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DEVELOPMENT OF CAMERA-BASED OFFLINE YORUBA OPTICAL CHARACTER RECOGNITION SYSTEM ON RECONFIGURABLE HARDWARE FOR AUTOMATIC DOCUMENT READING MACHINE.

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ABSTRACT

In-spite of the numerous reported successes of applications of optical character recognition in languages based on English alphabet, the same success story is not true of Yoruba language. Though the twenty-five basic characters of Yoruba alphabet are drawn from English alphabet, the performance of optical character

Introduction

Optical character recognition system (OCRS) is the process of conversion of grapheme (characters) of a language printed or handwritten to an editable character stream by a computer-based system. Conversion of printed or handwritten characters is important for making documents into machine-editable form, for accessibility and preservation. OCR systems find applications in many aspects of human endeavours. These applications include but are not limited to printed data records, e.g. in passport documents, institutional repositories and digital libraries, plate number recognition for security

recognition of Yoruba document is abysmally low because Yoruba is a tonal language. Hence acceptable performance is only guaranteed by expanding the Yoruba's basic character set to include characters with diacritical (tonal) marks. The focus of this project, therefore, is to develop a robust optical character recognition system for the expanded Yoruba alphabet. The proposed OCR system harnesses the pipelining and parallel processing capabilities as well as flexibility of an FPGA to achieve real-time character recognition for Yoruba document. To implement the system on an FPGA, hardware description languages VHDL (Very High Speed Integrated Circuit Hardware Descriptive Language) was employed to describe the system's architecture and functionality. The design is optimized to leverage the FPGA's parallelism and pipelining, thereby allowing for efficient processing of multiple characters concurrently. Experimental results showed the effectiveness and efficiency of the proposed Yoruba Optical Character System on the FPGA platform. The system achieves high recognition accuracy, even with challenging Yoruba characters diacritical (Tonal) marks. Furthermore, the real-time processing capability of the FPGA enables seamless integration into various applications, including document digitization, translation, and information retrieval.

Keywords: Optical Character Recognition (OCR), Normalization, Segmentation, Degradation, Restoration, feature extraction.

surveillance, invoices, and bank records, health care, and legal industries so that these documents can be electronically stored, edited, and searched. It also finds application in machine translation, text-to-speech synthesis, and text mining[1]. The predominantly existing optical character recognition is in Roman characters. This has made conversation in the English language (text and speech) across the globe easier and turned the world into a global village, these also have really led to the exchange of ideas and cultural values across the world. Languages that do not have access to this trend may face extinction as time goes by, such language cultural values will be forgotten and historical background may not be remembered [2].

Optical character recognition systems are classified into two types, these are

(1) Online character recognition system.
(2) Offline optical character recognition systems

Online OCR are typically real-time systems, whereby characters are recognized as they are written. The system employs a pen and a digitizer for its operation. The recognition process of online OCR include pen up, pen down, the number of strokes, sequence of strokes, the direction of movement of the pen on the digitizer for each stroke, and speed of writing within each stroke are part of dynamic information that are commonly accessible for online text recognition [3]. These are vital information that aids character recognition and typically leads to higher performing systems when compared to offline recognition.

Offline OCR on the other hand takes place after the writing has been completed, the document containing character is firstly digitized, then followed by document pre-processing steps this include smoothing, restoration (noise removal), de-skewing, morphological operation. Finally, character recognition steps is carried out, this step involves, segmentation, edge detection and feature extraction which serve as classification or recognition criteria. Feature extraction techniques are generally classified into three: Statistical method, Structural method and Global transformation method [4]. Statistical method is based on statistical pixel distribution of an Image, statistical method approach includes partitioning/zoning in regions, profile generation and projection as well as distance and crossing approach. Structural (geometrical) method uses the physical structure of an image (character) which has the following metrics: vertical and horizontal lines, numbers of loops, numbers of strokes, major and minor axis, aspect ratio and cross points [5],[6].

Related works

Yoruba as a tonal language, the tone of the pronunciation of phoneme defines its meaning. Words with the same orthography will have different meaning depending on the tone with which the phoneme is

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pronounced. For example, Odò (River), Odó (Mortar), Òdo (Zero) or Àjà (Dog), Ájá (Roof) etc. Basically Yoruba language has three tones, these are high tone or high pitch (/), this is called acute or acute accent, the mid tone is usually left unmarked, but sometimes marked with macron (̄) most especially when the writer desire to remove any ambiguity. The low tone or low pitch is indicated with grave or grave accent (\ ). All these three tonal marks called diacritical marks in Yoruba language are placed on vowel letters or character in each syllable of a word.

Yoruba Character Set

The Yoruba character set is made up of twenty-five characters or alphabets, derived from Roman characters or letters [7]. Out of these twenty-five characters, seven are vowels and the remaining eighteen are consonants. All the twenty-five letters in Yoruba character set can assume both upper and lower case.

The twenty-five Yoruba character set are as follows:

The upper case:

A B D E Ẹ F G GB I H J K L M N O Ọ P R S Ṣ T U W Y

The lower case:

a b d e ẹ f g gb i h j k l m n o ọ p r s ṣ t u w y

There are seven vowel letters in the Yoruba character set, these letters are as follows:

A E Ẹ I O Ọ U (Upper case)

a e ẹ i o ọ u (Lower case)

The letter 'GB' or 'gb' is the only diagraph in Yoruba orthography it is a combination of two consonant, this is a special case and the only situation when two consonant letters follows each other in Yoruba orthography. This combination will be taken as a single entity in Yoruba character recognition system, once these two letters subsequently followed each other.

Due to the naive nature of computer systems, pattern recognition is a difficult problem in computer vision. Pattern recognition has lately increased due to a slew rate of new applications that are not only difficult but also computationally intensive. This is clearly seen in optical character recognition. Yoruba optical character recognition will be more demanding due to its diacritical marks embedded on vowel letters.

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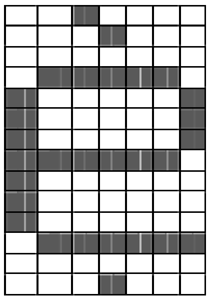
Fenwa, Omidiora, & Fakolujo, (2012) worked on Development of a writer independent online handwritten Yoruba character recognition system using modified hybrid neural network model. Character recognition was carried out using counter propagation which is a modified back propagation neural network. The result obtained showed that the learning rate parameter have adverse effect on the network performance. The smaller the value of the learning parameters, the higher the recognition accuracy, because weight update in the network were done in a more refined manner. The counter propagation is a hybrid network, it consists of an outer and a competitive filter network. The two training stages, involves the hidden and the output layers, this account for the slow learning rate. At large data size, input sets require a large topology network with a greater number of iteration and this have an adverse effect on recognition time and accuracy due to introduction of more noise as number of image (character) increases.
Oladele et al., (2017)[9] uses Support Vector Machine in realising OCR and achieved a recognition rate of 76.7%. SVM is known for its weakness in the classification of large datasets, large training time due to high computational complexities, and bad performance in the event of degraded character images.
Surajudeen Adewale Yekeen & Ibiyemi, (2019)[10] reviewed edge detection algorithms as one of the major steps in realising OCR. Other steps include pre-processing, segmentation, normalization, feature extraction and finally character recognition. The techniques of OCR realization are unlimited, the success of OCR system largely depends on the performance of each step's algorithm
ONI & ASAHIAH, (2020) developed Long Short Term Model (LSTM) using variant Recurring Neural Network (RNN) for Yoruba character recognition. A recurrent neural network (RNN) is a typical artificial neural network which uses sequential data or time series data. Its simplest form is One-to-One, which allows a single input and a single output. Other form of RNNs are One-to-Many, which gives multiple outputs when given a single input, Many-to-One, Many-to-Many. The downsides of RNN includes RNNs training complexities, the vanishing or exploding gradient problem. RNNs cannot be stacked up, Slow and Complex training procedures as well as Difficulties in processing longer sequences. This method may be cost effective in real practice.

Methodology

System Design

Optical Character Recognition System (OCRS) generally consists basically of four modules, these are image acquisition module, character pre-processing module, segmentation and feature extraction module and finally the recognition module. However, post processing module is sometimes included in order to fine tune the output for better results.
The recognition technique used in realization of Yoruba OCR in this work is template matching, the remaining modules or techniques were meticulously carried out to obtain a good result.
A database of template of Yoruba characters were created by plotting Seventy-eight (78) Standard Yoruba (SY) characters with DTM as a 14x7 grid matrix as a template for the character, the 7bit of each row of the binary character image were converted to two hexadecimal digits. The 14 bytes defining each character image were coded and stored in the database as the characters' template.



(a)

0	0	1	0	0	0	0
0	0	0	1	0	0	0
0	0	0	0	0	0	0
0	1	1	1	1	1	0
1	0	0	0	0	0	1
1	0	0	0	0	0	1
1	0	0	0	0	0	1
1	1	1	1	1	1	0
1	0	0	0	0	0	0
1	0	0	0	0	0	0
1	0	0	0	0	0	0
0	1	1	1	1	1	1
0	0	0	0	0	0	0
0	0	0	1	0	0	0

(b)

10
08
00
3E
41
41
41
7E
40
40
40
3F
00
08

(c)

Figure: 1 The system design for Yoruba Character data base (a) The bi-level image of Yoruba character ẹ̀, (b) the binary representation of the character in (a), (c) the character coding in two-digit hexadecimal byte of the character in (a)

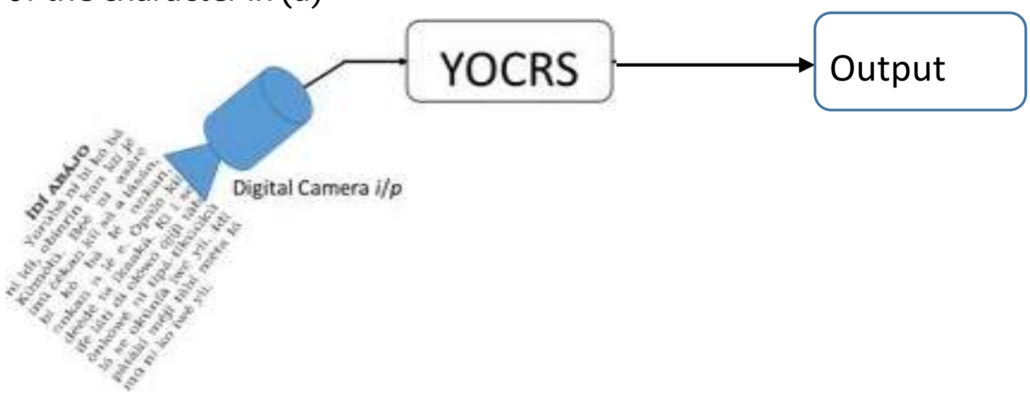


Figure 2 (a) Model design of the Yoruba Optical Character Recognition System (YOCRS) (b) Setup system

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The model design of the Yoruba Optical Character Recognition System (YOCRS) is shown in figure 2 and the flow chart is shown in figure 3

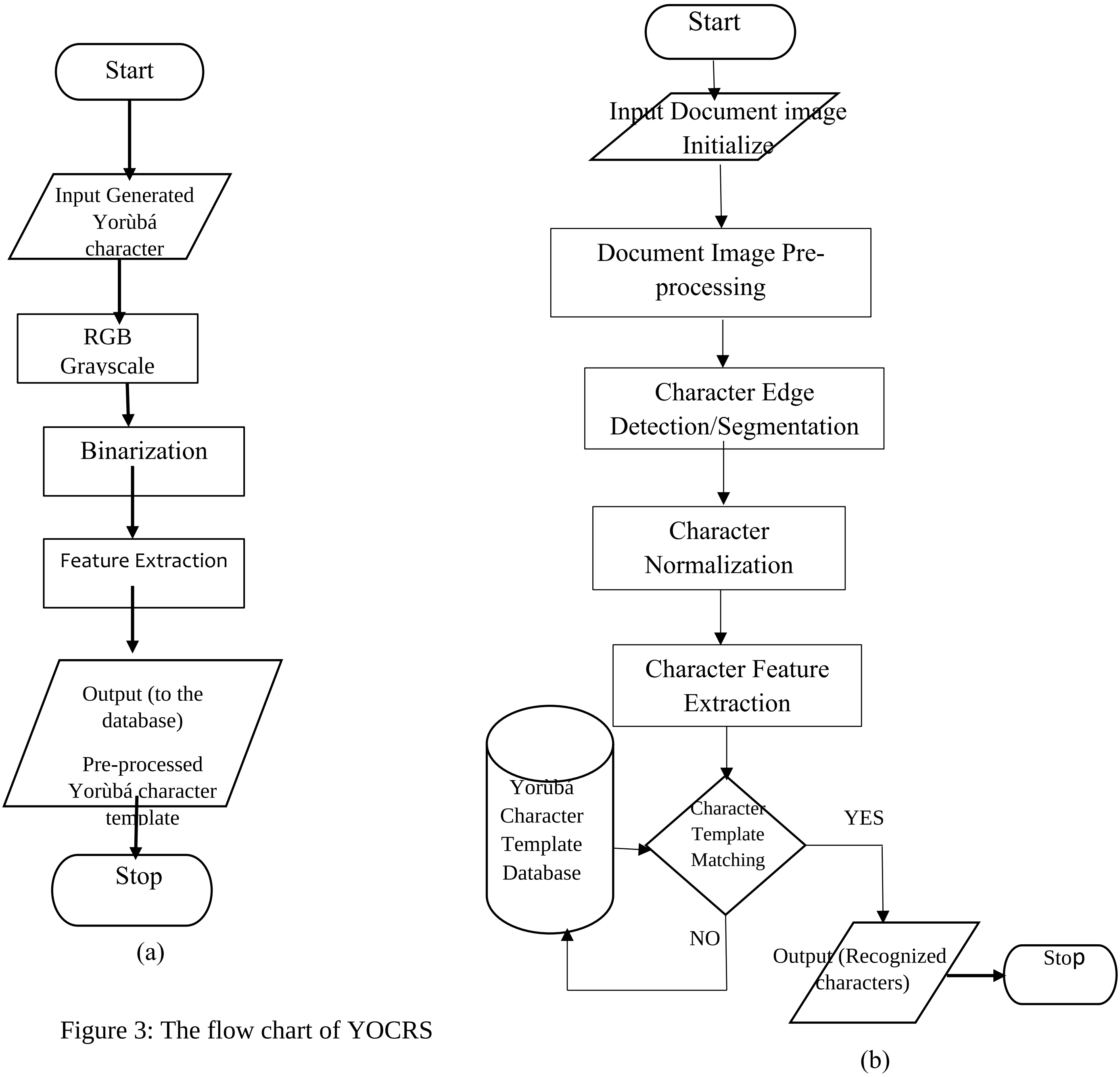

Figure 3: The flow chart of YOCRS

The document image pre-processing steps were carried out, these include document image colour-grayscale conversion, restoration, binarization, and morphological dilation. All these steps were taken to improve the recognition rate of the system. Luma correction algorithm was given precedence over averaging, saturation and decomposition method of colour to grayscale conversion of character image for its consideration of human perception of luminance of coloured image[10],[11]. The ITU-R BT.601, algorithm was implemented, this is given as

Grayscale = 0.0299Red + 0.0587Green + 0.0114Blue (1)

Binarization

Otsu's algorithm is implemented for the binarization in order to obtain a pure black and white image for a good contrast between character image and its background. Otsu algorithm assumes that the image consists of two classes of objects, these are the background and the foreground. The classes consist of pixel intensity at distinct values. An optimum threshold value is calculated such that their combined spread (intra class variance) is minimal[12]

$$S_{\omega}^{2}(t) = q_{1}(t)S_{1}^{2}(t) + q_{2}(t)S_{2}^{2}(t) \quad (2)$$

$where\ S_{\omega}\ weighted\ class\ variance$

$S_1 - Object\ class\ pixel\ mean\ intensity$

$S_2 - Backgroung\ pixel\ class\ mean\ intensity$

$q_1 - Object\ class\ probability$

$q_2 - Background\ class\ probability$

$$g(x,y) = \begin{cases} 1; & \text{if } f(x,y) \geq T \\ 0; & \text{if } f(x,y) < T \end{cases} \quad (3)$$

Algorithm for global thresholding

1) Select an initial estimate of the thresholding value T
2) Segment the image using T, this will produce two classes T_1 and T_2
3) Compute the mean intensity S_1 and S_2 for classes '1' and '2'
4) Determine the final threshold that will be used for Binarization

$$T = \frac{1}{2}(s_1 + s_2) \quad (4)$$

5) Repeat the process until

$$T < (T_1 - T_2) \quad (5)$$

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Otsu global thresholding algorithm given in equation (3) was used for the binarization of the digitized document image. The pixel intensity threshold was systematically chosen from pixel intensity variation of the digitized document, a threshold of 230pixel intensity was used as global threshold.

Segmentation

Segmentation is the partitioning of objects in an image from everything else, therefore, segmentation subdivides an image into its constituents regions or objects[13]. Document segmentation refers to partitioning of a document image into distinct entities namely text line [5], word, and characters. The level to which segmentation is performed depends on the problems at hand, segmentation stops when the object of interest in an application has been isolated.

There are various techniques that are employed in literatures for text line or row segmentation, these includes Hough transform technique, Row Line Smearing algorithm (RLSA) technique, projection profile segmentation technique (Priyanka, Srikanta and Mandal 2010), Gaussian method (Malakar, Das and Basu, 2011). Each of these techniques have their shortcomings, for geometrical constraint, its failure occurs when line space between text line are relatively small, it tends to give false line by combining two lines as one (Otsu 1979). Hough transform method is not flexible to follow variation in skew angle along the same text line (Chaki, Shaiku and Saeed, 2014).

This research work adopted horizontal projection profile. Projection is a histogram of the number of black pixel values accumulated along parallel lines taken through the document. The document image are enhanced and smoothed such that edge of each character in the text line are well defined, skew correction are also carried out, before the histogram of pixel intensity bins and valleys are identified.

The horizontal and vertical profile projection of document of column ‘n’ and row ‘m’ is given as

The horizontal projection profile is given as

$$P_x = \sum_{1\leq y\leq n}^{N} f(x,y) \qquad (6)$$

And for vertical projection

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$$P_y = \sum_{1 \le x \le m}^{M} f(x, y) \tag{7}$$

Each character in the document is a connected component. The centroid of each connected components is determined and the Euclidean distance between pairs of centroids are calculated. The expectation is that the inter word white spaces between characters are always larger than intra word white space. The Euclidean distance between two pixels in a two-dimensional image is given as

$$ED = \sqrt{\sum_{i=1}^{M} \sum_{j=1}^{N} (A(i,j) - B(i,j))^2} \tag{8}$$

Average distance (**AD**) is assumed between centroid of pairs of connected components for intra word white space and threshold Euclidean distance 'T' set. White pixel gap is categorised as intra word space if the Euclidean distance calculated satisfy the following condition.

$$0 < AD < T \tag{9}$$

Otherwise, the white space Euclidean distance is set to be inter word space.

Connected Component Analysis (CCA) was used to segment characters, each character is a connected component, 8-connectivity approach was adopted, the connectivity is defined such that every pixel can be reached from any other pixels through combination of moves in only eight directions.

Pixel connectivity algorithm

1 scan through all pixels of an object
2 if all four neighbours of a pixel are '0' assign a new label to P, else
3 if only one neighbour has v = {1} assign a new label to P, else
4 if more than one of the neighbours have v = {1} assign one of the labels to P and make a note of the equivalence.

After completing the scan, the equivalent pairs are sorted into equivalent classes and unique label is assigned to each class as a final step.

Character Size Normalization

Character size normalization improves the efficiency and robustness of character recognition systems for both hand and printed character

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recognition. Methods of image (Character) size normalization includes trained multilayer perceptron [3], second order moments [14] [15] and Bi-moment normalization based on
quadratic curve fitting [16]
In this research work, bilinear interpolation algorithm was adopted for size normalization of segmented character to the size of character templates in the database. The algorithm has the advantage of maintaining the aspect ratio of the character image and also invoke antialiasing, the computational cost is relatively low when compared with other methods mentioned above.
Bilinear interpolation is a resampling method that uses the distance between weighted averages of the four nearest pixel values to estimate a new pixel value. This simply implies that in order to increase the size of character image, the extra added pixels are filled with the average pixel intensity of its neighbours. The interpolation is applied on the character image on both width and height of the image. The algorithm is derived thus:

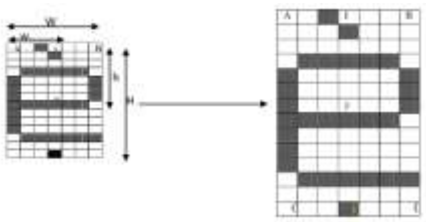

Figure 4: Character Normalization

Bilinear interpolation along the width of the image is given as

$$i = A + w(B - A) \tag{10}$$

$$\frac{i - A}{w} = \frac{B - A}{W} \tag{11}$$

$$\frac{j - C}{w} = \frac{D - C}{W} \tag{12}$$

$$j = C + w(D - C) \tag{13}$$

And along the height of the image is given as

$$\frac{y - C}{h} = \frac{D - C}{H} \tag{14}$$

$$y = C + h)D - C) \tag{15}$$

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Character Image Recognition

The core objective of the research work is to develop offline printed Yoruba character recognition system which will take into consideration the diacritical marks as well as under dots of Yoruba orthography. Having developed the Yoruba data base from the template described earlier in the previous. The character recognition was achieved using Normalized Cross Correlation Template Matching (NCCTM) algorithm. In Template matching, the matching block computes match metric values by sliding a template over a region or the entire image and then find the best match. The matching metrics include:

(i) Sum of Absolute Difference (SA)

$$d_p(x, y) = \sum_{i=1} (|x_i - y_i|)^{p^{\frac{1}{2}}} \tag{16}$$

(ii) Sum of Squared Difference (SSD)

$$d_2(I_i, T) = \sum_{i=1}^{n} | I_{i,j} - T_i |^2 \tag{17}$$

(iii) Maximum Absolute Difference (MaxAD)

$$d_\infty(I_{i,j}T) = \underset{i=1}{\overset{n}{MAX}} \; | I_{i,j} - T_j |^p \tag{18}$$

IMPLEMENTATION AND RESULTS ANALYSIS

4.1 System Implementation and Simulation

The system was developed on window based 64bits operating system. The configuration of the system is intel(R) core(TM) i5-04005u, the processor speed is 4.0 GHz and RAM size is 4.0GB.

The Camera-based Offline Yoruba Optical Character Recognition System

The user interface for Camera-based offline Yoruba optical character recognition system on reconfigurable hardware was developed using MATLAB GUI (graphical user interface). The GUI is user friendly and allows the user to perform each step of character recognition, starting from the data acquisition to recognition and documentation of recognized character. The initial users' GUI is shown in figure 5

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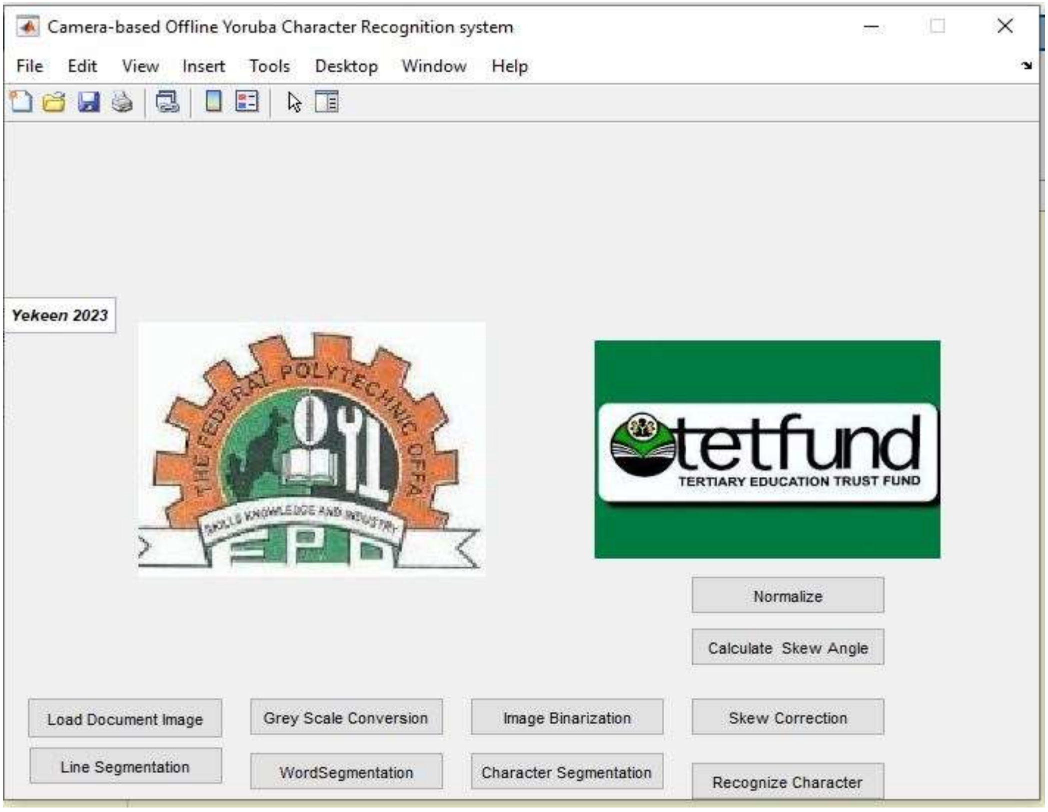
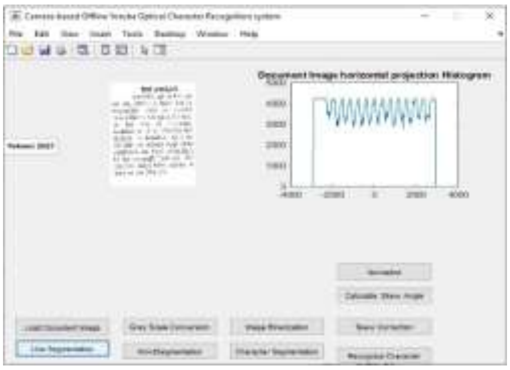


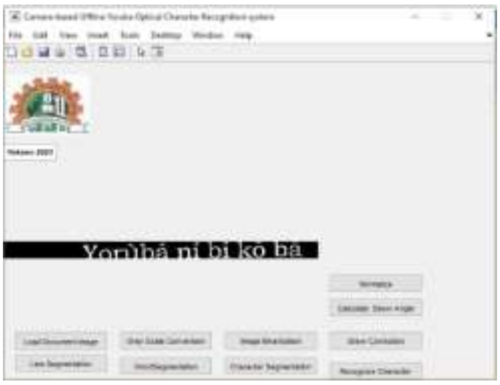
Figure 5: Guided User Interface (GUI) of Camera-based Offline Yoruba Optical Character Recognition System

The user interface of the Camera-based offline Yoruba optical character recognition system consists of nine modules. Each of the modules perform different stages of the character recognition, right from the data acquisition to the recognition of Yoruba character. The user is allowed to capture image of the document using a web camera attached with system in order to start the recognition process. The document image is converted to gray scale image, then followed by binarization of the document image. The skew angle detection and subsequent correction is done automatically by clicking the skew correction button.
The line or row segmentation was carried out using projection profile algorithm. The projection profile histogram was obtained, where each peak (histogram bin) shows the lines or rows in the document image while the valley between the peaks denotes the white space between the lines.
For line segmentation, we were able to achieve 100% success. The algorithm was tested on double, 1.5 and single line spacing of scanned printed Yoruba document.

Some of the test images were shown in figure 6

The system was tested with two lines of font size 24 and double line spacing, then thirteen lines, font size 14 and 1.5 line spacing and finally with twenty-six lines, font size 14 and single line spacing. In each case 100%line segmentation was achieved.





(b)

(a)

figures 6:(a) shows the segmented document image and the corresponding projection profile histogram (b) Shows the display of a segmented line

Word Segmentation

The Euclidean distance metric was used to group characters to form word. Each character is a connected component. The centroid of each connected components was determined and Euclidean distance between centroids were calculated. The calculated Euclidean distances between connected components of the same word ranges between 0.17mm – 0.21. Therefore, a threshold of 0.22mm was set as the maximum intra word white gap. If the calculated distance is greater than the threshold, the distance is set as inter word white space and all the previous connected components are grouped as word, otherwise, the distance is set as intra word white space. On word segmentation we were able to achieve a success rate of 98.8%. 263 out of 266 words were segmented correctly in the first image while 355 out of 360 words were segmented correctly in the second document image.

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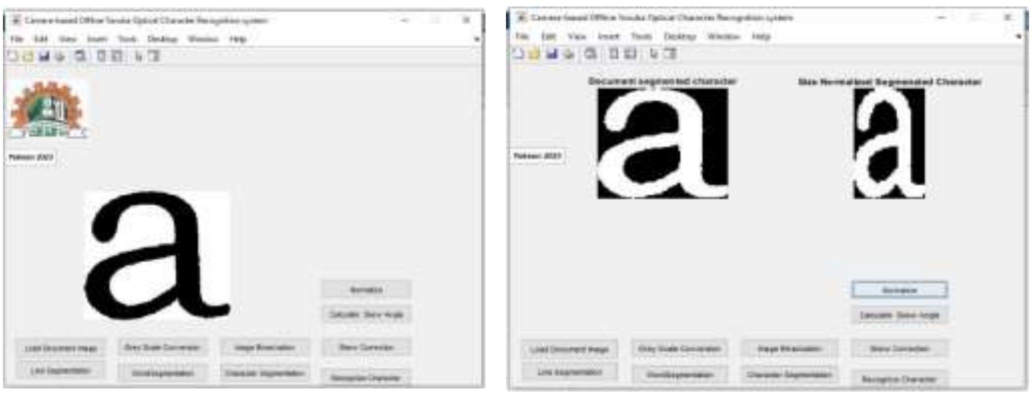
Table 1: Euclidean distances between connected components in segmented documenta

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
C1	0	0.156	0.192	0.387	0.429	0.684	0.743	0.917	1.155	1.176	1.385	1.613
C2	0.156	0	0.257	0.43	0.414	0.719	0.76	0.944	1.182	1.179	1.408	1.635
C3	0.192	0.257	0	0.195	0.259	0.492	0.552	0.725	0.963	0.986	1.193	1.421
C4	0.387	0.43	0.195	0	0.156	0.297	0.359	0.53	0.768	0.794	0.998	1.227
C5	0.429	0.414	0.259	0.156	0	0.333	0.353	0.54	0.775	0.766	0.999	1.223
C6	0.684	0.719	0.492	0.297	0.333	0	0.101	0.234	0.471	0.513	0.701	0.93
C7	0.743	0.76	0.552	0.359	0.353	0.101	0	0.188	0.423	0.435	0.649	0.876
C8	0.917	0.944	0.725	0.53	0.54	0.234	0.188	0	0.239	0.293	0.468	0.697
C9	1.155	1.182	0.963	0.768	0.775	0.471	0.423	0.239	0	0.175	0.23	0.459
C10	1.176	1.179	0.986	0.794	0.766	0.513	0.435	0.293	0.175	0	0.276	0.474
C11	1.385	1.408	1.193	0.998	0.999	0.701	0.649	0.468	0.23	0.276	0	0.229
C12	1.613	1.635	1.421	1.227	1.223	0.93	0.876	0.697	0.459	0.474	0.229	0

Character Segmentation

Connected Component Analysis (CCA) was used for character image segmentation, using pixel connectivity algorithm. 8-connectivity of pixel of each character was implemented and bounding boxes drawn around each segmented character. 97.5% accuracy was achieved with character segmentation. This low accuracy was as a result of morphological dilation of the character before segmentation, this has made the edges of the characters touching and as such two characters are seen as a single connected component.

The segmented characters were size normalized to the size of the character in the database and also taking to cognizance the aspect ratio of the characters. The segmented characters were size normalized to 14 X 7 graphical size. This is shown in figure 7



(a) (b)

Figures 7: (a) shows the segmented a segmented character (b) Shows the display of Size normalized character

Hardware Implementation of Algorithms

The algorithms were modelled by developing a prototype for deployment in FPGA with MATLAB Simulink. This was achieved by high level abstraction using conversion of MATLAB floating point values to fixed point in order to take advantage of pipelining and parallel implementation of algorithms in FPGA. The targeted device is Xilinx Spartan7 ISE FPGA board with following features Internal clock speeds exceeding 450MHz; 256 MB DDR3L with a 16-bit bus at 650 MHz,120 DSP Slices, 2,700Kbits of Block RAM, 5,200 Slices Flip-flops, and 8,150 Logic cells.

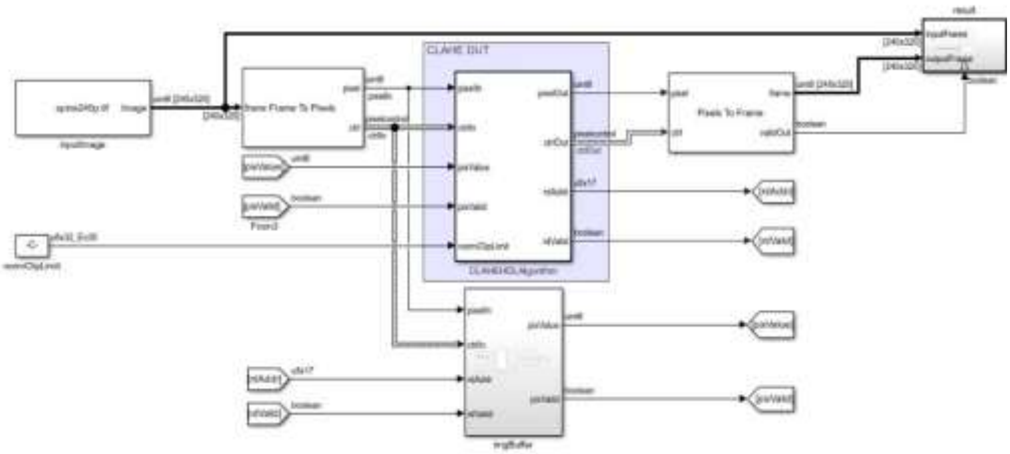


Figure 8: Prototype model block for Yoruba Optical Character Recognition System.

The prototype design block for implementation in MATLAB Simulink is as shown in figure 8

HDL coder of MATLAB R2019b was used to convert the MATLAB codes to VHDL, the resulting codes were verified and synthesized with the test-bench to ascertain similar output with implementation of algorithms.

5.0 Conclusion

The development of a Yoruba Optical Character Recognition System (Y OCRS) implemented on a Field Programmable Gate Array (FPGA) opens

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up exciting possibilities for preserving and utilizing the Yoruba language in the digital age. The combination of FPGA technology with Yoruba OCR algorithms showcases the potential for preserving cultural heritage, promoting language diversity, and enabling efficient text recognition and processing in the Yoruba language. The YOCRS on FPGA demonstrates remarkable speed, accuracy, and efficiency in recognizing Yoruba characters and converting them into editable and searchable text. Recognition rate of 98.7% was achieved within 10s when document of 195 words and 1560 Yoruba character i.e. 6.41ms per character, when the algorithms were simulated on the targeted FPGA platform. The results were aided by leveraging the parallel processing capabilities of FPGA, the system can handle complex Yoruba character recognition tasks in real-time, providing fast and reliable results. This capability has significant implications for applications such as digitization of Yoruba literature, automated data entry, Yoruba documents automation, and language-based machine learning models.

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