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Offline Gesture Recognition System for Yorùbá Numeral Counting

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Authors' contributions

This work was carried out in collaboration between all authors. Author KOJ designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Authors TMA and AAS managed the analyses of the study. Author OAA managed the literature searches. All authors read and approved the final manuscript.

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ABSTRACT

Aims: The study aimed to determine the specific features responsible for the recognition of gestures, to design a computational model for the process and to implement the model and evaluate its performance.
Place and Duration of Study: Department of Computer Engineering, Federal Polytechnic, Ede, between August 2017 and February 2018.
Methodology: Samples of hand gesture were collected from the deaf school. In total, 40 samples containing 4 gestures for each numeral were collected and processed. The collected samples were pre-processed and rescaled from 340 × 512 pixels to 256 × 256 pixels. The samples were examined for the specific characteristics responsible for the recognition of gestures using edge detection and histogram of the oriented gradient as feature extraction techniques. The model was implemented in MATLAB using Support Vector Machine (SVM) as its classifier. The performance of the system was evaluated using precision, recall and accuracy as metrics.

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Results: It was observed that the system showed a high classification rate for the considered hand gestures. For numerals 1, 3, 5 and 7, 100% accuracy were recorded, numerals 2 and 9 had 90% accuracy, numeral 4 had 85.67% accuracy, numeral 6 had 93.56%, numeral 8 had 88% while numeral 10 recorded 90.72% accuracy. An average recognition rate of 95% on tested data was recorded over a dataset of 40 hand gestures.

Conclusion: The study has successfully classified hand gesture for Yorùbá Sign Language (YSL). Thus, confirming that YSL could be incorporated into the deaf educational system. The developed system will enhance the communication skills between hearing and hearing impaired people.

Keywords: Yorùbá numeral counting; gesture recognition; sign language; edge detection.

1. INTRODUCTION

Human beings abstract facts and reality through only one channel which is language [1] and this affects the way people perceive or think about the reality. Sign language is an avenue through which hearing-impaired people communicate. Sign language uses gesture instead of speech to convey messages and meanings [2]. The design of the gesture recognition system has become an important part of everyday life among the deaf people, and their quality is of primary importance for numerous applications. The movement of the body parts, especially the hand or the head in a view to express an idea or meaning mostly refers to gesture. The gesture can originate from any bodily motion or state but usually from the face and hand. This study developed a gesture recognition system for Yorùbá numerals. This is with the view to make the computer understand hand gesture demonstration and develop a user-friendly system for communication flow between hearing and hearing impaired people. There are multitudes of sign language in the African continent which evolved outside the context of the deaf educational system. These include Yorùbá sign language (YSL), Hausa sign language and other indigenous sign languages. Yorùbá language is one of the languages in Nigeria that faces endangerment due to its fading popularities. It is spoken by the Benue-Congo phylum of African language and also by about 30 million Yorùbá speakers in Nigeria [3]. It is formally used in primary and secondary schools for instruction purpose and as a curriculum subject [1], except in hearing impaired schools where it has no recognition. YSL is known to be an indigenous sign language found in the community of deaf people in the Yorùbá speaking area of Southwestern Nigeria.

The speaking of fluent Yorùbá language requires a large amount of gesture demonstration [4] while communicating; this allows minimal communication between the deaf and the hearing. YSL incorporates many Yorùbá gestural signs and considerable articulation of Yorùbá words [4]. This sign language is yet to be integrated into the deaf education system and therefore depriving the deaf people the opportunity to learn Yorùbá language. This act has restricted the students to a certain language in their educational system. Also, most of the work in sign language has focused on the recognition of American Sign Language (ASL) because of its widespread use, and thus less complexity is required [2]. The need to salvage the loss of the Yorùbá language lies in its awareness among deaf schools where the popularity is at a minimal level. The YSL is more complex as it involves double hands and even foot in some cases. This study developed a gesture recognition system for Yorùbá numeral counting from 1 to 10.

The rest of this paper is arranged as follows. Related work described in Section 2. Sections 3 describe the materials and methods used to develop the work. Result and discussion were discussed in Sections 4. Section 5 concludes the paper.

2. RELATED WORK

Various gesture recognition systems involving hand have been reported to date. A number of techniques used include data gloves, stereo camera, time of flight (TOF) camera and Microsoft's Kinect sensor [5]. Two main methods have been identified in sign language recognition [6] and each aim at recognising gestures. These two approaches are glove-based and vision-based of which the former requires the signer to wear a colour or sensor glove for the segmentation process. The vision-based approach employs image processing techniques for the recognition process. These two approaches are mostly used by many authors who worked in the gesture recognition area. The data glove approach has recorded a better performance than some other systems, and the limitations of its popularity are due to the expensive and uncomfortable nature of its use [7]. The wearer of the data glove is roughly affected due to the installation of highly intense sensors [8], and also one person cannot use the glove of another person [9].

The potential of Kinect depth-mapping was examined by Zafrulla et al. [10] for the recognition of sign language. A total of 1000 ASL were used, and Hidden Markov Model was employed to recognise the gestures. The work of Kausar et al. [11] used the colour glove to identify finger-tips and joints of Pakistani sign language. The work employed fuzzy logic as its classifier, and the calculated angle between the finger-tip are used as the input into the fuzzy inference system for the recognition process. The drawback of this method is the wearing of the colour glove during the process, and the fuzzy logic suffers from the problem of a considerable number of rules required to accommodate all the features of the gestures [6]. In another work of Kalsh and Garewal [12], the author employed vision-based technique and applied edge detection as a feature extraction technique, and the classification of the gestures was achieved using MATLAB if-then rule. The recognition process was limited to only 6 sample images of English alphabets. The vision-based approach reported by Pramada et al. [13] used a colour marker to develop an intelligent sign language recognition for English alphabets.

The method is exposed to an accuracy problem because of difficulty in differentiating the skin and the marker from the background during image processing. More attention has been given to ASL as found in Shivashankara and Srinath [14] with the review of vision-based ASL recognition. Similar work was done by Nair and Bindu [2]. They discussed on various Indian Sign Language (ISL) recognition and the limitation and strength of most of the reviewed work that clearly stated for further improvement. Also, the hand gesture recognition system on a geometric model was developed for the Arabic language [15]. The system extracts geometric features from the hand gesture using only colour as a specific characteristic which limits the efficiency of the work for large datasets. Also in Ravikiran et al. [16], the detection of fingers for sign language recognition accomplished with boundary tracing and fingertip detection was introduced. The work is only limited to the extraction of fingertips using canny edge detection. The real-time gesture recognition [17] is an improvement over static gesture. The author recognised 37 signs of ASL using Artificial Neural Network with feed forward, back propagation algorithm, and accuracy of 94.32% was recorded. Also edge orientation histogram technique was adopted and 88.26% accuracy was obtained [18].

The problem of enormous search space in large vocabulary sign language was investigated by Gaolin and Wen, [19]. The work employed fuzzy decision tree with many classifiers, and the sign gesture responded differently to the various classifier which made the system to be computationally complex, although the classifiers were combined to generate classifier fusion model which reduces the complexity of the algorithm [20]. The use of fuzzy inference system and elliptical Fourier descriptor with principal component analysis for the recognition was demonstrated by Kishore and Kumar [21]. Apart from the large rule generated by the fuzzy system, the work considered only one feature for the ASL recognition process which reduces the accuracy rate of some recognised gestures. The Support Vector Machine has been used as a classifier in Nagashree et al. [22] with the histogram of the oriented gradient as feature extraction technique for the recognition of the 20 ASL hand gesture. The evaluation process of the work lacked accuracy as a limited number of gestures were collected and the performance evaluation process lacked standard evaluation metrics. In another work, the direction of sound was determined to aid hearing skill of the hearing impaired people [23]. Hardware system with four microphone inlets was developed and interfaced with the computer for the transfer of voice to the digital environment using vibration method to alert the user. The work provideed a robust means for hearing impaired people to sense the direction of the sound, but the work was only limited to sound recognition.

The reviewed works have used gestures of various languages, and it was shown that less attention had been given to YSL. The study developed a gesture recognition system for Yorùbá numerals with the view to enhance communication skills between hearing- impaired people in Yorùbá communities.

3. MATERIALS AND METHODS

The materials and methods used in formulating the recognition models are presented in this section.

3.1 Recognition Model

The recognition process was divided into stages which involved the feature extraction and classification stages. The feature extraction stage includes the pre-processing operation where the features were extracted using the histogram of the oriented gradient and edge detection techniques. The classification stages were achieved using Support Vector Machine (SVM) classifier. Classification problem involves associating an object with existing classes of objects. Classes may be defined as a set of objects, or by a set of rules, which define how objects are classified into given classes. In this study, the classifications of numerals are considered according to their respective gesture. Fig. 1 depicts a flowchart representing an automated gesture recognition model. Captured gesture images are the inputs to this model. The models first converted the image to grayscale and the images were pre-processed using various image processing techniques, then the edge was detected using canny edge detection algorithm for segmentation process and the feature vectors were extracted using Histogram of Oriented Gradient (HOG), the output of the extracted feature was trained using SVM classifier and the corresponding gesture type was recognised.

3.2 Image Processing

For training and recognition purpose, different samples of hand gesture were collected with a clear background. In total, 40 samples containing four (4) different images for each gesture were collected from the deaf school in Osogbo, Osun state. The samples were captured using a 14.1 Megapixels digital camera and after data capture, the samples were pre-processed using wavelet transform analysis in MATLAB. The data were rescaled and normalised to reduce redundancy with wavelet denoiser through wavelet soft thresholding. The pre-processing operation reduced noise and redundant data for the purpose of acquiring an optimum quality image that enhanced the recognition performance. In reducing the noise, the multi-scale decomposition of the image was done using wavelet transform and the noise variance σ^2 was estimated. For each level, scale parameter β was computed with Equation 1. The standard deviation and the threshold were computed using Equation 2. Soft thresholding was applied to the noisy coefficients and the multiscale decomposition was inverted to reconstruct the denoised image. The contrast and brightness of images were changed to enhance the appearance of the image. The colour of the images was modelled and processed in a digital domain. The images were then compressed using coefficient thresholding method to reduce the storage required saving the image. The collected samples were saved in Tagged Image File Format (TIFF) with an image size of 340 ×512. The captured images were converted from RGB (Red, Green and Blue) colour components to a grayscale image in order to extract the discriminatory information about the image and then thresholding using Otsu's method in MATLAB using image processing toolbox. Fig. 2 depicts the sample data of hand gestures collected for the recognition process.

$$\beta = \sqrt{\log\left(\frac{L_n}{J}\right)} \tag{1}$$

Where:

β is the scale parameter.
L_n Length of the subband at n^{th} scale.
n is the scale varying from 1, 2…..J and J is the total number of decomposition.

$$Th = \frac{\beta\sigma^2}{\sigma_y} \tag{2}$$

Th = Threshold;
σ^2 = noise variance and;
σ_y = Standard deviation of subband.

3.3 Feature Extraction Stage

Feature extraction is an essential step of sign language recognition. This is because the classifier accepts feature vectors obtained from the feature extraction process as an input. The techniques used for feature extraction extract the distinguishing characteristics about the gesture images. Feature extraction method used in this study serves two purposes, (1) to extract properties that can identify the number uniquely (segmentation process) and; (2) to extract features that differentiate between each gesture captured. It is an essential stage in sign recognition as its function improves the recognition rate and reduces the misclassification. Canny edge detection was used to obtain edges of the gesture images and histogram of the oriented gradient was employed to obtain the feature vector that was used to train the classifier. Three features were extracted, and they are broken into the following attributes:

i. Hand shape;
ii. Orientation and;
iii. Position

3.3.1 Canny edge detection

Canny edge detection is a Gaussian-based technique that searches for the zero crossing in the second derivatives of an image. Canny edge detection method was employed for the segmentation process. This is with the view of extracting features that uniquely identify the gesture images. Canny edge detection has a robust thresholding method when applied to the magnitude image array [24]. The algorithm used involved the following steps, (1) a Gaussian filter was applied to smooth the images to obtain a better-segmented edge. (2) The gradient of magnitude and orientation was computed using a finite-difference approximation for the derivatives and; (3) Non-maxima suppression was applied to the gradient magnitude. The image smoothening was computed as input $I_{i,j}$ image and the Gaussian filter was applied which are denoted as G [i, j, σ] where σ is the distribution of the Gaussian, and it also controls the degree of smoothing. The result obtained from the convolution of $I_{i,j}$ with G [i, j, σ] gives a set of smoothed data as shown in Equation 3.

$$S_{i,j} = G[i,j,\sigma] * I_{i,j} \tag{3}$$

The gradient was calibrated using the smoothed array $S_{i,j}$ which was then used to generate X and Y partial derivatives $X_{i,j}$ and $Y_{i,j}$ respectively as shown in Equation 4 and 5.

$$X_{i,j} = (S_{i,j+1} - S_{i,j} + S_{i+1,j+1} - S_{i+1,j})/_2 \tag{4}$$

$$Y_{i,j} = (S_{i,j} - S_{i+1,,j} + S_{i,j+1} - S_{i+1,j+1})/_2 \tag{5}$$

The X and Y partial derivatives were derived by averaging the finite difference over 2×2 matrix. The magnitude and orientation of the gradient were computed using Equation 6 and 7 respectively.

$$M_{i,j} = \sqrt{(X_{i,j})^2 + (Y_{i,j})^2} \tag{6}$$

$$\theta_{i,j} = \tan^{-1}(\frac{Y_{i,j}}{X_{i,j}}) \tag{7}$$

The pixel values were chosen based on the angle of the magnitude of the pixel and its surrounding neighbourhood. The Non-maxima suppression was evaluated using the magnitude of the image array. The situation with this approach is that the low threshold generates false edges, but a high threshold misses important edges. The threshold value was moderately selected to obtain a better edge orientation for the recognition process. This is because canny edge detection has a problem with the fixed value for thresholding.

3.3.2 Histogram of gradient

The histogram of oriented gradients descriptor was used for this study because of its high-performance record in human detection. The local gesture appearance and shape of the image were described by the local intensity changes obtained from the canny edge detection algorithm, and the image was divided into small connected regions called cells. The pixels around each cell were used and, the histogram of gradient directions was compiled as a feature vector which was later used for the training of the datasets. Fig. 3 shows the sample of the image obtained after the feature extraction process for numeral one.

3.4 Classification Stage

Image classification refers to the process of assigning pixels to an ordered set of related categories in which data are categorised according to its similarities. Image classification step categorises recognised objects into predefined classes using the suitable algorithm that compares the image patterns with the target patterns. SVM was employed as a classifier, and it is one of the best machine learning algorithms for image classification. The supervised learning algorithm serves to analyse the trained data and gives an inference called classifier. The output extracted from the feature extraction steps was used for the classification process, which classified the hand gestures to their corresponding numerals. For the classification process, 60% of the data were used to train the model, and 40% were used to test the model. Fig. 4 shows the implementation stage depicting the training and testing of the hand gestures recognition. Fig. 4(a) and Fig. 4(b) show the training and testing stages respectively. For the training stage, the extracted images were fed into the support vector machine and the training variables were saved. For the testing stage, the input image from the testing sets was pre-processed and compared with the saved training variables then output the result.

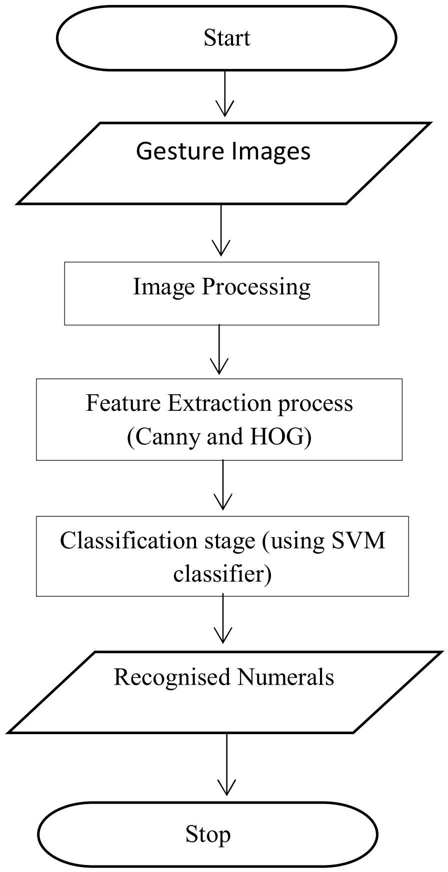


Fig. 1. Hand gesture recognition model

Fig. 2. Samples of hand gesture

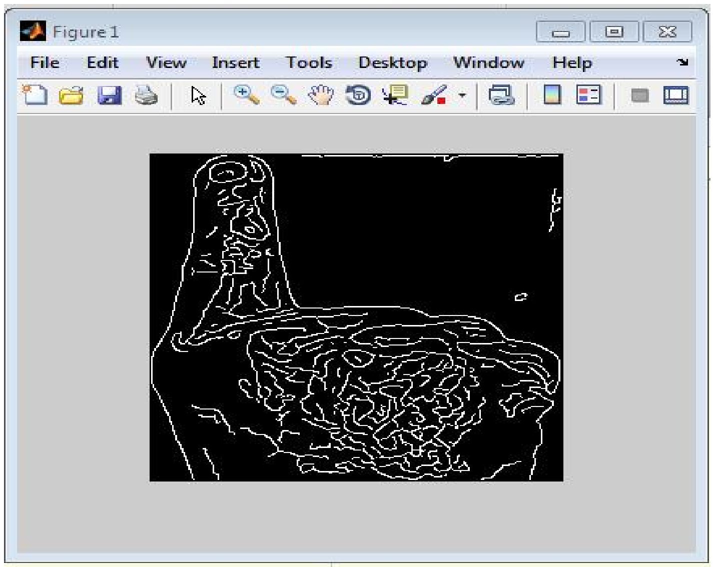


Fig. 3. Feature vector for hand gesture 1

4. RESULTS AND DISCUSSION

The hand gesture classification model was simulated in MATLAB R2015a environment. The sample of hand gesture data was rescaled from 340 ×512 to 256 ×256 pixels and processed on an Intel 1.90 GHz and 4GB RAM machine using the model developed in this study. A total of 40 samples containing 4 gestures for each numeral were collected and processed in MATLAB R2015a environment. MATLAB was adopted for programming because of its user-friendliness and scalability it provides. Fig. 5 shows the classification result for numeral 1and 2 respectively. Fig. 5 is the system design interface which displays the gesture recognition of Yorùbá numeral. The effectiveness of the algorithm used in this study is measured by inputting sample hand gesture images into the model, and its performance was recorded. The performance metrics used are recall rate, precision rate and accuracy which are defined in Equations 8, 9 and 10 respectively. Using the metrics defined in these equations, the classification efficiency of the model was recorded. Table 1 depicts the confusion matrix table for the overall recognition process. The accuracy of the model was recorded for each gesture classified and the overall recognition rate was obtained using the confusion matrix table. Table 2 shows the classification rate for the YSL for numeral 1 to 10. For numerals 1, 3, 5 and 7, 100% accuracy were obtained, numeral 2 and 9 had 90% accuracy, numeral 4 had 85.67% accuracy, numeral 6 had 93.56%, numeral 8 had 88% and numeral 10 had 90.72%. An average recognition rate of 95% was obtained over tested data.

$$Recall = \frac{T_P}{T_P + F_N} \tag{8}$$

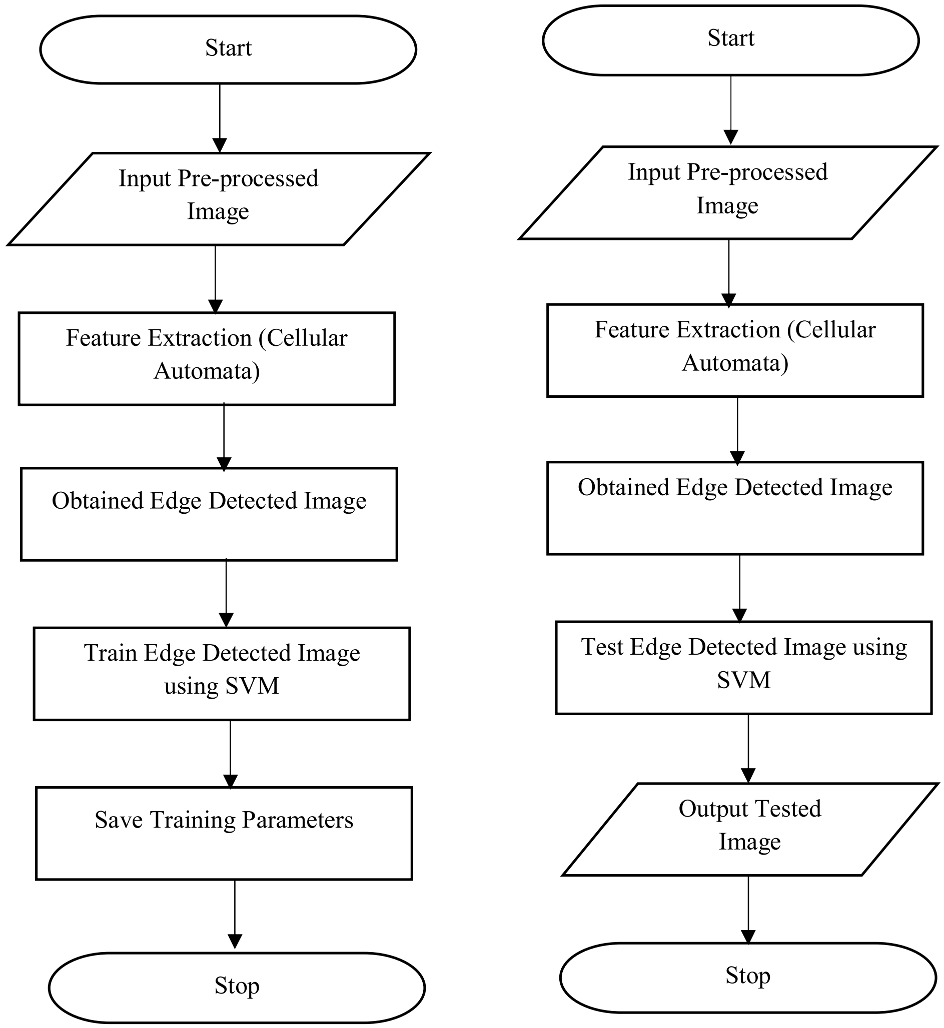
$$Precision = \frac{T_P}{T_P + F_P} \tag{9}$$

$$Accuracy = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \tag{10}$$

where *TP*, *FP*, *TN*, *FN* are equivalent to true positive, false positive, true negative, and false negative respectively.

Table 1. Confusion matrix for the overall recognition process

N = 40		Actual class		
Predicted Class	**Hand Gesture**	**Hand gesture**		
		24(T_P)	0 (F_P)	24
		2 (F_N)	14T($_N$)	16
		26	14	



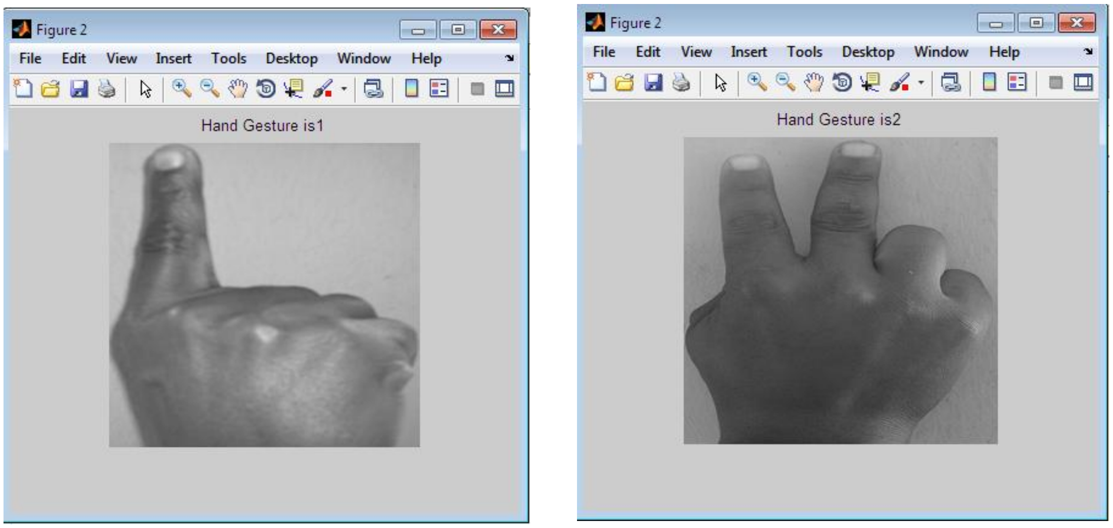
(a) Training Stage for Embroidery Recognition

(b) Testing Stage for Embroidery Recognition

Fig. 4. Implementation stage

Table 2. Classification rate for Yorùbá hand gesture

Sn	Yorùbá numeral	English meaning	Accuracy	Precision	Recall
1.	Ookan	One	100%	0.98	0.27
2.	Eeji	Two	90%	0.72	0.23
3.	Eeta	Three	100%	0.97	0.25
4.	Eerin	Four	85.67%	0.75	0.27
5.	Arun	Five	100%	0.91	0.24
6.	Eefa	Six	93.56%	0.93	0.26
7.	Eeje	Seven	100%	0.89	0.23
8.	Eejo	Eight	88%	0.75	0.26
9.	Eesan	Nine	90%	0.81	0.20
10.	Eewa	Ten	90.72%	0.90	0.26



(a) Classified Hand gesture for numeral 1 **(b) Classified Hand gesture for numeral 2**

Fig. 5. Classified hand gestures

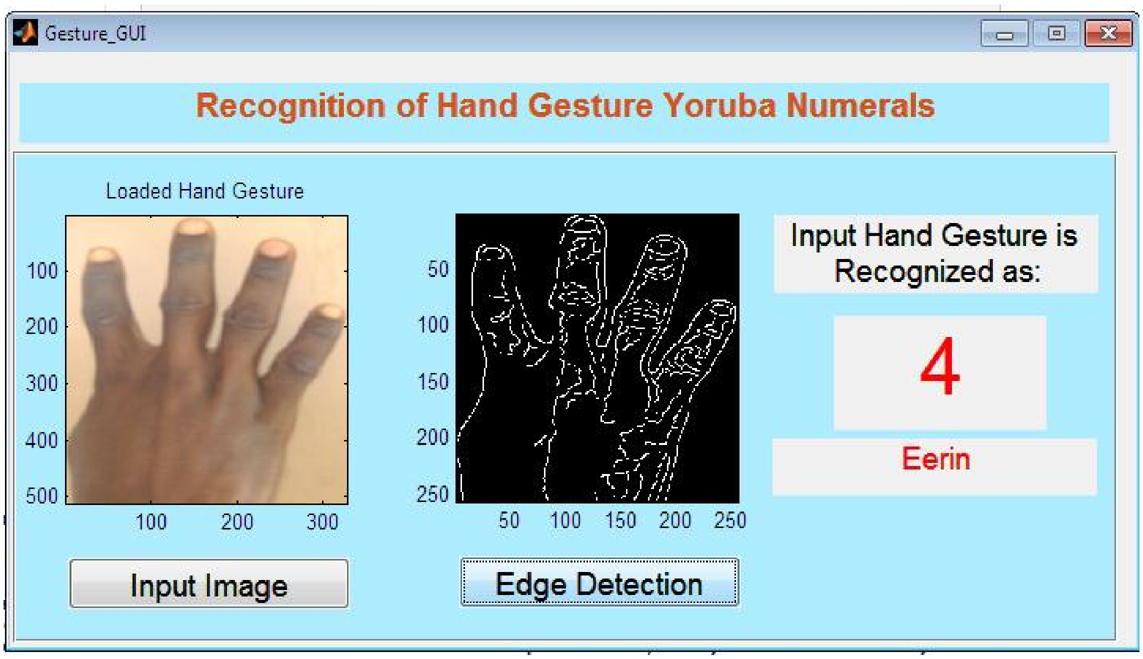


Fig. 6. System design Interface showing gesture recognition process

5. CONCLUSION

In this study, hand gesture recognition for Yorùbá numeral was developed. The study employed canny edge detector and histogram of oriented gradient as feature extraction method using support vector machine as its classifier. The developed system attempted to enhance the communication gap between hearing and hearing-impaired people in Yorùbá communities. The result produced from the evaluation of the performance of the system showed a robust output which indicated that the work can be incorporated into the deaf educational system. An overall recognition rate of 95% on tested data was recorded over a dataset of 40 gestures. The attributes extracted during feature extraction process enable the features to be unique for each gesture and this account for the variation in the accuracy of each Yorùbá numeral. For instance, numerals 1, 3, 5, and 7 which have 100% accuracy indicated that the numbers of vector processed for the gestures best describe the numerals. The method used in this study will be evaluated on a large dataset and comparison with other methods such as linear discriminant analysis, artificial neural network and principal component analysis for efficient performance will be done. Also, development of a real-time system will be considered for future work.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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