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# Emotion Based Music Playlist Recommendation System

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**Abstract:- Our lives anticipate music to play a significant role. However, because platforms for social media, like TikTok and Instagram have such a large influence on global music charts, consumers are only exposed to mainstream music, hence music streaming platform recommendations are not especially individualized. A recommendation algorithm based on emotions allows users to listen to music according to their emotions. Depending on the user's prior listening habits, current systems use audio and content - based filtering to make music suggestions. The suggested research project creates a tailored system that analyses the user's current emotion. Ascore is generated for each response based on the user's input, which adds up to a total score, which is utilized to generate the playlist. For playlist production and suggestion, the suggested recommendation system makes use of the Spotify platform andAPI usingValance Arousal dataset training the datasets into k-means clustering.**

***Keywords:-*** *TikTok, Instagram, Recommendation system, Valance Arousal dataset and K-Means clustering.*

## I. INTRODUCTION

People from different walks of life may communicate via music. This has been an essential part of human life from the dawn of time.People listen to music both on happy and terrible days. Music inspires us and enlightens us. From bird chirping to drum cadence, from harp to electrical guitar riffs, there are many distinct forms of music. Regardless of race, faith, or religion, music unites people. It brings people together and has a big influence on our lives. In adding to becoming a form of art and a language, music affects human mind and body. It gives our thoughts a boost.

Studies say that music has therapeutic properties, and they use different approaches to prove this. According to another study, tailored music-based medications should be used to treat mental health problems associated with aberrant emotional or temperamental brain action. Nowadays, people listen to music in a variety of methods, especially with the rapid development of downloading services and programs like TikTok. More people evaluate music based on its notoriety than on its quality. This stops the public from hearing incredible music by underappreciated artists. Not all musical creations are of the highest calibre. As a result, it's not always required for the user to choose music that he largely identifies with owing to current musical trends. Having music streaming service that is appropriate for our moods is essential, especially considering research showing thatindividualized music has a positive impact on the human mind. One of the most popular techniques for aiding computers in better comprehending people is human-computer interaction (HCL). Thisincreases the effectiveness of the system and guarantees that the user is aware of everything. Spotify is among the leading streamingservices in the world with 350 million active customers. It offers a web API that gives users full access to music data. Each song in the API has properties like Energy (which indicates the song's energy), Valence (which indicates whether the music is pleasant and joyous), dance-ability, acoustic-nests, and so on. Suchcharacteristics aid in our comprehension.

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In this idea music is prescribed to the client by distinguishing the constant catching of client's feelings. This procedure requires parcel of manual work thus, we proposed a framework to organize different music in various classes, for example, cheerful, miserable, or furious and so on. Emotion Based-music-player It's music player with chrome as front-End which can recognize feelings I.e, the substance of client. In light of the recognized client's mind-set tune rundown will be shown/prescribe to the client. This framework is primarily proposed on the grounds that music assume a crucial part as of late that is to lessen stress.so,in request to recognize the feeling we are involving face as a primary wellspring of information in light of the fact that regularly face demeanor characterizes the Emotion so as per the state of mind we play the music that it can change the client's temperament.

Individuals will generally communicate their feelings, mainly by their looks. Music has forever been known to change thestate of mind of a person. Catching and perceiving the inclination being voiced by an individual and showing proper melodies matching one's state of mind can progressively quiet the psyche ofa client and wind up giving a satisfying impact. The venture expects to catch the inclination communicated by an individual through looks. A music player is intended to catch human feelings through the web camera interface accessible on processingframeworks. The product captures the client's image, and then, with the use of picture handling and division methods, separates highlights from the substance of an objective individual and attempts to distinguish the feeling that the individual is attempting to communicate. The undertaking intends to ease up the mind-setof the client by playing tunes that match the prerequisites of the client by catching the picture of the client. Since old times, the best type of appearance investigation known to mankind is look acknowledgment. The most ideal manner by which individuals willoften break down or close the inclination or the inclination or the contemplation's that someone else is attempting to communicate is by appealing. Now and then, temperament modification may likewise assist in defeating circumstances by preferring melancholy and misery.

A great deal of exploration has been completed regarding music's driving effects on the physiological and close-to-home condition of a human. People see various sentiments from various kinds of music and, from ancient times, considered music to have an impact on the development of an individual person and the capacity to treat illnesses. Music listening essentially affects human sentiments, contemplations, and, subsequently, it impacts mental and actual well-being, and the subject of music prosperity support is acquiring fame. A great deal of estimation and exploration has been directed to grasping the effect of music on cerebral movement. Along with objective independent direction, feelings' perspectives have a significant impact on driving decisions. mindful suggestion framework would have the option to more likely comprehend individuals' prerequisites and sentiments and select the proper music pieces as indicated by the close to home setting. Music-related feelings are traditionally considered according to two principal points of view: feelings that can be seen in music (a cognitivist point of view) and feelings that are seen in music (an emotional viewpoint). In their exploration, Vempala and Russo thought about relationships between music and these two elective sorts of feelings. They prepared brain networks for the twoviewpoints with music highlights utilizing inputs. The results of these models were excitement and valence-based feelings, which were seen by music investigations and by mental criticism got from research members.

Table 1: Analysis of Current Works

| Paper Title | Dataset | Sentiment Analysis | Playlist Recommendation | Model Used |
|---|---|---|---|---|
| Amrita-CEN SentiDB 1: Improved Twitter Dataset for Sentimental Analysis and Application of Deep Learning | Twitter Dataset | Sentiment Positive and negative using the tone and expression towards a particular topic | No | LSTM |
| Emotion based Music Recommendation System | Images of facial expressions | Emotions were classified as Happy, Angry, Surprise, and Sad faces | Yes (Without per sonalized sugges tions) | Facial Action Coding System |
| Emotion Detection in Hinglish Hindi+English Code-Mixed Social Media Text | 12,000 Hindi English mixed texts | Emotions Happy, Sad, and Anger | No | CNN-BiLSTM |
| A personalized music recommendation system using convolutional neural networks approach | Million song dataset | No | Yes | CNN |
| Emotion Based Music Playlist Recommendation System using Interactive Chatbot | Twitter Dataset | Sentiment- Positive, Negative or Neutral | Yes (Including personal favourites) | Bidirectional LSTM |

## II. LITERATURE REVIEW

In a particular system V. P. Sharma, et.al.," [1] This researchpresents a neural network-based method for dealing with melody suggestions in which an individual's mood is determined by their appearance. A webcam or camera is used to take a picture of a person's face, and data is extracted from that image. This information is also used to determine a person's emotional condition. Two back-to-back CNN models are used in the proposed framework. The first CNN model was used to distinguishseven different types of moods, and the second CNN model was used to propose music based on those feelings. "S. Gilda et al.," [2] This music player contains three modules: the Emotion Module, the Music Classification Module, and the Recommendation Module. The Emotion Module takes a picture of the client's face asan input and utilizes profound learning calculations to recognize their mindset. The music order module specifically performs fundamentally well; it accomplishes high precision in the "furious" classification, while likewise performing considerably well in the "blissful" and "quiet" classes. By effectively planning the client's feelings to the right tune class with a general precision of 97.69%,it accomplishes hopeful outcomes for the four temperaments examined. "K. S. Naveenkumar et.al.," [3] This paper manages the information that has been taken from Twitter, the tweets fromTwitter, and we have named the gathered information "Amrita- CEN-SentiDB1". In this data set, just the positive and negative tweets are thought about. The gathered data set "Amrita-CEN-SentiDB1" is exposed to different non-straight message portrayal techniques with profound learning engineering, which performs better compared to the direct message portrayal with the AI calculations. "D. Ayata et.al.," [4] This paper proposes an "Inclination-based music suggestion structure that gains thefeelings of a client from the signs obtained by means of wearable physiological sensors. Specifically, the feeling of a client is characterized by a wearable figure gadget which is coordinatedwith a galvanic skin reaction (GSR) and photograph plethysmography (PPG) physiological sensor. This feeling data is fed to any cooperative or content-based suggestion motor as a strengthening mechanism. Information combination methods were applied to join information from GSR and PPG sensors, and FLF has been executed. "Shun-Hao Changa, et.al.," [6] In this paper, they have introduced a customized music suggestion framework in view of the CNN approach and cooperative separating calculation. They utilized the CNN way to deal with analysing music in light ofthe corresponding sound signs of the music. They extricated the client's data (like geological area, time, feelings, feelings, and so on) to give a superior music proposal that coordinated with the client's inclination. In addition, the utilization of other DNN approaches, for example, the GRU and the LSTM for performing music groupings concerning the CNN approach, can be considered to improve the accuracy of the client's music inclination expectation. "Sriram S, et.al.," [8] In this work, "The adequacy of two Deep Convolutional Neural Networks and crossover models is assessed for picture spam grouping-utilizing 3 unique datasets. The effects of using cost-sensitive learning are concentrated byallocating adjusted class loads, and moving learning is additionally concentrated by-utilizing a few pre-prepared CNN models". In ongoing work, the impacts of ill-disposed examples, which are equipped to deceive the model into making a mistaken expectation,can be contemplated. "Sneha, et.al.," [13] In this paper, a shrewd music framework is planned by perceiving the inclination by- utilizing voice discourse signal as an info source. The goal of the discourse feeling acknowledgment (SER) framework is to decide the condition of the feeling of a person's voice. This study perceives five feelings: outrage, uneasiness, weariness, bliss, and bitterness. The examination results show that this SER framework carried out north of five feelings gives fruitful profound grouping execution of 76.31%utilizing the GMM model and a general better exactness of 81.57% with the SVM model. "Kevin Patel, et.al.,"

[15] In the proposed strategy, "They use convolution brain organisation (CNN) for the feeling location task and fake brain organisation (ANN) for the tune order task. Try result says that our proposed model accomplishes 84% precision on the FER-13 dataset, which contains around 14k facial pictures. For the tune order task, we have utilised different melody highlights, which are removed from the Spotify music player". In our tune order task, weachieved an 82% precision. This framework is just like the Spotify music player. "Saurav Joshi, et.al.," [19] In this paper, different profound learning models like Long Short-Term Memory (LSTM), Convolution Neural Organization (CNN), CNN-LSTM, and LSTM-CNN Architectures" were ordered for recognising feelings. For example, cheerful, love, and miserable. The best was coordinated into the application. Thus, "Natural Language Processing and Deep Learning advances made it workable for machines to peruse and decipher feelings through texts by perceiving examples and tracking down connections. "Karthik Subramanian Nathan, et.al.," [20] "Here we are proposing an effective and exact model that would create a playlist in view of the current profound state and conduct of the client. Existing methods for automating the playlist ageing process are computationally slow, less precise, and sometimes require the use of additional equipment such as EEG or sensors".

## III. METHODOLOGY

The Emotion-based music playlist proposal framework is an application that focuses on executing constant mind-set location. A model of another item involves two primary modules: facial demeanor acknowledgment/mindset location and music proposal. The system architecture diagram shows the general layout of the software system, as well as the components' interactions, limitations, and boundaries. When the user first launches the Android app, the main screen appears, with three buttons: take a picture, use emoji, and play music. The camera opens when the user hits the "take snap" button, and the user takes a picture. This image is fed into a facial recognition algorithm. If no face is discovered or numerous faces are recognized, the user is given an appropriate error message.

*A. System Architecture Diagram*

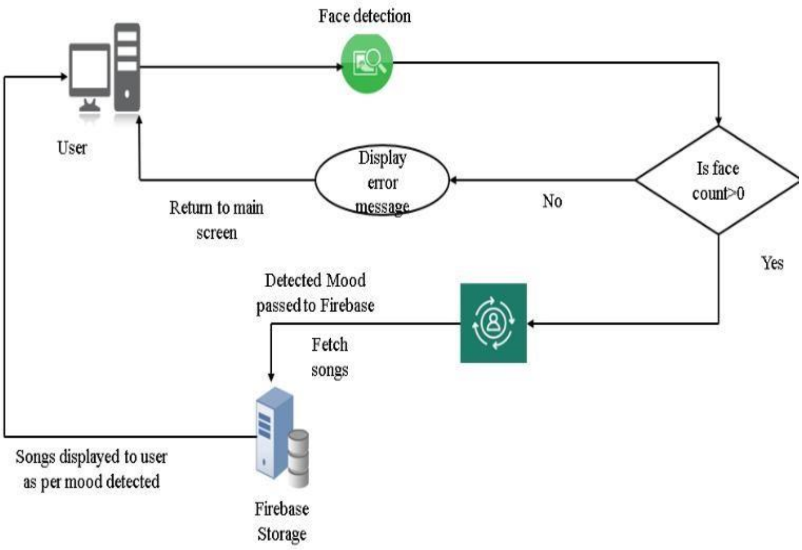


Fig. 1: Framework Architecture

The photo is sent as input to the mood detection module after successful single face detection. The user is then shown the identified mood, after which the "play tunes" button is enabled. On the playlist screen, as illustrated in Fig.9, the appropriate playlist for the identified mood is provided, and the user can select and play the song. When the user clicks the "use emoji" button, a screen with five emojis appears, as illustrated in Fig.10. The user can access the appropriate playlist by clicking on any emoji.

On Firebase, a project was made, and mp3 music was added to the storage section. In the real-time database area, these songs are organised by mood and language. The Firebase database was then connected to Android Studio.The tflite model methods were linked with the songs on Firebase and an appropriate UI for the Android application was constructed. Finally, the app was put through its paces to see whether it had any faults.

### *B. FACIAL EXPRESSION RECOGNIZER USING FER-USING DEEP NEURAL NET*

We use a variety of facial expressions in our daily lives, whether we realize it or not. Humans' emotional states are conveyed through these movements. The next person's mood and mental state can be judged by their facial expression. Ekman and Friesen defined "six" fundamental emotions in the early twentieth century.

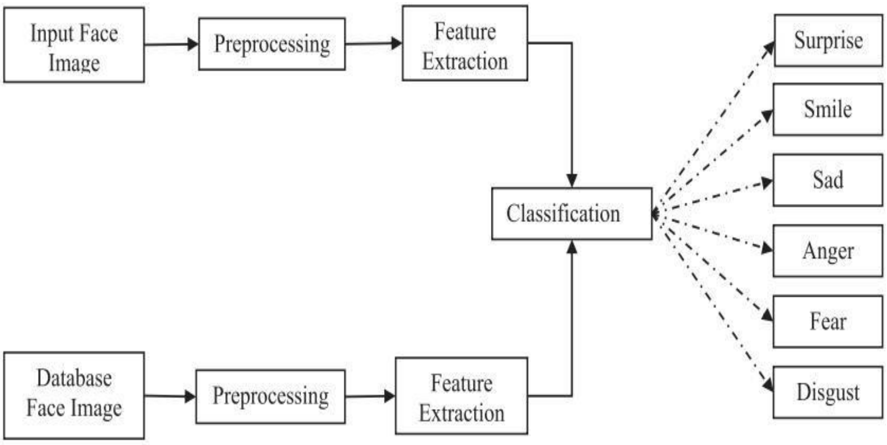


Fig. 2: Architecture of face expression recognition system

These expressions are universal and do not change with culture. These are the six facial expressions: Happiness, Sadness, Fear, Anger, Surprise, Disgust.

Justin Shenk created the Facial Expression Recognition Library. This library requires the installation of the OpenCV >=3.2 and Tensorflow >=1.7.0 dependencies on the system. The Haar Cascade classifier in OpenCV is used to detect faces.

- *K-MEANS ALGORITHM:*

The k-means clustering technique calculates centroids and iterates until the best centroid is found Presumably, the number of clusters is known.. It's also known as the "flat clustering algorithm". "In K-means, 'K' is the number of clusters identified from the data by the algorithm. The data points are assigned to a cluster in this technique in such a way that the sum of the squared distancebetween the data points and the centroid is as small as possible. It's important to remember that less variation among clusters means more comparable data points inside the same cluster".

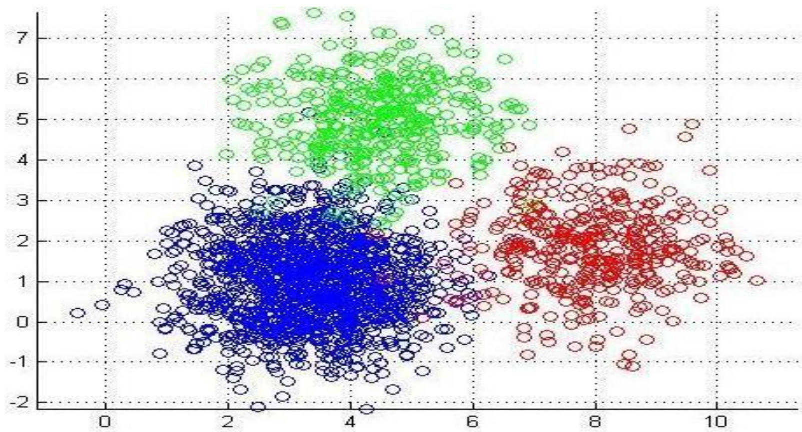


Fig. 3: K Means Clustering

➢ *Working of K-Means Algorithm*

The following stages will help us understand how the K-Means clustering technique works.

- Step 1: "We must first provide the number of clusters (K) that this method must generate".
- Step 2: "At random, select K data points and assign each to a cluster.To put it another way, categorise the data accordingto the number of data points".
- Step 3: "The cluster centroids will now be computed".
- Step 4: Continually iterate the steps below until we find the optimal centroid, which is the assignment of data points to clusters that do not change:
  - ✓ The sum of squared distances between data points and centroids would be calculated first.
  - ✓ Now we must allocate each data point to the cluster that is the most closely related to the others (centroid).
  - ✓ Next, calculate the cluster centroids by averaging each cluster's data point.

"To deal with the problem, K-Means uses the Expectation- Maximization method. The information focuses are assigned to the nearest bunch using the expectation-step, and the centroid of each group is registered using the maximisation-step".

➢ *K-MEDOIDS:*

The k-medoids problem, like the k-means problem, is a clustering problem. With their PAM algorithm, "Leonard Kaufman and Peter J. Rousseeuw" came up with the name. Both the k-means and k- medoids methods are partitional (that is, they divide the dataset into groups) and aim to reduce the distance between points classified as belonging to a cluster and a point designated as the cluster's centre. "Unlike

$$d(p,q)=\sum_{i=1}^{n}|p_i-q_i|=\|.\|^1$$

the k-means algorithm, k-medoids select actual data points as cluster centres (medoids or exemplars), allowing for more interpretability of cluster centres than k-means, which does not require the centre of a cluster to be one of the input data points (it is the average between the points in the cluster)".

"k-medoids is a traditional clustering partitioning approach that divides a data set of n items into k clusters", with the number k of clusters believed to be known a priori (which means the developer must define k before running a k-medoids process). Methods like the silhouette approach can be used to evaluate the "goodness" of agiven value of k. The medoid of a bunch is characterised as the item in the group whose typical difference to every one of the articles in the

$$argmin_C=\sum_{i=1}^{n}\sum_{i\in C_i}|x-median(C_i)|$$

group is negligible. That is to say, it is the most midway point in the bunch.

➢ *Algorithms*

In general, the *k*-medoids problem is NP-hard to solve exactly. Assuch, many heuristic solutions exist.

- Partitioning Around Medoids (PAM)

"Although PAM uses a greedy search strategy, it is speedier thanbroad search and may not get the best results.".

It works like this:

- (BUILD) Initialize: To reduce costs, choose k of the n data points as centroids greedily.
- Assign each single value to the medoid that is closest to it.
- (SWAP) while the configuration's cost decreases.
- For each medoid data point m and each non-medoid data set o.
- Consider swapping m and o and calculating the cost difference.
- Remember this m and o combination if the amount increase is the current best.
- If the cost function is reduced, execute the best swap of mbest and obest. Otherwise, the algorithm will stop working.

The runtime intricacy of the first PAM calculation per emphasis of (3) is O (k (n-k)2), by just processing the adjustment of cost. "A guileless execution recomputing the whole expense capability each time will be in O (n2k2). This runtime can also be reduced to O(n2)by dividing the expense change into three sections so that calculations can be shared or avoided (FastPAM). The runtime can additionally be decreased by enthusiastically performing trades (FasterPAM)", so, all in all, an irregular instatement turns into a practical choice to Construct.

➢ *K-MEDIANS:*

k-medians attempt to ease the awareness of k-means to exceptions by picking a different divergence metric. Rather than the Euclideandistance, we commonly use the outright contrast, also known as the L1 standard, the Manhattan distance, or the Taxicab distance (because it can be used to calculate the number of turns a taxi must take to reach its destination in a rectangular network of blocks).

This is considerably less delicate than exceptions on the grounds that these are just contributing with their genuine distance to the middle, rather than the square of the distance, as What is thesituation for euclidean distance?

The manhatten metric between two focuses, p and q, is For each aspect, ascertain the outright distinction between the focuses and their totals. This is additionally called the L1 standard. image bythe creator.

Nonetheless, various estimations, for instance, the Kullback- Leibler difference, could be utilised here assuming they are more suitable, for instance, to think about dispersals.To make it much stronger, we pick the centre as opposed to the mean for the core interests. So finally, we need to keep the following with this issue:

Numerical definition of the enhancement issue of k-medians Attempt to find a bunch of groups C that limit the outright distinction of each highlight to its having a place in group focus Ci.image by the creator The methodology of k-medians is basically the same as k-implies; it is again Llodyd's calculation. To summarize it briefly:

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*C. SPOTIFY API*

The Web API additionally gives access to client-related information, similar to playlists and music that the client saves in the Your Music library. Such access is empowered through particular approval by the client. The API provides a number of endpoints, each with its own distinct style. To get access to private information through the Web API, for example, client profiles and playlists, an application should get the client's authorization to access the information. Approval is through the Spotify Accounts administration.

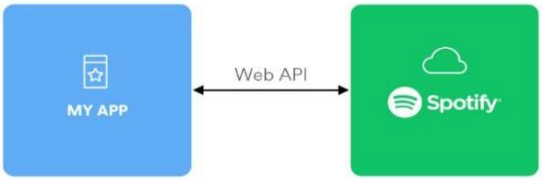


Fig. 4: Web API

This blog is in three parts:

- First, we enrol as a Spotify Developer and use our client certifications to obtain an entry token; second, we conduct some extremely basic research into things like collection posting or track properties; and third, we combine this into some seriously fascinating research.
- Getting client qualifications: Whether you'reutilizing Spotipyor moving your own, first you really want to get client qualifications for the Spotify API. If you already have a Spotify account (free or paid), make a beeline for Spotify for Developers and open your Dashboard. Click on "Make a Client ID" and deal with the checkboxes.
- Getting an entrance token: Presently, we should open up our Python climate of decision. At this moment, we simply have to send some GET and POST demands, so we should utilise the solicitations library, and save those client accreditations from our Spotify venture's page.

```
import requests

CLIENT_ID = 'yourclientid'
CLIENT_SECRET = 'yourclientsecret'
```

Fig. 5: Getting Client Credential

- *Authenticating with Spotipy*

There are two sorts of confirmation that we can perform with the Spotipy library. We, right off the bat, can confirm without a particular client as a main priority. This permits us to get to the general highlights of Spotify and see playlists. Without this, we can't see details intended for a client, like their following records and details of music paid attention to.

To verify without marking into a record, all we really want are the IDs, client and mystery. Then, at that point, we can make our "Spotify" object with the accompanying lines of code:

To validate with a record, we really want to provoke a client to sign in. This is finishedutilizing the "prompt_for_user_token" strategy in the "spotipy.utils" part of the bundle. As we don't involve this for this task, this will not be investigated. However, more can be learned about this in the documentation for the Spotipy bundle.

- *Extracting Tracks From a Playlist*

The principal strategy that we will use in removing highlights from tracks in a playlist is the "playlist_tracks" technique. This technique takes the URI from a playlist and returns JSON information containing all of the data about this playlist. Fortunately, the Spotipy bundle translates this for us, so we can parse through this information decently and Pythonically.

```
playlist_link =
"https://open.spotify.com/playlist/37i9dQZEVXbNG2KDcFcKOF?
si=1333723a6eff4b7f"
playlist_URI = playlist_link.split("/")[-1].split("?")[0]
track_uris = [x["track"]["uri"] for x in
sp.playlist_tracks(playlist_URI)["items"]]
```

Fig. 6: Extract the Track Data

While we're here, we can likewise separate the names of each track,the names of the collection that it has a place in, and the notoriety of the track (which we hope to be high for this situation — we're taking a gander at the most famous tunes internationally). We can glean a classification (though this is not absolute — specialists can create a wide range of music) and a craftsman prevalence scorefrom the craftsman.

```
for track in sp.playlist_tracks(playlist_URI)["items"]:
    #URI
    track_uri = track["track"]["uri"]

    #Track name
    track_name = track["track"]["name"]

    #Main Artist
    artist_uri = track["track"]["artists"][0]["uri"]
    artist_info = sp.artist(artist_uri)

    #Name, popularity, genre
    artist_name = track["track"]["artists"][0]["name"]
    artist_pop = artist_info["popularity"]
    artist_genres = artist_info["genres"]

    #Album
    album = track["track"]["album"]["name"]

    #Popularity of the track
    track_pop = track["track"]["popularity"]
```

Fig. 7: Extracting Tracks from a Playlist

➢ *Extracting Features from Tracks*

Since we have a rundown of track URIs, we can extricate highlights from these tracks to play out our investigation. From an examination of the sound, Spotify has a rundown of these elementsfor every one of its tracks. We can get to these with a solitary strategy for the spotify object 'audio_features (uri)'. This provides us with a rundown of generally mathematical elements that we can use for our examination.

Using: sp.audio_features(track_uri)[0]

There are a lot of different things that you can do with this item, including building and altering playlists, controlling your own Spotify playback, and getting to a wide range of items in Spotify.

```
{'danceability': 0.78,
 'energy': 0.719,
 'key': 3,
 'loudness': -3.613,
 'mode': 0,
 'speechiness': 0.0506,
 'acousticness': 0.302,
 'instrumentalness': 0.000196,
 'liveness': 0.0931,
 'valence': 0.336,
 'tempo': 127.962,
 'type': 'audio_features',
 'id': '5RwV8BvLfX5injfqYodke9',
 'uri': 'spotify:track:5RwV8BvLfX5injfqYodke9',
 'track_href': 'https://api.spotify.com/v1/tracks/5RwV8BvLfX5injfqYodke9',
 'analysis_url': 'https://api.spotify.com/v1/audio-analysis/5RwV8BvLfX5injfqYodke9',
 'duration_ms': 199604,
 'time_signature': 4}
```

Fig. 8: Extracted Features of the Data

## IV. RESULTS AND DISCUSSION

**In the first stage**, we authenticate or sign in using our Spotify developer user account; in the Spotify for Developers dashboard, we must create an APP to obtain the Client ID and Client Secret. By using Client ID and Client Secret, they start extracting tracks from the playlist and then finally extracting features from tracks such as **Id, Genre, Track_name, Artist_name, Valence** And **Energy** of songs, as shown in the figures below:

After Interfacing with the Developers for Spotify we get the data performed by the client Id and secret will find the several artist_names and finally all the required data is processed by the Spotify as shown figure below:

```
####################
## PROCESS DATA ##
####################

# Store data in dataframe
df = pd.DataFrame(data_dict)

# Drop duplicates
df.drop_duplicates(subset = "id", keep = "first", inplace
df.to_csv("valence_arousal_dataset.csv", index = False)

100%|██████████| 126/126 [44:57<00:00, 21.41s/it]

[ ] #@title
    data_dict

{'artist_name': ['Norah Jones',
  'Lulu & The Lampshades',
  'Various Artists',
  'Alice In Chains',
  'Eric Clapton',
  'The White Stripes',
```

Fig. 9: Process the data by client ID and Client Secret

| | id | genre | track_name | artist_name | valence | energy |
|---|---|---|---|---|---|---|
| 0 | 78xbGcjmm02TCbhsMJsuUn | acoustic | In the Morning | Keaton Henson | 0.2270 | 0.1700 |
| 1 | 6FjAGZp7c0Z2uaL3eHkXsx | acoustic | Turn Me On | Norah Jones | 0.5210 | 0.1720 |
| 2 | 451GvHwY99NKV4zdKPRWmv | acoustic | Banana Pancakes | Jack Johnson | 0.6150 | 0.3750 |
| 3 | 3LHg768dEKqJKht2uPTIVR | acoustic | Ghosts | Laura Marling | 0.7500 | 0.3680 |
| 4 | 11gqufRVufobe8jGNHmibY | acoustic | Gone Tomorrow | The Staves | 0.0933 | 0.2390 |
| ... | ... | ... | ... | ... | ... | ... |
| 11171 | 6B3Fr3kIWOOde0dFZPNDFp | world-music | Ghanan Ghanan | A.R. Rahman | 0.4100 | 0.5620 |
| 11172 | 2SvfiubxYXtDEhuXpWFqJ4 | world-music | M'bifé blues | Amadou & Mariam | 0.4050 | 0.4600 |
| 11173 | 70onHXBOZu4oL76aLDnbfF | world-music | Ayal-Ayale (The Handsome Hero) | Idan Raichel | 0.9620 | 0.7930 |
| 11174 | 4CappvVIBDtzTJzVeBcAOV | world-music | Chopin - Nocturne | Pet Music World | 0.3960 | 0.0501 |
| 11175 | 3paHCRsgqYToiZ89UTdnqh | world-music | Gina | Lu Colombo | 0.7190 | 0.3750 |

11176 rows × 6 columns

Fig. 10: Valence_arousal_data set

**In the Second stage**, We load the Valence_arousal_data set and perceive how the valence and energy upsides of two factors are plotted along two tomahawks by dissipation plot and K-Means bunching. It works out the amount of the square of the places and ascertains the typical distance. At the point when the worth of k - 6,as displayed beneath the figure, in k-means we marked every state of mind as k-means temperaments as:

**['0 - Depressed', '1 - Energetic', '2 - Misery', '3 - Excitement', '4 - Distressed', '5 - Contentment']**

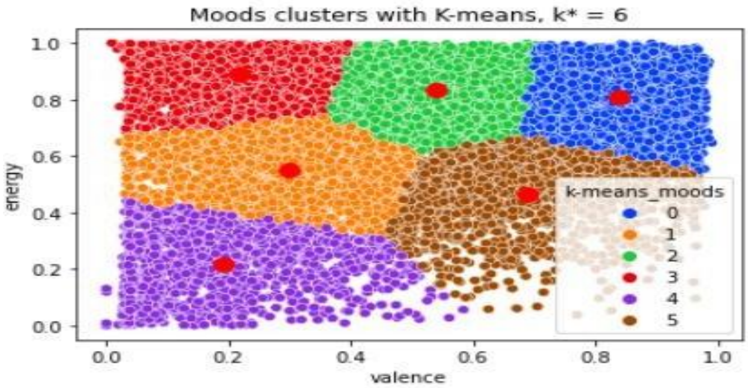


Fig. 11: Assigning moods as k-means moods

By K-Medians we create instance of k=6 and initial medians are feed to it where rather than working out the mean for each group to decide its centroid, one rather computes the middle, "**[0.19066008, 0.21390282], [0.29176613, 0.55255357], [0.67930098, 0.46349509], [0.21726171, 0.89302689], [0.83923924, 0.80557057], [0.53893319, 0.83543712]"** and finally Mood clusters with K-Medians, k* = 6 are created as show in above figure.

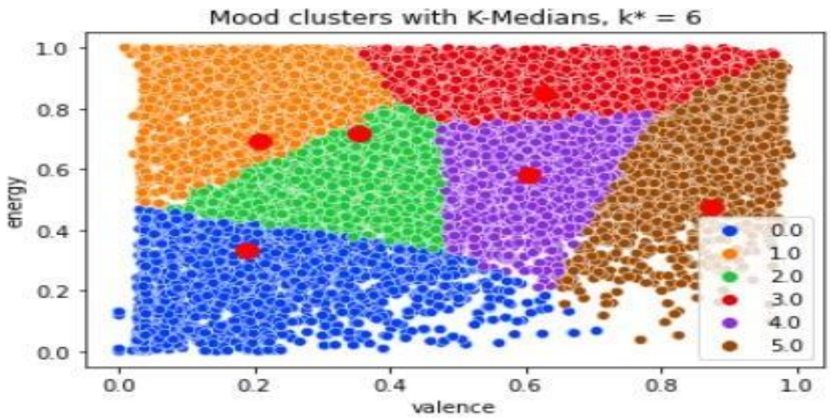


Fig. 12: Computation of single centroid for each cluster

"As opposed to the k-means calculation, k-medoids picks real data of interest as focuses (medoids or models)", and in this way, considers more prominent interpret ability of the bunch than in k- means.

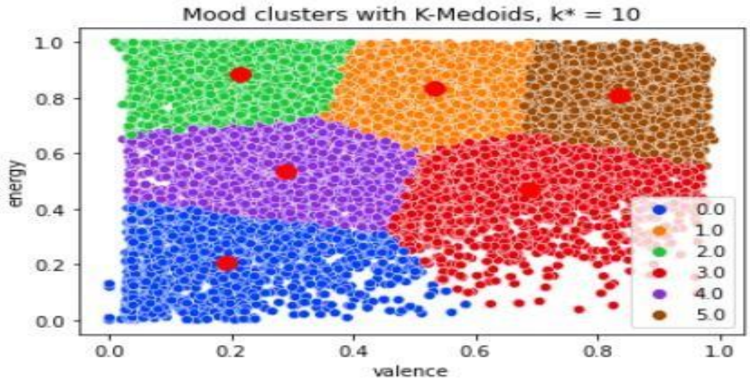


Fig. 13: Mood clustering by K-Medoids

```
mood_centroids
```

```
{'contentment': [0.67930098, 0.46349509],
 'depressed': [0.19066008, 0.21390282],
 'distressed': [0.21726171, 0.89302689],
 'energetic': [0.53893319, 0.83543712],
 'excitement': [0.83923924, 0.80557057],
 'misery': [0.29176613, 0.55255357]}
```

Fig. 14: moods assigned for each centroids

Where the point of a group isn't really one of the pieces of information data of interest (it is the typical between the focuses in the group). we initialize the membership of each point and label cluster membership for each point. And finally mood centroids has been assigned as shown above figure. After assigningcentroid for each cluster, Type of K-Means Moods and Types of mood labels are shown below:

'k-means_moods' == 0, 'moods_label' = 'Distressed' 'k-means_moods' == 1, 'moods_label' = 'Excitement' 'k-means_moods' == 2, 'moods_label' = 'Misery'

'k-means_moods' == 3, 'moods_label' = 'Energetic' 'k-means_moods' == 4, 'moods_label' = 'Depressed'

'k-means_moods' == 5, 'moods_label' = 'Contentment'

| | id | genre | track_name | artist_name | valence | energy | k-means_moods | moods_label |
|---|---|---|---|---|---|---|---|---|
| 0 | 2CjMm3TDd9BS8xAcvbe6yY | acoustic | Let Her Go (feat. Hannah Trigwell) | Boyce Avenue | 0.307 | 0.3330 | 4 | Depressed |
| 1 | 6bp1twiUg81a04GVGXHlsc | acoustic | Beach Baby | Bon Iver | 0.111 | 0.0774 | 4 | Depressed |
| 2 | 2r07lezrHUPEuhhBYW9JnC | acoustic | World Spins Madly On | The Shirelles | 0.337 | 0.3610 | 1 | Excitement |
| 3 | 51jy98I9q9Nk1xyA0W4ZBg | acoustic | If You've Gotta Go, Go Now - Bonus Track | Various Artists | 0.325 | 0.2170 | 4 | Depressed |
| 4 | 574GJ55EBM79W6n2V5bL5z | acoustic | Slow It Down | The Lumineers | 0.108 | 0.0640 | 4 | Depressed |
| ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 11139 | 4AdEld7iTSaADarHjqIXvT | world-music | Oualahila Ar Tesninam | Various Artists | 0.752 | 0.6980 | 0 | Distressed |
| 11140 | 79ILkqFf3SWvmWVMmznKF9 | world-music | Ausencia | Cesária Evora | 0.427 | 0.1320 | 4 | Depressed |
| 11141 | 4M6FuBh0zCSLFgoJ2SAWuw | world-music | Jama ko | Bassekou Kouyate | 0.904 | 0.6650 | 0 | Distressed |
| 11142 | 0V0CNmEzYPJRKeabBej6fu | world-music | Free (Sina Mali, Sina Deni) | Various Artists | 0.731 | 0.6540 | 0 | Distressed |
| 11143 | 1npXx6gwd9ZLUPHmjUo5cR | world-music | Pilentze Pee | Bulgarian State Television Female Choir | 0.104 | 0.3030 | 4 | Depressed |

11144 rows × 8 columns

Fig. 15: K-means moods and mood label are assigned for every single track.

**In the Final stage,** The sample video feed to it, loading and processing takes place, In the processing FER (Facial Emotion Recognition) Detects the face, then finds the same and opposite feeling of the face, and top emotion face, after the emotion found for the k-means moods, the top 10 songs are recommended as shown below figure:

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```
[ ]  button_click('opposite')

6603                  Mil Horas
10297      Lo Que Me Gusta A Mi
6531             Corazón partío
4177                   Rasputin
2193               Décalé Gwada
9520                    Rumbera
8307            Brave New World
5846                  party up!!
4993                    24 Deep
3717                 Muscle Man
Name: track_name, dtype: object
```

Fig. 16: Top 10 Songs recommended for the given sample

## V. CONCLUSION AND FUTURE WORK

Focusing on different variables, like specific settings, individual boundaries, sentiments, and feelings, is exceptionally vital to a dynamic course of suggestions. While recommending music, contemporary music proposal frameworks face a gap in personalization, human sentiments, logical inclinations, and close- to-home elements. In this paper, we proposed a feeling-driven suggestion framework as a means for customised inclinations and specific life and action settings. The methodology introduced in this study is focused on giving the greatest advantages to individuals from the music listening experience. It is vital to make the framework mindful of the way things are doing the suggestions,to further develop the music choice consistently. By taking care of the information from different sources, the framework is plannedto pay attention to every specific client and comprehend their motivations for tuning in, sentiments, and relevant inclinations to choose the most ideal music pieces for them. We saw what sort of information is required for the suggestion framework and how it tends to be gotten. Fundamental information-handling apparatuses are explained in the extent of this paper, and the exploratory model has been expounded.

In any case, to accomplish the most extreme precision in expectations and make them pretty significant, AI frameworks require a lot of information to prepare the models. As of now, the information assortment is in a dynamic cycle. Simultaneously, this sort of framework requires critical clinical examination and coordinated effort with clinicians to tune and test the model for genuine suggestions and decrease conceivable related chances. Further work on the execution and testing of the proposal motor, exact analyses, and effect assessments are considered for the following stage, when the fitting measure of the information willbe gathered. Music creation by falsely wise frameworks with specific music credits to move conditions of human feelings can beconsidered further elaboration work in this unique situation.

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