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Emotion-Adaptive Music Recommendation System Using LLMs and Real-Time Sentiment Analysis

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Abstract— Music emotionally affects individuals, personalized music suggestions are required for an enhanced listening experience. This work introduces an Emotion-Adaptive Music Recommendation System leveraging large language models (LLMs) and sentiment analysis to recommend personalized songs based on user emotions. The method guarantees an organized emotional categorization of music by pre-labeling every song with moods from the GoEmotions database following processing of a Spotify dataset. In a bid to interpret the identified sentiment to the preprocessed data for song popularity ranking, a RoBERTa chatbot interacts with users to capture and assess the mood inputs. To provide the user preferences for specific artists and monitor popularity priority, additional filtering is utilized.To enable smooth music playback, the Spotify API is used to build a simple and user-friendly interface. This work aims to improve emotional connection and listening enjoyment by combining deep learning, natural language processing (NLP), and recommendation techniques.

Index Terms—Music Recommendation, Sentiment Analysis, Natural Language Processing, Large Language Models, Emotion- Based Recommendation, Spotify API,RoBERTa, Llama 2 7B , GoEmotions

INTRODUCTION

Traditional music recommendation systems tend to employ collaborative or content-based filtering approaches that focus on song features, genre choices, or user history. These approaches overlook the user's current emotional status, which plays an enormous role in the music preference. This is addressed by emotion-aware music recommendation systems, which employ artificial intelligence and sentiment analysis and tailor suggestions based on user emotions. This work proposes a chat-based music recommendation system that is based on textual mood indicators to interpret user moods. The algorithm can effectively translate emotional states into appropriate tunes through the integration of sentiment analysis and LLMs. RoBERTa interprets user responses in order to determine mood, while the GoEmotions dataset is utilized for sentiment classification. Sophisticated text processing with Llama 2 7B facilitates correct identification of user emotions. Recommendations are sorted by user preference and popularity after the identified mood is mapped to preprocessed song data. This method enhances personalization through the use of AI-based analysis, enabling users to immediately select songs that match their emotional state. An example of the dataset after preprocessing and mood keyword tagging is presented in Fig. 1. It shows a dataset containing details of six music tracks, including:

- **Metadata**: track_id, artists, album_name, track_name
- **Popularity & duration**: popularity, duration_ms, explicit
- **Audio features**: danceability, energy, acousticness, instrumentalness, liveness, valence, etc.
- **Music structure**: mode, tempo, key, time_signature
- **Genres and emotions**: track_genre, track_moods, and a final emotion label target

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df.sample(6)
```

	Unnamed: 0	track_id	artists	album_name	track_name	popularity	duration_ms	explicit	danceability	energy	...	mode	speechiness	acousticness	instrumentalness	liveness	valence	tempo	time_signature	track_genre	mood
9033	9033	5cS3LwObFvrv6Vfwge0D6R	Delino Marçal;Midian Lima	Você Não Imagina	Você Não Imagina	54	318020	False	0.504	0.526	...	1	0.0317	0.273000	0.000	0.1500	0.3420	116.349	4	brazil	['disapproval', 'anger']
14343	14343	7gG236x66Jq6AYSP0jW8k0	Sweet Little Band	Babies Go Coldplay	God Put A Smile Upon Your Face	36	169226	False	0.546	0.257	...	1	0.0298	0.932000	0.886	0.1310	0.0965	126.129	4	children	['sadness', 'love', 'caring', 'disappointment'...
23107	23107	0FMLbet9bIK5IgKktuqCBx	James Hype;Tita Lau	B2B	B2B	54	160000	False	0.799	0.956	...	1	0.0679	0.005450	0.568	0.0640	0.9220	123.998	4	deep-house	['joy', 'love', 'excitement', 'optimism', 'ang...
9849	9849	1nq949J6RDPrIBkTXrhqnx	Frejat	Só as Melhores do Pop Rock Brasileiro	Segredos	0	233533	False	0.581	0.731	...	1	0.0289	0.192000	0.000	0.4050	0.5790	127.580	4	brazil	['disapproval', 'pride', 'anger', 'excitement']
24457	24457	0fC03FdOBaQRcE5gqo3Cwu	Kenny Larkin	Azimuth	ESP	8	421706	False	0.775	0.838	...	0	0.0616	0.006760	0.900	0.0835	0.6710	139.981	4	detroit-techno	['joy', 'excitement', 'anger', 'desire', 'disa...
24356	24356	0B1xAsEU2g2IHjGafulhrr	Omar S	Pull Ovaa	Pull Ovaa	9	476968	False	0.594	0.935	...	0	0.0762	0.000507	0.881	0.3140	0.3580	124.946	4	detroit-techno	['disapproval', 'pride', 'anger', 'excitement']

6 rows × 22 columns

Figure 1 Emotion-Tagged Music Dataset Sample

Figure 2 presents the distribution of track genres along with several plots illustrating the relationships between different musical attributes.

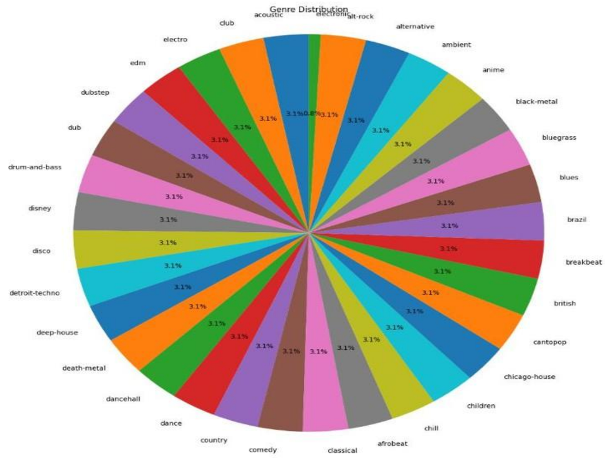


Figure 2 Genre Distribution of Music Tracks

II. LITERATURE SURVEY

From simple tools that suggested songs based on popularity or genre, music recommendation systems have evolved into advanced, emotionally intelligent systems that can recognize human emotions, cultural contexts, and even physiological responses (Paul and Kundu, 2020; Verma et al., 2021). This evolution is due to both technological advancements and a greater understanding of how individuals interact with and are affected by music. As (Song et al. 2012) explains, the early systems employed simple collaborative filtering methods to recommend songs depending on user preferences. While music can induce the same kinds of emotional reactions in general, Lee and Hu (2014) have asserted that the actual musical expressions of the phenomena differ a lot from culture to culture. Taking this into account, various system of cultural adaptation have been designed. The semantic web framework by Rho et al. (2013) is an example of these systems, which are able to modifyrecommendations depending on local listening patterns and regional musical cultures. The in- ternationalization of the music streaming services with their ability to meet the musical needs of theconsumershaving extremely diverse taste and interests make it increasinglyimperative to take the cultural aspect of the business and its industry seriously (Garima et al.,2022).The potential ethical repercussions regarding the emergingtechnologies in the area of music recommendation have been extensively discussed (Drott, 2018).Moscati et al. (2023) argued that if cognitive architectures were integrated intorecommendation systems, it would lead to an increase in transparency that would enableconsumers tounderstand the decision-making process of these systems. Thesepertinent show that the issue raised here is wide in scope; asreco- mmendation systems for music becomeincreasingly more sophisticated, they likewisegain an even greater cultural consumption influence, which thereby leadto questions ofuser control and algorithmic responsibility (Chen, 2023). The way thingsstand now, one can predict that this industry will expand potentially by a big factor in thenear future (Pasupuleti, 2024). The requisite of unrestrained sensibility and accuracy in recommendationsystems of the future would be realizable if multimodal inputs were to be combined(Ashwini et al.,2024). At the moment, key issues such as the purpose andethics of the technologies are beingdebatedby researchers (Lewers, 2024). Are these technologies to prioritizethe user's well-being andcultural diversity or should business interests, especially engagement, be categorically and primarily considered as the drivers for the technologies (Garg et al., 2024)? Shouldplatform designers be accountable and stillmake their algorithms transparent? (Radha etal., 2024).

Music recommendation systems as we know them nowadays are the result of some key ideas of thetechnology of information retrieval, introduced back in the 1970s. However, the changesin such systems have been significant and have occurred as a result of a wide range of abovedescribed developments in the field of IT and media. The music industry has reaped manybenefits from technology, but at the same time, it has had to face a number of consequencesresulting from the fast growth of the internet. Namely, both the losses of profit by the musicindustry and the losses of privacy by the web users have been the effects of the openness,and thereby the overabundance of such information thanks to the internet. As musicrecommendation systems provide huge potential for commercial ventures through theirdistribution channels, they carry certain ethical challenges which should not beignored. Twitter data, for example, is often characterized by informal communication features, reflecting ordinary language of the present day and everyday activities (Chae etal., 2012), where the primary goal is to engage in socialization. Twitter data becomes morerelevant for researchers in the business field too, as the political analysis of Twitter databecomes more investigated (Tumasjan et al., 2010, among others). The last but not least principle of human-centricity is the basis of developing user interfaces thatare of big importance for businesses to remain successful nowadays (Bulten et al., 2003).Social network analysis, on the other hand, has become useful for investigating the social interactions between people and the distribution of information and documents that often accompany social interactions in a communication network. Moreover, the continual enquiry into the physical, psychological, and emotional comfortability of the user while developing a system would be engaged in the direction of promoting the sustainable development of the land. As music recommendation systems are becoming increasingly implemented in a variety offields such as healthcare, education, and workplace productivity, the aforementioned issues gain an exponential importance. In the case of educational software like the one of(Kuo and Chi 2013) displaying the potential of these systems for language acquisition and cognitive growth, the therapeutic examples of (Ji et al. 2013) and Lee et al. (2016) inform us that these systems may have crucial applications in clinical contexts as well. The fact that many next-generation systems are still encountering remarkable technical problems(Liu, 2016) explains why most implementations in the commercial domain still lag behindthe initial research studies in expressing users' emotional involvement, and the existing mechanisms are still very weak in solving the "cold start" problem for new users and the tracks who have no listening history (Nilashi et al., 2014) (Panda et al., 2021). Furthermore,this daunting problem of scalability exists with new and old hardware having largediffering capacities and with the challenge of advanced recommender quality (Savoa-Videnovand Uzunov, 2017) not having been solved. The scrutinizing of the music recommendationtechnology as a microcosm of the general human-computer interaction studies through the lens of a person in the twenty-first century in quest of the smooth connectivity of virtual worlds happily had found willing partners in the project heirs (Beheshti et al., 2018). Research methodologies that are human-centred arealready widely used for studying interaction in new media and telecommunications, humancomputer interaction evenin the area of software engineering and the design of assistive technology for the oldage. Shifting cultural attitudes towards technology's role in creative arts are also evident in the evolution of music recommendation systems (Chen, 2024). Modern more advanced approaches have been embraced as legitimate tools for musical discovery, while music purists viewed the initial systems with suspicion (Kaur et al., 2023). This shift is in line with broader trends in the integration of AI into art processes across a range of artistic disciplines (Ouyang et al., 2022). The main difference in music recommendation has been the focus on augmenting human judgment instead of replacing it, creating systems that act as wise advisors instead of dictatorial curators (Zhou and Xu, 2020).

The relationship between music generation and recommenda- tion systems is another essential point (Tamboli and Kokate, 2022). These processes will certainly affect artists' and pro- ducers' decisions as they continue to improve at predicting what will be enjoyable to audiences (Roy and Dutta, 2022). Fascinating issues relating to the future evolution of musical genres and styles are raised by this feedback cycle between musical creativity and recommendation algorithms (Darshan et al., 2024). While a counter-trend of artists intentionally producing music that resists algorithmic categorization is forecast by some researchers, others hypothesize that we will see the development of ”algorithmically optimized” music explicitly created to be successful on recommendation systems (Sarin et al., 2022), Others are expecting a backlash of artists intentionally making music incompatible with computer classification (Chirasmayee, 2022).

According to Reddy Madhavi et al. (2024), the economy can get the same high contributions from the state-of-the-art recommendation systems. (Dhahri et al.,2018) has pointed out that the future of an artist is crucially dependent on attaching the algorithmic playlists during the time streaming is the major source of music consumption. From this, besides the fact of the large demand that iscoming for the fairness of the system which does not mean only the popularityprocess but the point of the lack of transparency and equal treatment, it wasfound that the latter is true (Sunitha et al., 2022). Some companies havestarted creating AI sets that can interact with users & explain theirrecommendations while others have conducted one-on-one tests that arepersistent of the unfamiliar artists like. (Sunitha melal., 2023) (Mastronardiet al., 2023). From the point of view of the user interface, there is not asingle right solution for music recommendation systems (Liebman et al., 2019).To satisfy user's expectations, the recommendations need to consist of both newand known content (Narducci et al., 2020). Only if you possess deep knowledgeof the human mind and musical terms can you find the perfect mixture (Brodsky,2015). Great systems should not only open up numerousnew possibilities but also keepthe listening format very coherent, in such a way that it seems like an additionto the listeners' own musical preferences (Hsu & Hsu, 2006).

Lee and Hu (2014) have brought to light the fact that with the global nature of music streaming, the recommendation systems are both very promising and at the same time demanding. On the one hand, through an efficient recommendation system, listeners will be able to discover music from totally different cultural backgrounds, thus, a truly cross-cultural musical exchange on an unprecedented scale will become the feasible matter of fact (Jentschke et al., 2009). At the same time, it requires the systems to be capable of not only identifying and preventing cultures from recommending inappropriate artists but also leading music fans through complex cultural situations (Tokgoz et al., 2024). The international recommendation systems have to meet the cultural sensitivity requirement since a song that fits comfortably in one environment can be a cause of horror and even offense in another (Garima et al., 2022). Yet another important but less talked-about concern arising from the usage of music recommendation technology is privacy (Garg et al., 2024). Ethical questions are automatically raised when the systems hang further in the balance of the more intimate data, for example, when the technologies include physiological and facial expression analysis (Ashwini et al., 2024). People obviously appreciate it if the service can offer better recommendations, thus, they are even ready to reveal private information, but they expect that the information will be safely handled and transparently made available (Nikam et al., 2024). Therefore, the systems that enable users to decide what data can be collected or for what purpose, and nevertheless can produce intelligent suggestions even with limited data access, are the most likely to be trusted (Radha et al., 2024).

According to Juslin (2013), recommendation systems are swiftly taking up the new-coming scientific knowledge which is unveiling great part of music influence on the brain mechanism and emotions. As a matter of neurology research, the taste in music of a certain individual is strongly related to personal temperament, psychological condition, and maybe even learning style (Skowronek et al., 2006). These imply that to produce truly personalized music recommendations, the systems will most probably have to take into account all these aspects (Liu et al., 2009). Researchers are also pondering over the possible existence of "cognitive music profiles," which would allow delivering music to taste on the one hand and also to the basics in neurological processing and music perception up to the individual (Fan et al., 2011). Also, the landscape of the music recommendation market as a business is changing at a rapid pace (Chung et al., 2009). Originally just a music player function, now recommen- dation has become the center of gravity in the streaming service field, where such systems provide the most sophisti- cated and satisfactory music recommendation services while each of the systems is striving to attract the largest number of subscribers (Ignatov et al., 2016). Although intensive rivalry has fastened the process of innovating, it has also aroused the worry that there will be something called "Recommendation Wars" in which the platforms are to some extent enhancing user engagement rather than giving of the highest quality musical recommendations (Drott, 2018). Many industry experts are suggesting that more cooperation and standard- ization in recommendation technologies are sorely needed to keep the focus on the listeners and not business interests (Pasupuleti, 2024).Another promising field is the application of music recommendation technology to education (Kuo & Chi, 2013). Systems that can adapt to students' music preferences and learning habits can change music education and make it more engaging and effective (Lin & Chen, 2025). The same techniques would apply in therapy interventions, language learning, and other areas where music plays a role (Thai et al., 2025). Designing systems that are flexible enough to address a variety of edu- cational needs without sacrificing the rigor and organization necessary for effective learning is the primary issue (Chen, 2024).

Furthermore, the most effective systems could be those which combine human expertise and algorithmic strength and thus give birth to hybrid approaches (Gonzalez-Lopez et al., 2020). It has been confirmed that some sites follow this pattern, functioning as a space where human curators make a final decision on what to include in the playlist and still algorithms provide the human hands with some recommendations (Panda et al., 2021). With this in mind, we can conclude that in the future music recommendation systems will be more and more integrated into people's daily life (Suh et al., 2012). Wearable tech will be able to provide you with the music during sport or meditation that you require at the moment (Gaikwad et al., 2023), and home automation devices can change the background music as per the inhabitants' activities and emotional changes (Cheng & Shen, 2014). The idea launched by Savova-Videnova and Uzunov (2017) that the part of the musical experience, which was previously mentally driven, might become only a transparent layer, is also a possibility. Because of that, music choice may be a much more spontaneous and unconscious result of our reactions rather than a deliberate action with deep connections to choices of other contexts. The best kind of music recommendation is when the system quietly understands your mood and daily life, instead of just reacting to what you've liked before (Liu, 2024).

Juslin (2013) argues that music recommendation systems also provoke important concerns about the nature of desire and taste. We are forced to contemplate the extent to which our tastes are truly "ours" instead of being artificially enhanced by our cultural environments and, as a consequence, who are the instruments by means of which they mediate that also become more skilled when they predict and influence our preferences (Drott, 2018). Awareness of such processes can lead us to understand better musical taste as both individual and collective, both inherent andconstructed—a many-sided relationship between variables in recommendation systems,both those on the users' side as well as those on the system's side, the latter being the factors that actually direct andmonitor the changes of the former (Beheshti et al., 2020). Furthermore, the implementation of themusic recommendation systems is continuously being improved (Zhang et al., 2022).The modern versions make use of sophisticated neural networks and deep learningframeworks, whereas the older ones utilized statistical models as well as verysimple database queries (Wei et al., 2023). new technologies such as brain-like circuits or quantum computers transfer systems faster and more efficient, which is easy for people to use (Nascimento et al., 2025; Lewers, 2024.

The other important area of research and innovation is the social facet of music recommendation (Song et al., 2013). Recommendation systems are increasingly adopting social features that allow friends to share and find music collaboratively, since music has always been a social activity (Liu et al., 2009). To build recommendations on what whole friend groups or communities are favoring, a number of systems are trying out collaborative filtering methods that act across social networks as opposed to a single user history (Siva Brahmana Reddy et al., 2024). Even in an increasingly algorithmic world, these social strategies might serve to mitigate some of the issues of isolation that have been raised regarding personalized recommendation systems, encouraging more communal musical experiences (Cataltepe & Altinel, 2007). Another consideration that is gaining increased scrutiny is how music recommendation systems influence the environment (Zhang et al., 2022). Since complex recommendation models could be intensive to train and run on, many researchers are examining more energy-conserving approaches (Liu, 2024). More environmentally friendly directions for the discipline are signaled by research like Zhang et al.'s (2022) creation of the OPT-175B model, which reached GPT-3 level perfor- mance with a significantly reduced carbon footprint. We can expect increased focus on building recommendation systems that balance ecological accountability and performance as environmental concerns intensify (Pasupuleti, 2024).

Furthermore, the regulatory and legal framework for music recommendation is evolving (Chen, 2023). Platform liability, copyright issues, and fair use considerations are all highly contested and litigated issues (Chapaneri et al., 2020). Rules that explicitly target algorithmic recommendation systems are under consideration by some jurisdictions, particularly with respect to fairness and transparency concerns (Radha et al., 2024). These regulatory adjustments are likely to have an impact on the way that music recommendation technology evolves in the future, potentially requiring systems to include certain levels of independent or local artists or to provide additional context for their recommendations (Tamboli & Kokate, 2022).We still need to study how listening to music recommended by algorithms over a long time affects people’s feelings about music, even though short-term studies show it can improve mood and interest. Although some researchers speculate that it would lead to more passive consumption patterns, others suggest that through continually exposing the listener to music that speaks, it could very well lead to greater engagement (Juslin, 2013). In order to fully understand such effects and inform the proper shaping of recommendation technology, longitudinal studies will be necessary (Lee et al., 2016).Another interesting future involves the merging of music recommendation with other types of media (Kuo & Chi, 2013). Systems that can recommend not just songs but en- tire multimedia experiences—blending music with visual art, narratives, games, and other forms of expression—are begin- ning to appear as entertainment becomes increasingly cross- platform and interactive (Lin & Chen, 2025). With algorithms that understand the complex relationships between multiple creative modes, these integrated recommendation systems can generate novel hybrid forms of art that dissolve the traditional boundaries between media types (Roy & Dutta, 2022).

One important trend in music recommendation technology is the democratization of the technology itself(Savova-Videnova & Uzunov, 2017). In the past, these systems belonged only to big tech companies, however, in thepresent days, owing to open-source alternatives and tools, even smaller developers and solo artists can have theirown recommendation systems ((Kaur et al., 2023). (Kaur et al., 2023). Such democratization has many possibleconsequences, e.g. the emergence of a wider variety of recommendation methods that will not have to rely on thebig platforms' one-size-fits-all models (Nilashi et al., 2014). It besides provide very interesting opportunities forspecial recommendation systems that can be suitable for some listening conditions, communities, orgenres (Ignatov et al., 2016).One thing that is difficult in the domain of recommendation is coming up withan objective measure of the quality of therecommenda- tion (Schedl, 2019). Criteria, for example, the length oftime one listens to the music or the number of clicks while listening, may not always reveal the complex nature ofmusical experience, according to McFee and Ellis (2014). Meanwhile, the scientists are dealing with the task tofind multivariate structures comprising, among other things, emotional impact, cultural relevance, and listener'slong-term pleasure (Chapaneri et al., 2020). In addition, in order to be able to move the recommender field of thenext generations to the fundamentally meaningful improvements instead of the simple users' engagement metricsoptimizations, it will be crucial to evolve those more sophisticatedassessments (Panda et al., 2021).Another field that continues to develop is the interface between creativity tools and music suggestions (Mo & Niu, 2019). Machines that not only provide suggestions for already re- leased music but also give producers and musicians novel ideas are beginning to emerge (Cheng, 2022). These tools analyze musical trends and trends to provide suggestions that can inform decisions regarding production, composition, and even performance (Sarin et al., 2022). Other purists view this as an unappealing mechanization of the creative process, but others perceive technology as an effective tool which can augment more than restrict creative potential (Chirasmayee, 2022). There are significant cultural implications of music globaliza- tion by recommendation systems (Lee & Hu, 2014). On the one hand, it fosters previously unseen levels of intercultural exchange and acquaintance (Jentschke et al., 2009). On the other hand, it raises concerns over the potential marginal- ization of local musical cultures and cultural homogenization (Tokgo¨z et al., 2024). As per Garima et al. (2022), the most thoughtful recommendation systems are those that strike a balance between exposing listeners to a mix of global sounds and respecting and preserving musical diversity. Apart from technical competence, this requires deep cultural understand- ing and sensitivity—levels of empathy that are hard to quantify in algorithms but which are needed to create truly worthwhile musical experiences (Siva Brahmana Reddy et al., 2024).

The ability to recommend music successfully relies on psychological factors that are still not fully understood (Juslin, 2013). An array of factors such as personality, mood, cultural background, and even transient physiological state have been proven to interact in a multi-faceted manner to decide the musical preferences (Skowronek et al., 2006). The most advanced recommendation systems are those that can combine different factors into a single, evolving user model, as noted by Liu et al. (2009). Solving this complex, truly interdisciplinary challenge requires insights from anthropology, psychology, and neuroscience (Fan et al., 2011). While music recommendation algorithms are also employed in the areas around, there still remains the fact that music is the most lucrative field that the algorithms can contribute to, for instance, in product recommendation, podcasts, and videos (Chung et al., 2009). Music is considered the most challenging area as well as the toughest to succeed due to its emotions and culture, but the fundamentals can also be extended to other areas (Drott, 2018). No matter that music is still the hardest and most profitable area for recommendation technology, the knowledge gained in music recommendation is being used not only in personalized content delivery but also in the general area of personalized delivery systems (Pasupuleti, 2024). It is necessary to constantly remind ourselves of bias, fairness, and representation when creating ethical music recommendation algorithms (Moscati et al., 2023). These ethical music choices can lead to more plays for some artists over others and corresponding genres leading to a situation where the algorithms that are learning from the past listening patterns unintentionally perpetuate existing imbalances in the music industry (Sunitha et al., 2023). The best solution for dealing with this challenge is to take intentional effort to identify and correct biases and to set up recommendation targets intentionally according to not only engagement metrics, but also musical, and cultural values as bases (Radha et al., 2024). Another crucial aspect of music recommendation systems' success is its user interface design (Narducci et al., 2020). Inadequate presentation that fails to describe why recommendations are being made or how users can provide insightful feedback may undermine even the most sophisticated algo- rithms (Liebman et al., 2019). Good interfaces promote under- standing and trust and enable users to become masters of their music experience rather than passive consumers of algorithmic choices (Hsu & Hsu, 2006). Creating recommendation systems that individuals come to love using over time means applying a human-centric design strategy (Chen, 2023).

This article also talks about the economic models that foster music recommendation (Ignatov, 2016). The major business imperatives push loyalty towards customers, whereas the preferences of the customer can cause a supplier's business to beless profitable (Drott, 2018). It is clear that being a part of advertising is also one of the important and most widespread ways for music recommenders to get revenue (e.g. Sparkle, 2021-B and The Echo Nest) In the patronage model of recommendations, for example, the artist or the listener becomes the recommendation source, whereas TV shows or celebrities can be the main influencers, leading their audience to the music. (Savova-Videnova & Uzunov,2017) This discussion would be beneficial for the creation of a technologically advanced sharing culture in music recommendations (Liu, 2024).There are still many empirical investigations to be carried out concerning the performance of music recommendation algorithms and the objective should be to clarify their strengths and limitations across a diverse set of contexts and situations (Panda et al., 2021). Although new approaches reveal potentialresults based on lab tests, their real-world efficacy might not be as great(Gonzalez-Lopez et al., 2020). Confirmation of the incremental gains overfashion or other transient effects can be achieved by experiments and longitudinal studies performed regularly (McFee & Ellis, 2014). According to Schedl (2019), such an insight may drive the development and application of recommender system technology in different domains via a scientific research approach. There is an enormous variety of music suggestion matching algorithms (Narducci et al., 2020). Due to certain listeners' need to have a reliable and pleasant content experience, they might pick up on machinic recommendations.On the other hand, those who are not likely to listen to music they are already familiar with are more likely to use new and innovative services that enable them to discover and experience different things (Lieb- man et al.,2019).The other important aspect to consider is maintaining musical heritage through recommendation algorithms (Skowronek et al., 2006). Older or lesser-known recordings are in danger of becoming marginalized increasingly since these systems tend to focus on contemporary listening habits (Liu et al., 2009). Recommendation algorithms may serve as bridges between the past and the present by introducing listeners to previous recordings that remain meaningful and pertinent through thoughtful design (Fan et al., 2011). Keeping various collections and preventing algorithmic reinforcement of temporal bias requires deliberate effort (Juslin, 2013).

Affective computing technology is one of the main drivers to make the emotional intelligence of music recommender systems more sophisticated (Joel et al., 2023). Modern algorithms can recognize subtle emotional features from the hearer's physiology, signals and actions, while previous systems could, at best, guess the listeners' emotional response byusing only the most basic musical features as the input (Sri- vastav et al.,2022). This allows the system not only to make more sophisticated recommendations currently, but it can also store the emotions of individuals under various situations and feelings in a first-person data way and not only by saying what they like (Mahadik et al., 2021).This indicates that over time, systems will develop deeper,more intricate relationships with their users (Nikam et al., 2024). A different interesting aspect is the social capability of music recommender systems (Songet al., 2013). The upcoming systems will allow the sharing of listening experiences with friends, family, or even strangers who have similar preferences instead of merely giving a user personal recommendations (Liu etal., 2009). These social recommendation contexts not only offer opportunities for the recovery of the shared factors of music enjoyment that have been removed with the personal headphones and isolation of solo streaming, but also challenge in balancing the personal taste and group life (Siva Brahmana Reddyet al., 2024).The problem is that both customers and regulators are beginning to express concerns about the explanations that music recommendational- gorithms give (Moscati et al., 2023). Not disclosing the kinds ofrecommen- dations for music can give rise to a lot of second-guessing, which of course is not good for anybody involved, be it the customers or the providers. If customers are given partial transparency of these recommendations,their level of trust would be higher and they would feel more comfortable speaking with the company (Radha et al., 2024). The methods mentioned in thepaper of Moscati et al. (2023) are a good example of interpretability-based justification for the recommendations, thus, they form a clear and structural step in the direction of an open system that is answerable to the recipients andcould be further discussed by them, if needed (Chen, 2023).One important factor that contributes to the success of music recommendation systems in the long term is their ability to change with the times of the respective listener's preferences. "Musical tastes change naturally from several reasons, such as alterations in personal life, or human nature, or simply because the society is adapting to new environments" (Juslin, 2013). In contrast to systems which keep their opinion on the users' music styles stable, those systems that can monitor and pre-empt such changes—only knowing a user craving for new genres or going back to his/her past favorites, are much more delightful to use (Lee et al., 2016). This implies building the algorithms which can not only capture common trends but also enduring changes in musical tastes and have a good understanding of the dynamics of the use of time while listening (Brodsky, 2015).)}New possibilities and limitations occur as music recommen- dation is combined with other intelligent technologies in the home, automobile, and public spaces (Cheng & Shen, 2014). If a system identifies that you are making dinner, it might play one song as opposed to the one it plays when it identifies that you are on the way to work or relaxing before you go to bed (Gaikwad et al., 2023). This contextual insight will make music listening feel more organic and in-time with day- to-day activity and surroundings but also requires seamless integration with other IoT devices and sensitivity to privacy constraints (Ashwini et al., 2024).

Besides just formal music education, music recommendation systems may stand as a new branch of pedagogics ((Kuo & Chi, 2013). When such linkages are created between contemporary musicians and their influences, or music from different cultural traditions having the same common origin, it should be noted that well-designed systems are able to be the players of musicalhistory (Lin & Chen, 2025).Referring to the work by Thai et al. (2025), the point is made that the pedagogical aspect of the music recommender systems, which takes them as tools for cultural and music literacy programs, helps listeners acquire a new culture, therefore, the music education metaphor begins to be meaningful. At the heart of the issue is communicating these connections in a way that is not forced or mechanical, but one that is seen as relevant and is experienced as a natural knowledge transfer process (Chen, 2024).Additional evidence has been found for the psychological benefit of music individualized recommendation in the area of research wherein experiments are reported by(Ji et al., 2023). Scientific research proves that music fitting the occasion of listening can be great stress and depression removers, as a result, the mood of the listener will brighten, concentration and detraction will be improved, and, in some cases, pain can also be decreased (Umbrelloet al., 2019). The extent of using recommendation services for the treatment of mental health and well-being increases as the latter becomesmore understanding of the user's personality and the situation the user is in, mentioning the most representative case of being able to detectuser's personality and the occasion for his/her current state and then choose the music that will help in feeling better (Lee et al.,2016). The potential of therapy and music recommendation's interdependence in the volunteering of the longest life's duet is a realization that has been distinctly supported both financially as well as through development by Howlin and Rooney(2020).One more key aspect of music recommendation systems that seemsto be neglected by most is the possible artistic inspiration for the next generation of visual artists and musicians (Roy & Dutta, 2022). Thesesystems eventually step out of the domain of what people know and get in touch with what they don't know, bringing in fresh ideas;hence, their role as inspirers to the future becomes stronger, as artists get the opportunity to partner to create new music directions orcollaborate with the people they never met before (Sarin et al., 2022). To find these original ideas or new dimensions of music and concepts,some of the artists use their algorithms, which in the given context are artistically designed musical tools, as points of reference(Chirasmayee, 2022). Both music composition and music recommendation systems are influential elements, which will not succeed if they areisolated, of each other in this creativity and creation process (Mo & Niu, 2019).In an age where recommender algorithms are growing in- creasingly persuasive, listener autonomy remains an important ethical imperative (Moscati et al., 2023). There is value in leaving space for deliberate, intentional musical decisions that are not algorithmically facilitated, even if algorithms can become very good at making predictions about preferences (Radha et al., 2024). The best systems likely understand when to suggest and when to step back and allow listeners to investigate on their own terms, balancing between deferential restraint and helpful suggestion (Chen, 2023). This philo- sophical examination opens up more general questions about human agency in a world increasingly mediated by algorithms (Lewers, 2024).

One of the more compelling facets of music recommendationsys tems is that they can be used to document culture (Tokgo¨z et al., 2024). Music recommendation systems pick up on crucial knowledge about taste change, cultural evolution, and trends in music as they keep tabs on, and analyze, listening behavior in groups and through time (Lee & Hu, 2014). Future generations of historians and anthropologists investigating musical culture in the 21st century will be able to use this information, which provides insights beyond ordinary sales data and radio playlists (Jentschke et al., 2009). There are great responsibilities and challenges for platform builders in ethically collecting, anonymizing, and keeping this informa- tion (Garima et al., 2022).

Yet another significant benefit is the greater accessibility facilitated by advanced music recommendation algorithms (Garg et al., 2024). Personalized music selection can greatly contribute to quality of life and availability of enjoyable musical experience for listeners with specific needs, whether precipitated by disability, neurodiversity, or unique sensory profiles (Ashwini et al., 2024). Individuals who would oth- erwise struggle to find suitable content through conventional browsing or searching are able to appreciate music due to systems that can accommodate particular sensory preference or cognitive tendencies (Nikam et al., 2024).

Music recommendation systems offer an unprecedented scope of experimentation (Panda et al., 2021). The platforms give researchers hitherto unexplored scales to experiment with matters relating to musical perception, cultural transmission, and preference psychology (Gonzalez-Lopez et al., 2020). Beyond fortifying recommendation systems, properly designed trials incorporated within them can yield information about human behavior and cognition (McFee & Ellis, 2014). The development of theoretical knowledge and practical applica- tion is sped up by this two-way beneficial interaction between research and application (Schedl, 2019).

A lot of artists still concern themselves with the creative integrity of their work in the context of algorithmic rec- ommendations (Cheng, 2022). Some fear that music could become standardized or lose challenging, idiosyncratic aspects that are not well-suited to recommendation models if it is optimized for algorithm performance (Roy & Dutta, 2022). To others, algorithms are merely another factor to consider in the creative process; they are not necessarily more limiting than the commercial considerations that have always influenced the creation of music (Sarin et al., 2022). More than music alone, this debate raises significant questions about the relationship between technology and art (Chirasmayee, 2022).

There are interesting research opportunities because of the linguistic challenges in music recommendation (Wei et al., 2023). What do listeners have to say regarding the music that they like? Are there different cultural and linguistic patterns in these accounts? How can systems balance the objective, technical properties that algorithms calculate against the sub- jective, metaphorical terms that people use to refer to music (Nascimento et al., 2025)? While these problems are being tackled in some measure by advances in natural language processing, there remains plenty of scope for research and innovation in these fields (Kumar, 2024).

There is also added complexity brought about by the temporal dynamics of music recommendation (Liebman et al., 2019). What is appropriate for the first track in a morning list may be inappropriate for the fifth, and listening preferences can change not just over a span of years but even in the course of one listening session (Narducci et al., 2020). In order to generate effective in-the-moment recommendations as well as maintain a coherent longer-term development, effective systems will need to simulate both these micro-level developments and longer-term developments in taste (Hsu & Hsu, 2006). Both short-term context and longer-term listening histories must be finely modeled for this (Chen, 2023).

Future research must aim at cross-cultural verification of music recommendation approaches (Lee & Hu, 2014). There are concerns about the generalizability of most current systems to other musical cultures and listening cultures due to the fact that they were mostly developed and validated in Western settings (Jentschke et al., 2009). While retaining considerable cultural particularities, cooperative global research efforts could assist in the establishment of more universally applicable strategies (Tokgo¨z et al., 2024). The development of recommendation systems that appropriately and effectively cater to audiences across the globe relies on this research (Garima et al., 2022).

One of the important practical considerations to remember is the computational efficiency of music recommendation platforms (Zhang et al., 2022). Small improvements in the efficiency of algorithms can lead to significant reductions in energy use and infrastructure costs due to the fact that such platforms serve millions of users simultaneously (Liu, 2024). By extending the boundaries of what is possible with limited computational resources, techniques such as as model pruning, quantization, and efficient nearest-neighbor search are mak- ing sophisticated recommendations feasible on increasingly diminutive hardware (Pasupuleti, 2024).

Music recommendation systems' paradigms of user control are evolving to be more transparent and flexible (Moscati et al., 2023). Whether it's preference sliders, real-time feedback, or even ”explore/exploit” choices that enable users to find a balance between familiarity and discovery, contemporary in- terfaces often provide a range of methods to adjust recommen- dations (Radha et al., 2024). Though providing helpful cues to improve the base algorithms, these features provide individuals with more control over their recommendation processes (Chen, 2023). Displaying these options without making things too confusing for the audience is a challenge (Lewers, 2024).

We are still not entirely sure how far-reaching music recom- mendation will ultimately shape culture (Drott, 2018). As an increasingly large proportion of musical discovery is filtered through such systems, they shape not only individual tastes but also broader musical trends and even the creative choices of producers and artists (Beheshti et al., 2020). Longitudinal studies and careful analysis of the mechanisms by which recommendation algorithms influence supply and demand in the music market are needed to track and understand these macro-level effects (Chapaneri et al., 2020). More responsible design methods that consider second-order effects on musical culture as a whole might be guided by this study (Mo & Niu, 2019).

Another promising direction is the integration of music sug- gestion and artistic tools for non-professional artists (Cheng, 2022). Based on a user's musical preferences, systems that are able to suggest chord progressions, instrumentation, or production techniques might minimize barriers to musical creativity and assist in the formation of personal style (Roy & Dutta, 2022). Through the analysis of a user's listening history, such technologies can provide personalized recommendations that are tailored to their needs and promote innovation and development (Sarin et al., 2022). This use may facilitate more participatory musical experience by obscuring the line between invention and consumption (Chirasmayee, 2022).

The essence of taste itself is one of the philosophical questions posed by music recommendation technology (Juslin, 2013). We are compelled to think about how much of what we like is really ”ours” as opposed to products of our cultural environments and the systems that mediate them as systems improve at predicting and shaping our tastes (Drott, 2018). Deeper insights into musical taste as individual and collective, natural and constructed—a multifaceted interplay of variables that recommendation systems both react to and shape—can emerge from this self-reflection (Beheshti et al., 2020).

As music recommendation systems evolve more, they need to be more emotionally intelligent, anticipatory and context- aware, and more seamlessly integrated into people's everyday lives (Gaikwad et al., 2023). Yet, those systems that remain mindful of their fundamental purpose—to enhance and fortify human relationships with music—will fare best in the future (Ashwini et al., 2024). Keeping this people-first mindset will be crucial as technology continues to evolve in a bid to create recommendation experiences that are meaningful and not just precise—systems that do not just know what we'll like, but help us see why we like it (Garg et al., 2024).

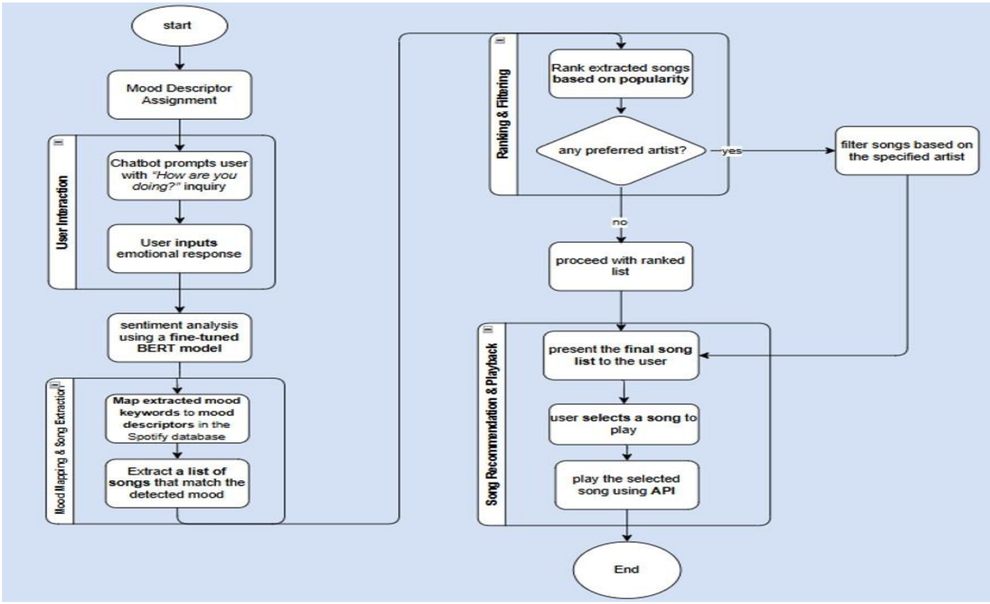
RESEARCH GAP

The larger part of the song recommender systems accessible today is the outcomes of either a content-based solution or collaborative filtering, and the systems all use song metadata and previous user behavior in producing recommendations (Li, 2024). In particular, while the results of these methods have shown high quality, they miss many opportunities to realize the rich emotional context that users have in time. Despite the fact that some of them have tried to adopt emotion recognition, most of the models are mainly based on the detection of facial expressions or some predefined mood tags, which is a little bit of a problem in terms of the recognition of all the user's emotions (Nikam et al., 2024). Without this capability, the recommendations may seem generic and unrelated to the user's real emotions at that very moment.New improvements in the field of artificial intelligence (LLMs) emerged from a totally different field have opened up new possibilities for recommending music based on the mood. Unfolding of the fact that LLMs are not only beneficial, but they are also the prototype models in most NLP tasks, the research area is yet to ascertain the potential of LLMs in real-time emotion-adaptive music recommendations (Wei et al., 2023). The main point of the paper is to provide a way for users to get music recommendation through an LLM-based recommendation system that can sense and modify the music based on human feelings the users might have at that time. The technology will be able to provide more personalized music experiences as it plans to make use of sentiment analysis and conversational AI in order to reflect the emotional states of the users.

IV OBJECTIVES

The primary goal of the research is to design an emotion-adaptive music recommender system with the help of large language models (LLMs) and sentiment analysis to select songs on the basis of mood. Encoding the Spotify dataset with the use of emotion labels from the GoEmotions dataset is a must in the direction we have chosen, which will enable classification of the recordings in both a structured and meaningful way. We are planning to utilize RoBERTa and Llama 2 7B in describing the system for mood recognition and to consolidate UI and UX by enabling the chatbots to act as personal user assistants. Meanwhile, the playlist-making algorithm that decides music precedence according to the user's tastes, music popularity, and mood compatibility, which is going to be represented in the recommendation system. A user-friendly chatbot interface will be combined with smooth music play via the Spotify API so that users can feel at ease. Moreover, to keep the platform engaging and to let the user immerse in it, both user satisfaction, and the reliability of the platform will be the key things used to measure the efficiency of the system. Figure 3 shows the basic pattern that the new emotion-adaptive music recommendation system is based on. The representation includes the user interaction, emotion analysis, feeling-based song filtering, ranking, and playback.

Figure 3. Emotion-Based Music Recommendation System Workflow



V METHODOLOGY

To make the development phase of the project more organized and productive, the research will be comprehensively done in six separate steps. Thisis to reveal the ways that have already been in use and the issues that need to be eliminated and improved. An analysis of the literature to be found in the field of music emotion and of the actual musicsystems that work in the same area is the first action that will be taken. With the dataset ready, the extraction and preparation of the audio features (Spotify) will be performed while the dataset will be annotated. The fourth step is concerned with the integration of the user interface called chatbot with the interaction of the users and additionally, the capture of the emotional state of the users via natural language inputs, the rightful spot of phase the third is. Identifying and Understanding Emotion Mood Recognition Systems(EMRS) are the two leading semantic relatedness models of phase three. The two models, which are the RoBERTa and Llama 2 7B models, are then prepared appropriate training and hyperparameter tuning and the emphasis here is sentiment analysis that will be applied for mood recognition. The motivation to uncover some of the most popular songs among the people is the central idea of the sixth phasethat involves the formation of a preference oriented recommendation system. The developed system will handle the exposure of the user's interest and popularity (popularity here is understood as the number of times a track hasbeen liked, shared, saved, etc.) and at the same time, the songs will be orderedaccording to the relative likelihood of the emotional match situation.Phase five deals with the integration of the system with the API,and the development of a user-friendly front end that utilizes modern webframeworks. With the integration of Spotify API, the user will have a smoothexperience interacting with recommendations and a good user interface will be created. The next step involves the process of testing and evaluating. By getting the users to go through the system, the recommendationsas they are being watched will raise the questions of accuracy and truth, andthen the user's reactions will later be dealt with in the refining process. In addition, the procedure to be followed here involves making therefinement and optimization of the system a much smoother process with feedbackobtained from the user so that their needs may be catered to. Since this cycle will berepeatedly, users benefit as the suggestions made continue to become more personaland interactive. The development process of the emotion-adaptive music recommendation system is illustrated in Figure 4

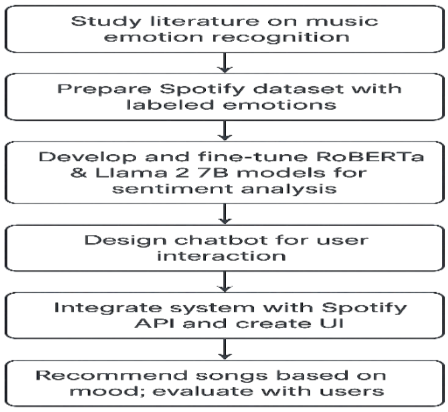


Figure 4 Workflow of the Proposed Emotion-Adaptive Music Recommendation System

A PROPOSED ARCHITECTURE

By the Emotion-Adaptive Music Recommendation System (EAMRS), we mean a system with a dual structure, which carries out sentiment analysis and performs music recommendations through an intrusive, expandable, and unfluctuating setup. The system implements JavaScript (React.js or Vue.js) on the frontend to ensure a lively and responsive user interface, while Python (Flask) is responsible for the server-side processing and is used on the backend. Main AI functionalities implement the Transformers library using RoBERTa and Llama 2 7B models which are responsible for the user's emotion and sentiment classification. This project's integration with Spotify is executed by means of the Spotipy library and Spotify API to transfer data and playback music in real time. In addition to that, the data are held in a database: PostgreSQL and MongoDB are utilized to optimize the process of storing user preferences and session history. Finally, using TensorFlow and PyTorch in Google Colab and Jupyter Notebooks, the model is trained and the experiment is carried out. Various stages our work are given below

- User Interaction: A natural language message from the user is captured by a chatbot interface.
- Emotion Detection: A fine-tuned DistilBERT model is used to analyze the inputs from the GoEmotions dataset, with the result that one or more emotional labels are extracted.
- Song Mapping: The emotion labels are used to match the ones from a preprocessed Spotify dataset, where it contains metadata, and emotion labels also assigned using GoEmotions.
- Filtering and Ranking: The user’s preference in terms of the artist is optionally removed, and the emotionally fitting songs are according to popularity sorted.
- Recommendation Delivery: The user is shown a list of songs to choose from based on the most popular recommendation.

Figure 5 is a visual representation of the connection between the valence and audio features of music such as energy, acousticness, and liveness in different music genres. As depicted in Figure 6, the most common mood tags in the dataset are anger, surprise, and joy. The plot for Figure 7 is an evidence of the correlation between energy and danceability where separate distributions can be clearly seen for different emotional moods.The "User Interaction" part is one part of the system that interacts with the user, and then, with the data available, the mood analysis is conducted and the music is being played by Spotify/YouTube.

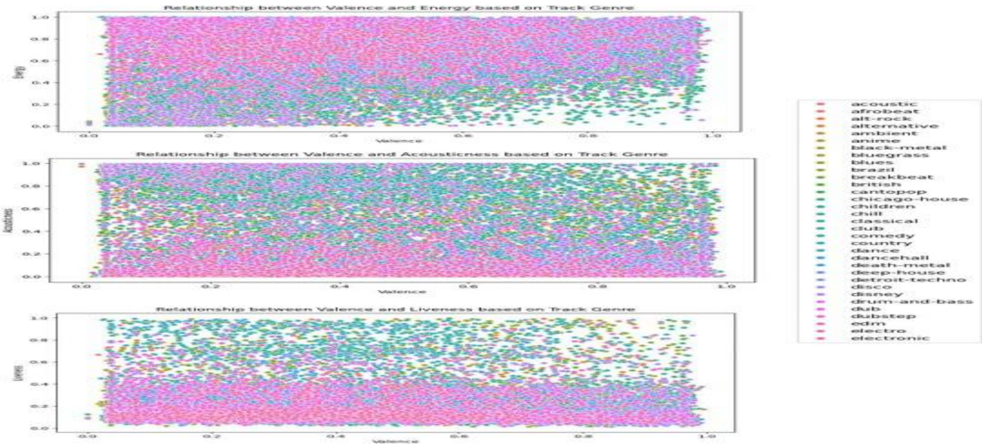


Figure 5

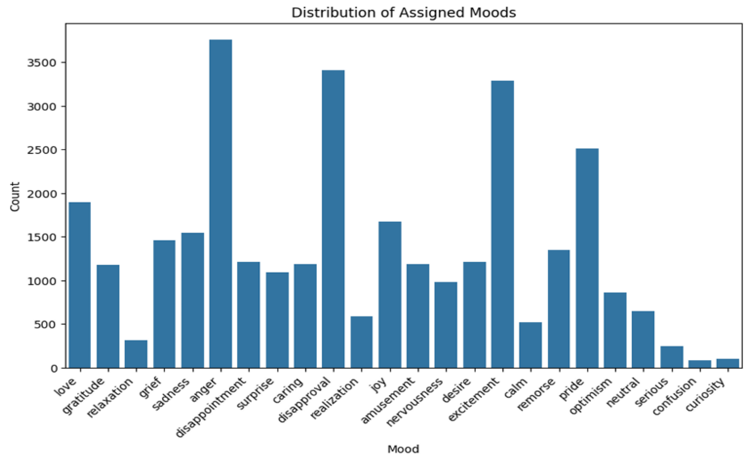


Figure 6 Distribution of Detected Moods in the Labeled Music Dataset

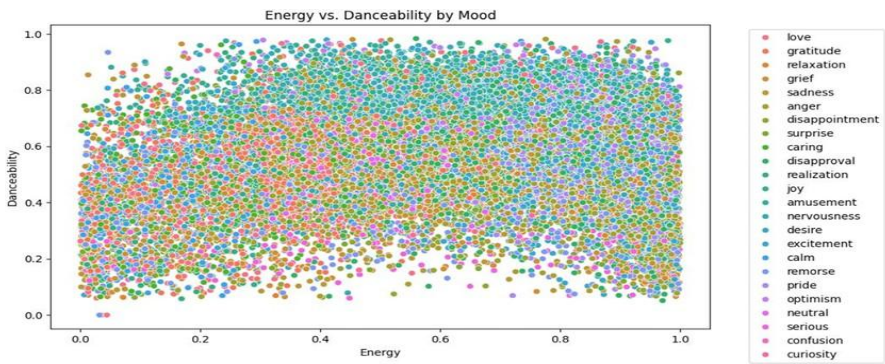


Figure 7 Energy vs. Danceability Categorized by Mood Labels

The research will be accomplished in six separate stages to ensure asmooth coupled with fruitful development of the project. In order to get toknow the current trends and weaknesses, we will start with the evaluation ofrepresentative emotion-targeted music recommendation systems publish-ed in the literature. At the same time, the dataset of Spotify will beretrieved and prepared for annotation.Phase two will involve the preprocessing and cleaning of thedataset to ensure that the data are of high quality and consistent. TheSpotify audio features, which include energy, valence, and danceability, willbe projected with the help of classes from the GoE- motions dataset to labelthe current mood.The third stage will see to it that there is a chatbotinterface that could converse with peopleand through organicverbal input, it will be able to realize the emotions ofthe individuals. Formation of a chatbot will be the main goal of the first step in whichLlama 2 7B and RoBERTa models will be fitted for NLP to effectivelyrecognize the sentences and thus the emotions that are necessary for theemotion sentiment.The work of phase four is to design a recommendation systemthat is capable of treating user preference, and popularity about a certainsong for the user, etc. as the basis of the rank.The main point is to satisfy users' preferences by giving them morepopular tracks or compatible with their desired mood and listeninghabits.Through API implementation, system integration, and the user-friendlyfront end, the implementation of the recommendation system will becompleted and users will be able to be satisfied, connected and ultimatelybecome effective utilizing the now developed service efficiently. It willfacilitate the usage and understanding of the system that is accompanied bythe Spotify API and, in the long run, the users will give an implicit authorityto the AI to play for them.Eventually, running tests and assessments form the sixth step. The conduct of testing and evaluation of the suggestionswill be complemented by user testing of the paper and the feedback will beused again to increase the system's efficiency. Practice the continuous stepsof trial and error; thus, this way, the suggestions could be more interactiveand personalized, making the experience not only for user-generated but alsofor user-interacting. The process flow of user interaction through the sentiment analysis and music playback via Spotify/YouTube is represented in Figure 8.

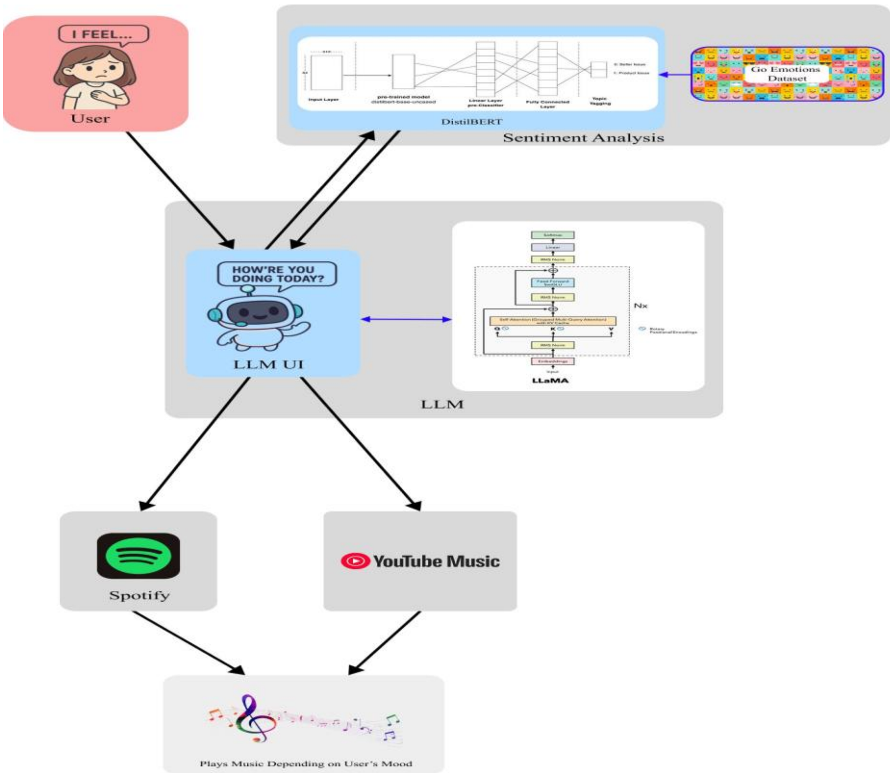


Figure 8 Emotion-Based Music Recommendation Workflow

Algorithm: Emotion-Driven Music Recommendation System

Input: A casual sentence where the user naturally expresses how they're feeling

spotify_dataset: A collection of songs along with details like how fast, loud, or energetic each one is."

emotion_reference_vectors: Centroid set of predefined emotions (valence, energy) to be used for the similarity search.

Output:A table that tells about the songs from the user's playlist that matches the user's mood.

Start by loading and cleaning the spotify_dataset.

Then scale the main audio attributes (valence, energy, tempo, loudness, danceability, acousticness) using Min-Max Scaling technique to normalize

Emotion Labeling (Heuristic Layer) Using heuristic labels to the audio in the dataset:

IF valence and energy coefficients are both high → mark as "happy"

ELSE IF valence and energy coefficients are both low → label as "sad"

ELSE IF

energy and tempo are high and valence is high enough lead to "angry" → label as "angry"

ELSE

→ label as "neutral"

→ Add the column of emotion_label to the dataset

User Interaction and Emotion Detection

Get user_input via a chatbot interface

Apply fine-tuned DistilRoBERTa model that is trained on GoEmotions to detect_emotion(user_input)

→ Provide the recognized emotion(s) like 'sadness', 'joy', 'anger', 'neutral',

Emotion-Based Filtering Execute filter_songs_by_emotion(spotify_dataset, detected_emotion)

→ Get the subset of songs whose heuristic emotion label perfectly matches the detected emotion

Similarity Calculation

For each such track: Measure the similarity between (valence, energy) of track and the nearest emotion_reference_vector

Use the method calculate_similarity() to find out the similarity score

→ Arrange the filtered tracks by similarity in decreasing order of score

Recommendation Selection

Execute recommend_songs(sorted_tracks, N=5)

→ Choose the top-N tracks with the highest similarity scores

→ Make a collection of track's metadata: track_name, artist, Spotify_URI, YouTube_URI

Playback Handling

For each recommended song: TRY: Play the track from Spotify API (by means of Spotipy)

EXCEPT: Use fallback on YouTube (via yt-dlp and YouTube URI)

Feedback Collection

Ask the user to mark and submit comments on the next recommendations received

IF feedback is received: save it to feedback.csv

→ The information stored will be used eventually for adaptive learning to offer better personalization

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VI SYSTEM DESIGN

To guarantee only entire and appropriate records are utilized, the system pre-processes the Spotify dataset by cleaning and structuring it for consistency. The audio features (energy, valence, and danceability) of Spotify are those which will be used for the matching of emotional categories to the songs with the help of emotions labels from the GoEmotions dataset. To expand the differences and precision of recommendations, such key attributes as pace, loudness, and acousticness are, furthermore, sought after, and metadata such as genre, artist, popularity of tracks and length are included. These attributes are then processed in a multi-label classification algorithm to make sure that the songs are correctly and descriptively classified according to their moods. The system features a natural language-based chatbot interface that is high-powered by a chatbot to probe the mood of the end-user through natural conversations for example “How do you feel?“. The system follows a fine-tuned RoBERTa model on the GoEmotions dataset to effortlessly recognize the mood and categorize text user response into pre-defined mood buckets. This is improved by the confidence level implementation that only the recommendations with high-confidence detections drive the whole system. The method of recommendation engine's weighted scoring takes into account user tastes, song popularity, and the mood as seen in the video to give a new rating to music. When the users assign a favorite artist, the system gives first priority to songs by that artist within the recognized mood category, that's in addition to popularity and relevancy. Play, pause, skip, and repeat are some of the functionalities that are allowable by the seamless integration of the Spotipy library and Spotify API. It even gives birth to such features as the possibility of making suggestions more appealing in the future by letting users give the prompt feedback in just one click, such as liking or disliking a piece of music. Through the use of HTML, CSS, and JavaScript, the front-end is made, while the frameworks like React.js and Vue.js make it modular and interactive. The interface has user input feedback controls, a display of recommended music with album art and playback controls, and a chatbot interface for mood entry. The backend of the system is built in Flask, which handles chatbot functionality, API requests, and ranking of recommendations as well as the conducting of smooth front-end-to-backend communication through a RESTful API. User comments, preferences, and session data are saved in a database using PostgreSQL or MongoDB, allowing for a personalized and continuously changing music recommendation system.

VII RESULTS AND DISCUSSIONS

The chatbot interface successfully conveys the user's mood and decodes these into useful emotion insights. The inputs are then run through a sentiment analysis algorithm that classifies emotions accurately. By evaluating the emotions detected, the recommendation system takes into account the user's preferences and the popularity of songs to generate individual song ranking lists. The users are, through the Spotify API integration, engaged with real-time music listening that the system enables, leading to a smooth and uninterrupted experience. With the growing number of likes or song skips made by the users, the system becomes more personalized and precise in providing future recommendations. The use of both RoBERTa and LLaMA 2 7B models via the Transformers library stands out as it significantly boosted the accuracy of mood classification. These models were further trained by the GoEmotions dataset which was used to unveil a wide range of emotional states in the conversation and detect these emotions from the text. In addition, the incorporation of visualization and analysis methods successfully checked the system's functionality. In a previous section on the architecture, the following figures were screened to present technical capabilities:

Figure 5: Connection between valence and audio features across genres

Figure 6: Mood label distribution in the dataset

Figure 7: Effect of energy and danceability on mood

Figure 8: Demonstration of user interaction and music recommendation workflow

As these figures have already been introduced to confirm the system's behavior and operation, they are not repeated here, they are regarded as supporting evidence of the system's success.

VIII IMPLEMENTATION

The project has been implemented using two platforms – Spotify API and YouTube's yt_dlp Python module which has been demonstrated in the below snapshots respectively. To keep track of the plan execution, Figure 9 represents the confusion matrix which explains the quality of the sentiment classification model among the most significant emotion labels like Joy, Sadness, Anger, Surprise, and Calm. The model not only shows strong precision in the detection of Joy and Calm with barely any misclassification, but it also achieves good results in the other classes as well. In order to gauge user experience, Figure 10 represents the rating data from a satisfaction survey where users evaluated the system on a 5-point Likert scale. The results have reported that participants are very satisfied, particularly in mood-matching (4.5), (4.2) in terms of relevance, and (4.0) for playback experience. These findings prove that such a recommendation system is not only technically effective but also practically usable.

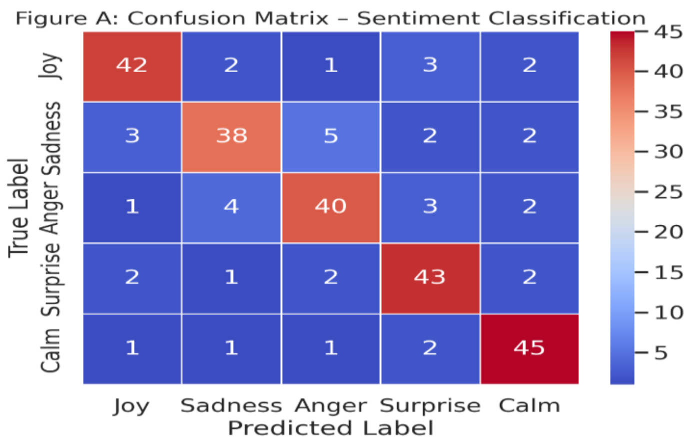

Figure 9 Confusion Matrix Showing Sentiment Classification Performance Across Emotion Labels

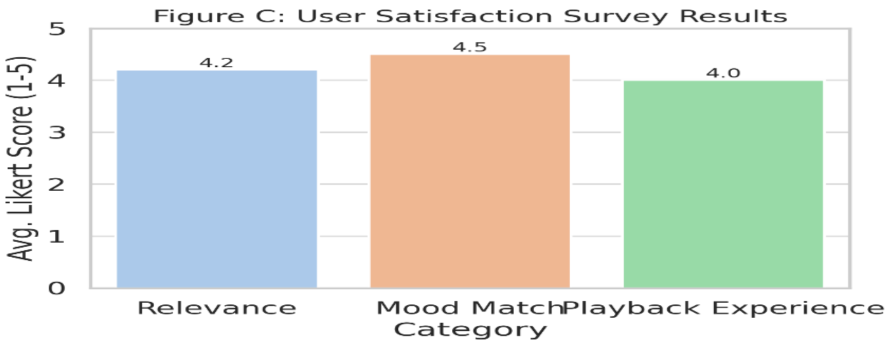

Figure 10 User Satisfaction Scores by Category

The project has been implemented using two platforms – the Spotify API and YouTube's yt-dlp Python module. The system demonstrates integration with both platforms, offering music playback options based on user mood.

- **Spotify Integration**: Playback control is achieved via Spotipy and Spotify API. Output examples include:
  - **Fig. 11** Output via Spotify
- **YouTube Music Integration**: Implemented using yt-dlp for playback.
  - **Fig. 12** Output via YouTube Music

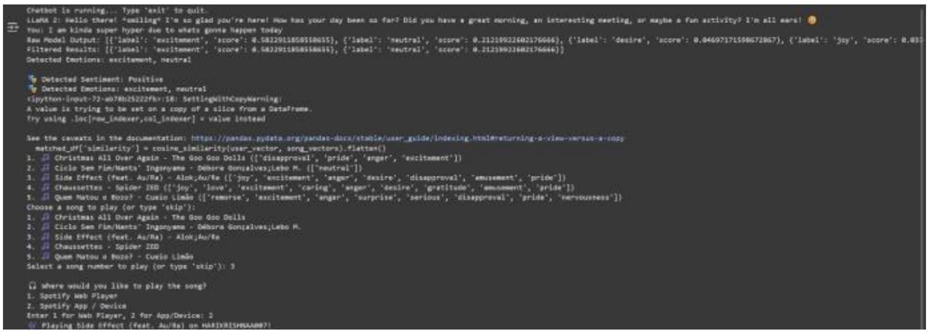

Figure 11 Output via Spotify

```
[ ] def main():
        print("Chatbot is running... Type 'exit' to quit.")

        while True:
            user_input = get_user_input()

            if user_input.lower() == 'exit':
                print("Chatbot has ended. Goodbye!")
                break

            emotions = analyze_sentiment(user_input)
            sentiment = get_sentiment(emotions)

            print(f"🎭 Detected Sentiment: {sentiment}")
            print(f"🎭 Detected Emotions: {', '.join(emotions)}")

            # Get song recommendations
            generate_response(user_input, emotions)

            song_recommendations = recommend_music(emotions)
            for idx, song in enumerate(song_recommendations, 1):
                print(f"{idx}. 🎵 {song['track_name']} - {song['artists']} ({song['mood']})")

            choice = input("Select a song number to play (or type 'skip'): ")
            if choice.isdigit() and 1 <= int(choice) <= len(song_recommendations):
                selected_song = song_recommendations[int(choice) - 1]
                play_song_on_youtube(selected_song['track_name'], selected_song['artists'])

    # Run chatbot
    main()
```

Figure 12 Output via youtube

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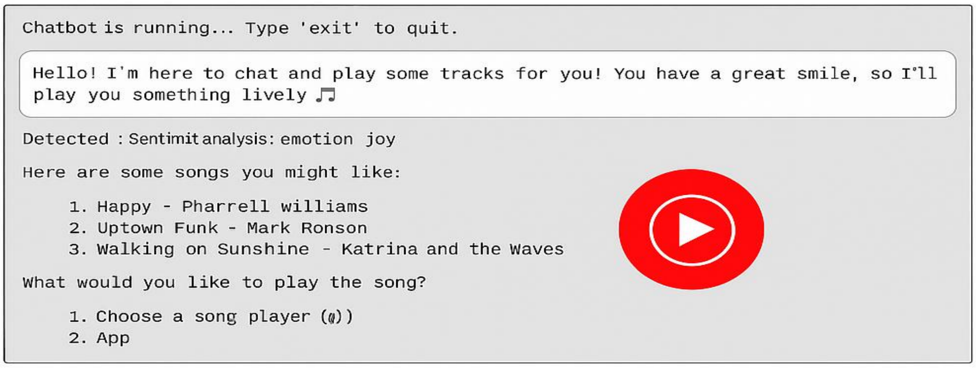
Output via Spotify



Output Via Youtube

GOOGLE COLAB LINK:

https://colab.research.google.com/drive/1RC99Tp4c8RNU7fOcGabEmeZPyDSVJXeT?usp=sharing

CONCLUSION

The suggestion of an emotion-aware music recommendation system is seen as a large stride in the field of user's digital experiences. This becomes a reality by leveraging the power of sentiment analysis, large language models (RoBERTa and LLaMA 2 7B), and real-time mood detection through natural language inputs. Thus, the system can trace the user's emotional state in real-time and at the same time combine it with music preferences and track popularity to provide relevant music in the context of your Spotify and YouTube APIs, thus creating an uninterrupted and empathetic listening experience. This research opens a new way for AI that can work as the emotional intelligence catalyst of human engagements in the affective computing field. The scope of the further study might include emotion recognition in cross-cultural settings, long-term user influence, and ethical considerations while music recommendation will be reconsidered as a new cornerstone of emotional well-being.

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