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A Review of the Emotion-Induced Music Recommendation Systems

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ABSTRACT

This review discusses the evolution, approaches, methodologies, features, and outcomes of emotion-induced music recommendation systems (MRS) in light of the growing demand for personalised music experiences. Traditional MRS often overlook the emotional context of users, making the integration of emotion recognition a promising enhancement for user satisfaction. The paper examines 32 studies published between 2011 and 2025, detailing how various inputs, such as facial expressions and physiological signals, can inform personalised music recommendations. It highlights the application of advanced machine learning techniques and the challenges that arise, including the cold-start problem and the need for real-time processing capabilities. The review categorises existing systems into content-based filtering, sequential recommendations, and emotion detection using physiological signals. Additionally, it emphasises the importance of context-aware recommender systems that factor in user environments. Future research is encouraged to address limitations in accuracy, scalability, and ethical considerations while exploring multimodal approaches for more robust MRS. Ultimately, the review highlights the transformative potential of emotion-based music recommendation systems (MRS) in enhancing user interaction and personalisation with digital music platforms.

Subject Categories and Descriptors: [H.5.5]: Sound and Music Computing; [H.5.2 User Interfaces]

General Terms: Music Recommender Systems, Emotion Analysis, Deep Learning

Keywords: Music Recommender Systems, Emotion-Based Recommendations, Psychological Music Influence, Personal Music Experience, Context-Based Recommendation, Facial Expression

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1. Introduction

The swift expansion of digital music platforms has underscored the need for sophisticated music recommendation systems (MRS) that cater to individual user preferences [1]. Earlier applications lacked

effective solutions for this issue, as they merely focused on generating playlists for users without accurately capturing their moods [2]. Recent studies have highlighted the significance of additional facets of the recommendation process, such as explanation, transparency, control, and overall user experience [3]. Tracking individual preferences and options has led to considerable progress in music recommendation systems (*MRS*), particularly those that incorporate emotion detection technologies [8]. By assessing user emotions through various inputs, such as facial expressions and physiological signals, these systems aim to enhance user satisfaction by providing context-aware music suggestions [9]. The integration of advanced machine learning approaches with emotion detection has created new pathways for personalised recommendations while also introducing distinct challenges [11, 8]. This paper evaluates 32 studies that investigate different methodologies for creating emotion-based music recommendation systems (*MRS*), focusing on how these systems utilise facial expressions, physiological signals, and other data to provide tailored music recommendations [4, 5, 6] [7]. We extract outcomes and inferences from these studies, presenting a comprehensive overview of the methodologies, challenges, and prospects in developing emotion-based *MRS* [10]. We seek to synthesise the current literature, emphasising the progression of these systems and pinpointing essential gaps that require attention [12, 13].

2. Early Studies

Research in music recommendation systems (*MRS*) over the last two decades has taken a significant direction, leading to the development of several new models and systems in music preferences. Many newer studies have primarily focused on using facial expression recognition to infer user emotions.

Afchar et al elaborated on how enhancing explain ability could refine music recommendation algorithms and improve the user experience. [14]. *MRS* involves creating multifaceted recommendation lists that consider intrinsic user characteristics, fairness in recommendation, explanation, evaluation, handling missing and negative feedback, user interface design, and open tools and data sources. [15].

Neural networks are especially effective at identifying the hidden factors of musical pieces from sound signals or metadata and recognising the sequential trends of musical items (such as tracks or artists) from playlists or listening activities. [8]. Libraries such as NumPy and Pandas were used to analyse the songs to reveal relationships between people and music. This allows us to suggest popular albums to individuals based on their past listening behaviour. [16].

Reinforcement learning challenge offers more promise for music recommendation by framing the exploration-exploitation dilemma. To understand user preferences, a Bayesian model is employed that considers both the audio characteristics and the novelty of the recommendations. [17]. When integrating deep learning architecture with IOT, the intelligent background music system is stable and effective. [18]. Kumar and Rakesh suggested a framework with three features: collaborative filtering, content-based, and a hybrid approach [19].

Present-day real-world Music Recommendation Systems (*MRS*) tend to be quite intricate and fine-tuned for accuracy in recommendations. They integrate multiple components that rely on collaborative filtering alongside content-based suggestions. This intricacy can hinder the ability to explain recommendations to users, which is especially crucial for suggestions that may be considered surprising or unsuitable. The emotions

and moods of users determine their music choices. Many researchers advocate for the emotion-based music recommendation system. [20-25].

Emotion-based recommendation systems can be recognised as intelligent music recommendation systems in a real sense. [20-25]. Hence, emotions are tapped using wearable devices. [4]. By integrating various artificial intelligence technologies with generalised music therapy techniques, a recommendation system is designed to assist individuals in selecting music tailored to different life circumstances, while supporting their mental and physical well-being. [26]. The affinity graph tends to sense the association between preferred music and emotions [27]. These systems employed convolutional neural networks (*CNN*) and Haar Cascade algorithms to detect emotions from facial images [28, 29].

Other research explored the use of physiological signals such as galvanic skin response (*GSR*) and photoplethy smography (*PPG*) to predict emotional states, which were then used to refine music recommendations [4]. More recent studies have integrated machine learning models like k-Nearest Neighbors (*KNN*), Support Vector Machines (*SVM*), and deep neural networks (*DNN*) to enhance the accuracy of emotion detection and recommendation quality [30, 31]. Several studies have also addressed the limitations of existing systems, such as the cold-start problem and the lack of real-time processing capabilities. Dual models that combine content-based and collaboration-based techniques, along with emotion detection, can effectively address the challenges discussed. [32].

Additionally, using context-aware recommender systems (*CARS*) that consider factors like time, location, and activity further enhances the relevance of music recommendations [33]. Various evaluations of the viability of deep learning models, such as Convolutional Neural Networks (*CNN*) and Recurrent Neural Networks (*RNN*), will be very incremental. [34].

3. Types and Techniques of Music Recommendation Systems

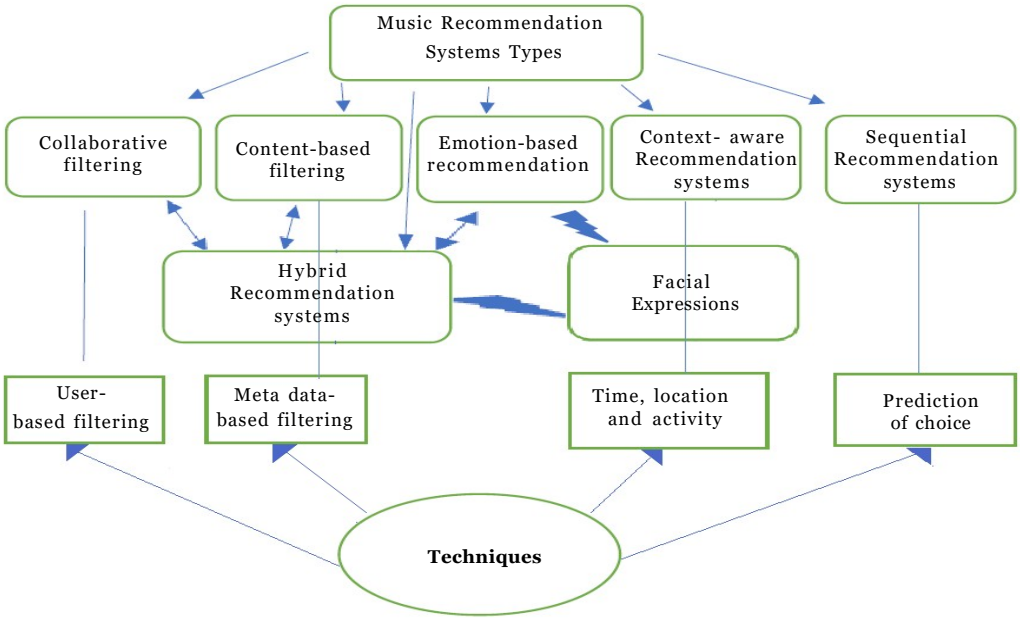

Figure 1. Types and Techniques of Music Recommendation Systems

There is no clear demarcation between the various music recommendation systems available, as they exhibit overlap. Also, one type is related to the other in terms of similar characteristics or features. Figure 1 expresses the types and techniques that enable us to understand its nature.

The methodologies employed in the reviewed studies vary widely, reflecting the diverse approaches to emotion-based music recommender systems (*MRS*).

There are three main categories of music recommender systems from a technical perspective: content-based filtering, sequential recommendation systems, and recently proposed approaches inspired by psychology [15]. However the below recommender systems are also identified.

3.1 Collaborative Filtering (CF): It represents a more advanced intelligent search technique for suggesting individual tastes in the Music Recommendation System (MRS). This method includes two primary strategies: user-based and item-based approaches [90]. It also enables the application of machine learning algorithms for recommending music and predicting ratings based on user preferences.

3.2 Facial Expression Recognition: This technique entails capturing and analysing facial images using *CNN*s or other deep learning frameworks to identify emotions. *CNN*s are employed for instantaneous emotion detection based on facial expressions, facilitating immediate music suggestions. The identified emotions are subsequently linked to appropriate music playlists, enabling timely, mood-based recommendations.

3.3 Content-based Filtering: Standalone acoustic feature analysis is one method of constructing a content-based music recommender system. The other method combines deep learning with computer vision to achieve better results [40]. Besides, a hybrid recommendation system analyses music using a few features and incorporates new features such as ELLT and DVS [41]. Content-based filtering uses metadata to extract features.

3.4 Sequential Recommendation: Recent studies have focused on two particular sequential recommendation tasks: predicting the following music selection and forecasting the next new music choice. These aim to anticipate the upcoming (new) music track that users may enjoy based on their previous listening history and prediction of choices [42].

3.5 Personalised Preferences: Certain systems, such as *GSR* and *PPG*, incorporate wearable sensors to track physiological signals. Wearable devices are utilised to monitor these signals, which are then analysed to predict the user's emotional condition and adjust music suggestions accordingly. The processed signals indicate the user's emotional state, which is then utilised to enhance music recommendations. This method often employs feature fusion techniques to combine data from multiple sensors, resulting in greater accuracy.

3.6 Machine Learning Algorithms: A variety of machine learning classifiers, including *KNN*, *SVM*, and *DNN*, are employed to categorize music genres and forecast emotions based on user data. Different classifiers, such as *KNN*, *SVM*, and Random Forest, are used to classify music genres and predict emotions based on user input. These models are frequently trained on datasets such as GTZAN and evaluated using metrics like accuracy, precision, recall, and F1-score.

3.7 Hybrid Approaches: A few systems employ a combination of content-based filtering, collaborative

filtering, and emotion recognition to enhance the quality of recommendations. Several hybrid methods enable the construction of highly reliable and accurate recommendation systems, combining facial expression recognition with collaborative filtering. These hybrid models combine user-item interactions with content attributes extracted from audio or visual inputs.

3.8 Context-Aware Recommender Systems: These systems enhance music recommendations by considering contextual elements, including time, location, and activity. These systems often conduct systematic literature reviews to identify and incorporate relevant contextual information into the recommendation.

4. Datasets and Analysis

For the selection of the core papers for investigation, we search, identify, extract, summarise and analyse them by resorting to an ideal scientific management system. When searching for a broad term, such as "Music Recommendation System," one can encounter hundreds of studies, making it a challenging task to select the most relevant source. We emphasise that the key aspects of scientific arguments are pertinent to the theme chosen. The review should analyse the framework of the research and interpret it from the perspective of the MRS. Its assessment should rely on recognised and established criteria that are selected, articulated, and clarified by the researcher performing the review. During the review process, it is also essential to utilise evidence to back up conclusions and viewpoints drawn from the evaluation of other scholars' works. Based on this premise, we searched the literature, which produced several hundred studies. To select the core literature,

S.NO	Work	Year	Methods	Outcome and Results	Approaches, dataset, and features used
1	Nofal, A [75]	2021	Recommender System for Music using K-Nearest Neighbors and Weighted Product Method	Systems Usability Score is 83.65	The Weighted Product Method (WPM) to weight the music criteria With the Kaggle dataset
2	Y. Zhang [56]	2022	Music Recommendation System and Recommendation Model Based on Convolutional Neural Network	The average accuracy rate of single-category user feature recommendations is 50.35 %, and the recommendation accuracy rate of multi-category user features is higher than that of single-category user features.	Features using spectrum and notes, design classification methods using convolutional neural networks

3	Volta, E [84]	2018	Performance-oriented systems, measuring physiological parameters, gesture recognition, and sensory mapping	Wearable systems impact musical contexts, from the design of multisensory instruments to systems that monitor key learning parameters.	Wearable technologies offer transformative potential for music performance and education
4	Chikaraddi, A [83]	2025	Emotion-Driven Music Recommender System with Deep Learning and Streamlit Integration	The system achieved a validation accuracy of 96% and a testing accuracy of 94% in detecting emotions	A combination of CNN, MTCNN and streaming APIs provides a scalable and efficient solution
5	Santosh Kumar Bharti S Varadhaganapathy Rajeev Gupta, Prashant Kumar Shukla, Koneru Lakshmaiah, Mohamed Bouye, Simon Karanja Hinga, Amena MahmoudAmena Mahmoud [66]	2022	Text-Based Emotion Recognition Using a Deep Learning Approach	Accuracy of 80.11%	A machine learning + deep learning model to identify emotions in text. Convolutional neural networks (CNNS) and Bi-GRUSare used as deep learning techniques. Support vector machine is used as a machine learning approach.
6	S. Chauhan [61]	2021	Movie recommender system from facial expression	Content-based and collaborative filtering offer more power for recommender systems.	Convolutional neural networks recognise each facial micro expression and content-based collaborative filtering offers more power for recommender systems.

7	Y. -J. Liu [63]	2018	Real-Time Movie-Induced Discrete Emotion Recognition from EEG Signals	Overall accuracy of 92.26 per cent in recognising high-arousal and valenced emotions from neutrality and 86.63 per cent in recognising positive from negative emotions.	A real-time movie-induced emotion recognition system for identifying an individual's emotional states through the analysis of brain waves. Real-time emotion recognition systems from EEG signals in terms of classification accuracy and recognising similar discrete emotions.
8	Á Lozano Murciego [12]	2021	Systematic Literature Review on Context-Aware Recommender Systems (CARS)	Not applicable	Reviewed context-aware systems in music; identified gaps in research and potential for better integration of Contextual factors.
9	S Metilda Florence, Uma Mohan [77]	2020	Emotional Detection and Music Recommendation System based on User Facial Expression	The classifier has an accuracy of more than 80 percent	Emotion - Audio Integration Module. Classification of facial landmarks
10	Aya Hassouneh [71]	2020	Facial Expressions and EEG based on machine learning and deep neural network methods	Maximum recognition rate of 99.81% using CNN for emotion detection using facial landmarks. The maximum recognition rate achieved using the LSTM classifier is 87.25% for emotion detection using EEG signals.	EEG) signals using a convolutional neural network (CNN) and long short-term memory (LSTM) classifiers by developing an algorithm for real-time emotion recognition using virtual markers
11	Su, H., Chang, Y., and Tseng, V. S. [67]	2016	Social content-based collaborative filtering for music recommendation	Outperforms RMSE (Root Mean Square Error) and NDCG (Normalised Discounted Cumulative Gain).	Multi-modal Music Recommender system (MMR), which integrates social and collaborative information to predict users' preferences Preferences.

12	Huilin Ge [69]	2022	Facial expression recognition based on deep learning	Combining facial action unit model and the pleasure arousal dimension model, and multimodal models, such as audio mode, 3D face depth information and human physiological information, is effective	Static facial expression recognition and dynamic facial expression recognition
13	Pandeya, Y.R [78]	2021	Deep-Learning-Based Multimodal Emotion Classification for Music Videos	The best classifier attained 74% accuracy, an F1-score of 0.73, and an area under the curve score of 0.926.	Music, video, and facial expression cues, use the audio–video information exchange
14	Wang, S [81]	2021	Emotion-aware music recommendatio-ns	The emoMR improved of 119.38% of Precision precision 175.60% of Recall recall 156.24% of F1F1 and 433.33% of HitRate HitRate.	A hybrid approach that combines content-based and collaborative filtering to generate emotion-aware music recommendations.
15	T. Gorasiya [82]	2022	Music Recommendat-ion based on Facial Expression using Deep Learning	Accuracy rate of 94 per cent	Used music dataset to create a user-specific music playlist (music recommen-dation model) witha Convo-lutional neural network to classify the users emotions in 7 different categories
16	R. L Rosa [65]	2015	Music recommendat-ion system based on users' sentiments	Reaching a rating of 91% of user satisfaction,	Presents a music recommendation system based on a sentiment intensity metric, named enhanced Sentiment Metric (esm), which is the association of a lexicon-based sentiment metric with a correction factor based on the user's profile. DL techniques in music recommendation, focusing on content-based and sequence-aware methods.

17	Bakariya, B [80]	2023	Facial emotion recognition and music recommendation system using CNN-based deep learning techniques	The model's accuracy is 73.02%	Two emotion recognition models using various combinations of these datasets with CNN model, predict six emotions: anger, fear, joy, neutral, sadness, and surprise.
18	Mojtaba Salehi [79]	2011	User behavior-based recommendation system	Sequential improved the quality of the recommend-ation	A preference matrix captures user preferences based on product attributes, and weighted association rules account for sequential purchasing patterns to enhance the accuracy of recommendations.
19	Ben Hayes [85]	2024	Digital signal processing for music and speech synthesis	Development ofhybrid models, which incorporate DDSP components	Differentiable audio signal processing, focusing on its use in music and speech synthesis.
20	Ting Zhang [78]	2024	Facial expression recognition with deep learning	High accuracy	Focused on real-time emotion-based music recommendation using facial expressions and deep learning.
21	Ran Zhang (68)	2023	Facial emotion detection based on improved VGG-16 Facial emotion d etection based on improved VGG-16	An accuracy of 68.0% is achieved An accuracy of 68.0% is achieved	VGG-16 convolutional neural networkmodel effectively recognises facial emotions and contributes in emotion detection research.
22	Dheeraj Hebri [76]	2024	k-nearest neighbours and long short-term memory algorithms	Accuracy 89% F1 score: 0.85	LSTM performed better than deep learning systems,
23	Shuting Zhang [72]	2023	Hybrid system combining content-based and collaborative filtering	0.95 weight of collaborative filtering	A hybrid recommendation system, combining 0.95 weight of collaborative filtering and 0.05 content-based recommendation system, achieves a good precision and diversity.

24	Pang Li [74]	2024	Deep Neural Networks (DNN) in Collaborative Filtering	Outperformed standard collaborative filtering	Deep Neural Networks (DNN) in Collaborative Filtering (CF) recommendation systems.
25	Fang, B [73]	2023	Facial expression analysis with a machine learning	Captured facial expression recognition and its application scenarios.	The framework consistsof various kinds of machine learning methods and published datasets.
26	V. Moscato [62]	2021	Emotional Recommender System for Music	A content-based filtering approach obtains more accurate and dynamic results	Use personality traits, moods, and emotions of a single user, starting from solid psychological observations recognized by the analysis of user behaviour within a social environment
27	Aryan Shirwadkar [70]	2022	Real-time emotion-based music recommendation	Accuracy: 85%	Used CNNs for facial expression recognition; suggested improving emotion detection and real-time Processing.
28	Yajie Hu [64]	2011	A Music Recommendation System Based On User Behaviour	The recommendation approach surpasses the baseline and our recommendation is effective	Music favoredness using user log
29	A Elbir [86]	2018	Music Genre Classification and Recommendation by Using Machine Learning Techniques	The GTZAN database was used, and the highest success was achieved with the SVM algorithm.	The acoustic features of music have been extracted by using digital signal processing techniques, and then music genre classification using machine learning methods. In addition, convolutional neural networks, which are deep learning methods, were used for genre classification and music recommendation.

30	Amil Khanzada [87]	2024	Facial expression recognition with deep learning	Demonstrated a state -of-the-art 75.8% accuracy on the FER2013 test set	A deep dive, implementing multiple deep learning models for facial expression recognition (FER).
31	Xu Ming Wang, [88]	2018	Facial expression recognition with deep learning	The result of the softmax activation function + SVM is better than that of the softmax activation function. The accuracy of facial expression recogniti on was 68.79% on the test set.	Static facial expression recognition with the FER-2013 dataset, using a CNN model. Employed SVM with softmax activation function.
32	Andres Ferraro [89]	2019	User behaviour analysis to combine multiple systems for music recommenda-tion	The ranking-fusion hybrid systems for nDCG@500 led to the best overall results, surpassing the baselines on most metrics	Combining multiple music recommender systems for each user individually, based on their expected perfor-mance. Use different fusion strategies to combine recommenda-tions.

Table 1. List of 32 core papers reviewed for this study

we applied several filters, including year, reviewed journals, and conferences, and adapted the *PRISMA* approach [86]. It is the evolution of the original *QUOROM* guideline for systematic reviews and meta-analyses of evaluations. *PRISMA* (Preferred Reporting Items for Systematic reviews and Meta-Analyses) was developed by a team of international researchers featuring experienced authors and methodologists. They outlined 27 criteria that a paper must meet to be considered eligible for review. Further filters are applied, such as recognised journal publications, citations from subsequent studies, and authorship. The list is presented in Table 1.

Extracting the deliverables from each paper is difficult, so we presented the essence of the discussions in the papers referred to earlier.

We summarise below the 32 research works on (Table 1) music and emotion-based recommendation systems, emotion recognition, and music classification, presenting the significant insights.

5. Consolidated Description of the Literature Reviewed

5.1 Music Recommendation Systems

Techniques used in the above studies, based on frequency, include K-Nearest Neighbours, Collaborative Filtering, Content-Based Filtering, Deep Neural Networks (*DNN*), and Hybrid Systems. We found that many models integrated emotional and contextual cues to enhance personalisation, such as emotion-aware filtering,

EEG, and facial expression analysis. The overall observation of accuracy and performance metrics varies, with some achieving validation and testing accuracy rates of up to 94–96%.

5.2 Emotion Recognition Data

The primary datasets used are explained in most studies, while a few, such as review papers, do not provide the dataset. The primary sources are Facial expressions, EEG signals, text, and multimodal (audio-video) data. The algorithms used to test the data are *CNN*s, *LSTM*s, *Bi-GRU*s, *SVM*s, *VGG*-16. In the inferences section, we found accuracy rates ranging from 68% to 99.81%, depending on the method and data modality.

5.3 User Behaviour Analysis

As the principal goal of this work is to tap the user behaviour, we studied the specific user emotions that include sequential use behaviour, sentiment intensity, and preferences. At the same time, the hybrid systems combining behaviour and content showed improvement in recommendation precision. These studies, particularly the recent ones published over the last four to five years, utilised real-time systems, wearable devices, and tools like Streamlit for interface development. The models deployed in the research relied on benchmark datasets like FER2013, GTZAN, and Kaggle. The emotion recognition accuracy reached a maximum level of 99.81%, whereas the EEG- based emotion detection achieved a peak of 92.26%. Systems based on hybrid and collaborative filtering achieved high user satisfaction and prediction accuracy.

We provide below the two comparison sets of the outcomes of both the emotion and hybrid approaches to MRS, together and separately. (Figures 2 and 3)

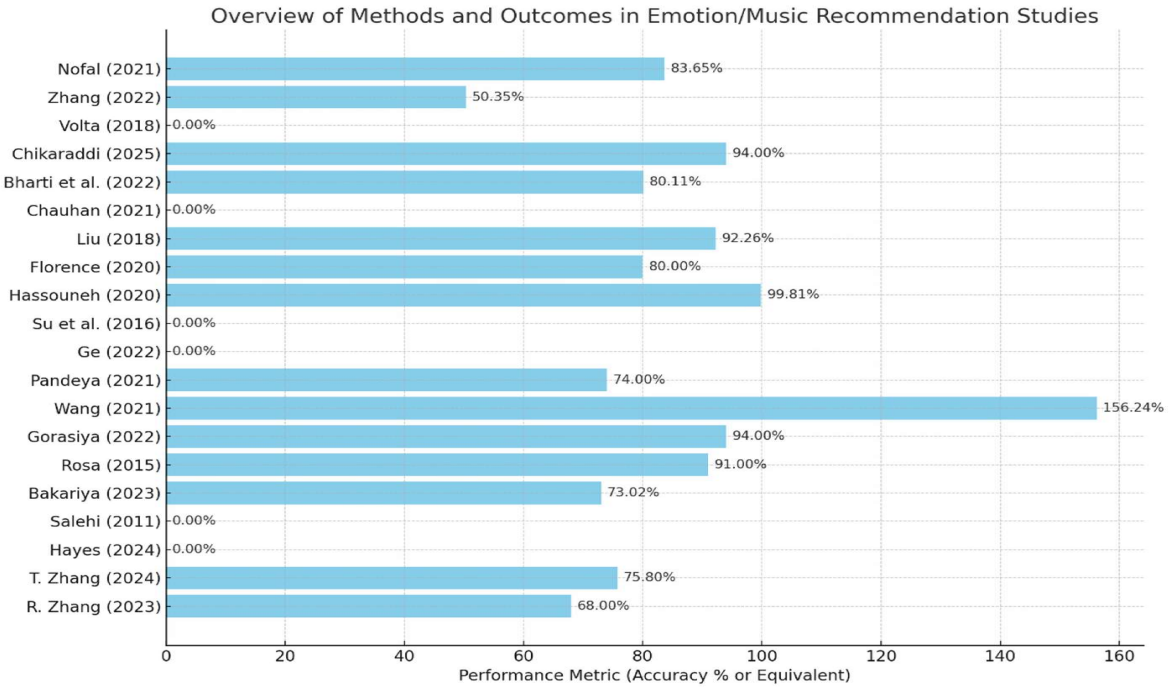

Figure 2. The performance outcome of the Music Recommendation Systems

Based on the results extracted from the analysis, we present a summary of the performance results associated with different testing scenarios for the Efficient Net model:

Scenario	Accuracy (%)
Initial Efficient Net Test Accuracy	71
After 70/30 Train-Test Split	72
After 80/20 Train-Test Split	74
With Augmented Data	87.15

The corresponding outcome is outlined in Figure 4.

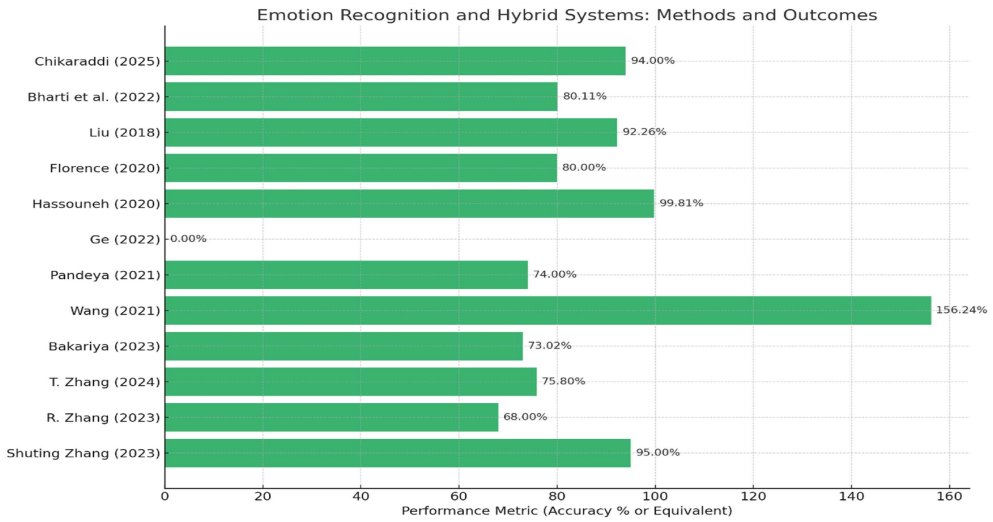

Figure 3. The methods and outcome of the Emotion Recognition and Hybrid Systems

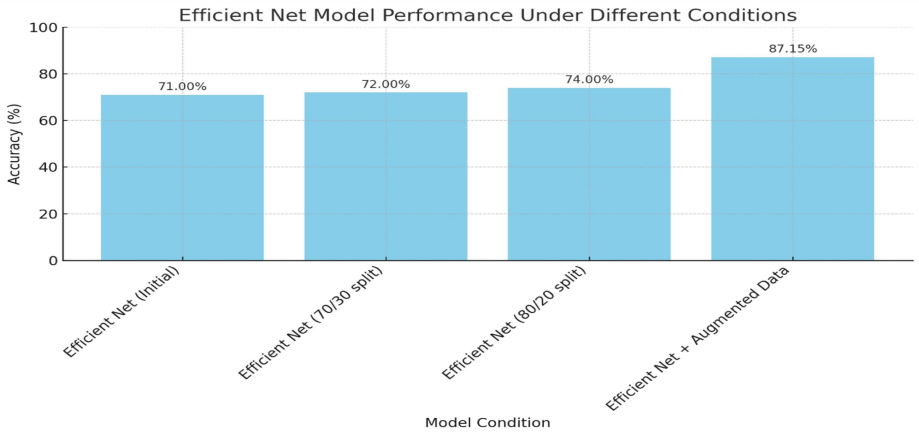

Figure 4. Efficient Net Model Performance Under Different Conditions

We plotted the values of the studies we used against the mean accuracy and displayed the result in Figure 4. The Efficient Net with augmented data approaches has attained notably higher accuracy than the rest when the Initial Efficient Net Test Accuracy and the efficient net results are at similar levels of accuracy.

6. Emotion-based MRS

This part examines the emotion-driven MRS by emphasising the characteristics, approaches, and challenges discussed in the research. Among the diverse methods utilised by scholars, several recent investigations introduced novel focuses, including sequential recommendations and those influenced by emotions. Nevertheless, when categorised, the emotion-driven research often falls into a limited number of overlapping groups. Studies centred on emotions are likely to influence upcoming music recommendation research.

A groundbreaking music suggestion system utilising reinforcement learning (RL) that can evoke emotions in users to enhance interaction across various scenarios, such as gaming, films, and intelligent environments. In this context, music systems influencing mood and feelings in our everyday lives are gaining significant attention. As a result, extensive research has been conducted within the affective computing field to understand the connection between music and emotions [38-41].

More broadly, the applications of affective computing research can be observed in various areas, including education, healthcare, entertainment, smart environments, multimedia retrieval, and the generation and retrieval of music. We have identified several studies that utilised various characteristics to gauge users' emotions when evaluating music recommendation systems. [42-51].

Some research focuses on identifying emotions through facial expressions, while others have examined EEG [52], physiological responses, and video data. These studies indicate that music recommendation is typically achieved by integrating physiological signals, including heart and breathing rates, as well as facial expressions, and generally employs AI techniques, predominantly deep learning methods, to interpret this data. Among the literature on this filtering approach, we discovered [53], where the authors introduce an emotion-driven music recommendation system that learns a user's emotional state from data gathered via wearable devices. Specifically, a user's emotion is evaluated by a wearable device that incorporates galvanic skin response and photoplethysmography sensors.

There is a broader scope for a neural network-based approach to music recommendation that incorporates facial expressions to detect users' moods [54].

7. Conclusion

Emotion-induced recommendation systems for music are the way to tap into personalised music preferences. Emerging evidence from the reviewed articles, aimed at advancing user satisfaction, suggests that an emotion recognition technique, when combined with conventional recommendations, can provide enhanced recommendations to users. However, some issues remain unresolved and may require further investigation before these systems can be deployed to their full potential. Processing in real time, data diversity, and ethical

concerns can become key threshold points in the further development of emotion-based MRSs, with a significant impact on human-computer interaction scenarios elicited on digital music platforms.

8. Future Work

Considering the diversity in music recommendations, future research should examine the different methodologies proposed in Music RS, taking a value-based approach. [60]. While advances are reported in terms of volume and veracity, numerous challenges remain in emotion-based MRS. Future investigations should focus particularly on improving the accuracy and scalability of these systems, as well as their ability to operate in real-time environments and accommodate user diversity. Increasing the diversity in the music and emotion datasets will enhance the relevance of these systems across various linguistic and demographic groups. In addition, consideration of the ethical issues concerning data privacy, in conjunction with the responsible use of emotion recognition technologies, is a must before the widespread application of these systems. User feedback, combined with multimodal methods that include facial expressions, physiological signals, and contextual data, can lead to more robust and concentrated MRS.

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