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CRISP-DM Method for Mood Classification in Indonesian Music 70 and 80 era

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***Abstract*— Large data processing is usually called a database. Databases in computer science often use the CRIS-DM method. This method has been around for 20 years. This method consists of several stages, namely business understanding, data understanding, data preparation, modeling, evaluation, deployment. This method is very suitable for processing data of more than 1000 cells. The data used is Indonesian music data from the era of 70 and 80. This data also only takes the chorus part because the implied message is conveyed in the chorus. The results of this study are the classification of music using the CRISP-DM method with categories of sad, happy and neutral.**

***Keywords*— Indonesian Music, , Mood, CRISP-DM**

INTRODUCTION

Listening to music is an activity that is mostly done by the community [1]. Music knows no age, beautiful music in all circles and every human being must love music. Music is something that cannot be separated from life itself [2]. The song gives the beauty of music lovers [3]. Mood is inseparable from music, a slow tempo can produce peace of mind. On the other hand, a depressed atmosphere can be produced from fast and loud music [4]. Multimodal representations such as audio, symbols, text (lyrics), images (images) and performances of musicians can be used as datasets [5]. Computer science on dataset processing in the form of lyrics and audio. the lyrics are stored in excel into a database. The audio is only taken from the chorus, processed by .wav using machine learning. It is possible to process large data using the CRISP-DM method..

LITERATURE RIVIEW

A.. Sound and Lyrics

The sound element is an important thing in music [6]. This element affects the quality of the music listened to [7]. Many studies in the field of analysis and modeling of musical sound [8]. Sound texture as a feature for visualizing and analyzing music [9]. So it is necessary to label the sound features with good and bad labels [10].

Lyrics are elements of a song in the form of an arrangement of words made for a musical composition. The lyrics in a song are a means to channel the songwriter's feelings or mood [11] so that every meaning in a lyric makes the song more lively [12]. Lyrics are one of the most important aspects of vocal music [13]. Some music researchers consider the lyrics of a song to be related to emotions, moods and musical genres [14]. Song lyrics are an important source of information about music [15]. Lyrics have also been shown to be a prominent musical component in listeners' minds [16]. Lyrics are essentially an expression of music creators using language that has similarities to musical elements such as pitch (pitch), duration (length), loudness (loundness) [17]. Many Indonesian music has a uniqueness in the lyrics of the songs they create with impressive delivery. Each type of music has its own characteristics and character to attract listeners [18]. Lyrics that are easy to understand for music listeners will make it easier for listeners to understand music; on the other hand, lyrics that are not easily understood by music listeners will cause listeners to not easily understand music [19]. In fact, several studies have concluded that music lyrics affect the sense of hearing when listening to the music [20].

Music can be viewed as a "document" that is conveyed through text and musical accompaniment that contains the story and "mood" that the songwriter wants to convey.

Based on a study of the content, there are five divisions of music [21]

a) *Intro:* usually the first 5-20 seconds usually do not contain song lyrics but only the sound of musical instruments as an opening;

b) *Verse:* the beginning of the main story in the lyrics of the song;

c) *Chorus (chorus):* the part that is repeated contains the essence of the song's lyrics;

d) *Bridge:* the 2/3rd part of the song is the closing part of the lyrics accompanied by music with changing tempos;

e) *Outro:* the end of the song usually does not contain lyrics but is a repetition of the sound of the instrument as a closing song

B. Mood on Music

Musical mood is the mood of music listeners caused by listening to the music. At this time the labeling (category) of mood on music is done manually by music experts after listening to the music. The rapidly increasing volume of music data from various genres makes labeling music categories inefficient. Therefore, a method that can be used to automatically label music moods into several categories is needed to support the production process and music analysis. One method of automatically classifying musical moods is using a machine learning model that is trained in a supervised manner with the input of a number of samples that have been manually labeled with musical moods. Each music sample used as training data is represented by several musical features. The training model is then used to predict the mood category of the music sample that does not have a musical mood label [22]. The mood categories used in labeling music can be seen in Table 2.2. In general, musical moods can be grouped into positive and negative moods. Furthermore, the category of positive mood can be further divided into several sub-moods from the highest level (excited) to the lowest (calm). Likewise, the negative mood category can be further divided into several sub-moods from the highest level (annoying) to the lowest (sleepy) [23][24]

TABLE 1.
MOOD GROUPING [23]

Category	Positive	Negative
High	Excited, Happy, Pleased	Annnoying, Angry, Nervous
Low	Relaxed, Peaceful, calm	Sad, Bored, Sleepy

C. CRISP-DM

CRISP-DM (Cross Industry Standard Process For Data Mining) was designed in 1996. CRISP-DM has six phases, namely business understanding, data understanding, data preparation, modeling, evaluation and deployment [25]. CRISP-DM is a complete and well-documented data mining method [26]. This method was adopted as an idea for a project by processing data mining and could also use statistical methods [27] This method is very suitable for processing large data. Where data science is a topic that is quite in demand and is of considerable concern [28].

Besides, CRISP-DM is widely used in various fields of science by clearly defining steps and tasks [29]

RELATED WORKS

Many studies that process large data and use the CRISP-DM method. These studies include data mining to predict the amount of coffee using the CRISP-DM method [30]. This study processed 170 datasets and the RMSE accuracy value was 0.3477. Another study tells about CRISP-DM which has been used for about two decades [31]. Research in the field of music itself uses the Naïve Bayes, K-NN and Random Forest methods with the highest accuracy in Nave Bayes, namely 58.91% [1]. The CRISP-DM method used in the health sector is for example the analysis of medical data without legs using the CRISP model with case studies of patients without legs [32]. This method is also suitable to be applied in the manufacturing sector with the aim of ensuring quality through the K. Nearest Neighbor classification algorithm [33]. CRISP-DM was used to analyze business data [34]. Corona analysis using the CRISP-DM method through the kaggle dataset [35] and there are many more cases using the CRISP-DM method.

THE PROPOSED MODEL

The stages in this study were adjusted to the stages of the CRISP-DM method [36] with a 6-phase process as shown in Figure 1.

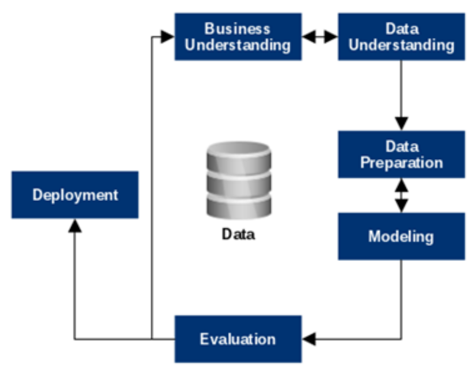

FIGURE 1. CRISP-DM MODEL

In this research, the stages of the method consist of 6 phases of Business Understanding, Data understangding, Data Preparation, Modeling, Evaluation, Deployment. The first phase is an important factor to achieve a success through business goals and requirements. The second phase of data collection. The third phase of data selection or data processing is certain. The fourth phase prepares the modeling technique. The fifth phase is evaluation by considering whether the results have achieved the goals well. The sixth phase is in the form of a final result report [37].

Results And Discussion

The first stage according to the model in Figure 2 is Business Understanding. This stage is done by studying the objectives of the research needs.

FIGURE 2. STAGES OF CRISP-DM MODEL

Where the next step becomes the initial plan to achieve these goals. Some of the research objectives are:

1) Develop the most optimal musical features to represent the mood of music across music genres.
2) Develop a machine learning-based classification model that has the most optimal performance for classifying the mood of music.
3) Selecting the most appropriate classification model performance metric to measure the performance of the mood classification model from the music dataset used.

The music feature that will be used for the classification of mood music is in the form of an audio feature, namely chromagram.. The lyric feature is a distributed document representation (sentence and document embeddings). The music content that will be explored is the chorus section. The target feature used is the mood category of the music in the form of sad and happy and neutral.

The second stage is Data Understanding. At this stage, data collection is carried out to form a dataset. The data collected was categorized by voting with 3 moods, namely sad, happy and neutral. Data collection consists of 2, namely lyric data and audio data. The data is collected manually via youtube. Then the song is converted to mp3 and cut by taking only the chorus. The chorus in the form of lyrics is stored in excel reff audio data is converted. wav. The third stage, namely Data Preparation, this stage the data begins to be processed. The song domains used are songs in Indonesia in the 70s and 80s. The main music samples that were chosen purposively were from the Pop category, namely Chrisye, The Rollies, Fariz RM, Koes Plus and Ballads/Country: such as Ebiet G. Ade, Iwan Fals.

Additional (alternative) music samples that were chosen purposively were from the Rock category, namely Achmad Albar and Dangdut/Malay: Rhoma Irama. The fourth stage is modeling or modeling. Mood classification model to be explored:

The next step is to create a model. Model that refers to the Chorus content or refrain. Where the Lyric feature uses sentence embedding. Audio or melody feature using chromagram. The lyric features are then processed into a text based classification model. Audio or melody is processed into a chromagram based classification model. So the final step is an ensemble based on transformer based Music Classification Mood which is shown in Figure 3

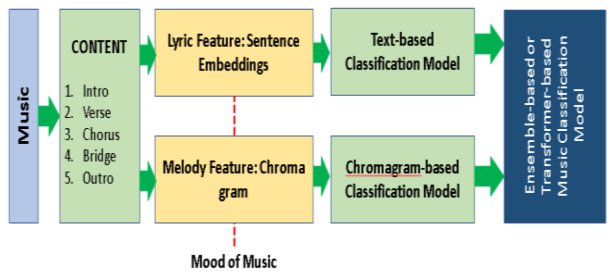

FIGURE 3. MODEL 1 MOOD RESEARCH APPROACH TO MUSIC

The fourth step is evaluation. Evaluation of this paper uses the Confusion matrix. The confusion matrix is another way to present generalization capabilities in more detail. In classification problems, model accuracy is not everything. To see the generalizability of the model, it is not seen in the training data, but in the testing data. Accuracy is how often the model formed can predict a problem correctly. Recall is how well the predictive model recognizes all positive observations. Specificity is how well the model predicts negative observations. Precision is the level of accuracy between the desired information and the answers given by the model. The results of the temporary confusion matrix for lyric data and audio data.

	precision	recall	f1-score	support
netral	0.86	0.77	0.81	120
sedih	0.76	0.76	0.76	120
senang	0.82	0.92	0.87	120
accuracy			0.81	360
macro avg	0.82	0.81	0.81	360
weighted avg	0.82	0.81	0.81	360

FIGURE 4. CONFUSION MATRIX RESULTS FOR LYRIC DATA

	precision	recall	f1-score	support
netral	0.62	0.89	0.73	9
sedih	0.75	0.43	0.55	14
senang	0.71	0.83	0.77	12
accuracy			0.69	35
macro avg	0.69	0.72	0.68	35
weighted avg	0.70	0.69	0.67	35

FIGURE 5. CONFUTION MATRIX RESULTS AGAINST AUDIO DATA

CONCLUSION

The results of the research are the most optimal musical features to represent the mood of music across music genres, namely the lyric feature in the form of text and the audio feature in the form of a chromagram. The machine learning-based classification model that has the most optimal performance for classifying the mood of music is the transformer model. The most appropriate classification model performance metric to measure the performance of the mood classification model from the music dataset used is the Confusion matrix.

REFERENCES

[1] Navisa S, Hakim L, Nabilah A. Komparasi Algoritma Klasifikasi Genre Musik Pada Spotify Menggunakan CRISP-DM. Jurnal Sistem Cerdas Vol. 4 No. 2. 2622-8254.2021.

[2] Dewi, K. C., & Harjoko, A. Kid's song classification based on mood parameters using K-Nearest Neighbor classification method and Self Organizing Map. International Conference on Distributed Frameworks for Multimedia Applications.2010

[3] Wieczorkowska, A., Synak, P., Lewis, R., & W. Raś, Z. Extracting emotions from music data. Foundations of Intelligent Systems, 456–465. https://doi.org/10.1007/11425274_47K. Elissa, "Title of paper if known," unpublished.. 2005

[4] Amirah, M. M. A., Widodo, A. W., & Dewi, C. Grouping Songs Based on Emotions Using Fuzzy Algorithm. Journal of Information Technology and Computer Science Development, Universitas Brawijaya, 1.J. Clerk Maxwell, A Treatise on Electricity and Magnetism, 3rd ed., vol. 2. Oxford: Clarendon, 1892, pp.68–73. 2017.

[5] Schedl, M., Gómez, E., & Urbano, J. Music Information Retrieval: Recent Developments and Applications. Foundations and Trends® in Information Retrieval (Vol. 8). https://doi.org/10.1561/1500000042. 2014.

[6] Song, H., W. Lin, Y. Lin, A.B. Wolf, R. Neggers, L.J. Donner, A.D. Del Genio, and Y. Liu, 2013: Evaluation of precipitation simulated by seven SCMs against the ARM observation at the SGP site. J. Climate, 26, 5467-5492, doi:10.1175/JCLI-D-12-00263.1

[7] Rentfrow, P. J., Goldberg, L. R., & Levitin, D. J. (2011). The structure of musical preferences: A five-factor model. Journal of Personality and Social Psychology, 100(6), 1139–1157. https://doi.org/10.1037/a0022406

[8] Frisson C, Dupont S, Yvart W, Riche N, Siebert X, Dutoit T. A Proximity Grid Optimization Method To Improve Audio Search For Sound Design. 15th International Society for Music Infrmation Retrieval Conference (ISMIR 2014)

[9] Strobl G, Eckel G, Rocchesso D. 2020. Sound Texture Modeling: A Survey. Sound Music Computing. https://hal.archives-ouvertes.fr/hal-03013639

[10] Bandiera G, Picas OR, Tokuda H. 2016. Good-Sounds.org: A Framework to Explore Goodness in Instrumental Sounds. Proceedings of the 17th ISMIR Conference, New York City, USA. https://good-sounds.org.

[11] Putri AA, Astri ND,Simanullang RSP, Tanjung T. 2007. Analisis Gaya Bahasa Dalam Lirik Lagu Fourtwnty: Kajian Stilistika. Jurnal Pendidikan Bahasa dan sastra Indo.nesia. 2614-4743

[12] Sudjiman, Panuti. 1993. Bunga Rampai Stilistik. Jakarta: Pustaka Utama Grafiti.

[13] Dzhambazov G, Srinivasamurthy A, Senturk S, Serra X. 2016. On The Use of Note Onset for Improved Lyrics-to-Audio Alignment in Turkish Makam Music. Proceedings of the 17th ISMIR Conference.

[14] Sasaki S, Yoshii K, Nakano T, Goto M, Morishima S. 2014. Lyricsradar: A Lyrics Retrieval System Based on Latent Topics of Lyrics. 15th International Society for Music Information Retrieval Conference ISMIR 2014.

[15] Kim J, Demetriou AM, Monolius S. 2020. Butter Lyrics Over Hominy Grit: Comparing Audio and Psychology-Based Text Features in MIR Tasks. Proceedings of the 21st ISMIR Conference.

[16] A. Demetriou, A. Jansson, A. Kumar, and R. M. Bittner. 2018. "Vocals in music matter: the relevance of vocals in the minds of listeners," in Proceedings of the 19th International Society for Retrieval Conference, ISMIR 2018, Paris, France, September 23-27, E. Gómez, X. Hu, E. Humphrey, and E. Benetos, Eds., 2018, pp. 514–520

[17] Suharto. S. 2011. Music And Language: A Stress Analysis of English Song Lyrics. Harmonia: Journal of Arts Research And Education. doi:http://dx.doi.org/10.15294/harmonia.v5 i3.821

[18] Purba, Antilan. 2009. Stilistika Sastra Indonesia Kajian Bahasa Karya Sastra. Medan: USU Press.

[19] brahim KM, Grunbrg D, Agres K, Gupta C, Wang Y. 2017. Intelligibility of Sung Lyrics: A Pilot Study. Proceeding of The 18th ISMIR Conference.

[20] Mori Kazuma and Makoto Iwanaga. 2014. Pleasure generated by sadness: Effect of sad lyrics on the emotions induced by happy music. Psychology of Music, 42(5).

[21] Tsai, W.H., Yu, H.M., Wang, H.M. and Horng, J.T., 2008. Using the Similarity of Main Melodies to Identify Cover Versions of Popular Songs for Music Document Retrieval. Journal of Information Science & Engineering, 24(6).

[22] Panda RES. 2019. Emotion Based Analysis and Classification of Audio Music. Thesis.Institution granting the academic degree: University of Coimbra, Faculty of Sciences and Technology.

[23] R. E. Thayer.1989. The Biopsychology of Mood and Arousal. New York, Ny: Oxford University Press.

[24] Bhattarai B and Lee J.2019. Automatic Music Mood Detection Using Transfer Learning and Multilayer Perceptron. International Journal of Fuzzy Logic and Intelligent Systems 2019;19(2):88-96

[25] Ayele WY. Adapting CRISP-DM For Idea Mining. INternational Journa of Advanced Computer Science and Application. Vol. 11, No. 6. 2020

[26] Darmawan T, Birawa AS, Eryanto E, Mauritsius T. Credit Classification Using CRISP-DM Method On Bank ABC Customers. Internationa; Journal of Emerging Trends in Engineering Research. Vol. 8. No. 6: 2347 - 3983. 2020

[27] Sharer C. The CRISP-DM Model:The New Blueprint for Data Mining. Journal of Data warehousing. Volume 5 Number 4. 2000

[28] Schröer C,Kruse F,Gómez JM. A Systematic Literature Review on Applying CRISP-DM Process Model. Prodecia Computer Science. vol 1:526-534. 2021

[29] CAZACU M, TITAN E. Adapting CRISPDM for Social Sciences. BRAIN. Broad Research In Artificial Intelligence and Neuroscienc. Volume 11: 2068-0473. 2020

[30] Khumaidi A. Data Mining For Predicting The Amount of Coffee Production using CRISO-DM Method. Jurnal Techno Nusa Mandiri Vol. 187, No. 1.2020

[31] Plumed FM, Ochando LC,Ferri C, Orallo JH, Kull M, Lachiche N, Quintana MJR, Flach P. CRISP-DM Twenty Years Later: From Data Mining Processes to Data Science Trajectories.IEEE Transaction on Knowledge and Data Engineering. 2020

[32] Alden ZS, Mousa AH. Limbless Medical Data Analyzing Using CRISP Model a Case Study of UK Limbless Patient. International Journal Of Engineering & Technology. 7 (4.19) 806-811. 2018.

[33] Huber S, Wiemer H, Schneider D, Ihlenfeldt S. DMME: Data mining methodology for engineering applications a holistic extension to the CRISP-DM model. 12th CIRP Conference on Intelligent Computation in Manufacturing Engineering. Procedia CIRP. 403–408: 2212-8271. 2018

[34] Exenberger E, Bucko J. Analysis of Online Consumer Behavior - Design of CRISP-DM Process Model. Agri on-line Papers in Economics and Informatics. Vol. 12 No. 3:1804-1930. 2020

[35] Rivai MA, Sfenrianto. Analysis of Coronavirus Spreading Uses The CRISP-DM as A Framework: Predictive Modelling. International Journal of Advanced Trends in Computer Science and Engineering. Volume 9, No.3 : 2278-3091. 2020

[36] Wirth, Rüdiger, and Jochen Hipp. "CRISP-DM: Towards a standard process model for data mining." In Proceedings of the 4th international conference on the practical applications of knowledge discovery and data mining, vol. 1, pp. 29-40. 2000.

[37] Shafique U and Qaiser. A Comparative Study of Data Mining Process Models (KDD, CRISP-DM and SEMMA). International Journal Of Innovation and Scientific Research No. 1 Vol. 12: 2351-8014. 2014

[38] Giri, K. C., Patel, M., Sinhal, A., & Gautam, D. (2019, April). A novel paradigm of melanoma diagnosis using machine learning and information theory. In 2019 International Conference on Advances in Computing and Communication Engineering (ICACCE) (pp. 1-7). IEEE.

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