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Emotion Detection using Text with Approaches of Machine Learning

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ABSTRACT
A system for automatic face identification or facial expression recognition has been developed by a human-computer interaction system. Researchers in psychology are paying closer attention to its languages, neurology, and other relevant field disciplines. An Automated Facial Expression is presented in this research. The suggested technique contains three stages: face detection, feature extraction, and identification of facial gestures The early phase the YCbCr colour system is used to detect the color of a person's skin model, lighting compensation to achieve face consistency, and morphological operations to keep the desired appearance portion. The first phase's output is used to extract data. AAM (Active Augmentation Method) was used to enhance facial features such as the eyes, nose, and mouth. The appearance Model is a method for calculating the appearance of a person. The automatic facial recognition stage is the third stage. Simple expression recognition is required. CLAHE (Contrast Limited Adaptive Histogram Equalization) is used for preprocessing in the recognition phase, then HOG, which is a classic technique for feature extraction. The test picture and the training images both have HOG features extracted. Finally, in this Naïve Bayes, KNN and CNN are used for categorization. The findings of this research demonstrate the feasibility and usefulness of improving facial recognition performance.

Keywords: Emotion detection, CNN, KNN, Naïve Bayes, ConvNet

INTRODUCTION
Identification of facial expressions (FER), which is related to machine learning, image processing, and cognitive process, has made significant advances over the past decade. As a result, automatic FER's effect and prospective use in numerous fields, such as Vehicle status monitoring, motion control, and communication module, has been rising [1]. However, strong facial expression identification from photos and videos remains a difficult task due to the difficulties in reliably taking the important emotional facts. These characteristics are frequently represented, including in static, dynamic, point-based geometric, and geographical area appearances. The motions of facial parts and

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muscles generate a facial movement feature, which includes changes in feature location and shape [2,3].

During emotional expression, muscles are flexed. When participants are exhibiting emotions, the facial components, particularly crucial elements, will constantly shift positions. As a result, the same feature appears in distinct photos at different times. Due to small facial muscle movements, the contour of the feature may be affected in rare circumstances. The mouths in the first two photographs, for example, have distinct forms than those in the third image [4].

As a result, the geometric-based location and appearance-based form of any component indicating a specific emotion in image databases and videos typically shift from one image to the next. This type of movement feature indicates a large group of both static and dynamic expression traits, all of which are important. The great bulk of previous FER research has ignored the dynamics of facial expressions. There have been some attempts to capture and use face movement. Most of the facts are taken on the basis of images[5,6,7].

Numerous Attempts are made to adapt the tracked geometric features. Face points (for example, shape vectors, face animation parameters, and so on trajectories), or appearance (distance, angular, and trajectories). As a result, there is a distinction between textured facial areas holistically or frames (e.g., optical flow and differential-AAM) and variations in mobility in specific facial regions (e.g. surface motion units, spatiotemporal descriptors, deformation pixel difference, and animation units). Despite the fact that promising outcomes, these methods frequently necessitate precision. The localization and tracking of face points is still a work-in-progress problem [8,9,10].

The similar argument can be made against surveillance equipment if criminals are still at large. Face-recognition security cameras can aid in the hunt for these individuals. The same monitoring systems can also be used to look for persons who have gone missing, but this requires both strong facial recognition software and a large collection of pictures. Finally, facial recognition has made an appearance in social media programs such as Facebook, where users are encouraged to tag friends who have been identified in photos [11]. It is apparent that facial recognition systems have a wide range of applications. Face detection, feature extraction, and model training are the steps that should be taken in general to accomplish this [12].

LITERATURE REVIEW

Many of researchers have applied many methods for emotion detection. Few of them has depicted over here. C Rahmad et al. [13] discovered that the Hog cascade algorithm is around 5% more accurate than the haar cascade algorithm. HOG features-based face recognition was proven to be more accurate than holistic approaches such as PCA or LDA by Dadi HS et al. [14] presented the AERSCIEA method for satellite color pictures, which is a binary search-based CLAHE that outperformed CLAHE by a long shot with the use of a binary tree classification strategy. Guo G et al. [15] depicted the facial recognition technique utilizing linear support vector machines. In comparison to the closest center strategy for face recognition, the experimental findings demonstrate that SVMs are a better learning algorithm. G Benitez-Garcia et al. [16] CLAHE was applied to PCA-based facial recognition. Anila S. et al. [17] devised a preprocessing approach that combined several preprocessing algorithms such as histogram equalization and gabber filter[18] By

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demonstrating the thalamic structures for emotion expression, Philip Bard enlarged Cannon's idea; this broad theoretical perspective later came to be known as referred to as the "Cannon-Bard Theory." This innovative theory contained that emotional triggers simultaneously cause both physical reactions like anxiety and emotional experiences like Candled et al. invented [19].

Data Set

In this work, Russell's Circumplex model is used on dataset to produce the structured data using a rule-based approach . According to Russell's Circumplex, emotions are circulated in a two-dimensional space with dimensions for pleasure (valence) and activation depicted in figure 1 (arousal) [20, 21].

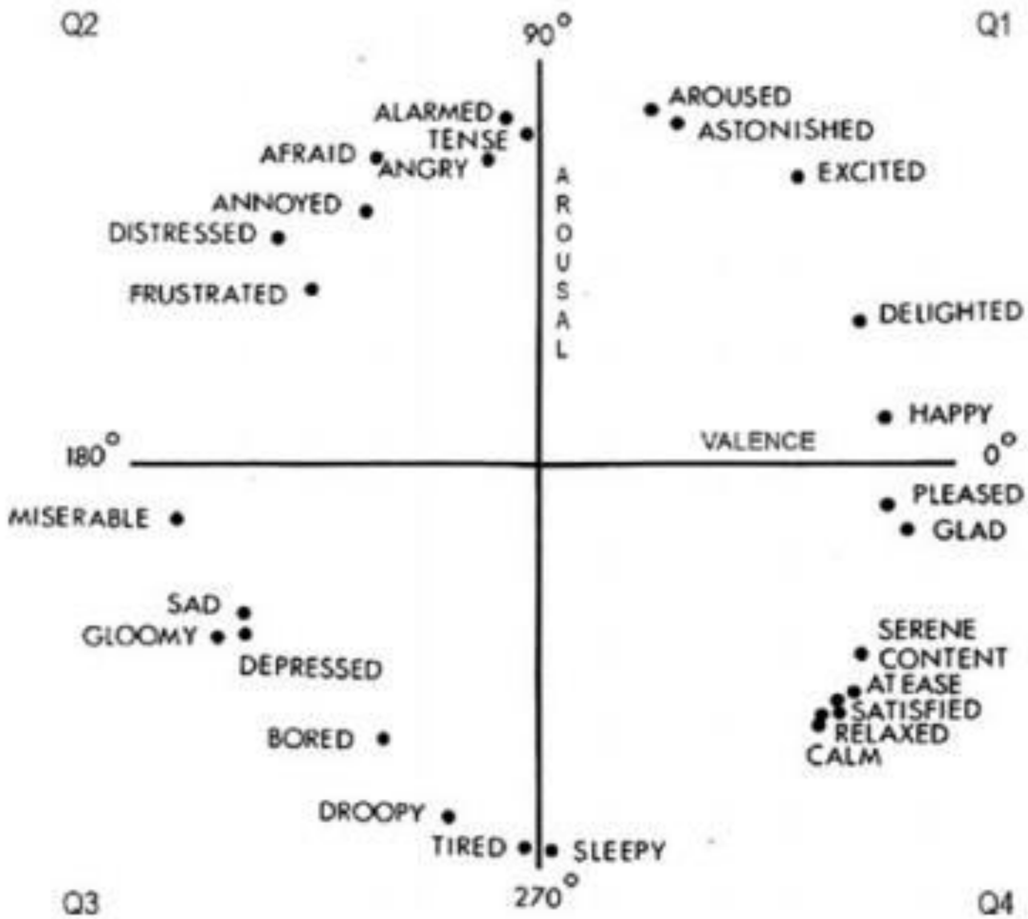

Fig 1 : Emotions Circumplex Model with dimensions

3.1NEGATED WORDS

Negated words are terms that carry a negation and can reveal a tweet's opposing side. Example of a Tweet: I'm not happy today. The aforementioned tweet truly carries the feeling of sadness, but if we omit the word "not" before joyful, It can mistakenly classify it as the happy emotion carrying class. Negation-carrying words must be given extra attention in order to lower the error rate because

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misclassification rates rise if we neglect the negated words. A separate list of negated words are kept for this reason shown in table 1.

TABLE 1 : Sample negated words

Do not	Have not	Could not	Was not	Does not	Would not	Should not	Cannot

Some of the emotions of dataset are shown in the following table 2.

Table 2 : Emotions Dataset

Sr. No	Emotions
1	Anger
2	Contempt
3	Disgust
4	Fear
5	Happy
6	Sadness
7	Surprise

METHODOLOGIES

For text categorization challenges in emotion detection, Machine learning algorithms have been used.

For the classification procedure, algorithms like Naive Bayes, k-nearest neighbor and Conventional Neural Network are employed.

4.1 Naïve Bayes

Bayes theorem is the basic key for this algorithm. A new tweet that the model has never seen is sent to it during the testing phase. The Bayes algorithm may categorize the tweets using the previously given information. During the training phase, the computer assigns each tweet to a certain category. It adopts the theory with the highest degree of likelihood [22].

$$P(label/features) = P(label) * P(features/label)/P(features)$$

where P(label) is the earlier probability of a sticker, P(features/label) is the preceding possibility of categorizing a specified feature set as a label, P(features) is the earlier probability of a specific image set occurring, and P(label/features) is the posterior certainty.

4.2 K-Nearest Neighbor Algorithm

Using KNN, 80 % of the tweets are utilized to give training to the model, and the rest 20% are used for testing. The proximity difference between a testing data point and a training data point has been considered in this instance. Every test data point is compared to every training data point in order to determine the similarity measure. The distance was determined using cosine similarity. After

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measuring, the tweets are assigned distance scores. Scores are arranged in descending order to establish the maximum comparable distance. The label of the tweet with the highest score was taken into account, and the same label was given to an unread tweet [23].

4.3 Conventional Neural Network

Neural networks can take many different topologies and are adapted to various of use scenarios and data types. It oftenly known as CNNs or ConvNets, are more commonly used for identification and image processing applications than recurrent neural networks, for example, which are frequently employed for audio and natural language processing. Prior CNNs, very intensive feature extraction techniques are needed to identify objects in photos. By leveraging matrix multiplication and other ideas from linear algebra to discover patterns in images, convolutional neural networks, on the other hand, now offer a more accessible way for categorizing photos and distinguishing objects. However, simulating them may need the use of graphics processing machines (GPUs) because they can be economically demanding.

It's a method that can take an image as an input, give various elements and patterns in the picture prominence (trainable values and biases), and be able to tell them apart. A ConvNet requires considerably less pre-processing than other classifiers do. ConvNets are able to learn certain filters and their features, in contrary to older hardware where filters had to be hand-engineered.

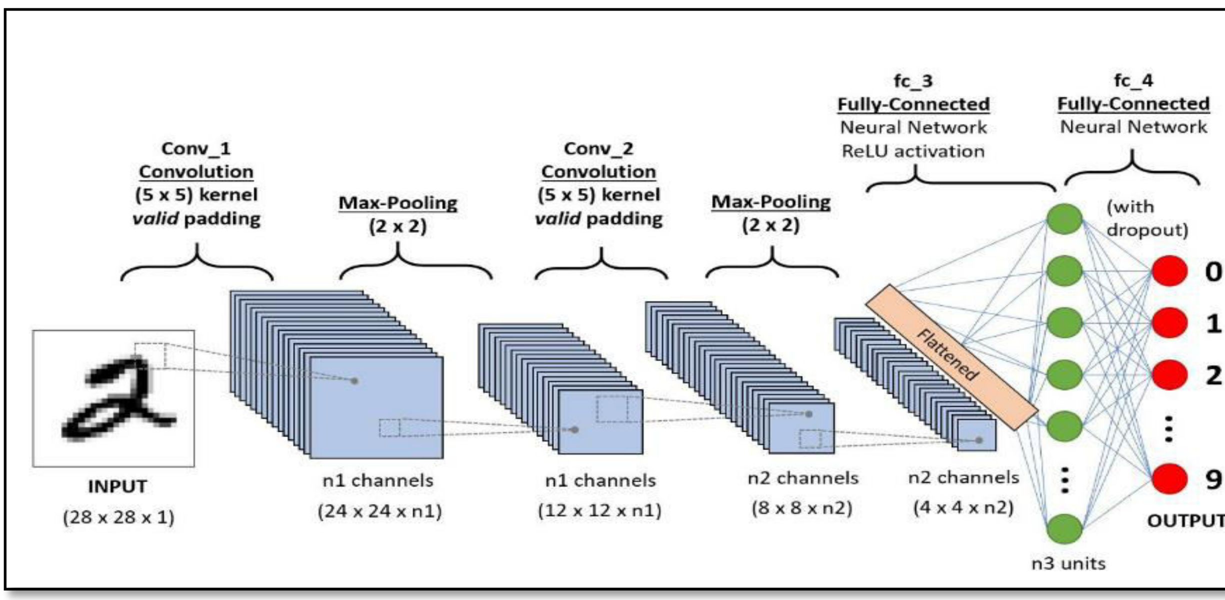

Figure 2 : A CNN sequence to classify the emotions data

It can identify one image from another by taking in an input data, assigning various qualities and entities in the image significance (trainable connection weights). In contrast to other different classifiers, there is no doubt that a ConvNet needs less pre-processing. ConvNets are able to learn these filters and their characteristics, in contrast to older systems where filters had to be hand-engineered.

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The organization of the Visual Cortex and the interconnecting matrix of neurons throughout the human brain both have an influence on the design of a ConvNet. Individual neurons only respond to stimuli in this restricted region of the visual field, known as the Receptive Field. These fields are gathered together as one and cover the whole.

RESULTS

The convolutional neural network uses two layers 4 layers and 3 layers as defines below with two level architecture :

- **4 Convolutional Layers**
- **2 Convolutional Layers**

They each include the following operations and by providing the above dataset some analysis has been done and shown with figure 3 and figure 4:

A convolution operator: preserves the spatial relationships between the pixels while extracting information from the input image using sliding matrices. The illustration below demonstrates how it operates:

To add non linearity to our CNN, we use the ReLU function. ReLU has really been discovered to out perform other factors like tanh or sigmoid in the majority of situations.
• Pooling is used to preserve the most critical data while reducing the proportions of each feature.

The same scaling function that is used for the convolutional step is applied to our data. Numerous functions, such as maximum, total, and mean, are available. The max function commonly shows better performance [24].

By using a Conventional neural network on emotion detection dataset, the following results are been achieved.

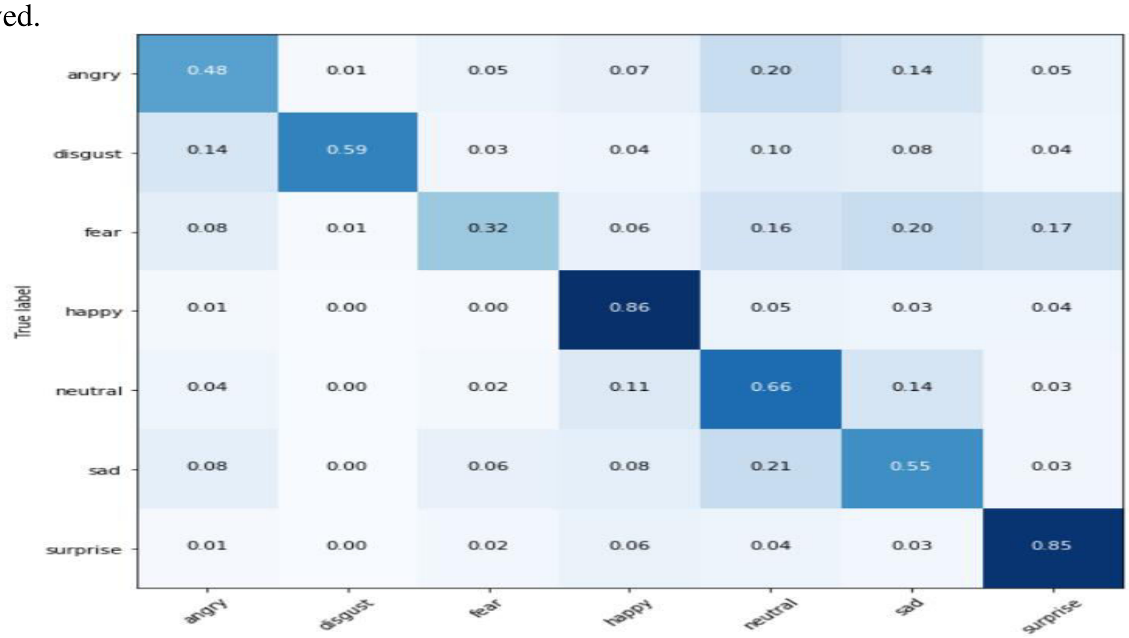

Figure 3. Confusion Matrix using CNN

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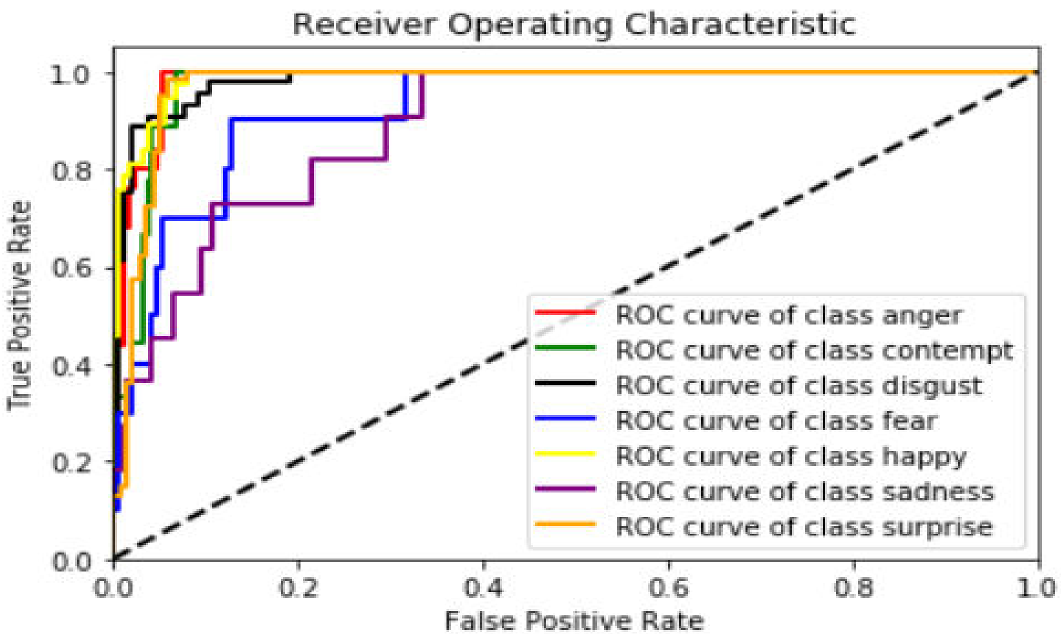

Figure 4. Result graph using CNN

So with the help of above figure 3 and figure 4, it could be check that how the human emotion dataset is analysed with Machine Learning Algorithms as in this research CNN is focused. The above graph shows the ROC curve for all dataset key points.

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