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Music Genre Classification using Deep Learning

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Abstract: ***Many subjects are affected by digital music production., including music genre prediction. Machine learning techniques were used to classify music genres in this research. Deep neural networks (DNN) have recently been demonstrated to be effective in a variety of classification tasks. Including music genre classification. In this paper, we propose two methods for boosting music genre classification with convolutional neural networks: 1) using a process inspired by residual learning to combine peak- and average pooling to provide more statistical information to higher level neural networks; and 2) To bypass one or more layers, use shortcut connections. To perform classification, the KNN output is fed into another deep neural network. Our preliminary experimental results on the GTZAN data set show that the above two methods, especially the second one, can effectively improve classification accuracy when compared to two different network topologies.***

I. INTRODUCTION

With day-by-day increasing internet penetration, huge amount of useful data is available at proximity to people. Although it seems that there is ease of access to data, but this exponentially increasing amount of data brings to table a new problem – most of this chunk is unclassified. We will create a deep learning project to automatically distinguish various musical genres from audio files in this project. We'll categorise these audio files based on their low-level frequency and time domain characteristics. We'll need a dataset of audio tracks of identical lengths and frequency ranges for this project. The KNN classification dataset is the most commonly recommended dataset for music genre classification projects, and it was collected specifically for this purpose. With the rise in popularity of personal multimedia devices in recent years, a vast amount of music has become available on a variety of platforms. Humans are finding it difficult to structure and organize such a vast volume of music. One of the current methods for structuring music content is genre grouping. To allow automated structuring and organizing of large music archives, an efficient and precise music genre classification system is urgently required. The musical genre is a kind of high-level mark. The standard phase of an automated genre classification system consists of three steps as a classification problem: 1) From the original audio signal, timbre, Spectro temporal, and statistical features are extracted; 2) To increase classification accuracy, several techniques are used to pick a meaningful subset of features or aggregate features.3) To automatically classify the input music into different genres, a machine learning-based classifier is trained over the selected features. Finding appropriate representations or features for the system is a critical component of its performance. Extraction of hand-crafted features from the original songs is a popular way to do this. This method necessitates technical know-how as well as engineering creativity. Neural net-works have become very successful in a variety of fields, including retrieving musical knowledge, thanks to the advancement of deep learning (MIR). With convolutional neural networks, we suggest two ways to increase the accuracy of music genre classification.:1) combining peak and average pooling to provide further statistical information to higher-level neural networks using a technique influenced by residual learning; 2) Bypassing one or even more layers with shortcut connections.

II. LITERATURE SURVEY

Hareesh Bahuleyan's novel Haree (2018). Using Machine Learning techniques, the researchers developed a method for automatically identifying music in a user's collection by assigning tags to the songs in their collection. In order to accomplish their goals, it explores both Neural Networks and traditional Machine Learning algorithms. The first approach uses a Convolutional Neural Network that is trained from beginning to end using audio signal Spectrogram features (images).

To classify the music into its genres, the second approach employs a range of Machine Learning techniques. Random Forest, Logistic Regression, Gradient Boosting (XGB), and Support Vector Machines are some of the ML algorithms that are used (SVM). After examining both approaches separately, they discovered that the VGG-16 CNN model had the best accuracy. A VGG-16 CNN and XGB ensemble classifier were used to create the optimized model, which had an accuracy of 0.894.

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Tzanetakis and colleagues (Tzanetakis et al., Tzanet (2002).They have looked at how to automatically classify audio signals into musical genres. They agree that these music genres are just human-made categorical labels used to group together pieces of music. Some general characteristics are used to classify them. All of these features are influenced by the instruments used, the rhythmic structures, and, most significantly, the harmonic nature of the music. To organize incredibly large online music collections, genre hierarchies are often used. They've proposed three different feature sets: timbral texture, rhythmic material, and pitch content. Researchers were able to examine proposed features in order to analyze their performance and relative significance by training statistical pattern recognition classifiers using real-world audio collections. In this paper, we look at both whole-file and real-time frame-based classification schemes. This model correctly classifies nearly 61 percent of ten music genres using the proposed feature sets.

Lu, L.et al., (2002).They presented their research on audio content segmentation and classification in content review for audio segmentation and classification. The type of audio or the speaker's identity are used to separate an audio stream into parts. Their plan is to build a robust model that can distinguish and segment audio signals into speech, music, ambient sound, and silence. This two-part grouping can be used for a number of purposes. The first move is to separate speech from non-speech discrimination. This paper introduces a new algorithm based on KNN (K-nearest-neighbor) and LSP-VQ (linear spectral pairs-vector quantization). After that, using a rule-based classification system, the non-speech class is divided into three categories: music, environmental sounds, and silence. They've used some unusual and innovative features, such as noise frame ratio and band periodicity, which are not only introduced but also thoroughly discussed. Also included and developed is a speaker segmentation algorithm. This is going on without any kind of oversight. It makes use of a new correlation analysis approach that combines quasi-GMM and LSP correlation analysis. The model will aid open-set speakers, online speaker modelling, and real-time segmentation without the need for any prior information.

Tom LH Li et al (2010). They've also created a speaker segmentation algorithm and used a convolutional neural network to extract musical pattern features automatically. This is a condition that is totally unsupervised. It uses a one-of-a-kind approach that combines quasi-GMM and LSP correlation analysis. Without any prior experience, the model can handle open-set speakers, online speaker modelling, and real-time segmentation. Audio clip-derived statistical spectral characteristics, rhythm, and pitch are less reliable, resulting in less accurate models. As a result, they took a different approach to CNN, focusing on musical data that is similar to image data and requires very little prior knowledge. The dataset in question was GTZAN. In total, there are ten genres with 100 audio clips in each. Each audio clip is 30 seconds long, with a 22050 Hz sampling rate and 16-bit resolution. When analyzing musical patterns with the WEKA system, several classification models were taken into account. At first, the classifier's accuracy was 84 percent, but it gradually improved. The CNN features were more reliable and generated better results than the MFCC, chroma, and temp features. The accuracy of parallel computation on different combinations of genres can also be improved.

Convolutional Neural Networks Improved Music Genre Classification, Weibin Zhang (2016) proposed two methods for boosting m usic genre classification with convolutional neural networks: 1) combining peak- and average pooling to provide more statistical knowledge to higher level neural networks using a method influenced by residual learning; 2) using shortcut connections to bypass one or more .The CNN's production is fed into a classification deep neural network. Our preliminary findings are based on a comparison of two network typologies. Our preliminary experimental results on the GTZAN data set, which compare two different network typologies, show that the above two methods, especially the second, can effectively improve classification accuracy.

Andreas Rauber and Thomas Lidy, they presented “Evaluation of feature Extractors, Psycho-Acoustic transformation for music genre classification,” a study on the importance of psycho-acoustic transformations for effective audio feature estimation. Rresults show which parts of the algorithm for Rhythm Patterns function extraction are critical and which parts are problematic. We introduce two new function representations in this context: Statistical Spectrum Descriptors and Rhythm Histogram functions. A music genre classification task, involving three reference audio collections, is used to evaluate both the individual and combined feature sets. On the same data sets, the findings are compared to previously reported steps. Psycho-acoustic transformations significantly increase classification accuracy in all environments, according to experiments.

M. Julia Flores, Jaime Ramirez The paper focuses on emerging machine learning developments as they apply to the issue of music annotation. They have a music genre classification experiment that uses an Audio collection to compare various machine learning models. This paper adds to the domain of music genre classification (MGC) by offering an up-to-date analysis of recent research from a variety of perspectives. A deep fully-connected neural network was used to create the Audio set baseline audio event multi-label classifier. The reference metric for standardized audio event classification with Audio set provided by Google is a mean AP of 0.314 and an average AUC of 0.959, with the top performing class music having an AP of 0.896 and AUC of 0.951 and the worst performing class "Rattle" having an AP of 0.020 and AUC of 0.796.

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They focused on supervised learning in the context of music classification for the purpose of this article. Ssupervised learning builds a theory based about how each sample's inputs relate to the related predicted output in order to accurately predict the output of new inputs.

Amelie Anglade, Rafael Ramirez, and Simon Dixon are among the artists who have contributed to this collection (2009). HARMONY RULES DERIVED FROM AUTOMATIC CHORD TRANSCRIPTIONS WERE USED FOR GENRE CLASSIFICATION. They demonstrated in this paper that our genre classification system, which is focused on harmony and first-order logic and has previously been tested on symbolic data, can learn classification models directly from audio data with classification accuracy well above chance level. Even when working with audio details, we can use a chord transcription algorithm to follow a high level representation of harmony. As a result of this high-level representation of harmony based on first-order logic, classification models that are human-readable, i.e. transparent, are possible. We improved clarity by implementing a new harmony representation scheme based on the western harmony representation, which defines chords in terms of degrees and chord categories. Not only is this representation musically more meaningful than the previous one we used, but it also yielded better classification results and enabled us to construct classification models faster.

In Alessandro L. Koerich, Carlos N. Silla Jr and Celso A. A. Kaestner (2008). AUTOMATIC MUSIC GENRE CLASSIFICATION USING A MACHINE LEARNING APPROACH. This paper presents a novel method for automatically classifying music genres. In the proposed solution, which is based on time and space degradation schemes, many feature vectors and a pattern recognition ensemble approach are being used. Regardless of the fact that categorizing music genres is a multi-class task, we solve it by combining the results of a collection of binary classifiers (space decomposition). Decomposition of the music samples is also done using the time segments extracted from the start, center, and ending portions of the original music signal(time-decomposition). To get the final classification from the collection of individual outcomes, a hybrid technique is used. Some of the really common machine learning algorithms include Nave-Bayes, Decision Trees, k Nearest-Neighbours, Support Vector Machines, and Multilayer Perceptron Neural Nets. The Latin Music Database, which contains 3,160 music parts split into ten musical genres, was used in the experiments. As per the results of the experiments, the proposed ensemble approach outperforms global and individual segment classifiers in the vast majority of cases. In addition, using the genetic algorithm model, some feature selection experiments were carried out. They show that the most significant features for classification differ depending on where they came from in the music signal.

III. THE METHODOLOGY

This section explains how we built this music genre classifier, which consists of three main measures. -

A. Data Preparation

Before diving right into feature analysis and classification, one needs to have an appropriate format of analyzable data. The GTZAN data-set has data in the ".au" format.

B. Extraction and Selection of Features

Any audio signal is made up of a variety of features. We must, however, remove the characteristics that are pertinent to the problem we are attempting to solve. Feature extraction is the procedure for extracting features in order to use them in research. The Mel frequency of a signal MFCCs are a small set of features (usually 10–20) that describe the overall shape of a spectral envelope in a concise manner. It is focused on the features of human vocalizations. Feature extraction is a dimensionality reduction technique that breaks down a large volume of raw data into manageable chunks. These large data sets often have a large number of variables. The large number of variables in these large data sets necessitates a lot of computational resources to process.

C. Categorization

Finally, our main goal is to identify the information provided. Audio dataset based on genre was accomplished by the classifier method been there.

We applied two most famous classifiers and found the best which helped us solve our problem. The two classifiers were

1) *KNNC (K-nearest neighbor classifier).*
2) *SVM (Support Vector Machine).*

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a) *KNNC:* k-Means is a term used to describe a group of people who Clustering is an unsupervised clustering algorithm, while KNN is a supervised classification algorithm. We ran the KNN algorithm several times with various K values to find the K that reduces the number of errors while maintaining the algorithm's ability to make accurate predictions when given data it hasn't seen before.

A few things to keep in mind:

- As K approaches zero, our predictions become less stable. Consider the situation where K=1 and the question point is surrounded by several reds and one green (I'm thinking of the top left corner of the colored plot above), but the green is the only one who is close to it. The query point should be red, but since K=1, KNN predicts it will be green.
- However, as we raise the value of K, our predictions become more stable, and therefore more likely to be accurate, due to majority voting/averaging (up to a certain point). The number of errors slowly starts to rise. At this point, we know we've shifted K's value too far.
- In cases where we take a majority vote among brands, we usually make K an odd number to have a tiebreaker (e.g. choosing the mode in a classification problem).

b) *SVM:* The formal description of an SVM (Support Vector Machine) is a discriminative classifier with a separating hyperplane. To put it another way, the algorithm produces an optimal hyper plane that categorizes new examples given labelled training data (supervised learning). In order to differentiate the two types of data points, we must select one of many hyper planes. Our goal is to find the plane with the greatest margin, or the greatest distance between data points from both classes. By increasing the margin difference, it becomes easier to distinguish possible data points. The position and orientation of the hyper plane are affected by support vectors, which are data points that are closer to the hyper plane. These help vectors are used to optimize the margin of the classifier. The path of the hyper plane would be changed if the support vectors were removed. These are the factors that will influence the development of our SVM. They have two key advantages over newer algorithms such as neural networks: they are faster and perform better with fewer samples (in the thousands). This makes the algorithm ideal for music genre classification problems, where a dataset of just a few thousand labelled samples is typically available.

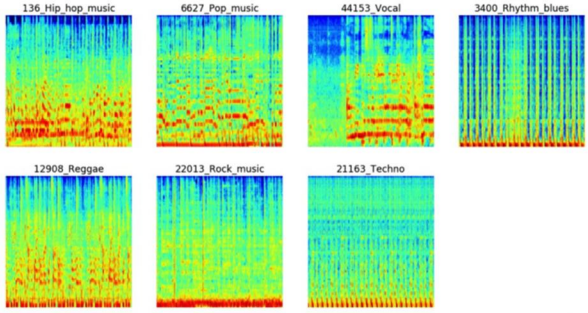


Figure 1: Spectrograms for audio signal.

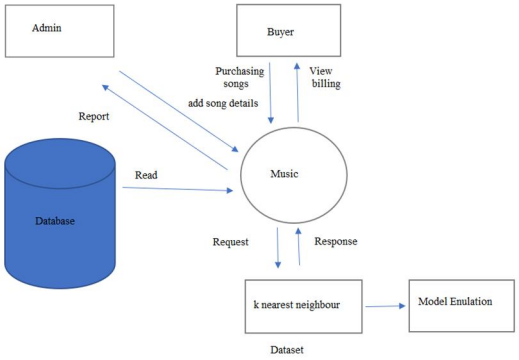


Figure 2: Aarchitectural Design

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IV. IMPLEMENTATION

In short, the supervised machine learning algorithm K-nearest neighbors is a technique which classifies a data point by calculating the distance between k labelled data points. The number of votes it gets from the k-nearest data points is used to calculate it. The user can get details about different songs using this restriction scheme. To use our framework, a user must first create an account. The server administrator will be in charge of adding, removing, and updating the song dataset. The system's administrator is in charge of overseeing its operation, after which the user can send the different songs to the system which he would want to know.
We make use of a protocol that is followed step-by-step from recording songs to giving the final data of the song asked by the user. Each step has its different use in our system.

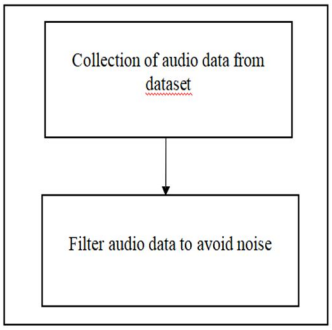


Figure 5.1 Steps in Pre- Processing

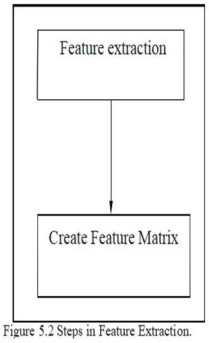


Figure 5.2 Steps in Feature Extraction.

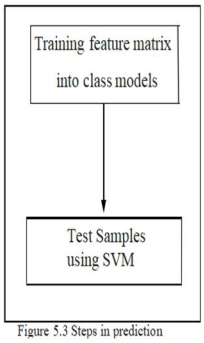


Figure 5.3 Steps in prediction

1) Pre- Processing is where we convert the data based on our need. Unwanted noise, blank spaces are removed in this step.
2) The most commonly used features for describing the spectrum of an audio recording in a concise and insightful manner are feature extraction and after which this data is stored in a matrix format for further use. For this purpose we make us of Librosa package of python. This contains many APIs that will help in fetching the features.
3) A function is an observable property or attribute of an observed phenomenon. Feature extraction begins with a feature which are intended to be descriptive and non-redundant array of calculated data and constructs, easing the learning and generalisation steps and, in some cases, resulting in better interpretations made by humans. SVM is used to analyze samples at a later date.

A. (SVM)Support Vector Machine

Pattern classification is normally dealt with by a support vector machine. Linear and non-linear patterns are two types of patterns. Linear patterns are patterns that are easily distinguishable or can be easily distinguished in low dimensions, whereas nonlinear patterns are patterns that are difficult to distinguish or cannot be easily separated, necessitating further investigation They've been exploited to make it simple to divide them. SVM's key concept is to construct an optimal hyper plane for linearly separable patterns that can be used for classification. The most suitable hyperplane for classifying patterns is the one that maximizes hyper plane's margin, i.e. The distance between the hyper plane and each pattern's closest point SVM's main goal is to optimize the margin so that it can correctly classify the given patterns; the greater the margin size, the more accurately it can classify the patterns.

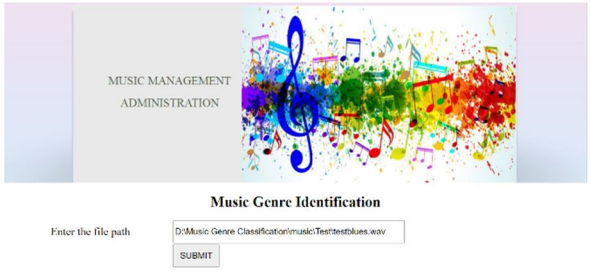
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1) Step 1: Imports
2) Step 2: Create a function to locate neighbors and calculate the distance between feature vectors.
3) Step 3: Determine who your immediate neighbors are.
4) Step 4: Make a model evaluation function.
5) Step 5: Extract features from the dataset and save them as a binary.dat file called “my.dat.”
6) Step 6: On the dataset, there is a train and test break.
7) Step 7: Make a forecast with KNN and see how accurate it is on real-world results.

Prediction is a phase where we test a single audio file against our trained dataset. Input audio file undergoes pre-processing and feature extraction process. Weight file is created. Compare model weights with input audio features. Obtained output (song name) is displayed in web application with few additional features of song.

V. RESULTS

The k-nearest neighbor (KNN) classification algorithm is a non-parametric classification that ballots the "k" nearest training points to a given test point and analyses the test point depending on their majority of votes. The KNN algorithm works well enough with data that is expressed by a series of dense clusters, each represents a distinct label. This algorithm, however, is easy to implement, it is vulnerable to inputs with a large number of dimensions. This section represents the result of our project. We have included few images of our system which are obtained using machine learning techniques like pre-processing, feature extraction and SVM.





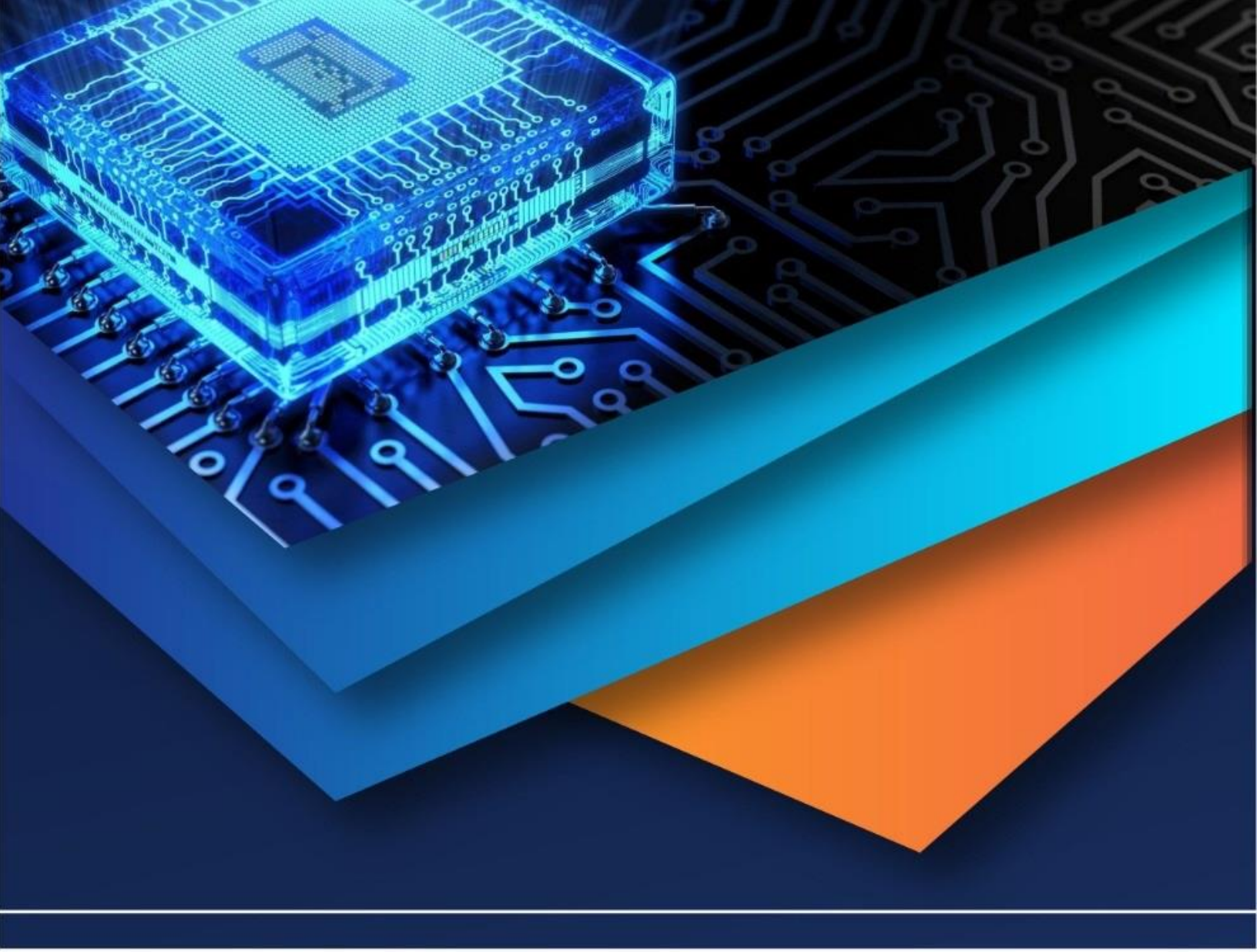
VI. CONCLUSION

Music genre classification is studied using the Free Music Archive small (fma_small) dataset. We proposed a simple approach to solving the classification problem and we drew comparisons with multiple other complex, robust models. We also compared the models based on the kind of input it was receiving. Two kinds of inputs were given to the models: Spectrogram images for CNN models and audio features stored in a csv for Logistic Regression and ANN model. Simple ANN was determined to be the best feature based classifier amongst Logistic Regression and ANN models with a test accuracy of 64%. CNN model was determined to be the best spectrogram-based model amongst CNN, CRNN and CNN-RNN parallel models, with an accuracy of 88.5%. CRNN and CNN-RNN models are expected to perform well if the dataset is increased. Overall, image based classification is seen to be performing better than feature based classification.

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