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Harmonizing Heritage: A Review of Advances in Indian Music Genre Classification

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The classification of Indian music genres represents a fascinating intersection of cultural richness and technological innovation. This review paper meticulously traces the evolutionary journey of music genre classification methodologies within the intricate domain of Indian music. Spanning from the foundational research in the early 2000s to the latest advancements in supervised, unsupervised, and deep learning approaches, we highlight seminal studies and their pivotal contributions. Our analysis encompasses the challenges and opportunities inherent in cross-cultural genre classification, fine-grained categorization, multimodal approaches, real-time classification, and resilience to noise and variability. Additionally, we explore novel deep learning architectures, genre evolution analysis, multilingual classification, and the critical role of open-access datasets. By synthesizing past achievements and elucidating future research directions and gaps, this paper serves as a beacon for further exploration, fostering interdisciplinary collaborations, and advancing our understanding and appreciation of the rich musical heritage of India. Through a critical lens, we identify significant research gaps and future directions,

including the need for fine-grained genre classification, robustness against noise and variability, and the exploration of multimodal approaches. By offering insights into the complexities of classifying Indian music genres and outlining a roadmap for future research, this paper aims to stimulate further investigations, foster interdisciplinary collaborations, and facilitate the development of more accurate and culturally sensitive classification systems. Ultimately, our goal is to enrich the understanding and appreciation of Indian music's profound cultural heritage through the lens of genre classification, paving the way for innovative applications in music recommendation, education, and digital archiving.

Keywords: Education, Genre, Learning, Music, Super Learning.

1. Introduction

Music is a profound expression of human culture, evolving distinctively across societies to become an integral part of our global heritage. Among the world's musical traditions, Indian music occupies a special place, renowned for its historical depth and cultural richness. Much research has been done on Western music compared to Indian music. So, we plan to extensively review Indian music genre classification in this current review paper. Distinct from the harmony-centric traditions of Western music, Indian music is celebrated for its melody-driven compositions, featuring an elaborate array of scales and ragas. These ragas, with their unique rules for crafting melodies, can invoke a broad spectrum of emotions, showcasing the complexity and vibrancy of Indian culture.

Indian music has a rich cultural heritage deeply rooted in ancient traditions. It is characterized by intricate melodies, rhythmic complexities, and emotive narratives, each offering a unique soundscape. Indian music is primarily melody-driven, with various scales and ragas evoking different emotions and moods. Technology and globalization have revolutionized how we access and experience music in the digital age. The multifaceted nature of Indian music, encompassing regional variations, improvisational elements, and the absence of standardized notations, poses significant obstacles in developing accurate and robust genre classification systems.

In today's digital era, how we access, experience, and categorize music has transformed dramatically. This shift presents unique challenges, especially in the genre classification of Indian music, marked by its intricate melodic structures, complex rhythms, and the improvisational nature of its performances. For instance, the emotive depth of 'Raga Bhairavi' or the celebratory feel of 'Raga Yaman' highlights the difficulties in pigeonholing such rich musical expressions into rigid categories.

Despite its significant cultural impact and global reach, Indian music has encountered notable obstacles in genre classification. These include a dearth of comprehensive datasets, a relative scarcity of research specifically targeting Indian music genre classification, and the challenge of achieving high accuracy in classification due to the music's diverse elements. This paper seeks to address these gaps by offering an in-depth look at both the historical and cultural contexts of Indian music and the technical hurdles in classifying its genres. Our goal

is to aid researchers and music enthusiasts by providing a thorough overview of existing studies, thereby paving the way for future research in this fascinating field.

In this complex landscape, gaining insights into the diverse sources of knowledge and research contributions in music genre classification becomes crucial. Figure 1 provides a visual representation of the distribution of paper publishers involved in studying music genre classification, underscoring this research's collaborative and interdisciplinary nature. It highlights how researchers have been blending traditional music knowledge with the latest technology, such as machine learning, to improve our understanding of music genres, particularly the unique sounds of Indian music.

Researchers have diligently explored innovative approaches, combining traditional music theory with cutting-edge machine learning (ML) algorithms. The development of feature extraction techniques tailored to the unique characteristics of Indian music has advanced classification accuracy. Moreover, leveraging domain knowledge from expert musicians has played a crucial role in enhancing the classification process.

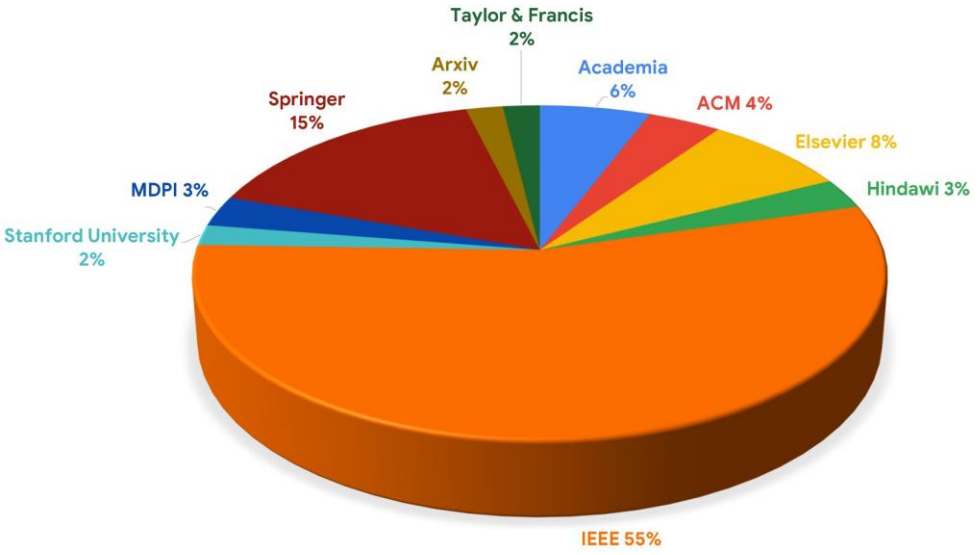

Figure 1. Distribution of Paper Publishers in Music Genre Classification Research

Building on this foundation, Figure 2 demonstrates a clear layout of our review's structure, focusing on the three primary classification methods explored in this study: supervised, unsupervised, and deep learning. By presenting the information in this manner, we aim to highlight the diverse techniques researchers use to classify music genres, simplifying the complexity of our investigation into the most effective ways to categorize Indian music. This structured approach aids in conveying the scope of our exploration, making it more accessible to those interested in the nuanced field of music genre classification.

The research rigorously investigates the complexities of classifying Indian music genres, emphasizing the potential for interdisciplinary cooperation and providing valuable perspectives on the broader evolution of Indian music genre classification. This review is helpful for researchers and scholars interested in classifying Indian music genres, providing a

foundation for future research and offering comprehensive analysis and commentary on this complex field.

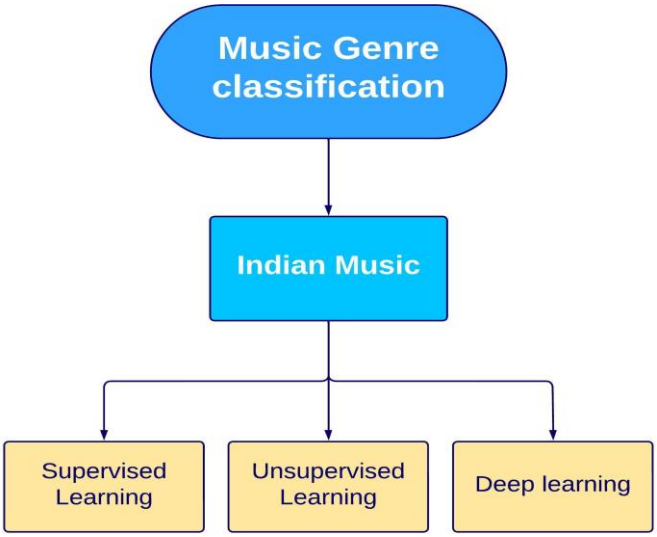

Figure 2. Methodology Classification Chart: A Visual Guide to Research Approaches in Music Genre Classification

Indian Music

Indian music is a testament to the rich cultural heritage of the subcontinent. It has roots and diverse traditions that have evolved. From the spiritual hymns of the Vedic period to the soul-stirring melodies of classical ragas and the energetic beats of Bollywood Indian music offers a wide range of sounds and emotions to its listeners. Every region in India from the northern Himalayas to the serene southern tip of Kanyakumari contributes its unique flavor to this musical tapestry. This diversity adds layers of depth and richness to music as a whole. Figure 3 gives an overview of the different genres within Indian music. It covers a spectrum, including lively rhythms found in folk music timeless charm found in classical compositions enchanting melodies in devotional songs, soul-stirring resonance in Sufi music captivating traditions like qawwali, and poignant narratives found in ghazals. Each genre offers an experience that showcases India's vast musical heritage.

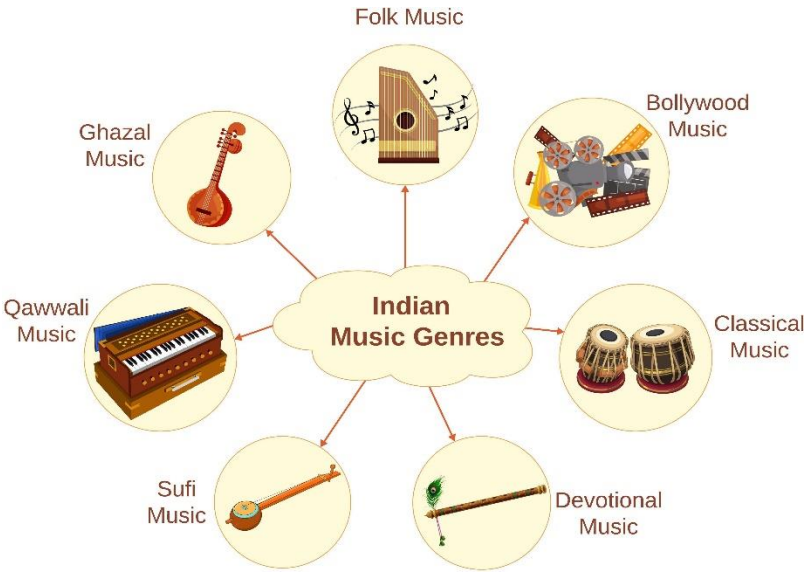

Figure 3. Mapping the Rich Tapestry of Indian Musical Genres

Genre classification in Indian music is a complex task that relies on understanding the intricate nuances present within each genre and subgenre. These nuances are influenced by elements such as rhythmic patterns (Taal) and melodic scales (Ragas). These elements intertwined with the time of day, seasons, and even emotions make Indian Music a unique experience. The beauty of Indian music lies not only in its vast variety but also in the intricacy of its rhythmic patterns and melodic scales. These elements are deeply woven into the fabric of music creating a profound and immersive experience. However, this richness and diversity also pose challenges when it comes to classifying the genres and sub-genres due to their unique nuances and subtleties. As we delve deeper into our exploration, we will uncover the captivating essence of music and gain insights, into the complexities involved in categorizing its vast array of genres.

This informative bar graph 4 showcases the changes in the accuracy of classifying genres of Indian music over the years. The graph demonstrates how approaches within ML, such as Supervised Learning, Unsupervised Learning, and DL have contributed to improving the classification accuracy specifically for Indian music. Over time these methodologies have adjusted to address the unique challenges posed by the diverse and vibrant landscape of Indian musical genres. By examining the trends in classification accuracy depicted in this graph we gain insights, into the advancements made in this field and the specific techniques that have proven successful in categorizing music genres. In subsequent sections, we will delve deeper into each methodology to develop a comprehensive understanding of the strategies and innovations that have shaped the domain of Indian music genre classification.

Supervised Learning for Indian Music Genre Classification

In the field of ML, one approach that stands out is supervised learning. This method follows a structured approach to problem-solving and proves to be a potent tool. Utilizing labeled datasets it enables models to identify patterns, make predictions, and categorize data with

increasing accuracy. When applied to the world of music, especially Indian music with its wide range of genres this systematic approach finds great resonance. Indian music is known for its depth and variety which pose both challenges and opportunities, for learning techniques. The challenge lies in classifying the numerous genres and sub-genres that come with their unique tonalities and rhythms. However, there is also an opportunity to leverage the power of learning to bring order, clarity, and structure to this vast musical landscape. In this section, we will delve into the advancements and contributions made in Indian music genre classification through supervised learning.

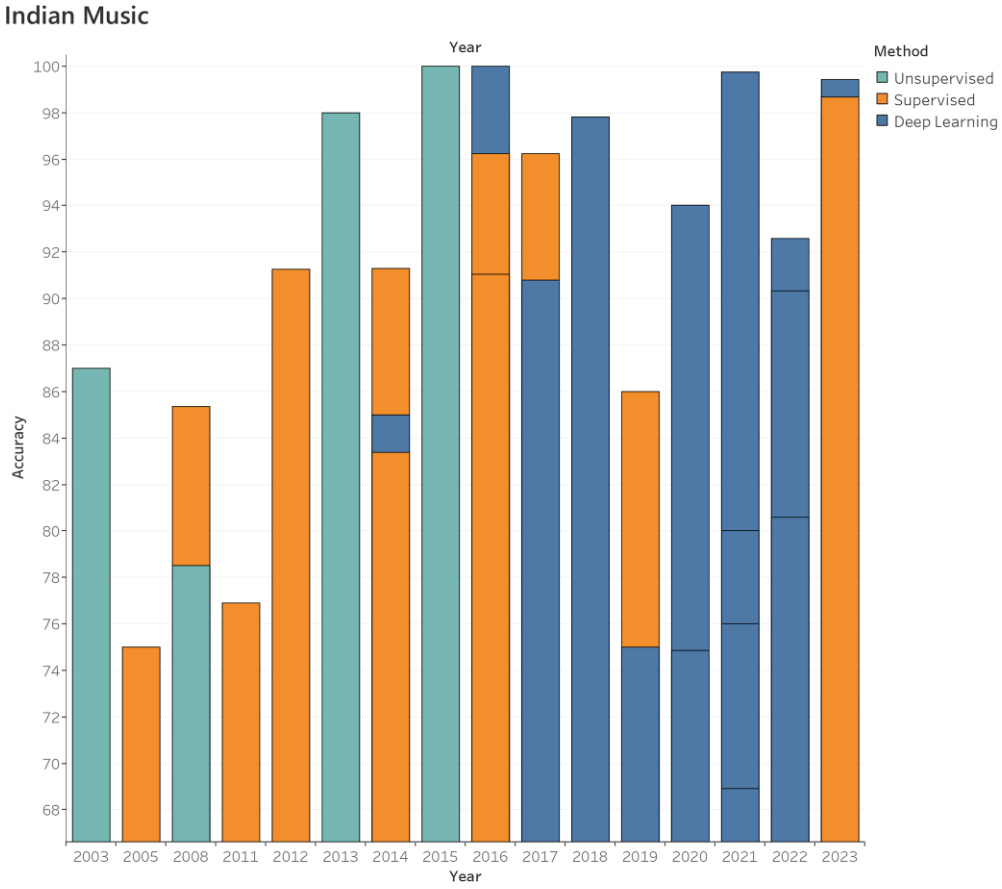

Figure 4. Harmonizing Indian Music Genre Classification: A Journey Through Accuracy Trends

The journey started back in 2005 when Norowi et al. (2005), conducted pioneering research on the significance of building classification systems for music. Their work focused on the complexities of learning in music classification highlighting a two-step process involving training and subsequent genre recognition testing. The training phase, as elucidated by Noris Mohd Norowi et al. is crucial as it involves using labeled data to educate the model, which is then evaluated for its ability to recognize genres. This foundational research paved the way, for studies that stressed the importance of a defined training phase, in supervised learning. It was a revelation that shed light on the nuances of using labeled data to train models

effectively.

By the year 2008, there was a broadening of discussion to include techniques, for classification techniques. Doraisamy et al. (2008) analyzed classifiers like IB1, J48, and SMO, and underscored the importance of choosing the classifier based on the specific requirements of the dataset. This highlighted how supervised learning was evolving where selecting a classifier became just as crucial as the data itself. In years there was a shift in focus towards feature extraction. In 2011 Kini et al. (2011) emphasized the significance of elements such as melody and rhythm in the classification process. This research shed light on how features and their extraction play a role in learning by suggesting that the accuracy of classification can be significantly influenced by the quality of features used. The emphasis on features brought forward the idea that the essence of a song, its very soul, could be captured and classified using the right features.

In 2012 Jothilakshmi and Kathiresan (2012) delved deeper into the world of music by exploring the nuances between short-term and long-term musical features. This distinction between immediate musical elements and broader perspectives, such as variations in spectral shape or beat information, added another layer to the supervised learning process. Building upon this work in 2013 Chordia P (2013) introduced a methodology that emphasized optimizing parameters and the importance of mapping training data into feature vectors. This approach highlighted the importance of understanding the distribution of data in supervised learning setting new standards in the field. The key takeaway from these studies was clear; to achieve results, with supervised learning one must have a thorough understanding of the data at hand.

In 2014, Kumar et al. (2014) highlighted the significance of data mining in genre classification, emphasizing the role of trained models in predicting song labels. This work laid the groundwork for understanding how data, when mined effectively, could enhance the supervised learning process. In parallel, Pandey and Dutta (2014) introduced novel techniques and algorithms, further expanding the horizons of supervised learning in music classification. The period was marked by rapid advancements and a deeper understanding of the intricacies involved.

Fast-forward to 2016, and the landscape of Indian music genre classification had evolved significantly. Kalapatapu et al. (2016) notably paper delved deeper into the intricacies of supervised learning techniques. It unraveled the potential of the Multilayer Perceptron Neural Network classifier (MLP) and the SVMs in accurately classifying Indian music genres. The research went beyond theory, showcasing concrete results that demonstrated the potential of supervised learning techniques.

In parallel, another research endeavor from the same year, attributed to Rajesh and Bhalke (2016) and Bhalke et al. (2017), further expanded the boundaries. This study explored various feature combinations with KNN and SVM classifiers, with a specific focus on Tamil genres. The findings were nothing short of remarkable, as they showcased that supervised learning, in tandem with the SVM and a feature set including spectral roll-off, flux, skewness, kurtosis, and fractional MFCC, achieved an astonishing accuracy of 96.05%. These results underscored the practical application of supervised learning in fine-tuning feature selection, further enhancing the accuracy of genre classification.

In 2019, a study by Chaudhary et al. (2019) highlighted the complexities of Indian music genres. These genres can be broadly classified into Classical (Hindustani or Carnatic) music, Semi-classical music (including Ghazals), and Light (including folk) music. The emotional content, referred to as "rasa" in Indian music, plays a pivotal role in the classification process. The study introduced a novel classification technique based on empirical mode decomposition (EMD) and demonstrated its efficacy in distinguishing between two genres of Indian music: Classical and Semi-Classical. The results indicated a significant increase in classification accuracy compared to previous works that utilized generic audio features.

The same year, another paper by Waghmare and Sonkamble (2019) emphasized the importance of exploring relevant features and classifiers for Indian music, given its diverse genres. While the nucleus of Indian music revolves around the concept of Raga, other genres such as bhajans (devotional songs) may or may not be based on raga. The study underscored the need for more focused research in the area of genre classification, especially considering the therapeutic potential of music.

Fast forward to 2023, advancements in the field, as presented by Sarkar et al. (2023), have led to the exploration of novel features for classification. One such study highlighted the application of EMD-based feature extraction, which resulted in significantly higher classification accuracy than previous methods. The study also touched upon the potential therapeutic effects of certain genres of Indian music, emphasizing the importance of accurate classification for therapeutic interventions.

The journey of supervised learning in Indian music genre classification over the past two decades underscores the synergy between technology and the arts. From the foundational research in the early 2000s to the innovative methodologies of the 2020s, there has been a consistent drive towards refining classification techniques to better understand the nuances of Indian music. As the field keeps progressing the focus remains on improving precision comprehending the complexities of genres and exploring the uses of these categorizations. Combining supervised learning with Indian music not only opens doors, for academic exploration but also has practical implications for the music industry, therapeutic interventions, and more. The future of this endeavor holds more advancements in store bringing together fragmented knowledge and nurturing a profound understanding of the vibrant world of Indian music.

Unsupervised Learning for Indian Music Genre Classification

In the world of music genre classification the shift, from supervised to unsupervised learning represents a paradigm shift. While supervised learning relies on labeled data to train models unsupervised learning explores the patterns and structures within the data without any existing labels. This approach has had a particular impact on Indian music genre classification as researchers aim to capture the diverse range of Indian musical genres.

In 2003 Pandey et al. (2003) embarked on an exploration of musicology applied to Indian classical music. Their work focused on the intricacies of music particularly emphasizing the concept of Ragas, which they represented as finite automata. This foundational research laid the groundwork for studies emphasizing the importance of understanding elements such as Pakad - A catchphrase - for each Raga that plays a crucial role in its identification. Their

approach achieved an accuracy rate of 77% as detailed in their findings.

By 2008 Doraisamy et al. (2008) extended the existing research by introducing Hidden Markov Models (HMM) as a tool, for modeling Ragas. Their study highlighted the versatility of unsupervised learning techniques in capturing the essence of Indian music genres. Their approach achieved an accuracy rate of 80% for Yaman Kalyan and 75% for Bhupali demonstrating the effectiveness of their approach.

Moving forward to 2011 Kini et al. (2011) emphasized the importance of feature extraction in their research. While they discussed both both short-time and long-time features it laid a foundation for understanding the significance of these features in unsupervised learning models. Notably, their exploration into tempo distribution and its impact, on classification accuracy garnered accuracies above 80% in genres.

In 2012 researchers Jothilakshmi and Kathiresan (2012) provided an overview of the techniques used in music genre classification. They discussed both supervised and unsupervised approaches highlighting the performance of classifiers, like MLP, which achieved an accuracy of 88.6%. The paper emphasized the potential of unsupervised learning in music genre classification as an area, for further exploration.

As the exploration into music genre classification deepened, the subsequent years witnessed a more nuanced understanding of unsupervised learning techniques tailored to the intricacies of Indian music.

In 2013 Agarwal et al. (2013) delved into the realm of SOMs to tackle the challenges associated with Indian classical music segmentation. Their research emphasized the pivotal role of data preprocessing in determining Pitch Class Profiles (PCP) for musical data. The onset detection emerged as a crucial tool in calculating key combinations based on available frequency spectrums. This method laid the groundwork for predicting ragas using SOM, which turned out to be a significant advancement in the field.

By 2014 Sharma et al. (2014) made improvements to this methodology. One noteworthy contribution was the incorporation of signal processing (DSP) as a preprocessing step. This transformation played a role in converting raw music signals from the time domain to the frequency domain making them optimal for SOM computation. The study also explored how to measure the distance between ragas by utilizing the Euclidean distance metric. Additionally, they introduced an updating rule for weight vectors in SOM highlighting how the learning process is dynamic and influenced by factors such, as time, learning rate, and neighborhood kernel.

By the year 2015, Daniel and Revathi (2015) took a holistic approach, in their research. They shifted towards the unsupervised domain utilizing methodologies such as k-means and hierarchical clustering. Unlike studies that primarily focused on classification methods this new direction explored the untapped potential of unsupervised learning for Indian music. The research also emphasized the importance of identifying features for music genre classification by employing techniques like Fourier analysis, cepstral analysis, and wavelet analysis. Unsupervised learning played a pivotal role, in shaping the landscape of Indian music genre classification.

Unsupervised learning played a pivotal role in shaping the landscape of Indian music genre

classification. Researchers during this period innovatively harnessed the power of unsupervised techniques, from Self Organizing Maps to hierarchical clustering, to delve deeper into the rich tapestry of Indian musical genres. These methodologies, tailored to capture the essence of Indian music, showcased the potential and adaptability of unsupervised learning in this niche domain. Surprisingly, post-2015, there appears to be a hiatus in the literature on this topic, indicating a potential area ripe for future exploration.

Deep Learning for Indian Music Genre Classification

Deep Learning, an advanced subset of ML, emulates the human brain's workings through interconnected nodes, akin to neurons, to model complex patterns in vast datasets. In the realm of Indian music, with its rich tapestry of genres and intricate nuances, DL offers a transformative approach. By harnessing this technology, researchers and musicologists can delve deeper into the multifaceted soundscape of Indian music, enabling precise genre classification and a better understanding of its diverse melodies and rhythms.

In 2014, Goel et al. (2014) ventured into automating genre classification of songs using the Parallel Multi-Layer Perceptron Network. Utilizing the Echonest libraries, they extracted distinctive audio features, subsequently feeding these into the neural network. Their model achieved an impressive 85% accuracy when classifying two distinct genres: Classical and Sufi. However, this work was confined to a database encompassing only 400 songs, highlighting the need for broader datasets for comprehensive genre classification.

Three years later, Bhatt and Patalia (2017) introduced a novel framework to classify Indian folk dance songs, focusing on four prevalent folk dances. Their methodology involved extracting audio from videos, computing the Mel-frequency Cepstral Coefficients (MFCC) and Linear Predictive Coding (LPC) coefficients, and subsequently employing the Scale Conjugate Gradient Neural Network for the final classification task. Demonstrating more than 90% classification accuracy, their work was, however, limited to folk dance songs.

By 2018, the realm of music genre classification witnessed a significant shift with Jawaherlalnehru et al. (2018) employing a Deep Neural Network. Their methodology, developed using the 'H2O' ML library, utilized log mel band energy features to classify music genres. Evaluated on the GENRE Dataset, their model achieved an outstanding accuracy of 97.8%. Nevertheless, the specificity of their work to this particular dataset raises questions regarding the model's generalizability.

In 2019, Lele and Abhyankar (2019) delved into the intricate domain of raga identification within Hindustani Classical Music. Through techniques like Fourier transforms, chromatogram, and spectrogram, they sought to identify ragas from samples of the santoor and light music. Despite achieving accuracies ranging between 70% to 80% for santoor samples, the model's performance dipped when subjected to songs from light music, emphasizing the challenges posed by the diverse expressions and intricacies in ragas.

The subsequent year, 2020, saw John et al. (2020) integrate DL with Indian Classical Carnatic music. They leveraged the CNN to classify ragas, using the pitch contour as a pivotal feature. While their methodology achieved a commendable 94% recognition rate across five ragas, it underscored the model's applicability to a select set of Carnatic ragas.

Continuing, Kumaraswamy and PG (2020) introduced an innovative approach to raga

recognition. Their model, a neural network classifier, was enhanced using the Grey Wolf Optimization algorithm. This approach, combined with weight optimization of the input feature set, showcased superior accuracy across multiple features. Notably, their model demonstrated significant improvements in pitch features, achieving an accuracy surpassing other neural network-based methodologies by up to 17.8%.

In 2021, Sharma et al. (2021) pioneered an analytical exploration into the realm of Indian Classical Music. Their primary focus lay in the delineation and classification of two paramount Raga-based genres: Hindustani and Carnatic. Employing Mel Frequency Cepstral Coefficients (MFCCs) as a principal feature, they adeptly harnessed a gamut of neural network architectures, ranging from Deep Neural Networks (DNN) to CNN and Recurrent Neural Networks (RNN) with LSTM cells. Their empirical results underscored the superior efficacy of RNN-LSTM and 3-layer CNN, achieving an unparalleled classification accuracy approaching 99%. This study not only illuminated the intricate dynamics of Indian Classical Music but also showcased the potential of leveraging DL models in discerning Raga motifs, an essential building block of Indian musical compositions.

Simultaneously, a collaborative effort by Kalapatapu et al. (2021) delineated the burgeoning necessity for adept music recommender systems, a need accentuated by the exponential surge in digitized music consumption. Through their judicious deployment of CNN models, trained rigorously on spectrograms derived from an equilibrated Indian Music dataset, they attained a commendable classification accuracy nearing 70%. Their findings underscored the nuanced heterogeneity of Indian music genres, which are intrinsically more regionalized and linguistically diverse than their Western counterparts.

In a parallel vein, Kiran (2021) elucidated the subtleties inherent in Indian Classical Music in 2021. His research underscored the pivotal distinction between the Hindustani and Carnatic branches, with an emphasis on the melodic essence encapsulated in Ragas. By ingeniously amalgamating neural network architectures with the state-of-the-art Dragonfly optimization algorithm, Kiran's methodology for raga recognition, especially within the Carnatic genre, rendered superior results, significantly outclassing traditional computational algorithms such as KNN and SVM.

Further enriching this academic discourse, Kumari et al. (2021) elucidated the challenges presented by the voluminous influx of music data. Their methodological approach, rooted in CNN architectures and pivotal feature extraction via MFCC, culminated in classification accuracies exceeding 75% across disparate datasets. This exploration, while highlighting the boundless potential of ML paradigms, concurrently underscored the exigency for comprehensive, well-curated datasets.

Transitioning to 2022, a groundbreaking paradigm was proposed by Hasan et al. (2021). Their research introduced an integrated computational framework tailored for the nuanced classification of Bangla music genres. The incorporation of CatBoost, a cutting-edge ensemble learning model, in tandem with judicious feature extraction from both time and frequency domains, yielded results that benchmarked the model's efficacy. CatBoost's consistent superiority over other classifiers accentuated its potentiality within the music industry, heralding a new era of enhanced algorithmic understanding and classification of music genres.

In 2022, the realm of Bengali music witnessed a significant advancement through the efforts of Hasib et al. (2022). While tools and methodologies had been developed for English music classification, the unique character of Bengali music remained relatively unexplored. Addressing this gap, the researchers introduced BMNet-5, a novel neural network model tailored for Bengali music genres. This model achieved an accuracy rate of 90.32%, showcasing its superiority when juxtaposed with traditional models such as KNN, SVM, and other deep neural networks.

Parallelly, the genre of Urdu music, intrinsic to Pakistan, experienced innovation spearheaded by Mughal et al. (2022) Harnessing the power of CNNs and emphasizing batch normalization, they achieved a commendable accuracy rate of 92.6%, paired with a

Minimal loss. Their methodology underscored the pivotal role of data augmentation and meticulous feature extraction in achieving these results.

The momentum of research carried forward into 2023 with a series of impactful studies. Chhetri et al. (2023) embarked on a meticulous exploration of ragas, an elemental facet of Indian classical music. Given the inherent complexity of ragas, their classification demanded a nuanced and sophisticated approach. Utilizing a combination of ML and DL models, and leveraging the feature extraction capabilities of the Librosa library, they attained an accuracy of 73% via an Artificial Neural Network model. This exploration illuminated pathways for musicologists, providing them with tools and methodologies to delve deeper into the intricacies of Carnatic music.

In a parallel exploration, Singha et al. (2023) leveraged the capabilities of CNN to further delve into raga classification. Their CNN, trained on an expansive set of 70 raga classes, highlighted the efficacy of DL in decoding the subtleties of Indian classical music, achieving a remarkable precision rate of 97.9%.

Concluding this chronological review, the study by Patil et al. (2023) presented a comprehensive perspective on Music Genre Classification (MGC). Their innovative approach, which extracted features from spectrographs of temporal music clips, yielded an accuracy of 99.41% on the GTZAN dataset and 93.44% on the Indian rhythms dataset. This study accentuated the versatility and adaptability of DL models across diverse datasets and genres.

Over the past decade, the integration of DL into Indian music genre classification has showcased remarkable advancements, both in methodology and accuracy. As the studies from 2014 to 2023 highlight, there's a compelling narrative of continuous innovation and refinement in this domain. The trajectory of these research endeavors not only underscores the potential of DL but also promises a future where the rich musical legacy of India is better understood, categorized, and appreciated through the lens of advanced technology.

Future Scope and Research Gaps

In the ever-evolving landscape of music genre classification, significant strides have been achieved, yet numerous avenues for prospective research and pertinent research gaps necessitate discerning exploration. This section expounds upon potential trajectories for further inquiry and delineates critical areas demanding additional investigation:

Cross-Cultural Music Genre Classification:

The prevalent focus on Western music genres in extant research calls for an expansion of horizons. Future investigations should encompass the classification of non-Western and cross-cultural music genres, including but not limited to Indian classical music, Chinese traditional music, and African music. These genres present distinctive intricacies owing to their unique characteristics and compositional structures.

Fine-Grained Genre Classification:

Present classification systems predominantly categorize music into overarching genres, such as rock, jazz, or classical. The path forward entails achieving granular and fine-grained genre classification. This necessitates the identification and delineation of sub-genres, stylistic variations, and regional nuances within broader musical categories, warranting the development of specialized models and datasets.

Multimodal Approaches:

The amalgamation of diverse modalities (audio, textual, and visual) presents an avenue for substantial advancement. Future research should scrutinize the fusion of lyrics, album art, and even sentiment analysis to cultivate a more comprehensive and nuanced understanding of music genres.

Real-Time Classification:

The challenge of real-time music genre classification remains a formidable frontier. Pioneering algorithms and models that can seamlessly classify music genres on the fly, with applications spanning from dynamic music recommendation to live event streaming, beckon as a compelling domain for future research.

Robustness to Noise and Variability:

Ensuring the resilience of music genre classification models against variations in audio quality, noisy recordings, and culturally diverse interpretations of genres stands as an imperative. Research endeavors should be poised to tackle these challenges, thus fortifying the reliability of genre classification.

Deep Learning Architectures:

The exploration of novel DL architectures and neural network structures specifically crafted for music genre classification merits scholarly scrutiny. Intriguing areas to delve into include transformers, graph neural networks, or capsule networks within this specialized context.

Genre Evolution Analysis:

In-depth research dissecting the evolution of music genres over time and their interplay in shaping one another promises insights into the dynamics of genre evolution and the prophesying of future genre trends.

Multilingual Music Genre Classification:

Expanding the purview of research to encompass multilingual music genre classification, encompassing music across diverse languages, assumes significance - especially in the

context of global music platforms seeking genre-based content categorization.

Open Access Datasets:

Championing the creation and dissemination of open-access, expansive, and diverse music genre classification datasets fosters a spirit of collaborative research and advances the collective knowledge in this domain.

In navigating the frontier of music genre classification, these technical future scopes and research gaps provide a robust roadmap for researchers and practitioners, paving the way toward ever-enhanced models and methodologies.

2. Conclusion

By identifying the gaps and potential research directions, we seek to contribute to the advancement of Indian music genre classification. Our objective is to stimulate further investigations, foster interdisciplinary collaborations, and facilitate cross-domain applications, ultimately enriching our understanding of the profound cultural heritage embodied in Indian music. Through this scholarly endeavor, we aspire to harmonize the computational realm with the melodic traditions, honoring the past while embracing the future of music genre classification. In light of our mission to advance Indian music genre classification, Figure 5 below illustrates the myriad applications of this technology across various fields. Music education, as illuminated in references Ceylan HC and H. (2021) and Xu (2022), has been a beneficiary, incorporating computational techniques to facilitate pedagogical advancements. Our journey ventures into the realm of mental healthcare and emotion recognition, where the insights from five scholarly contributions (references Sturm (2013), Markov and Matsui (2014), Rosa RL (2015), Rahman et al. (2021), Devi et al. (2022)) have harnessed genre classification for innovative diagnostic and therapeutic strategies.

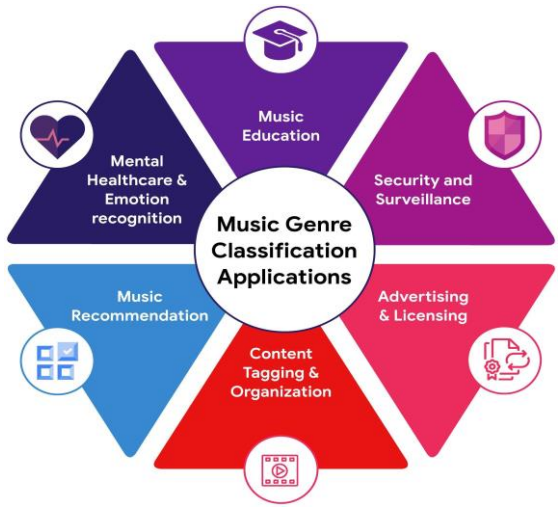

Figure 5. Harmonizing Melodies with Metrics: Music Genre Classification Across Diverse Disciplines

Three research endeavors (references Lampropoulos et al. (2012), Elbir A. (2018), and Alvarez P. (2020)) unfold the potential of music genre classification in the domain of music recommendation, offering listeners an enriched auditory experience. Additionally, the organization and retrieval of musical content find a formidable ally in this technology, as demonstrated by four studies (references Zhen and Xu (2010), Chen et al. (2009), Mayer et al. (2008), Oramas et al. (2017)) that showcase its role in content tagging and organization.

Notably, the industrial applications of music genre classification have not been overlooked, with two papers (references Sewell (2014), Tietche BH (2012), Rabaoui et al. (2008), Sharan and Moir (2015)) shedding light on its use in advertising, licensing, and security and surveillance. This comprehensive overview not only illuminates the multifaceted facets of music genre classification but also paves the way for interdisciplinary collaborations and cross-domain applications. We aspire to witness the harmonious convergence of computational ingenuity with the melodious heritage of Indian music, thus honoring its illustrious past while embracing a future enriched with genre classification possibilities.

In conclusion, this comprehensive review has traversed the rich tapestry of music genre classification, drawing from a plethora of methodologies spanning supervised learning, unsupervised learning, DL, and ensemble techniques. The examination unveiled the intricate web of feature extraction, data preprocessing, and audio signal processing techniques that underpin the diverse methods used for genre classification. These revelations serve as the foundation for not only enhancing classification accuracy but also for transcending into the realm of cross-genre classification and music recommendation systems.

Looking forward, we're excited about bringing together the timeless beauty of music with the endless opportunities offered by machine learning (ML). We hope to spark more research, connect experts from different fields, and find new ways to apply these insights, creating a future where music's rich traditions and cutting-edge technology play in harmony. This blend aims to cross the divides of culture, time, and tech, making sure that the study of music genres remains relevant and vibrant in our digital world.

We are in the process of developing a system for classifying Indian music genres, with aspirations to share our research very soon. As we look to the future, we're enthusiastic about merging the enduring beauty of music with the expansive potential of machine learning (ML). We aim to ignite further research, foster connections across diverse disciplines, and explore innovative applications. This endeavor seeks to harmonize music's rich heritage with the forefront of technology, bridging cultural, temporal, and technological divides. Our goal is to ensure the field of music genre classification remains dynamic and relevant in the evolving digital landscape.

Statements and Declarations

Compliance with Ethical Standards

The authors confirm that they do not have any conflicts of interest associated with this publication.

Competing Interests

The authors declare that they have no financial interest or non-financial interest in the

subject matter or materials discussed in this manuscript.

Availability of supporting data

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