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Artificial intelligence-based classification with classical Turkish music makams: Possibilities to Turkish music education

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ABSTRACT

Makams of Classical Turkish Music have been tried to be classified through various studies for the past years. Significant differences of opinion have emerged in the classification process of the makams in Music Education and Literacy from past to present. This situation creates problems in learning the makams related to music education and recognizing the makams heard. Additionally, there are uncertainties in the classification of the makam genre of the song, as individual mistakes were made while notating the musical notes. Apart from that, this situation constitutes a problem not only for the ones studying Turkish Classical Music but also for the ones interested in this certain type of Music. Therefore, the objective of the research is to contribute to the makam classification in Classical Turkish Music Education by developing an MIR system that determines the makam of the songs. Theoretically, we can extract the properties of sound signals with Time Wavelet Scattering Feature Extraction, classify them with SVM and distinguish between types of makams. In this study, upon eight different Makams, a Musical Information Retrieval system has been created via the Artificial Intelligence (AI) method of Support Vector Machines (SVM) and Time Wavelet Scattering Feature Extraction and through using a Graphics Processing Unit (GPU) accelerator for the sake of feature extraction. We performed the classification process by modeling it on the MATLAB program. The study's success rate was identified as 98.21% and it acquired a higher success rate compared to the other studies in the literature. After completing the classification procedure, the Makams were identified by sending samples belonging to different sound files from the system consisting of a database belonging to eight different Makams. In our study, the classification and detection processes were realized with nearly a hundred percent success. The difficulties encountered in classifying the makams in Classical Turkish Music mentioned above, with the application of artificial intelligence, the classification difficulty of individuals who have received this type of training or are interested in this subject has been overcome.

Keywords: Classical Turkish music makams, makam detection, artificial ıntelligence, support vector machine, musical education and literacy.

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INTRODUCTION

In Classical Turkish Music, the makam is a different concept from the tonal and modal scales in western music, with the combination of scale structure, interval structure and melodic features. The concept of 'seyir'[1] also has an important place for the makam. Makams are grouped under three headings and named as Simple, Combined, Şed (transposed). Combined makams are a combination of two or more simple makams, and Şed makams are formed by transposing certain makams into different pitches.

[1] It is the characteristic flow of makams in Turkish Classical Music

Although there are approximately 600 types of makams in Classical Turkish Music, performers can recognize around 30 makams. The melody can be classified into one of these 30 makams, while Western music includes two main classification groups, major and minör (Alpkoçak and Gedik, 2005). Below is given information about the studies on the concept and classification of makam.

In the literacy and education of Classical Turkish Music teachers, there are problems such as the existence of many approaches for makam classification, the mistakes concerning note writing, the free approach of people in performing the song, lack of knowledge and the experience required for classification. The mentioned difficulties cause difficulties in the recognition and classification of the makams, both those who receive this training and those who are interested in Classical Turkish Music. The aim of the study is to develop a solution to the mentioned problems by classifying with Artificial Intelligence application.

Classification studies of Classical Turkish Music and determination of makams in Turkish music came from the 15th century. In the 15th century, Abdülkâdir Merâgî (1353-1435) was acknowledged as the first musicologist to use the name makam in Classical Turkish Music. Musicologists before this period used the words "şed" or "devir" instead of the word makam (Safiyuddin, 1236, as cited in Yahya Kaçar, 2008).

With the 17th century, it was observed that musicologists started to take different approaches in the definitions, genres and classifications of makams and the musical characteristics of makams. As a result, new approaches emerged in the classification of Classical Turkish Music Makams (Arel, 1993).

The definition of makam by musicologists has been made in a more detailed way in recent years. Through examining the lines of change of Classical Turkish Music makams in the process, Kantemiroğlu Edvarı demonstrated that classification procedures have changed in the studies (Levendoğlu, 2004).

According to the expressions put forward in Kantemiroğlu Edvarı, the definition of makam became specialized until the 'çeşni'[2] and 'geçki'[3]. Arel's works in the 20th century defined makam as the feature of the pitch scales, which consists of the interaction of the sounds with the pauses (Karaduman, 2011).

Hüseyin Sadettin Arel (1880-1955), Suphi Ezgi (1869-1962) and Salih Murat Uzdilek (1891- 1967), who obtained 25 pitches by dividing an octave into 24 different intervals in Classical Turkish Music, developed a new approach. Starting from the "Kaba Çargâh" pitch to the treble part, 11 perfect fifth and 12 perfect fourth were placed on top of each other and pitches within an octave range were obtained. Hüseyin Sadettin Arel explains in detail the reason for dividing the octave into 24 different intervals and the ways of obtaining 24 sounds in his work titled "Türk Mûsikîsi Nazariyatı Dersleri" (Arel, 1993).

In addition, many famous musicologists such as Fârâbî, Urmevî, Seydî, Hızır bin Abdullah, Abdülbâkî Nasr Dede and Rauf Yekta have worked on the makams and structure of Classical Turkish Music and wrote 'edvars'[4]. The Arel-Ezgi-Uzdilek system continues to be the most widely used system in today's music education and literacy. In this system, makams are grouped under three headings and named as Simple, Combined, Şed (transposed). Combined makams are Combination of two or more simple makams, and Şed makams are formed by transposing certain makams into different pitches (Yahya Kaçar, 2008).

Inaccuracies and deficiencies arising from note writing in Classical Turkish Music pose an important problem for the course of musical education and literacy. Problems such as note writing that varies depending on different individuals or institutions, the absence of nuance signs, the absence of turning signs, the opposite of musical characteristics with the makam name indicated on the work frequently seen in similar makams, errors in the correspondence and so on can be listed as leading inaccuracies and deficiencies in this educational realm. These and similar problems are factors that make learning difficult and sometimes even impossible to learn (Ergöz, 2008).

In the educational process of Classical Turkish Music Makams, 'meşk'[5] has a very important position as a traditional teaching method. This teaching method, which has certain foundations and rules, cannot be explained only by a 'geçki'[6]. It is a method that literally reflects the instructor's own musical perspective to the student and encourages the student to progress in this direction. In this system, in which auditory memory occupies a very important place and musical talent is a prerequisite for selection, practice and execution as well as the theoretical knowledge in music education and literacy are of great importance. In the periods when the note writing process has yet to be done, the passage of the songs in musical education and literacy is carried out in two basic components as makam teaching and 'usul'[7] teaching, and then the parts of the songs are vocalized. In the mentioned period, even if the writing of the words is a reminder in educational studies, the practice is a teaching method that is largely based on auditory memory power. From this point of view, we see that the performance of the song has an important place in the method applied for

[2] Giving makam its unique character

[3] Parts of tone, mode or mode change in the song

[4] The name given to music theory books

[5] The method of learning and memorizing songs in Turkish Classical Music through vocalization

[6] Parts of tone, mode or mode change in the song

[7] The name given to rhythmic unity limited by certain orders and patterns in Turkish Classical Music

the teaching of makams in Classical Turkish Music. Today, this system, which is called as Turkish Music Theory and Solfeggio, has become very advantageous with the development of note writing, the use of note writing and the opportunity to listen to the musical works performed from various sources, unlike the way it was applied in previous periods. Developments in musical notation made it easier to learn and perform the makam in music education, with the writing of makam notation. However, despite of the developments in many subjects, the issue of Makams in Classical Turkish Music continues to be a subject that has been studied from the past to the present (Başuğur, 2016).

The subject of many studies on musical perception and auditory memory in Classical Turkish Music Makams has generally been the comprehension of the pitch part. However, it cannot be asserted that perception of sound and pitch is attainable only by musical talent. Musical ability is also associated with good musical perception and auditory memory. Musical perception can be possible by perceiving the components of music such as sounds, vocal intervals, rhythm, melody, and remembering through auditory memory. Studies investigating how the melody is recalled in auditory memory regarding the understanding of music as a whole have also shown that the melody line is very important in understanding the makams. What is important for auditory memory is the line of the melody, or in other words the 'seyir'[8] of the music (Yayla, 2006).

Auditory memory is an important and necessary feature even if the student is not performing the song but only playing the instrument. It is a feature that will be needed for most of his educational life, such as understanding the scales and distinguishing the differences from one another. The student needs a special effort and time to improve his auditory memory (Babacan, 2015).

The results of two experimental study on the recognition of Classical Turkish Music Makams are given below:

In the experimental study on recognizing the heard makams, according to the participants, having performed the song before and 'seyir'[9] are ranked the most important factor in recognizing a makam was heard. In the list where 17 factors were scored, the factor that experts and students thought had the least effect on recognizing makam was determined as internal knowledge (Başuğur, 2016).

In another experimental study on the subject, simple makam examples were created on students' recognition skills of simple makams. According to the students, it has been concluded that listening to the song before or having performed it before is important in recognizing the makams heard, as well as that internal information is relatively less important. As a result of the experiment conducted with the mentioned 3rd and 4th grade students, it was observed that the rank recognition success was 71.7% (Şen and Burç, 2016).

As can be seen in these two experimental studies, the experts and students have highlighted the factors of performance of song, mode of movement, and melodic line in recognizing the makam. This emphasizes an endless educational process for makam classification and recognition. As a result of these two experimental studies, it was observed that the people participating in the study could not achieve 100% success in the classification studies. Considering all these difficulties, the problems of classifying the makams, individual errors in the studies, experimental studies conducted on students and experts have shown the difficulty of the classification process. Our study aims to classify and identify the makams and to facilitate the problems of music learning in the computer environment, and to facilitate both students and people interested in Classical Turkish Music in recognizing and determining the makams.

Literacy can be defined, in its most basic form, as competence or knowledge in a particular field. On the other hand Music Literacy is the ability to read and understand notes even without a musical education. For people who do not have a musical education, it is very difficult to be able to read the notes. People who do not have music literacy also stay away from this area due to the difficulties they face. Education and Literacy of Classical Turkish Music Makams are difficult due to various problems mentioned. One of the reasons for the difficulty of classification is due to the makam transitions within the song.

Classical Turkish Music songs have been transferred to digital media and published on these media. Considering this situation and the developments in digital media technology (computer, internet, etc.), Classical Turkish Music songs have been digitized and more songs have been reached. Despite the mentioned developments, limited Classical Turkish Music makam samples or data set sources can be reached in digital media compared to Western Music. Dataset sources are divided into two types; symbolic and audio files. Using the symbolic data set, Alpkoçak and Gedik (2005) achieved a higher success rate in the literatüre with the N-Gram Classification method compared to those using both symbolic and sound files data sets. Kızrak and Bolat (2017) achieved the highest success rate with 96.57% in the literatüre with data sets consisting of voice files. In their study, more than one method was tried with a total of 93 songs in seven different makams, but they achieved the highest success rate using the DBN method. In addition, by examining the studies and success rates in different methods with symbolic and sound files data set in this field, success rates and methods are given in Table 1.

[8] It is the characteristic flow of makams in Turkish Classical Music
[9] It is the characteristic flow of makams in Turkish Classical Music

It is thought that our study will help organize the automatic makam classification process of the Music Information Retrieval (MIR) system, facilitate music education and literacy and later develop music recommendation programs. Additionally, to classify and identify Classical Turkish Music Makams in our application, it is expected that the sound files that are classified with GPU accelerator will be extracted by feature extraction and classified into makam by using Support Vector Machines and Wavelet Time Scattering features. The system is expected to perform this process as quickly as possible. The mentioned operations will be explained in detail in the method section.

MATERIALS and METHODS

Samplıng procedures

Symbolic data, polyphonic data and sound files performed with a single instrument were preferred in the studies conducted in the literature for the classification process of Classical Turkish Music Makams. Since there is not a large amount of voice-based data set in the studies, researchers conducting voice-based studies usually created their own data sets.

In our study, instrumental sound files performed with the use of more than one instrument (Oud, Qanun, Turkish Ney, Tanbur and Violin), which are available on the internet and have free access, were preferred to create a dataset.

We preferred songs performed with an instrument. However, there are separate performances of five different types of instruments among the songs we use (for example, the first sample oud and the second sample violin performance, etc.). In this way, our application compares the performances of five different types of instruments. As a result, performing more than one instrument instead of one type of instrument provides more reliable and accurate results for makam classification.

Files obtained from different musical instruments were performed in eight different makams (Hicazkar, Hüseyni, Hüzzam, Kürdi, Muhayyer, Nihavend, Saba, Segâh). The unique approaches of the performer of the song and possible tonal differences (bass-treble tones) can alter the sound signal. This situation may affect the signals belonging to the same makam. Instrumental sound files are preferred so that our artificial intelligence application is not affected. These eight makams constitute approximately fifty percent of the songs in the statistical archives of Trt (Turkish Radio Television) (Çevikoğlu, 2007). Among the makams, eight makams from which we could obtain the most instrumental samples were selected, also with the effect of their popularity. In summary, the reason we chose these eight makams for our study is that they are popular to a certain extent and we can obtain more samples. Although the different approaches of the performer are seen, each makam has a distribution of notes within itself.

Table 1. Current studies in the literature.

Authors	Method	Success rate (%)
Alpkoçak and Gedik (2005)	N-Gram Classification[10]	97.7
Kızrak and Bolat (2017)	Deep Belief Network[11]	96.57
Kalender et al. (2012)	Combined NN[12]	95.83
Ünal et al. (2014)	N-Gram Classification[10]	87.9
Demirel et al. (2018)	Chroma Features[13]	89.0
Öztürk et al. (2018)	Machine Learning Algorithms[14]	88.12
Gedik and Bozkurt (2010)	Pitch frequency histogram[15]	77.38
Ioannidis et al. (2011)	Chroma Features[16]	74.17
Kalaycı and Körükoğlu (2012)	K-Means[17]	70.0

[10] N-grams are N-character slices of a string. In N-gram-based text categorization, the system compares N-gram frequencies.
[11] Deep Belief Networks consist of multiple layers with the values that there is a relationship between layers. The main purpose is to help the system categorize data into different categories.
[12] Learning structure created by the combination of independent ANN models.
[13] Chroma, pays attention to twelve different classes of pitches. Chroma features, represent a powerful tool for the analysis of music and can be meaningful to classify and structure pitch approaching equally.
[14] Machine learning algorithm is a program with a specific way of setting its own parameters, given feedback on its previous performance while making predictions about a dataset.
[15] Pitch estimation method which combines the output of pitch estimation algorithms, takes advantage of the estimated pitch salience to refine the estimations.
[16] Chroma, pays attention to twelve different classes of pitches. Chroma features, represent a powerful tool for the analysis of music and can be meaningful to classify and structure pitch approaching equally.
[17] K-mean algorithm method is to divide a data set consisting of n data objects into k sets given as input parameters.

The note distributions of the specific 8 Turkish makams given above are given in Figure 1, respectively. Instrumental makam performances are available from YouTube (nd).

In addition, since more than one instrumental song is used, the effect of tone problems in the free approach of the performer on the classification is reduced in this way. The data obtained from the freely accessible internet environment as mp3 (file type .mp3), which is an audio file format, was converted into wav (file type .wav) format files, another audio file format, to be used in the MATLAB program.

After this process, equal-sized samples were taken from all wav formatted audio files. During the sampling study, the frequency of the audio files was chosen as 22050 Hz. To achieve a more realistic result, the entire audio file was used by dividing the entire audio file into non-overlapping parts.

After sampling, 56 samples in total, 448 wav extension audio files were obtained from each of the used makams to be used in the system and these are shown in Table 2.

Feature extractıon of the data set

After the dataset was sampled as wav format files, the feature extraction process was started to classify these data. The data that entered the classification process for feature extraction was obtained by the wavelet scattering method and converted to vector form to enter the multiple classifier of Support Vector Machines (SVM). In order to obtain scattering properties by wavelet scattering method to be used in the Support Vector Machines (SVM) method to be used in the classification and detection process, the natural logarithm of the scattering properties was obtained as part of 2^{19} training samples for each sample and the number of scattering windows was sub-sampled with 8.

As mentioned before, the wavelet scattering method was used for feature extraction of the data set. While feature extraction is made through wavelet scattering, the process is accelerated with a GPU accelerator. A GPU is a processor, most of which are made from smaller and more specialized cores. Cores work together to distribute and process the processing task among many cores, providing high performance. GPUs are used in areas such as deep learning and artificial intelligence. GPU or other accelerators are ideal for deep learning training with various neural network layers or highly specific data such as 2D visuals. The adoption of deep learning algorithms with an approach that accelerates the GPU has led to a significant increase in performance and, for the first time, feasible and valid solutions to many real-world problems.

The wavelet scattering method allows us to derive properties with minimal configurations, low variances from real-valued time series for use in machine learning and deep learning applications. The attributes are insensitive to the cycles of the input in the defined invariance scale and are continuous according to the distortions. The attributes are insensitive to the cycles of the input in the defined invariance scale and are continuous according to the distortions. The wavelet scattering method exhibits the features of multiscale contractions, linearization of hierarchical symmetries, and sparse representations. It also linearizes small distortions by separating varieties at different scales.

The lettering system used for mathematical modeling of the wavelet scattering method is as in Andén and Mallat (2011) and defined as f is input signal, ψ is wavelet function, ϕ is filtering process, $T = a^j$ maximum wavelet scale, $*$ convolution process and R_j wavelet module operator.

$$| f * \psi_j | * \phi_J (t) \tag{1}$$

With this convolution process, the signal amplitude covered by j is measured and averaged over t of the time $T = a^j$. To recover the information lost by the average, we can write it as the low-frequency component of the wavelet transform of the $| f * \psi_{j1} |$ account in the expression $| f * \psi_{j1} | * \phi_J$. Since the wavelet transform is reversible, the information lost in the convolution process with ϕ_J is recovered by the wavelet coefficients $| f * \psi_{j1} | * \psi_{j2}$. Averaged measurements are obtained by low-pass filtering of the modulus of these complex wavelet coefficients:

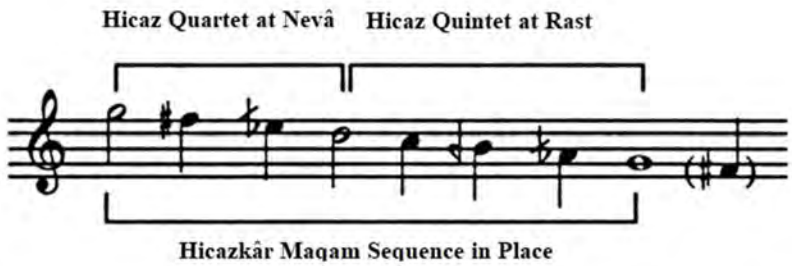
$$| f * \psi_{j1} | * \psi_{j2} | * \phi_J (t) \tag{2}$$

With this process, co-formation information is provided in a^{j1} and a^{j2} scales. These coefficients are called scattering coefficients because they compute the interferences of the signal f with two consecutive wavelets ψ_{j1} and ψ_{j2}, and measure the amplitude of the time variations of $| f * \psi_{j1} (t) |$ in the frequency ranges covered by ψ_{j2} wavelets.

Averaging the given second formula $| f * \psi_{j1} | * \psi_{j2} |$ with the ϕ_J again causes a high-frequency loss and this can be compensated by a new wavelet transform. The same procedure is repeated by defining a set of filter banks and module operators shown in Figure 2. In Figure 2, for the mathematical modeling of wavelet scattering, f input signal (audio file for our study) is defined as wavelet scattering function ψ_j and ϕ_J scaling function.

If $R_j f_{(t)}$ is the wavelet module operator that calculates the modulus of complex wavelet coefficients while keeping the phase of $f * \phi_J$, the scattering transformation in the convolution process first calculates $R_j f_{(t)}$ and subtracts the low-frequency signal $f * \phi_J$. In the next layer, each $| f * \psi_{j1} |$ is recycled by R_j, subtracts $|f * \psi_{j1} | * \phi_J$, and $| f * \psi_{j1} | * \psi_{j2}|'$ is calculated.

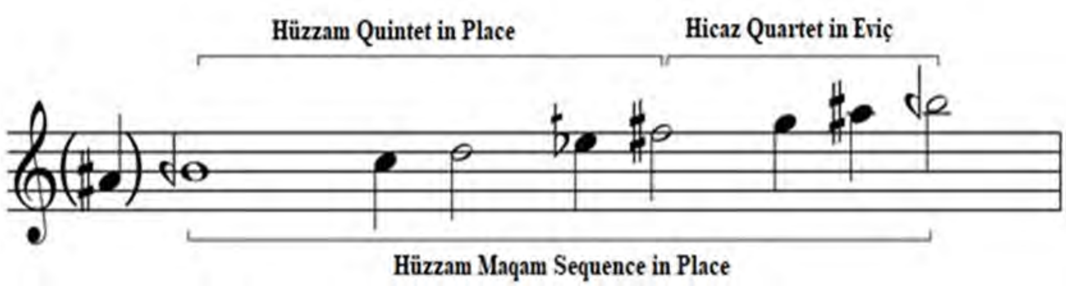
These coefficients are converted by $R_j f_{(t)}$ again and


Hicaz Quartet at Nevâ
Hicaz Quintet at Rast
Hicazkâr Maqam Sequence in Place

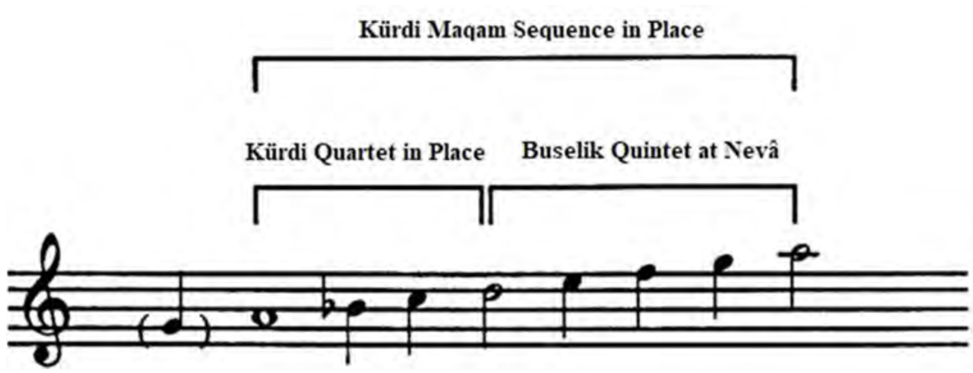
(a)


Hüseyni Quintet in Place
Uşşak Quartet at Hüseyni
Hüseyni Maqam Sequence in Place

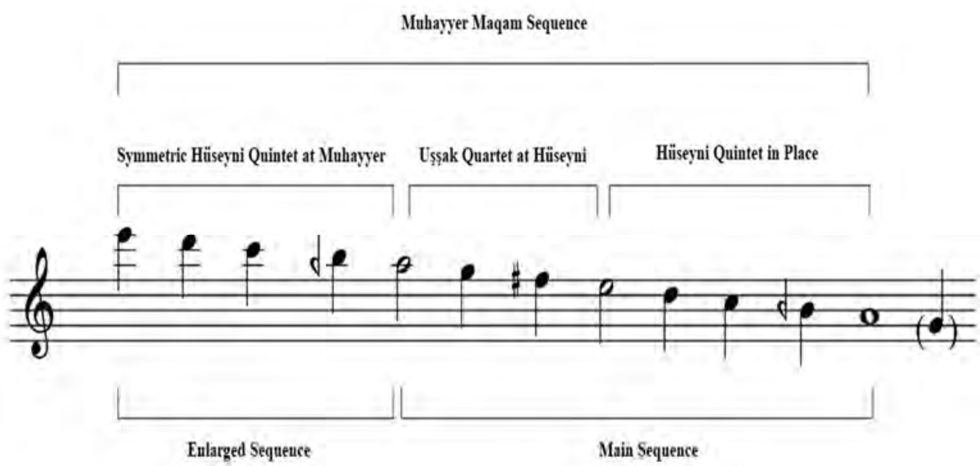
(b)


Hüzzam Quintet in Place
Hicaz Quartet in Eviç
Hüzzam Maqam Sequence in Place

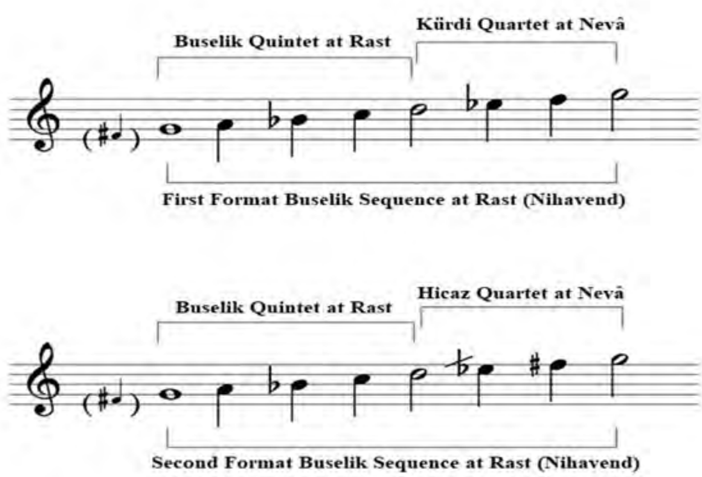
(c)


Kürdi Maqam Sequence in Place
Kürdi Quartet in Place
Buselik Quintet at Nevâ

(d)


Muhayyer Maqam Sequence
Symmetric Hüseyni Quintet at Muhayyer
Uşşak Quartet at Hüseyni
Hüseyni Quintet in Place
Enlarged Sequence
Main Sequence

(e)


Buselik Quintet at Rast
Kürdi Quartet at Nevâ
First Format Buselik Sequence at Rast (Nihavend)
Buselik Quintet at Rast
Hicaz Quartet at Nevâ
Second Format Buselik Sequence at Rast (Nihavend)

(f)


Zirgüleli Hicaz Sequence at Çargâh
Hicaz Quintet at Çargâh
Hicaz Quartet at Gerdâniye
Sabâ Quartet in Place

(g)

(h)

Figure 1. The sample note distributions of specifically chosen 8 Turkish Makams: (a) Hicazkar, (b) Hüseyni, (c) Hüzzam, (d) Kürdi, (e) Muhayyer, (f) Nihavend, (g) Saba, (h) Segâh.

Table 2. Sample numbers of makam types in the data set.

Makam type	Sample number
Hicazkar	56
Hüseyni	56
Hüzzam	56
Kürdi	56
Muhayyer	56
Nihavend	56
Saba	56
Segâh	56
Total	448

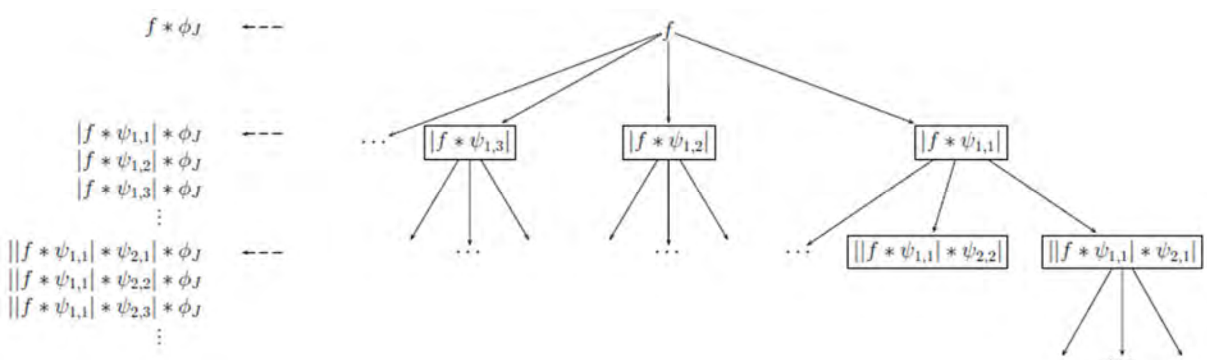


Figure 2. Tree modeling of wavelet scattering network.

generate the $| f * \psi_{j1} | * \psi_{j2} * | * \phi_J$ output and calculate the third-order wavelet signal. Repeating this wavelet transform for n times and removing the unfiltered coefficients by ϕ_J creates an n + 1 scattering vector at time t (Mallat, 2016).

Classifier

Support Vector Machines (SVM) are a supervised learning algorithm used for many classification problems such as signal processing, image and speech recognition applications. The purpose of Support Vector Machines (SVM) is to create a hyperplane separating data points between two classes. Hyperplane is the name given to the region between two classes. Sets the limit to the largest, allowing for a small number of misclassifications for most problems.

Helper vectors refer to a subset of training data that determines the position of the hyperplane separating the classes. Support Vector Machines (SVM) fall under the class of machine learning called the kernel method, where attributes are transformed with a kernel function. Kernel functions simplify the data set with boundaries in the higher dimensional mapped feature space for post-transformation classification. This way it performs well in the classification process.

Although Support Vector Machines (SVM) are formulated for binary classification, a multi-class SVM can be created by combining multiple binary classifiers. The kernel function makes Support Vector Machines more flexible and can be used to solve nonlinear problems. The steps followed for the multi-class mathematical approach of the described method to real problems are explained below (Vapnik, 1998).

In N binary classification operations $f_k(x)$ (k = 1, 2, …n), if we separate the education vectors for k classes from the education vectors of other classes:

$$f_k(x_i)=\begin{cases} if\ x\ belongs\ to\ k\ , & 1 \\ otherwise\ , & -1 \end{cases} \quad (3)$$

A classifier with n classes is created by selecting the class that corresponds to the largest value of the function.

$$f_k(x_i) = (x * \omega^k) + b_k \qquad k = 1, 2, \ldots. n \quad (4)$$

The operation m, which will separate the training data set without errors, creates n functions.

$$m = \text{argmax}[\,(x * \omega^1) + b_1\},\ldots,[(x * \omega^n) + b_n] \quad (5)$$

That is, the $(x_i^k * \omega^k) + b_k - (x_i^k * \omega^k) - b_m \geq 1$ inequalities are valid for all parameters (k=1,2,….n; m≠k ; i=1,…. l_k). We choose pairs (ω^k,b_k) and for k=1,2,….n the function $\sum_{k=1}^{n}(\omega^k * \omega^k)$ is minimum.

If the training dataset cannot be separated without error, the function subject to restrictions on the same parameters is minimized. To solve this optimization problem, we use the same technique as Lagrange multipliers and obtain the input vectors (the support vector of $f_k(x)$) determining the hyperplane:

$$\sum_{m\neq k}\left[\sum_{i=1}^{l_k}\alpha_i(k,m)(\chi * x_i^k) - \sum_{j=1}^{lm}\alpha_j\,(m,k)(x * x_i^m)\right] + b_k \quad (6)$$

It is necessary to determine the l(n1), α_i, (k,m),i=1,2,. l_k, $m \neq k$,k=1,2,…..n parameters in the $l = \sum_{k=1}^{l} l_k$ function simultaneously for multi-class Support Vector Machines.

As stated before, if the problem is not linear, the kernel function should be applied to the input vectors. To create Support Vector Machines, the $x_i^k * x_i^m$ expressions in the relevant equations must be replaced by $K\,(x_i^k * x_i^m)$. So the problem can be separated in transformed space:

$$K\,(x_i,x_j) = \varphi(x_i) * \varphi(x_j) \quad (7)$$

RESULTS

The data that we extracted with the Wavelet Scattering method are divided into two as test and learning data. In order to prevent both data sets from being processed in a certain order, they are mixed randomly within the application. The natural logarithm of the scattering properties was obtained for 2^{19} samples of each data set, and the number of scatter windows was sub-sampled up to 8. Attribute extraction is made for each data set to use in Support Vector Machines model. With the GPU implementation, the time taken to calculate the scattering properties is considerably reduced (Vapnik, 1998). The simulation process has been started for each data set using the Support Vector Machines (SVM) model. Support Vector Machines (SVM) used in simulation and parameters determined for data set formation are given in Table 3.

The Support Vector Machines (SVM) model prepared with the given parameters was used to match the scatter transformations of the training data to determine which makam type the test data belong to. If a makam in the application cannot be determined for the test data at the matching stage, it has been placed in a compartment (different makam) other than the makam types. Classification success was observed as 98.21% after the simulation. Among the eight types of makam included in our study, Hüseyni, Hüzzam, Kürdi, Muhayyer, Nihavend, Saba and Segâh were classified with a hundred percent and Hicazkar makam type was classified with 85.71% success rate. The success rate shows that we have achieved a more successful result than the studies found in the literature. The performance chart showing the determination of the makam types as a result of the simulation is given in Table 4.

The application can also be used for a sample taken from a sound file (.wav file type) other than the dataset for which the user wants to determine its makam. If the user wishes, he can upload the sound file belonging to the makam types within the scope of the study to the system and determine which makam it belongs to. When a different sample is loaded to the application by the user for the desired detection process, the same feature extraction process is repeated to be used in the Support Vector Machines (SVM) model for this sound file. The audio file whose attribute extraction is completed is compared with the makam types used in the classification process, and the output of which type of makam the loaded audio file belongs to is given apart from the results of the classification process. In addition, the detection process can be for a single audio file according

Table 3. Determined parameters.

Parameter type	Value
Frequency	22050 Hz
Invariance Scale	0.5
Order of Kernel Polynomial	3

Table 4. Makam type - correct classification percentage.

Makam type	Percentage of Correct Classification
Hicazkar	85.71%
Hüseyni	100%
Hüzzam	100%
Kürdi	100%
Muhayyer	100%
Nihavend	100%
Saba	100%
Segâh	100%

to the user's request, or if the user wants, it will perform the detection process by sending more than one audio file to the application. For the testing of the detection process, 10 audio files that were not included in the data set were sent to the system and all of them were correctly detected.

DISCUSSION

Artificial intelligence studies, which are becoming increasingly common today, help many scientific disciplines. As we mentioned before, the problems in the makam classification can be the basis for the studies in the makam classification area. As shown in Figure 1, makams contain certain rules of different makams. Simple, compound and transposed makams are included in our study. this situation makes it difficult for artificial intelligence to decide the classification process. To overcome this difficulty, the amount of data should be increased as much as possible. When the amount of data is high, the learning of the artificial intelligence application will also improve.

In our study, we divided the data set into two parts and formed a training and test set. We observed that if we increased the sample size in the training set, the percentage of success increased. When we tried with less sample size at the beginning, the success rate was 96.42%. When we increased the data set we used and obtained more samples and tested, we achieved a success rate of 98.21%. By changing the invariance scale constant, we found the optimum value with the highest performance. We observed that when we increased the kernel polynomial degree, the decision process of artificial intelligence was prolonged. As a result of this process, there were no significant changes in the percentage of performance. Based on the performance and the percentage of success of the artificial intelligence application, three were chosen as the optimum value.

The makams in our study largely overlap with other studies in the literature, with the effect of their usage rates. Of the 8 makams we used, 7 are the same as Ünal et al. (2014), Demirel et al. (2018) and Öztürk et al. (2018), 6 with Ioannidis et al. (2011), 5 with Gedik and Bozkurt (2010) and Kalender et al. (2012), 4 with Alpkoçak and Gedik (2005). Unlike other studies in the literature, we created a dataset with the wavelet scattering method and performed the classification process with support vector machines. Although the makams used are largely the same, we achieved a higher performance rate with the method difference.

To improve our work, we aim to observe the effects by using it with music education students and individuals who are interested in this type of music. By using our application in music education, we can observe its contribution to the targeted music education by examining its effects. In addition, it is aimed to classify other makams by increasing the number of makams and the data set we used. Finally, to improve our work, visual and auditory comparisons can be made by improving the audio signal processing study to observe the effect of classification problems caused by errors in note writing and comparing notes with the image processing method.

CONCLUSION

For the problems encountered in the literacy and education of Classical Turkish Music Makams, with the development of computer disciplines, the Music Information Retrieval (MIR) system was designed to facilitate the classification and determination of the makams.

A data set was created for the designed system using Wavelet Scattering Method. Support Vector Machines (SVM) classifier was used to classify the created data set. Our study and other studies in the literature have made a classification on similar makams by choosing popular makams from which they can obtain more samples. As a result of the classification, it has been observed that the success rate is 98.21%. Its success rate is higher than similar studies in the literature.

Considering the success of the classification, an application that will help music education and literacy in the face of difficulties such as classification problems encountered in the education of the Classical Turkish Music Makams individual errors in educational studies was obtained. In addition, since the work is done with the GPU, the time taken to calculate the scattering properties with the GPU application has decreased considerably (Gao et al., 2013).

In addition, our study provides convenience in music education for people who are educated in this field, and also provides convenience in terms of music literacy, as it can classify and identify makam types for both people who are educated and interested in this genre. This situation removes the difficulties of music literacy in those who do not have a musical education and contributes to music literacy in this field. Individuals who are interested in Classical Turkish Music and want to preserve this culture will better understand the features of makams by classifying the makam types of songs. This situation may lead the person to study Classical Turkish Music. Similarly, as it contributes to music literacy, it helps people who do not have musical education to engage in music by increasing their interest in this genre.

Thanks to the application, it will be easier to distinguish and classify certain Classical Turkish Music Makams for those who have music education and literacy or other people interested in this music genre. For individuals who cannot distinguish Classical Turkish Music Makams, as the songs they send to practice increase and determine the correct type of makam, their auditory memory will be strengthened and they will be able to make correct classification even if they have not educated in this field. In this way, it will also contribute to music literacy. If the sent audio file does not belong to one of the makam types in the application, our application distinguishes this file and produces the output that it does not belong to these makams. To develop the study, it is planned to expand the data set more and to add different makams.

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