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Genre Labelling Including Arabic Music Using Machin Learning

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ABSTRACT:

Music genre classification is a critical task in the digital age, essential for various applications such as personalized playlists and music recommendation systems. Among various machine learning algorithms, the K-Nearest Neighbors (KNN) algorithm has emerged as a robust technique due to its simplicity and adaptability. This paper explores the application of the KNN algorithm in music genre classification, delving into diverse feature extraction methods, distance metrics, and the impact of different K values on classification performance. Comparisons with other popular algorithms highlight the efficacy and potential of KNN in real- world music classification applications.

Keywords- K-Nearest Neighbors (KNN) algorithm, Feature extraction techniques, Distance metrics.

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I. Introduction

In the digital age, efficient music genre classification is crucial, with applications in recommendation systems, playlists, and search engines. The K-Nearest Neighbors (KNN) algorithm stands out for its simplicity and adaptability. KNN relies on similarity, comparing a new music piece to its nearest neighbors for genre prediction. It offers ease of implementation and adaptability to evolving music genres. Still, its performance depends on factors like distance metric, neighbor count (K), and feature representation. This paper explores KNN's application in music genre classification, examining feature extraction techniques, distance metrics, and the impact of different K values. Comparative analysis with other machine learning algorithms demonstrates KNN's effectiveness [1-4].

A. Existing System

Some of the existing systems in Music Genre Labelling are:

- Manual Classification.
- Automatic Classification using SVM
- Automatic Classification using CNN
- Automatic Classification using RNN

All of these systems are implemented on the original GTZAN dataset or some other datasets.

B. Drawbacks Of Existing System

The vast diversity of music styles, artists, and compositions results in significant variability within datasets. Music genres often have fuzzy and subjective boundaries, making it challenging to define clear rules for classification. The main problem with the existing systems is that almost all of those are implemented on the same 10 genres of GTZAN dataset, this restricts the diversity of the data and experimentation with new genres [5-9].

Proposed System

The proposed system uses KNN classifier, python speech features library. The dataset is a hybrid one which has all the 10 genres of GTZAN dataset with an additional Arabic music genre. First the music audio file input is given to the trained model through the interface by accessing the filesystem of the computer. The input audio file is compared with the trained data set to identify the genre using the machine learning algorithms. The features of new music file are compared with the features of all the labelled samples in the dataset by using various distance- based metrics. K nearest neighbors are selected from the feature space

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based on smallest distances, these K samples are the most similar to the new music sample given as input. The genre with the greatest number of neighbors among the K nearest neighbors is the predicted genre. The same will be displayed to the user through the interface.

C. Advantages Of Proposed System

- Diversification of the genre spectrum: In addition to the existing system, we broaden the dataset by adding an Arabic music genre.
- Adaptable to new genres and effective for small datasets
- No need of re-training of model
- Does not require extensive hyper parameter tuning.
- User friendly web interface

II.LITERATURE SURVEY AND IMPORTANCE OF THIS RESEARCH

In 2021 Music Genre Classification using Transfer Learning on log-based MEL Spectrogram was implemented. The methodologies used are Deep Learning and Transfer Learning. The paper discusses how Deep Learning techniques can be used to accurately classify music files, and features a detailed comparison of four transfer learning architectures for music genre classification (Resnet34, Resnet50, VGG16, and AlexNet). The project also mentions the use of statistical studies to identify music genres and the importance of music applications in providing easy access to songs and genres.

In 2020, a review of deep learning and traditional machine learning approaches was conducted. Ten different genres of the GTZAN dataset were used to train and test the previously used machine learning models and convolutional neural networks (CNN). 20 Mel Frequency Cepstral Coefficients (MFCC) of the three- or thirty-second feature set and extracted spectrograms.

In 2020, music genre classification using neural networks was implemented. TensorFlow was used to create a deep CNN network. The second modification involves modifying the DSP window function, which is used to transform the MP3 file into a spectrogram. The CNN architecture was changed, with levels of the CNN being added and removed. The dataset was adjusted, and the distribution of songs by genre was balanced.

In 2022, Convolutional Neural Networks Approach for Music Genre Classification was implemented. Use of CNN for music genre labelling based on Mel-spectrum assessment of audio files. Pre-processing of audio files using Librosa to convert into Mel spectrums. Majority voting approach applied to decisions made by 10 classifiers. Evaluation of model

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accuracy on the GTZAN dataset, with an average accuracy of 84% obtained.

In 2019, Music genre classification using machine learning algorithms was implemented. The first method employs a convolutional neural network that has been completely trained on the characteristics of spectrograms, or images, of the audio stream. The second method makes use of random forest and logistic regression. To categorize it into its genres, the MFCC, chroma characteristics, and spectral centroid Support Vector Machine (SVM) are utilized.

In 2021, Classification of Indian Classical Music with Time-Series Matching Deep Learning Approach was implemented. Three characteristics: The MFCC, Spectrogram, and Scalogram—are extracted in the first layer, and features are integrated in the second layer. The fourth layer compares model performance inside models by changing parameters, while the third layer compares model performance overall. There are two different ways used here. As one method, MFCCs, Spectrogram, and Scalogram features are combined into 3 channel configurations after which VGG-16, ResNet-50, and CNN models are trained. Another method for doing this involves integrating MFCCs into a single channel configuration and then training using CNN, DNN, SVM, and RNN-LSTM models.

In 2019, Machine learning for music genre: multifaceted review and experimentation with audio was implemented. Using an audio collection, to classify the musical genres. A series of tests have been run to see how various models perform when given a labelled dataset in order to learn more about how MGC functions in real- world situations. Thanks to its extensive library of samples from related musical genres, the audio set. The emphasis here is MGC, as opposed to earlier work with this novel dataset that was focused on broad audio event identification. Decision trees, NB classifiers, linear SVMs, DNNs, and RNNs are chosen for the studies. Deep learning techniques have been used in earlier work with Audioset.

III. DESIGN AND METHODOLOGY

Using KNN classifier and python speech features library, the input music file is given to the model which extracts its features and compares them to the features of the labelled samples using distance metrics. K nearest neighbors are selected from the feature space based on smallest distances, these K samples are the most similar to the new music sample given as input. The genre with the greatest number of neighbors among the K nearest neighbors is the predicted genre. The predicted genre is finally displayed to the user through the

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application's interface. The implementation follows the following steps:

- Uploading Music file: The function of uploading music files is enabled by the Image Upload Module. This module includes a wide range of components intended for handling, validating, and storing image data effectively and securely. It has features like managing picture files, data validation to assure the integrity and format of uploaded music files.
- Pre-processing: Preprocessing modules removing duplicates, corrupt files, dealing with missing values, normalization, data type conversions, etc.)

  To further examine the features, the music file is split into numerous little frames.
- Genre classification: The pre-processed audio files are thoroughly analyzed by this module, which uses trained models to categorize the audio file according to its genre. Model inference, feature extraction, and genre categorization are a few of the crucial elements that make up its functionality. The feature extraction component collects mid, high- and low-level features from the music file. Finally, the genre classification component sorts the files into distinct genres using the extracted attributes. Together, these components create an effective music genre classification system.
- User Interaction: The User Interface Module is crucial to the project since it provides a flexible and user- friendly web-based interface for smooth user interaction. This module consists of a wide range of elements designed to show users the user interface, make it easier to manage user input, and reveal the results of the genre classification.

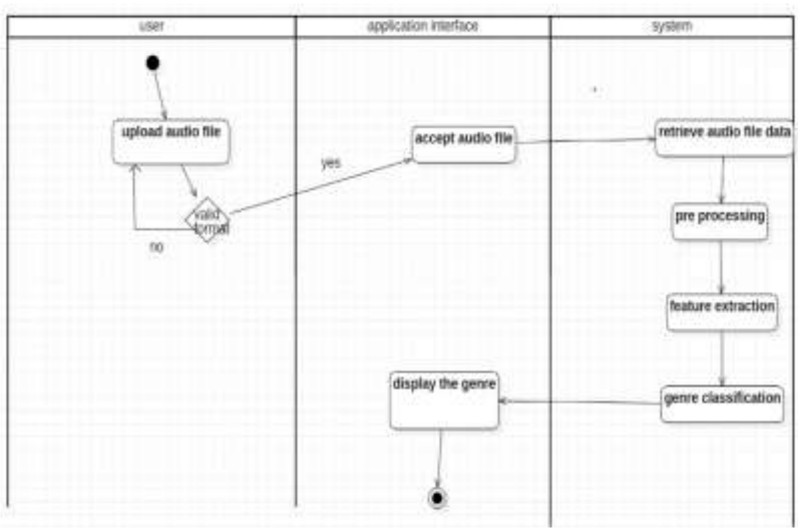

Figure 1. flow diagram

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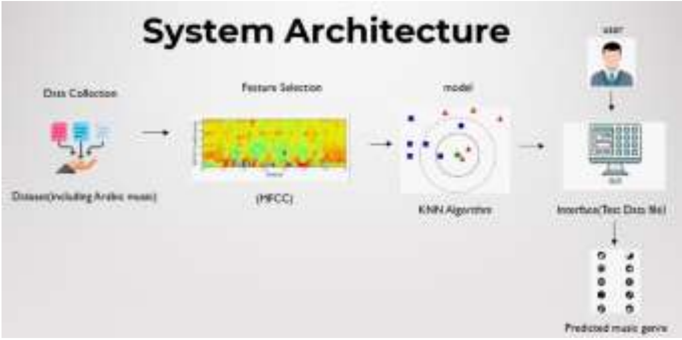

Figure 2. Architecture

A. *Dataset Description:*

The dataset used is a hybrid dataset that is primarily based on the GTZAN dataset. The novelty is the combination of the GTZAN dataset containing 10 genres with a new genre of Arabic music to make the hybrid dataset that is used in the project.

Pre-Processing:

Preprocessing modules removing duplicates, corrupt files, dealing with missing values, normalization, data type conversion.

B. ***Classifiers:***

KNN Classifier:

K-Nearest Neighbors (KNN) is a versatile machine learning algorithm used for both classification and regression tasks. It operates based on the principle of similarity in a feature space, making predictions by identifying the K nearest neighbors to a new data point. The choice of K, the number of neighbors to consider, is a critical hyperparameter that influences the algorithm's performance. KNN relies on distance metrics, such as Euclidean distance, to quantify the similarity between data points. It is well-suited for problems with complex, non-linear decision boundaries and can handle irregular patterns effectively. However, KNN can be computationally intensive for large datasets, and careful feature selection, normalization, and hyperparameter tuning are essential for optimal results. Its instance-based learning approach, lack of a distinct training phase, and robustness to outliers are among its notable features, making it a valuable tool in various machine learning applications, including text classification, recommendation systems, anomaly detection.K-Nearest Neighbors (KNN) stands out for music genre classification due to its simplicity, adaptability, and transparency. Its straightforward implementation and interpretability make it an excellent choice, particularly for those new to machine learning. KNN's ability to adapt to changing music trends, without necessitating a full model retraining, is invaluable in an ever-evolving industry. The absence of an extensive training phase and the quick classification of new music pieces make it suitable for real-time applications. Additionally, KNN's robustness to outliers and effectiveness with small datasets, common in music genre classification, contribute to its appeal. It can also handle multiclass problems often encountered in this task. However, it's essential to consider the choice of distance metric, the number of neighbors, and feature quality to harness KNN's full potential effectively. While other complex algorithms exist, KNN's versatility and ease of use make it a compelling choice for specific music genre classification scenarios.

C. Modules and Techniques Incorporated:

Feature Extraction: The process starts with extracting relevant features from the music audio. These features can include tempo, rhythm, spectral characteristics, harmonic content, and more. Feature extraction techniques like Mel-Frequency Cepstral Coefficients (MFCCs), Chroma features, and spectral contrast are commonly used. Feature selection and dimensionality reduction techniques may also be applied to improve model efficiency.

Dataset Preparation: A dataset of labeled music samples is crucial for training and testing the KNN model. The dataset should contain audio tracks with corresponding genre labels. It's important to maintain a balanced distribution of genres to ensure fair classification.

Data Preprocessing: Data preprocessing steps may involve standardization (scaling features to have a mean of 0 and a standard deviation of 1), normalization (scaling features to a specific range), or other techniques to prepare the data for KNN's distance calculations.

KNN Model Configuration: Configuring the KNN model involves selecting the value of K (the number of nearest neighbors to consider). The choice of distance metric, such as Euclidean distance, Manhattan distance, or others, is also an essential configuration step. Experimentation is often required to determine the optimal K and distance metric for the specific dataset.

Training: In the training phase, the KNN model stores the features and genre labels of the music tracks in the training dataset. As KNN is an instance-based learning algorithm, no model parameters are learned during this phase.

Testing and Classification: The testing phase involves taking new, unlabeled music samples and applying the KNN algorithm to classify them into predefined genres. KNN

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calculates the distances between the feature vectors of the new sample and those in the training set. The K nearest neighbors are selected based on these distances, and the majority genre among these neighbors is assigned to the new sample as its predicted genre. Evaluation: Model performance is assessed using various evaluation metrics, such as accuracy, precision, recall, F1-score, and confusion matrices, on a separate validation or test dataset. This step helps determine how well the KNN model classifies music genres.

Applications:

i. Healthcare: KNN is used in healthcare for patient classification, diagnosis, and treatment recommendations. For instance, it can help identify similar patient profiles for personalized treatment plans.

ii. Recommendation Systems: KNN plays a vital role in recommendation engines for e-commerce and streaming services. It suggests products, movies, or music based on user similarity to others with similar preferences.

iii. Anomaly Detection: KNN is employed in cybersecurity to detect anomalies and intrusions in network traffic by identifying patterns deviating from the norm.

Limitations of Model:

i. The input music file must be in .wav format only.

ii. The input file has to be around 30 seconds long for accurate classification.

iii. Performance Variability: The performance of KNN can be variable, and it may not consistently outperform other algorithms for music genre classification. The choice of distance metric, K value, and other parameters can significantly impact results.

Imbalanced Datasets: In music genre classification, datasets are often imbalanced, meaning some genres have significantly more samples than others. KNN might be biased toward the majority class, making it less accurate for underrepresented genres.

IV. RESULTS

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Figure. 3. User Interface

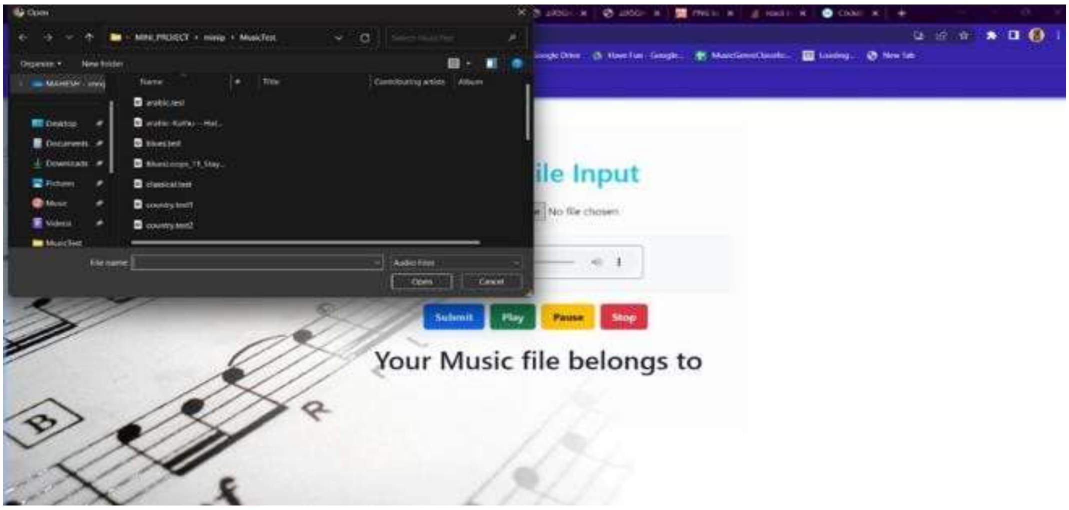

Figure. 4. File upload module

Figure.5. Arabic genre classification

CONCLUSION

The Music genre classification using K-Nearest Neighbors (KNN) has proven to be an effective approach, demonstrating the model's ability to discern similarities between different genres based on their feature vectors. By calculating the distance between data points and their nearest neighbors, KNN effectively categorizes music genres with a reasonable level of accuracy. However, its performance heavily relies on the appropriate choice of distance metric and the optimal value of K. While KNN serves as a simple and intuitive method for music classification, its effectiveness can be enhanced by integrating more sophisticated techniques, such as feature engineering and dimensionality reduction, to improve accuracy and efficiency. Despite its limitations, KNN remains a valuable tool for preliminary music genre classification tasks.

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