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RECOGNITION OF MUSICAL INSTRUMENT FROM AUDIO FILE

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ABSTRACT:- *The software involves a formal method of automatic ontology generation for web based audio signal processing application. Ontology is a set of concepts and category in audio file that shows their property and features. In this system various musical instrument from wind to string families are classified using timber features extracted from audio. To obtain models of the analyze instrument recordings k-means clustering is used to determine and optimize code book of line spectral frequencies (LSF) or met frequency spectral coefficient (MFCCs. To classification technique based on multi-layer perception(MLP) neural network and support vector machine (SVM)were tested. The input of software is music audio collection and output name of instrument with it's image.*

***Keywords** -Information Extraction, Data Mining, Bootstrapping, Ranking.*

I. INTRODUCTION

The entertainment industry has widely grown in recent years right form 1930s to till date. There are so many musical files that contain mixed songs as well solo instruments audios. There is always a need to sort these musical audios to particular category. The project aims to detect the musical instrument being played in the audio file. To detect the instrument correctly, the system uses data mining approaches. The system is made to work on these three algorithms. To evaluate the accuracy of each method, the musical instrument dataset is used where there are number of audio files for different instruments.

In machine learning, support vector machines (SVMs, also support vector networks) are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. Given a set of training examples, each marked as belonging to one or the other of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear (although methods such as Platt scaling exist to use SVM in a probabilistic classification setting). An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall. In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.

II. EXISTING SYSTEMS

There are many computational models such as Tuner-DaTuner, Tuner & Metronome etc. to detect musical instruments but they are not very accurate in identifying the instrument. The systems based on Formal Concept Analysis (FCA) and other well-known algorithms has been failed to perform the classification and prediction in musical instrument detection.

III. PROPOSED SYSTEM

The system takes audio file as an input. The audio file is parsed to get features of the audio. The features consist of many parameters that differ for all musical instruments. The system uses Small Vector Machine (SVM) for classification of the musical instrument being played in the audio. The standard dataset is used for testing the system. Dataset is collected from University of IOWA's Musical Instrument Samples (MIS) of different musical instruments. IOWA is a university where the dataset MIS is created.MIS dataset contains audio samples of various musical instruments.

A.SYSTEM ARCHITECTURE

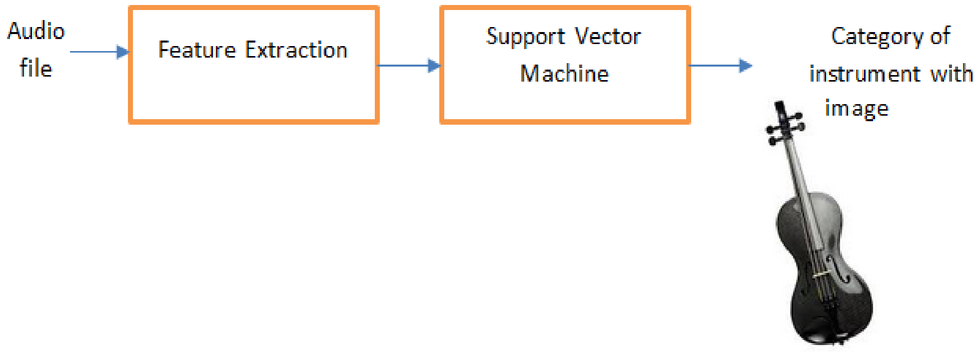

Fig.1 System Architecture

The system takes audio file as an input. The audio file consists of musical instrument played in the audio. The instruments may be, piano, flute, saxophone, violin, Tuba, oboe, etc. The audio file is parsed through a Java Library to get features of the audio. The features consist of many parameters that differ for all musical instruments. The features include: vibrating string, edge, vibrating air, etc. The system uses Support Vector Machine (SVM) for classification of the musical instrument being played in the audio. Support Vector Machine undergoes three main steps, training, testing and classification. SVM is considered as one of the best algorithm for classification. The standard dataset is used for testing the system. Dataset is collected from University of IOWA's Musical Instrument Samples (MIS) of different musical instruments.

IV. RELATED WORK

The aim of the proposed content-based automatic ontology generation system is to process information from audio files with a classification system and accurately extract the terminology related to musical instruments in order to analyze the conceptual structure and assist ontology engineers during the ontology construction process. Since the proposed system involves two different research areas, we will review both musical instrument identification and conceptual analysis studies.

A.MUSIC INSTRUMENT AND FAMILY IDENTIFICATION

To automate musical instrument identification, various approaches have been developed based on isolated notes, solo performances, or complex mixtures. The latter case is still in its early days. The results obtained depend on three main factors: the databases used during the learning and testing stages, the features selected to characterize the timbre of the instruments, and the classification methods.

The isolated note or solo performances present an advantage of simplicity and tractability, since there is no need to separate the sounds from different instruments. For example, Chétry et al. proposed a system based on Line Spectral Frequencies (LSF), which are derived from a linear predictive analysis of the signal and represent well the format structure of the spectral envelope. The instrument identification unit of our system is based on this model. K-means clustering is used to construct a collection of LSF feature vectors, called codebook (due to the use of LSF features in speech data compression). The principle of K-means clustering is to partition a n-dimensional space (here the feature space) into K distinct regions (or clusters), which are characterized by their centres (called codevectors). During the training stage, the K-means clustering is applied on the LSF feature vectors extracted fromseveral instrument recordings (isolated notes or solo performances). During the testing stage, the K-means clustering is applied on the LSF feature vectors extracted from the instrument recording to be identified. The collection of the K codevectors (LSF vectors) constitutes a codebook, whose function,within this context, is to capture the most relevant features to characterize the timbre of an audio signal segment. The classification decisions are made by finding which instrument minimizes the Euclidean distance between the LSF codebook associated with the audio sample to be predicted and the LSF codebook associated with the instrument (training stage). The system achieved 95% performance on a dataset comprising 4415 instrumental sound instances. In another study, Vincent and Rodent proposed a system based on Gaussian Mixture Models (GMM) which was trained and tested on isolated notes and solo recordings. The dataset was gathered by extracting 2 excerpts of 5 seconds from each of the 10 solo recordings used in the experiment. This approachyielded up to 90% of accuracy. Essid et al., proposed a system tested on a relatively large dataset. The same classification technique, GMM, was compared to Support Vector Machines (SVM) with different audio features. Their system obtained a 12% performance improvement compared to a system based on the SVM classifier, leading up to 87% of accuracy for 0.5 s-long audio segments. Furthermore, the performance of their system increased from 6% points up to 93% of accuracy, using SVM on 5 s-long audio segments. However, there are only a few studies where instrument recognition produces a hierarchical instrument structure. For example, Martin proposed a system which was based on three different hierarchical levels: 1) pizzicato (plucked) and sustained sounds, 2) instrument families such as strings, woodwinds, and brass 3) individual instruments for the corresponding instrument families. The recognition rate obtained with this system was

90% for instrument family and 70% for individual instruments, while the dataset consisted of 1023 solo tones samples from 15 instruments. Other hierarchical systems have been developed since then by Eronen, Kitahara et al. and Peeters. The overall correct identification rate of these systems are in the range of 35%to 80%for individual instruments, and 77% to 91% for instrument family recognition. In general, the problem with hierarchical classification systems is that the errors at each level propagate increasingly to the other levels of the hierarchy.

B.CONCEPTUAL ANALYSIS

Creating a class hierarchy is an important aspect of ontology design. Establishing such a hierarchy is a difficult task that is often accomplished without any clear guidance and tool support. Yet, the most commonly used hierarchical data mining techniques such as Hierarchical Agglomerative Clustering and Decision Trees do not take into account the relationships between objects. Therefore they do not provide an applicable solution to knowledge representation issues and the multi-relational hierarchical design of ontology systems. This problem becomes even more apparent considering the multi-relational nature of musical data. On the other hand, Formal Concept Analysis (FCA) allows to generate and visualise the hierarchies relying on the relationships of objects and attributes. FCA, also known as concept lattice, was first proposed by German mathematician Wille in 1982. It has been used in many software engineering topics such as the identification of objects in legacy code, or the identification and restructuring of schema in object-oriented databases. These works are important since ontologies provide the basis for information and database systems. Various specification techniques for hierarchical design in object-oriented software development have been proposed in. This study suggested alternative designs for FCA by not only utilizing attribute based categorizations but also using different levels of specification details (e.g., objects, attributes, methods) in order to obtain the class diagram of the software system. Furthermore, FCA has been used in conceptual knowledge discovery in collaborative tagging systems, and webmining studies in order to create adaptive web sites utilizing user access patterns extracted from Web logs. By offering a solution to bridge the gap between data and knowledge automatically, FCA has generated considerable research interest, recently one of the influential ideas of automatic ontology generation has been originally proposed by Maedche and Staad and can be described as the acquisition of a domain model from data. Other FCA-based systems have been developed since then by Cimiano, and Stumme. For instance, one crucial requirement in ontology learning is that the input data should represent the application domain very well.

V.REQUIREMENT ANALYSIS

Functional requirements for the system describe the functionality or services that should be provided by system functions in detail, its input and output expectation.

-Normal Requirements:

N1. Detect musical instruments

N2. Implement SVM algorithms

Expected Requirements:

Exp1. Attractive GUI design

Exp2. Correct identification of audio File.

-Exciting Requirements:

Ex1. Evaluate the system by using musical instrument dataset.

A. MINIMUM HARDWARE REQUIREMENTS

TABLE 1. MINIMUM HARDWARE REQUIREMENTS

Hardware	**Minimum Requirement**
Processor	Processor 2.0 GHz or above
Primary Memory	2GB or more
Secondary Memory	80GB or more
Internet Connection	Not Required
Other Hardware	Not Required

B.MINIMUM SOFTWARE REQUIREMENTS

TABLE 2. MINIMUM SOFTWARE REQUIREMENTS

Role	Software	Minimum Requirement
Development	**Platform (OS)**	Windows 8 or later
	Front End (Prog. Lang.)	Java 8
	Backend (DB)	MySQL 5.6
	Development Tool (IDE)	Netbeans 8.0.2
	Testing Tool	Manual
Deployment	**Execution Environment**	Windows 8 or later
	Browser	NA
	Server	NA
Documentation	**Documentation Tool**	Microsoft Office 2007 & Above
	Estimation Tool	SystemStar 3.0
Design	**UML Design**	StarUML
	DFD, ER, Flows	Edraw 6.1

VI. RESULT

We expect the following results from the system:

Accurate Detection of Musical Instrument: The foremost expectation form the system is to accurately detect musical instrument. The system must perform all the steps efficiently to get best results. The system is expected to identify around 20 different musical instruments namely, Flute, Saxophone, Clarinet, Tuba, Trombophone, Guitar, Piano, Violin, Viola, Trumpet, Vibraphone, Xylophone, Bass, Cello, Horn, Marimba, Oboe, Bass Flute, Bassoon, Alto Flute. The experiments will be performed on Musical Instruments dataset. This dataset contains different audio files for different instruments.

Correct Identification of audio file:
The audio file given input to the system must contain music only.

FIGURE 1:PROCEED

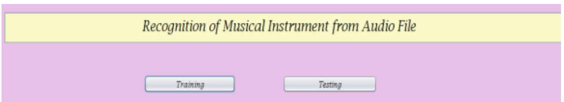

FIGURE 2: DECISIVE WINDOW

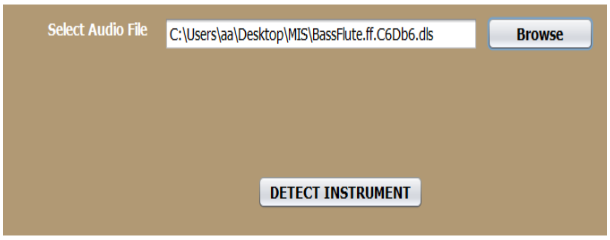

FIGURE 3:USER BROWSE AUDIO FILE FOR TRAINING

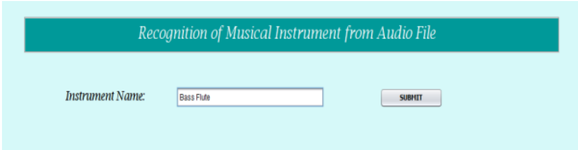

FIGURE 4:DISPLAY INSTRUMENT NAME

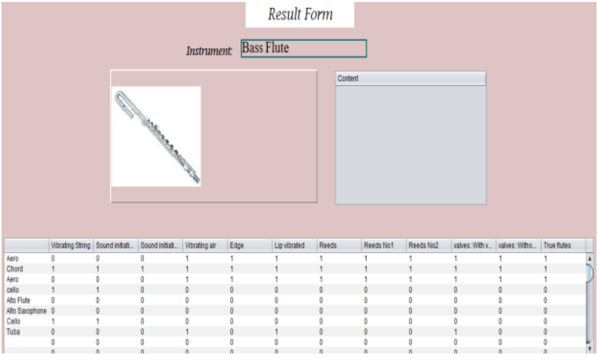

FIGURE 5:INSTRUMENT NAME WITH IMAGE AND FEATURES

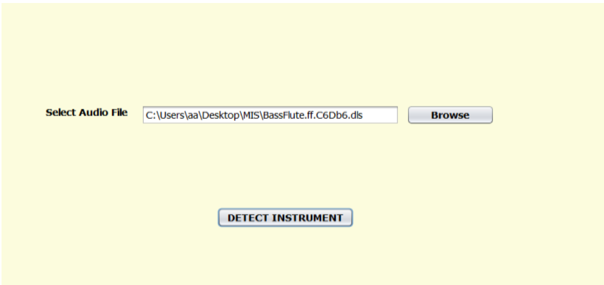

FIGURE 6:USER BROWSE AUDIO FILE

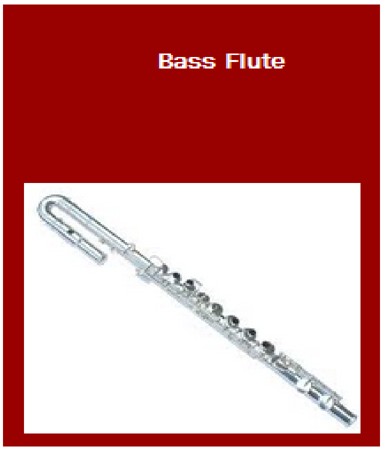

FIGURE 7:INSTRUMENT NAME DISPLAY WITH IMAGE

VII. CONCLUSION

The system is highly capable of detecting musical instruments of all kinds. Support Vector Machine is used for classifying the audio into different classes of instruments. The System accepts audio file as an input. Once the audio file is detected correctly, the system applies SVM on it. System then detects which category of musical instrument is played in audio. The system will be tested on MIS dataset having more than hundred audio files. The categories that musical instrument fall in are more than 20. Hence system will be capable of finding musical instrument of different categories very efficiently.

VIII. FUTURE SCOPE

The future scope of the system is aimed at take real time audio. The system must also take real music played to detect the musical instrument category. The proposed system takes only audio file but it should also take real time music through mic.

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