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Analysis the effects of games on cognitive activity of late adolescents using the electroencephalogram with the K-nearest neighbor method

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ABSTRACT

The influence of violent video games on child development continues to be a polemic, Various pros and cons also color this problem, because in adolescence not only adopt cognitive abilities in learning activities, but also various strategies related to managing activeness in learning, playing and socializing to improve cognitive abilities. Adolescents who are addicted to online games are included in the three criteria set by WHO (Word Health Organization), namely that they need games with symptoms of withdrawing from the environment, losing control, and not caring about other activities (Santoso and Purnomo, 2017). The purpose of this study is to analyze the cognitive activity of late adolescence between learning and playing games and knowing that games can have a good or bad impact on the cognitive activity of adolescents. The application of the K-Nearest Neighbor method to the system created can classify with prediction results on the influence of games on the cognitive activity of adolescents using Electroencephalogram (EEG) data and can also provide information in the form of new predictions on the respondent data obtained. The results of the analysis resulted in a percentage of accuracy in the game stimulus data of 80%, and in the cognitive stimulus data, namely SPM, it got an accuracy of 80% using the same K value in both stimuli, namely 1, 6, and 7. While the expert results on the system the percentage of superior but addicted respondents was 63.3% and the percentage of respondents who were average but addicted was 36.6% with a correlation rate between Games and SPM of 0.089822409. Based on the results of this study, it can be concluded that the percentage obtained from the comparison of the results of the expert to the results of the system and the comparison of the system itself does not have the influence of games on cognitive activity in late adolescence.

1. Introduction

The state of mind of a student when thinking about counting or when thinking about writing even when the student is not thinking about something can be known by conducting an evaluation that is using an Electroencephalogram (EEG). EEG devices work by capturing electrical activity on the surface of the scalp. The recording result signal from the EEG device is referred to as the EEG signal. Through EEG signals a person's state of mind can be known even if the person does not perform any physical movement [1].

Many variables can be reviewed to determine a person's state of mind based on EEG signals. In previous studies, EEG signals were used to distinguish between sleepy conditions and sleep states, alert states, emotional states, there were also those who used EEG signals to distinguish the condition of open eyes and closed eyes, moving external devices, identifying hand movements, moving the cursor through finger movements, knowing the writing and grasping conditions of the EEG signal, identifying Epilepsy disease. In addition, some stimuli can influence the results of the EEG signals obtained such as sound stimuli, musical stimuli that can affect the emotional state. However, EEG signal processing is not easy, the problems encountered in EEG signal processing are low amplitudes, easy noise accumulation during data recording and complicated patterns. Therefore, appropriate stages are needed in order to know a person's state of mind, starting from the extraction stage to the classification stage. The extraction stage is used to retrieve each trait present on the obtained EEG signal [1].

Activities carried out by humans will be responded to by the brain, including when listening to music, because sound can affect activities in the brain. To determine the activity in the brain, it can be seen through the Electroencephalogram (EEG) signal. EEG signals can be recorded through the cortex or scalp with the EEG tool. The cortex will flow low-frequency signals so that knowing the pattern of the signal is not easy. The EEG signal contains certain components, namely alpha waves (8-13 Hz) with a relaxed state, beta (14-30 Hz) with activity or thinking conditions, theta (4-7 Hz) with light sleep conditions or emotional stress, and delta (0.5-3 Hz) with deep sleep conditions, and gamma waves with a frequency of more than 30 Hz [2].

2. Previous Research

This research refers to research conducted by Hildegardi Dwi Alupan, Atti Yudiernawati, Susmini majoring in Nursing, Faculty of Health Sciences, Tribhuwana Tunggadewi University Malang 2017 with the title "The Effect of Play Therapy Education Gamer Computer on Cognitive Development in Pre-School Age Children in Shining Star Malang Kindergarten". This research method uses a pre-experimental research design. In this study, H1 was accepted, meaning that there was an influence after the provision of computer game education on cognitive development in pre-school-age children in Shining Star Kindergarten. The results of this study showed that: the results of the study found that as many as 18 children (45%) had sufficient cognitive abilities before being given an education game computer and as many as 35 children (87.5%) had good cognitive development after being given an education game computer [3].

In a study conducted by Galih Widyatmojo, Ali Muhtadi of TP PPs Study Program UNY, FIP Yogyakarta State University 2017 with the title "Development of Interactive Learning Multimedia in the form of Games to Stimulate Cognitive Aspects". This research uses a research and development (R&D) model which refers to the Alessi & Trolip model by going through 3 phases, namely standard, ongoing evaluation, and project management. The results of this study show that: games can be used to stimulate cognitive and language aspects in accordance with the school curriculum, consist of 4 types of games, are portable and standalone, can run with low-specification computers, the products produced meet the criteria very feasible to use, the products produced are very feasible to be used to stimulate the cognitive and language aspects of Group B kindergarten children in terms of usefulness [4].

Previous studies used Wavelet for EEG signal extraction at concentration level identification, Short-time Fourier for the extraction of imagined write conditions, and other studies using Autoregressive in extracting EEG signals for the detection of Epilepsy and non-Epileptic diseases. The extraction results are then passed on at the classification stage. At the classification stage it is used to measure the proximity of the obtained EEG signal to the state of mind that it wants to know. One of the methods that is quite widely used in the classification stage is Backpropagation.

While in other research, namely in research conducted by Irfan Herdiyansyah, Esmeralda C. Djamal, Agus Komarudin majoring in Informatics Engineering, Faculty of Mathematics and Natural Sciences, General Achmad Yani University 2017 with the title "Classification of EEG Signals against Three Conditions of Mind Using Autoregressive and Adaptive Backpropagation". This research in journal builds an EEG signal classification system against three states of mind using Autoregressive for EEG signal extraction and classification using Adaptive Backpropagation with the three states of mind reviewed being the conditions of calculating, writing and not thinking about something. The testing process in this study is divided into testing training parameters and testing the use of variations in Autoregressive order values used when conducting data extraction. The results of this study showed that: The test results showed the best accuracy obtained by extracting using order 30 with an accuracy of 82% of the 90 data sets used.

3. Methodology

3.1. Proposed Method

The proposed method is seen in a flowchart in Fig. 1.

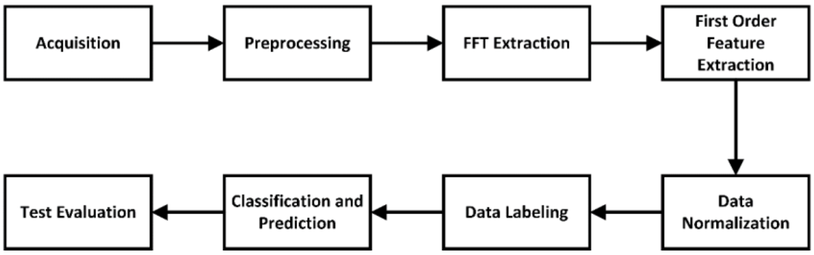

Fig. 1. Block diagram research stage

3.2. Standard Progressive Matrics (SPM)

Standard Progressive Matrices (SPM) is a tool for measuring a person's intelligence level The SPM test is oriented towards abstract relationships. The SPM test consists of 60 questions divided into five series, namely series A, B, C, D and E, each series consists of 12 questions in the form of pictures. The SPM test can be presented individually or classically and the serving time takes 30 minutes [5].

The results of SPM are presented in the form of an intellectual level in several categories as follows:

a. Grade I (Intellectually superior): subjects whose scores are in the > percentile 95.

b. Grade II (Definitely above the average in intellectual capacity): subjects whose values lie between the percentiles 75 - 95.

c. Grade III (Intellectually average): subjects whose values lie between the percentiles 25 - 75

d. Grade IV (Definitely below the average in intellectual capacity): subjects whose values lie between the 5th - 25th percentile.

e. Grade V (Intellectually defective): a subject whose value lies in the ≤ percentile 5.

3.3. Extraction of Statistical Traits

Trait extraction is a method of retrieval of traits based on the characteristics of the image histogram. From the values on the resulting histogram, several parameters of the first-order feature can be calculated, including mean, skewness, variance, kurtosis, and entropy [6].

a. Mean

Is the average of a record and is a measure of data centering. The mean can also show the size of the dispersion of an image. Can be seen in equation (1).

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n} \tag{1}$$

b. Standard Deviation (s)

Measuring the standard deviation of the data distribution, by first looking for the value of s squared first or the value of the variance. Can be seen in equation (2)

$$s^2 = \frac{(x_i + \bar{x})^2 + \cdots + (x_i + \bar{x})^2}{n} \tag{2}$$

$$s = \sqrt{s^2}$$

c. Skewness (sk)

Measuring the degree of inclination of the data distribution, can be seen in equation (3)

$$sk = \frac{\bar{x} - Median}{s} \quad (3)$$

d. Kurtosis (α_4)

Measuring the height of the data distribution, can be seen in equation (4)

$$\alpha_4 = \frac{\frac{1}{n}(x_i - \bar{x})^4}{s^4} \quad (4)$$

e. Entropy (H)

Measuring the irregularity of the shape of the data distribution, can be seen in equation (5)

$$Entropi\ (S) = \sum_{j=1}^{k} - p_j \, log_2 \ p_j \quad (5)$$

3.4. Acquisition

3.4.1. Block Diagram of Data Accumulation Stages

This stage of data capture is drawn using a flowchart. Here are the stages of data retrieval can be seen in Fig. 2.

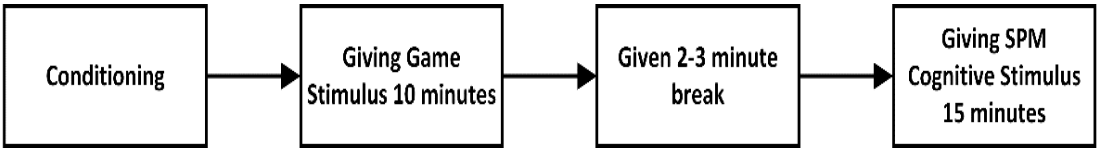

Fig. 2. Data acquisition phase

Data acquisition is a method of data retrieval using an EEG tool that is paired with a game stimulus and cognitive tasks in the form of SPM. In this study, three data collections were carried out, the time span of data retrieval from the first data retrieval to the second data collection was two weeks, with respondents numbering 30 people, age 18 - 21 years. In this data collection using the NeuroSky Mindwave tool with the number of sensors of one electrode in the Fp1 position and MyndPlayerPro software as a signal data recorder [7].

3.5. Preprocessing

At this stage, pre-processing of data is carried out which is the second step after the acquired signal data to the respondent data processing process to retrieve signal wave data that has been taken using the EEG tool. Before measuring brain waves, respondents will be asked to use a head-mounted EEG tool with recorded brain waves when given a game stimulus and SPM cognitive task questions to be able to retrieve the signal data on NeuroSky Mindwave after the recording is complete, it will be saved in the form of .log that is still unreadable, so that the data can be readable to export the log file to csv format using MyndPlayerPro. All data recorded by 30 respondents in the Export Log File to Ms. Excel data, after which the data from Ms. Excel is loaded into Matlab for further processing using Fast Fourier Transform [8].

3.6. Fast Fourier Transform Extraction

This stage aims to display the signal peak point with the highest Frequency every 0.25 Hz of the original signal FFT extraction and remove the baseline or baseline in the EEG signal to obtain the FFT extraction signal output. The results of the EEG signal were analyzed using Fast Fourier Transform to obtain a noiseless EEG signal to extract all important frequency components from the EEG signal such as: alpha, beta, gamma, delta, and theta. Fast Fourier Transform is used for grouping and detecting brain waves where the brain waves provide different features [9].

3.7. Feature Extraction of First-Order Traits

Furthermore, feature extraction from data that has been extracted with Fast Fourier Transform will then be extracted features to obtain features or features from each signal obtained. The extraction of this trait is carried out by applying statistics in the form of mean values, entropy, standard deviation, skewness, and kurtosis. In the extraction using first-order statistical features the function is to find out the features needed [10].

3.8. Data Normalization

The data normalization stage is the stage before classification is carried out so that the features obtained can be more stable. This stage of normalization uses a simple and widely used method of linear normalization by scaling within the range of [-1,1].

3.9. K-Nearest Neighbor

Classification using K-Nearest Neighbor is carried out to group training data and test data based on the proximity of the location (distance) of one data with other data with the Euclidien formula. To get the distance from the data searched for the category, the nearest K-data value to be used is determined. The K-Nearest Neighbor method is also used to predict the influence of a game on the cognitive activities of late adolescence. Determining the K value by observation in order to get a predictive value with good accuracy against the K value, the training data and test data used must also be good [11].

3.10. Testing Evaluation

Test evaluation is the final stage after the research is completed, this test evaluation stage aims to get accurate accuracy from the results of the system's predicted value. The results of the predicted values are then compared with the original data that the category already knows. In the final stage of this study, accuracy testing or performance testing using Confusion Matrix was used.

Evaluating a classification model requires a test dataset that does not exist or is not used in the Training Data. In conducting an evaluation, you can use certain measures where TP, TN, FP, and FN can be explained as follows:

a. TP is True Positive, which is the amount of positive data correctly classified by the system.
b. TN is True Negative, which is the amount of negative data correctly classified by the system.
c. FP is a False Positive, which is the amount of positive data but classified incorrectly by the system.
d. FN is a False Negative, that is, the amount of negative data but is classified incorrectly by the system.

An explanation of the above points can be explained as in Table 1 Evaluation Measurement.

Table 1. Evaluation measurement

	Predict	**Real**
True Positive	Positive (Y)	Positive (Y)
False Positive	Positive (Y)	Negative (N)
True Negative	Negative (N)	Negative (N)
False Negative	Negative (N)	Positive (Y)

The explanation of each term from the Confusion matrix above can be illustrated as in Table 2.

Table 2. Confusion matrix

		Prediction Class	
		True	**False**
Real Class	**True**	TP (True Positive)	FP (False Positive)
	False	FN (False Negative)	TN (True Negative)

Confusion matrix is very useful for analyzing the quality of classification models in recognizing the tuples of existing classes. TP and TN state that the classification model recognizes tuples correctly, meaning that positive tuples are recognized as positive and negative tuples are known as negative. In contrast, FP and FN state that the classification model is wrong in recognizing tuples, negative tuples are known as positive and negative tuples are known as positives. P' is the number of labels that are given a positive label (TP + FP) while N' number of labels that are given a negative label (TN + FN). Meanwhile the total number of tuples can be expressed as (TP + TN + FP + FN) or (P + N) or (P' + N') (SUYANTO, 2018).

4. Results and Discussion

The discussion of the results of this study will include several discussions related to data acquisition, preprocessing, feature extraction, implementation and classification, and evaluation of performance tests.

4.1. Data Acquisition

In the data acquisition process, it is carried out with 3 retrievals with a retrieval time span of 14 days or two weeks. In this study, there were 30 people who were willing to be respondents for their brainwave data collection by using game stimuli and cognitive task stimuli by pairing an EEG tool overhead when playing games with a time of 10 minutes and doing an SPM test with a time of 15 minutes. The grouping of experts can be seen in Table 3.

Table 3. Respondent data grouping

Name	Meeting 1	Meeting 2	Meeting 3
Respondent 1	G. 1	G. 1	G. 1
Respondent 2	G. 2	G. 2	G. 2
Respondent 3	G. 3	G. 3	G. 3
Respondent 4	G. 3	G. 2	G. 1
Respondent 5	G. 1	G. 1	G. 1
Respondent 6	G. 2	G. 2	G. 2
Respondent 7	G. 3	G. 3	G. 2
Respondent 8	G. 3	G. 3	G. 3
Respondent 9	G. 3	G. 2	G. 2
Respondent 10	G. 3	G. 2	G. 2
Respondent 11	G. 3	G. 3	G. 3
Respondent 12	G. 3	G. 3	G. 3
Respondent 13	G. 2	G. 3	G. 2
Respondent 14	G. 3	G. 3	G. 3
Respondent 15	G. 2	G. 2	G. 2
Respondent 16	G. 3	G. 3	G. 3
Respondent 17	G. 3	G. 2	G. 2
Respondent 18	G. 2	G. 3	G. 2
Respondent 19	G. 3	G. 3	G. 2
Respondent 20	G. 2	G. 2	G. 1
Respondent 21	G. 2	G. 2	G. 2
Respondent 22	G. 2	G. 1	G. 1
Respondent 23	G. 2	G. 2	G. 1
Respondent 24	G. 3	G. 2	G. 2
Respondent 25	G. 3	G. 3	G. 2
Respondent 26	G. 2	G. 2	G. 1
Respondent 27	G. 2	G. 1	G. 1
Respondent 28	G. 2	G. 2	G. 2
Respondent 29	G. 3	G. 2	G. 3
Respondent 30	G. 2	G. 2	G. 2

4.2. Preprocessing

The data that has been opened on MyndPlayerPro is exported to csv format (comma separated values) which is a data format in the database where each record is separated by a comma (,) or semicolon (;). In this study, the results of recording brain waves in .log format will be exported to csv to see the results of brain wave data obtained. For data export results in MyndPlayerPro will be three parts, including log data.csv, log.process.csv, and log.raw.csv data. Raw data can be processed on specific computer software for further analysis. The raw form of data can be a binary data set or a collection of data in another form. All data recorded by respondents during brainwave capture in Export Log File to .csv data.

4.3. Ekstraksi Fast Fourier Transform (FFT)

The results of the EEG signal were analyzed using Fast Fourier Transform to obtain a noiseless EEG signal to extract all the important frequency components of the EEG signal such as: alpha, beta, gamma, delta, and theta. The initial signal can be seen in Fig. 3.

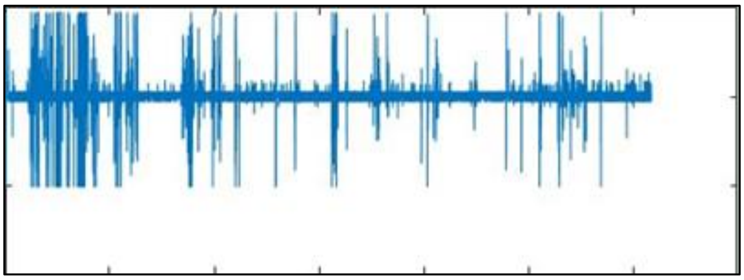

Fig. 3. Early signal

The FFT extraction result signal can be seen in Fig. 4.

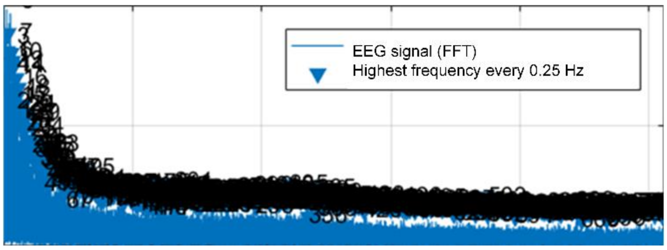

Fig. 4. FFT extraction results with the highest frequency every 0.25 Hz

4.4. Feature Extraction of First-Order traits

First-order feature extraction is used to determine statistical information in the form of mean, entropy, standard deviation, skewness, and kurtosis values. In extraction, it uses first-order statistical characteristics to find out the required features that can be found in the EEG data and are the parameters of each data. First-order feature extraction data can be viewed in Table 3.

4.5. Normalization of Data From Extraction of First-Order Feature Extraction

After performing the first-order feature e-blockage used to find out statistical information in the form of mean, entropy, standard deviation, skewness, and kurtosis values. Furthermore, the normalization process was carried out from the data of 30 respondents who had extracted first-order characteristic features, both game stimulus and SPM cognitive stimulus. The results of the game normalization data in the form of scatter graphic which can be seen in Fig. 5, Fig. 6, Fig. 7, Fig. 8 and Fig. 9.

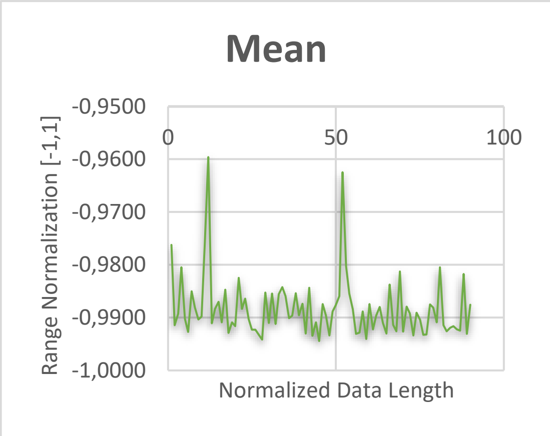

Fig. 5. Graph Mean Data Normalisasi

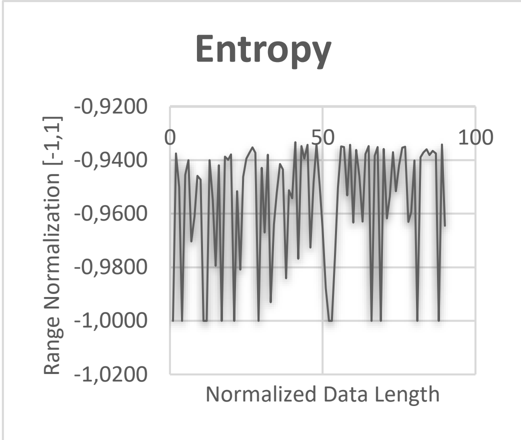

Fig. 6. Graph Entropy Data Normalisasi

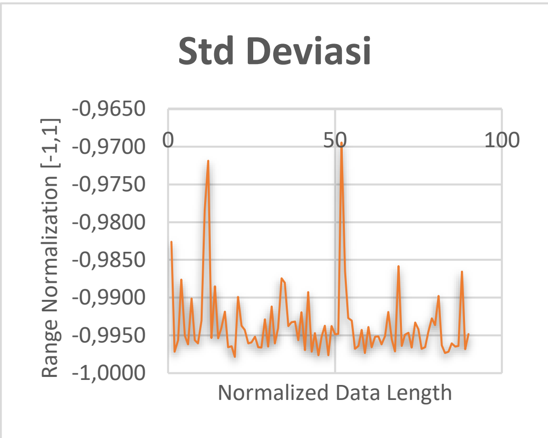

Fig. 7. Game Normalization Data Deviation Std Graphics

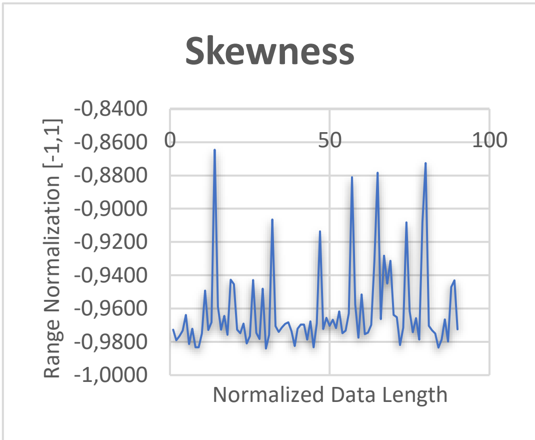

Fig. 8. Game Normalized Data Skewness Graph

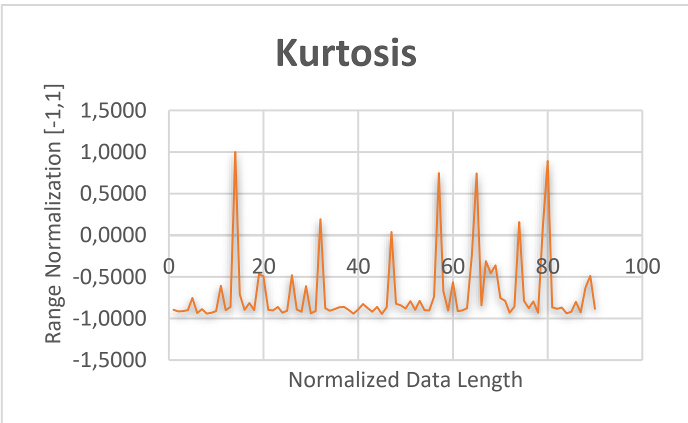

Fig. 9. Graph Kurtosis Data Normalisasi Game

While the SPM normalization results are in the form of a scatter chart image which can be seen in Fig.10, Fig. 11, Fig. 12, Fig. 13 and Fig. 14.

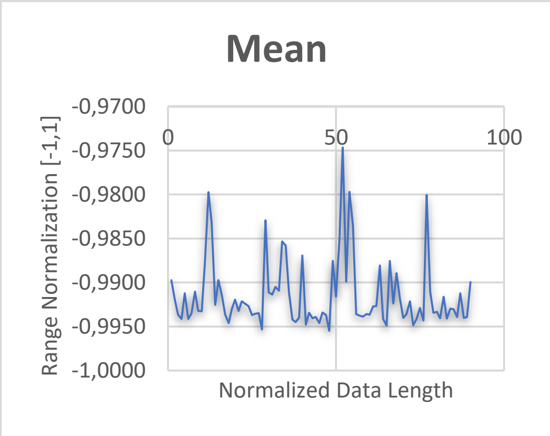

Fig. 10. SPM normalization data mean graph

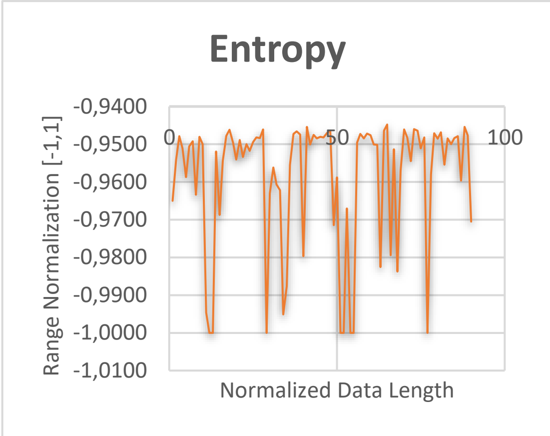

Fig. 11. SPM normalization data entopy graph

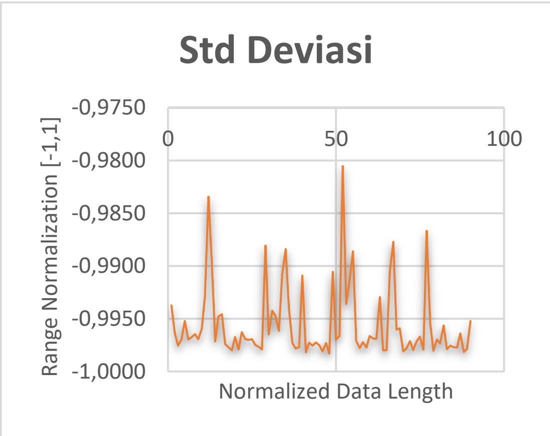

Fig. 12. SPM normalization data deviation std graph

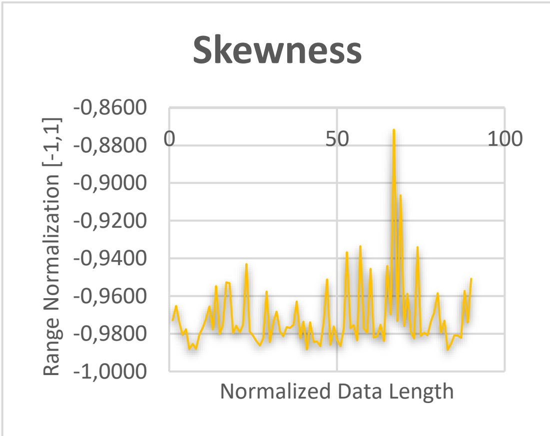

Fig. 13. SPM normalization data skewness graph

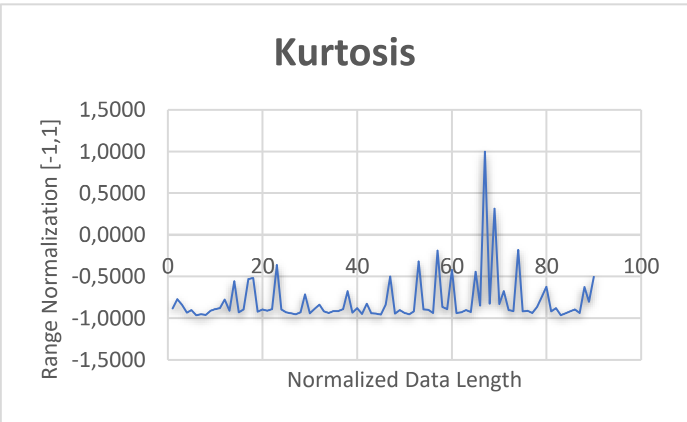

Fig. 14. SPM normalization data kurtosis graph

4.6. Implementation

At the implementation stage, the system is designed to fulfill all stages, from acquisition to classification and evaluation. The implementation interface can be seen in Fig. 15.

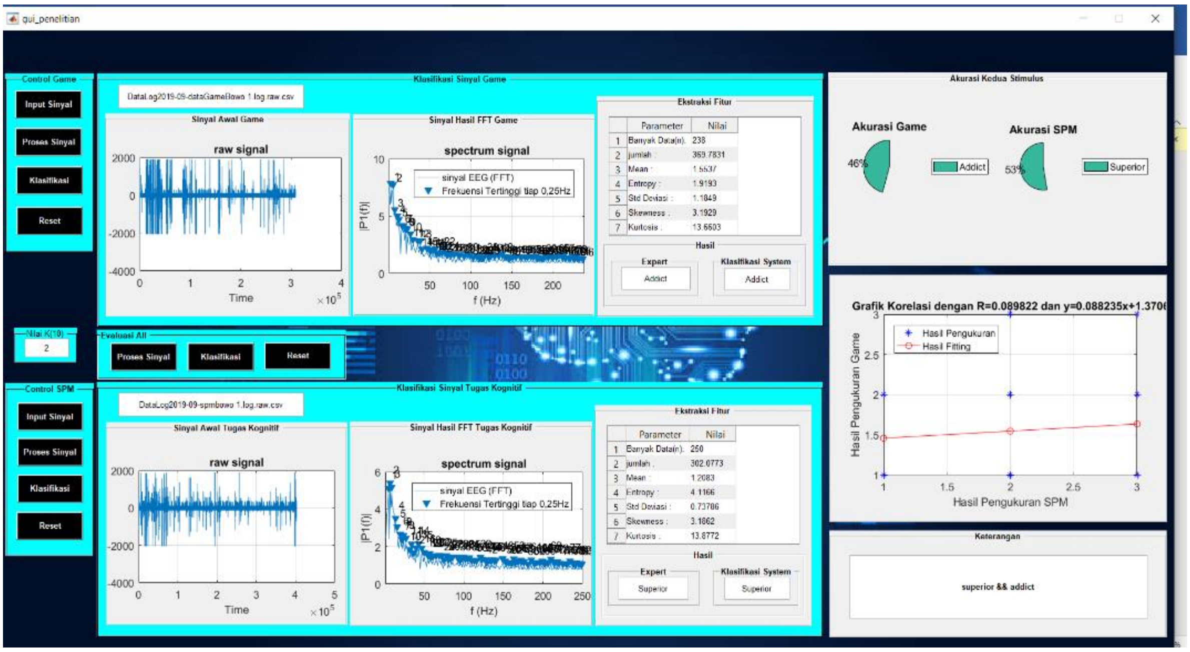

Fig. 15. Implementation View

4.7. Testing

a. Game Accuracy Level Testing

Before testing the accuracy of the results of testing the system with experts in each category. The category Table can be seen in Table 4 and the predicted number results with K 1, 6, and 7 in Table 4.

Table 4. Prediction Results in the Form of Numbers

K value	1	6	10
TP	24	24	24
TN	0	0	0
FP	6	6	6
FN	0	0	0

The calculation of accuracy in the prediction results of game data can be seen in Table 5 Game accuracy calculation results.

Table 5. Game Accuracy Calculation Results

K value	Account		
	1	**6**	**7**
Accuracy	$\frac{24+0}{24+0+6+0}\times 100\%$ $\frac{24}{30}\times 100\% = 80\%$	$\frac{24+0}{24+0+6+0}\times 100\%$ $\frac{24}{30}\times 100\% = 80\%$	$\frac{24+0}{24+0+6+0}\times 100\%$ $\frac{24}{30}\times 100\% = 80\%$
Precision	$\frac{24}{24+6}\times 100\%$ $\frac{24}{30}\times 100\% = 80\%$	$\frac{24}{24+6}\times 100\%$ $\frac{24}{30}\times 100\% = 80\%$	$\frac{24}{24+6}\times 100\%$ $\frac{24}{30}\times 100\% = 80\%$
Recall	$\frac{24}{24+0}\times 100\%$ $\frac{24}{24}\times 100\% = 100\%$	$\frac{24}{28+0}\times 100\%$ $\frac{24}{24}\times 100\% = 100\%$	$\frac{24}{24+0}\times 100\%$ $\frac{24}{24}\times 100\% = 100\%$

b. SPM Accuracy Rate Testing

After getting the results of new data predictions obtained from the system, the new data is then mixed on the data obtained from experts to see the level of accuracy of the new data. The process of comparing data to obtain accuracy on predictions in Table 6.

1) Accuracy rate at K 1, 6, and 7

Table 6. System performance results

K value	1	6	7
TP	24	24	24
TN	0	0	0
FP	6	6	6
FN	0	0	0

Table 7. System Accuracy Calculation Results

K value	Account		
	1	**6**	**7**
Accuracy	$\frac{24+0}{24+0+6+0} \times 100\%$ $\frac{24}{30} \times 100\% = 80\%$	$\frac{24+0}{24+0+6+0} \times 100\%$ $\frac{24}{30} \times 100\% = 80\%$	$\frac{24+0}{24+0+6+0} \times 100\%$ $\frac{24}{30} \times 100\% = 80\%$
Precision	$\frac{24}{24+6} \times 100\%$ $\frac{24}{30} \times 100\% = 80\%$	$\frac{24}{24+6} \times 100\%$ $\frac{24}{30} \times 100\% = 80\%$	$\frac{24}{24+6} \times 100\%$ $\frac{24}{30} \times 100\% = 80\%$
Recall	$\frac{24}{24+0} \times 100\%$ $\frac{24}{24} \times 100\% = 100\%$	$\frac{24}{28+0} \times 100\%$ $\frac{24}{24} \times 100\% = 100\%$	$\frac{24}{24+0} \times 100\%$ $\frac{24}{24} \times 100\% = 100\%$

The calculation of accuracy in the predicted results of game data can be seen in Table 8 SPM accuracy calculation results.

Table 8. System Accuracy Calculation Results

K value	Account		
	1	**6**	**7**
Accuracy	$\frac{24+0}{24+0+6+0} \times 100\%$ $\frac{24}{30} \times 100\% = 80\%$	$\frac{24+0}{24+0+6+0} \times 100\%$ $\frac{24}{30} \times 100\% = 80\%$	$\frac{24+0}{24+0+6+0} \times 100\%$ $\frac{24}{30} \times 100\% = 80\%$
Precision	$\frac{24}{24+6} * 100\%$ $\frac{24}{30} * 100\% = 80\%$	$\frac{24}{24+6} \times 100\%$ $\frac{24}{30} \times 100\% = 80\%$	$\frac{24}{24+6} \times 100\%$ $\frac{24}{30} \times 100\% = 80\%$
Recall	$\frac{24}{24+0} \times 100\%$ $\frac{24}{24} \times 100\% = 100\%$	$\frac{24}{24+0} \times 100\%$ $\frac{24}{24} \times 100\% = 100\%$	$\frac{24}{24+0} \times 100\%$ $\frac{24}{24} \times 100\% = 100\%$

5. Conclusion

a. System Accuracy Conclusion

The conclusion of the accuracy value on the manual calculation of the game stimulus and the SPM Cognitive stimulus can be seen in Table 9 Accuracy calculation results.

Table 9. System Accuracy Calculation Results

Data Stimulation	K Value	Category				
		suitable	Not suitable	Accuracy	Precision	Recall
Game	1	26	4	80%	80%	100%
	6	28	2	80%	80%	100%
	7	29	1	80%	80%	100%
SPM	1	24	6	80%	80%	100%
	6	23	7	80%	80%	100%
	7	24	6	80%	80%	100%

So, the result of the calculation of accuracy on the built system is 80% and 80%

b. Conclusion Accuracy Expert System

- The data of respondents who are Superior but Addict and respondents who are Average but Addict can be calculated percentages in Table 10 and can be seen in the Fig. 16 and Fig. 17.

Table 10. Expert Accuracy Calculation Results

	Category		
Sum	Superior & Addict	Average & Addict	total
	57	33	90
Percentage	63.3%	36.3%	

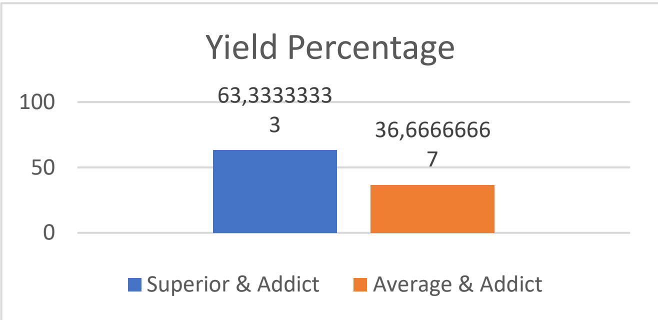

Fig. 16. Accuracy of Expert Results

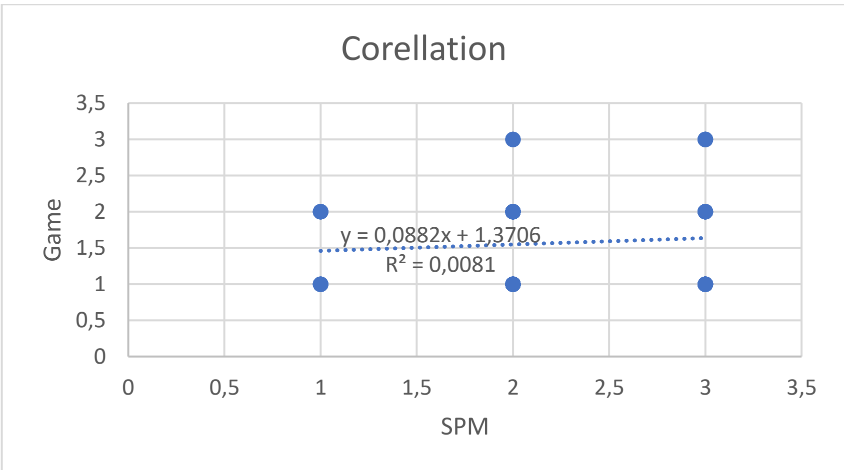

Fig. 17. Correlation of Both Stimuli

The results of the accuracy test of routine data retrieval by (3 takes) obtained an accuracy value of 80% of the game stimulus and 80% of the SPM stimulus. Meanwhile, the percentage of results from expert respondents who are superior but addict is 63.3% and the percentage of respondents who are average but addict is 36.6% with a correlation level between Games and SPM of 0.089822409.

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