Facial Expression Recognition System Using Neural Network based on LBP Features

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Abstract: *A novel expression recognition scheme is proposed to identify seven dissimilar facial emotions by using JAFFE (Japanese Female Expressions) database. Three different approaches of feature selection and extraction have been used for generation of optimal feature vector. Here, 2D-DCT (Two-Dimensional Discrete Cosine Transforms), uniform rotation-invariant LBP (Local Binary Patterns) and HOG (Histogram of Oriented Gradients) coefficients are employed in addition to image statistics parameters with a view to design a hybrid feature vector. The single hidden layer feed forward neural network has been used as a classifier in order to classify and also to recognize different emotions from frontal facial images. Three learning algorithms such as resilient back propagation, scaled conjugate gradient and gradient descent algorithm with momentum and adaptive learning rate have been compared. Major contribution of this research is in the design of an optimal feature vector comprising of uniform LBP based hybrid feature vector for encoding subtle texture information of images and also in the development of a simple neural network classifier containing a single hidden layer with carefully chosen number of neurons based on the experiments. The proposed neural network classifier trained with gradient descent algorithm with momentum and adaptive learning rate delivers the maximum average facial expression recognition accuracy of 97.2% along with the least number of connection weights and biases.*

***Keywords**:* **Facial Expressions, 2D DCT, LBP, HOG, Neural network, Classifier.**

1. Introduction

Expression is the most important mode of non-verbal communication between people. Facial expression conveys crucial information about the mental, emotional and even physical states of the conversation. Facial Expression Recognition (FER) has very broad applications, such as lie detection, behaviour prediction, user-friendly interface between man and machine and emotional robot, etc. However, these facial expressions (emotions) may be difficult to recognize by the untrained persons. It is necessary to understand the status of mind using face expression, because the situation of mind can be read by the person's mouth, eyes, eyebrows etc. With FER systems, it is possible to assess the human expressions depending on their effective state in the same way that human's senses do. The FER system can be applied in different areas of life such security and surveillance, they can predict the criminal's behaviour by analysing the images of their faces that are captured by the control-camcorder. Furthermore, the FER system has been used in communication to make the "answer machine" more interactive with people. FER has attracted increasing attention in computer vision, pattern recognition, and human-computer interaction research communities. The rest of the paper is organized as follows. Section II describes there view of related reported and published research work in the literature. The proposed research methodology has been explained in Section III. Computer simulation results are demonstrated in Section IV and finally, Section V highlights the conclusion.

2. Review of Related Work

Facial expressions and the changes in facial expressions provide important information about affective state of the person, his temperament and personality, psychopathological diagnostic information, information related to stress levels, truthfulness etc[1]. With growing terrorist activities all over the world, detection of potential troublemakers continues to be a major problem. The facial expressions tell us about concealed emotions which can be used to verify if the information provided verbally is true. These expressions representing the emotional state of a person can serve an important role in the field of terrorism control and forensics. Facial expression analysis can also be used effectively in psychopathology with regard to the diagnostic information relevant to depression, mania, schizophrenia and other disorders. The information relevant to the patient's response to the treatment could also be monitored with the facial expression analysis [2, 3]. Thus, expression analysis can be effectively employed for behavioural studies and medical rehabilitation. Stress detection through facial expression analysis can be useful in cases like monitoring stress levels in astronauts since other methods may not work in that environment [4]. Padgett [5] classified images into six or seven emotional categories. They trained neural networks from the data of 11 subjects and tested with the data from one subject. The training and testing dataset was interchanged and new networks were trained and tested. A classification accuracy of 86% was achieved in this study. Zhang et al., [6] used the JAFFE data base which consists of 10 Japanese female subjects. Although an accuracy of 90.1% was achieved; same data was used for training and testing. A 100 % recognition rate was achieved by Past works used different methods for feature extraction. G. Guo*et al.* [7] adopted Gabor and FSLP (Feature Selection via Linear Programming) for feature extraction process. Their appreciation rate is 91.0% using JAFFE database. Z. Wenming*et al.* [8] used KCCA (Kernel Canonical Correlation Analysis). Their recognition rate is 77.05% in JAFFE database. C. Zhengdon g*et al.* [9] used WMMC (Weighted Maximum Margin Criterion). Their recognition rate is

65.77%. C. Shan *et al.* [10] adopted Boosted-LBP. Their recognition rate is 81.0%for JAFFE database and 95.1% for CK database. Wang, Xun; Liu, Xingang; Lu, Lingyun; Shen, Zhixin et al. [11], have proposed a new FER system, which uses the active shape mode (ASM) algorithm to align the faces, then extracts local binary patterns (LBP) features and uses support vector machine (SVM) classifier to predict the facial emotion.

3. Proposed Research Methodology

The research problem undertaken is to develop a neural network based classifier system for identification of principal emotions (expressions) from human facial images with respect to standard benchmark database, namely, Japanese female expression database (JAFFE). All these images are frontal still gray images of the human faces, which will be used to develop an optimal neural network based classifier system with a view to correctly identify and recognize the expressed emotion by a person.

A unique hybrid image feature selection and generation scheme has been suggested with a view to achieve the best classification accuracy and the recognition. Features based on 2D DCT, LBP and HOG are augmented with features with regard to image statistics, entropy, texture, homogeneity, etc., so that every image is represented by a unique feature vector. Based on the annotations available and the visual inspection of the frontal still facial image of a person, the exact emotion is recognized, which is the target emotion. The facial image database is transformed to a knowledgebase to be used by a neural network, where a feature vector is followed by the expressed emotion. Primarily, three different feature extraction schemes based on 2D DCT, LBP and HOG are compared in order to determine the optimal feature vector of an image. Consequently, an optimal feature vector is designed. In a software environment available in MATLAB 2016a, codes are developed for accomplishing the tasks of feature extraction, development of a classifier based on neural network, etc.

For designing the optimal neural network based classifier, a network growing approach has been employed and in addition, a double loop design strategy has been followed. For ensuring simplicity of the neural network and also reduced time complexity and space complexity (hardware, number of connection weights including biases), a single hidden layer feed forward neural network is chosen, which is known as feed-forward neural network in MATLAB. The number of neurons (processing elements) in the hidden layer is increased gradually from 10 to 1000 in the increment of 10. For each value of the number of PEs (processing elements or neurons) in the hidden layer, ten different neural network candidates are configured and retrained with different random initialization of connection weights and biases as well as different random data partitioning into training, validation (cross validation) and testing subsets. This is necessary to ensure true learning without any prejudices and biases. Moreover, neural network learning has been made almost independent of any specific calculated choice of data partitioning into training, cross validation and testing datasets. Because of random partitioning of data into the training, validation and testing sets, each sample participates, on an average, an equal number of times to all these three sets. Because of small size of the dataset, 90% of the total samples are used as Training Dataset, different 5 % of the total samples as cross-validation (validation) dataset and remaining 5% of the total samples as testing dataset. Because of the fact that JAFFE database has 213 different images or samples, above distribution implies that 191 samples (exemplars) are used for training the neural network, other 11 samples are used for validation of the trained neural network and remaining 11 samples are used for testing the performance of the trained neural network.

Obviously, the performance of the neural network is always the best on the training dataset, because it is this dataset only which has been presented iteratively to the neural network in order to achieve learning and estimate the optimal values of the connection weights and biases of the neural network. Therefore, examination of the performance of the neural network on validation as well as the testing dataset is more important as neural network never sees these datasets during the process of learning. Cross-validation dataset is used for termination of the neural network training and as training proceeds, at the end of every iteration, it is ensured that both the error on training dataset and that on validation dataset go on decreasing with respect to the number of iterations (epochs). Though, the magnitude of these errors might be significantly different. It is generally noticed that the error on the training dataset is always much lower than that on validation dataset.

The magnitude of the error gradient and the number of validation checks are used to terminate the training. The number of validation checks represents the number of successive iterations that the validation performance fails to decrease. If this number reaches 6 (the default value), the training will stop.

All input features are normalized with zero mean and unit variance, so that the neural network based classifier models can run faster and better. Fig. 1 shows some sample facial images of JAFFE database. In the following figure the face expression is as following order Angry Disgust Fear Happy Neutral Sad Surprise.

Figure 1. Samples of images from the JAFFE benchmark database along with expressions (emotions)

For every setting of the number of neurons in the hidden layer, ten different trials of the neural network are run and during every trial, the results of the neural network are found to be drastically different most of the time. This is because of randomness in initialization of connection weights and biases and randomness in data partitioning into training, CV (cross-validation) and testing subsets at the beginning of every trial run. In addition, as this problem represents learning from data, the problem always has multiple non-optimal solutions (multiple local minima) and one optimal solution (global minimum). When training of the neural network proceeds, the learning algorithm often might get trapped to any one of the local minima and during every trial it can go on finding different local minima and thus further worsens the matter of finding a global optimal solution. Because of these complex situations, it is impossible to maintain exact reproducibility in the results produced by the same configuration of the neural network. For training of the neural network, three different learning algorithms, namely, Gradient descent with momentum and adaptive learning rate backpropagation (GDX) , Resilient backpropagation (RP) and Scaled Conjugate Gradient backpropagation (SCG) are used.

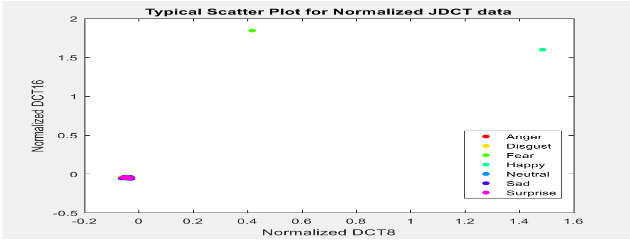
Because of the fact that input feature values are bipolar, 'tansig' activation function is used for the hidden as well as output layer neurons. Cross entropy error criterion is more appropriate for classification. The crux of the best design is the simplicity and the minimum time and space complexity of the neural network based classifier. The network with minimum number of free parameters (connection weights and biases) should be employed.

The performance of the neural network based classifier is recorded for all ten different trials (runs) with respect to cross-entropy error on training dataset, CV dataset and Testing dataset, Average Classification Accuracy on Training dataset, Average Classification Accuracy on CV dataset, Average Classification Accuracy on Testing dataset and Overall Average Classification Accuracy. Finally, the best performance measures are highlighted with an emphasis to the Average Classification Accuracy in comparison with cross-entropy error, because we are solving a classification problem. As overall average classification accuracy reflects the average classification accuracy on training, validation and testing datasets; the neural network configuration with the highest average overall classification accuracy is chosen.

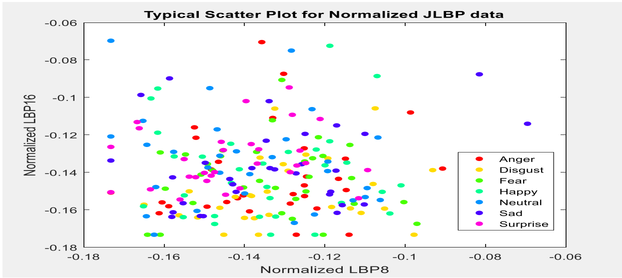
4 Experimental Results

4.1 Scatter Plots for Visualization of Decision Regions.

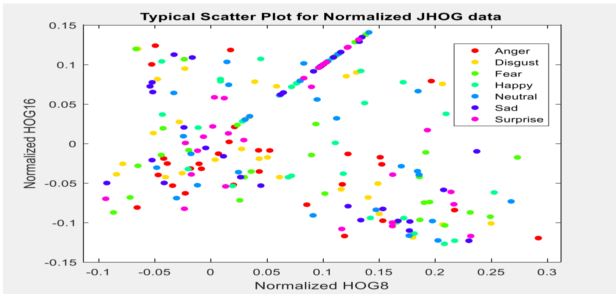
Scatter plots are plots of sample input feature vectors in input features space. They are excellent visualization tools for determining feature vector distribution in Rd, where d ≤ 3. They often facilitate natural or obvious clustering of class-specific feature data and the partitioning of Rd into suitable decision regions for classification.



(a) DCT16 vs. DCT8



(b) LBP16 vs. LBP8



(c) HOG16 vs. HOG8

Figure 2. Typical Scatter plots showing (a)Normalized DCT16 versus Normalized DCT8 (b)Normalized LBP16 versus Normalized LBP8 (c)Normalized HOG16 versus Normalized HOG8 for 7 different emotions.

The Fig. 2 (a) shows a typical scatter plot using features such as Normalized DCT16 and Normalized DCT8 for 7 different emotions in relation to JAFFE database. It is noticed that there exists overlapping between emotions, complete absence of many emotion-classes and also there does not exist sufficient clustering of emotion-class specific feature data. Therefore, decision regions cannot be estimated for classification into seven different classes. This seems to be an issue with 2D – DCT based features. In view of this, it is certain that these features are not able to provide reasonable classification accuracy. Results are the best if two classes have little or no overlap in feature space. Accordingly, it makes sense to include (combinations of) features that separate the classes as well as possible. The Fig 2 (b) shows the scatter plot using features such as Normalized LBP16 and Normalized LBP8 for 7 different emotions with respect to JAFFE database. It is seen that there exists somewhat clustering of emotion-class specific feature data with very little or no overlapping between different emotion classes. The emotion- classes are sufficiently disjoint. The decision regions are noticed as nonlinear; however, they can be estimated by an optimal neural network model for classification into seven different classes. As compared to input features based on 2D – DCT, the quality of input features based on LBP is much better. Similarly, Fig. 2 (c) depicts the scatter plot using features as Normalized HOG16 and Normalized HOG8 for 7 different emotions with respect to JAFFE database. It is noticed that there exists somewhat clustering of emotion-class specific feature data with very little overlapping between different emotion classes. As the decision regions are noticed as highly nonlinear; they can be estimated by a classifier based on a neural network for classification into seven different classes. This is possible, because the neural network has shown an ability to learn from input data (exemplars or instances) and with appropriate design, development and training of the neural network, facial expression recognition system can classify and recognize the human emotions with reasonable accuracy. As compared to input features based on LBP, the quality of input features based on HOG is slightly inferior. The proposed uniform LBP approach is very robust in terms of gray scale variations of images, immunity to contrast variations and rotation-invariant texture analysis of images. Hence, it is expected that the proposed LBP based hybrid feature vector would entail the best classification as well as recognition of the emotion.

4.2 Design of Neural Network based Classifier.

For the development of a classifier based on neural network, three different types of carefully designed feature vectors, such as, FVDCT and FVLBP and FVHOG have been employed. The feature vector, FVDCT based on 2D – DCT for JAFFE Database is comprised of 75 features, such that FVDCT = [DCT1, DCT2, DCT3, ...,DCT64, Average, SD, Entropy, moment2, moment3, median, variance, contrast, correlation, energy, homogeneity].

The feature vector, FVLBP based on LBP features for JAFFE Database is comprised of 72 features, so that FVLBP = [LBP1, LBP2, LBP3, ...,LBP59, Average, SD, Entropy, moment2, moment3, kurtosis, skewness, median, variance, contrast, correlation, energy, homogeneity].

The feature vector, FVHOG based on HOG for JAFFE Database is comprised of 75 features, so that FVHOG = [HOG1, HOG2, HOG3, ..., HOG64, Average, SD, Entropy, moment2, moment3, median, variance, contrast, correlation, energy, homogeneity].

First, input features based on 2D – DCT have been applied to the single hidden layer feed-forward neural network. As construed from the Scatter plot shown in Fig. 2 (a), the quality of FVDCT is very poor. Therefore, reasonable classification accuracy is no longer possible. In case of FVDCT, the maximum average overall classification accuracy is obtained for a neural network with a single hidden layer containing 520 neurons and trained with scaled conjugate gradient backpropagation algorithm. The maximum average overall classification accuracy is observed as only 42.253521% at the cost of formidable total number of connection weights and biases amounting to 43,167. In case of FVHOG, the maximum average overall classification accuracy is obtained for a neural network with a single hidden layer containing 610 neurons and trained with Gradient descent with momentum and adaptive learning rate backpropagation algorithm. The best average overall classification accuracy is observed as 92.9577% at the cost of formidable total number of connection weights and biases amounting to 50,637, which is certainly not pragmatic.

In view of this, neural network based classifier has been trained using FVLBP in order to achieve maximum average classification accuracy. The parameters of the neural network are designed a follows:

Input Layer: 72 Neurons

No. of PEs in Hidden Layer = 70 (optimal number decided after rigorous experimentation and re-training)

Output Layer: 7 Neurons as Seven emotion-classes are 1. Surprise, 2. Sad, 3. Neutral, 4. Happy, 5. Fear, 6. Disgust and 7. Anger

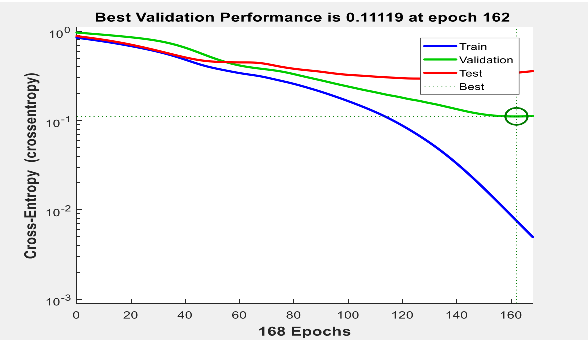
Architecture of patternnet: 72-70-7

Learning Algorithm: Gradient descent with momentum and adaptive learning rate backpropagation algorithm. For 70 neurons in the hidden layer, the neural network is re-trained ten times with different random initialization of connection weights including biases and random partitioning of the data into training, cross-validation and testing datasets (Training: 90%, Cross-validation: 5 % and Testing 5 %). Among ten different trials, during Trial 1, the maximum average overall classification accuracy is observed. Table I enlists the different performance measures of the optimal neural network delivering the maximum average overall classification accuracy for input features based on 2D – DCT, uniform LBP and HOG for three different learning algorithms, namely, GDX, RP and SCG.

Table 1. Performance Measures of Neural Network

FV	PE	Cross-Entropy Error			Maximum Average Classification Accuracy in %				LA	NCW
		Train	CV	Test	Train	CV	Test	Overall		
DCT (75)	680	0.2612	0.2600	0.2826	28.272251	18.181818	18.181818	27.230047	GDX	56447
	80	0.2336	0.2742	0.2747	35.602094	18.181818	9.090909	33.333333	RP	6647
	520	0.2333	0.3347	0.2733	43.455497	45.454545	18.181818	42.253521	SCG	43167
HOG (75)	610	0.0675	0.3997	0.5475	100	45.454545	18.181818	92.957746	GDX	50637
	170	0.0738	0.3745	0.5522	96.858639	54.545455	27.272727	91.079812	RP	14117
	860	0.0748	0.4007	0.7963	100	36.363636	27.272727	92.957746	SCG	71387
LBP (72)	70	0.032	0.11119	0.3427	100	72.727273	72.727273	97.183099	GDX	5607
	120	0.040972	0.393554	0.257441	100	54.54545	54.54545	95.30516	RP	9607
	380	0.034832	0.212824	0.248576	100	63.63636	54.54545	95.77465	SCG	30407

In the above Table 1, various acronyms are used, where FV denotes the feature vector, LA denotes learning algorithm and NCW denotes the total number of connection weights and biases present in the neural network. It is obvious that for feature vector, FVLBP, a neural network with 70 processing elements in the hidden layer, maximum average overall classification accuracy obtained is equal to 97.183099% for GDX training algorithm and the number of connection weights required are also very less i.e., only 5,607 as compared to other two algorithms. In case of the feature vector based on DCT data, i.e., FVDCT, the average classification accuracies are very poor (42.2535 %) for scaled conjugate gradient algorithm and the number of connection weights inclusive of biases required is enormous (43,167). Similarly, for feature vector, FVHOG, a neural network with 610 processing elements in the hidden layer, obtained maximum average overall classification accuracy is equal to 92.9577% for GDX training algorithm and the number of connection weights required is massive i.e., 50,637 as compared to other two algorithms.



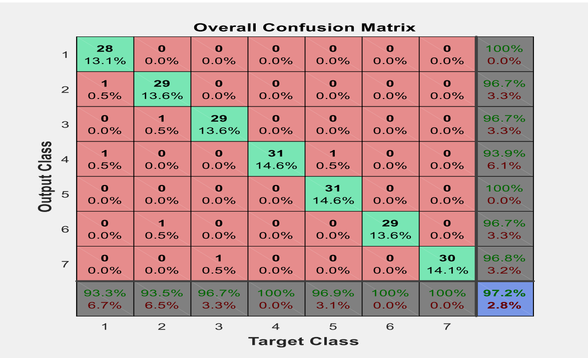


Figure 3. (a) Plot showing Cross-Entropy Error versus number of Epochs for training, cross validation and testing data, 3 (b) Overall Confusion Matrix for 72-70-7 Neural Network with GDX learning algorithm

In above graph shown in Fig. 3 (a), it is seen that the best validation cross-entropy error performance after six consecutive validation checks is 0.11119, which is obtained at epoch number 162. So at this instant, the training of the Neural Network is terminated. The Fig. 3 (b) shows the overall confusion matrix which combines classification accuracies of training, cross-validation and testing datasets for various emotions like surprise, sad, neutral, happy, fear, disgust and anger. So, it is noticed that the average overall correct classification accuracy is 97.2% for all the emotions.

It is seen from the Table 2 that 28 emotions are correctly recognized as surprise, one emotion is incorrectly recognized as sad and one emotion is incorrectly recognized as happy, resulting into the classification accuracy for surprise as 28/30, i.e., 93.3%. It is also observed that 29 emotions are correctly recognized as sad, one emotion is incorrectly recognized as neutral and one emotion is incorrectly recognized as disgust. Thus, out of total 31 emotions, only 29 emotions are correctly recognized as sad, resulting into the classification accuracy for sad of 29/31, i.e., 93.5%%. It is also noticed that 29 emotions are correctly recognized as neutral and one emotion is incorrectly recognized as anger, thus, leading to the classification accuracy for neutral as 29/30, i.e., 96.7%.

Table 2. No of correct classifications by the trained Neural Network (72-70-7, GDX)

No. of Recognized Emotion (Output)	**No. of Desired Emotions (Target)**						
	Surprise	**Sad**	**Neutral**	**Happy**	**Fear**	**Disgust**	**Anger**
Surprise	28	0	0	0	0	0	0
Sad	1	29	0	0	0	0	0
Neutral	0	1	29	0	0	0	0
Happy	1	0	0	31	1	0	0
Fear	0	0	0	0	31	0	0
Disgust	0	1	0	0	0	29	0
Anger	0	0	1	0	0	0	30
Correct Recognition	28/30	29/31	29/30	31/31	31/32	29/29	30/30
Classification Accuracy	93.3%	93.5 %	96.7%	100%	96.9 %	100%	100 %
Overall Average Classification Accuracy	97.2%						

In addition, it is also observed that all 31 emotions are correctly recognized as happy, thus, resulting into the classification accuracy with respect to happy as 100 %. Furthermore, 31 emotions are correctly recognized as fear and one emotion is incorrectly recognized as happy, entailing the classification accuracy for fear as 31/32, i.e., 96.9%. It is also obvious that all 29 emotions are correctly recognized as disgust, resulting into the classification accuracy in relation to disgust as 100%. Moreover, it is also evident that all 30 emotions are correctly recognized as anger, resulting into the classification accuracy for anger as 100%. The average overall classification accuracy for all emotions is computed as 97.2%.

5. Summary

The problem of recognition of facial expressions (emotions) from JAFFE database using neural network is investigated in this research work. Among 2D-DCT, uniform rotation invariant LBP and HOG based feature extraction schemes; FVLBP delivers the best classification performance of the neural network. The novelty of the research has been not only in the selection and generation of the most suitable input features from images resulting into the optimal feature vector in the anticipation of the best classification performance but also in the design of the optimal neural network classifier. Maximum average overall classification accuracy of 97.183099% is achieved for hybrid input features based on LBP, i.e., FVLBP (Total number of features

= 72) using a neural network with only 70neurons in the hidden layer and trained with Gradient descent with momentum and adaptive learning rate back propagation algorithm and the total number of connection weights inclusive of biases is only 5,607,which is very optimal as demonstrated in Table 1. This is the best ever reported maximum average overall classification accuracy on the JAFFE database, as no other researcher so far has reported such accuracy on the said database. In view of this, it is recommended to use the suggested optimal feature vector comprising of input features based on uniform LBP combined with image statistics and other features such as texture, entropy, etc. for training a neural network with a single hidden layer comprising of only 70 neurons. Though slightly slower in convergence, Gradient descent with momentum and adaptive learning rate back-propagation algorithm works superbly as compared to two other relatively faster algorithms.

6. Conclusion

In this paper, we have considered two datasets (Japan and cohn_kanade), and found the ROI for both. Then the various features like DCT, LBP and HOG along with image statistics are extracted as well as PCA's are also calculated for both datasets and these features are given as input to neural network for classification of emotions. The various training algorithms used for training ANN are SCG, RP and GDX and the parameters considered for classification are Confusion matrix and Cross Entropy Error.

For JAPAN dataset with LBP approach and GDX training algorithm, we obtained maximum classification accuracy of 97.183% with minimum number of connection weights, i.e.,5607 and for COHN KANADE dataset with LBP approach and RP training algorithm, we obtained maximum classification accuracy of 99.1% with minimum number of connection weights,i.e.,5465.

So by observing all the results we can conclude that the raw input features based on LBP provided best accuracy compared to DCT and HOG approaches with minimum number of connection weights and the training algorithm PR and GDX are very fast compared to SCG.

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