A Visually Impaired Mobile Application for Currency Recognition using MobileNetV2 CNN Architecture

[1*]Abraham Eseoghene Evwiekpaefe and [2]Habila Isacha

Department of Computer Science, Faculty of Military Science and Interdisciplinary Studies, Nigerian Defence Academy, Kaduna.

email: [1*]aeevwiekpaefe@nda.edu.ng, [2]isachahabila@nda.edu.ng

*Corresponding author

Received: 24 December 2024 | Accepted: 25 February 2025 | Early access: 10 March 2025

Abstract - *There are at least 2.2 billion people with visual impairment globally of which almost half of these cases could have been addressed or prevented. Visual impairment has both personal and economic impacts on individuals. It impacts negatively on the quality of life, especially among adults. Many visually impaired persons in our society today face a lot of challenges and one of these challenges is object recognition. The visually impaired persons need assistance so they can perform monetary transactions without being cheated. This work is aimed at developing a model for the recognition of Nigerian naira notes for visually impaired persons. The model was trained using the concept of transfer learning with a trainable layer built on the MobileNetV2 convolutional neural network architecture pre-trained model using python programming language on Spyder anaconda IDE. The model was saved and converted to TensorFlow lite format which was deployed into a mobile application coded in the java programming language in android studio. A total of 3615 image datasets were collected, including N5, N10, N20, N50, N100, N200, N500, and N1000 denominations and some random images of objects that constitute the non-currency class for the training of the model. The collected data was divided into 80% for training and 20% for testing. The model achieved an accuracy of 98%.*

Keywords: Currency, Naira, Visually Impaired, Transfer learning, Deep learning, MobileNetV2.

1 Introduction

There are at least 2.2 billion people with visual impairment globally of which almost half of these cases could have been addressed or prevented. Vision loss can affect people of all ages but majority of those with visual impairments are above 50 years of age. Visual impairment has both personal and economic impact on individuals. It negatively impacts the quality of life, especially among adults. In the case of older adults, visual impairment contributes to their social isolation, difficulty in walking and navigation, etc (WHO, 2021).

The Nigerian National Blindness and visual Impairment survey conducted between 2005 and 2007 in Nigeria, revealed that there are at least 1.13 million individuals aged at least 40 years who are currently blind while at least 2.7 million adults aged at least 40 years have moderate visual impairment. Therefore, Nigeria, which is the most populated African country with diverse ethnic and cultural background, faces a growing public health problem; blindness and visual impairments (Akano, 2017).

In our society today, the visually impaired persons face difficulties in identifying objects (Mallikarjuna et al., 2021). It is easy for people with a functional sight to recognize a currency, but this is not the case for the visually impaired. A visually impaired person is someone with either a partial or complete vision disorder. They face difficulties in their daily activities especially recognizing things they can't see (Samant et al., 2020). Currency transaction is an indispensable part of human civilization (Tasnim et al., 2021).

There are many assistive devices developed for the visually impaired recently with few solutions in place to help them recognize objects in their environments particularly indoors. Though research in object recognition and detection is gaining grounds, computer vision-based solutions seems to be promising because of their ease of accessibility. Visual impairment refers to vision loss that constitutes a significant limitation of visual capability resulting from disease, trauma, or a congenital or degenerative condition that cannot be corrected by conventional means, including refractive correction, medication, or surgery. Loss of vision has an extremely strong effect on an individual's ability to carry out certain activities for example, navigation, accessing information, and recognizing objects both animate and inanimate objects in his/her surroundings. With extremely weakened or non-existent of a sense of sight, visually impaired people have to depend on their memory and also rely on their senses such as hearing, touch, taste and smell in order to locate or identify objects in their surroundings. The amount of information that is received via human vision is much larger and its processing time takes less time as compared to the rest of the human senses, to depend on these other senses for perception can result in spending much time (Jafri et al., 2013).

Yadav et al. (2020) reported that people with visual impairments suffer from identifying currency values. Many visually impaired persons in our society today face a lot of challenges, one of these challenges is object recognition. Monetary transactions are very sensitive especially when it comes to trusting those handling it for one (Mallikarjuna et al., 2021). Technological advancements have brought about the increase in cases associated with counterfeit currencies around the world. In Nigeria, the issue of counterfeit currency is the biggest challenge faced in cash transactions (Ogbuju et al., 2020). According to Sarfraz et al. (2019) advancement in digital imaging technology which includes the ability to print highly coloured papers has made it possible to produce fake currency banknotes. The visually impaired persons need assistance so they can perform monetary transactions on their own or at least know the value of the currency that could be given to them. Another problem is that one may be given a counterfeit currency and may not be able to identify whether the currency is counterfeit or genuine which may lead to cheating those who accept these counterfeit currencies. This raises the need for currency recognition and detection system so the visually impaired can distinguish among the values of currencies. The proposed system will address the problem faced by the visually impaired in their ability to identify and recognize currency values in order to avoid them be cheated by a third party when given a currency. The visually impaired who cannot see nor identify objects properly can easily be cheated by simply giving them any currency note or even paper. Therefore, the proposed system should be able to identify eight (8) Naira currency denominations and voice out the value of the denominations in English language.

2 Literature Review

2.1 Convolutional Neural Network

A deep learning network design known as a convolutional neural network (CNN or ConvNet) learns directly from data and does away with the requirement for manual feature extraction. CNNs can recognize objects, faces, and scenes in photos by looking for patterns in the images. CNNs are mostly used in computer vision and object recognition applications such as self-driving cars, facial recognition, and systems for classifying and recognizing currencies. A CNN, like other neural networks, is made up of an input layer, an output layer, and numerous hidden layers in between as shown in Figure 1.

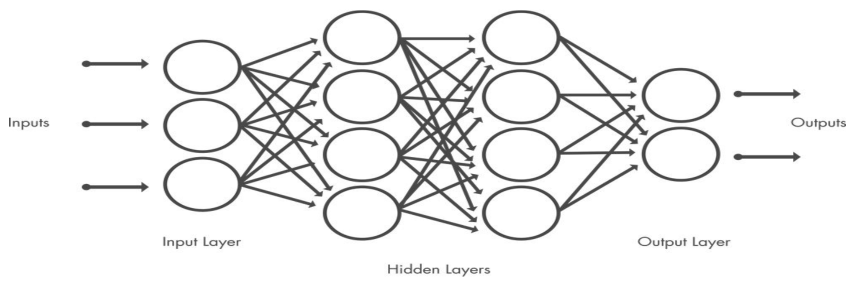

Figure 1: Typical CNN (Mathworks, 2021)

2.2 Transfer Learning

Is a concept that applies the known information or knowledge utilized or received from one operation to subsequent processes that are similar, which can drastically minimize the amount of data required and allow for a lightweight model design. E.g. MobileNet and RestNet (Zhu et al. 2021).

The workflow of the Transfer Learning Model is shown in Figure 2.

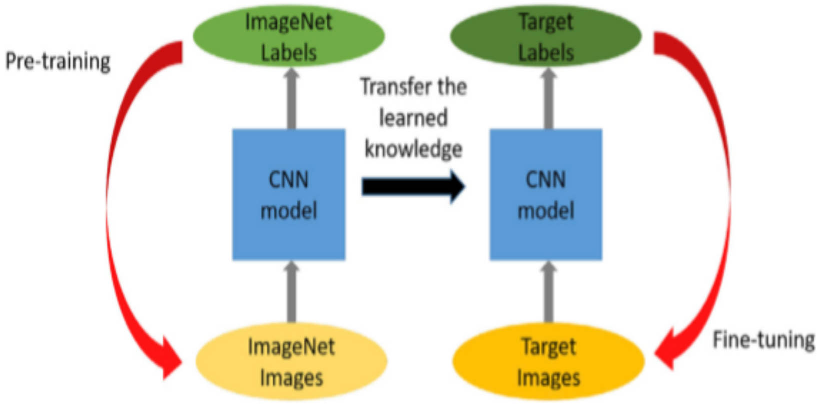

Figure 2: Transfer Learning workflow (Zhu et al. 2021)

In Figure 2, the transfer learning uses the pre-trained model based on the CNN architecture such as MobileNet or ResNet to obtain similar features from the data and train upon it. The transfer learning model gives room for fine-tuning the dataset in case the accuracy is low.

2.3 MobileNet CNN Architecture

The MobileNet model is based on depth wise separable convolutions which is a form of factorized convolutions which factorize a standard convolution into a depth wise convolution and a 1×1 convolution called a pointwise convolution. Depth wise convolution in MobileNets applies a single filter to each input channel. The depth-wise convolution's outputs are then combined using an 1x1 convolution by the pointwise convolution. A standard convolution both filters and puts together inputs into a new category of outputs in one stage. The depth wise separable convolution divides this into two layers, a different layer for filtering and another separate layer for combining. MobileNets are built on a simplified architecture that makes use of depth wise separable convolutions to build light weight. MobileNets are built primarily from depth wise separable convolutions and subsequently used in Inception models to reduce the computation in the first few layers. Down sampling is handled with stride convolution in the depth wise convolutions as well as in the first layer. A final average pooling reduces the spatial resolution to 1 before the fully connected layer. Counting depth wise and pointwise convolutions as separate layers, MobileNetV1 has 28 layers and MobileNetV2 has a total of 53 layers deep (Sandler et al., 2018).

Table 1: The MobileNetV2 architecture (Sandler et al., 2018)

Input	Operator	t	c	n	s
$224^2 \times 3$	conv2d	-	32	1	2
$112^2 \times 32$	bottleneck	1	16	1	1
$112^2 \times 16$	bottleneck	6	24	2	2
$56^2 \times 24$	bottleneck	6	32	3	2
$28^2 \times 32$	bottleneck	6	64	4	2
$14^2 \times 64$	bottleneck	6	96	3	1
$14^2 \times 96$	bottleneck	6	160	3	2
$7^2 \times 160$	bottleneck	6	320	1	1
$7^2 \times 320$	conv2d 1x1	-	1280	1	1
$7^2 \times 1280$	avgpool 7x7	-	-	1	-
$1 \times 1 \times 1280$	conv2d 1x1	-	k	-	

Table 1 shows the MobileNetV2 architecture, the parameter t is the expansion rate of the channels which uses a factor of 6, c is the number of input channels and n represents how often the block is repeated and s represents the first down sampling repetition of a block with a stride of 2. The architecture shows that input images have to be in the 224x224 dimension and in Red Green Blue (RGB) colour which is 3. As the training goes by, the architecture breaks down the dimension and for better high-level feature extraction (Sandler et al., 2018).

2.4 Review of Related Literature

2.4.1 Currency Detection for Visually Impaired Persons

According to Samant et al. (2020) it is easy for people who has functional sight to recognize a currency, but it is not the case for the visually disadvantaged. A visually impaired person is someone with either partial or complete sight disorder. They face difficulties in their daily activities especially recognizing things they can't see. They developed a system that is aimed at providing a cost-effective solution for visually impaired persons to be able to recognize currency using image processing techniques in form of an android application. The system works using voice commands and TensorFlow was used for the implementation. The system identifies and voices out the value of the currency.

According to Almu and Muhammad (2017) the manual method of identifying currency in Sokoto Metropolis is done manually by checking for certain features. This pose the challenge of differentiating between the original and fake currency. They developed a system using an image-based processing technique to help identify and recognize different currencies. The system was implemented using visual basic and Microsoft Access database management system. To test whether a currency is fake or not, the currency is fed into the system and the button start detection is clicked. The system returns a percentage of a match to a currency dataset. If the percentage of the match is high say 70 and above, the currency in question is considered genuine otherwise it Is considered as fake. The proposed future work includes the usage of two or more image processing algorithms to compare currencies for higher accuracy and the implementation on mobile devices and to identify bad or damaged currencies.

Suranya et al. (2020) implemented a currency counting system for visually impaired persons using SIFT algorithm along with ROI and OCR. The system scans a currency denomination and sums up the total then voices out the sum to the user. The system recognizes Indian currency. It is developed using the python packages and deployed into a hardware device which is assembled into a blind-stick with the camera on top of the sick for scanning the currency after which it is passed to the hardware device to echo the currency using a speaker. The hardware used was a raspberry pi with inbuilt Bluetooth and Wi-Fi. KNN algorithm was also used with 93.71% accuracy with good processing time but still has the limitation of differentiating the fake currency notes. This needs to be implemented in the system.

Ng et al. (2020) proposed an intelligent banknote recognition with assistive technology for visually impaired people using Hong Kong Dollar which is the main currency used in Hong Kong. Although the size of the banknotes differs but still it becomes difficult for the visually impaired to recognize them. Cheating can also be easier in case of monetary transactions involving the visually impaired. They applied a machine learning. The system has two parts: the first part is the pre-trained CNN model which was used for transfer learning which speeds up the time required for training. The system works by collecting input as a captured image, then image is pre-processed the feature extraction and the image passes through a binary classifier which determines whether the object is the Hong Kong banknote or not. If it is, then the note passes through a multi-class classifier which determines the denomination of the bank note. The application also checks the confidence level of the result of the classifier. If the confidence is not high enough say less than 70%, it requests the user to try again or else it gives voice and vibration feedbacks. The system was tested and has the accuracy of greater than 80% with the response time of less than 3 seconds. It was deployed using TensorFlow Lite Framework.

Islam et al. (2021) presented a new method for recognizing Bangladeshi currency using a Raspberry Pi 4 and the faster R-CNN model for the visually impaired. They built a smart blind glass that can recognize Bangladeshi currency and echo out the currency value in the blind man's ear. They also introduced a widely used model for object and face recognition which is the faster R-CNN approach. The faster R-CNN approach was used in training the dataset and has achieved a real-time accuracy of 97.8% which was considered high among the state-of-art research. They are with the opinion that visually impaired persons get cheated when it comes to monetary transactions. They used 4507 images as a dataset, these images are of different sizes and positions. 3571 images were used for training and 936 images for testing. The Pi camera captures the video immediately it senses the blind man holding money in his hand and the microprocessor processes the image and recognizes the amount then sends the sound of the amount to the speaker in the blind man's ear. The distance between the currency and the glass should be at last 60cm or less than that for proper focus. However, the blind man safety issues using voice recognition should be considered.

Tasnim et al. (2021) proposed an automated system for recognizing Bangladeshi currency using convolutional neural network for visually impaired persons. The datasets consist of 70, 000 bank notes of available Bangladeshi currency. The system has an accuracy of 92% and gives the result with both audio and text outputs. For the implementation technique, for both training and testing, the Keras framework was applied with TensorFlow as the background. The CNN contains architecture which includes two sections which are automatic feature extraction method and classification. ConvNets contains a sequential architecture used to create the model. The pre-processed dataset is divided into 80% training and 20% testing. However, there is a fluctuation of accuracy due to the nature of the datasets. There is also a need to integrate the system into a cost effective and lightweight mobile application that can help blind people in daily transactions, they also recommended testing the dataset with other classifiers.

According to Gamage et al. (2020) the distortion of currencies over time has become a major challenge for recognizing currency banknotes especially to the visually impaired in Sinhala. In order to address this problem, they conducted research and implemented a system which comprises of three modules which include a speech recognition module, currency recognition module and text to speech module. Which aim to achieve better accuracy in all the three modules using deep learning. Speech recognition neural network model was built using TensorFlow platform and Keras library and deep learning neural networks were used for the development of currency recognition and text to speech modules. They further opined that though there are many speech recognition applications in English, applications which are built in native languages are rarely developed that gave them the reason to develop a speech recognition system in Sinhala language for the Sri Lankan currency to help the visually impaired. 9000 images were used for training of the model with the final validation accuracy of 87.80% and 3000 images were used for testing with accuracy of 95.90%. Jupyter notebook was used to train the model. Many voices should be added and a mobile application integrating the three modules need to be implemented for the visually impaired people to use the system.

Veeramsetty et al. (2020) developed a novel lightweight CNN model to recognize Indian currency notes and were deployed into a web and mobile applications. The proposed model was developed using Tensorflow which is improved by the selection of optimal hyperparameter value and was compared with some well CNN architectures using transfer learning. The created datasets of Indian currency to be used in the system. They developed a mobile application which was created using MobileNet CNN architecture which provides both prediction probability and audio outputs for the visually impaired. The work can be further extended by incorporating the identification mechanism for counterfeit currency notes. This can be done by extracting the face value of currency note and other features which cannot be incorporate in counterfeit notes.

Naing et al. (2019) proposed a Smart Blind Walking Stick Using Arduino which was based on sensors and microcontroller. The system helps the blind persons navigate and identify obstacles and avoid collision. The system identifies objects on left, right, front and down directions in real time. The system was designed using the ultrasonic sensor, IR sensor and Arduino Mega 2560. Using the three components, the system can be attached to the stick of blind persons and capable of sensing distance with the sensors and sends the distance data to the Arduino Mega2560 controller which then alerts the blind person using a buzz. They used Arduino IDE and C programming language for the software implementation of the system. It has the advantage of being low cost and implementable for developing countries. However, there is need to add to the system the ability to detect drop off on the way, ensure sufficient information of the obstacle ahead and safety of the visually impaired person.

According to Chandankhede and Kumar (2019) the concepts of Machine Learning and Artificial Intelligence has offered great algorithmic advantages to the development of real-time applications. Deep learning is inspired by the human neural system. Object recognition and computer vision are some of the applications of machine learning. Object and image detection are better handled with the help of deep learning techniques of AI which can be used to serve the blind impaired persons. Computer vision trains the computer to understand and perceive the visual world. They uncovered that CNN is the leading object detection that shows high level of accuracy. They proposed a deep learning technique to help a visually impaired person by capturing images in real-time, preprocessing, boundary detection, 2000 images restriction based on where the user visits regularly, image captioning then voice output. CNN and ReLU can be used for the system implementation using camera, speaker and any other hardware that could be mobile. The existing system are bulky, white cane with camera module were developed, but the system needs constant sweep rate with ground for proper functioning, cannot work in a crowded area, some existing system depends completely on sensors. The proposed system relies heavily on new methods for recognizing the training of the classes (that are images derived as a result of survey).

Durgadevi et al. (2020) proposed a machine learning system for blind assistance which was implemented using a camera, Raspberry pi and a speaker as hardware components. The system enables the user to detect an object using the camera based on the trained dataset and voice the name of the object using the speaker after sending it to the Raspberry pi. They used a Neural Network model for the system. The system is cost effective simple and user friendly.

Legess and Seid (2020) proposed a CNN based model using a pre-trained model for the visually impaired persons to recognize Ethiopian currency banknotes in real time situations. 8500 images of Ethiopian currencies were collected as dataset. They evaluated the models with 500 real time videos under different views. They adopted Tensorflow object detection API, the faster-RNN and SSD MobileNet models. Transfer learning was used in the training of the datasets. Python language was used and opencv package was used for vision. For R-CNN 91.8% and for SSD MobileNet model has 79.4% accuracy. However, cannot detect fake currency notes.

Pathak and Aurelia (2019) proposed a mobile based smart currency recognition. The system was implemented in such a way that enables user to place their device against a currency and then the value of the currency can be known by giving the output as an audio signal and vibration formats using K-nearest neighbor and canny edge detection algorithm. The K-Means clustering algorithm to track points of interest on the currency, canny algorithm can be used to check for its edges of an object and finally use feature detection for valid currencies and perform currency matching by using feature matching algorithm available in MATLAB so as to finally show if the result if the image match accuracy is more than 75% else it requests the user to retake the image. The system was implemented only using Matlab and was not implemented in mobile, which appears more like a recommendation.

Yadav et al. (2020) are with the opinion that despite the availability of credit cards, electronic banking, internet, payment platforms, but still cash transactions are still going on because of its convenience and simplicity especially in rural areas where such transactions are unavailable. People with visual impairments suffer from identifying various currency values. Currency recognition can be of greatest help to the visually impaired persons. They proposed a currency recognition system for Indian rupees based on FAST and rotated YOLO V3 algorithm. They used six kinds of paper Indian currencies. The proposed system takes input of a given image, preprocesses it and coverts it from RGB to grayscale then a sober algorithm is applied for extraction of inner and outer edges. YOLO V3 algorithm is then used for clustering where clusters of features are made one by one, then it can recognize the feature of the image as either 200, 500, or 2000 depending on the input by comparing the same with the pre-trained dataset with the help of the YOLO V3 algorithm. The template matching is done using SURF key point detector on windows. The proposed system is camera based trained using image processing techniques on Indian currency dataset. The work can be extended to apply the classification to compare the original or counterfeit currency. It is possible to add foreign languages that can be used worldwide and to develop a recognition of currency notes on a low-end mobile phone for Visually Impaired persons and notify the user by voice note in regional language. It can be extended to recognize foreign currencies.

According to Mallikarjuna et al. (2021) many visually impaired persons in our society today face a lot of challenges and one of these challenges is object recognition. They can't navigate on their own, read and often feel isolated from their own community. There are exiting systems dressing such problems, but they have their own limitations. They proposed a solution to the problems faced by visually impaired by proposing a cost-effective system designed and implemented using IoT, machine learning and embedded technologies. The system was trained using Tensor Flow framework, camera to capture the image and a speaker to voice out the name of the object. A Raspberry pi was used to implement the system to which the camera sends the image after capturing, then it classifies the image then the type of the image is voiced out to the user via a speaker. Raspberry pi is trained using Tensor Flow machine learning framework for the classification of real-world object in python programming language. The proposed system helps identify four objects Car, Cat, Bus and Human being. They collected a set of 1615 images which forms the dataset. They used CNN algorithm and OpenCV software for pre-processing. The system is limited to object recognition only and the camera captures the image in one direction also, cannot work in the night. Therefore, the system can be extended for visual inspection of goods in industries, making a bionic eye.

The reviewed studies in this section demonstrate several approaches to aiding visually impaired individuals in currency recognition. Samant et al. (2020) and Almu and Muhammad (2017) showcase early systems using traditional image processing and manual feature extraction, which provide a low-cost solution but are limited by scalability and robustness. More recent works (e.g., Suranya et al. (2020) and Ng et al. (2020)) introduce deep learning often through transfer learning with CNN architectures to improve accuracy and processing speed. However, even these methods sometimes rely on limited datasets or face challenges when differentiating visually similar denominations. Overall, while deep learning methods have significantly increased recognition performance with many reporting accuracies above 95%, there remains a gap in addressing issues such as counterfeit detection and adapting to real-world variances like worn-out notes or varied imaging conditions.

2.4.2 Counterfeit Currency Detection

Bhatia et al. (2021) proposed a fake currency recognition using K Nearest Neighbour (K-NN) followed by image processing. They collected a high-quality image of both fake and genuine currencies as datasets using an industrial camera with 400x400 pixels dimension. They used a wavelet transform to extract features from the collected images. The attributes gathered after that includes Variance, skewness, kurtosis, Entropy, class of the currency. The data set has a total of 1372 images, out of which 610 are genuine and 762 are counterfeit currencies respectively. The further normalized the data to avoid biased classification due to some features on the currencies using MinMax Scaler which was imported from the sklearn. They trained the models using three (3) different algorithms including K-Nearest Neighbour (KNN) with the accuracy of 99.7%, Support Vector Classifier (SVC) with an accuracy of 97.5% and Gradient Boost Classifier (GBC) with 99.4% accuracy respectively. After the comparison, the KNN which has the highest accuracy was considered best algorithm for detecting counterfeit currencies based on the small amount of dataset used which may not be suitable for large datasets due its mode of operation which can be time consuming. As a future work, they proposed a Deep learning algorithm like CNN which can be suitable for large datasets and increasing the number of datasets. More so, more datasets should be added with high quality of real-world images and the use of convolutional neural network which have high accuracy in image processing scenarios. With the CNN the concept of wavelet transform can be removed as the CNN can analyse images from the input. Using CNN can also make the system more convenient and user friendly to use. In this case, the system can be improved and deployed for use by visually impaired persons by adding a voice note to detect the value and to distinguish between fake and genuine currencies.

According to Ogbuju et al. (2020) technological advancements has brought about the increase in cases associated with counterfeit currencies around the world. In Nigeria, the issue of counterfeit currencies is the biggest challenge faced in cash transactions. Therefore, it becomes important to utilize automatic means of counterfeit currency detections using machines to detect these fake currencies. They proposed a system that would help detect counterfeit banknotes and would contribute in curbing the menace of currency counterfeiting. To achieve this, they applied a deep learning approach using Faster Region Recurrent Neural Network (FRCNN) a class of CNN with 24 NN and 2 fully connected layers making a total of 76 nodes all together on the network to develop a naira detection model in Google Colab which was deployed to a mobile application called Real Naira. The system was tested with four (4) higher denominations of ₦100, ₦200, ₦500 and ₦1000 currency notes. They used a total of 730 images of the four (4) higher denominational currency notes. They extracted some relevant features that can be found on genuine currency banknotes and used these features for classification to identify the fake and genuine banknotes. The system is limited to detecting only the four higher currency banknotes using small number of datasets. Therefore, more datasets need to be added, with the addition of the four (4) lower currency banknotes ₦5, ₦10, ₦20, and ₦50 into system and possibly expanding the scope of the system to detect other African currencies.

According to Sarfaz et al. (2019) the advancement in digital imaging technology which includes the ability to print highly coloured papers has made it possible to produce fake currency Banknotes. The fake banknotes caused loss to anyone especially those involved in cash financial transactions. Therefore, there is a need to verify these currencies for smooth financial transactions. They proposed a cognitive computation-based approach for paper currency verification. They performed a scanning of both fake and original currencies to determine what both are made of using Scanning Electron Microscopy (SEM) and X-Ray Diffraction (XRD) analyses of counterfeit and genuine banknotes were performed. They used Support Vector Machine for classification based on the features like printing ink, chemical composition, and surface coarseness which they found a significant difference between the fake and the original currency. For experimentation and evaluation of performance purposes, they collected 195 Pakistani banknote images with 35 counterfeit banknotes. The system achieved 100% verification accuracy for well captured images. 60 genuine and 10 counterfeits of 500, 1000 and 5000 PKR each with threshold value of 0.4 were used for performance assessment and the system achieved 100% accuracy. However, more datasets should be added and can be deployed into web or mobile and another algorithm can also be used.

Rajebhosale et al. (2017) proposed a system based on image processing technique to identify fake currency notes automatically. They collected a dataset of 100, 500 and 1000 rupees using a camera, and they performed feature segmentation and template matching. Image processing was used to extract small parts of the images which matches the template image using template matching. Then they finally they deployed the template matching algorithm into a web application which enables the detection of both genuine and fake Indian rupees for the three denominations used. The goal of their work was to develop a friendly web application that can detect and recognize fake and genuine Indian rupees. They further propose that the method can be adopted and be used for real time recognition. The web application provides an interface to upload a currency note that the user would want to verify, and the system displays the uploaded image(input) alongside the processed(matched) version of the image with the statues of the image either being original or fake under the image. The technique can be very adaptive and can be implemented in a real time world.

Agasti et al. (2017) proposed an Indian currency recognition using image processing. The proposed system gave an approach to determine and verify fake Indian currency notes by extracting various features of the currency using MATLAB. The new system has advantage of simplicity and high speed. They used the concept of edge detection to identify and detect certain features and image segmentation which divides the images into sub-regions that could be used for feature matching and distinguishing the features of fake and genuine banknotes. They itemized the features which can be used to identify currencies as follows: security threads, serial number, latent image, watermark, identification mark, etc. The process involves image acquisition, grey scale conversion and edge detection, image segmentation, feature extraction and calculation of its intensity the finally, if the condition is satisfied with 70% threshold, then it is considered as genuine otherwise classified as fake.

Zhang (2018) proposed a Single Shot MultiBox Detector (SSD) model which was based on deep learning as a framework and employing the convolutional neural network (CNN) for feature extraction of paper currencies. They used two models for comparing the MobileNet and Faster R-CNN. However, they found out that the CNN performed suitably well for currency identification requirements. Even when a currency is tilted, moved front or back, it can still be identified. By using CNN and SSD with accuracy of 96.6%. They collected a total of 300 raw images of New Zealand dollars with 50 images of 6 denominations each. However, the data was not sufficient, so they performed data augmentation by rotating, resizing, randomly zooming the images and the total number of images increased to 300x25 which equals 7500 images. They created a 6-layer CNN model and chose to use quadrilateral box and set the initial weights to 1.0 for the currency recognition training. They finally compared and analyzed the three models they used which includes MobileNet, Faster R-CNN and SSD. The SSD model was the most accurate for currency recognition. In the future, there is a need to add many different country currencies, use serial number of the currencies and surface patterns, use other deep learning models such as RestNet-101, Inception_V2 model etc.

In this section, the focus shifts toward distinguishing genuine from counterfeit notes. Bhatia et al. (2021) used a K-Nearest Neighbour (K-NN) approach with wavelet-based feature extraction to achieve very high accuracy, yet this method may be computationally intensive and less scalable to larger datasets. Ogbuju et al. (2020) leverage deep learning using Faster R-CNN to detect higher denominations in Nigerian currency, but their approach is constrained by a small dataset and is limited to only a subset of denominations. Sarfaz et al. (2019) employed advanced imaging techniques (SEM and XRD) with SVM classification, achieving perfect accuracy in controlled conditions, though their reliance on high-quality, specialized imaging limits practical deployment. These studies indicate that while high accuracy is achievable in counterfeit detection, real-world application is hindered by dataset quality, processing demands, and the challenge of integrating such systems into user-friendly platforms.

2.4.3 Currency Recognition and Detection Using Deep Learning

Bhutada et al. (2020) proposed a currency detection system for staff working at the forex bank to identify currencies of various countries around the world. They used a machine learning technique such as image processing to help detect the origin, name, and denomination of various currencies around the world. As there are many currencies, they developed a system that can take a particular currency as an input, pre-processes the image to extract the Region of Interest (ROI) from the notes which includes the origin of the currency and denomination based on some features like dimension, pigment and text clipping. They deployed the model into web using Wampserver, Django and python. The results obtained show that the model was able to detect currencies with 93.3% accuracy. The system identifies the currency using template matching of the original currency. The value and denomination of the currency can be identified based on the color, size and text colors used to separate the various currencies. However, few country currencies tested. In the future there is a need to progress to maximum currencies.

Sindhu and Varma (2020) proposed a currency recognition by using image processing. They developed an automatic currency recognition system using digital image processing method. It helps users to recognize details on a particular currency such as currency value and currency name by using the main characteristics on a currency. The targeted currency includes the Indian Rupees and the US dollars. The system uses image processing techniques to extract information from a currency image as an input and then match it with template images. NumPy and OpenCV in python are two frameworks used in this work to perform image processing functionalities and Thinker for applet development of the application. The system accepts input as an image, performs template matching and processing them displays an output. However, the trained dataset is low therefore more improvements need to be made and real time currency detection should be made where the user detects the currency in real-time. There is a need to add more currencies as there are up to 180 currencies in 195 countries around the world.

Chakraborty et al. (2020) investigated various methods involved in currency recognition along with other techniques which can be applied in the process of identifying and recognizing currencies. They reviewed papers in order to identify recent developments in paper currency recognition. According to them, significant progress has been recorded over the years on currency recognition and detection as monetary transactions are inevitable part of our lives. Many people especially visually impaired persons who were most at times being deceived and being cheated because they cannot see. They pointed out some potential applications of currency recognition such as visually impaired assistance, counterfeit currency detection, Automatic selling goods, banking applications etc. though considerably much work has been done on currency recognition and detection, but there are still much vast opportunities to pursue in the future. Most of the models used for these works are Artificial Neural Networks (ANN) models with other kinds of neural networks such as Feed Forward, network, Back Propagation Neural Networks, Ensemble Neural Network. The framework of the existing methods is described, and the focus is on image acquisition, image localization, feature extraction, template matching and validating the output.

According to Linkon et al. (2020) an automatic detection and recognition of currencies can be very important for both the visually impaired persons and the bank because it can provide effective management for handling various paper currencies. They proposed an automatic approach for the detection and recognition of Bangladeshi Banknotes using a lightweight CNN architecture combined with transfer learning. They used ResNet152v2, MobileNet, and NASNetMobile as base models with two different datasets of Bangladeshi banknote images with one having 8000 images and the other 1970 images. They measured the performances of the models using the two datasets and obtained a maximum accuracy of 98.88% on 8000 image dataset using MobileNet, 100% on the 1970 images dataset using NASNetMobile, and 97.77% on the combined dataset (9970 images) using MobileNet. As a future work, increase the dataset, adjust the background of the images. Integration of fake currency banknote detection algorithms with the lightweight models.

Previous studies revealed that object recognition and detection using machine learning and deep learning has recorded a lot of progress. However, a model to recognize currency naira notes for four (4) higher denominations with the ability to distinguish between a genuine and a counterfeit note was proposed by Ogbuju et al. (2020). However, the work does not cover the recognition of lower currency naira notes. This work seeks to cover the currency recognition for eight (8) different naira currency denominations and voice out the values in English audio form using a mobile application.

This section reviews works that primarily apply deep learning techniques for recognizing and detecting currencies. Bhutada et al. (2020) and Sindhu and Varma (2020) explored models that combine image processing with machine learning to recognize multi-national currencies. Chakraborty et al. (2020) offer a broad review of deep learning methods, emphasizing that CNN-based models often enhanced through transfer learning provide the highest recognition rates. Linkon et al. (2020) further illustrates that lightweight CNN architectures can achieve high accuracy up to or above 98% and are suitable for mobile applications. Nonetheless, a recurring limitation is the need for large, diverse datasets to ensure model robustness and generalizability, especially under variable real-world conditions such as different lighting, angles, or wear of banknotes.

Across sections 2.4.1, 2.4.2 and 2.4.3, the literature reveals a clear trend: deep learning techniques, particularly CNNs augmented by transfer learning, have advanced the field of currency recognition, significantly outperforming earlier, traditional image processing methods. However, critical challenges remain, which includes

i. **Dataset Diversity and Quality:** Many studies rely on controlled or limited datasets, which may not fully capture the variability seen in real-world scenarios.
ii. **Computational Efficiency and Scalability:** While deep learning models achieve high accuracy, they often require substantial computational resources, making deployment on low-power or mobile devices challenging.
iii. **Robustness and Real-World Application:** Variations in image quality, lighting, and currency wear can adversely affect performance. Moreover, many systems do not yet robustly handle counterfeit detection alongside genuine currency recognition.
iv. **Integration for Practical Use:** Although high accuracies are reported in academic settings, translating these systems into accessible, user-friendly applications, especially for visually impaired persons, requires further work in terms of integration, real-time performance, and multi-language support.

These insights underline the need for future research to focus on building robust, lightweight, and scalable models that not only achieve high accuracy under controlled conditions but are also adaptable to the unpredictable variables of real-world usage.

3 Methodology

The methodology used for this work is deep learning. Many deep learning algorithms exist which have been used in object detection and classification. The most used which have proven to be more effective in vision-based systems and image processing systems is the convolutional neural network (CNN). The CNN concept has been applied in many real-world systems such as object recognition and detection, currency identification and classification, plant disease classification etc. Therefore, for the purpose of this work, a Deep Learning model based on transfer learning for Naira currency detection and recognition using MobileNetV2 CNN architecture was used after which the model was deployed into a mobile application using android studio for use on android mobile device.

3.1 System Flow Diagram

The system framework shows the processes involved in the development of the system from the start to the end. The process involved is captured in Figure 3.

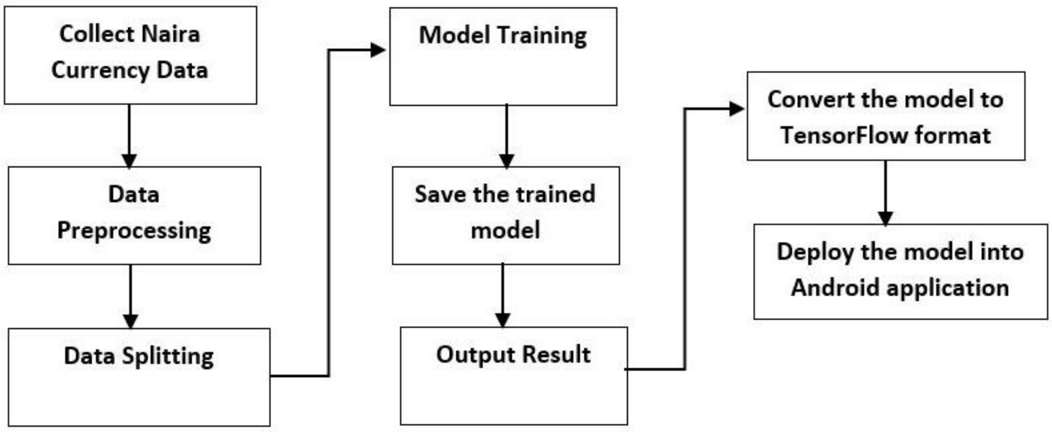

Figure 3: System Flow diagram

Figure 3 Shows the steps that is be followed to develop the system from getting the dataset, pre-processing, training, evaluation of training results and deployment into an android application for the user.

3.2 Dataset

The dataset was gathered using a mobile phone camera of 48Mega Pixels manually controlled, the dataset consists of eight denominations of Nigerian naira currency which includes: 261 five-naira denomination, 222 ten-naira denomination, 442 twenty-naira denomination, 269 fifty naira, 195-hundred-naira denomination, 362 two-hundred naira denomination, 572 five hundred naira denomination, 692 one-thousand naira denomination and 600 images of different objects for a non-currency class, making a total of 3615 images of naira notes based on the availability of the different currencies. The dataset collected are of 9 classes with each of the denominations making one class and the non-currency class, the images were named from 0, 1, 2, 3, 4, …, last. These images were resized to 224x224 pixels to make the suitable input dimension for the MobilenetV2 CNN architecture. The data was divided into 80% for training and 20% for testing respectively. The data augmentation method utilized includes the automatically generated augmentation while training the model and manual cropping of some of the data. The dataset used consists of nine classes, which were divided into 80% for training and validation and 20% for testing, making a total of 3615 images.

3.3 Training Environment Setup

The model was trained using python language in Spyder anaconda IDE. The trained model was converted to TensorFlow lite format making it ready to be deployed to a mobile device in the same Spyder anaconda IDE, the training was done on Windows 10 computer with 8GB RAM and 500GB HDD. The android app was designed and coded in android studio using Java programming language which was published to an android device for use.

3.4 System Model and Technologies

Figure 4 shows the model deployed into a mobile application which can detect a naira currency note and echo the value to the user. Python programming Language, MobileNetV2 CNN Architecture based on Transfer Learning, TensorFlow deep learning framework for training and Android studio for deploying the model into a mobile application were used.

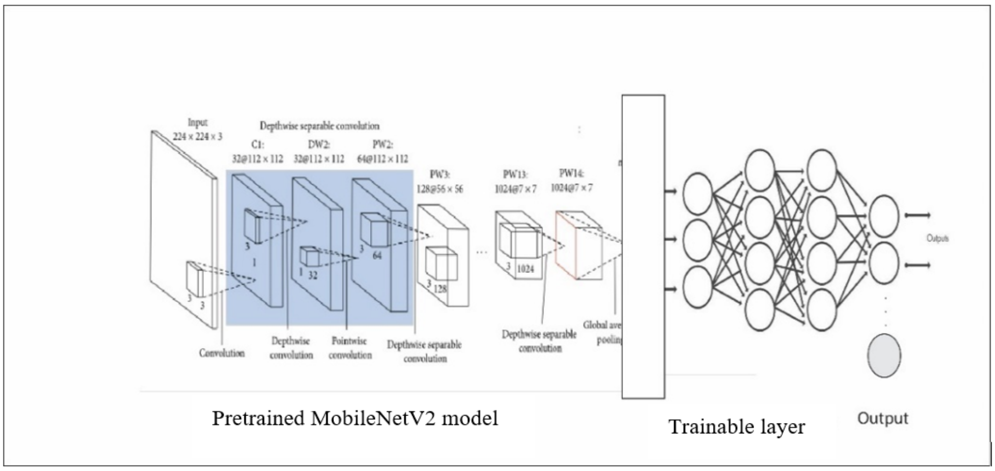

Figure 4: System Model overview (Howard et al., 2017)

Figure 4 shows how the MobileNetV2 pretrained CNN architecture used as a base upon which a layer containing the collected dataset is attached and trained using the concept of transfer learning. The first part is the fixed pretrained MobileNetV2 CNN architecture that is trained on ImageNet while the second part is the trainable layer which consists of the naira currency dataset with the input size of 224x224x3 attached at the output layer of the MobileNetV2 CNN architecture.

4 Results and Discussion

4.1 Results

The following results obtained from the training of the model using MobileNetV2 CNN architecture with 60 epochs (iterations) on the collected and preprocessed dataset. The pictural representation of the classification accuracy and cross entropy loss is shown in Figure 5 and Figure 6 respectively.

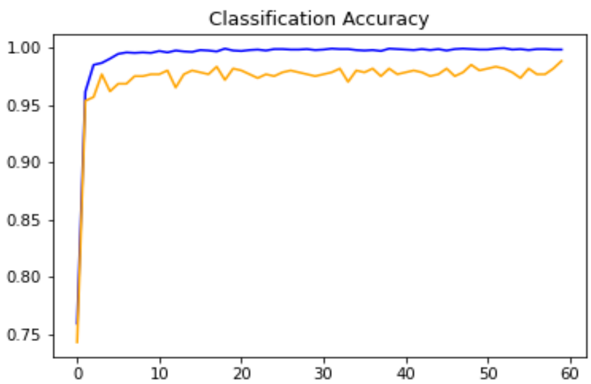

Figure 5: Classification Accuracy

Figure 5 shows the classification accuracy of the trained model. This accuracy is achieved after sixty (60) epochs.

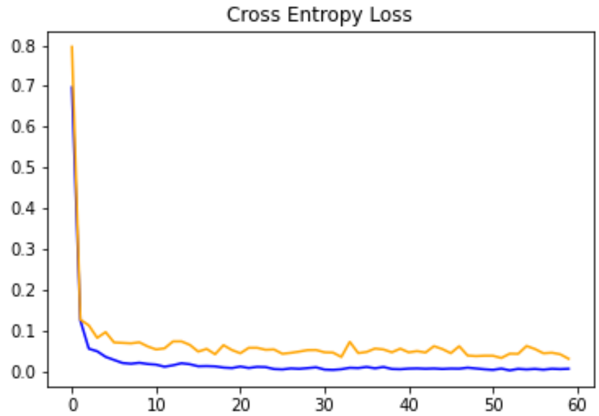

Figure 6: Cross Entropy loss

Figure 6 shows the cross-entropy loss of the trained model. This is the loss due to data imbalance and some factors associated with the trained model.

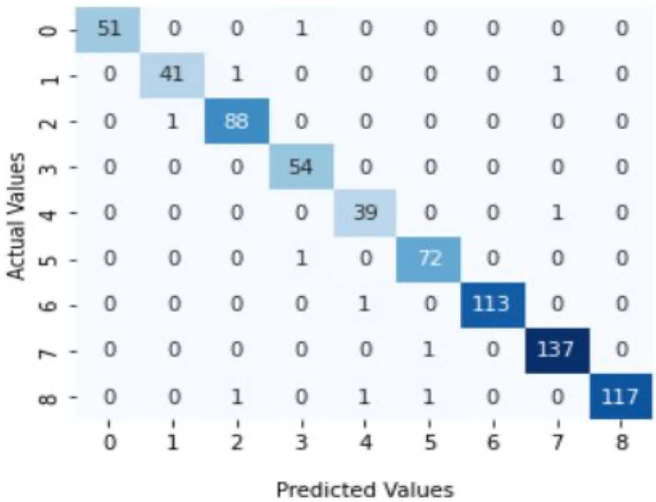

Figure 7: Confusion matrix for currency model

The confusion matrix in Figure 7 provides insight into the model's performance across different currency denominations based on the test data.
In the confusion matrix, each row represents an instance in a predicted class, and each column represents an instance in an actual class (Beheshti, 2022).

Table 2 shows the meaning of the list of classes in the confusion matrix in Figure 7.

Table 2: Classes and Meaning from Figure 7

Classes	Interpretation
0	Five (5) naira notes
1	Ten (10) naira notes
2	Twenty (20) naira notes
3	Fifty (50) naira notes
4	Hundred (100) naira notes
5	Two Hundred (200) naira notes
6	Five Hundred (500) naira notes

7	One Thousand (1000) naira notes
8	Noncurrency

In Figure 7, which presents the confusion matrix, the confusion matrix is used to ascertain the performance of the model as depicted in Table 3.

Table 3: Summary of the Performance Metrics

Class	Precision	Recall	F_1 – Score	Macro F_1 – Score	Accuracy
0	1.00	0.98	0.99		
1	0.98	0.95	0.96		
2	0.98	0.99	0.98		
3	1.00	1.00	1.00		
4	0.95	0.97	0.96		
5	0.97	0.99	0.98		
6	1.00	0.99	1.00		
7	0.99	0.99	0.99		
8	1.00	0.97	0.99		
				0.98	98%

The model achieves high precision and recall across all currency denominations, suggesting strong learning of distinguishing features. The model performed well across all classes, with precision and recall values ranging between 0.95 and 1.00, confirming its robustness. Focusing on class specific metrics, Class 3 which is Fifty Naira (₦50) achieved perfect classification, indicating that its unique features are well captured by the model.

Lower accuracy in non-currency classification suggests some non-currency objects may have textures or colors similar to currency notes which resulted in minimal missclassifications. The model performs exceptionally well, with F1-Scores above 0.95 for all classes. The results suggests high reliability in real-world applications. Though there are missclassifications in some of the classes, however, this is open to improvement.

4.2 Deployment Results

The model was deployed into a mobile application from Android studio and the results shown in figures 8 and 9. The model was trained and saved as model.h, and converted to Tensorflow lite format currency model.tflite using python language in Spyder IDE, the mobile application was coded using Java programming language.

This section shows results obtained from the model deployment and how it works on a mobile device. The system automatically opens the camera immediately it is launched, after which the user holding a naira currency can capture the image using the android's volume down button, then the system detects and echoes the naira currency value in audio form in English Language.

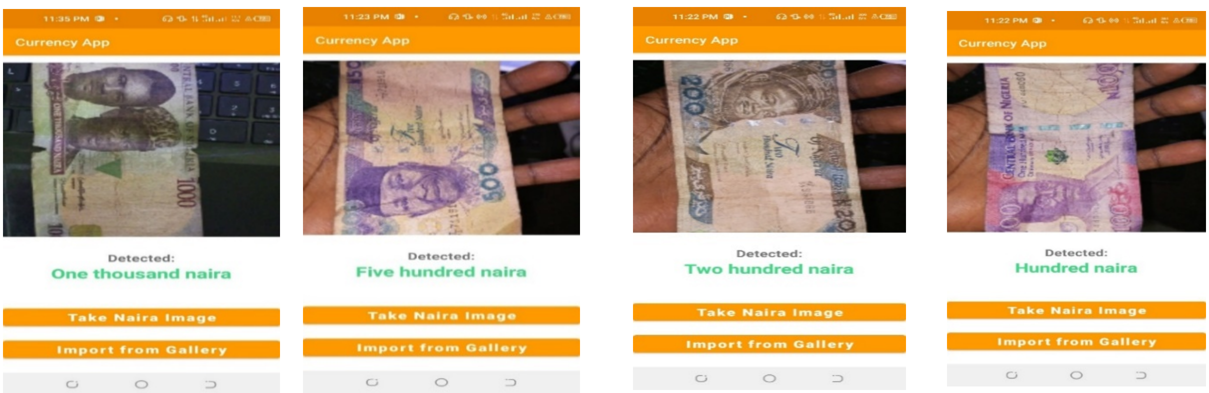

Figure 8: Detected images of one thousand, five hundred, two hundred and one hundred naira notes only

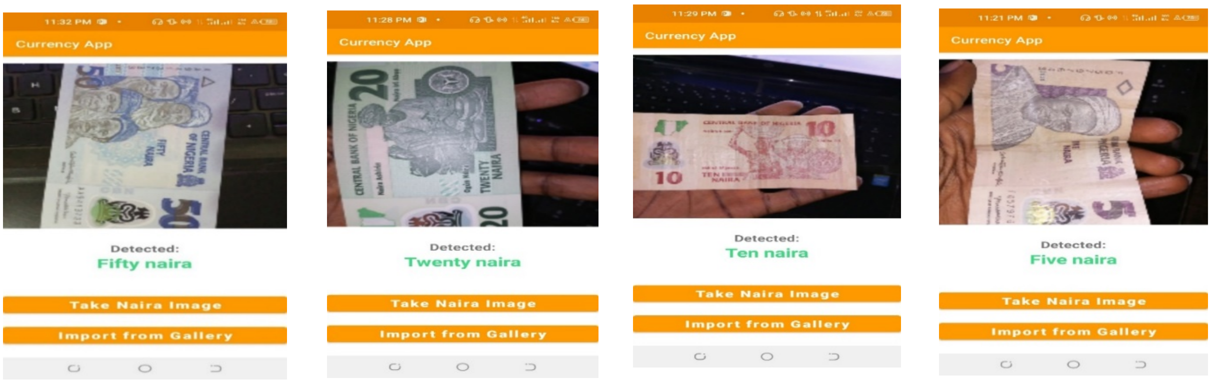

Figure 9: Detected images of fifty, twenty, ten and five naira notes

The results obtained from the training of the model using the mobileNetV2 CNN architecture is 98% accuracy. This indicates that the model's training accuracy is good. Also, the performance metrics shows that the model's performance is good. Most classes achieve recall (accuracy) levels between 97% and 99%, with Class 3 (Fifty naira notes) reaching 100%. The slight drop for Class 1 which has 95% accuracy suggests that Ten naira notes might be more challenging to distinguish, possibly due to visual similarities with adjacent denominations or variations in the note's appearance. Similarly, Classes 4 and 8 both at 97% accuracy shows a small degree of misclassification that might be due to subtle variations in design or imaging conditions.

Overall, the confusion matrix reveals an excellent classification performance across all classes, with only minor misclassifications that are within acceptable limits for real-world applications. This high level of accuracy indicates that the model is very reliable in recognizing the different currency notes and distinguishing them from noncurrency images.

Achieving such high accuracy suggests that the model have been trained on a well-balanced dataset, which suggests that its generalization to real-world conditions can be effective, though some of the classes have fewer datasets, however, automatic data augmentation has been used to increase the number of datasets during training. MobileNetV2 CNN Architecture have shown effectiveness in feature extraction even with few number of datasets since it is a pretrained model. Moreover, the model does not account for worn-out currencies which may affect real-world usability in such cases.

The deployment into the mobile application as seen in the results worked as expected and can be installed on mobile devices for detection of naira notes and voicing out the value of the corresponding classified naira currency in audio form in English Language. This work has added to the existing system more features such as dataset and audio integration which makes it suitable to be used by visually impaired persons. The system can also be used to teach about naira currency for children.

5 Conclusion

Looking at the state of art today, visually impaired persons need assistance to carry out their day-to-day activities especially when it has to do with financial transactions. This research explored the given problem and tries to address this problem which the visually impaired persons are faced with. Therefore, this research focused on the development of a model for the recognition of eight (8) denominations of Nigerian naira currency using deep learning CNN architecture MobileNetV2 model based on transfer learning for visually impaired persons. A total of 3615 images datasets were collected for the training of the model, the collected dataset was pre-processed, divided into 80% training and 20% testing, and the model was trained, saved, and converted into the TensorFlow format for deployment. The trained model achieved an accuracy of 98% which was trained using python programming language in the Spyder Anaconda IDE, the model was deployed into a mobile application which can be used by the visually impaired persons for the recognition of naira notes. The mobile application captures the currency image using the mobile phone's camera, then the captured image is sent to the currency model running at the application's background and the model classifies the currency image to its denomination. The mobile application then outputs the classified currency value both in text and in audio form. The user can listen to the value of the currency echoed by the mobile phone's speaker.

The system classifies only eight Nigerian naira currency denominations (5-1000). The work can further be extended to include the classification of Nigerian coins. Moreover, the result of currency classification voices out the values of Nigerian naira currency in English language, the work can be extended to add multiple languages used in Nigeria so that it can be used to learn about the naira currency in major Nigerian languages and for wider benefit and coverage.

References

Agasti, T., Burand, G., Wade, P., & Chitra, P. (2017, November). Fake currency detection using image processing. In IOP conference Series: materials Science and Engineering VIT University, Vellore, Tamil Nadu, India, 263(5), 1-8. IOP Publishing.

Akano, O. F. (2017). Vision health disparities and visual impairment in Nigeria: A review of the Nigerian National Blindness and Visual Impairment Survey. African Vision and Eye Health (AVEH): 76(1), 1-5. DOI:https://doi.org/10.4102/aveh.v76i1.345

Almu, A., & Muhammad, A. B. (2017). Image-Based Processing of Naira Currency Recognition. Annals, Computer Science Series: 15(1), 169-173.

Beheshti, N. (2022). Guide to Confusion Matrices and Classification Performance Metrics. Retrieved on 21st July, 2022 from https://towardsdatascience.com/guide-to-confusion-matrices-classification- performance metrics-a0ebfc08408e

Bhatia, A., Kedia, V., Shroff, A., Kumar, M., Shah, B. K., & Aryan. (2021). Fake Currency Detection with Machine Learning Algorithm and Image Processing. IEEE Proceedings of the Fifth International Conference on Intelligent Computing and Control Systems Vaigai College Engineering (VCE), Madurai, India: 755-760. DOI: 10.1109/ICICCS51141.2021.9432274.

Bhutada, S., Reddy, V. K., Chevva, A., Kadapala, S. & Gella, M. (2020). Currency Recognition Using Image Processing. *International Journal of Scientific Development and Research (IJSDR),* 5(4), 275-278.

Chakraborty, K., Basumatary, J., Dasgupta, D., Chandra J. K., Mukherjee, S. (2020). Recent Developments in Paper Currency Recognition System. *International Journal of Research in Engineering and Technology (IJRET)*, 2(11). Available @ http://www.ijret.org222 ISSN: 2319-1163.

Chandankhede, P. & Kumar, A. (2019). Deep Learning Technique for Serving Visually Impaired Person. IEEE 9th International Conference on Emerging Trends in Engineering and Technology - Signal and Information Processing (ICETET-SIP-19) Nagpur, India: doi: 978-1-7281-3506-9/19, 1-6.

Chaubey, N., Parikh, S., & Amin, K. (Eds.). (2020). Computing Science, Communication, and Security. Communications in Computer and Information Science. doi:10.1007/978-981- 15-66486

Daniel, U. (2020). Nigeria Association of the Blind (NAB). Retrieved on 25th October, 2021 from https://www.nigeriaassociationoftheblind.org/

Durgadevi, S., Thirupurasundari, K., Komathi, C. & Mithun, S. B. (2020). Smart Machine Learning System for Blind Assistance. IEEE International Conference on Power, Energy, Control and Transmission Systems (ICPECTS): 1-4 DOI: 10.1109/ICPECTS49113.2020.9337031

Gamage, C. Y., Bogahawatte, J. R. M., Prasadika, U. K. T., & Sumathipala, S. (2020). DNN Based Currency Recognition System for Visually Impaired in Sinhala. IEEE 2nd International Conference on Advancements in Computing (ICAC) Colombo, Sir Lanka: 1, 422-427. DOI: 10.1109/ICAC51239.2020.9357295

Geekforgeeks. (2019). Unified Modeling Language (UML) | An Introduction. Retrieved from https://www.geeksforgeeks.org/unified-modeling-language-uml-introduction/ on 21st July, 2022.

Howard, A. G., Zhu, M., Chen, B., Kalenichenko, D., Wand, W., Weyand, T., Andreetto, M. & Adam, H. (2017). MobileNets: Efficient convolutional neural networks for mobile vision applications. arXiv preprint arXiv: 1704.04861

Islam, M. T., Ahmad, M., & Bappy, A. S. (2021). Real-Time Bangladeshi Currency Recognition Using Faster R-CNN Approach for Visually Impaired People. In Communication and Intelligent Systems:147-156. Springer, Singapore.

Jafri, R., Abid, S. A., Arabnia, H. R. & Fatima S. (2013). Computer Vision-based Object Recognition for the Visually Impaired in an Indoors Environment: A Survey. Vis Comput Springer: DOI: 10.1007/s00371-013 0886-11 26

Legess, M. M. & Seid, H. W. (2020). Real-Time Ethiopian Currency Recognition for Visually Disable Peoples Using Convolutional Neural Network. Research square: 1-24. DOI: https://doi.org/10.21203/rs.3.rs125061/v1.

Linkon, A. H. M., Labib, M. M., Bappy, F. H., Sarker, S., Jannat, M. E., & Islam, M. S. (2020). Deep Learning Approach Combining Lightweight CNN Architecture with Transfer Learning: An Automatic Approach for the Detection and Recognition of Bangladeshi Banknotes. 2020 IEEE 11th International Conference on Electrical and Computer Engineering (ICECE) Buet, Dhaka, Bangladesh: 214-217.

Mallikarjuna, G. C. P., Hajare, R., & Pavan, P. S. S. (2021). Cognitive IoT System for visually impaired: Machine Learning Approach. Materials Today Proceedings. 1-7. doi: 10.1016/j.matpr.2021.03.666

Mathworks (2021). Convolutional Neural Network. Retrieved on 11th November, 2021 from https://www.mathworks.com/discovery/convolutional-neural-network-matlab.html

Naing, M., Nwe, N. O., & Thwe, M. O. (2019). Smart Blind Walking Stick using Arduino. International Journal of Trend in Scientific Research and Development (IJTSRD):3(5) August 2019 Available Online: www.ijtsrd.com e-ISSN: 2456 – 6470, 1156-1159.

Ng, S. C., Kwok, C. P., Chung, S. H., Leung, Y. Y., & Pang, H. S. (2020). An Intelligent BanknoteRecognition System by using Machine Learning with Assistive Technology for Visually Impaired People. 10th IEEE International Conference on Information Science and Technology (ICIST) Bath, London, and Plymouth, United Kingdom: 185-193. doi:10.1109/icist49303.2020.9202087

Ogbuju, E., Usman, W. O., Obilikwu, P. & Yemi-Peters, V. (2020). Deep Learning for Genuine Banknotes FUOYE. *Journal of Pure and Applied Sciences (FJPAS)*, 5(1), 56-67. ISSN: 2616-1419.

Pascolini, D., & Mariotti, S. P. (2012). Global estimates of visual impairment: 2010. British *Journal of Ophthalmology*, 96(5), 614-618.

Pathak, A., & Aurelia, S. (2019). Mobile Based Smart Currency Detection System for Visually Impaired. *Journal of Image Processing and Artificial Intelligence*, 5(3), 1–4. http://doi.org/10.5281/zenodo.3354669.

Rajebhosale, S., Gujarathi, D., Nikam, S., Gogte, P., & Bahiram, N. (2017). Currency Recognition System Using Image Processing. *International Research Journal of Engineering and Technology (IRJET)*, 4(3), 2559-2561.

Samant, S., Sonawane, S., Thorat, R., Shah, P. B., & Kulkarni, N. P. (2020). Currency Recognition System for Visually Impaired People. *International Journal of Advance Scientific Research and Engineering Trends*, 5(3), 31-35.

Sandler, M., Howard, A., Zhu, M., Zhmoginov, A., & Chen, L. C. (2018). Mobilenetv2: Inverted Residuals and Linear Bottlenecks. Proceedings Of the IEEE Conference On Computer Vision And Pattern Recognition (Iccvpr) Salt Lake City, Ut, Usa, 4510-4520: 10.1109/Cvpr.2018.00474.

Saranya, K. S., Badhan, A. K., Alekhya, A., Madhumitha, C., & Charmika, V. D. (2020). Currency Counting for Visually Impaired Through Voice using Image Processing. International *Journal of Engineering Research & Technology (IJERT)*, 9(5), 195-199.

Sarfraz, M., Sargano, A.B., & UI Haq, N. (2019). An Intelligent System for Paper Currency Verification using Support Vector Machines. Scientia Iranica, 26(1) (Special Issue on: Socio-Cognitive Engineering), 59-71: doi: 10.24200/sci.2018.21194

Simske, S. (2019). Meta-analytics: consensus approaches and system patterns for data analysis. Morgan Kaufmann.

Sindhu, R. & Varma, P. (2020). Currency Recognition System Using Image Processing. *International Journal of Scientific & Engineering Research,* 11(4), 1595-1601.

Tasnim, R., Pritha, S. T., Das, A., & Dey, A. (2021). Bangladeshi Banknote Recognition in Real-time using Convolutional Neural Network for Visually Impaired People. 2021 IEEE 2nd international Conference on Robotics, Electrical and Signal Processing Techniques (ICREST) American International University, Dhaka, Bangladesh: 388-393.

Veeramsetty, V., Singal, G., & Bidal, T. (2020). Coinnet: platform independent application to recognize Indian currency notes using deep learning techniques. Multimedia tools and applications, 79, 22569-22594

WHO. (14 October, 2021). Blindness and vision impairment. Retrieved on 25th October, 2021 from https://www.who.int/news-room/fact-sheets/detail/blindness-and-visual-impairment

Yadav, S., Ali, Z., & Gautam, K. S. (2020). Currency Detection for Visually Impaired. *Journal of Emerging Technologies and Innovative Research (JETIR)*, 7(5), 999-1002. www.jetir.org (ISSN-2349-5162)

Zhang, Q. (2018). Currency Recognition Using Deep Learning. A thesis submitted to the Auckland University of Technology in partial fulfilment of the requirements for degree of Master of Computer and Information Sciences (MCIS): I-95.

Zhu, W., Braun, B., Chiang, L. H., & Romagnoli, J. A. (2021). Investigation of transfer learning for image classification and impact on training sample size. *Chemometrics and Intelligent Laboratory Systems: An International Journal Sponsored by the Chemometrics Society*, *211*(104269), 104269. doi:10.1016/j.chemolab.2021.104269