Facial Expression for Emotion Detection using Deep Neural Networks

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Abstract*: *The imperative research part of the emotion recognition is the analysis of emotional state in the facial expression. The subject matter of this study is to aid the human – computer interaction more empathetic with the help of automatic emotion recognition system which will be a great step forward in the robotic field. This study proposes a novel method for the emotion detection where usage of Face detection using Haar feature-based cascade classifiers, saliency mapping and CNN architecture are implemented. The facial expression of the humans from the data set is fed into the Saliency using hyper-complex Fourier Transform (SHFT). The resulting saliency map has the extracted feature which is given as input to the CNN to perform feature modeling and output the emotional state of the human. We also exhibit that the proposed saliency model can emphasize on both minor and major salient regions more accurately than the other saliency models.

Index Terms*: *CNN classification, Emotion detection, Facial expression, feature extraction, Saliency using Hyper-complex Fourier Transform.

I. INTRODUCTION

KDD is an interdisciplinary area that basically center as around the efficient methods for procuring intriguing principles and examples from the information[1]. The noteworthy basic examples which are evaluated by intriguing quality measures incorporate affiliation principles and grouping rules. Affiliation govern mining (ARM), a standout amongst the most critical information mining strategies is broadly used for identifying fascinating connections between things. Colossal number of protocols dependably makes issue to prefer top among them. In this manner, the positioning of principles from the natural knowledge is indispenable zone [2]. The diverse rules of interestingness measures were proposed. In any case, these still create colossal number of continuous itemsets, and in this way these produce gigantic number of affiliation rules. Thus, more time is taken to execute these algorithms. In this proposed chapter, we have prompted a weighted rule mining method which has been produced utilizing two efficient measures rank-based weighted dense help and rank-based weighted consolidated certainty measures for removing rules from the information. Certain time it occurs that a gobs of rules may produce same support value with the same confidence. In this way, it takes considerably less time than the alternate calculations [3]. Another well-known advantage of RANWAR is that a portion of the tenets which hold low rank in conventional lead mining calculations, get great rank in RANWAR because of the contribution of qualities' weights (w.r.t. their significance) in the proposed measures, and adequate confirmations of biological implication of the genes based rules are obtained.

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II PROBLEM STATEMENT

In this proposed scenario, Temporal Apriori algorithm is implemented to handle the huge gene database efficiently. In this research, the gene database which includes Sequence Name, mcg, gvh, lip, chg, aac, alm1, alm2 are considered. Analyze the temporal database using time threshold. The time range is specified for support and confidence as min_ respectively. Then T-Apriori algorithm [2] is applied to produce frequent item sets and resultant temporal association rules. In many real time applications, the data consists of the attribute such as the time information and the data mainly has temporal relativity. This algorithm is also includes the preprocessing which associates numeric value along with discrete values to increase the performance of the scenario. This algorithm [5] is focused on the identifying the more number of dangerous gene among the total genes in the dataset. It discovers the minimum support count value and based on this values they can consider further gene which satisfies the support count and eliminates which gene support count is lesser than the support count. This proposed Apriori algorithm is retrieved the most frequent genes as well as significant one in the ranked association rule mining scenario. Hence this scenario is able to recognize the time datasets more superior with less computation time [6][7].

III EXISTING SYSTEM:

The large number of progressed rules of mining items by ARM techniques [7] makes misperception to the decision maker that how the top genes can be chosen. ARM technique is very effective technique but it lacks in minimizing the elapsed time.

IV PROPOSED SYSTEM:

We propose a weighted rule based mining technique that focus on two effective measures such as ranking based weighted support and ranking based weighted confidence that has been used for extracting the rules from the item set. Sometimes it occurs that resultant have the same support and confidence. It is very difficult to identify and differentiate them. Hence our proposed weighted technique can easily

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categorize them[4][8]. The main benefit of this effective technique is it generates less amount of frequent items compared to other existing association rule mining algorithms based on the same minimum input support values[9].

V SYSTEM ARCHITECTURE

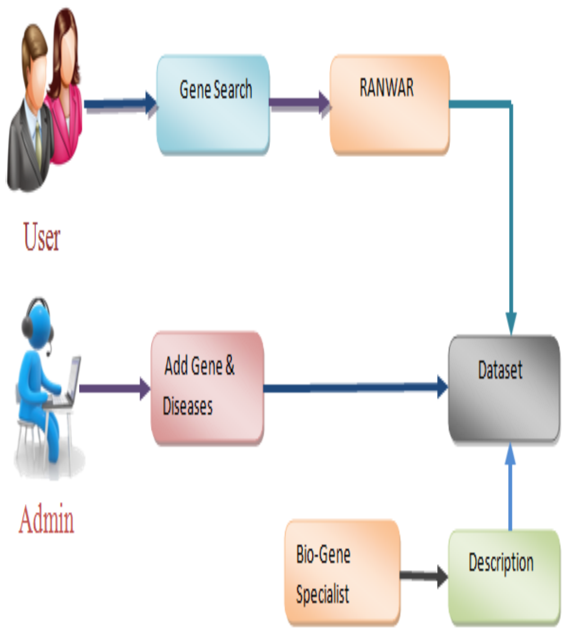

Fig 3.1 System Architecture

VI PRE-FILTERING

This pri-filtering process removes the low variance value from the genes[10][11][12] . The low variance value of the genes may cause and results in lower p-value which is insignificant even though it appears to be significant in nature[13][14[15]. The process of testing the overall variance of the item based on every gene is essential and to remove the genes data with precise low variance value[16][17][18].

VII WEIGHTED RULE MINING

Ranking based on weighted association rule mining method having two rule-interestingness trails such as weighted condensed support and weighted condensed confidence, [19][20] especially for microarray /bead chip data.The Microarray system is very worthwhile tool that measures the gene items through diverse experiments and control models. The experiment starts with pre-filtering stage which is applied on the data that is removing the low variance value the genes.

VIII GENE RANKING

Ranking the genes based on the variance value has significant effect in the overall result. This technique uses Limma test that provides a list of genes arranged according to the rank that is based on the p-values from best to worst case. The next process is to assign weights for each item that are ordered based on rank and the measures are added accordingly[21][22]. The measures that are added results in importance of every gene item set. The proposed method produces the measures that are in condensed form based on the support and confidence value [23][24]. Additionally, two gene countenance data items and two methylation item sets are effectively applied for testing the performance. The proposed approach is compared with the traditional Apriori technique and other existing approaches [25][26][27]. The identification of GO terms and KEGG path ways is applied for validating the rules. The highest number of GOs and the KEGG path ways are identified and stated for further biological benevolent measures[28][29][30]. The proposed approach shows significant reports that are top ranked rules that are produced and proves that it is more effective compared[31][32][33] to other traditional rule mining techniques[34][35][36].

IX RANWAR ALGORITHM IMPLEMENTATION

Input: GENE dataset
1: Strategy RANWAR
2: Normalize the gene information.
3: Calculate rank of gene (i.e., rank(:)) as indicated by unique quality rundown.
4: Assign weights wt(:) to all qualities as indicated by their positions rank(:).
5: Choose introductory seed esteems.
6: Discretize the esteem.
7: Apply post-discretization strategy.
8: Initialize k = 1.
9: Find visit 1-itemsets, wcs(i) ≥ min wsupp
10: repeat
11: k=k+1.
12: Generate applicant itemsets, CIk from FIk−1 itemsets.
13: for every applicant itemset, c ∈ CIk do
14: Calculate wcs(c) for every competitor itemset, c.
15: if wcs(c) >= min wsupp at that point
16: Generate rules, manage(:) 3rom the regular itemset, c.
17: Determine wcc(:) for each rule(:).
18: for each developed run, r ∈ manage(:) do
19: if wcc(r) >= min wconf at that point
20: Store the r in the subsequent govern list Rules with its wcs and wcc; Guidelines ← r, Rule Supp ← wcs(r) and Rule Conf ← wcc(r).
21: endif
22: endfor
23: endif
24: endfor
25: repeat until (FIk = ∅)
26: end strategy

XCONCLUSION AND FUTURE WORK:

The outstanding act of progressing rules of data by ARM algorithm marks misperception to the system that makes decision for choosing the top components. The two effective ranking-based weighted condensed rule-interestingness measures are proposed in this article. A rule-mining algorithm based on the weights has been built up depending upon on the bills especially for microarray/bead chip data. RANWAR is fully established on the statistical test, Limma technique is employed for calculating the each gene's P value (item), and some weight was given for each gene relevant to their p-value ranking. The two challenging

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datasets have been used for comparing the performance of RANWAR with the other existing algorithms. RANWAR algorithm generates only few frequent data sets compared to others so it cuts down the execution time. Another advantage of RANWAR is that close to most biological significant rules stand top here, which contain very low rank in Apriori. The validates of each rule are taken based on the GO-terms and KEGG pathways of genes.

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In the recent decades, one of the prominent complications in human-computer interaction is the determination of mutual empathy in communication between the machines and the humans, obligating to its implementation in various applications. Midst these problems, there have been a lot of reports on the study of emotional and empathetic communication between the humans and machines. This has gained a lot of recognition as an imperative component of human-computer interaction.

Facial expression is considered to be one of the most imperative and impulsive constituent to identify the emotional status of the human among all the emotional factors. By the existence of notable head movement, partial occlusions, temporal behaviors, the facial expressions are characterized in an impulsive interaction. However, the expressions on the human face is tough to determine the emotional states as the characteristics of the facial expression are sensitive to the external factors such as illumination conditions, etc.

There have been many techniques proposed to defeat these problems and yet the studies failed to be improved. One of the basic problems about the analysis of facial expression is the representation of visual information to produce the corresponding expression by the system.

The communication of human emotions is mainly carried out through Facial expression. According to a research, the message communicated is 55% effective through facial expression whereas the voice and the language comprises 38% and 7% of the effect respectively. In the recent years, the application of artificial intelligence and computer vision has increased in multiple fields [1 - 3], and the automated Facial Expression Recognition (FER) system made a significant advancement for different potentials in gesture language recognition, human behavior recognition, human-computer interaction, etc. There are six basic emotions as given by the experiments of Ekman: happiness, sadness, anger, fear, surprise and disgust [4].

To resolve gesture of different muscles on the face, the face motion is depicted by action units (AUs) through Facial Action Coding System (FACS) which was established by Ekman et al. Many FER systems have implemented the usage of AUs [5 - 6].

The Facial Expression Recognition system (FER) comprises of three fundamental stages: image procurement, feature extraction of face and classification. This paper proposes an advanced way to analyse the facial expressions for emotion detection using deep neural networks which will produce enhanced results. The proposed method implements detection of face by using the Haar feature cascade classifiers in a given data set, Saliency using hyper-complex Fourier Transform (SHFT) model to produce the saliency map and Convolutional Neural Network (CNN) to detect the complicated curves and to classify the emotion from the saliency map.

I. RELATED WORK

The most imperative element in the social communication is the human facial expressions. A normal communication comprises of both verbal and nonverbal communication. Through the facial expressions the nonverbal communications are expressed. The major phases in an ideal Facial Expression Recognition System (FER) are image pre-processing, extraction of feature and classification [16].

A.Pre-Processing

To enhance the operation of Facial Expression Recognition system, pre-processing of the image is done before the extraction of feature phase [19]. There are many types of image pre-processing such as contrast adjustment, image scaling and clarity and supplementary enhancement process in order to boost the frames of the expressions [20 - 21]. The image of the face is cropped and scaled using a technique where the midpoint is considered as the nose and other vital components of the face are embraced physically [22]. The reduction of the image of the face is carried out using Bessel down sampling which will also protect the features and perceptual value of native picture [23]. The Gaussian filter is employed to resize the input images which will smoothen the images [24].

The lowering of lighting and discrepancies of images of face are performed with the help of normalization which is also a type of preprocessing [25] which will use median filter to obtain a boosted image of face. The another imperative type of preprocessing technique is the Region Of Interest (ROI) segmentation which consists of three vital functions such as adjusting the dimensions of the face by division of color components and segmentation of mouth, forehead or eye regions [26]. The illumination variations are conquered by the histogram equalization technique [27, 28]. The histogram equalization technique is deployed for the purpose of improving contrast of face in the image and accurate illumination is used to increase the difference between intensities.

B. Feature Extraction

The extraction of features is the succeeding step in Facial Expression Recognition system. The process of detection and representation of supportive features in the input image is called feature extraction which is used for the succeeding processes. Feature extraction is classified into five different types which are the edge based method, geometric feature-base method, global and local feature-based method; texture feature-based method and patch-based method [12].

The Histogram of Oriented Gradients (HOG) is an edge-based feature descriptor which makes use of the gradient filter. The basis of edge information of recorded image the features are extracted. It separates the required visual

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features, for instance the visual feature for the smile expression is the curvature shaped eyes [29].

The feature descriptor which is a geometric feature-based method is the Local Curve-let Transform (LCT) that depends on wrapping mechanism. The mean, standard deviation and the entropy are the extracted geometric features [27].

The Principal Component Analysis (PCA) is one of the methods that extract features on the basis of global and local features. It extracts the global and low dimensional features. Another method is the Independent Component Analysis (ICA) which performs the process of feature extraction using multichannel observations [21].

Feature extraction using the texture descriptor is the Gabor filter which contains the phase and magnitude related data. The magnitude feature of Gabor filter contains the details of the arrangement of face image. The phase features encloses the details about intact explanation of magnitude features [20, 23, 26, 30, 31]. Another type of texture descriptor is the Local Binary Pattern (LBP) which produces the features with binary code and it is procured by thresholding between the center pixel and its locality pixels [28, 32].

The patch-based feature descriptor is employed by extracting the features of the facial movement as patches based on the distance characteristics. It is done through a couple of procedures like removing the patches and pairing it. The patch matching is done by rendering separated patches to distance attributes [22].

The detection of face by deploying Haar feature-based cascade classifier is a productive face recognition technique. This approach is based on machine learning where a number of positive and negative pictures of faces are given into a cascade function to train on. It is later deployed to detect faces on other images.

At first, in order to train the classifier, a various amount of positive and negative images of faces are fed into the algorithm and the feature extraction is performed. Different Haar features are used to implement feature extraction. It is more of the convolutional kernel. The sum of the pixels inside the white rectangle is removed from sum of pixels in the black rectangle to obtain the value of every feature which is a single value. Fig. 2 shows the different haar features for face detection.

Most of the picture has non-face region in an idle image. Therefore the window is checked to know if it is a non-face region. If it is a non-face region, drop the window in a single step, and do not process it again. Instead focus on regions where there is a possibility of face. This will make the process effective in inspecting the possible face regions. This is where Cascade of Classifiers is applied [7]. Rather than employing all 6000 features on a single window, the features are clustered as different phases of classifiers and implemented one by one. Discard the window if it fails the first phase and do not consider the remaining features it has. If it passes the first phase, then apply the next phase of features and continue the procedure. The face region is identified as the window which passes all the phases.

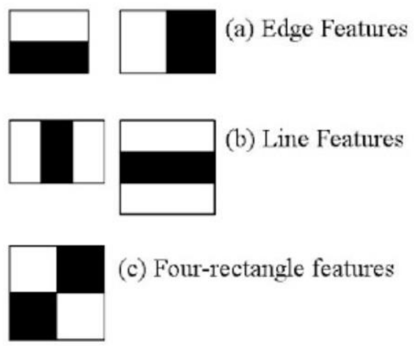

Figure 2: Haar features for face detection

A. Saliency Using Hyper-Complex Fourier Transform (SHFT)

The output of the face detection process is fed as the input into the saliency map. Saliency computation can be done using only one feature. But to yield better performance and results, more features such as color and motion information are required. According to [8], [9] and [10] the hyper-complex matrix is used to collaborate the multiple feature maps. As a result, the hyper-complex Fourier Transform is deployed in order to replace normal Fourier Transform.

The conventional discrete Fourier Transform has the input as a real matrix. The input matrix has every image pixel in it as a real number and as an element of the input matrix. Nevertheless, when more than a feature is combined to form a hyper-complex matrix, every element becomes a vector and the whole hyper-complex matrix becomes a vector field. Hence conventional Fourier Transform turns out to be unsuitable for computation. Given a hyper-complex matrix:

$$f(n,m)=a+bi+cj+dk \quad (1)$$

The HFT of (1) can be given in its discrete version as

$$F_H[x,y] = \frac{1}{\sqrt{MN}} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} e^{-\mu 2\pi\left(\left(\frac{my}{M}\right)+\left(\frac{nx}{N}\right)\right)} f(n,m) \quad (2)$$

where μ is a unit pure quaternion and $\mu^2 = -1$. Note that $F_H[x, y]$ is equally a hyper-complex matrix.

The opponent color space depiction for input image has these three feature maps. To compute the saliency mapping, the hyper-complex Fourier Transform $F_H[x,y]$ can be rewritten in polar form as given below:

$$F_H[x,y] = \|F_H[x,y]\| e^{\mu\phi(x,y)} \quad (3)$$

where $\|.\|$ refers to modulus of every element in the hyper-complex matrix. Its phase spectrum $P(x, y)$, amplitude spectrum $A(x,y)$ and eigen axis spectrum $X(x,y)$ are determined as given below.

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$$P(x, y) = \phi(x, y) = tan^{-1}\frac{\|V(F(x,y))\|}{S(F(x,y))} \quad (4)$$
$$A(x, y)=\|F_H(x, y)\| \quad (5)$$
$$X(x, y)=\mu(x,y) = \frac{V(F(x,y))}{\|V(F(x,y))\|} \quad (6)$$

where $X(x, y)$ is a pure quaternion matrix.

The spectrum scale space $\Lambda = \{\Lambda_k\}$ is manipulated by smoothing $A(x, y)$ with a sequence of Gaussian kernels while preserving the phase spectrum ($P(x, y)$) and eigenaxis spectrum ($X(x, y)$). The inverse transform of the saliecy map is performed at each scale from the smoothed amplitude spectrum (Λ_k) and the original phase and eigen axis spectra:

$$S_k = g^*\|F_H^{-1}\{\Lambda_k(x,y)e^{XP(x,y)}\}\|^2 \quad (7)$$

where g is the Gaussian kernel at each fixed scale. Now we get a sequence of saliency map $\{S_k\}$ and the absolute saliency map is chosen from the $\{S_k\}$by choosing the optimal scale k_p .

The optimal scale to choose the best saliency map is determined with the use of entropy.

$$k_p = arg_k min\{H(S_k)\} \quad (8)$$

Where $H(\mathrm{x})= -\sum_{i=1}^{n} p_i \log p_i$is the denotation of the entropy of x.

There is also another problem to focus on other than entropy while we choose a proper scale k. Using the border avoidance strategy, the saliency maps which has a robust response at the border area is chosen $\{S_k\}$ in SHFT. Therefore for every saliency map, a parameter λ is defined as follows.

$$\lambda_k = \sum\sum k(n, m).N(S_k(n,m)) \quad (9)$$

where k is the 2D centered Gaussian mask of equal size as $S, \sigma_w = W/4$, $\sigma_h = H/4$ and $k(n,m) = 1.N(.)$ and it is deployed to normalize S. This will make the total of all pixel values as 1. It is used to choose the optimal scale only and not for the remodeling of saliency map. Therefore the λ, k_p in (9) is rewritten as follows based on the definition of 2D entropy.

$$k_p = arg_k min\{\lambda_k^{-1} H_{2D}(S_k)\} (10)$$

B. Convolutional Neural Network (CNN)

The most dominant revolution in the department of computer science is the convolutional neural networks (CNN) [17]. It emulates the operation of brain of the human for the perceptible study as it is biologically stimulated from visual cortex. The implementation of CNN architecture is used which holds obvious supposition that inputs are in the form of images which will make it easy to apply particular attributes in the structure. The pre-processed picture is supplied to the network which will analyse the image features. The different layers of CNN are as follows:

Input Layer

The input layer has (w × h × c) as the value of pixels of the image where the variables w, h and c represents the width, height and number of colour channels of the image. The dimensions of the image in our study are 128×128×1.

Before we feed the pixels into the input layer, we have to pre-process the image as the dimensions are fixed.

Convolutional Layer

The convolutional Layer calculates the dot product of the weights and a small region where the neurons are attached to in the input layer [11]. One of the hyper attributes passed that are distinctive with arbitrarily produced weights is the number of filters. The filter is also known as kernel and it is combined with image. That is, the multiplication between the input pixel values and filter values is carried out element wise. This yields a feature map which behaves as a feature identifier that is reactive to edges and positions which represents the enhancement ways of the pixel values. As a result, we get (w× h× f), where f represents the total amount of filters deployed. In our study we have deployed 8, 16 and 32 filters in the first, second and third convolution layer respectively.

Extracting a specific data from the primary image matrix will have the weight matrix to behave as a filter. A weight combination might extract a certain color, while the one can extract edges, while the other one can simply smudge the undesirable noise. This type of extraction will lead to the right prediction in the network.

In the presenceof different convolutional layers, the generic features are extracted in the first layer and as the network becomes deeper, the weight matrices extract many complicated features and extra suitable to the difficulty at hand.

Pooling layer

In order to down sample the dimensions through the width and height for the reduction of manipulation time owing to a huge number of convolutional layers, a pooling layer is added to the convolutional layers. The reduction of dimensions of map is done by using Max Pooling and only the original feature map window's maximum pixel value is retained. In order for the profundity of image to remain unaltered, every depth dimension undergoes pooling. This pooling is done by applying max operation to every depth dimension of the twisted output. This helps in the reduction of parameters to a great scale.

After the process of pooling, the activation function called ReLU (Rectified Linear Unit) is implemented. This function will return 0 if it gets any negative values and for any positive value, it returns the same positive value. This will reduce the inconsistency in the convolutional layer and will decrease the computational time by going deeper to capture the micro-expressions in the image.

Dense Layer (Fully Connected Layer)

This layer is connected fully with the result of the preceding convolutional surface. These are usually employed in final phases of CNN architecture which is connected to output layer to build the required quantity of outputs. These

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features are transformed by connecting to layers with trainable weights.

The sophisticated features in the image are identified by this layer that fetches out the complete image. This is sometimes vulnerable to over fitting. In order to reduce the over fitting, a randomly selected portion of nodes have their weights set to zero by a dropout layer which is added during training. This selected portion will usually be less than 50%.

Output Layer

The output layer will give the required classes or their corresponding probabilities and it is connected the previous dense layer. Since, some emotions of humans are commonly a combination of various emotions which are calculated by the possibility of each emotion; we implement the soft-max layer to achieve this. The soft-max function is a much generalized logistic activation function which is used to classify multiple classes. Here in this study, the soft-max function will classify the given input as particular emotion depicted by the human.

II. MUG DATASET

The MUG database was developed by Multimedia Understanding Group [15]. This was developed to excel the restrictions of other databases indistinguishable to this that was existing at this time. The limitations were like uniform illumination, high quality, numerous subjects and numerous takes per subject. This MUG Data set aims to aid the researchers in the recognition of expression. This data set has 51 men and 35 women as participants who are aged within 20 to 35 years. Men are captured with and without beards. In the second half of the data set, Except 7 subjects are wearing glasses whilst the others are not. The database holds 38GB of images which has 52 participants made accessible to permitted internet users. 25 participants are accessible on requisition and the rest 9 are only obtainable in the MUG laboratory. This data set has two parts. The initial part consists of participants performing the seven fundamental expressions such as anger, disgust, fear, happiness, surprise, sadness and neutral. The following part comprises of laboratory induced emotions.

In the MUG database, there are three to four takes captured for every emotion for every subject. We have chosen the best take for every emotion depicted by every subject to produce the optimal result during classification.

III. EXPERIMENTAL RESULTS

The experiments were conducted in Intel i5 2.4 Ghz, 16GB RAM in MATLAB 2018b. The CNN learns image features from MUG image data set, and use those features to train an image classifier. Feature extraction is the easiest and fastest way to use the representational power of trained deep networks. The CNN network has three convolutional layers and one fully connected layer as shown in the Fig 1. In our experiment, the input data set is divided into 70% training and 30% test data.

The CNN requires input images of size 128-by-128-by-1, but the images in the image data stores have different sizes and images are normalized.

Fig. 3 shows the performance graph of our study. The total time taken by the training phase of the Facial Expression Recognition system is 38 minutes 10 seconds. We had a total of 15 epochs with 43 iterations per epoch. The total number of iterations were 645 iterations with a learning rate of 0.01 which was constant. The light blue line in the graph represents the training phase and the dark blue dotted line represents the testing phase. This experiment resulted in a validation accuracy of 96.07%.

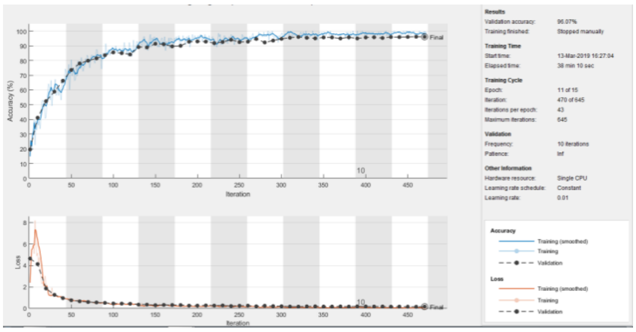

Figure 3: Performance graph

IV. CONCLUSION

The Facial Expression Recognition (FER) system through facial emotions is a great step ahead to smoothen the human-computer interaction. The FER has three main phases which are pre-processing of the image, feature extraction and classification. The pre-processing using Haar features to detect the face in a given image were used to extract features using saliency map which will help in identifying micro-expressions. These extracted features are given into the CNN to classify the emotion. Our experiment gave a validation accuracy of 96.07% which is more accurate when compared to other similar studies in the literature.

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