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Classification of 1D and 2D EEG Signals for Seizure Detection in the Newborn Using Convolutional Neural Networks

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Abstract
Unlike adults, neonates do not always show clinical symptoms during seizures. Therefore, uncontrolled seizures lead to severe brain damage. Timely recognition of seizures plays a crucial role for neonates. In this study, a deep transfer learning approach was proposed for automatic detection of seizures on the C4-P4 channel using electroencephalography (EEG) signals from neonates. The EEG signals were used in 1D and 2D dimensions to ensure performance, robust functionality, and a clinically acceptable level of detection accuracy. The pre-trained deep learning models Alexnet, ResNet, GoogleNet and VggNet were used in the study. Spectrograms were obtained by converting 1-dimensional signal data into 2-dimensional images, and then classification was performed for both the 1D and 2D datasets. For 1D classification, the highest performance was obtained by VggNet architecture with 91.67%, while 2D classification was obtained by AlexNet and ResNet architecture with 95.83%. The use of spectrograms significantly improved classification performance and made neonatal seizure detection and decision-making more clinically reliable.

1. Introduction

An epileptic seizure is a clinical condition resulting from sudden and irregular electrical discharges in all or part of the brain. Seizures in neonates are often caused by problems such as oxygen deprivation, hemorrhage, meningitis, infection, and stroke [1]. Seizures in neonates have different clinical symptoms than those in children and adults. In addition, they do not always show clinical signs during seizures. The fact that seizures in the neonatal period are often associated with severe illness makes special treatment necessary. Uncontrolled seizures cause severe brain damage and affect long-term prognosis. Visual scanning of EEG data is usually done within a few days and is a time-consuming process. In addition, a good specialist is needed to analyze the entire length of the EEG recordings and detect epileptic activity. If seizures are not recognized in time and if they are not treated, in some cases this can lead to death. Therefore, it is crucial to identify seizures in neonates urgently and initiate treatment. For these reasons, there is a need for computerized systems to assist experts in making decisions regarding the diagnosis of seizures [2].

Deep Learning is a class of machine learning algorithms that use multiple layers to progressively extract higher-level features from raw input. Most deep learning methods use neural network architectures. Convolutional Neural Networks (CNNs) eliminate the need for manual feature extraction in traditional machine learning methods, so you do not have to define the features used to classify images. CNNs work by extracting features directly from images. Relevant features are not pre-trained; they are learned while working on a network image collection. This automatic feature extraction makes deep learning models extremely accurate for computer vision tasks such as object classification. There are numerous clinical and technical studies in the literature for seizure detection [3, 4, 5]. In their study, Albayrak et al. aimed to detect the presence of epileptic activity in

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electroencephalogram (EEG) data and lay the foundation for software to aid in automatic diagnosis, with further software to be developed in the next phases [6]. Yıldırım et al. proposed a deep transfer learning approach for automatic diagnosis of diabetes mellitus (DM) using heart rate signals (HR) obtained from electrocardiogram (ECG) data. Signal analysis was performed in both 1D and 2D. In the study, the highest accuracy of 97.62% and sensitivity of 100% was achieved by using pre-trained deep learning methods [7]. In their study, Stevenson et al. determined the nonstationary periodic properties of electroencephalographic seizures by fitting their correlation estimates with time in both the time and time-frequency domains. It was integrated into a seizure detection algorithm (SDA) based on a support vector machine to detect episodes of seizures and unresponsiveness. The dataset used is from the Helsinki University Central Hospital. This dataset includes EEG recordings from neonatal and visual interpretation of the EEG by the specialist. The data were recorded from 79 neonatal using the NicoletOne EEG system. The recommended measures have high discriminatory power in detecting seizures [8]. Tuncer et al. a feature selection-based decision support system was developed to detect neonatal seizures using EEG signals. The highest performance was obtained by the C4-P4 channel with 98.8% [9]. Ullah et al. proposed a system for automatic diagnosis of epilepsy consisting of a collection of pyramidal one-dimensional convolutional neural networks. The proposed P-1D-CNN model is not only suitable for the detection of epilepsy, but can also be used in the development of robust expert systems for other similar diseases. In the study, 99% accuracy was achieved in almost all cases [10]. Yıldırım et al. proposed a new deep one-dimensional convolutional neural network (1D CNN) for automatic detection of normal and abnormal EEG signals. The developed model resulted in an error rate of 20.66% in classifying normal and abnormal EEG signals [11]. Hongshuai et al. designed a deep multiscale fusion CNN model based on an extended fusion kernel to classify these three states: normal, preictal, and ictal. The CNN model achieved 98.67% accuracy, 99% sensitivity, and 98% specificity [12]. In their study, Acharya et al. applied a 13-layer deep convolutional neural network (CNN) algorithm to detect the classes normal, preictal, and ictal. The dataset is from the University of Bonn, Germany. The data consists of continuous multichannel EEG recordings obtained from 5 patients. The proposed technique provided 88.67%, 90% and 95% accuracy, specificity and sensitivity, respectively [13]. Romero et al. showed that functional near infrared spectroscopy (fNIRS) can be used to predict epileptic seizures. The proposed method showed better results than EEG-based methods in detecting epileptic seizures. The study found that the deep learning application is suitable for this problem [14]. O'Shea et al. proposed a fully convolutional based model for neonatal seizure detection from raw EEG. The model showed better results than the latest technology without feature engineering [15]. Ryu et al. developed a new seizure detection algorithm using machine learning for single channel EEG [16].

This work is a continuation of our earlier work. Therefore, the results of other channels were not included in the study and the best results were obtained with the C4-P4 channel [9]. Therefore, Deep Learning methods were used only in the C4-P4 channel to detect epileptic seizures in Neonatal. For better performance, classification of the dataset was performed in both 1D and 2D using AlexNet, GoogleNet, ResNet, VggNet, pre-trained Deep Learning architectures. The EEG signal data was converted into spectrogram images for the pre-trained Deep Learning architectures. In this way, both higher classification accuracy and pre-trained Deep Learning architectures were trained with one dataset (40 normals and 40 patients).

1.1 Novelties and Contributions

In this article, pre-trained models using EEG signals are used to detect seizures in neonates. Additional studies were added to the literature. However, the application of the proposed method to the dataset used was not found.

Novelties;

-The use of spectrogram images obtained from EEG signals to detect seizures in neonatal is the most important innovation.

- Seizure detection was performed using the C4-P4 channel, which provided the highest accuracy value, rather than using all EEG channels.

Contributions of this study;

-Although manual feature extraction is effective, the use of CNN models provides high accuracy when evaluating complex signals such as EEG.

- Using spectrogram images from EEG signals is a simple and effective transformation. By using spectrogram images, higher accuracy has been

achieved compared to classification of 1D signals.
- The recommended approach to detect neonatal seizures is an alternative method that helps physicians.

2. Material and Method

Two different datasets were used for the study. The first dataset is from the NICU (Neonatal Intensive Care Unit) of the Finnish Children's Hospital, the central hospital of the University of Helsinki. The data consists of 79 full term neonatal. The sampling frequency of the data is 256 Hz and their average age is 3 days. The EEG recordings were evaluated by 3 experts and it was unanimously decided that 40 patients had seizures and 22 patients did not.

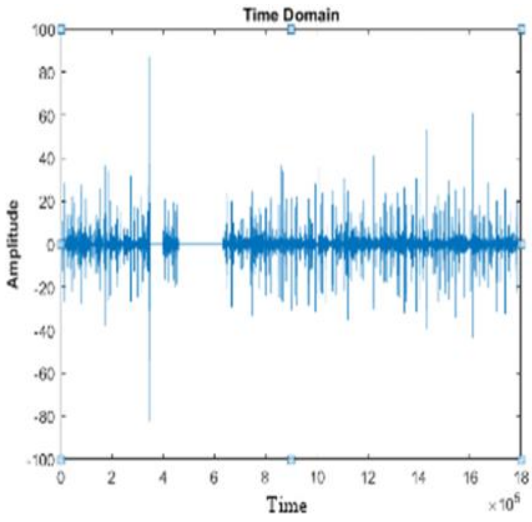

Figure 1. 1D EEG signal image

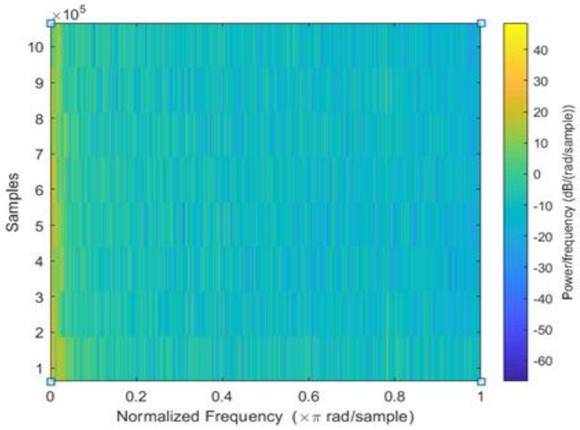

Figure 2. 2D EEG signal image

The second data set consists of data recorded during sleep hours of 18 neonatal without seizures, randomly selected from 100 records in 10 age groups. The data were recorded at the University of Jena in Germany as part of the project on automated EEG assessment of neonatal brain development. In total, the dataset includes 40 normal and 40 patient neonatal data. Figure 1 and Figure 2 show 1D and 2D signal images, respectively. The size of the images is 524 x 410 on average.

Classification is a data mining function that assigns features in a collection to specific categories or classes. The purpose of classification is to accurately predict the target class for each sample in the data. In this study, a CNN model, one of the most popular Deep Learning methods, was used to classify EEG signals from neonatal. A CNN combines learned features with input data and uses 2D convolutional layers, making this architecture very suitable for processing 2D data such as images. Spectrogram images are used to train and test pre-trained models. In this study, 1-dimensional EEG signal data was transformed into 2-dimensional spectrogram images using the pre-trained deep learning architectures AlexNet, GoogleNet, ResNet50, Vgg16 and Vgg19 with Short Term Fourier Transform and signal analysis was performed in both 1D and 2D. 70% of the data was used for training and 30% for testing. Figure 3 shows the application steps.

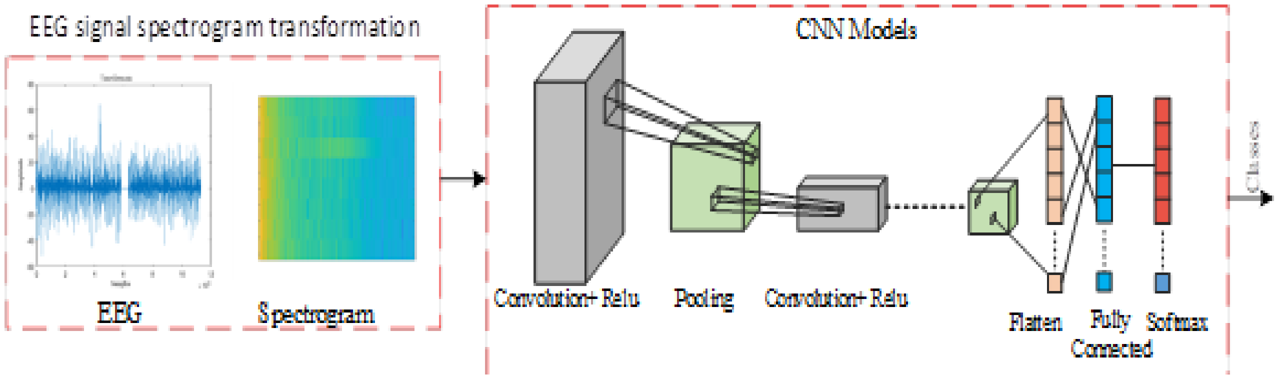

Figure 3. Application steps

2.1. 1D & 2D CNN Model

A pre-trained CNN model was used to classify EEG signals. 1-dimensional images of EEG signal data were obtained and trained and tested after introducing them into pre-trained Deep Learning architectures (AlexNet, GoogleNet, ResNet, VggNet). Figure 4 shows 1D signal images of a neonatal with and without seizures, respectively.

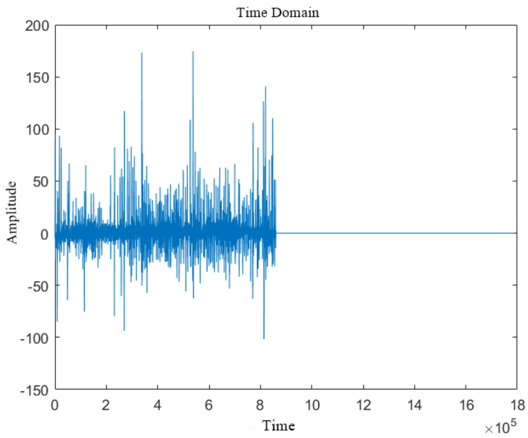

Figure 4.a) Sample 1D C4-P4 signal of a seizure neonates

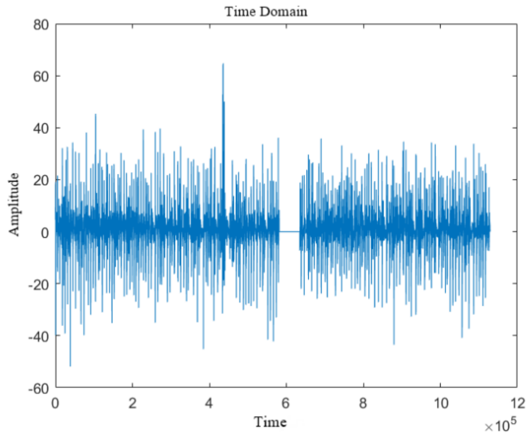

Figure 4.b) 1D C4-P4 signal of a seizure without neonates

EEG signals were converted into images that can be processed with pre-trained 2D CNN models to improve classification performance. Popular pre-trained models such as AlexNet, VggNet, GoogleNet and ResNet50 were trained and tested on this image data. Therefore, the short-time Fourier transform was applied to 1D EEG signals to obtain 2D images with visual representations of frequency spectrograms. When visually viewing the spectrogram images, it is difficult to distinguish between neonatal with and without seizures.

Deep learning can achieve the best recognition performance by extracting abstract features from these spectrogram images. Figure 5 shows spectrogram images of C4-P4 signals from a neonatal with and without seizures, respectively.

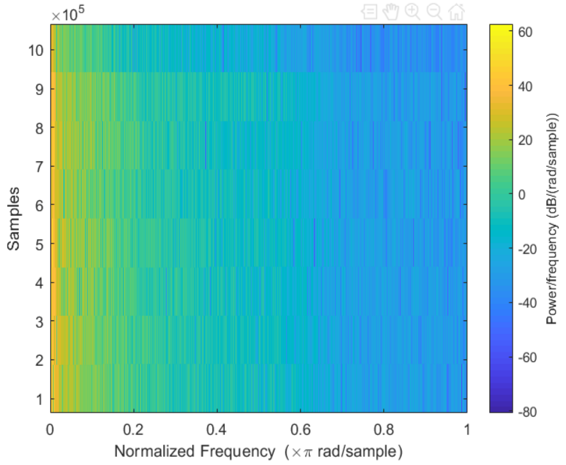

Figure 5.a) Spectrogram İmage of a seizure without neonates

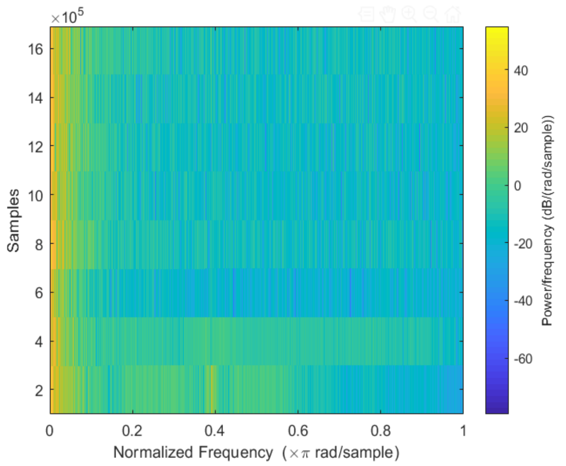

Figure 5.b) Spectrogram Image of a Seizure Neonates

2.2. Convolutional Neural Networks

The Convolutional Neural Network (CNN), a multilayer feedforward artificial neural network, is particularly used for image analysis. Alexnet is a deep learning architecture developed by Krizhevsky et al. and consists of 25 layers. It includes an input layer, five convolutional layers, three pooling layers, two dilution layers, three fully linked layers, seven ReLU layers, two normalization layers, and one classification layer. The input layer image is 227x227x3. ReLU is used as the activation function and maximum pooling is used in the pooling layer. The architecture of AlexNet is shown in Figure 6 [17].

A CNN combines learned features with input data and uses 2D convolutional layers, making this architecture well suited for processing

2D data such as images. CNNs eliminate the need for manual feature extraction, so you do not have to define features that are used to classify images. CNN works by extracting features directly from images. Associated features are not trained in advance; the network learns as it works with a collection of images. This automatic feature extraction makes Deep Learning models extremely sensitive to computer vision tasks such as object classification.

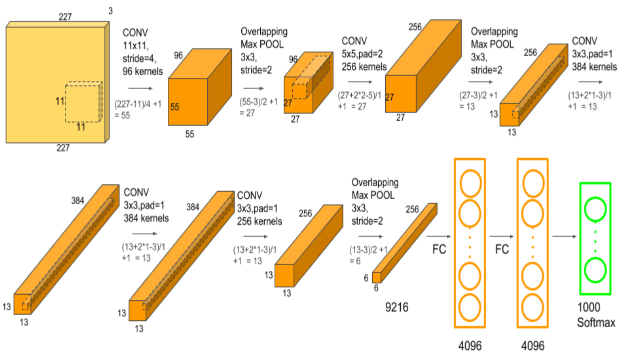

Figure 6. AlexNet architecture [18]

GoogleNet was the winner of the ILSVRC competition in 2014. GoogleNet (Inception) has a complex structure [19]. It achieved high performance with a low error rate of 5.7%. It has a depth of 22 layers and GoogleNet has a structure of 144 layers. By filtering in different dimensions with the inception module, it has revealed a formation that is different from the previously appeared Deep Learning architectures. To optimize the quality, the architectural decisions are based on the Hebbian principle and the intuition of multiscale processing.

It is a model developed by the Visual Geometry Group (VGG) at the College of Oxford. In Vgg16, smaller filters (3x3) were used in the convolutional layers instead of large filters (11x11, 9x9) as in AlexNet. VGG has 13 convolutional layers and 3 fully bound layers. There are 5 max-pooling layers with 2x2 dimensions and a softmax layer in the last layer. Vgg66, which uses ReLu as the activation function, contains 138 million parameters, while Vgg19 contains about 144 million parameters. It has 16 convulsive layers and 3 fully linked layers [20].

ResNet50 to solve the problem of training difficulty with increasing depth of network structure in CNNs. Instead of mapping the nonlinear function F(x) in normal CNNs, it adds the input value (x) to the function F(x) as an arithmetic function (F(x) + x) by linking from the input (x) to the output and bypassing certain layers. In this way, the training process is simplified. The Resnet50 model has a 50-layer structure [21].

2.3 Performance Evaluation

In the literature, many methods are used to evaluate the performance of the models. Therefore, the classification performances of the models in the study were evaluated using the indicators of sensitivity, specificity and AUC. Complexity Matrix was used in the calculation of the indicators. The calculation of the performance evaluation criteria is shown in Table 1 [22].

Table 1. Performance evaluation parameters

		Predicted Class		
		A ES (+)	A ES (-)	
Actual Class	A ES (+)	True Positive (TP)	False Negative (FN) Type II Error	Sensitivity $\frac{TP}{TP+FN}$
	A ES (-)	False Positive (FP) Type I Error	True Negative (TN)	Specificity $\frac{TN}{TN+FP}$
		Precision $\frac{TP}{TP+FP}$	F-measure $\frac{2TP}{2TP+FN+FP}$	Accuracy $\frac{TP+TN}{TP+TN+FP+FN}$

3. Results and Discussion

In this study, signal analysis was performed in both 1D and 2D. After training the 1D-CNN model, the best classification accuracy was achieved by the VggNet architecture with 91.67%, while the lowest classification accuracy was achieved by the GoogleNet architecture with 75%. Table 2 shows the classification performance of the different Deep Learning architectures according to the 1D-CNN model.

Table 2. 1D classification performance of deep learning methods

	TPR	SPC	P	FNR	F1	ACC
AlexNet	90.00 %	78.57 %	75.00 %	10.00 %	81.82 %	83.33 %
Google Net	80.00 %	71.43 %	66.67 %	20.00 %	72.73 %	75.00 %
Vgg16	91.67 %	91.67 %	91.67 %	8.33 %	91.67 %	91.67 %
Vgg19	100.00 %	85.71 %	83.33 %	0.00 %	90.91 %	91.67 %
ResNet 50	78.57 %	90.00 %	91.67 %	21.43 %	84.62 %	83.33 %

Figure 7 and Figure 8 show the graphs of training and testing accuracy and loss rate of AlexNet architecture according to 1D CNN classification. The CNN model completed the training process in three periods with no overcompatibility problems for one-dimensional EEG signals.

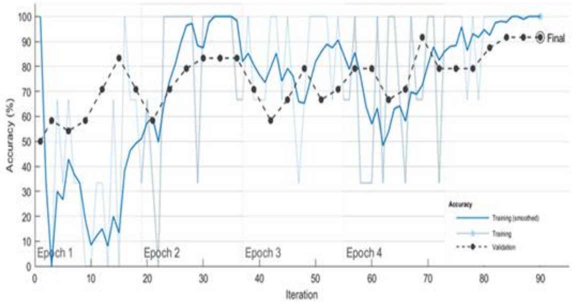

Figure 7. Training accuracy change of 1D CNN Model

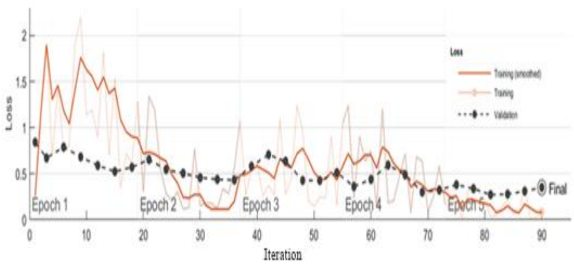

Figure 8. Training loss change of 1D CNN Model

After training, the best classification accuracy of the 2D CNN model from pre-trained deep learning architectures was achieved by the AlexNet and ResNet architectures with 95.83%, while the lowest performance was achieved by the GoogleNet architecture with 83.33%. Table 3 shows the classification performance of different deep learning architectures according to 2D CNN model.

Table 3. 2D classification performance of deep learning methods

	TPR	SPC	P	FNR	F1	ACC
AlexNet	100.00%	92.31%	91.67%	0.00%	95.65%	95.83%
GoogleNet	78.57%	90.00%	91.67%	21.43%	84.62%	83.33%
Vgg16	100.00%	85.71%	83.33%	0.00%	90.91%	91.67%
Vgg19	85.71%	100.00%	100.00%	14.29%	92.31%	91.67%
ResNet50	92.31%	100.00%	100.00%	7.69%	96.00%	95.83%

Figure 9 and Figure 10 show the graphs of training and testing accuracy and loss rate of the AlexNet architecture according to the 2D-CNN classification. The training process was completed in five periods

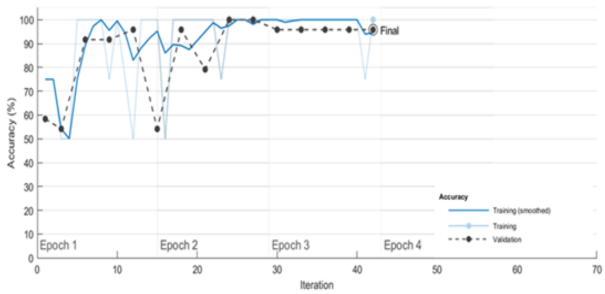

Figure 9. Training accuracy change of 2D CNN Model

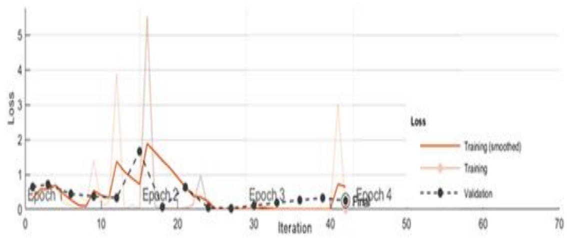

Figure 10. Training loss change of 2D CNN Model

In this study, using CNN, one of the Deep Learning methods, a single channel classification (on the C4-P4 channel) was performed from the EEG signals of neonatal with and without seizures. By converting 1-dimensional signal images into 2-dimensional signal images, signal analysis was performed in both 1D and 2D, and then their performance was compared. The study compared the performance of the models in classification using pre-trained deep learning architectures such as AlexNet, GoogleNet, Vgg16, Vgg19, ResNet50.

Since feature extraction is a process that directly affects classification performance, attempts are made to obtain better results by applying many CNN models to EEG signals. For the 1D CNN model, the highest classification accuracy of the pre-trained deep learning architectures was achieved by the Vgg16 and Vgg19 architectures with 91.67%, while the lowest classification accuracy was achieved by the GoogleNet architecture with 75%. (Table2). For the 2D CNN model, the highest classification accuracy of the pre-trained deep learning architectures was achieved by the ResNet50 architecture with AlexNet with 95.83%, while the lowest classification accuracy was achieved by the GoogleNet architecture with 83.33% (Table 3). The Vgg16 and Vgg19 architectures provided similar classification performance in both models. The GoogleNet architecture was found to be more unsuccessful in both models compared to other Deep Learning architectures.

All results showed that 2D signal analysis provides better performance than 1D signal analysis. The study showed that instead of using the features of all EEG channels, each channel was more successful in classification according to its individual features. The performance of all channels was evaluated and it was concluded that the best differentiation was obtained with the C4-P4 channel. This shows that the C4-P4 channel can represent the problem well. So the classification was done with less number of channels instead of all channels. The result obtained makes the study valuable in terms of reducing the cost and reducing the amount of data (Table 2).

Alexnet is a shallower model compared to ResNet and Densenet. When examining the results, one concludes that increasing the model depth does not always lead to a better result. In this case, we can assume that the Vgg19 model has a better feature vector than ResNet for the data used. (The loss function is the function that measures the error rate of the designed model as well as its performance. The last layer of deep networks is the layer where the loss function is defined). In Table 4, different studies using the same dataset were examined and compared.

Table 4. Studies on the same data set

Reference	Year	Method	Result
[8]	2019	In this study, a support vector machine-based seizure detection algorithm was used to detect periods of seizures and unresponsiveness.	**SVM=%95,5**
[9]	2020	In this study, a feature selection-based decision support system was developed to detect neonatal seizures based on EEG signals. The performance of all EEG channels and feature selection algorithms were tested.	**KNN=%98,8**
[16]	2020	In this study, four different machine learning-based seizure detection algorithms are compared, with the cosine K nearest neighbour algorithm showing the greatest potential for suitable clinical application for neonatal seizure detection.	**ROC = %91**

The advantages of the method are as follows:
-CNN models have been used to detect seizures in neonatal. The method is simple and useful.

-The C4-P4 channel, one of the EEG signals, has been used to detect seizures in neonatal.
-Classification results obtained by obtaining spectrograms of the EEG signals have higher accuracy than classification performed with raw EEG signals (1D).
-Developers and researchers can easily apply the proposed method to various problems.

4. Conclusions

In this study, a deep transfer learning-based approach was proposed using normal and spectrogram images from the C4-P4 channel in the EEG signals of neonatal with and without seizures. Signal analysis was performed in both 1D and 2D and then compared. In both approaches, the most popular pre-trained deep learning architectures Alexnet, GoogleNet, Resnet and VggNet were used. In the study, the highest classification accuracy was 91.67% in the 1D CNN model, while it increased to 95.83% in the 2D CNN model. Classification was performed using the data series used in the literature, but for the first time in this study, high performance was achieved by using Deep Learning methods.

Contributions of the authors

All authors contributed equally to the study.

Conflict of Interest Statement

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

The study is complied with research and publication ethics

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