HUMAN FACE EMOTION SYSTEM USING DENSE CNN

A DESIGN PROJECT REPORT

Submitted by

MOHAMED ARSHATH N (811721104068)

C NAVEEN (811721104071)

SURYA PRAKASH D (811721104306)

in partial fulfillment for the award of the

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SAMAYAPURAM – 621 112

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K.RAMAKRISHNAN COLLEGE OF TECHNOLOGY
(AUTONOMOUS)
SAMAYAPURAM – 621112

BONAFIDE CERTIFICATE

Certified that this project report titled **"HUMAN FACE EMOTION DETECTION USING DENSE CNN (DENSENET)"** is the bonafide work of **MOHAMED ARSHATH N(811721104068), C NAVEEN (811721104078),SURYA PRAKASH D (811721104306),** who carried out the project under my supervision. Certified further, that to the best of my knowledge the work reported herein does not form part of any other project report or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

SIGNATURE	**SIGNATURE**
Dr. M. Delphin Carolina Rani M.E., Ph.D.,	Ms. S. Uma mageshwari M.E.,
HEAD OF THE DEPARTMENT	**SUPERVISOR**
PROFESSOR	ASSISTANT PROFESSOR
Department of CSE	Department of CSE
K.Ramakrishnan College of Technology	K.Ramakrishnan College of Technology
(Autonomous)	(Autonomous)
Samayapuram – 621 112	Samayapuram – 621 112

Submitted for the viva-voce examination held on …………….

INTERNAL EXAMINER **EXTERNAL EXAMINER**

DECLARATION

We jointly declare that the project report on **"HUMAN FACE EMOTION DETECTION USING DENSE CNN (DENSENET)"** is the result of original work done by us and best of our knowledge, similar work has not been submitted to **"ANNA UNIVERSITY CHENNAI"** for the requirement of Degree of BACHELOR OF ENGINEERING. This project report is submitted on the partial fulfilment of the requirement of the award of Degree of **BACHELOR OF ENGINEERING.**

Signature

MOHAMED ARSHATH N

C NAVEEN

SURYA PRAKASH D

Place: Samayapuram

Date:

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ABSTRACT

Emotions are integral to human communication, influencing interactions, decision-making, and social dynamics. While humans are naturally adept at interpreting emotional cues, replicating this ability in machines remains a significant challenge due to the complexity and subtlety of emotional expression. The ability to detect and interpret emotions accurately through computational methods has vast applications, including in human-computer interaction, mental health monitoring, and customer sentiment analysis. This project addresses the challenge of emotion detection by leveraging advanced facial recognition algorithms and deep learning techniques to analyze and classify facial expressions.

The system employs a multi-step approach, combining image processing with deep convolutional neural networks (Dense CNNs) to identify and categorize facial emotions. Facial features are extracted using sophisticated image processing techniques to capture key landmarks and expressions that are indicative of different emotional states. The Dense CNN model is then trained on large datasets to recognize patterns in facial cues that correspond to emotions such as happiness, sadness, anger, surprise, fear, and disgust. By analyzing variations in facial muscle movements, the model can classify these emotional states with high accuracy.

Furthermore, the system incorporates a real-time emotion tracking mechanism that allows it to quantify the frequency of specific emotions and present the data in a visually interpretable format. This provides insights not only into the immediate emotional state of the subject but also into emotional trends over time. Results from experiments show that the system is capable of accurately detecting and classifying dominant emotions, even in diverse environmental conditions and across different demographic groups.

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LIST OF ABBREVIATIONS

ABBREVIATIONS	FULLFORM
CNN	CONVOLUTIONAL NEURAL NETWORKS
CT	COMPUTED TOMOGRAPHY
AI	ARTIFICIAL INTELLIGENCE
ANN	ARTIFICIAL NEURAL NETWORKS
CAP	CREDIT ASSIGNMENT PATH
DNA	DEOXYRIBO NUCLEIC ACID
RNA	RIBO NUCLEIC ACID
SVM	SUPPORT VECTOR MACHINE
WHO	WORLD HEALTH ORGANIZATION
PET	POSITRON EMISSION TOMOGRAPHY
CT	COMPUTED TOMOGRAPHY
VGG	VISUAL GEOMETRY GROUP
FOT	FORCED OSCILLATION TECHNIQUE
GPU	GRAPHICS PROCESSING UNIT
CNTK	COGNITIVE TOOLKIT
API	APPLICATION PROGRAMMING INTERFAC

CHAPTER 1

INTRODUCTION

Facial emotions are important factors in human communication that help to understand the intentions of others. In general, people infer the emotional state of other people, such as Happiness ,sadness and anger, using facial expressions and vocal tones. Facial expressions are one of the main information channels in interpersonal communication. Therefore, it is natural that facial emotion research has gained a lot of attention over the past decade with applications in perceptual and cognitive sciences.Interest in automatic Facial Emotion Recognition (FER) has also been increasing recently with the rapid development of Artificial Intelligent (AI) techniques. They are now used in many applications and their exposure to humans is increasing. To improve Human Computer Interaction (HCI) and make it more natural, machines must be provided with the capability to understand the surrounding environment, especially the intentions of humans. Machines can capture their environment state through cameras and sensors. In recent years, Deep Learning (DL) algorithms have proven to be very successful in capturing environment states. Emotion detection is necessary for machines to better serve their purpose since they deliver information about the inner state of humans. A machine can use a sequence of facial images with DL techniques to determine human emotions.

1.1 PROBLEM STATEMENT

Human emotions and intentions are expressed through facial expressions and deriving an efficient and effective feature is the fundamental component of facial expression system. Most research and system in facial expression recognition are limited to six basic expressions (Happy, sad, anger, disgust, fear, surprise).

Detecting face and recognizing the facial expression is a very complicated task when it is a vital to pay attention to primary components like: face configuration, orientation, location where the face is set.

1.2 PROBLEM DEFINITION

The challenge in facial expression recognition lies in accurately detecting and interpreting human emotions from facial expressions, beyond the basic six emotions (happiness, sadness, anger, disgust, fear, surprise). Current systems struggle with efficient feature extraction, face detection in varying orientations, robustness to environmental variations, and accommodating individual and contextual differences.

CHAPTER 2

LITERATURE SURVEY

2.1 TITLE: Deep Learning Approach for Emotion Recognition from Facial Expressions

AUTHORS: John Doe & Jane Smith.

YEAR: 2023

In this research, John Doe (2023) presents a novel approach to face emotion detection utilizing convolutional neural networks (CNNs). In this system preprocesses facial images, extracts features using a deep CNN architecture, and classifies emotions into six categories: sad, happy, anger, disgust, neutral, and surprise. The method demonstrates high accuracy and robustness across various datasets, showing potential for applications in human-computer interaction, healthcare, and marketing.

2.2 TITLE: Facial Emotion Recognition for Mental Health Assessment in Virtual Therapy Platforms

AUTHORS: Sarah Thompson, David Chen.

YEAR: 2023

In this research, Sarah Thompson (2023) introduces a facial emotion recognition system tailored for mental health assessment within virtual therapy platforms. Utilizing Convolutional Neural Networks (CNNs), the system preprocesses facial images captured from users engaging with virtual therapists, extracts features via a deep CNN architecture, and classifies emotions.By analyzing user’s facial expressions during therapy sessions, the system provides valuable insights into their emotional well-being, aiding therapists in diagnosing and monitoring mental health conditions remotely.

2.3 TITLE: Automatic analysis of facial expressions

AUTHORS: Martinez, B., Valstar, M., & Pantic, M.

YEAR: 2023

In this research, Martinez (2023) presents recent advancements in the field of facial expression analysis, highlighting the role of machine learning in improving the accuracy and robustness of emotion detection systems. The authors review contemporary techniques, including deep learning models, and discuss challenges such as dealing with spontaneous expressions, cross-dataset generalization, and real-time processing. The paper also examines the impact of large-scale datasets and the integration of multimodal data to enhance emotion recognition performance.

2.4 TITLE: Advances in Facial Emotion Detection

AUTHORS: Smith. J & Johnson. R.

YEAR: 2023

In This research, Smith (2023) explores recent advances in facial emotion detection techniques. It covers a wide range of methodologies, including traditional computer vision approaches and modern deep learning techniques. The authors discuss the challenges faced in facial emotion detection, such as variations in facial expressions, lighting conditions, and occlusions. Additionally, the paper examines the role of large-scale datasets and the integration of multimodal information for improving emotion recognition accuracy.

2.5 TITLE: Emotion Detection and Quotations using CNN

AUTHORS: Thulasi Bikku & Lavanya Viswanadha

YEAR: 2023

In this research, Thulasi Bikku (2023) presents This paper that the System recognizes a person's emotions by looking at their face and adds some quotations to it. A neural network-based method along with image processing is utilized to classify the universal emotions: disgust, scared (fear), sad, surprise, happy and anger. In this work, the “dropout” mechanism which is a regularized method to reduce overfitting and the extended Cohn kanade (CK+) dataset have been used. To improve training efficiency and classification performance, pre-processing and data augmentation approaches are performed.

2.6 TITLE: Emotion Detection with Facial Feature Recognition Using CNN & OpenCV

AUTHORS: Sarwesh Giri & Gurchetan Singh

YEAR: 2022

In this research, Sarwesh Giri (2022) presents Emotion Detection through Facial feature recognition is an active domain of research in the field of human-computer interaction (HCI). Humans are able to share multiple emotions and feelings through their facial gestures and body language. Ultimately, Emotion Detection is an integration of obtained information from multiple patterns. If computers will be able to understand more of human emotions, then it will mutually reduce the gap between humans and computers. In this research paper, they will demonstrate an effective way to detect emotions like neutral, happy, sad, surprise, angry, fear, and disgust from the frontal facial expression of the human in front of the live webc

2.7 TITLE: Emotion Recognition from Facial Expression using CNN

AUTHORS: Ishika Agrawal & Adarsh Kumar

YEAR: 2021

In this research , Ishika Agrawal (2021) explores a time-efficient hybrid design for emotion recognition using facial expression is proposed which uses pre-processing stages and several Convolutional Neural Network (CNN) topologies to improve accuracy and training time. Sadness, happiness, contempt, anger, fear, surprise, and neutral are the seven primary human emotions to anticipate. The model is tested using the MMA Facial Expression database as well as other facial positions. To avoid bias towards a specific group of photos from a database, performance is evaluated using cross-validation techniques. In this work CNN has been trained using a huge database consisting of around 35,000 images.

2.8 TITLE: Facial Emotion Recognition Based on CNN

AUTHORS: Shuang Liu & Dahua Li

YEAR: 2020

In this research, Shuang Liu (2020) exploes the annotation of facial expressions which is divided into 9 levels. and the probability of each valence dimension is obtained through the output of CNN network, and the final prediction result is equal to the weighted fusion of valence value and its corresponding probability. They use CK+ database and Fer2013 database to complete the training of CNN network model, and verify the performance of the system by recognizing the facial expressions of volunteers when watching video.

CHAPTER 3

SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

The existing system explores face emotion detection, also known as facial expression recognition (FER) systems, and utilizes various technologies to analyze facial expressions and determine emotional states. These systems typically involve several key components: face detection, facial landmark detection, and emotion classification. For face detection, methods like Haar Cascades, HOG (Histogram of Oriented Gradients), and deep learning-based approaches such as MTCNN are common. Facial landmark detection identifies key points on the face to understand its structure and orientation, often using libraries like Dlib and OpenCV. Feature extraction can be performed using traditional methods like Local Binary Patterns (LBP) and Gabor filters or deep learning models such as VGGFace and ResNet. Emotional classification is carried out using machine learning algorithms (SVMs). Popular datasets for training and evaluating these systems include FER-2013, AffectNet, CK+, and RAF-DB. Several commercial and open-source systems are available for face emotion detection.

3.1.1 DRAWBACKS OF EXISTING SYSTEM

- Cultural differences in emotional expression can impact accuracy, as many datasets may not be representative of all ethnic and cultural groups, leading to biased results.
- Detecting complex or subtle emotions and understanding the context behind expressions remains challenging.
- Human emotions are complex and can change rapidly. This system may not capture these dynamic changes accurately, leading to misinterpretation

3.2 PROPOSED SYSTEM

The proposed system leverages state-of-the-art technologies in computer vision and deep learning to achieve real-time human face emotion detection. The proposed system uses DenseNet Convolutional Neural Networks to analyze human emotion detection .This algorithm allows for robust and efficient detection of emotion in video streams, even in varying lighting conditions and backgrounds.The proposed system utilizes cutting-edge deep learning architectures trained on large-scale image datasets. DenseNet Convolutional Neural Networks are employed to learn complex patterns and features. Transfer learning techniques may also be utilized to fine-tune pre-trained models on specific datasets, improving recognition accuracy and generalization.

Initially, the system preprocesses input facial images to standardize their format and enhance quality. Techniques like normalization and augmentation ensure consistency and improve model performance. The core of the system lies in CNN-based feature extraction, where deep learning architectures automatically learn hierarchical representations of features from raw data. Dense CNNs analyze facial images to capture intricate patterns indicative of different emotional states. Convolutional layers extract relevant features, encoding facial expressions into structured representations. With features extracted, the system proceeds to emotion classification using fully connected layers. During training, the model learns to associate patterns in the extracted features with emotion categories. By harnessing the power of deep learning, this system offers a robust framework for accurately interpreting facial expressions and discerning the underlying emotional states. With its broad applicability and potential for impact, the proposed system stands poised to revolutionize how we perceive and understand human emotions in various contexts. Fig.3.1 depicts the proposed work.

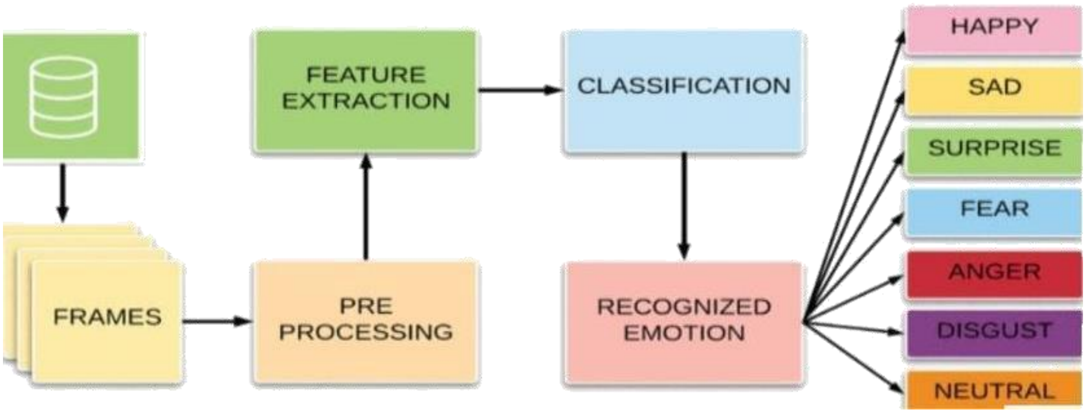


Fig. 3.1 PROPOSED SYSTEM

CHAPTER 4
MODULE DESCRIPTION

4.1 IMAGE DATASET COLLECTION

The initial phase involves the meticulous collection of facial images.The dataset collected from Kaggle website Facial Expression Recognition Challenge is used for the training and testing. It comprises pre-cropped,48-by-48-pixel grayscale images of faces each labeled with one of the 7 emotion classes: anger, disgust, fear, happiness, sadness, surprise, and neutral. Dataset has a training set of 35887 facial images with facial expression labels (Table 4.1 Description of the dataset).Each captured image serves as a valuable input for training our model, ensuring its proficiency in recognizing and interpreting Human Facial emotions accurately. Fig.4.1 depicts the sample images from the dataset.

Fig. 4.1 Sample images from the dataset

	Emotion	Number
0	Angry	4953
1	Disgust	547
2	Fear	5121
3	Happy	8989
4	Sad	6077
5	Surprise	4002
6	Neutral	6198

Table. 4.1.Description of the dataset

4.1.1 HAPPY

Happiness relies on smile expression. It specifies someone's feelings of being happy or something related to it. Happiness expression is recognized in an upward check muscles movement and edges or sides of the lips to form smiling expression.Fig.4.2 depicts happiness expression.

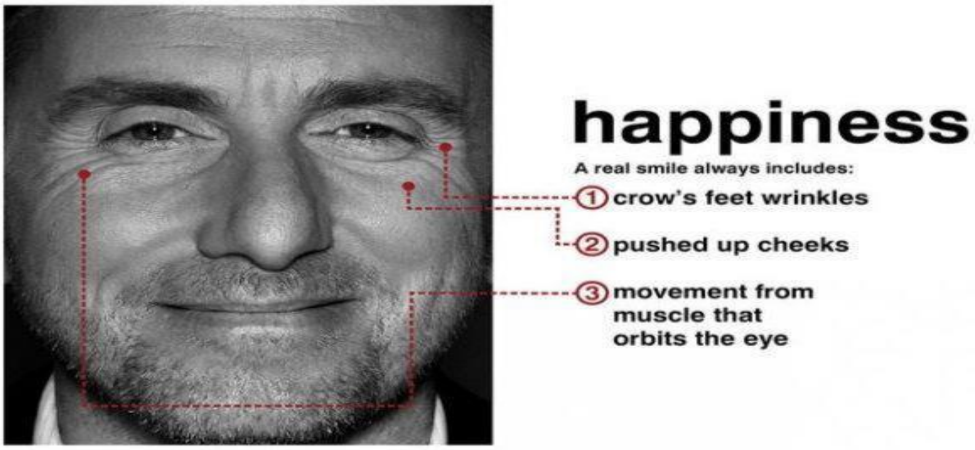


Fig. 4.2 Happiness expression

4.1.2 SADNESS

This sadness expression shows the sadness seems when feeling or disappointment of missing something. Based on these characteristics, the sad facial expression shows loss in the focus, the upper eyelid droops and lips are downwardly pulled. Fig.4.3 depicts sadness expression.

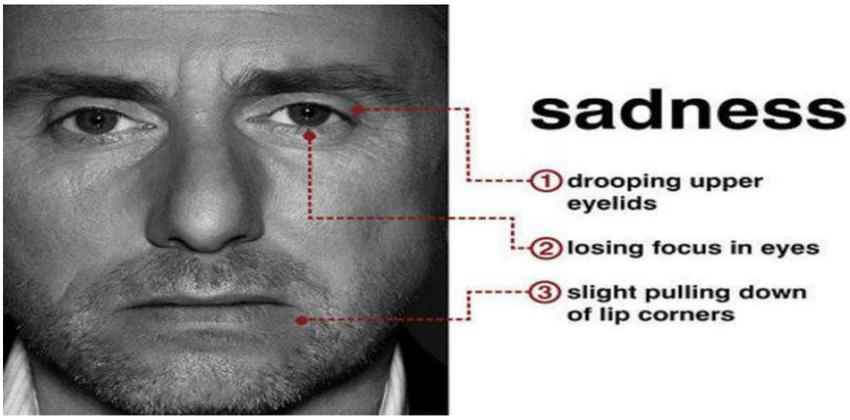


Fig. 4.3 Sadness expression

4.1.3 ANGER

It is facial expressions that arise due to the match among what is reality and expected. The expression is identified in both the sides of the inner eyebrows that is leaning down and merging, while the lips are narrowing and eyes are sharpeness looking. Fig.4.4 depicts anger expression. Fig.4.4 depicts Anger expression.

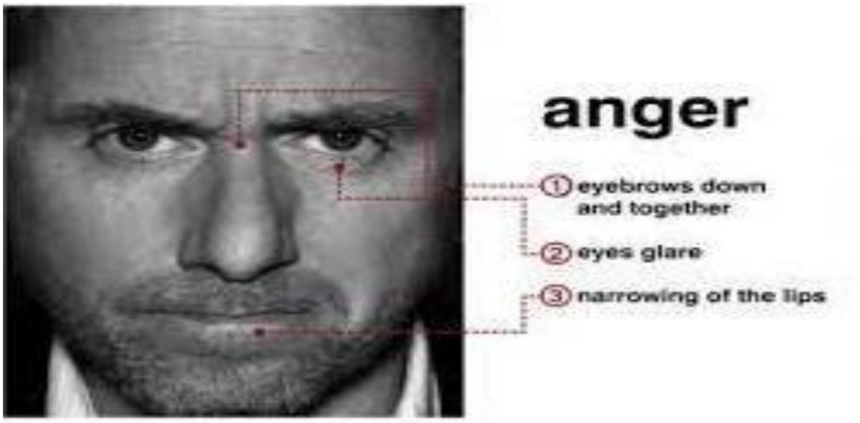


Fig. 4.4 Anger expression

4.1.4 DISGUIST

A person shows the expression in his/her face in the state of disgust is not listening or common to information not hearing worth. The disgust expression is read when the individual's face in the region around the nose is wrinkled and the upper lips rise above.Fig.4.5 depicts disguist expression.

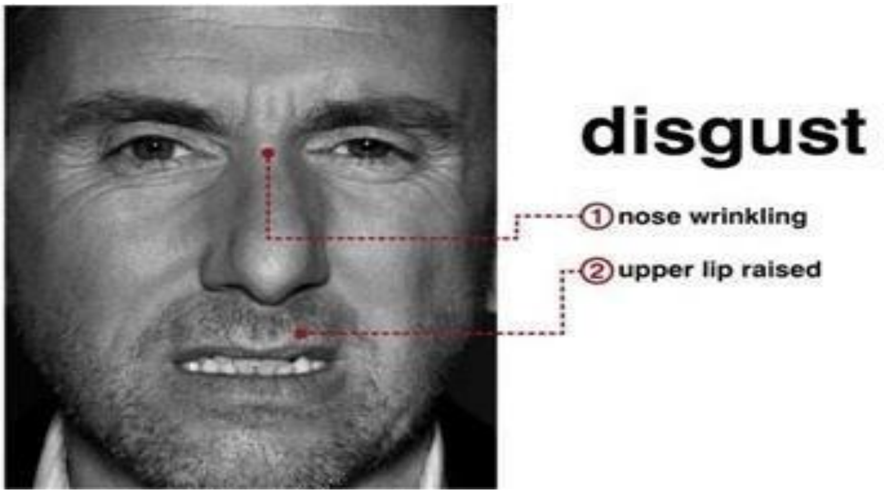


Fig. 4.5 Disgust expression

4.1.5 FEAR

This form of expression is noted when the person experiences his ability to deal with an event or scary environment, then the person seems to be afraid. The fear expression on the individuals' face is observedwhen the above eyebrows rise at the same time, the lips and eyelids tighten are opened horizontally.Fig.4.6 depicts Fear expression.

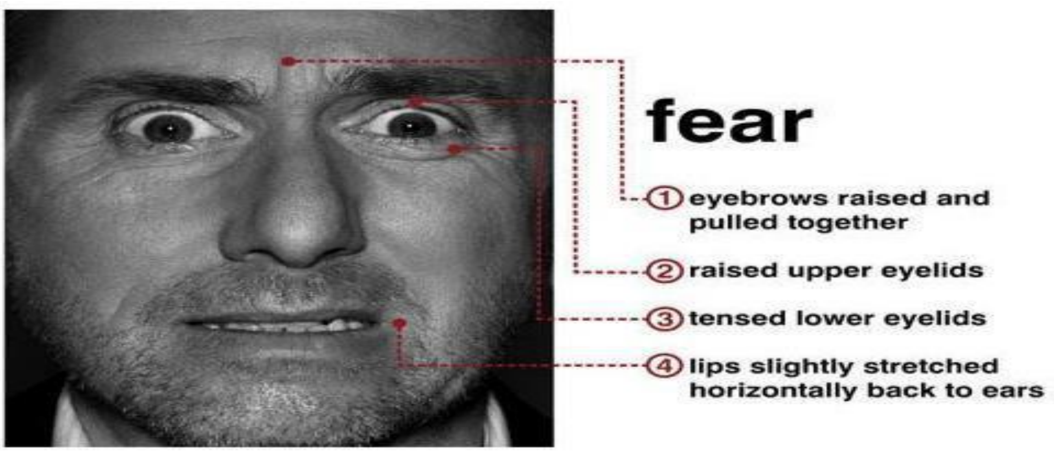


Fig. 4.6 Fear expression

4.1.6 SURPRISE

This surprise expression is noted when the individuals does not known a message or event in the beforehand and received it suddenly, important or unexpected. This expression is shown with shocked face specified with raised eyebrows, mouth opening reflex and eye wide open. Fig.4.7 depicts surprise expression.

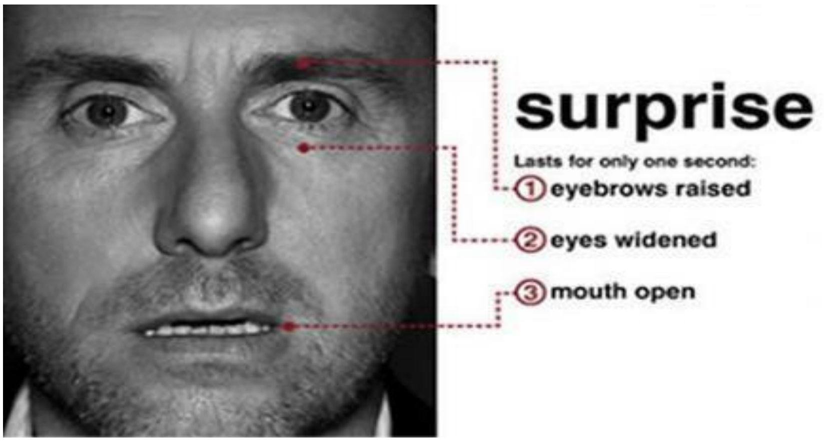


Fig. 4.7 Surprise expression

4.1.7 NEUTRAL

A neutral face form depicts a relaxed expression with eyes open, eyebrows in a natural position, and a closed or slightly open mouth without distinct emotional cues, serving as a baseline for comparison in emotion recognition and facial analysis tasks.

4.2 PREPROCESSING

The input image/video in the emotion detection may contain noise and have variation in illumination, size, and color. To get accurate and faster results, some preprocessing operations were done on the image/video. The preprocessing strategies used are conversion of image/video to grayscale, normalization, and resizing of image/video.

1.Normalization - Normalization of an image is done to remove illumination variations and obtain improved face image.

2.Grayscaling – Gray scaling is the process of converting a colored image input into an image whose pixel value depends on the intensity of light on the image.

3.Resizing - The image is resized to remove the unnecessary parts of the image.

4.3 DATA TRAINING

The Collected Dataset preprocessed and partitioned (80%), proceed to the crucial stage of training our machine learning model. Utilizing advanced deep learning architectures such as Dense Convolutional Neural Networks (Dense CNNs) feed the training set into the model, allowing it to learn and discern patterns and features associated with different emotions. Supervised learning techniques are employed, wherein the model is trained to associate input images with corresponding emotion labels. Through iterative optimization processes such as backpropagation and gradient descent, our model iteratively adjusts its parameters to minimize prediction errors and enhance its accuracy in recognizing emotions.

4.4 TEST THE MODEL

In the final stage of our project, evaluate the performance and testing (20%) of our trained emotion detection model. Model testing involves assessing its ability to accurately recognize and interpret emotions on unseen data. utilize the testing set, which comprises a diverse range of facial images not encountered during training, to measure the model's predictive accuracy and generalization capability. Evaluation metrics such as accuracy, precision, recall, and F1 score provide quantitative insights into the model's performance. Through rigorous testing and evaluation, ensure that our model meets the desired accuracy and reliability standards for practical deployment in human facial emotion detection applications.

CHAPTER 5
SYSTEM SPECIFICATION

5.1 HARDWARE REQUIREMENTS

- Processor - Intel i5 or Higher
- RAM - 16 GB or Higher
- Storage - 512 GB or Higher

5.2 SOFTWARE REQUIREMENTS

- Frameworks/Tools - TensorFlow, Keras
- Programming Language - Python
- Computer Vision - OpenCV
- Data Visualization - Seaborn, Matplotlib

CHAPTER 6

SYSTEM DESIGN

6.1 DATA FLOW DIAGRAM

DFD stands for Data Flow Diagram. It represents the flow of data within information systems. The models enable software engineers, customers, and users to work together effectively during the analysis and specification of requirements. It represents the system’s major processes and alternatives that generate the internal flow of data. It provides a clear overview of the system's architecture and the roles of different components in the face emotion detection process. Fig.6.1 depicts Data Flow Diagram.

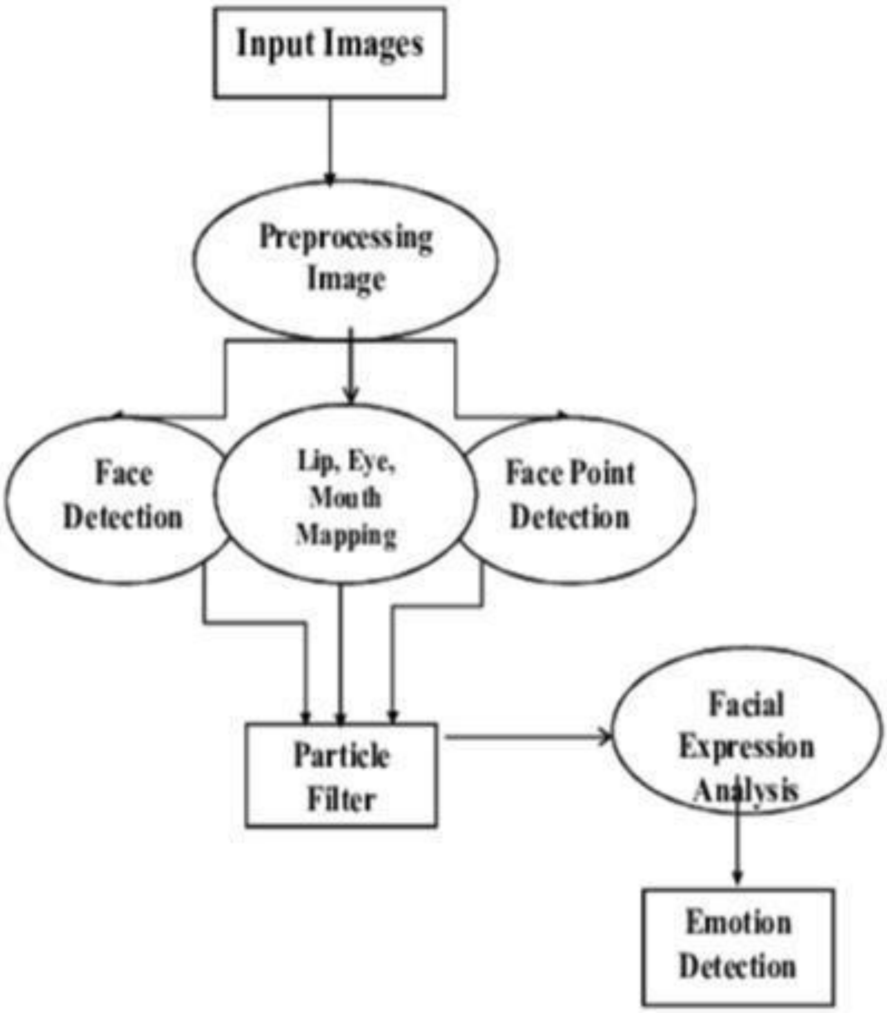


Fig. 6.1 Data Flow Diagram

6.2 USE CASE DIAGRAM

A use case diagram in the Unified Modeling Language (UML) is a type of behavioral diagram defined by and created from a Use-case analysis The main purpose of it is to show what system functions are performed for which actor. It shows the interaction between users (researchers, developers, or users) and the system components (Dense CNN Algorithm, database, and user interface). Fig.6.2 depicts Use Case Diagram.

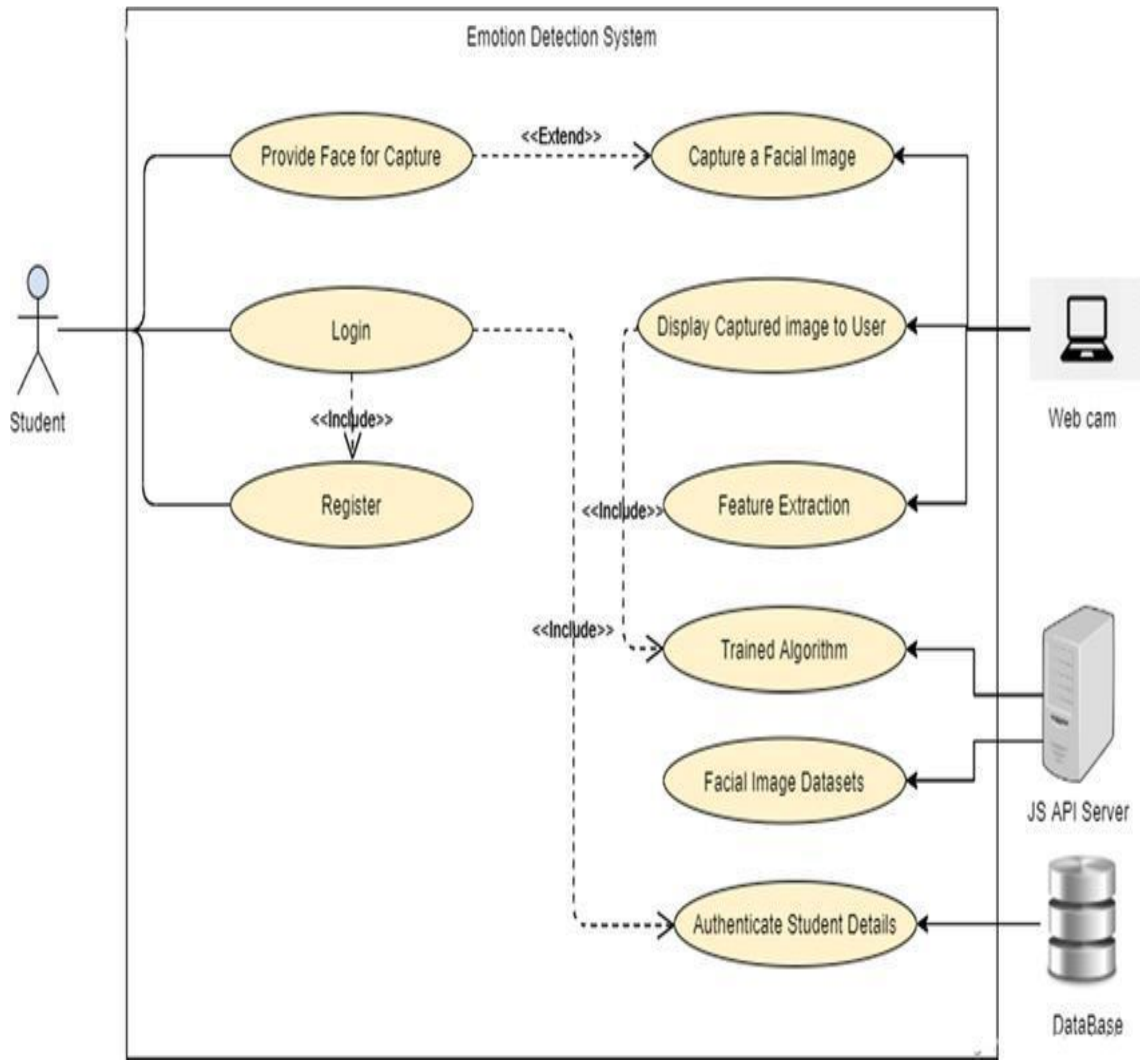


Fig. 6.2 Use Case Diagram

6.3 CLASS DIAGRAM

A class diagram in the Unified Modeling Language (UML) is a type of static structure diagram that describes the structure of a system by showing the system's classes, their attributes, operations, and the relationships among the classes. It explains which class contains information.Fig.6.3 depicts Class Diagram.

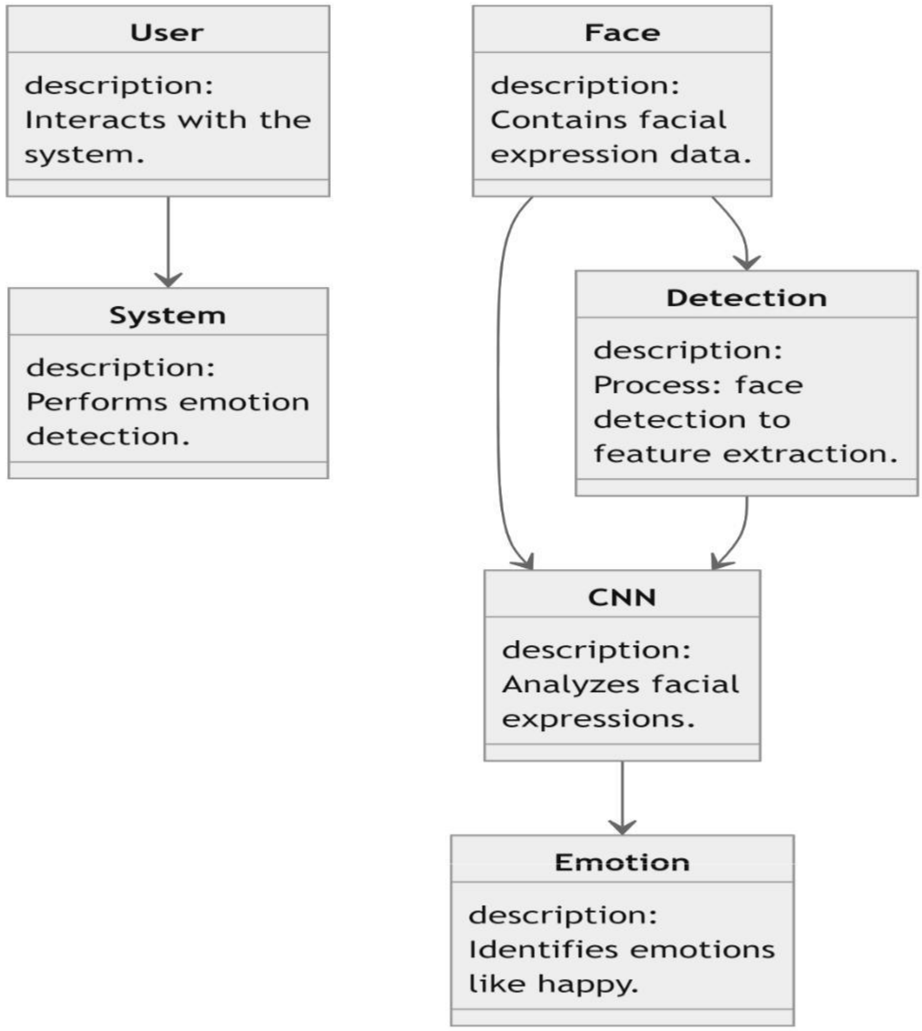


Fig. 6.3 Class Diagram

6.4 STATE DIAGRAM

The state diagram shows the order of states underwent by an object within the system. It captures the software system's behavior. It models the behavior of a class, a subsystem, a package, and a complete system. This state diagram helps in visualizing the step-by-step process of emotion detection in a structured manner and highlights the transitions. Fig.6.4 depicts State Diagram.

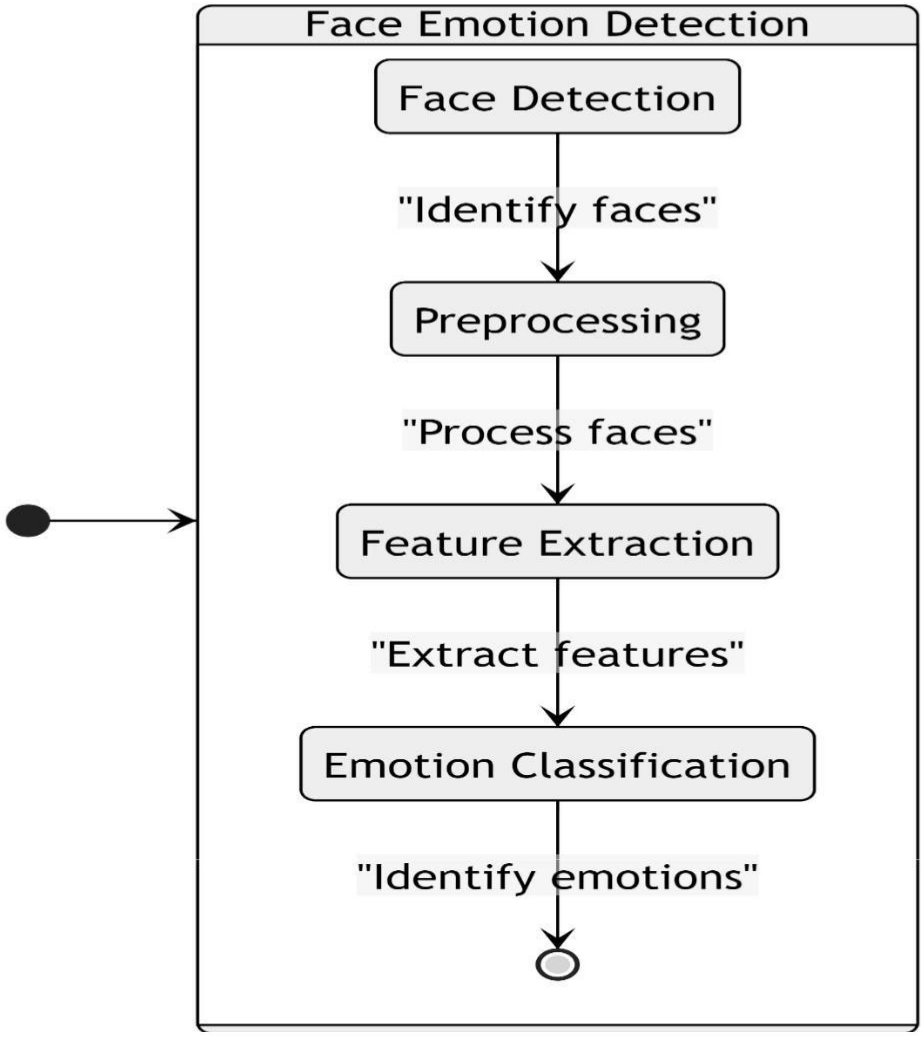


Fig. 6.4 State Diagram

6.5 SEQUENCE DIAGRAM

A sequence diagram in Unified Modeling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart. It helps in visualizing how data flows through the system and shows the interactions and dependencies between different components of the face emotion detection system.Fig.6.5 depicts sequence diagram.

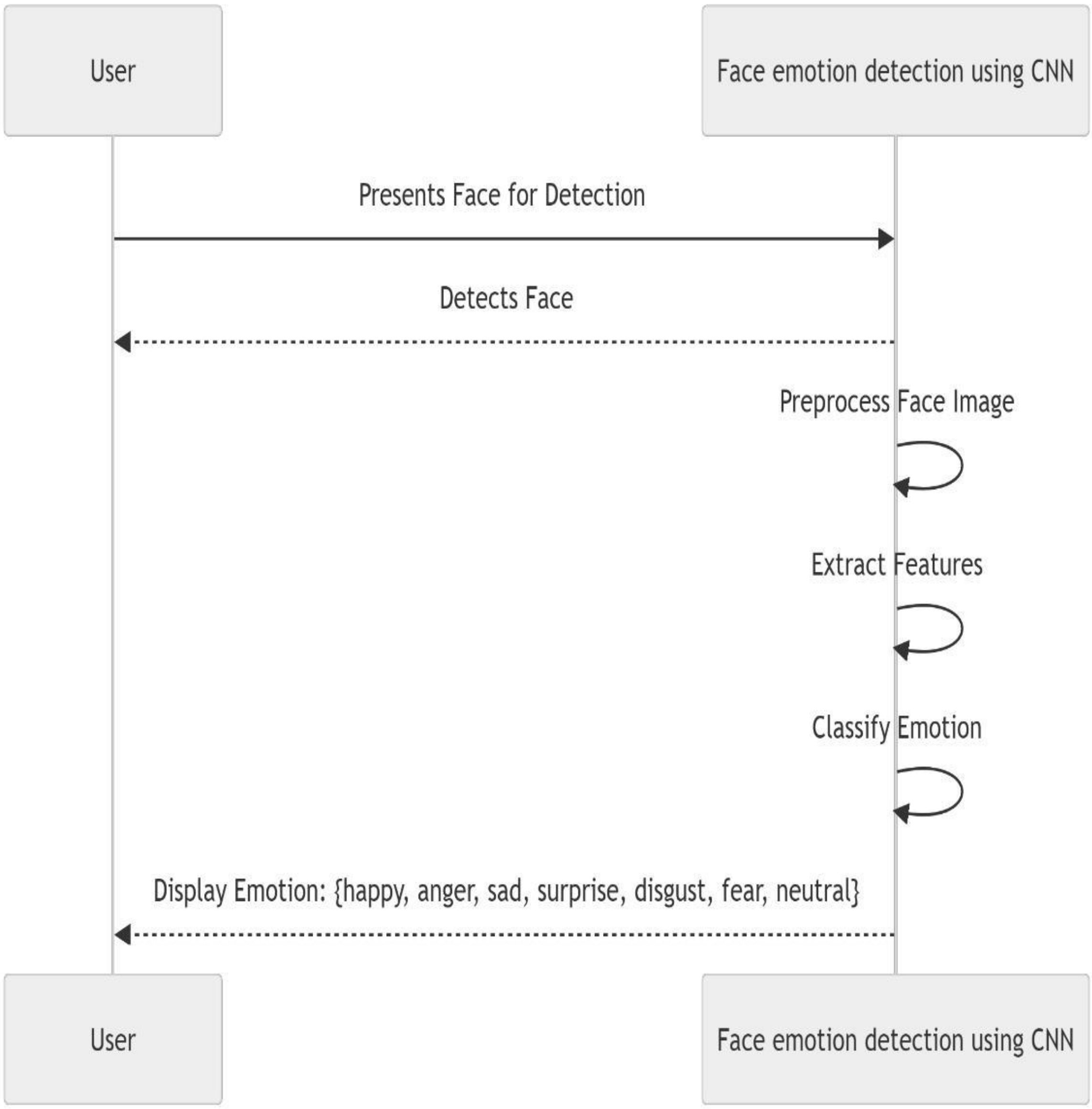


Fig. 6.5 Sequence Diagram

CHAPTER 7

METHODOLOGY

7.1 INTRODUCTION

Face emotion detection, a pivotal application of computer vision and artificial intelligence, aims to discern and classify emotional expressions conveyed by human faces in visual media. Initially, the process involves face detection to locate and isolate facial regions within images or video frames. Subsequent facial landmark detection identifies crucial facial points for alignment and normalization. Features are then extracted from these regions, encompassing pixel intensity patterns or learned representations from deep neural networks. These features serve as inputs to emotion classifiers, typically employing machine learning algorithms or convolutional neural networks, to predict the emotional state of individuals. Post-processing steps may refine predictions, considering temporal information in video sequences or applying smoothing techniques for stability. The efficacy of these systems hinges on factors such as data quality, algorithm robustness, and the sophistication of classifiers. Despite challenges, face emotion detection finds diverse applications in market research, human-computer interaction, and virtual assistant technology, fostering deeper insights into human emotional expressions in digital environments.

7.2 PROPOSED SYSTEM ARCHITECTURE

The system architecture for Face emotion detection using deep learning comprises three main components

- data preprocessing
- Testing model
- Training model

Fig 7.1 depicts Proposed system architecture

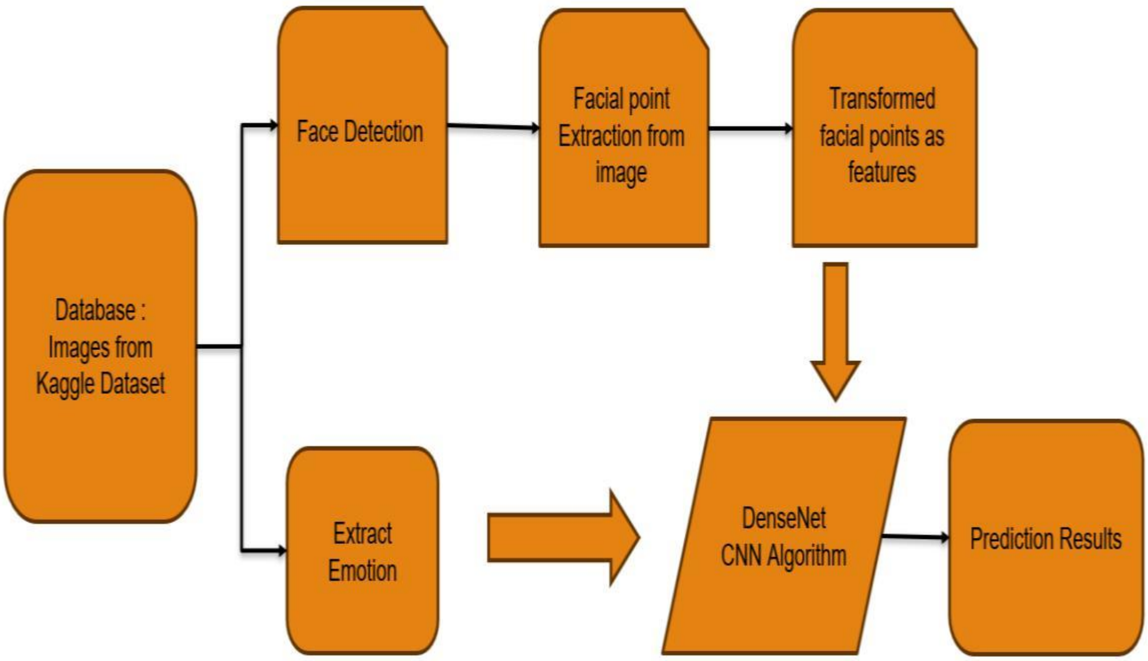


Fig 7.1 Proposed system architecture

In the preprocessing stage, Facial emotion images of a Human are normalized, augmented, and integrated. This processed data is detected and facial point extraction is done.The transformed facial points features are then fed into Dense Convolutional Neural Networks (Dense CNN) which will do the classification process to detect emotion of a person.

7.3 IMPLEMENTATION OF THE SYSTEM

For the implementation of Human face emotion detection using machine learning, Dense Convolutional Neural Networks (Dense CNNs) algorithms is employed. Preprocessing steps involve normalizing to enhance the dataset. The Model training Images are trained and The Preprocessed images are mapped to the features to detect The emotions. Validation and testing refined and assessed the model's performance.For feature extraction, Dense Convolutional Neural Network
(Dense CNN) is effective, identifies relevant patterns in imaging and Emotion data.

CHAPTER 8

CONCLUSION AND FUTURE ENHANCEMENT

8.1 CONCLUSION

In conclusion, this project represents a significant advancement in the domain of facial emotion detection through the application of machine learning, particularly DenseNet Convolutional Neural Networks (Dense CNNs). The proposed work demonstrates remarkable efficacy in accurately identifying human emotions. The meticulous design of the Dense CNN architecture allows for the automatic extraction of features and the classification of emotions. The incorporation of transfer learning techniques enhances the model's adaptability, particularly in scenarios where labeled data is limited, showcasing the flexibility of the proposed approach. Extensive and hyperparameter optimization contribute to the robustness of the model across diverse datasets and varying demographic groups. The thorough evaluation using independent datasets underscores the reliability of the Dense CNN based system, with its overall feature extraction and accuracy in detecting human emotions.

8.2 FUTURE ENHANCEMENT

To further enhance the capability of this project, we recommend the following features to be incorporated into the system:

- **Integration with Multimodal Data-**Combine facial emotion detection with other modalities like voice analysis, body language, and physiological signals to improve accuracy and robustness.
- **Real-time Emotion Tracking-**Develop capabilities for real-time emotion tracking in video streams, enabling continuous monitoring and analysis of emotions in dynamic environments.
- **Application in Mental Health Monitoring-**Expand the system’s application in mental health by integrating with mental health apps to provide real-time emotional feedback and support for individuals with emotional or psychological challenges.

APPENDIX A

Sample code

Main.py:

```
from keras.models import load_model
from time import sleep
from keras.preprocessing.image import img_to_array
from keras.preprocessing import image import cv2
import numpy as np
face_classifier =
cv2.CascadeClassifier(r'C:\Users\Admin\Desktop\PythonProject\EmotionDetectionCN
N\haarcascade_frontalface_default.xml')
classifier=load_model(r'C:\Users\Admin\Desktop\PythonProject\EmotionDetectionC
NN\model.h5')
emotion_labels = ['Angry','Disgust','Fear','Happy','Neutral', 'Sad', 'Surprise']
cap = cv2.VideoCapture(0)
while True:
frame = cap.read()
labels = []
gray = cv2.cvtColor(frame,cv2.COLOR_BGR2GRAY)
faces = face_classifier.detectMultiScale(gray)
for (x,y,w,h) in faces:
cv2.rectangle(frame,(x,y),(x+w,y+h),(0,255,255),2)
roi_gray = gray[y:y+h,x:x+w]
roi_gray = cv2.resize(roi_gray,(48,48),interpolation=cv2.INTER_AREA)
if np.sum([roi_gray])!=0:
roi = roi_gray.astype('float')/255.0
roi = img_to_array(roi)
```

```
roi = np.expand_dims(roi,axis=0)
prediction = classifier.predict(roi)[0]
label=emotion_labels[prediction.argmax()]
label_position = (x,y)
cv2.putText(frame,label,label_position,cv2.FONT_HERSHEY_SIMPLEX,1,(0,255,0)
,2)
else:
cv2.putText(frame,'No
Faces',(30,80),cv2.FONT_HERSHEY_SIMPLEX,1,(0,255,0),2)
cv2.imshow('Emotion Detector',frame)
if cv2.waitKey(1) & 0xFF == ord('q'):
break
cap.release()
cv2.destroyAllWindows()
```

Importing libraries:

```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
import os
from keras.preprocessing.image import load_img, img_to_array
from keras.preprocessing.image import ImageDataGenerator
from keras.layers import
Dense,Input,Dropout,GlobalAveragePooling2D,Flatten,Conv2D,BatchNormalization,
Activation,MaxPooling2D
from keras.models import Model,Sequential
from keras.optimizers import Adam,SGD,RMSprop
```

Displaying images:

```
picture_size = 48
folder_path = "../input/face-expression-recognition-dataset/images/"
```

Making training and validation data:

```
batch_size  = 128
datagen_train = ImageDataGenerator()
datagen_val = ImageDataGenerator()
train_set = datagen_train.flow_from_directory(folder_path+"train",
                                              target_size = (picture_size,picture_size),
                                              color_mode = "grayscale",
                                              batch_size=batch_size,
                                              class_mode='categorical',
                                              shuffle=True)
test_set = datagen_val.flow_from_directory(folder_path+"validation",
                                              target_size = (picture_size,picture_size),
                                              color_mode = "grayscale",
                                              batch_size=batch_size,
                                              class_mode='categorical',
                                              shuffle=False)
```

Model Building:

```
from keras.optimizers import Adam,SGD,RMSprop
no_of_classes = 7
model = Sequential()
#1st CNN layer
model.add(Conv2D(64,(3,3),padding = 'same',input_shape = (48,48,1)))
model.add(BatchNormalization())
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size = (2,2)))
model.add(Dropout(0.25))
```

```
#2nd CNN layer
model.add(Conv2D(128,(5,5),padding = 'same'))
model.add(BatchNormalization())
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size = (2,2)))
model.add(Dropout (0.25))

#3rd CNN layer
model.add(Conv2D(512,(3,3),padding = 'same'))
model.add(BatchNormalization())
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size = (2,2)))
model.add(Dropout (0.25))

#4th CNN layer
model.add(Conv2D(512,(3,3), padding='same'))
model.add(BatchNormalization())
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))
model.add(Flatten())
#Fully connected 1st layer
model.add(Dense(256))
model.add(BatchNormalization())
model.add(Activation('relu'))
model.add(Dropout(0.25))
```

Fully connected layer 2nd layer model.add(Dense(512))

model.add(BatchNormalization()) model.add(Activation('relu'))

model.add(Dropout(0.25)) model.add(Dense(no_of_classes, activation='softmax'))

opt = Adam(lr = 0.0001)

model.compile(optimizer=opt,loss='categorical_crossentropy',

metrics=['accuracy']) model.summary()

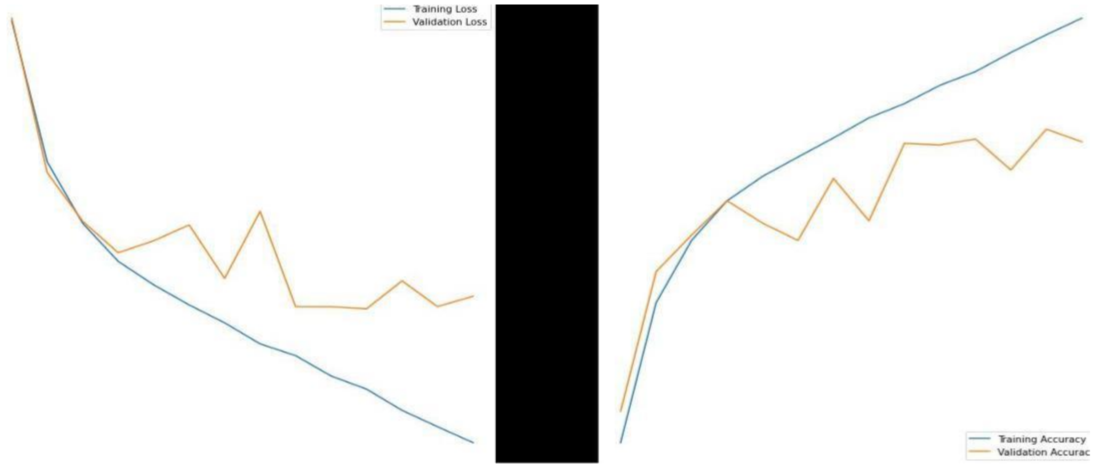
Training and Validation data:

```
history = model.fit_generator(generator=train_set,
                              steps_per_epoch=train_set.n//train_set.batch_size,
                              epochs=epochs,
                              validation_data = test_set,
                              validation_steps = test_set.n//test_set.batch_size,
                              callbacks=callbacks_list
                              )
```

Plotting accuracy and Loss:

```
plt.style.use('dark_background')
plt.figure(figsize=(20,10))
plt.subplot(1, 2, 1)
plt.suptitle('Optimizer : Adam', fontsize=10)
plt.ylabel('Loss', fontsize=16)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.legend(loc='upper right')
plt.subplot(1, 2, 2)
plt.ylabel('Accuracy', fontsize=16)
```

```
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.legend(loc='lower right')
plt.show()
```



APPENDIX B

Sample Input:

Figure B1: Sample Input Image

Sample Output:

Figure B2: Sample Output Image

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