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# Recognition of an Emotion using Independent Component Analysis of Leg Posture of a Human

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***Abstract: This paper explores recognition of hidden emotion of a human being expressed by the leg postures generated knowingly or unknowingly with respect to particular emotion. It is a non-verbal reflection of emotion by leg postures, formulated during various positions of legs during Sitting, Standing and Walking. To recognise an emotion based on leg posture, an image or a sequence of images of leg postures are normalized by different mathematical tools, then the Independent Components (ICs) of these normalized images are analysed are known as eigen features. Neural Network (NN), with Multi-Layer Feed Forward and Back Propagation Algorithm classifies this features against the seven basic emotions Neutral, Happy, Sad, Fear, Anger, Disgust and Surprise. The accuracy level of both Training and Testing processes along with error part is also measured.***
***Keywords*: Emotion, Leg Posture, ICA, Neural Network, Multi-Layer Feed Forward, Back Propagation.**

## I. INTRODUCTION

In a non-verbal communication whole body is remained interactive with its upper, middle and lower parts. In this paper, the lower expressive part of human body i.e. various posture of legs are considered. Legs provide balance to whole body so that it is widely used in the formation of posture in all situations [1]. The whole structure of human body and different shapes are dependent on the position of legs [2]. The different positions of legs support the creation of postures and also the variation in legs positions vary the interpretation of emotion. According to the variation of the position of the legs the Leg Language can be classified in three different categories, Leg-Sitting positions [LSI], Leg-Standing Positions [LST] and Leg-Walking Positions[LW] [3], [4]. The behaviour or the manners of a person is displayed in his sitting position. Whether you are crossing your legs, they are folded or remains to be straight, how much distance between two legs you maintained during sitting positions, many more positions of legs have their own emotion pattern accordingly they are positioned during sitting [3],[4]. Also, during communication with someone or facing any situation we take our position by standing posture. The positions taken by legs always have variation, whether they are straight or band, how much distance between two legs, they are overlapped or not, indicates many emotional status of a human being [6]. It is observed by psychologist that thought process becomes faster when a person walks even, new idea, feelings are generated a lot during walking that, directly change your walking pattern [4],[5]. Thus the different patterns of walk viz. jumping and leaping, dragging and tramping feet etc. are generated by hidden emotions [1], [3], [4]. Thus the successful analysis of these leg posture leads to become communication more successful

## II. INDEPENDENT COMPONENT ANALYSIS OF LEG POSTURE BASED MATHEMATICAL SYSTEM

The Independent Component Analysis of Leg Postures based Mathematical System architecture is shown in Fig. 1 where, the input image or sequence of images (Video) of leg posture related to an emotion is analysed in three different phases. (i) Image Normalization (ii) Feature (ICs) Extraction and (iii) Classification (by NN) and finally the entered leg posture is classified into basic seven emotions as mentioned above.

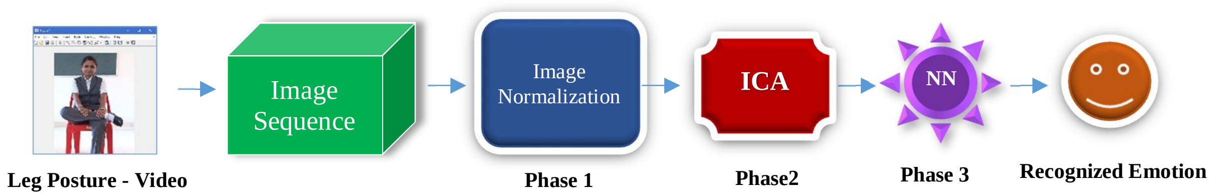


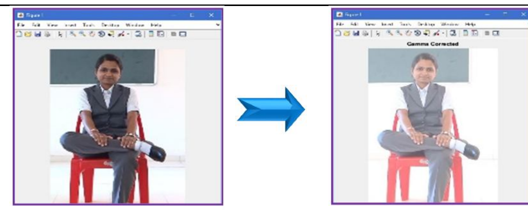
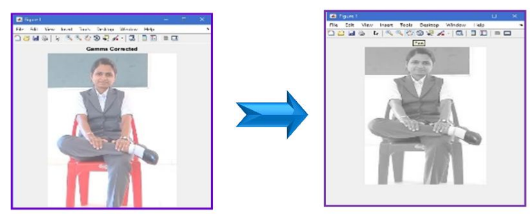
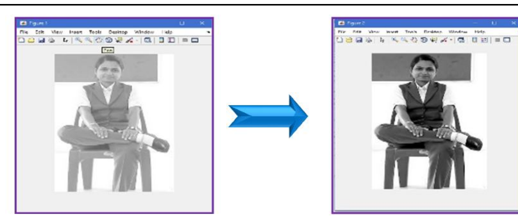
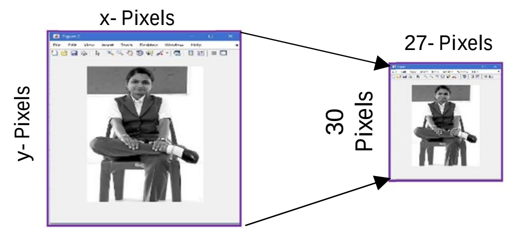

Fig. 1 Independent Component Analysis of Leg Posture based Mathematical System

In beginning of analysis process, a video of leg posture is converted into the sequence of image frames. Out of which some images have same appearance and some are significantly variant. We will consider only those leg posture images that are significantly differ from each other because these will give us a variety of expression for the same emotion. Thereafter, remaining phases of system will be performed as follows.

### *A. Phase-1: Image Normalization [9]*

In the classification of leg posture image into a class of emotion is mainly depended upon the quality of features obtained from the inputs. Thus, to improve the quality of ICs it is necessary to normalise the input images prior feature extraction. Normalisation of an input image means, Balance the light and darkness, Improve sharpness, Adjustment of Contrast, Dimension reduction of image pixel, fixing the Image dimension etc. For that, some Mathematical tools are used, which are described in Table I.

TABLE I
IMAGE NORMALIZATION

| Normalization | Mathematical Tool | Transformation Result |
|---|---|---|
| Balance darkness & lightness to improve the visibility | Gamma Correction:<br>$X_{New} = X^{Gamma}$ , Gamma = $(I_{out})/(I_{in})$,<br>$I_{in}$ = Image input and $I_{out}$ = Image output.<br>Gamma ∊ [0.0, 10.0], Where, 0.0 indicates lightness and 10.0 indicates darkness | <br>Original Image Gamma Corrected Image |
| Dimension reduction of image pixel to make classification faster | RGB to Gray Conversion:<br>ICs is irrespective to colour pixel such that,<br>$I_{(Gray)}$ = **0.2989 * R + 0.5870 * G + 0.01140 * B**<br>Pixel value ∈[0, 255] as per the intensity of gray value | <br>Gamma Corrected RGB Image Gray Image |
| Contrast Enhancement to differentiate variation in intensity of image pixel | Histogram Equalization:<br>$p(r_k) = \frac{h(r_k)}{n} = \frac{n_k}{n}$,<br>Where $r_k$ is the $k^{th}$ intensity level in the interval [0, G] and $n_k$ is the number of pixels in the image whose intensity level is $r_k$ and G = 255. | <br>Gray Image Histogram Equalized Gray Image |
| Image Dimension Reduction | Image Resizing:<br>A moderate size should be chosen that does not affect the recognition process.<br>For instance, [x, y] = [27, 30] is taken. | <br>Histogram Equalized Gray Image Resized Normal Image |

Now, the normalized image is ready for Phase – 2 to extract ICs features of leg posture images for further classification.

### *B. Phase - 2: Feature Extraction - ICA [7], [8]*

Many algorithms are available to perform ICA, here info-max algorithm by Bell and Sejnowski [10] is applied that was derived from the principle of optimal information transfer in neurons with sigmoidal transfer functions.

Let, the distribution of inputs is represented by $X$, an $n$-dimensional vector and Let $W$ is an $n \times n$ invertible matrix such that $U = W\,X$ and $Y = f(U)$ an $n$-dimensional variable representing the outputs neurons. If $f_1, f_2, f_3 \dots f_n$ are the components of function $f$ , is mapping real numbers into $[0, 1]$. Typically, the logistic function is used.

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$$f_i(u) = \frac{1}{1+e^{-u}} \quad (1)$$

Here, $U_1, U_2 \ldots . U_n$ are linear combinations of inputs, interpreted as presynaptic activations of $n$ neurons and $Y_1, Y_2 \ldots . Y_n$ are interpreted as postsynaptic activation rates, bounded by the interval $[0, 1]$.
The gradient update rule for the weight matrix W, in order to maximize the information between input $X$ and output $Y$ of NN is as follows.

$$\Delta W \propto \nabla W\ H(Y) = (W^T)^{-1} + E(Y'X^T) \quad (2)$$

where, $Yi' = fi''(Ui)/ fi'(Ui)$, E is an expected value, H(Y) is the entropy of $Y$, and $\nabla W\ H(Y)$ is the gradient of the entropy in matrix form, i.e., the cell in row i , column j of this matrix is the derivative of $H(Y)$ with respect to $W_{ij}$ .
Matrix inverse can be avoided by employing the natural gradient [14], and multiplying the absolute gradient by $W^T W$.

$$\Delta W \propto \nabla W\ H(Y) W^T W = (I + Y'U^T)W \quad (3)$$

Where, $I$ is the identity matrix. The logistic transfer function eq. (3) gives, $Y_i' = (1 - 2Y_i)$.
Now, to speedup algorithm sphering can be apply before learning, in which row means of $X$ are subtracted from each row, and then $X$ is passed through the whitening matrix $W_z$, which is twice the inverse square root of the covariance matrix.

$$W_z = 2 * (Cov(X))^{-(1/2)} \quad (4)$$

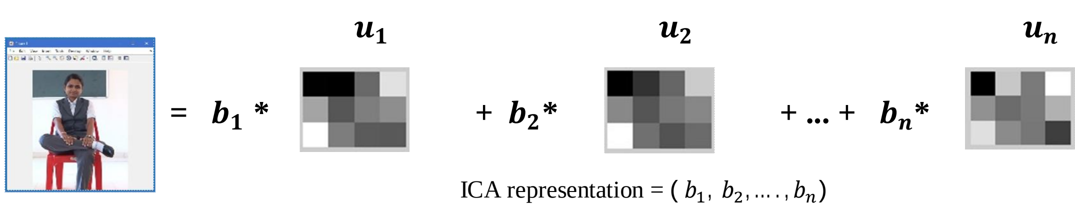
It will remove the first and the second-order statistics of the data by setting both mean and covariance to zero such that variances are equalized. Thus, in ICA the transform matrix $W_I$ is obtained by multiplying sphering matrix and the matrix learned by ICA.

$$W_I = WW_z \quad (5)$$

Also MacKay [7] and Pearlmutter [13] showed that the ICA algorithm converges to the maximum likelihood estimate of $W^{-1}$ for the following generative model of the data:

$$X = W^{-1}S \quad (6)$$

where $S = (S_1, \ldots, S_n)'$ is a vector of independent random variables, called the sources, with cumulative distributions equal to $f_i$ .
Thus, $W^{-1}$ is the source mixing matrix and the $U = WX$ variables can be interpreted as the maximum likelihood (ML) estimates of the sources that generates the data. The source images estimated by the rows of $U$ are used as basis images to represent Leg Posture and set of $b_i$ is the coefficients of linear combination of independent basis images $u_i$ of matrix $U$ can be seen in Fig. 2.




ICA representation = ( $b_1, b_2, \ldots, b_n$)

Fig. 2 The Independent Basis Image

Fig. 2 shows the Independent Basis Image Consisted of $b$ for the Linear Combination of Independent Basis Images $u$ that comprised each Leg Posture. ICs are corresponding with dimension of input images, thus in place of applying ICA on $n_r$ original images we will consider a set of m linear combinations of those images, where $m < n_r$ with assumption that the images in $X$ are a linear combination of a set of unknown statistically independent sources. To perform ICA, a linear combinations first m Principle Components (PCs) [15] of the image set have been chosen.
Let, $P_m$ denote the matrix having the first $m$ PCs in its columns and by performing ICA on ${P_m}^T$, a matrix of m independent source images in the rows of matrix U is obtained. Also, the coefficients $B = b_i$ can be determined by following procedure.
The PC representation of the set of zero-mean images in $X$ based on $P_m$ is defined as $R_m = XP_m$.
A minimum squared error approximation of $X$ is obtained by $\hat{X} = R_m {P_m}^T$.
The ICA algorithm produced a matrix $W_I = WW_z$, such that $W_I {P_m}^T = U$ , where $W$ is weighted matrix.

$${P_m}^T = {W_I}^{-1} U \quad (7)$$

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Therefore, $\hat{X} = R_m {P_m}^T$ becomes

$$\hat{X} = R_m {W_I}^{-1} U \quad (8)$$

Hence, $R_m {W_I}^{-1}$ the rows which contains the coefficients for the linear combination of statistically independent sources U that comprised $\hat{X}$ . The IC representation of the expression images based on the set of m statistically independent feature images, U was therefore given by the rows of the matrix

$$B = R_m {W_I}^{-1} \quad (9)$$

Similarly, The ICA representation for test images is obtained by using the PCs based on the training images,
$R_{test} = X_{test} P_m$ such that

$$B_{test} = R_{test} {W_I}^{-1} \quad (10)$$

Where, 'test' indicates the value of variable for test images.
The ICA based feature vectors of leg posture images can be seen in Fig. 3.

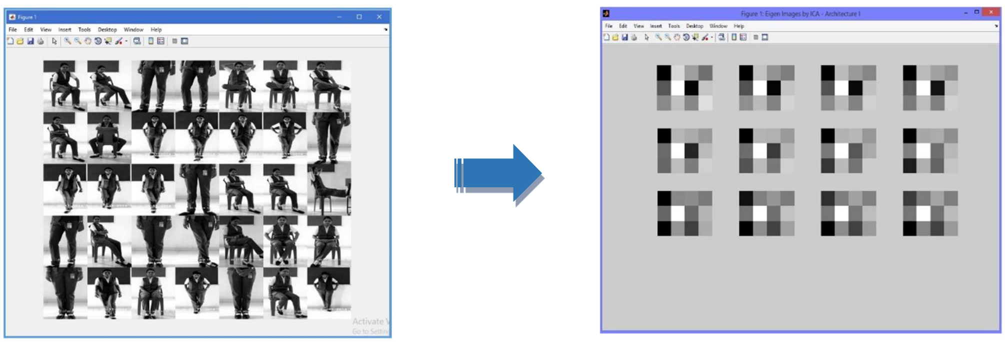

Fig. 3 Eigen Images by Independent Component Analysis

*C. Phase – 3: Classification [11], [12]*

The obtained ICA based eigen images of leg posture related to the emotion is classified by Neural Network using Multi-Layer Multilayer Perceptron (MLP) imply feed-forward networks and Back- propagation algorithm. MLP is one of the most popular neural network models widely used in classification because it has an ability to learn complex nature of pattern. Also, sigmoid function is very much ideal to train MLP shown in Fig. 4.

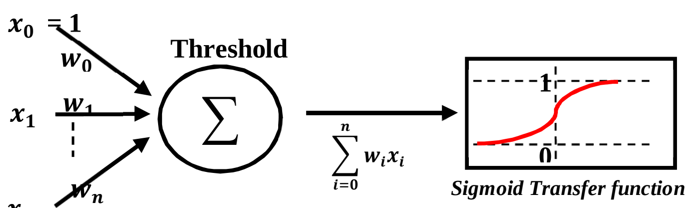


Fig. 4 Sigmoid Function for MLPs

When referring to MLPs, we imply feed-forward networks and Back-propagation algorithm. While inputs are fed to the NN forwardly, the 'Back' in Back-propagation algorithm refers to the direction to which the error is transmitted.

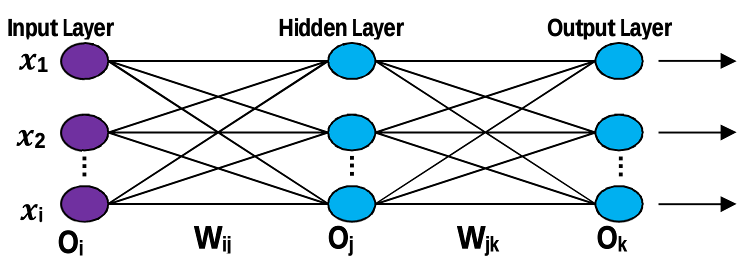


Fig. 5 Fully Connected, Feed-Forward MLP Network

Multilayer Perceptron with fully connected feed forward NN has three layers input, hidden and output. The input leg postures image set X = $x_1, x_2, \ldots, x_i$ is sent to input layer as input nodes and the classes of basic $k$ emotions are set to output layers as output nodes. While, $i$ input nodes are connected with $k$ output nodes with $j$ hidden layers. The $W_{ij}$ indicates the weighted connection of nodes form a unit $j$ in one layer to a unit $i$ in the previous layer. Here, output layer is trained to respond +1 for matching and 0 for others. But, in real practice outputs are vary between 0 and +1.

The NN algorithm can be converted to the standard gradient descent version of BACKPROPAGATION if the gradient becomes:

$\delta_k = \sum_{pattern}^{n} O_{n.k}(1 - O_{n.k})(t_{n.k} - O_{n.k})$, $n$ is the number of training patterns, $k$ is the number of output unit. (11)

TABLE II

BACKPROPAGATION ALGORITHM [12]

- ✓ Initialization network weights
- ✓ Until the termination**:**

{For each training example:

{Propagate the input forward to the network and compute the observed outputs.

Propagate the errors backward as: For each network output unit k calculate its error term $\delta_k = O_k(1 - O_k)(t_k - O_k)$

For each hidden unit calculate its error term $\delta_h = o_h(1 - o_h) \sum_{outputs}^{k} W_{kh}\delta_k$

Finally, update each weight $w_{ji} = w_{ji} + \Delta w_{ji}$ ,

Where $\Delta w_{ji} = -\eta.\delta_j x_{ji}$ }

} (Here, '$ji$' means from unit '$i$' to '$j$')

To train NN, some of the parameters on which NN is based on, must be set in prior, described as follows

TABLE III

NEURAL NETWORK PARAMETER [11], [12]

| NN Parameters | Description |
|---|---|
| Error Surface | The standard gradient descent error of Backpropagation is Sum of square of error; $E(\overline{w}) = \sum_{n\ pattern} \sum_{k\ outputs} (t_{n,k} - o_{n,k})^2$ Where, E is a function of the network's weight vector, t is targeted value and o is an output value. |
| Size of Hidden Layer | Usually, for pattern recognition one hidden layer is sufficient for classification. |
| Number of Neurons at hidden Layer | It is to be decided based on trial and error, also it is dependent on the values of other parameter, still an issue of research. |
| Learning rate | In backpropagation algorithm the weight is updated with rule $\Delta w_{ji} = -\eta.\delta_j x_{ji}$ High learning rate oscillates the algorithm and too small learning rate takes too long convergence. Thus, it is to be set by experiencing the training algorithm. |
| Momentum Term | By adding this term to the formula of the final step in Table II, the update rule will be: $\Delta W_{ji} = \eta\delta_j x_{ji} + \alpha\Delta W_{ji}(n-1)$. Therefore, the update in iteration is affected by the update in $n^{th}$ iteration multiplied by a factor 'α', called momentum. It helps to make convergence faster. |
| Input Standardization and Weights Initialization | In the MLP set the weight 0 at hidden layer nodes and random at output layer nodes which gives better appearance of leg posture than the other settings. |
| Training Stopping Criteria | It may be Fixed number of iterations (Epochs) to be performed, Use particular threshold for error, Use threshold for error gradient, Early stopping with validation error. |

## III.EXPERIMENTAL RESULTS

In the recognition of an emotion based on leg posture generated with respect to seven basic emotions of an individual, the ICs are used as eigen images to be classified by Neural Network, various leg postures of 10 individual persons are taken into the consideration. The leg postures related to an emotion are generated by during sitting positions, standing positions and walking positions by a human being. All these posture images are stored in the database with seven basic classes of the emotions Neutral, Happy, Anger, Sad, Disgust, Fear and Surprise. It is further classified as a training set and a testing set of expressions. Before train

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the Independent Component Analysis of Leg Postures based Mathematical System for training and testing-set, the basic parameters for NN have to set. Thus, the optimum topology of NN to classify an emotion based of leg posture is decided in Table IV.

TABLE IV
OPTIMUM TOPOLOGY OF NEURAL NETWORK FOR LEG POSTURE – SINGLE EMOTION

| Parameter | Expression |
|---|---|
| Data set | Leg Posture blocks 27 x 30 pixels |
| Training set | 94% |
| Test set | 6 % |
| Validation set | 0% |
| Input Standardization | ICA40 |
| Weight Initialization | Hidden Layer = 0 , Output Layer = random |
| Training Algorithm | Gradient Descent with Momentum |
| Transfer Function | Both layer use log-sigmoid |
| Neurons in Hidden Layer | 22 neurons |
| Learning rate | 1.2 |
| Momentum term | 0.6 |
| Minimum training MSE | 0.037009 |
| Maximum Epochs | 1600 |

With the consideration of above topology the performance output of the proposed system in MATLAB [16] is seen in Fig. 6.

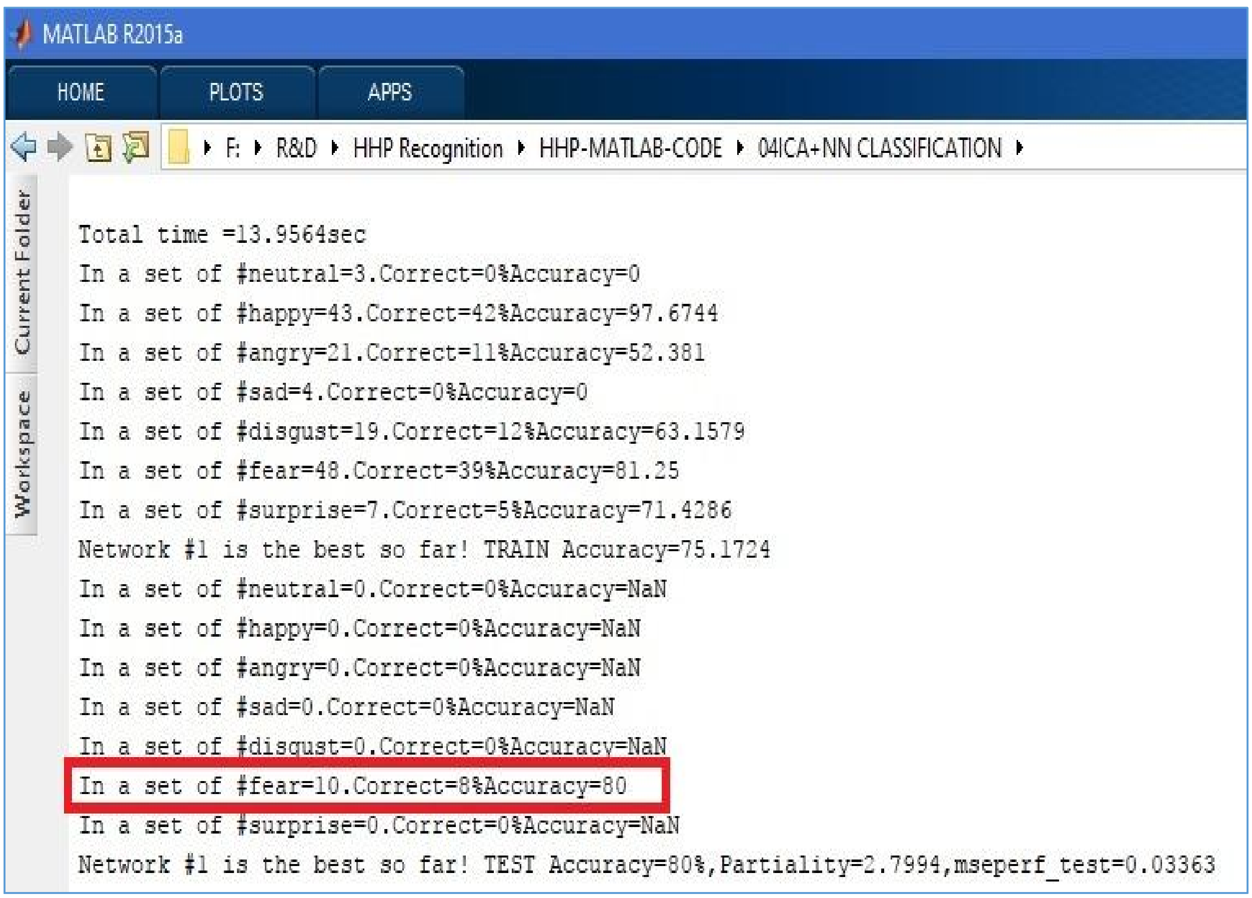

Fig. 6 MATLAB Output for the Emotion Fear of Subject 1

The Neural Network System architecture for the classification of the emotion can be seen in Fig. 7.

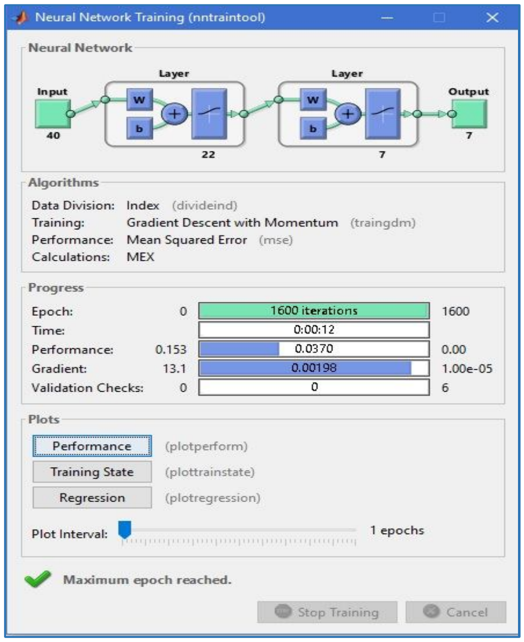


Fig. 7 Neural Network Architecture

The system architecture of NN shows that there are 40 input eigenvectors rather ICs are as input with setting of 22 neurons at hidden layer they are classified over 7 outputs (emotions). Also it shows the number of epochs performed, time taken, performance error and Gradient error as well.

The MATLAB output for the subject 1 for a single emotion "Fear" is summarized into following table.

TABLE V
MATLAB OUTPUT SUMMARY OF SUBJECT 1 FOR AN EMOTION FEAR

| Subject 1 | Emotion | Neurons in hidden layer | Eigen Images Taken | No. of Iteration (Epoch) | Train Accuracy | Train MSE | Test Accuracy | Test MSE |
|---|---|---|---|---|---|---|---|---|
|  | Fear | 22 | 40 | 1600 | 75% | 0.03701 | 80% | 0.03363 |

Similarly, the classification of all other emotions for subject 1 is tabulated as follows.

TABLE VI
MATLAB OUTPUT SUMMARY OF SUBJECT 1 FOR ALL BASIC SEVEN EMOTIONS

| Subject 1 | Emotion | Neurons in hidden layer | Eigen Images Taken | No. of Iteration (Epoch) | Train Accuracy | Train MSE | Test Accuracy | Test MSE |
|---|---|---|---|---|---|---|---|---|
|  | Neutral | 26 | 40 | 1600 | 76.3% | 0.03525 | 92.3% | 0.02568 |
| | Happy | 26 | 40 | 1600 | 78.9% | 0.03142 | 86.4% | 0.02942 |
| | Anger | 26 | 40 | 1600 | 72.0% | 0.03923 | 90.5% | 0.02763 |
| | Sad | 26 | 40 | 1600 | 84.3% | 0.02613 | 86.4% | 0.02942 |
| | Disgust | 26 | 40 | 1600 | 81.3% | 0.29264 | 85.3% | 0.30321 |
| | Fear | 26 | 40 | 1600 | 75.0% | 0.03701 | 80.0% | 0.03363 |
| | Surprise | 26 | 40 | 1600 | 83.3% | 0.02646 | 92.4% | 0.02532 |

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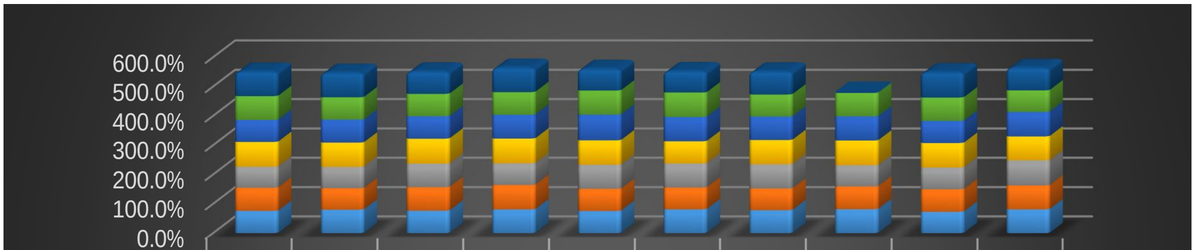
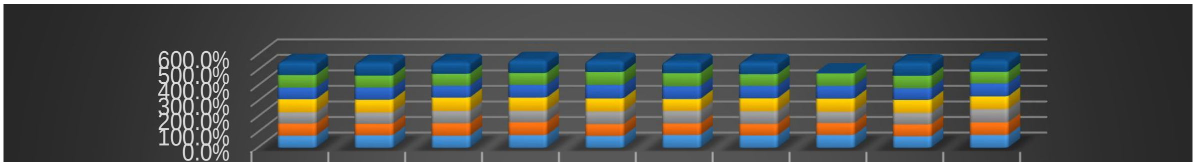
Similarly, the MATLAB output results of all 10 individuals for individual emotion over respective emotions are displayed graphically as follows.




| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Surprise | 83.3% | 83.4% | 75.9% | 82.6% | 73.3% | 72.5% | 78.0% | 0.0% | 86.2% | 76.3% |
| Disgust | 81.3% | 76.2% | 76.5% | 77.3% | 82.4% | 83.3% | 75.3% | 80.0% | 79.8% | 73.5% |
| Fear | 75.0% | 78.3% | 76.3% | 81.3% | 87.5% | 83.2% | 80.0% | 82.5% | 75.2% | 83.5% |
| Sad | 84.3% | 82.3% | 85.3% | 84.3% | 83.2% | 75.6% | 82.6% | 84.2% | 83.2% | 81.6% |
| Anger | 72.0% | 73.2% | 80.1% | 74.0% | 82.5% | 82.1% | 83.1% | 72.4% | 74.7% | 85.9% |
| Happy | 78.9% | 73.2% | 80.2% | 83.2% | 75.2% | 74.2% | 73.6% | 77.3% | 76.5% | 81.3% |
| Neutral | 76.3% | 80.3% | 76.9% | 81.2% | 76.0% | 81.6% | 78.8% | 82.1% | 73.3% | 81.6% |

Fig. 8 Percentage Train Accuracy ICA + NN Leg Posture

The experimental result shown in Fig. 8 indicates that the overall accuracy of training set is around 75%, which is better and has scope of improvement by updating more precise leg posture images of respective Emotions in training set.




| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Surprise | 83.3% | 83.4% | 75.9% | 82.6% | 73.3% | 72.5% | 78.0% | 0.0% | 86.2% | 76.3% |
| Disgust | 81.3% | 76.2% | 76.5% | 77.3% | 82.4% | 83.3% | 75.3% | 80.0% | 79.8% | 73.5% |
| Fear | 75.0% | 78.3% | 76.3% | 81.3% | 87.5% | 83.2% | 80.0% | 82.5% | 75.2% | 83.5% |
| Sad | 84.3% | 82.3% | 85.3% | 84.3% | 83.2% | 75.6% | 82.6% | 84.2% | 83.2% | 81.6% |
| Anger | 72.0% | 73.2% | 80.1% | 74.0% | 82.5% | 82.1% | 83.1% | 72.4% | 74.7% | 85.9% |
| Happy | 78.9% | 73.2% | 80.2% | 83.2% | 75.2% | 74.2% | 73.6% | 77.3% | 76.5% | 81.3% |
| Neutral | 76.3% | 80.3% | 76.9% | 81.2% | 76.0% | 81.6% | 78.8% | 82.1% | 73.3% | 81.6% |

Fig. 9 Percentage Test Accuracy ICA + NN Leg Posture

The results in Fig. 9 shows the test accuracy level of testing set of images of leg gesture with respect to emotion. It is around 85%, which is good, it is because of well-defined environment, in real phenomena it can be vary. But, still the variation can be overcome by taking only the posture of legs or body, the background and other portions can be avoided and the desired accuracy can be achieved.

## IV. CONCLUSION

The results of classification of an emotion for an individual human shows that, the combination of ICA as a feature extractor and Neural Network as a classifier has achieved the satisfactory accuracy of both training and testing set. Also, it should be remembered that this classification is vary from person to person and more precise expression of leg postures can have better result. Also, if it is timely updated for an individual then, the more accurate prediction can be obtained. This recognition of emotion through leg gesture of a human improves the understating level of human nature, which is an essence to deal with human during any kind of communication.

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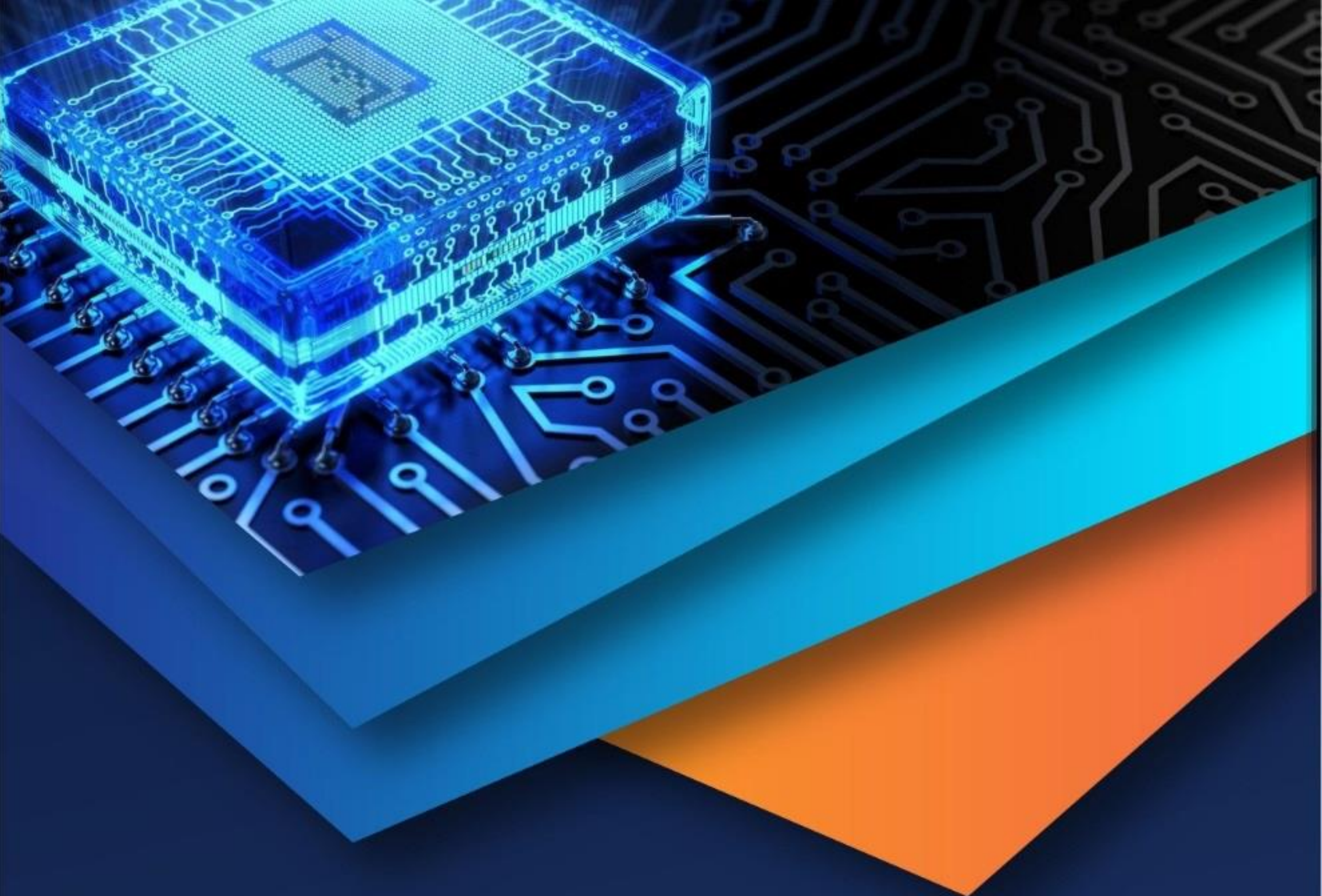

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