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Development of Serial Number Extractor for Nigerian Currencies

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Abstract

The need to track currency movement and validate currencies in circulation are two cogent reasons for developing a real-time currency serial number extractor. Due to significant technical innovation over the past few decades, currency counterfeiting issues have gotten progressively worse all over the world and it is presently one of the main issues in Nigeria. Hence, financial institutions and the general public often desire to know the authenticity of cash. Also, Government and security agencies often desire to track cash for the purpose of apprehending notorious kidnappers after ransom collection. This calls for a fast and accurate serial number extraction from currencies. Automatic serial number extraction can be segmented into three (3) phases, which include currency classification, region of interest extraction, and character recognition. In this paper, an optimized object identification model was proposed for currency classification. A pre-trained denomination-based region of interest algorithm was then applied for the extraction of the serial number region. We further utilized three (3) existing optical character recognition models: Pytesseract, Easy OCR, and Keras OCR for the character recognition. Accuracy, Levenshtein Distance, Jaccard Similarity, Character Error Rate, and Damerau Distance metrics were employed in this study for recognition performance measure. The currency bill classification yielded a 100% accuracy while the best accuracy of 81% was obtained with the EasyOCR framework at the character recognition phase. The recognition model performance can be considered poor for the targeted application. Hence, the need for customization of the general character recognition architecture for Nigerian currency bill serial number recognition.

Keywords: *Counterfeit currency, Currency tracking, Object Character Recognition, Pytesseract, Easy OCR, Keras OCR*

1. INTRODUCTION

The need for a real-time tracking of cash in circulation is more pronounced now than ever. Setting up a mechanism for tracking the movement of paper currencies can among other advantages provide the Central Bank of Nigeria with insight into the number of active currencies and the percentage that are possibly hoarded. Recent revelation by the apex financial regulatory body shows that a larger percentage of cash in circulation are being hoarded by individual [1]. This motivates the need to re-design higher denomination currencies. However, there is no data to support investigation into when and where these cash disappeared from circulation, which could be valuable for intelligence gathering. Also, the unprecedented rate of increase in kidnapping experienced across the nation can partially be attributed to the failure of the government and security agencies at curbing the menace. Individuals, families, organizations, and even government establishments are constantly being coerced by kidnapers to pay huge ransoms, in cash, in order to secure the release of their beloved ones; and these illegally acquired cash are often being spent without a means of tracking such [2]. Kidnapping and abduction has been tagged a thriving industry [3] and this has been attributed to the failure of concerned agencies to put in place radical deterrence mechanism [2]. Finally, in the year 2019, 84,934 pieces of banknotes valued at ₦64.71 million were declared counterfeits, while 67,265 pieces of phony notes worth at ₦56.83 million were documented as counterfeits in the year 2020, according to the body in charge of the issuing of

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these banknotes [4]. According to statistics, the global benchmark for the number of fake currency bills per million is 100, however in 2019 and 2020, the ratio of fake currency bills to the amount of total bank notes in circulation was 20% and 13% respectively [5]. Additionally, it was asserted that larger denomination banknotes, such as the ₦1,000 and ₦500, make up the majority of fake currency, representing 69.06 percent and 30.79 percent of all fake currency, respectively [6]. One possible solution to the problem above is to device a mechanism for automatic currency bill tracking. This involves the creation of a database of all printed currency bill, which include the year, serial number, and denomination. Banks, Automated Teller Machines, and other financial institution will then record inflow and outflow of cash by recording the serial number, and the ID of the client withdrawing or depositing such cash, and the location. These data can be mined for intelligence gathering for crime reduction [7].

Currency bill tracking is not an entirely new idea as there have been community of trackers for some foreign notes such as Dollar, Canadian Dollar, Euro, among others. One of such platform that tracks movement of $20 bill note is www.wheresgoerge.com. The site relies on manual entry of the currency bill serial number and other details of the custodian to generate the bill's traveling history. There is also a research that centers on the development of special IoT device for real-time tracking and location of stolen currency [8]. However, manual lodging of currency bill serial number will not be practically feasible and biases will be introduced. Also, the adoption of special tracking device will be both costly and limited in its applicability. Hence, the need for automatic serial number extraction. Banking system will be able to determining whether a note in circulation in the market was issued by their governing body, as the serial number of a bank note aids the Central Bank of Nigeria in determining the exact number of notes available to the market at any given time, as well as providing a platform for tracking and tracing each note through its supply chain. With current advances in deep learning and computer vision, currency bill classification and serial number extraction is expected to be achievable.

This paper investigates the degree of success achievable with existing state-of-the-arts techniques in computer vision and pattern recognition for automatic Nigerian currency bill classification and serial number extraction.

We proposed a methodology to create a technique for extracting serial numbers from every piece of paper money in Nigeria, with the aim of classifying the Nigerian banknotes using a convolutional neural network, detect the serial numbers on Nigerian Currency notes, and extract the serial numbers using optical character recognition.

The rest of this paper is organized as follows. In Section 2, we review related works i.e. the works related to fake banknote detection. In Section 3, we explain the proposed method in details. The experimental setup, results and conclusions are reported in Sections 4 and 5, respectively.

2. Related Works

This approach incorporates key findings from earlier studies. Prior works on extraction of serial numbers in currencies were reviewed, serving as the basis for the current task.

Ogbuju *et al.*, [9] used a deep learning technology to create a system that might help identify counterfeit banknotes and contribute to lowering the danger of money counterfeiting. The Faster Region Recurrent Neural Network (FRCNN) was used for fake naira currency recognition called Naira Real but their proposed model lacked accuracy due to minimal amount of image currency used.

To detect the serial number digits for Japanese Yen, Korean Won, and Euro Banknotes, Choi *et al.* [10] used a Joint Regression and Classification Machine Learning System. A sequential ROI identification and classification system was first built using the Convolutional Neural Network (CNN) to determine the ROI (Region of Interest) for the serial number from the input picture (the ROI detection CNN). Following this strategy, knowledge distillation and Bayesian optimization were used to improve the performance of machine learning-based serial number recognition for banknotes. The joint recognition technique was also found to be quicker than the sequential method while maintaining the same level of accuracy, implying that the convolution layers used for ROI detection and serial number identification might be shared.

Aseffa *et al.* [11] employed a CNN and an embedded platform to detect Ethiopian banknotes (mostly to recognize the banknotes and categorize them into denominations that may be used in automated processes). Different CNN models, such as Inception V3, Mobile NetV2, XceptionNet, and ResNet50, were also used to illustrate experimental analyses. For training, the suggested CNN architectures were combined with six distinct optimization techniques: Adam, SGD, RMSProp, Nadam, Adedelta, and Adagrad. Iterations were also run in parallel for 100 epochs. In a batch size of 64, the MobileNetV2 CNN architecture with RMSProp optimization approach has the best accuracy of around 96.80%.

Kumar *et al.* [12] used 7000 segmented offline handwritten Gurmukhi characters collected from 200 different writers in their study to examine offline handwritten pre-segmented character recognition in Gurmukhi script. The data dimension was decreased using a PCA-based feature selection technique and a 5-fold cross validation procedure after a set of 35 important characters from the Gurmukhi script were examined. K-NN, SVM (with four different kernels), and MLP classifiers were used as a comparison. In this experiment, they employed RBF-SVM to achieve a maximum recognition accuracy of 93.8 percent for the 35-class task.

Pham *et al.* [13] proposed a convolutional neural network-based technique for distinguishing between fake and real banknotes using visible-light images captured by smartphone cameras. On the self-collected banknote image datasets of EUR, USD, KRW, and JOD banknotes, a four-fold cross-validation approach was utilized, and the dataset of banknote images was randomly divided into four equal portions, three of which were used for training and the remaining one for testing. Four times, the training and testing procedure was applied, each time with a new dataset portion. The average categorization accuracy of the four testing results was used to assess overall performance. The suggested technique beats earlier classification algorithms based on various CNN architectures, according to the findings.

To work on character region segmentation based on aspect ratio and low-quality banknote serial number recognition, Jang *et al.* [14] employed a CNN as their deep neural network. A loss value trend analysis indicated that models with a large number of kernels in a deep configuration and models with a small number of kernels in a shallow configuration are both tiny and shallow, therefore the neural network was chosen. Data augmentation also aided in the improvement of performance in terms of lost value and recognition trends.

3 Methodology

3.1 Overview of Proposed Methodology

Figure 1 shows the overall procedure of the proposed method. A five-staged architecture comprising of the data acquisition or dataset collection, currency classification using VGG 16, cropping was used to detect where the serial numbers are, then image pre-processing (noise reduction and edge detection) was used on the cropped image after which serial number extraction was deployed which used libraries like Keras OCR, Pytesseract, Easy OCR. After the extraction has been completed, the performance of the libraries was evaluated using accuracy, Levenshtein distance, Jaccard Similarity, Character Error Rate (CER), Damerau distance.

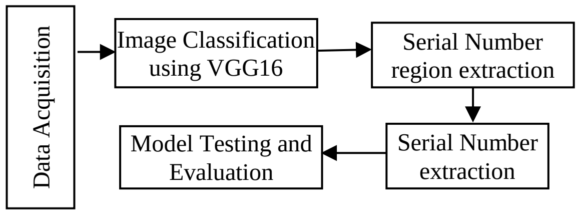


Figure 1: Architecture used for Extracting Serial Numbers from note

3.2 Dataset Acquisition

The dataset utilized in this investigation was created by Adeniyi *et al.*, [15]. There are a total of 580 banknote images. The monetary values shown in the photos are 5 naira, 10 naira, 20 naira, 50 naira, 100 naira, 200 naira, 500 naira, and 1000 naira. 10.34 percent of the photos are 5 Naira, 11.38 percent are 10 Naira, 6.55 percent are 20 Naira, 8.62 percent are 50 Naira, 17.93 percent are 100 Naira, 8.62 percent are 200 Naira, 12.76 percent are 500 Naira, and 10% are 1000 Naira. They were gotten from Mendeley, because no pre-processing has been done on the coin photos, they vary in size. The images are coloured RGB format and saved in JPEG format [15].

3.3 Currency Classification using VGG16

A Convolutional Neural Network named VGG16 was adopted for the purpose of identifying the denomination of various currency bill notes. A typical convolutional neural network model comprises of an input layer, several hidden layers and an output layer. VGG16 is a variation of the CNN model and has found its application in computer vision. VGG16 model showed a significant improvement over the state-of-the-art setups by analyzing the networks and enhancing the depth using an architecture with exceptionally small (3 3) convolution filters. With the depth extended to 16–19 weight layers, around 138 trainable parameters were produced. VGG16 is an object identification and classification algorithm that, when used to classify 1000 images into 1000 separate categories, has an accuracy rate of 92.7%. It is a popular method for categorizing photographs and is easy to use with transfer learning.

3.4 Region of Interest Detection
Cropping involves taking out unnecessary portions of a picture or drawing. The procedure normally entails removing portions of the image's outer areas in order to remove irrelevant details, improve framing, adjust the aspect ratio, or, in the case of this study, highlight or isolate the subject matter from its surroundings. Our Region of Interest is the specific location on each currency note that contains the serial number (ROI). To choose our ROI, we first predict which note it is, and then crop that portion of the image based on the position of the serial number of that particular note.

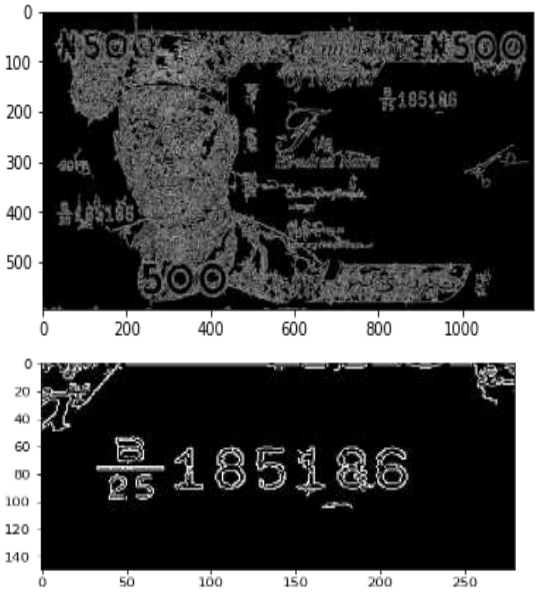


Figure 2: (a) Original Image (b) Cropped Image

3.5 *Noise Reduction and Edge Detection*
The picture pre-processing processes that were performed on the photos were Noise reduction and edge detection in order to improve the image data in an attempt to suppress unwanted distortions and highlight specific image features. Noise Reduction or Filtering is a stage in the image preparation process. Noise has a substantial influence on detection accuracy when it comes to identifying edges and contours. Therefore, noise must be eliminated, and pixel intensity must be managed. A better and more enhanced version of a picture is produced via image filtering, which takes out noise and undesirable components [16].

Edge detection is the technique of identifying the boundaries of the picture. Canny edge detection aids in the detection of image intensity gradients. Non-maximum suppression is used to remove erroneous edge detection replies. Use of a twofold threshold can be utilized to discover possible edges. These edges are established by comparing the brightness of the picture pixels [17].

3.6 Serial Number Extraction
The libraries used for the serial number extraction are Pytesseract, EasyOCR and Keras-OCR.

3.6.1 Pytesseract (Python tersseract)
Python-tesseract is a library for optical character recognition (OCR). The library receives an image as its input, and then attempts to identify and recognize text in the supplied image. Python-tesseract is a python wrapper for the Google's Tesseract-OCR Engine. It is useful as a standalone invocation script to tesseract since it can read any image type supported by the Pillow and Leptonica imaging libraries, including jpeg, png, gif, bmp, tiff, and others. Additionally, when used as a script, the library produced a real-time textual content rather than redirecting the output into file.

3.6.2 EasyOCR
An optical character recognition (OCR) library written in Python called EasyOCR can extract text from photos. More than 40 languages are supported by this ready-to-use OCR, including Chinese, Japanese, Korean, and Thai. It is an open source project with an Apache 2.0 license. EasyOCR carries out several pre-processing tasks (gray scaling, for instance) within its library before extracting the text. The CRAFT (Character Region Awareness for Text Detection) technique is also used to find the text. By looking at each character's affinity, the scene text identification system efficiently locates text areas. The recognition model employs convolutional recurrent neural networks (CRNN). Sequencing labelling is done using LSTM (Long Short-Term Memory) and CTC (Connectionist Temporal Classification), with CTC being used to label unsegmented sequence data with RNN.

3.6.3 Keras-OCR
In addition to having pre-built OCR models, Keras-OCR also has a full training pipeline for new OCR models. It is based on two popular neural network architectures: Convolutional

Neural Networks (CRN), which is used for text recognition, and Character Region Awareness for Text Detection, which is used for text detection (CRAFT). It is built on top of Tensorflow.

3.7 The Performance Evaluation Metrics

In this paper, five (5) metrics, which include: Accuracy, Levenshtein Distance, Character Error Rate, Jaccard Similarity, and Damerau-Levenshtein distance were used to evaluate the performance of the three OCR libraries.

Accuracy: Accuracy, which is just the proportion of properly predicted observations to all observations, is the most obvious performance statistic. Accuracy is represented in terms of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) as given in Equation 1:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (1)$$

Levenshtein Distance: A string metric called the Levenshtein distance is employed to compare two sequences. The distance between two words is known as the Levenshtein distance, which is a colloquial term for the number of single-character alterations (insertions, deletions, or replacements) required to change one word into the other [18]. The similarity of the strings increases with decreasing Levenshtein distance.

$$lev_{a,b}(i,j) = \begin{cases} \max(i,j) & if \min(i,j) = 0, \\ min \begin{cases} lev_{a,b}(i-1,j) + 1 \\ lev_{a,b}(i,j-1) + 1 \\ lev_{a,b}(i-1,j-1) + 1_{a_i \neq b_j} \end{cases} & otherwise \end{cases} \qquad (2)$$

Jaccard Similarity: The Jaccard Similarity developed by Paul Jaccard is a widely used proximity metric for determining how similar two objects, such as two texts, are. Two asymmetric binary vectors or two sets can be compared using the Jaccard similarity to see if they are comparable. Two sets will have a Jaccard Similarity Index of 1 if all of their members are identical. On the other hand, if they do not have any related members, their similarity will be 0. In literature, the concept of Jaccard similarity, represented by the letter J, is often referred to as Jaccard Index, Jaccard Coefficient, Jaccard Dissimilarity, and Jaccard Distance computed as:

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} \qquad (3)$$

Character Error Rate (CER): When calculating the Character Error Rate (CER), the total number of characters (n), including spaces, is compared against the minimum number of character insertions, replacements, and deletions required to provide the Ground Truth result for a particular page.

$$CER = \frac{S + D + I}{N} = \frac{S + D + I}{S + D + C} \qquad (4)$$

where S is the number of Substitutions, D is the number of deletions, I is the number of intersections, C is the number of correct characters, N is the number of character in references (N=S+D+C).

Damerau Distance: The Damerau-Levenshtein distance string metric may be used to calculate the edit distance between two sequences. The Damerau-Levenshtein distance between two words refers to the least amount of operations (consisting of insertions, deletions, or substitutions of a single character, or transposition of two adjacent characters) required to change one word into the other.

The Damerau-Levenshtein distance, which differs from the conventional Levenshtein distance in that it also accepts the three conventional single-character edit methods, allows transpositions as one of the authorized operations (insertions, deletions and substitutions).

$$d_{a,b}(i,j) = \begin{cases} \max(i,j) & if \min(i,j) = 0, \\ min \begin{cases} d_{a,b}(i-1,j) + 1 \\ d_{a,b}(i,j-1) + 1 \\ d_{a,b}(i-1,j-1) + 1 \\ d_{a,b}(i-2,j-2) + 1 \end{cases} & \begin{matrix} if\ i,j > 1\ \&\ a_i = b_{j-1} \\ if\ a_i \neq b_j\ \&\ a_{i-1} = b_j \end{matrix} \\ min \begin{cases} d_{a,b}(i-1,j) + 1 \\ d_{a,b}(i,j-1) + 1 \\ d_{a,b}(i-1,j-1) + 1 \end{cases} & \begin{matrix} otherwise \\ (a_i \neq b_j) \end{matrix} \end{cases} \qquad (5)$$

4. Results and Discussion

4.1 Data Preparation

Pre-processing simply means bringing our images into a form that is predictable and analysable for our task. It was done by first cleaning the images in the dataset and then resizing the images into a consistent form as can be accepted and is usable by the convolutional neural network for classification.

4.2 Training and Test Set Creation

The dataset that was acquired contains 580 images of Nigerian currency notes, for each of the currencies that were captured, there are two images, there is a front and a back image. Every Nigerian currency contains the serial numbers on either the front or the back, in the data cleaning, the one that does not contain the serial number was discarded as it contains no useful information relevant to the project. Sample image of the notes is as shown in Figure 3.

4.3 Resizing of Images

Images may be resized to be smaller or larger without losing any content or information. The image's dimensions are changed when it is resized, which often has an impact on the file size and image quality. The images were resized to a specific dimension in order to ensure that each of the images had the same width and height, the images were resized to a size of (550 * 1100) pixels.

4.4 Currency Bill Classification

After data cleaning, image separation and resizing the images, the classification of the notes in order to be able to automatically classify which denomination was each image was performed. The model is the product of making modifications to an already pre-trained model called VGG-16 available in the tensor flow library. The pre-trained VGG-16 model was already trained using the popular image-net dataset and has its weights already.

The top most layer from Vgg-16 was removed and replaced with our custom layers. One Batch Normalization layer, One Dropout layer, One Flatten layer, and One Dense layer were added to the pre-trained VGG-16 model. The optimizer used is Adam and the Loss is binary crossentropy. Accuracy was used as the internal evaluation metric. The model was then trained using 15% of the train set as the validation set and was trained for 50 epochs

The data was separated into train (0.8) and test (0.2) sets after being segmented into features (X) and target (Y) sets. Thus, the VGG-16 algorithm selected for the purpose of this task was trained on one set of data (along with validations that is usually performed with deep learning tasks in computer vision) and then tested out on a completely different set of data.

h

Figure 3: Sample naira notes (a) ₦5 (b) ₦10 (c) ₦20 (d) ₦50 (e) ₦100 (f) ₦200 (g) ₦500 (h) ₦1000

Due to the distinguished properties of the currency notes, the algorithm performed very well on the test set and had a very high level of accuracy 100%. The accuracy and loss curves of the VGG-16 architecture during picture training are shown in the Figure 4.

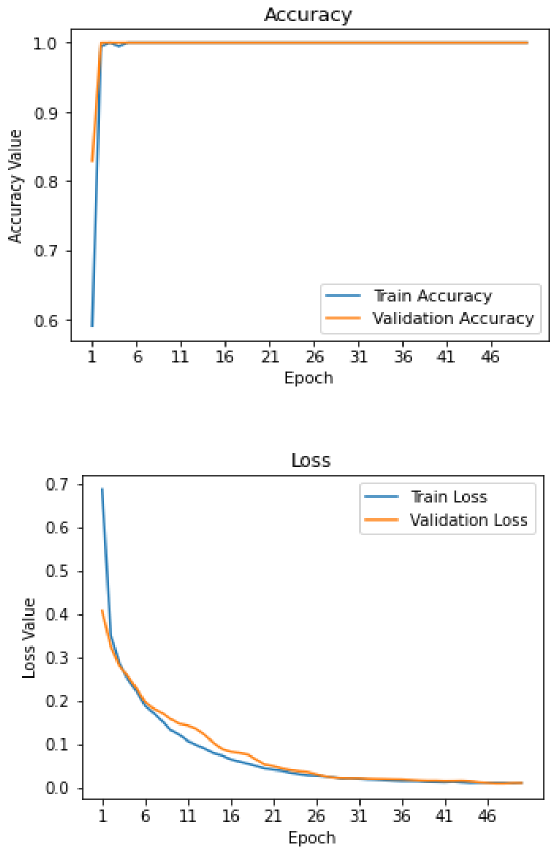


Figure 4: Accuracy and Loss plots for the CNN algorithm used for Currency classification

4.5 Dataset Description

The images used for this study were selected from the Nigerian currency dataset created by Adeniyi et al. [15]. There were originally 580 banknote images in all but after the cleaning and separation of the images, there were only 266 left. 30 five-naira notes, 33 10-naira notes, 19 twenty-naira notes, 60 fifty-naira notes, 52 100-naira notes, 25 200-naira notes, 37 500-naira notes, 29 one-thousand-naira notes.

4.6 Image Pre-processing

4.6.1 Result of Region of Interest Extraction

There is a Region of Interest (ROI) on each Naira note that bears the serial number, if it is at a location for one currency, then it is at that specific location for the other notes of that same currency. This knowledge is used to crop out (extract) the ROI of the image that contains the serial number after the classification of that note has been performed i.e. if the classification algorithm predicts that the note is a 10 naira note, then the part of the 10 naira note that contains the serial number can be extracted based on before known information. Figure 5 shows a ₦200 note currencies along with the part that contain the serial numbers extracted.

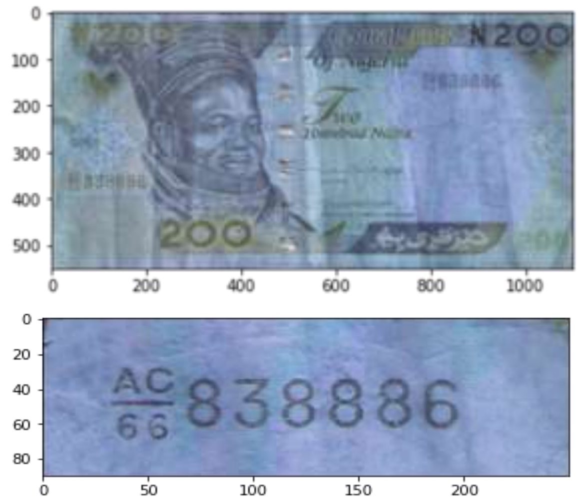
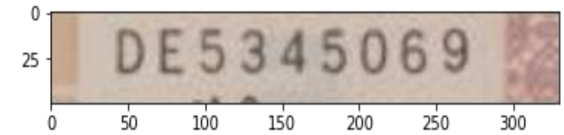


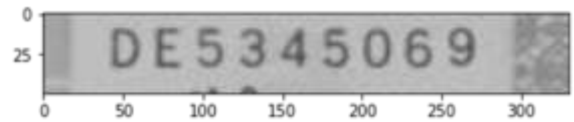
Figure 5: A 200 naira note along with its ROI cropped out

4.6.2 Result of Image Gray scaling

The clipped image is then turned into a grayscale version, which speeds up calculation and simplifies the procedure. Rather than working directly on color photos, extracting descriptors is frequently done via grayscale representations. The ROI before and after gray scaling are presented in Figure 6



(a)



(b)

Figure 6: Example of image before gray scaling(a) and image after gray scaling(b)

4.6.3 Result of Noise Reduction

Noise reduction is performed on the gray scale images, a bilateral filter is used for smoothening the images and reduce noise, while preserving edges. The OpenCV library in python contains a function that allows for this operation to be performed. Figure 7 shows a grayscale image in which a bilateral filter has been applied to.

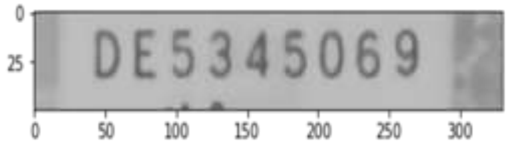


Figure 7: Image after Noise Reduction

4.6.4 Result of Edge Detection

Following noise reduction, edge detection is used to locate any places in the picture with strong discontinuities in brightness. A prominent edge detection technique used to perform edge detection and provide strong edges in the image is called Canny Edge Detection. Figure 8 shows an image which canny edge detection has been performed on.

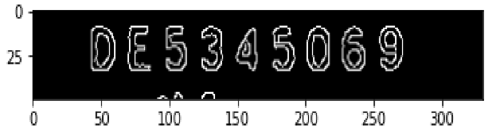


Figure 8: Image with Edge Detection.

4.7 Optical Character Recognition

The serial number extraction is the last phase of the framework. The results of the three different libraries used in this study for extracting the serial numbers for Nigerian currencies are summarized in Table 1.

EasyOCR had the best performance with an accuracy of 0.81. KerasOCR achieved the next best results with an accuracy of 0.60 while PyTesseract achieved the worst serial number extraction results in all metrics with an accuracy of 0.38.

The same performance trend is observed in the Jaccard similarity, character error rate, Levenshtein distance and Damerau distance between the recognized serial numbers and the ground truth. Figure 9 shows the performance of the three metrics whose values are between 0 and 1.

Examination of the test result revealed that currency bill with linear serial arrangement were generally well recognized while currency bills with fraction components in their serial numbers constitutes the failed recognition.

Table 1. Comparison of the three OCR tools

	Acc.	Lev Dist.	Jacc. Sim.	CER	Dam. Dist.
EasyOCR	0.81	3.11	0.74	0.39	3.11
KerasOCR	0.60	3.36	0.51	0.46	3.36
PyTesseract	0.39	5.96	0.24	0.80	5.96

4.8 Discussion of Results

The Nigerian currency bill classification phase of this research produced 100% accuracy, which is an improvement over the work of Ewetoye [19]. The currency classification model can be integrated into counting machines to obtain sum of multidenominational currency bundle. However, the results obtained for the serial number recognition show that existing OCR libraries do not produce acceptable result for Nigerian currency bill.

However, the result obtained from the serial number recognition phase cannot be utilized for real-time application due to high recognition error.

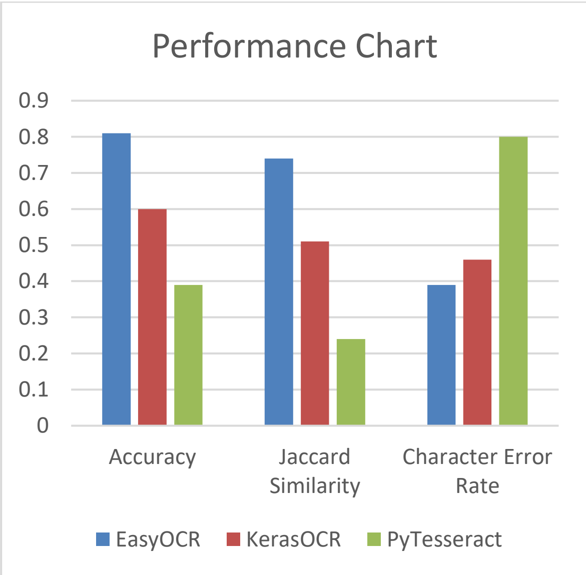


Figure 9: Performance of the OCR libraries

This calls for the development of deep neural network-based serial number recognition models trained on Nigerian currencies, especially the higher denominational notes. It is also worthy of note that the collection of the training set must be characterized by equal and sufficient occurrence of the alphabetical characters in the fraction part of the serial number. In addition, currency bills with single character in both numerator and denomination of the fraction, single character at the numerator with two characters at the denominator, two characters at the numerator with one character at the denominator, and two characters at both numerator and denominator should be well represented in the training set to enhance character segmentation accuracy. Further research is required in this domain to push the serial number recognition result to 100% as obtained in other currencies such as Japanese Yen, US Dollar, Indian Rupee, and South Korean Won [20].

5. Conclusion

In this research, we proposed a framework for extraction of serial numbers from all Nigerian paper currency, which followed a five-stage architecture, starting with data collection or acquisition, classification of currency using a deep learning algorithm, image pre-processing using noise reduction and edge detection, serial number detection using cropping, and serial number extraction using the Keras, Pytesseract, and EasyOCR libraries. Following extraction, accuracy, Levenshtein distance, Jaccard similarity, character error rate, and Damerau distance were used to assess the performance of the models. The results of the three different tools used in this study for extracting the serial numbers for Nigerian currencies show that EasyOCR had the best performance.

However, for a real-time currency tracking system, the accuracy must be near perfect to minimize false alarm rate in applications that relies on the data. A critical study of the wrongly recognized notes revealed that the libraries failed woefully on currency bills with fraction components in its serial number. This feature is common to 200, 500 and 1000 naira notes, which are the main notes of interest in some of the target application domain. This calls for a custom framework that will be capable of extracting, with high level of accuracy, serial number on these notes.

References

[1] Anudu, O., Popoola, N., Olatunji, S., & Isenyo, G., (2021). CBN plans Naira redesign to counter counterfeiting, kidnapping. *Punch Newspaper, 27th October, 2022. https://punchng.com/cbn-plans-naira-redesign-to-counter-counterfeiting-kidnapping/*

[2] Ugwuoke, C. U. (2011). Nigeria and the menace of kidnapping: The way forward. *The Nigerian Journal of Research and Production Volume*, *18*(2), 1-14.

[3] Hannatu, M., (2021). Kidnappings: when government dances with the devil. *Premium Times Newspaper, March, 03, 2021. Retrieved from https://www.premiumtimesng.com/opinion/446518-kidnappings-when-government-dances-with-the-devil-by-hannatu-musawa.html?tztc=1* on 22/01/2023.

[4] Umar, A. B., (2020). Currency Operation Department Annual Report 2020. Retrieved from https://www.cbn.gov.ng/Out/2021/CCD/2020%20COD%20Annual%20Report%20(FINAL%20APPROVED).pdf on 23/01/2023

[5] Ibemere, D. (2021). *Nigerian banks discovered N122.8m worth of fake Naira notes in two years- Report.* Retrieved December 22, 2022, from https://www.ripplesnigeria.com/nigerian-banks-discovered-n122-8m-worth-of-fake-naira-notes-in-circulation-last-year-report/

[6] Iyatse, G., (2021). CBN confiscates 67,000 counterfeit naira notes in 2020. Accessed from https://guardian.ng/business-services/cbn-confiscates-67000-counterfeit-naira-notes-in-2020/ on 23/01/2023

[7] Olatunde, T., Olabode, O., & Adetunmbi, A. (2021). Nigeria Paper Currency Serial Number Pattern Recognition System for Crimes Control, *Information and Knowledge Management*. Retrieved December 22, 2022, from https://doi.org/10.7176/IKM/11-3-04

[8] Fuller, R. & Grimm, P., (2006). Tracking System for Locating Stolen Currency. In *Proceedings of the 19th International Technical Meeting of the Satellite Division of the Institute of Navigation (ION GNSS 2006)*, Fort Worth, TX, September 2006, pp. 3094-3104.

[9] Ogbuju, E., Usman, W. O., Obilikwu, P., & Yemi-Peters, V. (2020). Deep learning for genuine Naira banknotes. *FUOYE Journal of Pure and Applied Sciences (FJPAS)*, *5*(1), 56-67.

[10] Choi, E., Chae, S., & Kim, J. (2019). Machine learning-based fast banknote serial number recognition using knowledge distillation and Bayesian optimization. *Sensors*, *19*(19), 4218.

[11] Aseffa, D. T., Kalla, H., & Mishra, S. (2022). Ethiopian banknote recognition using convolutional neural network and its prototype development using embedded platform. *Journal of Sensors*, *2022*, 1-18.

[12] Kumar, M., Jindal, M. K., Sharma, R. K., & Jindal, S. R. (2020). Performance evaluation of classifiers for the recognition of offline handwritten Gurmukhi characters and numerals: a study. *Artificial Intelligence Review*, *53*, 2075-2097

[13] Pham, T. D., Lee, Y. W., Park, C., & Park, K. R. (2022). Deep learning-based detection of fake multinational banknotes in a cross-dataset environment utilizing smartphone cameras for assisting visually impaired individuals. *Mathematics*, *10* (9): 1616.

[14] Jang, U., Suh, K.H., & Lee, E.C., (2020). Low-Quality Banknote Serial Number Recognition Based on Deep Neural Network. *Journal of Information Processing Systems,* 16(1):224-237.

[15] Adeniyi, J., Oladele T., Adebiyi, A., Adebiyi, M., Akande N., & Adeniyi T., (2021). ADEKCURR-DB, Mendeley Data, V1, doi: 10.17632/ywdtdzb99t.1

[16] Patil, S. (2019). Image Filtering— Using OpenCV. We Use Image Filtering To Remove Noise. Medium. Medium. https://soumyapatilblogs.medium.com/image-filtering-using-opencv-66b67e1bd968

[17] Kshirsagar, M., & Vaidya, G., (2021). Pre-processing with Computer Vision Part V: Edge Detection. Accessed from https://medium.com/perspectivesondatascience/preprocessing-with-computer-vision-part-v-edge-detection-1b51e37d5d3f on 15th December, 2022.

[18] Levenshtein, V. I. (1966). Binary codes capable of correcting deletions, insertions, and reversals. In Soviet physics doklady, 10 (8): 707-710.

[19] Ewetoye, I., (2019). Setting the template for Naira denomination detection. *International Journal of Research Publication,* 19(1): 1-5.

[20] Jang, W., Lee, C., Jeong, D.S., Lee, K, & Lee, E.C., (2022). Multi-currency integrated serial number recognition model of images acquired by banknote counters. *Sensors, 1-16, doi:* https://doi.org/10.3390/s22228612