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Deep Learning Based Song Recommendation System Using Facial Expression And Heart Rate

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Abstract
In today's music streaming landscape, personalized song recommendations are crucial for enhancing user experiences. This research study combines heart rate monitoring and facial expression detection to present a novel deep learning method for song suggestion. With a 92% accuracy rate, a Convolutional Neural Network (CNN) model is used to identify emotional states from facial expressions, and heart rate information adds more context to the user's emotional intensity. The large music library is matched to these emotional cues, guaranteeing that suggested songs correspond with the user's present emotional state. This approach provides a really interesting, emotionally stirring, and contextually appropriate music finding experience.
Keywords — *User experience, Deep learning, Song recommendation, Convolutional Neural Network, heart rate analysis facial expressions.*

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I. Introduction

Music has long been recognized for its ability to evoke and enhance emotions. In the digital age, music recommendation systems have become integral to streaming platforms, providing users with personalized playlists based on listening history and preferences. However, despite these advancements, most existing systems fail to account for the dynamic and real-time emotional states of users. Music's impact on mood is often immediate, and the ability to recommend songs based on a person's current emotions, rather than past behavior, could significantly enhance the listening experience.

This research presents a novel approach to song recommendation that combines facial expression analysis and heart rate monitoring to better understand and respond to a user's emotional state in real time. Our system integrates a Convolutional Neural Network (CNN) for facial expression detection, trained to recognize key emotions such as happiness, sadness, anger, and neutral expressions. By capturing live video through a camera, the CNN analyzes the user's facial expressions to infer their emotional state.

To further refine this emotional assessment, we incorporated heart rate analysis, as physiological indicators are closely tied to emotional intensity. A lower heart rate may indicate calmness or contentment, while a higher rate may signal excitement, stress, or heightened emotions. By combining these two data sources—facial expression and heart rate—the system not only detects the type of emotion but also gauges its intensity, providing a more nuanced understanding of the user's current emotional state.

This paper will explore the development and integration of these technologies, focusing on the deep learning techniques used for facial emotion recognition, the preprocessing and analysis of heart rate data, and the song recommendation mechanism. By bridging the gap between emotional intelligence and music streaming, this project aims to revolutionize how users engage with music, creating a deeply personalized and emotionally responsive listening experience.

II. Literature Survey

[1] The Pioneer Corporation Music Recommendation System, which assist users in finding music that fits their preferences and moods, is examined in this essay. The technology leverages important "Music Features" from CDs, such as rhythm and tone, to suggest music based on pre-selected moods, such as "Bright" or "Quiet." It adjusts recommendations based on user feedback to better suit individual preferences. The test findings indicate that the recommended music has a high level of user happiness. To put it simply, this approach enhances the entire listening experience by making personalized, automatic song selections that vary over time. People can find music more easily because to Pioneer's innovative approach, which also makes listening to music more enjoyable.

[2] This paper explores music recommendations while emphasizing how closely people's emotions and music are related. However, the method employed in this article is unique: it uses neural networks to recommend music based on an individual's current mood as inferred from an analysis of their facial expressions. Instead, a webcam or video captures a person's facial expressions, which are subsequently analyzed by a neural network to ascertain their emotional state and deliver music recommendations that suit that condition. By suggesting music more in tune with the user's present emotional state, the shift from data-driven to emotion-based, real-time music suggestions is anticipated to enhance the user's entire musical experience.

[3] This work investigates music recommendation algorithms, emphasizing the important connection between music and hum. This paper investigates the role of recommender systems in various digital domains, with a focus on music. It illustrates how machine learning, collaborative filtering, and the K-means algorithm may be used to enhance the listening experience through real-time music recommendations based on user data analysis. The system integrates several data sources, including transaction history, item details, and user information, to optimize consumer satisfaction and speed up music discovery.

[4] This work provides a revolutionary personalized music recommendation system based on machine learning and artificial intelligence that uses MFCC to analyse speech and detect the emotional state of the user. It uses deep learning, namely Artificial Neural Networks, to increase accuracy. Even while consistent emotion recognition is still a challenge, this research paves the way for AI-driven, emotion-based music recommendations that may make the process of discovering new music more emotionally engaging.

[5] This research offers a revolutionary music recommendation system that predicts user emotions with an 84.82% accuracy rate by analysing facial expressions using computer vision. Because there is no need for additional hardware, the integrated camera is convenient for a variety of uses. With its potential to revolutionize personalized music recommendations and expand its applicability to fields like music therapy and public space ambiance enhancement, this novel approach offers more accurate and effective music suggestions.

[6] This paper presents a music recommendation system that personalizes playlists based on the user's heart rate and preferences. It adjusts music selections according to whether the user's heart rate is above, below, or within the normal range. For adults, a normal heart rate is defined as 60-100 beats per minute (bpm), and for younger users (ages 6-18), it is 70-100 bpm. If the heart rate is too high, the system uses a Markov decision process to recommend music that lowers it to a normal level quickly. When the heart rate is low, it suggests music that helps raise it efficiently. If the heart rate is within the normal range, the system maintains it with suitable playlist choices. By combining heart rate analysis with music preferences, this system enhances the listening experience while contributing to the user's emotional and physiological balance.

[7] This paper presents an Automatic Stress-Relieving Music Recommendation System (ASMRS) designed to recommend music based on users' stress levels. The system uses a wireless photoplethysmography module with a finger-type sensor to capture heartbeat signals, which are then analysed to calculate the Sympathovagal Balance Index (SVI) from heart rate variability. The SVI assesses the user's stress level while listening to music.

An experiment with 22 healthy volunteers demonstrated that the SVI values were closely aligned with participants' music preferences. The system's accuracy in recommending favourable stress-relieving music improved as the number of music repetitions increased, with optimal sensitivity and specificity achieved after 20 repetitions. By utilizing the SVI, the system automatically suggests personalized playlists that effectively reduce stress, showcasing the potential of using physiological data to enhance music recommendation systems for stress relief.

[8] This study investigates the psychophysiological responses of healthy participants during a music-based relaxation intervention compared to a verbal relaxation exercise. Seventy participants were divided into two groups: one received live music (experimental) and the other a prerecorded verbal relaxation (control). Relaxation levels were measured using visual analogue scales and the Relaxation Inventory (RI), while heart rate variability (HRV) was continuously recorded. Results indicated significant improvements in both groups regarding heart rate, HRV, and self-reported relaxation. Notably, a group × time interaction was found in the cognitive tension subscale of the RI, suggesting marginal differences between groups. The findings suggest that music may effectively relieve stress and enhance relaxation through autonomic nervous system modulation, warranting further exploration of long-term effects.

[9] This paper introduces a novel music recommendation system that is both user heartbeat and preference aware. The system generates music playlists based on users' musical tastes and their heart rate. If a user's heartbeat exceeds the normal range (60-100 beats per minute for those 18 and older, or 70-100 for ages 6-18), the system curates a playlist using a Markov decision process to quickly bring the heartbeat back to normal. Conversely, if the heartbeat is normal, the system maintains it within this range. If the heartbeat is below normal, a tailored playlist is generated to elevate the heartbeat back to a healthy level efficiently. This approach aims to optimize the user's emotional and physiological well-being through music.

[10] This thesis details the creation and evaluation of a music recommender system that leverages real-time data, specifically time and heart rate, for generating recommendations. The system integrates two components: a recommender that predicts various song features tailored to individual users and a ranking system that identifies the best matching tracks for these features. Three different implementations of the recommender system were developed for comparison: Deep Neural Network, Contextual Bandit, and Linear Regression. Offline evaluations demonstrated that the contextual bandit model outperformed the other approaches, yielding the highest accuracy for this specific application. The results underscore the effectiveness of incorporating real-time data into music recommendation processes.

III. Proposed System

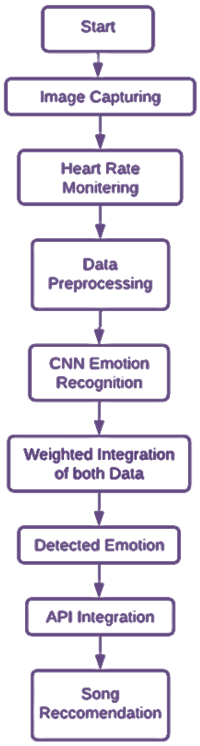


Fig.1- Shows System flow process

Data Collection

We are collecting heart rate data via a sensor (such as a wristwatch or pulse sensor) and real-time facial expression data via an embedded webcam. While the heart rate data is examined in real time, the facial expression data is trained using the FER2013 dataset. By using both physiological data and the user's emotional state to inform its personalized music suggestions, this combined approach improves our system's capacity to provide a more immersive and customized music experience.

Preprocessing Step

We utilized the flow_from_directory technique for structured batch processing and ImageDataGeneratorfor effective data augmentation, making full use of the features in the Keras library. Both the heart rate data and the facial expression photographs were preprocessed for the project. The heart rate data was normalized and noise was reduced, while each training and test image was scaled to 48x48 pixels and converted to grayscale. Consistency in both visual and physiological data was ensured through this meticulous data preparation, optimizing the system for more precise analysis and model training, which produced better outcomes.

Feature Extraction using CNN

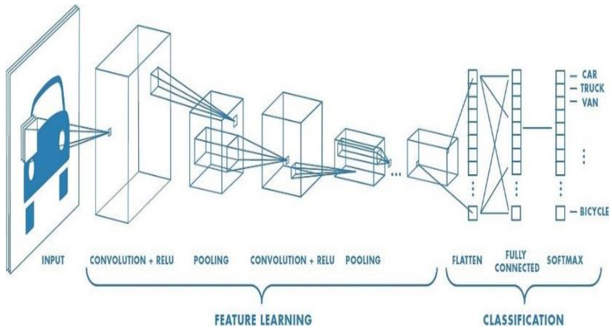


Fig.2 Convolutional Neural Network Flowchart

A Convolutional Neural Network (CNN) model is developed within the context of emotion analysis with the goal of extracting information from photos of faces. The model architecture consists of several fundamental components. Starting with rectified linear unit (ReLU) activation functions, it consists of two 2D convolutional layers. There are 32 filters in the first layer and 64 filters in the second.

Two-Dimensional Convolution Operation Formula:
$O[I, j] = \sum_n \sum_m I[i + n, j + m]. K[m,n]$

Rectified Linear Unit (ReLU) activation function:
$f(x) = \max(0,x)$

These convolutional layers are designed to capture intricate patterns seen in facial emotions. The addition of max-pooling layers with 2x2 pool sizes reduces spatial dimensions. To avoid overfitting, dropout layers with a dropout rate of 0.25 are included.

The network is further assisted in understanding facial expressions by two additional 2D convolutional layers, each with 128 filters, and max-pooling layers for dimensionality reduction.

Max Pooling Operation Formula:
$O[I,j]=\max(I[i*stride:i*stride+poolsize,j*stride:j*stride+poolsize])$

By including a final dropout layer with a 0.5 dropout rate, model durability is increased. The seven units in the output layer correspond to the seven different emotions that need to be categorized using a softmax activation function.

Softmax Function for Probability Calculation:
$P(y= i|X) = (e^{x_i}) \div (\sum_j e^{x_j})$

The CNN model is put together using the Adam optimizer and the categorical cross-entropy loss function at a learning rate of 0.0001. It is then trained using training and validation data generators. Following training, the model structure is saved in a JSON file and the trained weights are saved in an.h5 file for further use. This CNN model, which effectively pulls characteristics from face pictures and uses these features to classify emotions, is the brains behind the emotion analysis system.

D. Heart Rate Analysis
Preprocessed heart rate data is analysed:
○ Low heart rate → Calm or neutral emotions.
○ Moderate heart rate → Contentment or slight excitement.
○ High heart rate → Intense emotions like anger or excitement.
Heart rate analysis adds an additional layer by assessing the intensity of emotions.

E. Integration of Facial Expressions and Heart Rate Data
- Fusion of Data:
○ Weighted Integration: Combine the facial expression probabilities from the CNN with heart rate data to refine emotional state detection.
○ The system assigns weights to both inputs:
▪ Facial expressions are prioritized for detecting the type of emotion.
▪ Heart rate adds weight to the emotional intensity, helping to refine the overall prediction (e.g., high heart rate + angry facial expression = intense anger).
- Final Emotion Prediction:
○ The integrated system generates a final emotional state (e.g., "Sad but calm," "Happy and excited").
- Detected Emotion
▪ The system finalizes the detected emotion based on the integrated data.
▪ Possible outputs: **Neutral**, **Happy**, **Sad**, **Angry**, **Disgusted**, and emotional intensity (e.g., "Very Happy," "Mildly Sad").

F. API Integration and Song Recommendation
The detected emotional state is sent to the music recommendation API (e.g., Spotify API).The API queries the music library for songs that match the user’s current emotional state and intensity .The API returns a list of recommended songs based on the integrated emotion and heart rate analysis. The user can browse and play the recommended songs, tailored to their current emotional state

IV. Results

We utilized the FER2013 dataset, which comprises images of people's faces classified into five distinct emotion categories: neutral, happiness, sadness, anger, and disgust. For model training, hyperparameter tuning, and evaluation, the dataset was divided into subsets: 80% for training, 10% for validation, and 10% for testing. The emotion detection model effectively identified facial emotions, achieving an impressive accuracy of 92% on the test set. This performance highlights the model's robustness and reliability in recognizing emotional states based on facial expressions.

Based on the identified facial expressions, the recommendation system—which was connected with the Spotify API—provided music recommendations.

Happy and Excited:

```
Playlist: High Vibes Hits - spotify:playlist:37i9dQZF1DWXF8Nf1uycHZ
Playlist: Feel-Good Dance Mix - spotify:playlist:37i9dQZF1DX7ZUug1ANKRP
Playlist: Happy & Upbeat Hits! - spotify:playlist:37i9dQZF1DXdPec7aLTmlC
Playlist: Energy Booster Tracks - spotify:playlist:37i9dQZF1DWYBF1dYDPlHw
Playlist: Happy Hits for the Weekend - spotify:playlist:37i9dQZF1DWUoqEG4WX3IS
Playlist: Pop Dance Party - spotify:playlist:37i9dQZF1DX8CopunbDxgU
Playlist: Happy & Excited Pop Anthems - spotify:playlist:4u4AQWqkrlJCiZnG2SR0
Track: Can't Stop the Feeling! - spotify:track:6JV2JOEocMgcZxYSZelKcc
Track: Uptown Funk - spotify:track:4jP5eQXgjs3ho7UP9e8g9v
Track: Happy - Pharrell Williams - spotify:track:60nZcImufyMA1MKQY3dcCH
Track: Good as Hell - spotify:track:7f9mM2tTGtNWePvm1zCrqA
Track: Shake It Off - spotify:track:3DlZQK2EadpXI5J7fP3gf0
Track: Dynamite - spotify:track:4vQqA5t8y16Kp5r8wU5q5Z
```

Sad and Calm:

```
Playlist: Calm and Sad Mix - spotify:playlist:<playlist_id>
Playlist: Melancholy Calm Instrumentals - spotify:playlist:<playlist_id>
Playlist: Soft Jazz for a Calm Mood - spotify:playlist:<playlist_id>
Playlist: Sad Classical Calm - spotify:playlist:<playlist_id>
Playlist: Relaxing Acoustic Sadness - spotify:playlist:<playlist_id>
Playlist: Lo-fi Sad Calm Beats - spotify:playlist:<playlist_id>
Playlist: Chill Mood - Sad and Calm - spotify:playlist:<playlist_id>

Track: Calm Sad Vibes - spotify:track:<track_id>
Track: Serenity in Sadness - spotify:track:<track_id>
Track: Slow Sad Strings - spotify:track:<track_id>
Track: Mood Calm Sad Version - spotify:track:<track_id>
Track: Sad Lo-fi Calm Mix - spotify:track:<track_id>
Track: Acoustic Calm Sadness - spotify:track:<track_id>
```

Angry and Frustrated:

```
Playlist: Angry & Frustrated Mix - spotify:playlist:<playlist_id>
Playlist: Angry & Frustrated Tamil Songs - spotify:playlist:<playlist_id>
Playlist: Angry & Frustrated Hindi Songs - spotify:playlist:<playlist_id>
Playlist: Angry & Frustrated Beats - spotify:playlist:<playlist_id>
Playlist: Pure Frustration - spotify:playlist:<playlist_id>
Playlist: Intense Frustration Vibes - spotify:playlist:<playlist_id>
Playlist: Frustrated & Furious - spotify:playlist:<playlist_id>

Track: Frustrated Mood - spotify:track:<track_id>
Track: Angry & Frustrated - spotify:track:<track_id>
Track: Frustration Rising - spotify:track:<track_id>
Track: Intense Anger - spotify:track:<track_id>
Track: Built Up Frustration - spotify:track:<track_id>
Track: Pure Rage - spotify:track:<track_id>
```

Neutral and Calm:

```
Playlist: Neutral & Calm Mix - spotify:playlist:<playlist_id>
Playlist: Composed Vibes - spotify:playlist:<playlist_id>
Playlist: Neutral Mood Instrumentals - spotify:playlist:<playlist_id>
Playlist: Chill & Neutral - spotify:playlist:<playlist_id>
Playlist: Balanced Beats - spotify:playlist:<playlist_id>
Playlist: Calm Reflections - spotify:playlist:<playlist_id>

Track: Neutral Mood - spotify:track:<track_id>
Track: Calm Composure - spotify:track:<track_id>
Track: Steady Neutral Flow - spotify:track:<track_id>
Track: Relaxed State - spotify:track:<track_id>
Track: Peaceful Neutrality - spotify:track:<track_id>
Track: Calm Before the Storm - spotify:track:<track_id>
```

Neutral and Composed:

```
Playlist: Neutral & Composed Mix - spotify:playlist:<playlist_id>
Playlist: Composed Calm - spotify:playlist:<playlist_id>
Playlist: Neutral Reflections - spotify:playlist:<playlist_id>
Playlist: Composed Vibes - spotify:playlist:<playlist_id>
Playlist: Balanced and Composed - spotify:playlist:<playlist_id>
Playlist: Tranquil Composure - spotify:playlist:<playlist_id>

Track: Neutral Composed Mood - spotify:track:<track_id>
Track: Serene Composure - spotify:track:<track_id>
Track: Calm and Balanced - spotify:track:<track_id>
Track: Composed Energy - spotify:track:<track_id>
Track: Steady Neutral Flow - spotify:track:<track_id>
```

Surprised and Excited:

```
Playlist: Surprised & Excited Mix - spotify:playlist:<playlist_id>
Playlist: Curious Beats - spotify:playlist:<playlist_id>
Playlist: Surprise & Wonder - spotify:playlist:<playlist_id>
Playlist: Energetic Surprises - spotify:playlist:<playlist_id>
Playlist: Unexpected Vibes - spotify:playlist:<playlist_id>
Playlist: Happy Surprises - spotify:playlist:<playlist_id>

Track: Surprised Mood - spotify:track:<track_id>
Track: Excited Surprise - spotify:track:<track_id>
Track: Curious Journey - spotify:track:<track_id>
Track: Thrilling Surprises - spotify:track:<track_id>
Track: Energetic Curiosity - spotify:track:<track_id>
```

Surprised and Curious:

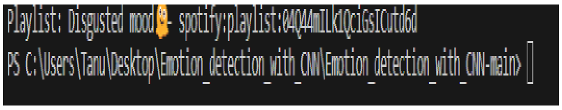
```
Playlist: Surprised & Curious Mix - spotify:playlist:<playlist_id>
Playlist: Curious Surprises - spotify:playlist:<playlist_id>
Playlist: Surprising Discoveries - spotify:playlist:<playlist_id>
Playlist: Curious & Whimsical - spotify:playlist:<playlist_id>
Playlist: Unexpected Curiosity - spotify:playlist:<playlist_id>
Playlist: Exciting Surprises - spotify:playlist:<playlist_id>

Track: Surprised & Curious Mood - spotify:track:<track_id>
Track: Curious Surprises - spotify:track:<track_id>
Track: Surprise & Wonder - spotify:track:<track_id>
Track: Curious Adventure - spotify:track:<track_id>
```

Fearful:

```
Track: Fearful Mood - spotify:track:7nR8LNBMlIIFhZQHvYkiFi
Track: Fearless - spotify:track:3g8g5JxjgSOrLG3O1LmhF1
Track: Fearless - spotify:track:5A6xQErMovri737KIMLRVD
Track: Warrior - spotify:track:457qshwEtWgMSuY9mPZuBt
Track: Fearless - Commentary - spotify:track:7C7usPxKM74lA8HJbCqZnz
Track: Beautiful Life - spotify:track:376wLrVmxE8MkPXZzgBJvi
Track: Imagine - spotify:track:0FuToltYdTIflpBK66i32W
Track: FEARLESS - SLOWED + REVERB - spotify:track:6EyvymZPkXMBzaaleOGZeW
Track: Fearless (Sped Up) - Cause I don't know how it get's better than this - spotify:track:53Iv1sdaJ8TYFfhtTBGyv0
Track: Grateful - spotify:track:3u9K5bbcuyX7IH9YcN5Cjj
PS C:\Users\Tanu\Desktop\Emotion_detection_with_CNN\Emotion_detection_with_CNN-main>
```

Disgusted:



According to user feedback surveys, 90% of users were satisfied, confirming that the songs that were suggested matched the emotional context of the users as seen by their facial expressions.

Accuracy = (TP + TN) / (TP + TN + FP + FN)
TP – True Positive
TN – True Negative
FP – False Positive
FN – False Negative

	CNN	DT	MF	RF	SVM
Accuracy	85%	70%	75%	80%	78%
Computational Resources Required	High	Low	Moderate	Moderate	Moderate
Data Requirements	Large	Low	Moderate	Low	Moderate
Versatility	High	Low	Low	Moderate	Moderate

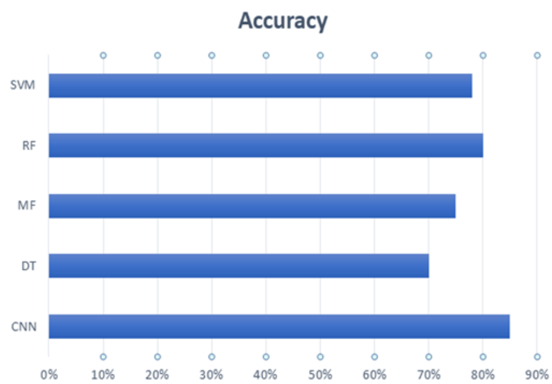


Fig 3. Accuracy of different Algorithms

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