Alcoholic EEG Classification Multichannel FFT Image

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Abstract. Long-term alcohol use can affect brain function. This is what prompted researchers to analyze the electroencephalogram (EEG) signal to recognize EEG signals in alcoholic or non-alcoholic persons. In this study, a method of classifying Alcoholic and non-alcoholic EEG signals using an image recognition approach is proposed. The EEG signal consisting of 64 channels is processed through a Fourier transformation process and arranged into an image-like plot with a 64 $\times$ N/2 size from the N-point FFT used. Furthermore, this plot is classified using a Convolutional Neural Network (CNN) to determine whether the EEG signal belongs to an alcoholic or non-alcoholic person. The test results showed the highest accuracy of 98.7% at 512-point FFT. This result is higher than the classification process using EEG signals in the time domain. The proposed method has great potential for EEG signal processing because of its simple computation.

Keywords: EEG · Alcoholic · Fast Fourier Transform · Convolutional Neural Networks · image classification

1 Introduction

EEG EEG signals, which are bioelectric signals generated by brain activity, play a crucial role in identifying various brain disorders, including epilepsy, anxiety, schizophrenia, and sleep disorders [1, 2]. Long-term alcohol consumption also impacts EEG signals [3, 4], leading to the development of methods for detecting alcoholism. Traditional approaches involve extracting signal components like the Gamma signal [5] or calculating entropy and statistical features [6, 7].

The resemblance of EEG signals to images, due to their multi-channel nature, has enabled the application of image processing techniques [8]. These techniques analyze the texture of multichannel EEG plots using methods such as the gray level co-occurrence matrix (GLCM) [9] and the gray level difference matrix (GLDM) [10]. Such methods focus on texture analysis to improve the detection of alcoholism from EEG data.

With the rise of artificial intelligence, deep learning has become a prominent choice for EEG alcoholic classification [11], offering the advantage of automatic feature extraction. Research by Farsi et al. demonstrated that combining raw EEG signals with long

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X(ω) represents the signal in the frequency domain, ω denotes the frequency in radians, and x(t) is the signal in the time domain. Equation 1 provides the FT for analog signals. For digital signals, the Discrete Fourier Transform (DFT) is utilized, as shown in Eq. 2.

$$X(k) = \sum_{n=0}^{N-1} x(n) W_N^{kn}, \text{ with } W_N = e^{-j\frac{2p}{N}} \tag{2}$$

$X(k)$ is the frequency domain, $x(n)$ is the time-domain signal. The FFT efficiently.

computes the TFD using symmetry properties of W_N. FFT is calculated at N-specific points where N is 2^m [15].

In our study, we explored N values from 64 to 512 for NFFT, impacting frequency resolution. We restricted N to a maximum of 512 to prevent generating an FFT plot larger than the original EEG signal data in the time domain, staying within the study's scope.

2.3 Convolutional Neural Network (CNN)

CNN is frequently used with picture data and has a high network depth. CNN is thus categorized as a Deep Neural Network type based on image data. CNN functions by simulating how the visual cortex of the human brain identifies items. A simple architecture of CNN is displayed in Fig. 2.

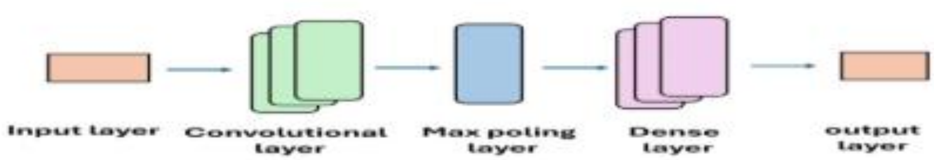

Fig. 2. CNN Architecture

The input layer of a neural network stores pixel values from the image. During feature extraction, convolution and pooling layers generate a feature map, which is then flattened into a vector before being processed by the fully connected layer. This layer connects all neurons to those in the next layer to produce the final classification. The output layer uses information from earlier layers to make class predictions, employing neurons to represent different classes and an activation function for categorization [16].

3 Results and Discussion

Figures 3(a) and (b) show data conversion from one dimension to two dimensions via a direct plot of 64 channels. Figures (c) and (d) depict the FFT results for the same 64 channels. Figure 4 presents the FFT plot of 64-channel EEG as an image. The FFT significantly changes the data by decomposing complex signals into their frequency components.

Table 1 illustrates that increasing the number of points in the FFT (N-FFT) improves model accuracy. The accuracy starts at 92.5% with N-FFT = 64 and rises to 96.6%

The proposed method achieves better accuracy compared to similar methods using 64 EEG signal channels in the time domain as presented in Table 2. Aprilia et al. used the Grey Level Difference Matrix (GLDM) for feature extraction, achieving a maximum accuracy of 73.3% [10], while another study utilizing Grey Level Cooccurrence Matrix (GLCM) and Random Forest reported an accuracy of 70% [9]. Both studies applied GLCM and GLDM at a sample distance of 2, with further efforts to increase accuracy through variations in distance and calculation angle, reaching 93.6% for GLDM and 86.8% for GLCM [13]. However, these results still fall short of the 98.7% accuracy achieved by the proposed method, which benefits from the inclusion of frequency domain information and the CNN classifier. The method shows strong potential for analyzing EEG signals across multiple channels and could be applied to different EEG cases in future research. A detailed frequency analysis of each signal channel will be a key focus of further investigation.

Table 2. Comparison with previous research

Ref	Dataset	Method	Feature	Classifier	Accuracy
[10]	UCI Machine Learning	Plot EEG Signal 64 Channel	GLDM	linear discriminant	73.3%
[9]	UCI Machine Learning	Plot EEG Signal 64 Channel	GLCM	RF	70%
[13]	UCI Machine Learning	Plot EEG Signal 64 Channel	GLCM & GLDM	ANN	93.6%
Proposed Method	UCI Machine Learning	Plot EEG Signal 64 Channel in frequency domain	–	CNN	98.7%

4 Conclusion

This study proposes a method for classifying alcoholism using EEG signals by generating FFT plots from each of the 64 channels. The FFT plot results in a $64 \times N/2$ matrix, resembling an image, which is then classified using CNN. The highest accuracy of 98.7% was achieved with 512-point FFT. This method effectively reduces variations due to data shifting by focusing on the frequency components of each EEG channel, making it suitable for analyzing EEG signals with multiple channels. Testing with higher N-FFT values was avoided to prevent exceeding the matrix size of the original signal.

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