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Transformer Model in Music Mood Classification

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***Abstract* - In recent years, artificial intelligence technology has developed rapidly and has become an inseparable part of life. Artificial intelligence has driven many activities in various sub-fields using machine learning. One of them is in the field of music. Every human being loves music. Music has become a part of human life. Music provides its own atmosphere to the listener which is called mood. There are so many elements of music that can be processed in machine learning, such as lyrics and audio. Lyrics and audio are saved into a music dataset. The author uses 1181 data on Indonesian music in the era of the 70s and 80s. The dataset only takes the refrain. The author uses the Transformer model where the lyrics management uses word embedding and audio processing uses the chromagram feature.**

***Keywords*— Indonesian Music dataset, , Mood, Transformer**

INTRODUCTION

Every human being loves music. Music knows no age, young or old, children and youth. All ages love music. Music is a subject in machine learning that can be studied further [1]. Music has many features. Music features include Spectograms, Cromagrams, and posters. Indonesia is a rich country besides being rich in natural resources, Indonesia is rich in culture [2] and 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 automatic music mood classification is using a machine learning model that is trained in a supervised manner with the input of a number of samples that have been labeled musical moods by collecting datasets manually. Indonesian music in the 70s and 80s is music that has many genres.

Among them dangdut, ballads, pop and struggle. The dataset used by the author is a dataset that is processed by himself by downloading songs from YouTube, converting to mp3 and cutting the song by taking only the chorus.

LITERATURE RIVIEW

Some topics that can be used for the use of transformer models in classifying moods in music, include:

A. Attributes to Music

The main musical features can be grouped into several categories as follows [3].

1. Music content is a music feature that is extracted from music audio signals. The main features of music content are rhythm (rhythm), timbre (tone color), melody (linear succession in music), harmony (a series of chords), loudness (loudness), and lyrics (song lyrics).
2. Music context is a music feature that is extracted directly from music audio. The main features of the music context are: semantic labels, performer's reputation, album cover artwork or posters, background artists, and music videos.
3. Music user context is a feature that represents the dynamic context of listeners/music connoisseurs. Music user context features consist of mood (such as feeling sad or happy), activities, social context, spatial temporal context, and other psychological conditions.
4. Music user property is a feature that represents dynamic characteristics of listeners/music connoisseurs such as music tastes, user opinions of players. The music user property features consist of: music preference, music training, music experience, demographics, opinions about musicians or performances, and popularity of musicians.

B. Classification of Mood in Music

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 [4]. The mood categories used in labeling music can be seen in Table 1. 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) [5][6]

Table 1
Mood Grouping [5]

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

Many researches on mood music have been carried out, for example research that uses mood as an access point for lyrics and audio [7]. Creating a music song mood dataset based on happy, angry, sad and relax categories. The creation of this dataset is based on Tags. last. Fm [8]. Another study explains that music can produce moods that can find suitable tracks in catalog and film productions [9]. Besides that, mood can also be used through many lyrics in OPM songs, where the method used is TF-IDF and the Key Graph keyword algorithm with an accuracy rate of 80%[10]. The implementation of mood in music is also processed with 1000 songs that have been annotated which in this study used multivariant regression reaching R to .70 and .50 [11]. The use of the mirex dataset is also carried out for detection of genre, mood and compuser by using audio features that are converted to mel spectrogram and CNN (Convolutional Neural Network) [12]. Besides that, mood is also studied as a person's concept in carrying out tasks such as driving, sleeping, romantic, confident, noisy, lively, noisy or others with various genres of jazz, comedy, gospel, sentiment, electronica, R & B Sensual, Blue, Blues, populist. Mood research on artists, genres was also carried out using dataset sources from AllMusicGuide.com, epinions.com and Last.fm [13].

C. Transformer Model

In essence, to solve sequential problems such as sentences, a transformer is needed which is an artificial neural network architecture [14]. Transformers are part of the Natural Language Process (NLP) in machine learning. The transformer is in charge of connecting the encoder and decoder to the text data [15]. input and output are interconnected through context vectors. Autoencoder is able to convert input into output. Besides being used in NLP transformers, it is also used in computer vision [16].

Several studies have used transformers, namely the Transformer Model to detect emotions in a social media conversation, for example on Facebook with the categories of happy, sad and angry [17]. Machine learning that uses a transformer model with 1000+ transformers to analyze health problems [18]. A transformer-based trial predicts the next 10 weeks with influenza case subjects [19]. The transformer model is also used in the detection of abusive language in Indonesian online news commentary. Text classification is done with the category of offensive, normal or non-ovensive [20]. In the health world, the transformer model is used for energy monitoring using the concept of algorithms in machine learning [21]. This study describes the use of the transformer method to analyze a person's stress [22]. Figure 1 describes the process of encoder and decoder through the input process and produces output. Transformer is also a mechanism that studies contextual relationships between words [23].

In Transformer there are two mechanisms, namely:

1. Encoder

The encoder is used to read all text input at once. The encoder consists of a stack of identical layers. Each layer has two sub-layers, namely self-attention layer and feed-forward neural network. With a self-attention layer, the encoder can help nodes not only focus on the word they are viewing but also to get the semantic context of the word. Each position in the encoder can handle all positions in the previous layer in the encoder.

2. Decoder

The decoder functions to produce a predictive output sequence. The decoder also consists of a stack of identifiable layers. Each layer consists of two sub-layers like those of the encoder, with an additional attention layer between the two layers to help the current node get to the key content that needs attention by performing multi-head attention on the output of the encoder. Similar to the encoder, the self-attention layer in the decoder makes each position in the decoder able to handle all the previous and current positions.

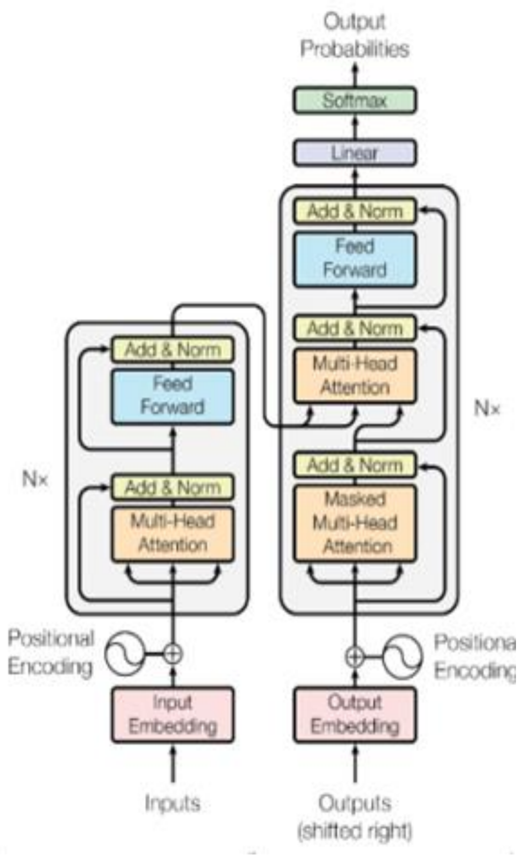


Figure 1. Transformer Model [23]

THE PROPOSED MODEL

The initial model or initial research framework used in the classification of moods with a database of Indonesian songs 70 and 80 eras is shown in Figure 2. The model in Figure 2 consists of the training music dataset and the testing music dataset. At the training stage, datasets are collected with data labels. Audio data will be processed into a vector value on the Chromagram, Lyrics data stored in excel will be processed using document embedding extraction. So that the resulting features in the form of chromagram features and lyric features. Chromagram data is the first training model. The lyric data is the second training model. The first and second training models will be combined into a trained ensemble model that will generate evaluation values. Likewise with the stages of data testing.

Figure 3 is a research framework with transformers. Where the stages are divided into 2, namely training music datasets and testing music datasets. This music dataset training involves music mood labels with audio and lyric data. Audio data will be processed into Chromagram. The lyric data will be processed through word embedding extraction. By using the transformer model, trained transformers are carried out which result in a performance evaluation.

Likewise with the music dataset testing stage which produces chromagram features and document embedding from audio and lyric data. Where the next step is a trained transformer model and generating a predicted Mood label.

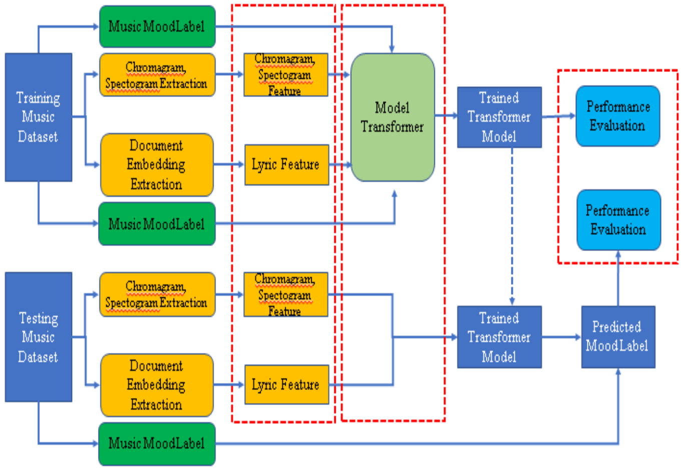

Music MoodLabel
Training Music Dataset
Chromagram, Spectogram Extraction
Chromagram, Spectogram Feature
Document Embedding Extraction
Lyric Feature
Music MoodLabel
Model Transformer
Trained Transformer Model
Performance Evaluation
Performance Evaluation
Testing Music Dataset
Chromagram, Spectogram Extraction
Chromagram, Spectogram Feature
Document Embedding Extraction
Lyric Feature
Trained Transformer Model
Predicted MoodLabel
Music MoodLabel

Figure 2. Initial research framework

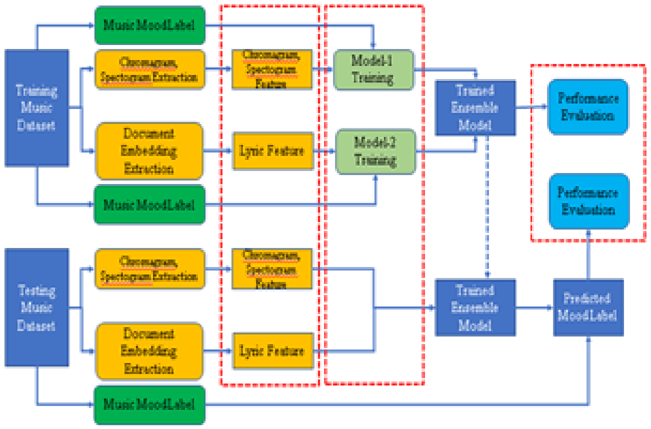


Figure 3. Research framework with transformers

RESULT AND DISCUSSION

Figure 4 is a Proposed Transformer Model Architecture as a Mood Classification. Where this image consists of input and output. Input has chromagram based feature vector and lyric based features. Figure 4 has many stages until it finally reaches the output. The first stage used is the same as the stages in the transformer, namely the vector encoder. The second stage is attention weight with weights of 0.5, 0.4, 0.3, 0.2, 0.1. The third stage is the context vector, the fourth stage is the decoder vector. Finally produces Output. The encoder and decoder get the input and convert it to a context vector and the decoder gets the context vector and converts it to an output.

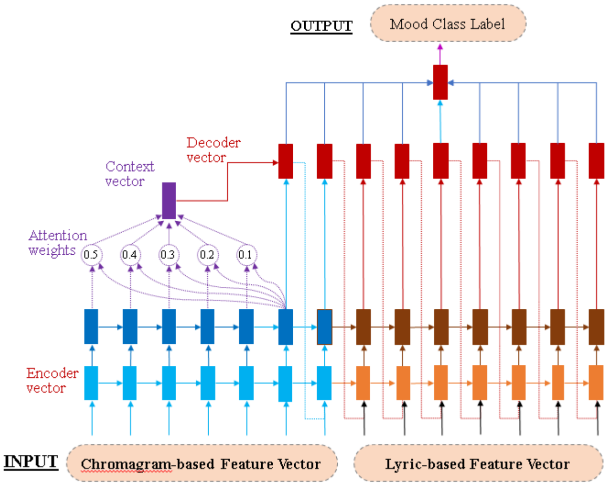


Figure 4. Proposed Transformer Model Architecture as Mood Classification

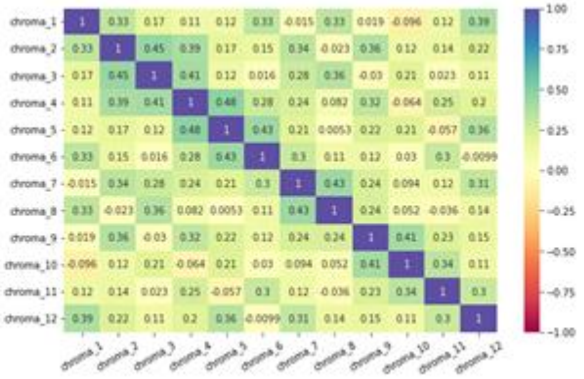
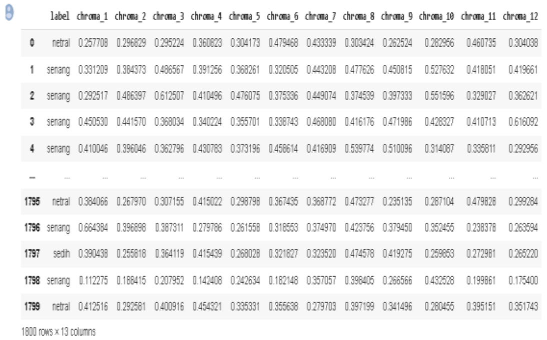


Figure 5. Correlation between chroma . columns

Figure 5 shows the degree of correlation between columns. Figure 5 only shows vector values in chroma 1 to chroma 12. Figure 6 is a data table of audio data containing vector values from the first chroma vector to the final data.



	label	chroma_1	chroma_2	chroma_3	chroma_4	chroma_5	chroma_6	chroma_7	chroma_8	chroma_9	chroma_10	chroma_11	chroma_12
0	netral	0.257708	0.296829	0.295224	0.360823	0.304173	0.479468	0.433339	0.303424	0.262524	0.282956	0.460735	0.304038
1	senang	0.331209	0.384373	0.486567	0.391256	0.368261	0.320505	0.443208	0.477626	0.450815	0.527632	0.418051	0.419661
2	senang	0.292517	0.486397	0.612507	0.410496	0.476075	0.375336	0.449074	0.374539	0.397333	0.551596	0.329027	0.362621
3	senang	0.450530	0.441570	0.368034	0.340224	0.355701	0.338743	0.468080	0.416176	0.471986	0.428327	0.410713	0.616092
4	senang	0.410046	0.396046	0.362796	0.430783	0.373196	0.458614	0.416909	0.539774	0.510096	0.314087	0.335811	0.292956
...	...	...	...	...	...	...	...	...	...	...	...	...	...
1795	netral	0.384066	0.267970	0.307155	0.415022	0.298798	0.367435	0.368772	0.473277	0.235135	0.287104	0.479828	0.299284
1796	senang	0.664384	0.396898	0.387311	0.279786	0.261558	0.318553	0.374970	0.423756	0.379450	0.352455	0.238378	0.263594
1797	sedih	0.390438	0.255818	0.364119	0.415439	0.268028	0.321827	0.323520	0.474578	0.419275	0.259853	0.272981	0.265220
1798	senang	0.112275	0.188415	0.207952	0.142408	0.242634	0.182148	0.357057	0.398405	0.266566	0.432528	0.199861	0.175400
1799	netral	0.412516	0.292581	0.400916	0.454321	0.335331	0.355638	0.279703	0.397199	0.341496	0.280455	0.395151	0.351743

1800 rows × 13 columns

Figure 6. Data table of audio data

Figure 7 is a visualization of the length of the lyrics from the text data. To train a model, the size of the data is very important. Figure 7 is a visualization of the length of each lyric.

The longest size of the lyric data is around 40 words in the chorus and the smallest size is about 3 words. This needs to be processed again so that it gets the maximum value.

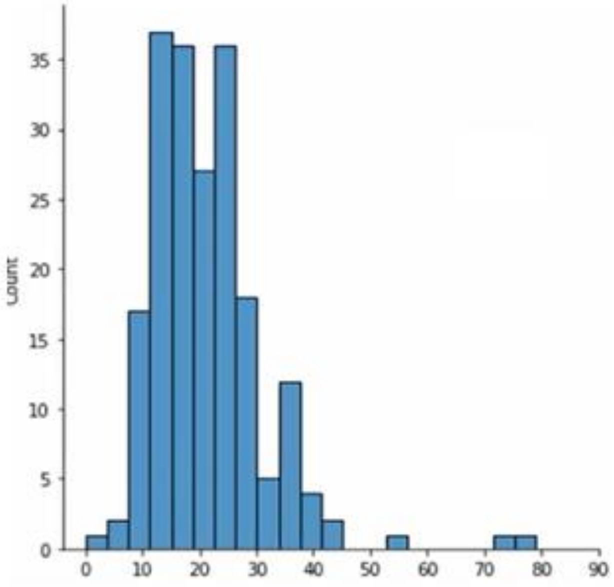


Figure 7. Visualization of text length

CONCLUSION

This study aims to develop a transformer model on music data using machine learning. Transformers are very important and need to be used in natural language processing with lyric data analysis on music datasets.

Transformer model used for processing voice data via audio. Lyrics data through chorus pieces stored in excel. For further research, you can use the intro or the ending section so that it can produce more datasets, high accuracy and more comparisons as well.

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