A report submitted in partial fulfilment of the requirements for the degree of Bachelor of Science (BSc) in

COMPUTER SCIENCE

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FACIAL EMOTION RECOGNITION FOR MUSIC RECOMMENDATION SYSTEM

By

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DECLARATION

I, Yie Nian Chu confirm that the work presented in this report is my own. Where information has been derived from other sources, I confirm that this has been indicated in the report.

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Yie Nian Chu

ABSTRACT

This project builds a facial emotion recognition model, and integrates it to a web application that provide music therapy service. The application uses machine learning and the PERN stack (PostgreSQL, Express, React and Node.js) to identify user's emotional states from their facial expressions, recommend and generate music playlist that aligns with their current emotion. The aim is to make music therapy more widely available and a useful tool for assistance outside of traditional settings. The machine learning model was trained with FER2013 and CK+ dataset to ensure it has the capability of emotion detection. Then it is enhanced with transfer learning technique to ensure broad demographic applicability and accuracy in emotion detection. The application's capability to correctly identify emotions and provide music recommendation was confirmed by the initial testing. It also brought attention to difficulties with expanding the application to support more different demographic users and integrating other music services. Future improvements will concentrate on expanding the scope of service integrations, and enhancing scalability and integrating user feedback to improve the recommendation algorithms. This report outlines the project's scope, from conception to testing and assessment, and discusses the potential future developments that could improve the application's contribution on mental health support. This project serves as an example of how technology can link in mental healthcare by providing a scalable, personalized solution that meet individual emotional requirements.

ACKNOWLEDGEMENTS

I have many people to thank for their invaluable advice and assistance which were crucial to the accomplishment of this project

First and foremost, I would like to express my sincere thanks to my supervisor, Mr. Craig Duffy, whose consistent support, insightful feedback, and guidance have been invaluable to me during this project. His thought not only influenced this work, but also aided in my intellectual growth.

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I am equally thankful to Ms. Kai Xin Phua for sharing her expertise in music classification. Her knowledge in music related field was essential in aligning the music recommendation system with the emotional analysis to enhance user experience.

My appreciation goes out to Ms. Megan Theng Ong, whose artistic abilities were instrumental in creating a visually striking and significant logo for the application. Her artistic contribution has greatly enhanced the project's UI and aesthetics.

Last but not least, I want to express my gratitude for my family's unwavering support, whose encouragement and belief in my capabilities have constantly motivated me during this journey.

ACRONYMS

AI Artificial Intelligence

AMTA American Music Therapy Association

CNNs Convolutional Neural Networks

Conv2D Convolutional Layer

EEG Electroencephalogram

EMG Electromyography

EOG Electrooculogram

ERD Entity-Relationship Diagram

FER Facial Emotion Recognition

FK Foreign Key

GD Gradient Descent

GDPR General Data Protection Regulation

JS JavaScript

k-NN K-Nearest Neighbors

LR Linear Regression

ML Machine Learning

MLP Multi-Layer Perceptron

MSE Mean Squared Error

NAMT National Association for Music Therapy

PK Primary Key

PTSD Post-traumatic Stress Disorder

RF Random Forest

SVM Support Vector Machine

TBI Traumatic Brain Injury

UI User Interface

WCAG Web Content Accessibility Guidelines

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1. INTRODUCTION

1.1. BACKGROUND AND SIGNIFICANCE

This project explores the relationship between technology and mental health by developing a web application that utilizes Facial Emotion Recognition (FER) to personalize music therapy sessions. The application tries to identify emotional signs from facial expressions by combining cognitive science and Machine Learning (ML), and it suggests music that might raise user's mood. This innovative approach might help to solve the practical problem of improving emotional well-being in areas where traditional therapy may not be available.

1.2. PROBLEM STATEMENT

The idea of this project lies in its potential to provide immediate, personalized therapeutic support. Although the benefits of music therapy for mental health are well known, but integrating it wil real-time emotion recognition technology provides an advanced approach for delivering presonalized care that changes depending on the user's emotional state.

1.3. OBJECTIVES

The main objectives of the project were to:

- Develop a FER system.
- Integrate this system with music therapy principles.
- Create a user-friendly interface that allows interaction and enhances user engagement.

1.4. LITERATURE REVIEW FINDINGS SUMMARY

From the literature review, many studies have been conducted separately on emotion detection and music therapy, not much have tried to combine the two for use in real-time applications. This gap highlights the project's imagination and its potential value to the fields of psychology and technology.

1.5. APPROACH AND METHODOLOGY

The approaches to solve this problem:

- Designing and training machine learning models to accurately recognize human emotions from facial expressions.
- Developing a system that uses emotional signs to generate playlist that corresponds to user's emotional state.
- Implementing the system within a web application to ensure accessibility and ease of use.

1.6. PROJECT OUTCOMES

The result of the project is a fully functional web application that identifies emotions and generate playlists based on user's emotional state. The system effectively integrates a music recommendation interface with an advanced ML algorithms for emotion recognition. While the application has went through testing to ensure its reliability and efficacy, but it has not yet been refined based on user feedback, which is a possible area for future iterations.

1.7. REPORT STRUCTURE

The report is structured as follow:

- **Chapter 2: Literature Review**: Provides an analysis of the studies on music therapy, emotion detection technology, and their applications in mental health.
- **Chapter 3: Requirements**: Details the functional and non-functional requirements that guided the development of the project.

- **Chapter 4: Methodology**: Discusses multiple methodologies and justify the reason of selecting the specific methodologies which employed in developing the FER model and the music recommendation system.
- **Chapter 5: Design**: Describes the system design such as the architecture, user interface of the web application, the model architecture such as the layers.
- **Chapter 6: Implementation**: Explain the steps taken in the implementation of building the ML model and web application.
- **Chapter 7: Project Evaluation**: Evaluates the trained models and the developed application, discusses limitations and potential improvements.
- **Chapter 8: Conclusion and Future Work**: Concludes the report with a summary of the project outcomes, and outlines possible future improvements to enhance the system's capabilities.

2. LITERATURE REVIEW

2.1. INTRODUCTION

As the field of therapeutic interventions has developed, music therapy has become a potent tool for treating a variety of psychological and emotional illnesses (Association, 2005). It is acknowledged as a clinical and evidence-based practice. Without demanding musical proficiency from participants, it strives to improve mental, emotional, physical, and cognitive abilities in a variety of contexts, including schools, mental health centers, hospitals, and nursing homes (Clinic, 2020). Scientific research suggest that novel activities such as vibroacoustic treatment, improvisation, singing popular songs, and composing can support personal growth and healing (Craig, 2019). As a result, music therapy is a very flexible and successful therapeutic approach. Its effectiveness stems from its ability to recognize and address each individual's emotional condition. This idea aligns with the potential of face expression recognition technologies.

FER technology bridges the gap between emotional understanding and technological innovation. It is a sophisticated version of facial recognition that uses Artificial Intelligence (AI) and ML to identify human emotions through facial expressions. Based on feature analysis, FER could identify emotions like happiness, sadness, anger and neutral (Huang et al., 2023). The ability to sense and react to individual emotional states makes it valuable in the healthcare sector, where it has the potential to transform patient care through monitoring emotional health, diagnosing illnesses and enabling more personalized treatment plans. Particularly in therapy, it provides a non-invasive way to gauge patient's emotional states which allows therapists to more precisely customize their approaches (Zharovskikh, 2020).

Building upon these foundational technologies, music recommendation systems represent another pivotal element in personalizing therapy sessions. These systems make music recommendations based on a number of variables, including user preferences, behavior, psychographic traits, and demographics. Additionally, it will categorise listeners into several groups such as savants, enthusiasts, causals and in differents, for more efficient tailoring in order to improve listening experiences (Song et al., 2012). Since music has a enormous effect on emotional and psychological health, these systems' accuracy becomes especially important in therapy (Schedl et al., 2021). Innovatively, AI-driven models have pushed the boundaries further by detecting patient's real-time emotions, and offering recommendations that not only match but also influence mood and psychological states (Babu et al., 2023). Technology plays a vital role in augmenting music's therapeutic potential, as evidenced by the introduction of AI into music recommendation systems, which bring in a new era of tailored therapy encounters.

2.2. MUSIC THERAPY

The history and theoretical foundations of music therapy track back thousands of years, but the field's practical development really took off in the 1940s. Following World War II, the US War Department published Technical Bulletin 187 in 1954 that detailed a program for rehabilitating service members through music (Barbara, 2014). With their emphasis on the use of music in a range of therapeutic settings, this curriculum established a standard for the official acknowledgement and advancement of music therapy as a profession. The National Association for Music Therapy (NAMT) was founded in 1950, which further cemented the path for the formal recognition and advancement of music therapy as a profession (Barbara, 2014). During this crucial time, the field of music therapy had substantial growth and advocacy, which resulted in the development of standards for training and application. The field then united to establish the American Music Therapy Association (AMTA) in 1998 (Barbara, 2014).

The theoretical foundations of music therapy are as varied and deep as its history, encompassing a wide range of psychological theories and studies such as developmental psychology, psychoanalysis, and John Bowlby's attached theory (Ackerman, 2018). These theories shows how music might be used therapeutically to promote safe attachments, improve social and emotional growth, and assist dynamic, patient-centered

therapy. The improvisational methods developed by Kenneth Bruscia place an additional emphasis on creativity and spontaneity, which facilitate the use of music to convey feelings and build interpersonal bonds (Bruscia, 1988).

Furthermore, empirical studies and neuroscientific discoveries that demonstate the effects of music on emotional regulation, stress response, and neuroplasticity reinforce the foundation of music therapy (Hillecke, 2005). According to this research, music therapy can benefit a wide range of people, including trauma survivors and infants. It also highlights the benefits of music therapy for mental health and cognitive development.

Music therapy's adaptability and relevance are highlighted by the inclusion of early educational programs and advocacy in addition to focused interventions for military groups (Barbara, 2014). According to Gooding and Langston (2019), music therapy has proven to have a deep ability to adapt to changing healthcare needs and societal demands as evidenced by its supportive role in post-war recovery from conditions such as Post-traumatic Stress Disorder (PTSD) and Traumatic Brain Injury (TBI) (Gooding and Langston, 2019), and its acceptance as a clinical profession(Garrison, 2021). With a strong foundation in evidence-based treatment and a profound comprehension of music's therapeutic potential, music therapy has come a long way from mystical conceptions to a scientifically validated practice.

2.2.1. Music and Emotion

Since ancient times, people have been fascinated by the paradoxical connection that exists between music and emotion. Even though music is an abstract art form that appears to be removed from everyday life, it has a profound potential to evoke strong emotional responses. This ability of music to trigger strong emotions is also demonstrated in other social circumstances, such as advertising. This encounter is further enhanced by the relationship that exists between music and our individual life experiences. Emotions, influenced by these encounters, provide our perception and thought processes a personalized meaning that connects the abstract quality of music to the concrete events of our everyday life. This complex tapestry that highlights the profound influence of music on our emotional environment is created by the blending of music, emotion, and human experience (Juslin and Sloboda, 2013).

Numerous musical elements that have been thoroughly explored are combined to convey emotions through music. Pace, mode, harmony, interval, rhythm, sound level, timbre, timing, articulation, accents, tone attacks and decays, and vibrato are some of these characteristics. Emotion in music is expressed through compositional elements as well as performance elements. Still, it's not an easy task to express feelings through music. Certain musical elements can be employed to convey a range of moods, showing that certain elements are not always reliable predictors of a certain emotion. The Lens Model (Juslin and Sloboda, 2013), which characterizes emotional expression in music as involving probabilistic and partially redundant auditory cues, sheds more light on this complexity. Listeners combine several cues for successful emotion recognition, and the redundancy of cues allows for a high level of emotion recognition through different combinations, offering room for creativity and personal expression (Pereira et al., 2011).

2.3. ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

2.3.1. Artificial Intelligence

AI is a broad field that includes using technology to build machines and computers that can replicate cognitive abilities connected to human intellect. These abilities include making recommendations, language understanding, data processing, and visual perception. AI should be viewed as a group of technologies incorporated into systems rather than as a stand-alone system that can understand, learn, and respond to complex problems (Cloud, 2023).

2.3.2. Machine Learning

ML is a branch of AI focused on enabling machines and systems to learn and enhance their performance through experience. Instead of relying on explicit programming, machine learning employs algorithms to analyze vast datasets, derive insights, and subsequently make informed decisions. These algorithms continually improve their performance as they are exposed to more data. The outcomes of this learning process are the machine learning models, which become more proficient with increased exposure to data (Google, 2021).

2.3.3. Machine Learning Algorithms

2.3.3.1. Linear Regression

Linear Regression (LR) is a supervised learning algorithm used to model the relationship between a dependent variable (target) and one or more independent variables (features). The fundamental assumption of LR is that there exists a linear relationship between the input variables and output (IBM, 2022*a*).

$$y = mx + b \tag{2.1}$$

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon \tag{2.2}$$

A LR model can be represented by the equation 2.2 where Y represented the dependent variable. β_0 is the y-intercept, $\beta_1, \beta_2, \cdots, \beta_3$ are the coefficients and the ϵ is an error term, representing the unobserved factors that affect Y but are not accounted for by the model. The logic of it is same as Linear Equation (See Equation 2.1) where using the gradient of the line (m), the value of x and the y-intercept (b) to get the value of y, which is what we are trying to predict.

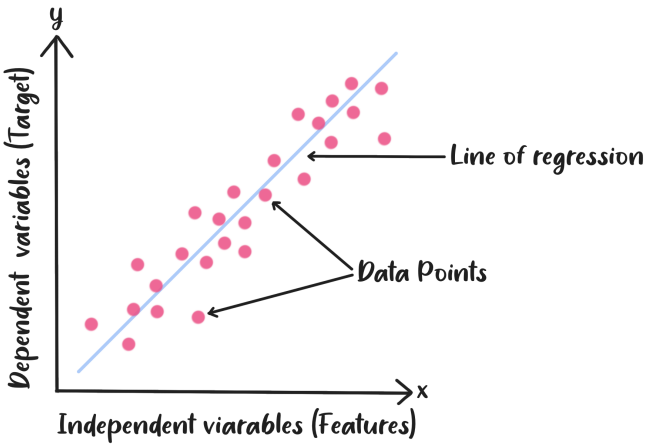


Figure 2.1: Linear Regression

While using LR, the main objective is to find the values of $\beta_0, \beta_1, ..., \beta_n$ that minimize the error between the predicted value ($\hat{Y}$) and the actual value (Y) in the training data.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \tag{2.3}$$

Therefore, Mean Squared Error (MSE), a cost function to measures the average squared difference between $\hat{Y}$ and Y, is introduced to quantify the goodness of fit of the model to the training data. If the current result is not optimized, Gradient Descent (GD), an optimization algorithm, will be used to adjust the coefficients, $\beta_0, \beta_1, ..., \beta_2$, towards the direction that minimizes the MSE until it reach the convergence (See Figure 2.2).

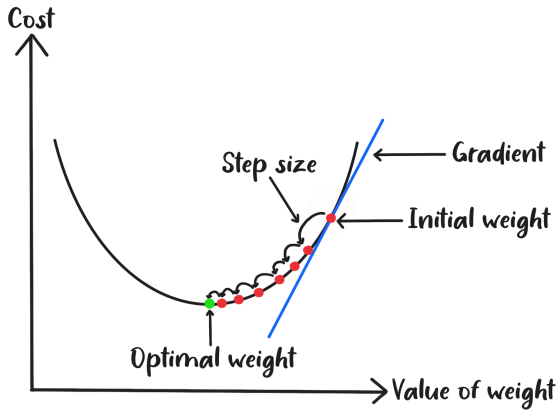


Figure 2.2: Gradient Descent

2.3.3.2. Support Vector Machine

Support Vector Machine (SVM) is a supervised ML algorithm where we used for classification, regression and outliers detection. The main goal of it is to find the hyperplane that best separates the data into different classes based on statistical approaches (Géron, 2017).

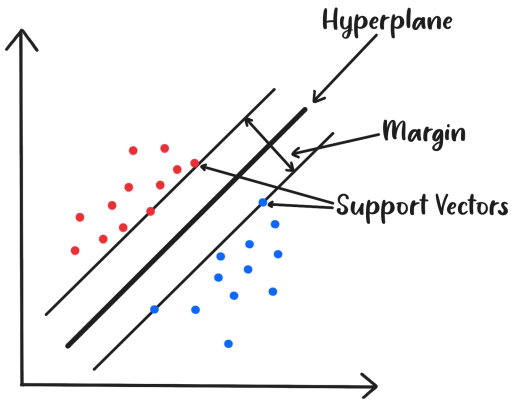


Figure 2.3: Support Vector Machine

While using SVM, the greater the margin, the better the result would be as it has better generalization to new or unseen data. There are two types of SVM for classification, which are Linear SVM and Non-linear SVM. A linear SVM finds the optimal hyperplane that maximizes the margin between classes for linearly separable data as shown in Figure 2.3.

$$f(x) = \text{sign}(\mathbf{w} \cdot \mathbf{x} + b) \tag{2.4}$$

The decision function of linear SVM (See Equation 2.4) is used to defines the ability to classify data points into different classes. When the result is greater than or equal to zero, the prediction would be positive. If $f(x)$ is less than zero, the decision function predicts the negative class.

$$f(x) = \text{sign}(\sum_{i=1}^{n} \alpha_i y_i K(x, x_i) + b) \tag{2.5}$$

$$K(x, x_i) = (x \cdot x_i + c)^d \tag{2.6}$$

$$K(x, x_i) = \text{exp}(-\frac{\| x - x_i \|^2}{2\sigma^2}) \tag{2.7}$$

$$K(x, x_i) = \text{tanh}(\alpha x \cdot x_i + c) \tag{2.8}$$

For non-linearly separable data, SVM uses kernel functions such as polynomial, sigmoid and radial basis function (RBF), to map the data into a higher-dimensional space where hyperplane can separate the classes. The equation 2.5 is the decision function of non-linear SVM. The kernel function, denoted by $K(x, x_i)$ in the equation, would be replaced by equation 2.6 if a polynomial kernel were used. Similar with the other kernels, if the RBF kernel is employed, it would be exchanged with equation 2.7, and for sigmoid kernel, it would be replaced with equation 2.8.

2.3.3.3. Random Forest

Random Forest (RF) is an ensemble learning algorithm that belongs to the family of decision tree-based methods. A group of decision trees that have been trained on various dataset subsets make up the forest of RF, and the final result is derived from averaging the predictions of each individual tree (IBM, 2023*b*).

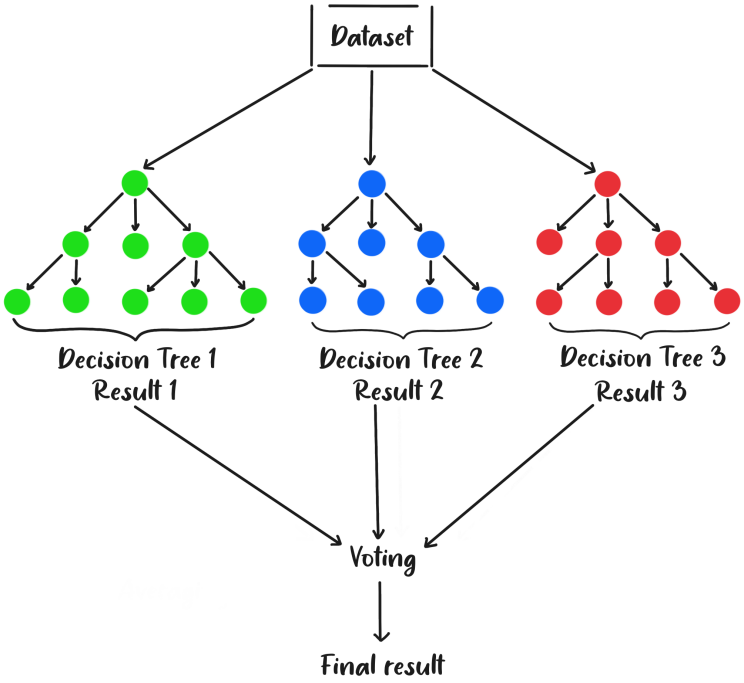


Figure 2.4: Random Forest

As shown in Figure 2.4, RF builds multiple Decision Trees and combines them to get a more accurate and stable prediction than any individual model. This process is called bagging which is one of a type of ensemble learning. In the process, the entire dataset is separated into subsets and each decision tree is trained individually on a subset that is selected at random. This adds variety and unpredictability to the trees. The training process will then generate results for each model, and the final output is determined by the "votes" for a class from each tree. The class with the majority of votes is chosen as the final prediction.

2.3.3.4. K-Nearest Neighbors

K-Nearest Neighbors (k-NN) is a intuitive supervised machine learning method used for both classification and regression tasks. The main idea of k-NN is to predict the label of new data point based on its k-nearest data points in the feature space (IBM, 2023*c*).

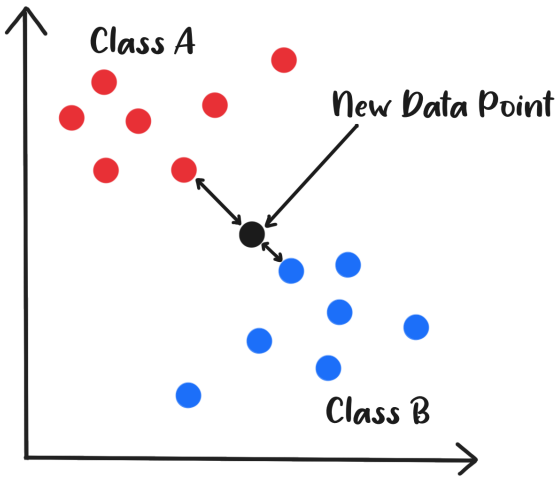


Figure 2.5: K-Nearest Neighbors

k-NN uses distance metric (See Equation 2.9) to calculate how similar two data points are to one another. k-NN finds the k training data points that, according to the selected distance metric, are closest to a given data point. In classification tasks, the majority class among a new data point's k-nearest neighbors predicts the class that the data point will fall into.

$$d(P,Q) = \sqrt{\sum_{i=1}^{n}(p_i - q_i)^2} \tag{2.9}$$

$$\hat{Y} = \text{argmax}_y \left(\sum_{i=1}^{k} I(y_i = y) \right) \tag{2.10}$$

The key hyperparameter of k-NN is the value of k (See Equation 2.10), representing the number of nearest neighbors to consider. The choice of k can significantly impact the performance of the algorithm, and it is often selected through cross-validation.

2.3.3.5. Neural Networks

2.3.3.5.1 Multi-Layer Perceptron

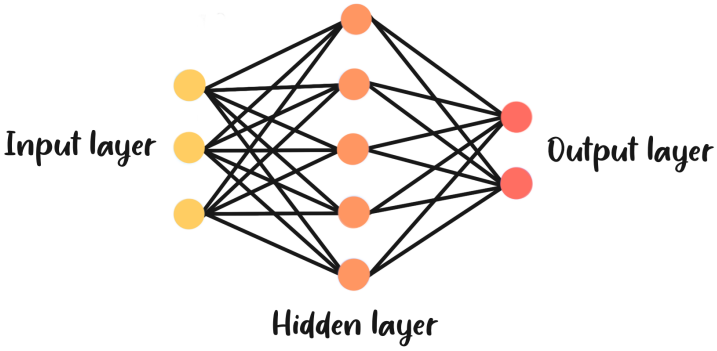


Figure 2.6: Multi-Layer Perceptron

An input layer, one or more hidden layers, and an output layer are the minimum number of nodes that make up a Multi-Layer Perceptron (MLP) feedforward artificial neural network type (See Figure 2.6). All nodes in these layers, aside from those in the input layer, are linked using a specific weight and employ a nonlinear activation function. Because of its nonlinearity, the network may learn and carry out more complicated tasks as well as represent intricate connections between the input and output. A MLP model is trained by comparing its output to the expected output and propagating errors back through the network to alter the weights. This process is known as backpropagation (Haykin et al., 2014).

2.3.3.5.2 Convolutional Neural Networks

Convolutional Neural Networks (CNNs) are a family of deep learning algorithms that are mostly utilized for processing input that has a grid structure, like images (Yamashita et al., 2018).

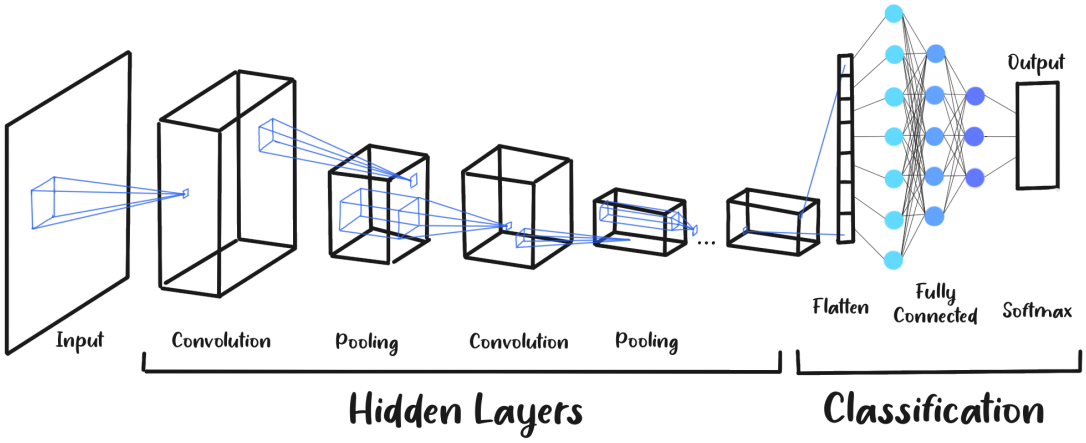


Figure 2.7: Convolutional Neural Networks

CNNs are designed to adaptively learn spatial hierarchies of features from the data. This learning process includes convolution layers, pooling layers, flatten layer, and fully connected layers. By applying filters, also known as kernels, to the input, these layers carry out the convolution process and produce feature maps. Local elements like textures and edges are captured throughout this procedure. Pooling layers, which come after convolutional layers, help to reduce the number of parameters and computation in the network by reducing the spatial dimensions (width and height) of the input volume.

The features from the input image are retrieved by the convolutional and pooling layers, and the next stage is to categorize the features which is done in flatten layer. The feature maps are converted into a one-dimensional vector in the flatten layer, which is necessary for fully connected layers. The flattened vector is then fed into the fully connected layers[1] for the classification task. These fully connected layers divide the image into discrete groups based on the high-level characteristics found in the preceding levels.

The last layer of layers in the network architecture play the crucial job of generating the output. The output layer typically uses a softmax activation function in multi-class classification settings to translate the network's raw output into probabilities given to each class. The output node with the highest probability is then chosen to determine the anticipated class.

[1]Fully connected layer resemble the standard neural network layers with fully connected nodes.

2.4. FACIAL EMOTION RECOGNITION

Human emotions can be inferred from facial expressions. Deciphering these signs of emotion has become a popular research topic in the fields of Human Computer Interaction and Psychology (Konstantina et al., 2021). The development of FER technology has been significantly aided by technological advancements, particularly with the introduction of ML and Pattern Recognition.

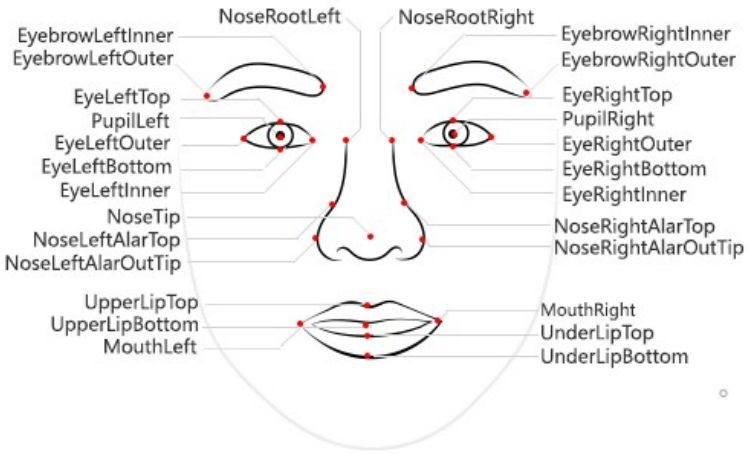


Figure 2.8: Facial Landmarks
(Farley, 2023)

FER is a broad field that intersects with Computer Science, AI, Psychology and other fields. It involves analyzing a person's facial expressions in still images and videos in order to determine their emotional state. A three-step approach is used in the methodology: face detection, facial expression identification, and categorization of the expression into a certain emotional state. Facial landmark (See Figure 2.8) detection and analysis of changes in their positions are key components of this complex process. FER attempts to offer insights into people's emotional experiences by identifying muscular contractions linked to various emotions from visual clues found in facial expressions.

Emotions	neutral	joy	surprise	anger	sadness	fear	disgust
neutral	881	125	2	155	340	48	101
joy	106	922	7	238	115	1	154
surprise	13	1	1135	8	8	390	13
anger	130	151	6	862	81	2	120
sadness	229	130	33	101	823	104	88
fear	41	0	220	5	88	871	4
disgust	76	147	73	107	21	60	996

(a) Confusion Matrix for k-NN Classifier

Emotions	neutral	joy	surprise	anger	sadness	fear	disgust
neutral	1160	75	9	29	644	61	41
joy	81	1178	0	57	141	0	129
surprise	3	0	1153	4	2	426	10
anger	58	137	0	1346	44	0	88
sadness	122	13	5	0	561	75	2
fear	8	1	308	1	74	910	2
disgust	44	72	1	39	10	4	1204

(b) Consfusion Matrix for MLP Classifier

(Tarnowski et al., 2017)

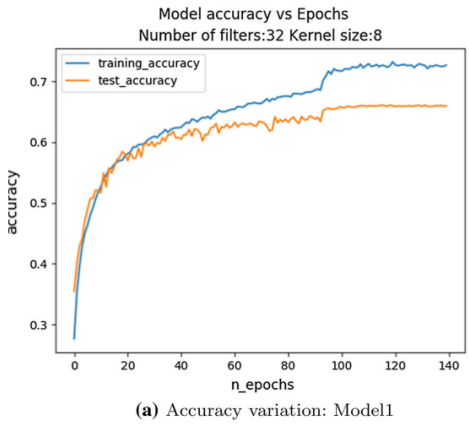
As stated by Tarnowski et al. (2017), the creative feature extraction from facial expressions using coefficients that detailed aspects of emotional states is what makes the research successful. They distinguished between seven different emotional states: happiness, sorrow, surprise, wrath, fear, and contempt, as well as the more subdued displays of neutrality. For featre computation, they employed a three-dimensional facial model as an alternative to conventional two-dimensional approaches. This enables them to collect more detailed and subtle data, which may improve the accuracy of identifying emotions. On top of that, they used the MLP neural network and the k-NN classifier to classify each emotional state. According to their research and comparative analysis, the MLP is more accurate than the k-NN in classifying emotional states, with a 73% classification accuracy compare to a 63% accuracy for k-NN (Tarnowski et al., 2017).

Mellouk et al. (2020) showed in their study that FER may be achieved with great accuracy and effectiveness by utilizing deep learning techniques. They provided a thorough analysis of multiple FER databases, emphasizing their diversity in terms of picture, video content, lightning circumstances, and demographic variances, all of which are important determinants of FER performance, in order to guarantee the credibly of the results.

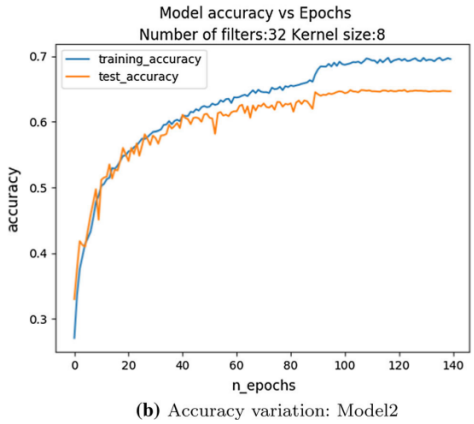
Traditional facial recognition techniques included manually defining and extracting features from facial photos, a procedure that was frequently less flexible and efficient. Examples of these techniques include Local Binary Patterns (LBP), Facial Action Coding System (FACS), Local Directional Patterns (LDA), and Gabor wavelet. CNNs and LSTMs can automatically extract and learn complex patterns from facial data, according to Mellouk et al. (2020), which will improve the reliability and accuracy of emotion recognition. Furthermore, the difficulties that traditional approaches faced, such as variances in facial characteristics due to diverse demographics, occlusions, and data diversity,

are resolved with the use of deep learning, increasing their versatility and effectiveness. The study also examines preprocessing methods including image scaling, cropping, normalization, and data augmentation that are crucial for improving the accuracy of these deep learning models.

With the help of deep learning and the preprocessing techniques they found, the outcome demonstrates proficiency in accurately classifying the fundamental emotions, with some models reaching over 90% accuracy under specific circumstances (Mellouk and Handouzi, 2020). It indicates that as machines improve at deciphering human emotions, interactions between humans and machines may become more intuitive and natural.



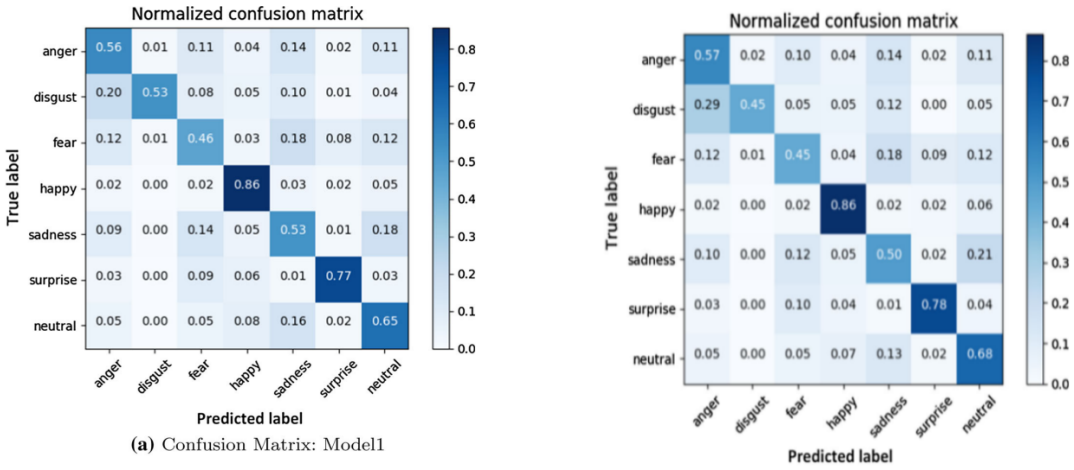
(a) Accuracy variation with 32 Filters and 8 kernel size for Model 1



(b) Accuracy variation with 32 Filters and 8 kernel size for Model 2

(Agrawal and Mittal, 2019)

Based on the findings of Agrawal et al. (2019)'s work, the kernel size and the number of filters significantly impact CNNs accuracy. Using the FER-2013 dataset as their primary emphasis, two CNN architectures is put forth after a thorough analysis of various kernel sizes and filter counts. To find the optimal set of parameters that could yield the best convergence and accuracy, Agrawal et al. (2019) ran tests with the combination of 6 different kernel sizes (2, 4, 8, ..., 64) and 8 different number of filters (2, 4, 8, ..., 256). They discovered that when network depth increased, a network with 32 filters and an 8 kernel size demonstrated a discernible gain in accuracy (See Figure 2.10a and Figure 2.10b).



(a) Confusion Matrix for Model 1

(b) Confusion Matrix for Model 2

(Agrawal and Mittal, 2019)

Even while Model 2 is simpler due to its constant kernel size, lack of dropout layers, and fully connected layers, it was nevertheless able to achieve an accuracy of 65% on the FER-2013 dataset, which is comparable to human performance (Agrawal and Mittal, 2019). Furthermore, in comparison with other emotions, the proposed models were able to categorize happiness and surprise with a higher degree of accuracy, which is consistent with people's challenges in picking out distinct emotions (See Figure 2.11a and Figure 2.11b).

Gestures	Recognition Accuracy
Neutral	99.00%
Smile	98.50%
Anger	98.50%
Scream	99.50%
Overall	98.88%

Figure 2.12: Linear Regression Classification Accuracies Table
(Naseem et al., 2010)

A pivotal study by Naseem et al. (2010) incorporates the analysis of facial expressions, recognizing them as crucial variations in appearance induced by internal emotions or social communications. In order to evaluate their LR Classification approach, they therefore took into account occlusion modes, brightness changes, and expressions such as scream, smile, rage, and neutral Notably, the LR Classification algorithm showed an excellent recognition accuracy for all facial expressions tested, averaging 98.88% in a 100D feature space (See Figure 2.12). For the screaming expression, the algorithm outperformed other accuracies by achieving an accuracy of 99.5% (See Figure 2.12).

This great accuracy demonstrates the reliability and efficacy of the LRC approach in handling a wide range of facial emotions.

	Facial Expression				Total
	Anger	*Happiness*	*Sadness*	*Surprise*	
Training (70%)	31	48	19	58	156
Testing (30%)	14	21	9	25	69
Total	45	69	28	83	225
Success	79%	95%	89%	96%	90%

Figure 2.13: Random Forest Classification Accuracy
(Munasinghe, 2018)

According to Munasinghe (2018), RF Classifier are capable of handling facial expression variability well and without overfitting. Also, the researcher asserts that facial landmarks (See Figure 2.8) provide an accurate feature extraction capability that capture subtle changes in facial emotions. A facial feature vector obtained from these landmarks and normalized to reduce variance in face size is used to discern emotions with a RF Classifier. With the aid of feature vector, the RF Classifier achieved an average success rate of 90% in classifying four different emotions: anger, happiness, sadness, and surprise (See Figure 2.13).

	happy	surprise	fear	angry	sad	disguise
h	144	7	5	10	11	23
s	21	147	6	10	1	15
f	1	5	143	8	19	24
a	11	2	21	132	26	8
s	6	14	18	27	119	16
d	12	13	24	21	6	124

Figure 2.14: Support Vector Machine Accuracy
(Xia, 2014)

Li Xia (2014) presented a unique method of facial emotion detection that employs multi-classification SVM. The study proposes a two-on-two classification method which is an innovative approach to overcome the limitations of traditional classification methods like one-against-one[2] and one-against-the-rest[3]. With this novel method, the classification process is faster with fewer sub-classifiers and reduced classification errors. The results of this study were impressive, showing the classifier in this investigation

[2]Classifier is trained for each pair of classes.
[3]Classifier is trained against all other classes combined.

demonstrated a high average recognition rate of 92.7% when six distinct emotions were considered, including happiness, surprise, anger, fear, disgust, and sadness.

2.5. MUSIC RECOMMENDATION BASED ON FER

From Chakrapani et al. (2023)'s approach, music recommendation system with deep learning algorithm could enhance the listening experience by accurately detect and interpret the user's emotions. This is achieved by using CNNs to analyze the user's age, gender, and facial emotion. Based on these data, the system would cater to the user's preferences and present mood. To ascertain the user's emotional state, they used the webcam to take pictures of the user and then processed the image using the CNNs models. The system then provided tailored music recommendations based on the predictions generated by the CNNs models. This approach offers a creative and user-centric alternative for music selection based on emotional cues while streamlining playlist construction and management (S et al., 2023).

Additionally, Athavle et al. (2021). discovered that using CNNs model helps a music recommendation system to accurately detect emotions and subsequently recommend music that aligns with the user's mood. They train a CNNs model for emotion detection in their work. While maintaining great precision, this method lowers total system costs and computing time. The system uses real-time emotion detection to work, and then sends the data to the CNNs model to classify the user's emotions. An appropriate playlist will be recommended as soon as the technology determines the user's current feeling, making the user experience engaging and responsive. In order to guarantee optimal classification accuracy and efficacy, they employed categorial cross-entropy as a loss function to manage missing and anomalous values inside the FER2013 dataset. Despite their result being less accurate than Chakrapani et al.'s work (71%), it nevertheless shows that the model is effective and trustworthy in identifying emotions from facial expressions (Athavle, 2021).

3. REQUIREMENTS

3.1. INTRODUCTION

To ensure that the project is built effectively, a comprehensive framework of functional and non-functional requirements that are carefully crafted to meet the objectives and user expectations should be created. Functional requirements provide the application's foundational architecture, dictating essential tasks such as playlist generation and user registration to ensure the application performs reliably and intuitively. Non-functional requirements, on the other hand, focused on performance quality and include things like system scalability, security, and efficiency.

3.2. FUNCTIONAL REQUIREMENTS AND NON-FUNCTIONAL REQUIREMENTS

3.2.1. Functional Requirements

Req. No.	Categories	Requirements	Priority
FR1	User Registration and Account Management	The system must allow user to register by providing a unique username, user's actual name, date of birth, email, and password.	High
FR2		The system must verify user accounts through an email verification process.	High

Req. No.	Categories	Requirements	Priority
FR3	User Registration and Account Management	Users must be able to login with their email or username and password. A "Remember Me" option should allow users to stay logged in for 7 days.	High
FR4		Users can access a settings page to update their name, date of birth, email, password, and profile picture. Usernames cannot be changed.	Medium
FR5		Users must be able to reset their passwords through a password reset feature on the login page.	Medium
FR6	Facial Emotion Recognition	The application integrates a machine learning model to recognize user's facial emotions via their device's camera.	High
FR7	Spotify Web Playback Integration	The system integrates with Spotify Web Playback SDK to play music within the web application.	High
FR8		The application must allow users to connect their Spotify account before accessing music playback services. This integration should facilitate authentication and authorization seamlessly within the web application.	High
FR9	Youtube API Integration	The system integrates with Youtube API to play music within the web application.	Medium

Req. No.	Categories	Requirements	Priority
FR10	Youtube API Integration	The application must allow users to connect their Google account before accessing music playback services. This integration should facilitate authentication and authorization seamlessly within the web application.	High
FR11	Music Recommendation System	The application must generate playlists based on the user's recognized emotion using an algorithm.	High
FR12	User Interface and Experience	The web application supports a toggle between light and dark themes, automatically detecting and applying the user's device theme upon first use.	Medium
FR13		The application supports multiple languages: English, Japanese, Chinese, Korean, and Malay.	Low

Table 3.1: Functional Requirements

3.2.2. Non-Functional Requirements

Req. No.	Categories	Requirements	Priority
NFR1	Compliance and Security	All user data, including passwords and personal information, must be encrypted.	High
NFR2		The application must implement secure authentication mechanisms to prevent unauthorized access.	High
NFR3		User data must be stored in a secure database with access strictly limited to the backend server. The database shall not be directly accessible from any public network (0.0.0.0/0).	High
NFR4		User passwords must be encrypted using a secure hashing algorithm (e.g., bcrypt) to ensure their safety even in the event of a data breach.	High
NFR5		All forms of data transmission involved in user authentication and registration must be over HTTPS, and sensitive information shall not appear in URLs or any part of the HTTP request visible to the client side.	High
NFR6		The application must comply with relevant data protection and privacy regulations, including General Data Protection Regulation (GDPR) where applicable, ensuring user's rights to privacy and data security are upheld.	High

Req. No.	Categories	Requirements	Priority
NFR7	Performance and Scalability	The application shall load within 3 seconds for 95% of its users under standard network conditions.	High
NFR8		The system must be scalable to support up to 100 concurrent users without significant degradation in performance.	High
NFR9	Usability	The application shall be designed with a user-friendly interface, ensuring ease of navigation and accessibility.	Medium
NFR10		User input fields should provide immediate feedback to correct errors or invalid data.	Medium
NFR11	Compatibility and Interoperability	The web application must be compatible with the latest versions of Chrome, Firefox, Safari and Edge browsers.	High
NFR12		The system must ensure seamless integration with the Spotify API and maintain compatibility with Spotify's update.	High
NFR13	Localization and Internationalization	The application must support multilanguage interfaces, allowing users to switch languages easily.	Medium
NFR14	Localization and Internationalization	Date and time formats should adapt to the user's selected language and region preferences.	Low
NFR15	Maintenance and Support	The system should be designed to allow easy updates and maintenance without significant downtime.	Medium

Req. No.	Categories	Requirements	Priority
NFR16	Maintenance and Support	Documentation must be provided for end-users and developers, detailing usage, integration features, and troubleshooting steps.	Medium
NFR17	Application Performance	The facial emotion recognition feature must provide a response within 5 seconds from the time of user's request under standard network conditions.	High
NFR18		The system should ensure a Spotify playback start time of less than 3 seconds after user selection or playlist generation.	High
NFR19		The web application's overall time to interactive (TTI) should not exceed 5 seconds for 90% of its users under standard network conditions.	High
NFR20	User Interface Design	The application must adhere to Web Content Accessibility Guidelines (WCAG) 2.1 AA standards for color contrast, navigability, and text size to ensure accessibility for users with disabilities.	High
NFR21		All user interface components (buttons, links, form elements) must be navigable using a keyboard in a logical order to support users with mobility or visual impairments.	High

Req. No.	Categories	Requirements	Priority
NFR22	Data Handling and Authentication	Implement OAuth 2.0 for secure authentication with Spotify, ensuring that user credentials are handled safety and in line with best security practices.	High
NFR23		Apply secure session management practices, including the generation of unique session tokens for users during login and their secure storage on the client side.	High

Table 3.2: Non-Functional Requirements

4. METHODOLOGY

4.1. INTRODUCTION

To effectively navigate the intricacies of software development and guarantee the project's success, choosing an appropriate approach is essential. The concepts, procedures, and practices that guide a project's development, implementation, and completion are collectively referred to methodology. The variety of alternative methods, each with specific advantages and applicability to various project types, means that selecting a methodology should be done with careful consideration. This section explores the reasoning behind the choice of an Agile-based methodology, with a particular emphasis on the Kanban methodology, made by the use of Notion application for project management. This decision was driven by the project's requirement for flexibility, continuous improvement, and a visual workflow management system. The following sections will outline the comparative comparison between various approaches, along with the reasoning behind choosing Agile due to its alignment with the project's objectives and task specifications.

4.2. RESEARCH METHODOLOGY

4.2.1. Waterfall methodology

Waterfall methodology, with its linear and sequential approach, stands as a traditional yet relevant framework for software development projects that require a clear, phased progression. Requirements, design, implementation, testing, development and maintenance are the steps in this process. They guarantee that one phase must be finished before moving on to the next, which makes them especially appropriate for projects with stable, well-defined requirements that are unlikely to change. Crespo-Santiago & de

la Cruz Dávila-Cosme (2022) highlight the Waterfall methodology helps maintain the scope of their library project within the requirements, estabilishing cost and time control, and documenting evidence of project governance.

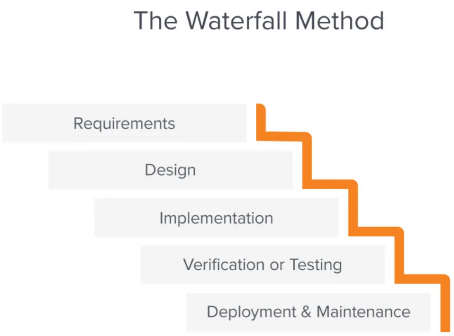


Figure 4.1: Waterfall Methodology (Team, 2022)

4.2.2. Spiral methodology

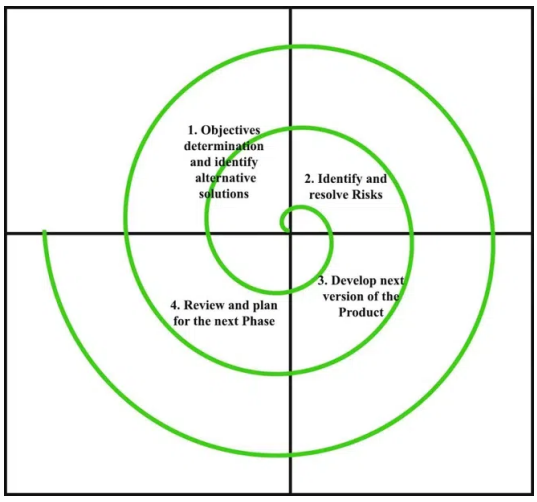


Figure 4.2: Spiral Methodology (Kumar Pal, 2018)

Spiral methodology, an evolutionary software development process introduced by Barry Boehm in 1986, is a model for process flexibility and risk control in software development (Boehm, 1986). The methodology is distinguished by its four-phase cycle approach, which includes planning, risk analysis, implementation, evaluation. This allows for ongoing iterations that involve setting project goals, identifying potential risks, carrying out development, and incorporating stakeholder feedback. Its iterative design ensures a flexible and adaptive development process by permitting incremental product

improvements based on changing needs and stakeholder input. The Spiral methodology provides a methodical approach to managing the complexities and uncertainties inherent in software development. It shines in contexts where project needs are ambiguous or subject to change because of its heavy emphasis on risk management.

4.2.3. Agile methodology

Figure 4.3: Agile Methodology (Laoyan, 2024)

Agile methodology, an approach originated from the Agile Manifesto, published in 2001 by a group of software developers, prioritizes adaptability, collaboration, customer satisfaction and timely delivery of high-quality software (Laoyan, 2024). While implementing Agile methodology, project is breaks into small, manageable pieces, known as iterations or sprints. Each sprint involves cross-functional teams working on various aspects like planning, design, coding, and testing, with a working iteration of the product delivered at the end of each cycle. This methodology works effectively for projects whose requirements are changing or unclear since it allows ongoing feedback and adjustment.

4.3. COMPARISON AND SELECTION

Software development can be approached differently using the Agile, Waterfall, and Spiral techniques, each with its own set of benefits and difficulties. As detailed in Table 4.1, Agile is highly flexible and adaptable, ideal for projects with evolving requirements, but may lead to unpredictable costs. Waterfall is straightforward and orderly, perfect for projects with well-defined requirements, but inflexible to changes. Spiral combines iterative development with focusing on risk management, but it could be costly.

The project's scale and the clarity of its needs determine which technique is best: Waterfall for its structure, Agile for its flexibility, or Spiral for its risk emphasis.

Table 4.1: Comparison of Methodologies

Aspect	Agile	Waterfall	Spiral
Pros	• High flexibility and adaptability to changes. • Frequent releases and feedback. • Enhanced customer satisfaction. • Reduced time to market.	• Simple and easy to understand and use. • Clear project milestones and deliverables. • Well-suited for projects with defined requirements.	• Focus on risk management. • Flexibility in design and development. • Suitable for large, complex projects with uncertain risks.
Cons	• Less predictable budget and timeline. • Requires close collaboration and customer involvement. • Not ideal for low-change projects or those with fixed requirements.	• Difficult to incorporate changes once the project has started. • Potential for late discovery of problems or errors. • Not suitable for projects where requirements may evolve.	• Can be complex and costly to implement. • Requires significant risk assessment expertise. • May lead to prolonged project duration due to iterative nature.

4.4. JUSTIFICATION FOR CHOOSING AGILE

The Agile methodology, particularly the Kanban variant, was chosen in order to satisfy the demand for an adaptable, graphical, and iterative developments process. Given the dynamic nature of the project and its ever-changing objectives, Kanban, which places a strong focus on continuous delivery and workflow efficiency, is an excellent fit.

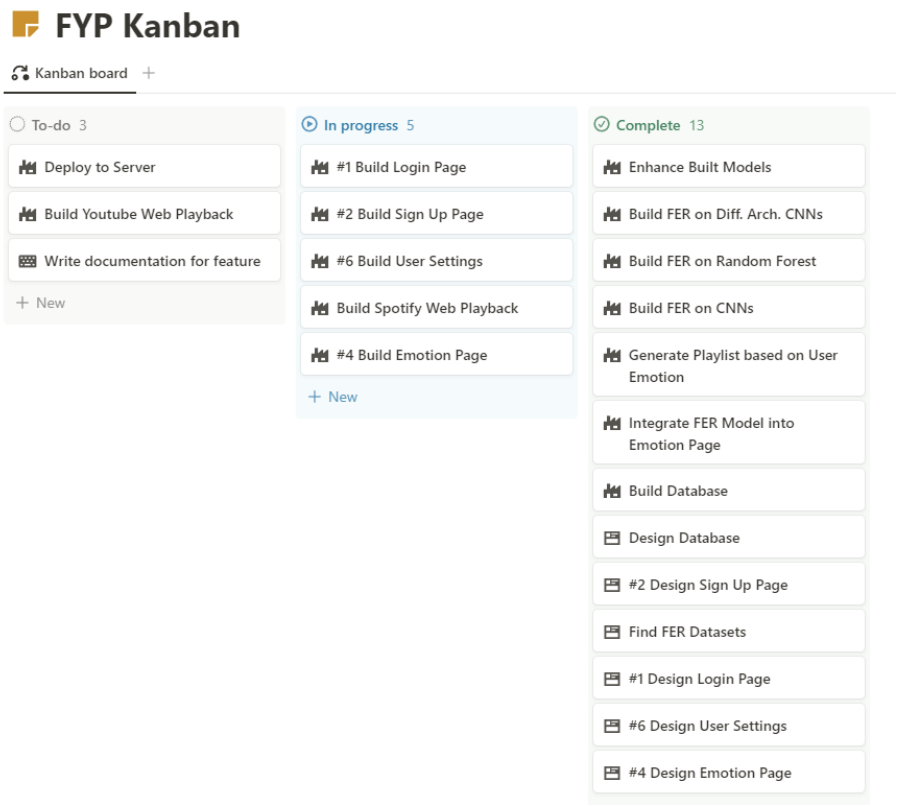


Figure 4.4: Kanban from Notion

In this project, Kanban is implementing using Notion. It gives tasks a visual representation, making it easier to organize and keep track of them as they go through various stages of development. Also, with the adaptability of Notion's platform, project plans could be updated easily which is crucial for keeping the plan responsive to changing project dynamics.

Kanban method's inherent simplicity and its focus on delivering work just-in-time are particularly beneficial for projects demanding flexibility and time efficiency. Kanban with Notion provides a clear picture of the project's progress, enabling developer to identify and resolve bottlenecks quickly, and efficiently manage task prioritization. Therefore, the combination of Notion's features with Agile Kanban creates a strong foundation for project management by fusing Kanban's visual clarity and streamlined efficiency with Agile's flexibility. Lastly, Gantt chart (See Figure G.1) is also used in this project to keep track on the progress.

5. DESIGN

5.1. INTRODUCTION

The design phase of the web application, focused on using emotion recognition to generate music therapy playlists, represents a bridge from theoretical concepts to a operational system. The varied design approaches that were used to develop an application with a solid technical framework and user-friendly interface are covered in this section.

The core aspect of the application is how it uses captured frame analysis to determine a user's emotional state by utilizing FER technology. This sense of emotional then guided the creation of customized music playlists, fusing the advanced machine learning techniques with the restorative properties of music to provide a unique advantageous user experience.

This project uses diagrams such as block diagram, use case diagram, sequence diagram and etc., where each focusing on a different aspect of the architecture and functionality of the system. Futhermore, this section delves into the visual and functional components of the application's user interface as illustrated by the Logo Design and Interface Design. The logo, as the visual cornerstone of the application's brand identify, have been thoughtfully designed to improve application usability and user engagement.

Additionally, the ML model architecture design, which describes the underlying algorithms and data processing methods used in FER, is also discussed in this section. This discussion covers the model's validation, training, and integration into the broader application ecosystem to ensure accurate emotional analysis.

All of these components provide a thorough explanation of the system's design, addressing structural, behavioral, and aesthetic factors from the abstract to the concrete.

5.2. WEB APPLICATION

This section explores the design decisions made for the web application's architecture and aesthetics. It describes how the architecture of the system was designed to optimize usability and functionality, ensuring seamless integration of the FER technology with the music recommendation system.

5.2.1. UML Diagrams

5.2.1.1. Block Diagram

Block diagram present a high-level overview of the system's architecture, highlighting the major components and their interactions (Freeman, n.d.). This offers insights into the overall system design and its flow.

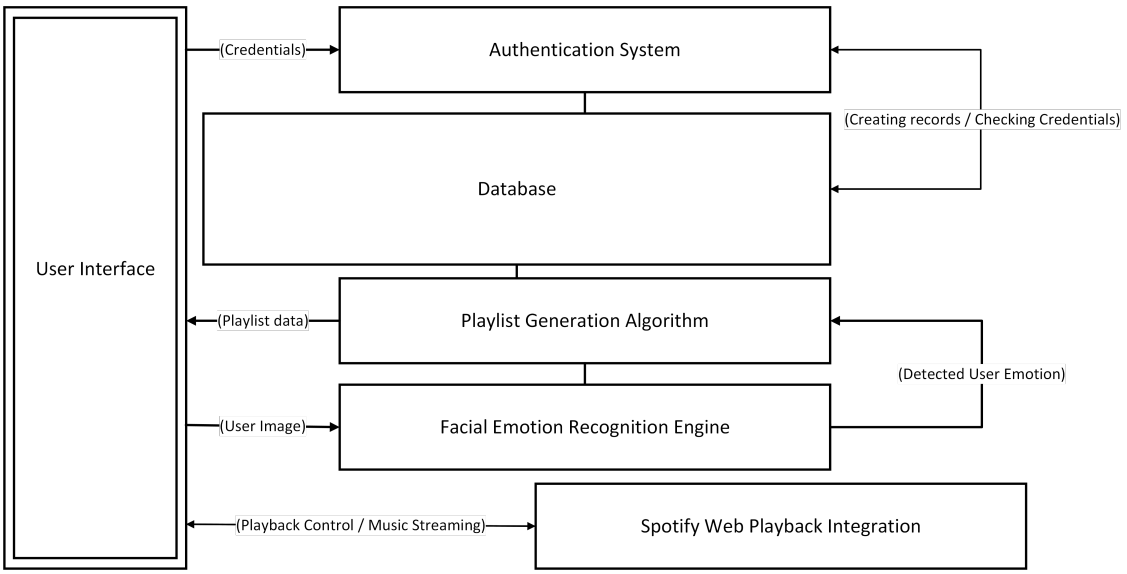


Figure 5.1: Block Diagram

As shown in Figure 5.1, there are different components and each component has its own responsibilities to enable FER and playlist generation for music therapy. User Interface (UI) is the gateway through which users interact with the application. It captures user inputs such as credentials for the authentication process, frames for emotion recognition, and user actions for music playback controls.

Authentication System manages user identity verification and access control. When user provides credentials, either username or email, and password to this component, it will validates them against stored data in the database. Upon successful validation, users can access the full functionality of the services. This component also handles account creation, where new user details are stored securely in the database.

Database stores and manages all persistent data, including user credentials, profile information, and any data pertinent to playlist generation processes. It ensures data integrity and provides efficient access for other components. FER Engine utilizes advanced algorithms and machine learning models. This engine analyses captured frame, which contains user's facial expression, to detect emotional states. The result of this analysis is then used to tailor the music playlist to the user's current emotional needs.

Playlist Generation Algorithm takes the detected emotion from the FER Engine and constructs a playlist that suits the identified mood and therapeutic requirements. It queries a database of songs, which stored internally, to select appropriate tracks. Then, Spotify Web Playback Integration acts as the music service interface. This component is responsible for fetching the actual music tracks from Spotify and controlling the playback within the application, such as playing, pausing, and etc. based on user input through the UI.

This diagram simplifies the conceptual understanding of the system and forms the architectural backbone of the application. It also outlines how user actions translate into system responses and result in a music therapy experience.

5.2.1.2. Use Case Diagram

Use Case diagram is a visual representation of the system's functionalities and the interactions that different types of users have with these functionalities (IBM, 2021).

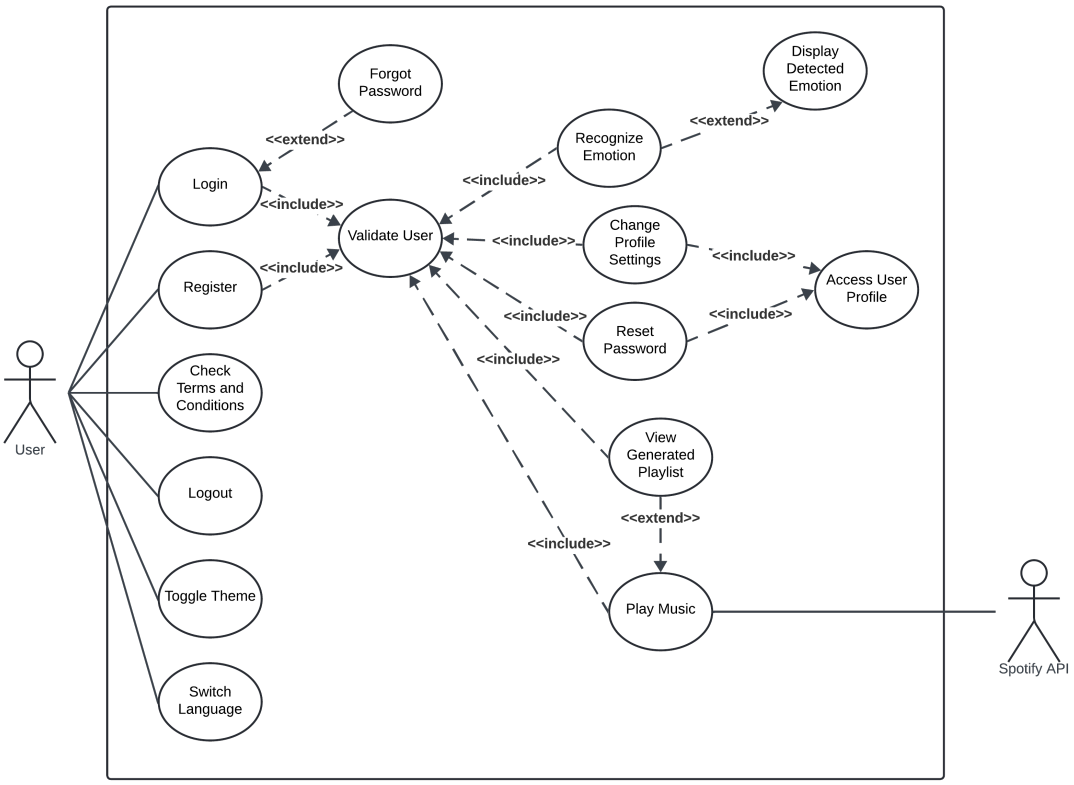


Figure 5.2: Use Case Diagram

As shown in Figure 5.2, there are two actors, ‘User’ and the ‘Spotify API’. The ‘User’ represents any individual who interacts with the application for its services. The ‘Spotify API’ acts as an external system that the application communicates with to stream music.

The use case diagram delineates the extent of the application’s capability from the ‘User’ point of view by illustrating the user interactions. This helps to understand what the system does, but not how it does it, thus separating the ‘what’ from the ‘how’ in system functionalities. When a use case incorporates another’s behavior or expands the behavior under some circumstances, it is represented by dashed lines with arrows labelled ‘includes’ and ‘extends.’ For example, several use cases in the application such as ‘Recognize Emotion’, ‘Change Profile Settings’, and ‘Play Music’, require the ‘User’ to be authenticated. This precondition is captured in the ‘Validate User’ use case, which is included in these use cases to ensure that the ‘User’ is logged in before granting access to the services.

5.2.1.3. Sequence Diagrams

Sequence diagrams provide an illustrative view of how various components of a system work together ot accomplish a process, acting as blueprints of interaction across time (Bell, 2004). They are especially helpful in understanding the flow of messages and actions between objects in response to software system events.

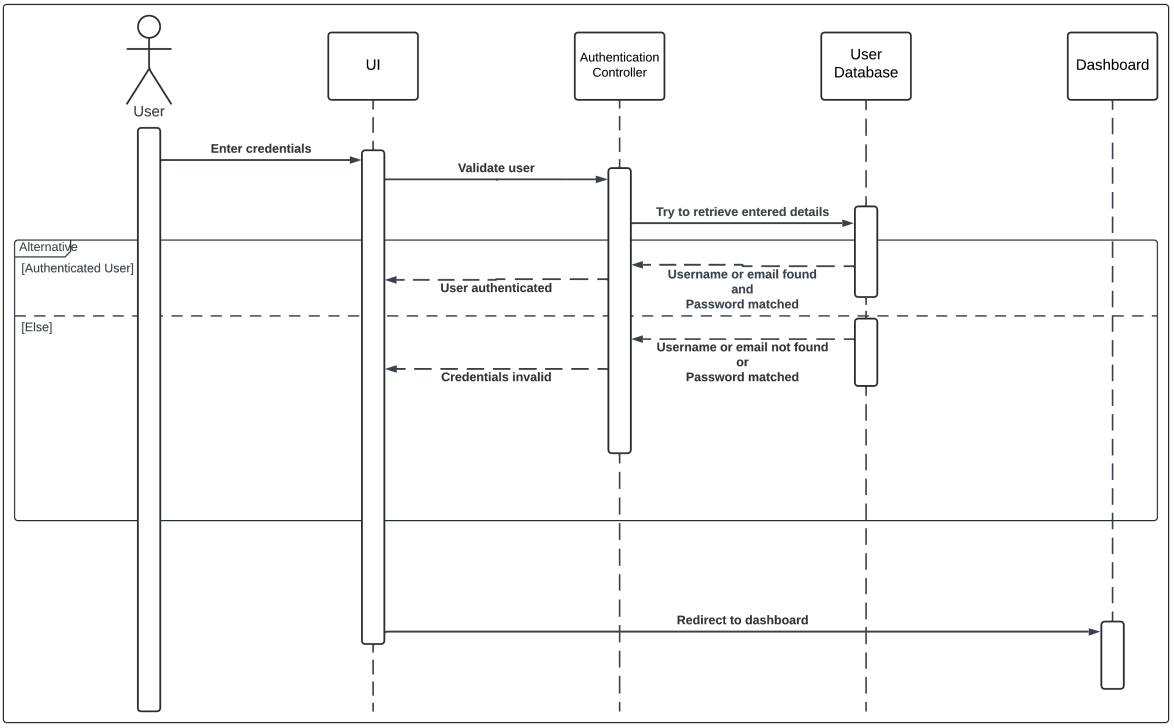


Figure 5.3: Login Sequence Diagram

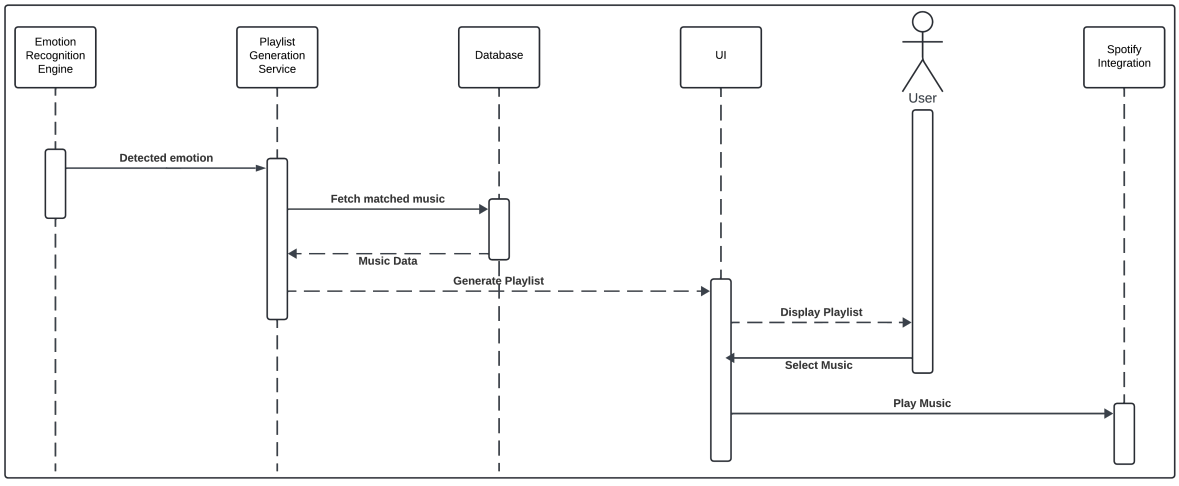


Figure 5.4: Playlist Generation Sequence Diagram

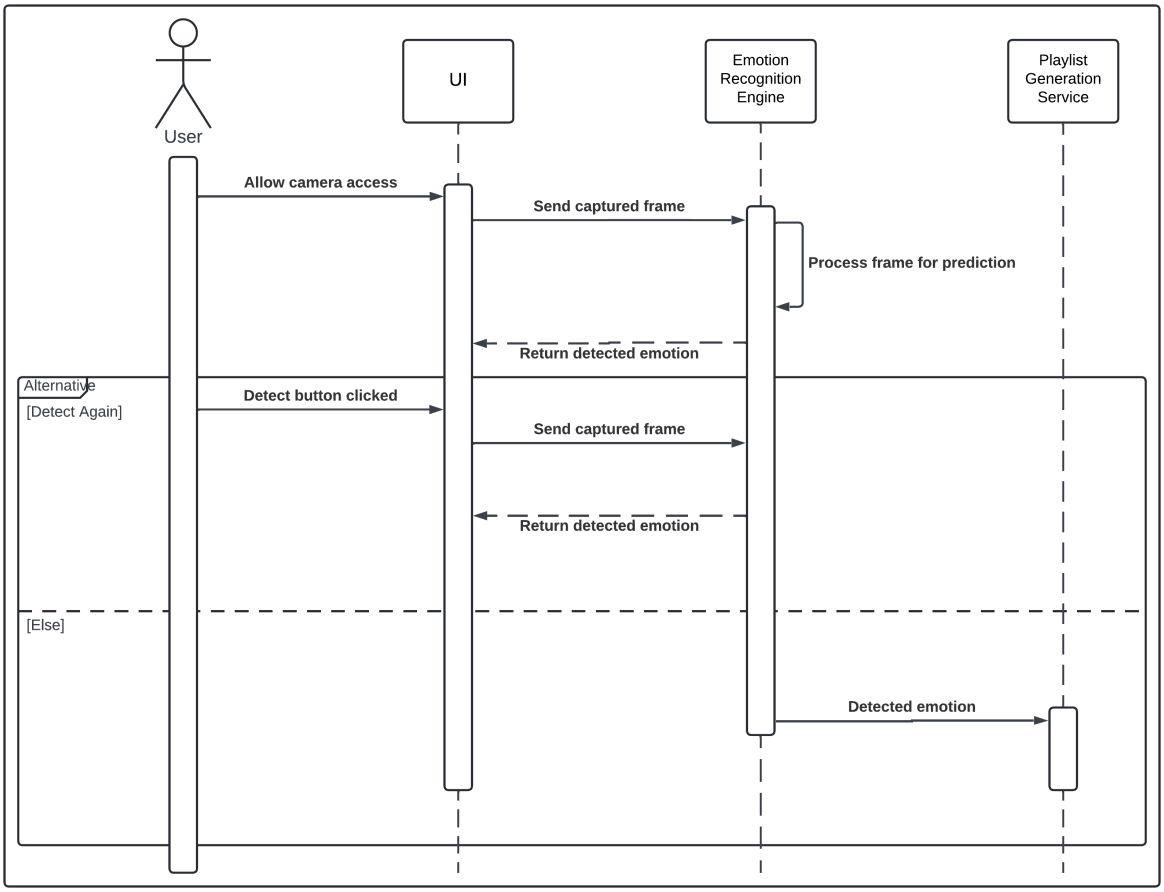


Figure 5.5: Emotion Recognition Sequence Diagram

Figure 5.5 presents the series of interactions that commence with capturing a user's facial expression and terminates when the system identifies the user's emotional state. The sequence is outlined from the user interface to the backend services, where the input is processed by the 'Emotion Recognition Engine' to identify emotion. The detected emotion will then influence the music playlist generation.

Figure 5.4 shows how the service uses the detected emotion from Figure 5.5 to choose and assemble a series of songs into a coherent playlist. From retrieving suitable songs based on the emotional analysis to returning the playlist to the user for playback through Spotify Web Playback service, it demonstrates the cooperation between the system's components.

5.2.1.4. Flowchart

Flowchart represent the process of a system, the decisions that need to be made, and the flow of control from one step to the next. Troubleshooting and system design are made considerably easier with the aid of flowchart as they make the sequential phase and logic paths in complicated processes visible (Lucidchart, 2019).

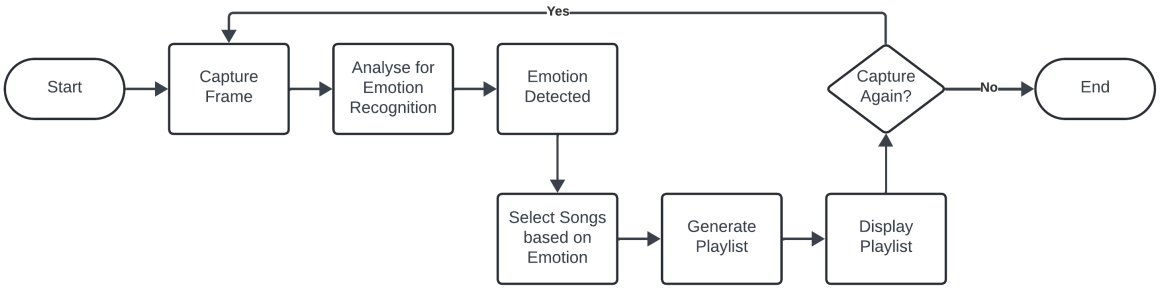


Figure 5.6: Flowchart For Emotion Recognition and Playlist Generation

Figure 5.6 shows the steps taken from the moment a user engages with the feature to capture their emotional state to the point where the system recognizes and outputs the detected emotion. Following the FER phase, the identified emotion is then used to select suitable music, creating playlist and presenting it to the user.

5.2.1.5. Entity-relationship Diagram

Entity-Relationship Diagram (ERD) is a structured representation of the data entities within the web application and the interconnections between them. This illustration outlines the database schema, which is foundational for storing, retrieving, and managing data that the application operates upon.

Figure 5.7 presents the ERD for the application. ‘User’ representing the application’s users, containing ‘UserID’, ‘Username’ and other personal details which could be modified in ‘User Settings Page’ (See Figure E.5). ‘Albums’, ‘Tracks’, ‘Audio Features’, ‘Track Popularity’, and ‘Artists’ are entities that stored music data from song title to information such as its tempo, its loudness and other audio features.

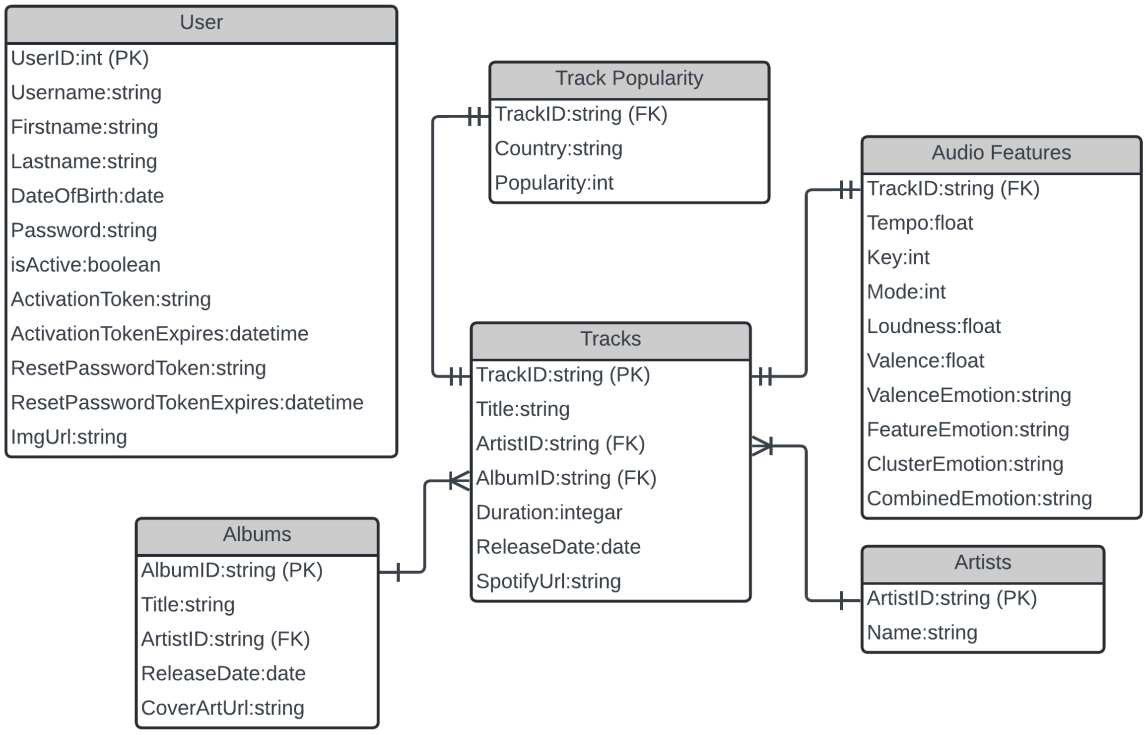


Figure 5.7: Entity-relationship Diagram

The relationship between entities are defined by Primary Key (PK) and Foreign Key (FK), enforcing referential integrity within the database. For example, a one-to-many relationship from ‘Artists’ to ‘Tracks’ indicates that one artist can have multiple tracks, whereas a one-to-one relationship between ‘Tracks’ and ‘Audio Features’ indicates that each track has its own unique features.

5.2.2. Logo Design

Figure 5.8a and Figure 5.9a is made up of stylized waves that reference the soothing rhythms of ocean waves while also visualizing the representation of an audio signal. This duality shows the fundamental purpose of the application, using the ability of music to evoke and influence emotions, providing a calming and therapeutic user experience.

Accompanying the logo, Figure 5.8b and Figure 5.9b incorporates the application’s name, ‘Sentirhy’, which itself is a portmanteau derived from ‘Sentiment’ and ‘Rhythm’. This naming convention shows the application’s focus on sentiment analysis and rhythm.

(a) Logo **(b)** Banner

Figure 5.8: Light Theme Logo

(a) Logo **(b)** Banner

Figure 5.9: Dark Theme Logo

5.2.3. Interface Design

UIs are created through the process of interface design. The arrangement of panels, as well as the style of components the user will interact with such as buttons, text fields and others are all included (See Appendix D).

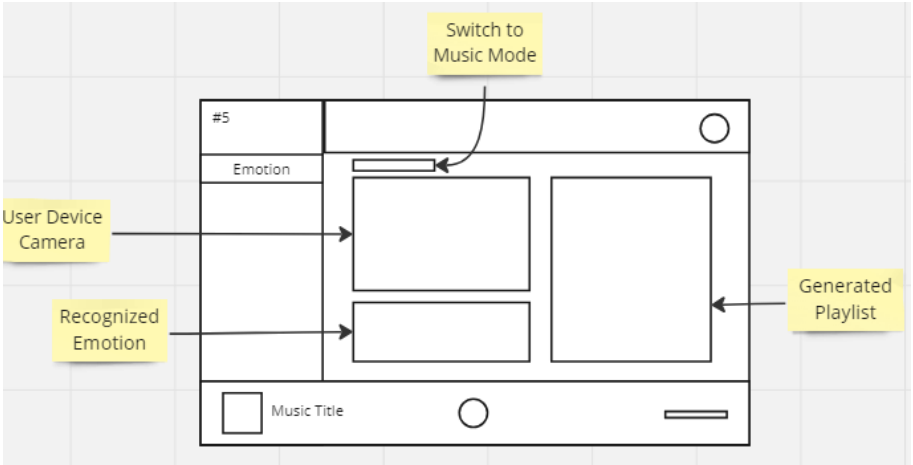


Figure 5.10: Emotion Recognition Page

5.3. ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

5.3.1. Models Architecture

In computer vision, a model's architecture is the basis that backs up its capacity for learning and generalization. The design decisions made when structuring a model determine not only its performance, but also its efficiency in extracting and understanding the complex patterns found in the data. A FER model must be able to manage the complexity of human facial emotions with ease. Therefore, the architectures explored and selected are designed with the goal of capturing a complex hierarchy of features.

Layer (Type)	Output Shape	Parameters
Input	(None, 48, 48, 1)	0
Conv2D (3x3x32)	(None, 48, 48, 32)	320
Conv2D (3x3x64)	(None, 48, 48, 64)	18,496
BatchNormalization	(None, 48, 48, 64)	256
MaxPooling2D (2x2)	(None, 24, 24, 64)	0
Dropout	(None, 24, 24, 64)	0
Conv2D (3x3x128)	(None, 24, 24, 128)	73,856
Conv2D (3x3x256)	(None, 22, 22, 256)	295,168
BatchNormalization	(None, 22, 22, 256)	1,024
MaxPooling2D (2x2)	(None, 11, 11, 256)	0
Dropout	(None, 11, 11, 256)	0
Flatten	(None, 30976)	0
Dense	(None, 1024)	31,720,448
Dropout	(None, 1024)	0
Dense (Softmax)	(None, 4)	4,100

Table 5.1: Detailed Architecture of the CNNs Model 1

Model 1 (See Table 5.1) is the first attempt at tackling the challenging issue of FER, based on the well-proven architectures similar to VGG-16 (Simonyan and Zisserman, 2014), which are intended to identify nad leverage the strengths of facial feature differentiation. The model started with a conservative number of filters in the Convolutional Layer (Conv2D), from 32 and incrementally increasing to 64, 128, and 256, to ensure the model is able to capture a spectrum of features from basic to complex. Those interspersed ‘Dropout’ layers are used to prevent over-fitting, which then giving the model greater generalization capabilities.

In order to reduce dimensionality, pooling layers are implemented throughout the architecture. This will compress the spatial volume of features before they are flattened into a format suitable for dense network processing. The learning process ends in the ‘Dense’ layers that, through a ‘Softmax’ activation, control the emotional categorization, converting the complex network of extracted features into perceptible emotional states.

Model 2 (See Table 5.2) is a refined version of the FER model. With the addition of L2 regularization and a varied number of filter sizes, this model differs from the first model. This version provides theoretical performance improvements, such as higher generalization in unseen data. Additionally, this model version is more similar to the VGG-16 model; but, because of resource constraints, the original VGG-16 model, which in theory should yield better results, is not implemented in order to use fewer computer resources.

Layer (Type)	Output Shape	Parameters
Input	(None, 48, 48, 1)	0
Conv2D (3x3x64)	(None, 48, 48, 64)	640
BatchNormalization	(None, 48, 48, 64)	256
ReLU Activation	(None, 48, 48, 64)	0
Conv2D (3x3x64)	(None, 48, 48, 64)	36,928
BatchNormalization	(None, 48, 48, 64)	256
ReLU Activation	(None, 48, 48, 64)	0
MaxPooling2D (2x2, stride 2)	(None, 24, 24, 64)	0
Conv2D (3x3x128)	(None, 24, 24, 128)	73,856
BatchNormalization	(None, 24, 24, 128)	512
ReLU Activation	(None, 24, 24, 128)	0
Conv2D (3x3x128)	(None, 24, 24, 128)	147,584
BatchNormalization	(None, 24, 24, 128)	512
ReLU Activation	(None, 24, 24, 128)	0
MaxPooling2D (2x2, stride 2)	(None, 12, 12, 128)	0
Conv2D (3x3x256)	(None, 12, 12, 256)	295,168
BatchNormalization	(None, 12, 12, 256)	1,024
ReLU Activation	(None, 12, 12, 256)	0
Conv2D (3x3x256)	(None, 12, 12, 256)	590,080
BatchNormalization	(None, 12, 12, 256)	1,024
ReLU Activation	(None, 12, 12, 256)	0
Conv2D (3x3x256)	(None, 12, 12, 256)	590,080
BatchNormalization	(None, 12, 12, 256)	1,024
ReLU Activation	(None, 12, 12, 256)	0
MaxPooling2D (2x2, stride 2)	(None, 6, 6, 256)	0
Flatten	(None, 9216)	0
Dense	(None, 4096)	37,752,832
BatchNormalization	(None, 4096)	16,384
ReLU Activation	(None, 4096)	0
Dense	(None, 4096)	16,781,312
BatchNormalization	(None, 4096)	16,384
ReLU Activation	(None, 4096)	0
Dense (Softmax)	(None, 4)	16,388

Table 5.2: Detailed Architecture of the CNNs Model 2

6. IMPLEMENTATION

6.1. INTRODUCTION

This section covers how the research was put into practice, with a particular emphasis on how machine learning models were put into practice and how they were integrated into a working web application for FER.

6.2. ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

The preparation of datasets, the training environment, and the computational resources employed will be discussed in the following section. Providing specific details about the measures taken to guarantee that the data was suitable for learning, the augmentation methods used to improve model performance, and the training approaches used to maximize model performance. The evaluation metrics and the outcome of testing the models on hypothetical data are also included in this ML section. See Appendix A for music classification model.

6.2.1. Setup and Preparation

6.2.1.1. Environment Setup

The models are developed with a robust software environment designed for advanced ML tasks. The preferred programming language was Python, which is well-known for its adaptability and power in data manipulation and machine learning. Then, the research and model training were carried out with Jupyter Notebook, which is an interactive computing environment that enables real-time code execution, analysis and visualization. The libraries used for model training are listed below.

- **Keras**: Chosen for its user-friendly API which operates on top of TensorFlow, it enabled to build and train neural network models with relative ease.
- **NumPy**: It is used for handling of numerical operations on array, forming the foundation of data structures in ML tasks.
- **Pandas**: This library provided robust data manipulation and cleaning capabilities which makes organizing tabular data and dataset transformation more easier.
- **Scikit-learn (sklearn)**: A broad range of machine learning tools, including cross-validation methods, model assessment, and preprocessing, are available in this library and aid in the improvement of learned models.
- **OpenCV (cv2)**: This library provided extensive image processing capabilities, which were crucial in manipulating and preparing facial images for training.
- **Matplotlib and Seaborn**: These libraries were used for data visualization. They allow findings to be converted into charts, which provide further insight into the functioning of the models.

6.2.1.2. Data Preparation

6.2.1.2.1 Data Collection

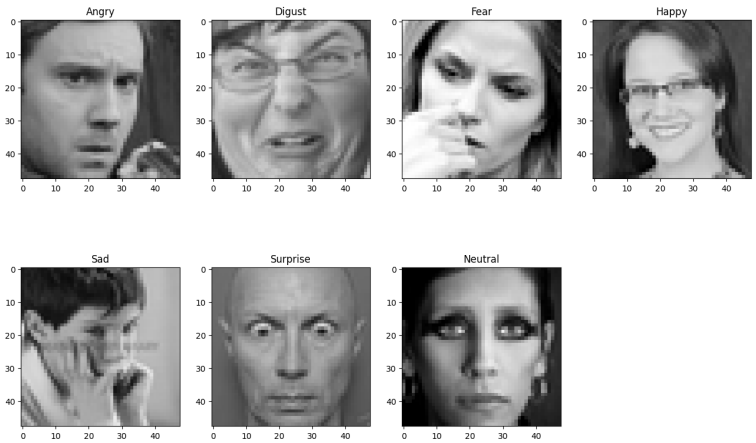


Figure 6.1: FER-2013 Dataset

A dataset capable of precisely capturing a wide range of human emotions through facial expression was needed for training the model. Therefore, the FER-2013 (Dumitru

et al., 2023) dataset which is a well-known benchmark in the field of FER from the Kaggle competition platform was chosen. A wide range of facial expressions are included in this dataset, and each of these grayscale images of faces are labelled with one of seven emotions. This makes it suited for training FER models.

Figure 6.2: CK+ Dataset

To increase the diversity of the data, CK+ (Lucey et al., 2010) dataset is included to the FER-2013. This dataset contains labelled facial expressions from varied populations and light scenarios. This addition was to provide the models a more comprehensive learning environment by exposing them to a greater variety of face emotions and characteristics.

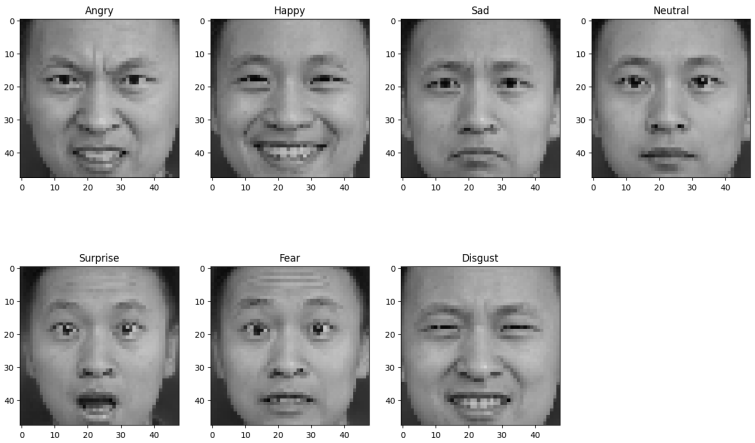


Figure 6.3: SZU-EmoDage Dataset

Moreover, SZU-EmoDage (Who, 2022) dataset was also included to the collection to ensure the models are capable of identifying facial expressions on Asian faces. With these additions, each dataset was integrated with a different set of challenges and viewpoints, which then improve the model's accuracy and practicality in real-world situation.

6.2.1.2.2 Preprocessing Steps

Those collected data went through a series of preprocessing stages to standardize input features and optimize them for efficient ML before training. Even though the data were already in grayscale, all images were first converted to grayscale using the '`cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)`' function to ensure that all data were in grayscale in order to simplify the input data and reduce computational cost. After conversion, all images were shrunk to 48x48 pixels. It is because neural networks require consistent picture sizes in order to handle batch data efficiently and handle all inputs equally during the learning process.

Following resizing, images were flattened from a format of 2D arrays to a 1D array with 2304 elements (48x48). This transformation is necessary because machine learning algorithms generally require a flat array of features for each sample to be handle and analyse. The flattened image data was then compiled into a pandas DataFrame, which made data handling and analysis in Python simpler. Before training models, pixel values from each image were standardized to lie within the range of [0,1]. This normalization make sure that all input characteristics contribute equally to the model's learning because having different scale will influence the results.

In order to simplify the model and better match the project with its use in music recommendation, the number of emotion categories was reduced from seven to four. The four categories were kept were 'Neutral', 'Happy', 'Sad' and 'Angry'. These emotions are more easily applied and useful for determining musical mood.

6.2.1.2.3 Augmentation

Keras' function '`ImageDataGenerator()`' is used to construct a strategic data augmentation process that improved the model's robustness and allowed it to generalize across a variety of face emotions and situations. The augmentation techniques that were used included random rotation of images up to $10°$. This mimics the natural tilts that occur in expressive moments. Additionally, width and height shifts, which translate images by up to 10% of their size in both directions. This helps with situations when faces are not in the center of the frame.

To help the model learn to identify emotions from faces at different camera distances,

random zooming was also applied to some of the images. Moreover, the images were arbitrarily rotated horizontally so that the model could be trained on mirror copies of faces, therefore double the range of face orientations the model saw in the training.

6.2.1.2.4 Dataset Splitting

A key phase in preparing for training and evaluation of ML models is splitting the dataset into training, validation, and testing sets. The training set was composed from the ‘Training’ data from FER-2013 and the complete CK+ dataset. This is to increase the model’s capacity to generalize across various demographic groups and emotional states by exposing it too a greater variety of facial expressions and environmental factors.

For validation, the ‘PublicTest’ subset of the FER-2013 was used. This collection is essential for adjusting the hyper-parameters of the model and for providing an unbiased evaluation of the model’s fit on the training dataset. The ‘PrivateTest’ subset of the FER-2013 was used to do the final evaluation of the model’s performance. In addition to the training, validation, and testing data, SZU-EmoDage dataset is used specifically for transfer learning purpose.

6.2.2. Training Process

In the training process, a common training framework was introduced for both models (See Table 5.1 and Table 5.2) to ensure consistency in the methodological approach. But some specific adjustments to address the unique characteristics of each model is allowed. The training process started with a thorough grid search to optimize hyper-parameters including dropout rates, kernel sizes, convolutional filter counts, and dense layer unit counts. Both models shared the same parameter grid as shown in Figure 6.4. This approach made it easier to explore the configuration space in an organized way, ensuring that each model was tuned to perform optimally.

```
param_grid = {
    'conv_1_filters': [32, 64],
    'conv_2_filters': [64, 96, 128],
    'conv_3_filters': [128, 192, 224],
    'conv_4_filters': [128, 160, 224, 256],
    'conv_1_kernel': [3, 6, 8],
    'conv_2_kernel': [3, 5, 8],
    'conv_3_kernel': [3, 5, 8],
    'conv_4_kernel': [3, 5, 8],
    'dropout_1': [0.1, 0.2, 0.4],
    'dropout_2': [0.0, 0.2, 0.3],
    'dropout_3': [0.0, 0.2, 0.3, 0.4],
    'dense_units': [512, 768, 1024],
    'l1_reg': [0.01, 0.001, 0.0001],
    'optimizer': ['adam', 'sgd'],
    'learning_rate': [1e-2, 1e-3, 1e-4],
    'epochs': [10, 50, 100]
}
```

Figure 6.4: Parameter Grid

After searching through the parameter grid (See Figure B.1 and Figure C.1), the process focuses on configuring each model's architecture to best capture the nuances of facial expression for FER. Model 1 (See Table 5.1) has a relatively simple architecture, which require careful tuning if dropout rates and filter sizes to balance feature learning against the risk of over-fitting. Model 2 (See Table 5.2) has more additional layers to capture a richer set of features before the final classification layer . But this led to a more thorough analysis required for the network's depth in relation to its performance on the validation set, which assisted in identifying when to add dropout and how to adjust the pooling layers.

```
es = EarlyStopping(monitor='val_accuracy', patience=5, restore_best_weights=True)
```

Figure 6.5: Early Stopping

To prevent over-fitting, early stopping mechanism, which configured as 'EarlyStopping' callback (See Figure 6.5), is integrated into the training to monitor validation accuracy and automatically halt training if no improvement was detected for five consecutive epochs. Most important of all, the callback (See Figure 6.5) was set to restore the weights form the epoch with the best validation accuracy, ensuring that the model

maintained any progress made prior to the plateau. This approach allows to train the model as long as beneficial, in the meantime, avoiding over-fitting and maintaining the optimal state achieved during training.

```
steps_per_epoch=len(train_X) / batch_size
```

Figure 6.6: Steps per epoch

Furthermore, the '`steps_per_epoch`' (See Figure 6.6) parameter was calculated to ensure that each epoch processed the entire dataset. With these techniques, early stopping and calculated epoch steps, the models were able to achieve a balance between computational prudence and strong learning. Consequently, the models were well-positioned for dependable performance in FER, having learned from training data efficiently and been prevented from the risk of over-fitting.

6.2.3. Models Evaluation

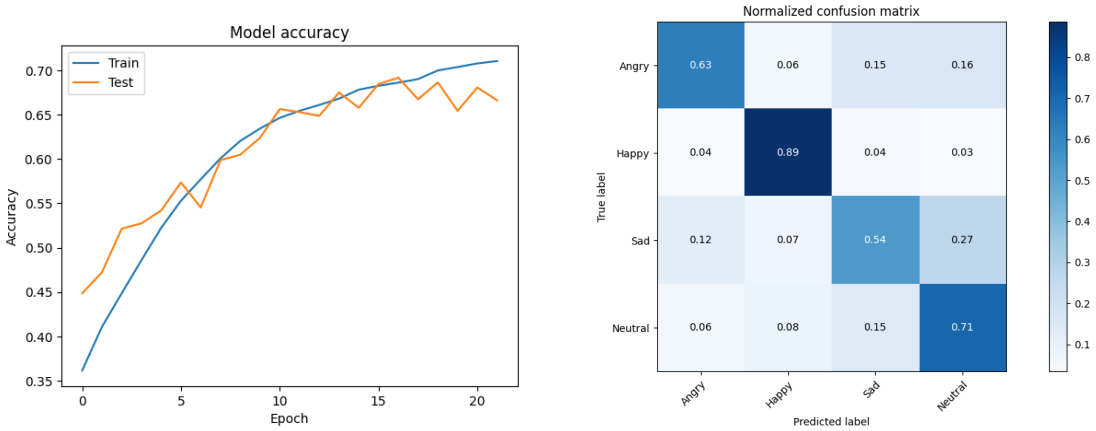
Analytical tools such as confusion matrices, accuracy graph over epochs, and classification reports are used to evaluate the effectiveness of the CNNs models. These insights will help in understanding the strengths and weaknesses of the models, and guide future improvements to improve the model's emotional intelligence.

6.2.3.1. Model 1

Category	Precision	Recall	F1-score	Support
Angry	0.68	0.63	0.65	491.00
Happy	0.86	0.89	0.87	879.00
Sad	0.61	0.54	0.57	594.00
Neutral	0.62	0.71	0.66	626.00
Accuracy			0.71	2590.00
Macro avg	0.69	0.69	0.69	2590.00
Weighted avg	0.71	0.71	0.71	2590.00

Table 6.1: Model 1 Classification Report

In the classification reports (See Table 6.1 and Table 6.2), the precision, recall, and F1-score for each emotion category provide insights into model performance for each specific emotion. While evaluating the performance of Model 1, the classification report (See Table 6.1) shows that the ‘Happy’ emotion achieved the highest precision of 0.86. It indicates a high ratio of correctly predicted happy instances relative to all predictions for happiness. Additionally, the recall for ‘Happy’ is 0.89, showing that the model is adept at identifying true happy states from the test data. With a balanced recall and prevision, the ‘Neutral’ category has an F1-score of 0.66, indicating an excellent performance in identifying neutral emotions. The model’s overall accuracy is 0.71 meaning that 71% of predictions were accurate.



(a) Model 1 Accuracy Variation

(b) Model 1 Confusion Matrix

Model 1 Graphs

The normalized confusion matrices (See Figure 6.7b and Figure 6.8b) offers a visual and numerical representation of the model’s performance, highlighting correct predictions along the diagonal and errors elsewhere. Confusion matrices provide a clear view of both true positives and true negatives, which indicate instances in which the model accurately identified the emotional states, as well as false positives and false negatives, which indicate instances in which the model confused one emotion for another.

The diagonal values (See Figure 6.7b) show the percentage of true positives, with ‘Happy’ and ‘Neutral’ emotions have higher values, at 0.89 and 0.71, respectively, suggesting that the model is more confidence in recognizing these emotions correctly. But, there are some misclassifications, for example, ‘Angry’ being misclassified as ‘Sad’ or ‘Neutral’, and ‘Sad’ being confused with ‘Neutral’. These off-diagonal parts shows

where more training data or fine-tuning are required to improve the model's ability to distinguish between emotions with small facial expression differences.

Accuracy graphs (See Figure 6.7a and Figure 6.8a) plot the models' performance over each training epoch for both the training and validation datasets. The graphs provide a clear picture of how the model improves or plateaus over time. The graphs also demonstrate the general trend that provides insights about the model's stability and learning capability, as well as the difference in accuracy between training and validation, which shows potential over-fitting. When the accuracy on the validation is noticeably lower than on the training set, this could be a sign of over-fitting, showing that the model may not generalize well to new data.

As shown in Figure 6.7a, the training dataset shows a noticeable improvement in accuracy with time, showing that model's capacity to pick up knowledge and get better at it. But, following some initial fluctuations, the test accuracy starts to plateau at about epoch 5, indicating that the model's learning has reached a stable state. This plateau can indicate that the model has learned as much as it can with the provided architecture and dataset. These insights give a thorough understanding of Model 1's performance and suggest possible improvements, including using data enrichment or model refinement to solve misclassifications.

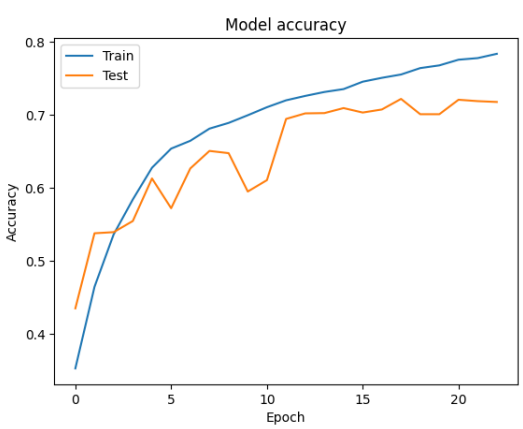
6.2.3.2. Model 2

Category	Precision	Recall	F1-score	Support
Angry	0.73	0.62	0.67	491.00
Happy	0.91	0.91	0.91	879.00
Sad	0.70	0.52	0.60	594.00
Neutral	0.60	0.82	0.69	626.00
Accuracy			0.74	2590.00
Macro avg	0.74	0.72	0.72	2590.00
Weighted avg	0.75	0.74	0.74	2590.00

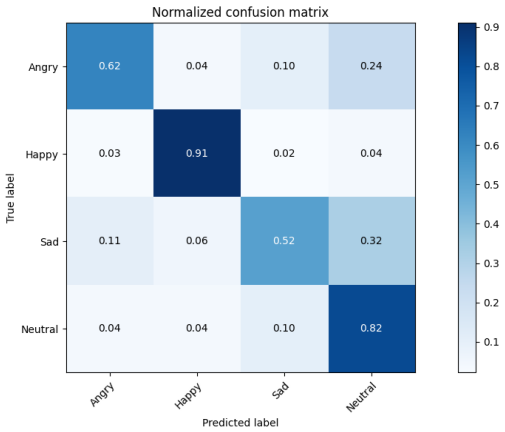
Table 6.2: Model 2 Classification Report

The classification report (See Table 6.2) shows that the model performs well in identifying ‘Happy’ expressions, with high precision (0.91) and recall (0.91) for the ‘Happy’ category. The precision of ‘Neutral’ is relatively lower at 0.60, indicating some misclassifications. ‘Angry’ and ‘Sad’ emotions show balanced precision and recall, which indicate that there is still potential for development in accurately identifying these emotions.

These findings are further supported by the confusion matrix (See Figure 6.8b), which shows the model’s capacity to accurately identify ‘Happy’ and ‘Neutral’ emotions with higher confidence. These categories are indicated by darker shades along the diagonal. The off-diagonal figures in the ‘Angry’ and ‘Sad’ sections, with the lighter shades, shows confusion, mainly with ‘Neutral’ expressions.



(a) Model 2 Accuracy Variation



(b) Model 2 Confusion Matrix

Figure Collection: Model 2 Graphs

Training and testing accuracy both steadily rise across epochs in the accuracy graph (See Figure 6.8a). The test accuracy plateaus at about the 15th epoch, indicating that continued training beyond this may not produce meaningful gains and may even worsen over-fitting problems.

All of these results shows that although Model 2 is quite good at identifying ‘Happy’, it struggles to identify ‘Angry’ and ‘Sad’. These issues could be resolved by improving the model’s generalizability by additional model tuning or data augmentation techniques.

6.2.4. Model Comparison and Selection

Property	Model 1	Model 2
Input shape	48 x 48 x 1	48 x 48 x 1
Weight layers	6	10
Conv layers	4	7
Kernel size	3x3	3x3
Training params	32,113,028	56,303,556
Model size (MB)	367	644
Accuracy (%)	71.35	74.32

Table 6.3: Comparison of Model 1 with Model 2

The performance of Model 1 and Model 2 is weighted to determine which is more suitable for deployment in this section. In addition to these variables, recall, accuracy, precision, and the F1-score for every emotional category, the architecture of the model, which depended on computational resources, is also taken into account in this decision making stage.

The comparative analysis between Model 1 and Model 2 (See Table 6.3) shows that Model 1 with fewer weight and convolutional layers, has much smaller in megabytes and has less training parameters compare to Model 2 which has more complex layers and greater model size. Besides, Model 2 achieves higher accuracy, which is an important consideration when choosing a model. It is because the project's objective is to accurately recognizing user's emotional states in order to provide music therapy.

Although Model 1 has the advantage of being a lighter model which may be beneficial in environments where computational resources are limited, the higher accuracy of Model 2 cannot be disregarded. The additional complexity of Model 2 is justified given the significance of accurate emotion detection in the context of the web application.

The decision between Model 1 and Model 2 will ultimately come down to balancing accuracy and computational efficiency. Despite its larger size and more parameters, Model 2 is the better option in terms of giving the best possible music therapy experience since its improved accuracy is more important in achieving the intended user experience.

Therefore, Model 2 is chosen, with further research and development to be done on optimization and efficiency issues.

6.2.5. Transfer Learning

Transfer learning, an approach that repurpose a pre-trained model for a different but related task, is implemented to fine-tune the selected Model 2 for better recognition of Asian facial features, which are underrepresented in the dataset primarily used for training - FER2013 (See Figure 6.1) and CK+ (See Figure 6.2). The integration of Szu-EmoDage (See Figure 6.3) aimed to address and improve the model's ethnic diversity-related limitations.

```
1     for layer in base_model.layers:
2         layer.trainable = True
```

Figure 6.9: Layer Trainable

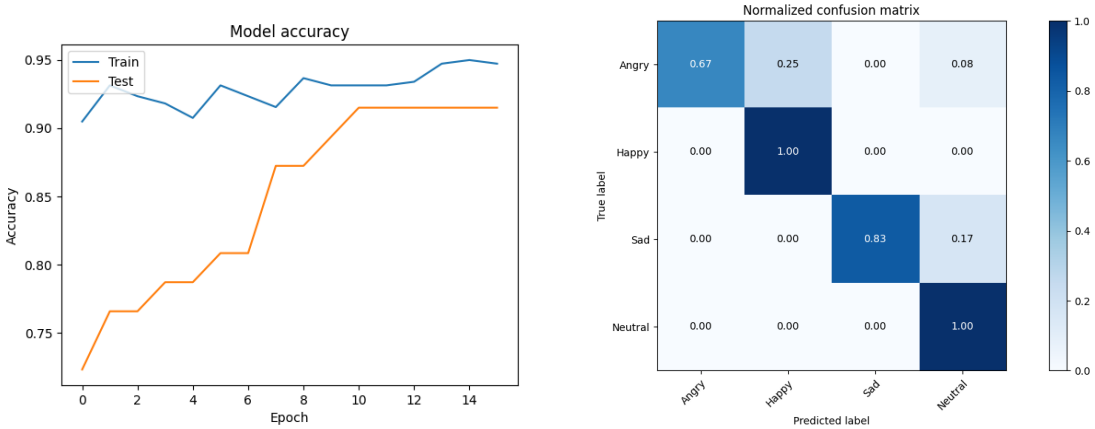
The transfer learning process involved retraining the model's layers, allowing it to learn from new features. During the fine-tuning stage, it is recommended to freeze certain layers of the model to preserve the knowledge it has acquired from the original datasets, while others were allowed to adjust their weights to the new data. However, all layers are set to trainable (See Figure 6.9) in this instance since Szu-EmoDage's size is significantly smaller than the original dataset which is less likely that it would overwrite the learned features from the original datasets.

The classification report (See Table 6.4) shows that the model achieved high precision across all emotions, particularly in identifying 'Angry' and 'Sad'. But, the recall for these emotions was lower, which indicates that the model occasionally missed some actual instances of these emotions.

The model accuracy graph (See Figure 6.10a), which peaks at 0.95 for the training set, shows a steady training process with high accuracy levels. The test set accuracy varies notably, but the model still perform well, indicating strong learning without over-fitting. This prove that the model generalizes the characteristics it has learnt from the original dataset, demonstrating its consistency in performance over varied inputs.

Category	Precision	Recall	F1-score	Support
Angry	1.00	0.67	0.80	12.00
Happy	0.80	1.00	0.89	12.00
Sad	1.00	0.83	0.91	12.00
Neutral	0.80	1.00	0.89	12.00
Accuracy			0.88	48.00
Macro avg	0.90	0.88	0.87	48.00
Weighted avg	0.90	0.88	0.87	48.00

Table 6.4: Transferred Learning Model Classification Report



(a) Transferred Learning Model Accuracy Variation

(b) Transferred Learning Model Confusion Matrix

Figure Collection: Transferred Learning Model Graphs

High true positive rates and a clear differentiation between ‘Happy’ and ‘Neutral’ is showed in the confusion matrix (See Figure 6.10b). This shows that the model is effectively recognizing these emotional states. However, it also shows that the model’s tendency to confuse the ‘Angry’ and ‘Neutral’, indicating a need for improved differentiation in these emotions.

6.3. WEB APPLICATION

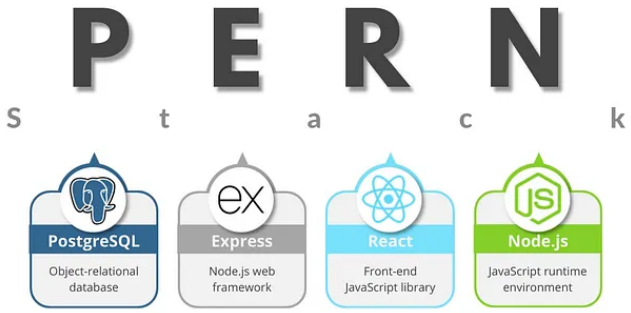


Figure 6.11: PERN Stack (Alves, 2023)

The web application uses the PERN stack (See Figure 6.11), which is an acronym for PostgreSQL, Express, React and Node.js. This set of technologies provides a comprehensive end-to-end foundation for creating dynamic web application.

The frontend was built with React.js, a widely-used JavaScript (JS) UI framework, which was chosen for its declarative and effective method of creating UI. For the backend, Node.js was chosen for its non-blocking, event-driven architecture. This architecture is well-suited for managing workloads that involve asynchronous operations, real-time applications and I/O-bound tasks. The backend API is then constructed using Express.js, a simple and adaptable Node.js web application framework. PostgreSQL is the chosen database system as it is well-known for its advanced features, data integrity and robustness.

6.3.1. Login and Registration

Users first provide their personal information, which consists of their date of birth, fist and last names, preferred username, and email address, to begin the registration process (See Figure 6.12). The entered data is then validated by cross-referencing it with existing entries in the ‘sentirhy.user’ table within the PostgreSQL database. If there is duplicated username or email, the user will be notified that the credentials have already been taken and the process will stopped. When there is no duplicate entry, the user’s password is securely hashed with ‘bcrypt’ (See Figure F.1 Line 9), and the ‘crypto’ module creates an unique activation token which will then send to the user’s email for

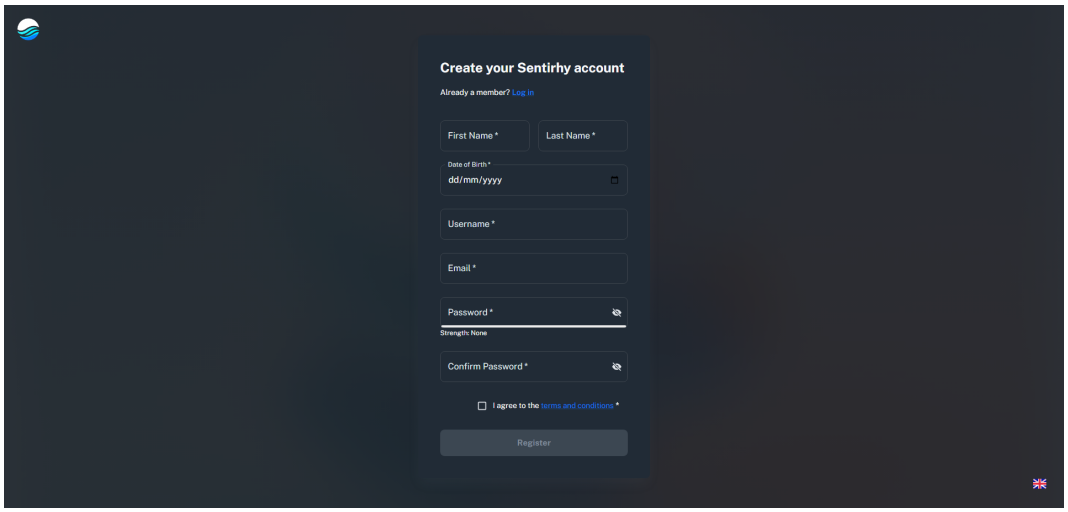


Figure 6.12: Register Page - UI

account verification. The generated token with an expiration date is also stored in the database with the user credentials for security purposes. An activation email (See

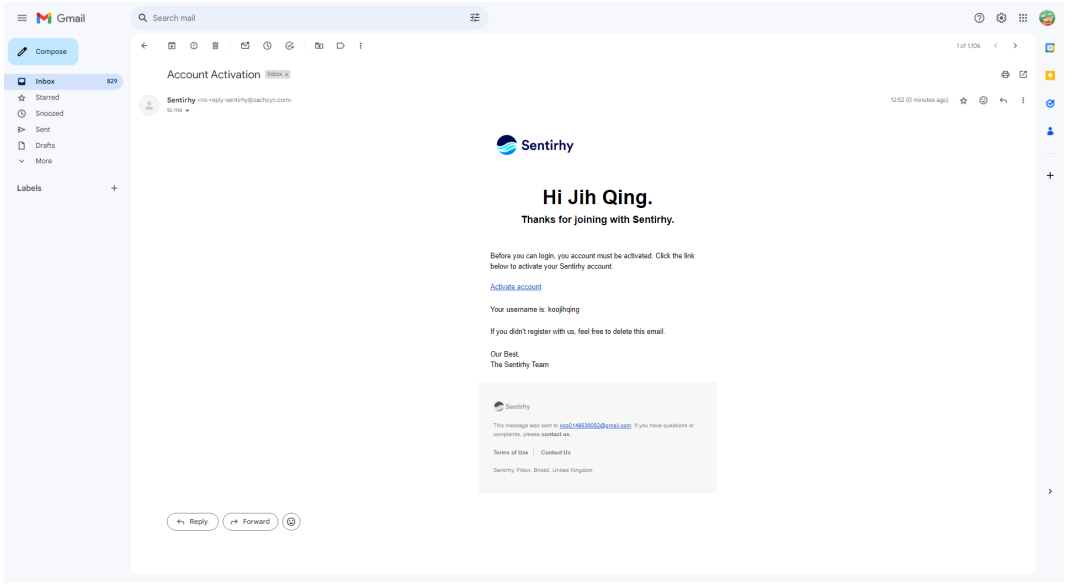


Figure 6.13: Account Activation Email - UI

Figure 6.13) is sent out using the ‘nodemailer’ after the new user’s database entry. For the login process (See Figure 6.14), the username and password are required. After user submitted the credentials, the system compares those credentials to those kept in the database. Then, access to the application is granted with a successful match and an activated account.

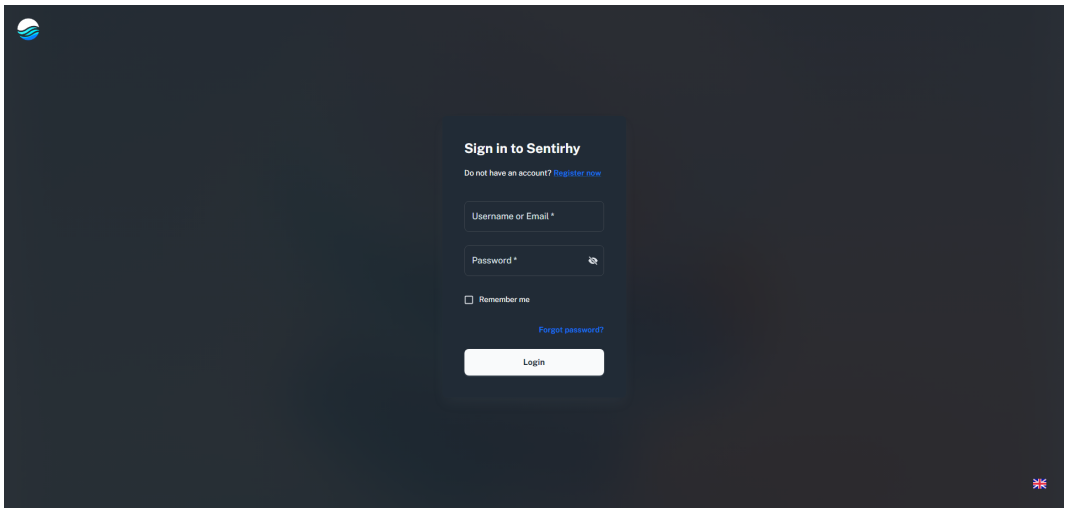


Figure 6.14: Login Page - UI

6.3.2. Integration with Music Services

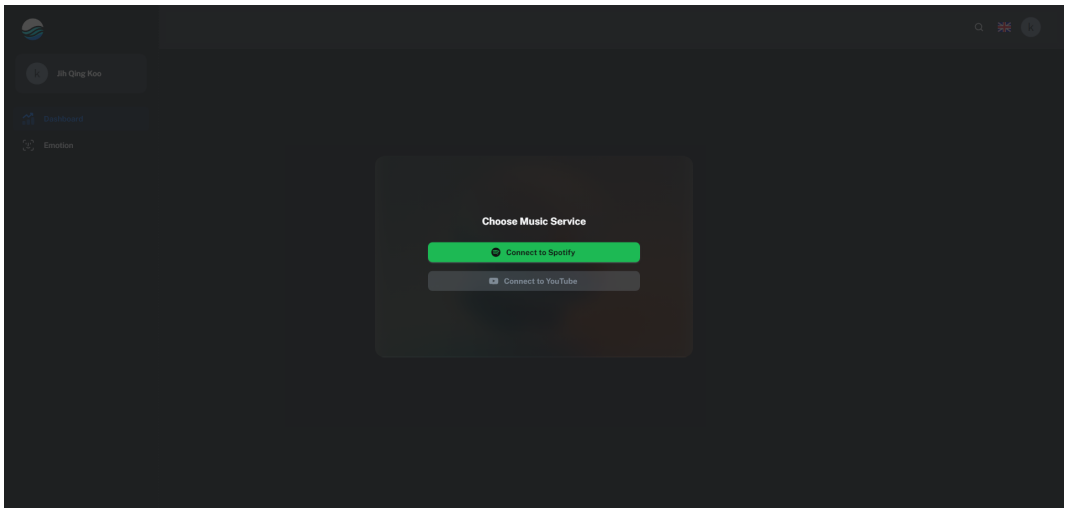


Figure 6.15: Music Services Connection - UI

As users log into the application, they are greeted with a dashboard. There will be a modal component (See Figure 6.15) showing on the dashboard, allowing users to connect to different music services, which is required to the app's function to play music. Users are redirected to Spotify's authorization interface through an OAuth 2.0 authorization flow in order to grant permissions when they choose to link their Spotify accounts. Once user's permission is acquired, an access token from Spotify's token endpoint gives the application the authority to request services from the Spotify API on the user's behalf, like playing music. Unfortunately, as of right now, the only integration that is operational is Spotify; Youtube connectivity is indicated as a planned addition.

6.3.3. Emotion Detector

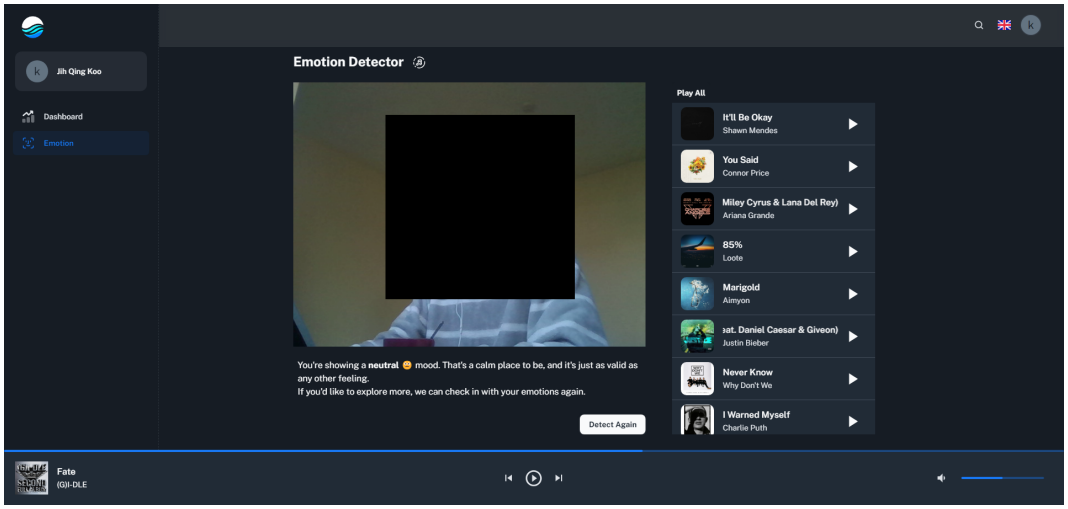


Figure 6.16: Emotion Detector - UI

When user enters the Emotion Detection page (See Figure 6.16), they encounter an interactive interface that requires access to the camera to proceed. With the user's permission, the application launches the Haarcascade frontal face identification algorithm and opencv.js, the JS library of OpenCV, enabling real-time face detection through the live video feed.

```
1    async function predictEmotion(imageFilename) {
2        const imagePath = path.join(__dirname, '/user_emotion/', imageFilename);
3        const model = await loadModel()
4        const imageBuffer = await fs.promises.readFile(imagePath);
5        const tensor = tf.node.decodeImage(imageBuffer).resizeBilinear([48,
         ↪  48]).mean(2).expandDims(-1).expandDims(0).toFloat().div(tf.scalar(255));
6        const prediction = model.predict(tensor);
7        const emotionIndex = prediction.argMax(1).dataSync()[0];
8
9        return emotions[emotionIndex];
10   }
```

Figure 6.17: Load Model and Preprocess data

The system is designed to identify faces quickly and captures the frame. The captured frame is then sent to the backend in a binary format appropriate for transmission

over the network. The backend, which has been configured with TensorFlow.js, awaits the binary format data to perform its function. It loads the trained model, then resize the image to 48x48 pixels, converted to grayscale, normalized to scale the pixel values, and batched for the model's evaluation in order to meet the model's needs (See Figure 6.17).

```
function generateProgressivePlaylist(user_emotion_tracks, neutral_tracks,
↪ happy_tracks, playlistLength) {

    const allTracks = user_emotion_tracks.concat(neutral_tracks, happy_tracks);
    allTracks.sort((a, b) => a.valence - b.valence);
    const step = Math.floor(allTracks.length / playlistLength);

    const selectedTracks = [];
    for (let i = 0; i < playlistLength && (i * step) < allTracks.length; i++) {
        selectedTracks.push(allTracks[i * step]);
    }

    return selectedTracks;
}
```

Figure 6.18: Generate Playlist

When the image is in an acceptable format, the model starts to recognize the user's current emotional state. Once the emotion is deciphered, the system responds by creating playlist that corresponds with the feeling (See Figure 6.18). The generated playlist is then dynamically displayed on the UI.

7. PROJECT EVALUATION

7.1. INTRODUCTION

Project evaluation allows to reflect on the project's successes and limitations. The end product was a responsive web application combined with advanced machine learning algorithms to create an emotion-based music recommendation system. CNNs model at the core of the system was trained on robust datasets and refined through transfer learning to improve recognition accuracy, especially for underrepresented demographics. This section is an opportunity to consider the feedback loop form supervisor, integrating their thoughts into the project's development.

7.1.1. Reflection on Project Phases

To improve the project's foundation, the research phase needs to include a deeper look into several key areas. First, integrating empirical research and well-established psychological theories will enrich the scientific basis of the emotion-music interaction, supporting the algorithmic approach for music recommendation. Additionally, adaptive algorithms that can customize recommendations based on user feedback should also be considered to improve user engagement and satisfaction.

To ensure the system's global applicability and adherence to ethical standards, especially privacy and cultural sensitivity, it is also essential to address ethical and cultural issues. Last but not least, by recognizing and addressing the limitations of current music therapy practices, the project may be positioned as a technical advancement that provides accessible and personalized therapeutic solutions.

The project was originally designed with a defined set of features that were essential for a music therapy application, such as user registration, emotion detection, music recommendations, along with an integration with Spotify's Web Playback API. However,

as the project developed, emerging challenges and deeper insights made it necessary to reevaluate and modify these requirements. As the appendix's Gantt chart (See Figure G.1) shows, the development of ML models and the integration with Spotify's API took longer than expected. The main cause of these delays was the unfamiliar with integrating API into web application and discovering the way to enhance the model's performance but still considering the amount of computational resources required.

Due to the delay which cause time constraints, the YouTube API integration was deprioritized and eventually not deployed. This decision is made to ensure the project could proceed gradually and the robustness and functionality of the core features, which were critical to the project's success, are developed on time.

During the implementation phase, a well-chosen technology stack and adaptable development techniques helped the project to be completed. The PERN stack was chosen for its reliability and scalability. The agile methodologies was chosen as it allows iterative improvements and flexibility in response to changing project requirements.

Using opencv.js for real-time face identification in the web application was one of the biggest obstacles, which required significant technical adjustments to ensure compatibility and efficiency. Another considerable challenge was the intensive hyperparameter tuning required for the models, especially the second one, for which it took approximately seven days to go through the parameter grid (See Figure 6.4). Then, the project timeline was impacted by this procedure, which was important but time-consuming.

7.1.2. Limitations and Test Results

In project evaluation, it is critical to address the limitations. One significant limitation in the emotion recognition system was its varying accuracy when exposed to different lighting conditions or when faced with unusual facial expressions, which may affect the accuracy of the results.

Additionally, even though the models work excellent on the dataset used, there were limits to the datasets themselves. For example, there were diversity issues with the datasets, FER2013 (See Figure 6.1) and CK+ (See Figure 6.2), especially with regard to ethnic representation. Also, the model may become biased towards to those more commonly represented categories, such as 'Neutral' faces in FER2013. This could limits the system applicability in real-world and diverse settings.

As shown in Table H.1, the project went through a set of testing that covered a wide range of functionality from backend operations to user interface interactions. The test showed the application's capability to handle user interactions and to interface with other services in an effective way. Tests for FER validated the face recognition algorithms' reliability, which is crucial for the project's core functionality. But, scalability testing, which is essential for evaluating the application's performance under various load conditions, is not part of the testing.

7.1.3. Supervisor's Feedback Utilization

The scope of the project was refined due to the frequent communication with the supervisor (See Table I.1). The project was previously intended to identify seven different emotions: angry, sad, neutral, happy, disgust, fear, and surprise. However, based on observations highlighting the importance of these fundamental emotions in music therapy, the scope was reduced to focus on the first four emotions. This modification ensured that the system was built with a clear focus on usability and efficacy for real-world applications, which also reduced the complexity and brought the project more directly in line with its therapeutic aims.

8. CONCLUSION AND FUTURE WORK

8.1. CONCLUSION

This study achieved its main goals of matching music selections to user's emotional states by effectively integrating music therapy and FER through a web application. It integrated advanced ML techniques for real-time FER and made use of the PERN stack for development. Despite acknowledging certain limitations, such as scalability and the unfinished Youtube API integration, the project adapted to feedback effectively, focusing on four main emotions to simplify and enhance the therapeutic aspects of the application.

8.2. FUTURE WORK

In order to improve the functionality of the application and user involvement, several initiatives are considered. The user experience will be improved by implementing a user feedback system, which enable the generation of personalized and adaptable music playlists. Enabling users to specify their nationality during sign-up will help with the suggestion of music that is culturally relevant, hence expanding the application's reach internationally.

Additionally, new features that let users remove their accounts and get their stored data will be implemented to ensure GDPR compliance (GDPR, 2018). Utilizing the emotional data gathered will also help the project by enhancing the FER model's responsiveness and accuracy. To dynamically modify music recommendation based on user interactions, it will be helpful to investigate advanced learning techniques such as reinforcement learning.

Lastly, a more thorough knowledge of users' emotional states will be possible by extending FER capabilities to incorporate with physiological and behavioral indications

such as speech patterns and brain signals[1]. Besides these indicators, body movements and gestures are also helpful in achieving accurate recognition of an individual's emotions.

8.3. CONCLUDING THOUGHTS

This project's multidisciplinary approach shows how cognitive science and technology may be used to address complicated problem in health and wellbeing. Although the application appears to have potential in matching music to identified emotional states, more testing is required to verify its effectiveness in improving emotional health. In addition to adding functionality to the application, the suggested future works aim to advance the field of emotion-sensitive interactive systems, which potentially offering benefits for users globally.

[1]This includes Electroencephalogram (EEG), Electromyography (EMG), and Electrooculogram (EOG) (Shin et al., 2018)

BIBLIOGRAPHY

Ackerman, C. E. (2018), ‘What is attachment theory? bowlby’s 4 stages explained.’.
URL: *https://positivepsychology.com/attachment-theory/*

Agrawal, A. and Mittal, N. (2019), ‘Using cnn for facial expression recognition: a study of the effects of kernel size and number of filters on accuracy’, *The Visual Computer* **36**, 405–412.
URL: *https://link.springer.com/article/10.1007/s00371-019-01630-9*

Alves, R. (2023), ‘Get started with the pern stack: an introduction and implementation guide’.
URL: *https://medium.com/@ritapalves/get-started-with-the-pern-stack-an-introduction-and-implementation-guide-e33c55d09994*

Association, A. M. T. (2005), ‘What is music therapy | what is music therapy? | american music therapy association (amta)’.
URL: *https://www.musictherapy.org/about/musictherapy/*

Athavle, M. (2021), ‘Music recommendation based on face emotion recognition’, *Journal of Informatics Electrical and Electronics Engineering (JIEEE)* **2**, 1–11.
URL: *https://jieee.a2zjournals.com/index.php/ieee/article/view/45*

Babu, T., Nair, R. R. and Geetha, A. (2023), ‘Emotion aware music recommendation system: Enhancing user experience through real-time emotional context’, *ArXiv (Cornell University)* **6**.
URL: *https://arxiv.org/abs/2311.10796*

Barbara, E. (2014), ‘Music therapy and military populations a status report and recommendations on music therapy treatment, programs, research, and practice

policy'.
URL: *https://www.musictherapy.org/assets/1/7/MusicTherapyMilitaryPops_2014.pdf*

Bell, D. (2004), 'Explore the uml sequence diagram'.
URL: *https://developer.ibm.com/articles/the-sequence-diagram/*

Berwick, R. (n.d.), 'An idiot's guide to support vector machines (svms) r. berwick, village idiot svms: a new generation of learning algorithms'.
URL: *https://web.mit.edu/6.034/wwwbob/svm.pdf*

Boehm, B. (1986), 'A spiral model of software development and enhancement', *ACM SIGSOFT Software Engineering Notes* **11**, 22–42.
URL: *https://dl.acm.org/doi/10.1145/12944.12948*

Bonthu, H. (2021), 'Detecting and treating outliers | how to handle outliers'.
URL: *https://www.analyticsvidhya.com/blog/2021/05/detecting-and-treating-outliers-treating-the-odd-one-out/*

Bruscia, K. E. (1988), 'A survey of treatment procedures in improvisational music therapy', *Psychology of Music* **16**, 10–24.

Clinic, C. (2020), 'Music therapy: What is it, types & treatment'.
URL: *https://my.clevelandclinic.org/health/treatments/8817-music-therapy*

Cloud, G. (2023), 'What is artificial intelligence (ai)?'.
URL: *https://cloud.google.com/learn/what-is-artificial-intelligence*

Craig, H. (2019), 'What are the benefits of music therapy?'.
URL: *https://positivepsychology.com/music-therapy-benefits/*

Crespo-Santiago, C. A. and Dávila-Cosme, S. d. l. C. (2022), 'Waterfall method: a necessary tool for implementing library projects', *HETS Online Journal* **1**, 81–92.
URL: *https://hets.org/ojournal/index.php/hoj/article/view/91*

Dumitru, Goodfellow, I., Cukierski, W. and Bengio, Y. (2023), 'Challenges in representation learning: Facial expression recognition challenge'.
URL: *https://www.kaggle.com/competitions/challenges-in-representation-learning-facial-expression-recognition-challenge*

Farley, P. (2023), ‘Face detection, attributes, and input data - face - azure ai services’.
URL: *https://learn.microsoft.com/en-us/azure/ai-services/computer-vision/concept-face-detection*

Freeman, J. (n.d.), ‘Block diagram | complete guide with examples’.
URL: *https://www.edrawsoft.com/block-diagram.html*

Gandhi, R. (2018), ‘Introduction to machine learning algorithms: Linear regression’.
URL: *https://towardsdatascience.com/introduction-to-machine-learning-algorithms-linear-regression-14c4e325882a*

Garrison, J. (2021), ‘Music & traumatic stress: Music therapy research and treatment with military populations’.
URL: *https://www.stress.org/music-traumatic-stress-music-therapy-research-and-treatment-with-military-populations*

GDPR (2018), ‘General data protection regulation (gdpr)’.
URL: *https://gdpr-info.eu/*

GeeksforGeeks (2018), ‘K-nearest neighbours - geeksforgeeks’.
URL: *https://www.geeksforgeeks.org/k-nearest-neighbours/*

Gooding, L. F. and Langston, D. G. (2019), ‘Music therapy with military populations: a scoping review’, *Journal of Music Therapy* **56**, 315–347.
URL: *https://pubmed.ncbi.nlm.nih.gov/31696919/*

Google (2021), ‘What is machine learning? | google cloud’.
URL: *https://cloud.google.com/learn/what-is-machine-learning*

Google (2022), ‘Descending into ml: Training and loss | machine learning crash course’.
URL: *https://developers.google.com/machine-learning/crash-course/descending-into-ml/training-and-loss*

Géron, A. (2017), *Hands-On Machine Learning with Scikit-Learn and TensorFlow*, 2nd edn, "O’Reilly Media, Inc.".

Harrison, O. (2018), ‘Machine learning basics with the k-nearest neighbors algorithm’.
URL: *https://towardsdatascience.com/machine-learning-basics-with-the-k-nearest-neighbors-algorithm-6a6e71d01761*

Haykin, S., York, N., San, B., London, F., Sydney, T., Singapore, T., Mexico, M. and Munich, C. (2014), ‘Neural networks and learning machines third edition’.
URL: *https://cours.etsmtl.ca/sys843/REFS/Books/ebook_Haykin09.pdf*

Hillecke, T. (2005), ‘Scientific perspectives on music therapy’, *Annals of the New York Academy of Sciences* **1060**, 271–282.
URL: *http://onlinelibrary.wiley.com/doi/10.1196/annals.1360.020/abstract*

Huang, Z.-Y., Chiang, C.-C., Chen, J.-H., Chen, Y.-C., Chung, H.-L., Cai, Y.-P. and Hsu, H.-C. (2023), ‘A study on computer vision for facial emotion recognition’, *Scientific Report* **13**.
URL: *https://pubmed.ncbi.nlm.nih.gov/37225755/*

IBM (2021), ‘Use-case diagrams’.
URL: *https://www.ibm.com/docs/en/rational-soft-arch/9.6.1?topic=diagrams-use-case*

IBM (2022*a*), ‘About linear regression | ibm’.
URL: *https://www.ibm.com/topics/linear-regression#: :text=Resources-*

IBM (2022*b*), ‘What is gradient descent? | ibm’.
URL: *https://www.ibm.com/topics/gradient-descent*

IBM (2023*a*), ‘What are convolutional neural networks? | ibm’.
URL: *https://www.ibm.com/topics/convolutional-neural-networks*

IBM (2023*b*), ‘What is random forest? | ibm’.
URL: *https://www.ibm.com/topics/random-forest#: :text=Random%20forest%20is%20a%20commonly*

IBM (2023*c*), ‘What is the k-nearest neighbors algorithm? | ibm’.
URL: *https://www.ibm.com/topics/knn#: :text=Next%20steps-*

Juslin, P. N. and Sloboda, J. A. (2013), ‘Music and emotion’, *The Psychology of Music* pp. 583–645.
URL: *https://psycnet.apa.org/record/2012-14631-015*

Konstantina, V., Anna, H. and Thomas, Z. (2021), ‘Facial emotion recognition’.
URL: *https://edps.europa.eu/system/files/2021-05/21-05-26_techdispatch-facial-emotion-recognition_ref_en.pdf*

Kumar Pal, S. (2018), ‘Software engineering | spiral model’.
URL: *https://www.geeksforgeeks.org/software-engineering-spiral-model/*

Kwiatkowski, R. (2021), ‘Gradient descent algorithm: a deep dive’.
URL: *https://towardsdatascience.com/gradient-descent-algorithm-a-deep-dive-cf04e8115f21*

Laoyan, S. (2024), ‘What is agile methodology? (a beginner’s guide)’.
URL: *https://asana.com/resources/agile-methodology*

learn, S. (2018), ‘1.4. support vector machines’.
URL: *https://scikit-learn.org/stable/modules/svm.html#: :text=Support%20vector%20machines%20(SVMs)%20are*

Lucey, P., Cohn, J. F., Kanade, T., Saragih, J., Ambadar, Z. and Matthews, I. (2010), ‘The extended cohn-kanade dataset (ck+): a complete dataset for action unit and emotion-specified expression’, *2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition - Workshops* pp. 94–101.
URL: *https://ieeexplore.ieee.org/document/5543262*

Lucidchart (2019), ‘What is a flowchart’.
URL: *https://www.lucidchart.com/pages/what-is-a-flowchart-tutorial*

Mali, K. (2021), ‘Linear regression | everything you need to know about linear regression’.
URL: *https://www.analyticsvidhya.com/blog/2021/10/everything-you-need-to-know-about-linear-regression/*

Mandal, M. (2021), ‘Cnn for deep learning | convolutional neural networks (cnn)’.
URL: *https://www.analyticsvidhya.com/blog/2021/05/convolutional-neural-networks-cnn/*

Mellouk, W. and Handouzi, W. (2020), ‘Facial emotion recognition using deep learning: Review and insights’, *Procedia Computer Science* **175**, 689–694.
URL: *https://www.sciencedirect.com/science/article/pii/S1877050920318019*

Mishra, M. (2020), ‘Convolutional neural networks, explained’.
URL: *https://towardsdatascience.com/convolutional-neural-networks-explained-9cc5188c4939*

Munasinghe, M. I. N. P. (2018), ‘Facial expression recognition using facial landmarks and random forest classifier’, *2018 IEEE/ACIS 17th International Conference on Computer and Information Science (ICIS)* pp. 423–427.
URL: *https://ieeexplore.ieee.org/document/8466510*

Naseem, I., Togneri, R. and Bennamoun, M. (2010), ‘Linear regression for face recognition’, *IEEE Transactions on Pattern Analysis and Machine Intelligence* **32**, 2106–2112.
URL: *https://ieeexplore.ieee.org/abstract/document/5506092?casa_token=Yu36FOKbkNoAAAAA:Ef2sB0dSZsqUG6bWOHcrtk-t9POgl6c169s0Jd9flh4dTQIwgHJSCl1Gu2c67tZj4tfi47ImXg*

Pereira, C. S., Teixeira, J., Figueiredo, P., Xavier, J., Castro, S. L. and Brattico, E. (2011), ‘Music and emotions in the brain: Familiarity matters’, *PLoS ONE* **6**, e27241.
URL: *https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0027241*

S, M. C. D., Iram, S., Bhat, R., Supritha, L. and Leelavathi, S. (2023), ‘Music recommendation based on facial emotion recognition’, *Nternational Journal of Advanced Research in Computer and Communication Engineering* **12**.
URL: *https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0027241*

Saha, S. (2018), ‘A comprehensive guide to convolutional neural networks: the eli5 way’.
URL: *https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53*

Saini, A. (2021), ‘Support vector machine(svm): a complete guide for beginners’.

URL: *https://www.analyticsvidhya.com/blog/2021/10/support-vector-machinessvm-a-complete-guide-for-beginners/*

Schedl, M., Knees, P., McFee, B. and Bogdanov, D. (2021), 'Music recommendation systems: Techniques, use cases, and challenges', *Springer eBooks* pp. 927–971.
URL: *https://link.springer.com/chapter/10.1007/978-1-0716-2197-4_24*

Scikit-learn (2018), 'sklearn.ensemble.randomforestclassifier : scikit-learn 0.20.3 documentation'.
URL: *https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html*

Shin, J., Maeng, J. and Kim, D.-H. (2018), 'Inner emotion recognition using multi bio-signals', *2018 IEEE International Conference on Consumer Electronics - Asia (ICCE-Asia)* pp. 206–212.
URL: *https://ieeexplore.ieee.org/document/8552152*

Simonyan, K. and Zisserman, A. (2014), 'Very deep convolutional networks for large-scale image recognition', *Computer Science* .
URL: *https://xueshu.baidu.com/usercenter/paper/show?paperid=2801f41808e377a1897a3887b6758c59&site=xueshu_se*

Song, Y., Dixon, S. and Pearce, M. (2012), 'A survey of music recommendation systems and future perspectives'.
URL: *https://www.semanticscholar.org/paper/A-Survey-of-Music-Recommendation-Systems-and-Future-Song-Dixon/e0080299afae01ad796060abcf602abff6024754*

Srivastava, T. (2019), 'Introduction to knn, k-nearest neighbors : Simplified'.
URL: *https://www.analyticsvidhya.com/blog/2018/03/introduction-k-neighbours-algorithm-clustering/*

Sruthi, E. R. (2021), 'Random forest | introduction to random forest algorithm'.
URL: *https://www.analyticsvidhya.com/blog/2021/06/understanding-random-forest/*

Tarnowski, P., Kołodziej, M., Majkowski, A. and Rak, R. J. (2017), 'Emotion recognition using facial expressions', *Procedia Computer Science* **108**, 1175–1184.

URL: *https://www.sciencedirect.com/science/article/pii/S1877050917305264?via%3Dihub*

Team, A. C. (2022), ‘Waterfall methodology: a complete guide’.
URL: *https://business.adobe.com/blog/basics/waterfall*

Who (2022), ‘A chinese face dataset with dynamic expressions and diverse ages synthesized by deep learning’, *osf.io* .
URL: *https://osf.io/7a5fs/*

Xia, L. (2014), ‘Facial expression recognition based on svm’, *Proceedings of the 2014 7th International Conference on Intelligent Computation Technology and Automation* pp. 256–259.
URL: *https://dl.acm.org/doi/abs/10.1109/ICICTA.2014.69*

Yamashita, R., Nishio, M., Do, R. K. G. and Togashi, K. (2018), ‘Convolutional neural networks: an overview and application in radiology’, *Insights into Imaging* **9**, 611–629.
URL: *https://insightsimaging.springeropen.com/articles/10.1007/s13244-018-0639-9*

Yiu, T. (2019), ‘Understanding random forest’.
URL: *https://towardsdatascience.com/understanding-random-forest-58381e0602d2*

Zharovskikh, A. (2020), ‘How face recognition and ai are used in healthcare’.
URL: *https://indatalabs.com/blog/ai-face-recognition-in-healthcare*

APPENDICES

APPENDIX A

To categorize music based on emotions, a detailed preprocessing and classification workflow was implemented. To convert the emotional labels into a numerical representation that could be used with ML algorithms, label encoder is implemented.

```
label_encoder = LabelEncoder()
df['combinedemotion'] = label_encoder.fit_transform(df['combinedemotion'])
```

Figure A.1: Label Encoder

```
classes = np.unique(df['combinedemotion'])
weights = compute_class_weight(class_weight='balanced', classes=classes,
↪  y=df['combinedemotion'])
```

Figure A.2: Label Encoder

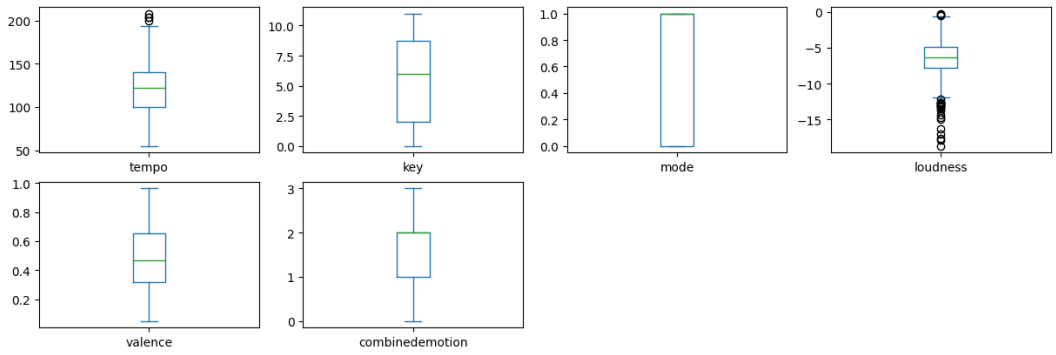


Figure A.3: Identify outliers with Box Plot

Then, to address data imbalances and ensure that each class had an equal impact on the model during training, compute class weight is used. By utilizing the inter-quartile

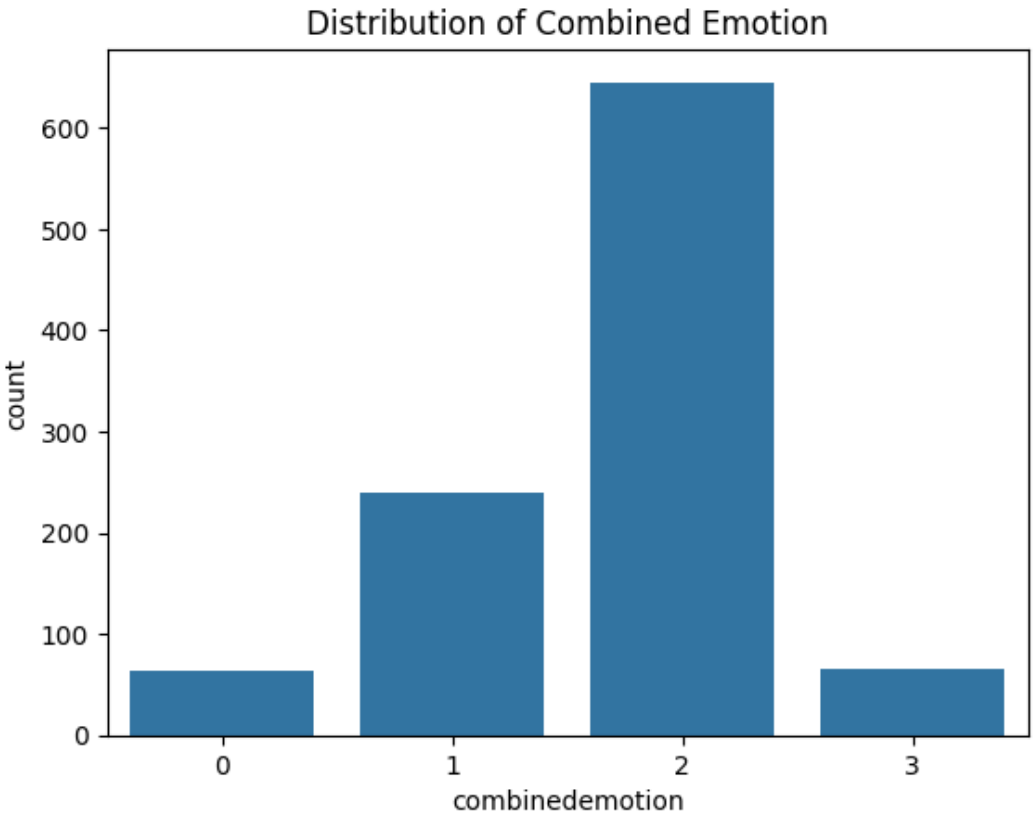


Figure A.4: Emotion Distribution Graph

range of tempo and loudness to identify and exclude the outliers[2], the dataset is refined which then helps the model to concentrate on more typical data points.

Then, we normalized selected features and employed one-hot encoding to transform categorical variables into binary matrices, which is important for classification algorithms. In order to improve the dataset and discover those hidden patterns, polynomial features were added to capture interactions between features. Tempo and loudness features are then scaled and grouped into quantile-based bins to prevent the model from being influenced by those extreme values.

Different ML algorithms such as RF, SVM, and Logistic Regression with a tailored approach to handle the class imbalance, were then employed to find out which would be the best algorithms for music classification. After evaluating different models, SVM

Table A.1: Accuracy comparison of machine learning models

Model	Random Forest	Support Vector Machine	Logistic Regression
Accuracy	0.82	0.71	0.75

[2]Data points that significantly differ from other observations in a dataset (Bonthu, 2021).

showed that it has the best performance compared to the others (See Table 6.3). Therefore, SVM model is further refined with grid search to optimize its parameters, which resulted in a significant improvement in the F1-score.

Category	Precision	Recall	F1-score	Support
0	0.67	0.33	0.44	12.00
1	0.93	0.75	0.83	157.00
2	0.82	0.94	0.88	121.00
3	0.57	0.50	0.53	8.00
Accuracy			0.83	198.00
Macro avg	0.75	0.63	0.67	198.00
Weighted avg	0.83	0.83	0.82	198.00

Table A.2: Music Classification Model Classification Report

In the classification report (See Table A.2), it shows an excellent result of 0.83 accuracy. However, classes 0 and 3 showed less-than-ideal performance metrics in the report. This could be due to the classes contain fewer data points which leads to data imbalanced, despite the fact that we applied class weights to account for imbalances. Therefore, in comparison to the more populated classes, these classes' insufficient data could not fully represent the complexity of their properties, leading to poorer accuracy and recall rates.

Moving forward, it will be essential to improve the dataset for these underrepresented classes. A more varied and collection of tracks for these emotions would likely to enhance the dataset and provide a model that is more sensitive and capable of generalization.

APPENDIX B

```
2023-12-27 23:22:26.546868:
Score: 0.5725693106651306
Params: {'conv_1_filters': 32, 'conv_2_filters': 64, 'conv_3_filters': 128, 'conv_4_filters': 128, 'conv_1_kernel': 3, 'conv_2_kernel': 3, 'conv_3_kernel': 3, 'conv_4_kernel': 3, 'dropout_1': 0.1, 'dropout_2': 0.0, 'dropout_3': 0.0, 'dense_units': 512, 'l1_reg': 0.01, 'optimizer': 'adam', 'learning_rate': 0.01}
2023-12-27 23:24:26.831029:
Score: 0.5765619874000549
Params: {'conv_1_filters': 32, 'conv_2_filters': 64, 'conv_3_filters': 128, 'conv_4_filters': 128, 'conv_1_kernel': 3, 'conv_2_kernel': 3, 'conv_3_kernel': 3, 'conv_4_kernel': 3, 'dropout_1': 0.1, 'dropout_2': 0.0, 'dropout_3': 0.0, 'dense_units': 1024, 'l1_reg': 0.01, 'optimizer': 'adam', 'learning_rate': 0.01}
2023-12-27 23:30:18.471026:
Score: 0.5906981825828552
Params: {'conv_1_filters': 32, 'conv_2_filters': 64, 'conv_3_filters': 128, 'conv_4_filters': 128, 'conv_1_kernel': 3, 'conv_2_kernel': 3, 'conv_3_kernel': 3, 'conv_4_kernel': 3, 'dropout_1': 0.1, 'dropout_2': 0.0, 'dropout_3': 0.2, 'dense_units': 512, 'l1_reg': 0.01, 'optimizer': 'adam', 'learning_rate': 0.01}
2023-12-27 23:45:27.23346:
Score: 0.3413424789905548
Params: {'conv_1_filters': 32, 'conv_2_filters': 64, 'conv_3_filters': 128, 'conv_4_filters': 128, 'conv_1_kernel': 3, 'conv_2_kernel': 3, 'conv_3_kernel': 3, 'conv_4_kernel': 3, 'dropout_1': 0.1, 'dropout_2': 0.0, 'dropout_3': 0.0, 'dense_units': 512, 'l1_reg': 0.01, 'optimizer': 'adam', 'learning_rate': 0.1}
```

Figure B.1: Model 1: Subset of Grid Search Results

APPENDIX C

```
2023-12-29 10:18:11.871023:
Score: 0.3413424789905548
Params: {'conv_1_filters': 32, 'conv_2_filters': 64, 'conv_3_filters': 128, 'conv_4_filters': 128, 'conv_1_kernel': 3, 'conv_2_kernel': 3, 'conv_3_kernel': 3, 'conv_4_kernel': 3, 'dropout_1': 0.1, 'dropout_2': 0.0, 'dropout_3': 0.0, 'dense_units': 512, 'l1_reg': 0.01, 'optimizer': 'adam', 'learning_rate': 0.01}
2024-01-01 03:45:22.236121:
Score: 0.6384439468383789
Params: {'conv_1_filters': 32, 'conv_2_filters': 64, 'conv_3_filters': 128, 'conv_4_filters': 128, 'conv_1_kernel': 3, 'conv_2_kernel': 3, 'conv_3_kernel': 3, 'conv_4_kernel': 3, 'dropout_1': 0.1, 'dropout_2': 0.0, 'dropout_3': 0.0, 'dense_units': 512, 'l1_reg': 0.01, 'optimizer': 'adam', 'learning_rate': 0.001}
2024-01-01 19:23:17.180239:
Score: 0.6926010847091675
Params: {'conv_1_filters': 32, 'conv_2_filters': 64, 'conv_3_filters': 128, 'conv_4_filters': 128, 'conv_1_kernel': 3, 'conv_2_kernel': 3, 'conv_3_kernel': 3, 'conv_4_kernel': 3, 'dropout_1': 0.1, 'dropout_2': 0.0, 'dropout_3': 0.0, 'dense_units': 512, 'l1_reg': 0.01, 'optimizer': 'adam', 'learning_rate': 0.001}
2024-01-05 23:07:41.103846:
Score: 0.6933638453483582
Params: {'conv_1_filters': 32, 'conv_2_filters': 64, 'conv_3_filters': 128, 'conv_4_filters': 128, 'conv_1_kernel': 3, 'conv_2_kernel': 3, 'conv_3_kernel': 3, 'conv_4_kernel': 3, 'dropout_1': 0.1, 'dropout_2': 0.0, 'dropout_3': 0.0, 'dense_units': 512, 'l1_reg': 0.01, 'optimizer': 'adam', 'learning_rate': 0.0001}
2024-01-11 11:14:23.678129:
Score: 0.7284515500068665
Params: {'conv_1_filters': 32, 'conv_2_filters': 64, 'conv_3_filters': 128, 'conv_4_filters': 128, 'conv_1_kernel': 3, 'conv_2_kernel': 3, 'conv_3_kernel': 3, 'conv_4_kernel': 3, 'dropout_1': 0.1, 'dropout_2': 0.0, 'dropout_3': 0.0, 'dense_units': 512, 'l1_reg': 0.001, 'optimizer': 'adam', 'learning_rate': 0.001}
```

Figure C.1: Model 2: Subset of Grid Search Results

APPENDIX D

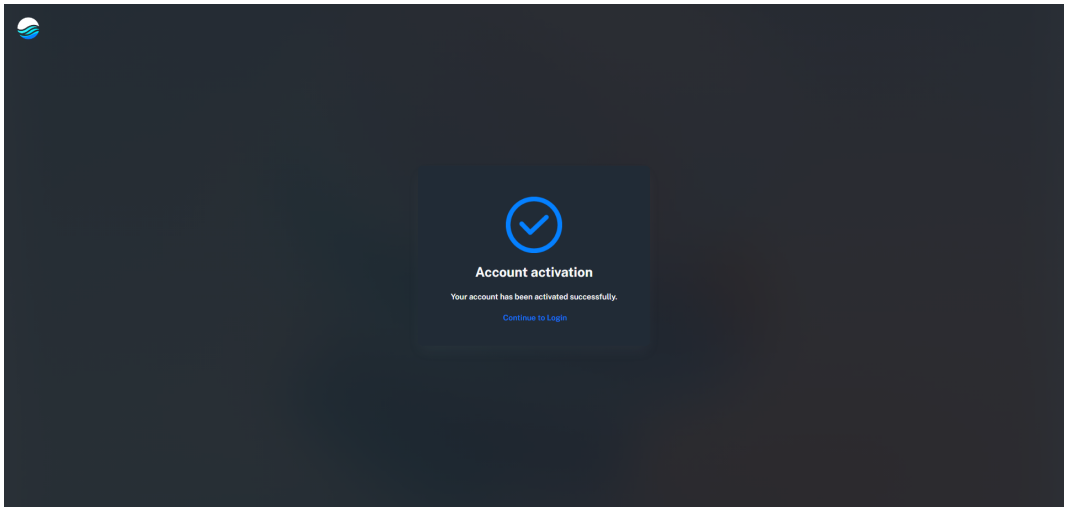


Figure D.1: Account Activated - UI

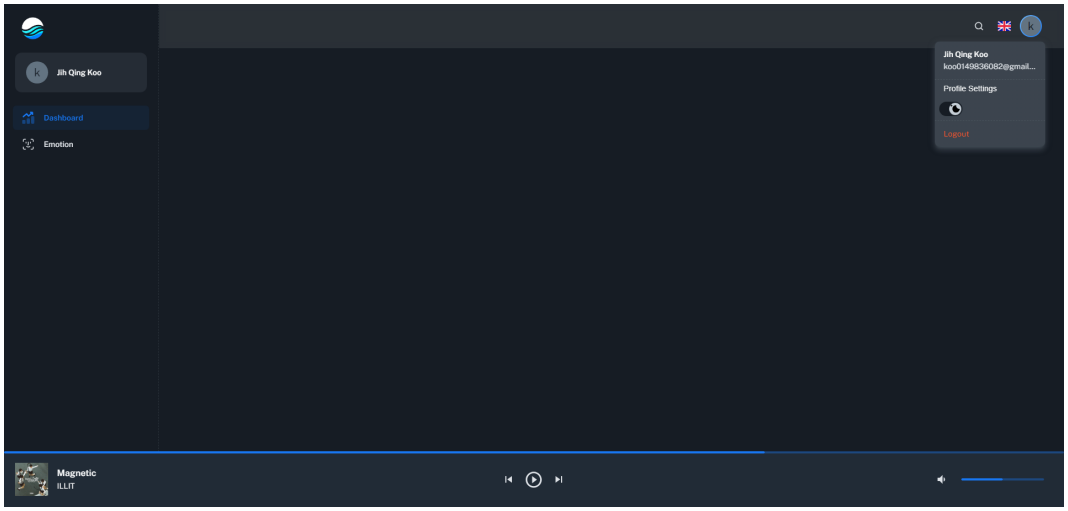


Figure D.2: Dashboard - UI

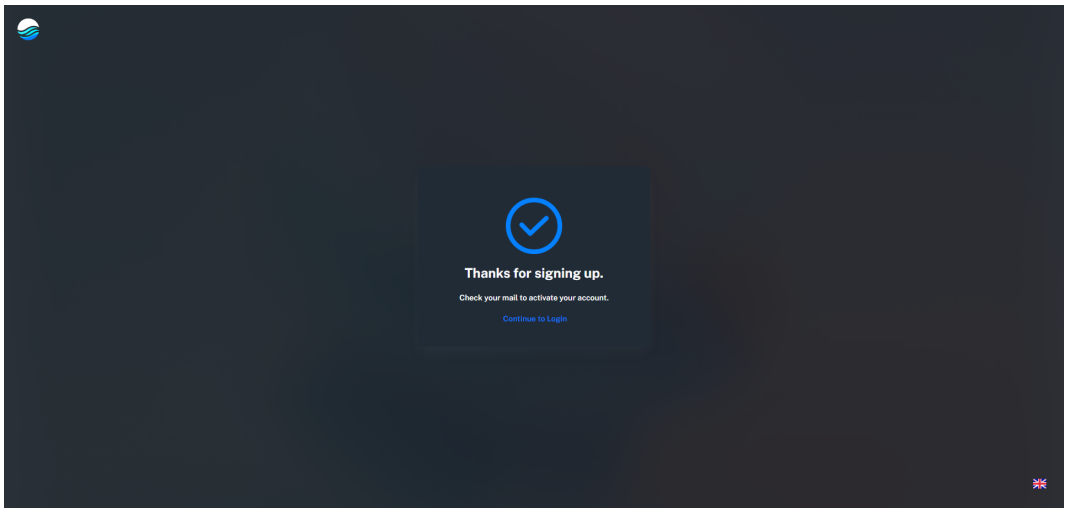


Figure D.3: Register Successful - UI

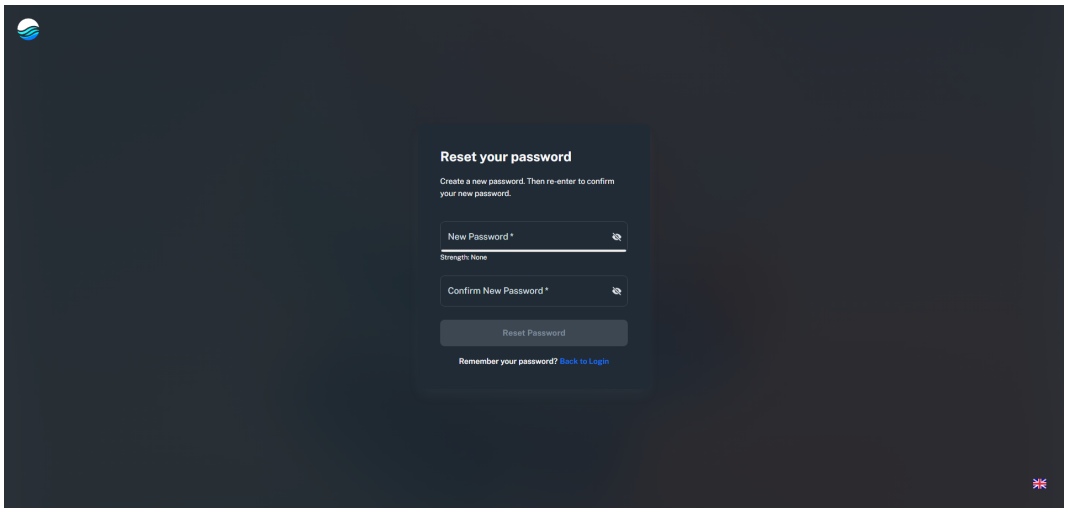


Figure D.4: Reset Password - UI

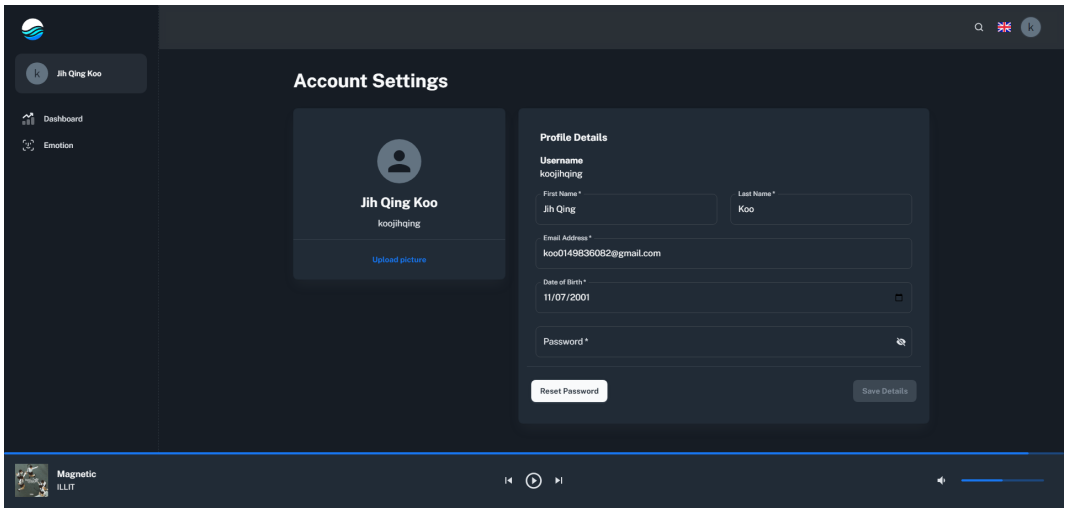


Figure D.6: User Settings - UI

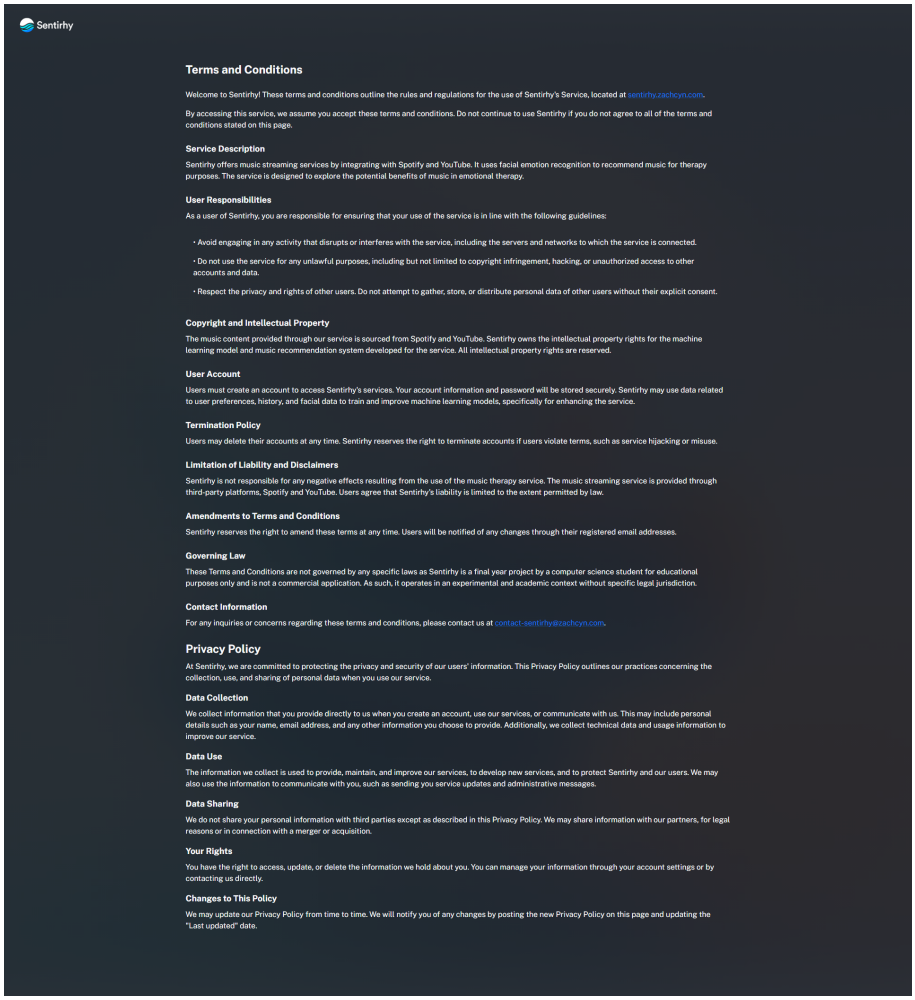


Figure D.5: Terms and Conditions - UI

APPENDIX E

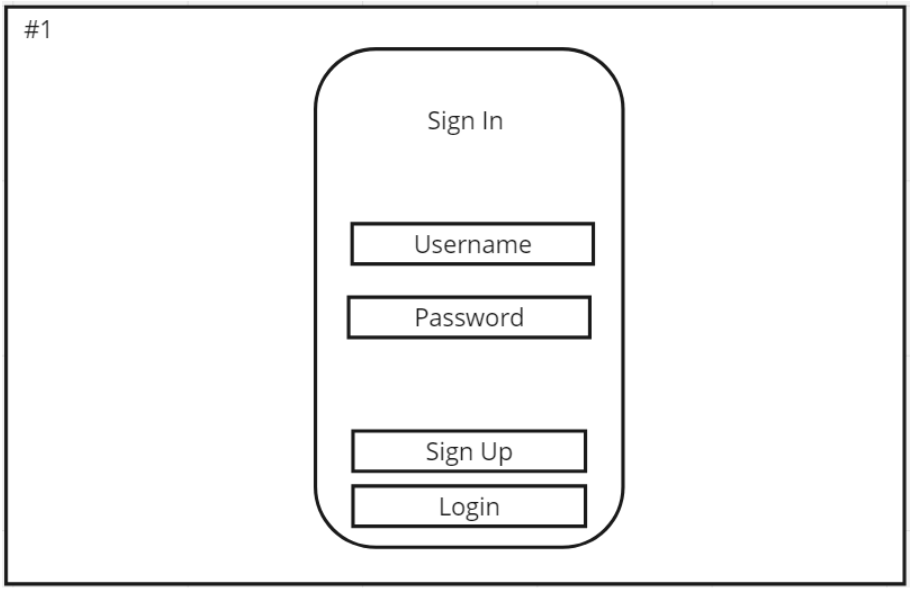


Figure E.1: Login Page

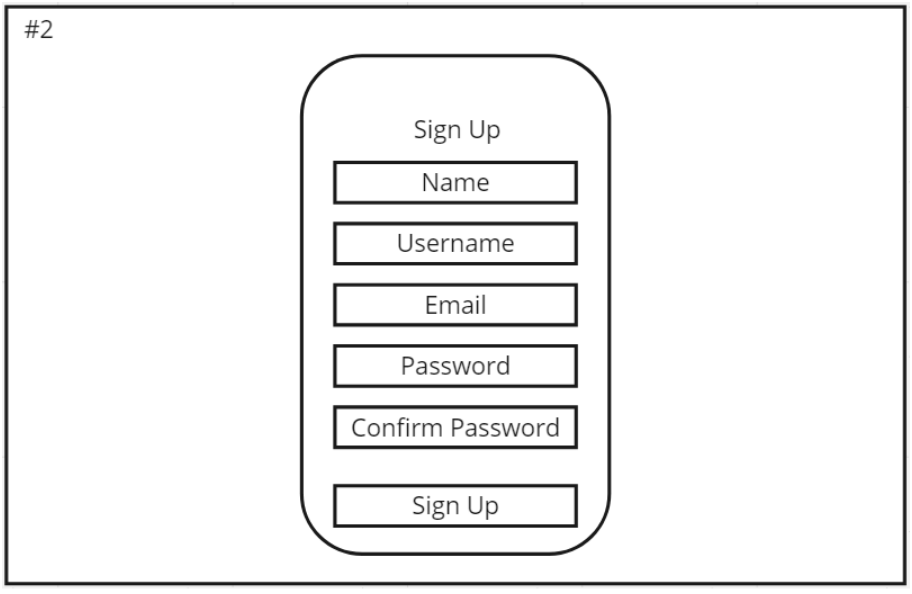


Figure E.2: Sign Up Page

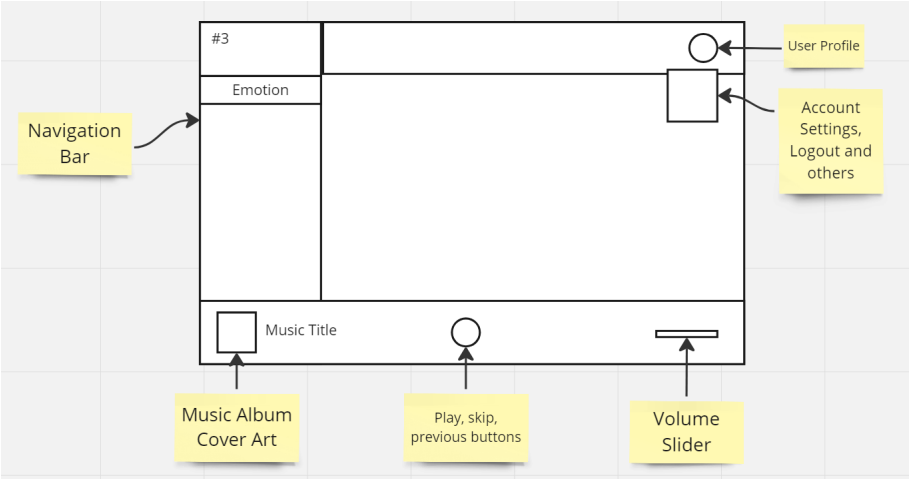


Figure E.3: Dashboard Page

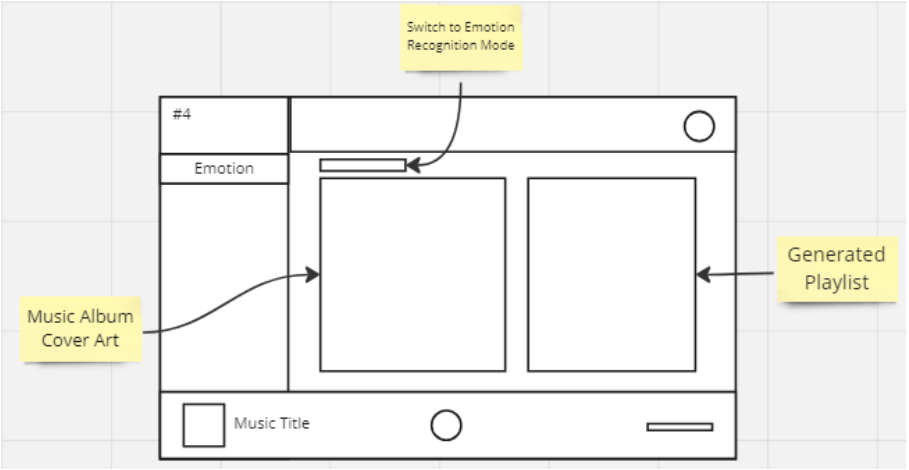


Figure E.4: Emotion Music Page

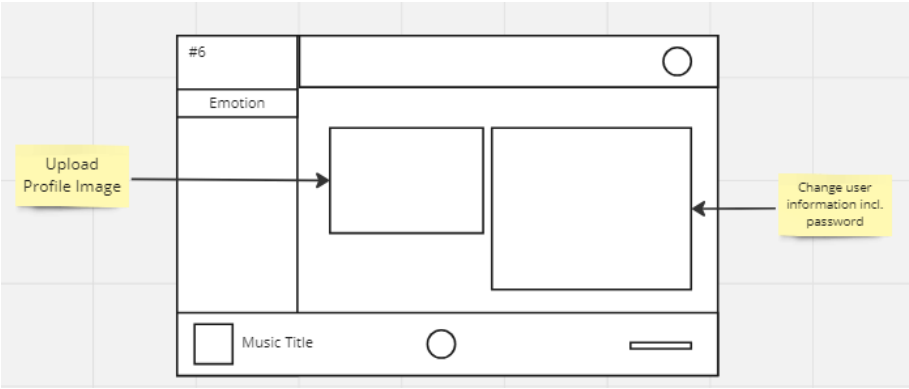


Figure E.5: User Settings Page

APPENDIX F

```
router.post('/register', async(req, res) => {
    try {
        const { fname, lname, dob, username, email, password, country } = req.body;
        const userCheckQuery = 'SELECT * FROM sentirhy.user WHERE email = $1 OR
        ↪  username = $2';
        const { rows: existingUsers } = await pool.query(userCheckQuery, [email,
        ↪  username]);
        if (existingUsers.length > 0) {
            return res.status(400).json({message:"Username or Email already in
            ↪  use."});
        }
        const hashedPassword = await bcrypt.hash(password, 10);
        const activationToken = crypto.randomBytes(20).toString('hex');
        const activationTokenExpires = new Date(Date.now() + 3600000).toISOString();
        const insertUserQuery = 'INSERT INTO sentirhy.user (fname, lname, dob,
        ↪  username, email, password, activationToken, activationTokenExpires) VALUES
        ↪  ($1, $2, $3, $4, $5, $6, $7, $8)';
        await pool.query(insertUserQuery, [fname, lname, dob, username, email,
        ↪  hashedPassword  , activationToken, activationTokenExpires]);
        const activationLink =
        ↪  `http://localhost:3030/activate?token=${activationToken}`;
        await sendEmail(email, "Account Activation", activateTemplate(username, fname,
        ↪  email, activationLink))
            .then(info => {
                console.log('Email sent successfully');
            })
            .catch(error => {
                console.log("Failed to send email:", error)
            })

        res.status(201).json({ message: "Registration successful. Please check your
        ↪  email to activate your account." });
    } catch (err) {
        console.error("Error in /register route: ", err);
        res.status(500).send("Error registering new user");
    }
});
```

Figure F.1: User Registration Process

APPENDIX G

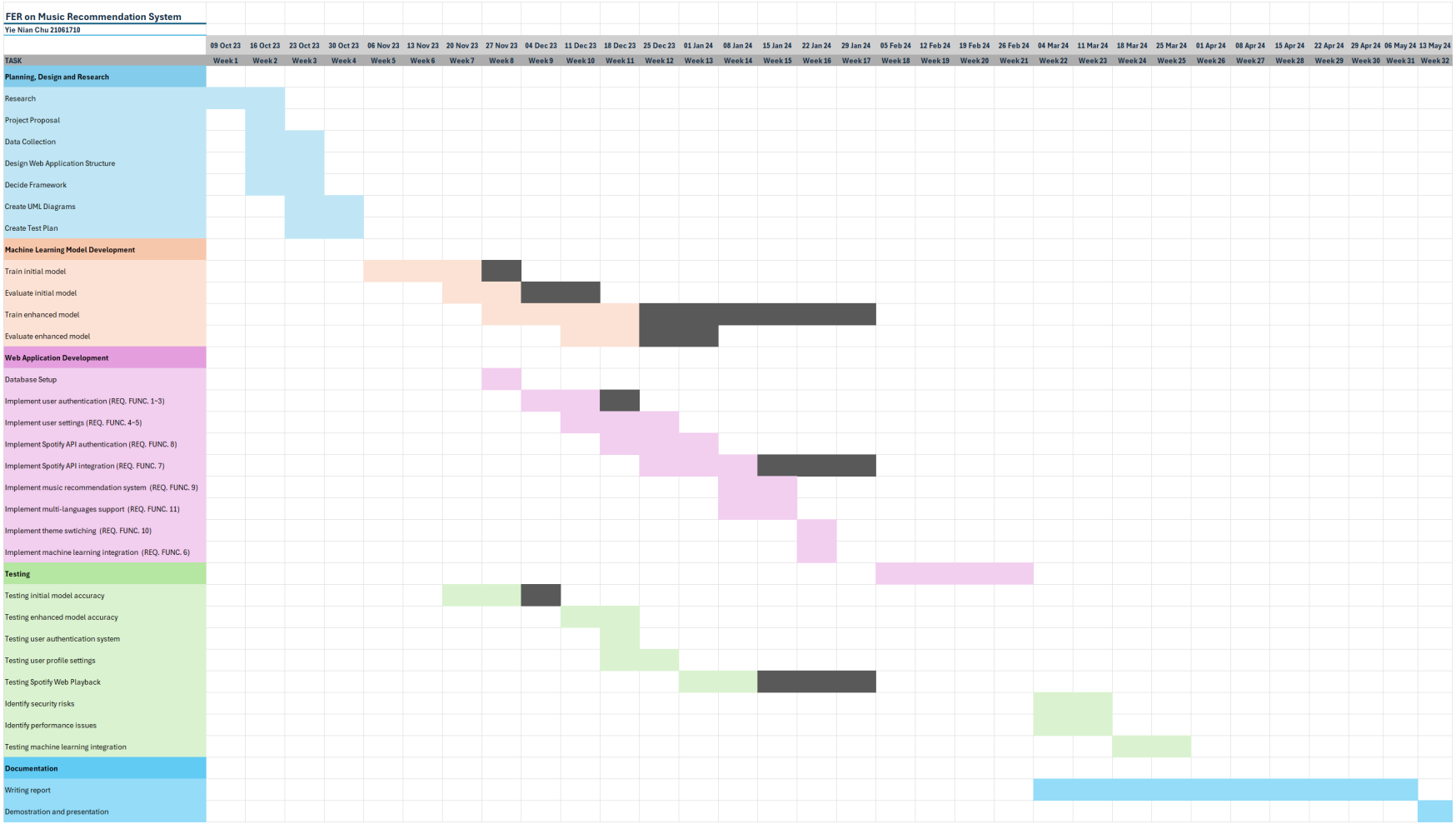


Figure G.1: Gantt Chart

APPENDIX H

Test No.	Cats.	Intention	Expected Result	Actual Result	Pass/Fail
1	UI	Registration	User registered	User registered and information added to database	Pass
2	UI	Login	User logged in	User logged in successfully	Pass
3	UI	Incorrect credentials upon login	User login failed and error message display	Error message displayed and user unable to login	Pass
4	UI	Account Activation	User received email and activate account from link	User activate account successfully from link	Pass
5	UI	Reset Password without Authentication	Reset link sent to user, and password reset successfully	Link sent, password reset successfully	Pass
6	UI	Connect Spotify API	Redirect user to Spotify Authentication Page, and redirect back to ‘Dashboard’	Granted permission from Spotify and brought user back to ‘Dashboard’	Pass
7	UI	Connect Youtube API	Redirect user to Youtube Authentication Page, and redirect back to ‘Dashboard’	Youtube API connection not implemented	Fail

Test No.	Cats.	Intention	Expected Result	Actual Result	Pass/Fail
8	UI	Play Music	Music play through Web Playback	Music played	Pass
9	UI	Skip Music	Skip music through Web Playback	Music skipped	Pass
10	UI	Previous Music	Play previous music through Web Playback	Previous Music played	Pass
11	UI	Adjust Volume	Volume higher or lower	Volume does adjusted through the slider	Pass
12	UI	Mute	Mute Web Playback	Music does muted	Pass
13	UI	Toggle light/dark theme	Theme switched when user pressed the button	Theme switched	Pass
14	UI	Detect user's system theme	Theme detected and switched to user's system theme	Theme switched accordingly	Pass
15	UI	Switch language	Web application language switched to user's preferred language	Language switched	Pass
16	UI	Change personal details in Settings	Update entered details to database	User's information is updated	Pass

Test No.	Cats.	Intention	Expected Result	Actual Result	Pass/Fail
17	UI	Change profile picture in Settings	Saved image to server and update the file path to database	Image saved and database updated	Pass
18	UI	Reset Password in Settings	Update new password to database	New password saved in database with encrypted	Pass
19	UI	Capture user's frame when face detected	Frame captured	Frame Captured with face showed clearly	Pass
20	ML	Detect 'Happy'	'Happy' detected on the captured frame	'Happy' detected	Pass
21	ML	Detect 'Sad'	'Sad' detected on the captured frame	'Sad' detected	Pass
22	ML	Detect 'Angry'	'Angry' detected on the captured frame	'Angry' detected	Pass
23	ML	Detect 'Neutral'	'Neutral' detected on the captured frame	'Neutral' detected	Pass
24	UI	Display recognized emotion on UI	Detected emotion is showed on user's screen	Detected emotion showing on user's screen	Pass
25	Server	Generate playlist	Generate playlist based on user's current emotion	Playlist generated based on user's current emotion	Pass

Test No.	Cats.	Intention	Expected Result	Actual Result	Pass/Fail
26	UI	Logout	User logged out, authentication token removed	Token removed and user logged out	Pass

Table H.1: Test Table

APPENDIX I

Date	Time	Location	Title	Attendees
16-10-2023	1505-1700	X Block	Project Idea and Aim Discussion	Yie Nian Chu, Ali Suhail, Martin Serpell
17-10-2023	1500-1515	2Q17	Project Idea and Aim Discussion	Yie Nian Chu, Craig Duffy
23-10-2023	1505-1605	X Block	Project Idea and Aim Disucssion	Yie Nian Chu, Ali Suhail, Martin Serpell
25-10-2023	1400-1430	Microsoft Teams	Final Decision on Project Idea	Yie Nian Chu, Craig Duffy
30-10-2023	1505-1520	X Block	Project Discussion	Yie Nian Chu, Ali Suhail, Martin Serpell
22-11-2023	1000-1030	Microsoft Teams	Progress Follow Up (Lit. Review)	Yie Nian Chu, Craig Duffy
06-12-2023	1000-1020	Microsoft Teams	Progress Follow Up (Lit. Review)	Yie Nian Chu, Craig Duffy
12-12-2023	1330-1400	2Q17	Development Discussion	Yie Nian Chu, Craig Duffy
16-01-2024	1500-1530	Microsoft Teams	Project Poster Discussion	Yie Nian Chu, Joseph Cauvy-Foster, Craig Duffy
06-02-2024	1600-1630	2Q17	Progress Follow Up (Dev)	Yie Nian Chu, Craig Duffy
05-03-2024	1200-1215	2Q17	Progress Follow Up (Dev)	Yie Nian Chu, Craig Duffy

Table I.1: Meeting Log

APPENDIX J

The source code and additional resources are hosted on GitHub and can be accessed at:

https://github.com/zachycn/sentirhy.