Modification of grey-level co-occurrence matrix for epileptic electroencephalogram signal classification

Donny Setiawan Beu[1], Achmad Rizal[1], Said Ziani[2], Triwiyanto[3]
[1]Master of Electrical Engineering Study Program, School of Electrical Engineering, Telkom University, Bandung, Indonesia
[2]Department of Health Technologies Engineering, Mohammed V University, Agdal, Morocco
[3]Department of Medical Electronics Technology, Poltekkes Kemenkes Surabaya, Surabaya, Indonesia

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ABSTRACT

Texture analysis is a fundamental approach in image processing for identifying specific patterns or structures. One widely used method is the grey-level co-occurrence matrix (GLCM), which computes the frequency of pixel value pairs at certain distances and angles. This study adapts the GLCM method for 1D electroencephalogram (EEG) signal analysis, focusing on extracting features such as contrast, energy, homogeneity, correlation, and entropy. EEG signals are normalized to the range 0–255, and the extracted features are classified using a support vector machine (SVM). Experimental results show that combining features across multiple distances (d=1 to 20) achieves classification accuracy of 78.8% for five classes (Z/O/N/F/S), 94.0% for three classes (O/F/S), and 94.3% for another three-class group (Z/N/F). The method shows strong performance for short to medium distances and fewer class combinations. However, performance declines when dealing with more complex class sets and longer distances, where texture features become less effective. The drop in accuracy for Z/O/N/F/S beyond d=5 underscores the challenges of maintaining feature robustness at extended distances. Despite this, GLCM remains a promising approach for EEG signal classification. Future work should focus on optimizing distance parameters and feature combinations to further enhance classification performance.

Corresponding Author:

Donny Setiawan Beu
Master of Electrical Engineering Study Program, School of Electrical Engineering, Telkom University
Bandung 40257, Indonesia
Email: donnysbeu@student.telkomuniversity.ac.id

1. INTRODUCTION

The Texture analysis is used in image processing to recognize specific patterns or structures within images [1]. This method has applications in various fields, such as pattern recognition [2], image classification [3], and object detection [4]. Texture analysis utilizes the statistical and spatial characteristics of pixels within an image to identify and describe the existing patterns [5]. Through texture analysis, valuable information from images can be extracted and used in diverse applications [6]. Various techniques for texture analysis have been developed, including gray level run length (GLRL) [7] and gray level difference matrix (GLDM) [8], [9]. A commonly utilized method is the grey-level co-occurrence matrix (GLCM) [10], which computes the frequency of pairs of pixels with specific intensities appearing at particular distances and angles in an image.

Several studies have employed GLCM as a texture analysis method. For instance, brain tumor analysis utilizes parameters such as energy, dissimilarity, homogeneity, and contrast [11]. Similarly, these parameters have been applied in research on bone X-ray images of musculoskeletal radiographs [12], demonstrating the versatility of GLCM across different domains. Other studies combined GLCM with first-order statistics, achieving a model with 97.00% accuracy when applied to three-class data [13]. However, most existing studies have focused on applying GLCM to two-dimensional medical images, whereas the current study explores its adaptation to one-dimensional EEG signals. Unlike conventional approaches that directly extract GLCM features from grayscale images, this study modifies GLCM to analyze the spatial relationships between signal amplitudes over time, effectively capturing temporal dependencies in EEG data.

In this study, we modified GLCM for application to 1D signals, similar to previous modifications of the GLDM. The features extracted from the GLCM will be used for epileptic seizure classification using an SVM. The classification features include contrast, energy, homogeneity, correlation, and entropy. The adapted GLCM method is expected to function as an alternative for analyzing EEG seizure signals through texture analysis.

2. METHOD

This study aimed to test the GLCM texture analysis method for EEG signal classification. Because EEG signals are 1D, whereas GLCM was originally designed for texture analysis of 2D images, a modification process was required. EEG signals were normalized or scaled to a range of 0-255. Subsequently, GLCM was computed only in the 0° direction. The features from the GLCM were extracted. The final step involved classification using SVM. Figure 1 illustrates the steps involved, and the details of each process are described in the following subsections.

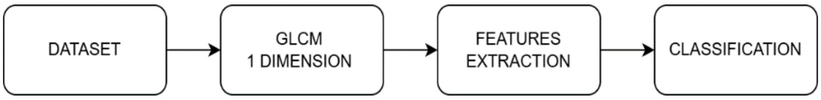


Figure 1. Block diagram for the system

2.1. Dataset

The EEG data used in this study were collected by Andrzejak *et al*. [14] from the University of Bonn, Germany, sampled at 173.61 Hz with an EEG device frequency range from 0.5 Hz to 85 Hz. To reduce noise artifacts, a low-pass filter (LPF) at 40 Hz was applied during the data-acquisition process. Each dataset consisted of 4096 samples with a total duration of 23.6 seconds. All category classes of data were included in this study and divided into various class-division scenarios for further analysis. The main objective of this study was to identify the most effective combination of data classes. Details regarding the types of classes within this dataset are presented in Table 1.

Table 1. EEG dataset description

Set	EEG signal	Name of file	Amount	Description
A	Normal	Z	100	Sets A and B contain surface EEG recordings conducted on five healthy volunteers using a
B	Normal	O	100	standardized electrode placement scheme. The volunteers were in a relaxed state with eyes open (A) and eyes closed (B).
C	Interictal	N	100	Data set C contains EEG recordings from the hippocampal formation in the hemisphere opposite the epileptogenic zone.
D	Interictal	F	100	Data set D contains EEG recordings from the epileptogenic zone. Both recordings from data set C and D were obtained during seizure-free periods.
E	Ictal	S	100	Set E is a collection of epileptic seizure activities recorded from the hippocampal focus.

2.2. Normalization

EEG signals represent electrical brain activity recorded on the scalp surface. These signals typically have many dimensions, are highly complex, and often require transformation or normalization for further analysis. In this approach, the one-dimensional EEG signal is transformed to a scale ranging from 0 to 255 to align it with the intensity range commonly used in digital images.

Normalization involves adjusting the amplitude values of the EEG signal to fit within the 0 to 255. This process involves adjusting the minimum and maximum values of the EEG signal to encompass the desired intensity range. By doing so, EEG signals, which originally had varying value ranges, could be standardized for further analysis using the GLCM. The normalization can be achieved using (1) [15]:

$$y(i) = floor\ \frac{x(i)-min(x)}{max(x)-\min(x)} x256 \tag{1}$$

2.3. Gray-level co-occurrence matrix

GLCM measures the frequency of pixel pairs with specific intensity values appearing in an image at specific distances and directions [16]. GLCM represents a matrix that illustrates how combinations of grayscale levels of these pixel pairs appear throughout an image [17]. $h(i_1, i_2|\theta)$ refers to the GLCM used to depict the frequency of occurrence of pixel pairs with intensities i_1, i_2 at the direction or angle θ within an image. The GLCM was first introduced in 1973 by Haralick, who introduced 14 basic features. Since then, GLCM has undergone various developments leading to the use of up to 20 or more features. Several commonly used features in GLCM are described in (2)–(6) [6], [18]. In (2) to (6) can be used to compute the features from the GLCM [6], [18]:

$$yASM = \sum_i \sum_j P(i,j)^2 \tag{2}$$

$$Contrast = \sum_{i_1} (i_1 - i_2)^2 p(i_1, i_2) \tag{3}$$

$$Homogeneity = \sum_{i_1} \sum_{i_1} \frac{p(i_1,i_2)}{1+|i_1-i_2|} \tag{4}$$

$$Energy = \sum_{i_1} \sum_{i_1} p^2(i_1, i_2) \tag{5}$$

$$Entropy = -\sum_{i_1} \sum_{i_1} p(i_1, i_2) \log p(i_1, i_2) \tag{6}$$

GLCM is generally used for texture analysis of images that utilize pixel values from [19], [20], and angle calculations in the image can be performed at angles of 0°, 45°, 90°, and 135°. This is a representation of an image that is basically in two dimensions so that the angles can be calculated. In addition, GLCM also has a distance parameter that defines how the value of the neighboring pixel pairs is set.

2.4. Modification of grey-level co-occurrence matrix

When the GLCM is applied to one-dimensional signals, it can use only one direction or angle, typically denoted by θ=0. Thus, it becomes $h(i_1, i_2|0)$. This notation provides an indication of how frequently two consecutive or nearby intensity values occur within a signal. Because the angle is only calculated at one angle, the use of GLCM in 1-dimensional signals is more prevalent. Figure 2 illustrates the conceptual difference between the 2D and 1D GLCM computations. Specifically, Figure 2(a) shows the calculation of the 2D GLCM at certain angles corresponding to 1. The first value (5,4) corresponds to the 0-degree angle, (7,2) corresponds to the 45-degree angle, (3,3) corresponds to the 90-degree angle and (4,2) to the 135-degree angle. In contrast, the 1D treatment considers only the 0-degree angle, as shown in Figure 2(b). There are several considerable distinctions regarding the dimensions of the processed data, the number of angles considered, and the number of conditions of the procedure. The 2D GLCM is meant for two-dimensional images such as paintings, in an attempt to calculate the GLCM matrix when the image is rotated at four different angles: 0°, 45°, 90°, and 135°. However, the 1D GLCM is for one-dimensional data, which is the signal; therefore, only one angle was considered. Both have the same intention of measuring the frequency of pairs consisting of intensity values placed a certain distance apart. However, the conditions of 1D GLCM are more straightforward and do not require as many conditions as 2D GLCM. Similar to images, once the GLCM is computed, the output undergoes a second procedure to extract the features of the GLCM using (2)-(6). This study used the Python programming language to help apply the GLCM to images.

The use of GLCM in direct one-dimensional signal processing, for example, during biometric data processing, including EEG signals, has led to significant developments in signal texture analysis. The GLCM obtains pairs of intensity values perpendicular to the angular position of the analyzed signal, which helps detect linear intensity change patterns. Such an approach increases the analysis speed by eliminating the need to convert 1D data to two-dimensional images. Modifying the GLCM transformation level is also novel for feature texture extraction, where subtle or complex variations are desired, thus facilitating accurate signal classification.

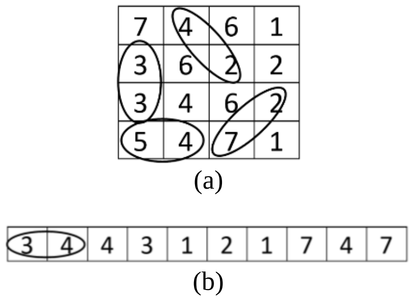


Figure 2. Illustration degree calculation for; (a) 2-dimensional and (b) 1-dimensional

The modified GLCM for one-dimensional data aims to overcome the limitations of the conventional GLCM designed for texture analysis in two-dimensional images. This approach adapts GLCM by considering the spatial relationship between data points in a 1D signal, for example, by constructing a co-occurrence matrix based on pairs of signal amplitude values within a certain time window. In addition, the variation in distance and orientation is adapted into the temporal domain to capture the dynamic patterns of EEG signals, allowing for more accurate detection of epilepsy patterns. By combining statistical features from 1D GLCM with machine learning or deep learning methods, this approach can improve the performance of epilepsy classification compared to conventional methods that only use frequency- or time-based features, making it more effective in capturing the complexity of EEG signals.

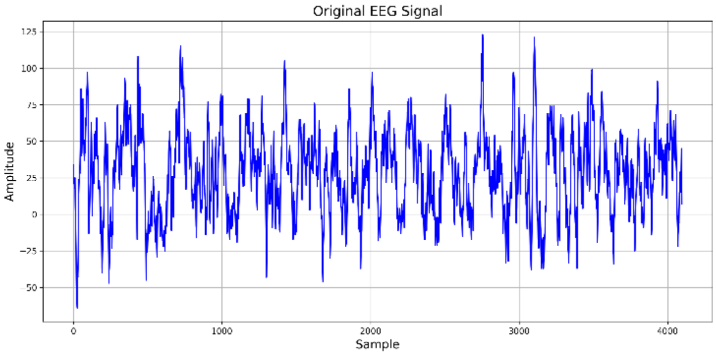
2.5. Support vector machine

Originally designed as a linear classifier, the support vector machine (SVM) has since been developed into a powerful solution for addressing nonlinear classification tasks. The SVM fundamentally seeks to discover the most suitable hyperplane that can effectively distinguish between two sets of data [21]. This hyperplane can be a straight line in the case of two-dimensional data or a linear surface in higher dimensions, separating the two groups of data [22]. The optimal hyperplane is determined by maximizing the margin, which is the distance between the hyperplane and the closest points of each class of data, referred to as the support vectors. To handle nonlinear classification problems, the SVM utilizes a method known as the kernel trick. This method allows the SVM to perform classification in feature spaces that have nonlinear shapes, such as circles or ellipses, without explicitly transforming the data into a higher-dimensional space.

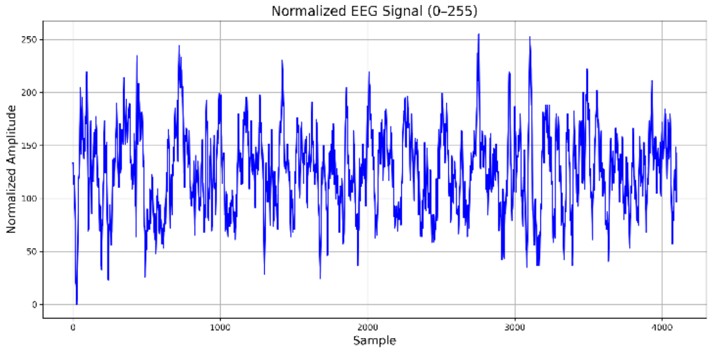
3. RESULTS AND DISCUSSION

Figure 3 shows the original and normalized EEG signals. Upon visual inspection, both graphs appear identical in terms of their graphical representation. However, the values of these two signals differed numerically. This difference may not be visually apparent but can affect further analysis of the EEG signal. The normalized EEG signal then proceeds to the GLCM computation. Figure 3(a) retains the same value as the original dataset, whereas Figure 3(b) is normalized using the min-max method. This normalization process transforms the value range of the EEG signal to a scale between 0 and 255. This step is crucial to ensure that the signal can be processed by the GLCM algorithm, which requires data in 2D format with limited intensity values.

Figure 4 (in Appendix) shows a box plot of the feature-extraction results at a distance of 10. As shown in Figure 4(a), Class Z exhibits the highest contrast values and significant variability, indicating considerable intensity differences in its texture. The homogeneity in Figure 4(b) shows that category F has greater variability, suggesting a less uniform texture than the other categories. Figure 4(c) shows that the correlation in categories Z and O has higher values with a broader distribution, indicating that pixel intensities in these categories are more correlated with each other. Category Z in Figure 4(d) also exhibits higher entropy values with a broader distribution, indicating a more random and complex texture. The energy values are shown in Figure 4(e), where all categories have very low values, but category Z has slightly lower values, suggesting that the texture might have more uniform intensities and lower energy. This explanation highlights the suitability of the SVM for classification in this study because it is effective in high-dimensional spaces and can be used for both linear and nonlinear classification.



(a)



(b)

Figure 3. Displays the sample data; (a) before normalization and (b) after normalization

The performance of the classification system at different distances shows both advantages and disadvantages, primarily influenced by the distance parameter's effect on classification outcomes. As shown in Table 2, the method achieves higher classification accuracy at shorter distances, particularly between d=1 and d=5, where texture features are more discriminative for EEG signal classes. For the five-class set Z/O/N/F/S, the highest accuracy reached was 68.2% at distances d=2–4. This is reasonable, given that the method performs best when local texture information is emphasized. However, as the distance increases, the classification accuracy declines, dropping to 44.2% at d=20. This decrease is attributed to the complexity of the five-class set, where increased distance leads to less distinguishable textures, reducing feature reliability.

Table 2. Classification accuracy

Distance	Accuracy		
	Z/O/N/F/S (%)	O/F/S (%)	Z/N/F (%)
d=1	63.2	90.3	87.0
d=2	68.2	92.0	86.7
d=3	68.2	91.0	88.3
d=4	68.2	90.0	89.7
d=5	67.8	90.0	90.0
d=10	54.6	72.7	77.3
d=15	50.4	76.3	70.0
d=20	44.2	66.7	68.0
d=1-20	78.8	94.0	94.3

In contrast, simpler class sets like O/F/S and Z/N/F maintained high classification accuracy across distances, exceeding 94%, although slight declines were noted at greater distances. These results suggest that the proposed method excels when classifying fewer categories with stronger, more consistent textures. The highest recorded accuracies were 94.0% for O/F/S and 94.3% for Z/N/F, based on averaged results over all distances. While GLCM provides more than just classification accuracy, offering insights into signal texture and subtle variations, it is also computationally efficient due to its operation on 1D signals. This enhances processing speed and emphasizes local texture patterns, which are essential for EEG signal analysis.

Nevertheless, the method's limitations become evident with increasing class complexity and distance. Therefore, improvements are needed—such as refining feature selection or adjusting the distance parameter—to enhance performance on complex datasets. Future work should aim to improve the method's robustness for broader class sets and greater distances, while maintaining high accuracy.

This research reveals varying performance results whereby distances are defined as scales, consistent with previous GLDM-related studies. In relation to studies that work with scale aspects, this study provided better results. As shown in Table 3, the relevance of the different feature extraction and classification methods resulted in different accuracies. The empirical mode decomposition (EMD) and extraction of desirable processes through entropy achieved 86.3% accuracy with classification using a SVM. On the other hand, another research embedded the EMD method supplemented with several entropy types, including Shannon entropy, spectral entropy and permutation entropy, and achieved 97.3% accuracy. This implies that the integration of multi-entropy types boosts classification efficiency.

Table 3. Comparison with previous research

Ref	Dataset	Method	Features extraction	Classifier	Result (%)
Wijayanto and Rizal [23]	Bonn University	EMD	Shannon entropy, spectral entropy, and permutation entropy	SVM	97.3
Wijayanto *et al.* [24]	Bonn University	-	Wavelet entropy	SVM	94.3
Rizal *et al.* [25]	Bonn University	Hjorth descriptor	-	SVM	99.5
Our work	Bonn University	GLCM modified	ASM, homogeneity, contrast, energy, and entropy	SVM	94.3

Classification using the wavelet packet decomposition (WPD) approach as well as extraction using Shannon and Renyi entropy, yielded an accuracy of 85.64%. This difference could be due to the differences in the data sets used. Interestingly, the Hjorth Descriptor approach applied to the Bonn University dataset yielded a very high accuracy of 99.5%. This shows that multi-scale descriptors are also highly effective in the classification of EEG signals in the case of epilepsy detection. This study, which modified the GLCM method with feature extraction, such as angular second moment (ASM), homogeneity, contrast, energy, and entropy, achieved an accuracy of 94.3%. These results demonstrate that this study competes well with previous studies using scale-based approaches and provides competitive outcomes for detecting epileptic seizures through EEG signal analysis.

Various techniques have been employed for EEG signal analysis, including EMD, wavelet entropy, WPD, and Hjorth descriptors. Wavelet entropy and WPD offer multi-resolution decomposition, making them effective in capturing irregular and transient frequency changes in EEG signals. Meanwhile, Hjorth descriptors focus on the temporal characteristics of signals, such as variations in amplitude, frequency, and signal complexity. Although each of these methods has distinct advantages, they tend to require high computational resources and may not effectively capture spatial relationships or texture patterns, especially when analyzing 1D EEG signals.

In contrast, the GLCM offers a simpler and more computationally efficient approach for analyzing spatial textures in 1D signals like EEG. GLCM captures the relative positioning of intensity value pairs, enabling the detection of linear intensity variations without converting 1D data into 2D structures. While GLCM may not fully capture frequency information, its speed and effectiveness in classifying EEG signals make it advantageous, particularly for applications that prioritize local texture patterns. Based on findings, the use of short distances (d=1 to d=5) in GLCM yields the highest classification accuracy, especially for simpler class sets like O/F/S and Z/N/F. However, accuracy tends to drop significantly with longer distances (d=10, d=15, and d=20), suggesting that texture features become less discriminative. Therefore, further optimization—such as refining distance parameters or combining GLCM with other feature extraction methods—is needed to enhance performance in more complex classification tasks involving longer spatial dependencies.

4. CONCLUSION

In this study, the GLCM was modified to analyze EEG signals. This technique involves measuring the frequency of the occurrence of pixel pairs with specific intensity values in an image at specified distances and angles. Five features were used to characterize each signal. The experimental results showed that using only one feature or a single distance did not yield a satisfactory accuracy. The best accuracy was attained by utilizing a combination of five features and incorporating distance ranges from 1 to 20, employing an SVM as the classifier. The distance parameters have a notable impact on the classification performance of the signals.

The use of GLCM in direct one-dimensional signal processing, for example, during biometric data processing, including EEG signals, has led to significant developments in signal texture analysis. The GLCM obtains pairs of intensity values perpendicular to the angular position of the analyzed signal, which helps detect linear intensity change patterns. Such an approach increases the analysis speed by eliminating the need to convert 1D data to two-dimensional images. Modifying the GLCM transformation level is also novel fot feature texture extraction, where subtle or complex variations are desired, thus facilitating accurate signal classification. The ability to apply GLCM directly to 1D signals, such as EEG, reduces the computational complexity and enhances the processing speed, offering a more efficient approach for real-time signal analysis. This study suggests using short distances (d=1 to d=5) to achieve maximum accuracy in EEG signal classification using GLCM. Although there is no conclusive method to ascertain the exact optimal distance leading to the highest accuracy, the suggested approach remains promising for future advancements. The classification performance can be significantly enhanced by exploring different signal manipulation techniques. Moreover, the direct application of GLCM to EEG signals presents the possibility of adapting this technique to other forms of time-series or sequential data analysis, thereby creating a wider range of applications in signal processing fields. However, this method still faces challenges in handling highly complex or noisy signal patterns, which may affect the accuracy at higher distances. Future work should aim to optimize the GLCM by refining the feature selection process and adapting the method to better handle noisy signals and larger, more complex datasets.

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AUTHOR CONTRIBUTIONS STATEMENT

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Donny Setiawan Beu	✓	✓	✓			✓		✓	✓	✓	✓			
Achmad Rizal	✓	✓		✓	✓		✓	✓		✓		✓	✓	✓
Said Ziani				✓		✓				✓	✓			
Triwiyanto				✓	✓					✓				

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

The dataset we collect from: https://www.upf.edu/web/ntsa/downloads/-/asset_publisher/xvT6E4pczrBw/content/2001-indications-of-nonlinear-deterministic-and-finite-dimensional-structures-in-time-series-of-brain-electrical-activity-dependence-on-recording-regi.

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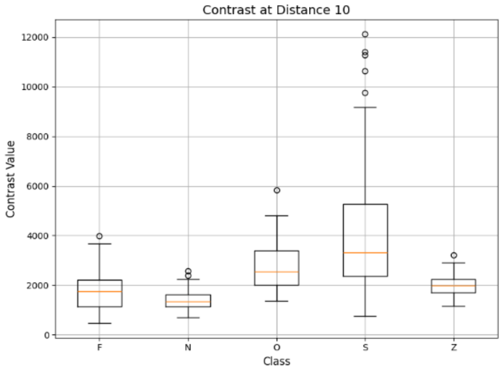
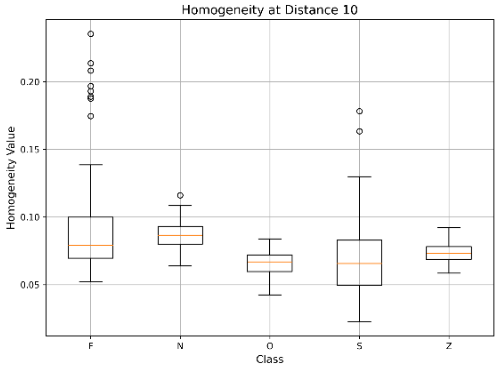
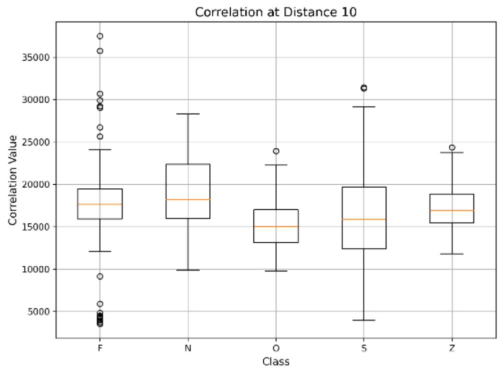
APPENDIX



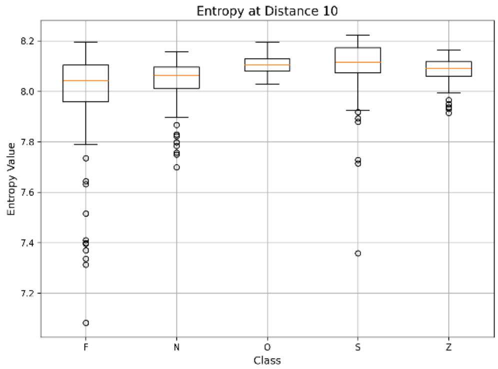
(a)



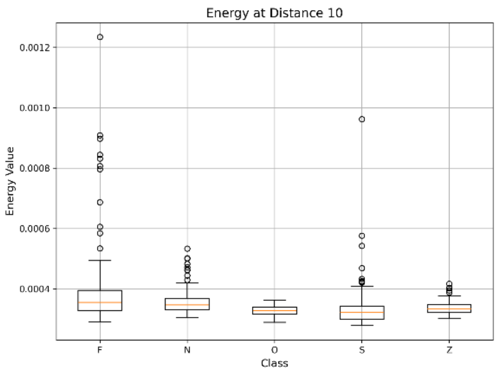
(b)



(c)



(d)



(e)

Figure 4. Features d=10; (a) contrast, (b) homogeneity, (c) correlation, (d) entropy, and (e) energy

BIOGRAPHIES OF AUTHORS

Donny Setiawan Beu received his bachelor's degree in Telecommunication Engineering from Telkom University in 2023. He is currently a master's student in the Department of Electrical Engineering at Telkom University. His research interests include research on signal processing focusing on biomedical signals. He can be contacted at email: donnysbeu@student.telkomuniversity.ac.id.

Achmad Rizal received Bachelor of Engineering in telecommunication engineering from STT Telkom (now, Telkom University), Bandung Indonesia in 2000. He received Master degree.in biomedical engineering from Institut Teknologi Bandung, Bandung, Indonesia in October 2006. Received Ph.D. degree from Universitas Gadjah Mada Yogyakarta, Indonesia. His research interests include biomedical signal processing, biomedical image processing, biomedical instrumentation, and telemedicine. Now he is a professor in the School of Electrical Engineering, Telkom University. He can be contacted at email: achmadrizal@telkomuniversity.ac.id.

Said Ziani is a professor at the Health Technologies Engineering Department at Mohammed V University (ENSAM), located in Rabat, Morocco. His research interests span a wide range of topics, including energy optimization, IoT for smart buildings, industrial applications, motor drives, renewable energy, FPGA and DSP applications, embedded systems, adaptive control, neural network control, automatic robot control, motion control, and artificial intelligence. He can be contacted at email: s.ziani@um5r.ac.ma.

Triwiyanto received his B.S. in Physics from Airlangga University, M.S. in Electronic Engineering from Institut Teknologi Sepuluh Nopember (2004), and Ph.D. in Electrical Engineering from Gadjah Mada University (2018), where he was awarded Best Doctoral Student. He has been an Associate Professor at the Medical Electronics Technology Department, Health Polytechnic Ministry of Health Surabaya since 2005. His research focuses on microcontrollers, biomedical signal processing, machine learning, rehabilitation engineering, and sEMG-based robot interactions. He also serves as Editor-in-Chief of several journals and chairs technical committees at international conferences. He can be contacted at email: triwi@poltekkesdepkes-sby.ac.id.