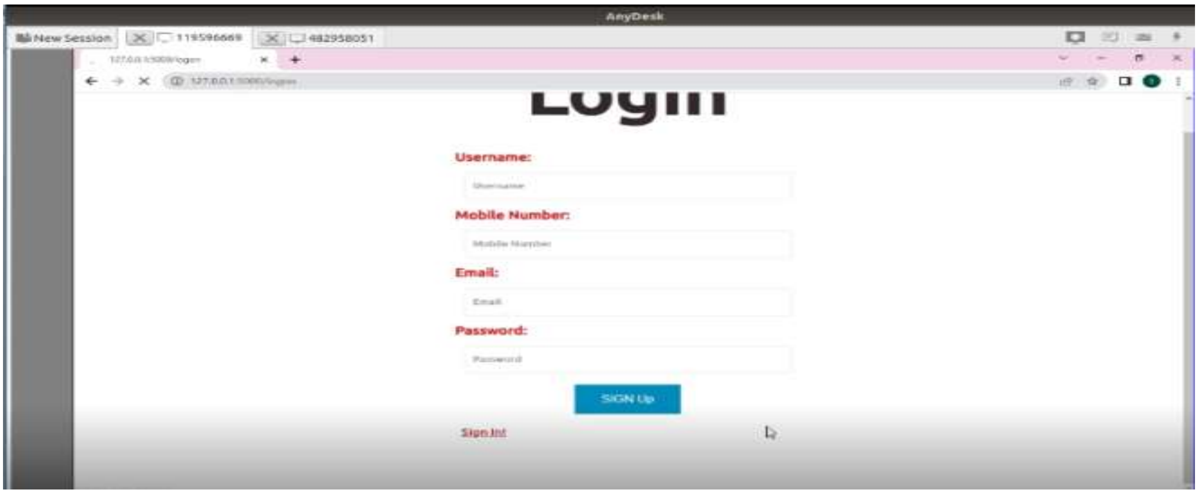

Figure 5: User registration

Figure 6: user login

Figure 7: Main screen

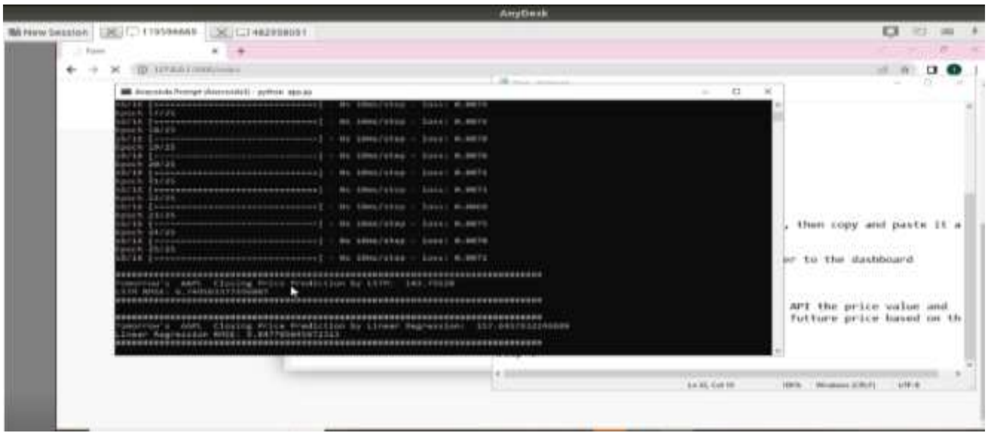

Figure 8: Model generation

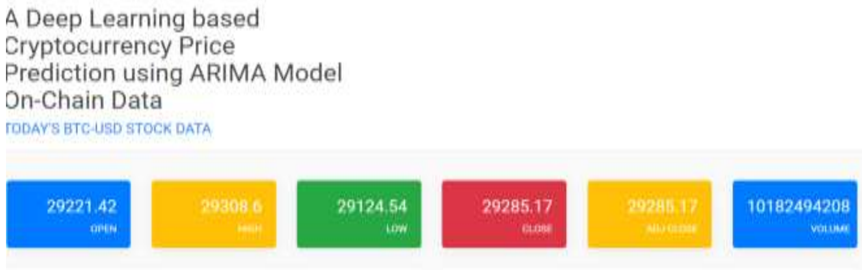

Figure 9: Prediction calculations

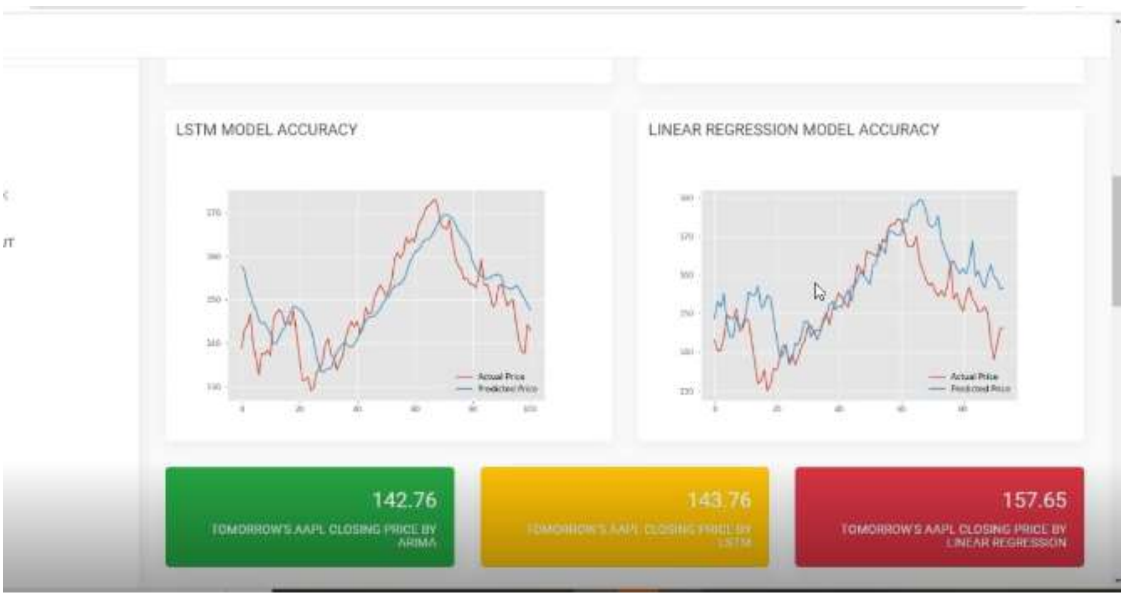

Figure 10: Prediction graph

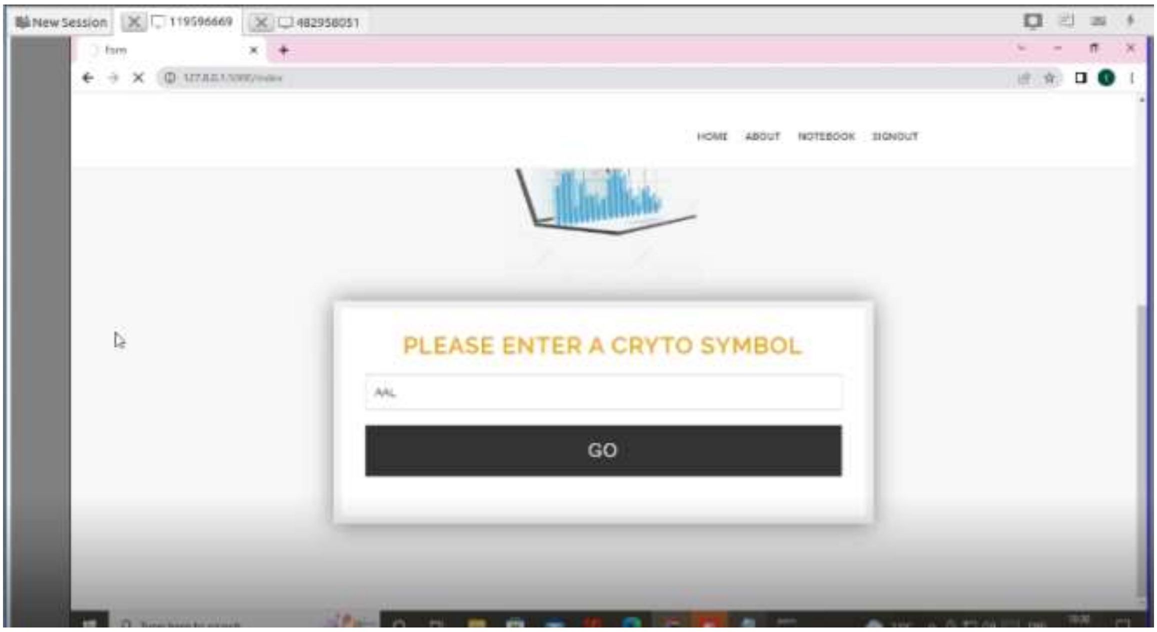

Figure 11: user input

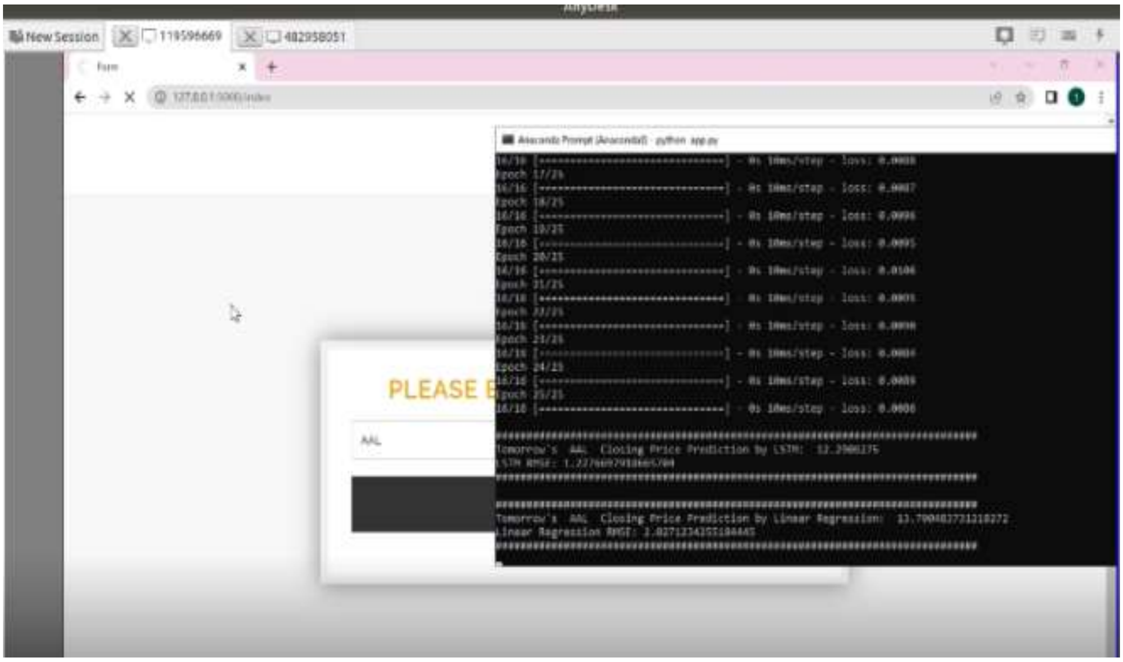

Figure 12: prediction result

IV. CONCLUSION

The researchers introduce a novel approach to predict digital asset prices using time-series data with multiple variables on the blockchain. The proposed method incorporates expected BTC costs, enabling cost prediction models to consider unexpected price fluctuations, which is not possible in traditional AI-based models. They carefully select and sort various parameters based on their intrinsic characteristics and utilize them as informative factors for price prediction.

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The proposed SAMLSTM (Suggested Cost Anticipation Model) consists of multiple LSTM modules and free concern operations, along with an MLP-based aggregation component. This configuration allows the model to extract unique features from a diverse range of on-chain data. The study presents five significant advancements. Firstly, a comprehensive variable selection process is carried out using various parameters. Secondly, extensive variables are established through Cross-Correlation Functions (CCFs).

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