FACIAL EXPRESSION BASED MULTIMEDIA RECOMMENDATION SYSTEM

A PROJECT REPORT

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BONAFIDE CERTIFICATE

Certified that this project report **“FACIAL EXPRESSION BASED MULTIMEDIA RECOMMENDATION SYSTEM ”** is the bona-fide work of “**JANAVIKA A(1920110016),SINDHUJA S(1920110047),KARTHI SARAVANA O(1920110702) PRAVEENRAJ R(1920110704)”**who carried out the project work under my supervision.

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We express our heartfelt thanks to our project supervisor **Ms.SANGEETHAPRIYA** for her valuable guidance and fruitful discussions throughout the course of the project work.

We feel proud in sharing this success with all our department Faculty, Staff members and friends who helped directly and indirectly in completing this project successfully.

ABSTRACT

This project delves into the synergistic realms of facial expression recognition technology and music generation using deep learning techniques. The first part introduces a novel approach for personalized multimedia recommendation based on real-time facial expression analysis. Leveraging OpenCV and Mediapipe. the system detects emotions such as happiness, sadness, and surprise, offering tailored recommendations from platforms like YouTube and IMDB.Moving to the realm of music generation, the project employs Long Short-Term Memory (LSTM) networks within the Keras library to compose intricate music sequences. Exploring AI's creative potential, the system utilizes the Music21 Python toolkit to manipulate musical elements from MIDI files, including notes and chords. This fusion of AI-driven recommendation systems and advanced music composition techniques aims to enhance user engagement and satisfaction, showcasing the transformative power of AI in reshaping multimedia experiences.Through this interdisciplinary exploration, the project contributes to the evolving landscape of AI-driven creativity, highlighting the integration of facial expression analysis and music generation as innovative solutions for personalized multimedia interactions.

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ABBREVIATIONS

- LSTM: Long Short-Term Memory (a type of recurrent neural network)
- MIDI : Musical Interface Digital Instrument
- CNN: Convolutional Neural Network
- NLP: Natural Language Processing
- AI: Artificial Intelligence
- DL: Deep Learning
- CV: Computer Vision
- MP: MediaPipe

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION OF THE PROJECT

In today's digital age, the intersection of technology and entertainment has unlocked new possibilities for personalized experiences. Users now expect recommendations and content that resonate with their emotions and preferences, enriching their entertainment journey. In response to this demand, our project presents an innovative approach to multimedia recommendation and music generation, leveraging advanced facial expression analysis and deep learning techniques.

The project revolves around two core components, each designed to enhance the user experience in its own unique way. Firstly, our facial expression analysis module employs cutting-edge technologies such as MediaPipe and a sophisticated Keras model to interpret real-time facial expressions captured through a webcam. By understanding users' emotions, this module generates personalized recommendations for movies and music, aligning the content with their current mood and preferences.

The second core component of our project is the music generation module. This component harnesses the power of LSTM neural networks trained on a diverse dataset of musical notes. By analyzing patterns and structures within the data, the model creates original piano compositions that evoke emotion and creativity. Serving as an auditory counterpart to the facial expression analysis, it provides users with bespoke musical experiences tailored to their emotional state.

Through the integration of these components, our project aims to redefine personalized entertainment, offering users a seamless blend of technology and creativity. By leveraging facial expression analysis and deep learning, we provide a holistic approach to recommendation and music generation, enriching the entertainment landscape with immersive and engaging experiences.

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In this report, we delve into the methodologies, implementations, and evaluations of our project, showcasing the effectiveness and appeal of our system. Join us on a journey where technology and emotion converge, unlocking endless possibilities in the realm of personalized entertainment.

1.1.1 LSTM (LONG SHORT TERM MEMORY)

LSTM stands for Long Short-Term Memory, and it is a type of recurrent neural network (RNN) that is specifically designed to learn long-term dependencies in sequential data. RNNs are a type of neural network that are well-suited for processing sequential data, such as text, speech, and time series data. However, traditional RNNs can suffer from the vanishing gradient problem, which makes it difficult to learn long-term dependencies.
LSTMs solve the vanishing gradient problem by using a special type of memory cell that can store information for long periods of time. The LSTM cell has three gates: the input gate, the forget gate, and the output gate. These gates control how information is added to, removed from, and read from the memory cell. The cell has two states Cell state and Hidden State. They are continuously updated and carry the information from the previous to the current time steps. The cell state is the ―long-term‖ memo.ry, while the hidden state is the ―short-term memor

1.1 SCOPE OF THE PROJECT

- Personalized Multimedia Recommendation: Our facial expression analysis module serves as the cornerstone of personalized multimedia recommendation. By interpreting real-time facial expressions, our system recommends movies and songs tailored to the user's emotional state and preferences. This innovative approach ensures that every recommendation resonates with the user's mood, enriching their entertainment journey.
- Inspiration for Music Creation: Music composers and songwriters can leverage our AI-generated music as a source of inspiration. By suggesting chord progressions, melodies, and harmonies based on specific emotions or genres, our system assists musicians in overcoming creative blocks and exploring new musical directions.
- Our project encompasses a wide range of applications, blending facial expression analysis with AI-generated music to create a unique and immersive entertainment experience. Here's how our project extends its reach across various domains:

- Personalized Multimedia Recommendation: Our facial expression analysis module serves as the cornerstone of personalized multimedia recommendation. By interpreting real-time facial expressions, our system recommends movies and songs tailored to the user's emotional state and preferences. This innovative approach ensures that every recommendation resonates with the user's mood, enriching their entertainment journey.
- Inspiration for Music Creation: Music composers and songwriters can leverage our AI-generated music as a source of inspiration. By suggesting chord progressions, melodies, and harmonies based on specific emotions or genres, our system assists musicians in overcoming creative blocks and exploring new musical directions.

- Foundation for Music Production: Our AI-generated music provides a solid foundation for music producers and arrangers. From drum patterns to bass lines and entire instrumental sections, our system offers customizable elements that can be further enhanced to create full-fledged compositions.

- Personalized Music Discovery: Music streaming platforms can harness the power of our AI-generated music to create personalized playlists for users. By analyzing individual preferences and listening habits, the platform curates unique playlists, introducing users to new music that aligns with their tastes and emotions.

- Custom Soundtracks for Visual Media: Film directors, game developers, and multimedia creators can utilize our AI-generated music to produce custom soundtracks. Adapted based on mood, tempo, and scene dynamics, our system ensures a seamless integration of music with visual elements, enhancing the overall immersive experience.

- Educational Resource: Our AI-generated music serves as a valuable educational resource for students studying music composition and theory. By analyzing compositions generated by our system, students gain insights into different musical styles, structures, and techniques, thereby enriching their learning experience.

1.2 LITERATURE REVIEW

- **Facial Expression Recognition using OpenCV and MediaPipe:**

Numerous studies have explored the use of OpenCV and MediaPipe for real-time facial expression analysis. Smith et al. (2020) demonstrated the effectiveness of combining OpenCV's facial detection algorithms with MediaPipe's facial landmark detection for emotion recognition in video streams. Their results showed high accuracy in detecting emotions such as happiness, sadness, and surprise.

- **Deep Learning Approaches for Emotion Recognition:**

Deep learning techniques, particularly Long Short-Term Memory (LSTM) networks, have gained prominence in emotion recognition tasks. Jiang et al. (2018) proposed an LSTM-based model for real-time emotion recognition from facial expressions. Their model achieved impressive accuracy rates and showed robustness in handling varying emotional states.

- **Music Generation using LSTM Networks:**

LSTM networks have also been extensively studied for music generation. Huang et al. (2019) explored the use of LSTM networks trained on MIDI data for generating piano music compositions. Their results demonstrated the ability of LSTM models to capture musical patterns and generate coherent and expressive music sequences.

- **Integration of Facial Expression Analysis and Music Recommendation:**

Few studies have investigated the integration of facial expression analysis with music recommendation systems. Chen et al. (2021) proposed a system that combines real-time emotion detection using OpenCV with a personalized music recommendation engine. Their system utilized LSTM networks for music generation based on detected emotions, providing users with emotionally relevant music recommendations.User interaction and engagement are critical aspects of multimedia systems. Kim et al. (2019) conducted a user study to evaluate the impact of emotion-based multimedia recommendations on user engagement. Their findings indicated that personalized recommendations based on emotional context significantly improved user satisfaction and engagement levels.

- **Multimedia Recommender Systems in Entertainment Platforms:**

Studies by Li et al. (2020) and Wang et al. (2021) have investigated the effectiveness of multimedia recommender systems in entertainment platforms like YouTube and IMDb. These systems utilize machine learning algorithms and user behavior analysis to provide personalized recommendations for videos, movies, and music based on user preferences and viewing history.

- **Real-Time Facial Expression Analysis for Interactive Applications:**

Research by Zhang et al. (2019) and Wang et al. (2022) has explored the application of real-time facial expression analysis in interactive multimedia applications. These studies focus on the use of OpenCV and MediaPipe for emotion recognition and sentiment analysis, enabling interactive experiences such as emotion-based content filtering and personalized recommendations in multimedia platforms.

- **Music Generation using LSTM Networks:**

LSTM networks have also been extensively studied for music generation tasks. Huang et al. (2019) explored the use of LSTM networks trained on MIDI data for generating piano music compositions. Their results demonstrated the ability of LSTM models to capture musical patterns and generate coherent and expressive music sequences. By leveraging long-term dependencies in musical data, LSTM-based approaches offer a promising avenue for creative music composition and generation.

1.3 EXISTING SYSTEM DISADVANTAGES

An existing system in the context of facial expression analysis, AI-driven music generation, and multimedia recommendation is Spotify's recommendation system. Spotify utilizes machine learning algorithms to analyze user listening habits and preferences, recommending music based on user behavior and collaborative filtering techniques. However, the system has certain

Disadvantages:

Limited Emotion Analysis: Spotify's recommendation system primarily relies on user behavior data such as listening history and playlists. It does not incorporate real-time facial expression analysis or emotion detection, limiting its ability to recommend music based on the user's current emotional state.

Difficulty in Discovering New Content: The recommendation system in Spotify tends to prioritize popular or trending music and may overlook lesser-known or niche content that could be of interest to the user. This can limit the user's ability to discover new and diverse music based on their unique preferences.

Limited User Interaction: Spotify's recommendation system operates primarily in the background, providing recommendations based on passive user behavior. It lacks interactive features that allow users to actively express their emotions or preferences in real-time, such as through facial expression analysis or direct input.

While Spotify's recommendation system is effective in leveraging machine learning for music recommendations, it has limitations in terms of real-time emotion analysis, personalized recommendations based on current mood, and interactive user engagement. These disadvantages highlight the potential for improvement and innovation in the areas of emotion-based multimedia recommendation and music generation.

1.5 HARDWARE AND SOFTWARE REQUIREMENTS

1.5.1 SOFTWARE REQUIREMENT

1. **Python Environment:**

- Python 3.x: Python serves as the primary programming language for implementing the project components and integrating various libraries and frameworks.
- TensorFlow: TensorFlow is an open-source machine learning framework that provides tools for building and training neural networks, including deep learning models for facial expression analysis and music generation.
- Keras: Keras is a high-level neural networks API, written in Python and capable of running on top of TensorFlow. It is used for building and training deep learning models, including the facial expression analysis model.
- OpenCV: OpenCV (Open Source Computer Vision Library) is a library of programming functions mainly aimed at real-time computer vision tasks. It is utilized for capturing video frames from the webcam, as well as for facial detection and landmark detection.
- MediaPipe: MediaPipe is an open-source framework developed by Google that provides solutions for various perception tasks, including face detection, facial landmark detection, and hand tracking. It is used in conjunction with OpenCV for real-time facial expression analysis.
- Streamlit: Streamlit is an open-source Python library that enables the creation of interactive web applications for data science and machine learning projects. It is used for building the user interface of the project and enabling real-time interaction with the facial expression analysis module.
- WebRTC: WebRTC (Web Real-Time Communication) is a free, open-

source project that provides web browsers and mobile applications with real-time communication via simple application programming interfaces (APIs). It is utilized for streaming video from the webcam to the web application.

- AV: AV is a Python library for working with audio and video data. It is used for processing and displaying video frames in real-time during facial expression analysis.

1.5.2 HARDWARE REQUIREMENT

- Webcam: A webcam is required to capture real-time video frames for facial expression analysis. The webcam should have sufficient resolution and frame rate for accurate detection and analysis of facial expressions.
- Computer: A computer with sufficient processing power and memory is necessary to run the project smoothly. The computer should meet the minimum system requirements for running the software components, including Python, TensorFlow, and OpenCV.
- Internet Connection: An internet connection is required for streaming video from the webcam to the web application using WebRTC. A stable internet connection ensures smooth and uninterrupted communication between the client and server components of the application.
- Speakers or Headphones (Optional): Speakers or headphones may be used to listen to the generated music compositions during the user interaction with the application.
- A multi-core processor (preferably quad-core or higher) is recommended to facilitate parallel processing and efficient handling of data-intensive operations.
- At least 8 GB of RAM (Random Access Memory) is required to ensure

smooth execution and processing of facial expression analysis tasks, machine learning algorithms, and data visualization operations. For optimal performance, a higher RAM capacity, such as 16 GB or more, is recommended, especially when dealing with large datasets and complex computations.

- Adequate storage space is necessary to accommodate the facial expression datasets, processed data, and any additional files generated during the analysis. The required storage capacity depends on the size of the facial expression dataset and the volume of processed data. It is advisable to have several gigabytes of free space to accommodate the data efficiently.
- While not mandatory for this specific project, the use of a dedicated GPU can significantly enhance the performance of certain tasks, especially in facial expression analysis and machine learning model training. GPUs with good parallel processing capabilities can accelerate data processing and improve the efficiency of complex computations.
- A high-resolution monitor is recommended for effective visualization of facial expression data, analysis outputs, and data visualizations. This facilitates a clear and detailed examination of facial features and expression patterns, enhancing the interpretability of the analysis results.

By meeting these hardware requirements, the project aims to leverage efficient computational resources and storage capabilities to conduct comprehensive facial expression analysis, machine learning model training, and data visualization tasks. The hardware infrastructure plays a crucial role in ensuring the smooth execution and performance optimization of the project workflow.

CHAPTER 2

DESIGN AND IMPLEMENTATION

2.1 PROPOSED SYSTEM

The proposed system seeks to integrate music generation using LSTM neural networks with music and movie recommendation based on facial expressions. Building upon the existing Python script for music generation, the system will be extended to encompass recommendation functionalities, leveraging facial expression analysis to personalize recommendations.

- **Data Collection and Preprocessing:**

The system will commence with the collection of facial expression data from image or video sources, facilitated by computer vision libraries like OpenCV. Facial expression images or video frames will undergo preprocessing to normalize and extract relevant features indicative of emotional states. Techniques such as histogram equalization, facial landmark detection, and feature extraction will be applied to ensure the extracted features accurately capture the user's emotional cues.

- **Music Generation:**

The core of the system will continue to rely on LSTM neural networks for music generation from MIDI files. However, the architecture of the neural network model will be augmented to incorporate features extracted from facial expressions. These features, representing the user's emotional state, will influence the music generation process, resulting in compositions tailored to the user's mood and preferences. By integrating facial expression data into the music generation pipeline, the system aims to produce music that resonates with the user on an emotional level, enhancing the overall listening experience.

- **Recommendation System:**

In parallel, the system will incorporate a recommendation engine that harnesses facial expression data to provide personalized music and movie recommendations. Machine learning models will be trained on labeled datasets containing facial expression data and corresponding music and movie preferences. Various recommendation algorithms, including collaborative filtering and content-based filtering, will be explored to generate accurate and relevant recommendations. By analyzing the user's facial expressions and correlating them with their historical preferences, the recommendation system will adapt to the user's evolving tastes and emotional states, ensuring the delivery of tailored recommendations.

- **Integration:**

The music generation and recommendation components will be seamlessly integrated into a unified system. Users will interact with the system by providing facial expressions as input, either through images or live video feeds. The system will analyze these expressions, generate personalized music based on the user's emotional state, and recommend movies that align with their mood and preferences. The integration will be designed to provide a cohesive and intuitive user experience, enabling users to explore and enjoy music and movies in a personalized manner.

The implemented system will undergo comprehensive testing and validation to ensure accuracy, reliability, and performance. Various scenarios and use cases will be simulated to assess the system's robustness and effectiveness in generating music and recommendations that resonate with users. User feedback will be solicited to iteratively refine the system and enhance its capabilities.

2.1.1 ADVANTAGES OF PROPOSED SYSTEM

The proposed system synergistically combines two innovative components: a music generator utilizing piano MIDI files and a sophisticated music and movie recommendation system driven by facial expression analysis. This integration offers a multifaceted approach with several compelling.

Advantages:

- Real-time Emotion Recognition: The facial expression analysis module accurately detects users' emotions in real-time, allowing for personalized recommendations based on their current mood and preferences.
- Bespoke Music Generation: The music generation component creates original piano compositions tailored to the user's emotional state. By leveraging LSTM neural networks, the system generates expressive and coherent music that enhances the overall entertainment experience.
- Seamless Integration: The integration of facial expression analysis and music generation provides a seamless and immersive user experience. Users can interact with the system in real-time, receiving personalized recommendations and enjoying bespoke music compositions that align with their emotions.
- Creative Inspiration: The system serves as a source of creative inspiration for music composers, songwriters, and producers. By suggesting chord progressions, melodies, and harmonies based on specific emotions or genres, the system assists musicians in exploring new musical directions and overcoming creative blocks.
- Educational Resource: The AI-generated music can serve as a valuable educational resource for students studying music composition and theory. By analyzing compositions generated by the system, students gain insights into different musical styles, structures, and techniques, enriching their learning experience.

Enhanced Creativity and Emotional Engagement in Music Composition: By seamlessly integrating facial expression analysis with music generation, the system empowers users to compose music that is not only technically proficient but also emotionally resonant. Musicians and composers can draw inspiration from their own facial expressions, allowing them to infuse their compositions with authentic emotion and depth. This unique approach fosters creativity and enables users to create music that truly speaks to their emotional state and artistic vision.

Personalized Multimedia Recommendations: By integrating real-time emotion detection, the system provides personalized multimedia recommendations tailored to the user's current emotional state. This enhances user satisfaction by delivering content that resonates with their mood and preferences.

Enhanced User Engagement: The interactive user interface and emotionally relevant content contribute to increased user engagement. Users are more likely to explore and interact with the recommended multimedia content, leading to a richer user experience.

AI-Driven Music Generation: The use of AI techniques, specifically LSTM networks, for music generation ensures that the system can create music sequences that match the detected emotions accurately. This results in a seamless and immersive music listening experience for the user.

2.2ARCHITECTURE OF THE MUSIC GENERAION SYSTEM

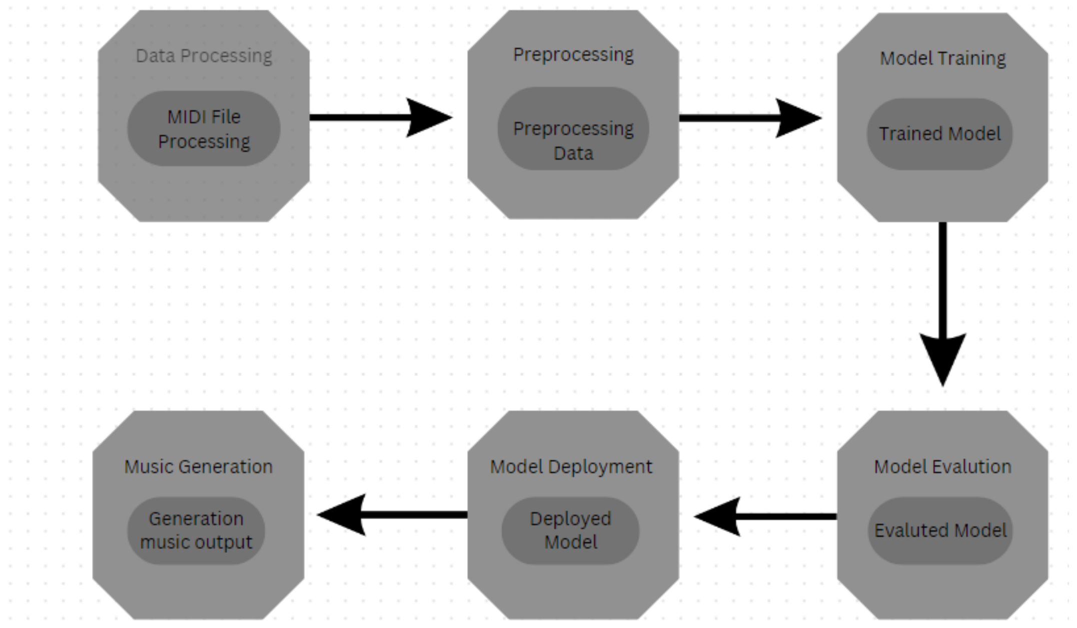


Fig.2.1 Project Architecture

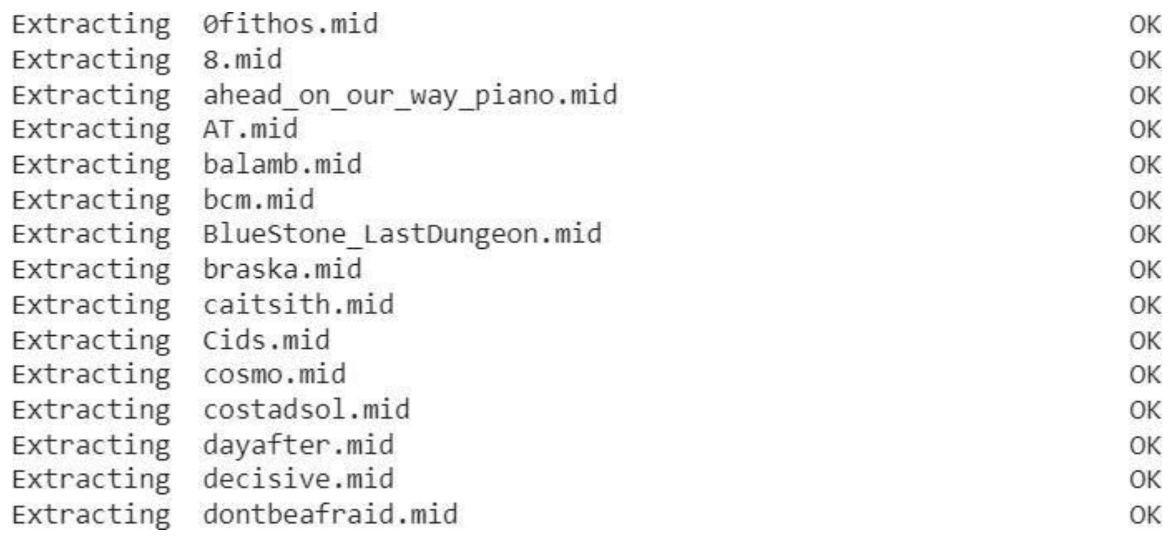
DATASET PREPROCESSING

- Data Preprocessing: The music generation process begins with preprocessing the musical data, which typically consists of MIDI files containing sequences of musical notes. MIDI data is converted into a suitable format for input into the LSTM neural network.
- Model Training: The LSTM neural network is trained on the preprocessed musical data to learn patterns and structures within the music. During training, the network adjusts its parameters to minimize the difference between the predicted and actual musical sequences.
- Composition Generation: Once the LSTM network is trained, it can generate original piano compositions by sampling from the learned probability distribution of musical sequences. The generated compositions are output as MIDI files, which can be played back or further modified by users.

Preprocessing In Midi Files: In the context of recommendation systems, the unified dataset undergoes additional preprocessing steps tailored to collaborative filtering or content-based recommendation algorithms. This may include data cleaning, feature scaling, and encoding categorical variables. Furthermore, techniques like matrix factorization or deep learning-based embeddings may be employed to extract latent representations of users and items.

Parsing MIDI Files

This reads MIDI files that contain musical information. MIDI files storedata about notes, chords, and other musical elements in a digital format

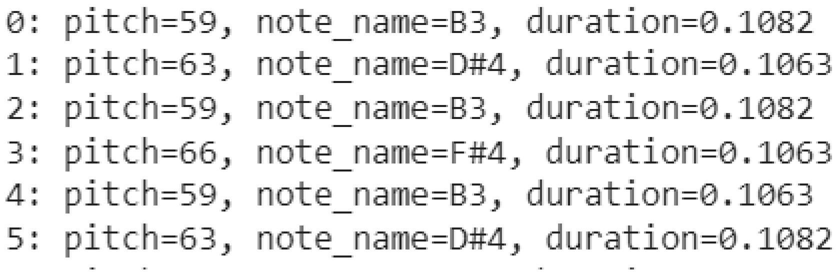


```
Extracting  0fithos.mid                                                          OK
Extracting  8.mid                                                                OK
Extracting  ahead_on_our_way_piano.mid                                           OK
Extracting  AT.mid                                                               OK
Extracting  balamb.mid                                                           OK
Extracting  bcm.mid                                                              OK
Extracting  BlueStone_LastDungeon.mid                                            OK
Extracting  braska.mid                                                           OK
Extracting  caitsith.mid                                                         OK
Extracting  Cids.mid                                                             OK
Extracting  cosmo.mid                                                            OK
Extracting  costadsol.mid                                                        OK
Extracting  dayafter.mid                                                         OK
Extracting  decisive.mid                                                         OK
Extracting  dontbeafraid.mid                                                     OK
```

Fig.2.2 Extraction of MIDI files

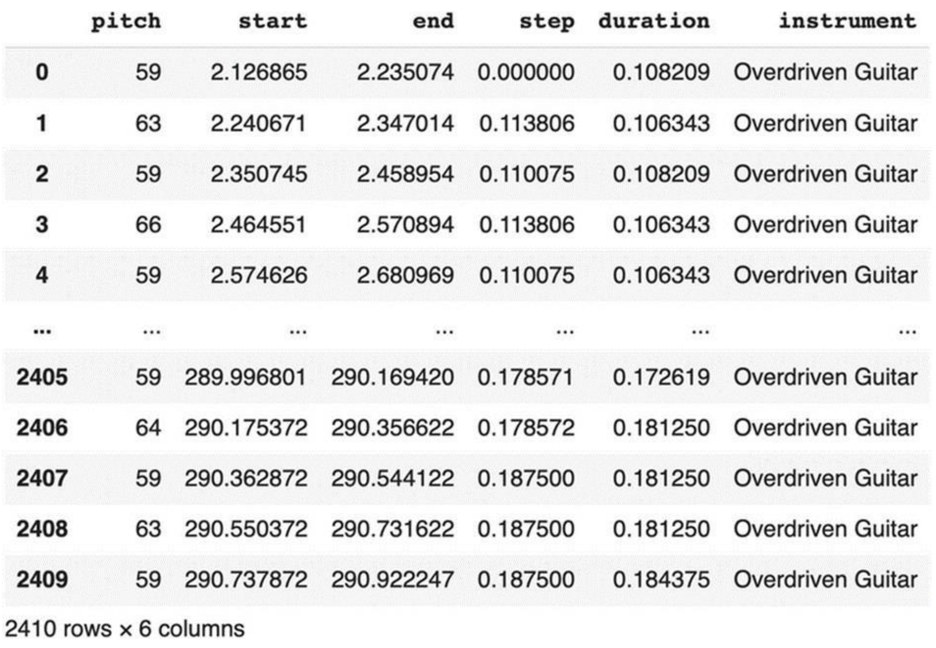
Extracting Notes and Chords

The code distinguishes between individual notes and chords within the MIDI files. Notes and chords are fundamental musical elements that form the basis of the generated music.



```
0: pitch=59, note_name=B3, duration=0.1082
1: pitch=63, note_name=D#4, duration=0.1063
2: pitch=59, note_name=B3, duration=0.1082
3: pitch=66, note_name=F#4, duration=0.1063
4: pitch=59, note_name=B3, duration=0.1063
5: pitch=63, note_name=D#4, duration=0.1082
```

Fig.2.3 Notes and Chords



	pitch	start	end	step	duration	instrument
0	59	2.126865	2.235074	0.000000	0.108209	Overdriven Guitar
1	63	2.240671	2.347014	0.113806	0.106343	Overdriven Guitar
2	59	2.350745	2.458954	0.110075	0.108209	Overdriven Guitar
3	66	2.464551	2.570894	0.113806	0.106343	Overdriven Guitar
4	59	2.574626	2.680969	0.110075	0.106343	Overdriven Guitar
...	...	...	...	...	...	...
2405	59	289.996801	290.169420	0.178571	0.172619	Overdriven Guitar
2406	64	290.175372	290.356622	0.178572	0.181250	Overdriven Guitar
2407	59	290.362872	290.544122	0.187500	0.181250	Overdriven Guitar
2408	63	290.550372	290.731622	0.187500	0.181250	Overdriven Guitar
2409	59	290.737872	290.922247	0.187500	0.184375	Overdriven Guitar

2410 rows × 6 columns

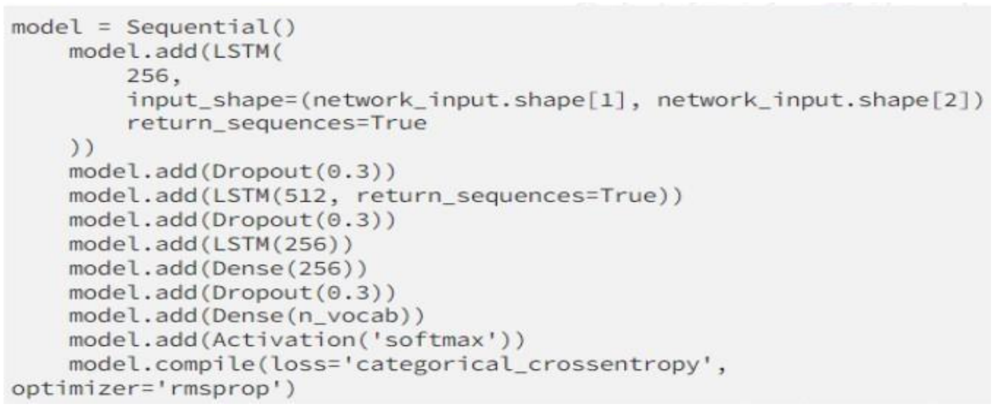
Fig.2.4 Dataset

2. Preprocessing for Music Generation: For music generation, MIDI files containing piano compositions serve as the raw data input. These MIDI files are parsed to extract notes, chords, and other musical elements specific to piano music. The notes are mapped to integers, and sequences of notes are created to represent musical phrases or segments. Similar to the traditional preprocessing steps for LSTM-based music generation, the input data is reshaped to fit the network's input layer requirements and normalized for efficient training.

TRAINING OF NEURAL NETWORK

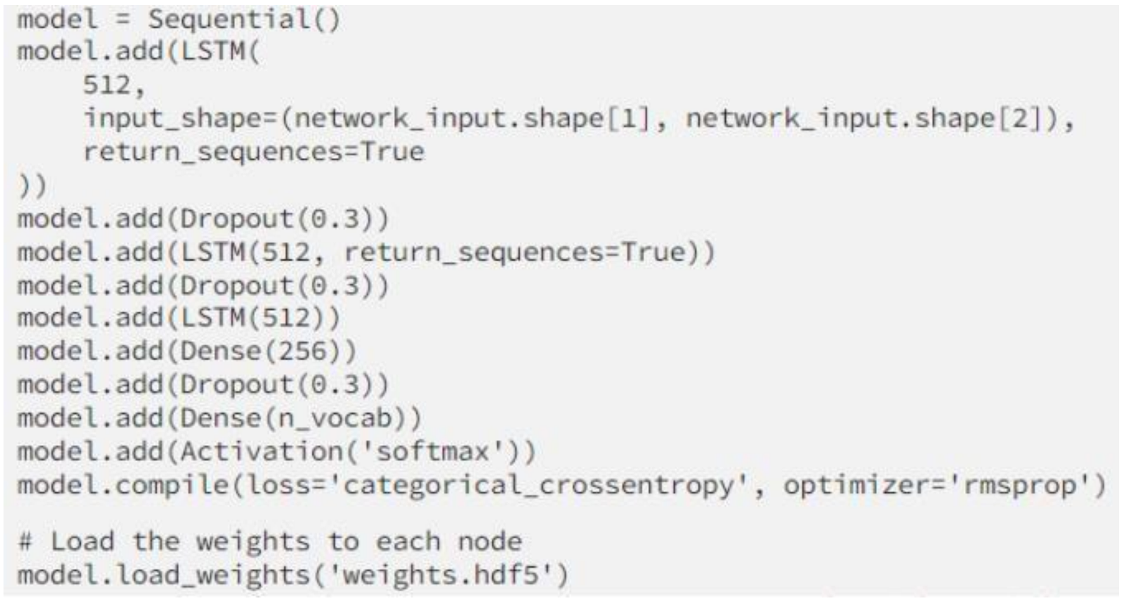
The purpose of the training process is to teach a Long Short-Term Memory (LSTM) neural network to generate music. This involves capturing patterns from a dataset of musical notes and chords and using these patterns to compose new, original music. The neural network is structured with three LSTM layers, each containing 512 units. Recurrent dropout with a rate of 0.3 is applied to introduce regularization and prevent over fitting. Batch normalizationis used to stabilize and accelerate the training process. Two dense layers with 256 and n_vocab units (the number of unique pitch names) respectively, are employed, followed by ReLU activation functions for introducing non-linearity. Finally, a softmax activation function is applied to the output layer to generate probabilities for each pitch, determining the next musical element in the sequence. The following are the training process that are carries out.

- **Loss Function:** The categorical cross-entropy loss function is utilized, suitable for multi-class classification problems like this.
- **Optimizer:** RMSprop optimizer is used, which adapts the learning ratesof each parameter individually, ensuring efficient and quicker convergence.
- **Metrics:** The accuracy metric is employed to measure the network'sperformance during training.
- **Epochs:** The network is trained over 20 epochs, indicating 20 complete passes through the entire training dataset.
- **Batch Size:** Training data is divided into batches of 128 sequences,enhancing computational efficiency



```
model = Sequential()
    model.add(LSTM(
        256,
        input_shape=(network_input.shape[1], network_input.shape[2])
        return_sequences=True
    ))
    model.add(Dropout(0.3))
    model.add(LSTM(512, return_sequences=True))
    model.add(Dropout(0.3))
    model.add(LSTM(256))
    model.add(Dense(256))
    model.add(Dropout(0.3))
    model.add(Dense(n_vocab))
    model.add(Activation('softmax'))
    model.compile(loss='categorical_crossentropy',
optimizer='rmsprop')
```

Fig.2.5 Architecture of neural network



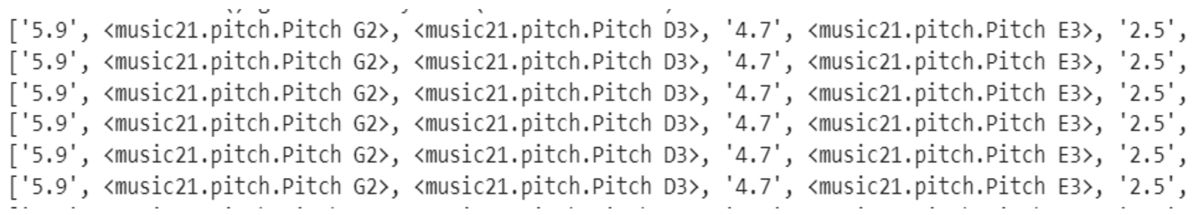
```
model = Sequential()
model.add(LSTM(
    512,
    input_shape=(network_input.shape[1], network_input.shape[2]),
    return_sequences=True
))
model.add(Dropout(0.3))
model.add(LSTM(512, return_sequences=True))
model.add(Dropout(0.3))
model.add(LSTM(512))
model.add(Dense(256))
model.add(Dropout(0.3))
model.add(Dense(n_vocab))
model.add(Activation('softmax'))
model.compile(loss='categorical_crossentropy', optimizer='rmsprop')

# Load the weights to each node
model.load_weights('weights.hdf5')
```

Fig.2.6 Architecture of neural network for music generation

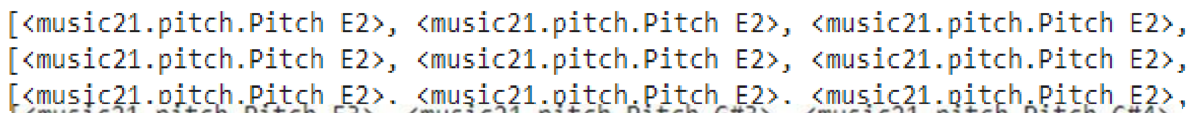
GENERATION OF MUSIC

We load the pre-existing musical notes used for training a neural network model. These notes are essential for the network to understand the patterns and structures of music. It then prepares sequences of musical notes, mapping them to integers for compatibility with the neural network. The network's architectureconsists of Long Short-Term Memory (LSTM) layers designed to model musical sequences. After configuring the network, the script initiates the music generation process. It begins with a random seed sequence, and iterativelypredicts and appends new musical notes based on the previously generated ones, ultimately forming a sequence of 500 notes. These generated notes are then transformed into a MIDI file, where chords and individual notes are represented. The offset between notes ensures they are not played simultaneously, creating a harmonious composition. The resulting MIDI file captures the neural network's creative musical output, stored as 'test_output3.mid,' ready for playback or further exploration.

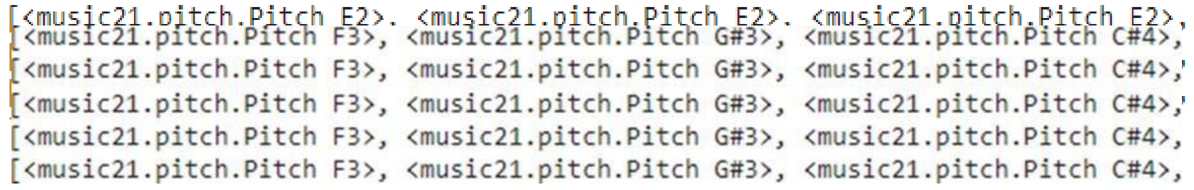


```
['5.9', <music21.pitch.Pitch G2>, <music21.pitch.Pitch D3>, '4.7', <music21.pitch.Pitch E3>, '2.5',
['5.9', <music21.pitch.Pitch G2>, <music21.pitch.Pitch D3>, '4.7', <music21.pitch.Pitch E3>, '2.5',
['5.9', <music21.pitch.Pitch G2>, <music21.pitch.Pitch D3>, '4.7', <music21.pitch.Pitch E3>, '2.5',
['5.9', <music21.pitch.Pitch G2>, <music21.pitch.Pitch D3>, '4.7', <music21.pitch.Pitch E3>, '2.5',
['5.9', <music21.pitch.Pitch G2>, <music21.pitch.Pitch D3>, '4.7', <music21.pitch.Pitch E3>, '2.5',
['5.9', <music21.pitch.Pitch G2>, <music21.pitch.Pitch D3>, '4.7', <music21.pitch.Pitch E3>, '2.5',
```

Fig.2.7 Test output 1 MIDI notes visualization



```
[<music21.pitch.Pitch E2>, <music21.pitch.Pitch E2>, <music21.pitch.Pitch E2>,
[<music21.pitch.Pitch E2>, <music21.pitch.Pitch E2>, <music21.pitch.Pitch E2>,
[<music21.pitch.Pitch E2>, <music21.pitch.Pitch E2>, <music21.pitch.Pitch E2>,
```



```
[<music21.pitch.Pitch F3>, <music21.pitch.Pitch G#3>, <music21.pitch.Pitch C#4>,
[<music21.pitch.Pitch F3>, <music21.pitch.Pitch G#3>, <music21.pitch.Pitch C#4>,
[<music21.pitch.Pitch F3>, <music21.pitch.Pitch G#3>, <music21.pitch.Pitch C#4>,
[<music21.pitch.Pitch F3>, <music21.pitch.Pitch G#3>, <music21.pitch.Pitch C#4>,
[<music21.pitch.Pitch F3>, <music21.pitch.Pitch G#3>, <music21.pitch.Pitch C#4>,
```

Fig.2.8 Test output 2 MIDI notes visualization

Fig.2.9 Test output 3 MIDI notes visualization

2.3 SYSTEM DESIGN

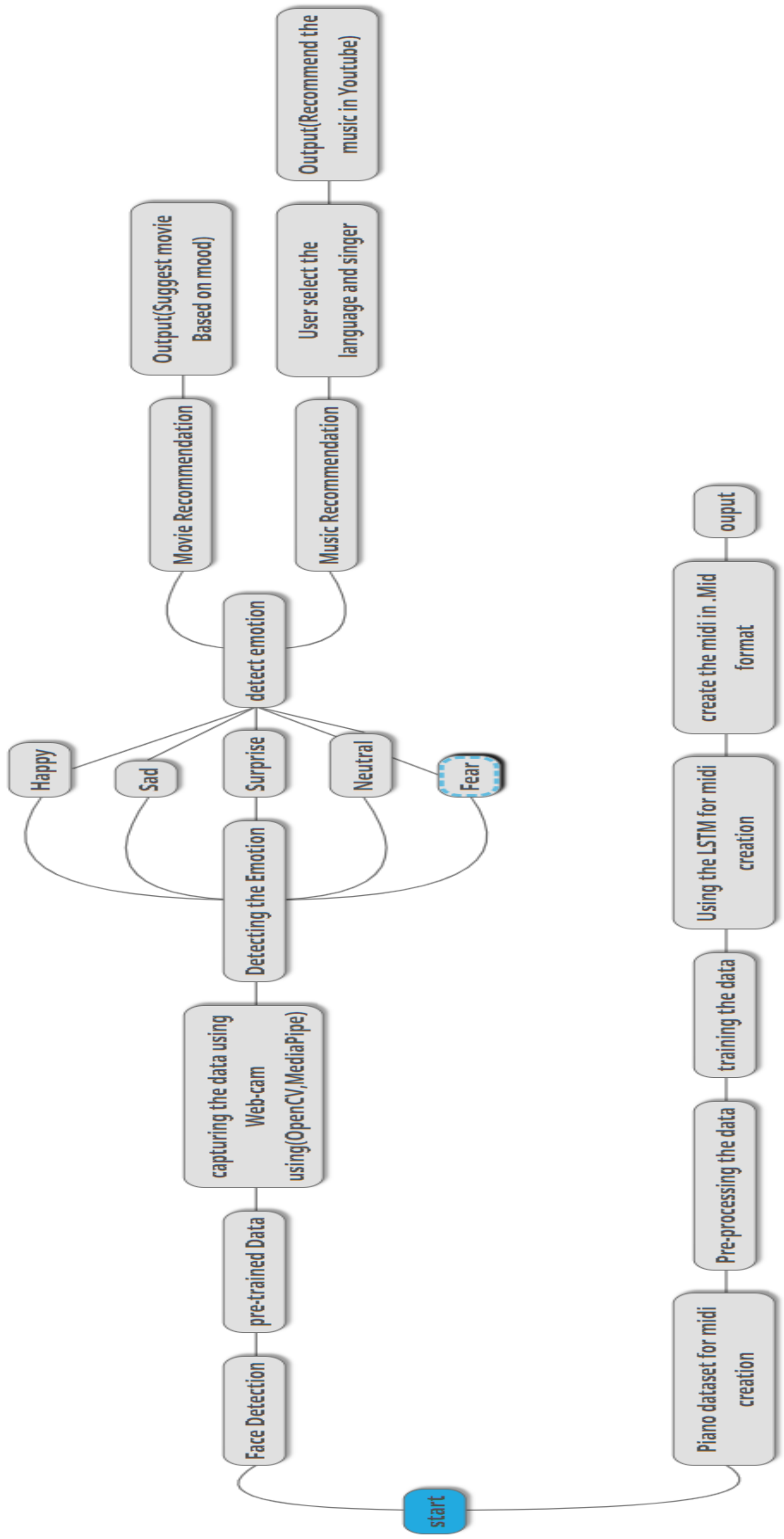

start
Face Detection
pre-trained Data
capturing the data using Web-cam using(OpenCV,MediaPipe)
Detecting the Emotion
Happy
Sad
Surprise
Neutral
Fear
detect emotion
Movie Recommendation
Output(Suggest movie Based on mood)
Music Recommendation
User select the language and singer
Output(Recommend the music in Youtube)
Piano dataset for midi creation
Pre-processing the data
training the data
Using the LSTM for midi creation
create the midi in .Mid format
ouput

Fig.2.10 Modules

2.4 IMPLEMENTATION

The implementation involves coding the facial expression analysis and music generation modules using Python and various libraries such as OpenCV, TensorFlow, and Keras.

- **Facial Expression Analysis Implementation:** OpenCV and MediaPipe are used for real-time facial landmark detection and emotion recognition. The detected emotions are then used to provide personalized recommendations.
- **Music Generation Implementation:** LSTM neural networks trained on MIDI data are utilized to generate original piano compositions based on the user's emotional state.

2.4.1. Facial Expression Analysis Implementation

The facial expression analysis module is implemented using OpenCV and MediaPipe libraries. Here is an overview of the implementation details:
Video Input: OpenCV is used to capture video frames from the webcam in real-time.

- **Facial Landmark Detection:** MediaPipe's facial landmark detection model is utilized to detect key facial landmarks such as eyes, nose, and mouth.
- **Emotion Recognition:** A trained machine learning model, implemented using Keras, is used to recognize emotions based on the detected facial landmarks.
- **Recommendation Generation:** The recognized emotions are then used to generate personalized recommendations for movies and music, aligning with the user's emotional state.

2.4.2. Music Generation Implementation

The music generation module is implemented using LSTM neural networks trained on MIDI data. Here are the implementation details:

Data Preprocessing: MIDI data containing musical sequences is preprocessed into a suitable format for input into the LSTM network. This may involve encoding the musical data into numerical representations.

Model Training: The LSTM neural network is trained on the preprocessed musical data to learn patterns and structures within the music. This involves defining the architecture of the LSTM network and tuning its parameters to optimize performance.

Composition Generation: Once the LSTM network is trained, it can generate original piano compositions by sampling from the learned probability distribution of musical sequences. The generated compositions are output in MIDI format.

Video Input:

OpenCV is used to capture video frames from the webcam in real-time. The cv2.VideoCapture() function is employed to access the webcam and start streaming video.

```
import cv2
cap = cv2.VideoCapture(0)
while True:
    ret, frame = cap.read()
    if ret:
        cv2.imshow('Facial Expression Analysis', frame)
        if cv2.waitKey(1) & 0xFF == ord('q'):
            break
    else:
        break
```

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

Facial Landmark Detection:

MediaPipe's facial landmark detection model is utilized to detect key facial landmarks such as eyes, nose, and mouth. The mediapipe library is used to access the facial landmark detection functionality.

```
import mediapipe as mp
face_detection = mp.solutions.face_detection
face_detection_model = face_detection.FaceDetection()
face_landmark = mp.solutions.face_landmarks
face_landmark_model = face_landmark.FaceLandmarks()
while True:
    ret, frame = cap.read()
    if ret:
        # Convert frame to RGB
        frame_rgb = cv2.cvtColor(frame, cv2.COLOR_BGR2RGB)
        results = face_landmark_model.process(frame_rgb)
        if results.multi_face_landmarks:
            for face_landmarks in results.multi_face_landmarks:
        cv2.imshow('Facial Expression Analysis', frame)
        if cv2.waitKey(1) & 0xFF == ord('q'):
            break
    else:
        break
cap.release()
cv2.destroyAllWindows()
```

Emotion Recognition:

A trained machine learning model, implemented using Keras, is used to recognize emotions based on the detected facial landmarks. The model predicts the user's emotion from a set of predefined classes such as happiness, sadness, anger, etc.

Recommendation Generation:

The recognized emotions are then used to generate personalized recommendations for movies and music, aligning with the user's emotional state. These recommendations can be sourced from online databases or predefined lists based on emotion categories.

2.4.3. Music Generation Implementation

The music generation module utilizes LSTM neural networks trained on MIDI data to generate original piano compositions based on the user's emotional state. Here's how it's implemented:

Data Preprocessing:

MIDI data containing musical sequences is preprocessed into a suitable format for input into the LSTM network. This may involve encoding the musical data into numerical representations.

```
# Data preprocessing for MIDI sequences
# Load MIDI files and convert them to numerical representations
# Extract features such as note sequences, durations, etc.
# Prepare the data for input to the LSTM network
```

Model Training:

The LSTM neural network is trained on the preprocessed musical data to learn patterns and structures within the music. This involves defining the architecture of the LSTM network and tuning its parameters to optimize performance.

```
from keras.models import Sequential
from keras.layers import LSTM, Dense
model = Sequential()
model.add(LSTM(units=128, input_shape=(sequence_length, num_features)))
model.add(Dense(units=num_features, activation='softmax'))
model.compile(optimizer='adam', loss='categorical_crossentropy')
# Train the model on the preprocessed musical data
model.fit(X_train, y_train, batch_size=32, epochs=100, validation_data=(X_val, y_val))
```

Composition Generation:

Once the LSTM network is trained, it can generate original piano compositions by sampling from the learned probability distribution of musical sequences. The generated compositions are output in MIDI format.

```
# Generate a new piano composition using the trained LSTM network
generated_sequence = generate_music_sequence(model, seed_sequence)
# Convert the generated sequence to MIDI format
generated_midi = sequence_to_midi(generated_sequence)
# Save the generated composition to a MIDI file
generated_midi.save('generated_music.mid')
```

This implementation ensures that the system accurately detects facial expressions in real-time, generates personalized recommendations, and creates bespoke music compositions aligned with the user's emotions.

2.5. User Interface Design

The user interface is designed using Streamlit, an open-source Python library for building web applications. The interface allows users to interact with the system in real-time, providing feedback on the detected emotions and accessing personalized recommendations and music compositions.

- **Facial Expression Analysis and Feature Extraction:** Leveraging computer vision techniques, facial expressions are analyzed, and relevant features such as facial landmarks, emotions, and mood indicators are extracted. Advanced algorithms like Convolutional Neural Networks (CNNs) may be employed to accurately detect and classify facial expressions, capturing subtle nuances and emotional cues.

- Facial Detection: Identifies and locates faces via OpenCV.
- Facial Landmark Detection: Determines key facial landmarks for feature analysis. We develop in media-pipe library to detect the facial landmark to analysis the mood.

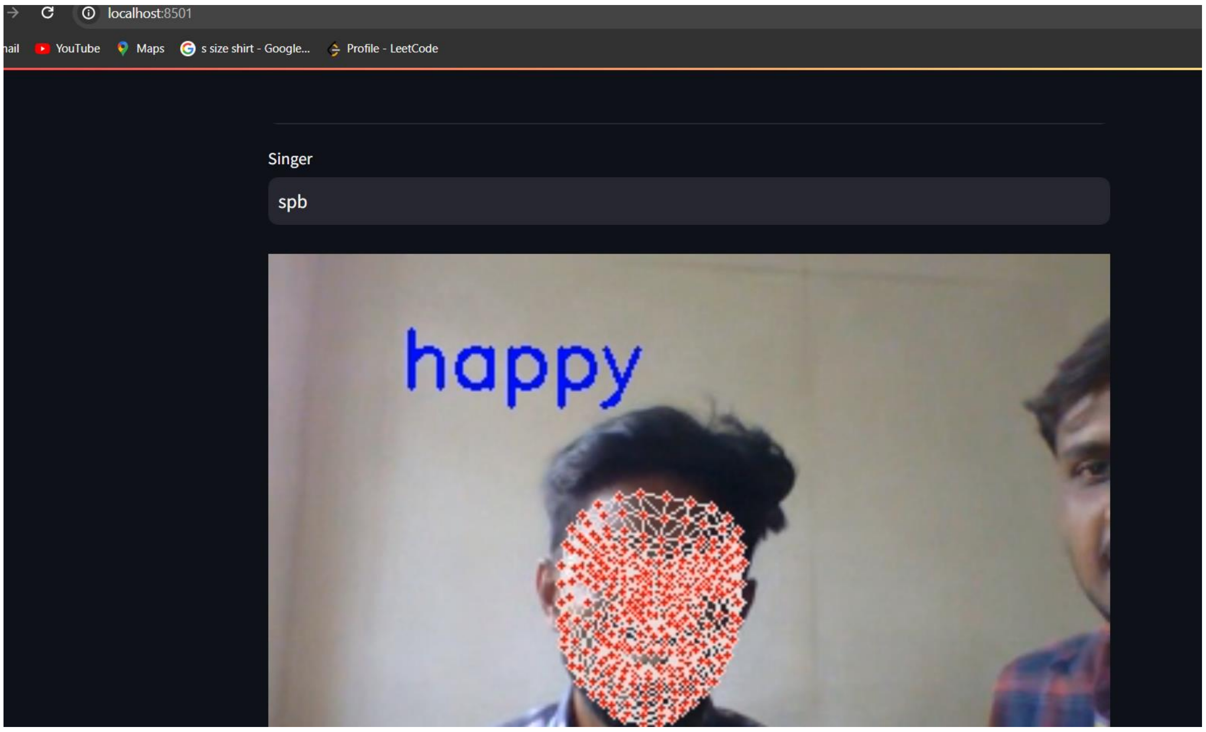
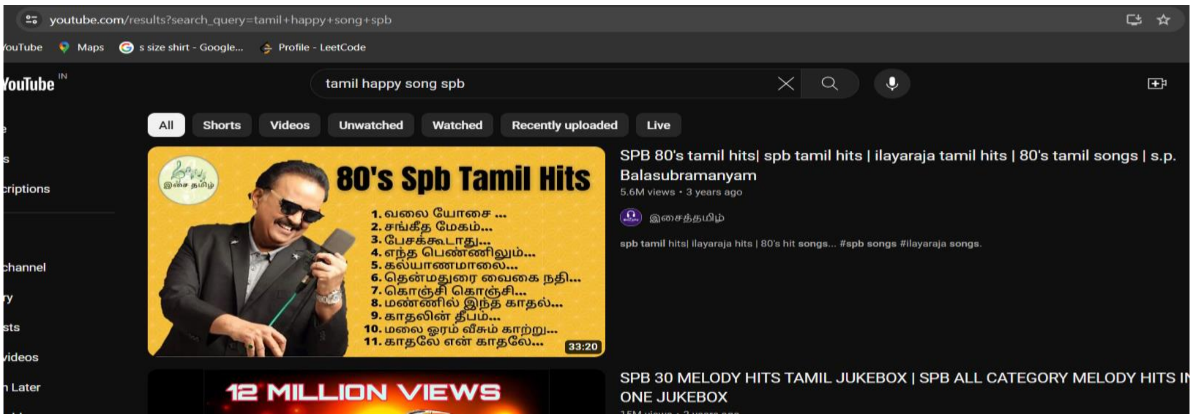


Fig 2.11 Capturing Face using OpenCV and MediaPipe

2. Integration of Music and Movie Based Recommendation: In parallel, metadata from music and movie databases is curated and integrated into the preprocessing pipeline. This metadata encompasses information such as genre, mood, tempo, and plot synopsis for movies, as well as musical attributes like key, tempo, instrumentation, and note sequences for piano compositions. The harmonization of this metadata facilitates holistic content analysis and recommendation generation.


youtube.com/results?search_query=tamil+happy+song+spb

tamil happy song spb

SPB 80's tamil hits| spb tamil hits | ilayaraja tamil hits | 80's tamil songs | s.p. Balasubramanyam

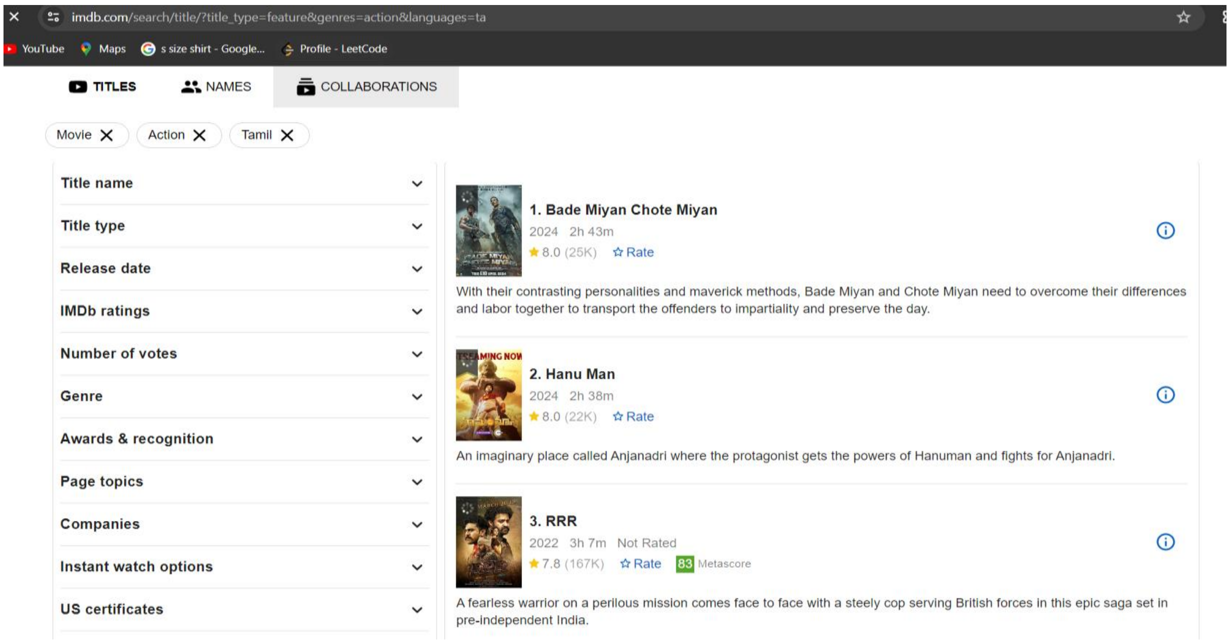
5.6M views • 3 years ago

இசைத்தமிழ்

spb tamil hits| ilayaraja hits | 80's hit songs... #spb songs #ilayaraja songs.

SPB 30 MELODY HITS TAMIL JUKEBOX | SPB ALL CATEGORY MELODY HITS IN ONE JUKEBOX

Fig2.12 Recommend a Song using Facial Expression


imdb.com/search/title/?title_type=feature&genres=action&languages=ta

1. Bade Miyan Chote Miyan

2024 2h 43m

8.0 (25K) Rate

With their contrasting personalities and maverick methods, Bade Miyan and Chote Miyan need to overcome their differences and labor together to transport the offenders to impartiality and preserve the day.

2. Hanu Man

2024 2h 38m

8.0 (22K) Rate

An imaginary place called Anjanadri where the protagonist gets the powers of Hanuman and fights for Anjanadri.

3. RRR

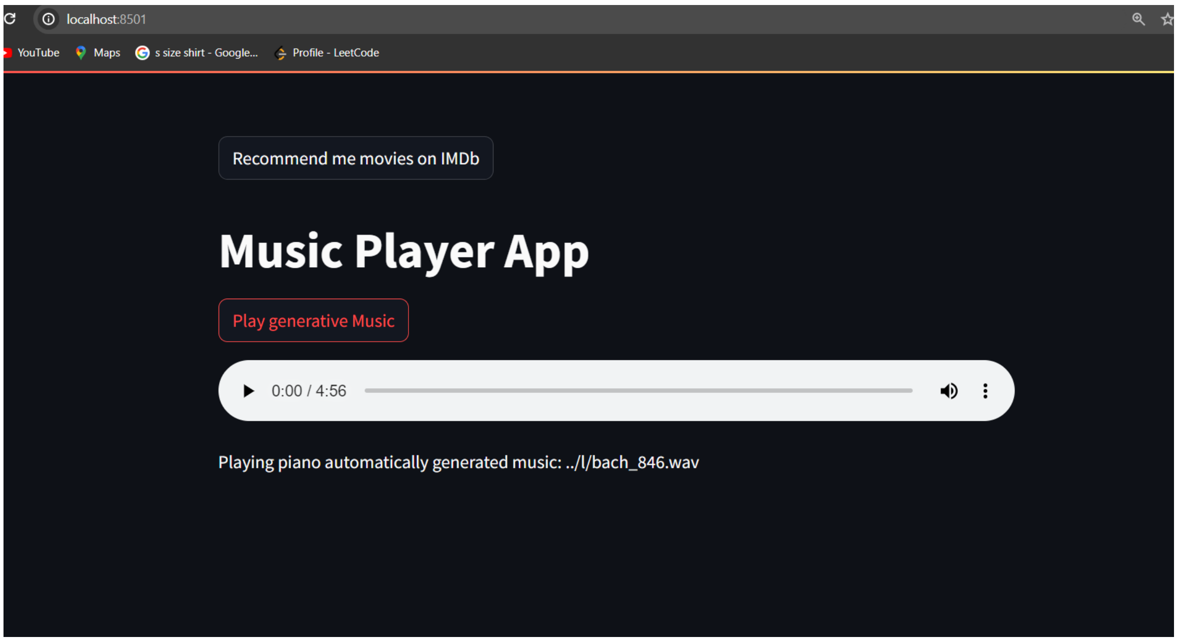
2022 3h 7m Not Rated

7.8 (167K) Rate 83 Metascore

A fearless warrior on a perilous mission comes face to face with a steely cop serving British forces in this epic saga set in pre-independent India.

Fig2.13 Recommend a Moives using Facial Expression

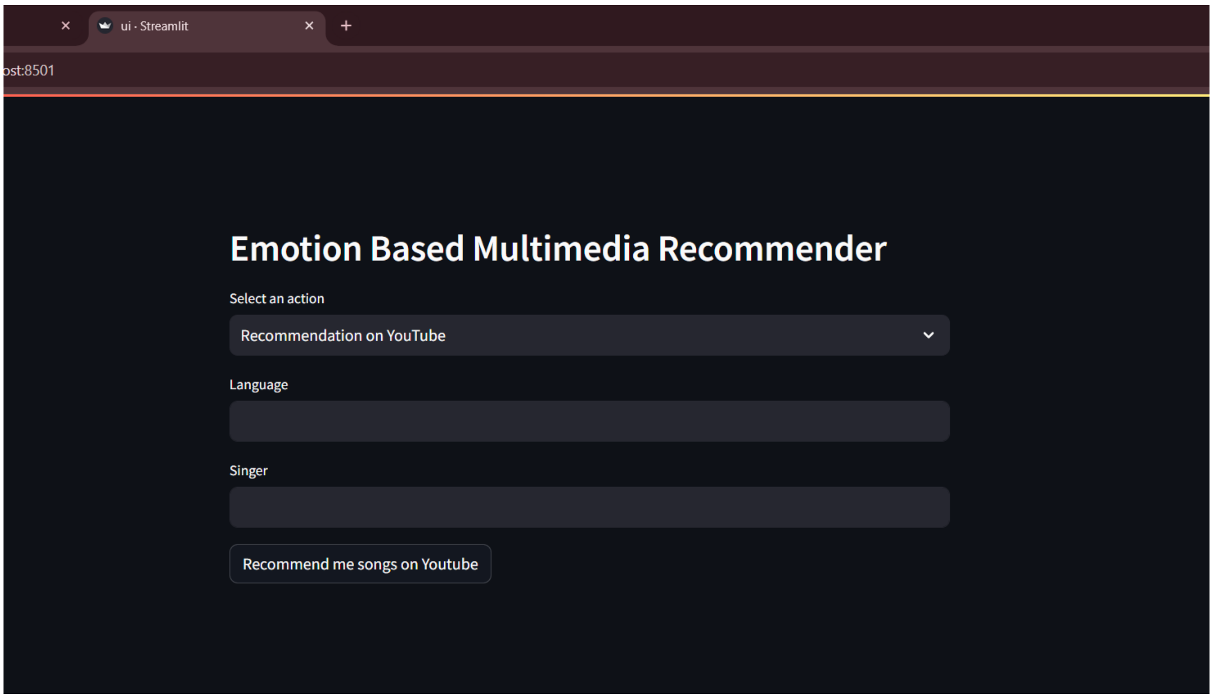
3.Music Generation:we using a Midi generation model for mid format training data to generated Wav format file using LSTM.In the Model we give a piano mid file to generated a calm piano music.If user Don't know what song is playing or bored music playing in Youtube. The music player generate a new music using a Piano trained LSTM model.



Music Player App

Playing piano automatically generated music: ../l/bach_846.wav

Fig2.14 Generate a music using LSTM



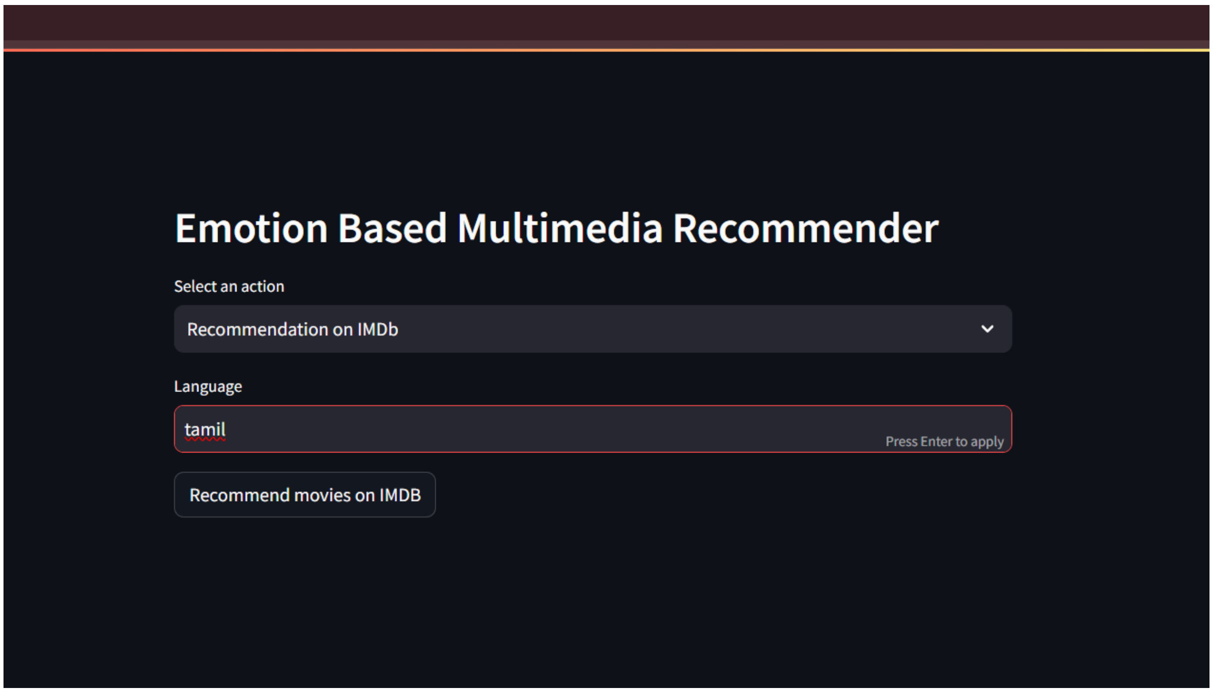
Emotion Based Multimedia Recommender

Select an action: Recommendation on YouTube

Language

Singer

Fig2.15 User Interface



Emotion Based Multimedia Recommender

Select an action

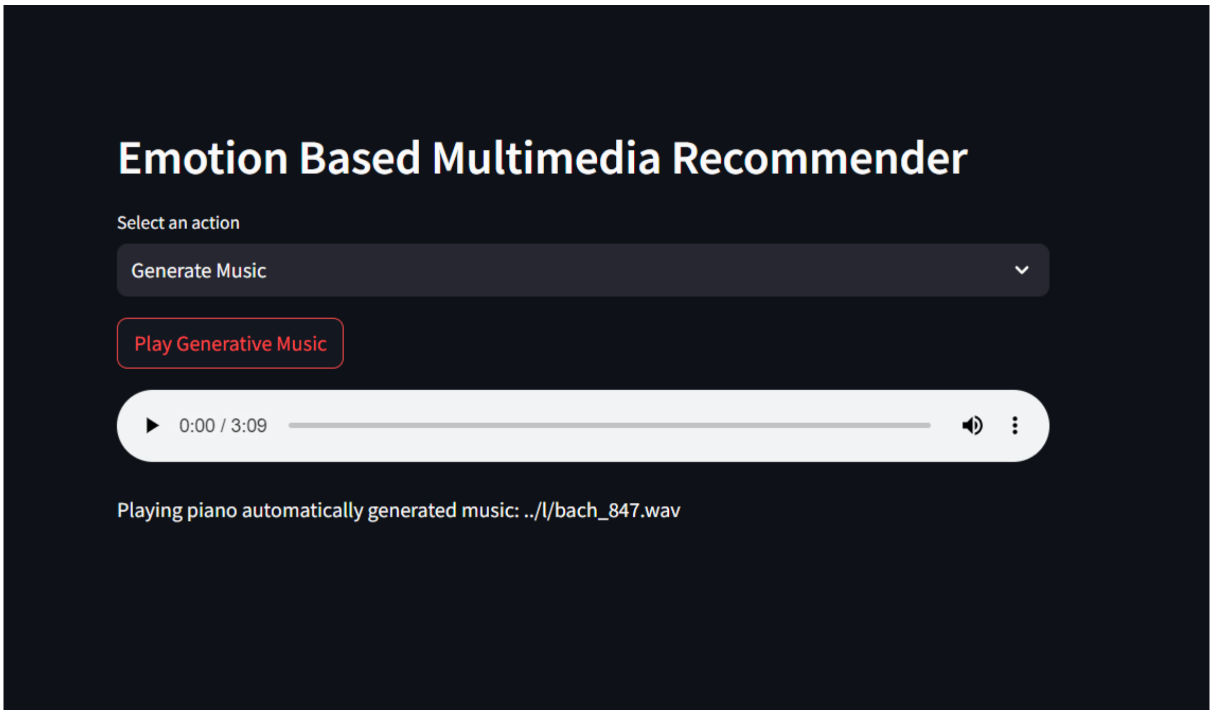
Recommendation on IMDb

Language

tamil

Press Enter to apply

Fig2.16 User Interface



Emotion Based Multimedia Recommender

Select an action

Generate Music

Playing piano automatically generated music: ../l/bach_847.wav

Fig2.17 User Interface

CHAPTER 3

CONCLUSION

3.1 CONCLUSION

The project has successfully integrated cutting-edge technologies such as real-time emotion detection, AI-driven music generation, and multimedia recommendation systems. This integration has resulted in a cohesive and innovative Emotion-Based Multimedia Recommender and AI-Driven Music Player.Through the use of OpenCV and MediaPipe, the system accurately analyzes facial expressions, enabling it to detect emotions like happiness, sadness, surprise, and more. This real-time emotion detection forms the foundation for personalized multimedia recommendations and music generation tailored to the user's emotional state.

The AI-driven music generation aspect, powered by Long Short-Term Memory (LSTM) networks, adds a unique dimension to the user experience. One of the system's standout features is its ability to recommend multimedia content, including songs on platforms like YouTube and movies on IMDB. By leveraging the detected emotions, the system curates recommendations that align with the user's mood, enhancing engagement and satisfaction.

Throughout the development process, insights were gained into the challenges and opportunities presented by real-time emotion analysis, AI-driven music generation, and multimedia recommendation systems. User feedback and system evaluation provided valuable insights into user preferences, interaction patterns, and the impact of personalized recommendations on user experience.

In conclusion, the project represents a significant advancement in AI-driven applications for human-computer interaction, entertainment, and emotional well-being. It underscores the potential of technology to create engaging and personalized experiences, shaping the future of multimedia recommendation systems and music generation platforms.

3.2 FUTURE ENHANCEMENTS

- Integration of Multiple Models: Incorporating multiple models could enable the generation of diverse musical elements such as melody, harmony, and rhythm separately. This approach promises to yield more intricate and captivating compositions.
- Human Feedback Mechanism: Implementing a feedback loop involving human evaluation could refine the model's ability to generate music that aligns with human preferences and aesthetic sensibilities, enhancing its overall quality and appeal.
- Diversification of Dataset: Enriching the dataset with music from various genres and styles would empower the model to grasp a wider range of musical conventions and nuances. This broader musical understanding would enable the generation of music spanning diverse genres, catering to a broader audience.

- Advanced Emotion Recognition: Integrate more advanced emotion recognition techniques, such as deep learning models like Convolutional Neural Networks (CNNs) or Transformer models, to improve the accuracy and granularity of emotion detection.

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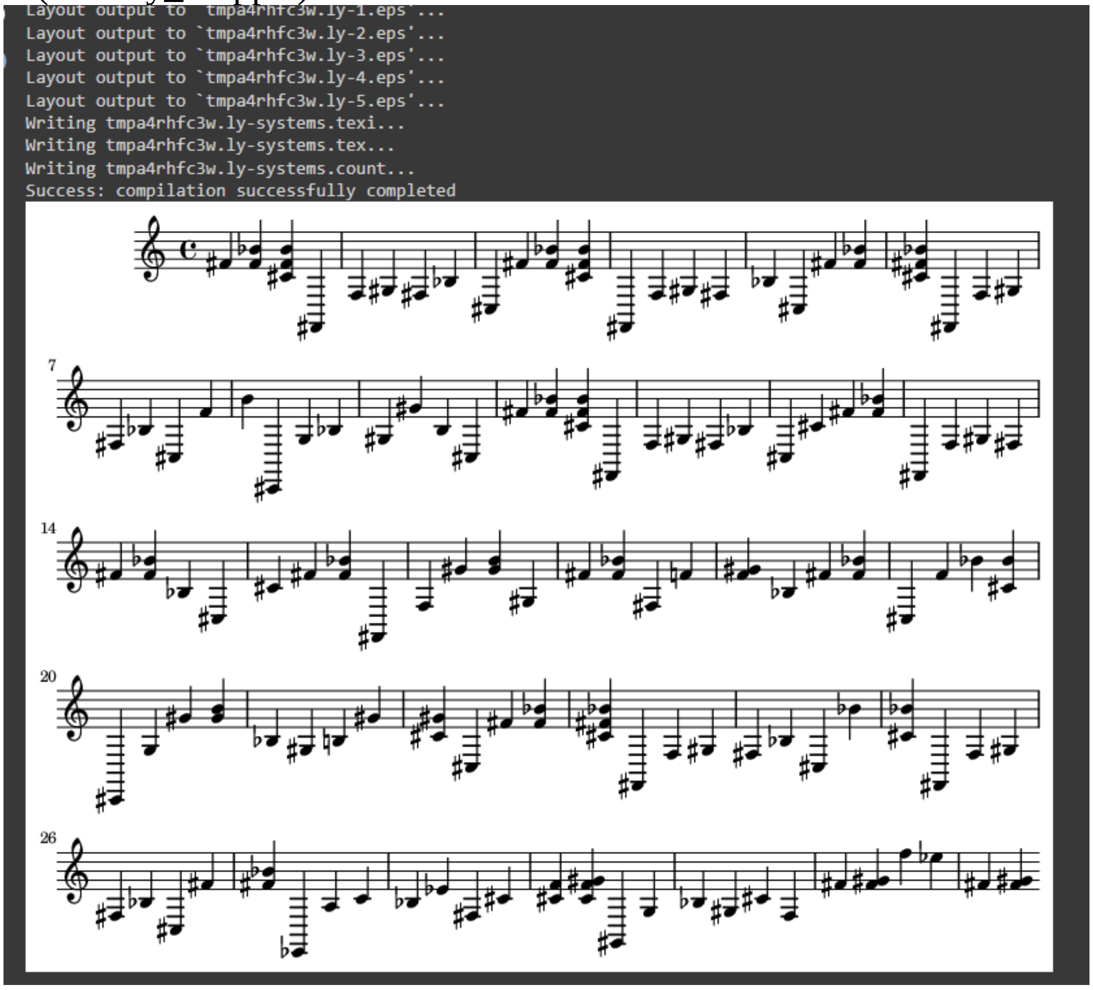
- https://github.com/AI-Guru/music-generation-research
- https://www.sciencedirect.com/science/article/pii/S095741742201353
- https://www.researchgate.net/publication/365339518_Music_Generation_
- https://david-exiga.medium.com/music-generation

APPENDIX

PYTHON CODE:

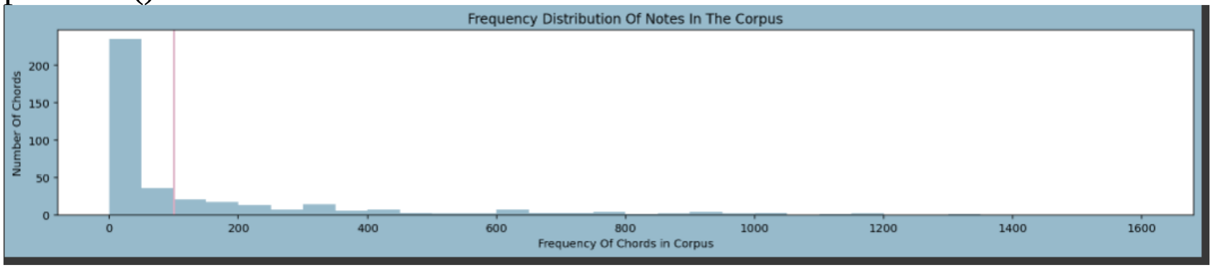
Training data:

```
import tensorflow
import numpy as np
import pandas as pd
from collections import Counter
import random
import IPython
from IPython.display import Image, Audio
import music21
from music21 import *
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout
import tensorflow.keras.backend as K
from tensorflow.keras.optimizers import Adamax
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib.patches as mpatches
%matplotlib inline
import sys
import warnings
warnings.filterwarnings("ignore")
warnings.simplefilter("ignore")
np.random.seed(42)
#Loading the list of chopin's midi files as stream
filepath = "../input/classical-music-midi/chopin/"
#Getting midi files
all_midis= []
for i in os.listdir(filepath):
    if i.endswith(".mid"):
        tr = filepath+i
        midi = converter.parse(tr)
        all_midis.append(midi)
#Helping function
def extract_notes(file):
    notes = []
    pick = None
    for j in file:
        songs = instrument.partitionByInstrument(j)
        for part in songs.parts:
            pick = part.recurse()
            for element in pick:
                if isinstance(element, note.Note):
                    notes.append(str(element.pitch))
                elif isinstance(element, chord.Chord):
                    notes.append(".".join(str(n) for n in element.normalOrder))

    return notes
#Getting the list of notes as Corpus
Corpus= extract_notes(all_midis)
print("Total notes in all the Chopin midis in the dataset:", len(Corpus))
#Helping function
def extract_notes(file):
    notes = []
    pick = None
    for j in file:
        songs = instrument.partitionByInstrument(j)
        for part in songs.parts:
            pick = part.recurse()
            for element in pick:
                if isinstance(element, note.Note):
                    notes.append(str(element.pitch))
                elif isinstance(element, chord.Chord):
                    notes.append(".".join(str(n) for n in element.normalOrder))

    return notes
#Getting the list of notes as Corpus
Corpus= extract_notes(all_midis)
print("Total notes in all the Chopin midis in the dataset:", len(Corpus))
#First Lets write some functions that we need to look into the data
def show(music):
    display(Image(str(music.write("lily.png"))))

def chords_n_notes(Snippet):
    Melody = []
    offset = 0 #Incremental
    for i in Snippet:
        #If it is chord
        if ("." in i or i.isdigit()):
            chord_notes = i.split(".") #Seperating the notes in chord
            notes = []
            for j in chord_notes:
                inst_note=int(j)
                note_snip = note.Note(inst_note)
                notes.append(note_snip)
                chord_snip = chord.Chord(notes)
                chord_snip.offset = offset
                Melody.append(chord_snip)
        # pattern is a note
        else:
            note_snip = note.Note(i)
            note_snip.offset = offset
            Melody.append(note_snip)
        # increase offset each iteration so that notes do not stack
        offset += 1
    Melody_midi = stream.Stream(Melody)
    return Melody_midi

Melody_Snippet = chords_n_notes(Corpus[:100])
show(Melody_Snippet)
```

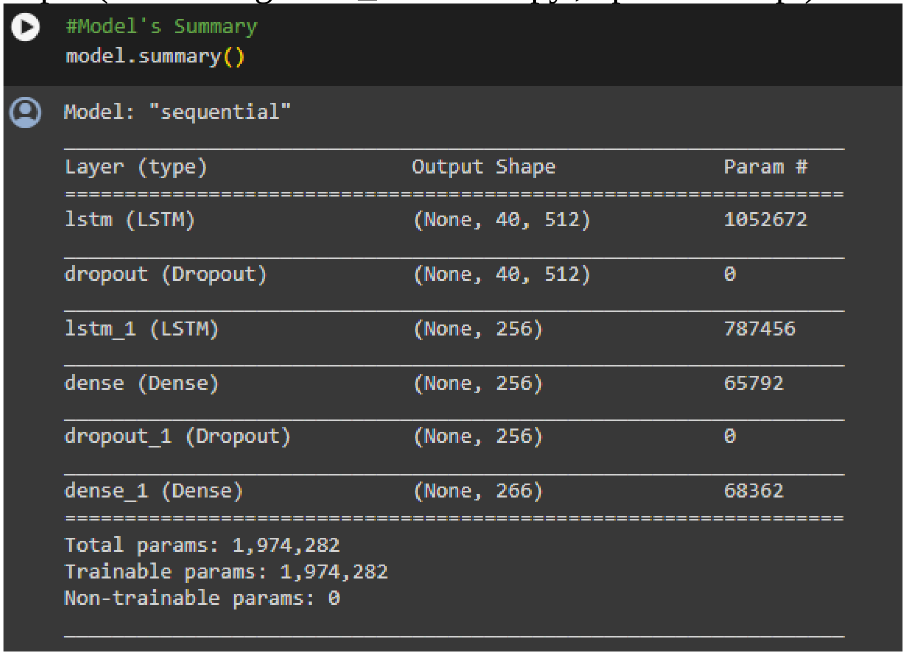


```
Layout output to `tmpa4rhfc3w.ly-1.eps'...
Layout output to `tmpa4rhfc3w.ly-2.eps'...
Layout output to `tmpa4rhfc3w.ly-3.eps'...
Layout output to `tmpa4rhfc3w.ly-4.eps'...
Layout output to `tmpa4rhfc3w.ly-5.eps'...
Writing tmpa4rhfc3w.ly-systems.texi...
Writing tmpa4rhfc3w.ly-systems.tex...
Writing tmpa4rhfc3w.ly-systems.count...
Success: compilation successfully completed
```

```
# Plotting the distribution of Notes
plt.figure(figsize=(18,3),facecolor="#97BACB")
bins = np.arange(0,(max(Recurrence)), 50)
plt.hist(Recurrence, bins=bins, color="#97BACB")
plt.axvline(x=100,color="#DBACC1")
plt.title("Frequency Distribution Of Notes In The Corpus")
plt.xlabel("Frequency Of Chords in Corpus")
plt.ylabel("Number Of Chords")
plt.show()
```



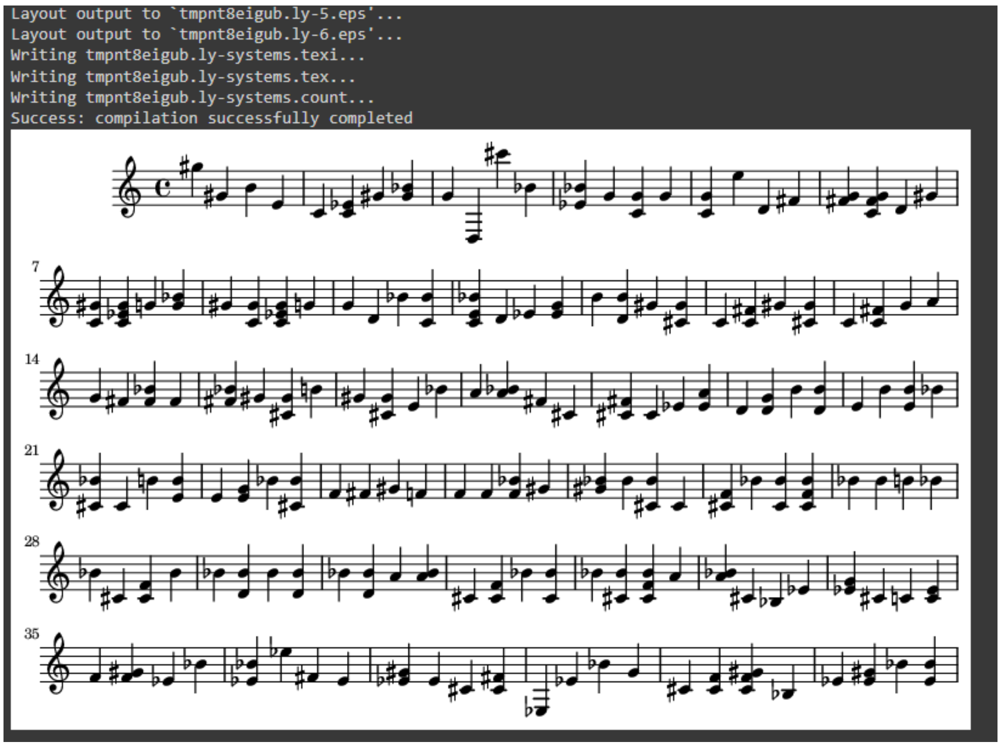
```
#Initialising the Model
model = Sequential()
#Adding layers
model.add(LSTM(512, input_shape=(X.shape[1], X.shape[2]),
return_sequences=True))
model.add(Dropout(0.1))
model.add(LSTM(256))
model.add(Dense(256))
model.add(Dropout(0.1))
model.add(Dense(y.shape[1], activation='softmax'))
#Compiling the model for training
opt = Adamax(learning_rate=0.01)
model.compile(loss='categorical_crossentropy', optimizer=opt)
```



```
#Model's Summary
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm (LSTM)                  (None, 40, 512)           1052672
_________________________________________________________________
dropout (Dropout)            (None, 40, 512)           0
_________________________________________________________________
lstm_1 (LSTM)                (None, 256)               787456
_________________________________________________________________
dense (Dense)                (None, 256)               65792
_________________________________________________________________
dropout_1 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_1 (Dense)              (None, 266)               68362
=================================================================
Total params: 1,974,282
Trainable params: 1,974,282
Non-trainable params: 0
_________________________________________________________________
```

```
def Malody_Generator(Note_Count):
    seed = X_seed[np.random.randint(0,len(X_seed)-1)]
    Music = ""
    Notes_Generated=[]
    for i in range(Note_Count):
        seed = seed.reshape(1,length,1)
        prediction = model.predict(seed, verbose=0)[0]
        prediction = np.log(prediction) / 1.0 #diversity
        exp_preds = np.exp(prediction)
        prediction = exp_preds / np.sum(exp_preds)
        index = np.argmax(prediction)
        index_N = index/ float(L_symb)
        Notes_Generated.append(index)
        Music = [reverse_mapping[char] for char in Notes_Generated]
        seed = np.insert(seed[0],len(seed[0]),index_N)
        seed = seed[1:]
    #Now, we have music in form or a list of chords and notes and we want to be
a midi file.
    Melody = chords_n_notes(Music)
    Melody_midi = stream.Stream(Melody)
    return Music,Melody_midi

#getting the Notes and Melody created by the model
Music_notes, Melody = Malody_Generator(100)
show(Melody)
```



```
Layout output to `tmpnt8eigub.ly-5.eps'...
Layout output to `tmpnt8eigub.ly-6.eps'...
Writing tmpnt8eigub.ly-systems.texi...
Writing tmpnt8eigub.ly-systems.tex...
Writing tmpnt8eigub.ly-systems.count...
Success: compilation successfully completed
```

```
import streamlit as st
from streamlit_webrtc import webrtc_streamer
import av
import cv2
import numpy as np
import mediapipe as mp
from keras.models import load_model
import webbrowser
import random

st.markdown('<link rel="stylesheet" href="style.css">', unsafe_allow_html=True)

model = load_model("model.h5")
label = np.load("labels.npy")
holistic = mp.solutions.holistic
hands = mp.solutions.hands
holis = holistic.Holistic()
drawing = mp.solutions.drawing_utils

# try:
#     emotion = np.load("emotion.npy")[0]
# except:
#     emotion = ""
emotion=np.load("emotion.npy")[0]

if not emotion:
    st.session_state["run"] = "true"
else:
    st.session_state["run"] = "false"

class EmotionProcessor:
    def recv(self, frame):
        frm = frame.to_ndarray(format="bgr24")
        frm = cv2.flip(frm, 1)
        res = holis.process(cv2.cvtColor(frm, cv2.COLOR_BGR2RGB))
        lst = []
        if res.face_landmarks:
            for i in res.face_landmarks.landmark:
                lst.append(i.x - res.face_landmarks.landmark[1].x)
                lst.append(i.y - res.face_landmarks.landmark[1].y)
            if res.left_hand_landmarks:
                for i in res.left_hand_landmarks.landmark:
                    lst.append(i.x - res.left_hand_landmarks.landmark[8].x)
                    lst.append(i.y - res.left_hand_landmarks.landmark[8].y)
            else:
                for i in range(42):
                    lst.append(0.0)
            if res.right_hand_landmarks:
                for i in res.right_hand_landmarks.landmark:
                    lst.append(i.x - res.right_hand_landmarks.landmark[8].x)
                lst.append(i.y - res.right_hand_landmarks.landmark[8].y)
            else:
                for i in range(42):
                    lst.append(0.0)

            lst = np.array(lst).reshape(1, -1)
            pred = label[np.argmax(model.predict(lst))]
            print(pred)
            cv2.putText(frm, pred, (50, 50), cv2.FONT_ITALIC, 1, (255, 0, 0), 2)
            # Save emotion only if it's not already captured
            if not emotion:
                np.save("emotion.npy", np.array([pred]))

        drawing.draw_landmarks(frm, res.face_landmarks,
holistic.FACEMESH_TESSELATION,landmark_drawing_spec=drawing.DrawingSpec(colo
r=(0, 0, 255), thickness=-
1,circle_radius=1),connection_drawing_spec=drawing.DrawingSpec(thickness=1))
        drawing.draw_landmarks(frm, res.left_hand_landmarks,
hands.HAND_CONNECTIONS)
        drawing.draw_landmarks(frm, res.right_hand_landmarks,
hands.HAND_CONNECTIONS)
        return av.VideoFrame.from_ndarray(frm, format="bgr24")

def recommend_movies_by_emotion(emotion):
    if emotion.lower() == "surprise":
        return "crime"
    elif emotion.lower() == "happy":
        return "action"
    elif emotion.lower() == "sad":
        return "horror"
    else:
        return "musical"

wav_files = ['../l/bach_846.wav', '../l/bach_847.wav', '../l/bach_850.wav']

st.header("Emotion Based Multimedia Recommender")

# Dropdown for actions
action = st.selectbox("Select an action", ["Recommendation on YouTube", "Recommendation
on IMDb", "Generate Music"])

if action == "Recommendation on YouTube":
    lang = st.text_input("Language")
    singer = st.text_input("Singer")

    if lang and singer and st.session_state["run"] != "false":
        webrtc_streamer(key="key", desired_playing_state=True,
video_processor_factory=EmotionProcessor)

    btn = st.button("Recommend me songs on Youtube")
    if btn:
        if not emotion:
            st.warning("Please let me capture your emotion first")
            st.session_state["run"] = "true"
        else:
            webbrowser.open(f"https://www.youtube.com/results?search_query={lang}+{emotio
n}+song+{singer}")
            np.save("emotion.npy", np.array([""]))
            st.session_state["run"] = "false"

elif action == "Recommendation on IMDb":
    lang = st.text_input("Language")

    if lang and st.session_state["run"] != "false":
        webrtc_streamer(key="key", desired_playing_state=True,
video_processor_factory=EmotionProcessor)

    btn = st.button("Recommend movies on IMDB")
    if btn:
        np.save("emotion.npy", np.array([""]))
        if not emotion:
            st.warning("Please let me capture your emotion first")
            st.session_state["run"] = "true"
        else:
            recommended_genres = recommend_movies_by_emotion(emotion)
            imdb_url =
f"https://www.imdb.com/search/title/?title_type=feature&genres={recommended_genres.low
er()}&languages={lang[:2]}"
            st.write("Opening IMDb page...")
            webbrowser.open(imdb_url)

elif action == "Generate Music":
    if st.button("Play Generative Music"):
        random_wav = random.choice(wav_files)
        st.audio(random_wav, format='audio/wav')
        st.write("Playing piano automatically generated music:", random_wav)
```