Journal of Statistics and Its Application, Likelihood Vol 1 No 2, December 2025

Comparison of Machine Learning and Deep Learning Models for Mental Condition Classification Based on Electroencephalogram Data

Saffanah Karimah [1]

[1] Institut Teknologi Sepuluh Nopember, Indonesia, email: saffanah.karimah@gmail.com

Abstract

Mental states refer to the state of mind that can be viewed from various perspectives, such as consciousness-based, intention-based, and functionalism-based. Among the various types of human mental states, those that are inherent in everyday life are concentration, relaxation, and a neutral state between the two. Concentration is a state that needs to be achieved in activities related to human cognitive abilities, while relaxation is necessary when not performing strenuous activities so that the body can feel comfortable. Therefore, the ability to achieve these two states when needed is very important. However, in reality, people with mental disorders or patients with neurological diseases often find it difficult to achieve the ideal state of concentration or relaxation. Therefore, immediate treatment is needed to overcome the existing effects. Treatment of patients often requires an assessment of their current mental condition. One method that can be used to detect mental conditions is to use electroencephalogram (EEG) brain wave signals. Understanding EEG patterns can provide a more objective picture of the body's condition because every neurological and mental condition in humans affects the brain wave patterns that appear. Brain wave signals have a complex structure and are rich in information. The application of machine learning and deep learning algorithms is considered capable of learning and recognizing patterns in EEGs so that characteristics that distinguish the patterns of each mental condition can be identified. In this study, by comparing the machine learning method, namely Multiclass Support Vector Machine (SVM) using the One-Against-One approach, and the deep learning method, namely Artificial Neural Network (ANN), it was found that the ANN method had a higher AUC value of 0.878 compared to the Multiclass SVM method with an AUC of 0.767. Therefore, the ANN method with Stochastic Gradient Descent optimization is the best method for classifying mental states of concentration, neutrality, and relaxation based on EEG data.

Keywords: *Brain Waves, EEG, Mental State, Multiclass SVM, Neural Network*

Introduction

Mental state refers to the state of mind that can be viewed from various perspectives such as consciousness-based, intention-based, and functionalism (Baron-Cohen, 1994). Among the various types of human mental states, the states that are inherent in everyday life are concentration, relaxation, and neutrality. A state of concentration is necessary when performing activities that require cognitive abilities, while a state of relaxation is important to achieve because in this state the body feels comfortable, relaxed, and free from constant tension.

However, individuals with mental disorders, such as depression, bipolar disorder, anxiety, posttraumatic stress disorder, dissociative disorder, and insomnia, as well as those with neurological diseases, such as Alzheimer's, stroke, vascular dementia, and Parkinson's disease, often find it difficult to achieve ideal conditions of concentration or relaxation. Therefore, immediate treatment is necessary so that these problems can be resolved quickly. In the management of mental disorders and clinical illnesses, it is often necessary to assess whether the patient is in a state of concentration, already relaxed, or still in the intermediate stage, which is neutral.

https://doi.org/10.30605/likelihood.1245

A person's neurological and mental condition can influence the frequency and type of brain waves that appear. This has become the basis for research on mental state detection based on brain waves, which is widely conducted to produce objective and more accurate results (Bhavsar and Banatra, 2012). The commonly used brain wave recording technique is electroencephalogram (EEG). EEG is a non-invasive method of recording electrical activity in the brain using electrodes attached to the scalp. Its ease of use, low cost, and minimal side effects make EEG a commonly used choice for measuring brain electrical activity (Mazher et al., 2018). Machine learning techniques are needed to read EEG recordings quickly and accurately. Classification is one method that can be used to analyze brain wave signals and divide them into several classes according to signal characteristics.

Brain wave signals have a complex structure, therefore, data pre-processing is required, namely signal filtering. In this study, the signal filtering method used is Finite Impulse Response (FIR) Hamming Windows. This refers to research by Romolo, Widasari, and Prasetio (Romolo et al., 2022) which compared the Finite Impulse Response (FIR), Infinite Impulse Response (IIR), and Discrete Wavelet Transform (DWT) filtering methods in conditions of mental fatigue based on EEG signals and concluded that the FIR method is the most efficient method of filtering. After filtering, features were extracted from each subband of the brain waves. The feature extraction results became predictor variables in the classification.

In EEG-based classification studies, several machine learning approaches have been applied. One of the commonly used statistical classification methods is logistic regression. Logistic regression is a probabilistic classification method that models the relationship between predictor variables and class labels using a logistic (sigmoid) function. Some studies that use binary logistic regression include (Zulfadhli et al., 2024; Otok et al., 2026; Zulfadhli et al., 2025; Achmad et al., 2025; Zulfadhli et al., 2025; Suriaslan et al., 2025; Zulfadhli et al., 2025; Zulfadhli, 2025). This method has the advantage of being simple, interpretable, and computationally efficient. Several recent studies have utilized logistic regression for EEG signal classification and mental state detection, showing satisfactory performance in binary classification contexts (Khan et al., 2023). However, logistic regression tends to have limitations in capturing complex non-linear patterns that commonly exist in EEG data, particularly when dealing with multiclass problems and high-dimensional feature spaces (Khan et al., 2023). Since EEG signals are inherently non-linear and non-stationary, linear models like logistic regression may underperform compared with non-linear classifiers or more flexible models in complex classification scenarios (Mwata-Velu et al., 2024).

Machine learning and deep learning approaches are the primary choices due to their ability to capture patterns relevant to classification purposes. Machine learning methods such as Multiclass Support Vector Machine (SVM) are widely used for multiclass classification and demonstrate good performance (Ravikumar and Thukaram, 2010). This method is suitable for application in mental state classification, which consists of three classes: concentration, neutral, and relaxed. The Multiclass SVM approach used is One-Against-One (OAO) because the classification data only consists of three classes. Meanwhile, deep learning methods such as Artificial Neural Network (ANN) offer the ability to capture non-linear and abstract patterns in complex data such as EEG.

Some of the author's latest research includes (Karimah, 2013; Purnami et al., 2025; El Dafi et al., 2025) With their respective characteristics and advantages, comparing Multiclass SVM and ANN is important to determine the most effective method for developing an EEG-based classification system. This research is also expected to assist medical professionals in classifying patients' mental states based on brain wave signals recorded by EEG.

Mental Condition

Mental state is a state of mind that can be viewed from various perspectives (Baron-Cohen, 1994). Mental states can be categorized into several areas. In this study, mental states were categorized into a state of concentration, which is a cognitive mental state; a relaxed state, which is a psychophysiological and emotional mental state; and a neutral state, which is a psychophysiological mental state.

Electroencephalogram

Electroencephalogram (EEG) is a method of recording electrical activity in the brain. Diagnosis of EEG recordings is often performed in the time domain by looking at waveform, wave sharpness, and wave complexity (Kobra and Amara, 2015). The placement of electrodes has a specific meaning related to the nature of the recorded signal waves. This study used the TP10 channel located in the temporo-parietal area of the brain. This channel is related to emotional aspects and is therefore associated with states of concentration, neutrality, and relaxation.

EEG recordings in the form of signals can be distinguished based on their frequency range. Brain signal waves are categorized into five basic waves, as shown in Table 1 (Boutros et al., 2011).

Table 1. Signal Wave Subband Frequency

Wave Subband	Frequency
Delta	0.1-3.5 Hz
Teta	4-7.5 Hz
Alfa	8-13 Hz
Beta	13.5-30 Hz
Gamma	30.5-100 Hz

Finite Impulse Response Filter

Signal filtering is a circuit that passes signals with frequencies that meet certain conditions, while signals with frequencies that do not meet those conditions are blocked. Finite Impulse Response (FIR) filters have a limited impulse response because there is no feedback within the filter.

Feature Extraction

Features are unique characteristics of an object. Feature extraction is a step to obtain features that will be used in the classification process as predictor variables. The following features can be extracted from EEG recording signals (Bird et al., 2018; Saputra et al., 2022; Avasiloaie et al., 2022; Dehnavi et al., 2020; Ali and Abdulghani, 2017; Alirezaei and Sardouie, 2017).

1. Minimum: The smallest sample value.
2. Maximum: The largest sample value.
3. Skewness: A measure of the asymmetry of the data distribution.
4. Kurtosis: A measure of the peak sharpness of the data distribution.

Multiclass Support Vector Machine

Support Vector Machine (SVM) is a machine learning method that works based on the principle of Structural Risk Minimization and can be used to solve classification cases with high dimensional spaces. Hyperplanes for linear cases are defined by equation (1) (Abe, 2010).

$$\boldsymbol{w}^T \boldsymbol{x} + b = 0 \tag{1}$$

In nonlinear cases, kernel functions are used to map the input space to a higher-dimensional feature space. There are several types of kernels, including linear kernels, polynomial kernels, Radial Basis Function (RBF) kernels, and sigmoid kernels. The matrix-forming functions of each kernel are shown in equations (2) to (4).

1. Linear Kernel

$$K\left(x_v, x_z\right) = \boldsymbol{x}_v{}^T \boldsymbol{x}_z \tag{2}$$

2. Polinomial Kernel

$$K(x_v, x_z) = (x_v^T x_z + r)^d \quad (3)$$

3. RBF Kernel

$$K(x_v, x_z) = exp(-\gamma \|x_v - x_z\|^2) \quad (4)$$

Description:

d : Degree parameter

γ : Gamma parameter

r : Coef0 parameter

Multiclass SVM merupakan pengembangan dari metode SVM yang semula hanya untuk kasus dengan data biner. Metode *Multiclass* SVM diterapkan dengan mendekomposisi data multikelas menjadi serangkaian masalah biner sehingga standar SVM dapat diterapkan. Salah satu pendekatan *Multiclass* SVM adalah *One-Against-One* (OAO). OAO merupakan metode membandingkan satu kelas satu kelas lainnya, sehingga apabila akan mengklasifikasikan data ke dalam e kelas/kategori, diperlukan membangun model biner SVM sejumlah e(e-1)/2. Prediksi kelas dari data x ditentukan berdasarkan nilai terbesar dari fungsi hyperplane, dapat dituliskan dengan persamaan (5) (Avasiloaie et al., 2022).

$$y(x) = arg \max_{p=1,2,\ldots,e(e-1)/2} \sum_{q=1,q\neq 1}^{e(e-1)/2} \text{sign}\left((w^{pq})^T \phi(x) + b^{pq}\right) \quad (5)$$

Artificial Neural Network

An Artificial Neural Network (ANN) is an intelligent system used to process information with a working system that resembles the working pattern of human neural networks (neurons) (C. Gershenson, 2003). Backpropagation is a learning algorithm in Artificial Neural Networks with two stages of calculation, namely forward calculation, which is performed to calculate the error between the ANN output and the desired target. The next stage is backward calculation, which uses the error obtained to correct the weights of all existing neurons.

Research Methodology

Data Source

The data in this study is secondary data in the form of brain wave signal recordings using Electroencephalography (EEG) obtained through GitHub at https://github.com/jordan-bird/eeg-feature-generation/tree/master/dataset/original_data (Avasiloaie, 2022). The data comes from 4 participants (2 women and 2 men), each of whom recorded each mental state (relaxed, neutral, and concentrated), resulting in a total of 22 recordings. The duration of the recording data used in this study was 40 seconds. The sampling rate of the recording was 256 Hz, so each data point would have 40 × 256 = 10,240 voltage difference points. The recording data used came from the TP10 channel.

Research Steps

The research steps taken in this study are as follows.

1. Analyzing the characteristics of the EEG recording signal data.
2. Filtering the EEG recording wave signal based on the frequency range using Finite Impulse Response Hamming Window.
3. Extracting the maximum, minimum, skewness, and kurtosis features.

4. Changing the data scale using Z-Score Normalization.
5. Classifying the data using the OAO approach Multiclass Support Vector Machine with GridSearch parameter optimization.
6. Classifying the data using Artificial Neural Network with several optimization functions.
7. Comparing the classification performance between the Multiclass SVM and ANN models and selecting the best method based on AUC, accuracy, sensitivity, and specificity values.

Analysis and Discussion

Characteristics of Mental Condition Signal Data

The total number of recordings was 22, consisting of seven concentration mental states, seven neutral mental states, and eight relaxed mental states. The Power Spectral Density (PSD) plot displays the spectral power density of the brainwave signal and illustrates the frequency energy distribution in the brainwave signal. An example of one PSD plot is shown in Figure 1. The PSD plot containing signal frequencies from 0 to 120 Hz shows that brain wave signals for concentration, neutral, and relaxed conditions have delta, theta, alpha, beta, and gamma wave subbands. Therefore, the preprocessing stage will begin with filtering, where the data will be separated into three wave subbands.

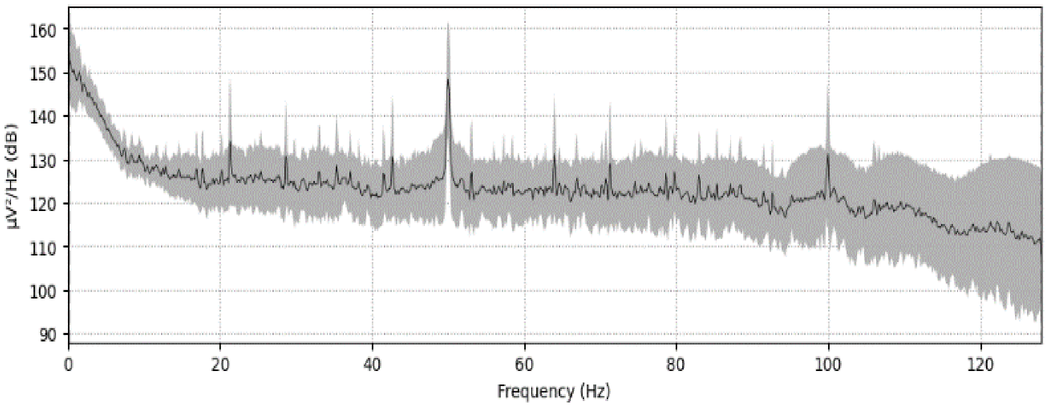

Figure 1. *Example of PSD Plot of Mental Condition Concentration Signal Data*

Filtration

The Finite Impulse Response (FIR) Hamming Windows filtering method is used to filter signals into five wave subbands based on frequency range. Each mental state contains five subbands, namely delta, theta, alpha, beta, and gamma. The higher the frequency range of the signal, the higher the signal density. Therefore, delta will have the lowest signal density, while gamma will have the highest signal density. In this study, filtering was performed to produce three subbands, namely theta, alpha, and beta, because these three subbands are related to concentration, neutrality, and relaxation.

Signal Feature Extraction

After the data segmentation process, feature extraction is performed to extract characteristics from the signal data. Feature extraction is performed on three wave subbands, with each subband extracted into four features, resulting in a total of 12 features for one channel.

Data Standardization

The feature extraction results show significant differences in the signal feature range. Therefore, data standardization is performed using Z-Score Normalization to provide a balanced impact on data modeling.

Classification Using Multiclass SVM OAO Approach

In the One-Against-One (OAO) approach to Multiclass SVM, one class is compared with another class. Three binary models are formed because the data consists of three classes. Multiclass SVM modeling is performed with optimal parameters obtained from GridSearch. The selection of the best model is based on the highest Area Under Curve (AUC) value, which is close to 1. The evaluation of the OAO approach to Multiclass SVM is shown in Table 2.

Table 2. *Evaluation of the OAO approach to Multiclass SVM*

Method	AUC	Accuracy	Sensitivity	Specificity
Linear	0.500	0.286	0.222	0.633
RBF	0.767	0.714	0.667	0.850
Polinomial	0.394	0.429	0.333	0.700
Sigmoid	0.456	0.571	0.500	0.767

The RBF kernel has the largest AUC compared to other kernels, so the best model for the OAO approach Multiclass SVM method is the model with the RBF kernel.

Classification Using Artificial Neural Networks

The ANN modeling architecture consists of an input layer, a hidden layer consisting of three layers, namely layer 1 has 128-unit neurons with ReLU activation function, Batch Normalization helps normalize inputs between layers, and Dropout of 30% to prevent overfitting. Layer 2 has 64-unit neurons and 20% dropout, and layer 3 has 32-unit neurons. It ends with an output layer with a Softmax activation function. The regularization strategy uses Dropout and Batch Normalization to prevent overfitting. EarlyStopping is used to control training so that it stops early if there is no improvement in performance and to adjust the learning rate.

The ANN modeling in this study compares the performance of various optimizations, namely Stochastic Gradient Descent (SGD) with momentum 0 and 0.9, Adam (Adaptive Moment Estimation), Adagrad (Adaptive Gradient Algorithm), and RMSprop (Root Mean Square Propagation). The results of the ANN modeling are shown in Table 3.

Table 3. *Evaluation of ANN*

Optimization	AUC	Accuracy	Sensitivity	Spesifisitas
SGD momentum 0	0.878	0.429	NaN	1,000
SGD momentum 0,9	0.233	0.429	NaN	NaN
Adam	0.444	0.286	1.000	0,000
AdaGrad	0.811	0.571	1.000	0,500
RMSprop	0.461	0.143	0.500	0,000

ANN dengan fungsi optimasi *Stochastic Gradient Descent* momentum 0 memiliki nilai AUC tertinggi dibandingkan ANN dengan fungsi optimasi lainnya. Maka, model terbaik metode ANN adalah dengan fungsi opmtiasi SGD momentum 0.

Selection of the Best Classifier

The selection of the best classifier between the Multiclass SVM and ANN methods was done by comparing the performance of the best models of each approach. The comparison of the two models is shown in Table 4. The ROC curve comparison between the two models is shown in Figure 2.

Table 4. *Comparison of Multiclass SVM and ANN Evaluations*

Optimization	AUC	Accuracy	Sensitivity	Specificity
Multiclass SVM	0.767	0.714	0.667	0.850
ANN	0.878	0.429	NaN	1.000

Table 4 shows that the ANN method has higher AUC and specificity values than the Multiclass SVM method. This indicates that the ANN method can classify multiclass mental conditions (concentration, neutral, and relaxed) better than the SVM method.

Figure 2 shows that the ANN method has a wider area under the curve than the Multiclass SVM method.

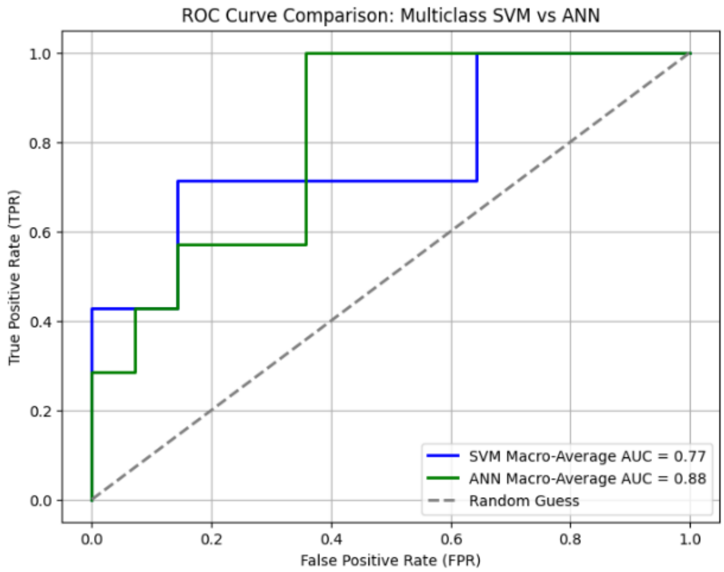

Figure 2. *ROC Curve Comparing Multiclass SVM and ANN Methods*

Conclusion

The conclusions drawn based on the analysis and discussion conducted are as follows. Classification using the machine learning method, namely Multiclass Support Vector Machine with various kernels and parameter combinations, yielded results indicating that the best kernel for mental condition classification is the RBF kernel with an AUC value of 0.767. Classification using the deep learning method, namely Artificial Neural Network with various optimization functions, shows that the best optimization function is Stochastic Gradient Descent with momentum 0 and an AUC value of 0.878. The results of comparing the performance of machine learning and deep learning methods in this study show that ANN is better at classifying mental states of concentration, neutrality, and relaxation based on electroencephalogram recording data.

Acknowledgment

The authors would like to express their sincere gratitude to Institut Teknologi Sepuluh Nopember (ITS) for the academic support, research facilities, and conducive research environment provided throughout the completion of this study.

References

Abe, S. (2010). *Support vector machines for pattern classification* (2nd ed.). New York: Springer.

Achmad, A. M., Zulfadhli, M., & Nurfaudzan, N. (2025). *Binary logistic regression on the status of unemployment rate in West Java Province in 2023. Likelihood: Journal of Statistics and Its Applications, 1*(1), 30–34.

Bhavsar, H., & Ganatra, A. (2012). A comparative study of training algorithms for supervised machine learning. *International Journal of Soft Computing and Engineering (IJSCE)*, *2*(4), 2231-2307.

Ali, A. M., & Abdulghani, A. M. (2017). Development of efficient algorithm to detect and classify alpha activity in real-time EEG signal using LabVIEW for mental state detection. In *Proceedings of the International Conference* (pp. 411–415).

Alirezaei, M., & Sardouie, S. H. (2017). Detection of human attention using EEG signals. In *Proceedings of the 2017 24th National and 2nd International Iranian Conference on Biomedical Engineering (ICBME)* (pp. 1–5).

Avasiloaie, A., Zîrnă, B. A., Oniga, M., Sultana, A. E., & Frunzete, M. C. (2022). Classification of mental effort vs. relaxation states using EEG signals. In *Proceedings of the 10th IEEE International Conference on E-Health and Bioengineering* (pp. 1–4).

Baron-Cohen, S., Ring, H., Moriarty, J., Schmitz, B., Costa, D., & Ell, P. (1994). Recognition of mental state terms. *The British Journal of Psychiatry*, 165(5), 640–649.

Bird, J. J., Manso, L. J., Ribeiro, E. P., Ekart, A., & Faria, D. R. (2018). A study on mental state classification using EEG-based brain-machine interface. In *Proceedings of the IEEE 2018 International Conference on Intelligent Systems (IS)* (pp. 1–6).

Boutros, N., Galderisi, S., Orefice, S., & Riggio, S. (2011). *Brain mapping in clinical psychiatry*. UK: John Wiley & Sons, Ltd.

Dehnavi, M. S., Dehnavi, V. S., & Shafiee, M. (2020). Classification of mental states of human concentration based on EEG signal. In *Proceedings of the IEEE International Conference on Information and Knowledge Technology (IKT)* (pp. 78–82).

El Dafi, A. A., Purnami, S. W., Andari, S., Maramis, M. M., Islamiyah, W. R., & Karimah, S. (2025, November). Comparative Analysis of Boosting Ensemble Methods for Classifying Depression Severity Using EEG Signals. In *2025 15th International Conference on Information & Communication Technology and System (ICTS)* (pp. 1-6). IEEE.

Gershenson, C. (2003). Artificial neural networks for beginners. *arXiv preprint arXiv:cs/0308031*, 1–8.

Karimah, S. (2013). *Klasifikasi Mental State Berdasarkan Data Rekaman Electroencephalography (EEG) Menggunakan Multiclass Support Vector Machine* (Doctoral dissertation, Institut Teknologi Sepuluh Nopember).

Khan, R. A., Rashid, N., Shahzaib, M., Malik, U. F., Arif, A., Iqbal, J., & Tiwana, M. (2023). *A novel framework for classification of two-class motor imagery EEG signals using logistic regression classification algorithm*. PLoS ONE, 18(9), e0276133.

Korba, H. B., & Amara, M. C. (2015). Application of empirical mode decomposition and artificial neural network for the classification of normal and epileptic EEG signal. *Biocybernetics and Biomedical Engineering*, 36(1), 285–291.

Mazher, M., Faye, I., Qayyum, A., & Malik, A. S. (2018). Classification of resting and cognitive states using EEG-based feature extraction and connectivity approach. In *Proceedings of the IEEE 2018 International Conference on Intelligent Systems (IS)* (pp. 1–6).

Mwata-Velu, T., *et al.* (2024). *Multiclass classification of visual electroencephalogram (EEG) signals: Deep learning and non-linear characteristi cs in EEG classifications*. Sensors, 24(12), 3968.

Otok, B. W., Zulfadhli, M., Pangesti, R. D., Kurniawan, M. I., Haryanto, A. E. P., & Kurniawan, I. (2026). *Comparison of binary probit regression and Fourier series nonparametric logistic regression in modeling diabetes status at Hajj General Hospital Surabaya. Barekeng, 20*(1), 255–270.

Purnami, S. W., Karimah, S., Andari, S., Wulandari, D. P., Hadiwidodo, Y. S., Islamiyah, W. R., ... & Zain, J. M. (2025). Mental state classification based on electroencephalogram (EEG) using multiclass support vector machine. *Medical Journal of Malaysia*, *80*(3), 352-358.

Ravikumar, B., & Thukaram, D. (2010). Comparison of multiclass SVM classification methods to use in a supportive system for distance relay coordination. *IEEE Transactions on Power Delivery*, 25(3), 1296–1305.

Romolo, D., Widasari, E. R., & Prasetio, B. H. (2022). Analisis perbandingan filter finite impulse response, infinite impulse response, dan discrete wavelet transform pada kondisi kelelahan mental berbasis sinyal electroencephalography. *Jurnal Pengembangan Teknologi Informasi dan Ilmu Komputer*, 6(9), 4580–4585.

Saputra, N. H., Wibawa, A. D., Purnomo, M. H., & Pamungkas, Y. (2022). EEG-based statistical analysis on determining the stress mental state on police personnel. In *Proceedings of the 2022 1st International Conference on Information System & Information Technology (ICISIT)* (pp. 181–186).

Suriaslan, A. S., Budiantara, I. N., Ratnasari, V., Zulfadhli, M., & Dhewy, R. C. (2025). *An empirical study on unmet need: A statistical inference framework for truncated spline nonparametric binary logistic regression (TSNLBR). Journal of Cultural Analysis and Social Change*, 10, 868–877. https://doi.org/10.20897/jcasc/2025.868

Zulfadhli, M., Budiantara, I. N., & Ratnasari, V. (2024). *Nonparametric regression estimator of multivariable Fourier series for categorical data. MethodsX, 13*, 102983. https://doi.org/10.1016/j.mex.2024.102983

Zulfadhli, M., Budiantara, I. N., Ratnasari, V., & Suriaslan, A. S. (2025). *Fourier series nonparametric regression estimator for modeling status of unmet need in East Java Province in 2023. Communications in Mathematical Biology and Neuroscience*, Article-ID 2025.

Zulfadhli, M., Budiantara, I. N., Ratnasari, V., Suriaslan, A. S., & Dhewy, R. C. (2025). *A statistical inference framework for FSNBLR: Modeling underdeveloped regional status in Eastern Indonesia. MethodsX*, 103746. https://doi.org/10.1016/j.mex.2025.103746

Zulfadhli, M., Budiantara, I. N., Ratnasari, V., & Suriaslan, A. S. (2025). *Semiparametric regression estimator of Fourier series for categorical data. IAENG International Journal of Applied Mathematics, 55*(7), 2157–2164.

Zulfadhli, M. (2025). *Estimator regresi nonparametrik deret Fourier multivariabel untuk data kategori* (Doctoral dissertation, Institut Teknologi Sepuluh Nopember).