

Music Recommendation System Based on Facial Expression

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Abstract

In the modern digital age, where users face an overwhelming array of music choices, personalized recommendations are crucial for enhancing the listening experience. Studies indicate that music significantly influences emotions, affecting mood, stress levels, and overall well-being. Over 60% of users struggle with decision fatigue when selecting music from their vast collections. To address this challenge, we propose a real-time music recommendation system that utilizes facial expression analysis through deep learning. The system employs a Convolutional Neural Network (CNN) trained on the FER-2013 dataset to analyze facial expressions captured via a webcam. Detected emotions are processed in real time, enabling dynamic music selection. Flask is used for backend API development and server management. Supabase functions as a cloud database. This emotion-driven approach streamlines the music selection process, saving time and reducing the stress of manual browsing.

Keywords: Emotion recognition, CNN, Facial Expression, FER-2013, Flask, Supabase, Music Recommendation.

1. Introduction

Music is a significant part of human emotions, influencing mood, behavior, and cognition. In today's digital age, music recommendation systems are a component of user experience augmentation through personalized playlists according to listening behavior and choice. However, classical systems are largely based on users' history and cannot react to current emotional states. Here, we introduce a Music Recommendation System Based on Facial Expressions, which would provide real-time and adaptive song suggestions based on the facial emotions of a person. The system is founded on deep learning techniques, utilizing a Convolutional Neural Network (CNN) to identify emotions from the FER-2013 dataset. Facial expressions are captured through a webcam and processed in real time by a trained model. Identified emotions are mapped to a music genre, providing a seamless and adaptive listening experience. The backbone of this system is a robust backend built with Flask, enabling real-time processing, and Supabase, a cloud database, for managing user preferences and storing recommendation history. The combination of such

technologies enables efficiency, scalability, and seamless user interaction. By translating facial expressions into informative content, the system enhances human-computer interaction, offering a natural and emotion-based way of music selection. The research aims to enhance accessibility, personalization, and interaction in music streaming, giving listeners a more interactive and richer experience. The report presents the system architecture, implementation, and performance evaluation, furthering the development of emotion-based recommendation systems. [1]

2. Methodology

2.1. Input Details

The system captures a face image through a webcam, processes it via a deep learning model, and classifies the emotion into predefined categories: Happy, Sad, Angry, Neutral, and Fear. The identified emotion is then mapped to a relevant song category. [2]

Dataset: The FER-2013 dataset, released at the ICML 2013 Challenge, is used for training the facial expression recognition model. The dataset has 35,887 48x48 grayscale images, each of which is annotated

with various emotional expressions.

Table 1 FER-2013 Dataset

Emotion	Training	Testing
ANGER	3995	958
SAD	4830	1247
HAPPY	7215	1774
FEAR	4079	1024
NEUTRAL	4965	1233

Model Architecture: A Convolutional Neural Network (CNN) is implemented for facial expression recognition. The architecture consists of:

- Input Layer: 48x48 grayscale images.
- Convolutional Layers with ReLU activation.
- Pooling Layers to reduce spatial dimensions.
- Fully Connected Layers for classification.
- Softmax Activation for the final emotion prediction. [3]

2.2. Working Process

- **Image Processing:** Webcam captures the user's face.
- **Preprocessing:** The image is resized and converted to grayscale.
- **Feature Extraction:** CNN extracts the facial features. [4]
- **Emotion Detection:** It classifies the image into an emotion category.
- **Music Recommendation:** The recommended song is based on the identified emotion.

3. Flow Chart

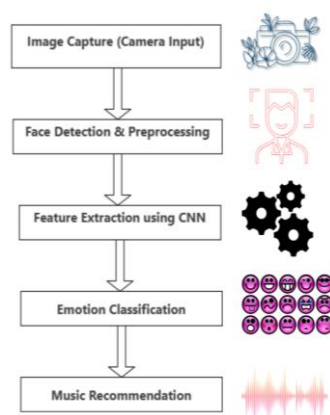


Figure 1 Flow Chart

3.1. Image Capture (Camera Input)

This is the initial stage where the system uses a webcam or any camera module to capture real-time images or video frames of the user's face. The camera input acts as the raw data source for further processing. This step is critical because the accuracy of subsequent processes heavily relies on the quality and clarity of the captured facial image. [5]

3.2. Face Detection & Preprocessing

Once the image is captured, the system detects the face using computer vision techniques such as Haar Cascades or pre-trained deep learning models (e.g., MTCNN or Dlib). After the face is located within the frame, preprocessing steps are applied which may include: [6]

- Converting the image to grayscale to reduce computational complexity.
- Resizing the face to a standard dimension (e.g., 48x48 pixels as required by the FER-2013 dataset).
- Normalizing pixel values to improve model performance.

This step ensures that the input to the neural network is clean, consistent, and focused solely on facial features. [7]

3.3. Feature Extraction using CNN

A Convolutional Neural Network (CNN) is applied to extract high-level features from the preprocessed image. CNNs are particularly effective in recognizing patterns in image data such as edges, shapes, and textures that represent different emotions. Through multiple layers of convolution, pooling, and non-linear activation functions, the network generates feature maps that encode essential details of the facial expression. [8]

3.4. Emotion Classification

The extracted features are then passed through fully connected layers and a softmax classifier within the CNN to predict the emotion class. Common emotion classes include:

- Happy
- Sad
- Angry
- Neutral
- Fear

The output is a probability distribution, where the

emotion with the highest confidence score is selected as the final detected emotion. [9]

3.5. Music Recommendation

Based on the classified emotion, the system maps the emotion to a predefined music category. For example:

- Happy → Upbeat or party songs
- Sad → Soft or comforting music
- Angry → Calm or soothing tracks
- Fear → Instrumentals or motivational music
- Neutral → Balanced or genre-mixed playlists

The recommendation engine (often using Supabase as your backend database) retrieves suitable songs based on the user's emotions and preferences. It may also log the interaction to personalize future recommendations. [10]

3.5.1.Convolutional Layers (Feature Detection)

- These layers apply filters (kernels) that slide over the input image to detect local features.
- Each filter learns to identify specific patterns like edges, corners, textures, and facial components (e.g., eyes, mouth, eyebrows). [11]
- Early layers detect low-level features (simple edges and curves), while deeper layers capture high-level abstract features, such as smiling lips, raised eyebrows, or frowning.

3.5.2.Activation Function (ReLU)

- After each convolution operation, the ReLU (Rectified Linear Unit) activation is applied.
- This introduces non-linearity, allowing the network to learn complex patterns beyond just linear combinations. [12]
- ReLU replaces negative values with zero, increasing training speed and reducing the chances of vanishing gradients.

3.5.3.Pooling Layers (Downsampling)

- Pooling (Max Pooling) reduces the spatial size of feature maps while keeping important information. [13]
- This makes the model faster, less sensitive to small variations and helps prevent overfitting.
- For example, if the position of the mouth changes slightly in different images, pooling still preserves the key features.

3.5.4.Flattening

- After multiple layers of convolution and pooling, the resulting 2D feature maps are flattened into a 1D vector. [14]
- This step prepares the data for classification through fully connected layers.

3.5.5.Fully Connected Layers (Dense Layers)

- These layers take the high-level extracted features and combine them to detect overall patterns associated with different emotions.
- The final fully connected layer outputs values corresponding to each emotion class, passed through a softmax function to produce a probability distribution. [15]

4. Result and Description

Output and Accuracy: The model was trained on FER-2013, achieving a validation accuracy of 65%. The classification performance is as follows:

Table 2 F1-Score Table

Emotion	Precision	Recall	F1-Score
Angry	40%	39%	39%
Fear	38%	25%	30%
Happy	68%	76%	72%
Neutral	46%	54%	50%
Sad	40%	40%	40%



Figure 2 Emotion



Figure 3 Precision

Conclusion

This study efficiently integrates deep learning and music recommendation techniques to maximize user experience. The system efficiently recognizes facial expressions and uses them to recommend appropriate songs, and hence, a personalized listening experience is achieved. The FER-2013 dataset and CNN model were used to achieve accurate emotion detection, with 65% validation accuracy. Integration of Flask for backend processing and Supabase for data storage offers scalable and smooth operations. The system provides real-time music suggestions, and manual choice of songs according to mood is not required. Flowchart-based methodology enhances understanding of the emotion detection and song recommendation working process. User interaction is significantly enhanced with the system dynamically adapting to real-time emotional states. Misclassification of similar emotions as a challenge highlights the need for dataset extension and hyperparameter tuning. Multi-modal emotion detection and integration of voice and gesture detection for enhanced accuracy are future enhancements. The system can be extended to other uses like mental health therapy, stress relief, and mood-based playlist generation. Using AI and deep learning, the project contributes to the burgeoning field of human-computer interaction and affective computing. Improved dataset quality and model optimization will further enhance system accuracy, and it will be an even more accurate music recommendation system. The project can be further enhanced by using multiple datasets and models, enhancing model robustness, and making it efficient and scalable.

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