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# Convolutional neural networks method for folded Naira currency denominations recognition and analysis

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## Abstract

Sorting banknotes automatically in payment facilities or freewill donation boxes involves many tasks such as recognizing banknote denomination, fitness classification, and counterfeit detection. Different studies have addressed these problems using foreign currencies. In other words, very few researches have been conducted on naira banknote denomination recognition. A few studies did not consider folded naira banknote denomination recognition. To overcome this, we propose a Machine Learning Based Folded Banknote Denomination Recognition System. The proposed system automatically extracts relevant features and characteristics of the naira currency denomination in different positions, orientations, and folds. This automatic representation of the naira currency denomination enables the proposed system to reduce over-reliance on suggested characteristics, improve performance accuracy, and generalize the proposed system to new problems. Moreover, the proposed system was modeled using object-oriented analysis and design methodology, and implemented in the Keras framework interfaced with Tensorflow. Then, the Softmax classification algorithm was used to classify each Naira banknote denomination. The proposed machine learning-based folded banknote denomination recognition achieved an average accuracy of 95%, which shows the generalization ability of the proposed system to recognize folded banknote denominations in different orientations, positions, and folded forms.

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## 1. Introduction

Despite a decrease in the use of currency due to the recent global expansion in electronic financial transactions, transactions in real money continue to be very vital in the global market [1]. While performing transactions in real money, touching and counting notes by hand is still a common practice in daily life.

Most religious organizations support their denomination with real money (cash) especially their offering or olfactory collection. The problem of accountability has been observed on several occasions. The use of automated machines has become essential for these transactions. However, the focus of most of the conventional currency recognition systems and machines is to use well-arranged/stretched banknotes for the recognition of banknote types, denominations, counterfeit detection, serial

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number recognition, and fitness classification. It is not enough for religious organizations where paper money is dropped in several folded positions. Conventional currency recognition machines such as automated self-service machines which include automated teller machines (ATMs) for cash deposits and withdrawals, as well as bill payments and transfer between accounts financial transactions, banknote counters, and coin counters, are mostly used in banks, and automatic vending machines, into which money is inserted to purchase goods cannot be used for this purpose. Therefore, these machines are responsible for specifically recognizing stretched paper currencies. However, any pieces of folded currency are not known and cannot be recognized by the system, but would be rejected in an ideal situation. Hence, it is necessary to develop banknote denomination recognition systems and bank machines that can not only carry out the conventional recognition and classifications for paper banknotes but also for folded banknotes.

Banknote recognition generally concerns the classification of banknotes by various denominations such as the banknote denomination amount of a note of a specific country. This classification also enables recognition of the year of printing, side, and input direction of the classified denomination. The reason for classifying direction and side in addition to denomination is that the position of a region of interest (ROI) within a banknote, which is used to implement the later process steps (serial number recognition, counterfeit banknote detection, and fitness classification), changes according to the direction and side of the banknote. Most of the studies in conventional banknote recognition utilize visible-light line sensors, such as contact image sensors (CIS) [1]. These sensors capture colored or black-and-white images and are used for the typical process flow of banknote recognition which includes preprocessing, feature extraction, classification, and verification [2]. Using a color image sensor is more advantageous because it provides more information than a black-and-white sensor, but its production cost is higher [3]. Image resolution, national currencies, and classification criteria are the factors influencing the efficiency of banknote recognition.

Automated Banknotes denomination recognition is one of the most challenging problems in computer vision [1]. This is because there are different denominations and currencies across various countries around the world. Even though recognizing banknote denominations of these multi-national currencies has become very essential in our daily lives. The applications have found their way into services such as automated teller machines, transaction management, automated vending machines, and automated payment online [4, 5]. Ensuring these financial services work efficiently as expected requires recognition of the currency denomination which helps to speed up and increase the amount of transaction. Moreover, banknote denomination is important in counterfeit detection, recognition of new and old banknotes, and currency denomination recognition for visually impaired individuals where the system helps to reduce the risk of becoming victims of deception during transactions either due to currency complexity or dishonesty by people. The transaction with fake currency would lead to economic loss.

In banknote recognition system, features of a specific country's currencies such as color, textures, values, etc. are extracted and fed to the recognition system to detect the country's currency and denomination values. However, most of the detectors designed for these currencies are country-specific and found it difficult to recognize or generalize to currency banknotes of other countries. Moreover, the recognition systems utilize magnetic and optic sensors that are difficult to acquire [6]. The customization of the systems makes it challenging to utilize currency features such as color, textures, and conventional machine learning algorithms of another country's national currency as the feature/characteristics may defer. To solve the problem, this thesis designed and implemented an automated banknotes denomination recognition system by utilizing the convolutional neural network. The developed system takes images captured with a mobile phone camera and automatically extracts the right features that would aid the recognition of the banknote denomination.

Consequently, the problems inherent in the current banknotes denomination recognition system include, first, the lack of sufficient dataset for Naira banknotes denomination recognition. Most of the banknotes datasets in recent studies [7] are related to Euro, dollars, Indian Rupee, etc., and has made developing an efficient Naira banknotes denomination recognition system challenging. Second, most of the studies in the banknote recognition system deploy conventional machine learning methods such as support vector machine, random forest, and k-nearest neighbors utilized that are not robust, and computationally intensive due to the high dimension of features vectors and attributes required to obtain high performance. The conventional models lie on manually extracted features/characteristics such as shape, size, and texture that tend to reduce the accuracy of the banknote recognition system. In addition, the existing banknote recognition systems utilize low-level feature representations such as color, shape, texture, and pictures to recognize and describe banknotes. The descriptions might be simple, but they lose semantic information and cannot achieve satisfactory results, especially for counterfeit and forgery detection purposes [8]. Finally, there is no definite number of ways that banknotes can be folded. Banknotes can be folded in multiple ways, at different locations and environments with poor illuminations. These stated conditions make banknote recognition challenging.

To proffer solutions to the identified issues, we developed a deep learning model termed *Machine Learning Based Folded Naira Banknote Denomination Recognition System* to improve the recognition rate of banknotes in different forms, positions, and folded angles. Specifically, the thesis developed a convolutional neural networks model to automatically extract attributes from raw naira banknote currencies captured using a camera and instantly recognize the values of the currencies. The main strength of the proposed system is its ability to automatically capture naira banknotes, and accurately recognize the denomination without human efforts.

The importance and relevance of the proposed banknotes denomination recognition system cannot be overemphasized. This is because the developed system can be used for various services such as automated teller machines (ATM), counting machines, vending machines, and social services such as providing means of recognizing genuine currency and denomination for visually impaired individuals. The proposed system utilizes convolutional neural networks (CNN) to extract relevant features and recognize banknotes denomination in real time.

The main contribution of this research to the body of knowledge are:

1. Developed comprehensive Machine Learning Folded Naira Banknote Denomination Recognition System to recognize naira banknote denominations;
2. Implement a data collection protocol to automatically collect a large number of naira banknote images;
3. Develop a module to preprocess the naira banknote for feature extraction;
4. Automatically extract relevant features from the collected banknote images using convolutional neural networks;
5. Accurately predict banknotes denominations using Softmax regression classification algorithm;
6. Evaluate the implemented deep learning-based banknote recognition system using appropriate machine learning model performance measures.

## 2. Review of related literature

This section discusses previous studies in machine learning for banknote recognition systems. The section is divided into convention and deep learning models for banknote denomination recognition.

### 2.1. *Conventional machine learning for banknote recognition*

A field of computer vision that provides the ability of computers to view and learn things without the system being programmed explicitly is called machine learning. It was developed because of the computation theory of learning in artificial intelligence. It identifies and classifies data such as images, objects, and videos. It builds an algorithm to analyze, learn from raw data, train, and make predictions. Conventional machine learning is a process where by computer learn from data by training and using an algorithm to develop a trained model. The algorithm used to develop a trained model is based on learning. The pre-trained model is used to recognize or classify the test dataset. A back-propagation algorithm of an artificial neural network was employed for Indian currency recognition [9].

### 2.2. *Deep learning methods for banknote recognition*

Five major types of deep learning methods have been used for various applications. These deep learning methods include the Restricted Boltzmann Machine, Deep Autoencoder, sparse coding, convolutional neural network, and recurrent neural networks.

#### 2.2.1. *Restricted Boltzmann Machines (RBMs)*

RBMs were invented by Geoffrey Hinton and can be used for dimensionality reduction, classification, regression, collaborative filtering, feature learning, and topic modeling. RBMs been a generative model serve as a building block in layer-by-layer feature learning and training of deep neural networks. The training of the model is with contrastive divergence (CD) which provides unbiased estimates of maximum likelihood learning [10]. To provide efficient feature extraction, several RBMs are stacked to form visible-to-hidden units, and the top layers are fully connected or embedded with classical machine learning to discriminate feature vectors [11]. The two Restricted Boltzmann Machine methods are Deep Belief Network and Deep Boltzmann Machine.

#### 2.2.2. *The auto-encoder*

The auto-encoder method produces the most discriminative features from unlabeled data by projecting them to lower dimensional space using an encoder and decoding units. The input values are replicated as output by the Autoencoder. To minimize the error rates. The auto-encoder is optimized by minimizing the reconstruction error, and the corresponding code is the learned feature during the process. The three important types of auto-encoders are sparse auto-encoder, denoising auto-encoder, and contractive auto-encoder.

Nweke *et al.* [10] proposed that Sparse coding is a machine learning technique for learning over a complete basis to produce efficient data representation. Having an effective means of reducing the dimensionality of data and dynamically representing the data as a linear combination of basis vectors enables a sparse coding model to capture the data structure and determine correlations between various input vectors. Some advantages of sparse coding include patterns with sparse features being more linearly separable, reconstructing the descriptor better by using multiple bases and capturing the correlations between similar descriptors which share bases, image patches are sparse signals and it is in line with the biological visual system, which argues that sparse features of signals are useful for learning [12].

### 2.3. *Recurrent Neural Network (RNN)*

RNN is a special type of deep learning adapted to work for time series data or data that involves sequences. RNN was developed to model sequential data such as time series or raw sensor data. RNN incorporates a temporal layer to capture sequential information and then learns complex changes using the hidden unit of the recurrent cell. RNN are developed by stacking multiple recurrent layers and allow control of the signal flowing from the upper layer to the lower layer. The mechanism is done by adaptively controlling based on the previously hidden state and assigning different layers with different timescales [10]. But among these deep learning models, convolutional neural networks are the most widely used in currency recognition [13–15]. This is because currency recognition uses an image processing approach and image processing mainly uses the CNN method.

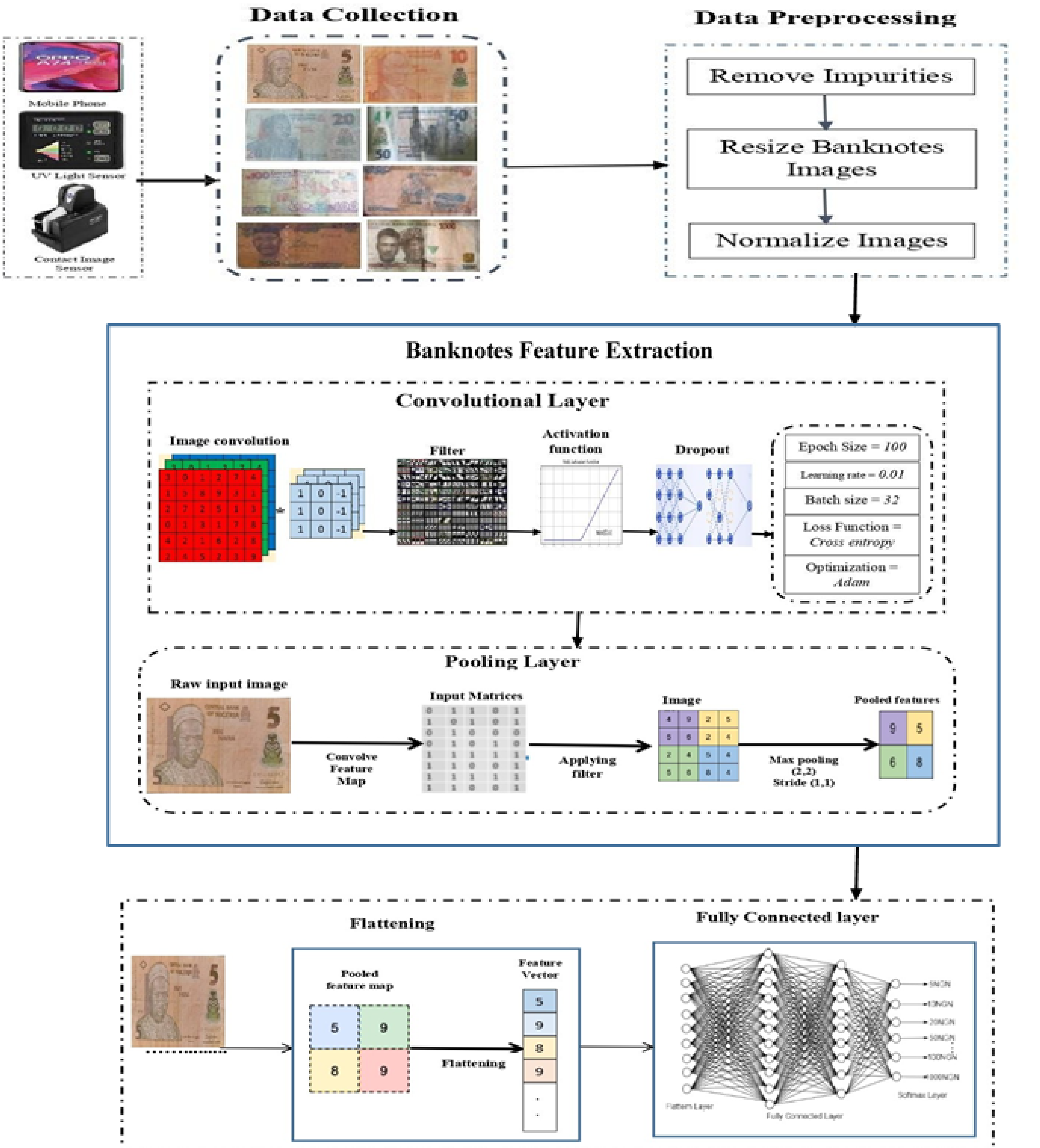


Figure 1. Machine learning-based folded banknote denomination recognition system architecture.

### 2.4. *Convolutional Neural Network (CNN)*

is a deep neural network with interconnected structures that performs convolution operations on raw data [10]. It is one of the most thriving deep learning approaches where multiple layers are trained in a very powerful way. CNN is most commonly used in Image processing and computer vision. Image Classification and Segmentation, Object Detection, Video Processing, Natural Language Processing, and Speech Recognition are some of the exciting application areas in CNN [16]. The use of multiple feature extraction in CNN made it a strong learn-


Figure 2. Sample Naira currency denomination. (a) five naira note, (b) ten naira note, (c) twenty naira note, (d) fifty naira note, (e) hundred naira note, (f) two hundred naira note, (g) five hundred naira note, and (h) one thousand naira note.

ing tool that can automatically learn representations from the data. The convolutional layer, pooling layer, and fully connected layer are the generally accepted components of a convolutional neural network. The fully connected layer is fused with the inference engine such as SoftMax, Support Vector Machine, or Hidden Markov Model that takes the feature vectors from data for currency recognition. To learn patterns across the input data in CNN, activation unit values are computed for each region of the network [17]. The convolutional layer captures the feature maps with different kernel sizes and strides and then pools the feature maps together to reduce the number of connections between the convolutional layer and the pooling layer. The pooling layer reduces the feature maps, and number of parameters and makes the network translational invariant to changes and distortion. In the past, different pooling strategies have been proposed for Convolutional Neural Network implementation in various areas of applications. These include max pooling, average pooling, stochastic pooling, and spatial pooling units [12]. Recently, theoretical analysis and performance evaluations of these pooling strategies have shown superior performance of max pooling strategies. Thus, the max pooling strategy is extensively applied in deep learning training. Other ideas that advanced CNN include architectural innovations, activation functions, regularization methods, Optimization strategies, etc. AlexNet, Clarifai, SPP, VGG, GoogLeNet are the categories or architecture of CNN [12]. These architectures were developed by the following researchers AlexNet [18], VGG [18], and GoogleNet [19]. Generally, the idea of a convolutional neural network (CNN) was inspired by Ref. [20] which noted that the human visual cortex consists of maps of the local receptive field that decrease in granularity as the cortex moves along the receptive fields [10]. Since the proposal, several other Deep CNNs achieved notable improvement in the representational capacity through architectural innovations.

## 3. Proposed methodology

This method describes the methodology adopted to develop the machine learning- based folded naira banknote denomination recognition system. The section is divided into different subsections and includes data collection, preprocessing, and a description of the proposed deep-learning model for banknote

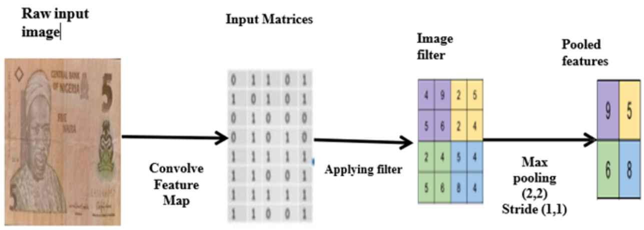


Figure 3. Polling layer of the proposed system.

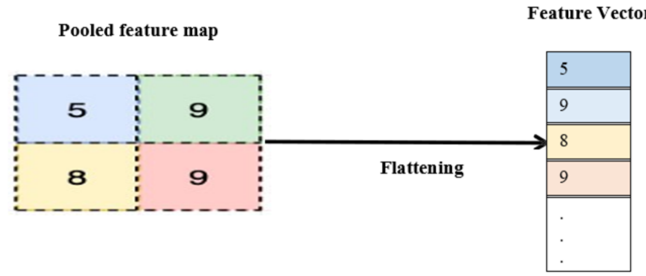


Figure 4. Flattened feature vectors.

recognition. Moreover, the section discusses the evaluation approaches adopted to evaluate the proposed bank recognition model. The architecture of the proposed system is shown in Figure 1.

### *3.1. Naira banknotes image collection*

In the implemented model, the data collection component of the system holds the raw naira banknote images in the form of (256X256 X 3) representing the dimension and color of the image. We collected different datasets of naira notes in different denominations, orientations, and positions. The denominations collected include N5, N10, N20, N50, N100, N200, N500 and N1000 notes. Different image sizes of this banknote denomination were also collected in different positions. Each naira banknote contains the Nigeria coat of arms, human pictures, denomination values written in English, Igbo, Yoruba, and Hausa language, serial numbers, and other objects. The images of these banknotes were captured using different mobile phones with high-resolution cameras from different backgrounds and viewpoints. Some of these images were folded once, twice, and many times to represent the natural usage of the banknotes. The banknotes were also captured on the front and back sides in arbitrary directions. The captured images were twenty-four thousand (24,000), three thousand for each denomination. A sample of the collected banknotes is shown in Figure 2.

### *3.2. Data preprocessing and cleaning*

The collected banknote currency image may be affected by noise or of different sizes and input shapes. This might affect the performance of the proposed deep learning models and the generalization of results obtained. Therefore, it is important to remove impurities from the images before feeding them to the models for feature extraction. We utilized approaches such as image resizing and normalization to clean the collected images' banknotes. Furthermore, Image resizing and normalization were necessary as the images captured vary in size, therefore, we ensure that each naira input parameter has a similar data distribution. The preprocessed banknotes images were saved, and then to be used as input to the proposed model.

### *3.3. Convolutional neural networks for folded Naira currency*

A convolutional neural network is a deep neural network with interconnected structures that performs convolution operations on raw data [10]. The method is the most important or the most implemented deep learning model that integrates multiple layers trained in a very powerful way. CNN is majorly implemented for tasks such as Image processing and classification of images and segmentation, computer vision, Object Detection, Video Processing, Natural Language Processing, Speech Recognition, etc. The convolutional neural networks consist of different layers and include a convolutional layer, a pooling layer, and a fully connected layer. These layers are explained following subsections.

#### *3.3.1. Convolutional layer*

The convolution layer (CL) is the first step in the process of extracting useful features from images. It is the most important operation in CNN [21] which uses convolution to extract relevant attributes from the banknotes images. Convolution performs linear operations that multiply a set of weights with the input, much like a traditional neural network. Given that the technique was designed for two-dimensional input, the multiplication is performed between an array of input data and a two-dimensional array of weights, called a filter or a kernel. The convolutional Layer applies a convolution operation to the input. These layers have filters (kernels) and strides that perform the convolution operation [22]. The output of the convolution layer is called a feature map. In the proposed machine learning-based banknotes denomination recognition systems, we developed three layers of convolutions with sixteen (16) channels, a 3 by 3 filter at the first layer, thirty-two channels and a 3 by 3 filter in the second layer, and sixty-four with 3 by 3 filters at the third layer. This enables the proposed system to extract deep and discriminant features from collected banknote images. Moreover, the convolutional layer has many hyper-parameters that might be tuned to extract more relevant features from images. These hyper-parameters include:

1. Filter: filter is used to detect spatial patterns in the edge of the banknote images by detecting the changes in their intensity values, positions, and orientation. Therefore, we defined a filter dimension of 3 by 3 which corresponds to a 3 by 3 matrix of data in the image's files. This enables the convolutional layer to detect image features.
2. Activation function: The activation function is an important parameter in convolutional neural networks that ensures the model extracts and separates useful features that accurately recognize banknote denominations. Therefore, it calculates the weights and biases of the networks

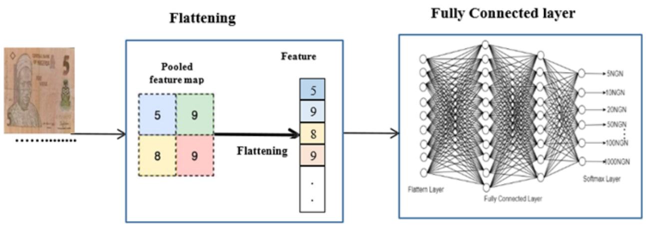


Figure 5. Fully connected layer of the proposed system.

and decides if network neurons should be activated or not. It helps the network to express the features extracted from the images and then improve prediction accuracy. In addition, it provides means to increase the non-linear ability of the network features and avoid gradient disappearance or gradient explosion after multiple network parameters iteration. There are many types of activation functions for deep learning implementation [23]. These include the sigmoid function, Tangent hyperbola (Tanh) function, and Rectified linear unit (RELU) function. However, among these activation functions, RELU provides broad applications for recognition and detection problems. Moreover, it is less computationally expensive as it involves simple mathematical operations compared to *Tanh* and sigmoid functions. Also, it activates a few neurons in the network making the network sparse, efficient, and easy for computation. Therefore, we proposed to apply a rectified linear unit (RELU) function in the proposed system. The activation function was applied in all the three layers of the convolutional layer.

3. Regularization: Convolutional neural networks extract large features from banknotes images which require the use of large weights and biases. The use of large weights would result in overfitting the model and its inability to generalize the developed model in new naira banknote images. Consequently, regularization techniques are used to penalize and reduce the weights of the proposed convolutional neural networks to prevent overfitting and control the model complexity. In this research work, we used the *dropout* regularization technique to prevent overfitting the model image data. It is also one of the most deployed regularization methods in the deep learning model. *Dropout* is a regularization technique that randomly drops some layers of the network with some probability. The essence is to reduce data variance, weights, and biases in the developed network and improve banknote recognition performance accuracy. With dropout, the convolutional neural network alters its connection and finds the best path to extract the required information from the banknote's images. In the proposed system, we set the dropout value to *0.2*.
4. Epoch: This defines the number of iterations required to achieve full training. In this study, we set the number of epochs during training the proposed system to 100. Setting the number of epochs to 100 enables the system to see all the partitions of the data and reduce bias in the currency identification.
5. Batch Size: This defines the number of training examples defined at one iteration. Choosing batch size during deep learning training is very important. If the batch size is too small, it may lead to a situation where the proposed system might not learn enough data examples to generalize to a new dataset. Also, if the batch size is large, it might lead to a high number of training time and computation complexity. In the thesis, we set the batch size to 32 training examples at every iteration of training.
6. Learning rate: In a deep learning problem, the learning rate is a hyper- parameter that defines the rate of adjusting the network weights with respect to the gradient descent. During training, choosing the appropriate learning rate is important as it controls the training procedure of the networks. If it is too low, the deep learning model will take a long time to converge while a large learning rate would make the deep learning model converge quickly and lead to suboptimal solutions. Consequently, to compensate for optimal convergence and good performance, we set the learning rate to 0.01.
7. Loss function: loss function is a deep learning hyper-parameter tuning metrics that compute the distance between the current output of the learning algorithm and expected outputs. The parameter evaluates how well the proposed algorithms model the naira currency denomination data. In this thesis, we set the loss function to categorical cross entropy which is popularly used in classification problems. Categorical cross-entropy is used for multi-class classification problems. In our dataset, we have multiple labels (5, 10, 20, 50, 100-, 200-, 500- and 1000-naira notes), and in our prediction, the prediction may belong to any of the class labels.
8. Optimization: optimization is the process of changing the attributes of a deep learning model such as weights, biases, and learning rate to reduce loss and improve algorithm generalization. In the proposed system, *adaptive moment estimation* (Adam) was used to as an optimizer in our proposed convolutional neural networks. The use of the Adam optimizer enables the deep learning model to converge fast and minimize high data variance.

### *3.3.2. Pooling layer*

A pooling layer (PL) is the next layer after activation functions have been applied to the feature map. The rectified feature map is fed into the pooling layer to learn several other features of the input. Different PLs use various filters to identify different parts of the objects in the image. The primary aim is to merge semantically similar features into one [23] and to reduce the size of the convolved feature map to reduce computation cost. Pooling layers are used to reduce the spatial dimension of image activation maps and the number of features without any loss of information [22]. In addition, the pooling layer helps to reduce over-fitting and increase the output generalization of the proposed deep learning- based Naira banknote recognition system. There are so many types of pooling operations and these

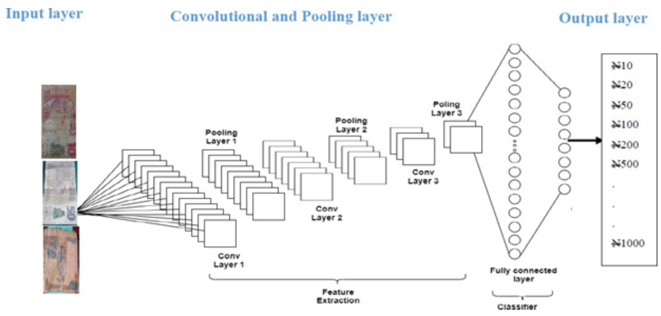


Figure 6. Architecture of the implemented convolutional neural networks.

```
Model: "sequential_5"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_16 (Conv2D)          (None, 254, 254, 10)      280

 max_pooling2d_14 (MaxPoolin  (None, 127, 127, 10)     0
 g2D)

 conv2d_17 (Conv2D)          (None, 125, 125, 20)      1820

 max_pooling2d_15 (MaxPoolin  (None, 62, 62, 20)       0
 g2D)

 conv2d_18 (Conv2D)          (None, 60, 60, 10)        1810

 max_pooling2d_16 (MaxPoolin  (None, 30, 30, 10)       0
 g2D)

 flatten_5 (Flatten)         (None, 9000)              0

 dense_10 (Dense)            (None, 250)               2250250

 dense_11 (Dense)            (None, 8)                 2008

=================================================================
Total params: 2,256,168
Trainable params: 2,256,168
Non-trainable params: 0
_________________________________________________________________
```

Figure 7. Inputs hyper-parameter settings.

include stochastic, spectral, spatial pyramid, max, multi-scale, and average pooling. In this thesis, we applied *max pooling* to extract the most discriminating features from the naira banknotes. In max pooling, the maximum element from the feature map covered by the specified filter is selected. This would enable the proposed system to extract the most discriminant and important features for the identification and recognition of the naira banknote denomination. The output of the pooling layer is called pooled feature map which passes through flattening before it is fed into a fully connected layer for banknotes denomination recognition. The pooling process is depicted in Figure 3.

### *3.3.3. Flattened layer*

A flattened layer (FL) is used when a pooled feature map is in a multidimensional or 2- dimensional array. It converts all the multidimensional arrays from pooled feature maps into a single continuous linear vector. The aim is to make multidimensional input one-dimensional. The flattened matrix is fed as input before passing it to a fully connected layer for recognition of different currency denominations. Figure 4 shows the flattening process.

### *3.3.4. Fully connected layer*

Fully connected layers (FCL) are generated when the flattened matrix from the pooling layer is fed as an input that classifies and identifies the Naira Banknotes denomination. It connects all the neurons in one layer to all neurons of the Softmax layer [22]. In addition, it converts a high-dimensional feature map to a one-dimensional by high- level reasoning that gives the probability that the feature belongs to a specific class. Softmax is an activation function that is used to classify objects in multiple classification problems. It computes the relative probabilities of each feature vector and determines the final problems of the likely features belonging to the target image class. The formula used by the Softmax layer to determine the relative probabilities of the feature vector is shown below.

$$Softmax(z_i) = \frac{\exp(z_i)}{\sum_j \exp(z_j)} \tag{1}$$

where z represents the different values of the neuron from the output layers of the proposed convolutional neural networks. Figure 5 shows the diagram of the fully connected layer.

## 4. Experimental setting

Figure 6 depicts the architecture of the implemented convolutional neural networks for naira notes currency denomination recognition. As depicted in the figure, the architecture is made up of an input layer that accepts the currency images, the convolutional and pooling layer that automatically represents and extracts relevant features, and an output layer that predicts the captured currency denominations using the Softmax classification algorithm.

We collected different datasets of naira banknotes in different denominations, orientations, and positions using different mobile devices to capture the data. The data was prepared and preprocessed by removing unwanted extensions from the dataset, resizing the images to 256x256 pixels, and scaling the image by dividing by 255. We mixed the denominations such as N5, N10, N20, N50, N100, N200, N500 and N1000 naira together. Then, the combined naira banknote images were split into 70% training, 10% validation, and 20% testing. The convolutional and pooling layers automatically extract relevant features, while the output layer predicts the capture currency denominations using the Softmax classification algorithm. The values of convolutional neural network parameters are shown in Figure 7.

### *4.1. Evaluation metrics*

To evaluate the performances of the proposed machine learning-based naira banknote recognition system, we computed three (3) performance metrics. These include Accuracy,

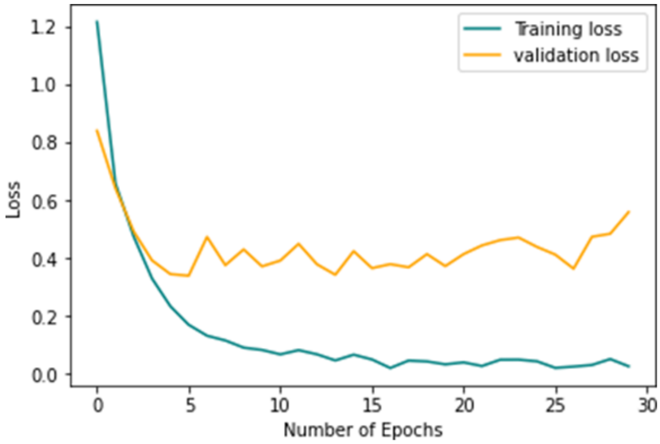


Figure 8. Training loss and validation loss recorded by the system.

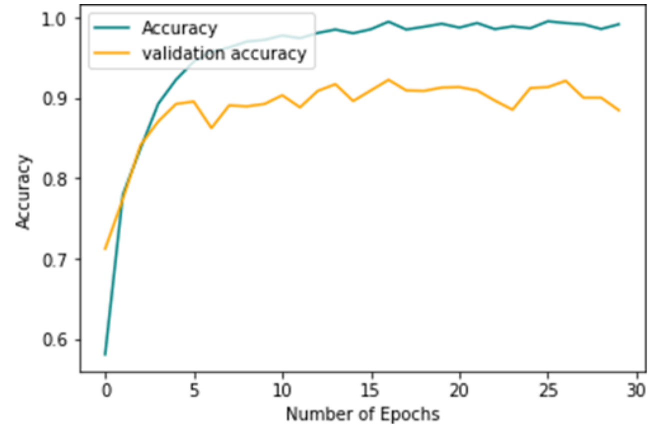


Figure 9. Training accuracy and validation accuracy.

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| NGN10 | 1.00 | 1.00 | 1.00 | 2 |
| NGN100 | 1.00 | 1.00 | 1.00 | 5 |
| NGN1000 | 1.00 | 1.00 | 1.00 | 3 |
| NGN20 | 1.00 | 1.00 | 1.00 | 7 |
| NGN200 | 1.00 | 1.00 | 1.00 | 4 |
| NGN5 | 1.00 | 1.00 | 1.00 | 4 |
| NGN50 | 1.00 | 1.00 | 1.00 | 3 |
| NGN500 | 1.00 | 1.00 | 1.00 | 4 |
| accuracy | | | 1.00 | 32 |
| macro avg | 1.00 | 1.00 | 1.00 | 32 |
| weighted avg | 1.00 | 1.00 | 1.00 | 32 |

Figure 10. Evaluation analysis.

Recall, and F-measure. For each naira denomination class, the predicted values were measured with the ground truth label. We calculated the number of true- positive (TP), True-Negative (TN), false- positive (FP), and false-negative (FN) with the aid of the confusion matrix of each prediction after testing. Here, N represents the total number of classes in the training sample.

1. Accuracy computes the rate of correctly classified domination classes out of the total number of denomination instances. Accuracy is calculated using equation (2).

$$\text{Accuracy} = \frac{1}{N}\sum_{i=1}^{N}\frac{(TP_i + TN_i)}{(TP_i + FP_i + TN_i + FN_i)} \quad (2)$$

2. Recall: This represents the average number of correctly predicted instances as positive instances. Recall rate is measured using equation (3).

$$\text{Precision} = \frac{1}{N}\sum_{i=1}^{N}\frac{TP_i}{TP_i + FP_i} \quad (3)$$

3. F-Measure: This computes the weighted harmonic mean of precision and recall. Equation (4) shows the formula for computing F-Measure as implemented in the study.

$$\text{F1 Score} = \frac{1}{N}\sum_{i=1}^{N} 2 \times \frac{TP_i}{2TP_i + FP_i + FN_i} \quad (4)$$

## 5. Results and discussion

The outputs from the dense layer are mapped to the eight (8) classes/labels of the Naira denomination images. The *softmax activation function* helps to get the probability value of the 8 classes that represent the Naira denomination to be able to predict the actual class (Naira denomination). So, we now have to compile the model using *Adam's optimization function* and *loss function* of *categorical cross entropy* because the multi- class label and accuracy were used as the model evaluation technique. After this, we now fit in the training data, into the model with 100 *epoch* and also pass in the validation data as well. So as the model is training, it is going to validate the training process using the validation data to ensure that the model is learning and capturing relevant features. At the end of the training, to save time, during the real testing of the model, it is important to save the developed model.

The expected result of the training is supposed to be a predictive class based on the currency fitted into the model. The classes have a label for all the Nigerian currency denominations. These classes are encoded to numbers such that:

1. $N5 \mapsto 0$
2. $N10 \mapsto 1$
3. $N20 \mapsto 2$
4. $N50 \mapsto 3$
5. $N100 \mapsto 4$
6. $N200 \mapsto 5$
7. $N500 \mapsto 6$
8. $N1000 \mapsto 7$

After the classes are predicted from the currency images that are been fit into the model, the *Softmax activation function* will now find the probability of the class which will be mapped to the class itself by determining the class number of the prediction. This is how the model understands and tends to accurately predict the currency denominations. We evaluate the

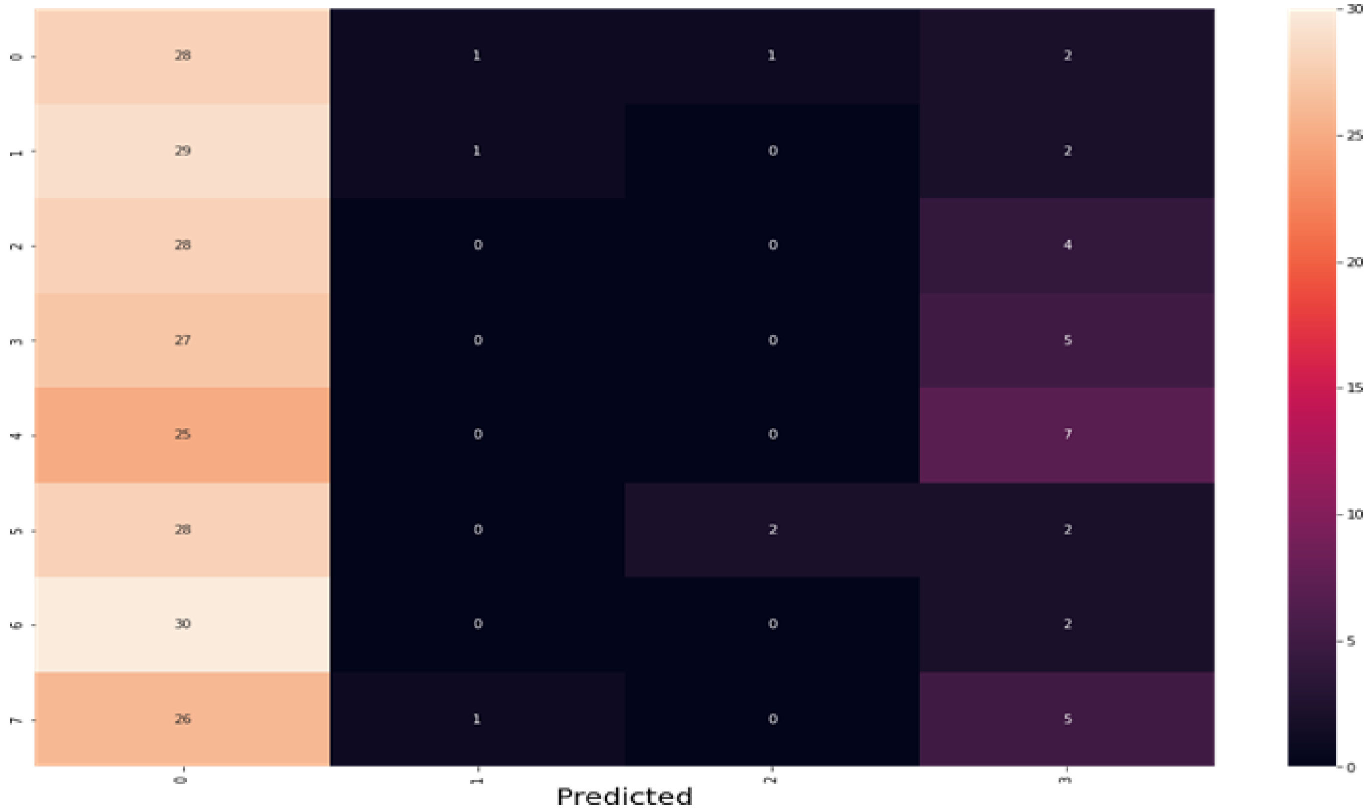


Figure 11. Confusion matrix of the model.

performance of the developed model using performance metrics such as average accuracy, training loss, validation loss, testing accuracy, and validation accuracy. Training loss shows the errors recorded by the model during training using the portions of the Naira note images. In addition, validation loss records the loss obtained while using the validation datasets. Figure 8 below shows the training loss and validation loss and Figure 9 below shows the training accuracy and validation accuracy respectively.

In the end, the model was found to perform well with an accuracy of 95.0% which is very good with precision of 1.0 and recall of 1.0 as well as an F1 score curve of 1.0 as shown in Figure 10.

For the class of 10 naira, the precision index was 1.0, recall 0.67, F1 curve 0.80. It is observed that the higher the scores obtained, the better the model. The overall accuracy of the model during the testing phase is 95.0%. The confusion metrics in Figure 11 show the performance accuracy of each Naira denomination.

## 6. Conclusion and future works

The Machine Learning-based Folded Banknote Denomination Recognition System will advance the identification of naira banknotes in different organizations. Therefore, to increase accountability and recognize folded banknote denominations, this study implemented a convolutional neural network-based banknote denomination recognition system to address the problems. The implemented system is an integrated platform that is developed to effectively capture banknote data and identify it in its different folded positions and orientations. It thereafter, predict denomination such as N5, N10, N20, N50, N100, N200, N500, or N1000 naira. An extensive evaluation showed that the developed system is scalable and reusable and can be deployed for large-scale banknote denomination recognition. In the future, we tend to collect a larger amount of naira denomination and implement cloud-based machine learning models.

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