



iJRASET

International Journal For Research in
Applied Science and Engineering Technology



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 6 Issue: III Month of publication: March 2018

DOI: <http://doi.org/10.22214/ijraset.2018.3207>

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Enhance Real Time Hand Gesture Recognition using FCM Clustering and Neural Network Approach

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Abstract: *Gesture Recognition is one of the most popular and viable solution for improving Human Computer Interaction and it has become very popular in the recent years due to its use in gaming devices like Xbox, PS4 and other devices like laptops, smartphones etc. Gesture Recognition and more specifically hand gesture recognition has usage in various application like medicine, accessibility support etc.*

Hand gesture recognition system can be used for interfacing between computer and human using hand gesture. This work defines a method for a human computer interface through hand gesture recognition that is able to recognize 25 static gestures from the American Sign Language hand alphabet.

In this research work, proposed there arises a great demand of overcoming the existing problems to achieve greater accuracy, faster response time and the difficulties faced in handling the training data inputs and testing outputs. Hence, gives the need to use such algorithms each of which is unique in its own effective and creative way and try to bring out the best possible results. Our proposed work focuses on segment the gesture using FCM algorithm, extracting the features using (SIFT) Scale Invariant Feature Transform algorithm and classifying the gestures using deep neural network. By doing this our system obtains better performance in terms of classification parameters (Accuracy, FAR, FRR and Recognize Speed) and faster response time or delayed outputs.

Keywords: *Hand Gesture Recognition, Applications, Neural Network Methods and Key points with SIFT feature extraction algorithm.*

I. INTRODUCTION

The main focus of constructing hand gesture recognition system is to generate a normal inter-action between human and computer where the recognized gestures can be used for controlling a robot or conveying meaningful information [1]. How to form the resulted hand gestures to be understood and well interpreted by the computer considered as the problem of gesture interaction. Every new device can be seen as an attempt to make the computer more intelligent and making humans able to perform more complicated communication with the computer.

This has been possible due to the result oriented efforts made by computer professionals for creating successful human computer interfaces [2]. The computer operator has been incredibly successful in easing the communiqué between computers and human. With the emergence of every new product in the market; it attempts to ease the complexity of jobs performed. For illustration, it has helped in enabling tele operating, mechanical use, better human control over complex work systems like cars, planes and monitoring systems. Earlier, Computer programmers were avoiding such kind of complex programs as the focus was more on speed than other modifiable features.

However, a change towards a user approachable environment has determined them to revisit the focus area. It is hard to settle on a specific useful definition of gestures due to its wide variety of applications and a statement can only specify a particular domain of gestures. Many researchers had tried to define gestures but their actual meaning is still arbitrary [3].

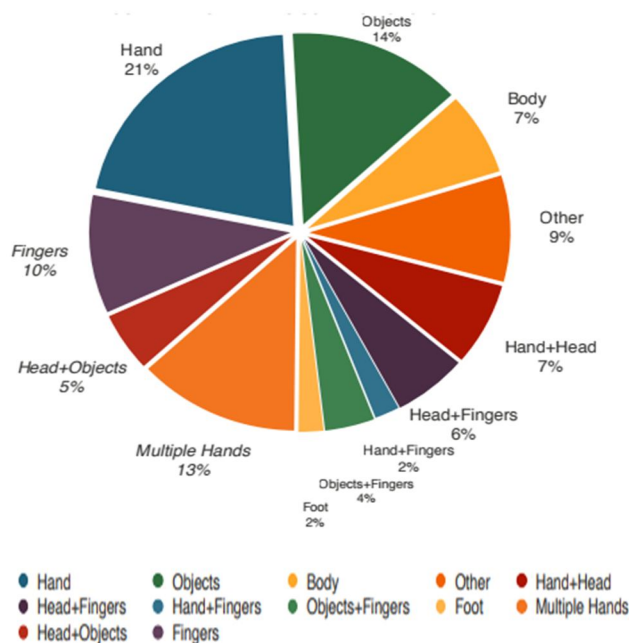


Figure 1. Body parts used for gesturing

Gesture recognition is important in the field of HCI and HCI plays an important role in applications like Gaming, User Interaction with software systems and accessibility support. We can use various body parts like hand, fingers, head and other objects to perform gestures, but this project focuses on hand gestures because as shown in figure 1 hands are used for performing 21% of gestures and along with other body parts they are used in a majority of the gesture performed [4].

Hand Gestures as the motion of the body that is intended to communicate with other agents. For a successful communication, a sender and a receiver must have the same set of information for a particular gesture. Gesture is defined as an expressive movement of body parts which has a particular message, to be communicated precisely between a sender and a receiver. A gesture is scientifically categorized into two distinctive categories: dynamic and static. A dynamic gesture is proposed to change over a epoch of time whereas a static gesture is experimental at the spurt of time. A waving hand means goodbye is an example of dynamic gesture and the stop sign is an example of static gesture. To appreciate a full message, it is needed to interpret all the static and active gestures over a period of time. This complex process is called gesture recognition. Gesture recognition is the process of recognizing and interpreting a stream continuous sequential gesture from the given set of input data [5].

II. REVIEW OF LITERATURE

Rishabh Agrawal et al., 2016 [6] presented that the most of the human computer interaction interfaces that are designed today require explicit instructions from the user in the form of keyboard taps or mouse clicks. As the complexity of these devices increase, the sheer amount of such instructions can easily disrupt, distract and overwhelm users. A novel method to recognize hand gestures for human computer interaction, using computer vision and image processing techniques, is proposed in this paper. The proposed method can successfully replace such devices (e.g. keyboard or mouse) needed for interacting with a personal computer. The method uses a commercial depth + rob camera called Senz3D, which is cheap and easy to buy as compared to other depth cameras. The proposed method works by analysing 3D data in real time and uses a set of classification rules to classify the number of convexity defects into gesture classes. This results in real time performance and negates the requirement of any training data. The proposed method achieves commendable performance with very low processor utilization.

Clementine Nyirarugira et al., 2016[7] Gesture recognition method derived from particle swarm movement for free-air hand gesture recognition. The Online gesture recognition is a difficult problem due to uncertainty in vision-based gesture boundary detection methods. They suggest automated process of segmenting meaningful gesture trajectories based on particle swarm movement. They proposed that the recognizer requires fewer computation resources; thus it is a good candidate for real-time applications.

Shruti Wale et al., 2016[8] Gesture recognition is finding a meaning attached to some motions. The main objective of hand gesture recognition from the real time video related to Gesture recognition techniques includes recognition of posture and human

behaviours. The problem faced in the gesture recognition is that a person will appear at different scales in videos. Movement of camera is another problem as the person holding it may shake it while shooting the video. Certain cases the camera may be mounted on something which moves with the person performing the action. The occlusions, background clutter, human variation and action variation are several issues faced. Gesture recognition also varies with person to person because every person has different skin texture and colour. The nonparametric histogram based on RGB model is used for the skin detection. In this system the gesture recognition is mainly divided into two phases: training phase and recognition phase. Feature extraction is the main function of both the phases. The fuzzy logic is used in this system for gesture recognition.

Lingchen Chen et al., 2013[9] discussed that the hand gesture recognition has become one of the key techniques of human-computer interaction (HCI). Many researchers are devoted in this field. In this paper, firstly the history of hand gesture recognition is discussed and the technical difficulties are also enumerated. Then, we analyse the definition of hand gesture and introduce the basic principle of it. The approaches for hand gesture recognition, such as vision-based, glove-based and depth-based, are contrasted briefly. But the former two methods are too simple and not natural enough. Currently, the new finger identification and hand gesture recognition technique with Kinect depth data is the most popular research direction. Finally, we discuss the application prospective of hand gesture recognition based on Kinect.

Luis A et al., 2017[10] proposed that intelligent system for translating sign language into text. An approach consists of hardware and software. The hardware is made by flex, contact, and inertial sensors mounted on a polyester-nylon glove. The software consists of a classification algorithm based on the k-nearest neighbours, decision trees, and the dynamic time warping algorithms. Proposed that the system is able to recognize static and dynamic actions. This system can classify the specific actions or patterns of an individual. The translating 61 letters, numbers, and words from the Ecuadorian sign language were used to test the proposed system. Experimental results demonstrate that our system has a classification accuracy of 91.55%. This result is a significant improvement compared with the results obtained in previous related works.

III. APPLICATION IN GESTURE RECOGNITION

The applications are broadly classified into two classes on the basis of their determination: multi-directional control and a symbolic language.

A. 3D Design

CAD (computer aided design) is an HCI which provides a platform for interpretation and manipulation of 3-Dimensional inputs which can be the gestures. Manipulating 3D inputs with a mouse is a time consuming task as the task involves a complicated process of decomposing a six degree freedom task into at least three sequential two degree tasks.

B. Tele Presence

Tele presence is that area of technical intelligence which aims to provide physical operation support that maps the operator's arm to the robotic arm to carry out the necessary task, for instance the real time ROBOGEST system [11] constructed at University of California, San Diego presents a natural way of controlling an outdoor autonomous vehicle by use of a language of hand gestures.

C. Virtual Reality

Virtual reality is applied to computer-simulated environments that can simulate physical presence in places in the real world, as well as in imaginary worlds. Most present virtual reality atmospheres are principally visual experiences, displayed either on a computer screen or through special stereoscopic display.

D. Sign Language

Sign languages are the most raw and natural form of languages could be dated back to as early as the advent of the human civilization, when the first theories of sign languages appeared in history. It has started even before the emergence of spoken languages. Since then the sign language has evolved and been adopted as an integral part of our day to day communication process. Now, sign languages are being used lengthily in universal sign use of deaf and dumb, in the world of sports, for religious practices and also at work places.



Figure 2. American Sign Language

A simple gesture with one hand has the same meaning all over the world and means either 'hi' or 'goodbye'. Many people travel to foreign countries without knowing the official language of the visited country and still manage to perform communication using gestures and sign language. These examples show that gestures can be considered international and used almost all over the world. In a number of jobs around the world gestures are means of communication.

Hand gesture recognition of representative words and decisions as they prepare in American and sign language [8] undoubtedly represents the most difficult recognition problem of those applications mentioned before. A functioning sign language recognition system could provide an opportunity for the deaf to communicate with non-signing people without the need for an interpreter. It could be used to generate speech or text making the deaf more independent. Unfortunately there has not been any system with these capabilities so far.

IV. FUZZY C-MEANS CLUSTERING

The fuzzy c-means (FCM) algorithm is a clustering algorithm developed by Dunn, and later on improved by Bezdek. It is useful when the required number of clusters is pre-determined; thus, the algorithm tries to put each of the data points to one of the clusters. What makes FCM different is that it does not decide the absolute membership of a data point to a given cluster; instead, it calculates the likelihood (the degree of membership) that a data point will belong to that cluster. Hence, depending on the accuracy of the clustering that is required in practice, appropriate tolerance measures can be put in place. Since the absolute membership is not calculated, FCM can be extremely fast because the number of iterations required to achieve a specific clustering exercise corresponds to the required accuracy.

A. Iterations

In each iteration of the FCM algorithm, the following objective function J is minimized:

$$J = \sum_{i=1}^n \sum_{j=1}^c \delta_{ij} \|x_i - c_j\|^2 \dots\dots\dots (i)$$

Here, N is the number of data points, C is the number of clusters required, c_j is the centre vector for cluster j , and δ_{ij} is the degree of membership for the i th data point x_i in cluster j . The norm, $\|x_i - c_j\|$ measures the similarity.

B. Degree of Membership

For a given data point x_i , the degree of its membership to cluster j is calculated as follows:

$$\delta_{ij} = \frac{1}{\sum_{k=1}^c \left(\frac{\|x_i - j\|}{\|x_i - ck\|} \right)^{2/m-1}} \dots\dots\dots (ii)$$

where, m is the fuzziness coefficient and the centre vector c_j is calculated as follows:

$$c_j = \frac{\sum_{i=1}^n \delta_{mij} .x_i}{\sum_{i=1}^n \delta_{mij}} \dots\dots\dots (iii)$$

In equation (3) above, δ_{ij} is the value of the degree of membership calculated in the previous iteration. Note that at the start of the algorithm, the degree of membership for data point i to cluster j is initialised with a random value θ_{ij} , $0 \leq \theta_{ij} \leq 1$, such that $\sum_j \delta_{ij} = 1$.

C. Fuzziness coefficient

In equations (2) and (3) the fuzziness coefficient m , where $1 < m < \infty$, measures the tolerance of the required clustering. This value determines how much the clusters can overlap with one another. The higher the value of m , the larger the overlap between clusters.

In other words, the higher the fuzziness coefficient the algorithm uses, a larger number of data points will fall inside a ‘fuzzy’ band where the degree of membership is neither 0 nor 1, but somewhere in between [12].

D. Termination Condition.

The required accuracy of the degree of membership determines the number of iterations completed by the FCM algorithm. This measure of accuracy is calculated using the degree of membership from one iteration to the next, taking the largest of these values across all data points considering all of the clusters. If we represent the measure of accuracy between iteration k and k + 1 with δ , we calculate its value as follows:[15]

$$c = \Delta \delta_{k+1} \delta_k \dots \dots \dots (iv)$$

where, δ_{k+1} and δ_k are respectively the degree of membership at iteration k and k + 1, and the operator Δ , when supplied a vector of values, returns the largest value in that vector [13,14].

V. METHODOLOGY

The system comprises of the training and the testing part where -in we have a numeric dataset of six different categories of hand images. The following steps present the different stages that need to be accomplished in order to match the hand gestures accurately.

A. Training Part

- Step-1 Start acquisition of hand gesture image required for the recognition process.
- Step-2 Upload a hand gesture image from the categories of hand images from the training data set images.
- Step-3 The uploaded image is segmented, made noise free, converted to grayscale and represented in the form of a histogram.

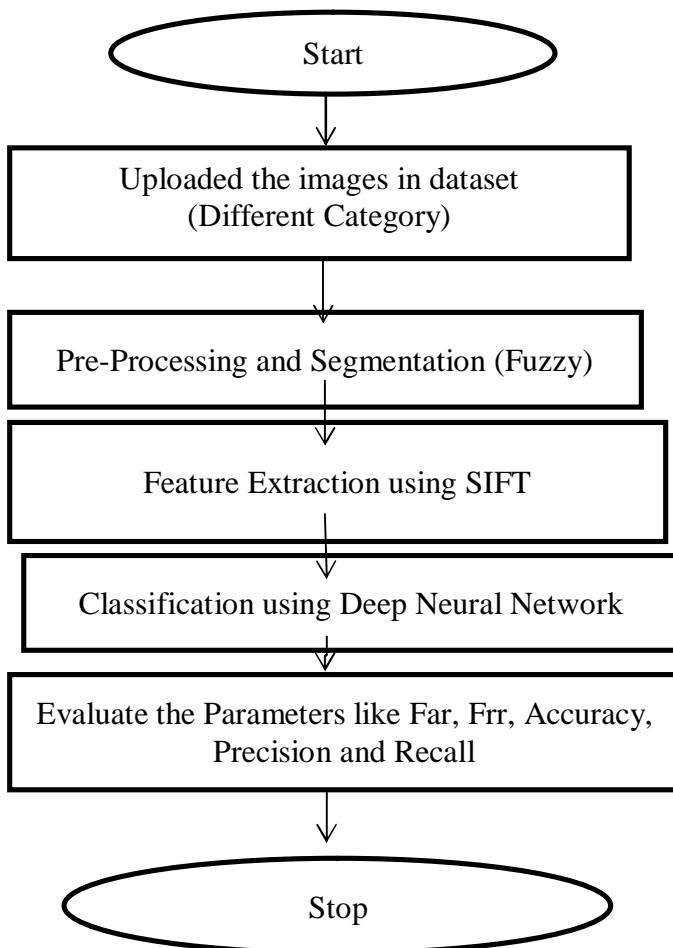


Figure 3. Proposed work flowchart

Step-4 the segmented image is used to generate key points or key features which are unique. This is achieved by extraction methods of Scale invariance feature transform algorithm.

Step5- The extracted features are classified to get the best results using deep neural network, making the system secure, the fit values are generated using its two sections which select the training and testing section.

Step-6 The results are saved to database. The whole process runs for all training data categories.

B. Testing Part

Step-7 Upload test data images from the testing data set categories of images.

Step-8 Repeat from step 3-6 for testing hand gesture images.

Step-9 Finally, implementation is carried out using deep neural network performing various validation checks and iterations to evaluate performance of training data and testing data modules followed by matching and non-matching checking of gesture image.

Step-10 Results are calculated based on performance parameters showing the mean square error, accuracy, false acceptance rate, false rejection rate and precision respectively. The values can be obtained from respective graphs of above parameters.

VI. PERFORMANCE EVALUATION

In this research work, various parameters have been used based on which our results are calculated such as, Mean Square Error, Accuracy, False Acceptance Rate(FAR), False Rejection Rate(FRR) and Recognize Time.

A. Mean Square Error (MSE)

Mean Square Error is defined as the sum of the averages of the squares of errors to the total number of errors. It is always non-negative and values closer to zero are better.

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [(I(i, j) - k(i, j))]^2$$

B. Accuracy

Accuracy is how close a measured value is to the actual (true) value. The accuracy factor defines the working performance of any algorithm. The high accuracy rate shows better performance of an algorithm. The proposed system has achieved an accuracy rate of 99% which earlier was 95%, thereby improving system performance.

C. False Acceptance Rate (FAR)

A system's FAR typically is stated as the ratio of the number of false acceptances divided by the number of identification attempts. It simply measures the likelihood of a biometric system to incorrectly accept an access from an unauthenticated user.

$$FAR = \frac{\text{Number of False acceptances}}{\text{Number of Identification attempts}}$$

D. False Rejection Rate (FRR)

A system's FRR typically is stated as the ratio of the number of false rejections divided by the number of identification attempts. It is the probability, that the system incorrectly rejects the access to an authenticated person.

$$FRR = \frac{\text{Number of false rejections}}{\text{Number of Identification attempts}}$$

E. Recognize Time






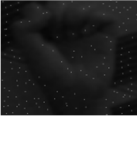





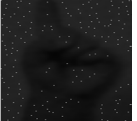





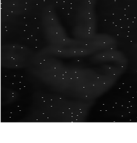





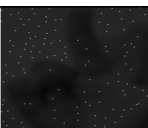





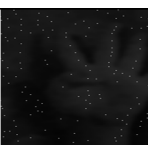
To identify from training, knowledge of appearance or features time.

VII. RESULTS AND DISCUSSION

Hand gesture recognition should be accurate and precise for better classification of hand gestures thereby improving performance of the system. In the proposed work, Scale invariant feature transform, Genetic algorithm and Back propagation neural network are used. Experimentally, it has been found that better results are yielded in terms of improved accuracy, mean square error, false acceptance rate followed by false rejection rate and recognize a time. The system has achieved 98.5% accuracy, using deep neural network. In the traditional method, RBF Neural Network had been used as a gesture classifier with support vector machine in voting for obtaining vector for classification which later lead to complexity for huge data space. The accuracy obtained in earlier approach was 94.7% showing our system is more accurate.

In proposed work, there are five different categories of images. The procedure goes as follows; the input image is uploaded from one of the categories of data set. The image undergoes segmentation for noise free clear image and transformed into gray scale and noise check in the image, filter the image and edge form after which the image appears in the form of histogram. The key features are extracted from this segmented image followed by reduction of extracting features. This makes the system secure and the process is followed by a classification of gestures in the end using Deep Neural Network.

Table 1 Results of proposed algorithm for hand gesture categories.

Cat no.	Original Name	Gray Scale	Edge Detection	Noisy Image	Segmented Image	Feature Extraction
Category 1						
Category 2						
Category 3						
Category 4						
Category 5						

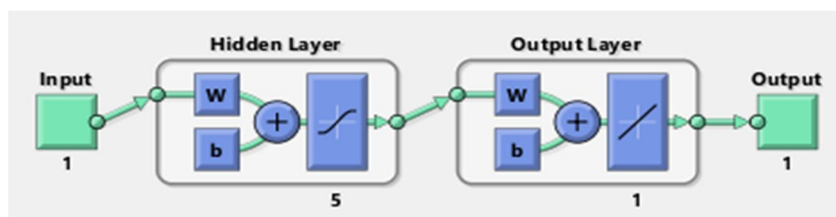


Figure 4: Neural Network

Above figure describe the performance of the recognition system, training module generate, classification. DNN uses the inbuilt function like levenbergmarquardt and find the average of the error. We have given the training of 1000 iteration but it complete in 10 iterations and it takes 0.0 seconds to complete and it shows the performance, Gradient, Mu, and validation checks. It plots the performance, training state and regression of the system.

In the following table below, the results of the above images are shown. In this, the following parameters FRR, FAR, ACCURACY and Recognize Speed are used. The output for each image is evaluated in tabular form with quantitative values of parameters for standard hand gesture images.

Table 2. illustrates the result of proposed algorithm and previous (BOW_SURF and Segmentation) for Various categories in Accuracy (previous and Proposed Work)

Gestures Category	Cat 1	Cat 2	Cat 3	Cat 4	Cat 5
Deep neural Network	98.7%	98%	99%	97.2%	98.6%
BOW-SURF	100%	96%	100%	80%	90%
BOW-SURF with threshold segmentation method	100%	97%	100%	95%	100%

Table 3. Different Features performance in self-built Database

Gesture Features		Accuracy (%)
Geometric Structure Features	FBA+FBA+FBA+FBA+FD	72.5%
Descriptors	BOW –SURF	88.5%
	SURF	78.75%
	BOW-SURF with Thresold Segmentation	97.9%
Texture Feature	LBP	12.5%
Image and Texture Feature	Key-points	98.7%

The above table 3. Defined that the gesture feature based on the accuracy, performance parameters (Geature features like Geometric Structure Fetaures, Descriptors, Texture Feature and Image and Texture Features) different in self built dataset.

Table 4. Different Classifier’s performance in BOW-SURF with threshold Segmenation and SIFTalgorithm

Classifiers	Accuracy	Recognize Speed
Voting SVM	97.5%	0.72
BP Neural Network	94.5%	0.2205
Deep Neural Network	98.7%	0.212

In this table 4.different classifier’s performance parameters in BOW-SURF with threshold segmentation and SIFT feature extraction with Deep Neural Network. The various classifiers like voting SVM, BP Neural Network and DNN (Deep Neural Network) with Accuracy and Recognize Speed.

Figure 5 illustrates the results of proposed algorithm and existing for Various categories in Accuracy (Base and Proposed Work)

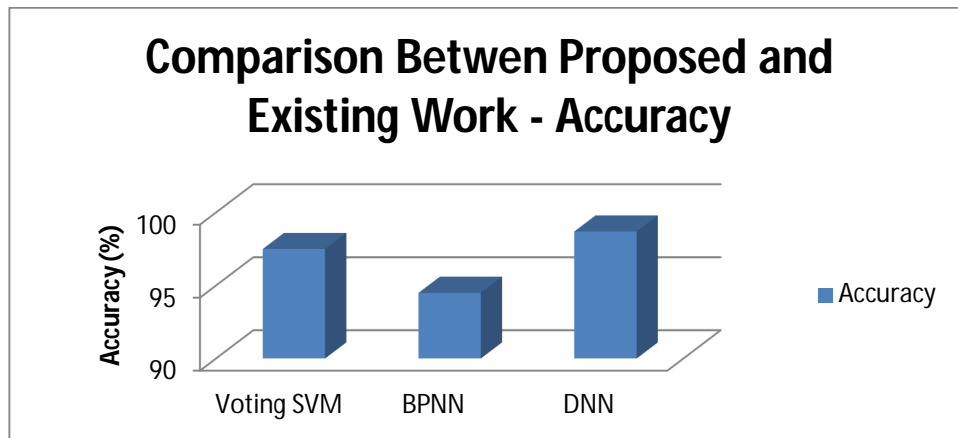


Figure 5. Accuracy Comparison (Existing and Proposed Work)

Figure 6 illustration results of proposed algorithm and existing for Various category in Recognize Speed (Base and Proposed Work)

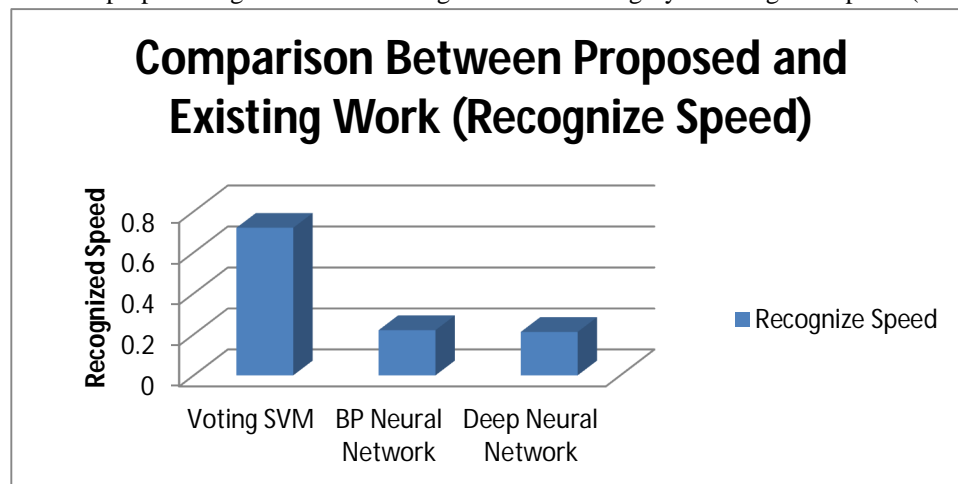


Figure 6. Recognize Speed comparison of (existing and proposed)

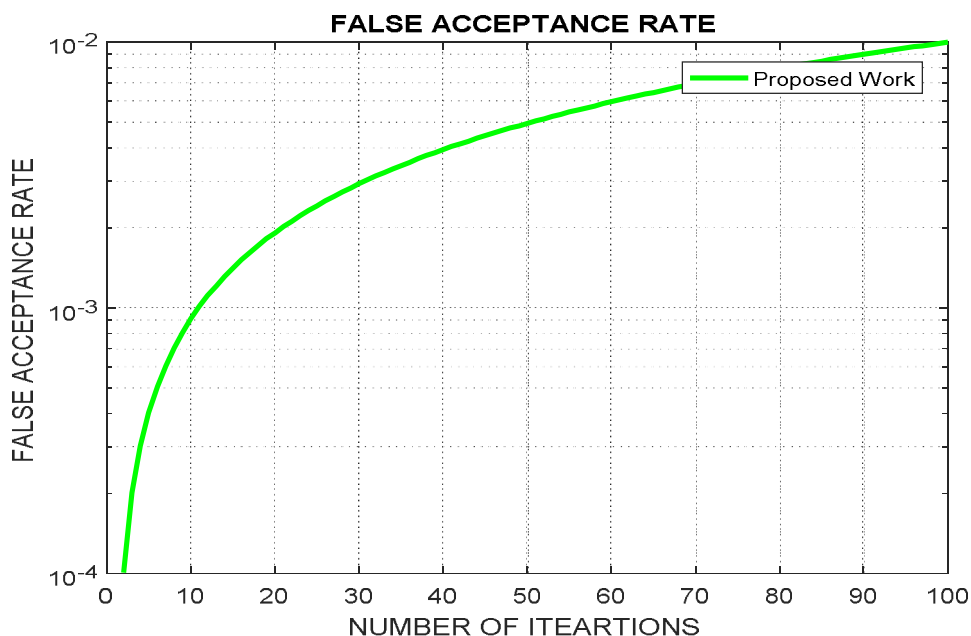


Figure 7. False Acceptance Rate in proposed work

The above figure defined that the false acceptance rate means false data acceptable in the original form. We check the wrong acceptance in the amount number of iterations in the hand gesture recognition.

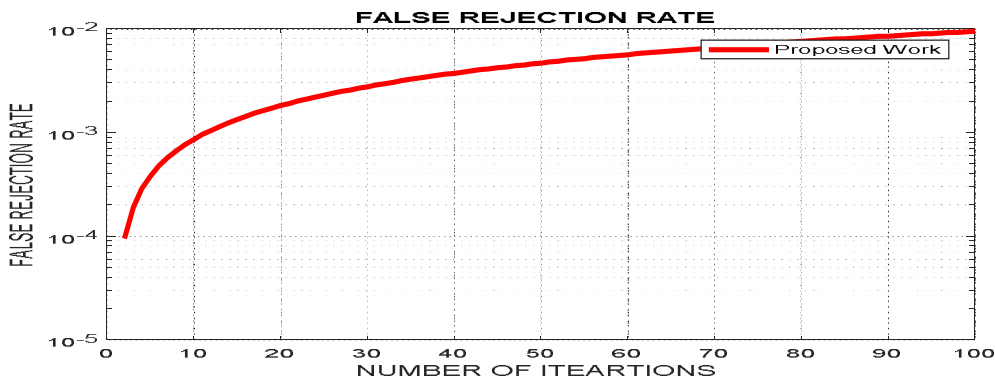


Figure 8. False Rejection Rate in proposed work

The above figure defined that the false rejection rate means false data reject able in the original form. We check the wrong data reject in the amount number of iterations in the hand gesture recognition.

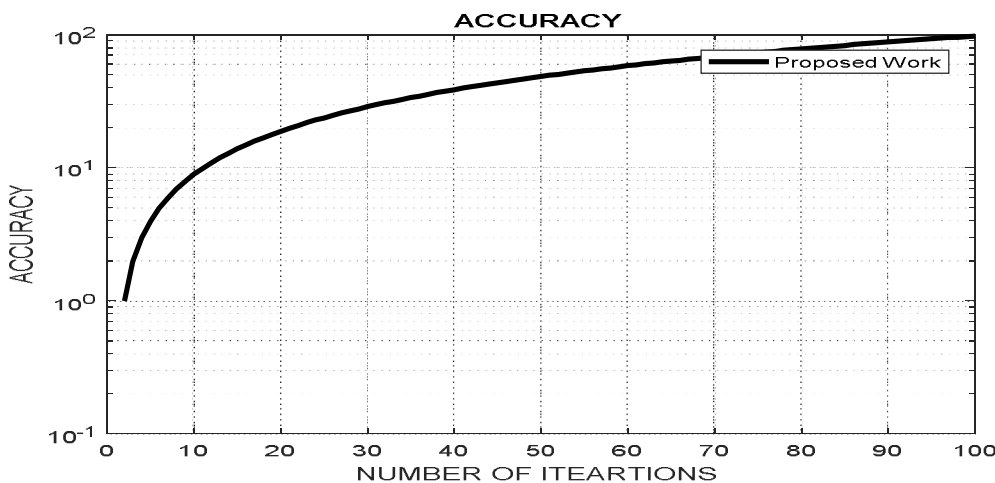


Figure 9. Accuracy in proposed work

The above figure shown that the accuracy in the proposed work. It evaluates the organization, accuracy in the hand gesture images according to the category.

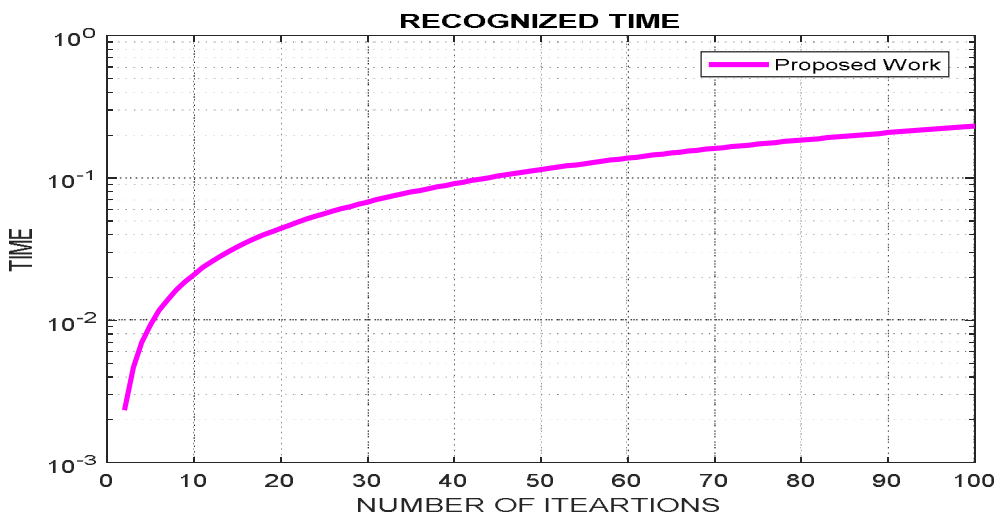


Figure 10. Recognize Time in proposed work

The above figure defined that the recognize speed. If we train all the categories in the training section. How much speed consumed to recognize the time in the training phase.

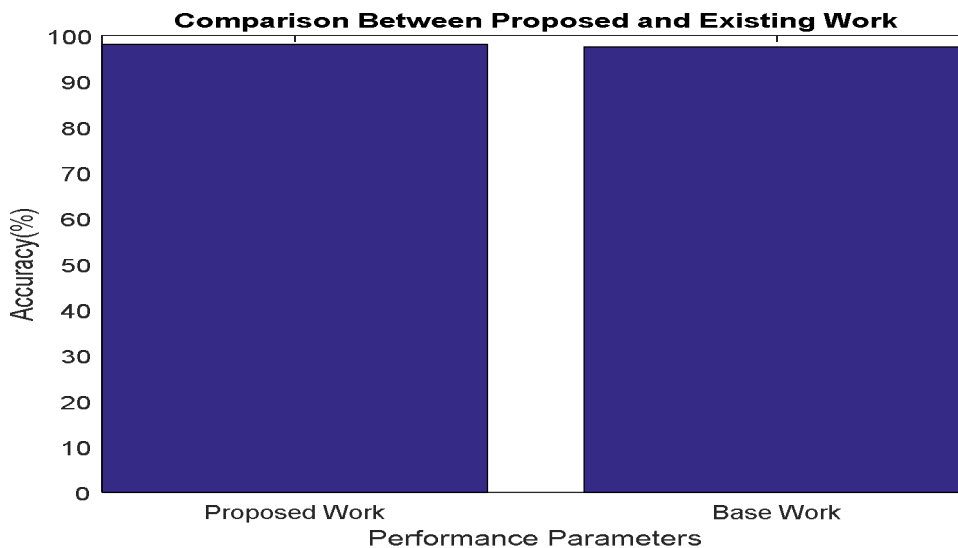


Figure 11. Comparison between Proposed and existing work (Accuracy)

The above figure showed that the comparison between RBF NN, SVM and Deep neural Network in the proposed work. The Proposed Work with Deep Neural Network accuracy value is 98.3% and Existing work with RBFNN and Voting SVM value is 94.5%.

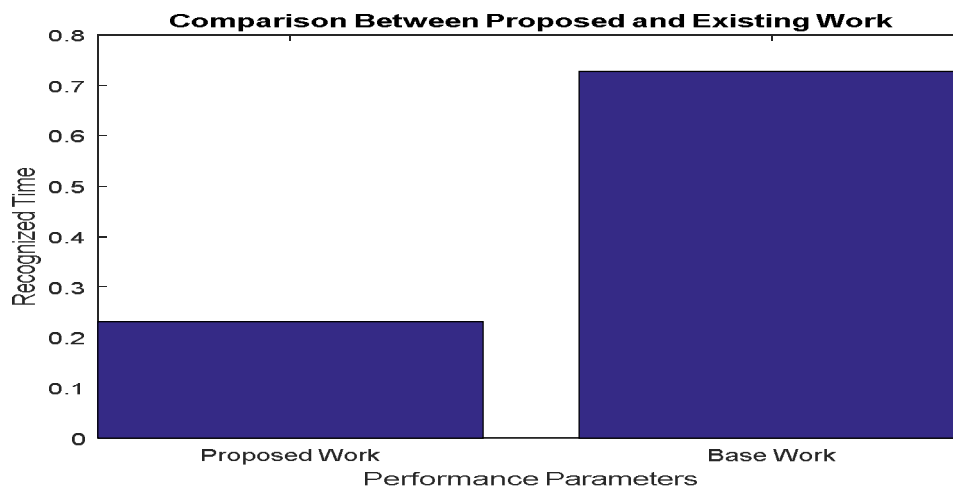


Figure 12. Comparison Between Proposed and Existing Work (Recognized Speed/Time)

The above figure 12 comparison between the proposed and existing work in recognizing speed. The proposed work recognition speed in the training case is 0.234 and existing work evaluate the recognize speed value is 0.77 sec.

VIII. CONCLUSION AND FUTURE SCOPE

The hand gesture recognition system that is considered is tested with different gestures and is able to categorize it correctly. The input image to be confident during testing phase has to be taken at the same distance as that of the training phase. The system is able to productively classify the hand gesture on behalf of number and the system can be further extended to recognize alphabets, expressions, etc. A new technique is planned to increase the accuracy of gesture recognition system using Deep Neural Network, Scale Invariant Feature Transform and Fuzzy C-means Clustering algorithm. We have compared proposed method with previous implemented method. From the results, it has been clearly seen that results for proposed methods are good in comparison to the prior method. As the purpose provides the flexibility to the users and especially physically challenge users to define the gesture according to their viability and ease of use.

Future work of hand gesture recognition can be enhanced to increase the presentation of the system. The planned system is able to classify only the static images which can be extended more to recognize the hand gesture in video as well.

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