Cureus Journal of Computer Science

Open Access Review Article

# Artificial Intelligence in Music Genre Classification: A Systematic Review of Techniques, Applications, and Emerging Trends

**Received** 04/21/2025
**Review began** 04/30/2025
**Review ended** 07/07/2025
**Published** 07/09/2025



**DOI:** https://doi.org/10.7759/s44389-025-04209-9

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## Abstract

Music has been an important means of expression and communication for centuries, and its genre classification is integral to its understanding, appreciation, and production. This meta-analysis evaluates the current cutting-edge approaches to music genre classification using a range of evaluation parameters: data sources, methods/techniques, approaches, study status, dataset, and place of publication. A total of 11 electronic databases were thoroughly searched, and 84 relevant articles were selected for closer examination and analysis. A quantitative review was conducted to pinpoint recent insights, measures, methods, and applications in this field, focusing on research published over the last seven years. This research reveals a significant insight: most music genre classification systems are still in the evaluation stage. This study further contributes to the field by developing a taxonomy of state-of-the-art methodologies. Researchers must explore other methods and algorithms for music genre classification to enhance further classification. The future recommendation is to exploit more deep learning techniques due to their unique features and increase the number of datasets used for African music classification, hence improving the performance of classifiers and reducing computational complexity.

**Categories:** AI applications, Deep Learning, Machine Learning (ML)
**Keywords:** african music, audio classification, genre identification, artificial intelligence, machine-learning, systematic literature review

## Introduction And Background

With digital entertainment on the rise, music has become a universal force, breaking down cultural barriers, uniting fans and artists, and redefining the music industry landscape [1]. Spotify, Apple Music, and other online streaming platforms have transformed the music industry, replacing magnetic cassettes and compact discs as the primary means of music storage and distribution [2], resulting in an enormous volume of music library databases and challenging song management [3].

A significant portion of the world's population now likely regularly downloads and buys music through internet music stores. Online music content distribution vendors have made large music libraries accessible, increasing user convenience for streaming and downloading music. Nevertheless, the vast array of music styles and genres creates a substantial obstacle to effective music indexing and retrieval [2]. Categorising music by genre enables efficient storage and retrieval. Hence, a reliable music genre classification (MGC) system is crucial for effective music content management and retrieval.

Numerous online music organisations have enthusiastically adopted the digital music revolution in recent years. These platforms operate various online music channels, provide entertainment services, and categorise similar tracks for easier discovery and client engagement. This analysis and classification enable informed decision-making. Notably, the International Federation of the Phonographic Industry (IFPI) [4] reports that online music streaming has become the primary revenue source, accounting for 62.1% of global recorded music revenues in 2020, with a 7.4% market growth, revenue of $ 21.6 billion, and about 443 million paid subscription users.

The migration of music to digital platforms underscores the importance of automating music classification for all parties involved, given that human responses to genre identification can be biased. Music can be categorised by genre, instruments, mood, and user preferences. Research indicates that users predominantly browse music by genre, thereby emphasising the need for accurate and efficient MGC [5].

Genre is a key factor in identifying and categorising music, and a conventional classifier for grouping pieces that share similar styles, traditions, or characteristics [6]. The diversity of music genres gave rise to varied musical preferences. Identifying musical styles or artists is a complex challenge. Musicians' creativity often blurs genre boundaries. The genre classification of some songs/artists remains ambiguous, as they incorporate diverse stylistic elements or innovate beyond established genre parameters. This issue is exacerbated by the lack of universal consensus on subgenre definitions, highlighting the need for innovative music classification and recommendation systems.

Music genre is a conventional category for understanding and categorising musical diversity, based on shared tradition, cultural, or historical attributes [6]. Examples are Jazz, Rock, Hip-hop, Fuji, Afrobeat, Juju, etc. Typically, these characteristics are often intrinsically linked to the music's rhythmic organisation, instrumental timbre, and harmonic composition. However, categorising music files into genres poses significant challenges in Music Information Retrieval (MIR), a field that focuses on navigating, organising, and querying vast music databases. Genre classification offers significant utility in addressing various music-related challenges, including song recommendation, related song retrieval, identifying target audiences, and informing survey research. Despite humans' capacity for MGC via auditory perception and cognitive processing, subjective biases undermine the reliability of such judgments [7,8], underscoring the importance of automated classification systems.

Automatic MGC uses computational algorithms to analyse and categorise music tracks into genres, providing an efficient and scalable solution for music classification [9]. The interdisciplinary approach of this research area has fuelled its rapid growth in recent years. By drawing on a broad range of disciplines, including music theory, digital signal processing, psychoacoustics, machine learning, and traditional computer science and numerical analysis, researchers can create innovative algorithms that are both effective and efficient [9].

Automatic musical genre classification offers a valuable enhancement to music information retrieval systems, potentially replacing or augmenting human classification [10]. This technology facilitates content-based analysis of musical signals, leveraging features derived from instrumentation, rhythmic structure, and texture [11].

Music classification poses significant challenges due to the complex selection and extraction of relevant audio features. Automated genre classification offers a faster and potentially more accurate solution than manual methods. This systematic literature review addresses the organisation of large music databases and the ambiguity of genre boundaries [12], aiming to catalogue existing measures and identify opportunities for improvement.

This research provides an in-depth review of MGC, focusing on (1) the different models or techniques available for MGCs, (2) the datasets used, (3) methods of feature extraction, and (4) the accuracies of existing models. Hence, it offers insight for academic, professional researchers and specialists in their quest to create and enhance current methods for precisely and successfully defining the music genre.

# Review

## Research objectives and questions

This study employed a multi-faceted research protocol, incorporating various search techniques, source identification, study selection, and execution methodologies. Prior searches were conducted to discover any systematic reviews that already existed and to gauge the number of possibly pertinent studies that would be included as sources. The primary objective of this study is to investigate and document state-of-the-art techniques for MGC. Identifying potential study gaps will help future studies to enhance the efficiency of music genre classifiers. To focus on the study, the following research questions were developed:

RQ1: What is the “state-of-the-art” in MGC?

RQ2: Which methods/techniques are often used for MGC?

RQ3: What common performance metrics can be used to evaluate music genre classifier techniques?

RQ4: Are there any public standard datasets that can be applied to examine MGC?

RQ5: Are there researchers who publish work on MGC in Africa?

## Search strategy and protocols

*Search Protocols*

The systematic literature search was informed by the following inclusion and exclusion criteria:

(1) Extract relevant phrases from the research questions using a systematic approach.

(2) Consider keyword alternatives and semantic analogues.

(3) Conduct a targeted literature review of papers published from 2017 to 2023, focusing on select keywords.

(4) Apply Boolean search syntax using "OR" and "AND" operators to connect major concepts.

The search results yielded the following outcome using the specified search terms: (Music Genre OR Automatic Music Genre OR Africa Music Genre) AND (Classifier ⟨OR⟩ classification).

*Systematic Search Procedure*

For this systematic review, a comprehensive search was conducted across prominent databases and research sources, including IEEE Xplore, Springer, ACM Digital Libraries, ScienceDirect/Elsevier, Wiley, MDPI, Sage Journal, SPIE, Stanford University, Taylor & Francis, and Google Scholar. Utilising the specified search terms, an advanced search was performed. The systematic review process and article selection methodology are visualised in the PRISMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses) flow chart (Figure 1).

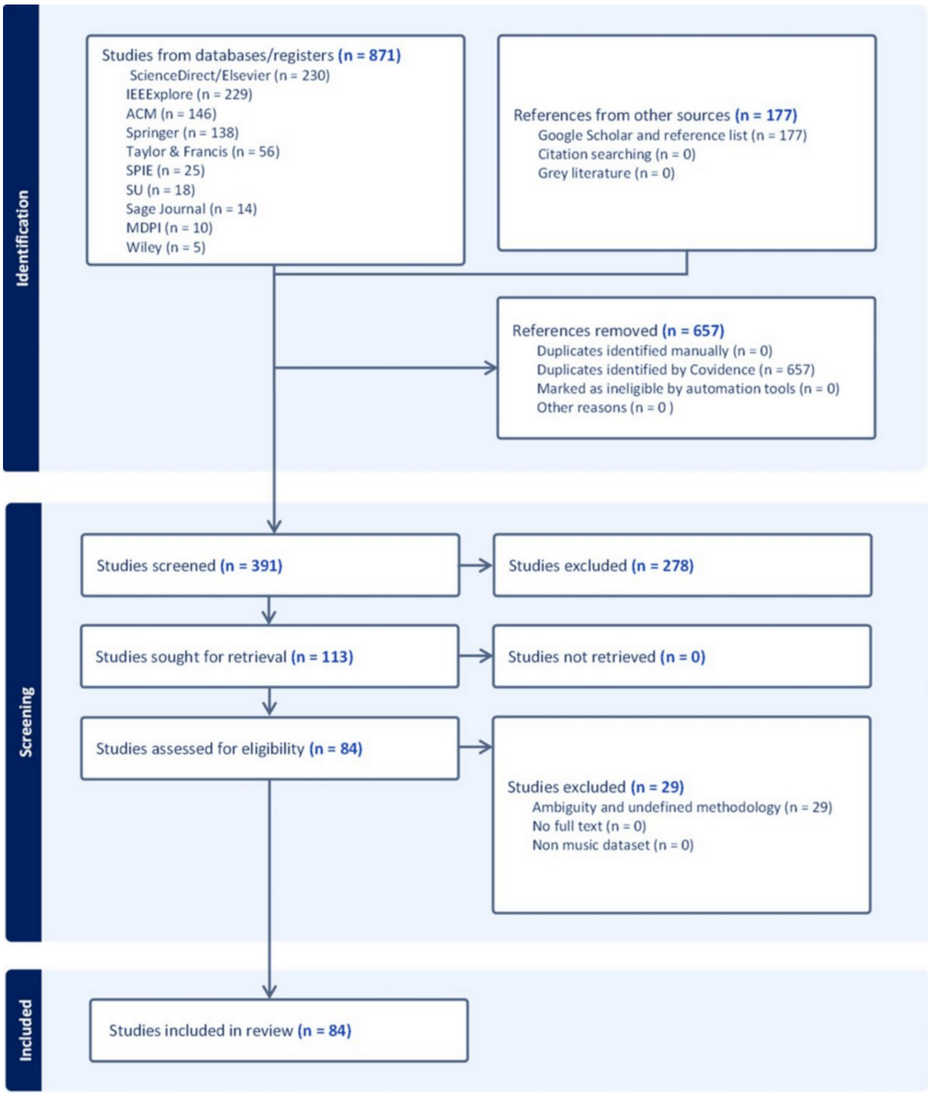



**FIGURE 1: PRISMA flowchart: Visualising Systematic Review Methodology and Article Selection.**

PRSIMA, Preferred Reporting Items for Systematic reviews and Meta-Analyses

After the delineation of data sources, procedures, and inclusion/exclusion criteria, a quantitative analysis was undertaken to identify novel contributions, metrics, methodology, or practical uses introduced by experts in this field over the past seven years.

(1) Step 1 (Identification): Eleven electronic databases were thoroughly searched, and the findings (articles) from each were summarised, totalling 1,048 articles. This identification process was concluded by removing duplicated articles; 657 were identified as duplicates during the database search, leaving 391 articles. Table *1* presents the potential articles identified for further assessment and graphically depicted in Figure *2*.

(2) Step 2 (Screening): The screening stage commenced by removing articles with no relevance to the titles of the papers or research being conducted. To accurately assess article relevance, a review of the full texts and their applied specific selection criteria was done. Out of the remaining 391 articles, a total of 278 articles were deemed irrelevant and removed from consideration, leaving 113 articles to be screened. Lastly, a total of 29 articles with ambiguous or unspecified methods were removed, leaving 84 articles.

(3) Step 3 (Inclusion): A quality evaluation of the remaining publications was done considering the research question mentioned above. After selection issues with the articles were overcome, 84 primary studies were taken into consideration for this systematic review.

| S/N | Research Database | Number of Publications |
|---|---|---|
| 1 | ScienceDirect/Elsevier | 230 |
| 2 | IEEE Xplore | 229 |
| 3 | Google Scholar & Others | 177 |
| 4 | ACM | 146 |
| 5 | Springer | 138 |
| 6 | Taylor & Francis | 56 |
| 7 | SPIE | 25 |
| 8 | Stanford University (SU) | 18 |
| 9 | Sage | 14 |
| 10 | MDPI | 10 |
| 11 | Wiley | 5 |

**TABLE 1: Database Search Results.**

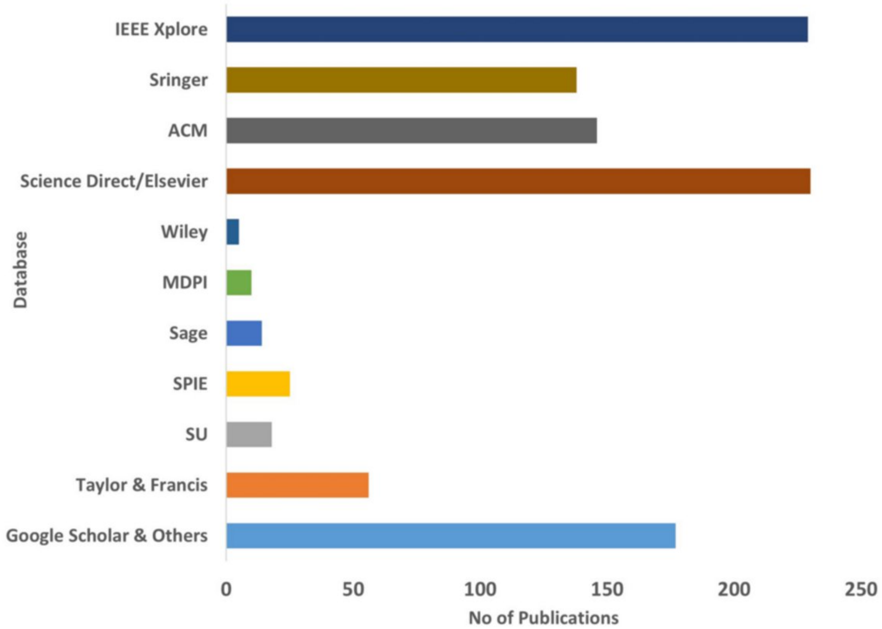



**FIGURE 2: Number of Publications From Each Digital Library.**

## Search technique

The search techniques utilised in this study are presented and discussed herein, based on a comprehensive review of 84 relevant papers.

The following are publications of the 84 relevant papers: 54 articles from journals, 27 articles from conference proceedings, 2 articles from workshops, and 2 articles from research theses, as shown in Figure *3*. To systematically assess the contributions of preceding scholars in this discipline, search techniques were stratified into six thematic categories: Data Sources, Methods/Techniques, Approaches, Study Status, Dataset, and Place of Publication.

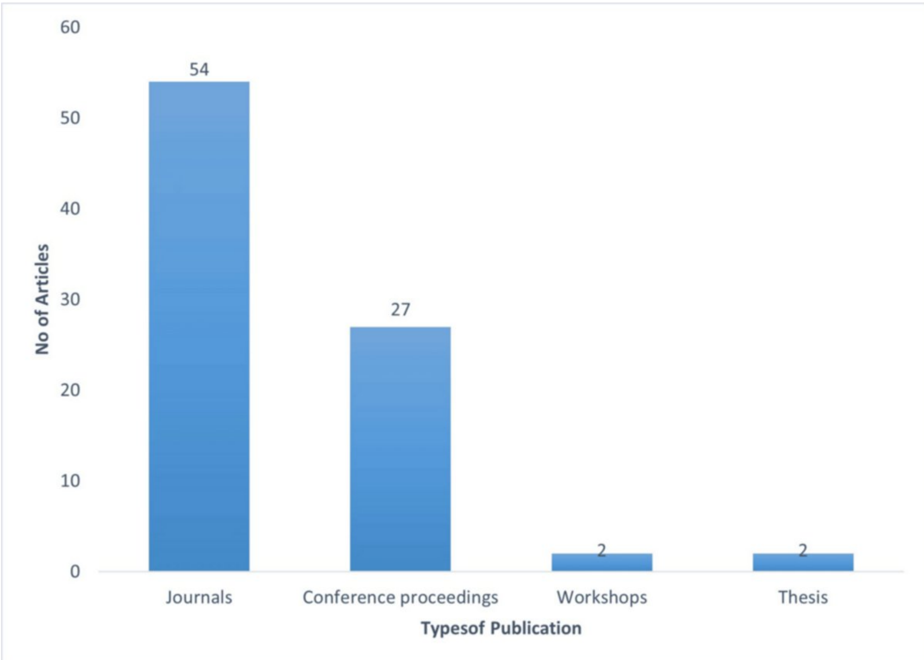



**FIGURE 3: Analysis of Collated Studies.**

*Data Sources*

A comprehensive literature search was conducted across 11 prominent digital databases, including IEEE Xplore, Springer, ACM Digital Library, ScienceDirect/Elsevier, Wiley, MDPI, Sage Journal, SPIE, Stanford University, Taylor & Francis, and Google Scholar. The search spanned articles published between 2017 and 2023, utilising title, abstract, and index term searches to identify relevant journal papers, conference proceedings, and other scholarly outputs. The results are summarised in Figure *3*.

*Methods/Techniques*

The methods or techniques utilised in the chosen papers are categorised in this section. Figure *4* illustrates the general architecture of MGC techniques, comprising two primary components: feature extraction and classification model [13].

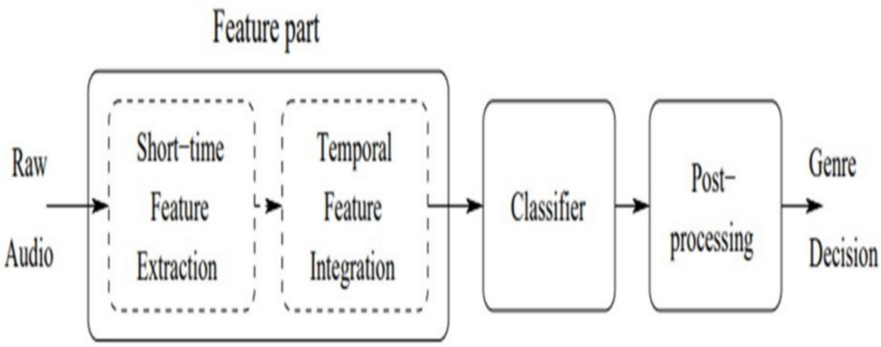



**FIGURE 4: Illustration of the Music Genre Classification Techniques.**

Source: [13]

Feature extraction: Feature extraction entails representing an audio clip as a compact numerical vector, involving the selection of dominant features from the dataset and the elimination of irrelevant elements. This process facilitates dimensionality reduction, accelerates processing, and enhances predictive accuracy [14]. It is particularly advantageous when preserving original feature units and meaning is essential for modelling objectives [15]. It is key when dealing with categorical data, and numerical transformations will not work. It simplifies large datasets like music data, reducing computational intricacy and speeding up processing. It is initially important to extract features from musical recordings that can be used as precepts when training a computer classifier. Simply feeding the recording to a classifier would result in a surplus of data, making the categorisation extremely slow and maybe impossible. By removing characteristics from recordings and giving them to classifiers, one can optimise data efficiency while emphasising parts of the recordings that, in theory, will be important for category categorisation. Unfortunately, selecting which features to employ is a challenging issue. Even while there has been a lot of effort put into analysing and defining specific forms of music, there has not been as much done on drawing features from music. The Canto Metrics Project [16], led by Alan Lomax and his associates, undertook a rigorous comparative analysis of thousands of songs from hundreds of cultural groups, employing 37 evaluative criteria. These attributes offer a solid foundation to build a library of high-level features. Although some other attempts to identify feature categories have been made, they tend to be extremely general. The "Checklist of Parameters" by Philip Tag from 1982 is still helpful as a general reference.

To recognise the distinctions between any given arbitrary pair of genres drawn from the vast superset of genres in general, a wide set of features must be developed. The usage of a hierarchical taxonomy allows for the performance of many classifications on various sub-trees of the hierarchy, each using specialised features, even though it is impractical from a classification standpoint to deploy all these features within a single classification operation. In other words, one may first create a broad classification using a specific collection of data and then create finer classifications using alternative sets of features. Music classification thus far has utilised features spanning several musical facets: timbre, pitch, harmony, and rhythm.

Music features are often grouped by musical aspect (e.g., pitch, rhythm), abstraction level (low to high), and localisation degree (short-term or long-term). The standard taxonomies are employed hierarchically in the categorisation of audio aspects provided by Fu et al. [17]. Research in symbolic music classification commonly employs a tripartite taxonomy, categorising music descriptors into pitch, timbre, and rhythm [18]. Figure *5* illustrates this classification. To enhance classification accuracy, various techniques are employed to select a relevant subset of features, a process commonly referred to as pre-processing [17].

Feature selection algorithms: The literature on feature selection algorithms delineates two fundamental paradigms: filter-based and wrapper-based approaches, each with distinct characteristics [14].

1. Filter-based algorithms: Filter-based algorithms employ a feature ranking strategy, assessing the utility of each feature for classification based on its information content. The ranking is computed using objective functions such as information gain and correlation, and the top N features are selected to form an optimal feature subset.

2. Wrapper-based algorithms: Wrapper-based feature selection embeds a classifier within an optimisation loop [19], assessing feature subset effectiveness through iterative perturbations. Due to the combinatorial explosion of possible feature sets, heuristic search strategies are employed to mitigate computational complexity.

| Feature Level | Symbolic based | | |
|---|---|---|---|
| High Level Features | **Pitch**<br>- pitch/pitch class histogram<br>- sequence of pitch/pitch class<br>- sequence of melodic intervals<br>- absolute/relative pitch contour<br>- melodic intervals histograms<br>- pitch extension/range<br>- number of pitch contour changes<br>- dominant pitch/pitch class prevalence<br>- pitch volume<br>- pitch class variety<br>- pitch bend fraction<br>- number/ proportion of specific intervals (e.g., major seconds)<br>- dominant melodic interval<br>- quantity of ascending or descending intervals<br>- number of notes<br><br>**Statistical functionals**<br>- descriptors from the top of pitch or pitch class histograms<br>- minimum, maximum, standard deviation and average pitch<br>- minimum, maximum, standard deviation and average of melodic intervals<br>- statistical features of repeated patterns<br>- minimum, maximum, and average of pitch volume | | |
| | **Rhythm**<br>- duration histogram<br>- sequence of Inter-Onset Interval (IOI)<br>- sequence of duration ratio or Inter Onset Interval Ratio (IOIR)<br>- sequence of tempo/meter changes<br>- sequence of time ratios<br>- sequence of duration contour<br>- time attacks<br>- duration range<br>- number of meter/tempo changes<br>- number of duration contour changes<br>- dominant time ratio, tempo, IOIR<br>- number of syncopations<br>- duty factor<br>- number of distinct IOI<br>- number of distinct note durations<br>**Statistical functionals**<br>- average time between attacks<br>- average, minimum, maximum and standard deviation of rests<br>- average, minimum, maximum and standard deviation of duration<br>- average metronome time | **Timbre**<br>- instrument patches<br>- instrument classes<br>- percussion sets<br>- prevalent instrument<br>- histogram of used instruments<br>- number of used instruments<br>- fraction of notes from unpitched instruments<br>- fraction of notes from pitched instruments<br>**Harmony**<br>- chord names/degree progression<br>- used tonal scales<br>- number of non-diatonic/diatonic notes<br>- number of accidental notes<br>- key changes<br>- number of distinct harmonic intervals<br>- dominant harmonic interval<br>- harmonic interval histogram<br>- chord dictionary/histogram<br>**Statistical functionals**<br>- average/standard deviation of accidental notes<br>- minimum, maximum, average and standard deviation of harmonic intervals | |
| | **Audio-based** | | |
| Mid-Level Features | **Rhythm Pitch Harmony**<br>- Beat histogram (BH)<br>- Beat-per-minute (BPM) | **Pitch**<br>- Pitch histogram (PH)<br>- Pitch class profile (PCP)<br>- Harmonic pitch class profile (HPCP) | **Harmony**<br>- Chord sequences (CS)<br>- Chord histogram (CH) |
| Low-Level Features | **Timbre**<br>- Mel-frequency cepstral coefficient (MFCC)<br>- Zero crossing rate (ZRC)<br>- Daubechies wavelet coefficient histogram (DWCH)<br>- Spectral rolloff (SR)<br>- Spectral centroid (SC) | **Temporal**<br>- Statistical moments (SM)<br>- Auto-regressive modeling (ARM)<br>- Frequency modulation (FM)<br>- Amplitude modulation (AM) | |

**FIGURE 5: Taxonomic Structure for Music Features: Audio and Symbolic Representations.**

Classification methods: A thorough examination of the literature revealed a dichotomy in MGC methodologies, with Machine Learning and Deep Learning techniques representing the two predominant paradigms, alongside hybrid models synthesising elements of both.

1. Machine learning techniques: Machine learning approaches employ learning paradigms and empirical validation to generate classification models, offering transparency into decision-making processes. Specifically, this study examines supervised and semi-supervised learning methodologies [20-23].

2. Deep learning techniques: The ascendancy of deep learning in scientific computing has been propelled by its capacity to tackle complex problems using artificial neural networks. By emulating the human brain's architecture and functionality, deep learning algorithms facilitate sophisticated data analysis [24].

Research in MIR has demonstrated that deep learning methods excel in genre classification tasks [25], surpassing machine learning techniques in accuracy and effectiveness, with ensemble methods further boosting classifier performance [26].

*Approaches*

Musical data can be represented in two primary approaches: symbolic representations (e.g., MIDI, piano rolls, scores) and audio recordings. These representations serve distinct purposes within the artificial intelligence community, with symbolic representations being predominantly used for algorithmic music composition [27,28]. Music classification tasks, including genre recognition [29,30] and mood classification [31,32], are commonly addressed in the audio domain. The analysis of 84 selected papers reveals that researchers employed two primary approaches: symbolic content representation and audio recording-based methods, with some studies leveraging hybrid approaches combining features from both.

*Study Status*

Based on the deployed status of the selected papers, five groups were created. The information outlined in Table *2* is utilised to determine the status of each paper included in the selection.

| S/N | Status | Description |
|---|---|---|
| 1 | Evaluated (E) | Pertains to studies that conducted comparative evaluations of existing algorithms using dataset assessments. |
| 2 | Implemented (I) | Pertains to studies that developed prototype systems by integrating existing algorithms. |
| 3 | Proposed (P) | Pertains to research introducing novel techniques or procedures without accompanying performance assessments. |
| 4 | Proposed and Evaluated (PE) | Pertains to research introducing novel methods/techniques, accompanied by systematic evaluations using established algorithms. |
| 5 | Proposed and Implemented (PI) | Pertains to research introducing novel methods, implemented using custom algorithms, and evaluated through expert feedback or appraisal. |

**TABLE 2: Existing Studies: Description and Status.**

*Dataset*

This subsection presents a quantitative examination of the publicly available datasets utilised in the 84 selected papers. Music genre datasets play a vital role in the development and evaluation of music classification systems and algorithms despite variations in genre and track numbers [14,33-35]. Hence, novel datasets were developed for those cultural music genres; some were made available for public use, and others remained private. A significant proportion of the music genre datasets employed in the selected papers relied on 31 publicly accessible datasets, as presented in Table *3*.

| S/N | Dataset | Description | Available Online |
| --- | --- | --- | --- |
| 1 | GTZAN | 10 genres; 100 tracks | https://www.kaggle.com/datasets/andradaolteanu/gtzan-dataset-music-genre-classification |
| 2 | Ballroom | 8 genres; 698 tracks | https://paperswithcode.com/dataset/ballroom |
| 3 | ORIN Dataset | 4 genres; 208 tracks | https://easy.dans.knaw.nl/ui/datasets/id/easy-dataset |
| 4 | Indian Folk Music | 15 genres; 606 tracks | enodo.org/record/6584021 |
| 5 | Extended Ball room | 13 genres; 4,180 tracks | https://hal.science/hal-01374567 |
| 6 | Tempo MTG | 1,159 tracks | http://mtg.upf.edu/node/3767 |
| 7 | Tempo LMD | 8 genres; 3,611 tracks | https://www.researchgate.net/figure/Genre-distribution-in-LMD-Tempo |
| 8 | ACM | 1,410 tracks | http://www.marsyas.info/tempo |
| 9 | ISMIR04 | 6 genres; 729 excerpts | https://paperswithcode.com/dataset/ismir-genre# |
| 10 | Hainsworth | 245 excerpts | http://www.marsyas.info/tempo/ |
| 11 | SMC Mirex | 217 excerpts | http://smc.inescporto.pt/research/data-2/ |
| 12 | Giantsteps | 664 files | https://github.com/GiantSteps/giantsteps-tempo-dataset |
| 13 | Million Song | A million tracks | http://millionsongdataset.com/#: |
| 14 | SLAC | 10 genres; 250 pieces | https://zenodo.org/record/4571050#.ZCjWStDMJPZ |
| 15 | Codaich | 55 genres; 26,420 songs | https://jmir.sourceforge.net/Codaich.html |
| 16 | Bodhidharma | 38 genres; 950 tracks | https://jmir.sourceforge.net/Bodhidharma.html |
| 17 | Cal10k | 153 genres; 10,870 tracks | https://paperswithcode.com/dataset/cal10k |
| 18 | Brazilian Music | 14 genres; 138,368 tracks | https://jcis.sbrt.org.br/jcis/article/view/515 |
| 19 | Lakh midi | 176,581 tracks | https://colinraffel.com/projects/lmd/ |
| 20 | Free Music Archive (FMA) | 161 genres; 106,574 tracks | https://paperswithcode.com/dataset/fma |
| 21 | Audioset | 2,084,320 tracks | https://research.google.com/audioset/index.html |
| 22 | Homburg | 9 genres; 1,886 tracks | https://github.com/fadymedhat/Homburg-for-MCLNN |
| 23 | Latin Music dataset | 10 genres; 3,160 songs | https://sites.google.com/site/carlossillajr/resources/the-latin-music-database-lmd |
| 24 | Carnatic | 176 pieces | https://www.britannica.com/art/Karnatak-music |
| 25 | Magna TagATune | 25,863 music clips; 147,295 songs | https://paperswithcode.com/dataset/magnatagatun |
| 26 | MuMu | 100 selected videos | https://www.upf.edu/web/mtg/mumu |
| 27 | Music Video dataset | 228,159 songs; 16 genres | http://www.ifs.tuwien.ac.at/mir/mvd/ |
| 28 | Spotify music dataset | 50,000 sound recordings | https://www.kaggle.com/datasets/mrmorj/dataset-of-songs-in-spotify |
| 29 | RMCA | 500 tracks; 5 genres | https://music.africamuseum.be/english/index.html |
| 30 | PMG-Net | 100 tracks | https://ir.linkedin.com/posts/nacer-farajzadeh-in_pmg-net-persian-music-genre-classification |
| 31 | DANGDUT music dataset | 100 tracks | https://www.linkedin.com/pulse/visualizing-spotify-dataset-indonesias-musical-taste-seaborn-renaldi/ |

**TABLE 3: Description of Existing Music Dataset.**

*Place of Publication*

Several research studies have been published on MGC; however, some continents are still lagging with respect to the 84 articles used for this research. An analysis of the countries with publications on MGC, based on the 84 selected articles, shows that 27 countries are represented, as displayed in Table 4.

| S/N | Country |
|---|---|
| 1 | United Kingdom |
| 2 | Nigeria |
| 3 | India |
| 4 | Brazil |
| 5 | China |
| 6 | Indonesia |
| 7 | Turkey |
| 8 | Italy |
| 9 | Slovak Republic |
| 10 | Taiwan |
| 11 | Spain |
| 12 | Sweden |
| 13 | USA |
| 14 | Iran |
| 15 | South Africa |
| 16 | United Kingdom |
| 17 | Canada |
| 18 | Korea |
| 19 | Australia |
| 20 | Finland |
| 21 | Sri Lanka |
| 22 | Denmark |
| 23 | South Korea |
| 24 | Greece |
| 25 | France |
| 26 | Japan |
| 27 | Bangladesh |

**TABLE 4: Countries With Music Genre Classification Publication in the Selected Articles.**

## Results

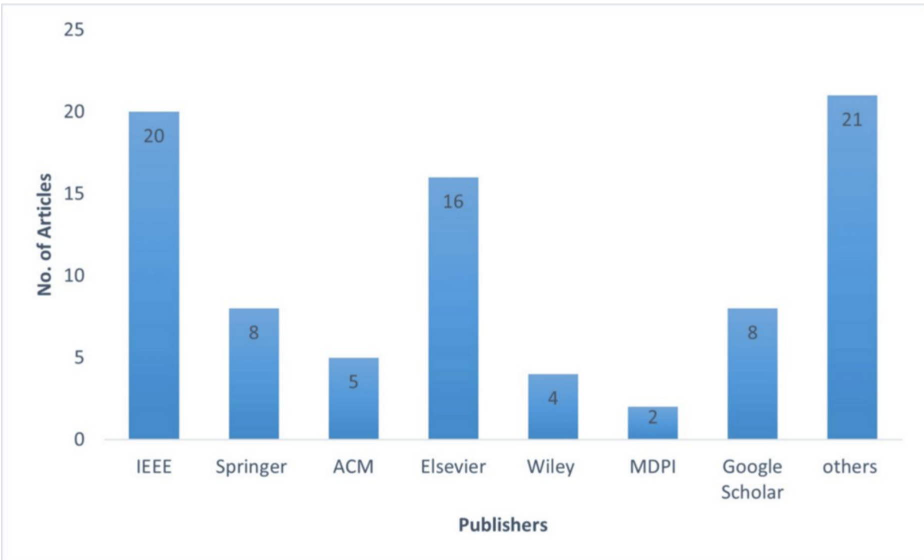
This section elucidates the study's findings, derived from a comprehensive analysis of six search strategies. The discussion is organised around the research questions, with succinct interpretations presented in dedicated subsections. A word cloud analysis revealed a prominent clustering of terms, including 'Genre', 'Music' and 'Classification', as depicted in Figure 6.


## FIGURE 6: A Word Cloud Illustrating the Thematic Emphasis of Reviewed Articles, Based on Title Keywords.

*Search Technique 1: Data Sources*

An initial literature search was conducted utilising a hierarchical search methodology to identify relevant publications related to MGC, leveraging paper titles and keywords. To address RQ1, a systematic literature search (2017-2023) was performed across leading databases: IEEE, Springer, ACM, Elsevier, Wiley, MDPI, Google Scholar, and others. Figures 7-9 present the findings.

As depicted in Figure 7, the top publishers of relevant articles were IEEE (20), Elsevier (16), Springer and Google Scholar (8 each), ACM (5), Wiley (4), MDPI (2), and others (21). Figure 8 illustrates the proportional distribution of relevant papers among the 84 collated publications, with IEEE accounting for the largest share (24%), followed by Elsevier (19%), Google Scholar and Springer (9.8% each), ACM (6%), Wiley (5%), MDPI (2%), and other publishers (25%).




## FIGURE 7: Number of Papers per Publication.

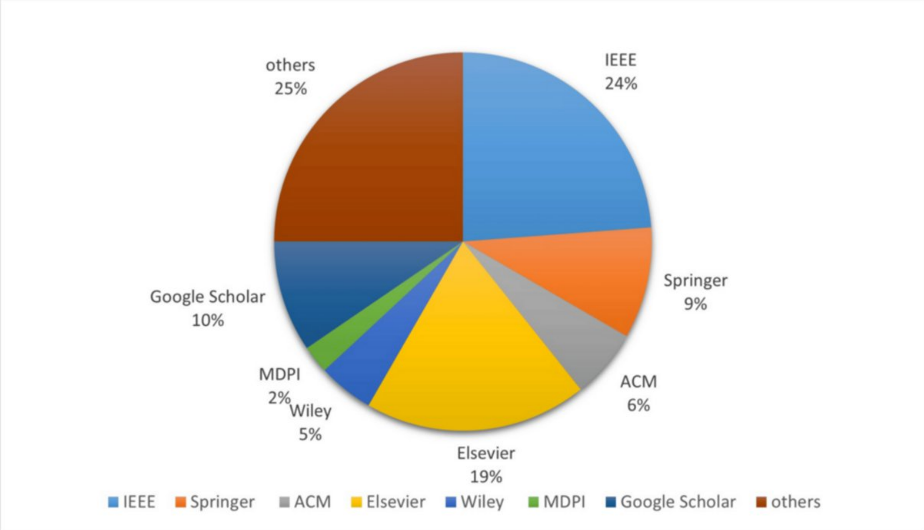



**FIGURE 8: Percentage of Papers per Publication.**

Figure 9 illustrates the annual distribution of relevant publications over the past seven years, with 2021 exhibiting the highest frequency (18 publications), whereas 2019 and 2023 recorded the lowest (7 publications each). Research is still ongoing in the area of classifications of music genres as new techniques are still emerging.

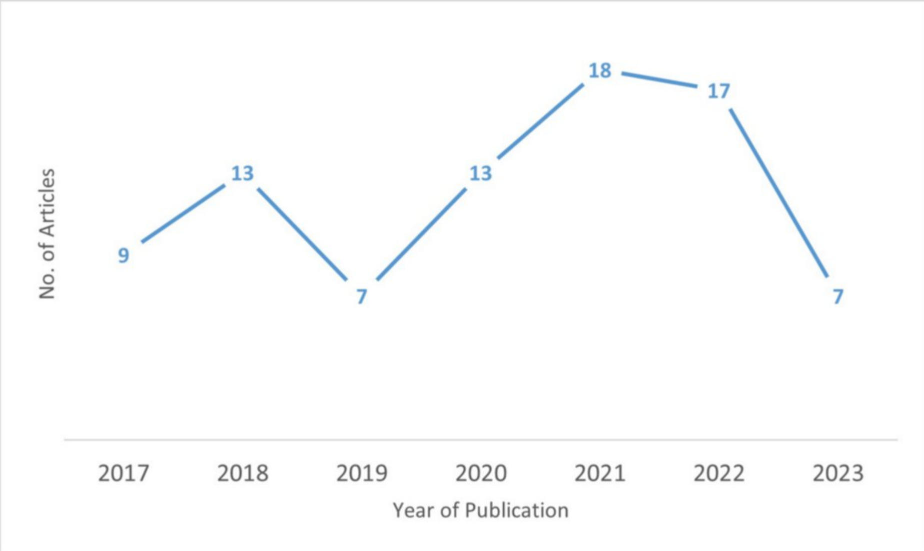



**FIGURE 9: Average Relevant Publication Rate per Annum (2017-2023).**

*Search Technique 2: Methods/Techniques*

This section's findings are categorised into two groups: classification algorithms and feature selection methods.

(1) MGC techniques can be categorised into three primary approaches: machine learning algorithms, deep learning algorithms, and hybrid methods. Both supervised and unsupervised machine learning algorithms have been employed to enhance MGC performance, as demonstrated in Figure 10. This subsection addresses RQ2, presenting an analysis of methods used in selected studies. Results indicate that 51% employed deep learning, 36% utilised machine learning, and 13% adopted hybrid approaches, with convolutional neural networks (CNNs) being the most frequently cited algorithm (Figure 11). Convolutional recurrent neural networks demonstrate superior performance in audio analysis tasks by effectively integrating spatial feature extraction and temporal sequence modelling, making them particularly well-suited for applications involving time-frequency representations such as spectrograms.

CNNs, while lacking explicit temporal modelling capabilities, exhibit strong performance in capturing local patterns within spectrogram-based inputs. Long short-term memory networks are proficient at modelling long-range temporal dependencies and are therefore highly effective for sequential audio processing tasks, including speech and emotion recognition. In contrast, traditional machine learning models such as XGBoost and Random Forest continue to serve as robust baselines when applied to tabular data or pre-extracted audio features (e.g., Mel-frequency cepstral coefficients, Chroma features), particularly in settings where data availability is limited or model interpretability is prioritised.

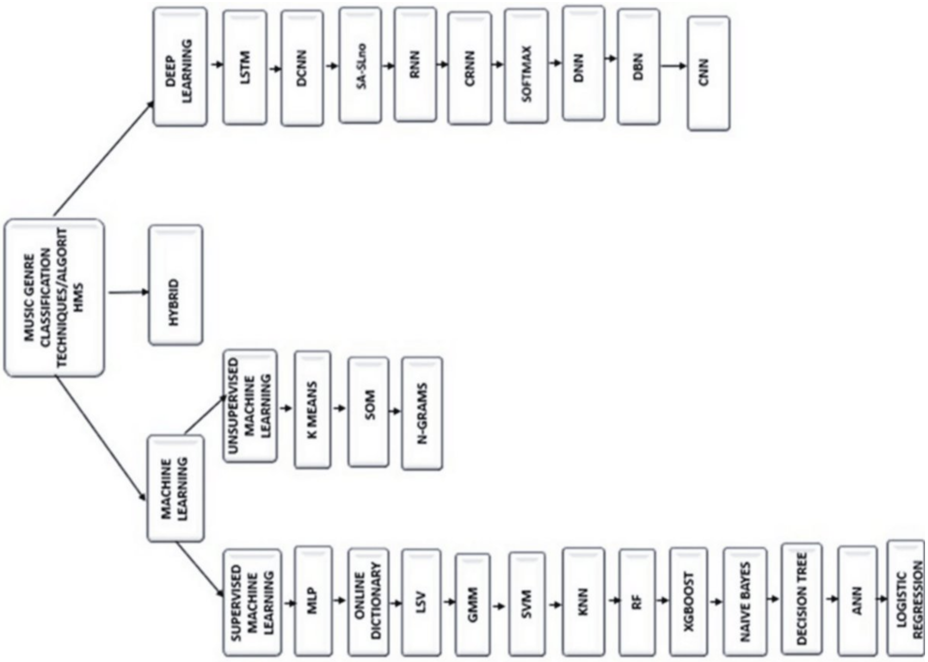



**FIGURE 10: Classification Techniques of the Selected Articles.**

LSTM, Long Short-Term Memory; DCNN, Deep Convolutional Neural Network; DBN, Deep Belief Network; CRNN, Convolutional Recurrent Neural Network; CNN, Convolutional Neural Network; DNN, Deep Neural Network; RNN, Recurrent Neural Network; SA-Sino, Self-Attention Sino; SOM, Self-Organizing Map; ANN, Artificial Neural Network; GMM, Gaussian Mixture Model; LSV, Least Squares Vector; RF, Random Forest; MLP, Multilayer Perceptron; SVM, Support Vector Machine; KNN, K-Nearest Neighbour

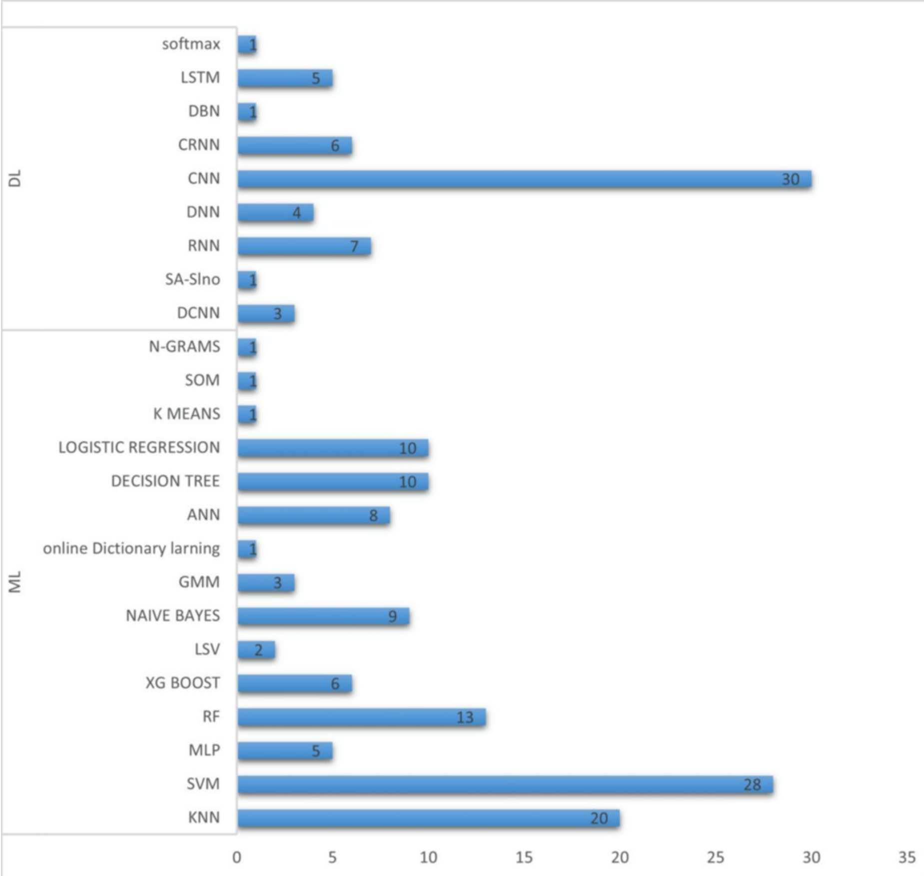



**FIGURE 11: Frequency of Classification Techniques Used in Selected Article.**

LSTM, Long Short-Term Memory; DBN, Deep Belief Network; CRNN, Convolutional Recurrent Neural Network; CNN, Convolutional Neural Network; DNN, Deep Neural Network; RNN, Recurrent Neural Network; SA-Sino, Self-Attention Sino; SOM, Self-Organizing Map; ANN, Artificial Neural Network; GMM, Gaussian Mixture Model; LSV, Least Squares Vector; RF, Random Forest; MLP, Multilayer Perceptron; SVM, Support Vector Machine; KNN, K-Nearest Neighbour

(2) This subsection presents a comprehensive analysis of feature selection techniques employed in 84 reviewed articles, revealing a total of 60 feature selection methods were identified. Figure *12* summarises the 16 most frequently used techniques, with MFCCs being the most cited (25 articles), followed by Zero-Crossing Rate (18 articles) and Spectral Centroid and Spectral Roll-off (16 articles each).

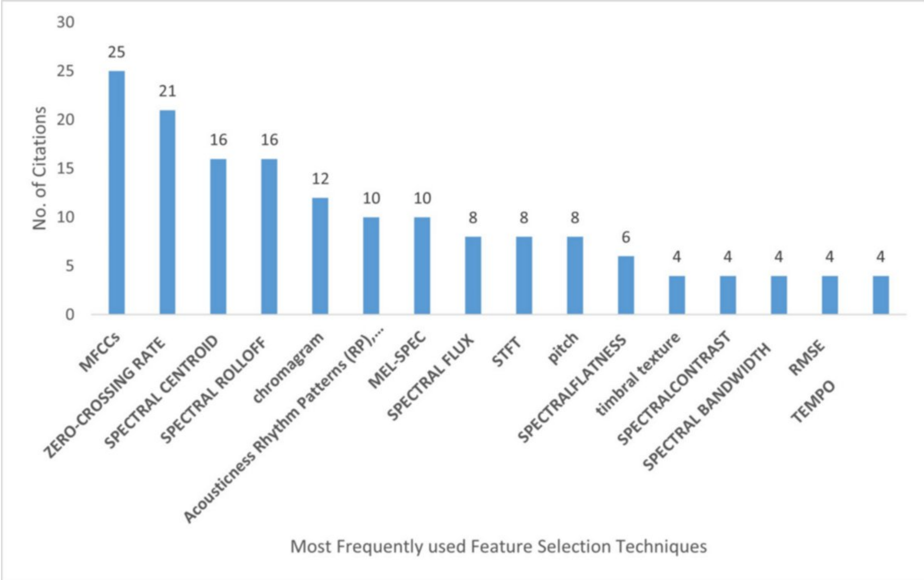



**FIGURE 12: Feature Extraction Techniques/Methods Utilised.**

Table *5* presents the mathematical formulations for select feature selection methods frequently employed in the literature [17,36].

| S/N | Commonly Used Feature Extraction Methods | Mathematical Expression |
| --- | --- | --- |
| 1 | Mel-Frequency Cepstral Coefficient | $f_{\text{mel}} = 2595 \log_{10}\left(1 + \frac{f}{700}\right)$ (Fu et al., 2011), where $f_{\text{mel}}$ is the Mel-frequency value (in mel), f is the frequency value (in Hz), log10 is Base-10 logarithm function. The inversion from mel scale to cent can be calculated as $f_{\text{cent}} = 700\left(\exp\left(\frac{m}{2595}\right) - 1\right)$, where $f_{\text{cent}}$ : Frequency value (in cents), m: Mel-frequency value (in mel), exp: Exponential function, 1125: A constant value used in the conversion formula. |
| 2 | Spectral Roll-off | $\sum_{n=1}^{R_t} S_t[n] = 0.85 \sum_{n=1}^{M} S_t[n]$, where n is the index variable, representing the n-th element in the sequence. $R_t$ is the right boundary of the summation, representing the total number of elements in the first summation. $S_t[n]$ is the signal value at index n, representing the n-th element in the signal sequence $S_t$ . 0.85 is a scaling factor or threshold used for comparison. M is the upper boundary in the second summation, representing the total number of elements considered in the full signal sequence. |
| 3 | Time Domain Zero Crossings rate | Here is the corrected explanation and the corresponding LaTeX representation of the formula: $DZC_t = \frac{1}{2}\sum_{n=1}^{M} \text{sign}(x[n] \cdot x[n-1])$, where $DZC_t$ : Zero-crossing rate (ZCR) at time t, a feature extracted from the signal that indicates the rate at which the signal changes sign. $\frac{1}{2}$: A scaling factor used to normalize the zero-crossing count. $\sum$ : Summation symbol, indicating that values are accumulated over a range. n: Index variable representing the n-th element in the signal sequence. M: Total number of samples or elements in the signal. x[n]: Signal value at index n. x[n-1]: Signal value at the previous index. $\text{sign}[\cdot]$ : The signum function, which returns: 1 if the input is positive, -1 if the input is negative, 0 if the input is zero. |
| 4 | Flux | $F_j = \sqrt{\sum_{i=1}^{M-1} \left(X_j(i) - X_{j-1}(i)\right)^2}$, where $F_j$ : Spectral flux (SF) at frame j, a measure of the amount of spectral change between consecutive frames. M: Total number of frequency bins or spectral components in the signal. i: Index variable representing the i-th frequency bin. $X_j(i)$ : Spectral magnitude of the ii-th frequency bin at frame j. $X_{j-1}(i)$ : Spectral magnitude of the same frequency bin at the previous frame (j−1). $\left(X_j(i) - X_{j-1}(i)\right)^2$ : Squared difference to emphasize spectral change. $\sum$ : Summation over all frequency bins to compute the total flux. Optionally, $\sqrt{\cdot}$ : Square root function, sometimes used to normalize or compute Euclidean distance-like spectral change. |

**TABLE 5: The Mathematical Underpinnings of Feature Extraction Methods.**

To further elucidate the study's findings, an analysis of various performance metrics was conducted on the selected articles, with the results presented in Figure *13*. This answers RQ3: What are common performance metrics that can be used to evaluate Music genre Classifier techniques? About 26 performance metrics were identified in the selected articles. The accuracy rate took the lead with 40 articles, followed by the confusion metric with 23, precision comes behind accuracy with 13 citations, followed by recall and N-fold cross-validation with 11 citations, respectively. To improve the real-world relevance of performance metrics in MGC, it is important to go beyond standard measures like accuracy and F1-score. Many songs belong to multiple genres, yet most MGC models assume a single-label structure. Adopting multi-label metrics such as Hamming loss, subset accuracy, and macro-averaged F1 better reflects genre blending in modern music. Additionally, incorporating confidence scores or probabilistic genre rankings enables systems to express uncertainty, which is crucial for applications like recommendation, where ambiguity can guide fallback strategies. Finally, genre distance-aware evaluation can differentiate between minor and severe misclassifications, offering a more nuanced assessment aligned with human perception.

*Search Technique 3: Approaches*

Previous research has categorised MGC approaches into two primary categories: symbolic content representation and audio recording-based methods. Notably, some studies have employed hybrid approaches, integrating features from both symbolic and audio-based representations. This study examined 84 existing music genre literature and found that the majority (87%, 73 articles) relied on audio-recorded approaches, while 8% (7 articles) used symbolic content representation and 5% (4 articles) employed hybrid approaches, as depicted in Figure 14.

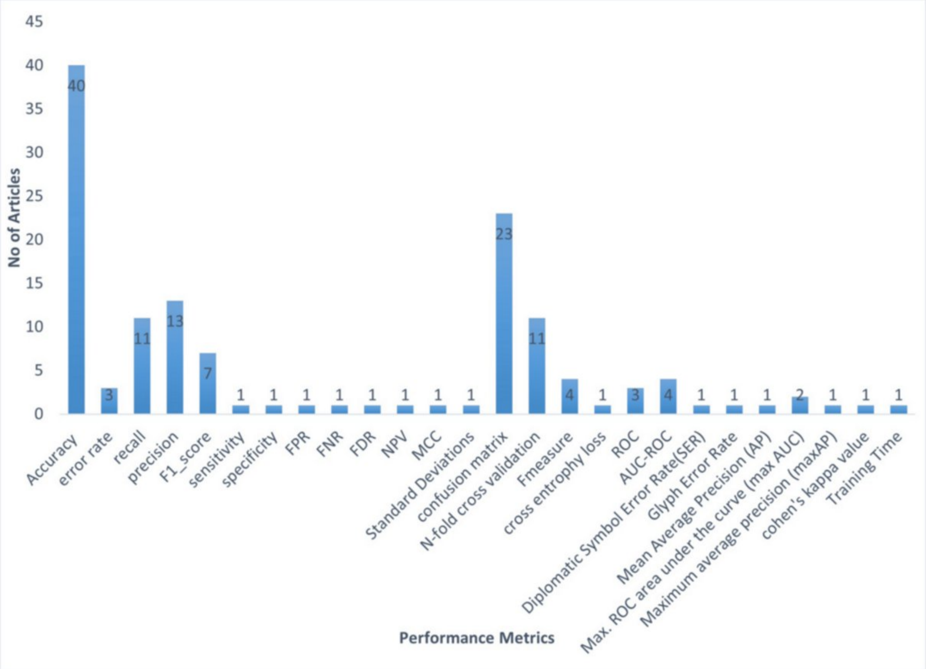



**FIGURE 13: Performance Metrics of the Selected Articles.**

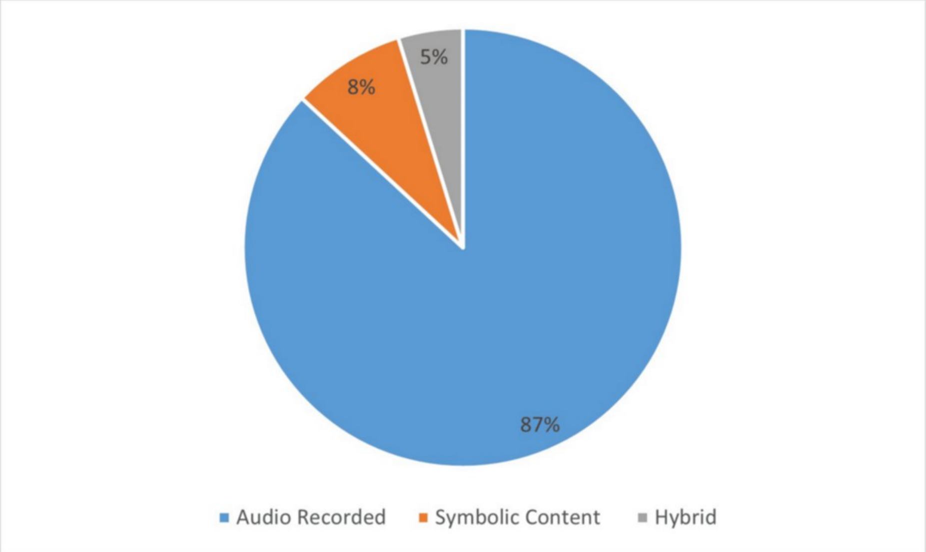



**FIGURE 14: Studies by Approach: Percentage Breakdown.**

*Search Technique 4: Study Status*

Figure 15 presents the outcomes of a categorical analysis of selected MGC publications, examining their status across five predefined categories. The analysis of 84 articles yields a classification status breakdown: 52% evaluation, 12% implementation, 6% proposal, 25% proposal and evaluation, and 5% proposal and implementation. Therefore, the status analysis reveals that the majority of existing MGC research is focused on evaluating existing algorithms.

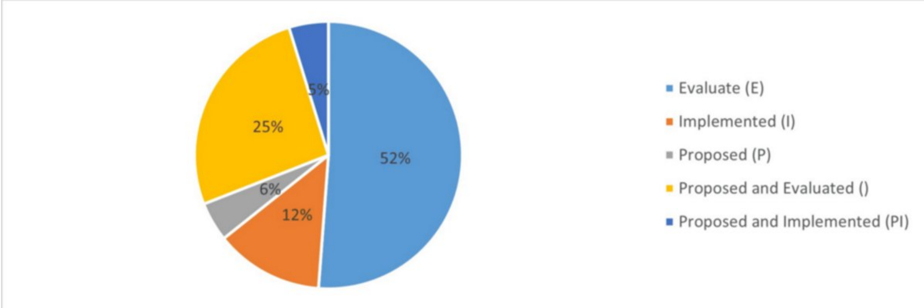



**FIGURE 15: Status of Selected Articles in Music Genre Classification.**

*Search Technique 5: Dataset*

This study's analysis is grounded in the 31 most widely utilised music genre datasets, identified from the 84 selected papers. Additionally, some authors collected proprietary datasets for MGC, while others employed random genre selections, which were not publicly available. Figure *16* presents the dataset usage distribution across the 84 selected studies. Notably, GTZAN was employed 48 times, followed by ISMIR04 (8), FMA 5 (5), LMD, MSD, and BALLROOM (4 each), and extended BALLROOM (3), with the remaining datasets used once or twice. It is important to note that GTZAN has known flaws, which include duplicated songs, mislabelling, and a lack of diversity, which more recent studies are trying to overcome using more robust datasets or by building custom ones.

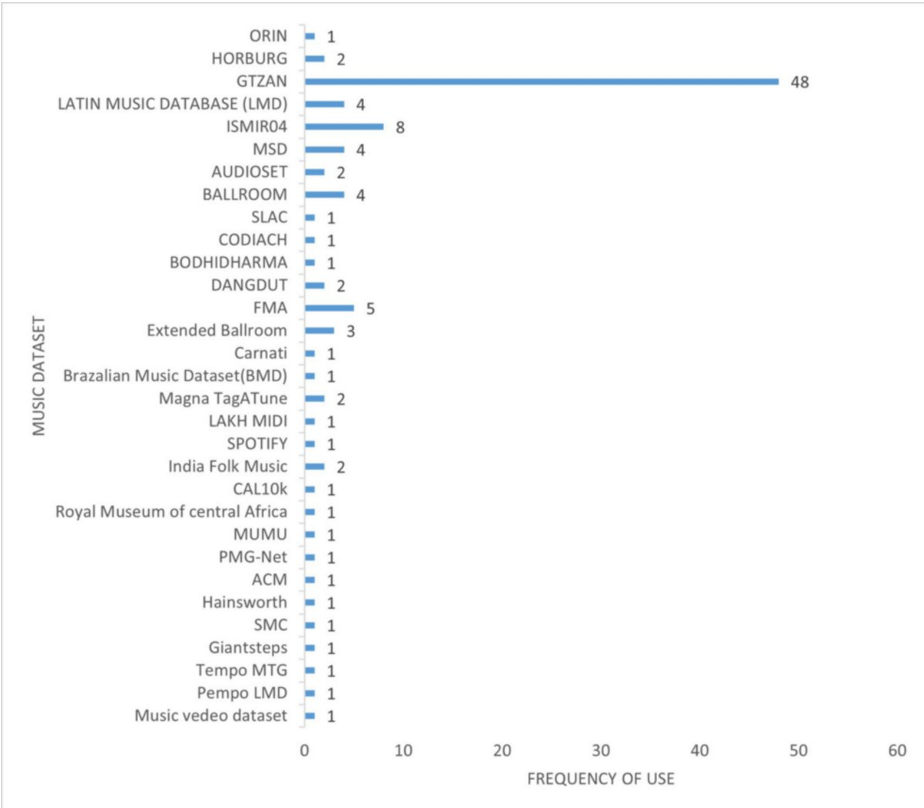



**FIGURE 16: Number of Selected Publications Using Identified Datasets.**

This section addresses RQ4, investigating the availability of public standard datasets for MGC. Figure *16* reveals that over 31 datasets meet this criterion.

*Search Technique 6: Place of Publication*

Substantial research has been conducted in the field of MGC. An analysis of the 84 selected research articles identified publications from 27 different countries, as illustrated in Figure *17*. This section specifically addresses RQ5: "Are there researchers who publish work on MGC in Africa?" According to the reviewed articles, Africa has indeed contributed to MGC research; however, only two African countries, Nigeria and South Africa, have published in this area, with two publications each, as highlighted in Figure *18*. India leads globally with 25 publications, followed by China with 14 publications.

All the countries that have publications according to the 84 selected articles are displayed in Figure *17*. African music possesses several unique characteristics that can be strategically leveraged to improve the accuracy of MGC. These features extend beyond conventional rhythm and melody and offer culturally rich, discriminative cues for modelling. Notably, African genres often incorporate indigenous instrumentation and timbres, such as talking drums, shekeres, balafons, and agogôs, which produce distinct acoustic signatures. Additionally, complex rhythmic structures, particularly polyrhythms, layered, simultaneous rhythmic patterns are a defining feature of many African musical traditions and are less prevalent in Western genres. Another key element is the common use of call-and-response patterns, either vocally or instrumentally, which provide a structured yet dynamic interaction within compositions. Explicitly modelling these features can significantly enhance genre differentiation and classification performance in African music datasets.

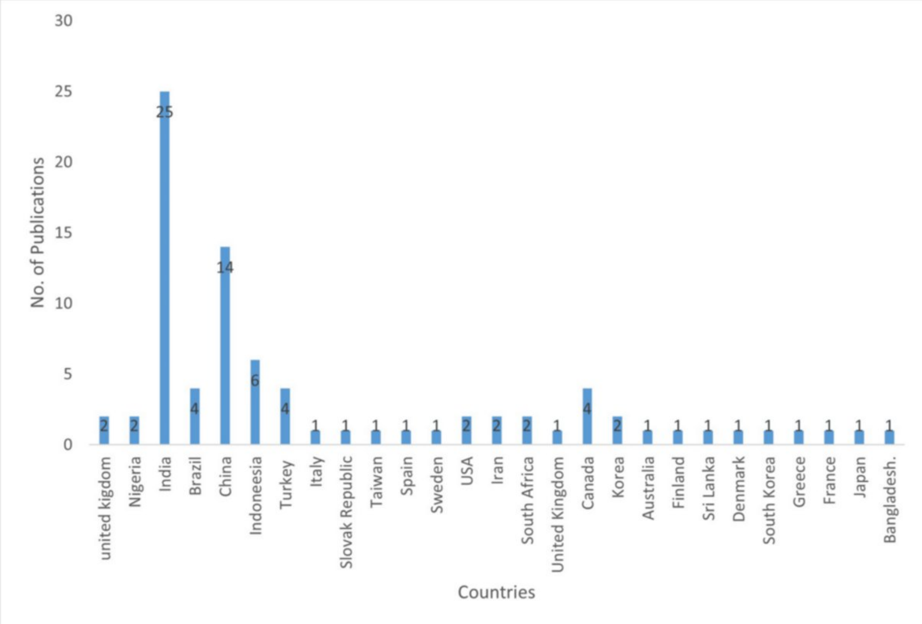



**FIGURE 17: Number of Music Genre Classification Publications per Country.**

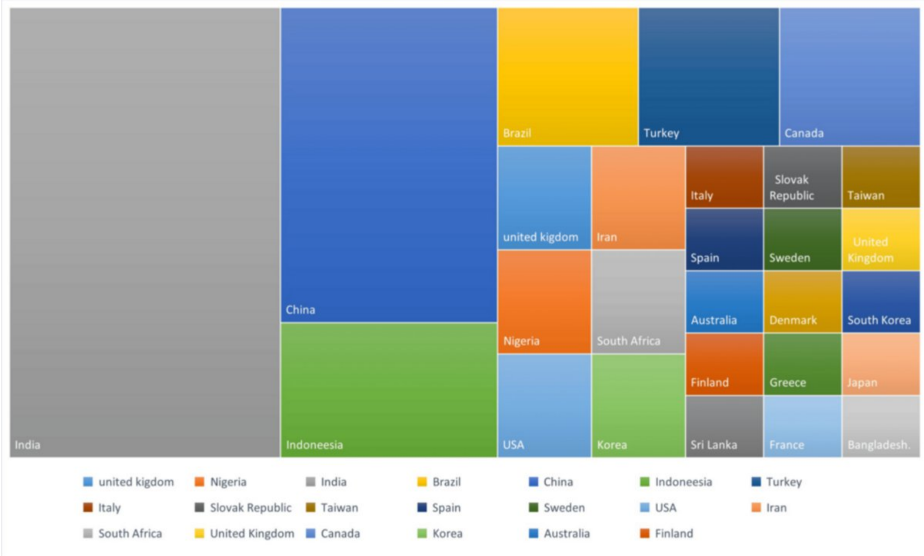



**FIGURE 18: Countries That Publish Articles in Music Genre Classification.**

*Comparison With Other Surveys and Threat to the Validity*

Several previous studies explored MGC using a range of methodologies and datasets, each contributing uniquely to the field. For instance, Silva et al. [36] proposed a music classification model designed to minimise intra-cluster distances and maximise inter-genre separation margins, with future plans to incorporate real-time user preferences via online learning algorithms.

To effectively integrate user preferences into real-time MGC systems, the system must continuously learn from user interactions and adapt dynamically. User actions such as playing, skipping, replaying, or adding songs to playlists provide valuable implicit feedback that can be used to infer evolving musical tastes. Beyond static genre classification, the system should also account for contextual listening patterns, such as time of day, location, or mood, to deliver more personalised predictions. This real-time adaptability ensures that the MGC system aligns not only with users' genre preferences but also with their situational listening behaviours.

Shkil et al. [37] introduced a practical MGC framework, leveraging FM band transmissions, featuring FPGA-optimised feature extraction followed by classification. Future efforts aim to develop a standalone FPGA-based platform integrating multichannel audio indexing and FM reception capabilities [38].

A separate study employs time-frequency representation learning within a CNN framework, demonstrating enhanced performance relative to traditional classifiers. The research includes comprehensive feature analysis across three music datasets, and future work is directed at applying spectrogram-based data augmentation and exploring broader music classification tasks to mitigate the limitations imposed by deep learning's data requirements [39]. Similarly, a CRNN-based music recommender system has been proposed, utilising feature similarity for personalised recommendations. By capturing both frequency and temporal patterns, the system demonstrates improved performance, particularly when genre information is integrated, underscoring the advantage of modelling diverse musical attributes [40].

Additionally, a hybrid ensemble method that fuses acoustic and visual features has been proposed to enhance classification robustness. The study outlines future directions involving dataset expansion to improve generalisation across genres. In parallel, a newly introduced dataset, ORIN, curated from Nigerian music, supports classification across five genres using models such as k-Nearest Neighbour, Support Vector Machine, XGBoost, and Random Forest. Future work for this dataset includes extending it to Nigerian English contemporary songs and incorporating tasks like artist recognition and mood detection [34].

In contrast to the reviewed studies, this study provides a systematic and comprehensive synthesis of the literature on MGC, offering a broader and more critical analysis of methods, feature engineering techniques, model architectures, and datasets used to date. Furthermore, this review explicitly highlights African contributions, an area underrepresented in most prior surveys. By presenting a novel categorisation of MGC research approaches, this study also offers a structured overview of the field's evolution, helping to identify methodological gaps and underexplored research directions.

Nevertheless, it is important to acknowledge potential threats to validity in this review. These include possible publication bias, language restrictions (e.g., exclusion of non-English studies), and the limitations inherent in database search coverage. While efforts were made to mitigate these risks through comprehensive inclusion criteria and transparent selection processes, some relevant studies may still have been inadvertently omitted. Future updates to this review could address these limitations by incorporating grey literature, expanding language inclusivity, and applying automated tools for broader search and classification.

*Limitations and Vulnerabilities*

This literature review acknowledges inherent limitations, including potential publication bias and the risk of inaccuracies during data extraction. The selection of studies was guided by a structured search process using specific keywords aligned with the research objectives. However, despite these exhaustive efforts, some articles may have been missed due to limitations in search parameters, as not all publications can be retrieved through title, abstract, or keyword searches. To enhance the comprehensiveness of the study, a secondary search was conducted by scrutinising the references of selected papers. Relevant studies were meticulously chosen based on rigorous quality assessment and methodological clarity criteria.

To mitigate the risk of publication bias, this study prioritised papers presenting comparative evaluations of existing techniques. Furthermore, rigorous scrutiny of selected publications was conducted to prevent overestimation of performance claims made by authors.

## Discussion, limitations and taxonomy

*Discussion*

This comprehensive survey highlights the significant research advancements in MGC, providing an in-depth overview of existing studies categorised by their cutting-edge methodologies, techniques, approaches, datasets/corpora, and publication venues. The diversity of music preferences among individuals, coupled with the existence of numerous distinct genres, necessitates effective music categorisation and recommendation systems in digital music platforms and applications. Automating the categorisation of music can make it simple to identify important information like trends, hot genres, and artists. The importance of MGC is multifaceted. This study's reviewed publications demonstrate the widespread adoption of machine learning techniques, while deep learning methods have emerged as a promising approach, leveraging their capacity to process vast amounts of data and extract essential features. While deep learning techniques are being extensively leveraged in domains such as text mining, image processing, and pattern recognition, the potential of Generative Adversarial Networks (GANs) remains relatively underexplored. GANs involve the concurrent training of two neural networks - a generator (G) and a discriminator (D) - with competing objectives, enabling the generation of enhanced output files.

A detailed evaluation of the strengths and weaknesses of MGC approaches is provided in Table *6*, synthesising the findings from the selected publications. In a study by Folorunso et al. [34], various machine learning algorithms were highlighted, including k-Nearest Neighbour, Support Vector Machine, XGBoost, and Random Forest, which have been successfully applied in diverse research domains for prediction, detection, and filtering tasks. Nevertheless, future research should explore the potential of GANs, a deep learning approach leveraging competing neural networks to enhance predictive accuracy [41]. Applying GANs to MGC presents several challenges. One major issue is class imbalance; when certain genres are overrepresented in the training data, GANs tend to generate samples biased toward those dominant classes, which can reduce overall classification performance. GANs may also struggle to capture the full diversity within each genre, often producing limited variations that fail to reflect the nuanced characteristics of real-world music. These limitations can hinder the effectiveness of GAN-based approaches in accurately modelling and classifying complex and diverse musical genres.

Symbolic music data, such as MIDI files, offers structured and noise-free representations of music, but it faces significant scalability challenges in large-scale MGC tasks due to limited availability and the technical complexity involved in creating such data. To address this limitation, a practical approach is to integrate symbolic data with audio-based representations, leveraging the widespread availability of audio recordings. This hybrid strategy enables broader coverage while retaining the structural advantages of symbolic formats. Additionally, rather than relying on full symbolic sequences, extracting high-level features, such as note density, rhythmic complexity, and key signatures, can make symbolic data more scalable and computationally efficient, facilitating its effective use in large-scale MGC systems.

| Areas | Sub-Areas | Strengths | Weaknesses |
|---|---|---|---|
| Approaches | Symbolic Content | Research highlights the paramount importance of pitch and rhythm in achieving exemplary music analysis results. Symbolic music representations offer an unparalleled advantage, affording precise high-level information, comprehensive instrumentation knowledge, and discrete instrument streams. | The symbolic representation paradigm is constrained by two primary limitations: the exclusion of vocal content and instrumentation restrictions. Furthermore, symbolic data lacks scalability. However, this representation enables precise analysis of music features, insulated from audio noise and extraneous properties. |
| | Audio Based | Audio features can capture subtle differences between genres, leading to more accurate classification. | Pitch and rhythm when used alone for audio recorded seem not to provide good enough results. |
| | Hybrid Approach | Combining feature approach improves classification performance. | Hybrid approaches often require more computational resources, which can be a limitation. |
| Feature Extraction | Filter-Based Algorithm | Computationally cheaper. Fast running time. Lower risk of overfitting. Ability of good generalisation. Easily scale to high dimensional dataset. | No interaction with classification model for feature selection. Mostly ignores feature dependency and consider each feature each feature separately in case of univariant techniques which may lead to low computational performance. |
| | Wrapper-Based Algorithm | Interacts with the classifier for feature selection. More comprehensive search of feature set space. Considers feature dependencies. Better generalization than filter approach. | High computational cost. Longer running time. High risk of overfitting. More computational unfeasible with increased number of features. No guarantee of optimality of the solution of prediction. |
| Methods/Techniques | Machine Learning | This approach facilitates the automatic identification of trends and patterns, eliminating the need for human intervention. Additionally, it enables continuous improvement and effectively handles complex, multi-dimensional, and multi-variety data, making it applicable across various domains. | Data acquisition presents several drawbacks, including substantial time and resource consumption. Difficulty in accurately interpreting algorithm-generated results. High susceptibility to errors. |
| | Deep Learning | Research demonstrates the efficacy of neural network-based approaches in automatically deducing and optimizing features, facilitating broad applicability across disparate domains and data types. Furthermore, the deep learning architecture exhibits remarkable flexibility, poised to tackle emerging challenges. | Deep learning necessitates an extensive dataset to surpass traditional techniques, posing a significant data requirement challenge. Furthermore, training complexities incur substantial costs. The absence of a standardized theoretical framework complicates the selection of optimal deep learning tools, requiring expertise in topology, training methods, and parameter tuning. |

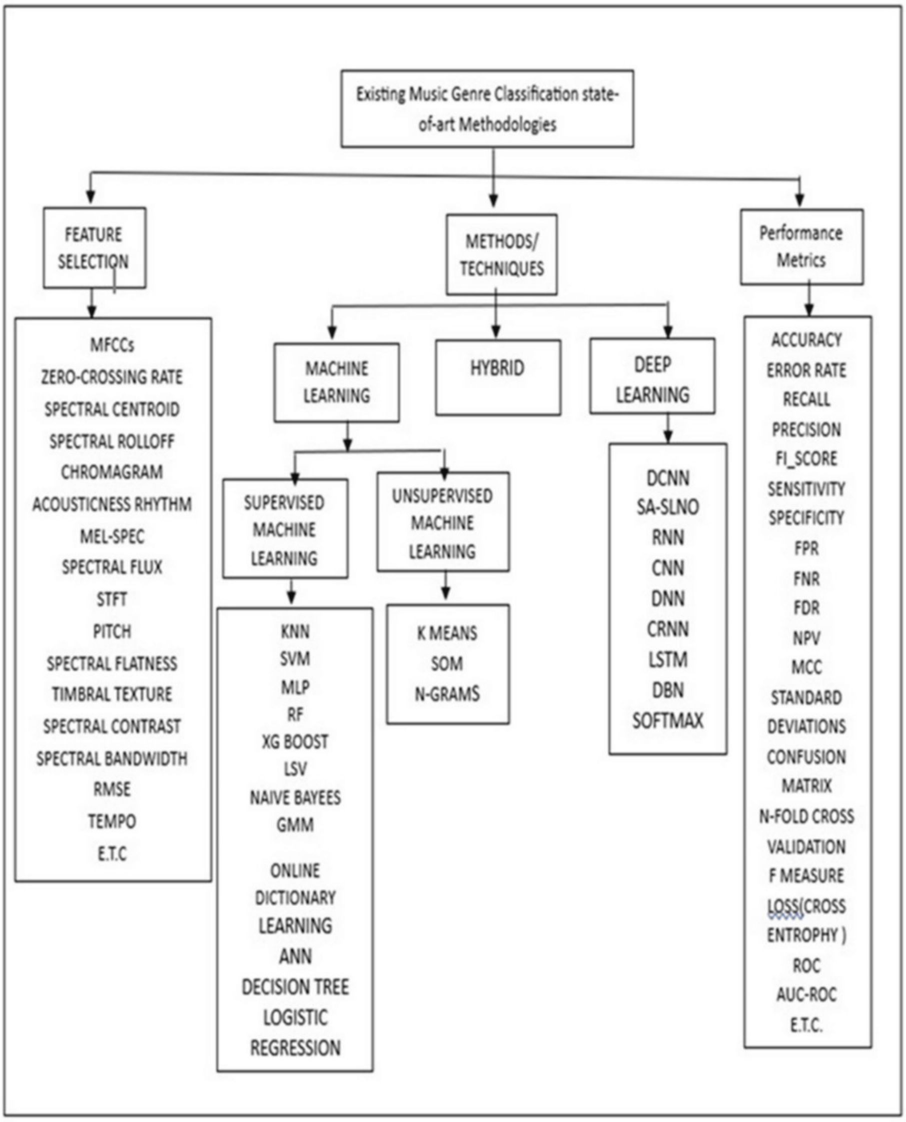
**TABLE 6: Summary of Strengths and Weaknesses Across Various Music Genre Classification Sub-Areas.**

*Limitations*

Following a rigorous review of the literature, this study identified 84 pertinent publications on MGC, published primarily between 2017 and 2023, which adequately addressed the research questions. However, due to the vastness of music genres and techniques, it is acknowledged that this study may not have exhaustively covered all relevant research. Additionally, the exclusion of non-English publications may have resulted in the omission of significant contributions.

*Taxonomy*

A systematic taxonomy was created to organise the state-of-the-art methodologies in MGC, based on the research outcomes. The taxonomy comprises three main classes: Feature Selection, Methods/Techniques, and Performance Metrics. Figure *19* illustrates the taxonomy in detail, while Table *7* summarises the relevant articles examined.




## FIGURE 19: Music Genre State-of-the-Art: A Taxonomy of Methods.

MFCC, Mel-Frequency Cepstral Coefficients; STFT, Short-Time Fourier Transform; RMSE, Root Mean Square Error; LSTM, Long Short-Term Memory; DCNN, Deep Convolutional Neural Network; DBN, Deep Belief Network; CRNN, Convolutional Recurrent Neural Network; CNN, Convolutional Neural Network; DNN, Deep Neural Network; RNN, Recurrent Neural Network; SA-SLNO, Self Adaptive-Sea Lion Optimization; SOM, Self-Organizing Map; ANN, Artificial Neural Network; GMM, Gaussian Mixture Model; LSV, Least Squares Vector; RF, Random Forest; MLP, Multilayer Perceptron; SVM, Support Vector Machine; KNN, K-Nearest Neighbour; FPR, False Positive Rate; FNR, False Negative Rate; FDR, False Discovery Rate; NPV, Negative Predictive Value; MCC, Matthews Correlation Coefficient; ROC, Receiver Operating Characteristic; AUC, Area Under the Curve

| SN | Author | Year | Method | | | Approach | | | Status | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | ML | DL | Hybrid | Audio Recorded | Symbolic Content | Hybrid | Evaluated | Implemented | Proposed | Proposed and Evaluated | Proposed and Implemented |
| 1 | Singh and Biswas [2] | 2022 | | * | | * | | | * | | | | |
| 2 | Bahuleyan [3] | 2018 | * | | | * | | | * | | | | |
| 3 | Ndou et al. [8] | 2021 | | * | | * | | | * | | | | |
| 4 | Kalapatapu et al. [14] | 2016 | * | | | * | | | * | | | | |
| 5 | Corrêa and Rodrigues [20] | 2016 | * | | | | * | | * | | | | |
| 6 | Nihalaani [21] | 2021 | * | | | * | | | * | | | | |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 7 | Qi et al. [22] | 2022 | • | | | • | | | • | | | | |
| 8 | Falola and Akinola [26] | 2022 | | • | | • | | | | | • | | |
| 9 | Oramas et al. [30] | 2021 | | • | | | | • | • | | | | |
| 10 | Peiris and Jayaratne [33] | 2017 | • | | | • | | | • | | | | |
| 11 | Folorunso et al. [34] | 2021 | • | | | • | | | | • | | | |
| 12 | Costa et al. [38] | 2017 | | • | | • | | | • | | | | |
| 13 | Adiyansjah et al. [39] | 2019 | | • | | • | | | • | | | | |
| 14 | Nanni et al. [40] | 2018 | | • | | • | | | | | | • | |
| 15 | Khamees et al. [42] | 2021 | | • | | • | | | • | | | | |
| 16 | Foleiss and Tavares [43] | 2020 | | | | | • | | | • | | | |
| 17 | Liu and Zhang [44] | 2022 | | • | | • | | | | | | • | |
| 18 | Setiadi et al. [45] | 2020 | • | | | • | | | • | | | | |
| 19 | Elbir and Aydin [46] | 2020 | • | | | • | | | • | | | | |
| 20 | Yu et al. [47] | 2020 | | • | | • | | | | • | | | |
| 21 | Chen and Steven [48] | 2021 | | | • | • | | | | | | • | |
| 22 | Choi et al. [49] | 2017 | | • | | • | | | • | | | | |
| 23 | Calvo-Zaragoza et al. [50] | 2019 | | • | | | • | | | | | • | |
| 24 | Siddavatam et al. [51] | 2020 | | • | | • | | | • | | | | |
| 25 | Jakubec and Chmulik [52] | 2019 | • | | | • | | | | | | | • |
| 26 | Shi et al. [53] | 2019 | | • | | • | | | • | | | | |
| 27 | Zheng [54] | 2022 | | • | | • | | | | | | • | |
| 28 | Cheng et al. [55] | 2020 | | • | | • | | | | | | • | |
| 29 | Elbir et al. [56] | 2018 | • | | | • | | | | | • | | |
| 30 | Kaur and Kumar [57] | 2017 | • | | | • | | | • | | | | |
| 31 | Castillo and Flores [58] | 2021 | • | | | • | | | • | | | | |
| 32 | Singhal et al. [59] | 2022 | • | | | • | | | • | | | | |
| 33 | Wei and Guobin [60] | 2022 | | • | | • | | | | | | | • |
| 34 | Foroughmand Aarabi and Peeters [61] | 2021 | | • | | • | | | • | | | | |
| 35 | Liu et al. [62] | 2022 | | | • | • | | | | | | • | |
| 36 | Liu et al. [63] | 2022 | | • | | • | | | • | | | | |
| 37 | Zhao et al. [64] | 2023 | • | | | • | | | • | | | | |
| 38 | Du et al. [65] | 2022 | | • | | • | | | | | | • | |
| 39 | Jiang and Zheng [66] | 2023 | | • | | | • | | | | | • | |
| 40 | Chaudhury et al. [67] | 2022 | • | | | • | | | • | | | | |
| 41 | Mahardhika et al. [68] | 2018 | • | | | • | | | • | | | | |
| 42 | Lefaivre and Zhang [69] | 2018 | • | | | • | | | | | | • | |
| 43 | Ghosal and Sarkar [70] | 2020 | | • | | • | | | • | | | | |
| 44 | Chillara et al. [71] | 2019 | • | | | • | | | • | | | | |
| 45 | Wong et al. [72] | 2018 | | • | | • | | | • | | | | |
| 46 | Shin et al. [73] | 2019 | | • | | • | | | | | | • | |
| 47 | Fathima et al. [74] | 2021 | | • | | • | | | | | | | • |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 48 | Rafi et al. [75] | 2021 | | • | | • | | | • | | | | |
| 49 | Thiruvengatanadhan [76] | 2018 | • | | | • | | | | • | | | |
| 50 | Elbir et al. [77] | 2018 | • | | | • | | | • | | | | |
| 51 | Tulisalmi-Eskola [78] | 2022 | • | | | • | | | • | | | | |
| 52 | Ghildiyal et al. [79] | 2020 | | • | | • | | | • | | | | |
| 53 | Ponlatha et al. [80] | 2021 | | • | | • | | | • | | | | |
| 54 | Qiu et al. [81] | 2021 | | • | | • | | | | | • | | |
| 55 | Martins de Sousa et al. [82] | 2017 | • | | | • | | | | • | | | |
| 56 | Zhuang et al. [83] | 2020 | | • | | • | | | | | | • | |
| 57 | Prabhakar and Lee [84] | 2023 | | • | | • | | | | | | • | |
| 58 | Dervakos et al. [85] | 2023 | | • | | | • | | | | | • | |
| 59 | Lattner et al. [86] | 2018 | | | • | | | • | | | | • | |
| 60 | Wu et al. [87] | 2019 | | • | | | | • | | | | • | |
| 61 | Pelchat and Gelowitz [88] | 2020 | • | | | • | | | • | | | | |
| 62 | Ma [89] | 2022 | | | • | • | | | • | | | | |
| 63 | Patil and Nemade [90] | 2017 | • | | • | | | | • | | | | |
| 64 | Chettiar and Kalaivani [91] | 2021 | | | • | | | • | • | | | | |
| 65 | Vishnupriya and Meenakshi [92] | 2018 | | • | | • | | | | • | | | |
| 66 | Farajzadeh et al. [93] | 2023 | | • | | • | | | • | | | | |
| 67 | Dias et al. [94] | 2022 | | | • | • | | | | • | | | |
| 68 | Falola et al. [95] | 2022 | | • | | • | | | • | | | | |
| 69 | Kiran and Veena [96] | 2022 | | | • | • | | | | | | • | |

**TABLE 7: Literature Review Summary: Relevant Articles**

ML, Machine Learning; DL, Deep Learning

## Conclusions

Despite advancements in music genre classification techniques, achieving complete accuracy remains challenging. This systematic literature review analysed contemporary methods, applications, and trends in the field, initially retrieving 1,048 articles and selecting 84 for in-depth analysis based on rigorous criteria. Among the methodologies identified, 51% utilised deep learning, with CNNs emerging as the most frequently cited algorithm. Machine learning methods accounted for 36%, while hybrid methods comprised 13%. Regarding content representation, 87% of studies analysed audio recordings, 8% symbolic content, and 5% employed hybrid methods. Evaluation of the reviewed literature indicated that 52% of articles were limited to performance evaluations of existing methods, suggesting that the domain remains under-explored in terms of algorithmic innovation and implementation. Additionally, the GTZAN dataset was identified as the most frequently used among 31 datasets cited across studies. Accuracy emerged as the predominant performance metric, featured in 40 studies out of approximately 26 metrics identified. Geographically, research was concentrated primarily outside Africa, with only Nigeria and South Africa contributing publications, highlighting significant geographical gaps. Specifically, the ORIN dataset from Nigeria remains the continent's only publicly available music genre classification dataset.

This review identifies critical research gaps, including limited representation of African music genres and insufficient datasets from the region. To address these challenges, future research should emphasise exploring advanced deep learning methods, particularly GANs, along with data augmentation techniques, to improve accuracy and broaden the representation and classification scope of African music genres. While the use of GANs in MGC is not yet widespread, they show strong potential for addressing data scarcity, enhancing feature representation, and improving robustness in genre-aware embedding systems.

# Additional Information

## Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

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## Disclosures

**Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

## Acknowledgements

Adebayo A. Abayomi-Alli and Adetunji A. Adeyanju acknowledge the support of the European Research Consortium for Informatics and Mathematics (ERCIM) and the Institute for Systems and Computer Engineering, Technology and Science (INESC TEC), as this work was carried out during the tenure of an ERCIM 'Alain Bensoussan' Fellowship Programme at INESC TEC.

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