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VISION BASED INDIAN SIGN LANGUAGE CHARACTER RECOGNITION

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ABSTRACT

Sign language recognition is helpful in communication between deaf or mute people with people who don't even know sign language. This has wide applications in communication at various public places. A system for computer-human interface of Indian Sign Language recognition in the domain of characters is proposed. This paper describes a system for automating recognition of Indian sign language static single handed and double handed character signs, in which a regular camera is used to capture the gestures. The system is designed to recognize isolated signs, i.e. each input image contains exactly one ISL character sign. To recognize images in real environment, two data sets are created, which contains 2600 images for single handed characters and 2340 gestures of double handed characters (A-Z). Structural features, local histogram features and direct pixel values of gray scale images extracted from these gestures are used as input to the recognition system. After extracting features from images, kNN classifier and neural network classifier are used to classify the gestures. In single handed data set 95.30% recognition rates are achieved, and in double handed data set 96.37% accuracy rates are achieved.

Keywords: *Indian Sign Language, Neural Network Classifier, kNN Classifier, Local Histogram Feature, Structural Feature, Direct Pixel Value Feature.*

1. INTRODUCTION

Sign language recognition can be helpful in communicating between deaf or mute people with people who don't know sign language, and also for building computer-human interaction in general. The proposed work describes a system for automatic recognition of Indian Sign Language (ISL) [1], with help of a camera and a computer system in the domain of single and double handed alphabet signs. The system is designed to recognize isolated signs; that is, each input image must contain exactly one character sign.

Usually the sign language is understandable by the signers and the persons who knows the language. But a person who does not know the sign language cannot understand the meaning of gestures. It is very difficult to exchange information between signer and non-signer community. There are various platforms in which a hearing impaired or hard hearing person want to communicate with a non-signer person and vice-versa. The public platforms in which such communication required are banks, public transport systems, educational establishments, etc. [1, 2]. In order to overcome these gaps in communication at public platforms, an interpreter is required to translate the gestures into text or speech. Due to unavailability of physical interpreters in all public places all the time, an automatic sign language recognition system will be helpful to both communities for communication purposes.

Indian sign language (ISL) has been standardized in the English language domain very recently [2]; the existing research works in its early stage on automatic computer recognition of ISL. Considering the challenges faced by deaf people in communicating with others who might be strangers to them, the objective is to develop an application in which an interface will be provided where the images of the ISL signs can be used as input and the system will display the corresponding alphabets, which the deaf person wants to express.

2. EXISTING WORK

Balakrishnan, G, Subha Rajam, P, et al [3] proposed a method of recognizing a 32 set of combinations, 10 for each up and down position of fingers to get corresponding Tamil sign letters. The method is used up/down position of fingers into decimal numbers, which is further categorized to recognize the Tamil alphabet. A set of static data in the form of images of sizes 640×480 pixels are captured. Palm image extraction is used to convert RGB to grayscale images. The experimental result is 96.87% for static method, and 98.75% accuracy rate is reported for dynamic method.

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Rekha, J, et al [4] proposed an approach to recognize ISL double handed static and dynamic alphabet signs. 23 static ISL alphabet signs from 40 signers are collected as training samples and 22 videos are used as testing samples. The shape features are extracted by the method of Principle Curvature Based Region Detector, texture features of hand are extracted by wavelet packet decomposition and features from fingers are extracted by complexity defects algorithms. Multi class non-linear SVM, kNN and DTW are used as sign classifiers. The recognition rate achieved are 91.30% for static signs and 86.30% for dynamic signs.

Goyal, S, et al [5] in their work described a model for recognition of ISL single handed alphabets. The database they developed contains 8 single handed ISL characters. They used SIFT algorithm as feature extraction from sign images. Key point matching algorithm is used to recognize the gestures which give 95.00% accuracy.

Deora, D and Bajaj, N [6] developed an Indian sign recognition system for 25 English alphabets (double handed signs) and nine numeral signs. The signers used for data acquisitions are required to wear blue and red gloves. They used segmentation and finger tip algorithm for feature extraction and PCA for classification of signs. The overall recognition rate reported is 94.00%.

In a paper by Singha, J, and Karen Das [7], a system is proposed that considers 24 alphabets of ISL, each alphabet consists 10 samples thus a total of 240 images existed in the database. The recognition system is divided into four parts namely, skin filtering, hand cropping, feature extraction and classification. The input RGB images are converted to the HSV images because RGB images are very sensitive to change in illumination condition. Next phase is the cropping of hand so that they detected the wrist and eliminated the undesired region. After cropped all images, feature extraction is performed. In feature extraction phase, Eigen values and Eigen vectors are extracted from cropped images. They used only five significant Eigen vectors out of 50 because all other Eigen vectors are very small, and they neglected the undesired Eigen vectors. This provides advantages like compression of data, dimensionality reduction without much loss of information, dropping the original variables into a lower number of orthogonal or non-correlated synthesized variables. A new classification technique Eigen value weighted Euclidean distance between Eigen vectors, which involved two levels of classification based on Euclidean Distance, and Eigen value weighted Euclidean distance are used in the experiments. With this new technique, recognition rate is 97.00%. When some images are tested with other database images then in the two levels of classification, the success rate has been improved from 87.00% to 97.00% with the use of the Eigen value weighted Euclidean distance between Eigen vectors.

Geetha, M, and U C Manjusha [8] proposed a vision based recognition of Indian Sign Language characters and numerals using B-Spline approximation. The data set contains 50 samples of each alphabet from A - Z and numbers from 0 - 5. The extracted boundary from the region of interest from image signs into a B-Spline curve by taking the Maximum Curvature Points (MCPs) as the Control points are used as features extraction technique. Support Vector Machine classifier is used to classify input signs, and the recognition result reported is around 90.00%.

After analyzing works of various authors, many drawbacks are found. The first drawback is the data set. There is no standard data set available in automating the recognition process of ISL. Furthermore, the experiments conducted by researchers are not clear. The recognition system we planned is for use in public places where the different background (noises) may present in acquiring signs. There are also diverse methods are available for classification and feature extraction, which always produces better results. Some authors used various methods for classification and feature extraction, which are not clear. In these works, the authors developed some laboratory-based systems.

3. METHODOLOGY

The proposed system is depicted in the figure 1. As mentioned above, no standard data set is available to experiment on automatic recognition of ISL gestures. Two data sets of ISL character signs are created. First set contains gestures belongs to singly handed ISL characters and the second set contains double handed gestures of ISL. The details of acquiring of data set is given in data set creation section. The input images are pre-processed before fed into feature extraction and classification phases of the proposed system.

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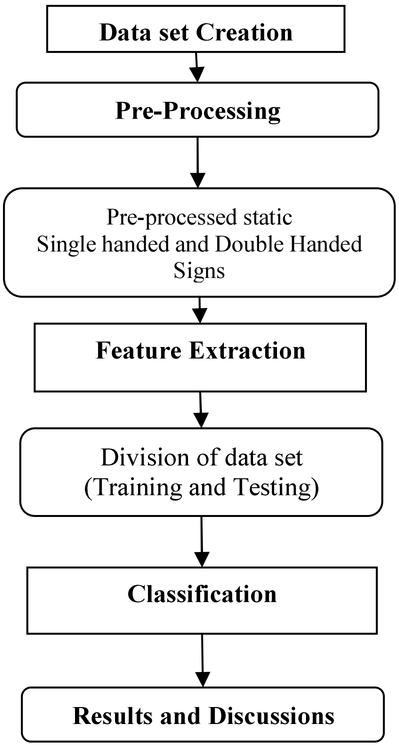

Figure 1: The Proposed ISL Single Handed and Double Handed Character Recognition System.

3.1 Data set Creation

Two data sets are created for the experiments. In the first data set (Figure 2), 100 signs of each single handed characters are captured using a digital camera. So, in this data set a total of 2600 images cropped to 200×300 RGB pixel sizes are collected. The images are collected from four males and six females. Each signer contributed 10 samples of each character. The backgrounds of sign images are dark, as only hand orientations are required for input to the feature extraction process. The images are stored in JPEG format because it can be easily exported and manipulated in different hardware and software environments. Each image requires nearly 25 KB of storage space with 72 dpi.

The second data set (Figure 3), contains 2340 images, collected from nine signers. The images are cropped to 250×160 RGB pixel sizes. The size of images of this data set differs from first data set is due to positions of both palms are required in this data set. Other features of this data set is similar with first data set. The memory space of an image from this data set is nearly 40 KB with 300 dpi.

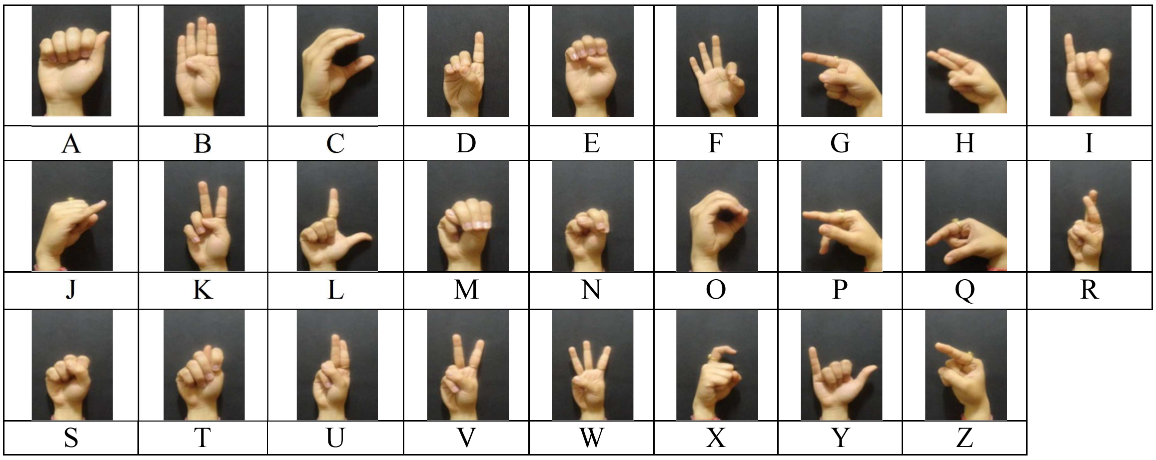

Figure 2: ISL Single Handed English Alphabet (Data Set I)

3.2 Pre-Processing

In the image pre-processing step, for each gesture, image background is estimated using morphological opening of the image. The image is structured as a flat rectangular shape. The structuring element members consist of all pixels whose centers are no greater than 15 away from the origin of each structured image. The axes of images are adjusted for normalization. The estimated backgrounds of the images are subtracted from all images. This provides images of uniform background to the system. As it is very difficult to extract features directly from a color image, the images are converted into the gray scale for input to the feature extraction phase.

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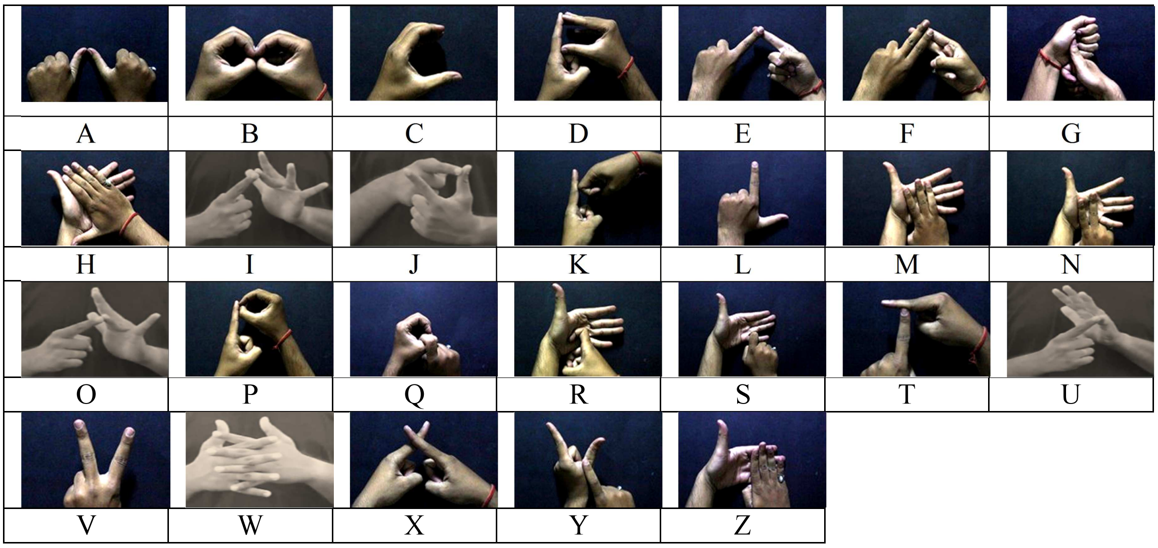

Figure 3: ISL Double Handed English Alphabet (Data Set II)

3.3 Feature Extraction

Images contain a large amount of information. The desired information can be automatically extracted from images in a process called feature extraction. This has a wide range of applications in computer vision. These systems called Content Based Image Retrieval (CBIR) have received intensive attention in the literature of image information retrieval since this area is started several years ago, and consequently, a broad range of techniques had been proposed.

The extraction task transforms rich content of images into various numerical features. Feature extraction is the process of collecting features to be used for image classification. Furthermore, feature selection reduces the number of features provided to the classification task. Those features which are likely to help in judgment are selected and used in the classification task. Useless features which are not selected are straightly discarded. Of these three activities, feature extraction is most critical because the particular features made available for discrimination directly influence the efficacy of the classification task.

Feature extraction techniques used in this research are Hierarchical Centroid [9], which uses the method of finding the centroid of the image, through that centroid, each image is partitioned into two different zones, based on balancing the number of pixels, i.e. left and right zones. Iteratively this method is performed at most seven times and then 256 features out of each image are extracted. The result of the feature extractor is a feature set, commonly called a feature vector, which constitutes a representation of the image.

Local histogram features [10] are extracted in the second feature extraction technique. The input to the feature extraction function is a gray-scale image, number of histogram bins, distance in pixels between nodes of neighborhood graph, radius of the histogram window, a 0-1 edge-map, same size as input image, where 1 entries are interpreted as edge locations. Outputs of this function are histograms - a matrix of local histograms. These matrices of local histograms are combined to represent the feature vector of each image.

In direct pixel value feature extraction method, the original images (200×300, in case of single handed alphabet, 250×160, in case of the double handed alphabet) are converted into gray-scale images and resized to 40×50 pixels. Then the image matrix is converted into one-dimensional array containing exactly 2000 elements for each gesture.

3.4 Classifier

The following classifiers are used for prediction of target class to which the test data samples belong to:

- k Nearest Neighbour (kNN)
- Neural Network Classifier

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3.4.1 kNN classifier

Instance-based classifiers like the kNN classifier [11] operate on the property that classification of unknown instances can be done by relating the unknown to the known according to various similarity or distance functions. The intuition is that two instances far apart in the instance space defined by the appropriate distance functions are less likely than two closely situated instances to belong to the same class.

Classification using an instance-based classifier can be a simple matter of locating the nearest neighbour in instance space and labeling the unknown instance with the same class label as that of the located neighbour. This approach is often referred to as a nearest neighbour classifier. The downside of this simple approach is the lack of robustness that characterizes the resulting classifiers. The high degree of local sensitivity makes nearest neighbour classifiers highly susceptible to noise in the training data.

More robust models can be achieved by locating k, where k > 1, neighbours and letting the majority vote decide the outcome of the class labeling. A higher value of k results in a smoother, less locally sensitive function. The nearest neighbour classifier can be regarded as a special case of the more general k-nearest neighbours' classifier, hereafter referred to as a kNN classifier. The drawback of increasing the value of k is of course that as k approaches n, where n is the size of the instance base, the performance of the classifier will approach that of the most straightforward statistical baseline, the assumption that all unknown instances belong to the class most frequently represented in the training data.

3.4.2 Neural network Classifier (NPRTool)

NPR Tool leads in solving a pattern recognition classification problem using a two-layer feed-forward pattern_net network with sigmoid output neurons. A variety of neurons are used on the hidden layer depending upon the size of input features. The network has twenty six output neurons because there are twenty six target values associated with each input vector. Pattern recognition networks are feed forward networks that can be trained to classify inputs according to target classes. The target data for pattern recognition networks should consist of vectors of all zero values except for a '1' in element '*i*', where '*i*' is the class they belong to. For classification, the input data is divided into three sets: Training, Validation and Testing.

Training data is used for adjusting the weight and biases. Validation is used to decide when to stop the training process, to avoid over fitting, which is a situation where the network memorizes the training data, rather than training the low that governs them. Testing data is used to measure the performance of the trained network. It is important that this data did not participate in the training process.

3.5 Results and Discussions

The experimental results on single handed and double handed character signs are explained below.

3.5.1 Results of Single handed characters

Table 1 shows results produced by kNN and neural network classifiers on single handed characters (A - Z). The higest recognition rate of kNN classifier is 59.48% and neural network classifier is 95.30%. The performance of neural network classifier is approximately 35% more than that of kNN irrespective of any feature vectors. We can easily conclude from *Table 1* that the combination of Neural Network classifier with histogram feature vector will be suitable for an automatic recognition system for ISL single handed characters. The performance of training, validation and testing parameters is depicted in figure 5. Number of hidden neurons used in the neural network is 65. At this point, the network performs maximum accuracy. Individual accuracy of results of each character sign is presented in table 2 and figure 4.

Table 1: Performance of classifiers kNN and Neural Network on single handed ISL characters

Feature Vector → Classifier↓	Direct Pixel Value	Hierarchical Centroid	Local Histogram	Sample Size	Data set
kNN	59.48%	51.02%	56.79%	26×100= 2600	Training = 70% Testing = 30%
Neural Network	92.52%	93.37%	95.30%	26×100= 2600	Training = 70% Validation=10% Testing = 20%

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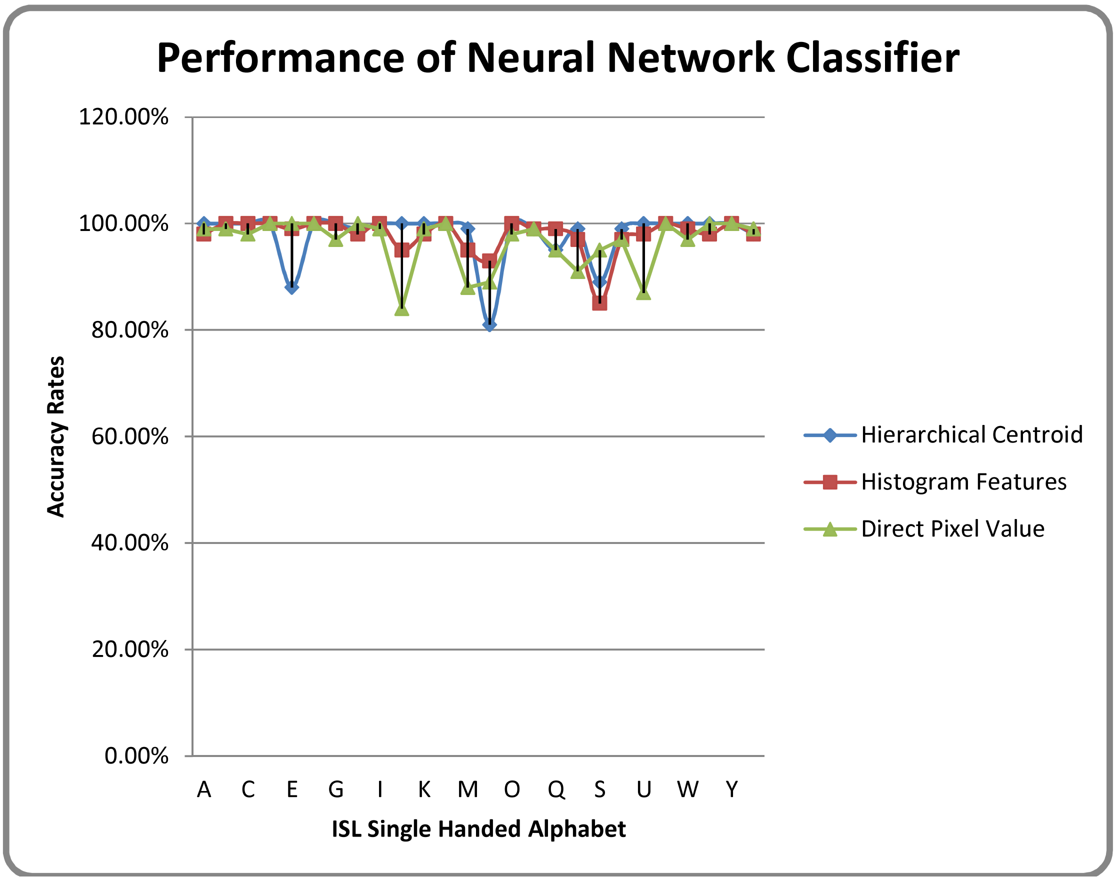

Figure 4: Performance of Neural Network classifier against all three Feature Vectors.

3.5.2 Results of the Double Handed Alphabet

The orientation of double handed characters of ISL is different than single handed characters. Same experiments are also conducted on the double handed alphabet as in single handed alphabet. But performance of kNN is far below our expectations on all feature vectors. So in result analysis of the double handed alphabet, the results obtained from kNN classifier are excluded. In this case, the performance of hierarchical centroid (HC) features (Table 3) is better than local histogram and direct pixel value feature vectors. Only 30 hidden neurons are needed in the neural network. At this point, the network performs better results. The combination of hierarchical centroid features with neural network classifier can be used for an automatic recognition system for double handed alphabets in ISL (Table 4 and figure 6). The performance of the training, validation and testing of the experiment is given in figure 7.

Table 3: Performance of Neural Network Classifier over three feature vectors

Feature Vector → Classifier↓	Direct Pixel Value	Hierarchical Centroid	Local Histogram	Sample Size	Data set
Neural Network	92.52%	96.37%	95.30%	26×90= 2340	Training = 70% Validation=10% Testing = 20%

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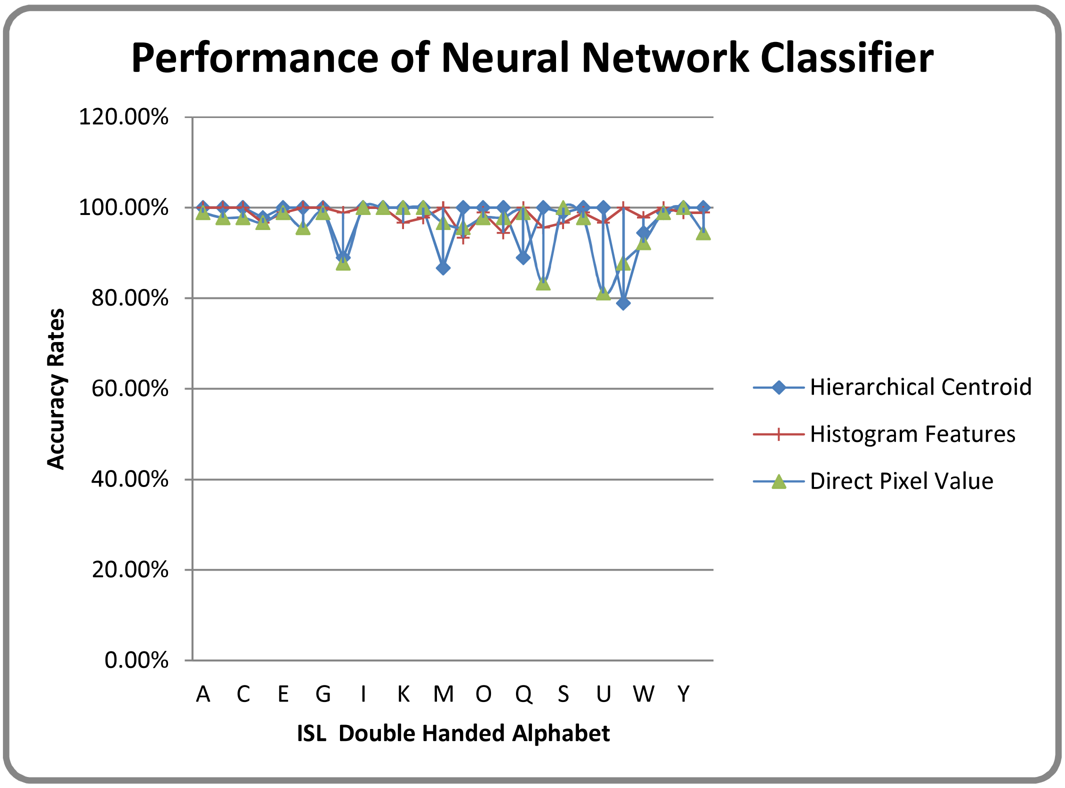

Figure 6: Performance of Neural Network Classifier with all Three Feature Vectors.

4. CONCLUSION

The proposed gesture recognition system can handle different types of characters in a common vision based platform. The system is suitable for complex Indian Sign Language (Alphabet) static signs. However, it is to be noted that the proposed gesture recognizer cannot be considered as a complete sign language recognizer, as for complete recognition of sign language, information about other body parts are essential. The experimental results show that the system is sufficient to claim a "working system" for native Indian sign language character recognition.

By using local histogram feature extraction technique with the neural network classifier result of 95.30% is achieved for single handed and the combination of hierarchical centroid feature vector with neural network classifier on the double handed alphabet is 96.37%. The achieved results are lower by only 5% from an ideal system, probably because of two reasons: one is limited data set, and the other is feature extraction algorithms adopted. Other feature extraction algorithms like Wavelet transform, Invariant moments, Zernike moments, Shapelets descriptor and others would have been tried for improvement in the results.

5. FUTURE SCOPE

In these experiments, training, testing and analysis on the limited number of users of similar age group are conducted. However, in the future to make the present system better a larger data set collected from various users of different age groups, including children, youngsters, middle-aged people and old people can be built. In the current system, the solid dark background for the images taken but this may not be the case everywhere. These features can be included in the future.

Thus, the proposed approach will be useful and will have a sufficient amount of accuracy to recognize hand sign gestures from ISL. This system can be extended to include the vision based recognition of dynamic gestures corresponding to words and sentences in ISL.

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Table 2: Confusion Matrix Of Neural Network Classifier Against Local Histogram Features(Singly Handed)

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z
A	98	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
B	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C	0	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
D	0	0	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
E	0	0	0	0	99	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F	0	0	0	0	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
G	0	0	0	0	0	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
H	0	0	0	0	0	0	0	98	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0
I	0	0	0	0	0	0	0	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
J	0	0	4	0	0	0	0	0	0	95	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
K	0	0	0	0	0	0	0	0	0	0	98	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0
L	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M	0	0	0	1	0	0	0	1	0	0	0	0	95	0	0	0	0	0	1	0	0	1	0	0	0	1
N	0	0	0	0	0	0	0	0	1	0	0	0	1	93	0	0	0	1	1	3	0	0	0	0	0	0
O	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0	0	0	0	0	0	0
P	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	99	0	0	0	0	0	0	0	0	0	0
Q	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	99	0	0	0	0	0	0	0	0	0
R	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	97	0	0	1	0	0	0	0	0
S	0	0	0	0	3	0	0	0	0	0	0	0	0	9	0	0	0	2	85	1	0	0	0	0	0	0
T	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	0	0	0	97	0	0	0	0	0	0
U	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	98	0	0	0	0	0
V	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0
W	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	99	0	0	0
X	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	98	0	0
Y	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0
Z	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	98

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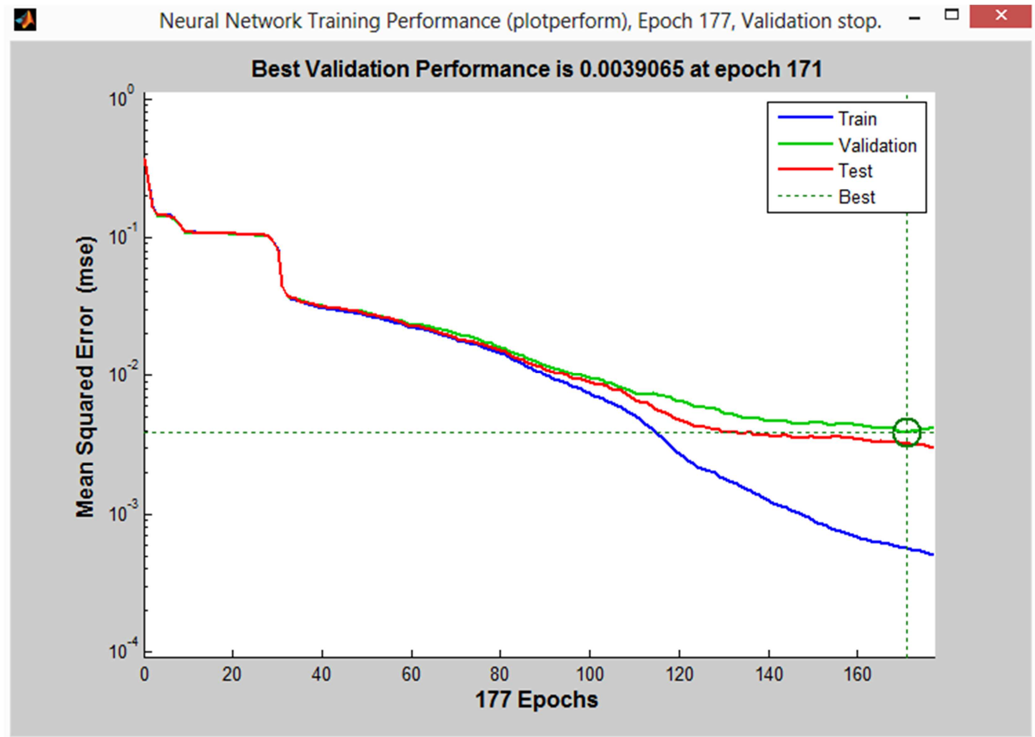

Figure 5: Performance Of Neural Network Classifier With Local Histogram Features (Single Handed).

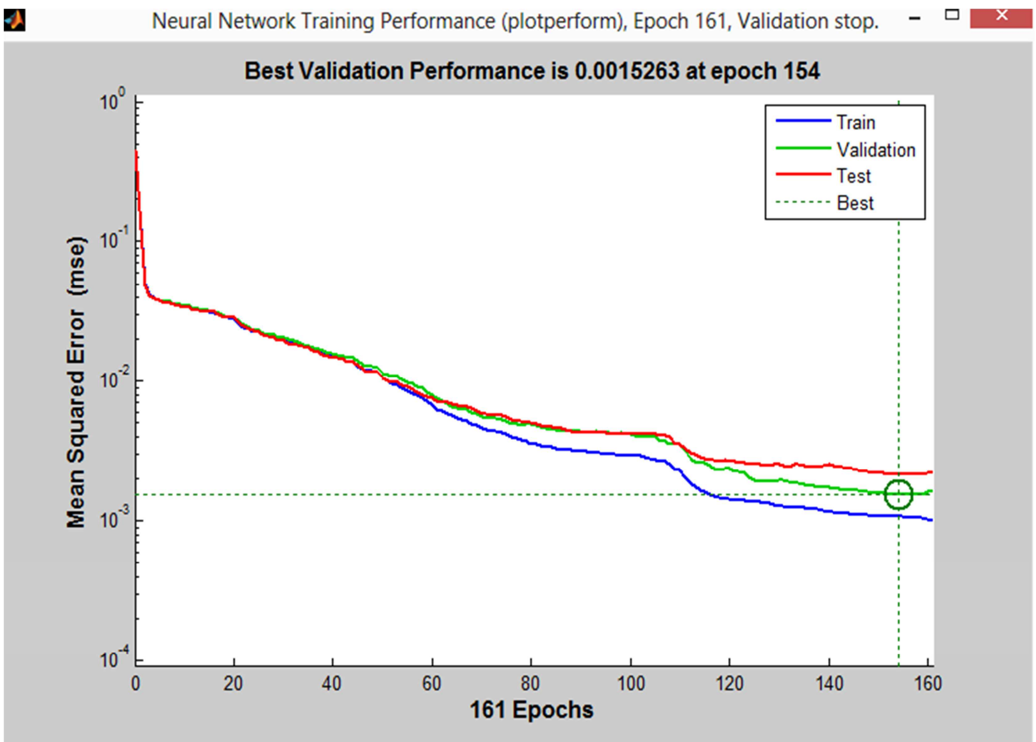

Figure 7: Performance Of Neural Network Classifier With Hierarchical Centroid Features (Double Handed).

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Table 4: Confusion Matrix Of Neural Network Classifier Against Hierarchical Centroid Features (Double Handed)

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z
A	90	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B	0	90	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C	0	0	90	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
D	0	0	0	88	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0
E	0	0	0	0	90	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F	0	0	0	0	0	90	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
G	0	0	0	0	0	0	90	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
H	0	0	0	0	0	5	0	80	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
I	0	0	0	0	0	0	0	0	90	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
J	0	0	0	0	0	0	0	0	0	90	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
K	0	0	0	0	0	0	0	0	0	0	90	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L	0	0	0	0	0	0	0	0	0	0	0	90	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M	0	0	0	0	0	0	0	0	0	0	0	0	78	8	0	1	0	0	3	0	0	0	0	0	0	0
N	0	0	0	0	0	0	0	0	0	0	0	0	0	90	0	0	0	0	0	0	0	0	0	0	0	0
O	0	0	0	0	0	0	0	0	0	0	0	0	0	0	90	0	0	0	0	0	0	0	0	0	0	0
P	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	90	0	0	0	0	0	0	0	0	0	0
Q	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	1	80	0	0	0	0	0	0	0	3	4
R	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	90	0	0	0	0	0	0	0	0
S	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	89	0	0	0	0	0	0	0
T	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	90	0	0	0	0	0	0
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	90	0	0	0	0	0
V	0	0	0	0	0	0	0	0	1	6	0	0	0	0	1	0	3	2	0	0	3	71	3	0	0	0
W	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	85	0	2	0
X	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	89	0	0
Y	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	90	0
Z	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	90

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