International Journal of Soft Computing and Engineering (IJSCE)
ISSN: 2231-2307, Volume-6 Issue-1, March 2016

Performance Analysis of Different Classifiers for American Sign Language Recognition

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Abstract: ***American Sign Language alpha-numeric character recognition without using any embedded sensor, color glove or without the constraints of an environment is a really difficult task. This paper describes a novel method of static sign recognition using a leap Motion sensor by obtaining feature set based on hand position, distance and angle between different points of hand. A feature set is later trained and tested using different classifiers like MLP (Multilayer Perceptron), GFFNN (Generalized Feed forward Neural Network), SVM (Support Vector Machine). We have collected dataset from 146 people including students of age 20-22 years and few elders age between 28-38 who have performed 32 signs resulting in total dataset of 4672 signs. Out of this 90% dataset is used for training and 10% dataset is used for testing/Cross validation. we have got maximum classification accuracy as 90% on CV/testing dataset using MLP Neural Network.***

Index Terms—ASL, MLP, GFFNN, SVM.

I. INTRODUCTION

As per figures from World Federation of the Deaf (WFD), the number of deaf people in the world is approximately 70 million. Sign Language is only the way for deaf-mutes to communicate with each other. Sign Language recognition Systems are mainly categorized in two classes as instrumented/Data Glove based and vision (Camera) based. However a combination of both is also tied by researchers. It is observed that hardware (Instrumented glove/Data Glove) based systems can recognize sign more correctly than vision as it has direct information of positioning of fingers and hand movement in coordinate format. Object identification is not the issue in instrumented based system as sensors are directly mounted on elbow, hand, fingers etc.

In comparison to this, vision based system need to first identify the object from an image based on color space selection may be based on skin color or color glove used in segmentation process. Skin color based segmentation is mainly done with plain background or with cloths of dark color where complete hand is covered and only palm, fingers are uncovered. However due to advancement in technology new devices like Leap Motion Sensor & Kinect have opened many ways for researchers to add new features to the existing research.

II. RELATED WORK

Fu-Hus Chou et al. [1] have worked on gesture image (1 to 5 numbers) detection and recognition. In detection process forearm and elbow is deleted after adjusting image. Later on in recognition phase first a model is constructed for static hand gesture and then unknown gesture image is identified by Gaussian Model match. It is observe that for the five numbers recognition, 300 gesture images are used to construct the GMM (Gaussian Model match) model & 200 test samples for each number gesture that has given average recognition rate 94%. Likewise M.S. Sinith et al. [2] have worked on recognition of few static signs (A, W, O, H, I and L, Six letters) of ASL. First color image is converted to gray scale image and then filter (Sobel filter) is used to get binary hand image. Longest three connected components of this image is considered as feature vector as a input to Support Vector Machine (SVM). Out of 30 letters given 28 is correctly recognized giving efficiency of 92.13%.

In [3], Hee-Deok Yang et al. have worked on recognition of Manual and Non manual sign American Sign Language (ASL) using color data glove. In Manual sign recognition hierarchical CRF (Conditional random field) is used to discriminate signer's signs, finger spelling and non-sign patterns using motion and location as features. BoostMap methods is used to recognize shape of hand. In Non manual sign recognition multiclass SVM is used to classify different facial expressions using 31 feature point and distance and angle as a measurement. While training user has to wear color glove and in testing there in so need. 98 Recorded videos are used in experiments which consist of 515 signs and 50 fingerspellings. In [4], Fahad Ullah et al. have worked on recognition of 26 alphabets of American Sign Language (ASL) using Cartesian Genetic Programming (CGP) where color image is converted to binary images of resolution 47*27 pixel which later on converted to linear array of size 1*1269 pixels vector. In programming 1269 inputs are used which gives five bit output representing exact number of familiar sign. 26 different equal number of binary images are used for training and testing. After recognition of alphabet it is kept in queue buffer which collect alphabet till it get sign for space. Then the word is displayed on monitor which signer wants to speak. Both training and testing results are above 90% accurate. However for testing same images those are used in testing are used with little modification.

In 2015, Asha Thalange et al.[5] proposed a method to detect static images of numbers 0-9 in American Sign Language (ASL). The feature vector is formed using number of open finger and distance between adjacent finger. Multi-layered feed forward back-propagation Neural is used for the categorization. The average classification accuracy of this technique is 92 %. On similar platform Priyanka Mekala et al. [6] have recognized all the English alphabets using combinational NN's design. Total 55 feature vector consists of 5 finger tip , 4 motion vector , 6 MV sequence and the remaining 40 are from the wavelet transform of the Fourier transformed image of a sign.

Revised Version Manuscript Received on March 05, 2016.

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In [7], Taehwan Kim et al. have worked on fingerspelling sequences which form words in American Sign Language (ASL) from a video where outputs of multilayer perception (MLP) classifiers are used as observations in a hidden Markov model (HMM)-based recognizer. It is observed that when segmentation is done using manual labels and signer specify the start and end of sign by pressing button. SIFT is used for feature extraction followed by PCA. Error rate observed is extremely small as HMMs & MLPs are trained by the tagged segmentation. For total three hundred words, the error rates are 2.6% & 0.6 % for Signer 1& 2 respectively .

Similar kind of approach is proposed by Dominique Uebersax et al. [8] have worked on American Sign Language (ASL) Recognition system for recognizing letters and finger-spelled words in real-time. System Test data was collected from 7 test subjects at a distance of approximately 80 cm from the MESA SR4000 TOF camera and two depth sensors. 3 users, each user perform sign so 50 samples are available per letter. For hand localization & segmentation depth data is used. For alphabet detection 3 methods that is average neighborhood margin maximization, depth difference and hand rotation are used. Average recognition rate for multiuser system is 76% and for single ser it is 88%. Some experiments based on instrumented glove and sensors also carried out by many researchers. Using a Immersion's 18 sensor Cyber Glove, Jerome M. Allen et al. [9] have designed a signer dependent system to recognize 24 static finger spelling letter of American Sign Language (ASL) and translate it to corresponding alphabet in printed and spoken English letters. Pattern recognition technique with perception network was used which gives the accuracy of 90%. Viselike E. Kosmidou et al. [10] suggested an analysis of the surface electromyogram signal for the detection of American Sign Language gestures. Total 16 attributes are acquired from the signer's forearm and assessed by the Mahalanobis distance principle. The number of features are reduced using discriminant analysis. The classification accuracy estimated is 97.7% for ASL. Using advanced technology C. S. Weerasekera et al. [11] have proposed a robust approach for recognition of bare-handed static sign language. Local Binary Patterns (LBP) histogram features based on color and depth information, and also geometric features of the hand are used as features. Linear binary Support Vector Machine (SVM) classifiers are used for recognition. In the case of multiple matches SVM is coupled with template matching. An accurate hand segmentation scheme using the Kinect depth sensor is also presented. After testing the algorithm on two fingerspelling datasets of ASL, 90% classification accuracy is observed. The system is vigorous to accept distance changes between user and camera and can handle likely difference in finger spelling among different users. Lucas Rioux-Maldague et al. [12] suggested a novel attributes extraction method for ASL fingerspelling (alphabets except J and Z) hand pose detection using intensity & depth images. Classification of fingerspelling carried using a Deep Belief Network. Results are evaluated using two situation, first using all identified users and second using an unobserved user. In first case 99 % recall and precision rate and for second case 77 % recall and 79 % precision rate is achieved.

A.S.Elons et al. [13] have captured hands and fingers movements in 3D digital format using Leap motion. The sensor throws 3D digital information in each frame of movement. These temporal and spatial features are fed into a Multi-layer perceptron Neural Network (MLP). The system was tested on 50 different dynamic signs (distinguishable without non manual features) and the recognition accuracy reached 88% for two different persons.

L. Nanni et al. [14] have proposed a system using Kinect sensor for few ASL hand gesture recognition based on distance and curvature Features computed on the hand shape. A combination of SVM classifiers and rotation boosting has given better accuracy as compared to performance of single one. It is observed that due to fusion, accuracy of 97.9 and 88.7 is obtained on two different datasets. Similarly Cao Dong et al. [15] recognized 24 static ASL alphabets using localize hand joint with 92% accuracy. Feature vector consist of 13 key angles of the hand skeleton to build Random Forest (RF) classifier for recognition of sign.

Giulio Marin et al. [16] proposed a novel ASL static hand gesture recognition scheme using Leap motion and Kinect. Feature set of leap Motion consists of Fingertips distances, Fingertips angles and Fingertips elevations. Feature set of Kinect consists of Curvature, Correlation. A Multi-class SVM classifier is used to recognize the performed gestures. It is observed that due to combination of Leap and Kinect, the recognition accuracy achieved is 91.28% for 10 static signs. Using Leap Motion, Makiko Funasaka et al. [17] recognized 24 ASL alphabets (except J and Z) using the decision tree. 16 kinds of conditions that focus on the characteristics of hand and finger are considered for tree. By changing the order of the conditional branches, a different decision tree is generated with a different average recognition rate for the finger spelling. The average recognition rate obtained is 82.71% .

III. EXPERIMENTATION SETUP

A. Data Acquisition and collection

The Leap Motion sensor is a little USB device structured to be kept on a hard surface pointing up. The device has 2 IR cameras and 3 IR LEDs with a approximately hemispherical region which work up to a distance of around one meter [12]. Leap Motion sensor is easy to use and of low cost as shown in Fig 1.

Fig. 1. Leap Motion Controller

This sensor can track the finger's joints and their movements. These details are provided by device Vendors "https://www.leapmotion.com" [18]. It is observed while performing signs that Leap Motion Sensor doesn’t show the sign properly in Visualizer, a software tool released with Leap Motion. However when we kept Leap Motion we 10 degrees inclined as shown in Fig 2 we have got better visualization of performed sign.

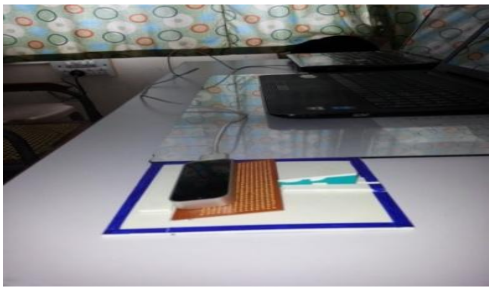
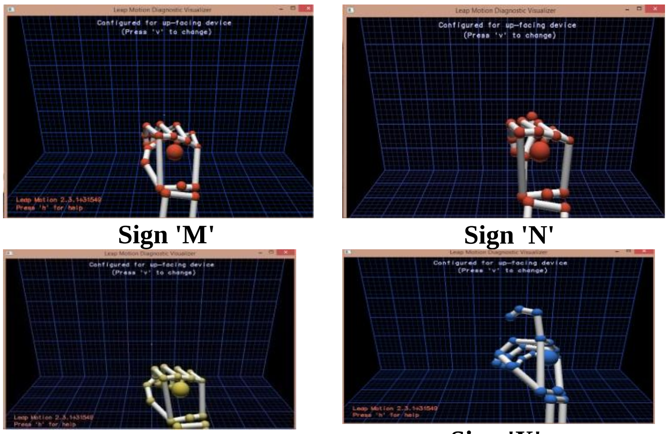


Fig. 2. Leap Motion Controller kept on self designed stand

Samples of signs on Visualizer tool of Leap Motion Sensor is as shown in Fig. 3.



Sign 'M' Sign 'N'

Sign 'S' Sign 'X'

Fig. 3. Sample of some signs of ASL on visualize tool of Leap Motion

As shown in Fig. 4, the 3D co-ordinates of each finger tip and palm is accessed using Leap Motion API.

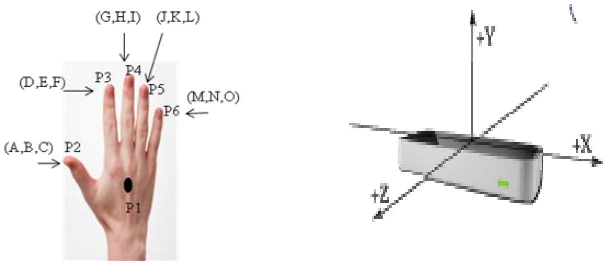


Fig. 4. Points of interest for feature extraction

We have collected signs from 146 users who have performed 32 signs only once resulting in total dataset of 4672 signs.

B. Feature Selection

The feature set consists of positional values of each finger and palm, distance between positional values, angle between positional vales with respect to plane. Understanding the fact that every person has different hand shape and size, a database is created so as to have all possible samples of hand pose for concern posture. We have calculated 15 Euclidean distances for all combination of 6 points p1 to p6

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$$D1 = \sqrt{(P-A)^2 + (Q-B)^2 + (R-C)^2} \quad (1)$$

$$D2 = \sqrt{(P-D)^2 + (Q-E)^2 + (R-F)^2} \quad (2)$$

$$D3 = \sqrt{(P-G)^2 + (Q-H)^2 + (R-I)^2} \quad (3)$$

$$D4 = \sqrt{(P-J)^2 + (Q-K)^2 + (R-L)^2} \quad (4)$$

$$D5 = \sqrt{(P-M)^2 + (Q-N)^2 + (R-O)^2} \quad (5)$$

$$D6 = \sqrt{(A-D)^2 + (B-E)^2 + (C-F)^2} \quad (6)$$

$$D7 = \sqrt{(A-G)^2 + (B-H)^2 + (C-I)^2} \quad (7)$$

$$D8 = \sqrt{(A-J)^2 + (B-K)^2 + (C-L)^2} \quad (8)$$

$$D9 = \sqrt{(A-M)^2 + (B-N)^2 + (C-O)^2} \quad (9)$$

$$D10 = \sqrt{(D-G)^2 + (E-H)^2 + (F-I)^2} \quad (10)$$

$$D11 = \sqrt{(D-J)^2 + (E-K)^2 + (F-L)^2} \quad (11)$$

$$D12 = \sqrt{(D-M)^2 + (E-N)^2 + (F-O)^2} \quad (12)$$

$$D13 = \sqrt{(G-J)^2 + (H-K)^2 + (I-L)^2} \quad (13)$$

$$D14 = \sqrt{(G-M)^2 + (H-N)^2 + (I-O)^2} \quad (14)$$

$$D15 = \sqrt{(J-M)^2 + (K-N)^2 + (L-O)^2} \quad (15)$$

Similarly a Cosine angle between every two positional values is calculated as shown below for all possible combination of point p1 to p6. As an example, cosine angle between point p1 and p2 is calculated as

Costheta1=dot(P1,P2)/(norm(P1)*norm(P2)) (16)

thetha_deg1= acos (Costheta1)*180/pi (17)

Likewise for all possible combination of point p1 to p6, total 15 angles (thetha_deg1, thetha_deg2,...,…,…, thetha_deg15) are calculated. Thus for one sign we get 18 positional values, 15 distance values and 15 angle values resulting in feature vector of size 48. This way for all signs we get feature matrix of size 4672 × 48.

C. Classification using Neural Network

1) Multilayer Perceptron Neural Network:

Following trials have been performed on Multilayer Perceptron Neural Network (MLP) to get optimal parameters for minimum MSE and maximum percentage Average Classification Accuracy. Feature vectors are divided into two part as 90 % for training (TR) and 10% for Cross validation (CV). By keeping only one hidden layer, first network is tested to search number of Processing Element (PE) required in Hidden Layer which gives minimum Mean Square Error (MSE) on training dataset. Fig. 5 shows that minimum MSE is given by processing element (PE) number 27. Different transfer function (T.F.) like Tanh, LinearTanh, Sigmoid, LinearSigmoid, Softmax and Learning rules (L.R.) like Step, Momentum, Conjugate Gradient (C.G.) , Quick Propagation, Delta Bar Delta are varied in hidden Layer to get maximum percentage classification accuracy as shown in Fig. 6.

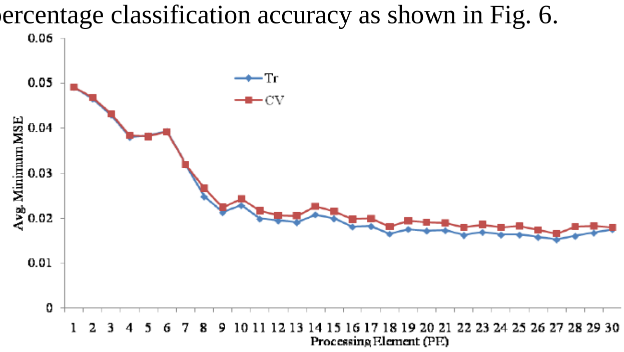

Fig. 5. Processing Element (PE) Vs Minimum MSE

Published By:
Blue Eyes Intelligence Engineering
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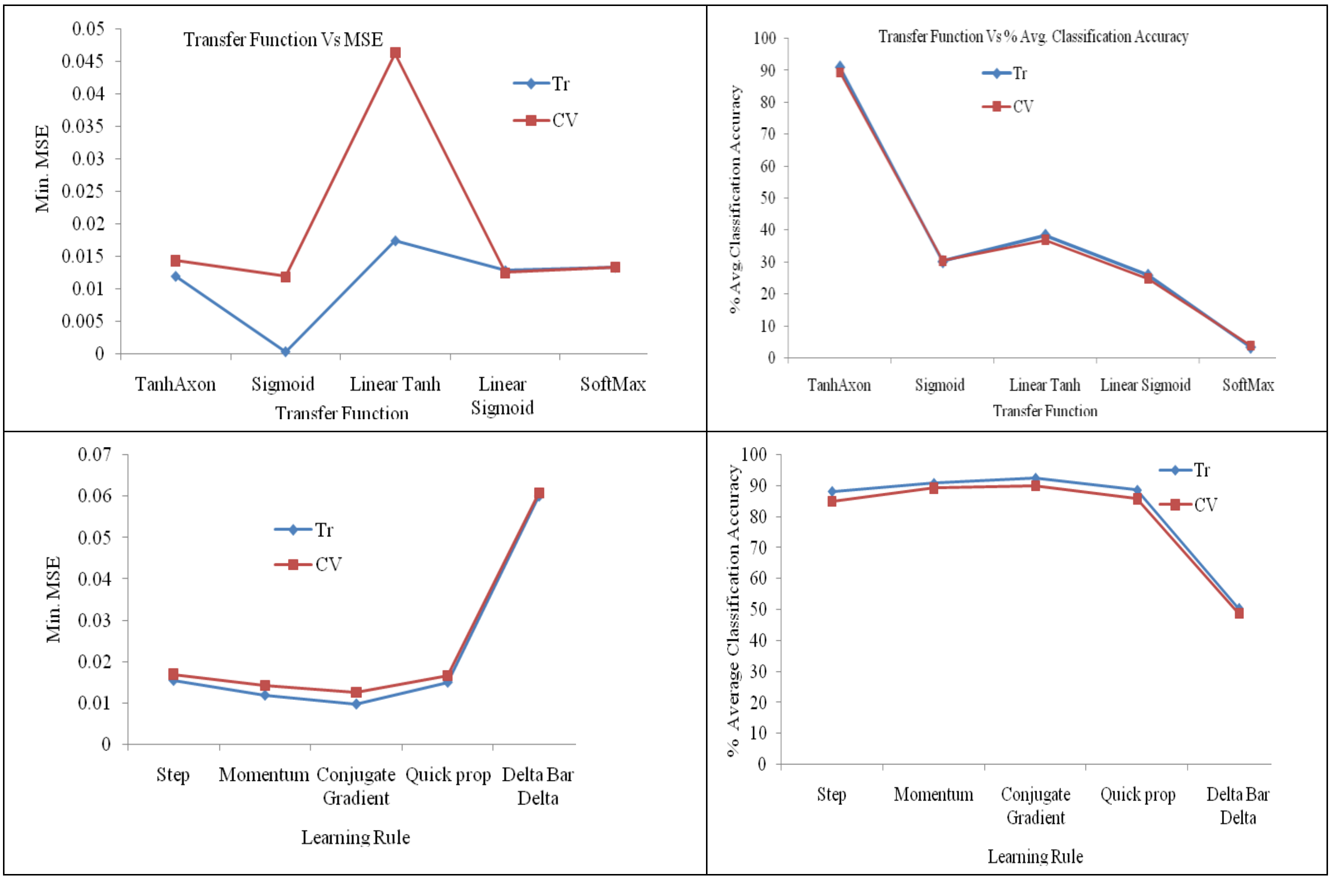

Fig. 6. Variation of Minimum MSE and Percentage Average classification Accuracy with different transfer functions and learning rules

MLP with the following parameter setting gives maximum Percentage classification accuracy of 92.66 % on training and 90 % on CV dataset.

Tagging of Data: 90% for Training & 10% Cross validation
Input Processing Element: 48 Output PE's:32
Exemplars: 4205
Hidden Layer:
Processing Elements - 27
T.F. - Tanh
L.R. - C.G.
Output Layer:
T.F.- Tanh
L.R. - C.G.

2) Generalized Feed Forward Neural Network:

Like MLP Neural Network we have performed similar trials using GFFNN. With the following parameter setting we have got maximum Percentage classification accuracy of 92.28 % on training and 89.27 % on CV dataset.

Tagging of Data: 90% for Training & 10% Cross validation
Input Processing Element: 48 Output PE's:32
Exemplars: 4205
Hidden Layer: Processing Elements: 21
T.F.-: Tanh L.R.: Momentum
Step Size- 0.2 Momentum: 0.7
Output Layer:
T.F.- Tanh L.R.- Momentum
Step Size - 0.2 Momentum- 0.7

3) Support Vector Machine:

We have varied epoch & number of runs by fixing the step size at 0.1. It is observed that from epoch 10 onwards, there is very little change is MSE as shown in Fig 7.

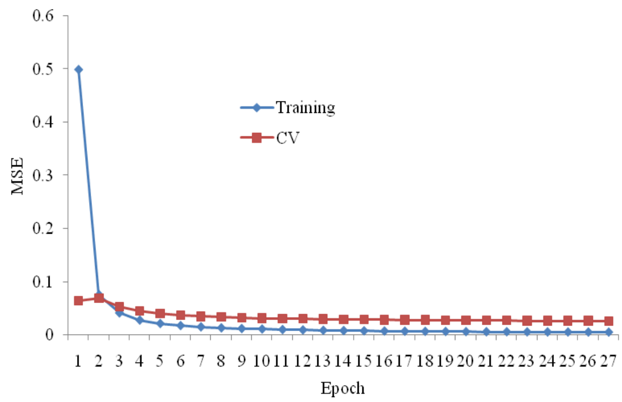

Fig. 7. Step Size Vs % Classification Accuracy

After fixing the number of epoch as 10, we have varied step size from 0.1 to 1 to check the maximum classification accuracy as shown in Fig. 8

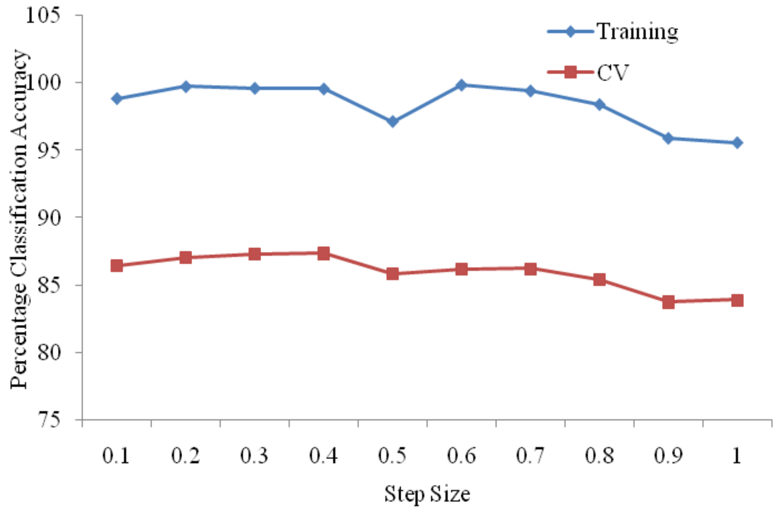

Fig. 8. Step Size Vs Percentage Classification Accuracy

After experimentation we have observed that the best result is i.e. 99.57 % on training and 87.37 % on CV data set with optimal parameter setting as below.

Tagging of Data: 90% for Training & 10% Cross validation
No. of Epoch: 10 No. of Runs: 1 Processing Elements: 32 Exemplars: 4205 Step Size: 0.4 Kernel Algorithm: Adatron

Table 1. Confusion Matrix for Cross Validation (CV)/Testing data set using MLP Neural Network

Output / Desired	1	3	4	5	7	8	9	10	A	B	C	D	E	F	G	H	I	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y
1	10	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
3	0	11	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	0	0	0	0	0
4	0	0	15	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	13	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	15	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	0	0
8	0	0	0	0	1	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
9	0	0	0	0	0	0	8	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
A	0	0	0	1	0	0	0	0	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
B	0	0	0	1	0	0	0	0	0	20	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	0	0	0	0	0	0	0	0	6	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
D	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	2	1
E	0	0	0	0	0	0	1	0	0	0	0	0	13	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	0	1	0	0	0	0	0	0	16	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	0	0	0	0	0	0	0	0	20	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	2	0
H	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
I	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	17	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	0	0	0	0	0	0	0	18	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	0	0	0	0	0	0	0	14	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	1	0	0	0	0	0	0	8	2	0	0	0	0	2	1	0	0	0	0	0
N	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	14	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	1	0	0	0	0	1	1	7	0	0	0	0	0	0	0	0	0	0
P	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15	0	0	0	0	0	0	0	0	0
Q	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16	0	0	0	0	0	0	0	0
R	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	1	0	2	0	0	1	0
S	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	3	0	0	0	0	16	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	0	0	0	0	0	0	1	12	0	0	0	0	0
U	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	13	1	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	0	0	0	0	0	0	0	13	0	0	0
W	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	0	0	0	0	14	0	0
X	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	13	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	0	0	0	0	0	0	0	9

Table 2. Performance Matrix for Cross Validation (CV)/Testing data set using MLP Neural Network

Sign	1	3	4	5	7	8	9	10	A	B	C	D	E	F	G	H	I	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y
% Correct Classification	100	100	100	86.67	93.75	85.71	66.67	100	100	90.91	85.71	81.82	92.86	88.89	95.24	100	94.44	81.82	100	72.73	66.67	100	100	100	90.91	76.19	92.31	81.25	92.86	100	72.22	90

IV. RESULT

We have obtained maximum Average classification accuracy as 90 % on Cross Validation data with the optimal parameter setting as explained earlier using MLP Neural network as shown in Table 3. While comparing our result with other researcher Giulio Marin et al. [16] had received 80.86% overall accuracy for 10 signs by using leap motion sensor. it can be observed from confusion matrix shown in Table 1 that few signs like M, N, S, X has lot of similarity in posture so the result for these signs are not much satisfactory. Similarly posture of sign F and 9 is much similar so these signs pull down the overall classification accuracy as shown in Table 2. We have not considered dynamic signs like J, Z. However static signs 2 & 6 are also not considered because of exactly similar posture like V and W respectively.

Table 3: Performance measure of different classifiers

Sr. No.	Classifier	% Average Classification Accuracy	
		Training	CV
1	MLP	92.66%	90
2	GFF	92.28	89.27
3	SVM	99.57	87.37

V. CONCLUSION

To solve the problem of similarity in posture, more features can be consider like angle between two fingers and considering third finger as a reference or distance ratio of finger with respect to another finger. However same or other classifiers can be tested with distinct features.

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