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Differentiating Trauma from Normal Human Emotion using Recurrent Neural Network

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Abstract: In this paper Trauma identification has been done by using the Recurrent Neural Network, which will be greatly helpful in understanding the human normal emotional condition (happy, anger, sad, neutral, disgust, fear), as well as the network will efficiently differentiate the Traumatic condition of the person from the normal condition.

Keywords: Neural Network, helpful in understanding the human normal emotional condition (happy, anger, sad, neutral, disgust, fear),

I. INTRODUCTION

Emotions recognition can be done through different modalities, such as speech, facial expression, body gestures etc. Emotion recognition through facial expression has attracted a lot of interest in last few decades. Expression of our face says a lot without speaking.

In the year 1972 Ekman, Friesen and Ellsworth works on the idea of Darwin and found that according to psychology perspective facial expression were culture specific like any culture had its own verbal language; emotion had its own language of facial expression. Mc carter and Tokmins in the year 1964 gives the first study demonstrating that facial expressions were reliable associate with certain emotional state. In the psychological research one can express his feelings and attitude by speaking i.e., by saying up to 7% through his vocal expressions upto 98% and 55% through his facial expressions as stated by A.Meharabian (1968). This shows that facial expression plays an important role for an individual too express their intention attitude, feelings and emotional state and other non-verbal messages in speech communication. Facial expression shows the mood or emotional state of an individual how he is feeling at a particular moment like sad, happy, anger.

Twisha Patel[1] investigates about various facial feature extraction techniques which is good review. [2] gives the various algorithms and their link with the facial expression detection. Yingle et. al., discusses about the facial changes and their relating emotions, and their challenges[3].

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Paper [4]uses LBP technique for feature extraction and SVM (Support Vector Machine)and ANN(Artificial Neural Network) for classification.paper[5] uses Backpropagation Neural network for identification of the face.Yeong [6]discusses about how efficient the neural in identifying human emotion. Kiran talele [7]discusses about facial feature extraction using LBP(Local Binary Pattern) and classification using NN(Neural Network).

Paper[8] discusses about various techniques of feature extraction and its efficiency when used by KNN classifier. Nazia et al., [9] explains about facial expression recognition through

machine learning and the paper [10] discusses about the neural efficiency in identifying emotion.

II. II. IMAGE DATASET

The images were obtained from the online public resource available on the internet: JAFFE (Japanese Female Facial Expression). The database contains 10 unique females. Each one has 6 poses for 6 different expressions. Therefore, a total number of expressions 180 images are used for this developed system for emotion recognition. Sample images are shown in Fig. 3.1 and for the Trauma recognition the same system uses the database PICS (Psychological Image Collection at Stirling), which has 63 images with 7 expression total of 9 women’s

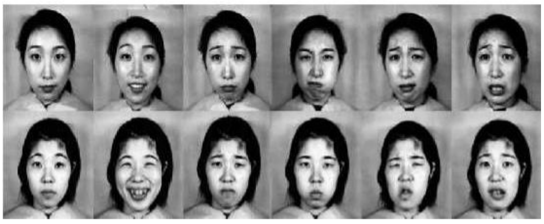

Fig.1 Samples of dataset images from JAFFE

Fig. 2 Sample Database from PICS

III. III. THE PROPOSED SYSTEM METHODOLOGY

This work presents how the Recurrent Neural Network recognize different types of facial expressions such as happy, sad, anger, neutral, disgust and fear. The images are not directly fed into the neural network, however, an image processing phase takes place first in order for the used images to be filtered and remove some useless components.

In this image processing, the images are cropped with only a face part and after doing preprocessing steps only the features such as the eyes, eyebrows, and mouth were extracted and their dimensions are measured and they are given as the input for the various network for training and testing purpose for identification of the normal human emotion and trauma condition. The images used for training and testing purposes of the network are obtained from the JAFFE database (the Japanese Female Facial Expression Database) and the PICS (Psychological Image Collection at Stirling).

IV. IV. Feature Extraction

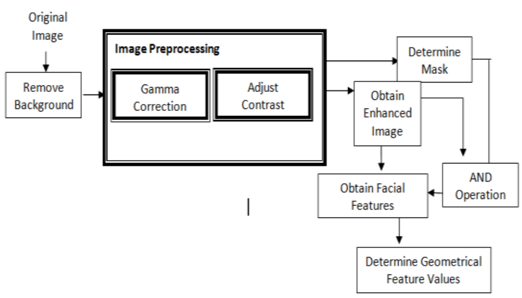

Fig. 3 Feature Extractions by Image Processing

3.3.2 Dimension Measurement

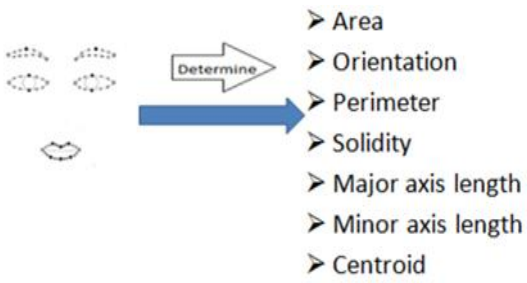

Fig. 4 Geometrical Features Measured

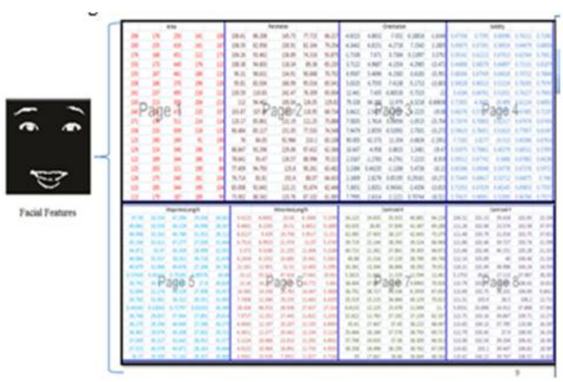

Fig. 5 Values of Measurements

After measuring the various parameters and these measurements are given as input and their performance has been evaluated using various neural networks for identifying the emotion and after ensuring the performance of BRRNN in identifying the emotion with greater accuracy which we have given in our earlier paper [11] we have given the PICS database in which trauma image is present and we tested for differentiating the trauma state of the person from normal emotion using Bayesian Regularized Recurrent Neural network with various two different types of algorithm and by varying the number of epochs.

V. V. TRAUMA IDENTIFICATION WITH RNN-BPN BY VARYING NUMBER OF

EPOCHS TO 100 AND 1000

A. Confusion Matrix for Trauma Identification with RNN-BPN

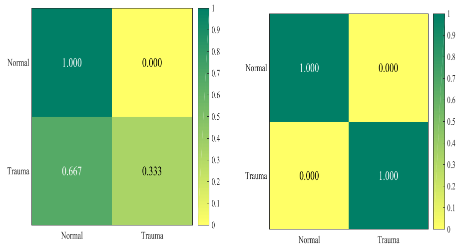

Fig.6 Confusion Matrix for Epochs 100 and 1000 for Trauma Identification with RNN-BPN

In the above two confusion matrix for the epochs 100 the normal human emotion has been achieved upto 100% correct identification, but the system could identify trauma only upto 33.3%, but when we increase the number of epochs to 1000 the network performance gets increased upto 100% identification both the normal and trauma state for the given facial features.

B. Target Vs Output Plot for Trauma Identification with RNN-BPN

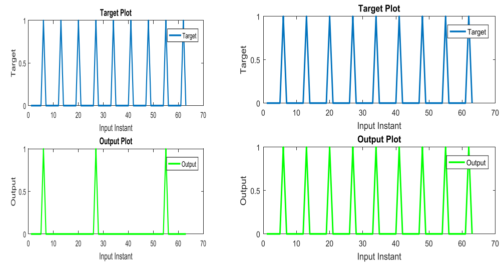

Fig. 7 Target Vs output plot for 100 Epochs and 1000 Epochs for Trauma Identification with RNN-BPN

Similar to the confusion matrix here in target vs. output plot also the network performs well for epochs 1000 compared to epochs 100, which indicates the perfect matching between the target and the output plot.

C. Regression Plot for Trauma Identification with RNN-BPN

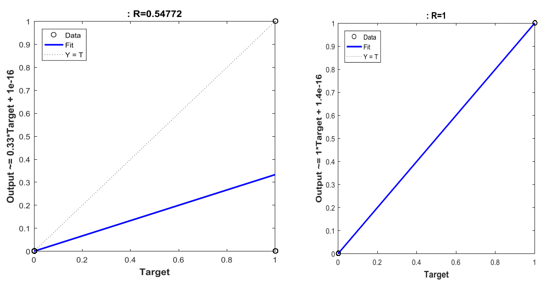

Fig.8 Regression Plot for Epochs 100 and 1000 for Trauma Identification with RNN-BPN

Here we have two equations given by the regression plot
For epochs 100: the equation is, Output=0.33*Target+1e-16, Let's assume the target as 1 then the output will be 0.33 which is not out desired output (our desired output is 0 for normal condition and 1 for trauma condition), which indicates for the epochs 100 the network does not work efficiently with the gives the R value as 0.5477.
For epochs 1000: the equation is, Output=1*Target+1.4e-16, (Assume Target as 1)

Output=1*1+1.4e-16=1, which is our desired output to indicate the trauma condition.

So the network works efficiently for epochs 1000 for the BRRNN with BPN algorithm with the R value equal to 1, which indicates the perfect fit between the Target and the output

D. Error Plot for Trauma Identification with RNN-BPN

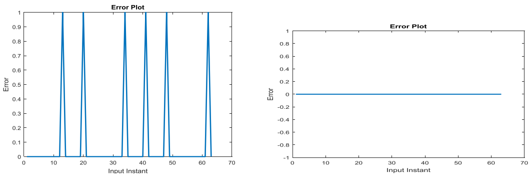

Fig. 9 Error Plot for epochs 100 and 1000 for Trauma Identification with RNN-BPN

The error plot for the epochs 1000 indicates the zero error and for the epochs 100 the error span is from 0 to 1.

E. Error Histogram for Trauma Identification with RNN-BPN

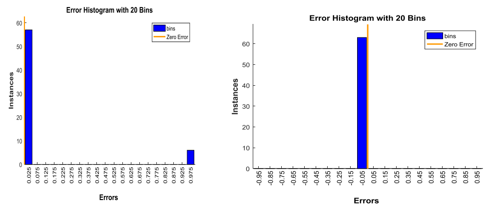

Fig. 10 Error Histogram for 100 epochs and 1000 Epochs for Trauma Identification with RNN-BPN

Error histogram for the epochs 100 shows the maximum error lie in the zero range but some of the error lie out of the zero range also which indicates the misclassification in identification of the emotions. And for the epochs 1000 it indicates the maximum error lie in the zero range and none of the error occur other than that which indicates perfect identification of emotion.

Table 3: Performance Evaluation of RNN with BPN algorithm

Parameters	Epochs 100	Epochs 1000	Description
Error	0.0952	0	Incorrect Identification for epochs 100. Ideal value is zero has been achieved for epochs 1000
Accuracy	0.9048	1	Closeness of identification to original expression of a class Ideal value is 1 has been achieved for epochs 100, and the ideal value of 1 has been achieved for epochs 1000
Precision	1	1	Closeness of identification to original expression of a class and identification of expression not belonging to the same class. Ideal value is 1 and it has achieved for epochs 1000
Specificity	1	1	Correct identification of objects not belonging to a class Ideal value is 1.
Sensitivity	0.333	1	Correct identification of objects belonging to a class Ideal value is 1.

VI. PERFORMANCE EVALUATION OF RNN-BR ALGORITHM FOR TRAUMA IDENTIFICATION

With Varying Number Of Epochs 100, 1000

A. Confusion Matrix for RNN-BR Algorithm for Trauma Identification

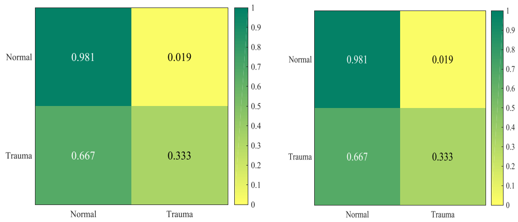

Fig. 11 Confusion Matrix for Epochs 100 and 1000 for RNN-BR Algorithm for Trauma Identification

in this condition for both in the lower end (epochs 100)and higher end (epochs 1000)the performance of the network remains the same for the all evaluation parameters. For both the epochs the normal emotion of the person has been identified upto 98.1 % and the trauma has been identified upto 33.3%.

B. Target Vs Output Plot for RNN-BR algorithm for Trauma Identification

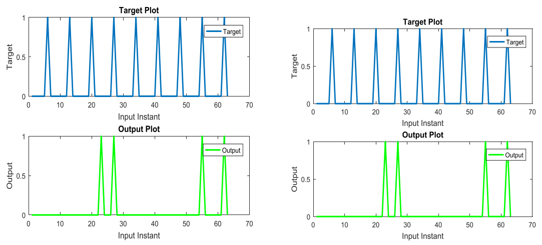

Fig. 12 Target Vs Output plot for 100 Epochs and 1000 Epochs for RNN-BR Algorithm for Trauma Identification

For both the epochs 100 and 1000 the target Vs. Output plot doesn't indicate the perfect fit, which indicates the misidentification of emotion with help of the given features.

C. Regression Plot for RNN-BR Algorithm for Trauma Identification

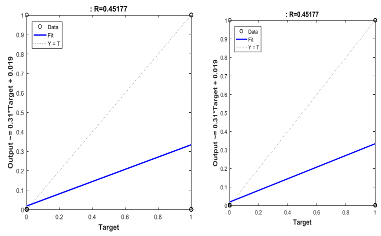

Fig. 13 Regression Plot for Epochs 100 and 1000 for RNN-BR Algorithm for Trauma Identification

Here for both the epochs the equation is given as, Output=0.31*Target+0.019,Let's assume target as 1, therefore will be Output=0.31*1+0.019=0.401, which is not our desired output, our desired output. And also we can see poor value for R given by the plot where R= 0.45177

D. Error Plot for RNN-BR algorithm for Trauma Identification

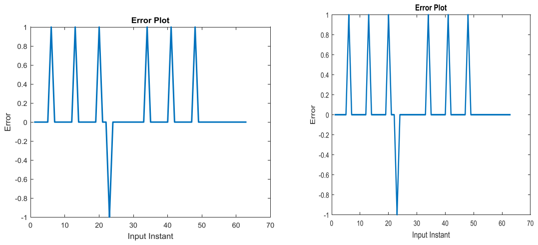

Fig. 14 Error Plot for Epochs 100 and Epochs 1000 for RNN-BR Algorithm for Trauma Identification

The error plot of horizontal line indicate the zero error but here both graph indicate the error span of -1 to +1.

E. Error Histogram for RNN-BR algorithm for Trauma Identification

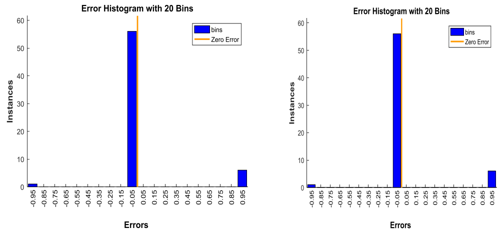

Fig. 15 Error Histogram for 100 Epochs and 1000 epochs for RNN-BR Algorithm for Trauma Identification

Here in both the plot the maximum error falls in near the zero error and we can also see some of the bins fall beyond the zero range which indicates the network performance in identifying the emotion and trauma can be achieved maximum.

Table 4: Performance Evaluation of RNN-with BR Algorithm

Parameters	Epochs 100	Epochs 1000	Description
Error	0.11	0.11	Incorrect Identification. Ideal value is zero
Accuracy	0.89	0.89	Closeness of identification to original expression of a class Ideal value is 1.
Precision	0.75	0.75	Closeness of identification to original expression of a class and identification of expression not belonging to the same class. Ideal value is 1.
Specificity	0.9815	0.9815	The network almost can Correctly identify the objects not belonging to a class where the Ideal value is 1.
sensitivity	0.333	0.333	The network poorer in Correct identification of objects belonging to a class Ideal value is 1.

VII. VII. CONCLUSION

With testing the performance of RNN by various algorithms such as BPN and BR and also by varying the number of epochs, and at RNN with BPN algorithm with epochs 1000 shows the ideal performance. So this research work can be greatly used in the medical field for identifying the emotion of the person at various stages and also it can efficiently differentiate the traumatic state of the person from other emotions. We thoroughly believe that this research work of identifying the trauma will be very useful to the mankind, as they use only frontal face for identification, which avoids various techniques which induces side effects and helps better understanding of doctors in identifying the Trauma patients as well as the mood of the patients.

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