RNN Classifier to Identify the Influence of Oud Master on the Way to Play of Oud Player

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Abstract: We propose in this work, a model for recognizing the effect of the famous Oud masters on the Oud player's style, and for identifying which Oud academy, an Oud player belongs to, based on extracted attributes using deep learning classification algorithm RNN. The subsequent enhancements are often focused on the integration of a screening mechanism for the optimum properties. In this initiative, functional cases have also been built to assess the validity and reliability of our model.

1 INTRODUCTION

The Oud is the lute's and guitar's forefather. It's a fretless string instrument that's been used in several oriental musical styles

Many works in literature explain how to identify a singer without discriminating between instrumental and singing sounds. (Ratanpara and Patel, 2015) We consider an investigation into how artificial neural networks can be trained on a large corpus of melodies and converted into automatic music composers capable of providing new phrases that are consistent with the style on which they were trained, and (Colombo and al, 2016) we consider an examination into how artificial neural networks could be trained on a large corpus of phrases and transformed into audio data composers able to produce new compositions that are compatible with the genre on which they were trained. On (Bahatti and al, 2013), a series of sinusoidal descriptors are described with the aim to characterize musical signals and recognize the maximum information included in that signal. Various learning techniques were developed and tested in (Herrera and al, 2003), (Kaminsky and al, 1995), (Peeters, 2003), (Dhanalakshmi et al, 2008), (Hochreiter, 1998) to accomplish audio identification work. In the learning process (Gers and al, 1999), (Graves and al, 2013), (Chung and al, 2014), (Sutskever and al, 2014), (Graves , 2013) the neural networks are going to be very helpful. The algorithmic composition model (Karpathy, 2015) provides a deep (multilayer) method of monophonic melodies based on neural RNN networks with gated recurrent units (GRUs). However, the RFE-SVM is egoism, which only seeks to determine the optimal combination of classification (Lamine and al, 2012). There appears to have been a consensus among many techniques, based on its versatility, computational effectiveness, the capability of handling high-density data, and the revenue for selection of characteristics, using Superstar Vectors (SVM) (Guo and Li, 2003), (Zhiquan and al, 2013), (Moraes and al, 2012). The (Bahhati and Bouattane, 2016) model is an efficient audio classification system based on SVM to recognize the composer. In (Zhar and al, 2020) authors present an algorithm that allows to artificially compose oriental music based on calculated features. In (Zhar and al, 2020), we find a new mechanism to classify the influence of oud master on the way of play of oud player, this model is based on the KNN algorithm. In (Zhar and al, 2020), we find an artificial algorithm of oriental music composition based on oriental gramma.

In this work, we propose a classification model to identify the degree of influence of master styles on oud players. To do that, we chose three famous oud schools:

- The oriental school: 'Farid EL ATTRACHE'.
- The modern school: 'Naseer SHAMMA'
- The Iraqi school: 'Munir BASHIR'.

Our approach is to propose a model that provides audio from the musical components of the three Oud

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masters noted above. Distinctions in play style can then be identified for each Master, showing holes and alterations, and then predicting how Oud Master Play affects the Oud Player. The impact percentage helps to classify the Oud Player according to playing style.

The majority of the article has the following structure: The classification algorithms are presented in Section 2. Section 3 describes in detail the extraction techniques, the reduction dimensionality technique, and the application of a classification algorithm solution consisting of audio segmentation. Section 4 includes descriptions of the practical application. Finally, we end the article in Section 5 and discuss appropriate future studies.

2 DEEP LEARNING ALGORITHM (RNN)

An artificial neural network with recurrent connections is a recurring neural network. An ongoing neural network is composed of non-linear interconnected units (neurons) for whom there is a structure with at least one cycle. The units are connected by weight-rich arcs (synapses). The neuron's output is a non-linear combination of input. Neural recurring networks are appropriate for variable-size input data. They are especially suitable for analyzing time series.

3 PROPOSED MODEL

Our proposal focuses on six key components, namely audio segmentation, mathematical attributes analysis extraction, standardization, and data normalization, attributes selection, and the use of the greatest precise algorithm in-depth classification method RNN and finally the prediction. The diagram illustrating our plan appears in Figure 1.

3.1 Audio Segmentation

The fragments are divided into different periods between 5 seconds and 100 seconds then the whole of the proposed model classification algorithm has been completed in several tests, with the aim to build the maximum precision time frames. Duration with the perfect time is 5 seconds.

3.2 Extraction Attributes

Our method consists of exploring the parameters of an audio signal via mathematical equations of signal processing. A lot of information has been extracted with the help of signal processing elements as an example :

Zero-Crossing Rate, Energy, Entropy of Energy, Spectral Centroid, Spectral Spread, Spectral Entropy, Spectral Flux, Spectral Rollof, MFCCs, Chroma Vector, Chroma Deviation.

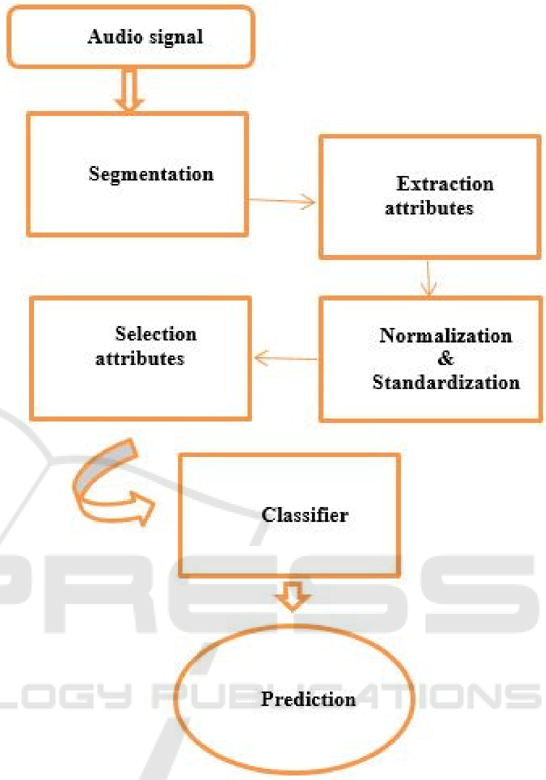

Figure 1: Block diagram of our classification process

3.3 Normalization & Standardization

Auto-learning algorithms will not function correctly without normalization. The range of all entities must therefore be normalized to ensure that each entity leads to the final interval approximately and proportionately.

We converted then the data to a level [0, 1] using the formula for the aim to make better use of the information's generated and start reducing the range of values:

Xsc is the normalized value, where X is an original value.

$$X_{sc} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

3.4 Selected Attributes

In this model, the Univariate Feature Selection uses certain statistical tests, such as chi-square, F-test, Mutual information to determine the force of the connection among each factor and the target variable. The characteristics of the model are classified systematically according to their strength with the results. All functions are deleted from the current function space, other than a predisposed number of markers. The other characteristics are then used for the training, testing, and validation of machine models. The figure below illustrates the filtering mechanism used.

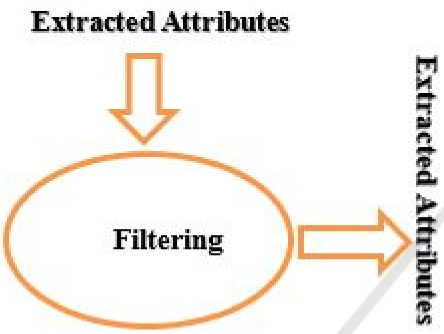

Figure 2: The features selection approach

3.5 Classification Algorithm

In this part, we chose to design a deep learning-based classifier RNN to produce performance with greater accuracy after passing all segmentation, extraction, normalization, and parameter selection steps.
For training and testing, the data was split into 80% and 20%. After testing several training opportunities between 10% and 90%, this division is the best solution.
Accuracy established is: **73%**

4 PROCESS IMPLEMENTATION

The following table shows the pieces used:

Table 1: Pieces used for classification.

Oud Player	Durations	Number of inputs of 5 seconds
Farid EL ATTRACHE	02 : 15 : 34	1 629
Mounir BACHIR	05 : 07 : 57	3 700
Nasseer Shamma	05 : 03 : 09	3 645

The table below describes the wave format inputs of our model, we have here 3 master oud players that we will study in depth.
After testing a series of differentiation times between 2 and 20, we chose a 5 second for every piece to discover the perfect choice.

Table 2: Accuracy and Loss for 100 epochs.

Accuracy	100 epochs	73 %
Loss	100 epochs	58 %

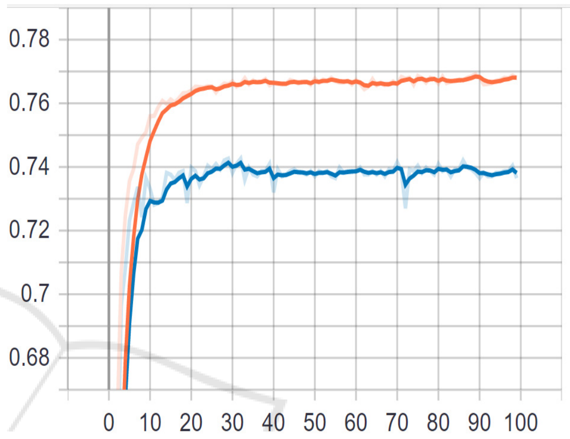

Figure 3: Train and validation epoch accuracy.

the figure below illustrates the accuracy for training and testing according to the epoch

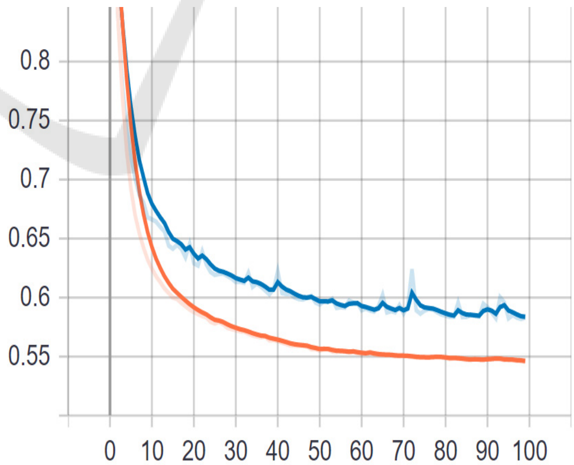

Figure 4: Train and validation epoch loss.

the figure below illustrates the loss for training and testing according to the epoch.

5 CONCLUSIONS

In this manuscript we presented a model of categorization of the effect of oud master on oud players, this model is based on a deep learning approach including an input layer, a middle layer, and an output layer. All layers contain several nodes for each layer based on several tests, the practical results show that the system is capable to classify according to a rate of accuracy equal to 73 percent and loss equal to 58 percent, this result remains to be improved, that's why we opt in the perspectives of conceptualizing other models for the aim to reach an accuracy more than 90 percent and loss least than 20 percent.

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