# Fake Currency Detection using Modified Faster Region-Based Convolutional Neural Network

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*Abstract:* - Significant technological advancements in the printing and scanning industries exacerbated the counterfeiting problem. As a consequence, counterfeit currency has an impact on the economy and diminishes the value of genuine currency. Therefore, it is essential to detect the counterfeit currency. The majority of previous methods rely on hardware and image processing techniques. Using these methods to detect counterfeit currency is inefficient and time-consuming. We have proposed a system for the detection of counterfeit currency using a modified faster region-based convolution neural network (Faster R-CNN) to circumvent the aforementioned issue. This study identifies counterfeit currency by analyzing images of currency. One thousand images of currency note are used as dataset to train a Faster-RCNN model on inception V2 architecture to learn the feature map of currencies. Upon successful training and validation of the model, 500 images of counterfeit currencies were used to test the model. The proposed method efficiently identifies 96% of counterfeit currency images tested. Other evaluation means such as mean average precision and detection accuracy show that the developed system has an accuracy of 97%.

*Key-Words:* - Fake currency detection, Nigerian currency, Faster R-CNN, Feature extraction.

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## 1 Introduction

Paper currency is one of many types of legal tender, but it is particularly useful as a medium for conducting business transactions [1], [2]. According to [3], [4], currency features can be broken down into two categories: internal and external. The breadth and size of the currency are both considered to be exterior properties, and they are included in the category of physical aspects of the currency. The color of the currency is the internal characteristic that can be taken into consideration. Because currencies are moved from person to person through a variety of methods, internal features are not dependable. During this procedure, we may acquire wrong results as a result of the notes becoming dirty, which also happens during the process. The process of recognizing currencies is made significantly more challenging when those currencies have been worn down to the point where they are torn, old, or faded [5].

CNN is a generally prominent technique utilized for the purposes of image detection and recognition [6], [7]. Faster R-CNN has been utilized for object detection in related literature because of its high level of accuracy and its ability to automatically extract features. Image processing and neural networks are two of the more common types of technology that are utilized in the process of existing currency identification systems available in literature. However, the amount of processing time required for all of these methods is rather extensive [8].

Considering the traditional hardware systems which made use of optoelectronic devices to analyze the light that is refracted by the banknote in order to identify specific features, this study leverage on the potency of Faster R-CNN to extract and identify those specific. This paper describes the design, implementation, and evaluation of fake currency detection system, there are also descriptions of the techniques used for image acquisition, image processing, and currency detection using Naira notes as case study. The remainder of the paper is structured as follows. The second section is the literature review of image acquisition, image preprocessing, and currency detection. The third section focuses on the methods employed in the investigation. Results are analyzed and discussed in the fourth section. The final section of the paper concludes with suggestions for future research.

## 2 Review of Related Works

Since there are numerous ways to implement a system that distinguishes currency images, it was necessary to examine other algorithms and previously implemented works to acquire a deeper understanding of the proposed system's objectives and outcomes. Currency recognition system using image processing was proposed in [9], the study describes a method for identifying the denomination of banknotes. This system is compatible with 20 distinct national currencies. This system first identifies the country based on certain predefined conditions, such as template matching based on vacant areas and region of interest, and then identifies the denomination of the banknote based on characteristics such as size, color, and text extraction. This system can identify the country and denomination of a banknote in an average of 5.3 seconds and with a nearly 93% degree of accuracy [9].

Authors in [10] conducted a study on the detection and recognition of counterfeit banknotes based on Deep Learning. The extant system operates on two types of images, one of which is the front side of the original image and the other a backside image. The verification is based on these two images. In the comparison study, the extraction of features from scanned images of currency notes is a crucial step. Then, a comparison of characteristics is performed to distinguish between counterfeit and authentic items. Certain parameters, such as image segmentation and elimination of linked elements from binary images with fewer than P pixels, which results in the creation of an additional binary image, are used to evaluate performance. The investigations were conducted to distinguish between Indian and Saudi currency notes. The distinction between authentic and counterfeit currency images was based on their dissimilarities. The extracted features were used to detect counterfeit currency. After comparing the features of two banknotes, it was determined whether a bill was genuine or counterfeit [10].

In [6], paper currency detection system based on combined speeded up robust features (SURF) and local binary pattern (LBP) features was proposed. The dataset for the proposed method consisted of 1600 images representing eight classes of four distinct currencies and 200 images used to denote a negative class. There were a total of 1800 images utilized for nine courses (8 positive and 1 negative). The dataset contains images of paper currencies in various orientations and angles, allowing the system to accurately detect rotated or misaligned notes. Combining SURF and LBP features, this system can detect paper currency. The first phase of the proposed system emphasizes image enhancement through pre-processing techniques. Processing of each image frame was accomplished by use of the sliding window method. Features from SURF and LBP were retrieved separately for each frame. In a subsequent step, two features were fused and SVM was applied to identify frames within the region of interest. The system's average accuracy was determined to be 92.6%.

Authors in [1] conducted a research based on Yemen's currency notes. The study made use of a support vector machine (SVM) to train the model based on features such as; colour and texture extracted from the dataset. There were two classes in the dataset: actual and false. After that, principal component analysis (PCA) was employed to decrease the data using texture feature approaches such as SURF, and discrete wavelet transform (DWT). The technique made use of colour and size of Yemeni currency note along with security elements such as microprints, serial numbers, and watermarks. To classify the data, SVM was employed. During performance evaluation, 80% of the counterfeit notes tested were detected.

In [8], researchers looked on the topic of counterfeit currency detection. Detecting edges, extracting features, and identifying the authenticity of the currency notes. The mechanisms of the proposed algorithm consist of the combination of three image processing techniques. Optical character recognition (OCR) is the process of extracting letters from an image. Using this method, the micro-printing feature of banknotes was extracted. The "Bangabandhu" watermark was extracted using a rudimentary object recognition model consisting of mixed-scale dense (MSD) method. The MSD algorithm outperformed PCA in terms of precision and speed. Since ultraviolet lines were absent from the counterfeit note, the Hough transformation was used to extract ultraviolet line features. OCR has the lowest accuracy of the three image processing techniques with 73.33 percent across all models. The proposed procedure has an approximate overall accuracy of 93.33 percent and an average execution time of 6-7 seconds [8].

Automated System for Indian banknote recognition using image processing and deep learning was conducted in [3]. This paper proposed a method for identifying the denomination of Indian currency using deep learning and image processing techniques. The method described in this paper involves first pre-processing the banknote and then using template matching techniques to determine whether the banknote is an Indian banknote or not. This system employs Normalized Cross-correlation as its template matching algorithm. If the input banknote is Indian, then color, contrast, correlation, energy, and homogeneity characteristics are extracted. Two distinct methods, k-NN (k-Nearest Neighbors) and Convolutional Neural Network (CNN), are utilized to classify the various denominations. The accuracy of the k-Nearest Neighbors classifier is 91.18%, whereas the accuracy of the Convolutional Neural Network is one hundred percent.

## 3 Proposed Method

The segments of the developed system are model training and implementation. As depicted in Figure 1, each phase is comprised of a number of effectively completed tasks. The process of training includes validating the model to prevent over-fitting and training the model for optimal fit. During the implementation phase, the model is extracted and then deployed on the entire system.

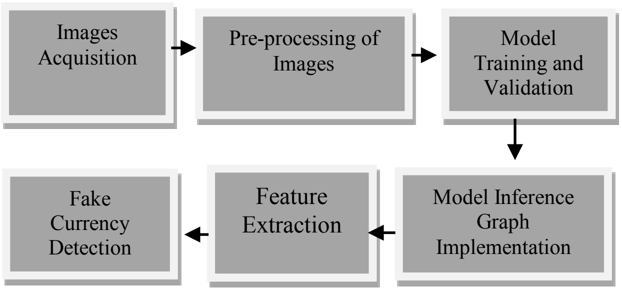


Fig. 1. Proposed system overview

### 3.1 Image Acquisition and Preprocessing

Obtaining fake currency images is the initial process of the entire system. The images are then prepared for further enhancement, and the model is trained and validated. During the model testing phase, the acquisition of fake currency images precedes image pre-processing in order to detect counterfeit notes. After detecting the notes, the images were reprocessed using template matching techniques to effectively recognize the basic features of the notes. The final step in the implementation phase is storing the extracted, recognized notes in a database.

### 3.2 Model Training and Validation

Faster region-based convolutional neural network (Faster R-CNN) with Inception V3 architecture was used to develop the detection model due to its reduced complexity and ability to learn faster with limited number of datasets. Convolutions in the original model were more effective in terms of computational complexity because of the employment of clever "factorization techniques". The Inception V3 model factorizes a convolution of 7×7 and uses an additional classifier to propagate information about labels. The network's performance improved as a result of convolution factorization. For instance, a 3×3 convolutions with the same number of filters is computationally 49/9 = 5.44 times more expensive than a 7×7 convolution over a grid with 'n' filters and 'm' filters. Utilizing a momentum optimizer, the faster-RCNN Inception V3 model was trained. Here, 250 images were utilized to validate the model, after 750 images were utilized to train the model using 15 epochs.

The region proposal network (RPN) received its input from the final convolution layer of the CNN. Regression box differences with regard to anchors were predicted by the RPN together with "objectness". To produce proposals, these offsets were positioned alongside the anchors. The region of interest (ROI) align layer, followed by the classifier and "bbox regressor", received the RPN proposal. The architecture of faster R-CNN is shown in Figure 2. Numerous quantization procedures must be performed to map the generated proposal to precise indexes during ROI pooling implementation. These quantization operations introduce misalignments between the ROI and extracted features. This, however, has some negative impact on object detection. To address the misalignment issue, ROI align was used to remove all possible quantization operations in the network.

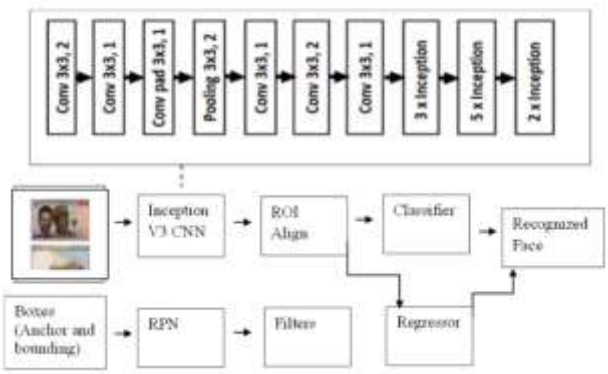


Fig. 2. Faster R-CNN Model on Inception V3 backbone

### 3.3 System Implementation

The inference graph generated after a successful model training was implemented on Jupyter notebook, an open-source web application that permits the creation and implementation of documents that contain codes, algorithms, visualizations, and narrative texts. In order to achieve good results from the detector, the extracted bank note images were further subjected to image processing. Scale uniformity through rescaling of the extracted images has been performed using a suitable equation. Image "binarization" was also performed using a suitable equation to remove a certain number of unwanted details from the extracted bank note images.

### 3.4 System Evaluation

Accuracy of training and validation processes was obtained from the loss function curve.. Training and validation losses were also computed by the model. These losses amount to the trained model classification loss, which is a measure of the predictive inaccuracy of the model. The overall loss function of the model is obtained from the model classification loss. After a successful training procedure, the system was validated with 250 images (positive and negative).

After validating the model, the entire system was tested in real-time with 50 bank notes comprises of 20 counterfeit notes. The system was evaluated using specificity and accuracy as defined in equation 1 and equation 2.

$$Specificity = 100\frac{TN}{TN + FP} \quad (1)$$

$$Accuracy = 100\frac{(TP + TN)}{(TP + FP + TN + FP)} \quad (2)$$

where TN is "true negative", FP is "false positive" and TP is "true positive".

In this study, TP is defined as the number of currency notes correctly detected; TN is defined as the number of fake currency detected; FP is defined as the number of currency falsely detected as fake.

## 4 Results

To demonstrate how the model responded to the training and validation datasets, the training accuracy, training loss, validation accuracy, and validation loss per epoch curves were automatically computed using the model prediction. The results of the 15 training and validation epochs are shown in Tables 1 and 2.

**Table 1**. Accuracy and loss results for model training

| Epochs | Training Accuracy | Training Loss |
|---|---|---|
| 1 | 0.7550 | 0.8710 |
| 2 | 0.9450 | 0.2600 |
| 3 | 0.9750 | 0.2000 |
| 4 | 0.9600 | 0.1900 |
| 5 | 0.9550 | 0.1600 |
| 6 | 0.9700 | 0.1450 |
| 7 | 0.5200 | 0.1000 |
| 8 | 0.9660 | 0.0900 |
| 9 | 0.6680 | 0.0800 |
| 10 | 0.9600 | 0.0700 |
| 11 | 0.9720 | 0.0650 |
| 12 | 0.9750 | 0.0670 |
| 13 | 0.9770 | 0.0690 |
| 14 | 0.9770 | 0.0500 |
| 15 | 0.9800 | 0.0400 |

**Table 2**. Accuracy and loss results for model validation

| Epochs | Validation Accuracy | Validation Loss |
|---|---|---|
| 1 | 0.9245 | 0.3050 |
| 2 | 0.9450 | 0.1860 |
| 3 | 0.9525 | 0.1500 |
| 4 | 0.9645 | 0.1650 |
| 5 | 0.9670 | 0.1000 |
| 6 | 0.9680 | 0.1400 |
| 7 | 0.9690 | 0.1000 |
| 8 | 0.9655 | 0.1600 |
| 9 | 0.9700 | 0.1400 |
| 10 | 0.9710 | 0.1050 |
| 11 | 0.9720 | 0.1000 |
| 12 | 0.9750 | 0.1060 |
| 13 | 0.9670 | 0.1002 |
| 14 | 0.9756 | 0.1003 |
| 15 | 0.9780 | 0.1056 |

After 50 iterations, the loss curve shown in figure 4 was obtained. The plot clearly shows that a highest accuracy of 0.9800 as the loss function reached a minimum value of 0.02. This is the highest validation accuracy for best fit. It's noteworthy to state that the validation accuracy drooped after the 43th iteration, this is an indication of over fitting at 44th and 45th iterations.

## 5 Conclusion

In this study, a fake currency detection system was developed using an improved Faster-Region based Convolutional Neural Network with Inception V3 architecture. The system leverage on the unique features of Region of Interest align to resolve the issues of misalignments caused by the use of Region of Interest Pooling engaged in the traditional Faster R-CNN. The techniques and the developed system were implemented using a Python-based integrated development environment called "Anaconda Navigator". Regardless of skin tone or gender, the developed fake currency detector achieved an accuracy of 96% during evaluation of the system in real-time. A robust system with the capacity to capture and process a wide range of area at a time may be included in future research and development on fake currency detection systems.

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**Conflict of Interest**
The author have no conflicts of interest to declare that are relevant to the content of this article.