A Project Report

On

MUSIC GENRE CLASSIFICATION BY AUDIO FREQUENCY USING CONVOLUTION NEURAL NETWORK AND MEL- SPECTROGRAMS

Submitted to

JAWAHARLAL NEHRU TECHNOLOGICAL UNIVERSITY ANANTAPUR, ANANTHAPURAMU

In Partial Fulfillment of the Requirements for the Award of the Degree of

BACHELOR OF TECHNOLOGY

In

COMPUTER SCIENCE & TECHNOLOGY

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This is to certify that the project work entitled "**MUSIC GENRE CLASSIFICATION BY AUDIO FREQUENCY USING CONVOLUTION NEURAL NETWORK AND MEL-SPECTROGRAMS**" is a bonafide work carried out by

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This is to certify that the B.Tech Project report titled, "**Music Genre Classification By Audio Frequency Using Convolution Neural Network And Mel- Spectrograms**" submitted by **Gopa Vamsi (19691A28G9), B. Sasidhar Reddy (19691A28C9), D Shifayath AliKhan (19691A28D4), N J Vinay Chandra Singh (19691A28H2**) has been evaluated using **Anti-Plagiarism Software, URKUND** and based on the analysis report generated by the software, the report's similarity index is found to be 10 % .

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We hereby declare that the results embodied in this project **"Music Genre Classification By Audio Frequency Using Convolution Neural Network And Mel-Spectrograms"** by us under the guidance of **Mr. V. Naveen**, **Assistant Professor, Dept. of CST** in partial fulfillment of the award of **Bachelor of Technology** in **Computer Science & Techology** from **Jawaharlal Nehru Technological University Anantapur, Anantapur.** and we have not submitted the same to any other University/institute for award of any other degree.

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TABLE OF CONTENT

ABSTRACT

The modern song involves different instruments and it combines different genres as well. Genre classification of music plays a crucial role to provide the different instrumental behaviours of a song. Mel-spectrogram is a technique used to represent an audio signal to a visual form of spectrum. Commonly musical genre annotations are performed manually apart from that some automatic machine learning algorithms including Decision Trees, K Nearest Neighbours, Support Vector Machines and Naïve Bayes to classify genres. Convolutional Neural Network is an advanced algorithm used for image processing. We are proposing a CNN algorithm to classify musical genre audio signal from GTZAN dataset and analyse the performance. GTZAN dataset consists of 1000 audio tracks each 30 seconds long. It contains 10 genres and each represented by 100 tracks. Blues, Classical, Country, Disco, Hip-hop, Jazz, Metal, Pop, Reggae and Rock are the 10 genres of dataset.

List of Figures/Screens/Tables

CHAPTER-1
INTRODUCTION

1.1 MOTIVATION

One of the primary issues with music type arrangement is that genres are in many cases liquid and not entirely clear. For instance, a tune might be delegated having a place with one type by one individual, and one more kind by someone else. This is on the grounds that types are many times characterized by emotional models, like the individual taste. Thusly, it is frequently challenging to make a conclusive rundown of classifications or to group a melody conclusively as having a place with one sort. Thus, there is a need for a framework to group the music into various genres which can be utilized in some genuine applications to order the music into their particular kind without human mediation. Consequently, a profound learning model is made to characterize the music into different types.

1.2 PROBLEM DEFINITION

Make a model that resolves the issue of naturally characterizing music into its significant genres and to further develop the subsequent model's precision rate in contrast with prior endeavours and current models. It is important to make a pertinent model for the diversion area given the quickly growing AI capacities.

1.3 OBJECTIVE OF THE PROJECT

➢ To develop a model with a better precision rate that groups the information sound example or melody into the music type in which it has a place so it very well may be utilized progressively in applications.

➢ To diminish or supplant the association of manual assignments in the music-kind characterization.

1.4 LIMITATIONS OF THE PROJECT

The GTZAN is the broadly utilized dataset in Music Data Recovery (MIR) works. It is still broadly utilized in research connected with music, however, the dataset contains just the ten genres.

The genres are not refreshed from starting it actually contain the genres when it is gathered. Furthermore, the dataset likewise contains a lesser number of records They needed more information, to sum up, the genres' different examples and there is the question that the framework fits the cutting-edge music as a smaller number of kinds are utilized and there could be no other dataset really standard utilized for music data retrieval.

1.5 ORGANISATION OF DOCUMENTATION

1.5.1 Feasibility Study

Primer examination inspects project attainability; the probability the framework will be helpful to the association. The principal objective of the practicality review is to test the Specialized, Functional and Prudent plausibility for adding new modules and investigating old running framework. All frameworks are plausible assuming they are given limitless assets and boundless time. There are viewpoints in the attainability concentrate on part of the starter examination:

1. Technical Feasibility
2. Operation Feasibility
3. Economic Feasibility

1.5.1.1 Technical Feasibility

The specialized issue normally raised during the feasibility phase of the examination incorporates the accompanying:

- Does the fundamental innovation exist to do what is recommended?
- Do the proposed system have the specialized ability to hold the information expected to utilize the new framework?
- Will the proposed framework give sufficient reaction to requests, no matter what the number or area of clients?
- Might the framework at any point be updated whenever created?
- Are there specialized assurances of exactness, dependability, straightforward entry, and information security?

1.5.1.2 Operation Feasibility

The functional Feasibility incorporates Ease of use, unwavering quality, security, compactness, availability, and viability of the product utilized in the task.

1.5.1.3 Economic Feasibility

Examination of an undertaking expenses and income with an end goal to decide if it is consistent and conceivable to finish.

CHAPTER-02

LITERATURE REVIEW

2.1 INTRODUCTION

As per the mood, instrument utilized, or consonant substance of the information, sort classification can bunch tantamount kinds of data into a solitary character and give that personality a name. As the music business develops quickly with new mechanical advancements, scientists are likewise extending their advantage in the field of music. Different profound learning arrangements are proposed by various creators to order various kinds of music.

2.2 LITERATURE SURVEY

In the research conducted by Md Sabbir Ahmed, Md Zalish Mahmud and Shamim Akhter "**Musical Genre Classification on the Marsyas Audio Data Using Convolution NN** [1]". Mel Frequency Cepstral Coefficients (MFCC) spectrogram is utilized to take care of neural organization. CNN or profound NN performs better with fewer info boundaries, and with this speculation, they created the class waveform to Mel Frequency Cepstral Coefficients (MFCC) spectrogram. MFCC spectrogram is a component generally utilized in programmed discourse and speaker acknowledgment. They utilized MFCC spectrograms to arrange the Marsyas Dataset. They effectively planned and executed CNN with the MFCC spectrogram.

In the research conducted by Nirmal M R and Dr. Shajee Mohan B S "**Music Genre Classification using Spectrograms** [2]". In their work, the music signals are first switched over completely to their comparing spectrograms. These spectrograms are then given as a contribution to the classifier. The classifier utilized in their work is a Convolutional Neural Network (CNN). Two CNN models are examined in their paper: A client characterized CNN model and a pre-prepared convert. Pre-prepared convnet utilizes the ideas of tweaking and moving learning. The exhibition of the classifier was assessed utilizing execution measures like disarray lattice and arrangement precision. They utilized just Three music kinds, for example, blues, old style, and rock from the GTZAN dataset for trial and error. Their model characterization precision was viewed as great.

In the research conducted by Pelchat and Craig M. "**Neural Network Music Genre Classification** [3]", The GTZAN dataset's tunes were arranged into seven classes. The sound system channels were then consolidated into one mono channel, and the music information was changed over into a spectrogram utilizing the SoX (Sound eXchange) order line music application utility, which was then cut into 128x128 pixel pictures, and the marked spectrogram was utilized as contributions to the dataset, which was parted into 70% preparation information, 20% approval information, and 10% test information. Every one of the loads was presently instated utilizing the Xavier introduction strategy. The initial four layers are convolutional layers with a part size of 2x2 and a step or two, trailed by a maximum pooling layer. Following the initial four layers is a completely associated layer wherein each result of the past layer is taken care of into each contribution of the completely associated layer. This yields a vector of 1024 numbers. From that point onward, a SoftMax layer is applied to produce seven results, one for every sort. The CNN execution had all the earmarks of overfitting, as the exactness for the preparation information was 80% versus 47% for the test information.

In the research conducted by K. Meenakshi "**Automatic Music Genre Classification using Convolution Neural Network** [4]", They used to prepare the framework by sorting the music data set into various classifications. From that point onward, every melody should go through a pre-handling stage. Highlight Vector Extraction is acted in Python utilizing the librosa bundle, otherwise called MFCC. The Mel Scale Filtering is then performed to get the Mel Recurrence Range by [4]. They acquired two sorts of element vectors: Mel Range with 128 coefficients and MFCC coefficients. ConvNet architecture is assembled utilizing three sorts of layers: Convolutional Layer, Pooling Layer, and fully Connected Layer. The data set in this way gotten is the MFCC, with a classification exhibit size of 10 clusters. The information comprises 1000 melodies with ten genres. The vector of elements for MFCC The Boa constrictor Python bundle was utilized for the assessment. The learning exactness of the Mel Spec highlight vector and the MFCC include vector was viewed as 76% and 47%, individually.

In the research conducted by Yandre M.G. Costaa, Luiz S. Oliveira b, Carlos N. Silla Jr. c in their paper "**An evaluation of Convolutional Neural Networks for music classification using spectrograms** [5]"distributed in the year 2017 proposed music type grouping framework by utilizing Convolution Neural Network and Backing Vector Machine calculation. They utilized three datasets: Latin Music Dataset [LMD], ISMIR, and African Music Data set. LMD comprised three 3,277 full-length music bits of 10 distinct sorts. ISMIR 2004 comprised 1,458 music pieces. This dataset was separated into half preparation and half testing. In this paper result of the two calculations is consolidated to get more precision. The outcome acquired is the combination of CNN and SVM which gives 83% Accuracy.

In the research conducted by Hareesh Bahuleyan "**Music Genre Classification using Machine Learning Techniques** [6]", the correlation between two classes of models is carried out. The first is a profound learning approach wherein a CNN model is prepared start to finish, to foresee the class mark of a sound sign, exclusively utilizing a spectrogram. The subsequent methodology utilizes both hand-made highlights from the time-space and recurrence area. In this manner, these cycle includes that serve the most in the characterization of assignments are laid out. Here two distinct methodologies are utilized to tackle the issue. The main methodology creates a spectrogram of the sound sign regarding it as a picture. A CNN-based picture classification model, in particular, VGG16 is likewise gifted on these pictures to gauge the music sort which depends on the spectrogram picture. The subsequent methodology was to separate the time-space and recurrence area highlights from the sound signs followed by preparing a customary AI classifier in light of the removed elements. XGBoost was utilized as a classifier to report the main elements. Additionally, collecting the CNN and XGBoost model was done and it ended up being valuable

In the research conducted by Dong, M., "**Convolutional neural network achieves human-level accuracy in music genre classification** [7]" creators utilized the CNN model having two convolution layers with Mel-spectrogram highlights which thus provided them with an exactness of around 70%. They split the sound documents into more modest pieces of 3sec length.

In the research conducted by kostrzewa, D., Kaminski, P. furthermore, Brzeski, R., "**Music Genre Classification: Looking for a Perfect Network** [8]" they have dealt with various structures like CNN, CRNN, and LSTM. They got the most noteworthy exactness of 52% with a CNN model involving Mel-spectrograms as an input..

In the research conducted by Wibowo and Wihayati (2022) "**Detection of Indonesian Dangdut Music Genre with Foreign Music Genres Through Features Classification Using Deep Learning** [9]", proposed a profound learning approach for the characterization of music types. The creators investigated the GTZAN dataset with ten foreign music classifications. The profound learning model got an order precision above 90%. In the following stage, an extra dataset as well known as the dangdut music sort was added for the ID of the dangdut music type among Western music classes. It was seen that the exhibition of the profound learning model with the dangdut music type diminished to around 76%. The outcome featured that dangdut music is not quite the same as other unfamiliar music types, yet scarcely any music classifications, for example, jazz and pop were recognized.

In the research conducted by Puppala and Muvva (2021) [10] "**A Novel Music Genre Classification Using Convolutional Neural Network**", they planned a convolutional neural network utilizing a profound learning approach for the preparation and order of music kinds from the GTZAN dataset. The Mel frequency cepstral constant (MFCC) highlight vector was removed and used for the order cycle. The dataset was partitioned into 60% for preparation and 40% for the end goal of testing. The preparation and testing accuracies were 97% and 74%, separately, with this methodology

In the research conducted by Kumar and Chaturvedi (2020) [11], "**An Audio Classification Approach using Feature extraction neural network classification Approach**", They expounded a sound order approach utilizing a counterfeit neural organization. The creators accentuated sounder component extraction draws near, like chroma-or centroid-based highlights, Mel frequency cepstral coefficients (MFCCs), and direct prescient coding coefficients (LPCCs), to comprehend the way of behaving of the sound sign. An effective neural network classifier was utilized for the grouping of sound signs at a high accuracy rate.

In the research conducted by minwei, luiang (2020) "**Music Genre Classification Using Transfer Learning**[12]" In this paper, our center are labels related to western music types. Considering that best in class auto-labeling models center around top-50 labels of a dataset, they can't identify music with labels that are out of the main 50, for example, "old style music" in the Million Melody Dataset1 (MSD), and "blues" in the MagnaTagATune Dataset2 (MTT). To settle this, we propose an exchange learning approach. The information acquired from the pre-prepared music auto-labelling models can be applied to the objective assignment of music sort arrangement. We exhibit the viability of our strategy in 1100 sound accounts comprising of 11 types: Rock, Pop, Rap,Country, Society, Metal, Jazz, Blues, R&B, Electronic Music furthermore, Old style Music3.

In the research conducted by Jaime Ramirez Castillo And M. Julia Flores "**Web-Based Music Genre Classification for Timeline Song Visualization and Analysis** [13]"(2020). 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 behaviour of the models, which at the same time, is an interesting way to detect undesired or rare predictions.

In the research conducted by Wing W. Y. Ng , Weijie Zeng , And Ting Wang, "**MultiLevel Local Feature Coding Fusion for Music Genre Recognition**[14] "(2020). In this work, we propose an outfit approach for music classification acknowledgment in view of the combination of significant level component sets gained from various sorts of low-level elements. A staggered include coding network utilizes a CNN with self-consideration and NetVLAD to learn undeniable level elements for each low-level element. The NetVLAD extricates additional predominant aspects by catching nearby data from various include levels while the self-consideration learns long haul conditions across levels. The proposed model is compelling in catching discriminative highlights, in this manner yielding the best test precision on GTZAN, ISMIR2004, and Broadened Dance hall dataset.

In the research conducted by Leisi Shi ,Chen Li "**Music Genre Classification Based on Chroma Features and Deep Learning**"[15](2020) sort order has an incredible connection with congruity, yet has no relationship with human tone, volume, outright pitch, and so forth. These superfluous factors significantly influence the improvement of order precision. In this way, how to overlook these variables in the calculation and spotlight on the portion factors that vitally affect the arrangement of music sorts is our fundamental errand. In light of this thought, we develop a structure for music order utilizing the chroma include and further developed VGG16 profound learning organization in this paper.

2.3 EXISTING SYSTEM

In the existing System, a large number of them are utilizing AI (ML) algorithm like K nearest neighbours (k-NN) to characterize the genre, and the vast majority of the genre grouping review centres around tracking down the least difficult arrangement of worldly elements, changes, and channels that best address the music. What's more, a considerable lot of the frameworks that are utilizing the deep learning models have utilized the MFCC sound portrayal and prepared a music design extractor to characterize the genre.

2.4 DISADVANTAGES OF EXISTING SYSTEM

The current models slack in the component extraction of music records. We accept that this essentially restricts the exhibition of models on the grounds that these highlights are eventually removed by people and that we will be feeling the loss of a few significant elements that would be extricated by a neural organization. And, surprisingly, the contribution to the profound neural networks matters in deciding the exhibition of the created framework since the execution of the framework while involving Mel-spectrograms as info will be more when contrasted with MFCC's as contribution to the model, on the grounds that MFCC is an entirely compressible portrayal, frequently utilizing only 20 or 13 coefficients rather than 32-64 bands in Mel spectrogram. The MFCC is a smidgen more decorrelated, which can be helpful with direct models like Gaussian Blend Models. With heaps of information and solid classifiers like Convolutional Neural Organizations, Mel-spectrogram can frequently perform better.

2.5 PROPOSED SYSTEM

By considering the above frameworks we are Proposing a model that is superior to the previously mentioned work. We are proposing a CNN design in which we are taking care of the Mel-Spectrograms created from the music documents. In the first place, we split the 30-second music record into 3-second documents then we get 10 music tests from every music document. We do this on the grounds that from hearing a 3-second music record a human can anticipate the class of music same applies to the neural networks, so we create the Mel-spectrograms from the 3-second music record for preparing the created model. In our work, we are involving 10 genres for preparing the model (blues, classical, country, disco, hip jump, metal, pop, reggae, and rock).

2.6 ADVANTAGES OF PROPOSED SYSTEM

In the proposed system we are utilizing the Mel-spectrograms which consolidates the most extreme highlights of the info music document as the contribution to the CNN engineering planned with the goal that the model concentrates every one of the elements of the music and learns better about it. As we are utilizing a profound learning model it disposes of the human undertaking of recovering the music including physically and it learns better about music as the CNN can extricate the features which there is an opportunity for the people to miss for extraction.

CHAPTER-03
ANALYSIS

3.1 INTRODUCTION

It is a difficult errand given that the information we really want to characterize is audio, which is a type of simple information. The sound record's immediate computerized design can't be used to classify the sound. Subsequently, we should show the audio examples in a manner that is more proper. In our undertaking, we feed the convolutional neural network utilizing a Mel Spectrogram portrayal of the sound input.

3.1.1 Neural Networks

A neural network (NN) is an AI procedure that is as often as possible effective in extricating significant qualities from immense informational indexes and making an item or model that precisely addresses those viewpoints. The model is first prepared to utilize NN utilizing the preparation information base. After model preparation, NN might be utilized to isolate information utilizing a learned model on new or already unselected data of interest.

3.1.2 Convolutional Neural Networks

A specific class of focal organization called a Convolutional Neural Network (CNN) is made to examine pictures that have similar individuals on various sides. The essential contrast between double characterization and order in numerous classifications utilizing CNN is the number of result classes. A picture classifier can be prepared to utilize an information assortment of creature pictures, for example. The picture's pixel esteem vector and the vector's predetermined shape fragment are shipped off CNN (human, animal, bird, and so on.).

3.1.3 Model Architecture

Model Architecture characterizes the consistent associations of different layers utilized in model creation and preparing. The different layers utilized in our model are:

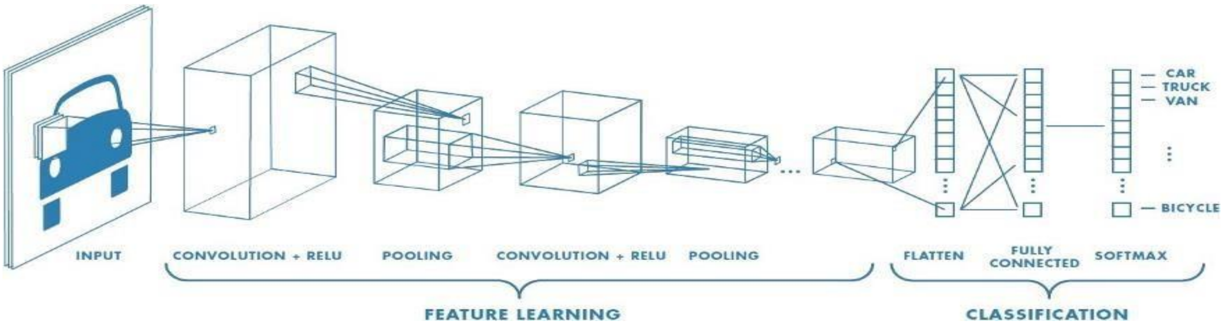


Fig 3.1 General Schematic of Convolutional Neural Network

- **Convolution layer:** In this layer, we think about a specific number of channels, and we take one channel and convolve them (slide them) around the whole picture simultaneously duplicating the pixel worth of the picture with the relating pixel worth of the channel adding them up and isolating by the complete number of pixels to get the result. In this way, we will get the results equivalent to the quantity of channels we pick.

- **Rectified linear unit (ReLu) layer:** ReLu change capability possibly initiates a hub when the result is over a specific amount, in the event that the info is under nothing, the result will be zero just, when the info goes over a specific worth, it has a direct relationship with the reliant variable. Subsequently in this layer, the qualities under zero will become zero and the qualities over zero will stay for what it's worth in the result got from the Convolution layer.

- **Pooling layer:** In this layer, we diminish the picture stack to a more modest size. The pooling can be of the greatest, least, or normal worth.

- **Fully connected (Dense) Layer**: In the wake of going the picture through a heap of convolution, ReLu and pooling the result shows up at the last layer known as the completely associated layer. Here definite characterization occurs. Here we take our separated and contracted pictures and put them into a solitary rundown. In the rundown, there will be a sure worth high for a specific sort which helps in its type grouping.

- **Dropout layer:** The dropout layer haphazardly disposes of x% of the accessible qualities given as the information. The worth of the x is determined by the client and is indicated between the reaches 0.0 to 1.0.

- **Flatten Layer**: The straighten layer changes over the 2 layered 'm x n' exhibit into a solitary layered 'm + n' cluster basically leveling the information into a direct structure.

- **SoftMax Layer:** This layer is utilized for multiple results and gives each result a worth from 0 to 1, the expansion of every one of these results is likewise 1 and the result which has most extreme worth is the anticipated result. The worth of result given by still up in the air by the quantity of hubs in its past layer.

3.2 HARDWARE REQUIREMENTS

3.2.1 Minimum Requirements

- CPU- Intel Core i3 5th gen/ AMD Ryzen 3 1300 or above.
- GPU- Nvidia GTX 1050 or above.
- RAM- 4 GB or above.
- HDD- 4 GB free space.

3.2.2 Recommended Requirements

- CPU- Intel Core i3 8th gen/ AMD Ryzen 5 2600 or above.
- GPU- Nvidia GTX 1660 or above.
- RAM- 8 GB or above.
- HDD- 8 GB free space.

3.3 SOFTWARE REQUIREMENTS

- Operating System: Windows 7/8/8.1/10 (32 bit/64 bit) or Ubuntu Linux or Mac OS

- Programming Language: Python with Librosa, Keras & TensorFlow libraries installed

- Platform: Google Colaboratory

3.4 PYTHON PACKAGES

Let us see in detail about the python packages that we mentioned above.

1. Librosa

Librosa is a strong Python library worked to work with sound and perform examination on it. It is the beginning stage towards working with sound information at scale for a great many applications like distinguishing voice from an individual to tracking down private qualities from a sound.

It assists us with carrying out:

- Sound sign examination for music.
- Reference execution of normal strategies.
- Building blocks for Music data recovery (MIR).

2. Matplotlib

Matplotlib is an exceptionally well known Python library for information perception. Like Pandas, machining Learning isn't straightforwardly related. It especially proves to be useful when a developer needs to picture the examples in the information. It is a 2D plotting library utilized for making 2D diagrams and plots. A module named pyplot makes it simple for software engineers for plotting as it gives elements to control line styles, textual style properties, designing tomahawks, and so on. It gives different sorts of diagrams and plots for information perception, viz., histogram, blunder outlines, bar visits and so on. It gives a MATLAB like point of interaction and is uncommonly easy to use. It works by utilizing standard GUI tool stash like 12 GTK+, wxPython, Tkinter or Qt to give an object oriented Programming interface that assists developers with inserting charts and plots into their applications.

3. TensorFlow

TensorFlow is an open-source library created by Google essentially for profound learning applications. It additionally upholds customary AI. TensorFlow was initially created for enormous mathematical calculations without remembering profound learning. Nonetheless, it ended up being extremely valuable for profound learning advancement too, and in this manner Google publicly released it. TensorFlow acknowledges information as multi-layered varieties of higher aspects called tensors. Complex exhibits are extremely helpful in dealing with a lot of information. TensorFlow chips away at the premise of information stream charts that have hubs and edges. As the execution system is as diagrams, executing TensorFlow code in a conveyed way across a bunch of PCs while utilizing GPUs is a lot simpler.

4. Keras

Keras is one of the main undeniable level neural networks APIs. It is written in Python and supports numerous back-end neural network calculation motors. Keras was made to be easy to understand, particular, simple to expand, and to work with Python. The Programming interface was "intended for individuals, not machines," and "follows best practices for decreasing mental load."Neural layers, cost capabilities, streamlining agents, instatement plans, initiation capabilities, and regularization plans are all independent modules that you can join to make new models. New modules are easy to add, as new classes and works. Models are characterized in Python code, not isolated model setup documents. The most compelling motivations to utilize Keras originate from its core values, basically the one about being easy to understand. Past simplicity of learning and simplicity of model structure, Keras offers the upsides of expansive reception, support for an extensive variety of creation organization choices, coordination with no less than five back-end motors (TensorFlow, CNTK, Theano, MXNet, and PlaidML), and solid help for various GPUs and conveyed preparing.

CHAPTER-4

DESIGN

4.1 INTRODUCTION

The Plan objectives comprise of different plan which we have executed in our framework Music sort grouping utilizing CNN. This framework has worked with different plans, for example, information stream graph, arrangement outline, class outline, use case graph, part graph, action chart, state graph, sending chart. Subsequent to doing these different outlines and in light of these charts we have done our project

Model: A model is nothing but simplified representation of thing/product.

UML: UML is a language for Visualizing, Specifying, Constructing, and Documenting artefacts of a software project.

4.2 UML DIAGRAMS

Diagram: The gathering of things and relationship is known as outlines". To all the more likely comprehend to a model (or) a framework there are different in UML each outline gives different data about framework. Each product contains primary perspectives along with conduct angles to address this the outlines.

Diagrams are categorized into two parts.

- Static/structural diagram
- Dynamic/behavioural diagram

STATIC DIAGRAMS:

- Class diagram
- Object diagram
- Component diagram
- Package Diagram

DYNAMIC DIAGRAMS:

- Use Case diagram

- Activity diagram

4.2.1 Class Diagram

Class Diagram are the outlines of our framework. You can utilize this chart to demonstrate the items they make up the framework, to show the connection among objects, and furthermore to depict what those articles do and benefits that they give. Class chart isn't just utilized for envisioning, portraying, and recording various parts of a framework yet in addition for building executable code of the product application. These class outlines are valuable in many phases of framework plan.

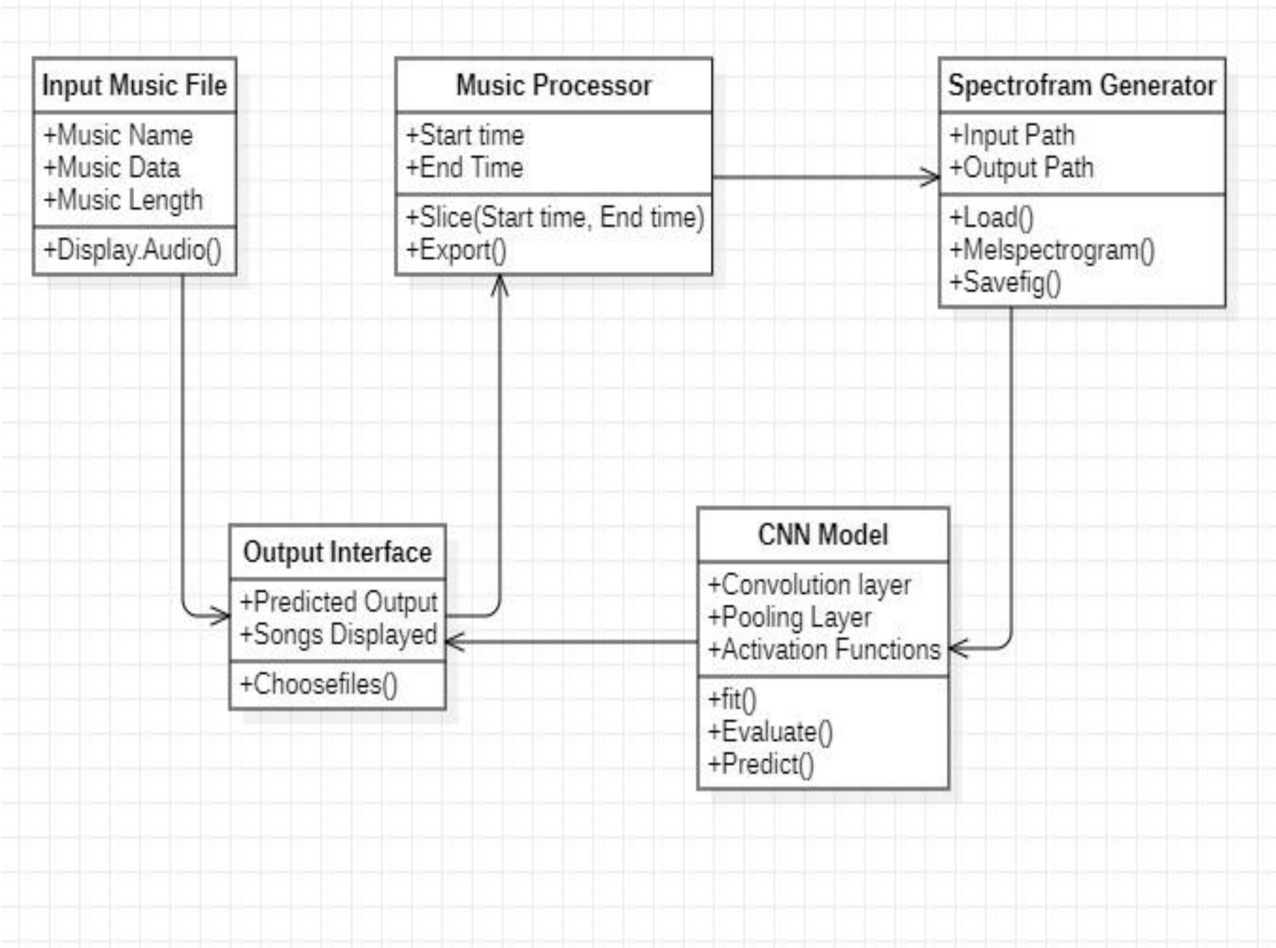


Fig 4.1 Class Diagram

4.2.2 Object Diagram

An Object Diagram shows the connection between launched classes and characterized classes, and the connection between these articles in the framework. These item charts are helpful to portray more modest segments of framework when your framework class outline is complicated.

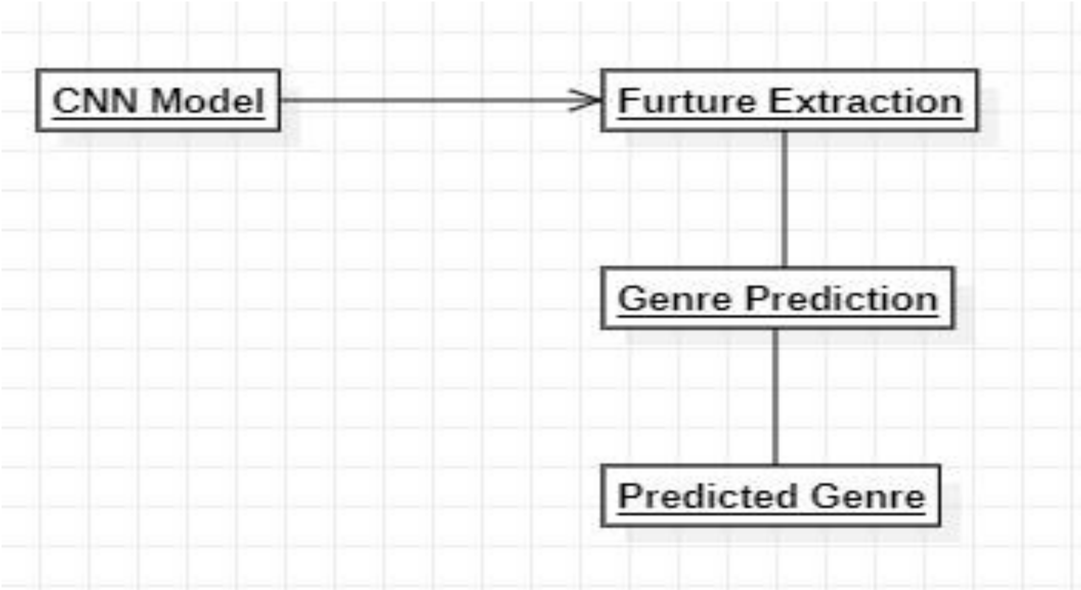


Fig 4.2 Object Diagram

4.2.3 Component Diagram

A Component Diagram, otherwise called an UML part chart, depicts the association and wiring of the actual parts in a framework. Part graphs are frequently attracted to assist with displaying execution subtleties and twofold check that each part of the framework's necessary capability is covered by arranged advancement. Here part outline comprises of all significant parts that is utilized to fabricate a framework. These outlines help to show the connection between various parts in framework. In our framework we have various parts like Dataset, Pre-processor, CNN Framework, highlight extractor and this multitude of parts connected to one another on the grounds that smooth working of one part relies upon the other part.

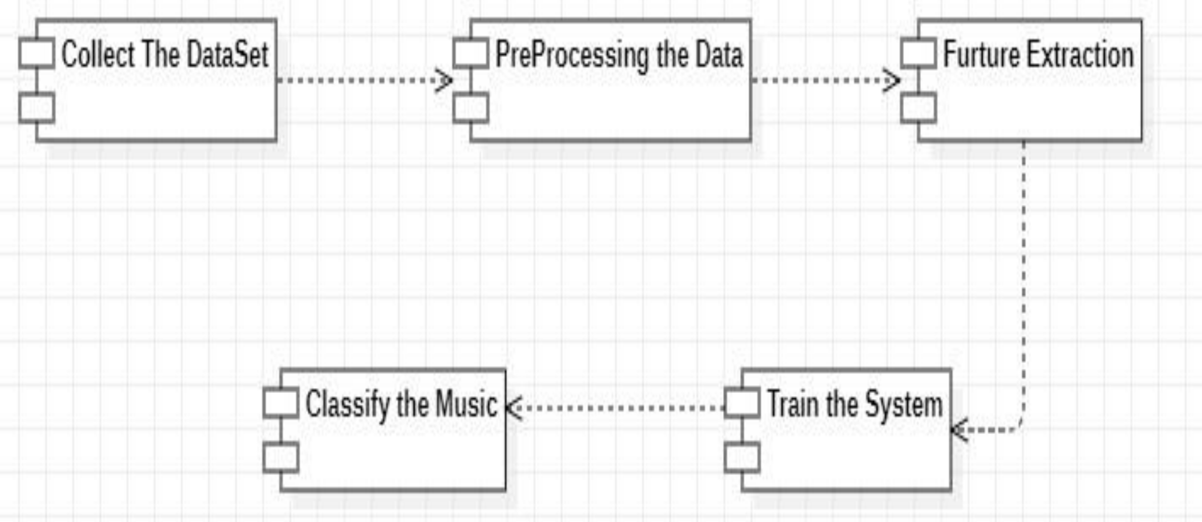


Fig 4.3 Component Diagram

4.2.4 Use Case Diagram

A Use Case Diagram is a graphical portrayal of a client's potential communications with a framework. A utilization case graph shows different use cases and various sorts of clients the framework has and will frequently be joined by different kinds of outlines too.

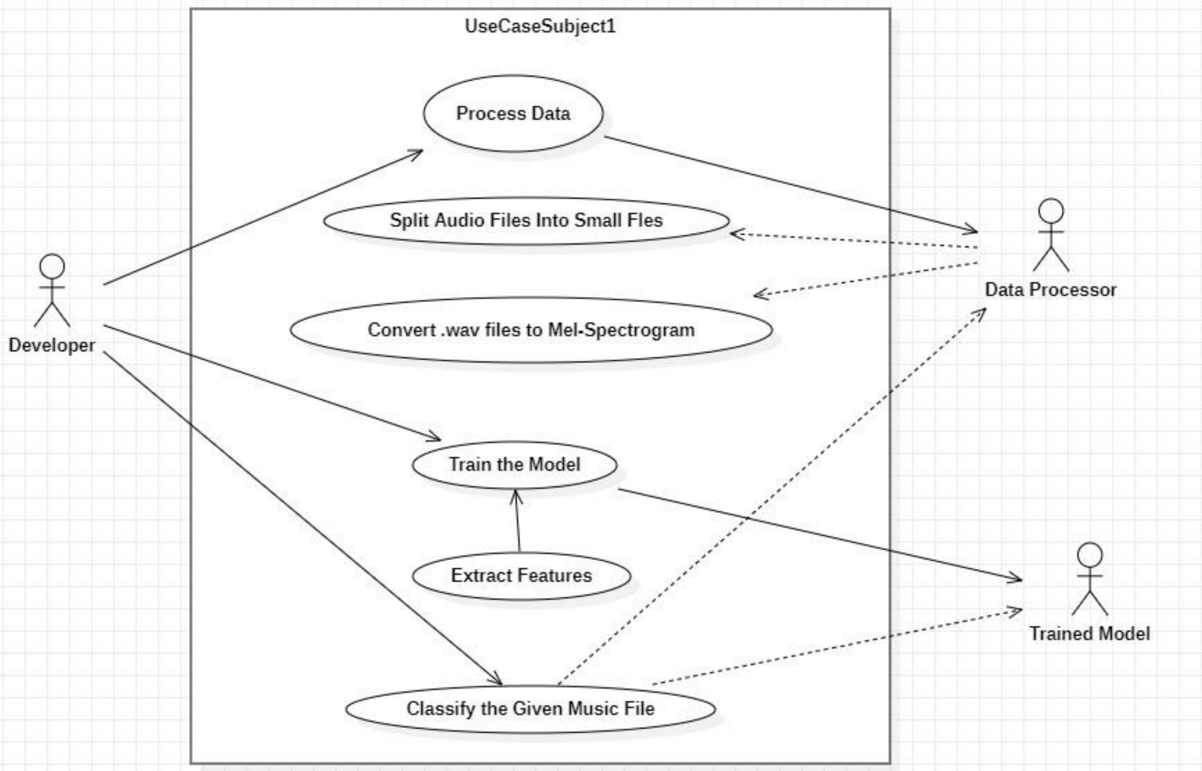


Fig 4.4 Use Case Diagram

4.2.5 Activity Diagram

Activity Diagram is one more significant outline in UML to portray the powerful parts of the framework. Action chart is fundamentally a flowchart to address the stream starting with one movement then onto the next action. The action can be portrayed as an activity of the framework. The control stream is attracted starting with one activity then onto the next. Here in our framework initial a dataset is gathered, and it is handled and parted into train and test then the model is prepared with train dataset and checked for execution on the off chance that not fulfilled then modify and retrain the model once done an obscure music is taken and process it and feed it to the model to get classification of that music record.

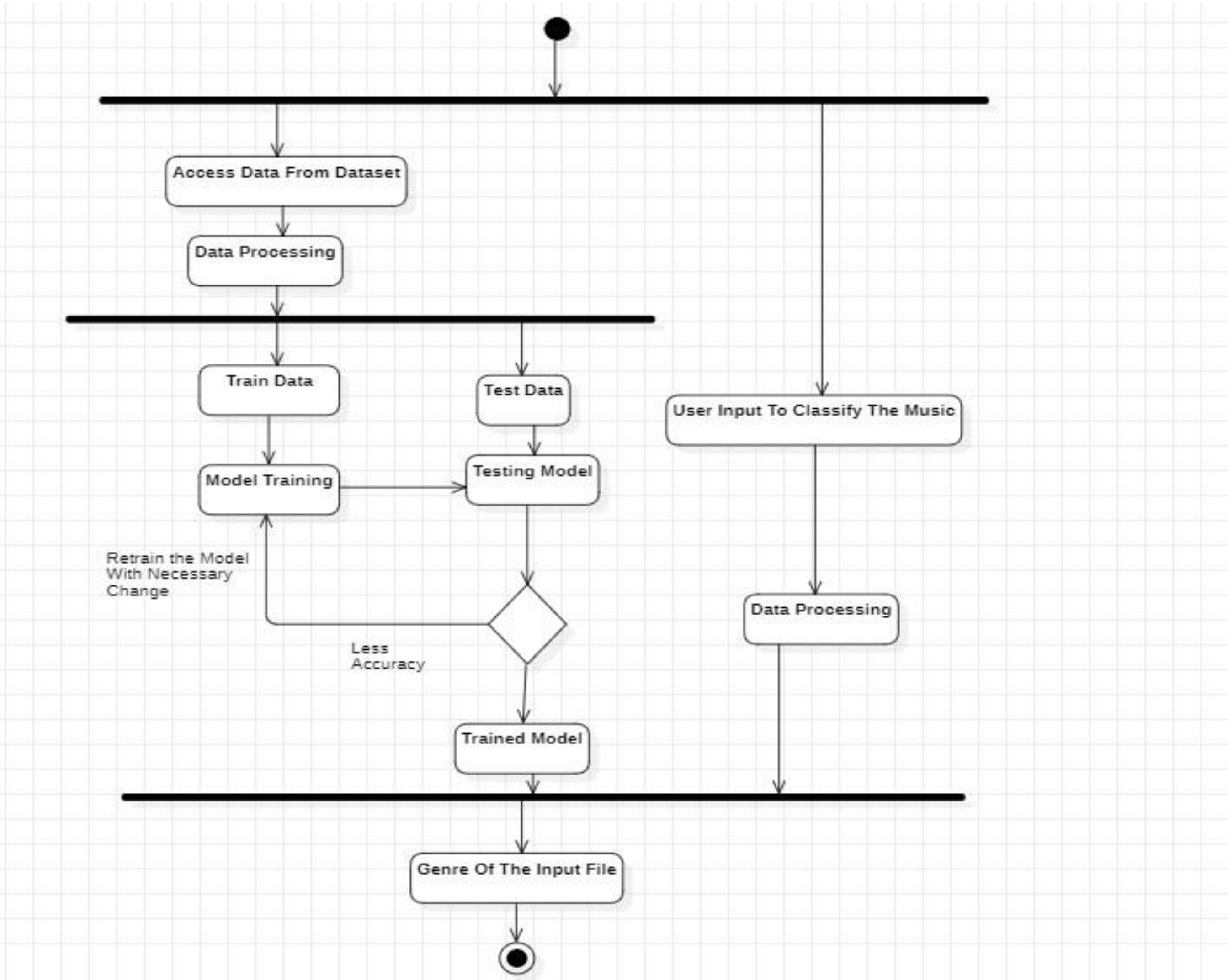


Fig 4.5 Activity Diagram

4.2.6 Package Diagram

A Package Diagram in UML portrays the conditions between the bundles that make up a model. In our undertaking we have bundles like Dataset, CNN model and the CNN model is reliant upon sub bundles like Keras and so forth and both the bundles are expected to prepare the framework.

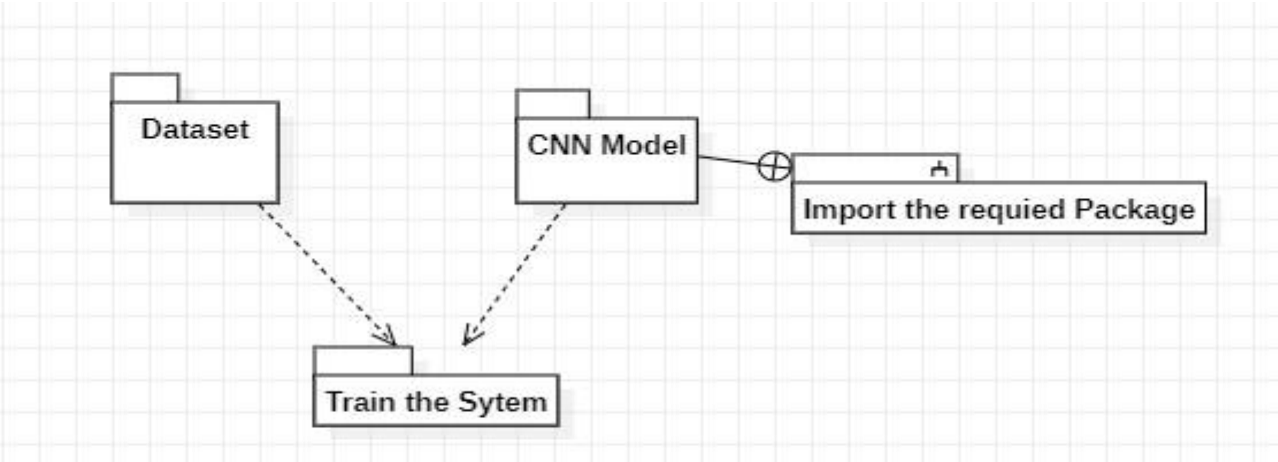


Fig 4.6 Package Diagram

4.3 SYSTEM ARCHITECTURE

Music Genre Classification utilizing CNN groups the given information music record into fitting class. The design of the framework utilizes the GTZAN dataset which contains the music documents of various sorts. In the pre-handling stage it first cuts the large sound record into sound document of three seconds each and afterward Mel-spectrograms are produced with that cut music records and the pictures created are parted into train and test datasets and the model is prepared over train dataset and when client gives the obscure music records the framework requires initial three seconds of the record and converts it to Mel-spectrograms and took care of to show then the model concentrates the highlights and gives the class of that music as the result. An engineering chart is a graphical portrayal of a bunch of ideas, that are important for a design, including their standards, components, and parts. As displayed in fig 4.1 the outline makes sense of about the framework programming in impression of outline of the framework.

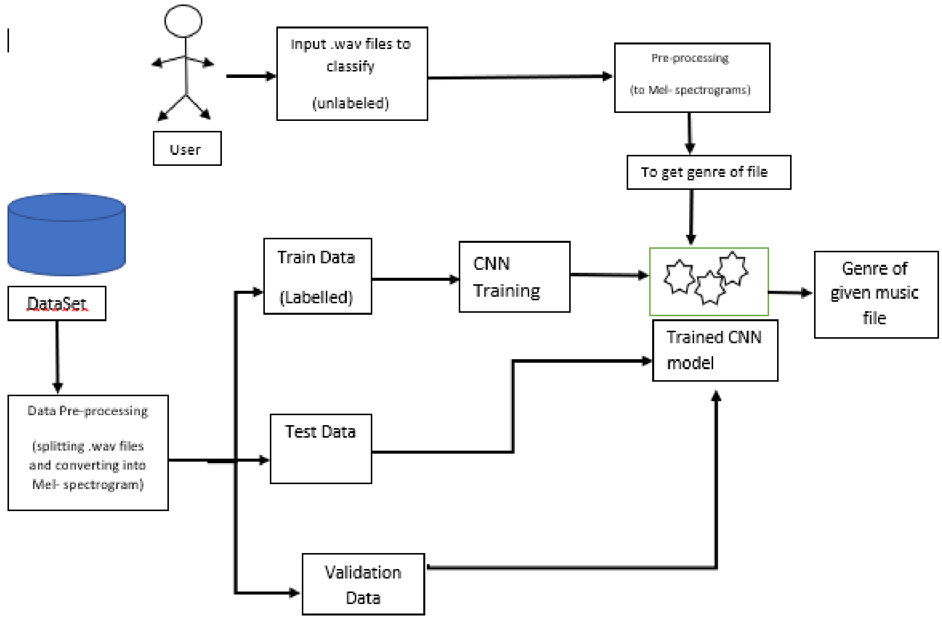


Fig 4.7 System Architecture

4.4 MODULE DESIGN AND ORGANISATION

1) Module 1 (Music File Slicing)

All the music documents in the dataset are cut into more modest records to get more information for training.

i.e., 30-second music document is made into 10 records of 3 seconds each utilizing a sound section from the Pydub library.

2) Module 2 (Generating Mel-spectrograms)

Every one of the created 3 seconds records of all genres are changed over into Mel-spectrograms utilizing the librosa to give them as a contribution to our planned convolutional neural organization.

3) Module 3 (Divide dataset into Train and Test Sets)

The created Mel-spectrograms are parted into Preparing Dataset, Approval Dataset, Testing Dataset in the proportion that is fitting for the model to be productive.

4) Module 4 (Defining path to pass images to CNN model)

Every one of the ways of the Train, Approve, Test are joined to the factors utilizing the capability "train_gen.flow_from_directory(path,target_size ,batch_size=,class_mode=)" with the goal that the pictures from individual ways can be taken care of to the model as indicated by the group size.

5) Module 5 (CNN Model Training)

The CNN model is constructed utilizing the Keras successive engineering with convolutional layers, pooling layers, smooth, thick layers and afterward it is incorporated with a reasonable enhancer and a gaining rate and prepared with a train dataset from picture generator module.

6) Module 6 (Getting Genre of Unknown Music File)

The music document that is taken as information is first changed over into Mel-spectrogram and afterward took care of into the model to get the name of the music record.

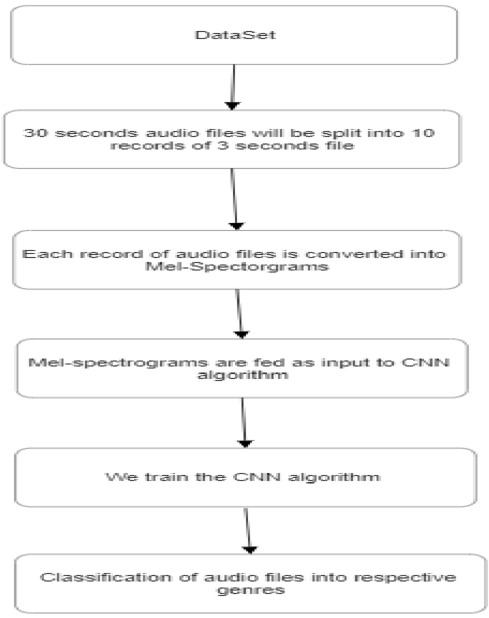


Fig 4.8 Data Flow Diagram

4.5 CONCLUSION

In light of the relative multitude of charts we can plan the necessary functionalities and the progression of information that will be kept up with between every one of them. By doing this we can keep up with the framework with next to no bugs and blunders. We had the option to construct a model with great execution. Every one of the graphs that are created show us the functionalities of the model and the framework created on top of it.

CHAPTER-5

IMPLEMENTATION AND RESULTS

5.1 INTRODUCTION

Execution is the phase of the task when the hypothetical plan is transformed out into a functioning framework. Those can be viewed as the most basic stage in accomplishing a fruitful new framework and in giving the client certainty that the new framework will work and be compelling. The execution stage includes cautious preparation, examination of the current framework and its imperatives on executions, planning of techniques to accomplish change over and assessment of progress over strategies. Our venture "music type characterization utilizing CNN" is executed utilizing python totally.

5.2 METHOD OF IMPLEMENTATION

For execution we want to follow the accompanying advances:

1. Import the required modules like Tensor Stream, Keras, matplotlib, Pydub and so on.
2. Download the dataset and store it in the drive
3. Slice the sound record and store it in the envelope made for Mel-spectrograms in the drive.
4. Split the pictures produced into the train, validation, and test sets and store them in particular genres.
5. Develop the CNN model utilizing the Keras API Programming interface with every one of the required layers.
6. Use picture information from dataset capability to take care of the pictures present in organizers to the CNN model.
7. Test the model with the pictures in the test dataset.
8. Take the obscure music document and require its initial three seconds and produce its Mel-spectrogram and feed it to display the model giving the class of that music record as a result.

"""**Importing Dataset from Kaggle**"""

```
!pip install -q kaggle
from google.colab
import drive
drive.mount('/content/dr
ive') from google.colab
import files
files.upload() ! mkdir
~/.kaggle
! cp kaggle.json ~/.kaggle
! chmod 600 ~/.kaggle/kaggle.json
! kaggle datasets download -d andradaolteanu/gtzan-dataset-music-genre-classification
```

"""**Unzipping Dataset**"""

```
! unzip gtzan-dataset-music-genre-classification.zip
```

"""**Importing Required packages**"""

```
!pip install pydub import os
import matplotlib.pyplot as plt
from tensorflow import keras
from keras.layers import *
from keras.models import *
from keras.preprocessing
import image
from keras.preprocessing.image
import ImageDataGenerator
import shutil
import tensorflow as tf
import numpy as np
import scipy from PIL
import Image
import librosa from keras.applications.imagenet_utils
import preprocess_input
import pydot from keras.utils.vis_utils
```

import model_to_dot from matplotlib.backends.backend_agg

import FigureCanvasAgg as FigureCanvas

"""**Slicing 30 sec audio into 10 files with 3 second each**"""

```
from pydub import AudioSegment
newSong = 'newSong'
i=0:
 for g in genres: j=0 print(f"{g}") for filename in
os.listdir(os.path.join('/content/Data/genres_original',f"{g}")):
song = os.path.join(f'/content/Data/genres_original/{g}',f'{filename}') j = j+1 for w in
range(0,10):
i = i+1 #print(i) t1 = 3*(w)*1000 t2 = 3*(w+1)*1000 newAudio =
AudioSegment.from_wav(song) new = newAudio[t1:t2]
```

#create a directory for 3seconds audio files

```
new.export(f'/content/drive/MyDrive/Project/audio3sec/{g}/{g+str(j)+str(w)}.wav',
format="wav")
```

"""**Creating Mel-Spectrograms**"""

```
import numpy as np import
librosa.display, os import
matplotlib.pyplot as plt def
create_spectrogram(audio_file,image_fi
e):
    fig = plt.figure()     ax =
fig.add_subplot(1, 1, 1)     y, sr =
librosa.load(audio_file)     ms =
librosa.feature.melspectrogram(y, sr=sr)
canvas = FigureCanvas(fig)     log_ms =
librosa.power_to_db(ms, ref=np.max)
plt.imshow(log_ms)
plt.savefig(image_file, transparent = True,
bbox_inches = 'tight', pad_inches = 0)
plt.close(fig) def
create_pngs_from_wavs(input_path,
```

```
output_path): if not
os.path.exists(output_path):
os.makedirs(output_p
ath) dir =
os.listdir(input_path)
for i, file in
enumerate(dir):
input_file = os.path.join(input_path, file) output_file =
os.path.join(output_path, file.replace('.wav', '.png'))
create_spectrogram(input_file, output_file)

create_pngs_from_wavs('/content/drive/MyDrive/Project/audio3sec/blues',
'/content/drive/MyDrive/Project/spectrograms3sec/blues')
create_pngs_from_wavs('/content/drive/MyDrive/Project/audio3sec/classical',
'/content/drive/MyDrive/Project/spectrograms3sec/classical')
```

"""**splitting the Mel-spectrograms in spectrograms folder to train, validation and test folders**"""

```
directory =
"/content/drive/MyDrive/Project/spectrograms3sec/" for g in
genres:
filenames =
os.listdir(os.path.join(directory,f"{g}")) for f in
filenames:
shutil.move(directory + f"{g}"+ "/" + f,"/content/drive/MyDrive/Project/train/" +
f"{g}")

import random directory =
"/content/drive/MyDrive/Project/train/" for
g in genres:
filenames =
os.listdir(os.path.join(directory,f"{g}"))
```

random.shuffle(filenames) test_files =
filenames[0:200] for f in test_files:
shutil.move(directory + f"{g}"+ "/" + f,"/content/drive/MyDrive/Project/valid/" +
f"{g}") """**Specifying the train, validation and test paths**""" from
tensorflow.keras.utils import load_img from tensorflow.keras.utils import
img_to_array train_path = "/content/drive/MyDrive/Project2/train" val_path =
"/content/drive/MyDrive/Project2/valid" test_path =
"/content/drive/MyDrive/Project2/test" image_categories =
os.listdir('/content/drive/MyDrive/Project2/train') print(image_categories)

"""**feeding the cnn model with images using image_dataset_from_directory function in keras**"""

IMAGE_HEIGHT = 237
IMAGE_WIDTH = 246
BATCH_SIZE = 64
N_CHANNELS = 3
N_CLASSES = 10

"""**CNN Model**""" model = Sequential() model.add(Conv2D(32, kernel_size =
(3, 3), activation='relu', input_shape=(237,246,3)))
model.add(BatchNormalization()) model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Conv2D(64, kernel_size=(3,3), activation='relu'))
model.add(BatchNormalization()) model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Conv2D(128, kernel_size=(3,3), activation='relu'))
model.add(BatchNormalization()) model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Conv2D(256, kernel_size=(3,3), activation='relu'))
model.add(BatchNormalization()) model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Conv2D(512, kernel_size=(3,3), activation='relu'))
model.add(BatchNormalization()) model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.2)) model.add(Flatten()) model.add(Dense(512,
activation='relu')) model.add(Dropout(0.5))
model.add(Dense(9,activation='softmax'))
model.summary() """Model compilation"""
model.compile(

```
loss='sparse_categorical_crossentropy',
optimizer=tf.keras.optimizers.Adam(learning_rate=0.0
001),     metrics=['accuracy'],
)
"""Model training""" history = model.fit(train_ds,
epochs=40, validation_data=valid_ds)
model.evaluate(test_ds)
max(history.history['val_accuracy'])
max(history.history['accuracy'])
plt.plot(history.history['val_loss'])
plt.plot(history.history['loss'])
plt.title("Model Loss")
plt.ylabel("Loss") plt.xlabel('Epochs')
plt.legend(['val_loss', 'loss'],
loc='upper left') plt.show()

plt.plot(history.history['val_accuracy'])
plt.plot(history.history['accuracy'])
plt.title("Model Accuracy")
plt.ylabel("accuracy") plt.xlabel('Epochs')
plt.legend(['val_accuracy', 'acc'],
loc='upper left') plt.show()

directory =
"/content/drive/MyDrive/Project2"
name = 'musicclassifier1.h5' path =
os.path.join(directory, name)
model.save(path)
 print('Saved trained model at %s ' %
path)
```

 # **Input music file processing**

```
audio= "/content/drive/MyDrive/Unknown/in-the-now-123545 (1).wav"
#Load & decode the audio as a time series, where sr represents the
```

sampling rate data , sr = librosa.load(audio) print(type(data), type(sr))
import IPython
IPython.display.Audio(data,
rate=sr """take first three seconds
of audio file""" from pydub
import AudioSegment t1 =
3*(w)*1000
t2 = 3*(w+1)*1000 newAudio =
AudioSegment.from_wav("/content/drive/MyDrive/Unknown/in-the-now-123545 (1).wav") newAudio = newAudio[t1:t2]
newAudio.export('/content/drive/MyDrive/Unknown/Slices/in-the-now-123545.wav', format="wav") audio = "/content/drive/MyDrive/Unknown/in-the-now-123545 (1).wav" #Load & decode the audio as a time series, where sr represents the sampling rate data , sr = librosa.load(audio) print(type(data), type(sr))

IPython.display.Audio(data, rate=sr) #Create Spectrogram
of input music File
create_pngs_from_wavs('/content/drive/MyDrive/Unknown
/Slices',
'/content/drive/MyDrive/Unknown/Spectrograms')

 # Predicting a genre of known music file from keras_preprocessing
import image
image_path="/content/drive/MyDrive/Project2/train/classical/classical100.png" img = image.load_img(image_path, target_size=(237,246,3))
plt.imshow(img) plt.show() x = image.img_to_array(img) x = np.expand_dims(x, axis=0) images = np.vstack([x])
pred = model.predict(images, batch_size=64) label = np.argmax(pred, axis=1) print("Actual: "+image_path.split("/")[-2]) print("Predicted: "+class_names[np.argmax(pred)]) # predicting genre of unknown music file from keras_preprocessing import image
image_path="/content/drive/MyDrive/Unknown/Spectrograms/Spectrogra

ms.png" img = image.load_img(image_path, target_size=(234,246,3))
plt.imshow(img)
plt.show() x = image.img_to_array(img) x
= np.expand_dims(x, axis=0) images =
np.vstack([x]) pred =
model.predict(images, batch_size=64) label
= np.argmax(pred, axis=1)
print("Predicted:
"+class_names[np.argmax(pred)])

5.3 OUTPUT SCREENS AND ANALYSIS

```
! unzip gtzan-dataset-music-genre-classification.zip

Archive:  gtzan-dataset-music-genre-classification.zip
  inflating: Data/features_30_sec.csv
  inflating: Data/features_3_sec.csv
  inflating: Data/genres_original/blues/blues.00000.wav
  inflating: Data/genres_original/blues/blues.00001.wav
  inflating: Data/genres_original/blues/blues.00002.wav
  inflating: Data/genres_original/blues/blues.00003.wav
  inflating: Data/genres_original/blues/blues.00004.wav
  inflating: Data/genres_original/blues/blues.00005.wav
  inflating: Data/genres_original/blues/blues.00006.wav
  inflating: Data/genres_original/blues/blues.00007.wav
  inflating: Data/genres_original/blues/blues.00008.wav
  inflating: Data/genres_original/blues/blues.00009.wav
  inflating: Data/genres_original/blues/blues.00010.wav
  inflating: Data/genres_original/blues/blues.00011.wav
  inflating: Data/genres_original/blues/blues.00012.wav
  inflating: Data/genres_original/blues/blues.00013.wav
  inflating: Data/genres_original/blues/blues.00014.wav
  inflating: Data/genres_original/blues/blues.00015.wav
  inflating: Data/genres_original/blues/blues.00016.wav
  inflating: Data/genres_original/blues/blues.00017.wav
  inflating: Data/genres_original/blues/blues.00018.wav
  inflating: Data/genres_original/blues/blues.00019.wav
  inflating: Data/genres_original/blues/blues.00020.wav
```

Fig 5.1.1 Dataset pulling and unzipping the music files in it

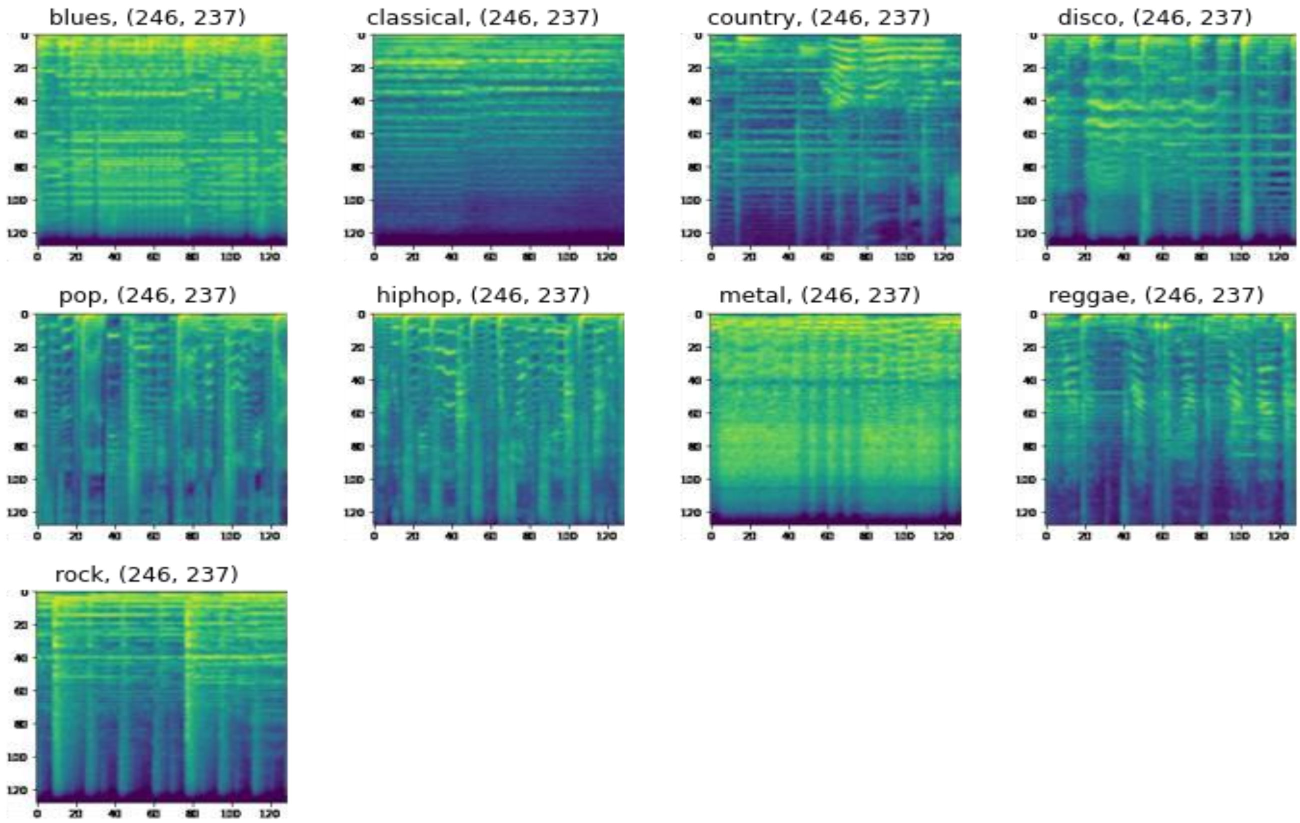


Fig 5.2 Generated Spectrograms of different genres

```
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_10 (Conv2D)          (None, 235, 244, 32)      896

 batch_normalization_10 (Bat  (None, 235, 244, 32)     128
 chNormalization)

 max_pooling2d_10 (MaxPoolin  (None, 117, 122, 32)     0
 g2D)

 conv2d_11 (Conv2D)          (None, 115, 120, 64)      18496

 batch_normalization_11 (Bat  (None, 115, 120, 64)     256
 chNormalization)

 max_pooling2d_11 (MaxPoolin  (None, 57, 60, 64)       0
 g2D)

 conv2d_12 (Conv2D)          (None, 55, 58, 128)       73856

 batch_normalization_12 (Bat  (None, 55, 58, 128)      512
 chNormalization)

 max_pooling2d_12 (MaxPoolin  (None, 27, 29, 128)      0
 g2D)

 conv2d_13 (Conv2D)          (None, 25, 27, 256)       295168

 batch_normalization_13 (Bat  (None, 25, 27, 256)      1024
 chNormalization)

 max_pooling2d_13 (MaxPoolin  (None, 12, 13, 256)      0
 g2D)

 conv2d_14 (Conv2D)          (None, 10, 11, 512)       1180160

 batch_normalization_14 (Bat  (None, 10, 11, 512)      2048
 chNormalization)

 max_pooling2d_14 (MaxPoolin  (None, 5, 5, 512)        0
 g2D)

 dropout_4 (Dropout)         (None, 5, 5, 512)         0

 flatten_2 (Flatten)         (None, 12800)             0

 dense_4 (Dense)             (None, 512)               6554112

 dropout_5 (Dropout)         (None, 512)               0

 dense_5 (Dense)             (None, 9)                 4617

=================================================================
Total params: 8,131,273
```

Fig 5.3 Model Summary

```
model.evaluate(test_ds)

8/8 [==============================] - 3s 69ms/step - loss: 1.1564 - accuracy: 0.8689
[1.1563860177993774, 0.8688889145851135]
```

We have obtained a testing accuracy of 86.88 for the genre classification

Fig 5.4 Model testing accuracy

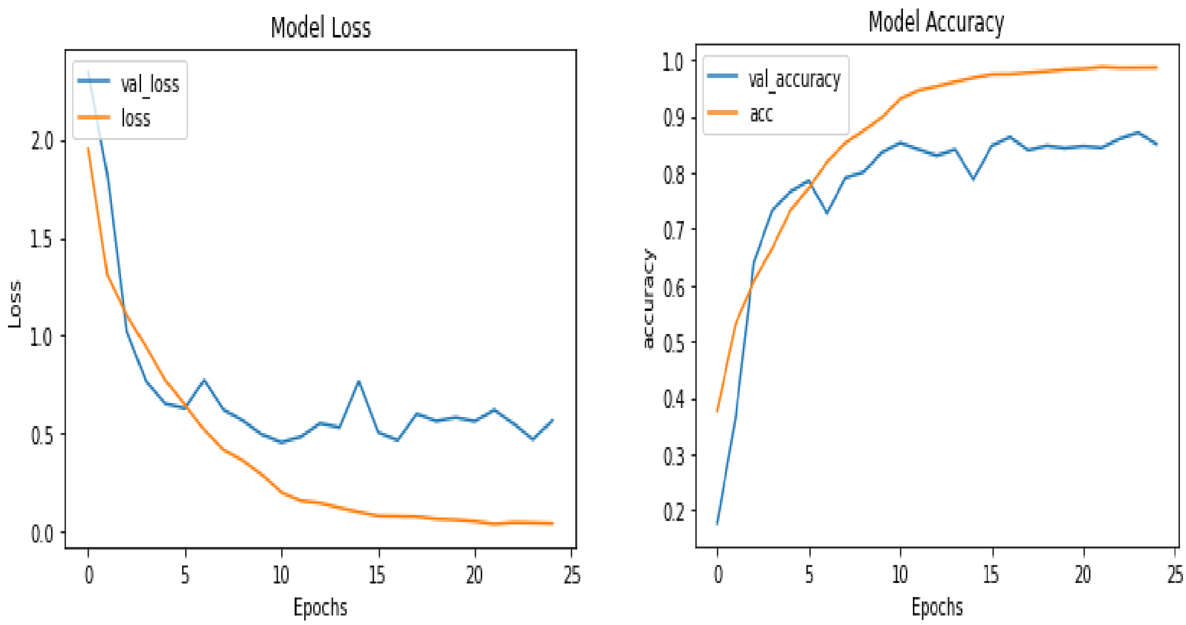


Fig 5.5 Model Loss and Accuracy curves up to 25 epochs

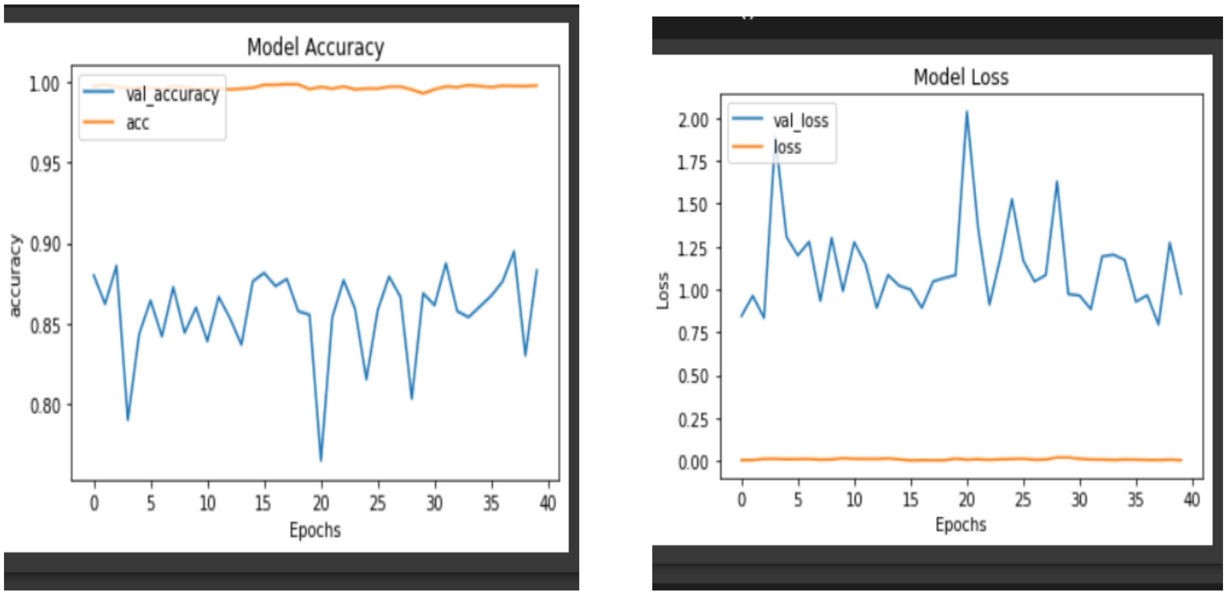
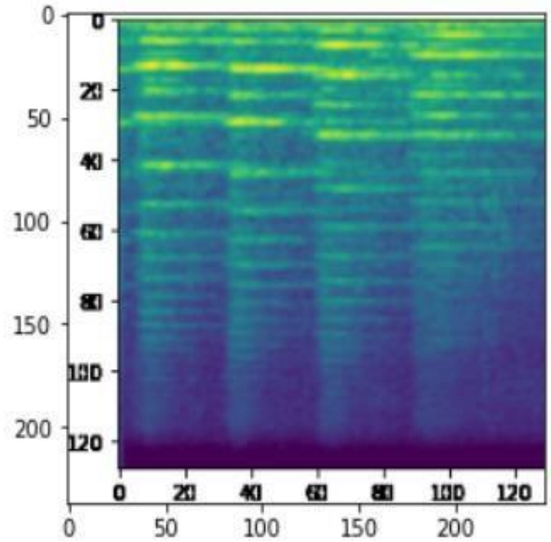
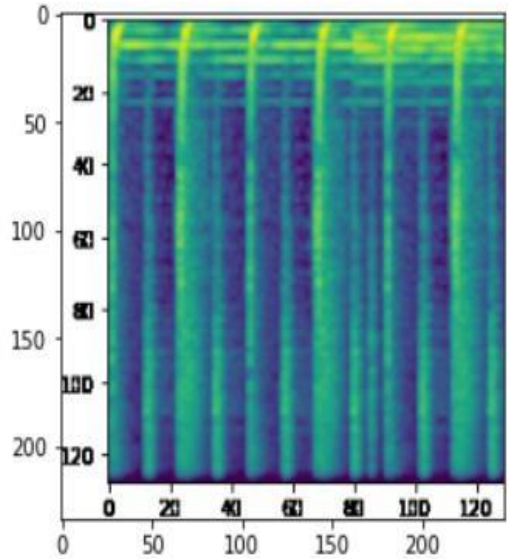


Fig 5.6 Model Loss and Accuracy curves up to 40 epochs



```
1/1 [==============================] - 0s 129ms/step
Actual: classical
Predicted: classical
```

Fig 5.7 Prediction of genre of known music file



```
1/1 [==============================] - 0s 96ms/step
Predicted: disco
```

Fig 5.8 Prediction of genre of unknown music file

5.4 CONCLUSION

The CNN design that we utilized in our work has shown a maximum accuracy of 82.11 on the test data. We have trained our model up to 20 epochs we have gotten a maximum training accuracy of 95.7 and a maximum validation accuracy of 83.1 and an 84.77 testing precision and when prepared up to 40 epochs preparing exactness of 99.8, approval precision of 88.25 and a testing accuracy of 86.88.

CHAPTER-6

TESTING AND VALIDATION

6.1 INTRODUCTION

INTRODUCTION TO TESTING

Testing is a cycle which uncovers the blunders in the program. The model is accurately grouping the class of the music document or not. By giving info pictures in the testing organizer in colab journal, the testing is finished. The model is tried for exactness which is determined by the quantity of information sources it is arranging accurately to the quantity of records utilized for testing. It addresses a definitive survey of particular, plan, and age.

UNIT TESTING

Unit testing includes the plan of experiments that approve that the inward program rationales working appropriately, and that program inputs produce legitimate results. All choice branches and interior code stream ought to be approved. It is the trying of individual programming units of the application. It is finished after the consummation of a singular unit before joining. This is a primary testing, that depends on information on its development and is obtrusive. Unit tests perform fundamental tests at part level and test a particular business interaction, application, as well as framework design.

INTEGRATION TESTING

Integration tests are intended to test coordinated programming parts to decide whether they run as one program. Testing is occasion driven and is more worried about the fundamental result of screens or fields. Coordination tests exhibit that albeit the parts were exclusively fulfilment, as shown by effectively unit testing, the blend of parts is right and reliable. Incorporation testing is explicitly pointed toward uncovering the issues that emerge from the blend of parts.

VALIDATION TESTING

An engineering validation test (EVT) is performed on first engineering prototypes, to ensure that the basic unit performs to design goals and specifications. It is important in identifying design problems and solving them as early in the design cycle as possible, is the key to keeping projects on time and within budget. Too often, product design and performance problems are not detected until late in the product development cycle — when the product is ready to be shipped. The adage holds true: It costs a penny to make a change in engineering, a dime in production and a dollar after a product is in the field.

SYSTEM TESTING

Framework testing of programming or equipment is trying led on a total, incorporated framework to assess the framework's consistence with its predetermined necessities. Framework testing falls inside the extent of black box testing, and in that capacity, ought to require no information on the inward plan of the code or rationale.

6.2 DESIGN OF TEST CASES AND SCENARIOS

Module under test	Prediction of genre
Description	User needs to input the music file of which genre needs to be known and that music is converted into Mel-spectrogram by program
INPUT	Input music file and the Mel-spectrogram of that music is fed into the CNN model
OUTPUT	System outputs the genre of the input music file. The accuracy of the system depends on the quality of the music file if the music file is good without any noise, then the system returns the correct genre.

Remarks	Test Successful

Table 6.1 Test case for prediction of genre

6.3 CONCLUSION

We set off to make a framework that naturally characterizes the given info music record into its individual class. We were fruitful in making a model which performs better compared to the current models. our work has shown a most extreme precision of 85.11 on the test information. We have prepared our model up to 25 ages we have gotten a most extreme preparation precision of 98.7 and a greatest approval exactness of 87.1 and an 83.77 testing exactness and when prepared up to 40 ages preparing exactness of 99.2, approval precision of 87.25 and testing exactness of 85.11 were achieved.

CHAPTER-7
CONCLUSION

7.1 CONCLUSION

In our Project, we are putting out a strong and productive framework for ordering music classifications that can characterize the submitted sound record into various classes. Our proposed framework even decreases the assignment of recovering every one of the singular elements of the sound physically expected for the models to learn. This undertaking presents a neural network-based application for grouping music classifications. There are different strategies for removing sound elements, but it was resolved that Mel-spectrograms would turn out best for our motivation. We utilized CNN calculations to prepare our model and complete the arrangement of our dataset. This venture fills in to act as an illustration of a neural network-based framework for grouping melodic kinds. Marks are given to melodic perspectives, including type, as a component of the movement of music groupings in music information retrieval (MIR). The Python-based librosa module supports highlight extraction and consequently gives proper boundaries to organize preparation. As a result, our procedure appears to guarantee for ordering a colossal music library into the right classification.

7.2 FUTURE ENHANCEMENT

The future scope of this proposed framework is to basically work progressively under circumstances as it is quite possibly the main application. Furthermore, the ongoing work of this undertaking will be exceptionally useful in numerous applications when the framework is connected to the expected utilization. In future work, we attempt to foster different models by utilizing different neural networks like CRNN and foster a GUI and coordinate it with the created classifier. We'll continue working on the model's precision while consolidating streaming media and web crawlers to join our CNN design, which will make it more extensive, and help particular artists and music students in decreasing their learning time and augmenting their efficiency.

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