EMOTION RECOGNITION FROM FACIAL EXPRESSIONS USING ARTIFICIAL INTELLIGENCE

[1] **K Prasanna Lakshmi, Professor, Information Technology, Gokaraju Rangaraju Institute of Engineering and Technology, Email id: prasannakompalli@gmail.com**

[2] **Kompalli Sri Divya Muktha, Sri Chaitanya Jr College, Email id: sridivyakompalli@gmail.com**

[3] **K Archana, Assistant Professor, Information Technology, Gokaraju Rangaraju Institute of Engineering and Technology, Email id: archana.buddaraju@gmail.com**

[4] **P Gopala Krishna, Associate Professor, Information Technology, Gokaraju Rangaraju Institute of Engineering and Technology, Email id: gopalakrishna@griet.ac.in**

[5] **K Avinash Bhargav, Computer Science, SRMIST, Email id: kompalliavinash@gmail.com**

Abstract

The human face is crucial in determining an individual's mood. From the last 10 years there have been many applications that come under in order to detect the facial expressions of a person. The required input is instantaneously taken from a human face via a webcam. One of the applications of this input could be to extract data in order to determine a person's mood. The goal of the project is to create a model that can recognize emotions of a person using AI algorithms. The major steps that were used in this project are Face Detection, Extraction, Classification, and Recognition. In order to detect the emotion, the mouth region of a person is split using any of the segmenting techniques and then facial expressions are graded based on the white pixel values. To train the images the supervised learning and reinforcement learning approaches are used in this project. Face recognition algorithms commonly employ supervised learning, which requires more time and effort to compute whereas reinforcement learning is continually attempting to improve the outcomes. In this scenario, the training dataset is used to produce the result of face emotion.

1. Introduction

In order express the emotions or feelings of a person facial expressions plays a major role. Many applications have been introduced till now to detect the emotion of a person. Emotion recognition is very essential to developeffective Human Computer Interaction. Humanemotions are recognized by various non-verbal cues likefacial expressions, gestures, body posture or speech.Among them facial expressions is easy to obtain. These emotional expressions can result with or without the self-consciousness of a person. People, on the other hand, are likely to have conscious control over their emotional expressions; they do not need to be aware of their mental or affective state to display empathy.

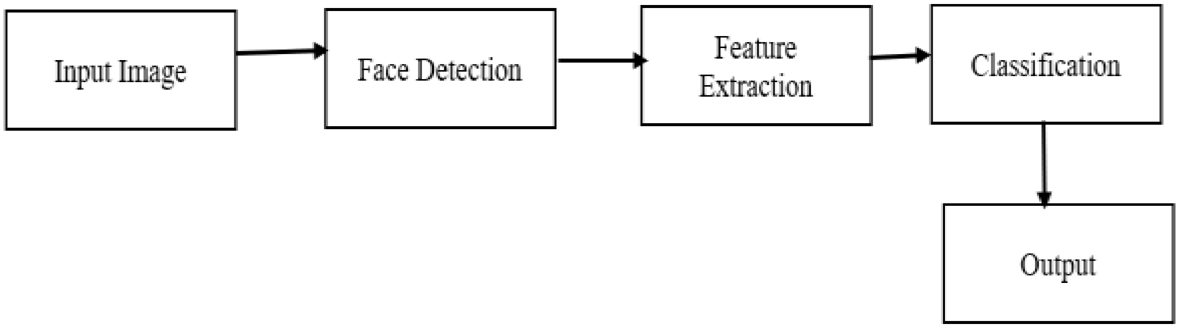


Fig 1: Procedure of Facial Expression Recognition.

The emotions of a person include the following:

Happy is the emotion induced by happiness, wealth, or good fortune, or the chance of receiving what one desires: passion manifested or screened. Sadness is an emotion typically characterized by accompanying feelings, like loss, disappointment, disinterest, a low mood, helplessness and hopelessness. Surprise is one of the seven universal emotions and arises when we encounter sudden and unexpected sounds or movements. Anger is an emotion when a person's boundaries are breached or violated, he or she may get enraged.

The severe motor loss leads due to a brain stroke, cerebral palsy and other neurological problems. People who cannot speak and cannot use their hands to operate a traditional input device such as a mouse, and key boards find it very difficult to communicate with outside environments. Invasive and non-invasive type BCI techniques are available for observing brain activity. The p300 is one of the components in the EEG, which is used to transfer the user's intent into input command There are 6 different types of frequency band data that are measured from the scalp. A non-invasive type technique is proposed in this paper to measure the electrical activity of neurons; this technique is also termed as electroencephalography (EEG). NeuroSky's Mind wave EEG device is used to record the electrical activity of the brain, Electromyogram (EMG) and Electrooculogram (EOG) signals are related to muscle movement and eyeball movement. Bacivarov, Ionita, and Corcoran (2008) developed a statistical active appearance model to track blinking of the eyes and the location of the eyes in various expression or poses. Khushaba developed an algorithm to extract various physiological signals to detect driver drowsiness/fatigue. used neural network classification for detecting the p300 responses to make decision-making. The weakness of the P300 was a low transfer rate. Improving the transfer rate is also possible by using Bayesian approach with threshold for taking adaptive decision about input signals The source for the EOG signal is Cornea-retinal potential and is generated due to the movements of eyeballs within the conductive environment of the skull. While recording the EOG signal, it will be contaminated by the Electromyography (EMG) signal. As the EOG is a non-stationary signal, the multi resolution analysis using wavelet decomposition offers the best solution to the noise and feature extraction of EOG signals The model is designed to be robust to variations of a head pose or gaze. The model parameters, which encode the variations caused by blinking, are analyzed and determined. This paper presents a machine learning approach to detect eye movements and blinks from EEG data and maps them as intents to control external devices like a computer desktop or a wheel chair (Gupta, Soman, & Govind Raj, 2012). The objective is to control the direction (left or right) of an electric wheelchair by using a recursive training algorithm to generate recognition patterns from EEG signals a cursor control on a monitor screen. To move the cursor to a target on the monitor screen the target selection or rejection functionality is implemented using a hybrid feature from motor imagery and the P300 potential. To select the target of interest, the user must focus his or her attention on a flashing button to evoke the P300 potential. Gandhi and Prasad (2014) proposed a real-time implementation of a novel iAUI design for a mobile robot control task. The major advantage with the iAUI is the user-centric graphical user interface design that presents all the control options to the BCI user at all times. A new modality-independent interface can be used to command a robotic wheelchair. The wheelchair can be controlled by eye blinks, eye movements, head movements, brain waves and can also navigate in an autonomous mode, taking the user from the current location to a desired one, and it can also operate like an auto-guided vehicle by following metallic tapes. RFID was used to calibrate the odometer and to provide location feedback to the user. This was introduced by Bastos-Filho & Cheein, 2014. Yom-Tov and Inbar (2003) proposed that Brain-Computer Interface is a device for enabling patients with severe motor disorders to communicate with the world. One method for operating such devices is to use movement-related potentials that are generated in the brain when the patient moves or imagines a movement of, one of his limbs. The mental motor imagery movement provides the enhanced alpha band desynchronization. It might be a useful aid in the identification and training of BCI signals a P300 BCI based on a 12 x 7 matrix and new paradigmatic approaches to flashing characters designed to decrease the number of flashes needed to identify a target character. The results indicate that 16-flash pattern is better than other patterns. RC approach and performance of an online P300 BCI can be significantly improved by selecting the best presentation paradigm for each subject. examined the role of mental practice and concentration skills on the EEG control during the imaginative hand movements. The results show that the mental practice and concentration can generally improve the classification accuracy of the EEG patterns. It is found that mental training has a significant effect on the classification accuracy over the primary motor cortex and frontal area. focused on the problems of dimensionality reduction by means of Principal Component Analysis (PCA) in the context of single-trial EEG data classification. The principal components with the highest variance, however, do not necessarily carry the greatest information to enable discrimination between the classes. An EEG data-set is presented where the principal components with high variance cannot be used for discrimination. In addition, a method based on linear discriminant analysis, is introduced that detects principal components which can be used for discrimination, leading to data sets of reduced dimensionality but similar classification accuracy. In this paper, the real time Raw EEG sensing is carried out by using a bio-sensor head set, also called NeuroSky's mind wave mobile. It is a device with portable EEG sensors. The personalized GUI contains different task such as Wheelchair control, personalized music player, personalized movie player, Home appliances control, Help and Personalized web browser. The user can access any task from the personalized GUI by blinking their eyes. Analysis of variance is done to find the significant signals influencing the subject to improve the motion characteristics of brain computer interface-based system. ANOVA gives clearly how the parameters affect the response of the particular subject signal generation and the level of significance of the factor considered.

2 Literature Survey

An emotion identification system that is both real-time and very accurate is required to achieve such an application. Emotion recognition with good performance for mobile apps is suggested in this research. A smart phone's integrated camera captures face video in the suggested method. A face detection module is used to extract the face areas in the frames after certain representative frames have been taken from the movie. To categorize the mood, the dominating bins are given into a Gaussian mixture model-based classifier. The suggested system provides excellent recognition accuracy in an acceptable amount of time, according to experimental data. This model has improved identification characteristics, is easier to deploy, and responds quickly.

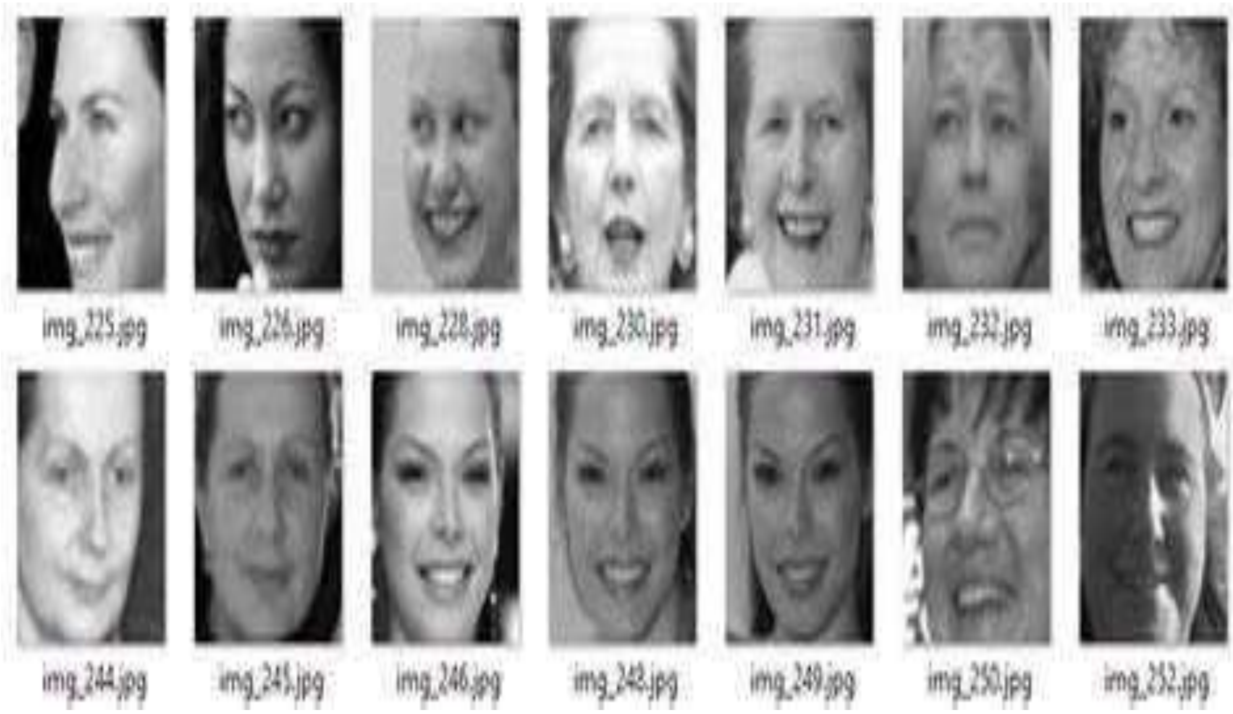
Emotion recognition is important in affective computing, according to Jian Guo et al. A compound facial emotion is more comprehensive than the seven traditional facial emotions since it comprises dominant and complimentary emotions (e.g., happily-disgusted and sadly-fearful) (e.g., happy, disgust, and soon). The iCV-MEFED dataset, which comprises 50 classes of compound emotions and labels evaluated by psychologists, was provided to solve these issues. Due to the significant similarity of compound facial emotions from several categories, the work is difficult. The suggested data collection, on the other hand, may open the way for more study into compound facial emotion identification. The model yields precise feature extraction outcomes.

Understanding people's emotions through natural language, according to Xin Kang et al, is a difficult challenge for intelligent systems based on the Internet of Things (IoT). The main difficulty is from a lack of fundamental understanding of emotion expressions in a range of real-world situations. In this research, a Bayesian inference approach is provided for investigating latent semantic dimensions as contextual information in natural language and learning emotion

In this paper we introduce an important new businesscustomer relation paradigm titled Emotional Business Intelligence (EBI), outline its relevance, and envisage one concrete technological enabler and impact example called FeelingsExplorer. At this stage in our research, our solution is mostly on Proof of Concept level and the presentation of evidence resembles therefore that of a “Gedankenexperiment” about future business system intelligence in dealing with its human dimensions. Throughout history it is obvious that the homo economicus has been the dominating model for describing and explaining human and organizational behavior in commerce contexts. This homo economicus is rational and logical, cognizant and utilitarian, deterministic and computational, and therefore—and this is important—assumingly computable, predictable, and controllable. All of these attributes, alongside its fit to the popular human information processor model [1] [2], made the homo economicus seemingly an archetypical business companion, and an ideal inhabitant of the knowledge society in a digital age. Above all, the homo economicus is a very Business Intelligence (BI)-friendly notion, considering that BI (by providing analytical processing and practical presentation of business data) traditionally supports rational decision making [3] [4] [5] [6] [7]. However, humans in- and outside business organizations cannot be aptly described and understood in rational terms alone, and for this reason the homo economicus is a fallacious abstraction that undermines the mission of raising businesscustomer proximity as well as the validity and power of business-relevant decision-making models. This conclusion per se is not new, and has —implicitly and explicitly— accompanied the discourse between economic and psychological takes on decision-making throughout history [8]. Here we claim that introducing emotions into the business equation is an opportunity to generate new value with customers and employees. And on top of this it is a necessity not only to enhance the naturalistic model validity but importantly also to deal with the future data load of BI. In this vein, we have recently started witnessing welcomed changes in how companies, products and services, as well as people's relation to these, are conceptualized. These changes have been driven by a rise of emotion-related themes, emphasizing on hedonic and symbolic product and service meanings, user and customer experiences (see e.g., [9]'s research agenda), and intangible organizational assets (e.g., [10]). Yet, as popular as these changes have been with business evangelists, they have often proven difficult in practice. Our paper is a contribution to reinforce the valuable evolution towards experience-centricity by offering for it a conceptual handle and boosting the business practical relevance. The proposed conceptions intend to challenge incumbent business models in general, and at their core, they urge to review the functioning and aptness of BI as an organization's central data processing nervous system. To do so, we inquire about the role of experiences (particularly emotions) in business and outline the future of BI in this emerging emotional context, calling it EBI.

Methodology System

In the proposed system, the mood of a user is determined by recording his/her's face through webcam and predicting its emotion using our emotion recognition model which includes extraction of the features of the image. This model is developed using the techniques Face Detection, Extraction, Classification, Recognition and Segmentation.

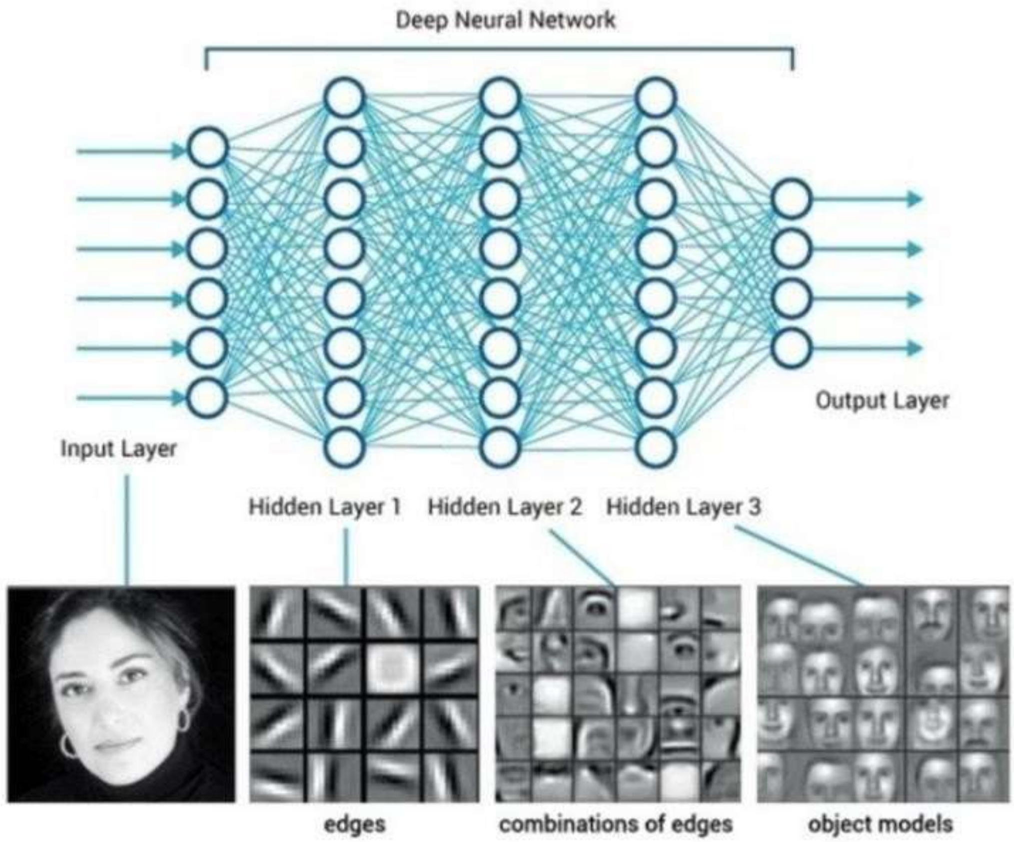


Data Pre-processing

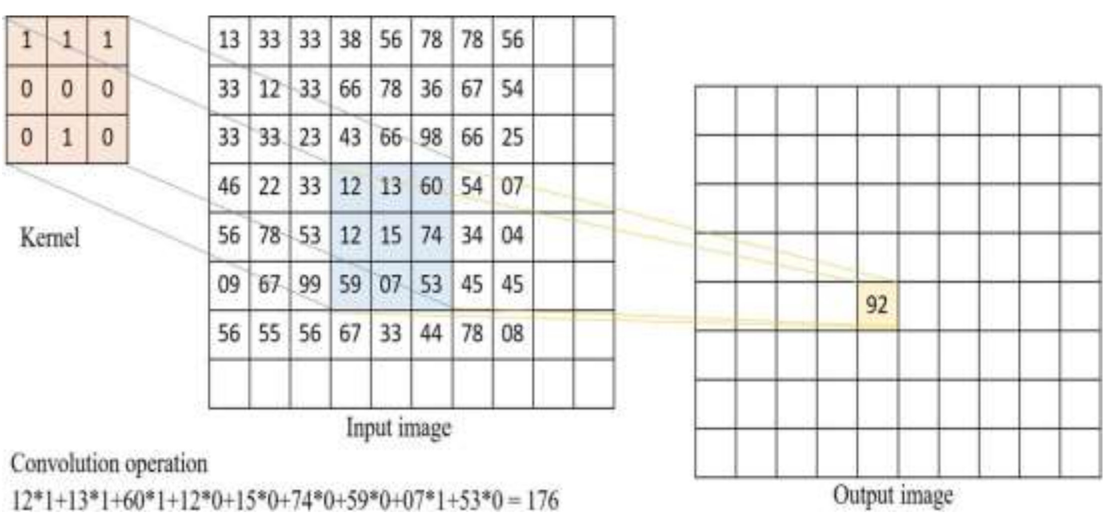
Data preprocessing is the process of converting raw data into an easy-to-understand format. This is also an important step in data mining, as you cannot work with raw data. Before applying machine learning or data mining algorithms, you need to verify the quality of your data.

Data Exploration

Data exploration is the first step in data analysis and is used toexamine and visualize data to gain insights from the beginning and to identify areas and patterns that can be further explored.



6.1.1 Dimensions of images



4 Results

Execution:

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Windows PowerShell
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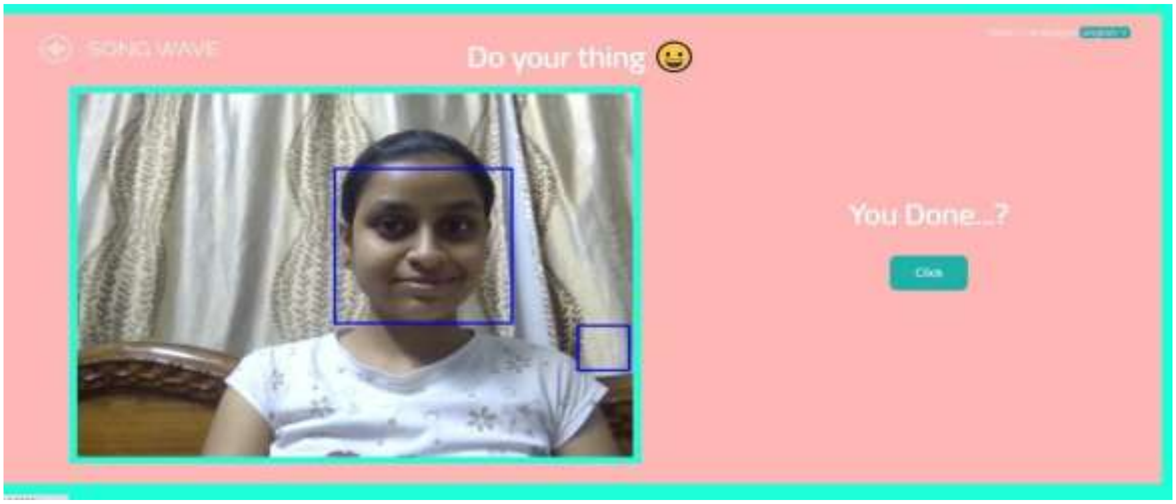
Try the new cross-platform PowerShell https://aka.ms/pscore6

PS C:\Users\PoojaM\Downloads\emotion-based-music-player-main> & 'C:\Users\PoojaM\AppData\Local\Programs\Python\Python310\python.exe' 'c:\Users\PoojaM\.vscode\e
xtensions\ms-python.python-2022.4.1\pythonFiles\lib\python\debugpy\launcher' '60251' '--' 'c:\Users\PoojaM\Downloads\emotion-based-music-player-main\index.py'
2022-04-12 19:37:40.746227: W tensorflow/stream_executor/platform/default/dso_loader.cc:64] Could not load dynamic library 'cudart64_110.dll'; dlerror: cudart64
_110.dll not found
2022-04-12 19:37:40.750447: I tensorflow/stream_executor/cuda/cudart_stub.cc:29] Ignore above cudart dlerror if you do not have a GPU set up on your machine.
 * Serving Flask app 'index' (lazy loading)
 * Environment: production
   WARNING: This is a development server. Do not use it in a production deployment.
   Use a production WSGI server instead.
 * Debug mode: on
INFO:werkzeug: * Running on http://127.0.0.1:5000 (Press CTRL+C to quit)
INFO:werkzeug: * Restarting with stat
2022-04-12 19:37:48.493261: W tensorflow/stream_executor/platform/default/dso_loader.cc:64] Could not load dynamic library 'cudart64_110.dll'; dlerror: cudart64
_110.dll not found
2022-04-12 19:37:48.501494: I tensorflow/stream_executor/cuda/cudart_stub.cc:29] Ignore above cudart dlerror if you do not have a GPU set up on your machine.
WARNING:werkzeug: * Debugger is active!
INFO:werkzeug: * Debugger PIN: 139-327-916
```

Output Screen



Conclusion

In this project we have created a model using MT CNN and trained the model using haarcascade dataset. We have used technologies like python, flask, in this. The major purpose of this project is to detect users' emotions and play music that corresponds to them using Deep Learning.There are various projects on emotion recognition. As a result, we've incorporated a music suggestion system to our emotion recognition system.It is both time and cost efficient. Our algorithm, which has a 75 percent accuracy rate, can accurately detect seven moods: anger, disgust, fear, joyful, sad, surprise, and neutral; and our Android application can play music that is appropriate for the discovered mood.

Future enhancements

Many studies and researches on Emotion Recognition and Deep Learning Techniques for Recognizing Emotions have been undertaken using data sets. In the future, a model like this, with considerably higher accuracy and reliability, will be necessary, as it has several applications in a variety of sectors.

This paper investigates some of the CNN-based facial emotion recognition systems. This research aids in the understanding of various face emotion detection models as well as the development of new CNN architectures for improved performance and accuracy.

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