A Project report on

Human Face Emotion In 3D

A Dissertation submitted to JNTU Hyderabad in partial fulfillment of the demic requirements for the award of the degree.

Bachelor of Technology

in

Computer Science and Engineering

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CERTIFICATE

This is to certify that the Major Project Phase I report entitled **"Human Face Emotion In 3D"**being submitted by V. Mahesh (20H51A0526), N. Keerthi (20H51A0542), T. Ajay(20H51A05M0)in partial fulfillment for the award of **Bachelor of Technology in Computer Science and Engineering** is a record of bonafide work carried out his/her under my guidance and supervision.

The results embodies in this project report have not been submitted to any other University or Institute for the award of any Degree.

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ABSTRACT

Emotion recognition is one of the trending research fields. It is involved in several applications. Its most interesting applications include robotic vision and interactive robotic communication. Human emotions can be detected using both speech and visual modalities. Facial expressions can be considered as ideal means for detecting the persons' emotions. The main idea is to generate key points using CNN algorithm, which is based on real-time deep learning. This phase is deployed to enhance the accuracy of emotion detection. Finally, the decomposed features are enrolled into a Machine Learning (ML) technique that depends on a Support Vector Machine (SVM), k-Nearest Neighbor (KNN), Naïve Bayes (NB), Logistic Regression (LR), or Random Forest (RF) classifier as an efficient deep neural network technique. The presented techniques are evaluated on different datasets with different evaluation metrics. The simulation results reveal that they achieve a superior performance with a human emotion detection accuracy of 97%, which ensures superiority among the efforts in this field.

CHAPTER 1
INTRODUCTION

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Introduction

One of the major components of behavioral biometrics is the recognition of facial emotion and its intensity. In the industry and academic research, physiological traits have been used for identification through biometrics. Any level of biometrics could not be performed without good sensors, and when it comes to facial emotion intensity recognition, apart from high-quality sensors (cameras), there is a need for efficient algorithms to recognize emotional intensity in real time. With the increased use of images over the past decade, the automated facial analytics such as facial detection, recognition, and expression recognition along with its intensity has gained importance and are useful in security and forensics. Components such as behavior, voice, posture, vocal intensity, and emotion intensity of the person depicting the emotion, when combined, help in measuring and recognizing various emotions. Primarily, 3D facial images are the most thoroughly researched and predictions are made by the available systems based on the features that were extracted from the images for emotion and intensity recognition. The intensity of emotion is often directly associated with the intensity of facial muscle movements. This, in turn, indicates that the intensity of muscle movement represents the index of the intensity of emotional state, implying the intensity of the emotion that is being experienced. Such intensities can be measured in both spontaneous and posed expressions. Posed facial expressions of emotions, on the other hand, are used on a large-scale for studies involving the intensity of facial emotions. Algorithms that have been used for feature extraction span from classical techniques such as Convolutional Neural Network(CNN) ,SVM, Random Forest and KNN to modern techniques such as machine learning (ML) and artificial neural networks (ANN) .

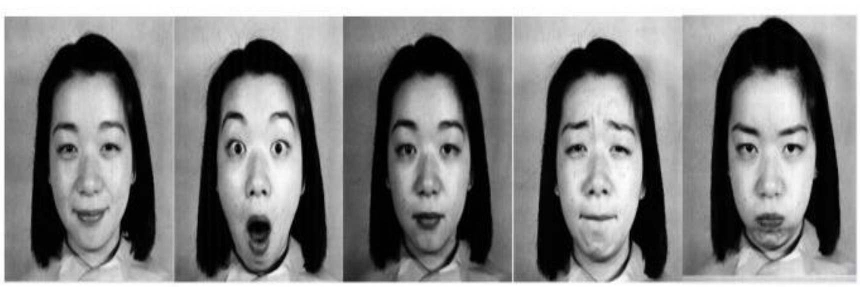

Fig 1.1 : Emotions

1.1 Problem Statement

The objective of this study is to develop a neural network-based intelligent system capable of identifying children's emotions. Most of the time human expresses feelings spontaneously that causes automatic change in shape and size of different semi movable parts of our face like chick, eyebrow, tongue, lips, eye size etc. A precise recognition system greatly helps doctors and parents to understand physical and mental health of the child. According to surveys 7% meaning of a message is understandable through verbal statement, 38% is understood from vocal analysis and most amazingly remaining 55% is attained from facial expression.

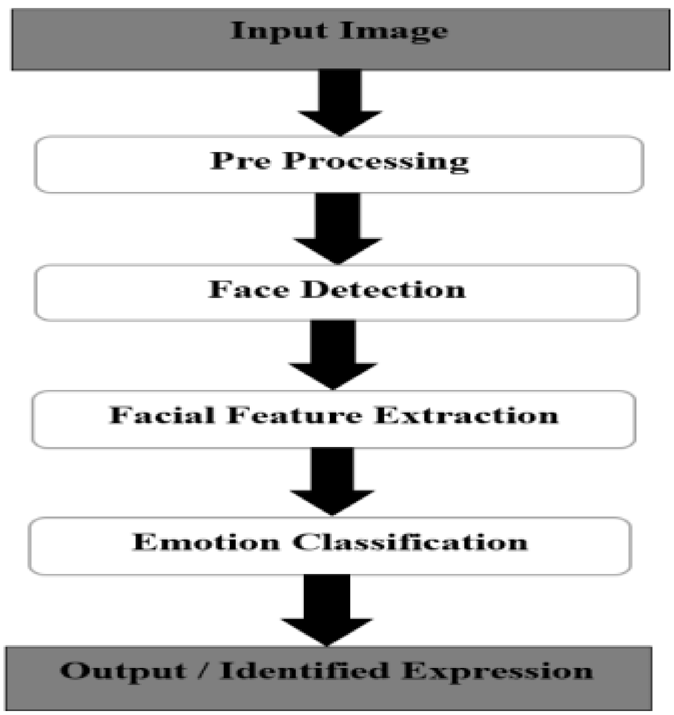

Fig 1.2: Flow chart

1.2 Research Objective

One of the primary goals of this study is to correctly recognize human precisely toddler's emotions from real time videos and photographs. We have used here Deep Convolution Network; input frames are taken from real-time video as input image. This study uses the kaggle fer 2013 labeled dataset. We are using this dataset to classify above mentioned seven emotional classes.

1.3 Scope and Limitations

The scope and limitations of representing human emotion in 3D

1. Visual Realism: 3D technology allows for the creation of visually realistic representations of human emotions..

2. Expressiveness: 3D models and animations can convey a wide range of human emotions, from happiness and excitement to sadness and fear.

3. Interactivity: In virtual environments and video games, 3D technology can enable interactivity with emotionally responsive characters or settings.

4. Research and Therapy: 3D representations of human emotion have applications in psychological research and therapy.

5. Data and Animation: Creating emotionally expressive 3D models and animations often requires a significant amount of data, time, and expertise.

6. Technology Limitations: The capabilities of hardware and software can place constraints on the quality and real-time rendering of 3D emotional representations.

7. Privacy and Security: In virtual environments, the collection and analysis of data related to users' emotional responses can raise privacy and security concerns.

CHAPTER 2
BACKGROUND WORK

CHAPTER 2
BACKGROUNDWORK

2.1. Facial Expression Study Based on 3D Facial Emotion Recognition

2.1.1 Introduction

Three-dimensional reconstruction refers to the establishment of a mathematical model suitable for computer representation and processing of three-dimensional objects. It is the basis for processing, operating and analyzing its properties in a computer environment. It is also a key technology for establishing virtual reality in the computer to express the objective world. Compared with 2D image features, 3D feature-based methods have stronger robustness and recognition capabilities, and 3D-based analysis methods allow us to examine the fine structure of general and complex expressions. This technique is used by many methods and has achieved good results, but this method still has limitations because it Not suitable for reconstructing 3D features from shadows. In the traditional classroom teaching method, the teacher can observe the facial expression and physical state of each student through his own eyes and know the learning effect and quality of the student in the course of listening to the class etc. So as to use computer technology to replace the teacher's facial expression recognition and analysis of online learning students, accurately judge the real-time learning effect and quality of students and lay a scientific foundation on the theoretical level.

Fig 2.1: Classification of Emotion

The ability to confidently detect human emotions can have a wide array of impactful applications, and therefore emotion recognition has been a core area of research in computer vision. We wanted to focus on the issue of emotion recognition, and build a real-time emotion detection system.

Suppose $I(x,t)$ is an image profile at location x at time t. If the image undergoes a translational motion with a displacement function $\delta(t)$, the image is given by :

$I(x,t) = = f(x + \delta(t))$ and $I(x,0) = f(x)$

Pixel intensity I of a magnified motion is computed as follows, where $B(x, t)$ is difference of intensity and given that

$I(x,t) = I(x) + B(x,t)$ $\hat{I}(x,t) = I(x) + \alpha * B(x,t)$, where α = magnification factor,

I can be approximated by the first-order Taylor series as follows

$\hat{I}(x, t) \approx f(x) + \sum k \alpha B(x, t)$,

where k is pass band of a temporal filter with a corresponding attenuation factor γk and $B(x, t)$ is output of temporal band pass filter:

$B(x, t) = \sum \gamma k \, \delta(t) \, \delta f(x) / \delta x$

Once the expressions are exaggerated using A-EMM or P-EMM and with magnification factor α, Local Binary Pattern with Three Orthogonal Plane (LBP – TOP) is used for feature extraction. For LBP-TOP feature extractions, the following steps are followed :

1) Spatially resize image to 320 x 240 pixels resolution

2) Partition images into non-overlapping 5 x 5 blocks

3) Blocks are stacked up in 3-D volumes

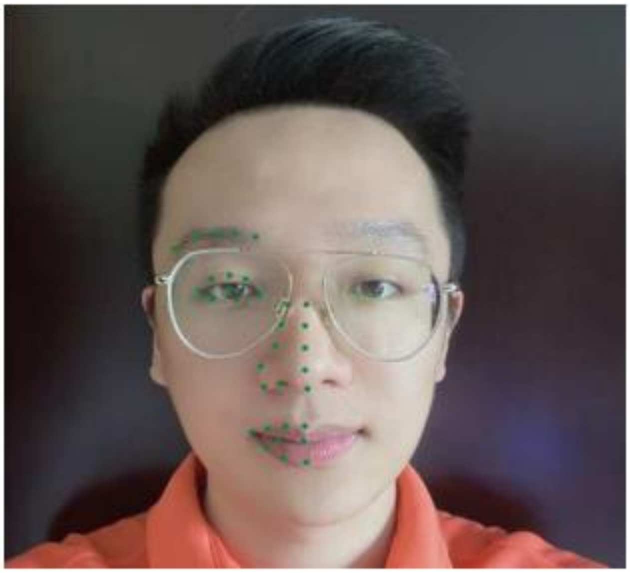

Fig 2.2: Feature selection and face detection

Fig 2.3: Depth Prediction

2.1.2 Merits and Demerits

Some of the Benefits are:

- **High Accuracy:**

  3D facial emotion recognition can offer higher accuracy compared to traditional 2D methods. It captures depth information, allowing for a more precise analysis of facial features and expressions.

- **Multimodal Analysis:**

  By combining 3D data with other modalities like audio and physiological signals, a more comprehensive understanding of emotions can be achieved, improving overall accuracy.

- **Applications in Healthcare:**

  It has potential applications in healthcare, particularly in aiding the diagnosis and monitoring of conditions like autism and depression, where recognizing subtle facial expressions is crucial.

- **Enhanced Security:**

  3D facial emotion recognition can be used for secure access control, as it is difficult to spoof compared to 2D facial recognition.

- **Human-Computer Interaction:**

  It can enhance human-computer interaction by allowing devices and systems to adapt to users' emotional states, leading to more personalized and effective experiences.

Some of the Drawbacks are:

- **Complex Data Capture:**
  3D facial recognition often requires specialized hardware like depth-sensing cameras, making data capture more complex and potentially limiting its widespread adoption**.**

- **Privacy Concerns:**
  The 3D mapping of faces raises significant privacy concerns, as it can capture highly detailed facial features, potentially compromising individuals' privacy and data security**.**

- **Resource Intensive:**
  Processing 3D facial data can be computationally intensive, requiring significant resources for real-time applications, which can be a limitation in certain contexts.

- **Data Bias:**
  If training data used for 3D facial emotion recognition is biased, it can result in inaccurate recognition and reinforce stereotypes or biases in technology.

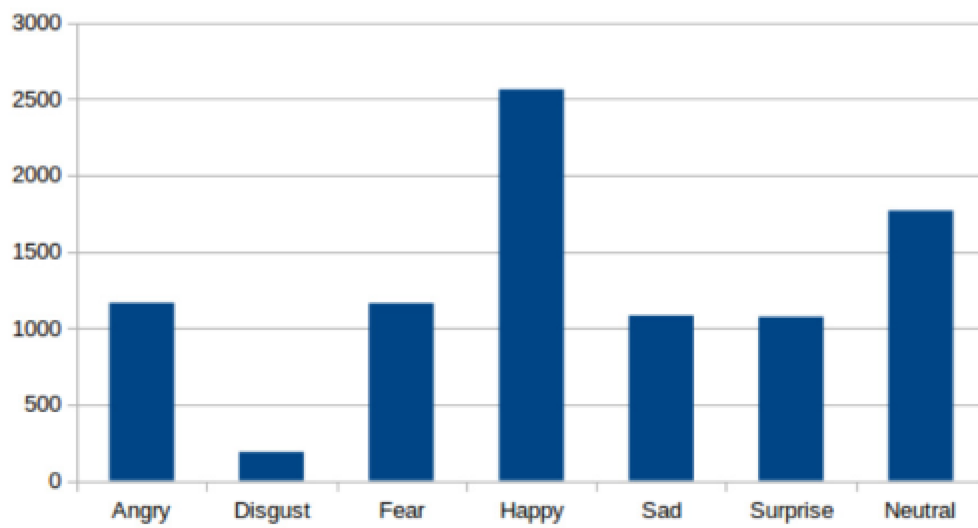

Fig 2.4: No. of images per emotion in training set

2.1.3 Implementation

Facial expression based on 3D facial emotion recognition propose two new methods. The first method is to reconstruct a single two-dimensional image into a three-dimensional image. The method consists of three steps: The first step is to use the supervised descent method (SDM) and Convolution Neural Network to detect the facial features such as the mouth, nose and eyes of the half face, and to detect the face based on these facial features. The second new method is to use the camera to capture the changes in the learner's facial expressions to judge the learner's state after completing the construction of the 3D face model, and then judge the learner's learning effect and the degree of mastery of the knowledge points.

First stage of our method is to find the required features. For this purpose, a method named SDM is used which has good results and robust in nature. It works simply by minimizing a function which is called nonlinear least square function. The main benefit of this algorithm is that while minimizing nonlinear square function, it uses learned decent direction which don't need Hessian or Jacobian for computations process. The difference between us and them is that because the camera of the learner is often at a relatively fixed position during learning, we only select the feature points of half of the face.

When constructing the 3D face model, we mirror the selected feature points. You can get a complete face feature point, which will reduce a lot of repeated calculations, make the system faster, and also provide speed support for subsequent facial expression recognition. In order to develop our Convolutional Neural Network, we decided to utilize pre-trained models. We believed that this would lead to better results for our project, since these pre-trained networks are much deeper that we could develop, and would thus have much better feature-detection power. In researching existing networks, we couldn't find any that dealt directly with facial detection or recognition, so we chose to use networks with varying initial applications. Since many of the most successful emotion recognition applications used CNN's, we also decided to use CNNs as our model to target the emotion recognition problem.

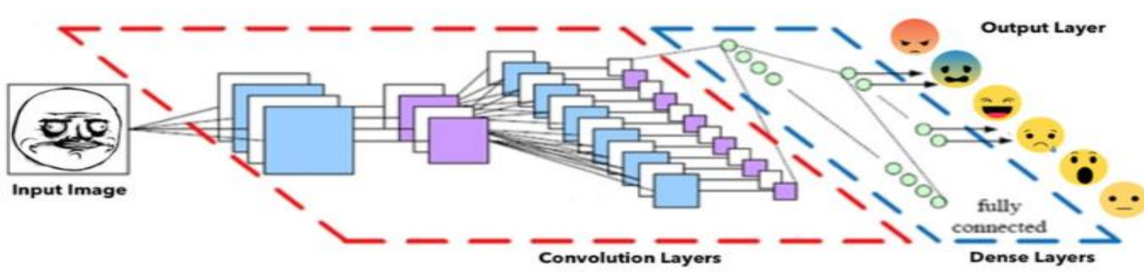

Fig 2.5: Convolution Layer Model

2.2. Visual Expression of Emotion In Dynamic 3D System Based on Emotion Synthesis Model

2.2.1 Introduction

Emotion is a unique ability possessed by human beings as advanced creatures. Emotions give people a unique physical and mental experience. Assigning emotions to computer systems is one of the latest topics in artificial intelligence research. The purpose is to allow machines to achieve natural coordination between humans and computers. This article focuses on the visual expression of emotion in the dynamic three-dimensional painting system, creating an intelligent painting system and realizing a good user experience. In this paper, the discrete method is used to qualitatively analyze emotions, and the continuous method is used to quantify basic emotions, and emotional modeling and emotional quantitative analysis are proposed to realize quantitative analysis of emotions. Combining these two methods, a comprehensive method is proposed, which uses a continuous method to quantify the basic emotions of each discrete dimension, and finally superimposes them into a comprehensive emotional synthesis model. Borrowing the relationship between emotion synthesis model and visual emotion elements, this article puts forward the concept of qualitative and quantitative visual emotion elements, and expounds that the multidimensional superposition of visual emotion elements makes dynamic three-dimensional painting system emotions. This can indicate that different subjects have different feelings and evaluations of this emotional visualization. As long as the difference is within a reasonable range, this emotional visualization also has practical value, and has the ability to convey or suggest emotions.

Understanding emotional facial expressions accurately is one of the determinants in the quality of interpersonal relationships. The more one reads another’s emotions correctly, the more one is included to such interactions. The problems in social interactions are shown in some psychopathological disorders may be partly related to difficulties in the recognition of facial expressions. Such deficits have been demonstrated in various clinical populations. Nonetheless, with respect to facial expressions, there have been discrepant findings of the studies so far.

Fig 2.6: Base Model

2.2.2 Merits and Demerits

Some of the benefits are include:

- Easy to understand conceptually – standard architecture for CNNs
- Well researched and widely used. Great for understanding CNN concepts.
- Available in most popular machine learning libraries
- Good performance at image classification and generalizes well to related tasks
- Trained for weeks on millions of images
- Better security. Face detection augments surveillance tactics and forms the basis of the identification process of terrorists and criminals.
- Easy to integrate. Most face detection¬ solutions are compatible with security software.
- Automated identification. Face detection lets facial identification be automated, thus increasing efficiency alongside a heightened rate of accuracy.

Some of the drawbacks are include:

- Research has continued since 2014 and there are often better-performing CNN architectures available
- With over 100 million trained weights, the model size is large. ~500MB on disk.

- Training for a different task (transfer learning) can be difficult due to the deep network and vanishing gradient problem.
- Huge storage requirements.
- Machine learning technology requires powerful data storage.
- Detection can be vulnerable.
- We’ve outlined the way in which facial detection can be thrown off; Potential privacy issues.
- There is disagreement on whether face detection is compatible with human privacy rights.

2.2.3 Implementation

The specific detection method is to first select multiple samples of the tested object, and experience some related states after experiencing this emotionalized 3D dynamic website. To achieve the purpose of emotion detection, we preset a number of detection concerns, including: the emotional state of the object, the transmission of website emotions, the experience of the website, the contagiousness of website emotions, and the acceptance of three-dimensional websites. After the subject completes this emotional visualization experience, they will use questionnaire surveys to collect answers to related questions regarding these concerns. As shown in Table 3, for each point of interest, five values are used to scale the value of the corresponding point of interest. A smaller value means that the value of the corresponding point of interest is biased toward negative, and a larger value means that the value of the point of interest is biased toward positive..

Fig 2.7: Different Face Emotions

The detection process of a single sample is divided into 3 stages. The first stage introduces the purpose and meaning of this visual expression of emotion to the test subject; the second stage, the test subject answers the first question, that is, the current emotional state. Afterward, the test subjects experience the visual expression system for emotions; in the third stage, the test subjects give the other four points of attention corresponding to the scores based on the second stage experience. Facial Emotion Recognition is essential to recognize the emotions in many cases like in criminal investigation, E-learning, gaming and psychology. In criminal investigation, it is used to identify the criminals based on their facial expressions. Similarly in E-learning, this can be used to conclude whether a student understands a concept or not and in other applications it ensures the understanding of a person’s emotional condition. The classification of the facial expressions was performed using Convolution Neural Network and Haar Cascade Classifier Algorithm. The image is uploaded which is then converted as a grey scale image. The face is detected using Haar Cascade Classifier which is then classified by the model that displays the image along with its emotion as the output.

2.3. Detection and Recognition of Human Emotion using Neural Network

2.3.1 Introduction

Human emotion and face expression is one of the most powerful tool of communication. Facial expression are very expressive. It is found that the linguistic component of a message contributes to only a meagre 7% of the total significance of the effect of the message, whereas the tone indicates about 38% of the total signal and the remaining in turn signified or portrayed 55%. of the total message. Feature Extraction of the facial features is a very widely sought after implementation in the fields of surveillance (video or images),biometrics as well as HCI(human computer interface. Here facial image is used as a medium to read human emotion. The research on human’s emotion can be traced back to the Darwin’s pioneer working and since then has attracted a lot of researchers to this area. There are seven basic emotions that are universal to human beings. Namely, neutral, angry, disgust, fear, happy, sad, and surprise and these basic emotions can be recognized from human’s facial expression. Solving the problem of recognising facial features is not a very simple job since each individuals face varies from person to person. There are a lot of factors influencing the features like physical characteristics as well and sex, genes and age. Therefore because of intense variability the challenge is not easy. There are many factors that have to be taken while developing a emotion recognition system. The main stage in any face processing system is to detect the face accurately and classify them. The facial expression recognition system should work in all diverse environment like change in surrounding light and different illumination problems, use of spectacles, presence of facial hair etc. These are some problems that the system should be able to overcome to create an ideal system. A general a biometric process has four stages of process flows: face detection , preprocessing , Feature Extraction, and Face Recognition.

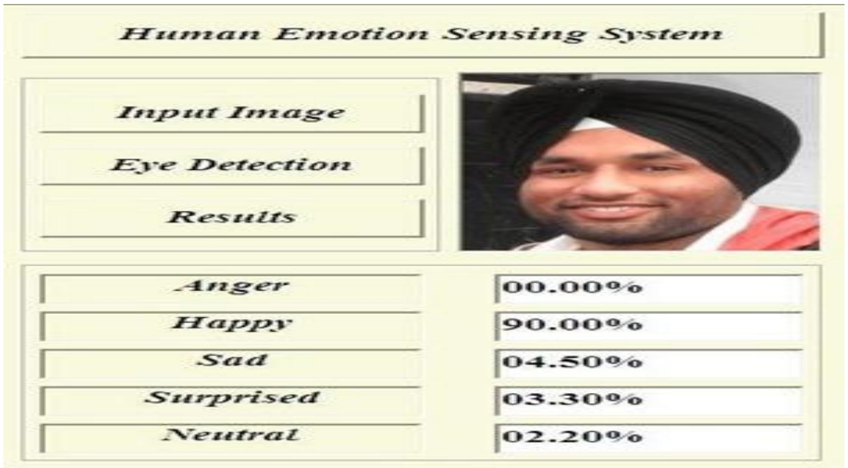

Fig 2.8: Human Emotion Sensing System Result

2.3.2 Merits and Demerits:

- **High Accuracy:** Neural networks, particularly deep learning models, have shown impressive results in emotion recognition tasks.
- **Adaptability:** Neural networks can adapt to various data sources and modalities, such as text, images, audio, and physiological signals.
- **Feature Learning:** Neural networks can automatically extract relevant features from raw data, eliminating need for manual feature engineering. This is especially valuable in emotion recognition, relevant features can be complex and dependent.
- **Real-time Processing:** With hardware acceleration and optimized models, neural networks can process data in real-time, making them suitable for applications like emotion-aware interfaces and virtual reality.
- **Transfer Learning:** Pretrained neural network models, such as those used in computer vision or natural language processing, can be fine-tuned for emotion recognition tasks, reducing the need for large labeled datasets.
- **Scalability:** Neural networks can be scaled to handle large datasets and can be trained on distributed computing clusters, enabling the development of highly accurate emotion recognition systems.

- **Demerits:**
- **Data Dependency:** Neural networks require large labeled datasets for training, and The quality of the data greatly influences the model's performance. Obtaining accurate and diverse emotional data can be challenging.
- **Computational Resources:** Training deep neural networks can be computationally intensive and time-consuming , requiring powerful hardware like GPUs or TPUs. This may limit the accessibility of these methods.
- **Interpretability:** Neural networks are often criticized for their lack of interpretable Understanding why a model made a particular emotion prediction can be challenge which is a concern in applications where interpretability is crucial.
- **Overfitting**: Neural networks are prone to overfitting when the model becomes too complex relative to the size of the dataset. Regularization techniques are often needed to mitigate this issue.
- **Bias and Fairness:** Neural networks can inherit biases present in the training data, leading to potential issues in fairness and equity in emotion recognition systems. Careful data duration and model evaluation are necessary to address these concerns.
- **Generalization:** While neural networks can achieve high accuracy in specific dataset, they may not generalize well to new or diverse contexts, which can limit their real -world applicability.
- **Ethical Concerns:** Emotion recognition technology raises significant privacy and ethi -cal concerns , as it can be used for surveillance and monitoring without consent. There are ongoing debates about the responsible use of such technology.

Accuracy Detection Model	
Emotion	Accuracy(Percent)
Happy	67
Neutral	72
Surprised	71
Sad	34
Anger	25

Fig 2.9 : Table of Emotions v/s Observed Accuracy

2.3.3 Implementation

The problem statements we have are having robust and automated face detection, analysis of the captured image and its meaningful analysis by facial expressions, creating data sets for test and training and then the designing and the implementation of perfectly fitted classifiers to learn underlying classifiers to learn the vectors of the facial descriptors. We propose a model designing which is capable of recognizing up to six models which are considered universal among all walks of cultures. Mainly being fear, happiness, sadness, surprise, disgust and lastly surprise. Our system would be to understand a face and its characteristics and then make a weighted assumption of the identity of the person. This algorithm is mainly helped from the most widely used algorithms at this task, known as the Viola-Jones algorithm. The concept of neural networks is biologically inspired paradigm which allows a computer to learn from the given data. Using tflearn as the frontend and the tensor flow as the backend, we creating a neural network model that is used to train the facial emotion which are in the FER-2013 dataset and then validate, evaluate and then test the model. The model which is being used is a Convolutional Neural Network which sufficient dropout layers as well as pooling to prevent overfitting of the model as well as increase efficiency.

Human emotion can be recognized by analyzing the human face or verbal communication. It is crucial for public interaction to know how people are feeling. Facial expressions are essential for recognizing human emotions. Through identifying emotions, we can understand what humans are thinking. Surveys have found that humans interact socially through emotion and universal language. Through facial expressions, people convey information to one another. The mental well-being of a person can be seen through the expression on their face. Hence, automatic recognition of emotion using Image processing, cyber security, robotics, psychological studies, and virtual reality applications, to mention a few, can all benefit from high-quality sensors.

Fig 2.10: Implementation Test(Neutral)

Fig 2.11 : Implementation Test(Happy)

2.4. Emotion Detection using Machine Learning

2.4.1.Introduction

Facial expression recognition (FER) has been dramatically developed in recent years, thanks to the advancements in related fields, especially machine learning, image processing and human cognition. Accordingly, the impact and potential usage of automatic FER have been growing in a wide range of applications, including humancomputer interaction, robot control and driver state surveillance. However, to date, robust recognition of facial expressions from images and videos is still a challenging task (1)due to the difficulty in accurately extracting the useful emotional features. These features are often represented in different forms, such as static, dynamic, point-based geometric or region-based appearance. Facial movement features, which include feature position and shape changes, are generally caused by the movements of facial elements and muscles during the course of emotional expression. The facial elements, especially key elements, will constantly change their positions when subjects are expressing emotions. As a consequence, the same feature in different images usually has different positions. In some cases, the shape of the feature may also be distorted due to the subtle facial muscle movements. For example, the mouth in the first two images in presents different shapes from that in the third image. Therefore, for any feature representing a certain emotion, the geometric-based position and appearance-based shape normally changes from one image to another image in image databases, as well as in videos. This kind of movement features represents a rich pool of both static and dynamic characteristics of expressions, which play a critical role for FER. The vast majority of the past work on FER does not take the dynamics of facial expressions into account. Some efforts have been made on capturing and utilizing facial movement features, and almost all of them are video- based. These efforts try to adopt either geometric features of the tracked facial points (e.g. shape vectors, facial animation parameters, distance and angular, and trajectories), or appearance difference between holistic facial regions in consequent frames (e.g. optical flow, and differential-AAM), or texture and motion changes in local facial regions (e.g. surface deformation, motion units, spatiotemporal descriptors, animation units, and pixel difference). Although achieved promising results, these approaches often require accurate location and tracking of facial points, which remains problem

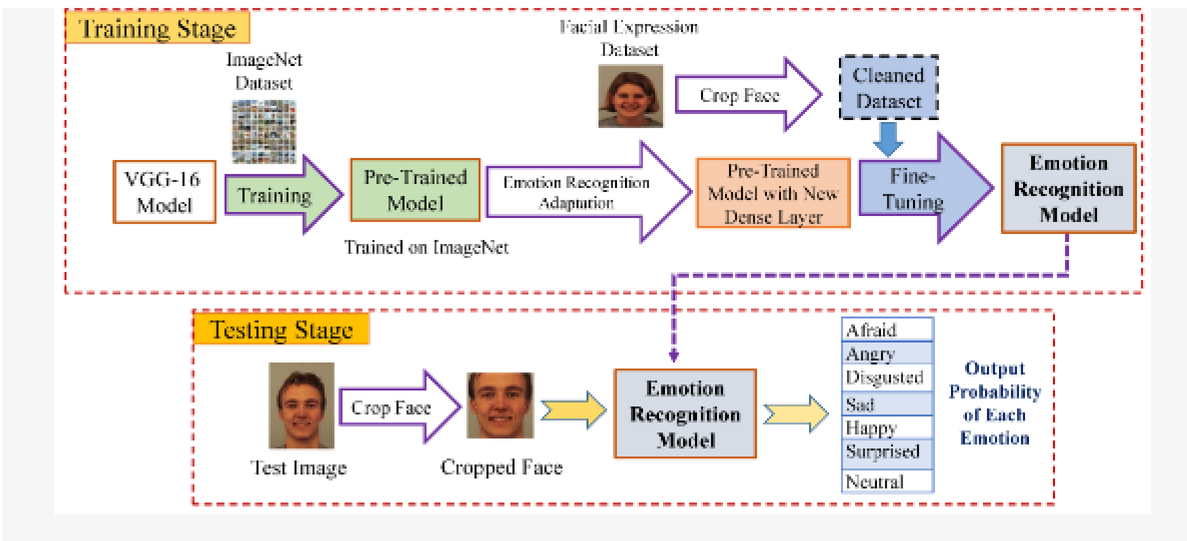

Fig.2.12: Flow Chart of FER

2.4.2 Merits and Demerits:

➢ **Merits**

One advantage of using these color spaces is that most video media are already encoded using these color spaces. Transforming from RGB into any of these spaces is a straight forward linear transformation

1. Face detection,
2. Feature extraction and
3. Facial expression recognition.

The first phase of face detection involves skin color detection using color model, lighting compensation for getting uniformity on face and morphological operations for retaining the required face portion.

- **Demerits:**
    1. The system plays a communicative role in interpersonal relations because they can reveal the affective state, cumulative activity, personality, intention and psychological state of a person.
    2. The proposed system consists of three modules.
    3. The face detection module is based on image segmentation technique where the given image is converted into a binary image and further used for face detection.

2.4.3 Implementation

To improve the recognition rate of the system, further modification in the third phase is done using Artificial Neuro-Fuzzy Inference System (ANFIS). In this method, the static images as well as video input can be given for testing the expressions. Here, neuro-fuzzy based automatic facial expression recognition system to recognize the human facial expressions like happy, fear, sad, angry, disgust and surprise has been proposed. Initially a video showing different expressions is framed into different images. Then the sequence of selected images is stored in a database folder. Using AAM method, the features of all the images are located & stored in the form of .ASF files. Then a mean shape is created for all the images in data folder. The change in the AAM shape model according to the change in facial expressions measures the distance or the difference between Neutral and other facial expressions. These values are stored in a MAT file & a specific value is assigned for each individual expression for training the ANFIS. These difference values are then given as input to the ANFIS (Artificial Neuro-Fuzzy Inference System). Using the ANFIS tool available in Mat lab, the system is trained for the different images and their video input sequences for different expressions. To improve the recognition rate of the system, further modification in the third phase is done using Artificial Neuro-Fuzzy Inference System (ANFIS). In this method, the static images as well as video input can be given for testing the expressions. Here, neuro-fuzzy based automatic facial expression recognition system to recognize the human facial expressions like happy, fear, sad, angry, disgust and surprise has been proposed. Initially a video showing different expressions is framed into different images. Then the sequence of selected images is stored in a database folder. Using AAM method, the features of all the images are located & stored in the form of .ASF files. Then a mean shape is created for all the images in data folder. The change in the AAM shape model according to the change in facial expressions measures the distance or the difference between Neutral and other facial expressions. These values are stored in a .MA T file & a specific value is assigned for each individual expression for training the ANFIS. These difference values are then given as input to the ANFIS (Artificial Neuro-Fuzzy Inference System). Using the ANFIS tool available in Mat lab, the system is trained for the different images and their video input sequences for different expressions.

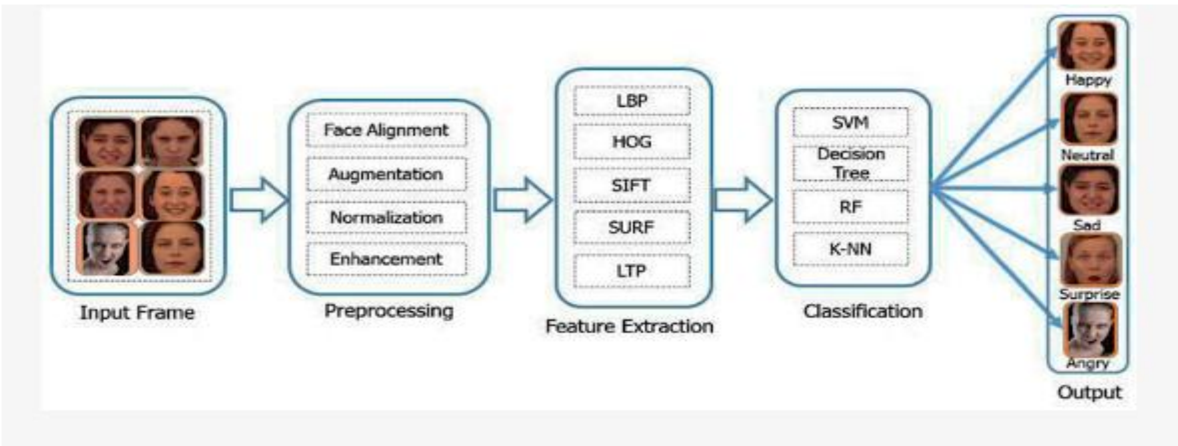

Fig 2.13: Implementation Model

CHAPTER 3
RESULT AND DISCUSSION

CHAPTER 3
RESULTS AND DISCUSSION

3.1 Result

We introduce 3D facial expression model into our work and restore the 3D facial model from 2D images. With the 3D facial models and fused images, a random forest which integrates two regressions for both 3D landmarks tracking and emotion estimating simultaneously is constructed. The experimental results showed that our real-time approach is powerful to achieve preferable result in continuous emotion estimation. Furthermore, the high efficiency of our system make it possible to provide intelligent responds timely in human-computer interactions. Although our algorithm is based on 3D facial model, only 2D images or 2D video stream are used as inputs, which gets rid of the bondage of equipments. Due to the usability of our system, it is promising to deploy our system on mobile devices such as smart phones, tablet personal computers and so on. The image features extracted in our work are intensity of images, which are the simplest features of an image. In future work, we will try to use more robust features such as ones extracted from restored 3D facial model, which may lead to a better performance. The proposed system provides a low complexity and is suitable for real time implementations, such as real time facial recognition.

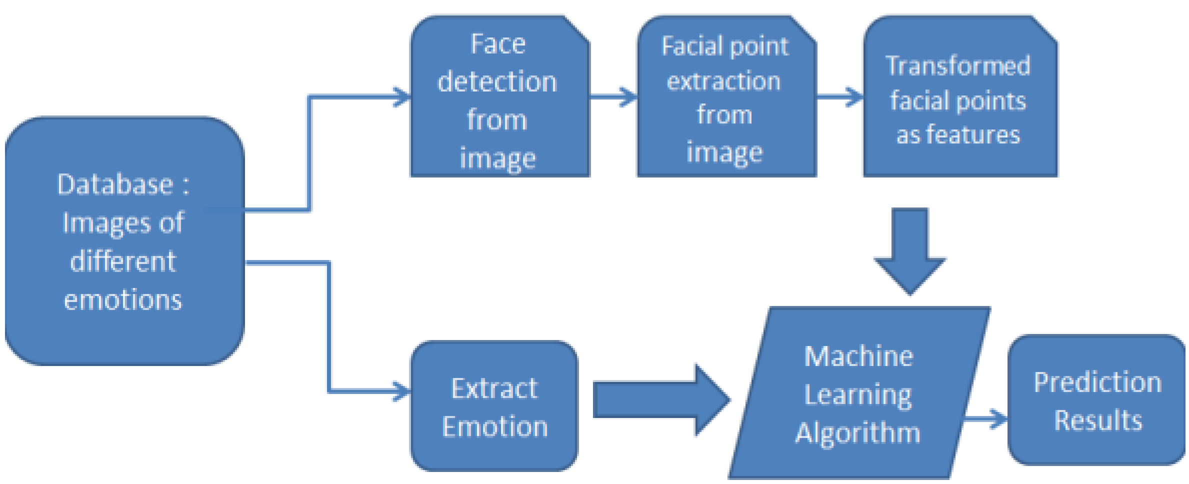

Fig 3.1: Implementation Flow chart

- We Present the outcomes of our Deep Learning model.
- We are trying to evaluate its accuracy and efficiency.
- We Compare its performance with traditional methods and existing methods, showcasing how it outperforms them.

CHAPTER 4
CONCLUSION

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The result obtained from the proposed model gives the accuracy of the expressions is included in a range between 60% and 90%. Some expressions, like anger and fear, generally have the lowest recognition rates. Indeed, the motions of these expressions are moderate compared to happiness or surprise, and thus more challenging to recognize. Regarding the action units, the experiments reached recognition rates in a broader range, between 50% and 95%. The number of features for each AU to be detected will be increased to achieve more accurate results, and the neural networks will gradually be used more and more in the field of facial expression recognition. The purpose of this work was not to get conclusive results but to bear out the main challenges and difficulties involved in emotion detection from facial expressions. The project helps in identifying the different emotions of a person which are angry, disgust, happy, sad, fear, surprise and neutral. These facial emotions can be mainly used in E-learning, criminal investigation, online gaming, psychology and many other applications. Using a public dataset of train and test samples for seven different classes of human emotions.

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