# Literature review

Soft computing methods are vital for effective audio analysis since they help classify different music genres. Music genre automatic classification plays major roles in multiple audio applications including music recommendation structures as well as individual playlist creation and efficient music retrieval systems. The extraction process of relevant audio features remains a basic challenge together with the requirement to handle noise from the data and the presence of incomplete datasets (George & Perry, 2022). Previous research studies related to feature selection approach and classification techniques and methods directed at resolving challenges with noisy and incomplete inputs in music genre categorization receive investigation. The automatic categorization of music works as a fundamental component of music information retrieval tools since it helps streams and digital libraries organize their song collection for efficient recommendations and search functions.

Music organization together with personalized music recommendations benefits from automatic genre categorization of songs. This study creates a machine learning system for sorting music into different genre categories by using acquired audio feature information. Through the use of a Kaggle dataset, the research shows how to discover vital features that produce the most accurate classifications while solving problems due to data imperfections (Nirmal, Hemang, & Nirav, 2020).  The study examines multiple methods for choosing features together with data cleaning approaches which help enhance model performance. The dataset requires Python libraries from sci-kit-learn NumPy and pandas to cleanse data extract features and transform it for training Random Forest and XGBoost classifiers. A successful model assessment includes checking its classification accuracy which needs to reach at least 85% performance. The project explores techniques to deal with incomplete and damaged audio data for improving stability during practical application.

The success of classification systems relies on performing suitable feature selection because it leads to better accuracy and operational efficiency. A variety of audio-based features were evaluated in previous research investigations. Acoustic properties which are basic elements constitute the domain of low-level features since these properties originate from raw audio signals. Sound frequencies become perceptible to humans as MFCCs do due to their status as a leading acoustic characteristic extraction method. Three spectral features namely spectral centroid spectral roll-off and spectral flux serve as essential factors for identifying timbral characteristics (Fathima, Sagar, & Shreya, 2021). The pitch content included in chroma features supports the identification of harmonic distinctions between different musical genres. Music content becomes easier to represent through high-level features at an abstract level. The rhythmic features consisting of tempo beat strength and onset rate assist in distinguishing rhythm patterns that define jazz and rock genres from each other.

The identification of musical genres becomes more efficient when music includes features related to key as well as chord progression and harmonic complexity. Manual and automated deep learning extraction of Timbre features enables the detection of musical instruments together with texture in songs. Proper selection of important features serves two important purposes decreasing dimensions and preventing model overfitting. PCA enables high-dimensional feature spaces to obtain lower dimensions while maintaining the data variance (Navneet, Shikta, Gunj, & Ameya, 2021). The machine learning model Support Vector Machines (SVM) uses Recursive Feature Elimination (RFE) to select its most informative features. Random Forest and XGBoost tree-based models deliver important feature identification that enables users to identify crucial classification features. Machine learning and deep learning exist as multiple techniques that researchers apply to identify music genres. Support Vector Machines (SVMs) function effectively within high-dimensional spaces thus they are standard tools used for music classification (Snigdha, Kavitha, Shwetha, Shreya, & Vidyullatha, 2019). XGBoost operates as a gradient-boosting algorithm that provides boosted predictive functionality and manages data incompleteness effectively. The classification of spectrograms uses extensive Convolutional Neural Networks (CNNs) alongside other deep learning methods. The audio signal treatment requires Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTMs) because they enable the detection of temporal relationships.

The presence of noise as well as missing data among audio datasets makes it extraordinarily difficult to execute music genre classification. Multiple methods have been introduced to handle this set of problems. Spectral subtraction serves as a noise reduction technique that allows users to separate background noises from audio signals before signal enhancement. Z-score analysis together with IQR filtering serves as a statistical method to detect outlier samples and remove them from the dataset through automated processes. Lifeless datasets from music recordings receive remedy through mean/median imputation approaches by inserting feature average or median elements into missing spots (Prajwal, Shubham, Prasanna, & Sugna, 2021). The algorithm of KNN imputation implements the k-nearest neighbors mechanism for value completion and deep learning autoencoders achieve reconstruction of missing features by discovering data latent dimensions. The process of expanding audio training data via pitch shifting along with time stretching remains standard practice in audio processing systems because it maintains the fundamental musical attributes. Two augmentation techniques Mix-up and Spec Augment combine multiple audio data or transform spectrogram elements to achieve better generalization abilities in modelling behavior.

For assessing the performance of classification models standardized metrics must be utilized. The proportion of songs accurately placed by the system measures Accuracy. Model performance assessments for datasets with imbalance use precision, recall, and F1-score. The evaluation of misclassification trends through confusion matrix analysis leads to better model interpretability by visualizing classification errors (Bharat, Vinayak, Mujahid, & Varsha, 2021). Model robustness relies on cross-validation which verifies how different subset divisions of the dataset affect performance measurements. The modern research field develops progressive methods to boost both classification precision along robustness performance. The pretraining of models through self-supervised learning occurs with large music datasets before training with labelled data. Neural networks with implemented attention mechanisms focus their analysis on important time-frequency segments of audio signals through attention layers.

By applying graph neural networks (GNNs) the representation of different musical elements as graphs allows the discovery of their interconnections. Genre classification performance receives additional benefits through Multimodal learning because it integrates audio data with lyrics information and metadata (Ponlatha, Mathisalini, Deepthisri, Kalaiyarasi, & Kowshika, 2021). Music genre classification represents a complicated system whose solution depends on selecting the best features while implementing strong classification models together with noise handling in incomplete datasets. Rand Forests and Standard Vector Machines (SVMs) represent traditional machine learning methods that producers have widely adopted for the task while deep learning models namely CNNs and RNNs have delivered better outcomes. Developing reliable classifiers requires attention to noise-related issues alongside missing data issues using data cleaning methods and imputation and augmentation techniques.

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