UNIVERSITATEA "ALEXANDRU-IOAN CUZA" DIN IAȘI

FACULTATEA DE INFORMATICĂ

LUCRARE DE LICENȚĂ

Music Recognition Using Convolutional Neural Networks

propusă de

Andrei Vavilov

Sesiunea: Iulie, 2021

Coordonator științific

Conf. Dr. Vitcu Anca

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Contents

Motivation

In the age of big data and immense computational power, artificial intelligence has come to be the new standard in the computer science field. Various types of data can be understood, learnt, predicted and even produced by a well-tuned neuronal network, making the principles of machine learning a must for a scientist nowadays.

Applications of neuronal networks can be found in any discipline: from medicine to physics, social sciences and languages. The purpose of this thesis is to depict how artificial intelligence can find it's place and purpose in a previously profoundly human field: art.

Introduction

The current thesis is an attempt to materialize the intersection of artificial intelligence and arts, especially, music.

The application consists of two major parts:

- First, the machine learning component, represented by a neuronal network framework, implemented from scratch (i.e. without the explicit support of existent frameworks or libraries). The module presents the necessary functionalities for constructing a neuronal network: layers, activation functions, metrics, optimizers, models and support for data generation and preprocessing.

- Second, the visual support, compound of two illustrative animations, created in Autodesk Maya 2019, and a Graphical User Interface, in which a hypothetical user can interact with the application by feeding it an YouTube link of a song. As a result, the application will decide whether the input song is played on a piano or not (prediction Piano/Other). Depending on the decision of the neuronal network, the corresponding Maya animation will be played.

0.1   Context

The first analogy between the way computers can process information and the way the human brain works (as we know, at least, to this day), has been made by Warren McCullough and Walter Pitts in 1944, who later became the founding members of what is sometimes called the first cognitive science department [8]. The primary idea

is elegant in it's simplicity: the neuron, the basis of the human cognitive apparatus, can be modelled in machine learning as an unit in a network.

Since then, numerous studies and breakthroughs have been made, as well as various frameworks and tools which make implementing a neuronal network accessible without possessing the full mathematical background needed prior.

0.2 Purpose and modus operandi

One of the purposes of this thesis is to implement the functionalities and the logic behind a neuronal network ab initio, as well as creating and fine-tuning a model. In order to complete this task, we consulted multiple sources(e.g. [10],[15],[13]) which presented the theoretical and mathematical aspects of constructing the aforementioned classifier. The implementation was constructed with the support of various tools from the Python programming language (e.g. Numpy, Librosa, Tenserflow Keras, Kapre), which will be extensively discussed in the following chapters.

As discussed before, the second component of the thesis regards the visual part of the application. For obtaining a interactive use of the project, we used Autodesk Maya 2019 (for creating the animations) and Python tkinkter for creating a simplistic GUI.

The logical flow of the pipeline is as follows: the user feeds an YouTube link of a song to the GUI. The model (previously trained and saved) computes a prediction regarding the category under which the input falls (Piano/Other). Given this result, the corresponding animation is played.

0.3 Personal contributions

Numerous attempts of creating a medium between artificial intelligence and other disciplines have been made since the rise of this field. Arts, especially music, is no exception.

The particularity of the current thesis is the approach we had in completing the task: implementing from scratch the neural network framework, and, implicitly, understanding the mathematical and theoretical subtleties of it, as well as creating the visual aid which aims to touch on (although briefly) 3D animations.

0.4 Structure

The structure of the present thesis follows the major constituent parts described before and is as follows:

1. Chapter One

    - Similar applications : in which other akin projects are mentioned;

2. Chapter Two

    - Technologies used : in which technologies needed for creating the application and their purpose and functionalities are discussed;

3. Chapter Three

    - Architecture and implementation : in which the actual implementation is discussed explicitly. This section contains technical and theoretical aspects of the thesis and showcases relevant code;

4. Chapter Four

    - Use cases: in which the functionalities of the project are presented.

0.5 Acknowledgements

I would like to express my special thanks of gratitude to the academical staff of the Faculty of Computer Science Iași for the opportunity to do this project.

Obviously, the present thesis would not be possible without the help and guidance of the professor that directed it, PhD. Anca Vitcu.

Chapter 1

Similar applications

Neural Network Models as well as Machine Learning algorithms provide various versatile and adaptive methods for non-linear problem solving. Because of these reasons , there are numerous applications which perform the task of musical/audio classification using the aforementioned techniques. We will discuss in the following sections about three of those applications.

1.1   Spektrum

Spektrum is a multi-platform music genre classificator and music recommandation system developed in the context of the course "Application Challenges for Machine Learning on the example of IBM Power AI", by the team consisting of Marte Vinje, Moritz Klimmek, Thomas Salzer, Aaron Hümmecke, Lukas Vorwerk [14] . The application consists of two parts:

- Music Genre Classification: Performed by a Convolutional Neural Network Model which analyzes the MEL spectogram of a given input song.

- Music Recomandation: Generating suggestions by making use of a combination collaborative filtering and content based filtering.
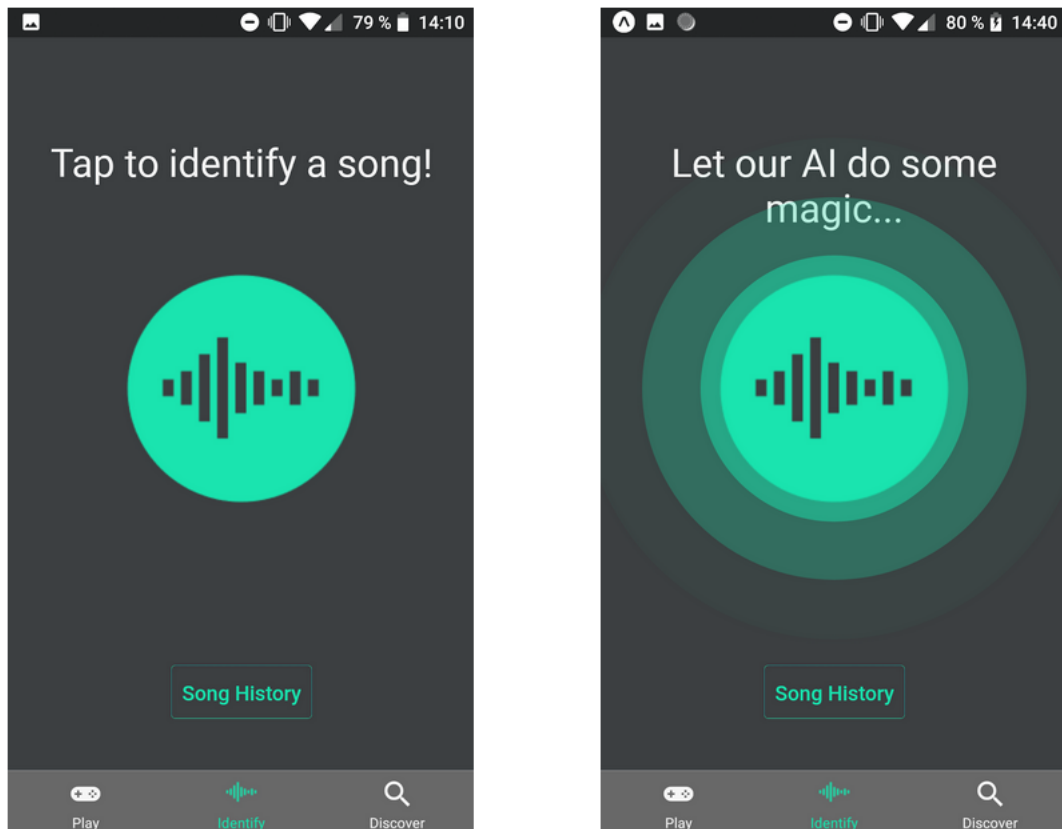
Figure 1.1: The interface of the Spektrum application (Photo source: [14])

1.2 MuseNet

MuseNet is a Deep Neural Network Framework developed by OpenAI that can generate 4-minute snippets of original musical composition with up to 10 different instruments, combining various styles ranging from Mozart to The Beatles. MuseNet creates music by determining the patterns over a given style as input, generating the respective sequence of notes and chords. It also computes a relational graph between the its various current styles, in order to incorporate as many related musical features as possible.
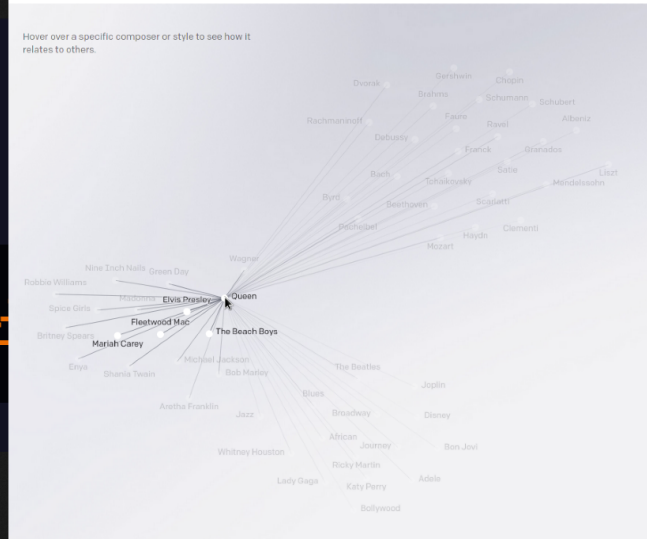
Figure 1.2: An illustration of the MuseNet's functionalities

1.3 Magenta

Magenta is an open source project (started by a group of engineers from the Google Brain team), based on deep learning and reinforcement learning used for generating and creating art. Based on Google's Tensorflow as well and Magenta.js, the produce original songs, images, drawings and material textures.
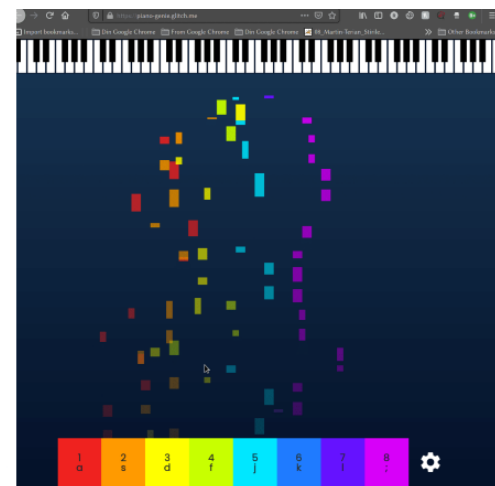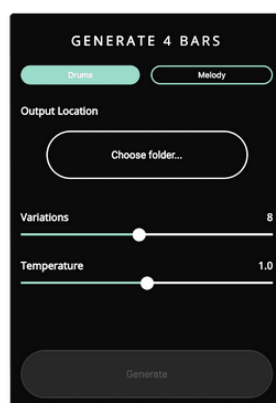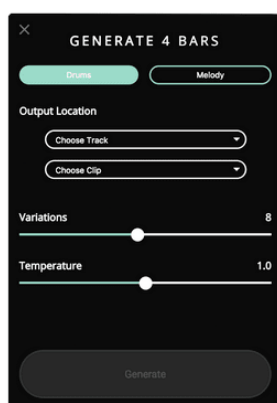

Figure 1.3: Applications based on Magenta

Chapter 2

Technologies used

Python provides many modules for numeric calculus, data processing and manipulation as well as tools for user interaction. In the following chapter we will breafly touch on the modules and libraries used for achieving the goal of the application, instrument classification.

2.1 Scipy

SciPy is a Python-based ecosystem of open-source software for mathematics, science, and engineering. The SciPy library contains a collection of numerical algorithms and domain-specific toolboxes, including signal processing, optimization, statistics, and much more.[4] The aforemetioned library's submodule *Input and output* provides a variety of ways of reading and writing data in numerous file formats. For the data processing part of the application, we had choosen the *scipy.io.wavfile.read* function because it facilitates the data manipulation process by being compatible with the numpy module, mentioned below (the output of the *scipy.io.wavfile.read* function is a tuple consisting of the sample rate(int) and the audio data(as a *ndarray*).

2.2 NumPy

Numpy is a Python library (part of the SciPy ecosystem) that provides the needed tools in order to perform the mathematical operations behind the Neural Network Framework. The core of the module is the *ndarray* object, which encapsulates an optimized n-dimensional array. Thus, we use *ndarray* objects for computing and storing

the various operations performed throughout the application (e.g. the dot product, the data reshaping). The *ndarray* array is represented as a matrix, whose dimensions are referred as *shape*. Some of the advantages brought by the numpy module are:

- Forward and backward operation compatibility for the various objects contained withing the application

- Fast execution time caused by the optimization of the library [3] (by using pre-compiled C code)

- Support for large number/big data processing.

2.3   TensorFlow

TensorFlow is an end-to-end open source platform for machine learning. It has a comprehensive, flexible ecosystem of tools, libraries and community resources that lets researchers push the state-of-the-art in ML and developers easily build and deploy ML powered applications.[5] From the vast amount of methods and submodules contained within TensorFlow, we used Keras, an utilitary library built on top of the TensorFlow API. In order for the Neural Network Framework to be able to handle large amounts of data, we inherited in our custom *DataGenerator class* the *tensorflow.keras.utils.Sequence* class. The *Keras DataGenerator class* along with the custom Neural Network Framework *DataGenerator* provide among other functionalities the *getitem* method, which yields a batch of data at a given index, thus overcoming the big data handling problem.

2.4   Kapre

Kapre (Keras Audio Preprocessors) is an audio data preprocessing library built on top of *Keras*, specialized on audio signal handling.[1] Kapre facilitates sound transformation by efficiently performing various operations (e.g. *Short Time Fourier Transformation, Magnitude*) in a GPU optimized consistent manner . For the input data modeling we had chosen the *get mel spectogram layer* function from the module *kapre.composed*. It applies sequentially *STFT, Magnitude and mel filterbank* transformations over the given input data, returning a mel spectogram with an user specified sample rate and output shape.

2.5   Librosa

Librosa is a python package for music and audio analysis. It provides the building blocks necessary to create music information retrieval systems. [11] Out of the Librosa API we have choosen the following tools :

- *resample*: A function that resamples an audio file from its original rate to an user given sample rate.

- *to mono*: A function which converts a multi channel signal to mono signaling by averaging the sample values.

2.6   youtube-dl

Youtube-dl is an open source tool for downloading videos and songs from the YouTube platform. In the context of the final application, the youtube-dl module provides the end user with the possibilty of classifying a song just by inserting a link to a YouTube video.

2.7   Tkinter

Tkinter is the standard Python GUI Toolkit, a simple yet versatile module was used for the minimalistic Graphic User Interface of the final application.

Chapter 3

Architecture and implementation

The application is divided into three parts:

- The Neuronal Network Engine

- The User Input Handling and Processing

- The Application-User interaction via the GUI

We will continue this chapter by entering into the details of each of the aforementioned component.

3.1   The Neuronal Network Engine

The the Neural Network Engine was developed using the Neural Network Framework which we implemented from scratch. The main application problem can be reduced to a binary classification problem (the engine has to predict if a given input falls into the category Piano or Other), thus we choosen the following architecture:
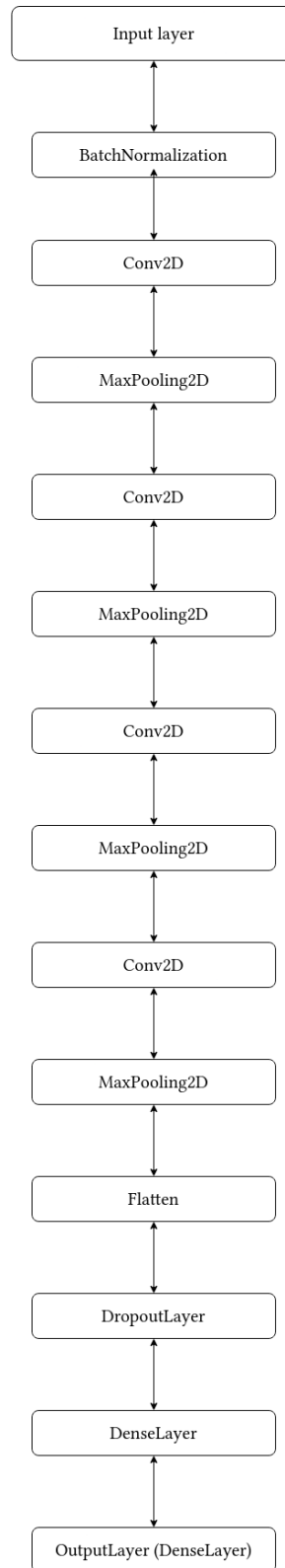
Figure 3.1: A summary of the model architecture

The model is composed of layers, which fall into two categories: trainable (Conv2D, MaxPooling2D, DenseLayer), and non-trainable (InputLayer, FlattenLayer, Dropout-Layer, BatchNormalization). The difference between the two categories is the type of the operations performed, and whether or not they facilitate the learning process.

For the trainable layers we choosen the *RMSProp*(Root Mean Squared Propagation) optimizer, which works by using a moving average of squared gradients to normalize the gradient. This normalization balances the step size(momentum), decreasing the step for large gradients to avoid exploding, and increasing the step for small gradients to avoid vanishing.[6]

The activation function we had choosen for the trainable layers is *ReLU*(Rectified Linear Unit), while for the activation layer we preferred the *SoftmaxActivation* because, unlike linear activation functions, the aforemetioned activation function returns the probability values normalized between 0 and 1, handling very small negative or exploding values by penalizing them.

The metrics measured throughout the learning process are computed using *CategoricalAccuracy* and *CategoricalCrossentropy*.

The Neural Network Engine consists of a model, which is a binary serialized file containing the weights and biases of the trainable layers from the figure 3.1.

The model values and its performance are the result of the training process, which consisted of five epochs over 33602 inputs values (one second wav audio snippets), presented to the model in the form of *batches* provided by the custom *Data generator*, with each batch containing 32 samples.

The data was gathered by web scraping various YouTube playlists, thus obtaining a diverse and feature rich dataset. The "Piano" category consists of isolated tracks which only contain piano snippets(any other combination of instruments will not be classified as expected by the model), while the "Other" category contains every other category of sounds.

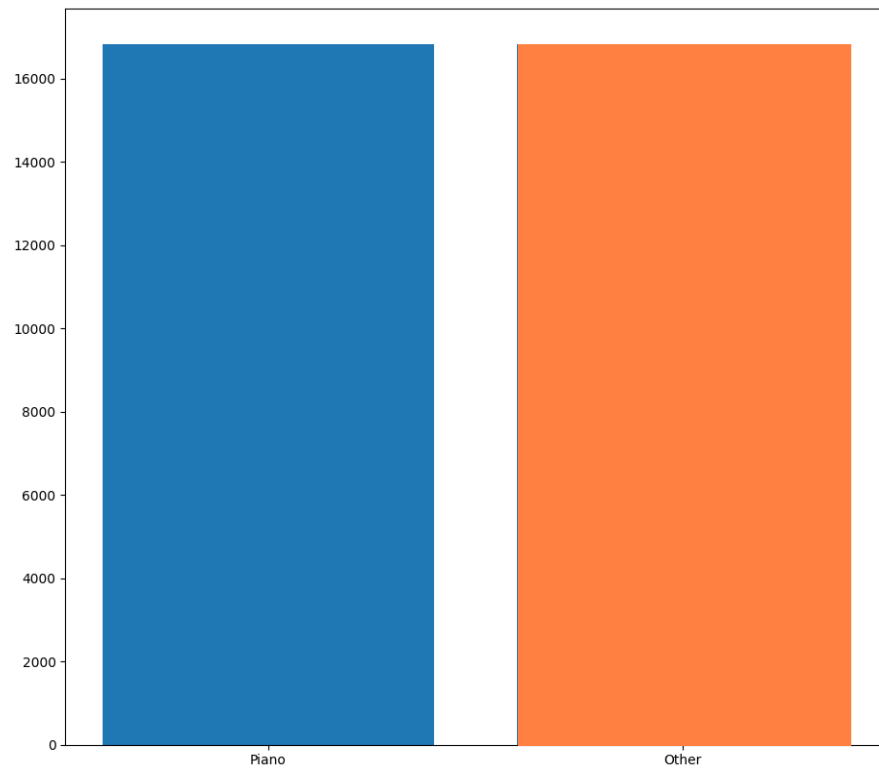The distribution of the data is presented in the below figure:

Figure 3.2: Data distribution by number of samples.

Initially we approached the problem without using Convolutional Operations, but after testing numerous configurations the results were below satisfying (with the loss stagnating at a value of about 0.5) and the accuracy fluctuating between 40-60
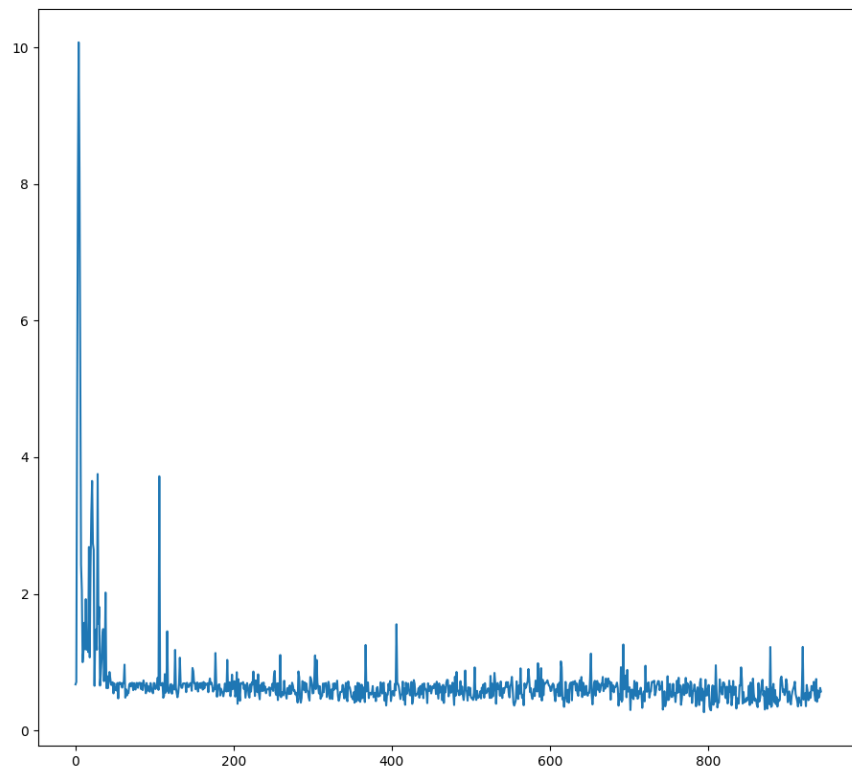
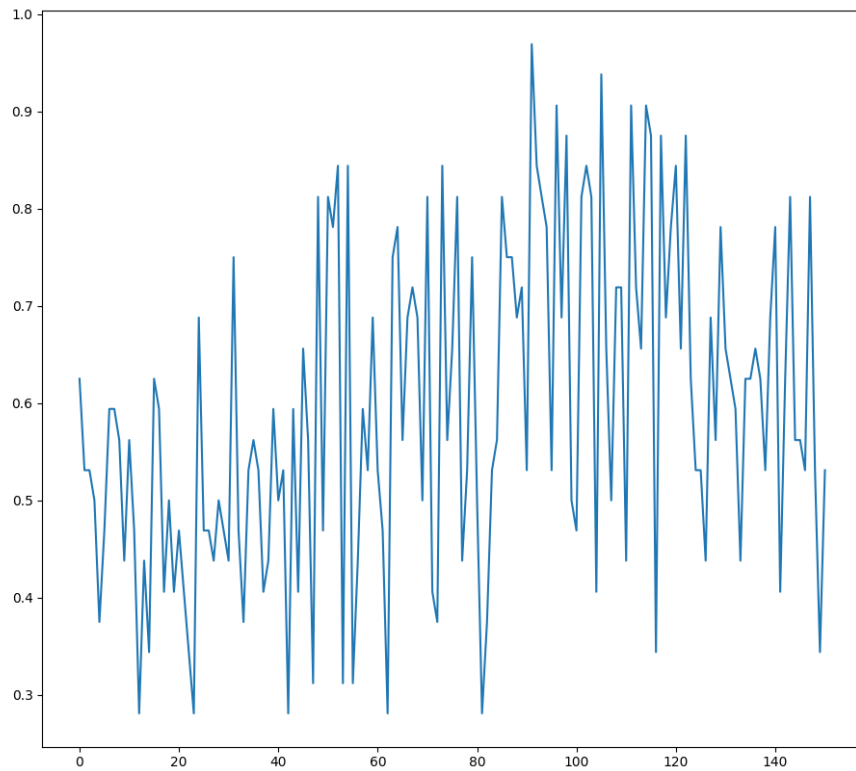Figure 3.3: Model loss before adding Convolutional Operations to the Model

Figure 3.4: Model accuracy before adding Convolutional Operations to the Model

By incorporating the Convolutional Operations and Layers into the Neural Network Framework, the model accuracy as well as the loss improved at a visible rate, as shown below.
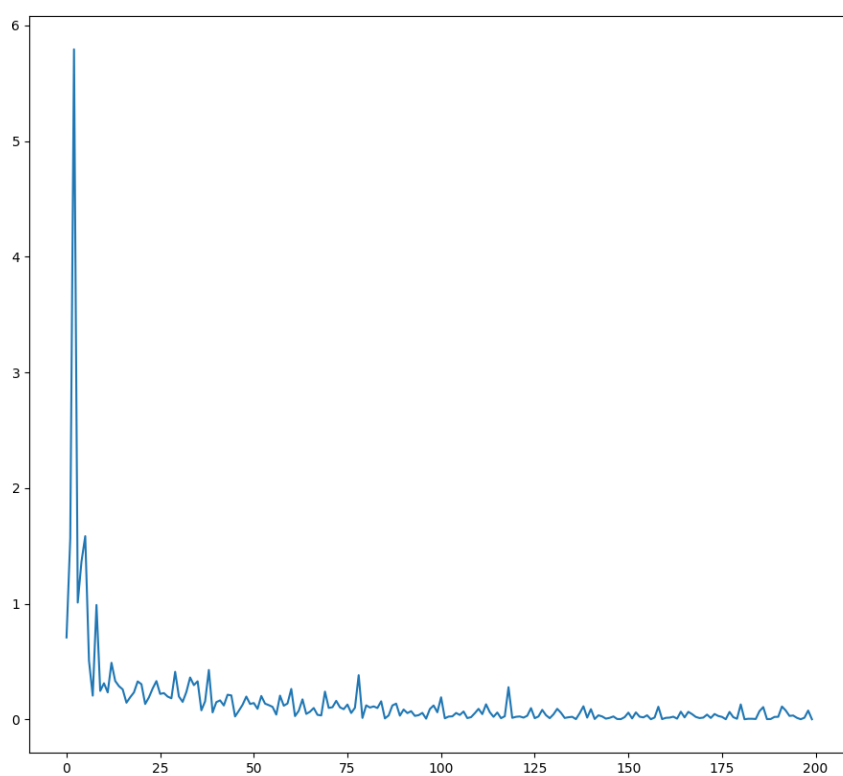
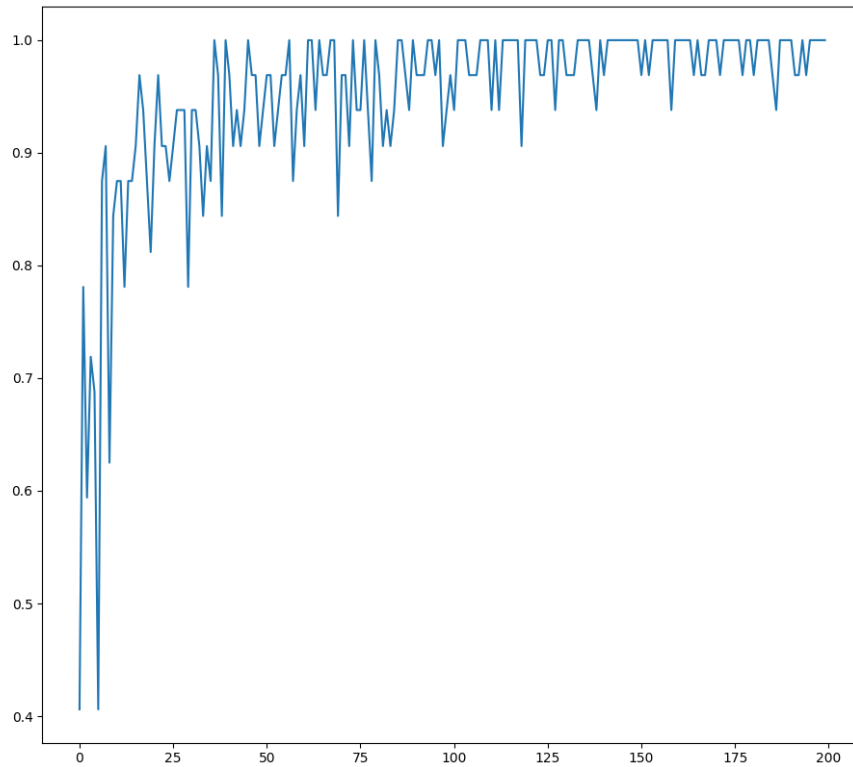Figure 3.5: The model loss after incorporating Convolutional Layers

Figure 3.6: The model accuracy after incorporating Convolutional Layers

The general flow of the data in the Neural Network Framework is based on the forward-backward propagation principle, specific to the *Convolutional Neural Network* architecture. Each of the trainable model's layers have the following methods:

1. :function:forward(inputs): A method which takes the previous layer output as the parameter(inputs) and perform the specific operations, thus performing the forward data processing.

2. :function:backward(derivated values): A method which takes the previous layer output, which consists of the gradient of the forward propagation end result(derivated values), performing the inverse computations in regards to the forward method, and then propagating the end result to the next layer.

3. :parameter:output: A *ndarray* where the *forward* function computations are stored.

4. :parameter:derivated input: A *ndarray* where the *backward* function computations are stored.

The following diagram ilustrates the forward-backward propagation of the Neural Network Model.
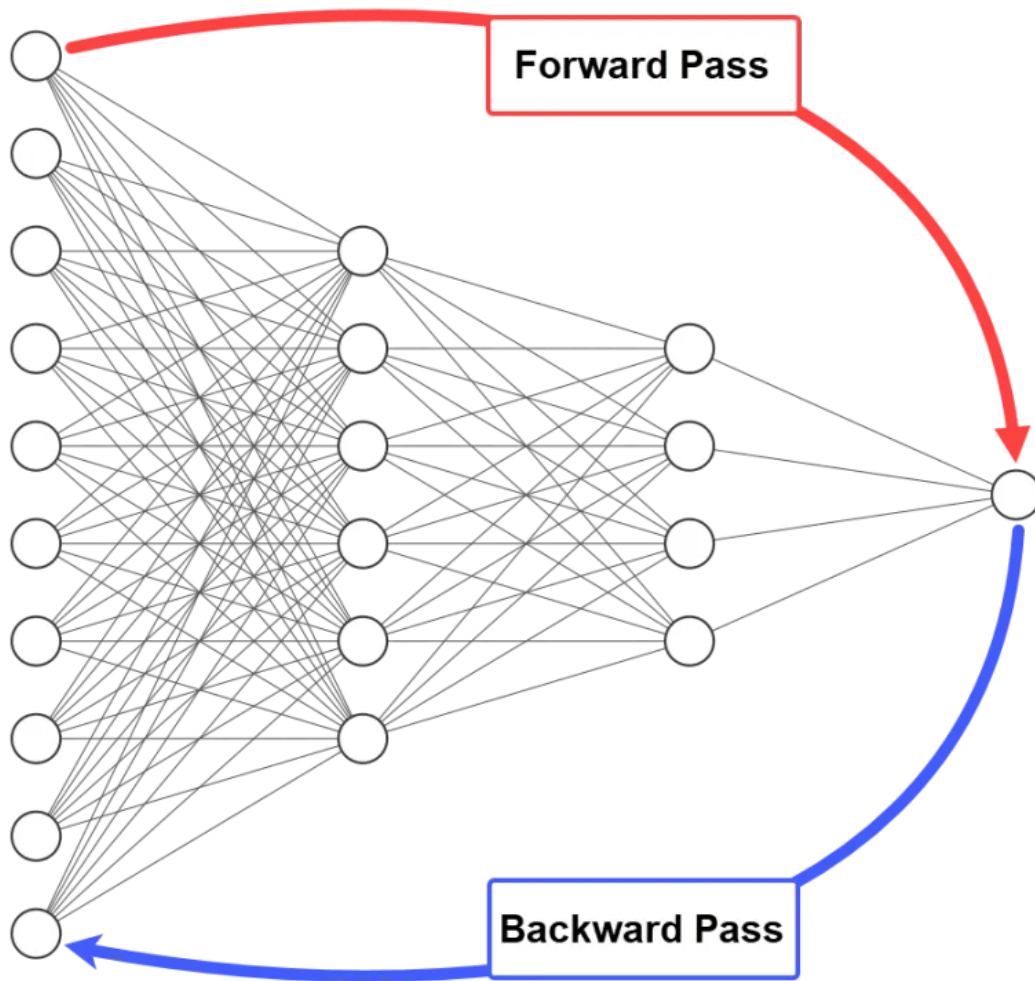

Figure 3.7: Data flow throughout the model (image source [12])

Because the model of the Neural Network Engine is effectively a Convolutional Neural Network, the training process follows the following schema:
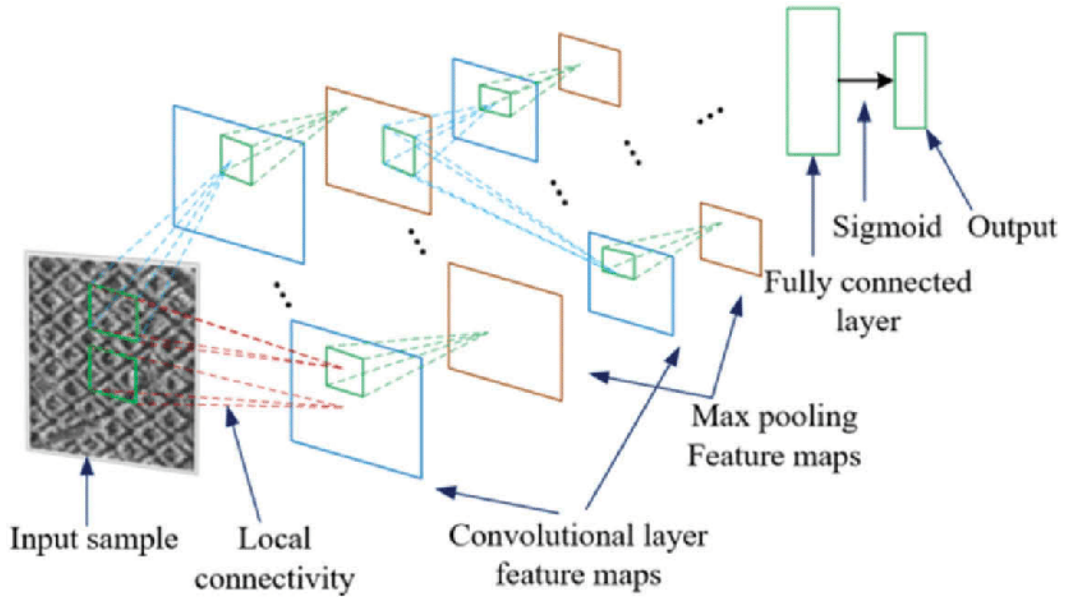
Figure 3.8: Generic Convolutional Neural Network architecture (image source [7])

At the end of each iteration the model has to classify unseen data (the *validation data*), and based on the results of the classification, the model *metrics* are computed, in the form of loss (computed with *Categorical CrossEntropy*) and accuracy (computed with *CategoricalAccuracy*).

3.2 User Input Handling and Processing

The modus operandi of the input handling and processing pipeline is presented in the following diagram.
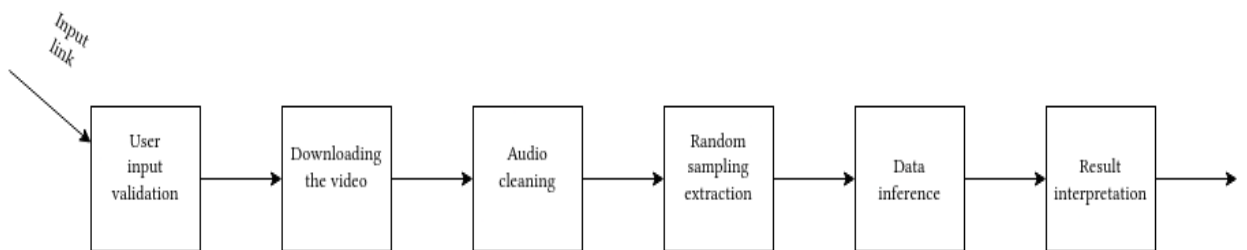

Figure 3.9: User input handling pipeline

The steps performed in order process the user input are as follows:

1. Validating the user input : Checking if the input link inserted by the user is a valid YouTube link to either a video or a playlist.

2. Downloading the video : Saving and converting the video at the specified link in a temporary folder. The *youtube-dl* utility facilitates this step by downloading the file using a list of specified configuration parameters such as audio quality and the output format. After this step, we will have obtained an audio file of format wav in a temporary folder, which will be deleted after the finish of the prediction operation.

3. Audio file cleaning: Given the reason that the model was trained on 1 second snippets of audio files of sample rate of 16000, the following operations are necessary to be performed to the audio file in order for it to be compatible with the Neural Network Engine:

   - Downsampling the wav file to mono: Reducing the number of channels of the file to mono with the function *to mono* from *librosa*.
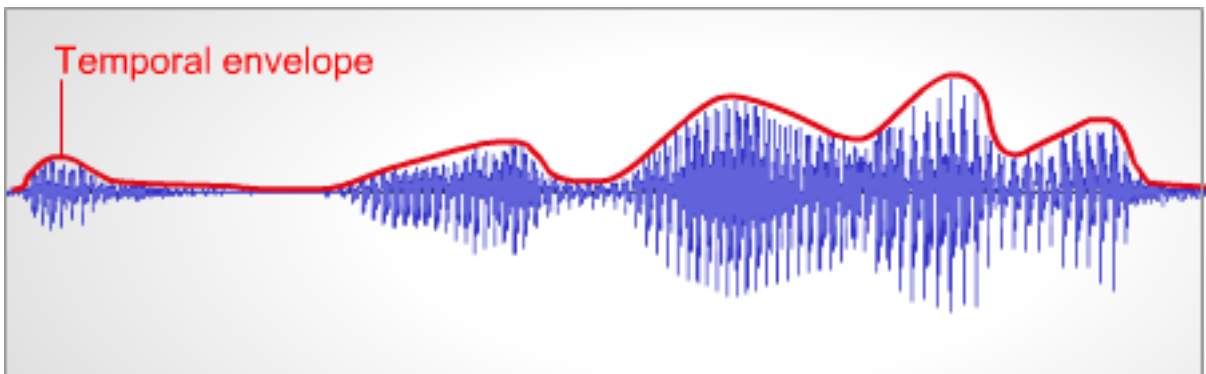
   - Cleaning the wav file by sound envelope.

Figure 3.10: Sound envelope example (Source [2])

   The sound envelope (presented in the figure 3.10), represents the changes in audio frequency over a period of time. The *split wav by sound envelope* function computes a *filtered mask* of the audio file by comparing each value of the sound envelope to a given threshold, thus eliminating the audio noise(such as crowd cheering and silence), keeping only the relevant audio information.

   - Splitting the masked audio file: After the first two steps of the audio processing, the audio file has to be splitted into 1 second samples and converted to a sample rate of 16000.

4. Extracting a number of random sound samples: In order to offer an accurate

prediction and reduce the time cost required by the Neural Network Engine, we randomly extract a number of samples from the splitted audio file.

5. Loading the random sound samples into the model: The Neural Network Engine also presents the *inference* functionality. The inference/prediction is performed by transforming the input data (transformation performed by the input layer), then performing the forward-backward data propagation once. The transformations applied by the input layer are:

  - Short Time Fourier Transformation

    Short Time Fourier Transformation is a mathematical transformation technique used for decomposing a function relative to its spatial and temporal dependencies. Since the audio signal is composed of sound wave which only ilustrate the amplitude of a recording, the Fourier transform allows for the creation of an illustration of a frequency over time,called spectrum. [9]
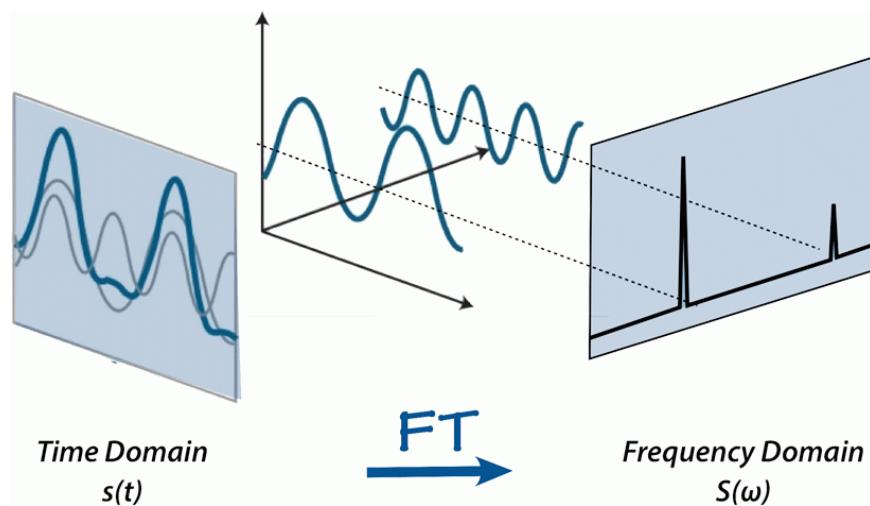

Figure 3.11: Fourier transformation (Source [9])

  - MEL Filterbank transformation

    The *MEL* scale is a reprezentation of the sounds that can be heard and distinguished by the human ear. The *MEL spectogram* is a graphical representation of the sound variations and intensities of the a given audio sample. With the *MEL Filterbank transformation* we effectively represent the relevant information of the input data, thus transforming the problem from an audio classification into an image classification one.
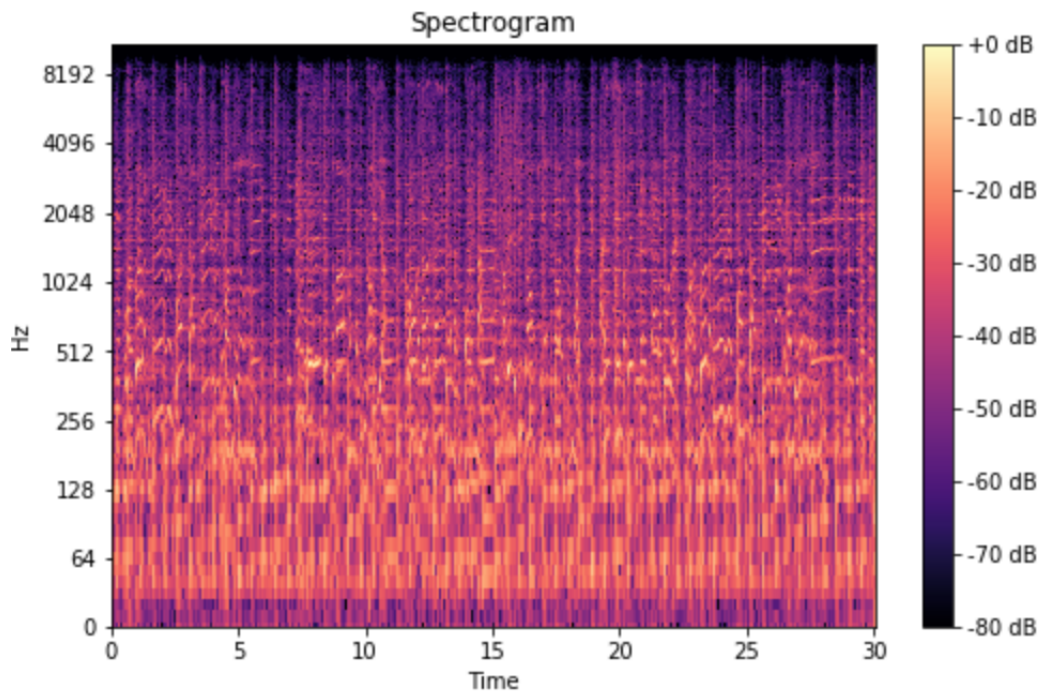
Figure 3.12: MEL Spectogram example

The output of the transformation is a *ndarray* containing the MEL spectogram of the input sample which represents the neural network model's input.

The inference output is an array containing floating point numbers which represent the confidence value of the model prediction.

The predicted label is computed by extracting the *argmax*(the index of the element with the biggest value), then mapping it to the specific class name.

6. Interpreting the result and returning the final prediction: The output label is stored for each prediction extracted from the random samples batch. The final label is computed by extracting the prediction which was suggested most often.

3.3 The Application-User Interaction

The application provides a minimalistic Graphic User Interface which offers the end user the means for classifying an YouTube song, as well as visualise the specific 3D Animation depending on the model prediction. The following figure illustrates some of the application states.
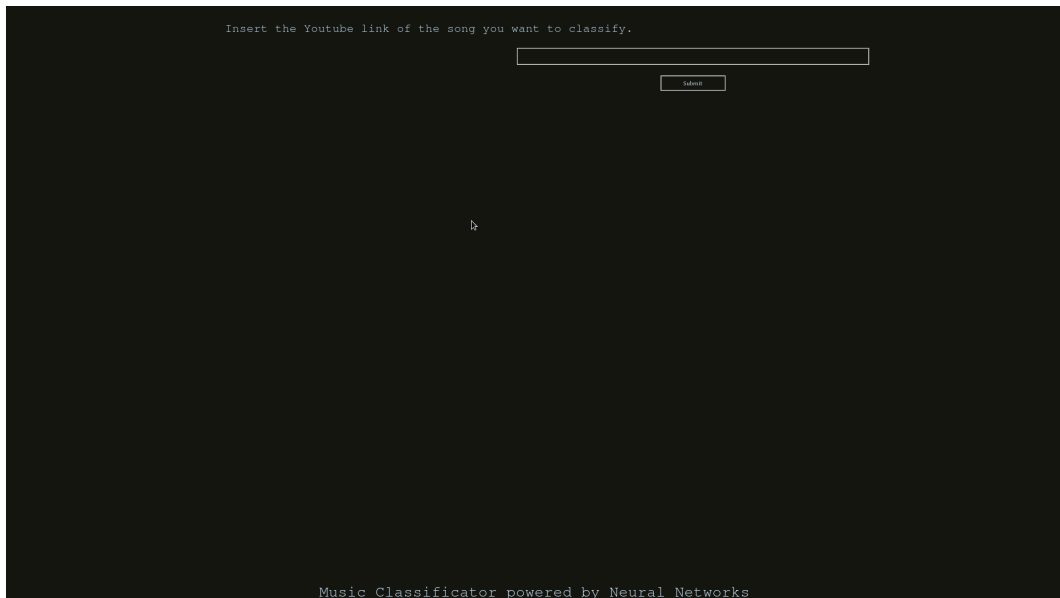
Figure 3.13: The Graphic User Interface at the start of the application
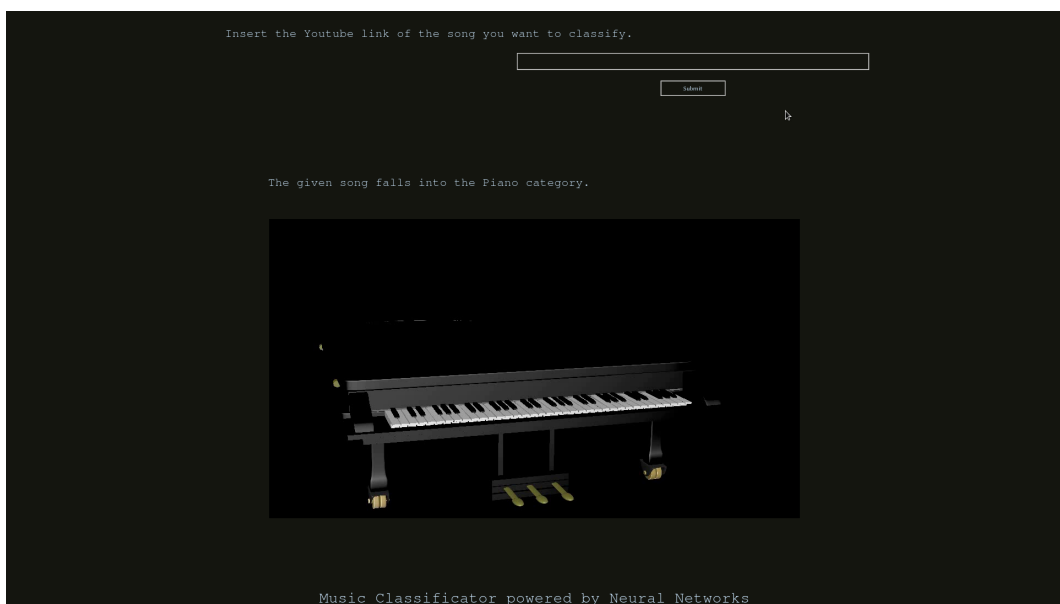

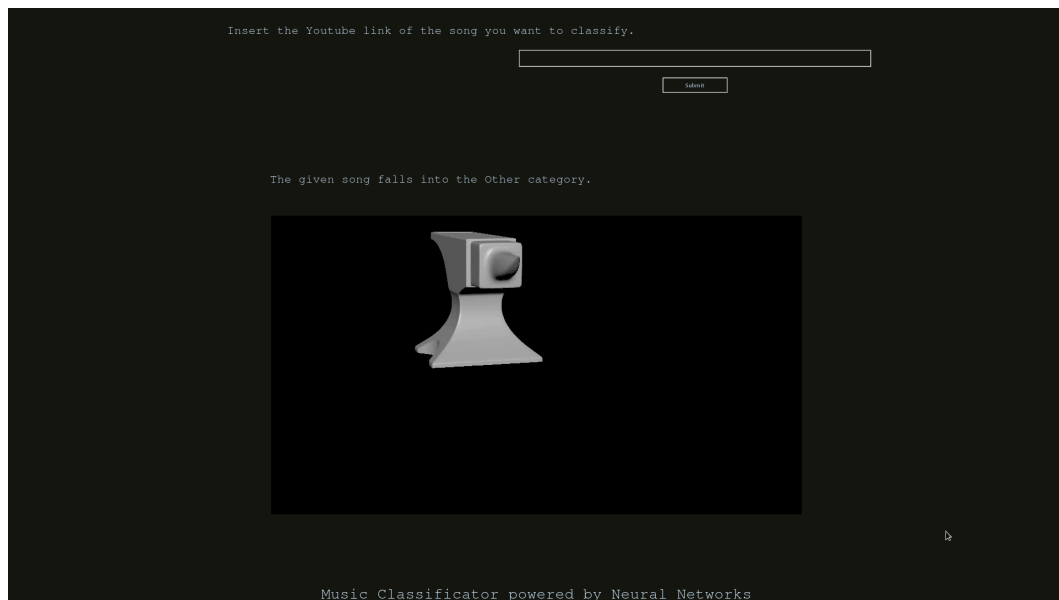Figure 3.14: The Graphic User Interface after predicting a song as a piano song.

Figure 3.15: The Graphic User Interface after classifying a song as other.

Chapter 4

Use cases

For illustrating the functionality of the aplication, we propose the following three use cases:
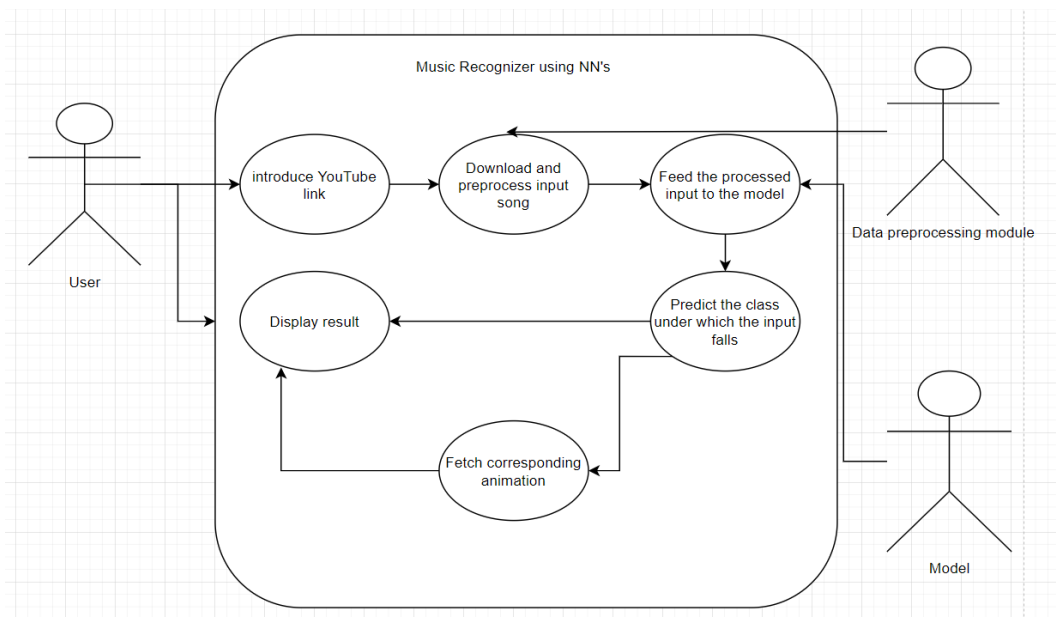
4.1   First use case

Figure 4.1: Illustration of the application behaviour when the user inputs a correct link.

The application has the expected behaviour.
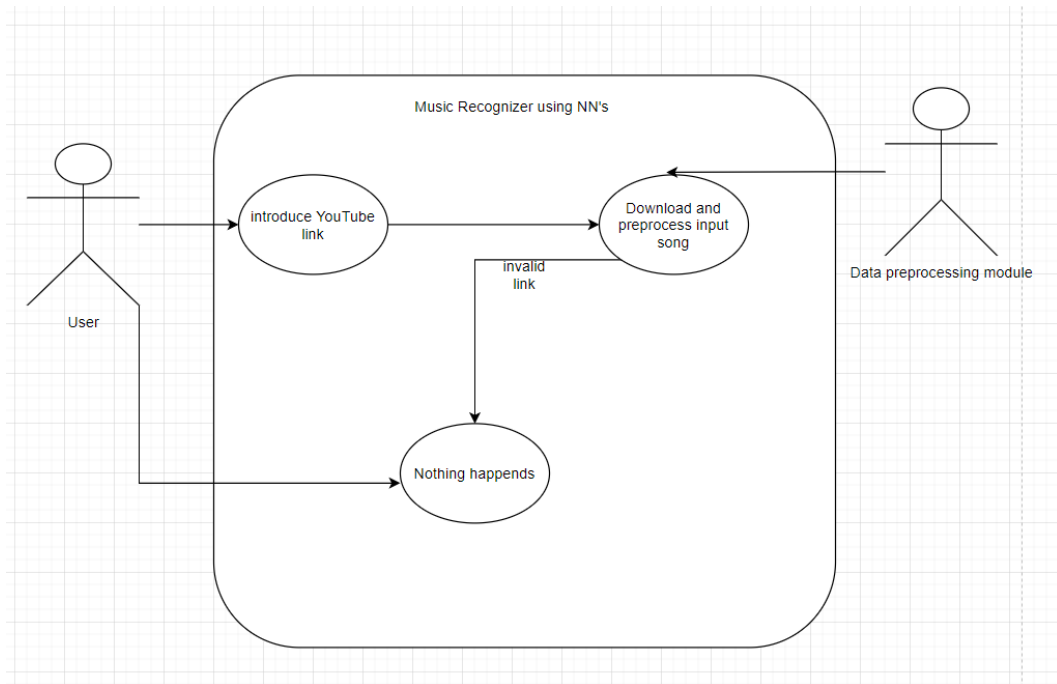
4.2 Second use case

Figure 4.2: Illustration of the application behaviour when the uses inputs an invalid link.

The link introduced by the user is invalid. The youtube-dl library will throw an exception and the execution will be ceased, given that the input cannot be fetched.
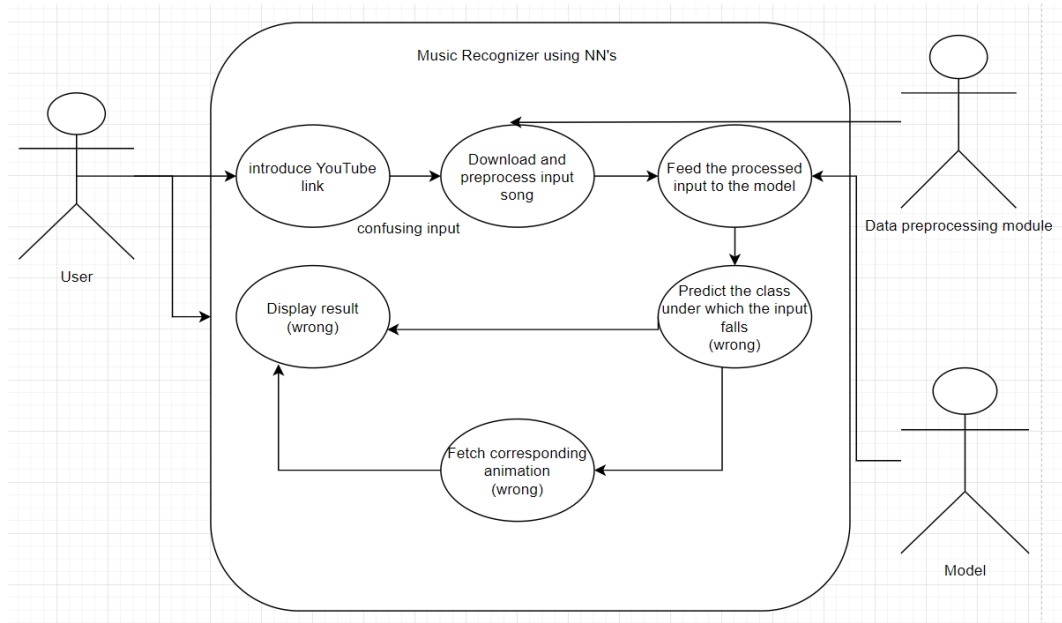
4.3 Third use case

Figure 4.3: Illustration of the application behaviour when the user inputs a confusing song to the application.

The input is confusing (e.g. a symphonic concert containing multiple other instruments beside a piano). Given that the model has been trained on piano-only samples, the prediction for such an input will be 'Other'.

Final conclusions

The three constituent parts of the application (as presented in Chapter 3 of the current paper) form a project that serves its purpose: to both create a middle way between arts and computer science, making the applications of machine learning interesting, yet engaging and to get a deeper understanding, by implementing the neuronal network framework from scratch, of the mathematical and theoretical subtilities of artificial intelligence.

The application succeeds in creating the liaison between an intuitive and friendly user experience and the complex background of the custom machine learning framework. Therefore, we believe that the current thesis corresponds with the initial ambition of the project.

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