A Deep Learning App for Counterfeit Banknote Detection in the WAEMU

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Abstract. In West Africa, counterfeit CFA banknotes impact the economic growth of states. Because of this scourge, we are witnessing a decline in the purchasing power of the population. However, some hardware kits for detecting counterfeit CFA banknotes are available on the market. These kits are expensive for the actors of the informal sector. For them, these kits are not easily portable and also frequently break down. In this work, we propose an approach based on deep learning for the detection of counterfeit CFA banknotes through an Android application. Furthermore, the proposed approach is a first one in the WAEMU in the field of research for the CFA banknote forgery detection. We use an image dataset of over 4000 genuine and counterfeit ten-thousand CFA banknote for our model training. The images of the banknotes are taken by a smartphone camera. We use the convolutional neural network Alexnet for banknote classification. The accuracy of the training model reaches 99.7% for the detection of counterfeit CFA banknotes.

Keywords: Counterfeit detection, CFA banknotes, Deep learning, Convolutional Neural Network, Android

1 INTRODUCTION

The CFA franc is the common currency of eight West African countries that are members of the West African Economic Monetary Union (WAEMU). CFA banknotes have several security features that ensure their reliability and authenticity. These features also facilitate the detection of counterfeit banknotes. Despite these security features, the Central Bank of West African States (BCEAO) is always attentive to the evolution of counterfeit CFA bills. To help the BCEAO in these tasks, we propose in this document, a mobile solution for automatic detection of counterfeit CFA banknotes based on deep learning.

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To facilitate the detection of counterfeit banknotes, some instruments such as the Safescan 45, the Valorisatrice CAT800 detector, the Fiducontroles exist on the market. These tools are generally used by merchants, banks and financial institutions. But the major problem is that most of the informal sector actors do not use these tools because they are expensive, immobile and frequently broken-down. If nothing is done, this can reduce the incessant checking of banknotes at these entities and increase the likelihood of counterfeits entering the country's economy. In the informal sector, small traders, grocery stores, restaurants, petrol stations, carpenters and others appreciate mobile solutions to the problem of forgery. In reality this solution is portable and easy to carry as application in an android phone.

In this work, our purpose is to design a mobile application using a machine learning algorithm specifically on convolutional neural networks for CFA banknotes authentication [1]. To do this, we use Alexnet's algorithm [2] based on convolutional neural networks. Thus, we obtain a global accuracy of 99.8% for the classification of banknotes of 10000 FCFA and 99.7% for the detection of counterfeit. In section 2 we present the literature review, then the proposed methodology in section 3, the results in section 4 and finally the conclusion and perspectives in section 5.

2 STATE OF THE ART

A large number of work in the litterature propose many approaches for counterfeit banknote detection in machine learning. For example, Martin et al. [3] propose an approach based on artificial neural networks. With some images of Chinese banknotes, they use techniques such as translations, rotations, scaling, brightness variation, gaussian blur, random figures on images and others to augment the data. They use a deep learning model of the AlexNet network with an architecture consisting of five convolution layers and three strongly connected layers. For training the AlexNet neural network model, 5000 samples were generated. The size of the images was 150×150 of 3 RGB channels (Red Green Blue). The result of the training of the model was 94% accuracy. This approach is simple and effective for the detection of forgery in Chinese banknotes. Also, the advantage of this approach is that it is generally appliable to other banknotes in the world.

Yan et al. [4] proposed in 2013 to extract the color features and texture features of the banknotes and train a forward propagation neural network. As a result, thanks to this convolutional neural network, the training of the model reached 98.6% accuracy. Indeed, this type of network is a good candidate for the classification of banknotes where the color of the images is a differentiating factor. That approach helps us to understand the performances of CNN models in banknotes recognition.

Syed et al. [5] focus on the GAN (Generative Adversarial Networks) algorithm for there Deep-Money approach. In that solution Seyd et al. use a generative model composed of a generative network and a discriminator network. The discriminator is trained on the basis of the generated data and the training data. In addition, the discriminator has a classifier function to recognize the images, but collaborating with the generator. In the process, the generator generates an image and sends it to the discriminator, which tries to recognize it. If this image is recognized it produces an output, if not the discriminator returns the image to the generator for improvement. Then the generator regenerates the image by improving it and sends it back to the discriminator for recognition. This process is looped until the model is optimal by generating the same good image perfectly classifiable. In the case of the recognition of counterfeit banknotes, the generator generates the counterfeit banknotes and the discriminator makes sure that the data it receives comes from either the generator or the training data. Seyd et al. obtain an accuracy of 80% as a result of the training on data. This solution does not give a good accuracy in distinguishing counterfeit bills from real ones.

In Ethiopia, A. Shefraw [6] has set up a banknote recognition system. In his method, he uses an HP jet 2710 scanner to scan the banknotes. Then he resizes the images to 640×312 pixels. Furthermore, he converts the RGB (Red Green and Blue) format to the grayscale format of the image. The method proposed by Shefraw is composed of eight convolution layers and two fully connected layers. Between each convolution layer, there is a ReLU activation layer. In the first convolution layer, filters extract features from the image to detect parts of it. This process also occurs as the image passes through the filters in the different layers of the network.
In practice, Shefraw collected images of Ethiopian banknotes of 5, 10, 50 and 100. In his model, he combines ANN, SVM and KNN classification systems. The training time of the model is longer than the time needed to extract the features. In the classification of Ethiopian banknotes, an accuracy of 99.4% was achieved with the FFANN network. For the verification of counterfeit banknotes an accuracy of 96% has been achieved.

Lee et al. [1] propose an algorithm based on a two-layer convolution model with a ReLU activation function, a max-pooling layer, two fully connected layers with a dropout function and finally a SoftMax function. After training the model, over 25 epochs the accuracy rate reached 100%. In this approach, Lee et al do not refer to a standard model such as ResNet, LeNet, VGGNet, AlexNet or GoogleNet. They proposed their own empirical algorithm according to the results of the model. Also the network is not deep enough for deep feature extraction of banknote images.

In there approach, Mohamad et al. [7] rely on artificial neural networks. After acquiring the banknote images, they apply the operations of gray level image conversion, wavelet transforms for determining the variances, skewness, entropy and class of the images. Then they segment the images of the bills and proceed to the training of the model. In their network, they define the activation functions, the biases, the weights and the initial values of the parameters are generated. The default algorithm is the Levenberg-Marquardt or trainml.

Laavanya et al.[8] used the convolutional neural network AlexNet as a method for recognizing and classifying counterfeit Indian banknotes. The model was trained on a dataset of 100 Indian banknote images and 50 augmentation images. As a result they obtain a recognition accuracy of 81.5% for real banknotes and 75.0% for fake banknotes.

In the study published by Dittimi et al. [9] in 2018, they mention the problem of detection as related to visually impaired people. This is because while using banknotes, people detect fakes by inspecting the images, words, numbers, distinguishing marks, consistency and size of the banknotes. This technique is not reliable because of possible human errors. Dittimi et al. have developed a purely mobile version of the counterfeit bill recognition application. For this research, 2310 genuine and 2048 fake Nigerian bills were collected, ranging from five to one thousand naira. Thus, they present a mobile application for banknote identification and authentication using OCR in conjunction with a KNN adaptation. The proposed system had a recognition rate of 99.27%, and a detection accuracy of 94.70% with a processing time of 0.02 ms. This approach is interesting because it offers a mobile solution that can be useful for the informal sector. We use this possibility for the proposal of a deep learning algorithm.

In this paper, Omatu et al. [10] propose an empirical model based on Principal Component Analysis (PCA), Learning Vector Quantization (LVQ) and an algorithm that relies on the Gaussian density assumption. PCA is intended feature extraction from banknote image data. LVQ represents the main classifier of the recognition model. As an alternative classifier, they use the hidden Markov model. For the classification result, they achieve a recognition accuracy of 100% after applying the LVQ method.

3 PROPOSED METHODOLOGY

3.1 Dataset

Our dataset includes images of counterfeit and genuine CFA banknotes. Thus, to obtain the data we used three sources which are:

- The platform [1] of the world banknotes images dataset;
- Through our own bills scanned by a smartphone;
- And in the finance office of Nazi BONI University.

In sum, we collect one hundred and fourteen (114) images of banknotes of five hundred, one thousand, two thousand, five thousand and ten thousand francs mixed front and back. As for the counterfeit bills, we have collected nearly two hundred and seven (207) images front and back using a smartphone as show in table 1. But, our study focuses only on the 10,000 CFA franc banknotes.

Table 1: Banknote dataset

Genine Banknotes	fake Banknotes	Total Dataset
114	207	321

[1] http://www.banknote.ws

3.2 Data augmentation

In deep learning, the data augmentation technique allows to increase the size of the data and to diversify it. This is done thanks to some geometric transformation operations in image processing. This technique is necessary in our context as our images are not numerous. After data augmentation process the global dataset reaches more than 4000 images. The augmentation methods used are described in the table 2.

Table 2: Preprocessing and data augmentation

Data preparation	Geometric transformation
Size standardization	Image rotation
Image segmentation	Image zooming

- Image size standardization
Image standardization is used to define the size of CFA banknote images. According to Asfaw Alene Shefraw in [6], the recommended size is 1122×570 or 640×312 for banknote image classification. Even compared to the computational complexity of the algorithms, the 640×312 size is better [4]. So, we normalize all our images to a size of 640×312.

- Image rotation
It is a geometrical transformation that allows to obtain an image of the initial figure based on the sliding around a point called center of rotation defined according to an angle and a direction. This makes it possible to obtain different images with different angles of rotation [3]. All these operations allow to force the model to scan everywhere on an image and to take into account the image capture positions by the users.

- Image zooming
This operation allows to change the magnification and the angle of view of an image without moving it. It allows to increase the data with variable parameters.

- Image segmentation
In our context we choose to adopt the segmentation based on the classification or thresholding of pixels according to their intensity. This operation consists in dividing the image into different zones, so that an object or a color zone can be better distinguished. This operation will allow the neural network to better identify the objects, the color zones, the contours and their arrangements on the banknotes [7].

3.3 Architecture

In deep learning, neural networks are a good candidate for image classification. Thus, we propose an adapted classification model based on the Alexnet architecture [3]. This model consists of a first input layer, five convolution layers, four pooling layers each exposed after a convolution layer, a vector linearization layer, at least one fully connected layer consisting of three dense layers. The

convolution layer includes the convolution and the network activation operations.
AlexNet is a convolutional neural network designed by Alex Krizhevsky and his collaborators. AlexNet algorithm was successful in the ImageNet challenge for visual object recognition called ImageNet Large Scale Visual Recogniton Challenge (ILSVRC) in 2012. It achieved the best recognition result compared to other traditional approaches. In addition, AlexNet has a fairly deep network with eight layers containing five convolution layers. It can be used on the ImageNet database which contains more than one million training sets of images. An input image belongs to one of a thousand different classes and the output of the network is a vector of a thousand classes. Also, it is basically designed for the recognition and classification of large-scale images. For these reasons, AlexNet algorithm motivates us to adopt it for CFA banknote classification. In our proposed model, we only keep the original design of AlexNet by modifying the number of parameters and the size of the convolution kernels. During the training of the model we faced the performance limits of the computer used. Thus, we reduced the number of parameters of the network as we went along to allow the computer to support the training of the model. The chosen parameters are presented in the figure 1. Our model is in the case of a binary classification in view of the number of classes we want to predict. We therefore have only two classes, namely the counterfeit bills and the genuine bills [2]. The reduction of the parameters of the algorithm allows it to be adapted in a binary classification framework. Also, this adaptation of the Alexnet network allows to reduce the computational load and the training time of the network.

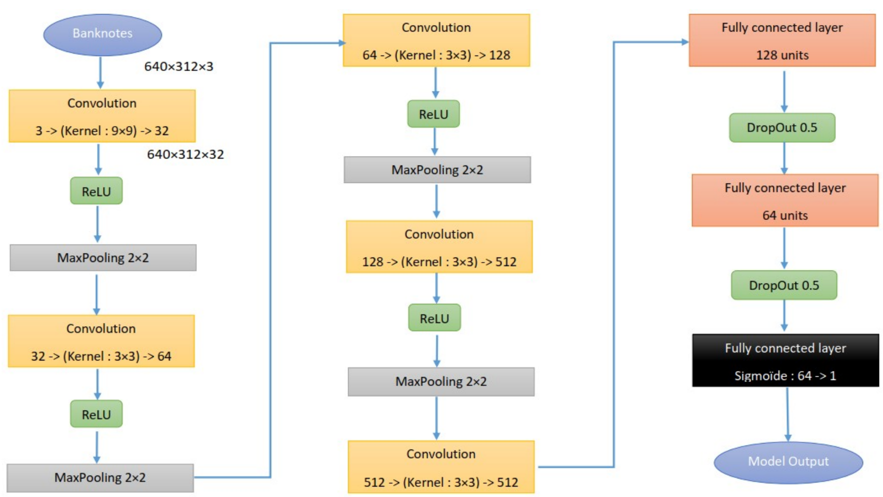

Fig. 1. Neural network architecture

The input layer and the output layer correspond respectively to the input image and the result of the discrimination. In all layers, the activation function used is the ReLU function. The configuration of our neural network used is illustrated in the figure 1.

3.4 Banknote authentication process

The CFA banknote authentication mobile app scans banknotes through the camera. When the user logs into the application, he scans the image of the banknote. Then the quality of the image is checked by calculating the Peak Signal to Noise Ratio (PSNR). The PSNR is commonly used to measure the quality of reconstruction of compression codecs in image processing [11]. If the image quality is right, it is sent to the banknote classification module. This module embeds the trained model that classifies a bill as genuine or counterfeit as described in Figure 2.

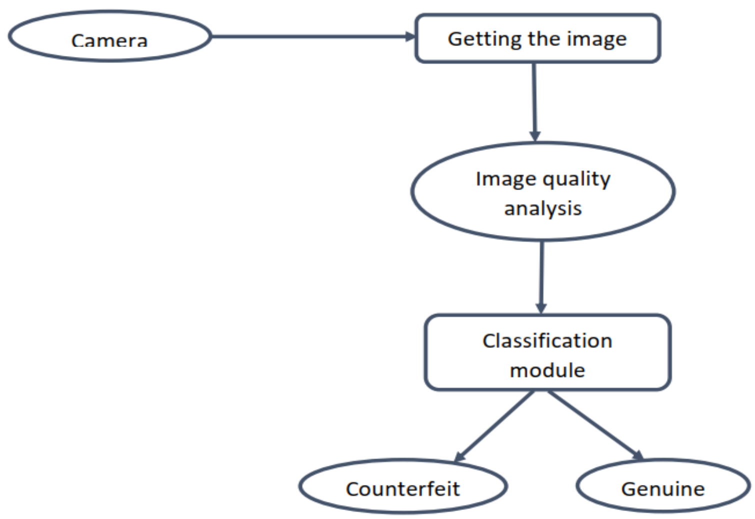

Fig. 2. Banknote authentication process

4 EXPERIMENTAL RESULTS

This section explains the experimental setup and analyzes the results obtained. Here we evaluate the performance of the proposed model. As discussed earlier, the dataset is divided into 70%, 15% and 15% subsets for training, testing and validating, respectively. We used a computer brand HP i5 intel CPU of 2.6 GHz. We increased the size of the RAM memory to 50 GB for training the model.

4.1 Model training and testing results

The model classifies the banknotes into two groups: one group representing the label of good banknotes, the other label representing fake banknotes. We classify a good bill by 1 and a fake bill by 0. The test reveals a consistently high f1-score for bills labeled 1, i.e. for genuine banknotes. The overall fair prediction score of the model is 99.85%.

Table 3: Model qualification metrics

Metrics	Definition - formulation	Value in %
Precision	TP / (TP + FP)	99.7%
Accuracy	(TP + TN) / (TP + FP + TN + FN)	99.84%
Recall	TP / (TP + FN)	100%
F1-score	2*TP / (2*TP + FP + FN)	99.85%

Where TP : True Positive, TN : True Negative, FP : False Positive and FN : False Negative After training our neural network model, we obtained an accuracy of 99.84% on the training data. For the validation data, we reached 99% accuracy (see figure 3 and 4). In order to show the results

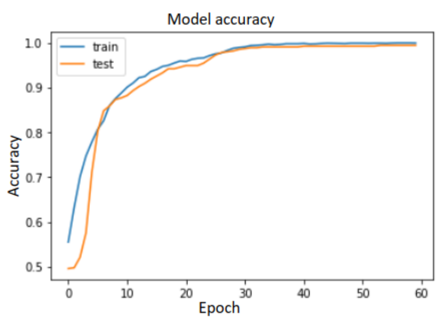

Fig. 3. Training/validation accuracy

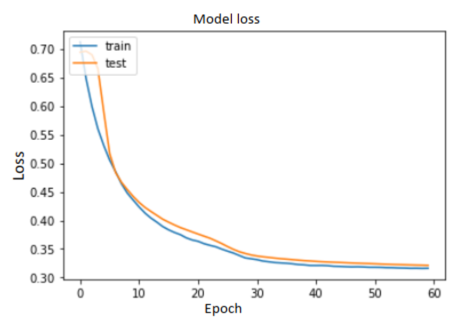

Fig. 4. Training/validation Loss

obtained from the model, we illustrate in the table 3 the results in terms of accuracy and error as well as the confusion matrix.

Our dataframe contains more than 4000 images of authentic and counterfeit CFA banknotes. In the test dataset there are 652 banknotes of which 343 are genuine and 309 are counterfeit (and recognized as such) on the rows in the table 4. After the prediction, we obtain in column of the matrix a recognition of the set of authentic banknotes as such. For the counterfeit banknotes, a prediction error appears on all the 309 banknotes.

In this section, we show a comparison with another models on banknotes recognition. Thus, we present the achievements and classification performance of our approach in the table 5.

Table 4: Confusion matrix

		Predicted classes	
		Authentic banknotes (class 1)	counterfeit banknotes (class 0)
Current classes	Authentic banknotes (class 1)	343	0
	counterfeit banknotes (class 0)	1	308

Table 5: Models comparison

Authors	Papers	Models	Accuracy	Android
Martin et al.	A Deep Learning Model for Chilean Bills Classification	AlexNet	94%	No
Yan et al.	An empirical approach for currency identification	Feedforward Neural Network	98.4%	No
Dittimi et al.	Mobile app for detection of counterfeit banknotes	KNN	99.27%	Yes
Seyd et al.	DeepMoney: counterfeit money detection using generative adversarial networks	Generative Adversarial Networks	80%	No
Our model	A Deep Learning App for Counterfeit Banknote Detection in the WAEMU	AlexNet	99.7%	Yes

4.2 Description of the model output

To describe the observed output of our training model, we choose the Shapley value method of cooperative game theory. This approach allows us to explain the output of machine learning models [12]. We can express the Shapley value of a banknote image as the expected value of the weighted marginal contribution to a random sample S of images from our entire training set excluding this image, rather than an exhaustive weighted sum. In our dataset we choose a few banknote images to describe the Shapley value (in Fig. 5). We use this algorithm to determine the features that distinguish genuine from counterfeit banknotes.

Figure 5 shows a model output for seven banknote images. The first three images are genuine bills and the last four are counterfeit bills. On the three genuine banknotes, the red pixels increase the model output. On the counterfeit banknotes, the blue pixels decrease the output of the model.

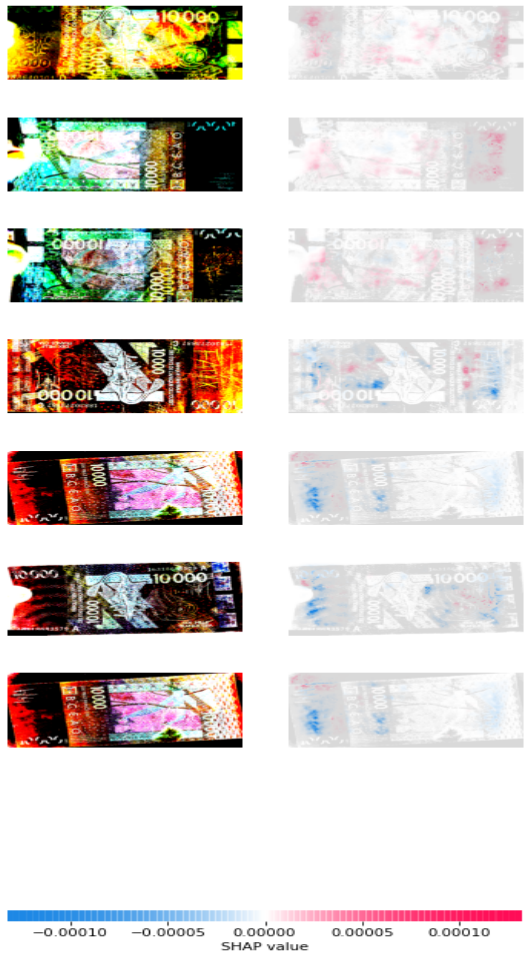

Fig. 5. Shapley values

These colored pixels therefore represent the feature areas that allow the model to classify the banknotes as counterfeit or genuine.

4.3 Mobile app

Banknotes authentication is a mobile application that allows users to register and then authenticate. On the home page, the user can select open camera (by pressing ”SWIPE UP”) to start scanning a banknote image. The scanning page is presented in figures 6 and 7.

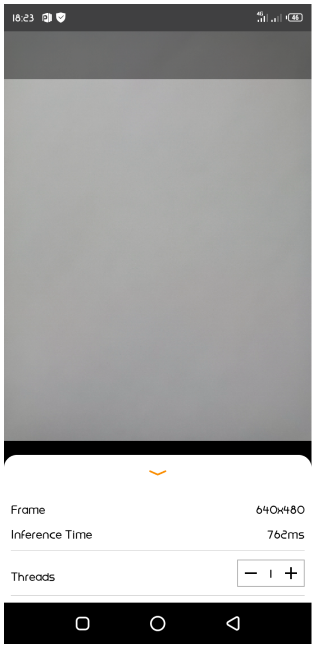

Fig. 6. Scan page

Fig. 7. Prediction test of 10,000F CFA banknote

When the user performs the scan, it is shown the prediction score of the banknote and the label corresponding to a counterfeit or genuine banknote. In the example of the figure 7 one notices that the banknote of ten thousand francs CFA is predicted among the label of the good banknotes (authentic) with a prediction score of 95.25%. In general, the prediction score is between 90% and 99%. This result is due to that the sharpness of the image is difficult to have in real time. The variable execution time is 836 milliseconds (ms). On average the execution time of prediction of CFA banknotes is 800 ms.

5 DISCUSSION

The results obtained after evaluation of our classification model show the model performance. The accuracy of our classification model reached 99.84% for the training. Thus, this means that the model has learned the features of the banknote images in our dataset well. The classification phase of the sets of fake and good banknotes is therefore clean and accurate. The model is therefore able to be accurate when sent any new banknote in terms of class prediction. But in the mobile version, the execution time of the banknote predictions needs to be improved in order to reduce it.

The second limitation concerns the data of the banknote images. Indeed, we were able to come into possession of few images of counterfeit bills. Traders and households are immediately suspicious when the subject of counterfeit CFA bills is raised. They have counterfeit bills, but their fear outweighs their reason. The only counterfeit notes that we were able to come into possession of were available at the Financial Department of the Nazi BONI University. These counterfeit bills are 10 in number. However, the presence of a small number of image data can bias the model and play on the convergence of the metrics of the classification model.

Also, the capture of the images by our smartphone can be a limitation for obtaining a more reliable model. In addition, there is a major memory space problem when training our model. In fact, training it requires a memory space of at least 20 GB of RAM. This prevents us from applying the cross-validation technique on our training set because it requires a huge size of RAM storage. Thus, this lack of resource may be crucial in the finality of our results.

6 CONCLUSION AND PERSPECTIVE

In this paper, we proposed a convolutional neural network model based on the AlexNet model architecture for banknote authentication. After training the model we successfully made predictions on a new dataset of images of fake and good CFA banknotes. The overall accuracy of the model reached 99.84%. Subsequently, we designed the mobile platform for the prediction and detection of counterfeit banknotes. This application embeds the light version of the counterfeit banknote detection model. Thus, this application is able to authenticate CFA banknotes by scanning the banknote image with an average execution time of 800ms. This mobile solution helps traders in the informal sector to continuously check the authenticity of CFA banknotes.

The evaluation tests of our model gave an approximate score of 99.85%. The results obtained show a good distribution of our data in the different classes. This represents a good approach to solving the problem of counterfeit CFA banknotes detection. In the future, we plan to include counterfeit and good bills of five hundred, one thousand, two thousand and five thousand CFA francs in our dataset. As an approach to improve the classification model we recommend an improvement of the recognition model using neural network architectures such as GoogLeNet or LeNet with a larger dataset including 5000, 2000, 1000 and 500 CFA banknote images.

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