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Method to Profiling the Characteristics of Indonesian Dangdut Songs, Using K-Means Clustering and Features Fusion

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Abstract: There have been numerous studies that discuss profiling for various subjects, including criminal profiling, consumer profiling, and employee profiling, among others. However, song profiling is a relatively rare and underexplored area. In fact, profiling songs can provide us with new insights. Dangdut, one of the most popular musical genres in Indonesia, is a unique blend of musical rhythms from Arabic, Malay, Indian, and local music, and has the ability to captivate listeners and get them dancing and swaying along. In this study, we utilized feature selection techniques and feature fusion in conjunction with the K-Means clustering method to profile 281 Dangdut songs into two groups of clusters, with the best Silhouette score of 0.646. Additionally, we compared our method with non-Dangdut song data and obtained a Silhouette score of 0.549.

Keywords: Song Profiling, Clustering, Features Selection, Dimension Reduction, Dangdut Song, Features Fusion

1. INTRODUCTION

We live in the computer age, where computers have become a part of human life. With the help of computers, humans can do almost anything, not only limited to office work but also in many aspects of human life. From calculating balance sheets to providing entertainment, computers can handle all of these tasks. One of the biggest advantages of computers is their speed. They are capable of performing millions of calculations in just seconds.

With the increasing speed of computers and widespread availability of internet connections, it has become easier for people to access various types of songs. Many of us enjoy spending our time listening to songs. When we hear a song, whether it is at a concert, on the radio, online, or through other media, we sometimes notice subtle similarities between one song and another. These similarities may be in the form of tone, musical color, arrangement, style, tempo, and so on.

There are various kinds of popular culture in Indonesia, one of which is "Dangdut". Dangdut is one of the most popular music genres in Indonesia. Compared to Rock, HipHop, RnB or Pop music, Dangdut has a broader appeal and is enjoyed by all levels of society. It is often performed at several major national events.

Dangdut is very unique and has a long history. Starting from the early 70s [1], dangdut songs began to gain popularity among the public. Dangdut itself is a blend of musical rhythms from Arab, Melayu, India, and local music, as well as the use of modern musical instruments from the West. The lyrics of Dangdut songs often convey popular messages, both Islamic and secular [2].

In the early days of the emergence of Dangdut music, the songs were often associated with the lower classes. However, gradually there was a significant change and Dangdut became accepted by all levels of society. Dangdut songs have unique rhythms and characters that can "hypnotize" the listeners and invite them to dance and sway along with the music.

As time goes by, there is an evolution in Dangdut music itself. In the era of the 2000s, and with the influence of "techno dance" music, Dangdut music was transformed into "Dangdut koplo". It is characterized by its distinctive drum pattern and fast tempo [3].

In this study, we conducted a comprehensive study to profile the characteristics of Indonesian Dangdut songs using a computer science approach, particularly the machine learning method. The purpose of this paper is to contribute to science, especially computer science, by:

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- Provides a dataset of Indonesian Dangdut songs.
- Proposes a method to profiling the characteristics of Indonesian Dangdut songs.
- Presents the results of profiling the characteristics of Indonesian Dangdut songs.

2. RELATED WORK

What comes to our mind when we hear the word ”profiling”, there can be many possibilities, and it can be about crime, banking, customers, employees, disease and so on. But what if this profiling is related to the song?, this is something interesting that needs to be explored further.

The word “profiling” itself means an action to collect information about someone or something so that we can obtain a meaningful description of it. To the best of our knowledge, the research related to profiling a song using a computer science approach is still not well explored. However, there are several previous studies using a computer science approach to profiling other things.

A. Common Cases Profiling

There have been several studies conducted on profiling using a computer science approach, such as criminal profiling. In criminal cases, profiling is utilized to aid law enforcement in predicting the characteristics of criminals. The machine learning approach employed, utilizing the Bayesian network method, has successfully profiled criminals with a relatively high degree of accuracy [4]. Additionally, crime patterns can be predicted by profiling supporting attributes [5], such as date, time, and location.

Consumer profiling is commonplace in the business world. This is done by obtaining information related to anything that can affect consumer interest and loyalty to a product or service. Classification techniques such as Naive Bayes, Random Forest, and Decision Tree are used to identify suitable customers for offering banking products [6]. For fashion customers, profiling is very helpful in determining the most purchased products related to the current season [7]. Additionally, consumer profiling to determine their opinions regarding a product can help the industry build a more intimate relationship with the consumers for the products or services offered [8].

In the industrial world, a computer science approach is used in recruiting prospective employees. One of the most popular computer science approaches is Deep Learning, which helps to profile the right prospective employees and prevent threats that may come from the employees themselves [9]. Additionally, the implementation of text mining is very helpful in profiling prospective employee applications [10]. In the world of medicine, a computer science approach such as Random Forest, Naive Bayes, and Support Vector Machine, is used for drug discovery profiling [11].

Regarding human health, genome profiling with the help of machine learning can contribute to predicting possible diseases in humans [12], such as cancer and heart disease diagnostics [13]. Meanwhile, the use of convolutional neural network (CNN) can help analyze cytokine storms in COVID-19 patients [14].

B. Music Profiling

Many of us may think that music and songs are the same thing, but actually they have different definitions. Music can be defined as organized sound [15], while a song is a combination of melody, linguistic information, and the vocalist’s emotions [16]. A song is a type of music that is created to be sung by a singer. Although there are different definitions of music and song, several musical attributes also exist in songs, such as tonality, timbre, and rhythm [17].

Music Information Retrieval (MIR) is a method in computer science that can be used to solve problems related to music [18]–[20]. These methods enable the retrieval of information contained in the music for further processing [21].

There have been several studies related to music profiling, such as music recommendations and music similarity. Music recommendations work by extracting important information from music and providing recommended songs or music that match the user’s preferences [22]–[25].

Meanwhile, music similarity is the concept of grouping several pieces of music or songs into the same group or cluster [26], which have the same characteristics. Those characteristics include tempo, rhythm, pitch, melody, harmony, and timbre [27].

Several studies related to the similarity of music have been conducted, such as identifying ”cover song” similarity in music [28], [29], similarity of classical music composers [30], and similarity of Indian music [31].

3. METHOD

In this study, the unsupervised learning method [32], which is a part of machine learning methods, was used to perform profiling of the characteristics of Indonesian Dangdut songs. The clustering technique chosen for this study is the K-Means clustering algorithm [33]. Our novelty in this study is that we tailored the K-Means clustering algorithm with a feature selection technique and used a dimension reduction technique to fuse multiple feature variables.

There are nine stages in this method to profile the characteristics of Indonesian Dangdut songs. These stages include audio data collection, audio preprocessing and segmentation, feature extraction, feature selection, data scaling, dimension reduction, determining the optimal number of clusters, clustering, and visualization.

The nine stages of this method are crucial and must be carried out in the correct sequence. To illustrate the process, we have presented it in Figure 1. Additionally, we will provide a more in-depth explanation of each stage in the following section.

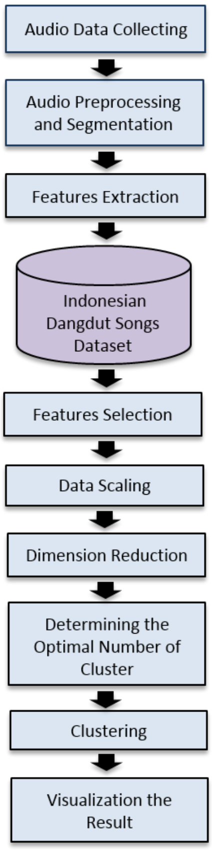

Figure 1. Nine stages for Profiling the Characteristics of Indonesian Dangdut Songs

A. *Audio Data Collecting*

At this stage, a total of 281 Dangdut songs were collected from several periods, ranging from the 1970s to the 2000s, each of which was a popular title in its respective era. All collected songs were in MP3 audio format and were obtained from various sources on the Internet. Each audio recording contains vocals and musical accompaniment. For further details, the list of Dangdut songs used can be seen in Table I.

TABLE I: List of Dangdut Song Titles

Song Name	
1001 Macam	Cuma Kamu
135.000.0000	Cuma Satu
5 Centi	Dana Asmara
Abang Ghoib	Darah Muda
Abang Goda	Debu Jalanan
ABG Tua	Depan Belakang
Acong Jadi Amir	Derita
Adu Domba	Derita Tiada Akhir
Aisah Jamilah	Di Tikung Teman
Aku Buka Wifi	Dia Lelaki Aku Lelaki

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TABLE I: List of Dangdut Song Titles (Continued)

Song Name	
Aku Bukan Pengemis Cinta	Diam Bukan Tak Tahu
Aku Jijik	Diam Diam Jatuh Hati
Aku Mah Apa Atuh	Dibalas Dusta
Aku Tak Biasa	Digenjot Cinta
Aku Tak Mau	Dinding Pemisah
Alamat Palsu	Do Mi Sol
Anak Siapa	Dokter Cinta
Antara Benci Dan Rindu	Dosa Kau Anggap Madu
Antara Dusta dan Cinta	Dua Dua
Antara Teman Dan Kekasih	Duda Anak 2
Awet Muda	Duh Engkang
Ayu Sari	Duyeh
Baju Satu Kering di Badan	Emansipasi Wanita
Bang Mandor	Enaknya Dikamu
Bang Toyib	Engkau Penggoda
Baru 6 Bulan	Gadis Atau Janda
Bayang Bayang	Gadis Malaysia
Begadang	Gak Ada Waktu Beib
Bekas Pacar	Galau Ting Ting
Belah Duren	Gali Lobang Tutup Lobang
Benci	Gantengnya Pacarku
Berdiri Bulu Romaku	Gantung Aku Di Monas
Berkelana	Gembala Cinta
Bibir Bermadu	Gitar Tua
Bimbang	Goyang 2 Jari
Biru Hatiku	Goyang Dombret
Bojo Galak	Goyang Dumang
Bujangan	Goyang Inul
Buka Pintu	Goyang Nasi Padang
Bukan Tak Mampu	Goyang Pantura
Bukan yang Pertama	Goyang Pokemon
Bulan Purnama	Gubuk Bambu
Cerita Lama	Guruku Yang Cantik
Cie Cie	Haji
Cikini Gondangdia	Haram
Cincin Putih	Harga Diri
Cinta Abadi	Hati Terluka
Cinta Basi	Hati Yang Luka
Cinta Ganjil Genap	Hello Sayang
Cinta Kurang Gizi	Hey Siapa Kamu
Cinta Pertama	Hitam
Cinta Putih	Hitam Bukan Putih

Continued on next page

TABLE I: List of Dangdut Song Titles (Continued)

Song Name	
Cinta Sabun Mandi	Hitam Manis
Cinta Satu Malam	Hitam Putih Fotomu
Cinta Tak Terbatas Waktu	Ibu Kota
Cinta Terpendam	Ilalang
Cinta Tulalit	Ini Dangdut
Cintaku Dan Cintamu	Istilah Cinta
CKC Cuma Kamu Cin	Iwak Peyek
Coba Coba	Izinkanlah
Colak Colek	Jablai
Cowok Ayam Kampung	Jacky
Cuit Cuit Witwiw	Jagung Bakar
Jagung Rebus	Pacar Baru
Janda Kembar Dua	Pacar Dunia Akhirat
Jandaku	Pacar Satu Satunya
Jangan Mengharap	Pagar Makan Tanaman
Jangan Pura Pura	Pak Pos
Janji	Pandangan Pertama
Janji Suci	Pangeran Dangdut
Janur Kuning	Pasrah
Jaran goyang	Payung Hitam
Jelita	Penantian
Jeritan Hati	Penasaran
Jhonny	Penonton
Jogja Bandung	Perawan Atau Janda
Judi	Pergilah Kasih
Judul-Judulan	Pernikahan Dini
Kamu Pelakor	Pertemuan
Kangen	Pesan Ibu
Karna Su Sayang	Piano
Kata Pujangga	Prasangka
Kau Segalanya	Pura Pura Bahagia
Kau Tercipta Bukan Untukku	Pusing Pala Berbie
Kau Tercipta Untukku	Putri Panggung
Ke Pasar Minggu	Racun Asmara
Kejam	Ramina
Kembalikanlah Dia	Rani
Keong Racun	Ratapan Doa
Kereta Malam	Rembulan Malam
Khana	Rena
Klepek Klepek	Rindu
Kocok Kocok	Rindu Berat

Continued on next page

TABLE I: List of Dangdut Song Titles (Continued)

Song Name	
Konco Mesra	Romantika
Kost Kostan	RT 05 RW 03
Kucing Garong	Sakit Sakit Hatiku
Kuper	Sakitnya Luar Dalam
Kupinta Maafmu	Salam Terakhir
Kupu Kupu Dan Bunga	Sambalado
Lagi Syantik	Santai
Lagu Kenangan	Sapu Tangan Merah
Laksamana Raja di Laut	Sarmila
Lari Pagi	Sebelas Duabelas
Lebih Baik Sakit Gigi	Secangkir Kopi
Lelaki Pendusta	Sejengkal Tanah
Lima Menit	Sekedar Bertanya
Lirikan Matamu	Sekuntum Mawar Merah
Mabuk Judi	Selamat Malam
Madu Merah	Selfie
Magdalena	Senyum Membawa Luka
Makan Hati	Setangkai Bunga Padi
Malam Terakhir	Si Miskin Bercinta
Mama Minta Pulsa	Sianida
Mandi Kembang	Siapa Kau
Mandi Madu	Siksa Kubur
Masih Adakah Cinta	Sinden Jaipong
Maya	Sirin Farhat
Mbah Dukun	Sisa-Sisa Cinta
Melanggar Hukum	SMS
Menanti Kasih	Suamiku Kawin Lagi
Menanti Majikan	Sudah Cukup Sudah
Menghitung Bintang	Suling Bambu
Menunggumu Sumpah	Aku Nggak Sakit
Mirasantika	Surat Cinta
Ojo Lali	Surat Merah
Ojo Suwe Suwe	Suratan Cintaku
Susah Move ON	Terong Dicabein
Tak Butuh Cinta	Terpaksa
Tak Ingin Sendiri	Terpengaruh
Tak Sanggup Lagi	Tersesat
Takdir	Tiada Guna
Tamu Tak Diundang	Tidak Semua Laki Laki
Tang Ting Tong Dher Tua	Tua Keladi
Teganya	Undangan Mantan
Tembok Derita	Undangan Palsu

Continued on next page

TABLE I: List of Dangdut Song Titles (Continued)

Song Name	
Terbayang Bayang	Untukmu Wanita
Tercantik di Dunia	Wakuncar
Tercyduk	Ya Nasib
Terimalah	Yank Haus
Terlena	Zaenal
Termiskin di Dunia	

B. Audio Preprocessing and Segmentation

At this stage, the raw data in the form of audio files is manually checked to ensure that all collected files are not damaged or corrupted. We also check the beginning and end of each song, and remove any parts without a sound signal. Next, we convert the audio signal to mono format with a sampling rate of 22 kHz.

Before proceeding to the next stage, we perform segmentation by dividing each audio file into 20 smaller segments, and for each segment, we only extract the first few seconds of the audio signal. In Figure 2, we mark the segments with a red dotted line, while the light blue dotted line represents the initial 15 seconds that we used.

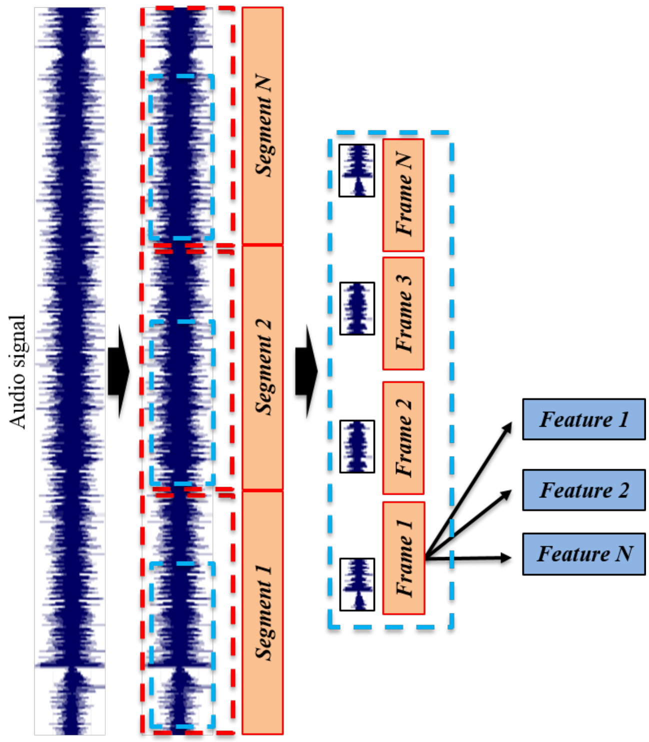

Figure 2. Audio segmentation for Indonesian Dangdut Songs

For each segment, we counted the total number of frames and then proceeded with feature extraction.

C. Features Extraction

Feature extraction is one of the most vital and important steps in machine learning [34]. The main purpose of feature extraction is to obtain important information, usually in the form of statistical values or numbers, which are useful for machine learning models. In this study, 67 features based on time and frequency domains were used. We utilized PyAudioAnalysis [35] for feature extraction purposes.

We present the details about the features that we used in this dataset in Table II.

TABLE II: List of Features Used

Feature Name	Dimensions
Energy	2
Energy Entropy	2
Zero Crossing Rate (ZCR)	2
Spectral Centroid	2
Spectral Spread	2
Spectral Entropy	2
Spectral Flux	2
Spectral Rolloff	2
Mfcc1 to Mfcc13	26
Chroma1 to Chroma12	24
Chroma Deviation	1

Energy is related to the perceived sound intensity, and this feature is used to estimate loudness. Following is the equation:

$$E(i) = \frac{1}{W_L} \sum_{n=1}^{W_L} |X_i(n)|^2 \tag{1}$$

Energy entropy can be interpreted as a measure of the spontaneity or suddenness of a change. Following is the equation:

$$H(i) = -\sum_{j=1}^{K} ej.log_2(ej) \tag{2}$$

Zero crossing rate (ZCR) measures the number of times that the amplitude of the signal changes sign per unit of time in a section or frame. ZCR can be interpreted as a measure of the noise of a signal. Following is the equation:

$$Z(i) = \frac{1}{2W_L} \sum_{n=1}^{W_L} |sgn[x_i(n)] - sgn[x_i(n-1)]| \tag{3}$$

Spectral centroid can be used to measure the ”brightness” of a sound and relates to the timbre of music. Following is the equation:

$$C_i = \frac{\sum_{k=1}^{Wf_L} kX_i(k)}{\sum_{k=1}^{Wf_L} X_i(k)} \tag{4}$$

Spectral spread can be interpreted as the variance of the average frequency in the signal. Following is the equation:

$$S_i = \sqrt{\frac{\sum_{k=1}^{Wf_L}(k-c_i)^2 X_i(k)}{\sum_{k=1}^{Wf_L} X_i(k)}} \quad (5)$$

Spectral entropy is used to measure the size of the distribution of power or spectral power. Following is the equation:

$$H = -\sum_{f=0}^{L-1} nf.log_2(nf) \quad (6)$$

Spectral flux is to describe the change in power or power spectrum successively between each frame. Following is the equation:

$$Fl_{(i,i-1)} = -\sum_{k=1}^{Wf_L}(EN_i(k) - EN_i(k))^2 \quad (7)$$

Where:

$$EN_i(k) = \frac{X_i(k)}{\sum_{l=1}^{Wf_L} X_i(l)} \quad (8)$$

Spectral Rolloff can be used to distinguish certain parts contained in music. Following is the equation:

$$\sum_{k=1}^{m} X_i(k) = C\sum_{k=1}^{Wf_L} X_i(k) \quad (9)$$

The role of MFCC can be used to model the sound color or timbre of music. Following is the equation:

$$C_m = \sum_{k=1}^{L}(log\tilde{O}_k)cos[m(k-\frac{1}{2})\frac{\pi}{L}] \quad (10)$$

Chroma is representation the scale of the tone, according to western music standards. Following is the equation:

$$V_k = \sum_{n\in S_k}\frac{Xi_{(n)}}{N_k}, k \in 0 \quad (11)$$

The Hamming window method [36], [37] was used in this study with overlapping frames [38], [39]. The window size was set to 0.050 msec, and the window step value was set to 0.025 msec. The equation for the Hamming window method is given below:

$$w(k) = \alpha - \beta\cos(\frac{2\pi k}{N-1}) \quad (12)$$

Where N is the length of the filter and $k = 0,1,\ldots, N\text{-}1$.

D. Features Selection

After extracting all the features, the next step is to select the top 20 features that have the best scores and remove any weak features that don't meet certain criteria. To achieve this, we will use the Chi-square test method for feature selection [40], [41].

Chi-square for feature selection works by calculating x^2 between each feature and target, and then selecting the desired number of features with the best x^2 score value. The equation is as follows:

$$X^2 = \sum_{i=1}^{n}\frac{(O_i - E_i)^2}{E_i} \quad (13)$$

Where: O_i is the i^{th} observation in an event. E_i is the i^{th} expectation in an event, indicating that there is no relationship between the feature and the target.

E. Data Scaling

The purpose of data scaling is to transform the data into a specific scale. This is important because several features, after the features extraction process, result in different data scales. In addition, data scaling can help to improve the results of machine learning (ML) algorithms [42].

In this study, the data will be scaled using built-in preprocessing libraries provided by Scikit-learn tools: StandardScaler. The equation for standardization is as follows:

$$z = \frac{x-\mu}{\sigma} \quad (14)$$

With mean:

$$\mu = \frac{1}{2}\sum_{i=1}^{N}(x_i) \quad (15)$$

For standard deviation:

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i-\mu)^2} \quad (16)$$

F. Dimension Reduction

The purpose of dimension reduction is to reduce the projection of variable inputs in high dimensional spaces and also to avoid the "dimensionality curse" phenomenon. Currently, there are many methods for dimension reduction, but for this study, Principal Component Analysis (PCA) will be used for dimension reduction purposes [43], [44].

G. Determining the Optimal Number of Cluster

For profiling purposes in this study, the clustering method will be used. Therefore, to determine the optimal number of clusters, we will use the Silhouette method [45]. This method is one of the methods that can be used to validate the consistency of data grouping. The way the Silhouette method works is by measuring the similarity of an object to its own group (cohesion) and comparing it to other groups (separation).

Silhouette values range from -1 to +1, where a high value indicates that the object fits into its own group and does not fit into any other group. If most of the objects have high values, then the process of determining the number of clusters is considered appropriate. However, if many object points have negative or low values, then the process of determining the number of clusters may have too few or too many clusters.

By using the Euclidean distance metric and the clustering method using K-Means clustering, the Silhouette method can be formulated that for each object point i element of C_I (the i^{th} object point in C_I cluster), for example:

$$a(i) = \frac{1}{|C_I| - 1} \sum_{j \in C_{I, i \neq j}} d(i, j) \tag{17}$$

be the average distance between i and all object points in the same cluster, where $|C_I|$ is the number of points belonging to cluster i, and $d(i,j)$ is the distance between object points i and j in cluster $|C_I|$ (divided by $|C_I|$-1 because the distance to it self $d(i,i)$ doesn't count). It can be interpreted that $a(i)$ is a measure of how well i is placed in its group, where the condition applies that the smaller the value, the better the placement. Then to define the average difference for object point i to several clusters C_J as the average distance from i to all points C_J (where C_J not equal C_I), if all object points are i element of C_I, then for example:

$$b(i) = \min_{J \neq I} \frac{1}{|C_j|} \sum_{j \in C_j} d(i, j) \tag{18}$$

Furthermore, the Silhouette value for each object point i can be calculated as follows:

$$S(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}}, if |C_I| > 1 \tag{19}$$

and $S(i) = 0$, if $|C_I| = 1$, where a = the average distance between each object point in a cluster, b = average distance between all clusters.

H. Clustering

Clustering is a method of unsupervised learning that works by dividing the data population into smaller groups by minimizing the distance between each point in the group and maximizing the distance between one group and another. The main purpose of clustering is to group data based on certain criteria. K-Means clustering [46] will be used in this study. In general, the steps of the K-Means clustering algorithm are:

1) Determines the number of K to be created, where K refers to the number of clusters or groups.
2) Randomly choose a starting point or centroid that will act as the initial cluster.
3) Calculating the distance of each data to the nearest centroid using the Euclidean distance method.
4) For each data that has the closest distance to the centroid, it will become part of the cluster group.
5) Update centroid value.
6) Repeat steps 3-5 until the centroid point doesn't change anymore.

I. Visualization the Result

The results of clustering will be displayed in this stage. Visualization in the form of a chart will be very helpful to be able to understand profiling results and the characteristics of Indonesian Dangdut songs. A radar chart will be used to display the results.

4. RESULTS AND DISCUSSIONS

In this section, we will present the structured results of our study and compare them with other song data. The experiment was conducted on a computer with 3 GHz speed processor, 16 GB of system memory, 8 GB of graphics card memory, and a 64-bit operating system. system.

A. The Dataset

The dataset used in this study consists of a total 71 columns and there are 281 records. The data type used in this dataset is float64, except for "Artist", `"Song_Name"`, and "Period", the data type used is string. There are no data with NULL values in this dataset.

B. Features Selection

After performing feature extraction, the next step is to select features that have the best ranking. In this case, we use the top 20 features with the highest score. In Table III, we show the selected features.

TABLE III: Top 20 Features For Profiling Indonesian Dangdut Songs

Variabel Name	Score
Chroma7_mean	6.835
Chroma7_std	5.972
Mfcc1_std	2.355
Chroma5_std	2.206
Chroma_Deviation_mean	1.871
Mfcc13_std	1.650
Energy_Entropy_std	1.621
Spectral_Flux_std	1.599
Energy_Entropy_mean	1.593
Mfcc2_std	1.531
Chroma8_std	1.510
Mfcc12_std	1.287
Chroma8_mean	1.208
Spectral_Centroid_std	1.197
Chroma11_mean	1.107
Chroma5_mean	0.889
Spectral_Spread_mean	0.877
Chroma9_std	0.860
Spectral_Flux_mean	0.787
Chroma3_mean	0.772

C. Features Fusion

At this stage, we group the top features that have been selected into the same group, and then we combine the features into new features using dimension reduction technique. Rather than using a single dimension reduction technique, we apply several dimension reduction technique to each groups. For each PCA, we set the output to produce only one component. Three new features were created as the result of feature fusion. We named the three new features: Dynamics, Timbre, and Harmony, which forms the foundation of the characteristics of a song. We illustrate this process in Figure 3.

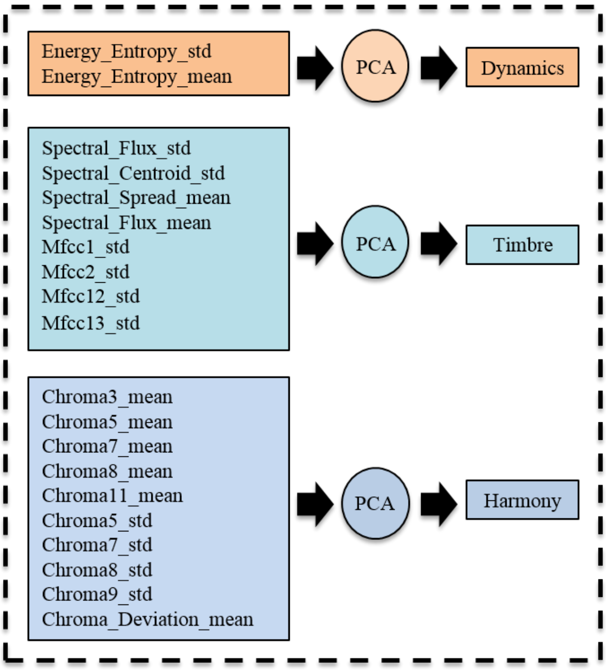

Figure 3. Features Fusion using PCA for Profiling the Characteristics of Indonesian Dangdut Songs

D. Determining the Optimal Number of Cluster

To determine the optimal number of clusters before the clustering process, we used the Silhouette method and limited the clusters to ten groups. We found that increasing the number of clusters did not improve the Silhouette score significantly. As shown in Table IV, the highest score of 0.646 was achieved when the number of clusters was set to two groups. We then illustrated the clustering process with two groups in Figure 4.

TABLE IV: Comparison Of Silhouette Scores For Different Numbers Of Clusters in Indonesian Dangdut Songs

Number of Clusters	Silhouette Score
2	0.646
3	0.626
4	0.632
5	0.615
6	0.542
7	0.556
8	0.507
9	0.480
10	0.479

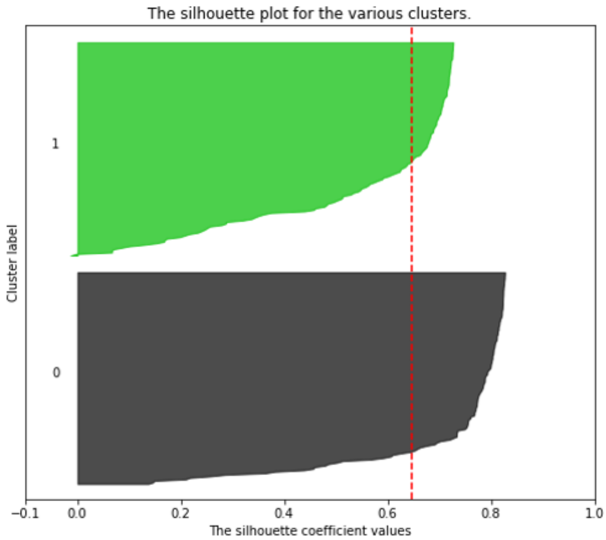

Figure 4. Silhouette plot k=2

E. Clustering and Profiling

To enhance the findings of this study, we present the clustering results of Indonesian Dangdut songs with the number of cluster groups set to two. We then proceed to profile these clusters to describe their characteristics. Firstly, we examine the distribution of songs, which appears to be evenly distributed when the cluster is set to two. The details can be seen in Figure 5.

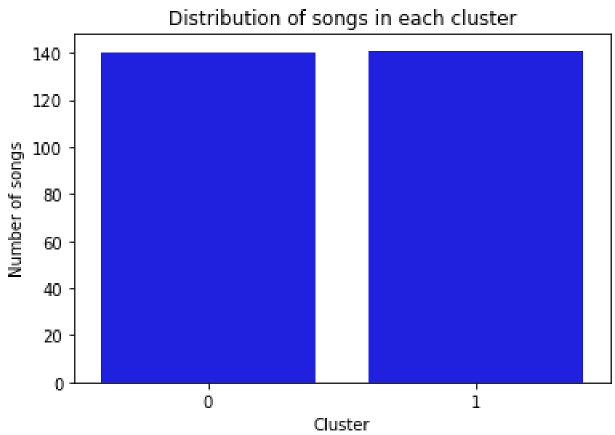

Figure 5. Songs Distribution k=2

To visualize the centroid point formed during the clustering process, we present a visualization of the clustered data in Figure 6, where each cluster is marked with a different color. In Table V, we provide the mean values for the feature variables after fusion, based on the selected clusters. The characteristics of Indonesian Dangdut songs are further analyzed in Figure 7 using two clusters. Figure 7 is explained as follows: each row represents a cluster, while each column represents a feature. The grey bars show the distribution of features, whereas the blue bars represent the distribution of features in each cluster, allowing for comparison between clusters. By examining the distribution, we can determine whether a cluster has high or low levels of certain features. This is indicated by the position of the blue bar relative to the grey bar (on the right for high and on the left for low). By profiling these characteristics, we can even identify distinct cluster identities. Table VI summarizes the profiled characteristics of Indonesian Dangdut songs.

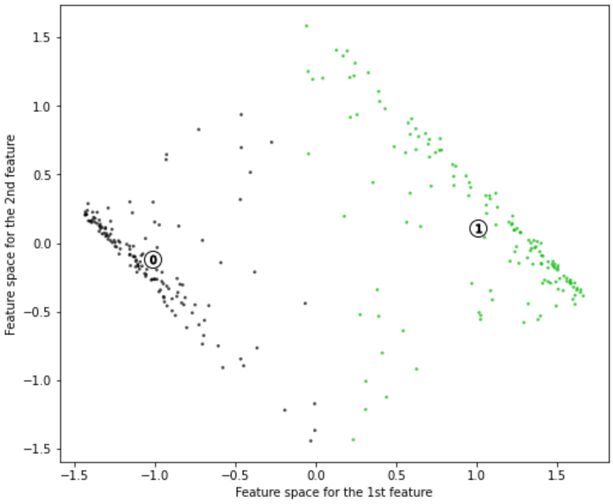

Figure 6. The Visualization of the Clustered data k=2

TABLE V: Mean Values of Energy, Mfcc, Spectral and Chroma Features After PCA Fusion For Indonesian Dangdut Songs

Number of Clusters	Cluster	Dynamics	Timbre	Harmony
2	0	0.051	0.279	0.287
	1	0.903	0.692	0.696

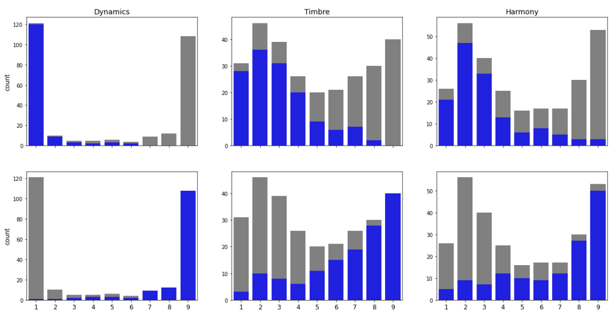

Figure 7. Bar Chart Comparison for The Characteristics of Indonesian Dangdut Songs

TABLE VI: Summary of Profiling the Characteristics of 281 Indonesian Dangdut Songs

K-Means	Cluster	Dynamics	Timbre	Harmony
2	0	Low	Low	Low
	1	High	High	High

F. Visualization Results

We use a radar chart, shown in Figure 8, to provide a better visual understanding of the profiling results. In addition, we demonstrate the output examples of 20 Indonesian Dangdut song lists that underwent the clustering process and belong to either cluster 0 or cluster 1, as illustrated in Tables VII and VIII.

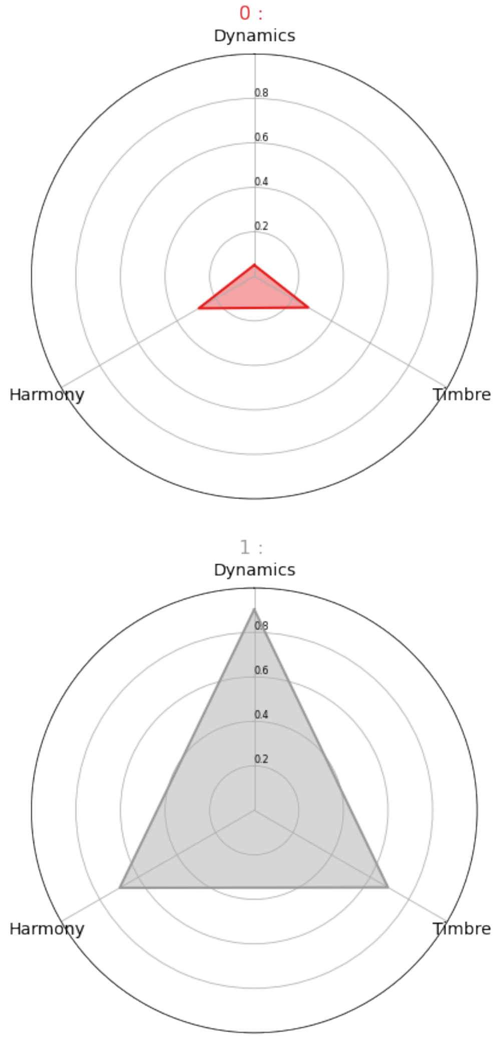

Figure 8. Visualization the Characteristics of Indonesian Dangdut Songs using Radar Chart

TABLE VII: Indonesian Dangdut Songs in Cluster 0

Artist	Song Name	Period
Siti Badriah	Undangan Mantan	2000’s
Rhoma Irama	Awet Muda	80’s
Rhoma Irama	Ibu Kota	80’s
A. Rafiq	Pandangan Pertama	70’s
Mansyur S & Maghdalena	Cintaku Dan Cintamu	70’s

Continued on next page

TABLE VII: Indonesian Dangdut Songs in Cluster 0 (Continued)

Artist	Song Name	Period
Elvy Sukaesih	Menghitung Bintang	80's
Asep Irama	Kembalikanlah Dia	90's
Muchsin Alatas	Derita	80's
Ikke Nurjanah	Bibir Bermadu	90's
Meggy Z	Gubuk Bambu	90's
Rhoma Irama	Darah Muda	70's
Abiem Ngesti	Pangeran Dangdut	90's
Mansyur S	Dua Dua	80's
Rhoma Irama & Elvy Sukaesih	Ke Pasar Minggu	70's
Iis Dahlia	Payung Hitam	90's
Mansyur S	Ramina	80's
Mansyur S	Sejengkal Tanah	90's
Hamdan ATT	Secangkir Kopi	70's
Jaja Mihardja	Penantian	70's
Camelia Malik	Rindu Berat	80's

TABLE VIII: Indonesian Dangdut Songs in Cluster 1

Artist	Song Name	Period
Ratu Idola	Kamu Pelakor	2000's
Caca Handika	Undangan Palsu	90's
Salsiah	Enaknya Dikamu	2000's
Siti Badriah	Terong Dicabein	2000's
Nita Thalia	Bang Mandor	2000's
Nella Kharisma	Hitam Putih Fotomu	2000's
Rhoma Irama	Emansipasi Wanita	80's
Dinda Permata	Tak Sanggup Lagi	2000's
Yus Yunus	Gadis Malaysia	90's
Asmin Cayder	Tembok Derita	80's

Continued on next page

TABLE VIII: Indonesian Dangdut Songs in Cluster 1 (Continued)

Artist	Song Name	Period
Desy Ning Nong	Tercyduk	2000's
Cucu Cahyati	Mabuk Judi	90's
Ona Sutra	Sisa-Sisa Cinta	90's
Susi Legit	Ya Nasib	2000's
Nais Larasati	Takdir	90's
Cita Citata	Perawan Atau Janda	2000's
Ratu Idola	Dibalas Dusta	2000's
Sandrina	Aku Jijik	2000's
Caca Handika	Cincin Putih	80's
Lilis Karlina	Sinden Jaipong	90's

G. Comparison Using Other Songs

In this section, we present the comparison results of our method using non-Dangdut songs data. We evaluate the performance based on various metrics and provide a detailed analysis of the results.

To evaluate our method, we selected 172 songs from a variety of existing music genres, including Blues, Dance, Disco, J-POP, K-POP, Rap, Rock, and Techno. Table IX provides the details of the songs used in this evaluation.

TABLE IX: List of Non-Dangdut Song Titles

Song Name	
30 Minutes	Celebration
99 Problems	Changes
9PM (Till I Come)	Chime
A Big Man	Chooker
Acperience 1	Counting Stars
Ai Uta	Crazy Train
All About That Bass	DADDY! DADDY! DO!
All Eyez On Me	Dancing Queen
Around The World	Dark Is The Night-Part 1
Attention	Dear Mama
Back in Black	Disco Inferno
Back In My Life	Dominato
Bad Boy	Don't Leave Me This Way
Bad Guy	Don't Stop
Belfast	Don't Stop Believin'
Better Off Alone	Don't Stop 'Til You Get Enough
Blood Sweat and Tears	Draggin My Tail

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TABLE IX: List of Non-Dangdut Song Titles (Continued)

Song Name	
Blue (Da Ba Dee)	Dream On
Bodyrock	Dynamite
Bohemian Rhapsody	Electric Shock
Bombayah	Empire State Of Mind
Boogie Wonderland	Energy Flash
Boom, Boom, Boom, Boom	Enter Sandman
Breathe	Every Day I Have The Blues
Bubble Pop	Everything's Gonna Be Alright
Caf del Mar	Fantastic Baby
Calfornia Love	Fight the Power
Fire	Natural Blues
Firework	New Order
Forever Love	No Tears Left To Cry
Freestyler	Not Gonna Get Us
Funky Town	November Rain
Gangnam Style	Odoru Ponpokorin
Get Down Tonight	Out of Space
Gin and Juice	Outside Help
Go	Pacific State
Got To Move	Paprika
Ground Hog Blues	Paradise City
Growl	Phuture
Happy	Pretender
Hate To See You	Rapper's Delight
Heart Shaker	Regulate
Heaven Must Be Missing an Angel	Ring Ding Dong
Hey Boy, Hey Girl	Rock You Like A Hurricane
High Hopes	Romeo
Honey	Sakura
Hotel California	Say You Won't Let Go
Hotline Bling	Sayonara Elegy
How Blue Can You Get	Sekai ni Hitotsu Dake no Hana
Hypnotize	September
I Am The Best	Shake For Me
I Feel Love	Shake Your Groove Thing
I Get Around	Shape of You
I Got My Mojo Working	Smells Like Teen Spirit
I Need U	Smokestack Lightnin
I Wanna Walk	Someone Like You
I Will Always Love You	Sorry Not Sorry

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TABLE IX: List of Non-Dangdut Song Titles (Continued)

Song Name	
I Will Survive	Sorry Sorry
Insomnia	Stairway to Heaven
It Was Good Day	Stakker Humanoid
Juicy	Stay
Kibou No Uta	Stay The Night
Kimi No Na Wa Kibou	Stay With Me
Kiroro	Stayin' Alive
Kiseki	Straight Outta Compton
Kiss	Strings of Life
Koi	Sugar
LaBelle	Sugar Mama
Le Freak	Sweet Child O Mine
Leave Home	The Age Of Love
Let's Groove	The Bells
Life	The Boys
Lion Heart	The Final Countdown
Little Baby	The Joker
Little Red Rooster	The Message
Living On a Prayer	Tomorrow Never Knows
Lollipop	Tom's Diner
Lose Yourself	U.S.A
Love Me Like You Do	We Found Love
Love Scenario	We Will Rock You
Lovers Again	Welcome To The Jungle
Mabataki	Where's Your Head At
Mean Old World	Window Licker
Model 500	Wrecking Ball
My First Wife Left Me	You Should Be Dancing
My Name Is	New Order

Then we selected the top 20 features with the highest scores and listed them in Table X. We also performed feature fusion with a small adjustment, which is demonstrated in Figure 9.

TABLE X: Top 20 Features From Non-Dangdut Songs

Variabel Name	Score
Chroma7_std	2.578
Chroma7_mean	2.493
Chroma10_mean	2.249
Energy_std	2.009
Chroma3_std	1.960
Chroma_Deviation_mean	1.877

Continued on next page

TABLE X: Top 20 Features From Non-Dangdut Songs (Continued)

Variabel Name	Score
Energy_mean	1.834
Spectral_Flux_mean	1.804
Spectral_Rolloff_std	1.789
Energy_Entropy_std	1.763
Chroma3_mean	1.648
Chroma6_std	1.626
Energy_Entropy_mean	1.615
Chroma9_std	1.551
Spectral_Centroid_std	1.511
Spectral_Flux_std	1.497
Chroma9_mean	1.491
Spectral_Spread_mean	1.461
Mfcc11_std	1.459
Spectral_Entropy_mean	1.425

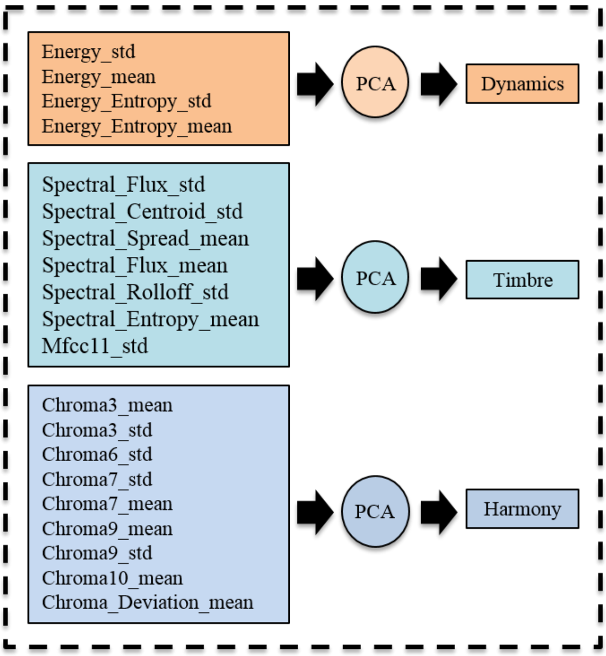

Figure 9. Features Fusion using PCA for Non-Dangdut Songs

We conducted a clustering analysis to determine the optimal number of clusters and found that the highest score of 0.549 was achieved when we set the number of clusters to four groups. In Table XI, we provide the mean values of the feature variables after fusion, based on the selected clusters, and illustrate the clustering process into four groups in Figure 10. Additionally, Figure 11 shows the visualization of the clustered data. We also present the results of the characteristics profiling using non-Dangdut songs data in Figure 12 and summarize the profiling results in Table XII.

To further illustrate the clustering results, we provide examples of 20 non-Dangdut songs that have undergone the clustering process and belong to either cluster 0 or 1. These examples are listed in Tables XIII and XIV.

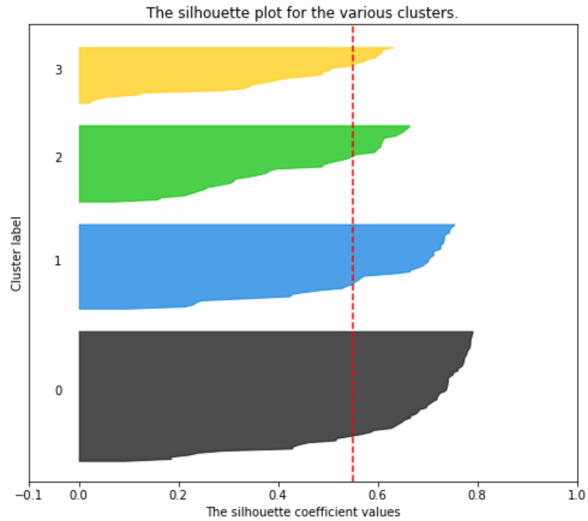

Figure 10. Silhouette plot k=4

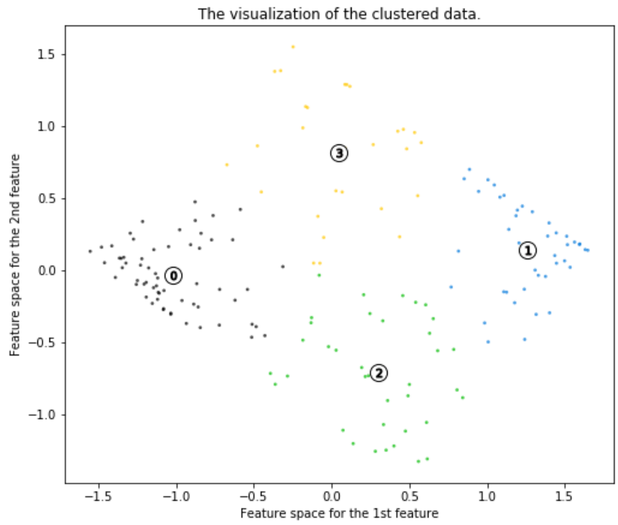

Figure 11. The Visualization of the Clustered data k=4

TABLE XI: Mean Values of Energy, Mfcc, Spectral and Chroma Features After PCA Fusion For Non-Dangdut Songs

Number of Clusters	Cluster	Dynamics	Timbre	Harmony
4	0	0.118	0.205	0.185
	1	0.880	0.771	0.865
	2	0.250	0.702	0.755
	3	0.777	0.379	0.264

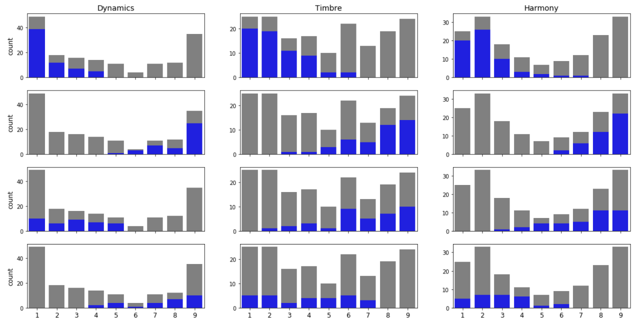

Figure 12. Bar Chart Comparison for the Characteristics of Non-Dangdut Songs

TABLE XII: Summary of Profiling the Characteristics of 172 Non-Dangdut Songs

K-Means	Cluster	Dynamics	Timbre	Harmony
4	0	Low	Low	Low
	1	High	High	High
	2	Low	High	High
	3	High	Low	Low

TABLE XIII: Non-Dangdut Songs in Cluster 0

Artist	Song Name	Genre
BB King	How Blue Can You Get	Blues
Mr. Children	Tomorrow Never Knows	Jpop
Little Walter	Mean Old World	Blues
Bon Jovi	Living On a Prayer	Rock
GReeeeN	Ai Uta	Jpop
ABBA	Dancing Queen	Disco
John Mayall	A Big Man	Blues
Little Walter	Everything's Gonna Be Alright	Blues
Queen	Bohemian Rhapsody	Rock
Earth, Wind & Fire	Boogie Wonderland	Disco
Howlin Wolf	Shake For Me	Blues
Nirvana	Smells Like Teen Spirit	Rock
The Trammps	Disco Inferno	Disco
BB King	Outside Help	Blues
Eagles	Hotel California	Rock
Ellie Goulding	Love Me Like You Do	Pop
X Japan	Forever Love	Jpop
Guns N Roses	November Rain	Rock

Continued on next page

TABLE XIII: Non-Dangdut Songs in Cluster 0 (Continued)

Artist	Song Name	Genre
Scorpions	Rock You Like A Hurricane	Rock
Muddy Waters	I Got My Mojo Working	Blues

TABLE XIV: Non-Dangdut Songs in Cluster 1

Artist	Song Name	Genre
Demi Lovato	Sorry Not Sorry	Pop
2NE1 ft. BIGBANG	Lollipop	Kpop
BLACKPINK	Bombayah	Kpop
The Prodigy	Breathe	Techno
Jay-Z ft. Alicia Keys	Empire State Of Mind	Rap
Meghan Trainor	All About That Bass	Pop
f(x)	Electric Shock	Kpop
Jay-Z	99 Problems	Rap
PSY	Gangnam Style	Kpop
Eminem	My Name Is	Rap
Nas	N.Y. State of Mind	Rap
BTS	Fire	Kpop
2NE1	I Am The Best	Kpop
BTS	Blood Sweat & Tears	Kpop
2Pac ft. Big Syke	All Eyez On Me	Rap
BTS	Dynamite	Kpop
Vengga Boys	Boom, Boom, Boom, Boom	Dance
Drake	Hotline Bling	Rap
Alice DeeJay	Back In My Life	Dance
Bomfunk MCs	Freestyler	Dance

H. Discussion

The aim of this study was to profile the characteristics of Indonesian Dangdut songs using a set of audio features. We then compared the profiling results with those obtained from non-Dangdut songs. In this section, we will discuss the main findings and their implications.

The results of our study showed that Indonesian Dangdut songs have distinct song characteristics compared to non-Dangdut songs. Our feature selection process revealed that some of the most important features for profiling Dangdut songs were spectral flux, spectral centroid, spectral spread, and mfcc. These features are related to the timbral characteristics of the audio, which are important in determining the characteristics of the song. Using the selected features, we conducted a clustering analysis to group the Dangdut songs into two clusters. The profiling results showed that Cluster 1 had the highest mean values for most of the selected features, indicating that this cluster represented the most typical characteristics of modern Dangdut songs.

We also compared the profiling results of Dangdut and non-Dangdut songs using the same set of audio features. The results showed that the selected features were effective in differentiating Dangdut songs from non-Dangdut songs. In particular, the feature of spectral was found to be highly discriminative. The bar chart visualization of the profiling results provided a clear representation of the audio characteristics of Dangdut and non-Dangdut songs.

The clustering analysis of non-Dangdut songs resulted in four clusters, with pop and rock songs dominating two of the clusters each. When comparing the characteristics between Dangdut and non-Dangdut songs, it was found that Dangdut songs tended to have higher values for mfcc, chroma, and spectral features, while having lower energy levels. This indicates a more harmonic sound with less loudness. Conversely, non-Dangdut songs tended to have higher energy, chroma, and spectral features, while having less mfcc, indicating a more dynamic sound with less emphasis on harmony.

5. CONCLUSION AND FUTURE WORK

In this study, we performed a comprehensive analysis of the characteristics of Indonesian Dangdut songs using machine learning techniques. We utilized audio segmentation, feature extraction, feature fusion, and clustering analysis to profile the characteristics of Dangdut songs. Our results showed that Dangdut songs have unique characteristics compared to non-Dangdut songs, with higher emphasis on harmonics and lower emphasis on loudness.

We also conducted a comparison analysis between Dangdut and non-Dangdut songs, where the latter was dominated by pop and rock songs. The comparison showed that non-Dangdut songs tend to have a more dynamic and less harmonic sound compared to Dangdut songs.

Our study contributes to the understanding of the unique characteristics of Dangdut songs, which can potentially benefit music enthusiasts, composers, and producers. The methodology we used in this study can also be applied to other music genres to further investigate their distinct characteristics.

Overall, our study provides insights into the audio characteristics of Indonesian Dangdut songs and their differences from non-Dangdut songs. The results can be used to develop automatic music genre recognition systems and to enhance the understanding of Indonesian music. However, there are some limitations to this study. Firstly, the dataset used in this study was limited to a specific time period and may not represent the entire history of Dangdut songs. Secondly, the feature selection process and clustering analysis were based solely on audio features, and other factors such as lyrics and cultural context were not considered. Future studies can address these limitations by including a larger and more diverse dataset, as well as by incorporating other factors into the analysis and open up new avenues for future research.

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