Prediction of Drug Users Addiction Level with Methadone Treatment based on Brainwave Maximum Amplitude using ANFIS Method

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Keywords: Methadone, EEG, drugs, and ANFIS.

Abstract: The use of drugs outside the doctor's instructions tends to damage nerve function in users. The ability to detect drug users early is a major obstacle in overcoming drug abuse. If the brain system in humans is damaged, it usually causes permanent disability and is difficult to repair. In this study, a classification method to identify the level of brain damage in drug users was proposed. In the experiment, drug images were randomly displayed to stimulate the subjects' memory of using certain drugs. Recorded brain signals from eight subjects (addiction, methadone treatment (rehabilitation), and control) were performed. Brain waves in the form of alpha, beta, theta, and delta are used as features for the classification process using the ANFIS method. The classification results related to drug use with an accuracy rate of 96.97% were achieved.

1 INTRODUCTION

This study aims to determine the level of addiction of a drug user after using methadone on the brain. The brain is the central regulatory structure that regulates most of the movement, behavior, and body functions such as heart rate, blood pressure, body fluid balance, and body temperature for every living thing, especially humans. The large part of the brain can be divided into four lobes, namely the front (frontal), back (occipital), middle (parietal), and side (temporal) brain.

The cerebral cortex is the outermost layer of the brain, which extends in two hemispheres and is connected by the corpus callosum. Overall, each hemisphere is divided into four lobes namely frontal, parietal, temporal and occipital. This division shows that each lobe works based on their respective functions. The frontal lobes are separate from the parietal, and temporal lobes, where they are connected by central and lateral sulci, respectively. The frontal lobe generally functions to regulate emotional regulation, planning, reasoning, and problem solving. The parietal lobe functions to connect all sensory information such as touch, temperature, pressure, and pain. The temporal lobe functions to process sensory information from the parietal lobe such as hearing, recognizing language, and forming memories. The occipital lobe is the main center for processing information in the form of visuals such as interpreting the depth, distance, location, and identity of the object seen.

The information content in each brain activity according to its function can be recorded and processed for various needs such as disease detection, robot applications in the form of wheelchairs (Turnip et al, 2015), games, entertainment, and others (Turnip, Hidayat & Kusumandari, 2017; Simbolon et al, 2019). Of the many medical instrumentations, electroensephalogram (EEG) is a tool that can be used to study information from recorded electrical activity in the brain, including recording and interpretation techniques. EEG signals contain information on electrical activity in the brain, including the state of electrical and mental disturbances in nerves. EEG signals have a complex shape, are easily buried by

Turnip, A., Sitompul, E., Michael T., G., Iskandar, S., Novita, D. and Kusumandari, D.
Prediction of Drug Users Addiction Level with Methadone Treatment based on Brainwave Maximum Amplitude using ANFIS Method.
DOI: 10.5220/0010370603010307
In *Proceedings of the International Conference on Health Informatics, Medical, Biological Engineering, and Pharmaceutical (HIMBEP 2020)*, pages 301-307
ISBN: 978-989-758-500-5

noise, small amplitudes and do not have a standard pattern, so visual analysis is not easy.

There are many types of EEG signals, one of which is the P300 signal type (Karamacoska & Barry, 2019). EEG signals can also be interpreted in the form of delta (δ), theta (θ), alpha (α), beta 1 (β1), beta 2 (β2), and gamma (γ) waves. Delta waves (δ) are conditions that arise when a person is sleeping well. Theta wave (θ) is a condition that occurs when a person is lightly sleeping, and in a happy state. Alpha waves (α) are conditions that appear when a person is relaxed and their eyes are closed. Beta waves (β) are conditions that appear when a person is doing activities in terms of remembering such as a state of thinking. Gamma waves (γ) are conditions in which brain activity integrates various stimuli (Neto & Rosa, 2017).

Several previous studies related to the use of EEG for interpretation of brain signal information have been done (Simbolon et al, 2015; Turnip et al, 2019). Research on methadone was conducted using the fuzzy method as a classifier in the journal entitled Drug Abuse Identification based on EEG-P300 Amplitude and Latency with Fuzzy Logic Calssifier compiled by (Turnip, Kusumandari, & Pamungkas, 2018). This study aims to determine the level of a person's addiction to drugs using fuzzy logic. EEG Signal Classification Using AAR and SVM with Eeggyroscope Sensor of Emotiv Epoc was conducted to determine the results of the EEG signal classification using the AAR and SVM methods. This study also links ICA as one of its methods. The accuracy of this study shows that the number is quite high, namely 92%.

Furthermore, in the literature entitled An Adaptive Method for Feature Selection and Extraction for Classification of Epileptic EEG Signal in Significant States, feature selection and extraction to get good classification results are carried out (Harpale & Bairagi, 2018). This study also uses the ANFIS method as a classifier with approximate accuracy 96,48%

EEG signal classification using the K - Means algorithm and Fuzzy C Means Clustering in a study entitled EEG Signal Classification using K-Means and Fuzzy C Means Clustering Methods is proposed (Hegde, Nagananda, & Harsha, 2015). Drug-related research entitled The Effects of Methadone Maintenance Treatment on Heroin Addicts with Response Inhibition Function Impairments: Evidence From Event-Related Potentials discusses the effects of methadone on the brain response of heroin users (Yang, et al., 2015). The results of this study indicate that there are differences in brain response after using methadone. A similar study using methadone, namely Aging Opioid Users' Increased Risk of Methadone-Specific Death in the UK explains the level of risk of death caused by excessive methadone use (Pierce, Millar, Robertson, & Bird, 2018). Subsequent research studies (Characteristics of Adherence to Methadone Maintenance Treatment Over A 15-Year Period among Homeless Adults Experiencing Mental Illness) proved that adherence to methadone maintenance treatment over a 15 year period (among homeless adults with mental illness) provided significant improvement.

Risks of Methadone use as Substitute Therapy for Opioid Addiction during Pregnancy and use of Clonidine as a Plausible Alternative by (Munin, Iqbal, & Stowe, 2016) discusses the risks of using methadone in therapy during pregnancy. Another study in the form of EEG Signal Classification Using PSO Trained RBF Neural Network for Epilepsy Identification discusses the classification of EEG signals using the RBF Neural Network method with an accuracy of 98% (Satapathy, Dehuri, & Jagadev, 2017). The application of the ANFIS method to detect brain tumors was also successfully carried out in a study entitled "Brain Tumory Detection Using Artificial Neural Network Fuzzy Inference System (ANFIS) (J.Deshmukh & Khule, 2014). However, the accuracy of this study is still relatively low, namely 50-60%.

In this study, the use of the ANFIS method to predict drug users addiction levels in rehabilitation patients using methadone was proposed. The predictors that are developed are expected to be able to assist the medical team in providing methadone doses to patients, so that the suspicion of over or under-dosage can be overcome. Either over or under dosage will slow down the process of eliminating dependence on drug use. Even over dose is thought to cause death or at least will increase dependence on drugs.

2 METHOD

The process of this research is divided into 4 stages, namely: Signal Recording, Filtering Process, Data Extraction, and Data Classification. Recording of the EEG signal was carried out at Hasan Sadikin Hospital Bandung. The tools used are Electro-cap, Electro-gel, electro-gel special syringe, Mitsar EEG-202, computer, MatLab 2020 software.

Brain recording data of the subjects used were as many as 8 subjects after fasting to consume methadone for 8 hours before the experiment. Each subject was subjected to 2 tests, namely different pre and post stimuli. The different pre and post were the subjects' EEG recording data before and after using the methadone, respectively. Stimulus different is a collection of pictures, one of which contains pictures of drugs. The image set consists of 4 images of non-target stimuli (different images with drugs) and 1 target stimulus (drug-like) in 10 different sequences (20 seconds total). Each subject was recorded with the condition before and one hour after consuming methadone. The recorded data is then extracted based on the brain wave. Figure 1 is EEG Mitsar 201 and experimental scenario.

Each subject will be assigned an Electro-cap that has been given Electro-gel for each channel. Recording is done using the Mitsar EEG-201 device which is connected to a computer and has WinEEG software. Prior to recording, the electrode impedance calibration for each channel was performed with an impedance less than 5k□. Raw data that is recorded is an EEG signal which is very sensitive to noise. Therefore, the signal will be preprocessed to sort out the data that will be considered noise.

The signal that has been extracted from the filtered signal will study the pattern of changes from before and after consuming methadone. The pattern obtained is then used as input for the classifier to produce a decision on the outcome of each subject. The classification used is ANFIS logic as a method for machine learning decision making.

Figure 1: Recording process using Mitsar - EEG 201

Artificial Neuro Fuzzy Inference System (ANFIS) is an architecture that is functionally the same as the fuzzy rule base Sugeno model. ANFIS architecture is also the same as a neural network with radial functions with certain limitations. It can be said that ANFIS is a method in which setting rules use a learning algorithm for a set of data. ANFIS also allows the rules to adapt. The first order ANFIS structure is shown in Figure 2. In the Figure there are 5 layers with different functions for each layer. The box symbol represents an adaptive node, meaning that its parameter values can change with learning. Meanwhile, the circle symbol represents a non-adaptive node whose value is fixed.

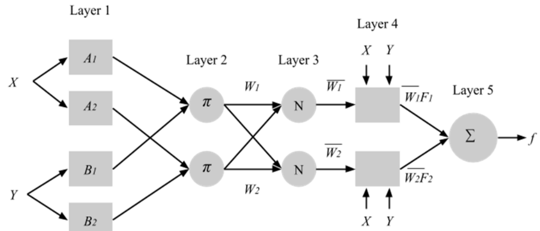


Figure 2: Structure of ANFIS prediction model

3 RESULTS AND DISCUSSIONS

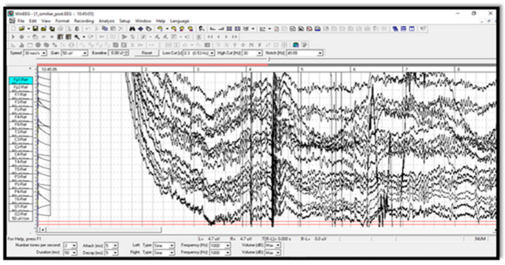
3.1 EEG Signal Pre-processing

The signal is filtered using a Band Pass Filter in the frequency range 0.5 Hz - 70 Hz (signal frequencies outside this range will be considered noise). Figure 3 is the EEG signal raw data with background noise content. The portions that are marked with red colour are known as artefacts.

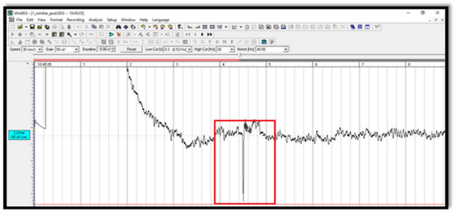
The filtered EEG signal is then extracted. Extraction is carried out to obtain brain waves in the form of alpha, beta, theta, delta, beta, and gamma waves. Signal extraction was carried out using EEG Spectra method from WinEEG application. EEG Spectra produces extraction data in the form of amplitude, power spectrum, and percent of the EEG signal. The extraction results are then known as features to be used as input to the classifier. The feature chosen in this study is the average percentage of the maximum amplitude of each wave. Table 1 is the percentage of the maximum amplitude of each channel for one subject in one experiment, namely before consuming methadone. The same was done for each subject both before and one hour after taking methadone. The results from each subject were then averaged to obtain a single amplitude value for each subject in each experiment.

3.2 Clasification Process

After going through the recording process using an EEG signal recording device, data will be obtained in the form of numbers from the translation of the recorded brain signal. The selected feature is the difference in the average percentage of the maximum amplitude, namely in Tables 2 and 3 which consists of six variables, namely Delta, Theta, Alpha, Beta1, Beta2, and Gamma (S is the subject). The value of each wave was obtained from the difference in the average maximum amplitude before (Table 2) and after one hour (Table 3) consuming Methadone for each subject.



(a) Hasil Perekaman



(b) Bentuk Noise pada sinyal

Figure 3: Shape of the brain signal

Table 1: Maksimum amplitudo of one subject for each channels

	Delta		Theta		Alpha		Beta1		Beta2		Gamma	
	%	Hz	%	Hz	%	Hz	%	Hz	%	Hz	%	Hz
Fp2-F8	31.97	1.46	7.98	3.91	8.47	10.50	3.73	18.80	6.93	29.30	9.89	33.20
F8-T4	19.34	1.46	7.01	3.91	18.16	9.52	10.69	18.80	9.32	19.78	7.19	37.35
T4-T6	13.68	1.46	6.06	3.91	38.60	9.52	14.83	18.55	7.57	19.78	3.99	31.49
T6-O2	18.40	1.46	9.21	4.39	40.44	9.52	11.55	18.31	6.17	19.78	1.70	30.76
Fp1-F7	29.90	1.46	8.70	3.91	6.55	7.32	3.05	19.04	4.98	22.95	4.75	38.82
F7-T3	29.26	1.46	7.24	3.91	10.28	11.47	3.28	18.80	4.07	20.02	2.73	33.69
T3-T5	18.26	1.46	6.26	3.91	23.62	9.52	8.68	18.80	4.71	19.78	1.49	29.79
T5-O1	14.87	1.46	7.10	3.91	44.29	9.52	15.05	18.55	6.17	19.78	1.40	30.03
Fp2-F4	29.32	1.46	7.27	3.91	7.89	9.52	3.30	19.78	8.62	20.02	10.98	33.20
F4-C4	26.17	1.46	8.81	3.91	24.78	10.74	6.63	19.53	7.95	20.75	2.08	30.03
C4-P4	22.34	1.46	7.70	3.91	35.46	10.01	9.20	18.80	5.51	20.02	1.12	30.27
P4-O2	18.85	1.46	9.53	3.91	37.37	9.52	11.90	18.80	7.58	19.78	1.46	29.79
Fp1-F3	35.15	1.46	10.47	3.91	8.19	9.28	2.91	19.29	4.39	22.22	3.10	38.82
F3-C3	22.39	1.46	9.44	4.15	28.46	11.47	6.65	18.80	8.95	20.02	2.74	31.01
C3-P3	15.54	1.46	7.22	4.39	44.52	9.52	11.73	18.80	7.44	20.02	1.60	30.03
P3-O1	11.10	1.46	6.24	7.32	49.13	9.52	16.38	18.55	7.09	19.78	1.04	30.03
Fz-Cz	19.50	1.46	7.13	3.91	13.06	11.47	3.35	19.78	4.73	22.46	15.64	38.82
Cz-Pz	17.52	1.46	8.73	6.59	43.84	11.23	9.59	18.80	6.60	20.02	1.67	30.03

Table 2: Average maximum amplitude before Methadone consumption

S	δ	θ	α	$\beta 1$	$\beta 2$	γ
S1	1,6	5,4	1,8	0,8	1	13,7
S2	1,7	4,3	0,5	0,8	6,7	7,1
S3	1,7	3,9	8,2	0,7	0,9	7,2
S4	2	4,6	5,7	0,7	1	21,8
S5	1,5	6,9	5,3	0,8	1	20,4
S6	1,8	4,2	5,5	0,6	11,2	21,4
S7	2,1	4,1	6,4	0,8	0,9	14,4
S8	1,6	5,3	9	0,7	6,3	1,5

Table 3: Average maximum amplitude after one hour Methadone consumption

S	δ	θ	α	$\beta 1$	$\beta 2$	γ
S1	2,2	5,1	6,8	0,8	1	1,3
S2	1,6	5,1	0,5	0,7	1	15,6
S3	1,9	5	6,9	0,7	1,1	1,4
S4	1,7	6,5	2,3	0,7	0,9	1,4
S5	1,9	6,1	3,7	0,7	1	8,5
S6	1,9	4,9	1,9	0,7	11,4	15
S7	1,7	4,1	3,6	0,8	0,9	28,3
S8	1,7	5,2	4,1	0,7	1	8,5

The classification results are used to detect the level of a person's addiction to drugs in relation to the administration of methadone doses in rehabilitation patients. The results from the difference in maximum amplitude from Table 3 to Table 2 for each subject are used as input in the ANFIS method as in Table 4.

Table 4. Difference of average maximum amplitude

S	Delta (δ)	Theta (θ)	Alpha (α)	Beta1 ($\beta 1$)	Beta2 ($\beta 2$)	Gamma (γ)	Output
S1	1	0.5	9.9	0.1	5.7	8	25.20
S2	0.3	1.6	4.9	0	0	28.9	35.70
S3	0.6	1.9	3.6	0.1	5.9	14.6	26.70
S4	0.1	2.7	1.5	0.1	5.6	0	10
S5	0.8	0	3.3	0	5.7	8.5	18.30
S6	0.5	1.5	1.3	0.2	5.9	14	23.40
S7	0	0.8	2.1	0.1	5.7	34.3	43
S8	0.5	0.7	0	0.1	0.4	27.4	29.10

The column output data in Table 4 is used as a reference for the classifier. The value ranges are grouped into 4 categories, where for each category the value are:

- HA (Heavily Addicted): >40
- MA (Moderate Addicted): <40 - ≥ 30
- SA (Slightly Addicted): <30 - ≥20
- NA (Not Addicted): <20 - ≥ 0

The grouping of values for each feature (Delta, Theta, Alpha, Beta1, Beta2, and Gamma) is a predictive output related to the addiction level of rehabilitation patients. This data is the difference from the signal before consuming methadone and after consuming methadone. The six waves will later become input in this classification process. Classification process Based on the image above, the following is an explanation for each description in Figure 4: (a) how to input training data in the ANFIS algorithm, (b) showing the ANFIS display, (c) showing the input and output design on the classification for each category predefined, (d) iterates 100 times on the data. (e) shows the comparison of training data and tested data.

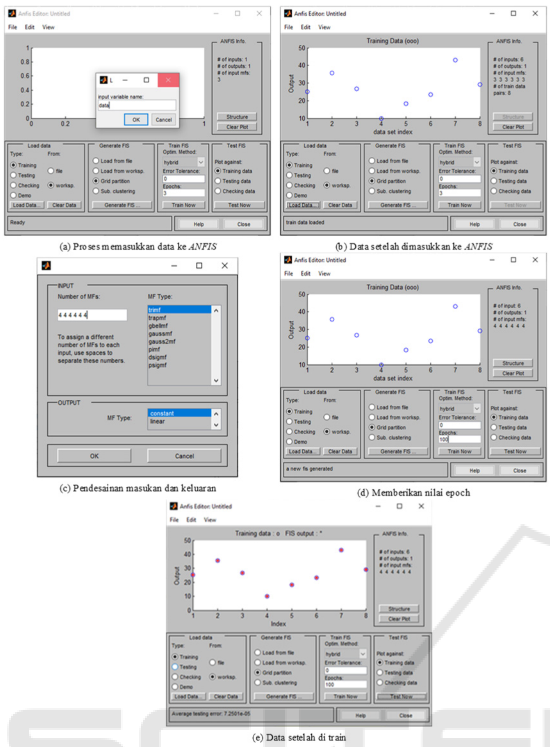


Figure 4: Clasification process using ANFIS method

Each input requires the maximum and minimum value of the data for the smallest and largest input variables. Based on Figure 5, the following is an explanation for each description of the input settings: (a) Delta variable, the value range starts from 0 to 1. Each category gets a value of 0.25, (b) the Theta variable, the range of values starts from 0 up to 3. Each category gets a value of 0.75, (c) the Alpha variable, the range of values starts from 0 to 10 with the category of getting a value of 2, 5, (d) the Beta1 variable, the range of values starts from 0 to with 0.02 with each category getting a value of 0.05, (e) the Beta2 variable, the value range starts from 0 to 6 with each category getting a value of 1.5, (f) the Gamma variable, the range of values starts from 0 to 35, with each category getting a value of 8.75.

Figure 6 shows the Rule Viewer of the input and output model design in the ANFIS classifier. A hybrid training algorithm is used where a combination of the gradient descent algorithm and a least squares algorithm is used for an effective search for the optimal parameters. The main benefit of ANFIS is that it converges much faster, since it reduces the search space dimensions of the backpropagation method used in neural networks. 4096 If-then rules and threemf type of membership function are used. The developved predictor model designed by ANFIS method is shown in Figure 7. This study started from recording brain signals before and after 1 hour of consuming methadone from 8 subjects who were drug addicts. There will be a comparison of the results of the two recordings starting from the increase and decrease in the subject's brain signal. This comparison becomes the data that we will process for classification. To get a comparison of the two data, the difference between the two experiments was calculated. After getting the difference between the two data, the classification process in the ANFIS prediction model application that has been built is carried out. The iteration process of 40 epochs was carried out to increase the accuracy of the prediction model. Furthermore, the input form is redesigned to improve the accuracy results before testing the prediction model.

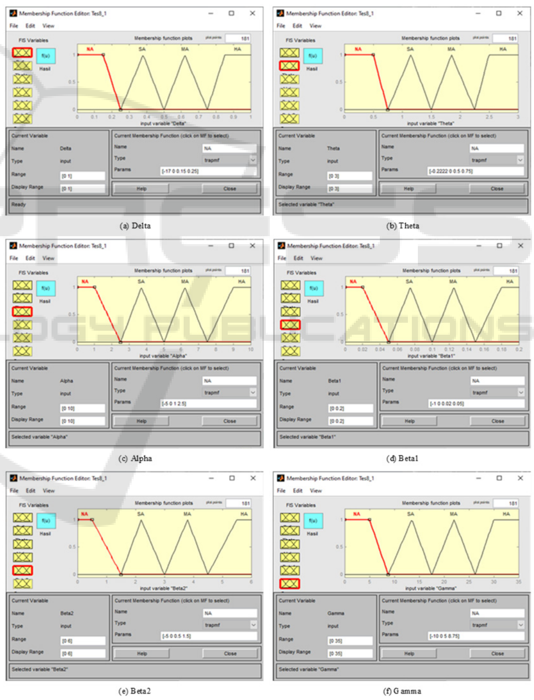


Figure 5: Design input on ANFIS

The comparison of clasification results using ANFIS method and calculation process is shown in Figure 8. It can be seen that both result almost the same except subjects 4 and 5. The slightly different of the classification results on those subject was suspected that both subjects consumed methadone before the experiment. However, generally the classification results of 96.97% is shows that this prediction model can be used to predict the addiction level of a drug user. Table 4 shows the predicted addicted level for all subjects. It were obtained that only one subject was highly addicted. Six subject were moderate addicted and one subject was not addicted.

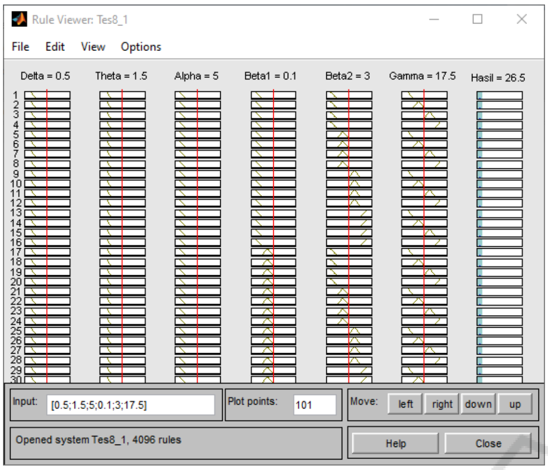


Figure 6: Viewer IF-Then rules

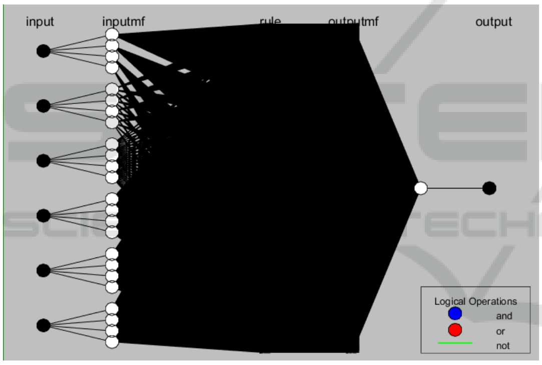


Figure 7. Developved ANFIS Structure

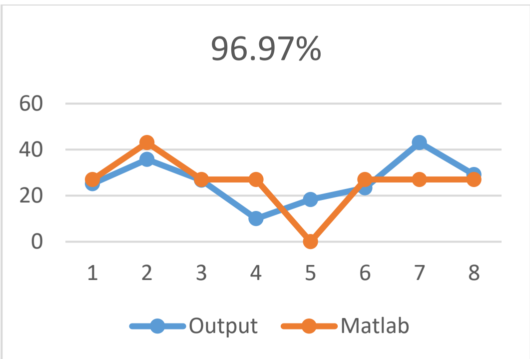


Figure 8. Comparison of Addiction level of calculated data with predicted by ANFIS method.

Methadone-induced increased brain signal activity resulted in several different patterns of enhancement for each subject. Each pattern was evaluated in each subject to determine the level of dependence of a patient on drugs in this study represented by methadone. The increase in the amplitude value of several brain waves before and after consuming Methadone indicates an increase in brain signal activity in certain parts. Some of the unusual enhancements to the subject are indicated by numbers soaring higher than other subjects. This is thought to be due to interference in recording brain signals.

Table 4: Classification results

S	ANFIS	Calculation	Addiction level
S1	25,20	27,0	MA
S2	35,70	43,0	HA
S3	26,70	27,0	MA
S4	10,00	27,0	MA
S5	18,30	0,0	NA
S6	23,40	27,0	MA
S7	43,00	27,0	MA
S8	29,10	27,0	MA

4 CONCLUSIONS

The classification of brain signal activity before and after 1 hour of consuming Methadone using the ANFIS process resulted in a fairly good prediction. Using 4 categories to determine the addiction level of each input resulted in an accuracy rate of 96.97%. This high degree of accuracy makes ANFIS modeling feasible for medical needs. However, the drawback is in the spike in brain signal values that fluctuate based on disturbance or stimulation when the ANFIS determines the category associated with the desired value. ANFIS predictor represent a useful tools for solving the non linearity problem of drug user prediction level prediction. Training data for the present study of ANFIS prediction was randomly collected from several simulations in MATLAB. The simulation results proved that ANFIS predictor can be applied successfully to predict the drug user addiction level because of its effectiveness and fast processting time.

ACKNOWLEDGMENTS

This research was supported by Technical Implementation Unit for Instrumentation Development, Indonesian Institute of Sciences, and

Department of Electrical Engineering, Universitas Padjadjaran, and Toba Research Center, Indonesia.

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