Application of Hybrid Filtering Strategies in Music Recommendation System

Surekha Lanka

Head, IT Department, Stamford International University, Bangkok, Thailand

E-mail: surekha.lanka@gmail.com

Abstract

Everyone has their own distinct musical preferences; it's safe to assume that each music will find an appreciative audience. It's important to note that there isn't a single human society that has ever survived without music. There are two major gains from this study. Initially, a multi-strategy approach is taken to develop hybrid recommendation algorithms that give more accuracy than the existing algorithms. Also this hybrid algorithm is used to find new music in real time. This allows the algorithm to make an educated guess as to which musician and song best suit the user. As a second step, a general context-aware and emotion-based customized music framework is offered to facilitate the quick growth of context-aware music recommendation systems and to shed light on the whole recommendation procedure. Multiple methods exist for responding to requests, and a general framework is required for both collecting these methods and interpreting them within the context of the proposed framework. The kind of recommendation algorithm used is decided by the format of the input.

Keywords: Music recommender systems, hybrid approach, neural network, emotion-aware, context-awareness.

1. Introduction

The Internet has emerged as the go-to place to find any kind of multimedia content, whether it is a video, an idea, a book, a piece of music, or anything else. Listening to music is a common pastime because people value music highly and see it as an integral part of their life. The challenge, however, is now in how to handle and catalog the millions of songs that have been created. It is essential for a good Music Recommendation System (MRS) to be able to automatically recognize preferences and create playlists in accordance with those findings. The suggested technique uses musical similarities to identify instances of possible plagiarism. The plagiarism detection algorithm reads the input and looks for a musical

passage that sounds similar to the one in the query, which indicates that the query includes copied music. At the same time, the rise of recommendation systems presents a great chance for the sector to attract a larger audience with a shared interest in musical content. The greatest music-recommendation systems use KNN or Machine Learning to create predictions based on the listener's individual preferences [1-6].

There isn't a single human society that has lived without music, despite the fact that the music business may prefer some genres of music more than others. Everyone, whether they are professional musicians, karaoke enthusiasts, or casual listeners, may benefit much from music. There are too many songs for one person to listen to them all [7].

As the contemporary Internet has grown, tailored services have flourished, which utilize the diverse material. The purpose of recommender systems is to guide users to content that is tailored to their specific needs [8-11]. The immense volume of digital music material presents an enormous potential for song recommenders. To improve their suggestions, current music recommendation systems employ a user-item matrix that includes characteristics about users and music items, as well as context-aware data users [12, 13]. However, the recommendation of music has the ability to affect human emotions and cognition, since it serves as a kind of emotional input. Thus, academic and commercial sectors have shown interest in studying the effects of music suggestions on human emotions.

Mood prediction makes it simple to provide personalized music recommendations to users. Mood may be anticipated in a number of ways, including lyric analysis, face expression recognition, and so on. Here, the similarity score and suggested music have been determined depending on the predicted mood based on the lyrics.

Systems that propose music might be seen as double-edged swords. They provide value for both the recipient and the service provider. They reduce the user's workload by narrowing down the available options and keeping the user interested via the discovery of interesting music in the form of suggestions. They provide the opportunity to listen to and learn about new kinds of music that the user may not have known that it existed before. Because it's a song suggestion, there's never any dull moments.

2. Literature Survey

Quadrana et al., (2018) provided a comprehensive review of sequence-aware recommender systems. It was a very up-to-date study, although the writers don't zero down

on the musical field. Automatic music playlist production is a vital job in MRS research, since it involves creating a meaningful sequence of musical songs (APG). Less attention was paid to content-based tactics [14].

Previous researchers Bonnin and Jannach [2014] analyzed APG in a survey. This examination looks at the fundamentals and agree that APG is a significant barrier to entry for content-based MRS. It detailed the present survey on how content characteristics may be included comprehensive and up-to-date evaluation. Unfortunately, the importance of music suggestions is little in that poll [15].

An overview of Content-Based Music Information Retrieval was provided by Murthy and Koolagudi [2018]. The authors examined the primary tasks associated with Music Information Retrieval (MIR), such as identifying artists, classifying musical genres, and recognizing emotions, as well as the typical acoustic properties utilized in MIR (harmony, pitch, and rhythm). Despite the importance of issues and duties related to MRS, the writers focused primarily on content-based music aspects [16].

Last but not least, Deldjoo et al., (2020) provided a comprehensive review of RS applications that make use of audio, video, text, and/or a mix of these types of media. Multimedia query servers are the focus of a subset of that survey. However, the study doesn't provide a comprehensive examination at the many forms, functions, and significance of content in MRS beyond discussing a small number of works [17].

There has been a lot of development in the area of emotionally-aware music suggestions, but there are still some issues with the current models and approaches. To begin, current research represents music emotions, with examples being Park and Polignano et al., [18,19] who used the six Ekman fundamental emotions. Though the six fundamental emotions were widely recognized, research has shown that there are many more kinds of emotions, and that continual modeling of emotions is preferable.

Shen et al., [20] noted that the recommendation is related to be a proxy for the user's emotional state or musical preference at discrete moments in time. Emotions are responsible for a time-variant, but short-term choice [21]. Consequently, there is a requirement for ongoing emotion state identification throughout time; even though the recommender should create suggestions every time, the user accesses the system. And third, it's been shown that events, especially large-scale social events, have an impact on people's emotions [22], but this data isn't being included into the present depictions of thought.

In this research, a deep neural network-based technique has been offered for recommending music that takes into account the listener's mood and surrounding environment. This study focuses on primary problems like continually representing music's emotional states, creating recommendation activity, etc. It has developed a music emotion representation model [23] that recommends emotion through valence-arousal model. This approach seems to be able to provide more effective emotional music suggestions, as seen by the findings. Emotions in music and users' preferences for music emotions during specific emotional states are presented. The result is a wider range of feelings covered by music suggestions.

3. Methodology

Web technology has advanced to the point where people have access to an unparalleled quantity of music online for a set cost or for free. Users of streaming services have access to ever-expanding music libraries, but this makes it more challenging for them to discover fresh music. When there are ambiguities or numerous versions of the same item, finding a certain piece of music might be like hunting for a needle in a haystack.

3.1 Context-based Information Retrieval

A context-based information retrieval model employs user ratings for music discovery and recommendation [26], as opposed to acoustic characteristics in a content-based model and ratings in collaborative filtering. Websites like Facebook 10, YouTube 11, and Twitter 12 have proliferated with the rise of social media because of the wealth of information they make available about people [27]. Therefore, issues such as artist likeness, genre classification, emotion detection, semantic space, and others are supported by context-based information retrieval, which use web/document mining algorithms to filter out relevant information. Furthermore, a number of studies have claimed that social information utilization has been more successful than content-based models. However, the same issues that plague collaborative filtering also ensure that popular music will always outperform the long tail in terms of public opinion [28]. Eventually, a popularity bias issue will arise when high-quality music receives high-quality reviews.

3.2 Emotion-based Model

When used to express oneself, music is universally greeted with warmth. Music is rich in substance and expression, therefore traditional methods of retrieving musical

information are insufficient. The study of music's emotional impact has become the dominant paradigm in the realm of music discovery and recommendation. Using the basic emotion model (2D valence-arousal) discovered by psychologists, a commercial online service called "Musicovery" may recommend songs based on the user's emotional state. Users may plot their anticipated feelings of valence (positive or negative) and arousal (how excited or tensed they are) in a two-dimensional space (how exciting or calming).

There are a variety of audio cue patterns linked with feeling distinct emotions, much as the content-based paradigm suggests. Numerous extra perceptual variables, such as energy, rhythm, temporal, spectral, and harmonic harmony, have been exploited for emotion identification.

3.3 Hybrid Model Information Retrieval

The goal of a hybrid model is to improve the performance of the combined models. Burke listed a number of techniques for creating a hybrid model, including weighted, switching, mixed, feature combination, and cascade. A well-designed hybrid model would do better than using each individual component alone, since it would be able to reap the advantages of both while avoiding either's inherent weaknesses.

The goal of this method is to train it to determine whether or not a user will find value in a given item, such as whether they will play a certain music or not. Ratings may be used for this purpose. Explicit and implicit methods exist for gathering user feedback. The K-Nearest Neighbors Algorithm is used.

3.3.1 Explanatory Score

This implies a rating will be directly requested from the user. To what extent a user enjoys music is revealed here more than by any other means. The definition of "explicit" in the dictionary is "clear and detailed." As the name implies, precise feedback data is a hard number that a customer has assigned to a product. Customers' ratings of movies on Netflix and goods on Amazon are two instances of direct feedback.

3.3.2 Implicative Rating Scale

Factors such as how long and how often a user listened to music is considered to infer whether or not they like it. An example of an implicit rating is the user's attention, which may be gauged by whether or not they listen. How long did the user spend reading content related

to music, if any? Implicit ratings are preferred since they require no extra effort on the part of the rater other than taking a quick glance at the object in question [29].

3.3.3 User-based approach

The term "user-based approach" (or user-item) describes the method that locates the groups of people who have similar tastes and preferences using the data from users' listening habits. As an alternative, it may take into account the user's past preferences and likes to suggest further music that they may appreciate; this is known as the item-based method (or item-item).

4.   Results and Discussion

Most users clearly started out giving poor ratings to the suggested songs when they were recommended without the mood option; as users started selecting their mood, they started providing higher ratings, indicating that they approved the suggestions. This research article contains three student named Tesfalem, Luwan and Micheal for this recommendation test. The average recommendation rating was 4.5 (without the mood option) and 4.6 (with the mood selection), indicating that the majority of the test participants enjoyed the music that were suggested to them through various rating by various examiners which is contained in table 1.

Table 1. Recommendation Testing Sample

| Listener ID	Methods	No. of Recommendation Without / With Mood	Average Recommendation without Mood (for rating)					Average Recommendation with Mood (for rating)					Avg. Rating Without Mood	Avg. Rating With Mood	Overall rating
Tesfalem	Context Based	5	2.8	3.2	3.1	3.8	4	2.9	3.2	3.2	3	4.1	3.38	3.28	3.33
	Information retrieval	5	3	3	3.1	3.5	3.6	3.7	3.8	3.3	3.2	4.2	3.24	3.64	3.44
	Hybrid Filtering	5	4	4.1	4.5	4.2	4.5	4.5	4.7	4.8	4.4	4.5	4.26	4.58	4.42
Luwam	Context Based	5	2.5	2.6	2.9	3.4	3.1	2.1	3.5	3.7	3.8	4.4	2.9	3.5	3.2
	Information retrieval	5	3	3.5	3.6	3.7	3.8	3.8	4.2	4.6	3.9	4.8	3.52	4.26	3.89
	Hybrid Filtering	5	4	4.4	4.7	4.6	4.8	4.5.	4.5	4.4	4.7	4.8	4.5	4.58	4.54
Micheal	Context Based	5	3	3.5	3.6	3.7	3.2	3	3.5	3.4	3.3	3.2	3.4	3.28	3.34
	Information retrieval	5	2.9	3	3.2	3.4	4	3.5	3.6	3.9	4.5	4.8	3.3	4.06	3.68
	Hybrid Filtering	5	4	4.3	4.2	4.7	4.8	4.5	4.8	4.9	4.9	4.8	4.4	4.78	4.59

The data have been evaluated and some encouraging conclusions have been made. It has already been established that CAP Music takes into account the user's musical preferences and other information when making recommendations; consequently, it is hoped

that the system's recommendations will become more precise and the user's level of satisfaction with them will rise as time goes on. The chart below provides supporting evidence for this theory by demonstrating that participants' average rating for each song grew as they made more frequent use of the suggestion request. Figure 1a, b and c show the performance measures chart of 3 participants.
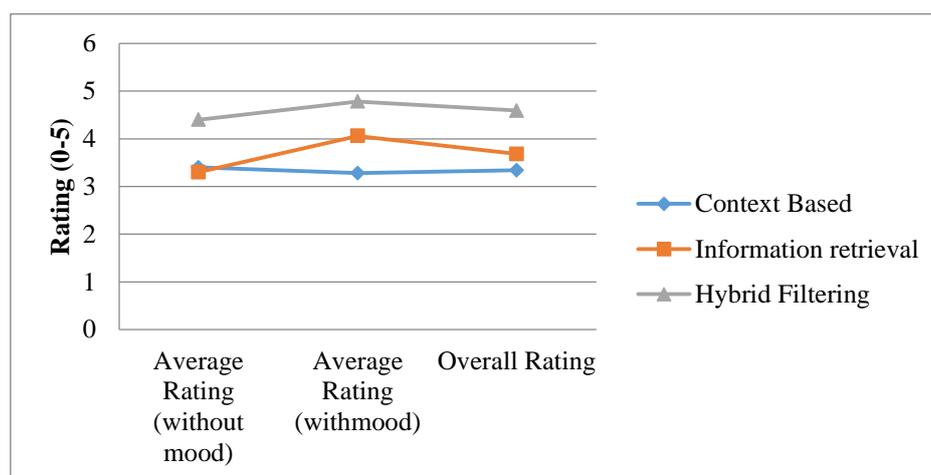
It is the job of the playlist function to create a musical set list according to the user's tastes. This feature allows the user to create a personalized playlist. The best way for users to build their own playlists is to actively search for music and add them.
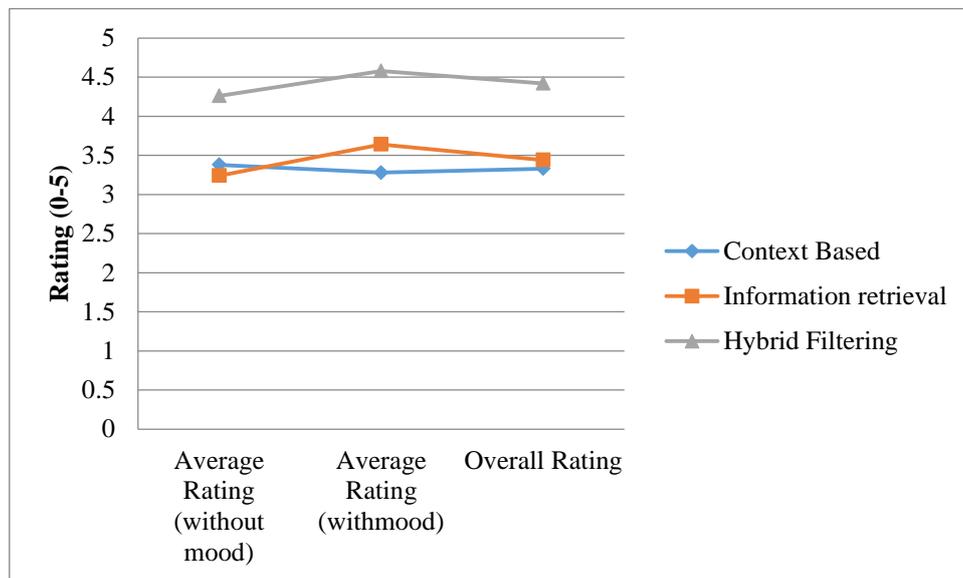
Figure 1a. Performance Measures Chart of Tesfalem
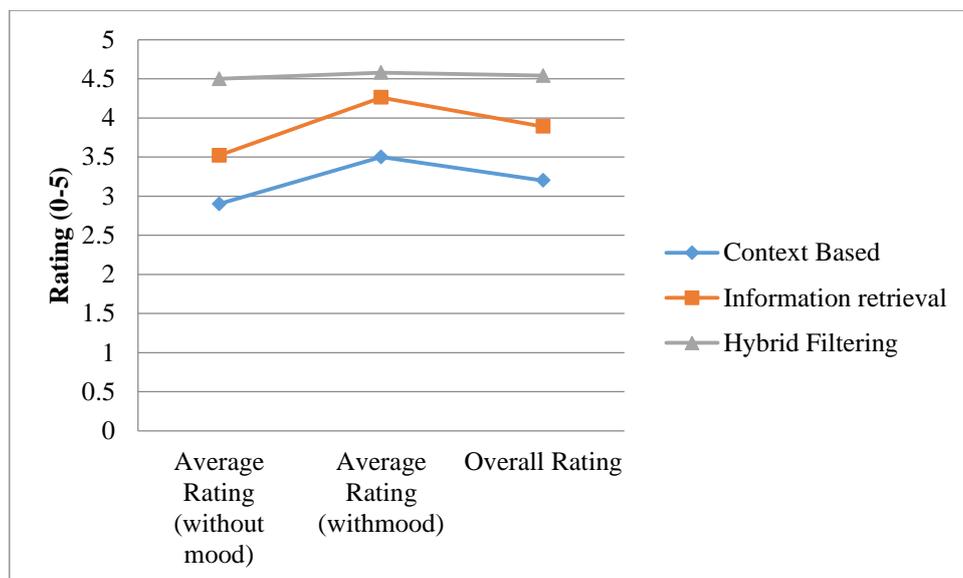
Figure 1b. Performance Measures Chart of Luwam

Figure 1c. Performance Measures Chart of Michael

Playlists may have custom names and descriptions written by the user. After the user has listened to too many songs through best recommendation, it is noted in the performance measures chart.

5. Conclusion

This article proposes an original approach to fixing the Cold-Start issue in music recommendation systems. This study's suggested solution may give users, both new and old, with a simple method for learning about and listening to new music, as well as tailored recommendations, i.e., suggestions of songs that are most likely to appeal to the user. A general framework called the Context-Aware Personalised Music system has been built to aid in the creation of similar context-aware music recommendation systems. The term "data collection" refers to the steps taken to gather pertinent information about the user's context from various data sources with the purpose of creating a dynamic user profile. More research has to be done to fully understand how a user's unique traits affect how they interpret and respond to ratings for suggested songs. The nearly 1000 Tigrinya songs (Eritrea and Ethiopia Country peoples are listening) are used in this study, which is hardly a representative sample. A more extensive investigation with a bigger sample of the music is unlikely, but the first results seem promising. Mood is lifted, tension is reduced, and memory is jogged for the accompanying movie or music video, and so on, as shown in studies of psychology. The primary advantages of music listening have been noted in empirical trials in sports, including increased work production, improved performance, detachment from negative emotions, etc. Athletes, for instance, go toward music that is more traditional in speed and intensity rather

than thoughtful and sophisticated. Psychologists' discovery that consumers' musical tastes reflect their individual traits is a major finding. It's also important to note that quick, energetic music has a stimulating impact, while calm, soothing music has a sedative one. All of these examples show how a music suggestion may be a helpful and soothing resource in a variety of situations. The literature based on these empirical findings is, to the best of our knowledge, sparse.

References

[1] L. Wang, "Design and implementation of hybrid music recommendation system based on music gene," in Proceedings of the 2020 International Conference on Computers, Information Processing and Advanced Education, pp. 121–124, ACM, Ottawa, Canada, October 2020.

[2] D. Hou, Z. Zhao, and S. Hu, "Multi-label learning with visual semantic embedded knowledge graph for diagnosis of radiology imaging," IEEE Access, vol. 9, Article ID 15730, 2021.

[3] M. Alam, A. Gangemi, V. Presutti, and D. R. Recuperp, "Semantic role labeling for knowledge graph extraction from text," Progress in Artificial Intelligence, vol. 10, no. 3, pp. 309–320, 2021.

[4] J. Wang, Y. Yang, T. Wang, R. S. Sherratt, and J. Zhang, "Big data service architecture: A survey," Journal of Internet Technology, vol. 21, no. 2, pp. 393–405, 2020.

[5] P. Nitu, J. Coelho, and P. Madiraju, "Improvising personalized travel recommendation system with recency effects," Big Data Mining and Analytics, vol. 4, no. 3, pp. 139–154, 2021.

[6] X. Wen, "Using deep learning approach and IoT architecture to build the intelligent music recommendation system," Soft Computing, vol. 25, no. 4, pp. 3087–3096, 2021.

[7] D. Paul and S. Kundu, "A survey of music recommendation systems with a proposed music recommendation system," Advances in Intelligent Systems and Computing, Springer, Singapore, pp. 279–285, 2020.

[8] M. Pulis and J. Bajada, "Siamese neural networks for content based cold-start music recommendation," in Proceedings of the Fifteenth ACM Conference on Recommender Systems, pp. 719–723, ACM, Amsterdam, ,e Netherlands, October 2021.

[9] D. Wu, "Music personalized recommendation system based on hybrid filtration," in Proceedings of the 2019 International Conference on Intelligent Transportation, Big Data & Smart City (ICITBS), pp. 430–433, IEEE, Changsha, China, January 2019.

[10] M. Wada, T. Asada, Y. Yoshitomi, M. Tabuse, Music recommendation system using peripheral skin temperature as input data, Proceedings of the Human Interface Symposium, Human Interface Society, Kyoto, Japan, 2019, pp. 736–739

[11] Su, J.H.; Chang,W.Y.; Tseng, V.S. Effective social content-based collaborative filtering for music recommendation. Intell. Data Anal. 2017, 21, S195–S216.

[12] Xiang, K.; Xu, C.; Wang, J. Understanding the relationship between tourists' consumption behavior and their consumption substitution willingness under unusual environment. Psychol. Res. Behav. Manag. 2021, 14, 483–500.

[13] Shuai Zhang, Lina Yao, Aixin Sun, and Yi Tay. 2019. Deep Learning Based Recommender System: A Survey and New Perspectives. ACM Comput. Surv. 52, 1 (2019), 5:1–5:38.

[14] Massimo Quadrana, Paolo Cremonesi, and Dietmar Jannach. 2018. Sequence-Aware Recommender Systems. ACM Comput. Surv. 51, 4 (2018), 66:1–66:36.

[15] Geoffray Bonnin and Dietmar Jannach. 2014. Automated Generation of Music Playlists: Survey and Experiments. ACM Comput. Surv. 47, 2, Article 26 (November 2014), 26:1–26:35 pages.

[16] Y. V. Srinivasa Murthy and Shashidhar G. Koolagudi. 2018. Content-Based Music Information Retrieval (CB-MIR) and Its Applications Toward the Music Industry: A Review. 51, 3 (June 2018), 45:1–45:46.

[17] Yashar Deldjoo, Markus Schedl, Paolo Cremonesi, and Gabriella Pasi. 2020. Recommender Systems Leveraging Multimedia Content. ACM Comput. Surv. 53, 5 (2020), 106:1–106:38.

[18] Park, T.; Jeong, O.R. Social network based music recommendation system. J. Internet Comput. Serv. 2015, 16, 133–141.

[19] Polignano, M.; Narducci, F.; de Gemmis, M.; Semeraro, G. Towards Emotion-aware Recommender Systems: an Affective Coherence Model based on Emotion-driven Behaviors. Expert Syst. Appl. 2021, 170, 114382.

[20] Shen, T.; Jia, J.; Li, Y.; Ma, Y.; Bu, Y.;Wang, H.; Chen, B.; Chua, T.S.; Hall,W. Peia: Personality and emotion integrated attentive model for music recommendation on social media platforms. In Proceedings of the AAAI Conference on Artificial Intelligence, New York, NY, USA, 7–12 February 2020; Volume 34, pp. 206–213.

[21] Cowen, A.S.; Keltner, D. Self-report captures 27 distinct categories of emotion bridged by continuous gradients. Proc. Natl. Acad. Sci. USA 2017, 114, E7900–E7909.

[22] Gunes, H.; Schuller, B.; Pantic, M.; Cowie, R. Emotion representation, analysis and synthesis in continuous space: A survey. In Proceedings of the Face and Gesture 2011, Santa Barbara, CA, USA, 21–25 March 2011; pp. 827–834.

[23] White, C.; Ratcliff, R.; Vasey, M.; McKoon, G. Dysphoria and memory for emotional material: A diffusion-model analysis. Cogn. Emot. 2009, 23, 181–205.

[24] Corthaut, N.; Govaerts, S.; Verbert, K.; Duval, E. Connecting the Dots: Music Metadata Generation, Schemas and Applications. In Proceedings of the 9th International Conference on Music Information, Philadelphia, PA, USA, 14–18 September 2008; pp. 249–254.

[25] Tallapally, D.; Sreepada, R.S.; Patra, B.K.; Babu, K.S. User preference learning in multi-criteria recommendations using stacked auto encoders. In Proceedings of the 12th ACM Conference on Recommender Systems, Vancouver, BC, Canada, 2 October 2018; pp. 475–479.

[26] Zarzour, H.; Al-Sharif, Z.A.; Jararweh, Y. RecDNNing: a recommender system using deep neural network with user and item embeddings. In Proceedings of the 2019 10th International Conference on Information and Communication Systems (ICICS), Irbid, Jordan, 11–13 June 2019; pp. 99–103.

[27] Liu, Z.; Guo, S.;Wang, L.; Du, B.; Pang, S. A multi-objective service composition recommendation method for individualized customer: hybrid MPA-GSO-DNN model. Comput. Ind. Eng. 2019, 128, 122–134.

[28] Xu, C.; Ding, A.S.; Zhao, K. A novel POI recommendation method based on trust relationship and spatial-temporal factors. Electron. Commer. Res. Appl. 2021, 48, 101060.

[29] Ayata, D.; Yaslan, Y.; Kamasak, M.E. Emotion based music recommendation system using wearable physiological sensors. IEEE Trans. Consum. Electron. 2018, 64, 196–203.

Author's biography

Surekha Lanka is currently working as a Head in the IT Department at Stamford International University, Bangkok, Thailand. Her area of research includes artificial intelligence, networks, and cloud computing.