Research Article

Design of Deep Learning Network Model for Personalized Music Emotional Recommendation

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Music is a way for people to express their inner thoughts, and it is an art form to express their feelings and send their emotions. In modern society, people are more and more inclined to listen to music as a form of leisure and entertainment, and different types of music hold different feelings of listeners and trigger different emotional resonances. In this study, we propose an algorithmic model based on the two-layer attention mechanism, which includes the processing of textual convolutional neural network for music name and music label text data and the processing of two-layer attention mechanism, where the two-layer attention mechanism refers to the first layer of attention mechanism that learns the user’s preference for each music feature from the feature level and the second layer of attention mechanism that learns the user’s preference for each piece of music in the history listening list from the item level. The experiments show that the NDCG value of this method is improved by about 0.08, and the overall quality of the recommendation list is improved, which indicates that the user interest model constructed based on the fusion of various things has good characterization ability and is helpful to alleviate data sparsity.

1. Introduction

Music is a way for people to express their inner thoughts, and it is an art form to express their feelings and send their emotions. In modern society, people are more and more inclined to listen to music as a form of leisure and entertainment, and different types of music hold different feelings of listeners and trigger different emotional resonances. Some studies have shown that people listen to music more frequently in their daily social life compared to the behaviors of reading books and watching fixed movies that require a fee [1–3]. At the same time, also because music generally lasts for a short period of time, and listening has a coherent nature. Users are more likely to finish listening to multiple pieces of music at once. In recent years, digital multimedia technology has enabled the rapid development of both online and mobile music. In earlier years, music existed mainly in the form of CD albums, but in recent years it is gradually changing to digital storage, and albums are mostly becoming digitally distributed, the size of music databases is expanding rapidly, and the number of users of music websites and music applications is growing rapidly [4].

The application of a recommendation system in a certain field needs two bases: first, the data volume of the field is so large that users cannot select their favorite items by understanding and contacting all items; second, the user needs cannot be described exactly. Those that meet these two conditions are mainly concentrated in the pan-entertainment field, such as e-commerce, music, video, etc. The music field happens to have the above two characteristics [5]. First, the current library of each mainstream music platform contains at least tens of millions of different types of music, and the library is updated very fast, so it is unrealistic for users to listen to all the music and then choose their favorite music; second, the demand for listening to music is not clear, and usually in a certain context, users may like a certain type of music, but there is no specific demand for a certain music item that Fuzzy recommendations can be made [6]. For users, because listening to music online is generally free and the duration of each piece of music is short, the time cost and economic cost are lower compared to other forms of leisure.
and entertainment that require a fee, such as books and movies. Online music websites can meet users’ personalized listening needs through music recommendation systems, and music recommendation systems can also help improve service levels and user stickiness. Therefore, the research on personalized music recommendation systems has great practical value [7].

The effect of applying personalized music recommendation algorithms on domestic and international music websites is remarkable, and personalized music recommendations that meet users’ emotional needs have helped music websites greatly increase the number of users and the length of time they use. The powerful role of personalized music recommendations cannot be underestimated [8].

Although a variety of music recommendation methods have emerged, there are still some common problems that have not been solved in the field of music recommendation, such as the real-time problem. Most of the existing recommendation methods only consider the basic information of users and combine with the overall historical behavior of users to achieve recommendations, but they do not divide the historical behavior of users into long-term and short-term, and short-term interest preferences are closer to the real-time needs of users. Therefore, the existing algorithms are less capable of making recommendations based on users’ real-time emotions and state of mind, causing the problem of real-time recommendations [9].

2. Related Work

2.1. Music Recommendation. Initially, some attribute features of the music itself were analyzed to generate recommendation results, such as analyzing the acoustic data of the music’s spectrum, short-time over-zero rate, etc. This method requires professional knowledge of signal processing and acoustics, and the complexity of the algorithm is also high. [10] Research was conducted on content-based recommendation methods to realize a personalized music recommendation system, which obtains information such as the rhythm and melody of the user’s preference. The user’s preference is obtained through the rhythm and melody of the user’s preferred music, the music is classified according to the melody classifier, and then the classified music with a similar rhythm is recommended to the user. [11] The lyrics information was transformed and downscaled using the vector space model, the frequency cepstrum coefficient features of music was extracted, multimodal fusion with lyrics information as a complement to collaborative filtering recommendation was performed, and a multimodal-based music recommendation system was realized. [12] A dynamic music similarity metric strategy to recommend music through the tags of music using content features, as well as user access patterns was proposed. [13] A music recommendation model based on MFCC and GMM, combining frequency central coefficients and Gaussian mixture model to first extract the speech features of music was proposed, and then the GMM algorithm to generate templates for music was used. This method can also analyze the user rating and review data of music, and since these data are generated by users, the recommendation results can be personalized [14]. The used text input is analyzed, including the user’s personal information, and descriptive information about the music, and the user’s own data is combined with content-based recommendations to recommend music that matches the user [7]. Music items and predicted users considering the Gaussian distribution of user ratings, in addition to also improving the performance of recommendations using audio features are grouped.

Tag-based music recommendation mainly refers to tags established for different types of music, such as music genres, music styles, etc. Tags can be generated either by experts or by users, tags make music libraries that can be structurally represented and can help to complete the recommendation of a certain type of music, but the generation of tags costs more and is also prone to tag imbalance [15] based on the social tags of music, which are first mapped into three semantic spaces of genre, sentiment, and contextual information, respectively, to calculate the user and the music. The similarity of users and music is calculated, and then the similarity of the three spaces is fused by different methods to recommend songs to users. [16] The user history and download records, combined with LDA method are analyzed [17], and a music recommendation model based on LDA-MURE is proposed. [18] A recommendation method combining LDA is proposed, which achieved better results.

2.2. Attentional Mechanisms. Attention mechanism is a mechanism used to improve the effectiveness of Encoder + Decoder model, which is summarized based on the habitual pattern of human observation. It was first proposed by Google Deep-Mind team in 2014 to solve the image processing problem, and the error rate of image classification was significantly reduced by introducing the attention mechanism in the recurrent neural network, and it was verified in the MNIST classification task [19], which reduced the error rate by 4%. This proved the effectiveness of adding the attention mechanism to image processing. After that, the attention mechanism also began to be applied to the field of machine translation, [12] was the first to apply the attention mechanism in the field of machine translation, used the attention mechanism to solve the problem of aligning source languages of different lengths in machine translation, and performed machine translation while aligning the source languages, which led to a significant improvement in the performance of neural network machine translation models, demonstrating the usefulness of the attention mechanism in the field of natural language processing. The attention mechanism was introduced based on [20], and the sentence modeling was implemented using the convolutional neural network with the addition of the attention mechanism [21]. Later, the Google machine translation team fused the attention mechanism and the sequence converter network [22] to achieve better text translation, which is different from the previous combination of attention mechanism and recurrent neural network or CNN, and proved the feasibility of the fusion method of multiple attention mechanisms. Li et al. [23] designed and implemented a dynamic attention
network based on cascading attention, borrowing the idea of alternating cooperative attention mechanisms, and the iterative process enabled the model to recover from the initial local maxima corresponding to wrong answers, achieving good results in a machine reading quiz task.

2.3. Music Recommendation Algorithm Based on a Two-Layer Attention Mechanism. To address the problems of sparse data and poor recommendation real-time of previous algorithms, this study combines a music recommendation system and a deep learning method and designs a music recommendation method based on a two-layer attention mechanism, which makes full use of multiple features of users and music, such as user gender, age, nationality, music name, music tag, artist, etc., as well as users’ historical music listening records by adding a two-layer [24]. The deep learning model with attention mechanism learns multiple source data and processes the input multiple data from feature-level and item-level, respectively, with the feature set and music itself as minimum processing units to obtain a nonlinear multilevel abstract feature representation, combining the learned user’s interest preference for each music feature and the user’s interest preference for each music in the historical music listening list and constructs. Finally, the output of the attention mechanism is fed into the fully connected layer to calculate the music with higher similarity and generate a personalized music recommendation list for the user to achieve the final music personalization recommendation function.

2.4. Music Text Feature Processing. In the field of machine learning, it is crucial to convert data into machine language that can be processed by computers and to represent the data effectively with features. In natural language processing problems, common approaches are Word Embedding or Distributional vectors, both of which transform the data into computationally understandable vectors or matrices. Training methods for word embedding are divided into unsupervised or weakly supervised pretraining and end-to-end supervised training. Word2vec and auto-encoder are typical representatives of unsupervised training methods, which can represent words in natural language as low-latitude distributed word vectors. Word2vec technique does not take the trained model results as the most important content, but characterizes the word vectors with the parameter matrix of the hidden layer. Each row of the word vector matrix represents a word, and the number of columns of the matrix indicates the dimensionality of the word vector, which is generally between 100 and 300. The unsupervised training process is relatively simple, and it is easy to obtain the implicit semantic information, but it is less

![Figure 1: Structure diagram of two-layer attention mechanism model.](image-url)
specific in dealing with different problems, and it needs to be adjusted by using manually labeled samples after training out the model, as shown in Table 1. The supervised training model, or end-to-end training model, is based on a deep neural network, where the natural language is input to the chin-in layer, and the semantic information is learned through multiple convolutional layers. The word embedding layer can be interpreted as a dictionary lookup, where different weights are assigned to different word vectors, adjusted by back-propagation, and finally, the trained word vectors are returned, but the algorithm is more expensive due to the complex structure [26].

| Unsupervised | Supervised |
|--------------|------------|
| word2vec and auto-encoder | Embedding layer |
| Simple process and weak pertinence | Complex structure, high accuracy and strong pertinence |

Natural language texts, such as music names and music tags, contain some deep-level features of music, especially music tags, which can be generated by both experts and users, and can be used to distinguish genres and styles of music, as well as to describe the emotion of music and users’ listening experience. If we only analyze music tags statistically, we can only get the user’s interest information to a certain extent. By combining with neural networks, we can analyze these text data to learn deeper user preference characteristics, which can help to build a more complete user interest model.

In this study, for music name and music tag text data, unsupervised word vector training Word2vec technique is used to convert them into distributed word vectors for feature extraction, and then input to text CNN for feature processing; for other user features and music features, considering that the end-to-end training model has a clear task orientation and the learned word embedding vectors are often more accurate, therefore, the end-to-end model using the neural network word embedding layer is used for feature extraction.

The parameter matrix obtained after training is the word vector matrix, which represents the music name and music label, with low-dimensional dense characteristics, and the word vector is obtained with semantic information. Then, the word vectors of music names and labels obtained by Word2vec technique are input to the text of CNN for feature extraction since the convolutional neural network has the feature of local connectivity, spatial sampling, and weight sharing. After the features of the music name and music label text are obtained in the convolutional layer, the features are further extracted and downsampled using the pooling layer spatial sampling method, which reduces the computational effort and enhances the robustness at the same time. Similar to biological neural networks, CNN also has the feature of weight sharing, which can avoid a large amount of data preprocessing work and complex data reconstruction process, and therefore has been more widely used in the field of natural language processing [7].

Therefore, in this study, text CNN is chosen to process music name and music label text.

2.4.1. Two-Tier Attention Mechanism

(1) First layer attention mechanism. After inputting the user feature set and music feature set into the word embedding layer respectively, the vectorized table of user features and music features is obtained.

The user set is represented as

\[ U = \{u_1, u_2, u_3, \ldots, u_m\}, \]  

where

\[ u_i = \sum_m u_f. \]

The user feature set is represented as

\[ u_f = \{u_f_1, u_f_2, u_f_3, \ldots, u_f_n\}. \]

The music collection is represented as

\[ M = \{m_1, m_2, m_3, \ldots, m_N\}. \]

Among them

\[ m_f = \sum_n m_f. \]

The set of musical features is denoted as

\[ m_f = \{m_{f_1}, m_{f_2}, m_{f_3}, \ldots, m_{f_n}\}. \]

Through the fully connected network, the features of each user and each piece of music are obtained \( U_f \). The attention mechanism learns the user’s preference function for music features \( M_f \), i.e., attention:

\[ a_{ij} = \tanh(w_{ij}h_{mj} + b_{ij}), \]

where \( \{h_{m_1}, h_{m_2}, \ldots, h_{m_N}\} \) is the hidden layer state value corresponding to the music feature set \( \{m_{f_1}, m_{f_2}, m_{f_3}, \ldots, m_{f_n}\} \), \( w_{ij} \) and \( b_{ij} \) are parameters obtained by model training, \( w_{ij} \) represents the weight of user \( u_i \) on the music \( m_k \) features, and \( b_{ij} \) represents the bias.

After normalization using the Softmax function:

\[ a_{ki} = \frac{\exp(\sum_{j=1}^n a_{ij})}{\sum_{j=1}^m \exp(\sum_{i=1}^n a_{ij})}. \]

The preference \( C \) of the user \( u_i \) for the features of each music is obtained by multiplying and adding the hidden layer vector \( \{h_{m_1}, h_{m_2}, \ldots, h_{m_N}\} \) of the music features and the weight coefficient points:

\[ C = \sum a_{ki}h_{m_i}. \]

The output of the first layer of attention mechanism results in different preferences of users for each music feature:
\[ U_a = H\left(C, h_m, m_f\right). \] (10)

(2) Second layer of attention mechanism. Input data: user’s preference for each music feature \( U_a = \{U_{a1}, U_{a2}, U_{a3}, \ldots\} \), user’s historical music listening list \( L_u = \{m_{u1}, m_{u2}, m_{u3}, \ldots, m_{uk}\} \). Unlike the first layer of attention mechanism, this layer of attention mechanism takes each music as the minimum operational unit and learns from the music item level to get the user’s preference for each music in the historical listening list.

The attention mechanism learns the different preferences of users for each track in the listening history list:

\[ a^k_u = \tanh(w_k m^k_u + b_k), \] (11)

where \( m^k_u \) denotes the \( k \)th track in the user’s listening history list, \( w_k \) and \( b_k \) are the model parameters to be trained, \( w_k \) denotes the bias of user \( M \) towards a particular track, and \( m^k_u \) denotes the bias amount.

Normalization using the Softmax function yields \( u_i \) preferences for music \( k \):

\[ a_k = \frac{\exp(a^k u)}{\sum_k \exp(a^k u)}, \] (12)

where \( u_i \) is the initialization weight and the final output of the second layer of the attention mechanism is a weight vector summed over the preferences of the user’s \( u_i \) historical music listening list:

\[ \phi = \sum_k m^k a_k. \] (13)

Then the weight vector output from the second layer of the attention mechanism is input to the fully connected layer, and the music vector with higher similarity is calculated and composed into a music recommendation list to realize the function of music recommendation. In the model training process, the adaptive moment estimation Adam optimization method is used. Adam algorithm is a first-order gradient optimization method for stochastic objective function, which has high computational efficiency and small memory requirement, and is suitable for attenuating the noise of the model, and the learning rate is set to 0.001 in this model.

### 3. Music Recommendation List Building

The output of the two-layer attention mechanism is the user’s interest preference vector, which characterizes the user’s recent music listening interest preference model. After obtaining this result, the next task is to generate a personalized recommendation list for the user based on the user’s interest weight vector, and this paper uses the vector cosine similarity method to calculate the similarity between the user’s interest weight vector and the music vector, and selects the Top-\( N \) music for users to generate personalized music recommendation list [14].

**Table 2: Last.fm360Kusers dataset contains data.**

|                          | Last. Fm360 users dataset |
|--------------------------|----------------------------|
| Unique users             | 35,347                     |
| Artists with MBID        | 16,642                     |
| Artists with MBIDID      | 10,373                     |
| Total lines              | 17,59,50                   |

For the user interest vector \( \phi \), calculate the similarity with the music vector \( m_j \):

\[ \text{Sim}(\phi, m) = \frac{\sum_{U,j \in M} \phi m_j}{\sqrt{\sum_i \in U, j \in M \phi^2 \sum_i \in U, j \in M m_j^2}}. \] (14)

In the above equation, \( \phi \) represents the interest weight vector of user, \( m_j \) represents the vector representation of certain music, the music with higher similarity is calculated, and the top 7 music are selected to build the recommendation list for the user.

### 4. Experiment

#### 4.1. Data Set for This Study

Last.Fm360K users dataset contains data of nearly one million music songs for free. MSD dataset has collected and organized the information of some famous music websites, mainly including Second Hand Songs dataset and Musi Xxnatch dataset. It contains comprehensive information about user characteristics and music characteristics. In this study, we use Foundation dataset, which contains basic information about users, music listening history, and various music characteristics. Since the Last.Foretaste dataset contains a large amount of data that is inconvenient to handle, some researchers have trimmed down the data contained in it and taken some of the more complete user and music information to obtain Last.Fm360Kusers dataset, which contains the following data as shown in Table 2.

The Last.fm360K users dataset has two files.

1. **Listen to the song** (user-id-timestamp-artid-artname-traid-traname.tsv).
2. **User information** (user-id-profile.tsv) The listening record file is the historical music listening records, playing time, playing times, etc. Of nearly 360,000 users, as well as information related to the music itself such as music name, artist, music ID, artist ID, etc. The user information file records all users’ basic information such as user ID, age, gender, country, and registration time.

The listening record file contains field descriptions as shown in Table 3.

The user file contains field descriptions as shown in Table 4.

Since the Last. Fr360K users dataset does not contain music tag information, we need to extract music tags from...
The Last fantastic dataset. Since MSD has set a unified track id for the integration of music from different music sites, for the songs in the Last. Fr360 Users dataset, we only need to find its music tag according to the triad and create a new music ID-music tag file according to the traid-tag method.

5. Experimental Environment

Eras is an open-source neural network library that can be used as a high-level API for Tensor flow [20], which is the most widely used framework for deep learning. Eras is modular and scalable and contains algorithms commonly used in artificial intelligence, such as support vector machines and plain Bayes, as well as deep learning models such as CNN used in this study, which are convenient to use due to their highly integrated nature, and can also be switched between CPU and GPU, making it easy for researchers to efficiently construct the neural network structures needed for different tasks, as shown in Table 5. The neural network structure required for different tasks can be efficiently constructed.

6. Results and Comparative Analysis

For the two evaluation indexes, hit-rank and normalized discount cumulative gain (NDCG), this study takes the ranking list truncation index $K = 10$. Therefore, for the test set containing 1 positive case and 99 negative cases, hit-

Figure 2: Comparison of hit-ranking values of each algorithm.
recommendation list, we designed a comparison experiment, and the results are shown in Figures 4 and 5. For the deep learning method with the attention mechanism, when the number of music in the user’s history list is greater than or equal to 15, a more complete user’s interest preference can be obtained, and the method without the attention mechanism does not achieve the maximum value in the range of 0–20 songs. The method without the attention mechanism does not achieve the maximum value in 0–20 songs, and there is still room for improvement, which indicates that more user listening information is needed to get better recommendation results. This verifies the effectiveness of adding the attention mechanism to the deep learning method, which helps to improve the accuracy of the recommendation and reduce the complexity of the calculation.

7. Conclusions

The proposed algorithm model based on the two-layer attention mechanism includes the processing of text convolutional neural networks for music name and music label text data. After obtaining the user’s interest weight vector, the vector cosine similarity method is used to calculate the music with high similarity and generate personalized recommendation lists for the users. Experiments show that the NDCG value of this method is improved by about 0.08, and the overall quality of the recommendation list is greatly improved.

Data Availability

The dataset used in this study is available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

[1] D. Izidio, A. Ferreira, and H. R. Medeiros, “An embedded automatic license plate recognition system using deep learning,” Design Automation for Embedded Systems, vol. 24, no. 7, 2020.
[2] S. Zhang, H. Liu, J. He, S. Han, and X. Du, “A deep bi-directional prediction model for live streaming recommendation,” Information Processing & Management, vol. 58, no. 2, p. 102453, 2021.
[3] G. Cai, Y. Fang, J. Wen, S. Mumtaz, Y. Song, and V. Frascolla, “Multi-carrier M-ary DCSK system with code index modulation: an efficient solution for chaotic communications,” IEEE Journal of Selected Topics in Signal Processing, vol. 13, no. 6, pp. 1375–1386, 2019.
[4] K. Merceron and A. Prouteau, “Évaluation de la cognition sociale en langue française chez l’adulte: outils disponibles et
recommendations de bonne pratique clinique,” *L’Évolution Psychiatrique*, vol. 78, no. 1, pp. 53–70, 2013.

[5] S. Nagi Alsubari, S. Deshmukh, A. Abdullah Alqarni et al., “Data analytics for the identification of fake reviews using supervised learning,” *Computers, Materials & Continua*, vol. 70, no. 2, pp. 3189–3204, 2022.

[6] D. Graupe, “Deep Learning Neural Networks (Design and Case Studies),” *FRONT MATTER*, 2016.

[7] S. A. Saeedinia, M. R. Jahed-Motlagh, A. Tafakhori, and N. Kasabov, “Design of MRI structured spiking neural networks and learning algorithms for personalized modelling, analysis, and prediction of EEG signals,” *Scientific Reports*, vol. 11, no. 1, p. 12064, 2021.

[8] W. Shenhao, M. Baichuan, and Z. Jinhua, “Deep neural networks for choice analysis: architecture design with alternative-specific utility functions,” *Transportation Research Part C: Emerging Technologies*, vol. 112, pp. 234–251, 2020.

[9] C. H. Cao, Y. N. Tang, and D. Y. Huang, *IBIE: An Improved Identity-Based Encryption Algorithm for WSN Security*, p. 2021, Security and Communication Networks, 2021.

[10] N. A. Charaniya and S. V. Dudul, “Design of neural network models for daily rainfall prediction,” *International Journal of Computer Application*, vol. 61, no. 14, pp. 23–27, 2013.

[11] H. Nassar and H. Al-Mahdi, “Design and analysis of a TDMA call assignment scheme for cellular networks,” *Computer Communications*, vol. 32, no. 7–10, pp. 1200–1206, 2009.

[12] S. Rho, S. Song, Y. Nam, E. Hwang, and M. Kim, “Implementing situation-aware and user-adaptive music recommendation service in semantic web and real-time multimedia computing environment,” *Multimedia Tools and Applications*, vol. 65, no. 2, pp. 259–282, 2013.

[13] R. Reed, A. Bilgic, and R. Gotzheim, “Model-Driven development of time-critical protocols with SDL-MDD,” in *Proceedings of the sddl: design for motes & mobiles*, *International Sdl Forum*, pp. 34–52, Springer-Verlag, Bochum, Germany, September, 2009.

[14] A. Radwan, M. F. Domingues, and J. Rodriguez, “Mobile caching-enabled small-cells for delay-tolerant e-Health apps,” in *Proceedings of the 2017 IEEE International Conference on Communications Workshops (ICC Workshops)*, pp. 103–108, IEEE, Paris, France, 2017.

[15] D. Wu, C. Zhang, L. Ji, R. Ran, H. Wu, and Y. Xu, “Forest fire recognition based on feature extraction from multi-view images,” *Traitement du Signal*, vol. 38, no. 3, pp. 775–783, 2021.

[16] A. A. El-Saleh, A. Alhammadi, I. Shayea et al., “Measuring and assessing performance of mobile broadband networks and future 5G trends,” *Sustainability*, vol. 14, no. 2, p. 829, 2022.

[17] R. Ali, S. Lee, and T. C. Chung, “Accurate multi-criteria decision making methodology for recommending machine learning algorithm,” *Expert Systems with Applications*, vol. 71, pp. 257–278, 2017.

[18] C. Weih, U. Liggies, F. Mörchen, and D. Müllensiefen, “Classification in music research,” *Advances in Data Analysis and Classification*, vol. 1, no. 3, pp. 255–291, 2007.

[19] S. Palanisamy, B. Thangaraju, O. I. Khalaf, Y. Alotaibi, and S. Alghamdi, “Design and synthesis of multi-mode bandpass filter for wireless applications,” *Electronics*, vol. 10, no. 22, p. 2853, 2021.

[20] J. Xie, F. Zhu, M. Huang, N. Xiong, S. Huang, and W. Xiong, “Unsupervised learning of paragraph embeddings for context-aware recommendation,” *IEEE Access*, vol. 7, pp. 43100–43109, 2019.

[21] M. Zaslows, T. Halle, L. Martin et al., “Child outcome measures in the study of child care quality,” *Evaluation Review*, vol. 30, no. 5, pp. 577–610, 2006.

[22] J. Du, C. Jiang, Z. Han, H. Zhang, S. Mumtaz, and Y. Ren, “Contract mechanism and performance analysis for data transaction in mobile social networks,” *IEEE Transactions on Network Science and Engineering*, vol. 6, no. 2, pp. 103–115, 2017.

[23] H. Li, D. Zeng, L. Chen, Q. Chen, M. Wang, and C. Zhang, “Immune multipath reliable transmission with fault tolerance in wireless sensor networks,” in *Proceedings of the International Conference on Bio-Inspired Computing: Theories and Applications*, pp. 513–517, Springer, Singapore, 2016.

[24] R. Anand, R. S. Sabeenian, D. Gurung, R. Kirthika, and S. Rubeena, “June). AI based music recommendation system using deep learning algorithms,” *IOP conference series: earth and environmental science*, vol. 785, no. 1, p. 012013, 2021.

[25] K. Chandra, A. S. Marcano, S. Mumtaz, R. V. Prasad, and H. L. Christiansen, “Unveiling capacity gains in ultradense networks: Using mm-wave NOMA,” *IEEE Vehicular Technology Magazine*, vol. 13, no. 2, pp. 75–83, 2018.

[26] C. Musto, F. Narducci, M. Polignano, M. De Gemmis, P. Lops, and G. Semeraro, “MyrrorBot: a digital assistant based on holistic user models for personalized access to online services,” *ACM Transactions on Information Systems*, vol. 39, no. 4, pp. 1–34, 2021.