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# EEG-Based of Drug Addiction Levels Using Adaptive Neuro-Fuzzy Inference

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**ABSTRACT**

*Drug addiction influences the brain with varying levels of intensity. After being consumed, the active compounds in drugs are transported through the bloodstream to the brain, where they interfere with neural mechanisms and weaken impulse regulation. These substances primarily affect the limbic system, producing emotional reactions and sensations of pleasure that alter an individual's mental condition. Electroencephalogram (EEG) analysis provides a reliable means of studying addiction, as it reflects brainwave patterns associated with addictive behavior. The classification of drug addiction levels in this research was conducted using ANFIS, with input features obtained from the five brainwave ranges of delta, theta, alpha, beta-1, and beta-2. The approach achieved an accuracy rate of 94.2%, highlighting its effectiveness in detecting neural markers of addiction and its potential contribution to the development of more precise diagnostic tools and intervention methods.*

**Keywords:** Drugs, EEG, ANFIS, Classification.

**Mathematics Subject Classification:** 62J12, 62G99

**Computing Classification System:** I.4

## 1. INTRODUCTION

Narcotics are substances that may originate from natural, synthetic, or semi-synthetic sources and are known to produce effects such as reduced levels of consciousness, hallucinations, and heightened excitability. As stated in Article 1, Paragraph 1 of the Narcotics Law, such substances, either plant-based or synthetically produced, have the potential to induce hallucinations, reduce consciousness, and create dependency, which in excessive consumption frequently results in addiction. Although narcotics are sometimes prescribed for therapeutic purposes such as pain management and relaxation, their misuse carries legal consequences (National Narcotics Agency (BNN), 2019). The intricate link between neuroscience and addictive behavior has motivated researchers to seek innovative methods for understanding and addressing drug dependence. One promising avenue is the classification of electroencephalogram (EEG) signals, which provides valuable insights into the brain mechanisms underlying addiction. Since drug addiction has both physical and psychological dimensions, it represents a significant health concern. EEG, which measures the brain's electrical activity, also serves as a dynamic tool for examining complex neural functions and responses related to addictive behaviors.

This research was conducted on inmates with a background of drug-related offenses, a population considered at risk because of their likelihood to relapse after serving prison sentences. One method that has gained increasing attention is the use of electroencephalogram (EEG) analysis to identify alterations in brain activity patterns caused by substance use. To enhance classification performance, the K-Nearest Neighbors (KNN) algorithm has been applied, which categorizes data based on training examples determined by a selected number of closest neighbors (Turnip, Esti, Amri, et al., 2017; Borra, Mondini, Magosso, Müller-Putz, 2023). EEG has also been utilized to investigate whether Magnetoencephalography (MEG) can provide spatial information comparable to, or even better than, the less invasive Stereo-electroencephalography (SEEG) in localizing the Epileptogenic Zone (EZ) for surgical planning, an area that remains relatively underexplored (Vasilica, Litvak, Cao, et al., 2023; Da Silva Lourenco, Tjepkema-Cloostermans, van Putten, 2023). Furthermore, while EEG is recognized as a valuable diagnostic tool for Alzheimer's disease (AZD), its interpretation is complicated by the rapid and unpredictable progression of AZD-related brain changes. To address this limitation, the Flexible Analytic Wavelet Transform (FAWT) has been introduced due to its ability to adapt to dynamic variations (Khare, Acharya, 2023). Another approach, Continuous Wavelet Transformation (CWT), has been used to produce EEG-based image representations across time and scale intervals, and when combined with transfer learning, it shows strong potential in seizure detection (Kaur, Gandhi, 2023; Laurent, Ko, Mensah-Brown, Mavroudis, et al., 2023; Lih, Jahmunah, Palmer, et al., 2023). In neuropathic pain research, a non-parametric statistical model combining the Brief Pain Inventory (BPI) with both linear and nonlinear EEG features has been implemented (Zolezzi, Alonso-Valerdi, Ibarra-Zarate, 2023). To eliminate artifacts in EEG recordings, a hybrid denoising approach utilizing Canonical Correlation Analysis (CCA) as a blind source separation method has been proposed (Satyender, Dhull, Singh, 2023). Moreover, the ANFIS model, which integrates neural networks with fuzzy inference principles, is acknowledged for its flexibility in handling various types of input data and its robust ability to model complex systems across different domains.

In this work, the ANFIS method is introduced as a sophisticated approach for classifying EEG signals collected from individuals with a history of drug consumption. By combining the reasoning capability of fuzzy logic with the adaptive learning strength of neural networks, ANFIS establishes a robust framework for analyzing complex data. When applied to EEG measurements, the method enables the identification of distinctive brainwave patterns and markers that separate drug users from non-users. The classification relies on five principal five distinct neural frequency bands: delta, theta, alpha, beta-1, and beta-2 allowing a comprehensive evaluation of brain activity associated with addictive behaviors. Considering multiple features enhances both accuracy and sensitivity, offering deeper insights into the brain's unique responses to substance exposure. Beyond detecting neural patterns, the use of ANFIS aims to contribute to the design of targeted interventions and individualized treatment strategies. However, its broader application also raises ethical considerations regarding the utilization of neural data for classification and therapy. Overall, this study represents a significant step in linking neuroscience with addiction research, delivering knowledge that may support the advancement of more accurate diagnostic tools and effective therapeutic solutions.

## 2. METHOD

This research was carried out through a collaborative effort involving Universitas Prima Indonesia, Universitas Padjadjaran in Bandung, and a correctional institution located in North Sumatra Province, Indonesia. The experimental procedure comprised several stages, beginning with EEG data acquisition and concluding with the classification of addiction levels. A total of 21 male subjects, aged between 20 and 30 years, participated in the study. The primary objective was to evaluate the addiction levels of each inmate. Prior to data collection, participants were provided with detailed explanations regarding the procedures to be followed. In addition, researchers conducted interviews to gather personal information and background records from each subject. All data obtained during this phase were treated with strict confidentiality and securely protected, as any disclosure could potentially affect the participants' legal status.

In this study, EEG recordings were obtained using a Mitsar EEG 202 amplifier together with a 17-channel electro-cap. The electrodes were placed at specific positions—F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, P2, P4, T6, O1, and O2—as illustrated in Figure 1(b). The experiment was conducted while participants remained in a relaxed state with their eyes closed for two minutes. To ensure reliable data collection, precise fitting of the electro-cap, shown in Figure 1(a), was essential. Besides the scalp electrodes, two auricular references (A1 on the left ear and A2 on the right ear) were employed in a blended reference configuration. In total, 17 scalp electrodes and 2 auricular electrodes were utilized. The experimental tools consisted of electro-caps, an amplifier, conductive gel, and EEG Win software. The electro-cap acted as the primary sensor to detect electrical activity from the scalp, while the amplifier enhanced the signals for more accurate measurement. Conductive gel was applied to improve electrode–scalp contact and to ensure high-quality signal transmission (Jin, Peng, Qin, Li, Kong, 2023; Dehghani, Soltanian-Zadeh, Hossein-Zadeh, 2023).

A Brain-Computer Interface (BCI) refers to a technological framework that enables direct interaction between the human brain and external devices, including computers and other electronic systems. The operation of a BCI follows a sequence of interconnected stages that describe how neural data is captured and processed. The first stage, known as signal acquisition, records brain activity using specific measurement techniques. The collected digital signals are then subjected to pre-processing before relevant features are extracted during the feature extraction phase. These features are subsequently analyzed in the classification stage to interpret the user's mental state, intentions, or actions. The outcomes of classification generate BCI output signals, which can be applied to control external devices or perform specific tasks. Overall, the BCI framework consists of several integrated processes, including signal acquisition, pre-processing, feature extraction, classification, and application deployment. A schematic overview of this workflow and its stages is depicted in Figure 2 (Turnip, Rizqywan, Kusumandari, Turnip, Sihombing, 2018).

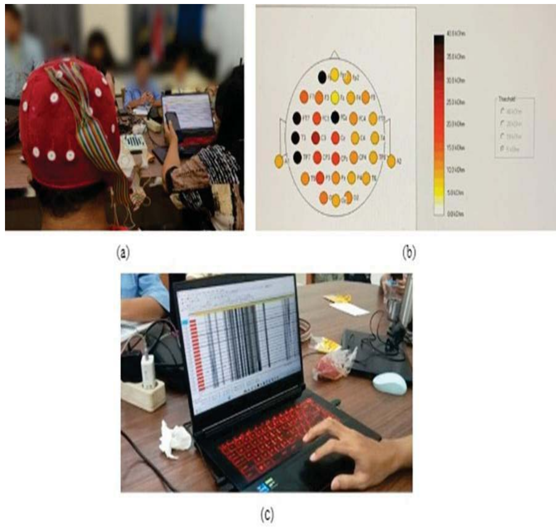



**Figure 1.** (a) devices and materials, (b) electrocup channels, (c) waves of electrical activity in the brain.

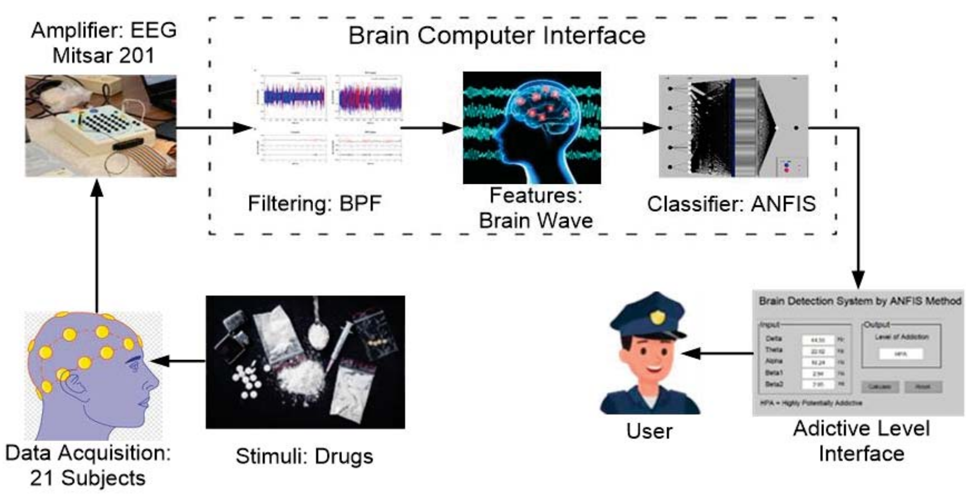



**Figure 2.** Brain Computer Interface

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is a type of neural network model that combines the principles of fuzzy inference, originally introduced by Sugeno, with adaptive learning capabilities. In this framework, two input variables, denoted as x and y, are mapped to produce a single output variable, z. When utilizing a first-order Sugeno approach, the system can be expressed through two fuzzy rules, as illustrated below (Almumtazah, Kiromi, Ulinnuha, 2023):

$Rule\ 1: If\ x\ is\ A1\ and\ y\ is\ B1, then:$

$$f\,1 = P\,1 + q1 + r)$$

$Rule\ 2: If\ x\ is\ A2\ and\ y\ is\ B2, then:$

$$f\,2 = p\,2 + q2 + r$$

## 3. RESULTS AND DISCUSSIONS

After the EEG signals were recorded, the raw data still contained considerable noise. A Band Pass Filter (BPF) operating in the range of 0.5–50 Hz was utilized to improve the signal quality. This filter is designed to retain brainwave components of interest—such as alpha, beta, and other relevant frequencies—while suppressing signals outside that range. The primary purpose of this process is to eliminate unwanted disturbances, enabling researchers or clinicians to concentrate on specific neural activities. As illustrated in Figures 3(a) and 3(b), the application of the Band Pass Filter significantly reduces noise and improves the clarity of the EEG signals being analyzed.

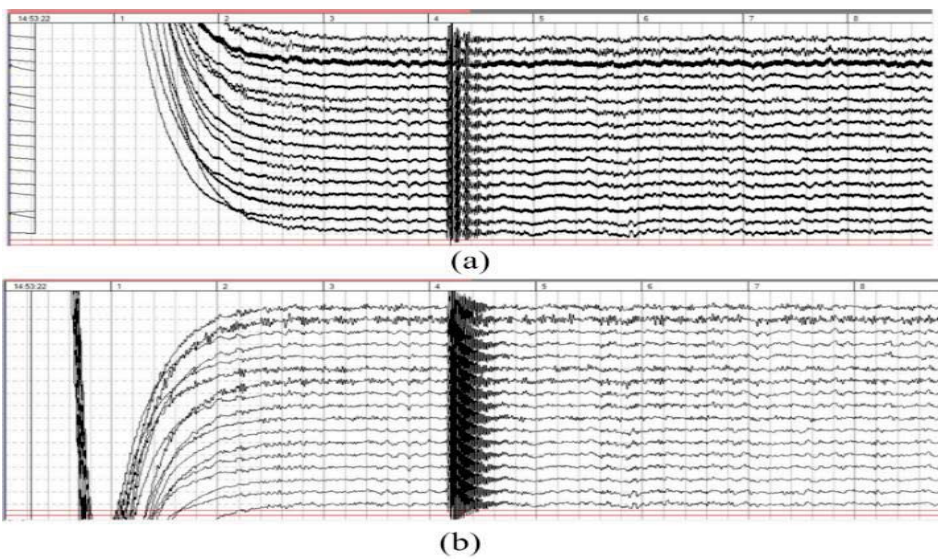


**Figure 3.** The recorded signal (a) Before (b) See has been Filtered.

This research analyzed five categories of brainwave activity: delta, theta, alpha, beta-1, and beta-2. When participants were blindfolded, theta activity was generally dominant, reflecting states of drowsiness or light sleep. Alpha rhythms, in contrast, commonly emerged when individuals reached a relaxed or calm resting condition. Beta waves became more pronounced during active cognitive engagement, such as carrying out daily tasks or engaging in social interaction. The mean amplitude values derived from the feature extraction process for each subject are presented in Table 1.

*Table 1:* Feature extraction results for each subject

| Subjects | Delta | theta | alpha | beta1 | beta2 | Class |
|---|---|---|---|---|---|---|
| S1 | 2,72 | 2,70 | 4,85 | 1,37 | 1,31 | 12,95 |
| S2 | 3,99 | 3,19 | 5,48 | 1,76 | 1,58 | 16,00 |
| S3 | 2,55 | 1,90 | 3,01 | 1,08 | 1,06 | 9,61 |
| S4 | 12,64 | 8,78 | 15,90 | 3,73 | 1,98 | 43,02 |
| S5 | 2,47 | 1,95 | 4,74 | 1,67 | 1,75 | 12,58 |
| S6 | 5,76 | 3,87 | 5,04 | 2,04 | 2,09 | 18,79 |
| S7 | 2,10 | 1,81 | 3,91 | 1,54 | 1,55 | 10,90 |
| S8 | 1,61 | 1,79 | 2,94 | 1,37 | 1,75 | 9,46 |
| S9 | 5,02 | 2,97 | 6,45 | 1,98 | 2,53 | 18,95 |
| S10 | 11,37 | 6,11 | 5,38 | 1,84 | 1,87 | 26,57 |
| S11 | 11,25 | 5,00 | 7,74 | 1,13 | 1,74 | 26,86 |
| S12 | 9,61 | 10,00 | 47,05 | 4,85 | 2,78 | 74,30 |
| S13 | 16,94 | 3,15 | 3,86 | 0,73 | 0,86 | 25,54 |
| S14 | 12,79 | 9,97 | 5,95 | 2,98 | 1,85 | 33,54 |
| S15 | 2,96 | 1,21 | 2,55 | 0,68 | 1,14 | 8,54 |
| S16 | 15,98 | 6,78 | 14,84 | 3,42 | 2,72 | 43,74 |
| S17 | 18,67 | 9,97 | 12,07 | 1,69 | 1,42 | 43,82 |
| S18 | 9,28 | 3,67 | 10,35 | 1,71 | 1,66 | 26,67 |
| S19 | 5,71 | 2,66 | 7,01 | 1,35 | 1,47 | 18,19 |
| S20 | 3,52 | 2,29 | 3,01 | 1,71 | 1,74 | 12,28 |
| S21 | 3,07 | 2,33 | 3,50 | 1,73 | 1,94 | 12,57 |

Table 1 displays the average EEG measurements for each subject, covering multiple frequency bands, namely Delta, Theta, Alpha, Beta1, and Beta2. Every subject is assigned a class label, which aids in identifying patterns related to neurological conditions, cognitive states, or other relevant factors. The data reveal noticeable variations in EEG band values among subjects, with participants such as S4, S12, S13, S16, and S17 showing higher amplitudes in several bands, indicating possible differences in neural activity patterns. The “Class” column denotes specific categories or labels associated with each subject, providing useful information about their characteristics. Examining the EEG values in relation to these class labels can help uncover correlations with certain conditions and may highlight underlying trends. In particular, S12, S16, and S17 exhibit consistently high values across several EEG bands, suggesting distinctive brain activity patterns. Further analysis of these subjects could yield deeper insights into the neurological traits linked to their respective class labels.

Exploring correlations between different EEG frequency bands can enhance our understanding of brain activity patterns. For instance, variations in Delta or Theta may be associated with different cognitive states compared to changes in Alpha or Beta bands. Recognizing these inter-band relationships contributes to a more nuanced interpretation of EEG data. Subjects displaying extreme values in specific EEG bands, such as S12 in Alpha and Beta2 bands, may be potential outliers, necessitating careful consideration of their impact on the overall analysis. The data, exhibiting potential for machine learning applications, especially in classification, is primed for further analysis. A predictive model, like a classifier, will be trained using the normalized EEG data from Table 1 to predict associated class labels. The data will be categorized into four classes: non-addictive (NA: less than 33.37), moderate addictive (MA: 33.37 – 61.53), potentially addictive (PA: 61.54 – 89.72), and highly potentially addictive (HPA: more than 89.72). The classification intervals were determined through a division based on the minimum and maximum values, ensuring a comprehensive and accurate classification approach.

For the classification process, the dataset was divided into three portions: 50% for training, 25% for testing, and 25% for validation, ensuring a reliable evaluation of the model's performance. Interval values were applied to determine the overall results across the classification categories. Following the initial classification, the data was re-analyzed using the ANFIS approach to verify accuracy. Proper organization and distribution of the input data play a crucial role, as they directly influence the predictive strength of the ANFIS model. The ideal number of training epochs is determined by both task complexity and the volume of available data. An excessive number of epochs may result in overfitting—where the model adapts well to training data but fails with unseen inputs—while too few epochs can lead to suboptimal performance. This trade-off between epochs and model effectiveness is illustrated in Figure 4.

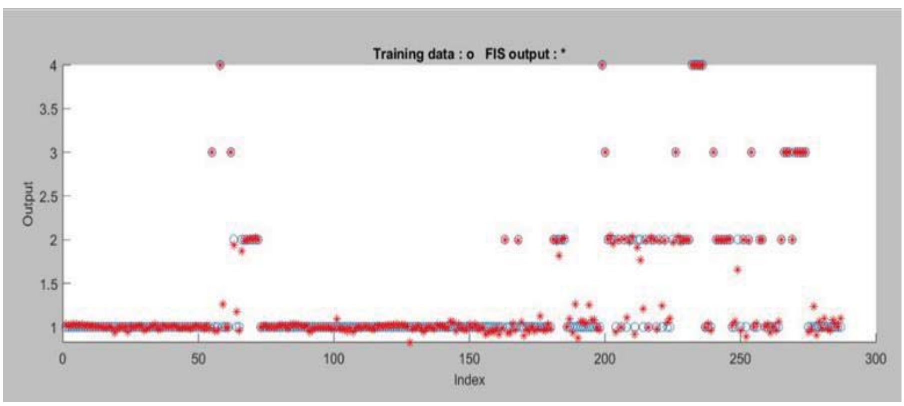



**Figure 4.** Data dissemination

The accuracy of ANFIS in the training data is depicted in the ANFIS graph editor. A blue circle signifies the data training process, while a red circle represents the results of ANFIS training. The presence of increasing red stars within the blue circle indicates that ANFIS is effectively training on the input data. The ANFIS model architecture comprises multiple layers and parameters, which can be adjusted based on input and output data, as illustrated in Figure 5.

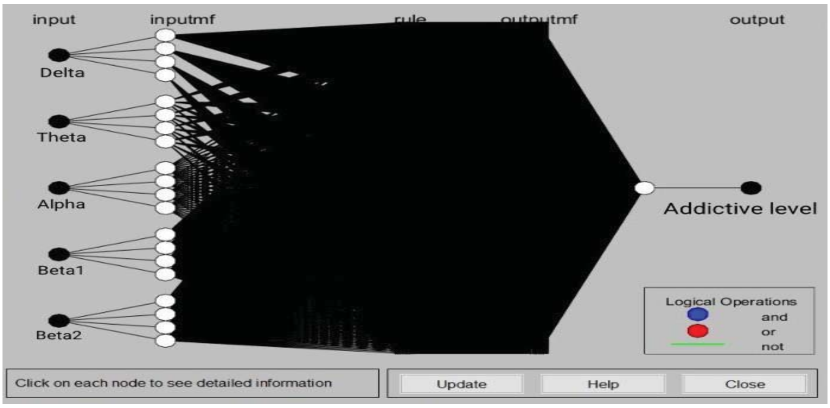



**Figure 5.** Anfis Model architecture for modeling relationship between input and output variables

During the training phase, the system adjusts several components, including membership function parameters, rule weights, and other related settings. This adaptability enables the ANFIS model to align itself with the given dataset, producing accurate fuzzy inference results suited to the specific task. A Fuzzy Inference System (FIS) is defined by key features that reflect the principles of fuzzy logic, as shown in Figure 6. Within ANFIS, membership functions are essential in mapping the relationship between input and output variables. They specify fuzzy sets and assign a degree of membership that indicates how strongly an input belongs to each set. Each input variable is associated with a group of linguistic terms represented by fuzzy sets, and the membership functions quantify the extent to which the input corresponds to these categories. Together, the membership functions and their parameters form the fundamental rule base of the fuzzy inference system. Through this structure, ANFIS employs fuzzy logic to connect inputs with outputs, handle uncertainty, and perform approximate reasoning in the decision-making process.

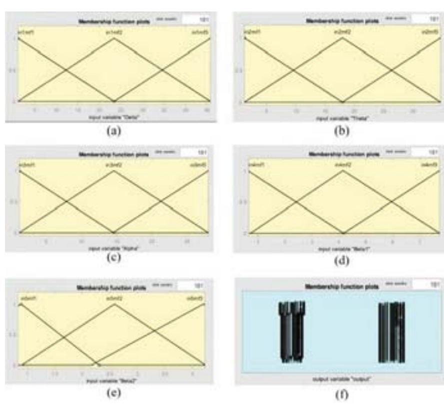
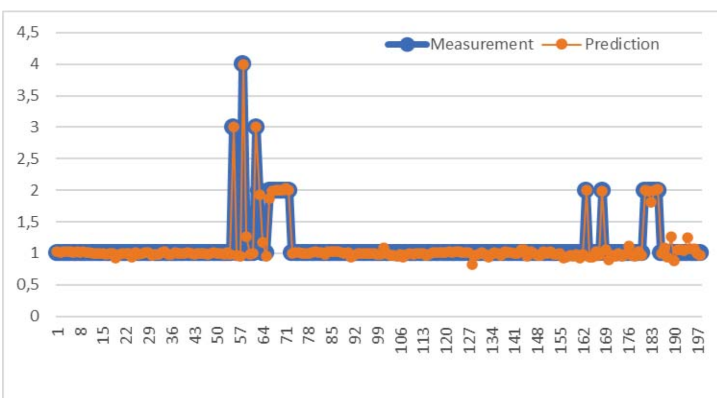


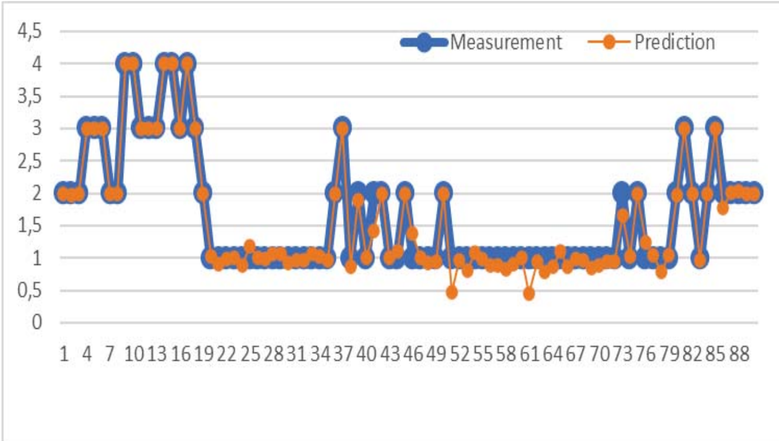

**Figure 6.** Membership functions (a) Deltha (b) Theta (c) Alpha (d) Beta 1 (e) Beta 2 (f) Output

The Fuzzy Inference System (FIS) emerges as a robust methodology designed to navigate and address the challenges posed by uncertainty and ambiguity in data processing. It incorporates a set of essential elements, including inference rules, fuzzy sets, membership functions, and mechanisms that establish the connections between inputs and outputs within the framework of fuzzy inference. This holistic approach enables FIS to effectively capture and model complex relationships in situations where traditional methods may fall short. In the context of EEG classification, the ANFIS method has been employed to leverage the capabilities of FIS for pattern recognition and classification tasks. The results of this approach are promising, as reflected in the achieved accuracy rates. During the training phase, the model demonstrated an impressive accuracy rate of 97.1%, showcasing its ability to learn and adapt to the intricacies of the provided data. The testing phase further substantiates the model's robustness, yielding an accuracy rate of 92.7%. The validation phase, crucial for assessing the model's generalization capability, resulted in an accuracy rate of 94.2%. These high accuracy rates across various phases indicate the proficiency of the ANFIS method in effectively classifying EEG data.

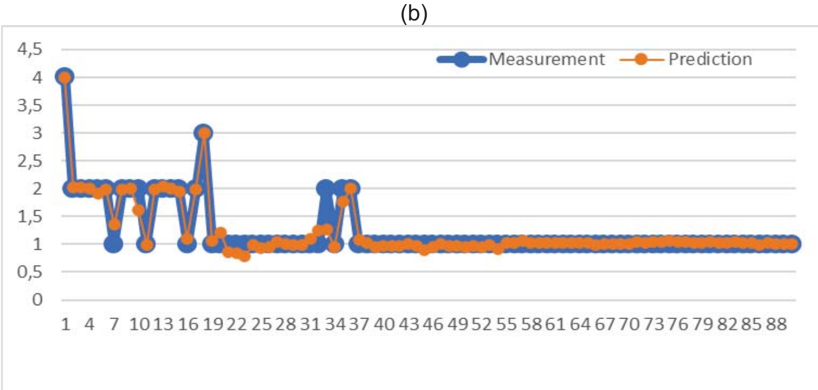
Figures 7(a) - (c) visually encapsulate the outcomes of EEG classification obtained through the ANFIS method. This graphical illustration offers an understanding of the unique patterns and trends revealed by the model throughout the various stages of data analysis. The efficacy of ANFIS in achieving high accuracy rates not only underscores its potential for EEG classification but also highlights its adaptability and robustness in handling complex and uncertain data. Moreover, these results pave the way for discussions on the practical applications of ANFIS in real-world scenarios, such as healthcare, where EEG classification plays a crucial role in diagnosing neurological conditions. The ability of ANFIS to handle uncertainty in EEG data makes it a promising tool for improving the accuracy and reliability of diagnostic systems. Generally, the successful application of the ANFIS method within the FIS framework demonstrates its effectiveness in EEG classification, providing accurate and reliable results across training, testing, and validation phases. The integration of fuzzy logic principles in data processing, as exemplified by FIS and ANFIS, holds great potential for advancing pattern recognition and classification tasks in fields where uncertainty and ambiguity are inherent.




(a)




(b)




(c)

**Figure 7.** (a) Prediction data training (b) Prediction data testing (c) Prediction data validation.

This part describes the design and implementation of a Brain Detection System that relies on a predefined rule set, achieving an accuracy of 94.2%. To improve usability, a graphical user interface (GUI), illustrated in Figure 8, was created. The primary objective of the system is to determine brain states through the analysis of five input features: Delta, Theta, Alpha, Beta-1, and Beta-2. Using these inputs along with the specified rules, the system generates an output category. In the example shown, the classification result is “Highly Potentially Addictive (HPA).” In practice, users input EEG measurements, and the system applies its rule-based mechanism to determine the appropriate brain state classification. With its simple and user-friendly design, the Brain Detection System is intended to facilitate rapid and accurate detection, as well as evaluation of neural patterns associated with addiction risk.

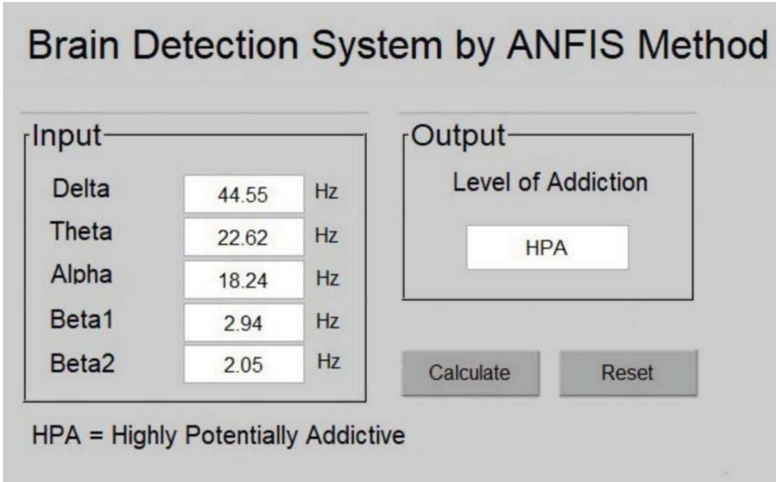



**Figure 8.** Brain Detection System by ANFIS Method

## 4. CONCLUSION

The Brain Detection Addiction Level system developed using the Adaptive Neuro-Fuzzy Inference System (ANFIS) has shown strong effectiveness in classifying levels of drug addiction from EEG data, reaching an overall accuracy of 94.2% across training, testing, and validation phases. By utilizing five major brainwave characteristics—delta, theta, alpha, beta-1, and beta-2—and combining the reasoning ability of fuzzy logic with the adaptive learning of neural networks, the system is capable of modeling intricate brain activity patterns related to addictive behaviors. The addition of a user-friendly graphical interface (GUI) enables straightforward data entry and real-time classification, enhancing its practicality for research, clinical diagnostics, and rehabilitation programs. With its high accuracy, consistent performance, and accessible design, the system holds considerable promise as a neuroscience-based approach for evaluating addiction levels. Future improvements may include expanding the dataset, refining fuzzy rule sets, and broadening its application in clinical environments.

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