ISTANBUL TECHNICAL UNIVERSITY
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A Music Recommendation System Based On Personality

Graduation Project

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Statement of Authenticity

I hereby declare that in this study

1. all the content influenced from external references are cited clearly and in detail,
2. and all the remaining sections, especially the theoretical studies and implemented software/hardware that constitute the fundamental essence of this study is originated by my individual authenticity.

İstanbul, June 2019

Orçun Özdemir

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A Music Recommendation System Based On Personality

(SUMMARY)

Data plays an important role in the advancement of humanity year to year. There are lots of data streams that continue to accumulate over the internet. In some aspects, having a large amount of data in digital world seems an advantage for users, but data has to be processed and filtered to get beneficial results from it. However, the amount of data that is not categorized collected on the internet is increasing rapidly.

Hence, as a result of increasing total size of data in digital world, users and consumers cannot find and use their desired requests in variety of fields easily. To overcome this problem, information filtering systems which filter unwanted and unnecessary data for some specific users are working on many areas in the internet. Overload of the data can be reduced with the help of filtering systems.

In addition, recommendation systems are great subsets of information filtering mechanisms. Recommendation systems provide relevant data to users and customers by filtering most of the data that are calculated and seem as redundant for a specific person.

This project is aimed to create a music recommendation system based on psychological personality. Correlation between big five personality traits in psychology and musical genre tastes are used to provide relevant songs for users. In the proposed system, users are able to give these five values manually or they can answer 44 questions to leave big five personality traits calculations to the application side. After that generated genre interest matrix for the user will be matched to most similar songs with the help of k nearest neighbors (KNN) algorithm and predicted normalized genre values by deep learning musical genre classifier model which uses audio features of songs that were fetched from Spotify API.

Furthermore, three different feedback mechanisms were implemented in this project related to song dissatisfaction, song genre suggestion, and general genre suggestions. With the help of song dissatisfaction feedback, we are able to validate model by analyzing satisfaction/dissatisfaction rate of our recommendations, also general genre suggestions help to collect data to create a model to bypass references papers and build a custom layer for recommended songs according to big five personality traits. Moreover, song genre suggestion helps to improve and correct predicted genre of song when there is any inconsistency occurred in genre classifier model predictions. So, the general system is able to improve, feed, and evaluate itself continuously when monitoring and utilizing feedback system.

Although, there is no exact and precise boundaries in musical genre classification, classifier deep learning model of this project achieved to understand some crucial differences between songs, and converged them to mostly accurate genres. With the help of data preprocessing, personality to genre interest values mapping, and k nearest

neighbors algorithm, this recommender system was able to recommend relevant songs for the user amongst nearly 600 thousands of songs in database.

Kişilik Temelli Müzik Öneri Sistemi

(ÖZET)

Veri insanlığın gelişiminde yıldan yıla daha da artan önemli bir rol oynamaktadır. İnternet üzerinde dolaşımda olan çok fazla veri akışı kaynağı bulunmaktadır. Dijital dünyada çok fazla verinin toplanması ve birikmesi bazı açılardan kullanıcılar için faydalı gibi gözükse de toplanmış olan verilerden faydalı sonuçlar üretilebilmesi için bunların işlenmesi ve filtrelenmesi gerekmektedir. Fakat internetteki kategorilenmemiş veri sayısındaki artış giderek yükselmektedir.

Bu nedenle, dijital dünyadaki toplam veri boyutunun artmasının bir sonucu olarak, kullanıcılar ve tüketiciler ihtiyaçlarını çeşitli alanlarda kolayca bulamıyor ve bunlardan yararlanamıyorlar. Bu sorunun üstesinden gelebilmek için, bazı spesifik kullanıcılar için istenmeyen ve gereksiz verileri filtreleyen bilgi filtreleme sistemleri internetteki birçok alanda çalışmaktadır. Verilerin gereksiz şekilde kullanıcıların önüne çıkması, filtreleme sistemlerinin yardımıyla azaltılabilir.

Ek olarak, öneri sistemleri bilgi filtreleme mekanizmalarının büyük alt gruplarıdır. Öneri sistemleri, belirli bir kişi için gereksiz olarak hesaplanan verilerin çoğunu filtreleyerek kullanıcılara ve müşterilere alakalı veriler sağlar. Bu sistemler genellikle üç kategoriye ayrılır: işbirlikçi filtreleme, içerik tabanlı filtreleme ve hibrit sistemler. Bu proje için çalışma yaklaşımı hem içerik tabanlı hem de işbirlikçi filtrelemeyi kullanır, bu nedenle ikisi birlikte kullanıldığı için hibrit bir sistemin kullanıcılar için öneriler oluşturmak için kullanıldığı söylenebilir.

Bu proje psikolojik kişiliğe dayalı bir müzik öneri sistemi oluşturmayı amaçlamaktadır. Psikolojideki beş büyük kişilik özelliği ile müzik türü zevkleri arasındaki korelasyon, kullanıcılara alakalı şarkılar sağlamak için kullanılmaktadır. Kullanıcılar bu beş değeri manuel olarak verebilirler ya da sisteme büyük beş kişilik özellik değeri hesaplamasını bırakmak için 44 soruyu cevaplayabilirler. Bundan sonra, kullanıcının bulduğu türün içsel matrisi, en yakın komşular kullanılarak en benzer şarkılarla eşleştirilecek ve Spotify API'den getirilen şarkıların ses özelliklerini kullanan derin öğrenen müzik türü sınıflandırma modeliyle normalize edilmiş tür değerleri tahmin edilecektir.

Ayrıca, bu projeye üç farklı geri bildirim mekanizması implemente edilmiştir bunlar: şarkı memnuniyetsizliği, şarkı türü önerisi ve genel tür önerileridir. Şarkı memnuniyetsizliği geri bildiriminin yardımıyla, önerilerimizin memnuniyetini/memnuniyetsizlik oranını analiz ederek modeli doğrulayabiliriz, ayrıca genel tür önerilerini sağlamak için baz alınan akademik çalışmaları atlamak için bir model oluşturmaya, veri toplamaya ve şarkılara göre şarkı önermek için özel bir katman oluşturmaya yardımcı olur büyük beş kişilik özellikleri. Ayrıca, şarkı türü önerisi, tür sınıflandırma model tahminlerinde herhangi bir tutarsızlık olması durumunda, öngörülen şarkı türünün iyileştirilmesine ve düzeltilmesine yardımcı olur. Böylece, genel sistem, geribildirim sistemini izlerken ve kullanırken sürekli kendini geliştirebilir, besleyebilir ve değerlendirebilir.

Her ne kadar, müzik türü sınıflandırmalarında kesin ve keskin bir sınır olmasa da,

bu projenin müzikal tür sınıflandırıcı derin öğrenme modeli, şarkılar arasındaki bazı önemli farklılıkları anlamaya başlamış ve bunları çoğunlukla doğru türler olarak tahmin edebilmiştir. Veri ön işleme, ilgi alanı değer değerlerinin haritalanmasına yönelik kişilik ve en yakın komşu algoritması k nearest neighbors ile bu öneri sistemi, kullanıcı için veritabanındaki yaklaşık 600 bin şarkı arasından ilgili şarkıları önerebildi.

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1 Introduction and Project Summary

In today's world, many companies use recommendation systems to increase their revenue, customer experience and user experience by filtering lots of redundant data in the internet. Chute et al. published a paper which pointed out that total data size of digital universe is at 2.25 x 1021bits (281 exabytesor 281 billion gigabytes) which is bigger than predictions of researches. Generally, the growth in data comes as a result of advancement in replications of data. Moreover, in 2008, it is estimated that by 2011, total digital data size will be 10 times the total size of data. [2]. In digital services world, there are lots of different alternatives for every company and service, hence this leads companies to serve only the most relevant contents to satisfy their users. For example, YouTube shows suggested videos section to their users when watching a video continuously. These suggested videos are selected by using customer's activity, liked, disliked, and watched videos according to customer which interacts with the platform. So, In 2010, Zhou et al. shows that suggested videos section is one the most significant source for the majority of videos. Some investigations in how video views are driven by the recommendation system, a powerful correlation between the view count of a video and the average view count of its top referrer videos is found [3]. Moreover, other major companies like Amazon, Netflix, and Spotify use recommendation systems as a subset of information filtering systems to provide high-quality user experience. To exemplify, Spotify shows users *Made For You* library which has lots of different playlist created after analyzing users' listening characteristics combined with trend musics.

This project aimed to create a music recommendation system for music streaming field of the digital industry using personalities and the results from a research by Schwartz and Foutz pointed that personality profiles are directly derived from the essential findings and their connections with main music preferences [4]. However, there are lots of models and psychological inventories to identify personalities of people. One of the significant model is named big five personality. Big five personality has five main labels to classify individuals' behaviors and characteristics. Goldberg states that big five personalities traditionally labeled as follow: extraversion (surgency), agreeableness, conscientiousness (dependability), emotional stability (neuroticism), and openness (culture) [5].

Ali explains big five personality trait labels as listed below:
Extraversion: Which individuals engage with the outer world and experience ardor and other positive affections.
Agreeableness: Which individuals value cooperation and social harmony, honesty, decency, and trustworthiness. Agreeable individuals also tend to have an sanguine sight of human nature.
Conscientiousness: Which individuals esteem planning, have the quality of perseverance, and are accomplishment-oriented.
Neuroticism: Which individuals experience negative affections and their propensity to emotionally overreact.
Openness to Experience: Which individuals exhibit intellectual interest, self-awareness, and individualism/non-conformance. [6].

Chamorro et al. points out that the big factor model is necessary to provide an extensive view of an individual's behavioral tendencies, including their coherent affective and cognitive designs. With these theoretical advances in mind, recent studies have begun the missions of scientifically investigating the **Big Five Personality** framework in relation to music uses and preferences [7].

Moreover, another research by Rentfrow et al. indicates that for example, a person which is tend to new experiences may like to listen styles of music that reinforce his or her view of being artistic and sophisticated [8]. Additionally, people may search for particular styles of music to compose their emotional states; for instance, depressed people may prefer genres of music that maintain their melancholic mood. While the numerous psychological and social processes influencing individuals' music preferences are precisely complicated, it is acceptable to suppose that examining the ties between basic personality traits and music preferences could explain on why people listen to music.

Pearson et al. pointed out that numerous number of studies show that extraversion personality type heavily influenced music preferences. Hence, researchers have showed relationships between music preference and personality using some tools like the Eysenck Personality Questionnaire and neuroticism extraversion openness personality inventory [9].

Therefore, a lot of academic studies assert that there is a correlation between psychological personalities and musical preferences. These studies have been conducted using different personality inventories and classifications. In this project, we used big five personality framework and its inventory to develop a recommendation system, because there is a research done by Ferwerda et al. which calculated Spearman's correlation values between music genres and personality traits over age groups, and analyzed 1415 users with their music listening histories [1].

Furthermore, this project also offers a good solution for cold start problem in music recommendation systems using academic researches that give correlation values between musical genres and personalities and a deep learning model which classifies songs by genres using their important musical features given by Spotify's application programming interface (API). Also, the proposed application collects user feedback to retrain itself and give more accurate results and to satisfy more users by filtering redundant songs. User's genre correlation matrix is calculated after he/she gives it manually or gives answers of 44 personality identifier questions, then this genre correlation matrix search its nearest neighbors on song genre prediction table using k nearest neighbors algorithm. Figure 1.1 depicts the Gantt chart of scheduled and carried out project tasks.

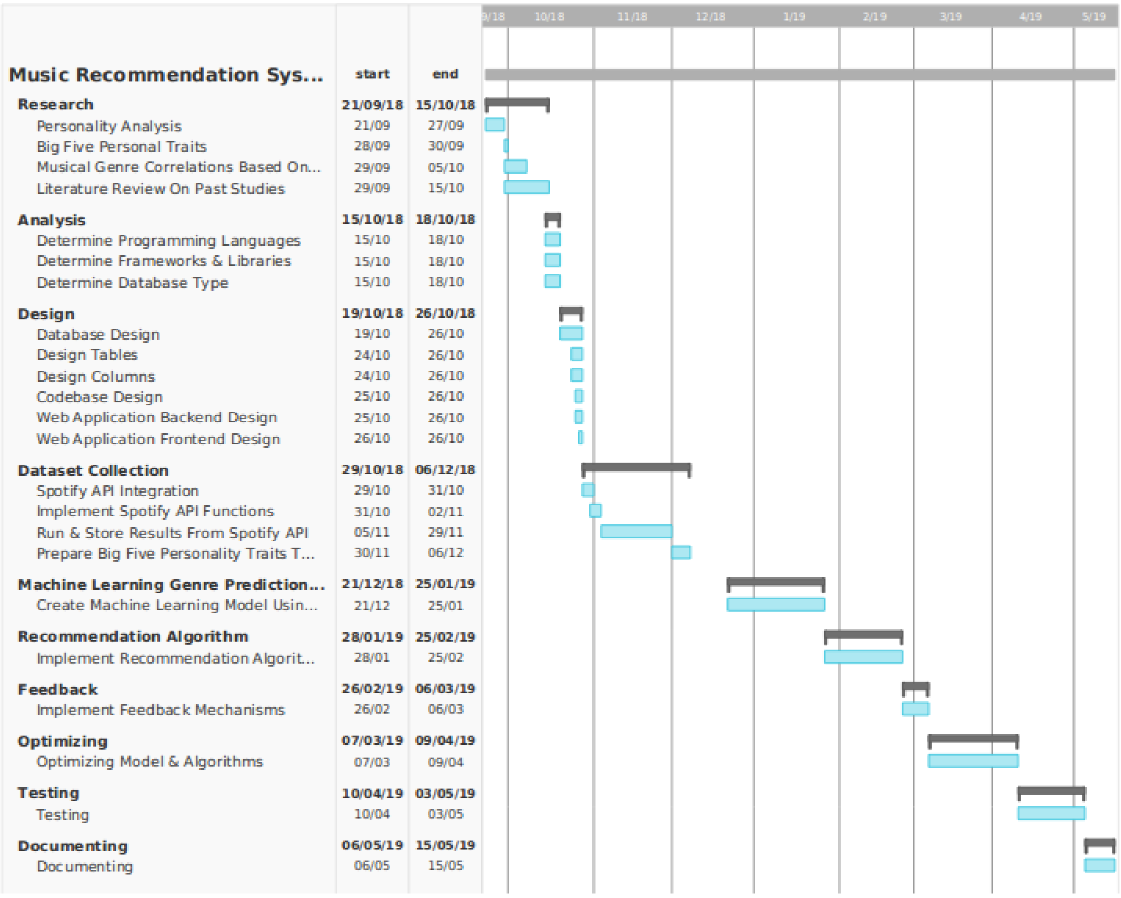

Figure 1.1: Gantt chart of project schedule

2 Existing Work

2.1 Background on Personality Research

There are various indicators to calculate individual's personality scores. This thesis carried out using a big five inventory quiz, which contains 44 different questions which has a scoring system; every answer has 1 to 5 points that indicates "disagree strongly", "disagree a little", "neither agree nor disagree", "agree a little", "agree strongly" respectively. After creating scale scores by averaging item scores, big five personality values can be computed [10, 11]. Users can select advanced mode to answer big five personality inventory questions and get recommended songs from the system, or there is a quick mode option for users who know his/her big five personality values and want to give them manually.

Table 2.1: Big five personality scoring chart [10, 11]

Extraversion	Agreeableness	Conscientiousness	Neuroticism	Openness
1	2R	3	4	5
6R	7	8R	9R	10
11	12E	13	14	15
16	17	18R	19	20
21R	22	23R	24R	25
26	27R	28	29	30
31R	32	33	34R	35R
36	37R	38	39	40
	42	27R		41R
				44

Mapping between question numbers as a positive or reverse (negative) keys to big five personalities can be seen in Table 2.1. R indicates reverse-score items which can be calculated substracting by 6, and the others have value as same as user answer between 1 to 5 [10, 11].

After computing big five personality values, the most crucial part of the system is calculating musical genre interest according to personalities and age groups. Regarding to a academic paper which suggested a solution for cold start problem in music recommendation systems used myPersonality.org dataset and combined them with Last.fm user listening histories, demonstrated genre correlation values according to big five personalities and age groups [1]. This research has helped for mapping 5 personalities and 3 age groups over 18 musical genres. Musical genre interest correlation values regarding to age group and personality can be shown in Figure 2.1.

	Openness			Conscientiousness			Extraversion			Agreeableness			Neuroticism		
	12-19	20-39	40-65	12-19	20-39	40-65	12-19	20-39	40-65	12-19	20-39	40-65	12-19	20-39	40-65
R&B	-.019	-.004	-.053	-.026	-.009	.150	**.106**	.065	**.326**	-.049	.047	.326	.027	-.001	-.175
Rap	-.019	-.011	-.205	-.085	-.065	.059	.030	**.108**	.052	-.070	.062	.052	.003	-.072	-.158
Electronic	.046	**.106**	-.138	-.043	-.031	.152	.015	.038	-.246	-.090	-.050	-.246	.036	-.023	.133
Rock	-.075	**-.104**	.095	-.058	.016	-.124	-.085	**-.102**	-.182	.070	-.031	-.182	.014	.053	.182
New Age	**.142**	**.105**	.133	.037	-.053	.006	-.022	**-.184**	-.209	.008	.011	-.209	-.062	-.064	-.143
Classical	.080	.038	.266	.028	-.060	.261	**-.136**	**-.146**	-.136	-.070	-.010	-.136	-.015	-.005	-.080
Reggae	-.015	.046	.185	**-.102**	-.059	-.059	.039	.025	.046	-.032	.051	.046	.028	-.042	-.138
Blues	**.130**	**.167**	**.358**	-.048	-.046	.321	.060	.032	.252	-.006	.018	.252	-.054	-.005	**-.552**
Country	**.117**	**.126**	.325	-.067	-.073	.154	.005	.005	.128	.062	**.184**	.128	.049	-.027	-.109
World	**.114**	**.217**	.201	-.016	-.009	.217	**-.102**	-.054	.028	-.056	-.025	.028	.061	-.014	-.236
Folk	**.230**	**.231**	**.368**	-.014	**-.114**	-.268	.066	-.040	.181	**.101**	**.110**	.181	-.064	.004	-.217
Easy Listening	.084	.060	-.161	.020	.024	.256	.041	-.019	.212	-.073	.041	.212	.035	-.012	.006
Jazz	**.139**	**.106**	-.124	-.047	-.025	**.510**	.005	-.010	.062	-.053	-.068	.062	-.039	.004	-.106
Vocal (a cappella)	**.132**	**.170**	.282	.059	-.007	.125	.038	-.013	.136	-.074	-.001	.136	-.014	.002	-.091
Punk	-.032	-.008	.089	**-.130**	**-.103**	.081	**-.111**	-.029	-.074	.005	.006	-.074	**.101**	.049	.220
Alternative	**.131**	**.116**	.154	**-.108**	**-.165**	**.507**	-.010	-.052	-.027	.018	.029	-.027	**.129**	**.137**	.070
Pop	.021	.000	-.157	.045	.005	.052	.064	.017	.287	-.017	**.194**	.287	.040	-.010	-.275
Heavy Metal	-.033	-.044	-.117	-.005	-.012	.038	**-.148**	**-.126**	**-.339**	-.058	**-.105**	**-.339**	-.030	-.030	**.372**

Figure 2.1: Correlation between music genres and personality traits over age groups [1]

2.2 Previous Studies

There is also a research which combines musical genre classification and personality diagnosis. It uses both content-based and collaborative filtering techniques and creates a mobile middleware as a push service for mobile music recommendation systems. In their research, Lampropoulos et al. applied genre classification for each song using support vector machine (SVM) algorithm, and they expected music files from user [12]. This project achieves 0.7557 mean accuracy over 10 folds cross-validation analysis for genre classification process, yet they included only 4 main genres which are blues, classical, country, and disco. In contrary, in this thesis, there are 18 different genres. Moreover, in our project's genre classifier phase, users do not have to send their favorite music files, besides not a support vector machine but a deep learning model using 12 main song feature values fetched from Spotify's application programming interface as classes is used. Moreover, Lampropoulos et al. do not diagnose personalities with big five personality model, they consider and get the active user's known ratings of music items to assume different personality types and apply collaborative filtering methods. Sending music files to push service is a time consuming process for users [12].

Another research conducted by Cheng et al. using music tags for classifying songs suffered from synonymy and polysemy problems [13]. There is not an exact musical genre taxonomy study in data science this leads to myriad numbers of different genres and sub-genres which have lots of similarities. For example, alternative rock covers thousands of different genres, but there are lots of names such as art rock, avant-garde rock, singer-songwriter music that are another branches of alternative rock, but represented as different musical tags. Cheng and Tang heavily used MPEG layer 3 (MP3) as music format rather than popular musical instrument digital interface (MIDI) corpora used for similar researches. They focused on three main groups in musics which are timbre texture, rhythmic and pitch, also considered musical acoustic features such as centroid, flux, mel frequency cepstral coefficients (MFCC), pitch, rolloff, rhythm and used support vector machine (SVM) algorithm as a classifier method [13]. Similar music recommendation projects differ from this thesis according to dataset diversities, because our proposed recommendation system uses 588.787 songs and their precalculated feature values from Spotify API, but other projects use short data sets to analyze. For example, this project's dataset only has 120 pieces of music to be worked on which could cause errors classifying rare musical items.

A research carried out by Shan et al., assumed that music components which influence the emotional state enclose melody, rhythm, tempo, mode, key, harmony, dynamics and tone-color [14]. Within these music components, melody, mode, tempo and rhythm have robust influences on individual's emotions. Mostly, major scale is brighter, happier than minor; rapid tempo is more exciting or more stretched than slow tempo. They used these musical elements to extract musical features in their research. Also, in this thesis, deep learning genre classifier model contains valence, key, mode, tempo, energy features as labels which are similar to emotionally dominant musical elements selected in Shan's research.

In addition, previous study by Paudel et al. focused on personality based music recommendation system similar in this thesis in a way that they also selected to use big five personalities (five factor model) as a personality identifier and used myPersonality.org dataset to create recommendation system's model [15]. On the other hand, Paudel's recommender system needs Facebook profiles to find user's big five personality traits while fetching status updates and creates a feature vector will be the input of Naive Bayes classifier and logistic regression. Their system applies machine learning application to calculate big five personality traits, yet in our proposed project, a multilayer perceptron-based deep neural network is used only to classify genre of songs not finding personalities.

3 Design and Implementation of the System

This chapter gives information about the models of the project's system in various aspects such as database entity relationship (E-R) diagram, behavioral model, activity diagram, algorithms' structures, and workflows. It contains general approaches, presentations, user diagrams, and numerous mock-ups of the recommendation system from backend, frontend, and database sides of the project.

3.1 General Overview of the System

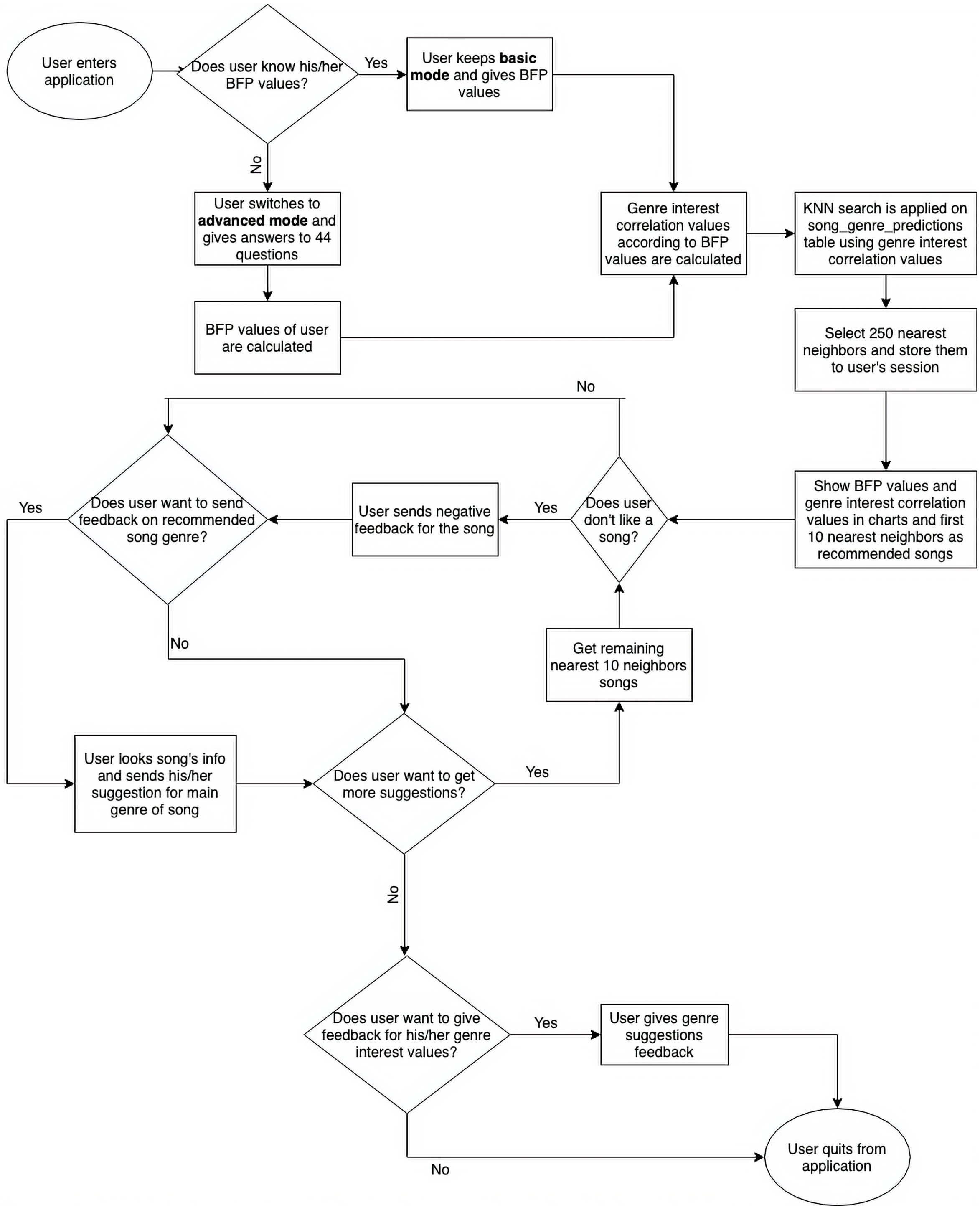

Figure 3.1: General user flow diagram of the application

In Figure 3.1, all user scenarios from beginning of the application to the end of the application are presented on user flow diagram. Figure 3.2 shows an example of big five personality matrices to genre interest correlation matrices conversions with KNN to get recommended songs.

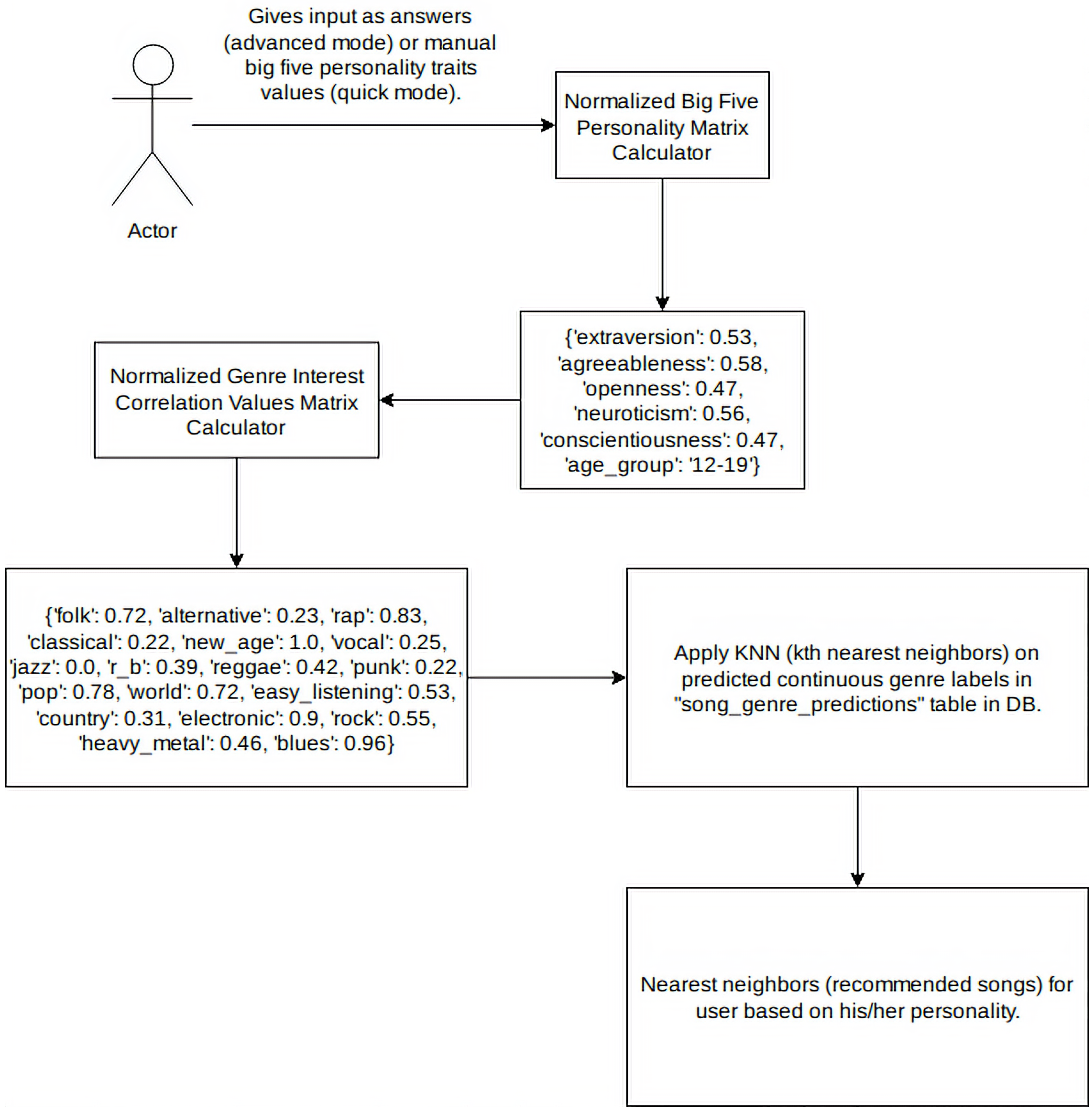

Figure 3.2: Example of big five personality matrix to interest correlation matrix conversion

3.2 Data Model of the System

Chen states that database E-R diagram contains some semantic information about the real world and it is a special visualization technique for database design tasks [16]. Entity relationship diagrams can be used as a basis for unification of different views of data: the network model, the relational model, and the entity set model. The entity-relationship model applies a more natural view that the real world contains entities and relationships.

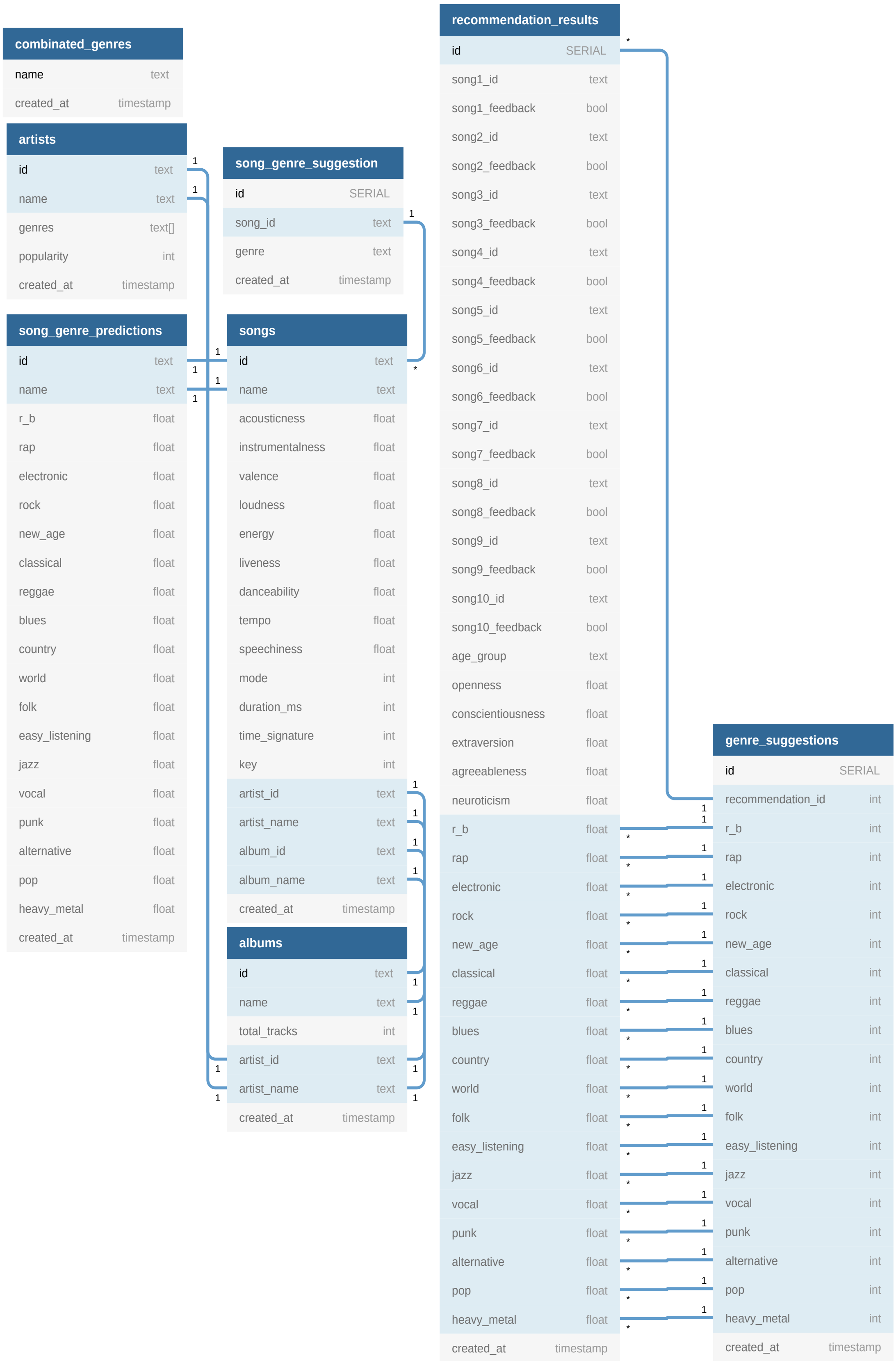

Figure 3.3: Database entity relationship diagram of the system

As shown in Figure 3.3, there are 8 tables in this project's database. Artists table contains artist information such as **Spotify artist identification (ID)**, **artist name**, **artist genres**, and **popularity**. All information has taken from Spotify's application programming interface (API). Artist popularity used to filter some artists which have low popularity in database seeding phase of the project. Artist ID is used as a primary key, because Spotify API gives unique ID for each artist. Albums table contains **album identification (ID)**, **album name**, **total tracks**, **artist ID**, and **artist name** columns. One of the most significant table in this project's database design is **songs** table, because it contains 12 crucial song features which are used in genre classifier neural network features in deep learning stage. These important features are precalculated by Spotify artificial intelligence team, and served via representational state transfer (REST) API.

These 12 main features are listed in Table 3.1.

Table 3.1: Audio features that are used as features in genre classifier model

acousticness
instrumentalness
valence
loudness
energy
liveness
danceability
tempo
speechiness
mode
time_signature
key

Key, *mode*, and *time_signature* features are integer values, and the others give a floating point number value between 0.0 and 1.0 except loudness. *Loudness* has values between 0.0 and -60.0. Key indicates the estimated overall key of the track. Integers map to pitches using standard pitch class notation. For example, 0 = C, 1 = C#/Db, 2 = D. Mode shows modality of track, 1 indicates track has major mode, but 0 indicates that minor mode is dominant. Time signatures specifies how many beats per each bar. High frequencies give low *acousticness* value. *Danceability* looks for musical components such as tempo, rhythm stability, beat strength, and overall regularity. *Energy* is another floating number value which analyses fast, loud, and noisy elements in audio. *Instrumentalness* looks for spoken words. For example, songs by Sebastian Bach or Mozart give high *instrumantalness* values because they are mostly classical music without a vocal sound, but rap/hiphop songs give low *instrumantalness* value due to high vocality in songs. *Liveness* is determined by seeking for presence of an audience in the recording. Loudness is the quality of a sound that is the primary psychological correlate of physical strength (amplitude). *Speechiness* detects the presence of spoken words in a track. For example, audio books, podcasts, poetries etc. *Valence* shows emotional positiveness in a track. For instance, nice, cheerful, happy songs have high valence value; however, depressing and angry songs have low valence value. *Tempo* indicates Beat Per Minute (BPM) value [17].

Moreover, 18 different main genres of artists are used as song descriptors for deep learning models. Every user is able to send genre suggestions according to his/her interests scoring each genre between 1 to 5. Hence, system is able to collect all suggestions with personality values, then in the future, system will retrain itself to converge and recommend more accurate songs to users.

They can be shown in **recommendation_results** and **genre_suggestions** as shown in Table 3.2.

r_b
rap
electronic
reggae
alternative
rock
new_age
classical
blues
country
world
folk
easy_listening
jazz
vocal
punk
heavy_metal

Table 3.2: Musical genres that are used as classes in genre classifier model

Another important table is *recommended_songs* which contains 10 songs and user's normalized genre correlation values with big five personality traits that are openness, extraversion, agreeableness, conscientiousness, and neuroticism. After, a recommendation request for a user is created, recommendation row is inserted into this table. A user can get more suggestions using a dedicated button, then other recommendations will be loaded from session of the user, and feedback fields of each song will be given as **true** by default. When a user clicks **dissatisfied** button which is placed below for each song, feedback field will be updated as **false** which points that user sent negative feedback for the underlying song.

Furthermore, **song_genre_predictions** table is used for storing data which come from the prediction function of musical genre classifier deep learning model for each song in the database, if the user wants to see predicted genre values he/she can select info button that is placed below each song, and he/she can use form to send genre suggestion for mispredicted main genre of any song. To exemplify, when a user see that a song from Justin Bieber highly predicted as heavy metal genre, user can select pop and send feedback to help system to collect and analyze user feedbacks in the future.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1	genres	song_id	song_name	acousticness	instrume	valence	loudness	energy	liveness	danceabilit	tempo	speechines	mode	duration_ms	time_signatu	key
2	['classic soundtrack', 'theme']	3fXDycJkTxN	En Garde, Bent	833	459	112	-14028	195	337	317	178861	0.0374	1	124373	4	5
3	['canadian hardcore', 'canadiar	6IvpTBRFV0v	Led By Hand - H	0.0459	0.0435	0.07	-6469	932	375	224	89759	0.0948	1	236707	4	7
4	['edm', 'progressive house', 'pr	549eOcszWcJ	A State Of Tran	0.0999	0.0	891	-8449	734	261	608	129523	404	0	31290	4	6
5	['edm', 'progressive house', 'pr	38WEB4yynG	Looking Back T	0.00129	0.94	0.0379	-8726	882	387	509	130.0	0.0435	1	211284	4	7
6	['deep melodic euro house', 'ge	3QfVrqbJH1N	Freakin' - Robert	0.00101	0.0262	928	-7207	756	0.0759	752	125008	0.0696	1	431938	4	6
7	['glam rock', 'rock']	6HFIzqXPJrx4	Bohemian Rhap	881	0.00713	107	-9713	719	802	283	141251	0.0562	1	62040	4	3
8	['denpa-kei']	5wEn2SYsIbZ	呼べよ嵐	0.0126	0.0	567	-2854	982	419	536	96507	114	1	201680	4	9
9	['progressive house', 'progress	13MGIswQYY	If It All Stops -	9.48e-05	143	347	-6045	911	177	516	123943	37	1	263280	4	5
10	['album rock', 'glam metal', 'ha	4Ao8NIbAGZY	Light It Up	0.000941	146	176	-6148	915	69	362	132958	0.0944	0	370120	4	4
11	['disco house', 'progressive ho	1DOh7g0S7T4	A Love That's H	0.00674	0.38	199	-4404	0.82	0.0744	704	124995	32	0	227370	4	5
12	['big room', 'edm', 'progressive	5oad3aS3i6Pg	Soldier	0.0389	0.000482	0.0498	-6464	687	589	572	128027	0.0647	1	203434	4	4
13	['canadian hardcore', 'canadiar	57v2p66uLbyT	Dose Your Drea	0.0162	566	433	-7126	878	202	563	107011	0.0427	0	329747	4	11
14	['album rock', 'glam metal', 'ha	13D9RXm49yv	Praise You	0.0168	0.00508	382	-6.64	0.73	354	361	153373	0.0397	1	274293	4	1
15	['classical piano', 'hollywood', '	1KI7iv27YON9	Pièces froides: -	981	881	128	-29198	0.0516	73	206	81368	0.0464	0	67427	4	9
16	['german techno', 'minimal tec	0QcqnnzypeL	Paniklevel	0.0155	892	483	-10796	533	107	0.85	125004	0.15	1	520320	4	9
17	['scorecore', 'soundtrack']	4zWfuLWtYfH	Mouserinks	659	876	0.0577	-23415	0.0907	82	243	107923	0.0384	0	252747	4	7

Figure 3.4: Sample labeled CSV file to be used for deep learning model's input

3.3 Abstract Model of the System

In this section, deep learning model's structure and some important workflows of the project are represented. As presented in Figure 3.4, from database seed using Spotify API to create predictions, calculating user's personality values, genre interest correlation matrix, and searching the most similar matrices over **song_genre_predictions** table with k nearest neighbors algorithm to recommend songs, there are lots of layers and modules in the project.

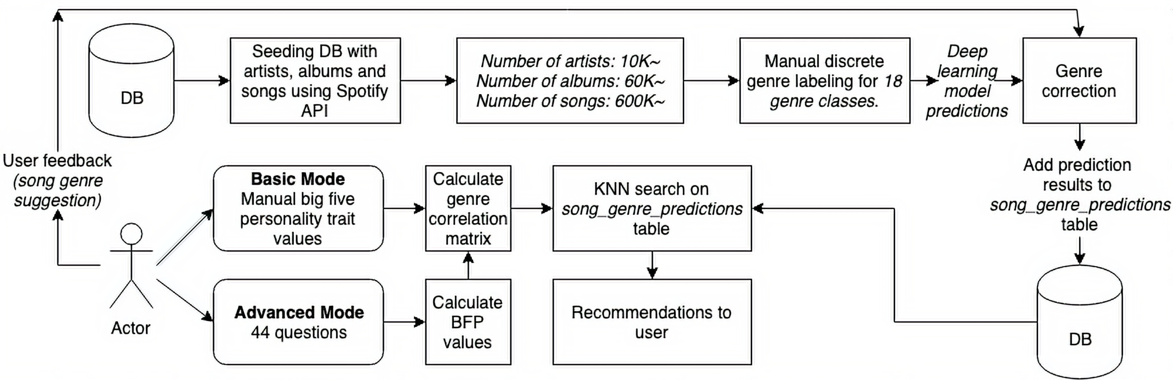

Figure 3.5: General workflow structure of the project

After seeding database using Spotify API's gathering artist, album, and song functions, a CSV file was created to use as a dataset for deep neural network input. Spotify API gives multiple artist genres for some popular artists, nevertheless, it does not give album or song genres. Thus, in this project, we selected to use artist genres as a label of every song of the artist. As mentioned in Section 3.2, 12 significant audio features that were served via Spotify API's audio features function are used as data for each genre label. In Figure 3.5, there is an example labeled CSV file which was read by Pandas library, after some preprocessing stages this file can be used for genre classification model as an input. Figure 3.6 shows this background processes briefly.

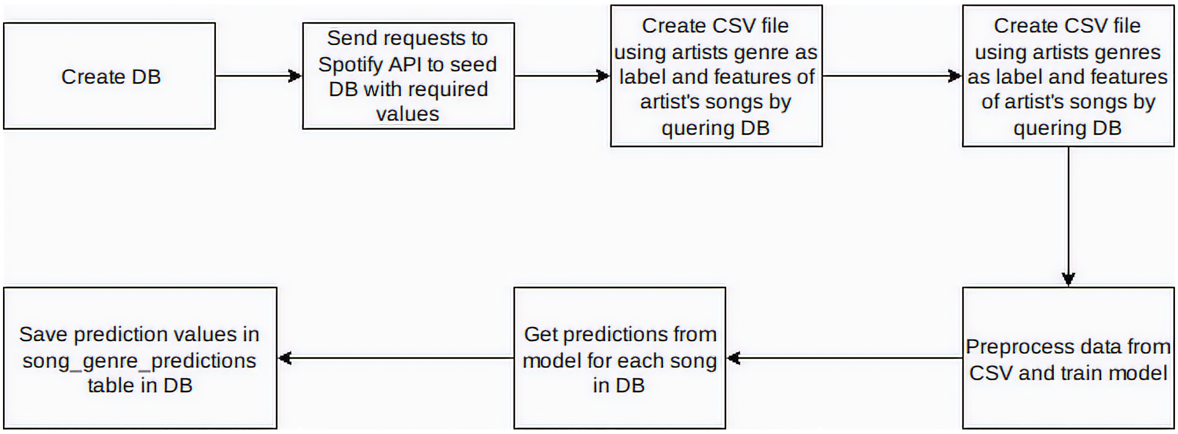

Figure 3.6: Background processes from creating DB to storing predicted genre values on DB

At preprocessing stage, thousands of different sub-genres grabbed from Spotify API mapped to 18 main genres which are r & b, rap, electronic, alternative, punk, heavy metal, pop, blues, world, folk, reggae, easy listening, vocal, new age, classical, rock, country and encoded by one hot encoder to transform a single variable with n observations and d distinct values, to d binary variables with n observations each. Each observation indicates the presence (1) or absence (0) of the dichotomous binary variable [18]. In Table 3.3, mapping dictionary of genres and, in Table 3.4 output of one hot encoding can be seen.

Sub-genre	**Main Genre**
pop, teen	*pop*
r&b	*r&b*
hardstyle, house, tech, edm, electro, disco, trance, hi-nrg, wave, deep, dance	*electronic*
hollywood, soundtrack, downtempo, harmony, comedy, game music, movie, monastic	*easy_listening*
metal, grunge, glam, brutal	*heavy_metal*
garage, rock, indie, singer-songwriter, lo-fi, alternative rock, emo, surf, art	*rock*
jazz	*jazz*
blues, funk, soul	*blues*
country, texas, outlaw, gospel	*country*
rap, hip hop	*rap*
singing, vocal, choral, choir, opera	*vocal*
folk, choro, bolero, tango, traditional, flamenko, mambo	*folk*
world, christian, mexican, latin, tropical	*world*
new_age, ambient, anime, meditation, melancolia	*new_age*
punk, hardcore, skate, noise	*punk*
classical, orchestra, broadway, ensemble, violin, dreamo	*classical*
reggae, ska, fusion	*reggae*
alternative	*alternative*

Table 3.3: Mapping sub-genres to main genres

In Figure 3.7, you can see a general overview of fully connected multilayer perceptron neural network architecture.

String Representation	One Hot Encoded Representation
r&b	[1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
rap	[0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
electronic	[0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
rock	[0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
new_age	[0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
classical	[0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
reggae	[0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
blues	[0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
country	[0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0]
world	[0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0]
folk	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0]
easy_listening	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0]
jazz	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0]
vocal	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0]
punk	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0]
alternative	[1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0]
pop	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0]
heavy_metal	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1]

Table 3.4: One hot encoding of main genres

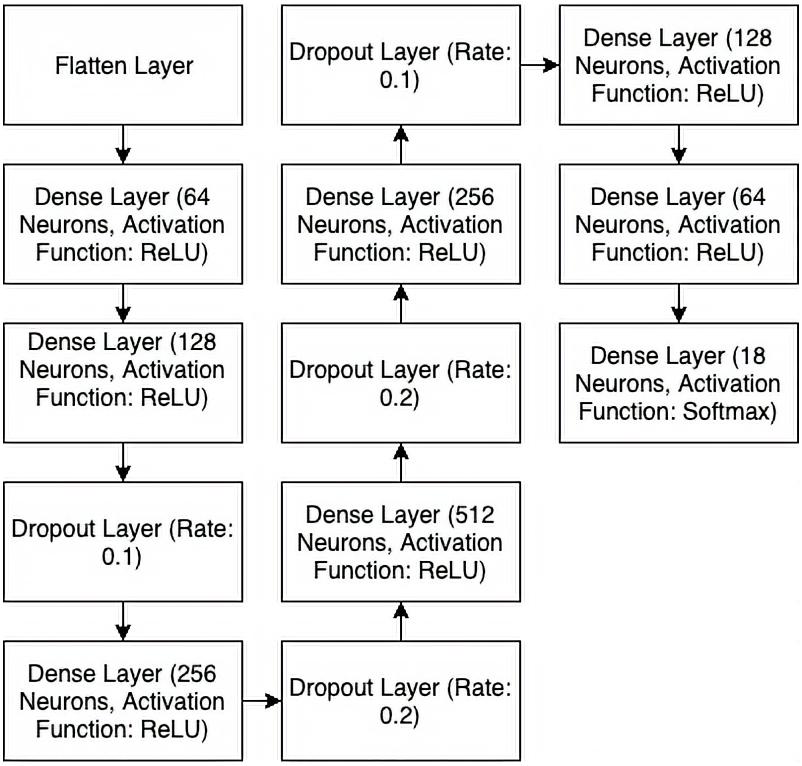

Figure 3.7: Densely connected multilayer perceptron neural network overview

Deep learning model which can be seen in Figure 3.7 works as a musical genre classifier, uses categorical_crossentropy function as a loss function and Adam as an optimization algorithm. In additionly, rectified linear unit functions (ReLU) used as an activation functions, and softmax function was used to predict classes at the last layer of neural network. This model is predicting song genres online, as can be shown in Figure 3.4, it predicts continuous song genre labels before application is gone live and be ready for production. In the future, after collecting some solid user feedbacks on genre interests and song label corrections, this model is aimed to retrain itself to get more accurate genre labels for the recommender system.

4 Testing and Evaluation

4.1 Software Features

In this project, technological stack for experimentation environment contains elements are shown in Table 4.1.

Programming Language	Python
Web Framework	Django
Frontend (CSS) Framework	MaterializeCSS
Frontend Dynamic Features	Javascript, JQuery
Web Server	Nginx
Operating System	Ubuntu 16.04
Database	PostgreSQL
Cache Server	Redis
Deep Learning Frameworks	Tensorflow and Keras
KNN and Preprocessing Library	Scikit-learn
CSV Processing Library	Pandas
Array Processing Library	NumPy

Table 4.1: Technological system of the proposed project

Experimentation environment was built on a Virtual Private Server (VPS), background jobs such as gathering data from Spotify API, predict song genre values, and inserting them to database, labeling songs using artist genres and writing them to CSV files are handled on a virtual private server.

Moreover, individualsymphony.com domain name is selected and prepared to be deployed on. Project frontend user interface can be seen on Figure 4.1, is user-friendly and focuses on user experience. Informative and helpful buttons are supported by flash messages after clicking any button also can be seen on Figure 4.2. In case of error, user can see error messages as flash message which is triggered by Javascript.

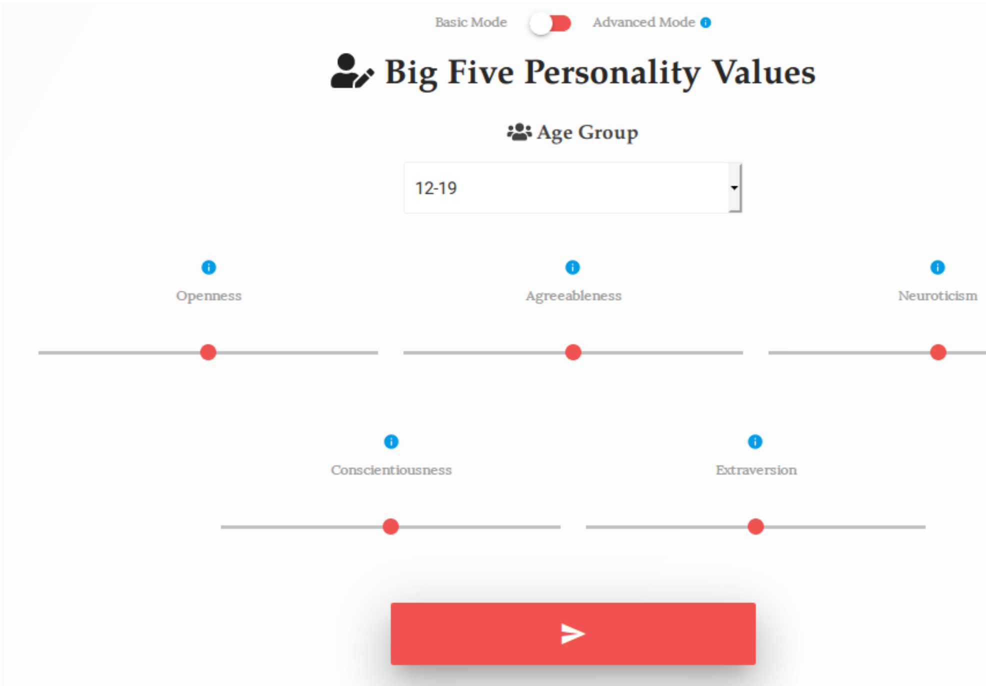

Figure 4.1: Informative and minimal user interface for experimentation environment

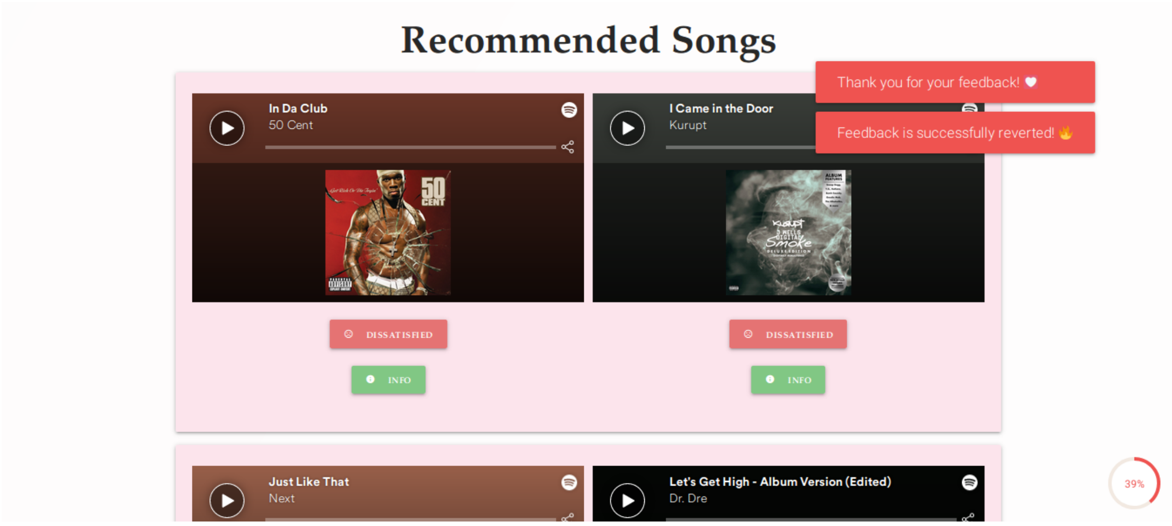

Figure 4.2: Helpful flash messages and buttons for better user experience

4.2 Evaluation and Discussion

In this thesis, a deep learning model is aimed to classify songs to 18 main genres, however, there is no exact taxonomy about musical genres and is still unknown. 12 audio features that model used mentioned in Section 3.2 classifies some important changes in songs, but training accuracy results in 0.4304. However, in 18 main genres, some of them are really close each other. For example, world music and folk music are similar in various ways, also alternative rock and rock genres do not have exact differences and features which help to identify one from the another. On experimentation platform, individualsymphony.com creates recommendations 276 times to users which is equal to 2760 recommended songs and only 341 times users sent negative feedback over 2760 songs. Therefore, this results in 0.88 evaluation accuracy against real users.

Furthermore, when we take consideration of 4 artists 6ix9ine, Justin Bieber, Nirvana, and Radiohead make music mostly in genres respectively rap/hiphop, pop/rap, punk/rock, and rock/electronic. Hence, some song genre predictions of model show that they have accurate correlation between predictions and their dominant genre. For example, in Figure 4.3 and 4.4 show that songs of Radiohead's electronic dominant album *Hail To The King* have high value of electronic prediction from the model.

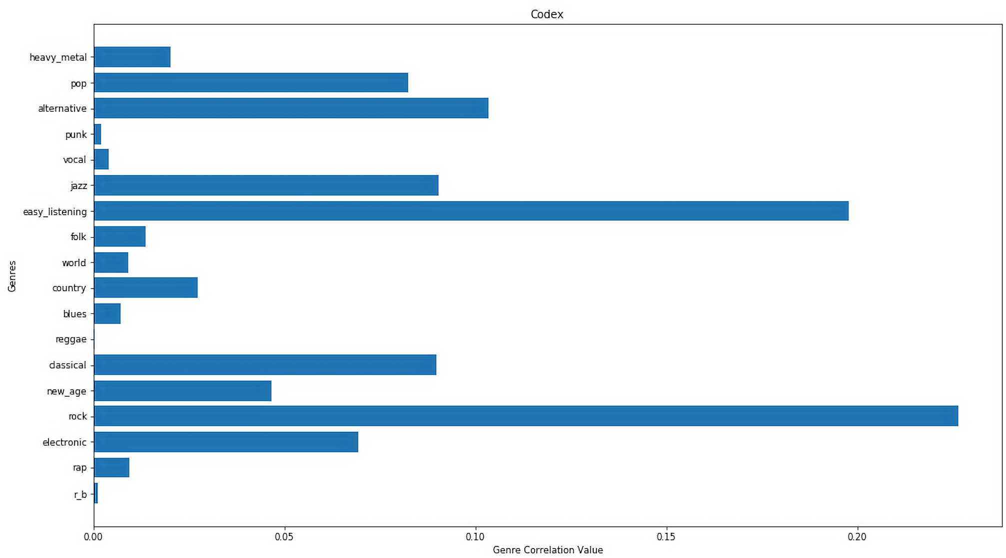

Figure 4.3: Radiohead - Codex genre prediction values

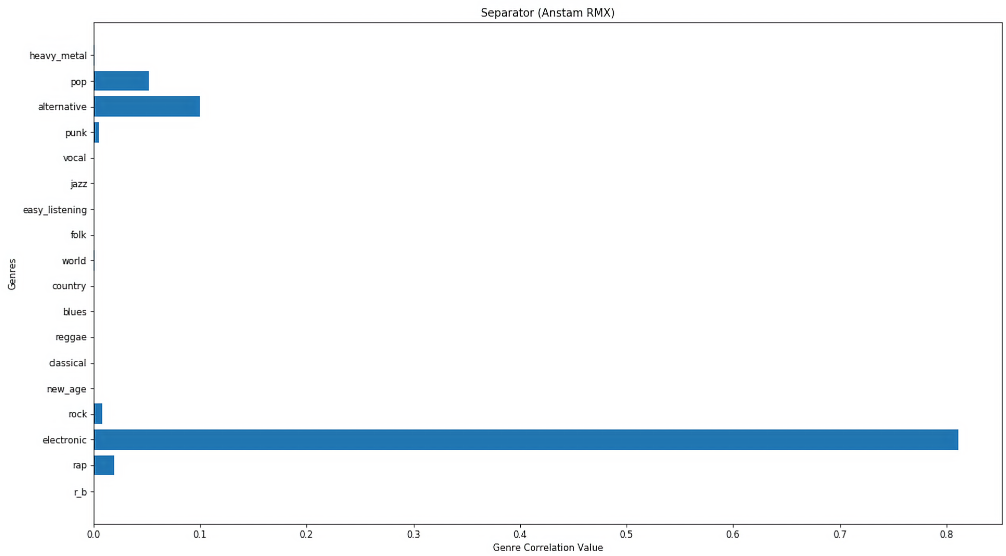

Figure 4.4: Radiohead – Seperator genre prediction values

Moreover, Justin Bieber is known as a pop music artist, but his one of the most popular song *Baby* is by featuring Ludacris who is a rap artists, so the song is not only a pop song but also has some rap characteristics due to Ludacris. Figure 4.5 depicts that model achieves to identify this song has 2 primary genres which are pop and rap that is an accurate prediction which shows strength of the model.

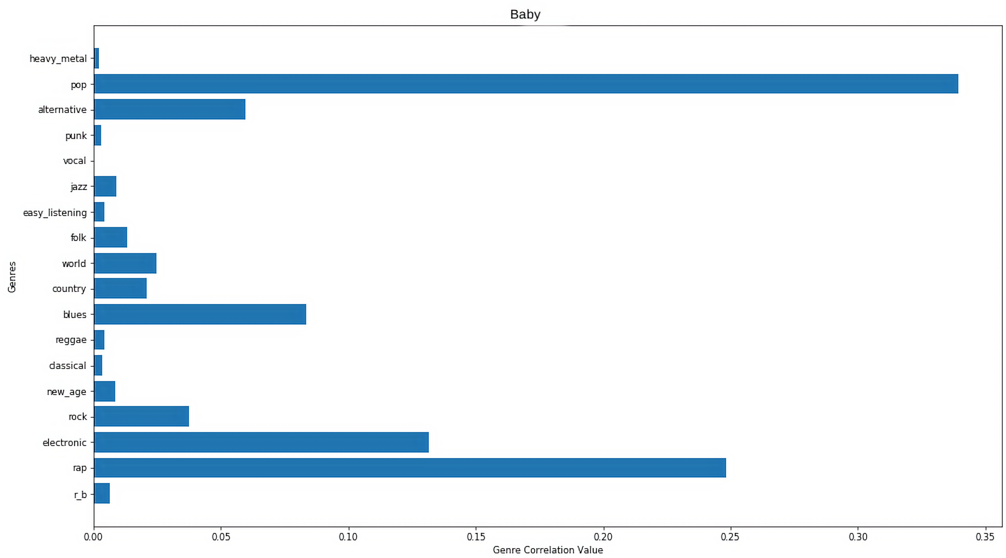

Figure 4.5: Justin Bieber ft. Ludacris – Baby genre prediction values

Also, model can understand difference between live and album versions of same song. For example, *Breed* by Nirvana is an alternative rock song which is not so noisy, nonetheless, live version of Breed seems more loud and energetic, and the differences can be seen in Figure 4.6 and Figure 4.7. Live version has more rock and heavy metal elements which can be interpreted as a correct prediction.

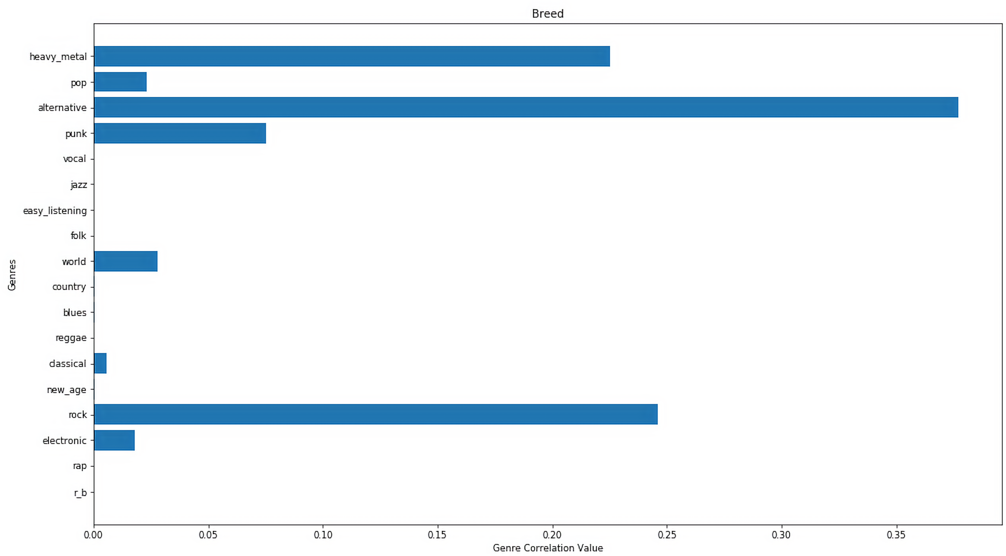

Figure 4.6: Genre predictions of album version of Breed by Nirvana

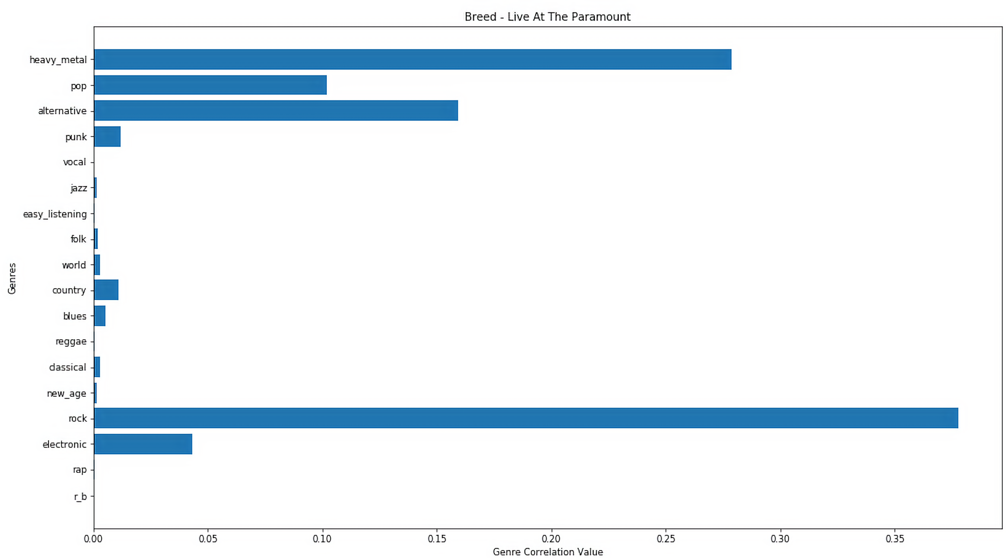

Figure 4.7: Genre predictions of live version of Breed by Nirvana

5 Conclusion and Future Work

Firstly, in this thesis, we proposed a music recommendation system that is based on big five personalities. With the help of correlation between big five personality and musical genre interests, we could construct genre interest matrices to search on predicted genre values in database to get nearest song matrices to recommend them to users.

Finally, this proposed project has significant potential to grow and to be extended using feedback mechanism values collected by users. 3 different feedback features focus on to create general validation of product, more accurate predicted genre values of songs, and better accuracy in correlation between big five personality traits and musical genre interests. Project's user interfaces and user experiences encourage users to give feedbacks on genre interest values regarding to their big five personality traits, indicating dissatisfaction about recommended songs, and valid genre suggestion for a recommended song if seems inaccurate for user. After the increase of the number of users of this application, total number of feedback values which are stored in database will increase and project advance itself retraining models, detecting, analyzing unliked songs and changing algorithm behind musical genre correlation values and big five personality traits. Although, now project is based on 2 references to calculate big five personality traits and musical genre correlation values regarding to these traits, in the future, these references knowledge could be changed and converged to more accurate real-world statistics.

Another feature that can be implemented to this project is creating a personalized user platform system where users are able to sign up to platform and continuously give feedbacks about their interests and liked songs, and genres. After that each user will have a personalized user area where they can find fresh and updated recommended songs that are fetched regarding users continuous activities and feedbacks, also this platform can work as a social media platform and apply better collaborative filtering using friends of users' and other similar users' interests. For example, musical tastes of people who have similar big five personality values and joined the network before the current user, can be used as a reliable collaborative source to calculate recommended songs for the current user. Furthermore, growing number of satisfied users will increase popularity of this application, and because this project came up with a solution for cold start problem in recommendation systems, it could draw attention later for big companies which focus on streaming music industry.

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