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Decision tree method to classify the electroencephalography-based emotion data

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Abstract — [C1] Electroencephalography (EEG) data contains recordings of brain signal activity divided into several channels with different impulse responses that can detect human emotions. In classifying emotions, EEG data needs to be parsed or signal processed into values to help recognizes emotions. Research related to electroencephalography has been carried out previously and has experienced success using the Fuzzy C-Means, Multiple Discriminant Analysis, and Deep Neural Network methods. This study classifies human emotions from electroencephalography data on 10 participants. Here, each participant carried out 40 trials of testing using the Power Spectral Density (PSD) at the initial classification stage. Then, we apply Discrete Wavelet Transform (DWT) methods and the Decision Tree method as the final method that can improve the accuracy of the two methods at the initial classification stage. The results of this study were the finding of 2 participants (3 trials) who were unmatched from a total of 10 participants (400 shots), which were analyzed using the decision tree method. The decision tree method can correct this error and increase the classification result to 100%. The DWT method is used as a reference in the classification of emotions, considering that the DWT method has an output of arousal and valance values . In contrast, the PSD method only has a combined result.

Keywords – Electroencephalography (EEG), Power Spectral Density (PSD), Discrete Wavelet Transform (DWT), Decision Tree.

I. INTRODUCTION

Emotions are reactions to events that happen to a person.. The word emotion comes from the French émouvoir, which means joy. Emotion is a psychological state in the human consciousness related to identity, mood, character, and temperament. Each individual has a variety of emotions expressed depending on the feelings and thoughts that are unique to each individual. A person's emotions are complicated to predict, and some human-computer interaction systems are still very lacking in interpreting emotional information [1]. On the other hand, emotion is one of the critical factors to improve the welfare of human life.

Emotional analysis can apply Human Computer Interaction (HCI), with later displayed in electroencephalography (EEG). Many research developments have been related to emotion recognition based on EEG signals [2]. However, artefacts in the raw EEG signal can cause noise, resulting in inaccurate EEG signal readings [3]. The preprocessing step analyzes the core of the original signal and reduces the noise needed to improve the accuracy of the EEG signal. The stages of preprocessing EEG are Re-reference/down-sample, filter data, reject component artefacts and reject wrong channels.

Several previous studies related to identifying electroencephalography signals in determining emotions have been carried out using various methods [4]–[12]. Researchers [4], [10] used machine learning and deep learning approaches to compare emotional categories. Furthermore, EEG also uses the stacking emotion classification method to analyze the results obtained, where this method provides recognition accuracy of 77.19% for HA/LA and 79.06% for HV/LV.

Research on EEG was also conducted by [6], where they used a conditional framework (CTL) to facilitate the positive transfer. In addition, emotion recognition from EEG can use a discrete wavelet transform approach [7] and also use the power spectrum and frequency band features [11], [12]. The differential entropy method shows effective results for EEG processing [9]. Researchers [8] also performed an EEG emotion classification by combining several decisions at the segment level.

Decision Tree is one of the modern solutions for problem decision making by studying data from the problem domain and building a model to predict an event with the support of systematic analysis. [13]. Decision Tree has the concept of converting data into decision requirements that can shorten the process of making complex decisions into simple ones so that that decision making will provide more solutions to the problems experienced. Decision Trees can also find the relationship between the input and target variables, which is very good in making decisions. [B3, C2]In this study, we apply Decision Tree as a method of classifying emotions from emotional output. Where previously we have tested 10 participant datasets using the Power Spectral Density (PSD) method and the Discrete Wavelet Transform (DWT) method. Several previous studies have applied the Decision Tree Method in research that requires a decision-making process [14]–[18].

II. RESEARCH METHODS

In this study, we propose the Decision Tree method for analyzing EEG signals and the Independent Component Analysis (ICA) method for correcting artifacts and removing various artifacts from EEG data with linear decomposition as a preprocessing method. Then test the classification results from the Decision Tree decision method used.

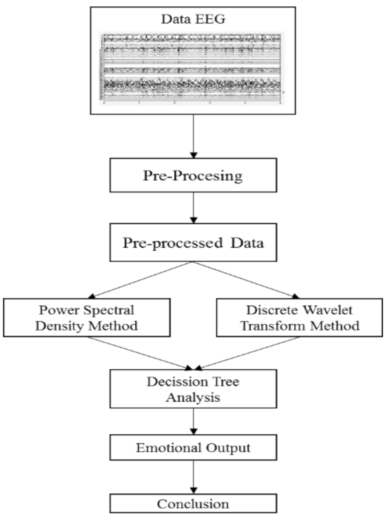


Fig.1. Research Method

Figure 1 shows the flow design of the classification method using Decision Tree as a method of classifying emotions from emotional output. We apply Power Spectral Density (PSD) and Discrete Wavelet Transform (DWT) methods.

A. Power Spectral Density

Power Spectral Density (PSD) analyzes power distribution across the frequency range. The main purpose of using this method is to estimate the spectral density from the given data.

[C4]$$\lambda = \log 10 \left(\frac{Average\ Power}{Sum\ Power}\right) \quad (1)$$

Calculating the Fourier transform of the signal can be used as a stochastic process to determine the signal strength [19]. A PSD function based on a standard sinusoid or complex exponential base set must have the following characteristics:

a) To facilitate the analysis should be a continuous signal.

b) Having the interpretation G(fx) is directly proportional to the power in the sinusoidal component of the signal with frequency fx Hz.

c) The integral of the power spectral density at possible frequencies equals the average signal

B. [C5]Discrete Wavelet Transform

Discrete Wavelet Transform (DWT) is a transformation that decomposes a given signal into several sets. Each set is a time series of coefficients describing the time evolution of the movement in the appropriate frequency band [20]. The first results using wavelet analysis of EEG signals to obtain univariate hypnotic depth descriptors [21]. The resulting index, called the wavelet-based an aesthetic value for the central nervous system (WAVCNS), was clinically validated with success, later by Bibian et al. [22-23], Lundqvist et al. [24], and Zikov et al. [25]. the NeuroSENSE Monitor has integrated WAVCNS technology into its system. Like the BIS, WAVCNS uses the same 0-100 scale to represent a patient's hypnosis depth. Particular attention is paid to the WAVCNS technology to avoid nonlinearity and the use of non-minimum phase elements. WAVCNS technology does not add additional computational delay, making it virtually delay-free. The dynamic behavior of WAVCNS is linear and the second-order time-invariant linear transfer function is fully functional (LTI). However, WAVCNS may provide inaccurate data in deeper hypnotic states [26].

C. Decision Tree

Decision Tree is one of the modern solutions for problem decision making by studying data from the problem domain and building models to predict outcomes by systematic analysis. [13]. The decision Tree represents the various alternative solutions available to solve a problem. How to illustrate often proves to be decisive when making choices. Decision tree analysis answers several questions after each affirmative or negative answer until making a final selection. The decision tree classifies the samples by arranging them from the root node to the leaf node. Each non-leaf node in the tree represents a test for attribute values, and each leaf node represents a category classification. The root node is the highest node of the decision tree. The sample class can be determined when all leaf nodes give the same classification results [27].

Several ways to display a decision tree, lines, boxes, and circles usually represent this analysis. Squares represent decisions, lines represent consequences, and circles represent uncertain outcomes by keeping the lines as far apart as possible.

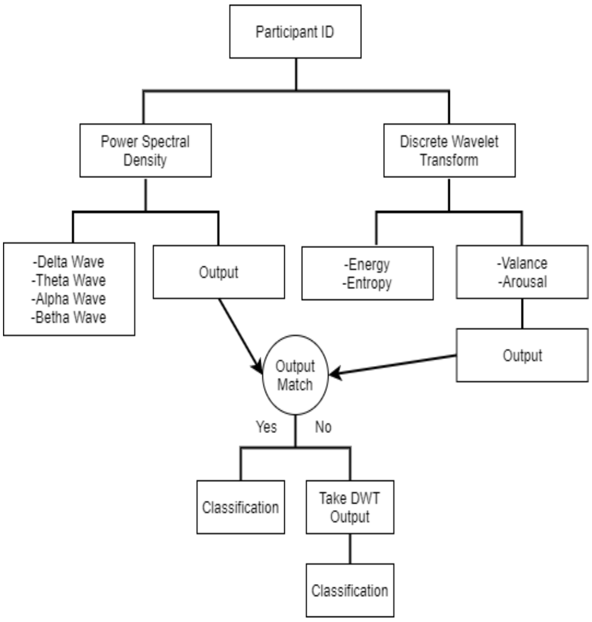


Fig.2. Classification with Decision Tree

Arousal and valance values range from 1-9 with a median value. For the low category, the values range from 1-4.99, and the high category is worth 5-9.

Table 1. Arousal and Valance Value Range

Value	Valance	Value	Arousal	Emotion
1 s.d 4,99	Low	1s.d 4,99	Low	Sad
	Low		High	Angry
5 s.d 9	High	5 s.d 9	Low	Calm
	High		High	Happy

The division of emotional groups is divided according to the provisions. If the arousal value is high and the value is high, it will produce happy emotion output, and if the arousal value is high. The deal is low, it will produce angry emotion output, if the arousal value is low and the value is high, it will produce emotional output calm, and if the arousal value is low. The deal is low, it will have soft emotion output.

D. A. Fasich tested the classification of eight emotions using fuzzy c-means clustering with the result that the silhouette index and rand index values tended to decrease when the C parameter increased. The parameter C = 2 has the highest accuracy with a value of 57.66% [4]. Based on this research, Hopefuly, using the decision tree classification method can improve accuracy better.

III. RESULT

In this study, we carried out two stages of testing: the Power Spectral Density (PSD) test and the Discrete Wavelet Transform (DWT) test. We conducted the test using the DEAP dataset containing the results of the EEG signal test from 32 participants. Each participant will get tested 40 times with the provisions of each trial by getting a different video. The output of the two tests is in the form of an analysis text file using Matlab R2019a.

A. Power Spectral Density Test

The EEG signal provided by the DEAP dataset was analyzed for each participant using Matlab R2019a and resulted in the delta, theta, alpha, and beta wave values as follows:

- Participant 1

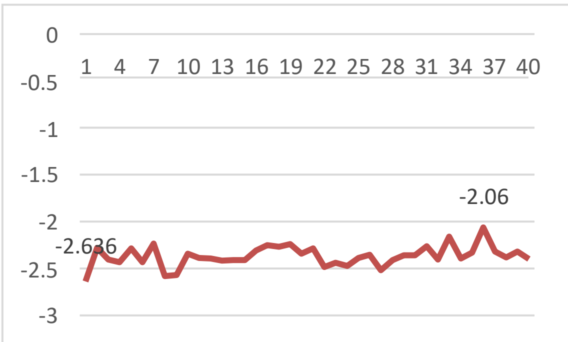


Fig.3. Delta Wave of Participant 1

Delta waves occur when participants are unconscious or in a state of not thinking. As shown in Figure 3, the highest value is in the 36th video trial and the lowest value is in the 1st video trial with values of -2.06 and -2.636.

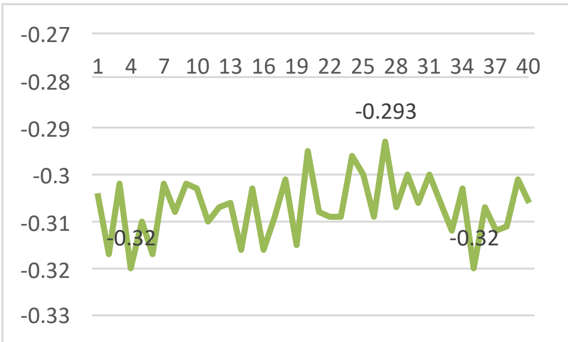


Fig.4. Theta Wave of Participant 1

Theta waves occur when participants experience drowsiness. Figure 4 shows the theta wave values in participant 1, the highest in the 27th video trial and the lowest in the 4th video trial with values of -0.293, and -0.32.

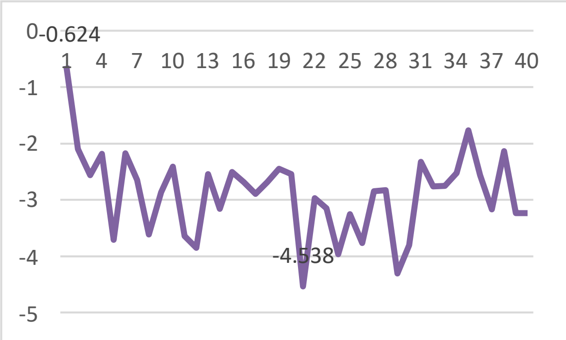


Fig.5. Alpha Wave of Participant 1

As shown in figure 5, Alpha waves occur when the participant is relaxing or resting. As highlighted, in Figure 5 the highest alpha wave value is in video trial 1 and the lowest is in video trial 21 with a value of 0.624, and a value of -4,538.

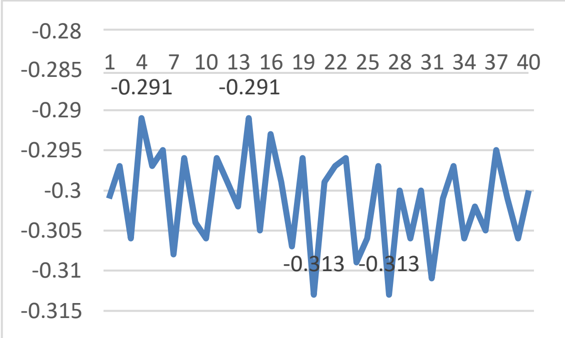
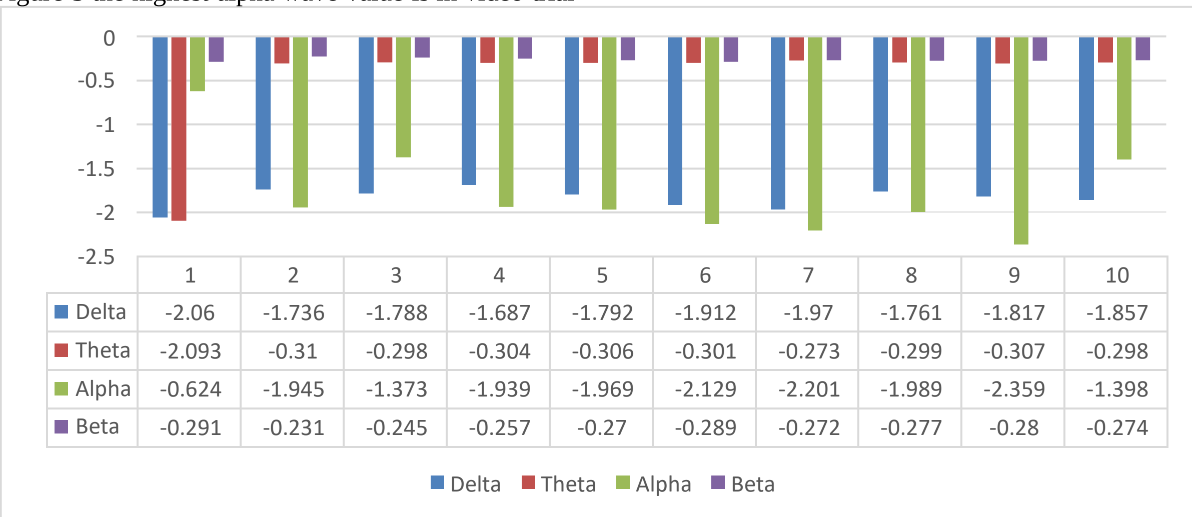


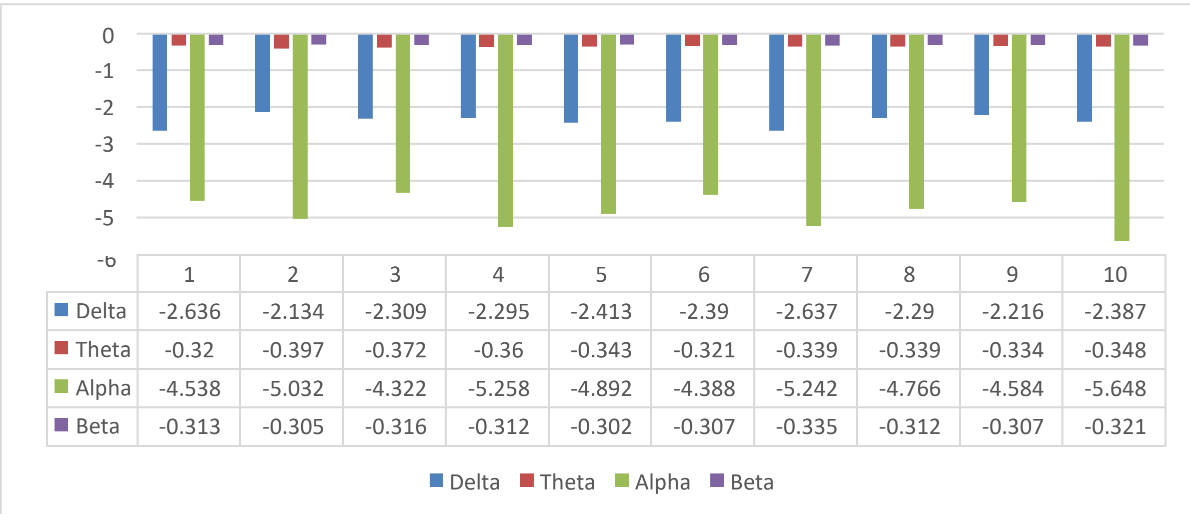
Fig.6. Beta Wave of Participant 1

Turning to figure 6, Beta waves occur when participants experience fully awake activities. In participant 1, the highest delta wave value was obtained in the 4th, and 14th video trials with a value of -0.291, and the lowest occurred in the 20th and 27th video trials with a value of -0.313.



	1	2	3	4	5	6	7	8	9	10
Delta	-2.06	-1.736	-1.788	-1.687	-1.792	-1.912	-1.97	-1.761	-1.817	-1.857
Theta	-2.093	-0.31	-0.298	-0.304	-0.306	-0.301	-0.273	-0.299	-0.307	-0.298
Alpha	-0.624	-1.945	-1.373	-1.939	-1.969	-2.129	-2.201	-1.989	-2.359	-1.398
Beta	-0.291	-0.231	-0.245	-0.257	-0.27	-0.289	-0.272	-0.277	-0.28	-0.274

Fig 7. Maximum Value of Power Spectral Density



	1	2	3	4	5	6	7	8	9	10
Delta	-2.636	-2.134	-2.309	-2.295	-2.413	-2.39	-2.637	-2.29	-2.216	-2.387
Theta	-0.32	-0.397	-0.372	-0.36	-0.343	-0.321	-0.339	-0.339	-0.334	-0.348
Alpha	-4.538	-5.032	-4.322	-5.258	-4.892	-4.388	-5.242	-4.766	-4.584	-5.648
Beta	-0.313	-0.305	-0.316	-0.312	-0.302	-0.307	-0.335	-0.312	-0.307	-0.321

Fig 8. Minimum Value of Power Spectral Density

Fig.7 and Fig 8. show the Power Spectral Density values, which consist of 4 types of waves with maximum and minimum values for 10 participants with the following information:

a) Delta waves refer to the slowest brain waves recorded in humans. The more mature humans are, the fewer delta waves are produced during deep sleep. Because delta waves are associated with the most profound relaxation and restorative healing level. A thinking disability or severe ADHD can cause high values of delta waves. In contrast, low delta waves can be due to the inability to revitalize the brain [28].

b) Theta waves are when humans feel deep and raw emotions. Theta waves benefit from increasing intuition creativity and helping to boost natural awareness. Depression, hyperactivity, and inattention are causes of high theta wave values, while anxiety and stress are triggers for low delta waves. [28].

c) Alpha waves refer to feelings of deep relaxation and help promote calmness. The causes of high alpha wave values are daydreaming, unfocused, and overly relaxed. At the same time, alpha waves are low and their causes are anxiety, high stress, and insomnia [28].

d) Beta waves refer to conscious, logical thinking and tend to stimulate influence. High beta wave values due to states of anxiety, arousal, and inability to relax. At the same time, the causes of low beta waves are daydreaming, depression, and poor cognition [28].

B. Discrete Wavelet Transform Test

Discrete Wavelet Transform as a filter can synthesize EEG signals in energy, entropy, valance, and arousal values. The results of the synthesis of the EEG signal are as follows:

a) Participant 1

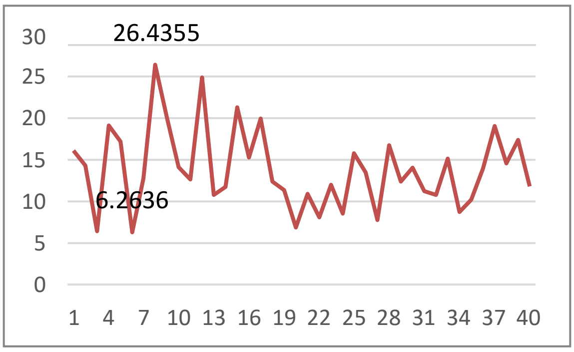


Fig 9. Energy in Participant 1

Energy is the lower area of the box of magnitude, and in EEG signal analysis, energy with high values is the true value (not noise). For example, for lodging 1 participants, the highest energy value occurred in the 8th video trial with a value of 26.4355, and the lowest energy value occurred in the 6th video trial with a value of 6.2636.

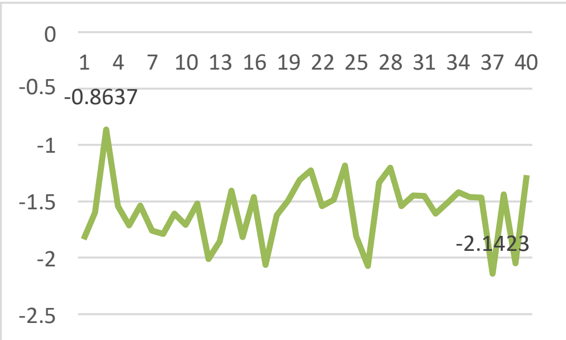


Fig 10. Entropy in Participant 1

Entropy is a measure of uncertainty and can also measure the degree of chaos. Therefore, higher entropy represents higher uncertainty and chaos. For example, in participant 1, the highest entropy value occurred in the 3rd video trial with a value of -0.8637, and the lowest entropy value occurred in the 37th video trial with a value of -2.1423.

https://doi.org/10.20895/infotel.v14i1.750

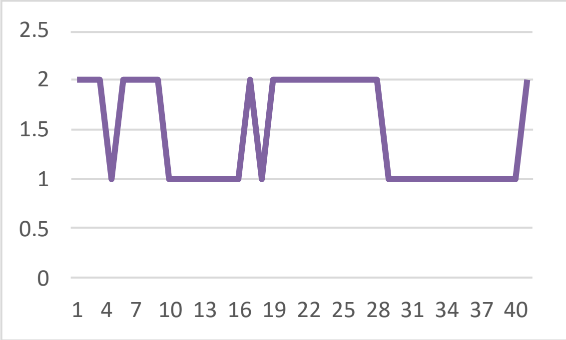


Fig 11. Valance in Participant 1

For the valance results in participant 1, valance values of 1 or 2 are obtained in each trial, as shown in Figure 4.23. A valance value of 1 refers to a valance value that is low or less than 5, and a valance value of 2 refers to a valance value that is high or greater than 5.

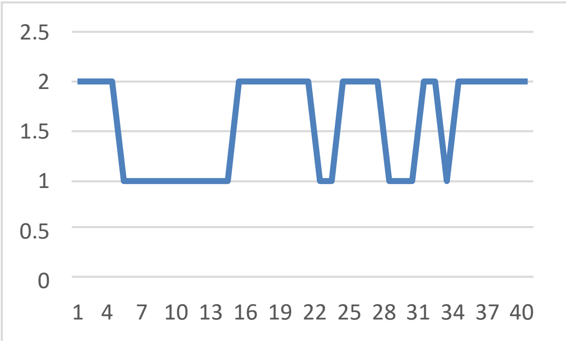
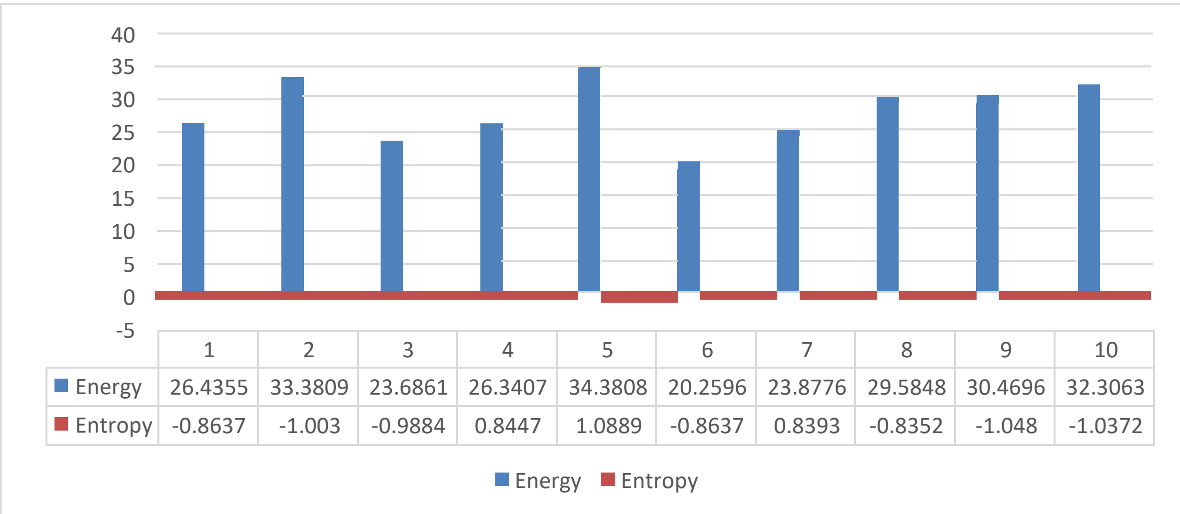


Fig 12. Arousal in Participant 1

For arousal outcomes in participant 1, Figure 4.12 shows arousal values of 1 or 2 in each trial. Arousal value 1 refers to a passion value that is low or less than 5. Then, arousal value 2 indicates a high arousal value greater than 5.



	1	2	3	4	5	6	7	8	9	10
Energy	26.4355	33.3809	23.6861	26.3407	34.3808	20.2596	23.8776	29.5848	30.4696	32.3063
Entropy	-0.8637	-1.003	-0.9884	0.8447	1.0889	-0.8637	0.8393	-0.8352	-1.048	-1.0372

Fig 13. Maximum Value of Discrete Wavelet Transform

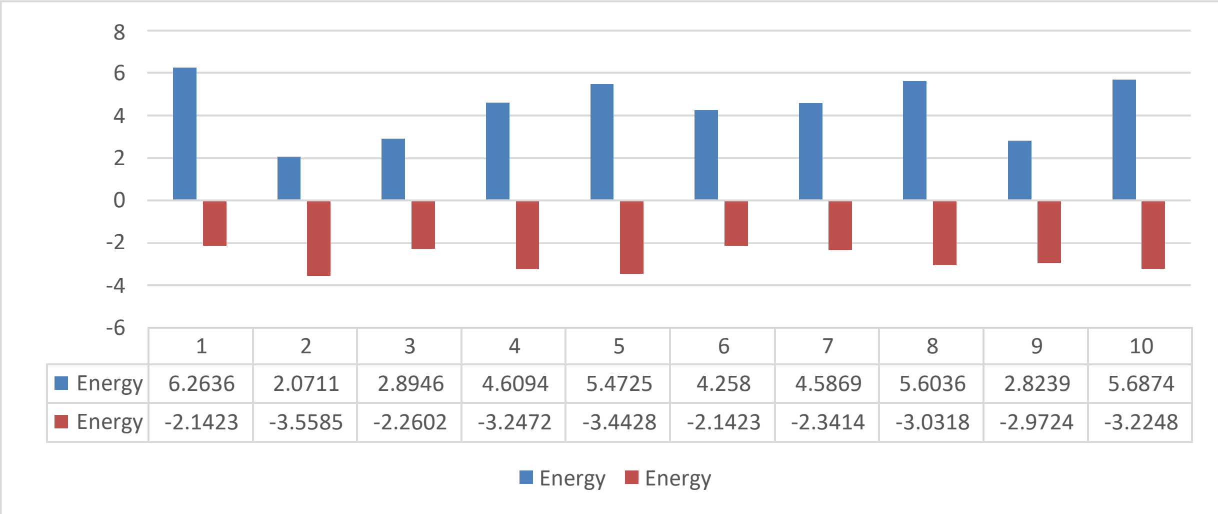


Fig 14. Minimum Value of Discrete Wavelet Transform

Figure 13 and Figure 14 show the value of Discrete Wavelet Transform with two parameters, namely energy and entropy, with maximum and minimum values obtained for 10 participants. The EEG represents the amount of activity in the frequency band between coherent electrodes in the brain region in terms of energy. Energy with a high value is as the actual value (not noise) [29]. Meanwhile, in entropy, EEG is a statistical way to measure the amount of uncertainty or randomness in the pattern of information contained in the signal. The entropy value means implicit assumptions regarding important signal aspects, vector distances between segments, and spectral elements. Entropy with high values represents higher uncertainty and chaos [29].

C. Comparison of PSD Output and DWT Output

This stage is a comparison stage between the output of the power spectral density test and the output of the Discrete Wavelet Transform test. The output of the two tests is in the form of values 1-4, which represent the following emotions:

Table 2. Description of Emotions Based on Test Output

Output	Valance	Arousal	Emotion
1	Low	Low	Sad
2	Low	High	Angry
3	High	Low	Calm
4	High	High	Happy

The following is a comparison between PSD and DWT outputs in graphic form:

a) Participant 1

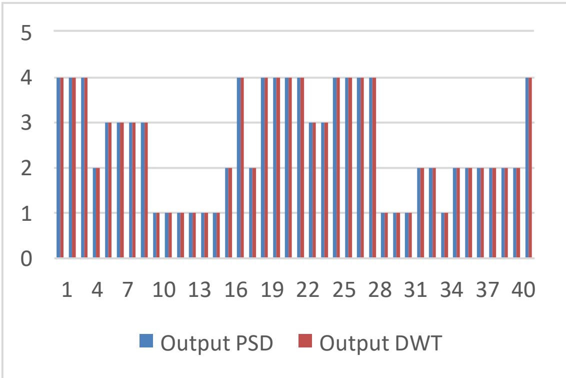


Fig. 15. Comparison Output PSD and Output DWT of Participant 1

Fig.15. shows the comparison of PSD output and DWT output in participant 1 with the same output results between PSD and DWT. We will explain in more detail as follows::

- The PSD and DWT output values for participant 1 were happy (output 4) in 13 trials, namely trials 1, 2, 3, 16, 18, 19, 20, 21, 24, 25, 26, 27, and 40.
- The PSD and DWT output values for participant 1 were calm (output 3) in 6 trials, namely in trials 5, 6, 7, 8, 22, and 23.
- The PSD and DWT output values for participant 1 were angry (output 2) in 11 trials, namely trials 4, 15, 17, 31, 32, 34, 35, 36, 37, 38, and 39.
- The output value of PSD and DWT for participant 1 was sad emotion (output 1) in 10 trials, namely in trials 9, 10, 11, 12, 13, 14, 28, 29, 30, and 33.

b) Participant 2

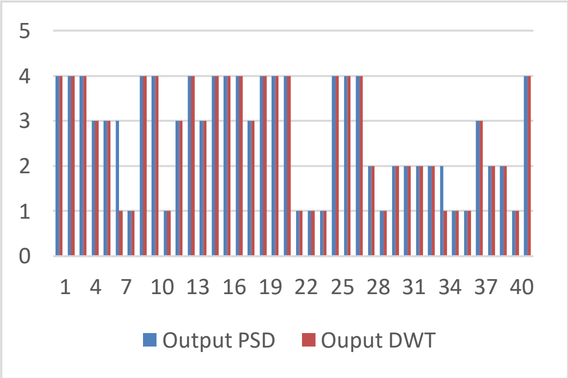


Fig. 16. Comparison Output PSD and Output DWT of Participant 2

Fig.16. is a comparison of PSD output and DWT output in participant 2 with 38 similar outputs and two different outputs between PSD and SWT:

• The output value of PSD and DWT of participant 2 obtained happy emotions (output 4) in 16 trials, namely in trials 1, 2, 3, 8, 9, 12, 14, 15, 16, 18, 19, 20, 24, 25, 26, and 40.

• The PSD and DWT output values for participant 2 were calm (output 3) in 6 trials, namely in trials 4, 5, 11, 13, 17, and 36.

• The output values of PSD and DWT of participant 2 were angry (output 2) in 7 trials, namely 27, 29, 30, 31, 32, 37, and 38 trials.

• The output value of PSD and DWT for participant 2 was sad emotion (output 1) in 9 trials, namely trials 7, 10, 21, 22, 23, 28, 34, 35, and 39.

Based on our results, participant 2 received 2 trials with different outcomes between the PSD and DWT methods. Where, in the 6th trial, we get a value of 3 on the PSD output, and a value of 1 on the DWT output. Furthermore, in the 33rd trial, we get a value of 2 on the PSD output and a value of 1 on the DWT output. Participant 3

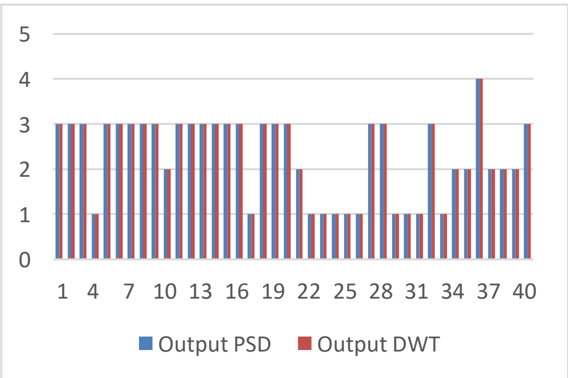


Fig. 17. Comparison Output PSD and Output DWT of Participant 3

Fig. 17. is a comparison of PSD output and DWT output in participant 3 with the same production between PSD and DWT:

• The output values of PSD and DWT for participant 3 are happy emotions (output 4) in 1 trial, namely 36 trials.

• The PSD and DWT output values for participant 3 were calm (output 3) in 21 trials, namely in trials 1, 2, 3, 5, 6, 7, 8, 9, 11, 12, 13, 14, 15, 16, 18, 19, 20, 27, 28, 32, and 40.

• The output values of PSD and DWT for participant 3 were angry (output 2) in 7 trials, namely in trials 10, 21, 34, 35, 37, 38, and 39.

• The output value of PSD and DWT for participant 1 was sad emotion (output 1) in 11 trials, namely trials 4, 17, 22, 23, 24, 25, 26, 29, 30, 31, and 33.

c) Participant 4

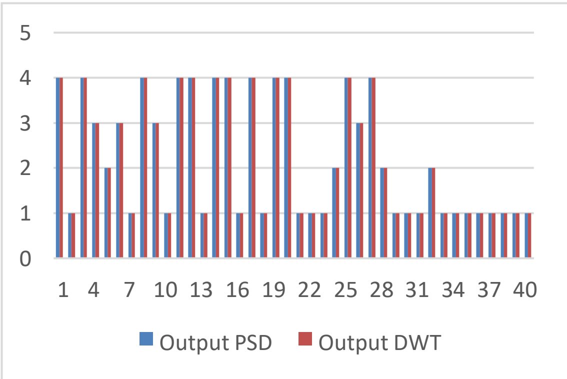


Fig.18. Comparison of PSD Output and DWT Output of Participants 4

Fig. 18 is a comparison of PSD output and DWT output in participant 4 with the results:

• The output values of PSD and DWT for participant 4 were happy emotions (output 4) in 12 trials, namely trials 1, 3, 8, 11, 12, 14, 15, 17, 19, 20, 25 27.

• The output values of PSD and DWT for participant 4 were calm (output 3) in 4 trials, namely trials 4, 6, 9, and 26.

• The output values of PSD and DWT for participant 4 were angry (output 2) in 4 trials, namely trials 5, 23, 28, and 32.

• The output value of PSD and DWT for participant 4 was sad emotion (output 1) in 20 trials, namely in trials 2, 7, 10, 13, 16, 18, 21, 22, 23, 29, 30, 31, 33, 34, 35 , 36, 37, 38, 39, and 40

d) Participant 5

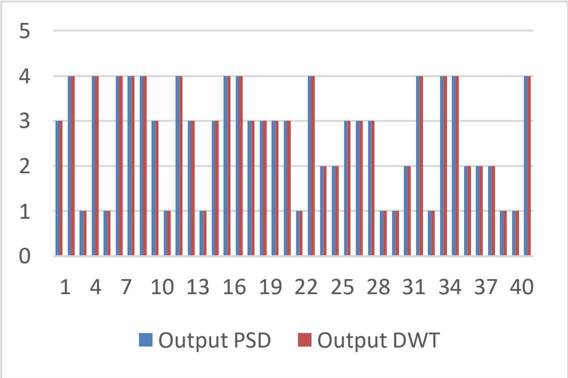


Fig.19. Comparison Output PSD and Output DWT of Participant 5

Fig.19. is a comparison of PSD output and DWT output in participant 5 with the results:

• The output values of PSD and DWT for participants 5 were happy emotions (output 4) in 13 trials, namely trials 2, 4, 6, 7, 8, 11, 15, 16, 22, 31, 33, 34, and 40.

• The PSD and DWT output values for participants 5 were calm (output 3) in 11 trials, namely trials 1, 9, 12, 14, 17, 18, 19, 20, 25, 26, and 27.

• The output values of PSD and DWT for participants 5 were angry (output 2) in 6 trials, namely in trials 23, 24, 30, 35, 36, and 37.

• The output value of PSD and DWT for participant 5 was sad emotion (output 1) in 10 trials, namely trials 3, 5, 10, 13, 21, 28, 29, 32, 38, and 39.

e) Participant 6

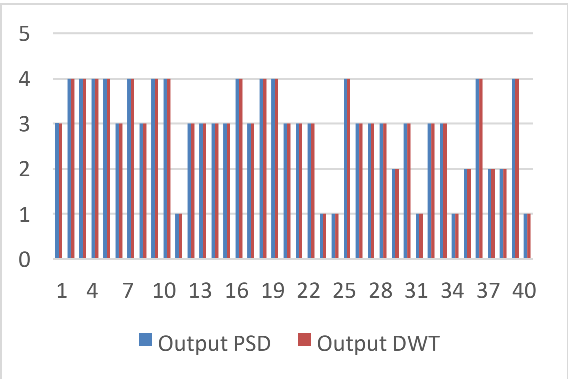


Fig.20. Comparison Output PSD and Output DWT of Participant 6

Fig. 20. is a comparison of PSD output and DWT output in participant 6 with the results:

• The output values of PSD and DWT for participants 6 were happy emotions (output 4) in 13 trials, namely trials 2, 3, 4, 5, 7, 9, 10, 16, 18, 19, 25, 36, and 39.

• The output value of PSD and DWT of participants 6 obtained calm emotions (output 3) in 17 trials, namely in trials 1, 6, 8, 12, 13, 14, 15, 17, 20, 21, 22, 26, 27, 28, 30, 32, and 33.

• The output values of PSD and DWT for 6 participants were angry (output 2) in 4 trials, namely 29, 35, 37, and 38 trials.

• The output value of PSD and DWT for 6 participants was sad emotion (output 1) in 6 trials, namely in trials 11, 23, 24, 31, 34, and 40

f) Participant 7

Fig. 21. is a comparison of PSD output and DWT output in participant 7 with the results:

• The output values of PSD and DWT of 7 participants were happy emotions (output 4) in 18 trials, namely in trials 2, 4, 5, 6, 7, 8, 10, 11, 14, 19, 20, 31, 35, 36, 37 , 38, 39, and 40.

• The output value of PSD and DWT for 7 participants was calm emotion (output 3) in 10 trials, namely in trials 1, 3, 9, 12, 13, 15, 17, 18, 27, and 29.

• The output values of PSD and DWT for 7 participants were angry emotions (output 2) in 7 trials, namely in trials 16, 21, 24, 30, 32, 33, and 34.

• The PSD and DWT output values for 7 participants were sad emotions (output 1) in 5 trials, 22, 23, 25, 26, and 28.

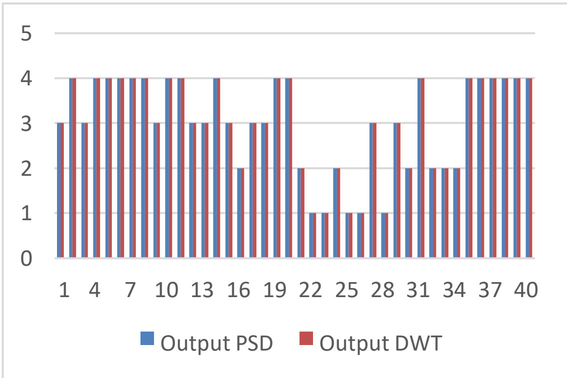


Fig.21. Comparison Output PSD and Output DWT of Participant 7

g) Participant 8

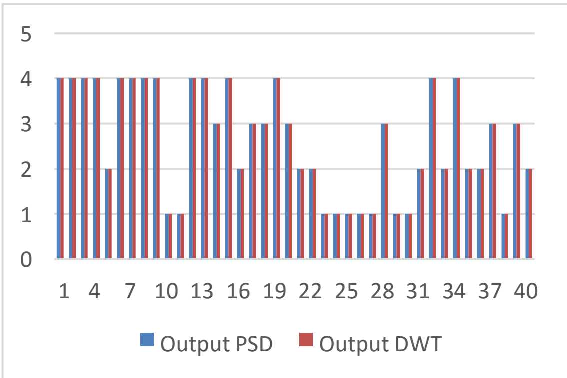


Fig.22. Comparison Output PSD and Output DWT of Participant 8

Fig. 22. is a comparison of PSD output and DWT output in 8 participants with the results:

• The PSD and DWT output values of 8 participants obtained happy emotions (output 4) in 14 trials, namely in trials 1, 2, 3, 4, 6, 7, 8, 9, 12, 13, 15, 19, 32, and 34.

• The PSD and DWT output values of 8 participants obtained calm emotions (output 3) in 7 trials, namely trials 14, 17, 18, 20, 28, 37, and 39.

• The output values of PSD and DWT of 8 participants were angry (output 2) in 9 trials, namely trials 5, 16, 21, 22, 31, 33, 35, 36, and 40.

• The PSD and DWT output values for 8 participants were sad emotions (output 1) in 10 trials, namely in trials 10, 11, 23, 24, 25, 26, 27, 29, 30, and 38. Participant 9

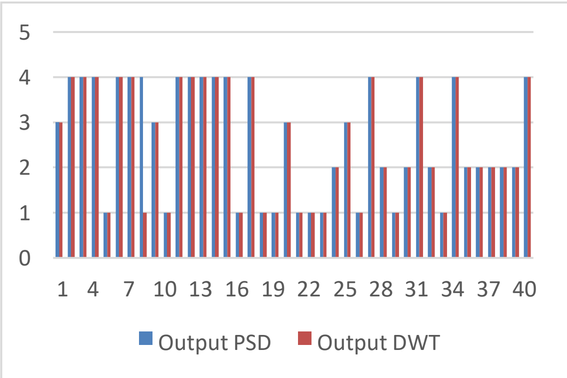


Fig.23. Comparison Output PSD and Output DWT of Participant 9

Fig. 23. is a comparison of PSD output and DWT output in participant 9 with 39 the same work and one different creation between PSD and DWT:

• The PSD and DWT output values of 9 participants obtained happy emotions (output 4) in 15 trials, namely in trials 2, 3, 4, 6, 7, 11, 12, 13, 14, 15, 17, 27, 31, 34, and 40.

• Participants' PSD and DWT output values obtained calm emotions (output 3) in 4 trials, namely in trials 1, 9, 20, and 25.

• The output values of PSD and DWT for 9 participants were angry emotions (output 2) in 9 trials, namely trials 24, 28, 30, 32, 35, 36, 37, 38, and 39.

• The output values of PSD and DWT for 9 participants were sad emotions (output 1) in 11 trials, namely in trials 5, 10, 16, 18, 19, 21, 22, 23, 26, 29, and 33.

In participant 9, we got one trial with a different output between the PSD and DWT methods, namely in trial 8 with a value of 4 on the PSD output and a value of 1 on the DWT output.

h) Participant 10

Fig. 24. is a comparison of PSD output and DWT output in 10 participants with the results:

• The PSD and DWT output values for 10 participants were happy emotions (output 4) in 11 trials, namely trials 1, 4, 5, 6, 7, 9, 10, 11, 19, 32, and 40.

• The PSD and DWT output values for 10 participants were calm (output 3) in 9 trials, namely trials 3, 8, 12, 13, 14, 15, 18, 20, and 24.

• The PSD and DWT output values for 10 participants were angry (output 2) in 11 trials, namely in trials 2, 21, 30, 31, 33, 34, 35, 36, 37, 38, and 39.

• The PSD and DWT output values for 10 participants were sad emotions (output 1) in 9 trials, namely trials 16, 17, 22, 23, 25, 26, 27, 28, and 29.

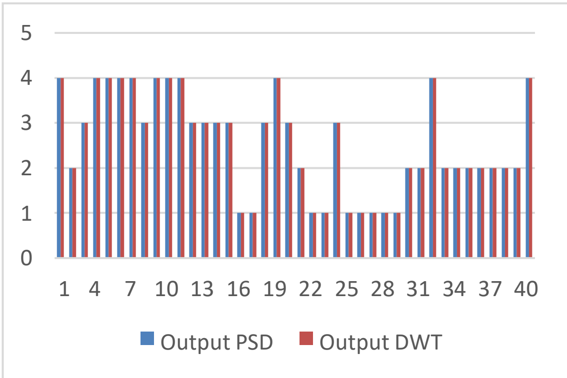


Fig.24. Comparison Output PSD and Output DWT of Participant 10

D. *Calculation of Method Accuracy*

In calculating performance accuracy, we use discrete wavelet transform method as a reference in emotion classification. This is because the DWT method has output in the form of arousal and valance values, while the power spectral density method only has a combined output (emotion) without knowing the values of arousal and indolence. The formula for calculating method accuracy is as follows:

$$\left(\frac{\text{Total Trial}-\text{Trial Error}}{\text{Total Trial}}\right) \text{x } 100\% \qquad (2)$$

IV. DISCUSSION

The decision tree analysis is carried out to make decisions about emotional output from classifying emotions using the power spectral density method and the discrete wavelet transform method. From a total of 32 participants that we tested, researchers only took 10 participants as samples for decision tree analysis. The results are as follows: Participants 1, 3, 4, 5, 6, 7, 8, and 10 of the 40 trials we have tested have emotional outputs that match the power spectral density method and the discrete wavelet transform method. So, according to the research flow in Figure 3.7, it can be directly classified into emotions. Furthermore, in participants 2 and 9, we found emotional outputs that did not match the power spectral density method and the discrete wavelet transform method, namely trial 6 and trial 33 for participant 2 and trial 8 for participant 9. So, according to the research flow in Figure 3.7, the classification of emotions was carried out based on the output of the discrete wavelet transform method. The results of the classification changed as follows:

a) Participant 2

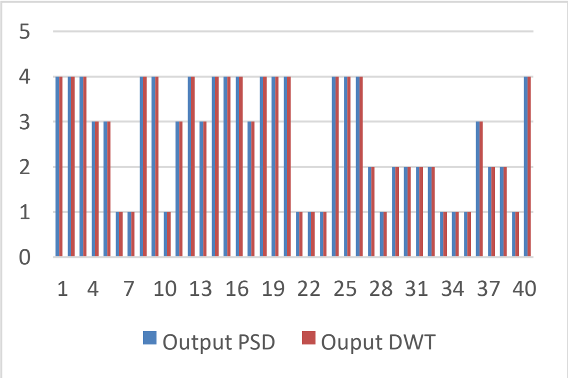


Fig.25. Comparison Output PSD and Output DWT of Participant 2 After Decision Tree

Fig. 25. is a comparison of PSD output and DWT output in participant 2 after the decision tree analysis:

• At the output of PSD and DWT participant 2 obtained happy emotions (output 4) in 16 trials, namely in trials 1, 2, 3, 8, 9, 12, 14, 15, 16, 18, 19, 20, 24, 25, 26, and 40.

• At the output of PSD and DWT, participant 2 obtained calm emotions (output 3) in 6 trials, namely trials 4, 5, 11, 13, 17, and 36.

• In the output of PSD and DWT, participant 2 obtained angry emotions (output 2) in 7 trials, namely trials 27, 29, 30, 31, 32, 37, and 38.

• In the output of PSD and DWT, participant 2 obtained sad emotions (output 1) in 11 trials, namely in trials 6, 7, 10, 21, 22, 23, 28, 33, 34, 35, and 39.

b) Participant 9

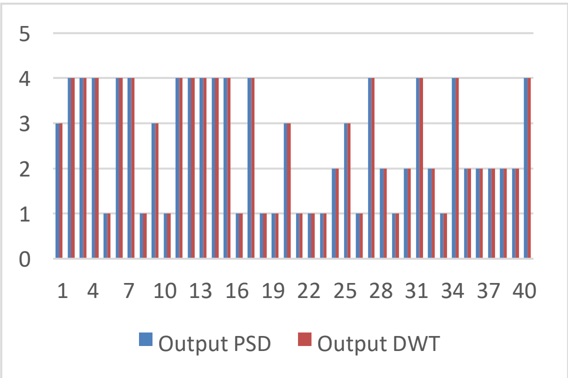


Fig.26. Comparison of Output PSD and Output DWT Participant 9 after Decision Tree

- Fig. 26. reveals a comparison of PSD output and DWT output in 9 participants after the decision tree analysis:
- The output value of PSD and DWT of participants 5 obtained happy emotions (output 4) in 15 trials, namely in trials 2, 3, 4, 6, 7, 11, 12, 13, 14, 15, 17, 27, 31, 34, and 40.
- The PSD and DWT output values for participants 5 were calm (output 3) in 4 trials, namely trials 1, 9, 20, and 25.
- The output values of PSD and DWT for participants 5 were angry (output 2) in 9 trials, namely trials 24, 28, 30, 32, 35, 36, 37, 38, and 39.
- The output values of PSD and DWT for participants 5 were sad emotions (output 1) in 12 trials, namely trials 5, 8, 10, 16, 18, 19, 21, 22, 23, 26, 29 33.

V. CONCLUSION

We have successfully applied the discrete wavelet transform method as one of the emotion classification methods. The DWT method has output in the form of arousal and valance values, while the power spectral density method only has combined results (emotions) without knowing the arousal and valance values. In terms of accuracy, the decision tree method can increase the accuracy of the power spectral density method to 100%, which was originally 99.25%, because of 400 trials conducted on 10 participants. There is only a difference in output in 3 shots.

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