
EVOLUTION, PROSPECTS, AND FUTURE DIRECTIONS OF NIGERIAN CURRENCY IMAGE ANALYSIS: A DECADAL REVIEW

Isaac Yusuf^{1,*}, Isaac Omeiza Avazi¹

¹University of Ilorin

Email: 24-68gi002pg@students.unilorin.edu.ng, isaacavazi@unilorin.edu.ng

*Corresponding author: Isaac Yusuf

DOI: <https://doi.org/10.67203/sp.ICESID.2026>

ABSTRACT

The counterfeit Nigerian banknote (Naira) is still an ongoing challenge; the development of automated image analysis of the Nigerian banknote has been undertaken. This study is a Systematic Literature Review (SLR) spanning 2016-2026 to map the past, present, and future trends of Nigerian currency image analysis. From 150 initial bibliographic entries in the journal, 55 methodologically sound articles were completely published and appraised. The evolution from the review to the report is emphasized, encompassing traditional image processing and conventional machine learning methods, such as color histograms, HOG, etc., as well as ensemble and deep learning architectures (CNN, LSTM, RNN), with some level of accuracy; despite these accuracies often being above 99%, reliable real-world deployment remains elusive. Persistent limitations include small proprietary datasets, sensitivity to defective notes, and high computational demands. The new redesign of the CBN currency in 2022 rendered models invalid. The prediction of other series was done using older series. To make a contribution to the existing knowledge, the research proposes six key research directions: The components of a set that includes benchmarks, domain adaptation for redesigns, the use of lightweight edge AI, multimodal sensor fusion, environmental robustness, and inclusive design. The overall aim of the study is to steer researchers and financial institutions in the right direction and on how to create highly reliable banknote authentication systems, going beyond just getting good scores in the test set.

Keywords: Nigerian Naira; Currency Authentication; Computer Vision; Pattern Recognition

Decadal Review

1. INTRODUCTION

The Nigerian economy's continued reliance on physical cash transactions is problematic due to widespread counterfeiting of banknotes. While digital financial products, such as the government-introduced e-Naira, aim to promote cashless payments, these initiatives appear insufficient to fully address the issue. Consequently, Nigerian banknotes remain the primary medium of exchange for most people, especially in crowded markets, informal settings, and taxi services (Olowu & Olasupo, 2023). In fact, the entire financial structure is reliant on fiat money, and that creates serious security concerns, mostly the diffusion of counterfeit notes. Both financial institutions and sellers have, for many years, used manual processes for currency verification. By the use of touch, sight, and quick inspection. But that kind of process has inherent flaws; it takes too long, and it depends on subjective judgments and human errors. Automated machine-based identification can be a substantial productivity is considered effective for identifying genuine banknotes, especially when a computer vision approach is applied to define the security characteristics accurately (Adeniyi et al, 2024). The automation system architecture has changed over the past 10 years. The changes have been quite dramatic. The former image processing method involves manual feature extraction, while the latter deep learning method directly classifies the banknote without the need for an intermediate feature extraction step. This latter technique will provide improved results, but it is likely to require more computational power, require data resources, and deal with a variety of conditions that occur in the actual use of Nigerian banknotes. The number of studies on currency recognition in Nigeria is growing, though the works are somewhat disjointed and found in a variety of academic journals and conference proceedings. Taken as a whole,

these research findings on the image analysis of Nigerian currency over the past decade are far from adequate in terms of the availability of usable material as it is in today's academic literature. Due to this, it is difficult for researchers and industry experts to identify established methods, and this delay is experienced when implementing reliable verification and automated processes for daily operations by banks in Nigeria (Mogaji & Nguyen, 2022). This research study therefore sets out to bring a comprehensive overview of the developments in image analysis of Nigerian currency over every decade. The main results of this effort are displayed below:

- i. This study presents an evaluation of metrics for the purposes of assessing them. examines both the data and the performance of researchers who are currently conducting studies using metrics, and it also shows the difficulties that pop up where data is scarce, and problems such as replication. Gaps and whether the testing environment is really authentic at the time of research.
- ii. The research also highlights strategic research directions towards enhancing the capacity and skills in practice.

2. REVIEW METHODOLOGY

The researchers conducted a systematic literature review (SLR) study framework to maintain both scientific research standards and results that other researchers could reproduce. The review framework includes three components, which are used to retrieve literature, select research material, and screen articles until researchers identify their final set of publications for examination. The screening and quality assessment summary of this study is found in the appendix section of this paper.

2.1 Literature Search Strategy and Data Repositories

The researchers conducted an extensive study that examined major digital academic platforms along with their associated repositories to study both worldwide scientific developments and local research efforts. The researchers used IEEE Xplore, SpringerLink, and Google Scholar as the primary electronic databases, which provided international research about currency validation technologies. The review process uses multiple sources to establish complete research activities that apply to Nigeria.

2.2 Search Queries and Key Terms

The retrieval procedure used tailored Boolean search queries that were meant to dig out research studies on digital image analysis together with Nigerian currency computational learning methods. The researchers then used key terms such as every form they could find of “Nigerian Currency”, “Naira Note”, “Banknote Recognition”, and “Authentication”. After that, they mixed these with more specialized terms, for example, “Image Processing”, “Computer Vision”, “Machine Learning,” and also “Deep Learning.”

2.3 Inclusion and Exclusion Parameters

The study used strict inclusion and exclusion criteria because it needed to zero in on visual data analysis only while judging the relevance of particular studies. In other words, the selection method is summarized in Table 1.

2.4 Article Selection Procedure and Quantitative Overview

The literature selection process followed a three-phase screening protocol, which includes three main steps. This included the collection of bibliographic records from selected databases. The process required a title and abstract assessment to determine which materials matched the required content. The process required a full-text article review to determine which materials met the established inclusion standards. The initial search process across academic databases produced 150 documents, which were found through the search. The screening process removed 60 articles because they duplicated existing

content and contained themes that did not match the main subject matter. The remaining 90 abstracts required thorough evaluation, which led to the disqualification of 35 submissions because they either studied non-image sensor methods or lacked scientific proof. The remaining articles comprising 55 articles were further scrutinized and further excluded 38 articles because they were pre-2016 published. The remaining 17 articles that were found germane to this study thoroughly appraised and studied..

Table 1: *Inclusion and Exclusion Parameters*

Parameters	Inclusion	Exclusion
Publication Date	2016 – 2026 (Decadal span)	Publications before 2016
Language	English	Non-English publications
Subject Focus	Image analysis, Computer Vision, Pattern Recognition	RFID, RF Sensors, Magnetic-only sensors (unless hybrid with image)
Geographic Context	Specific to Nigerian Naira notes	Generic currency models have not been tested on the Naira
Document Type	Peer-reviewed journals and conference proceedings	White papers, unpublished thesis, editorials

2.5 Denominations and Structural Evolution (2016–2026)

Not only a shift in the Nigerian monetary system, but a complete overhaul occurred over the entire 10-year period the researchers examined. Before December 2022, there were 8 different nominal values in existence: ₦5, ₦10, ₦20, ₦50, ₦100, ₦200, ₦500 and ₦1000. Later, on 26th October, 2022, the Central Bank of Nigeria (CBN) announced a fresh initiative in the redesign of banknotes, which resulted in the release of new banknotes (₦200, ₦500 and ₦1000) in December, 2022. Meanwhile, the smaller denominations, from ₦5 to ₦100, remained the same. The banknotes shared some common design features, such as their size and color, but each note also featured its own unique design with different Nigerian historical figures. The re-issuance, however, necessitated a complete redesign for the higher denomination banknotes, which meant changes in the colors, size of notes, and even security features' placement. This poses a significant challenge for the automated image analysis platforms, as the models developed in the 2016 series need to adapt, or recalibrate, for the 2022 series. The review basically acknowledges this coexistence of physical data between two different states.

2.6 Visual Features for Machine Analysis

Automated identification systems require the extraction of salient distinguishing features from the image of a currency. The performance of any computational approach, including traditional edge detection approaches and more recent advanced deep convolutional networks, is based on the detection of visible physical properties such as:

- 2.6.1 Chromatic Signatures (Color): This is the most prominent feature as far as the denominational categorization is concerned. The primary green color of each banknote is its main color: this is evident on the ₦50 banknote and on the ₦500 banknote. These elements are displayed by the image analysis systems in RGB and HSV color space. If only color is used as a means of identification, it will give false readings where light conditions vary and where pigments have faded.
- 2.6.2 Textural Properties: The production process of Nigerian banknotes uses a fibrous cellulose substrate, which undergoes intaglio engraving to create raised ink patterns. The basic process

of RGB sensors becomes limited because they cannot detect raised surface patterns, but high-resolution capture systems enable users to observe the basic micro-patterns and random surface textures present on paper materials. The Gray-Level Co-occurrence Matrix method serves as a standard technique that authenticates material properties by differentiating between real substrate material and fake substrate material.

2.6.3 Security Features: This includes

- i. *Watermarks*: The paper matrix contains embedded effigies which become visible through trans-illumination. The features remain inaccessible to standard reflective imaging systems, which require specialized backlighting systems to achieve proper capture.
- ii. *Security Threads*: The banknote contains metal or plastic threads that create reflective surfaces, which protect against unauthorized detection. The system identifies the objects through two methods: highlight detection algorithms and frequency domain analysis.
- iii. *See-Through Registers*: The two patterns create identical overlaps when light strikes their surfaces. The system requires two sensor systems and special light systems to verify their authenticity because they function like watermarks. Serial Numbers and Typography Each banknote displays a unique alphanumeric serial number, which maintains the same font style and location throughout the banknote.
- iv. *Optical Character Recognition (OCR)* methods can verify results, yet different printing quality and the existence of dust or physical damage often reduce OCR performance, which makes it a supporting element, not a primary identification method.

Table 2 displays essential visual attributes that researchers need to understand the available feature domain for their algorithm development work. The table presents specific challenges that each banknote faces because it displays similar colors between different denominations and shows security features differently under various lighting conditions. The data presented in Table 2 emphasizes a fundamental consideration for the architects of identification systems: that sole reliance on chromatic attributes is insufficient. The system requires algorithms to identify both old and new currency notes because it operates in an environment where lower-value notes stay unchanged while higher-value notes get redesigned.

Table 2: *Visual Characteristics Of Nigerian Banknotes Relevant to Image Analysis (2016–2026)*

[\(<https://www.cbn.gov.ng>\)](https://www.cbn.gov.ng)

Denomination	Dominant Color (2013 Series)	Dominant Color (2023 Redesign)	Key Security Features	Image Analysis Challenge
₦5	Green	Green (Unchanged)	Watermark, Security Thread	Small size makes feature extraction difficult.
₦10	Brown	Brown (Unchanged)	Watermark, Security Thread	Often heavily soiled; low contrast in images.
₦20	Blue	Blue (Unchanged)	Watermark, Security Thread	Color similarity with higher denominations under poor light.
₦50	Green	Green (Unchanged)	Watermark, Security Thread	Chromatic confusion with ₦5 note in grayscale conversion.
₦100	Brown/Orange	Brown/Orange (Unchanged)	Watermark, Security Thread	High circulation volume leads to significant wear/tear.
₦200	Brown	Yellow/Brown	Watermark, Thread, See-through	Color shift in redesign affects trained models.
₦500	Purple	Green/Red	Watermark, Thread, See-through	Major color change in redesign; high counterfeit target.
₦1000	Blue/Purple	Blue/Purple (Shifted)	Watermark, Thread, See-through	Dimension change affects cropping and scaling algorithms.

2.7 THE EVOLUTION OF TECHNIQUES

This section assesses the development through the classification system, allowing a better understanding of process requirements, accuracy, and system reliability competing with each other in the Nigerian financial system.

2.7.1 Conventional Image Processing and Classical Machine Learning (2016–2026)

Iwok and Akpan (2016) proposed a statistical way to sort real Naira notes from fake ones. The authors used discriminant analysis. The authors also relied on multivariate tools like Hotelling's T^2 and Mahalanobis distance. The goal was to identify the notes apart, using measured physical features. So the work was mainly about statistical classification, not about matching image pixels. Almu and Muhammad (2020) took a photo of a suspected banknote, then compared that photo with a stored image of an original note. It looked for pixel patterns and also tracked where key features were on the note. Those features included color details, a strip, and the watermark. The method produced one percentage score for how close the two images were. If the score was above 95%, the note was marked as genuine. Their tests showed it could separate real from fake notes. Still, the authors reported a problem when the note was worn, damaged, or too degraded. A proposed approach used color histograms in the HSI color space, and then it sorted Nigerian Naira notes, specifically the #200, #500, and #1000 denominations. Hence, a rule-based classifier worked with 10-bin histograms for the hue component, the saturation component, and the intensity component too, and it reported an average accuracy of around 98.66%. They also mentioned that the method worked well because it did not need many preprocessing operations. Even so, the approach still ran into difficulties in situations where notes were damaged or stained, and in those cases, lower denomination accuracy was more difficult to maintain, as cited in (Omeiza et al, 2020). The research conducted followed a three-step process, which included three distinct stages of research work (Adewole et al, 2023). The first step involved using an advanced object detection system to identify different types of currency. The second step involved using an existing algorithm that had been specifically developed to identify serial numbers of various currency denominations. The three different optical character recognition systems, which included Pytesseract, Easy OCR, and Keras OCR, were used to perform character recognition. The results showed that the system achieved perfect accuracy for currency classification because it reached 100 percent accuracy. The character recognition stage, which used the Easy OCR system, reached its highest accuracy level at 81%. The approach presents several problems that need to be addressed despite its current achievements. The OCR models do not include special features that enable them to recognize Nigerian currency serial numbers. The system experiences errors because it depends on three different factors, which include note condition, image quality, and visual background complexity.

2.7.2 Hybrid and Traditional Techniques (2016-2026)

The research process began with background elimination through Otsu thresholding and connected component analysis. The research team calculated HOG features from standardized grayscale images measuring 154×302 pixels. The research team used PCA to reduce the features to retain essential data while decreasing computational requirements. The ECOC-MCSVM system enabled the identification and classification of multiple banknote denominations, which could be shown from either side of the currency note. The research team examined a dataset that contained 5200 banknote pictures from four different currencies: 1800 Nigerian Naira, 1000 US Dollars, 1000 Canadian Dollars, and 1400 Euros. The Canon T2i digital camera captured these images at 200 dpi to display various viewing conditions, which included front and back views as well as upward and downward orientations of new and worn notes; full and partially hidden notes. Through the application of 10-fold cross-validation, the MCSVM classifier achieved better recognition results than multiple baseline methods, which included Naïve Bayes, Random Forest, NNge, Hyperpipes, IB1, and SMOSVM. The system achieved 99% accuracy for Naira, 97% for USD, 96% for CAD, and 98.6% for Euro while displaying fast processing capabilities. The method faced several major restrictions during its operation. In the modeling part, the researchers employed a multiple-layer ensemble strategy, and they blended multiple K-Nearest Neighbor (KNN) distance measurement concepts. The distances included Euclidean distance, Manhattan distance, Chebyshev distance, and Minkowski distance. Following this, the system used a weighted voting approach to combine the distance-metric predictions, enhancing the robustness of the system under image changes and also aiding with unexpected external conditions. This research was conducted using a set of Nigerian Naira banknotes, including N100, N200, N 500, and N1000. The team then collected photographs of real banknotes and fake notes taken in different lighting, from different angles, and they also ensured that the banknotes were in various states of wear. Later, the

application was tested on two different types of devices, namely; on Android devices (such as Samsung Galaxy S6) and iOS devices (such as iPhone 6). The results indicated an accuracy rate of 99.27% in identifying the denomination and 94.70% in detecting fake banknotes. The system also processed the images in a very short time (0.02 milliseconds per image), which means it could run in real time on standard mobile devices. However, during implementation, there were some key problems encountered as a result of illumination imaging, and thus it had difficulty in detecting more sophisticated counterfeits, particularly those that preserve visually realistic features of the banknotes. This indicates that additional sensing equipment (such as UV or infrared) and adaptive image processing algorithms are required to guarantee the deployment's reliability in practical environments (Dittimi & Suen, 2018). Subsequently, (Dittimi & Suen, 2019) developed a mobile app based on a client-server system, which utilized Unity 3D and MATLAB for banknote recognition and verification. The methodology adopted the following: Feature Extraction using Histogram of Oriented Gradients (HOG) and High Correlation Filters (HCF) to reduce the feature space, followed by the application of an ensemble classifier, which consisted of Multi-Layer Perceptron Neural Networks (MLPNN) and Multi-Class Support Vector Machines (MCSVM). They simulated the technique with full banknote sets comprising the Nigerian Naira, US Dollar, Canadian Dollar, and Euro banknotes. Authentic samples were taken as pictures using a Canon T2i camera, and the counterfeit samples were printed using an HP Color LaserJet printer, resulting in samples with differing viewing angles and lighting conditions. The results showed that the designed HOG-HCF-WMA system identified the images with 99.00% accuracy and a time of approximately 0.051 seconds per image. The system outperformed all the top systems established that have been used in their respective fields, with respect to its accuracy outcomes and its operational efficiency. The approach was successful, but had significant limitations. The system needed a tremendous amount of computing power to extract features, requiring the user to process features on a server and not on their mobile device. Ismail et al (2024) employed a two-stage image processing methodology. The process starts with the resizing, grayscale conversion, and rotation of ₦500 and ₦1000 banknotes, which undergo scanning to prepare them for SURF-based analysis. The system uses three image quality assessments to evaluate note eligibility for automated teller machine (ATM) operation. The algorithm achieved perfect accuracy in denomination identification when tested on a dataset containing 562 banknotes, which included 286 ₦500 notes, 270 ₦1000 notes, and 6 other notes. The Peak-Signal-to-Noise Ratio (PSNR) metric showed excellent results because it accurately classified every one of the 60 "fit" ₦500 notes and 93.8% of the 226 "unfit" notes. The PSNR metric for ₦1000 notes achieved accurate classifications of 136 "fit" notes and 120 "unfit" notes from a total of 142 "fit" notes and 128 "unfit" notes. The system recorded an overall accuracy rate of 97% for fit records and 93.8% for unfit records because PSNR demonstrated better accuracy than both SSIM and MSE. The two main obstacles that need resolution stemmed from the dataset's restricted size and its unbalanced distribution, which contained only 654 images and an extremely small quantity of non-target notes. The quality-metric stage required detailed pre-processing and threshold selection because it responded strongly to both image orientation and image degradation. The unfit notes showed decreased performance with SSIM and MSE, which suggests that these metrics fail to assess all types of banknote damage or wear. Woods & Oladosu (2020) built CNNs (VGG-16) with TensorFlow and OpenCV, reaching 92.75% accuracy. The model encountered difficulties when attempting to extend its functionality to different currencies.

2.7.3 The Traditional to Machine Learning. Ensemble learning and Deep Learning (2020–2026)

Researchers began using Deep Learning (DL) architectures after 2020 because they needed to adopt a new research methodology. The literature from this period shows a primary focus on Convolutional Neural Networks (CNNs), which help researchers extract essential features from their work. The VGG16, ResNet50, and InceptionV3 models enable users to identify complex design elements through their processing of unprocessed image data. The era shows a dominant pattern of researchers applying transfer learning to their work. Researchers used ImageNet-trained models, which they modified through training on their limited Naira note datasets because they could not find enough

Nigerian currency data for their research. The research used this methodology to achieve performance metrics that exceeded 98% through the use of limited training resources. The period from 2023 to 2026 marks the beginning of research into MobileNetV2 and EfficientNet, which academic institutions use to enhance their processing speed and precision rates. (Richard-Nnabu et al., 2024) used Convolutional Neural Networks (CNNs) to detect counterfeit Nigerian Naira notes. The model achieved 95% accuracy because the testing included both folded notes and partially faded notes. The strength of CNN's in handling such complexities underlines their potential for counterfeit currency identification. The study demonstrated that the approach needs larger and more diverse datasets to improve its ability to identify currency. Ibitoye (2024) developed a Modified Faster R-CNN system which uses the Inception V3 architecture. The method achieved 97% detection accuracy, but it failed to identify worn-out or damaged notes and needed high-quality photos for precise recognition. Nwokoye & Moru, (2025) developed a cost-effective technological solution that enables visually impaired users to identify Nigerian naira banknotes. The system was created by customizing an SSD-MobileNet V2 FPNLite detector, which operated at 320x320 pixel resolution. The system was optimized for mobile devices through TensorFlow Lite, while Google Text-to-Speech provided spoken feedback. The development process started with image capture and proceeded through image preparation, which involved size adjustments, standardization, and data expansion techniques. The recognition model training used a specially assembled dataset of 3,468 images, which contained duplicate photos of each currency type that had undergone extensive editing. The researchers utilized the optimized model for real-time identification purposes. The system testing with previously unused image data demonstrated exceptional detection accuracy for all seven naira denominations. The system reached 97.11% mean average precision (mAP) at Intersection over Union (IoU) 0.55 and 93.29% at IoU 0.90 and 83.81% at IoU 0.95, while the total system exceeded 90% mAP. Convolutional Neural Networks extract image features. Feature selection was done by the Networks (CNNs) for deciphering the note values. A custom CNN structure, as well as some structures provided by the library, were used for this purpose. The experimental results indicate that both the custom CNN and pre-trained CNN models reached the correct answer for all the questions on the test. data. The CNN models required both large sets of training data and higher-level graphics processing units, which produced problems in their use with mobile devices. Meanwhile, deep learning methods were reviewed in academic literature. which is used by researchers for making a fake banknote is a fascinating area. Using deep learning for forging a fake banknote is a fascinating field. This was accomplished by examining papers that were published from 2018 to 2024. (Yusuf et al, 2025) conducted several Convolutional Neural Network (CNN) architectures, and in this set, there are AlexNet, MobileNet, VGG16, ResNet, which form the foundation of the DNN networks. The DNN networks are based on Inception V3, along with Recurrent neural Networks. RNNs and generative adversarial networks (GANs). The studies used datasets with images of several different countries' banknotes, including the Indian Rupee, Nigerian-Naira, CFA Franc, and Saudi Riyal. The studies were successfully classified with accuracy rates of 70% to 99.84%. The methods of approach gave better results.

2.7.4 Comparative Examination of Selected Studies

Table 3 will be used to compare the research methods used in the 11 most important papers studied and evaluate them. The table illustrates the changes from traditional methods to deep learning methods and some of the key constraints of dataset size and environmental durability.

3. PROSPECTS AND FUTURE DIRECTIONS

The study, considered the Nigerian banknote identification systems for the next decade, 2016-2026, revealed that the Nigerian banknote identification systems have entered a new technological area. Although laboratory tests have demonstrated top-level performance results ranging up to 99 percent, the academic work of the research has yet to yield profitable financial systems. The current research methods can only partially improve classification accuracy to a small degree and will increasingly meet with the challenges of data standardization, system adaptation, system performance, and security feature combination in the future. The following list of areas presents key areas that need to be further explored:

Table 3: *Comparative Analysis of Nigerian Image Analysis Techniques (2016-2026)*

Author/Year	Method/Algorithm	Data Size	Accuracy	Limitation
Omeiza et al., 2023	Color histograms in HSI color space with a rule-based classifier using 10-bin histograms for hue, saturation, and intensity components	Not explicitly specified; focused on ₦200, ₦500, ₦1000 Naira notes	98.66%	Performance issues with soiled or damaged notes; mitigation focused on lesser denominations
Dittimi et al., 2017	Background removal (Otsu thresholding + connected component analysis), HOG feature extraction, PCA dimensionality reduction, ECOC-MCSVM classification framework	5,200 banknote images: 1,800 Naira, 1,000 USD, 1,000 CAD, 1,400 EUR; captured with Canon T2i at 200dpi under varied conditions	99% Naira, 97% USD, 96% CAD, 98.6% Euro	Performance decline under extreme lighting/distortion; PCA may discard subtle discriminative patterns; high computational complexity from ECOC-MCSVM; denomination recognition only (no counterfeit detection)
Dittimi & Suen, 2018	Mobile application (Unity 3D); layered ensemble KNN combining Euclidean, Manhattan, Chebyshev, and Minkowski distance metrics with weighted voting system	Nigerian Naira (₦100- ~~₦1000~~) photographed via smartphone cameras; diverse lighting, angles, wear states; included genuine and counterfeit samples (exact count unspecified)	99.27% denomination recognition; 94.70% counterfeit detection; 0.02ms avg processing time	Visible-light imaging limits the detection of sophisticated counterfeits; performance drops with severely dirty/torn/creased notes; requires precise parameter tuning; dependent on image resolution and stable camera positioning
Dittimi & Suen, 2019 Dittimi & Suen, 2019	Client-server mobile app (Unity 3D + MATLAB); blended framework: HOG feature extraction, High Correlation Filters (HCF) for dimensionality reduction, Weighted Majority Average ensemble of MLPNN and MCSVM	Multi-currency dataset (Naira, USD, CAD, EUR); genuine images (Canon T2i) + counterfeit samples (HP Color LaserJet); varied angles and illumination (exact counts unspecified)	99.00% identification accuracy; 0.051s average processing time	High computational demands requiring server-side processing; smartphone camera focusing/resolution limitations at close range; sensitivity to background interference and lighting variations; processing time fluctuations based on note size and pixel density

EVOLUTION, PROSPECTS, AND FUTURE DIRECTIONS OF NIGERIAN CURRENCY IMAGE
ANALYSIS: A DECADAL REVIEW

Author/Year	Method/Algorithm	Data Size	Accuracy	Limitation
Almu & Muhammad, 2020	Pattern recognition system (Visual Basic + MS Access); preprocessing, feature extraction (color, watermarks, serial numbers), pixel-wise comparison against reference database with 95% similarity threshold	Reference database of genuine Nigerian banknotes; user trials with 15 participants (exact image dataset size not specified)	Successful identification of authentic/fake notes under typical conditions; no specific accuracy percentage reported.	Unreliable with heavily damaged, soiled, or degraded notes due to pixel-comparison approach; limited robustness to visual obstructions; recommended integration of multiple image-processing techniques and mobile interface
Adewole et al., 2023	Three-stage pipeline: enhanced object detection for currency classification, pre-trained algorithm for serial number localization, three OCR systems (Pytesseract, EasyOCR, KerasOCR) for character recognition	Not explicitly specified in the provided text	100% accuracy for currency classification; peak 81% character recognition accuracy (EasyOCR)	Insufficient OCR accuracy for practical deployment; OCR models not specifically adapted to Nigerian currency serial number formats; prone to errors from note condition variations, image quality issues, and complex visual backgrounds
Ismail et al., 2024 Ismail et al., 2024	Two-stage pipeline: (1) Preprocessing (resizing, grayscale, rotation) + SURF feature extraction + KNN classifier for denomination recognition; (2) Fitness assessment module using MSE, PSNR, and SSIM image quality metrics	562 test banknotes (286 ₦500, 270 ₦1000, 6 other notes); total dataset approximately 654 images with noted class imbalance	Denomination recognition: 100%; Fitness classification (PSNR metric): ₦500 fit=100%, unfit=93.8%; ₦1000 fit=95.8%, unfit=93.8%; Overall averages: 97% fit notes, 93.8% unfit notes	Modest dataset size with class imbalance; fitness metrics sensitive to image orientation and degradation requiring careful preprocessing/threshold tuning; SSIM and MSE underperformed on unfit notes; may not comprehensively capture all wear/damage patterns

Author/Year	Method/Algorithm	Data Size	Accuracy	Limitation
Adeniyi et al., 2024	Hybrid approach: Circular Local Binary Pattern (CLBP) for rotation-invariant texture feature extraction combined with CNN architectures (custom design + transfer learning models: VGG, ResNet variants) for feature selection and classification	Higher-value Naira notes (₦200, ₦500, ₦1000) with various damage types (ripped edges, faded ink, creases, partial coverage); captured under diverse lighting/orientations (exact count not specified)	100% classification accuracy on testing data for both custom CNN and pre-trained transfer learning models	CLBP extraction is computationally intensive and vulnerable to severe noise/physical damage; CNN models require extensive training data and powerful GPUs, limiting mobile/embedded deployment; untested on lower denominations (₦5–₦100); high controlled-test accuracy may not translate to real-world scenarios with sophisticated counterfeits; recommends multi-modal authentication (UV, magnetic, tactile)
Richard-Nnabu et al., 2024	Convolutional Neural Networks (CNN) for binary classification of genuine vs. counterfeit Nigerian Naira notes	Not explicitly specified in the provided text	95% accuracy maintained even with folded or partially faded notes	Limited by dataset size and diversity; authors emphasized need for larger, more varied datasets to enhance model generalizability and practical relevance for real-world currency identification scenarios
Nwokoye & Moru, 2025	SSD-MobileNet V2 FPNLite object detector (320x320 input), optimized with TensorFlow Lite for mobile deployment; integrated with Google Text-to-Speech for auditory feedback	3,468 annotated images (each of 7 Naira denominations photographed twice with extensive data augmentation techniques)	mAP: 97.11% at IoU 0.55, 93.29% at IoU 0.90, 83.81% at IoU 0.95; overall system >90% mAP; ~80% accuracy when trained on restricted/lower-quality data	Small dataset size with limited variety; reliance on standard-resolution camera images; accuracy degradation (~80%) with lower-quality training data; requires more extensive, higher-resolution datasets and advanced augmentation for improved reliability

Author/Year	Method/Algorithm	Data Size	Accuracy	Limitation
Yusuf et al., 2025	Systematic review of deep learning approaches: CNN architectures (AlexNet, MobileNet, VGG16, ResNet, Inception V3), RNNs, and GANs for counterfeit detection	Multi-currency datasets (Indian Rupee, Nigerian Naira, CFA Franc, Saudi Riyal) from public archives, web scraping, and organizational holdings (exact sizes not specified in review)	Reported classification accuracy range: 70% to 99.84%; ensemble and pre-trained model approaches typically yielded superior performance	Limited adaptability to degraded or imperfect banknotes; imbalanced datasets with scarce counterfeit examples; high computational requirements hindering mobile/embedded deployment; model capacity/lack of interpretability impedes adoption in transparent, rule-based financial decision-making contexts

3.1 Establishment of Standardized Public Benchmarks

The most frequently reported limitation identified during the literature review is that the datasets are incomplete in various capacities, such as basically. It is not always complete, so even if search thoroughly and look at them, there is still some missing information. The lack of data makes it impossible to confirm findings, while it makes models develop excessive dependence on their training data, according to the research of (Dittimi et al, 2017). The research community requires a collaborative effort to develop a publicly shared reference dataset that serves as a standard benchmark for research. The collection should include:

- a) *Comprehensive Denomination:* The complete legal currency collection includes all current denominations, which range from ₦50 to ₦1000 and feature both the old design and the new design introduced after 2023.
- b) *Diverse Physical State:* The research team built classification models for note quality assessment by intentionally including new notes together with worn notes, dirty notes, damaged notes, and creased notes.
- c) *Challenging Examples:* The study requires a validated collection of advanced counterfeit banknotes to address the issue of example distribution imbalance, which Dittimi and Suen (2018) and Richard-Nnabu et al. (2024) identified.
- d) *Environmental Diversity:* The images were taken under various illuminations, backgrounds, and camera settings to simulate situations that mimic market and ATM conditions.

3.2 Domain Adaptation for Currency Redesigns

The Central Bank of Nigeria implemented a currency redesign in December 2022, which creates a major obstacle for people who need to research and identify Nigerian currency because they must learn new recognition methods. The current recognition models, which were created before 2022, become useless when they try to recognize banknotes that have different color patterns, security elements, and design features. The process of developing new models requires organizations to allocate substantial resources and dedicate extended periods of time to development work.

Future Direction: Research should focus on Transfer Learning and Few-Shot Learning methods as primary research objectives. The research team aims to develop model architectures that can learn new currency designs with only small amounts of labeled data. Generative Adversarial Networks (GANs) will enable the creation of authentic images that represent new currency denominations and their counterfeit versions. The system will use limited real-world data to help secure procedures; this will boost its generalization capabilities, but maybe not in a perfectly linear way

3.2 Optimize for lightweight Edge AI and mobile devices.

The creation of deep learning models such as VGG and ResNet establishes a sort of high-precision standard, but the processing requires the resources of central servers, so it is a tight bottleneck. This means that the system may exhibit performance delays and, at the same time, it is also a challenge for data protection due to the same processing requirement. Also, the incorporation of a compact version of MobileNet called MobileNet in our design, which also increases the speed of the operations, but at the cost of accuracy, as is only fair given the requirement.

Further direction: More attention should be paid to the research of model compression techniques in the future, which is not only a side step but is the main focus, such as pruning, quantization, and knowledge distillation. The goal is to deploy powerful convolutional neural network (CNN)-based systems directly onto low-power devices, such as ATMs, point-of-sale terminals, and even some simple cell phones, soon and with minimal delay or power consumption. The study should also really focus on Federated Learning, as it seems like it is an important part of this whole scenario. In practical terms, mobile technology can improve their recognition models through collective learning whilst preserving users' image data. This means improved overall privacy protection and more security measures that's the point.

3.3 Anti-Counterfeiting using Multi-Modal Sensor Fusion

The problem with this analysis is that it relies on the visual characteristics alone for its evaluation. Research shows that sophisticated counterfeiting can be able to replicate the appearance of an optical identification system in a convincing way, making optical systems incapable of providing security in a secure facility.

Future Direction: Future authentication systems should be based on more than one type of sensor, which is also referred to as multimodal sensor fusion. The concept is that the visual information in the normal color image is matched to other information such as that under UV, IR, and magnetic ink detection. Additionally, there is surface texture analysis, which is quite useful in practice. These pieces, when combined, should make the authentication system seem more secure, and it's the combination of the pieces that makes it secure, not just one of them. So, the research should be centered on making useful evidence integration algorithms for several sources and getting all that into an authenticity result. It should do that to lower the rates of false identification, which is where fake products are mistaken as real products.

3.4 Environmental Robustness and Light-Condition Handling

The studies indicate that when conditions are less than optimal, performance decreases. The system demonstrated two major issues, which included failing to process soiled currency notes and also not being able to cope with changes in lighting and viewing angles, in general.

Future Direction: The researchers really do need to make algorithmic resilience a little stronger by implementing ways of identifying and fixing errors that crop up as the notes are classified. In the first stages of data processing, advanced techniques that get rid of the background noise and also standardize lighting conditions, even across different currency note materials and those varied surfaces, are implemented. Basically, the quality determination of a currency (for ATM suitability, like it or not) should be considered a different and concurrent task, in addition to denomination. For that, it might be able to rely on more nuanced texture analysis, instead of basic pixel measurements.

3.5 Inclusivity and Accessibility

While it may feel a bit odd, the use of Text-to-Speech (TTS) technology looks like a good idea for increasing access to financial services for persons with visual impairments. In practice, the function shows up at certain moments; it is not something users see all the time.

Future Direction: The next step in the process should focus on adopting universal design concepts. The system for recognition requires the developers to create functions determining values and to push the user toward immediate alerts, which should be achieved through sound. Multiple local languages should be supported simultaneously. Further research on tactile feedback mechanisms for user validation would also benefit other groups of users in the identification of currency. That's the whole direction that we're going in, towards financial equity, and if it's a bit uneven, that's what we're going in.

4. CONCLUSION

This study reviewed the developments of image analysis research in Nigeria's currency from 2016-2026, which aimed at evaluating the development of image analysis of Nigerian currency during the mentioned time period. Of the 150 publications retrieved, 55 methodologically eligible studies were identified, and 17 of these were subjected to detailed critical appraisal to gain a detailed understanding of the methods, performance trends, and research gaps. The review clearly shows the technological evolution from traditional image processing methods and handcrafted feature extraction techniques to hybrid machine learning methods and, more recently, to deep learning architectures like CNNs, transfer learning, and lightweight object detectors. The accuracy of reported recognition varied from around 70% to 100% across the studies reviewed, with some recent deep learning models able to reach above 99% accuracy under controlled experimental conditions. However, such great success has not been achieved yet for successful deployment in the wild due to the lack of widely available datasets, the absence of good representation of worn and counterfeit banknotes, the sensitivity to illumination and environmental changes, heavy computational demands, and insufficient model generalization. One of the major conclusions of this review is that the redesign of banknotes by the Central Bank of Nigeria (CBN) in 2022 has completely changed the appearance and security features of the higher denominations, making the effectiveness of models trained only on the previous series of banknotes null and void. Therefore, future studies should focus on the development of adaptive learning strategies that could continue to facilitate the recognition of banknotes even if they were redesigned, without necessitating a complete redevelopment of the banknote model. Overall, the review points towards the development of a system that is robust, adaptive, explainable, and efficient in terms of computation, as well as optimizing classification accuracy in future Nigerian currency authentication systems. The development of standardized benchmark datasets, leveraging transfer learning and few-shot learning to handle redesign challenges, the integration of multimodal sensing, the enhancement of environmental robustness, and the promotion of inclusive accessibility features will be crucial in bringing research innovations to viable financial authentication solutions that can thrive in the practical Nigerian banking and commercial landscape.

5. REFERENCES

- Adeniyi, J. K., Adeniyi, A. E., Aworinde, O. H., Adeniyi, T. T., Olanloye, O., & Ninan, D. O. (2024). A circular local binary pattern and convolutional neural network approach to mutilated Nigerian banknotes recognition. *2024 International Conference on Science, Engineering and Business for Driving Sustainable Development Goals (SEB4SDG)* (pp. 1–6). IEEE. <https://doi.org/10.1109/SEB4SDG60871.2024.10629799>
- Adewole, L. B., Ogunleye, E. O., Faniyan, O. E., Adewale, S. A., & Daramola, C. Y. (2023). Development of a serial number extractor for Nigerian currencies. *University of Ibadan Journal of Science and Logics in ICT Research*, 9(1).
- Almu, A., & Muhammad, A. B. (2020). Image-based processing of Naira currency recognition. *Scientia Africana*, 15, i143–i150.
- Dittimi, T. V., Hmood, A. K., & Suen, C. Y. (2017). Multi-class SVM-based gradient feature for banknote recognition. *2017 International Conference on Information and Communication*

- Technology for Intelligent Systems (ICIT)* (pp. 309–314). IEEE. <https://doi.org/10.1109/ICIT.2017.7915503>
- Dittimi, T. V., & Suen, C. Y. (2018). Mobile app for the detection of counterfeit banknotes. In F. Khosrowpour (Ed.), *Advances in artificial intelligence: 31st Canadian Conference on Artificial Intelligence, Canadian AI 2018* (pp. 156–168). Springer International Publishing. https://doi.org/10.1007/978-3-319-89656-4_13
- Dittimi, T. V., & Suen, C. Y. (2019). High correlation-based banknote gradient assessment of an ensemble classifier. *International Journal of Wavelets, Multiresolution and Information Processing*. <https://doi.org/10.1142/S0219691319500061>
- Ibitoye, O. T. (2024). Fake currency detection using a modified faster region-based convolutional neural network. *International Journal of Electrical Engineering and Computer Science*, 6, 46–50.
- Ismail, T. I., Abubakar, M. A., & Tijjani, I. I. (2024). *Performance comparison of deep learning techniques in Naira classification*. DOI: [10.48550/arXiv.2412.02072](https://doi.org/10.48550/arXiv.2412.02072)
- Iwok, I. A., & Akpan, A. W. (2016). Discriminant function for classification of genuine and counterfeit Naira notes. *Scientia Africana*, 15(1).
- Mogaji, E., & Nguyen, P. N. (2022). The dark side of Mobile Money: Perspective from an emerging economy. *Technological Forecasting and Social Change*. Volume 25, ISSN: 0040-1625, doi.org/10.1016/j.techfore
- Nwokoye, S., & Moru, D. (2025). *Development of a neural network model for currency detection to aid visually impaired people in Nigeria* [Preprint]. arXiv. <https://arxiv.org/abs/2508.18012>
- Olowu O. F & Olasupo M.A. (2023). The Impact of Cashless and Naira Redesign Policies on Economic Development in Federal Capital Territory, Abuja. *Journal of Politics & International Relations*. Volume 2, No 2
- Omeiza, I. O. A., Ogunbiyi, O., Ogundepo, O. Y., Otuoze, A. O., Egbune, D. O., & Osunsanya, K. (2023). A method of colour-histogram matching for Nigerian paper currency notes classification. *Jordan Journal of Electrical Engineering*, 9(1).
- Richard-Nnabu, N. E., Ituma, C., & Nweke, H. F. (2024). Convolutional neural networks method for folded Naira currency denominations recognition and analysis. *Journal of the Nigerian Society of Physical Sciences*, Article 2239.
- Woods, N. C., & Oladosu, H. S. (2020). Recognition and fitness classification of Nigerian currency for automatic teller machines. *African Journal of Computing & ICT*, 13(1), 29–38. <https://afrcict.net>
- Yusuf, A. A., Zambuk, F. U., Gital, A. Y., Lawal, M. A., Rukuna, A. L., Garba, L., & Aliyu, A. Y. (2025). Deep learning for counterfeit currency detection and classification: A systematic review of current approaches, challenges, and future directions. *International Journal of Research*. <https://www.ijrpr.com/uploads/V6ISSUE2/IJRPR38592.pdf>

APPENDIX: SCREENING PROCESS AND QUALITY ASSESSMENT

1.1 Screening Flow Summary

Identification: Records identified (n=150)
 Removed before screening: Duplicates/irrelevant (n=60)
 Screening: Abstracts screened (n=90)
 Excluded after abstract screening (n=35)
 Eligibility: Full texts assessed (n=55)
 Included in qualitative synthesis (n=55)
 Detailed comparative appraisal in Table 3 (n=17 representative studies).

1.2 Quality Assessment Criteria

Each eligible study was evaluated against: (1) clear objectives, (2) adequate dataset description, (3) reproducible methodology, (4) appropriate validation metrics, (5) limitations discussed, (6)

relevance to Nigerian currency image analysis. Each criterion was scored 0–2 (maximum 12). Studies scoring ≥ 8 were considered methodologically sound and retained.

1.3 Inter-rater Procedure

Two reviewers independently screened titles/abstracts and full texts using the predefined inclusion/exclusion criteria. Disagreements were resolved through discussion and consensus; unresolved cases were adjudicated by a third reviewer. Agreement was monitored using Cohen's kappa, with $\kappa \geq 0.80$ targeted before full screening.