Subject Independent Emotion Recognition Using Electroencephalogram Signals with Continuous Capsule Network Method

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Abstract –Emotions play an essential role in human reasoning. Researchers have made various efforts to improve emotion classification methods. Based on the several emotion classification methods studied in previous studies, the Continuous Capsule Network method produced the highest accuracy compared to other classification methods. This method can maintain spatial information from electroencephalogram signals so they are not reduced. However, this method has only been tested subject-dependently. Based on this study, the Continuous Capsule Network method will be applied to classify emotions in the Faculty of Engineering and Vocational Studies, Universitas Pendidikan Ganesha students. The number of participants involved in this study was 17 people (10 men and 7 women). Through six subject-independent test scenarios, the Continuous Capsule Network method produced accuracy, precision, recall, and F1 scores of 99.31%, 99.34%, 99.20%, and 99.27, respectively. At the same time, the loss value was 0.88%. In addition, the Continuous Capsule Network method produced an average training and validation time of 401.17 seconds and an average testing time of 4.67 seconds for the six test scenarios.

Keywords: classification; continuous capsule network; electroencephalogram; emotion.

I. INTRODUCTION

Emotions play an essential role in human life [1]. Emotions can be measured and classified through the application of artificial intelligence. EEG or electroencephalogram is a technique for analyzing electrical impulses emitted by the brain [2]. The signal is obtained by attaching metal electrodes to several points on the scalp [3]. In the EEG device, electrical impulses emitted by the brain to the skin, one of which is the scalp, are recorded by the electrodes and translated into digital signals [3]. These signals can be studied by artificial intelligence models and used in various ways. One application uses electroencephalogram signals to test usability to validate emotional methods [4] and other approaches, such as emotion classification [5].

Several researchers carried out the emotion classification process before using the EEG tool. Emotions based on human voice can be classified by extracting features from human voices and then classifying them using an artificial neural network [6]. Research involving electroencephalogram signals uses the recurrent neural network model [5]. Various improvements are always made, one of which is reducing the EEG signal's baseline to increase the classification process's accuracy level [7].

A continuous capsule network modifies the capsule network method to overcome the loss of spatial data during the convolution process [8]. This study also combines a capsule network, using an architecture inspired by previous research [9]. This network can capture spatial information from EEG signals for emotion recognition. However, the convolution process can sometimes result in a loss of spatial data between channels in different frequency bands. The continuous convolution approach is combined with the continuous capsule network architecture to mitigate this problem. This combined architecture is specifically designed to recognize four categories of emotions [8]. The evaluation results show higher accuracy when compared to similar studies in recognizing four quadrants of emotions based on arousal and valence [8]. However, this method is only tested based on subjects. Therefore, it is crucial to test this method on independent subjects. Independent testing of subjects is essential to obtain a method that can recognize emotion patterns more generally.

Referring to several previous studies that have been presented, this study will re-implement the continuous capsule network method into the emotion recognition of students of the Faculty of Engineering and Vocational (FTK) of Universitas Pendidikan Ganesha and re-evaluate the performance of the process that will be implemented with primary data, not using secondary data from previous research datasets so that this provides flexibility in improving the quality of the dataset produced through better procedures and considerations. The research subjects determined the students in Universitas Pendidikan Ganesha. This scenario is done to avoid distrust of the research subjects if conducted externally at Universitas Pendidikan Ganesha. This study will produce outputs in the form of emotion recognition datasets of students of the Faculty of Engineering and Vocational, Universitas Pendidikan Ganesha, and evaluation of the performance of the continuous capsule network method on primary data.

II. METHOD

This research is a series of activities carried out by researchers, including problem formulation, literature review, ethical clearance, determination of population and sample, selection of stimulus media, data acquisition, and data analysis consisting of several sub-processes in the continuous capsule network algorithm that has been developed [8], and concluding as in Fig. 1.

A. Data Preparation

Data preparation includes determining the population and sample, selecting stimulus media, and conducting the data acquisition. The sub-activities are explained below.

Determining Population and Sample: The population in this study consists of active students from the Faculty of Engineering and Vocational Education, Universitas Pendidikan Ganesha. They will be given a Big Five Inventory personality trait questionnaire [10]. His study will use two types of samples: a supporting sample and a primary sample. The supporting sample will select the stimulus media shown to the primary sample to obtain the desired dataset. Determining the sample begins by calculating the level of representation of the subject's personality in the population using the Euclidean distance calculation.

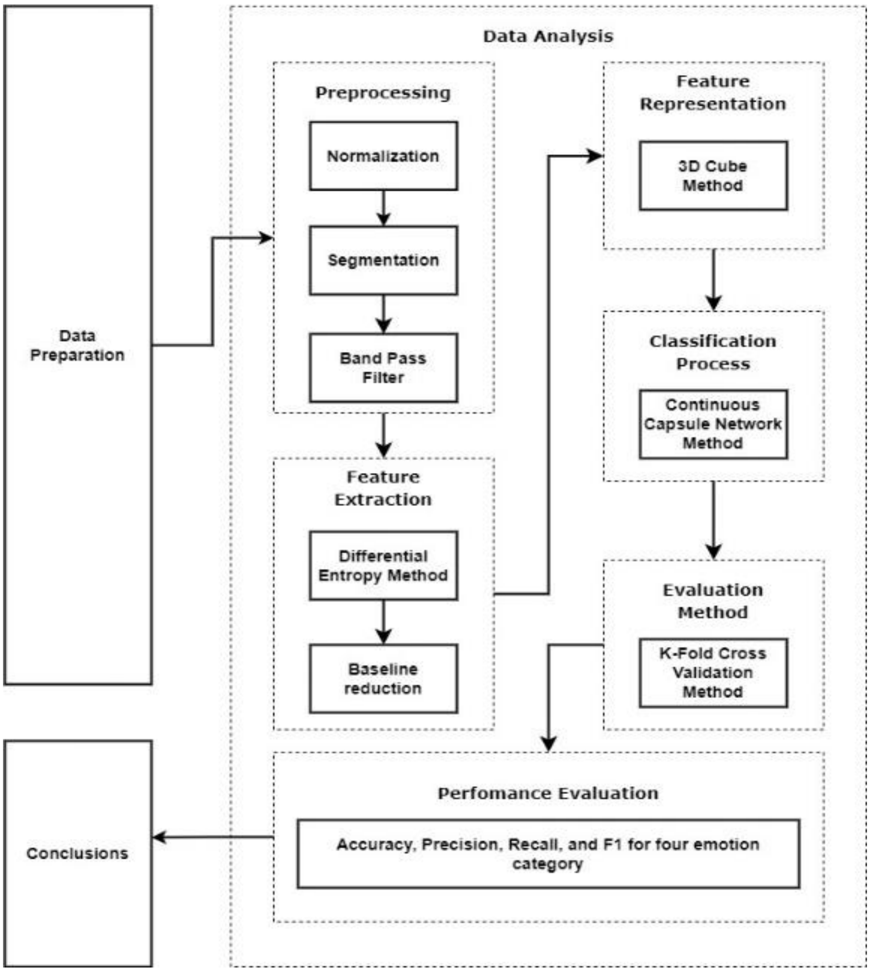


Fig. 1 Research procedure

The results of the euclidean distance calculation were continued with purposive sampling to obtain a sample of 17 people. Purposive sampling will be used with two criteria, namely, first, the prospective sample is in the first to third year of studying at FTK in Universitas Pendidikan Ganesha, and second, the prospective sample is willing to be a research sample, and finally, the prospective sample will only be included in one type of sample, either the primary sample or the supporting sample so that if there is a prospective sample that has been included in the supporting sample, it will be eliminated from the selection of the primary sample and vice versa. The two types of samples are separated. The author is concerned that if the primary sample is included in the selection of stimulus media, the emotions the primary sample feels will not be the same because they have previously witnessed the stimulus media. The sample determination process described above is described in Fig. 2.

1) Media Stimuli Selection: The selection of stimulus media began with 32 stimulus media, divided into eight media per emotional quadrant according to the Russell circumplex model [11]. The author made the first selection personally; then, the author will involve a supporting sample to rank the stimulus media for each quadrant. The supporting sample will be invited to gather and watch all the prepared stimulus media together, and then they will be rated individually. Before the assessment, the sample will monitor their body temperature and be given hand sanitizer when entering the room. The sample will fill out the attendance list and briefly explain the process to be carried out. This series of activities is a form of implementation of the author's commitment to research ethics. The data collection instrument for selecting stimulus media is an online questionnaire filled out on the spot, with the contents of the questionnaire guided by self-assessment manikin (SAM). The data that has been collected will be analyzed using Cronbach's alpha calculations to obtain the best stimulus media in each quadrant [12].

Data Acquisition: After obtaining the best stimulus media from each quadrant, the primary sample will be instructed to watch the stimulus media while wearing an EEG signal measuring device, the Emotiv Epoc X 14-channel. Before recording, the participant's health condition will be monitored first by measuring body temperature. Body temperature checks will be performed using an infrared body temperature measuring device. After being declared healthy, an EEG signal recording device will be installed, and the stimulus media will be broadcast while the EEG signal recording is carried out. The stimulus media is provided through the YouTube platform. This recording flow refers to previous research [7]. The implementation of data recording in this study went without significant obstacles, primarily related to the health condition of the primary sample. After recording, the sample's condition was also monitored using the hamilton rating anxiety scale questionnaire [13]. The data to be collected in this study were from 17 participants consisting of 10 men and seven women. Data recording used an EEG measuring device called the Emotiv Epoc X. Information on the device can be accessed at https://www.emotiv.com/collections/all/products/epoc-x. This Emotiv Epoc x tool will place points as in Fig. 3.

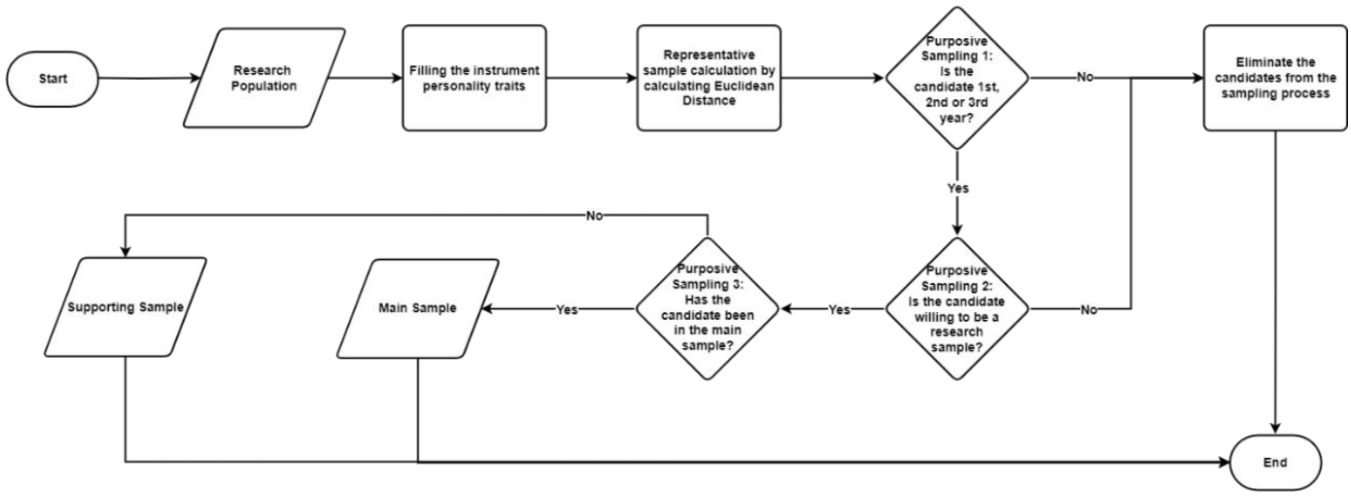


Fig. 2 Sample selection flowchart

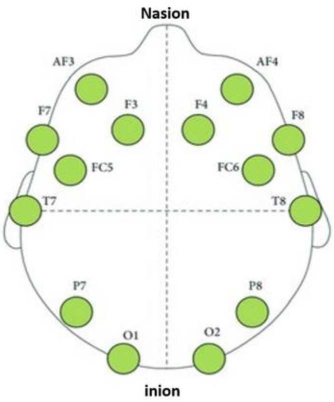


Fig. 3 Position of placement of 14 channels at the participant's head

In Fig. 3, nasion is the front of the participant's head starting from the forehead, while inion is the back of the participant's head. The F code at that point is the front or can be called frontal, the T code is temporal, the P code is parietal, and the O code is occipital. The data sequence of each channel is depicted in **Error! Not a valid bookmark self-reference.**.

Some data information, including the channel list, is packaged into a single file with the extension .mat for each participant. This file can be accessed using the MATLAB application, as shown in Fig. 4.

As seen in Fig. 4, the channel variable contains 14 EEG channels. The Fs variable represents the sampling rate per second of the data, 128, and the merged_data variable represents the EEG recording data for the eight scenarios. Furthermore, the label_assessment variable is a collection of Self-Assessment mannequin data from the eight scenarios. Finally, the subject variable represents the participant ID. Fig. 5 The combined data variable below has 8 data matrices with 14 columns. The 14 columns represent the number of channels, and the rows represent the recording duration (1-second x 128 sampling rates). This dataset is publicly accessible via the link https://data.mendeley.com/datasets/6cjgr5xthm/1.

Each participant will carry out eight scenarios, where the total data generated for one participant is 312,448.

A. Data Analysis

The data analysis process will apply the continuous capsule network algorithm [8]. The data analysis steps are shown in the outline below.

1) *Preprocessing:* At this stage, the raw EEG signal from the dataset is normalized. This process reduces the amplitude of EEG signal outliers caused by artifacts. The normalization process uses the z-score method. The normalized EEG signal results are then segmented. The segmentation process aims to separate the baseline signal and the trial signal in the EEG. The baseline signal is used as a benchmark for changes in activity in the EEG signal. This signal is essential for seeing signal activity to stimuli and tasks given to participants. In this process, the baseline signal is set at seconds 1 to 5, while seconds 6 to the last second are used as trial signals. This process will be carried out for each channel in eight trials from each participant. After segmenting, the signal is decomposed to extract theta, alpha, beta, and gamma bands using the bandpass filter method. The decomposition process is a process for extracting signals into specific types of frequencies, including four frequencies: Gamma, Betta, Alpha, and Theta. These frequencies are done for each channel in the EEG trial signal. In this study, 14 channels will go through a decomposition process through four frequency bands (γ, β, α, θ) so that their dimensions will increase and produce 56 features. In contrast, the Delta frequency reflects the condition of the brain when someone is in deep sleep, so it is not considered in this study.

TABLE I
LIST OF CHANNELS PAIRED WITH EEG SIGNAL RECORDING POINTS

No	Channel	No	Channel
1	AF3	8	O2
2	F7	9	P8
3	F3	10	T8
4	FC5	11	FC6
5	T7	12	F4
6	P7	13	F8
7	O1	14	AF4

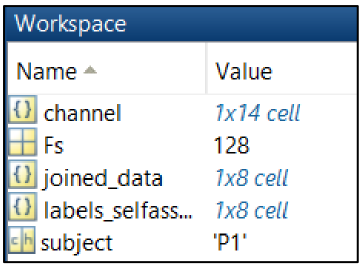
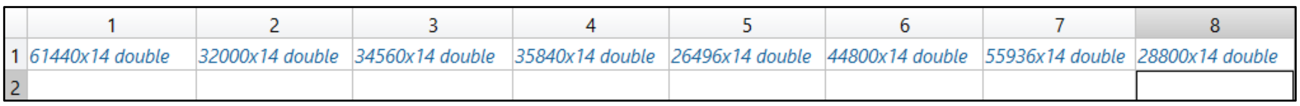


Fig. 4 Variable structure in .mat files



	1	2	3	4	5	6	7	8
1	61440x14 double	32000x14 double	34560x14 double	35840x14 double	26496x14 double	44800x14 double	55936x14 double	28800x14 double
2								

Fig. 5 Contents of the joined_data variable

2) Feature Extraction: The feature extraction stage is carried out for each second, frequency, and channel using different entropy methods. Each second will obtain a different entropy value. After the features are extracted, a data reduction process is carried out to refine the data and ensure it is well-focused. The feature extraction will be done for each channel segment and frequency band. The wavelength per second will be extracted, which will produce one feature. The signal extraction process is carried out using the differential entropy method. The Differential Entropy value at each frequency is then averaged again to create the average Differential Entropy value in four frequency ranges and 14 channels for each signal second. The Differential Entropy value can be calculated using (1).

$$h(X) = \frac{1}{2}\log\left(2\pi e \delta^2{}_i(X)\right) \tag{1}$$

Where e is Euler's constant, $\delta^2{}_i$ is the variance at second i for the EEG signal segment, and $h(X)$ is the DE value at second i for the EEG signal segment [8].

3) Feature Representation: Due to the spatial characteristics of EEG signals, selecting an appropriate method for feature representation is critical before classification. This process is applied to each frequency band in all channels to preserve the spatial relationship between adjacent channels. The 3D cube method effectively preserves spatial information in all frequency bands and channels.

4) Classification Process: The classification process will utilize the continuous capsule network method [7], divided into three stages: continuous convolution, primary capsules, and emotion capsules. The following is the architecture of the proposed continuous capsule network method, as shown in Fig. 6.

Based on Fig. 6, the structure of the continuous capsule network method generally consists of several parts:

- Continuous convolution. At this stage, the convolution process is carried out from the input matrix data, and the activation process is carried out with the ReLu activation function.
- Primary capsule. At this stage, the reshape and the second convolution processes are carried out from the output produced by the first convolution process. In the primary capsule stage, the feature map data obtained from the fourth continuous convolution process is divided into eight blocks, each measuring 9 × 9 × 8. The result of this process is a vector value u_i, which is used as input for the emotion capsule process.
- In the emotion capsule stage, affine transformation, weighted sum, dynamic routing, and squashing are applied [14]. Several stages of the process are carried out based on the capsule network method architecture. [15]:

Input vector ($\boldsymbol{u_i}$). In the capsule network method, the value of the input node is a vector. The input vector comes from nodes $\boldsymbol{u_1}$, $\boldsymbol{u_2}$, ***and*** $\boldsymbol{u_3}$ or is generated from the previous capsule layer. The capsule network method does not use bias values as input.

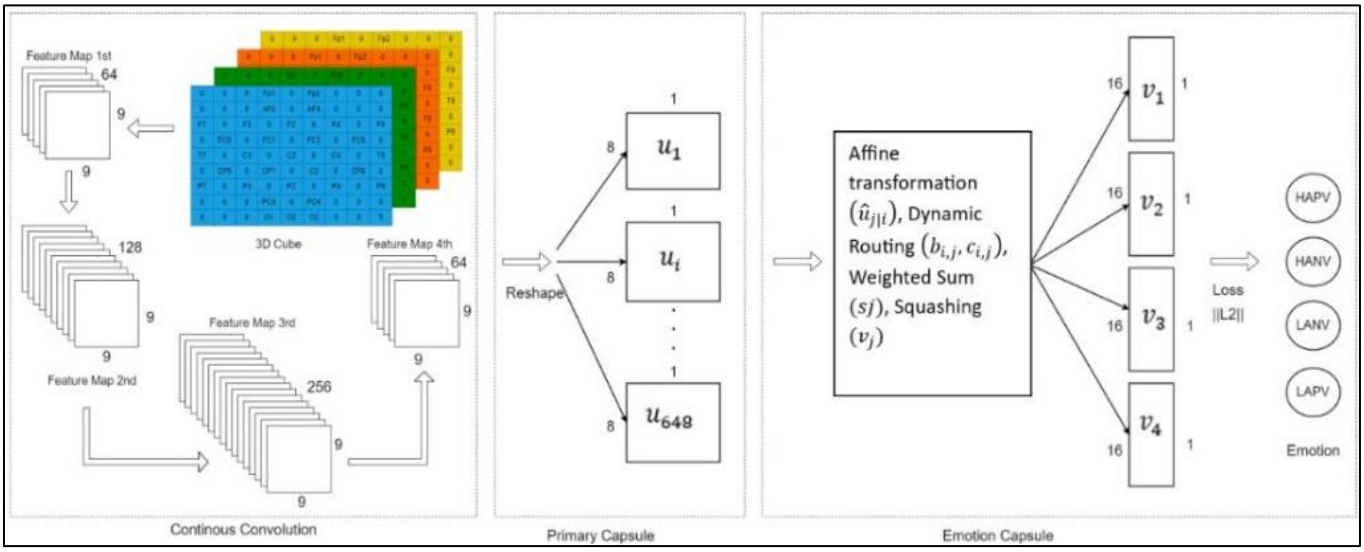


Fig. 6 The architecture of the Continuous Capsule Network method [14]

- *Affine transformation*. This step applies the matrix transformation $\boldsymbol{W_{i,j}}$ ($\boldsymbol{W_{1,j}}$, $\boldsymbol{W_{2,j}}$, $\boldsymbol{W_{3,j}}$) to the vectors $\boldsymbol{u_1}$, $\boldsymbol{u_2}$, $\boldsymbol{u_3}$ from the previous input layer or Capsule layer to produce the vector $\boldsymbol{\hat{u}_{j|}}$ I ($\boldsymbol{\hat{u}_{j|1}}$, $\boldsymbol{\hat{u}_{j|2}}$, $\boldsymbol{\hat{u}_{j|3}}$). For example, the matrix $\boldsymbol{W_{1,j}}$ of size 16 × 8, and the input vector $\boldsymbol{u_1}$, size 8 × 1, are transformed into the vector $\boldsymbol{\hat{u}_{j|1}}$ of size 16 × 1. It can be illustrated as follows (p × k) × (k × 1) ⟹ p × 1. Equation 2 represents the affine transformation process.

$$\hat{u}_{j|i} = W_{i,j} u_i \qquad (2)$$

where $\boldsymbol{u_i}$ is the input vector of the lower-level capsule (i), $\boldsymbol{W_{i,j}}$ is the weight matrix, and $\boldsymbol{\hat{u}_{j|i}}$ is the upper-level capsule (j) prediction vector. This transformation aims to represent the spatial relationship between sub-objects (i) of all objects in the higher layer (j). In this way, whether these sub-objects are correlated with objects at a higher level can be predicted.

- *Weighted Sum process* ($\boldsymbol{s_j}$). This process aims to project several prediction vectors ($\boldsymbol{\hat{u}_{j|i}}$) that represent sub-objects using coupling coefficients ($c_{i,j}$) to produce the Weighted Sum ($\boldsymbol{s_j}$) value. For example, the calculation of $\boldsymbol{s_j}$ s produced through the addition process of the multiplication process of c_{ij} (scalar value) with $\boldsymbol{\hat{u}_{j|i}}$ (vector value), as follows $\boldsymbol{s_j}$ = $c_{1j*}\boldsymbol{\hat{u}_{j|1}} + c_{2j*}\boldsymbol{\hat{u}_{j|2}} + c_{3j*}\boldsymbol{\hat{u}_{j|3}}$. The ci,j value is determined using the dynamic routing process.

5) Evaluation Method. To test the reliability of the continuous capsule network method, researchers designed 6 test scenarios with independent subjects. All data from 17 participants were combined into one data unit with 5,311,616 data. All of this data is divided into three parts: the part for training data, the part for validation data, and the part for testing data. These three parts of data will be used for model testing. Six testing scenarios will be applied in this study. The following Fig. 7 is a visualization of the as-in-testing scenario.

The dataset from each participant will be proportioned into X% for training and validation data and Y% for testing data. The comparison of the percentage of the division is shown in Fig. 8.

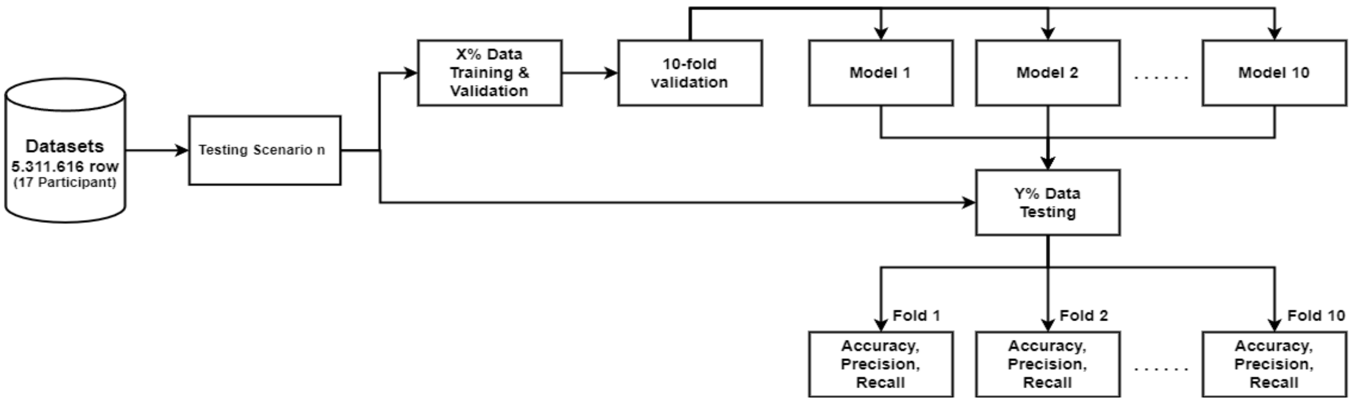


Fig. 7 Six model testing scenarios

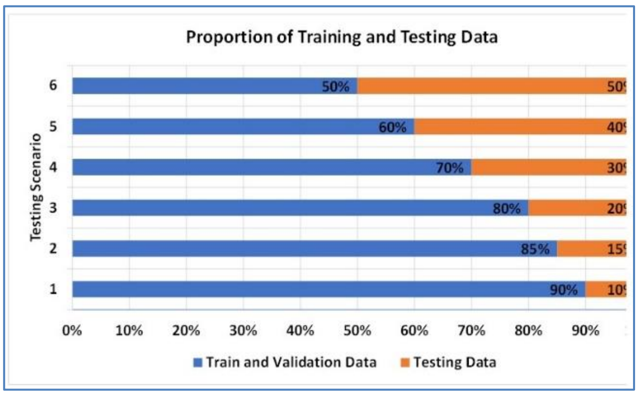


Fig. 8 Proportion between testing data with train and validation data

After proportioning, X% of the training and validation data will be trained using the k-fold cross-validation method, with a value of k = 10, to produce 10 models. Each model will be tested by Y% of the testing data and produce accuracy, precision, and recall values. This process is repeated as many times as the number of participants.

6) Performance Evaluation: After carrying out the processes above, the accuracy value will be calculated by dividing the true label value by the sum of the true and false labels. Naming true labels is based on the results of recording testing data, which can identify precisely which emotional quadrant it falls into. Meanwhile, the

K-Fold Cross Validation technique is used for the training and validation, where the specified K value is 10.

III. RESULT AND DISCUSSION

The research sample selection process began by distributing the Big Five inventory questionnaire online to the population through the Google form platform. Forty-seven people were obtained who were willing to be research samples. The 47 people were then divided into 30 supporting samples to rank the stimulus media, and 17 other people were the primary sample that would participate in the EEG signal recording. The process of determining who was included in the 30 supporting and 17 primary samples began by defining the representative level of the sample to its population using the Euclidean distance calculation against the value of the Big Five inventory questionnaire that each sample had collected.

Euclidean distance calculation applies two centroids and groups the candidate samples into classes A and B. Each candidate sample will be ranked in its class. Based on their ranking, the first half of the members in each class show a high representativeness to the population. They are included in the supporting sample group assessing the stimulus media. In contrast, the rest will be included in the primary sample group undergoing EEG recording. The process of evaluating the stimulus media by the supporting sample is shown in Fig. 9.

The process of selecting stimulus media by supporting participants is done by watching the stimulus media that will be assessed together, as in Fig. **9**. At the end of each stimulus media, the supporting sample will fill out a SAM questionnaire that assesses what each supporting sample feels about the stimulus media displayed. There are eight stimulus media for each emotional quadrant. The list of stimulus media that will be displayed is presented in Table II.

Fig. 9 Support sample reviewing media stimuli

TABLE II
SELECTED MEDIA STIMULI BASED ON CRONBACH'S ALPHA SCORE

No	Media	Score
1	Media K1.5	0,799
2	Media K1.6	0,869
3	Media K2.3	0,742
4	Media K2.4	0,739
5	Media K3.1	0,587
6	Media K3.5	0,215
7	Media K4.3	0,000
8	Media K4.6	0,025

The list of selected stimulus media includes the two best stimulus media in each emotional quadrant. The selected stimulus media will be shown to the primary sample based on cronbach's alpha calculation value. After each showing of the stimulus media, the primary sample will also fill out a SAM questionnaire as material for the data training process. The EEG recording process is documented in Fig. 10.

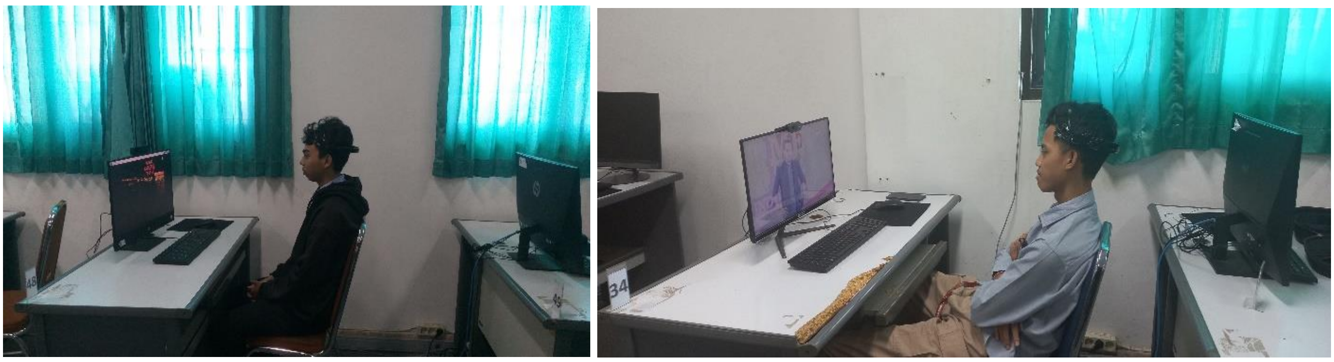


Fig. 10 Main sample watching media stimuli while EEG recording

The results of the data recording will be analyzed further. The analysis will use the continuous capsule network method to recognize high arousal positive valence (HAPV), high arousal negative valence (HANV), low arousal negative valence (LANV), and low arousal positive valence (LAPV) emotions. All participants were combined into 1 data set (independent subjects) to test the reliability of this method. All data are divided into train, validation, and testing data. To optimize the performance of this method, several parameters, such as batch size, learning rate, and epoch, were given values of 2, 0.001, and 20, respectively. The accuracy for each fold for six test scenarios is in Fig. 11, Fig. 12, and Fig. 13.

Based on the six test scenarios that have been carried out, the continuous capsule network method has proven to recognize four classes of emotions in FTK student participants at Universitas Pendidikan Ganesha well. This method consistently produces accuracy, precision, recall, and F1 scores above 97% in 10-fold testing, as shown in TABLE III.

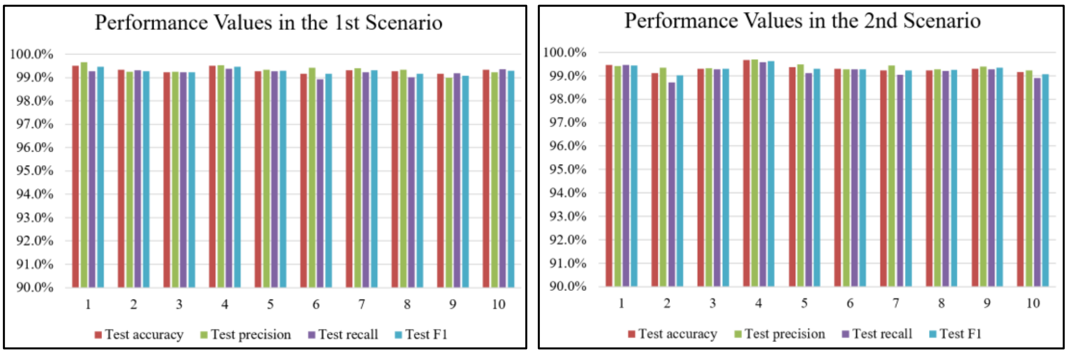


Fig. 11 Accuracy, precision, recall, and F1 score values for the first scenario (left) and for the second scenario (right)

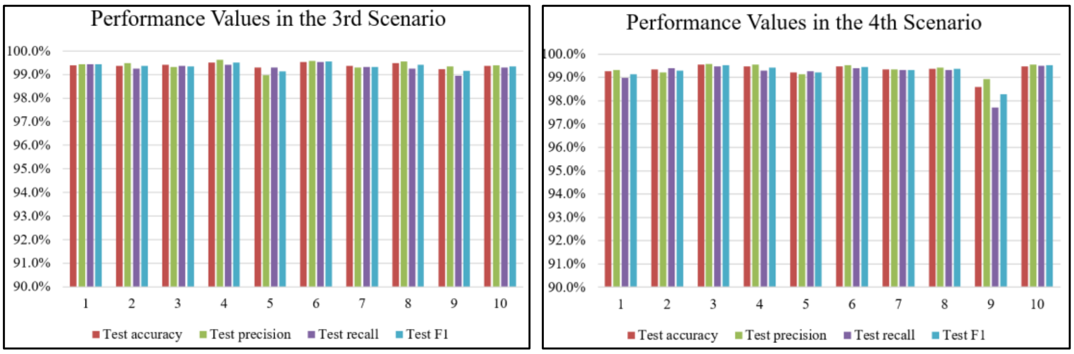


Fig. 12 Accuracy, precision, recall, and F1 score values for the third scenario (left) and for the fourth scenario (right)

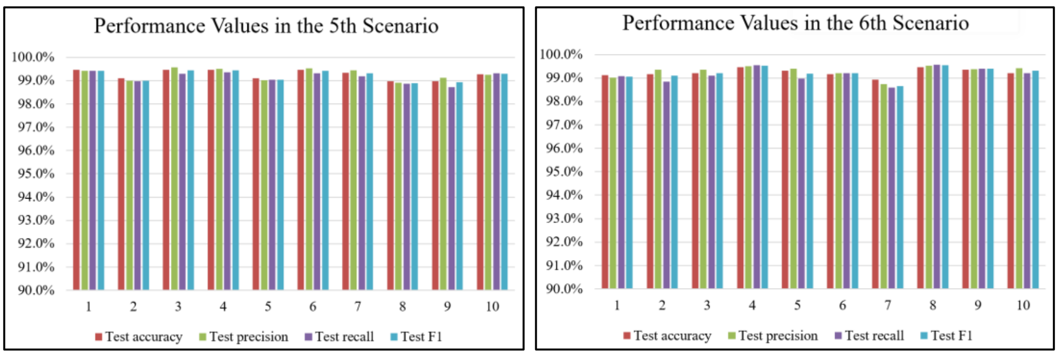


Fig. 13 Accuracy, precision, recall, and F1 score values for the fifth scenario (left) and for the sixth scenario (right)

TABLE III
RECAPITULATION OF THE AVERAGE VALUES OF ACCURACY, PRECISION, RECALL, F1 SCORE, TRAIN TIME, AND TEST TIME FOR ALL SCENARIOS

	acc	precision	recall	F1 score	loss	train time	test time
The 1st Scenario	99.31%	99.34%	99.22%	99.28%	0.84%	465.49	5.67
The 2nd Scenario	99.31%	99.39%	99.19%	99.28%	0.82%	487.02	5.28
The 3rd Scenario	99.39%	99.40%	99.31%	99.35%	0.87%	445.25	5.08
The 4th Scenario	99.31%	99.36%	99.17%	99.26%	0.88%	442.77	4.52
The 5th Scenario	99.26%	99.28%	99.16%	99.22%	0.92%	304.56	3.99
The 6th Scenario	99.24%	99.29%	99.15%	99.22%	0.99%	261.94	3.46
Mean	99.31%	99.34%	99.20%	99.27%	0.89%	401.17	4.67

The continuous capsule network method tested on primary data with a subject-independent testing scenario has an accuracy value that is not much different from research with secondary data. Spatial data maintained during the convolution process can increase measurement accuracy with primary and secondary data [8]. Based on the research results presented, this method has the potential to be used in various fields as an emotion recognition approach.

IV. CONCLUSION

Through the acquisition of emotional data on students of the Faculty of Engineering and Vocational Studies in Universitas Pendidikan Ganesha, 17 participants were obtained who were willing and had health conditions suitable for the EEG signal recording process. The data that had been received was analyzed to recognize EEG signal patterns representing four emotional quadrants. The data analysis process includes classification. By using the continuous capsule network method, the classification of four emotional quadrants was successfully carried out. The emotional classification process obtained an average accuracy, precision, recall, and F1 score of 99.31%, 99.34%, 99.20%, and 99.27% for six test scenarios, respectively. Furthermore, the loss value was 0.88% for six test scenarios. Based on 17 data used for the training, validation, and testing processes, the continuous capsule network method produced an average training and validation time of 401.17 seconds and an average testing time of 4.67 seconds for six test scenarios.

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