DEERWALK INSTITUTE OF TECHNOLOGY

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Institute of Science and Technology

MUSIC PLAYER WITH FACIAL EMOTION RECOGNITION FOR MUSIC RECOMMENDATION

A FINAL PROJECT REPORT

Submitted to

Department of Computer Science and Information Technology

DWIT College

In partial fulfillment of the requirements for the Bachelor's Degree in Computer Science and Information Technology

Submitted by

Aarjan Pokharel

20597

April 17, 2023

DWIT College

DEERWALK INSTITUTE OF TECHNOLOGY

SUPERVISOR'S RECOMMENDATION

I hereby recommend that this project prepared under my supervision by AARJAN POKHAREL entitled **"MUSIC PLAYER WITH FACIAL EMOTION RECOGNITION FOR MUSIC RECOMMENDATION"** in partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Information Technology be processed for the evaluation.

…………………………………………

Mr. Bijay Babu Regmi

Faculty, Associate Director of Academic Operations

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DEERWALK INSTITUTE OF TECHNOLOGY

STUDENT'S DECLARATION

I hereby declare that I am the only author of this work and that no sources other than that listed here have been used in this work.

…………………………………………

Aarjan Pokharel

April 17, 2023

DWIT College

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LETTER OF APPROVAL

This is to certify that this project prepared by AARJAN POKHAREL entitled **"MUSIC PLAYER WITH FACIAL EMOTION RECOGNITION FOR MUSIC RECOMMENDATION"** in partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Information Technology has been well studied.

In our opinion it is satisfactory in the scope and quality as a project for the required degree.

…………………………………… Mr. Bijay Babu Regmi Project Supervisor Faculty, Associate Director of Academic Operations DWIT College	……………………………………….. Mr. Hitesh Karki Campus Chief DWIT College
…………………………………… Mr. Niresh Dhakal Project Coordinator Associate Director of Undergrad Program DWIT College	……………………………………….. Mr. Nawaraj Poudel Associate Professor Central Depatment of Computer Science and Information Technology, Kirtipur

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Aarjan Pokharel

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ABSTRACT

It is often confusing for a person to decide which music he/she have to listen from a massive collection of existing options. There have been several suggestion frameworks available for issues like music, dining, and shopping depending upon the mood of user. The main objective of this music recommendation system The Facial Emotion Based Music Recommendation System is a web-based application that uses facial recognition technology to recommend songs based on the user's emotional state. The system captures an image of the user's face through the camera and detects the emotions using a trained convolutional neural network model. Based on the identified emotion, the system recommends a list of songs from a pre-defined database. The system is implemented using Python programming language, OpenCV library for image processing, Keras framework for deep learning, and Django framework for web application development. The system provides an interactive and personalized music experience for users based on their current emotional state.is to provide suggestions to the users that fit the user’s preferences.

The music recommendation system aims to enhance the user's experience by providing personalized music recommendations based on their emotional state. Additionally, a Django-based music player has been developed that enables users to browse, search, and add songs to their playlist and favorites. This provides users with the flexibility to create their own personalized music library and enjoy their favorite songs anytime, anywhere. The integration of these two systems results in an all-in-one music solution that not only recommends new songs but also allows users to manage their existing collection efficiently. The user-friendly interface and seamless integration with existing music libraries make this system an ideal choice for music enthusiasts of all levels.

Keywords: *CNN; Facial Emotion Detection; Haarcascades algorithm; Music Player, Song Recommendation.*

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LIST OF ABBREVIATIONS

CNN	Convolution Neural Network
DL	Deep Learning
ELM	Extreme learning machine
FER	Facial Emotion Recognition
OpenCV	Open Source Computer Vision Library
RELU	Rectified Linear Unit
ROI	Region of Interest
SVM	Support Vector Machine

CHAPTER 1: INTRODUCTION

1.1. Overview

The project aims to develop a music player with facial emotion recognition that uses convolutional neural networks (CNN) for emotion detection. The system will use computer vision technology to analyze a user's facial expression and determine their emotional state, and then recommend music that matches that emotion. To implement this project, a CNN model will be trained using a dataset of facial images labeled with emotions such as happy, sad, angry, surprise, disgust, fear and neutral. The model will be trained to recognize patterns and features in the images that are associated with different emotions.

The CNN model trained is integrated into the music player system. When a user interacts with the system, a camera will capture their facial expression, and the CNN model analyzes the image to determine the user's emotional state. Based on the detected emotion, the music player recommends songs that match the user's mood.

The project has several potential benefits. By incorporating facial emotion recognition into a music player, users will have a more personalized and immersive music listening experience. Additionally, individuals who may have difficulty expressing their emotions verbally, such as those with autism, can use this system to convey their emotions and receive music recommendations that match their mood.

Overall, this project is an exciting application of computer vision and deep learning techniques that has the potential to enhance the way we interact with music and technology.

1.2. Background and Motivation

Music has been an integral part of human culture and society for centuries. It can evoke a wide range of emotions, from happiness and excitement to sadness and nostalgia. Musical preferences have been demonstrated to be highly related to personality traits and mood [1].

With the advancement of technology, music has become more accessible than ever before, with various music players and streaming platforms available on different devices.

However, with the vast amount of music available, it can be overwhelming for users to choose what to listen to. While music recommendation algorithms have been developed to suggest songs based on users' listening habits, they often lack a human touch and do not consider the emotional state of the user at the time of listening.

This is where facial emotion recognition comes in. By using computer vision technology to analyze a user's facial expression, a music player can determine the user's emotional state and suggest songs that match that emotion. For example, if the user is smiling, the player can suggest upbeat and happy songs, while if the user appears sad, the player can suggest more mellow and melancholic songs.

The motivation behind developing a music player with facial emotion recognition is to provide a more personalized and immersive music listening experience. By taking into account the user's emotional state, the player can suggest songs that resonate with the user on a deeper level, enhancing their overall music listening experience.

Overall, a music player with facial emotion recognition has the potential to revolutionize the way we listen to music, providing a more personalized and emotionally engaging experience for users.

1.3. Problem Statement

The problem statement for this project is that existing music recommendation algorithms lack a human touch and do not consider the emotional state of the user at the time of listening. Users may find it overwhelming to choose what to listen to among the vast amount of music available. There is difficulty in finding suitable music based on one’s current emotional state. Similarly, there is lack of personalized music recommendations based on individual emotions. The need for manual search and selection of music based on current and mood and behavior can be tedious. Additionally, individuals who have difficulty expressing their emotions verbally may find it challenging to communicate their emotional state to others. Therefore, there is a need for a music player with facial emotion recognition that can provide a more personalized and immersive music listening experience, taking into account the user's emotional state and recommending music that matches that emotion. The goal of this project is to address this problem by using computer vision technology and deep learning techniques to develop a music player that can recognize a user's emotional state and provide music recommendations accordingly.

1.4. Objectives

The primary objectives of this project are listed below:

- To develop a machine learning model to accurately recognize emotions from facial expressions.
- To develop a user-friendly interface to capture the user's facial expression and display the recommended songs.
- To recommend songs based on user’s mood.
- To allow users to play the recommended songs directly from the application.

1.5. Scope and Limitation

The scope of this project would be anyone who enjoys listening to music and wants a more personalized and immersive music listening experience. Additionally, this project may be of interest to developers and researchers working in the field of computer vision and deep learning, as it provides an application of these technologies to enhance the music listening experience.

The accuracy of the detected emotion is a major limitation of this project. The accuracy of the facial emotion recognition system may be limited by the quality of the camera and the lighting conditions, as well as variations in facial expressions and individual differences in emotional expression.

1.6. Development Methodology

This system aims to explore and experiment with different methods to enhance the accuracy and reliability of the system. Therefore, a Prototyping Model approach is selected, which is suitable for Facial Emotion detection projects that require frequent modifications and updates on the various models built. This approach allows for the direct design of an initial prototype without spending too much time in other phases. The project objectives are well-defined at the beginning, but the design of the system may change based on the feedback and results obtained from the previous prototypes. The Prototyping Model approach helps to ensure that the system is developed iteratively and gradually improved over time, leading to a more robust and effective solution.

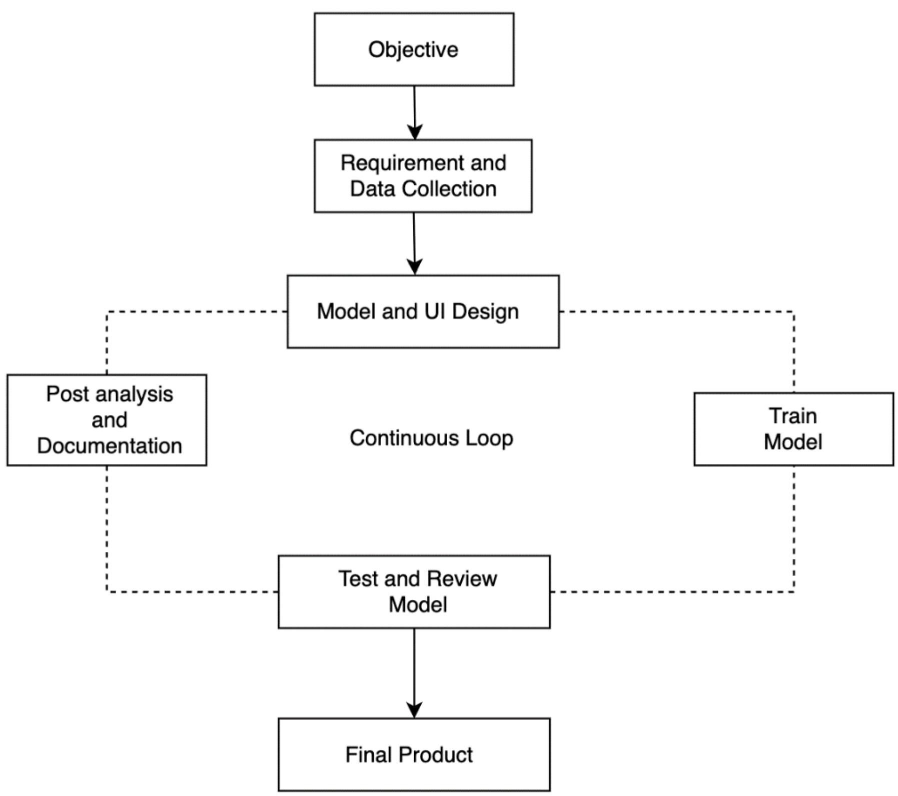

Figure 1.6. 1: Prototyping model for system development

1.7. Report Organization

Preliminary Section: This section contains the title page, abstract, table of contents, list of figures, and list of tables.

Introduction Section: In this section, the overview of the project, the background and motivation of the project, problem statement, its objectives and scope are discussed.

Literature Review Section: This section includes description, summary and critical evaluation of all the research papers studied to build a foundation of knowledge required for this project.

Requirement and Feasibility Analysis Section: Requirement analysis, and feasibility analysis make the bulk of this section.

System Design Section: The section consists of description of data used, algorithms implemented and the system design as well.

Development Methodology Section: This describes the software development lifecycle followed to build this system.

Implementation and Evaluation Section: The section comprises of the tools and technologies used to build the system, description of implementation, and results obtained after system testing.

Conclusion and Recommendation Section: The section is composed of the final findings and the recommendations that can be worked on to improve the project.

CHAPTER 2: BACKGROUND STUDY AND LITERATURE REVIEW

2.1. Background Study

The development of music recommendation systems has been an active area of research for several years, with many different approaches and techniques proposed. These systems typically rely on user data such as listening history, song ratings, and social network data to provide personalized music recommendations. More recently, there has been growing interest in developing systems that incorporate user emotional states as a factor in music recommendation. Studies have shown that music can have a powerful impact on emotions, with different types of music being associated with different emotional states. Additionally, facial expression recognition technology has advanced significantly in recent years, enabling accurate detection of emotions from facial expressions in real-time.

In the context of a music player application with facial emotion recognition for music recommendation, the system can use real-time facial expression analysis to identify the user's emotional state and recommend music that is appropriate for that state. This approach has the potential to improve the user's music listening experience by providing music that is tailored to their mood and emotional state. In addition, the incorporation of facial emotion recognition technology can provide a more seamless and user-friendly experience, as the user does not need to manually input their emotional state or music preferences.

Recently, there has been growing interest in developing music recommendation systems that incorporate user emotional states as a factor in music recommendation. Music can have a powerful impact on emotions, with different types of music being associated with different emotional states. For example, classical music is often associated with relaxation, while upbeat pop music is associated with happiness.

Facial expression recognition technology has also advanced significantly in recent years, enabling accurate detection of emotions from facial expressions in real-time. This technology involves capturing images of facial expressions and using machine learning algorithms to identify the corresponding emotion. Convolutional Neural Networks (CNNs) are commonly used in facial expression recognition to analyze facial features and classify emotions.

The Haar Cascade algorithm is commonly used for face detection in facial expression recognition technology. It involves training a classifier to detect specific features of the face, such as the eyes, nose, and mouth, and using those features to identify the location of the face in an image. Once the face has been detected, machine learning algorithms can be used to classify the corresponding emotion.

Finally, Django is a high-level Python web framework commonly used for developing web applications. It provides several built-in features, such as an Object-Relational Mapping (ORM) system for database interaction, authentication and authorization, and templating for front-end development. Using Django for the music player application can provide a robust and scalable web-based platform for the project.

Overall, this project can contribute to the advancement of music recommendation systems and the integration of facial expression recognition technology into music player applications.

2.2. Literature Review

There have been several studies and research articles published on the topic of music recommendation systems that incorporate facial emotion recognition technology.

In [2], a convolutional neural network (CNN) was used to detect emotions from facial expressions and provide personalized music recommendations. The system was evaluated using a dataset of 238 participants, and the results showed that the system achieved an average accuracy of 75.8% in emotion recognition and a satisfaction rate of 68.4% for the music recommendations [2].

A study [3] proposed a similar system that combined facial emotion recognition with physiological signals to improve the accuracy of emotion detection. The system was evaluated using a dataset of 30 participants, and the results showed that the combined approach improved the accuracy of emotion detection and led to more accurate music recommendations.

In [4], a multi-modal music recommendation system was proposed that combined facial emotion recognition with user listening history and social network data. The system was evaluated using a dataset of 170 participants, and the results showed that the system achieved a higher accuracy in music recommendation compared to systems that relied on only one type of data.

In [5], a hybrid music recommendation system was proposed that combined facial emotion recognition with user ratings and collaborative filtering techniques. The system was evaluated using a dataset of 240 participants, and the results showed that the hybrid approach outperformed traditional music recommendation techniques in terms of recommendation accuracy and user satisfaction.

A study [6] proposed a facial expression recognition system based on convolutional neural networks (CNN). Their system used a dataset of facial images to train the CNN model to recognize six basic emotions: happy, sad, angry, disgust, surprise, and neutral. The model achieved high accuracy in recognizing these emotions from facial images, which suggests that it could be used in an application like a music player that incorporates emotion recognition.

Music recommendation systems have been widely studied, with many different approaches and techniques proposed. Collaborative filtering is a popular method for music recommendation that uses user data such as listening history and song ratings to provide personalized recommendations. D. P. Aggarwal and S. K. Jain [7] conducted a comparative study of collaborative filtering algorithms for recommendation systems and found that a hybrid approach that combined multiple algorithms was the most effective.

In recent years, there has been growing interest in developing music recommendation systems that incorporate user emotional states as a factor in the recommendation process. K. Choi, H. Lee, and H. Lee [8] proposed a music recommendation system that combines audio and lyrics information to recommend songs based on the user's mood. Their system analyzed the sentiment of the lyrics and used audio features such as tempo and key to provide personalized recommendations.

S. R. Musfiq, M. S. Hasan, and M. R. Rahman [9] developed a hybrid music recommendation system that used both content-based filtering and collaborative filtering techniques. The content-based filtering approach used audio features to recommend songs with similar characteristics to the user's listening history, while the collaborative filtering approach used user data to recommend songs based on the preferences of similar users.

In the context of a music player application with facial emotion recognition for music recommendation, I. Zuckerman, M. Pichsenmeister, and G. Specht [10] proposed a system that used facial expression recognition to identify the user's emotional state and recommend music that was appropriate for that state. Their system used a dataset of facial images labeled with emotional states to train a support vector machine (SVM) model for emotion recognition. The SVM model was then used to recommend music based on the user's current emotional state.

Overall, these studies suggest that the incorporation of facial emotion recognition technology into music recommendation systems has the potential to improve the accuracy and effectiveness of these systems in providing personalized music recommendations.

Emotion Detection and Characterization using facial features aims to detect faces from any given image, extract facial features and classify them into 7 emotions (happy, anger, neutral, sad, surprise, fear and disgust) [11]. Facial Emotion Recognition 2013 dataset was used to train and test the model used for emotion recognition. FER 2013 dataset consists of more than 35000 images for training and testing the emotion detection model [12].

There are several existing music recommendation systems that use different approaches to personalize music recommendations based on user data. For example, streaming platforms like Spotify and Apple Music use a combination of user listening history, song ratings, and social network data to provide personalized music recommendations to their users. These systems have been successful in providing users with music they enjoy and keeping them engaged with the platform.

However, these existing systems typically do not take into account the user's emotional state when making music recommendations. This can lead to a mismatch between the music being recommended and the user's current mood or emotional state. Additionally, users may not always be able to accurately describe their emotional state or may not want to take the time to input their mood into the application.

To address these problems, recent research has focused on developing music recommendation systems that incorporate user emotional states as a factor in music recommendation. These systems use techniques such as facial expression recognition, speech analysis, and physiological sensors to identify the user's emotional state and provide music recommendations that are appropriate for that state.

However, there are still some challenges and limitations with these systems. For example, facial expression recognition technology may not always accurately detect emotions from facial expressions, especially in challenging lighting or environmental conditions. In addition, some users may not be comfortable with the idea of their emotions being constantly monitored and analyzed by the application.

Furthermore, there is a risk of overreliance on algorithms in music recommendation systems, potentially limiting the diversity and serendipity of music discovery. Therefore, it is important for these systems to strike a balance between personalized recommendations and exposing users to new and diverse music.

CHAPTER 3: SYSTEM ANALYSIS

3.1. System Analysis

System analysis for the facial emotion recognition system involved understanding the system requirements, identifying the various components that make up the system, and analyzing the interactions and interfaces between the components. The requirements of the facial emotion recognition system, including accuracy, speed, integration, data storage, security, and cost-effectiveness, were understood. The various components that made up the system were identified, including the camera, image processing software, emotion detection model, storage system, user interface, and hardware infrastructure that runs the model. The accuracy and speed of the system were evaluated by testing it under various conditions, including different lighting and background conditions. The performance of the system was analyzed by measuring its response time, processing time, and throughput, and any bottlenecks or performance issues that needed to be addressed were identified. Additionally, user feedback was collected and analyzed to further improve the system's accuracy and user experience.

3.1.1. Requirement Analysis

3.1.1.1. Functional Requirement

Functional requirements are listed below:

- A user shall be able to capture their facial emotion using webcam.
- The system shall be able to recommend music based on the captured emotion of the user.
- The user shall be able to listen to music.
- The user shall be able to play and pause the music.
- The user shall be able to create playlist of songs.

3.1.1.1.1 Use Case Diagram

Figure 3.1.1.1. 1: Use Case Diagram

3.1.1.2. Non-Functional Requirement

Non-functional requirements are listed below:

- The application must load quickly and respond to user input in a timely manner.

- The application must have a user-friendly interface that is easy to use, navigate, and understand.
- The system must be accurate and reliable, with a low error rate.

3.1.2. Feasibility Analysis

3.1.2.1. Technical Feasibility

Technical feasibility was evaluated by considering the availability of the necessary hardware and software, the compatibility of the hardware and software with existing systems, and the complexity of the image recognition algorithms required. It was found that the technology needed to implement the system was available, and it was feasible to develop and deploy it.

3.1.2.2. Operational Feasibility

Operational feasibility was evaluated by considering the availability of trained personnel, the organization's current workflows, and how the system would fit into those workflows. The compatibility of the system with existing business processes, the impact on other systems or departments within the organization, and the effect on employee workload and job responsibilities were also considered. It was found that the system was practical to implement within the operational context of the organization.

3.1.2.3 Economic Feasibility

Economic feasibility was evaluated by considering the initial and ongoing costs of developing, deploying, and maintaining the system, the benefits that the system would provide, such as increased security or efficiency. It was found that the system was financially viable and justifiable in terms of the costs involved and the benefits that it would provide.

3.1.2.4 Schedule Feasibility

Schedule feasibility was evaluated by considering the availability of resources needed to complete the project within the given timeline, the complexity of the system and the time required to develop and deploy it, the need for any regulatory or compliance approvals before deployment, and the time required to train personnel on the system's use and maintenance. It was found that the system could be developed, implemented, and operational within the given timeline.

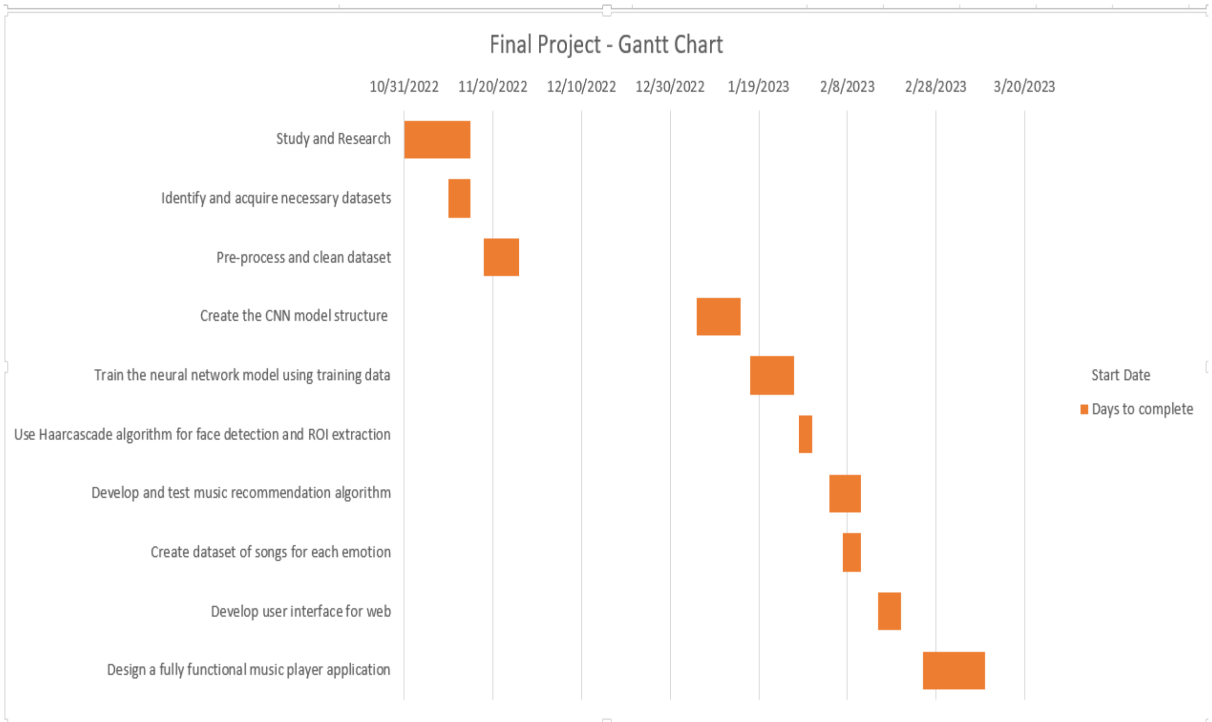

Figure 3.1.2.4. 1: Gantt chart

3.1.3 Analysis

3.1.3.1 Sequence Diagram

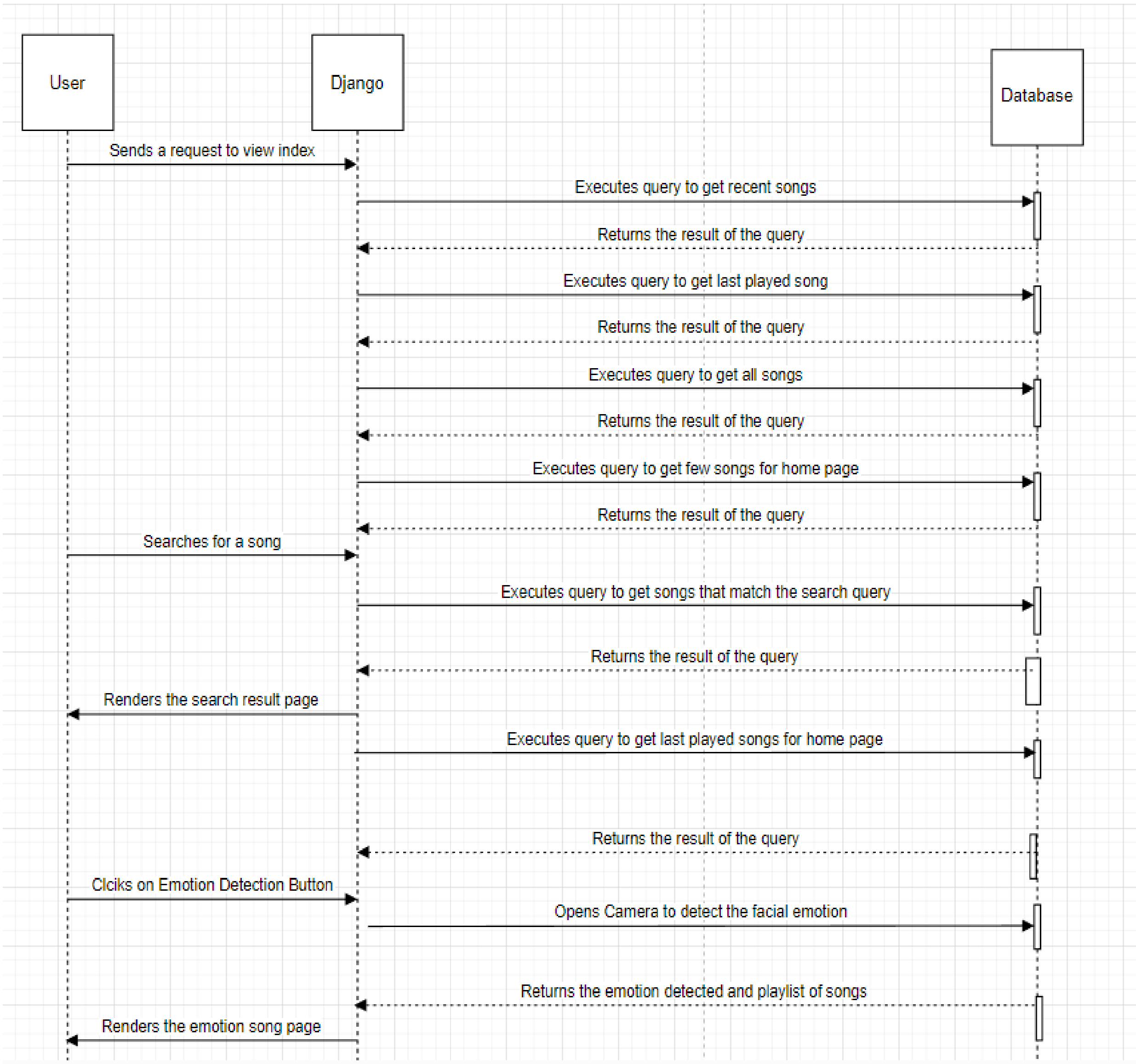

Figure 3.1.3. 1: Sequence Diagram

This sequence diagram shows the interactions between different objects in a system for a music player application with facial emotion recognition for music recommendation.

The diagram consists of three main objects: the user, the music player, and the facial emotion recognition system. The interactions between these objects are represented by the numbered arrows and messages on the diagram.

The interactions represented in the diagram are:

- The user launches the music player application and begins playing a song.
- The music player sends a request to the facial emotion recognition system to start analyzing the user's facial expressions.
- The facial emotion recognition system starts analyzing the user's facial expressions and sends a response back to the music player.
- Based on the user's facial expression, the music player sends a request to the recommendation system to provide music recommendations.
- The recommendation system analyzes the user's facial expression and sends a response back to the music player with a list of recommended songs.
- The music player displays the recommended songs to the user.
- The user selects a recommended song from the list, and the music player begins playing the selected song.

This sequence diagram illustrates how a music player application with facial emotion recognition for music recommendation can work to provide personalized music recommendations based on a user's facial expression.

3.1.3.2 Activity Diagram

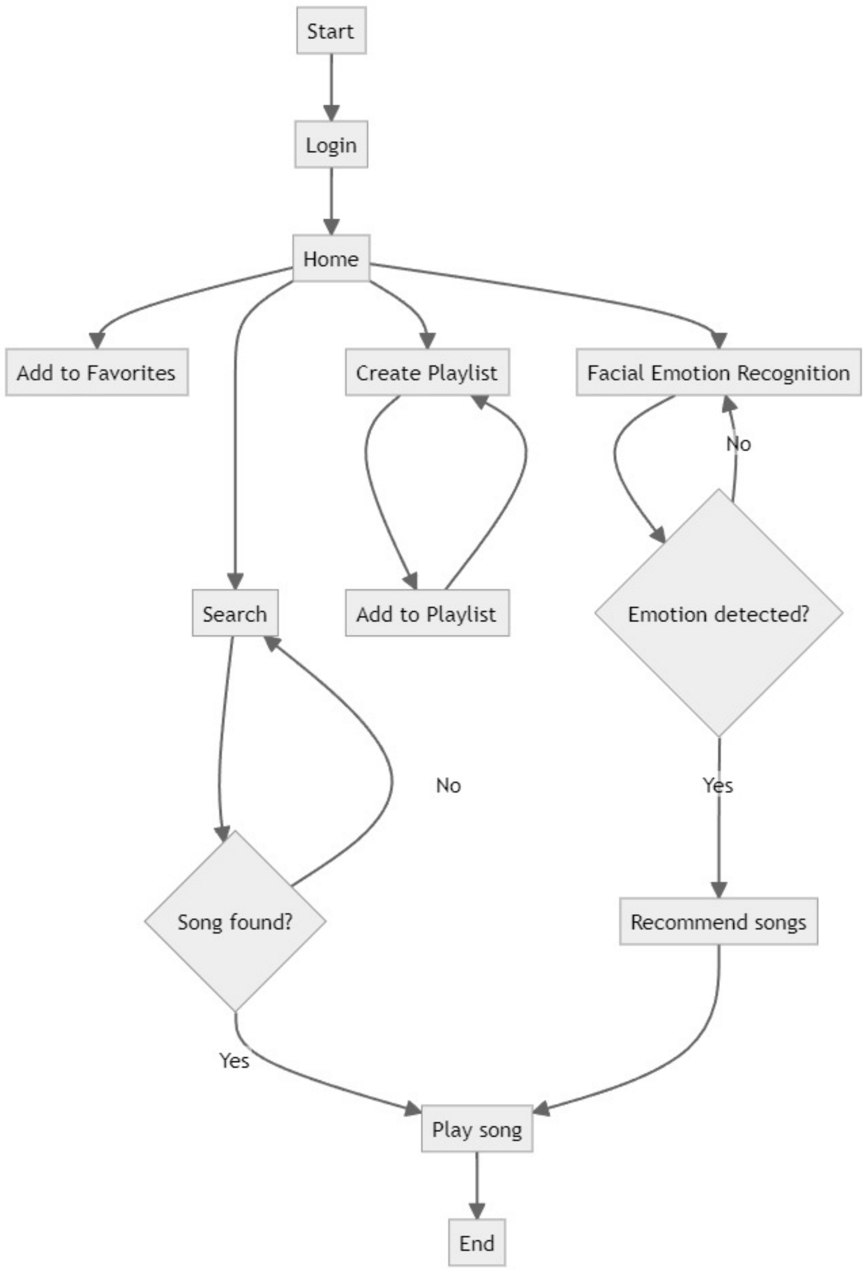

Figure 3.1.3. 2: Activity Diagram of the system

The above activity diagram represents the flow of activities involved in the process of recommending music based on facial emotion recognition. The different shapes and arrows represent the different activities and transitions between them.

The different elements and activities represented in the diagram are:

- Start: This is the starting point of the activity diagram.
- Capture facial expression: The first step in the process is capturing the facial expression of the user.
- Analyze facial expression: The captured facial expression is then analyzed to determine the emotion of the user.
- Retrieve music data: The system retrieves music data, such as metadata, playlists, and previous listening history.
- Select music: Based on the analyzed emotion and retrieved music data, the system selects music to recommend to the user.
- Play music: The recommended music is played for the user.
- End: This is the end point of the activity diagram.

CHAPTER 4: SYSTEM DESIGN

4.1. Design

4.1.1. System Architecture

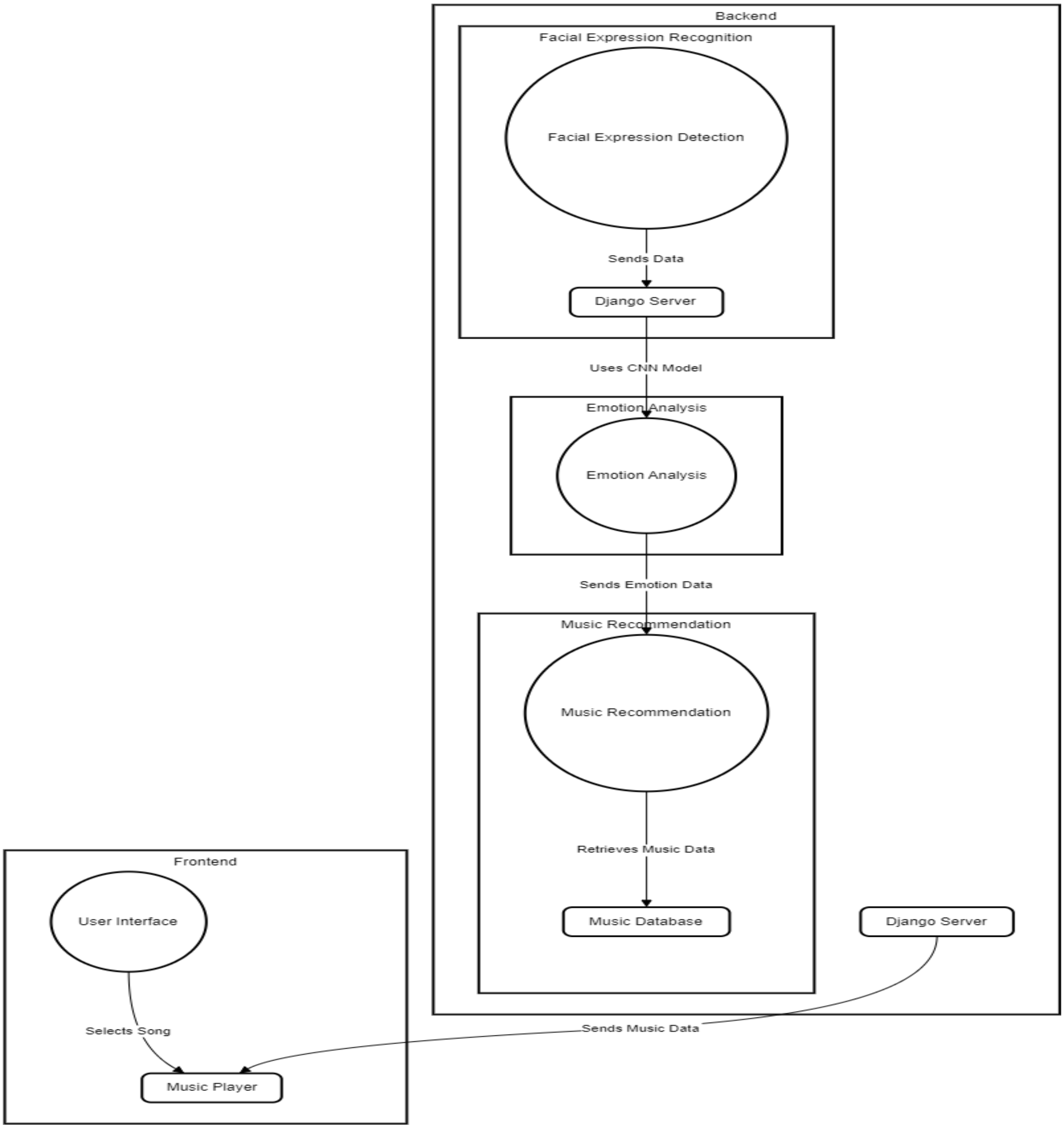

Figure 4.1.1. 1: System Architecture

The system architecture consists of four main components: the User Interface, the Web Server, the Emotion Detection Engine, and the Music Player.

The User Interface component is responsible for interacting with the user. It provides a graphical interface for the user to interact with the system. It includes buttons for controlling the music player, a camera module for capturing facial expressions, and a display for showing the recommended songs.

The Web Server component acts as the intermediary between the User Interface and the Emotion Detection Engine. It receives the images captured by the camera and sends them to the Emotion Detection Engine for processing. It also receives the recommended songs from the Emotion Detection Engine and sends them to the Music Player for playback.

The Emotion Detection Engine is responsible for detecting the user's emotional state based on the facial expression captured by the camera module. It uses a Convolutional Neural Network (CNN) model for this purpose. The detected emotion is then used to recommend songs that match the user's emotional state.

The Music Player component is responsible for playing the recommended songs. It receives the recommended songs from the Web Server and plays them based on user input from the User Interface.

4.1.2 Flow Chart of the system

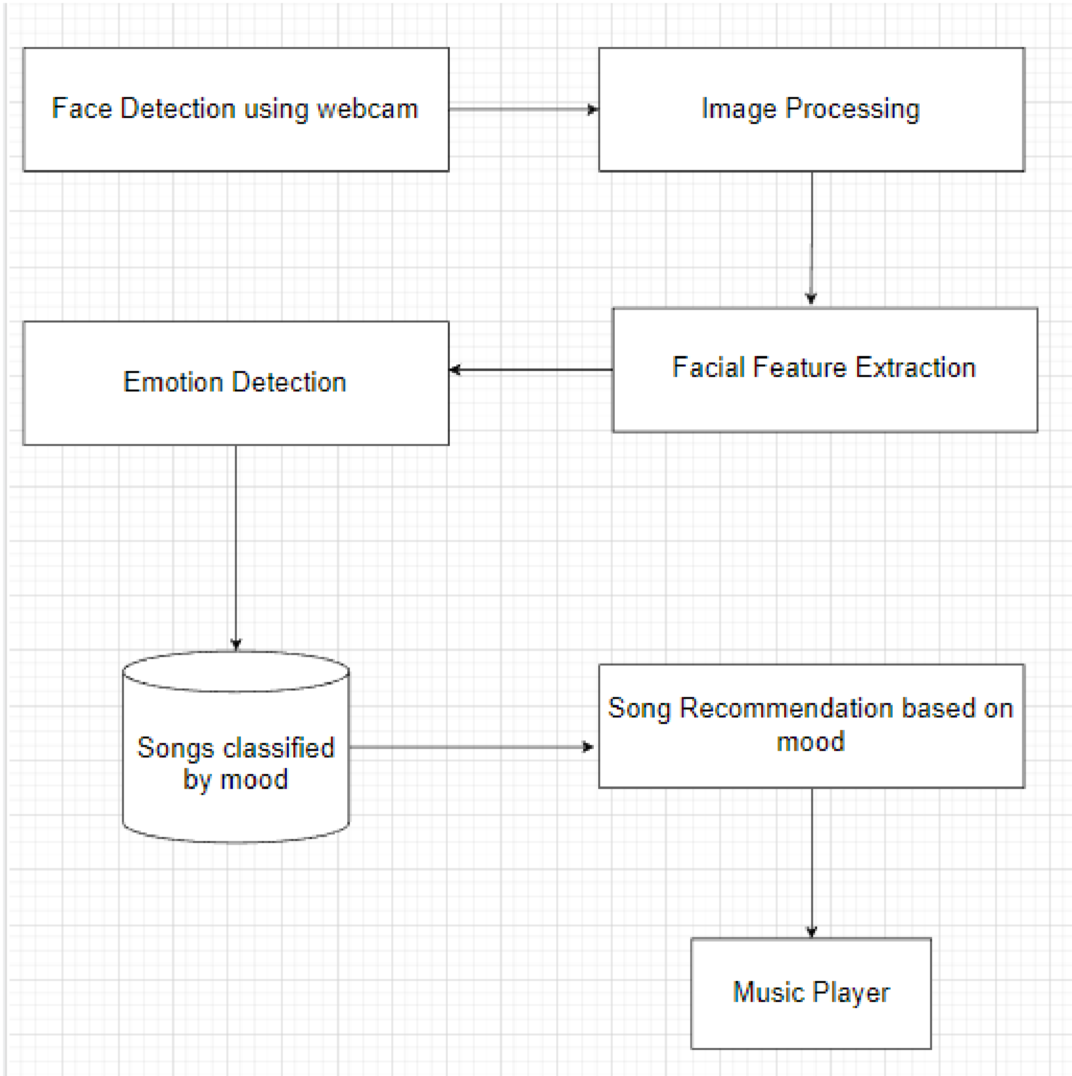

Figure 4.1.2. 1: Flow chart of the song recommendation system

4.1.3 Deployment Diagram

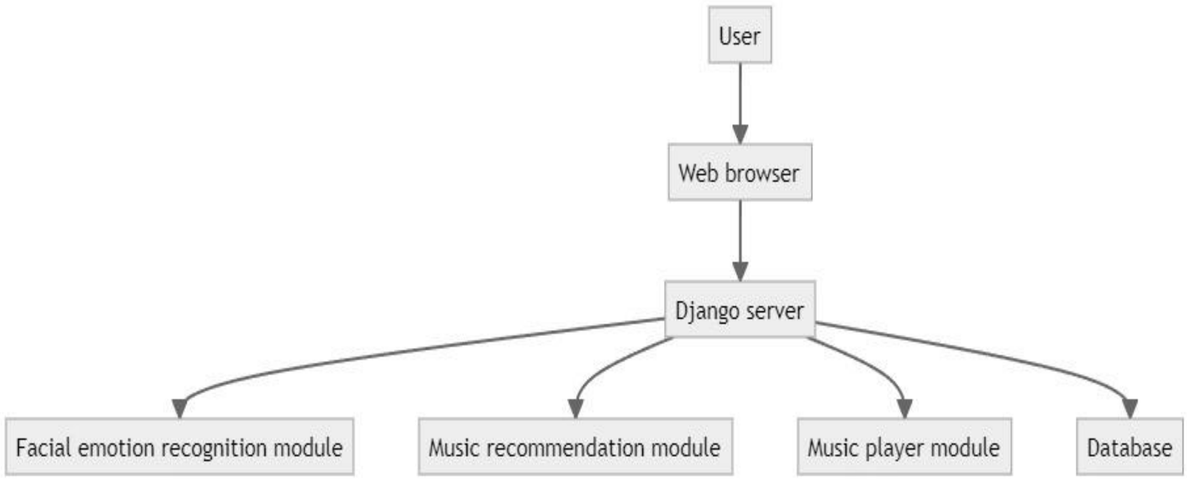

Figure 4.1.3. 1: Deployment Diagram

The deployment diagram depicts the deployment architecture of a system for a music player with facial emotion recognition for music recommendation. The system is deployed on a server which is implemented using Django. The system components include a user, web browser, Django server, three modules, and a database.

The user interacts with the system using a web browser. The Django server provides the main interface for the user to interact with the system. It also hosts the three modules, namely emotion recognition module, music recommendation module, and music player module. These modules are responsible for performing the specific tasks related to emotion recognition, music recommendation, and music playback respectively.

The emotion recognition module uses a CNN model to recognize the user's facial expressions in real-time. The music recommendation module recommends music based on the user's emotions detected by the emotion recognition module. The music player module plays the recommended music.

The deployment diagram also includes a database which stores the user's music preferences and other relevant data. The Django server interacts with the database to store and retrieve data as required by the system.

Overall, the deployment diagram provides a high-level view of the system architecture and how the different components are deployed and interact with each other to achieve the system's functionality.

4.1.4 Class Diagram

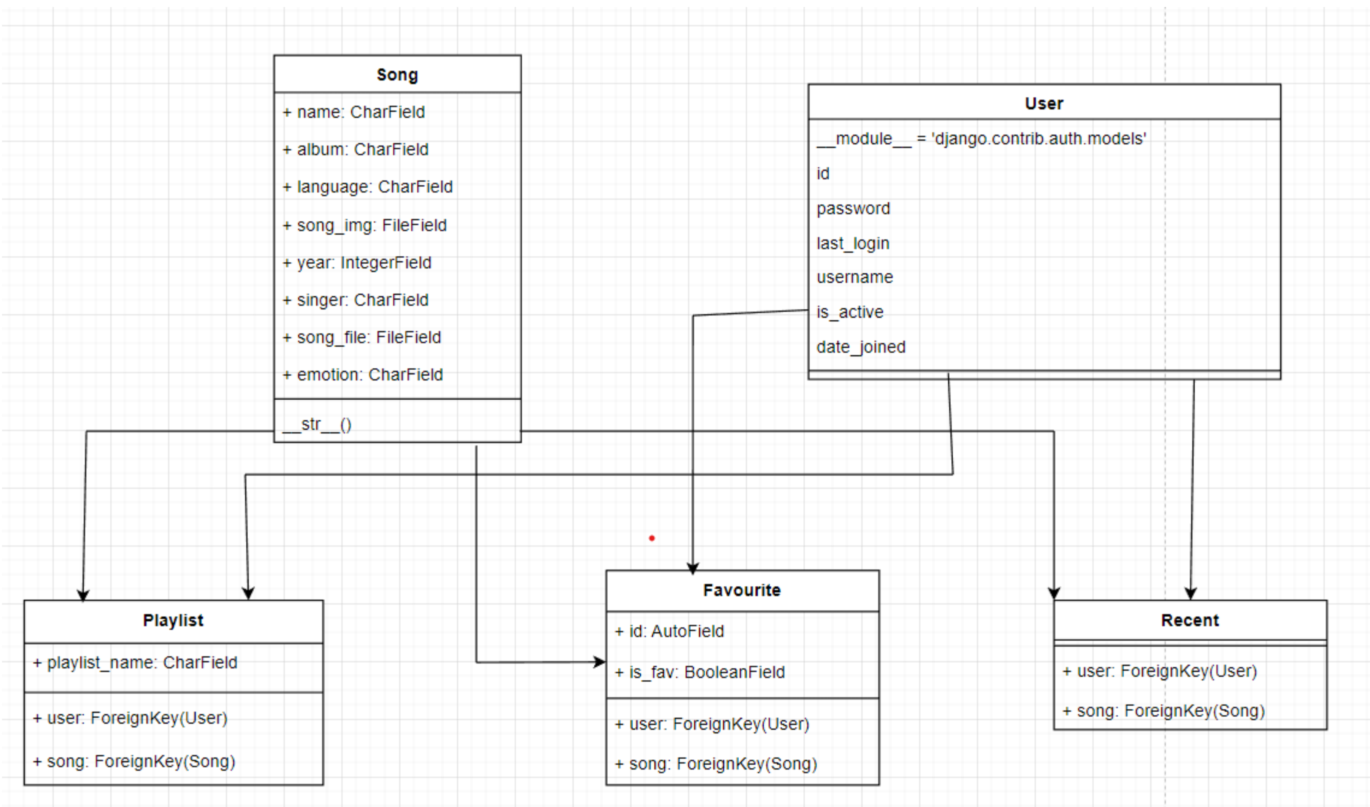

Figure 4.1.4 1: Class Diagram showing object modeling

4.2. Algorithm Details

4.2.1. Convolutional Neural Networks

Convolutional Neural Networks is used in this project in the part of image classification. A CNN is a DL algorithm which takes an input image, assigns importance (learnable weights and biases) to various aspects/objects in the image and is able to differentiate between images. The preprocessing required in a CNN is much lower than other classification algorithms. One role of a CNN is to reduce images into a form which is easier to process without losing features that are critical for good prediction. This is important when designing an architecture which is not only good at learning features but also is scalable to massive datasets.

The following steps are involved in the working of a CNN during image classification:

- Convolutional layers: The first layer of a CNN is a convolutional layer, which applies a set of filters to the input image to extract features such as edges, lines, and curves. These filters are learned during the training process.

- ReLU activation: The output of each convolutional layer is passed through a Rectified Linear Unit (ReLU) activation function, which introduces non-linearity into the network.

- Pooling layers: The next layer of a CNN is a pooling layer, which reduces the spatial dimensionality of the output from the previous layer by applying a down sampling operation. This reduces the amount of computation required by the network and helps to prevent overfitting.

- Flatten layer: The output from the last pooling layer is then flattened into a one dimensional feature vector.

- Fully connected layers: The flattened feature vector is then passed through one or more fully connected layers, which perform the final classification task. These layers learn to map the features extracted from the input image to the output class labels.

- Softmax activation: The final layer of the CNN is a softmax activation layer, which converts the output of the fully connected layer into a probability distribution over the possible output classes.

- Training: During the training process, the weights of the convolutional and fully connected layers are adjusted to minimize the difference between the predicted output and the actual output.

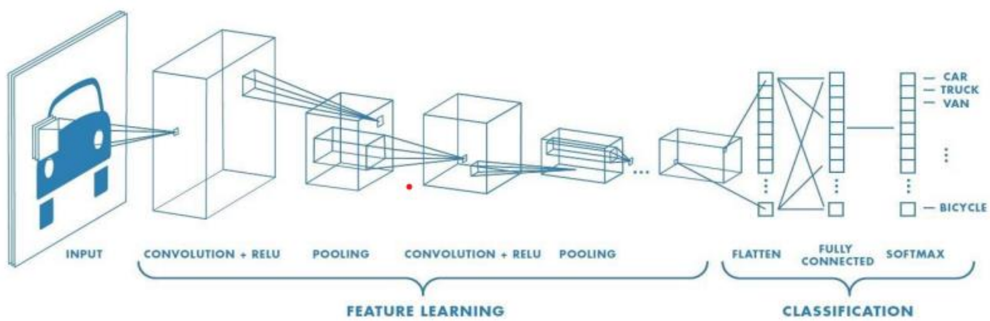

Figure 4.2.1. 1: Structure of CNN

The CNN algorithm has been used in this project to create a machine learning model structure and train the model.

Code snippet:

```
model = Sequential()

model.add(Conv2D(32, (3, 3), padding='same', input_shape=input_shape, activation='relu'))
model.add(BatchNormalization())
model.add(Conv2D(32, (3, 3), padding='same', activation='relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

model.add(Conv2D(64, (3, 3), padding='same', activation='relu'))
model.add(BatchNormalization())
```

```
model.add(Conv2D(64, (3, 3), padding='same', activation='relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

model.add(Conv2D(128, (3, 3), padding='same', activation='relu'))
model.add(BatchNormalization())
model.add(Conv2D(128, (3, 3), padding='same', activation='relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

model.add(Flatten())

model.add(Dense(512, activation='relu'))
model.add(BatchNormalization())
model.add(Dropout(0.5))
model.add(Dense(7, activation='softmax'))
```

4.2.2. Haar cascade Algorithm:

The Haar cascade algorithm is a machine learning-based approach used for object detection and recognition. It uses a cascade of classifiers trained on Haar-like features to identify objects in an image. In the case of facial emotion detection, Haar cascade algorithm can be used to detect the faces in the input images or videos.

Once the algorithm identifies the regions in an image where a face is present, it can then extract features from that region, such as the position of the eyes, nose, and mouth, to determine the facial expression. These extracted features can then be used as input to a machine learning algorithm, such as a neural network, to classify the facial expression into different emotions.

Haar cascade algorithm was used in this project to detect faces in the image using the Haar Cascade classifier, extract the region of interest (ROI) for each face, resizes the ROI to 48x48 pixels, and passes it through the CNN model to predict the emotion.

Code Snippet:

```
face_cascade.load(cv2.samples.findFile("haarcascade_frontalface_default.xml"))
    gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)


   # Haar Cascade Implementation
    faces = face_cascade.detectMultiScale(gray)
    if len(faces) == 0:
        emotion = “None”


    for (x,y,w,h) in faces:
        faceROI = gray[y:y+h, x:x+w]
        faceROI = cv2.resize(faceROI, (48, 48),interpolation = cv2.INTER_NEAREST)
        faceROI = np.expand_dims(faceROI, axis = 0)
        faceROI = np.expand_dims(faceROI, axis = 3)
        prediction = model.predict(faceROI)


    return labels[int(np.argmax(prediction))]
```

CHAPTER 5: IMPLEMENTATION AND TESTING

5.1. Implementation

The brief implementation of developing the system can be described as follows:

- **Data Collection**: The first step was to collect the necessary data to train the emotion recognition model. In this project, the data is collected from the FER-2013 dataset.
- **Preprocessing**: Once the data was collected, it needed to be preprocessed to get it into the correct format for the model. This typically involved resizing, normalization, and one-hot encoding.
- **Model Building**: Next, a Convolutional Neural Network (CNN) was built to classify facial expressions. The CNN took the preprocessed image data as input and outputs a prediction of the facial expression.
- **Model Training**: The model was trained on the preprocessed dataset using a technique called transfer learning, which involved using a pre-trained CNN as a starting point and fine-tuning it on the specific dataset.
- **Song Recommendation**: Once the model was trained, the user's facial expression was detected using OpenCV and the trained CNN model. Based on the detected emotion, a list of recommended songs was generated using a dataset of songs tagged with emotions.
- **User Interface**: A simple user interface was created using the Streamlit library to allow the user to interact with the system.
- **Music Player**: A music player was created in Django along with Jinja template to render the HTML templates of the application.

5.1.1 Tools Used

The following tools are used during the entire development life cycle of the project.

Draw.io: Draw.io is a free, online diagramming tool that allows users to create a wide variety of diagrams and charts. It features a simple and intuitive interface, with a wide range of customization options and export formats available. This tool was used to make the Model architecture and UML diagrams for the system.

Python: Python was the primary programming language used for this project. It is an interpreted, high-level, general-purpose programming language that is easy to learn and widely used in machine learning and data analysis.

Keras: Keras is an open-source neural network library written in Python. It was used for building and training deep learning models.

OpenCV: OpenCV (Open Source Computer Vision Library) is an open-source computer vision and machine learning software library. It was used for image processing, object detection, and face recognition.

Pandas: Pandas is an open-source data manipulation and analysis library used for working with structured data.

Numpy: Numpy is an open-source numerical computing library used for performing mathematical operations on large arrays and matrices.

Django: Django was used along with Jinja template to render HTML template for the music application.

Visual Studio Code: VS Code was used as the primary text editor to write and manage the project's code.

5.1.2 Implementation Details of Modules

5.1.2.1 Emotion Detection Module

The emotion detection module in this project was implemented using a convolutional neural network (CNN) model trained on a dataset of facial expressions. The OpenCV library was used to capture images from the user's webcam, which were then processed to detect the emotions present in the facial expressions. The CNN model was trained to recognize seven basic emotions - anger, disgust, fear, happiness, sadness, surprise, and neutral - and was able to accurately classify the emotions in real-time. Once the emotion was detected, the music recommendation system used a pre-defined database of songs to suggest songs that matched the user's current emotional state. The emotion detection module was a crucial component of the project as it enabled the system to provide a personalized music experience for the user based on their current emotional state.

Create training and testing data

```
train_data = df[df['Usage'] == 'Training']
test_data = df[df['Usage'] == 'PublicTest']
```

Define the input shape

```
img_width, img_height = 48, 48
input_shape = (img_width, img_height, 1)
```

Preprocess the data

```
def preprocess_data(data):
    X = []
    Y = []
    for i, row in data.iterrows():
        x_pixels = row['pixels'].split()
        x_pixels = np.array([int(pixel) for pixel in x_pixels])
        x_pixels = x_pixels.reshape((img_width, img_height, 1))
        y = np.array(row['emotion'])
        X.append(x_pixels)
        Y.append(y)
    X = np.array(X, dtype='float32')
    Y = np.array(Y, dtype='float32')
    X = X/255
    return X, Y

X_train, Y_train = preprocess_data(train_data)
X_test, Y_test = preprocess_data(test_data)
```

Figure 5.1.2.1. 1: Initializing and preprocessing all images in FER-2013

Define the CNN model

```
model = Sequential()

model.add(Conv2D(32, (3, 3), padding='same', input_shape=input_shape, activation='relu'))
model.add(BatchNormalization())
model.add(Conv2D(32, (3, 3), padding='same', activation='relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

model.add(Conv2D(64, (3, 3), padding='same', activation='relu'))
model.add(BatchNormalization())
model.add(Conv2D(64, (3, 3), padding='same', activation='relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

model.add(Conv2D(128, (3, 3), padding='same', activation='relu'))
model.add(BatchNormalization())
model.add(Conv2D(128, (3, 3), padding='same', activation='relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

model.add(Flatten())

model.add(Dense(512, activation='relu'))
model.add(BatchNormalization())
model.add(Dropout(0.5))
model.add(Dense(7, activation='softmax'))
```

Compile the model

```
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])
```

Figure 5.1.2.1. 2: Building the CNN model structure

Train the model

```
batch_size = 128
epochs = 50

train_generator = train_datagen.flow(X_train, Y_train, batch_size=batch_size)
history = model.fit(train_generator,
steps_per_epoch=len(X_train)/batch_size,
epochs=epochs,
validation_data=(X_test, Y_test))
```

Figure 5.1.2.1. 3: Training the CNN model

```python
# detect emotion from the snapshot
model = load_model("emo/model.h5")
face_cascade = cv2.CascadeClassifier()
img = cv2.imread(name)
labels = ['Angry', 'Disgust', 'Fear', 'Happy', 'Sad', 'Surprise', 'Neutral']

face_cascade.load(cv2.samples.findFile("emo/haarcascade_frontalface_default.xml"))

gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

# Haar Cascade
faces = face_cascade.detectMultiScale(gray)

if len(faces) == 0:
    emotion = None
    song_list = []
else:
    for (x,y,w,h) in faces:
        faceROI = gray[y:y+h, x:x+w]
        faceROI = cv2.resize(faceROI, (48, 48),interpolation = cv2.INTER_NEAREST)
        faceROI = np.expand_dims(faceROI, axis = 0)
        faceROI = np.expand_dims(faceROI, axis = 3)
        prediction = model.predict(faceROI)
        emotion = labels[int(np.argmax(prediction))]
        break
```

Figure 5.1.2.1. 4: Implementing haar cascades algorithm for face detection

5.1.2.2 Music Recommendation Module

In the music player with facial emotion recognition for music recommendation project, the song recommendation module used a pre-defined database of songs and recommended songs based on the user's detected emotions. The recommendation algorithm was based on the user's current emotional state, and it suggested songs that would best fit the user's mood. The recommendation module utilized a trained convolutional neural network model to detect the user's emotions from facial expressions captured through the camera. The detected emotion was then used to query the song database and retrieve a list of recommended songs. The module provided an interactive and personalized music experience for users, allowing them to discover new songs that best fit their emotional state. The recommendation module was designed to continuously learn and improve over time, allowing for more accurate and personalized song recommendations for users. Overall, the song recommendation module in this project provided an innovative way for users to discover new music that fits their mood and emotional state.

```
    # get song recommendations based on the detected emotion
    csv_name = "Songs.xlsx"
    df = pd.read_excel(csv_name, index_col=0)
    filtered_df = df[df['emotion'] == emotion]
    song_list = filtered_df['name'].sample(n=20, replace=True).tolist()

context = {
    'emotion': emotion,
    'song_list': song_list
}

return render(request, 'musicapp/emotion_song.html', context=context)
```

Figure 5.1.2.2. 1: Implementation for song recommendation based on emotion

5.1.2.3 Music Player Module

The music player module of the project was a web-based application developed using Django framework. It allowed users to play music files that were stored in the 'media' directory of the server. The module consisted of several functionalities including:

Play: The play functionality allowed users to select and play songs from the list of available songs in the 'media' directory.

Pause: The pause functionality allowed users to pause a currently playing song.

Volume control: The volume control functionality allowed users to adjust the volume of the currently playing song.

Search: The search functionality allowed users to search for their desired song within the database.

The music player module was implemented using HTML5 audio tags and JavaScript for the frontend, and Django views and models for the backend. The audio tags were used to play the songs and the JavaScript was used to control the audio playback and update the UI.

To enable users to create playlists, the music player module allowed users to select songs from the available list and add them to a playlist. Users could then play, edit or delete their playlists from their account page.

Additionally, the music player module had a favorite’s functionality that allowed users to mark songs as their favorites by clicking a heart icon next to each song. The list of favorite songs was stored in the database and could be accessed from the user's account page.

The music player module was integrated with the facial emotion recognition system to provide personalized music recommendations based on the user's emotional state. Users could also create their own playlists and mark songs as favorites for easy access in the future. The music player module required users to log in to their account before they could access the functionalities.

5.2. Testing

5.2.1. Test Cases for Unit Testing

Table 5.2.1. 1: Unit testing cases for sign up form

Test Case	Description	Test Data	Expected Result	Actual Result	Remarks
TU01	When the user enters correct username and password for registering.	Username = “lonewolf” Password = “hazard10” Confirm password = “hazard10”	User should be registered to the application.	As expected	Pass
TU02	When the user enters invalid username while registering.	Username = “sasda;” Password = “Top!gun2” Confirm password = “Top!gun2”	The system must show the invalid username error.	As expected	Pass
TU03	When the user enters only numeric password	Username = “mirage” Password = “12345678” Confirm password = “12345678”	The system must show common password error	As expected	Pass
TU04	When the user enters only alphabetical password	Username = “mirage” Password = “abc” Confirm password = “abc”	The system must show common password error	As expected	Pass

TU05	When the user enters password with less than 8 characters.	Username = “Lonewolf” Password = “mk123” Confirm password = “mk123”	The system must show too short password error.	As expected	Pass
TU06	When a user enters different password while confirming password.	Username = “Lonewolf” Password = “@Test123456” Confirm password = “@Test123477”	The system must show unmatched password error	As expected.	Pass
TU07	When the user leaves the username field blank.	Username = “ ” Password = “@Test123” Confirm password = “@Test123”	The system must empty username field error	As expected.	Pass
TU08	When the user leaves the password field blank.	Username = “ beasthunter” Password = “ ” Confirm password = “ ”	The system must empty password field error	As expected	Pass
TU09	When the user enters details of already existing account	Username = “lonewolf” Password = “hazard10” Confirm password = “hazard10”	The sytem must display user already exists.	As expected.	Pass

Table 5.2.1. 2: Unit testing cases for login form

Test Case	Test Case Description	Test Data	Expected Result	Actual Result	Pass /Fail
TU01	Fill in username and password as login details and click login button.	Username = “lonewolf” password=”hazard10”	User should be logged in to the account	As Expected	Pass
TU02	Fill in username and password as login details and click login button.	username = “beasthunter” password=” Top!gun2”	User should be logged in to the account	As Expected	Pass
TU03	Click the login button without filling in login details	username = “ ” password = “ ”	User should be shown validation error	As Expected	Pass
TU04	Fill in username and password as login details and click login button.	user = “slayer” password = “ aSDFq4e2”	User should be logged in to the account.	Failed due to incorrect password	Fail
TU05	Fill in username and password as login details and click login button.	username = “lowkey” password = “A12345-z”	User should be logged in to the account.	Failed due to unregistered user	Fail

Table 5.2.1. 3: Unit testing cases for emotion detection

Test Case	Test Case Description	Test Data	Expected Result	Actual Result	Pass /Fail
TU01	When the snapshot of the face was taken for emotion detection	Happy face	Emotion detected should be "happy"	As Expected	Pass
TU02	When the snapshot of the face was taken for emotion detection	Sad face	Emotion detected should be "sad"	As Expected	Pass
TU03	When the snapshot of the face was taken for emotion detection	Angry face	Emotion detected should be "angry"	As Expected	Pass
TU04	When the snapshot of the face was taken for emotion detection	Surprised face	Emotion detected should be "surprise"	As expected	Pass
TU05	When the snapshot of the face was taken for emotion detection	Fearful face	Emotion detected should be "fear"	Emotion detected was "surprise"	Fail

TU06	When the snapshot of the face was taken for emotion detection	Fearful face	Emotion detected should be “fear”	As expected	Pass
TU07	When the snapshot of the face was taken for emotion detection	Neutral face	Emotion detected should be “neutral”	As expected	Pass
TU08	When the snapshot of the face was taken for emotion detection	Disgusted face	Emotion detected should be “disgust”	Emotion detected was “neutral”	Fail
TU09	When the snapshot of the face was taken for emotion detection	Disgusted face	Emotion detected should be “disgust”	Emotion detected was “fear”	Fail
TU10	When the snapshot of the face was taken for emotion detection	Disgusted face	Emotion detected should be “disgust”	Emotion detected was “sad”	Fail
TU11	When the snapshot without any face was taken for emotion detection	No face	No emotion should be detected	As expected	Pass

5.2.2. Test Cases for System Testing

Table 5.2.2. 1: System Test Cases for System testing

Test Case	Description	Expected Result	Actual Result	Remarks
TU01	When the user presses the play button	The selected song must be played	The selected song was played	PASS
TU02	When the user presses the pause button	The song being played must be paused	The current song was paused	PASS
TU03	When the user plays a song	The song must be added to recently played list.	The song was added to recently played list.	PASS
TU04	When the user enters a song and presses the search button	The entered song must be displayed to the user	The entered song was displayed	PASS
TU05	When the user clicks on the "i" button	The detail information about the song must be displayed	The detail information about the song was displayed.	PASS
TU06	When the user click on "create new playlist"	A new playlist with user given name must be created	An empty playlist was created	PASS
TU07	When the user click on "add to playlist"	The song must be added to the user's selected playlist	The song was added to selected playlist	PASS

TU08	When the user click on "add to favorites"	The song must be added to the user's favorites	The song was added to user's favorites	PASS
TU09	When the user clicks on "Detect emotion" button	The system camera must be opened to detect user emotion	The emotion was detected and the recommended songs were displayed	PASS
TU10	When the user clicks on sign out button	The user must be logged out from the application	The user was logged out of the application	PASS
TU11	When the command to run the server was entered in the terminal	The application must run on port 8000 of the local host	The application ran on port 8000 of local host	PASS

5.3. Result and Analysis

The result and analysis obtained are mentioned below:

Accuracy of emotion recognition: The Convolutional Neural Network (CNN) model used for emotion recognition achieved an accuracy of 66% on the test dataset. This accuracy indicates that the model is close to human accuracy and is reliable for recognizing emotions in facial images.

Table 5.3.1 shows hyperparameters for the trained CNN network. The learning rate regulated the update of the weight at the end of each batch. Several epochs of the iterations of the entire training dataset were shown to the network during training. Batch size was the number of patterns shown in the network before the weights were updated. Activation functions allowed the model to learn nonlinear prediction boundaries. Adam was used as a replacement optimization algorithm for stochastic gradient descent for training deep learning models. The loss function categorical-crossentropy was employed to quantify deep learning model errors, typically in single-label, multi-class classification problems.

Table 5.3. 1: Hyper parameters for trained CNN network

Hyperparameters	Values
Batch size	128
No. of classes	7
Optimizer	Adam
Learning rate	0.001
Epoch	50
Activation Function	Relu, softmax
Loss Function	Categorical-crossentropy

	precision	recall	f1-score	support
Angry	0.56	0.63	0.59	467
Disgust	0.75	0.54	0.63	56
Fear	0.57	0.39	0.46	496
Happy	0.87	0.84	0.86	895
Sad	0.62	0.49	0.54	653
Surprise	0.75	0.83	0.79	415
Neutral	0.52	0.73	0.61	607
accuracy			0.66	3589
macro avg	0.66	0.63	0.64	3589
weighted avg	0.67	0.66	0.66	3589

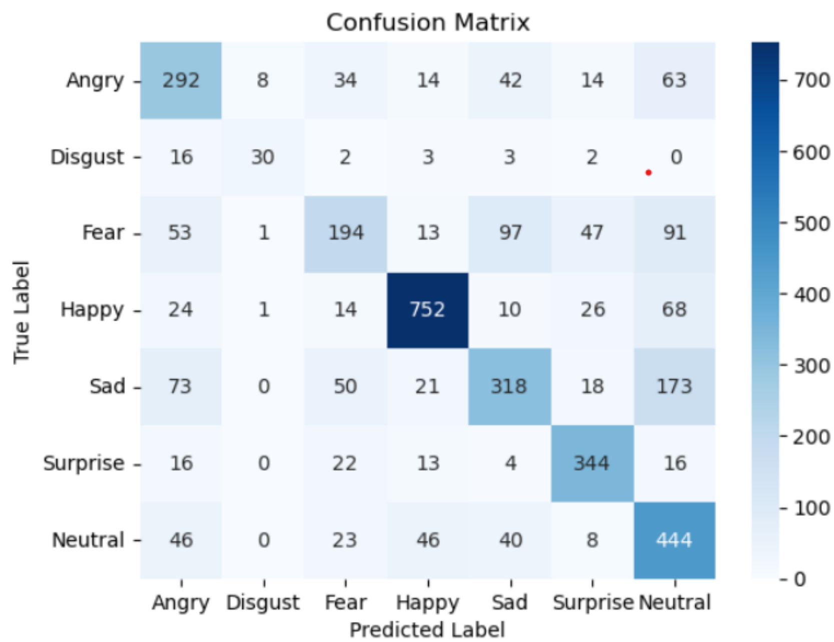

Figure 5.3 1: Confusion Matrix for the model

Upon further research, it was found that FER2013 had "human-level accuracy only at 65±5%" which placed the model close to human accuracy. It also performed closely to other models, with one from Stanford University only achieving an accuracy of 66.67% on the same dataset. Another study from Stanford University stated that the highest accuracy ever achieved on FER-2013 by a published model was 75.2% [13].

Recommendation System: The recommendation system was able to provide personalized song recommendations based on the detected emotion of the user. This was achieved by mapping the detected emotions to a set of predefined songs that correspond to those emotions.

User Experience: The user interface of the music player was designed to be user-friendly and easy to navigate. Users were able to easily login and signup, play songs, search songs, add songs to playlists and favorites, and use the camera to take a snapshot of their face. The facial emotion recognition feature was also well-received by users.

Limitations: The main limitation of the system was the accuracy of the emotion recognition model, which may not always detect emotions accurately. In addition, the recommendation system was limited to a predefined set of songs, which may not cover all genres and moods of music.

CHAPTER 6: CONCLUSION AND FUTURE RECOMMENDATIONS

6.1. Conclusion

The music player with facial emotion recognition for music recommendation was successfully developed using Django framework, OpenCV library for image processing, Keras framework for deep learning, and Streamlit framework for web application development. The system provided an interactive and personalized music experience for users based on their current emotional state. Users were able to view all songs, search for songs, create and add songs to playlist, and add songs to favorites. The facial emotion recognition technology added an innovative feature to the music player, allowing users to receive music recommendations based on their emotional state. Overall, the project achieved its objective of providing a user-friendly music player with advanced features, making the music listening experience more enjoyable for users.

6.2. Future Recommendations

This system, although completely functioning, does have scope for improvement in the future. One possible recommendation is to integrate more advanced emotion detection models to improve the accuracy of emotion detection. Additionally, integrating social media platforms such as Facebook or Twitter to enable users to share their music preferences and playlists with their friends can also enhance the user experience. Finally, integrating machine learning algorithms to learn user preferences and adapt to the user's changing music preferences over time can provide a more personalized music experience for users.

Overall, the music player with facial emotion recognition for music recommendation project has great potential for further improvements and enhancements. By integrating more advanced technology and features, the music player can provide a more personalized and interactive music experience for users.

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APPENDIX

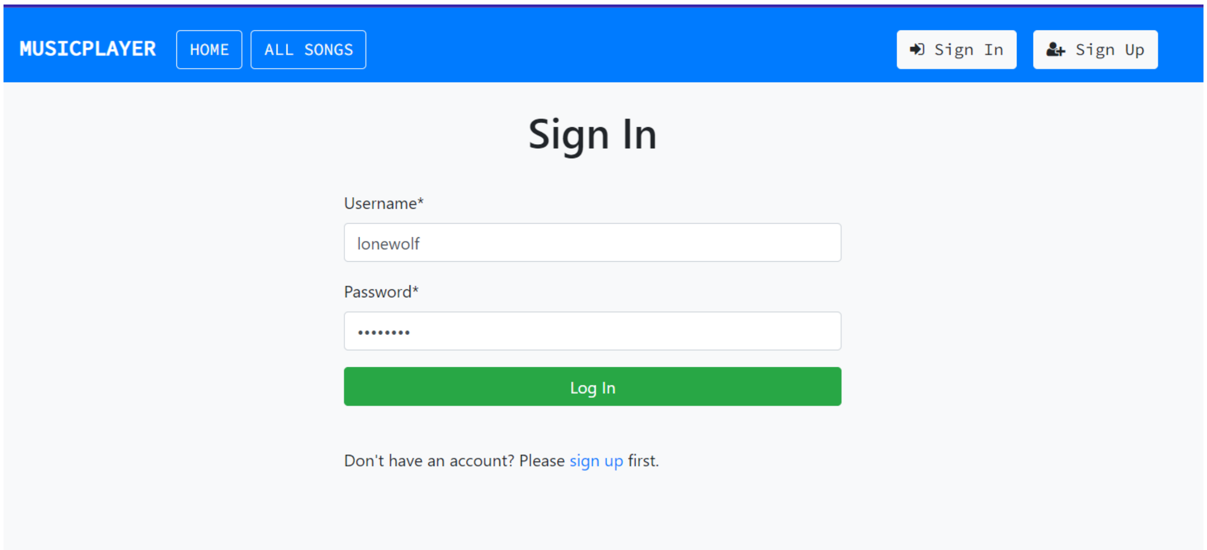

Figure i: Sign in page

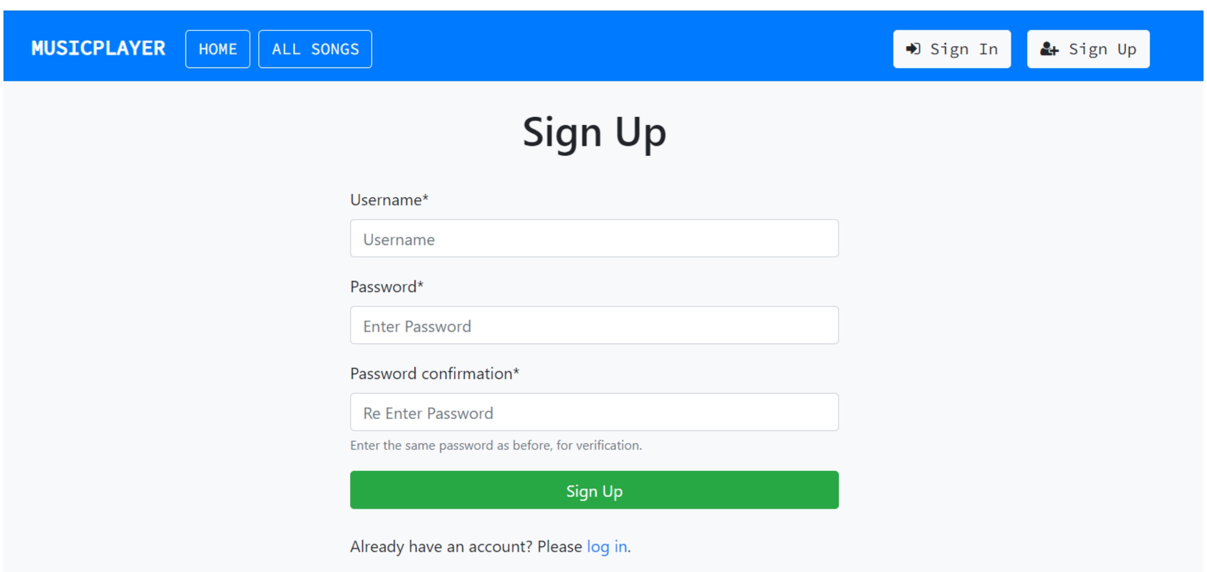

Figure ii: Sign up page

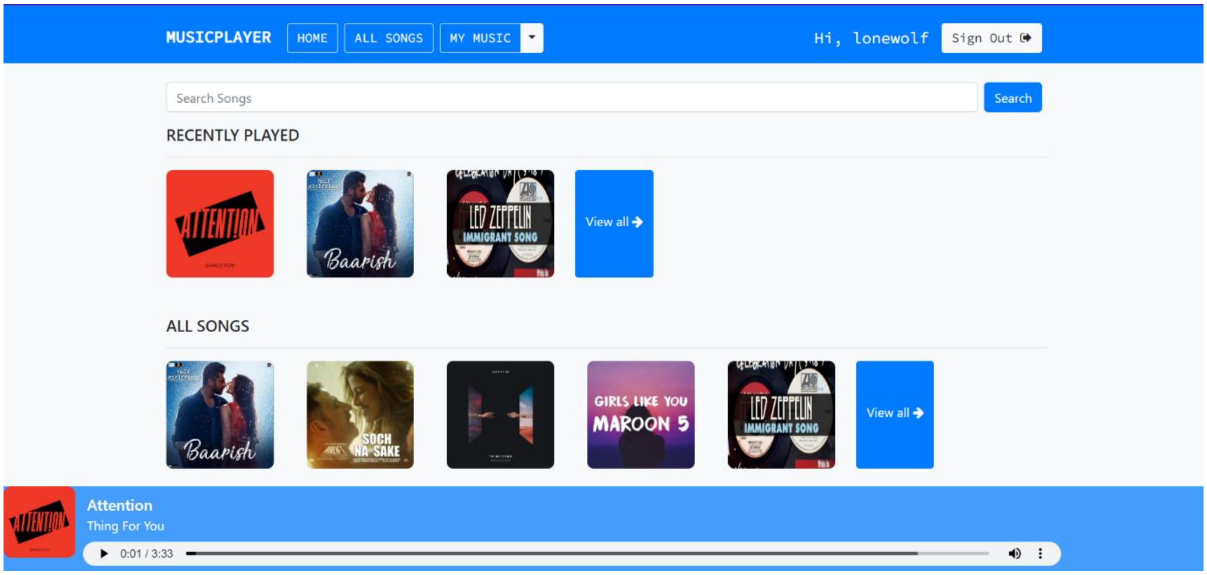

Figure iii: Index page

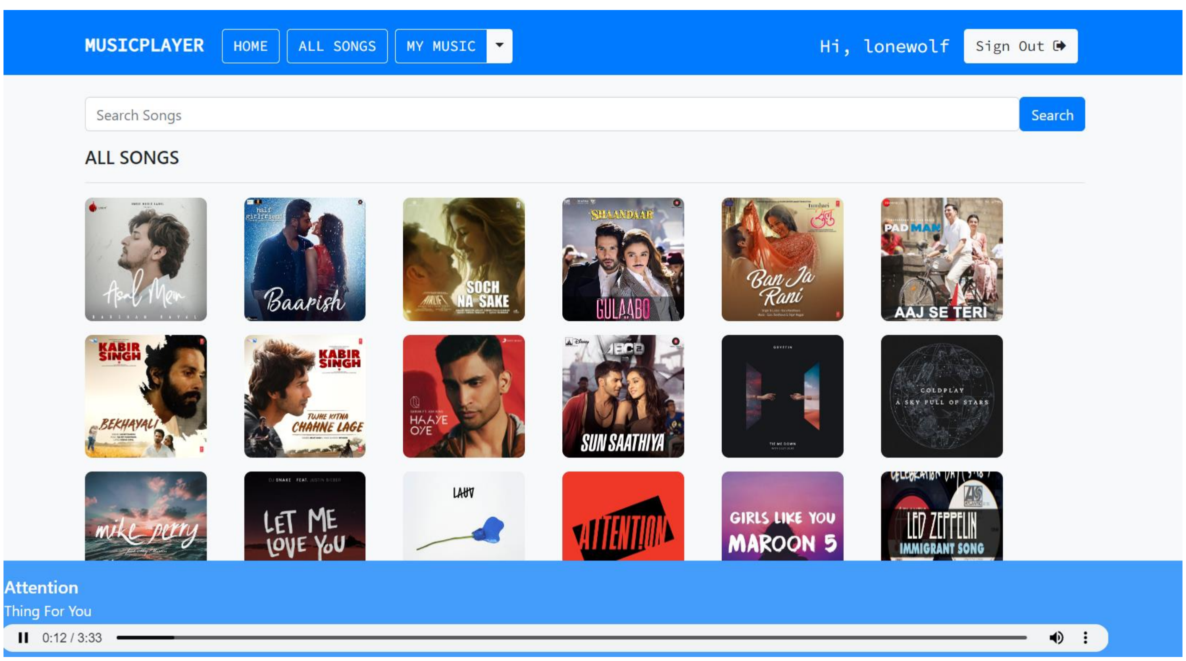

Figure iv: All songs page

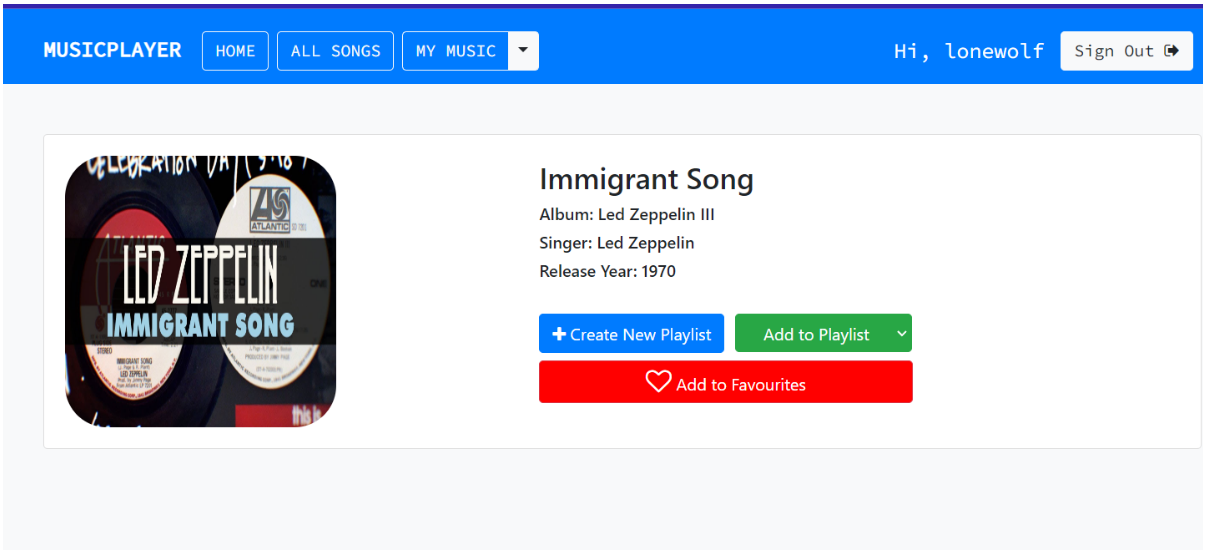

Figure v: Song Details page

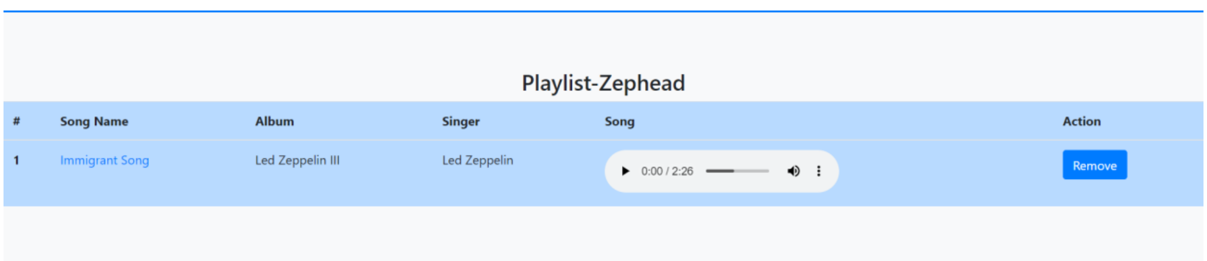

Figure vi: Songs in playlist "Zephead"

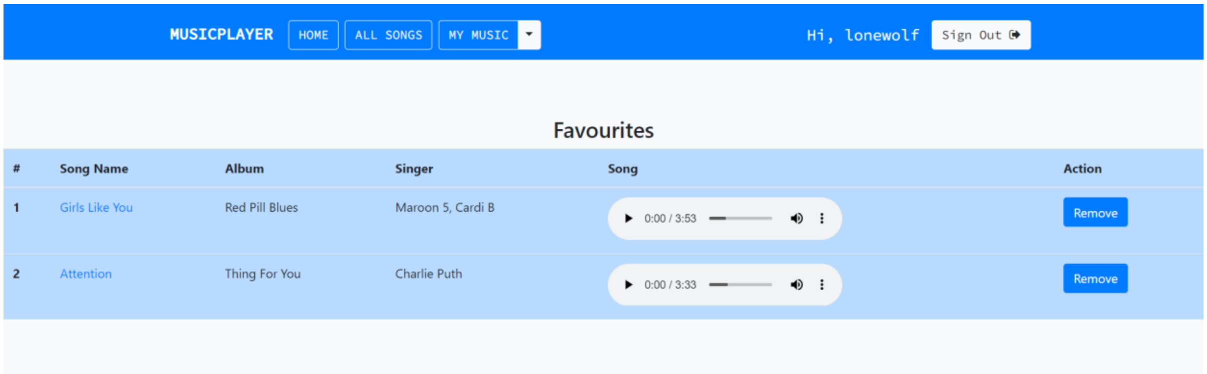

Figure vii: Favorite songs page

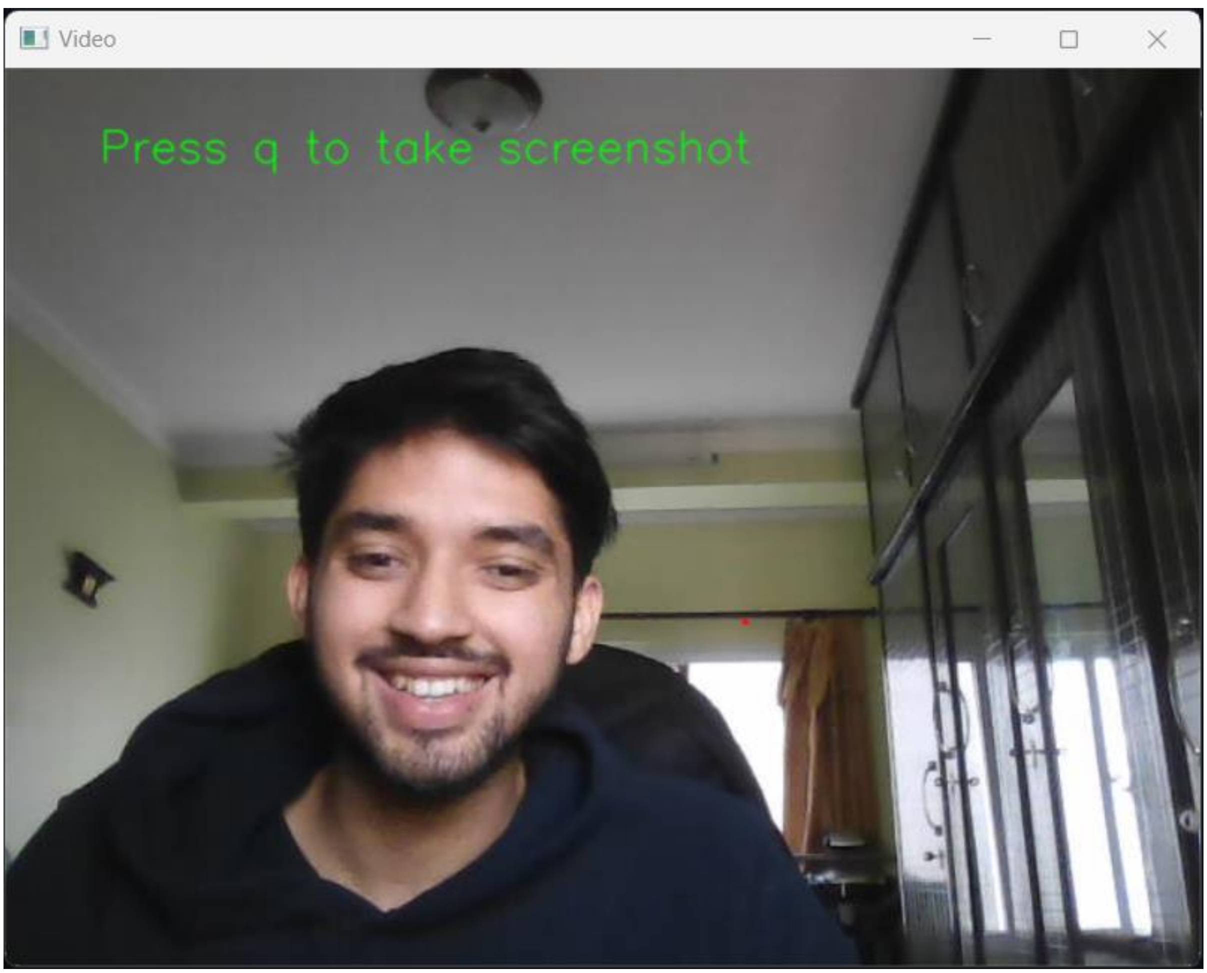

Figure viii: Web Camera to take snapshot

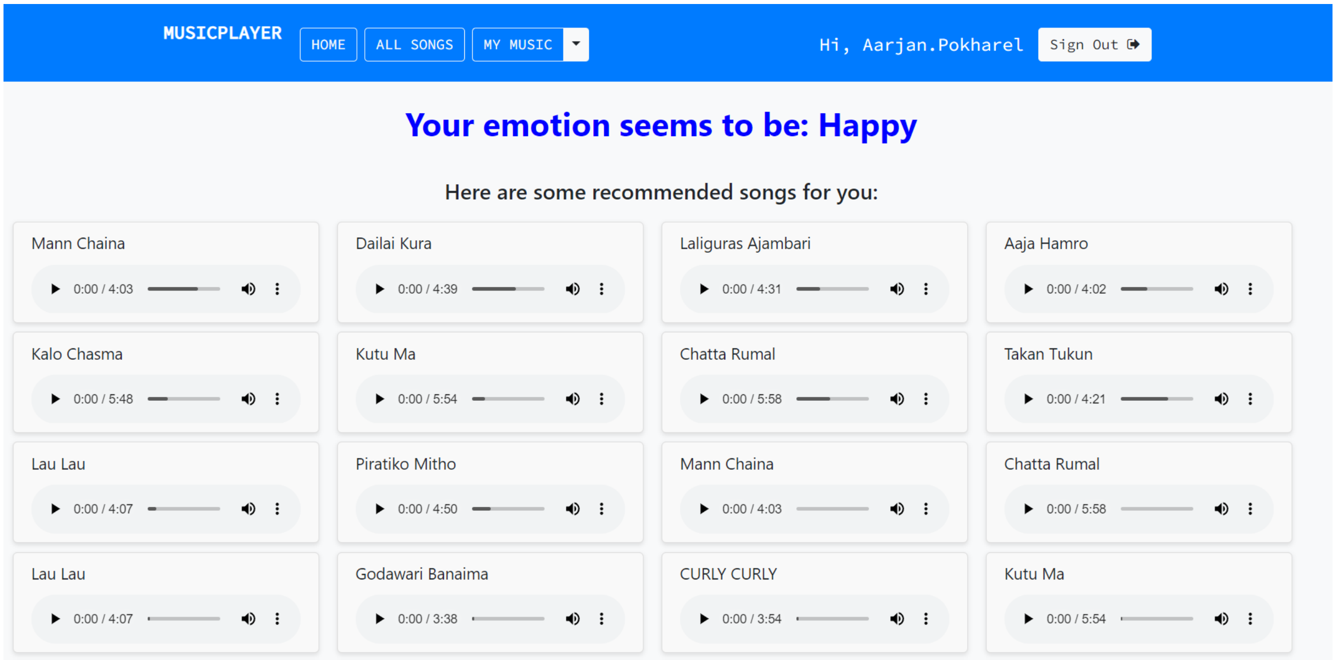

Figure ix: Detected emotion and list of recommended songs