DeepFakesUG: Detecting Counterfeit Ugandan Banknotes Using Deep Learning

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Abstract. Despite the rise of digital transactions, paper money remains vital in regions such as Uganda and other parts of Sub-Saharan Africa. The persistent challenge of counterfeit banknotes undermines economic stability and public trust. Traditional detection methods, often reliant on manual inspection, are inadequate against sophisticated counterfeiting techniques. This paper introduces DeepFakesUG, a deep learning system using convolutional neural network (CNN) to identify counterfeit Ugandan banknotes from smartphone images. This study assessed CNN architectures including ResNet50V2, InceptionV3, Xception, and ResNet152V2, and demonstrates that ResNet152V2 and ResNet50V2 excel in detecting subtle counterfeit patterns. Furthermore, we have integrated the ResNet152V2 model into a smartphone application that performs on-device analysis, verifying the authenticity of banknotes in under five seconds without the need for internet access. This study offers a practical, accessible, and efficient alternative for counterfeit currency detection during everyday financial transactions.

Keywords: Paper money · Convolutional neural network (CNN) · Deep learning · Counterfeit currency

1 Introduction

Digital financial transactions are increasingly becoming common around the world. However, the use of paper money is still prevalent in many parts of the world including Uganda and other parts of the Sub-Saharan region. This is mainly because of their simplicity and reliability, especially in the developing economies. The use of paper currency has been associated with counterfeit banknotes in circulation which poses a significant threat to the economy, undermining financial stability and public confidence in the monetary systems [12,18]. Traditional methods [6,12,18] of counterfeit banknote detection often rely on manual inspection and basic technological tools and are proving inadequate in the

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presence of sophisticated counterfeiting techniques. Banknote-counting machines can recognize the type of banknote and denomination, detect counterfeits, classify fitness, and identify serial numbers using image processing techniques [18]. Financial institutions in the developing world sometimes launch social campaigns to inform their clients about ways to identify counterfeit currencies in circulation based on security features on banknotes. However, these features can be hard to recognize by touch or with the human eye [1] especially when the notes are very old, dirty, and torn.

Counterfeit detection techniques use various features including security threads, anti-copier patterns, and watermarks (hologram patterns). The existing detection approaches rely on detection sensors inclusive of magnetic, infrared (IR), or ultraviolet (UV) sensors making detection complex [18]. Several studies propose machine-assisted systems based on generative adversarial networks (GANs) [1], ensemble learning methods including AdaBoost and voting classifiers [14], machine learning algorithms such as thresholding, K-means clustering, and support vector machines [5], and snapshot-based hyperspectral imaging (HSI) algorithm that converts RGB images to HSI images [15] for counterfeit currency detection. The widespread circulation of counterfeit bills complicates the ability of everyday users to quickly and reliably verify the authenticity of banknotes in their daily transactions.

This study investigates the application of deep learning models [3,8–10], in particular, convolutional neural networks (CNNs) [13] in the detection of counterfeit Ugandan banknotes. CNNs have demonstrated capabilities in identifying intricate patterns and features in images that are imperceptible to the human eye. This study utilizes state-of-the-art CNN architectures to improve counterfeit banknote detection accuracy and reliability. Specifically, the performances of ResNet50V2, InceptionV3, Xception, and ResNet152V2 [17,22] have been evaluated in detecting counterfeit Ugandan banknotes. These models have unique architectural features that make them suitable for image classification tasks as in this study.

This study makes the following contributions:

- We propose DeepFakesUG, a simple counterfeit currency detection system for Ugandan banknotes. This system employs a CNN-based method that uses visible-light images of the banknotes captured with smartphone cameras. This approach offers greater convenience compared to previous methods that require multiple sensors and specialized equipment for image capture.
- This study compares ResNet50V2, InceptionV3, Xception, and ResNet152V2 models for the task of counterfeit banknote detection. By evaluating these models on a dataset of Ugandan banknotes consisting of images of legitimate banknotes and counterfeits, we report ResNet152V2 and ResNet50V2 as consistent and effective architectures for detecting counterfeit Ugandan banknotes.
- We illustrate the incorporation of a CNN model into a smartphone application, leveraging on-device machine learning capabilities to improve accessibility for everyday users. The application can detect counterfeit Ugandan

banknotes in under five seconds without requiring an internet connection, thereby enabling users to swiftly verify the authenticity of banknotes and make informed decisions.

The rest of the paper is organized as follows: Sect. 2 presents studies related to counterfeit banknote detection. Section 3 presents the methodology used in this study. Results are discussed in Sect. 4, while conclusions are made in Sect. 5.

2 Related Work

Several studies have explored the detection of counterfeit banknotes using CNN architectures [18], ensemble learning algorithms [12], and genetic fuzzy systems [6] among other things. However, state-of-the-art deep learning models have shown to be more accurate in image classification tasks when compared with other methods [3,8–10].

Tuyen et al. [18] proposed a fake-banknote detection method that uses CNN and banknote images captured by a smartphone camera. The dataset used in the study included images of EUR, USD, KRW, and JOD banknotes. The study relied on the creation of fake notes out of images of genuine notes rather than gathering existing counterfeits in circulation. The study reported that CNN models performed well in classifying banknotes. They intend to improve their approach to facilitate the localization and detection of banknotes from images taken using smartphone cameras as well as integrate counterfeit detection with denomination classification. Our methodology is similar to the methodology used in this study [18] except our study experimented with counterfeit detection of Ugandan banknotes using diverse data collected from the markets (in circulation) and we demonstrate the usage of the resulting model among everyday users.

A study by Khairy et al. [12] used ensemble learning algorithms including Adaboost and voting for the detection of counterfeit banknotes. Swiss Franc dataset comprising fake and legitimate banknotes was used in the study and they reported a high accuracy in banknote classification. This approach illustrates the evolving complexity and efficacy of these detection systems in correctly identifying counterfeit currency notes [14]. However, our study differs from that study [12] since we leverage state-of-the-art deep learning models (CNN-based architectures) including ResNet152V2 among other models for the detection of counterfeit banknotes.

Genetic fuzzy systems have also been used in this domain to detect counterfeit currency notes [6]. This approach requires huge amounts of high-quality training data. Besides, variations in lighting, angle, and wear and tear of banknotes can easily affect the performance of genetic fuzzy systems for this task.

Another study [21] identified the authenticity of currency notes based on characteristics extracted from images of banknotes using common classification algorithms. The study reported K-nearest neighbors as the most consistent algorithm for counterfeit currency detection at an accuracy of 99.8%.

A snapshot-based hyperspectral imaging (HSI) algorithm that converts RGB images to HSI images has also been used for counterfeit currency detection [15].

This has been demonstrated to detect fake Taiwanese currency notes, whereby the notes were differentiated based on the mean gray values (MGV) within shorter wavelengths, though these MGV become similar in longer wavelengths. The primary attributes of this module include its compact and portable design, affordability, the absence of mechanical parts, and the elimination of the need for image processing, among other things.

In study [5], machine learning algorithms such as thresholding, K-means clustering, and support vector machines (SVM) were employed to detect counterfeit currency based on intensity values. The effectiveness of these algorithms was evaluated using a 50-image dataset, achieving an impressive accuracy rate of 96%.

DeepMoney [1] system illustrates the use of GANs for the detection of counterfeit banknotes. These networks utilize unsupervised learning for training, which enables them to make supervised predictions, effectively using unlabeled data for training while still providing accurate predictions. Applied to Pakistani banknotes, the system integrates state-of-the-art image processing and feature recognition to differentiate between genuine and counterfeit notes and achieved an overall accuracy of 80% in the detection of counterfeit notes.

Using CNN-based architectures [3,8–10] with Ugandan banknote images captured using a smartphone camera and demonstrating the efficacy of the most consistent model to everyday users provides insights into the adaptation of these models for banknote detection using any part of the notes. Nonetheless, our study introduces a practical and accessible system as an alternative for the detection of counterfeit currency notes during everyday financial transactions.

3 Materials and Method

3.1 Dataset

The dataset used in this study included images of Ugandan banknotes in the denominations of 1000, 2000, 5000, 10000, 20000, and 50000. Image data collection involved taking photos of banknotes using a smartphone camera and the default resolutions were maintained throughout the exercise for consistency with everyday usage. The currency notes, especially the counterfeits, were gathered from mobile money agent shops, micro-finance institutions, and banks in the country and their images were captured using a smartphone camera.

Unlike some related studies that created their own counterfeit banknotes from images of genuine notes [18], we collected the fake notes from financial institutions in Uganda. We ensured a diverse representation of banknotes in the dataset, including dirty and old notes sourced from the local markets. Each banknote image was preprocessed by digitizing the photo at an appropriate resolution that is sufficient to capture significant forensic features for authentication. A sample of the datasets is shown in Fig. 1. The dataset comprises a total of 1538 images of Ugandan banknotes, with 50.3% genuine notes and 49.7% counterfeits as shown in Table 1, which was preprocessed and used for model training. Owing to relatively small size of the dataset, this study used transfer learning approach instead of training the deep learning models from scratch.

Fig. 1. Sample image dataset of Ugandan banknotes.

Obtaining large samples of high-resolution counterfeit banknotes can be challenging. This is because of the criminal nature of counterfeiting, these banknotes are usually confiscated and documented in small quantities, making access to large volumes for research difficult without specific legal permissions.

3.2 System Workflow and Use Case Diagram

A workflow of the banknote detection system is shown in Fig. 2. It includes gathering images of banknotes that are preprocessed and used for training and validating the banknote detection model. The resulting optimized model for banknote classification is deployed on a mobile device as a smartphone application that can be used for inference. Using the Unified Modeling Language [11], a use case diagram of the banknote detection system was drawn and it details the activities carried out by users of the system as shown in Fig. 3. The user of the system takes photos of currency notes using the smartphone camera, or they can upload an image from the gallery that is then processed by the detection model

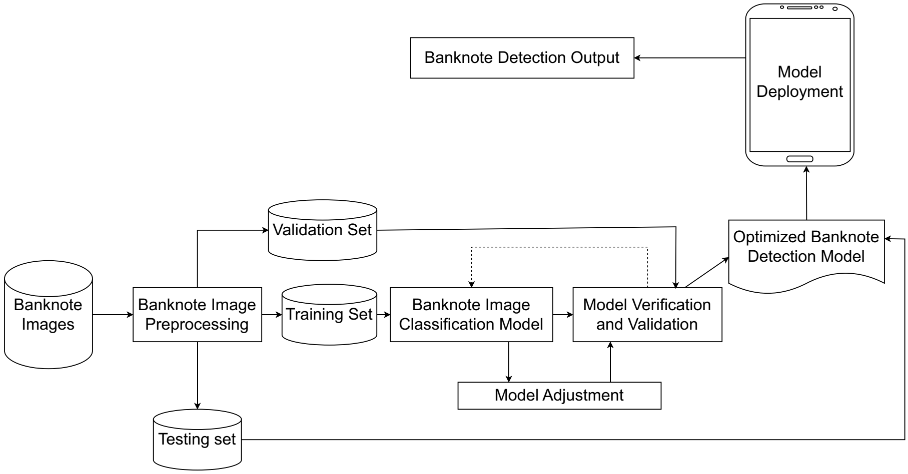


Fig. 2. Workflow of banknote detection system.

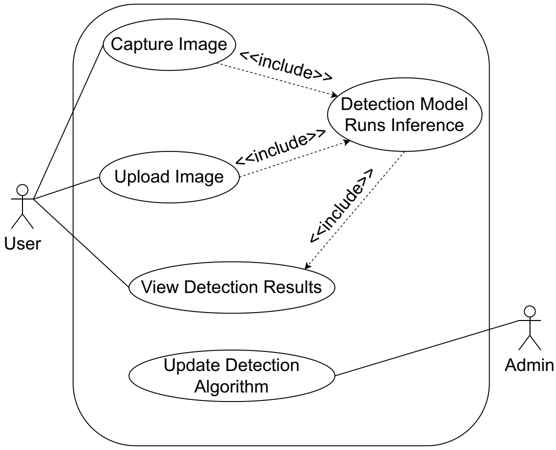


Fig. 3. Use case diagram for banknote detection system.

using a pre-trained model. The detection model runs inference and displays the result of whether the banknote is genuine or counterfeit on the screen of the device. The administrator can update the detection algorithm to improve its accuracy in classifying banknotes.

3.3 Data Preprocessing

Every banknote image was rescaled to a uniform size of 224×224 pixels. This allowed for consistency across the datasets before model training. Besides, the pixel values were normalized to range between 0 and 1 to aid in the convergence of the neural network during training. To improve the ability of the model to generalize, data augmentation including rotation of the images at $\pm 10^{\circ}$ and horizontal flipping was performed. The dataset was split into the training set, testing set, and validation set. The training set contained 618 genuine banknotes and 610 counterfeits. The testing set contained 78 legitimate banknotes and 76 counterfeits. The validation set contained 78 genuine and 78 counterfeit banknotes. Nonetheless, with 50.3% genuine banknote images and 49.7% counterfeits in the dataset, this study achieved a fairly balanced dataset to avoid bias towards one class. Table 1 shows the summary statistics on the dataset.

Table 1. Summary of dataset.

Dataset	Genuine	Counterfeit
Training set	618	610
Testing set	78	76
Validation set	78	78
Total (%)	50.3	49.7

3.4 Model Training and Evaluation

This study adopted a transfer learning approach and CNN-based models with validated feature extraction capabilities to identify patterns and intricacies within the image dataset [3,8–10]. These models included ResNet50V2, InceptionV3, Xception, and ResNet152V2 with all their architectures capable of differentiating between genuine and counterfeit banknotes. This allowed for precise analysis of subtle forensic markers on the banknotes that are critical for authentication.

In our experiments, each model was initialized with weights pre-trained on the ImageNet dataset. We replaced the lower layers of every network with a global average pooling layer, followed by a fully connected dense layer, strengthening the feature selection abilities of the models from our data. Below this, a dropout layer was put in place as one of the countermeasures to prevent the models from overfitting. Finally, it was followed by a dense layer to tailor the models to the binary classification task (counterfeit and genuine).

Model training relied on the preprocessed images of the banknotes, employing a binary cross-entropy loss function optimized with the Adam optimizer. We carried out iterative model training over multiple epochs with early stopping implemented to prevent overfitting. This reduces the computational cost by halting the training process once the model performance ceases to improve, or starts degrading, on a validation dataset while also ensuring that the models learn thoroughly from the dataset [4,19]. An epoch represents a complete pass through the entire training dataset. Several epochs allowed the models to refine their weights and biases progressively based on the gradient descent optimization algorithm, thereby enhancing the ability of the models to make accurate predictions. Thus, early stopping rigorously monitors the performance of a model on a validation set after each training epoch. More specifically, it terminates training when the validation error consistently fails to decline or starts to rise, indicating potential overfitting [4,19]. This approach makes the model generalize to new data as well as optimizes computational resources by terminating the training process at an optimal point.

The performance of the trained models was validated using a separate validation set. The trained models were evaluated on a hold-out test set that was not exposed to the models during the training process. This study used common model performance metrics in literature [20] including accuracy, precision, recall, and f1-score to evaluate all of the models [16].

3.5 Model Packaging

This study packaged the most capable model for detecting Ugandan banknotes in a mobile application. We call the banknote detection system DeepFakesUG. The RestNet152V2 model was converted into a TensorFlow Lite (TFLite)[1] format. This conversion allowed deploying the model on mobile devices, as TFLite models are optimized for such environments. In particular, the trained TensorFlow model was exported as a SavedModel, which includes both the model architecture and weights, and the SavedModel was converted into a TFLite model using the TensorFlow Lite Converter[2]. Besides quantization during the conversion allowed us to optimize the model for mobile deployment by reducing the model size and computational demands without significantly affecting accuracy.

The mobile application was developed using Flutter [2,7], an open-source UI toolkit developed by Google for crafting high-fidelity applications across mobile, desktop, and web platforms from a single codebase. The logic for integrating the TFLite model was implemented using the Dart programming language[3]. The key components of the application include a user interface designed to allow users to easily take photos of currency notes using the smartphone camera or select images from the gallery. This interface also displays the predictions of the model on whether the note is genuine or counterfeit. Real-time camera functionality was implemented using the Flutter Camera plugin and it supports camera operations such as capturing images, which are then used as input for the model. The TFLite Flutter plugin[4] was used to load the TFLite model into the application. This

[1] TensorFlow Lite: https://www.tensorflow.org/api_docs/python/tf/lite.

[2] TensorFlowLite Converter: https://www.tensorflow.org/api_docs/python/tf/lite/TFLiteConverter.

[3] The Dart Programming Language: https://dart.dev/.

[4] TensorFlow Lite Flutter Plugin: https://pub.dev/packages/tflite_flutter.

plugin handles the interfacing between the Dart code and the underlying TFLite model, enabling the application to perform inference directly on the device. Whenever a user captures a photo of a currency note, the image is preprocessed to meet the input requirements such as resizing and normalization, of the TFLite model. The model then predicts whether the note is counterfeit or genuine, and this is displayed to the user in less than 5 s.

This packaging and demonstration offer ease of use, especially among everyday users. This study reveals a high-level architectural design of the banknote detection system including the RestNet152V2 (the most capable model for this task) in Fig. 4. The model can be extended for similar tasks in other countries that are cash-dependent.

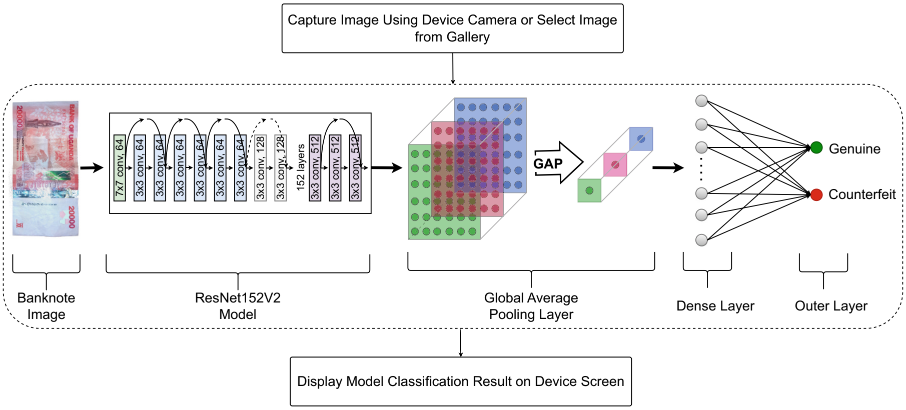


Fig. 4. High-level architecture of banknote detection system for identifying counterfeit Ugandan banknotes.

4 Results and Discussion

4.1 Model Performance Results

Table 2 shows the performance of each model used in this study on the testing set. ResNet152V2 outperformed all the other models with an accuracy of 96% and precision, recall, and f1-score at 95%, demonstrating superior performance in identifying counterfeit Ugandan banknotes.

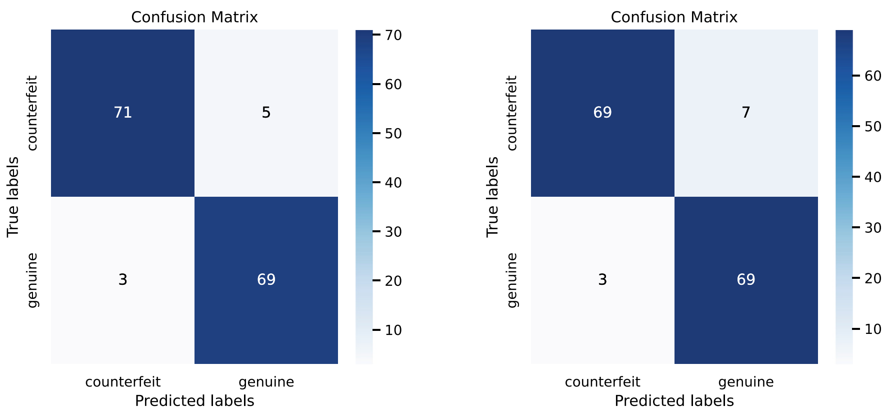
ResNet152V2 is a deeper network compared to ResNet50V2, InceptionV3, and Xception. It contains 152 layers (see high-level architecture in Fig. 4), which allows it to learn more complex features at various scales. Besides, ResNet152V2 uses residual connections to overcome the vanishing gradient problem in deep neural networks. With a vast number of layers and parameters, ResNet152V2 can learn complex patterns in currency note images compared to other simpler models [3,8–10]. Meanwhile, ResNet50V2 achieved an accuracy of 93%,

Table 2. Model performance on the testing dataset.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
ResNet152V2	96	95	95	95
ResNet50V2	93	93	93	93
InceptionV3	89	90	89	89
Xception	86	86	86	86

with precision, recall, and f1-score also at 93%, demonstrating consistent performance in distinguishing between genuine and counterfeit Ugandan banknotes. InceptionV3 achieved an accuracy of 89%, with precision, recall, and f1-score hovering around 89%, showing competitive performance but slightly lower than ResNet50V2. Xception attained an accuracy of 86%, with precision, recall, and f1-score all at 86%, displaying moderate performance in detecting counterfeit banknotes when compared to all other models used.

We show the confusion matrices for the consistent models (ResNet152V2 and ResNet50V2) for this task in Fig. 5.



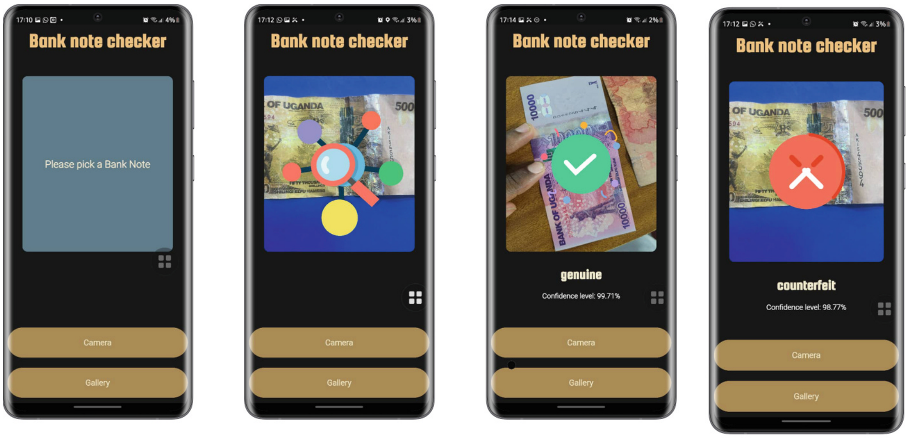
(a) ResNet152V2 (b) ResNet50V2

Fig. 5. Confusion matrices for consistent CNN models.

ResNet152V2 model showed superior performance to the ResNet50V2 model, which had an overall accuracy of 93% on the test dataset. This particular test dataset had 148 images, of which the ResNet50V2 model correctly classified 138 and misclassified 10. Notably, it misclassified 7 counterfeit notes as genuine, as shown in Fig. 5b. In contrast, the ResNet152V2 model achieved a higher accuracy of 96%, correctly classifying 140 images. It misclassified only 5 counterfeit notes as genuine, demonstrating better performance than the ResNet50V2, as shown in Fig. 5a. Both models misclassified 3 genuine notes as counterfeits. Misclassifications primarily occur due to variations in lighting and image quality, which are dependent on the smartphone camera used for capturing the images. Improving the accuracy of the model will involve collecting a more extensive dataset for model training.

4.2 DeepFakesUG Demo

To demonstrate the usage of the CNN-based model in detecting counterfeit Ugandan banknotes among everyday users, we selected the ResNet152V2 model and packaged it in a mobile application even though ResNet50V2 showed consistent results and could still be used for the same task. Figure 6 shows a user-friendly interface of the packaged model as a smartphone application, with Fig. 6a showing the initial screen having an option to capture image of a banknote using the device camera or select an image from the gallery of the smartphone.



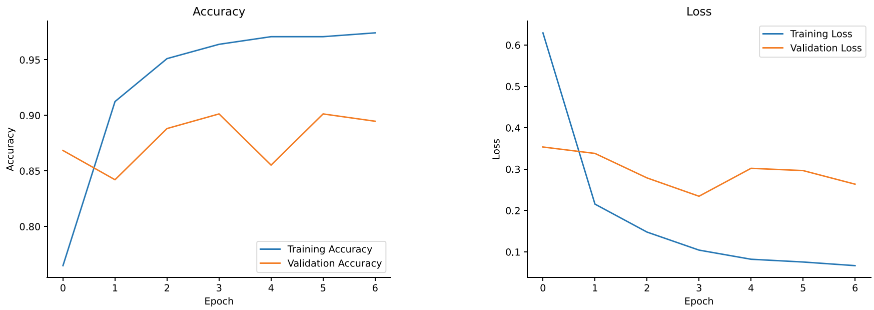
(a) Initial screen (b) Detection (c) Genuine (d) Counterfeit

Fig. 6. ResNet152V2 model packaged in a mobile application for everyday usage.

Processing of the image by the ResNet152V2 model, behind the scenes takes place in 6b in less than 5 s. The result of the classification of the banknote image is shown in Fig. 6c (for a genuine prediction) or Fig. 6d (for a counterfeit prediction). We observed faster processing of the image since this was designed to happen on device (locally) without having to connect to internet service and this makes it low-cost to everyday users.

Figure 7 shows the accuracy and loss curves for ResNet152V2. In particular, Fig. 7a indicates that ResNet152V2 model achieved a remarkable accuracy of nearly 99% on the training dataset by the 6th epoch, showcasing its ability to effectively learn from the training data to make accurate predictions. However, the validation accuracy reached a peak of 91% by the 3rd epoch. This implies that while the model was able to generalize well to the validation set, it did not achieve the same level of accuracy as on the training set. The decision to halt training at the 6th epoch suggests a recognition that further epochs may lead to overfitting, where the model becomes too specialized to the training data and fails to generalize effectively to new data. By stopping training at this point, we retain the balance between training and validation performance, whereby the model can generalize to unseen data as well as maximize performance on the training set.

Figure 7b indicates that the ResNet152V2 model achieved its minimum training loss, close to zero, by the 6th epoch. This finding suggests that the model effectively minimized its error on the training dataset while achieving a high level of fit to the training dataset. Nevertheless, the validation loss reached its minimum value, approximately 0.23, by the 3rd epoch. Thus the performance of the model on the validation dataset was also optimal at this point, with relatively low error. Generally, the loss curves of the model indicate effective training, as both training and validation losses decrease across epochs, reaching minimal values by the final epoch.



(a) Accuracy (b) Loss

Fig. 7. Accuracy and loss curves for ResNet152V2 model.

This study provides a visual example of correctly and incorrectly classified Ugandan banknote images by the ResNet152V2 model in Fig. 8. The model made these consistent predictions under varying lighting conditions and image quality with high accuracy ranging from 90% to 96%. The model correctly identified subtle features indicative of counterfeit banknotes including irregular patterns and discrepancies in texture. These findings corroborate with results from a recent and related study [18], providing further validation and consistency to our research outcomes.

Fig. 8. Predictions with ResNet152V2 model on test dataset.

5 Conclusions

This study proposes a simple counterfeit currency detection system for Ugandan banknotes called DeepFakesUG. In particular, a mobile application that packages a CNN model (ResNet152V2) and classifies genuine and counterfeit images of Uganda banknotes.

A dataset containing 1538 images of Ugandan banknotes was used and a transfer learning approach was preferred to training the CNN-based models from scratch due to the size of the dataset. The dataset contained 50.3% images of legitimate notes and 49.7% counterfeits captured using a smartphone camera at the default resolution. ResNet50V2, InceptionV3, Xception, and ResNet152V2 models [17,22] were trained and evaluated on this dataset. The accuracy of the models ranged from 86% to 96% on the testing set.

This study reports ResNet152V2 and ResNet50V2 as consistent and effective deep learning models for classifying Ugandan banknotes. We demonstrated the usage of ResNet152V2 in a smartphone application for the detection of counterfeit banknotes among everyday users by taking images of any part of a banknote. ResNet152V2 uses residual connections to overcome the vanishing gradient problem in deep neural networks and it can learn complex patterns in banknote images compared to other simpler models [3,8–10]. This study demonstrates the efficacy of deep learning in accurately identifying counterfeit Ugandan banknotes using visible-light images captured with a smartphone camera. This capability can empower everyday users to reliably detect fake currencies during their routine transactions. The findings of this study are consistent with results obtained by similar studies [1,18] and can be replicated to cover other currencies, especially in cash-dependent settings for similar tasks.

Despite the promising results, this study relied on a relatively small size of dataset. Additionally, further analysis is needed on the misclassifications that resulted either due to variation in image quality or the patterns the model was able to learn from the data. More algorithms should be trialed for the same task, as well as training the models from scratch, other than using the transfer learning approach.

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