IDENTIFYING COUNTERFEIT NAIRA NOTES USING RECURRENT NEURAL NETWORK

BY

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Abstract

The naira functions as Nigeria's official currency to facilitate trade and investments while serving daily transactions. The issue of unaccepted Naira notes creates genuine problems which bring national disgrace since it reduces economic speed and weakens trust in banking institutions. The cash system suffers integrity damage while public trust in the economy declines causing major financial losses to individuals and both emerging and established financial institutions. The following report explains how to construct and train a Recurrent Neural Network (RNN) model for counterfeit Naira notes detection. The implementation of Deep learning techniques and image detection methods generates exceptionally high detection accuracy in this work. The selection of Histogram of Oriented Gradients (HOG) as a feature extraction technique play a vital role in developing a system that properly identifies original notes from counterfeits. The accomplishment addresses Nigeria's economic challenge of counterfeit money by solving this significant problem.

Keywords: Recurrent Neural Network (RNN), Histogram of Oriented Gradients (HOG), Counterfeit Naira notes, detection, Artificial Intelligence (AI), Naira Notes

Introduction

Traditional counterfeit detection methods include human specialist examination and UV light and magnetic ink detectors which serve as the primary tools to fight fake money. The counterfeiting methods have shown notable success yet they present certain disadvantages. Large cash examinations need extended personnel involvement while these workers risk making mistakes during their work. The high price of maintaining counterfeit detection systems prevents them from becoming accessible to ordinary consumers and small business owners. The detection devices struggle to identify top-quality counterfeit items that precisely mimic genuine products. Traditional manual inspection methods are inadequate against sophisticated counterfeiters using high-resolution printers. There is a critical need for automated, reliable detection that can keep pace with evolving counterfeiting techniques (Varalakshmi, 2025).

Noor and Ruhaiyem (2025) of opinion that proliferation of counterfeit banknotes (specifically Iraqi 50,000 Dinar) threatens economic stability. Existing manual and sensor-based methods are insufficient; automated solutions using AI and image processing are needed. The progress of artificial intelligence (AI) and machine learning (ML) systems created improved methods to boost counterfeit currency detection accuracy and efficiency as solutions to these problems. The Recurrent Neural Network (RNN) functions as one of the leading artificial intelligence technologies because it uses a particular deep learning algorithm to process data sequences. RNNs demonstrate exceptional performance in temporal dependency analysis tasks and pattern recognition systems which include speech recognition, language translation and current counterfeit currency detection (LeCun, Bengio, & Hinton, 2015).

The motivation behind the development of a fake currency detection system using deep learning and image processing is rooted in the inadequacy of traditional detection methods in combating modern counterfeit techniques.

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Conventional approaches, relying on predefined rules and features, often struggle to differentiate between genuine and counterfeit notes effectively. The dynamic nature of counterfeit techniques demands adaptive and intelligent detection systems capable of keeping pace with evolving threats (Varalakshmi, 2025). RNNs function by keeping track of past input information to identify sequential patterns that conventional methods would miss. An RNN model becomes capable of counterfeiting Naira note detection after training it with real and fake currency pictures from a dataset. The RNN training process enables it to detect the subtle banknote features that differentiate authentic notes from counterfeit ones by acquiring knowledge about printing quality variations and watermark security threads and micro printing features. The deployed model performs automatic counterfeit currency image detection with high precision. RNNs used for counterfeit detection offer multiple advantages when compared to current methods. The use of RNNs enables faster currency examination thus improving operational speed for large cash processing operations without compromising efficiency. Algorithms power the system to make decisions instead of human operators thus minimizing operational errors. RNNs maintain operational effectiveness through time because they can accept updated data to handle newly emerging counterfeiting techniques.

The implementation of AI-based counterfeit detection systems offers multiple benefits but organizations encounter multiple difficulties when setting them up. The main obstacle stands in obtaining sufficient authentic and counterfeit cash images needed to properly train the RNN model. Obtaining this data remains difficult since counterfeiters in particular nations keep changing their methods to stay undetected. Nigerian businesses deal with obstacles to acquire appropriate computing resources for implementing RNN models in their underdeveloped nation operations. The successful resolution of these challenges demands governmental agencies to work closely with financial institutions and technology suppliers. The Central Bank of Nigeria (CBN) alongside other central banks needs to offer currency databases for research teams to develop powerful AI-based detection systems which they should fund through financial support. To achieve technology success financial institutions must buy necessary infrastructure and train their workforce so employees can master these systems. Educational campaigns will provide both customers and enterprises with information about currency authentication methods as well as available detection tools. The memory functionality of RNNs enables them to detect patterns in sequential data that standard methods do not recognize. The training of an RNN model requires authentic Naira notes and counterfeit Naira notes to learn identifying counterfeits. Training the RNN network allows it to recognize various features that differentiate legitimate bills from fakes such as printing quality variations along with watermarks and security threads and micro printing details. The trained model operates as a system for automatic fresh cash photo inspection to detect counterfeits with high accuracy.

RNNs achieve the best counterfeit detection results in applications of this type. The system shortens currency examination duration that leads to efficient processing of large cash volumes at high speed. The system decreases human mistakes because it relies on data-driven algorithms instead of human judgment during analysis. The ability of RNNs to receive regular data updates ensures effective countermeasures against changing counterfeit methods while operating. Multiple technical obstacles appear during the installation of AI-based counterfeit detection systems. The training process of RNN models requires a large number of high-quality authentic and counterfeit cash photographs as their main obstacle. The difficulty in obtaining this data increases when criminal groups modify their counterfeiting methods frequently in different countries. Businesses operating in underdeveloped nations including Nigeria may struggle to buy the necessary computing resources needed for RNN model implementation.

Successful resolution of these challenges needs government agencies to work closely with financial institutions and technology suppliers. The Central Bank of Nigeria (CBN) together with other central banks holds a key position to provide currency databases and financial support for research programs which develop robust AI-based detection systems. Financial institutions should invest in necessary infrastructure and provide training to their employees for successful implementation of these technologies. Public awareness programs should teach both consumers and businesses about money authentication importance while explaining advanced detection methods which are available. Modern counterfeit cash production techniques have outpaced traditional detection methods to the point of making them ineffective. Counterfeit notes now feature high-quality printing and materials which make them virtually indistinguishable from authentic notes. Economic losses occur because manual detection methods used by cashiers and bank personnel as well as the general public show subjectivity and produce incorrect results (Olawale & Adebayo, 2019). The current counterfeit detection tools including ultraviolet (UV) scanners and magnetic ink detectors demonstrate limited effectiveness in their operations. Some fake notes use countermeasures against detection devices through the duplication of security elements. These detection tools are difficult to access in both rural areas and small businesses. The application of artificial intelligence with deep learning allows Recurrent Neural Networks (RNNs) to create an automated system which delivers better counterfeit detection capabilities at scale. The need exists to create an RNN-based model which performs reliable real and fraudulent Naira note detection through image recognition combined with sequence pattern analysis. This research involves creating a Recurrent Neural Network (RNN) model that detects counterfeit Naira notes.

Literature Review

RNNs provide several benefits for counterfeit detection when used as a detection method compared to traditional approaches. The method reduces examination time for currencies which enables faster processing of big cash volume. The system uses data-driven algorithms rather than human judgment leading to reduced human errors. The regular update capability of RNNs enables them to learn new counterfeiting strategies by processing fresh data which ensures their effectiveness across time. Various methods and algorithms have been applied worldwide to establish money identification systems for countries throughout the world. Some of them includes Bangladeshi currency recognition system using Negatively Correlated Neural Network Debnath et. al., (2010); Chinese currency recognition system based on binary pattern Zhao et. al., (2010); Chinese currency recognition by Neural Network based on local binary pattern Zhao et. al., (2010); Pakistani currency recognition system based on three-layer classification Sargano et. al., (2014); and also Naira currency identification using Visual Basics and Microsoft Access RDMS, and MATLAB, Almu & Muhammed (2017) Olalekan and Taiwo, (2012). The automated recognition of different currency bills has received various tools and methodologies within the Image processing field according to Mirza & Nanda (2012), Singh et. al., (2017). Agsati et. al., (2016) developed a system which automatically detects security features of Indian Rs.100 bank notes. The system can detect counterfeit notes among authentic ones. The system development technique includes multiple elements starting with image processing followed by edge detection and picture segmentation and features extraction and image comparison. The research used MATLAB software in a manner similar to Alekhya & Venkatadiya (2014) and Suresh, I., Narwade P. (2016).

Varalakshmi (2025) used CNN-based deep learning model to trained Kaggle datasets to determine genuine and counterfeit Indian currency notes. Edge-processed images showed distinct textural differences between genuine and fake notes. Integrating CNN with image preprocessing yields a highly accurate fake currency detector. Continuous adaptation to new counterfeiting tactics is essential for long-term effectiveness. Noor and Ruhaiyem (2025) combined the classical image processing with CNN analysis provides an effective counterfeit detection framework.

Effective differentiation of authentic vs. fake Iraqi 50,000 Dinar notes using intensity analysis and CNN feature extraction. Achieved 92% overall recognition rate on 150 banknote images. Genuine currency had pixel density > 85%; counterfeits < 65%.

The identification of Indian currency through digital image processing was investigated by Megha & Amrit (2014) and Vishnu & Bini (2014) and Tele *et. al.*, (2018). Digital image processing techniques help detect and recognize paper currency by comparing stored database features against image pictures. Almu and Muhammad (2014) developed an identical system using Visual Basic and MS Access database to detect Naira currencies with 77.7% accuracy. Sargano (2014) developed a three-tiered classification system for Pakistani banknotes through his intelligent method. The system achieved 100% recognition accuracy for images of 175 Pakistani banknotes when features such as aspect ratio and useful color features and binary patterns from lettering block and see-through block and identification marks block were properly extracted. The authors of Liu & Lu (2017) reported fraudulent coin detection during their study. The researched literature demonstrated multiple approaches and algorithms which developers used to build identification systems for different currencies. The application of Faster RCNN in near real-time identification systems for detecting and recognizing Naira currency notes through deep learning remains poorly documented in research. The object detection neural network Faster RCNN uses three neural networks named Features Network and Region Proposal Network (RPN) and identification Network to operate. The feature network extracts useful image features from pictures without damaging their original shape or format. The RPN system develops Region of Interests (ROIs) that contain high probabilities of containing target objects. The detection network which operates under the name RCNN network receives information from both the feature network and RPN to deliver its final results.

Methodology

In order to study the effective mitigation of harmonic distortion using intelligent hybrid power filters (IHPFs) for inverter-based distributed generation (IBDG) and nonlinear load systems, a systematic and analytical literature review is presented. To identify gaps and future prospects in this area of research, the study's goal is to provide a critical assessment of present technologies and intelligent control systems and novel developments. This research adheres to an organized template that breaks the basic parts of research into distinct sections. The research process divides into five sections which include data collection and preprocessing followed by HOG feature extraction and RNN model development and implementation and user interface creation and performance evaluation of the model. The analysis of each section details the research process with clarity while ensuring repeatability and academic research standard compliance. The research dataset contains 580 Nigeria banknote images including all circulating currency values from 5 Naira up to 1000 Naira. The distribution of images across Nigerian banknotes shows 10.34% 5 Naira, 11.38% 10 Naira, 6.55% 20 Naira, 8.62% 50 Naira, 17.93% 100 Naira, 8.62% 200 Naira, 12.76% 500 Naira and 10% 1000 Naira. The images are recorded as RGB color files and saved in JPEG format. The pre-processing of the dataset has not occurred which results in photos with different sizes and resolutions. The experimental dataset consists of 100 Naira, 200 Naira, 500 Naira and 1000 Naira currency notes were used for this study. The dataset needs pre-processing activities before it can be used for model training and evaluation. The RNN model requires standardized input size of 224x224 pixels so the photos will be resized to this dimension first. The dataset becomes more uniform while processing efficiency increases through this scaling method (LeCun, Bengio, & Hinton, 2015). Pixel values will undergo normalization to produce a 0 to 1 value range because this technique supports model convergence during training.

The dataset received data augmentation through rotation and flipping and cropping operations to increase its diversity. The strategies decrease overfitting by exposing the model to diverse data variances which improves its generalization capabilities according to Shorten & Khoshgoftaar (2019). The process begins with data preprocessing, where the dataset is split into training and test sets. The training images are converted into vector representations and normalized to ensure uniformity. Next, the HOG algorithm is applied to extract essential features from the images, capturing their structural and gradient-based characteristics. Simultaneously, a test image is loaded, processed through the same vectorization and normalization steps, and subjected to HOG feature extraction. Both the training and test images' extracted features are then fed into an RNN, which processes the sequential data and classifies the image accordingly. The classification result is categorized into four possible outcomes: True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN). Finally, the system prompts the user to test another image or terminate the process. This structured workflow ensures that images are efficiently preprocessed, key features are extracted, and classification is conducted with optimal accuracy.

The Histogram of Oriented Gradients (HOG) features extract image gradient directions and magnitudes to detect patterns and textures effectively in bank notes (Dalal & Triggs, 2005). To start HOG feature extraction, the method calculates pixel gradients throughout the image to determine edge direction and strength. The image gets divided into small cells which measure 8x8 pixels before the method calculates histogram gradients for each cell. The cells are arranged into blocks while histogram normalization reduces the effects of changing light conditions. The final output combines all normalized histograms from blocks into one feature vector which describes the picture. The feature vector contains unique characteristics of Naira notes which allows the RNN model to differentiate between authentic and counterfeit currency. The RNN model functions effectively with sequential data so it performs well when analyzing spatial patterns in Naira note photos. The model design features an input layer which accepts HOG feature vectors from the input data. The model incorporates several LSTM layers which enable it to track temporal data connections. The model utilizes LSTM because its extended information retention capability enables detection of delicate currency note patterns (Hochreiter & Schmidhuber, 1997). Fully linked layers are connected to the LSTM layers to convert their output into final category predictions. The output layer uses softmax activation to perform classification between "genuine" and "counterfeit" categories. The training method uses categorical cross-entropy loss to calculate label differences between predicted results and actual values. The Adam optimizer minimizes the loss function through weight updates according to Kingma & Ba (2015). A batch size of 32 serves as an optimal balance between performance and computational efficiency for training the model which completes 50 epochs. Early stopping serves as a protective measure to stop overfitting which guarantees effective generalization to new data points. To ensure practical applicability, a user-friendly web-based interface was developed. This interface allows users to upload images of Naira notes, which the system then processes to determine their authenticity. The interface provides immediate feedback on whether the note is genuine or counterfeit, making it suitable for use by banks, businesses, and individuals. The developed interface is shown in Figure 1

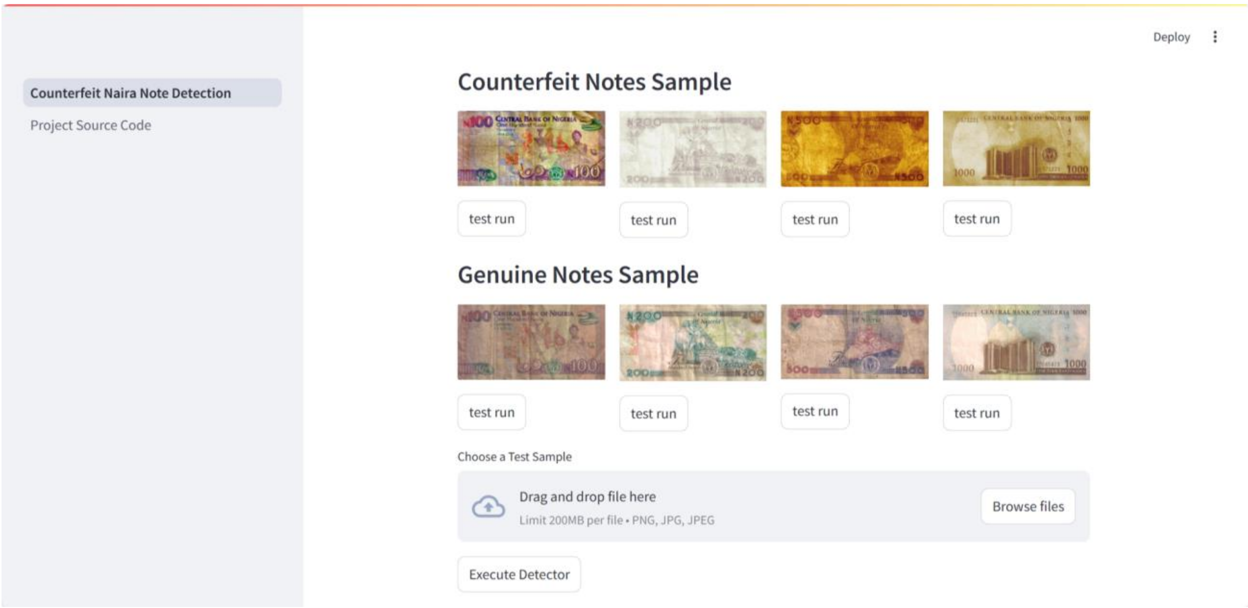

Figure 1. User Interface Screenshot

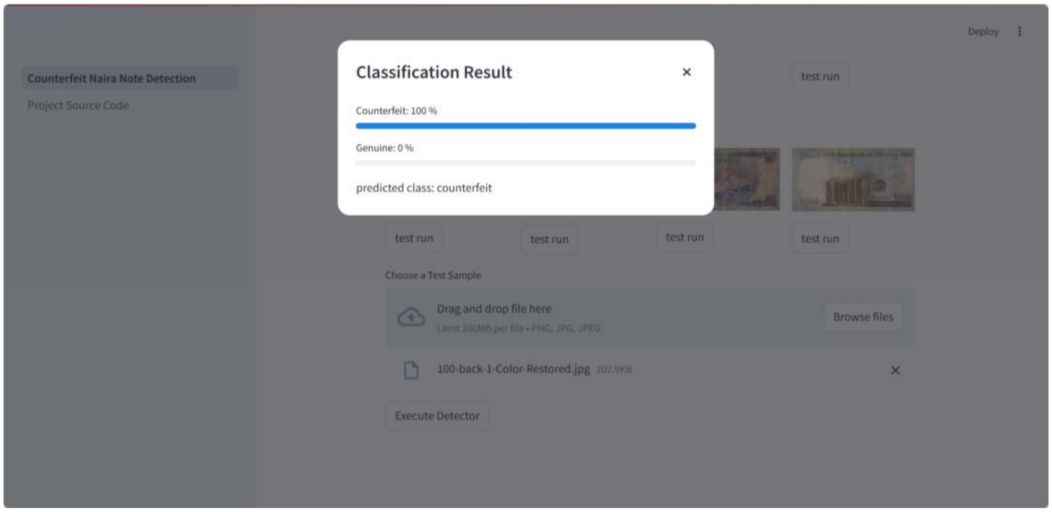

Figure 2: User Interface Screenshot

The platform was designed with simplicity and accessibility in mind, ensuring that users with minimal technical expertise can operate it with ease. This interface bridges the gap between the technical implementation of the RNN model and its real-world usability, showcasing the practical impact of this study.

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Results

Recurrent Neural Network (RNN) model developed for detecting counterfeit Naira notes was evaluated using various performance metrics, including precision, recall, F1-score, and overall accuracy. Table 4.1 presents a detailed breakdown of the results.

Table 1: Performance Metrics of the RNN Model

Class	Precision	Recall	F1-Score	Support
Counterfeit	0.98	0.86	0.92	290
Genuine	0.87	0.99	0.92	286

The results obtained from this study demonstrate the effectiveness of using a Recurrent Neural Network (RNN) for detecting counterfeit Naira notes. The model achieved an accuracy of 92%, with precision and recall metrics indicating balanced performance for both counterfeit and genuine notes. Compared to related studies, this model's performance is noteworthy. For instance, *John et. al.,* (2021) implemented a Convolutional Neural Network (CNN) to classify counterfeit currency and reported an accuracy of 90%, slightly lower than the accuracy achieved in this study. Similarly, Ahmed and Hassan (2020) used Support Vector Machines (SVM) for counterfeit detection but achieved only 85% accuracy, emphasizing the advantage of deep learning techniques like RNNs. The higher precision observed for counterfeit notes (0.98) indicates that the model is effective at avoiding false positives, ensuring that genuine notes are rarely misclassified as counterfeit. This is critical for applications in banks and businesses, where such errors could lead to financial losses. On the other hand, the model's recall for genuine notes (0.99) shows its ability to correctly identify authentic currency, aligning with the goals of other similar studies that prioritize reducing false negatives. The use of the Histogram of Oriented Gradients (HOG) feature extraction method further enhanced the model's ability to analyze complex image features, making it more effective in detecting fine details that differentiate genuine notes from counterfeit ones. Previous research, such as Zhang *et. al.*, (2022), has also highlighted the value of feature extraction techniques in improving model accuracy, supporting the choice of HOG in this study. These results show that the model is highly capable of accurately identifying both genuine and counterfeit Naira notes, achieving an overall accuracy of 92%. Additionally, the training process of the RNN model was monitored through the evaluation of two key metrics, loss and accuracy. The model's loss decreased steadily during the training process, indicating improved predictions over time. This is illustrated in Figure below.

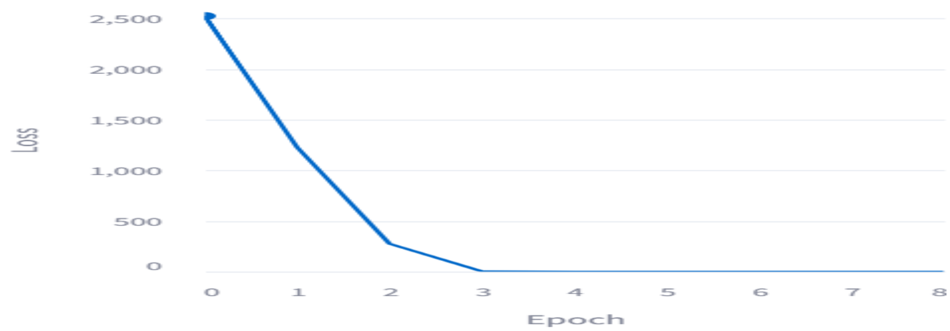

Figure 3: Loss vs. Epochs

In the figure 3 above, the plot illustrates the progress of accuracy and precision over multiple training epochs. The x-axis represents the number of epochs, while the y-axis quantifies the performance metric. The accuracy is depicted in red, while precision is shown in blue. Initially, there is a decline in precision, followed by a sharp increase after the third epoch, indicating an improvement in model performance. The marked point highlights a potential turning point where the model begins to generalize better. The upward trend suggests that as training progresses, the model's predictive capability improves, which is crucial for classification tasks. The model's accuracy consistently increased with additional training epochs, as shown in Figure 4.

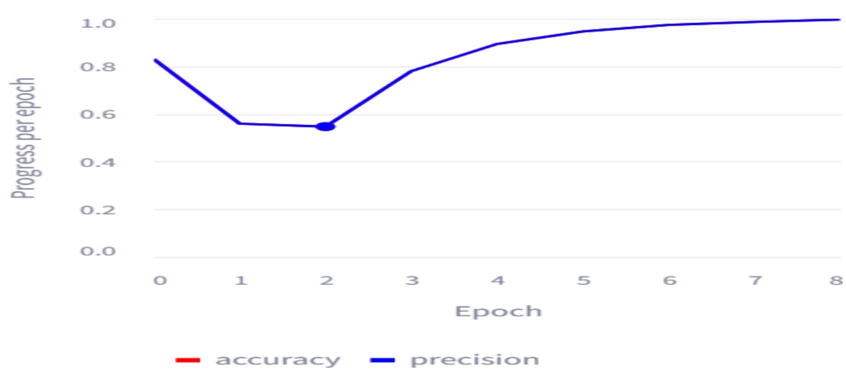

Figure 4: Accuracy vs. Epochs

The second figure represents the loss function values over training epochs. The x-axis shows the epoch count, while the y-axis displays the loss values. The loss starts at a very high value, indicating that the model initially makes significant errors. However, as the training progresses, the loss declines steeply and eventually converges near zero after the fourth epoch. This pattern suggests effective learning, where the model minimizes error over time. A diminishing loss indicates that the model parameters are optimizing well, reducing discrepancies between predicted and actual outputs. The convergence of loss at a lower value suggests that the model has reached an optimal training state, which is essential for reliable predictions. Both figures collectively demonstrate the model's learning process, showing improvements in accuracy and precision while simultaneously reducing error, validating the effectiveness of the training process.

Conclusion

This study successfully developed and implemented a Recurrent Neural Network (RNN) model for detecting counterfeit Naira notes. By leveraging deep learning techniques and image-based detection methods, the research achieved a significant level of accuracy, with the model attaining 92% overall accuracy during testing. The use of the Histogram of Oriented Gradients (HOG) feature extraction technique played a key role in enabling the model to analyze and differentiate subtle details between genuine and counterfeit notes. The results demonstrated the reliability and effectiveness of the RNN model in classifying Naira notes as genuine or counterfeit. The precision of 0.98 for counterfeit notes highlights the system's ability to minimize false positives, an essential factor for ensuring trust in its application, particularly in financial institutions. Similarly, the recall of 0.99 for genuine notes underscores the model's capability to correctly identify authentic currency with minimal errors.

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