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Grey Level Differences Matrix for Alcoholic EEG Signal Classification

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***Abstract*— Electroencephalogram (EEG) signals can provide information on abnormalities in a person's brain and characterize brain activity. Brain injury or diseases can manifest as brain disorders. Trauma or the use of specific chemicals or medications, such as alcohol, can result in brain damage. Previous research has demonstrated variations in the patterns of EEG signals between alcohol-using and non-drinking people. Various techniques, including wavelet and entropy, have been developed to detect alcoholic EEG using event-related potential (ERP) testing. This work proposes a feature extraction technique based on texture analysis for the classification of alcohol EEG signals because ERP-measured EEG often involves many channels. An NxM image is thought to be equivalent to an EEG signal with N channels and a recording duration of M samples. The NxM matrix is formed by channelizing the N-channel EEG signal in this investigation. Normalization is then used to get a matrix value of 0-255 or an 8-bit image in the following step. Five features are measured in four directions, and the Grey Level Difference Matrix (GLDM) approach is utilized for feature extraction. Using five grey-level difference matrix (GLDM) features and linear discriminant analysis as a classifier, the maximum accuracy was achieved at 73.3%. Image processing can still be used to increase accuracy even though the final product is less accurate than the earlier technique. The suggested approach can still be adjusted to work with biomedical signals or image processing techniques like the Grey Level Co-occurrence Matrix (GLCM).**

***Keywords*— Electroencephalogram; alcoholic; grey-level difference matrix; classifier.**

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I. INTRODUCTION

An alcoholic, often referred to as alcoholism, tends to hurt individuals, both on the social aspects and on the mental and physical health of the individual. On the health aspect, alcoholism's body and brain condition are influenced by usage patterns. A hallmark symptom of alcoholism is impaired motor coordination, suggesting disruptions in brain functions responsible for movement control. Long-term usage of alcohol can alter brain function, cause several nerve connections to break, and even cause the brain to shrink. It can further lead to the forming of diseases such as dementia [1].

EEG signals are electric signals produced by brain activity. Activities that involve thought processes can be identified by the EEG signals. Some brain disorders can be identified by EEG signal patterns, e.g., in cases of epilepsy [2] or Alzheimer's [3]. Certain chemicals can be consumed over a prolonged period to affect a person's EEG signal. Moreover, in alcohol or psychotropic drug users, assessment of these abnormalities is often done through a measurement called the event-related potential (ERP) [4]. In the ERP, subjects are given a specific test, and the EEG generated is recorded for analysis.

Another research translated EEG signals into a different domain [5]. Discrete Wavelet Transform (DWT) is used by Gopan et al. [6]. The wavelet coefficient is the consequence of this process. The feature value is then obtained by recalculating the coefficient value. The feature extraction process used the Fast Fourier Transform (FFT) [7]. The spectral entropy value is calculated using a signal converted to the frequency domain. The feature extraction stage in [8] similarly used the signal transformation. The signal was decomposed into the approximation coefficient and detail coefficient using WPD. Another wavelet-based method of research was conducted by Ekaputri et al. [9]. Multilevel wavelet packet entropy was calculated in each channel to produce an accuracy of up to 77.8%. In the study, the researcher chose a support vector machine (SVM) as a classifier.

Palaniappan and Ravendran [10] conducted research employing the time domain feature. However, the accuracy obtained in those trials is less than 95%. Improved classification accuracy can be achieved by exploiting features that effectively capture the differentiation between EEG signals of alcoholics and non-alcoholics.

Several researchers proposed various methods for the classification of EEG signals for alcoholics and control using ERP results. Spectral entropy in the gamma subband was employed as a feature of the visual ERP of a multichannel EEG signal [11]. Meanwhile, in another study, the relative wavelet bi-spectrum feature was used, which produced an accuracy of up to 90% [5]. Several studies have explored wavelet decomposition features, including entropy, interquartile range, energy, and median absolute deviation of each sub-band, for classifying alcoholic and control EEG signals. [7]. The data set used was different from the two previous studies. A more straightforward method was proposed by Widadi et al., who used statistical features of the gamma subband obtained from the elliptic filter [12]. The highest accuracy achieved through this method reached 96%. All previous techniques used the signal processing method on many EEG signal channels. Multichannel signals can be seen as 2D or image signals. Using conversion, an image was produced to represent the multichannel signal.

In this study, the multichannel EEG signals were converted into images to classify alcoholic and non-alcoholic EEG signals. A 64-channel EEG signal with a length of 256 produced a 64x256 image. Feature extraction in this study used a texture analysis known as the GLDM [13]. It is expected that the difference between alcoholic and non-alcoholic EEG signals would be distinguishable when the features of the converted image texture are shown.

The following is how the paper is organized in this paper. Section 2 discusses the EEG signal data set, signal conversion process, calculation of GLDM features, and classification. Section 3 discusses the test results and discussion, while the final part of this paper concludes what has been presented in this paper.

II. Materials and Method

Figure 1 shows the design scheme to classify alcoholic EEG signals and non-alcoholic EEG signals.

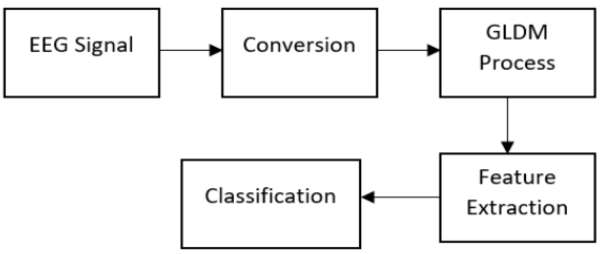
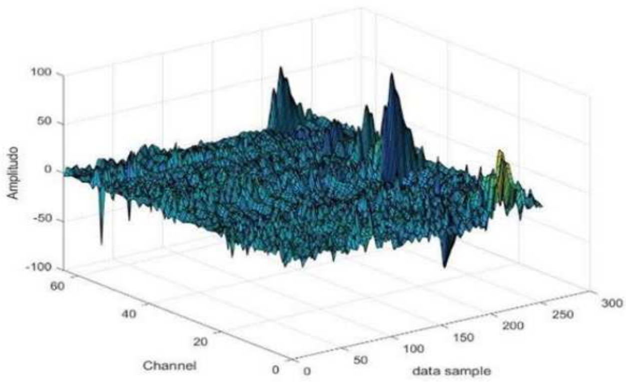


Fig. 1 Proposed Method

The EEG signals from 64 channels were arranged as shown in Figure 2 and Figure 3. Because the images were a 2-dimensional matrix, they would be converted to greyscale images. Then, the GLDM process was carried out as proposed [13], and the five GLDM features were calculated. The classification process was then performed to test whether the resulting features could distinguish the two classes of EEG data used. Details of each process are explained in the following subsection.



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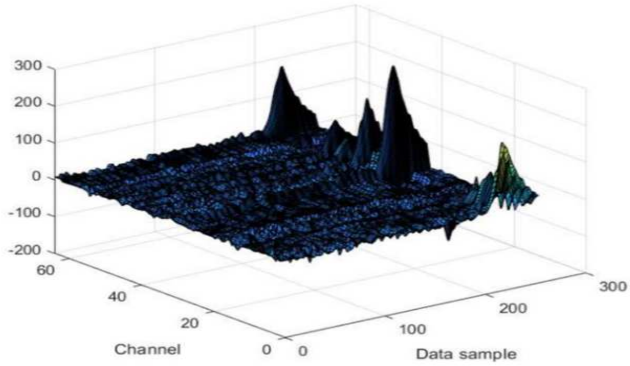

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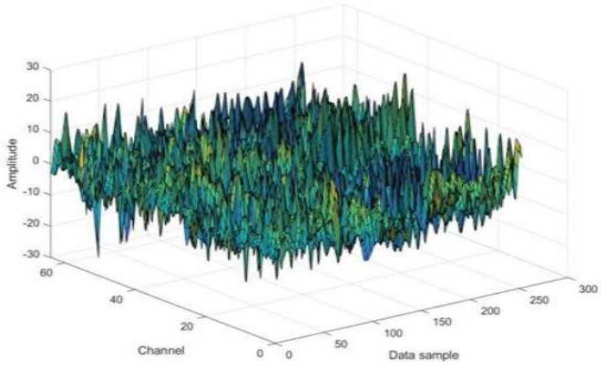
Fig. 2 Example of alcoholic EEG signal



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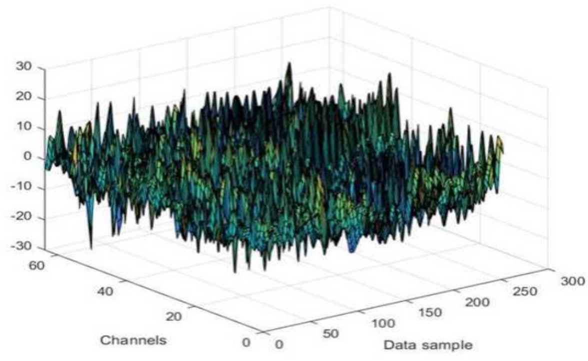

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Fig. 3 Example of non-alcoholic EEG signal

A. EEG Dataset

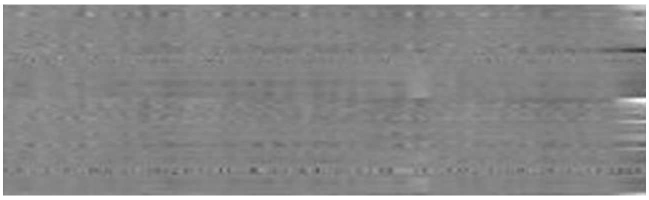
According to Zhang et al. [14], EEG signal data was obtained from the UCI Machine Learning Repository. One second of signal was recorded for 64 channels at a sample frequency of 256 Hz. EEG data were recorded when the participant was presented with either a single stimulus (S1) or two stimuli (S1 and S2). Both conditions are observed: S1 differs from S2, and S1 matches S2. Each of the 120 individuals receives 120 trials. Just 600 EEG signals for each alcoholic and standard EEG signal were collected for this study [9]—figures 2 and 3 display examples of EEG signals from brains belonging to alcoholics and non-alcoholics.

B. Signal Conversion

The EEG signal from the 64 channels plotted would produce a matrix with dimensions of 64 × 256. Therefore, the matrix could be treated as an image. Then, it would be converted using a scaling process. If *X (m, n)* is an EEG signal with m channels and n samples, the converted image will be expressed as shown in Equation (1).

$$y(m,n) = floor\frac{x(m,n)-\min(x)}{\max(x)-\min(x)} \times 256 \qquad (1)$$

From the process above, we would get an image with a size of m x n with a range of values from 0-255, which was equivalent to a grey-scale image with a depth of 8 bits [15]. Converted images are shown in Figure 4 and Figure 5.



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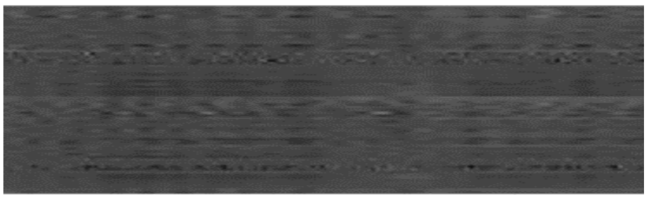

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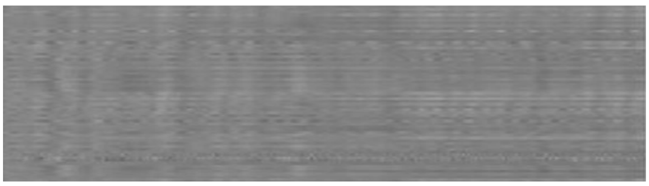
Fig. 4 Converted image from signal in Fig. 2



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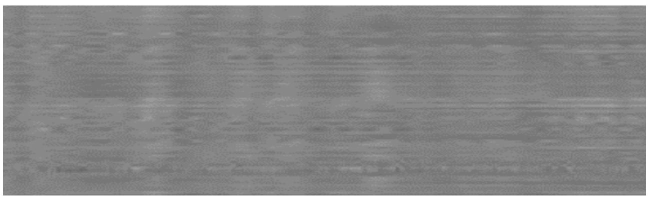


(b)

Fig. 5 Converted image from signal in Fig. 3

C. Grey Level Different Matrix (GLDM)

Wezka et al. [13] described GLDM as differences between adjacent pixels. Weszka et al. observed the intensity change in an image by measuring the absolute value differing of two neighboring pixels in all the vertical, horizontal, and diagonal axes [16]. The number of neighboring pixels with an absolute difference value of g in the direction of θ is represented by H(θ). The likelihood of neighboring pixels in the direction θ to the difference g's absolute value. Equations (2) to (6), which represent gradient contrast, gradient second moment, gradient entropy, gradient mean, and inverse-differences moment, respectively, can be used to compute the image's features based on GLDM [17]:

$$Gradient\ contrast\ (GC) = \sum_g g^2 h(g|\theta) \qquad (2)$$

$$Gradient\ second\ moment\ (GSM) = \sum_g [h(g|\theta)]^2 \qquad (3)$$

$$Gradien\ entropy\ (GE) = -\sum_g h(g|\theta)\log\big(h(g|\theta)\big) \qquad (4)$$

$$Gradient\ mean\ (GM) = \sum_g h(g|\theta) g \qquad (5)$$

$$inverse - diffrence\ moment\ (IDM) = \sum_g \frac{h(g|\theta)}{(g^2+1)} \qquad (6)$$

In this study, the directions of 0°, 45°, 90°, and 135° of the five different features were calculated. In addition, we calculated an average of the four directions' features. The total features produced were 25.

D. Classification

In this study, four classifiers were used to test the accuracy of the features produced. The classifiers used were SVM, logistic regression, K-NN, and linear discriminant. SVM is a classification method oriented to training data. SVM forms a hyperplane to separate two data classes called support vectors [18]. The hyperplane formed depends on the kernel used, such as linear, cubic, quadratic, etc. In statistics, logistic regression is a technique that matches data to the logistic function of the log curve to estimate the likelihood of an event occurring [19]. Logistic regression was considered appropriate for this case because the data consisted of two classes, namely alcoholic and control.

KNN is a classification method that uses distance measurement to see data similarity. The distance will be measured by the training data and calculated by the number of K training data closest to the test data. The most data classes in K data are considered data classes from test data [20]. Fisher's Linear Discriminant, commonly known as Linear Discriminant Analysis (LDA), is another classification technique that uses each unique item [21]. The LDA approach finds linear projection to maximize the between-class covariance matrix while reducing the within-class covariance matrix. With this method, members in the class are distributed more sparsely, which may ultimately increase the classification's success.

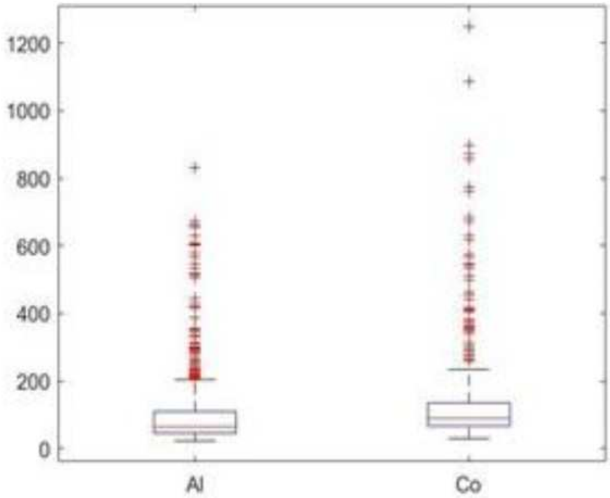
The performance measured in the test is the accuracy stated by Equation (7).

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \qquad (7)$$

where TP and TN are EEG signals appropriately classified according to their class, while FP and FN are misclassified EEG signals.

III. Results and Discussion

Figure 6 displays the features produced by GLDM in the 90° direction. Gradient contrast, as in Figure 6, had the broadest range of order in the hundreds, while the ASM Gradient had the smallest range of values. This difference in value ranges will affect the classification process using total distance measurements such as KNN. Features with small value will be covered by features with a significant mathematical and statistical operations calculation to separate each class of data by statistical properties for enough value.



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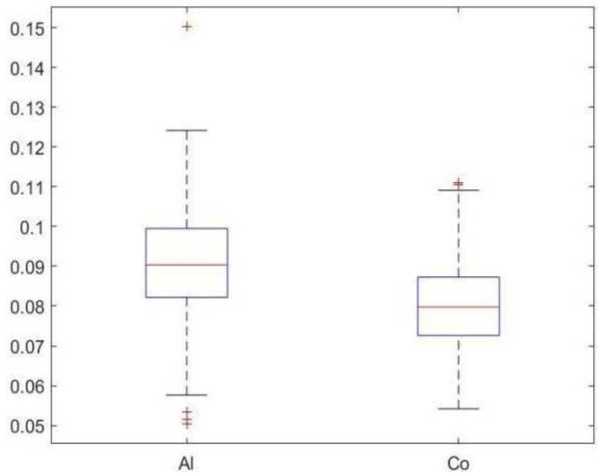

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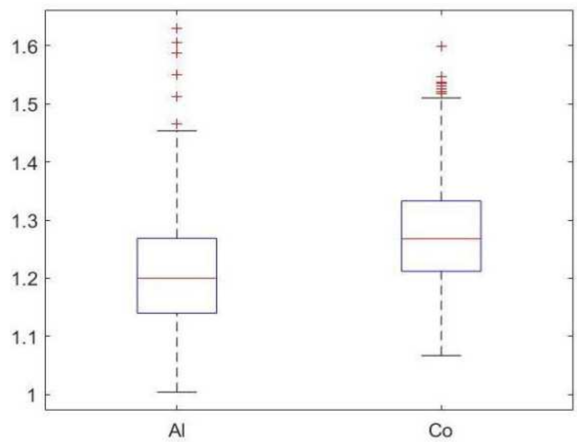

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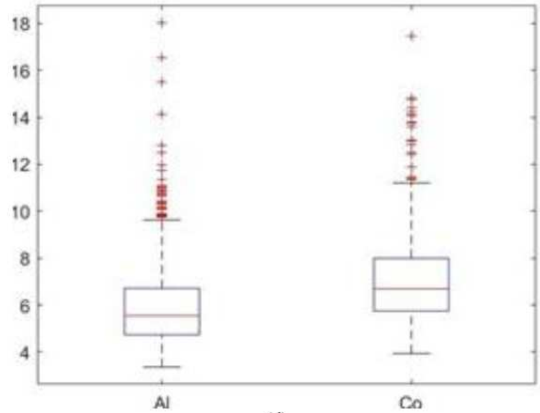
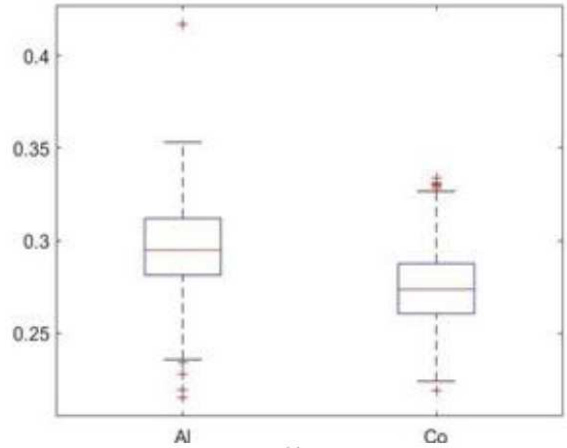


(d)



(e)

Fig. 6 Features in 90° direction (a) Gradient contrast (b) Angular second moment (c) Gradient entropy (d) Gradient mean (e) Gradient IDM.

Figure 6 shows that the values of the feature tend to overlap and are not explicitly separated. Presumably, the image generated from the conversion process tends to have a relatively small contrast. The image enhancement process was not carried out, so the pixel value tends to gather in the middle and not scattered. It cannot be distinguished between the form of the image resulting from an alcoholic EEG signal and EEG control. With such conditions, the possibility of classification results will not be high enough.

TABLE I
VALIDATION RESULT OF THE PROPOSED METHOD

Classifier	Direction			
	0°	45°	90°	135°
Gaussian SVM	67.1	70.3	71.8	70.9
Logistic Regression	67.3	71.5	73.3	71.3
KNN	66.3	69.3	72.5	70.5
Linear Discriminant	66.2	71.6	73.3	71.2

These are the highest results for various SVM and KNN kernels, which did not produce the highest accuracy. The highest accuracy of 73.3% was generated by logistic regression, and LDA used GLDM with 90° directions and five features. This result was better than using the average value of the five features. The 90° direction produced high accuracy due to several things. The image of the EEG signal had a size of 64x256. The 90° direction showed the direction of GLDM orientation upward, which was the channel difference. For 0°, the direction followed the order on one channel, so sometimes the signal change would not be big enough. This study used d

= 1, so the signal change was too insignificant, making GLDM results slightly small.

The accuracy results in this study were still lower than in previous studies using gamma waves [12]. However, the proposed method still leaves much potential for development. Image conversion results in this study have not been through improved image quality, such as increased contrast. Another thing that can be done is calculating GLDM at various distances, as in [22]. The modified GLDM was measured at multiple distances before calculating the feature in the form of the Hjorth descriptor. In this study, the selection of relevant characteristics can still be made using various existing methods. The combined exploration of multiple methods to improve the performance of the proposed system became an exciting topic in the future.

IV. Conclusion

This research describes the performance of the Alcoholic EEG system for categorization by converting a 64-channel EEG signal into a grayscale image. GLDM was used to extract features at a distance of d = 1. In this work, picture analysis was carried out directly, without the need for earlier image processing. The result was a low-contrast image after conversion. Converting multiple channels of signals to an image has advantages, such as image processing methods that can provide many alternative feature extraction and other signal processing techniques. Thus, there will be many alternative ways to improve accuracy besides using machine learning for classifiers. Exploration that can be done in future studies includes channel selection, image enhancement methods, or other feature extraction methods.

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