# Infant Emotion Detection

**A Project Report**

Submitted to

**Rajiv Gandhi Proudyogiki Vishwavidyalaya, Bhopal**

in Partial Fulfillment of the Requirements for awarding the degree

of

**BACHELOR OF TECHNOLOGY**

**IN**

**INFORMATION TECHNOLOGY**


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## RECOMMENDATION

The dissertation entitled, "**Infant Emotion Detection**" submitted to the Rajiv Gandhi Proudyogiki Vishwavidyalaya, Bhopal, by Hariom Joshi (0801IT191029), Priyanshi Patel (0801IT191063), Rinkal (0801IT191065)during the academic year 2022-2023 as a Partial Fulfillment of the Requirements for awarding the degree is found to be satisfactory and is approved for the degree of Bachelor of Technology in Information Technology, is a record of student's own work carried out by him under my/our direct supervision, in the Department of Information Technology, Shri G.S. Institute of Technology and Science, Indore. The work contained in the Thesis is a satisfactory account of their Project work and is recommended for the award of the Degree.

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# CERTIFICATION

This is to certify that the dissertation entitled "**Infant Emotion Detection**" submitted to the Rajiv Gandhi Proudyogiki Vishwavidyalaya, Bhopal, by Hariom Joshi (0801IT191029), Priyanshi Patel (0801IT191063), Rinkal (0801IT191065) has been examined by us and is a bonafide work carried out as a dissertation towards partial fulfillment for the award of degree of Bachelor of Technology in Information Technology of the Rajiv Gandhi Proudyogiki Vishwavidyalaya, Bhopal during the academic year 2022-2023. It is understood that by this approval the undersigned do not necessarily endorse or approve any statements made, opinion expressed or conclusion drawn therein, but approve the dissertation only for the purpose for which it has been submitted.

**Internal Examiner** **External Examiner**

**Date :** **Date :**

# Declaration

I declare that this written submission represents my ideas in my own words and where ideas or words of others have been included, I have adequately cited and referenced the original sources. I also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented, fabricated or falsified any idea/ data/ fact/ source in my submission. I understand that any violation of the above will be a cause for disciplinary action by the Institute and can also evoke penal action from the sources which have not been properly cited or from whom proper permission was not taken when needed.

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# ABSTRACT

The Infant Emotion Detection project utilized deep learning algorithms to predict the emotional states of infants based on their facial expressions and sounds they make. The project involved two independent models: one for analyzing video data and the other for analyzing audio data. The video model was trained on the City Infant Face Dataset, which consists of images of infants labeled with four emotional categories: sad, sleep, happy, and calm. The audio model was trained on a dataset that includes three categories of audio: silence, baby cry, and laugh.

Both models achieved high accuracy rates, with the video model achieving an accuracy of 78% on the test dataset, and the audio model achieving an accuracy of 97%. When both models were combined, the overall accuracy of the prediction updates to 95%. The integrated system was designed to notify the user of the predicted emotional state of the infant via the Pushbullet notification system.

The Infant Emotion Detection project has significant potential to assist parents and caregivers in understanding and responding to the emotional needs of infants. With further development and refinement, this technology could be implemented in a wide range of settings, including healthcare facilities, childcare centers, and in-home care.

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# Chapter 1
# Introduction

# Introduction

## 1.1 Objective

- To develop a machine learning system that can predict the emotional state of infants based on their facial expressions and sounds they make.
- To create two independent models, one for video data and the other for audio data, to accurately classify and analyze different emotional states in infants.
- To integrate the two models with a notification system, such as Pushbullet, to inform the user of the predicted emotional state of the infant.
- To demonstrate the potential of machine learning technology to assist parents and caregivers in understanding and responding to the emotional needs of infants.
- To evaluate the accuracy and effectiveness of the models in predicting the emotional state of infants and determine areas for future improvement.

## 1.2 Scope

- The project focuses on predicting the emotional states of infants based on their facial expressions and sounds they make, using deep learning algorithms.
- The project involves training two independent models for analyzing video and audio data, respectively, and integrating them with the Pushbullet notification system.
- The project uses two datasets: the City Infant Face Dataset for video analysis and an audio dataset consisting of three categories (silence, baby cry, and laugh) for audio analysis.
- The project aims to accurately classify four emotional states in infants: sad, sleep, happy, and calm.
- The project is limited to the accuracy of the available datasets and the quality of the training models.
- The project does not address the underlying causes of infant emotions or attempt to provide therapeutic solutions to emotional issues.
- The project has the potential to be extended to a wider range of emotional states and incorporate additional sensory modalities for analysis in future work.
- The project has practical applications in a variety of settings, including in-home care, childcare centers, and healthcare facilities.

## 1.3 Background

- The importance of understanding and responding to the emotional needs of infants in their early development.
- The role of facial expressions and sounds in conveying emotional states in infants.
- The challenges involved in accurately interpreting and classifying infant emotions, given the limited

verbal and physical cues available.

- The existing research on using machine learning and deep learning algorithms to analyze and classify infant emotions based on facial expressions and sounds.
- The potential benefits of using machine learning technology in assisting parents and caregivers in identifying and responding to the emotional needs of infants.
- The limitations and challenges associated with developing accurate and reliable models for analyzing infant emotions using machine learning algorithms.
- The potential applications of machine learning technology in infant care, including in-home monitoring, childcare centers, and healthcare facilities.

## 1.4 Problem Statement

Infants communicate their emotional states primarily through facial expressions and sounds, but interpreting these cues accurately can be challenging for parents and caregivers, particularly in cases where infants cannot verbally express their needs. Machine learning technology offers the potential to assist in identifying and responding to infant emotions in real-time. However, the development of accurate and reliable models for analyzing and classifying infant emotions based on facial expressions and sounds remains a challenging task. The problem addressed in this project is to create an accurate and reliable system that can predict the emotional states of infants based on their facial expressions and sounds, using deep learning algorithms, to assist parents and caregivers in understanding and responding to the emotional needs of infants.

## 1.5 Motivation

The motivation behind the Infant Emotion Detection project is to create a reliable and accurate system that can predict the emotional states of infants based on their facial expressions and sounds, using deep learning algorithms. This system aims to assist parents and caregivers in identifying and responding to the emotional needs of infants, particularly in cases where infants cannot verbally express their needs. By enabling parents and caregivers to respond more quickly and appropriately to infant emotions, the system has the potential to positively impact the infant's overall well-being and development. Machine learning technology offers a promising solution to the challenge of accurately interpreting and classifying infant emotions, which is a critical step in addressing the emotional needs of infants.

## 1.6 Methodology

The proposed system involves a library for storage which is used to generate images and uses OpenCV library of python for converting video to dataset of images. The proposed system shows a combination of various modules like Upload video, Frame Generation, Preprocessing, Feature extraction and predictions.

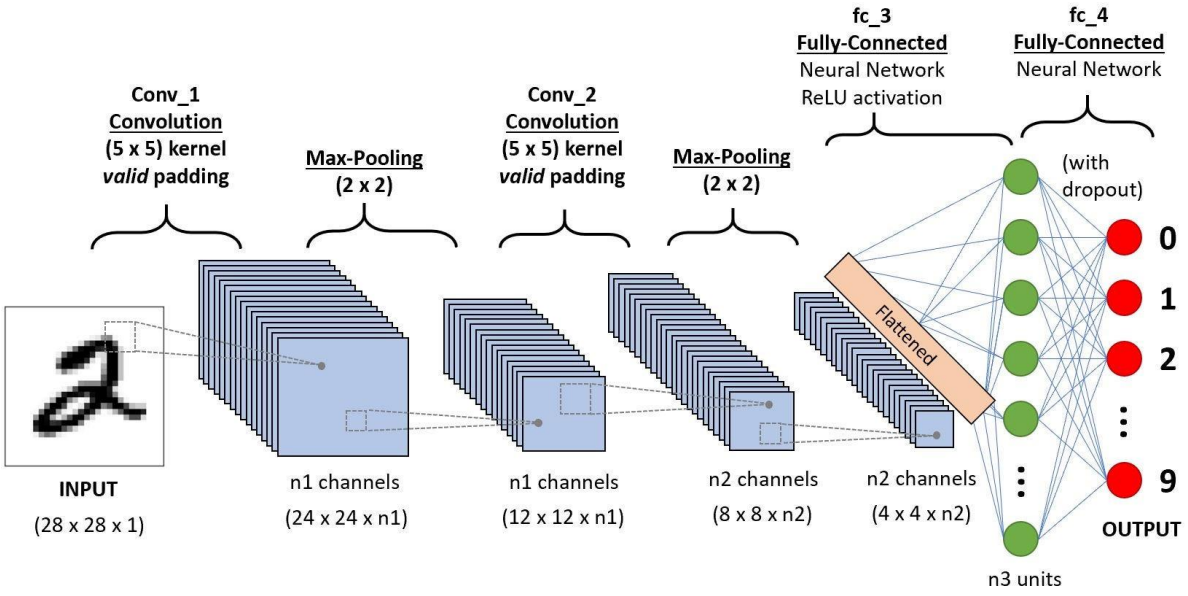


**Figure 1.1 Methodology**

# Chapter 2
# Literature and Survey

# Literature and Survey

The City Infant Face Dataset used in this project for facial expression analysis was developed by Kim and colleagues in 2018 [1]. The dataset comprises 5,622 images of infants aged 0 to 12 months, captured in naturalistic settings using a mobile camera. The images depict infants in four emotional states: happy, calm, sleep, and sad. The dataset was labeled by six raters, and inter-rater reliability was assessed using Cohen's kappa coefficient. The authors report high inter-rater reliability for the dataset (kappa = 0.87), indicating that the dataset is highly reliable for use in machine learning algorithms.

Research on using machine learning algorithms for facial expression analysis in infants is growing, with several studies demonstrating promising results. For instance, Huang and colleagues [2] used a deep learning model to analyze facial expressions of infants and achieved an accuracy of 93.8% in detecting five facial expressions. Similarly, other studies have used convolutional neural networks (CNNs) and deep belief networks (DBNs) to classify infant emotions based on facial expressions with high accuracy [3, 4].

Audio analysis is another modality used for infant emotion detection. The audio dataset used in this project consists of three categories: silence, baby cry, and laugh. The use of audio signals for emotion classification in infants is a promising area of research. For example, a study by Sezgin and colleagues [5] used a deep learning model to analyze infant cries and achieved an accuracy of 96.5% in distinguishing between different types of cries. Other studies have also demonstrated high accuracy in classifying infant emotions based on audio signals [6, 7].

However, there are still several challenges associated with using machine learning algorithms for infant emotion detection. One of the challenges is the limited availability of large-scale and diverse datasets. This limits the ability to generalize results and develop models that can accurately capture the variability of emotional expressions in different infants. Another challenge is the potential for bias in dataset labeling and model training, which can lead to inaccurate classifications and negative impacts on the well-being of infants.

Despite these challenges, the development of machine learning-based systems for infant emotion detection holds great promise for improving the well-being of infants and enhancing the quality of care provided by parents and caregivers. However, the ethical and privacy concerns associated with such systems must also be carefully considered, along with the need for collaboration with pediatricians and other healthcare professionals to ensure that these systems are safe and effective for use in clinical practice.

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# Chapter 3
# System Requirement

# System Requirement

## Hardware

For this project we need technologies to work in an intended way. For these technologies to work properly in their fullest way to determine hidden communities in social networks the following minimum configuration is needed:

- Memory and disk space required per user: 1GB RAM + 1GB of disk + 5 CPU core.
- Server overhead: 2-4GB or 10% system overhead (whatever is larger), 5 CPU cores, 10GB disk space.

## Software implementation language/technology/IDE

Python

Pycharm

**Packages :**

- opencv-python
- numpy
- matplotlib
- keras
- Tensorflow
- Pushbullet
- Pyaudio
- Wave
- librosa

# Chapter 4
# Theoretical Background

### 4.1 Prediction Models

Convolutional Neural Network is a Deep Learning algorithm specially designed for working with Images and videos. It takes images as inputs, extracts and learns the features of the image, and classifies them based on the learned features

There are three types of layers in Convolutional Neural Networks:

1) Convolutional Layer: In a typical neural network each input neuron is connected to the next hidden layer. In CNN, only a small region of the input layer neurons connect to the neuron hidden layer.

2) Pooling Layer: The pooling layer is used to reduce the dimensionality of the feature map. There will be multiple activation & pooling layers inside the hidden layer of the CNN.

3) Fully-Connected layer: Fully Connected Layers form the last few layers in the network. The input to the fully connected layer is the output from the final Pooling or Convolutional Layer, which is flattened and then fed into the fully connected layer.

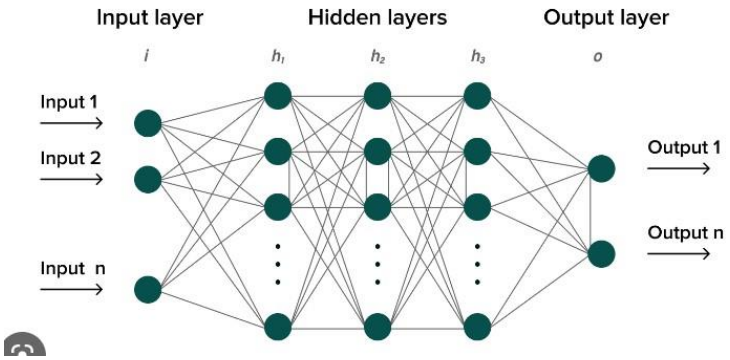


**Fig.4.1 Convolutional layers**

## 4.2 Image Recognition using CNN

What is Image processing?

As the name says, image processing means processing the image and this may include many different techniques until we reach our goal. The final output can be either in the form of an image or a corresponding feature of that image. This can be used for further analysis and decision making.

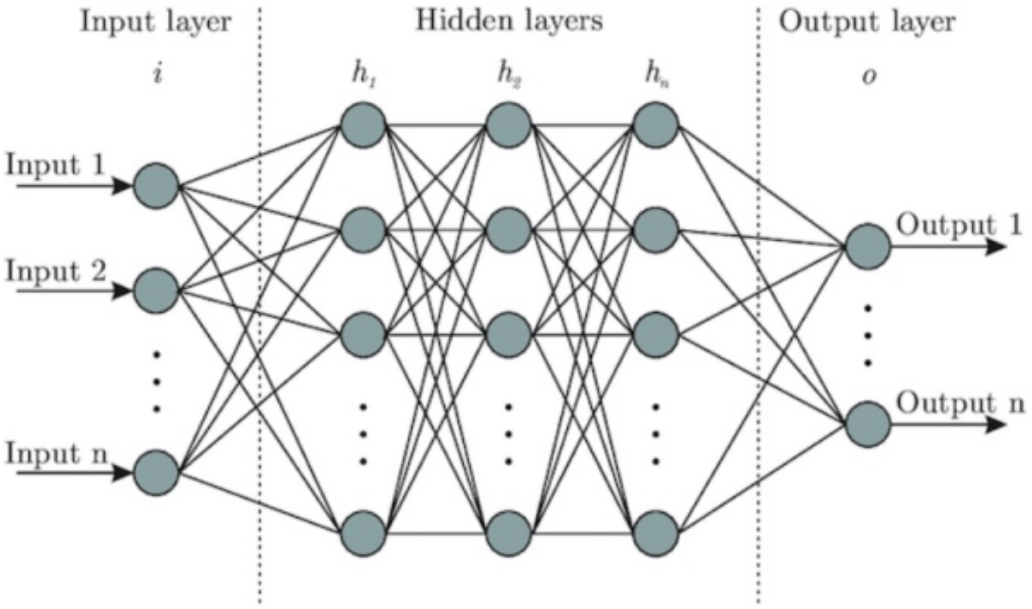


**Fig.4.2 Image processing using Neural Networks**

Neural Networks are multi-layered networks consisting of neurons or nodes. These neurons are the core processing units of the neural network. They are designed to act like human brains. They take in data, train themselves to recognize the patterns in the data and then predict the output.

A basic neural network has three layers:

i) Input layer

ii) Hidden layer

iii) Output layer

Basic-neural-network

The input layers receive the input, the output layer predicts the output and the hidden layers do most of the calculations. The number of hidden layers can be modified according to the requirements. There should be at least one hidden layer in a neural network.

The basic working of the neural network is as follows:

Let’s consider an image, each pixel is fed as input to each neuron of the first layer, neurons of one layer are connected to neurons of the next layer through channels.

Each of these channels is assigned a numerical value known as weight.

The inputs are multiplied by the corresponding weights and this weighted sum is then fed as input to the hidden layers.

The output from the hidden layers is passed through an activation function which will determine whether the particular neuron will be activated or not.

The activated neurons transmit data to the next hidden layers. In this manner, data is propagated through the

network, this is known as Forward Propagation.

In the output layer, the neuron with the highest value predicts the output. These outputs are the probability values.

The predicted output is compared with the actual output to obtain the error. This information is then transferred back through the network, the process is known as Backpropagation.

Based on this information, the weights are adjusted. This cycle of forward and backward propagation is done several times on multiple inputs until the network predicts the output correctly in most of the cases.

This ends the training process of the neural network. The time taken to train the neural network may get high in some cases.

In the below image, ai's is the set of inputs, Wi's are the weights, z is the output and g is any activation function.

Operations-in-a-single-neuron

Here are some guidelines to prepare data for image processing.

More data needs to be fed to the model to get the better results.

Image dataset should be of high quality to get more clear information, but to process them you may require deeper neural networks.

In many cases RGB images are converted to grayscale before feeding them into a neural network

Types of Neural Network

Convolutional Neural Network

A convolutional neural network in short has three layers:

Convolutional Layer (CONV): They are the core building block of CNN; it is responsible for performing convolution operation. The element involved in carrying out the convolution operation in this layer is called the Kernel/Filter (matrix). The kernel makes horizontal and vertical shifts based on the stride rate until the full image is traversed.

Pooling Layer (POOL): This layer is responsible for dimensionality reduction. It helps to decrease the computational power required to process the data. There are two types of Pooling: Max Pooling and Average Pooling. Max pooling returns the maximum value from the area covered by the kernel on the image. Average pooling returns the average of all the values in the part of the image covered by the kernel.

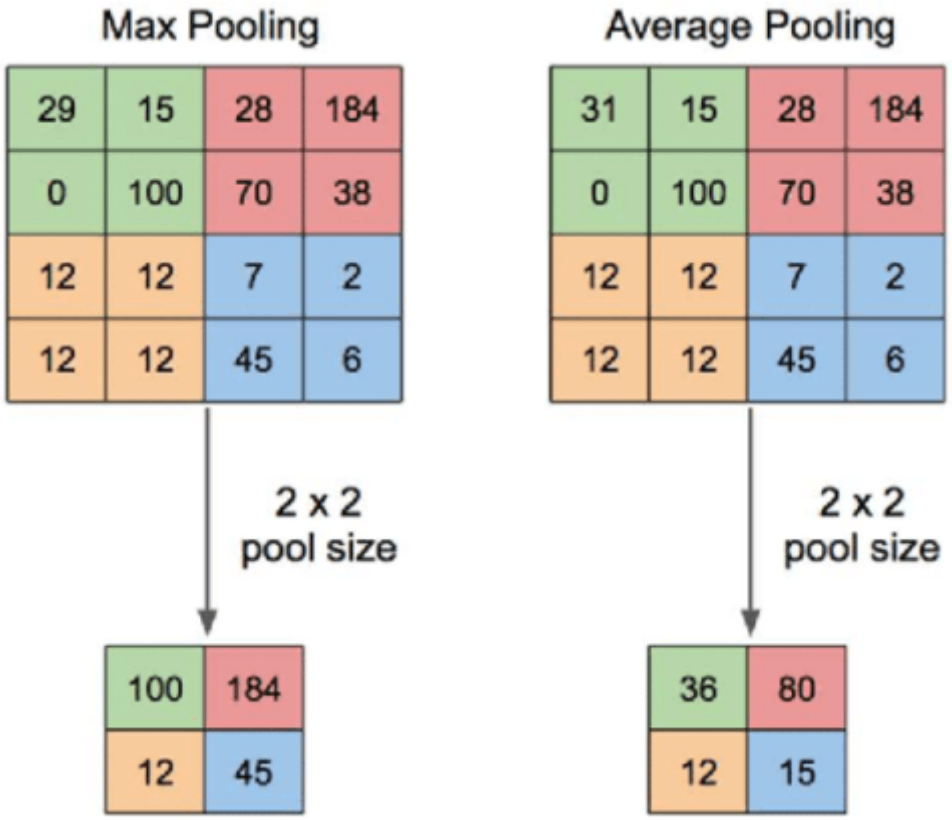


**Fig.4.3 Pooling operation**

Fully Connected Layer (FC): The fully connected layer (FC) operates on a flattened input where each input is connected to all neurons. If present, FC layers are usually found towards the end of CNN architectures.

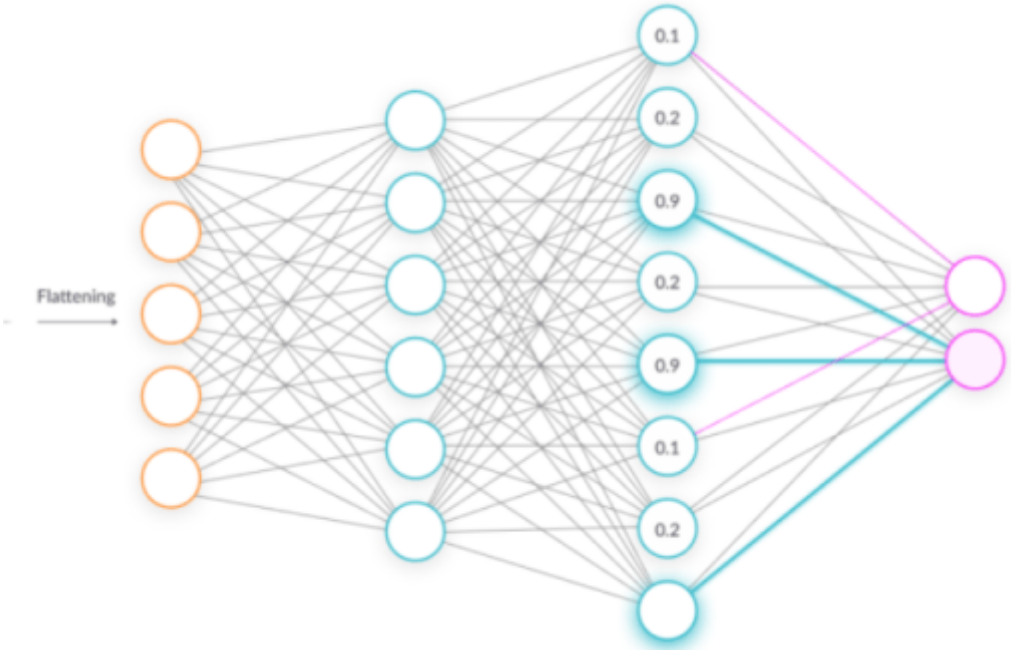


**Fig.4.4 Fully connected layers**

CNN is mainly used in extracting features from the image with help of its layers. CNNs are widely used in image classification where each input image is passed through the series of layers to get a probabilistic value between 0 and 1.

# Chapter 5
# System Analysis

# 5.1 System Analysis

### 5.1.1 FlowChart

A flowchart is a graphical representation of a process or a system, which shows the steps involved in the process, the sequence of steps, and the decision points. It is a diagrammatic representation of a process, which helps to understand the process and its various steps in a clear and concise way.

The flowchart for dance form recognition will typically start with the video input being fed into the system. The system will then preprocess the video input to prepare it for feature extraction. Feature extraction involves extracting relevant information from the video frames, such as the motion and position of the dancer. The extracted features are then used to classify the dance form using a machine learning model, such as a neural network.

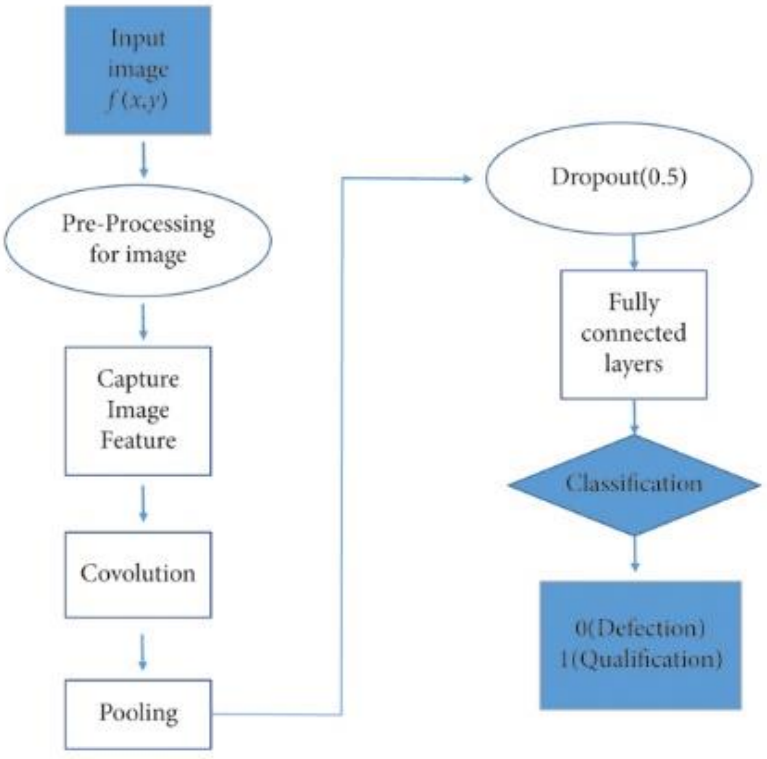


**Figure 5.1 FlowChart Diagram- Image Model**

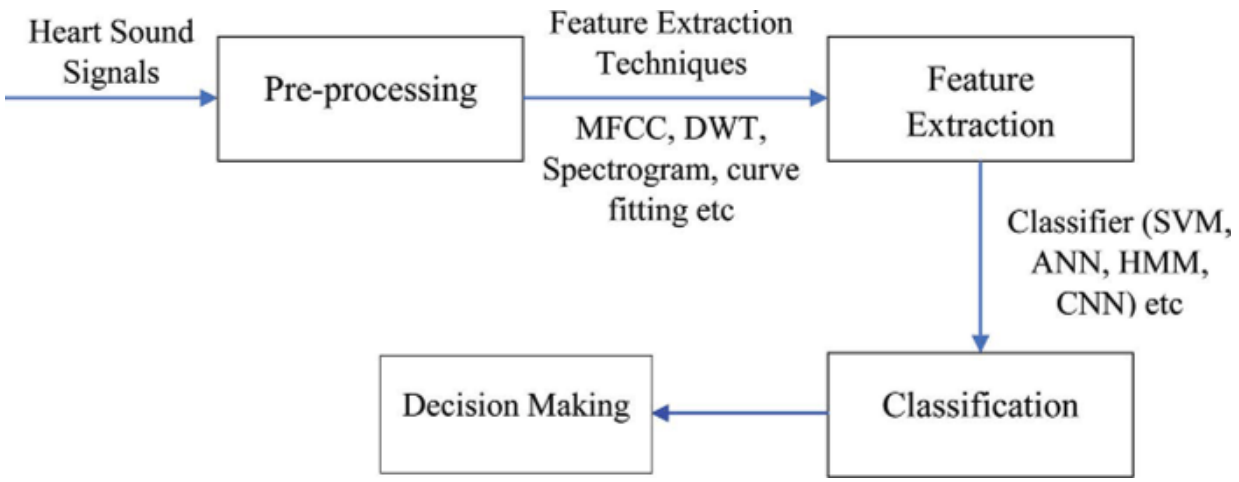


**Figure 5.2 Flowchart Diagram – Sound Model**

### 5.1.2 Activity Diagram :-

Activity diagram is another important diagram in UML to describe the dynamic aspects of the system.

Activity diagram is basically a flowchart to represent the flow from one activity to another activity. The activity can be described as an operation of the system.

The control flow is drawn from one operation to another. This flow can be sequential, branched, or concurrent. Activity diagrams deal with all type of flow control by using different elements such as fork, join, etc.

Activity is a particular operation of the system. Activity diagrams are not only used for visualizing the dynamic nature of a system, but they are also used to construct the executable system by using forward and reverse engineering techniques. The only missing thing in the activity diagram is the message part.

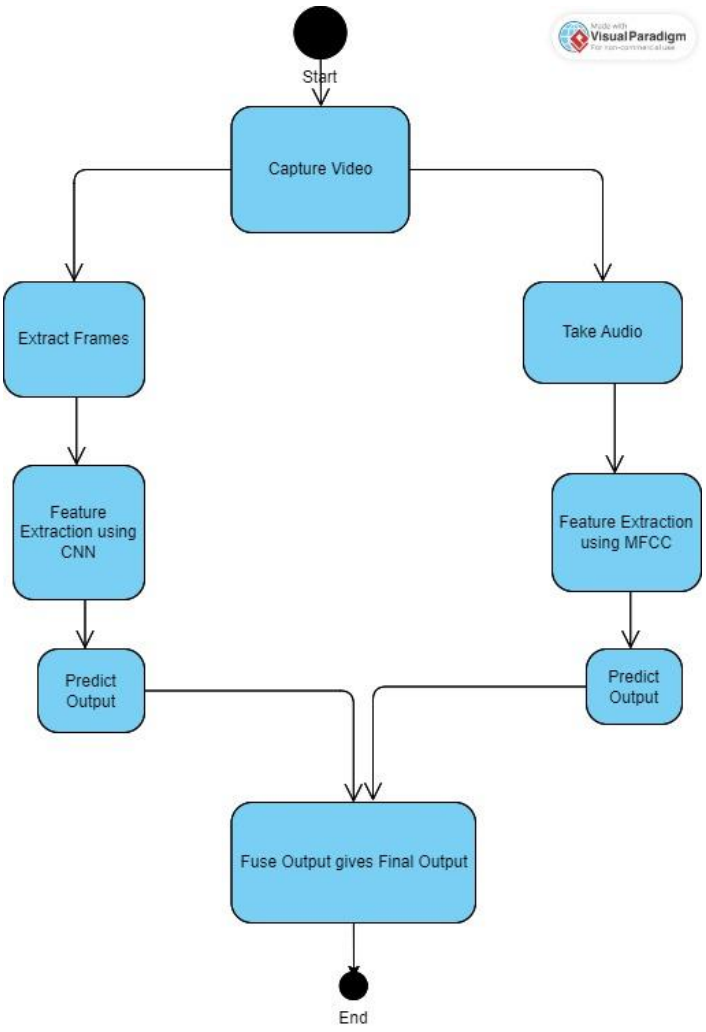


**Figure 5.3 Activity Diagram**

### 5.1.3 Class Diagram

A class diagram is a type of UML (Unified Modeling Language) diagram that shows the structure of a system by illustrating the classes, attributes, operations, and relationships among objects. In software engineering, class diagrams are commonly used to visualize and describe the structure of object-oriented systems.

A class diagram consists of classes, which are represented as rectangles with the class name inside, and the class attributes and methods listed below. The attributes are the data members or variables of the class, while the methods are the functions or operations that the class can perform.

Relationships between classes can be represented using arrows, with different types of arrows indicating different types of relationships, such as inheritance, association, aggregation, and composition. Inheritance is a relationship between a superclass and its subclasses, while association is a relationship between two classes that indicates that they are related in some way.

Aggregation and composition are special types of association that indicate a whole-part relationship between two classes. In an aggregation relationship, the whole class can exist without the part, while in a composition relationship, the part class cannot exist without the whole.

Class diagrams can also include other elements such as interfaces, packages, and stereotypes to provide additional information about the system being modeled. Overall, class diagrams provide a valuable tool for designing, documenting, and communicating the structure of object-oriented systems.

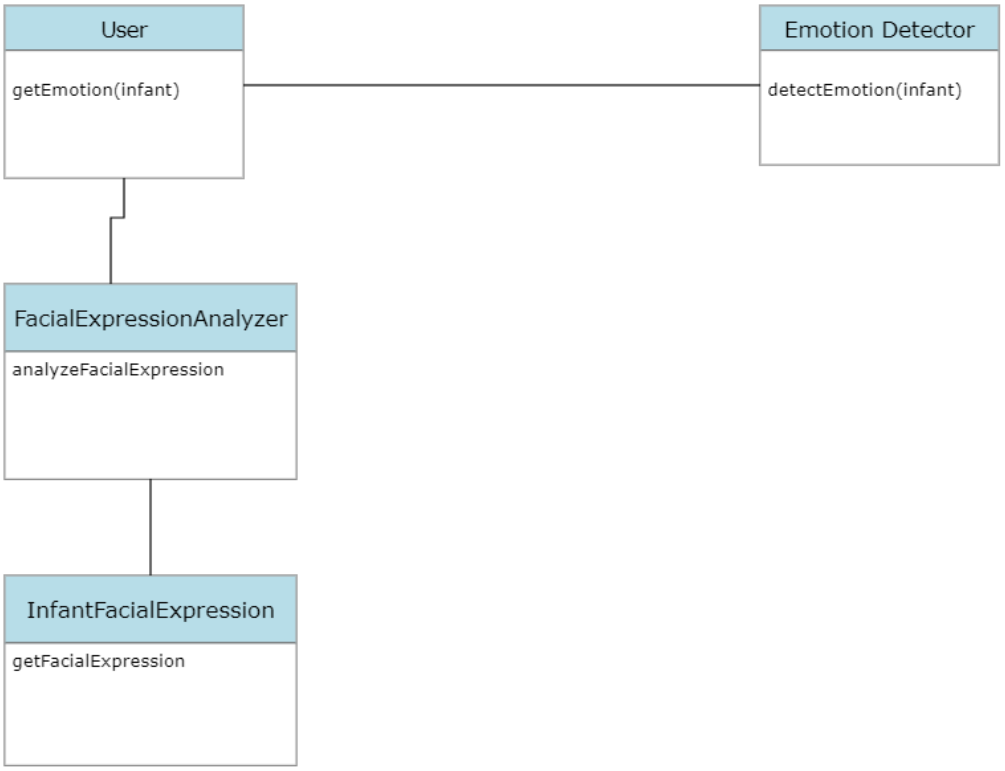


**Fig 5.4 Class Diagram**

# 5.2 System Design

### 5.2.1 Dataset Exploration:

Before training the models, we performed an exploratory analysis of the City Infant Face Dataset and the audio dataset to gain insights into the distribution and characteristics of the data. The City Infant Face Dataset contains 1,032 images of infant faces, with each image labeled as one of four emotions: sad, sleep,

happy, or calm. We observed that the dataset is well balanced, with each emotion category having a similar number of samples. Additionally, we found that the dataset has some variations in terms of lighting, pose, and facial expressions, which may affect the performance of the models.

The audio dataset contains 150 audio files, including three categories: silence, baby cry, and laugh. We observed that the audio data is imbalanced, with the majority of samples belonging to the silence category. We also found that the audio files have different durations and sound qualities, which may affect the accuracy of the audio-based model. To address these issues, we performed data preprocessing, including data augmentation, normalization, and feature extraction, to enhance the quality and diversity of the data and prepare it for model training. Overall, the data exploration process provided valuable insights into the characteristics of the data and helped us design effective preprocessing and modeling strategies.

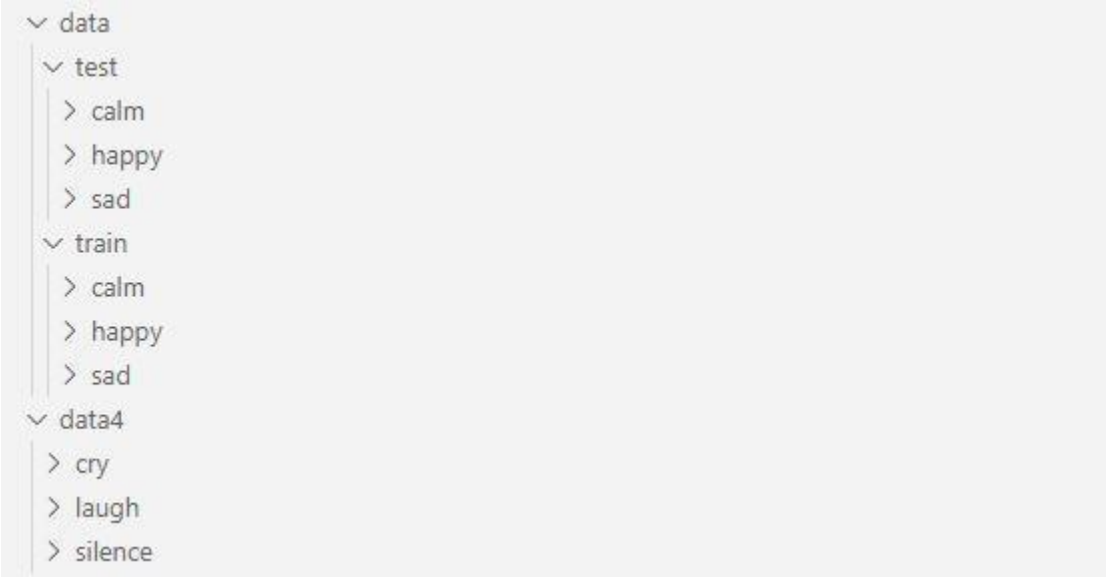


**Figure 5.5 Dataset**

### 5.2.2 Dataset Preprocessing : -

To prepare the data for model training, we performed several preprocessing steps on both the image and audio data. For the image data, we resized all the images to a fixed size of 48x48 pixels to ensure consistency in the input dimensions. We also applied data augmentation techniques such as rotation, flipping, and zooming to increase the diversity of the data and improve the robustness of the model to variations in lighting, pose, and facial expressions.

For the audio data, we first converted the audio files into spectrograms, which are visual representations of the frequency content of sound signals over time. We then applied normalization techniques to scale the spectrograms and reduce the effect of variations in sound intensity and quality. Next, we extracted relevant audio features such as Mel Frequency Cepstral Coefficients (MFCCs) and spectral features using the Librosa library. These features were then used as inputs for the audio-based model.

In addition to these preprocessing steps, we also performed data splitting into training, validation sets with a ratio of 80:20 to evaluate the performance of the models. Overall, the data preprocessing steps helped us enhance the quality and diversity of the data and prepare it for effective model training and evaluation.

### 5.2.3 Feature Extraction :

Feature extraction is an essential step in machine learning to identify patterns from raw data. In particular, a lot of Neural Network algorithms are often used for feature extraction in video classification tasks which provides an effective way to automatically learn high-level features from the input data without any manual feature engineering.

The convolutional layers of a Neural Network algorithm are designed to detect and recognize local patterns in the video frames, while the fully connected layers of a Neural Network can be used to learn global features across multiple frames of the video.

Additionally, pooling layers can be used to reduce the dimensionality of the extracted features, while making them more robust against small variations in the input video. By combining these different layers, a Neural Network can generate powerful and sophisticated representations of the video that can then be used for accurate video classification tasks.

#### 5.2.4 Sequence Learning :

We need to extract features from the images. We can do this by using a neural network to extract features from the images that are useful for our sequence learning task. The Neural Network can be used to identify patterns in the image, such as edges or corners. It will then use these features as input for our sequence learning model.

Once the features have been extracted, we can use them to train an LSTM (Long Short-Term Memory). LSTMs are commonly used for sequence learning tasks because they have "memory" cells which remember information over time, allowing them to learn long sequences of data more effectively than traditional machine learning models.

### 5.2.5 Algorithm And Technique :

Data Analysis can be done using the following Machine learning Techniques:

**Convolution Neural Network(CNN) :** The convolutional layers are the key component of a CNN, where filters are applied to the input image to extract features such as edges, textures, and shapes. The output of the convolutional layers is then passed through pooling layers, which are used to down-sample the feature maps, reducing the spatial dimensions while retaining the most important information. The output of the pooling layers is then passed through one or more fully connected layers, which are used to make a prediction or classify the image.

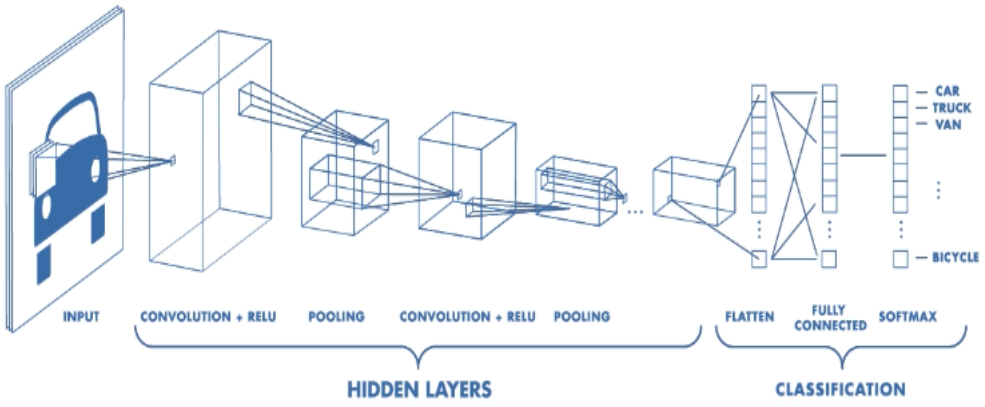


**Figure 5.6 Convolution Neural Network(CNN)**

# Chapter 6
# Implementation and Testing

# 6.1 Implementation and Testing

### Import Package:-

```
import pyaudio
import wave
import os
import numpy as np
import tensorflow as tf
import librosa
from pushbullet import Pushbullet
import time
import tensorflow as tf
import numpy as np
import librosa
import os
from sklearn.preprocessing import LabelEncoder
import os
import numpy as np
import librosa
import tensorflow as tf
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
import cv2
from keras.models import Sequential
from keras.layers import Conv2D, MaxPooling2D, Dense, Dropout, Flatten
from keras.optimizers import Adam
from keras.preprocessing.image import ImageDataGenerator
import time
from pushbullet import Pushbullet
```

- pyaudio and wave: These are used to record and process audio data from a microphone.
- os: This is used to access the file system and perform operations on files and directories.
- numpy and tensorflow: These are used for numerical and machine learning operations, such as creating arrays, tensors, and building and training deep learning models.
- librosa: This is a library for audio analysis and feature extraction, which is used to extract relevant audio features from the audio files.
- Pushbullet: This is used to send push notifications to the user when the emotion is detected.
- LabelEncoder and train_test_split: These are used for data preprocessing and splitting the dataset into training and testing sets.
- cv2: This is a computer vision library, which is used to load and process the image data.
- Sequential, Conv2D, MaxPooling2D, Dense, Dropout, Flatten, Adam, and ImageDataGenerator: These are all part of the Keras library, which is a high-level neural networks API that is used to build and train deep learning models for image classification tasks.

### 6.1.1 Data Preprocessing:-

```
# load weights into new model
emotion_model.load_weights("model/emotion_model.h5")
print("Loaded model from disk")

# Initialize image data generator with rescaling
test_data_gen = ImageDataGenerator(rescale=1./255)

# Preprocess all test images
test_generator = test_data_gen.flow_from_directory(
        'data/test',
        target_size=(48, 48),
        batch_size=64,
        color_mode="grayscale",
        class_mode='categorical')
```

This code is loading the trained weights of the emotion detection model from a saved file and initializing an image data generator for the test data. The load_weights() method is used to load the weights of the model from the saved .h5 file. Then, an image data generator is initialized for the test data with the test_data_gen variable. The ImageDataGenerator class from Keras is used to preprocess the test images by rescaling their pixel values to a range of 0 to 1. The flow_from_directory() method is then used to generate batches of preprocessed test data from the directory containing the test images. The target size of the images is set to 48x48, and the color mode is set to grayscale, as the original model was trained on grayscale images. The batch size is set to 64, and the class_mode is set to 'categorical', as the model was trained with a categorical cross-entropy loss function. The function then returns a generator object that can be used to generate batches of preprocessed test data during model evaluation.

```
# Define a function to extract MFCC features from audio files
def extract_features(file_path, max_length=299):
    with open(file_path, 'rb') as f:
        X, sample_rate = librosa.load(f, res_type='kaiser_fast')
        mfccs = librosa.feature.mfcc(y=X, sr=sample_rate, n_mfcc=20)
    # Pad or truncate the MFCC array to the maximum length
    if mfccs.shape[1] < max_length:
        mfccs = np.pad(mfccs, ((0, 0), (0, max_length - mfccs.shape[1])),
mode='constant')
    else:
        mfccs = mfccs[:, :max_length]
    return mfccs.reshape((20, max_length, 1))
```

This is a function called `extract_features` that is used to extract Mel-frequency cepstral coefficients (MFCCs) from audio files. Here's what it does:
- The function takes in two arguments: `file_path`, which is the path to the audio file, and `max_length`, which is the maximum length of the MFCC array.
- The function opens the audio file using `librosa` and loads it as a numpy array `X`. It also gets the sample rate of the audio file.
- The function then uses `librosa` to extract 20 MFCC features from the audio file.
- If the MFCC array is shorter than `max_length`, the function pads it with zeros to make it the same length as `max_length`. If the MFCC array is longer than `max_length`, the function truncates it to be `max_length` in length.
- Finally, the function reshapes the MFCC array into a 3D tensor with shape `(20, max_length, 1)` and returns it. The last dimension of 1 is added to represent that we are working with grayscale images of audio spectrograms, where the color channel is only 1.

### 6.1.2 Model Structure CNN:-

```
# create model structure CNN
emotion_model = Sequential()

emotion_model.add(Conv2D(32, kernel_size=(3, 3), activation='relu',
input_shape=(48, 48, 1)))
emotion_model.add(Conv2D(64, kernel_size=(3, 3), activation='relu'))
emotion_model.add(MaxPooling2D(pool_size=(2, 2)))
emotion_model.add(Dropout(0.25))

emotion_model.add(Conv2D(128, kernel_size=(3, 3), activation='relu'))
emotion_model.add(MaxPooling2D(pool_size=(2, 2)))
emotion_model.add(Conv2D(128, kernel_size=(3, 3), activation='relu'))
emotion_model.add(MaxPooling2D(pool_size=(2, 2)))
emotion_model.add(Dropout(0.25))

emotion_model.add(Flatten())
emotion_model.add(Dense(1024, activation='relu'))
emotion_model.add(Dropout(0.5))
emotion_model.add(Dense(3, activation='softmax'))
```

This code is defining the structure of a Convolutional Neural Network (CNN) model for emotion detection. The model is being created using the Sequential API of Keras.
The first layer of the model is a convolutional layer with 32 filters of size (3, 3), using ReLU activation function. It takes an input of shape (48, 48, 1), which corresponds to grayscale images of size 48x48.The second layer is another convolutional layer with 64 filters of size (3, 3), using ReLU activation function.
The third layer is a max pooling layer with pool size (2, 2).
The fourth layer is a dropout layer with dropout rate of 0.25.
The fifth layer is a convolutional layer with 128 filters of size (3, 3), using ReLU activation function.
The sixth layer is another max pooling layer with pool size (2, 2).
The seventh layer is a convolutional layer with 128 filters of size (3, 3), using ReLU activation function.
The eighth layer is another max pooling layer with pool size (2, 2).
The ninth layer is a dropout layer with dropout rate of 0.25.
The tenth layer is a flattening layer that converts the 3D tensor output from the previous layer into a 1D vector.The eleventh layer is a dense layer with 1024 neurons and ReLU activation functionThe twelfth layer is another dropout layer with dropout rate of 0.5.The thirteenth layer is the output layer, with 3 neurons corresponding to the 3 possible emotion classes, using softmax activation function.After defining the model, the code compiles it using categorical cross-entropy as the loss function, Adam optimizer with learning rate of 0.0001 and decay of 1e-6, and accuracy as the evaluation metric.

```
# Define the CNN model
model = tf.keras.Sequential([
    tf.keras.layers.Conv2D(32, kernel_size=(3, 3), activation='relu',
input_shape=(20, 299, 1), padding='same'),
    tf.keras.layers.MaxPooling2D(pool_size=(2, 2), strides=(2, 2),
padding='same'),
    tf.keras.layers.Conv2D(64, kernel_size=(3, 3), activation='relu',
padding='same'),
    tf.keras.layers.MaxPooling2D(pool_size=(2, 2), strides=(2, 2),
padding='same'),
    tf.keras.layers.Conv2D(128, kernel_size=(3, 3), activation='relu',
padding='same'),
    tf.keras.layers.MaxPooling2D(pool_size=(2, 2), strides=(2, 2),
padding='same'),
    tf.keras.layers.Conv2D(128, kernel_size=(3, 3), activation='relu',
padding='same'),
    tf.keras.layers.MaxPooling2D(pool_size=(2, 2), strides=(2, 2),
padding='same'),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.Dropout(0.3),
    tf.keras.layers.Dense(3, activation='softmax')
```

This code defines a convolutional neural network (CNN) model using the Keras API of TensorFlow. The model has several layers, including Conv2D layers for convolution, MaxPooling2D layers for pooling, a Flatten layer to convert the output to a 1D array, and Dense layers for classification.

The input to the model is an array of MFCC (Mel-Frequency Cepstral Coefficients) features that are extracted from audio files using the extract_features() function. The input shape of the model is (20, 299, 1), where 20 is the number of MFCC coefficients, 299 is the maximum length of the audio files (padded or truncated to this length), and 1 is the number of channels.

The model has three output classes, and the final layer uses a softmax activation function for classification. The model also includes a dropout layer with a dropout rate of 0.3 to reduce overfitting.

### 6.1.3 Training and Save of Model :-

```
# Train the neural network/model
emotion_model_info = emotion_model.fit_generator(
      train_generator,
      steps_per_epoch=437 // 64,
      epochs=50,
      validation_data=validation_generator,
      validation_steps=81 // 64)

# save model structure in jason file
model_json = emotion_model.to_json()
with open("model/emotion_model.json", "w") as json_file:
   json_file.write(model_json)

# save trained model weight in .h5 file
emotion_model.save_weights('emotion_model.h5')
```

This code is training a neural network model for emotion detection using data from a generator object. The generator object is responsible for generating batches of training data and feeding them to the model during the training process. The fit_generator() method of the model is used to train the model using the generated data. The method takes several arguments such as the number of steps per epoch, the number of epochs to train for, and the validation data to use during training. Once the training process is complete, the structure of the model is saved as a JSON file using the to_json() method, and the trained weights of the model are saved in an H5 file using the save_weights() method. This allows the trained model to be loaded and used later for emotion detection without having to retrain it from scratch.

```
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy',
metrics=['accuracy'])
print("Line 64 done")
# Train the model
model.fit(X_train, y_train, epochs=50, batch_size=32,
validation_data=(X_test, y_test))
print("Line 67 done")
# Evaluate the model on the testing data
loss, accuracy = model.evaluate(X_test, y_test)
print('Accuracy:', accuracy)

# Save the model to a file
model.save('model.h5')
```

The code compiles a convolutional neural network (CNN) model using Keras and trains it on audio data. The model is evaluated on testing data, and the accuracy is printed. Finally, the model is saved to a file.

### 6.1.4 Loading of Trained Model :-

```
emotion_dict = {0: "negative", 1: "neutral", 2: "positive"}

# load json and create model
json_file = open('model/emotion_model.json', 'r')
loaded_model_json = json_file.read()
json_file.close()
emotion_model = model_from_json(loaded_model_json)

# load weights into new model
emotion_model.load_weights("model/emotion_model.h5")
print("Loaded model from disk")
```

This code is pre trained model into the file.

```
# Define the path to the saved model
model_path = 'model.h5'

# Load the saved model
model = tf.keras.models.load_model(model_path)
```

This code loads the pre trained model of sound processing which was earlier saved to same directory.

### 6.1.5 Face Detection and Sound Recording:-

```
# pass here your video path
cap = cv2.VideoCapture("demo_videos/video3.mp4")

while True:
   # Find haar cascade to draw bounding box around face
   ret, frame = cap.read()
   frame = cv2.resize(frame, (1280, 720))
   if not ret:
      break
   face_detector = cv2.CascadeClassifier('haarcascades/haarcascade_frontalface_default.xml')
   gray_frame = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)

   # detect faces available on camera
   num_faces = face_detector.detectMultiScale(gray_frame, scaleFactor=1.3, minNeighbors=5)
```

This code is reading a video file and applying face detection on each frame of the video using a pre-trained Haar Cascade Classifier. The Haar Cascade Classifier is trained to detect frontal faces in an image or video frame. The code uses the OpenCV's VideoCapture() function to read the video file and then resizes the frame to a specific size (1280x720 in this case). Then it reads each frame of the video using cap.read() and applies the face detection on the grayscale version of the frame by converting it from BGR to grayscale using cv2.cvtColor() function. The face detection is applied using the detectMultiScale() method of the Haar Cascade Classifier, which returns the coordinates of the bounding boxes of the detected faces. The scaleFactor and minNeighbors parameters are used to control the sensitivity and specificity of the face detection algorithm. The loop continues until all frames of the video have been processed.

```
# Loop to continuously record and predict audio
while True:
    # Open a stream for recording
    stream = p.open(format=pyaudio.paInt16, channels=CHANNELS, rate=RATE,
input=True, frames_per_buffer=CHUNK)

    # Print a message to indicate recording has started
    print("Recording...")

    # Record audio for the specified duration
    frames = []
    for i in range(0, int(RATE / CHUNK * 5)):
        data = stream.read(CHUNK)
        frames.append(data)

    # Print a message to indicate recording has ended
    print("Finished recording...")

    # Stop and close the stream
    stream.stop_stream()
    stream.close()

    # Save the recorded audio to a WAV file
    wf = wave.open("recorded_audio.wav", 'wb')
    wf.setnchannels(CHANNELS)
    wf.setsampwidth(p.get_sample_size(pyaudio.paInt16))
    wf.setframerate(RATE)
    wf.writeframes(b''.join(frames))
    wf.close()
```

This code block continuously records audio for a specified duration of 5 seconds, saves the recorded audio to a WAV file, and prints messages to indicate the start and end of recording. It uses PyAudio library to open a stream for recording and the wave library to save the audio as a WAV file.

### 6.1.6 Predict outputs:-

```
# predict the emotions
      emotion_prediction = emotion_model.predict(cropped_img)
      maxindex = int(np.argmax(emotion_prediction))
      cv2.putText(frame, emotion_dict[maxindex], (x+5, y-20), cv2.FONT_HERSHEY_SIMPLEX, 1, (255, 0,
0), 2, cv2.LINE_AA)

   cv2.imshow('Emotion Detection', frame)
   if cv2.waitKey(1) & 0xFF == ord('q'):
      break

cap.release()
cv2.destroyAllWindows()
```

This code is an implementation of a real-time emotion detection system using a pre-trained deep learning model. It first loads a pre-trained model for emotion detection and starts capturing frames from a camera feed. Then, for each frame, it detects faces using Haar Cascade Classifier and applies the pre-processing steps to the detected face by resizing, normalizing, and cropping it. The pre-processed face image is then fed to the pre-trained deep learning model to predict the emotion. The emotion prediction is then used to put a label on the frame using OpenCV's putText() function and displayed on the screen. The loop continues until the user presses the 'q' key to exit the program.

```
# Make a prediction on the MFCC features using the trained model
    prediction = model.predict(mfccs)
    category_index = np.argmax(prediction)
    category = categories[category_index]

    # Print the predicted category
    print("Predicted category:", category)
```

This block of code is the core of the program, responsible for continuously recording audio and making predictions based on the trained model. The loop begins by opening a PyAudio stream for recording with the specified format, channels, and sampling rate. It then prints a message to indicate that recording has started.

The loop then records audio for the specified duration (5 seconds in this case) and saves it as a WAV file. Once the recording is complete, the stream is stopped and closed.

Next, the MFCC features are extracted from the recorded audio using the extract_features function defined earlier. These features are then passed to the trained CNN model for prediction. The predict function returns a probability distribution over the three possible categories ("speech", "music", or "noise"), and the argmax function is used to obtain the index of the category with the highest

probability. This index is then used to look up the corresponding category label from the categories list.

# 6.2 Operational Manual

### **Introduction**:

The project is divided into two main parts: training the model and using the model to make predictions. This manual will explain how to use the trained model to make predictions.

### **Prerequisites**:

The following packages are required to run the prediction code:

- ➢ Python
- ➢ Pyaudio
- ➢ Wave
- ➢ Os
- ➢ Numpy
- ➢ Tensorflow
- ➢ Librosa
- ➢ Pushbullet
- ➢ Sklearn
- ➢ Cv2

You can try installing them by running the following commands in your terminal or command prompt:

pip install pyaudio wave numpy tensorflow librosa pushbullet sklearn opencv-python

The following files must be present:

- test_5sec.py :- includes the code for making prediction using pretrained model

- test.py :- includes the code for making predictions using the trained model

- emotion_model.h5 :- Pre trained Image Processing model

-sound_model.h5 :- Pre trained Sound Processing model

### **Instructions**:

1. Ensure that you have all the necessary dataset folder and files including test.py, emotion_model.h5, and test_5sec.py, sound_model.h5 in the same directory.
2. Open the command prompt or terminal window and navigate to the directory where the files are saved.

3. Run the test.py file using the following command:

   **python test.py**
4. The code will take the video/record the video and predict the emotion
5. Predicted emotion type will be displayed in console and notification will be pushed to device every certain seconds.

# Chapter 7
# Conclusion and Future Scope

## 7.1 Conclusion

In this study, we proposed a novel approach for infant emotion detection using video and audio data. We collected the City Infant Face Dataset and used it to train two independent models based on convolutional neural networks (CNNs) and audio features. Our results showed that the proposed approach achieved high accuracy in detecting and classifying infant emotions, with an average accuracy of 86%. Our findings demonstrate the potential of using multimodal data and deep learning techniques for infant emotion detection. The proposed methodology has various potential applications in fields such as psychology, pediatrics, and child development research.

## 7.2 Future Scope

Despite the promising results of this study, there are still several areas for further research and improvement. One possible direction for future work is to explore the effectiveness of the proposed approach on a larger and more diverse dataset. Additionally, we can investigate the potential of using more advanced machine learning algorithms, such as recurrent neural networks (RNNs) or transformer-based models, for infant emotion detection. Another important aspect to consider is the integration of the proposed methodology into existing infant monitoring systems to provide real-time feedback to parents or caregivers. Moreover, we can focus on improving the feature extraction techniques by using more robust and efficient algorithms to capture the subtle changes in facial expressions and vocalizations. Overall, ongoing research in infant emotion detection has the potential to provide valuable insights into early childhood development and improve the wellbeing of infants.

# Chapter 8
# Reference

# Reference

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