IJIREEICE
ISSN (O) 2321-2004, ISSN (P) 2321-5526
International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering
Impact Factor 8.414 ≍ Peer-reviewed & Refereed journal ≍ Vol. 13, Issue 10, October 2025
DOI: 10.17148/IJIREEICE.2025.131022

Performance Of Deep Learning Model For Prediction Of Cryptocurrency Adoption In Nigeria

Sulaiman Umar S.Noma[*1], Salihu Alhassan[2], Sadiq Abubakar Zagga[3] and Shamsu Sani[4]

Department of Computer Science, Kebbi State Polytechnic, Dakingari, Kebbi State. Nigeria[1-4]

*Corresponding Author

Abstract: The use of cryptocurrencies is rapidly increasing in developing countries as governments and financial institutions become more aware of them. With millions of people actively transacting in digital assets, Nigeria is a global leader in the adoption of cryptocurrencies. Our knowledge of the socioeconomic elements influencing adoption is still lacking, despite this. Gaps remain in understanding the socio-economic drivers of adoption. This study explores cryptocurrency adoption in Nigeria by using Convolutional Neural Networks (CNN) for predictive analytics. We develop and evaluate a CNN model using adoption-related datasets to classify and predict adoption trends. The CNN model was evaluated on five (5) performance evaluation metrics and achieved 92% accuracy, 90% precision, an 86% recall score, an 86% F1 score and a 95% ROC-AUC. Therefore, results indicate that CNN can effectively capture nonlinear relationships in adoption patterns, outperforming traditional machine learning models in accuracy and generalisation. The study revealed that Convolutional Neural Networks (CNN) can accurately estimate and forecast Nigeria's adoption of cryptocurrency and provides insights for policymakers, financial institutions and technology innovators.

Keywords: Deep learning, Cryptocurrency, Convolutional Neural Network (CNN), Adoption, Nigeria.

I. INTRODUCTION

Cryptocurrency, often known as digital currency, is a virtual currency used to exchange and transfer assets. Unlike traditional currencies, which rely on central banking institutions, cryptocurrencies are based on the principle of decentralised control. As a result, a cryptocurrency is utilised to transfer funds electronically without the intervention of a central or governmental authority. Cryptocurrency trading has gained popularity in recent years, owing to its unregulated and anonymous nature. The industry has risen considerably for financial transactions and trading around the world (El-Berawi *et al.*, 2021). Cryptocurrencies have gained popularity worldwide because of their decentralisation, immutability, and security. They are built on confidence in technology infrastructure, allowing financial resources to be delivered from anywhere with near-zero latency while network users provide the necessary authentication procedures. This novel model thus combines the advantages of transaction anonymity with the speed and ease of electronic transactions without a central management entity (Oyedele *et al.,* 2022). Deep learning is an algorithm model that uses several deep neural networks. The ultimate goal of deep learning is to enable robots to analyse and learn like humans while also recognising data such as text, photos, and sounds. Deep learning is a complicated machine learning process that has led to major improvements in speech and image recognition. Deep neural networks, unlike typical machine learning methods, require data preprocessing and feature extraction before training. In addition, deep neural networks use a cascade of multilayer nonlinear processing units to extract and transform features automatically. This improves neural networks' ability to uncover nonlinear correlations between data and their learning ability with respect to the original dataset. In recent years, based on the big data collected from information sets, the parallel processing capabilities of graphics processing units (GPUs), and new families of convolutional neural networks, deep learning methods have achieved great success in many different applications, including image classification, object detection, and time series prediction (Zhang, 2023). Emerging economies confront particular obstacles, such as volatile national currencies, inadequate banking infrastructure, strict capital controls, and large unbanked populations. Cryptocurrencies can address these issues by offering low-cost, borderless, and inflation-proof financial tools. However, adoption patterns differ greatly between countries, implying that domestic economic, legal, and technological circumstances determine primary factors (Onohwakpo & Onyeanuforo, 2025). Nigeria's position as a major player in the global digital economy is reflected in the country's quick increase in cryptocurrency acceptance. Nigeria consistently ranks among the top three nations in the world for Bitcoin usage. Adoption is influenced by a number of factors, including high remittance costs, currency instability, inflation and youth-driven technological engagement. Despite widespread adoption, not much research has been done to predict or categorise adoption patterns in Nigeria using deep learning techniques. Convolutional Neural

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Networks (CNN), a popular deep learning architecture in computer vision, are used in this study to extract features from intricate adoption datasets.

II. REVIEW OF THE RELATED LITERATURES

Udo and Akpan (2024) investigated what drives technology/ICT businesses in Uyo City to adopt cryptocurrencies. Factors include transaction speed**,** transaction security**,** value stability**,** low transaction cost, etc. This is relevant for business level adoption rather than individual. Irmiya *et al.* (2023) analysed how regulatory restrictions by the Central Bank of Nigeria affect ongoing adoption. Finds that restrictions (especially banking transaction bans, limits on payment channels) negatively impact adoption, create psychological and practical barriers for owners/traders. Highlights the trade-offs between regulation and innovation. Blockchain & crypto can promote financial inclusion among Small & Medium-Scale Enterprises (SMEs) in Ogun East district of Ogun State. Finds that crypto/blockchain improve accessibility, affordability, usability of financial services; but also identifies challenges such as regulation, skills, network and security (Adebayo *et al.,* 2024). Akila *et al.* (2023) proposed a deep-learning approach based on LSTM networks for cryptocurrency price prediction. The approach takes into account historical price data and technical indicators as inputs to the LSTM network, which learns the underlying patterns and trends in the data. However, predicting cryptocurrency prices accurately is not a straightforward task due to their highly volatile nature and sudden changes. They address this issue, by incorporating a change point detection technique with the usage of Pruned Exact Linear Time (PELT) algorithm. Samson *et al.* (2025) published a study that forecasts Bitcoin's daily closing price movements (up or down) using an ensemble machine learning model that combines logistic regression and XGBoost via historical price data and technical indicators (SMA_50, SMA_200 and RSI), the model selects features via hyperparameter tuning, correlation analysis and RFE. Time Series Split cross-validation maintains temporal integrity. The developed ensemble outperforms baseline models by achieving 90.4% test set accuracy, with precision, recall and F1-scores greater than 0.89. Sani *et al.* (2025) developed a supervised machine learning model to forecast bitcoin adoption in Nigeria using datasets scraped from Twitter and Facebook. The goal is to investigate public mood, social behaviour, and cryptocurrency adoption patterns in the region using a robust prediction methodology. They acquired data from relevant social media discussions, and preprocessing techniques were used to clean and turn the information into organised formats appropriate for analysis. Support Vector Machines (SVM) and Naive Bayes algorithms were used to create two models because of their efficiency in text classification and predictive analytics. Both models were trained, validated and tested using social media datasets, and their performance was assessed using important metrics such as accuracy, precision, recall, and F1 score. Suganthini *et al.* (2023) extended dataset for sentiment analysis by incorporating semantic concepts for each retrieved element. This strategy may improve the accuracy of the categorisation model. Agama (2023) investigated the causes driving fast cryptocurrency adoption in Nigeria and examines investor protection concerns raised by this development. The increase in crypto assets poses a new problem for Nigerian policymakers. The existing literature suggested the use of deep learning algorithms for cryptocurrency adoption in Nigeria. This is because most of the published articles used traditional methods (qualitative, quantitative, survey, systematic literature review, etc.) or machine learning algorithms to predict cryptocurrency adoption. This study proposed the use of deep learning algorithms, specifically Convolutional Neural Networks (CNN), to develop a robust model that predicts cryptocurrency adoption in Nigeria.

III. METHODOLOGY

Figure 1 depicts how the model is comprised of integrated components. The dataset is first preprocessed to make it suitable for the evaluation. After processing, the data is passed via a semantic analyser, which removes stop words and applies normalisation. During the feature extraction stage, feature vectors are generated from the processed datasets. The dataset is then separated into subgroups for training, validation and testing purposes. After the validation and testing data are analysed in the classification model, the training data is used to build the model. This approach divides the results into low, medium and high categories and predicts the cryptocurrency adoption in Nigeria. Figure 1 represent the model architecture.

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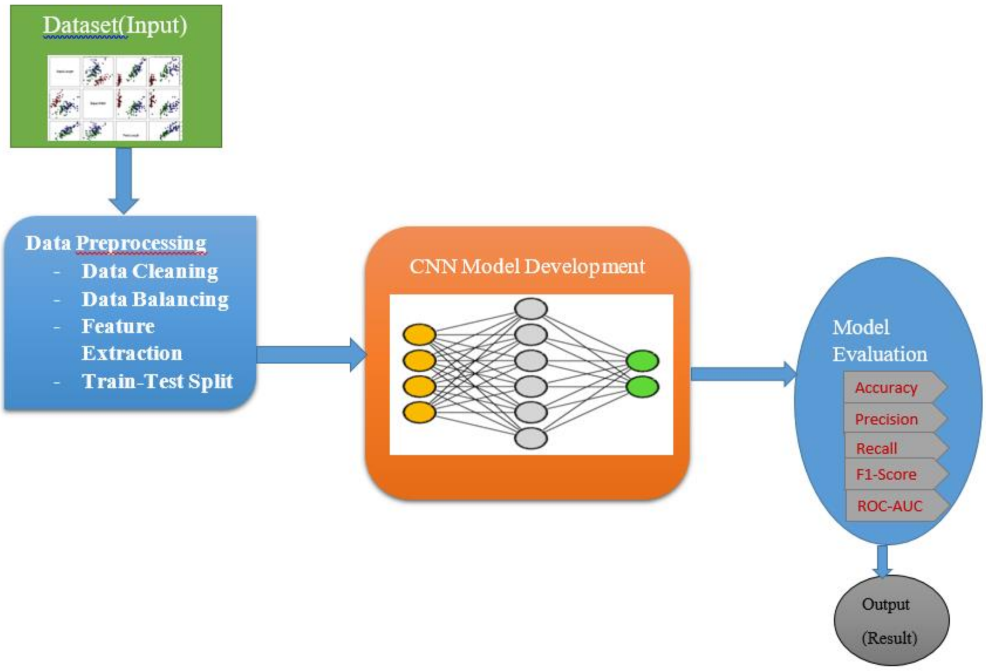

Figure 1: Model Architecture

a. Basic Theory of Convolutional Neural Network (CNN) Model

CNN is a deep learning algorithm commonly used for picture detection and processing. CNNs use convolution to discover associations in visual and sequential data, focussing on local features. It can also identify patterns in time series data. CNNs have revolutionised image processing and can now work with one-dimensional time series data, capturing temporal relationships while retaining the benefits of convolutional operations (Farag, 2022; Köse *et al.,* 2025; Wu *et al.*, 2022). The architecture of CNNs allows them to process data in parallel, which can lead to quicker training times and greater performance compared to classic sequential models such as RNNs (Shang *et al.*, 2023). CNNs normally consist of three fundamental layers: convolutional, pooling and fully connected layers. The convolutional layer derives feature maps from input and identifies local patterns. In this layer, kernels apply a sliding window to learn characteristics in each region. Equation (1) defines the convolution process, which involves learning the relationship between input data and filter.

$$(X * K)(i, J) = \sum_m \sum_n X(i + m, j + n).K(m, n) \quad (1)$$

Where:

X is the input data
K is the kernel
i, j is the location where the convolution process is applied.

After the convolution layer, the ReLU (Rectified Linear Unit) activation function is typically used. After activation, pooling is done. For example, maximum pooling is the process of applying a window to each filter and calculating the maximum value. This procedure is illustrated in Equation (2).

$$y = \max(x_1, x_2, \ldots, x_n) \quad (2)$$

Selecting the maximum value in each window minimises size and improves information density. However, feature maps are flattened to a completely linked layer.

Equation (3) illustrates the final output generation for a classification or prediction task of the model.

$$y = W. x + b \quad (3)$$

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Where:

$W =$ weight matrix

$x =$ input vector

$b =$ bias term.

CNNs may discover local patterns in different regions of data using filters. This functionality offers a significant advantage, particularly for image and time series data. CNNs can learn features automatically, unlike older approaches that need manual extraction. The pooling layer and convolution procedure minimise data dimensions and network parameters, leading to lower computing costs. However, CNNs have several downsides. CNNs perform better with larger data sets. Small data sets pose a considerable danger of overfitting. CNNs demand substantial processing resources to handle massive amounts of data and filters.
CNN's deep structure increases the model's complexity and parameter count (Köse *et al.*, 2025).

b. Data Collection
A dataset consisting of 25,890 items was gathered using the https://www.scrapy.org/ web scraper. The user-generated perspectives in this dataset, which includes postings, comments, and interactions, are diverse and provide a plethora of data for the current study. The scraping process entailed capturing relevant keywords such as "Demographics Information", "Technological Factors", "eNaira", "cryptocurrency", "Psycological Factors", "Behavioural Factors", "Nigerian digital currency", "Nigerian money", "financial inclusion", "eWallet", "adoption", "Nigerian technology" and all user opinions relevant to the study's subject, confirming that the information gathered is comprehensive and representative of the general public's opinion on three major social media networks, Facebook, Instagram and Twitter.
The dataset contained attributes such as:

- Demographics include age, gender, region, economic category, and education level.
- Technological factors include smartphone ownership, internet usage frequency, and digital literacy score.
- Psychological and behavioural factors include faith in digital banking, perceived risk, understanding of crypto rules, peer influence, and more.
- Low*:* does not own crypto (Owns_Crypto = 0)
- Medium*:* owns crypto but rarely/occasionally uses it (Owns_Crypto = 1 and Daily_Usage = 0).
- High*:* owns and uses crypto daily (Owns_Crypto = 1 and Daily_Usage = 1)

The CNN model learnt nonlinear correlations between these features to predict adoption.

1	Age	Gender	Education	Income_C	Awarenes	Owns_Cry	Daily_Usa	Preferred	Adoption_
2	56	Male	Secondary	Medium	1	0	0	Stablecoir	Low
3	46	Male	Secondary	High	1	1	0	Ethereum	Medium
4	32	Female	Tertiary	Low	1	0	0	Ethereum	Low
5	25	Female	Secondary	Medium	1	0	1	Stablecoir	Low
6	38	Male	Tertiary	High	1	1	0	Ethereum	Medium
7	56	Female	Secondary	Low	1	0	0	Stablecoir	Low
8	36	Male	Tertiary	Low	1	1	0	Ethereum	Medium
9	40	Male	Tertiary	Medium	1	1	0	Bitcoin	Medium
10	28	Male	Postgradu	High	1	0	0	Bitcoin	Low
11	28	Male	Secondary	Low	0	0	0	Bitcoin	Low
12	41	Female	Tertiary	Medium	1	0	0	Bitcoin	Low
13	53	Female	Postgradu	Medium	1	0	1	Bitcoin	Low
14	57	Female	Secondary	Medium	0	0	0	Ethereum	Low
15	41	Male	Postgradu	Medium	1	0	0	Bitcoin	Low
16	20	Male	Tertiary	Medium	1	0	1	Bitcoin	Low
17	39	Male	Tertiary	Medium	0	0	1	Stablecoir	Low
18	19	Female	Postgradu	Medium	1	1	1	Others	High
19	41	Male	Secondary	Medium	1	1	0	Stablecoir	Medium
20	47	Female	Tertiary	Medium	1	0	0	Others	Low
21	55	Female	Postgradu	High	1	0	0	Ethereum	Low
22	19	Female	Secondary	Low	1	1	0	Bitcoin	Medium
23	38	Female	Tertiary	High	1	1	0	Ethereum	Medium

Figure 2: Dataset

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c. Data Preprocessing
i. Data Cleaning
To enhance the quality of the data, data cleaning involves identifying and eliminating errors and discrepancies from the data. Inadequate data cleaning procedures can result in failures, flawed analysis, dataset inaccuracies and ultimately incompatible datasets for predictive modelling applications. The procedure used includes:

i. Load & Inspect dataset.
ii. Clean: Fix invalids and drop duplicates.
iii. Split into train/validation/test using stratified sampling (do this before imputation if you want to avoid leakage).
iv. Impute missing values (fit imputer on training set only; apply to val/test).
v. Encode categorical variables: Fit encoders or embedding maps on training data only.
vi. Feature engineering (create derived features) fit any scalers/transforms on the training set.
vii. Scale/normalise continuous features (fit scaler on training set).
viii. Resample or calculate class_weights on the training set only to handle imbalance.
ix. Arrange features into model input shape (n_samples, n_features, 1) or (n_samples, sequence_length, channels).
x. Serialise preprocessing objects (imputer, encoders, scalers) for reproducibility.

iii. Data Balancing
This stage used a Synthetic Minority Oversampling Technique (SMOTE) to balance the dataset in order to have equal distribution of low, medium and high attributes to avoid bias in model training.
iv. Data Training-Validation-Testing set Split
The dataset was divided into three (3) parts: 70% of the data was used for training the model, 15% was used for validation and the remaining 15% was used for testing.
d. Performance Metrics
The following performance evaluation metrics was used to measure the prediction performance of the model.
i. Accuracy
Accuracy measures the proportion of correctly predicted samples among the total samples evaluated.

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \times 100 \qquad (4)$$

ii. Precision
Precision quantifies how many of the predicted positive (adoption) cases were actually positive.

$$Precision = \frac{TP}{TP+FP} \qquad (5)$$

iii. Recall (Sensitivity)
Recall measures the model's ability to identify all actual positive samples.

$$Recall = \frac{TP}{TP+FN} \qquad (6)$$

iv. F1-Score
The F1-score represents the harmonic mean of precision and recall.

$$F1\ Score = 2\ x\ \frac{Precision\ x\ Recall}{Precision+Recall} \qquad (7)$$

v. Roc-auc (receiver operating characteristic – area under curve)
ROC-AUC quantifies the model's ability to discriminate between different adoption levels.
A perfect model scores 1.0, while a random guess scores 0.5.
ROC curve plots the trade-off between:

i. True Positive Rate (TPR) how many actual positives are correctly predicted.
ii. False Positive Rate (FPR) how many negatives are incorrectly predicted as positives.

The AUC (Area Under the Curve) measures the entire two-dimensional area underneath the ROC curve it represents how well a model distinguishes between classes.

(a) True Positive Rate (TPR) (also called *Recall* or *Sensitivity*):

$$TPR = \frac{TP}{TP+FN} \qquad (8)$$

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(b) False Positive Rate (FPR)

$$FPR = \frac{FP}{FP+TN} \tag{9}$$

Where:

TP = True Positive

TN = True Negative

FP = False Positive

FN = False Negative

The ROC curve is a parametric plot of **TPR** versus **FPR** at various threshold levels θ of prediction probability. For each threshold θ:

$$(\text{FPR}(\theta), \text{TPR}(\theta)) \tag{10}$$

The **AUC** can be approximated using the **trapezoidal rule** over all points of the ROC curve:

$$AUC = \int_0^1 TPR\,(FPR)d(FPR) \tag{11}$$

In discrete form (numerical approximation):

$$AUC \approx \sum_{i=1}^{n-1}(FPR_{i+1} - FPR_i) \times \frac{TPR_{i+1}+TPR_i}{2} \tag{12}$$

Where n = number of threshold steps.
This equation computes the trapezoidal area under the ROC curve by summing over all consecutive pairs of (FPR, TPR) points.

IV. RESULT AND DISCUSSION

Table 1: CNN Configuration Setup

Parameter	Description
Optimizer	Adam optimizer (learning rate = 0.001)
Loss Function	Categorical Crossentropy
Metrics	Accuracy, Precision, Recall, F1-score and ROC-AUC
Batch Size	32
Epochs	100 (with early stopping if validation loss stops improving)
Train-Val-Test Split	70/15/15 training, validation and testing

Table 2: Confusion Matrix

Actual/Predicted	Low	Medium	High
Low	190	20	10
Medium	23	215	17
High	12	19	194

Table 2 shows the model's confusion matrix; the created CNN model accurately sorted the majority of samples into the appropriate adoption groups. Minor confusion arose between "medium" and "high," indicating overlapping behavioural patterns among semi-active users.

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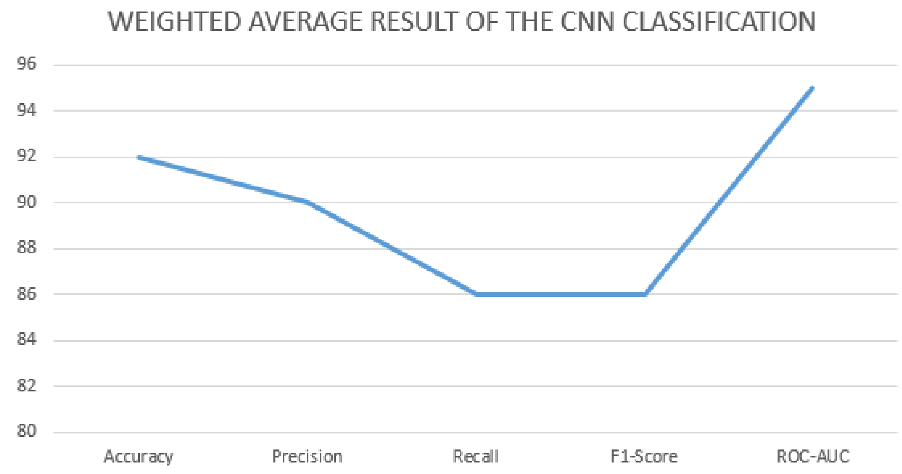

Figure 3: Result of the CNN Classification

Figure 3 shows the performance of the Convolutional Neural Network (CNN) designed to predict cryptocurrency adoption in Nigeria was assessed using various conventional performance metrics, including accuracy, precision, recall, F1-score and ROC-AUC. These metrics together provide insight into how well the model distinguishes between low, medium and high adoption classes, as well as its capacity to generalise over previously encountered data. The CNN model attained 92% accuracy, demonstrating that it successfully captures complicated nonlinear interactions between socioeconomic, demographic and behavioural factors such as education, income and awareness. The high accuracy in Figure 3 demonstrates that the CNN's convolutional layers successfully learnt relevant feature interactions such as the combination of education level, awareness and income as strong predictors of widespread cryptocurrency adoption. The CNN achieved a 90% precision rate for the "High Adoption" class, indicating that 90% of those projected as adopters were actually adopters. The model's high precision suggests that it makes few false-positive mistakes, which is critical for policy or marketing purposes because it ensures that resources targeted at potential adopters reach the intended audience. The model had a recall rate of 86% across all adoption classes. This shows that the CNN accurately identifies the majority of adopters, even when feature patterns differ (for example, differing education or income levels). The high recall ensures that the model is inclusive and reduces false negatives; thus, potential adopters are rarely neglected in prediction or policy formulation. CNN earned an F1 score of 86%, indicating an ideal balance between detecting actual adopters and reducing incorrect classifications. This balanced performance implies that the model is suitable for real-world decision-support systems, such as national cryptocurrency awareness campaigns or FinTech acceptance metrics. The CNN model had an ROC-AUC of 95%, indicating excellent separation amongst adoption classes (low, medium, and high). This demonstrates the CNN's superior capacity to distinguish between adopters and non-adopters based on input attributes. In practice, governments and FinTech firms can rely on such a model to appropriately rank individuals or regions in terms of adoption likelihood.

V. CONCLUSION

This study concluded that, Convolutional Neural Networks (CNN) are capable of precisely estimating and forecasting Nigeria's adoption of Cryptocurrency. In terms of accuracy and generalisation, CNN performs better than conventional machine learning algorithms. These findings highlight the value of cutting-edge AI technologies in financial analytics, particularly in developing countries with complex adoption trends. The results imply that using such advanced models could greatly improve the decision-making procedures involved in investing in cryptocurrencies. Therefore, integrating these technologies could help Nigerian financial institutions and policymakers better understand market dynamics and create more efficient regulatory frameworks. Stakeholders can learn more about market trends and consumer behaviour by adopting these cutting-edge approaches. In the end, this might result in a more secure financial system and increased investor trust in the rapidly developing cryptocurrency market.

VI. FUTURE RESEARCH WORK

This study suggested the following for further investigation by the researchers:

i. Development of an ensemble deep learning models for cryptocurrency adoption in Nigeria and other African countries.

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DOI: 10.17148/IJIREEICE.2025.131022

ii. Hybridising two or more deep learning model in order to enhance the models on cryptocurrency adoption in Nigeria and other African countries.
iii. Future research should also use real-time transactional datasets and expand to additional African countries for comparative analysis.

ACKNOWLEDGEMENT

The authors appreciated Tertiary Education Trust Fund (TETFund) for financial sponsorship under 2025 Institutional Based Research (IBR) intervention in Kebbi State Polytechnic Dakingari, Kebbi State, Nigeria.

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