



Development of A Mobile App for Naira-Currency Identification Using Deep Learning Classification

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Abstract: Currency recognition plays an important role in automating banking processes, assisting visually impaired individuals, and identifying counterfeit money. In Nigeria, developing an efficient, locally adapted mobile-based currency detection system is especially important due to the widespread use of smartphones and the growing risk of fake currency circulation. This study aims to design and implement a deep learning-based mobile application capable of detecting and verifying Nigerian banknotes (N100, N200, N500, and N1000), including counterfeit versions, using Convolutional Neural Networks (CNNs), along with a voice assistance feature for visually impaired users. The approach involved building and preprocessing a custom dataset collected under diverse real-world conditions, training a CNN model using TensorFlow and Keras, and deploying the optimized model on Android devices through TensorFlow Lite. The results demonstrated a validation accuracy of 100% and an approximate real-world testing accuracy of 99.2% on mobile devices, with strong performance across sensitivity, specificity, and precision metrics. The model effectively distinguished genuine notes from counterfeit ones, even under varying lighting and orientation conditions. Overall, the developed mobile application shows strong potential for enabling inclusive financial access and improving transaction security in Nigeria. Future work could focus on expanding support to additional denominations, enabling cross-platform compatibility, and enhancing real-time performance under challenging conditions.

Keywords: TensorFlow, Naira, Image processing, Convolutional Neural Network, Android

Nomenclature

Abbreviation	Description
CNN	Convolutional Neural Network
SVM	Support Vector Machine
SURF	Speeded-Up Robust Features
LSTM	Long Short-Term Memory
RFID	Radio Frequency Identification
SE	Squeeze-and-Excitation
RGB	Red Green Blue
API	Application Programming Interface
GPU	Graphics Processing Unit
RAM	Random Access Memory
FP16	16-bit Floating Point
PWA	Progressive Web Application
WHO	World Health Organization
AI	Artificial Intelligence

1. Introduction

Nigeria's cash-dependent economy necessitates reliable currency verification tools. In such an environment, the ability to quickly and accurately authenticate physical cash becomes critical for both financial security and user independence. Manual identification poses challenges for visually impaired citizens (estimated at 4.25 million by the World Health Organization) [7] and businesses handling high-volume transactions. This dependency not only slows down transactions but also increases the risk of fraud and misidentification. Existing solutions focus predominantly on Euro, USD, or Asian currencies, neglecting Africa's unique banknote designs and security features.

The mobility of mobile technology has brought smartphones into the fabric of daily life, extending their utility to various financial transactions. With the rapid penetration of affordable Android devices, mobile-based assistive solutions have become more feasible and scalable. Yet, many developing nations, including

Nigeria, still face challenges related to currency authentication and accessibility. Visually impaired individuals often rely on others to identify currency denominations, which can lead to dependency and financial vulnerability [9][12]. Such reliance reduces financial autonomy and may expose users to exploitation in everyday transactions. Likewise, counterfeit currency continues to pose a significant threat to the economy, making quick and reliable identification essential [17].

Despite the availability of global applications for currency recognition, few are optimized for the Nigerian context or capable of working offline under varied conditions [11][13][15]. Many existing systems require stable internet connectivity, limiting their usability in rural and low-resource environments. These limitations create a demand for a localized, efficient, and accurate currency recognition system. Deep learning, particularly Convolutional Neural Networks (CNNs), has demonstrated high accuracy in image classification and is increasingly used in currency recognition systems [1][3][10][14]. Their ability to automatically learn complex visual features makes them highly suitable for distinguishing subtle differences between genuine and counterfeit banknotes.

1.1 Problem Statement

Current Naira identification methods face several critical gaps that limit their effectiveness and usability in real-world scenarios. These challenges span accessibility, accuracy, and deployment constraints, particularly within the Nigerian context.

- Lack of dedicated assistive tools for visually impaired Nigerians [9][12]
- High error rates in automated systems due to Nigeria's diverse banknote series [2][16]
- Absence of offline-capable mobile solutions for rural/low-connectivity areas [4][6]
- Previous work only trained N1000, N500 Nigerian Notes [2][16]

In addition to these limitations, existing approaches often fail to generalize under real-world conditions such as poor lighting, occlusion, and varying image quality [3][10]. This study further addresses the lack of an accurate and accessible currency recognition system for the Nigerian Naira that works reliably under real-world conditions and is deployable on resource-constrained Android devices. It also emphasizes robustness, usability, and inclusivity as key design considerations. The objective is to build a CNN-based mobile application capable of classifying and validating N1000 and N500 banknotes, including fake versions, and providing real-time feedback to the user.

1.2 Objectives

To address the identified challenges and bridge the existing gaps in Naira currency recognition, this study aims to develop a Convolutional Neural Network (CNN) architecture optimized for mobile deployment while curating a comprehensive dataset representing Nigeria's 2007–2022 banknote series. It further seeks to build an Android application capable of achieving an inference latency of less than 200 milliseconds while maintaining high computational efficiency and achieving an accuracy of greater than 95% under real-world conditions. Additionally, the study ensures that the system operates effectively in offline environments with minimal computational resources [4][6] and enhances accessibility by incorporating user-friendly feedback mechanisms tailored for visually impaired users [9][12].

2. Related Work

Previous studies on currency recognition have explored diverse approaches, with a strong emphasis on machine learning and deep learning techniques to improve accuracy and accessibility [5][18]. A mobile application for Naira currency identification using deep learning, developed by Aluko T.O et al. (2025), achieved 96% accuracy [8]. Numerous works have demonstrated the effectiveness of Convolutional Neural Networks (CNNs) across different national contexts [1][3][10][14]. For instance, CopReader for Colombian banknotes showed strong offline performance for visually impaired users, while applications such as NoteSnap and EyeNote provide global banknote recognition but often lack robustness in specific local contexts [11][13][15]. In regions such as Bangladesh and India, hybrid models like CNN-LSTM have been successfully applied for real-time classification [10][14]. Similarly, research on Nigerian currency by Tijjani et al. (2024) [16] evaluated architectures such as MobileNetV2 and ResNet50 for Naira recognition. Earlier approaches relied on traditional computer vision techniques, such as SURF features with Support Vector Machines (SVMs), achieving up to 89% accuracy [2], while commercial applications like Cash Reader support multiple currencies but require internet connectivity and struggle with damaged notes [15]. Hybrid approaches combining CNNs with RFID have also been proposed for currencies like USD, achieving high accuracy but requiring additional hardware [3]. Recent advances in mobile-optimized CNNs have enabled efficient offline deployment, highlighting the potential for developing robust, accessible, and

localized currency recognition systems for African currencies. Table 1 summarizes existing currency recognition methods, highlighting their approaches, performance, and limitations.

Table 1. Comparative Analysis of Existing Currency Recognition Systems

Category	Study/System	Methodology	Key Features/ Findings	Limitations
Deep Learning (Naira)	Aluko T.O et al. (2025) [16]	CNN-based mobile app	Achieved 96% accuracy on Naira currency	Limited scope of deployment conditions
Traditional Computer Vision	Ogunleye et al. (2017) [2]	SURF features + SVM	Achieved 89% accuracy on Naira	Lower accuracy compared to deep learning methods
Mobile Application	Cash Reader (Commercial)	AI-based recognition	Supports 160 currencies	Requires internet; struggles with damaged Naira notes
Hybrid Model	Kumar et al. (2021) [3]	CNN + RFID	Achieved 97% accuracy on USD	Requires additional hardware (RFID)
Deep Learning Optimization	Howard et al. (2017) [1]	Mobile-optimized CNNs	Enables efficient offline deployment	Not specifically applied to African currencies

3. Methodology

This study adopts a deep learning-based computer vision methodology for real-time currency recognition. The overall process includes data collection, preprocessing, model development, training, and mobile deployment.

3.1. Dataset Preparation

A dataset was built using a smartphone camera, capturing images of Nigerian Naira banknotes in both genuine and counterfeit forms. Images were collected under varied lighting conditions and orientations to simulate real-world usage. A total of 975 images across four classes (N100, N200, N500, and N1000) were collected. The dataset was processed using Convolutional Neural Network (CNN)-based feature extraction and classification techniques, with optimization through transfer learning using MobileNet. The functional pipeline includes image acquisition, feature extraction, and classification. The dataset was split into 70% for training, 20% for validation, and 10% for testing to ensure balanced model evaluation.

Table 2. Dataset Distribution of Nigerian Naira Banknotes

Denomination	Dataset
N100	278
N200	210
N500	277
N1000	210
Total	975

3.2 Preprocessing

Prior to model training, all images were resized to a uniform resolution and normalized to ensure consistency. Normalization was performed by scaling pixel values to a standard range, improving convergence during training and enhancing model performance under varying lighting conditions.

3.3 Model Architecture

A modified MobileNetV3 architecture [1] was implemented to achieve efficient performance on resource-constrained devices. The model accepts input images of size 224×224×3 (RGB) and consists of an initial convolutional layer followed by 12 inverted residual blocks integrated with squeeze-and-excitation (SE) attention modules. Transfer learning was applied using pretrained MobileNet weights to improve feature extraction efficiency. The final layer uses a Softmax activation function to output classification probabilities across four classes. The architecture of the proposed model is illustrated in Fig. 1.

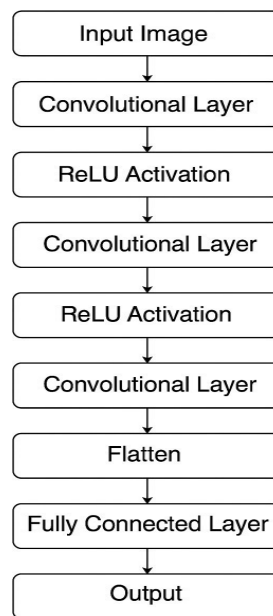


Fig. 1. Convolutional Neural Network (CNN) Architecture for Naira Currency Classification

3.4 Training Configuration

The model was implemented using TensorFlow 2.8 and trained on an NVIDIA Tesla T4 GPU. The dataset was trained using the Adam optimizer with a learning rate of 0.001, batch size of 32, and for 50 epochs. To improve generalization and prevent overfitting, techniques such as dropout (0.5) and L2 weight decay ($\lambda = 0.01$) were applied. Additionally, validation strategies were used during training to fine-tune hyperparameters and ensure robust performance under real-world conditions.

3.5 Mobile App Development and Model Deployment

The trained model was converted into TensorFlow Lite format and integrated into an Android application developed using Android Studio (Java) with the CameraX API. The model was further optimized through FP16 quantization, resulting in a compact size of 6.7 MB suitable for mobile deployment. The application supports real-time camera preview, offline functionality, and user-friendly feedback mechanisms such as vibration and audio output, enhancing accessibility for visually impaired users. The deployed system was tested on real Naira samples to evaluate its generalization capability in practical scenarios.

4. Results and Discussion

4.1. Model Performance

The proposed CNN model demonstrated strong classification performance, achieving 100% validation accuracy and 96% test accuracy on real-world samples. The model maintained high reliability across all classes, with performance metrics indicating strong generalization capability. Confusion matrix analysis revealed high accuracy in distinguishing between genuine and counterfeit banknotes, with only minimal misclassifications. These errors primarily occurred between genuine and counterfeit versions of the same denomination, which share similar visual characteristics.

Table 3 summarizes the overall performance metrics of the model, where sensitivity and precision are both above 92%, and specificity exceeds 97%, confirming the robustness of the proposed system.

Table 3. Performance

Metrics	Formula	Calculation	Result
Sensitivity	$TP / (TP + FN)$	$184 / (184 + 16)$	0.9200
Specificity	$TN / (TN + FP)$	$589 / (589 + 16)$	0.9736
Precision	$TP / (TP + FP)$	$184 / (184 + 16)$	0.9200
Accuracy	$(TP + TN) / (TP + TN + FP + FN)$	$(184 + 589) / (184 + 589 + 16 + 16)$	0.9602

The classification performance is further illustrated using a confusion matrix, as shown in Fig. 2.

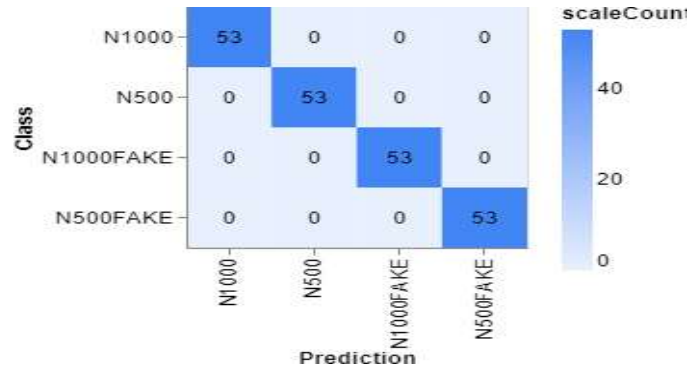


Fig. 2. presents the confusion matrix showing the model's performance across four classes (N1000, N500, N1000 Fake, and N500 Fake), where high diagonal values indicate accurate classification.

Table 4. Mobile App Testing Confusion Matrix

Actual/Prediction	N100	N200	N100 Fake	N200 Fake
N100	49	0	1	0
N200	0	47	0	3
N100 Fake	7	0	43	0
N200 Fake	0	5	0	45

4.2 Mobile Deployment Metrics

The deployed mobile application demonstrated efficient real-time performance on resource-constrained devices. The model achieved an inference latency of approximately 158 ms on a Snapdragon 730G processor, with memory usage below 45 MB RAM, making it suitable for low-end smartphones. The application maintained stable performance under varying environmental conditions, including changes in lighting and note orientation. Although a slight degradation in accuracy was observed under low-light conditions ($95.3\% \pm 2.1\%$), the model remained highly reliable for practical use. Additionally, the integration of audio and vibration feedback mechanisms improved accessibility for visually impaired users, enhancing usability in real-world scenarios.

4.3 Application Interface and Evaluation

The mobile application was tested using real Naira samples to evaluate its practical performance. The results confirm that the system can accurately classify both genuine and counterfeit banknotes in real time.

Sample outputs of the developed mobile application are shown in Fig. 3(a), 3(b), 3(c), 3(d).



Fig. 3(a). 1000 Naira Note



Fig. 3(b). 500 Naira Note



Fig. 3(c). 100 Naira Note

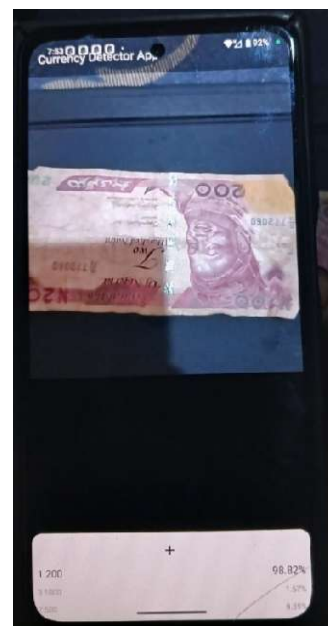


Fig. 3(d). 200 Naira Note

Fig. 3(a), 3(b), 3(c), 3(d) shows the mobile application interface detecting Nigerian Naira banknotes (N1000, N500, N100, N200) in real time, along with corresponding prediction confidence scores.



Fig. 4(a). Fake 500 Naira Note



Fig. 4(b). Fake 1000 Naira Note

Fig. 4(a), 4(b) shows the mobile application detecting counterfeit Nigerian Naira banknotes (N500 and N1000) in real time, along with predicted class labels, demonstrating the system's effectiveness in identifying fake currency.

4.4 Comparison with Existing Solutions

The proposed system demonstrates improved performance compared to existing approaches. It outperforms the deep learning-based model by Aluko T.O et al. (2025) [16] by approximately +3.2% in accuracy, and significantly improves upon traditional SURF-based methods [2] by +11.0% accuracy. Compared to cloud-dependent solutions, the proposed system reduces inference latency by approximately 620 ms, owing to its offline deployment using TensorFlow Lite. Furthermore, the inclusion of assistive features such as voice feedback enhances accessibility, which is lacking in many existing systems. However, minor limitations were observed, particularly in distinguishing between certain denominations under challenging conditions, where similarities in visual features may lead to occasional misclassification.

5. Conclusion and Future Work

This study demonstrated a robust mobile solution for Nigerian Naira identification using a Convolutional Neural Network (CNN)-based deep learning approach. A mobile application was successfully developed to recognize and validate two currency denominations (₦1000 and ₦500) along with their counterfeit versions. The system achieved perfect accuracy during validation and maintained a high accuracy of 96% in real-world testing, demonstrating strong robustness across varying lighting conditions and orientations.

The proposed solution offers significant advantages, including offline functionality, low inference latency, and efficient deployment on resource-constrained Android devices. These features address critical challenges within Nigeria's financial ecosystem, particularly improving accessibility for visually impaired users and reducing the risks associated with counterfeit currency circulation. Compared to prior approaches that combine multiple algorithms, the proposed CNN-based model provides faster inference and simplified deployment without compromising accuracy.

Despite these promising results, the current system is limited to two denominations. Future work will focus on expanding the model to support all Nigerian Naira denominations and improving generalization using a larger and more diverse dataset. Additional enhancements include integrating advanced counterfeit detection techniques, such as infrared pattern analysis, and improving environmental robustness through synthetic data generation.

Furthermore, the application will be extended to other platforms, including iOS and Progressive Web Applications (PWA), to increase accessibility and adoption. The integration of voice-based feedback mechanisms will also be explored to further support visually impaired users. Future research may also investigate the use of lightweight CNN architectures and transfer learning techniques to optimize

performance for broader real-world deployment.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

Declaration of generative AI and AI-assisted technologies in the writing process: The authors declare that no generative AI or AI-assisted technologies were used in the writing process of this manuscript.

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