AUTOMATIC MUSIC INSTRUMENT RECOGNITION

by

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THEJASVINI. S | **AKSHAJ PRASAD**

ABSTRACT

Musical instruments come in various sizes and shapes and the characteristics of them can sound very similar or sometimes very distinct. The same type of musical instrument can make a wide variety of sounds based on the material it is made of and the way it is used. Automatic sound source recognition plays an important role in developing automatic indexing and database retrieval applications. These applications have potential in saving the humans from time taking searches through huge amounts of digital audio material available today.

In this project we have shown that musical instruments come in various sizes and shapes and can make a wide variety of sounds based on the material it is made and the way it is used. We have used machine learning models to compare different characteristics of musical instruments and study its ability to distinguish different instruments. The project pipeline involves obtaining musical instrument data by using MFCC and DFT in processing frequency domain and feature classification. Monophonic and monotimbral signals were classified while eliminating noise and silence.

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1. INTRODUCTION

1.1 OBJECTIVES AND GOALS

The main aim of the project is to achieve Musical Instrument Recognition using signal processing in frequency domain and feature classification. Computer audition is the general study of the systems and methods necessary for audio understanding by a machine. In a sense, computer audition concerns itself with the study of designing computers that can “hear” as humans do.

The ultimate goal is a machine that can organize what it hears; learn names for recognizable objects, actions, events, places, musical styles, instruments, and speakers; and retrieve sounds by reference to those names. We aim to classify monophonic and monotimbral signals from the input audio while eliminating the presence of noise and silence in the same.

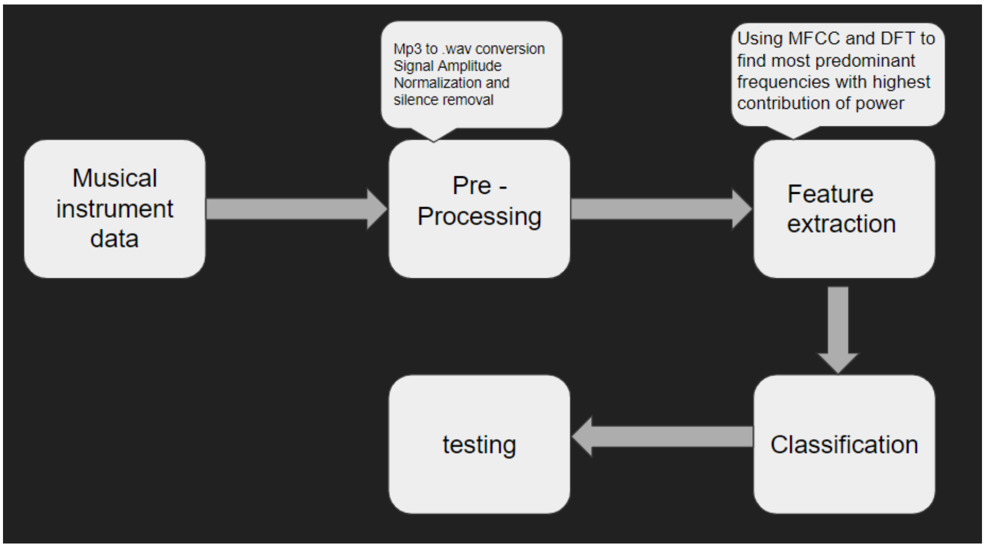
1.3 APPLICATIONS

Musical instrument recognition and sound source recognition are essential parts of computational auditory scene analysis (CASA). In this field, the goal is to analyse complex acoustic environments, including the recognition of overlapping sound events, and thus their sources. In musical synthesis, the model parameters are often analysed from an acoustic signal. There might be potential in combining these two fields, using physical model synthesis parameters for musical instrument recognition and bringing new methods for feature extraction from musical instrument recognition to physical modeling.

Musical instrument recognition is related to many other fields of research. The methods used in implementing musical instrument recognition systems are drawn from different technical areas. The pre-processing and feature extraction techniques can be taken from speech and speaker recognition. Commonly, classification is performed with statistical pattern recognition techniques. Neural networks and other soft computing techniques have also been applied in many cases.

2. DESIGN

2.1 BLOCK DIAGRAM



2.2 SOFTWARE ANALYSIS

The datasets were trained and tested after which four machine learning models namely, SVM, Ridge, Linear Regression and Lasso, were employed in order to calculate precision.

DATA SET

The dataset used was derived from the following website :
https://philharmonia.co.uk/resources/sound-samples/

This data set consists of 7 musical instruments which are :

Cello - 889 samples

Clarinet - 846 samples

Flute - 878 samples

Guitar - 106 samples

Saxophone - 732 samples

Trumpet - 485 samples

Violin - 1502 samples

LANGUAGES & TOOL KIT

These were the Languages/Modules that were used for this project

- Bash
- Matlab
- Python
- Communications Toolbox (Matlab)

4. SOFTWARE OVERVIEW

4.1 MATLAB CODE

NOISE ADDITION:

```
function count = NoiseAdd(snr)

    count = 0 ;

    %directory_in=input('enter directory path of the dataset of each instrument: ','s');
    directory_in = 'D:\Matlab\DSP project\data\';

    %directory_noisy=input('enter directory path for the noisy data of each instrument:
','s');
    directory_noisy = 'D:\Matlab\DSP project\n_data';

    d = dir(directory_in);
    isub = [d(:).isdir];
    nameFolds = {d(isub).name}';
    nameFolds(ismember(nameFolds,{'.','..'})) = [];
```

```
    for i = 1:size(nameFolds)
        nums = [nameFolds{i,:}];
        s = strcat(directory_in,nums);
        count = count+1;
        allFiles = dir(s);
        allNames = {allFiles.name};
        allNames(ismember(allNames,{'.','..'})) = [];

        [rows, columns] = size(allNames);

        for j = 1:columns
            count = count+1;
            audio_path = strcat(s,'\',[allNames{:,j}]);
            [y,Fs] = audioread(audio_path);

            %adding white guassian noise to y

            yy = awgn(y,snr);
            c = strcat(directory_noisy,"\",nums,"\",[allNames{:,j}],".wav");

            %writing a new file

            audiowrite(c,yy,Fs);
        end
    end
end
```

MACHINE LEARNING MODELS USED:

SVM*:*

```
function precision = SVM()
    [train,test,res] = createtbl();
    mdl = fitcecoc(train,res);
    res_test = predict(mdl,test);
    precision = PRECISION(res,res_test);
end
```

RIDGE:

```
function precision = RIDGE()
    [train,test,res] = createtbl();
    b = ridge(table2array(res),table2array(train),5,0);
    res_test = round(b(1) + table2array(test)*b(2:end));
    precision = PRECISION(res,res_test);
end
```

LINEAR REGRESSION:

```
function precision = LR()
    [train,test,res] = createtbl();
    mdl = fitlm([train res]);
    res_test = round(predict(mdl,test));
    precision = PRECISION(res,res_test);
end
```

LASSO:

```
function precision = LASSO()
    [train,test,res] = createtbl();
    [B,FitInfo] = lasso(table2array(train),table2array(res),'Alpha',0.75,'CV',10);
```

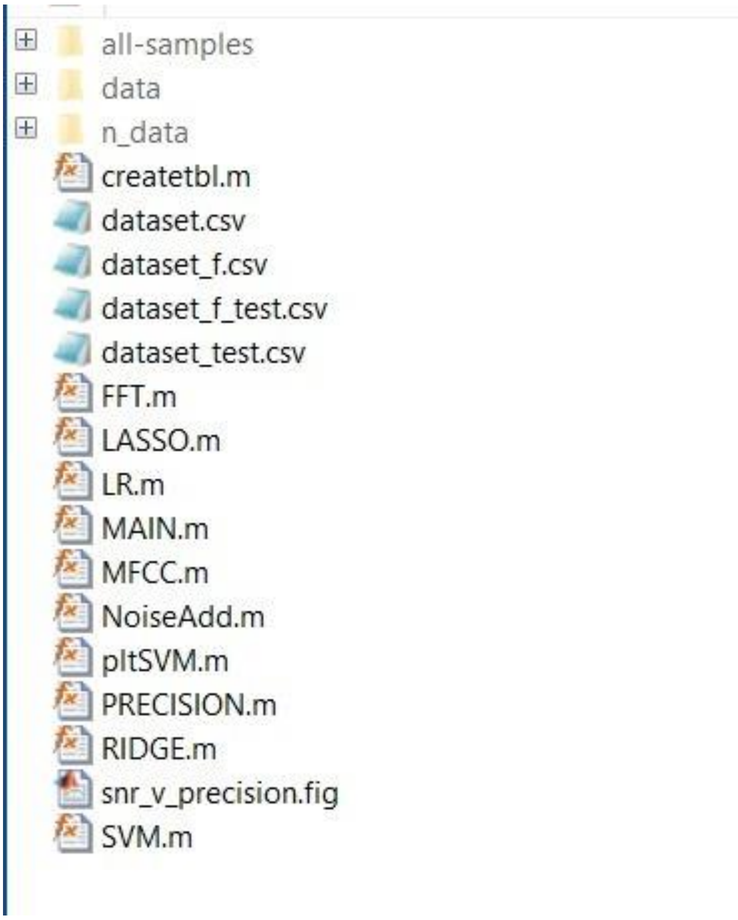
```
    idxLambda1SE = FitInfo.Index1SE;
    coef = B(:,idxLambda1SE);
    coef0 = FitInfo.Intercept(idxLambda1SE);
    XTest = table2array(test);
    yhat = round(XTest*coef + coef0);
    precision = PRECISION(res,yhat);
end
```

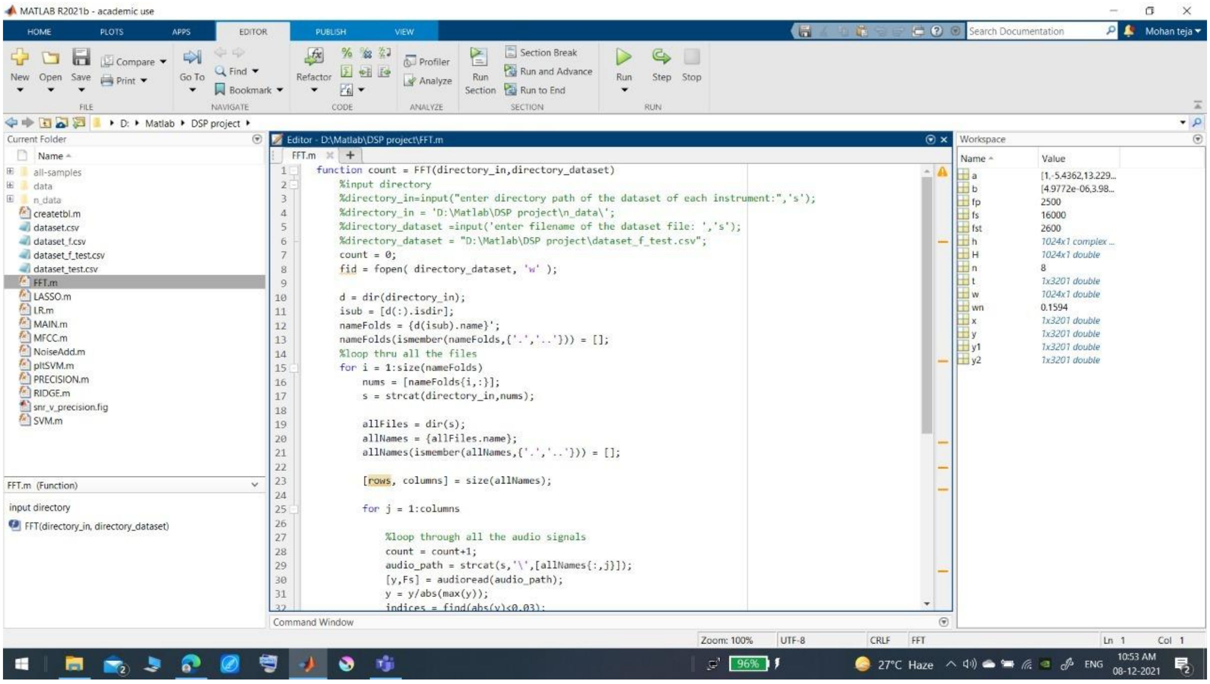
PRECISION CALCULATION:

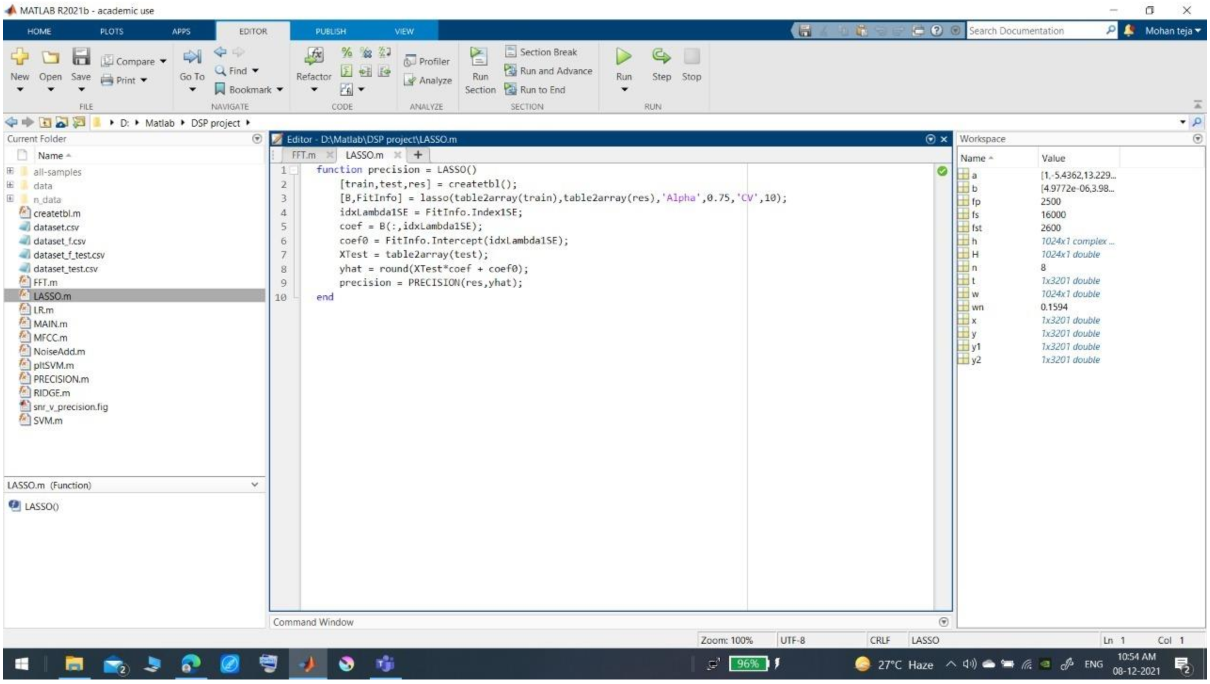
```
function precision = PRECISION(res,res_test)
    count=0;
    same =0;
    for i=1:height(res)
        count= count+1;
        if(res_test(i,:)==res{i,:})
            same= same+1;
        end
    end
    precision = same*100/count;
end
```

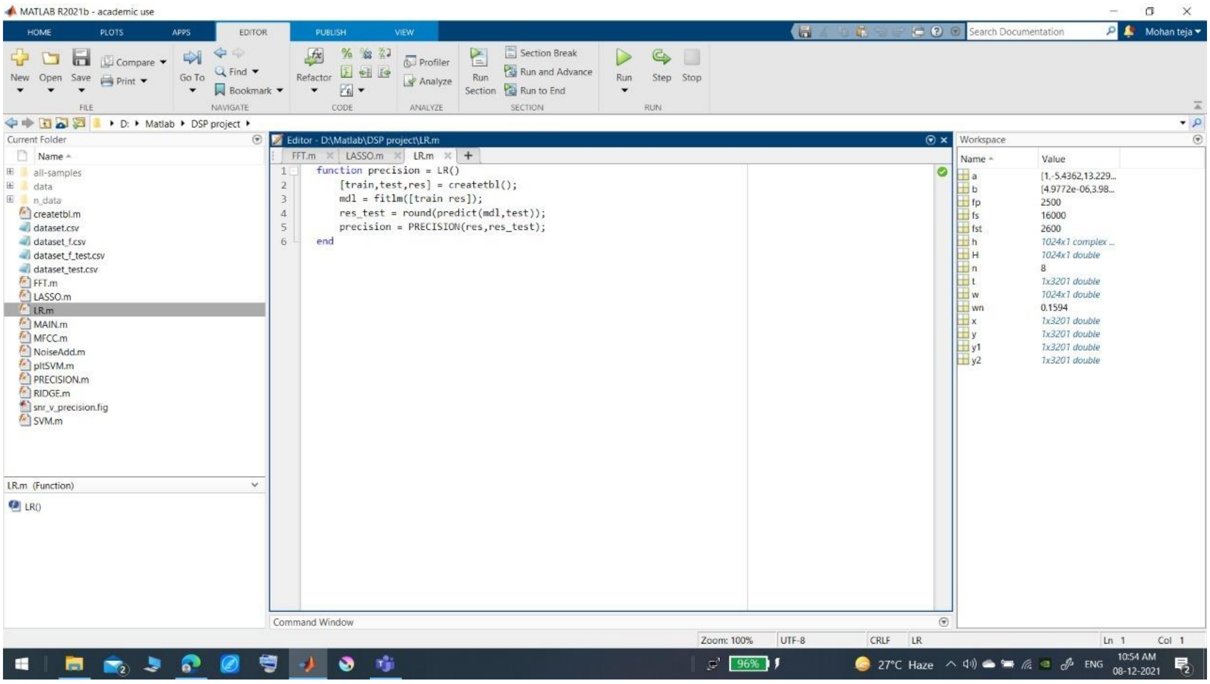
5. RESULTS

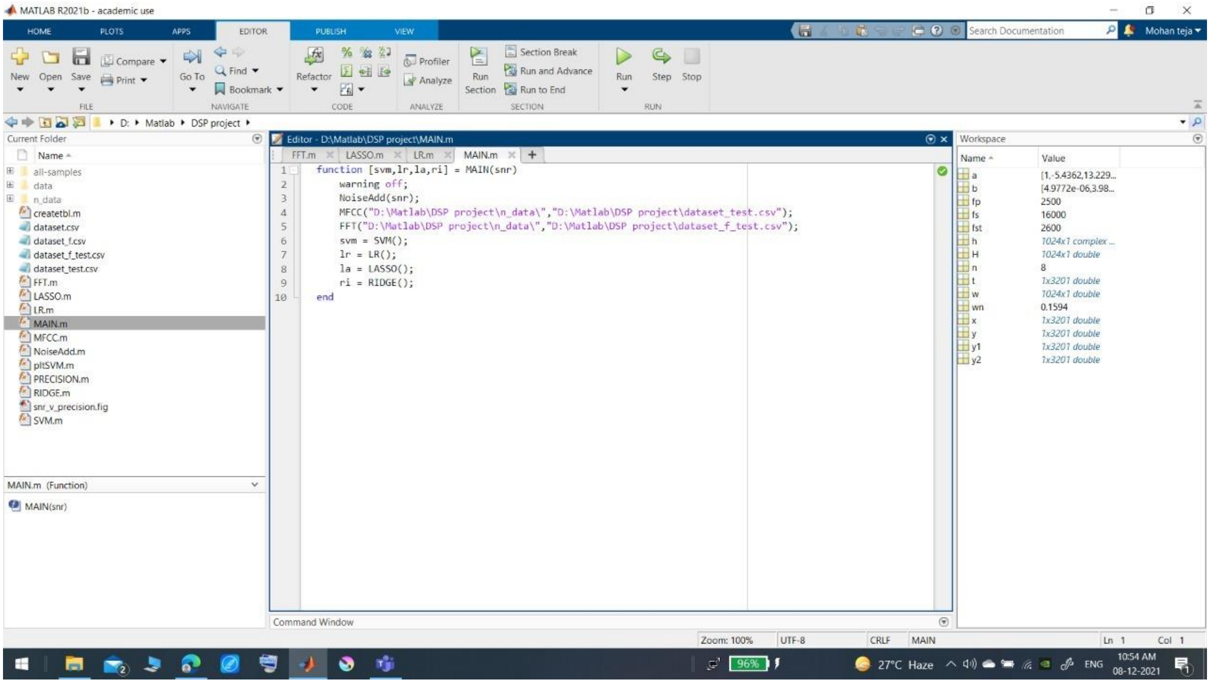
MATLAB SNAPSHOTS:

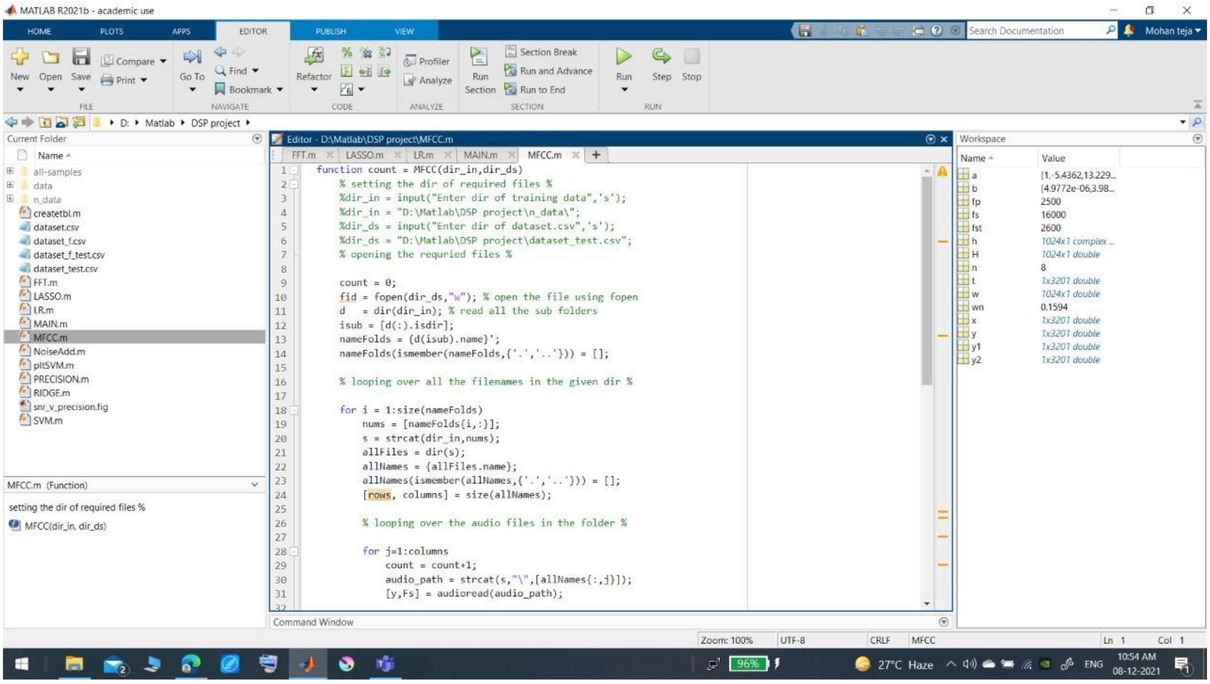


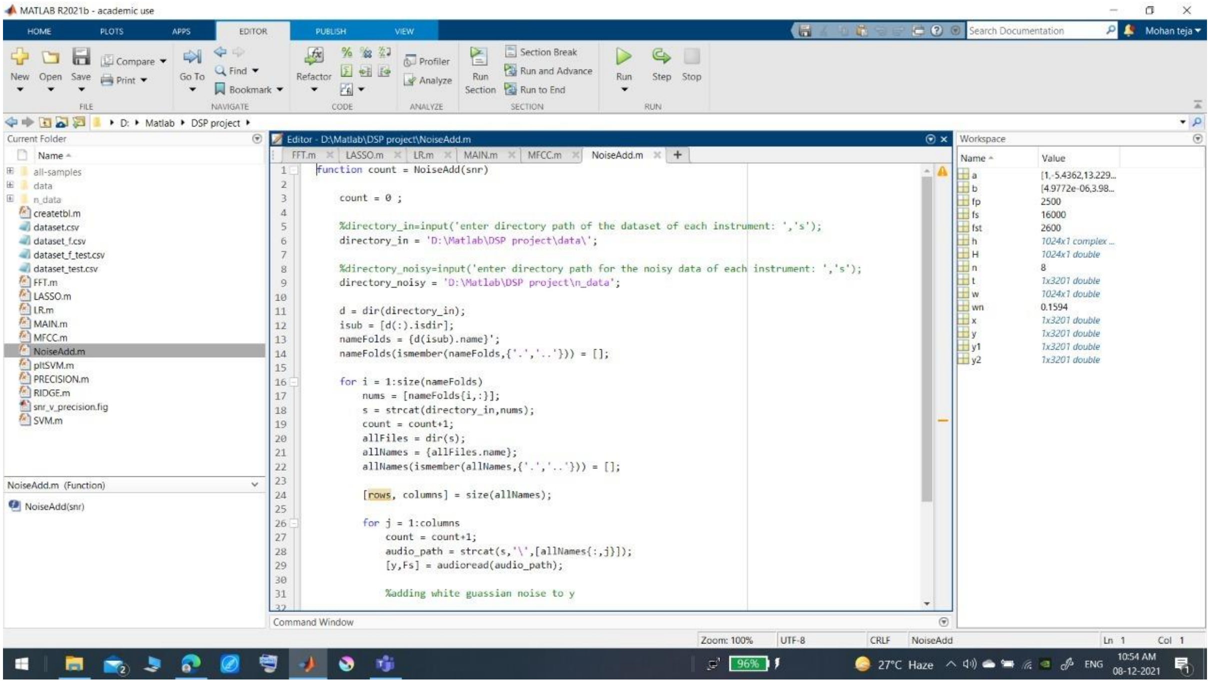


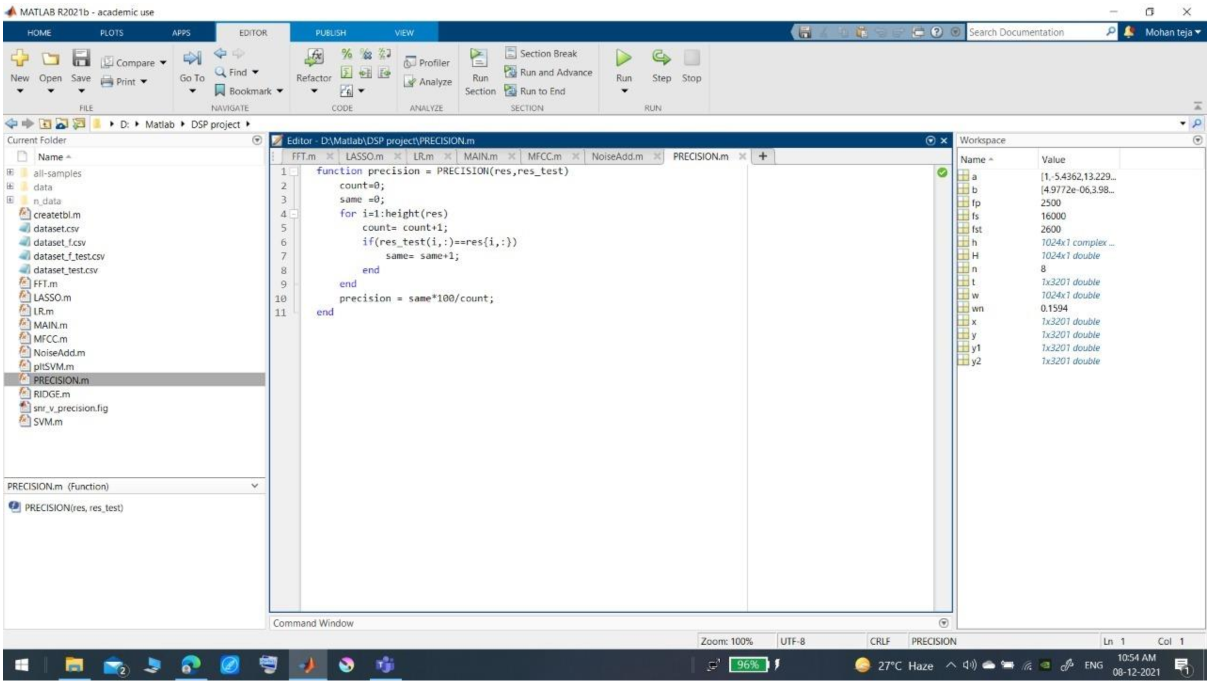

MATLAB R2021b - academic use
Editor - D:\Matlab\DSP project\LASSO.m
FFT.m
LASSO.m
function precision = LASSO()
[train,test,res] = createtbl();
[B,FitInfo] = lasso(table2array(train),table2array(res),'Alpha',0.75,'CV',10);
idxLambda1SE = FitInfo.Index1SE;
coef = B(:,idxLambda1SE);
coef0 = FitInfo.Intercept(idxLambda1SE);
XTest = table2array(test);
yhat = round(XTest*coef + coef0);
precision = PRECISION(res,yhat);
end

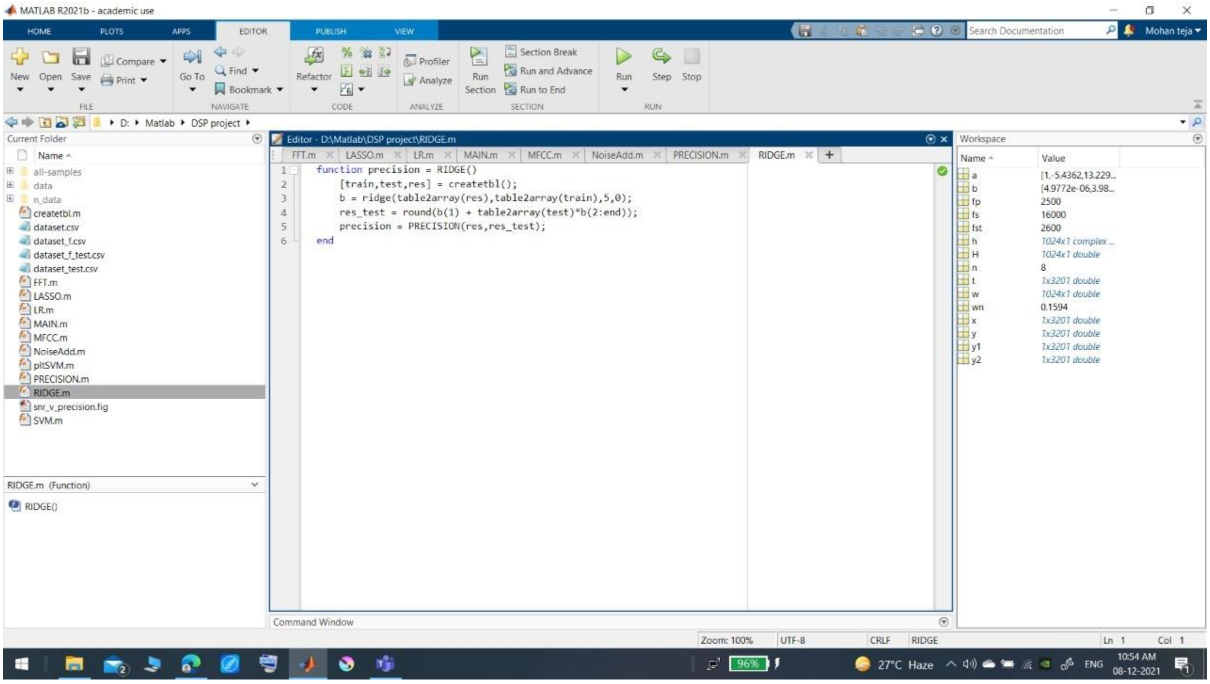

MATLAB R2021b - academic use
Editor - D:\Matlab\DSP project\LR.m
FFT.m
LASSO.m
LR.m
function precision = LR()
[train,test,res] = createtbl();
mdl = fitlm([train res]);
res_test = round(predict(mdl,test));
precision = PRECISION(res,res_test);
end

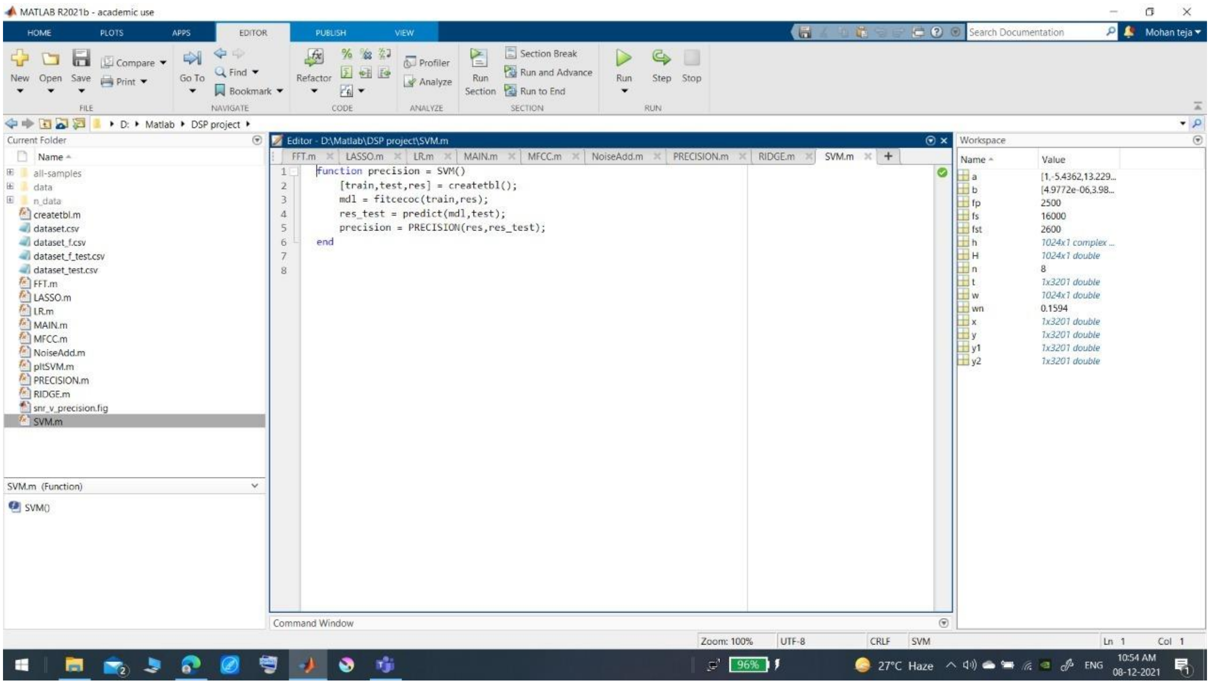

MATLAB R2021b - academic use
Editor - D:\Matlab\DSP project\MAIN.m
function [svm,lr,la,ri] = MAIN(snr)
warning off;
NoiseAdd(snr);
MFCC("D:\Matlab\DSP project\n_data\","D:\Matlab\DSP project\dataset_test.csv");
FFT("D:\Matlab\DSP project\n_data\","D:\Matlab\DSP project\dataset_f_test.csv");
svm = SVM();
lr = LR();
la = LASSO();
ri = RIDGE();
end


MATLAB R2021b - academic use
Editor - D:\Matlab\DSP project\MFCC.m
function count = MFCC(dir_in,dir_ds)
% setting the dir of required files %
%dir_in = input("Enter dir of training data",'s');
%dir_in = "D:\Matlab\DSP project\n_data\";
%dir_ds = input("Enter dir of dataset.csv",'s');
%dir_ds = "D:\Matlab\DSP project\dataset_test.csv";
% opening the requried files %
count = 0;
fid = fopen(dir_ds,"w"); % open the file using fopen
d = dir(dir_in); % read all the sub folders
isub = [d(:).isdir];
nameFolds = {d(isub).name}';
nameFolds(ismember(nameFolds,{'.','..'})) = [];
% looping over all the filenames in the given dir %
for i = 1:size(nameFolds)
nums = [nameFolds{i,:}];
s = strcat(dir_in,nums);
allFiles = dir(s);
allNames = {allFiles.name};
allNames(ismember(allNames,{'.','..'})) = [];
[rows, columns] = size(allNames);
% looping over the audio files in the folder %
for j=1:columns
count = count+1;
audio_path = strcat(s,"\",[allNames{:,j}]);
[y,Fs] = audioread(audio_path);


Editor - D:\Matlab\DSP project\NoiseAdd.m
function count = NoiseAdd(snr)
count = 0 ;
%directory_in=input('enter directory path of the dataset of each instrument: ','s');
directory_in = 'D:\Matlab\DSP project\data\';
%directory_noisy=input('enter directory path for the noisy data of each instrument: ','s');
directory_noisy = 'D:\Matlab\DSP project\n_data';
d = dir(directory_in);
isub = [d(:).isdir];
nameFolds = {d(isub).name}';
nameFolds(ismember(nameFolds,{'.','..'})) = [];
for i = 1:size(nameFolds)
nums = [nameFolds{i,:}];
s = strcat(directory_in,nums);
count = count+1;
allFiles = dir(s);
allNames = {allFiles.name};
allNames(ismember(allNames,{'.','..'})) = [];
[rows, columns] = size(allNames);
for j = 1:columns
count = count+1;
audio_path = strcat(s,'\',[allNames{:,j}]);
[y,Fs] = audioread(audio_path);
%adding white guassian noise to y


Editor - D:\Matlab\DSP project\PRECISION.m
function precision = PRECISION(res,res_test)
count=0;
same =0;
for i=1:height(res)
count= count+1;
if(res_test(i,:)==res{i,:})
same= same+1;
end
end
precision = same*100/count;
end


MATLAB R2021b - academic use
Editor - D:\Matlab\DSP project\RIDGE.m
function precision = RIDGE()
[train,test,res] = createtbl();
b = ridge(table2array(res),table2array(train),5,0);
res_test = round(b(1) + table2array(test)*b(2:end));
precision = PRECISION(res,res_test);
end
Current Folder
Workspace
Command Window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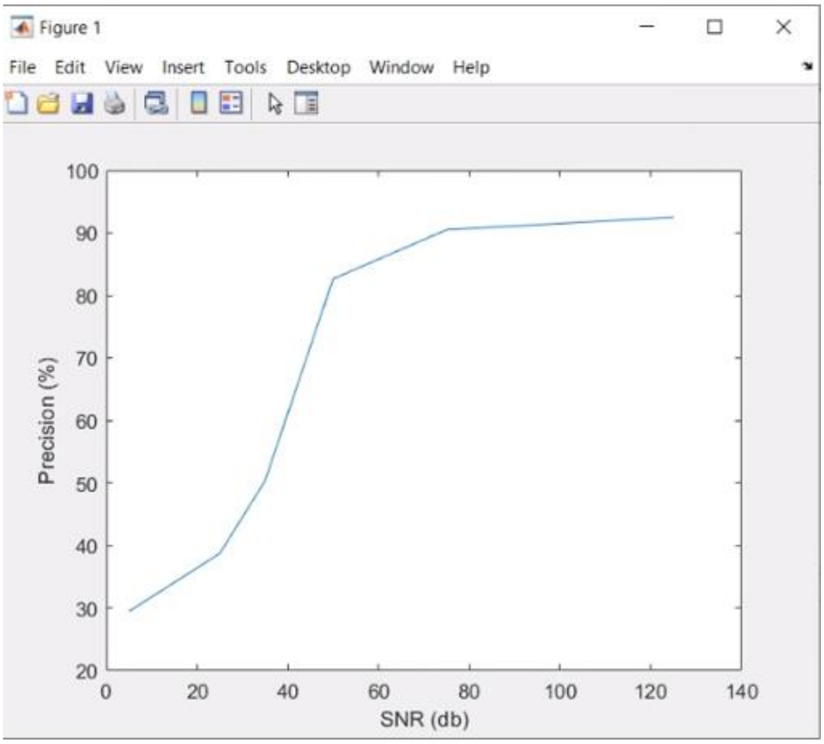
Editor - D:\Matlab\DSP project\SVM.m
function precision = SVM()
[train,test,res] = createtbl();
mdl = fitcecoc(train,res);
res_test = predict(mdl,test);
precision = PRECISION(res,res_test);
end
Current Folder
Workspace
Command Window

PRECISION PERCENTAGES:

```
>> [svm,lr,la,ri] = MAIN(100)

svm =

   83.5476


lr =

   96.7609


la =

   95.0643


ri =

   81.1311
```

In comparison, it is observed that maximum precision was achieved using the linear regression model.

PRECISION VALUES WITH RESPECT TO SNR:



6. CONCLUSION AND FUTURE WORK

This paper presents different types of classification schemes used to identify musical instruments. It can be said that these techniques are not the verge of the story of musical instrument recognition, and that there is lot of scope for expansion.

Based on the test, the MFCC and machine learning methods can classify the sound source of the instrument with an accuracy of 83.54%, 96.76%, 95.06% and 81.13%, with linear regression being the most accurate. It can be concluded that MFCC and machine learning models can be implemented in classifying sound sources on musical instruments with good accuracy.

FUTURE WORK:

This project can be further expanded to design and employ models and algorithms that have an optimized performance and work with more accuracy. It can also be expanded to classify and identify instruments from real-time music using the spontaneous data that is being obtained from the same.

Music content analysis in general has many practical applications, including structured coding, automatic musical signal annotation, and musicians' tools. Automatic musical instrument recognition is a crucial subtask in solving these difficult problems, and may also provide useful information in other sound source recognition areas, such as speaker recognition and much more.

7. REFERENCES

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