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A Hybridized Feature Extraction Model for Offline Yorùbá Document Recognition

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

Document recognition is required to convert handwritten and text documents into digital equivalents, making them more easily accessible and convenient to store. This study combined feature extraction techniques for recognizing Yorùbá documents in an effort to preserve the cultural values and heritages of the Yorùbá people. Ten Yorùbá documents were acquired from Kwara State University's Library, and ten indigenous literate writers wrote the handwritten version of the documents. These were digitized using HP Scanjet300 and pre-processed. The pre-processed image served as input to the Local Binary Pattern, Speeded-Up-Robust-Features and Histogram of Gradient. The combined extracted feature vectors were input into the Genetic Algorithm. The reduced feature vector was fed into Support Vector Machine. A 10-folds cross-validation was used to train the model: LBP-GA, SURF-GA, HOG-GA, LBP-SURF-GA, HOG-SURF-GA, LBP-HOG-GA and LBP-HOG-SURF-GA. LBP-HOG-SURF-GA for Yorùbá printed text gave 90.0% precision, 90.3% accuracy and 15.5% FPR. LBP-HOG-SURF-GA for Handwritten Yorùbá document showed 80.9% precision, 82.6% accuracy and 20.4% (FPR) LBP-HOG-SURF-GA for CEDAR gave 98.0%

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precision, 98.4% accuracy and 2.6% FPR. LBP-HOG-SURF-GA for MNIST gave 99% precision, 99.5% accuracy, 99.0% and 1.1% FPR. The results of the hybridized feature extractions (LBP-HOG-SURF) demonstrated that the proposed work improves significantly on the various classification metrics.

Keywords: Yorùbá; feature extraction; document recognition; feature selection; language processing; machine learning.

1. INTRODUCTION

Recognition system plays a vital role in object, text or patterns identification. The importance of the field is reflected by an increasing number of efforts that have been made on the development of the Handwritten recognition systems [1-3]. Document recognition emanates from the need to transform handwritten and text document to their digital equivalent, thereby making the document easily storable and accessible in a more efficient manner. This becomes necessary to preserve historical heritages and cultural values among other numerous benefits. There is an advanced OCR technology for the development of Handwritten Recognition System for Languages such as Latin, Arabic, German, Falsi and Chinese [4,5] The same cannot be said for Yorùbá - which is a language spoken by south western people of Nigeria and other countries like Brazil, Cameroun, Togo and Cuba. Yorùbá consists of twenty-five characters which contains 18 consonants and 7 vowels characters. The vowels characters contain tone marks which makes its recognition challenging [6,7]. Yorùbá vowels contains variant of vowel characters which add up to the Yorùbá alphabet totalling thirty-one (31) characters. Yorùbá text recognition is more challenging than printed English text because it contains three tonal signs, which are; acute (áéíóú), mid (âêîôû), and grave (àèìòù). Other reasons that posed lots of challenges for machine to recognize Yorùbá written and printed text are the diacritic signs which are not common in English language [5,8,9], also, lack of generic algorithm that works for all the language and the implication of diacritic signs omission or misplacement which affects to the interpretation and meanings of the language [10,11].

Some of the available works on Yorùbá Language recognition focuses on characters, typed text and written words [12]. However, effort is still required to improve performance of the recognition accuracy when applied to Yorùbá document. To improve the classification performance, optimal feature extraction methods are developed. The feature extraction is considered as a form of dimensionality reduction [13]. The process of getting the most active properties from the original input while concurrently minimizing the variability within a class and maximizing the variability across classes can be referred to as feature extraction or feature selection [14].

Most of the research carried out on Yorùbá handwritten recognition focused on the classification accuracy and mostly with one algorithm for feature extraction techniques [15-17]. However, from literatures, a hybridized approach has proven to be more effective [18-20], hence this research explores the effectiveness of the hybridized feature extraction techniques over recognition accuracy when feature construction is made and feature optimization is also carried out on the classification algorithm. This study employs three feature extraction techniques, which are Local Binary Pattern [21], Histogram of Gradient [22] and Speeded-Up-Robust Feature [23] algorithms with Genetic Algorithm as feature selection technique [24] and Support Vector Machine as classifier [25]. The proposed feature extraction techniques improve the recognition accuracy of Yorùbá document, hence, the contribution of this paper.

2. RELATED CONCEPTS

The following are the concepts related to this research work:

2.1 Local Binary Pattern (LBP)

Local Binary Pattern (LBP) algorithm uses counter clockwise binary number to detect features of an image, which consists of digits that are close to the center pixel [26,27]. This binary code, known as the LBP-central pixel code, is employed as a distinctive local texture, which is given as:

$$LBP(yp_n, yp_h) = \sum_{p=0}^{p-1} h(yp - yc) \times 2^p \quad (1)$$

where yc is the central pixel intensity, yp is the intensity of neighboring pixel with index p , where h is expressed as:

$$h(n) = \begin{cases} 1 & if \ n \geq 0 \\ 0 & if \ n < 0 \end{cases} \tag{2}$$

The radius R of the circle sampling points is used to determine the method's spatial resolution and also its quantization by computing the interpolation estimates of the gray values outside the pixel's center.

2.2 Histogram of Gradient

Histogram of Gradient (HOG) is the technique that counts occurrences of gradient orientation of an image [28,29]. The HOG descriptor focuses on the shape of an object to produce histograms of the image using the magnitude and orientations of the gradient. The steps in using HOG for extracting features of Yorùbá document are as follows:

Step 1: The Yorùbá printed or handwritten input word image and resized into an image of 64x128 pixels.

Step 2: The gradient of the image is computed as:

$$G_q(y,n) = I(y,n+1) - i(y,n-1) \tag{3}$$

$$G_z(y,n) = I(y-1,n) - I(y+1,n) \tag{4}$$

where G_q and G_z is calculated for each pixel.

where y, n refer to rows and columns respectively. The magnitude and angle are represented as:

$$Magnitude(\mu) = \sqrt{G_q^2 + G_z^2} \tag{5}$$

$$Angle(\theta) = \left| \tan^{-1}\left(\frac{G_q}{G_z}\right) \right| \tag{6}$$

Step 3: Computed histogram using 9-point as:

$$Number\ of\ bins = 9\ (ranging\ from\ 0^o\ to\ 180^0\ ) \tag{7}$$

$$Therefore, \quad step\ size(\Delta\theta) = \frac{180^0}{Number\ of\ bins} = 20^o \tag{8}$$

Each Jth bin has $[\Delta\theta.j, \Delta\theta.(j+1)]$ and the bin's value, C_j, is given as :

$$C_j = \nabla\theta(j + 0.5) \tag{9}$$

Step 4: Compute value jth value using the formulae:

$$j = \left\lfloor \left(\frac{\theta}{\Delta\theta} - 0.5\right) \right\rfloor \tag{10}$$

$$V_j = \mu . \left[\frac{\theta}{\Delta\theta} - 0.5\right] \tag{11}$$

$$V_{j+1} = \ \mu . \left[\frac{\theta - C_j}{\Delta\theta}\right] \tag{12}$$

Step 5: The histogram was calculated: $b_1, b_2, b_3, \ldots, b_{36}\ \ for\ a\ single\ 36 \times 1\ matrix$ to append the value of vectors V_j and V_{j+1} with index of jth and (j+1)th respectively.

Step 6: The root of the sum of squares, k, is normalized using the formula:

$$k = \sqrt{b_1^2 + b_2^2 + b_3^2 + \cdots + b_{36}^2} \tag{13}$$

$$Normalised\ vector, fbi = \left[\left(\frac{b_1}{k}\right).\left(\frac{b_2}{k}\right).\left(\frac{b_3}{k}\right).\cdots.\left(\frac{b_{36}}{k}\right)\right] \tag{14}$$

$$where\ i = 1,2,3,\ldots,36\ for\ a\ single\ 36 \times 1\ matrix$$

Step 7: After the histogram is computed, the blocks are combined to form a (2×2) block. The value of f_b is computed using the norm given as:

$$f_b \leftarrow \frac{f_{bi}}{\sqrt{\left\|{f_{bi}}^2\right\| + \epsilon}} \tag{15}$$

To avoid zero division error, a small value, ϵ, is added to the square of f_b.

2.3 Speeded -Up-Robust Feature (SURF)

Speeded-Up Robust Features (SURF) is a novel scale- and rotation-invariant detector and descriptor [30,31]. The Integral Pixel is an efficient and rapid method for determining the total pixel values in an image. It is mostly used to compute the average intensity of an image. This expedites the computation of convolution filters of the box type. The entry of a complete image at I(x). x = $(x,y)^T$ indicates the sum of all pixels within a rectangle region created by the origin. x is given as:

$$I_{\Sigma(x)} = \sum_{i=o}^{i\leq x} \sum_{j=0}^{j\geq y} I(i,j) \tag{16}$$

It takes four additions to determine the sum of intensities over any upright, rectangular region computed, regardless of the area's size. The Hessian matrix is given:

$$H(f(x,y)) = \begin{bmatrix} \frac{\partial^2 f}{\partial x^2} & \frac{\partial^2 f}{\partial_x \partial_y} \\ \frac{\partial^2 f}{\partial_x \partial_y} & \frac{\partial^2 f}{\partial y^2} \end{bmatrix} \tag{17}$$

A Gaussian kernel is computed as at point X = (x, y), the Hessian matrix H(x, σ) in x at scale σ which is defined as:

$$H(X,\sigma) = \begin{bmatrix} L_{xx}(x,\sigma) & L_{xy}(x,\sigma) \\ L_{xy}(x,\sigma) & L_{yy}(x,\sigma) \end{bmatrix} \tag{18}$$

where $L_{xx}(x, \sigma)$ is the convolution of the second-order Gaussian derivative with the image I at x, and correspondingly for $L_{xy}(x, \sigma)$ and $L_{yy}(x, \sigma)$.

To calculate the determinant of the Hessian matrix, convolution with a Gaussian kernel is utilized, followed by second-order derivative. Using integral images and regardless of size, the approximated second-order Gaussian derivatives may be evaluated at a very minimal computational cost, which is part of the reason why SURF is so quick. These approximations are given as D_{xx}, D_{yy}, and D_{xy}. The determinant is represented as Hessian as:

$$\det(H_{approx}) = D_{xx}D_{yy} - (\omega D_{xy})^2 \tag{19}$$

2.4 Related Works

An offline Yorùbá character recognition system based on the Freeman chain code and the K-Nearest Neighbor algorithm (KNN) was presented by [5]. The k-nearest neighbor classifier and other classification algorithms have been used in the majority of Latin word recognition and character recognition. The same recognition capability on Yorùbá characters was being researched. The performance of the KNN was compared to that of other classification algorithms that recognized Yorùbá characters using Support Vector Machine (SVM) and Bayes classifier. The k-nearest neighbor classification algorithm and Freeman chain code were found to have a recognition accuracy of 87.7%, outperforming the aforementioned classifiers. [12] created a Yorùbá character recognition system using SVM. The system was tested with 600 handwritten images using 480 for training and 120 for testing. The training time was 45.842 seconds, the recognition rate was 76.7%, and the rejection rate was 23.3%. The work can be expanded to include lower case Yorùbá characters as well as words. Also, the Yorùbá handwriting character database can be designed in such a way that large amounts of data are available for testing. [32] presented a novel technique for developing a Yorùbá alphabet recognition system using deep learning. Although it is limited to Yorùbá characters, this study developed a deep convolutional network called YORBNET for detecting Yorùbá alphabets, taking into account all factors and metrics. [33] presented a transfer learning-based framework for the development of an offline Yorùbá handwritten character recognition system using AlexNet. The AlexNet pre-trained model was used in this study to recognize Yorùbá handwritten character. The transfer learning workflow was used to create the framework. As a result, the reporting network accuracy is 82.8%. Furthermore, computational modelling of an optical character recognition system for Yorùbá printed text was presented by [16]. The study observed Yorùbá language as one of those languages on the verge of extinction. One method proposed for preserving the language was to create a digital library of books and literature. The goal of the optical character recognition (OCR) systems was to convert a large number of printed or handwritten documents. Yorùbá's OCR system can be improved by creating a more robust language model that can function as an error correction subsystem. The model's performance demonstrates that the greater the distance between an image text font and the font(s) used in training the network, the higher the character error rate. To address the problem of low recognition accuracy for Yorùbá document recognition for both handwritten and printed text, the we developed a novel extraction of local features over distinct characters, taking into account the unique characteristics of Yorùbá documents. The proposed hybridized feature extraction strategies emphasized the usage of combined feature extraction techniques and the evaluation of their impact on the classification algorithm.

3. METHODOLOGY

In order to achieve the objectives of this research work, the following methods are used: Data acquisition, preprocessing, feature extraction, feature selection and classification.

3.1 Data Acquisition

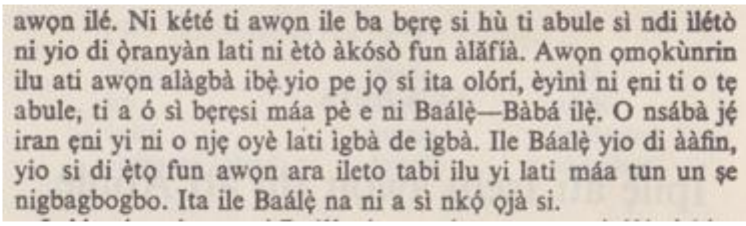
Ten Yorùbá Literature books were acquired from the archive of Kwara State University Library and the handwritten Yorùbá document was written by ten literate writers from the Literature Books in order to provide handwritten dataset document with correct diacritic marks that will be used as testbed for the developed recognition system. Other text dataset was also acquired from MNIST and CEDAR to evaluate the performance of the developed system. Though the variability of printed of text is not too obvious, since, the printed text is typed using the same font but the handwritten shows different variations in human handwritings. Samples of Yorùbá documents acquired for both printed text and handwritten text is shown in Fig. 1.

3.2 Data Pre Processing

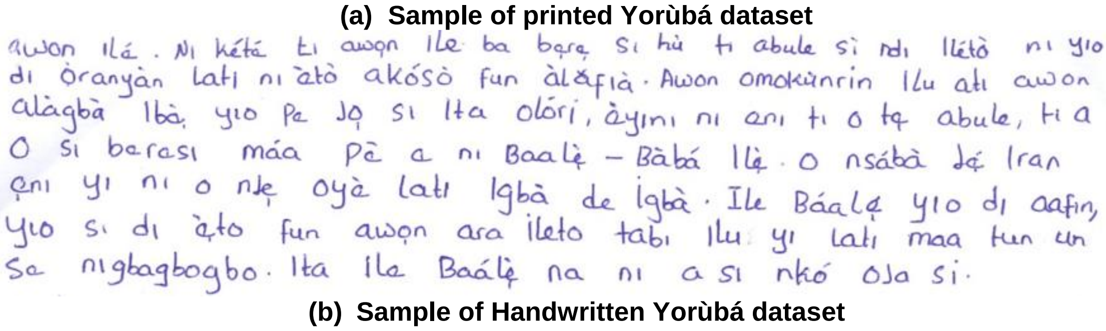
In the Digitization phase the printed or hand written dataset was converted into the digital form by scanning the given document. The acquired images were subjected to some level of pre-processing for the removal of perturbations and make it suitable for the next level of the recognition process. The Yorùbá documents were converted to grayscale representation, the grayscale images were binarized using Otsu's method and the binarized images were subjected to word level segmentation.

3.3 The Hybridized Model

This work developed a hybrid feature extraction technique for Yorùbá document recognition. Three features extraction techniques Local Binary Pattern (LBP), Histogram of gradients (HOG) and Speeded-Up Robust Features (SURF) algorithm were used due to the fact that most of these feature extraction techniques have proven to be effective for extraction of low level detail representation that will enhance the recognition accuracy. The three extracted feature algorithm were used individually and later subjected to Genetic Algorithm (GA). This gives LBP-GA, HOG-(GA) and SURF-GA. From these three feature extraction techniques, two of the feature extraction techniques were also combined resulting into these combination LBP-HOG-GA, LBP-SURF-GA, HOG-SURF-GA, and the three feature extraction techniques were also combined to form LBP-HOG-SURF-GA. The result of the reduced dimension feature vectors served as input to Support Vector Machine for classification. The model is grouped into five classification such as: The document acquired


awọn ilé. Ni kété ti awọn ile ba bẹrẹ si hù ti abule sì ndi ilétò ni yio di ọ̀ranyàn lati ni ètò àkósò fun àlăfíà. Awọn ọmọkùnrin ilu ati awọn alàgbà ibẹ̀ yio pe jọ sí ita olórí, èyini ni ẹni ti o tẹ abule, ti a ó sì bẹrẹsi máa pè e ni Baálẹ̀—Bàbá ilẹ̀. O nsábà jẹ́ iran ẹni yi ni o njẹ oyè lati igbà de igbà. Ile Báalẹ̀ yio di ààfin, yio si di ẹ̀tọ fun awọn ara ileto tabi ilu yi lati máa tun un ṣe nigbagbogbo. Ita ile Baálẹ̀ na ni a sì nkọ́ ọjà si.

(a) Sample of printed Yorùbá dataset


awon ilé. Ni kétá ti awọn ile ba bẹrẹ si hù ti abule sì ndi ilétò ni yio di ọranyàn lati ni àtò akósò fun àlăfià. Awon omokùnrin ilu ati awon alàgbà ibẹ̀ yio pe jọ si ita olóri, àyini ni eni ti o tẹ abule, ti a o si berasi máa pè a ni Baalẹ̀ – Bàbá ilẹ̀. o nsábà jẹ́ iran ẹni yi ni o njẹ oyà lati igbà de igbà. Ile Báalẹ yio di aafin, yio si di ẹ̀to fun awọn ara ileto tabi ilu yi lati maa tun un sa nigbagbogbo. Ita ile Baálẹ̀ na ni a si nkó oja si.

(b) Sample of Handwritten Yorùbá dataset

Fig. 1. Sample of the acquired (a) Sample of printed Yorùbá and (b) Handwritten Yorùbá dataset

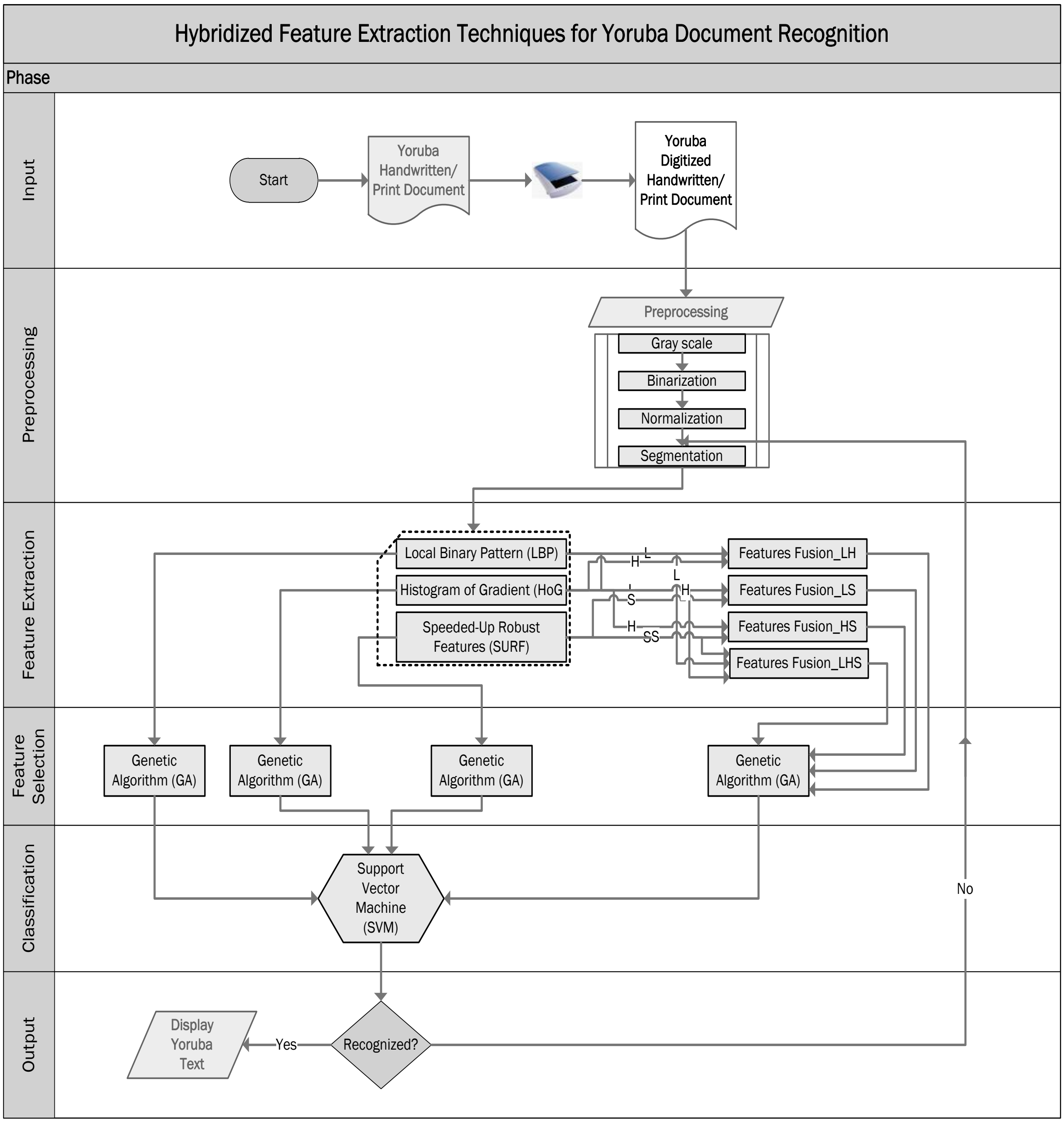


Fig. 2. Developed model for the hybridized features extraction techniques

converted to it digitized format for both printed and handwritten Yorùbá document, the digitized Yorùbá document were subjected to some level of preprocessing such as grey scale, binarization and segmentation. The result of the word level segmentation served as input to the feature extraction techniques combined in 7 different forms. The resulting feature vector form the various FET was passed to Genetic algorithm and the reduced feature were subjected to support vector machine. The description of the model of the hybridized feature extraction techniques is shown in Fig. 2.

3.3.1 Combination of LBP, HOG and SURF Algorithm

A 3×3 windows was used to extract features of each of the words where the central pixel is picked and the neighbouring pixel was used to compute the LBP code. The code generated was added up to produce the feature vector for the Yorùbá document. For HOG, the image was resized into 64×128 size and the size of the image was divided by 8×16 grid and each of the grid contains 8x8 size. Each of the grid was used to compute the gradient and magnitude of the

Yorùbá words. The feature vector is divided into nine different bins, which was added up to form the feature vector of the Yorùbá words. The SURF algorithm is very good at detecting the interest point and generate a reduced feature vector. Because it in invariant to scaling and dimension. The integral image was derived from the image, from the integral image the hessian matrix is given to compute the gaussian kernel and the determinant of the hessian matrix is also. This was done to get the feature vector of SURF algorithm on the Yorùbá document. The three-feature vector from the three algorithms were combined to form the hybridized feature extraction techniques were passed to genetic algorithm. Algorithm 1 shows the hybridization of the three techniques using 1-combination, 2-Combinations and the 3-combinations.

Algorithm 1: Hybridization of Extracted Features

```
Procedure HB ← HIBRID (IMG, SURF, LBP, HOG, GA)
img ← preprocess (orimg)
imgsize ← size(img)
for cnt ← 1: imgsize do
   bw ← charcrop (img {cnt})
   [rowbw colbw] ← size (bw)
  if rowbw<10 | colbw<10 then
       bw←round(rand(0,0))
  else
       bw←bw
  end if
end for
    charvec ← figresize(bw)
for i ← j-1 to -1: size do
    points ← detectSURFFeatures(bw)
    [features, validPoints] ← extractFeatures(bw,points)
 end for
bfeatures←gafeature(features)
for i ← j-1 to -1:size do
   features←extractLBPFeatures(bw)
end for
bfeatures←gafeature(features)
for i ← j-1 to -1:size do
   features←extractHOGFeatures(bw)
end for
bfeatures←gafeature(features)
for i ← j-1 to -1:size do
   if     features←extractLBPFeatures(bw) then
          lbpfeatures←gafeature(features)
   else if
features←extractHOGFeatures(bw)
hogfeatures←gafeature(features)
    else
points ← detectSURFFeatures(bw)
[features, validPoints] ← extractFeatures(bw,points)
     end if
surffeatures←gafeature(features)
cfeatures← [surffeatures hogfeatures lbpfeatures]
bfeatures←gafeature(cfeatures)
 end do
 out(: , cnt) ← charvec
 outfeat(: , cnt)←charvec
end
```

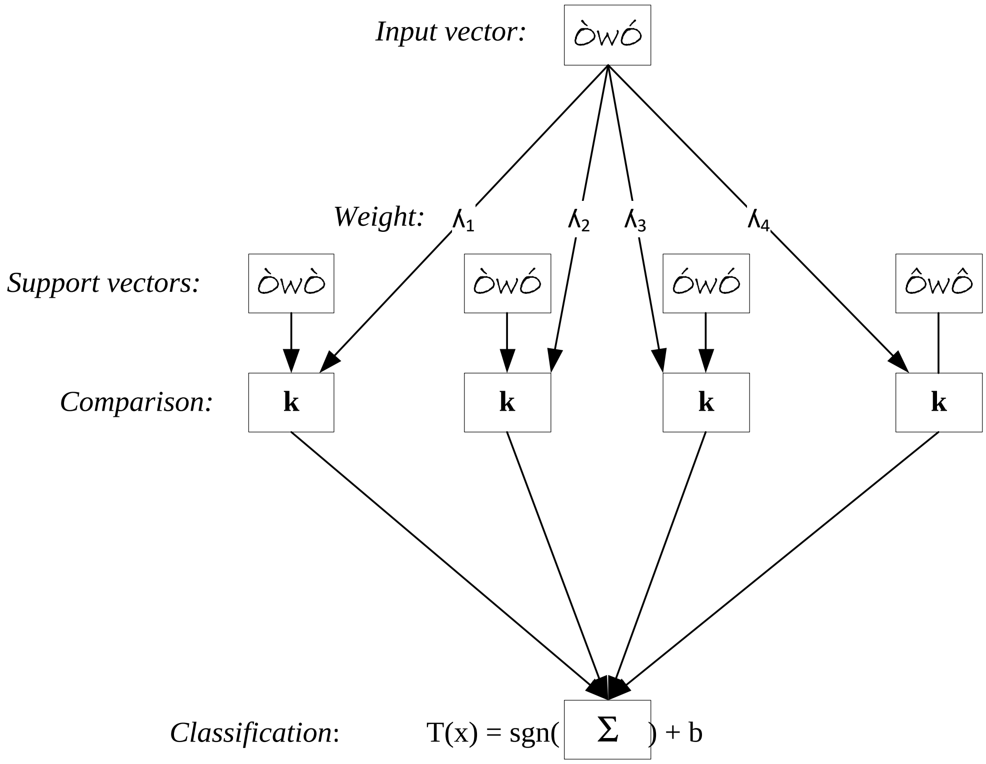


Fig. 3. SVM model for Yorùbá document recognition (Source: adapted from [34])

3.4 Feature Selection

In order to improve the performance of the classification algorithm, the feature vector from the hybridized feature extraction techniques were subjected to feature selection technique so as to reduce and optimize the feature parameters. Genetic algorithm is a type of metaheuristic algorithm used in machine learning to handle optimization problems. It is one of the most essential algorithms because it assists in solving complex problems. Genetic Algorithm feature selection techniques was used with a fitness function of $\sum(f_{i-1} - f_i)$. This fitness function was used to select chromosomes that will crossover to new offsprings. Genetic algorithm is shown in Algorithm 2.

2: Genetic Algorithm for the combined features

parameter(w) : W -set of words
Initialization1=0
*Initialize Pi to random individuals from w**
EVALUATE FITNESS-GA(W, PI)
while termination condition not met

$$\textbf{do}\begin{Bmatrix} Select\ individauls\ from\ Pi(fitness\ prortional) \\ Recombine\ individauls \\ Mutate\ individuals \\ EVALUATE - FITNESS(w, modified\ individuals) \\ P_{i+1} \xrightarrow{yields} newly\ created\ individuals \\ \end{Bmatrix}$$

return (Words derived from best individual in Pi
PROCEDURE EVALUATE FITNESS-GA(W..P)
W-Set of Words
P-population of individuals
for each individual $i \in P$

$$\boldsymbol{do}\left\{\begin{array}{c} generate\ derived\ words\ w(i) \\ m \xrightarrow{yields} all\ set\ of\ words\ from\ W\ that\ are\ not\ considered\ by\ a(i) \\ w'(i) \xrightarrow{yields} concatenation\ of\ w(i) and\ m \\ fitness(i) \xrightarrow{yields} \sum_{i=1}^{m}(f_{i+1} - f_i) \end{array}\right\}$$

3.5 Classification

The result of the optimized parameters served as input to the classification algorithm. Support Vector Machine is the classification algorithm used, which takes input data from the vectors of input data generated from GA. Four different Support Vector similar to the input vector were used and comparison was made with the kernel of the input vector with the support vectors to maximize the hyperplane based on the constraint on how close the classified words is close to the original image. Fig. 3 shows an adapted model of SVM for classifying Yorùbá document. The first layer contains the input words to be classified and the weights are added subset of the training set (the Support Vectors) which classifies the input words by adjusting the sigmoid of the decision function and add a bias, it then returns the maximum hyperplane of the words. Detail of this is shown is Fig. 4. The algorithm for the Support Vector Machine is shown in Algorithm 3 [34].

Algorithm 3: Algorithm for SVM (Source: [34])

Step 1: Input the optimized parameters from GA

Step 2: Find the decision function

$$maximixe\ S(\gamma) = \sum_{i=1}^{n} \gamma_i - \frac{1}{2}\sum_{i,j=1}^{n} \gamma_i\gamma_j\beta_i\beta_j\langle x_i x_j\rangle$$

$$where\ \ \gamma \in \mathbb{R}^n$$

$$subject\ to\ \gamma_i \geq 0, i = 1, \dots\dots, n$$

$$and\ \sum_{i=1}^{n} \gamma_i\beta_i = 0$$

Step 3: if k is positive, $Q_{IJ} = (\beta_i\beta_j\langle x_i x_j\rangle)_{ij}$ is a positive definite matrix which provides a convex problem that can be solved efficiently as:

$$\sum_{i.j=1}^{n} \gamma_i\gamma_j\beta_i\beta_j\, k(x_i x_j) = \left(\langle\sum_{i=1}^{n} \gamma_i\beta_j\emptyset(x_i)\rangle, \langle\sum_{j=1}^{n} \gamma_i\beta_j\emptyset(x_i)\rangle\right) \geq 0$$

$$for\ all\ \gamma \in \mathbb{R}^n$$

Step 4: Compute the hyperplane decision function as:

$$T(x) = sgn\left(\sum_{i=1}^{n} \gamma_i\beta_j\,(x, x_i)\right) + b$$

Step 5: return the optimal margin hyperplanes as T(x)

4. RESULTS AND DISCUSSION

The proposed hybridized feature extraction technique has a feature vector length limit of 256 bins. The proposed LBG-GA, HOG-GA, SURF-GA, SURF-HOG and LBP-HOG-SURF-GA was tested on Yorùbá handwritten, printed text, MNIST and CEDAR dataset using a 10-folds cross validation. The computed feature vector is used to determine the best probe match score for the handwritten and printed images in the lexicon of Yorùbá document. The efficiency of the developed hybridized feature extraction methods was evaluated using False Positive Ratio (FPR), Specificity (SPE), Sensitivity (SEN), Accuracy (ACC) and Precision (PREC) on the SVM with threshold 0.23 across 7 forms of Feature Selection Techniques (FET). The FET are LBP-GA, HOG-GA, SURF-GA, LBP-HOG, LBP-SURF, HOG-SURF and LBP-HOG-SURF-GA. The following subsections present the results of the hybridized feature extraction techniques for Printed Yorùbá text, handwritten Yorùbá text, CEDAR dataset and MNIST dataset.

4.1 Assessment of FET on the Printed Yorùbá Document

The results presented in Table 1 and Figs. 4, 5, and 6 provide an overview of the recognition accuracy of the developed document recognition systems for printed Yorùbá documents. The study evaluated different combinations of feature extraction techniques, including LBP, HOG, and SURF, and found that LBP outperformed the other techniques. The study also showed that combining two or more feature extraction techniques could further improve recognition accuracy. The highest recognition accuracy was achieved using the LBP-HOG-SURF-GA combination, with an accuracy of 90.3%. The study also showed that LBP-HOG was more effective than LBP-SURF and HOG-SURF combinations for recognizing printed Yorùbá documents. Figs. 4, 5, and 6 provide a detailed analysis of the sensitivity and precision of the recognition accuracy of the developed Yoruba printed text recognition system for different combinations of feature extraction techniques. The figures also show that the proposed hybridized feature extraction techniques outperform the 1 and 2-combinations of feature extraction techniques.

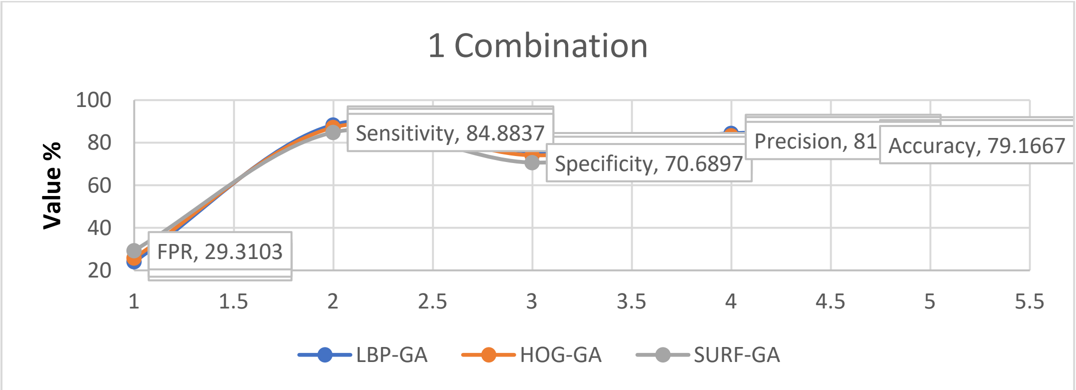


Fig. 4. Performance Evaluation of LBP-GA, HOG-GA and SURF-GA for printed Yorùbá Document

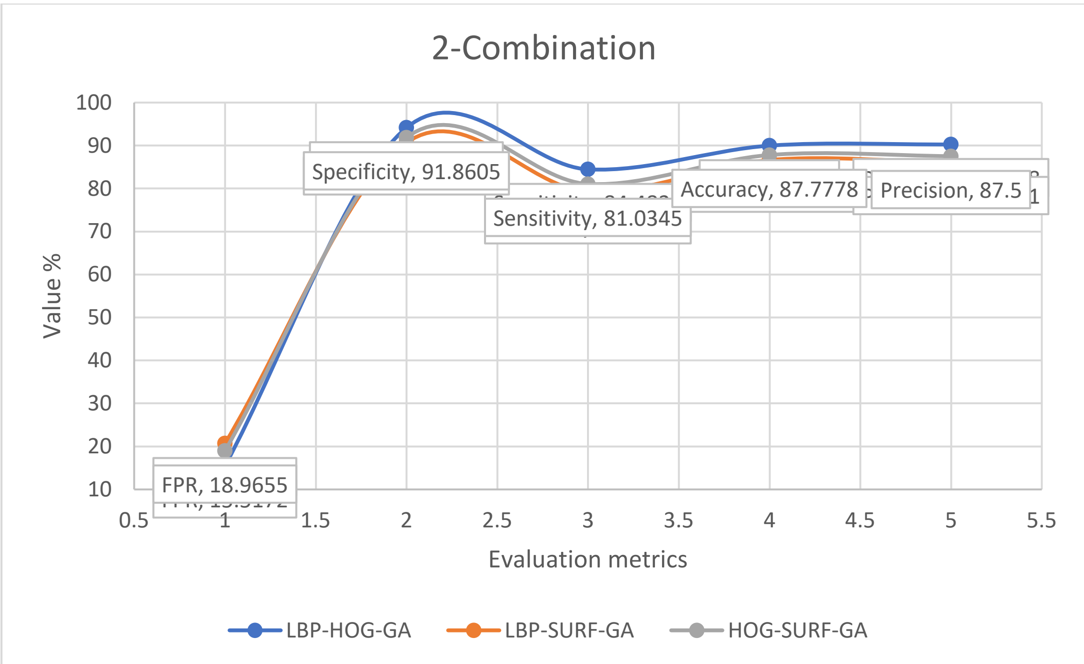


Fig. 5. Performance Evaluation of LBP-HOG-GA, HOG-SURF-GA and LBP-SURF-GA for Yorùbá Printed text

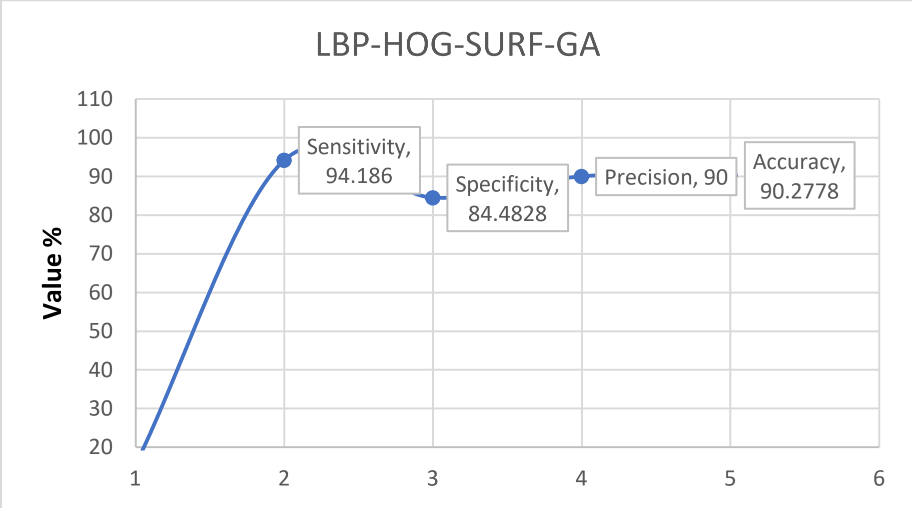
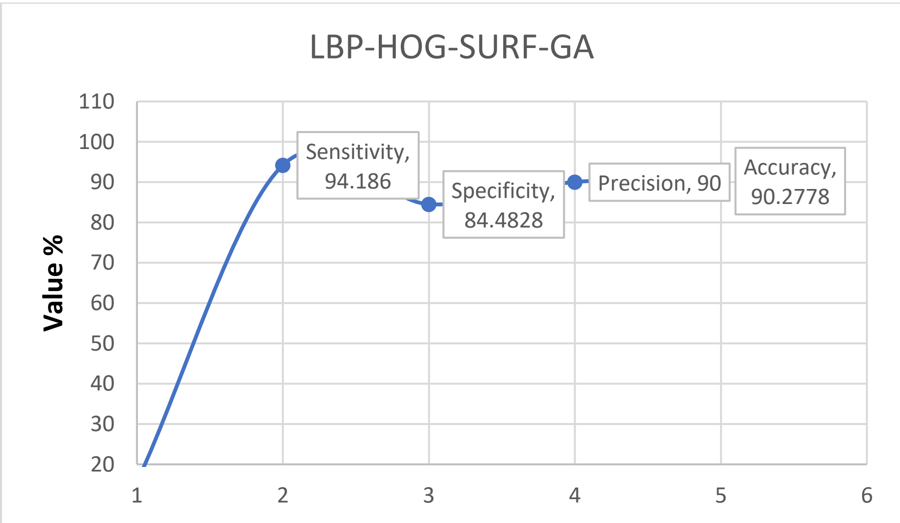


Fig. 6. Performance Evaluation of LBP-HOG-SURF-GA printed Yorùbá Document



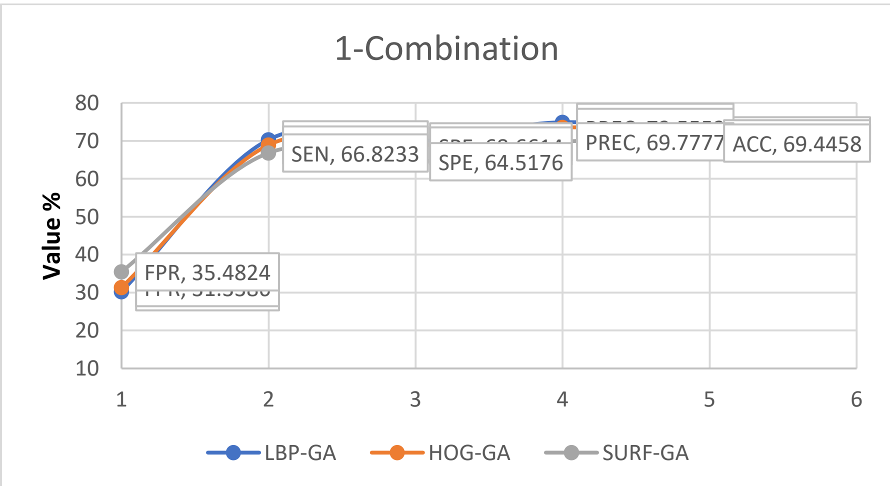


Fig. 7. Performance Evaluation of LBP-GA, HOG-GA and SURF-GA for Handwritten Yorùbá Document

Table 1. The hybridized feature extraction techniques on Yorùbá Printed text

FET	FPR	SEN	SPE	PREC	ACC	THRES	TIME	CLASSIFIER
LBP-GA	24.1379	88.3721	75.8621	84.4444	83.3333	0.23	89.2869	SVM
HOG-GA	25.8621	87.2093	74.1379	83.3333	81.9444	0.23	78.4679	SVM
SURF-GA	29.3103	84.8837	70.6897	81.1111	79.1667	0.23	76.4213	SVM
LBP-HOG-GA	20.6897	90.6977	79.3103	86.6667	86.1111	0.23	118.4426	SVM
LBP-SURF-GA	18.9655	91.8605	81.0345	87.7778	87.5	0.23	117.9911	SVM
HOG-SURF-GA	22.4138	89.5349	77.5862	85.5556	84.7222	0.23	113.0266	SVM
LBP-HOG-SURF-GA	15.5172	94.186	84.4828	90.0000	90.2778	0.23	175.735	SVM

Table 2. The hybridized feature extraction techniques on Yorùbá handwritten text

FET	FPR	SEN	SPE	PREC	ACC	THRESHOLD	TIME	CLASSIFIER
LBP-GA	30.2439	70.2834	69.7561	74.8888	71.3341	0.23	100.4678	SVM
HOG-GA	31.3386	68.9135	68.6614	73.5552	70.5584	0.23	86.9733	SVM
SURF-GA	35.4824	66.8233	64.5176	69.7777	69.4458	0.23	84.8885	SVM
LBP-HOG-GA	28.6843	80.3241	71.3157	73.6666	75.3328	0.23	150.3456	SVM
LBP-SURF-GA	26.9348	81.4844	73.0652	72.4441	76.9834	0.23	146.2315	SVM
HOG-SURF-GA	29.5821	74.4532.	70.4179	69.5555	73.7782	0.23	140.3248	SVM
LBP-HOG-SURF-GA	20.3945	84.3842	79.6055	80.8888	82.5674	0.23	200.8945	SVM

Table 3. The hybridized feature extraction techniques on CEDAR dataset

FET	FPR	SEN	SPE	PREC	ACC	THRESHOLD	TIME	CLASSIFIER
LBP-GA	7. 2243	95.3346	92.7757	93.6675	93.1111	0.23	70.6578	SVM
HOG-GA	9.7683	93.6749	90.2317	92.5541	92.4441	0.23	65.3465	SVM
SURF-GA	10.2345	89.6897	89.7655	90.7861	91.5783	0.23	63.5787	SVM
LBP-HOG-GA	5.4785	97.5876	94.5215	96.7769	97.1222	0.23	80.3454	SVM
LBP-SURF-GA	6.9655	96.9874	93.0345	95.6861	96.8881	0.23	83.7645	SVM
HOG-SURF-GA	8.4138	96.7344	91.5862	94.7743	95.0000	0.23	85.6634	SVM
LBP-HOG-SURF-GA	2.5624	98.2332	97.4376	98.3323	98.4321	0.23	90.4557	SVM

Table 4. The hybridized feature extraction techniques on MNIST dataset

FET	FPR	SEN	SPE	PREC	ACC	THRESHOLD	TIME	CLASSIFIER
LBP-GA	3.1132	98.8777	96.8868	98.4453	97.5000	0.23	70.6578	SVM
HOG-GA	3.2658	97.9125	96.7342	97.3554	97.4448	0.23	65.3465	SVM
SURF-GA	4.7688	96.2551	95.2312	96.3236	95.5666	0.23	63.5787	SVM
LBP-HOG-GA	1.6431	99.5	98.3569	98.5677	98.5	0.23	80.3454	SVM
LBP-SURF-GA	1.8796	98.4321	98.1204	98.2311	98.5667	0.23	83.7645	SVM
HOG-SURF-GA	2.4564	97.6332	97.5436	97.8889	98.1111	0.23	85.6634	SVM
LBP-HOG-SURF-GA	1.1112	99.0000	98.8888	99.5000	99.0000	0.23	90.4557	SVM

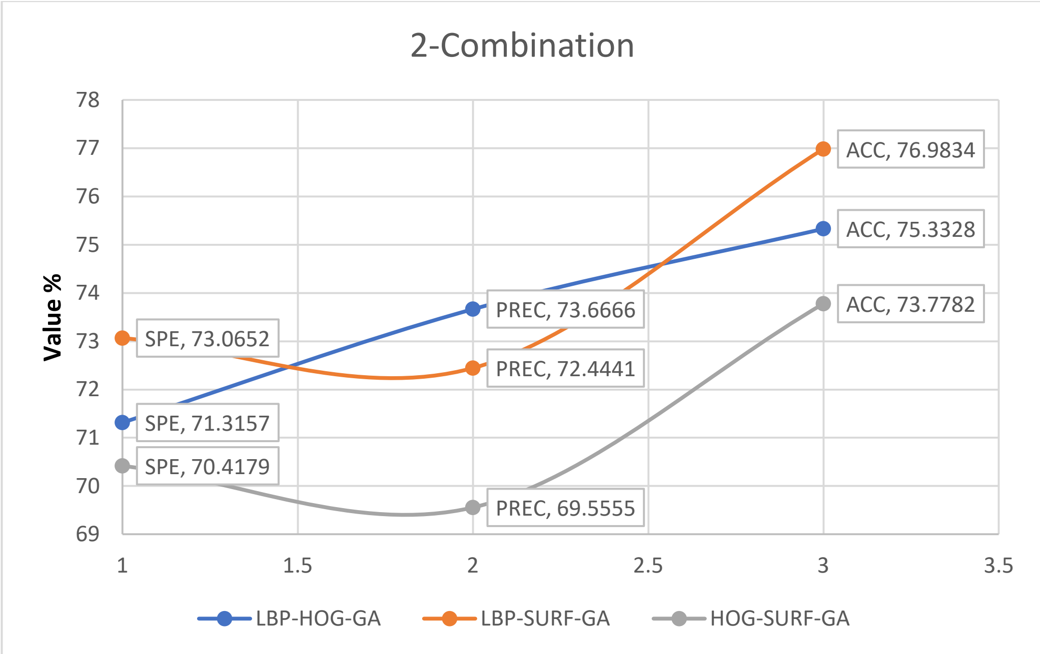


Fig. 8. Performance Evaluation of LBP-HOG-GA, LBP-SURF-GA, HOG-SURF for Handwritten Yorùbá Document

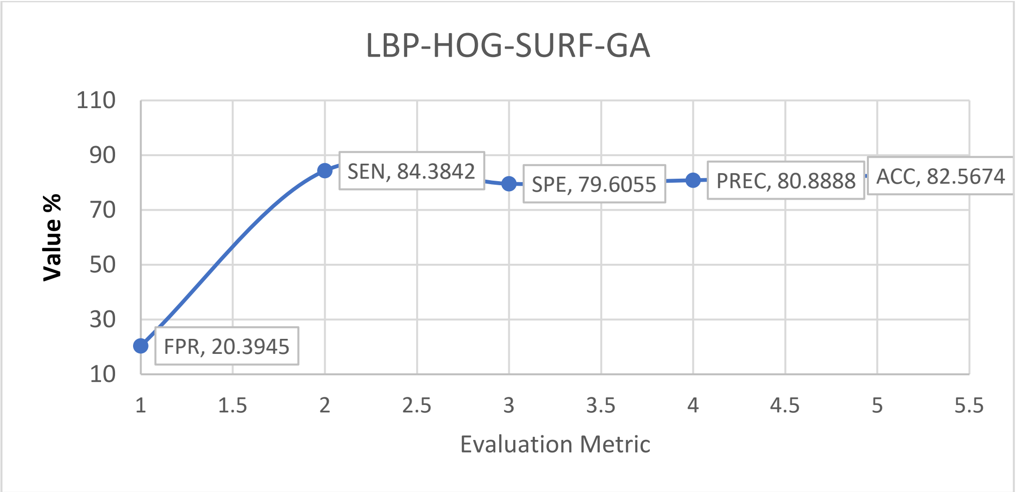


Fig. 9. Performance Evaluation of LBP-HOG-SURF-GA for Yorùbá Handwritten Document

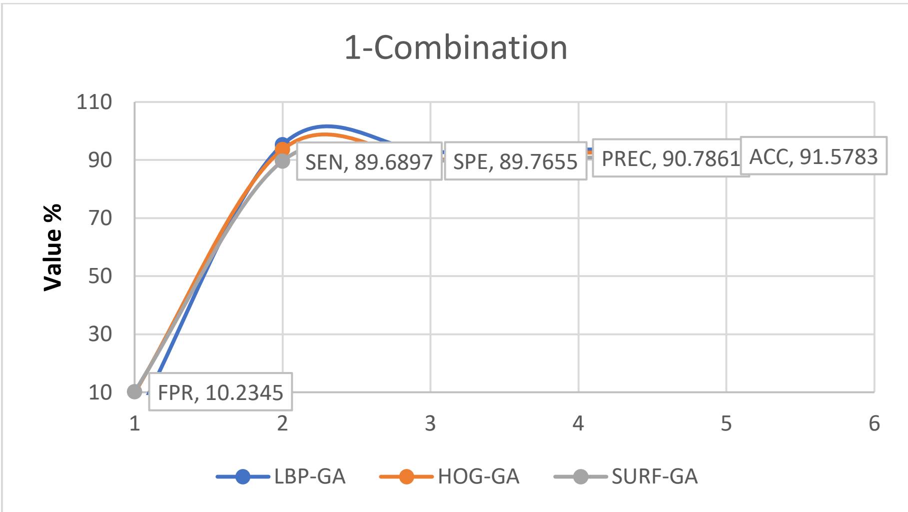


Fig. 10. Performance Evaluation of LBP-GA, HOG-GA and SURF-GA for CEDAR Text Document

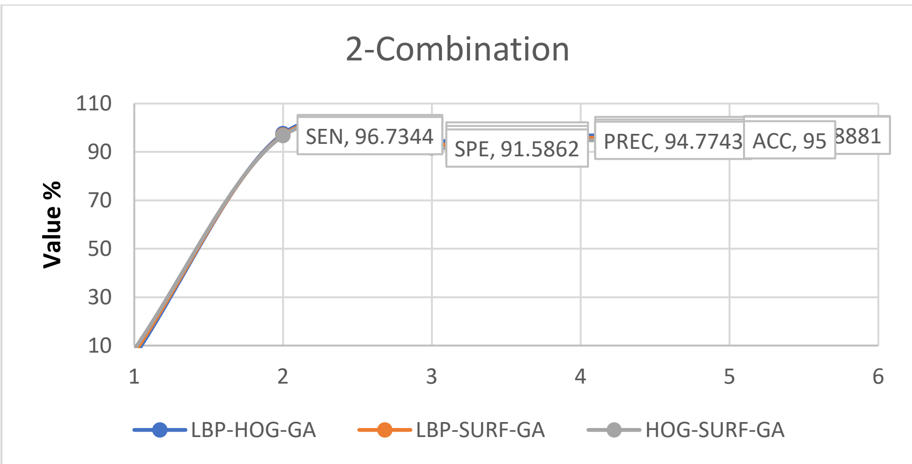


Fig. 11. Performance Evaluation of LBP-HOG-GA and LBP-SURF-GA and HOG-SURF for CEDAR Text Document

4.2 Assessment of the FET on Yorùbá Handwritten Document

The recognition accuracy for Yorùbá handwritten document is presented in Table 2 as follows: LBP-GA is 71.3%, HOG-GA is 71.0% and SURF-GA is 69.4%, LBP-HOG-GA is 75.3%, LBP-SURF-GA is 77.0%, HOG-SURF-GA is 73.8% and LBP-HOG-SURF-GA is 82.5%. Figs. 7, 8 and 9 show the sensitivity and precision of the Yoruda handwritten document recognition system. Fig. 7 shows LBP-GA (70.2%, 74.8%), HOG-GA (68.9%, 73.5%), SURF-GA (66.8%, 69.7%). Fig. 8 shows LBP-HOG-GA (80.3%, 73.6%), LBP-SURF-GA (81.4%, 72.4%) and HOG-SURF-GA (74.4%., 69%). Fig. 9 shows LBP-HOG-SURF-GA (84.3%, 80.8%). The results showed that the proposed hybridized feature extraction model outperform the LBP-GA, HOG-GA, SURF-GA(1-combination) and LBP-HOG-GA, LBP-SURF-GA , HOG-SURF-GA (2-combinations) of feature extraction techniques.

4.3 Assessment of FET on CEDAR Handwritten Document

The recognition accuracy for CEDAR dataset is presented in Table 3 as follows: LBP-GA is 93.1%, HOG-GA is 92.4% and SURF-GA is 91.5%. Also, LBP-HOG-GA is 97.1%, LBP-SURF-GA is 96.8%, HOG-SURF-GA is 95% and LBP-HOG-SURF-GA is 98.4%. The result showed that the proposed hybridized feature extraction model outperform 1 combination and 2 combinations of feature extraction techniques. Detail of this is shown in Figs. 10, 11 and 12, which shows the sensitivity and the precision of the recognition system developed for CEDAR

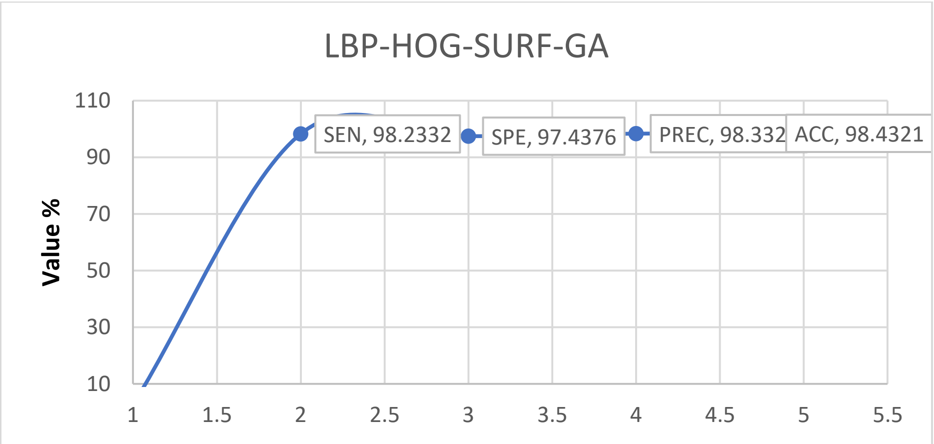


Fig. 12. Performance Evaluation of LBP-HOG-SURF-GA for CEDAR Text Document

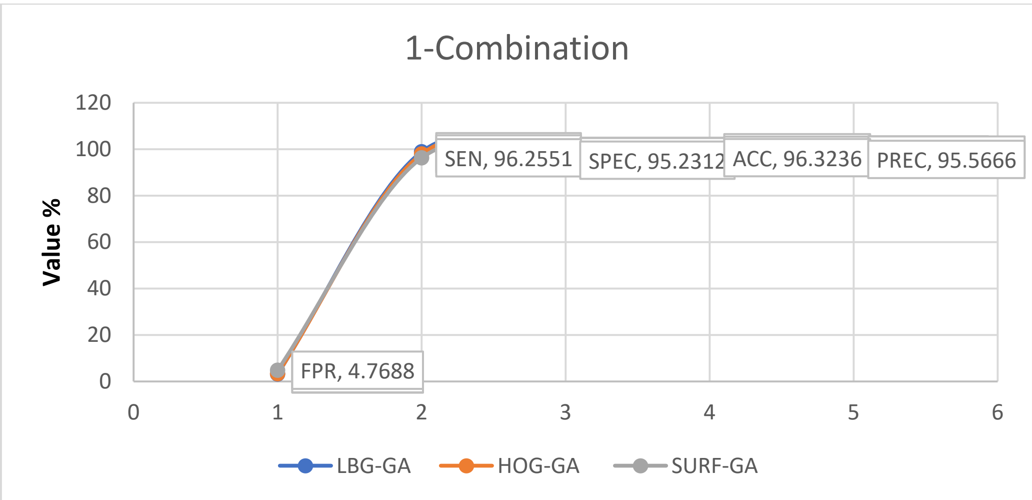


Fig. 13. Performance Evaluation of LBP-GA, HOG-GA and SURF-GA for MNIST Digit Document

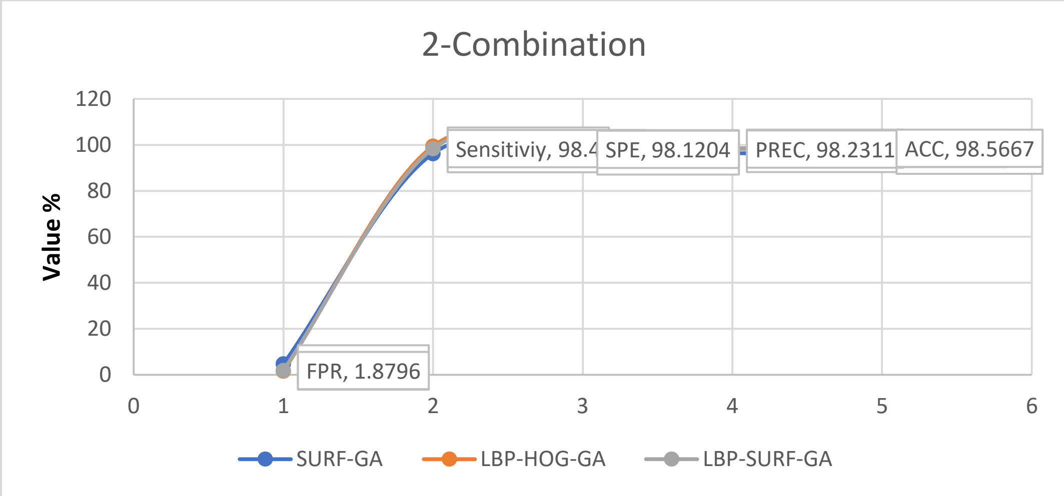


Fig. 14. Performance Evaluation of LBP-HOG-GA, LBP-SURF-GA and HOG-SURF-GA for MNIST digit Document

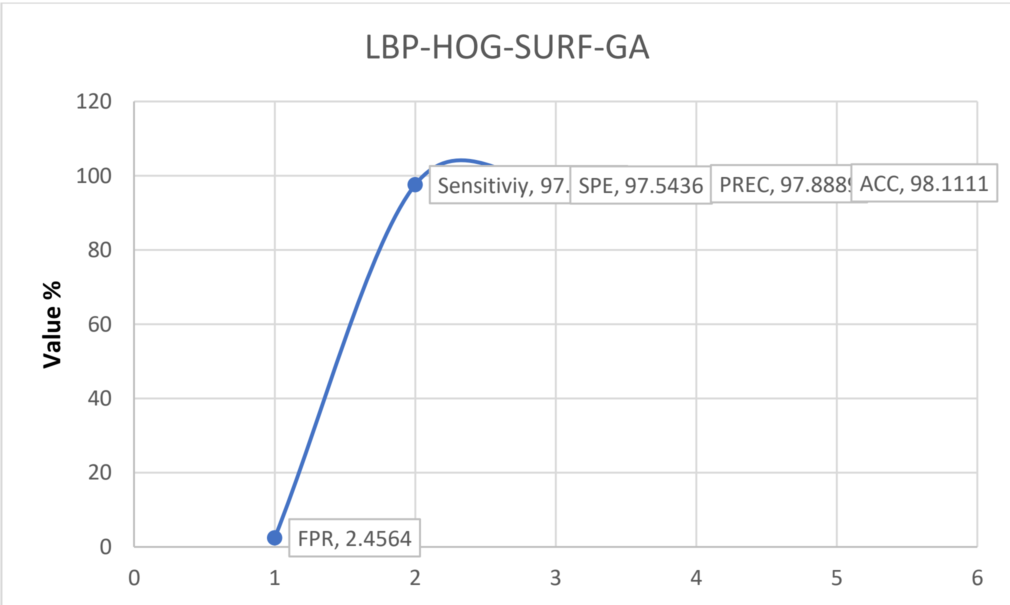


Fig. 15. Performance Evaluation of LBP-HOG-SURF-GA for MNIST digit Document

dataset. The proposed hybridized model gave better performance in terms of accuracy, sensitivity and precision. Details of these are shown in Figs. 10, 11 and 12 respectively.

4.4 Assessment of FET on MNIST handwritten Document

The result of the recognized MNIST dataset was tested on the Yoruba document recognition system to show the validity of the system. The recognition accuracy for MNIST dataset is shown in Table 4. LBP-GA is 97.5%, HOG-GA is 97.4% and SURF-GA is 95.5%. Also, LBP-HOG-GA is 98.5%, LBP-SURF-GA is 98.5%, HOG-SURF-GA is 98.1% and LBP-HOG-SURF-GA is 99%. The result showed that the proposed hybridized feature extraction Model outperform 1 and 2 combinations of feature extraction techniques. Figs. 13, 14 and 15 shows the sensitivity and precision of the recognition module.

5. CONCLUSION

In this research work, a hybridized based feature extraction techniques were proposed for Yorùbá

Handwritten and printed text Recognition system. Based on some of reviewed articles, the results have shown that previous works focused on the classification accuracy, not much attention was on how effective is it if two or more techniques of feature extraction were used. The result obtained, it shows a clear indication that, combination of several feature extraction technique gave an appreciable recognition accuracy, considering the recognition time shown on Tables 1, 2, 3 and 4. The hybridized model recognition time is higher compared to 1-combination and 2-combination feature extraction techniques. Therefore, the time is traded off for the recognition accuracy which is the goal of this research work.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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