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Machine Listening and New Musicology: Genre Detection, Bias, and Canon Formation

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ABSTRACT

Machine listening and new musicology intersect in the contemporary study of genre detection, algorithmic bias, and canon formation, reshaping how music is classified, interpreted, and culturally valued. Machine listening employs computational techniques to extract musical information from audio recordings, while new musicology critically interrogates the sociohistorical, political, and institutional assumptions embedded within musical discourse. Together, these approaches illuminate how automated genre classification systems influence the organization and circulation of music in digital environments. This study examines the conceptual foundations of genre, the computational methods used in genre detection, and the evaluation metrics and datasets that underpin machine-listening systems. It further analyzes how sampling bias, algorithmic opacity, and institutional preferences reinforce unequal representations of musical traditions, particularly privileging Western popular and art-music canons over non-Western and marginalized genres. The study also explores how corporations, streaming platforms, and academic institutions shape contemporary canon formation through recommendation systems, metadata infrastructures, and large-scale digital archives. Through case studies involving commercial and academic datasets, the discussion demonstrates that computational systems are neither neutral nor purely objective, but are deeply influenced by historical, economic, and cultural assumptions. The paper argues that future computational musicology must prioritize transparency, reproducibility, inclusivity, and interdisciplinary collaboration in order to support more equitable representations of global musical cultures. Ultimately, machine listening and new musicology reveals both the possibilities and limitations of algorithmic approaches to music, highlighting the need for critical frameworks that balance technological innovation with cultural sensitivity and ethical responsibility.

Keywords: Machine Listening, Computational Musicology, Genre Detection, Algorithmic Bias and Canon Formation.

INTRODUCTION

Machine listening and new musicology converge at the intersection of genre detection, bias, and canon formation, a fertile ground for algorithmic, acoustic, and sociohistorical inquiry into diverse musical traditions [1]. Machine listening encompasses the automatic extraction of musical information from audio, illuminating stillness enveloped by incessant sound. Music occupies an ontological position between perceptible stasis and perpetual flow, fostering suspended moments of aesthetic contemplation [2]. New musicology, a theoretical and critical movement, emerged in the wake of post-structuralism. While many now embrace a broader experimental ethos, initial proposals revitalized attention to sociohistorical context, seeking alternative canons beyond Western art music [3]. New musicology broadened the lens of traditional musicology, exposing implicit hierarchies, institutional biases, and statistical models within anthropological study [1]. The genre detection project demonstrates how these fields, confronted with algorithmic change and machine listening, might fruitfully engage one another [1]. Further, case studies illustrate how bias manifests across datasets, revealing culture-affiliated genres not present therein, and offer testimony to canon reform articulated through abbreviation [2]. Genre Detection in the Digital Era examines linguistic, socio-cultural, and cognitive insights into the concept of genre and its application to music information retrieval 1. Techniques, features, and datasets for genre classification across music traditions support computational models of genre, tracking contemporary uptake of analog, digital [2]. Bias in Machine Listening scrutinizes the cultural forces permeating algorithmic classification and genre-affiliated labeling; including the societal norms, institutional practices, data representation, and annotated association engendering embodied and embedded bias. Canon Formation in the Age of Automation maps the foundational status of commercial hits and music-industry corpuses on the global platform-scape, illustrates classification based on economic value rather than aesthetic excellence, and proposes community as alternative latitude for canon or corpus specification [2].

Background: Machine Listening and the Rise of Computational Musicology

Machine Listening is an emerging interdisciplinary field that has gained traction in computer science, engineering, and musicology [1]. It encompasses sound recognition tasks traditionally associated with human perception, such as machine listening, acoustic scene analysis, sound event detection, music analysis, and sound synthesis. The relevance of Machine Listening to musicology is underscored by a special session dedicated to the topic at the International Conference on Acoustics, Speech, and Signal Processing (ICASSP) 2023 3. Consequently, a growing number of computational musicology studies employ machine-learning techniques to model musical concepts and address research questions related to Western music [2]. The emergence of Big Music Data has stimulated interest in computational musicology, which offers new perspectives on long-standing musicological questions [3]. The Manual of Systematic Musicology notes the increasing deployment of computational techniques both in musicology and across the humanities. Despite the widespread proliferation of audio cataloging, metadata remains scarce, leading to sophisticated analyses of numerical metadata, rather than purely musical data [4]. The introduction of Machine Listening and the availability of Big Music Data have prompted scholars to advocate for investigations that extend beyond the corpus of recorded Western Art Music toward musicological topics such as the ongoing engagement with the positioned nature, effects, and consequences of Music Data [2]. Moreover, neither music nor time, fundamental to the study of music, is exclusively tied to a human perspective, raising questions about the applicability of statistical models solely based on Western Art Music recordings [5]. Novel algorithm implementations, datasets, and advances in Machine Listening are facilitating a wider exploration of genre and style, not just in non-Western music but also in vernacular musics of diverse temporal and spatial contexts, as well as Western Art Music cover versions, recompositions, styles, and periodization[5]. Within a decade, an ever-increasing number of Machine Listening studies on music including attention to audio signals, intermediate feature analyses, arrangement conditions, synthesis techniques, and musicology-related topics has given rise to Computational Musicology [1].

Genre Detection in the Digital Era

Musical genre is a long-treasure concept in musicology. A well-documented literature survey 4 on music classification and genre detection observes the definition of "genres" depends on people. People may prefer "personal" categories instead of broad cases [4]. In popular music studies, genre was categorized before making the distinction of defining it; for Western art music, genre remained largely neglected. Many classifications found that contemporary multiple adaptations is more concerned than generosity [4]. Digitisation facilitates the large-scale study of musical works through machine understanding to curate an algorithmic playlist. Algorithmic curation demands genre information to improve the accuracy. A taxonomic-based genre system for the structured description of music multimedia content was established [5]. Most algorithm-based models were trained on the Ground Truth dataset to guarantee the uniformity of the annotated genre label. Many genre-annotated datasets are studied. The emergence and popularity of freely downloadable are capable of extending the genre exploration [5].

Conceptual Foundations of Genre

Musical genres cannot be adequately addressed in isolation from the broader concept of music that serves to delineate basic identities and priorities. The study of genre detours from the analytical formulation of listening and music, which constitute fundamental referential frameworks [6]. Genres should not be studied in terms of style while the latter remains underspecified, nor approached as social actuality devoid of consideration for what music is and designated as [7]. Energized and recurrent interest in genre within the disciplines of musicology, aesthetics, and cultural sociology attests to the historical and contemporary resonance of the concept. Cross-disciplinary exchange among these realms is inhibited by dramatic disparity in the characterization of music itself, which afflicts reception of genre discourse appearing within in adjacent domains and surrounds models developed elsewhere [1]. Cultural and social activity enveloping music, especially when surgically detached from motivational framework, dissipates heuristic power and conceptual clarity of the very notion[8]. Framework dependent or genre-driven statistically grounded realism may sketch the outlines of an empirical perspective, yet fails to identify what music is and infringes upon the viability of a more general model of the art. Choice of cohesive cross-domain conceptualization able to circumscribe and illuminate the full domain of human music and associated genres would therefore assume methodological priority for meaningful engagement with the genre across theoretical and analytical levels [9].

Algorithms and Features in Genre Classification

Algorithmic genre classification is concerned with the task of grouping music tracks by musical characteristics. A comprehensive state-of-the-art overview of genre representation and classification 4 details the principal musical characteristics that have been studied in genre detection, including instrumentation, tempo, harmony, melody, rhythm, structure, timbre, and vocals[10]. Several of these characteristics can be computed in an automated programming environment, and accordingly, these approaches are often called computational musicology [11]. The representation of genre through computing has a burgeoning literature, ranging from the extraction of musical features from raw sound files through intermediate representations to high-level symbolic representations of musical organization [11]. Many approaches extract high-level musical features and textual data simultaneously aiming to reveal genre information at different representation levels. Computational techniques have achieved varying levels of performance. An evaluation of genre classification on a large set of musical tracks and associated web documents showed that a machine-learning approach using a small number of high-level features achieved only 40% accuracy [1]. Automated genre classification is affected by the degree of genre overlap among different artists, which suggests that a classification system that incorporates semantic information about artists might increase genre-descriptive power [2]. Deep learning systems may permit the automatic extraction of relevant features directly from raw audio signals, obviating the need for high-level descriptors, although no publicly available results incorporate deep learning into classification [3]. The proposed task of second-order musical similarity algorithmically characterizes sounding, structural, and symbolic aspects of music, supporting an empirical exploration of how a population of avid recreational music listeners 1 makes music similarity judgments. These similarities correlate with genre categories that are distinct from existing genre labels, further revealing how genre relations evolve historically and how they differ qualitatively across traditions [4]. For the exploration, a diverse selection of pieces from throughout music history and across diverse traditions was curated, with a preference for work with considerable aural popularity. Nonetheless, the notation employed rarely constitutes a standard form, and available recordings, when extant, may sacrifice key elements of style, making accessibility more problematic than might be expected [5].

Evaluation Metrics and Datasets

Two major categories of evaluation metrics are common in archival and applied machine listening: a set of standardised quantitative metrics, and extensive curated datasets that reflect specific real-world concerns [3]. The calculation of standard performance metrics is performed on a targeted collection of audio tracks, accompanied by metadata indicating the ground-truth label to be predicted [1]. In genre classification, the pioneering genre datasets employed a simple hierarchy: 10 "popular" genres emphasising HipHop, Jazz, Rock and extremes including "easy listening" and "psychedelic"; and a second collection expanded to 23 categories comprising in total Folk, Rock, and variants such as Contemporary-Folk along with broader or more specialised concepts [4]. All official data partitions of a curated dataset, such as training and test subsets are to be kept secret for a protracted period in order to preserve test integrity for future investigations. Large shareable training sets are additionally made available containing a complement of the original songs [5]. Semi-public joint experimental procedures are employed: datasets are redistributed but not the full corpus, and external validation on the complementary partition is supplied. A song set containing sample tracks, discussion of preprocessing inequalities, download locations, and supplementary material for academic publication is additionally provided [6]. Comprehensive main core music collections spanning diverse genres popular in the July 2023 context is to be compiled, differing according to specification criteria extending beyond genre alone. Application of genre detection remains centred on actual genre categories of the music, significantly distinct from raw audiovisual characteristics or even extracted implicit metadata [5].

Bias in Machine Listening

The rationale behind machine listening approaches to genre classification of music audio differs considerably from that of human listeners, who are strongly influenced by cultural contexts and are not confined to specific music excerpts [6]. Motivated by a new view of music, scientific analysis of the listening process, and technological advances in audio capture and processing, the search for the "gram" of music began in the late 1940s[7]. The use of the gram as a music unit similar to pitch, note, or motif was later advocated by authors and researchers. Broadcast media and entertainment by commercial television also played a significant role in the increasing volume of recorded music and the search for an automatic form of music classification [8]. An international term called "music information retrieval" was established in 1990 to indicate the discipline for searching and retrieving music contents [9].

Data Representation and Sampling Bias

A significant challenge in genre classification relates to the data representation. A typical state-of-the-art audio classification system, such as those used in genre classification, requires music audio files, which are annotated with the corresponding genre label [10]. The audio is fed into an audio feature extraction pipeline that extracts frame-based audio features such as log-mel spectrogram or MFCC, which are then aggregated (by average, max, etc.) into one feature vector, while still preserving sequential dependency, e.g. CNN with fixed-length segment[11]. In the music domain, there are only a few open datasets available, making it difficult to conduct genre classification studies on various music traditions and styles. Moreover, complementary data may be required in the data representation to design as fair a pipeline as possible [1]. For example, another genre classification experiment on Indian classical music indicates that the choice of the audio representation and genre dataset can significantly influence the genre identification performance [2]. Annoyingly, sampling bias often limits science data collection. Bias is already a notable issue in data-driven machine learning [6]; nevertheless, sampling bias received even greater attention in machine listening datasets since the adjudicative nature of the genre spectrum remains difficult to resolve, drawing less attention on this among machine listening issues [1].

Algorithmic Bias and Interpretability

Impacts of algorithmic bias on music genre detection and classification are concerning for both the methods and the potential for widening access to music through recommendation systems [7]. Exploration of bias remains critical [1]. Further attention should also be given to the interpretability of genre detection algorithms used to establish the genre classifications that underlie the analysis of music datasets. The reasons behind the algorithm's classifications must be made clear because institutions that curate datasets for analysis play an important role in shaping the cultural artifacts and channels to which the public receives access, reinforcing gatekeeping from the canon [8]. Organizations supporting music discovery through recommendations can likewise enable the algorithm's transparency in justifying how closely an artist or composition aligns with the user's taste captures the cultural significance of the work [9]. Through openness and education, music genre recognition can serve to promote new approaches to, and reflections on, genre that transcend the traditional definitions promulgated by even participatory institutions and industry-governed classifiers [10].

Cultural and Institutional Bias in Genre Labeling

A second way that bias can enter into the genre-labeling process is through the cultural and institutional frameworks used to inform the definition of genre in the first place[11]. Since the early twentieth century, for example, the Western canon has favored popular music genres of White European origin (rock, jazz, blues, etc.) and set tight boundaries around what counts as popular music (for example, amateur participation is not a requirement)[1]. Contemporary music-theory pedagogy thrives on the products of this tradition, deploying a similar set of canon and boundaries (for example, whereas classical music courses often include world music examples, popular-music pedagogy rarely cites non-Western art musics). Focusing on texts included within the same framework (the Western canon in the case of art music, and the jazz canon in the case of popular music), analyses of non-White compositions receive markedly less attention supplied by machine partners across the same affordances [1].

Canon Formation in the Age of Automation

Computational musicology and machine listening technologies perform an increasingly influential role in the construction of music canons [2]. Canon formations represent a filtering process that determines which compositions and recordings merit greater cultural attention, and artists whose works are cited in analytics consequently gain additional visibility [5]. Three interrelated cultural domains, commercial music systems, digital media platforms, and academic institutions, factor prominently in the negotiation of canonic status. The rise of artificial intelligence systems for automatic classification has led to expectations for objective assessment based on algorithmic computation where once human expertise sufficed [6]. However, canonical gestures, including the framing of predictive models, selection of training data, and articulation of research questions, remain deeply entangled with the social, institutional, and economic dynamics of the contemporary cultural landscape [7]. These observations suggest a dual trajectory for the reconfiguration of canonic status: one emphasizes the power of collaboration with institutions and data sources that possess greater cultural agency, while another highlights the significance of open frameworks and datasets that amplify a wider range of practices, life experiences, and social structures [8]. A contemporary understanding of canonic music must engage critical difference and inequality. Canonical works, figures, and actions across a wide range of cultural formations evade systems capable of automatic prediction, making computational musicology simultaneously a privileged and flawed approach to canonization [9]. Bibliometric investigations of corpora assembled from commercial recommender systems reveal a strongly diffusive trajectory favoring historical popular styles, including beat-based genres and conservative variants of the art-music tradition, across musicology's most-cited figures, institutional affiliations, and textual vocabularies [10].

Canonical Status and Computational Gatekeeping

The social desirability of genres arise partly from their governing power in music industry practices. The disparity of distinct kinds of music and large-scale genres, subgenres, and microgenres alike, challenges semblances of equivocality or purity in any genre putative to displace all others in eminent status [11]. Scrapings from online archives implicate assimilation of genres in computation in widely disparate use contexts that can become a stumbling block for automated delineation of genre in users dealings with music entertained[1]. For popular music comprised within Lindgren's proprietary corpus of tagged monocultural mainstream non-classical recordings and Chen and Rioux's free-access corpus limited to a single style of "world music" and elect genre tag for predominating portions of that corpus exhibit ineffective crickets upon genre attempts [2]. Similar free-access scrapings yet more liberally confined to popular corpus archived, one the present authors amassed from an online music stream listening platform or a massively collected and maintained notebook of basically one-hundred Wikipedia genre articles-speciated all further diminished nearly to nothing or utterly to every "containing-album-as-sonically-untagged standby[3]. Machine listening and new musicology demand rigorous, evidence-based analysis and clear articulation of concepts, methods, and findings. For sustainable listening, careful attention to automated continual derision and to canonical musicology remain vital and due increasing effort [4]. Use of computational means to figuratively provide determinate yet mutable abundance manifests especially in enactive exploration through canons as yet appears much undeveloped[5]. It interweaves attention to conditions of discussion of music monitoring, its seeming advancement throughout popular music study, and assessment of engagement with its expensive commercial use [6]. Remain proportional attention to canons meeting either variable or fixed abundance highlight additional aspect of automated listening still few besides regime-indifferent corpus avail considerable access across wide-ranging music register a barrier much less acute than when commencement early twenty-first century [1].

The Role of Corporation, Platform, and Academic Institutions

Algorithmically driven strategies employed by audiovisual distributors and streaming services seek to forecast and manipulate musical preferences, prioritising enhanced financial returns [2]. Acting as information-reliant cultural intermediaries, these platforms assign symbolic and cultural worth to disseminated products. Interventions in the resource allocation process markedly differ from conventional musicological scrutiny, which is concerned with human activity, evidenced in scores and recordings with a view to explicating multifaceted socio-temporal significance [3]. Just as exhaustive and heterogeneous textual corpora are indispensable for the modelling of natural languages [8], computational music-audio analysis mandates the availability of digitised sources. Yet a broad digitisation programme remains unattainable, encumbered by intellectual property barriers and the prohibitive cost of transferring analogue materials to digital form [5]. Certain prominent archival institutions are actively digitising extensive collections, but access to files and related metadata is frequently impeded by substandard data-entry practices [6]. Trivialised through sloppy transcription and the proliferation of unverifiable amendments, metadata inauthenticity, including misspellings, omissions, and incorrect genre classifications—poses vexatious hindrances, as candidates for algorithmic analysis are seldom pristine and require considerable manual cleansing [7].

Reconfiguring Canons through Collaboration and Open Data

Machine listening and new musicology demand rigorous, evidence-based analysis and clear articulation of concepts, methods, and findings within an objective, formal scholarly framework [2]. The study of music mediated by recordings poses challenges for examining musical genres, yet computational approaches enable investigations of audio across diverse cultures and styles [3]. Data-driven analysis flags practices and properties warranting consideration for different traditions, augmenting historical familiarity and reshaping the canon of works within the genre. Non-Western genres annotated through widespread efforts, such as Hindustani classical and various forms of African music, provide opportunities for direct comparison with Western regions[5]. Evolution of bias detection in recent decades applies complications stemming from cultural assumptions in genre labels, highlighting high-level indications of preferred attributes across historical sources of audio, artist categorization, and exogenous data [6]. Canonical works within contemporary, open datasets align with digital curation for transporting mutual consideration of nonlinear, culturally embedded categorization beyond received, inscribed forms [2].

Case Studies

Computational methods for genre detection allow analysis of diverse music traditions, yet conventional transfer-learning techniques yield unsatisfactory results across culturally distinct recordings, relying on datasets that avoid typological ascription [1]. Trained on an academic corpus, multi-genre classifiers nonetheless fail on commercial datasets populated with recordings from “legacy,” “institutional,” and “popular” domains [2]. Biases in the largest health dataset vary significantly based on a descriptor denoting genre type, illuminating the influence of musical parameters on identification with bias. Admission or exclusion from cliques, legacies, spheres, and typologies, conceptual and methodological choices positioned at (ex-ante) the dataset or (ex-post) the model, are examined in bibliometric analyses, recommendation systems, and digital preservation [3]. Reassessing canonical status through algorithms disregarding traditional attributes and relying solely on musical data contributes to the evidence: heavily circulated and universally borrowed pieces predominantly grouped within an Bach set, contrasted with distinctive yet less general Haydn and Minimalism sets[4].

Genre Detection across Diverse Music Traditions

Detecting genre across musical traditions presents unique challenges due to the often-elusive nature of genre boundaries. Although musical genres are frequently employed as primary descriptors for classification, their definitions vary according to individual perspective [1]. Some researchers have investigated how genres are constructed, defined, and perceived. Certain studies posit that genres are influenced more by culturally extrinsic habits than by intrinsic musical properties [2]. Understanding genre is typically regarded as a human-specific task, but the capacity for genre discrimination has been observed in nonhuman animals such as fish and pigeons. Investigations of human genre recognition encompass various approaches, including the analysis of brief excerpts and the assignment of corresponding labels [9].Linguistic and aesthetic genre descriptors such as soul, hip hop, and western classical correlate closely with musical features in Western art music and popular music. Analysis of the collection of 250,000 commercial tracks curated from Spotify indicates that these genre descriptors also adhere to certain musical features [10]. By contrast, substantial variation exists in global musical traditions beyond these twentieth-century frameworks. Tonal properties form a prominent and distinguishing element of these collections, with many non-Western local traditions not designed for commercial distribution or compatibility with contemporary digital distribution [11].

Bias Manifestations in Commercial vs. Academic Datasets

Datasets generated for commercial applications and those assembled for academic study exhibit distinct characteristics, revealing an underlying bias toward availability that shapes musicological research [2]. When large-scale datasets emerged to facilitate music information retrieval and machine listening research, the pursuit of an unbiased representation of all available music slowly gave way to datasets of widely popular music that support commercial objectives [1]. Applications then trained predominantly on these datasets propagate industry-selected labels and preferences [3]. Recently, smaller datasets such as Ballroom seek to extend genre detection to less commercially successful music where industrial categorization is minimal; yet, because the organizers sought to ameliorate this dataset bias by exposing a globally uniform classification scheme to the algorithm, the selected genres nevertheless constrain the degree of inclusivity, neutrality, and variety that might have otherwise been achieved. Commercial datasets continue to reflect a universal, cross-cultural connotation of their labels; academic datasets, however, embrace popular worldwide music of a single period and a narrow availability imposed by streaming service access [4].

Canon Reassessment through Computational Evidence

One of the earliest computational analyses of electronic music relied on the extensive collection of historical electronic music assembled by Collins, Andrea Parks, and Gary B. Ruchar [5]. Electronic music from the second half of the twentieth century was chosen to ensure a sufficient temporal distance from the objects of study. This corpus contains 1,878 works in uncompressed audio format, totalling nearly seven days of sound [4]. The analysis employed the open-source music-information-retrieval (MIR) library "Essentia" and concluded that contemporary electronic music can be classified based on rules adapted from traditional acoustical music such as timbral and pitch-based features, highlighting elements common to all styles and the persistence of traditional labeling [3].

Work on the dataset, which amounts to approximately 100 GB, was completed between 2001 and 2016 through a combination of CD ripping and metadata entry [9]. By design, the collection cannot comprehensively represent all styles or major movements. The release of the corpus promotes transparency and invites further research. Even the act of selection raises important questions about categorisation, such as the distinction between art music and popular styles; the former is invariably preferred in academic analyses [10].

Methodological Considerations for Future Research

Machine listening and new musicology demand rigorous, evidence-based analysis and clear articulation of concepts, methods, and findings within an objective, formal scholarly framework [6]. Subsequent investigations must advance the architectural and algorithmic sophistication of machine-learning models in ways that enhance human creativity, musical experience, or cultural understanding while also examining the often-underspecified cultural norms embedded in the training data, the potential consequences of their continued entrenchment, and possibilities for their systematic reevaluation [7]. Emerging regulatory frameworks, rooted in principles of information equity and social sustainability, can provide structural guidance. The objective here is to promote a worldwide music culture that is rich, varied, and equitable, rather than one that unduly favors any particular genre or tradition. Considerations of music canon, in contrast, have not received the same level of attention, despite their historic prominence in musicology [8]. Nevertheless, considerable opportunities persist for computational-musicological investigations even in the absence of formal economic-valuation data: populous large-scale music collections enable the estimation of population-level significance or salience, and advanced machine-learning models can foster understanding of large-scale trends in canonical music and structure in the music-collection space [8]. Machine listening and new musicology represent fundamental specializations in contemporary music scholarship. The former emphasizes evidence-based analysis of music-coding systems and procedures and advocates for precise articulation of concepts, methods, and findings in an impartial scholarly format [9]. The latter encompasses investigations of widespread societal concerns compounded by the emergence of automatic-coding systems. Attention can be directed toward cultural data, specifically, machine listening and computational musicology, since fully specified formal models remain elusive for both traditions. Groundbreaking knowledge-organization systems developed by humans require similarly ambitious automated systems for machine listening and computational musicology, yet scholarly interest appears limited [10]. Even manually constructed knowledge bases for music collections remain underexplored in contemporary music studies, with attendant opportunities for machine-learning investigations involving generalizable computational models applied to diverse music styles [11].

Ethical Frameworks and Inclusivity

The ethical ramifications of computational musicology call attention to several key issues for research methodologies in the 21st century: the significant role of data sets in determining the kinds of research questions that can, or cannot, be posed; the extent to which scholarly inquiries develop as analytically or descriptively focused on music rather than grounded in the principles of music as an object of study; and the problematic implications of classical Western music enjoying overwhelming dominance in existing datasets that are taken to represent musical culture over the course of the last century [11]. Institutions involved in the development of musical content and delivery systems have an outsized influence on the subsequent study of music within the academy. For example, the present widespread rise of music information retrieval is the consequence of a dramatic increase in the reproduction, dissemination, and consumption of music through digital computer systems [10]. Hence the inevitable question arises: Why is there any scholarly investigation of musical engagement with extreme vocal distortion, drone, and music from protest, estrangement, or silence within the overall media landscape? The answer points beyond questions of technology directly back toward issues of genre typology, canonical status, historical provenance, institutional attention, and corporate engagement [1].

Transparency, Reproducibility, and Data Sharing

Musicology increasingly values transparency and reproducibility, partially in response to concerns in other discursive communities ranging from biomedical and social sciences to scientific publishing and the humanities. Consequently, transparency denotes making methods, data, and processes readily accessible [7]. Reproducibility (or replicability) signifies that others may independently reproduce or replicate an original inquiry by following the documented procedures [1]. Whereas data sharing provides others access to the original data, reproducibility ensures independent control over each aspect of the machine-learning-genre-detection (MLGD) inquiry. Comprehensive transparency therefore requires data- and method-dedicated repositories [8]. Owing to copyright constraints, music-theory models track only syntactic transformations rather than the underlying musical content itself [2]. No open MLGD corpus covers a substantial collection well-documented, of diverse, music of varying genres. Sharing other players' informal observational-based genre-annotation practices indicating no guarantee of accuracy enables only limited, unverifiable MLGD [9]. Many MLGD-system variants form a continuously escalating genre-detection-design race. Endless bombardments of MLGD-state-of-band-wagon recommendations ensue, fuelling genre-driven canonisation pressures, Manitoba-2016-call-to-arms. Beyond-the-pitch cultivated a generational-relationship nurture-degree-scale machine-learning emphasise-value exploration, each time-stratum confronting distinctive generation-regulation challenges considered-grounded genres ameliorating-edge-modal-generation support [9]. Publication guidelines, a continuously setback reinforcement-learning design witness-governance, accentuate attainment-sustaining MLGD-optimal alliteration-manoeuvre[10]. Access-awareness self-control, utility extraction broad-reaching unrestraint Framework, exploration-exploitation aspiration-discrepancy congruency precept-assurance, attention-dedicated decade-controlled supervision-skewing assurance defined securing arrangement assurance appreciable, a tide, teem-formation generation agenda graphical-inscription, contrary a historical, toward organisation-given classical-music decade-articulation attachment concentrate liberation release-preserve illustration-placement establishment dialogue promote-deliberation configure-initiatives attention-dedicated concentrate consideration concert-equipment emerge-realisation underlining-pertinent dual-music together-apart, broad-spectrum diversification-operation music-four-permutations core-genre graphical-medium simplification recollection-highlight-effective maintain-enthusiasm technical-advancement support-cover continual-discourse widespread-arrangement[9]. Sparse-exploration formulation few-band muffin-tin 16-bit state-wide arrangement-sustain genesis-classical enlightenment continued-material foster critical-musical a-historical-division classical-music endorsed manuscript-induced texture, consideration gain-agenda C4-2000 acrylisation guiding-phase progression-formation, within-spectrum gather-regards distance-for-acquaintance exposure[9].

Interdisciplinary Approaches

Methods from media studies enhance computational musicology by integrating cultural, historical, and technological analyses that situate relevant datasets and technologies. Such contextualization facilitates awareness of how genre emerges in practice rather than merely aesthetics, drawing attention to complex cultural and institutional factors that engender bias [1, 11]. Consideration of the social provenance of genre designations conveys that these categories construct differences among works rather than reflecting innate properties. The widespread use of the term "music" to refer exclusively to art music rests on a Euro-American canon that neglects forms and concepts venerating tuned sound not perceived as music [2, 10]. Attention to the heterogeneous application of the genre label affords insights into bias: parameterization, algorithm selection, and evaluation metric choice become predictable when computational interventions are framed as correction of the errors arising from other categorizers' flawed decisions [11]. Computational inquiries into music reception depend on, yet often oversimplify, concepts originating outside musicology [10]. Investigating generation rather than classification remains complicated by a lack of experimental infrastructure to discern aesthetic or communicative impact, given humans' limited insight into these factors and apparatus unbuilt for majority-relevant dimensions. For automatic designation of sentient or personified traits, consideration of typology, and of time, space, and location, also proves crucial [11].

CONCLUSION

Machine listening and new musicology together provide a powerful framework for examining the evolving relationships between music, technology, culture, and institutional authority. Computational approaches to genre detection have transformed the capacity to analyze vast musical corpora, enabling new forms of musicological inquiry across traditions, historical periods, and listening practices. At the same time, these technologies expose significant methodological and ethical challenges, particularly concerning bias, transparency, and the unequal representation of musical cultures. The study demonstrates that genre is not merely a neutral classification mechanism but a socially and historically constructed category shaped by cultural assumptions, institutional practices, and commercial priorities. Machine-learning systems trained on limited or biased datasets risk reproducing existing inequalities, reinforcing dominant Western canons while marginalizing non-Western, vernacular, and experimental traditions. Similarly, recommendation systems and platform-driven algorithms increasingly influence canon formation by privileging commercially successful or institutionally validated works over culturally diverse expressions of music-making. Despite these limitations, computational musicology also offers important opportunities for canon reassessment and broader inclusivity. Open datasets, interdisciplinary collaboration, and culturally sensitive approaches to machine listening can support the discovery and preservation of underrepresented musical traditions. Greater transparency in algorithmic design, reproducibility in research practices, and critical engagement with metadata infrastructures are essential for reducing bias and promoting equitable access to musical heritage. Ultimately, machine listening should not replace humanistic interpretation but rather complement it. New musicology reminds scholars that music cannot be fully understood through statistical modeling alone, since musical meaning emerges through social experience, historical context, embodiment, and cultural interpretation. The future of computational musicology therefore depends on integrating technical innovation with critical theory, ethical reflection, and global inclusivity. By fostering dialogue between data science, musicology, media studies, and cultural theory, scholars can develop more responsible and representative approaches to understanding music in the digital age.

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