International Journal of Computer Applications (0975 – 8887)
Volume 186 – No.66, February 2025

Real-Time Depression Detection using Emotion Recognition Techniques

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ABSTRACT
When it comes to health, mental health is a very widespread problem today. health, where nearly 25% of the world's population suffers from some mental illness. Artificial Intelligence (AI) is a concept that has evolved considerably and is expected to soon bring improvements and help to people in various fields. The mental health field is not excluded, so artificial intelligence can help in the performance of health services, whether by medical staff or patients. Within mental health, it has been observed that by recognizing facial expressions, depression, schizophrenia, or other similar conditions. However, for machine learning, a large data set is required for good accuracy. In this paper, presented a facial expression recognition method using only a few training datasets, the accuracy of this training dataset was 94%. This precision is stored as the depression-detector model name.h5. The proposed model (FEDA) will facilitate the understanding of people's mental state. Human image data models have helped understand emotions and provided new application concepts in health, security, business, and education, which can be used remotely via a web application.

Keywords
Emotion Recognition, AI, DL, ML, CNN, OpenCV, Kera's, TensorFlow, Depression Detection Model.

1. INTRODUCTION
According to a current survey, mental illness accounts for at least 25% of the total and the annual cost is estimated may reach 6 trillion dollars by 2030 [1]. Currently, almost every public health institute promotes the prevention of mental disorders, prevention of the impact of mental disorders on society, and mental well-being. In this sense, the question of using gesture analysis, expressions, and analysis of speech fragments to identify possible mental disorders was raised. So, it is expected to recognize the remarkable results of artificial intelligence depression, anxiety, mental alienation, or other similar conditions. Through the branch of artificial intelligence focused on learning from data - machine learning is a very promising tool to help predict mental health [2]. Facial expression is a powerful communication element that can voluntarily or even involuntarily add information to the communication process. Therefore, research into emotions from facial expressions obtained by image and video analysis increased, especially for psychiatric applications. To get a suitable algorithm for this area of exercise, emotions theory was developed. Based on "basic emotions", it has automatic emotion detection was developed. On the other hand, facial expression or reduction of emotions may be symptoms or negative symptoms of mental disorders such as schizophrenia, autism, or depression, for example, people with schizophrenia scored higher in ambiguity, the degree of conditional entropy in the expression of a single emotion [3], but patients may also show signs of fear, sadness or apathy confusion or disorientation and even displays of anger or aggression.

1.1. Proposed system
According to previous work [4], in this paper have implemented an experiment for real-time emotion detection using a convolutional neural network (CNN) model. based on various functions such as activation function Sequential (), Conv2D (), MaxPooling2D () or ReLU [5].

1.2 Related work
In this paper, work has been done to identify problems such as emotions or depression. Data analysis has been done to detect situations based on facial expressions. A model has been demonstrated by training with a very large data input dataset. It is necessary to have high accuracy due to improved results by the data train model, by using epoch 100 the accuracy has been brought up to 94%. That means very good results can be obtained through this model. This model system is primarily designed to detect facial depression. In this order: 7087 images are included. And CNN network has been used for sentiment recognition. The work of running a data train model and CNN network on the Python platform has been done. To get better results from the data model, work has been done to import libraries like OpenCV, Keras, TensorFlow, and Haarcascade. An attempt has been made to find out whether the mental state of humans is depressed or natural through a real-time emotion detection process using the webcam.

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2. METHODS
2.1 Emotion Recognition System
The emotion recognition system is divided into 3 stages: face location determination, feature extraction, and emotion classification. After the face is located using a face detection algorithm, knowledge of the symmetry and shape of the face

combined with image processing techniques is used to process the face region to determine the location of the features. These stages are further processed to extract the emotion feature points needed for the emotion classification stage. From the extracted feature points, the distances between the features are calculated and given as input to the neural network for the classification of the contained emotions. A convolutional neural network was trained to recognize 2 universal emotions for mental health.

Using an emotion recognition system, artificial intelligence (AI) can detect human emotions through facial expressions [8], [9]. Detected emotions can fall into one of two main emotion data: depression (or stress) and natural. For example – negative emotions in a human can be identified by AI as depressing or stressful.

2.1.1 Face Location Determination Stage.

The system offers two face detection methods using different knowledge-based techniques, and temple-based techniques can be developed for face localization, and the invariant function approach based on skin color is chosen as the first method because of its flexibility and simplicity in face localization. several algorithms for different color spaces can be found in skin color regions [10], [11]. These algorithms are listed in Table I below.

TABLE I: Skin color segmentation algorithms in different color spaces

Color Space	Criteria
RGB	$R > 95$ and $G > 40$ and $B > 20$ and {Max (R, G, B) – Min (R, G, B)} and $\|R-G\| > 15$ and $R > G$ and $R > B$
RGB normalized	$r/g > 1.185$ and $(r*b) / (r+g+b)2 > 0.107$ and $(r*g) / (r+g+b)2 > 0.112$
HSV	$I > 40$ and If ($13 < S < 110$ and $0^\circ < H < 28^\circ$) and $332^\circ < H < 360^\circ$ If ($13 < S < 75$ and $309^\circ < H < 331^\circ$)
YCbCr	$77 \leq Cb \geq 127$ and $133 \leq Cr \geq 173$

For accurate face identification, the largest connected area that meets various conditions is selected and further refined. Refinement selects the center of the region and selects the densest area of skin color pixels around the center as the face region.

2.1.2 Feature Extraction Stage.

The extracted selected face region is further processed to extract the emotion classification phase of the desired feature points. Several feature points were identified as important at this stage and were extracted for use in the classification stage. The extraction phase can be divided into two parts: Feature area extraction and feature point extraction [12].

2.1.3 Feature Region Extraction.

Face detection phase, the detected face is used to identify the eye, eyebrow, nose, and mouth regions [13]. First, the likely Y coordinates of the eyes are identified, and then the area around this Y coordinate is processed to identify the extracted eye regions. Later, eyebrow and mouth regions were also extracted based on the eye regions. Finally, the corner point detection algorithm obtains the desired corner points from the feature regions.

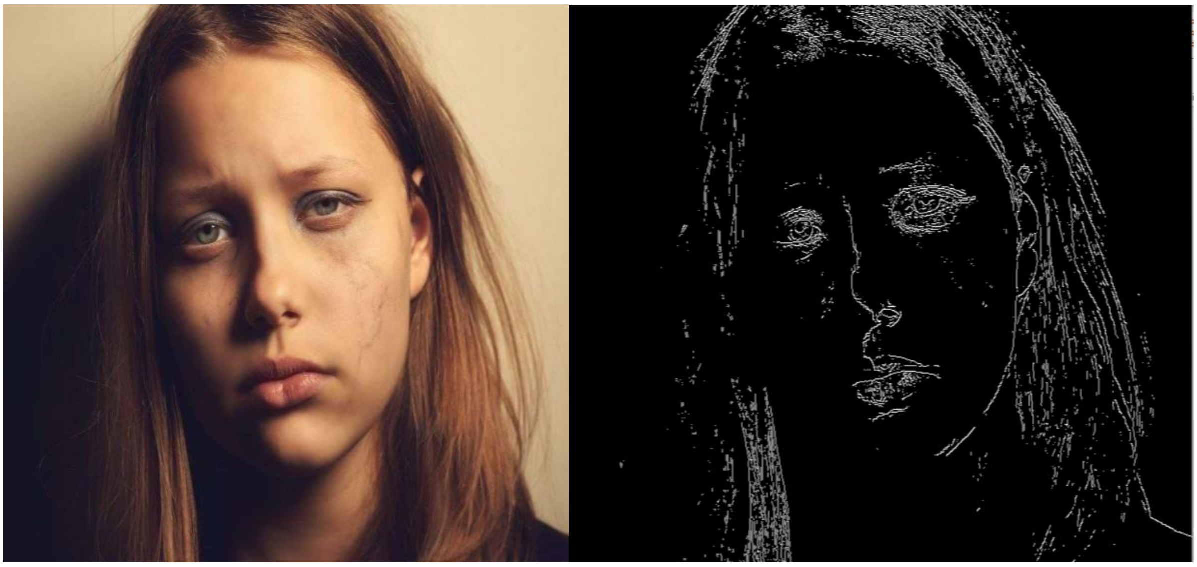


Fig.1 (a) Original image, (b) Region detection edge image.

2.2 Emotion Classification

The extracted feature points are processed to obtain inputs for the neural network. Neural is trained to recognize natural and depressive emotions. 35887 images of individuals have been taken from a database of facial expressions and emotions that are used to train the network. These 35887 images consist of images of an individual representing these 2 emotions. The inputs given by the neural network are as follows.

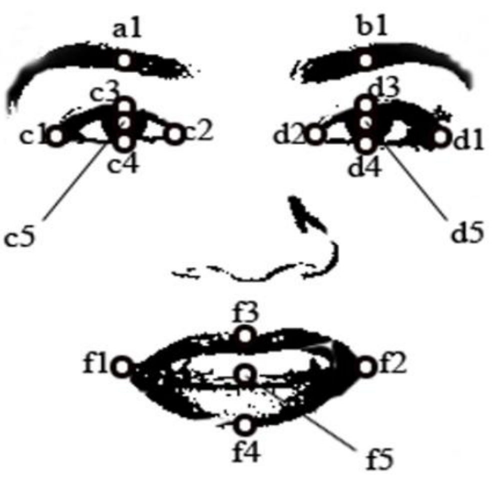


Fig.2 Feature points extracted by the feature point extraction stage.

- Eye height = (Left eye height + Right eye height) / 2

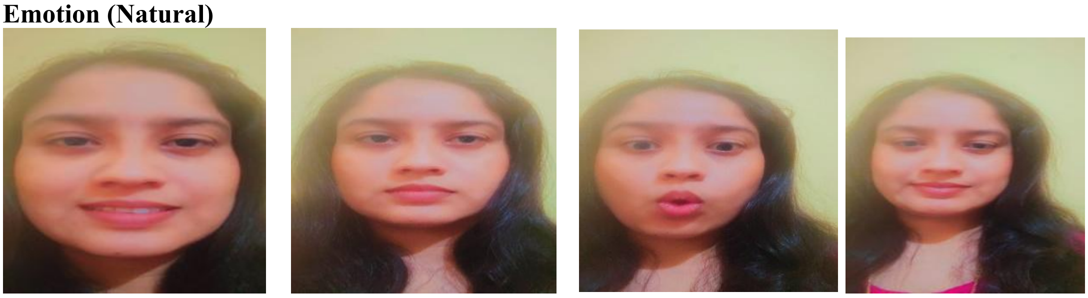
  $= [(c4 - c3) + (d4 - d3)] / 2$
- Eye width = (Left eye width + Right eye width) / 2

  $= [(c2 - c1) + (d1 - d2)] / 2$
- Mouth height = $(f4 - f3)$
- Mouth width = $(f2 - f1)$
- Eyebrow to Eye center height = $[(c5 - a1) + (d5 - b1)] / 2$
- Eye center to Mouth center height = $[(f5 - c5) + (f5 - d5)] / 2$
- Left eye center to Mouth top corner length
- Left eye center to Mouth bottom corner length
- Right eye center to Mouth top corner length
- Right eye center to Mouth bottom corner length
- Eye width/ Eye height
- Mouth width / Mouth height
- Eyebrow to Eye center height / (Eyebrow to Eye center height + Eye center to Mouth center height).

2.3 Classification Evaluation

based on the phase of emotion classification and facial point detection, positive or negative emotions can be easily recognized because the height, width, and distance values of eye, eyebrow, and mouth landmarks differ for different emotions [13].

Positive Emotion (Natural)



Negative Emotion (Depressive)

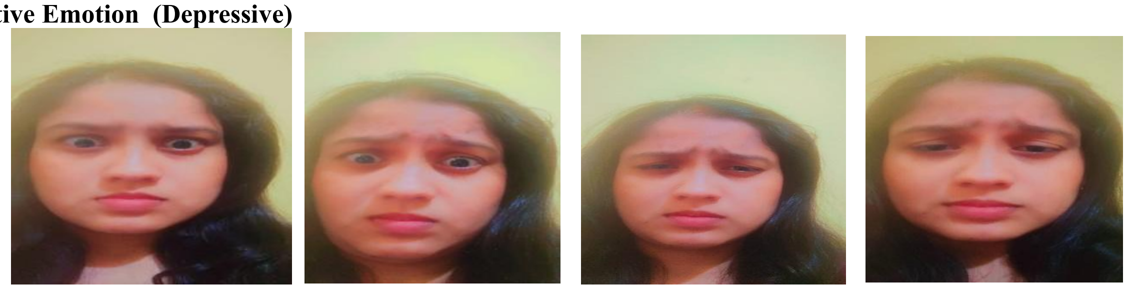


Fig.3 Positive (Natural) and Negative (Depressive) Emotion Classification.

To train the network, for each of these 35887 images, manually labeled feature points and emotions contained in each face were obtained. Then the obtained feature points were processed to calculate the inputs mentioned earlier. Finally, the inputs and emotions were fed to a supervised neural network.

The neural network contained a hidden layer with multiple neurons. The network was trained with a learning rate of 0.1 to reach the goal.

2.4 Dataset and Data Preparation

In this research, used the FER-2013 dataset for depression detection [16]. Since the dataset is divided into 7 emotion classes, researcher cannot use it directly, so first this dataset was divided into 2 emotion classes based on the emotion of depression. The dataset was converted to a depression dataset based on the positive and negative datasets, as negative emotions represent depression or stressful emotions and positive emotions represent natural or neutral emotions. It is based on two different classifications starting with index labels 0 to 1, which are described in the table.

TABLE II: Number of data in the Depression dataset.

	Depressive	Natural	Total
Training	3229	3858	7087
Testing	3229	3858	7087

The next step is to change the scale of the images. The OpenCV library has built-in support for performing this operation. Cropping was done in two values: 48 pixels × 48 pixels. The goal is to compare them during training. Before converting this set of images to a binary file, these images are converted to grayscale images. Python Images Library (PIL) is the chosen tool to accomplish this task.

The technique of preprocessing image data sets. It is the most important stage of the methodology. Here, the emotion dataset has been used for mental health. This dataset has been run on a Python Jupyter Notebook and the Keras library and OpenCV has been used for image classification. FIGURE 4 shows the classification of the image data set [17].

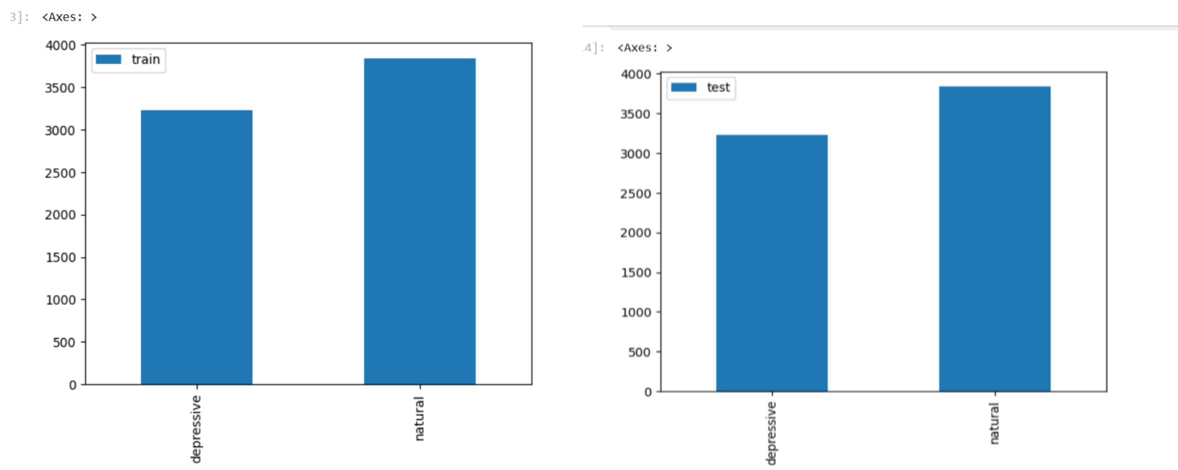


Fig.4 Shows the depressive and natural image dataset classification

2.5 Training Dataset

The training dataset is the dataset of examples used during the learning process and is used to adapt the parameters of the classifier. For classification tasks, a supervised learning algorithm looks at a training data set to determine, or learn, the optimal combination of variables that will produce a good predictive model.

2.6 Convolutional Neural Network (CNN) Model

Here CNN classification was used Creating a convolutional neural network (CNN) model using the Keras API for image categorization and in real-time "Sequential()" created an empty sequential model that allowed layers to be added in sequential order [18]. The "Conv2D()" function with 128 filters, 3x3 kernel size, and ReLU activation function is used to add the first convolutional layer, and the shape of the training data is used to define the input shape. The "MaxPooling2D()" function selects the highest value in each pool size area (2x2) to reduce the sample size of object maps. By randomly removing some input units, a Dropout() function is added to stop the overflow, and the second convolutional layer has the same structure with "max pooling" and "dropout" afterward. Then a second convolutional layer is added with 258 filters, a 3x3 kernel, and a ReLU activation function. Then a third convolutional layer is added with 512 filters, a 3x3 kernel, and a ReLU activation function. The same settings are applied to the fourth convolutional layer.

The 2D output from the previous layer is then converted to a 1D vector using the "Flatten()" function. Two fully connected layers, each with 512 neurons and a ReLU activation function, are added to minimize switching, and Dropout is implemented after each fully connected layer. A dense output layer with a softmax activation function having the number of neurons equal to the output classes is added to obtain the class probabilities. The model is designed for use by the Adam optimizer with the categorical cross-entropy acting as a loss function (typically used for multi-class classification problems) and the accuracy serving as a performance metric to assess the fiction of the model's effectiveness during training. The optimizer, loss function, and metrics are configured as part of the model compilation process using the "compile()" method. The "fit()" function can be used to train the model after it has been built.

The Keras function called "model.summary()" is also used to create a list of neural network model layers and parameters. The type of each model layer, the output shape, and the number of trainable parameter values are listed in a line for each layer in the summary. The output shape of each layer is presented as a tuple in which the first value indicates the batch size and the remaining values indicate the output size tensor.

Compile and train the model

```
]: history = model.fit(x= x_train,y = y_train, batch_size = 128, epochs = 100, validation_data = (x_test,y_test))

Epoch 1/100
WARNING:tensorflow:From C:\Users\Sonal\AppData\Local\Programs\Python\Python310\lib\site-packages\keras\src\utils\tf_utils.py:492: The name tf.ragged.Ragged
TensorValue is deprecated. Please use tf.compat.v1.ragged.RaggedTensorValue instead.

WARNING:tensorflow:From C:\Users\Sonal\AppData\Local\Programs\Python\Python310\lib\site-packages\keras\src\engine\base_layer_utils.py:384: The name tf.exec
uting_eagerly_outside_functions is deprecated. Please use tf.compat.v1.executing_eagerly_outside_functions instead.

56/56 [==============================] - 335s 6s/step - loss: 0.6979 - accuracy: 0.5360 - val_loss: 0.6906 - val_accuracy: 0.5431
Epoch 2/100
56/56 [==============================] - 716s 13s/step - loss: 0.6896 - accuracy: 0.5431 - val_loss: 0.6893 - val_accuracy: 0.5431
Epoch 3/100
56/56 [==============================] - 335s 6s/step - loss: 0.6891 - accuracy: 0.5431 - val_loss: 0.6876 - val_accuracy: 0.5431
Epoch 4/100
56/56 [==============================] - 1419s 26s/step - loss: 0.6897 - accuracy: 0.5347 - val_loss: 0.6899 - val_accuracy: 0.5431
Epoch 5/100
56/56 [==============================] - 316s 6s/step - loss: 0.6900 - accuracy: 0.5431 - val_loss: 0.6875 - val_accuracy: 0.5431
Epoch 6/100
56/56 [==============================] - 1492s 27s/step - loss: 0.6860 - accuracy: 0.5545 - val_loss: 0.6867 - val_accuracy: 0.5553
Epoch 7/100
56/56 [==============================] - 274s 5s/step - loss: 0.6839 - accuracy: 0.5612 - val_loss: 0.6788 - val_accuracy: 0.5800
Epoch 8/100
56/56 [==============================] - 279s 5s/step - loss: 0.6817 - accuracy: 0.5616 - val_loss: 0.6751 - val_accuracy: 0.5870
Epoch 9/100
56/56 [==============================] - 1891s 34s/step - loss: 0.6752 - accuracy: 0.5843 - val_loss: 0.6668 - val_accuracy: 0.5994
Epoch 10/100
56/56 [==============================] - 275s 5s/step - loss: 0.6716 - accuracy: 0.5956 - val_loss: 0.6602 - val_accuracy: 0.6136
Epoch 11/100
56/56 [==============================] - 615s 11s/step - loss: 0.6692 - accuracy: 0.5954 - val_loss: 0.6620 - val_accuracy: 0.6001
Epoch 12/100
56/56 [==============================] - 308s 5s/step - loss: 0.6660 - accuracy: 0.5922 - val_loss: 0.6566 - val_accuracy: 0.6230
Epoch 13/100
56/56 [==============================] - 279s 5s/step - loss: 0.6660 - accuracy: 0.5987 - val_loss: 0.6564 - val_accuracy: 0.6069
```

Fig.5 Compile and train the model.

In the last part of the realtimedepressiondetection.py file, save the architecture and weights of the depressiondetector.h5 model.

2.7 Testing Dataset

A test dataset is a dataset that is independent of the training dataset and follows the same probability distribution as the training dataset.

If the model fits the training dataset, also the dataset well first. There was minimal reassembly. A better fit to the training data set, as opposed to the test data set, usually indicates overfitting.

Thus, the test set is a set of examples used only to access the performance of a fully specified classifier. To test the data, followed the following steps- Evaluate the model and find the final accuracy of 94%.

```
56/56 [==============================] - 288s 5s/step - loss: 0.1553 - accuracy: 0.9404 - val_loss: 0.0161 - val_accuracy: 0.9983
Epoch 100/100
56/56 [==============================] - 299s 5s/step - loss: 0.1375 - accuracy: 0.9454 - val_loss: 0.0171 - val_accuracy: 0.9989
```

Fig.6 Shows model accuracy and loss.

2.8 Train Model Validation Accuracy and Loss

Training includes updating model weights based on training data and calculation accuracy and focusing on loss using training and validation data. The "history" variable kept track of previous occurrences of these values. As Figure 7 shows, the performance of the model is recorded and displayed in the notebook command "%matplotlib inline". The history object returned after training the model is used to obtain the training loss and validation and precision metrics and plots the training loss, data loss, and training precision into separate plots along with the validation precision and creates a new figure for each plot using the plt.figure() function provided.

In the prediction of the facial depression emotion recognition model, the highest accuracy was 94% and the loss was 13%, the highest value accuracy was 99% and the loss was 1%.

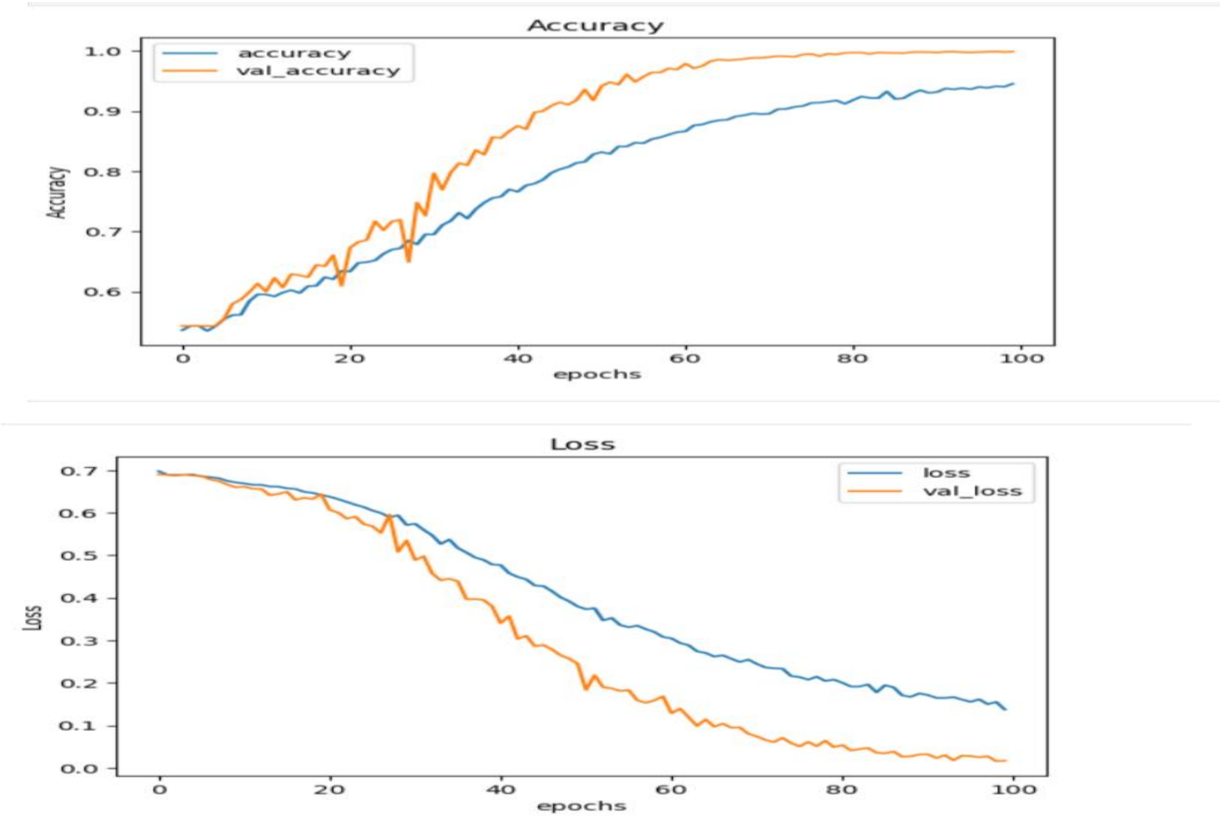


Fig.7 Visualization of the performance of the trained model during the training process.

3 REAL-TIME EMOTION DETECTION FOR DEPRESSION RECOGNITION.

Using a convolutional neural network (CNN) recognition model, a facial emotion recognition model was developed to distinguish human depressive or stressful emotions and made this idea the central focus of this work. Here, a human face dataset was used and a system was created. Python programming language and OpenCV library and using a computer webcam to determine the desired result based on the data set. The real-time facial emotion recognition component was developed and completely run in a Jupyter Notebook. As for the emotion recognition dataset component training, two image datasets were created for the model.

3.1 Real-Time Depression or Natural Emotion Recognition from Webcam-

In this step, checking the result was performed by running the cell on the Jupyter Notebook. And the webcam light was turned on to check the result. An attempt was made to depict emotions in real-time, that is, when a person is present at that time. The emotion prediction accuracy scores have reached a trend, which is also a good sign for the model if the performance is consistently high. The emotion prediction result is shown in FIGURE 8.

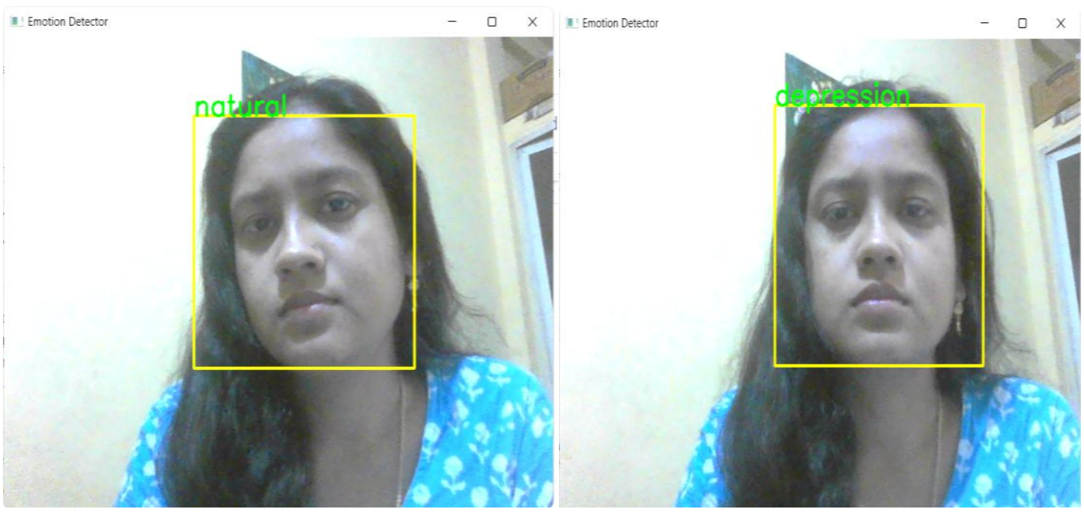


Fig.8 Displayed results on webcam and performance for depression and natural emotion recognition.

3.2 Train Test and Validation Confusion Matrix

The confusion matrix reports the proportion of faces classified correctly or incorrectly. On the vertical and horizontal axis of the matrix are the actual and predicted face labels. The diagonal of the confusion matrix shows the proportions of faces classified correctly and faces misclassified everywhere [19],[20].

Confusion matrix on Training Set-

A training set is a set of data used to train a model. It includes a large part of the available data and is the basis for estimating model parameters. The training set must contain all possible inputs that the model can process.

```
89/89 [==============================] - 51s 554ms/step
Confusion Matrix
[[1101 1483]
 [1362 1709]]
Classification Report
              precision    recall  f1-score   support

  depressive       0.45      0.43      0.44      2584
     natural       0.54      0.56      0.55      3071

    accuracy                           0.50      5655
   macro avg       0.49      0.49      0.49      5655
weighted avg       0.50      0.50      0.50      5655
```

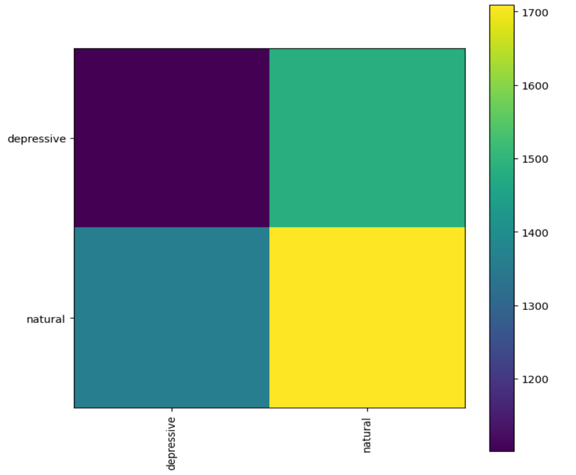


Fig.9 Training set Confusion Matrix.

Confusion matrix on Testing Set-

The test set is a separate subset of the data retained during the training phase. It is an unbiased benchmark for evaluating model performance after training.

```
111/111 [==============================] - 61s 542ms/step
Confusion Matrix
[[1384 1845]
 [1665 2173]]
Classification Report
              precision    recall  f1-score   support

  depressive       0.45      0.43      0.44      3229
     natural       0.54      0.57      0.55      3838

    accuracy                           0.50      7067
   macro avg       0.50      0.50      0.50      7067
weighted avg       0.50      0.50      0.50      7067
```

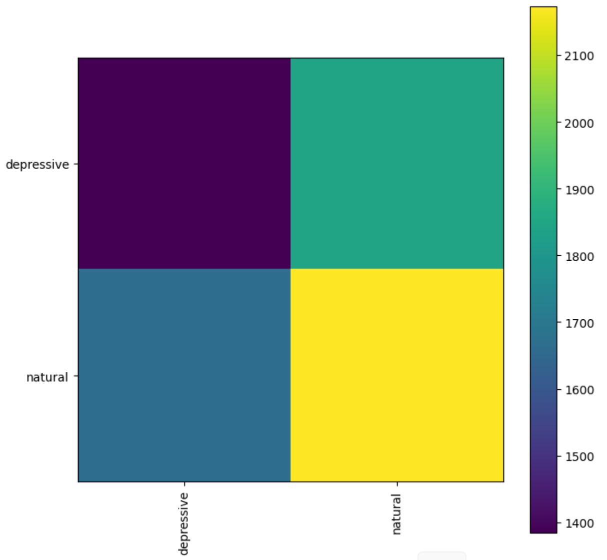


Fig.10 Testing set Confusion Matrix

Confusion matrix on Validation Set-

The validation set, sometimes called the development set, is an intermediary between the training set and the test set. Its primary purpose is to fine-tune the model's hyperparameters and assess its performance during training.

```
23/23 [==============================] - 13s 529ms/step
Confusion Matrix
[[283 362]
 [340 427]]
Classification Report
              precision    recall  f1-score   support

  depressive       0.45      0.44      0.45       645
     natural       0.54      0.56      0.55       767

    accuracy                           0.50      1412
   macro avg       0.50      0.50      0.50      1412
weighted avg       0.50      0.50      0.50      1412
```

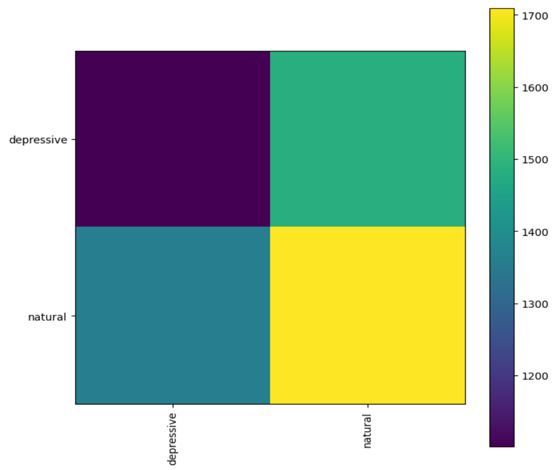


Fig.11 Validation set Confusion Matrix.

3.3 The confusion matrix predicts on True or False image dataset.

In this step, the true and false predictions of the prediction model are evaluated through the confusion matrix. Color =("green" if predict_index == true_index else "red") if the model predicts the true index, it will give a 'green' text format, if it is false, it will give a 'red' text format. This is shown in FIGURE 6.6.

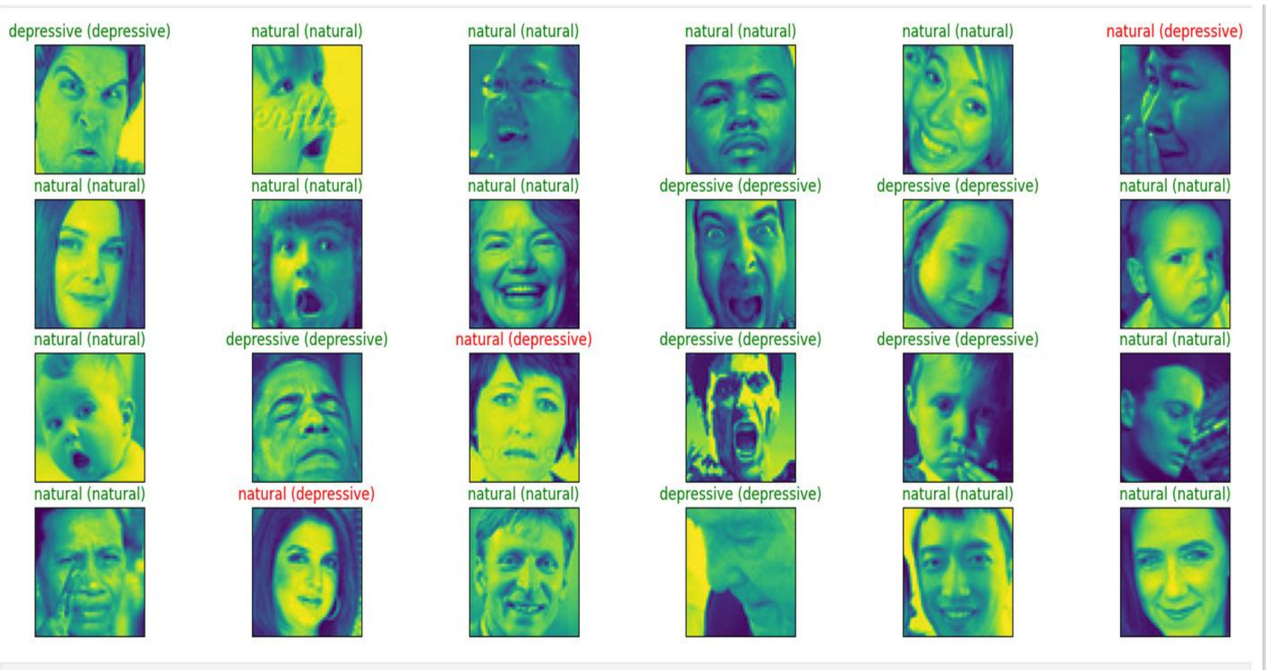


Fig.12 Shows True and False predictions.

3.4 Results and Discussion

In this research, trained a convolutional neural network model with our modified dataset which includes natural emotions (happy, Natural, and surprise) and depressive emotions (sad, anger, fear). The size of the recognizable characters has been made 48×48 pixels. A new depression detection model.h5 has been generated. The accuracy of this depression detection model has been achieved at 94%. Through the code, an attempt has been made to identify the emotions of the human being in real-time using a webcam, whether the human is depressed or not. A Python package for all this methodology provides useful and better results. figure 1 shows the corner point or image edge of the face in the inputted image. Through which different emotions can be identified. Figure 2 shows the main points of a face which clearly shows the (top and bottom) height and length of corner points of the eyes, mouth, eyebrows, etc. Figure 3 shows positive and negative emotions. Figure 4 shows the depression and natural dataset through a graph that shows how many classes the data has been placed in. Figures 5 and 6 show the compiled game data model and its total accuracy. Figure 7 shows the accuracy and loss value of the trained model through a graph. Figure 8 shows the result, in which human emotion depressive is natural has been recognized. Figures 9,10,11 show the confusion matrix associated with the train, test, and validation datasets. Figure 12 shows where the model got confused in the inputted image dataset and how often it got confused. Through this research work, by understanding the process and accuracy of the model, researchers can work to improve it in the future.

4 CONCLUSIONS

Depression is a serious mental health condition that can affect a person's daily life, workability, and relationships, so it is important to diagnose human depression. Users can timely identify and solve the problems of a depressed person by improving technology. In this research paper, an experimental model has been proposed using AI, and ML with a Python package to easily identify problems like depression or stress during human emotions. An attempt has been made to identify depressed emotions. This model has been used with a webcam so that real-time emotion can be recognized and the patients can be identified and treated with the help of doctors, counselors, and therapists.

5 FUTURE WORK

In the future, complete software can be created to identify and trace stress in humans. The mental health of employees, students, and elders can be easily identified daily, and treatment can be done through emotion recognition in the modern world. And efforts can be made to achieve more advanced development in mental health and other areas.

6 REFERENCE

[1] Astha Sharma (M. Tech Scholar) and Surender Kumar Grewal, August 2019, Implementation of human emotion recognition system, SSN NO: 1301-2746, Volume 8, Issue 8.

[2] P. J. Bota et al. September 2019, Review, Current Challenges, and Future Possibilities on Emotion Recognition Using ML and Physiological Signals, IEEE.

[3] Sonali Singh and Prof. Navita Srivastava, June 2021, Emotion Recognition using AI Techniques: A Review, Volume 8, Issue 6, ISSN-2349-5162, JETIR. https://www.jetir.org/papers/JETIR2106764.pdf

[4] Paul Ekman, 1992, An argument for Basic Emotions, cognition, and Emotion, 169-200.

[5] Neha et al., Aug 2020, Emotion Recognition and Depression Detection using Deep Learning, Volume 7, Issue 8, ISSN-2395-0056, IRJET.

[6] Vedhas Vinjamuri et al., April 2018, Emotion Recognition Using Real-Time Face Recognition, Volume 6, Issue 2, ISSN- 2320-2882, IJCRT.

[7] Barathi Subramanian et al., July 2022, Digital Twin Model: A Real-Time Emotion Recognition System for Personalized Healthcare, Volume 10, IEEE.

[8] Emotion recognition: introduction to emotion reading technology, Dubai Internet City Building 3, https://recfaces.com/articles/emotion-recognition

[9] Khamar Basha Shaik et al., 2015, Comparative Study of Skin Color Detection and Segmentation in HSV and YCbCr Color Space, International Conference on Recent Trends in Computing, http://creativecommons.org/licenses/by-nc-nd/4.0/

[10] S. Kolkur et al., 2017, Human Skin Detection Using RGB, HSV and YCbCr Color Models, Vol. 137, Pp. 324-332, The authors. Published by Atlantis Press, http://creativecommons.org/licens)es/by-nc/4.0/

[11] Jin Hyun Cheong et al., August 2023, Py-Feat: Python Facial Expression Analysis Toolbox, Springer, doi.org/10.1007/s42761-023-00191-4.

[12] Hamid Golzadeh et al., 2018, Emotion Recognition using spatiotemporal features from Facial Expression Landmarks, IEEE.

[13] Fuzail Khan, Jul 2020, Facial Expression Recognition using Facial Landmark Detection and Feature Extraction via Neural Networks, arXiv:1812.04510v3 [cs.CV].

[14] Moon Hwan Kim et al., 2015, Emotion Detection Algorithm Using Frontal Face Image, KINTEX, Gyeonggi-Do, Korea, ICCA.

[15] Tanusree Podder et al., August 2022, Time efficient real-time facial expression recognition with CNN and transfer learning, Indian Academy of Sciences, https://doi.org/10.1007/s12046-022-01943-x.

[16] Zeeshan Farhan Hanif et al., May 2023, Emotional Analysis using OpenCV, Volume 8, Issue 5, SSN-2456-4184, IJNRD.

[17] Jianqiang Xu et al., January 2020, Intelligent Emotion Detection Method Based on Deep Learning in Medical and Health Data, Volume 8, IEEE.

[18] Mr. Rohan Appasaheb Borgalli and Dr. Sunil Surve, April 2022, Deep Learning Framework for Facial Emotion Recognition using CNN Architectures, IEEE, doi: 10.1109/ICEARS53579.2022.9751735.

[19] Sunil MP and Hariprasad. S.A, June 2023, Facial Emotion Recognition using a Modified Deep Convolutional Neural Network Based on the Concatenation of XCEPTION and RESNET50 V2, IJEEE, Vol.10, doi.org/10.14445/23488379/IJEEE-V10I6P110.