Black Sea Journal of Engineering and Science
doi: 10.34248/bsengineering.1125590

Open Access Journal
e-ISSN: 2619 – 8991

Research Article
Volume 5 - Issue 4: 151-157 / October 2022

YORÙBÁ CHARACTER RECOGNITION SYSTEM USING CONVOLUTIONAL RECURRENT NEURAL NETWORK

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Abstract: Handwritten recognition systems enable automatic recognition of human handwritings, thereby increasing human-computer interaction. Despite enormous efforts in handwritten recognition, little progress has been made due to the variability of human handwriting, which presents numerous difficulties for machines to recognize. It was discovered that while tremendous progress has been made in handwritten recognition of English and Arabic languages, very little work has been done on Yorùbá handwritten characters. Those few works, in turn, made use of Hidden Markov Model (HMM), Support Vector Machine (SVM), Bayes theorem, and decision tree algorithms. To integrate and save one of Nigeria's indigenous languages from extinction, as well as to make Yorùbá documents accessible and available in the digital world, this research work was undertaken. The research presents a convolutional recurrent neural network (CRNN) for the recognition of Yorùbá handwritten characters. Data were collected from students of Kwara State University who were literate Yorùbá writers. The collected data were subjected to some level of preprocessing such as grayscale, binarization, and normalization in order to remove perturbations introduced during the digitization process. The convolutional recurrent neural network model was trained using the preprocessed images. The evaluation was conducted using the acquired Yorùbá characters, 87.5% of the acquired images were used for the training while 12.5% were used to evaluate the developed system. As there is currently no publicly available database of Yorùbá characters for validating Yorùbá recognition systems. The resulting recognition accuracy was 87.2% while the characters with under dot and diacritic signs has low recognition accuracy.

Keywords: Handwriting recognition, Yorùbá, Convolutional recurrent neural network, Document analysis, Deep learning

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Received: June 08, 2022
Accepted: September 08, 2022
Published: October 01, 2022

Cite as: Ajao JF, Yusuff SR, Ajao AO. 2022. Yorùbá character recognition system using convolutional recurrent neural network. BSJ Eng Sci, 5(4): 151-157.

1. Introduction

Optical character recognition is a subset of pattern recognition that employs a computer to recognize human handwriting. Handwriting recognition is one of the most fascinating and difficult research areas in image processing and pattern recognition, stemming from the need for humans to automate handwritten text recognition and enable computers to receive and interpret it (Mithe et al., 2013). Different writers have different writing styles; many people do not write distinct letters with clear spacing between them, making the characters more difficult to distinguish. Handwriting recognition is still considered an open research problem, owing to the wide range of individual differences in appearance. This issue has been extensively researched, and numerous viable solutions have been discovered (Chaudhari and Thakkar, 2019). Humans can read and write, as well as recognize artistic writings and graphics. Unconstrained handwriting recognition is still a difficult and critical problem for machines to solve (Graves et al., 2008). Aside from the usual problems in handwriting recognition, such as inter-writer abnormality and variation within-writer, character and word segmentation, the presence of diacritic signs presents a significant challenge for Machine recognition (Darwish et al., 2021). Furthermore, the processing of scanned images of historical documents is hampered by variables such as poor image quality, difficult text-ink versus background separation, unknown styles for which no labelled training data sets exist, highly connected patterns that are difficult to segment horizontally and vertically, and ancient or peculiar language material for which no statistical dictionaries exist (Gatos et al., 2004; Likforman-Sulem et al., 2007, Nina et al., 2011). Numerous algorithms with varying degrees of precision have been developed to tackle these tasks (Chacko et al., 2012; Das and Behera, 2017). High precision performance on Latin, Arabic, Falsi, Chinese, and other languages has been achieved as a result of these efforts (Srihari et al., 2007; Srihari and Ball, 2012; Garoot et al., 2017). However, only a minor portion of Yorùbá language recognition accuracy has been achieved. The integration of information technology into the Yorùbá language is critical to preventing the language's extinction. Yorùbá handwriting technology can also be made available to the entire population. Yorùbá speakers

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predominate in Nigeria's western region. Yorùbá mythology holds that all Yorùbá people are descended from a hero named Oodua or Oduduwa. The Yorùbá alphabet has 25 characters, 18 consonants, and 7 vowels. The vowel characters have diacritic signs such as acute, grave, and under dot, which are unique to Yorùbá alphabet. All twenty-five letters in the Yorùbá character set can be upper or lower case (Bamgbose, 2000; Ojo, 2007; Peel, 2009). The goal is to create an offline Yorùbá handwriting character recognition algorithm for recognizing handwritten characters in scanned documents and images using a Convolutional recurrent neural network. This paper is divided into six sections. The introduction is followed by related work. The third section depicts the proposed architecture, and the fourth section describes the system's methodology. The results of the experiments are shown in the following section of the paper, followed by a conclusion.

1.1. Related Works

Different solutions available in the literature to solve this problem have been reviewed. Asahiah (2014) developed, implemented, and evaluated a computational system for restoring missing diacritics in a digital text of the Standard Yoruba. Oladele et al. (2020) investigated offline Yorùbá handwritten word recognition system (OYHWR), which recognizes uppercase Yorùbá alphabets.

Various handwritten characters written by different writers were obtained using the paint application and M708 graphics tablets. Oni and Asahiah (2020) developed a Yorùbá character image recognition model using a dataset of scanned images of Standard Yorùbá printed text. The developed model was implemented and its performance was evaluated in order to create an Optical Character Recognition (OCR) model for Yorùbá printed text images. Dewa et al. (2018) developed a software that employs digital image processing methods and a convolution neural network module for offline handwritten Javanese character recognition in a computer-aided design environment.

On the basis of invariances such as translation, rotation, and scale, Oyedotun and Dimililer (2016) investigated and reviewed the performance of convolutional networks and their variant, convolutional auto encoder networks, when tasked with recognition problems involving translation, rotation, and scale. In the research, handwritten Yoruba vowel characters were used to represent the vowels.

Altwaijry and Al-Turaiki (2021) presented Hijja, a new dataset of Arabic letters written solely by children aged 7–12. The dataset includes 47,434 characters written by 591 people. Furthermore, the author proposed a model for automatic handwriting recognition based on convolutional neural networks (CNN). Hijja and the Arabic Handwritten Character Dataset (AHCD) were used to train the model. Wang et al. (2021) proposed a novel method for Chinese text recognition using cellphone-shot ID card images. It has two main contributions: A conditional adversarial generative network designed to generate million-level synthetic ID card text line images, which preserve the diversity of synthetic data and also the inherent template pattern of ID card images. A more effective convolutional recurrent neural network (CRNN) is presented, with DenseNet using VGGNet as a replacement to extract more complex spatial features. Calvo-Zaragoza et al. (2019) proposed the use of convolutional recurrent neural networks, which have been shown to be effective in other similar domains such as handwritten text recognition. Ly et al. (2017) present a Deep Convolutional Recurrent Network (DCRN) model for recognizing offline handwritten Japanese text lines without the need for explicit character segmentation.

Bluche et al. (2014) conducted a comparison of Bidirectional LSTM-RNNs and Deep MLPs. The authors conducted experiments on two public databases of multi-line handwritten documents: Rimes and IAM, both of which are available online. They demonstrated that the proposed hybrid systems achieve performance comparable to that of the state-of-the-art regardless of the type of features used (hand-crafted or pixel values) or the optical model used (neural network) (Deep MLP or RNN)

In this study, we proposed Yoruba handwritten character Recognition system based on convolutional recurrent neural networks (CRNN).

2. Materials and Methods

2.1. Methodology

The method used for the research work are as follows:

- Data acquisition
- Image preprocessing
- CRNN module for classification

2.2. Dataset Acquisition

Data were collected from fifty literate indigenous writers who writes under a guided format. The peculiarities of Yorùbá alphabets are that, besides the twenty-five characters, there are additional variations of the vowel characters which are 11 total 36 such that, a vowel characters can carry underdot, grave accent, acute accent, and it can also combine both underdot with any of the diacritic signs which makes the total alphabet Thirty-six. The 36 characters that make up Yoruba characters were written by 50 people which amount to 1800 characters. This acquired images were digitized and replicated, since CRNN required large training dataset. Figure 1 shows samples of the digitized image.

Figure 1. Sample of digitized image.

2.3. Image Pre-processing

The data was manually labeled, and each character is made up of approximately 200 images, because deep learning requires large datasets for training. The collected sample data was replicated to form 400 images used for training. This is shown in Figure 2.

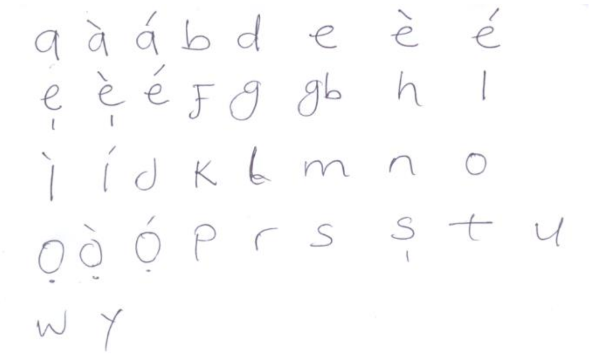

Figure 2. Sample of resized image.

2.4. RGB Image Channel Values

The acquired RGB images were preprocessed to Grayscale images each value of the grayscale value refers to a certain shade of gray with the absolute value referring to white and minimal representing black. The graysacle image was converted to binary image using Otsu method. Samples of the binarized image is shown in Figure 3.

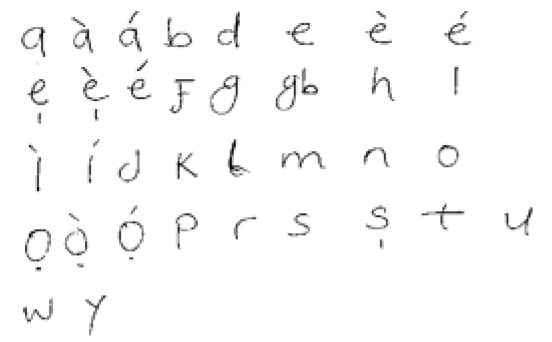

Figure 3. Binarized image

2.5. Image Normalization

In this research work, we used scale between 0 and 1 and this was achieved, by dividing our image by 255 which is the maximum possible value for any pixel.

2.6. Image Resizing

Most neural networks architectures used a fixed array shape, in our model the images were designed to use a 32×128 size image as input, so all the images were in that dimension. The implementation of the network was done using Tensor flow and keras. Figure 4 shows the model structure of CRNN. The CRNN model uses a convolutional neural network (CNN) to extract visual features, which are reshaped and fed to a long short term memory network (LSTM). The CNNLSTM were integrated using a sigmoid function through the maxpooling layer, this was passed with bias. The output of the LSTM is then mapped to character labels space with a Dense layer of softmax.

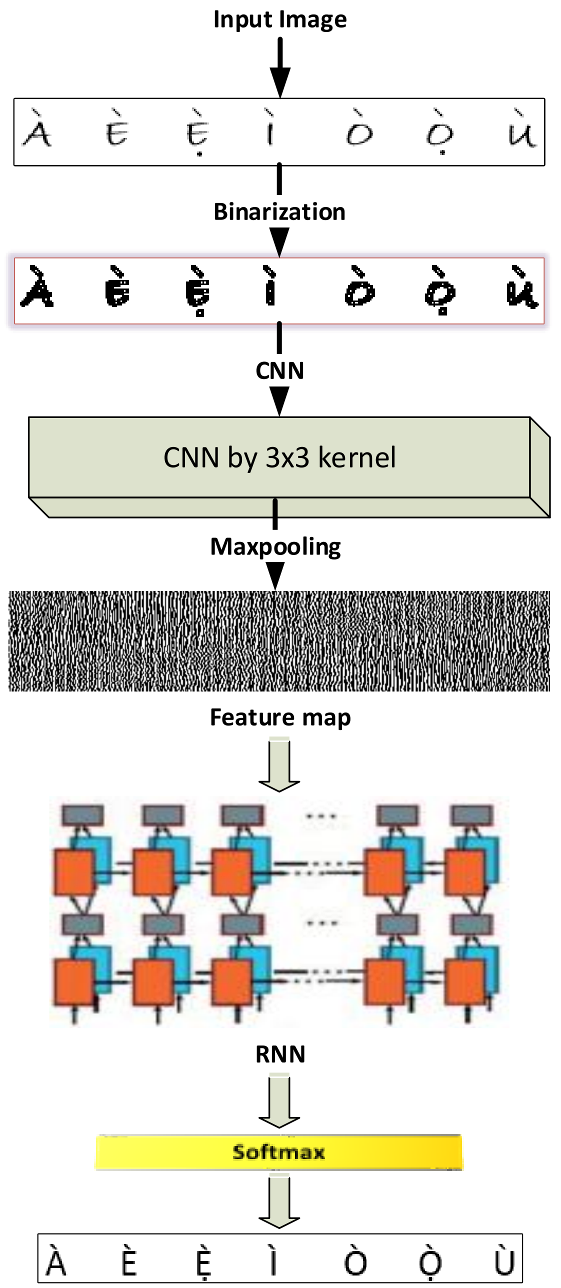

Figure 4. The CRNN architecture for Yorùbá character recognition.

Three input characters of the same character with different diacritic signs were supplied to the CNN with a filter of 3×3 for each of the characters to produce a feature sequence of size 16×16 that was also subjected to maxpooling to reduce the dimension of the data and to also reduce the training time and the testing time. After series of convolution and maxpooling of the feature vector, the final output of the maxpooling resulted into a reduced feature vectors which serve as input to the fully connected network of Recurrent Neural Network. The Convolution process is shown in Equation (1) to Equation (9)

Convolution Layer 1

$$C1_{i,j}^{k} = \left(\sum_{m=0}^{4} \sum_{n=0}^{4} w_{m,n}^{k} * I_{i+m,j+m} + b^{k} \right) \quad (1)$$

Where $C1^k$ is the feature map of the convolution layer, k is the filter number, m,n are the indices of the k^{th} filter. The training of the Convolution Neural Network was carried out as explained in equation 2.

Convolve 2: is a max-pooling layer. The output of the convolution layer C1 is fed to max-pooling layer. The max-pooling layer takes six features' maps from C1 and performs max-pooling operations on each of them. The max-pooling operations on $C1^K$ is given as *Q2 = MaxPool ($C1^k$).* For each features map in $C1^K$, max-pooling performs the following operations:

$$Q2_{i,j}^{k} = \max \begin{pmatrix} C1_{(2i,2j)}^{k}, C1_{(2i+1,2j)}^{K} \\ C1_{(2i,2j+1),}^{K}, C1_{(2i+1,2j+1)}^{K} \end{pmatrix} \quad (2)$$

where (I,j) are the indices of kth features map of output, and k is the features map index.

Convolve 3 is the second convolution layer which produces 16 features maps as given in Equation 3.

$$C3_{i,j}^{k} = \sigma \left(\sum_{d=0}^{5} \sum_{m=0}^{4} \sum_{n=0}^{4} W_{m,n}^{k,d} * P2_{i+m,j+n}^{d} + b^{k} \right) \quad (3)$$

where $C3^K$ represent the 16 output features maps of convolution layer C3, *k* is the index of the output features map, (*m,n*) are the indices of filter weights, (*I,j*) are the indices of output, and d is the index of the number of channel in the input.

Convolve 4 is a max-pooling layer which produces 16 features maps $P4^K$. The max-pooling operations is given as $P4^K$ = MaxPool($C3^k$)

$$P4_{i,j}^{k} = max \begin{pmatrix} C3_{(2i,2j)}^{K}, & C3_{(2i+1,2j)}^{k} \\ C3_{(2i,2j+1)}^{k}, & C3_{(2i+1,2j+1)}^{k} \end{pmatrix} \quad (4)$$

where (i,j) are the indices of kth features map of output, and k is the features map index.

Convolve 5 is the third convolution layer that produces 120 output feature maps and is given by;

$$C5_{i,j}^{k} = \sigma \left(\sum_{d=0}^{15} \sum_{m=0}^{4} \sum_{n=0}^{4} W_{m,n}^{k,d} * P4_{i+m,j+n}^{d} + b^{k} \right) \quad (5)$$

where $C5^k$ represents the 120 output features maps of convolution layer C5 of size 1 x 1, *k* is the index of the output features, (*m,n*) are the indices of filter weights. *d* is the index of the number of channels in input and (*i,j*) are the indices of output, since output is only 1 x 1, the index (*i,j*) remains (0,0) for each filter. This formular can be simplified as the filter size is equal to the size of input,so no convolution stride happens.

$$C6_{i,j}^{k} = \sigma \left(\sum_{d=0}^{15} \sum_{m=0}^{4} \sum_{n=0}^{4} W_{m,n}^{k,d} * P4_{m,j}^{d} + b^{k} \right) \quad (6)$$

Convolve 6 is the fully connected layer. It consists of neurons for different classes, which is defined in equation 6.

$$F6^{k} = \sum_{i=1}^{120} w_{i}^{k} * C5^{i} \quad (7)$$

The activation functions used is softmax function given as Z^k = softmax($F6^k$). The softmax function is defined as;

$$Z^k = \text{softmax}(F6^k) = \frac{e^{F6^{k}}}{\sum_{i=1}^{10} e^{F6^{i}}} \quad (8)$$

The softmax activation function produces the final output of the neurons in the range [0,1] and all outputs add up to 1. Each of the output represents the probability of the input belonging to a particular class. Where Z^k is the vector of size containing final output of the network.

2.7. Loss Layer

The obtained output is compared against the actual output to compute the loss function. The calculated error is then used to update the weight of the network. The process is repeated until the error is minimized. The Mean Squared Error (MSE) of CNN model can be given as. Loss = E(Z, *target*). The loss function E is defined as;

$$E(Z, \text{target}) = \frac{1}{10} \sum_{k=1}^{10} \left(Z^{k} - \text{target}^{k} \right)^{2} \quad (9)$$

where Z^k is the *k*th output (in this case the networks will produce 10 outputs representing class probabilities) generated by the CNN and the *target* is the ground truth of the input. E(Z, *target*) is the error/loss which represent how far the prediction of the network is from actual target. The number of convolution layers, the nodes in the convolution layer, the layer layout, the neurons in the fully connected layers, the activation functions, and the loss function and its parameters are all optimized in our model for a fully connected network,

The data was into divided into two categories. The model was trained using 87 %of the data. The model was created using Google's open-source deep learning library tensor flow, and it contained approximately (400 x 36) character parameters, as well as convolutional, Maxpooling, LSTM, and Dense layers.

Softmax is constant along diagonals: this is the dimension that is removed, and it corresponds to the softmax output being independent of the translated input scores (a choice of 0 score). To normalize the scores, the number of input scores can be used. The primary advantage of recurrent neural networks is that they have a directional circle that can recollect previous data and apply it to the current output. The samples of convolution performed on the preprocessed Yoruba image, the maxpooling to reduce the selected features, and the number of training and non-trainable parameters are shown in Table 1. On the output shape, several convolutional layers were applied, and the total number of trainable parameters was determined at each level. The reduced feature map was passed to the bidirectional recurrent neural network with LSTM at the end of the series of convolution and maxpooling to recall and produce the output characters. 1886 parameters were trained, while 114 could not be trained.

Table 1. The numbers of training parameters and non-trainable parameters with different maxpooling layers

Layer Type	Output shape	Parameters
Input Layer	32,128, 1	0
Con2d-1	32,128,64	640
Maxpooling_1	16, 64, 64	0
Con2d-1	16,128,128	1118
Maxpooling_2	8, 64, 64	0
Con2d_3	8,32,256	1566
Maxpooling_1	8, 32, 256	0
Trainable parameters	1886	
Non-trainnable	114	

The Connectionist Temporal Categorical (CTC) loss function is the objective function used to minimize the loss. As the input image varies in nature, CTC loss is specially designed to optimize both the length of the predicted sequence and the classes of the predicted sequence. During the back-propagation procedure, the convolution filters and LSTM weights are jointly learned. The Adam optimizer was used for training, with initial learning rates ranging from 0.001 to 0.002 and 0.003 to 0.005. The module was passed to the CRNN module, which runs the ROI image through a forward pass with the pre-trained model, resulting in encoded values, each of which represents a character in the Yorùbá alphabet. The encoded values from the CRNN module are received by the decoder module and decoded into Yorùbá characters.

The steps involved for the recognition process;

- Acquired the digitized image
- Preprocessed the digitized image by converting it to grey scale and binary image
- Resize and normalize the preprocessed image into 32 × 128
- Convolve the normalized image using 3x3 kernel
- Perform maximum pooling to reduce the feature map
- The feature map was passed to RNN
- The output of the RNN was passed to softmax to produce the text equivalent of the recognized characters.

3. Results and Discussion

The performance of our proposed recognition system for Yorùbá alphabet, which consist of 36 lower case characters with variant diacritic signs and under dot was evaluated. This dataset contains more than 1800 images that are classified into training and testing classes. The proposed system was implemented by taking 87.5% of character images from the class of dataset as training data and 12.5% images for the class as testing dataset. The recognition accuracy was evaluated using CRRN as shown in Table 2. The ROC curve in Figure 5 depicting the trade-off between sensitivity and specificity indicates an excellent performance of the recognition system. The resulting recognition accuracy was 87.2% while the characters with under dot and diacritic signs has low recognition accuracy.

Table 2. Recognition accuracy of Yoruba character

Yorùbá characters	Training dataset	Testing dataset	Recognized	NR
a	350	50	50	0
à	350	50	50	0
á	350	50	50	0
b	350	50	48	2
d	350	50	45	5
e	350	50	50	0
è	350	50	46	4
é	350	50	47	3
ẹ	350	50	30	20
ẹ̀	350	50	26	24
ẹ́	350	50	15	25
f	350	50	49	1
g	350	50	50	0
gb	350	50	35	15
h	350	50	48	2
i	350	50	50	0
î	350	50	47	3
ǐ	350	50	43	7
j	350	50	48	2
k	350	50	50	0
l	350	50	46	4
m	350	50	49	1
n	350	50	49	1
o	350	50	50	0
ô	350	50	48	2
ǒ	350	50	46	4
ọ	350	50	25	25
ọ́	350	50	13	37
ọ̀	350	50	20	30
p	350	50	49	1
r	350	50	50	0
s	350	50	50	0
ṣ	350	50	38	12
t	350	50	49	1
u	350	50	50	0
ù	350	50	48	2
ǔ	350	50	46	4
w	350	50	48	2
y	350	50	50	0

NR= not recognized

An effectiveness of the normalization along with the classification technique was further supported by the area under the ROC curve (AUC) of the classification performance of the recognition systems in Table3. The normalization yielded AUC of 95% confidence interval. The performance of our model was compared with other Yoruba character recognition system as our model shows a better improvement over machine learning approach.

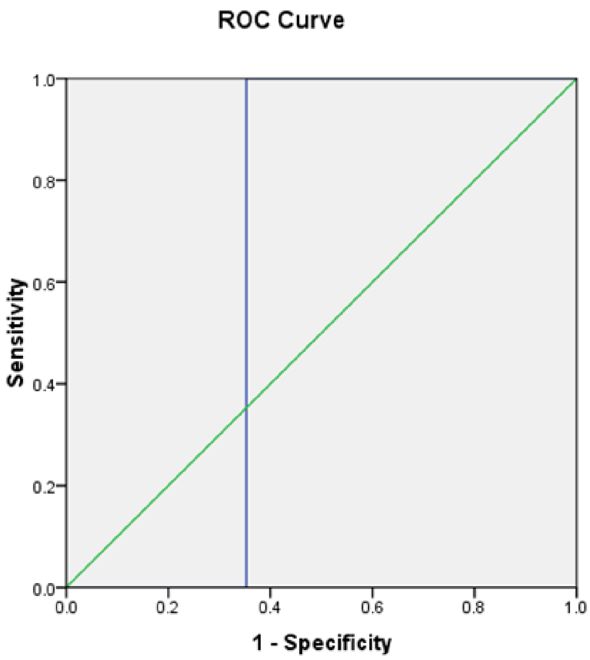

Figure 5. ROC of recognition accuracy of Yoruba character.

Table 3. Area under curve of the recognition accuracy

Area	Std. Error[a]	Asymptotic Sig.[b]	Asymptotic 95% Confidence Interval	
			Lower Bound	Upper Bound
.647	.082	.294	.486	.808

a. Under the nonparametric assumption

b. Null hypothesis: true area = 0.5

Table 4. Performance evaluation of Yoruba character recognition using CRNN and other character recognition

Author	Classifiers	Database	RA
Oladele et al. (2017)	Support Vector Machine (SVM)	Yoruba Character database	76.7%
Mathias et al. (2020)	Geometric features and Support Vector Machine(SVM)	Yoruba character database	85.7%
Oyeniran and Oyebode (2021)	Transfer Learning Model(Alextnet)	Yoruba Character database	91.4%
Our Model	Convolutional Recurrent Neural Network(CRNN)	Yoruba character datatabse	87.2%

RA= recognition accuracy

4. Conclusion

Offline Yorùbá character recognition was implemented using CRNN, from the result, it was observed that characters that have peculiar features of Latin characters have 100% recognition accuracy. Those characters that carries unique features that are peculiar to Yorùbá characters have less recognition accuracy, those few of the characters that were recognized have the underdot and the diacritic written far apart from the characters, the characters that were written correctly with underdot directly under the characters and the diacritic signs above the characters were not recognized correctly. The recognition accuracy achieved is high compared to other classification algorithm that carries out separate feature extraction techniques separately.

Author Contributions

Concept: J.F.A. (35%), S.R.Y. (30%) and A.O.A. (30%), Design: J.F.A. (35%), S.R.Y. (30%) and A.O.A. (30%), Supervision: J.F.A. (35%), S.R.Y. (30%) and A.O.A. (30%), Data collection and/or processing: J.F.A. (35%), S.R.Y. (30%) and A.O.A. (30%), Data analysis and/or interpretation: J.F.A. (35%), S.R.Y. (30%) and A.O.A. (30%), Literature search: J.F.A. (35%), S.R.Y. (30%) and A.O.A. (30%), Writing: J.F.A. (35%), S.R.Y. (30%) and A.O.A. (30%), Critical review: J.F.A. (35%), S.R.Y. (30%) and A.O.A. (30%). Submission and revision: J.F.A. (35%), S.R.Y. (30%) and A.O.A. (30%). All authors reviewed and approved final version of the manuscript.

Conflict of Interest

The authors declared that there is no conflict of interest.

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