Development and Comparison of Two Classifiers for Offline Recognition of Yoruba Handwritten Characters

Adepoju, T.M., Oladele, M.O., Olatoke, O.O. & Ajah, O.N.
Department of Computer Engineering Technology
Federal Polytechnic Ede
Ede, Osun State, Nigeria
*E-mails: atemilola@gmail.com
Phone: 07037659707

ABSTRACT

Handwriting recognition is the ability of a computer to receive and interpret handwritten input from sources such as paper documents, touch screens, digital devices and so on. Typing Yoruba handwritten documents is time consuming, hence there is a need for an efficient recognition system which can recognize Yoruba alphabets and convert it to digital format. This paper developed a Yoruba handwritten recognition system for upper case characters using multilayer perceptron and naïve Bayes classifiers. The results showed a recognition rate of 88.3% and 85.8% for multilayer perceptron and naïve Bayes respectively when tested with 120 characters.

Keywords: Handwriting, Multilayer Perceptron, Naïve Bayes, Neural Network, Yoruba.

SMART-iSTEAMS Conference Proceedings Paper Citation Format
Adepoju, T.M., Oladele, M.O., Olatoke, O.O. & Ajah, O.N. (2018): Development and Comparison of Two Classifiers for Offline Recognition of Yoruba Handwritten Characters. Proceedings of the 10th SMART-iSTEAMS Multidisciplinary Conference, February, 2018, Ogwuashi-uku, Delta State, Nigeria. Pp 27-34

1. BACKGROUND TO THE STUDY

Handwriting is a unique style of writing of an individual [1]. There has been speculations that handwriting can be mimicked thereby resulting into forgery but there is certain level of individuality and uniqueness which cannot be mimicked or forged such as the way of holding the pen, the strokes used in the writing, the amount of pressure put on paper and so on [2]. Handwriting recognition is the ability of a system to understand an individual's handwritten input from different sources such as paper, documents, photographs and other devices [1]. It is applicable in various fields such as authentication of signatures in banks, recognizing ZIP codes addresses on letters, forensic evidence and so on. Handwriting recognition can be divided into two different categories namely offline and online recognition. In offline recognition, writing is usually captured optically by a scanner and the completed writing is available as an image. The online system represents the two dimensional coordinates of successive points as a function of time and the order of strokes made by the writer are also available [3].

The offline handwritten recognition system accepts images of handwritten documents as input and the recognized characters from document image are generated as output while the online handwritten recognition system accepts signals from electronic devices, such as smartphone and tablet dynamically, and recognized characters are presented as output [4].

Also, characters or words are determined in a digital image in offline recognition while in online recognition, characters are determined on writing device with digital pen or plotter [1]. There are various methods that can be used for handwriting recognition such as neural network, statistical, template matching, structural, character decomposition, wavelets and so on but the template based and structural method are not so commonly used in the area of character recognition [1], [5]. The several challenges involved in handwriting recognition such as varying writing styles and shapes, unconstrained writings, cursive handwritings, noise and unnecessary markings and so on [1].

Multilayer perceptron (MLP) is a feedforward neural network that uses a supervised learning approach known as backpropagation neural network for training. It consists of one input layer, one or more hidden layers and one output layer [1]. Naïve Bayes is a statistical classifier that can be used to predict class membership probabilities, such as the probability that a given sample belongs to a particular class. It is based on Bayes theorem [6]. Naïve Bayes is one of the most effective and efficient classification algorithm that uses the hypothesis that the values of the variables $\langle x_1, x_2, \ldots x_n \rangle$ are conditionally independent given a target value V .

This research is targeted to recognize Yoruba handwritten characters for uppercase letters only using MLP and Naïve Bayes to help to convert Yoruba handwritten text to digital format and to evaluate the performance of MLP and Naïve Bayes based on recognition rate and rejection rate. There have been several studies on handwriting recognition for various languages such as English, Arabic, Devanagari, Nepali and so on but there are few ones on Yoruba language. Few of the existing works are highlighted in this sub-section. Pant, Panday, and Joshi [1] conducted a research on offline Nepali handwritten character recognition using MLP and Radial Basis Function (RBF), three datasets for Nepali handwritten characters were created namely for numerals, vowels and consonants and it was discovered that RBF had a better accuracy than MLP.

Fenwa, Omidiora and Fakolujo [7] presented a hybrid feature extraction techniques using geometrical and statistical features. A hybridized classification model was developed to train the neural network using modified counter propagation and modified backpropagation learning algorithms. A recognition rate of 96% was achieved. Ajao, Olabiyisi, Omidiora and Odejobi [8], presented an evaluation of preprocessing attributes of Yoruba handwriting word recognition. The approach is aimed at assessing the intrinsic measure of some of the preprocessing stages. From the experiment carried out, it was observed that the entropy measure of handwritten word is higher than the typewritten word. Another Yoruba handwritten character recognition was carried out by Oladele et al. [9]. Support Vector Machine (SVM) was used for the recognition on Yoruba uppercase letters and achieved a recognition rate of 76.70%.

2. STATEMENT OF THE PROBLEM

Typing Yoruba handwritten documents is time consuming, hence there is a need for an efficient recognition system which can recognize Yoruba alphabets and convert it to digital format.

3. OBJEJCTIVE

The main aim of this study is to develop a Yoruba handwritten recognition system for upper case characters using multilayer perceptron and naïve Bayes classifiers.

4. METHODOLOGY

The framework of the developed system is shown in Fig. 1. Handwritten character from different individuals was collected using the paint application and the characters were preprocessed and the important features were extracted from each characters. The system was developed using MATLAB 2015a.

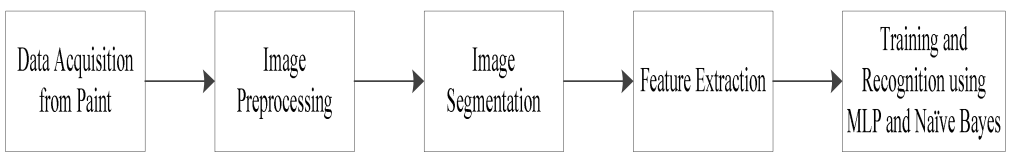

Fig. 1: Framework of Yoruba Handwritten Character Recognition

Data Acquisition

As a result of the limited scope of work being done in the area of Yoruba character recognition, standard handwritten dataset is not readily available. Hence, the dataset is generated by taking handwritten upper case samples from twenty-five different individuals using the paint application. These characters were further divided into two sets: training and testing set. Fig. 2 shows the acquired sample images.

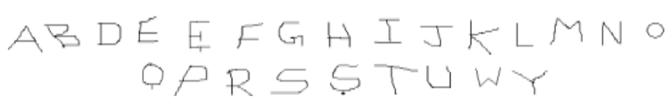

Fig. 2: Sample Images

Image Preprocessing

The second stage of the character recognition is the image preprocessing stage. It helps to extract relevant information from the characters, enhances the image and prepares them for segmentation, feature extraction and classification. Image preprocessing performs series of operation on the handwritten characters such as grayscale conversion, image resize, edge detection, binarization, image dilation and erosion. Grayscale conversion: This converts a 24-bit RGB image to 8-bit grayscale image. Grayscale image are more compact to process than the RGB image. The MATLAB function rgb2gray was used for grayscale conversion. The equation for grayscale conversion is given by:

$$G(x, y) = 0.299 \times (R + 0.587) \times (G + 0.114) \times B \quad (1)$$

Where $G(x, y)$ is the grayscale image, R, G and B are the red, green and blue components of the RGB image respectively.

Image resize
Resizing is the reduction of the size of the image so as to reduce lots of noise in the original image. It also helps to get a uniform dimension for the character image. The images used in this work were resized into 60 × 60. The MATLAB function imresize was used to resize these images.

Binarization
This refers to the conversion of grayscale image to binary image. It tends to separate the pixel values into two groups: white as background and black as foreground. Only two colors, white and black, can be present in a binary image. Binarization helps to reduce unwanted information present in the image and as well keeping the useful information. It also eliminates the background noise linked with the image in a helpful way. The MATLAB function im2bw was used for binarization.

Image Segmentation
Segmentation is used to find boundaries of the characters and divides the character images into definite area that has all pixels for image analysis and interpretation. It separates the characters from the background image and helps to analyze and transform the image into something more significant and easy to analyze.

Feature Extraction
In feature extraction stage, the relevant features needed for recognition was extracted from each character image. The feature extraction used was based on zoning and gradient features extraction. High recognition performance deals with the feature extraction method that was used. To apply zoning, individual characters were resized into a size of 60×60 pixel and thereafter divided into 9 zones i.e. 3×3 pixels, then gradient feature extraction was used to extract the features in each zones.

Gradient is a vector quantity i.e. it has both magnitude and direction. These magnitude and direction are computed by applying its derivatives in both horizontal and vertical directions. For an image, gradient can be calculated by using either the Sobel, Roberts or Prewitt operator. But the Sobel operator was used in the work. Also, the twelve directional planes were used. The extracted gradient features were then used to train the classifiers. A total of 108 features (12 directional planes × 9 zones) were used for this study Fig. 3 shows the Sobel masks for vertical and horizontal gradient.

1	2	1
0	0	0
-1	-2	-1

-1	0	1
-2	0	2
-1	0	1

Fig. 3: Sobel mask for vertical and horizontal gradient

Training and Recognition

Training: The training was done using two classifiers the MLP and naïve Bayes. MLP is a neural network classifier with three layers: input, hidden and output layers. The naïve Bayes is a statistical classifier used to predict class membership probabilities. 480 characters were used to train the classifiers and 120 were used for testing. For MLP, we have 108 inputs, 55 nodes in the hidden layer and 24 outputs. The 24 outputs signify the number of Yoruba characters. There are a total of 25 characters in Yoruba language but 24 was used because one of the characters i.e. "GB" is classified as two different characters "G" and "B". In naïve Bayes classifier, the characters were grouped into 24 classes and a new observation is assigned to the most probable class, assuming the features are conditionally independent given the class value.

Recognition

The system was tested with 180 handwritten characters i.e. 5 images per character using MLP and naïve Bayes. The unicode representation of the characters was displayed as output since the Yoruba alphabets are not on the standard keyboard. The flowchart of the system is shown in Fig. 4 on the next page (pg 32)

The metrics used to evaluate the performance of the system are the training time, testing time, recognition rate and rejection rate. Training time is the total time taken to train the classifier. Testing time is the total time taken to recognize the characters. Recognition rate is the ratio of correctly classified characters to the number of tested characters. Rejection rate is the ratio of incorrectly classified characters to the number of tested characters. The formula for recognition rate and rejection rate is shown in (2) and (3).

$$\text{Re}\,cognition\ rate = \frac{Number\ of\ correctly\ classified\ characters}{Total\ number\ of\ testing\ characters} \tag{2}$$

$$\text{Re}\,jection\ rate = \frac{Number\ of\ incorrectly\ classified\ characters}{Total\ number\ of\ testing\ characters} \tag{3}$$

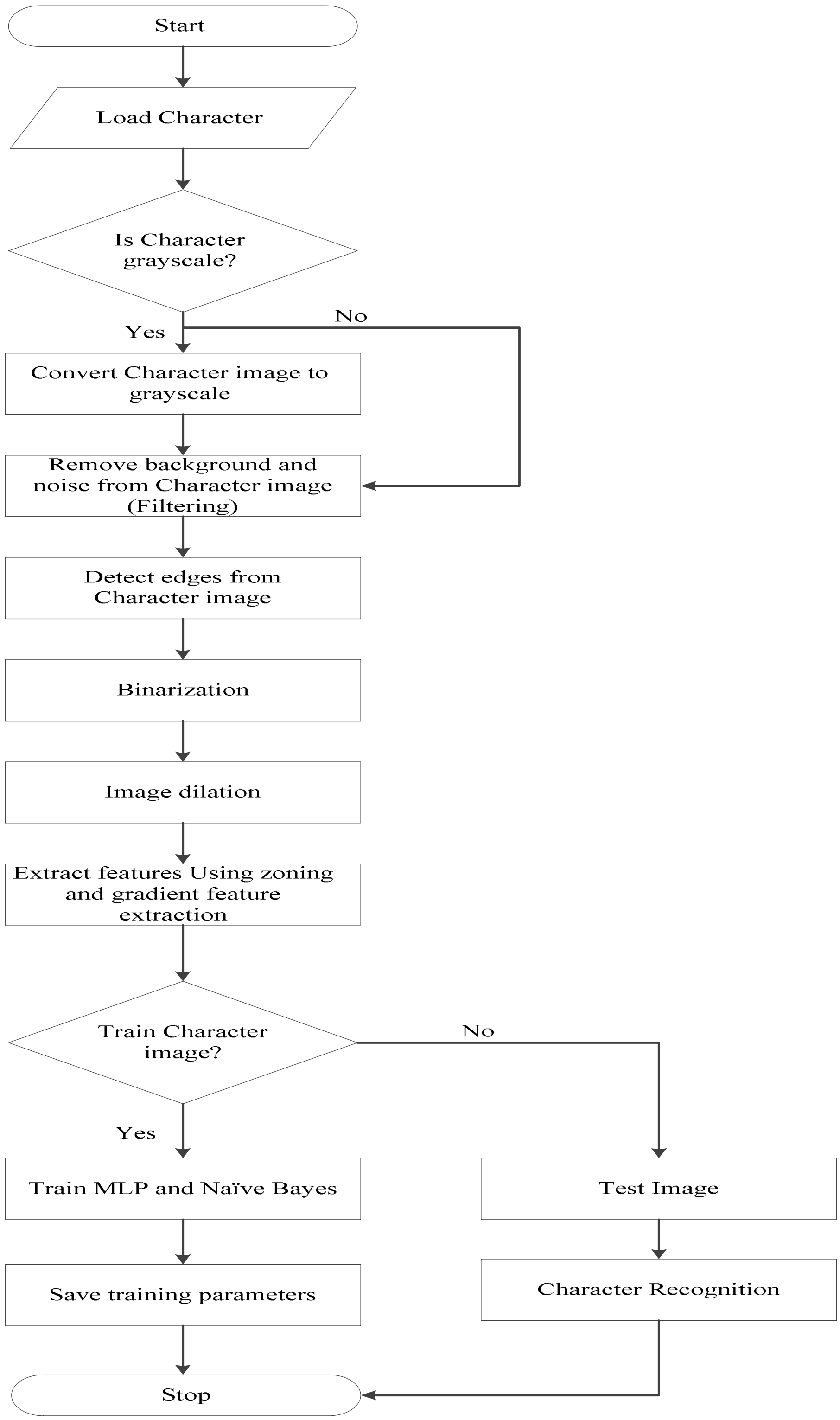

Fig. 4: Flowchart of the developed Yoruba handwritten recognition system

5. DATA PRESENTATION

Table 1: Results of the character recognition system

Character	MLP Recognition Rate	Naïve Bayes Recognition Rate
A	100%	20%
B	60%	100%
D	80%	40%
E	80%	100%
Ẹ	80%	100%
F	100%	80%
G	100%	100%
H	60%	60%
I	100%	100%
J	100%	100%
K	80%	100%
L	60%	40%
M	100%	100%
N	60%	60%
O	100%	100%
Ọ	100%	100%
P	100%	80%
R	100%	100%
S	100%	100%
Ṣ	100%	100%
T	100%	100%
U	80%	80%
W	80%	100%
Y	100%	100%

6. DISCUSSION OF RESULTS

The system was tested on a 6GB RAM, Intel core i5 and 2.40GHZ CPU speed HP pavilion laptop computer and the results obtained shows a training time of 9.747 and 9.141secs, testing time of 5.550 and 3.556 seconds, recognition rate of 88.3% and 85.8%, rejection rate of 11.7% and 14.2% for MLP and naïve Bayes respectively. It was observed that MLP has a higher recognition rate of 88.3% compared to naïve Bayes 85.8%, but the training and testing time is higher than naïve Bayes. Table I shows the recognition result of MLP and naïve Bayes respectively.

7. CONCLUDING REMARKS

Comparison of classifiers for offline Yoruba handwritten character recognition system was presented and evaluated. It was observed that MLP has the highest recognition rate of 88.3% as against 85.8% for naïve Bayes.

8. CONTRIBUTION TO KNOWLEDGE

This work has contributed to the body of knowledge by identify Yoruba symbols which can also be extended to Yoruba words and lower case characters. The classifiers can also be combined to give a better recognition rate.

REFERENCES

[1] A. K. Pant, S. P. Panday, and S. R. Joshi, "Off-line Nepali handwritten character recognition using Multilayer perceptron and Radial basis function Neural network," 3rd Asian Himalayas International Conference on Internet, Kathmandu, Nepal, November 2012.

[2] P. S. Rao, and J. Aditya, "Handwriting recognition – "Offline approach", Modern Trends in Intelligent Computing Systems, 2005.

[3] J. Pradeep, E. Srinivasan and S. Himavathi, "Diagonal based feature extraction for handwritten alphabets recognition system using neural network", International Journal of Computer Science & Information Technology (IJCSIT), Vol 3, No 1, pp. 27 – 38, February 2011.

[4] C. N. Manisha, E. S. Reddy, and Y. K. S. Krishna, "Role of offline handwritten character recognition system in various applications", International Journal of Computer Applications, Vol 135, No 2, pp. 30 - 33, February 2016.

[5] L. C. Munggaran, S. Widodo, A.M. Cipta and Nuryuliani, Handwritten pattern recognition using Kohonen neural network based on pixel character", International Journal of Advanced Computer Science and Applications, Vol. 5, No. 11, 2014.

[6] M. Kantardzic, "Data Mining - Concepts, Models, Methods, and Algorithms", IEEE Press, Wiley-Interscience, 2003, ISBN 0-471-22852-4.

[7] O. D. Fenwa, E. O. Omidiora, and O. A. Fakolujo, "Development of a Feature Extraction Technique for Online Character Recognition System", Innovative Systems Design and Engineering, Vol. 3, No. 3, 2012.

[8] J. F. Ajao, S. O. Olabiyisi, E. O. Omidiora, and O. A. Odejobi, "Yoruba Handwriting Word Recognition Quality Evaluation of Preprocessing Attributes using Information Theory Approach", International Journal of Applied Information Systems (IJAIS), Vol. 9, No. 1. pp. 18 – 23, 2015.

[9] M. O. Oladele, T. M. Adepoju, E. O. Omidiora, A. A. Sobowale, O. A. Olatoke, and E. C. Ayeleso, "An offline Yoruba handwritten character recognition system using support vector machine" International Conference of Science, Engineering and Environmental Technology (ICONSEET), Vol 2, No 13, pp 95 -103, 2017.