Neurological Disorder Diagnosis through Deep Residual Network-based EEG Signal Analysis

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Abstract—

Quantifying anomalies in brain signals can reveal various brain conditions and pathologies. Most recent studies on neurological disorders diagnosis such as epilepsy and autism spectrum disorder (ASD) based on electroencephalogram (EEG) rely on custom feature extraction techniques. Traditional methods of feature extraction approaches are time-consuming and provide limited accuracy. So, to balance accuracy and efficiency, more ability is required in the choice of such significant features. This study introduces a feature extraction model based on a deep residual network (ResNet) capable of automatically extracting representative features from EEG signal to address this issue. This proposed method consists of three steps: signal preprocessing using a static filtering method, hidden pattern extraction from EEG signals using the ResNet model, and classification using a SoftMax layer. EEG data sets from the UBonn University database and King Abdulaziz University (KAU) are used in this study. The ResNet model's results are evaluated using accuracy, sensitivity, and specificity. In this study, the proposed diagnostic system achieves a classification for 3 classes accuracy of 100% for Epilepsy in offline diagnosis and an accuracy of 95.5% for Autism in a three-class classification.

Keywords— Residual network (ResNet), Electroencephalogram (EEG), Computer-Aided Decision Systems (CADS), Feature extraction.

1. INTRODUCTION

Computer-based systems play a crucial role in the medical domain, encompassing various applications like electronic health records (EHR) and computer-aided diagnosis (CAD) systems. These systems are utilized by medical professionals to assist in diagnosing disorders by automatically analyzing medical images [1] and physiological signals, such as electroencephalography (EEG) signals [2]. Medical diagnosis often requires significant expertise and effort from healthcare practitioners. However, with advancements in signal processing and machine learning techniques, computer-based systems have become increasingly proficient in performing intricate tasks, including EEG signal analysis. These automated processes save time and enhance the overall accuracy of diagnosis on a global scale.

Examining abnormalities in brain signals holds promise for understanding various brain conditions and pathologies. EEG, capable of capturing signals from the human brain, offers significant potential for analyzing brain activity and conditions. While EEG recordings have traditionally been employed as a diagnostic tool for epilepsy [3], recent research has extended their utility to diagnose conditions like autism spectrum disorder (ASD) [4] and Alzheimer's [5], among others. Despite their relatively low spatial resolution, EEG recordings boast advantages such as high temporal resolution, simplicity, cost-effectiveness, and widespread availability.

The conventional diagnostic system utilizing EEG generally comprises three primary phases: preprocessing of EEG signals, extraction of features, and classification. Preprocessing aims to filter out undesired EEG signals. Following this, essential features are derived from the processed EEG signal and then utilized in the subsequent decoding or classification phase. Numerous studies have been conducted to understand and analyze these signals [7], revealing that feature extraction, statistical analysis, classification, and the choice of the best classifier are key steps in the EEG signal diagnosis process [7].

In this work, autism and epilepsy are diagnosed using a deep learning method. As a matter of fact, epilepsy affects around thirty percent of people with autism spectrum condition, according to the American Epilepsy Society. It's unclear, therefore, if there are any obvious similarities between epileptics and autistic people. In this way, we have addressed the difficulties in diagnosing these various neurological conditions. This technique seeks to evaluate our deep learning methodology's applicability to various neurological disorders.

Conversely, multi-neurological disorders exhibit varied biomedical EEG data, frequently demonstrating imbalance and nonstationary, and encompassing specific unusual conditions. So, our proposed model incorporates many hidden layers, trained with extensive sets of labeled EEG data, facilitating direct learning and extracting of significant features. Moreover, the applied deep learning approach contributes to a more cohesive integration of diagnosis and prognosis protocols [8].

In this particular context, we explore using the ResNet model for feature extraction in conjunction with EEG classification techniques to aid in diagnosing epilepsy and autism spectrum disorder (ASD). The primary advantage of using deep learning (DL) methods is their ability to extract features from signals automatically. Through the training process, the network autonomously learns to extract relevant features, thereby enhancing the efficiency and effectiveness of

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supervised learning. ResNet, a specialized form of neural network architecture, proves particularly adept at handling intricate DL tasks and models. ResNet can achieve superior performance within neural network architectures by employing networks with numerous layers, thereby mitigating the "vanishing gradient" problem.

The proposed method is delineated into three complementary phases: signal pre-processing, extraction of hidden patterns from EEG signals, and classification. This research employs the Kaiserwin filtering method to preprocess the raw EEG data. Furthermore, a deep Residual Network is devised to unearth significant features concealed within EEG signals automatically. These extracted deep ResNet features are subsequently utilized as input for the SoftMax classifier. A comprehensive exposition of the methodologies discussed is presented in Section 2, elucidating the rationale behind their inclusion in this study.

2. .MATERIALS AND METHODS

a. *Applied Dataset Description*

This study validates the proposed methods using various EEG datasets, beginning with the initial dataset sourced from the University of UBonn, Germany. This dataset comprises five distinct sets labeled A, B, C, D, and E, each containing 100 single-channel EEG signals with a duration of 23.6 seconds. The EEG signals were digitized at a sampling rate of 173.61 Hz. Sets A and B consist of standard signals obtained from five volunteers in states of eyes opened and closed, respectively. Sets C and D capture EEG signals from the pre-ictal region, recorded respectively from the epileptogenic and left areas of the hippocampus. Set E encompasses EEG signals associated with the ictal region. Datasets A and B employ the 10–20 scalp EEG standard for recording signals, while datasets C and D utilize intracranial EEG recorded with depth electrodes. Set E utilizes both depth and strip electrodes [9].

The second dataset was provided by King Abdulaziz University (KAU),[10] Saudi Arabia. It comprises recordings from ten normal subjects (males aged 9–16 years) and nine autistic subjects (six males and three females aged 10–16 years). The EEG data were collected in a relaxed state, using a 16-channel EEG system at a sampling rate of 256 Hz.

b. *Methodology*

Feature extraction is crucial in deep learning (DL) models for automatically extracting compelling features, which is beneficial for large volumes of data. The proposed DL model consists of three stages, as illustrated in Figure 1: (1) signal preprocessing, (2) feature extraction, and (3) classification.

The first stage involves signal preprocessing, where noise in EEG signals is eliminated using a static filtering method. The second stage includes feature extraction from denoised signals using the deep Residual Network model to enable efficient extraction.

The final stage, which involves feeding the retrieved deep features into a SoftMax classifier, completes the classification operation. Below is a thorough explanation of each of the three stages:

c. *Preprocessing signal:*

The EEG signals inherently unpredictable and contain many types of artifacts. These disturbances can skew signal analysis, potentially resulting in inaccurate findings [26]. The primary objective of preprocessing is to mitigate or eradicate noise and artifacts from the signals, thereby standardizing the data for effective model development. This research uses a static filter to diminish and eliminate noise in EEG data.

This study employs an IIR filter. These filters demonstrate considerable effectiveness, delivering comparable amplitude responses with fewer coefficients or reduced sidelobes for an equivalent number of coefficients. We use the Kaiser Window Filter order four; the window length mainly affects the transition band, while the roll-off coefficients (the shape factor) control the size of the passband and stopband ripples. Therefore, by keeping the window length constant, we can adjust the shape factor to achieve the appropriate passband and stopband ripple level [11].

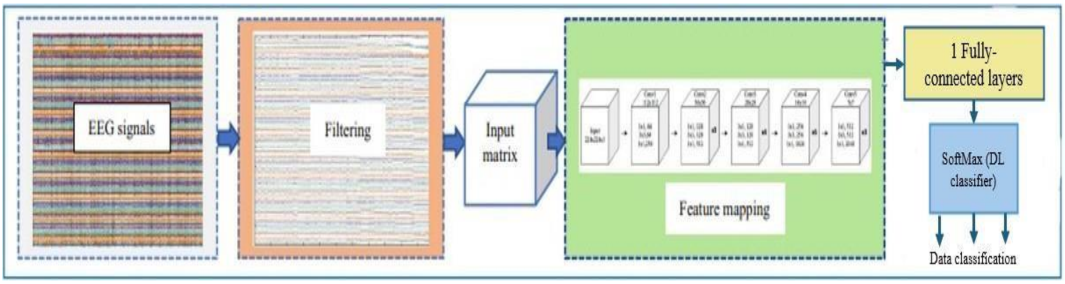

Figure 1. The structure of the deep Residual Network model proposed in this study.

To enhance the outcomes, the dataset undergoes a feature scaling process. The subsequent section delineates various techniques employed for feature scaling, aiming to standardize the data.

The above-mentioned filters have been designed to have a passband region between (8.0-31.0 Hz) [12], exclusively covering the α and β bands of the EEG frequency spectrum, which have been proven to contain patterns associated with a specific neurological disorder [14], [14].

d. Extraction feature by Residual network model:

This section is dedicated to extracting significant features from EEG data in a robust and automated manner, facilitating efficient detection. Feature extraction represents a crucial step in classification tasks Involving the conversion of denoised EEG signals into a concise collection of task-specific data known as features. Traditional manual feature extraction methods involve tedious and unsophisticated selection of features from data. In contrast, DL-based methods automatically extract meaningful features directly from EEG data, yielding better recognition performance than traditional approaches in less time.

In this research, a novel deep ResNet framework is proposed to extract significant features from denoised EEG signals. At the same time, this method has been applied to image recognition [15] [16]. The deep ResNet model's motivation lies in its development as part of extremely deep architectures, demonstrating high accuracy and favorable convergence behavior with increased depth. This model employs advanced residual units and full pre-activation, addressing vanishing/exploding gradient issues through skip layer styles [17], [18].

The deep ResNet elevates network performance through the addition of numerous layers, establishing a structured hierarchy of distinctive features. Its distinctive design guarantees that the feature representation of any deeper unit comprises a fusion of the features from shallower units alongside the cumulative sum of preceding residual responses. This approach notably enhances performance, particularly in ultra-deep networks boasting over 1000 layers, when compared to earlier residual techniques [19]. Essentially, ResNet is founded upon feedforward deep neural networks, integrating diverse operations within each layer to glean insights from preceding layers. Skip connections, also known as shortcuts, are employed to bypass certain layers [15]. The structure includes convolutional layers, rectified linear units (ReLU) layers, batch normalization layers, and skip connections, as illustrated in Figure 2

Figure 2 provides an example of the residual learning module, where 'X' represents the input mapping, and F(X) is the residual function. The figure demonstrates two branches, depicting the input mapping 'X' and the residual function F(X).

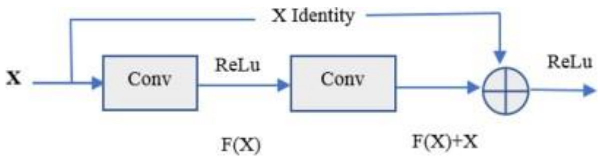

Figure 2. Residual Blocks

When unified, these components undergo a non-linear alteration via the ReLu activation mechanism to constitute the integral residual learning unit. Illustrated in Figure 2, the input is labeled as X, with a shortcut introduced thereafter. Subsequently, the block's output is merged with the input, yielding F(X)+X. Thus, the network's weight parameters are tasked with learning the function F(X). Figure 2 underscores the crucial role of the 'skip connection' in preserving identity mapping, where the previous layer's output is directly added to the subsequent layer without introducing extra parameters [20].

In our proposed model, residual blocks serve as the fundamental units of the entire deep ResNet network, defined as follows [15]:

$$Y = F(X, \{W_i\}) + X \qquad (1)$$

Here, X stands for the input vector, Y represents the output vector of the specified layers, and the function F(X, {Wi})) signifies the residual mapping awaiting acquisition. Equation (1) explicitly states the requirement for the dimensions of X and F to match.

In this paper, we have structured the ResNet model for implementation as outlined in Table 1. This table illustrates the network's configuration and how it is implemented with a substantial number of parameters in the current study. The feature extraction process involves five convolutional layers with various kernels, where the activation function operates on the convoluted results to generate feature maps. The average pooling layer uses the average values from every neuron cluster in the previous layer to compile features from the prior layers. Lastly, fully connected layers are used, and the classification task's SoftMax function receives the outputs from these layers.

This work trained the model using classical backpropagation (BP) [14] with a batch 32. Backpropagation facilitates the computation of the loss function gradient for updating the network weights. The model was tested for 150 training epochs, with validation performed after each epoch using 10% of the training data to prevent overfitting of the model.

The residual network architecture is presented in Table 1, where the hyperparameters are set as follows: we fixed a learning rate of 10^{-3}, MSE as the loss function, and a considerable batch of 32. As for the optimizer, "Adam Optimizer" has been chosen as one of the widely used optimizers in DL models.

Table 1. Explanatory table of the proposed ResNet model used in this study.

Block number	**Layers**
Conv1	Conv1d_0 BatchNormalization_0 Activation_0
Conv2_x	Conv1d_1 BatchNormalization_1 Activation_1 Conv1d_2 BatchNormalization_2 Conv1d_3 Activation_2 BatchNormalization_3
Conv3_x	Conv1d_4 BatchNormalization _4 Activation_3 Conv1d_5 BatchNormalization _5 Conv1d_6 Activation_4 BatchNormalization _6
Conv4_x	Conv1d_7 BatchNormalization _7 Activation_5 Conv1d_8 BatchNormalization _8 Conv1d_9 Activation_6 BatchNormalization _9
Output	Global_average_pooling1d_1 Dense Dense

3. RESULTS AND DISCUSSIONS

The proposed EEG signal chain integrating dynamic filtering and ResNet has demonstrated interesting performance in tasks related to images [20]. These networks facilitate the automatic learning of discriminative features from input data, eliminating the need for manual feature extraction. Given their inherent complexity, nonlinearity, and non-stationarity, this characteristic makes the Resnet model particularly well-suited for analyzing EEG signals [22].

In this phase, we assess the effectiveness of the proposed model using established metrics such as accuracy, sensitivity, specificity, precision (positive predictive value), false positive rate, false negative rate and F1 score [23].

The comprehensive classification outcomes for the extracted deep features utilizing the SoftMax classifier of the deep ResNet model (DL classifier) are displayed in Table 2. This table showcases the overall performance in terms of accuracy, sensitivity, specificity, precision, and F1- score. The findings from Table 3 demonstrate that the proposed Residual Network features yield superior performance compared to previous studies.

Table 2. Evaluation Results of the Proposed Technique

	Data of Bonn	Data of KAU
Accuracy	99.99%	99.52%
Precision	99.38%	95.60%
Sensitivity	97.41%	90.26%
Specificity	98.41%	92.66%
F1-score	97.63%	89.01%

These results highlight the potential of our model in the automated classification of EEG signals. The model's performance is assessed and displayed using metrics presented in Table 2. Figure 3 illustrates the convergence of the loss function towards optimal weights, with a final loss of 10-6 for the categorical cross-entropy function, confirming the effectiveness of the proposed method.

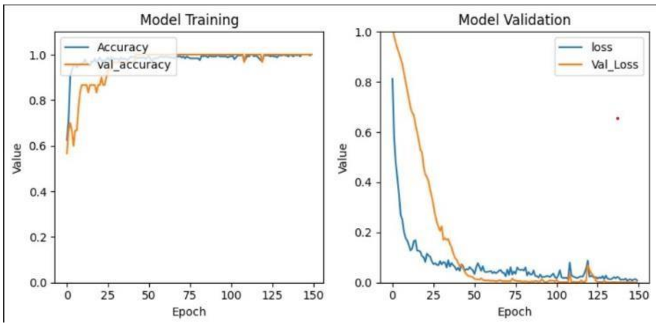

Figure 3. Evaluation.

Table 3 showcases the performance evaluation of the proposed model in comparison to existing methods.

Table 3. Results comparison with similar works

Author	DL Network	Dataset	Accu.
D.Taha [24]	ResNet	TUH (Temple University Hospital)	96.49%
H. Abbasi [22]	Resnet	--	98.7%
S. Siuly [25]	Resnet	database from Kaggle	99.23%
Our work	static filter + Residual Network	Bonn	100%
		KSU	99.52%

4. Conclusion

This research introduces a novel deep-learning framework utilizing a Residual Network model to enhance the extraction of robust feature representations from EEG signals. The objective is to automatically differentiate individuals with EEG signals, automatically enhancing classification accuracy. The convolutional layers, residual connections, average pooling, and fully connected layers are all smoothly combined in the suggested network architecture. This integration enhances convergence efficiency and elevates overall performance. This model can automatically extract compelling features, which is particularly beneficial for analyzing large-scale datasets. This work involves extracting deep features through the Residual Network model and employing them as input to the SoftMax function for classification purposes. The performance of the proposed method was evaluated with two datasets, first from university of UBonn and the second from KSU.

The effectiveness of the proposed technique for extracting features from EEG signals has been demonstrated in this work. Consequently, the diagnostic system proposed in this study achieves an average accuracy of 100% for epilepsy in offline diagnosis, utilizing the data of UBonn. Moreover, when applied to autism diagnosis with the KAU dataset, the same system yields an average accuracy of 99.52%.

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