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A CONTEMPLATION ON MUSIC RECOMMENDATION SYSTEMS BASED ON EMOTION DETECTION

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***Abstract*—Rise of music streaming platforms have attracted large number of users. This increase in the userbase has given birth to competitive market and competition to pull more number of users by providing quality service. Quality of service on these streaming platforms can be achieved by sensing the user needs and customizing the dashboards or playlist as per their need. This responsibility of customized recommendation lies on the recommendor system, an integral part of streaming platforms. In the absence of an effective recommender system, users have to waste lot of time in finding what they want, sometimes this is very frustrating and may lead to loss in revenue. It is found that "Emotion" play an important role in user music preferences, yet there is very little work done in this sector. In this paper, we have discussed taxonomy of a recommender system,critically analyzed the prominent existing models and have proposed a new hybrid model. The proposed model is an amalgamation of emotion detected from face, lyrical recommendation system and users history.**

***Index Terms*—Recommendation Systems, Types of Recommendation System, Emotion-based recommendation System, Face based emotion detection.**

I. Introduction

Music is an integral part of human life, it can uplift someone's mood, provide happiness and even sets the tone for any enjoyable festivities. It is one of the biggest forms of human entertainment. Music Therapy is another key application in improving human health. It has been found that music therapy improve patients' recovering from autism, and depression [1]. With rapid digitalization and the upsurge of the internet, there is an exponential growth in the availability of music on streaming platforms. This has created a new problem of recommending the right music to suit the needs of particular users at particular times. The aim of music recommendation systems is to help users to discover the music that they want and it does this by using specifically designed algorithms for the task [2]. Platforms such as Spotify, Gaana and Apple music have an inherent need to use music recommendation systems because they consist of millions of tracks, and searching for the right music would be like finding a needle in the haystack. This makes music recommendation systems an extremely important part to carry out their day-to-day operations as they help in. They help in recommending songs appropriately and efficiently.

As we know that music recommendation systems help us in recommending better music for everyone, but they also come with their own challenges. Some of the prominent challenges are covered by [3]. Every human is uncertain, and they might love a type of melody one day but may love an entirely different music next day . Swing in mood, interest and emotions make it very challenging to recommend a the most suitable music. All recommender systems, at their core, depend upon the user's interactions by recording their activity when they interact with a service or system. The most widely used categories of music recommendation systems are: content-based, collaborative-based, context-based, metadata-based, and emotion based[3]. Most of the music recommendation systems that we use in modern times are generally the hybrids of these techniques or their sub-category. Organizations choose the level of influence of each technique on their whole recommender system and recommend music to users accordingly.

The flow of this paper is as follows: Section-II, discusses the recommendation system in general and its taxonomy. It also discusses emotion based recommendation system and its sub categories. Section-III, discusses types of recognizable emotions, popular machine learning based classification techniques in user and some of the public data sets for the same. Section-IV, describes the proposed hybrid model and section-V concludes the work.

II. Recommender Systems

Commercially, music recommendation systems are inseparable part of music streaming platforms like Spotify, Saavn, Wynk, Apple Music, and Pandora. All these platforms use various recommendation systems but more or less they use a hybrid of all the techniques combined. This process is hard as they cover defects with the benefit of other techniques and increase the accuracy of their system by incorporating different techniques. Every single technique's particular influence over the whole is decided as per organization's policy and choice.

The broad categories of recommendation systems are shown in fig.(1) and discussed briefly in the following section.

A. Content-Based Recommendation

In content-based recommendation system [4], the music is suggested based on the juxtaposition between the contents of the song and a users' profile information. There are a number of issues that must be addressed when executing a content-based recommendation. Primarily, the items should be represented in such a way that the

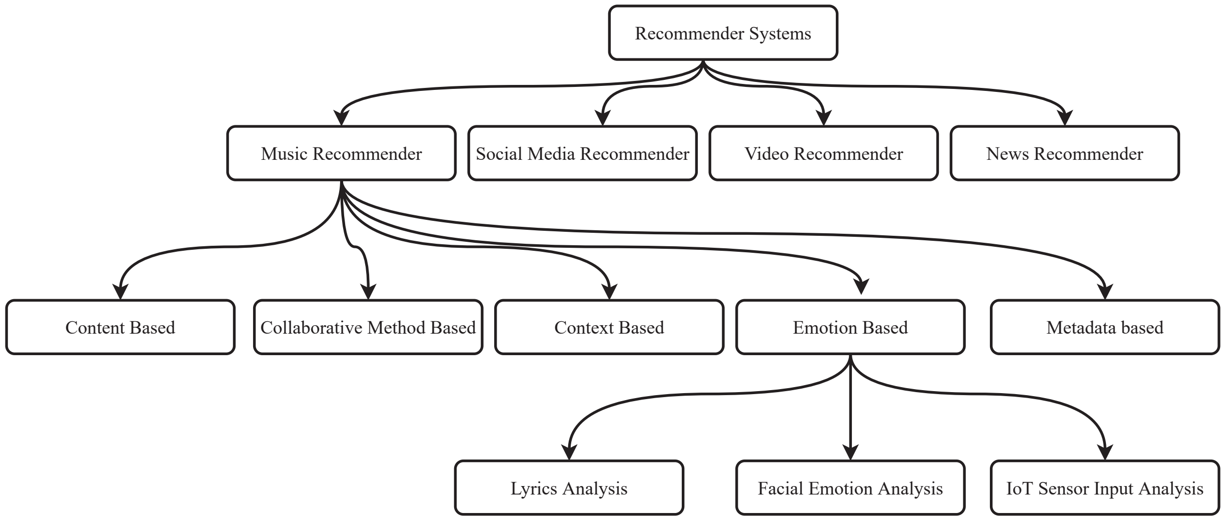

Fig. 1: Taxonomy of Recommender Systtem

user profile and elements could be significantly compared. And then, to make recommendations, a learning algorithm should be selected which would be able to learn from users' profile on the basis of given data points and could make proper recommendations accordingly. The contents of each song are presented as a collection of descriptors or items, that crop up in a profile. The acoustic characteristics of the song such as volume, tempo, rhythm, and stamp are evaluated to recommend songs. A huge shortcoming of the content-based model is that it relies on the truthfulness of the song model. The Glass-ceiling effect is also a big problem, and also that this technique is unable to differentiate among similar music.

B. Collaborative Method Based Recommendation System

In this method [5] new recommendations for users are obtained by collecting their social-collective choices and tags from other users and this is all done by gathering social ratings by other users for a particular song. A method of creating self-contained predictions regarding a user's choices by obtaining proclivity about information from a variety of uses. This recommendation technique uses user ratings for its recommendation. Collaborative systems are made upon the presupposition that users like what their peers like and the wisdom of the crowd always plays a huge role in determining the rating of the music.

The K-Nearest Neighbor algorithm is a major recommendations algorithm used in this system. Ratings could be sorted between two categories explicit or implicit. The illustration of explicit ratings is a five-star rating process which is used by e-commerce sites and the number of likes used by music streaming services like Spotify, Saavn, Wynk apple-music, etc. All of these ratings are separately provided by users when they like or give ratings to a song. Implicit ratings are gathered by extracting and evaluating user behavior. Retention rates and CTR[1] could be utilized for implicit rating values. When a song gets played many times by many users, it automatically gets a better implicit rating value. The immense disadvantage of this system is that it makes ineffective recommendations at the beginning of service. In particular, for upcoming new music with very few ratings, recommendations made in such a manner are not very effective. This is also called the cold-start problem [6]. When an initial user interacts with the software, the system is unable to give coherent recommendations because users are yet to rate anything down, so the system has no idea what to suggest. Human endeavor is another opposition to that system. The more work it takes to create a recommendation, the less likely it is that users will be assess the system for long.

[1]Click-through rate

C. Context-Based Recommendation System

In the context-based models [7], a public hype is used to evaluate a song's rating and it is then recommended accordingly. Here we use social media apps and sites like Facebook, Instagram, Tumblr, Twitter, and Reddit and videos sites like YouTube, Netflix, Prime Video etc., to collect data regarding the public hype of a song and suggest the song to users accordingly. It uses the collective user history of users in an area and recommends the music accordingly. It is constructed upon the retention of the songs on the social media websites. Organizations like Apple Music, Saavn, Wynk, and Spotify utilize leaderboards or similar ways, where the songs which are being listened to by most user-base are considered as well as the tracks that see the most social media hype are added to that list. The context-based model can produce a "Your Mix" section for the users, constructed on users' engagement history and social media hype of various musical tracks. Another way to use a context-based model is to use location and recommend songs on that basis.

D. Metadata-Based Recommendation System

When we use the data tags such as artist name, genre, and album name to recommend music it is called metadata-based recommendation system [8]. Here, the system utilizes metadata to suggest music to the users. It is one of the most initial forms of recommender

TABLE I: Emotion based recommendation systems

Technique	Advantages	Disadvantages
Lyrics Based	(i) Multiple NLP, transformer, multi-modal, etc, techniques can be used. (ii) No data sparsity as there are huge amounts of data that already exist.	(i) Lyrical copyrights and accessing the data cost-free. (ii) Keywords are essential to define item features.
Face Emotion Based	(i) It could be made highly profitable on social media apps on video calling in dating apps. (ii) A lot of face emotion recognition techniques are there, so it would be easy to implement the most accurate one.	(i) As it is very new it would be really hard to get users to start using this method for song recommendation (change resistance of users) (ii) It suffers from cold-start problem.
Using IoT Sensors	(i) A novel approach and something that is growing by the day. (ii) Using medical signals would make it extremely powerful and yet being so economic because of the mass availability of the sensors	(i) A huge data sparsity problem because of the extreme novelty of the framework. (ii) Privacy concerns of users.

system that is still quite prominent. Although the recommendations are comparatively less effective, because they can only suggest songs based on metadata, none other user info is considered here.

E. Emotion-Based Recommendation System

Humans and music are deeply connected to one another [9], music is one of the most fundamental things in this world that can change or amplify particular emotion in humans. So, it is necessary to use a recommendation system that recommends music on the basis of emotional tags, subtlety is the key here. Commercial and academic sectors both have huge ongoing research on human emotion and what affects them, but this research in music, is still fairly new [10]. Various acoustic factors of the musical tracks are utilized to discover the emotions that a track could generate. When it comes to music it has been shown time and time again that the mood of the user highly affects the users' song preference and accordingly the retention of the app(or service). Music-streaming apps construct playlists that are calibrated on human emotions accordingly to better suit an emotion a user is feeling. The biggest upside of the emotion-based recommender technique is also the biggest downside as this method demands huge collections of data and more efforts accordingly.

Listed below are major sub-categories of emotion-based music recommendation techniques.

1) Lyrics Based Approach: Lyrics heavily affect the emotions of music [11]. It is based on lyrical keyword extraction that is associated with a particular emotion. Keywords' emotions are captured using the valence-arousal method. This approach uses multiple NLP, transformer, and multimodal based techniques. These days huge amount of data is available for applying this approach. Lyrical copyright and access to cost free data is a challenge in addition to accuracy of keywords.

2) Face Emotion Recognition Based Approach: Using facial emotions to predict music is a relatively new technique which is very promising [12]. As we know currently there are a lot of face emotion recognition systems, if we could combine face recognition in a music recommender it can create a hybrid that would be very novel and could help in starting research in this field. This approach would find out facial emotion, then the recognized emotion will go into the music recommender and the music recommender will recommend the music accordingly.It could be made highly profitable on social media apps and video calling in dating apps.A lot of face emotion recognition techniques have already been proposed by different researchers, so it would be easy to implement the most accurate one.

3) Using IoT Sensors: It is one of the modern techniques where emotion of the user is detected using wearable device [13]. This device may be integrated with a Galvanic skin response (GSR) and Photo plethysmography physiological sensors(PPG), the output of this device is forwarded to a supplementary recommendor system such as collaborative or context based recommendor system.

III. Emotion Recognition

Emotion recognition is one of the hottest topics and has found its application in many areas such as health care [14], safe driving [15], social security etc. Ekman [16] considers 6 basic emotions: Anger, Happy, Sad, Fear, Surprise and Disgust, and believes that other emotions are output of reactions and combination of these basic emotions. Plutchik's [17] wheel model addresses 8 basic emotions: Joy, Surprise, Trust, Anger, Fear, Sadness, Disgust and Anticipation. Here, author has also addressed strength of emotions and mixing of emotions. Ezard in [18] has considered 10 basic emotions: Interest, Joy, Surprise, Sadness, Fear, Shyness, Guilt, Angry, Disgust, and Contempt, which he considers have naturally evolved during the process of evolution. Gyanendra K. Verma *et al.* [19] have proposed a system where there are 13 recognizable emotions namely: Terrible, Love, Hate, Sentimental, Lovely, Happy,Fun, Shock, Cheerful, Depressing, Exciting, Melancholy, and Mellow. In the following section we discuss popular algorithms in use for classification of emotions, some popular available public data sets and methods for recording emotions.

A. Popular Classification Algorithms

One of the steps in emotion detection process is to assign the signals to a particular class of emotions i.e. classification. There are many classification techniques proposed by the researchers out of which the most commonly used techniques for emotion detection are: Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), K-nearest neighbor (KNN), Random Forest (RF), Support Vector Machine (SVM), Particle Swarm Optimization (PSO), Probabilistic Neural Network (PNN), Long-Short Term Memory (LSTM) and Deep Learning (DL). A survey of some of the prominent work and the classifier used is tabublated in table (II).

B. Public data sets

Some of the publicly available databases for human emotion analysis are: DEAP [31],MANHOBA [32], SEED [33], BioVid Emo DB [34],AffectNet [35], Ascertain [36], and Extended Chohn-Kanade [37].

C. Recording Emotions

Emotion recognition can be broadly classified in two categories: Based on external signals and internal signals. External signals or physical signals can be used to read facial expressions, speech, gesture, posture,eye ball etc. These are relatively easy to collect compared to internal signals. Internal signals or physiological signals are captured through temperature, EEC, ECG, EMG, GSR, respiration etc.

There are various emotion extraction techniques out there but the most relevant ones for our proposed model are the following. The reason for choose these is that these require minimal or no binding of monitoring device to users body.

1) Eye-tracking: The eyes are important indicators of our thoughts and emotions [38]. A simple arrangement is Pupil dilation. With the help of eye-tracking, we could be highly precise in our recommendations, although this is not feasible for the current time being in Music recommendations, it could be pursued in the future.

2) Skin Conductance (EDA/GSR): The emotional arousal of humans changes according to the change in stimulus [39]. When using sensors, emotions can be recognized via sensorial inputs and we could recommend music accordingly. This method could look computationally expensive but it has already started to happen in many industries like health and fitness, so it can even be received in music.

3) Facial Expressions: One of the most prominent emotion indicators is the human face[18]. the amount of information revealed by the human face in terms of emotions is impeccable. That is why there are a lot of facial emotion recognition systems available out there, but as we know facial emotions used in music recommendation is a very novel approach so it is very promising, and could yield far greater results in the long term.

IV. PROPOSED HYBRID MODEL

Commercial recommendation templates utilize a hybrid recommendation variant system. When a user registers for the first time, the systems asks for certain basic details and choices, there after the system tracks the user through their unique id. Generally the unique ids are email id, mobile number, user id or any combination of these. The initial preference choices may include: language, genre, artist, and time period. Over time, as the user listens to an increasing number of songs, the system uses history for recommending songs via session tracking.

A. Data Gathering

Though there are many publicly available data sets (as discussed in section III-B) for the testing of this model, but our model can also capture the data through a capturing device.

B. Data preprocessing

After gathering the data, preprocessing of the data set is very important. Denoising and preparing data for the operations are done in this stage. In this stage splitting the data set into three parts is done, training, testing, and validation. Model is trained on the training data set, evaluated on validation dataset, and when the model is ready then tested on the test data set. In preprocessing, formatting is also done to suit the needs of the model. In preprocessing of the data, there is another key factor to look and that is to either remove missing data or impute the missing values to introduce uniformity in the data set. In using the image dataset, as an example we have 0.4 million faces in the AffectNet dataset, that's why we need to sample our data because too much data can also increase the chance of overfitting.

The proposed system is shown in fig. (2), It is a hybrid emotion-based recommendation system that uses two of the most popular emotion recognition techniques such as facial emotion recognition and lyrical emotion recommendation system. The proposed model first scans the subject via visual input (generally camera), then after the acquired images are passed to "Image Processing" phase where these images are pre-processed before apply pre-trained CNN Model for detection of emotion. The detected emotion along with the text based input from the "lyrical dataset" and users history is fed to the Amalgamation and Filtering Unit. The lyrics based emotion recommendation system uses keywords or the words with higher frequency of usage in the song. The "Users History" database has the history of the user, how many times the user has listened a particular song. The amalgamation and filtering unit processes these three inputs and gives the filtered output.

For computing similarity between the tracks from the lyrical data set and historical data of the user we use track similarity. Let us assume that each track is represented as a vector $\alpha_i = (c_1, c_2, c_3, ..., c_n)$, where c_k represents the number of times user k has listened to this track.where $k \in U$ and $|U| = N$ is the total number of users. The track similarity is estimated using the following expression [40]

$$TS(\alpha_1, \alpha_2) = \frac{\sum_{k=1}^{n}((\alpha_1, k - \bar{c}_k).(\alpha_2, k - \bar{c}_k)}{\sqrt{\sum_{k=1}^{n}(\alpha_1, k - \bar{c}_k)^2}.\sqrt{\sum_{k=1}^{n}(\alpha_2, k - \bar{c}_k)^2)}} \quad (1)$$

The $\bar{c}_k$ is obtained from users listening history.

There are many applications of our proposed model with suitable modifications,it could be used while playing video games, live streaming, and online dating. The best part of the proposed model is that the users do not require any device to be binded to their body like recommendations systems designed to detect emotions based on psychological signals.

V. CONCLUSION

While surveying the music recommendation systems, it is found that even though a lot of work has been done in music recommenders still there is a huge potential in sentiment analysis research for recommender systems especially when it comes to music and how emotions affect our music choices. We know good music can change a person's emotions but it can also be reversed as emotions can also predict what kind of music is required. If we find that sad emotion is there and we recommend a happy playlist the user's mood can change into positive. If any emotion is detected and accordingly the playlist is provided, then it will increase the user retention and also makes it highly enjoyable for the user.

In this paper, we have survey different types of recommendation systems and emotion capturing systems. We have also listed popular emotion classification algorithms in use. Finally, we have

TABLE II: Summary of prominent emotions and the classifiers used

Author	Emotions	Classifier
Foteini Agrafioti *et al.* [20]	Valence and Arousal	LDA
Peiyang Li *et al.* [21]	Positive, Neutral, and Negative	SVM and GELM
Ping Gong *et al.* [22]	Joy, Anger, Sadness and Pleasure	C4.5 Decision Tree
Yi Ding *et al.* [23]	Arousal and Valence	SVM and KNN
Gyanendra K. Verma *et al.* [19]	Terrible, Love, Hate, Sentimental, Lovely, Happy,Fun, Shock, Cheerful,Depressing, Exciting, Melancholy, and Mellow	KNN, MMC, SVM, MLP,
Jianhua Zhang*et al.* [24]	Joy, Happiness, Anger and Sadness	KNN, NB, SVM, and RF
Wei Long *et al.* [25]	Happy, Sad, Fear, and Neutral	SVM
Yong Peng *et al.* [26]	Happy, Sad, Fear, and Neutral	SWSC
Cong Zong *et al.* [27]	Joy, Anger, Sadness and Pleasure	SVM
Xiang Li *et al.* [28]	Valence and Arousal	LSTM
Zirui Lan *et al.* [29]	Positive and Negative	SVM
Chi-Keng Wu *et al.* [30]	Love, Sadness, Joy, Anger and Fear	KNN5

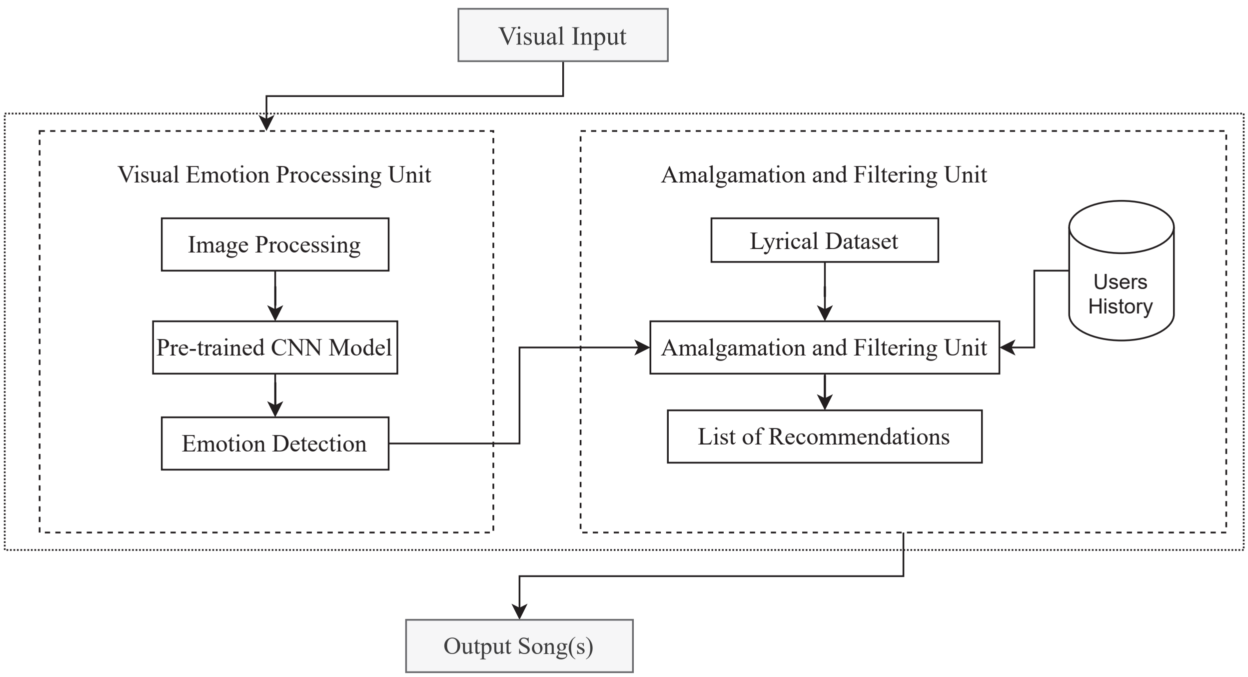

Fig. 2: Proposed Hybrid Model

proposed a hybrid face based music recommendation system. The proposed model's amalgamation and filtering unit considers 3 factors for recommending music: Emotion detected from visual emotion processing unit, output from lyrical data set and users history. The implementation of this model is in progress.

As a future work, psychological methods of emotion capturing can be a complementary part of this model, with an option to the user if they want devices to be attached to their body or not. Another extension to this work could be inclusion of pupil dilation technique.

REFERENCES

[1] M. Casellas, J. Segura, C. Andres, P. Berbel, and Y. Lopez, "Effects of music therapy as a distance therapeutic technique for cancer patients. pilot test with a relaxing music model," *Aloma-Revista De Psicologia Ciencies De L Educacio I De L Esport*, pp. 21–34, 2021.

[2] D. Paul and S. Kundu, "A survey of music recommendation systems with a proposed music recommendation system," in *Emerging Technology in Modelling and Graphics*, pp. 279–285, Springer, 2020.

[3] M. Schedl, H. Zamani, C.-W. Chen, Y. Deldjoo, and M. Elahi, "Current challenges and visions in music recommender systems research," *International Journal of Multimedia Information Retrieval*, vol. 7, no. 2, pp. 95–116, 2018.

[4] K. Yoshii, M. Goto, K. Komatani, T. Ogata, and H. G. Okuno, "Hybrid collaborative and content-based music recommendation using probabilistic model with latent user preferences.," in *ISMIR*, vol. 6, pp. 296–301, 2006.

[5] P. Darshna, "Music recommendation based on content and collaborative approach & reducing cold start problem," in *2018 2nd International Conference on Inventive Systems and Control (ICISC)*, pp. 1033–1037, IEEE, 2018.

[6] N. A. Abdullah, R. A. Rasheed, M. H. Nizam, and M. M. Rahman, "Eliciting auxiliary information for cold start user recommendation: A survey," *Applied Sciences*, vol. 11, no. 20, p. 9608, 2021.

[7] B. Yapriady and A. L. Uitdenbogerd, "Combining demographic data with collaborative filtering for automatic music recommendation," in *International Conference on Knowledge-Based and Intelligent Information and Engineering Systems*, pp. 201–207, Springer, 2005.

[8] Y. Song, S. Dixon, and M. Pearce, "A survey of music recommendation

systems and future perspectives," in *9th International Symposium on Computer Music Modeling and Retrieval*, vol. 4, pp. 395–410, Citeseer, 2012.

[9] A. V. Iyer, V. Pasad, S. R. Sankhe, and K. Prajapati, "Emotion based mood enhancing music recommendation," in *2017 2nd IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT)*, pp. 1573–1577, IEEE, 2017.

[10] Y. Agrawal, R. G. R. Shanker, and V. Alluri, "Transformer-based approach towards music emotion recognition from lyrics," *arXiv preprint arXiv:2101.02051*, 2021.

[11] J. Choi, J.-H. Song, and Y. Kim, "An analysis of music lyrics by measuring the distance of emotion and sentiment," in *2018 19th IEEE/ACIS International Conference on Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing (SNPD)*, pp. 176–181, IEEE, 2018.

[12] S. Gilda, H. Zafar, C. Soni, and K. Waghurdekar, "Smart music player integrating facial emotion recognition and music mood recommendation," in *2017 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET)*, pp. 154–158, IEEE, 2017.

[13] D. Ayata, Y. Yaslan, and M. E. Kamasak, "Emotion based music recommendation system using wearable physiological sensors," *IEEE transactions on consumer electronics*, vol. 64, no. 2, pp. 196–203, 2018.

[14] R. Guo, S. Li, L. He, W. Gao, H. Qi, and G. Owens, "Pervasive and unobtrusive emotion sensing for human mental health," in *2013 7th International Conference on Pervasive Computing Technologies for Healthcare and Workshops*, pp. 436–439, IEEE, 2013.

[15] S. De Nadai, M. D'Incà, F. Parodi, M. Benza, A. Trotta, E. Zero, L. Zero, and R. Sacile, "Enhancing safety of transport by road by online monitoring of driver emotions," in *2016 11th System of Systems Engineering Conference (SoSE)*, pp. 1–4, Ieee, 2016.

[16] P. Ekman, "An argument for basic emotions," *Cognition & emotion*, vol. 6, no. 3-4, pp. 169–200, 1992.

[17] R. Plutchik, "The nature of emotions: Human emotions have deep evolutionary roots, a fact that may explain their complexity and provide tools for clinical practice," *American scientist*, vol. 89, no. 4, pp. 344–350, 2001.

[18] C. E. Izard, "Basic emotions, natural kinds, emotion schemas, and a new paradigm," *Perspectives on psychological science*, vol. 2, no. 3, pp. 260–280, 2007.

[19] G. K. Verma and U. S. Tiwary, "Multimodal fusion framework: A multiresolution approach for emotion classification and recognition from physiological signals," *NeuroImage*, vol. 102, pp. 162–172, 2014.

[20] F. Agrafioti, D. Hatzinakos, and A. K. Anderson, "Ecg pattern analysis for emotion detection," *IEEE Transactions on affective computing*, vol. 3, no. 1, pp. 102–115, 2011.

[21] P. Li, H. Liu, Y. Si, C. Li, F. Li, X. Zhu, X. Huang, Y. Zeng, D. Yao, Y. Zhang, *et al.*, "Eeg based emotion recognition by combining functional connectivity network and local activations," *IEEE Transactions on Biomedical Engineering*, vol. 66, no. 10, pp. 2869–2881, 2019.

[22] P. Gong, H. T. Ma, and Y. Wang, "Emotion recognition based on the multiple physiological signals," in *2016 IEEE International Conference on Real-time Computing and Robotics (RCAR)*, pp. 140–143, IEEE, 2016.

[23] Y. Ding, N. Robinson, S. Zhang, Q. Zeng, and C. Guan, "Tsception: Capturing temporal dynamics and spatial asymmetry from eeg for emotion recognition," *arXiv preprint arXiv:2104.02935*, 2021.

[24] J. Zhang, Z. Yin, P. Chen, and S. Nichele, "Emotion recognition using multi-modal data and machine learning techniques: A tutorial and review," *Information Fusion*, vol. 59, pp. 103–126, 2020.

[25] W.-L. Zheng, W. Liu, Y. Lu, B.-L. Lu, and A. Cichocki, "Emotionmeter: A multimodal framework for recognizing human emotions," *IEEE transactions on cybernetics*, vol. 49, no. 3, pp. 1110–1122, 2018.

[26] Y. Peng, W. Kong, F. Qin, F. Nie, J. Fang, B.-L. Lu, and A. Cichocki, "Self-weighted semi-supervised classification for joint eeg-based emotion recognition and affective activation patterns mining," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–11, 2021.

[27] C. Zong and M. Chetouani, "Hilbert-huang transform based physiological signals analysis for emotion recognition," in *2009 IEEE international symposium on signal processing and information technology (ISSPIT)*, pp. 334–339, IEEE, 2009.

[28] X. Li, D. Song, P. Zhang, G. Yu, Y. Hou, and B. Hu, "Emotion recognition from multi-channel eeg data through convolutional recurrent neural network," in *2016 IEEE international conference on bioinformatics and biomedicine (BIBM)*, pp. 352–359, IEEE, 2016.

[29] Z. Lan, O. Sourina, L. Wang, and Y. Liu, "Real-time eeg-based emotion monitoring using stable features," *The Visual Computer*, vol. 32, no. 3, pp. 347–358, 2016.

[30] C.-K. Wu, P.-C. Chung, and C.-J. Wang, "Representative segment-based emotion analysis and classification with automatic respiration signal segmentation," *IEEE Transactions on Affective Computing*, vol. 3, no. 4, pp. 482–495, 2012.

[31] S. Koelstra, C. Muhl, M. Soleymani, J.-S. Lee, A. Yazdani, T. Ebrahimi, T. Pun, A. Nijholt, and I. Patras, "Deap: A database for emotion analysis; using physiological signals," *IEEE transactions on affective computing*, vol. 3, no. 1, pp. 18–31, 2011.

[32] M. Soleymani, J. Lichtenauer, T. Pun, and M. Pantic, "A multimodal database for affect recognition and implicit tagging," *IEEE transactions on affective computing*, vol. 3, no. 1, pp. 42–55, 2011.

[33] W.-L. Zheng and B.-L. Lu, "A multimodal approach to estimating vigilance using eeg and forehead eog," *Journal of neural engineering*, vol. 14, no. 2, p. 026017, 2017.

[34] L. Zhang, S. Walter, X. Ma, P. Werner, A. Al-Hamadi, H. C. Traue, and S. Gruss, ""biovid emo db": A multimodal database for emotion analyses validated by subjective ratings," in *2016 IEEE Symposium Series on Computational Intelligence (SSCI)*, pp. 1–6, IEEE, 2016.

[35] A. Mollahosseini, B. Hasani, and M. H. Mahoor, "Affectnet: A database for facial expression, valence, and arousal computing in the wild," *IEEE Transactions on Affective Computing*, vol. 10, no. 1, pp. 18–31, 2017.

[36] R. Subramanian, J. Wache, M. K. Abadi, R. L. Vieriu, S. Winkler, and N. Sebe, "Ascertain: Emotion and personality recognition using commercial sensors," *IEEE Transactions on Affective Computing*, vol. 9, no. 2, pp. 147–160, 2016.

[37] P. Lucey, J. F. Cohn, T. Kanade, J. Saragih, Z. Ambadar, and I. Matthews, "The extended cohn-kanade dataset (ck+): A complete dataset for action unit and emotion-specified expression," in *2010 ieee computer society conference on computer vision and pattern recognition-workshops*, pp. 94–101, IEEE, 2010.

[38] J. Z. Lim, J. Mountstephens, and J. Teo, "Emotion recognition using eye-tracking: taxonomy, review and current challenges," *Sensors*, vol. 20, no. 8, p. 2384, 2020.

[39] M. Ragot, N. Martin, S. Em, N. Pallamin, and J.-M. Diverrez, "Emotion recognition using physiological signals: laboratory vs. wearable sensors," in *International Conference on Applied Human Factors and Ergonomics*, pp. 15–22, Springer, 2017.

[40] T. Hornung, C.-N. Ziegler, S. Franz, M. Przyjaciel-Zablocki, A. Schätzle, and G. Lausen, "Evaluating hybrid music recommender systems," in *2013 IEEE/WIC/ACM International Joint Conferences on Web Intelligence (WI) and Intelligent Agent Technologies (IAT)*, vol. 1, pp. 57–64, IEEE, 2013.