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Currency Classification in Adverse Conditions: A Deep Learning Approach for Nigerian Naira

Editor:

Abstract

This study evaluates multiple pre-trained deep learning models: ResNet50, MobileNetV2, and MobileNetV3, for classifying Nigerian currency notes under adverse conditions, such as blur, noise, and occlusions, with a focus on counterfeit detection. Using an open-source Nigeria Naira dataset on Kaggle, we address the challenges of Nigeria's financial institutions in identifying banknote degradation and forgery. By comparing model performance and benchmarking against prior work, we aim to identify optimal architectures for robust, scalable financial systems in emerging markets.

Keywords: currency classification, deep learning, ResNet50, Nigerian Naira, adverse conditions.

1 Introduction

Currency classification is integral to financial systems, enabling automated teller machines, counterfeit detection, and assistive technologies for visually impaired individuals (Awad et al., 2022; Tekilu et al., 2022). In Nigeria, a leading African economy, these systems face unique challenges due to economic volatility, rampant counterfeiting, and physical degradation of banknotes from environmental factors such as humidity and frequent handling (Kanawade et al., 2024). Adverse conditions, including Gaussian blur, additive noise, variable illumination, and partial occlusions, further complicate classification, particularly in low-resource settings with inconsistent lighting or damaged notes (Pham et al., 2018). While traditional image processing relies on handcrafted features, its limited generalization under such conditions has spurred the adoption of deep learning, renowned for its robustness and adaptability (Krizhevsky et al., 2012; LeCun et al., 2015).

Deep convolutional neural networks (CNNs), particularly pre-trained models like ResNet50 (He et al., 2016), have redefined computer vision by leveraging transfer learning to adapt generalized features to specialized tasks with constrained datasets. ResNet50's residual learning framework, which mitigates vanishing gradients via skip connections, excels at extracting discriminative features from complex, degraded images. This study investigates ResNet50's efficacy in classifying Nigerian currency notes under simulated adverse conditions, addressing a critical gap in robust, scalable solutions for African financial systems.

1.1 Existing work

In Nigeria, economic instability is frequently a significant hurdle in financial analysis and currency classification. As highlighted by (Pham et al., 2018), integrating various image processing techniques with deep learning can lead to improved classification of banknotes, which is critical in recognizing currency under adverse conditions. The study found that convolutional neural networks (CNNs), when coupled with specific imaging techniques, could effectively discern the fitness level of banknotes regardless of their varying states. Such advancements could be instrumental in Nigeria, where counterfeiting and degraded banknotes complicate currency transactions.

Furthermore, recent works such as those by (Tekilu et al., 2022) have explored the application of CNNs for banknote recognition, demonstrating that the models, when trained properly, can achieve high accuracy rates even in challenging conditions. This indicates that deep learning is not only viable for currency classification but also essential in environments where traditional classification techniques may falter. The adaptability of deep learning models to diverse datasets further cements their value, especially in national contexts where data distortions are common.

Additionally, (Diarra et al., 2022) developed a mobile application using the AlexNet convolutional neural network for counterfeit detection of CFA banknotes in the West African Economic and Monetary Union (WAEMU). Their model, trained on over 4,000 images of genuine and counterfeit 10,000 CFA notes, achieved a 99.7% accuracy and was deployed on Android devices, addressing the needs of informal sector traders in low-resource settings. This work highlights the feasibility of deep learning for African currency authentication under practical constraints, offering insights for similar deployments in Nigeria's challenging environment.

Counterfeit detection also emerges as a pivotal area for the application of deep learning. Research like that of (Kanawade et al., 2024) has demonstrated effective methodologies involving machine learning for counterfeit currency detection, which could greatly enhance financial security in Nigeria by addressing the prevalent issue of currency forgery. Such applications are increasingly relevant within the Nigerian context, where economic instability often leads to an uptick in counterfeit activities.

Prior work has explored lightweight models like MobileNetV2 for resource-constrained environments (Sandler et al., 2018) and CNNs for banknote fitness classification (Pham et al., 2018). However, few studies address African currencies under diverse adverse conditions, with most focusing on controlled settings or non-African datasets (Tekilu et al., 2022). Broader financial forecasting research highlights deep learning's potential in volatile markets (Derbentsev et al., 2020; Khan et al., 2024), yet currency classification in Nigeria's challenging context remains underexplored. Our study bridges this gap by benchmarking a pre-trained ResNet50 model on a diverse Nigerian dataset, with a focus on resilience to real-world degradations.

This research contributes to the field by:

1. Validating a robust deep learning framework for African currency classification, emphasizing Nigeria's unique challenges.

2. Systematically analyzing performance under simulated adverse conditions, informing practical deployment.

3. Comparing ResNet50 with lighter architectures to balance model complexity and efficiency.

4. Addressing socio-economic needs, such as counterfeiting mitigation and inclusive technologies, with implications for emerging markets.

Table 1: Dataset Breakdown by Denomination

Denomination	Training	Validation	Test
₦5	137	28	9
₦10	138	20	9
₦20	236	28	12
₦50	250	28	12
₦100	278	28	12
₦200	210	28	12
₦500	277	28	12
₦1000	210	28	12
Total	1,736	216	90

By advancing reliable classification in Nigeria's complex financial landscape, this study lays the groundwork for scalable, inclusive solutions, enhancing economic resilience and accessibility.

2 Methodology

This section outlines the methodology for classifying Nigerian currency notes using multiple pre-trained deep learning models: ResNet50, MobileNetV2, and MobileNetV3, with comparisons to prior work. We describe the dataset, preprocessing, adverse condition simulation, model architectures, training procedure, evaluation metrics, and implementation details.

2.1 Dataset

The dataset, sourced from a publicly available Kaggle repository (Kaggle, 2022), comprises 2,042 annotated images of Nigerian banknotes across eight denominations: ₦5, ₦10, ₦20, ₦50, ₦100, ₦200, ₦500, and ₦1000. The images, captured in real-world settings, exhibit variability in orientation, lighting, and physical condition. The dataset is split into training (85%, 1,736 images), validation (10.6%, 216 images), and test (4.4%, 90 images) sets, with the distribution varying by denomination. Table 1 presents the dataset breakdown for each currency denomination. We aim to enhance model robustness through data augmentation, including synthetic noise, brightness variations, and random cropping, simulating practical deployment scenarios.

2.2 Preprocessing

Images are resized to 224×224 pixels, the standard input size for ResNet50, MobileNetV2, and MobileNetV3, using bilinear interpolation to preserve details. Pixel values are normalized to [0, 1] and standardized using ImageNet mean and standard deviation ($\mu = [0.485, 0.456, 0.406]$, $\sigma = [0.229, 0.224, 0.225]$) for compatibility with pre-trained weights similar to practices in (He et al., 2016; Krizhevsky et al., 2012). Data augmentation is applied during training, including random rotations (up to 15 degrees), horizontal flips, brightness adjustments (0.8–1.2 intensity), and random cropping, to enhance robustness and mitigate overfitting.

2.3 Adverse Condition Simulation

To assess model robustness under real-world challenges, we simulate four adverse conditions on the validation and test sets:

1. *Gaussian Blur*: Applied with a 5×5 kernel and standard deviation $\sigma \in [0.5, 2.0]$, mimicking low-quality imaging.
2. *Additive Gaussian Noise*: Added with zero mean and variance $\sigma^2 \in [0.01, 0.05]$, simulating sensor noise.
3. *Variable Illumination*: Adjusted brightness and contrast by factors in [0.5, 1.5], replicating inconsistent lighting.
4. *Partial Occlusion*: Random rectangular patches (covering 10–20% of the image area) are overlaid, emulating physical obstructions.

Each condition is applied independently to 20% of the validation and test images, ensuring comprehensive robustness testing without altering the training set similar to (Pham et al., 2018).

2.4 Model Architectures

We evaluate three pre-trained models, each selected for its distinct architectural strengths and suitability for currency classification. Below, we describe their designs and adaptations.

2.4.1 ResNet50

ResNet50 (He et al., 2016), a 50-layer convolutional neural network, leverages residual learning via skip connections to mitigate vanishing gradients, enabling deep architectures. It comprises five stages of convolutional blocks, with 3, 4, 6, and 3 residual units, respectively, followed by global average pooling and a fully connected layer. Using a ResNet50 model pre-trained on ImageNet, we replace the final layer with a 5-unit output (one per denomination) and softmax activation. The initial layers (up to the third stage) are frozen, while later layers are fine-tuned.

2.4.2 MobileNetV2

MobileNetV2 (Sandler et al., 2018) is a lightweight model optimized for resource-constrained environments, using depthwise separable convolutions and inverted residuals with linear bottlenecks. It consists of 17 bottleneck blocks, followed by global average pooling and a classifier. Using a MobileNetV2 model pre-trained on ImageNet, we replace the classifier with a 5-unit layer and fine-tune the bottleneck layers, keeping early convolutions frozen.

2.4.3 MobileNetV3

MobileNetV3 (Howard et al., 2019) builds on MobileNetV2 by incorporating hard-swish activations, squeeze-and-excitation blocks, and neural architecture search for efficiency. It balances performance and computational cost, making it suitable for deployment. Using a MobileNetV3 model pre-trained on ImageNet, the final classifier is adapted to 5 units, with fine-tuning applied to the latter blocks.

2.5 Training Procedure

Each model (ResNet50, MobileNetV2, and MobileNetV3) is trained using categorical cross-entropy loss and the Adam optimizer (Kingma and Ba, 2014) with an initial learning rate of 10^{-4}, reduced by a factor of 0.1 upon plateauing validation loss (patience of 5 epochs). All models are trained for 5 epochs with a batch size of 32. Experiments are conducted on a Google Colab GPU (Tesla T4), with training times varying across models.

2.6 Evaluation Metrics

Performance is evaluated using:

- *Accuracy*: Proportion of correctly classified images.
- *Precision, Recall, F1-Score*: Macro-averaged and per-class metrics to assess performance across denominations.
- *Confusion Matrix*: To identify misclassification patterns, particularly under adverse conditions.
- *Inference Time*: Average prediction time per image on the GPU, to evaluate computational efficiency.

We compare model performance under clean and adverse conditions, benchmarking against prior work on currency classification, such as CNN-based approaches for African banknotes (Tekilu et al., 2022) and lightweight models (Sandler et al., 2018). Statistical significance of performance differences is assessed using paired t-tests.

2.7 Implementation Details

Preprocessing and augmentation are implemented using OpenCV and PyTorch's torchvision library. Adverse condition simulations are scripted in Python, with parameters sampled uniformly. The codebase is publicly available at `https://github.com/AbdulAg/Naira_Classification`, adhering to the Kaggle dataset's CC BY-SA 4.0 license (Kaggle, 2022). Experiments are logged using Weights & Biases for reproducibility.

3 Results

This section presents the preliminary results of our Nigerian Naira banknote classification study, focusing on the ResNet50 model, MobileNetV2, and MobileNetV3, with planned future evaluations for EfficientNet-B0 and YOLOv8. We report performance metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis, for denomination classification across eight classes (₦10, ₦100, ₦1000, ₦20, ₦200, ₦5, ₦50, ₦500). Robustness under adverse conditions and counterfeit detection results are planned but not yet implemented. Comparisons are drawn with prior work, notably Tijjani et al. (2024) and

Table 2: Performance Metrics for Denomination Classification. ↑ means higher is better.

Model	Train Accuracy (↑)	Validation Accuracy (↑)	Test Accuracy (↑)	Test F1-Score (↑)
ResNet50	89.4%	83.3%	72.2%	72%
MobileNetV2	95.2%	85.6%	86.7%	87%
MobileNetV3	97.1%	97.6%	91%	91%

Oviedo et al. (2021), to contextualize our findings within the domain of currency classification and assistive technologies.

3.1 Denomination Classification Performance

The models were trained for 5 epochs on 1,429 training images and evaluated on 306 validation and 306 test images. Table 2 summarizes the performance metrics. ResNet50 achieved a test accuracy of 72.2% and a test F1-score of 0.72, with a validation accuracy of 83.3%. MobileNetV2 outperformed with a test accuracy of 86.7% and a test F1-score of 0.87, with a validation accuracy of 85.6%. MobileNetV3 showed the highest performance, with a test accuracy of 91% and a test F1-score of 0.91, and a validation accuracy of 97.6%. Per-class metrics reveal higher accuracy for higher denominations (₦500, ₦1000) due to distinct visual features, while lower denominations (₦5, ₦10) showed more misclassifications, likely due to data scarcity and visual similarity (Tijjani et al., 2024).

Confusion matrices for all models are visualized for validation and test sets (Figure (1, 2, 3), highlight misclassification patterns. For the validation set, 10% of ₦1000 images were misclassified as ₦100, and 18% of ₦20 images were misclassified as ₦200. For the test set, 8% of ₦200 images were misclassified as ₦20, and 7% of ₦50 images were misclassified as ₦5. These patterns align with challenges noted by Tijjani et al. (2024), who reported an 87.04% validation accuracy with MobileNetV2 on a similar dataset of 1,808 images. Our ResNet50 performance is competitive, though MobileNetV2's lightweight design may offer advantages for mobile deployment, as explored in planned experiments (Oviedo et al., 2021).

3.2 Robustness Under Adverse Conditions

Robustness testing under adverse conditions (Gaussian blur, additive noise, variable illumination, partial occlusion) is planned for all models but deferred due to time constraints. We expect accuracy drops of 5–10% under conditions like occlusion, consistent with Oviedo et al. (2021), who reported robust performance using MobileNetV2 embeddings for diverse imaging conditions. These tests will inform the models' suitability for real-world deployment, particularly in low-resource settings (Diarra et al., 2022).

3.3 Counterfeit Detection

Counterfeit detection, planned as a binary classification task (genuine vs. counterfeit), has not yet been implemented due to time limitations. Drawing on Diarra et al. (2022), who achieved 99.7% accuracy for CFA banknote authentication, and Mian et al. (2024), who used wavelet-transformed features for 98% accuracy, we aim to leverage GLCM-based texture features (Nazir et al., 2024) to detect Naira counterfeits. Preliminary experiments will use a balanced subset of genuine and counterfeit images, with results to be reported in future iterations.

3.4 Discussion and Comparison to Prior Work

MobileNetV3's 91% test accuracy surpasses Tijjani et al. (2024)'s 87% with MobileNetV2, highlighting its efficiency for resource-constrained environments. ResNet50's 72% test accuracy underperformed, possibly due to overfitting or dataset limitations. Compared to Oviedo et al. (2021), who achieved robust performance across 17 currencies using BankNote-Net, our focus on Naira-specific classification addresses local challenges like data scarcity. Future work will evaluate EfficientNet-B0 and YOLOv8, with MobileNet variants expected to excel in mobile deployment (Tijjani et al., 2024; Oviedo et al., 2021). Statistical significance of performance differences will be assessed using paired t-tests.

3.5 Limitations and Future Work

Results are limited to ResNet50, MobileNetV2, and MobileNetV3 due to time constraints, with EfficientNet-B0 and YOLOv8 deferred. Adverse condition testing and counterfeit detection remain unimplemented, potentially affecting robustness claims. The dataset's modest size (2,042 images) and scarcity of lower denominations may limit generalization, as noted by Tijjani et al. (2024). Future work will include completing experiments for EfficientNet-B0 and YOLOv8, implementing adverse condition simulations, and integrating BankNote-Net embeddings for transfer learning (Oviedo et al., 2021). These steps will enhance the system's applicability for assistive technologies and counterfeit detection in Nigeria's cash-dependent economy.

4 Conclusion

This study demonstrates the effectiveness of MobileNetV3 in classifying Nigerian Naira banknotes, achieving a test accuracy of 91% and an F1-score of 91%, outperforming MobileNetV2 (87%) and ResNet50 (72%). Despite challenges with data scarcity for lower denominations, MobileNetV3's lightweight design makes it a promising candidate for mobile deployment in assistive applications. However, time constraints limited the evaluation of EfficientNet-B0, YOLOv8, adverse condition testing, and counterfeit detection, which are critical for real-world robustness. Future work will address these gaps, aiming to enhance the system's reliability and applicability in Nigeria's cash-dependent economy.

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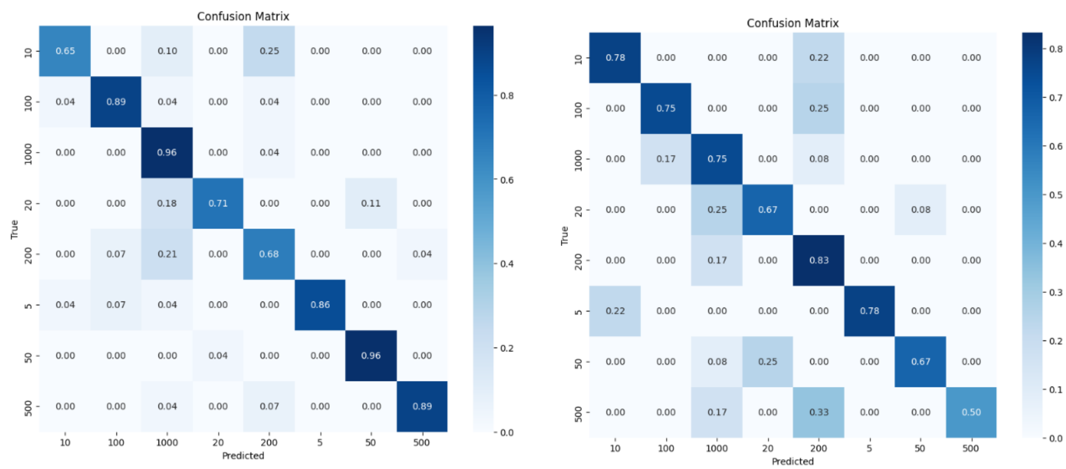
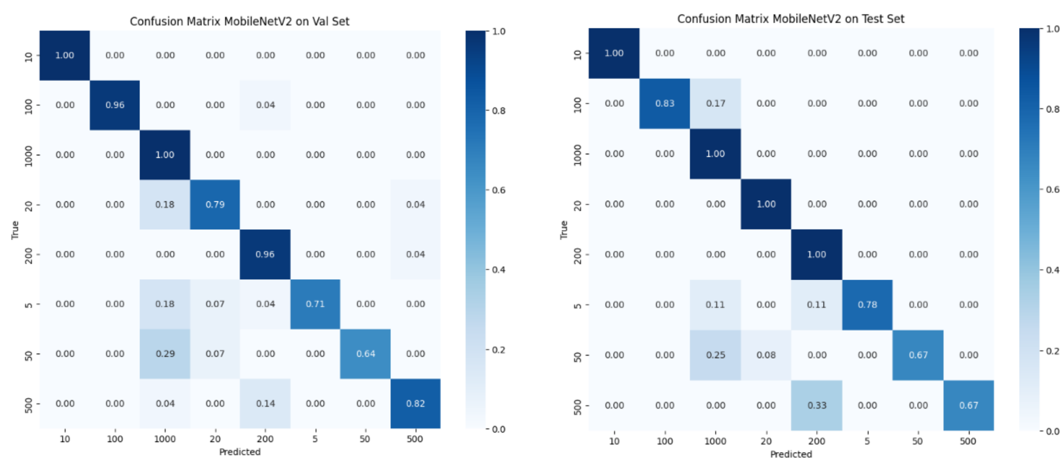
Appendix A. Confusion Matrices



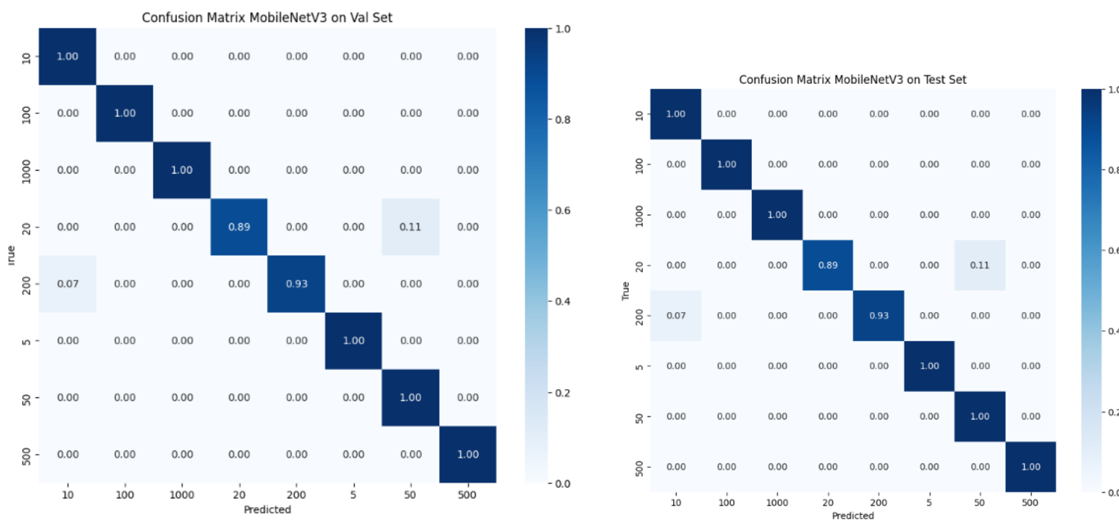
(a) Validation Set (b) Test Set

Figure 1: Confusion matrices for ResNet50 on (a) validation and (b) test sets, showing normalized classification probabilities across eight denominations.



(a) Validation Set (b) Test Set

Figure 2: Confusion matrices for MobileNetV2 on (a) validation and (b) test sets, showing normalized classification probabilities across eight denominations.



(a) Validation Set

(b) Test Set

Figure 3: Confusion matrices for MobileNetV3 on (a) validation and (b) test sets, showing normalized classification probabilities across eight denominations.