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WEB-BASED MUSIC GENRE CLASSIFICATION FOR TIMELINE SONG VISUALIZATION AND ANALYSIS

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ABSTRACT

This paper presents a web application that retrieves songs from YouTube and classifies them into music genres. The tool explained in this study is based on models trained using the musical collection data from Audioset. For this purpose, we have used classifiers from distinct Machine Learning paradigms: Probabilistic Graphical Models (Naive Bayes), Feed-forward and Recurrent Neural Networks and Support Vector Machines (SVMs). All these models were trained in a multi-label classification scenario. Because genres may vary along a song's timeline, we perform classification in chunks of ten seconds. This capability is enabled by Audioset, which offers 10-second samples. The visualization output presents this temporal information in real time, synced with the music video being played, presenting classification results in stacked area charts, where scores for the top-10 labels obtained per chunk are shown. We briey explain the theoretical and scientific basis of the problem and the proposed classifiers. Subsequently, we show how the application works in practice, using three distinct songs as cases of study, which are then analyzed and compared with online categorizations to discuss models performance and music genre classification challenges.

Keywords: Password, graphical, high security.

I.INTRODUCTION:

Research in Music Information Retrieval (MIR) [1] comprises a broad range of topics including genre classification, recommendation, discovery and visualization. In short, this research line refers to knowledge discovery from music and involves its processing, study and analysis. When combined with Machine Learning techniques, we typically try to learn models able to emulate human abilities or tasks, which, if automated, can be helpful for the nal user. Computational algorithms and models have even been applied for music generation and composition [

Music genre classification (MGC) is a discipline of the music annotation domain that has recently received attention from the MIR research community, especially since the seminal study of Tzanetakis and Cook [5]. The main objective in MGC is to classify a musical piece into one or more musical genres. As simple as it sounds, the Feld still presents challenges related to the lack of standardization and vague genre definitions. Public databases and anthologies do not usually agree on how each genre is dened. Moreover, human music perception, subject to opinions and personal experiences, makes this agreement even more difficult. For example, when a song includes swing rhythms, piano, trumpets and improvisation, we would probably define it as jazz music. However, if we introduce synthesizers in the same song, should the song be classied as electronic music as well? If we only consider acoustic characteristics, the answer is probably yes. But different listeners can perceive the piece from their own perspective. Whereas some might categorize the song as jazz, others might consider it electronic music or even a combination of both.

In an effort to provide a tool that gives more insights about how each genre is perceived, we have trained several classi- cation models [6] and embedded them in a web application that allows the user to visualize how each model ``senses" music in terms of music genre, at particular moments of a song. Note that experimentation details for each model are beyond the scope of this article and can be found in [6]. These models have been built using common machine learning techniques, namely, Support Vector Machines (SVM), Naive Bayes classifiers, Feed forward deep neural networks and Recurrent neural networks. Whereas Bayesian and SVM methods have historically delivered good results as general purpose machine learning models, the results achieved with deep learning techniques in arterial perception (arterial vision, speech recognition, natural language processing, among others) have delivered remarkable results, approaching human-like accuracy [7]. By comparing deep learning with more traditional machine learning techniques, we also aim to compare its performance for music genre classification.

II.MACHINE LEARNING FRAMEWORK

Machine Learning (ML) is an area of Computer Science that involves the application of Artificial Intelligence techniques to learn from data. In our case, we perform the task of supervised classification. Taking a set of songs as input, labeled by genre, we have learned different models. The songs are characterized by specific features and the labels will guide the learning process. In this case, one song can be labeled with multiple genres, and they are classified in excerpts, as we will explain later. So, the problem that we approach in this work is the annotation of music genres present in a music clip, with the purpose of comparing the performance of different machine learning models when applied to this specific problem. To this end, we use the Audio set repository and its music genre samples to train the following set of models.

III.LITERATURE SURVEY

1.music information retrieval

Authors: Roberto Raieli, in Multimedia Information Retrieval, 2013

The status of AR systems is covered in the Survey of Music Information Retrieval systems, presented at the Sixth International Conference on Music Information Retrieval in 2005.27 In illustrating a summary of 'Music Information Retrieval (MIR)', a distinction is made between the content-based search systems of general 'audio data' and search systems for 'music based on the notes'. Alongside these are the 'hybrid' systems, which in the early treatment of any type of audio data were converted into a symbolic version of the notes.

2.The bach doodle: Approachable music composition with machine learning at scale

Authors: Cheng-Zhi Anna Huang, Curtis Hawthorne, Adam Roberts, Monica Dinculescu, James Wexler, Leon Hong, Jacob Howcroft

To make music composition more approachable, we designed the first AI-powered Google Doodle, the Bach Doodle, where users can create their own melody and have it harmonized by a machine learning model Coconet (Huang et al., 2017) in the style of Bach. For users to input melodies, we designed a simplified sheet-music based interface. To support an interactive experience at scale, we re-implemented Coconet in TensorFlow.js (Smilkov et al., 2019) to run in the browser and reduced its runtime from 40s to 2s by adopting dilated depth-wise separable convolutions and fusing operations.

3.Deep learning techniques for music generation A survey

Authors: Jean-Pierre Briot, Gaëtan Hadjeres, François-David Pachet

This paper is a survey and an analysis of different ways of using deep learning (deep artificial neural networks) to generate musical content. We propose a methodology based on five dimensions for our analysis: Objective - What musical content is to be generated? Examples are: melody, polyphony, accompaniment or counterpoint. - For what destination and for what use? To be performed by a human(s) (in the case of a musical score), or by a machine (in the case of an audio file). Representation - What are the concepts to be manipulated? Examples are: waveform, spectrogram, note, chord, meter and beat. Piano automatic computer composition by deep learning and blockchain technology

4.musical genre classification of audio signals

Musical genres are categorical labels created by humans to characterize pieces of music. A musical genre is characterized by the common characteristics shared by its members. These characteristics typically are related to the instrumentation, rhythmic structure, and harmonic content of the music. Genre hierarchies are commonly used to structure the large collections of music available on the Web. Currently musical genre annotation is performed manually. Automatic musical genre classification can assist or replace the human user in this process and would be a valuable addition to music information retrieval systems.

IV.EXICITING SYSTEM:

We have used classifiers from distinct Machine Learning paradigms: Probabilistic Graphical Models (Naive Bayes), Feed-forward and Recurrent Neural Networks and Support Vector Machines (SVMs). All these models were trained in a multi-label classification scenario. Because genres may vary along a song's timeline, we perform classification in chunks of ten seconds. This capability is enabled by Audio set, which offers 10-second samples. The visualization output presents this temporal information in real time, synced with the music video being played, presenting classification results in stacked area charts, where scores for the top-10 labels obtained per chunk are shown. We briey explain the theoretical and scientific basis of the problem and the proposed classifiers. Subsequently, we show how the application works in practice, using three distinct songs as cases of study, which are then analyzed and compared with online categorizations to discuss models performance and music genre classification challenges.

V.PROPOSED SYSTEM:

In this paper author is using various machine learning algorithms such as Linear SVM and Ensemble Decision Tree and have also experiment with deep learning algorithms such as Feed Forward Neural Networks and LSTM (long short term memory) to classify music genre (type of music like HIP HOP, JAZZ, Disco or etc. In all algorithms LSTM is giving better accuracy. To implement this project author has used YouTube dataset called AUDIODATASET and we are also using same dataset to implement this project.

VI.METHODOLOGY

MODULES:

1) User Login:

Using this module user can login to application and after login can train with SVM, LSTM and then classify music genre

2) New User Signup Here:

Using this module user can signup with the application and then can login

3) Train SVM:

Using this module we extract features from dataset using MFCC algorithm and this extracted features will get train with SVM and then will calculate accuracy, average precision, AUC and recall with confusion matrix graph. Here extracted features dataset will be split into train and test where 80% data used for training and 20% for testing

4) Train Decision Tree:

Using this module we extract features from dataset using MFCC algorithm and this extracted features will get train with Decision Tree and then will calculate accuracy, average precision, AUC and recall with confusion matrix graph. Here extracted features dataset will be split into train and test where 80% data used for training and 20% for testing

5) Train LSTM:

Using this module we extract features from dataset using MFCC algorithm and this extracted features will get train with LSTM and then will calculate accuracy, average precision, AUC and recall with confusion matrix graph. Here extracted features dataset will be split into train and test where 80% data used for training and 20% for testing

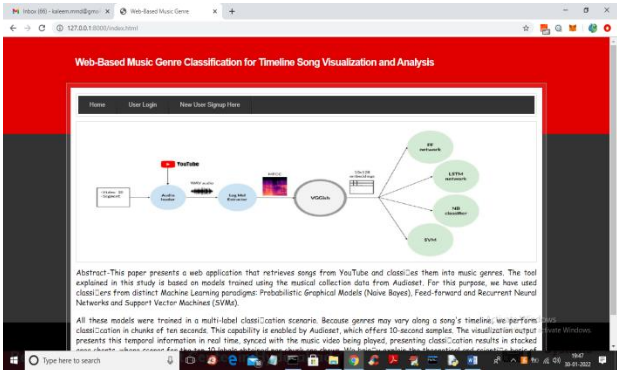
6) Train Feed Forward Network:

Using this module we extract features from dataset using MFCC algorithm and this extracted features will get train with Feed Forward Neural Network and then will calculate accuracy, average precision, AUC and recall with confusion matrix graph. Here extracted features dataset will be split into train and test where 80% data used for training and 20% for testing

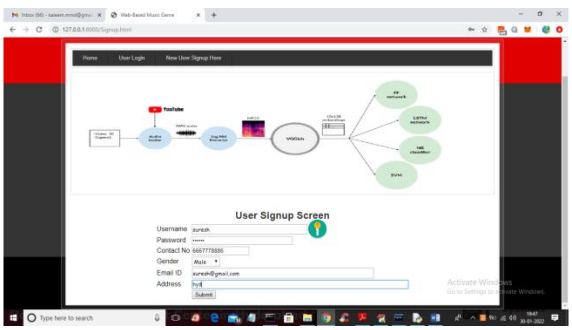
7) Music Genre Classification:

Using this module user can upload test audio files from ‘test Music Files’ folder and then LSTM will predict/classify type of that uploaded music Genre

VII.OPERATION:

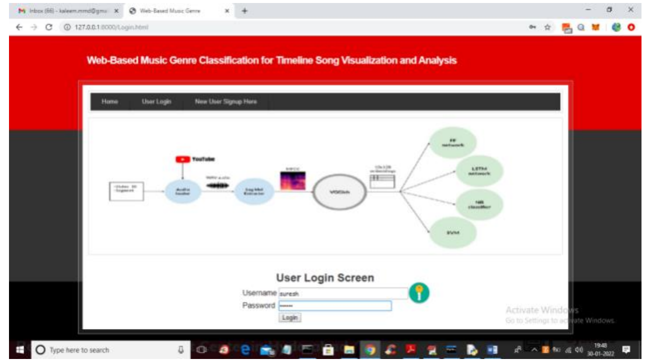


In above screen click on 'New User Signup Here' link to get below screen

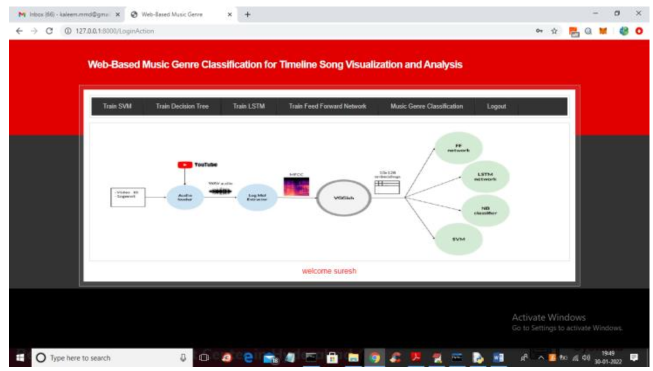


In above screen user is entering signup details and then click on 'Submit' button to get below screen

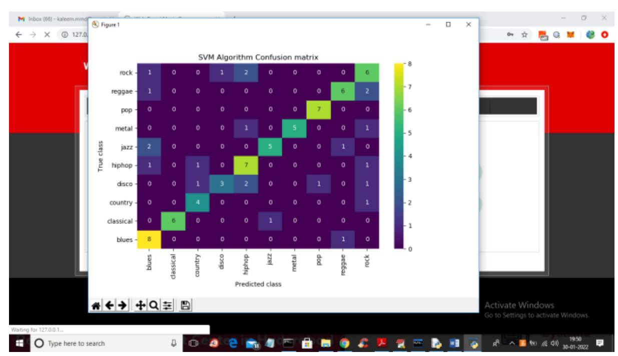
In above screen signup task completed and now click on 'User Login' link to get below login screen



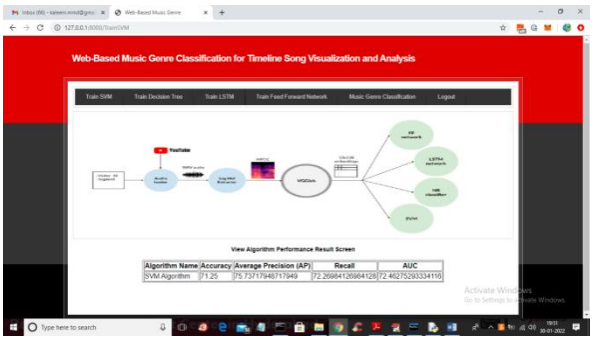
In above screen user is login and after login will get below screen



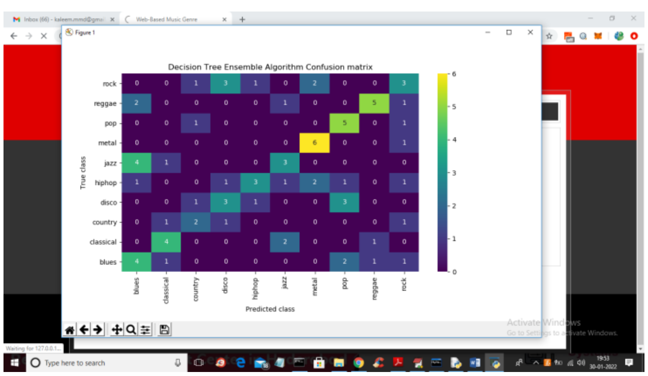
In above screen user can click on 'Train SVM' link to train SVM algorithm and get below classification result on test data using SVM



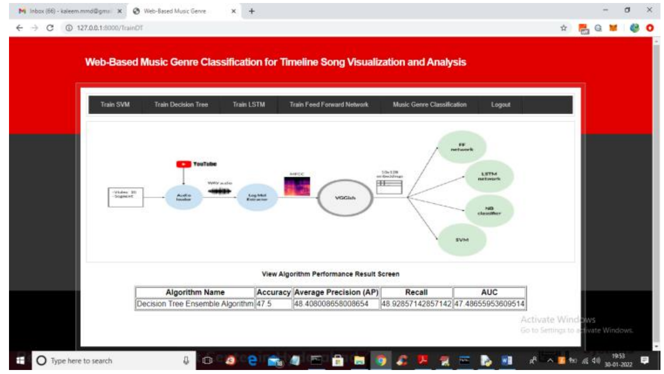
In above SVM confusion matrix graph x-axis represents predicted music genre classes and y-axis represented TRUE test classes and all values in horizontal part are correct prediction by SVM remaining values greater than 0 in other boxes are the wrong prediction and we can see SVM has predicted so many wrong classes and now close above graph to get below SVM precision value



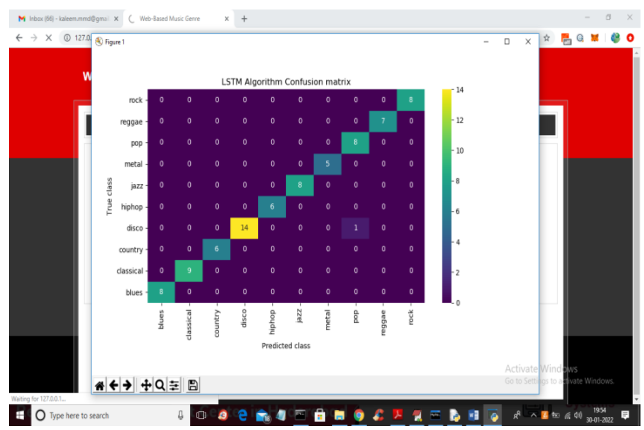
In above screen with SVM we got precision value as 75% and now click on 'Train Decision Tree' link to train decision algorithm and get below graph



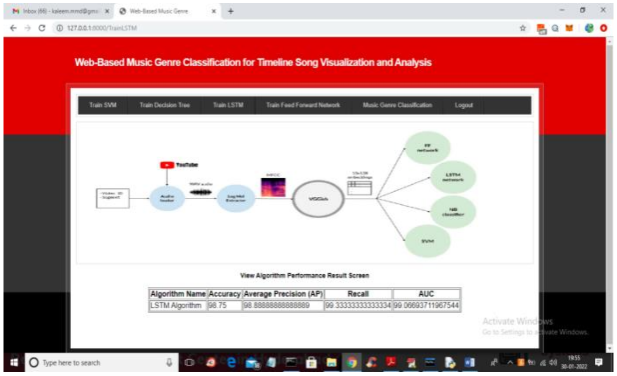
In above screen with decision tree also so many wrong classes are predicted and now close above graph to get decision tree precision



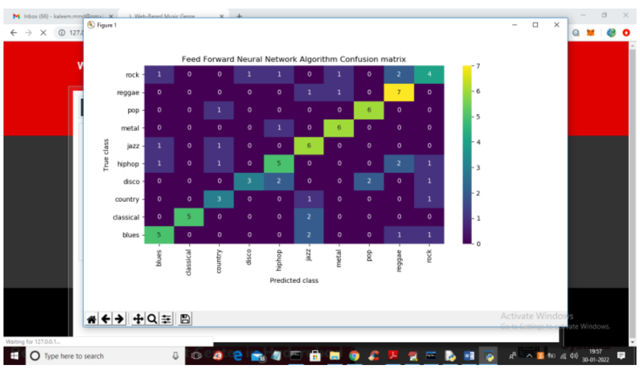
In above screen with decision tree algorithm we got 48% precision so its performance is not good and now click on 'Train LSTM' to train LSTM and get below output



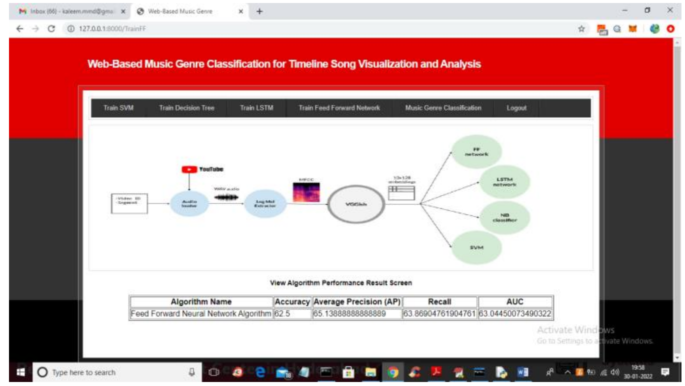
In above LSTM confusion matrix in diagnol boxes all classes are correctly predicted and only 1 class in other boxes is wrongly predicted so LSTM is good in performance and now close above graph to get below LSTM precision



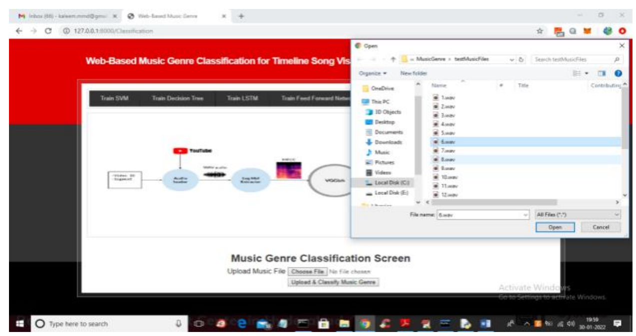
In above screen with LSTM we got 98% precision so its performance is best compare to other algorithm and now click on 'Train Feed Forward Network' link to get below output



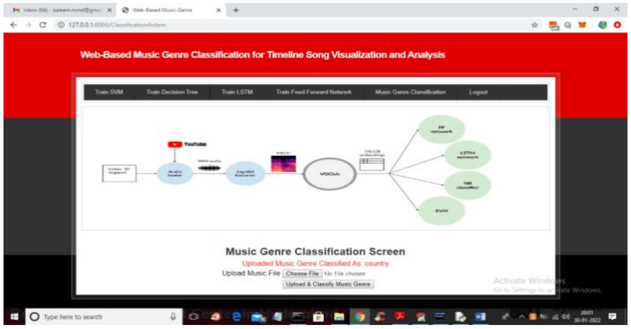
In above screen with feed forward neural network we can see in diagnol only few classes are correctly predicted so its performance also not good and now close above graph to get feed forward output



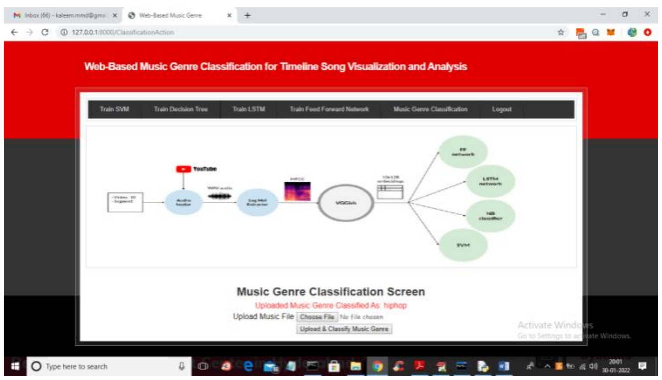
In above screen with Feed Forward we got precision as 65% and we can see in all algorithms LSTM got better performance and in paper also author saying LSTM is better in performance and now click on 'Music Genre Classification' link to get below screen



In above screen browsing and uploading '6.wav' file and then click on 'Open' button to load audio file and then click on 'Upload & Classify Music Genre' button so LSTM can predict or classify music Genre from uploaded audio like below screen



In above screen in red colour text we can see uploaded music genre classified as ‘Country’ and now test other files



In above screen another audio genre classified as ‘hiphop’ and similarly you can upload other files and classified them

VIII.CONCLUSION

The article presents a web application to discover music genres present in a song, along its timeline, based on a previous experimentation with different machine learning models [6]. By identifying genres in each 10-second fragment, we can get an idea of how each model perceives each part of a song. Moreover, by presenting those data in a stacked area timeline graph, the application is also able to quickly show the behavior of the models, which at the same time, is an interesting way to detect undesired or rare predictions.

We believe that this application could be a supporting tool for the traditional evaluation metrics in MGC, especially when manual introspection of questionable results is required beyond classic performance metrics, such as average precision or AUC.

It is, in any case, a challenge to establish a formal way to validate genre predictions, particularly when trying to compare them with categorizations from other sources, such as online music platforms, because there is no standard or formal way of defining genres. Last.fm, to name an example, has a completely different set of tags, which, in many cases, do not correspond or exist in the Audio set ontology.

The application is also a first step towards an eventual user-centered MGC tool, in which the users can submit feedback about the correctness of the predictions. To our knowledge, there is no visual tool that provides this level of verification on genre classification results for different fragments of the song.

The design of the precision/sensitivity metric, and its use for comparing the models' results, is an additional contribution of this paper. The incorporation of available tags from public and online services enabled the proposed evaluation method. We believe that the extension and tenement of these metrics and matching algorithms is a promising future line of work and deserves attention. As mentioned throughout the paper, a consensus for a standardized taxonomy for music genre categorization is an open challenge for MGC. We plan to open a research line approaching this issue, and we feel we should incorporate semantic elements and ontology-based information to properly tackle the genre-mapping problem across different taxonomies.

IX.REFERANCES

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