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One-Dimensional EEG Artifact Removal Network Based on Convolutional Neural Networks

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Abstract. *The electroencephalogram (EEG) serves as a significant tool in the realms of clinical medicine, cerebral investigation, and neurological disorders research. However, the EEG records we obtain are often easily contaminated by various artifacts, which can blur or distort the underlying EEG signals and make data interpretation difficult. Generally speaking, removing EEG artifacts is considered an essential step in brain signal analysis. Therefore, removing artifacts is crucial for obtaining accurate and reliable EEG signals for subsequent analysis. Recently, deep learning techniques have found widespread application across various domains for denoising tasks, including image denoising and EEG denoising. Many advanced algorithms have been developed in image denoising, which has achieved good results in enhancing low-quality images. Moreover, it has shown superior performance in EEG denoising. In contrast, few people have devoted themselves to studying EEG denoising, and existing convolutional neural network EEG denoising methods still have problems of overfitting and poor denoising effect in Electromyograph(EMG) and ElectroOculoGram(EOG) artifact removal. Therefore, this paper proposes a method called DWINet (De-artifacting with Image-based Network for EEG Signals) based on an image dehazing network DRHNet for removing artifacts from EEG signals. Specifically, our approach DWINet, addresses the de-artifacting issue in EEG signals by converting it as an image dehazing problem and utilizes the image dehazing capability of DRHNet to enhance the denoising performance of EEG signals. Experimental results demonstrate that the proposed method outperforms the compared algorithms in removing the ocular artifact in EEG signals and exhibits higher accuracy and robustness.*
Keywords:Electroencephalogram (EEG) artifact removal, CNN, end-to-end, deep learning

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1. **Introduction.** An electroencephalogram (EEG) is a technique used to record the electrical responses of cerebral neurons in the cortical region of the brain. Typically, it involves the insertion of electrodes into the cranium of the patient to gather EEG data [1]. Because EEG signals can be employed to explore cerebral functions, such as cognitive processes, emotions, and behaviours, it has been extensively utilized in neuroscience research. This information can help detect potential problems associated with brain disorders. An EEG tracks and records brain wave patterns, which can show abnormal spikes in epilepsy or slow waves in lesions. An EEG is useful for diagnosing and monitoring conditions such as seizures, tumors, stroke, brain injury, and sleep disorders. Nevertheless, while capturing neural activity, electroencephalograms are susceptible to interference from extraneous noise or artifacts, including eye artifacts [2], muscle artifacts [3, 4], cardiac artifacts [5], and non-physiological noise [6, 7]. These noises and artifacts can affect the accuracy of EEG signal measurements, leading to biased research results. Using EEG signal denoising techniques can help eliminate these effects, thereby improving measurement accuracy, which can foster the progress of neuroscientific research and clinical diagnostics. However, the fluctuations of artifacts are very similar to those of the original EEG signals [8], making EEG artifact removal a highly challenging task.

In EEG signal denoising, the most prevalent method is artifact removal, which is capable of recognising and eliminating artifacts from the signal while preserving the original signal's neurological characteristics and phenomena [9, 10]. Generally, there are two main implementation methods for artifact removal algorithms: One is based on regression and filtering methods, and the other is through the use of existing EEG denoising methods, such as autoencoders [11], generative adversarial networks [12], regression-based methods [13], Blind Source Separation (BSS) methods [14], wavelet transforms [15], and methods that separate or decompose noise data into other domains to achieve artifact removal [16], among others. In addition, EEG signals are typically feeble, in the range of 20 mV, and thus require enhancement. However, the enhancement of signals also enhances artifacts, highlighting the necessity of removing artifacts during EEG signal analysis. The artifact removal stage is crucial for eliminating artifacts in the original EEG signal while preserving the brain's neural activity [17]. Existing methods for removing artifacts from EEG signals have several limitations. Numerous artifact removal techniques rely on the number of EEG channels or electrodes used for data capture, which is a significant disadvantage. Consequently, algorithms that exhibit high performance on multi-channel EEG data may not demonstrate the same effectiveness when applied to single-channel EEG recordings or could be because of the nonlinearities of the noise being added in the EEG signal [18].

In this work, to tackle the challenges associated with inadequate artifact removal and the limited techniques available for one-dimensional EEG signals, we explore the feasibility of image-denoising networks in EEG signal artifact removal by using the convolutional neural network image de-rain and de-fog network DRHNet as an example. Convolutional neural networks are among the most commonly used methods for image denoising. They have a high representation ability and can automatically learn complex image features to reduce noise. While the model of image denoising is usually based on spatial or frequency domain features of images, the model of EEG signal denoising is usually based on temporal or frequency domain features of EEG signals. Therefore, there are significant differences between EEG signal and image denoising, and they cannot be regarded as the same or similar problems. Image denoising models based on deep learning may have the following advantages: 1) They can automatically learn valuable feature representations in EEG signals without manual feature extractors. 2) They can adapt to different types and degrees of EEG signal noise and preserve important but weak information in EEG signals. 3) They can use a large amount of existing or synthesized EEG signal data with different types and degrees of noise. Specifically, we first reduce the two-dimensional network to one dimension and then change the original Torch version to the Tensorflow version. We also introduce the BN layer and fully connected layer and adjust the network structure appropriately to improve the ability of the network to capture complex relationships between input and output signals.

The main contributions of this paper are summarized as follows:

1) We unify the essence of image denoising and EEG denoising as the same underlying problem and propose a novel approach for EEG denoising based on an image dehazing network. This approach solves the problems of overfitting and poor denoising in traditional neural networks and promotes the development of the previously limited EEG denoising field, creating more possibilities for future research.

2) By applying a two-dimensional image denoising network to the one-dimensional EEG signal denoising field, we have provided a novel approach for adapting two-dimensional image networks to one-dimensional EEG signal data and features. This method offers a valuable insight into borrowing algorithms from similar tasks in different dimensions, providing a new strategy for future research.

3) We demonstrate the feasibility and effectiveness of our proposed model through qualitative and quantitative comparative experiments. Compared with the traditional convolutional neural networks, When it comes to reducing ocular artifacts from EEG signals, the outcomes obtained by our model are more effective.

2. Related Work.

2.1. Existing EEG Denoising Techniques.

Independent Component Analysis (ICA) [19] is a frequently employed technique for removing anomalies from Electroencephalogram (EEG) signals. The basic principle of ICA is to decompose the mixed EEG signal into independent components corresponding to different sources, including brain activity and noise. The noise and artifact components can be identified and removed, while the brain-related components can be preserved. By identifying and removing artifact-related components, ICA can effectively remove many artifacts from EEG signals. Wavelet-based Denoising [20] is a technique that divides EEG signals into subbands of varying frequencies by employing wavelet transformation as the key transformational tool. The artifacts can be removed by applying threshold processing to the subbands' coefficients. It has been proven effective in removing various types of noise and artifacts, including baseline drift and high-frequency noise.

In deep learning, Convolutional Neural Networks (CNNs) [21] and Recurrent Neural Networks (RNNs) [21] can learn the complex features of EEG signals and adaptively remove artifacts. However, methods such as ICA may require a large number of computing resources and may be sensitive to the choice of initial conditions, making it challenging to effectively separate artifacts from EEG signals. Similarly, wavelet-based methods are sensitive to changes in signal amplitude and frequency, which makes it difficult to remove some types of artifacts and can lead to significant distortion of the signal. Overall, existing techniques for removing artifacts from EEG signals have some limitations, and there is still a long way to go in the field of EEG artifact removal [22].

2.2. Convolutional Neural Network-based Denoising Techniques.

CNN is an essential part of deep learning and has gained widespread interest in the past few years [23]. Deep learning techniques have gained extensive utilization in the domain of EEG denoising, offering performance comparable to traditional methods. Convolutional networks are commonly used in image processing, yet their effectiveness extends beyond this domain. An illustrative example is their successful application in text classification within the field of natural language processing (NLP) [24, 25], with performance comparable to RNN-based networks. Compared with Conventional methods, CNNs are superior not only in terms of precision but also rapidity. In addition, CNNs can automatically extract and learn the most advantageous features from unprocessed signals, enabling adaptive design. Importantly, CNNs can effectively exploit the spatiotemporal structure of the EEG signals that they receive as input while having advantages such as weight sharing and deformation robustness [26]. In practical applications, an autoencoder structure can be used to train the CNN, that is, designing a network to map the noisy signal to the original signal. The trained network can learn the rules for removing noise and can be used for actual signal denoising. However, this method also has some drawbacks, such as the number of CNN hidden layers increases but the change of individual hidden layer re-temporal order is not considered. Different CNNs have different effects [21], and the CNN introduced in this paper is also a network that differs from traditional CNNs.

2.3. **DRHNet.** As deep learning techniques continue to evolve, deep learning models are able to process large amounts of data, extract useful information from it, and perform with surprising accuracy in a variety of tasks. For example, Zhang et al. proposed A learning vector quantized neural network based on quantum genetic algorithm optimization can effectively predict short-term traffic changes in urban transportation networks [27]. Zhang et al. proposed a motion classification and recognition algorithm based on linear discriminant and support vector machine (SVM) is proposed, which effectively solves the nonlinear problem, expands the sample variance, and reduces the dimensional operation efficiency of the vector space [28]. Ma et al. proposed a new deep transfer learning architecture, combining convolutional neural networks (CNN) and sparse coding, for false positive reduction in lymph node detection [29]. The DRHNet [30] is a deep learning-based image dehazing algorithm that uses Convolutional Neural Networks (CNN) and Generative Adversarial Networks (GAN) to estimate the atmospheric light and transmission matrix and restore a clear image. The initial objective of DRHNet was to understand the residual between hazy and haze-free images accurately. First, a module for context-aware extraction of features was proposed for gathering relevant information and incorporating it into maps of features. The proposed transformation module was then used to derive high-level characteristics decoded using a deblurring decoder to calculate the residual image [30].

Since the residual between blurry and haze-free images are primarily negative in most areas, the haze-free image can be recovered by taking the blurry image and subtracting the learned map of harmful residuals. The dual-branch network structure consisting of CNNs and GANs handles different degrees of haze, and the final output is synthesized using a fusion module. The GAN branch is used to enhance the image quality, consisting of a generator and a discriminator. The generator component of a GAN learns to create new samples by taking random noise as input and transforming it into data that resembles the training examples. It learns to generate realistic images by minimizing the difference between its generated images and the real images from the training dataset. The discriminator component, on the other hand, acts as a binary classifier. It learns to distinguish between the real images from the training dataset and the generated images from the generator. DRHNet made a context-aware feature extraction module to collect information about the context better and used the new activation function RPReLU to speed up convergence. Therefore, the network achieves good results in image dehazing and deraining. Special attention was paid to contextual information and residual learning, which can also be applied to EEG denoising tasks.

The structure of DRHNet can provide helpful ideas and inspirations for EEG artifact removal tasks, especially in the following areas:

Feature extraction: Feature extraction is a data dimensionality reduction technique that can extract useful information from raw data for subsequent analysis or processing. DRHNet created a context-aware extraction of features module for gathering contextual data. Context awareness is a computer vision technique that can use global information in an image to enhance local information, thereby improving image quality or understanding. In EEG artifact removal tasks, a similar context-aware feature extraction module can help the network extract the spatiotemporal features of EEG signals and better capture the artifacts caused by various sources of interference or signal processing in EEG signals.

Residual learning: Residual learning is a deep learning technique that can improve model performance by avoiding gradient vanishing and overfitting problems by adding skip connections in the network. DRHNet is an image dehazing method based on residual learning, which can restore clear and haze-free images from hazy images. It does this by using residuals to understand the difference between hazy and haze-free images, and the desired dehazing effect is then achieved by removing the negative residual mapping out of the blurred image. Similar to how it may be applied to EEG denoising tasks, residual learning can enable the network successfully capture the difference between the signal and the noise, then subtract it to restore clean EEG signals. However, this does not mean that residual learning can completely eliminate noise or retain all useful information. The signals generated by residual learning may have some errors or distortions, thus requiring further evaluation and validation.

GAN: The deep learning model Generative Adversarial Networks (GAN) consists of a generator and a discriminator [31], which generates new data through adversarial training. It is a GAN-based image super-resolution method that can restore clear and haze-free images from hazy images. Similarly, GAN can also be applied to EEG denoising tasks to help the network generate clearer, more natural, and more realistic EEG signals.

Transformation module: The transformation module is a type of deep learning module that can transform input data from one domain to another, such as from the image domain to the feature domain. DRHNet uses a Convolutional Neural Network (CNN)-based transformation module to extract high-level features of EEG signals, and estimating the residual map by decoding the feature maps. Superior characteristics of EEG signals refer to abstract and semantic information extracted from the raw signal, such as brain wave frequency, brain region activity, cognitive state, and so on. These features can help the network better understand and process EEG signals. Similarly, in EEG denoising tasks, this CNN-based transformation module can be used to extract high-level features of the signal to better remove noise and artifacts.

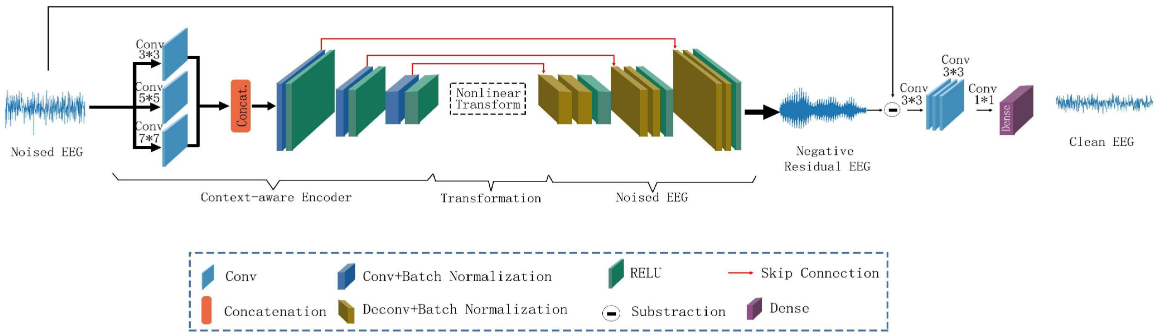

Figure 1. DWINet

3. Methodology.

3.1. Introduction to The Overall Model Design Idea. As illustrated in Figure 1, our network is composed of three components: a context-aware encoder (left), a transformation module (middle), and a denoising decoder (right). In the one-dimensional EEG denoising task, DWINet directly learns the residual between the clean signal and the noisy signal. This approach re-expresses network layers as residual functions, reducing the computational burden [32]. In the EEG denoising task, the clean signal is the output of the layer, and the noisy signal is the input of the layer. DWINet aims to remove noise and interference from EEG signals more effectively by learning residuals and preserving key features of the signal. The model employs multiple feature extraction, attention mechanisms, and regularization techniques to improve denoising performance and generalization ability. The core idea is to improve denoising performance by learning the differences between clean and noisy signals. In this process, DWINet learns how to transform the input signal to make the output signal closer to the clean signal and remove noise and interference. The denoising result generated by DWINet can be represented as the clean signal of EEG signals plus the residual, the generated EEG signals after removing artifacts and noise can be expressed as follows:

$$D = DWINet(C) + C \tag{1}$$

The output of *DWINet*, denoted by *DWINet(C)*, represents the denoised version of the input EEG signal with artifacts C. The resulting artifact-free signal, denoted by D, is obtained by adding the output of DWINet to the original noisy signal C.

The model architecture is based on a combination of convolutional blocks and residual blocks. The model takes EEG data with a length of 512 time points and 1 channel as input. The first layer performs one-dimensional convolution with three different kernel sizes on the input, followed by batch normalization and leaky ReLU activation. Then there are two convolutional layers with 128 and 256 filters, respectively. Next, there are 7 residual blocks, each composed of 3 convolutional layers with different filter sizes, followed by batch normalization and ReLU activation. The output of the last residual block is fed into three one-dimensional transpose convolutional layers, with the number of filters decreasing, followed by batch normalization and a custom activation function, OurRelu. Finally, the output is flattened and passed through a dense layer consisting of 512 neurons and a dropout layer.

BN layer:

In deep learning, the parameters of neural networks are updated through the backpropagation algorithm. However, during the training process, when the network parameters are updated, the distribution of the input data to a certain layer may change, leading to the problem of internal covariate shift. This may cause slow convergence, gradient vanishing, and other issues that can compromise the ability of neural networks to learn complex patterns in the data. This change can seriously affect the network's generalization ability and training speed, making it more difficult to saturate non-linearities. To address this issue, we introduce Batch Normalization(BN) [33].

The BN method normalizes the activation outputs of a layer using a batch normalization layer for each batch. With this approach, BN can avoid the need for special parameter initialization to achieve faster convergence, better generalization ability, and higher stability. Internal covariate shifts refer to changes in the network activation distribution due to changes in the network parameters during training. Internal covariate shifts slow down the training process, require lower learning rates and careful parameter initialization, and make it difficult to train models with saturating nonlinearities [33]. The principle of batch normalization is to normalize the data for each batch, making the input data distribution more stable for each layer in the network and reducing the impact of internal covariate shift. Additionally, batch normalization can also serve as a form of regularization, helping to prevent overfitting of the network. Therefore, to optimize DWINet, we propose using BN layers after the convolutional layers.

Resnet: When constructing a network, there are three crucial factors that significantly influence its performance: the depth of the network, its breadth, and the size of the filters utilized [34]. Traditional CNN enhancement Techniques only emphasized increasing the depth of the network to improve its capability of processing features. However, because of the issues of gradient explosion and degradation, even the deeper the network is, the more difficult it is to get a good result. So we introduced resnet to solve this problem. [32]. Zagoruyko and Komodakis [35]have demonstrated that broad and shallow network models outperform narrow and dense network models, and the effectiveness of a model does not necessarily depend solely on the depth of the network. While depth has its advantages, it must be used judiciously. The addition of a ResNet can solve the problem of gradient explosion and degradation in deep networks through residual connectivity, making the training and optimization of deep networks easier and more efficient.. Furthermore, longer convolutions do not necessarily lead to better results; excessive convolutions can increase training time and reduce effectiveness.

Dense: The fully connected layer is generally found at the end of the CNN network and can be used to handle the feature extraction and classification tasks of the signal during model training [36]. In the case of an end-to-end EEG signal, the input to the model is a noisy signal containing EEG activity and unwanted artifacts, while the output is a clean signal containing only EEG activity. The fully-connected layer in the model learns to extract relevant features from the input signal, such as the frequency and amplitude of the EEG waves while filtering out unwanted artifacts. The full junction layer has a significant impact on EEG artifact removal. The model can effectively capture high-level information about EEG signals and artifacts using the full junction layer to better distinguish and remove artifacts from EEG signals. Compared with traditional EEG artifact removal methods that rely on manual features and signal processing techniques, the fully connected layers enable the network to learn complex representations and capture intricate patterns in the data, making them a fundamental component in various neural network architectures. The absence of the fully connected layer in the original network has a significant impact on its overall performance. Simply replicating the architecture without modifications may lead to poor performance, thus making artifact removal much less effective.

1D-Conv /Deconv+ReLU layer: To address the time-varying nature of EEG, we consider the observation of local characteristics about the convolution kernel and construct a model. In this one-dimensional model, the input features are one-dimensional vectors, and we treat the one-dimensional convolution kernel as a sliding window over a time series to extract short-term features between the sequences to deal with the time-interval features efficiently. The first layer of our 1D model performs a 1D convolution operation on the input EEG raw signal, followed by deconvolution, which increases the length of the signal and extracts deeper feature information. Such processing aims to fully use the temporal information in the EEG data, enabling the model to understand the dynamic changes in EEG activity better.

3.2. **Context-aware Encoding.** The most remarkable feature of the EEG signal is that the fluctuating regions of different zones of the EEG signal are affected by different degrees of noise and artifacts, but each affected time period is extremely near to its neighboring regions. Therefore, it is necessary to use multi-scale convolution to extract features of the blurred images. The kernel sizes of the context-aware encoder components are set to 3×3, 5×5, and 7×7 to aggregate contextual information. EEG signal denoising and artifact removal is an important denoising processing task with high requirements for the validity of EEG information [16]. Parallel convolution can extract features from objects of different sizes by using multiple parallel convolution branches, and this structure can significantly improve the generalization ability of the network [37]. We use context-aware coding to efficiently extract the features of EEG signals using three parallel convolutional extractions of 3, 5, and 7. In the proposed DWINet's first layer, contextual information is aggregated using a module for context-aware feature extraction. The subsequent layer is derived from the preceding layer's convolution with a kernel size of 3 and a step size of 2. In the context-aware encoder component, there are only three convolutional layers.

The EEG signal feature size of the subsequent convolution is half the EEG signal feature size of the preceding convolution.

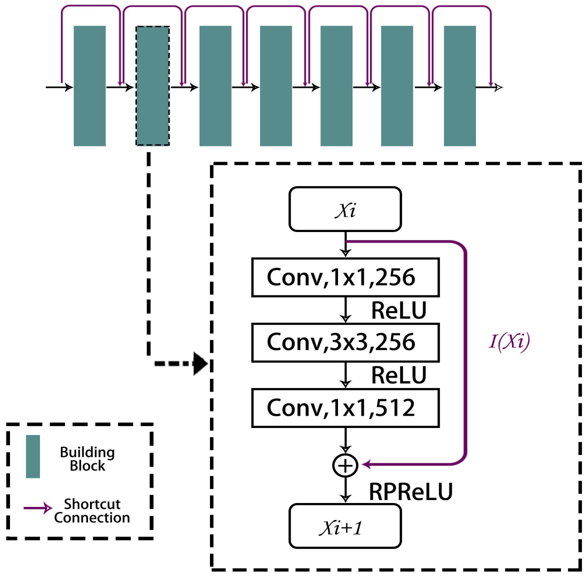

FIGURE 2. Transformation component framework

3.3. **Transformation Component.** The depth of Convolutional Neural Networks (CNN) has an important impact on the denoising performance of electroencephalogram (EEG) signals. In this work, He et al. provide numerous experiments demonstrating that Using bottleneck construction blocks to derive features simplifies optimising deep networks [32]. To further improve the performance of DWINet, this network uses bottleneck building blocks as transformation components to learn residual functions from reference layer inputs instead of learning unreferenced functions. Since the relationship between noisy EEG signals and residuals is nonlinear, the transformation component converts blurry information into high-dimensional residual information to remove noise better. Unlike traditional CNNs, the transformation component of DATNet consists of seven bottleneck building blocks, which can better extract features. DATNet can more effectively remove noise and more accurately analyze EEG signal data through these optimisations.

Removing artifacts from EEG signals presents various challenges, such as the complexity of the methods and the nonlinearity of the noise added to the EEG signals. Due to the nonlinearity of the artifacts, it is hard to extract them without losing the actual neuronal data. In the case of one-dimensional EEG artifact removal, the nonlinearity of the signal needs to be considered. To address this issue, as shown in Figure 2, we propose a transformation component that converts the original artifact-contaminated signal into a high-dimensional residual signal. The transformation component consists of seven bottleneck building blocks [32], each of which performs a mapping that extracts the nonlinear features of the signal. Unlike traditional CNNs, the design of the bottleneck building blocks allows for the extraction of more effective signal features while maintaining a lightweight model. The mapping performed by the bottleneck building blocks is as follows:

$$x_i + 1 = RPReLU(F(x_i, w_i) + I(x_i)) \tag{2}$$

In each bottleneck building block, the input and output are represented as $\hat{x}_i$ and $\hat{x}_i$ +1, respectively. The set of weights and biases associated with block i is denoted by $\hat{w}_i$, while the identity function is denoted by *I(.)*. where activation function (denoted as RPReLU) can be written as:

$$\mathrm{RPReLU}(x) = \begin{cases} ax_i, & \text{if } x > 0 \\ x_i, & \text{otherwise} \end{cases} \tag{3}$$

where the coefficient a is set to 0.1. To balance computational efficiency and the accuracy of the model, we choose to set the size of the bottleneck block to 512. This dimension selection allows us to achieve a favorable trade-off between the complexity of the model and its performance.

3.4. **Noise Decoder.** The main motivation of DWINet is to learn the residual between noise-free one-dimensional EEG signals and noisy one-dimensional EEG signals accurately. To improve the denoising performance of DWINet, the features extracted from the shallow modules are crucial. Therefore, it is essential to attach the noise decoder component's extracted features to the transformation component. In addition, the RELU activation function is also utilised in the noised decoder component, as its primary function is to assess the map of residual using advanced characteristics. Since the structure of DWINet is symmetric, the noise decoder component's parameter settings are identical to those of the context-aware encoder component. The noise decoder finally outputs the noise signal and the signal residual, and the clean signal output can be calculated by adding the residual signal to the original input signal utilising an equation.

3.5. **Loss Function.** We use an end-to-end training approach for the networks, where the contaminated EEG segment is normalized and input directly into the neural networks. The network's output is the EEG segment with noise removed. The network for denoising is trained to learn a nonlinear function f, which maps the polluted EEG $\hat{y}_i$ to the denoised EEG $\tilde{x}_i$, with the objective of removing noise from the input EEG signal:

$$\tilde{x} = f(\hat{y}, \theta) \tag{4}$$

Where $\hat{y} \in R^{1\times T}$ denotes the contaminated EEG segment, $\hat{x} \in R^{1\times T}$ as the output of the neural network (the denoised EEG segment), and the vector θ contains all parameters to be learned.

Using an appropriate loss function is crucial for the performance of many data-driven EEG denoising networks. In this regard, Mean Squared Error (MSE) is a widely used loss function [21, 26]. It quantifies the difference between the network's predicted output and the true output and optimizes the network parameters to minimize this difference. To achieve the learning process of the EEG denoising task, we chose MSE as the loss function LMSE(f). By using gradient descent, our goal is to minimize the error between the denoised signal and the true clean signal. This process involves backpropagation and optimization of the network parameters to improve the performance and generalization ability of the denoising network. In this way, we can better train our model to improve its resistance to complex noise and artifacts, resulting in higher denoising quality and better signal restoration results. Therefore, the loss of mean squared error can be expressed as:

$$LMSE = \frac{1}{N}\sum_{i=1}^{N} \|\tilde{x}_i - \hat{x}_i\| \tag{5}$$

Where N represents the number of time samples in each segment; $\tilde{x}_i$ denotes i^{th} sample of the output of the neural network; $\hat{x}_i$ denotes the i^{th}sample of the ground truth x.

4. **Experiments.**

4.1. **Experimental Specifications.** All experiments are conducted using TensorFlow 2.4.0 on an Ubuntu 20.04 system, with NVIDIA RTX 3080Ti GPU to optimize the training speed. For each task, we compared with the five contrast algorithm methods separately. All the contrast algorithm models were trained for 60 epochs, and our network model was trained for 5 epochs. By default, we train our model with batch size 40 using the Adam optimizer [38], and the parameters were set to $\alpha = 5e - 5$, $\hat{\beta}_1 = 0.5$, and $\hat{\beta}_2 = 0.9$. The default initial learning rate is set to 0.00005.

4.2. **Data Source and Processing.** Data is crucial for an experiment, Chen et al. proposed a new algorithm, UHUOPM, for mining efficient use-occupancy patterns in uncertain databases [39]. Wu et al. proposed a privacy-preserving data mining framework for federated enterprise industrial collaboration activities. The approach protects the privacy of datasets while providing high accuracy compared to traditional data mining techniques [40]. Gan proposed a new anomaly detection framework called DUOS, which is able to discover useful anomalous sequence rules from a set of sequences [41].The dataset we used is from EEGdenoiseNet [21], which is specifically designed for deep learning-based EEG denoising tasks.The dataset contains 4514 pure EEG segments as ground truth, 3400 pure EOG segments as ocular artefacts, and 5598 pure EMG segments as muscle artefacts. To generate pristine EEG, EOG, and EMG segments, the data were initially preprocessed. Each segment was then rescaled to have the same variance. The segment's duration was set to 2 seconds. A 2-second segment is sufficient to recover the time and frequency characteristics of the EEG, EOG, and EMG. Due to sporadic blinking or movement, it is challenging to obtain artifact-free EEG segments longer than 2 seconds. The contaminated signals were generated by linearly combining a segment of pure EEG with a segment of EOG or EMG artefact, yielding the following formula:

$$y = x + \lambda n \tag{6}$$

In the equation, y represents the one-dimensional mixed signal of EEG and artifact, x represents the clean EEG signal as the ground truth, n represents the (ocular or muscular) artifact, and λ is a hyperparameter that controls the Signal-to-Noise Ratio (SNR) of the contaminated EEG signal y. The formula for SNR is:

$$SNR = 10 \log_{10} \frac{RMS\,(x)}{RMS\,(x \cdot n)} \tag{7}$$

The definition of the root-mean-square (RMS) value is:

$$RMS(g) = \sqrt{\frac{1}{N} \sum_{i=1}^{N} g_i^2} \tag{8}$$

The contaminated signals were synthesized by combining clean EEG signals with clean noise signals. The semi-synthetic EOG contaminated signals were generated using 3400 EEG segments and 3400 EOG segments, with 80% of the segments used for the training set, 10% for the validation set, and 10% for the testing set. EMG signals were generated using the same technique.

4.3. **Noise Reduction Analysis.** The time domain of EEG signals refers to the changes of signals over time. EEG signals are dynamic and exhibit complex temporal patterns, including oscillations, transients, and evoked responses. These temporal patterns are related to different cognitive and physiological processes in the brain. When denoising EEG signals, the goal is to remove noise while preserving and analyzing the real signals. Therefore, by observing the changes in the temporal patterns of EEG signals before and

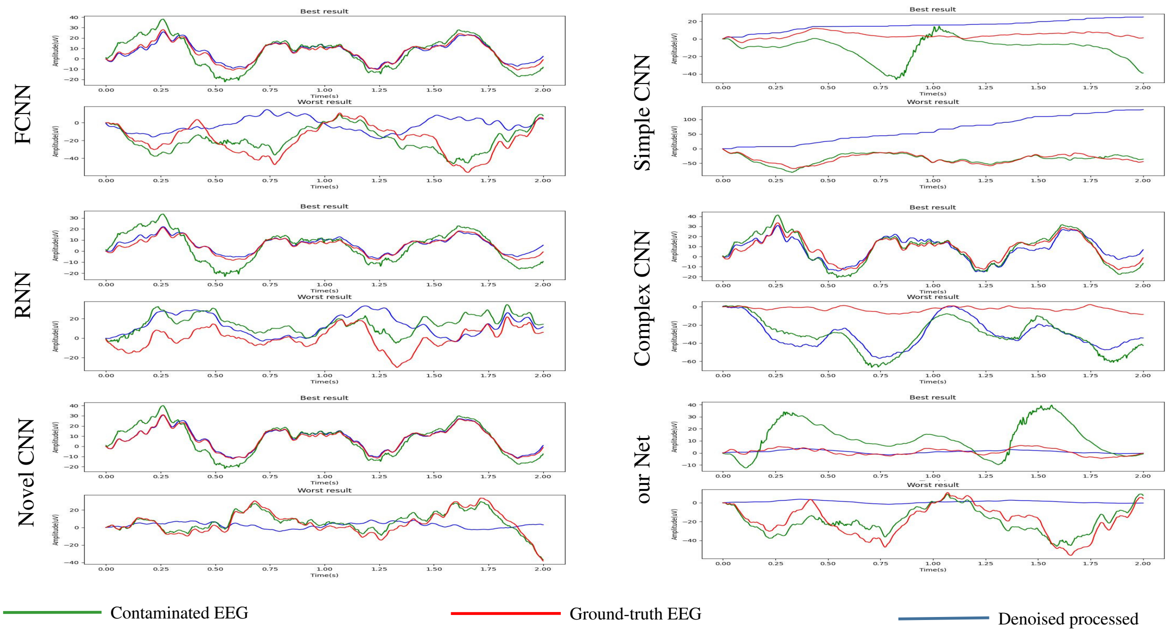

Figure 3. Examplary segments of the performance in temporal domain for myogenic artifact removal., where the orange, green, and blue lines represent the ground truth EEG, noisy EEG, and cleaned EEG using the proposed method, respectively.

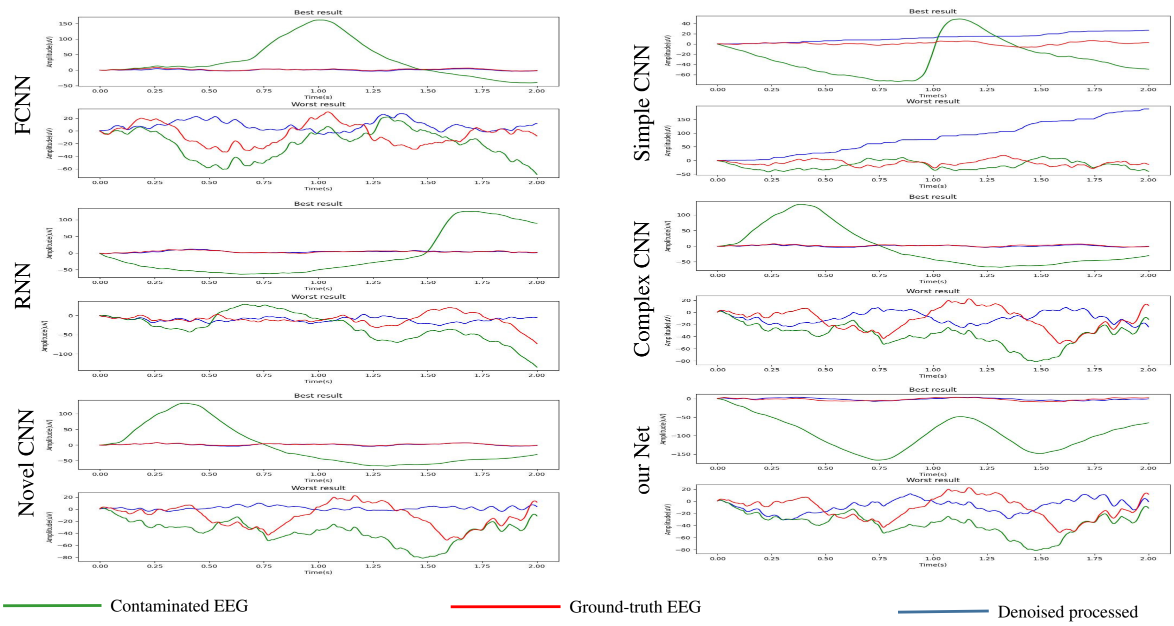

Figure 4. Examplary segments of the performance in temporal domain for ocular artifact removal, where the orange, green, and blue lines represent the ground truth EEG, noisy EEG, and cleaned EEG using the proposed method, respectively.

after denoising, the effectiveness of denoising can be evaluated [21, 42, 43]. In order to compare the performance of DWINet with five other networks, namely FCNN, RNN, Novel CNN, Simple CNN, and Complex CNN, the denoising results were evaluated.

We used the same performance evaluation method to demonstrate the muscle artifact removal (EMG) results of our DWINet on two examples from the test set (one best case and one worst case) in Figure 3. We observed that the high-frequency artifact was effectively reduced in both cases. In the best case, the output was generally close to the ground truth EEG, while in the worst case, the correlation with the ground truth EEG was poor, with only some time points showing a slight correlation.

For our eye artifact removal (EOG) results shown in Figure 4, we can clearly observe that the output in the best case almost overlaps with the ground truth, while in the worst case, the correlation has significantly improved compared to the EMG case, but the artifact in the high-frequency range is still significantly reduced. The two time-domain plots demonstrate that our network has achieved good results, which are weaker than other networks in removing muscle artifact, but superior to other convolutional neural networks except for RNN in removing eye artifact.

4.4. **Convergence Analysis.** We have examined the results of quantitative analysis and first presented the convergence of these five networks. MSE loss is the sum of squared errors, which can clearly indicate the size of the gap between predicted values and actual values. MSE is sensitive to errors because of its squared term and is particularly sensitive to small errors. Even small errors can have a significant impact on the value of MSE. Therefore, the use of MSE can effectively reflect the performance of EEG signal denoising algorithms. As the loss function, we make use of the mean squared error, often known as LMSE. The gradient descent algorithm is used to implement the learning process in order to reduce the gap between the noise level and the ground truth and to validate the denoising impact [21].

Let us begin by examining the myogenic artifacts in Figure 5. From the visual analysis, it is apparent that the Complex CNN and CNN networks suffer from severe overfitting, which adversely affects their performance. The models' effectiveness is limited due to this issue. In the case of FCNN, Novel CNN, and RNN, their losses rapidly declined to the minimum value within 10 epochs. However, after that, their losses started to increase, indicating overfitting, leading to the loss of generalization ability of the models. On the other hand, our proposed network demonstrated faster and more stable fitting with no overfitting, making it stand out from the other networks. These results suggest that our model performs exceptionally well.

Moving on to Figure 5, where we focus on the loss of ocular artifacts. From the results, we can see that CNN, Complex CNN, and Novel CNN networks exhibited a rising trend in their losses, indicating severe overfitting and poor model performance. Similarly, the FCNN model's loss started to increase after the first epoch, also indicating overfitting. In contrast, the RNN model demonstrated a reverse increase at the 19th epoch, further demonstrating the overfitting issue. Our proposed DWINet, on the other hand, maintained a stable downward trend, indicating its robustness and strong convergence speed in removing ocular artifacts. Consequently, our model showcases outstanding generalization ability and resilience. Overall, the test loss results reflect the superior performance of our model in removing both myogenic and ocular artifacts.

4.5. **Power Ratio Analysis.** The power ratio in different frequency bands after EEG denoising can be an important evaluation index. EEG signals are generated by synchronous electrical activity of large numbers of neurons in the brain. Different frequency bands of EEG signals correspond to different neural processes. EEG signals can be divided into different frequency bands, such as delta, theta, alpha, beta and gamma. Each frequency

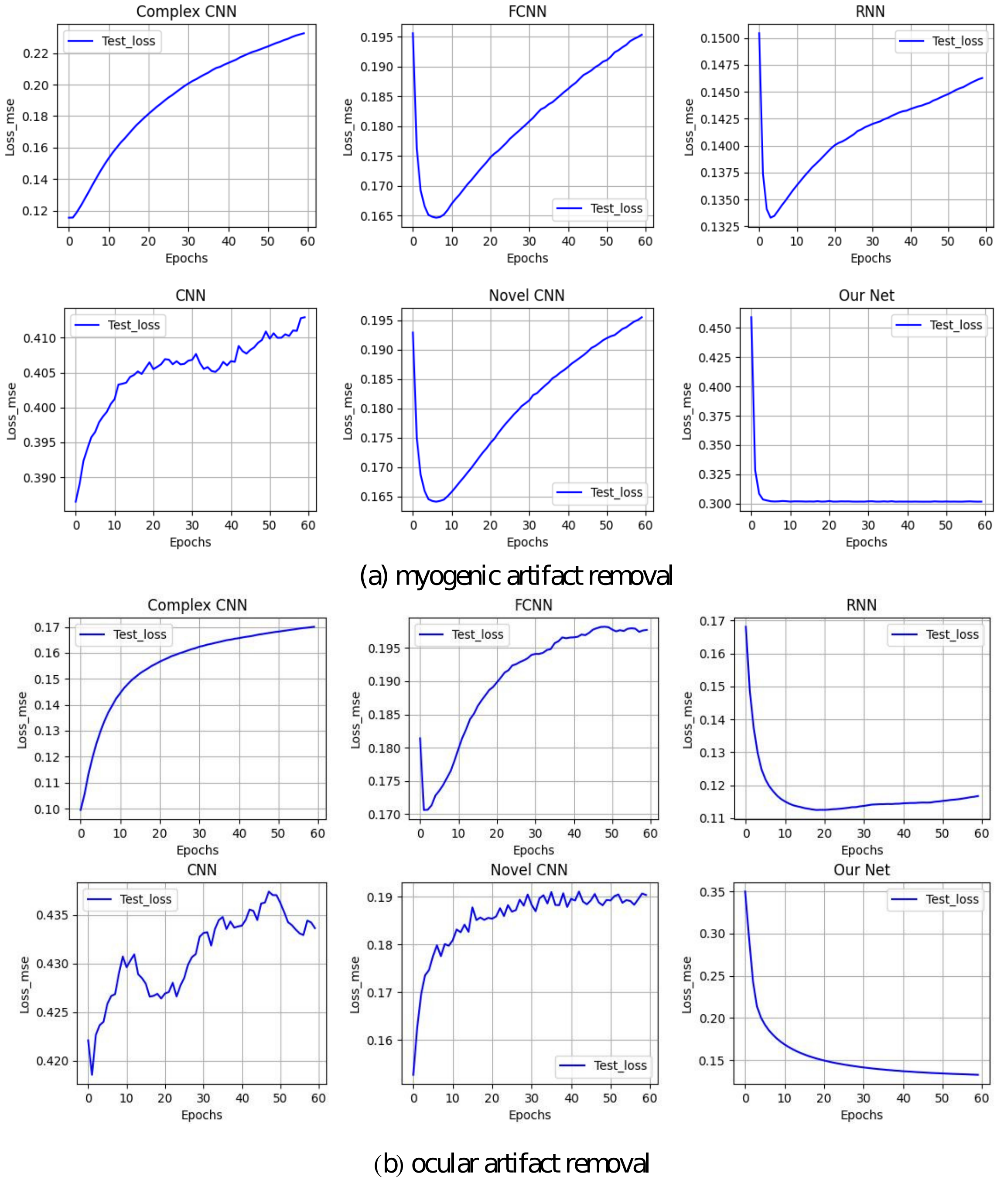

Figure 5. The MSE loss as a function of the number of epochs: (a) myogenic artifact removal,(b) ocular artifact removal. The blue line for the Test set.

band is related to different brain states or activities, such as delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and gamma (>30 Hz), corresponding to different aspects of brain functions, and can provide insights into the relative strength of different neural processes in the brain. For example, an increase in the power ratio of the alpha band may indicate a relaxed state of the subject, while a decrease in the power ratio of the beta band may indicate increased cognitive processing [21, 44].

From Tables 1 and 2, we can see that the increase of myogenic and ocular artifacts increases the beta and gamma power ratio while decreasing the other three power ratios.

In Table 1, it can be seen that six denoising methods were used to remove myogenic artifacts, and the power ratios of different frequency bands before and after removal were compared with ground truth and contaminated signals. It can be observed that RNN is closest to ground truth in delta and beta, Simple CNN is closest to ground truth in theta and alpha, and Novel CNN is closest to ground truth in theta and gamma.

From Table 2, we can see that Complex CNN is closest to ground truth in theta and beta, while our net is closest to ground truth in delta and theta.

Table 1. Power ratios of different frequency bands before and after myogenic artifact removal

Denoising method	delta	theta	alpha	beta	gamme
FCNN	0.207	0.151	0.070	0.207	0.365
RNN	**0.215**	0.165	0.076	**0.210**	0.335
Simple CNN	0.201	**0.182**	**0.081**	0.213	0.323
Complex CNN	0.149	0.130	0.067	0.216	0.438
Novel CNN	0.258	**0.182**	0.069	0.197	**0.293**
Ours	0.027	0.041	0.041	0.230	0.662
Ground Truth	0.235	0.206	0.090	0.211	0.259
Contaminated signal	0.098	0.097	0.057	0.223	0.524

Table 2. Power ratios of different frequency bands before and after ocular artifact removal

Denoising method	delta	theta	alpha	beta	gamme
FCNN	0.246	0.191	0.081	0.205	0.278
RNN	0.237	0.195	**0.084**	0.206	0.278
Simple CNN	0.210	0.185	0.083	0.218	0.303
Complex CNN	0.232	**0.199**	0.083	**0.212**	0.273
Novel CNN	0.270	0.195	0.078	0.201	**0.257**
Ours	**0.233**	**0.199**	0.082	0.204	0.285
Ground Truth	0.235	0.206	0.090	0.211	0.259
Contaminated signal	0.098	0.095	0.057	0.236	0.514

5. **Conclusions.** This paper proposes a one-dimensional Electroencephalogram (EEG) artifact removal method called DWINet based on an image denoising network. This

method reduces the dimensionality of the image network to adapt it to the one-dimensional EEG signal data structure. At the same time, the BN layer and dense layer are added to the network. The BN layer can solve the internal covariate shift problem, thereby accelerating the training process and improving generalization ability and stability. The dense layer can map the feature maps extracted by convolutional layers and pooling layers to a low-dimensional space, thereby realizing the identification of artifact components in input signals. In this way, DWINet can remove artifacts from EEG signals and output processed signals. We conducted three comparative experiments on the EEGdenoiseNet dataset and conducted detailed experimental analysis and comparative research on DWINet and five traditional neural network EEG denoising methods. The results show that DWINet can remove eye artifacts while retaining more original EEG signals, improving the quality of EEG signals. However, in terms of removing muscle artifacts, DWINet performs poorly. In the future, we will continue to explore how to improve image network design based on the characteristics of EEG signals to solve this problem.

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