EMOTION CLASSIFICATION OF FACIAL ELECTROMYOGRAM SIGNALS BASED ON NEURAL NETWORKS

Charlyn Pushpa Latha. G[1], Mohana Priya[2]

Abstract

Signal processing using statistical methods is a remarkable area in the field of practical applications in Mathematics to investigate and mine the most essential facts from the signals. It removes the unwanted noise, deals with their statistical properties like standard deviation, covariance, median, average etc. Being a versatile feature extraction method, it is also used in different areas such as natural language processing, bio signal processing, sonar. In this work, we have examined the facial electromyography signals (FEMG) by applying the statistical features in order to extract the necessary features for categorizing the six emotional conditions namely happy fear, neutral, sad, disgust and anger. 20 subjects took part in this FEMG study. The statistical features namely kurtosis, skewness, moment, range, median absolute deviation and mean were used in this work to draw the features. In order to classify the emotive conditions, the four neural network models namely Cascade Neural Network model, Elman Neural Network model, Layered Recurrent Neural Network model and Feed Forward Neural Network model were modelled accordingly. Outcomes of this work indicate the highest classification accuracies of 94.5%, 87.56%, 97.58% and 98.33% to categorize these emotional conditions.

Key Words: Electromyography, Statistical Feature Extraction,, Elman Neural Network model, Feed Forward Neural Network model, Cascade Neural Network model, Layered Recurrent Neural Network model, Facial Electromyography

I. Introduction

Emotions are intensely innate and discrete to a specific event or condition. The emotional experience varies from person to person even in same situations at variable instances of time Emotional collaboration is the foremost quantity dealing with social communications in persons, and it explicitly rests on facial muscle movements. It has also been defined as a critical state that lasts for a comparatively minimum span of period relating to a specific occurrence [1]. Studies on emotion have improved considerably over years with various arenas subsidizing to different fields comprising, medicine, history, neuroscience, endocrinology sociology etc. Relating with functioning, emotions are principally termed as arguments in a bi-coordinates emotional area comprising emotional arousal factor and valence factor. Valence factor symbolizes global loveliness of emotional capabilities fluctuating between negative to positive, whereas arousal factor denotes emotional strength, oscillating between calm emotion and

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excited emotion.[2-3]. Various possibilities have been discovered by the investigators to endow emotional skill in computers in the areas of human to computer interaction (HCI). Hence an emotion recognition system could be entailed in the existing environment which is trustworthy, perfect, simple and pliable in nature.

Nonverbally discrete emotions is being depicted by the human facial model which is an interesting feature recently. The fundamental emotional intellectual factor is the capability of the intensive analysis of expressions on the face. Inorder to detect the facial emotions accurately, scientists are aiming on Facial Electromyogram signals (FEMG) signals [4]. Facial expressions are comparatively efficient on comparing with other nonverbal frequencies of communications like that of unwritten variations and body postures. Facial expressions seem to be highly inspiring sensations focussed to sentient control [5]. Facial lexes and speech systems based emotion recognition were also described in the former studies [6]. A Coding System based on facial muscle reactions centered on distinct emotional conditions and hypothetical perception are modelled by Ekman and Friesen which aimed at rating the explicit facial muscle movements [7-8].

Professionals around the world have been renowned for developing several techniques related to sensors such as Electroencephalogram, Heart Rate, Skin Conductance, Respiration Rate, and EMG signals [9]. EMG shows a chief part in identifying the emotional reactions from the face when compared to all other physiological signals. Six different emotional conditions namely happy, anger, fear, disgust, sad and neutral were used in this work. The emotional data was obtained in a well-equipped location by the auditory – pictorial stimuli. The emotional features could be derived from the FEMG signals by way of the statistical parameters namely median absolute deviation value, mean value, range value, skewness value, moment value , and kurtosis parameters were used. The statistical features could be applied to the following four neural networks namely Cascade Neural Network model, Feed forward Neural Network model, Elman Neural Network model and Layered Recurrent Neural Network model. These models segregate these six emotional conditions from the obtained statistical features. This work is planned as below. Some of the current related methods for supporting the work is illustrated in Part II. Part III examines some of the. FEMG data collection techniques, pre-processing methods and feature extraction technique. Part IV demonstrates the experimental outcomes. The arguments on the methods with the certain inferences obtained are illustrated at the end of this work.

II. Previous work

Emotions are highestly independent and explicit to an individual occurrence or state. Similar individual may not experience similar emotional strength to similar conditions at various phases. This segment defines certain related methodologies which used FEMG signals for identifying the emotional conditions. G. Rigas et al [10] used the classification algorithms namely Random Forest classifiers and K – Nearest Neighbour (K-NN) for happiness, disgust and fear emotional factors . They have designed an emotion recognition system by obtaining a recognition rate of 48%, 68% and 69% for the three emotional states happy, disgust emotion and fear consecutively. Wee Ming Wong et al [11] went on with the emotional features sad, angry pleasure and joy. He derived the highest recognition rate of 89.25% with Particle Swarm Optimization of synergetic neural classifier Shanxiao Yang et al [12] derived 62.5% and 91.67% recognition rate for the emotions happiness and disgust after comparing Support Vector Machine (SVM) and standard Backpropogation (BP) neural network classifier .

Hamedi. M et al [13], took the emotional conditions namely rest, smile, frown, rage, and pulling up eyebrows. He attained an highest recognition rate of 90.8% after examining with Fuzzy C-Means Classifier. He also developed a technique for distinguishing 5 separate facial muscle movements Principal Component Analysis and higher order statistics were adopted by Jerritta et al [14] to design a technique for categorizing the emotional states from facial EMG signals In addition to that, they also acquired the classification rate of 69.5% after using the K-nearest neighbour (KNN) classifier in order to detect the emotional conditions of the FEMG signals. The scientists Jonghwa. K and Ande .E [15], identified the 4 emotional conditions namely anger, sad, pleasure and joy and achieved 95% and 70%, the improved average recognition rate using extended LDA classifier.

III. FEMG Data Acquisition and Methodology

a) FEMG Signal Acquisition

Depressor Anguli Oris muscle

Emotional factors can be prompted either through (a) visual [16] or by (b) audio-visual [17] or by (c) remembering former emotional incidents [18] and (d) only audio clips [19]. This work in particular goes ahead with the audio - visual method for inducing the facial emotions. FEMG data are chronicled with the help of an ADI Bio signal Amplifier.

In order to avoid any motion artifacts, the face of the participants should be cleaned properly. 5 electrodes which are coated in gold are positioned on the facial muscle locations such as Depressor Anguli Oris muscle, Corrugator Supercilli muscle, Levator muscle Labii Superioris muscle, Orbicularis Oris muscle and at the reference point. The facial muscles from which the activity of the FEMG signals [20] are recorded are as follows:

- Corrugator Supercilli muscle is chosen which shakes the eyebrow to the middle end and down.
- Levator Labii Superioris muscle shrinks the nose, enlarges nasal divisions and uplifts the upper lip.
- Orbicularis Oris muscle restricts the skin around the eye.
- Depressor Anguli Oris muscle has the control over the size and shape of the mouth openings.

At the edge of the hairline, a reference electrode is positioned as in Fig. 1. The sampling frequency of the FEMG signals is set as 200Hz. These works used the audio -visual clippings from the movies modelled by Tomarken et al.[21]. 11 males and 9 females by age ranging from 21-25 years agreed to be the participants for the experimental testing. For the six emotions namely happy, anger, disgust, fear, sad and neutral the FEMG signals are noted. Each and every FEMG recording persists for five seconds with ten trials each. The FEMG signal is documented in two slots. For a single time slot, five trials are logged. Hence for two slots, ten trials are noted. 10 minutes halt is given to the subjects in-between the slots. The halt among the slots makes the participant to relax at the time of the testing and counterbalance any reaction from the past emotion provocations. The experimentation is reiterated for all the six emotional conditions. Before the initiation of the experimentation, the participants were asked to maintain a free mind and focus on the audio-video clippings so as to attain best FEMG data. Neural Networks are modelled to analyse the classification rates of the FEMG signals.

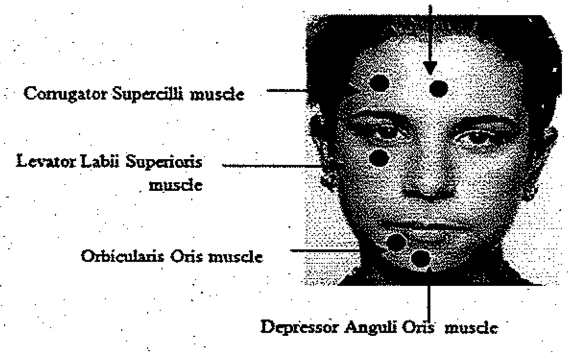

Figure 1 Positions of Electrodes in FEMG

b) Initial FEMG data Cleaning and Mining using Statistical Features

The initial facial data have noises that arise due to power line intrusion. Hence they are primarily treated using a notch filter. Using chebyshev filter, the FEMG signals are band pass filtered to generate the ten frequency groups ranging as following: The groups are split as follows 0.1-1Hz, 1-2Hz, 2-3Hz, 3-4Hz, 4-5Hz, 5-6Hz, 6-7Hz, 7-8Hz, 8-9Hz and 9-10Hz consecutively. The spectral analysis of the signals determine the frequency groups. Fig.2 demonstrates the frequency bands of the obtained FEMG signal. For eg, sad emotion has the frequency range within 10Hz. For efficient pattern recognition or classification, the feature mining is very much essential in any signal handling procedure.

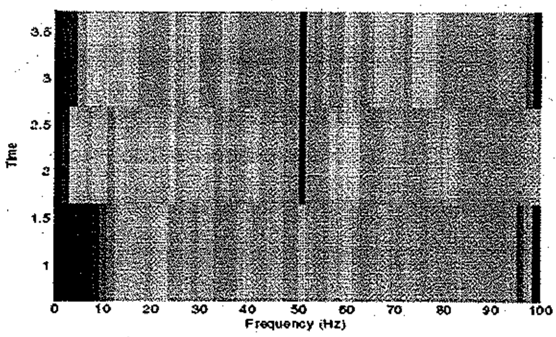

Figure 2 Spectral Analysis of Sad emotion

In this work, bi – channel data is used for signal recording. 120 parameters are derived from a single FEMG signal.6 statistical parameters namely mean value, median absolute deviation value, range value, moment, value, skewness value and kurtosis value of the 10 frequency groups are formed. For all the 6 emotional factors, the testing is iterated. The mathematical formulations of the mined features using statistical methods are explained in Eqns [1] – [10].

Mean Value

This statistical parameter computes the average rate of the FEMG signal [22].

The procedure used for the estimation of mean is :

$$\mu_m = 1/T\sum_{b\approx 1}^{T} Z_b \qquad (1)$$

where, $Z_b, b = 1,2,3...T$ is the initial FEMG data

T denotes size of initial FEMG value.

Median Absolute Deviation Value

This parameter evaluates the mean absolute deviation value of the FEMG data which is the middling value of total variations between every data in signal group along with middling all the data containing in that particular signals group. Extraction of the middling deviancy is done using median value or mean value. The reason why median value is opted is because the summation of group deviancy when observed from median value is the least on ignoring the signs [22].

The formula used for calculation is:

$$\text{Mean Deviation Formula} = \sum \frac{|Z_b - MD|}{T} \qquad (2)$$

where, T indicates size of the initial FEMG value

$Z_b = 1,2,3...T$ is the initial FEMG value

MD indicates the median of the signal

Median value is derived by

$$\text{Median value (MD)} = \left[\frac{b+1}{2}\right]^{th} \text{factor, if signal strength is of odd value} \qquad (3)$$

$$\text{Median (MD)} = \frac{\left[\frac{b}{2}\right]^{th}\text{factor} + \left[\frac{b+1}{2}\right]^{th}\text{factor}}{2} \qquad (4)$$

When the entire signal strength is of even value

Range Value

The variation of the highest and least data of the signal value in the signal collection is referred as the signal range [22].

Formula used for calculation is:

Range Value = Highest signal value – Least signal value (5)

Moment Value

Principal Moment value of order k of a signal [21] is

$$x_k = E(b-\mu)^u \qquad (6)$$

where, $E(b)$ is the estimated value of b which is the dimension of the mid probability function. Mean gives the derived formula value.

b represents the discrete value

μ denotes average value of the signal value

u represents the signal order for individual column

$$E(b) = b_1l_1 + b_2l_2 + b_3l_3 + ..b_nl_b \qquad (7)$$

where, $l_1, l_2, l_3 ... l_b$ represents likelihood signal chances.

$$l_b = \frac{no\ of\ signal\ favourable values}{Net\ values} \quad (8)$$

Skewness Value

The standardized forms of third and fourth term cummulants are Skewness and Kurtosis [22]. The asymmetry degree of a circulation about their average is symbolized by Skewness which describes the distribution shape. It represents also the third central moment of X, divided by the cube of its standard deviation.

The formula for calculation is:

$$\text{Skewness}\,(\upsilon_3^{\wedge}) = \frac{\sum_{b=1}^{T} (Z_b - \mu_m)^3}{(T-1)\sigma^3} \quad (9)$$

where, μ_m is the average

σ_m is the standard deviation of the pre-processed signal Z_b

T represents size of the initial value of the FEMG signal

Kurtosis Value

The degree of comparative immensity of the end of a dissemination in connection to the normal dissemination is referred to as kurtosis. It also represents the fourth central moment of X, divided by fourth power of its standard deviation [22].

The formula used :

$$\text{Kurtosis}(\upsilon_4^{\wedge}) = \sum_{n=1}^{N} \frac{(Z_b - \mu_m)^4}{(T-1)\sigma_m^{\ 4}} - 3 \quad (10)$$

c) Recognition of Facial Electromyogram Signals :

Categorization based on the signal behavior is referred to Classification of signals. FEMG data were collected from 20 participants and the 6 statistical parameters mean value, median absolute deviation value, range value, moment value, skewness value and kurtosis value were derived from the participants. The testing is iterated for 10 trials with an outcome of 120 parameters. 120 derived parameters are fed to the classifier. The 4 neural network models namely FFNN, ENN, CFNN and LRN are modeled with 120 input neuron values, 3 output neuron values and 15 hidden neuron valuese selected by way of experimental verification process. In order to train and test the above networks, 75% of the data values and 100% of the data values are used consecutively. The testing and training error rate is set as 0.05 and 0.0001 respectively.

The 4 network models namely Layered Recurrent Neural Network model (LRN), Cascade Neural Network model (CNN), Feed Forward Neural Network model(FFNN), and Elman Neural Network model (ENN) are adopted to recognize the six emotional conditions from the values of the facial electromyogram signals.

The static, utmost renowned and generally used inspired grouping system is the FFNN classifier [23] which is also a robust and the artificial neural network model developed in the earlier times. Data pass in at the inputs and traverses along the network after each and every layer, and it reaches the outputs. They are named as feed forward neural networks as there is no feedback among the individual layers. FFNN practices a supervised learning technique. It is also known as back propogation neural networks as the variations between the real output values and the ideal output values are broadcasted back from the first layer to next layers which use these values to alter the connection values.

The energetic recurring network model comprising a bi-level back propagation network model is ENN. It is also called as feedback neural networks because it has an extra feedback association starting from the output value of the hidden level up to its input level. It has 4 levels namely input level, output level, hidden level and context level. This network also acts as a finite state machine which studies what condition to recollect. The context layer of the ENN network permits the exchange of the hidden layer values to the input layer.

Cascade forward networks are same as feed-forward networks, except that it comprises a linkage from the input layer to each and every past layers to the consecutive layers. The prime usage of this network is that each and every layer of neurons is related to all past layer of neurons. In order to obtain the enhanced status of the network, the tan-sigmoid transfer function was opted.

Layered recurrent neural networks are alike feed forward networks, apart from the condition that each and every layer has a intermittent linking with a tap interruption connected with it which makes the network to have a boundless active reaction to input data. This network resembles the time delay and the distributed delay neural networks, which have fixed input reactions.

IV Experimental Results

a. Comparison of average Classification Accuracies based on the nature of the proposed neural network models

Four neural network models namely FFNN model, ENN model, LRN model and CFNN model are used for categorizing the FEMG signals. Of these 4 neural network models designed for categorization, ENN Model and LRN models belong to the dynamic and feedback type of the network model while CFNN and FFNN models belong to the static type of neural networks.

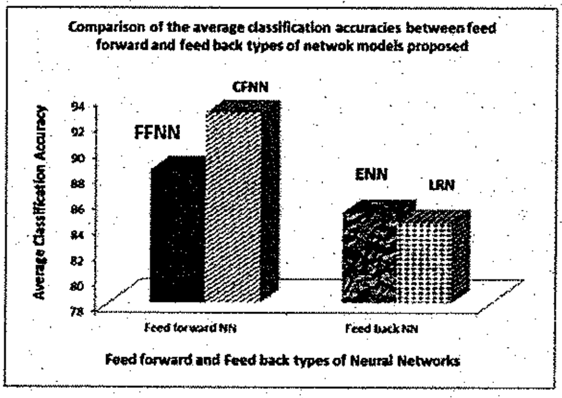

Figure 3. Comparison of average classification accuracies based on the nature of network models

Six emotional conditions namely anger, disgust, fear, happy, neutral and sad are classified with the derived 120 parameters.Fig.3 illustrates the evaluation chart of average classification accuracies of all the 4 proposed network models. Comparing feed forward and feedback neural network models, the average classification accuracy is higher for the feed forward type of neural networks when compared with the feedback neural networks. CFNN network model gives the highest average recognition rate of 92.74% which is a type of feed forward network model. FFNN model achieved an average rate of 88.32%. On the other hand, ENN model derived an average classification rate of 85.01% and LRN has an average accuracy of 84.23%.

b. Comparison of Highest Classification Accuracies based on the nature of the proposed neural network models

The proposed neural network models are LRN model, CFNN model, ENN model and the FFNN model. Fig4 shows the highest classification rates of all the four models. On evaluation, LRN network has the highest accuracy of 98.33%. Next the CFNN network gives the next highest accuracy of 97.58%. Following the 2 networks, FFNN gives the highest rate of 94.5% and ENN a rate of 87.56%. Concluding, recognition rate is highest for LRN model which is a type of the Feedback network model.

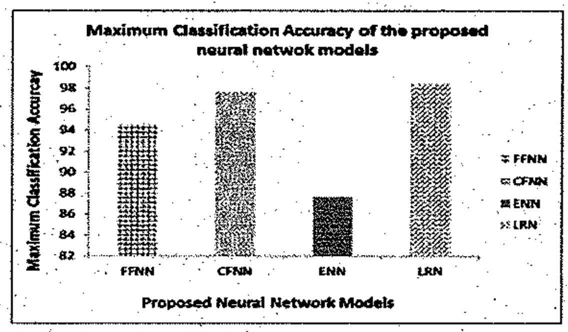

Figure 4. Comparison of highest classification accuracies based on the nature of network models

c. Comparison of classification accuracies of the network models based on the gender

i) FFNN based classification:

Gender plays a major role in classification of human emotional states. Fig5 depicts the gender based classification for FFNN. On considering FFNN, in males, Subject2 gives the highest recognition rate of 90.42% and Subject18 gives the least classification accuracy of 82.54%.

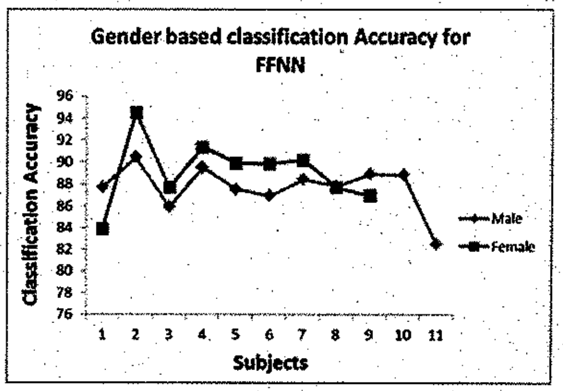

Figure 5. Gender based classification accuracy for FFNN

On the other hand, while comparing with females, Subject4 gives the highest recognition rate of 94.5% while Subject3 gives the lowest classification rate of 83.88%. On the whole, Subject4 is a female which gave the highest classification accuracy rate.

ii) ENN based classification:

Fig6 shows the classification for ENN for gender. For males, the highest classification accuracy is 87.56% for Subject2 and the minimum classification accuracy is 82.33% for Subject8. Considering females, Subject7 gives the highest recognition rate of 87.22% and Subject4 gives the lowest classification accuracy of 81.79%. The overall highest classification accuracy is obtained for Subject2 who is a male.

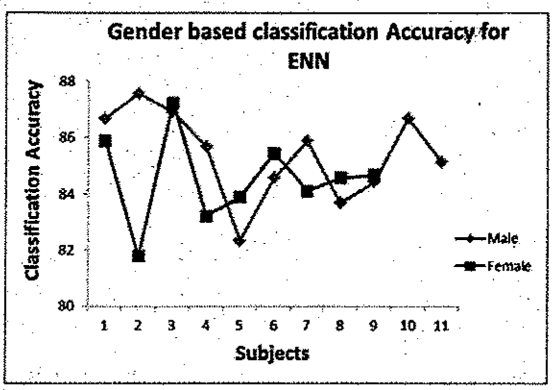

Figure 6. Gender based classification accuracy for ENN

iii) CFNN based classification:

Fig7 describes the gender based classification for CFNN network. While considering males, the highest classification accuracy is obtained for S14 with 97.58% and the lowest classification accuracy is obtained for Subject16 with 89.92%. On considering females, the highest classification accuracy is 97% for Subject17 and lowest classification accuracy is 80.83% for Subject3. The overall highest classification accuracy is 97.58% for Subject14 which is a male subject.

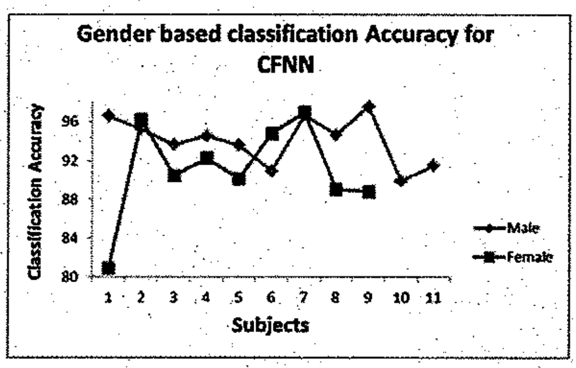

Figure 7. Gender based classification accuracy for CFNN

iv) LRN based classification:

Fig8 describes the gender based classification for LRN network. While considering males, the highest classification accuracy is obtained for S2 with 87.67% and the lowest classification accuracy is obtained for Subject6 with 79.92%. On considering females, the highest classification accuracy is 98.33% for Subject4 and lowest classification accuracy is 82.17% for Subject12. The overall highest classification accuracy is 98.33% for Subject4 which is a female subject.

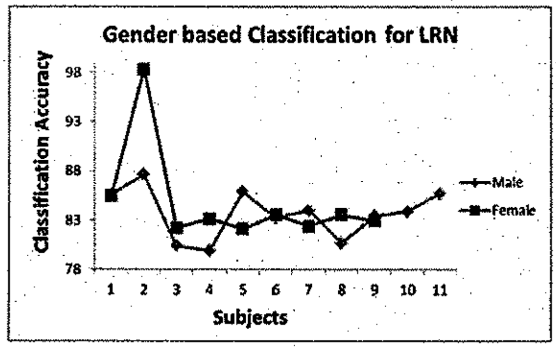

Figure 8. Gender based classification accuracy for LRN

After analysing the results of all the networks, we summarize that Subject4 who is a female subject gives the highest classification accuracy of 98.33% for LRN networks and Subject6 which is a male subject gives the lowest classification accuracy of 79.92% with LRN networks.

c. Comparison of classification accuracies of the network model based on age factor

Table1 illustrates the evaluation of the classification accuracies based on the age factor. On viewing table1,it is found that the highest accuracy of 98.33% is found for Subject4 for the network model LRN with age 18. The lowest accuracy is 79.92% for the Subject6 for the network model LRN with age 23. Comparing group wise classification rate, the participant in the age group of 41-50 achieved the highest average recognition rate of 97% on comparing all the 4 network model. of From the table it is also inferred that higher the age of the subject, the emotional response is higher.

Fig 9 shows the comparison of classification accuracies among age groups of the participants. On inferring Fig9, participant in the age group of 41-50 gives the highest classification accuracy. Subject4 have better reacted to the emotional clippings when matched with the other participants. The main reason for the Subject6 to react worse is primarily due to the findings that the personal behaviour of each and every emotion differ from each and every individual where the strength and the valence of the emotion produced varies.

The main reason for the difference in the emotional response is due to the dissimilar change in emotive reaction of person from period to period and also on the dependency of age factor etc. Also, all humans have diverse emotional reactions for the same incidents and happenings. In order to authenticate the reliability of the proposed methods in categorizing the specific emotional conditions, real time investigations are mandatory. In addition to that extensive study of the parameters had to be necessarily analyzed so as to develop an efficient system.

V. Inferences

Recognizing the individual emotional condition by way of FEMG signals have drawn recent consideration. FEMG analysis may be a well - thought and delicate method for analysing the individual's particular emotional condition. Anyhow, it has drawbacks for some real life claims due to its protrusiveness and the action of the facial muscle movements have an impact by lot of not affecting, negotiating parameters. The work analyzed the statistical parameters method by classifying the six facial emotional reactions disgust, fear, anger, neutral, sad and happy using 4 neural network models namely CFNN model, LRN model, ENN model and FFNN model. Highest classification rates of 94.5%, 87.56%, 97.58%% and 98.33% were achieved for the network models namely FFNN model, ENN model, CNN model and LRN model respectively. On inferring the experimentation process, it is observed that the results of LRN model is comparatively better than all the other 3 neural network models. The motivation of our forthcoming analysis is to be done by enhancing the classification rate of the emotional classification model by way of using novel and improved features and classification algorithm.

S.No	Age Group	Subject No	Age	Classification Accuracy Table Network Models				Group wise Average Classification Accuracy			
				FFNN	ENN	CFNN	LRN	FFNN	ENN	CFNN	LRN
1	10 -20	S4	18	94.5	81.79	96.25	98.33	88.90	84.56	93.5	86.73
		S5	19	85.92	86.89	93.67	80.42				
		S7	19	87.67	87.22	90.5	82.25				
		S8	20	87.5	82.33	93.58	85.92				
2	21-30	S1	30	87.67	86.67	96.58	85.67	87.95	85.33	91.23	83.94
		S2	22	90.42	87.56	95.25	87.67				
		S3	26	83.88	85.89	80.83	85.5				
		S6	23	89.5	85.67	94.58	79.92				
		S9	30	91.33	83.22	92.25	83.17				
		S10	24	86.92	84.56	90.94	83.25				
		S12	26	89.92	83.89	90.17	82.17				
		S15	23	89.83	85.44	94.83	83.58				
		S16	29	88.83	86.67	89.92	83.92				
		S18	23	82.54	85.11	91.5	85.75				
		S19	24	87.67	84.56	89.08	83.58				
		S20	23	86.92	84.67	88.83	83				
3	31-40	S11	38	88.42	85.89	96.67	84	88.39	84.67	96.31	82.70
		S13	31	87.83	83.67	94.67	80.67				
		S14	31	88.92	84.44	97.58	83.42				
4	41-50	S17	45	90.17	84.11	97	82.42	90.17	84.11	97	82.42

Table 1 Comparison of Classification Accuracy Ranges based on age factor

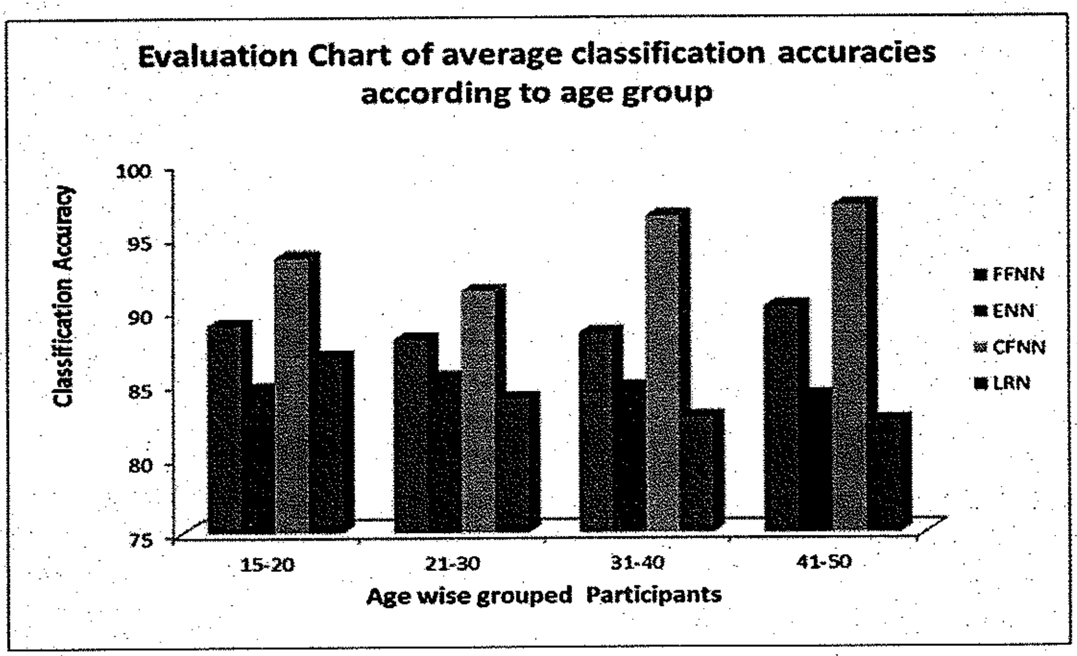

Fig.9. Age group based classification accuracy for FFNN, ENN, CFNN and LRN

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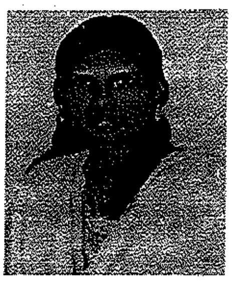
Authors Biography



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