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# **Emotion Modeling for Emotion-based Personalization Service**

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#### Abstract

This study suggests the emotion space modeling and emotion inference methods suitable for personalized services based on psychological and emotional models. For personalized emotion space modeling taking into account the subjective disposition based on the empirical assessment of the personal emotions felt by the personalization process of emotion space was used as a decision support tool, the Analytic Hierarchy Process. This confirmed that the special learning to perform personalized emotion space modeling without considering the subjective tendencies. In particular to check the possible reasoning based on fuzzy emotion space modeling and sensitivity for the quantification and vague human emotion to it based on the inherent human sensitivity.

Keywords : Analytic Hierarchy Process, Choquet Fuzzy Integral, Emotion Space, λ-Fuzzy, Sugeno Fuzzy Integral

### 1. Introduction

Development of IT has made human environments easier and faster leading it to pursue the convenience and realize maximized improvement. This is how continuous IT has been improved evolving to automate and simplify complicated environment. Such evolving IT service environment has been developed to realize high quality service by reflecting preferences or emotion of individuals along with the research conducted on emotion Information Communication and Technology (ICT)industry according to emotion User Experience (UX). Especially, researches have been actively conducted on various intellectual systems for individualized systems reflecting personal preferences<sup>[1,2]</sup>.

Reflection of personal propensity requires to consider emotion of individuals beyond the discovery of simple profile-based patterns, learning, or the scope of prediction. At the same time, it is required to expand the scope of service to be provided and improve the quality of it. For this, it is required to come up with inference methods and establish personalized emotion space to infer proper emotion of human on the emotion-based personalized service.

In this study, relative importance of Valence and Arousal is evaluated on emotion-expressing language as a way of establishing personalized emotion space model that reflects personal propensity while summarizing them in the use of Analytic Hierarchy Process<sup>[3-5]</sup>. In addition, personalized and internalized emotion space model reflecting empirical and subjective propensity was established without collecting biological data such as biological signals. For the emotion-based personalized service in the established personalized emotion space model, it is required to be able to proceed appropriate inference on emotion. However, various inference methods are available depending on the applied areas for emotion-based service. As for emotion inference from establishing personalized emotion model in the use of various biological data as suggested earlier, different methods can be applied depending on the field and scope of application.

For this, Sugeno Fuzzy inference method,  $\lambda$ -Fuzzy Measure, Choquet Fuzzy Integral, and Sugeno Fuzzy Integral were used in this study for the establishment of light and swift emotion model and emotion inference in consideration of personal propensity to implement personalized emotion space modeling and evaluate the results<sup>[6,7]</sup>. With them, internalized complicated emotion of humans were expressed proceeding fast emotion inference in personalized emotion space from vague inputs.

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## 2. Personalized Emotional Space Modeling Using Analytic Hierarchy Process

Various researches have been conducted to model human emotion in psychological or emotion-inference. Especially, emotion of humans contains subjective propensity. Due to significant difference of it from individuals, there is a difficulty in modeling them<sup>[8,9]</sup>. In this study, personalized emotion space was established in the use of psychological emotion model, while implementing emotion inference in the established emotion space. Stage for them is as shown in the Fig. 1.

Analytic Hierarchy Process, the subjective decision making supporting tool, was used as a way for individualization of Valence-Arousal emotion space according to personal propensity. Analytic Hierarchy Process is a decision making supporting tool that reflects personal propensity as a way of quantitatively measuring the relative importance of subjective propensities through pair-wise comparison if subjective propensities are strongly applied when measuring the importance of subjects in comparison.

Analytic Hierarchy Process was used as a way of individualization measuring relative importance on Valence-Arousal values with specific emotion on total 12 types of emotion on Positive and Exciting.

The relative importance of the 12 emotions to positivity and excitement was measured. As an interpretation of the result, (2.0), which is the relative importance between Pleased and Happy for the positive, means that Pleased is 1/2 more important than Happy (Happy is



Fig. 1. Personalization emotional space establishment and inference phase.

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more important than Pleased by 2.0). In other words, when evaluating the relative importance between Happy and Pleased for positive aspects, respondents in this survey turned out to feel more positive emotion on Happy than on Pleased. However, having 2.0 of relative scale means that the indices of positiveness on these two types of emotion are very similar in 9-score criteria by Saaty.n addition, among all the emotions on the positive side, the emotion with the greatest weight (L) value, which is the relative importance, was Happy (L: .234), followed by Pleased (L: .199). On the contrary, the emotions with the lowest relative importance were Angry (L: .015) and Sad (L: .016). On the other hand, the emotion with the lowest relative importance turned out to be Angry (L: .015) and Sad (L: .016). In this case, the meaning of the magnitude of relative importance means that Happy and Pleased are the most positive emotions for the survey respondents, and their intensity can be compared with the magnitude of relative importance. In the same way, the emotion with the greatest relative importance among all emotions in terms of Exciting was Excited (L: .230).

Personalized Valence-Arousal emotion space was established with normalization of relative importance among sensitivities reflected with personal propensity. There was a difference depending on types of emotion or personal propensity, but the distribution of Valence-Arousal values of emotion turned out to be identical with the Valence-Arousal emotion by Thayer. Being happy is that Valence value is strongly positive, and Arousal is strongly related to Exciting. On the other hand, being said is that Valence value is strongly negative, and Arousal is strongly calm. In other words, this means that it is possible to establish Valence-Arousal emotion space in the use of results of relative importance among sensitivities in the use of Analytic Hierarchy Process on aforementioned types of emotion. Especially, the importance value of derived emotion reflects the personal and subjective propensity, and it is feasible to establish personalized emotion space when using them.

Fig. 2 represents to normalize the relative importance derived from Analytic Hierarchy Process to Valence-Arousal emotion model and also to calculate positive and negative values of Pleased emotion.

When normalizing the results from Analytic Hierarchy Process, it is confirmed how it is properly converted

Pleased	Positive	Value

- = Pleased\_Weight / ( MAX ( Pleased\_Weight, Happy\_Weight, Excited\_Weigth )
- + MIN ( Pleased\_Weight, Happy\_Weight, Exctied\_Weight ) )

### Pleased\_Negative Value

= 1 – Pleased\_Positive Value

Fig. 2. Valence-Arousal emotional model normalization.

to Valence-Arousal emotion model. Especially, results of normalization at this time were derived by using decision making outcomes on personal propensity of individuals as a personalized emotion space model reflected with each emotion. Human psychological emotion model has "Wheel of Emotion" emotion space model by Plutchik other than Valence-Arousal emotion model by Thayer<sup>[10,11]</sup>. In this study, emotion model by Plutchik was re-established with two-dimensional emotion space model with Valence-Arousal values as a main component followed by the creation of personalized emotion model. The biggest difference between the emotion model by Plutchik and by Thayer is a type of emotion to be expressed. Especially, Plutchik model is able to express 32 types of emotion unlike the Thayer model that can only express 12 types of emotion. In addition, color theory was applied on emotion expressing how it was feasible to synthesize sensitivities. For the establishment of personalized emotion space model, each of the models was separated into 4 areas based on Valence-Arousal. At the same time, relative importance of all types of emotion was derived using Analytic Hierarchy Process to quantify the strength of internalized and psychological emotion.

Analytic Hierarchy Process evaluation was implemented on the middle group of sensitivities with same colors, Trust, Joy, Anticipation, Anger, Disgust, Sadness, Surprise, and Fear among 32 types of emotion defined in the emotion model by Plutchik. When deriving the evaluation values of the middle group, it is feasible to predict sensitivities that are either stronger or weaker than them.

Table 1 represents the Analytic Hierarchy Process evaluation results on emotion model by Plutchik. Strength was higher in an order of Trust and Joy in the Positive aspects, and also of Joy and Anger in the Exciting aspect. These values mean that Joy is to be selected when Positive and Exciting value becomes higher.

	Emotion tuna	Valence – Arousal		
	Emotion type —	Positive	Exciting	
Ι	Joy	0.292	0.272	
	Trust	0.038	0.399	
II	Anger	0.235	0.024	
	Anticipation	0.293	0.080	
III	Sadness	0.042	0.039	
	Disgust	0.152	0.026	
IV	Fear	0.099	0.025	
	Surprise	0.050	0.134	

Table 1.	Analytic	Hierarch	y Process	evaluati	on result	for
Plutchik	emotional	model (	Positive.	Exciting	side)	

Normalized\_Value ( Trust ) = Trust\_Weight / ( Trust\_Weight + Joy\_Weight ) Normalized\_Value ( Joy ) = Joy\_Weight / ( Trust\_Weight + Joy\_Weight )

Fig. 3. Normalize weight by emotion.

Like the way of establishing personalized emotion space in the use of emotion model by Thayer, emotion model by Plutchik is feasible to model 2D-type personalized emotion space based on Valence-Arousal values according to weights on each type of emotion derived from Analytic Hierarchy Process.

In order to express the result of Analytic Hierarchy Process evaluation, weights on each type of emotion, in Valence-Arousal emotion space model, they were normalized in the values between 0 and 1. At this time, negative and calm values were calculated by subtracting 1 from each of the Positive and Exciting values. Trust and Joy were derived by the Fig. 3 so that the value added with importance from both values became 1 as they were sensitivities falling in to the same 1st quadrant.

## 3. Emotional Inference Using Fuzzy Scale and Fuzzy Integral

In this study, Fuzzy criteria and Fuzzy integral were used on emotion model by Thayer and Plutchik inferring complicated sensitivities from the Valence-Arousal inputs with the determination of comprehensive importance on the current emotion.

In conclusion, when Positive, Negative, Exciting, and Calm values are given on personalized emotion space,

inference is made on ambiguity for how sensitivities are developed. Therefore, inference results may become significantly different depending on the basic form of emotion space.

Fuzzy rule-based Sugeno inference system makes it difficult to be individualized as it is required to adjust the entire system when establishing and immediately reflecting personalized emotion space. However, inference system in the use of Fuzzy measure and integral adjusts evaluation values in personalized emotion space and also swiftly derive overall importance of current emotion if providing Valence-Arousal weights needed for determining proper sensitivities in the current environment.

 $\lambda$ -Fuzzy measure was applied to derive Fuzzy criteria on weights needed for determining emotion. Here,  $\lambda$ represents a way to consider interaction on weights and is defined as followed in the Equation 1.

$$g(\mathbf{A} \cup \mathbf{B}) = g(\mathbf{A}) + g(\mathbf{B}) + \lambda g(\mathbf{A})g(\mathbf{B}) \tag{1}$$

When  $\lambda \in (-1,\infty)$ , regular set function g by P(X) is referred to as  $\lambda$ -Fuzzy measure if fulfilling the following conditions on all pairs of A and B as a subset without common elements.

If  $\lambda$  is negative value, both are in negative subset relation while showing positive subset interaction, in other words; positive synergic effect. In this case, the entire evaluated value by Fuzzy integral is calculated to be less. On the other hand, if  $\lambda$  is a negative value that is greater than -1, both sets have positive subset relation and can be replaceable with each other, while showing negative subset interaction and increasing the entire evaluated value.

Singleton Fuzzy Measure Ratio Standard algorithm was used as an identification algorithm to derive Fuzzy measure in the use of interaction coefficient,  $\lambda$ , in this study, and the algorithm is as follows.

In case of  $\lambda > -1$ , if  $\lambda$ -Fuzzy measure is defined to be  $\mu_{\lambda}$ , Equation 2 is identified as follows.

$$\mu_{\lambda}(A \cup B) = \mu_{\lambda}(A) + \mu_{\lambda}(B) + \lambda \mu_{\lambda}(A) \mu_{\lambda}(B)$$
(2)

At this time, if  $\mu(X) = 1$ ,  $A \cap B = \emptyset$ , and  $\mu(A) \in [0,1]$ ,  $\forall A \in 2^x$ .

In addition, when the weight, w, is shown in the Equation 3 to calculate Fuzzy-measure, algorithm for

 Table 2. Singleton fuzzy measure ratio standard algorithm

When *p*∈(0,1) and μ({1,2,...,*n*}) = 1
1. Normalize weights where max *w<sub>i</sub>* 1
2. *p*:=0.5
3. μ({*i*}): = *pw<sub>i</sub>*, ∀*i*4. Calculate for *j* = 2, ..., *n*  u({1,2,...,*j*}): = μ({1,2,...,*j*-1})+μ({*j*}) + λμ({1,2,...,*j*-1})μ({*j*})
5. If μ({1,2,...,*j*}) > 1 for a j then decrease the p and go to 3
6. If μ({1,2,...,*j*}) < 1 then increase the p and go to 3</li>
7. If If μ({1,2,...,*j*}) = 1 then stop the algorism

calculating monotonic fuzzy measure is as follows in Table 2.

$$\mu_{\lambda}(\{1\}):\mu_{\lambda}(\{2\}):\cdots\mu_{\lambda}(\{n\})=w_{1}:w_{2}:\cdots:w_{n} \quad (3)$$

Fuzzy integral is a way to synthesizing evaluation values on each item in the use of Fuzzy measure when assessing certain subjects with various measures. In this study, Choquet integral and Sugeno integral were used to derive overall evaluation values in each type of emotion.

First of all, the method of derivation with Choquet integral is defined as follows.

Fuzzy measure of the set X is defined to be g. At this time, Choquet integral on Fuzzy measure g of the function,  $h:X \rightarrow [0,1]$ , is as follows in the Equation 4.

$$S(h(x_1)), \cdots h(x_n)) = \sum_{i=1}^n (h(x_{(i)}))$$
(4)  
- h(x\_{(x-i)})) × g(H\_{(i)})

At this time, x(i) satisfies  $0 \le h(x_{(1)}) \le ... \le h(x_{(n)})$ , and  $f(x_{(0)}) = 0$ . In addition, it means  $H_{(i)} = \{x_{(i)}, ..., x_{(n)}\}$ .

Sugeno integral is defined as follows.

Fuzzy measure on the set X is defined to be g. At this time, Sugeno integral on Fuzzy measure g of the function,  $h:X \rightarrow [0,1]$ , is as follows in the Equation 5.

$$\int h(X) \circ g(\cdot) = \bigvee_{i=1}^{n} \left[ h(x_i) \wedge g(A_i) \right]$$
<sup>(5)</sup>

At this time,  $Ai = \{x \mid f(x) \ge f(x_i)\}$ .

### 4. Experiment and Evaluation

In this study, emotion from Valence-Arousal input weight is inferred in emotion space by Thayer and Plut-

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Normalized\_Positive = Positive\_Weight / ( Positive\_Weight + Negative\_Weight ) Normalized\_Exciting = Exciting\_Weight / ( Exciting\_Weight + Calm\_Weight )

Fig. 4. Weights value as input stimulus.

chik. For this, rule-based Sugeno Fuzzy Inference System is established according to non-individualized psychological emotion model, while attempting to proceed emotion inference from Valence-Arousal values. In addition, personalized emotion space by Analytic Hierarchy Process is established on random subjects for Fuzzy integral and Fuzzy inference in personalized emotion space using Fuzzy measure and Fuzzy integral to infer emotion from Valence-Arousal input values in pre-established personalized emotion space. At the same time, emotion modeling results on these three methods were compared.

Emotional inference was attempted according to Valence-Arousal input in the rule-based Sugeno fuzzy inference system. In consideration of a total of 17 situations, the experiment was conducted by defining the weights value, which is the stimulus of the input. At this time, Sugeno FIS system uses Valence and Arousal values between 1 and -1 for the inputs. Therefore, the system was normalized according to these values. Fig. 4 has been used for normalization.

This study has implemented emotion inference on emotion model by Thayer and Plutchik and evaluated the results. Fig. 5 and 6 represent results from ValenceArousal inputs in the emotion space modeled by Sugeno FIS.

As shown in the Fig. 5 and 6, it is confirmed that emotion is selected, and strength of it is inferred in each quadrant from emotion model according to the results of emotion inference by Sugeno FIS. As shown in the Fig. 3, each quadrant of emotion model by Thayer is comprised of 3 types of emotion. Therefore, it is confirmed that emotion strength is inferred on 3 types of emotion according to Valence-Arousal values. In addition, as shown in the E15 and E16, Exciting in the 1st quadrant and Annoying in the 2nd quadrant do not exist in the same quadrant, but it is difficult to distinguish the emotion if Valence value is very small.

As for emotion model by Plutchik, 2 types of emotion were modeled in each quadrant. Especially, types of emotion change depending on the strength of emotion in emotion model by Plutchik. Therefore, it is feasible to express new emotion in the use of threshold. emotion strength on Trust from E1 is 0.741. Therefore, it is available to express it in the strength of upper level of emotion, Admiration.

In summary, there might be an issue of accurate inference of emotion in the boundary of quadrants according to types of emotion and modeling method of each quadrant for emotion space modeling that uses rule-based Fuzzy inference system in the space of two sensitivities. In addition, seeing as how human emotion is expressed in complicated forms, there is an insufficiency for it to only express emotion and the strength of it in the quadrant.



Fig. 5. Emotion inference result by Sugeno FIS (Thayer emotion model).



Fig. 6. Emotion inference result by Sugeno FIS (Plutchik emotion model).

In order to resolve these issues, Fuzzy measure and Fuzzy integral-based emotion inferring model has been suggested. Especially, it was intended to confirm how emotion inference was feasible in personalized emotion space in the experiment.

Personalized emotion space is established first to infer emotion in personalized emotion space. Like FISbased emotion inference method, individualization has been implemented on both emotion space models by Thayer and Plutchik. Analytic Hierarchy Process was implemented to derive relative importance among sensitivities to establish personalized emotion space experiment in the use of emotion model by Thayer. Analytic Hierarchy Process was implemented in Positive and Exciting aspects of the emotion.

As a result of the evaluation, in terms of positive, it was analyzed that there was a positive tendency toward the emotions of Pleased (L: .197), Happy (L: .179), and Peaceful (L: .175). In the Exciting aspect, it was analyzed to have strong stimulation on sensitivities of Exciting (L: .249), Annoying (L: .148), and Angry (L: .191).

As an interpretation of emotion space established by experiment results, Angry turned out to be expressed in Exciting (0.761) and Negative (0.675) values. This is a strength of stimulation needed to feel the Angry emotion from Valence-Arousal values in the emotion space from the 2nd quadrant. In other words, Annoying was not sensitive with changes in Negative, and Nervous turned out not to be sensitive with changes in Exciting. However, Angry was sensitive with Exciting that it is available to infer with the current emotion if there is a strong stimulation on both Negative-Exciting.

In this study, it is intended to analyze results of emotion inference by  $\lambda$ -Fuzzy measure and Fuzzy integral (Choquet and Sugeno). At this time, Fuzzy measure value represent distinctive features in each area of 0 (additive), > 0 (multicative),  $0 > \lambda > -1$  (subtitive). Therefore, results of Fuzzy integral show the difference. Hereupon, this study has derived results of emotion inference and analyzed them in each  $\lambda$  area.  $\lambda$  values to be used in the experiment are 0, -0.3, and 0.3.

It is available to confirm how the scale of emotion derived from changes in the interaction coefficient,  $\lambda$  values, changes. However, it is also confirmed that only the scale of it changes without type of emotion. Using such results, it is confirmed to be feasible to adjust sensitivity on emotions inferred from changes in  $\lambda$  values.

In the same way, the result of sentiment inference by Sugeno fuzzy integration showed a characteristic that the value was relatively larger than that by Choquet fuzzy integration. Especially, unlike the results by Choquet Fuzzy integral, when  $\lambda$  is equal to 0, resulting values turned out to be the most widely spread. Therefore, according to overall performance, Sugeno integral is inappropriate for emotion inference, and it is judged to be effective in using Choquet integral.

According to the results of analysis, emotion inference based on Choquet integral was implemented for Plutchik emotions as shown above confirming the

results thereafter.  $\lambda$  value used at this time was 0.3. At this time, due to the difference of personalized emotion space and emotion expressing languages used at this time, there is a difficulty to directly compare with aforementioned results of inference.

Unlike emotion model by Thayer, emotion model by Plutchik uses 32 types of emotion, and it is also possible to infer new emotions through synthesis of emotions. Emotions inferred from E3 to E7 turned out to be all Surprise. However, the maximum strength of it reaches up to 2 times of the one of minimum strength. In this case, they are divided into three emotions according to the strength from emotion model by Plutchik and processed into Amazement, Surprise, and Distraction.

In the case of Love and Remorse, it belongs to the opposite emotion within the model as a mixed sensibility of a specific emotion. It is also possible to infer them through proper calculation between emotions used for synthetic emotions. Average was used in this study as the simplest form for inference.

Based on this study, following plans are available to be established. First of all, emotional agent in the imitation of personalized emotion Avatar, emotional game NPC, or human emotions that are appropriate in mobile environment, or emotional pet or robot that reacts in recognition of emotions of an owner from emotional sharing are available. Especially, it is available to establish the emotion space comprised of very simple outcomes. Therefore, it is very advantageous to share them in personalized emotion space. Hereupon, it is judged to be convenient in realizing virtual objects or agents that resemble a certain character or understand them in particular forms.

In addition, it is feasible to provide personalized service based on whether it is required to consider particular location, space, or weather condition by using preestablished personal emotion space. In fact, research has recently been conducted on emotion service based on various situations. If it is available to recognize proper and accurate circumstances, it seems to be feasible to swiftly establish emotion space and realize service without having to learn as needed to provide appropriate personalized service.

### 5. Conclusions

In this study, personalized emotion space modeling

has been implemented using Analytic Hierarchy Process based on two-dimensional emotion space model by Thayer and Plutchik, a psychological emotion model on humans. In addition, Fuzzy Inference System, Fuzzy and Fuzzy Measure applied in MCDM techniques, and Fuzzy Integral-based emotion inference were implemented on emotions from input stimulants in personalized emotion space.

As a result, it was confirmed to be available to infer emotions from Valence-Arousal values as an input. However, it also turned out to be difficult to adjust the entire system as individualization was only available after going through learning such as the establishment of Neuro-Fuzzy System. It is difficult to deal with subjective decision making process, or especially decision making process with multiple measures, and also to quantitatively process and evaluate ambiguity of subjective propensity. For this, MCDM, etc. attempted to resolve ambiguity of decision making process in the use of logic-based Fuzzy Measure or Fuzzy Integral. This study also attempted to quantitatively evaluate ambiguity of internalized emotions of humans and establish personalized emotion space from them. At the same time, it was confirmed to be feasible to model emotion space and establish inference system from Valence and Arousal values as an input stimulant.

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#### References

- A. Esposito, L. Fortunati and G. Lugano, "Modeling emotion, behavior and context in socially believable robots and ICT interfaces," Cognitive Computation, Vol. 6, No. 4, pp. 623-627, 2014.
- [2] K. K. Chow, D. Fox Harrell, K. Yan Wong and A. Kedia, "Provoking imagination and emotion through a lively mobile phone: a user experience study," Interacting with Computers, Vol. 28, No. 4, pp. 451-461, 2016.
- [3] D. Garg and K. G. Verma, "Emotion Recognition in Valence-Arousal Space from Multi-channel EEG data and Wavelet based Deep Learning Framework," Procedia Computer Science, Vol. 171, pp. 857-867, 2020.

- [4] J. Song, X. Zhang, Y. Sun, and C. Jiang, "Establishment of emotional speech database based on fuzzy comprehensive evaluation method," Modern Electronics Technique, Vol. 39, No. 13, pp. 51-54, 2016.
- [5] X. Hu, H. Zhang, Y. Yuan, Y. Chen and M. Zhong, "A model for reappraisal with personality in emotion regulation," International Journal of Computer Integrated Manufacturing, pp. 1-11, 2020.
- [6] Z. Xu, "Choquet integrals of weighted intuitionistic fuzzy information," Information Sciences, Vol. 180, No. 5, pp. 726-736, 2010.
- [7] P. Bosc, L. Liétard and O. Pivert, "Sugeno fuzzy integral as a basis for the interpretation of flexible queries involving monotonic aggregates," Information processing & management, Vol. 39, No. 2, pp. 287-306, 2003.

- [8] J. Yang, "Study on emotion spaces with centrality measure," New Ideas in Psychology, Vol. 35, pp. 11-17, 2014.
- [9] K. B. Sim, K. S. Byun, and C. H. Park, "Emotional expression system based on dynamic emotion space," Journal of Korean Institute of Intelligent Systems, Vol. 15, No. 1, pp, 18-23, 2005.
- [10] Y. An, S. Sun, and S. Wang, S. "Naive Bayes classifiers for music emotion classification based on lyrics," In 2017 IEEE/ACIS 16th International Conference on Computer and Information Science (ICIS), pp. 635-638, 2017.
- [11] Z. Ahanin and M. A. Ismail, "Feature extraction based on fuzzy clustering and emoji embeddings for emotion classification," International Journal of Technology Management and Information System, Vol. 2, No. 1, pp. 102-112, 2020.

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