Analyzing Emotional Responses through Sinhala Comments on Sinhala Music: A Dataset Study

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Research Supervisor - Dr. Nisansa de Silva

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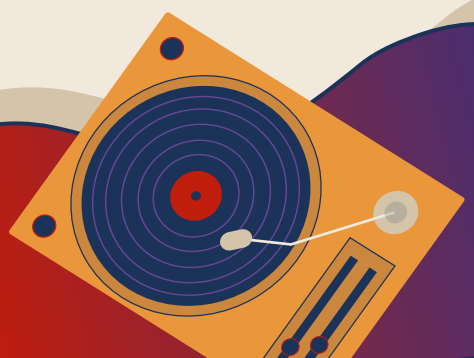


01

Introduction

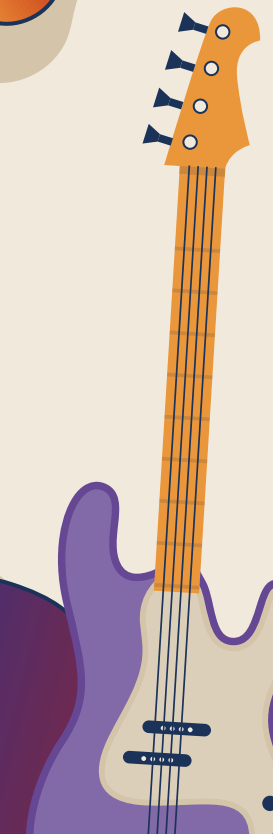
Introduction

- **Music Information Retrieval (MIR)** is the field concerned with extracting, analyzing, and understanding information from music data [1]
- **Music Emotion Recognition (MER)** is a subfield of **MIR** that focuses on the development of computational methods for the automatic identification and analysis of the emotional content present in music applying machine learning and signal processing techniques [2].
- The objective of MER is to *enable* the recognition and response to the emotional distinctions of music [3].
- MER represents a growing area of research at the intersection of musicology, psychology,and computational science [4].
- The pursuit of MER is deeply rooted in the historical and theoretical exploration of the relationship between music and emotions. From the ancient Greeks' belief in the emotive power of music to the modern-day endeavours of psychologists and musicologists [5].

[1] C. Plachouras, P. Alonson-Jiménez, and D. Bogdanov, "mir_ref: A representation evaluation framework for music information retrieval tasks," arXiv preprint arXiv:2312.05994, 2023.
[2] S. Hizlisoy, S. Yildirim, and Z. Tufekci, "Music emotion recognition using convolutional long short term memory deep neural networks," Engineering Science and Technology, an International Journal, vol. 24, no. 3, pp. 760–767, 2021.
[3] Y. E. Kim, E. M. Schmidt, R. Migneco, B. G. Morton, P. Richardson, J. Scott, J. A. Speck, and D. Turnbull, "Music emotion recognition: A state of the art review," in Proc. ismir, vol. 86, 2010, pp. 937–952.
[4] Y. Deldjoo, M. Schedl, and P. Knees, "Content-driven music recommendation:Evolution, state of the art, and challenges," arXiv preprint arXiv:2107.11803, 2021.
[5] Y.-H. Yang and H. H. Chen, "Machine recognition of music emotion: A review,"ACM Transactions on Intelligent Systems and Technology (TIST), vol. 3, no. 3, pp. 1–30, 2012.

02

Related Work



Related Work

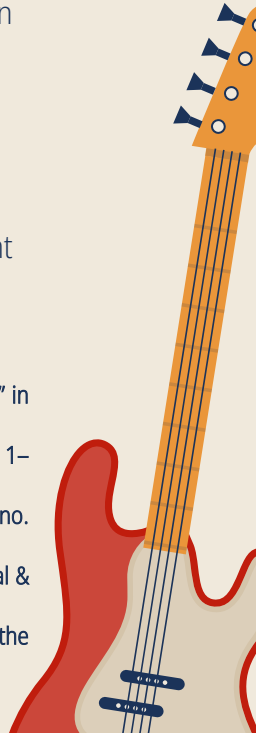
Importance of MER Studies

- Importance lies in its potential to deepen our understanding of the emotional aspects of music, enhance user experiences, and contribute to the development of emotionally intelligent technologies [2].
- MER can inform personalized music recommendations, contribute to affective computing [3].
- Extensive research spanning fields such as medicine, neuroscience, psychology, and music consistently attests to the efficacy of music therapy across a spectrum of populations, including medical, psychiatric, and sub-clinical settings [6, 7].
- In conjunction with these clinical applications, music has various applications for emotion regulation in everyday life [8].

[2] S. Hizlisoy, S. Yildirim, and Z. Tufekci, "Music emotion recognition using convolutional long short term memory deep neural networks," Engineering Science and Technology, an International Journal, vol. 24, no. 3, pp. 760–767, 2021.
[3] Y. E. Kim, E. M. Schmidt, R. Migneco, B. G. Morton, P. Richardson, J. Scott, J. A. Speck, and D. Turnbull, "Music emotion recognition: A state of the art review," in Proc. ismir, vol. 86, 2010, pp. 937–952.
[6] K. R. Agres, R. S. Schaefer, A. Volk, S. van Hooren, A. Holzapfel, S. Dalla Bella, M. Müller, M. De Witte, D. Herremans, R. Ramirez Melendez et al., "Music, computing, and health: a roadmap for the current and future roles of music technology for health care and well-being," Music & Science, vol. 4, p.2059204321997709, 2021.
[7] D. Han, Y. Kong, J. Han, and G.Wang, "A survey of music emotion recognition," Frontiers of Computer Science, vol. 16, no. 6, p. 166335, 2022.
[8] M. V. Thoma, S. Ryf, C. Mohiyeddini, U. Ehlert, and U. M. Nater, "Emotion regulation through listening to music in everyday situations," Cognition & emotion, vol. 26, no. 3, pp. 550–560, 2012.

Related Work
Challenges in MER Studies

- Cross-cultural differences in music perception and emotional expression can have significant implications for MER [9].
- Cultural differences in musical training and exposure can affect the ability to recognize and express emotions in music [3].
- Subjective perception of emotions, making consensus on recognition results difficult [5, 10, 11].
- Significant challenges lie in acquiring reliable emotion annotations essential for training and evaluation [11].
- The absence of a standardized annotation protocol further complicates the comparison and evaluation of different MER systems [5, 10].



[3] Y. E. Kim, E. M. Schmidt, R. Migneco, B. G. Morton, P. Richardson, J. Scott, J. A. Speck, and D. Turnbull, “Music emotion recognition: A state of the art review,” in Proc. ismir, vol. 86, 2010, pp. 937–952.
[5] Y.-H. Yang and H. H. Chen, “Machine recognition of music emotion: A review,”ACM Transactions on Intelligent Systems and Technology (TIST), vol. 3, no. 3, pp. 1–30, 2012.
[9] X. Wang, Y. Wei, and D. Yang, “Cross-cultural analysis of the correlation between musical elements and emotion,” Cognitive Computation and Systems, vol. 4, no. 2, pp. 116–129, 2022.
[10] F. H. Rachman, R. Sarno, and C. Fatichah, “Music emotion classification based on lyrics-audio using corpus based emotion.” International Journal of Electrical & Computer Engineering (2088-8708), vol. 8, no. 3, 2018.
[11] Y. S. Can, B. Mahesh, and E. André, “Approaches, applications, and challenges in physiological emotion recognition—a tutorial overview,” Proceedings of the IEEE, 2023.

Related Work

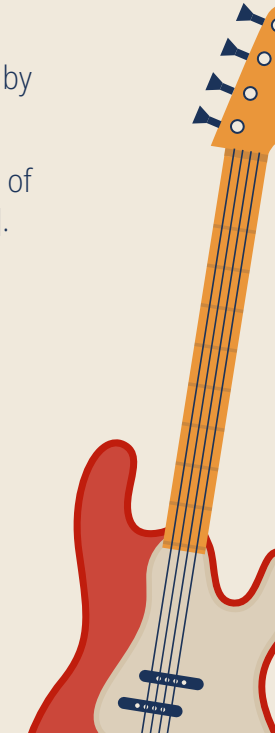
Emotion Categorization in Music Psychology [7, 12]

- The classification of emotions has long been debated within psychological research, primarily revolving around two prominent models.
  - *Categorical Model*
  - *Dimensional Model*
- Categorical models advocate for discrete classification, delineating emotions into distinct categories such as happiness, sadness, anger, fear, and disgust.
- Dimensional models propose a continuum-based classification, emphasizing valence (positive/negative) and arousal (high/low) as core dimensions for describing emotions.

[7] D. Han, Y. Kong, J. Han, and G.Wang, “A survey of music emotion recognition,” Frontiers of Computer Science, vol. 16, no. 6, p. 166335, 2022.
[12] X. Hu, J. S. Downie, and A. F. Ehmann, “Lyric text mining in music mood classification,” American music, vol. 183, no. 5,049, pp. 2–209, 2009.

Related Work
Categorical Model

- Emotion categorization model introduced by Hevner is a systematic approach to understanding the affective value and expressiveness of music through the categorization of adjectives based on their feeling-tone [13].
- Arrange adjectives into groups that share similar emotional characteristics [13].
- This arrangement allows for a comprehensive and nuanced understanding of the emotional nuances conveyed by music [7, 12].
- This approach not only simplifies the analysis of emotional content in music but also facilitates the comparison of results across various compositions, contributing to a deeper understanding of the affective value of music [7, 12].



[7] D. Han, Y. Kong, J. Han, and G.Wang, "A survey of music emotion recognition," Frontiers of Computer Science, vol. 16, no. 6, p. 166335, 2022.
[12] X. Hu, J. S. Downie, and A. F. Ehmann, "Lyric text mining in music mood classification," American music, vol. 183, no. 5,049, pp. 2–209, 2009.
[13] K. Hevner, "Experimental studies of the elements of expression in music," The American journal of psychology, vol. 48, no. 2, pp. 246–268, 1936.

Related Work
Categorical Model (Cnt.)

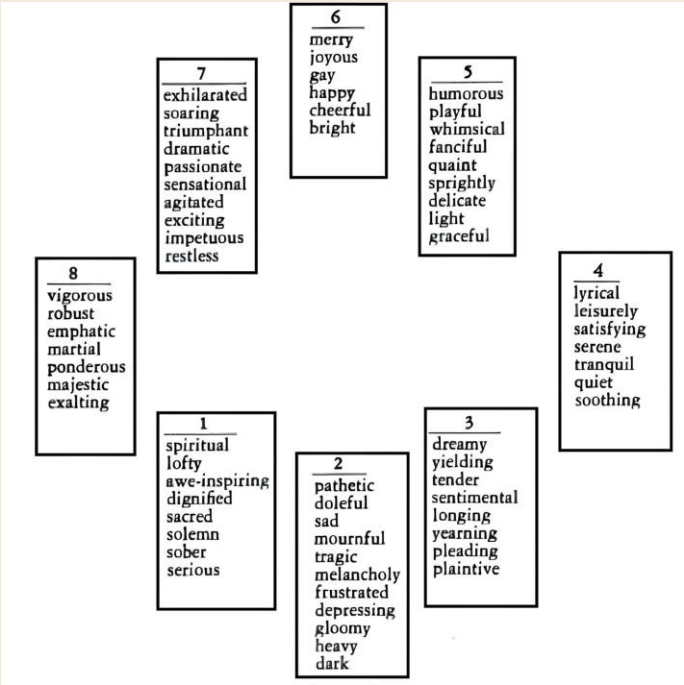


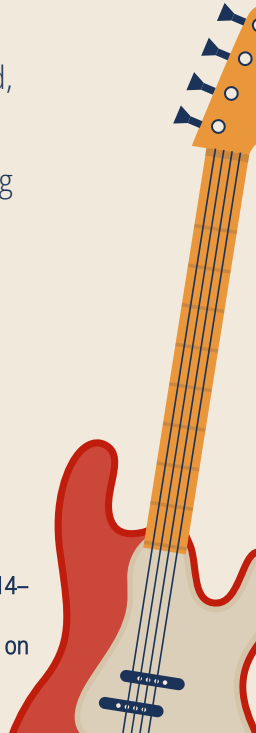
Fig. 1: Hevner's eight clusters of affective terms [13]

- Since categorical models may oversimplify the complex nature of emotional experiences, this has inherent limitations [6, 11].
- The subjective variation in how people experience and perceive emotions introduces complexity and makes categorical models less flexible when applied to a variety of populations [6, 11].
- Limited ability to capture nuanced emotional reactions hinders their effectiveness in tailored interventions [6, 11].

[6] D. Han, Y. Kong, J. Han, and G.Wang, "A survey of music emotion recognition," Frontiers of Computer Science, vol. 16, no. 6, p. 166335, 2022.
[11] X. Hu, J. S. Downie, and A. F. Ehmann, "Lyric text mining in music mood classification," American music, vol. 183, no. 5,049, pp. 2–209, 2009.
[13] K. Hevner, "Experimental studies of the elements of expression in music," The American journal of psychology, vol. 48, no. 2, pp. 246–268, 1936.

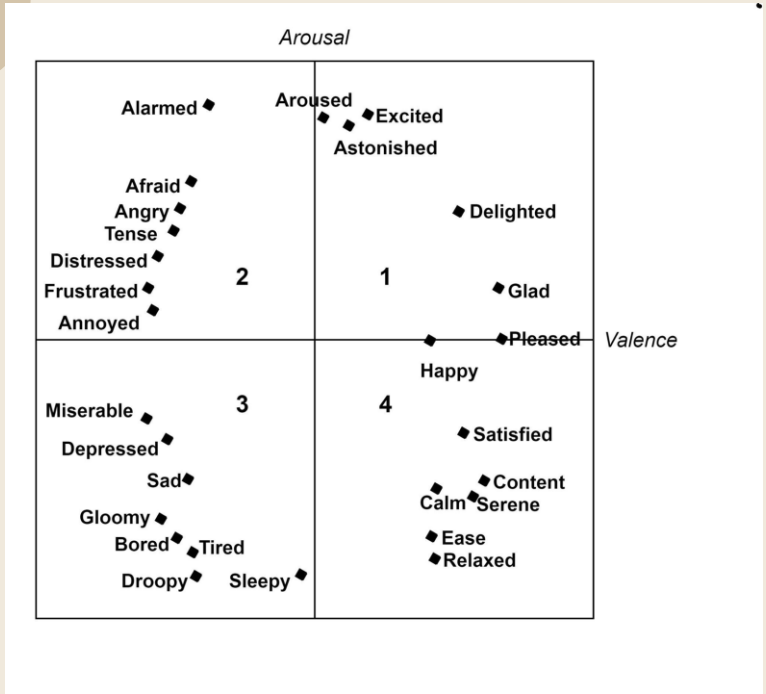
Related Work
Dimensional Model

- Valence-arousal model by Russell [14] is a widely accepted dimensional model used to represent and understand emotions [7].
- According to this model, emotions are characterized along two primary dimensions: valence and arousal [15, 16].
- Valence refers to the degree of pleasantness or unpleasantness of an emotion, Arousal, on the other hand, represents the level of physiological activation or energy associated with an emotion [15].
- By combining these two dimensions, a two-dimensional space is formed, creating a framework for understanding and categorizing a wide range of emotional states [15].



[7] D. Han, Y. Kong, J. Han, and G.Wang, "A survey of music emotion recognition," Frontiers of Computer Science, vol. 16, no. 6, p. 166335, 2022.
[14] J. A. Russell, "A circumplex model of affect." Journal of personality and social psychology, vol. 39, no. 6, p. 1161, 1980.
[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] R. L. Rosa, D. Z. Rodriguez, and G. Bressan, "Music recommendation system based on user's sentiments extracted from social networks," IEEE Transactions on Consumer Electronics, vol. 61, no. 3, pp. 359–367, 2015.

Related Work
Dimensional Model (Cnt.)



- The combination of valence and arousal dimensions results in a two-dimensional space that can be divided into four quadrants [16].
- It has been widely used in various fields, including psychology, affective computing, and music emotion recognition, to analyse and classify emotional states [15].

Fig. 2:The 2D valence-arousal emotion space [14]

[14] J. A. Russell, "A circumplex model of affect." Journal of personality and social psychology, vol. 39, no. 6, p. 1161, 1980.
[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] R. L. Rosa, D. Z. Rodriguez, and G. Bressan, "Music recommendation system based on user's sentiments extracted from social networks," IEEE Transactions on Consumer Electronics, vol. 61, no. 3, pp. 359–367, 2015.

Related Work

Sinhala Sentiment Analysis

- Sinhala language is spoken by 20 million people in Sri Lanka, Sinhala is the mother tongue for 16 million, with 79.7% literacy. It belongs to the Indo-Aryan branch in the Indo-European language tree and has a unique writing system [17, 18].
- In linguistic contrast to English's Germanic branch, Sinhala is classified as a class 01 language according to Joshi et al. [19], subsequently Ranathunga and de Silva [20] categorise this as class 02 language.
- The lack of resources, including annotated datasets and sentiment lexicons, poses a major obstacle in creating reliable Sinhala-specific sentiment analysis models. The complexities of Sinhala sentiment expression, influenced by contextual and cultural factors, add layers of difficulty [21].
- Despite challenges, there are rich opportunities for academic research and real-world applications in Sinhala sentiment analysis [17, 21].

[17] N. De Silva, "Survey on publicly available sinhala natural language processing tools and research," arXiv preprint arXiv:1906.02358, 2019.
[18] V. Dhananjaya, P. Demotte, S. Ranathunga, and S. Jayasena, "Bertifying sinhala–a comprehensive analysis of pre-trained language models for sinhala text classification," arXiv preprint arXiv:2208.07864, 2022.
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[21] V. Jayawickrama, G.Weeraprameshwara, N. de Silva, and Y.Wijeratne, "Seeking sinhala sentiment: Predicting facebook reactions of sinhala posts," arXiv preprint arXiv:2112.00468, 2021.

Related Work

Traditional ML Approaches for Music Emotion Recognition

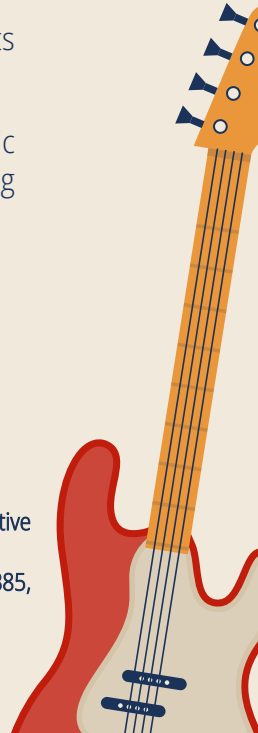
- Using appropriate text pre-processing methods (tokenization, stop word removal, stemming, lemmatization, etc) including data transformation and filtering can significantly enhance the performance of the sentiment classifier [22].
- Researchers combined the bag of words technique with term frequency–inverse document frequency and Chi-square methods in sentiment analysis, aiming to extract the most relevant features and enable a comprehensive analysis [23].
- Studies have utilized a diverse set of machine learning algorithms, including Naïve Bayesian, Support Vector Machine Classifier (SVM), Stochastic Gradient Descent (SGD), Linear Regression (LR), Random Forest, and Decision Tree, to classify reviews based on sentiment orientation [23].
- Evaluation of classifiers involved multiple performance metrics such as accuracy, precision, recall, and F1 score [23].

[22] E. Haddi, X. Liu, and Y. Shi, "The role of text pre-processing in sentiment anal-ysis," Procedia computer science, vol. 17, pp. 26–32, 2013.28
[23] T. U. Haque, N. N. Saber, and F. M. Shah, "Sentiment analysis on large scale amazon product reviews," in 2018 IEEE international conference on innovative research and development (ICIRD). IEEE, 2018, pp. 1–6.

Related Work

Traditional ML Approaches for Music Emotion Recognition (Cnt.)

- SVM is effective in handling high-dimensional data and deciphering complex decision boundaries [24].
- Random Forest is esteemed for its resilience against over-fitting and adeptness in managing extensive datasets [24].
- Conventional algorithms, such as SVM and Random Forest, face challenges in capturing intricate semantic relationships and contextual subtleties in natural language, emphasizing the superior performance of deep learning models in sentiment analysis [23, 24].



[23] T. U. Haque, N. N. Saber, and F. M. Shah, “Sentiment analysis on large scale amazon product reviews,” in 2018 IEEE international conference on innovative research and development (ICIRD). IEEE, 2018, pp. 1–6.
[24] A. Yadav and D. K. Vishwakarma, “Sentiment analysis using deep learning architectures:a review,” Artificial Intelligence Review, vol. 53, no. 6, pp. 4335–4385, 2020.

Related Work

DL Approaches for Music Emotion Recognition

- There is a Increase in use of Deep Learning-based models, driven by the surge in neural network utilization for text classification tasks, particularly sentiment analysis [25].
- Ray and Chakrabarti [26] utilized a seven-layer deep Convolutional Neural Network (CNN) for aspect term extraction and sentiment classification, complemented by rule-based techniques to improve accuracy.
- Introduction of models BERT [27], RoBERTa [28], mBERT [27] (a multilingual extension of BERT), and XLM [29] ; addressed the challenge of text classification across diverse languages, especially those with limited linguistic resources.
- Multiple studies [27, 30, 31] have shown that the implementation of a hybrid deep learning model - The bidirectional LSTM followed by a CNN produces promising results compared to BERT followed by Bi-LSTM and CNN.

[25] M. M. Agüero-Torales, J. I. A. Salas, and A. G. López-Herrera, "Deep learning and multilingual sentiment analysis on social media data: An overview," Applied Soft Computing, vol. 107, p. 107373, 2021.
[26] P. Ray and A. Chakrabarti, "A mixed approach of deep learning method and rule based method to improve aspect level sentiment analysis," Applied Computing and Informatics, vol. 18, no. 1/2, pp. 163–178, 2022.
[27] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "Bert: Pre-training of deep bidirectional transformers for language understanding," arXiv preprint arXiv:1810.04805, 2018.
[28] Y. Liu, M. Ott, N. Goyal, J. Du, M. Joshi, D. Chen, O. Levy, M. Lewis, L. Zettlemoyer,and V. Stoyanov, "Roberta: A robustly optimized bert pretraining approach,"arXiv preprint arXiv:1907.11692, 2019.
[29] G. Lample and A. Conneau, "Cross-lingual language model pretraining," arXiv preprint arXiv:1901.07291, 2019.
[30] C. Colón-Ruiz and I. Segura-Bedmar, "Comparing deep learning architectures for sentiment analysis on drug reviews," Journal of Biomedical Informatics, vol.110, p. 103539, 2020.
[31] M. U. Salur and I. Aydin, "A novel hybrid deep learning model for sentiment classification," IEEE Access, vol. 8, pp. 58 080–58 093, 2020.

Related Work

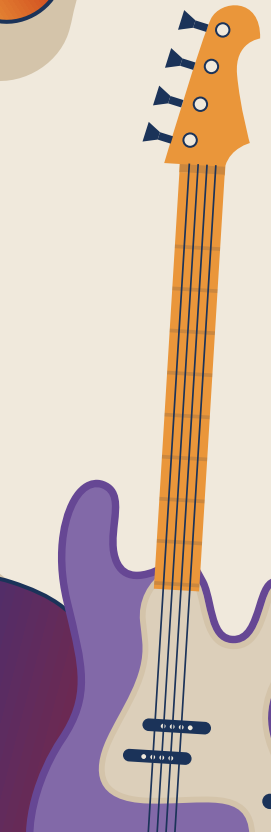
DL Approaches for Music Emotion Recognition (Cnt.)

- XLM-R [32], developed by Facebook:
  - *Surpasses its predecessors (mBERT and XLM) across various tasks such as classification [32].*
  - *Achieves unprecedented excellence in cross-lingual understanding, enabling training in one language and seamless application to others without the need for additional training data [33].*
  - *Stands out as a pioneering multilingual model, exhibiting remarkable efficacy in low-resource language scenarios [32, 33].*
- DL models are adept at capturing long-term dependencies and contextual information, making them highly suitable for tasks involving natural language data [24].

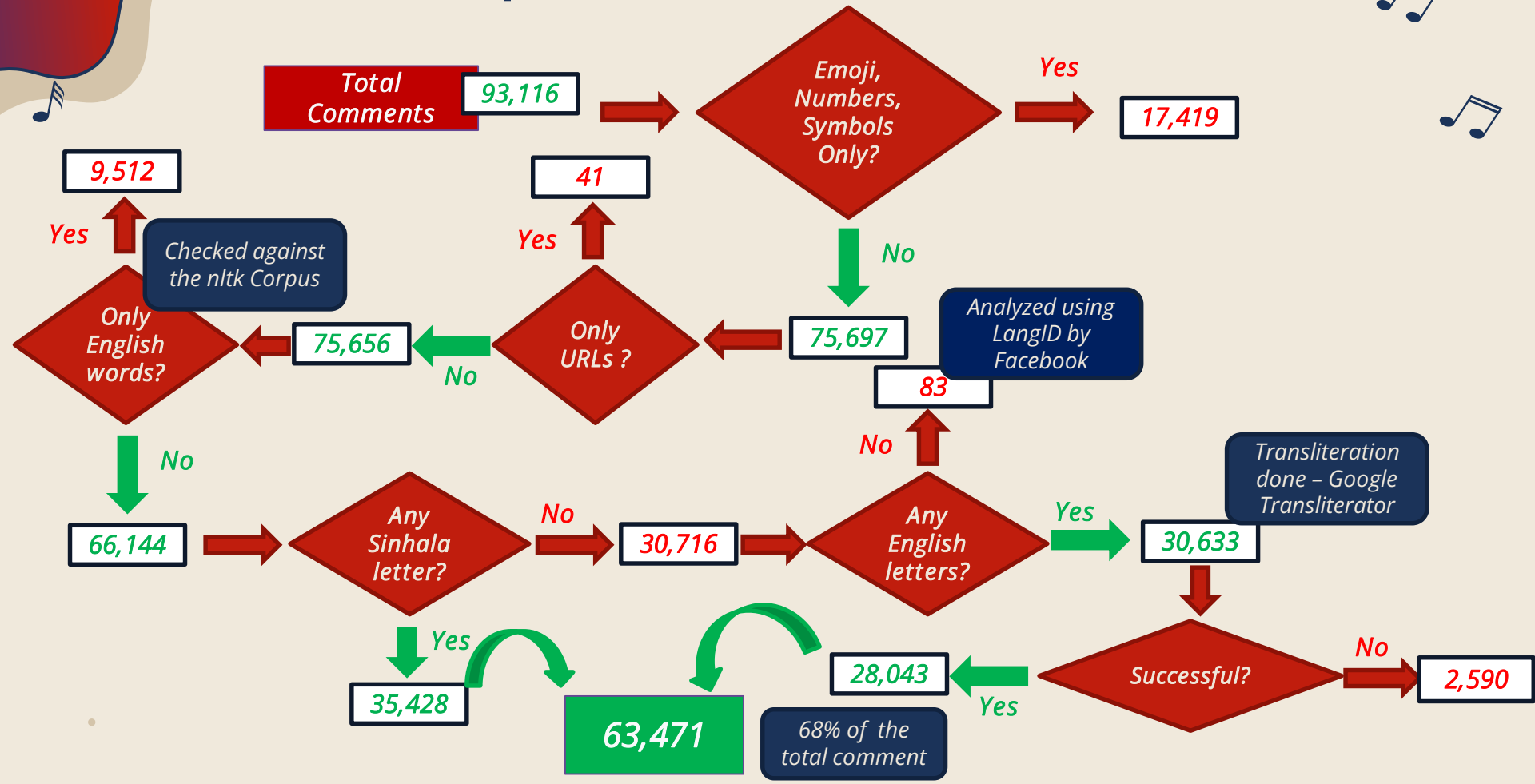
[24] A. Yadav and D. K. Vishwakarma, "Sentiment analysis using deep learning architectures:a review," Artificial Intelligence Review, vol. 53, no. 6, pp. 4335–4385, 2020.
[32] A. Conneau, K. Khandelwal, N. Goyal, V. Chaudhary, G. Wenzek, F. Guzmán,E. Grave, M. Ott, L. Zettlemoyer, and V. Stoyanov, "Unsupervised cross-lingual representation learning at scale," arXiv preprint arXiv:1911.02116, 2019.
[33] Y. K. Wiciaputra, J. C. Young, and A. Rusli, "Bilingual text classification in english and indonesian via transfer learning using xlm-roberta." International Journal of Advances in Soft Computing & Its Applications, vol. 13, no. 3, 2021.

03

Data Preparation

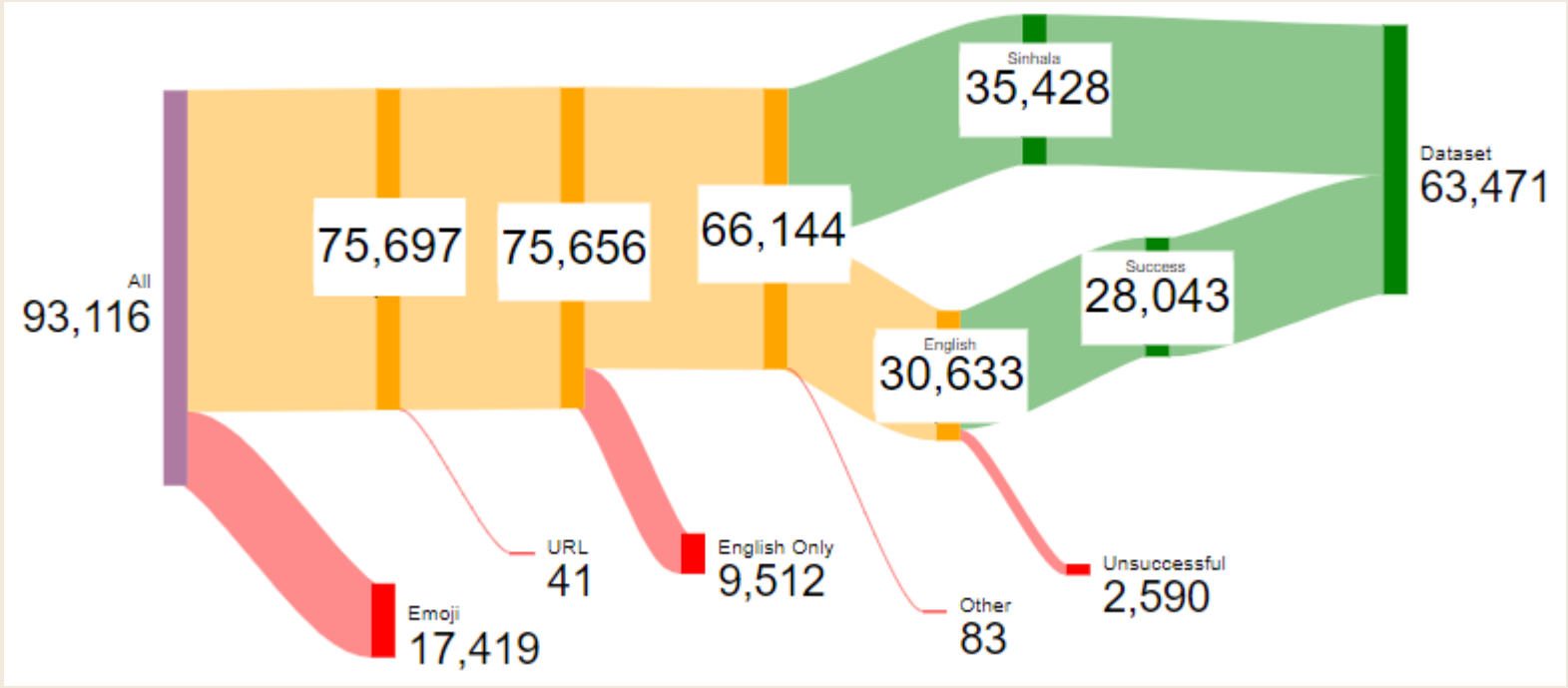


Data Preparation



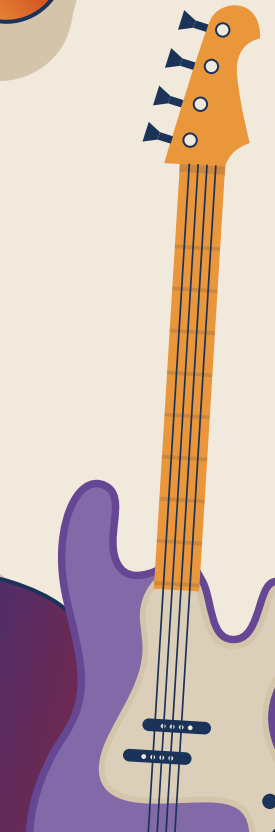
Data Preparation

- Final Distribution of the comments.



04

Data Analysis



Data Analysis

Artist	Song	No of Sinhala Comments
Thisara Weerasinghe	Ansathu Oba	14095
Sarith and Surith	Salli Salli	12251
Dinesh Gamage	Danena Thuru Maa	5377
Methun SK	Kaari Naa Sanda	3935
Saman Lenin	Amude	3753
BnS	Unmada Prema Geeya	3289
Danith Sri	Ehema dewal na hithe	2824
Sanuka Wick	Perawadanak	2633
Raini Charuka	Kaluwarata Hitha Baya	2596
Ridma	Sobana	2057
Prageeth Perera	Komaliya	1870
Abisheka and Mihdu	Dannawada Adare Neethiya	1721
Sanuka Wick	Saragaye	1502
Sandeep Jayalath	Nuraavi	1370
Sanuka	Mohini	1318
Saman Lenin	Ambaruwo	809
Victor Rathnayake	Thaniwennata mage lowe	790
Nanda Malini	Ma sadata kamathi bawa	735
Victor Rathnayake	Ape hagumwalata	387
Ashanthi	Piyanani	130

Language	No of Comments
Arabic	1
Armenian	3
Assamese	1
Bangla	2
Bulgarian	1
Catalan	1
Chinese	19
English	18
Esperanto	1
French	3
Galician	1
German	2
Hindi	3
Japanese	8
Korean	2
Malayalam	5
Marathi	1
Neapolitan	1
Russian	2
Tamil	6
Turkish	1
Ukrainian	1
Grand Total	83

	Sinhala sent Count Bucket	Frequency
0	1	42137
1	2	11226
2	3-5	8330
3	6-15	1553
4	more than 16	196

Sinhala Word Count Bucket	Frequency
1-5 words	34463
6-15 words	20543
15-25 words	4606
25-50 words	2721
more than 80 words	579
50-80 words	530

Data Analysis Cont.

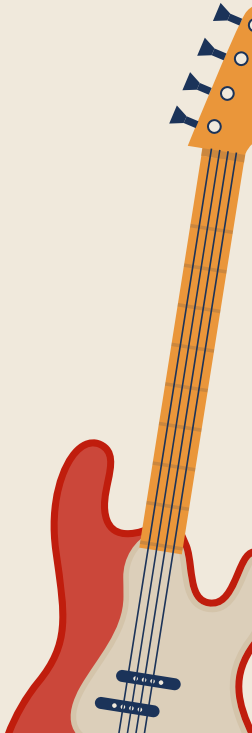
- IQR for the word count.

0%	25%	50%	75%	100%
1	3	5	10	755

- Word distribution and word pair distribution.

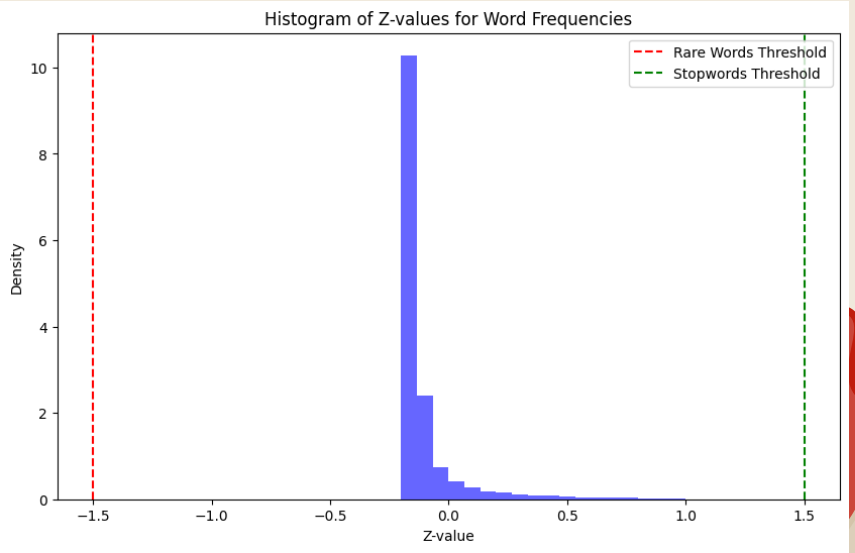
Word	Frequency
මේ	6692
එක	5761
ඒ	4731
නෑ	4161
වගේ	3025
ලස්සනයි	2938
සෝන්ග්	2800
නම්	2770
එකක	2644
ලස්සන	2635

Word Pair	Frequency
මේ වගේ	930
කියන්න වචන	761
කොච්චර ඇහුවත්	630
මේ සින්දුව	625
හරිම ලස්සනයි	617
ඇහුවත් එපා	586
කාරි නෑ	564
ඔබ වෙත	555
වචන නෑ	496
සෝන්ග් එක	472



Data Analysis Cont.

- There were 115,115 unique words.
- Below patterns were removed.
  - Words containing numbers in between and only numbers.
  - Words containing English letters in between and only English letters.
  - Words containing symbols in between and only symbols.
- Final unique word count 46,795.
- Z- Score for word frequency is as follows.

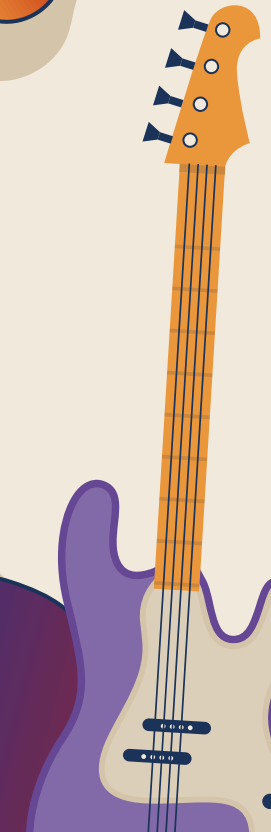


Data Analysis Cont.

- The words with Z- Score > 1.5 were categorized as stop words.
- Identified **379** stop words.
- Translated stop words were compared against the nltk – stop word list for English : **98** were included.
- Checked against the common stop words in Sinhala general domain.
    - *Extracted data from other Sinhala web sites (Sinhala Wikipedia, Diwaina Online news paper)*
- Comparison of Z- Score value of unique words of general Sinhala words **(Z_2)** with the Z- Score value of Sinhala YouTube Comments **(Z_2).**
- Identified **375** stop words specific to the domain.

05

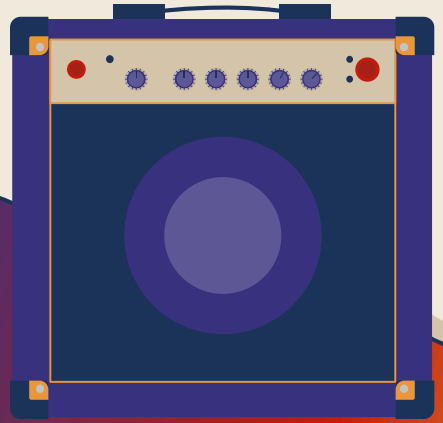
Conclusion



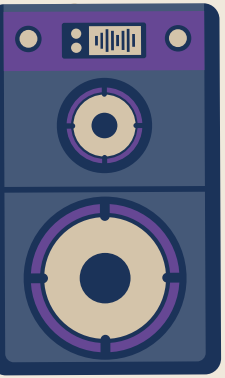
Conclusion

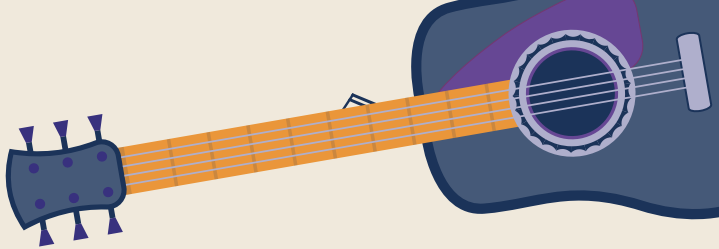
- Advanced filtering and transliteration techniques resulted in a refined dataset of 63,471 Sinhala comments, crucial for emotion analysis.
- 379 Sinhala-specific stopwords were identified, enhancing sentiment analysis precision.
- Out of above 98 were included in English stopword list when translated and compared.
- 375 Domian specific Sinhala stopwords were identified.
- Dataset serves as a resource for MIR and MER studies specific to Sinhala music.
- Integration of linguistic analysis and computational methods deepens understanding of Sinhala music emotions.
- Opens avenues for further exploration and innovation in computational musicology and emotion recognition within diverse cultural traditions.

Thank You!



Q & A





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