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Classification algorithms to recognize the influence of the playing style of the Oud masters on the musicians of the Oud instrument

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ABSTRACT

In an effort to recognize the influence of the famous Oud masters on the style of the Oud player game, and for the aim to classify which Oud school, an Oud player belongs to, in this work, we are proposing a model for recognizing the influence of Oud Master Player based on extracted features using for multiple machine learning classification algorithms KNN, Decision Tree and SVM.
The improvement brought about by this work is also based on the integration of a procedure for selecting the optimal characteristics.
Practical cases were also developed in this work in order to test the relevance and efficiency of our model.

Key words: Machine learning, Classification, Features, Selection, KNN, Decision Tree, SVM, Univariate Feature Selection, Timbre.

1. INTRODUCTION

The Oud is the ancestor of the lute and the guitar. It is a fretless string instrument used in many oriental musical traditions. There are exotic stories about the Oud and its origins. The oldest known Ouds are around 3000 years old. It is believed that Ziryab added the 5th string to the Oud. Today's Oud player plays essentially the same instrument as Ziryab, with just one slight modification: a sixth string. The sixth string was introduced in the 20th century by Munir Bashir. There are three large Oud schools in the world of music, the Iraqi school, the oriental school and thirdly the modern school. Each school represents a unique and different style of play. The way the musician positions his fingers in the handle of the Oud, the way to hold the feather, the force of the strike on the strings, the movements of the feather, the series of notes and the speed of the game, all - mixing and more - of methods represents the style and manner of playing of each Oud player regardless of the genre of the Oud, its method of making and the timbre of the sound generated. Each Oud school is represented by a grandmaster:

- **Iraqi school: Munir BASHIR.**
- **Oriental school: Farid EL ATTRACHE.**
- **Modern school: Naseer SHAMMA**.

In the field of Artificial Intelligence, the application of Machine Learning-based classification algorithms brings good results in terms of recognition, which is why we have opted for a classification model based on three supervised classification algorithms. The objective of our approach is to propose a system capable of generating relevant audio characteristics from the musical pieces of the three Oud masters mentioned above, and then to be able to detect the difference in the playing style of each one by highlighting the gaps and differences that exist and then to be able to predict the influence of the playing style of these masters on the Oud Player. The rate of influence will allow us to classify the Oud Player by playing style.
The remainder of this paper is structured as follows: Section 2 discusses the prior works as state-of-the-art on the collection of automated audio classification algorithms and the features selection. Section 3 introduces the three common classification algorithms. Section 4 deals with the conceptual solution consisting of audio segmentation, extraction characteristics, data standardization and explains the reduction dimensionality strategy in detail, as well as explains the implementation of classifier algorithms. The details of the realistic application are set out in Section 5. Lastly, in Section 6, we conclude the paper and discuss relevant future research.

2. STATE OF THE ART

To recognize a singer without separating instrumental and singing sounds [1] use audio features like timbre coefficients, pitch class, Mel frequency Cepstral coefficients (MFCC) and [2] we consider an investigation into how artificial neural networks can be trained on a wide corpus of melodies and converted into automatic music composers capable of producing new melodies that are compatible with the style on which they were trained. The proposed method for characterizing a musical signal is explained on [3] by extracting a set of sinusoidal descriptors which reflect the maximum information contained in that signal. To achieve an audio recognition task, different classification algorithms have been designed and tested in [4], [5], [6], [7], [8], [9]. Neural networks will be very useful in the learning process [10], [11], [12], [13], [14]. In [15] a deep (multilayer) model for the algorithmic composition of monophonic melodies based on neural RNN networks with gated recurrent units (GRU) is provided. Yet the RFE-SVM is a selfish system that only aims to find the best possible classification combination [16]. Between many methods, a consensus seems to have been formed through the use of Support Vector Machines (SVM) [17],[18],[19] due to their versatility, computational performance, the ability to handle high-dimensional data and the feature selection income. The model described in [20] is an Effective Audio Classification System based on Vector Support Machines designed to identify the composer. In [21], a system of the artificial composition of oriental music allowing to generate derived words based on the original pieces of a chosen composer. In [22], the authors highlight the capability of SVM on a popular audio database consisting of 409 sounds from 16 classes, a comparison of the SVM-based classification with other common approaches has been developed while suggesting a new criterion for audio recovery, called Boundary Deviation (DFB).

3. CLASSIFICATION ALGORITHMS

In this section, we introduce the basic theory of classification algorithms in Machine Learning.

3.1 Basic Theory of K-Nearest Neighbors (KNN)

K-Nearest Neighbors (KNN) is a system for the classification of cases based on their similarities to other cases, cases that are mutually neighbors.

The KNN Algorithm:

1- Pick a value for K

2- Calculate the distance of unknown cases from all cases.

The Euclidean distance:

- The distance which calculates the square root total of the square differences between the two-point coordinates:

$$D_e(x,y) = \sqrt{\sum_{j=1}^{n}\left(x_1 - y_j\right)^2} \tag{1}$$

3- Choose the k-observations, which are nearest to the unknown data point in the training data.

4- Predict unknown data point answers using the most common response value from the nearest k-nearest neighbors.

3.2 Basic Theory of Decision Tree

The decision tree is a type of supervised learning algorithm (with a predefined target variable) that is often used in classification issues. It functions on all input and output categorical as well as continuous variables. Via this technique we split the population or sample into two or more homogeneous sets (or sub-populations) depending on the most important splitter/differentiator input variables.

Entropy:

Entropy is the amount of disorder of information or the amount of randomness in the data. The node entropy depends on how much random data that node contains and is calculated for each node. In the decision trees, We look for trees with the lowest entropy in their nodes. Entropy is used to measure the sample homogeneity within that node. When the samples are fully homogeneous, the entropy is zero and if the samples are split evenly it has one entropy. Entropy is classified in terms of:

$$\text{Entropy} = -\,p(A)\log(p(A)) - p(B)\log(p(B)) \tag{2}$$

$$H = -\sum p(x)\log\, p(x) \tag{3}$$

Information gain:

Information gain is a metric measuring the expected reduction in collection S impurity, caused by splitting the data according to any given attribute. When constructing the decision tree, the ID3 algorithm uses the knowledge gain metric to pick the best attribute at-stage, the attribute that provides the "best split". The information gain Gain(S, A) is defined as:

Information Gain = (Entropy before split) – (weighted entropy after split)

$$Gain\,(S,A) = Entropy\;(S) - \sum \frac{|S_e|}{|S|} - Entropy\;(S_e) \tag{4}$$

3.3 Basic Theory of Support Vector Machines (SVM)

Support Vector Machines (SVM) is a supervised algorithm that classifies cases by finding a separator, then mapping data to high-dimensional characteristics and then finding a separator.

We are interested in a (possibly non-deterministic) phenomenon F which,

- From a certain set of inputs x,
- Produce an output y = F(x)

The aim is to find F from the single observation of a certain number of pairs input-output $\{(x_i, y_i): i = 1, \dots, n\}$

We consider a pair (X, Y) of random variables with values in X x Y. Only the case Y = {-1, 1} (classification) interests us here (we can easily extend to the case of |Y| = m > 2 and in case Y = R).

- Data: a sample is observed S = {(X1, Y1), …, (Xn,Yn)} of n independent copies of (X, Y).
- Goal: build a function $h : X \rightarrow Y$ such as $P(h(X) \neq Y)$ is minimal.

The linear model is defined by:

$$F(x) = w.x + b \tag{5}$$

The Hyperplane is defined by:

$$w.x + b = 0 \tag{6}$$

The distance from a point to the plane is given by:

$$d(x) = \frac{|w.x + b|}{\|w\|} \tag{7}$$

4. PROPOSED APPROACH

Our proposed model is based on five essentials steps: segmentation of the audio, feature extraction based on a set of mathematical features, normalization and standardization of the data, feature selection through a filtering method and finally the exploitation of supervised classification algorithms (KNN, Decision Tree and SVM) to choose the algorithm offering the highest accuracy. The diagram illustrating our proposal is shown in Figure 1.

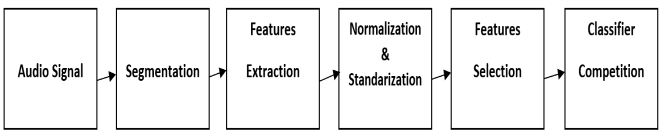

Figure 1: Block diagram of our classification process

4.1 Segmentation Audio

A series of tests were carried out to segment the pieces into different durations between (5s and 100s) and then going through the whole proposed classification model in order to define the duration generating the highest accuracy. The most optimal duration is D = 5 seconds.

4.2 Extracted Features

The principle of our approach is based on the Features of the musical signal as shown in the diagram in figure 1.1. The Features are classified according to their nature:

- A family of interesting features that reflect the transition segments between successive notes in the musical signal
- Features to generate additional information on power, bandwidth, and envelope.

The features play a key role in solving any machine learning problem.

Extraction is the first step in the pre-processing phase of our dataset. Feature extraction is essential to remove irrelevant and redundant values from the raw data so that the learning model can work well. In this work, time, frequency and cepstral domain, as well as other characteristics from our audio library, were extracted.

- Time characteristics (characteristics 1) generates information on the time evolution of the signal.

Energy characteristics (characteristics 2 and 3): represents information referring to various signal energies.

Spectral characteristics (characteristics of 4-34, except MFCC): these characteristics are calculated from the time-frequency representation of the signal without a previous waveform model.

- Cepstral characteristics (MFCC) (characteristics from 8 -20): represents the shape of the spectrum with coefficients using Mel bands instead of Fourier spectra.

Table 1: List of Features Related to the Musical Audio

Features ID	**Features Name**	**Description**
1	Zero Crossing Rate	The rate of signal transition over the length of a given frame.
2	Energy	The sum of the signal values squares, multiplied by the length of the corresponding frame.
3	Entropy of Energy	The entropy of normalized energies of the subframes. It can be construed as a measure of sudden changes.
4	Spectral Centroid	The optical center of gravity.
5	Spectral Spread	The spectrum 's second Key Moment.
6	Spectral Entropy	The entropy of the spectral energies uniform for a subframe package.
7	Spectral Flux	The square difference of the two successive frames between the normalized magnitudes of the spectra.
8	Spectral Rollof	The frequency at this is centered 90 per cent of the spectrum's magnitude range.
9 –21	MFCCs	Mel Frequency Cepstral Coefficients form a cepstral representation where the frequency bands are measured according to the mel-scale rather than linear ones.
22-33	Chroma Vector	A 12-element representation of the spectral energy where the bins reflect the 12 groups of Western-type music (semitone spacing) in equal-tempered pitch.
34	Chroma Deviation	The standard deviation of coefficients of 12 chromiums.

In this work, we extracted data from the signals related to oriental music produced by the lute instrument. These signals are relatively short, non-stationary, characterized by an almost percussive sound. The elements of extraction are as follows: Spectral characteristics, cepstral characteristics are calculated on the basis of a short term Fourier transform which is expressed as follows:

$$S(t, F_k) = \int_{-\infty}^{+\infty} S(\tau - t) w(\tau) \exp(-j2\pi.F_k.\tau) d\tau \tag{8}$$

An average calculation has been applied to all the figures generated by the extraction functions in order to standardize the results obtained, optimize the processing operation, and increase the efficiency of the model:

$$Average\ (s(t)) = \frac{sum\,(s(t))}{number\ (s(t))} \tag{9}$$

4.3 Features Standardization

Since the range of values of the raw data varies considerably, the auto-learning algorithms will not work properly without normalization. Many classifiers calculate the distance between two points by the Euclidean distance. If one characteristic has a wide range of values, the distance will be governed by that particular characteristic. Therefore, the range of all entities must be normalized so that each entity contributes approximately and proportionally to the final distance.
For better exploitation of the generated data and in order to reduce the range of values, we transformed the data to a scale [0, 1] using the equation:

$$X_{sc} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{10}$$

Where **X** is an original value, $\mathbf{X_{sc}}$ is the normalized value**.**

4.4 Selected Features

Since not all the parameters calculated are relevant for classification, they must be pre-processed to reduce dimensionality in order to retain only the relevant candidates and thus facilitate the task of classification. In view of this fact, the approach adopted is to combine simplicity and precision through the integration of a filtering module.
Filtering methods aim to determine the most relevant characteristics by analyzing the relationship between the entities and the target class. Filtering methods provide a ranking for all features rather than selecting the best subset of features. This ranking is based on the scores obtained by each feature/target combination in a statistical test or inter/intra-class distances between instances of the dataset and can be used to select the best scoring features that can be used with any classifier to improve its performance and efficiency. The filtering method used in this work is: Univariate Feature Selection.

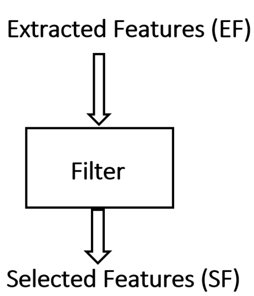

Figure 1: Schematic view of the features selection approach.

Univariate Feature Selection helps to determine the strength of the relationship between each individual characteristic and the target variable, using certain statistical tests such as chi-square, F-test, Mutual Information etc. Features are ranked according to the strength of their relationship with the result. All features other than a predetermined number of markers are removed from the current feature space. The remaining features are then used to train, test, and validate the machine learning models. Univariate Feature Selection is used as a preprocessor before applying an estimator model to the data set. F-test and Mutual Information are the two statistical tests used in our work.
F-test: it uses hypothesis tests to check whether the characteristic and the target variable are significantly different. The correlation between the feature and the target is calculated and converted to the F-score to obtain the p-value. Features with high F-score are selected for modeling.

$$F = \frac{\text{VBT}}{\text{VWT}} \tag{11}$$

VBT: the variance between treatments.
VWT: the variance within treatments.

$$F = \frac{\text{MS}_{\text{Treatments}}}{\text{MS}_{\text{Error}}} = \frac{SS_{Treatments} \big/ (I-1)}{SS_{Error} \big/ (n\tau - I)} \tag{12}$$

Variance between treatments is:

$$\sum\nolimits_{i=1}^{k} n_i (\overline{Y}_i - \overline{Y})^2 / (k-1) \tag{13}$$

Where Yi is the average of the sample in the groups, ni is the number of observations in the groups, Y is the overall average of the data and K is the number of groups.
Variance within treatment is:

$$\sum\nolimits_{i=1}^{k} \sum\nolimits_{j=1}^{ni} (Y_{ij} - \overline{Y}_i)^2 / (N-K) \tag{14}$$

Where Yij is the jth observation in the jth out of K groups and N is the overall sample size.
A test on the number of features from 1 to 34 was performed in order to choose the number generating the highest precision, the best compromise found is 7 features.
The 7 feature selection chosen after applying the filter module are shown in the table below:

Table 2: Selected Features

Features ID	Features Name
1	Chroma STF
4	Spectral bandwidth
6	Zero crossing rate
9	mfcc3
14	mfcc8
16	mfcc10
18	mfcc12

4.5 Classification Algorithms

In this part and after having passed all the steps of segmentation, extraction, standardization, and selection of the parameters, we opted for competition between 3 supervised classification algorithms namely: KNN, Decision Tree, and SVM in order to choose the algorithm generating the highest precision.
The data was divided into 80% for Training and 20% for Testing and this is the most adequate division after testing a set of possibilities between (10% and 90%) for Training.
The table below illustrates the established accuracy of each algorithm.

Table 3: Accuracy of Each Classification Algorithm

Algorithms	KNN	Decision Tree	SVM
Accuracy	95.22%	81.15%	74.85%

5. PROCESS IMPLEMENTATION

This work exploits the data generated from the monophonic musical pieces of the lute instrument played by three masters recognized worldwide:
- **FARID EL ATTRACHE**, which represents a purely oriental, traditional style and is characterized by the depth of sound, the strength and the sequence of the notes.
- **MUNIR BACHIR**: which represents the Iraqi school of playing influenced by the Turkish style of playing of its master HAIDAR, this style is characterized by the sharpness of the notes, the economic feather, and the inverted feather.
- **NASSER SHAMMA**: which represents the modern school of the lute, influenced by the Western guitar playing and by the Iraqi school, this playing is characterized by the sharpness of the notes, the use of chords and arpeggios in the playing.

In order to realize this model, it was essential to exploit all the existing musical and monophonic pieces of these three lute stars.
The table below illustrates the information on the pieces used:

Table 4: Audio Input

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

We opted for a 5-second segmentation time for each piece after testing a set of segmentation times [2, 20] to find the best choice.
As mentioned before, the algorithm offering better accuracy is KNN.

The table below illustrates the tests performed to find the best K value generating the highest precision. **K = 8** offers a precession of **0.9500891265597148**.

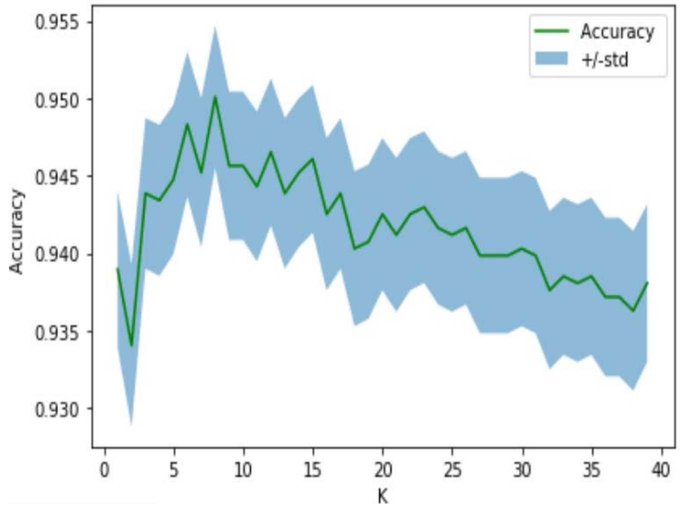

Figure 3: KNN Accuracy as Function as K.

Part of the list of accuracy as a function of K:

Table 5: Accuracy Table as Function as K

K	Accuracy
1	0.93894831
2	0.93404635
3	0.94385027
4	0.94340463
5	0.94474153
6	0.9483066
7	0.94518717
8	0.95008913
9	0.9456328
10	0.9456328
11	0.9442959
12	0.94652406
13	0.94385027
14	0.94518717
15	0.94607843
16	0.94251337
17	0.94385027
18	0.9402852
19	0.94073084
20	0.94251337
21	0.94117647
22	0.94251337
23	0.942959
24	0.9416221
25	0.94117647

26	0.9416221
27	0.93983957
28	0.93983957
29	0.93983957
30	0.9402852
31	0.93983957
32	0.93761141
33	0.93850267
34	0.93805704
35	0.93850267
36	0.93716578
37	0.93716578
38	0.93627451
39	0.93805704
40	0,93614523

In this part, we practically tested the relevance of our model. Four musicians played 100 songs of 5 seconds each, the degree of effect was calculated based on the sum of all predictive outcomes of all the components. The table below describes some of the results obtained.

Table 6: Prediction Table

Musicians	Results (in %)	Masters of Oud
Mehdi ZHAR	78 %	Farid EL ATTRACHE
Mohammed CHOUROUK	62 %	Mounir BACHIR
Fouad BENELCAID	68 %	Farid EL ATTRACHE
Younes AZALI	81 %	Naseer SHAMMA

6. CONCLUSION AND FUTURE WORKS

In these papers, we have proposed a model for recognizing the influence of the great Oud masters on the playing style of Oud players through the data extraction, normalization and filtering methods we have adopted. The resulting data were processed by three supervised classification algorithms KNN, Decision Tree and SVM, the best accuracy was generated by applying the KNN model with k=8. This allowed us to predict results with a very high accuracy rate. The case studies showed the efficiency and relevance of our approach, the rate of influence of the Oud masters on the Oud players has been measured on the basis of several pieces played, each Oud player belongs to a school of play, this will also help the Oud players to know the lacks they have in relation to a school of play and proceed to learn the adequate techniques to increase the rate in relation to the desired school. In perspective, we propose to study the use of other types of extraction functionalities, explore other feature selection algorithms based on these classification models as well as other Deep Learning models.

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