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IRSD: Indonesian Regional Song Dataset

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Abstract: Dataset is a very important role in music information retrieval (MIR), it widely used for several task, such as: music classification, music recognition and music identification. Indonesia is an archipelago country, consisting of 38 provinces, where each of province in Indonesia has its own regional songs. In Indonesian culture, regional song is part of the cultural identity and culture of the local community, also have influence in their respective cultures. The motivation of this study is to facilitate researchers in the field of MIR by presents the methods used in the creation of Indonesian regional song dataset. The IRSD aims to overcome this hurdle by providing feature extraction from 500 tracks of Indonesian regional song, from 10 provinces with total 67 features were extracted.

Keywords: Dataset, Folks Song, Feature Extraction, Music Information Retrieval

1. INTRODUCTION

Music Information Retrieval (MIR) is one of the most interesting and hot topics in the field of computer science today, where the methods found in computer science can be used to solve problems in the music domain area. This field involves several backgrounds, for example: music, psychology, informatics, machine learning and signal processing are the fields involved in MIR.

One aspect that is quite important in MIR is dataset. The use of the dataset is to train and evaluate the model and has a very important role in the whole process. Without an adequate dataset, we will have experience difficulties and challenges while doing the tasks in MIR.

Indonesia is an archipelago country that stretches from the west of the island of Sabang to the east of Merauke, and in the north by the island of Miangas to the south by the island of Rote. With an estimated number of ethnicities around 1,340 ethnic groups spread across 38 provinces in Indonesia, the cultural wealth is very diverse, including one of them is the richness of regional songs. Each province in Indonesia, has its own regional song, where this is part of the cultural identity and culture of the local community.

The purpose of this paper is to facilitate researchers in the field of MIR by:

- Contributing a publicly available of Indonesian regional song dataset.
- Propose the methods used in the creation of Indonesian regional song dataset.

2. RELATED WORK

There are several datasets that are quite widely used today for research needs, especially in the field of computer science. Some of these datasets are used and become references in research today.

A. Non Audio Datasets

For general purposes in machine learning we recognize several dataset, such as: ImageNet [1], this dataset used for visual object recognition purposes, which contains 1,281,167 training images and 100,000 test images. IMDB-Wiki [2] is a dataset consisting of 500,000 images of human faces that are distinguished by gender and age, this dataset is used for computer vision.

MS Coco [3] is dataset used for object detection and contains 330,000 images. MNIST [4] is dataset contains handwritten digits, consisting of 60,000 images for training and 10,000 images for testing. Meanwhile, the dataset used for the health sector, there is breast cancer dataset [5], EEG dataset [6], and diabetes dataset [7].

B. Audio Datasets

Dataset have important role in MIR and it widely used for several task, such as: music genre classification and recognition [8], [9], [10], [11], [12] music emotion recognition [13], [14], [15], music instrument recognition [16], [17], music regional classification [18] and music generation [19].

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In MIR there are also several datasets that are quite popular, such as: MSD [20], this dataset contains over 1,000,000 songs from various genres of music. What is given to this dataset is limited to extracted audio features only.

GTZAN [21] is a dataset that contains of 1000 clips from 10 genres where this dataset includes audible audio. Urban sound [22] is a dataset for environmental sound, contains 8732 labeled sound with duration 4s of each clips. This dataset divided into 10 classes, such as: air conditioner, car horn, children playing, dog bark, drilling, engine sound, gun shot, jackhammer, siren and street music.

NES-MDB [23] this is dataset consists of 5278 songs from game soundtracks of Nintendo Entertainment System (NES). This dataset comes in MIDI format.

Greek music [24], is dataset of 1400 Greek music in the form of both features and raw MIDI files. FMA [25] is dataset of 106,574 music from 161 genres. Ryerson [26] is dataset contains emotional speech and song.

3. METHOD

There are four steps in this method to create IRSD. These stages include: data collection, audio preprocessing, audio segmentation, and feature extraction. Each stage in this method has its own role, where each stage is related to one another.

The four steps that we have mentioned, have very important role in this study. Every step must be done correctly, so creation of the dataset can be completed properly. To make it clearer, we describe and show it in the Fig.1. Furthermore, we will explain each step more clearly in the next section.

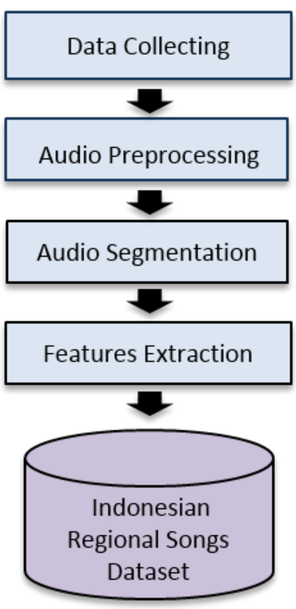

Figure 1. Four steps in making Indonesian regional song dataset

A. Data Collecting

At this stage, we started by collecting the songs from each province, a total of 500 Indonesian regional songs were collected from various sources on the Internet. All songs that have been collected are in MP3 audio format, with an average duration about four minutes long. In this regional song, each audio contains vocals and accompaniment music. For this study, we limit only to 10 province, they are:

TABLE I: Province Name List

No	Province Name	Short Name
01	DI Aceh	ACEH
02	Jawa Barat	JABAR
03	DKI Jakarta	JAKARTA
04	JAWA Tengah	JATENG
05	Kalimantan Barat	KALBAR
06	Maluku	MALUKU
07	Papua	PAPUA
08	Riau	RIAU
09	Sulawesi Utara	SULUT
10	Sumatera Barat	SUMBAR

From each province, we collected 50 songs each and the list of songs that have been collected, we display in groups based on regional origin. For more details, the songs list can be seen starting from table II to table XI respectively.

TABLE II: List of Songs From Province of ACEH

Song Name	
Beu Sare Sare	Peubeut Suroh
Bungong Nanggro	Peuranan Hareuta
Bungong	Tajak Ugle
Hasan Husein	Jodoh
Jak Tabeudoh	Asai Bak Punca
Nyang Na	Babah Pintoe
Paro Tulo	Bungong Jeumpa
Peumulia	Doda Idi
Rabbani	Geulumbang Raya
Ya Allah Biha	Jambo Jambo
Hikayat Putroe Bungsu	Kisah Seudeh
Jamboe Nyoe	Lembah Alas
Katidhein	Likok Cewek
Keuneubah Endatu	Likok Pulo
Kutidhieng	Lon Sayang
Mala Bayeun	Pileh
Putroe Bungsu	Ranup Lampuan
Seulayang	Salem

Continued on next page

TABLE II: List of Songs From Province of ACEH (Continued)

Song Name	
Bungong Jeumpa	Sulouh
Bungong Seulanga	Tanpa Judul
Ceptaan Tuhan	Tari Saman
Dibabah Pino	Tari Seudati
Engat Keuh Ensan	Tarian Laweut
Hudep Meusampee	Tawar Sedenge
Meukeumat Gaseh	Tueng Seumangat

TABLE III: List of Songs From Province of JABAR

Song Name	
Adumanis	Colenak
Amplop Biru	Degung Ayun Kaheman
Angle	Deungkleung
Banondari	Duh Indung
Beuger Pakokolot	Jeruk Manis
Daun Pulus Lalambaran	Kembang Bungur
Jatining Hirup	Kukupu
Kalangkang Heulang	Kumalayang
Karumaosan	Ngalagena
Kembang Goyang	Nyawang Bulan
Kembang Ros Bodas	Nyoreang Katukang
Nikmat Duriat	Pegat Duriat
Panggeuing Batin	Puspa Jala
Pucuk Cemara	Sarakan Pangbalikan
Remis Janari	Senggot
Rukun Iman	Tamperan Kaheman
Sangsara Dihaja	Tokecang
Sedih Prihatin	Anjeun
Taman Priangan	Dua Saati
Wangsit Siliwangi	Geter Panineungan
Geter Panineungan	Girimis Kasorenakeun
Angin Peuting	Jeruk Manis
Balebat Ngejat	Mojang Bandung
Bubuka Tepang Asih	Budak Leutik Bisa Ngapung
Cianjuran Gunung Sari	Neng Geulis

TABLE IV: List of Songs From Province of JAKARTA

Song Name	
Abang Pulang	Si Denok
Arisan	Sinyo Kemayoran

Continued on next page

TABLE IV: List of Songs From Province of JAKARTA (Continued)

Song Name	
Bini Tua	Sungguh Jauh
Buat Siapa	Tebak Tebakan
Bul Bul Efendi	Tega
Buntut Punya Main	Tukang Jamu
Gampang Gampang Susah	Tuntunan Puasa
Gara Gara Anak	Aturan Asyik
Gurudut	Badminton
Hari Kenangan	Begini Begitu
Helicak	Di Patil Ikan Sembilang
Indung Indung	Disini Aje Timbel
Ingin Kenalan	Hujan Gerimis
Item Manis	Keroncong Kemayoran
Jande Kembang	Kompor Meleduk
Janji Setia	Lampu Merah
Kecil Kecil Kunyit	Minta Duit
Konde Jatuh	Ondel Ondel
Main Congklak	Si Ridon
Main Enjot Enjotan	Surilang
Pasang Koni	Tukang Tuak
Penganten	Sirih Kuning
Perkutut	Gado Gado Jakarta
Petik Kelapa	Jali Jali
Sayang Sayang	Ondel Ondel v2

TABLE V: List of Songs From Province of JATENG

Song Name	
Ayak Ayakan	Ketawang Santimulyo
Ayo Ngguyu	Ketawang Subokastowo
Bengawan Sore	Kembang Kecubung
Bowo Pangkur Banyumasan Itrus Eling Eling	Kecik Kecik
Caping Gunung1	Langit Mendhung
Caping Gunung2	Lelo Ledhung
Caping Gunung3	Lir Ilir
Cublak Cublak Suweng	Mari Kangen
Dadi Ati	Ngimpi
Digilir Cinta	Ngujiwat
Gambang Suling No1	Ojo Sembrono
Gambang Suling No2	Padang Wulan
Gending Dolanan Lelagon Gelang Kalung	Panbuka Prabu Mataram 1978

Continued on next page

TABLE V: List of Songs From Province of JATENG (Continued)

Song Name	
Gending Ketawang Kodok Ngorek	Roso Madu
Gending Ketawang Laras-moyo	Rujak Jeruk
Gending Ketawang Tirto-kencono	Sekar Pucung
Gending Ldr Gleyong	Sido Asih
Gending Ldr Sekartejo	Sido Opo Ora
Gending Ldr Wilujeng	Suwe Ora Jamu
Giwankusuma1 1978	Tak Eling Eling
Giwankusuma2 1978	Tak Enteni
Jaranan	Teh Poci Gula Batu
Ketawang Langengito	Walang Kekek
Ketawang Mijil Wigaringtyas	Wuyung
Kagok Semarang	Yen Ing Tawang

TABLE VI: List of Songs From Province of KALBAR

Song Name	
Alok Galing	Hari Hari Mengumpan Babi
Alon Alon	Jit Thiau Sim
Amoi Kai Thung Khu	Kain Lunggi
Ayo ke Singkawang	Kalau Jodoh Tak Kemana
Bantellan	Kapal Belon
Bie Shuo Wo De Yan Lei Ni Wu Suo Wei	Mesjid Jami
Berantah Mate	Nerapak Tunggol
Binua Garantung	Ng Jung Ji Chim Tui Siong
Bujang dan Dare	Ngabayotn Sabinuo
Bujang Nadi Dare Nandong	Ngapeme
Bubbor Padas	Ngeremo
Batu Ballah	Paguh Benua Borneo
Cemburu Butak	Panton Pinangan
Ci Ci Sun Sun Loi Pai Nyi	Pantun Binua Landak
Ca Uncang	Perau Jukong
Cik Cik Periuk	Pun Khoi Cai Co Ho Phen Jiu
Cinte Kau Duakan	Saerah
Cinte Yang Terlarang	Sambas Kebanjiran
Dara Muning	Sebukit Rama
Dare Si Barang	Senandung Perantau
Galaherang	Si Bukit Rama

Continued on next page

TABLE VI: List of Songs From Province of KALBAR (Continued)

Song Name	
Kalimantan Thi Fong	Sungai Kapuas
Khiu Thien Pok Hiau Khoi Lu	Takkor Tolen
Khon Kia Nyin Ho Sim Kon Ng Cun	Tanda Sambas
Ki Pe Te	Tikannang Urang Tue

TABLE VII: List of Songs From Province of MALUKU

Song Name	
Aniong Mama	Beta Ingin Mau Pulang
Atanase	Buka Pintu
Baku Sayang	Bulan Pake Payung
Bawa Lari Bini	Bumaku
Beta Rindu Ingin Pulang	Goro Goro Ne
Cukup Jua	Hela Rotan
Cuma Par Ale	Hoehate
Gandong EE	Hura Hura Cincin
Ingin Pulang	Kota Ambon
Jinak Merpati	Ladju Ladju
Ka Laut	Nona
Katong Seng Sangka	Nona Manis
Lembe Lembe	Nona Padede
Mangaku Bujang	Ole Ole
Naik Kereta	Ouw Ulat Ee
Ole Sio	Panggajo e Pangganjo
Pangkuan Ibu	Pantai Waijam
Sarjana	Papaceda
Saule	Ramai Dendang
Seng Bisa Pele	Rasa Sayange
Sirimau	Seng Sangka
Su Jodoh	Sioh Mama
Talalu Saki	Suli
Waktu Hujan Sore Sore	Waktu Potong Padi

TABLE VIII: List of Songs From Province of PAPUA

Song Name	
Asa asa Teluk Odori	Yospan
Ayabunara	Angin Tiup Kapas Melayang
Babenasan	Asaibori Kena Duri

Continued on next page

TABLE VIII: List of Songs From Province of PAPUA (Continued)

Song Name	
Biak Kota Jase	Cincin Emas
Dormomo	E Mambo Simbo
Inseri Swani Wanda	Fyaduru
Insos Rosmina	Jantung Hati
Insoso	Karui Swaf
Juma Kuya	Kasun
Ketika Purnama	Lepas Tangan Dari Cintaku
Mambo Yesina	Mandira
Myos Mandun	Mgun Ido
Myos Soren	No Title
Ori Syun	No Title
Paik Inseri	No Title 1
Permaisuri Padwa	No Title 2
Sanerido	Pengiring Tarian
Srar Yesi	Rostina Yo
Sye Mambesak	Sirawaya
Syo Jauh	Suster Yolanda
Wamo Wambarek	Waisamba No 1
Yado Yaraswan	Waisamba No 2
Yakonda	Wara
Yayun Yarabe	Weri
Yenaiwa	Wonggor Binyeri

TABLE IX: List of Songs From Province of RIAU

Song Name	
Anak Pulau	Makan Sirih
Anak Rengat	Pancaran Senja
Anak Tiung	Penyengat Sayang
Ayam Putih Pungguk	Pulau Bintan
Bakti Riau	Puteri Tujuh
Cik Minah Sayang	Raja dan Dayang
Datin Suri Perdana	Rentak 106
Dedap Durhaka	Seganteng Lade
Hitam Manis	Sekapur Sirih Seulas Pinang
Hujan Malam	Selayang Pandang
Indragiri	Selayang Pandang Ver2
Indragiri Hulu	Sempaya
Joget Anak Kala	Seri Langkat
Joget Karimun	Sri Banang
Junjung Budaya	Sri Deli

Continued on next page

TABLE IX: List of Songs From Province of RIAU (Continued)

Song Name	
Kota Lama	Surga Di Telapak Kaki Ibu
Kota Tanjung Pinang	Syair Melayu
Kuala Deli	Tanjung Katung
Laksamana Raja Di Laut	Timbalan Riau
Lancang Kuning	Tujuh Malam
Lancang Kuning Ver2	Untukmu Kekasih
Lingga Bunda Tanah Melayu	Zapin Anak Negeri
Majulah Kepri	Zapin Batam
Mak Inang Kampung	Zapin Negeri
Mak Inang Pulau Kampai	Zapin Sembulang

TABLE X: List of Songs From Province of SULUT

Song Name	
Ado Sayang	Luri Wisako
Apa Boleh Buat	Mama Papa
Apakan Niko Tare	Mareng Ambenang
Batelpon	Mawole Wole Mokan
Berdoa	Menyesal
Bubur Manado	Miara Si Bujang
Bulan Depan	Nasib Diriku
Bunga Rosi	Niko Mokan
Burung Pisok	Ina Ni Keke
Cintaku	Oh Ina Sa'ku Liniur Numo
Cuma Ngana	Oh Weta
Cuma Sandiwara	Paneselen
Dapa Inga Dulu	Pele Jalanku
Disana Gunung	Pete Cingkeh
E Sayang	Pulang Kampung
Esa Mokan	Roong Sonder
Hatiku Sakit	Sapa Mo Tahang
Ibu	Sapa Suru Datang Jakarta
Ika Genang	Satoro Mama
Jalan Jalan Sepanjang Jalan	So Ada Yang Punya
Kita Mo Tanya	Sumengkor Sepuluh Tahun
Kita Nda Mo Lupa	Tuhan Tolong Hidupku
Kita Ndak Sangka	Tinggal Dikobong
Kita Pe Nasib	Toyope
Lolombulan Manembonembo	Tuan Dan Nyonya

TABLE XI: List of Songs From Province of SUMBAR

Song Name	
Andam Denai	Malereang Tabiang
Andiang	Mudiak Arau
Banda Sapuluah	Ombak Mamatjah
Batang Kampar	Padang Pulau
Badindin	Pariaman Kini
Bapikek Balam	Riak Siboga
Batang Arau	Riak Tanjuang Sani
Bayang Salido	Sungai Pua Baru
Badorai	Taluak Rengat
Buai Anak	Gadih Minang
Bujang Marantau	Tingkuluak Usang
Denai Sansai	Palayaran
Dendang Sayang	Untung Mambaok Jauh
Indang Pariaman	Si Upik Siti Rabiatun
Indang Payakumbuh	Sungayang Baru
Indang Sari Lamak	Parantian Pak Bawang
Indang Singguling	Ranalah Anjuk
Indang Payokumbuah	Ratok Mandeh
Kadja Bakadja	Sayang Ka Uda
Kelok Sambilan	Singgalang Baparak Lobak
Kambanglah Bungo	Singgalang Oyak Kapua
Kamang Bakaju	Sungayang Baru
Kelok Sembilan	Tangih Mande
Lenggang Paninggahan	Tanpa Judul
Lenggang Kursi	Tari Piring

B. Audio Preprocessing

In this part, we did manual preparation for the audio data, this includes converting the audio to mono with a sampling rate of 22 kHz, and also removes the silent part of the sound that found at the beginning and end of the song. In order to get the loudness level at the same level, we do audio normalization with the loudness level set at -16 dB.

C. Audio Segmentation

Audio segmentation is part of preprocessing, which aims to divide the song into small parts. The goal is to group the parts of the song, which have similarities and closeness to each other in the range of time duration in the audio signal. For example, the intro of a song will be different from the outro of a song, so it's better to separate the intro and outro into separate segments.

The song structure generally has sections such as: intro, verse, chorus and outro. But the structure of Indonesian regional songs is different from the structure of songs in general. There are several song from several region, where in the middle of the song, there is a poem. So in order to extract audio features properly and relevant information can be obtained, audio segmentation will be performed in this study.

We do segmentation by spliting the audio file into several parts. In this study, the audio file is divided into 20 parts or we can call segment and then for each segment, we only take the first 10 seconds of the audio signal, which we marked with a green dotted box that can be seen visually in Fig.2.

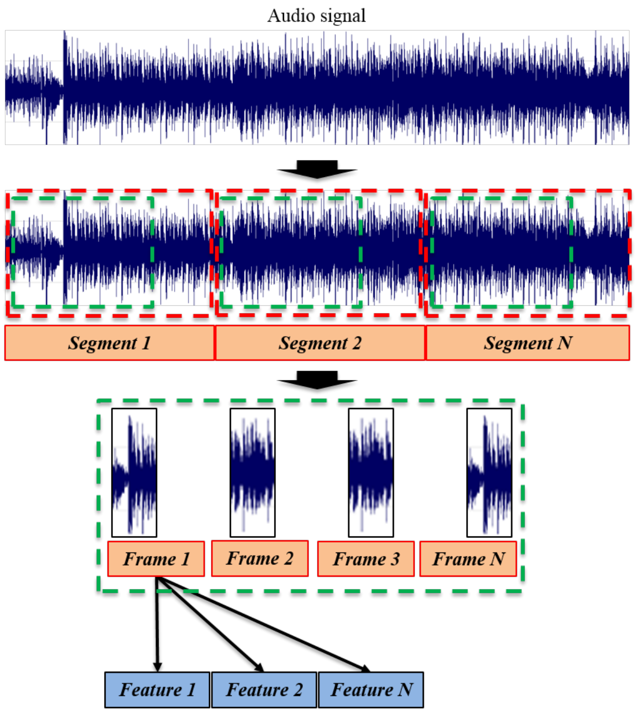

Figure 2. Audio segmentation for Indonesia regional songs

After the audio file has been divided into several segment, we calculate the number of frames that found in that segment. For each frame, we perform the required feature extraction. By segmenting the song, the information contained in it can be retrieved evenly.

The algorithm for audio segmentation that we use, is describe it as follows:

```
audio_data <- load audio_file.mp3
number_of_segment <- a
segment_duration <- m
audio_chunk <- len(audio_data)/number_of_segment
audio_segment <- []
counter <- 0
for x in range (number_of_segment) then
   counter <- audio_chunk * (x+1)
   audio_segment_temp <- audio_data[:counter]
   if (x == 0):
       audio_segment[x] <- audio_segment_temp[:counter]
       audio_segment[x] <- audio_segment[x][:segment_duration]
   end if
   if (x != 0):
       audio_segment[x] <- audio_segment_temp[-counter:]
       audio_segment[x] <- audio_segment[x][:segment_duration]
   end if
end for
end
```

D. Feature Extraction

The purpose of feature extraction is to get the statistical value of each existing feature, so that it can be used at later stage in classification or clustering. In this study we use overlapping frames method for feature extraction. We set the windowing size to 0.050 msec, and the windowing step value to 0.025 msec.

For window functions, the hamming window coefficients is used. Following is the equation:

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

Where N is the length of the filter and k = 0,1,. . . , N-1.

The algorithm for feature extraction that we use, is describe it as follows:

```
audio_features <- [list_of_audio_feature]
extracted_features <- []
feature_value <- []
frame_features <- []
window_size <- d
window_steps <- e
feature_average_value <- []
number_of_segment <- a
audio_segment <- []
for x in range (number_of_segment) then
  audio_segment[x] <- computeAudioSegment
  audio_frames <- computeAudioFrame (audio_segment[x])
  for p in (audio_frames) then
    for t in (audio_features) then
        feature_value <- computeFeature (window_size,
                 window_steps, audio_features[t],
                audio_frames[p], audio_segment[x])
        extracted_features[t] <- append(feature_value)
    end for
    frame_features[p] <- append(extracted_features[t])
  end for
  feature_average_value[x] <- append(average
                                  (frame_features[p]))
end for
end
```

A total of 67 features were extracted for the creation of this dataset. We use features based on time domain and frequency domain. PyAudioAnalysis [27] was used for features extraction. For more details about the features that we use in this dataset, we show in the table XII:

TABLE XII: Features List

Feature Name	Domain	Dimensions
Energy	Time	2
Energy Entrophy		2
Zero Crossing Rate (ZCR)		2
Spectral Centroid	Frequency	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, this feature is used to estimate loudness and as an indicator for new events in audio segmentation. Energy entrophy can be interpreted as a change that occurs spontaneously or suddenly.

Zero Crossing Rate (ZCR) is measures the rate of change of the amplitude value, over a certain period of time in a section or frame. ZCR can be interpreted as a measure of the noise of a signal.

Spectral centroid is the center of gravity of the magnitude spectrum, that is the frequency band in which most of the energy is concentrated. Can be used to measure the ”brightness” of a sound and relates to the timbre of music.

Spectral spread is a derivative of the spectral centroid, which can be interpreted as the variance of the average frequency in the signal. Spectral entropy is used to measure the size of the distribution of power or spectral power. Spectral flux is used to describe the change in power or power spectrum successively between each frame.

Spectral Rolloff is defined as the frequency below a certain percentage of the magnitude distribution of the concentrated spectrum. Can be used to distinguish certain parts contained in music.

Mel Frequency Ceptral Coefficients (MFCC) is a spectrum representation where the frequency band is not linear but is distributed according to the Mel scale. Chroma is representation of the scale of the tone according to western music standards.

4. RESULT

This dataset has 71 columns and there are 500 records. The data type used in this dataset is float64, except for ”Artist”, "Song_Name", and ”Region”, the data type used is string. There are no data with NULL values in this dataset. We display the results of this dataset, with an explanation of the columns that used in this dataset, divided into two tables. Table XIII explain about features variables, while table XIV explain about target variables.

TABLE XIII: Features Variables

Column	Description	Example
ZCR_mean	The mean value of ZCR.	0.08994
Energy_mean	The mean value of energy.	0.11974
Energy_Entropy_mean	The mean value of energy entropy.	3.15201
Spectral_Centroid_mean	The mean value of spectral centroid.	0.18227
Spectral_Spread_mean	The mean value of spectral spread.	0.19968
Spectral_Entropy_mean	The mean value of spectral entropy.	0.69706

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TABLE XIII: Features Variables (Continued)

Column	Description	Example
Spectral_Flux_mean	The mean value of spectral flux.	0.00397
Spectral_Rolloff_mean	The mean value of spectral rolloff.	0.19464
Mfcc1_mean	The mean value of mfcc1.	-22.02289
Mfcc2_mean	The mean value of mfcc2.	1.40641
Mfcc3_mean	The mean value of mfcc3.	0.03916
Mfcc4_mean	The mean value of mfcc4.	0.29722
Mfcc5_mean	The mean value of mfcc5.	0.23777
Mfcc6_mean	The mean value of mfcc6.	0.14408
Mfcc7_mean	The mean value of mfcc7.	0.10514
Mfcc8_mean	The mean value of mfcc8.	-0.38933
Mfcc9_mean	The mean value of mfcc9.	-0.04098
Mfcc10_mean	The mean value of mfcc10.	0.0192
Mfcc11_mean	The mean value of mfcc11.	-0.07619
Mfcc12_mean	The mean value of mfcc12.	0.10236
Mfcc13_mean	The mean value of mfcc13.	0.10285
Chroma1_mean	The mean value of chroma1.	0.01512
Chroma2_mean	The mean value of chroma2.	0.00405
Chroma3_mean	The mean value of chroma3.	0.03087
Chroma4_mean	The mean value of chroma4.	0.00748
Chroma5_mean	The mean value of chroma5.	0.01925
Chroma6_mean	The mean value of chroma6.	0.02703
Chroma7_mean	The mean value of chroma7.	0.0161
Chroma8_mean	The mean value of chroma8.	0.00732
Chroma9_mean	The mean value of chroma9.	0.01149

Continued on next page

TABLE XIII: Features Variables (Continued)

Column	Description	Example
Chroma10_mean	The mean value of chroma10.	0.01461
Chroma11_mean	The mean value of chroma11.	0.03957
Chroma12_mean	The mean value of chroma12.	0.00646
Chroma_Deviation_mean	The mean value of chroma deviation.	0.02187
ZCR_std	The standard deviation value of ZCR.	0.03118
Energy_std	The standard deviation value of energy.	0.07864
Energy_Entropy_std	The standard deviation value of energy entropy.	0.14911
Spectral_Centroid_std	The standard deviation value of spectral centroid.	0.04734
Spectral_Spread_std	The standard deviation value of spectral spread.	0.02687
Spectral_Entropy_std	The standard deviation value of spectral entropy.	0.4102
Spectral_Flux_std	The standard deviation value of spectral flux.	0.00375
Spectral_Rolloff_std	The standard deviation value of spectral rolloff.	0.07461
Mfcc1_std	The standard deviation value of mfcc1.	1.70473
Mfcc2_std	The standard deviation value of mfcc2.	0.81659
Mfcc3_std	The standard deviation value of mfcc3.	0.68592
Mfcc4_std	The standard deviation value of mfcc4.	0.55571
Mfcc5_std	The standard deviation value of mfcc5.	0.45627
Mfcc6_std	The standard deviation value of mfcc6.	0.3743

Continued on next page

TABLE XIII: Features Variables (Continued)

Column	Description	Example
Mfcc7_std	The standard deviation value of mfcc7.	0.32098
Mfcc8_std	The standard deviation value of mfcc8.	0.33951
Mfcc9_std	The standard deviation value of mfcc9.	0.37378
Mfcc10_std	The standard deviation value of mfcc10.	0.27536
Mfcc11_std	The standard deviation value of mfcc11.	0.27851
Mfcc12_std	The standard deviation value of mfcc12.	0.27793
Mfcc13_std	The standard deviation value of mfcc13.	0.31066
Chroma1_std	The standard deviation value of chroma1.	0.01615
Chroma2_std	The standard deviation value of chroma2.	0.01148
Chroma3_std	The standard deviation value of chroma3.	0.04623
Chroma4_std	The standard deviation value of chroma4.	0.01507
Chroma5_std	The standard deviation value of chroma5.	0.01906
Chroma6_std	The standard deviation value of chroma6.	0.01484
Chroma7_std	The standard deviation value of chroma7.	0.01725
Chroma8_std	The standard deviation value of chroma8.	0.01302
Chroma9_std	The standard deviation value of chroma9.	0.02042
Chroma10_std	The standard deviation value of chroma10.	0.01371

Continued on next page

TABLE XIII: Features Variables (Continued)

Column	Description	Example
Chroma11_std	The standard deviation value of chroma11.	0.04254
Chroma12_std	The standard deviation value of chroma12.	0.0124

TABLE XIV: Target Variables

Column	Description	Example
Artist	The name of the singer who performed the song.	Ida Widawati
Song_Name	Song title.	Ole Sio
Region	The name of the province of origin of the song.	PAPUA
Tempo	Is the speed of the song when sung. Tempo measure in beats per minute (BPM).	100

5. CONCLUSION

The IRSD is a dataset of Indonesian regional songs that can help researchers to conduct research in the MIR field. This research uncovers barriers to the need for a publicly accessible regional song dataset originating from Indonesia.

For researchers in the MIR field who are interested in using this dataset, it can be accessed publicly at (without quotes): "https://www.kaggle.com/datasets/ferdym/irsd-indonesian-regional-song-dataset".

During the process of creating this dataset, we learned that there are many regional songs from various regions in Indonesia that we have not been able to make into a dataset, but we hope that in future research, we can develop this research by increasing the number of regional songs, so that it can enrich research in this field.

References

[1] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein *et al.*, "Imagenet large scale visual recognition challenge," *International journal of computer vision*, vol. 115, no. 3, pp. 211–252, 2015.

[2] R. Rothe, R. Timofte, and L. Van Gool, "Deep expectation of real and apparent age from a single image without facial landmarks," *International Journal of Computer Vision*, vol. 126, no. 2, pp. 144–157, 2018.

[3] T.-Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, P. Dollár, and C. L. Zitnick, "Microsoft coco: Common objects in context," in *European conference on computer vision*. Springer, 2014, pp. 740–755.

[4] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, “Gradient-based learning applied to document recognition,” *Proceedings of the IEEE*, vol. 86, no. 11, pp. 2278–2324, 1998.

[5] D. Dua and C. Graff, “UCI machine learning repository,” 2017. [Online]. Available: http://archive.ics.uci.edu/ml

[6] A. Babayan, M. Erbey, D. Kumral, J. D. Reinelt, A. M. Reiter, J. Röbbig, H. L. Schaare, M. Uhlig, A. Anwander, P.-L. Bazin *et al.*, “A mind-brain-body dataset of mri, eeg, cognition, emotion, and peripheral physiology in young and old adults,” *Scientific data*, vol. 6, no. 1, pp. 1–21, 2019.

[7] J. W. Smith, J. E. Everhart, W. Dickson, W. C. Knowler, and R. S. Johannes, “Using the adap learning algorithm to forecast the onset of diabetes mellitus,” in *Proceedings of the annual symposium on computer application in medical care*. American Medical Informatics Association, 1988, p. 261.

[8] K. Markov and T. Matsui, “Music genre and emotion recognition using gaussian processes,” *IEEE access*, vol. 2, pp. 688–697, 2014.

[9] C. Senac, T. Pellegrini, F. Mouret, and J. Pinquier, “Music feature maps with convolutional neural networks for music genre classification,” in *Proceedings of the 15th international workshop on content-based multimedia indexing*, 2017, pp. 1–5.

[10] S. Oramas, F. Barbieri, O. Nieto Caballero, and X. Serra, “Multimodal deep learning for music genre classification,” *Transactions of the International Society for Music Information Retrieval. 2018; 1 (1): 4-21.*, 2018.

[11] M. Jakubec and M. Chmulik, “Automatic music genre recognition for in-car infotainment,” *Transportation Research Procedia*, vol. 40, pp. 1364–1371, 2019.

[12] F. Mahardhika, H. L. H. S. Warnars, Y. Heryadi *et al.*, “Indonesian’s dangdut music classification based on audio features,” in *2018 Indonesian association for pattern recognition international conference (INAPR)*. IEEE, 2018, pp. 99–103.

[13] F. Zhang, H. Meng, and M. Li, “Emotion extraction and recognition from music,” in *2016 12th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD)*. IEEE, 2016, pp. 1728–1733.

[14] S. Kwon, “A cnn-assisted enhanced audio signal processing for speech emotion recognition,” *Sensors*, vol. 20, no. 1, p. 183, 2019.

[15] R. Panda, R. Malheiro, and R. P. Paiva, “Novel audio features for music emotion recognition,” *IEEE Transactions on Affective Computing*, vol. 11, no. 4, pp. 614–626, 2018.

[16] T.-A. Anderson, “Musical instrument classification utilizing a neural network,” in *2017 12th International Conference on Computer Science and Education (ICCSE)*. IEEE, 2017, pp. 163–166.

[17] M. Mitrovic and M. Misic, “Classification of musical instruments with convolutional neural networks,” in *2018 26th Telecommunications Forum (TELFOR)*. IEEE, 2018, pp. 1–4.

[18] J. Li, J. Luo, J. Ding, X. Zhao, and X. Yang, “Regional classification of chinese folk songs based on crf model,” *Multimedia tools and applications*, vol. 78, no. 9, pp. 11 563–11 584, 2019.

[19] N. Hewahi, S. AlSaigal, and S. AlJanahi, “Generation of music pieces using machine learning: long short-term memory neural networks approach,” *Arab Journal of Basic and Applied Sciences*, vol. 26, no. 1, pp. 397–413, 2019.

[20] T. Bertin-Mahieux, D. P. Ellis, B. Whitman, and P. Lamere, “The million song dataset,” 2011.

[21] G. Tzanetakis and P. Cook, “Musical genre classification of audio signals,” *IEEE Transactions on speech and audio processing*, vol. 10, no. 5, pp. 293–302, 2002.

[22] J. Salamon, C. Jacoby, and J. P. Bello, “A dataset and taxonomy for urban sound research,” in *Proceedings of the 22nd ACM international conference on Multimedia*, 2014, pp. 1041–1044.

[23] C. Donahue, H. H. Mao, and J. McAuley, “The nes music database: A multi-instrumental dataset with expressive performance attributes,” *arXiv preprint arXiv:1806.04278*, 2018.

[24] D. Makris, I. Karydis, and S. Sioutas, “The greek music dataset,” in *Proceedings of the 16th International Conference on Engineering Applications of Neural Networks (INNS)*, 2015, pp. 1–7.

[25] M. Defferrard, K. Benzi, P. Vandergheynst, and X. Bresson, “Fma: A dataset for music analysis,” *arXiv preprint arXiv:1612.01840*, 2016.

[26] S. R. Livingstone and F. A. Russo, “The ryerson audio-visual database of emotional speech and song (ravdess): A dynamic, multimodal set of facial and vocal expressions in north american english,” *PloS one*, vol. 13, no. 5, p. e0196391, 2018.

[27] T. Giannakopoulos, “pyaudioanalysis: An open-source python library for audio signal analysis,” *PloS one*, vol. 10, no. 12, p. e0144610, 2015.

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