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Design of a Currency Counting System with Integrated Counterfeit Currency Detection

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ABSTRACT
Counterfeit currency circulation remains a persistent threat to Hu integrity, particularly in cash-dependent economies where manual verification is both time-consuming and error-prone. This paper presents the design and simulation of a currency counting system integrated with an automated counterfeit detection mechanism. The proposed system employs image processing techniques including grayscale conversion, Gaussian blur, Canny edge detection, and Contrast Limited Adaptive Histogram Equalization to extract discriminative features from scanned currency note images. Four feature categories are utilized: color histogram, texture, edge, and Oriented FAST and Rotated BRIEF keypoint features. A Random Forest classifier, trained on a labelled dataset of genuine and counterfeit Nigerian Naira note images, performs binary classification of each uploaded note. The system subsequently counts total notes, segregates genuine from counterfeit samples, and computes the aggregate monetary value of authenticated notes only. A web-based interface, developed using Streamlit, provides an accessible and interactive platform for real-time note scanning and result visualization. Experimental testing confirmed that the system correctly processes uploaded images, applies the trained classification model, and returns accurate counting and valuation outputs. The findings demonstrate that a software-based prototype integrating machine learning with image analysis can effectively simulate the core functions of a physical counterfeit-detecting banknote counter. Future work will incorporate ultraviolet, infrared, and magnetic sensor modules alongside hardware implementation using a microcontroller-driven mechanical platform.

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INTRODUCTION

Currency remains one of the most important instruments of daily economic exchange. Despite the global proliferation of electronic payment systems, physical cash continues to be widely used across markets, financial institutions, educational establishments, transportation businesses, and retail outlets. This widespread reliance on cash has, however, created favorable conditions for the production and circulation of counterfeit banknotes, which pose a significant threat to financial integrity and public confidence in monetary systems.

Counterfeit currency is defined as money produced without legal authority and designed to imitate genuine notes (Ali et al., 2019). PachÃ³n et al. (2021) observed that modern counterfeit banknotes increasingly resemble authentic ones, rendering manual inspection unreliable for individuals who lack specialized training. The proliferation of high-resolution digital printers, scanners, and image-editing software has further lowered the technical barrier to counterfeiting, making automated detection an urgent necessity (Saxena et al., 2018).

Conventional counterfeit detection relies on inspecting visual and tactile security features embedded in genuine banknotes, including watermarks, security threads, microprinting, ultraviolet-reactive inks, infrared-absorptive patterns, magnetic ink, and specialized paper texture. While these features remain effective, their manual examination is susceptible to fatigue-related error, especially in high-volume cash-handling environments. Currency counting machines address the speed and accuracy limitations of manual counting; however, standalone counters that lack authentication capability remain vulnerable to counterfeit notes passing undetected.

Research into automated counterfeit detection has explored diverse methodologies. Bruna et al. (2013) demonstrated that near-infrared imaging can reveal banknote features invisible under normal light, enabling simultaneous denomination identification and forgery detection. Baek et al. (2018) showed that multispectral imaging achieves high accuracy across multiple currency types. In the domain of image processing, Patil et al. (2018) applied feature-space comparison with support vector machine classification to detect forged Indian Rupee notes, while Salem and Elmadani (2019) extracted Hu moments from Libyan Dinar images for error-based classification. More recently, deep learning approaches particularly convolutional neural networks have demonstrated strong performance in banknote authentication (PachÃ³n et al., 2021; Pham et al., 2020), and generative adversarial networks have been explored for data augmentation and detection (Ali et al., 2019).

Despite these advances, many proposed systems either focus exclusively on counterfeit detection without integrating a counting function, or require expensive sensing hardware that is unsuitable for low-cost prototype development. This study addresses that gap by designing and simulating a currency counting system that integrates automated fake currency detection through image processing and machine learning. The system is applied to Nigerian Naira denominations and is implemented as a software prototype using Python, OpenCV, Scikit-learn, and Streamlit, providing a practical and accessible foundation for subsequent hardware realization.

Research Objectives

The objectives of this study are to:

i. Design a system capable of accurately counting currency note images submitted for analysis.
ii. Incorporate an automated counterfeit detection mechanism based on image processing and machine learning.
iii. Identify discriminative currency security features suitable for distinguishing genuine from counterfeit notes.
iv. Develop a control and classification unit that processes image signals and returns an authenticated result.
v. Provide an output interface displaying note count, counterfeit status, and total genuine monetary value.
vi. Evaluate the performance of the designed system using samples of genuine and suspected counterfeit note images.

Research Questions

This study is guided by the following research questions:

i. How can a currency counting system be designed to count notes accurately from image input?
ii. What image-based currency features can reliably distinguish genuine notes from counterfeit ones?
iii. How can the counting and counterfeit detection functions be effectively integrated in a single system?
iv. To what extent does the designed system reduce error in cash counting and note verification?

Literature Review

Currency Counting Systems

Automated banknote processing machines have evolved from simple mechanical counters to sophisticated multi-function devices. Lee et al. (2017) surveyed banknote recognition methods employed in automated teller machines, vending machines, and banknote counters, categorizing their capabilities into denomination recognition, counterfeit detection, serial number recognition, and fitness classification. Their survey underscored that modern cash-handling systems must simultaneously address counting efficiency and authentication accuracy. Traditional currency counters rely on optical sensors and mechanical rollers to detect note passage events, incrementing a count for each detected sheet; however, these systems inherently lack the ability to assess authenticity.

Counterfeit Currency and Security Features

Counterfeit currency poses documented economic risks at both macro and micro levels. Saxena et al. (2018) attributed the growing prevalence of sophisticated fake notes to advances in color printing and scanning technologies. Security features incorporated into genuine banknotes including watermarks, security threads, UV-fluorescent inks, IR-absorptive patterns, magnetic ink, and specialized paper substrates serve as primary means of authentication. Bruna et al. (2013) demonstrated that near-infrared imaging effectively reveals features invisible under visible light, enabling both denomination identification and forgery detection in Euro banknotes. Baek et al. (2018) extended this approach using multispectral imaging, achieving high detection accuracy across Euro, Indian Rupee, and US Dollar denominations.

Sensor-Based Detection Approaches

Sensor-based authentication systems detect the physical and optical properties of currency notes using ultraviolet, infrared, magnetic, or optical sensors. Each sensor type targets a specific class of security feature, and combining multiple sensor modalities improves overall detection robustness (Lee et al., 2017). Harjunowibowo et al. (2012) implemented a UV-light detection system paired with a Learning Vector Quantization neural network, demonstrating that ultraviolet fluorescence signals can be processed intelligently to classify notes as genuine or counterfeit. Kang and Lee (2016) further combined visible-light and infrared multispectral sensing, achieving real-time performance suitable for in-line counterfeit detection.

Image Processing Approaches

Image processing methods analyze digitally acquired currency images to extract discriminative features without requiring specialized hardware beyond a standard camera. Patil et al. (2018) proposed a dissimilarity-space representation of Indian Rupee images, using local keypoint descriptors and a Support Vector Machine (SVM) for binary classification of genuine and counterfeit notes. Salem and Elmadani (2019) applied Hu moment feature extraction to Libyan Dinar images, computing mean square error and root mean square error between test images and genuine reference templates. Kumar et al. (2020) combined edge detection, segmentation, and image comparison techniques to identify counterfeit notes across multiple denominations, demonstrating the generalizability of image processing pipelines to different national currencies.

Machine Learning and Deep Learning Approaches

Supervised machine learning models offer a systematic means of learning discriminative patterns from labeled datasets of genuine and counterfeit note images. Han and Kim (2019) proposed a joint banknote recognition and counterfeit detection model incorporating explainable artificial intelligence, enabling simultaneous denomination identification and authenticity classification. PachÃ³n et al. (2021) benchmarked convolutional neural network architectures for fake banknote recognition and reported strong classification performance, noting that deep feature learning obviates the need for handcrafted feature engineering. Pham et al. (2020) developed a smartphone-based CNN detection system for visually impaired users, demonstrating the accessibility of deep learning-based currency authentication. Ali et al. (2019) introduced DeepMoney, leveraging generative adversarial networks for both counterfeit detection and data augmentation.

Gap in the Literature

A review of the existing literature reveals that most prior systems address either counterfeit detection or denomination recognition in isolation, without integrating a counting function. Additionally, approaches employing deep learning or multispectral imaging typically require computational resources or hardware costs that exceed the constraints of a low-cost prototype. There is a demonstrable need for a unified, affordable system that performs note counting and counterfeit detection simultaneously using standard image processing and machine learning techniques. The present study addresses this gap.

MATERIALS AND METHODS

System Design and Methodology

This study adopted a simulation-based design approach. The currency counting and counterfeit detection system was developed and evaluated as a software prototype prior to any physical hardware realization. The prototype accepts digital images of currency notes as input, applies image processing and machine learning algorithms, and produces classification, counting, and valuation outputs through a web-based interface.

System Architecture

The proposed system comprises five functional modules: (1) image acquisition, (2) image preprocessing, (3) feature extraction, (4) machine learning classification, and (5) counting and output display. The general processing pipeline is as follows:

Currency Image Input Image Preprocessing Feature Extraction Random Forest Classification
Genuine/Counterfeit Decision Note Counting and Value Aggregation Interface Output

In a physical implementation, currency notes would be fed through a mechanical transport mechanism equipped with an optical camera or sensor array. In the present simulation, users upload image files representing individual notes through the Streamlit interface.

Dataset Preparation

The dataset was organized into two categories: genuine currency note images and counterfeit currency note images, stored in separate directories. The directory structure is presented below:

data/genuine/ - images of authentic Nigerian Naira notes
data/fake/ - images of counterfeit or suspected counterfeit notes

Images placed in each folder were automatically assigned class labels during the training phase. Supported image formats included .jpg, .jpeg, .png, .bmp, and .webp. Dataset quality - in terms of image resolution, lighting consistency, and class balance was identified as a critical determinant of model performance.

Correction Integrated

The dataset used for the prototype was obtained from the project simulation folders data/genuine and data/fake. At the time of training, the dataset contained 12 Nigerian Naira note images: 6 genuine images and 6 fake or suspected counterfeit images. Each image was treated as one currency note sample.

Table 1: Distribution and Sample Filenames of the Currency Note Dataset

Class	Number of images	Sample filenames
Genuine	6	200 genuine.jpg; download.jpg; genuine note .jpeg; genuine note 1.jpeg; genuine old 1.jpeg; genuine old 2.png
Fake/Suspected counterfeit	6	200 fake old.jpg; 200 naira note.jpg; fake naira 2.jpg; fake naira 3.jpg; Fake-Naira-2.webp; New-Naira-notes.webp

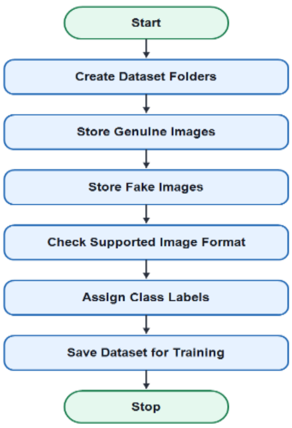

Figure 1: Dataset Preparation Flowchart

Image Preprocessing

Each uploaded image was subjected to a standardized preprocessing pipeline prior to feature extraction. The preprocessing stages and their rationale are described in Table 2.

Specific Preprocessing Method Used in the Software

- i. Resize each uploaded image to 420 x 220 pixels.
- ii. Convert the resized BGR image to grayscale.
- iii. Apply a 5 x 5 Gaussian blur to suppress image noise.
- iv. Apply Canny edge detection with lower and upper thresholds of 80 and 180.
- v. Apply CLAHE contrast enhancement with clipLimit = 2.0 and tileGridSize = 8 x 8.

Gray(x,y) = 0.299R(x,y) + 0.587G(x,y) + 0.114B(x,y)
G(x,y) = (1 / 2*pi*sigma^2) exp(-(x^2 + y^2) / 2*sigma^2)
M(x,y) = sqrt(Gx^2 + Gy^2), where M is the edge gradient magnitude.

Table 2: Image Preprocessing Stages

Stage	Operation	Purpose
1. Resizing	Resize to 420 Ã— 220 pixels	Standardizes input dimensions across all images
2. Grayscale Conversion	RGB to grayscale transformation	Reduces dimensionality; focuses on luminance features
3. Gaussian Blur	Gaussian smoothing filter	Suppresses high-frequency image noise
4. Edge Detection	Canny edge detection algorithm	Identifies printed borders and structural patterns
5. Image Enhancement	Contrast Limited Adaptive Histogram Equalization (CLAHE)	Improves local contrast to reveal latent security features

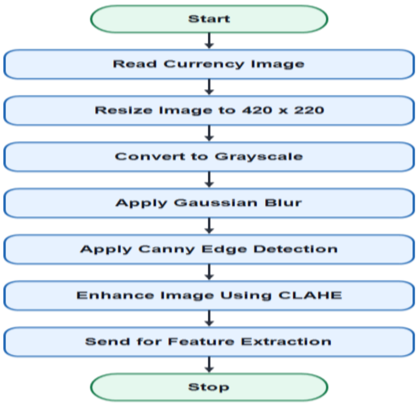

Figure 2: Image Preprocessing Flowchart

Feature Extraction

Following preprocessing, four categories of features were extracted from each processed image and concatenated into a single feature vector for classifier input:

Detailed Feature Extraction Method and Equations

Color histogram: the resized image was converted to HSV color space and an 8 x 8 x 8 histogram was computed over the H, S, and V channels.

$H_i = n_i / N$, where n_i is the number of pixels in bin i and N is the total number of pixels.

Texture features: mean intensity, standard deviation, entropy, and Laplacian variance were computed from the grayscale image.

$\text{Mean} = (1/N) \sum I_i$

$\text{Standard deviation} = \sqrt{(1/N) \sum (I_i - \text{Mean})^2}$

$\text{Entropy} = - \sum p_i \log_2(p_i)$

$\text{Laplacian variance} = \text{Var}(\text{Laplacian}(I))$

Edge features: edge density, contour count, and normalized contour area were computed from the Canny edge image.

Edge density = number of edge pixels / total number of pixels

Normalized contour area = sum contour areas / total number of pixels

ORB features: ORB descriptors were extracted from the CLAHE-enhanced grayscale image. The descriptor matrix was averaged into a 64-value vector; if no descriptor was detected, a zero vector of length 64 was used.

Final feature vector: X = [color histogram, texture features, edge features, ORB descriptor mean].

i. ***Color Histogram Features:*** Represent the distribution of pixel intensity values across the image, capturing differences in ink quality, color balance, and tonal range between genuine and counterfeit notes.
ii. ***Texture Features:*** Comprise statistical measures including mean brightness, standard deviation, entropy, contrast, and Laplacian variance, characterizing the surface grain and printed quality of the note.
iii. ***Edge Features:*** Derived from the Canny edge map, including edge density, contour count, and total contour area, capturing structural and geometric regularity of printed patterns.
iv. ***ORB Keypoint Features:*** Oriented FAST and Rotated BRIEF descriptors identify locally distinctive image regions associated with fine-detail security printing features.

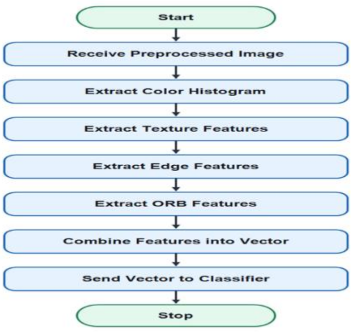

Figure 3: Feature Extraction Flowchart

Machine Learning Classification

A Random Forest classifier was selected for binary classification of currency note images as genuine or counterfeit. Random Forest is an ensemble learning algorithm that aggregates predictions from multiple decision trees trained on bootstrap samples of the training data (Breiman, 2001). It was chosen for its robustness to overfitting, suitability for structured tabular feature data, and inherent support for probability-based confidence scoring.

Detailed Random Forest Model Design

The Random Forest classifier was implemented using Scikit-learn's RandomForestClassifier. The model used n_estimators = 250, max_depth = None, random_state = 42, and class_weight = balanced. A 0.25 test split was used only when the dataset size permitted stratified splitting; otherwise, the available small dataset was used for training.

$\text{Gini}(D) = 1 - \sum p_k^2$

$\hat{y} = \text{mode}(T_1(X), T_2(X), ..., T_m(X))$

$P(c|X)$ = number of trees predicting class c / total number of trees

Table 3: Details of Random Forest Design

Model item	Implementation detail
Classifier	RandomForestClassifier
Number of trees	250
Class balancing	class_weight = balanced
Saved model	models/currency_detector.joblib
Output	Genuine/fake label and prediction confidence

The training procedure comprised the following steps: (i) loading all images from the genuine and fake directories; (ii) applying the preprocessing and feature extraction pipeline to each image; (iii) assigning binary class labels; (iv) fitting the Random Forest model on the resulting feature matrix; and (v) persisting the trained model to disk using Joblib (models/currency_detector.joblib). At inference time, the saved model is loaded and applied to each newly uploaded note image without retraining.

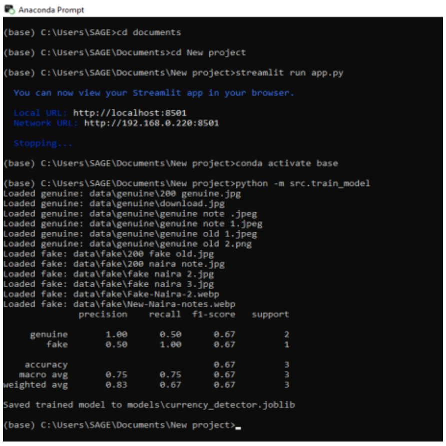

Figure 4: Model Training

Figure 1 shows an Anaconda Prompt terminal session documenting the model training process for the fake currency detection system. The command python -m src.train_model was executed, which loaded the dataset 6 genuine and 6 fake Nigerian Naira note images from their respective folders. Upon completion, the trained model was saved to models/currency_detector.joblib for later use by the application.

Currency Counting and Valuation

The system supports batch processing of multiple simultaneously uploaded images, with each image treated as a single currency note. For each uploaded image, the system records the classifier output and increments one of three counters: total notes scanned, genuine notes, or counterfeit notes. Prior to scanning, the user specifies the denomination of each uploaded note from the set {NGN 5, NGN 10, NGN 20, NGN 50, NGN 100, NGN 200, NGN 500, NGN 1000}. The aggregate monetary value is computed by summing the denominations of notes classified as genuine only; counterfeit notes are excluded from the valuation total.

Counting and Recognition Software Design

The implemented system treats each uploaded image as one currency note. Therefore, a single image containing many overlapping notes is outside the current implementation scope unless the notes are first segmented into separate note images. A future extension can handle many notes in one image using thresholding, contour detection, perspective correction, and note-by-note segmentation before classification.

N = total number of uploaded images

G = sum 1[y_i = genuine]

F = sum 1[y_i = fake]

V = sum d_i * 1[y_i = genuine], where d_i is the selected denomination of note i.

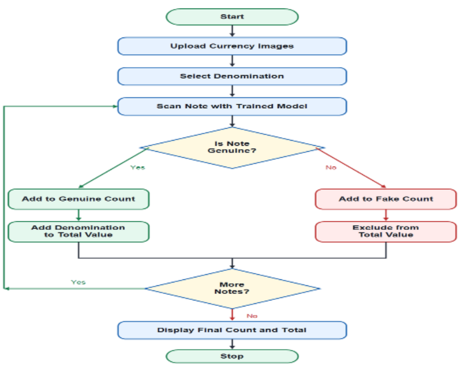

Figure 5: Currency Counting and Evaluation Flowchart

Use Case Diagram

Software Design Method

The software was organized into four main modules: feature extraction, model training, prediction, and user interface. The feature extraction module loads images, preprocesses them, and extracts color, texture, edge, and ORB features. The training module collects labelled images, trains the Random Forest classifier, and saves the model. The prediction module loads the saved model and returns the class label, confidence, and probabilities. The Streamlit interface provides upload, denomination selection, scanning, preview, and summary display.

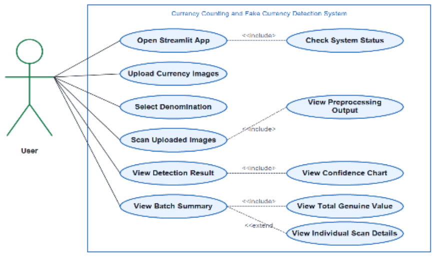

Figure 6: Use Case Diagram for User Interface Design

System Algorithm

The procedural algorithm governing system operation is as follows:

i. Step 1: Load the trained classification model from the model directory.
ii. Step 2: Accept one or more currency note image uploads; assign denomination values per note.
iii. Step 3: For each uploaded image: resize, convert to grayscale, apply Gaussian blur, Canny edge detection, and CLAHE enhancement.
iv. Step 4: Extract color histogram, texture, edge, and ORB features; construct the feature vector.
v. Step 5: Apply the trained Random Forest model; obtain class prediction and confidence score.
vi. Step 6: If genuine, add the note's denomination to the aggregate genuine value. If counterfeit, increment the fake counter only.
vii. Step 7: Upon completion of all images, display the batch summary and individual results.

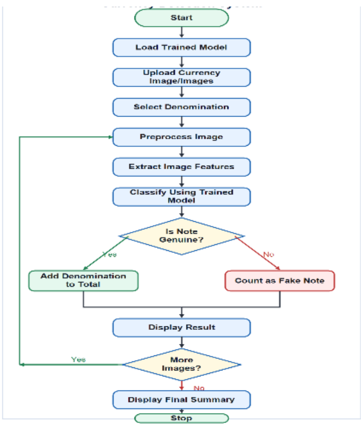

Figure 7: System Flowchart

RESULTS AND DISCUSSION

Results

The implemented system was evaluated through functional testing using uploaded images of genuine and suspected counterfeit Nigerian Naira notes. The primary objective of testing was to verify correctness of preprocessing, classification, counting, and valuation outputs. The key outputs assessed during testing are summarized in Table 2.

Classification Evaluation Metrics

The model evaluation is based on true positive (TP), true negative (TN), false positive (FP), and false negative (FN) values obtained from the confusion matrix.

Accuracy = (TP + TN) / (TP + TN + FP + FN)

Precision = TP / (TP + FP)

Recall = TP / (TP + FN)

F1-score = 2 * (Precision * Recall) / (Precision + Recall)

Specificity = TN / (TN + FP)

Training accuracy = correct predictions on training set / total training samples

Testing accuracy = correct predictions on testing set / total testing samples

The implementation uses Scikit-learn's classification_report to compute precision, recall, F1-score, and support when a test split is possible. The Streamlit interface also displays prediction confidence using the Random Forest predict_proba output.

Table 2. System Functional Test Summary

System Function Evaluated	Expected Output	Observed Outcome
Image upload and format acceptance	All supported formats accepted	Confirmed
Preprocessing pipeline display (grayscale, edges, CLAHE)	Visual outputs rendered in tabbed panels	Confirmed
Genuine note classification	Labelled GENUINE with confidence score	Confirmed
Counterfeit note classification	Labelled FAKE with confidence score	Confirmed
Total note count (all uploaded images)	Equals total images submitted	Confirmed
Counterfeit exclusion from genuine total	Fake notes not counted in value sum	Confirmed
Aggregate genuine monetary value computation	Sum equals denominations of genuine notes only	Confirmed
Batch summary display	Totals displayed correctly in summary panel	Confirmed

All eight functional test criteria were successfully met. The system correctly accepted images in all supported formats, rendered preprocessing outputs in tabbed panels, applied the trained Random Forest model to produce binary classification labels with associated confidence scores, incremented note counters accurately, excluded counterfeit notes from the total value computation, and displayed the complete batch summary. Error handling mechanisms such as the absence of a trained model or failure to upload an image produced appropriate user-facing messages, confirming the robustness of the interface design.

In terms of classification behavior, notes classified as genuine received the label GENUINE accompanied by a probability confidence score output from the Random Forest classifier's predict_proba function. Notes assessed as counterfeit were labeled FAKE and their denominations were withheld from the aggregate total. The system's probability output enables users to assess the reliability of individual classification decisions, which is particularly informative for borderline cases.

Discussion

The results confirm that a software-based simulation can effectively replicate the core functional behavior of a physical currency counting machine equipped with counterfeit detection capability. The integration of image processing and a Random Forest classifier within a single pipeline addresses the principal limitation identified in the literature namely, the separation of counting and authentication functions in existing systems (Lee et al., 2017; Han and Kim, 2019).

The feature extraction strategy employed in this study combines complementary sources of discriminative information. Color histograms capture global tonal and ink-quality differences; texture features characterize surface printing patterns; edge density and contour metrics quantify structural regularity; and ORB keypoints encode local fine-detail patterns associated with security printing. This multi-feature approach aligns with the multi-modal sensing principles documented in the sensor-based literature (Lee et al., 2017; Harjunowibowo et al., 2012), translated into the image-processing domain.

The selection of Random Forest as the classification algorithm reflects a deliberate trade-off between predictive performance and implementation simplicity. While convolutional neural network architectures have demonstrated superior accuracy in banknote recognition tasks (PachÃ³n et al., 2021; Pham et al., 2020), they impose substantial computational and dataset requirements that are incompatible with a low-resource prototype setting. Random Forest, by contrast, achieves competitive performance on handcrafted feature vectors, supports probability-based confidence scoring, and imposes minimal computational overhead during inference characteristics that are advantageous for a prototype intended to scale toward hardware deployment.

A notable practical contribution of this system is its denomination-specific valuation function. Existing image-based counterfeit detection systems predominantly output a binary genuine/fake label without integrating a counting or valuation mechanism. The present system extends the utility of classification by aggregating the monetary value of authenticated notes, which directly supports the operational needs of cash-handling environments such as retail outlets, financial institutions, and small businesses in the Nigerian context.

Several limitations must be acknowledged. The system's classification accuracy is bounded by the size and diversity of the training dataset; small or class-imbalanced datasets increase the risk of overfitting and reduce generalizability to unseen note conditions. The image-only approach does not replicate the detection capabilities of UV, infrared, or magnetic sensors, which can identify security features invisible in standard visible-light images (Bruna et al., 2013; Baek et al., 2018). Furthermore, image quality factors including illumination variation, motion blur, note folding, and soiling can degrade feature extraction fidelity and, consequently, classification performance.

These limitations define the primary directions for future development. Enlarging and diversifying the training dataset, incorporating transfer learning from pre-trained CNN models, and integrating hardware sensor modules would substantially improve detection robustness. Automatic denomination recognition eliminating the current requirement for user-specified denomination input represents an additional capability enhancement applicable through standard image classification techniques.

CONCLUSION

This paper presented the design and simulation of a currency counting system integrating automated counterfeit detection through image processing and machine learning. The system accepts digital images of Nigerian Naira notes, applies a five-stage preprocessing pipeline, extracts four categories of discriminative image features, and classifies each note as genuine or counterfeit using a trained Random Forest classifier. The system subsequently counts notes, segregates genuine from counterfeit samples, and computes the aggregate value of authenticated notes, with all outputs presented through an accessible Streamlit web interface.

Functional testing confirmed that the system correctly performs image acquisition, preprocessing, classification, counting, and valuation across all tested note images. The results demonstrate the feasibility of a software-simulated currency counting system that integrates counterfeit detection without requiring specialized sensing hardware.

The primary contributions of this study are: (i) the demonstration of a unified counting-and-authentication pipeline applicable to Nigerian Naira; (ii) a multi-feature image analysis approach combining color, texture, edge, and keypoint descriptors; and (iii) a denomination-specific valuation mechanism that extends the operational utility of binary counterfeit classification. The prototype provides a solid foundation for subsequent hardware implementation involving microcontroller integration, mechanical note transport, and multi-modal sensor augmentation.
Future research should address the current limitations by expanding the training dataset with verified genuine and counterfeit samples across all Naira denominations, integrating UV and infrared sensor inputs, developing automatic denomination recognition, and validating the system under real-world cash-handling conditions using a physical prototype.

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