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PAM: Cultivate a Novel LSTM Predictive analysis Model for The Behavior of Cryptocurrencies

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Abstract: The popularity of cryptocurrencies has skyrocketed in the last several years due to the introduction of blockchain technology (BCT). Herein, we are navigating the intersection of sustainable market investment and cryptocurrency predictive analysis against the backdrop of a dynamic and evolving financial landscape marked by the surge of digital assets. This study's goal is to construct the predictive analysis model (PAM) which incorporates Long Short-Term Memory (LSTM) capabilities to predict the price of Bitcoin with high accuracy the next day and to identify the variables that influence price. In constructed PAM, we are using a comprehensive methodology to study temporal correlations within minute-by-minute bitcoin data using preprocessing, sophisticated machine learning algorithms, and data exploration. Our findings demonstrate the effectiveness of the LSTM model in forecasting bitcoin behavior, offering detailed information that is essential for long-term market investing.

Keywords: Sustainable investment, Cryptocurrency analytics, Predictive Analysis mode, Market sustainability, financial decision-making, Blockchain Technology, Long Short-Term Memory

1. Introduction

The cornerstone of each nation is its economy. This study attempted to showcase the issues and criticisms of the nation's economy through conducted surveys for prior studies related to our scope. One of these issues is an economic meltdown that may have detrimental effects on numerous facets of life. The National Bureau of Economic Research claimed in [1] that the worst catastrophe in recent decades was the global financial crisis that lasted from 2007 to 2009. Economic and social aspects were impacted by this crisis, including inequality, poverty, and social conflicts. Ultimately, this resulted in political instability and the need for more economic reforms. Awotunde et al. [2] discussed another economic concern which entailed anxiety regarding the stocks that are chosen to optimize investment and boost earnings. Hence stock market investors in [3] must understand when to purchase and sell stocks to maximize their investment return. Hence [4] stated that Price prediction is currently one of the main subjects of discussion in finance. However, the efficient market hypothesis in [5] demonstrated that price prediction is meaningless for maximizing the profit. Nonetheless, it has tried to respond favorably.

Also, [6] highlighted another criticism of the present-day monetary system which has several imperfections. The scholars of [6] described the monetary system's imperfections as a lack of tangible backing for currencies which can lead to problems like income inequality and hyperinflation. Additionally, transactions are frequently carried out through middlemen like financial institutions and credit card firms, resulting in expensive fees and lengthier transfer times. Meanwhile, the traditional ledgers used to record transactions are vulnerable to manipulation and violations. This may result in people losing ownership and control over their data.

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Moreover, these criticisms forced academics and stakeholders in the financial system to adopt a new transaction method that can successfully foster confidence across all parties. As a result, [6] attempts to treat these issues and criticisms by introducing blockchain technology (BCT). Whilst This technology according to [7] achieved credibility where monetary transactions are performing via the public internet without the need for intermediaries and facilitate transactions through utilizing digital currency or in other word cryptocurrency. Due of the significance of cryptocurrency, [8] defined it as a virtual currency unaffected by outside influence or legal restrictions also, [9] grants a system with a high level of security and makes it exceedingly difficult to fake or modify. Thus, cryptocurrency [10] has significant ramifications for emerging economies and the global economy as a whole. Confirmation of that Livieris et al.[11] stated that one of the most well-liked and prospective categories of lucrative investments is the trade of cryptocurrencies. Still, there is a lot of volatility and substantial price swings in a continually expanding financial sector. And [12] clarified that the growing recognition of environmental, social, and governance (ESG) factors in investment decisions underscores the urgency of integrating sustainability into financial strategies. So that [11, 12] served as inspiration and motivation for many investors and academics forecasting cryptocurrency. Notwithstanding, [13, 14] claimed that the forecasting of cryptocurrency prices is often regarded as one of the most difficult time-series prediction issues because of the numerous unknown variables and the high volatility of cryptocurrency values, which thereby producing intricate temporal dependencies.

Posteriorly, scholars of [15, 16] deployed deep learning techniques (DL) for the purpose of forecasting. due to DL in [17] has shown to be helpful in a variety of domains and is capable of processing chaotic data. Therefore, deep learning is a sophisticated neural network type that more closely resembles the functioning of the human brain. For instance, [6] suggested deep learning models for providing trustworthy price prediction models that, using previous data, cryptocurrency investors and speculators can depend on. in the same vein, Long Short-Term Memory Neural Networks (LSTM) in [2] captured patterns with a significant degree of generality, making them more suitable for sequential data such as time series. Also, [18] implemented Multi-Layer Perceptron (MLP) and Long Short-Term Memory (LSTM) as predictors techniques for Bitcoin, Ethereum, and Litecoin. Herein, we are leveraging the capabilities of DLT and employing its capabilities to analyze the cryptocurrency's behavior and predict its future behavior through constructing predictor model based on LSTM technique. The objective of the predictive analysis model (PAM) is to orient decision-makers and investors in the direction of the right investment by analyzing data on cryptocurrency and its potential worth.

The study is constructed according to several sections. Each one represents certain information related to our study as the prior studies and methodologies which exhibited and implemented in our interested area in section 2. Hence, we exploited these methodologies to construct our novel PAM in section 3. Moreover, we discussed PAM's results and findings in section 4. Finally, we recorded our conclusions and visions in section 5.

2. Comprehensive Study for Cryptocurrency Prediction

This section showcases various artificial intelligence (AI) techniques of regressions, machine learning (ML) and DLT by scholars in earlier studies.

Market indicators and societal attitudes employed in [19] which utilized as independent factors and price as the dependent variable in the framework of price prediction based on multivariate regression model. Also, [20] indicated that there was a favorable relationship between social emotion and changes in the price of Bitcoin. The authors of [20] analyzed this relationship by constructed model of polynomial and linear regression to forecast the prices. other studies as [21] harnessed artificial neural network (ANN's) potential to forecast the trend either upward or downward using the bitcoin market data over the past 50 days,. in the same vein, [22] Used Multi-Layer Perceptron (MLP) as branch of ANN to estimate the value of Bitcoin (BTC), the most well-known and powerful cryptocurrency, in Turkish Lira (TL) using the exchange rate between the US dollar (USD) and the Turkish lira (TL) and date characteristics. Along the same lines, [23] anticipate the erratic time-series data of the amount of Bitcoin transactions in Nigeria through leveraging Backpropagation Algorithm (BPA) and MLP. ANN, a random forest (RF), and a binary autoregressive tree (BART) model are utilized in [14] to simulate the short-term movements of the top three cryptocurrency capitalizations of Bitcoin, Etherium, and Ripple. Chowdhury et al. [24] used a robust ensemble learning models, ANNs, gradient boosted trees, and k-nearest neighbor among other machine learning methods. The objectives of utilizing these models are forecasting cryptocurrency future values.

others as [18] embraced another perspective entailed in cryptocurrency price forecasting is a sequential activity by nature. A new type of neural networks called recurrent neural networks (RNNs) emerged to handle time-dependent data. Nevertheless, once a sequence reaches a certain length, RNNs can no longer capture long term dependencies. Hence, Hochreiter et al [25] proposed an effective new architecture is LSTM. Confirmation of this ,LSTM utilized in [26] In order to mitigate risks ,the decision-making process involved in the investment process must make the proper choice at the appropriate moment. Hence, hybrid cryptocurrency prediction system founded on LSTM and GRU is demonstrated, concentrating on Litecoin and Monero[27] .

Ultimately, drawing from a synopsis of earlier research. We concluded that LSTM is a branch or technique of DLT. Thereby, we are leveraging the ability of LSTM to analyze cryptocurrency behavior to predict future cryptocurrency behavior through constructing Predictive Analysis Model (PAM).

3. Predictive Analysis Model Methodology

In this section, we detail the comprehensive methodology employed to guide our investigation into sustainable market investment using predictive analysis of cryptocurrency data. In our methodology, we adopt Long Short-Term Memory (LSTM) as a fundamental tool for modeling cryptocurrency data due to its inherent ability to capture and learn complex temporal dependencies within sequential data. LSTM networks are a class of recurrent neural networks (RNNs) designed to address the challenges of learning long-term dependencies in sequential data.

The primary design theory revolves around the incorporation of memory cells, input gates, output gates, and forget gates. These components enable LSTMs to selectively store and retrieve information, making them particularly suited for capturing intricate temporal patterns present in cryptocurrency data. The memory cells maintain a hidden state, preserving information over extended sequences, while the gates regulate the flow of information, preventing the vanishing gradient problem that can hinder the training of traditional RNNs. The LSTM architecture, with its unique design elements, provides an effective solution for modeling the dynamic and non-linear nature of cryptocurrency trends. To implement the LSTM model for cryptocurrency predictive analysis, we follow a systematic set of steps:

- Initial step is data processing where raw dataset is organized into sequences suitable for training the LSTM [16, 28–30].
- This process includes scaling features, handling missing values, and creating input sequences with corresponding target values. Subsequently, the LSTM architecture is configured, specifying the number of layers, neurons, and activation functions.
- The model is then trained using historical cryptocurrency data, and hyperparameters are fine-tuned through iterative testing to optimize performance.
- During training, the LSTM learns the temporal dependencies within the data, enabling it to make informed predictions based on historical patterns.
- To ensure the model's robustness and generalization, we evaluate its performance using separate validation and test datasets, assessing key metrics namely mean square error (MSE).

-This comprehensive methodology allows us to harness the power of LSTM networks for predictive analysis, offering a principled approach to modeling cryptocurrency trends in the context of sustainable market investment.

```python
import torch
import torch.nn as nn
import torch.optim as optim

# Define the LSTM model class
class LSTM(nn.Module):
    def __init__(self, input_size, hidden_size, num_layers, output_size, dropout_prob, directions=1):
        super(LSTM, self).__init__()

        # Initialize parameters
        self.num_layers = num_layers
        self.hidden_size = hidden_size
        self.directions = directions

        # LSTM layer
        self.lstm = nn.LSTM(input_size, hidden_size, num_layers, batch_first=True, dropout=dropout_prob)

        # Dropout layer to prevent overfitting
        self.dropout = nn.Dropout(dropout_prob)

        # Fully connected layer for output
        self.linear = nn.Linear(hidden_size, output_size)

    # Initialize hidden states for LSTM
    def init_hidden_states(self, batch_size):
        state_dim = (self.num_layers * self.directions, batch_size, self.hidden_size)
        return (torch.zeros(state_dim).to(device), torch.zeros(state_dim).to(device))

    # Forward pass through the model
    def forward(self, x, states):
        x, (h, c) = self.lstm(x, states)

        # Apply dropout to the output
        x = self.dropout(x)

        # Fully connected layer
        out = self.linear(x)
        return out, (h, c)

# Define model, loss function, and optimizer
model = LSTM(
    NUM_FEATURES,
```

```
    HIDDEN_SIZE,
    NUM_LAYERS,
    OUTPUT_SIZE,
    DROPOUT
).to(device)

# Mean Squared Error Loss
criterion = nn.MSELoss()

# AdamW optimizer with weight decay
optimizer = optim.AdamW(model.linear.parameters(), lr=LEARNING_RATE, weight_decay=0.01)
```

4. Results and Discussion

In this pivotal section, we showcase the outcomes of our empirical investigations at the intersection of sustainable market investment and cryptocurrency predictive analysis.

Our experimental investigations rely on a public dataset, wherein temporal information is represented in Unix timestamps, denoting the number of seconds elapsed since 1970-01-01 00:00:00.000 UTC, with each timestamp reflecting minute-by-minute data due to their multiples of 60. The dataset includes the Asset_ID, signifying the identification of various cryptocurrencies (e.g., Asset_ID = 1 for Bitcoin), with the mapping detailed in the asset_details.csv. The parameters encompass Count, indicating the total number of trades within the last minute; Open, denoting the opening price of the time interval in USD; High, representing the highest price reached during the interval; Low, indicating the lowest price observed during the time interval; Close, reflecting the closing price in USD; Volume, quantifying the quantity of the asset bought or sold in base currency USD; VWAP, portraying the asset's average price over the interval, weighted by volume, as an aggregated form of trade data. Additionally, the dataset features Target, providing residual log-returns for the asset over a 15-minute horizon, constituting a comprehensive set of variables for our analytical pursuits. Table 1 provides a comprehensive summary of key statistical metrics derived from our empirical analysis of cryptocurrency data. This table encapsulates essential descriptive statistics, offering insights into the central tendencies, dispersion, and shape of the dataset. Parameters such as mean, median, standard deviation, and quantiles are presented, providing a concise overview of the distributional characteristics of the analyzed variables.

Table 1: Summary Statistics of Cryptocurrency Dataset

	count	**mean**	**std**	**min**	**25%**	**50%**	**75%**	**max**
timestamp	2.42E+07	1.58E+09	3.32E+07	1.51E+09	1.55E+09	1.58E+09	1.61E+09	1.63E+09
Asset_ID	2.42E+07	6.29E+00	4.09E+00	0.00E+00	3.00E+00	6.00E+00	9.00E+00	1.30E+01
Count	2.42E+07	2.86E+02	8.67E+02	1.00E+00	1.90E+01	6.40E+01	2.21E+02	1.65E+05
Open	2.42E+07	1.43E+03	6.03E+03	1.17E-03	2.68E-01	1.43E+01	2.29E+02	6.48E+04
High	2.42E+07	1.44E+03	6.04E+03	1.20E-03	2.68E-01	1.43E+01	2.29E+02	6.49E+04
Low	2.42E+07	1.43E+03	6.02E+03	2.00E-04	2.67E-01	1.43E+01	2.28E+02	6.47E+04
Close	2.42E+07	1.43E+03	6.03E+03	1.17E-03	2.68E-01	1.43E+01	2.29E+02	6.48E+04
Volume	2.42E+07	2.87E+05	2.43E+06	-3.66E-01	1.41E+02	1.30E+03	2.73E+04	7.60E+08
VWAP	2.42E+07	NaN	NaN	-inf	2.68E-01	1.43E+01	2.29E+02	inf
Target	2.35E+07	7.12E-06	5.68E-03	-5.09E-01	-1.69E-03	-4.29E-05	1.60E-03	9.64E-01

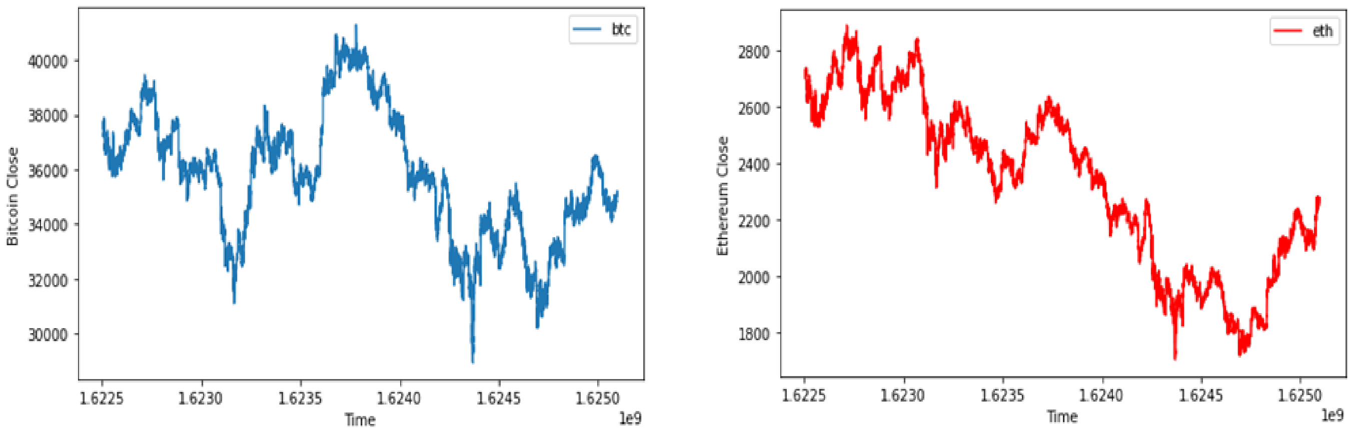

Figure 1. Temporal Dynamics of Cryptocurrency Market

According to Figure 1, key aspects of our dataset are presented visually through insightful visualizations. Utilizing the provided timestamps, the figure illustrates minute-by-minute trends in cryptocurrency trade frequencies, price movements, and related parameters. The comprehensive visualization encapsulates the temporal dynamics of the dataset, offering a graphical representation of the interplay between various factors crucial to our framework. This figure serves as a foundational visual aid for understanding the intricate patterns within the cryptocurrency market data, laying the groundwork for the subsequent analyses and discussions in this study.

Hence, Figure 2 presents a visual exploration of the correlation dynamics between Bitcoin (BTC) and Ethereum (ETH) over time. This graphical representation sheds light on the interdependent movements of these prominent cryptocurrencies, offering insights into their synchronized or divergent behavior across different temporal intervals. The visualization captures the nuanced relationship between BTC and ETH, providing a comprehensive depiction of how their respective market values fluctuate in tandem or deviate over the observed timeframe. This figure serves as a crucial visual tool for understanding the dynamic correlation patterns between Bitcoin and Ethereum, contributing valuable information to the broader narrative of cryptocurrency market dynamics.

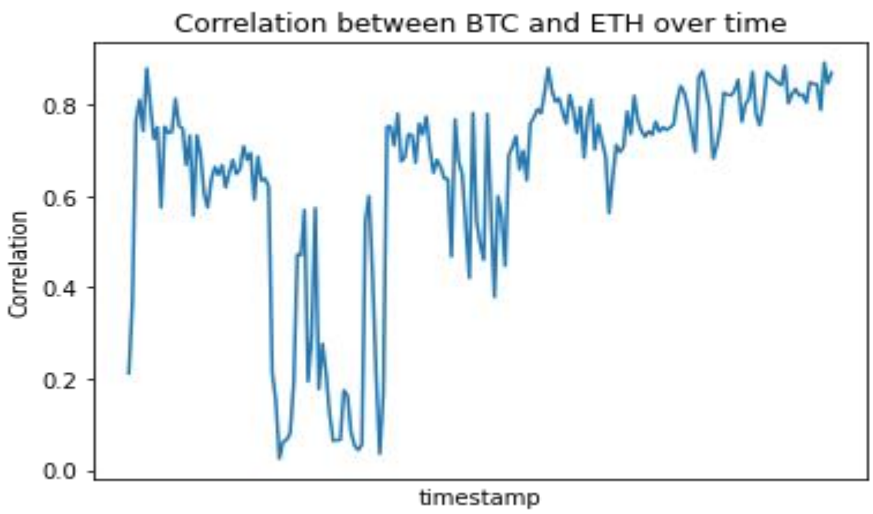

Figure 2. A visual representation of the correlation trends over time between Bitcoin (BTC) and Ethereum (ETH).

Figure 3 illustrates the learning curves derived from our predictive analysis model, depicting the evolution of performance metrics over successive iterations. The visualization showcases the convergence and stability of the model as it learns from the dataset, providing valuable insights into the training process's efficiency and effectiveness. This visual representation serves as a crucial tool for assessing the model's performance evolution, guiding a nuanced understanding of its convergence patterns, and informing discussions on the efficacy of the predictive analysis approach in the context of sustainable market investment.

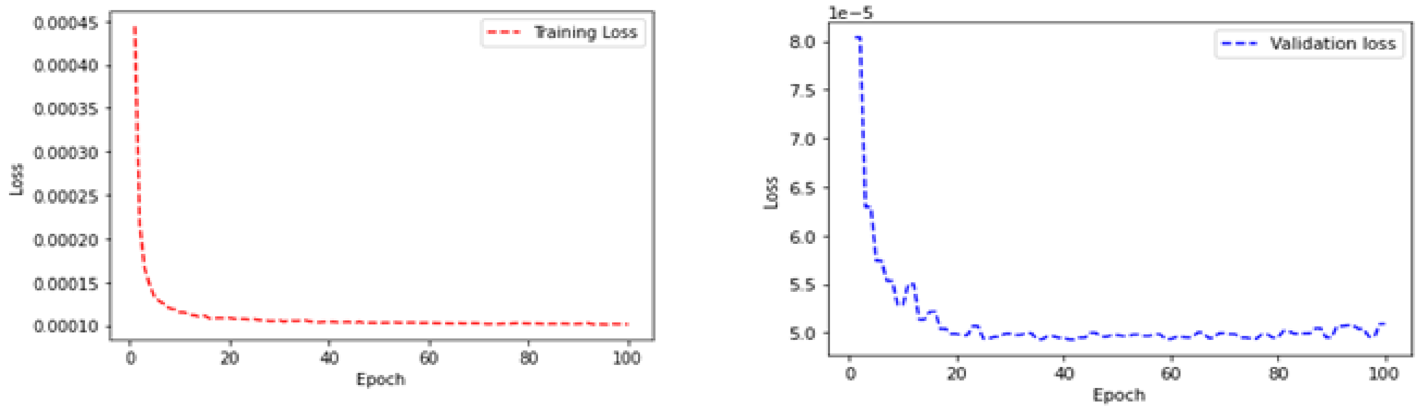

Figure 3. Learning Curves of Predictive Analysis Model

5. Conclusions and Future Directions

The acronym of cryptocurrency is used frequently in modern times, nonetheless there are a lot of problems associated with digital currency, so it's critical to figure out how to lower or eliminate the risks that individuals who deal with it face. Thus, predicting the future behavior and transactions of cryptocurrency based on current and historical behavior is crucial for stakeholders and decision makers to making accurate decisions related to investments and sustainability of market. The predicting process is a complex task, it needs powerful technique has ability to predict dependent variables from independent variables.

Based on conducted surveys for earlier studies, Deep learning is a popular technique for handling challenging situations when sophisticated financial transaction prediction is needed. Herein, we are volunteering this technique especially, RNNs which differentiate from DLT. Whilst in RNNs, the model's parameters are altered in addition to producing an output value when data is swapped into it. Following that, LSTM is proposed as branch of RNNs. This technique characterized by Long-term dependencies are provided by adding a new memory cell state and gating functionality, which regulates what data is inserted and removed.

Herein, we constructed PAM based on LSTM to analyze cryptocurrency behavior to predict the next event or behavior for cryptocurrency. Our PAM adepts at capturing intricate temporal dependencies, showcases promising results in forecasting cryptocurrency behavior. generally speaking, along with contributing to understanding of cryptocurrency dynamics, this study's methodology and perceptive assessments provide the groundwork for future investigations into the nexus between developing financial technologies and sustainable market investment.

Supplementary Materials

Not applicable.

Author Contributions

All authors contributed equally to this work.

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Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

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