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A secure framework of blockchain technology using CNN long short-term memory hybrid deep learning model

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ABSTRACT

Generation Z is embracing blockchain technology, which is appropriate for the digital age. Internet of things (IoT) can benefit from blockchain technology IoT. The proliferation of IoT technology has led to breakthroughs in distributed system architecture. For the blockchain network to store, communicate, and exchange data, it needs a randomized data management system. This shows how difficult it may be to provide consistent and safe data replication in a distributed system, an issue blockchain technology may overcome. We need a solid prediction model that improves results. This article describes an innovative way to overcome the limitations of third-party transactions using Bitcoin. In this article, convolutional neural networks-long short term memory (CNN-LSTM) deep learning forecasting models are introduced. Convolutional layers help extract relevant data from instances. It has an long short-term memory (LSTM) layer, which lets it find long-and short term dependencies. The experiment's goal was to test the multivariate statistical model we suggested and compare its performance to well-established models. The addition of convolutional layers to a forecasting model may improve its accuracy, according to an experiment. The research shows that this strategy has a better chance of success and is more trustworthy than others.

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1. INTRODUCTION

In today's world, blockchain has grown to be a hugely popular and effective approach. Blockchain proponents argue that the technology has nearly limitless applications in a variety of industries, including banking, power, IoT, wellness, entertainment, and more [1]. Blockchain technology, a fully decentralized ledger that may be used to securely keep ever-growing lists of data recordings and payments, has recently swept the globe. Public or less approved, private or authorised, and consortium are the three basic requirements for blockchain identity and connectivity. The most crucial and distinguishing feature of the blockchain idea is that the data is completely protected within the blocks of the blockchain's operations. Reliability, vitality, and flexibility are the three major elements of its decentralised consensus model [2]–[4]. Blockchain, in its most basic form, is a distributed ledger. Utilizing encryption as well as decentralised algorithms, transactions on the blockchain are almost tamper-proof. Consumers may generally access transaction details supplied by a blockchain, but changing historical transactions inside the ledger is practically difficult. This is partially attributable to its dispersed nature, but it is also due to other factors [5]. The general ledger of a blockchain functions in a decentralized, peer-to-peer form the majority of the time. Any modifications made to an existing record, such as a transaction from the past, must be communicated to the great majority of ledger holders. Machines that have a lot of processing power must be prevented from altering the ledger history in order for this update to succeed. Blockchain technology has also proved that it has the capacity to protect and enhance the reliability of a wide range of information systems. In the early 2000s, the concept of blockchain was initially introduced to the general public. By disseminating records broadly, there would always be a reliable source for verifying the integrity and correctness of any given collection of records. The notion was simple and predicated on this principle. Because of this, it was assumed that there would always be at least one reliable and widely accepted source of information. Due to the lack of actual blockchain-based services at the time, it took some time for the concept to gain widespread acceptance. Bitcoin [6] was originally published in 2009 and introduced the notion of a digital currency built on the blockchain. It has been a hot topic ever since. Electronic currency transactions might be completely self-contained and checked against anybody else's records that had been retained prior to the transaction. One of the most important aspects of Bitcoin's success is that it has ushered blockchain technology into the mainstream. In spite of the fact that a great number of people were effective in identifying useful purposes and advantages, there were also cases and experiences that brought to light a number of unpleasant and inconvenient outcomes associated with the blockchain. Because of the public trust that blockchain technology supports, it is possible to do away with intermediary third parties altogether. Transactions and confirmations can also be fine-tuned at the granular level. This simplification makes it possible to make a significant alteration to the architecture of transaction verification. Interactions of this kind provide more reliable data trails in many information systems. As a result, it's expected that future market analyses and reactions will be able to go into greater depth. Smart contracts can be used to implement the idea in a real-world setting.

Without a question, blockchain's most well-known feature, its lack of trust, has had a significant influence on present and future real-world applications. The fundamental security and transparency of blockchains eliminates the need for third-party financial intermediary and, as a result, the necessity for trust among users in decentralized and untrustworthy situations [7]. However, blockchain is not a replacement for trust; rather, it is a new type of trust that aims to eliminate reliance on individual entities [8]. Deep learning has made significant progress in numerous application areas during the last few of years. Deep learning techniques and approaches have been successfully deployed in a range of applications for real-world difficulties like time series forecasting [9]. With these methods, forecasts are more accurate and dependable because of their ability to deal with the world's most unexpected and erratic natures. In-depth learning models such as long short-term memory (LSTM) and convolutional neural networks (CNN) are the most extensively used and well-established [10]. LSTM models are more efficient in generating the sequence outline, whereas CNN models are better at filtering input noise and collecting critical characteristics. This is the primary purpose of using these models in time series issue resolution [11]. When it comes to complex temporal correlations, standard CNNs are unable to handle them. Instead, the LSTM makes use of the properties of the training dataset and is capable of handling temporal relationships. Because of this, a time series model that integrates both of these deep learning models can improve overall prediction results. For numerous aspects that might impact the blockchain system, this article discusses several existing solutions and blockchain applications. Due to its decentralization, durability, anonymity, and auditing properties, blockchain technology has drawn significant industry and academic interest. The development of a revolutionary deep learning model that benefits blockchain technology in a secure manner is examined in this study.

2. RELATED WORKS

Three layers of a recurrent neural network (RNN) are comprised of the input, hidden layer and output [12]. There are no surprises when it comes to chained calculations, as they all accomplish the same thing. Feed-forward neural networks can only map input to output. Recurrent neural networks may be able to encode each and every output in an unfurled typical network vector [13]. For example, mapping one sequence to another is a method for doing so. Several systems communicate with each other, each of which sends a signal to the next one. Only a few steps in the past are actually available for it to use as a reference point (more on this later). One input unit, one output unit, and one repeating hidden unit make up a typical network when it is fully unfolded. By separating the RNN into three inner-cell gates, some LSTM networks create so-called "memory cells" to handle gradient disappearance [14].

When it comes to time series forecasting, the LSTM model is one of the most powerful [15]. The first to use the told model to predict tourist drift was Tian *et al.* [16]. In their research, they use this method to predict the flow of tourists. According to them, LSTM's long-term accuracy may be better than that of back propagation neural network (BPNN) and autoregressive integrated moving average (ARIMA) models. Time series forecasting is more accurate when compared to other methodologies, as demonstrated by the experimental results. Chua and Roska [17], the Bi-LSTM model and Gaussian LDA were used to classify a wide range of inputs, including software, labels, banking information, and other relevant information. Bi-LSTM is used to capture grammar rules and contextual knowledge in source code, despite the fact that this work uses a gaussian LDA model for comment creation. The attention methodology was used to focus on the most relevant components of smart contracts for tagging and to combine account information to provide further categorization information. Consequently, this system of categorization has gained widespread acceptance.

For image identification, CNN is one of the most widely used deep learning algorithms [18]. However, a 2019 experiment shows that this network is equipped to deal with time-series data patterns and is also well suited for fault prediction [19]. Although it individually has a low predictive performance, when used in hybrid scenarios, it improves transmission accuracy. Dwork *et al*. [20] utilised CNN, multi layer perceptron (MLP), and LSTM to forecast the stock prices of four community-owned businesses in the United States for 2020. This study's results were more accurate in predicting outcomes than prior studies.

Wu *et al*. [21] for speech recognition, Yang presented a novel decentralized feature extraction method in federated learning. An end-to-end RNN model is used for the acoustic model to extract features from the data. A specialized RNN model in the near vicinity then recognizes the encoded attributes. In the proposed decentralized architecture, advances in fractional learning are employed to defend models and limit attacks on privacy preservation. This model's speech recognition performance was shown to be comparable to the performance of standard deep neural network (DNN)-based acoustic model (AM) models while learning with the same neural kernel size. Decentralizing prediction models is a key component of the recommended VFL-based ASR architecture, but additional statistical privacy techniques will be applied to strengthen the proposed models from various data security viewpoints [21].

Wei *et al*. [22] is working on recognizing addresses that belong to socializing services in order to tackle Bitcoin money laundering. A feature-based network analysis approach developed throughout the study was used to identify network, account, and transactional statistics. Address-specific transactional patterns have been described using the term attributed temporal heterogeneous (ATH) motifs. Themes associated with the ATH A "positive and unidentified learning dilemma" has been coined in an effort to solve the issue of inaccurate labeling due to the assessment of attributes. Real Bitcoin datasets were used in the trials to demonstrate the identification model's effectiveness and the utility of hybrid motifs in mixture recognition. An Address-address interaction network (AAIN) and transaction-address interaction network (TAIN) were created to show the similarity between addresses and the linkage between addresses and money transfers in order to study transaction records in greater detail. The usage of network motifs has made many network mining tasks easier. As a result, we've developed a brand-new method for figuring out how the Bitcoin transaction network's dynamic operations function. Temporal homogeneous motifs in AAIN can be used to identify mixing services, however ATH motifs in TAIN cannot be used in the same way.

Kim and Cho [23] introduced the CNN-LSTM hybrid model for journey time prediction. Milo *et al*. [24] suggested the same for the house's energy usage. TAIN is better able to clearly illustrate the power of money transfer when compared to AAIN. It has been demonstrated in [14], [25] that network motifs, also known as recurring subgraph patterns in networks, may be utilised to characterise higher-order interactions and gain an understanding of many facets of complex systems. In this part of the article, the characteristics of addresses from the first, second, and third levels are discussed. When it comes to data analysis, grid-based architectures work very well for deep learning models like CNN [26]. The only data that could be received was that coming from input nodes. RNNs are distinct from other neural networks in that they are able to perform computations on both the input space and their own internal state space [27]. Image data, in contrast to temporal information, has a topology that is just two-dimensional. This model may be used to time series prediction with great performance, as demonstrated by this state-of-the-art research [28]. Cell state ct and filtered input ot control the output layer, which selects the result. As a result of its excellent estimation accuracy and application in a variety of load forecasting requests [29], this topology has attracted a lot of interest. Riswantini and Nugraheni [30] introduced it for predicting the strength of typhoons.

As a direct result of the global epidemic caused by the coronavirus infection COVID-19, online education is gaining popularity throughout the world. Participation by 799 students representing a wide range of schools, colleges, and universities demonstrates the study's success in examining online education's quality [31]. Diabetes mellitus (DM), one of the most lethal health problems affecting people all over the world, cannot be effectively treated without first receiving an accurate diagnosis. Now, patients who have diabetes may be detected through the use of a number of different methods [32]. Changes in the environment on a worldwide scale have had an impact on the development of infectious diseases, viral mutations, and new diseases, making it challenging to tackle these threats with technological advances alone [33]. A multi-agent robot system, or MARS, is one of the most hotly debated topics in the world today. The core of this system relies on the collaborative and shared efforts of its participants (robots). It combines two major systems, the multi-agent system (MAS) and the multi-robot's system (MRS) [34]. Developing computer-assisted diagnostic assistance systems was an absolute necessity in light of the fact that skin cancer can rapidly spread to other regions of the body. The most up-to-date technology employs something called CNNs to classify photographs in order to detect skin cancer. "Internet of things" (IoT) refers to a system of interconnected physical items that may be used to provide a wide range of services. The number of connected devices is growing rapidly, and this has positive effects in many different fields. The Hajj is widely considered as both a major religious observance and a significant cultural event across the world. The Hajj is a religious pilgrimage that takes place once a year in Mecca and typically lasts between five and six days during which participants visit various sites across the city. Hence from the above discussed related works, AAIN and ATH motifs in TAIN are used for the feature extraction and CNN-LSTM hybrid model is chosen for the prediction.

The primary purpose of this study is: i) to extract characteristics of the addresses from network, address and transaction level and visualizing; ii) to give a deep-leaning-based solution to improve overall prediction in blockchain technology; and iii) to evaluate the suggested methodology's performance.

3. METHOD

The proposed technique was defined and presented in depth in the following section. For assessment, here a Kaggle dataset is usedwe. You'll find information on blockchain blocks and transactions in this resource. The bigquery-public-data: crypto Bitcoin dataset contains all historical data. Every ten minutes, it is refreshed. The information may be combined with past kernel pricing. The input dataset is first imported and preprocessed. You'll find information on blockchain blocks and transactions in this dataset. The data properties are then standardised before being provided to the model during pre-processing. The raw data is cleaned up via a pre-processing method or to put it another way, a multitude of data sources are used to get the raw data, making analysis more difficult than it should be. In order to reduce the amount of data to a manageable size, pre-processing is used: i) imprecise data (missing data)-missing data might be due to a lack of ongoing data collection, a data entry error, or technical issues; ii) the inclusion of noisy data (incorrect statistics and misfits)-The causes for the presence of noisy data might be a high-tech issue with the data collection device, or a human error during data input; and iii) conflicting data-data redundancy, manual database administration, mistakes in codes or names, i.e., data restrictions violations, and other reasons all contribute to the incidence of discrepancies.

As a result, data pre-processing is used to handle raw data. Let's move further and carry EDA process on preprocessed data. Exploratory data analysis (EDA) is then used to extract insights from the data by visualizing diverse patterns, relationships, and anomalies in the data using statistical graphs. The next stage is to use AAIN and TAIN from transaction data for feature extraction, which will extract features from several layers. The dataset is divided into two parts after the transactions are seen in Figure 1. The first set is used to train the CNN-LSTM hybrid deep learning model, while the second set is used to test it. Finally, the models are evaluated for effectiveness.

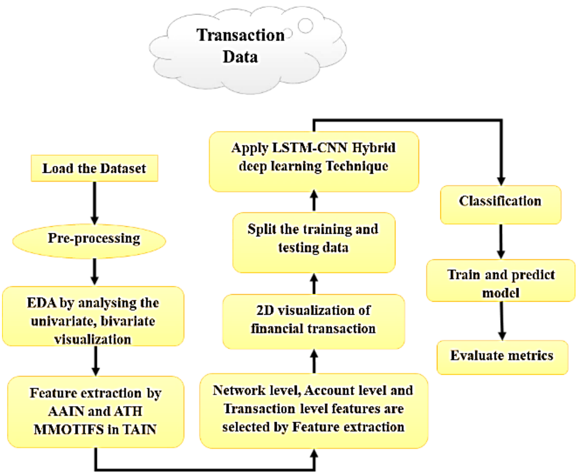

Figure 1. Overview of proposed model

3.1. AAIN and TAIN motifs for feature extraction

There are several ways to think about Bitcoin transactions as a large and complex network, each node representing a Bitcoin address and each edge representing a transaction. This fundamental modeling tool examines the interaction patterns of addresses using the homogenous AAIN. Use the TAIN to describe transaction amount information in this diagram showing the links between address pairings because Bitcoin transactions frequently have several inputs and outputs. In comparison to AAIN, TAIN is able to clearly demonstrate the power of money transfer that network motifs, or repeated subgraph patterns in networks, can be used to describe higher-order interactions and understand diverse aspects of complex systems. In this section, the properties of addresses from three tiers are outlined.

3.1.1. Network features

This section collects information from both AAIN and TAIN. There are a number of network motifs used to identify interaction patterns and show network functions. Tiny subgraph patterns that appear more frequently than in random networks are known as network motifs [25]. It is possible to determine the statistical significance of a pattern's differences using the z-score.

$$z - score = \frac{n_{real} - \bar{n}_{random}}{std\ (n_{random})} \tag{1}$$

Where nreal is the probability of the design appearing in a network connection, $\bar{n}_{random}$ and std(nrandom) denote the mean and variance of the pattern occuring frequencies in a collection of random networks, respectively.

3.1.2. Account features

In order to provide a description of the current state and level of activity associated with an address, account attributes were developed. This was done as a result of the fact that the status and activity level of an address may expose its category in a number of different settings. This was done as a result of the fact that this was done. For example, addresses that are linked to cryptocurrency exchanges experience a jump in the number of transactions, despite the fact that the number of transactions carried out by a single user is far lower. This is because cryptocurrency exchanges have access to a larger pool of users. The reason for this is because Bitcoin exchanges have access to a wider user base than traditional financial markets.

3.1.3. Transaction features

Because of this, transaction characteristics are used to track the behavior of addresses in relation to transactions. Using an intermediary address (such as a hub) may be necessary since it would be visible if the funds were delivered to the same recipients in subsequent blocks, as is the case with fund separation and assimilation solutions. This is due to the implementation of money separation and assimilation. Bitcoins from transaction sources will be dispersed to those who are legally authorized to receive them once a sufficient number of intermediate addresses has been utilized to do so.

3.2. Proposed deep learning technique CNN-LSTM

A precise structure in the input data is required by deep learning models such as LSTM and CNN, which necessitates a preset format for the data. Using a one-dimensional CNN network is therefore beneficial. It consists of three layers: a convolutional (CL), a pooling (PL), and a fully connected (FC) layer. A great deal of information about a time series can be obtained by utilizing the CL and PL strata. An RNN model known as the LSTM is a deep learning model with a long history of use. Its gates, which will be discussed in further detail, are the main strength of the system. They performed brilliantly on numerous time series applications. While the LSTM model succeeds at eliminating temporal features, the CNN model shines at extracting spatial properties.

3.2.1. Convolutional neural networks

Deep learning models like CNN thrive at analyzing data with grid-like architectures. Unlike time information, image data has a two-dimensional topology. Linear operations that replace standard matrix multiplication are utilized in at least one of its levels, such as convolutions. Multi-channel and multi-headed architectures have also been developed as a result of the advancement in CNN technology. Many of them, on the other hand, follow the same basic structure. Pre-processing methods such as data normalization and standardization are frequently employed in data analysis. One, two, and n-channel data types are all supported by CNN models. A 1-D input data form is used in this study's proposed model.

3.2.2. Long short-term memory

No information could travel from the input nodes to hidden layers to the output layers of traditional feed-forward neural networks; only data from input nodes could be received. RNNs are unique in that they can operate on both the input and internal state spaces. The RNN paradigm has two flaws that need to be addressed: gradient disappearance and velocity explosion. To address these issues, the LSTM architecture was intended to incorporate input and output gates. Similar to the RNN, the LSTM model is built on the same foundations. Recurrent-neuron gates such as the forget gate f, update gate, and output gate are all distinct from one another. Each gate in the cell has a distinct purpose. The job of the forget gate is to remove any past data and output from the top-hidden units ht1 that are no longer required. Update gates add new items to the state, while the cell filters the current condition and distinguishes desirable and undesirable data so that the outer loop can select the most useful data. The memory cell reads the value of the variable xt, which contains information crucial to the computation of energy production projections.

3.2.3. CNN-LSTM

Two convolutional layers with 32 and 64 filters, PL, underlying LSTM layer, and output layer are proposed in our model. The model's accurate design can be found in the following:

The Input Gate: $I_t = \sigma(W_I x_t + A_I h_{t-1} + b_I)$ (2)

Forgot Gate: $P_t = \sigma(W_P x_t + A_P h_{t-1} + b_P)$ (3)

Output gate: $O_t = \sigma(W_O x_t + A_O h_{t-1} + b_O)$ (4)

New memory cell: $c_t = W_t c_{t-1} + I_t \tilde{c}_t$ (5)

Final memory cell: $\tilde{c}_t = tanh(W_C x_t + W_C h_{t-1} + b_C)$ (6)

Final output: $h_t = O_t \tanh(c_t)$ (7)

where W_I, W_P, W_O, and W_C represents input weight vectors, while A_I, A_P, A_O, and A_C represent upper output weight vectors. Then b represents bias vectors; σ=sigmoid function. After prediction, evaluation of different metrics like accuracy, precision and recall was carried out to ensure the performance efficiency of proposed system.

4. RESULTS AND DISCUSSION

The investigational fallouts show that the suggested design has a positive overall influence on forecast accuracy, ensuring that model resilience and prediction outcomes are excellent. This study includes the training times for each of the models in order to provide researchers with more information. To begin, load the dataset for data preparation. Data as shown in Figure 2, pre-processing is used to eliminate the source of unformatted real-world data. There are three options: ignore the missing record, manually fill in the missing information, or use calculated values to fill in the gaps.

```
 #   Column                                          Non-Null Count  Dtype
---  ------                                          --------------  -----
 0   Date                                            2913 non-null   object
 1   btc_market_price                                2882 non-null   float64
 2   btc_total_bitcoins                              2913 non-null   float64
 3   btc_market_cap                                  2913 non-null   float64
 4   btc_trade_volume                                2892 non-null   float64
 5   btc_blocks_size                                 2913 non-null   float64
 6   btc_avg_block_size                              2913 non-null   float64
 7   btc_n_orphaned_blocks                           2913 non-null   int64
 8   btc_n_transactions_per_block                    2913 non-null   float64
 9   btc_median_confirmation_time                    2913 non-null   float64
 10  btc_hash_rate                                   2913 non-null   float64
 11  btc_difficulty                                  2913 non-null   float64
 12  btc_miners_revenue                              2913 non-null   float64
 13  btc_transaction_fees                            2913 non-null   float64
 14  btc_cost_per_transaction_percent                2913 non-null   float64
 15  btc_cost_per_transaction                        2913 non-null   float64
 16  btc_n_unique_addresses                          2913 non-null   int64
 17  btc_n_transactions                              2913 non-null   int64
 18  btc_n_transactions_total                        2913 non-null   int64
 19  btc_n_transactions_excluding_popular            2913 non-null   int64
 20  btc_n_transactions_excluding_chains_longer_than_100 2913 non-null   int64
 21  btc_output_volume                               2913 non-null   float64
 22  btc_estimated_transaction_volume                2913 non-null   float64
 23  btc_estimated_transaction_volume_usd            2913 non-null   float64
 24  btc_trg_class                                   2913 non-null   int64
dtypes: float64(17), int64(7), object(1)
memory usage: 569.1+ KB
```

Figure 2. Data before preprocessing

Then correlation relationship of every variable is viewed as given in Figure 3. Then, the time frequency analysis is done for extracted features like address, transaction and network values and plotted as given below Figure 4. The recovered features of the financial transaction are depicted in a two-dimensional format in Figure 5, which shows how these qualities relate to the frequency of the transaction.

```
df.isnull().sum()
```

```
Date                                              0
btc_market_price                                  0
btc_total_bitcoins                                0
btc_market_cap                                    0
btc_trade_volume                                  0
btc_blocks_size                                   0
btc_avg_block_size                                0
btc_n_orphaned_blocks                             0
btc_n_transactions_per_block                      0
btc_median_confirmation_time                      0
btc_hash_rate                                     0
btc_difficulty                                    0
btc_miners_revenue                                0
btc_transaction_fees                              0
btc_cost_per_transaction_percent                  0
btc_cost_per_transaction                          0
btc_n_unique_addresses                            0
btc_n_transactions                                0
btc_n_transactions_total                          0
btc_n_transactions_excluding_popular              0
btc_n_transactions_excluding_chains_longer_than_100  0
btc_output_volume                                 0
btc_estimated_transaction_volume                  0
btc_estimated_transaction_volume_usd              0
btc_trg_class                                     0
dtype: int64
```

Figure 3. Preprocessed data with null values

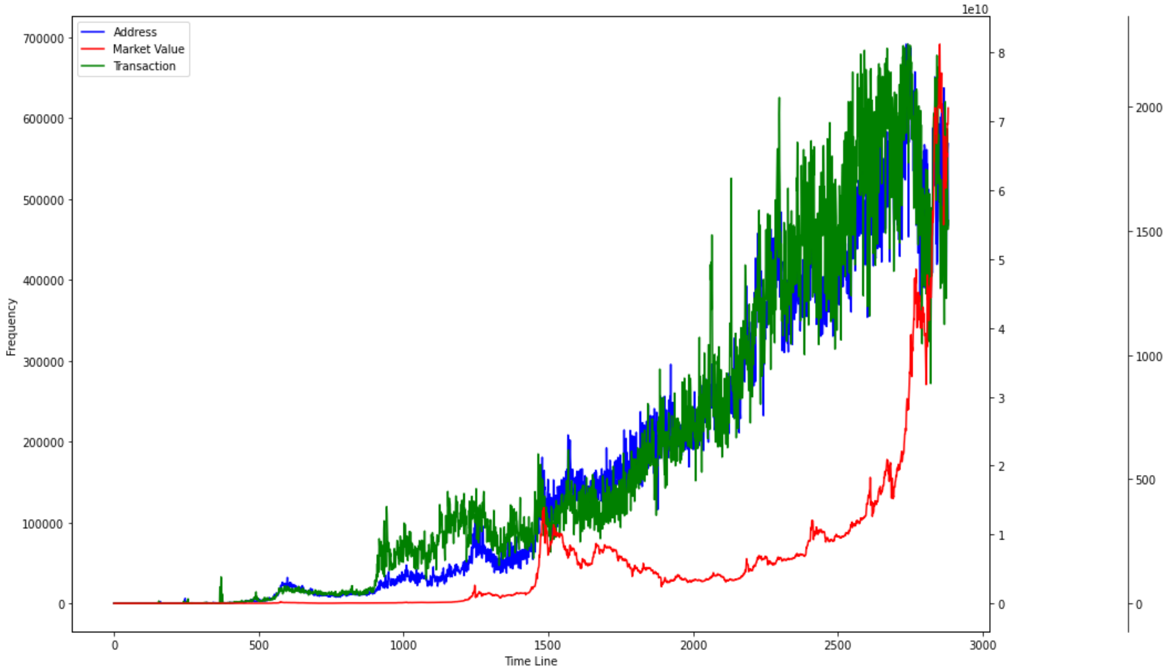

Figure 4. Time frequency analysis of extracted features

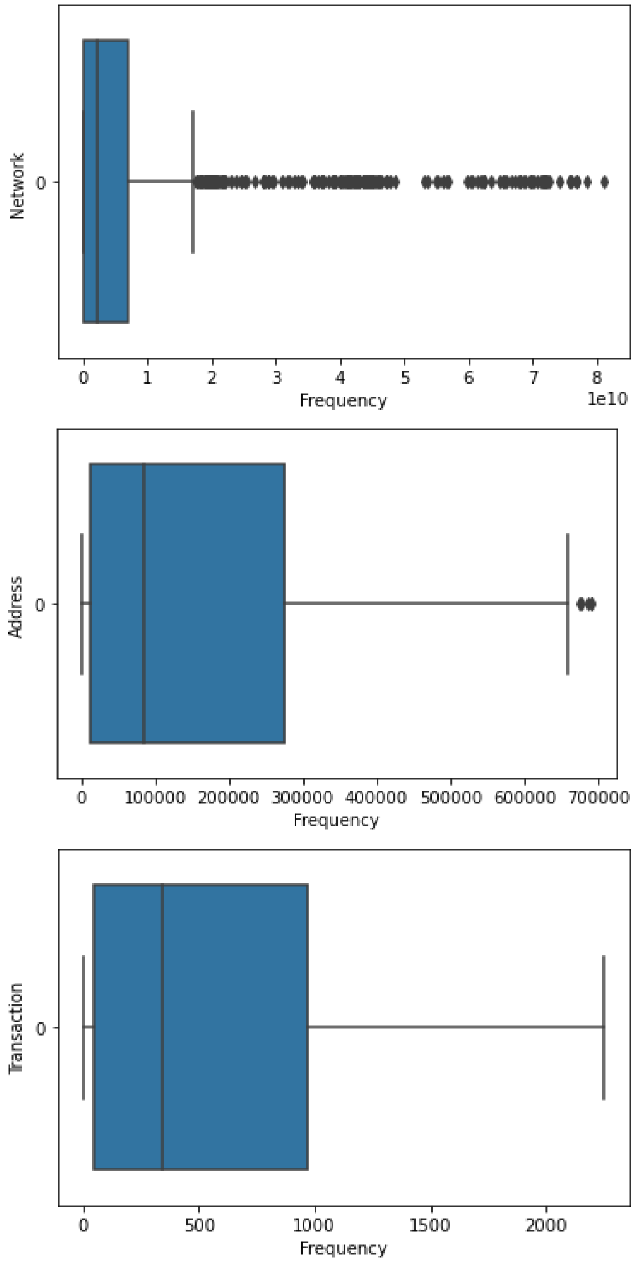

Figure 5. 2D visualization of extracted features

Then the dataset is divided into training and testing data. Then the proposed CNN-LSTM deep learning algorithm is performed over the given dataset. It has been determined how well the proposed system would perform in contrast to the present system for the assessment metrics. When compared with the accuracy of predictions made by other deep learning models, this model's accuracy stands out (decision trees (DT), random forests (RF), Fast region-based convolutional network (Fast-R-CNN)) in Table 1. The efficiency of the models was assessed, and Figure 6 provides a graphical depiction of the findings that can be found further down in this article.

Table 1. Comparative table for evaluation metrics

	DT	RF	FAST_R_CNN	CNN_LSTM
Accuracy	0.819653	0.890173	0.926400	0.967800
F1_score	0.511540	0.470948	0.912426	0.953250
Precision	0.512142	0.446118	0.993075	0.994521
Recall	0.511212	0.498705	0.915913	0.962300

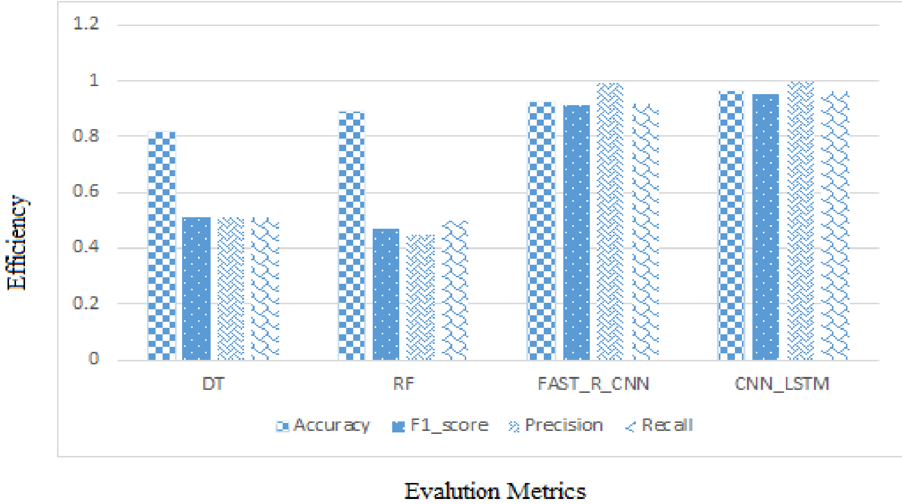

Figure 6. Performance analysis of CNN-LSTM

5. CONCLUSION

For Bitcoin transactions, this artifact provides a reliable and effective hybrid CNN-LSTM model leveraging blockchain technology. A distributed system's replication of data must be both consistent and safe, and this design provides a practical solution. The proposed architecture beats single models in forecasting, according to the statistical data. There are many reasons for this, including because CNN-LSTM topology incorporates both CNN and the LSTM, both of which are capable of extracting spatial characteristics from datasets. Hybrid designs, according to these studies, outperform single models in the vast majority of cases. The accuracy, precision, f1-score, and recall all played a role in the trial's evaluation. There is still a need for more study to better understand user behavior features and make use of the information acquired to improve security model prediction.

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