

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

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.

References

- S. Awad, B. Sharef, A. Salih, and F. Malallah. Deep learning-based iraqi banknotes classification system for blind people. *Eastern-European Journal of Enterprise Technologies*, 1(2(115)):31–38, 2022. doi: 10.15587/1729-4061.2022.248642.
- Aboudramane Diarra, Tegawendé F. Bissyande, and Pasteur Poda. A deep learning app for counterfeit banknote detection in the WAEMU. In *Proceedings of JRI 2022*, pages 1–13, Ouagadougou, Burkina Faso, November 2022. EAI. doi: 10.4108/eai.24-11-2022.2329802. URL <https://doi.org/10.4108/eai.24-11-2022.2329802>.
- Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 770–778, 2016.
- Andrew Howard, Mark Sandler, Grace Chu, Liang-Chieh Chen, Bo Chen, Mingxing Tan, Weijun Wang, Yukun Zhu, Ruoming Pang, Vijay Vasudevan, et al. Searching for mobilenetv3. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, pages 1314–1324, 2019.
- Kaggle. Nigerian currency recognition dataset. <https://www.kaggle.com>, 2022.
- M. Kanawade, S. Jangade, A. Mane, and T. Kurne. Counterfeit currency detection using machine learning. *International Journal of Scientific Research in Science Engineering and Technology*, 11(3):399–405, 2024. doi: 10.32628/ijrsrset24113139.
- Felipe Oviedo, Srinivas Vinnakota, Eugene Seleznev, Hemant Malhotra, Saqib Shaikh, and Juan Lavista Ferres. Banknote-net: Open dataset for assistive universal currency recognition. Manuscript submitted to ACM, April 2021. URL <https://arxiv.org/abs/2204.03738>.
- T. Pham, D. Nguyen, W. Kim, S. Park, and K. Park. Deep learning-based banknote fitness classification using the reflection images by a visible-light one-dimensional line image sensor. *Sensors*, 18(2):472, 2018. doi: 10.3390/s18020472.
- Mark Sandler, Andrew Howard, Menglong Zhu, Andrey Zhmoginov, and Liang-Chieh Chen. Mobilenetv2: Inverted residuals and linear bottlenecks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 4510–4520, 2018.
- D. Tekilu, H. Kalla, and S. Mishra. Ethiopian banknote recognition using convolutional neural network and its prototype development using embedded platform. *Journal of Sensors*, pages 1–18, 2022. doi: 10.1155/2022/4505089.
- Ismail Ismail Tijjani, Ahmad Abubakar Mustapha, and Isma’il Tijjani Idris. Performance comparison of deep learning techniques in naira classification. *SSRG International Journal of Recent Engineering Science*, 11(5):131–139, October 2024. doi: 10.14445/23497157/IJRES-V11I5P113. URL <https://doi.org/10.14445/23497157/IJRES-V11I5P113>.

Appendix A. Confusion Matrices

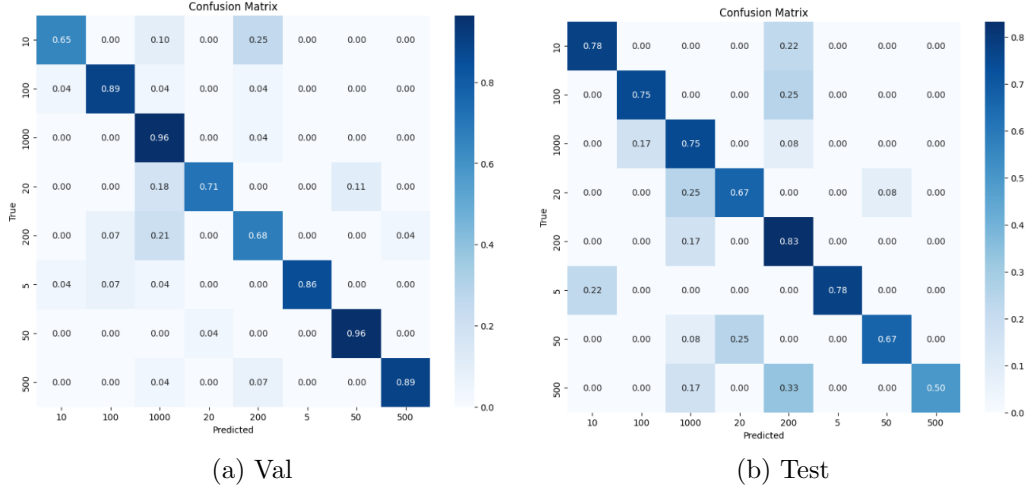


Figure 1: ResNet50 confusion matrices.

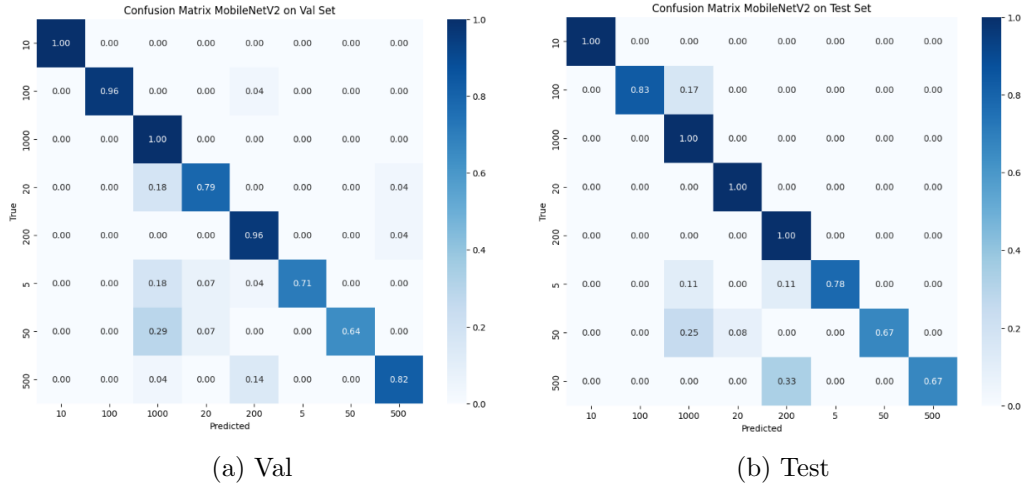


Figure 2: MobileNetV2 confusion matrices.

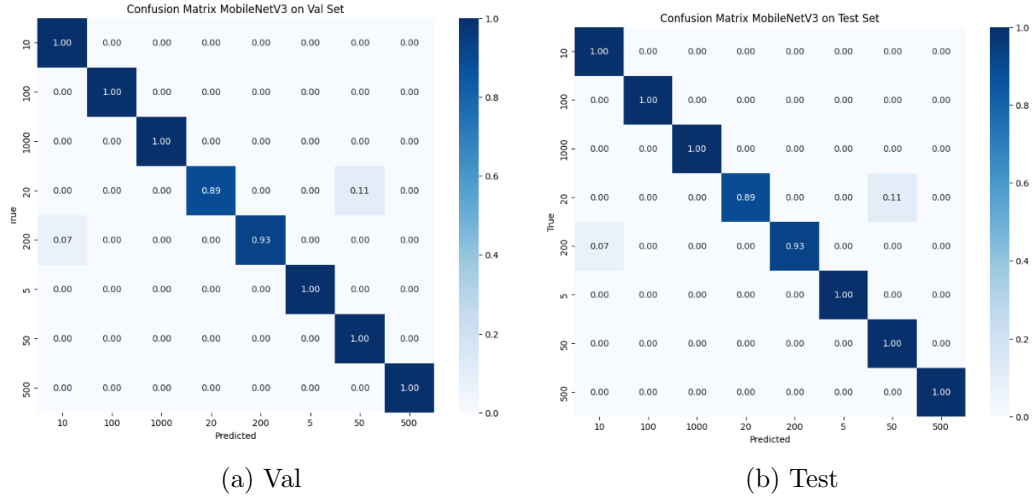


Figure 3: MobileNetV3 confusion matrices.