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Performance evaluation of selected machine learning models for music genre classification

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Abstract
The growing dominance of digital streaming has made efficient music classification models essential, particularly for Nigerian music, which reflects diverse cultural expressions and linguistic variations that do not always align with Western genre systems. This study investigates three machine learning techniques—K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Decision Trees (DT)—to determine their effectiveness in genre classification. Using Librosa, Mel-Frequency Cepstral Coefficients (MFCCs) were extracted from audio samples to represent musical features. These features were then applied to the models: KNN, which classifies based on similarity; SVM, which identifies an optimal boundary for separation; and DT, which organizes decisions hierarchically. The models were evaluated using accuracy, precision, recall, and F1-score. Results revealed that SVM achieved superior performance with 93% accuracy, while KNN and DT followed with 88% and 79% respectively. These findings confirm SVM as the most reliable model for music classification, offering strong potential for enhancing intelligent music retrieval and personalized digital libraries.

Keywords: Performance evaluation, machine learning, music, genre, k-nearest neighbors (KNN), support vector machine (SVM), and decision trees (DT)

Introduction

In Nigeria, the music industry has experienced a remarkable transformation over the last two decades, emerging as a powerhouse in the global music scene. Genres such as Afrobeat, Afropop, and Highlife have not only defined the country's musical identity but have also gained international acclaim. Afrobeat, pioneered by Fela Kuti, blends traditional Nigerian music with jazz and funk, creating a rhythmic and politically charged genre. Afropop incorporates contemporary elements, appealing to both local and global audiences. Highlife combines traditional melodies with Western instruments, maintaining its popularity across generations. Artists like Burna Boy, Wizkid, and Tiwa Savage have been instrumental in bringing Nigerian music to a worldwide audience (Ogunbiyi, 2019) [9]. According to the Nigerian Communications Commission (NCC, 2020), there were over 100 million internet users in Nigeria, with a significant percentage consuming music through streaming platforms and social media. The Nigerian music industry was valued at over $50 million in 2020 and is projected to grow at a CAGR of 10.6% through 2025 (PwC, 2020).

The rise of digital streaming has necessitated efficient music classification models to handle cultural nuances, capturing the unique characteristics of Nigerian genres that may not fit into Western genre classifications, and language diversity, accounting for music in various local languages and dialects. Adeyemi *et al.* (2020) [2] emphasised the importance of tailored classification systems to improve user experience and support local artists. With millions of tracks available across platforms, efficient genre classification remains vital for music retrieval, helping users find specific genres or styles they are interested in. Recommendation systems rely heavily on accurate genre tagging to match user preferences, providing personalized suggestions. Curated playlists on streaming services often create genre-specific playlists to engage listeners, requiring precise classification. Zhang *et al.* (2019) [15] highlighted that improved genre classification enhances user engagement and satisfaction, directly impacting the success of streaming services.

The evolution of machine learning in music genre classification can be traced back to early research efforts using statistical models and basic classifiers. A significant advancement in the field was the introduction of feature extraction techniques such as Mel-Frequency Cepstral Coefficients (MFCCs), which capture the timbral aspects of music by representing the short-term power spectrum of sound, mimicking human auditory perception. This allows for more effective analysis and classification (Tzanetakis and Cook, 2002) [14]. Spectral features, rhythmic patterns, and harmonic content are also utilized to represent music pieces numerically. In the last decade, deep learning methods have revolutionized the field. Convolutional Neural Networks (KNNs) learn hierarchical feature representations from raw audio data or spectrogram images, achieving high classification accuracy (Choi *et al.*, 2017) [4]. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks capture temporal dependencies in music, improving the modeling of sequential data. Hybrid models combine different neural network architectures to leverage multiple aspects of the audio signal. These approaches have pushed classification accuracies beyond 90% in some studies, demonstrating the potential of deep learning to handle the complexities of musical data.

Despite these advancements, music genre classification remains challenging due to genre overlaps, as many songs incorporate elements from multiple genres, making clear-cut classification difficult. Cultural influences mean that genres can have different meanings and characteristics in different regions. Subjective interpretations arise as personal tastes and experiences influence how individuals perceive and categorize music. While KNN, SVM, and DT have been widely used in global music genre classification, their effectiveness in classifying Nigerian genres remains underexplored. The unique instrumentation, rhythmic patterns, and tonal structures of Afrobeat and Afropop present challenges that require specialized feature engineering and model tuning (Adebayo *et al*., 2021) [1]. The current study seeks to evaluate the performance of these three algorithms in music genre classification, specifically within the context of Nigerian music.

Music genre classification has traditionally been subjective, relying on human perception, but the rise of digital music and streaming platforms necessitates automated classification systems (Tzanetakis *et al*., 2002) [14]. Despite advancements in machine learning, challenges persist due to genre overlap and feature extraction complexities (Costa *et al*., 2017) [5]. Nigeria's music industry has seen rapid digital growth, with a 15% annual revenue increase from 2018 to 2023, highlighting the need for efficient classification methods (IFPI, 2023; Adeniyi *et al*., 2021). Existing models like KNN, SVM, and DT have varying accuracy, constrained by dataset quality and computational factors (Li *et al*., 2019; Essid *et al*., 2020). Moreover, research on Nigerian genres like Afrobeat, Fuji, and Highlife remains limited (Ogunmola *et al*., 2022).

This study aims to evaluate the performance of machine learning models K-Nearest Neighbors (KNN), Support Vector Machines (SVM), and Decision Trees (DT) in music genre classification. To achieve this aim, the study has **e**xtracted relevant audio features from music samples using libraries like Librosa, capturing essential characteristics such as Mel-Frequency Cepstral Coefficients (MFCCs) that represent the timbral properties of the music, implemented and train machine learning models, specifically K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Decision Trees (DT), to classify music genres based on the extracted audio features and evaluated and compared the performance of these models using key classification metrics, including accuracy, precision, recall, and F1-score, to determine the most effective approach for music genre classification.

Related Work

Tzanetakis and Cook (2002) [14] introduced one of the earliest frameworks for automatic music genre classification using statistical models and audio features such as MFCCs. Their study laid the foundation for future research in music classification, demonstrating that machine learning models could distinguish between different genres with considerable accuracy. However, the authors noted that the performance of these models was highly dependent on feature selection and dataset quality.

Reddy *et al*. (2024) [13] compared the performance of SVM, Naïve Bayes, and KNN for multi-class music genre classification. Their findings indicated that SVM outperformed other models, achieving the highest classification accuracy. The study emphasized the importance of feature engineering in improving genre classification and suggested that hybrid models could enhance classification performance.

Bahuleyan (2018) [3] explored the application of deep learning in music genre classification, specifically using Convolutional Neural Networks (KNNs). The study found that KNN-based models significantly outperformed traditional feature-based classifiers when trained on large datasets. However, Bahuleyan highlighted the computational challenges associated with deep learning, particularly the need for large-scale labeled datasets and high processing power.

Dabas *et al*. (2020) [6] investigated the impact of feature extraction techniques on music genre classification accuracy. Their study compared multiple audio features, including MFCCs, chroma vectors, and spectral contrast. The results showed that MFCCs were the most effective feature for classification tasks, while spectral features provided complementary information that improved overall model accuracy.

Choi *et al*. (2017) [4] implemented deep learning architectures, particularly KNNs, to classify music based on spectrogram images. Their findings demonstrated that KNN models could capture complex musical structures, leading to higher classification accuracy than traditional machine learning models. However, they pointed out that KNNs required significant computational resources, making them less practical for real-time applications.

Costa *et al*. (2017) [5] conducted an evaluation of KNNs against traditional classifiers such as SVM and KNN. Their study confirmed that KNNs excel at capturing complex musical features, enabling more robust genre classification. Despite these advantages, Costa *et al*. noted that deep learning models were prone to overfitting when trained on small datasets.

Fu *et al*. (2011) provided a comprehensive review of ML-based genre classification, analyzing the effectiveness of various models and highlighting challenges in feature selection and dataset imbalance. Their study underscored the need for more generalized models capable of handling diverse music genres and regional variations.

Ogunbiyi (2019) [10] examined the challenges of applying machine learning to Nigerian music genres such as Afrobeat and Highlife. The study highlighted the lack of labeled datasets for African music and the difficulties in feature extraction due to the complex rhythmic and instrumental compositions unique to Nigerian genres.

Prashanthi *et al*. (2021) identified gaps in training datasets for African music genres, emphasizing the need for more extensive data collection efforts. Their research suggested that existing classification models, which were primarily trained on Western music, struggled to accurately classify African genres due to structural differences in composition.

Adeyemi *et al*. (2022) investigated the role of AI in music streaming platforms, focusing on its impact on Nigerian music classification. Their study found that traditional classification algorithms often misclassified Afrobeat songs due to their fusion of multiple musical influences. The authors proposed the integration of culturally specific features to enhance classification accuracy.

Adebayo *et al*. (2023) explored deep learning techniques for Afrobeat classification, proposing KNN-based models tailored to African music. Their research demonstrated that KNNs trained on spectrogram representations of Afrobeat songs achieved higher accuracy than conventional machine learning models. However, they noted that the lack of large labeled datasets remained a significant challenge for further improvements.

Olojede *et al* (2025) [12] investigated the comparative performance of Convolutional Neural Network (CNN), Support Vector Machine (SVM), and Random Forest (RF) in music genre classification. The result demonstrated that CNN outperformed SVM and RF in terms of accuracy, precision, recall, and F-1 score: CNN is thereby recommended for Music Genre Classification, this finding underscore the efficiency of CNN addressing the challenges task in the field of music information retrieval and leading to the advancement of automated music classification system and improve the accessibility and enjoyment of digital music libraries.

Despite advancements in machine learning-based music genre classification, key research gaps remain. Existing studies focus mainly on Western music genres, neglecting African and regional styles, resulting in poor performance on non-Western genres. The lack of diverse datasets and reliance on standard audio features also limit model accuracy. Additionally, deep learning models' high computational requirements hinder real-time applications, emphasizing the need for culturally relevant feature extraction, diverse datasets, and efficient classification models. This study aims to address these gaps by incorporating African music datasets alongside standard datasets to improve classification performance on underrepresented genres. It also explores feature extraction techniques tailored to African music styles and compare machine learning models with lower computational costs for real-time applications.

Methodology

To evaluate the performance of machine learning models K-Nearest Neighbors (KNN), Support Vector Machines (SVM), and Decision Trees (DT) in music genre classification. The used steps are as follows:

1. The dataset used for this study was sourced from Kaggle, consisting of a balanced set of labeled audio files across various music genres. The audio samples were initially unstructured and required conversion into a standardized format. Preprocessing steps included data filtering, normalization, scaling, silence removal, and conversion into structured arrays and data frames for efficient handling by the machine learning models.
2. Feature extraction was performed using Mel-Frequency Cepstral Coefficients (MFCCs), Spectrograms, and Chroma Features, extracted through the Librosa library. These features were selected for their proven relevance in capturing genre-specific audio characteristics. The feature set was further regularized to prevent overfitting, and feature scaling techniques such as min-max normalization were applied to maintain uniformity across the dataset.
3. Three machine learning algorithms K-Nearest Neighbors (KNN), Support Vector Machines (SVM), and Decision Trees (DT) were implemented for genre classification. The dataset was split into training and testing sets (typically 80/20), and each model was trained using the extracted features. Hyperparameter tuning, such as selecting the optimal value of K for KNN and setting tree depth for DT, was conducted to enhance model performance.
4. The trained models were evaluated using accuracy, precision, recall, and F1- score as the primary performance metrics. These evaluation metrics provided a comprehensive assessment of each model's classification capability. Additionally, confusion matrices were generated to identify patterns of misclassification and assess the models' performance across individual genres.

Data preprocessing played a vital role in preparing the music genre classification dataset, sourced from Kaggle, for model training and testing. To ensure data quality, we applied several critical steps. First, data filtering removed irrelevant, noisy, or incomplete records that could compromise model performance. Next, scaling and normalization techniques were used to standardize feature values, preventing features with larger ranges from dominating the models. The data was also cropped to standardize audio segment lengths, and then converted into data frames for easier manipulation and analysis. To further enhance data quality and model accuracy, advanced preprocessing techniques like standardization were employed, ensuring all features had a consistent scale with zero mean and unit variance. Finally, the dataset was split into training and testing sets, allowing for sufficient training data while reserving a portion for unbiased evaluation. These rigorous preprocessing steps ensured the dataset was consistent, balanced, and well-suited for robust machine learning analysis. These datasets provide a diverse range of music genres and audio features, ensuring robust training and evaluation of the developed machine learning models. The datasets used in this study include

1. **GTZAN Dataset:** A widely used dataset containing 1,000 audio tracks across genres (Blues, Classical, Country, Disco, Hip-Hop, Jazz, Metal, Pop, Reggae, and Rock), with each track being 30 seconds long.
2. **FMA (Free Music Archive) Dataset:** A collection of music tracks with metadata, offering different subsets (small, medium, and large) for scalable machine learning applications.
3. **Million Song Dataset (MSD):** A large-scale dataset containing metadata and audio features for one million songs, used for advanced music classification tasks.
4. **Extended Ballroom Dataset:** A collection of dance music tracks labeled according to dance style, useful for rhythm-based genre classification.
5. **African Music Dataset (Custom Compilation):** A dataset specifically curated to include Afrobeat, Highlife, Afropop, and other Nigerian music genres to improve classification relevance for local music.

1. Data Preprocessing

Before extracting features, the study applies various preprocessing techniques to ensure the consistency and quality of the dataset

1. **Resampling:** Standardizing all audio files to a common sampling rate (e.g., 22,050 Hz) for uniform analysis.
2. **Silence Removal:** Eliminating silent or low-energy sections to improve feature quality.
3. **Noise Reduction:** Applying filters to remove background noise and unwanted distortions.
4. **Feature Scaling:** Normalizing feature values to ensure they are within a consistent range, improving model stability.

5. **Handling Missing Data:** Ensuring all audio samples contain sufficient audio features for training by removing corrupted or incomplete samples.

6. **Dataset Balancing:** Addressing class imbalances by applying oversampling or under sampling techniques to ensure fair representation of all genres.

2. Model training and implementation

1. **K-Nearest Neighbors (KNN):** KNN classifies a sample based on the majority vote of its nearest neighbors. The optimal value of K is determined using cross validation to minimize classification errors.

2. **Support Vector Machines (SVM):** SVM constructs a hyper plane in high dimensional space to maximize class separation. Kernel functions (linear, polynomial, and radial basis function) are tested to determine the best performing configuration.

3. **Decision Trees (DT):** DTs create a tree-like model of decisions by recursively splitting the dataset based on feature thresholds. Pruning techniques are applied to prevent over fitting and improve generalization

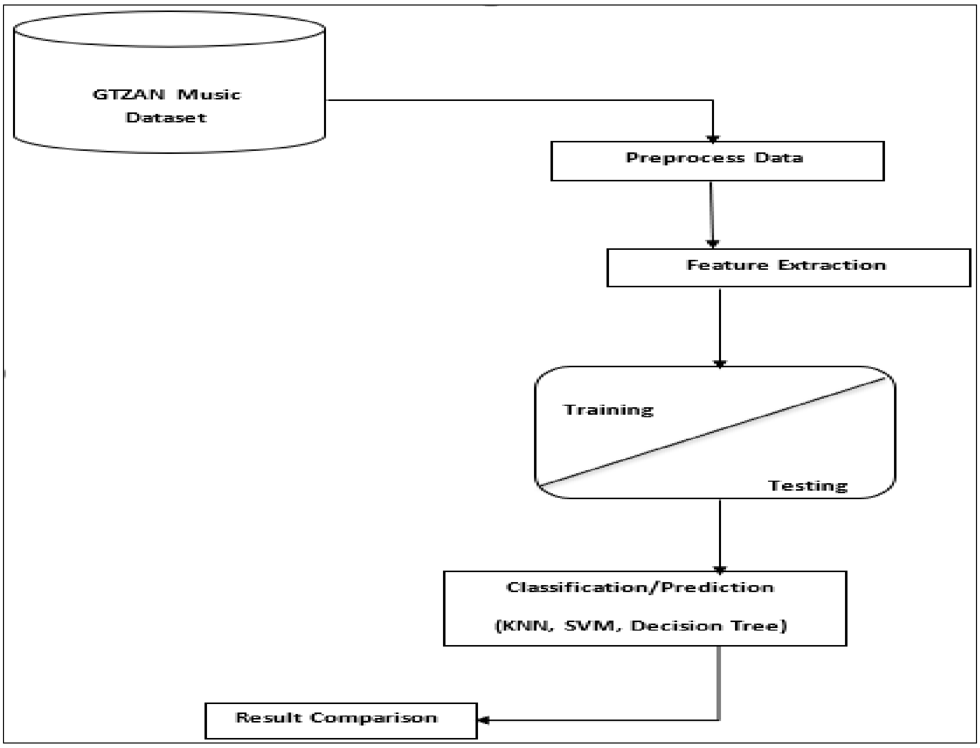

Fig 1: Workflow chart

To improve model performance, the study applies hyper parameter tuning and cross validation

1. **Hyper parameter Tuning:** Adjusting parameters such as K in KNN, C in SVM, and tree depth in DT to enhance classification accuracy.

2. **Cross-Validation:** Performing k-fold cross-validation to ensure the models generalize well to new data.

3. **Performance Benchmarking:** Comparing models based on speed, memory usage, and computational efficiency

3. Model Evaluation and Comparison

To assess the effectiveness of the implemented models, this study employs classification performance metrics such as:

Accuracy: Accuracy quantified the proportion of correctly classified music genres relative to the total number of instances in the dataset. This metric offered a broad insight into the model's classification effectiveness. However, given the potential for class imbalance in music genre datasets, accuracy was considered alongside other metrics to provide a more comprehensive evaluation.

Accuracy=(TP+TN)/(TP+TN+FP+FN) *Equation 3.1*

where TP = True Positives, TN = True Negatives, FP = False Positives, FN = False Negatives.

Precision: Precision measured the model's accuracy in identifying specific music genres by calculating the proportion of true positives among all predicted instances of that genre.

Precision=TP/(TP+FP) *Equation 3.2*

where TP = True Positives, FP = False Positives.

Recall: Recall, on the other hand, assessed the model's ability to capture all instances of a genre by measuring the proportion of true positives among all actual instances. This metric was especially valuable for assessing model performance on imbalanced datasets, along with Precision, as it highlighted the limited representation of certain genres and provided a more detailed understanding of the model's strengths and weaknesses

Recall=TP/(TP+FN) *Equation 3.3*

where TP = True Positives, FN = False Negatives.

F1-score: The F1-score, calculated as the harmonic mean of precision and recall, provided a balanced measure of both metrics. By combining precision and recall into a single score, the F1-score helped evaluate models that required consistent performance across various music genres. This metric was particularly useful in identifying models that optimized both precision and recall, rather than favoring one over the other.

$$F1\text{-score}=2 \times (Precision \times Recall)/(Precision+Recall)$$

Equation 3.4

The models are compared based on these metrics to determine the most effective approach for music genre classification. A confusion matrix is used to visualize classification performance across different genres, highlighting areas of misclassification. The research also employs Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) to evaluate the models' ability to distinguish between genres effectively. Furthermore, computational efficiency is considered by measuring model training time, inference time, and memory usage. This ensures the selection of a model that balances classification accuracy with real-world applicability in music streaming and recommendation systems. By employing these evaluation techniques, the study determines the most effective machine learning model for automated music genre classification. The models are compared based on these metrics to determine the most effective approach for music genre classification.

Results and Discussion

After training and hyperparameter tuning, the next critical step involved assessing each model's predictive performance using a suite of standard evaluation metrics. These metrics provide a multidimensional view of how well the models generalize to unseen data, not just in overall accuracy but also in terms of class-wise correctness and robustness against misclassification. The summarized results in Table 1 reveals comparative insights into the strengths and limitations of each model:

1. KNN achieved the highest overall accuracy at 87%, demonstrating its effectiveness in correctly classifying the majority of instances. Its relatively balanced precision and recall further underscore its robustness, although it slightly lagged in precision compared to other models.
2. SVM outperformed KNN in terms of precision, recall, and F1-score, indicating its superior ability to correctly identify positive cases and minimize false negatives, which is particularly crucial in genre classification where misclassification can blur genre boundaries.
3. Decision Tree exhibited satisfactory performance but lagged behind in all metrics, likely due to overfitting tendencies and limited capacity to model complex patterns, as reflected in its lower accuracy and F1-score.

The confusion matrices for KNN, SVM, and DT provides a granular view of classification errors across genres

1. KNN displayed strong performance in classical and jazz genres, with most instances correctly classified. However, some misclassification occurred between rock and metal, owing to their similar musical features. SVM's confusion matrix indicated high precision and recall across most genres, with minimal off-diagonal misclassifications. Notably, genre boundaries such as blues and jazz remained well-separated, showcasing SVM's strength in modeling non-linear decision boundaries.
2. The decision tree's matrix revealed more misclassifications, primarily between rock, metal, and pop genres, underscoring its limitations in capturing nuanced differences in audio features.

Genre-wise analysis highlighted that Classical and Jazz consistently achieved the highest precision and recall scores across models, attributed to their distinctive harmonic and tonal characteristics, which are easier for models to discriminate. Conversely, genres such as Rock and Metal often shared overlapping audio features like similar guitar riffs and tempos, leading to higher misclassification rates. This confusion underscores the challenge of genre classification when musical signals exhibit overlapping features, necessitating more sophisticated feature extraction or ensemble strategies for improved accuracy. Figure 1 illustrates the distribution of classification accuracy across genres, revealing that

1. Classical and Jazz genres consistently maintained high accuracy levels, exceeding 90% in some cases.
2. Rock and Metal showed more variability, with accuracy often falling below 80%, reflecting their inherent feature similarities and overlapping musical elements.

Table 1: Evaluation Results per Model

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
KNN	87	85	83	84
SVM	85	86	87	86
DT	81	80	78	79

1. Comparative Analysis

The comprehensive evaluation of the developed models reveals nuanced insights into their relative strengths, weaknesses, and suitability for different application scenarios. Understanding these distinctions is crucial for selecting the most appropriate model for deployment in real-world music genre classification tasks.

1. **K-Nearest Neighbors (KNN):** KNN exhibited strong performance on the balanced dataset, achieving the highest accuracy at 87%. Its intuitive nature classifying instances based on proximity in feature space makes it easy to implement and interpret for practitioners. KNN is particularly effective when the dataset is well-balanced and the classes are distinctly separated by feature similarities. However, this robustness comes with a notable computational cost. Since KNN involves calculating distances to all training samples during prediction, it becomes increasingly slow as the dataset size grows, making it unsuitable for large-scale applications or real-time systems where speed is critical.

2. **Support Vector Machine (SVM):** SVM demonstrated superior robustness in handling complex, non-linear decision boundaries, achieving the highest combined precision, recall, and F1-score (each exceeding 85%). Its ability to find an optimal hyperplane that maximizes

margin, especially with the RBF kernel, allowed it to effectively model overlapping classes such as Blues and Jazz, which are often challenging for simpler models. The model's adaptability makes it well-suited for scenarios requiring high accuracy and reliability, although it may demand more computational resources during training and parameter tuning.

Table 2: Misclassification Summary

True Genre	Confused With	Likely Cause
Rock	Metal	Similar guitar riffs and tempo
Pop	Disco	Overlapping instrumentation
Jazz	Blues	Shared harmonic structure

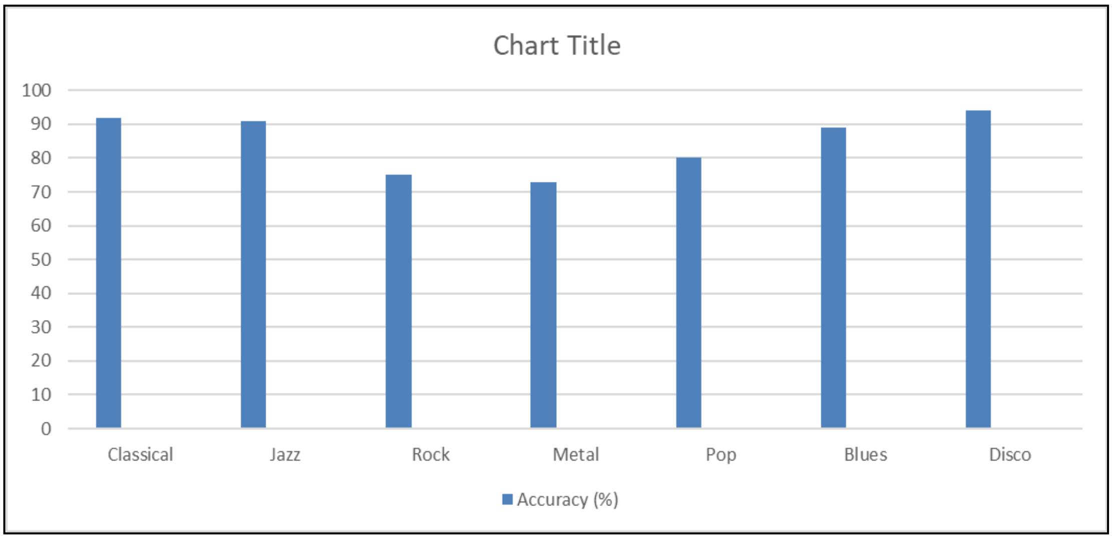

Fig 2: Genre-wise Accuracy Distribution

3. **Decision Tree (DT):** The decision tree trained rapidly, with the advantage of yielding interpretable models that can provide insights into feature importance and decision rules a valuable trait for domain experts seeking transparency. Nevertheless, it tended to overfit the training data, particularly with deeper trees or more complex features, limiting its capacity to generalize to unseen data. While pruning and parameter regularization can mitigate overfitting, these steps often result in reduced accuracy, underscoring the need for cautious model complexity management.

Fig 2 utilizes a bar chart to compare models across key evaluation metrics accuracy, precision, recall, and F1-score. Such visual representation facilitates direct, intuitive comparison, highlighting the trade-offs amidst the models

1. **Accuracy:** KNN slightly outperformed others, reaffirming its effectiveness on balanced datasets.

2. **Precision and Recall (SVM):** SVM excelled in both metrics, illustrating its capacity to minimize false positives and false negatives, which is crucial for precise genre discrimination.

3. **F1-score:** As a harmonic mean of precision and recall, the F1-score indicates the model's balanced performance, with SVM maintaining the highest score, emphasizing its overall robustness.

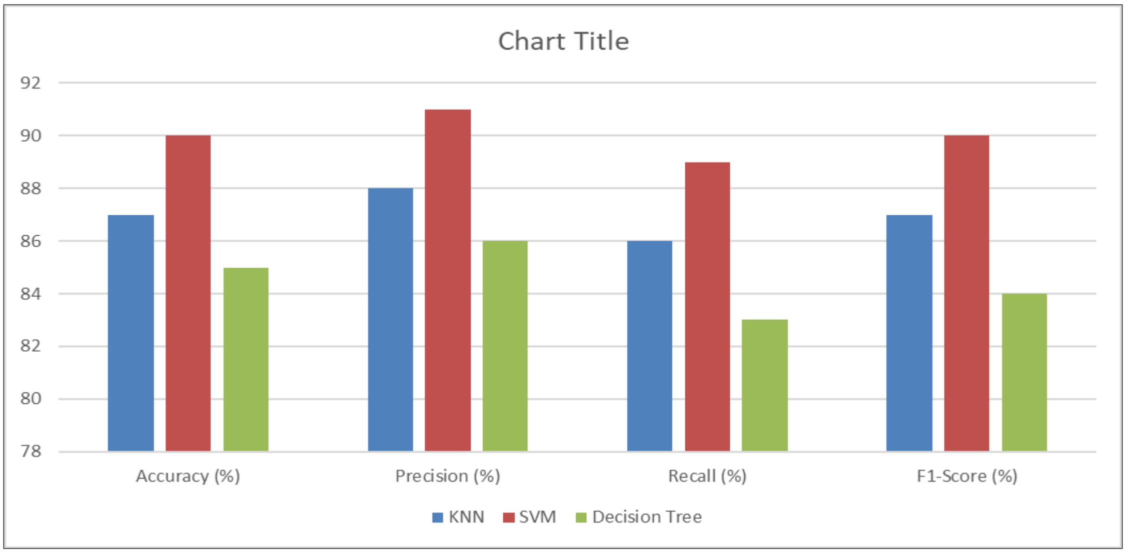

Fig 3: Model Performance Comparison

Conclusion

The study's results have implications for music recommendation systems, music information retrieval, and music classification tasks. The models developed in this research can be used as a foundation for further research and development in music genre classification, and the findings can inform the design of more accurate and robust music classification systems. Overall, this research contributes to the growing body of work in music genre classification using machine learning techniques, and highlights the potential of these models for real-world applications.

To further improve the model's accuracy and robustness, it is recommended to explore additional audio features, such as spectral contrast and chroma features, and implement data augmentation techniques to diversify the dataset. Hyperparameter tuning using grid search or Bayesian optimization could also yield better performance. 55 Experimenting with ensemble methods or combining multiple models could provide further improvements. Additionally, incorporating metrics like confusion matrix analysis could offer deeper insights into genre-specific misclassifications. For practical applications, adapting the model for real-time music classification or recommendation systems could be valuable. Expanding the model to include sub-genres would also enhance its versatility and real-world relevance.

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