FACIAL EMOTION DETECTION USING NEURAL NETWORK

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Abstract- Emotional responses are mental states of sentiments that arise spontaneously rather than via conscious effort and are accompanied by physiologic changes in facial muscles that result in facial expressions. Nonverbal communication techniques such as facial gestures, eye gaze, and gestures are widely employed in various aspects of human-computer interaction. Facial emotion is one of the most commonly used since it expresses people's emotional states and sentiments. Emotion recognition is a difficult endeavor since there is no precise demarcation between the expressions on the face, and there is also a great deal of complexity and unpredictability. Because certain essential extracted characteristics are employed for modeling the face in the machine learning method, it will not attain a precision for emotion identification because the elements are arm and rely on past information. This study constructed convolutional neural networks to recognize facial emotional expressions. Facial expressions are important in nonverbal communication because they represent a person's interior sentiments. A great deal of study has been done on computer modeling of human emotion by many types of researchers. However, it is still far behind human vision. The Viola-Jones technique was employed in this article to recognize the eye as well as lips zone from a face, followed by the neural network. Emotion recognition is also accomplished through the use of Machine Learning methodologies, Deep Learning models, and Neural Network algorithms. The posture of the lips and eyes were used to determine the mood in this study. An effective method for detecting anger, contempt, disgust, fear, pleasure, sorrow, and surprise will be proposed in this study. These are anjuyu7 j, bill the seven emotions depicted in a human being's frontal facial picture.

Keywords: Feature Extraction, Neural Network, Emotion Detection, Facial Recognition, Emotion Recognition, Emotions, Viola-Jones

I. INTRODUCTION

Facial expressions are important for interpreting and recognizing emotion. Even the phrase "interface" implies the importance of face in communication between two entities. According to research, interpreting facial expressions may drastically influence the understanding of what is said as well as determine the course of a discussion. The capacity of humans to read emotions is critical to efficient communication; the sentiment of an entity accounts for up to 93 percent of communication in a typical discussion. Machines should be able to read human emotion for perfect human-computer interactions (HCI). As a result, the focus of this study is on how computers can accurately identify mood using multiple sensors. This method has been used to read human moods using a facial picture. Human emotion study may be dated directly to Darwin's pioneering work and has subsequently drawn a large number of scholars to this field. Seven fundamental emotions are shared by all humans. These fundamental emotions include neutral, angry, disgusted, fearful, pleased, sad, and surprised, and they may be detected by a human's facial expression. This study presents a method for detecting surprise, neutral, sad, and happy emotions in frontal facial expressions. Various approaches for emotion identification have been presented throughout the last decade. Many techniques have been proposed to construct enhanced service delivery that can identify emotions extremely effectively. Computer applications might improve communication by adjusting replies based on the psychological level of human users from different encounters. A person's emotion can be inferred by his or her voice, demeanor, or even gesture. The study described in this paper investigates the identification of facial expressions. Traditional techniques for facial emotion detection generally start with a face image that is differentiated from an information picture, and then facial fragments or milestones are identified from the face regions. These face portions are then split into several spatial and worldly highlights. Finally, a classifier, such as Keras library's random forest, is developed to generate recognition results based on the segregated highlights. This study is an application of a deep learning model. Deep learning is a well-established pattern recognition methodology. It employs the Keras package and a Convolutional Neural Network (CNN) method. CNN is a type of neural network that employs a machine-learning unit.CNN may be used to identify objects, recognize faces, and analyze images, among other things. A deep convolutional neural network (DCNN) is a neural network layer-by-layer compilation. It is also capable of extracting relevant characteristics from data.

II. LITERATURE REVIEW

Facial expression is a universal signal that all humans use to communicate their moods. Many attempts have been made to create autonomous facial emotion analysis tools because they have applications in a variety of sectors including robotics, healthcare, drivers assist systems and lie detectors. Ekman et al. defined seven primary emotions in the twentieth century, irrespective of the society in which a person grows up with the seven manifestations. Sajid et al. discovered the influence of facial disproportion as a signal of age estimate in a recent study using the facial recognition software dataset. According to research findings, right face symmetry is preferable to left face symmetry. The appearance of facial poses is still a major concern with face detection. Ratyal et al. proposed a solution to the problem of diversity in face position appearance. They employed a three-dimensional posture invariant technique with subject-specific descriptors. Convolutional networks are used to handle a variety of problems, including excessive makeup, stance, and emotion. Recently, researchers have achieved amazing success in the detection of facial expressions, which has led to advancements in neurology and cognitive neuroscience that fuel the growth of work in the domain of facial expressions. In addition, advances in machine learning and computer vision have made emotion recognition more efficient and made it available to the general public. As a result, face expression detection as a semi of image analysis is quickly expanding. Human-computer interaction, psychiatric observations, intoxicated driver recognition, and, most importantly, lie detection are just a few of the potential uses. Several domains, including machine learning, natural language processing, neurology, and others, have made contributions to the subject of emotion detection research. In prior investigations, they combed through facial expressions, voice characteristics, and textual information as global markers of emotions. Happiness, sorrow, contempt, rage, fear, and surprise are some of the static categorizations of emotion. Later works benefit from merging picture, voice, and textual information. The merging of this data produces the most accurate outcome. This sort of fusion can take three forms: initial, later, or hybrid. Other ethos includes emotional aspects and cooperation between emotional responses and other intellectual operations.

III. IMPLEMENTATION TECHNIQUE

The complete system is the training element of this study, which considers the major difficulty encountered by machine learning. Where the system must be trained using real-world human face data reactions. The re-training technique was utilized to familiarize the system with these feeling categories. The data for re-training was gathered in the actual world. The re-training portion of this method was the most difficult. There are several additional components to the system. Machine learning is a powerful technique that allows for more efficient and rapid data processing of massive databases. This improves the accuracy with which emotion may be detected. The system did not wait for the outcome in the future, thus the image had to be saved. Neoteric data mining techniques, with the aid of contemporary computers, can examine thousands of data points in a relatively short period, saving several hours. Furthermore, the cost of utilizing and installing such products is substantially lower. If correctly adjusted, these data mining algorithms can produce better results than a person. This paper presented a broad and viable framework for emotion data mining that uses machine learning to discover emotion patterns. The algorithm was proposed in this work using a Deep Learning model with computer vision emotion identification. For this paper, the proposed method employs the CNN algorithm. This presented a more advanced system than CNN's, which only detected seven emotions. The following are the four phases of their deep learning-based emotion detection system.

(1) Using CNN to train the public face database.

(2) The extraction of seven probabilities for each face frame.

(3) For each image in the dataset, the single-frame probabilities are aggregated into fixed-length image descriptors.

(4) Classification of all pictures using a support vector machine (SVM) trained on the competition training set's image descriptors.

A. Importing Libraries and Dataset

This is utilized in both real-world and online media to acquire as much data as possible throughout the data collecting processes. Different forms of emotional photographs of relatives and friends, cousins, and some recognized unknown people's facial expressions may be found in the real world. They filtered data that had been saved for further analysis. The data set comes from kaggle.com and is gathered from internet media. This site has the most reliable set of emotional data. This turned the data into grayscale pictures of faces at a resolution of 48x48 pixels. It is split into two categories: pixels and sentiments. The mood part has a number code ranging from 0 to 6. Furthermore, the pixel section has a string embedded in statements for each image. Furthermore, the image should only be a portrait of a face. As a result, the gathered images are scaled and cropped portraits of people's faces and a clear image.

B. Training phase using deep learning

Building a convolution neural network(CNN) is a wonderful approach to utilizing deep learning to identify photos. The Keras package in Python makes creating a CNN straightforward. Pixels are used by computers to see pictures. In most cases, pixels in a picture are linked. For example, a collection of pixels might represent an image's edge or another pattern. This is used by convolutions to assist identify pictures. The batch size is taken as 128. A convolution multiplies a pixel matrix with a filter matrix, or 'kernel,' and adds the results. The convolution then moves on to the next pixel, repeating the process until all of the picture pixels are covered. This procedure is depicted in the diagram below.

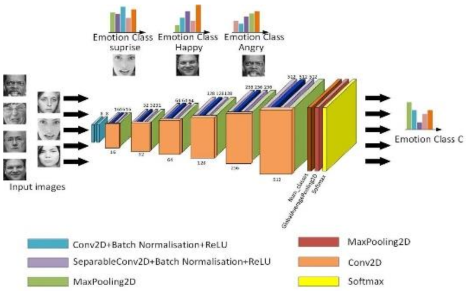


Figure: Emotion detection using CNN

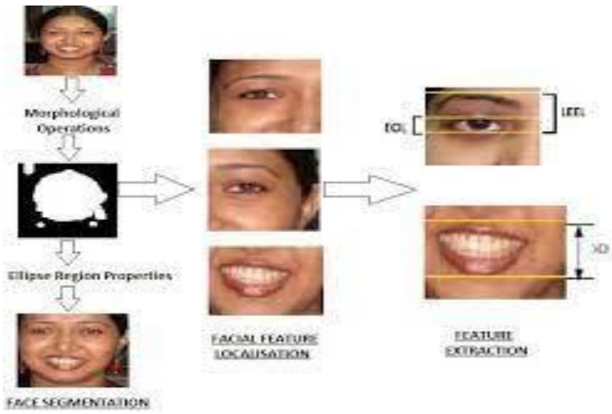
Sequential will be the model type we'll be employing. In Keras, the simplest technique to create a model is sequential. It helpes you to train a new model layer by layer. To add layers to our model, we utilize the 'add ()' method. Our first two layers are Conv2D. These are the convolution layers that will be used to deal with our input photos, which are represented by two-dimensional matrices The number of nodes in each layer is 64 in the first layer of the model and 32 in the second layer of model. Depending on the size of the dataset, this value might be modified to higher or lower. In this project, 64 nodes and 32 nodes work nicely together, so we'll remain with them for the time being. For our convolution, the kernel size equals the size of the filter matrix. We'll have a 3x3 filter matrix with a kernel size of 3. For a refresher, go return to the introduction and the first image. The layer's activation function is called activation. The

Rectified Linear Activation (ReLU), will be the activation function for our first two layers. This activation function has been demonstrated to be effective in neural networks. Our first layer accepts an input shape as well. As stated before, this is the form of each input picture, 28,28,1, with 1 indicating that the photos are greyscaled. There is a Flatten layer (which helps to calculate task easily) between the Conv2D layers and the dense layer. Flatten acts as a bridge between the convolution and thick layers. Flatten is used to link the convolutional and dense layers. After that, the model will provide a forecast based on the choice with the highest likelihood. After that, you'll need to assemble the model. The model is built using three parameters: optimizer, metrics, and loss. The learning rate is controlled by the optimizer. The 'adam' optimizer is going to be used in this. For the most part, Adam is a nice optimization to employ. Throughout the training, the Adam optimization changes the learning rate. The learning rate controls how quickly the model's optimum weights are computed. A slower learning rate may result in more accurate weights, but it will take longer to compute the weights. For our loss function, we shall employ 'categorical cross-entropy.' It is the most commonly used categorization method. A lower score suggests that the model is working more effectively. To make things even easier to understand, while training the model, it will utilize the 'accuracy' measure to see the accuracy score on the testing dataset. It will train using the 'fit ()' function with the following parameters: training data (train X), target data (train y), testing dataset, and the number of epochs. It will utilize the test set supplied in its dataset for validation data, which has been divided into the X test and y test. The model cycle on the given data determined by the number of epochs. The model will improve overtime as we run additional epochs, up to a point. After this, the model will remain same and accuracy will not increase over the epochs. The number of iterations in our model will be set to three. On that validation set, it has achieved 93 percent accuracy after three epochs.

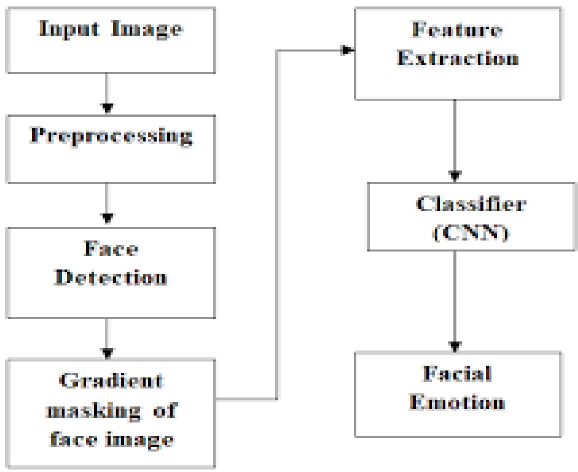
C. Model Building

The K-means clustering algorithm was utilized, with several clusters set to two. The largest value across all rows is discovered as well as its average is calculated here. Similarly, the smallest value in each row is determined, and its average value was taken. Using these two locations as a starting point, the pixel values closest to the greatest average value are gathered into one cluster, while the pixel values closest to the minimum average value are clustered into another. The total number of attributes in the image is computed based on the clustering result. The person's eyes are segregated first using the bounding box function, based on the number of components. The eyes are segmented first since they are the first element encountered while exploring the pixel values column-wise. Other face elements are separated using a distance-based technique employing the eye matrix. The picture obtained after doing k-means clustering for various phrases is exhibited.

The Viola-Jones method is a popular technique for detecting objects. The key advantage of this technique is that it is slow to train yet rapid to detect. The Haar basis element is used in this technique. Haar characteristics are the ones that are important for face detection.



Layers are commonly used to structure neural networks. Layers are made up of multiple linked nodes, each of which has an activation function. Patterns are supplied to the network through the input nodes, which communicate with one or more hidden layers, where the real processing is performed via a weighted connection mechanism. The face expression recognition system's method is broken into three steps. Face and facial parts identification using the Viola-Jones technique, facial expression extraction, and features segmentation using CNN are all part of image pre-processing. Keras is a python-based open-source neural network that may be used for preprocessing, modeling, assessing, and optimizing data. It's for high-level APIs, which are handled by the backend. It's made for creating models with loss and optimization functions, as well as training with the fit function. It is meant for combination and low-level computing in the backend using tensors or TensorFlow. The following python libraries are used for preprocessing, modeling, optimization, testing, and displaying emotion with the highest proportion. It employs a sequential model and several layers, including image pre-processing, pooling layers, convolution layers, dense layers, flattens layers, ReLU, and activation. The initial part of the proposed system is image preprocessing, which includes Face Identification and FPs detection and extraction. The Viola-Jones face detection framework is employed, which is a technique that includes the capability of analyzing photos in real-time circumstances. This technique finds the face region despite variations in the raw input image's size, backdrop, brightness, and spatial transformation. Face FP detection is accomplished by merging classifiers in a cascade structure that improves detection efficiency while lowering computing complexity. The final classifier is a linear combination of all weak classifiers that differentiate the positive and negative in terms of weighted error (each learner's weight is proportionate to its accuracy). Face components (both eyes and mouth) are recognized, cropped, extracted, and normalized to a size of 64 × 64 pixels before being removed from the normalized facial picture. The retrieved face portions are reduced to 32 x 64 pixels in size. The lower image scale reduces the amount of information that the network must learn while also making moves to make and with less memory expense. Convolution layers will be added to improve accuracy while working with huge datasets. The dataset is gathered from a CSV file, transformed into photos, and then used to identify emotions based on their expressions. With 34,488 photos for the training data and 1,250 for testing, emotions are categorized as joyful, sad, angry, surprise, neutral, disgust, and fear. Each emotion is communicated by many facial characteristics such as lifted brows, opening the lips, elevated cheeks, creases around the nose, wide-open eyes, and many more. The big dataset was trained for higher accuracy, and the outcome is the object class for source images. Pooling is a notion that goes hand-in-hand with convolution in deep learning visual object detection. A local neural network feature detector maps an area of an image to a feature map, according to the theory. A 5x5 array of pixels, for example, might be translated to aligned edge features. When you compress all Photoshop elements to one backdrop layer, this is known as flattening. Layers can increase the size of a file while also using processing resources. You may combine several layers or even compress the actual picture to one background layer to save file size. The dense layer is a conventional strongly linked neural network layer. It is the most popular, optimized and often utilized layer. The dense layer performs the following operation on the argument and outputs the result. The activation value is transported from node to node based on connection strengths (weights), inhibition or excitement, and transfer functions. Each node adds the output value it gets and alters the value using its transfer function. Dropout may be implemented in Keras by including Dropout layers into our network architecture. Every batch, each Dropout layer will remove a user-defined hyperparameter of units from the preceding layer. Keep in mind that with Keras, the input layer is presumed to be the initial layer and is not added with the add command. After the convolution layers and before max pooling, ReLU is one of the most frequent kinds of nonlinearity to utilize in neural networks. All negative image pixels in the feature map are replaced with zero. After the convolutional layer, it's usually employed. Adam is an optimization technique that, instead of the traditional stochastic gradient descent procedure, may be used to iteratively update network weights based on training data. It has been discovered that several efforts have been made to assess emotions using various automated approaches. However, most of them are found without any set structure or indication of how to use them appropriately. Understanding and maintaining emotion analysis skills, in particular, can assist law enforcement authorities inefficiently using a machine learning approach to track and recognize emotion trends.

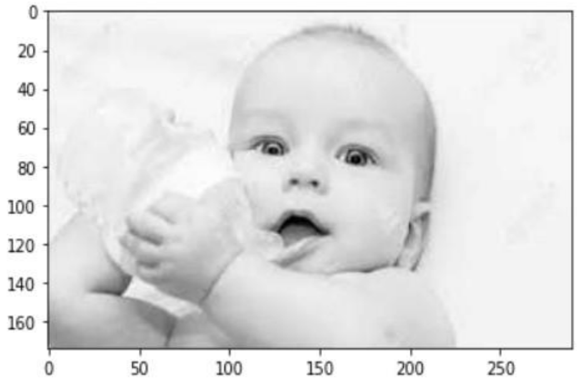


To summarize the above image Take the photograph from the user first, then clean it up. Then isolate a person's face and apply the Haar characteristics to it. The picture should then be compared to the prior training dataset. Python's Keras package is used here. It employs a convolutional neural network (CNN). A sequential model is used by CNN.

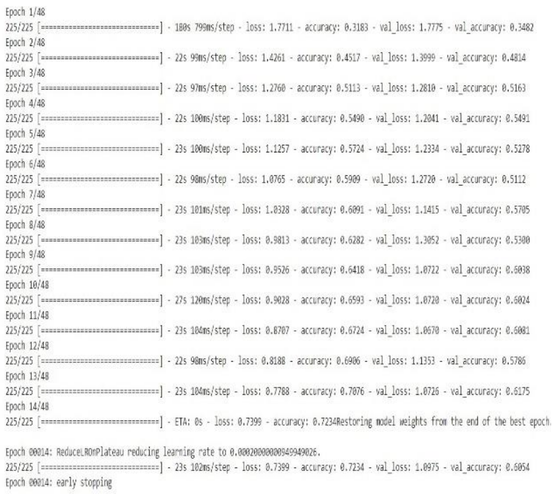
Conv2D, MaxPooling2D, AveragePooling2D, Dense, Activation, Dropout, and Flatten are some of the other layers used. These layers choose the emotion from the categorization set after the approach. This is the finished product. The normalized facial picture is submitted to the feature extraction phase after some pre-processing to locate the essential characteristics that will be utilized for classification. In other words, this module is in charge of creating a feature vector that is good enough to represent a facial image. Following this comparison, the facial picture is classed as having one of the seven expressions (disgust, contempt, anger, sorrow, surprise, fear, or happiness).

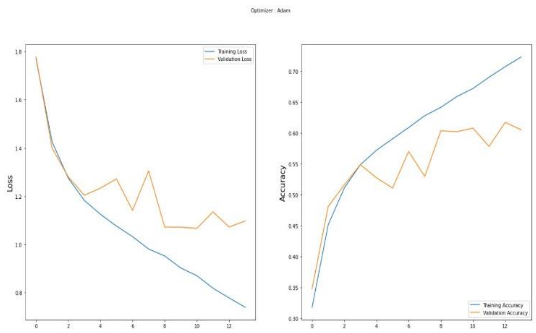
IV. RESULT AND ANALYSIS

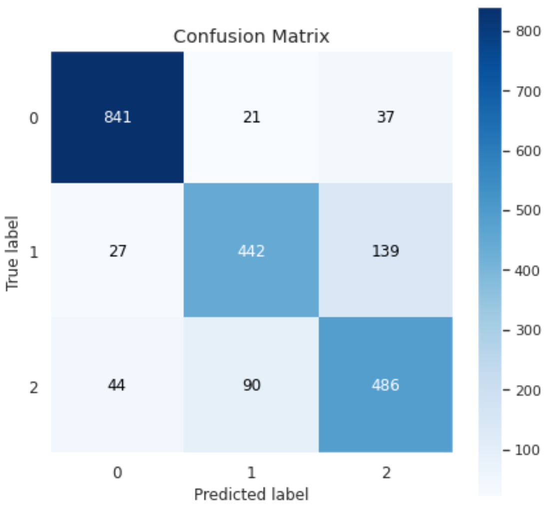
We have used a large data to train our model and to get the best accuracy over the correct predictions. This technique began with a pre-planned approach and calibrated this model using put-away information acquired from the real world. A series of preliminary studies confirmed the hypothesis that facial recognition would be more useful in highlight extraction. Some models make good use of such systems.



On datasets of a few hundred highlights or segments, machine learning methods operate effectively. The system accurately detects a picture, classifies its sentiment, and selects the appropriate emotion for the image. The choice of the deep learning classifier is based on the fact that it processes data across many layers. A deep learning algorithm, on the other hand, might be effective for less unexpected difficulties because it has access to a large amount of data. For photos, the standard benchmark for developing deep learning models for wide picture recognition is more than 2.1 million images. A decision tree was employed for a flawless display of sentiment analysis pattern analysis. The nodes and levels of the decision tree indicate the character, while the branch represents the outcome of the experiment. The decision tree has the advantage of making it extremely easy to see and comprehend the feeling and the outcome. A decision tree's operation is simple to comprehend. If the data has been categorized based on their movement, responses, and order, which ideally corresponds to different sorts of emotions. This has also been categorized into trees and sub-trees, which represent whether the individual is sad, furious, or pleased, and so on. If only there was a way to categorize their use of these approaches in a more straightforward manner. To do this, a retrain approach was utilized, which remembered the pattern and satisfied the criterion. Continue to the end of the tree when any of the conditions are met. It will cease checking and report "The emotion cannot be recognized" if none of the requirements meet the intermediate condition. The emotion is a mystery. Emotions are difficult to comprehend. The same feeling can be expressed in a variety of ways. For the same feeling, various people have different ways of expressing it. Modern machine learning software can enhance law enforcement authorities in detecting emotion so that the computer can comprehend human emotion and behave and act more like humans. This emotional data was gathered from several online and offline sources. For example, Google's kaggel.com website. Friends and relatives, strangers, and so on. The Keras library was used to initially categorize and evaluate the emotion and obtain the data. The emotion is then identified using Haar features and Numpy. And with the assistance of Anaconda's platform. It creates output from raw data, and the outcome is displayed in real-time. The decision tree is a hierarchical data mining process that aids in the generation of probability judgments by calculating several characteristics that are originally used to define the emotion pattern. It also performed effective field research to gather more individuals and diverse types of people, as well as varied emotional deferent expressions and a variety of faces, in addition to online and offline data collection. The data set for online data gathering comes from kaggel.com. They deliver high-quality data sets. They used the numerical quantity of the photographs to transform the photos into pixel grayscale. As a consequence, it provides excellent data as well as the best possible outcome. Both experts agreed that this sentiment analysis may assist detect emotions more precisely and help take proper actions in the name of accurate emotion identification. It would give additional information about the many sorts of expressions of their feeling, and also the proportion of each existing type of emotion. While working on this project, we discovered that a vast amount of testing datasets and keywords are required for improved accuracy. A scarcity of original data is also necessary to prolong the study activity. If you wish to handle a huge amount of test data in the quickest amount of time, you'll need a high-configuration graphics processing unit (GPU) certified computer. So, if this receives enough data and a powerful computer, it'll be much easier to increase the accuracy to more than 97 percent. It will also be able to apply that method to a new platform and get a different result, as well as assist in determining the emotion expression profile.







V. BACKGROUND WORK

The goal of FER is to recognize a human face's emotion. That is, given a human face, the system must automatically determine whether the face is joyful, angry, disgusted, afraid, delighted, sad, or surprised. Due to the enormous number of applications that employ FER directly or indirectly, several research has been undertaken in this field. FER may be employed in a variety of fascinating and beneficial applications, including security monitoring, medical treatment, marketing research, and e-learning.

A fuzzy emotion identification approach based on aspects of the eyes and lips has been presented. It has been proposed to use a multimodal facial recognition algorithm. The influence of various kernels on FER performance has been studied. Different kernels, such as linear, polynomial, sigmoid, and RBF kernels, are explored for the study. The suggested approach is utilized to automatically detect the emotion type from video recordings. The video clips are from the actual world, and several classifiers such as SVM, logistic regression, and appropriate statistical approaches are employed. proposes a method for identifying unfamiliar people's facial expressions. In addition to the type of emotion recognized, whether the feeling is favorable or negative is also detected. In, an approach that employs line-based caricatures is suggested that is suitable for real-time applications. A decision tree-based facial expression categorization method that is computationally economical is proposed. Another innovative technique for FER that employs Gabor filter-based features and LVQ-based classification.

In, a new face area identification approach based on the YCbCr color model and Maximum Morphological Gradient Combination is suggested (MMGC). Once the face region has been identified, the search for emotion is confined to that area. Viola-Jones, a well-known face area identification technique, is used to detect facial regions, and then KNN is used to classify the type of emotion elicited from the facial structure.

VI. CONCLUSION

By observing and staring at another person, an experienced human may frequently recognize his or her emotions. Machines, on the other hand, are growing more clever in this modern age. Machines have been attempting to mimic human behavior for some time. If the computer has been programmed to act on account of human feelings at the moment. The machine may then think and behave like a person. On the other side, if the computer can recognize emotions, it can avoid a lot of things from happening. Data mining, with increasing competency and errorless computing emotion, can support correct expression patterns, allowing robots to identify and behave more effectively like humans. This thesis or framework was constructed or structured using extensive study and field studies to establish the emotion manifestation patterns. This method followed the blueprint process to achieve the desired result. The deep learning CNN algorithm, coupled with Keras, Tensorflow, as well as retraining principles, was utilized to follow the framework and more successfully recognize emotional expression patterns. It was feasible to detect emotions, as well as the kind of emotion, in an actual photograph using these approaches. To better visualize the results and methods, decision tree approaches were implemented, which aid in determining which emotions percentages are high and which emotions percentages are low. Now, a large majority of feelings receive the most real emotions conceivable. And those with a small proportion of emotions have a worse likelihood of survival. It is now feasible to detect correct emotions as a result of this research. And robots can more correctly discern emotion and, as a result, provide a suitable reaction while also helping prevent the same unintended occurrence. This machine may also be used to replace humans.

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