

MUSiNET: A Complex Network Model to Explore Underlying Relationship among Musics

Avijit Gayen

Indian Institute of Information Technology Guwahati

Avik Mondal

Techno India University

Praswasti Sharma

Indian Institute of Information Technology Guwahati

Angshuman Jana

`angshuman@iiitg.ac.in`

Indian Institute of Information Technology Guwahati

Research Article

Keywords: Music network, Complex network, Graph theory, Music Information Retrieval, Music recommendation.

Posted Date: September 9th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-7527327/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

MUSiNET: A Complex Network Model to Explore Underlying Relationship among Musics

Avijit Gayen^{1,2}, Avik Mondal², Praswasti Sharma¹
and Angshuman Jana^{1*}

¹Department of CSE, Indian Institute of Information Technology
Guwahati, Bongora, Guwahati , 781015, Assam, India.

²Department of CSE, Techno India University, West Bengal,
EM-4, Sector V, Salt Lake, Kolkata, 700091, West Bengal, India.

*Corresponding author(s). E-mail(s): angshuman@iiitg.ac.in;
Contributing authors: avijit.gayen@iiitg.ac.in;
374avikmondal@gmail.com; praswasti1310@gmail.com;

Abstract

Music transcends cultural and linguistic boundaries, serving as a universal medium of expression. Traditional approaches to analyzing musical relationships often rely on subjective feedback or basic genre classifications, which fail to capture deeper, nuanced connections. In this paper, we present MUSiNET, a novel music network model that integrates computational analysis with musicology to explore complex relationships within musical datasets. We construct a weighted, undirected graph where nodes represent songs and edges reflect similarity scores derived from both intrinsic (e.g., tempo, energy) and extrinsic (e.g., artist, language) features using cosine similarity. Our analysis spans three hierarchical levels: micro (node centrality), meso (community detection), and macro (global topology). Key findings reveal: (1) network hubs are dominated by recent, algorithmically promoted tracks (e.g., K-pop), while bridges often consist of older, cross-cultural music; (2) a giant component comprising 99.58% of the nodes indicates strong integration across languages; and (3) assortativity varies significantly with popularity, duration, and release year. These insights demonstrate

MUSiNET's potential as a data-driven framework for music recommendation, cross-cultural discovery, music therapy, and plagiarism detection, offering a robust alternative to traditional classification systems.

Keywords: Music network, Complex network, Graph theory, Music Information Retrieval, Music recommendation.

1 Introduction

Music is the part and parcel of human culture since the early age of human civilization across the world. According to archaeological evidence, music was first developed in human society around 1400 BC [1]. The existence of evidence of musical instruments around 40,000 years ago suggests their primitive nature, which is not only connected to the culture of human society but also serves as a means to fuel the emotional needs of human beings. Music has a great influence on human society. It fosters patriotism in the minds of the country's people, thus playing a pivotal role in national integration. Music has not only been developed for recreation and amusement, but it also has a long-term and deep impact on mass communication as music has its melody as well as the remembrance of its content by rhythm [2]. On the other hand, understanding the cognitive brain mechanisms and the influence of music on this complex cognitive process becomes the primary goal of neuroscience of music. Nowadays, music therapy [3] has become popular in this context. The existence of a strong economic impact of music in any society can not be ignored. As music development, preparation, and further distribution create an involvement of a large set of people, which in turn develops the music industry. It creates a generation of jobs that not only include music composers but also audio engineers, sales and marketing personnel, and others, for the music industry.

Music has been an integral part of human culture, resonating across languages and geographical boundaries. Although the music has its language and attempts to convey messages to its listeners, it possesses an inherent universality that is intrinsic to its composition. Therefore, language is not always a barrier to music. It has been observed that music has its universality and is acceptable across the language barrier [4]. On the other hand, based on the intrinsic property of the music, over the years, researchers have been fascinated by the relationships between various musical elements, driving advancements in music analysis [5]. This relationship among the music not only corroborates the universal nature of music but also helps identify similar music that might be of interest to the listener across different languages, cultures, and ethnicities.

Traditional methods for studying music relationships often rely on subjective measures like user feedback or basic genre classification. The relationships among songs often remain hidden and are not easily discernible through conventional classification or clustering methods, which may miss subtle connections between the music. In some earlier studies [4], people primarily used

the concept of collaborative filtering, where listener demographic similarities were mainly focused on for music recommendations. These limitations have prompted researchers to explore data-driven approaches that utilize audio and metadata features to derive objective and accurate insights. Though there exists very few works [6] where the authors used the concept of a graph model to explore the similarities among the music to recommend music, they ignore the dynamics of relationship among the music and nature of the evolution of the music network which might be crucial for understanding the growth of the music industry, role of individual player in the music industry, etc. Thus, there is a strong requirement for the development of a music network that can capture the nuances of inter-relationships among music across languages, genres, popularity, and other factors. Further analysis of the network may reveal hidden dynamics within the music network.

In this work, we propose a novel idea to develop music network **MUS $\dot{\mathbf{i}}$ NET($\mathbf{M}$, $\mathbf{S}$)** from complex network perspectives where $\mathbf{M}$ set stands for the music which contains all the music and $\mathbf{S}$ set represent the weighted edge which represent the similarity score between the music to explore the role of inter-relationship among the music across the language, genre and popularity. We have considered every individual piece of music as a node in the network, and the edges between the nodes in the network represent the inter-relationship among the music. The feature similarity score between any two music nodes can be considered as the edge weight. Here, we raise two central research questions as follows in the context of the proposed music network:

- What is the extent of the universality of music that could be measured from the proposed music network?
- Is the similarity score a useful measure to recommend music for various purposes?

Network analysis has become a powerful tool for understanding the dynamics of complex systems. The proposed music network would help us to establish connections among people based not only on similar languages but also on similar feelings and agendas. The proposed network would work as an underlying architecture not only for the music recommendation system but also as a platform to develop a music-based community. This proposed network could also be an integrated part of the mental health improvement system through music therapy. Our proposed music network would not only be able to address the well-known exploitation theory of over-popularization of promoted music [7], but it would also help in the exploration of new music that might be accessible to the broader audience. The proposed music network could be used as an underlying architecture for music plagiarism checks across languages, countries, and communities.

The major challenges to develop proposed music network are as follows:—
a) music is inherently diverse, encompassing a wide range of genres, languages, and cultural influences, b) musical preferences are highly subjective and vary significantly from person to person, c) the perception of music can differ based

on the same audio stimuli, influenced by contextual, emotional, or cultural factors. To address these challenges, we require an approach that analyzes and connects music not only through explicit metadata, such as artist and album, but also via intrinsic audio features, e.g., tempo, danceability, energy, valence, etc.

In this work, we considered the dataset [8] which consists of 20405 pieces of music information, including the audio file, metadata, as well as the intrinsic properties of music. Initially, to develop the network, we explore the relationships among 5000 songs across five different languages: English, Bengali, Hindi, Spanish, and Korean. By leveraging intrinsic features of music, e.g., danceability, energy, loudness, etc., along with the extrinsic metadata attributes, e.g., artist name, album name, popularity, etc., we calculate pairwise similarity scores using the cosine similarity method. A threshold value of similarity score is determined via the Hyperlink-Induced Topic Search (HITS) algorithm to filter meaningful connections. To visualize and analyze these relationships, we construct an undirected graph using the NetworkX library. We analyze the proposed music network from three levels of network visualization: a) Micro level, b) Meso level, and c) Macro level. This analysis not only reveals the structural position of the music track in the network but also its interrelationship across the language and community. We summarize the contribution of the work in this paper as follows—

- Propose a novel music network that identifies the relationship among the music.
- Detailed analysis of network from micro, meso, and macro levels.

We organize the paper as follows: In the next section, we discuss the detailed literature related to our proposed music network, which outlines the earlier works as well as identifies the scope of our work. Next, in section 3, we describe the mathematical model of our proposed music network. In section 4, we describe the methodology of development of the proposed music network, which includes a dataset description and analysis of the method of the music network. In section 5, we discuss the detailed results obtained and interpret them from the perspective of the objective of the work. Finally, we conclude in section 6 and put the remarks regarding the future direction of the work. In the paper, we have used the terms "music" and "song" synonymously. Although, "music" term could have a broader aspect, in our work, we have kept it as each individual recorded tracks available in our dataset.

2 Related Works

In this section, we explore prior research relevant to the study of music similarity and network-based approaches to understanding the relationships between songs. Emphasis is placed on contributions in music information retrieval, recommendation systems, genre classification, and network modeling, which form the foundation for this work.

Music information retrieval (MIR) studies have focused heavily on audio feature extraction for classification, clustering, and recommendation. Traditional approaches utilize features like timbre, rhythm, pitch, and loudness to predict genres or moods[9]. Hybrid models that combine acoustic features with usage data[10, 11] and advances leveraging AI and blockchain[12] demonstrate the field’s shift toward personalization and security. MIR has also benefited from alternative input modalities such as Query-by-Humming[13] and has leveraged big data and cloud infrastructures[14]. While existing MIR systems focus on isolated tasks (e.g., retrieval, classification), MUSiNET integrates both intrinsic and extrinsic features into a unified network structure to uncover deeper, structural patterns across music datasets.

Music recommendation networks models have evolved from basic collaborative filtering to complex architectures involving deep learning[15, 16] and graph-based learning[17, 18]. Recent studies have introduced domain-specific layers (e.g., genre, lyrics) to improve transparency and personalization[19, 20]. However, our proposed approach diverges from traditional recommender systems by focusing on the network topology of similarity rather than user preferences. This allows it to support novel use cases such as cross-cultural discovery and music therapy. Unlike prior models, MUSiNET does not depend on explicit user behavior or collaborative filtering; it identifies latent relationships by analyzing both acoustic and contextual metadata through network structures.

Music collaboration networks models have also been used to study artist collaborations. These networks often exhibit small-world and scale-free properties[21, 22]. Multiplex modeling and Graph Neural Networks (GNNs) have enhanced predictions of potential collaborations[23, 24]. Unlike artist-centric collaboration graphs, MUSiNET models song-level similarity, enabling track-level discovery rather than networked artist prediction. Moreover, MUSiNET shifts focus from co-creation to inherent content similarity, offering a complementary approach to understanding musical relationships.

Music genre classification networks advances in genre classification often use CNNs and Transformers trained on spectrograms[25, 26]. Attention mechanisms and transfer learning have further improved accuracy and generalizability[27, 28]. MUSiNET does not rely on supervised classification. Instead, it analyzes emergent genre patterns via unsupervised network clustering, potentially revealing hybrid genres overlooked by traditional models. By not being constrained to predefined labels, MUSiNET supports discovery-driven exploration of genre-blending music.

Music influence networks studies have modeled influence propagation through centrality metrics and directional graphs to explore genre evolution and artist dominance[29, 30]. These models quantify cultural impact but are often limited to artist-level granularity. Note that, MUSiNET complements influence studies by offering a similarity-based model that captures influence at the song level, including potential cross-genre or temporal bridges. It highlights how intrinsic musical characteristics may indirectly propagate cultural influence.

The emotional character of music has been examined using multimodal sentiment models combining audio and lyrics[31, 32]. Deep learning models can both classify sentiment and generate emotionally coherent music[33]. While MUSiNET does not explicitly model sentiment, its feature-based similarity network inherently reflects emotional tone through features like valence, energy, and tempo.

Though the existence of plethora of works related of music in terms of music information retrieval, collaboration network, music recommendation etc, that enrich a lot of the concerned domain of music from the perspective of data analytics, no such significant work address the universality nature of music which could be understood from the perspective of complex network. Our proposed model introduces a distinct contribution by integrating intrinsic and extrinsic features into a unified graph framework. Unlike existing works that emphasize supervised learning or artist-focused relationships, MUSiNET provides a structural lens to understand song-level similarity across time, language, and genre—offering new insights for recommendation, music therapy, and plagiarism detection.

3 Proposed Music Network

We model **MUSiNET** as a **weighted undirected graph** $G = (M, S, W)$, where:

- M is the set of **nodes** representing individual music tracks.
- S is the set of **edges** representing relationships (similarity) between tracks.
- $W : S \rightarrow \mathbb{R}^+$ is a **weight function** that assigns a similarity score to each edge.

3.1 Node Representation

Each music track $m_i \in M$ is represented as a feature vector $\mathbf{v}_i$, composed of **intrinsic** and **extrinsic** attributes:

$$\mathbf{v}_i = [i_1, i_2, \dots, i_n, e_1, e_2, \dots, e_m]$$

where:

- $i_1, i_2, \dots, i_n$ are intrinsic audio features (e.g., tempo, danceability, loudness, energy, valence).
- $e_1, e_2, \dots, e_m$ are extrinsic metadata features (e.g., artist, album, genre, language, popularity).

3.2 Similarity Measure

The similarity between two music tracks m_i and m_j is calculated using **cosine similarity**:

$$\text{Sim}(m_i, m_j) = \frac{\mathbf{v}_i \cdot \mathbf{v}_j}{\|\mathbf{v}_i\| \|\mathbf{v}_j\|}$$

where $\cdot$ represents the dot product, and $\|\mathbf{v}\|$ is the Euclidean norm.

3.3 Edge Formation and Weight Assignment

An edge $(m_i, m_j) \in S$ exists if $\text{Sim}(m_i, m_j)$ exceeds a predefined threshold τ :

$$(m_i, m_j) \in S \quad \text{if} \quad \text{Sim}(m_i, m_j) \geq \tau$$

The weight function is defined as:

$$w(m_i, m_j) = \text{Sim}(m_i, m_j)$$

where higher weights indicate stronger similarity.

3.4 Graph Representation

The resulting **MUSiNET** is represented as an **adjacency matrix** A :

$$A_{ij} = \begin{cases} w(m_i, m_j), & \text{if } (m_i, m_j) \in S \\ 0, & \text{otherwise} \end{cases}$$

3.5 Network Properties and Analysis

To analyze the structure of the music network, we categorize our analysis into three levels: **Micro (Node Level)**, **Meso (Cluster Level)**, and **Macro (Network Level)**.

3.6 Micro-Level Analysis (Node-Level)

Micro-level analysis focuses on individual nodes (music tracks) and their roles in the network. The key metrics include:

3.6.1 Centrality Measures

- **Degree Centrality** $d(m_i)$: Measures the number of connections a node has.

$$d(m_i) = \sum_j A_{ij}$$

This identifies popular songs that have high similarity with others.

- **Betweenness Centrality** $BC(m_i)$: Measures how often a node acts as a bridge between other nodes in the shortest paths.

$$BC(m_i) = \sum_{s,t} \frac{\sigma_{st}(m_i)}{\sigma_{st}}$$

where σ_{st} is the total number of shortest paths from node s to t , and $\sigma_{st}(m_i)$ is the number of those paths passing through m_i .

- **Closeness Centrality** $CC(m_i)$: Indicates how close a node is to all other nodes in the network.

$$CC(m_i) = \frac{1}{\sum_j d(m_i, m_j)}$$

- **Eigenvector Centrality** $EC(m_i)$: Assigns higher scores to nodes connected to other important nodes.

$$EC(m_i) \propto \sum_j A_{ij} EC(m_j)$$

3.6.2 Clustering Coefficient

The clustering coefficient of a node C_i measures the tendency of its neighbors to be connected:

$$C_i = \frac{2T_i}{d(m_i)(d(m_i) - 1)}$$

where T_i is the number of triangles that include m_i .

3.6.3 Assortativity Score

The assortativity coefficient r measures the tendency of nodes to connect based on similar attributes. It is defined as:

$$r = \frac{\sum_{(i,j) \in S} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{(i,j) \in S} (x_i - \bar{x})^2}$$

where x represents the attribute under consideration. We compute assortativity for the following attributes:

$$x \in \{\text{duration}, \text{release_year}, \text{popularity}, \text{language}\}$$

3.7 Meso-Level Analysis (Cluster-Level)

Meso-level analysis focuses on the structural properties of clusters within the network. A cluster C_k is a subset of nodes where intra-cluster connections are denser than inter-cluster connections. We analyze the following properties:

3.7.1 Cluster Size Distribution

The size of a cluster C_k is given by:

$$C_k = \sum_{i \in C_k} 1$$

The average cluster size is:

$$\bar{C} = \frac{1}{K} \sum_{k=1}^K C_k$$

where K is the total number of clusters.

3.7.2 Edge Density of a Cluster

The edge density within a cluster C_k is defined as:

$$D(C_k) = \frac{2E_k}{\|C_k\|(\|C_k\| - 1)}$$

where E_k is the number of intra-cluster edges.

3.7.3 Inter-Cluster Connectivity

The inter-cluster connectivity between two clusters C_k and C_l is given by:

$$IC(C_k, C_l) = \frac{\|E_{kl}\|}{\|C_k\|\|C_l\|}$$

where E_{kl} is the number of edges connecting nodes in cluster C_k to nodes in cluster C_l .

3.7.4 Cluster Similarity Statistics

To quantify how clusters group similar songs, we define the average pairwise similarity within a cluster as:

$$S(C_k) = \frac{1}{\|C_k\|(\|C_k\| - 1)} \sum_{i,j \in C_k, i \neq j} w(m_i, m_j)$$

Where $(w(m_i, m_j))$ is the similarity weight between songs (m_i) and (m_j) .

The global average cluster similarity is given by:

$$\bar{S} = \frac{1}{K} \sum_{k=1}^K S(C_k)$$

3.8 Macro-Level Analysis (Network-Level)

Macro-level analysis examines the global properties of the network.

- **Average Centrality:** Measures the mean centrality values across all nodes to assess the distribution of influence in the network.

$$\bar{C} = \frac{1}{M} \sum_{i \in M} C_i$$

where C_i can be any centrality measure.

- **Average Clustering Coefficient:** Measures the overall tendency of the network to form tightly knit groups.

$$\bar{C} = \frac{1}{M} \sum_{i \in M} C_i$$

where C_i is the clustering coefficient of node i .

4 Proposed Method

In this section, we describe the methodology adopted to develop the proposed network model. Initially, we outline the detailed dataset description which include the snippet of the raw data in the dataset, general information and statistics of the dataset. Further, we outline the statistical analysis performed on the raw dataset based on the various meta data of the each data points. We also describe the several featured used in formation of the proposed network. Finally, we outline the detailed method of network formation.

4.1 Dataset

In our work, we have used the dataset of the well-known audio listening platform spotify [34]. The spotify dataset [8] is publicly available for the purpose of research. It contains **20405** numbers of musics in **.mp3** format. To reduce the computational complexity of handling such a large size of data, we have randomly selected $\approx 5,000$ songs evenly distributed across five languages—English, Bengali, Hindi, Spanish, and Korean. We have chosen these five different languages to keep it a well mix of Indian language i.e., Hindi which is spoken in PAN India as well as the regional language i.e., Bengali. We also kept two foreign languages i.e., Spanish and Korean along with internationally accepted language i.e., English. The rationale behind this language selection in our sample dataset is to observe the network formation in cross language and further understanding of the dynamics of edge formation among intra-language and inter-language. It contains nearly a century spanned long released songs, starting from 1920 to 2024. The dataset contains metadata e.g., track-ID, track-name, artist name, album name, release year, duration, language, genre and popularity. The description of the metadata has been shown the table 1. Further, we describe the detailed statistical information of the raw dataset in table 2.

We perform the preprocessing on the raw dataset for various purposes, e.g., scaling features, filling in missing metadata, and standardizing audio metrics. The balanced mix of languages and existence of large set genres make it ideal for exploring cross-cultural and multilingual music relationships. The raw dataset stored in the **.csv** file format. For the detailed understanding of the raw dataset, we have shown the snippet of files in table 3.

Attribute	Description
track-id	Unique identifier for each song in the dataset
track-name	Title of the song
artist-name	Name of the artist or group
album-name	Album to which the song belongs
release-year	Year the song was released
duration-ms	Duration of the song in milliseconds
popularity	Score representing the song’s popularity
genres	Musical genre(s) like pop, rock, or jazz
language	Primary language of the song’s lyrics
Audio-file name	Name of the Mp3 file

Table 1: Meta data of the Sportify dataset [34].

Attribute	Description
Lang. of songs	English, Bengali, Hindi, Spanish, Korean
Release Period	1920 – 2024
Unique Genres	531
Most occurred Genre	filmi
Popularity Range	0 – 85
Avg. Popularity	9.34
Duration Range	0.52 – 86.56 mins.
Avg. Duration	3.58 mins.
Top 5 Artist (Song’s Count)	Tayo the Little Bus, Pororo the little penguin, Lata Mangeshkar, Jinyoung Kim, Harmony River
Top 5 Artist (Album’s Count)	Lata Mangeshkar, Rockit Music, Pororo the little penguin, Tayo the Little Bus, Korean Comic

Table 2: General Statistics of Sportify dataset [34].

4.2 Statistical Analysis

In this section, we perform the various statistical analysis of the meta data of the music dataset used in our work to reveal the breath of the dataset used for this analysis. We observe the various statistical analysis on extrinsic features, i.e., popularity, duration. release year, artist name, album name. In our study, we exclude ‘genre’ feature from our statistical analysis to reduce the complexity that could overwhelm the reader as there exist a large set of genre in the dataset.

Popularity

In this section, we observe the distribution of the popularity of the music in our dataset. We observe the overall distribution of the popularity of the music across the languages as well as the distribution of the popularity in each language. In figure 1, we show the popularity distribution of the music of the dataset used in our proposed network model. The figure shows that the popularity distribution across multiple languages exhibits a right-skewed, long-tail pattern. It indicates that a small number of music attain high popularity while the majority remain relatively obscure. This trend suggests the presence of highly popular music alongside a vast pool of low popular music. Notably, the

track id	track_name	artist_name	album_name	release year
01.	Pop Muzik	M, Robin Scott	Pop Muzik	2022
02.	Tum Hi Ho	Arijit Singh	Ultimate Love Songs	2020
03.	Chokher Aaral Hoile	Runa Laila	Bengali Songs	1982
04.	Sueño Español	Sueño Profundo Club	Música para Dormir	2018
05.	Song Of Youth	Lee Heemoon, Prelude	Korean Men	2017

duration (ms)	popularity	genres	Language	Audio_File Name
200682	61	synthpop	English	Pop_Muzik_Robin_Scott.mp3
261974	56	filmi, modern bollywood	Hindi	Tum_Hi_Ho_Arijit_Singh.mp3
159760	2	classic bangla pop	Bengali	Chokher_Aaral_Runa_Laila.mp3
136830	27	musica de fondo	Spanish	Sueno_Espanol_Sueno_Profundo.mp3
369600	7	joseon pop, k-indie, korean minyo	Korean	Song_Of_Youth_Prelude.mp3

Table 3: Music Dataset Table

peak probability and the rate of decay in the distribution vary across languages. It implies that differences in content engagement and consumption diversity across the languages. Some languages(e.g., Bengali and Korean) show a sharper concentration at low popularity levels. On the other hand though the Hindi and Spanish music’s follows similar behavior in popularity distribution, it has more thicker tail that indicates the presence of significant number of highly popular musics. Explicitly, musics of English language exhibits significant shift of the distribution nature of the popularity. It shows a right skewed normal distribution. It might be the reflection of adoption of English language as international language that in turn makes the music to reach larger set of audience which increases the popularity of the each individual music in that concerned language.

Duration

In this section, we observe the distribution of the duration of the music in our dataset. We observe the overall distribution of the duration of the music

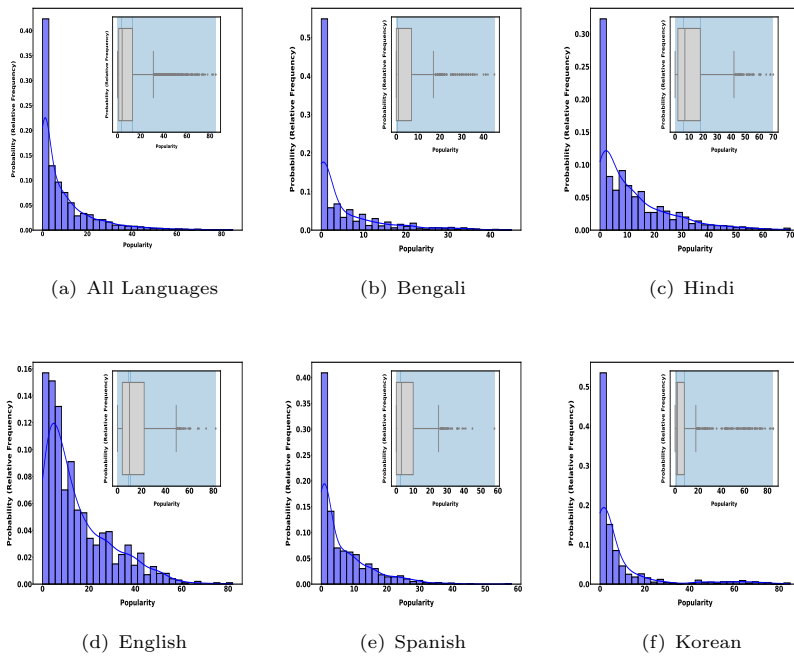


Fig. 1: It represents the popularity distribution of the music of the dataset used in our work. Along x-axis, we plot the popularity score and along y-axis, we plot the probability value of the corresponding popularity score. In the inset of the each figure, we show the box-plot of the same distribution.

across the languages as well as the distribution of the duration in each language. In figure 2, we show the duration distribution of the music of the dataset used in our proposed network model. The duration distribution across five languages—English, Bengali, Hindi, Korean, and Spanish—reveals notable differences in content consumption preferences based on duration of music. English and Spanish users tend to favor shorter content, with their distributions peaking between 2 to 4 minutes and showing a steep decline thereafter. It might be the indication of a strong preference for brief engagement. In contrast to that, Bengali, Hindi, and Korean content displays a much wider duration spread. Bengali shows a peak around 7-8 minutes, while Hindi and Korean exhibit a relatively uniform distribution that extends up to 60–70 minutes, with significant probabilities sustained even at longer durations. These patterns suggest that users in Bengali, Hindi, and Korean linguistic communities are more inclined toward longer content, possibly due to cultural or contextual factors. These differences underscore the importance of language-specific strategies in content creation, recommendation, and user engagement design.

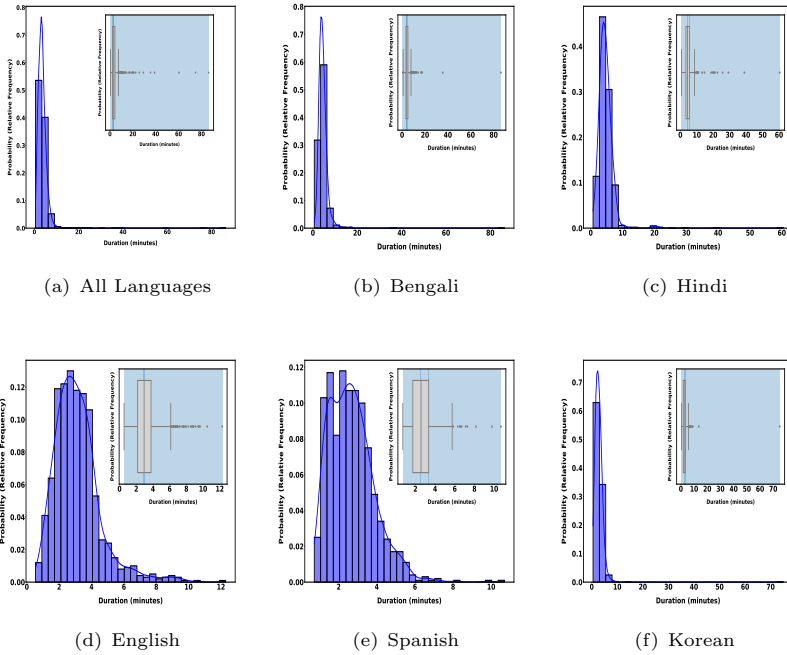


Fig. 2: It represents the duration distribution of the music of the dataset used in our work. Along x-axis, we plot the duration(ms) and along y-axis, we plot the probability value of the corresponding duration value. In the inset of the each figure, we show the box-plot of the same distribution.

Release Year

In this section, we observe the distribution of the music over the period of time. To understand the time period of release of the music across the different languages, we plotted the data in a comparative bar graph. As our dataset contains the music across a century(1920-2020), we have observed the count of the music released across different languages on each decades. In figure 3, we show the comparative distribution of the release yr of the music across the five languages in our dataset. The bar chart illustrates the logarithmic (base 10) distribution of the number of songs produced per decade across five languages—Bengali, English, Hindi, Korean, and Spanish in the duration of 1920-2020. A clear upward trend is evident in all languages, especially from the 1960s onward, indicating a significant increase in global song production over time. English songs consistently lead in quantity across most decades. It shows the dominant role of English in the global music industry. This might be due to global presence and acceptance of English. We observe that Korean and Spanish songs have shown rapid growth since the 1980s and 1990s respectively, highlighting the global rise of K-pop and Latin music in recent decades. On

the other hand, Hindi and Bengali also display steady growth that reflects the expanding music scene in the Indian subcontinent. The logarithmic scale emphasizes exponential growth in song production that shows the stronger role of technological advancements, globalization, and increased access to music creation and distribution platforms.

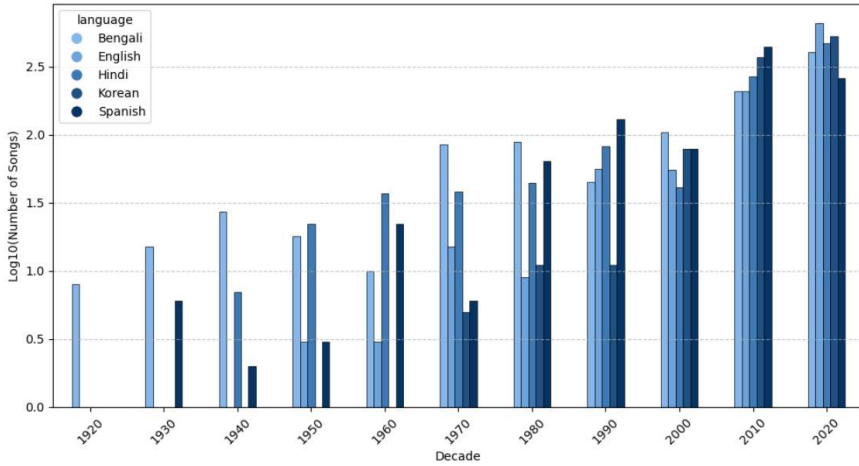


Fig. 3: Figure shows the distribution of the release year of the music. Along x-axis, we plot the release decade and along y-axis, we represent the count of music released in that concerned year.

Artist Name

To observe the details of artists of our music dataset, we figure out the top 5 popular artists in language. We also list the top 5 popular artists in each decade starting from 1970-2020. Though our dataset contains musics across a century(1920-2020), we have considered recent 50 years for observation without populating it across the century. This observation not only reveal most popular artists across the language but also list down top popular artists contemporary to the concerned decades.

In figure 4(a), we show the most popular artist in the dataset across five different language. We find that the top five popular artists in Bengali, English, Hindi, Korean, Spanish respective as follows— Bengali: 1) Lagnajita Chakraborty 2) Minar Rehaman 3) Bagdhara 4) Arindam 5) hatipool Session, English: 1) The Weeknd 2) Elvis Presley 3) Charley Brown Junior 4) Asap Rockey 5) M Robinscott, Hindi: 1) Pritam 2) Arijit Singh 3) Jubin Nautiyal 3) Vishal-Shekhar 5) Udit Narayan, Korean: 1) Odetari 2) KATSEYE 3) ILLIT 4) The Weeknd 5) NewJeans, Spanish: 1) Pancho 2) Pol Sebastian 3) Akapellah 4) Canciones Infantiles 5) Manuel de falla. The key observation of this figure states that regional language artists like Bengali is comparatively less popular

than Hindi. This reflects the smaller audience set than that of Hindi. Whereas the English and Korean language artist has larger and broader audience base which makes them most popular.

In figure 4(b), we show the most popular artist in the dataset across five decades(1970-2020). We find that the top five popular artists in 1970s, 1980s, 1990s, 2000s, and 2010s respective as follows— 1970s: 1) Bill Conti(English) 2) M.Nick Launay(English) 3) Eddie Rabbitt(English) 4) Mukesh(Hindi) 5) The Band(English), 1980s: 1) Bill Conti(English) 2) S.P. Balasubramaniam(Hindi) 3) Alabama(English) 4) Juan Antonio Alvarez Parejo(Spanish) 5) Antonio Molina(Spanish), 1990s: 1) Elvis Presley(English) 2) Alka Yagnik (Hindi) 3) Udit Narayan(Hindi) 4) Jamiroquai(Spanish) 5) Thierry(English), 2000s: 1) Sonu Nigam(Hindi) 2) Gwen Stefani(English) 3) Project Pat(English) 4) NSYNC(English) 5) Chris Brown(English), 2010s: 1) Pop Smoke(English) 2) Jack Stauber(English) 3) Travis Scott(English) 4) Charlie Brown Jr. (English) 5) Alka Yagnik, Arijit Singh(Hindi). The result shows some very interesting facts—1) There is a shift in popularity score of the top five artists after 1990. This may be due to growth of technology which promotes the distribution of music across the world. 2) Though the Korean and Spanish artists are also popular compared to Hindi, they are not featured in top list of the every decade. 3) English artists show their domination in top list of every decade, though Hindi artists also take a good position in the top popular artist list of every decade.

Album Name

In this section, we observe the details of albums of our music dataset. We figure out the top 5 popular albums in each language. We also list the top 5 popular albums in each decade starting from 1970-2020. Though our dataset contains musics dataset span across a century(1920-2020), for our observation, we have considered most recent 50 years.

In figure 5(a), we show the most popular albums in the dataset across five different languages. We find that the top five popular albums in Bengali, English, Hindi, Korean, Spanish respectively as follows— Bengali: 1) Ekanoborti 2) Dur theke 3) Proticchobi 4) Fida 5) Upo, English: 1) Poppular HBO 2) Platinum 3) Musica 4) GTA V 5) Pop Muzik, Hindi: 1) Keriya 2) Love forever with Arijit Singh 3) Tum hi ana 4) Ghungroo 5) Kabhi Khushi Kabhi Gham, Korean: 1) FROSTBYTE 2) Touch 3) SUPER REAL ME 4) Popular HBO (Kr.) 5) NewJeans 'Super shy', Spanish: 1) Mis 30 Aniversario 2) Las Mejores Canciones 3) Funky Fresco 4) Canciones Infantiles 5) Falla. The similar behavior of the popularity of the album is observed as seen in the artists across the language. It might be reflection of the popularity of the artist which carries in their album. Though popularity score of the top five albums are very close to each other.

In figure 5(b), we show the most popular albums in the dataset across five decades(1970-2020). We find that the top five popular artists in 1970s, 1980s, 1990s, 2000s, and 2010s respective as follows— 1970s: 1) Rocky II(English) 2) New York(English) 3) Rocky Mountain Music(English) 4) Kabhi

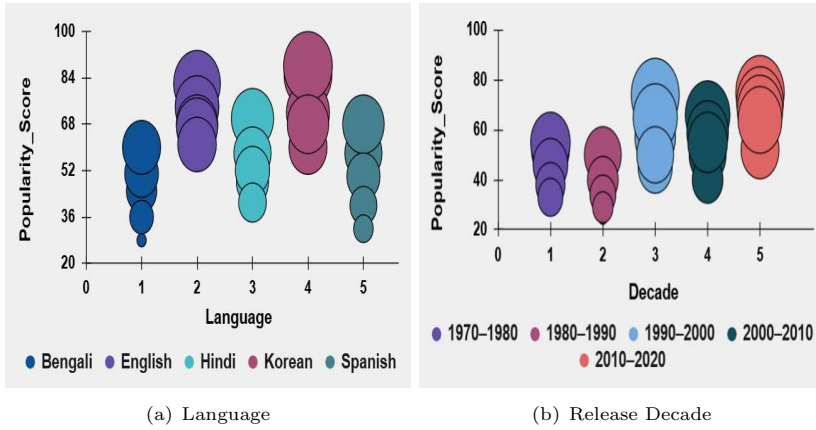


Fig. 4: Figure shows the Top 5 artists based on their popularity score. In figure 4(a), it represents the top popular artists in different languages. Similarly in fig 4(b), it show the top popular artists in every decades starting from 1920 to 2020 respectively.

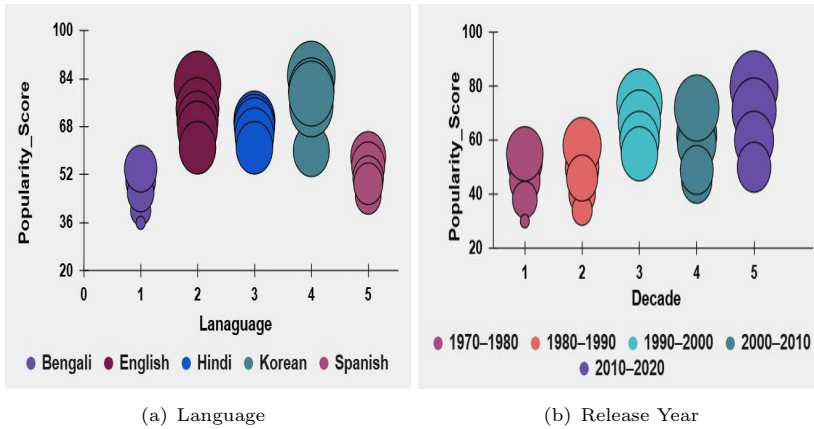


Fig. 5: Figure shows the Top 5 albums based on their popularity score. In figure 5(a), it represents the top popular albums in different languages. Similarly in fig 5(b), it show the top popular albums in every decades starting from 1920 to 2020 respectively.

Kabhie(Hindi) 5) Rock Of Ages(English), 1980s: 1) Rocky III(English) 2) Maine Pyar Kiya(Hindi) 3) Livin' Lovin' Rockin' Rollin'(English) 4)Canciones Españolas(Spanish) 5) Antología de la Canción Española(Spanish), 1990s: 1) Platinum - A love in Music(English) 2) Pehchan(Hindi) 3) Kuch Kuch Hota Hai(Hindi) 4) Modern Era(English) 5) Pop Muzic(English), 2000s: 1) Kabhi Khushi Kabhi Gham(Hindi) 2) Love. Angel. Music. Baby.(English) 3) Most Known(English) 4) Celebrity(English) 5) Chris Brown(English), 2010s:

1) Meet the woo(English) 2)Pop Food(English) 3)JACKBOYS(English) 4) Edição Luxo(Spanish) 5)Roll or Die(English). It has been observed that across the decade Hindi and English albums dominate in measure of popularity. Eventually popularity of the albums have a positive shift after 1990 as same seen in the artist's popularity. It also shows that the Korean, Spanish and Bengali albums are not able to get the top positions across the decades. English albums are dominating across the decades that might be the reflection of English speaking people across the globe, though that language is not always native one. On the other hand, Hindi albums popularity reflect its melodious nature that attracts across the world.

4.3 Feature Identification

To develop our proposed music network, we primarily focused on two categories of features of the each individual music— a) Intrinsic audio features and b) Metadata features. To extract intrinsic audio features such as tempo, danceability, energy, acousticness, etc. characteristics, we have used **Librosa**[35]. Additionally, metadata including artist name, album, genre, release year, and language was integrated to provide a comprehensive representation of each track. In table 5, we have highlighted the different features used and their brief description.

4.4 Network Formation

In this section, we describe the network formation method. To understand the flow of the steps, we describe it by a schematic diagram presented in figure 6. We constructed the proposed music network by following a structured methodology that integrates data retrieval, feature extraction, similarity computation, and network formation.

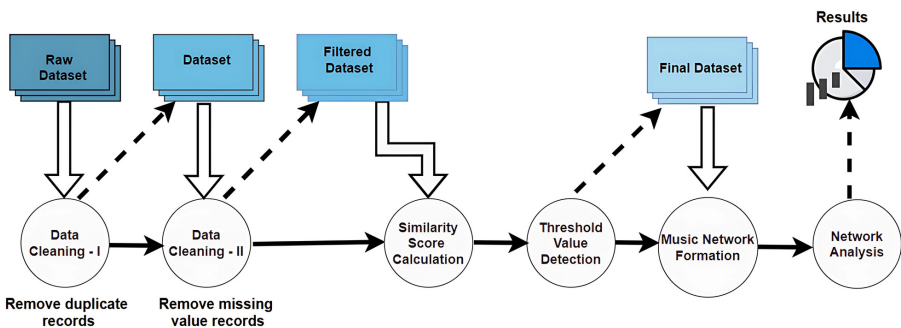


Fig. 6: Figure shows the schematic diagram of the flowchart followed in the proposed methodology.

Initially, we randomly select ≈ 5000 songs across five languages—English, Bengali, Hindi, Spanish, and Korean using the Spotify API [34]. To ensure

Table 4: Intrinsic Features of music used in proposed Music Network Model.

Features (Intrinsic)	Description
Danceability	The ability of a piece of music to encourage physical movement and coordination in a rhythmic manner. It reflects how easily a listener can engage with the music through body movements, making it enjoyable for dancing.
Energy	The intensity and drive a piece of music conveys, influencing how lively or powerful it feels. It reflects the overall sensation of movement and excitement, often making a song feel more dynamic or calm.
Loudness	The perceived strength or intensity of sound, determining how soft or powerful it feels to the listener. It is influenced by the force of sound production and how it is experienced in different environments.
Speechiness	The degree to which a piece of audio resembles spoken words rather than sung or purely instrumental sounds. Higher speechiness indicates more clear and prominent spoken content, such as in podcasts or rap verses.
Acousticness	The quality of a sound that reflects its natural, unprocessed, or organic nature, typically produced without electronic modification. Higher acousticness indicates a greater presence of traditional, non-synthesized instruments and sounds.
Instrumentalness	The extent to which a piece of music lacks vocal content, focusing primarily on instrumental sounds. Higher instrumentalness indicates minimal or no sung or spoken words in the track.
Liveness	The degree to which a recording captures the presence of a live performance, including audience sounds and ambient acoustics. Higher liveness suggests a stronger sense of a concert-like or real-time experience.
Valence	The measure of how positive or negative a piece of music feels, influencing its overall emotional tone. Higher valence indicates a happier, more uplifting sound, while lower valence suggests a darker or more melancholic mood.
Tempo	The speed at which a piece of music progresses, influencing its sense of movement and energy. It is typically measured in beats per minute (BPM), affecting how fast or slow the music feels.
Key	The tonal foundation of a piece of music, determining the set of notes and chords that create its harmonic structure. It defines the overall mood and feel, such as major keys sounding bright and uplifting, while minor keys feel darker or more somber.
Mode	A specific arrangement of musical notes that defines the character or mood of a piece, beyond just major or minor. Different modes, such as Ionian or Dorian, create unique tonal atmospheres and emotional expressions.
Time-Signature	A numerical notation that defines the rhythmic structure of a piece of music, indicating how beats are grouped within each measure. It consists of two numbers: the top number shows the number of beats per measure, and the bottom number represents the note value that gets one beat (e.g., 4/4, 3/4, 6/8).

a comprehensive representation of musical relationships, we retrieved both intrinsic audio features and extrinsic metadata attributes for each track. The dataset was obtained using the Spotipy Python module, which enabled authentication, track searches, artist details, and audio feature retrieval. To handle the API rate limits, we introduced delays using the time module and implemented a pagination mechanism that allowed us to fetch tracks in batches of

Table 5: Extrinsic Features of music used in the proposed Music Network Model.

Features (Extrinsic)	Description
Artist-name	The official or stage name of the performer, composer, or music creator associated with a track. It helps in identifying, categorizing, and attributing musical works to specific individuals or groups.
Album-name	The title of a collection of recorded tracks released together as a single entity. It serves as a thematic or conceptual representation of the music within, often reflecting artistic intent.
Release-year	The official year on which a song or album is made available to the public. It helps in tracking the historical context, popularity trends, and relevance of the music.
Duration	The total length of a song from start to finish, measured in minutes and seconds. It influences how the music is consumed and experienced in different settings.
Popularity	A measure of how widely a song or artist is recognized and appreciated, often based on metrics like streaming counts, chart rankings, and audience engagement.
Genre	A classification that groups music based on shared characteristics such as instrumentation, rhythm, and cultural influence. Examples include rock, jazz, classical, and electronic music.
Language	The linguistic medium in which a song's lyrics are written and performed, influencing its cultural context and audience reach. It plays a key role in conveying meaning, emotion, and storytelling within the music.

50 per request. This iterative process ensured the retrieval of a diverse set of songs while preventing data loss due to API constraints.

Once the dataset was collected, we extracted two primary categories of features: intrinsic audio properties and extrinsic metadata attributes. The intrinsic features included tempo, danceability, energy, loudness, valence, etc. which were derived directly from the raw audio files using the Spotify API's audio analysis tools [8]. Meanwhile, the extrinsic metadata attributes consisted of artist names, album details, release years, popularity scores, genres, and language information, providing essential contextual details about the music. To refine the dataset, we performed data deduplication by identifying and removing duplicate track IDs and names, ensuring the uniqueness of each song in the network. This preprocessing step was crucial in maintaining the integrity of the dataset and avoiding redundant connections in the subsequent network formation.

Afterward, we computed pairwise similarity scores between tracks using the cosine similarity measure [36], which allowed us to quantify the relationships based on their audio and metadata features. To enhance the accuracy of these relationships, we applied the Hyperlink-Induced Topic Search (HITS) algorithm [37] to determine a threshold of similarity score, to filter out weak connections and retaining only meaningful links between songs. We then represented the resulting connections as weighted edges in the network, where the

To construct the music network, we modeled it as a weighted undirected graph using the NetworkX library. In this representation, each node corresponded to an individual music track, while the edges signified similarity-based relationships between tracks. The weight assigned to each edge reflected the strength of similarity between the connected songs. We structured the graph to allow for the analysis of various musical properties at different scales, from individual song relationships to broader structural patterns in the network. The resulting network provided a comprehensive view of the underlying connections between songs, revealing clusters of similar music and cross-language interactions. To understand the proposed music network, we represent the schematic diagram of the proposed network in figure 7. For the clear observation of the network, we have kept only few nodes and edges in the figure. Though the figure shows the schematic representation, these nodes are taken as sample from our dataset. On the other hand, the edges and their edge weights are computed at the time of network formation.

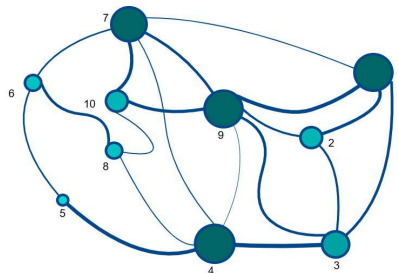


Fig. 7: The figure represents the schematic view of the proposed music network. The node represents the individual music and edge represents the relation between the music. Size and thickness of node and edge respectively show the degree and weight of the corresponding entities in the network. To generate the network the following musics has been used. The name of the musics represented in the nodes are as follows: 1) Popular by Playboy Carti and Madonna 2) Magic in the Hamptons 3) Sietecanciones 4) Kings n Queens 5) Dorimin 6) Pop Muzic 7) Eresalta y delgada 8) Dil ne dil se kaha 9) Touch 10) Bondhure.

4.5 Network Analysis

In this section, we describe the various observation techniques adopted in our work to analyze the network in details. We conducted a multi-level analysis to explore its structural and dynamic properties. In our study, we analyze the network from three levels—a) Micro-level, i.e., node level b) Meso-level, i.e., cluster level c) Macro-level, i.e., Network level.

Micro-level

Micro-level analysis focuses on the role of individual music tracks within the proposed network. It examines their structural influence through centrality measures and clustering coefficients. This granular perspective is motivated by the need to identify key songs that act as bridges between disparate genres or languages, thereby validating the universality hypothesis raised in the introduction section. By computing degree, betweenness, closeness and eigenvector centrality, we can pinpoint tracks with high connectivity, which may serve as ideal candidates for cross-cultural recommendation. Additionally, the clustering coefficient reveals local cohesion, indicating whether songs with similar acoustic features (e.g., high energy or valence) form tightly knit subgroups. Potential findings of the node level analysis would include the identification of “hub” songs that defy traditional genre or language boundaries, suggesting their broader appeal. While low-clustering nodes may highlight niche or experimental tracks with limited similarity to others.

Meso-Level

To uncover the latent groupings that transcend explicit metadata like genre or language, we perform the meso-level analysis on our proposed music network. This analysis is driven by the hypothesis that intrinsic audio features (e.g., tempo, danceability) may create unexpected affinities between seemingly unrelated tracks. Using modularity-based clustering algorithms, we quantify intra-cluster density and inter-cluster connectivity to assess whether traditional classifications align with data-driven communities. For instance, clusters dominated by high danceability scores might merge pop songs across languages, while sparse inter-cluster edges could reveal cultural or temporal divides. Anticipated outcomes include the discovery of hybrid genres (e.g., K-pop-infused Spanish tracks) and the quantification of cross-cultural fusion, which could inform more nuanced recommendation systems that prioritize acoustic similarity over metadata.

Macro-level

The macro-level investigation evaluates the global topology of proposed music network. This analysis would help us to probe its small-world or scale-free properties to understand how musical influence propagates system-wide. The assortativity metrics would critically reveal whether nodes preferentially connect based on attributes like language or popularity. It might be able to expose

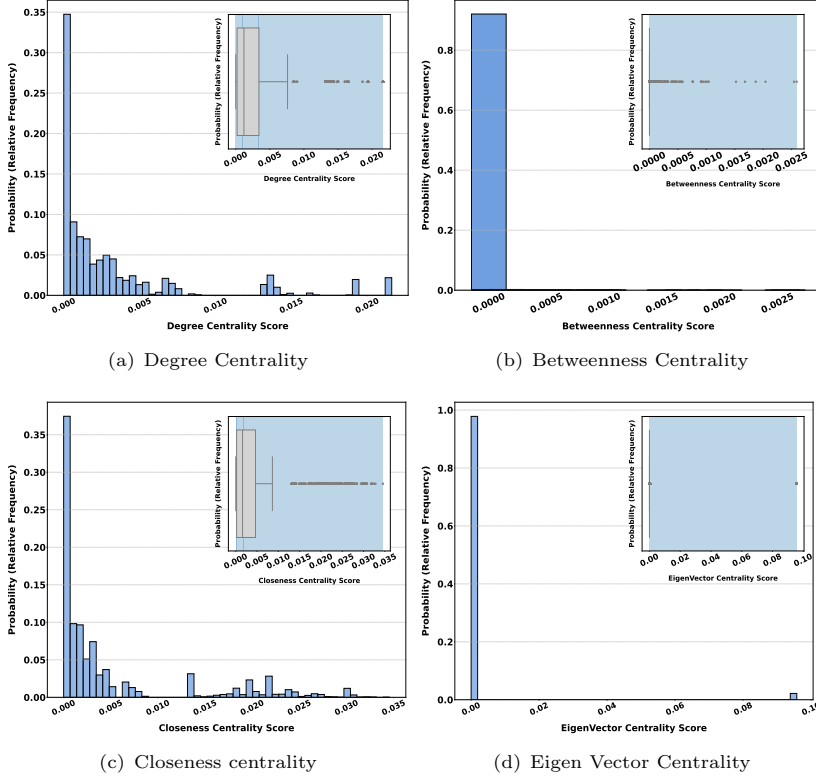


Fig. 8: The figure represents the distribution of four centrality score i.e., degree, betweenness, closeness and eigen vector centrality of the proposed music network. Along x-axis, we plot the centrality score and along y-axis, we plot the probability value of the corresponding centrality score. In the inset of the each figure, we show the box-plot of the same distribution.

the biases in music production or consumption. For example, disassortative mixing by language would support the universality of music, while high assortativity in release years might indicate temporal silos. The potential findings of macro-level analysis would disclose the nature of the network. It might include the scale-free degree distribution of the proposed network that might be able to explore the “rich-get-richer” dynamics in music popularity, and low assortativity in the network, which would underscore the network’s capacity to bridge cultural divides.

5 Results & Discussions

In this section, we present the empirical findings derived from our multi-level analysis of our proposed music network. We mainly focus on the structural

and relational properties of the music network. Our experiments are organized into three hierarchical levels: Micro, Meso, and Macro, each offering unique insights into the network’s dynamics. At the Micro-level, we examine individual nodes (music tracks) through centrality measures and clustering coefficients to identify influential songs and local cohesion patterns. The Meso-level analysis explores cluster formations, revealing how intrinsic audio features and metadata shape communities within the network. Finally, the Macro-level investigation evaluates global topological properties, such as assortativity and small-world characteristics, to understand the network’s overarching behavior. These analyses collectively address our research questions about the universality of music and the efficacy of similarity-based recommendations. Preliminary results underscore the network’s ability to bridge linguistic and cultural divides, highlighting its potential for applications in music discovery, therapy, and plagiarism detection.

5.0.1 Micro Analysis

The Micro-level analysis focuses on individual nodes (music tracks) to examine their structural roles in MUSiNET. We conducted experiments using centrality measures—degree, betweenness, closeness, and eigenvector centrality—along with the clustering coefficient and edge weight distribution. These experiments aim to identify influential tracks, bridge nodes, and tightly connected communities. This experiment addresses our research question on the universality of music by quantifying how songs transcend genre and language barriers. The rationale behind these metrics is to uncover hidden patterns in musical relationships that traditional classification methods may overlook.

In fig. 8(a), we observe the probability distribution of degree centrality of the nodes in the MUSiNET. Degree Centrality measures the number of connections per node. It reflects a song’s similarity in terms of intrinsic and extrinsic features to others. The distribution reveals a few highly connected tracks—likely cross-cultural popular music tracks, while most songs exhibit moderate connectivity. This suggests that while certain tracks act as universal bridges, most remain confined to localized clusters. It reinforces the idea that music universality is applicable to some certain extends based on the intrinsic quality of it.

The Betweenness Centrality metric identifies those nodes that act as bridges between disparate clusters. The fig. 8(b) shows the heavily right-skewed distribution. It indicates that only a small fraction of tracks facilitate cross-genre or cross-language connections. These high-betweenness songs are critical for network cohesion, supporting the hypothesis that some music inherently transcends cultural boundaries.

In fig. 8(c), we represent the probability distribution of closeness centrality of nodes in the proposed network. Closeness Centrality evaluates how quickly a node can reach others in the network. A narrow distribution suggests that most tracks are similarly accessible, with minor variations for highly central songs.

This implies that while certain tracks are more influential, the network lacks extreme hierarchies, allowing diverse music to coexist without rigid dominance.

Figure 8(d) highlights the distribution of Eigen Vector Centrality. This network parameter estimates the probability of connectivity of a node to other influential nodes. It exposes the “elite” tracks that shape musical trends. The distribution shows a few high-scoring songs—likely by globally popular artists, while most exhibit lower influence. This result aligns with real-world music dynamics, where a handful of artists disproportionately impact industry trends.

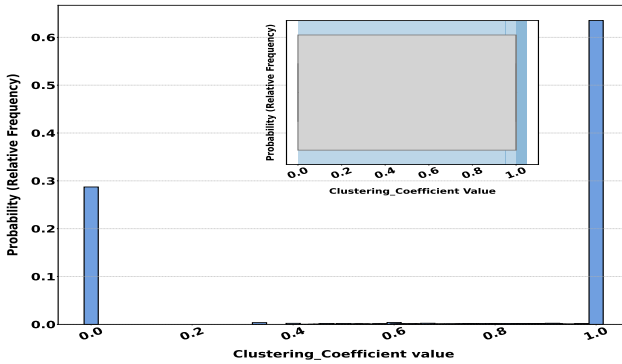


Fig. 9: Clustering Coefficients

To reveal the local group cohesiveness of the music tracks in the proposed music network, we have observed the probability distribution of the clustering coefficient. The distribution of clustering coefficient (as shown in Fig. 9) highlights the existence of it with higher values that indicates tightly connected neighborhoods. The distribution reveals that songs with similar acoustic features (e.g., tempo, energy) cluster together, even across languages. It reinforces the universality of certain musical attributes.

In music network formation, we have kept only edges which has significant edge weight i.e., (similarity score > 0.024). This threshold value has been estimated using HITS algorithm [38], which identifies authoritative nodes in a network by iteratively assigning hub and authority scores, allowing us to isolate musically significant connections based on similarity strength. We show the edge weight distribution in fig. 10 that reflects the similarity scores between tracks. The distribution shows a long tail, with most edges having moderate weights and a few strong connections. This confirms that while many songs share subtle similarities, only a subset exhibits deep acoustic or thematic parallels, supporting the need for threshold-based filtering in recommendation systems. Collectively, these findings validate MUS_iNET’s ability to uncover latent relationships beyond metadata labels, offering a data-driven framework for cross-cultural music discovery and recommendation accurately.

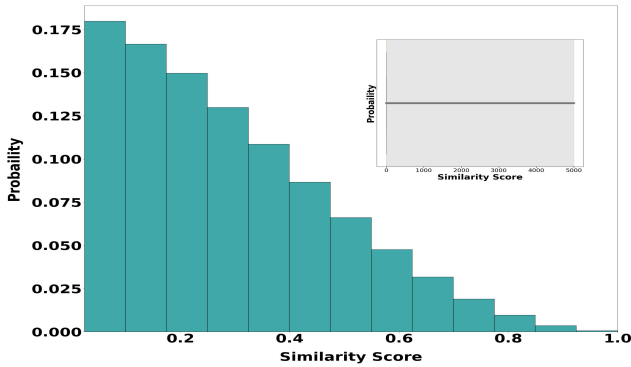


Fig. 10: The figure shows the edge weight distribution of proposed music network. Along x, we plot the edge weight in terms of similarity score and along y axis, we plot the probability of the edge weight. In inset of the figure, we show the box plot of the same distribution.

5.0.2 Meso Analysis

In this section, we focus on the Meso-level analysis of the proposed music network. This analysis uncovers the community structures within the proposed music network. It reveals how songs cluster based on shared intrinsic and extrinsic features. This analysis bridges the gap between individual node properties (Micro-level) and the global network topology (Macro-level), offering insights into the formation of musical communities that transcend traditional genre or language boundaries. Initially, we identify the hubs and bridges nodes that either dominate their clusters or connect disparate communities. This observation helps us to better understand the underlying dynamics of musical similarity and influence. Additionally, we performed community detection techniques on the music network using Louvain method [39]. It quantifies the modularity of these clusters and visualizes their distribution. Further, we elucidate how music naturally groups into cohesive yet interconnected communities.

Hubs & Bridges Analysis

Hubs and bridges play a pivotal role in the structure and function of the music network. Hubs are highly connected nodes that dominate their local clusters, while bridges act as critical links between otherwise isolated communities. To identify hubs and bridges in the proposed music network, we employed two key centrality measures: a) degree Centrality is used to identify hubs in the network. We have selected the top 2% of nodes [40] with the highest degree centrality, as these nodes represent the most connected tracks in the network, acting as central points within their communities., b) betweenness Centrality has been employed to detect bridges in our proposed music network. We considered the top 1% of nodes [41] with the highest betweenness centrality, as these nodes serve as critical connectors between otherwise disconnected

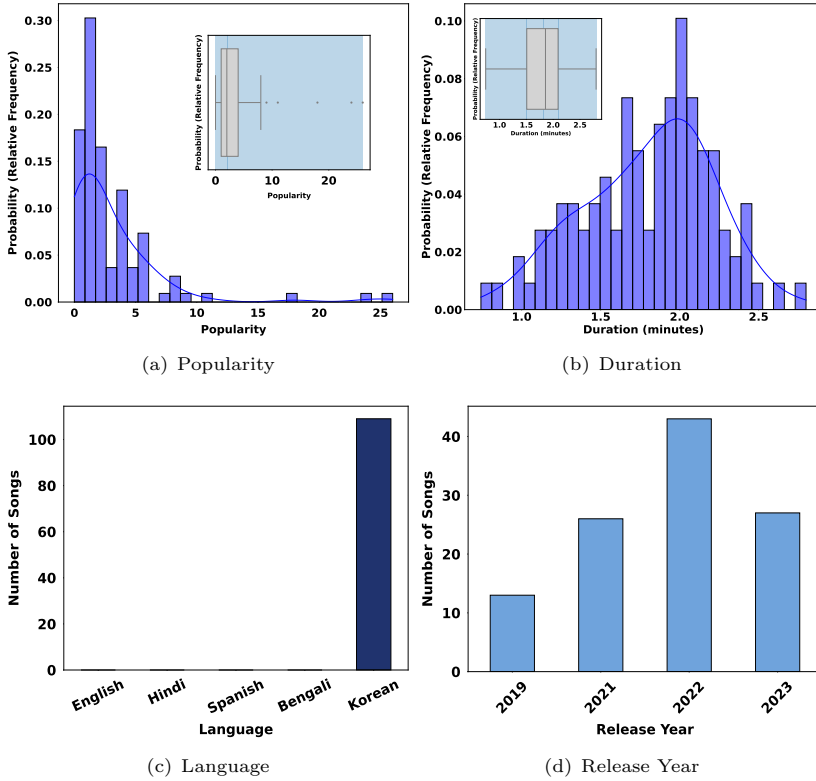


Fig. 11: The figure represents the distribution of four extrinsic features i.e., popularity, duration, language and release year of the HUBs in the network. Along x-axis, we plot the popularity, duration, language and release year in fig. 11(a), 11(b), 11(c) and 11(d) respectively. Along y-axis, we plot the probability value of the corresponding extrinsic features of those HUB nodes in the network. In the inset of the each figure, we show the box-plot of the same distribution.

clusters, facilitating cross-genre or cross-language musical relationships. The distributions of degree and betweenness centrality (Fig. 8(a) and 8(b)) revealed a heavy-tailed structure, confirming that only a small fraction of nodes exhibit exceptionally high connectivity or bridging capacity. Figure 11 and 12 illustrate the distribution of extrinsic features—popularity, duration, language, and release year—for these key nodes.

The detailed study of hub nodes in the music network reveals several noteworthy patterns about contemporary music consumption. We observe in fig. 11(a) that though there exists majority nodes with popularity ranges between 1-10, these hubs demonstrate a strong concentration among highly popular tracks (popularity ranges between 0-25 of all hubs in the network),

sl no	track_name	artist_name	album_name	language
01.	Popular (with Playboi Carti & Madonna) -	The Weeknd, Playboi Carti, Madonna	Popular(HBO)	English
02.	Run	Calvin Jenkins	Pop Music 2020	English
03.	Popular	Kidz Bop Kids	KIDZ BOP 2024	English
04.	July	Claire Bell	Top Pop Music	English
05.	Mind Control	Just Relax Music Universe	Hindi Songs for Relaxation and Meditation	Hindi
06.	Uttar Dakshin	Alka Yagnik, Sonu Nigam, Javed Akhtar	Aur Pyar Ho Gaya (Original Motion Picture Soundtrack)	Hindi
07.	Bengali Song [Lofi]	Hindi Dance Vibes, New Traditions Crew, Lofi Beats India	Sad Hindi LoFi – Chillout At Night: Alone & Broken	Hindi
08.	Asha	Anish Kumar	Bollywood Super Hits!	Hindi
09.	Bengali Song [Lofi]	Hindi Dance Vibes, New Traditions Crew, Lofi Beats India	Sad Hindi LoFi – Chillout At Night: Alone & Broken	Bengali
10.	Uttar Dakshin	Sabina Yasmin	Bengali Songs - Sabina Yasmin	Bengali

Table 6: Top 10 Hubs in the Music Similarity Network

with a pronounced peak in the 15-25 popularity score range. Though this nature does not fully align with the "rich-get-richer" phenomenon where already popular songs accumulate even more connections, we find some highly popular song tracks which are very well connected. Interestingly, these central nodes tend to be shorter in duration than average, typically between 1.5-2.5 minutes(as shown in fig. 11(b)), which may reflect the prevalence of attention-grabbing hooks and viral snippets in today's streaming-dominated music landscape. The language distribution shows a surprising dominance of Korean tracks among hubs, highlighting the global reach and platform-friendly nature of K-pop. In figure 11(d), we observe that all identified hubs come from the post-2019 period. It might be underscoring how streaming algorithms and playlist culture have created a new class of super-connected, algorithmically boosted tracks that form the backbone of modern music networks.

In contrast, the bridge nodes which are the critical connectors between different communities, shows a different aspect of musical connectivity. These

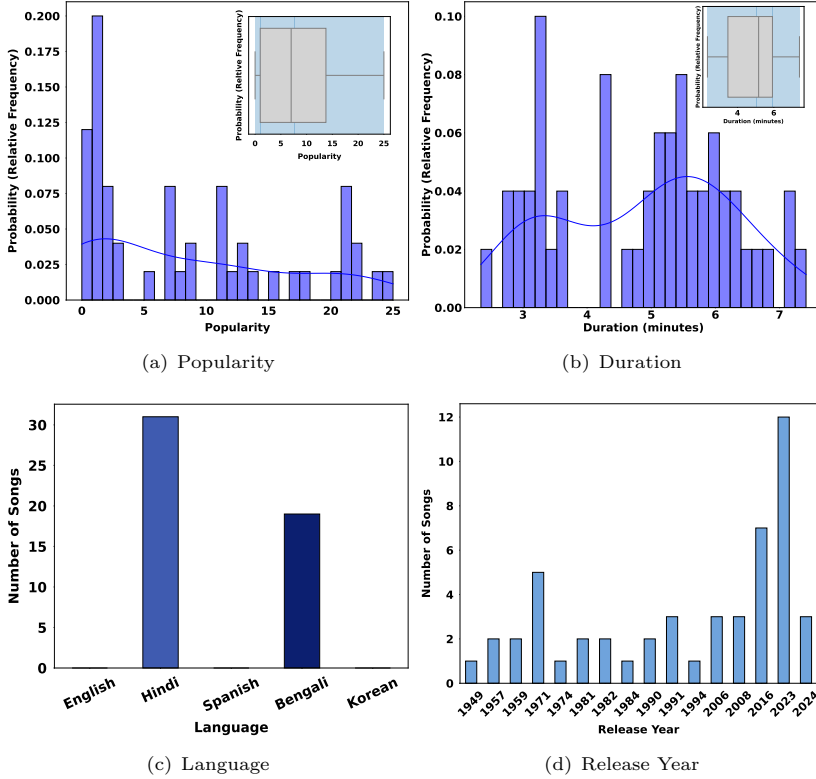


Fig. 12: The figure represents the distribution of four extrinsic features i.e., popularity, duration, language and release year of the Bridges in the network. Along x-axis, we plot the popularity, duration, language and release year in fig. 12(a), 12(b), 12(c) and 12(d) respectively. Along y-axis, we plot the probability value of the corresponding extrinsic features of those Bridge nodes in the network. In the inset of the each figure, we show the box-plot of the same distribution.

nodes show a bimodal popularity distribution (as shown in fig. 12(a)) with peaks in both mid-range and low popularity scores. This suggests that while some moderately popular songs serve as bridges, many connections are actually facilitated by less mainstream tracks. We observe the duration distribution of the bridges in fig. 12(b). The duration distribution of bridges is notably broader than hubs, with many bridge tracks falling in the 3-7 minute range and a secondary peak around 6 minutes, indicating that longer, more complex compositions often serve as connectors between genres or styles. Linguistically, Hindi and Bengali tracks are overrepresented among bridges as shown in figure 12(c). It suggests that South Asian music plays a particularly important role in linking disparate musical communities. Perhaps most remarkably,

sl no	track_name	artist_name	album_name	language
01.	Ori Ori Baba (From "Bali- daan")	Usha Uthup	Best of Bangla Music By Bappi Da	Bengali
02.	Aladin Dao Aladin	Usha Uthup	Bengali Mod- ern Songs	Bengali
03.	Tujhe Apne Paas Bulati Hai (remastered)	Talat Mah- mood	Classic Bolly- wood Music Hits (Digitally Remastered)	Hindi
04.	Sab Lal Pathor (From "Mandira")	Lata Mangeshkar	Best of Bangla Music By Bappi Da	Bengali
05.	Amraye Bhubon Ayiam (From "Priya")	Kumar Sanu	Best of Bangla Music By Bappi Da	Bengali
06.	Chirodini Tumi Je Aamar (Male Version)	Kishore Kumar	Best of Bangla Music By Bappi Da	Bengali
07.	Yaad Rakhna Chand Taro (remastered)	Lata Mangeshkar	Classic Bolly- wood Music Hits (Digitally Remastered)	Hindi
08.	Duniya Badal Rahi Hai (remastered)	Lata Mangeshkar	Classic Bolly- wood Music Hits (Digitally Remastered)	Hindi
09.	Jetha Ramd- hanu Othe Hese	Talat Mah- mood	Bengali Mod- ern Songs	Bengali
10.	Tumi Sundar Jodi Nahi Hao	Talat Mah- mood	Bengali Mod- ern Songs	Bengali

Table 7: Top 10 Bridges in the Music Similarity Network

bridge tracks span seven decades of release dates, with significant representation from the 1970s-1990s(as shown in fig. 12(d)). This nature reveals how certain musical elements maintain their connective power across generations.

Insight of the Analysis These findings reveal that hubs represent the concentrated power of algorithmic promotion and contemporary hit-making music tracks in recent times. It creates dense clusters around recent, platform-optimized music tracks. On the other hand, bridges demonstrate the enduring, organic connections that form through shared intrinsic musical properties, where older tracks, regional genres, and less commercial works maintain the network's connectivity. This duality suggests that while streaming platforms may amplify certain types of music to hub status, the underlying web of

musical relationships remains rich and multidimensional. For music recommendation systems, these insights point to the value of balancing the visibility of current hits with pathways that leverage these natural bridges, potentially leading to more diverse and satisfying listening experiences that honor both contemporary trends and music’s deeper connections.

Network Properties	Values
No. of Communities	11
No. of nodes in giant community	4,979
No. of edges in giant community	12,392,731
Size of giant community(in % of whole network)	99.58%
Modularity Score	0.0001
Extrinsic features of giant community	
No. of distinct language	5
Popularity range	0 - 85
Duration range	0.52 - 86.36
Release period	1929 - 2024

Table 8: Statistics of Communities in the proposed music network.

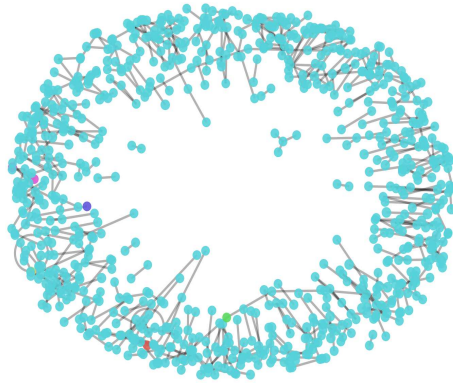


Fig. 13: Figure represents the communities in the proposed Mus_inet. The nodes having the same color represent their belongingness into the same community.

Community Analysis

In this section, we perform the detailed analysis of communities existing in the proposed music network. This section explores the meso-level structure of the proposed music network by identifying and characterizing communities i.e., groups of songs that share stronger connections with each other than with the rest of the network. We have used the Louvain method [1] for community detection in complex networks. We uncover clusters of songs that exhibit

high intra-group similarity in terms of intrinsic audio features (e.g., tempo, energy, valence) and extrinsic metadata (e.g., genre, language, release year). This analysis aims to answer whether musical relationships align with traditional genre/language classifications or reveal unexpected cross-cultural and cross-temporal affinities. By quantifying modularity, cluster size distribution, and inter-cluster connectivity, we assess the network’s tendency to form cohesive yet interconnected communities, providing insights into the universality of music and the potential for data-driven music discovery.

The Louvain method identified 11 distinct communities in the network, with a dominant “giant component” encompassing 99.58% of all nodes (Table 8 and figure 13). This near-complete connectivity suggests that the music network is highly integrated, with most songs linked through direct or indirect similarity paths. Although the low modularity score (0.0001) indicates weak intra-community cohesion, where songs within the same cluster share moderate acoustic or thematic similarities. Notably, the giant component spans a wide range of languages, popularity scores, and release years, reflecting the network’s capacity to bridge diverse musical attributes. However, the sparse representation of very long-duration tracks (>6 minutes) in communities hints at niche listening preferences or algorithmic biases against unconventional song lengths. We also observe that the inter-language edges (212,989) are fewer than intra-language edges (582,386) (Table 9), suggesting that linguistic boundaries still influence community formation, though intrinsic musical features often transcend them.

In figure 14, we observe the distribution of languages across the communities in the music network. We represent the distribution by heatmap that highlights how languages distribute across communities. Our observation figured out that english language moderately dominates most clusters that reflects its global influence, of the language. While Bengali and other regional languages appear in smaller, tightly knit groups. Interestingly, some communities exhibit strong cross-language mixing (e.g., Korean-Spanish), revealing unexpected acoustic or thematic similarities. We further observe the popularity distribution heatmap (figure 15) among the communities. It shows that high-popularity tracks tend to concentrate in a few communities, while low and medium popularity songs form smaller, niche clusters. It is notable that “Very High” popularity tracks rarely appear in isolation, instead acting as hubs that bridge multiple communities.

Insight of Community The strong interconnectedness in the proposed network reveals latent universality of the music. For instance, communities dominated by danceability or valence may merge pop songs across languages, while sparse inter-cluster edges highlight cultural or temporal divides. These findings challenge rigid genre/language classifications and support hybrid recommendation systems that prioritize acoustic similarity over metadata labels. The persistence of older tracks (pre-2000s) in communities alongside recent hits further suggests that certain musical elements (e.g., chord progressions, rhythmic patterns) transcend temporal trends, enabling timeless connections.

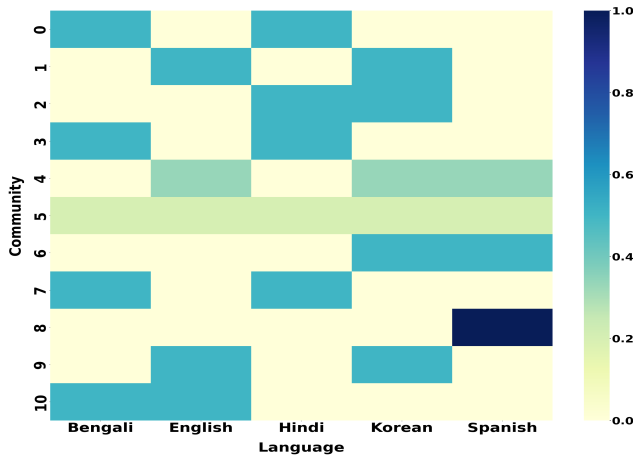


Fig. 14: Figure represents distribution of language among the communities in the proposed music network. Along x-axis, we plot the five distinct languages and along y-axis, it represents the communities marked as 0-10.

5.0.3 Macro Analysis

In this section, we perform the macro-level analysis of the proposed music network. We focus on the uncovering the global structural properties of the network and examining assortative mixing patterns—how nodes preferentially connect based on shared attributes. Initially, We summarize the fundamental network metrics which provides an overview of the network’s scale, connectivity. Following this, we investigate the assortative nature of node attachments by analyzing four key attributes: popularity, language, duration, and release year. Each experiment of assortative mixing serves a distinct purpose: (1) Popularity assortativity tests whether popular songs form hubs, reinforcing preferential attachment dynamics; (2) Language assortativity evaluates cultural and linguistic clustering; (3) Duration assortativity examines if song length influences connectivity; and (4) Release year assortativity explores temporal trends in musical evolution. Together, these analyses reveal how metadata and intrinsic features shape the network.

Initially, we overview the fundamental network metrics which has been summarized in the table 9. We observe that the network consists of 4,990 nodes with 582,386 intra-language edges and 212,989 inter-language edges. It indicates a densely connected structure where cross-cultural links are substantial yet slightly fewer than within-language connections. The average degree centrality of the network shows the moderate connectivity, while the low betweenness centrality implies that only a few tracks serve as critical bridges between clusters. Further, the very low value of average closeness and eigen vector centrality might reflect that influence is distributed rather than concentrated, with no single song dominating the network. We observe that the network have high clustering coefficient. It confirms strong local cohesion,

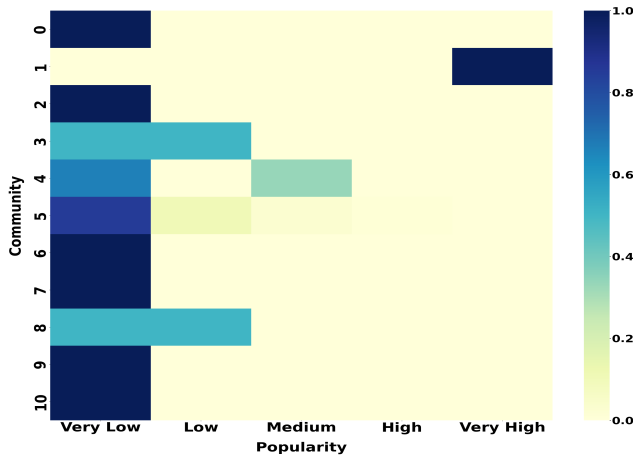


Fig. 15: Figure represents distribution of popularity among the communities in the proposed music network. Along x-axis, we plot the popularity in five categorical scale (very low (bottom 25%), low (25% to 5% below median), medium (5% below of median to 5% above median), high (5% above the median to 75%), and very high (top 25%)) and along y-axis, it represents the communities marked as 0-10.

Network Properties	Values
No. of nodes	4990
No. of intra-language edges	582386
No. of inter-language edges	212989
Avg. val. of Node Prop.	
Degree centrality	3.156×10^{-3}
Betweenness centrality	1.1×10^{-5}
closeness centrality	5.09×10^{-3}
Eigen-vector centrality	2.096×10^{-3}
Clustering coefficient	0.691

Table 9: Properties of the proposed network developed on the music dataset [34] used in our work.

where songs with similar features form tightly knit groups. These properties collectively suggest that the proposed music network exhibits small-world characteristics, balancing localized clustering with broader, cross-cultural linkages.

To investigate the assortative nature of the nodes in the proposed music network in terms of four basic meta information: 1) popularity 2) Language 3) Duration 4) Release year. To conduct this experiment, we first categorized songs into five popularity levels based on their streaming performance: very low (bottom 25%), low (25% to 5% below median), medium (5% below of median to 5% above median), high (5% above the median to 75%), and very high (top 25%). We then mapped how frequently songs from each popularity

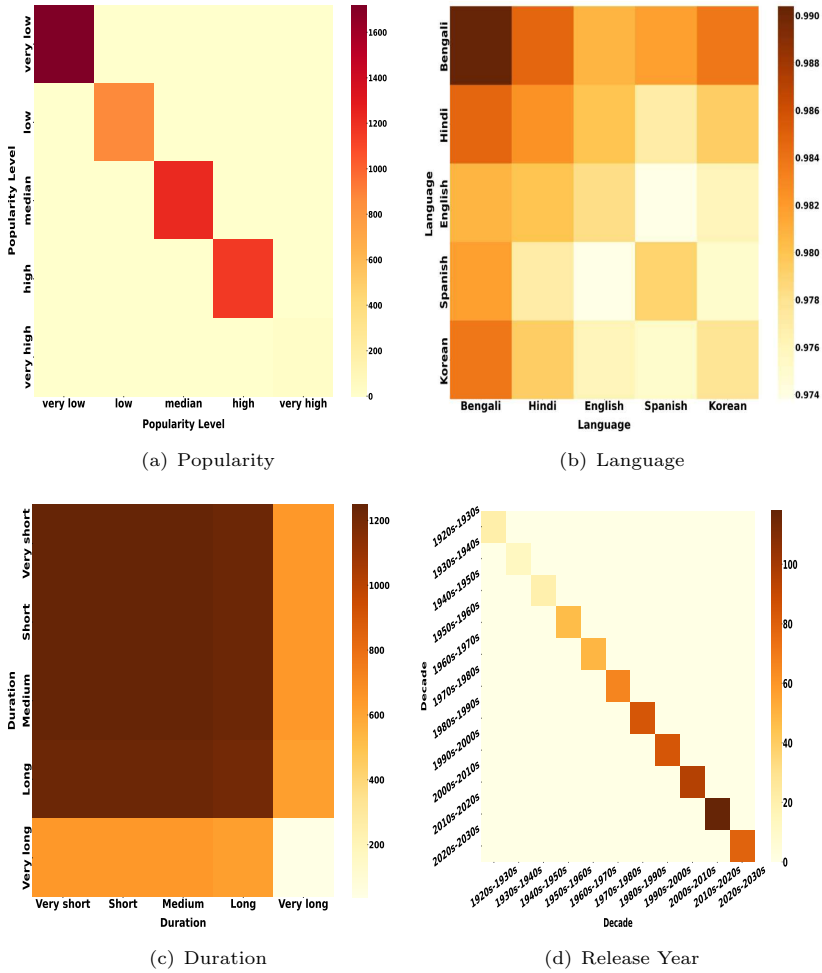


Fig. 16: The heatmap represents the assortative mixing nature of nodes in the proposed music network with respect to four major extrinsic properties of music, i.e., popularity, language, duration and release year of each individual music.

level connect with others in the network, creating a heatmap where brighter colors indicate stronger connections. The analysis focused on both the density of connections within each popularity group (showing how similar songs link together) and between different groups (revealing how music discovery might flow across popularity levels). By examining these connection patterns, we could identify which songs serve as hubs or bridges in the network, and how popularity influences a song's role in music recommendation pathways.

This method allowed us to move beyond simple popularity rankings to understand how different tiers of popularity actually interact in listeners' music exploration.

The heatmap analysis(as shown in the fig. 16(a)) reveals clear patterns in how songs of different popularity levels connect within the network. Highly popular songs form tight clusters with many mutual connections, while less popular songs have fewer links overall. Medium-popularity songs emerge as important bridges, connecting both to popular hits and lesser-known tracks. This suggests that while popular songs naturally attract more attention (the "rich get richer" effect), medium-popular tracks play a crucial role in helping listeners discover new music. The sparse connections among very low-popularity songs indicate they often get overlooked, though some do connect to more popular groups. These findings demonstrate how popularity influences music spread through networks, with top hits dominating but mid-tier songs serving as key connectors. For music recommendation systems, this means focusing solely on the most popular songs might create repetitive listening patterns, while strategically including medium-popular tracks could better balance mainstream hits with fresh discoveries. The structure also suggests that combining popularity with other factors like musical similarity might optimize recommendations for both listener satisfaction and artist exposure.

In figure 16(b), we observe the assortative mixing of the nodes in the music network. The language heatmap reveals fascinating patterns in how songs from different languages connect. English songs show the strongest internal connections. It reflects their global popularity, while Korean and Spanish display surprisingly strong musical similarities despite their linguistic differences. Hindi and Bengali tracks naturally connect well with each other due to shared cultural roots. Interestingly, all languages maintain some connection with English, making it a central hub in the network. These patterns show that while language is important, music transcends linguistic boundaries through shared rhythms, production styles, and cultural influences. For music recommendations, this means systems should consider both language preferences and these hidden musical connections to better guide listeners between familiar favorites and exciting new discoveries across different cultures. The strong Korean-Spanish connection especially highlights how modern music is creating unexpected bridges between seemingly unrelated languages.

The duration heatmap (as shown in fig. 16(c)) reveals several key insights about how song length affects musical connections in our network. We observe the strongest connections occur between songs of similar durations. It is also observable that the assortative mixing among the very long duration music tracks comparatively low that could be reflection of very fewer existence of very high duration music in the network. Particularly, the medium-length range (3-4 minutes) music tracks form the densest cluster. Interestingly, very short songs (under 2 minutes) show some connection to very long tracks (over 6 minutes), suggesting that unconventional durations may share certain musical

qualities despite their length differences. The map also shows that medium-duration songs act as bridges, connecting to both shorter and longer tracks. These patterns imply that while duration influences musical similarity, it's not an absolute barrier - songs can connect across duration categories through shared rhythmic patterns, instrumentation, or structure. This duration analysis complements our language and popularity findings to give a more complete picture of how different musical characteristics interact in the network.

Finally, we observe the assortative linkage between the music in the proposed music network from the perspective of release year. As our dataset contains the music tracks over a century, to observe the assortative mixing across the release year, we have marked the music tracks under decades i.e., 1920-1929, 1930-1939, etc. The motivation of this decade wise cluster came from the music pattern of the released music across the decade which get attention the contemporary audience. The result is shown in figure 16(d) in heat map. We observe strong diagonal patterns showing songs most frequently connect with contemporaries from the same 5-10 year period, confirming that era-specific production styles create natural musical similarities. The strong era clustering confirms release year should be weighted alongside other features in recommendation systems to maintain stylistic coherence. The secondary bands shows connections between songs separated by 20-30 years (e.g., 1980s hits linking to 2010s retro revivals). It suggests cyclical trends in musical influence. The revival patterns reveal opportunities to build "then-now" recommendation pathways that connect classic songs with their modern reinterpretations. Certain transitional periods (particularly the late 1990s) show unusually broad connections to both older and newer music. It potentially represents evolutionary bridges in music technology. This observation suggests that certain historical moments may be particularly fruitful for studying musical evolution through network dynamics. This temporal analysis completes our multidimensional understanding of MUSiNET by showing how music connects not just through sound (duration) and culture (language), but also through historical lineage - creating a rich, time-aware framework for music discovery and analysis.

6 Conclusion and Future works

Music, as a universal language, reveals intricate and often overlooked connections across genres, languages, and cultures—connections that traditional classification methods frequently miss. To explore these deeper relationships, we developed MUSiNET, a data-driven network model that transcends subjective genre labels by capturing both intrinsic audio features such as tempo and energy, and extrinsic metadata including artist and language. Through the construction of a weighted, undirected graph and a three-level analysis (micro, meso, and macro), we discovered that hubs in the network tend to be recent algorithm-boosted songs, while bridges often consist of older, cross-cultural

tracks. A large connected component encompassing 99.58% of tracks underscores music's inherent interconnectedness, and assortativity patterns highlight both expected groupings (e.g., by language or popularity) and surprising cross-genre affinities. These findings support the idea that music's universal nature can be meaningfully modeled through structural and content-based features. Nevertheless, our study has limitations: the dataset includes only five languages, the choice of similarity thresholds can influence outcomes, and the model's scalability is constrained by computational demands. Moreover, the reliance on Spotify data introduces potential biases related to regional content and popularity, while the absence of lyrics and textual metadata limits the system's ability to capture semantic and emotional dimensions. Future work will address these gaps by incorporating textual and lyric-based analysis, broadening the multilingual and cultural scope of the dataset, and improving computational efficiency. Crucially, we recognize the need for real-world validation, and therefore plan to conduct a user study involving participants from diverse linguistic and musical backgrounds. These users will evaluate MUSiNET's song recommendations based on perceived relevance, novelty, and emotional or cultural resonance, with quantitative metrics such as top-K precision, recall, and Mean Opinion Score (MOS) used to assess performance. We also aim to benchmark MUSiNET against traditional approaches like collaborative filtering and genre-based classifiers, which will not only validate its effectiveness but also help refine similarity thresholds and weighting strategies, thereby enhancing its applicability in practical music recommendation contexts.

Declarations

- **Funding:** No funds, grants, or other support were received to conduct this study.
- **Conflict of interest/Competing interests:** On behalf of all authors, the corresponding author states that there is no conflict of interest.
- **Data availability:** Publicly available.
- **Author contribution:** **Avijit Gayen:** Conceptualization, Methodology, Experiment, Writing. **Avik Mondal:** Data collection, Experiment. **Praswasti Sharma:** Data collection, Experiment. **Angshuman Jana:** Supervision, Writing review & editing.

References

- [1] Killin, A.: The origins of music: Evidence, theory, and prospects. *Music & Science* **1**, 2059204317751971 (2018)
- [2] Toussaint, G.T.: The Geometry of Musical Rhythm: What Makes A" Good" Rhythm Good? CRC Press, ??? (2019)

- [3] Särkämö, T., Tervaniemi, M., Huotilainen, M.: Music perception and cognition: development, neural basis, and rehabilitative use of music. *Wiley Interdisciplinary Reviews: Cognitive Science* **4**(4), 441–451 (2013)
- [4] Hesmondhalgh, D.: *Why Music Matters*. John Wiley & Sons, ??? (2013)
- [5] Tan, S.-L., Pfordresher, P., Harré, R.: *Psychology of Music: From Sound to Significance*. Routledge, ??? (2017)
- [6] Oramas, S., Nieto, O., Barbieri, F., Serra, X.: Relating user and item perspectives in hybrid music recommendation systems. In: *Proceedings of the 2nd Workshop on Knowledge Graphs and Semantics for Text Retrieval, Analysis, and Understanding (KG4IR)*, pp. 22–26 (2018). <https://www.upf.edu/web/mtg/kgrec>
- [7] Abdollahpouri, H., Burke, R., Mansoury, M.: Unfair exposure of artists in music recommendation. *arXiv preprint arXiv:2003.11634* (2020)
- [8] Silva, M., Willemsen, M., van de Ven, M., Hanjalic, A.: Musicoset: A dataset for music content analysis. In: *Proceedings of the Data Science Workshop (DSW)* (2019)
- [9] Sturm, B.L., et al.: The use of deep learning in music genre classification. *IEEE Transactions on Multimedia* (2021)
- [10] Shao, Y., *et al.*: Hybrid music recommendation with acoustic features and user data. *ACM Transactions on Information Systems* **37**(4), 1–23 (2019)
- [11] Chen, Y.: Music recommendation systems in music information retrieval: Leveraging machine learning and data mining techniques. *Applied and Computational Engineering* **87**, 197–202 (2024)
- [12] Cheng, Y.: Music information retrieval technology: Fusion of music, artificial intelligence and blockchain. In: *2020 3rd International Conference on Smart Blockchain (SmartBlock)*, pp. 143–146 (2020). IEEE
- [13] Putri, R.A., Lestari, D.P.: Music information retrieval using query-by-humming based on the dynamic time warping. In: *2015 International Conference on Electrical Engineering and Informatics (ICEEI)*, pp. 65–70 (2015). IEEE
- [14] Kostek, B.: Music information retrieval—the impact of technology, crowd-sourcing, big data, and the cloud in art. *Journal of the Acoustical Society of America* **146**, 2946–2946 (2019)
- [15] Zhang, S., *et al.*: Deep learning-based hybrid collaborative filtering for music recommendations. *IEEE Transactions on Knowledge and Data*

- Engineering **32**(3), 484–496 (2020)
- [16] He, X., Liao, L., Zhang, H., Nie, L., Hu, X., Chua, T.-S.: Neural collaborative filtering. In: Proceedings of the 26th International Conference on World Wide Web (WWW), pp. 173–182 (2017). International World Wide Web Conferences Steering Committee
 - [17] Bevec, M., Tkalcíč, M., Pesek, M.: Hybrid music recommendation with graph neural networks. *User Modeling and User-Adapted Interaction*, 1–38 (2024)
 - [18] Liu, X., Yang, Z., Cheng, J.: Music recommendation algorithms based on knowledge graph and multi-task feature learning. *Scientific Reports* **14**(1), 2055 (2024)
 - [19] Deldjoo, Y., Schedl, M., Knees, P.: Content-driven music recommendation: Evolution, state of the art, and challenges. *Computer Science Review* **51**, 100618 (2024)
 - [20] Singh, J., Bohat, V.K.: Neural network model for recommending music based on music genres. In: 2021 International Conference on Computer Communication and Informatics (ICCCI), pp. 1–6 (2021). IEEE
 - [21] Tandon, R., *et al.*: Analyzing collaboration networks in the music industry. In: *Complex Networks and Their Applications*, pp. 345–358. Springer, ??? (2018)
 - [22] Bush, R.A.M.: Analysis of a spotify collaboration network for small-world properties. *arXiv preprint arXiv:2503.09526* (2025)
 - [23] Martínez, J.H., Boccaletti, S., Makarov, V.V., Buldú, J.M.: Multiplex networks of musical artists: The effect of heterogeneous inter-layer links. *Physica A: Statistical Mechanics and its Applications* **510**, 671–677 (2018)
 - [24] Dhanushya, M., PK, G.N., Lavanya, G., Arya, A.: Anticipating collaborative trends in spotify music using variants of graph neural networks. In: 2023 10th International Conference on Soft Computing & Machine Intelligence (ISCMI), pp. 96–100 (2023). IEEE
 - [25] Costa, Y.M., *et al.*: An evaluation of convolutional neural networks for music classification using spectrograms. *Applied Soft Computing* **52**, 28–38 (2017)
 - [26] Wu, P., Gao, W., Chen, Y., Xu, F., Ji, Y., Tu, J., Lin, H.: An improved vit model for music genre classification based on mel spectrogram. *PloS one* **20**(3), 0319027 (2025)

- [27] Ding, Y., Zhang, H., Huang, W., Zhou, X., Shi, Z.: Efficient music genre recognition using ecas-cnn: A novel channel-aware neural network architecture. *Sensors* **24**(21), 7021 (2024)
- [28] Ghildiyal, A., Singh, K., Sharma, S.: Music genre classification using machine learning. In: 2020 4th International Conference on Electronics, Communication and Aerospace Technology (ICECA), pp. 1368–1372 (2020). IEEE
- [29] Singh, A., et al.: Quantifying and predicting music influence and similarity in online social networks. *Journal of Cultural Analytics* **4**(1) (2019)
- [30] Zhang, X., Ren, T., Wang, L., Xu, H.: Music influence modeling based on directed network model. arXiv preprint arXiv:2204.03588 (2022)
- [31] Schedl, M., et al.: Sentiment analysis in music: A survey. *IEEE Transactions on Affective Computing* (2019)
- [32] Panda, R., Paiva, R.P.: Lyrics-based music genre classification using a hierarchical attention network. *Neural Computing and Applications* **33**, 1–14 (2021)
- [33] Ferreira, L.N., Whitehead, J.: Learning to generate music with sentiment. arXiv preprint arXiv:2103.06125 (2021)
- [34] Spotify Tracks Dataset (full)
- [35] McFee, B., Raffel, C., Liang, D., Ellis, D.P., McVicar, M., Battenberg, E., Nieto, O.: librosa: Audio and music signal analysis in python. *SciPy* **2015**, 18–24 (2015)
- [36] Gunawan, D., Sembiring, C., Budiman, M.A.: The implementation of cosine similarity to calculate text relevance between two documents. In: *Journal of Physics: Conference Series*, vol. 978, p. 012120 (2018). IOP Publishing
- [37] Meadi, M.N., Babahenini, M.C., Ahmed, A.T.: New use of the hits algorithm for fast web page classification. *Turkish Journal of Electrical Engineering and Computer Sciences* **25**(3), 2015–2032 (2017)
- [38] Giannoulakis, S., Tsapatsoulis, N.: Filtering instagram hashtags through crowdtagging and the hits algorithm. *IEEE Transactions on Computational Social Systems* **6**(3), 592–603 (2019)
- [39] Bhowmick, A.K., Meneni, K., Danisch, M., Guillaume, J.-L., Mitra, B.: Louvainne: Hierarchical louvain method for high quality and scalable network embedding. In: *Proceedings of the 13th International Conference on*

Web Search and Data Mining, pp. 43–51 (2020)

- [40] Kumar, P., Jain, R., Chaudhary, S., Kumar, S.: Solving community detection in social networks: A comprehensive study. In: 2021 5th International Conference on Computing Methodologies and Communication (ICCMC), pp. 239–345 (2021). IEEE
- [41] Mo, Y., Goursaud, C., Gorce, J.-M.: On the benefits of successive interference cancellation for ultra narrow band networks: Theory and application to iot. In: 2017 IEEE International Conference on Communications (ICC), pp. 1–6 (2017). IEEE