ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL OF ARTS AND SOCIAL SCIENCES

AUDIO BASED CLASSIFICATION OVER MUSICAL PRODUCTION PERIOD: A STUDY ON MUSICS OF BARIŞ MANÇO AND HIS CONTEMPORARIES

M.A. THESIS

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İSTANBUL TEKNİK ÜNİVERSİTESİ ★ SOSYAL BİLİMLERİ ENSTİTÜSÜ

MÜZİK PRODÜKSİYON DÖNEMİ ÜZERİNE SES TABANLI SINIFLANDIRMA: BARIŞ MANÇO VE ÇAĞDAŞLARININ MÜZİKLERİ ÜZERİNE BİR ÇALIŞMA

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EYLÜL 2019

Metehan KÖKTÜRK, a M.A. student of ITU Graduate School of Arts and Social Sciences, student ID 409151104, successfully defended the thesis entitled "AUDIO BASED CLASSIFICATION OVER MUSICAL PRODUCTION PERIOD: A STUDY ON MUSICS OF BARIŞ MANÇO AND HIS CONTEMPORARIES", which he prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

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Date of Submission : **26 August 2019**
Date of Defense : **11 September 2019**

To my family,
To the memories of my brother, whom I lost at the begining of this master program,
To the memories of my grandfather, whom I lost at the end of this master program,

FOREWORD

I always found interesting the effect of the time period over the produced music, in means of technological availabilities and limitations, which is generally expressed with terms such as ”the sound of seventies” or ”the sound of eighties” etc. I wanted to take Barış Manço as a reference point, who is considered as one of the most influential figures of Turkish rock music, and move further with his contemporaries who are as influential and valuable as him. Among their valueable musical works, I aim to study on an audio classification implementation for evaluating the music production history of Turkey via today's informatical possibilities and modern scientific study areas such as Music Information Retrieval and Machine Learning.

For their guidance during this study, firstly I would like to thank to my thesis consultant Assoc. Dr. Can Karadoğan, and the jury members Dr. Taylan Özdemir and Dr. Ali Boyacı.

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ABBREVIATIONS

rpm	: Revolutions Per Minute
Hz	: Hertz
kHz	: Kilohertz
dB	: Decibel
SPL	: Sound Pressure Level
DAW	: Digital Audio Workstation
LR	: Logistic Regression
SVM	: Support Vector Machines
KNN	: K-Nearest Neighbors
GTB	: Gradient Tree Boosting
RF	: Random Forest
MLP	: Multi-Layer Perceptron
EVC	: Ensemble Vote Classifier

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AUDIO BASED CLASSIFICATION OVER MUSICAL PRODUCTION PERIOD: A STUDY ON MUSICS OF BARIŞ MANÇO AND HIS CONTEMPORARIES

SUMMARY

This thesis will be focused on an audio classification implementation over musical production periods based on the low-level audio features that are extracted from the musical works which can be considered under the umbrella term Anatolian Rock or so called Turkish Psychedelic Rock. This approach is derived from the idea that the technological opportunities and resources has an effect on the characteristic and the output quality of produced music. This phenomenon can be observed on the sound of the music over decades. Calculated with a sufficient precision, informatical outputs of a classification based on production period will have an importance and influence forevaluating today's music production quality and aesthetics. The audio collection is gathered from the musical works of Barış Manço, who is one of the most influential figures in music history of Turkey, and his contemporary artists who are as valuable as himself. Essentia library is selected among several audio feature extraction tools for information retrieval from the collection. Among the extracted information, low-level audio descriptors are chosen to work on, since they are more related to signal level qualities rather than tonal or rhythmical descriptors. Recursive feature elimination is applied over the extracted features to reduce the dimension of feature space to see whether the similar prediction capacities can be achieved with lesser amount of total features. Classifier models are implemented individually among 6 generally used machine learning algorithms from Scikit-Learn library. As an additional approach, Ensemble Vote Classifier is implemented as a combination of these 6 algorithms. After the classifier models are trained and tested on Barış Manço's musics, the best 3 classifiers are selected. These classifier models are trained and tested again on the dataset extended with the musics of artists who produced similar kind of music within the similar eras to see the accuracy of the approach.

MÜZİK PRODÜKSİYON DÖNEMİ ÜZERİNE SES TABANLI SINIFLANDIRMA: BARIŞ MANÇO VE ÇAĞDAŞLARININ MÜZİKLERİ ÜZERİNE BİR ÇALIŞMA

ÖZET

Bu tez, Anadolu Rock ya da Türk Psychedelic Rock adı altında düşünülen müzik eserlerinden elde edilen düşük seviyeli ses özelliklerine dayanan, müzik üretim dönemlerine göre bir ses sınıflandırma uygulamasına odaklanacaktır. Bu yaklaşım, teknolojik imkan ve kaynakların üretilen müziğin karakteristiği ve çıktı kalitesi üzerinde etkili olduğu fikrinden türetilmiştir. Bu fenomen, belli dönemlere ait müziğin duyumu üzerinde gözlemlenebilir. Yeterli bir hassasiyetle hesaplandığında, üretim sürecine dayalı bir sınıflandırmanın bilişimsel çıktıları, günümüzün müzik yapım kalitesinin ve estetiğinin değerlendirilmesinde de önemli ve etkili olacaktır. Ses koleksiyonu, Türkiye'nin müzik tarihinin en etkili figürlerinden biri olan Barış Manço'nun ve yine onun kadar değerli olan çağdaşlarının müziklerinden toplanmıştır. Çeşitli ses özelliği çıkarma araçları arasından Essentia kütüphanesi, koleksiyondan ses niteliklerini çıkarmak üzere seçilmiştir. Çıkarılan niteliklerden düşük seviyeli ses tanımlayıcıları, tonal ve ritmik tanımlayıcılara göre sinyal seviyesi ile daha yakın ilişkili olduklarından ötürü, üzerlerinde çalışmak için seçilmiştir. Çıkarılan nitelikler üzerinde, benzer tahmin kapasitelerinin daha az nitelik kullanılarak elde edilip edilemeyeceğini görmek üzere, özellik alanının boyutunu azaltmak için rekürsif nitelik azaltma uygulanmıştır. Sınıflandırıcı modeller, Scikit-Learn kütüphanesinden genel olarak kullanılan 6 makine öğrenme algoritması arasında ayrı ayrı olarak uygulanmıştır. Ek bir yaklaşım olarak, Topluluk Oy Sınıflandırıcısı bu 6 algoritmanın bir kombinasyonu olarak uygulanmıştır. Sınıflandırıcı modeller Barış Manço'nun müzikleri üzerinde eğitilip test edildikten sonra, en iyi 3 sınıflayıcı seçilmiştir. Bu sınıflandırıcı modeller, yaklaşımın doğruluğunu görmek için benzer dönemlerde benzer türde müzik yapan sanatçıların müzikleriyle genişletilen veri setinde tekrar eğitilir ve test edilmiştir.

1. INTRODUCTION

Considering the history of music production, the improving technology and development of new audio devices in the last decades constitute a range of possibilities to expand the production decisions and the audio aesthetics that will be created by the producers, audio engineers and even recording artists. The usage of these possibilities and the decisions of the production make clear traces of the characteristic sound of the music work, the album, the musician or the band.

When it is considered in the perspective of the music's affect on listeners, decisions made by audio engineers and producers during the sound design, mixing and mastering phases have a significant importance as much as the composition, arrangement or the musical performance. The quality of the musical production is as important as the composition and performance by the listeners, especially in the sense of preference of the music to listen.

Careful and focused listeners may perceive the sonic details and the production aesthetics of a playing track or an album to guess the production period of the work such as 60's, 70's, 80's or 90's etc. This awareness may affect the listeners to classify the sound of choice over decades for their preference of listening repertoire. As an example, while for some rock music fans, the golden age of the rock music is the 70's, whereas some others are expecting to the hear the snare sound with the gated reverb effect from the 80's. At the end of a music production process which is shaped by the perspective of these sonic details and aesthetics, it is possible to create a nostalgia effect even on the music produced today.

The aim of this thesis is to focus on audio classification based on the umbrella term Anatolion Rock or so called Turkish Psychedelic Rock genre over the production periods as 60's, 70's, 80's and 90's. An audio data set will be created by collecting short excerpts from the musical works of Barış Manço and his contemporary artists or bands that produced music in different decades. Music information retrieval methods will be used to extract features from this data set related to the sonic details of production characteristics. Among these features, state of the art machine learning algorithms will be used to implement a classification approach over the decades that the musics are produced. The main idea is to test various classification algorithms on the features extracted from the audio files via latest music information retrieval methods which are related with production characteristics and run different case studies in order to see the usefulness of this approach.

The classification approach developed as an outcome of this study will be discussed to see the possibility of developing a test tool for today's musicians, audio engineers and producers who are willing to create a nostalgic effect on their works to reflect the aesthetics of a specific production decade.

2. BARIŞ MANÇO AND HIS CONTEMPORARIES

Within the scope of this study, music pieces of Barış Manço are used as an initial audio collection. As a second step, audio collection is extended with the musics of various artists who are the contemporaries of Barış Manço and can be considered under the umbrella term Anatolian Rock.

2.1 Barış Manço's Music Career

Harmoniler was the band that Barış Manço recorded his first vinyls with. Together they recorded eight pieces and released three singles in 45-rpm disc format between years 1962 and 1963. For these three singles, they were working with Grafson Plak company.

With Jacques Denjean Orchestra, Manço released three other 45-rpm disc from Rigolo company in 1964. Years between 1966-1967, he was working with the band Les Mistigris and released three singles. First two released from Sahibinin Sesi company and the last one from Sayan Plak. Produced at this period, the piece "Je Te Retrouverais" was released from Sayan Plak in 1972.

After Les Mistigris, Manço worked with the band Kaygısızlar, which also includes young guitarists Mazhar Alanson and Fuat Güner, who will be known as MFÖ after many years. Together they recorded a renewed version of Kol Düğmeleri, which was and is one of the most famous hits of Manço. The band was influenced by the gradually rising psychedelic music movement, which is known for its proximity to both Anatolian themes and eastern motifs. While interpreting folk songs like Bebek, Kağızman, they also composed English songs like Trip, Runaway, Flower Of Love. Together they released eight singles from Sayan Plak in 45-rpm disc format years between 1967-1969. Of these, Ağlama Değmez Hayat has been sold more than fifty thousand and let Manço to won his first Golden Record. The band recorded Fairground and Susanna pieces in France with the Philips label, but they were not released for a long time.

With a group of musicians from different nations, Manço founded the band Ve in 1970 in France. Together they recorded and released Küçük Bir Gece Müziği, Derule and the famous hit Dağlar Dağlar from Sayan Plak.
In 1971, western influenced Barış Manço and anatolian rock band Moğollar came together with an aim to gain a reputation in Europe with Turkish music. Also known as "ManςoMongol", the band released İşte Hendek İşte Deve in 45-rpm disc format from Sayan Plak in 1971. Working both with Moğollar and Kaygısızlar, Binboğanın Kızı was also released from the same company in 1971. Murat Ses, the keyboardist of Moğollar, later took part in Kurtalan Ekspres.
Taken its name from the train that worked in Haydarpaşa Kurtalan line, Kurtalan Expres is the band that Barış Manço founded in 1972 and worked together until his decease. Established with Murat Ses, Ahmet Güvenç, Celal Güven and Ömür Gidel, the band continued with Bahadır Akkuzu after 1978. Various musicians played within the band through its career. Along with the concert stages, Barış Manço worked with Kurtalan Ekspres also for his television shows. (Url-1)

2.2 Bands that Barış Manço Worked with

Through his forty years of musical life, Barış Manço worked with a total of seven bands; five local and two international. Below is listed the bands and years they work together

- Kafadarlar: in 1958
- Harmoniler: between 1962 and 1963
- Jacques Denjean Orchestra: in 1964
- Les Mistigris: between 1966 and 1967
- Kaygısızlar: between 1968 and 1969
- Ve : in 1970
- Moğollar : in 1971
- Kurtalan Ekspres : between 1972 and 1999 (Url-1)

2.3 Record Companies that Barış Manço Worked with

Barış Manço released thirty singles in 45-rpm disc between 1962-1981, and fourteen albums between 1975-1999. Through this journey, he worked with eight different record company.

- Grafson Plak: between 1962-1963
- Rigolo Music: between 1964-1964
- Sahibinin Sesi Plakçılık: between 1966-1966
- Sayan Plak: between 1967-1971
- Türküola Plak: between 1972-1983
- Yavuz Burç Plakçılık: between 1973-1989
- Sony Music: between 1976-1976
- Emre Plak: between 1985-1999 (Url-2)

2.4 Barış Manço Discography

List of musical pieces of Barış Manço which are used in this study are listed under Appendix A.

2.5 Contemporaries of Barış Manço

An additional audio collection is created from various artists who are contemporaries of Barış Manço and can be considered under the umbrella term Anatolian Rock. These artists include Erkin Koray, Cem Karaca, İlhan İrem, Mazhar Fuat Özkan, Selda Bağcan, Özdemir Erdoğan, Moğollar, Fikret Kızılok, Nejat Yavaşoğulları, Cahit Oben, Asia Minor, Tünay Akdeniz, Zafer Dilek, Kardaşlar, Haramiler, Kaygısızlar, L.S.D. Orkestrası, Silüetler, Stephan Umutyan and various others. As denoted in Chapter 2.1 and Chapter 2.2, many of these artists and bands also have collaborative musical outputs with Barış Manço. Used musical pieces from these artists are listed under Appendix B.

3. AUDIO FEATURE EXTRACTION TOOLS

In order to accomplish an algorithmic classification on audio signal, one of the most important steps is to gather the contextual information out of it. These informations extracted from audio signal are commonly referred to as audio features or descriptors. This study is done under the topic of audio feature extraction or music information retrieval. Basically, audio features can be grouped as low level and high level features. MPEG-7 standard had defined seventeen temporal and spectral descriptors, which have a very general applicability in describing audio (Manjunath, 2002). With the Cuidado project which includes the design of appropriate description structures and the development of extractors for deriving high-level information from audio signals, total number of these features are extended (Peeters, 2004).

3.1 Overview for Modern Audio Feature Extraction Tools

Many audio feature extraction libraries and toolkits have been developed with different capabilities and purposes. Some of them are listed below.

- **Aubio** is a free and open source extraction library written in C language and released under the GNU/GPL license. It also has a Python interface. It mainly focused on extracting high level features such as pitch detection, beat and tempo tracking, onset detection. Aubio offers the possibility to work both real time or non-real time (Url-3).

- **Librosa** is an application programming interface for audio and music signal processing in Python which aims to ease the transition of MIR researchers into Python, and also to make core MIR techniques readily available to the broader community of scientists and Python programmers (McFee, 2015).

- **LibXtract** is a "simple, portable, lightweight library of audio feature extraction functions. The purpose of the library is to provide a relatively exhaustive set of feature extraction primatives that are designed to be 'cascaded' to create a extraction hierarchies (Bullock, 2007)".

- **MIRToolbox** is a free function library for Matlab for the purpose of extracting musical features such as tonality, rhythm, structures, etc. It is released under GNU General Public License. Designed as an object-oriented modular framework; "the different algorithms are decomposed into stages, formalized using a minimal set of elementary mechanisms, and integrating different variants proposed by alternative approaches – including new strategies we have developed –, that users can select and parametrize (Lartillot, 2007)."
  "The toolbox was initially conceived in the context of the Brain Tuning project financed by the European Union (FP6-NEST). One main objective was to investigate the relation between musical features and music-induced emotion and the associated neural activity (Url-4)."

- **YAAFE** (Yet Another Audio Feature Extractor) is a low level feature extraction library with a focus for computational efficiency, usage simplicity and capability to process long audio files. It is working on command line with the input of provided audio files and feature extraction plan. Extraction process can be done in a batch mode, outputting to a CSV or H5 file. Pyhton or Matlab can be used also for extraction (Mathieu, 2010). Yaafe source is released under GNU LGPLv3 License and compilable on Linux and Mac Os X operating systems (Url-5).

- **Essentia** is an open-source, cross-platform C++ library for analysis and audio feature extraction, which is also wrapped in Python. It supports Linux, Mac OS X and Windows operating systems. It released under the Affero GPL license. Consists of reusable algorithms for the implementation of I/O functions, digital signal processing blocks, high level and low level descriptors such as spectral, temporal and tonal.
  "Essentia is designed with a focus on the robustness of the provided music descriptors and is optimized in terms of the computational cost of the algorithms. The provided functionality, specifically the music descriptors included in-the-box and signal processing algorithms, is easily expandable and allows for both research experiments and development of large-scale industrial applications(Url-6)."

Essentia can output the results as yaml or json, which are the most common serialization and interchange format for data (Bogdanov, 2013).

- **Meyda** is a real-time clientside audio feature extractor for use with the JavaScript Web Audio API. "These initial features were chosen with influence from the set of features implemented in the YAAFE Audio Feature Extractor for Python, filtered by what was feasible in the context of the Web Audio API." Initially influenced from the feature set implemented in YAAFE, consisting feautres can be grouped as perceptual, time domain, and spectracl domain features. The Meyda project, including source code and documentation is released under a MIT license (Rawlinson, 2015).

3.2 Evaluation of Audio Feature Extraction Tools

Among these audio feature extraction toolboxes and libraries, an evaluation is done by David Moffat, David Ronan and Joshua D. Reiss from Center of Digital Music of Queen Mary University of London. They used Cranfield Model, which is a six point scale for measuring and evaluating information retrieval systems. In their paper, they present an evaluation based on the following criteria:

- Coverage: List of audio descriptors and features provided by a tool, pre or post processing functionality.
- Effort: User experience for each tool, complexity of performing a new specific query or modify queries, and reference documentation.
- Presentation: Output file format availability and software interfaces for different software languages.
- TimeLag: Computational efficiency based on elapsed time for a task of each tool (Moffat, 2015).

The variety of the features to extract can be considered as coverage in context of audio feature extraction libraries and tools. Tools are compared by their total list of unique features. Feature set provided by each library and the coverage of MPEG-7 and

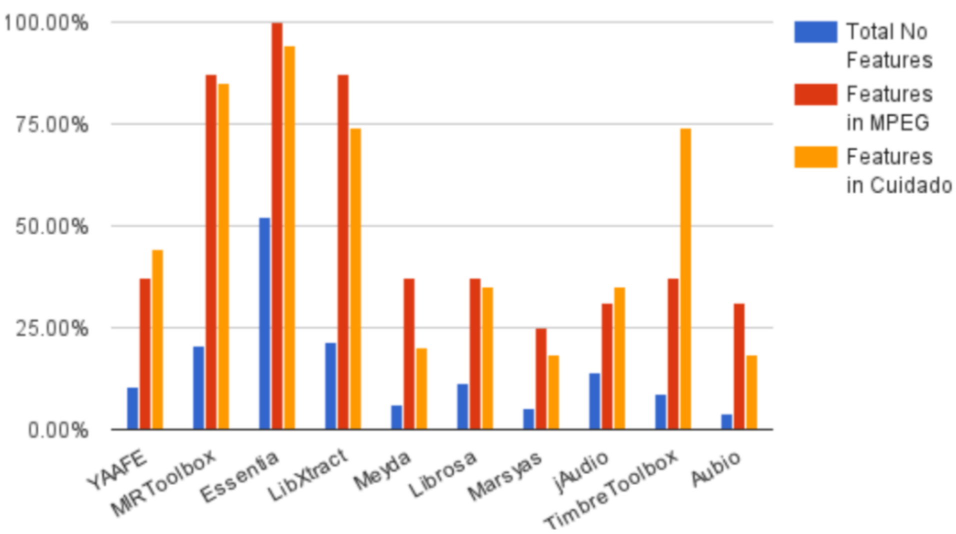

Figure 3.1 : Coverage Percentage of MPEG-7 & Cuidado Standarts (Moffat, 2015).

	Aubio	Essentia	jAudio	Librosa	LibXtract	Marsyas	Meyda	MIR	Timbre	YAAFE
High level Features	Y	Y	N‡	Y	N	Y	N	Y	Y	Y
Low Level Features	N*	Y	Y	Y	Y	Y	Y	Y	Y	Y
Resample	Y	Y	Y	Y	N	Y	Y†	Y†	Y†	Y
Filter	N	Y	N	N	N	N	Y†	Y†	Y†	N
Clustering	N	Y	N§	N	N	Y§	N	Y§	N	N
Similarity	N	N	N	N	N	N	N	Y	N	N
Real Time	Y				Y	Y	Y			
Vamp Plugin	Y	N	N	N	Y	Y	N	N	N	N
GUI	Y^{+}	N	Y	N	Y^{+}	Y^{+}	N	N	N	N
CLI	Y	Y^{E}	Y	N	Y^{+}	Y	N	N	N	Y
APIs	C/C++ Python R PD	C/C++ Python Matlab^{O} PD/Max-MSP	Java	Python	C/C++ Supercollider PD/Max-MSP Java	C/C++ Python Java Lua	JS	Matlab	Matlab	Matlab Python C/C++
Output	Vamp	YAML JSON	XML ARFF	CSV	Vamp XML	Vamp CSV ARFF		TSV ARFF	TSV	CSV HDF5

* = Except MFCC and FFT Statistics,
‡ = Some Mid-high level features but very limited,
† = As part of environment, not toolbox,
$^{+}$ = As result of being Vamp plugin,
§ = Can produce ARFF files, designed for being read directly into Weka.
^{E} = CLI is produced through C 'Extractor' files, with some examples provided.
^{O} = A project for calling Essentia from Matlab has been developed.

Figure 3.2 : Capabilities of Audio Feature Extraction Tools (Moffat, 2015).

Cuidado standard audio descriptor sets are evaluated for total list of available features from each library. Results for this evaluation are shown in Fig. 3.1.

Effort can be considered as the user experience complexity of a system. Effort need to use a tool is evaluated relative to the user interface that is provided, whether it is a Graphical User Interface (GUI), Command Line Interface (CLI) or an Application Program Interface (API). Reference documentation quality and case examples are evaluated in order to identify how intuitively a tool's interface is presented to a user. Presentation of the resulting information is an important aspect of any information retrieval system. The output formats and interfaces shown in Fig. 3.2.

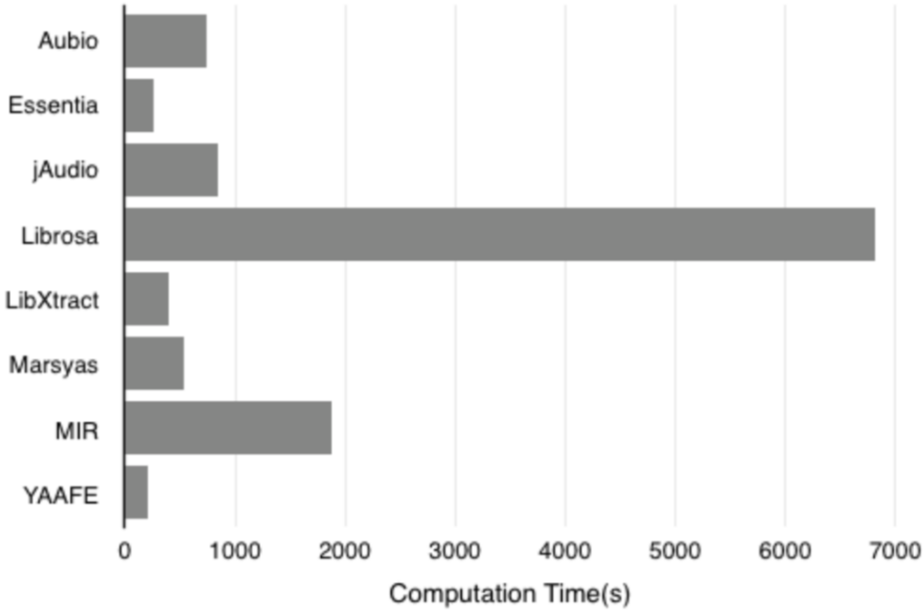

Figure 3.3 : Comparison of Elapsed Time of Feature Extraction Process. (Moffat, 2015)

Time lag is the elapsed time of a given task to complete. Especially for analysing large data sets, awareness of time necessity for performing a task and the comparison of the relative speeds are important informations for choosing the right system to use. Elapsed time comparison results is shown in Fig. 3.3.

3.3 Selected Feature Extraction Tool for This Study

Considering the results of evaluation done by Moffat, Ronan and Reiss from Center of Digital Music of Queen Mary University of London, Essentia library is selected to be used in this study. While each of the tools have their own advantages in different use cases, Essentia library suits the most for the scope of this study due to its compatibility with Python language, flexibility of output format, computational cost and the coverage of features in MPEG-7 and Cuidado standards.

4. METHODOLOGY

Methodology of this study is explained step by step in this section. Audio collection from Barış Manço's discography, used technologies, feature extraction and machine learning algorithms that are going to be used for the project are declared and defined.

4.1 Audio Collection

Music excerpts that are used for this study are prepared in two sections. Music pieces Barış Manço are used for training and validation classifier models. Musics of various artists over the same eras are used to extend the dataset to test the classifier models in a wider perspective.

Collection used in this study is consisting of .mp3 format audio files in various bit rates since most of them are not available or easily findable as uncompressed .wav files in standart compact disc quality. Because of their signature sound characteristics for the eras they are popularly used, other distribution formats such as cassettes and vinyls are planned to be used in early stages of this study. Yet this approach has been waived out since they were not easily accessible in means of rarity and priciness.

4.1.1 Music Pieces of Barış Manço

Among the discography of Barış Manço, all 14 studio albums are collected in mp3 format. Four compilation albums which are released by the record labels in his life time are added to the collection. Names of the compilation albums are Ben Bilirim, Dağlar Dağlar, Dünden Bugüne and Sakla Samanı Gelir Zamanı. Additionally, a new compilation album named 1962-1963, which contains his first single releases is also added. Within this discography, a total number of 224 musical pieces are collected.

4.1.2 Music Pieces of Barış Manço's Contemporaries

A total number of 190 different musical piece from other artists who are could be considered under the umbrella term Anatolioan Rock between 1960 and 1999 are collected in mp3 format. These new excerpts will be combined with Barış Manço dataset to have an extended sample space for Anatolian Rock. Best resulting classifiers will be trained and tested on this extended dataset to see whether the classification of musical production period over low-level features approach is applicable in a wider spectrum.

4.2 Technologies Used

Pyhton 3.7 is used as the programming language for this study. As a coding environment Jupyter Notebook is used for the sake of its modularity and interactivity. Popular open source Pyhton libraries such as Pandas (Python Data Analysis Library) and NumPy are used for data structures, data analysis and scientific computation purposes. As a high level interface for drawing and visualization of data, Seaborn library based on Matplotlib is used. Essentia library is used for the audio feature extraction process. Scikit-Learn, which is a popular open source library, is used for the machine learning and feature reduction algorithms. To create an ensemble voting classifier among the used machine learning algorithms, Mlxtend, which is a machine learning extensions library written in Python, is used.

4.3 Feature Extraction from Audio

All audio features and their statistical measurements available by music extractor algorithm of Essentia library are extracted from 30 seconds long divisions from each track. For each 30 seconds long frame, two separate files are saved in json format; one for the audio feature vectors of the frame and one for the statistical measures of related feature vectors such as mean, variance, standard deviation etc. As a naming convention, each sample file is named as Albumname_TrackName_FrameStartTime_FrameEndTime. These audio feature files consist of information in four categories: Metadata, Low-Level descriptors which are related with signal level properties, rhythmic descriptors and tonal descriptors. Since the focus of this study is to predict the music production, only the low level descriptors are used. Additionally, metadata information is used for labeling the dataset.

Below are the explanations of the low-level audio features extracted by Essentia.

- **Spectral Centroid:** In digital signal processing, spectral centroid is a dimension to define a spectrum by pointing out its center of the mass. For human perception, it has a direct relation with the sense of brightness for a sound (Grey,1978). For calculation, by using Fourier transform, magnitudes of the frequencies in a given signal are taken as weights and the weighted mean is equal to spectral centroid (Peeters,2004).
  In application, since it is accepted as a good predictor for the brightness of audio, it is common to use spectral centroid as a dimension of musical timbre (Schubert, 2004).

- **Spectral Spread:** Following the definition of spectral centroid, spectral spread defined as the spread of the spectrum around its mean value, a variance of the distribution of frequencies and their probabilities to be observed in normalized amplitude (Peeters, 2004).

- **Zero-Crossing Rate:** For a given signal, zero-crossing rate is the measure of the sign change from positive to negative or vice versa. The total number of times that the value cross the zero axis. It is one of the most commonly used audio features which holds a key role to classify percussive sounds (Peeters, 2004).

- **Spectral Skewness:** Spectral skewness is the dimension to define the degree of asymmetry of the spectral distribution around its mean value. When skewness equals to 0, it indicates that distribution over spectrum is symmetric. Skewness lower than 0 means more energy on the right side and being higher than 0 means more energy on the left side (Peeters, 2004).

- **Spectral Kurtosis:** Spectral kurtosis is the dimension to indicate peakedness or flatness of the spectral distribution around its mean value. When the kurtosis equals to 3, the distribution is normal. Below 3 indicates a flatter distribution while above 3 indicates a peaker distribution (Peeters, 2004).

- **Spectral Slope:** Calculated via linear regression over the amplitude of the spectrum, spectral slope gives out the quantity of the decrease of spectral amplitude (Peeters, 2004).

- **Spectral Decrease:** Formulated around perceptual studies and so more correlated to human hearing, spectral decrease is another representation for the decrease of spectral amplitude (Peeters, 2004).

- **Spectral Roll-off:** Spectral roll-off indicates a frequency point where the 95% energy of the signal is contained below. This point has a correlation with the harmonic/noise cutting frequency (Peeters, 2004).

- **Spectral Flux:** Calculated via Euclidean distance between the spectra of two successive frames to measure the change in the power spectrum of a signal. It is not dependent with overall power since there is a normalization process. Mainly for onset detection and determination of the overall timbre of an audio, spectral flux can be used for various applications (Giannoulis, 2013).

- **Spectral Entropy:** Entropy is the measure for the peakiness of a spectral distribution. In automatic speech recognition area, this feature is used for deciding a signal is voiced or unvoiced (Misra,2004).
  In Essentia, Shannon entropy is default.

- **Spectral Strong Peak:** Spectral strong peak is the ratio between the maximum peak's magnitude in the spectrum and the bandwith of that peak above a threshold, which is the half of its amplitude (Gouyon, 2001).

- **Spectral RMS:** RMS stands for root mean square as a mathematical term, and calculated as the square root of the mean square. For a continuous-time waveform, square of the defining function is the RMS (Url-7).

- **Spectral Complexity:** For a given input spectrum, spectral complexity is defined as the number of the peaks (Laurier, 2010).

- **Energy:** In terminology of signal processing, the area under squared magnitude of a given continuous-time signal is defined as energy (Url-8). Essentia's standard algorithm outputs energy for different frequency bands such as high, middle-high, middle-low, low.

- **Spectral Contrast:** For music type classification, spectral contrast is a strong discriminative feature because its focus of spectral peak, spectral valley and the

differences of them among sub-bands. Spectral peaks have a rough correlation with harmonic contents while spectral valleys can monitor non-harmonic material or noises. So this feature is a rough reflection of the relative distribution for harmonic and non-harmonic material for a given spectrum (Jiang, 2002).
Essentia's standard algorithm outputs the spectral contrast coefficients and the magnitudes of the valleys seperated.

- **Pitch Salience:** To avoid inconsistent pitch estimation in sound analysis, a given frame should be known whether it is pitched or not. The inconsistency between the analysed signal's magnitude spectrum and the ideally best matched harmonic pattern can be used to measure pitchness for harmonic pattern recognition. Given audio signal is accepted as inharmonic due to the largeness of this inconsistency. The ratio of the highest peak's amplitude of auto correlation and the total power of the signal gives the pitch salience, which is a dimension of tone sensation. For harmonic sounds this ratio approaches to 1, while it approaches to 0 for non-harmonic sounds. This feature can be used in applications that aim to characterize percussive sounds (Ricard, 2004).

- **HFC:** Stands for high frequency content, HFC is a basic feature to determine the amount of the high-frequency content of a given signal via a short-time Fourier transform. Used for applications such as onset detection, this measure is not directly correlated with human hearing, Rather it has some similarities with spectral centroid feature (Url-9).
Essentia library offers three different computation method such as Masri, Jensen and Brossier.

- **Dissonance:** Different from theoretical or musical dissonance, sensory dissonance is a feature for percepted roughenss of a sound. For a given audio signal, it is calculated by the roughness of the spectral peaks (Url-10).

- **Dynamic Complexity:** Related to the dynamic range and the fluctuation amount in loudness, dynamic complexity is calculated with the average absolute deviation from overall loudness as dB (Streich, 2006).

- **Silence Rate:** This feature indicates an estimation whether a given frame is silent. Can be calculated for a list of given thresholds and output a boolean response to whether the frame's instant power is below the thresholds or not. By default, Essentia calculate silence rates for thresholds 20dB, 30dB and 60dB (Url-11).

- **Loudness EBU R128:** This feature and its sub-branches are related to EBU R128 loudness descriptors of a given audio signal. A K-weighting filter, which consists of two stages as shelving and high-pass filters, is applied to the given signal. Four different sub descriptors are defined as momentary loudness, short-term loudness, integrated loudness and loudness range (Url-12).

- **Psychoacoustical Scales:** Psychoacoustical scales that derived from perception study experiments. Rather than musical compositions, these scales are used for studying perception (Url-13).

  – **Bark Scale:** In 1961, Eberhard Zwicker proposed the Bark scale, and named after Heinrich Barkhausen who proposed the first subjective measure for loudness.
    Generally they are almost logarithmic for frequencies above 500 Hz but nearly linear below 500 Hz. Related with the 24 critical bands of hearing Bark scale is ranged from 1 to 24 (Url-14).

  – **ERB Scale:** ERB stands for Equivalent Rectangular Bandwith, a psychoacoustic measure which is based on non-real but simple modelling as rectangular band-pass filters to make an estimation for the filters' bandwith for human hearing (Url-15).

  – **Mel Scale:** Derived from the word melody to point out this scale is an analogy for pitch sense, mel scale is evaluated by listeners to perceptually scale the pitches as guessing in equal distance with each other. A perceptual 1000 mels is assigned to 1000 Hz tone as reference point (Url-16).

4.4 Dataset of Low-Level Features

A low level feature dataset of Barış Manço is created by using Pandas Library from the output feature files of Essentia Music Extractor which contains statistical measures of selected low level feature vectors. An additional test dataset is created via the same procedure from musical works of Barış Manço's contemporaries for further test purpose.

4.4.1 Extracted Excerpts from Barış Manço's Works

Among 224 musical pieces from the selected albums of Barış Manço, a total number of 1720 excerpts are created via Essentia library. These excerpts are labelled based on their release dates such as 60's, 70's, 80's and 90's. Tracks in studio release albums are labeled with the album release date. Tracks in compilation albums are labeled with the release year of each track individually. Figure 4.1 represents the number of 30 second long excerpts based on decades. Consisting of the extracted features of these 1720 excerpts, a 404-dimensional feature space is created. Figure 4.2 is the 2-dimensional Umap projection of the 404-dimensional feature space.

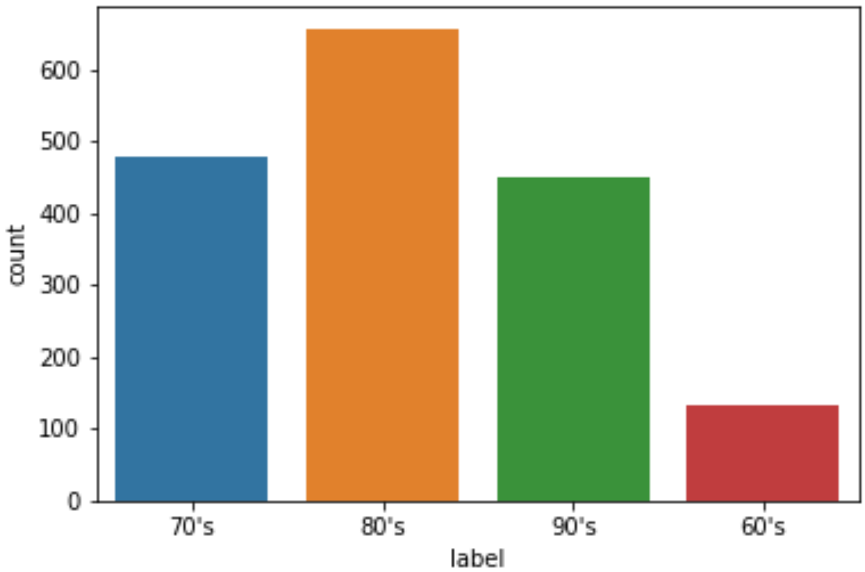

Figure 4.1 : Excerpt Counts for Decades from Barış Manço Dataset

4.4.2 Extracted Excerpts from Musics of Barış Manço's Contemporaries

To extend the dataset for further testing, a total number of 1393 excerpts are extracted via Essentia library from 190 selected musical pieces of various artists. These excerpts are labelled based on their release dates such as 60's, 70's, 80's and 90's. Figure 4.1 represents the number of 30 second long excerpts based on decades for these excerpts. Consisting of the extracted features of these 1393 excerpts, a 404

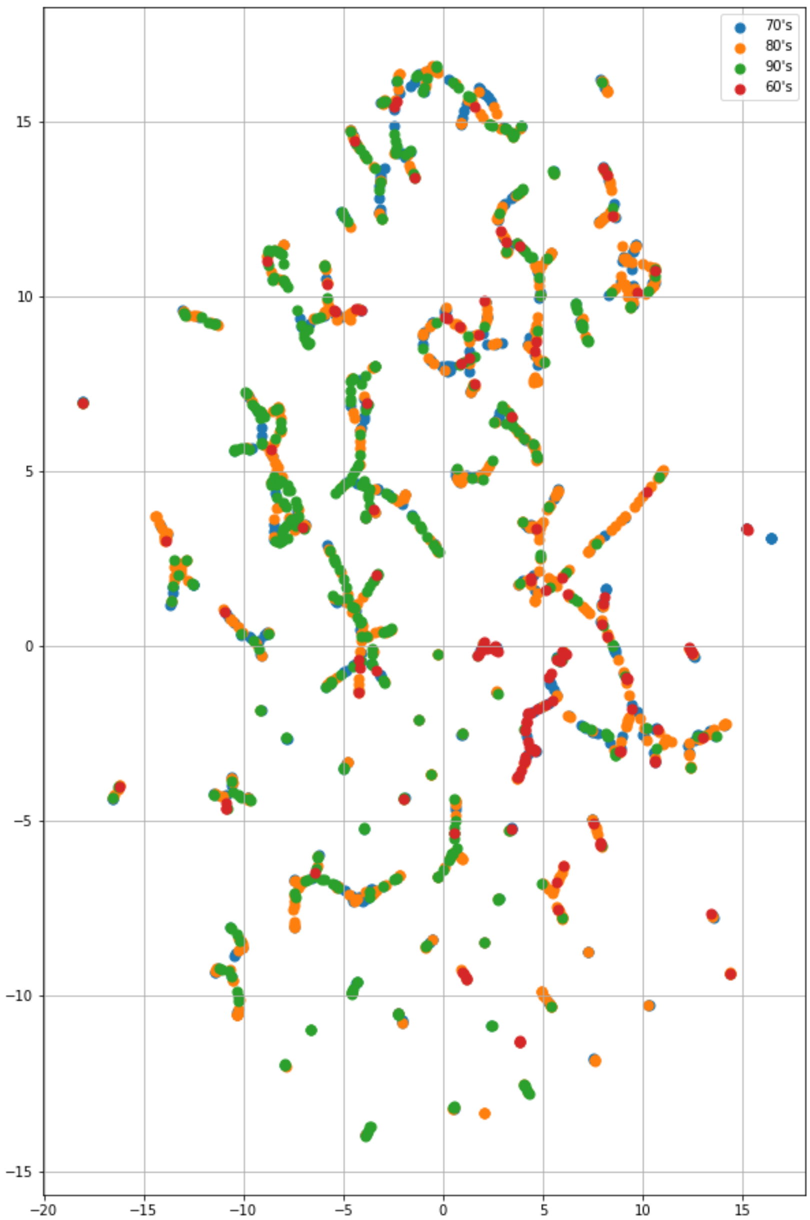

Figure 4.2 : 2-dimensional Umap Projection of Barış Manço Dataset

dimensional feature space is created. Figure 4.2 is the 2-dimensional Umap projection of the 404-dimensional feature space for these excerpts.

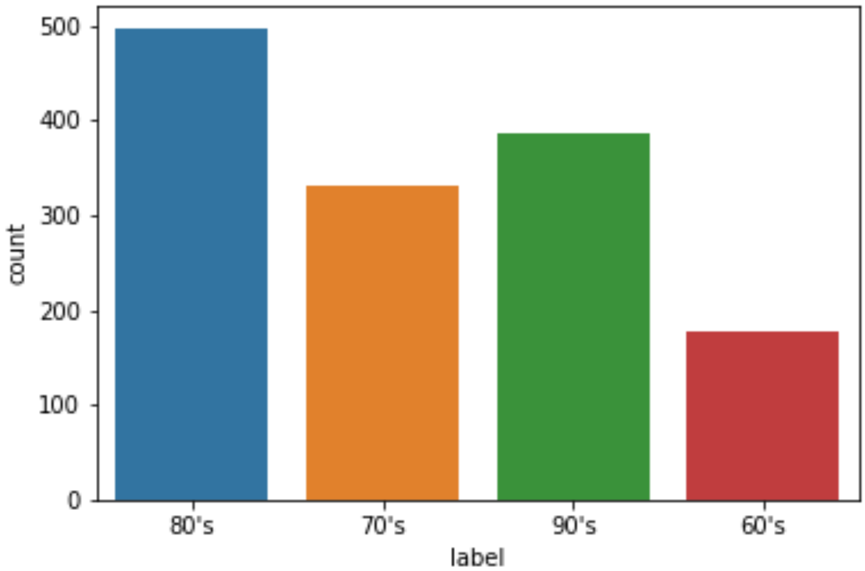

Figure 4.3 : Excerpt Counts for Decades of New Excerpts

4.5 Feature Selection

Among the descriptors that Essentia tool can extract, 47 different audio descriptors are included in this study. Statistical calculations due to vector type descriptors also added to the overall feature vector. Putting together, the low level feature dataset used in this study consists of a 404-dimensional feature space. A total of 1720 different samples extracted from the audio collection, which makes the number of samples higher than the number of features. This section will focus on elimination of the features to avoid the curse of dimensionality. As the name suggest, curse of dimensionality occurs when working on data with high dimensional spaces (Url-17). The success rate of the classifier will increase until some optimal number of features and will decrease further on if the number of training samples will not increase accordingly (Url-18). Following approaches are combined for reducing the dimension of the feature space.

4.5.1 Removing Redundant Features

First step is to remove the features with no variance, which has no effect over the classification process. After removing the zero variance features, Pearson method of the Pandas library is used to calculate standard correlation coefficient and remove the highly correlated features. 95% is used for a threshold for this step.

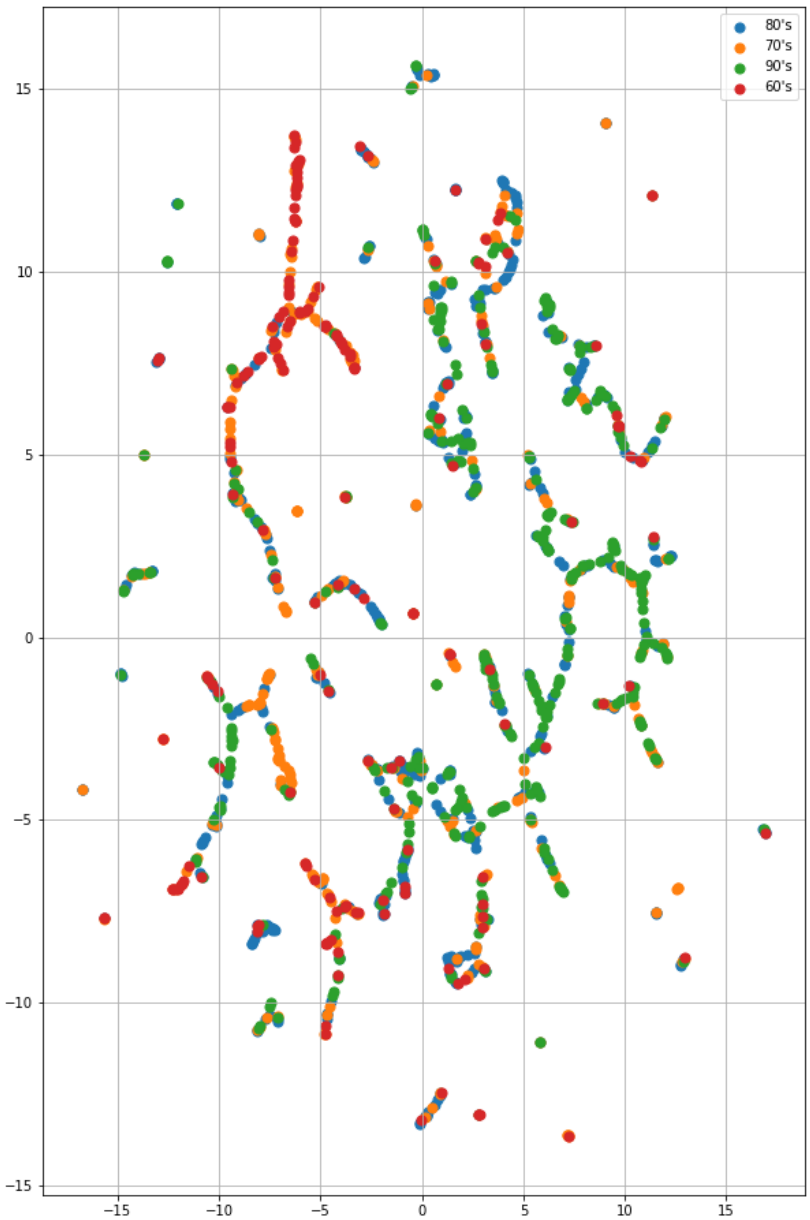

Figure 4.4 : 2-dimensional Umap Projection of New Excerpts

4.5.2 Recursive Feature Elimination with Cross Validation

Recursive feature elimination with cross-validation algorithm (RFECV) from Scikit-Learn library applied on the remaining features. RandomForestClassifier algorithm with cross validation used for estimator for scoring accuracy. In each iteration, 10 fold cross validation applied and one feature eliminated. Outputs of this step are that the features with the best rank due to their importance and an optimal number of features for a saturated score is calculated.

4.5.3 Feature Importances with Forests of Trees

From the output of recursive feature elimination, features which are ranked as 1 are saved as an other dataset of best features. Importance of these best features are calculated with tree-based feature selection approach. ExtraTreesClassifier algorithm is used from Scikit-Learn library.

4.6 Machine Learning Algorithms

Machine learning algorithms that are used in this thesis study are briefly explained in this section.

4.6.1 Logistic Regression (LR)

Even though it has regression in its name, Logistic Regression is used for classification problems. The main idea is to determine whether something is true or false by drawing a logarithmic line which discriminates outcome variables on extreme ends (Url-19). The regression in the name comes from the Logistic Regression will calculate the probability of belonging to a given class for a given example (Url-20). Logistic Regression uses the logistic function, also called the sigmoid function, as the main approach of the method. Developed by statisticians to define the properties of a given set, logistic function is an s-shaped curve which can map any real-valued number into a binary value such as 0 and 1 (Url-21). It uses the maximum likelihood approach to differentiate the class densities and the priors (Fu, 1968). Within the focus of this study the expected classification outputs are the labels for music production decade.

Since there is more than two values, they will be modeled by multi-nominal logistic regression. Among the given low level audio features, logistic regression will try to fit a logistic function to determine the relation between the audio features and the labels such as 60's 70's 80's and 90's.

4.6.2 Support Vector Machines (SVM)

Being another simple yet efficient algorithm, which is suitable both for regression and classification problems, SVM has a popularity because of its remarkable accuracy with lesser computational cost (Url-22). In the main idea, SVM is a classification approach for linearly separable binary sets. By looking at the sets given, the goal of the SVM is to draw an optimal decision boundary, which is referred as a hyperplane that separates the training data in two classes. The closest datapoints from each class to the opposite are referred as support vectors. Best boundary is selected as the hyperplane which has the maximum margin from both classes, which can metaphors as the widest street to separate the examples. One of the main advantages of the Support Vector Machines is the efficiency in high dimensional spaces, like in the example of the dataset used in this thesis study. For the higher dimensional feature spaces computational cost is very expensive. To reduce the computational cost, support vector machines uses a kernel function, which is also referred as the kernel trick, that dot products the vectors in the feature spaces. Thus, a non-linear space transformed to a linear space. The three general kernel functions are polynomial, radial basis function(rbf) and sigmoid kernels. For various decision functions, different kernels could be implemented.

4.6.3 K-Nearest Neighbors (KNN)

K-Nearest Neighbors algorithm is a non-parametric method in pattern recognition used for classification and regression (Altman,1992). KNN is a very simple algorithm for supervised machine learning, which depends on the similarity of the features. Works on the assumption that similarity has a direct proportion with proximity, and similar things exists together, KNN classifies a given sample based on the classification of its surroundings. Because it is a lazy learner, which memorizes all the training data instead of learning a discriminative function among them, KNN approach fits mostly to the small, labelled and noise-free datasets. It keeps all accessible instances and classify fresh instances based on measure of resemblance. To calculate the proximity with the neighbors and find the nearest ones, in general the euclidean distance is used. K is the parameter that relates to the amount of neighbors closest to majority voting. To achieve a better accuracy in the output, optimal k should be chosen with parameter tuning. As a starting point, squareroot of the total number of data samples may be chosen. Better to select and odd value of k to prevent confusion between two classes (Url-23).

4.6.4 Gradient Tree Boosting (GTB)

Another branch of ensemble techniques is boosting algorithms where the predictors works sequentially, gaining experience from their predecessors. The idea of boosting is whether a weak learner such as decisions trees, where the prediction is slightly better than random guessing, could be improved for a better learning. Decision trees, regressors or classifiers can be used as prediction models for boosting technique. It will take less time or iterations to reach to the resulting prediction since the predictors are learning from the errors done by the priors, but still it is a key point to choose an optimal stopping criteria to avoid the overfitting on training data (Url-24). Among other boosting algorithms, the difference of Gradient Tree Boosting is that it trains models gradually, additively and sequentially. Gradient boosting will identify the deficiencies of the weak learners by using gradients in the loss function, which measures how good the coefficients of the model are when the underlying information are fitted (Url-25).

4.6.5 Random Forests (RF)

As a model, Random Forest consists of a large number of decision trees, a tree-like approach to decision making problems, as building blocks. Decision trees can be thought as a series of boolean questions over data which end up to predict a class or continuing value of regression (Url-26). One of the key points is that to create uncorrelated or at least low correlated decision tree models to output a crowd decision which are more precise than the individual predictions (Url-27). While using multiple decision trees, random forest does not simply take the average of results. While creating trees, it uses the samples randomly as training data points and makes decisions over random subsets of features (Url-26). Choosing features with the consideration of some predictability and the optimized tuning of hyper parameters will impact the resulitng correlations (Url-27).

4.6.6 Multi-Layer Perceptron (MLP)

Influenced by the biological neural network of human brain, artificial neural networks consist of many nodes to process information, which are also called as neurons, connected to each other to send and receive signals. Multi-layer perceptron is a feedforward instance of artificial neural networks and consists of neurons that are arranged in different layers to perform different kind of transformation on its input. Arbitrary number of layers between the input and the output layers are called as hidden layers, which are the computational core of the Multi-Layer Perceptron (Url-28). When applied to supervised learning problems, MLP will try to learn the correlation between features and the labels by training on dataset. Inputs of the neurons are calculated as weights, summed and transferred through a function, called as activation or transfer function (Url-29). Using non-linear activation, MLP can learn and differentiate data which is not linearly separable.

4.6.7 Ensemble Vote Classifier (EVC)

This classifier can be defined as a meta-classifier which combines various classifier algorithms to achieve decision over voting based on majority or plurality. Aim of this approach is to achieve a better classifier with higher success in prediction than the individual classifiers. With the EnsembleVoteClassifier of Mlxtend library, an ensemble classifier is created from the six classifier algorithms used in this study. Each algorithm has its own capacities and approach for classification problems. Ensemble classifier aims to have a voting mechanism among the predictors. This classifier may implement two different types of voting approach. Prediction based on most frequent answers is referred as hard voting while the average of the answers referred as soft voting. Weights of the votes are configurable for giving privilege to better predictors (Raschka, 2018).

5. RESULTS AND EVALUATION

Results of this thesis study are declared and discussed in this chapter. Outputs of feature selection process are presented. Outputs of the classification algorithms and usability of the extracted features from the audio excerpts are evaluated depending on their success rates and their contribution in classifying the production period of the related excerpt.

5.1 Feature Selection Results

Redundant features are eliminated and most effective features are selected. Following subsections are explaining the results for each step in feature selection.

5.1.1 Removing Redundant Features

In this step the number of features reduced to a total 399 features by removing 5 features with 0 variance. Pearson method with a threshold of 95% is applied for removing highly correlated features, 147 features are eliminated and the feature space is reduced to 252 dimensions.

5.1.2 Recursive Feature Elimination with Cross Validation

After removing features that have 0 variance and high correlation, recursive feature elimination is applied with cross validation. Over remaining 252 features, 5 iterations are applied to reduce the dimension space to a saturated optimal number of features. Table 5.1 shows the results of each iteration.

As it is shown in Table 5.1, recursive feature elimination approach comes to a saturation point between 20 and 30 features with a negligible variation of maximum accuracy. Figure 5.1 represents the result of the second iteration for number of features selected and the related accuracy score. During this process, three additional feature

Table 5.1 : Results of Recursive Feature Elimination Iterations

	Total #Features	Optimal #Features	Maximum Accuracy
Iteration 1	252	72	86.41%
Iteration 2	72	39	86.58%
Iteration 3	39	25	86.35%
Iteration 4	25	23	86.34%
Iteration 5	23	23	85.93%

spaces are created additional to the whole feature space among the optional feature numbers as 72, 39, 25 to compare the classifier results for each.

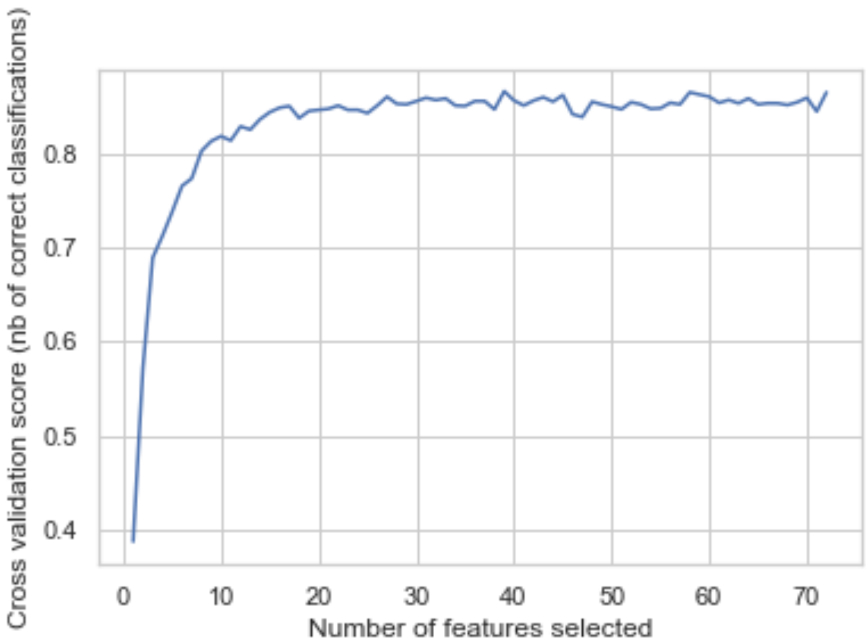

Figure 5.1 : Result of Iteration 2

5.1.3 Feature Importance with Forests of Trees

Among the selected features, Figure 5.2 shows the best features sorted by their importance which are calculated by Forests of Trees. After sorting the selected 25 features due to their importances, it is observed that the best discriminative features for the musical production decades are consisting of the statistical calculations of psychoacoustic scales such as ERB scale and EBU 128 loudness metrics. As it is explained in Chapter 4.3, psychoacoustical scales are directly related with the outputs of perception study experiments. Rather than musical compositions, they are used to estimate the human hearing tendencies over the frequency spectrum. Other than spectral qualities, perception of the dynamics in a given musical piece, which can be calculated via loudness metrics has an important role for human hearing as well. It is also observed that the other spectral features such as spread, roll-off, complexity, skewness, energy and strongpeak are existing in the important features list. It already can be seen in other audio classification studies that these features have a high discriminative role in audio classification.

5.2 Results of the Machine Learning Models

Classification success rates of the introduced machine learning algorithms are declared in this section. To have a detailed comparison and see the efficiency of the feature selection approach, each algorithm are fed separately with both full features and resulted optimal number of features for first three iterations of recursive feature elimination process. Table 5.2 shows the success rates for each classifier model with different number of features. Top 3 success rates are obtained from Ensemble Vote, Random Forest and SVM classifiers. In the following subsections, confusion matrices are reported for each classifier, which are produced on 39-dimensional feature space as an arbitrary selection.

Table 5.2 : Success Rates of Classifier Algorithms with Different Number of Features

	404 Features	**72 Features**	**39 Features**	**25 Features**
Logistic Regression	84.01%	75%	67.44%	65.4%
Support Vector Machines	84.01%	84.88%	85.17%	83.13%
K-Nearest Neighbors	80.23%	82.84%	83.13%	82.26%
Gradient Tree Boosting	82.84%	81.97%	79.94%	79.94%
Random Forest	84.3%	84.59%	84.59%	82.55%
Multi-Layer Perceptron	77.32%	72.38%	67.44%	71.51%
Ensemble Vote	88.37%	87.79%	86.33%	86.04%

5.2.1 Logistic Regression

It is observed on Table 5.2 that while the feature space is getting narrower, the accuracy score of LR classifier is decreased remarkably. Figure 5.3 shows the distribution among actual labels and predicted labels by LR classifier. LR's prediction has the best accuracy for predicting 90's with 78%, while 18% of the excerpts from 90's are confused with 80's. It shows similar prediction rates for 80's and 70's, again its confusion concentrates on neighbor decades but mostly on each other. For 60's, LR

	FeatureName	Importance
0	erbbands_flatness_db_min	0.065493
1	loudness_ebu128_integrated	0.061199
2	erbbands_flatness_db_mean	0.054093
3	loudness_ebu128_loudness_range_dmean_dmean2_dv...	0.052348
4	barkbands_flatness_db_min	0.048309
5	spectral_spread_dmean	0.042473
6	spectral_rolloff_max	0.041833
7	melbands_kurtosis_median	0.040620
8	spectral_spread_mean	0.040056
9	spectral_complexity_dvar	0.039259
10	spectral_skewness_mean	0.038563
11	erbbands_spread_mean	0.037821
12	loudness_ebu128_loudness_range_dmean_dmean2_dv...	0.037513
13	pitch_salience_mean	0.037172
14	barkbands_crest_dvar	0.036941
15	spectral_spread_min	0.036304
16	melbands_crest_dmean	0.035845
17	spectral_energyband_high_stdev	0.034152
18	spectral_energyband_low_dmean	0.033960
19	spectral_energyband_low_max	0.032940
20	melbands_crest_dvar	0.031678
21	spectral_energy_dvar	0.031599
22	pitch_salience_dvar	0.031224
23	spectral_energy_max	0.030127
24	spectral_strongpeak_dvar	0.028478

Figure 5.2 : Most Important Features Sorted

only predicted half of the excerpts correctly while it confused the 60's with the 70's for most of the other half.

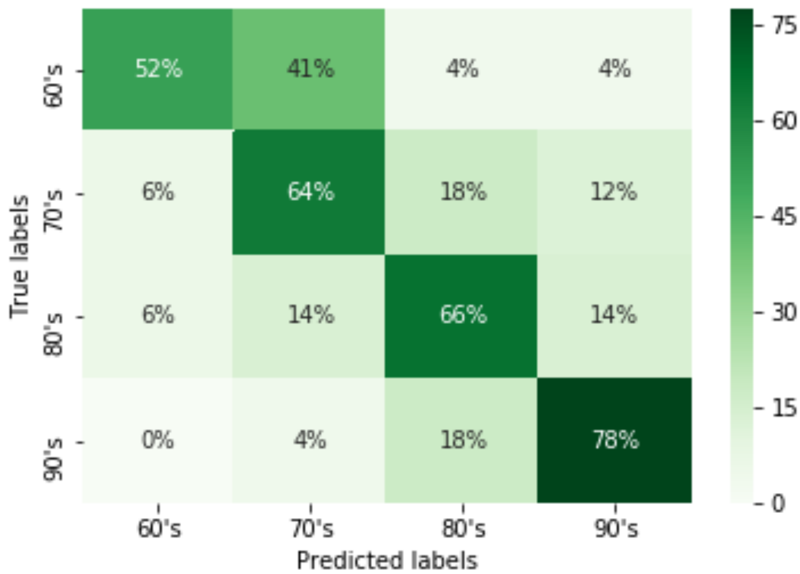

Figure 5.3 : Confusion Matrix for LR

5.2.2 Support Vector Machines

It is observed on Table 5.2 that while the feature space is getting narrower, the accuracy score of SVM classifier is increased. SVM produced the best score on the 39-dimensional feature space. It is also observed that for excerpts from 1960's, SVM produced the best classification result by 0 confusion with 1980's and 1990's. Figure 5.4 shows the distribution among actual labels and predicted labels by SVM classifier. SVM have high and balanced prediction accuracies over production decades, alternating between 80% and 90%. SVM confusion for given production decades are mostly concentrated on preceding or subsequent decades. Confused predictions for 70's and 80's are mostly concentrating on each other and very less for 60's and 90's. For the excerpts of 60's, it is remarkable to see that SVM has no confusion with 80's or 90's. All wrong predictions for 60's are on 70's, which is the direct subsequent decade.

5.2.3 K-Nearest Neighbors

It is observed on Table 5.2 that while the feature space is getting narrower, the accuracy score of KNN classifier is increased. Similar to SVM, KNN produced the best score on 39-dimensional feature space. SVM outputted the 3rd highest output. Figure 5.5 is the confusion matrix that shows the distribution among actual labels and predicted labels

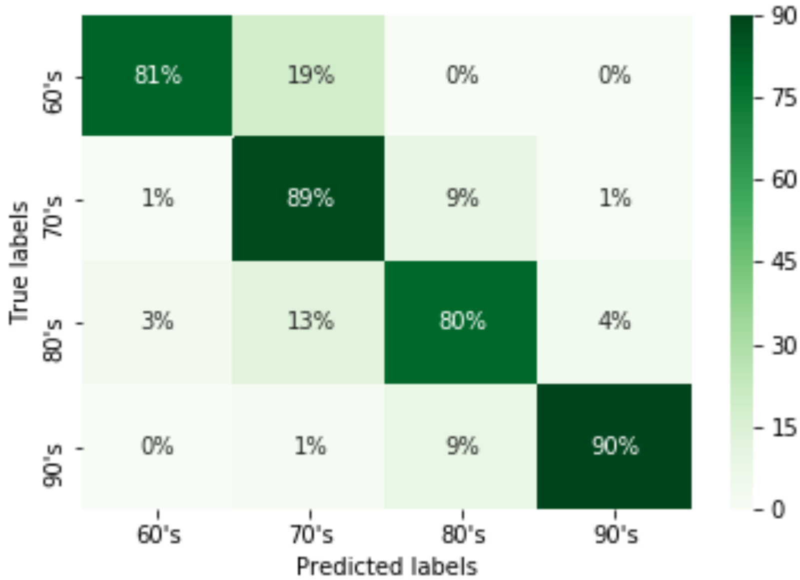

Figure 5.4 : Confusion Matrix for SVM

by KNN classifier. KNN has a very strong prediction accuracy for 90's with 94% while it does not show the same accuracy for other decades. Since the prediction logic of KNN is depending on the similarity of the features, these results can be interpreted as the features of excerpts from 90's shows more similarities compared to other decades. KNN shows no confusion among the excerpts of 60's and 90's between each other. This result can be understood as there are no or very less similarity between the features of 60's and 90's. Confusions for 70's and 80's are mostly concentrated on each other, which denotes a closer similarity among their features. While the prediction success is not as balanced as SVM's for all eras, KNN's prediction is still better than Logistic Regression for overall.

5.2.4 Gradient Tree Boosting

As it is shown in Table 5.2, while it is not as drastic as in LR, the accuracy score of GTB classifier is also decreased as the feature space is getting narrower. Still, the success rates can be considered as similar. Confusion matrix in Figure 5.6 shows the distribution among actual labels and predicted labels by GTB classifier. GTB predicts only the half of the excerpts of 60's correctly while it has an ascending prediction rate for 70's, 80's and 90's respectively. Still, there is no confusion with 90's for the excerpts of 60's. Confused predictions belong to 70's and 80's are mostly concentrated

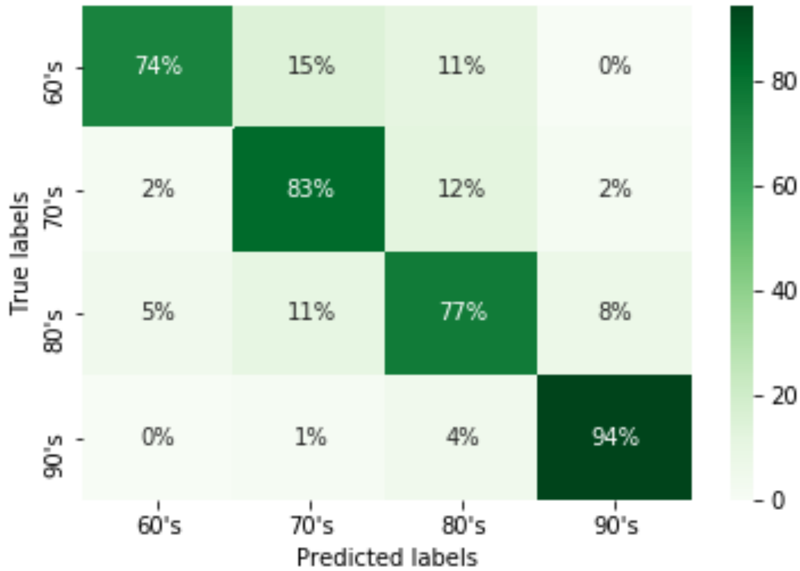

Figure 5.5 : Confusion Matrix for KNN

on each other. For the excerpts of 90's, most of the wrong predictions are on 80's, which is the preceding decade, while only 1% confusion on 70's and none on 60's.

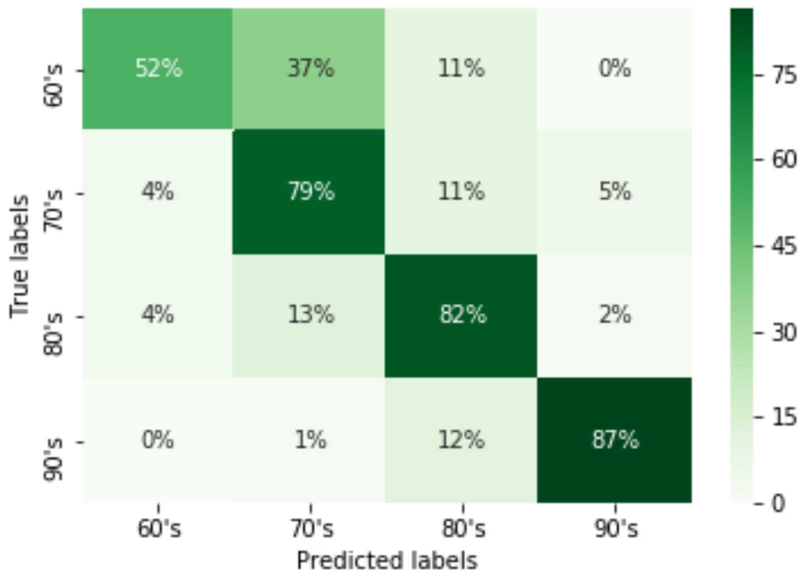

Figure 5.6 : Confusion Matrix for GTB

5.2.5 Random Forests

As it is shown in Table 5.2, accuracy scores are better on 72 and 39 features than 404 features. For 25 features, accuracy score is lower than the others. The best score was on the 39-dimensional feature space. RF outputted the second highest output.

However, RF's prediction on excerpts 1960's is not as good as SVM's. Yet for excerpts from 80's and 90's, RF shows 0 confusion with 60's. Confusion matrix in Figure 5.7 shows the distribution among actual labels and predicted labels by RF classifier. While having 52% success like GTB for the excerpts of 60's, RF classifier shows a very strong prediction accuracy for other decades. While it has a 33% confusion with 70's for the excerpts of 60's, there is no confusion with 60's for the excerpts of 70's. With 90%, RF classifier has its strongest accuracy for excerpts of 70's, while the confusion for these excerpts are equally distributed between 80's and 90's. For the excerpts of 80's and 90's, confusion is generally concentrated on preceding decades.

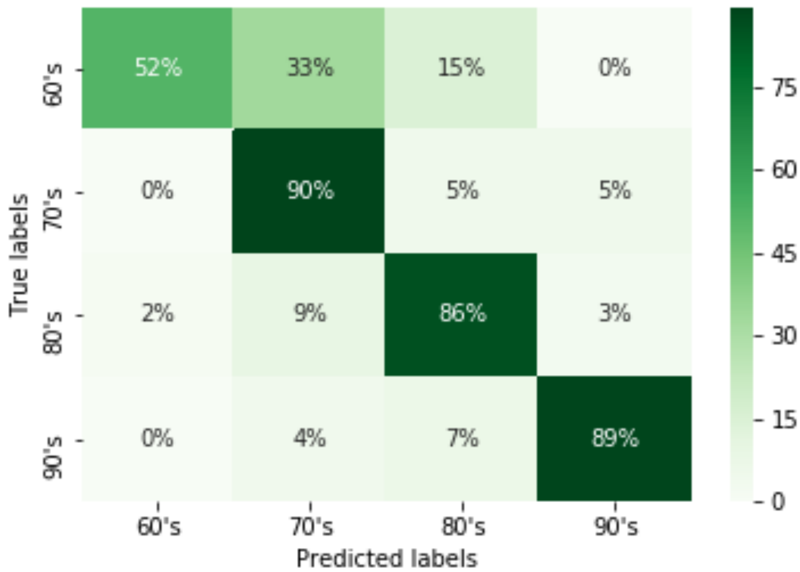

Figure 5.7 : Confusion Matrix for RF

5.2.6 Multi-Layer Perceptron

As it is shown in Table 5.2, MLP classifier resulted with the lowest accuracy scores among all other classifiers for all dimension spaces. The accuracy score of MLP classifier is decreased as the feature space is getting narrower. MLP's lowest accuracy score is produced on 39 features. Figure 5.8 is the confusion matrix that shows the distribution among actual labels and predicted labels by MLP classifier. It is observed that somehow MLP had zero success for predicting excerpts from 60's. Yet it also didn't had a confusion resulted with 60's. Seems like MLP could not learn a pattern for 60's within the given dataset. As it can be seen on the confusion matrix, MLP cannot find a distinguishing pattern for the excerpts of 60's. While it has 0 correct predictions on 60's, it did not confused with 60's for the excerpts of other decades. Still, it is interesting to see that most of the excerpts of 60's predicted as 70's with a 89% accuracy. MLP's prediction confusion for 70's and 80's are concentrated on each other, as it is observed in other classifiers results too. Strongest prediction accuracy of MLP is for excerpts of 90's with 87% accuracy, while 13% of confusion with 80's and no confusion with 70's and 60's.

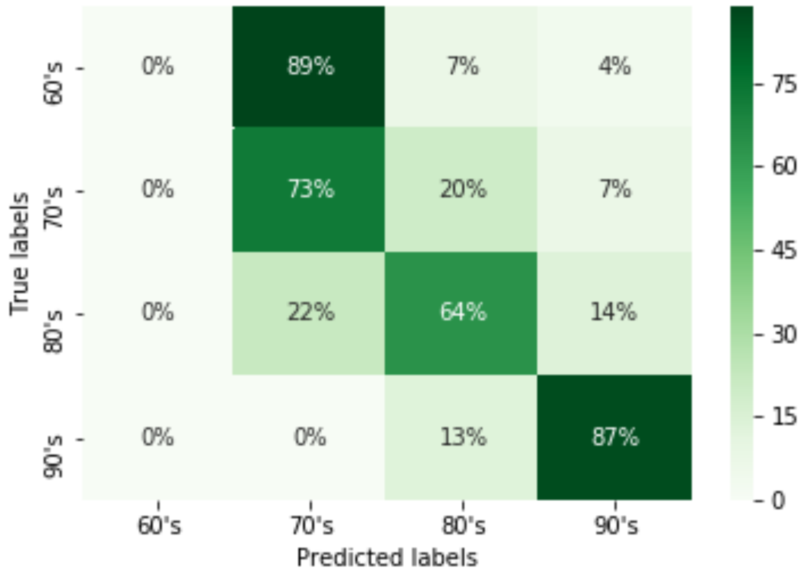

Figure 5.8 : Confusion Matrix for MLP

5.2.7 Ensemble Vote Classifier

Ensemble vote classifier is created by using the previous six classifier algorithms used in this study. The two best resulting algorithms SVM and RF are weighted as 2 while the others weighted as 1. This weighting configuration is chosen since it produce better results than giving equal weights for all six algorithms. EVC resulted with the highest scores for all dimension spaces as it can be seen on Table 5.2. The overall prediction accuracy is increased with a remarkable amount. Confusion matrix in Figure 5.9 shows the distribution among actual labels and predicted labels by EVC. With an acceptable confusion for predicting the excerpts of 60's, Ensemble Vote Classifier shows the best accuracy scores among the other classifiers since it is a decision mechanism that consisting of the previous individually used classifiers. It can be said that the ensemble vote approach brings together the distinctive prediction strengths of different classifiers on different eras.

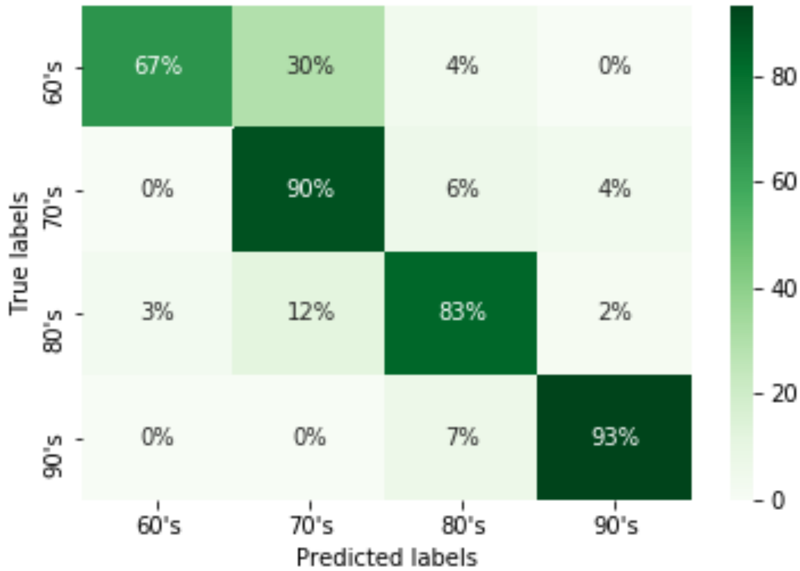

Figure 5.9 : Confusion Matrix for EVC

5.3 Testing the Best Resulting Classifiers on Extended Dataset

For further testing purpose, the initial dataset is extended with various artists, which are contemporaries of Barış Manço and can be defined with the umbrella term Anatolian Rock. Total count of excerpts are raised to 3113.

The three highest scoring classifiers, which are EVC, RF and SVM respectively, are trained and tested on this extended dataset. Table 5.3 shows the accuracy scores both on Barış Manço dataset and the extended dataset for comparison. It is observed that these three classifiers increased their accuracy scores on the extended dataset. In the following subsections, confusion matrices are reported for the three classifiers, which are produced on 39-dimensional feature space as an arbitrary selection.

Table 5.3 : Comparison of Success Rates for Best 3 Classifiers on Both Datasets

	404 Features	**72 Features**	**39 Features**	**25 Features**
SVM on Barış Manço Dataset	84.01%	84.88%	85.17%	83.13%
SVM on Extended Dataset	84.43%	88.44%	85.71%	85.07%
RF on Barış Manço Dataset	84.3%	84.59%	84.59%	82.55%
RF on Extended Dataset	85.71%	84.91%	85.07%	83.94%
EVC on Barış Manço Dataset	88.37%	87.79%	86.33%	86.04%
EVC on Extended Dataset	89.24%	89.88%	87.96%	86.67%

5.3.1 Support Vector Machines on Extended Dataset

Figure 5.10 shows the distribution among actual labels and predicted labels by SVM classifier on extended dataset. While it produced its best score on 72 features, 39 and 25 features also resulted better than 404 features. While the overall prediction accuracy of the SVM is raised on the extended dataset, it showed different tendencies when the results are breakdown to different eras.

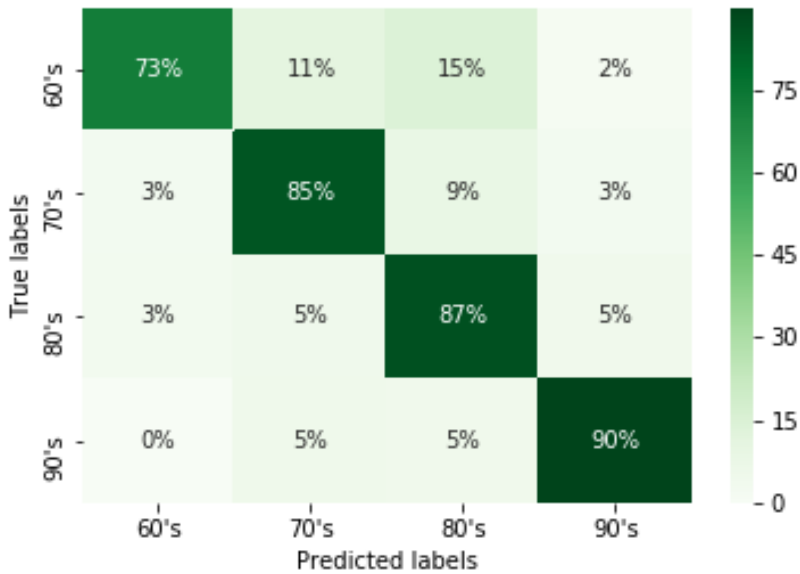

Figure 5.10 : Confusion Matrix for SVM on Extended Dataset

5.3.2 Random Forests on Extended Dataset

Confusion matrix in Figure 5.11 shows the distribution among actual labels and predicted labels by RF classifier on extended dataset. Accuracy scores on diverse dimension spaces differ in small percentages. Prediction accuraccy is raised remarkably for 60's while it has a slight decrease for 70's.

5.3.3 Ensemble Vote Classifier on Extended Dataset

As a combination of prediction powers of all 6 classifiers, EVC again resulted with the highest scores for all dimension spaces of extended dataset. While its best score is on 72 features, it resulted with lesser success rate on 39 and 25 features than the 404. Confusion matrix in Figure 5.9 shows the distribution among actual labels and predicted labels by EVC on extended dataset. It is also observed that EVC has 0

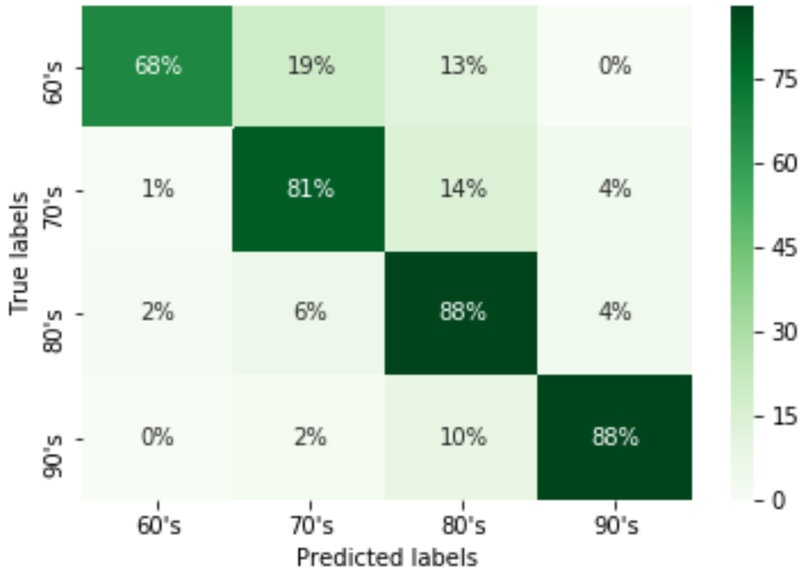

Figure 5.11 : Confusion Matrix for RF on Extended Dataset

confusion for the excerpts that belongs to 1990's with 1960's and 1970's. EVC shows very high prediction accuracy which is balanced over different eras.

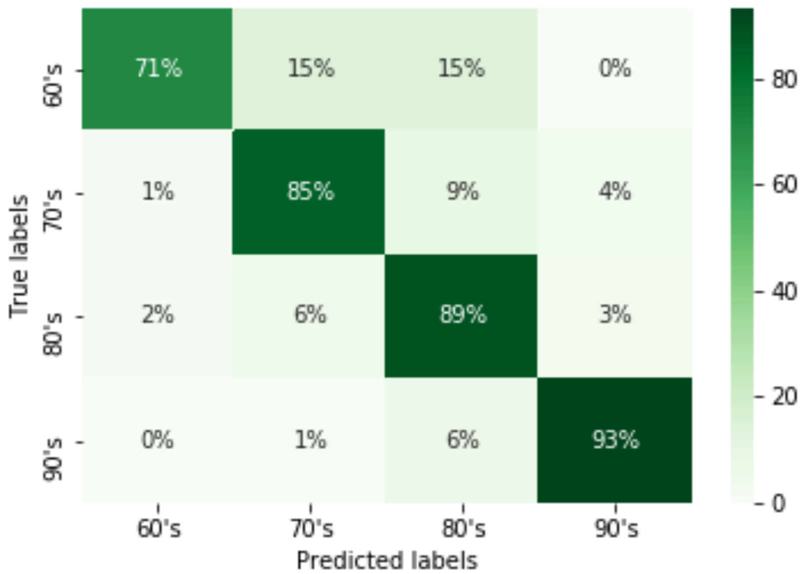

Figure 5.12 : Confusion Matrix for EVC on Extended Dataset

6. CONCLUSION

The aim of this thesis study is to implement an audio classification approach on musical production period by using low-level audio features. As an initial step, audio features from 224 Barış Manço music pieces are extracted via Essentia library. Each piece is divided in 30 second long frames. Among the 404 low-level features extracted from 1720 excerpts, a Barış Manço dataset is created by labeling each piece with its production year. Recursive feature elimination is applied to the feature space iteratively for trying to reduce the total number of features used while keeping the classification accuracy similar. Six generally used classification algorithms are applied on this dataset. An ensemble voting classifier is created to increase the prediction accuracies by combining the decision powers of these six classifiers.

Among these six individual classifier models that are trained and tested on Barış Manço dataset, Random Forest and SVM algorithms resulted with the highest accuracies respectively. As a combination of all algorithms used in this study, Ensemble Vote Classifier resulted with the highest scores among all. It is also observed that the increase of accuracy by using ensemble voting approach is remarkable.

Applying the recursive feature elimination process on Barış Manço dataset, similar prediction accuracies obtained for 404, 72, 39 and 25-dimensional feature spaces. Most important 25 features are sorted by their importance and listed on section 5.1.3.

For a wider training and test purpose, an extension dataset is created out of 190 music pieces from Barış Manço's contemporaries who can be considered under the umbrella term Anatolian Rock. Similar framing, feature extraction, labelling and dataset creation procedures applied with Barış Manço dataset to these music pieces. New dataset of 1393 excerpts and 404-dimensional feature space is combined with the Barış Manço's excerpts to extend the initial dataset. Selected features by applying recursive feature elimination on Barış Manço dataset also tested with the new extended dataset.

Best three resulting classifier algorithms, EVC, RF and SVM, are trained and tested on the extended dataset. It is observed that the accuracy of the predictions are similar or even higher since the data count increased.

Even though the feature selection process is done only on Barış Manço dataset, with 25 features selected by their importance classifier models also resulted with similar prediction scores on extended dataset. It shows the resulting descriptors of feature selection process have a general applicability for audio classification over musical production eras.

It is also observed on the confusion matrices that are discussed on Chapter 5.2 and Chapter 5.3, predictions can be confused on the distinction between neighbor decades. Since the effects of the technological improvements on changing production approach are not that sharp, tendencies could be similar between preceeding or subsequent decades.

6.1 Practical Application of This Study

Gathered information from the thesis will practically lead us to observe the quality and the characteristics of Anatolian Rock Music of Turkey due to the production decades. Resulting classifier models can be used for defining the unknown production date for a given audio excerpt belonging to Anatolian Rock genre.

This classification approach may extend the perspective of musicological studies in terms of music production capabilities. Considering the affection of technological improvements over music production, thus the music itself, I think the informatical output of such evaluation will hold a musicological importance. As well as the Anatolian Rock, other musical production styles of other genres may also be evaluated via this approach, to have a better understanding of the genre itself. Results of this study can also be evaluated under other interdisciplinary studies of music such as psychoacoustics or music cognition.

Resulting classifier models can be used to build a quality check software for the musicians, sound engineers and music producers to evaluate the quality of their creative output in means of a desired production period or different production aesthetics. Additional breakdowns for audio recommendation engines can be implemented via considering the so called sound of a specific artist, band or an era. Other then the music production perspective, different classification approaches on different audio features, like tonal or rhythmical descriptors, can be applied on further ethnomusicological studies.

6.2 Further Work

The approach of classification over production period can be applied to other artists from other countries as well as Turkey, to have an international evaluation and comparison on the music production technology and quality over the last decades.

At the conceptual stage of the study, resources were considered as direct digital conversion from cassette, vinyl or compact disc to reflect the consummation standards of each related era. However, because of resource limitations, actually used media files were consisting of .mp3 files with various bit depth qualities found over internet. As a further study, a collection from resources such as cassettes, vinyls or compact discs is planned to be created to have the same approach could be applied for a more detailed comparison.

Having a relatively small dataset for training the classifiers was another limitation for this study. Also the machine learning algorithms were chosen with the consideration of working on small datasets consisting less than 10000 data samples. The trained classifiers were also tested on different styles of musics from various other artists who are not considered in the scope of this study. It is observed that these classifiers could not perform the same prediction accuracies for any given musical recording. To overcome this generalization problem, classifiers are trained and tested again in a wider dataset and better results had been achieved with a wider dataset containing more variant musical artists with different musical aesthetics. As a further study, better prediction accuracies for a wider musical scope can be achieved via training deep learning models with a dataset which is not limited only to Turkish Anatolian Rock but from a global and genre independent audio collection.

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APPENDICES

Appendix A. List of Pieces from Barış Manço

Album | Piece | Year

- 1962-1963 | Lets Twist Again | 1962
- 1962-1963 | The Jet | 1962
- 1962-1963 | Do the Twist | 1962
- 1962-1963 | Twistin USA | 1962
- 1962-1963 | Cit Cit Twist | 1963
- 1962-1963 | Dream Girl | 1963
- 1962-1963 | Kizilciklar Oldu Mu | 196-
- 1962-1963 | Urfanin Etrafi Dumanli Daglar | 196-
- 2023 | 2023 | 1975
- 2023 | Acih'da Baga Vir! | 1975
- 2023 | Baykoca Destani | 1975
- 2023 | Kayalarin Oglu | 1975
- 2023 | Kol Basti | 1975
- 2023 | Tavuklara Kisst De | 1975
- 2023 | Uzun Ince Bir Yoldayim | 1975
- 2023 | Yine Yol Gorundu Gurbete | 1975
- 2023 | Yolverin Agalar Beyler | 1975
- Baris Mancho | Blue Morning Angel | 1976
- Baris Mancho | Dragon Fly | 1976
- Baris Mancho | Emerald Garden | 1976
- Baris Mancho | Lady of the Seventh Sky | 1976
- Baris Mancho | Little Darlin' | 1976
- Baris Mancho | Lonely Man | 1976
- Baris Mancho | Lucy Road | 1976
- Baris Mancho | Nick the Chopper | 1976
- Baris Mancho | Old Paulin' | 1976
- Baris Mancho | Ride on Miranda | 1976

- Baris Mancho | Tell Me Old Man | 1976
- Yeni Bir Gun | 2024 | 1979
- Yeni Bir Gun | Anliyorsun Degil Mi | 1979
- Yeni Bir Gun | Aynali Kemer Ince Bele | 1979
- Yeni Bir Gun | Bir Kelebegin Yasam Oykusu | 1979
- Yeni Bir Gun | Bir Selam Sana Gonul Daglarindan | 1979
- Yeni Bir Gun | Coban Yildizi | 1979
- Yeni Bir Gun | Elveda Olum | 1979
- Yeni Bir Gun | Gesi Baglari | 1979
- Yeni Bir Gun | Ham Meyvayi Kopardilar Dalindan | 1979
- Yeni Bir Gun | Ikinci Yolculuk | 1979
- Yeni Bir Gun | Ne Koy Olur Benden Ne Kasaba | 1979
- Yeni Bir Gun | Ne Ola Yar Ola | 1979
- Yeni Bir Gun | Sari Cizmeli Mehmet Aga | 1979
- Yeni Bir Gun | Yeni Bir Gun Dogdu Merhaba | 1979
- 20. Sanat Yili Disco Manco | Anliyorsun Degil Mi | 1980
- 20. Sanat Yili Disco Manco | Ben Bilirim (Disko) | 1980
- 20. Sanat Yili Disco Manco | Daglar Daglar (Disko) | 1980
- 20. Sanat Yili Disco Manco | Dragon Fly (Disko) | 1980
- 20. Sanat Yili Disco Manco | Egri Bugru | 1980
- 20. Sanat Yili Disco Manco | Elveda Olum | 1980
- 20. Sanat Yili Disco Manco | Gamzedeyim (Disko) | 1980
- 20. Sanat Yili Disco Manco | Huseyni Selam | 1980
- 20. Sanat Yili Disco Manco | Iste Hendek Iste Deve (Disko) | 1980
- 20. Sanat Yili Disco Manco | Katip Arzuhalim (Disko) | 1980
- 20. Sanat Yili Disco Manco | Kervan Taksim | 1980
- 20. Sanat Yili Disco Manco | Kolbasti (Disko) | 1980
- 20. Sanat Yili Disco Manco | Nazar Eyle (Disko v1) | 1980
- 20. Sanat Yili Disco Manco | Nazar Eyle (Disko v2) | 1980

- 20. Sanat Yili Disco Manco | Ne Koy Olur Benden Ne Kasaba | 1980
- 20. Sanat Yili Disco Manco | Ne Ola Yar Ola | 1980
- 20. Sanat Yili Disco Manco | Nick The Chopper (Disko) | 1980
- 20. Sanat Yili Disco Manco | Taksim | 1980
- 20. Sanat Yili Disco Manco | Yemen Turkusu | 1980
- 20. Sanat Yili Disco Manco | Yeni Bir Gun | 1980
- Sozum Meclisten Disari | 2025 (Ucuncu Yolculuk) | 1981
- Sozum Meclisten Disari | Ademoglu Kizgin Firin Havva Kizi Mercimek | 1981
- Sozum Meclisten Disari | Ali Yazar Veli Bozar | 1981
- Sozum Meclisten Disari | Alla Beni Pulla Beni | 1981
- Sozum Meclisten Disari | Arkadasim Essek | 1981
- Sozum Meclisten Disari | Bahcede Hanimeli | 1981
- Sozum Meclisten Disari | Cacik | 1981
- Sozum Meclisten Disari | Ce Sera Le Temps | 1981
- Sozum Meclisten Disari | Donence | 1981
- Sozum Meclisten Disari | Gulpembe | 1981
- Sozum Meclisten Disari | Hal Hal | 1981
- Sozum Meclisten Disari | Hamburger | 1981
- Sozum Meclisten Disari | Sehrazat | 1981
- Estagfurullah... Ne Haddimize! | Aman Yavas Aheste | 1983
- Estagfurullah... Ne Haddimize! | Bal Sultan | 1983
- Estagfurullah... Ne Haddimize! | Cit Cit Cetene | 1983
- Estagfurullah... Ne Haddimize! | Eski Bir Fincan | 1983
- Estagfurullah... Ne Haddimize! | Gecti Dost Kervani | 1983
- Estagfurullah... Ne Haddimize! | Halil Ibrahim Sofrasi | 1983
- Estagfurullah... Ne Haddimize! | Kazma | 1983
- Estagfurullah... Ne Haddimize! | Kol Dugmeleri | 1983
- Estagfurullah... Ne Haddimize! | Ninni Bebek | 1983
- Estagfurullah... Ne Haddimize! | Selahaddin Eyyubi'nin Yegeni Aslan Yurekli Risar'ın Kiz Kardesine Karsi | 1983

- 24 Ayar | Abbas Yolcu | 1985
- 24 Ayar | Bugun Bayram | 1985
- 24 Ayar | Dort Kapi | 1985
- 24 Ayar | Dut Agaci | 1985
- 24 Ayar | Gibi Gibi | 1985
- 24 Ayar | La Casba Della Mamma Tulipano | 1985
- 24 Ayar | Lahburger | 1985
- 24 Ayar | Mahkum | 1985
- 24 Ayar | Old Pavlin | 1985
- 24 Ayar | Soyle Zalim Sultan | 1985
- 24 Ayar | You And I | 1985
- Degmesin Yagli Boya | Al Beni | 1986
- Degmesin Yagli Boya | Duriye | 1986
- Degmesin Yagli Boya | Iste Hendek Iste Deve | 1986
- Degmesin Yagli Boya | Nerede | 1986
- Degmesin Yagli Boya | Olmaya Devlet Cihanda | 1986
- Degmesin Yagli Boya | Osman | 1986
- Degmesin Yagli Boya | S.O.S. Aman Hocam | 1986
- Degmesin Yagli Boya | Super Babaanne | 1986
- Degmesin Yagli Boya | Unutamadim | 1986
- Ful Aksesuar'88 Manco Sahibinden Ihtiyactan | Affet Beni | 1988
- Ful Aksesuar'88 Manco Sahibinden Ihtiyactan | Ahmet Bey'in Ceketi | 1988
- Ful Aksesuar'88 Manco Sahibinden Ihtiyactan | Anahtar | 1988
- Ful Aksesuar'88 Manco Sahibinden Ihtiyactan | Gonul Ferman Dinlemiyor | 1988
- Ful Aksesuar'88 Manco Sahibinden Ihtiyactan | Kalpler Beraber | 1988
- Ful Aksesuar'88 Manco Sahibinden Ihtiyactan | Nane Limon Kabugu | 1988
- Ful Aksesuar'88 Manco Sahibinden Ihtiyactan | Omrumun Sonbaharinda | 1988
- Ful Aksesuar'88 Manco Sahibinden Ihtiyactan | Sahilde | 1988
- Ful Aksesuar'88 Manco Sahibinden Ihtiyactan | Sakiz Hanim ile Mahur Bey | 1988

- Ful Aksesuar’88 Manco Sahibinden Ihtiyactan | Zehra | 1988
- Darisi Basiniza | 7’den 77’ye Delikanli Gibi | 1989
- Darisi Basiniza | Can Bedenden Cikmayinca | 1989
- Darisi Basiniza | Domates Biber Patlican | 1989
- Darisi Basiniza | Gule Gule Oglum | 1989
- Darisi Basiniza | Gunaydin Cocuklar | 1989
- Darisi Basiniza | Hatirlasana | 1989
- Darisi Basiniza | Hayir | 1989
- Darisi Basiniza | Kara Sevda | 1989
- Darisi Basiniza | Kezban | 1989
- Mega Manco | Allah’im Guc Ver Bana | 1992
- Mega Manco | Ayi | 1992
- Mega Manco | Ayrilik | 1992
- Mega Manco | Diral Dede’nin Dudugu | 1992
- Mega Manco | Gel | 1992
- Mega Manco | Hemserim Memleket Nire | 1992
- Mega Manco | Suleyman | 1992
- Mega Manco | Tut-i Mucize Guyem | 1992
- Mega Manco | Yine Bir Gul Nihal | 1992
- Musaadenizle Cocuklar | Al Beni | 1995
- Musaadenizle Cocuklar | Bal Bocegi | 1995
- Musaadenizle Cocuklar | Benden Ote Benden Ziyade | 1995
- Musaadenizle Cocuklar | Beyhude Gecti Yillar | 1995
- Musaadenizle Cocuklar | En Buyuk Mehmet Bizim Mehmet | 1995
- Musaadenizle Cocuklar | Gul Bebegim | 1995
- Musaadenizle Cocuklar | Musaadenizle Cocuklar | 1995
- Musaadenizle Cocuklar | Saril Bana | 1995
- Musaadenizle Cocuklar | Yol | 1995
- Musaadenizle Cocuklar | Yolla Yarim Tez Yolla | 1995

- Live in Japan | Daglar Daglar | 1996
- Live in Japan | Domates Biber Patlican | 1996
- Live in Japan | Donence | 1996
- Live in Japan | Gulpembe | 1996
- Live in Japan | Hemserim Memleket Nire | 1996
- Live in Japan | Kara Sevda | 1996
- Live in Japan | Nane Limon Kabugu | 1996
- Live in Japan | Toki No Tabibito | 1996
- Live in Japan | Unutamadim | 1996
- Live in Japan | Yine Yol Gorundu Gurbete | 1996
- Mancoloji | 40 Yil | 1999
- Mancoloji | Alla Beni Pulla Beni | 1999
- Mancoloji | Anliyorsun Degil Mi | 1999
- Mancoloji | Aynali Kemer | 1999
- Mancoloji | Ben Bilirim | 1999
- Mancoloji | Beyhude Gecti Yillar | 1999
- Mancoloji | Can Bedenden cikmayinca | 1999
- Mancoloji | Daglar Daglar | 1999
- Mancoloji | Domates Biber Patlican | 1999
- Mancoloji | Donence | 1999
- Mancoloji | Gibi Gibi | 1999
- Mancoloji | Gul Bebegim | 1999
- Mancoloji | Gulpembe | 1999
- Mancoloji | Hal hal | 1999
- Mancoloji | Halil Ibrahim Sofrasi | 1999
- Mancoloji | Iste Hendek Iste Deve | 1999
- Mancoloji | Kara Sevda | 1999
- Mancoloji | Kol Dugmeleri | 1999
- Mancoloji | Nazar Eyle | 1999

- Mancoloji | Nick the Chopper | 1999
- Mancoloji | Sakiz Hanim ile Mahur Bey | 1999
- Mancoloji | Sari Cizmeli Mehmet Aga | 1999
- Mancoloji | Unutamadim | 1999
- Mancoloji | Yolla Yarim | 1999
- Ben Bilirim | Ben Bilirim | 1975
- Ben Bilirim | Bir Bahar Aksami | 1974
- Ben Bilirim | Burasi Mustur | 197-
- Ben Bilirim | Ce Sera le Temps v1 | 1981
- Ben Bilirim | Dere Boyu Kavaklar | 1975
- Ben Bilirim | Estergon Kalesi | 1974
- Ben Bilirim | Gamzedeyim Deva Bulmam | 1972
- Ben Bilirim | Gonul Dagı | 1973
- Ben Bilirim | Gulme Ha Gulme | 1975
- Ben Bilirim | Hey Koca Topcu | 1973
- Ben Bilirim | Kalk Gidelim Kuheylan | 1973
- Ben Bilirim | Lambaya Puf De | 1973
- Ben Bilirim | Nazar Eyle Nazar Eyle | 1974
- Ben Bilirim | Olum Allahin Emri | 1972
- Daglar Daglar | Aglama Degmez Hayat | 1969
- Daglar Daglar | Anadolu | 1969
- Daglar Daglar | Ay Osman | 1971
- Daglar Daglar | Bin Boganin Kizi | 1971
- Daglar Daglar | Daglar Daglar | 1970
- Daglar Daglar | Derule | 1970
- Daglar Daglar | Iste Hendek Iste Deve | 1971
- Daglar Daglar | Kagizman | 1969
- Daglar Daglar | Katip Arzuhalim | 1971
- Daglar Daglar | Kirpiklerin Ok Eyle | 1969

- Daglar Daglar | Kol Dugmeleri | 1967
- Daglar Daglar | Seher Vakti | 1967
- Daglar Daglar | Unutamiyorum | 1969
- Dunden Bugune | Aglama Degmez Hayat | 1969
- Dunden Bugune | Anadolu | 1969
- Dunden Bugune | Daglar Daglar I | 1970
- Dunden Bugune | Derule | 1970
- Dunden Bugune | Iste Hendek Iste Deve | 1971
- Dunden Bugune | Kagizman | 1969
- Dunden Bugune | Katip Arzuhalim Yaz Yare Boyle | 1971
- Dunden Bugune | Kirpiklerin Ok Ok Eyle | 1969
- Dunden Bugune | Kol Dugmeleri | 1967
- Dunden Bugune | Kucuk Bir Gece Muzigi | 1970
- Dunden Bugune | Lory | 1966
- Dunden Bugune | Seher Vakti | 1967
- Sakla Samani Gelir Zamani | Ben Bilirim | 1975
- Sakla Samani Gelir Zamani | Gonul Dagi | 1973
- Sakla Samani Gelir Zamani | Hey Koca Topcu | 1973
- Sakla Samani Gelir Zamani | Kalk Gidelim Kuheylan | 1973
- Sakla Samani Gelir Zamani | Lambaya Puf De | 1973
- Sakla Samani Gelir Zamani | Nazar Eyle | 1974
- Sakla Samani Gelir Zamani | Olum Allahin Emri | 1972
- Sakla Samani Gelir Zamani | Rezil dede | 1976

Appendix B. List of Pieces from Contemporaries of Barış Manço

Artists or Band | Album | Piece | Year

- Asia Minor | - | Mahzun Gozler | 1979
- Cahit Oben | - | 36 24 36 | 1965
- Cahit Oben | - | Ala Gozlerini Sevdigim Dilber | 1973
- Cahit Oben | - | Her Gun Kavga | 1966
- Cahit Oben | - | Hereke | 1965
- Cahit Oben | - | Karakoyun | 1973
- Cahit Oben | - | Makaram Sari Baglar | 1965
- Cahit Oben | - | Ozlenen Sevgi | 1975
- Cahit Oben | - | Sey | 1966
- Cem Karaca, Apaslar Kardaslar | - | Dadaloglu | 1970
- Cem Karaca, Apaslar Kardaslar | - | Demedim Mi | 1971
- Cem Karaca, Apaslar Kardaslar | - | Felek Beni | 1969
- Cem Karaca, Apaslar Kardaslar | - | Kara Sevda | 1971
- Cem Karaca, Apaslar Kardaslar | - | Kara Yilan | 1971
- Cem Karaca, Apaslar Kardaslar | - | Lumune | 1971
- Cem Karaca, Apaslar Kardaslar | - | Niksar | 1969
- Cem Karaca, Apaslar Kardaslar | - | Tatli Dillim | 1971
- Cem Karaca, Apaslar Kardaslar | - | Zeyno | 1969
- Cem Karaca | Bekle Beni | Bekle Beni | 1982
- Cem Karaca | Bekle Beni | Delikanli Sevdasi | 1982
- Cem Karaca | Bekle Beni | Nem Alacak Felek Benim | 1982
- Cem Karaca | Bekle Beni | Ogluma | 1982
- Cem Karaca | Bekle Beni | Peynir Gemisi | 1982
- Cem Karaca | Bekle Beni | Sakin Reddetme | 1982
- Cem Karaca | Bindik Bir Alamete | Allah Yar | 1999
- Cem Karaca | Bindik Bir Alamete | Bindik Bir Alamete | 1999
- Cem Karaca | Bindik Bir Alamete | Deser De Gecer | 1999

- Cem Karaca | Bindik Bir Alamete | Hudey Hudey | 1999
- Cem Karaca | Bindik Bir Alamete | Kerkuk Zindani | 1999
- Cem Karaca | Bindik Bir Alamete | Obur Dunya | 1999
- Cem Karaca | Bindik Bir Alamete | Olum | 1999
- Cem Karaca | Bindik Bir Alamete | Sakin Donme | 1999
- Cem Karaca | Bindik Bir Alamete | Yolumuz Gurbete Dustu | 1999
- Cem Karaca | Merhaba Gencler | Bedava Yasiyoruz | 1987
- Cem Karaca | Merhaba Gencler | Bidanem | 1987
- Cem Karaca | Merhaba Gencler | Canim Benim | 1987
- Cem Karaca | Merhaba Gencler | Carki Felek | 1987
- Cem Karaca | Merhaba Gencler | Ceviz Agaci | 1987
- Cem Karaca | Merhaba Gencler | Iste Geldik Gidiyoruz | 1987
- Cem Karaca | Merhaba Gencler | Peynir Gemisi | 1987
- Cem Karaca | Merhaba Gencler | Yarim Porsiyon Aydinlik | 1987
- Cem Karaca | Nerde Kalmistik | Islak Islak | 1992
- Cem Karaca | Nerde Kalmistik | Raptiye Rap Rap | 1992
- Cem Karaca | Nerde Kalmistik | Sen Duymadin | 1992
- Cem Karaca | Nerde Kalmistik | Sende Basini Alip Gitme | 1992
- Cem Karaca | Nerde Kalmistik | Suskunluk | 1992
- Cem Karaca | Tore | Aksam Erken Iner Mapushaneye | 1988
- Cem Karaca | Tore | Dur Be Yeter | 1988
- Cem Karaca | Tore | Money Money | 1988
- Cem Karaca | Tore | Ogluma | 1988
- Cem Karaca | Tore | Resimdeki Gozyaslari | 1988
- Cem Karaca ve Apaslar | Anadolu Oyun Havasi | 1965
- Cem Karaca ve Apaslar | Hudey | 1967
- Cem Karaca ve Apaslar ve Kardaslar | Bu Son Olsun | 1969
- Cem Karaca ve Dervisan | Maden Ocagının Dibinde | 1977
- Cem Karaca ve Dervisan | Tamirci Ciragi | 1975

- Erkin Koray | - | Allah Askina | 1977
- Erkin Koray | - | Anma Arkadas | 1967
- Erkin Koray | - | Bir Eylul Aksamı | 1966
- Erkin Koray | Devlerin Nefesi | 13 Ve Ben | 1999
- Erkin Koray | Devlerin Nefesi | Ask Oyunu | 1999
- Erkin Koray | Devlerin Nefesi | Copculer | 1999
- Erkin Koray | Devlerin Nefesi | Krallar | 1999
- Erkin Koray | Devlerin Nefesi | Memurum Ben | 1999
- Erkin Koray | Devlerin Nefesi | Mesk Oyunu | 1999
- Erkin Koray | Devlerin Nefesi | Sen Yoksun Diye | 1999
- Erkin Koray | Devlerin Nefesi | Seni Her Gordugumde | 1999
- Erkin Koray | Elektronik Turkuler | Cemalim | 1974
- Erkin Koray | Elektronik Turkuler | Hele Yar | 1974
- Erkin Koray | Elektronik Turkuler | Inat | 1974
- Erkin Koray | Elektronik Turkuler | Karli Daglar | 1974
- Erkin Koray | Elektronik Turkuler | Korkulu Ruya | 1974
- Erkin Koray | Elektronik Turkuler | Sir | 1974
- Erkin Koray | Elektronik Turkuler | Turku | 1974
- Erkin Koray | Elektronik Turkuler | Yalnizlar Rihtimi | 1974
- Erkin Koray | Gaddar | Anladin Mi | 1986
- Erkin Koray | Gaddar | Cemilem | 1986
- Erkin Koray | Gaddar | Doktor | 1986
- Erkin Koray | Gaddar | Gaddar | 1986
- Erkin Koray | Gaddar | Kavak | 1986
- Erkin Koray | Gaddar | Kervan Yurur | 1986
- Erkin Koray | Gaddar | Raziyim | 1986
- Erkin Koray | Gaddar | Tamam Artik | 1986
- Erkin Koray | Gaddar | Topik | 1986
- Erkin Koray | Gaddar | Zalim Gaddar | 1986

- Erkin Koray | Gun Ola | Akrabin Gozleri | 1996
- Erkin Koray | Gun Ola | Gokteki Yildizlar | 1996
- Erkin Koray | Gun Ola | Gun Ola Harman Ola | 1996
- Erkin Koray | Gun Ola | Melek Misin | 1996
- Erkin Koray | Gun Ola | Mezarlik Gunleri | 1996
- Erkin Koray | Gun Ola | Ofke | 1996
- Erkin Koray | Gun Ola | Sakin Gitme | 1996
- Erkin Koray | Hay Yam Yam | Cemile Kiz | 1989
- Erkin Koray | Hay Yam Yam | Haftanin Yedi Gunu | 1989
- Erkin Koray | Hay Yam Yam | Ham Yam Yam | 1989
- Erkin Koray | Hay Yam Yam | Hayat Katari | 1989
- Erkin Koray | Hay Yam Yam | Konusuluyorduk | 1989
- Erkin Koray | Hay Yam Yam | Sen Bana Sabir Ver | 1989
- Erkin Koray | Hay Yam Yam | Soyle Boyle | 1989
- Erkin Koray | Hay Yam Yam | Yok Yok | 1989
- Erkin Koray | Hay Yam Yam | Yolcu Yolunda Gerek | 1989
- Erkin Koray | - | Kizlari Da Alin Askere | 1967
- Erkin Koray | - | Krallar | 1974
- Erkin Koray | - | Mechul | 1968
- Erkin Koray | - | Mesafeler | 1973
- Erkin Koray | - | Sana Birseyler Olmus | 1969
- Erkin Koray | - | Sandalci | 1977
- Erkin Koray | - | Seni Her Gordugumde | 1969
- Erkin Koray Dortlusu | - | Cicek Dagi | 1965
- Fikret Kızılok | - | Leylim Leylim | 1972
- Haramiler | - | Aya Bak Yildiza Bak | 1968
- Haramiler | - | Camlica Yolunda | 1965
- Ilhan Irem | Bezgin | Cokuntu | 1981
- Ilhan Irem | Bezgin | Olmus Icimde Hasret | 1981

- Ilhan Irem | Bezgin | Saclarim Sarmasiklar | 1981
- Ilhan Irem | Bezgin | Yemyesil Bir Deniz Gozlerin | 1981
- Ilhan Irem | Bezgin | Yolgecen Hani | 1981
- Ilhan Irem | Bezgin | Yorgun Argin | 1981
- Ilhan Irem | Hayat Opucugu | Ali Veli Maria | 1998
- Ilhan Irem | Hayat Opucugu | Bak Su Aynaya | 1998
- Ilhan Irem | Hayat Opucugu | Gezgin | 1998
- Ilhan Irem | Hayat Opucugu | Iste Hayat | 1998
- Ilhan Irem | Hayat Opucugu | Terazi | 1998
- Ilhan Irem | Kopru | Birak Kalsin Oylece | 1985
- Ilhan Irem | Kopru | Birseyin Bitisi | 1985
- Ilhan Irem | Kopru | Donuk Yolculuk | 1985
- Ilhan Irem | Kopru | Goruntuler | 1985
- Ilhan Irem | Kopru | Kovalamaca | 1985
- Ilhan Irem | Kopru | Kucuk Hesaplar | 1985
- Ilhan Irem | Kopru | Serpintiler | 1985
- Ilhan Irem | Romans | Gul Kokulu Ceviz Sandigi | 1994
- Ilhan Irem | Romans | Ninni Sevgilim | 1994
- Ilhan Irem | Romans | Sampiyon | 1994
- Ilhan Irem | Romans | Surgun Gibi | 1994
- Kardaslar | - | Deniz Ustu Kopurur | 1973
- Kaygısızlar | - | Sasirdim | 1969
- Kaygısızlar | - | Son Gece | 1969
- Kontlar | - | Arpa Bugday Taneler | 1965
- Korkut Koray | - | Yalnızlar Rıhtımı | 1969
- L.S.D. Orkestrası | - | Donmeyen Sevgili | 1967
- L.S.D. Orkestrası | - | Neye Geldim Dunyaya | 1967
- MFO | Ele Gune Karsi | Bu Sabah Yagmur Var Istanbulda | 1984
- MFO | Ele Gune Karsi | Deli Deli | 1984

- MFO | Ele Gune Karsi | Ele Gune Karsi | 1984
- MFO | Ele Gune Karsi | Gullerin Icinden | 1984
- MFO | Ele Gune Karsi | Yalnizlik Omur Boyu | 1984
- MFO | Geldiler | Alaturka | 1990
- MFO | Geldiler | Ali Desidero | 1990
- MFO | Geldiler | Atesi Aska | 1990
- MFO | Geldiler | Mecburen | 1990
- MFO | Geldiler | Sude | 1990
- MFO | MVAB | Aglamadan | 1995
- MFO | MVAB | Bilmem Nedendir | 1995
- MFO | MVAB | Leylayim | 1995
- MFO | MVAB | Manzeretim Var Asabiyim Ben | 1995
- MFO | MVAB | Para Gelince Aska | 1995
- MFO | MVAB | Sakin Gelme | 1995
- MFO | Peki Peki | Diday Diday Day| 1985
- MFO | Peki Peki | New York Sokaklarinda | 1985
- MFO | Peki Peki | Peki Peki Anladik | 1985
- MFO | Turkuz | Adımız Miskindir Bizim | 1973
- MFO | Turkuz | Gullerin Icinden | 1974
- MFO | Turkuz | Hekimoglu | 1974
- MFO | Turkuz | Mevsimler | 1974
- MFO | Turkuz | Nerde Hani | 1973
- MFO | Turkuz | Seviyorum Seni Canim | 1974
- MFO | Turkuz | Sur Efem Atını | 1973
- MFO | Turkuz | Turkuz Turku Cagiririz | 1974
- MFO | Turkuz | Upside Down | 1974
- MFO | Vak The Rock | Adimiz Miskindir Bizim | 1986
- MFO | Vak The Rock | Hep Ayni | 1986
- MFO | Vak The Rock | Vak The Rock| 1986

- Mavi Cocuklar | - | Tamzara | 1965
- Mogollar | - | 78 98 | 1975
- Mogollar | - | Alageyik Destanı | 1972
- Mogollar | - | Sessiz Gemi | 1969
- Nejat Yavasogullari | Yalniz Kalma | 1975
- Ozdemir Erdogan | - | Ac Kapiyi Gir Iceri | 1974
- Ozdemir Erdogan | - | Gurbet | 1972
- Selda Bagcan | - | Ince Ince Bir Kar Yagar | 1976
- Selda Bagcan | - | Yaz Gazeteci Yaz | 1975
- Siluetler | - | Kasik Havasi | 1965
- Siluetler | - | Lorke Lorke | 1966
- Siluetler | - | Sis | 1965
- Stephan Umutyan | - | Bekleyis | 1965
- TPAO Batman Orkestrası | - | Seker Alalım | 1968
- Tulay German | - | Burcak Tarlası | 1964
- Tunay Akdeniz ve Grup Cıgrısım | - | Salak | 1975
- Yabancılar | - | Agıt | 1967
- Zafer Dilek | - | Yekte | 1976

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