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Facial Expression Recognition using Discrete Differential Operator and CNN

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Abstract: The facial expressions display the mood of a person which reflect his/her state of mind. Emotions can be positive or negative. The negative emotions affect the mental health as a result of depression, stress and anxiety. In this study, seven emotions, i.e. happy, sad, disgust, surprise, contempt, fear and angry are considered under a study of facial expressions recognition (FER). To this end, a CNN architecture containing two convolutional, two pooling and two dense layers are utilized with some additional features between the two convolutional layers. The output of the first convolutional layer called the feature map is multiplied by the original resized image and then fed to the next convolution layer of CNN to generate the information set based feature map. With this model, an accuracy of 98.63 % is achieved. On the other hand, the use of Prewitt and Sobel operators on the input images to produce the preprocessed images followed by the application of CNN on them leads to the recognition accuracy of 99.31%.

Keywords: Facial Expression Recognition, CNN, CK+ dataset, Sobel operator, Prewitt Operator

1. INTRODUCTION

The detection of human emotions reflecting the state of mind can be made through Facial Expression Recognition (FER). Moreover, Human Computer interaction (HCI) facilitated by FER has several applications, i.e. identification of the positive and negative emotions, lie detection, in healthcare system for patient monitoring to check the pain intensities and to make depression analysis. The main objective of this paper is to recognize the seven basic human emotions in order to deter their negative impact on a person.

Gera and Balasubramanian [1] have proposed a Spatio-Channel Attention Net (SCAN) that provides the local and the global attention per channel without using the landmark detector information. An Efficient Channel Attention (ECA) reduces the redundancies in the facial features.

Zhenghao Xi et al. [2] have developed a parallel neural network by using the Convolutional Neural Network (CNN), capsule network and residual network. This parallel network combines the eight texture features of the Gray Level Co-occurrence Matrix (GLCM).

Khalil et al. [3] have done a systematic literature review (SLR) on facial analysis system to investigate the effect of bias. Kai Wang et al. [4] have presented an efficient Self Cure Network (SCN) that suppresses the uncertainty due to self attention and avoids the use of relabeling mechanism.

Tian Xu et al. [5] have used an attribute-aware approach to disentangle the existing approaches along with the data augmentation. This approach gives an improved accuracy over that of the baseline approach.

Nonis F. et al. [6] have analyzed the constraints and the strengths of Facial Expression Recognition (FER) approaches. The accuracy of FER is improved using 3D facial data over that of 2D facial data, but it is not free from limitations that can be overcome by a multimodal 2D+3D approach. Ko [7] has presented a review of two FER schemes; one based on the conventional approach and another, the deep learning approach. The latter approach has some limitations, i.e. they require large datasets, a large memory and high computing power. They are also very time-consuming at the training and testing phases.

Two issues are covered by Deep FER systems which include over fitting caused because of insufficient training data and the unrelated variations in facial expressions [8] caused due to the varying illumination, the identity bias and

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head pose.

Liu X et al. [9] have proposed a FER approach called Identity- Disentangled FER Machine (IDFERM) wherein an identity is disentangled by utilizing the differences between a query sample and the reference samples.

Otberdout N. et al. [10] encode the local and global Deep Convolution Neural Network (DCNN) features using a compact local and global covariance descriptor. Deep covariance descriptor is proved to be more effective than the standard CNN classification models containing the fully connected dense layers and Softmax activation function.

Chen et al. [11] have developed a Facial Motion Prior Network (FMPN). In FMPN, a branch is added to generate a facial mask that focuses on the moving regions of the facial muscles. The prior domain knowledge in the form of the average of differences between the neutral and expressive faces is incorporated into the network.

Burrows et al. [12] have given a solution for the reduction of stress and to improve the mental fitness of system users. CNN is used to identify the negative emotions and Generative Adversarial Network (GAN), to produce media by which a user attempts to reduce their advese effects.

Arya et al. [13] make use of the local triangular coded pattern (LTCP). Moreover, the local binary descriptors are widely employed for many computer vision applications. In their work an accuracy of 97.52 % is secured on CK+ dataset having 6 classes. A low calorie net CERN (Compact Expression Recognition Net) proposed by Darshna Gera et. al. [14] performs well under occlusions and the pose variations. Liu et al. [15] have developed the Expression Snippet Transformer (EST) that gives good performance.

We present two approaches on FER in this work. In the first approach, the facial expression images are preprocessed using the Prewitt and Sobel operators and the preprocessed images are fed to the CNN. In the second approach, a CNN with the proposed modifications is used for FER.

The organization of the paper is as follows: Section 2 provides the explanation of dataset used and the methodology involving the preprcessing and CNN is explained in Section 3. The results are described in Section 4. Conclusion and future scope are discussed in Section 5.

2. DATA SET USED

The Extended Cohn-Kanade dataset [16] (CK+ dataset) containing 7 classes, i.e., Happy (HA), Disgust (DI), Sadness (SA), Anger (AN), Fear (FE), Contempt (CO) and Surprise (SU) is taken from [17]. This dataset contains 593 sequences on 123 subjects. A total of 981 images with each gray scale image of size 48x48 is used in this work. This database is split into the training, testing and validation sets with the ratios of 7:1.5:1.5. A few sample images of seven emotions are shown in Figure 1. Some general expansion methods vouch for the operations such as horizontal flip,

Figure 1. Images from CK+ dataset

Figure 2. The expanded dataset after data augmentation

zoom range of 0.2, rotation range of 30 and shear range of 0.2 to create a number of training, validation and testing samples as shown in Figure 2.

3. METHODOLOGY

A. *Preprocessing*

The Prewitt and Sobel operators are the simple edge detectors. The pixels with large gradient values are considered to be the edge pixels in the gradient images produced by applying these detectors on the facial images. The edge pixels with the highest gradient values can be traced perpendicular to the gradient direction. The image gradients can also be used to match the facial features and textures of two images with a considerable facial accuracy.

The Prewitt and Sobel operators are applied on the subimages to perform the convolution operation in the horizontal, vertical and diagonal directions. Figure 3(a) and (b) show the Prewitt operator and Figure 3(c) and (d) show the Sobel operator in the horizontal and the vertical directions respectively. The choice of the Sobel operator is made because of its high noise suppression trait. Figure 4 (a)-(d) show the Prewitt and Sobel operators for detecting

-1	-1	-1
0	0	0
1	1	1

(a)

-1	0	1
-1	0	1
-1	0	1

(b)

-1	-2	-1
0	0	0
1	2	1

(c)

-1	0	1
-2	0	2
-1	0	1

(d)

Figure 3. Prewitt (a,b) and Sobel (c,d) masks for detecting horizontal and vertical edges

0	1	1
-1	0	1
-1	-1	0

(a)

-1	-1	0
-1	0	1
0	1	1

(b)

0	1	2
-1	0	1
-2	-1	0

(c)

-2	-1	0
-1	0	1
0	1	2

(d)

Figure 4. Prewitt (a, b) and Sobel (c, d) masks for detecting diagonal edges

the diagonal edges. The outcome of the first order gradient operator on a facial image is revealed in the form of fine lines. As the facial expressions are the portrayal of fine curves on a face; a gradient operator enhances these features that are fed to the CNN architecture for further modification by the kernel functions/filters [18]. We now present the mathematical expression for the computation of gradient value. The squared values of G_x that is the gradient along the x-direction and G_y that is the gradient along the y-direction are summed up and then the square root of the sum is the gradient value, as given by

$$\nabla(x, y) = \sqrt{G_x^2 + G_y^2} \tag{1}$$

The implementation of the Prewitt and Sobel operators on the facial images is illustrated in Figure 5 in which (a)-(d) show the effect of these operators in the horizontal, vertical and diagonal directions respectively and (e) shows the original image. Figures (f), (g) show the gradient images in the horizontal, vertical and diagonal (45deg, -45deg)

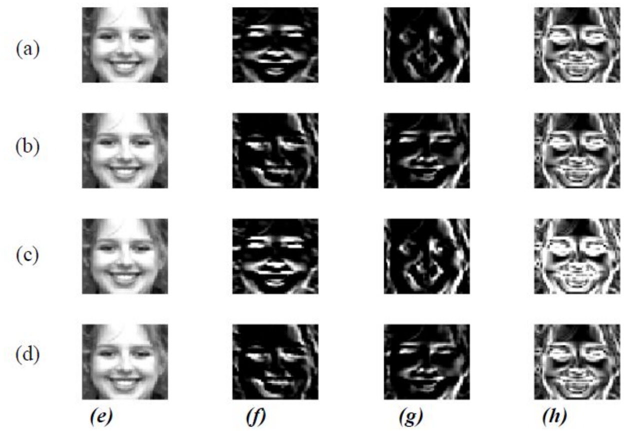


Figure 5. Effect of Prewitt (a) horizontal and vertical, (b) diagonal and Sobel Operators (c) horizontal and vertical, (d) diagonal on Images (e) original image, (f) G_x, (g) G_y, (h) $\sqrt{G_x^2 + G_y^2}$

directions from which the final gradient image is obtained as shown in Figure 5 (h).

B. The CNN Architecture

The two main tasks that are performed by CNN are feature extraction and classification.The convolution operations expressed by Eq. (2) are carried out in the two convolutional layers. Next, the max operation expressed by Eq. (3) is carried out in the pooling layer. The output of the pooling layer is fed to the two dense layers of size 512 and 128 nodes with dropout of 25 % along with ReLU activation function and next is the output layer with 7 nodes for 7 classes with Softmax activation function. The OpenCV and Tensor flow in Python are applied on this architecture.

$$F_{c_1}(x, y) = ReLU\left[\sum_{j=1}^{K_1} z_{c_1,j} w_{c_1,j}\right] \tag{2}$$

$$I_p(x, y) = Max\left[F_{c_1}\right]_{k_1 \times k_1} \tag{3}$$

It may be noted that in Eq. (2) z and w denote the pixel intensities and kernel parameters respectively. The subscript c1 is the convolution layer-1, whereas in Eq. (3) the maximum value is selected from a window of size k1xk1 from the convoluted image F. The results of two approaches are now analyzed.

a) In the first approach, preprocessing is done on the facial images. The preprocessed images are then fed to the convolutional layer of CNN. The Prewitt and Sobel operators are used for preprocessing. The complete architecture is shown in Figure 6.

b) In the second approach, no processing is done on the input facial image which is directly fed to the first convolutional layer. The output of this layer is a set of

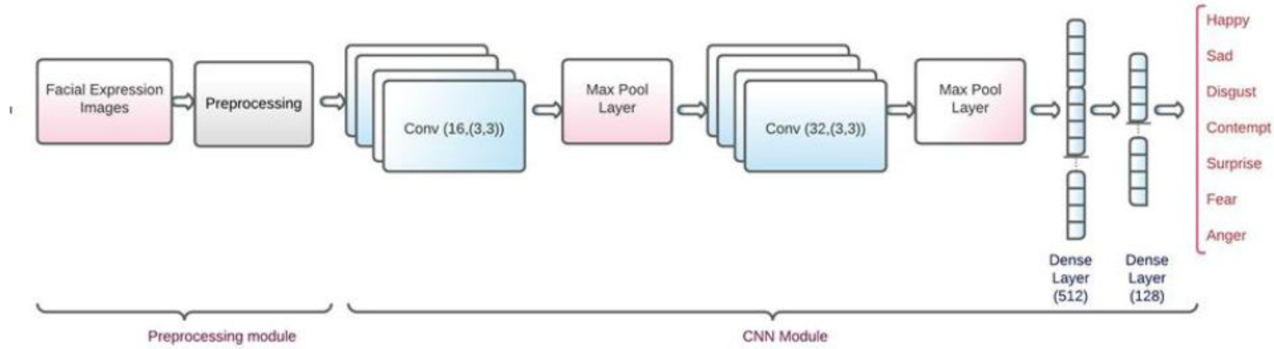


Figure 6. CNN Archtecture used with the preprocessing step

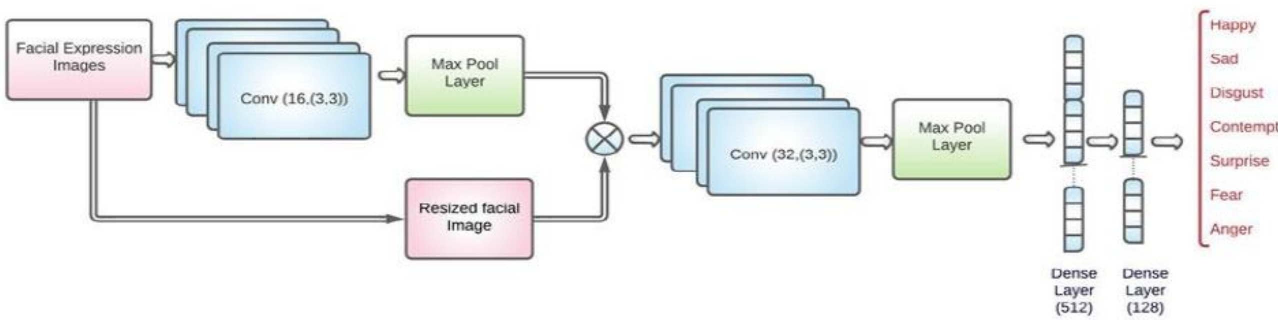


Figure 7. CNN Archtecture with the proposed modification

feature maps whose sizes are reduced at the first max pooling layer. The reduced feature maps are multiplied with the resized original image and then fed to the second convolutional layer as shown in Figure 7. This process called the conversion of feature maps and the reduced original input image into the information set based feature maps is explained as follows: Let I(x,y) be the facial image that is fed to the first convolutional layer of size (32(3,3)) and then its outcomes are fed to the max pooling layer yielding $I_p(x, y)$. The input image I(x,y) is resized to the size of $I_p(x, y)$ and then both are multiplied to get what we call the information set based feature maps expressed by Eq.(4).

$$I_m(x, y) = I_p(x, y)I_r(x, y) \tag{4}$$

$$F_{c_2}(x, y) = ReLU\left[\sum_{j=1}^{K_2} I_{m,j}w_{c_2,j}\right] \tag{5}$$

$$P_{c_2}(x, y) = Max\left[F_{c_2}\right]_{k_2\times k_2} \tag{6}$$

Where $I_p(x, y)$ is the output of max pooling layer and $I_r(x, y)$ is the resized facial image. $I_m(x, y)$ is fed to the second convolutional layer c2 thus modifying the information set based feature maps as in Eq.(5). It can be proved that when a kernel function is convolved with an input image it yields a feature map. We get as many feature maps as the number of kernels functions applied. Each feature map consists of the membership function values. According to the information set theory, multiplication of the attribute values (here grey levels) and the corresponding membership function values are termed the information values the sum of which gives the certainty of these values to a concept (in this case it refers to a particular expression). We use the following function to identify an emotion by finding the highest value.

$$\sigma\left(\vec{z}\right)_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_i}} \tag{7}$$

Eq. (7) represents the softmax function, where z_i is the output vetor of the second dense layer, K is the number of classes, that is 7 in this study. The exponential function gives the positive value even for the negative input value. $\sum_{j=1}^{K} e^{z_i}$ is used to get the normalized output.

4. RESULTS

The effectiveness of the proposed model can be noticed from the results in Table I. The overall classification accuracy achieved without pre-processing is 97.27%. When the Sobel operator is applied on the input image as a preprocessing step before inputting to the CNN model the accuracies jump to 99.31% and 97.95%, which correspond to the use of the operator in the vertical-horizontal directions and diagonal directions, respectively. Similarly, the accuracies obtained with Prewitt operator in the horizontal

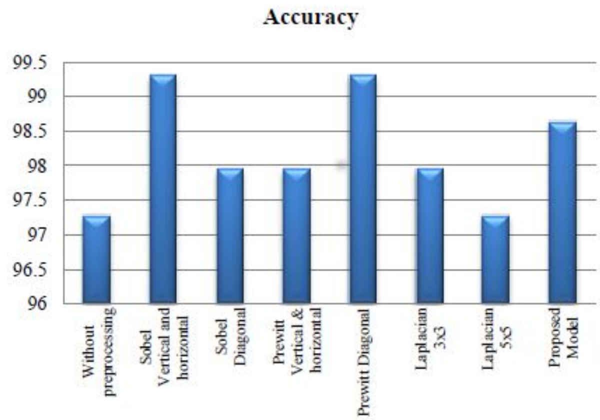


Figure 8. The Recognition accuracies with different methods

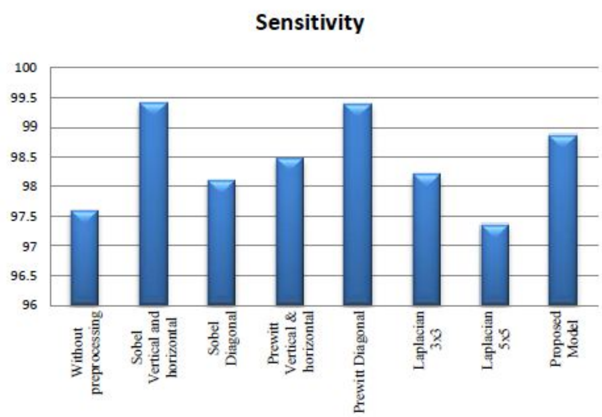


Figure 9. The results of sensitivity due to different methods

and vertical directions are 97.95% and 99.31% respectively. In the second approach 98.63% accuracy is obtained.

As can be seen in Table I that F1 score attains a value of 0.9938 by using the Prewitt operator on diagonal elements of facial sub-image by achieving an accuracy of 99.31 % using the same approach. Preprocessing step includes the application of either one of the Sobel and Prewitt operators on the facial images before inputting them into the CNN.

We have also modified the CNN architecture using information set concept and the results are improved. The accuracy and sensitivity due to different approaches appear in Figure 8 and Figure 9 respectively.

Figure 10 shows the training and validation accuracies for (a) Simple CNN, (b) Preprocessed by Sobel operator (horizontal and Vertical), (c) Preprocessed by Prewitt operator (Diagonal), (d) CNN with the proposed model respectively. Figure 11 shows the plots of the training and validation losses for (a) Simple CNN, (b) Preprocessed by Sobel operator (horizontal and Vertical), (c) Preprocessed by Prewitt operator(Diagonal), (d) CNN with the proposed model. The confusion matrices for the seven emotions due to different methods are given in Figure 12.

Table II shows a comparison of various models on different datasets. Gera et. al. [1] have used the spatio channel attention on FER plus dataset and achieved 89.42 % accuracy, while Xi et al. [2] have applied parallel neural network and achieved 98.14 % accuracy on CK+ dataset. Wang et al. implement FER plus dataset on the self cure network and achieve 89.35% accuracy on 8 classes. The methods in [19], [20], and [21] use the CK+ dataset and achieve the accuracies of 95.7 %, 93.46 % and 97.32 % respectively. In [22] Ritanshi et al. have applied Laplacian of Gaussian at the preprocessing step on the images and then they fed the preprocessed images to CNN to obtain the accuracy of 99.32 %. Ritanshi et al. have used the horizontal flip only for augmentation whereas we have used rotation, zoom and shear along with the horizontal flip for augmentation. We have obtained 99.31 % accuracy by applying Prewitt's diagonal (D) and Sobel's horizontal and vertical (HV) operators before CNN. Sun. Z, et al. [23] have achieved 98.1 % accuracy by utilizing the improved conditional GAN and discriminative loss function, while Bisogni et al. [24] have obtained the recognition accuracy of 97.83 %. In [25], Kumar et al., have obtained the accuracy of 94.5%.

5. Conclusions and Future Work

A. Conclusions

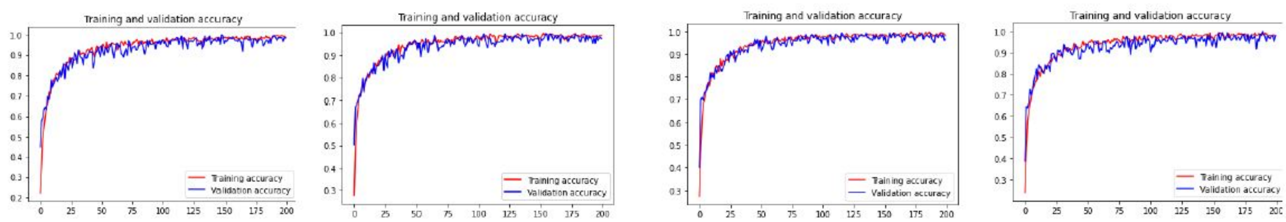
This work exhibits the influence of the edge operators, Prewitt and Sobel on the facial images at the pre-processing step. The resulting gradient images are fed to the CNN architecture containing two convolutional layers with 2 pooling layers and 2 dense layers leading to a recognition accuracy of 99.31 % with Sobel HV - CNN combination and Prewitt D - CNN combination. Using the discrete differential operators like Sobel operator or Prewitt operator on the facial images at the preprocessing step highlights the facial expressions. It is observed that by applying these operators on images before inputting into CNN, the performance of the proposed model is improved. Also, the results of the proposed model involving the combination of differential operator and CNN are better than thoseof the simple CNN architecture with the same number of convolutional and pooling layers. This paper demonstrates the influence of discrete differential operator on images. It is concluded from experiments that Sobel HV and Prewitt D operators make a considerable change in the facial expression images by way of revealing the facial curves.

B. Future Scope

The facial expressions are the reflection of the status of mind of a human being. It is evident that a significant size of population suffers from the problem of poor mental health [12]. The poor mental state is the result of a number of factors, i.e. difficult obligations, hard lifestyle, lack of physical activity and work environment. The only way

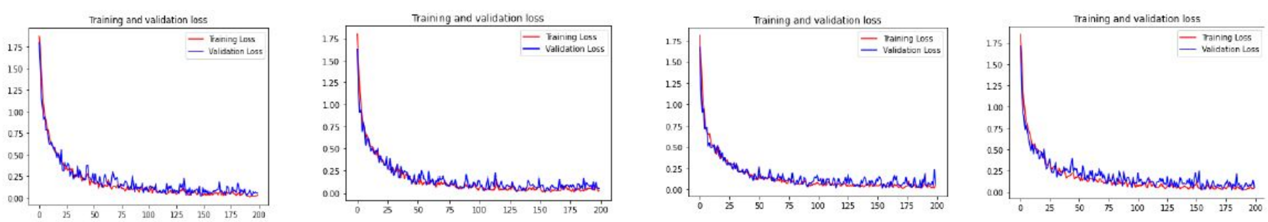
TABLE I. The results of preprocessing by the Sobel and Prewitt operators on emotions recognition

-	Accuracy(%)	Loss	Sensitivity	Specificity	F1 Score
CNN Model	97.27	0.0731	97.57	99.28	0.9759
Sobel HV	99.31	0.0283	99.4	99.93	0.994
Sobel D	97.95	0.0695	98.10	99.60	0.981
Prewitt HV	97.95	0.0427	8.47	99.63	0.9847
Prewitt D	99.31	0.0289	99.38	99.89	0.9938
Laplacian 3x3	97.95	0.0921	98.21	99.35	0.9821
Laplacian 5x5	97.27	0.1261	97.35	99.54	0.9735
CNN with proposed model	98.63	0.0566	98.87	99.66	0.9887
				*D Diagonal	* HV Horizontal Vertical



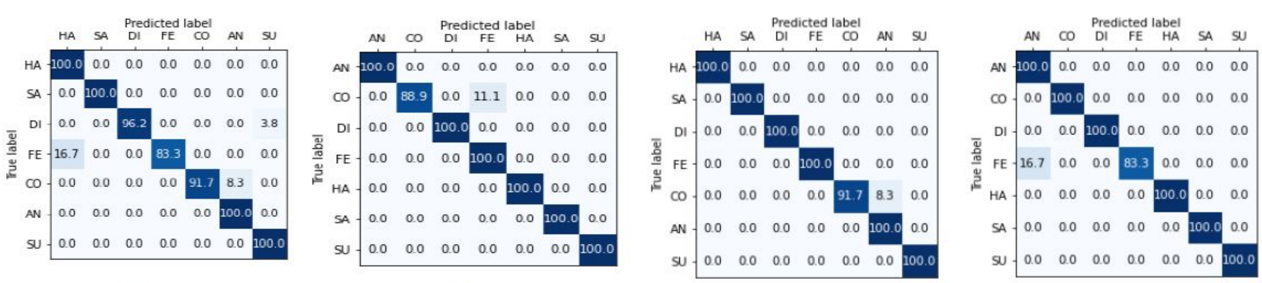
(a) (b) (c) (d)

Figure 10. Training and validation accuracies for (a) Simple CNN, (b) Preprocessed by Sobel operator (horizontal and Vertical), (c) Preprocessed by Prewitt operator(Diagonal), (d) CNN with proposed model



(a) (b) (c) (d)

Figure 11. Training and validation loss for (a) Simple CNN, (b) Preprocessed by Sobel operator (horizontal and Vertical), (c) Preprocessed by Prewitt operator(Diagonal), (d) CNN with proposed model



(a) (b) (c) (d)

Figure 12. Confusion Matrix for (a) Simple CNN, (b) Preprocessed by Sobel operator (horizontal and Vertical), (c) Preprocessed by Prewitt operator(Diagonal), (d) CNN with the proposed modification

TABLE II. A Comparison of various Models on different datasets

Method Used	Year	Dataset Used	No. of Classes	Accuracy (%)
Spatio Channel Attention [1]	2021	FER Plus	8	89.42
Parallel Neural network [2]	2020	CK+	7	98.14
Self cure Net [4]	2020	FER Plus	8	89.35
FMPN [11]	2019	CK+	7	89.06
HiNet [19]	2019	CK+	7	95.7
DCMA-CNN [20]	2019	CK+	6	93.46
LBP CNN [21]	2020	CK+	7	97.32
Gaussian CNN [22]	2021	CK+	7	99.32
Im-cGAN [23]	2023	CK+	7	98.1
CNN [24]	2022	CK+	7	97.83
HOG LPQ [25]	2023	CK+	7	94.5
Prewitt D + CNN		CK+	7	99.31
Soel HV + CNN		CK+	7	99.31

to mitigate the poor mental health that arises whenever negative emotions start overpowering is to adopt a stress free life.

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