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Offline Handwritten Character Recognition for Igbo Alphabets Using Convolutional Neural Networks

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ABSTRACT

Most Latin word and character recognition systems have numerous classification algorithms to automate the identification of handwritten characters. However, despite extensive research on various Latin-based languages, relatively limited attention has been given to the recognition of handwritten text in Nigerian indigenous languages. Handwritten character recognition is challenging due to the variations in shape and style. In addition to that, these characters naturally vary among individuals. This work presents an offline character recognition system for Igbo handwritten alphabets using convolutional neural networks. In this study, a dataset comprising 9,000 character images was created, with 250 distinct samples for each of the 36 letters in the Igbo alphabet. Of these, 200 samples per character (a total of 7,200 images) were pre-processed, binarized, and normalized for training two Convolutional Neural Network (CNN) models. The remaining 50 samples per character (1,800 images) were reserved for testing. Model 1 and Model 2 achieved recognition accuracies of 83.5% and 85.0%, respectively. The proposed approach demonstrates potential for enhancing the automation and digitization of handwritten Igbo texts into machine-readable formats.

Keywords: Optical Character Recognition, Igbo Handwritten Characters, Nigerian, Indigenous, Convolutional Neural Network

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I. INTRODUCTION

Optical Character Recognition (OCR) has been described as the art of detecting, segmenting and identifying characters from images [1]. However, despite extensive efforts already made, character recognition is still an active research area because of its complex nature [2][3]. According to Surya Nath and Afseena [4], achieving 99.9% accuracy in OCR is quite a challenging task. OCR represents a compelling subfield within pattern recognition and artificial intelligence, attracting growing interest due to its broad applicability across mobile technologies, office automation systems, and various industrial domains [4] [5].

Cun et al [6] defined character as the basic building block of any language which can be used to develop different language structures. Characters are simply a universal set of alphabets from which lexical structures such as words, strings, sentences, paragraphs and so on can be developed. OCR is the recognition of optically processed characters. In OCR, a digital camera or scanner can be used to capture different types of documents (like paper documents, PDF files and character images) and convert these captured documents into machine-editable formats.

1.1 Classification of OCR

Surya Nath and Afseena [4] classified OCR into two categories, which are: Handwritten Character Recognition (HCR), the recognition of intelligible handwritten input from sources such as paper documents; and Printed Character Recognition (PCR), the recognition of text characters from printed documents.

Furthermore, based on the acquisition source, HCR systems can be subdivided into two categories, namely: On-Line Character Recognition system and Off-Line Character Recognition system. On-line character recognition is the conversion of text written on a digitiser or personal digital assistant automatically where an electronic pen is used to write characters on the digitiser and based on the pen movements. Here, the computer recognises the characters as they are drawn, real-time. In off-line character recognition, the image of the written text is scanned and processed off-line, this means that the optical recognition is performed after the writing or printing has been completed [7].

1.2 The Igbo Language

The Igbo people constitute one of the largest ethnic groups in Nigeria, predominantly inhabiting the southeastern region of the country [7]. Representing approximately 17% of Nigeria’s total population, Igbo communities are also present in notable numbers in neighbouring countries such as Cameroon and Equatorial Guinea. The language spoken by this ethnic group is known as Igbo, and the language uses a total of 36 characters, including digraphs. Traces of Igbo culture and language are present in the South-Southern and South-Western geopolitical regions of Nigeria, in states such as Lagos, Rivers, Akwa-Ibom, Bayelsa and Ogun States [8].

1.3 Handwriting recognition

Handwriting recognition across different languages is often treated as a distinct challenge by researchers, primarily due to the unique character sets and language-specific features inherent to each script. These variations pose significant difficulties in developing a universal algorithm capable of effectively handling handwriting recognition for all languages. Despite the intensive research efforts on the automatic character recognition of many Latin languages, only a few works have been done concerning indigenous languages, especially the Nigerian native languages [9]. Although a lot of research works have been published on Yoruba handwritten characters, there is obviously still a lot of work to be done [10] [11]. Consequently, further research is needed for the offline automatic recognition of handwritten characters in Nigerian indigenous languages.

This research proposes an offline handwritten character recognition system using two models of convolutional neural networks to recognise handwritten Igbo characters.

2. RELATED WORKS

Many researchers have worked in the area of handwriting recognition, and numerous techniques and models have been developed to recognise handwritten text both online and offline. Extensive research efforts have particularly focused on languages such as English and Arabic, resulting in a substantial body of published literature in these domains. Similarly, considerable research works for handwritten character recognition in are available for Latin and many Indian scripts such as Tamil, Devnagari, Telugu, Hindi, Gurumukhi, Marathi, and Gujarati [12] [13] [14]. In Nigeria, several works have also been published on Yoruba handwritten characters, however, there are few literature on the Igbo character recognition.

Being that cursive handwritings are connected, Saha and Jaiswal [12] worked on recognition of cursive handwriting of different languages, using segmentation. In their work, they used line segmentation to extract sentences; word segmentation to extract words and character segmentation to extract individual letters. This involved dividing the input image based on contours by setting different kernel size. For classification, they used convolution neural networks and achieved an experimental accuracy of 79.3% for the E-MNIST and 93% for UCI Devanagari dataset.

Siddhartha and Saravanan [14] discussed the mechanical or electronic conversion of scanned images, containing text and graphics, and the recognition of images where characters may be broken or corrupted. They applied different preprocessing techniques to remove noise from the background of the image, and converted the labelled data into grayscale images. They then trained the classifier and generalised it using the validation set to reduce any kind of validation error. Finally, they developed a desktop-based OCR application using Python 3.0, and reported a 97.82% accuracy when applied on different datasets.

Olaniyi et. al. [9] in their research, considered Igbo vowels character recognition with different handwritings. The authors created and trained a multilayer feedforward Neural Network (NN) using backpropagation algorithms. The network was simulated after the training, and the authors reported that the simulation gave a recognition rate of 90.2%.

According to Ahmed et al [15] most research on HCR are dedicated to English-language only, therefore they focused their work on developing Offline Arabic Handwriting Recognition (OAHR). They opined that OAHR is a very challenging task, due to some unique characteristics of the Arabic script such as its cursive nature, ligatures, overlapping, and diacritical marks. Several effective Deep Learning approaches have been proposed to develop efficient automatic handwriting recognition systems, and their paper surveyed emerging technologies with some insight on OAHR background, challenges, opportunities, and future research. Jyoti et al [16], on the other hand, presented a review of articles that focused on exploring the functionality of Offline Handwritten Text Recognition systems of Indian language text with emphasis on the Hindi language/ Devanagari script within the timeframe from 2018 to 2023.

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As noted by Durayhim et al [17], less research has focused on recognizing children's Arabic handwriting. They proposed two deep learning-based models for the recognition of children's Arabic handwriting. The proposed models, a CNN and a pre-trained CNN (VGG-16) were trained using Hijja, a dataset of Arabic children's handwriting. Their results indicate that their proposed CNN outperforms the pre-trained CNN (VGG-16) model.

A Support Vector Machine (SVM)-based Yorùbá character recognition system for Yorùbá alphabets was developed by [10]. The researchers divided the process into four stages: the preprocessing, segmentation, feature extraction, and classification stage. The developed system was experimented with 600 handwritten images for Yorùbá alphabets. Their results showed a recognition rate of 76.7% and rejection rate of 23.3%.

Ajao et al. [11] modelled a recognition system for offline Yoruba characters recognition using Freeman Chain Code and K-Nearest Neighbour (KNN). They collected data from adult indigenous writers and pre-processed scanned images to enhance the quality of the digitised images. They used Freeman Chain Code to extract the features of the digitised images and KNN to classify the characters based on feature space. From their research, the authors observed that the recognition accuracy of the KNN classification algorithm and the Freeman Chain Code peaked at 87.7%.

Khan et al. [2], presented an intelligent recognition system for handwritten Pashto letters. The authors used a dataset of 4488 images, collected from 102 unique samples for each of the 44 letters in Pashto. The recognition framework extracted zoning features, followed by KNN and NN for classifying individual letters. Based on the evaluation, the system achieved an overall classification accuracy of approximately 70.05% by using KNN, while an accuracy of 72% was achieved through NN at the cost of an increased computation time.

3. METHODOLOGY

This work was carried out using the Python programming language and the Jupyter notebook development environment. The Jupyter notebook comes with libraries used in our development process. This research focuses on creating and automating the process behind an OCR program for Igbo character set recognition, using two Convolutional Neural Network models. The framework for the proposed recognition system for Igbo characters is shown in Figure 1. The steps followed were the acquisition of data, digitisation of collected data, storage of digitised data in a database, image preprocessing, feature extraction, model training, classification and recognition.

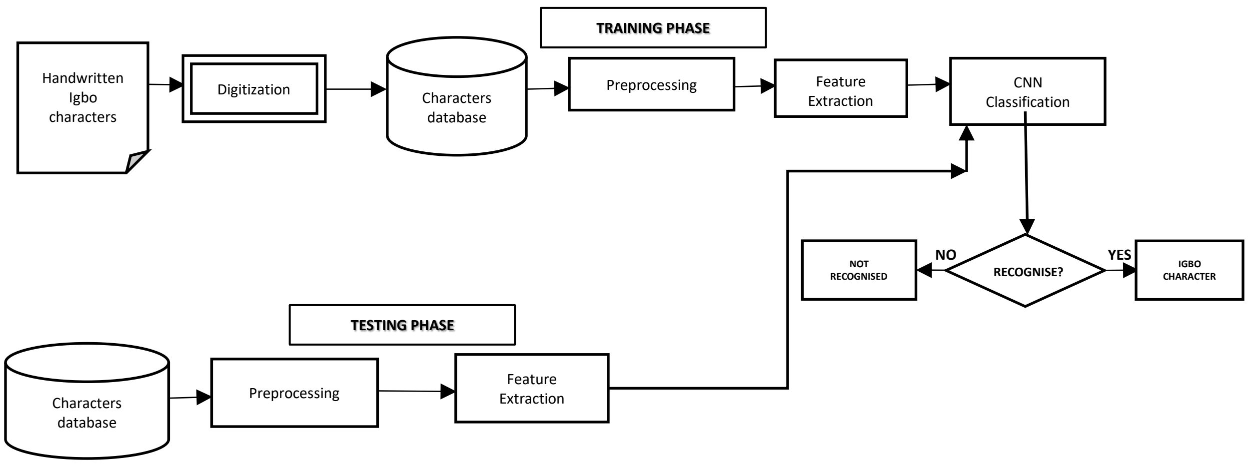

Figure 1: Framework for the Igbo Character Recognition System

3.1 Data Acquisition

For this study, a total of 250 unique samples for each of the 36 lowercase characters in Igbo alphabet were collected from different individuals as input data for the research. This made the total number of handwritten samples collected 9,000 individual characters. These characters were handwritten under supervision by students aged between 12 to 17years, from Monatan High School, Wofun-Iyalode; T.L. Oyesina High School, Alabebe-Monatan; Bishop Philips Academy, Iwo Road; and students of the Department of Computer Science, University of Ibadan. A guiding template was used to collect various handwriting samples. A sample of the handwritten images is shown in Figure 2. These images were scanned using a digital camera with 72 dpi resolution. The scanned images of the handwritten characters were then converted into Portable Network Graphics (PNG) format and subsequently stored in a database.

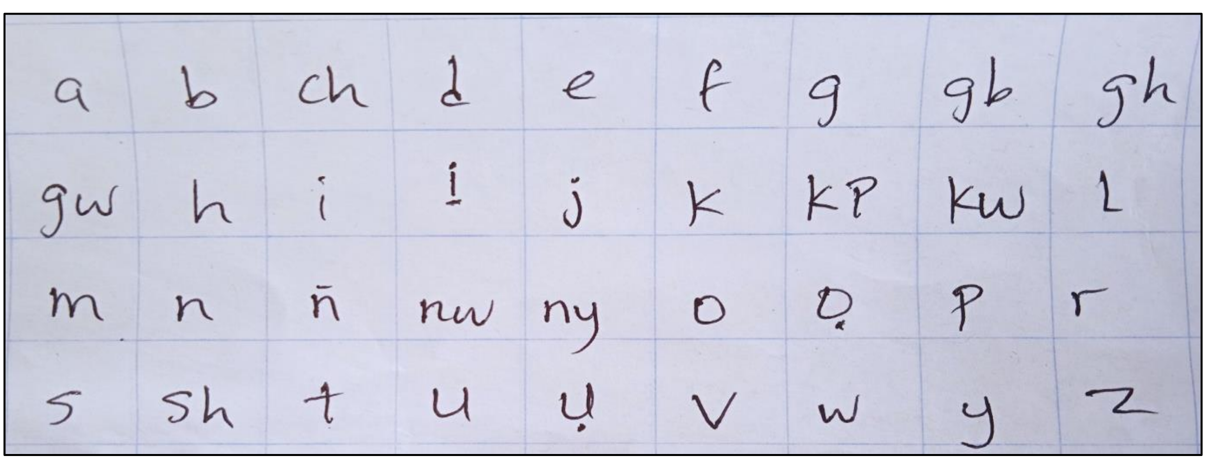

Figure 2: A sample of handwritten characters collected from a student

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3.2 Image Preprocessing

A series of preprocessing operations were carried out on the captured and digitised image for the enhancement of the images for further processing. These included data cleaning tasks such as character isolation, where each character was cropped out and isolated from each character set so that each character was an image of its own. The isolated images were then denoised, converted to grayscale, binarized and normalised in order to achieve the necessary preprocessing requirements and make the data images suitable for feature extraction and classification. Figure 3 shows some of the binarised images after they have been pre-processed and optimised for training the models.

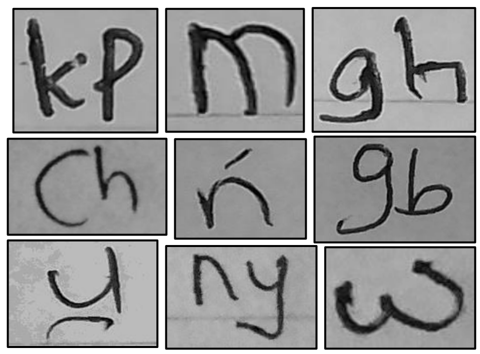

Figure 3: Binarised images of characters

3.3 Implementation of the Convolutional Neural Networks (CNN)

Two distinct CNN models were developed and evaluated to recognise handwritten Igbo characters from images. These models were designed to address the challenges of limited research and digital resources available for Indigenous African languages such as Igbo. The models are referred to as **Model 1: Custom CNN** and **Model 2: VGG19 Transfer Learning CNN**.

Model 1: Custom CNN

The Custom CNN model was developed to handle the peculiarities of the Igbo character dataset. The dataset comprised 36 classes of Igbo characters, some of which include diacritics and unique combinations not found in the standard English alphabet. For this model, the input images were resized to 64x64 pixels with three colour channels (RGB). The architecture, shown in Figure 4, consisted of multiple convolutional layers: two initial Conv2D layers with 64 filters (5x5 kernel size), followed by two Conv2D layers with 128 filters, and two additional Conv2D layers with 256 filters (3x3 kernel size). Each pair of convolutional layers was followed by MaxPooling layers to reduce dimensionality while preserving important features. After the convolutional blocks, the network included a flatten layer to convert the 2D feature maps into a 1D feature vector. This was followed by fully connected dense layers with 512, 128, and 64 neurons respectively, each utilising ReLU activation functions. Finally, the output layer was a dense layer with 36 neurons corresponding to the 36 Igbo classes, using softmax activation for multi-class classification. The model was compiled using the RMSprop Optimizer with a learning rate of 0.001, employing categorical cross-entropy as the loss function. Early stopping and learning rate reduction callbacks were applied during training to prevent overfitting and improve convergence.

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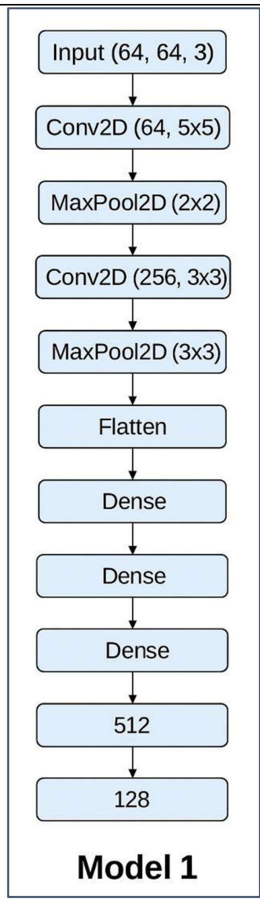

Figure 4: Schematic Diagram of the Custom CNN model

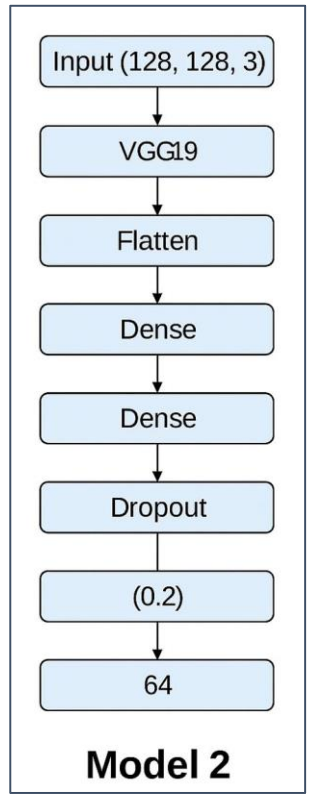

Figure 5: Schematic Diagram of the VGG19 Transfer Learning CNN

Model 2: VGG19 Transfer Learning CNN

The design for the second model, VGG19 Transfer Learning CNN leveraged the power of pre-trained models to improve performance with limited data. The architecture is shown in Figure 5. The VGG19 model, which had been pre-trained on the ImageNet dataset, was used as a fixed feature extractor by freezing its convolutional base layers. The input images for this model were resized to 128x128 pixels to match the expected input size for VGG19. After passing through the frozen VGG19 layers, the output was flattened and fed into additional custom Dense layers with 512, 256, and 64 neurons, respectively. Dropout regularisation (with a rate of 0.2) was added to reduce overfitting. The final output layer again used 36 neurons with softmax activation.

The VGG19-based model was compiled using the Adam Optimizer with a learning rate of 0.001 and categorical cross-entropy loss. This transfer learning approach provided a more robust feature extraction capability, which resulted in improved performance compared to the custom CNN.

3.4 Training Phase

The offline handwritten character recognition system used in this study comprised the two models described in the previous section. These two models were trained to classify different kinds of handwritten lowercase Igbo alphabets. Although 9,000 images were collected for this work, 7,200 images from the pre-processed dataset, consisting of 200 images per character, were used to train both models. 50 testing images for each alphabet, amounting to a total of 1,800 images, were reserved for testing the models.

The training of the models ran through 15 epochs because of the limited capacity of the CPU used, and it took a little over 6 hours. This meant that the learning capacity of our models was restricted to a very small number of 15 cycles. To optimise computational resources, we used an early-stopping mechanism to stop the learning if the validation loss is not reduced after 5 rounds, at which point it can be assumed the model is no more learning. This can also help prevent over-fitting.

3.5 Evaluation Metrics

For this research, the evaluation metrics used are Precision, Recall and F-Measure. These metrics are described briefly as follows:

a. Precision: Precision is the proportion of true positives to the cases that are anticipated as positive. It is the level of chosen cases that are right.

$$\boxed{Precision(P) = \frac{True\ Positive}{True\ Positive + False\ Positive}}$$

b. Recall: Recall is the proportion of true positives to the truly positive cases. It is the level of chosen cases that are selected.

$$\boxed{Recall(R) = \frac{True\ Positive}{True\ Positive + False\ Negative}}$$

c. F-Measure: F-measure is the mean of Precision and Recall. It takes both false positives and false negatives into account.

$$\boxed{F\text{-}Measure = 2\frac{PR}{P+R}}$$

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4. RESULTS AND DISCUSSION

A lookup table containing the indices of the Test Set Data for the models was generated. The first character "a" was labelled with index 0, while the last character in the dataset "z" was labelled with 35. Feature extraction of the pre-processed images was carried out and compared with the trained feature vectors. If two feature sets were similar, it looked up for the right character in the lookup table and displayed the corresponding digital equivalent of the handwritten character if found, or displayed a False Negative result if not found.

Evaluation metrics were analysed during the classification and recognition stages. The recognition of Igbo handwritten characters was performed on the handwritten database created. The two models designed recognised 36 Igbo alphabets distinguished based on diacritical marks. After evaluating each of the test sets on each of the two models, the results are presented in Table 1. From Table 1, we see that the custom CNN model achieved an accuracy of 83.5% on the test dataset, with a validation accuracy of 91.8%. Precision, recall, and F1-score were also computed, yielding values of 84.2%, 83.5%, and 83.4%, respectively. The VGG19 Transfer Learning Model achieved a higher test accuracy of 85.3%, with a validation accuracy of 92.69%. Precision, recall, and F1-score were 86%, 85.3%, and 85%, respectively, outperforming the custom CNN in all evaluation metrics.

Table 1: Summary of metrics for both models

Model	Custom CNN	VGG19 Transfer Learning CNN
Accuracy	83.50%	85.30%
Precision	84.20%	86.00%
Recall	83.50%	85.30%
F1-Score	83.40%	85.00%
Validation Accuracy	91.80%	92.69%

Classification Evaluation

The classification report for the Custom CNN Model (Model 1) is shown in Figure 6. From the figure, it can be deduced that precision is highest (1.00) for the characters indexed 12 and 18, which correspond to **ị** and **m,** respectively and lowest (0.35) for character indexed 3, which corresponds to **d**.

The recognition metrics for the Custom CNN model (Model 1) are shown in Figure 7. This means that the model demonstrated strong recognition capabilities (83.5%). However, evaluation metrics such as precision (84.2%), recall (83.5%), and F1-score (83.4%) indicated that while the model could recognise most characters correctly, its performance was moderately affected by occasional misclassification. This suggests that while the model achieved the goals of system design and implementation, its ability to fully recognise handwritten Igbo scripts has room for improvement.

Classification Report for Model 1

	precision	recall	f1-score	support
0	0.63	0.78	0.70	37
1	0.41	0.54	0.47	39
2	0.82	0.92	0.87	39
3	0.35	0.24	0.29	46
4	0.63	0.83	0.72	53
5	0.92	0.83	0.87	53
6	0.88	0.51	0.65	43
7	0.96	0.76	0.85	29
8	0.89	0.80	0.84	20
9	0.95	0.95	0.95	20
10	0.76	0.89	0.82	36
11	0.86	0.67	0.75	27
12	1.00	0.94	0.97	36
13	0.70	0.84	0.76	62
14	0.85	0.85	0.85	71
15	0.95	0.91	0.93	57
16	0.93	0.85	0.89	46
17	0.88	0.90	0.89	100
18	1.00	0.93	0.97	46
19	0.93	0.96	0.95	54
20	0.79	0.97	0.87	35
21	0.97	0.83	0.90	42
22	0.90	0.90	0.90	21
23	0.88	0.95	0.91	79
24	0.96	0.89	0.93	56
25	0.96	0.78	0.86	69
26	0.82	0.86	0.84	70
27	0.86	0.86	0.86	64
28	0.95	0.89	0.92	45
29	0.82	0.95	0.88	44
30	0.75	0.74	0.75	70
31	0.87	0.87	0.87	39
32	0.76	0.81	0.79	48
33	0.90	0.91	0.91	58
34	0.84	0.81	0.82	58
35	0.91	0.90	0.90	68
accuracy			0.83	1780
macro avg	0.84	0.83	0.83	1780
weighted avg	0.84	0.83	0.83	1780

Figure 6: Classification Report for Custom CNN Model (Model 1)

Classification Report for Model 2

	precision	recall	f1-score	support
0	0.62	0.54	0.58	37
1	0.65	0.56	0.60	39
2	0.95	1.00	0.97	39
3	0.73	0.70	0.71	46
4	0.74	0.81	0.77	53
5	1.00	0.89	0.94	53
6	0.72	0.79	0.76	43
7	0.59	0.83	0.69	29
8	1.00	0.25	0.40	20
9	0.76	0.80	0.78	20
10	0.91	0.81	0.85	36
11	0.90	0.67	0.77	27
12	0.79	0.92	0.85	36
13	0.89	0.77	0.83	62
14	0.93	0.79	0.85	71
15	0.98	0.91	0.95	57
16	0.90	0.96	0.93	46
17	0.87	0.94	0.90	100
18	1.00	0.89	0.94	46
19	0.96	0.98	0.97	54
20	0.92	0.94	0.93	35
21	0.85	0.93	0.89	42
22	0.90	0.90	0.90	21
23	0.82	0.95	0.88	79
24	0.79	0.96	0.87	56
25	0.97	0.93	0.95	69
26	0.89	0.84	0.87	70
27	0.79	0.89	0.84	64
28	0.86	0.80	0.83	45
29	0.84	0.95	0.89	44
30	0.80	0.81	0.81	70
31	0.71	1.00	0.83	39
32	0.91	0.83	0.87	48
33	0.88	0.86	0.87	58
34	0.90	0.64	0.75	58
35	0.97	0.99	0.98	68
accuracy			0.85	1780
macro avg	0.85	0.83	0.83	1780
weighted avg	0.86	0.85	0.85	1780

Figure 8: Classification Report for VGG19 Transfer Learning CNN (Model 2)

The Classification Report for VGG19 Transfer Learning CNN (Model 2) is shown in Figure 8. From the figure, it can be deduced that precision is highest (1.00) for characters indexed 5 and 18, which correspond to **f** and **m,** respectively and lowest (0.59) for character indexed 7, which corresponds to the digraph **gb.**

The recognition metrics for the VGG19 Transfer Learning CNN model are shown in Figure 9. This means that the model demonstrated superior ability and robustness in recognising handwritten Igbo characters (85.3%). The F1-score of 85% reflects a better balance between precision and recall compared to Model 1. Its improved performance is largely due to the power of transfer learning—leveraging pre-trained convolutional layers from VGG19, which are adept at feature extraction and classification, and by extension, the recognition.

5. CONCLUSION

In this research, we developed an offline character recognition system for handwritten Igbo script. Although the employed algorithms demonstrated reasonable accuracy, the findings indicate that increasing the volume of training data significantly enhances recognition performance. Specifically, the number of correctly classified characters improved as more training samples were incorporated into the dataset. This underscores the importance of enabling the models to learn the distinctive features of each character, thereby improving their ability to differentiate visually similar letters. The overall effectiveness of an HCR system is strongly influenced by both the quality of feature extraction and the capacity of the classifier to learn from those features. In addition to expanding the training dataset, careful identification and integration of unique character features during the training phase can further improve classification accuracy, particularly for characters with similar visual structures. The proposed approach demonstrates potential for enhancing the automation and digitization of handwritten Igbo texts into machine-readable formats.

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