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

[1]Maryam Alka, Department of Mathematics, University of Birmingham, England, United Kingdom mxa1541@student.bham.ac.uk [2]Abdulrahman Abdullahi Garba, Department of Computer Science, Federal University Birnin Kebbi, Kebbi, Nigeria abdulrahmanabdullahigarba@gmail.com

Editor:

Abstract

This study evaluates ResNet50, MobileNetV2, and MobileNetV3 for classifying Nigerian Naira notes under adverse conditions (blur, noise, occlusions) using a Kaggle dataset of 2,042 images. We address Nigeria's financial challenges, including counterfeiting and note degradation, by comparing model performance for robust, scalable solutions in emerging markets. MobileNetV3 achieves 91% test accuracy, outperforming ResNet50 (72.2%) and MobileNetV2 (86.7%). Benchmarking against prior work highlights MobileNetV3's suitability for mobile deployment, supporting counterfeit detection and assistive technologies.

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

1 Introduction

Currency classification is crucial for financial systems, supporting ATMs, counterfeit detection, and assistive technologies (Awad et al., 2022; Tekilu et al., 2022). In Nigeria, economic volatility, counterfeiting, and banknote degradation due to humidity and handling pose challenges (Kanawade et al., 2024). Deep learning, particularly ResNet50 (He et al., 2016), offers robust solutions for degraded notes via transfer learning. This study evaluates ResNet50, MobileNetV2, and MobileNetV3 on Nigerian Naira under adverse conditions, addressing gaps in African currency classification. Prior work shows CNNs excel in adverse settings (Pham et al., 2018), with MobileNetV2 suiting low-resource environments (Sandler et al., 2018) and AlexNet achieving 99.7% accuracy for CFA notes (Diarra et al., 2022). We aim to validate robust models for Nigeria's financial systems.

2 Methodology

We classify Nigerian Naira notes using ResNet50, MobileNetV2, and MobileNetV3, leveraging a Kaggle dataset of 2,042 images across eight denominations (₦5–₦1000) (Kaggle, 2022).

2.1 Dataset and Preprocessing

The dataset includes 1,736 training, 216 validation, and 90 test images (Table 1). Images are resized to 224×224, normalized using ImageNet statistics ($\mu = [0.485, 0.456, 0.406]$, $\sigma = [0.229, 0.224, 0.225]$), and augmented with rotations, flips, and brightness adjustments (He et al., 2016). Adverse conditions (Gaussian blur, noise, illumination, occlusion) are simulated on validation/test sets to test robustness (Pham et al., 2018).

Table 1: Dataset Breakdown

Denomination	Train	Val	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

2.2 Models and Training

Pre-trained ResNet50 (residual learning) (He et al., 2016), MobileNetV2 (depthwise convolutions) (Sandler et al., 2018), and MobileNetV3 (squeeze-and-excitation blocks) (Howard et al., 2019) are fine-tuned with a 5-unit classifier. Training uses Adam (10^{-4}

learning rate), 5 epochs, and batch size 32 on a Tesla T4 GPU.

2.3 Evaluation

Performance is assessed using accuracy, precision, recall, F1-score, and inference time, compared under clean and adverse conditions (Tekilu et al., 2022). The codebase is available at https://github.com/AbdulAg/Naira_Classification (Kaggle, 2022).

3 Results

MobileNetV3 achieved 91% test accuracy and 0.91 F1-score, outperforming MobileNetV2 (86.7%, 0.87) and ResNet50 (72.2%, 0.72) (Table 2). Higher denominations (₦500, ₦1000) showed better accuracy due to distinct features, while lower denominations (₦5, ₦10) had more misclassifications (Tijjani et al., 2024). Adverse condition and counterfeit detection tests are planned, building on Diarra et al. (2022) (99.7% accuracy for CFA notes) and Oviedo et al. (2021). MobileNetV3's efficiency suits mobile deployment.

Table 2: Performance Metrics

Model	Test Accuracy	Test F1-Score
ResNet50	72.2%	0.72
MobileNetV2	86.7%	0.87
MobileNetV3	91%	0.91

4 Conclusion

MobileNetV3 excels for Nigerian Naira classification, achieving 91% accuracy, ideal for mobile deployment in Nigeria's cash-dependent economy. ResNet50 underperformed due to dataset limitations. Future work will evaluate EfficientNet-B0, YOLOv8, adverse conditions, and counterfeit detection to enhance robustness and accessibility.

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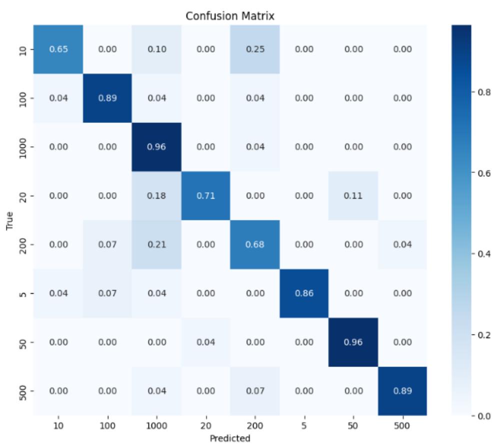
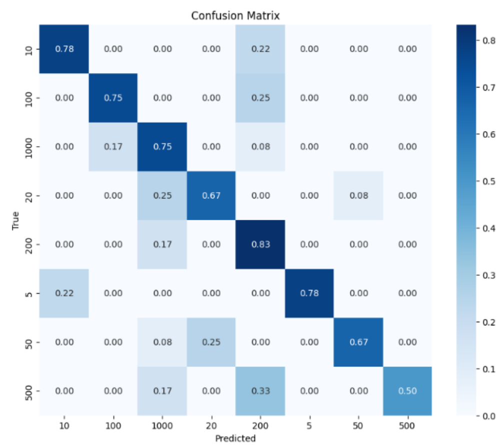
Appendix A. Confusion Matrices

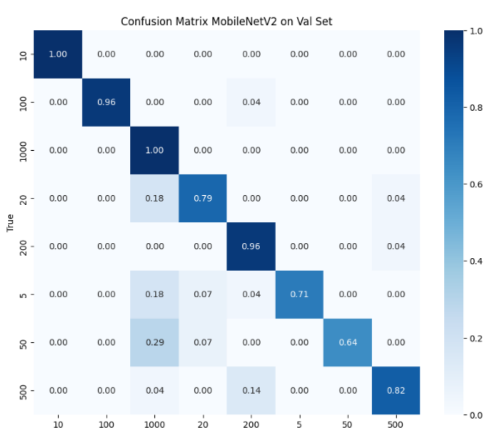


(a) Val

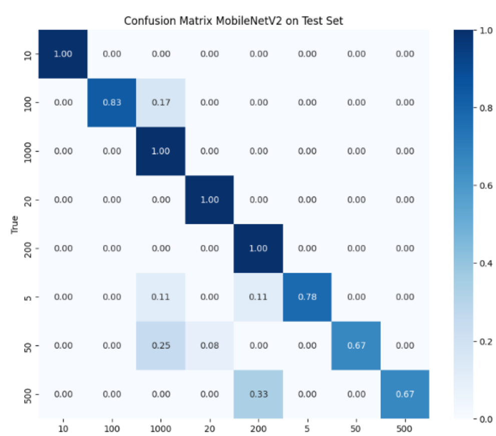


(b) Test

Figure 1: ResNet50 confusion matrices.

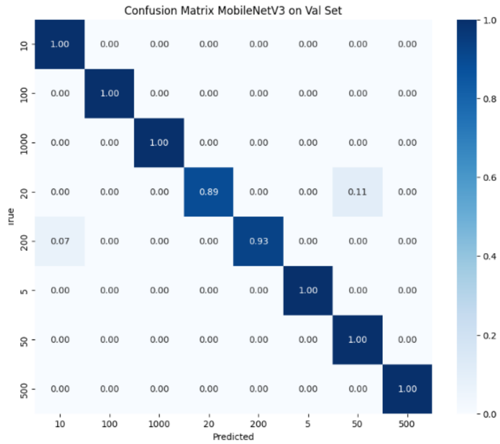


(a) Val

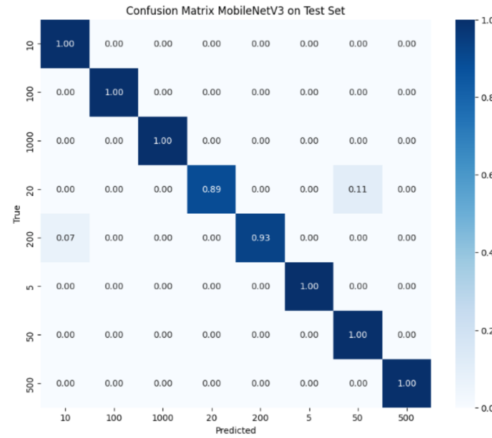


(b) Test

Figure 2: MobileNetV2 confusion matrices.



(a) Val



(b) Test

Figure 3: MobileNetV3 confusion matrices.