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CLASSIFICATION OF EEG SPECTROGRAM IMAGES WITH DEEP LEARNING MODELS FOR ALCOHOLISM DETECTION

ÖZNUR YILDIRIM[1], YAHYA CIHAT SÖKER[2] MEHMET ZAHID YILDIRIM[2*] AND EMRAH ÖZKAYNAK[2]

[1] *TOBB Technical Sciences Vocational School, Karabük University, 78050, Karabük, Türkiye*
[2] *Computer Engineering Department, Karabük University, 78050, Karabük, Türkiye*

ABSTRACT. **Electroencephalogram (EEG) signals are time series that play an essential role in understanding the electrical behavior of the brain. The complex structure of the brain makes the interpretation of EEG signals difficult. In this study, the classification of EEG signals based on image processing with deep learning is performed differently from traditional methods. Images of EEG signals obtained for the detection of alcoholism were used to classify healthy and alcohol-addicted individuals using a Convolutional Neural Network (CNN). Three models have been implemented in the experiments conducted on the EEG images: Resnet50, Xception, and custom CNN. The findings demonstrate that Xception achieves the best accuracy with 100% classification success.**

1. INTRODUCTION

Electroencephalography (EEG) is a method that records electrical brain activity [1]. This method provides feedback related to brain activity by detecting time-dependent frequency information [2,3]. According to the data provided, pre-diagnostic systems have been developed for several nervous system diseases such as epilepsy [4], Alzheimer's [5], emotion analysis [6] and alcohol addiction [7]. Due to the complexity and multidimensional structure of EEG signals, plenty of methods have been proposed to analyze the signals. Fourier and Wavelet Transformations are classical methods that aim to reveal the spectral features of EEG signals with their frequency-based approaches. These methods have been frequently applied to track the frequency components of EEG signals over time and to detect specific events in the signals [8, 9]. In addition, feature extraction techniques such as Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), and Independent Component Analysis (ICA) have been used to reduce noise in the signal and analyze the significant components [10] . However, these methods are inadequate, especially in the detection of nonlinear features. In recent years, the preliminary diagnosis and classification of nervous system diseases has become much faster and easier, especially with

E-mail address: oznuryildirim@karabuk.edu.tr, yahyacihat@protonmail.ch, m.zahidyildirim@karabuk.edu.tr(*), eozkaynak@karabuk.edu.tr.
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machine learning-based algorithms applied to large and complex data. In particular, deep learning-based methods are more successful than traditional methods for complex and difficult-to-analyze data, such as EEG signals [11]. Deep learning methods applied to EEG signals can be divided into two different concepts. The first is based on recurrent neural networks (RNN). RNN-based methods such as Long Short-Term Memory (LSTM) can be used to model temporal dependencies in EEG signals [12, 13]. Second, CNN-based methods can be used to process EEG signals in image format [14]. CNN models are deep learning models that can work specifically on images. These models are algorithms that can extract features from images and classify them at the same time.

In this study, alcoholism detection is performed using images obtained from EEG signals. The time-dependent frequency features of EEG signals are converted into spectrogram images, and CNN-based classification is performed. Popular CNN-based algorithms, Resnet50 and Xception models, and a custom CNN model were applied to the spectrogram images. Among these methods, the Xception model achieved 100% classification success in detecting alcoholism on spectrogram images in the experimental studies and gave more successful results compared to other methods. This success in classifying spectrogram images of EEG signals with the CNN model seems promising for classifying complex and multidimensional signals with more straightforward methods.

2. METHODS

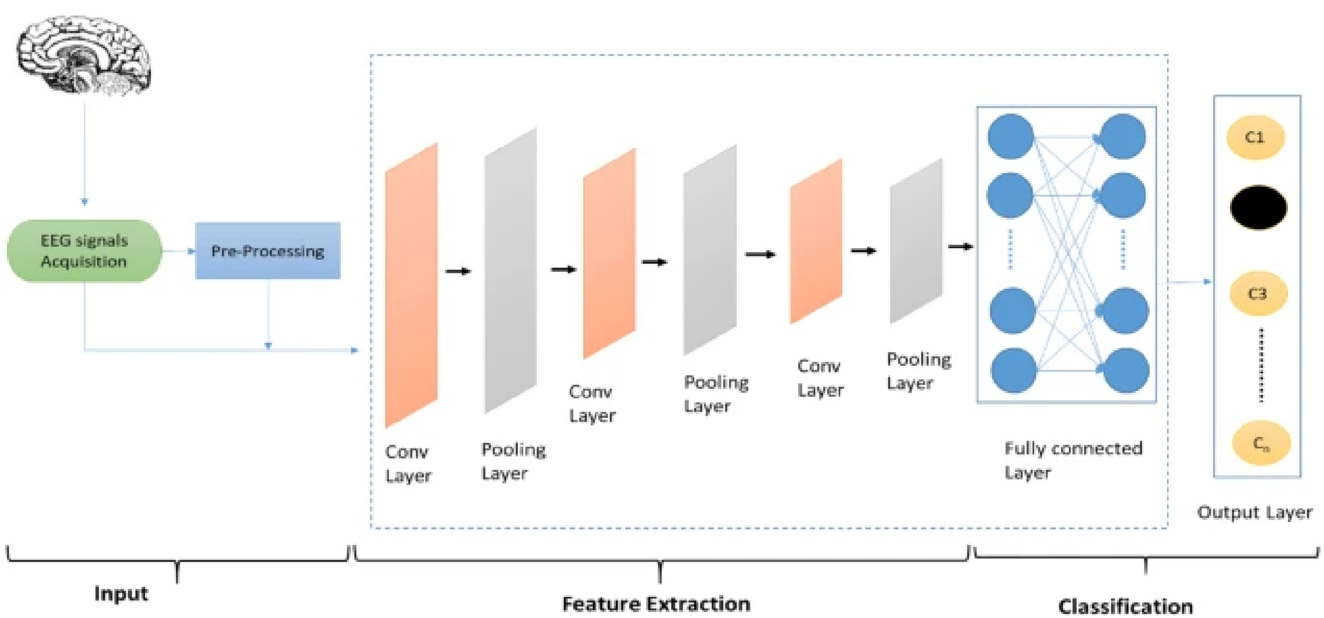

FIGURE 1. **A typical CNN architecture used for EEG analysis [15] .**

CNN is a deep-learning algorithm commonly used in image processing. It is able to detect and classify features in images through the operations performed in its different layers. The input data passes through convolutional, pooling, and fully connected layers, respectively. Figure 1 shows a general CNN architecture used in EEG signal processing.

The convolutional layer is where various filters are used to extract meaningful features from images. This layer passes filters over the entire image to extract feature maps. In the pooling layer, dimension reduction is performed to reduce the computational cost. The fully connected layer passes the extracted features to a classifier.

The CNN algorithm, with its layered structure, extracts important features from the data without the need for manual feature selection. It also provides more effective learning by preserving spatial and temporal features in the data [16] . Many special models of the CNN algorithm have been developed in accordance with the structure of the data used. ResNet50 and Xception are some of the most popular ones [17].

ResNet50 and Xception are two deep-learning models usually used for image recognition. The ResNet50 model consists of 50 layers. Each layer provides a transferred copy of its output to the following layer via unique connections known as "residual connections." The structure of the ResNet50 model enables the establishment of deeper networks, which means the learning of the network is faster and more efficient. Xception is a modified version of the Inception model. This model requires less computation and parameter selection with an unusual technique called "depthwise separable convolution," which enables this method to operate faster alongside high performance. Both methods are very efficient and widely desired, especially in image classification problems [17]. Additionally, a custom CNN model is implemented in this paper. This model consists of three convolutional layers: a pooling layer, a flattening layer, and a fully connected output layer. The first three layers of the model are 3x3 convolutional layers with 64, 128, and 256 filters. The ReLU activation function is used at the output of each convolutional layer in Equation 1.

$$f(x) = \max(0, x) \tag{1}$$

After the third convolution layer, a max pooling layer is added. This layer reduces the size of the feature maps by selecting the highest values of the image at a given filter size. The max pooling process is expressed as follows, as given in Equation 2.

$$P(i, j) = \max(S(x, y)) \tag{2}$$

After the pooling layer, the flattened layer transforms the multidimensional feature maps into a one-dimensional vector. It then prepares this vector to be transferred to the fully connected layer. The final layer of the model is a fully connected layer consisting of two neurons. It converts the output of the model into a value between 0 and 1 using the sigmoid activation function given in Equation 3.

$$\sigma(z) = \frac{1}{1 + e^{-z}} \tag{3}$$

The binary cross-entropy function is used to optimize the model and calculate the losses. The Adam optimization algorithm is also used to update the parameters of the model.

2.1. **Evaluation Metrics.**

The complexity matrix is used to evaluate the model performance in detail. The complexity matrix provides four main components by comparing the true and predicted classes. Precision indicates how many of the positively classified examples are actually positive, as seen in Equation 4. Recall indicates how many of the positively classified examples are correctly classified as positive, as seen in Equation 5. F1-Score is a metric that expresses the balance between Precision and Recall, as seen in Equation 6, and is calculated with the harmonic mean. Accuracy is the rate of correct classification of all examples, as seen in Equation 7 [18].

$$Precision = \frac{TP}{TP+FP} \tag{4}$$

$$Recall = \frac{TP}{TP+FN} \tag{5}$$

$$F1-Score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{6}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{7}$$

2.2. **K-Fold Cross Validation.**

In order to evaluate the performance of the models used in the study more consistently and to minimize the bias in the dataset, a 4-step (4-fold) K-fold cross validation method was applied. This method consists of the following steps as shown in Figure 2.

- The dataset is divided into 4 equal subgroups (folds).
- In each iteration, one of these subgroups is used as the test dataset and the rest as the training dataset.
- The model is trained in each iteration and evaluated on the test dataset.
- The evaluation metrics of all iterations are calculated and the average is taken and the overall performance of the model is evaluated.

This method is an effective strategy to obtain an overall view of model performance and reduce the risk of overfitting.

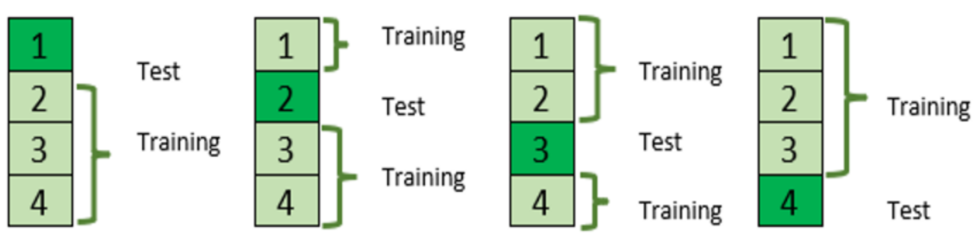

FIGURE 2. **K-Fold Cross Validation for k=4.**

3. EXPERIMENTAL STUDY

In this study, a dataset of EEG spectrogram images created for alcoholism detection was used [19] . The dataset consists of 7200 one-second images from 12 different brain channels. 5400 images were used for training, 900 of the remaining 1800 images were used for testing, and 900 were used for validation. There are equal numbers of alcohol-dependent and normal subjects in the training and test data. Figure 3 shows examples of normal subjects and dependent on alcohol.

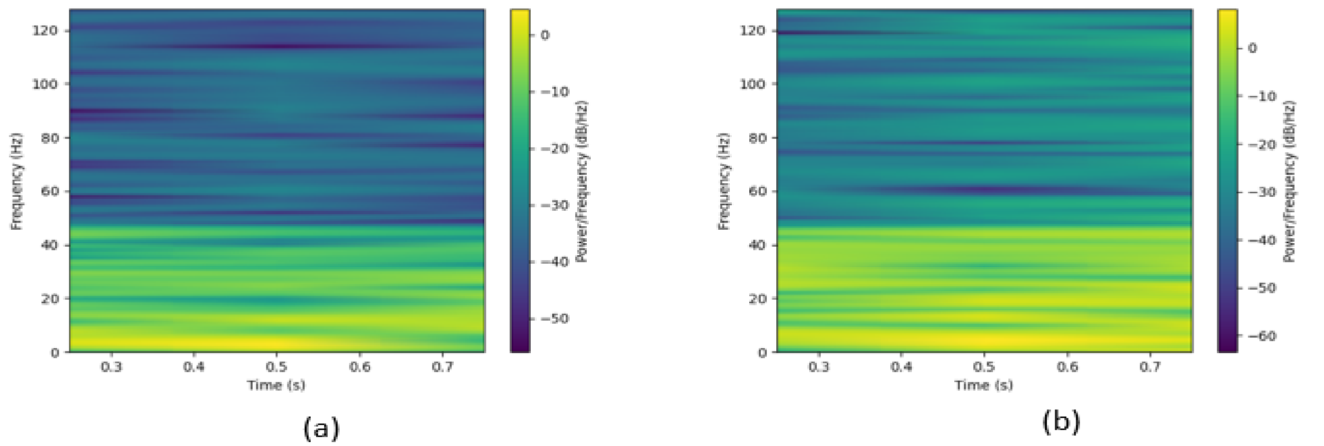

FIGURE 3. **Spectrogram image of EEG signal. (a) alcoholism (b) normal.**

The success of deep learning in image classification has influenced the preference for deep learning methods in artificial intelligence technologies in recent years. Unlike traditional machine learning methods, the ability of deep learning methods to extract features directly from images through deep neural networks has been effective in the preference of deep learning methods in our study. ResNet50, Xception, and custom CNN models, which are among the most preferred deep learning models in image classification, were used.

The hyper parameters given in Table 1 were selected in the training process of the deep learning models used in the study.

TABLE 1. **Hyperparameters used in training the models.**

Parameter	Parameter Selection
Initial Learning Rate	1
Rho(ρ)	0.95
Epochs	120
Cluster Size	5400

Learning rate shows how fast the network parameters are updated. In case of using adaptive optimization algorithms, this value is learned automatically during learning and is constantly changing. The constant ρ value is a measure used in updating the parameters in the backpropagation phase of the network. Epoch number is the number of iterations. Cluster size shows the number of training data processed in a single step in an epoch during the training phase.

TABLE 2. **Classification results of EEG spectrogram images**

Algorithm	Precision	Recall	F1-score	Accuracy
Resnet50	100%	86%	92%	97%
Xception	100%	100%	100%	100%
Custom CNN	99%	99%	99%	99%

In the results of the experimental study in Table 2, the classification of spectrogram images of EEG signals with deep learning models had a high success rate. Among the applied models, it is seen that the Xception model gives the most successful results in the detection of alcoholic individuals. The successful performance of the Xception model is also seen in the Complexity matrix given in Figure 4, where it has high sensitivity and accuracy in addiction detection, and there are no false positive or false negative classification rates. The deep discrimination capacity of the Xception model and the harmonious optimization of its parameters have been an important factor in the high performance of this model in classification accuracy.

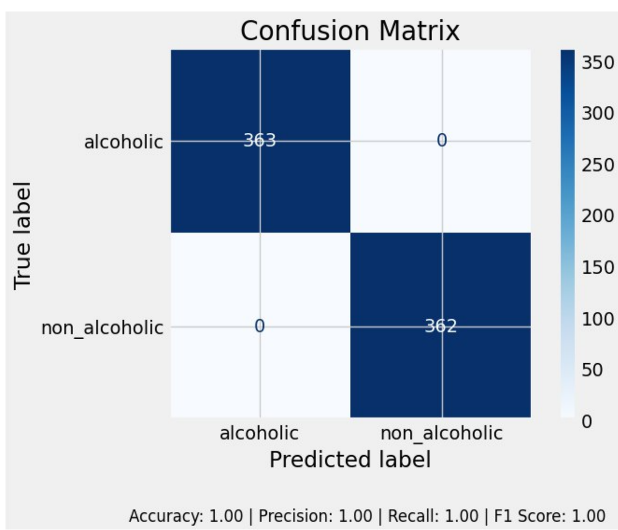

FIGURE 4. **Complexity matrix of the Xception model according to classification results.**

The box plot in Figure 5 shows the consistency of the results obtained with the 4-step K-fold method of the Xception model. The graph shows that the model offers a high and constant success rate in each fold, thus the generalization ability of the model is quite strong. No anomalies or large variances are observed in the graph, indicating the stable performance of the model.

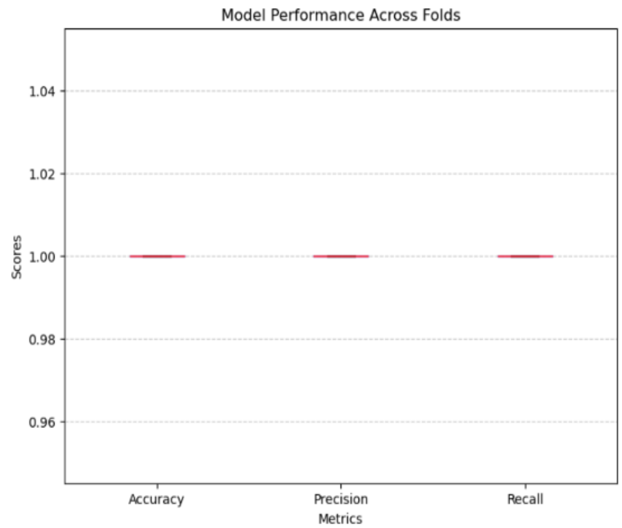

FIGURE 5. **Box plot of the results of the Xception model.**

Table 2 shows that the second most successful model for alcoholism classification is custom CNN. The Custom CNN model, which is close to the Xception model with 99% success in all metrics, correctly classified alcoholic individuals at a very high rate. As can be seen in the complexity matrix given in Figure 6, a performance loss of 1% is due to the fact that it could not classify very few test data correctly due to not learning some spectral variations sufficiently. This shows that the custom CNN model works quite effectively for alcoholism detection, but the Xception model outperforms it by a small margin due to the depth of optimization and parameter adjustments.

The ResNet50 model, another deep learning model used in the study, is seen to be lagging behind among the compared models, although it yields successful results as seen in Table 2. Although the ResNet50 model reached 97% in the accuracy rate, it only achieved 86% in the sensitivity metric. This result shows that the ResNet50 model has difficulty in correctly identifying some dependent individuals in the classification process and causes missing detections. The success rate of 92% for the F1-Score metric can be attributed to the relatively low sensitivity. The complexity matrix in Figure 7 shows that this decrease in the success of the ResNet50 method is due to the classification of non-alcoholic individuals as alcoholics.

The experimental results show that the Xception model shows the most successful performance among the deep learning models ResNet50, Xception and custom CNN models applied for classification. The experimental results also show that the Xception model has the best accuracy and reliability in classifying

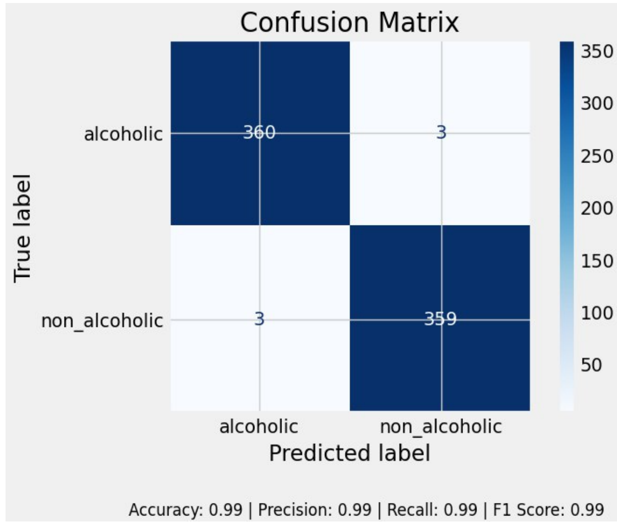

FIGURE 6. **Complexity matrix of the Custom CNN model according to classification results.**

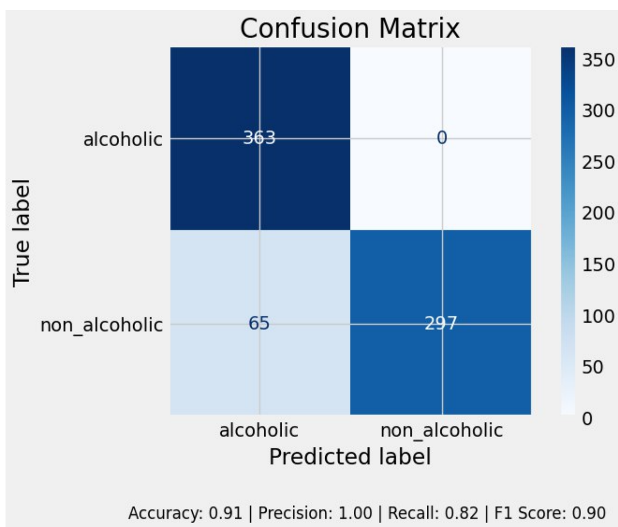

FIGURE 7. **Complexity matrix of ResNet50 model according to classification results.**

spectrogram images obtained from EEG signals for alcoholism analysis. The parameter optimization of the Xception model, its in-depth layered structure and its ability to effectively learn the intrinsic properties of the data have provided superiority over other models in classification success.

4. CONCLUSION

This study aims to classify EEG signals for alcoholism detection by converting their time-dependent frequency features into spectrogram images. It is shown that alcoholism can be successfully classified with deep learning models. The applied ResNet50, Xception, and custom CNN models achieve 91%, 100%, and 99% classification success, respectively. The Xception model shows superior performance in classification by achieving 100% sensitivity and 100% F1-score as well as classification accuracy. The Custom CNN model is close to the Xception model, achieving 99% sensitivity and 99% F1-score. The ResNet50 model, on the other hand, achieved 97% accuracy, but underperformed with 86% in sensitivity and 92% in F1-score. These results indicate that the parametric fit and the deep structure of the Xception model improve the classification performance. The results prove that analyzing spectrogram images of EEG signals with deep learning algorithms is a powerful tool for the detection of nervous system diseases. In future studies, since the conversion of EEG signals into spectrograms can reveal more details in the image format, this approach may be potentially useful in the diagnosis of other neurological disorders and other areas requiring signal analysis.

DECLARATIONS

- **Contribution Rate Statement:** All authors have contributed equally.
- **Conflict of Interest:** The authors report no declarations of interest.
- **Data Availability:** Dataset is available online.
- **Statement of Support and Acknowledgment:** None.

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