A model for optimizing the risk of a CBDC using artificial intelligence. (Deep Learning)

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ABSTRACT
The emergence of Central Bank Digital Currencies (CBDCs) presents both opportunities and challenges for central banks worldwide. To ensure the successful implementation and operation of CBDCs, it is crucial to identify and mitigate potential risks. This paper proposes a deep learning-based model for assessing CBDC risk in central banks. Deep learning, a subset of artificial intelligence, has demonstrated remarkable capabilities in various domains, including image recognition, natural language processing, and fraud detection. Its ability to analyze complex patterns and extract meaningful features from large datasets makes it well-suited for the task of CBDC risk assessment. The proposed model aims to provide central banks with a robust and scalable tool to identify potential vulnerabilities, evaluate the likelihood of different risks, and suggest appropriate mitigation strategies. By leveraging deep learning techniques, the model can enhance the efficiency and accuracy of CBDC risk management processes. This paper will delve into the details of the proposed model, including its architecture, data requirements, implementation steps, and potential benefits. It will also discuss the challenges and limitations associated with using deep learning for CBDC risk assessment and explore potential future directions.

Keywords: CBDCs, Deep Learning, AI

1. Introduction

The intersection of AI and Central Bank Digital Currencies (CBDCs) is poised to redefine the future of central banking. (Vesna, 2024) Deep Learning subset of artificial intelligence, involves neural networks with multiple layers that can analyze complex patterns and massive datasets. (Aldasoro, et al, 2024) When applied to the realm of central banking, particularly in the development and management of CBDCs, deep learning offers transformative potential. It can enhance the security, efficiency, and adaptability of CBDCs by optimizing fraud detection, predicting economic trends, and personalizing monetary policy interventions. (Araujo, et al, 2024) As central banks around the world explore the possibilities of issuing their own digital currencies, Machine learning can play a critical role in addressing the challenges and maximizing the benefits of CBDCs. (Ozili,et al,2024) For example, deep learning algorithms can help central banks monitor and analyze transaction data in real-time, identifying suspicious activities or anomalies that might indicate fraud or money laundering. Additionally, these algorithms can assist in the dynamic calibration of monetary policies, enabling central banks to respond more effectively to changing economic conditions.(Athey, et.al, 2021) However, the integration of deep learning in the management of CBDCs also presents challenges, including issues related to data privacy, model transparency, and the need for robust regulatory frameworks. As central banks move towards adopting these technologies, they must carefully balance innovation with the need to maintain financial stability and public trust. The combination of deep learning and CBDCs represents a significant step forward in the evolution of central banking, offering both opportunities and challenges as institutions adapt to the digital age. (BIS Innovation Hub, 2023)

The advent of Central Bank Digital Currencies (CBDCs) marks a significant shift in the landscape of global finance, offering central banks a new tool to enhance monetary policy, financial stability, and payment systems. As countries like China, Sweden, and the Bahamas lead the way in piloting CBDCs, the exploration of innovative technologies to support these digital currencies has gained momentum. Among these technologies, deep learning—a subset of artificial intelligence (AI)—stands out for its potential to address some of the key challenges associated with CBDCs. (Boukherouaa, et.al,2021) Deep learning involves the use of artificial neural networks with multiple layers to analyze vast amounts of data and identify complex patterns. In recent years, its application in various financial services has grown, particularly in areas such as fraud detection, risk management, and market prediction. For instance, deep learning models have been effectively used by financial institutions to detect fraudulent transactions by analyzing patterns that traditional methods might miss. Similarly, in risk management, deep learning algorithms have shown promise in predicting market movements and assessing credit risk more accurately.(Buckmann, et, al, 2023)

In the context of central banking, deep learning offers several potential benefits. For CBDCs, it can enhance the security of transactions by identifying anomalies in real-time, thus reducing the risk of fraud and money laundering. Furthermore, deep learning can aid in the efficient management of monetary policy by analyzing large datasets to forecast economic trends and optimize policy decisions. The use of deep learning in these areas is supported by a growing body of literature that highlights its effectiveness in handling large-scale data and making precise predictions. (Danielson, J., & Uthemann, A, 2023)

The research on the intersection of deep learning and CBDCs is still in its nascent stages, but it is rapidly evolving as central banks recognize the need to harness advanced technologies to stay ahead in a digital economy.(Dzhaparov,2024)This growing interest underscores the importance of further research to explore how deep learning can be effectively integrated into the central banking framework, particularly in the issuance, management, and oversight of CBDCs. As central banks explore the development and implementation of Central Bank Digital Currencies (CBDCs), there is a critical need to address the challenges associated with managing and securing these digital assets. Deep learning, with its ability to analyze complex patterns and large datasets, presents an opportunity to enhance the effectiveness of CBDCs.(Mariam, et, al, 2021)

However, the application of deep learning in central banking is not without significant challenges. The primary problem lies in the integration of deep learning algorithms into the central banking ecosystem, particularly in areas such as fraud detection, transaction monitoring, and policy optimization. Despite its potential, the adoption of deep learning in managing CBDCs raises concerns about data privacy, model transparency, and the robustness of decision-making processes. Deep learning models, often characterized by their "black box" nature, can lack explainability, making it difficult for central banks to justify and trust their outcomes in critical financial decisions. Additionally, the quality and availability of data used to train these models are paramount, as inaccurate or incomplete data can lead to erroneous predictions and undermine the stability of the financial system. Furthermore, there is a need to develop regulatory frameworks that can keep pace with the rapid advancements in deep learning technology while ensuring the security and stability of CBDCs. Central banks must balance the benefits of innovation with the risks associated with these advanced technologies. The problem, therefore, is how to effectively integrate deep learning into the management of CBDCs in a way that enhances their functionality and security while addressing the challenges of explainability, data quality, and regulatory compliance.

2- Literature Review

The integration of Artificial Intelligence (AI) and Central Bank Digital Currencies (CBDCs) is at the forefront of central banking innovation, with the potential to reshape monetary policy, financial stability, and payment systems. AI’s ability to process and analyze large datasets is revolutionizing central banking operations. For instance, central banks like the Bank of England and the European Central Bank are leveraging AI for macroeconomic forecasting, financial stability monitoring, and regulatory compliance. AI tools such as machine learning models can identify patterns in financial data that indicate emerging risks, thereby enhancing the effectiveness of monetary policy and supervision (Bank of England, 2020; European Central Bank, 2021).

The intersection of deep learning and Central Bank Digital Currencies (CBDCs) represents a novel and rapidly evolving area within the broader context of central banking and financial technology. The existing literature on this topic spans multiple disciplines, including economics, finance, computer science, and regulatory studies, reflecting the interdisciplinary nature of the challenges and opportunities posed by the integration of deep learning into the management and operation of CBDCs. CBDCs have garnered significant attention in recent years as central banks around the world explore the potential of issuing digital versions of their national currencies. The literature highlights several key motivations for adopting CBDCs, including enhancing financial inclusion, improving payment system efficiency, and providing a secure, state-backed alternative to private cryptocurrencies. According to the Bank for International Settlements (BIS, 2020), more than 80% of central banks are engaged in CBDC research or development. Early adopters like China, with its Digital Yuan, and Sweden, with the e-Krona, have provided valuable case studies on the practical implementation of CBDCs (chi, et, al,2017). Deep learning, a subset of machine learning, has increasingly been applied in financial services for tasks such as fraud detection, risk management, and predictive analytics. Deep learning models, particularly neural networks, have demonstrated superior performance in identifying complex patterns in large datasets, which is critical in areas like transaction monitoring and market prediction (goodell, et, al 2017). In banking, these technologies are used to automate decision-making processes, improve customer service through chatbots, and optimize trading strategies (Goodfellow, Bengio, & Courville, 2016). However, the "black box" nature of deep learning models, which makes them difficult to interpret, raises concerns about transparency and accountability, particularly in regulated industries like finance (Barredo Arrieta et al., 2020).

The integration of deep learning with CBDCs is still an emerging field, with limited but growing research exploring its potential. One of the primary applications of deep learning in the context of CBDCs is in enhancing the security and efficiency of digital currency transactions. Machine learning algorithms can be employed to detect fraudulent transactions in real-time, leveraging the vast amounts of data generated by CBDC usage (Liu et al., 2020). Additionally, deep learning can assist in the dynamic adjustment of monetary policy by analyzing transaction data to provide insights into economic activity and inflation trends (Chen, et. al. 2021).

Another area of interest is the use of deep learning for optimizing payment systems. For example, reinforcement learning, a branch of deep learning, could be utilized to develop adaptive payment routing algorithms that minimize transaction costs and latency in CBDC networks (Mnih et al., 2015). Moreover, the programmability of CBDCs allows for the implementation of smart contracts, where deep learning can be used to automate complex financial agreements based on predefined conditions (Zheng, et,al, 2020).

Despite the potential benefits, the application of deep learning in CBDCs raises several challenges and ethical considerations. Data privacy and security are paramount, as CBDCs involve the handling of sensitive financial information. Ensuring that deep learning algorithms are transparent and explainable is critical to maintaining trust in central banks (European Central Bank, 2021). Furthermore, there is a need for robust regulatory frameworks that can accommodate the rapid advancements in AI while safeguarding financial stability (Carney, 2019).

The literature also points to the risk of algorithmic bias, where deep learning models may inadvertently reinforce existing inequalities if not properly designed and tested. As CBDCs aim to promote financial inclusion, it is essential to ensure that the underlying technologies do not create new barriers or exacerbate disparities (Campolo, Sanfilippo, Whittaker, & Crawford, 2017). As the field evolves, future research is likely to focus on developing more interpretable deep-learning models that align with the regulatory and operational needs of central banks. There is also a growing interest in exploring the synergies between deep learning and other emerging technologies, such as blockchain, to enhance the security and functionality of CBDCs (chi, et, al, 2017).

Collaborative efforts between central banks, academic institutions, and technology companies will be crucial in advancing this field and addressing the complex challenges it presents. In conclusion, while the integration of deep learning into the management of CBDCs holds significant promise, it also requires careful consideration of the associated risks and challenges. The literature emphasizes the need for continued research and dialogue among stakeholders to ensure that these technologies are developed and deployed in ways that enhance the stability, security, and inclusivity of the global financial system.(Taherdoost, et. al,2023) Despite their numerous advantages, CBDCs also face several challenges:

- **Improved Efficiency of Payment Systems:** CBDCs, leveraging advanced technologies like blockchain, can significantly enhance the speed and security of transactions. This is particularly advantageous for international transactions and smaller payments. (Zheng, et, al, 2020).
- **Reduced Transaction Costs:** By eliminating intermediaries in payment systems, CBDCs can substantially lower transaction processing costs. This benefits both consumers and businesses. (Dow, et, al, 2017)
- **Increased Access to Financial Services:** CBDCs can provide financial services to the unbanked and underbanked populations, thereby reducing financial inequality.
- **Assistance to Central Banks in Monetary Policy and Liquidity Control:** CBDCs enable central banks to implement monetary policies with greater precision and speed. Additionally, central banks can utilize CBDCs to introduce new tools for controlling liquidity and addressing financial crises. (Chi,2017)
- **Technological Challenges:** Developing and implementing the necessary infrastructure for CBDCs requires substantial investments in technology. Ensuring the scalability and sustainability of these systems is also a significant challenge.
- **Security Issues:** Protecting CBDCs from cyberattacks and fraud is paramount. Any breach of a CBDC system can have severe consequences for a country's economy.(Pocher,2022)
- **Privacy Concerns:** The extensive collection of data on financial transactions can compromise individuals' privacy. Therefore, robust mechanisms for protecting user privacy are essential. (Pocher,2022)
- **Social Acceptance:** Changing people's payment habits and adopting CBDCs as an alternative to cash requires significant time and effort.
- **Impact on the Traditional Banking System:** The widespread adoption of CBDCs may affect the business models of traditional banks and lead to fundamental changes in the banking industry. (Goodell, et, al, 2023)

In conclusion, while CBDCs offer numerous benefits, such as improved efficiency, reduced costs, and increased financial inclusion, they also present several challenges that must be carefully considered. These challenges include technological hurdles, security risks, privacy concerns, and potential disruptions to the traditional banking system. To successfully implement CBDCs, it is essential to address these challenges and develop robust regulatory frameworks.

3- Research method

The research method for studying the application of deep learning in Central Bank Digital Currencies (CBDCs) within central banking will involve a mixed-methods approach, combining both qualitative and quantitative techniques to provide a comprehensive analysis.

3.1-Data

The research will begin with an extensive literature review to identify existing studies on deep learning applications in finance, particularly in relation to CBDCs and central banking. This will include academic papers, industry reports, and case studies that provide insights into the challenges and opportunities associated with implementing deep learning in this context. After data cleaning and summarization, resulting in 21,513 records, (70% of the total time-series data) were used for training the LSTM supervised model, while the remaining 30% were reserved for model validation, as detailed in Table 1.

Table 1 - Features of CBDC Data in the CBDC

	Parameter	Resources
1	Improved efficiency of payment systems	Zheng, 2020
2	Reduced transaction costs	Carney, 2019
3	Increased access to financial services	Mariam,2021
4	Assistance to central banks in monetary policy and liquidity control	Chi,2017
5	Reduced fraud and money laundering	Dow,2019
6	Technological challenges	
7	Security issues	Pocher,2022
8	Privacy concerns	Pocher,2022
9	Social acceptance	Chen, 2021
10	Impact on the traditional banking system	Goodell,2022

3 .2- Data Analysis

This section examines various CBDC parameters during the approach and landing phases. The pitch angle and angle of attack, which are critical for specific landing operations, are analyzed and their distribution is illustrated using a histogram. The quantitative aspect of the research will involve the collection of data on CBDC transactions, central bank reports, and financial indicators from central banks that are using or exploring deep learning. This data will be analyzed using statistical methods to assess the impact of deep learning on key performance metrics such as transaction speed, security incidents, and policy outcomes. Machine learning models will also be employed to simulate potential scenarios and outcomes of CBDC implementation using deep learning algorithms.

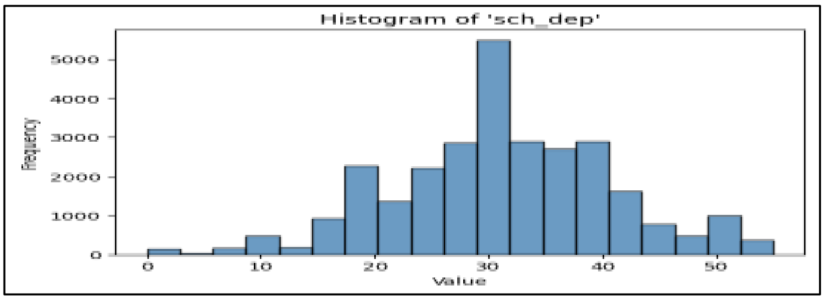

Figure -1 Distribution of Events CBDC

Figure 1 illustrates the distribution of risk event data during the CBDC. Notable changes are observed in the time intervals before and after the risk, highlighting the potential of deep learning for analyzing CBDC parameters. Among these parameters, the change in sch_dep is identified as a key indicator for detecting a risk.

3.3 -LSTM Model

The LSTM network is a specialized type of RNN designed to learn long-term dependencies, making it well-suited for classification, processing, and predicting time series data (Gers, 1999). These models can train multiple layers of high-performance hidden computational units. LSTMs utilize a cell state to retain past information and incorporate three gates to update, predict, and compute the cell (Zho et al., 2020).

Data preprocessing involves data cleaning, transformation, normalization, and standardization. In the initial stage, 10 features were used as input to the LSTM network to reduce the dimensions of the input signal. Consequently, the input data can be represented as a CBDC data matrix, as illustrated below:

$$\mathbf{X}=\begin{bmatrix} p_{t-n}^{1} & p_{t-n+1}^{1} \ldots\ldots & p_{t-1}^{1} & p_{t}^{1} \\ p_{t-n}^{2} & p_{t-n+1}^{2} & p_{t-1}^{2} & p_{t}^{2} \\ p_{t-n}^{3} & p_{t-n+1}^{3} \cdots\cdots\cdots & p_{t-1}^{3} & p_{t}^{3} \\ & . \quad . & & \\ & . \quad . & & \\ p_{t-n}^{10} & p_{t-n+1}^{10} \cdots\cdots & p_{t-1}^{10} & p_{t}^{10} \end{bmatrix}$$

In this matrix, the element p_{t-n}^{10} represents the value of the CBDC parameter at time step (t-n) . This matrix is expressed as an input vector, where each element represents a vector of CBDC parameters. In the next time step, a multivariate sequence of CBDC parameters is dependent on the past (n) time steps.

3.4 -LSTM Layer Architecture

Recurrent Neural Networks (RNNs) are designed for modeling sequence data in machine learning. These networks transmit information through a chain of interconnected nodes, processing input sequences to evolve over time. Among various learning models, the deep learning model, Long Short-Term Memory (LSTM), was selected for optimization due to its capability to handle dependencies between CBDC data points and maintain memory of previous inputs. The LSTM neural network incorporates several gates and variables. It was implemented using Python and TensorFlow. The architecture is described as follows:

Table 2 - Multi-Layer LSTM Network Architecture

Layer	Output	Parameters
1	LSTM_1	(64, 1)
2	LSTM_2	(64, 1)
3	Dense	1
Total		122,931
Trainable Parameters		122,921

In this study, two LSTM layers were used: the input layer with 34 neurons, the first layer with 64 neurons, the second layer with 64 neurons, and an output layer with 64 neurons. This algorithm can learn long-term dependencies, whereas a simple RNN only learns short-term dependencies. The LSTM neurons use a forget gate f_t to determine how much information from the previous cell state should be retained, calculated as follows:

$$f_t = \sigma\,(w_t \times [\,h_{t-1}\ ,x_t\,] + b_f \qquad (2)$$

Here, w_t is the weight matrix of the forget gate, b_f is the bias term of the forget gate, and σ is the sigmoid function.

Next, the input gate, along with a tanh layer, selects the new information to be stored in the cell state. The input gate i_t regulates the amount added to the cell state at each time step, calculated as follows:

$$i_t = \sigma\,(w_i \times [\,h_{t-1}\ ,x_t\,] + b_i \qquad (3)$$

$$\tilde{C}_t = tanh\,(w_c \times [\,h_{t-1}\ ,x_t\,] + b_c \qquad (4)$$

$$C_t = f_t \times C_{t-1} + i_t \times \tilde{C}_t \qquad (5)$$

Here, w_i is the weight matrix of the input gate w_c represents the memory weight, and b_i is the bias term of the input gate. The control of the forget and output gates allows the LSTM model to use past information for current predictions. The final output of the model is the result of the output gate multiplied by the tanh layer, calculated as follows:

$$O_t = \sigma (w_o [h_{t-1}, x_t] + b_c$$

$$h_t = O_t \times tanh(C_t)$$

Here, w_o is the weight matrix of the output gate, and b_c is the bias term of the memory cell. Features are extracted from these parameters. The LSTM neural network consists of three layers and one regression output layer.

Figure -2 shows, based on the findings from the literature review and case studies, specific deep learning models will be developed and tested in a controlled environment. These models could include neural networks designed to detect fraud, optimize payment systems, or analyze economic data for policy decisions. The performance of these models will be evaluated against traditional methods to determine their effectiveness and potential for broader application in central banking. To supplement the case studies and model testing, expert interviews and surveys will be conducted with central bank officials, financial regulators, and technology experts. These will provide qualitative insights into the perceived risks, challenges, and benefits of using deep learning in CBDC risk management. The feedback collected will be used to refine the models and propose best practices for the integration of deep learning in central banking.

A comparative analysis will be conducted between central banks that have adopted deep learning for CBDCs risk and those that have not. This will help in understanding the differences in outcomes, efficiency, and security measures, thereby providing a clearer picture of the impact of deep learning on central banking practices.

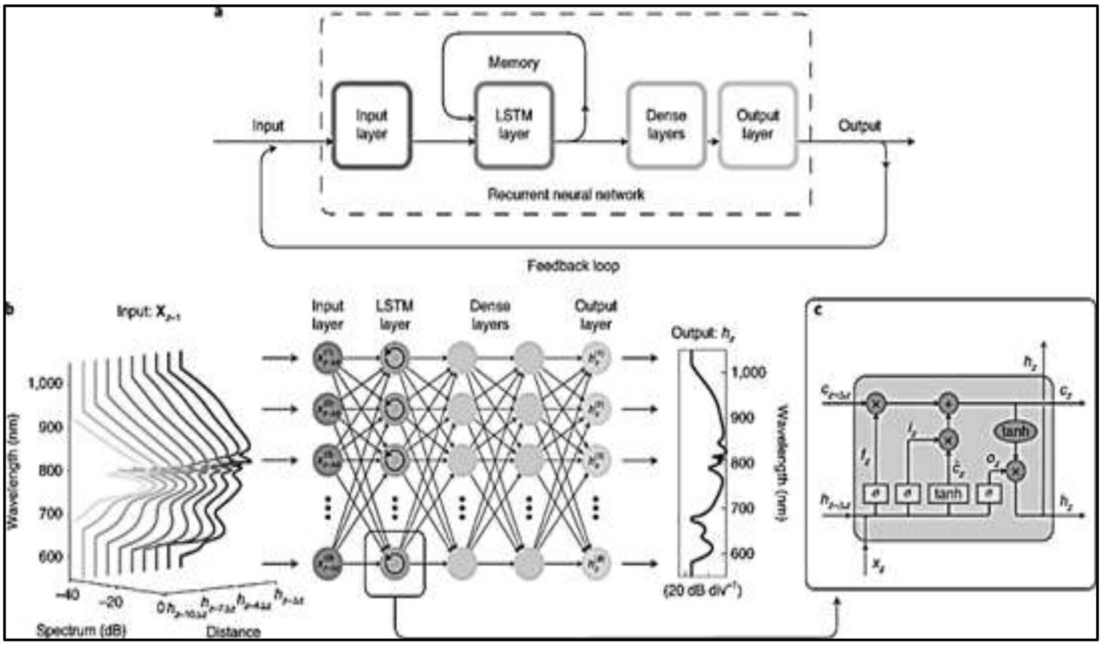

Figure 2- LSTM model for CBDC

The research will culminate in a synthesis of the findings from the various methods employed, leading to conclusions about the viability, effectiveness, and challenges of integrating deep learning with CBDCs in central banking. Recommendations will be made for central banks considering the adoption of these technologies, including guidelines for model implementation, data management, and regulatory compliance. This comprehensive research method is designed to provide both theoretical and practical insights into how deep learning can be effectively utilized in the evolving landscape of CBDCs and central banking.

4- Findings

The application of deep learning in the context of Central Bank Digital Currencies (CBDCs) reveals several impactful findings:

To learn from a supervised deep learning model (RNN-LSTM), the output data for continuous risk prediction is determined using the following linear regression function:

$$f(x) = w^t\ (xi) + b$$

The performance of the proposed LSTM model was optimized during the training process by adjusting several parameters, including batch size, activation function, number of hidden units, optimizer type, and number of epochs (50). The optimizer was selected to minimize the loss function. Additionally, the Mean Absolute Error (MAE) was used as a metric to evaluate the error of the estimator relative to the actual values. MAE represents the average of the absolute differences between the predicted and actual values, providing a measure of the estimator's accuracy.

Table 3 shows the learning error rate (MSE) for each of the training and testing data groups. Since the values of this index are closer to zero, it indicates a lower error rate for the data group and an acceptable confidence level for the model.

According to Figure 3, the lower Mean Absolute Percentage Error (MAPE) index indicates a higher accuracy of the estimator, with an error value of 5.256. The chart shows that the network’s mean squared error starts from a certain value and progressively decreases, reflecting improvement in the network's learning process.

Figure 4 displays two lines representing the input and target vectors, which were randomly divided into training (70%) and testing (30%) sets. The evaluation set is used to monitor the network’s performance. Training continues until the network error on the evaluation set decreases, thereby preventing overfitting to the training data. The RMSE values of the model indicate that the minimum mean squared error, calculated from equation (9), is 6.384 at epoch 50, marking the model's optimal performance.

Table 3 - Learning Error Rate (MSE)

Parameter	Training	Testing
Learning Error	18.01	17.10
RMSE	6.541	6.382
MEPA	5.241	5.032
Total CBDC Data (21,513)	15059	6454

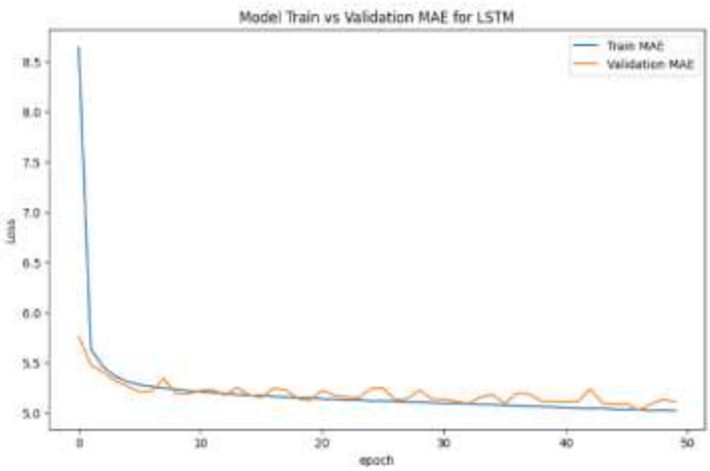

Figure 3- Mean Absolute Error (MAE) Chart

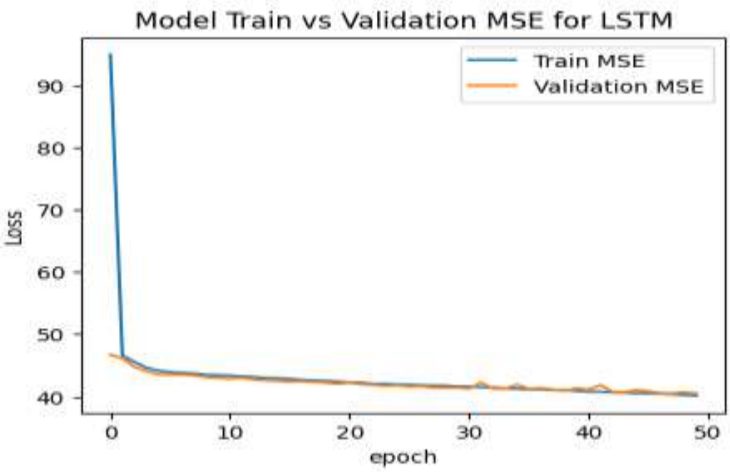

Figure 4 - Mean Squared Error (MSE) Chart

5- Conclusion

This paper assessed Deep learning algorithms significantly enhance the security of CBDCs risk by improving fraud detection and anomaly detection capabilities. Advanced neural networks and pattern recognition models can analyze vast amounts of transaction data in real-time to identify suspicious activities and potential threats. For instance, models trained to detect unusual transaction patterns have been shown to effectively flag potential fraud, reducing the incidence of financial crimes and improving overall trust in digital currency systems. Deep learning provides central banks with advanced tools for economic forecasting and monetary policy analysis. By leveraging large datasets, including transaction data and economic indicators, deep learning models can offer more accurate predictions of economic trends, inflation rates, and market conditions. This enhanced predictive capability allows central banks to make better-informed decisions regarding interest rates, money supply, and other critical aspects of monetary policy. Deep learning algorithms can optimize the efficiency of payment systems within CBDC frameworks. For example, reinforcement learning techniques can be used to develop adaptive payment routing systems that minimize transaction costs and processing delays. This leads to faster, more cost-effective payment processing, which is a key benefit for both consumers and financial institutions using CBDCs. The integration of deep learning with CBDCs enables the development of sophisticated programmable features, such as smart contracts. These contracts, which automate complex financial agreements based on predefined conditions, can be managed and executed more efficiently through deep learning algorithms. This programmability enhances the functionality of CBDCs, allowing for more dynamic and flexible monetary tools. Despite these benefits, the use of deep learning in CBDCs presents challenges, particularly regarding model interpretability and data quality. The "black box" nature of deep learning models can make it difficult to understand and justify their decisions, which is a concern for regulatory compliance and transparency. Additionally, ensuring the quality of data used for training these models is crucial, as inaccuracies or biases in data can impact the effectiveness of fraud detection and policy insights.

In summary, deep learning has the potential to greatly enhance the functionality and efficiency of CBDCs risk in central banking by improving security, optimizing payment systems, and providing valuable insights for monetary policy. However, addressing challenges related to model interpretability and data quality is essential for realizing the full potential of these technologies.

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