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A Hybrid Study for Epileptic Seizure Detection Based on Deep Learning using EEG Data

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Abstract: Epilepsy, a neurological disease characterized by recurrent seizures, can be diagnosed using Electroencephalogram (EEG) signals. Traditional diagnostic methods often face limitations, leading to delays and potential misdiagnoses. In response, researchers have been developing low-cost assistive systems to enhance diagnostic accuracy and reduce life-threatening risks for epilepsy patients. In this study, a hybrid approach is proposed to diagnose epilepsy disease. To validate the success of the proposed algorithm, Hauz Khas and Bonn data sets were used. AlexNet, GoogleNet, VGG19, ResNet50, and ResNet101 classifiers were employed in this study along with the Continuous Wavelet Transform (CWT) and Short Time Fourier Transform (STFT). To increase the generalization capability, 10-fold cross-validation method was used in the classification process. Firstly, the preictal and ictal moments in the Hauz Khas dataset was classified with 99.5% success rate by CWT method and Resnet101. Similarly, 99.8% accuracy was achieved in the binary classification of the Bonn dataset using the CWT method with Resnet101. Finally, for the classification with the AB-CD-E group, 99.33% classification success rate was achieved by using the CWT method with the Resnet-101 model. These findings underscore the potential of the proposed assistive system to significantly improve the diagnosis and management of epilepsy, demonstrating high accuracy and reliability across different datasets and classification techniques.

Keywords: EEG, epilepsy diagnosis, STFT, CWT, transfer learning.
Categories: I.4.7, I.5, I.6.4, I.2.6
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1 Introduction

Epilepsy can be defined as a type of disease that occurs suddenly in the brain and cannot be controlled, although its effect does not last very long in general, but has a high probability of causing damage due to the existing contractions or uncontrolled states on the patient who had the seizure during the seizure [Duru et al., 10, Çelebi and Güllü, 19]. The result of these uncontrolled seizures can sometimes result in the death of exposed patients. Researchers shared that the mortality rate of epilepsy patients living in countries with a low level of development in the world, where the level of development is directly proportional to the treatment opportunities, is quite high, and the most prominent reason for this increase is the distance of the patients from treatment [Pal et al., 00]. In addition, epilepsy is among the most common diseases in the brain, which puts the disease on the agenda of research [Tzallas et al., 12]. Research on the disease shows that 1% of the world population suffers from these disorders in the brain [Thijs et al., 2019]. In line with the shared statistics, it can be said that the increase in the incidence of the disease from year to year in the world is an effective factor in the fact that epilepsy has an important field of study in the literature [Görgülü and Fesci, 11]. Considering this increase and the financial difficulties in underdeveloped countries that make it difficult to access treatments, early diagnosis of epileptic seizures through helpful ideas may have a significant impact on reducing the permanent damage and deaths that the disease may cause.

Human nature has potential to make mistakes when it comes to interpretation. To reduce the misdirections that these errors can cause, a helpful idea can be offered to the experts [Kaya and Bilge, 14]. These helpful ideas push researchers to focus on brain signals obtained from the brain, called Electroencephalography (EEG) [Noachtar and Rémi, 09]. EEG can be defined as a signal series that is accepted as a measure of the electrical activity in the brain and provides signal-based monitoring of the reactions occurring in the brain [Kirschstein and Köhling, 09]. By using EEG signals, it can be observed what kind of electrical activity in the brains of epilepsy patients during seizures. The ability to be observed is seen as one of the main reasons why EEG signals are frequently preferred in studies on the current conditions of epilepsy patients [Maganti and Rutecki, 13].

In today's literature studies, many studies are carried out and new models continue to be developed. Chua et al. carried out the feature extraction method by making use of high-order spectra in their study to detect during and before epileptic seizures from EEG signals. Then, the authors subjected the data, which was digitized and ready for classification, to the Gaussian mixture model and Support Vector Machines methods, in line with the information coming from the algorithm they developed in order to determine the most suitable classifier for classifying the data. While the authors achieved a success rate of 92.56% with the help of Support Vector Machines in the classification they made on two different labeling, seizure and before, they shared that this rate increased to 93.11% in the Gaussian mixture model [Chua et al., 11]. Türk and Özerdem aimed to provide high accuracy in the diagnosis of epileptic seizures with the help of artificial intelligence methods by applying the Continuous Wavelet Transformation (CWT) method to the data set they had in line with the method they were trying to develop. In this direction, the authors visualized the data set, which is one of the main pillars of the study, with the help of CWT and applied artificial intelligence methods to the picture sets in their hands. In this context, the authors achieved a general classification success of 93.60% in the data set containing 5 different subject groups [Türk and Özerdem, 19]. In their study, Ahmad et al. aimed to present an approach for the diagnosis of epilepsy. The dataset that used, consists of EEG signals from 24 subjects and has a recording time of 916 hours. The authors aimed to obtain features that would increase the accuracy of the classification process by applying the Discrete Wavelet Transform (DWT) method on this data set. Then, the authors extracted statistical features such as mean and standard deviation from the data they applied DWT and optimized the data by removing the data that had no effect on the classification with the feature selection method called Principal Component Analysis (PCA). After these processes, the authors obtained an average accuracy of 94.8% with the Support Vector Machines (SVM) method [Ahmad et al., 14]. In their study, Kaya and Ertuğrul aimed to present a method for determining the determinants of EEG signals in order to affect the classification success. In this context, the authors benefited from the BONN data set, which was also mentioned in previous studies. The authors, who wanted to subject the data set to machine learning algorithms, first benefited from the local triple pattern feature extraction method, which was based on image processing, in order to digitize the data. In line with this method, the authors, who obtained two different feature groups as lower and upper features, subjected each feature group separately to 6 different machine learning-based classifiers: Random Forest (RF), SVM, BayesNet, Artificial Neural Networks (ANN), Clusters and functional trees. The first aim of the authors in the data set, which was taken from healthy people with a diagnosis of epilepsy and lettered between A and E, was to distinguish the E group belonging to the epileptic seizure patient from other groups. In this direction, the authors who performed the classification process with group A, which belonged to a healthy person with open eyes, with 100% accuracy, also achieved classification successes of 97.5%, 97.5% and 94.5%, respectively, in the classification process of groups B, C, and D with group E. Finally, the authors achieved a classification success rate of 95.7%, rather than comparing EEG data from healthy people (A), EEG data from subjects with epilepsy with eyes open (D), and EEG data collected during epileptic seizures. The authors, who obtained these results with the help of sub-attributes, shared that the results they obtained with the help of upper-features had classification success rates close to this ratio [Kaya and Ertuğrul, 18]. Acharya et al. have benefited from a 13-layer Convolutional Neural Network (CNN) deep learning classifier, which they think that it can be more effective than machine learning methods in order to detect seizure states, pre-seizure and normal states in epilepsy patients. The authors, who preprocessed and optimized the data with the help of Z-score normalization, standard deviation and zero mean methods before applying it to the classifier, aimed to minimize the data irregularities in the data that would affect the incorrect training. The authors, who applied the 13-layer CNN deep learning algorithm to the data set ready for classification, shared that they reached an accuracy rate of 88.67% at the end of the study [Acharya et al., 18]. Sagga et al. have presented an approach through deep learning-based classifiers in order to prevent the harm that may occur due to the uncontrolled state of the patient during the seizure by predicting the seizures of people with epilepsy through the CHB-MIT dataset. In this context, the authors subjected the model to a pre-training stage by applying 1-layer CNN to the EEG signals in the dataset. Then, the authors applied the Resnet and VGGNet classifiers to the pre-trained data using the CNN method. As a result of these procedures, the authors shared that they achieved classification success of 97.6% and 97.32% from Resnet and VGGNet classifiers, respectively [Sagga et al., 20]. Malekzadeh et al. have made a detailed approach on the Bonn data set within the scope of their study. The authors aimed to classify the A, B, C, D, E groups of the data set for 6 different conditions, primarily A-E, B-E, C-E, D-E, ABCD-E, AB-CD-E. The authors first applied a feature extraction process to extract statistical features from the EEG signal data in the data set. Then, the Intensity Weighted Average Frequency (IWMF) method was applied to obtain the frequency-based properties. Finally, in order to obtain entropy properties, they performed feature extraction by using several methods. The authors subjected the data groups consisting of these features to SVM, K-Nearest Neighbor (KNN) and CNN-based SVM (CNN-SVM) classifiers. As a result of these processes, it was seen that the highest success was obtained by using the CNN-SVM classifier. The authors obtained 99.61%, 99.46%, 99.51%, 99.82%, 99.78%, 99.71% accuracy for groups A-E, B-E, C-E, D-E, ABCD-E, AB-CD-E, respectively [Malekzadeh et al., 21].

As seen above, there are many approaches in the literature for diagnosing epileptic seizures with the help of artificial intelligence methods. In this study, it was aimed to diagnose epilepsy using various transfer learning models. To propose a robust and effective model, two data sets that are frequently used in the current literature were used. These are the Hauz Khas and Bonn Epilepsy datasets, respectively. STFT and CWT methods were used to transform 1-dimensional (1D) data into 2-dimensional (2D) data. Then, the obtained 2D images were presented as input to the proposed transfer learning models. In this way, changes in signals could be expressed more clearly. Then, the classification process was performed with 10-fold cross-validation using various transfer learning models. When the classification results were evaluated for both datasets, promising accuracy rates were obtained.

2 Experimental Setup and Data Set

Within the scope of this study, an epileptic seizure diagnosis approach was carried out by using two different data sets, the Bonn epilepsy data set and The Hauz Khas data set.

2.1 Bonn Epilepsy Data Set

The Bonn Epilepsy dataset, also known as the University of Bonn Electroencephalogram (EEG) database, is a widely used dataset in the field of epilepsy research. It is a collection of EEG recordings obtained from epilepsy patients. The dataset was compiled by the Department of Epileptology at the University of Bonn Medical Center in Germany [Andrzejak et al., 12].

The details of the groups of the data set obtained from 5 different groups are given in Table 1.

Group	Description
A	This signal group consists of the signals of healthy and open-eyed subjects.
B	This signal group consists of signals from healthy and blindfolded subjects.
C	These are the signals collected from epilepsy patients with eyes open but without seizures.
D	These are the signals collected from epilepsy patients with eyes closed but no seizures.
E	These signals belong to the moments when subjects with epilepsy had seizures.

Table 1: Bonn Epilepsy Data Set Details

Some sample of signals belonging to each of the 5 different groups is given in Figure 1.

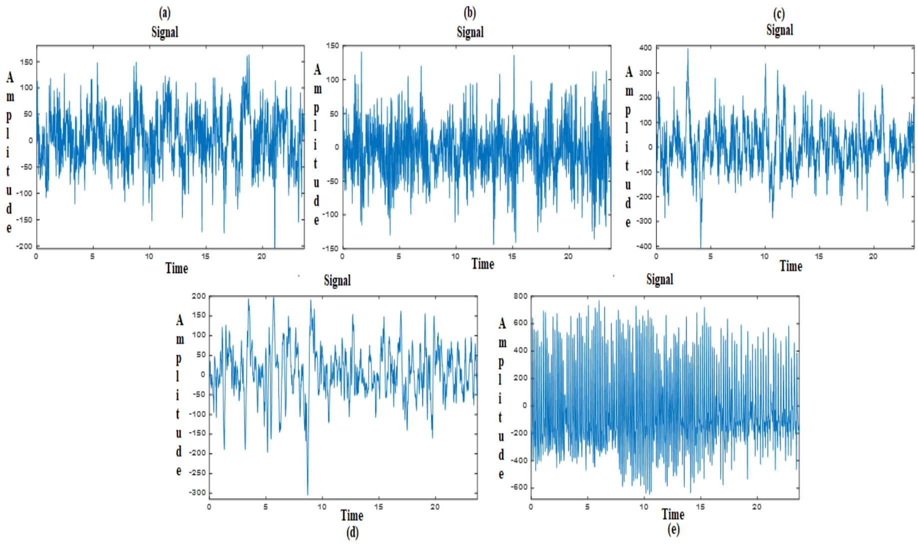

Figure 1: Examples of Bonn dataset groups: (a): Group A, (b): Group B, (c): Group C, (d): Group D, E: Group E

2.2 The Hauz Khas Data Set

The Hauz Khas dataset was collected through the Neurology and Sleep Center and made available to researchers to conduct studies on epilepsy errors. In addition, EEG signals were collected with the 10-20 electrode placement system, which is the most common method. A band-pass filter was applied to all the data to filter the obtained signals in the 0.5-70 Hz frequency band. While the data collection time is 5.12 seconds in total, each signal data contains 1024 samples [Swami et al., 16]. The shared data consists of 3 groups as Preictal, Ictal and Interictal and each group contains 50 EEG signal samples. These 3 groups and the state they represent are described in Table 2.

Group	Description
A	This signal group consists of the signals of healthy and open-eyed subjects.
B	This signal group consists of signals from healthy and blindfolded subjects.
C	These are the signals collected from epilepsy patients with eyes open but without seizures.

Table 2: Details of The Hauz Khas Delhi data set

An example of signals belonging to each of the 3 different groups is given in Figure 2.

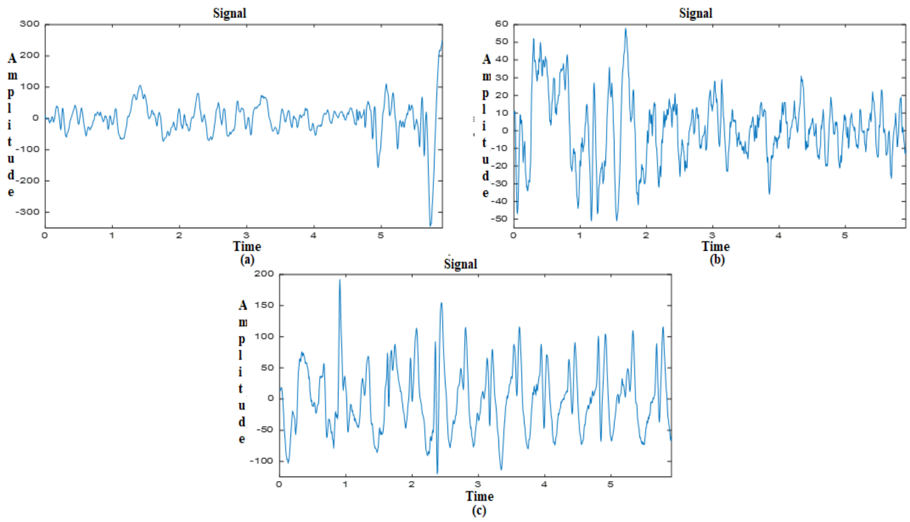

Figure 2: Examples of The Hauz Khas dataset groups: (a): Preictal (b): Ictal, (c): Interictal

3 Method

3.1 Transformation Methods

Although deep learning methods perform transfer learning process thanks to the convolutional network structure it contains, applying the right transformation method to the data has a positive effect on the classification success. Since Resnet-50, Resnet-101, GoogLeNet, AlexNet and VGGNet deep learning-based methods to be used in this study show successful performance on visual classification, Short-Time Fourier Transform (STFT) and Continuous Wavelet Transform (CWT) methods has been applied to The Hauz Khas and Bonn epilepsy data sets.

3.1.1 Short-Time Fourier Transform (STFT)

The Short-Time Fourier transform is frequently used in signal-based studies in the literature as an analysis method that allows us to analyze signals over time through frequency components. The Short Time Fourier Transform (STFT) method, which allows to observe the change of the signal over time, has the opportunity to perform this process in 4 stages [Kıymık et al., 05].

In the first stage, a temporal segmentation is performed and these are divided into windows and these windows generally have a fixed time interval. In addition, the overlapping windows method is used to eliminate the deficiencies that may arise in the transition between windows. Within the scope of STFT methods, 5 different window types are used, namely Rectangle, Hanning, Hamming, Blackman and Kaiser [Sameer and Gupta, 22]. In this study, the analysis of the signals was carried out by using the Kaiser window.

The Kaiser window is one of the most frequently used window types in spectrum analyzes because it controls the balance between the width of the main lobe and suppressions from the side lobes. The mathematical expression of the Kaiser window is given in Equation 1.

$$W(n) = \frac{I_0(\beta\sqrt{\frac{1-4n^2}{(M-1)^2}}}{I_0\beta} \tag{1}$$

Parameters I_0, β, n and M given in Equation 1 represent Bessel function value, shape factor, window length and filter order, respectively.

After the window selection process, the Fouirer Transform (FT) process is applied to the signal groups remaining in each of the selected windows separately. The output of the FT method applied for each window is the signal spectrum [Zabidi et al., 12]. Spectograms are formed as a result of the process of combining the signals by coloring them based on their amplitudes. In Figure 3, Figure 4, Figure 5 and Figure 6, the output of The Hauz Khas dataset with 128 window intervals Kaiser window output, the Bonn epilepsy data set with 128 window intervals Kaiser window output, The Hauz Khas data set with 256 window intervals Kaiser window output. and Kaiser window output of the Bonn epilepsy dataset with 256 window intervals is given.

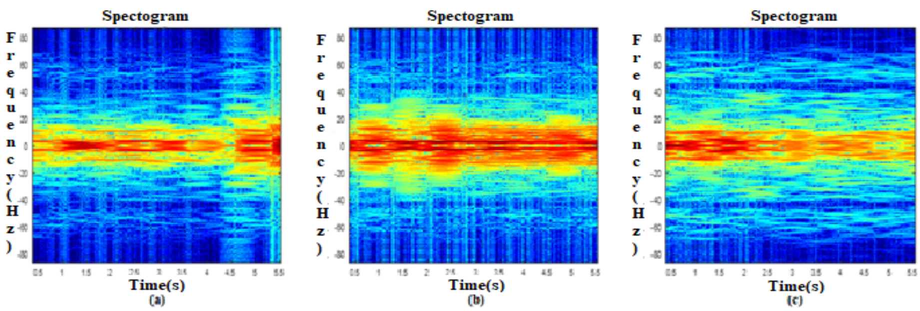

Figure 3: The Hauz Khas dataset Kaiser method based STFT output samples with 128 window size. (a): Preictal state, (b): Ictal state, (c): Interictal state

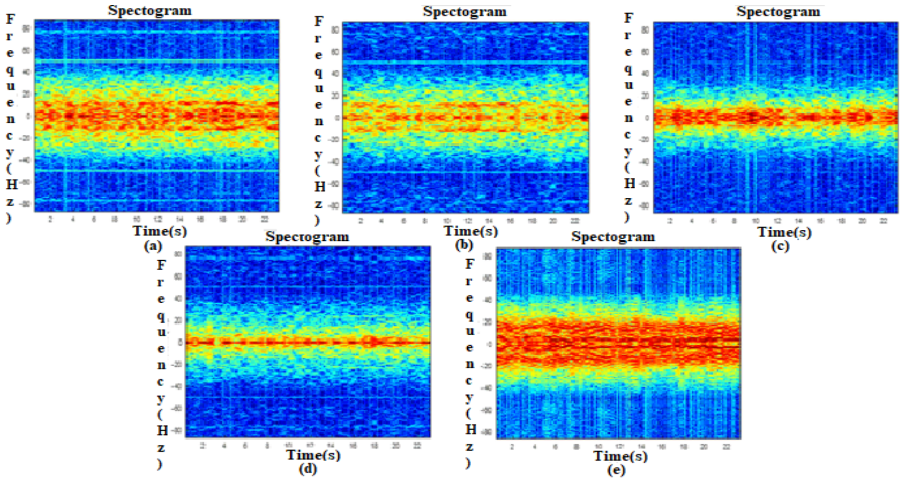

Figure 4: The output samples of STFT method based on Kaiser method with Bonn data set 128 window size: (a): Group A, (b): Group B, (c): Group C, (d): Group D, (e): Group E

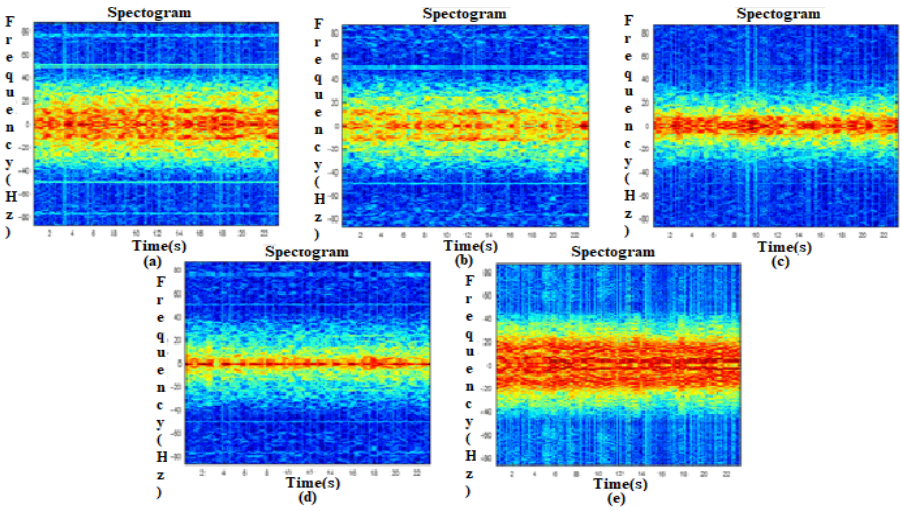

Figure 5: The output samples of STFT method based on Kaiser method with Bonn data set 128 window size: (a): Group A, (b): Group B, (c): Group C, (d): Group D, (e): Group E

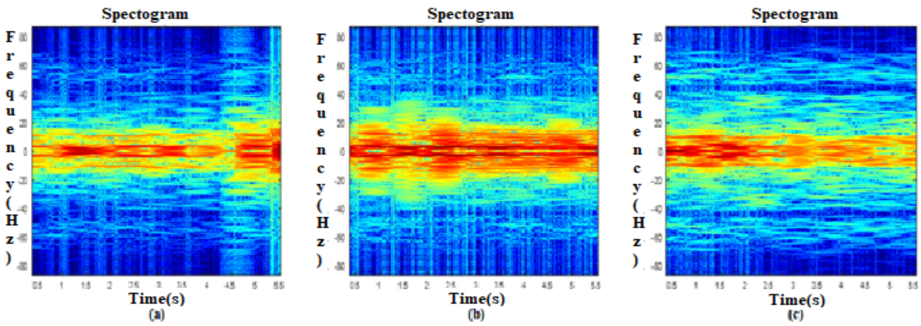

Figure 6: The Hauz Khas dataset Kaiser method based STFT output samples with 128 window size. (a): Preictal state, (b): Ictal state, (c): Interictal state

3.1.2 Continious Wavelet Transform (CWT)

Continuous Wavelet Transform (CWT) is an analysis method that allows the time and frequency components of a signal to be processed jointly. In other words, this method allows to examine how the frequency values of the signal of interest change over time [Jadhav et al., 2020]. The CWT method, which can analyze time and frequency components at different resolution values thanks to the wavelets that it has taken its name from, consists entirely of short-term and oscillating wavelet forms. The mathematical expression in which the CWT analysis method has performed the transformation is given in Equation 2.

$$T(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\varphi \frac{(t-b)}{a} dt \qquad (2)$$

Given in Equation 2, a represents the scaling parameter, b represents the transform position, wavelet function, and x(t) the input signal.

The function transformed by this equation is transformed for each scale one by one. It is then converted to a spectrogram as in the STFT method. On the basis of CWT, the equivalent of this spectrogram is called Scalogram [Roy and Islam, 20]. The scalogram is a density map representing the energy and coefficient magnitude of the CWT coefficients obtained with the help of Equation 2. It performs the process of obtaining an image from the signal by performing the coloring process in line with the intensity of this energy and the size of the [Meintjes et al., 18]. In Figure 7 and Figure 8, an example of the images obtained as a result of applying CWT to each group of Bonn and The Hauz Khas data sets is shown. Artificial Neural Network (ANN), Logistic Regression (LR) and Random Forest (RF) models are used to obtain performance metrics.

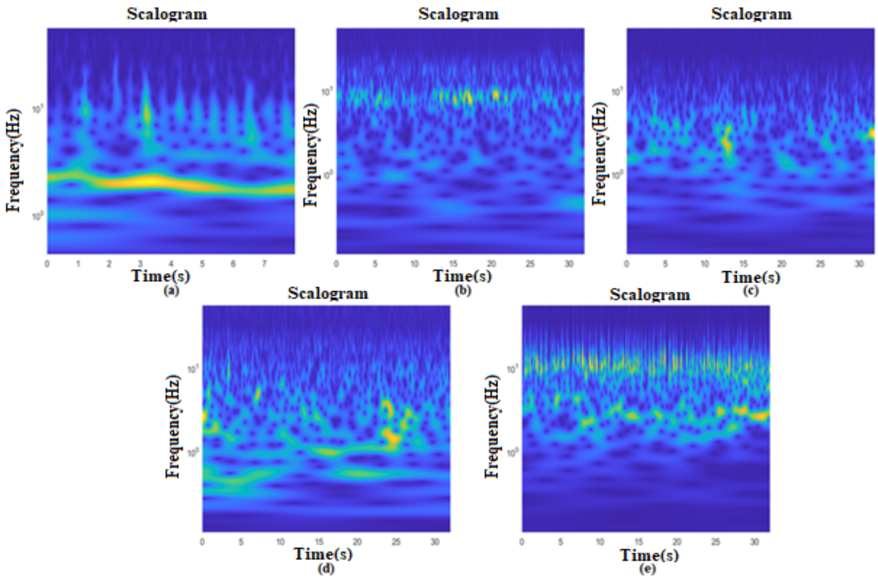

Figure 7: Samples obtained as a result of Bonn data set CWT-based analysis: (a): Group A, (b): Group B, (c): Group C, (d): Group D, (e): Group E

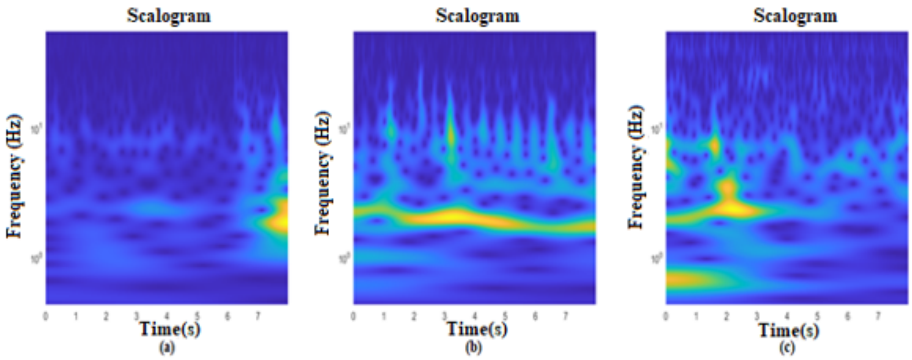

Figure 8: Samples obtained as a result of CWT-based analysis of The Hauz Khas dataset (a): Preictal state, (b): Ictal state, (c): Interictal state

3.2 Deep Learning

Deep learning is a collection of learning methods that are inspired by the human brain and consist of networks, classified as a specialized sub-branch of machine learning. These methods, which aim to give computers the ability to think and make decisions like humans, are among the methods frequently used today due to their high success on complex data with high dimensions where machine learning is insufficient [LeCun et al., 15]. Deep learning methods, inspired by neural networks and having a layered structure, offer an optimal learning path by analyzing the data entering the layers one by one and transferring the necessary information to the next layer. This arrangement also provides a lot of convenience in the processing of big data [Schmidhuber, 15].

3.2.1 Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNN) is a deep learning method that is often preferred to perform its tasks on image processing in general. Since CNN-based methods have more layers than other deep learning methods in order to perform feature extraction, their frequency of use in studies is high [Rusk, 16].
Convolutional Neural Networks (CNN), one of the most frequently used branches of deep learning methods in the literature, have methods that are frequently used in the classification of signals.
CNN algorithms have the potential to perform feature extraction and classification operations together due to the different tasks undertaken by the layers in their structure. CNN-based approaches that perform feature extraction operations through convolutional layers make use of filters when applying this process. Then, the data entering the pooling layers as input in order to reduce the size of the obtained data becomes smaller after this stage. This can be considered as one of the most important processes that enable the system to gain speed. After the realization of these two processes, the classification layers come [Alzubaidi et al., 21]. The customizations made in these layers also enabled the diversification of CNN-based methods. In this study, 5 different CNN-based classifiers were used.

3.2.1.1 Resnet-101

The ResNet101 classifier, known as ResNet and belonging to the classifier family, which means Residual Network, is a CNN-based method designed and introduced in 2015 by a group of researchers working in the Microsoft Research team. The general purpose of the classifier is image processing, object detection and segmentation of images [Khan et al., 18]. Besides, the main reason why the network is called the Residual Network is that the learning process is now taking place. It is a method designed to solve the gradient problem that occurs in networks with high learning depth. With this method, the network now performs the learning of matches. It does this by making use of jump and shortcut links. The number '101' at the end of the classifier represents the number of layers it contains. However, in general, Resnet 101 classifier consists of 33 residual blocks, which includes 4 different types of layers: convolutional layers, pooling layers, fully connected layers and layers that provide shortcut connections. 29 of these 33 blocks are fed with residual information from the previous layer [Ghosal et al., 19]. The architectural structure of Resnet 101 is given in Figure 9.

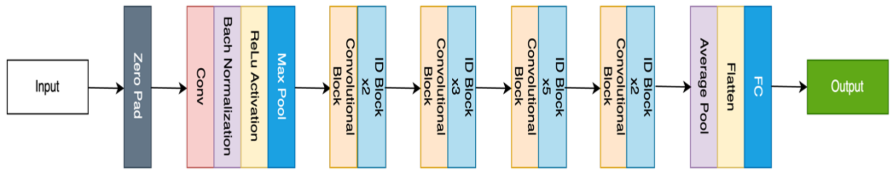

Figure 9: Architecture of the Resnet-101 classifier

As shown in Figure 9, the Resnet-101 classifier does not follow a direct path from input to output as in traditional structures, but thanks to the mapping capability provided to the layers, layer outputs are residual obtained as a result of collecting the information coming from the networks at the layer input. This feature frees the network from the burden of learning from scratch, allowing the network to work with residuals at hand that are easier to optimize. In addition, when Figure 9 is examined, it is seen that the Resnet-101 classifier is obtained by adding the residual blocks side by side. These residual blocks contain layers with normalization and Rectified Linear Units (ReLU) activation functions [Feng et al., 20]. In addition to the inter-block connection, the transfer of residual information to the input of the next layer is also shown in the figure. In line with its success, the Resnet 101 classifier, which is frequently used in the classification of images in the literature, has a more intensive use area day by day.

3.2.1.2 Resnet-50

The ResNet-50 classifier, like ResNet-101, is one of the classifiers developed by Microsoft Research team members to perform image learning. The year this classifier was introduced is 2015, as in ResNet-101 [Wen et al., 20]. ResNet50 algorithm, which has 50 layers, also has a trained infrastructure to successfully perform image segmentation and object recognition tasks. The infrastructure of this learning is also derived from the data in ImageNet. In this way, he is involved in the task to be performed in a pre-trained manner. As in ResNet-101, the ability to recover the gradients that have disappeared in this structure with residual networks is among the most prominent features of ResNet50.

3.2.1.3 Alexnet

AlexNet is frequently used in the literature as a CNN-based classifier, which plays a very important role in making progress in the field of deep learning and computer vision. AlexNet, which was developed by Alex Krizhevsky, Ilya Sutskever and Geoffrey Hinton in 2012 and won the ImageNet Large-Scale Visual Recognition Competition (ILSVRC) in the same year, consists of 8 layers, 3 fully connected layers and 5 convolutional layers [Yu on et al., 16]. AlexNet is trained by its designers with a dataset of thousands of classes and millions of images on ImageNet. Also, taking advantage of the GPU power during the training phase, AlexNet has taken its place among the methods that demonstrate the success of deep learning methods in fulfilling this task with its successful performance in classifying images. In addition, this success paved the way for the use of CNN-based applications in applications involving image processing.

3.2.1.3 GoogleNet

Like the other classifiers described in GoogLeNet, it is a deep learning-based method, also known as Inception-v1, which is supported by the CNN algorithm and designed and introduced by Google in 2014 [Yoo, 15]. The word Inception, which gives the network its name, actually originates from the most important feature of the GoogLeNet network. While this layer performs the filtering process with the help of the filters it contains, it also performs the size reduction process with the help of the 1x1 convolutional layer in its structure. In other words, it is characterized by the name of this layer because it performs both dimension reduction and feature learning in this layer. This combination gives speed to the model by reducing the computational complexity and also adds a high efficiency to the network [Kim et al., 19]. In addition, GoogLeNet, which strengthens its architecture with intermediate layers as well as the main layers, performs the process of eliminating the gradient extinction problem, which the Resnet-101 network has realized with the inclusion of the networks in the next stage, with the help of small classifiers added to the layers. GoogLeNet, which also has regulatory middleware that prevents over-compliance, aims to eliminate the problem that may arise during the learning phase by following this practical way. GoogLeNet has become a very interesting model as a result of its higher success with the help of fewer parameters compared to other models it has been compared to. This pushed the designers of the model to make various studies on the model.

3.2.1.5 VGG-19

The VGG-19 method takes its name from the English abbreviation of the name Visual Geometry Group. VGG-19, like other classifiers used in this study, is CNN-based and was developed by members of the Visual Geometry Group working at Oxford University. This method is a continuation of the VGG-16 architecture produced by the same group and managed to attract attention by performing at a high level in the Large-Scale Visual Recognition Competition (ILSVRC) organized by ImageNet in 2014 [Bagaskara and Suryanegara, 21]. Compared to the other classifiers mentioned, the VGG-19 classifier draws attention with its simplified structure. This architecture, which is formed as a result of combining 16 convolutional, 5 pooling and 3 fully connected layers, takes the suffix '19' from the numbers of these layers [Shaha et al., 18]. As it can be understood from the Visual Geometry Group, which is named VGG-19, it has a structure designed to perform image segmentation and object detection tasks like the ResNet network. The disadvantage of the architecture, which aims not to miss local patterns with the 3x3 filter that it has in its structure to strengthen these processes and is constantly active throughout the network, is that it has many parameters and the computational and memory load it brings. A simple representation of the VGG-19 architecture is shown in Figure 10.

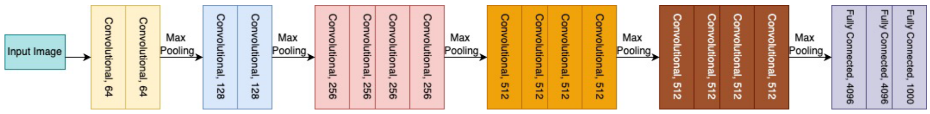

Figure 10: VGG-19 Architecture

3.3 Performance Metrics

In order to evaluate the success of the presented method on the detection of epileptic state from the EEG-based data performed in this study, accuracy, f-measures, sensitivity and precision parameters were used. The basic values used in the calculation of the mentioned parameters are given in Table 3.

		Real Values	
		Positive	**Negative**
Estimated Values	**Positive**	True Pozitif (TP)	False Pozitif (FP)
	Negative	False Negative (FN)	True Negative (TN)

Table 3: Information on Performance Criteria

The information given in the table is based on the correct or incorrect classification of the data in the classification process. In the light of these parameters, the obtaining of the parameters we used in the thesis is explained below.
Accuracy: Accuracy is one of the most basic criteria and is obtained by the ratio of correctly classified data to all data during the classification process.

$$\text{Accuracy} = \frac{\text{TN+TP}}{\text{TN+TP+FN+FP}} \tag{3}$$

Sensitivity: Sensitivity is a measure of success in classifying positive examples of a model. It is obtained as a result of evaluating true positive data together with false negative data.

$$\text{Sensitivity} = \frac{\text{TP}}{FN+TP} \tag{4}$$

Precision: The precision criterion is obtained by dividing the correctly predicted positive data obtained as a result of the classification process made by the model to the overall positive data.

$$\text{Precision} = \frac{\text{TP}}{FP+TP} \tag{5}$$

F -1 Score: Although F measures are also known as F1 score, they are obtained as a result of joint evaluation of precision and sensitivity information. It is the result of a detailed evaluation on the performance of the model.

$$\mathrm{F-1\ Score} = \frac{\mathrm{TP}}{FP+TP} \tag{6}$$

4 Experimental Results

The process of diagnosing epileptic seizures by using EEG data is obtained as a result of combining various steps. If this process is to be done through a machine learning classifier, while making it ready for the classifier with the help of various pre-processes and then feature extraction methods; If this diagnostic process is performed with deep learning methods, the feature extraction process changes according to the path followed by the researcher who carried out the study. The transfer learning process, which deep learning algorithms have performed due to its layered structure, already performs the feature extraction process within its own structure. However, by using various transformation algorithms, the available data can be used to increase the learning success of deep learning methods.

In this study, it is aimed to diagnose epileptic seizures with the help of deep learning-based classifiers. In this direction, Hauz Khas and Bonn epilepsy datasets were used and STFT and CWT transformation methods were applied to the data to convert these datasets from 1D to 2D format. In order to measure the effect of tranformation methods on classification, 5 different CNN-based classifiers were used. The performance parameters obtained by applying these classifiers to the STFT and CWT data using the 10-fold cross-validation method and the success of the classification method and transformation method pairs were measured. For perform these calculations, the MATLAB 2022 and the NVIDIA GeForce GTX 1080 TI computer graphics card was used. Additionally, the hyperparameters of the classification methods used in the study are given in Table 4.

Model / Parameters	Resnet-50	Resnet-101	AlexNet	GoogleNet	VGG-19
Mini-Batch Size	10	10	10	10	10
Max Epochs	6	6	6	6	6
Optimizer	sgdm	sgdm	sgdm	sgdm	sgdm
Initial Learning Rate	0.0003	0.0003	0.0003	0.0003	0.0003
Validation Frequency	2	2	2	2	2

Table 4: Hyperparameter values of the classification methods

First of all, STFT method was applied to The Hauz Khas dataset with the help of Kaiser window and the window interval was determined as 128. The success rates obtained as a result of applying this process to preictal, ictal and interictal signals in The Hauz Khas data set are shared in Table 5.

Classifier	Accuracy	Precision	Sensitivity	F1 Score
Resnet 101	**0.905**	**0.896**	**0.898**	**0.897**
Resnet 50	0.818	0.802	0.810	0.806
AlexNet	0.740	0.802	0.824	0.813
GoogLeNet	0.747	0.676	0.780	0.728
VGG 19	0.640	0.640	0.546	0.593

Table 5: Success rates of classification of preictal, ictal and interictal groups (results obtained as a result of applying STFT with Kaiser window with 128 window size)

When Table 5 is examined, it is seen that the highest accuracy rate obtained as a result of the triple classification process belongs to the Resnet-101 classifier. After this process, a binary classification process was applied on The Hauz Khas dataset in order to perform a diagnosis by making use of the differences between the preictal and ictal moments, and the Kaiser window with 128 window intervals of the STFT classifier was used as the transformation method in this classification process. The results obtained are shown in Table 6.

Classifier	Accuracy	Precision	Sensitivity	F1 Score
Resnet 101	**0.993**	**0.994**	**0.990**	**0.992**
Resnet 50	0.947	0.926	0.930	0.928
AlexNet	0.690	0.696	0.650	0.673
GoogLeNet	0.866	0.856	0.880	0.868
VGG 19	0.780	0.744	0.756	0.750

Table 6: Success rates of classification of preictal and ictal groups (results obtained as a result of applying STFT with Kaiser window with 128 window size)

As can be seen in Table 6, Resnet-101 classifier completed this process with 99.3% success. In addition to the data obtained with the help of Kaiser window with 128 window size, classification process was performed by increasing the window interval to 256 in order to test the effect of Kaiser window size on the classifier on the data set. As in the previous classification process, this classification process was performed for two different data groups. The results of the triple classification process are shared in Table 7, and the results of the binary classification process are shared in Table 8.

Classifier	Accuracy	Precision	Sensitivity	F1 Score
Resnet 101	**0.856**	**0.856**	**0.874**	**0.865**
Resnet 50	0.796	0.816	0.830	0.823
AlexNet	0.740	0.750	0.764	0.757
GoogLeNet	0.729	0.715	0.767	0.741
VGG 19	0.711	0.686	0.722	0.704

Table 7: Success rates of classification of preictal, ictal and interictal groups (results obtained as a result of applying STFT with a 256 window size Kaiser window)

Classifier	Accuracy	Precision	Sensitivity	F1 Score
Resnet 101	0.905	0.908	0.922	0.915
Resnet 50	**0.920**	**0.918**	**0.924**	**0.921**
AlexNet	0.787	0.814	0.820	0.817
GoogLeNet	0.867	0.864	0.890	0.877
VGG 19	0.867	0.867	0.867	0.867

Table 8: Success rates of classification of preictal and ictal groups (results obtained as a result of applying STFT with Kaiser window with 256 window size)

When Table 7 is examined, it is seen that the highest classification success was obtained with the Resnet-101 method, but another point to be considered is the decrease in accuracy rates. When Table 8, which represents the results of binary classification, is examined, it is seen that the highest success rates are obtained by Resnet-50 method as a result of this process, but lower classification accuracy is obtained compared to the classification process performed on the data obtained using the 128-dimensional Kaiser window.

The last operation on The Hauz Khas dataset is Continuous Wavelet Transform (CWT), which is applied to determine the effect of transformation methods. In order to make an accurate comparison, classification was carried out on the data set on double and triple groups. The results of the classification process performed on the triple group are shared in Table 9, and the results of the classification process on the double group are shared in Table 10.

Classifier	Accuracy	Precision	Sensitivity	F1 Score
Resnet 101	**0.955**	**0.940**	**0.968**	**0.954**
Resnet 50	0.852	0.832	0.844	0.838
AlexNet	0.822	0.826	0.846	0.836
GoogLeNet	0.843	0.796	0.850	0.823
VGG 19	0.809	0.804	0.844	0.824

Table 9: Success rates of classification of preictal, ictal and interictal groups (results obtained as a result of CWT application)

Classifier	Accuracy	Precision	Sensitivity	F1 Score
Resnet 101	**0.995**	**0.996**	**0.994**	**0.995**
Resnet 50	0.993	0.993	0.995	0.994
AlexNet	0.987	0.987	0.989	0.988
GoogLeNet	0.967	0.972	0.966	0.969
VGG 19	0.891	0.884	0.912	0.898

Table 10: Success rates of classification of preictal and ictal groups (results obtained as a result of CWT application)

When Table 9 is examined, it is seen that the highest classification accuracy was obtained with the Resnet-101 classifier at a rate of 95.5% in line with the triple classification process, and this accuracy increased to a higher level when compared to the other 2 methods.

When Table 10, which shows the characteristics of the classification processes performed after the CWT transformation applied to the data groups containing the preictal and ictal moment signals, is examined, it is seen that 99.5% accuracy was obtained by using Resnet-101. In the studies conducted on the Hauz Khas data set, it is seen that the classification success of the Resnet-101 method is at the highest level in case the transformation methods change. In addition, when the classification success of the transformation methods is examined, it can be said that the CWT method has a more positive effect on the classification accuracy than the other two methods. Figure 11 and Figure 12 show the ROC and Loss curves for the highest classification success scenarios obtained through Resnet-101 on the preictal-ictal-interictal groups and preictal-ictal groups of the Hauz Khas dataset, respectively.

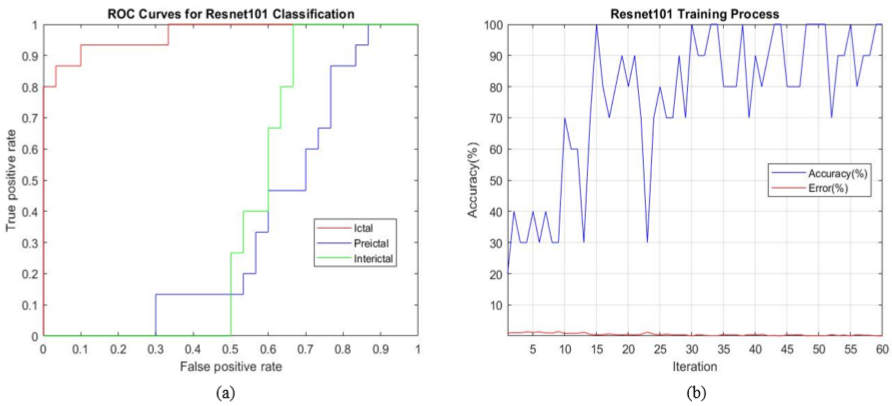

Figure 11: Graphs of the classification process for the Preictal-Ictal-Interictal groups; (a): ROC curve, (b): Loss curve

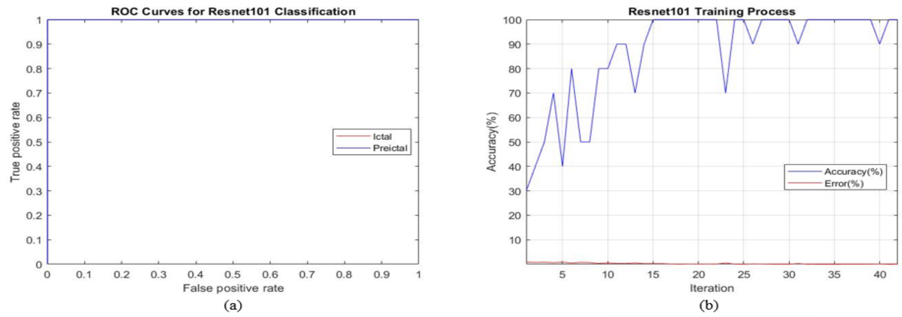

Figure 12: Graphs of the classification process for the Preictal-Ictal groups; (a): ROC curve, (b): Loss curve

In another phase of the proposed approach, Bonn data set, which is a larger data set compared to The Hauz Khas data set, was used. Classification processes were carried out based on the A, B, C, D, E groups specified in the material section on the Bonn data set. These classification processes are grouped as A-E, B-E, C-E and D-E in order to detect epileptic seizures and other conditions. In addition to these dual classification processes, AB-CD-E grouping was used to be used in the classification process after the diagnosis of healthy subjects, subjects with epileptic disease but not epileptic seizures, and subjects whose signal data were collected during seizures. In these classification processes, transformation and classification methods used in The Hauz Khas data set were used.
First, Kaiser window with 128 window size was applied on the Bonn data set in order to measure the contribution of the STFT transformation method to the classification process. The data that was ready for the classification process was subjected to classifiers and the classification success of the methods is shared in Table 11.

Classifier / **Data Groups**	**Resnet- 101 (Accuracy Precision, Sensitivity F1 Score)**	**Resnet-50 (Accuracy, Precision, Sensitivity F1 Score)**	**AlexNet (Accuracy, Precision, Sensitivity, F1 Score)**	**GoogLeNet (Accuracy, Precision, Sensitivity, F1 Score)**	**VGG-19 (Accuracy, Precision, Sensitivity, F1 Score)**
A-E	0.983 0.983 0.985 0.994	0.983 0.983 0.984 0.983	0.988 0.988 0.990 0.989	**0.994** **0.994** **0.996** **0.995**	0.867 0.867 0.895 0.881
B-E	**0.983** **0.983** **0.984** **0.983**	0.979 0.978 0.980 0.979	0.950 0.948 0.952 0.950	0.978 0.978 0.980 0.979	0.971 0.971 0.972 0.971
C-E	**0.989** **0.989** **0.987** **0.988**	0.983 0.983 0.984 0.983	0.978 0.978 0.980 0.979	0.986 0.984 0.988 0.986	0.800 0.720 0.783 0.750
D-E	0.950 0.950 0.952 0.951	**0.994** **0.993** **0.995** **0.994**	0.961 0.961 0.960 0.961	0.961 0.962 0.961 0.962	0.877 0.900 0.904 0.901

AB-CD-E	**0.944** **0.948** **0.952** **0.950**	0.916 0.920 0.924 0.922	0.891 0.902 0.904 0.903	0.931 0.918 0.922 0.920	0.901 0.908 0.911 0.909

Table 11: Classification successes obtained from the Bonn dataset with STFT applied using Kaiser window with 128 window intervals.

When Table 11 is examined, it is seen that different classifier performances show superiority in each group. The GoogLeNet method has a 99.4% success rate in the A-E classification process, while Resnet-101 achieved 98.33% and 98.9% accuracy in the classification of B-E and C-E groups, respectively. The Resnet-50 classifier has the highest success rate of 99.4% in the classification of D-E groups and finally, the Resnet-101 classifier has the highest accuracy rate of 94.4% in the classification of AB-CD-E groups.

In order to measure the classification performance of the window sizes on the Bonn data set, the window interval of the Kaiser window was increased to 256, and the STFT transformation method was applied to the data and again subjected to deep learning-based classifiers. The performance criteria of the classification process are shared in Table 12.

Classifier / Data Groups	**Resnet- 101 (Accuracy Precision, Sensitivity F1 Score)**	**Resnet-50 (Accuracy, Precision, Sensitivity F1 Score)**	**AlexNet (Accuracy, Precision, Sensitivity, F1 Score)**	**GoogLeNet (Accuracy, Precision, Sensitivity, F1 Score)**	**VGG-19 (Accuracy, Precision, Sensitivity, F1 Score)**
A-E	0.972 0.975 0.977 0.976	**0.983** **0.983** **0.984** **0.983**	0.917 0.924 0.914 0.919	0.972 0.975 0.979 0.977	0.942 0.944 0.946 0.945
B-E	**0.983** **0.983** **0.984** **0.983**	0.981 0.982 0.980 0.981	0.972 0.975 0.979 0.977	0.928 0.904 0.940 0.922	0.867 0.867 0.882 0.874
C-E	0.967 0.967 0.969 0.968	0.979 0.972 0.978 0.975	0.978 0.974 0.980 0.977	**0.983** **0.983** **0.984** **0.983**	0.900 0.900 0.907 0.904
D-E	**0.972** **0.966** **0.972** **0.969**	0.961 0.964 0.968 0.966	0.950 0.952 0.950 0.951	0.939 0.944 0.936 0.940	0.867 0.866 0.882 0.874
AB-CD-E	**0.973** **0.973** **0.975** **0.974**	0.966 0.966 0.968 0.967	0.946 0.954 0.946 0.950	0.933 0.933 0.939 0.936	0.917 0.924 0.914 0.919

Table 12: Classification successes obtained from the Bonn dataset with STFT applied using Kaiser window with 256 window intervals.

Table 12 shows a similar picture to Table 11. While the classifiers achieved close accuracy rates, the Resnet-50 classifier achieved the highest classification accuracy for the groups by classifying the A-E group with 98.33% accuracy. In addition, the Resnet-101 classifier achieved the highest success rate of 98.3% in the classification of group B-E, while the highest accuracy rate of 98.3% was obtained using the GoogLeNet classifier in the classification of group C-E. Finally, the highest success rates for the classification of the D-E and AB-CD-E groups were 97.2% and 97.3%, respectively, using the Resnet-101 classifier.

Finally, the CWT method was applied on the Bonn data set to compare the STFT and CWT methods, and the scalogram images obtained as a result of this process were subjected to each of the 5 classifiers. Classifier performance criteria for each grouping are shared in Table 13.

Classifier / Data Groups	**Resnet- 101 (Accuracy Precision, Sensitivity F1 Score)**	**Resnet-50 (Accuracy, Precision, Sensitivity F1 Score)**	**AlexNet (Accuracy, Precision, Sensitivity, F1 Score)**	**GoogLeNet (Accuracy, Precision, Sensitivity, F1 Score)**	**VGG-19 (Accuracy, Precision, Sensitivity, F1 Score)**
A-E	0.990 0.994 0.992 0.993	**0.996** **0.995** **0.997** **0.996**	0.983 0.983 0.984 0.983	**0.996** **0.995** **0.997** **0.996**	0.833 0.850 0.864 0.857
B-E	0.978 0.982 0.980 0.981	0.993 0.995 0.993 0.994	0.987 0.984 0.986 0.985	**0.997** **0.998** **0.996** **0.997**	0.983 0.983 0.984 0.983
C-E	**0.998** **0.998** **0.996** **0.997**	0.993 0.994 0.992 0.993	0.983 0.983 0.984 0.983	0.987 0.983 0.991 0.987	0.800 0.720 0.783 0.750
D-E	**0.997** **0.994** **0.998** **0.996**	0.993 0.993 0.991 0.992	0.983 0.983 0.984 0.983	0.950 0.939 0.951 0.945	0.900 0.900 0.916 0.907
AB-CD-E	**0.993** **0.993** **0.994** **0.993**	0.982 0.984 0.982 0.983	0.980 0.984 0.986 0.983	0.961 0.954 0.966 0.960	0.927 0.914 0.936 0.925

Table 13: Classification achievements obtained from the CWT applied Bonn dataset

When Table 13 is analyzed, the increase in classifier success is remarkable. Groups A-E, B-E, C-E were correctly classified by the classifiers at the highest rates of 99.6%, 99.7% and 99.8% respectively. The D-E group was correctly classified by the Resnet-101 method with 99.7% accuracy. The data consisting of AB-CD-E groups were correctly classified by Resnet-101 classifier with 99.33% accuracy. Figure 13 shows the ROC and Loss curves for the highest classification success scenario obtained through Resnet-101 on the AB-CD-E groups of the Bonn dataset.

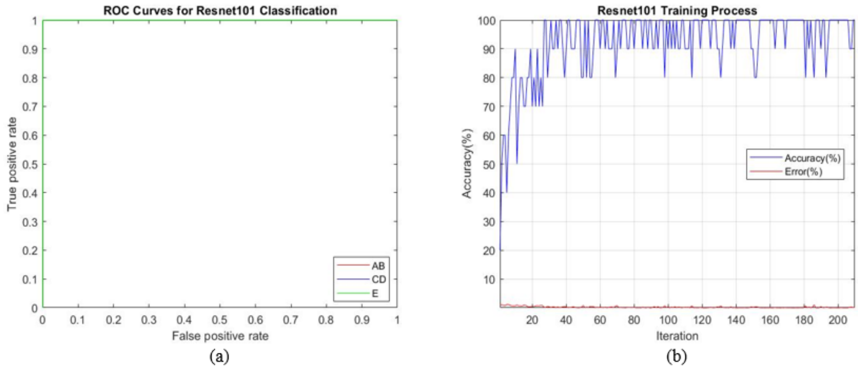

Figure 13: Graphs of the classification process for AB-CD-E groups; (a): ROC curve, (b): Loss curve

In this study, an approach to the diagnosis of epilepsy was carried out using two different data sets, two different transformation methods and 5 different deep learning-based classifiers.

5 Discussion and Conclusion

Due to the increasing prevalence of epilepsy disease, it is the subject of many academic studies today. The rate of increase in the disease is also one of the main factors that show the continuity of studies on this subject. With the help of EEG signals becoming more efficient, epilepsy has also created a field of study for research groups that produce artificial intelligence-based systems that frequently deal with signals. Researchers aimed to develop various auxiliary systems to assist expert ideas by extracting features from time-varying EEG signals and presented approaches in this context.

In this study, it is aimed to present a deep learning-based approach by using Hauz Khas and Bonn epilepsy datasets to design an assistive system. The main reason why deep learning is preferred is that it allows operations to be performed faster. Within the scope of this study, which aims to increase the classification success by applying a transformation process instead of classifying the raw data, STFT and CWT methods were applied to the data and their effects on the classification performance of the methods were observed. These two methods are among the frequently used conversion methods to visualize data and reveal the spectrum created by amplitude and frequency-based changes in EEG signals.

When an evaluation is made about the transformation methods used; First of all, the effect of window spacing in the Kaiser window based STFT transformation method needs to be examined. In this context, it can be said that the classification accuracy of STFT spectrograms obtained with the help of the Kaiser window with a window range of 128 in both data sets is higher. However, the sharpness of the images obtained with the help of CWT in terms of evaluation was effective in increasing the success rate of the classification process, and this method provided remarkable capabilities in the approximation of nonlinear feature mappings.

Carrying out the classification process in this study by using STFT and CWT transformations allowed finding the correct transformation method for the data sets. In addition, by evaluating classification algorithms combined with transformation methods, it has become easier to identify algorithms that give good results on data sets. In this way, both classification algorithms and transformation methods could be evaluated as a single piece. Additionally, when compared to studies in the literature, this study has shown that it is preferable in light of the accuracy rates obtained. Therefore, it seems that the high accuracy rates of epilepsy diagnosis made with the help of EEG signals have a positive impact on the purpose of designing the assistive system.

The approaches taken in the literature on the subject are shown in Table 14 and compared with this study. It is seen that the success rates obtained in this study are at high levels when compared to the studies in the literature.

Name, (Year)	**Method**	**Dataset**	**Success**
Kaya, Y., and Ertuğrul, Ö.F. (2018)	One-Dimensional Triple Patterns (1D-TP)	Bonn Dataset (A-E,B-E,C-E,D-E)	%100, %97.5, %97.5, %94.5
Ullah, I., et al. (2018)	-Adam optimizer, 1D-CNN, 10-fold cross validation,	Bonn Dataset (A-E, B-E, C-E, D-E, AB-CD-E)	%100, %99.6, %98.5, %98.8, %94.33
Türk, Ö., and Özerdem, M.S. (2019)	CWT	Bonn Dataset (A-E,B-E,C-E,D-E)	%99.5, %99.5 %98.5, %98.5
Malekzadeh, A., et al. (2021)	- Statistical features, frequency based features, entropy, SVM,KNN,CNN-RNN	Bonn Dataset (A-E, B-E, C-E, D-E, AB-CD-E)	%99.61, %99.46, %99.51, %99.82, %99.71
Du, R., et al. (2022)	Combination of CNN-based feature extraction and SVM classifier (CNN-SVM)	The Hauz Khas Dataset	%98.0
Zhang, Y., et al. (2019)	- Statistical features -KNN	Bonn Dataset (AB-CD-E)	%92.2
This Study	**-STFT, CWT, Resnet-101, Resnet-50, AlexNet, GoogLeNet, VGG-19**	**The Hauz Khas Dataset (Preictal-Ictal) (Preictal-Ictal-Interictal) --- Bonn Dataset (A-E, B-E, C-E, D-E, AB-CD-E)**	**%99.5 %95.56 --- %99.6 %99.7 %98.8 %99.7 %99.3**

Table 14: Classification successes obtained from the Bonn dataset with STFT applied using Kaiser window with 256 window intervals.

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