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**| RESEARCH ARTICLE**

# Language Preservation through Popularization of Regional Indian Music: A Data-Driven Approach

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**| ABSTRACT**
The increased global connectivity due to internet penetration has resulted in the dominance of international languages and the decline of regional languages. To help preserve these languages, this study identifies the non-native regions in India that offer the most promising opportunities for expanding the popularity of music for each of the 14 regional languages. It analyses the audio features of 41,000 songs from 14 Indian languages on Spotify, employing two approaches – clustering algorithms and Random Forest Regressors. An overlap between the regions identified by both methods for any given language is considered a robust result, providing greater confidence in the results. The results show that while geographical proximity is a significant factor in determining non-native market fits for the music of a given language, alignment in preferences of audio features driven by cultural similarities plays an integral role as well. The findings have important implications for music industry stakeholders, including artists, management, digital platforms, and governments, who can leverage this data to devise strategies to expand the reach of regional music. This includes designing targeted marketing strategies, fostering cross-regional artist collaborations, and optimizing content recommendation algorithms, among others.

**| KEYWORDS**

Regional Music, Ethnomusicology, Spotify, Language Preservation, Clustering, Random Forest Regressor.

**| ARTICLE INFORMATION**

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## 1. Introduction

### *1.1 Cultural Diversity and Language Preservation in India*

India's rich cultural diversity is both a source of national pride and a complex challenge. With 22 officially recognized languages and hundreds of dialects, the country represents a microcosm of linguistic diversity. However, the rapid globalization and dominance of certain languages like Hindi and English have led to the endangerment of many regional languages. According to Annamalai, regional languages are increasingly under threat, with fewer young speakers, leading to a gradual decline in cultural practices tied to these languages (Annamalai, 2004, p. 151-162).

Music has historically played a crucial role in the preservation of culture and language. Ethnomusicologists like Nettl argue that music is not only a form of artistic expression but also a repository of cultural memory (Nettl, 2005, p. 131-133). In the Indian context, music in regional languages serves as a vital tool for maintaining linguistic diversity. It encapsulates the identity, history, and traditions of a community, acting as a bridge between the past and the present.

### *1.2 The Role of Music in Cultural Exchange*

The concept of using music as a medium for cultural exchange is well-established. "Musicking" has been studied as a social practice that fosters community and shared understanding (Keil, 2009, p. 221-223). In India, music in regional languages has the potential to transcend linguistic barriers, particularly among the youth, who are increasingly exposed to diverse cultural influences through digital platforms like Spotify and YouTube.

Studies have shown that younger audiences are more open to listening to music in languages they do not speak (Ulea, 2024). This openness is partly due to the accessibility of global music and the decreasing relevance of language as a barrier to musical enjoyment. The Indian music industry is witnessing a growing trend of cross-regional musical appreciation, where songs from one language gain popularity in regions where that language is not spoken (Chaudhry, 2024).

### *1.3 Computational Ethnomusicology: Machine Learning in Musical Studies*

Computational ethnomusicology "refers to the use of computational techniques for the study of music from around the world" (Tzanetakis, 2014). With advancements in technology and artificial intelligence, this field has experienced substantial progress and found several interesting applications. Analysis of similarities in musical rhythms and beat patterns has helped researchers unearth historical connections between Greek and African civilizations as well as Turkish and Indian societies (Antonopoulos et al., 2007) (Srinivasamurthy, 2014, p. 94-114). It has also been used to classify songs into musical genres and has shown particularly strong efficacy in identifying Latin and Flamenco music (Volkel, 2010) (Guastavino, 2009, p. 129-138).

The Spotify API provides data about a range of audio feature metrics like "danceability," "tempo," "liveness," and "speechiness", among others. Several studies, including this one, have used this large trove of data for computational ethnomusicology research. It has helped us understand the musical characteristics that determine a song's popularity (Nijkamp, 2018) (McLeod, 2023) (Gulmatico, 2022). The API has also provided insight into the relationship between a listener's mood or personality traits and the types of songs they prefer (Hongpanarak & Mongkolnavin, 2021) (Duman et al., 2022). Furthermore, researchers have developed song recommendation algorithms based on personal user preferences with the Spotify API data (R et al., 2022, p. 422-426) (Bakhshizadeh et al., 2019).

## 2. Methodology

The research question of this paper is as follows: "Which non-native regions in India offer the most promising opportunities for expanding the popularity of music for a specific regional language?" While computational ethnomusicology and Spotify API data have been used for a variety of use cases, this paper's application of the concept to predicting cross-regional music popularity is innovative and unexplored in academic literature. Additionally, this study makes a valuable contribution to understanding the dynamics of music in endangered Indian regional languages, which have been largely ignored by the computational ethnomusicology academic landscape. This paper uses two methodologies – Clustering and Random Forest Regression – that are independent of each other and finds overlapping findings between the two, increasing confidence in the robustness of the conclusions.

### *2.1 Data Collection and Pre-Processing*

The dataset comprised the top 41,000 Spotify songs from 2000 to 2023, representing 14 different regional Indian languages. Each song was characterized by various audio features, including "popularity," "danceability," "energy," "instrumentalness," "key," "liveness," "loudness," "speechiness," "tempo," and "valence." The data was preprocessed by standard-scaling these features and using one-hot encoding for the mode. The time signature and duration were excluded from the analysis, as they were found to be consistent across languages and less relevant to song popularity.

### *2.2 Clustering*

The clustering phase of the methodology was a critical step in understanding the distribution of song types across different regional languages in India. It involved two layers of clustering – the first aimed to identify five main genres that all 41,000 songs can be classified into, and the second grouped the 14 languages into five groups based on similarity in distribution of their songs across the genres identified in the first stage.

The K-means clustering algorithm was employed to categorize the songs into five distinct cluster genres based on their audio features. K-means is a widely used clustering method that partitions the data into K clusters, where each data point belongs to the cluster with the nearest mean. The algorithm iteratively adjusts the cluster centroids to minimize the within-cluster variance, resulting in more coherent clusters.

The number of clusters (K=5) was determined through the Elbow Method, which involves plotting the sum of squared distances from each point to its assigned cluster centre (inertia) for different values of K. The "elbow" point on this plot, where the rate of decrease sharply slows down, suggests the optimal number of clusters. In this study, K=5 provided a balance between cluster granularity and interpretability.

Once the five cluster genre were formed, the next step was to analyse the distribution of songs within each genre for every regional language. This analysis revealed the dominant genres of songs in each language based on the centroid characteristics of the clusters they most frequently fell into. For example, one cluster genre might represent high-energy, high-tempo songs, while another might represent softer, more acoustic-driven songs.

After clustering the songs, the 14 regional languages were grouped into five broader clusters based on the similarity of their song distributions across the five identified cluster genres. This grouping was performed using another iteration of the K-means clustering algorithm. For example, languages that fell into Group C tended to have no songs in Genre 1 and the largest proportion in Genres 4 and 5.

### *2.2 Predictive Modelling*
The predictive modelling phase of this study focused on forecasting the potential popularity of regional songs in non-native markets using a Random Forest Regressor. The aim was to identify regions where songs in a specific regional language might find success despite the language not being native to that region.

For the purpose of this study, a non-native market is defined as a market that does not speak the song language being considered. Popularity, as defined by Spotify, is influenced by the total number of plays and the recency of those plays, with scores ranging from 0 to 100. The challenge was to use audio features to predict this popularity in markets where the language of the song is not spoken.

The first step involved identifying the features that are the best predictors of song popularity in a given market. The audio features of the market's native language were used as proxies. For example, Malayalam songs reveal the preferences of the Kerala market. For each market, a Random Forest Regressor was run on every possible permutation set of features as predictors for song popularity. The "Optimal Model" for each market was determined by selecting the combination of features that yield the lowest mean-squared error in predicting popularity.

For each language, its songs were inputted into the "Optimal Model" of each non-native market to see where the language's songs have the highest mean popularity. This helped determine which non-native markets are best suited for each language.

## 3. Results
### *3.1 Clustering*
Table 1 represents the properties of the centroid of each of the five genre clusters found. Each value represents the number of standard deviations of the centroid from the mean for a given audio feature.

| | Genre 1 | Genre 2 | Genre 3 | Genre 4 | Genre 5 |
|---|---|---|---|---|---|
| **Danceability** | 0.182 | -0.931 | 0.850 | 0.871 | -0.880 |
| **Acousticness** | 0.021 | 0.014 | 0.008 | -0.041 | -0.032 |
| **Energy** | -0.019 | -0.022 | -0.033 | 0.015 | 0.013 |
| **Liveness** | -0.002 | 0.033 | -0.025 | 0.015 | -0.023 |
| **Loudness** | -0.012 | -0.025 | 0.034 | -0.002 | 0.001 |
| **Speechiness** | -0.026 | 0.045 | 0.013 | 0.040 | 0.024 |
| **Tempo** | 1.530 | -0.339 | -0.489 | -0.111 | -0.091 |
| **Mode** | 0.619 | 0.897 | 0.897 | -1.115 | -1.115 |
| **Valence** | -0.044 | 0.006 | 0.037 | 0.011 | -0.024 |

*Table 1*

By focusing on the larger magnitude values under each genre, the key features of each genre are extracted and depicted in Table 2.

| Genre | Features |
|---|---|
| Genre 1 | Low speechiness, high tempo |
| Genre 2 | Low danceability, low tempo |
| Genre 3 | Low speechiness, major mode |
| Genre 4 | High acousticness, minor mode |
| Genre 5 | High energy, low danceability |

*Table 2*

For each regional language, the distribution of their songs across the five genre clusters are displayed in Fig 1.

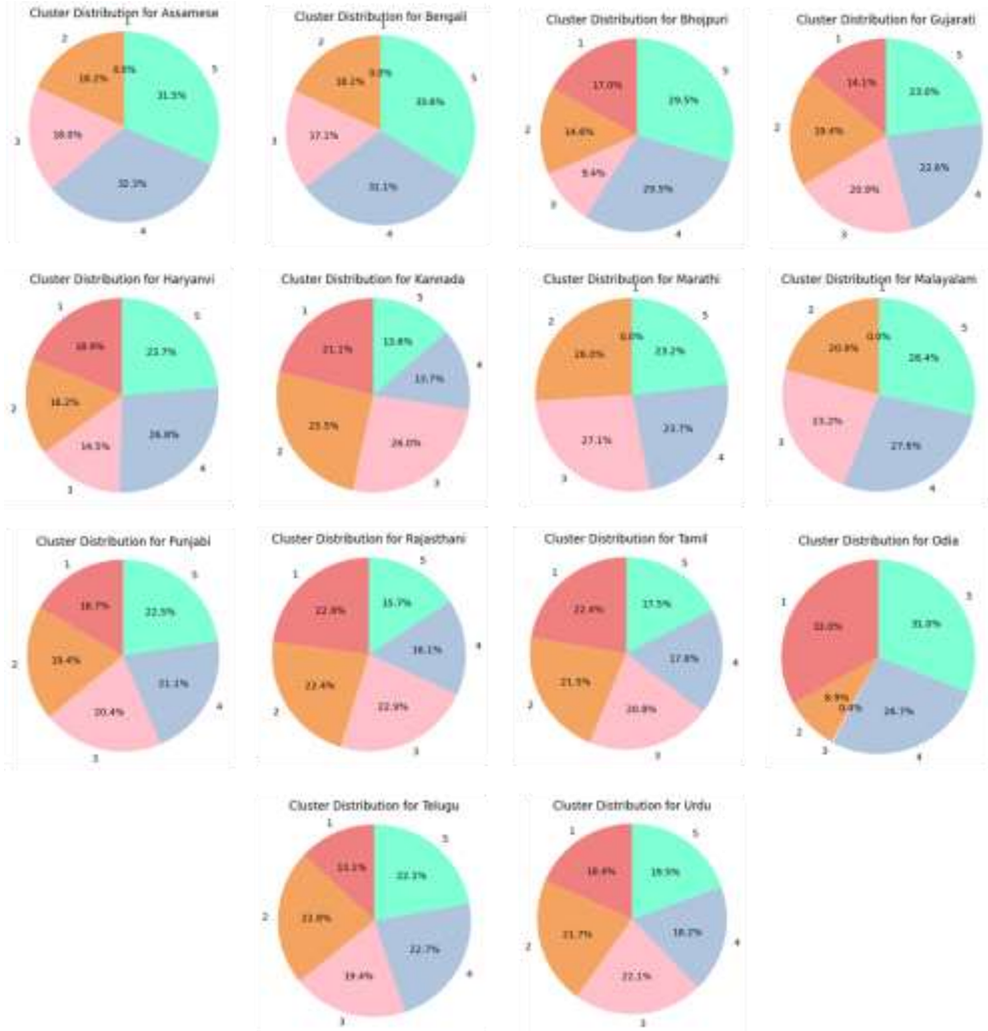


*Fig 1*

Based on the distribution of songs across genre clusters for each language, the fourteen languages were clustered into given groups, as depicted in Table 3 and Fig 2.

| Group | Languages |
|---|---|
| A | Gujarati, Marathi, Punjabi, Telugu |
| B | Odia |
| C | Assamese, Bengali. Malayalam |
| D | Kannada, Urdu, Rajasthani, Tamil |
| E | Bhojpuri, Haryanvi |

*Table 3*

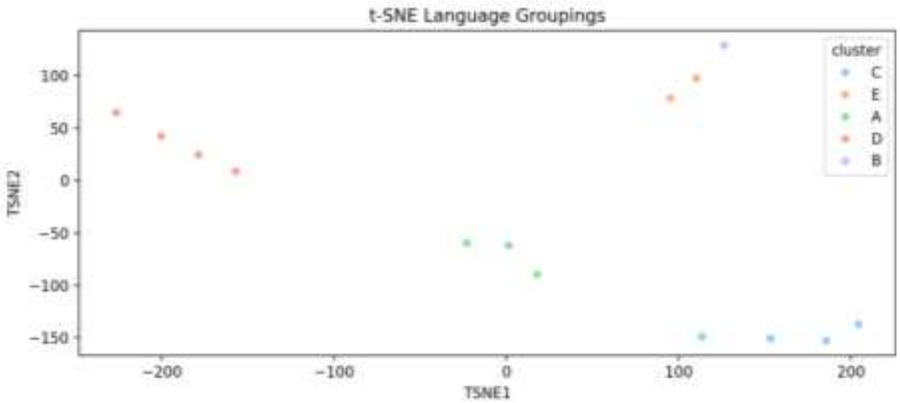


*Fig 2*

### *3.2 Prediction*

Fig 3 displays the input parameters for the 'Optimal Model' of each native market, with the y-axis representing the 'Feature Importance' as determined by the Random Forest regressor.

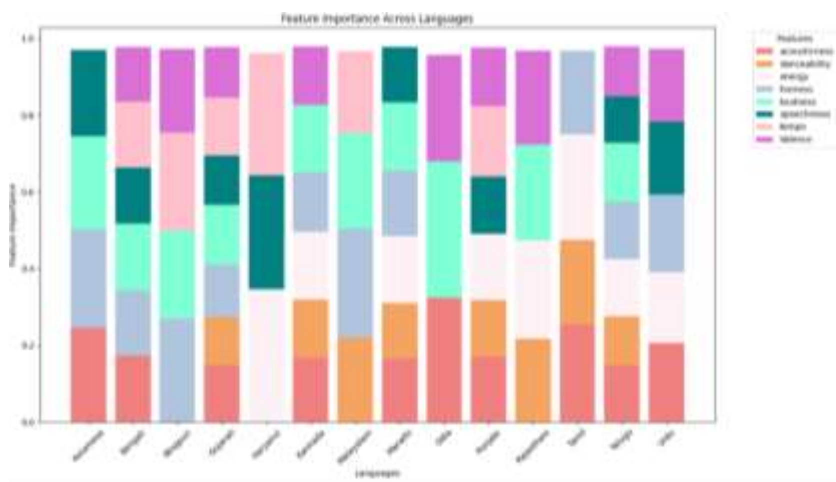

*Fig 3*

For each language, its songs were inputted into the Optimal Model of each non-native market. Based on the highest predicted mean song popularity, the three best non-native market matches for each song language are displayed in Table 4.

| Song Language | Non-Native First | Non-Native Second | Non-Native Third |
|---|---|---|---|
| **Assamese** | Telugu | Malayalam | Bengali |
| **Bengali** | Assamese | Kannada | Malayalam |
| **Bhojpuri** | Odia | Haryanvi | Bengali |
| **Gujarati** | Marathi | Punjabi | Kannada |
| **Haryanvi** | Bhojpuri | Odia | Urdu |
| **Kannada** | Odia | Rajasthani | Bengali |
| **Malayalam** | Tamil | Assamese | Odia |
| **Marathi** | Gujarati | Haryanvi | Telugu |
| **Odia** | Bengali | Rajasthani | Urdu |
| **Punjabi** | Assamese | Gujarati | Marathi |
| **Rajasthani** | Kannada | Assamese | Urdu |
| **Tamil** | Odia | Kannada | Bengali |
| **Telugu** | Marathi | Bengali | Assamese |
| **Urdu** | Marathi | Tamil | Rajasthani |

*Table 4*

## 4. Discussion

### *4.1 Trends in Results*

This study uses two approaches – Clustering and Random Forest Regression – to answer the research question, "Which non-native regions in India offer the most promising opportunities for expanding the popularity of music for a specific regional language?" To draw conclusions with reasonable confidence, the author believes that the most reliable matches between a regional language and a non-native market are those that appeared in the same group in the clustering method and in the top three matches in the prediction approach. Table 5 summarizes these overlaps.

| Song Language | Non-Native Market(s) |
|---|---|
| Assamese | Malayalam, Bengali |
| Bengali | Assamese, Malayalam |
| Bhojpuri | Haryanvi |
| Gujarati | Marathi, Punjabi |
| Haryanvi | Bhojpuri |
| Kannada | Rajasthani |
| Malayalam | Assamese |
| Marathi | Gujarati, Telugu |
| Odia | N/A |
| Punjabi | Gujarati, Marathi |
| Rajasthani | Kannada, Urdu |
| Tamil | Kannada |
| Telugu | Marathi |
| Urdu | Tamil, Telugu |

*Table 5*

These findings reinforce the argument that geographical proximity significantly influences the suitability of non-native markets for regional music. In India, neighbouring states often share deep cultural and linguistic ties, making them more receptive to music from each other's regions compared to more distant states. Several examples from this study illustrate this point. For instance, Haryanvi and Bhojpuri emerge as strong matches. Both languages are part of the Hindi Belt, a region where local languages, despite their differences, are heavily influenced by Hindi and are largely mutually intelligible (Government of India, 2001). This shared linguistic background likely facilitates the cross-market success of their music. Moreover, both regions produce high-energy, powerfully vocal music, which aligns with their representation in Genres 4 and 5 – clusters characterized by high energy levels.

Similarly, the analysis identifies the neighbouring North-Eastern states Assam and Bengal as strong musical matches. Assamese and Bengali are the only two Indian languages that use the Eastern Nagari script, and they are mutually intelligible (Salomon, 1998). A large part of their musical traditions, including Baul songs from Bengal and Deh Bichar songs from Assam, emphasizes storytelling through mystical, devotional, and metaphorical narratives (Borah, 2019, p. 712-722). This narrative focus could explain why neither Assamese nor Bengali songs were clustered into Genre 1, which is the only cluster characterized by low speechiness.

Additionally, Tamil and Kannada, spoken in neighbouring southern regions, share common Dravidian linguistic roots, including core vocabulary and grammatical structures (Krishnamurti, 2003). The classical music traditions in these regions, which heavily feature vocal performances and traditional instruments like the veena, mridangam, and flute, prioritize acoustic richness over modern electronic effects (Benary, 1972, p. 42). This likely accounts for the high proportion of Tamil and Kannada songs found in Genres 1, 2, and 3, which are distinguished by high acousticness.

An intriguing conclusion from the study is the identification of regions where regional songs from specific languages gain popularity despite significant geographical distance. Examples of this occurrence include the predicted success of Malayalam songs in Assam and Rajasthani songs in Karnataka. This phenomenon highlights the complex interplay between musical preferences, cultural exchanges, and technological advancements, suggesting that factors other than geographical proximity can influence the cross-market success of regional music.

The study underscores that the appeal of regional music can transcend geographic boundaries when certain musical elements resonate on a broader scale. For example, the Assamese market – where acousticness, liveness, loudness, and speechiness are important predictors of popularity according to Fig 3 – may be a suitable opportunity for expansion for Malayalam music, which has a strong alignment with Assamese preferences along these dimensions. Songs with universal themes or musical elements that evoke strong emotional responses can bridge cultural divides and foster appreciation across diverse regions.

### 4.2 Factors Facilitating Cross-Cultural Music Exchange

The proliferation of digital platforms such as Spotify, YouTube, and regional music streaming services has significantly enhanced the reach of regional music beyond its geographical origins. These platforms enable users to discover and access music from different linguistic and cultural backgrounds with ease. For instance, the rise of YouTube as a global music platform has allowed South Indian music to gain popularity in non-South Indian regions and even internationally. The accessibility of global music and the decreasing relevance of language as a barrier to musical enjoyment have contributed to the growing cross-regional popularity of songs.

Bollywood, India's premier film industry, plays a pivotal role in promoting cross-cultural musical exchange. Bollywood films often incorporate musical elements from various regional traditions, thereby introducing audiences to diverse musical styles. For example, the use of Punjabi folk music in Bollywood soundtracks in recent years has broadened its appeal across different linguistic regions.

Collaborative music projects and fusion genres represent another significant factor in cross-cultural musical exchange. Artists frequently collaborate across regional and linguistic boundaries, creating music that blends various styles and traditions. An example of this is the collaboration between Indian classical musicians and contemporary artists, which results in innovative music that resonates with diverse audiences. The fusion genre, which blends traditional Indian music with Western influences, has also gained popularity, exemplified by artists like A. R. Rahman, whose music combines elements from various regional and international styles.

Cultural festivals and music events provide platforms for regional music to reach broader audiences. Festivals such as the NH7 Weekender and SulaFest showcase a diverse array of musical acts from different parts of India, allowing regional music to be appreciated by attendees from across the country. These events not only highlight regional musical traditions but also foster interactions among artists and audiences from different cultural backgrounds.

Socioeconomic mobility and urbanization contribute to the spread of regional music. As individuals migrate to urban centres for education and employment, they bring their cultural preferences with them, creating opportunities for regional music to reach new audiences. The urbanization of cities like Bangalore and Mumbai has led to a more diverse cultural landscape where regional music from different parts of India can find new listeners.

### 4.3 Limitations and Future Research

While the study provides valuable insights into cross-cultural musical exchange through the analysis of data from Spotify, it is essential to acknowledge several limitations that may impact the comprehensiveness of the findings.

The study relies predominantly on data from Spotify, a leading music streaming platform. While Spotify offers a substantial amount of data, it represents only one facet of the broader music consumption landscape. Other platforms, such as YouTube Apple Music, and regional streaming services like Gaana and JioSaavn, may have different user bases and listening patterns that could provide additional insights into music popularity and cross-cultural exchange. For example, regional streaming services often feature music that is more specific to local tastes and preferences, which might not be as prominently represented on Spotify.

The analysis focuses primarily on audio features while excluding the lyrical content of songs. Lyrical themes play a significant role in regional music, particularly in genres like Tamil film music, where local cultural references, storytelling, and language contribute substantially to the music's appeal and resonance with audiences. For instance, Tamil film songs often include references to local customs, mythology, and contemporary social issues, which can enhance their regional relevance and emotional impact. The exclusion of lyrical content may, therefore, limit the study's ability to fully capture the factors driving regional preferences and cross-cultural exchange.

Marketing strategies also play a crucial role in shaping the popularity of music across regions. Promotional activities, artist collaborations, and media coverage can significantly influence the reach and success of musical releases. However, the current study does not account for these marketing factors, which could affect the generalizability of the findings regarding cross-cultural musical exchange.

To address these limitations, future research could adopt a multi-platform approach, incorporating data from a variety of streaming services, social media, and other digital platforms. This broader dataset could provide a more comprehensive view of music popularity and cross-cultural exchange. Additionally, incorporating lyrical analysis and examining the impact of marketing strategies would enrich the understanding of regional music dynamics and their influence on cross-cultural interactions.

### *4.4 Implications for Music Industry Stakeholders*

The insights from this study present several valuable opportunities for various music industry stakeholders, including artists, their management teams, digital platforms, and the government. Understanding cross-regional music preferences and cultural dynamics can help shape more effective strategies for expanding the reach of regional music across diverse markets.

Cross-regional collaborations between artists can amplify the appeal of regional music. By collaborating with artists from non-native regions where there is promising potential for growth, musicians can blend styles and cultural elements to create fusion genres that appeal to wider audiences. For example, an Assamese artist collaborating with a Malayalam singer could introduce Assamese music to Kerala and vice versa in an organic and engaging way, broadening the audience for both. Additionally, the growing acceptance of regional music in non-native markets can open new avenues for touring and live performances. Artists can strategically plan live events in regions where their music is showing increased adoption, fostering stronger fan bases and increasing revenue streams. Furthermore, artists can take advantage of the study’s analysis of audio features, such as tempo, energy, and acousticness, to better understand what makes certain regional music genres resonate in non-native markets. By identifying which audio features are favored in particular regions, producers can fine-tune their music to cater to these preferences, potentially increasing the likelihood of success in new markets. For instance, if high-energy, rhythm-driven songs are popular in Gujarat, producers can incorporate these characteristics into their music when targeting that market, regardless of the region’s native language.

Music producers and marketers can use the insights from this study to design highly targeted, data-driven marketing campaigns. By identifying non-native regions with a demonstrated affinity for specific regional music genres, marketers can focus on those markets with the highest potential for adoption. For instance, if Bengali music is shown to resonate well in Assam, marketing efforts and resources can be tailored to capitalize on the cultural connections and musical preferences of that region. For record labels and distributors, this research presents an opportunity to invest in emerging regional markets where music from non-native regions is gaining traction. By understanding which regions are showing increased interest in specific music genres, labels can prioritize distribution efforts in those areas.

Digital music platforms like Spotify, YouTube, and Apple Music play a pivotal role in expanding the reach of regional music. These platforms can leverage the study’s findings to optimize their content curation and recommendation systems by focusing on the cultural and geographical proximity between regions. Regional playlists, personalized suggestions, and curated collections can increase the visibility of non-native music and encourage listeners to explore unfamiliar genres.

For government bodies and organizations focused on cultural preservation, the cross-regional adoption of music provides an opportunity to promote regional languages and traditions. By actively supporting the production and dissemination of regional music, stakeholders can help ensure that endangered languages and cultures remain relevant and vibrant, even in non-native regions. Collaborations with streaming platforms and local artists to promote regional content can also contribute to cultural preservation efforts. These initiatives can be backed by educational campaigns and sponsorships to increase awareness and appreciation of the diverse cultural landscape of India.

## 5. Conclusion

This study offers significant insights into the predicted cross-regional popularity of regional music within India, highlighting the role of both geographical and cultural proximity in shaping musical preferences. Through the use of Clustering and Random Forest Regression, the author identified promising non-native markets where regional language music may thrive, suggesting that cultural similarities in audio feature preferences can transcend geographical boundaries and resonate with distant audiences. Overall, this paper offers an innovative approach to preserving endangered regional languages by expanding the reach of their music in non-native markets.

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