Time-ResNeXt for epilepsy recognition based on EEG signals in wireless networks

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Abstract

To automatically detect dynamic EEG signals to reduce the time cost of epilepsy diagnosis. In the signal recognition of electroencephalogram (EEG)of epilepsy, traditional machine learning and statistical methods require manual feature labeling engineering in order to show excellent results on a single data set. And the artificially selected features may carry a bias, and cannot guarantee the validity and expansibility in real-world data. In practical applications, deep learning methods can release people from feature engineering to a certain extent. As long as the focus is on the expansion of data quality and quantity, the algorithm model can learn automatically to get better improvements. In addition, the deep learning method can also extract many features that are difficult for humans to perceive, thereby making the algorithm more robust. Based on the design idea of ResNeXt deep neural network, this paper designs a Time-ResNeXt network structure suitable for time series EEG epilepsy detection to identify EEG signals. The accuracy rate of Time-ResNeXt in the detection of EEG epilepsy can reach 91.50%. The Time-ResNeXt network structure produces extremely advanced performance on the benchmark dataset (Berne-Barcelona dataset), and has great potential for improving clinical practice.

Full Text

Due to technical limitations, full-text HTML conversion of this manuscript could not be completed. However, the manuscript can be downloaded and accessed as a PDF.

Figures

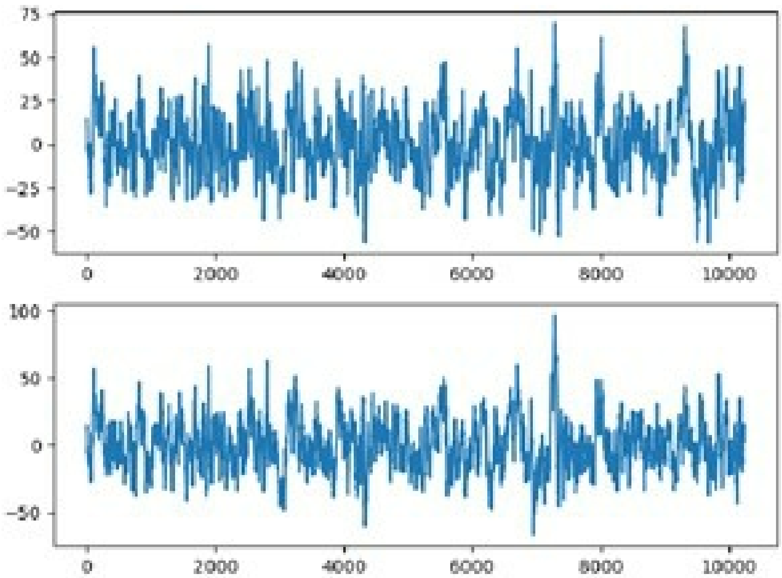

Figure 1

Part of the EEG image：An example of ECG time series data for two channels. The sequence length is 10240, the sampling frequency is 512Hz, and the time is 20s.

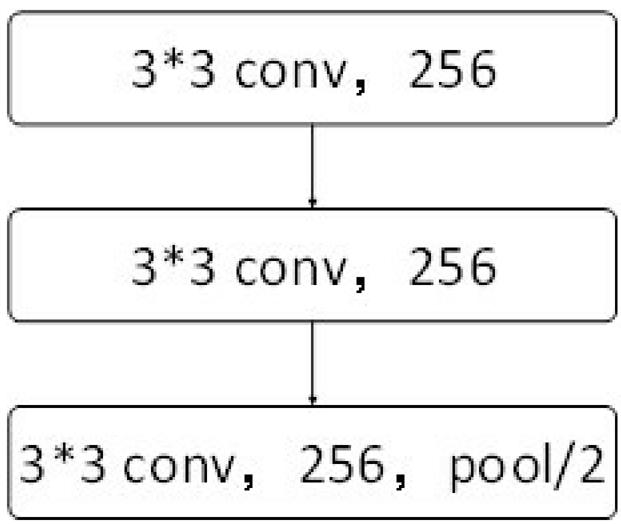

Figure 2

Structure of key modules of VGG network：The typical structural unit of the VGG model has four layers. The first three were 3 * 3 convolutional layers, with 256 channels. The fourth layer is a 3 * 3 convolution layer plus a pooling layer.

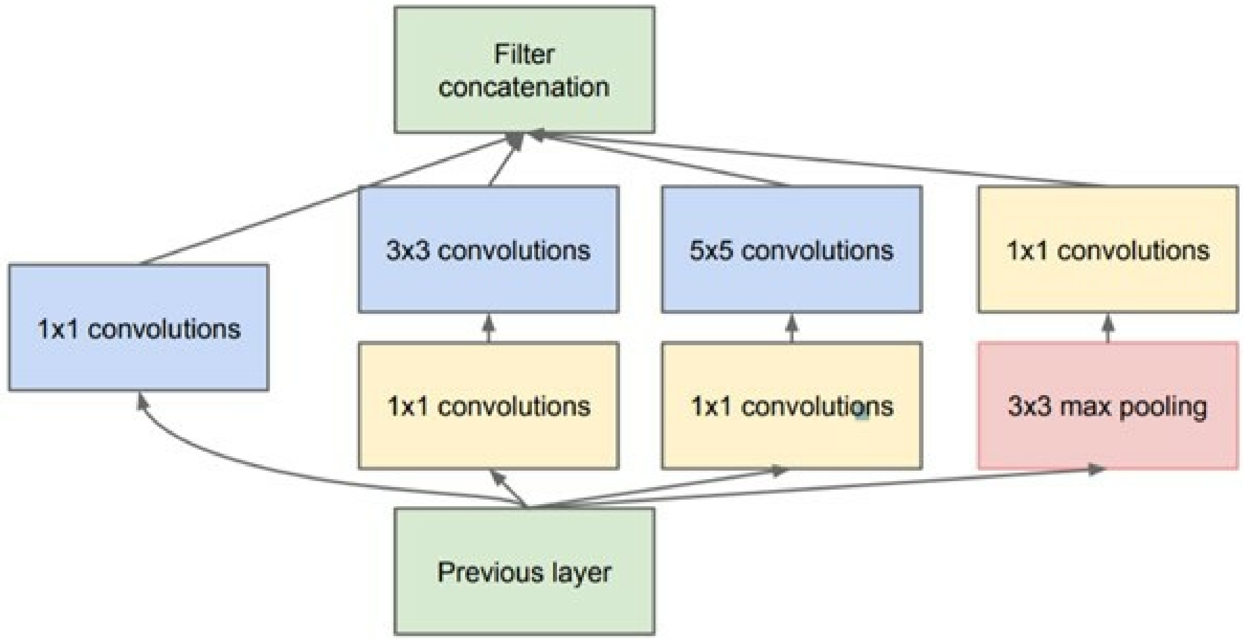

Figure 3

The structure of the key modules of the Inception network：The structural unit of the inception network performs multi-selection links based on the ordinary network structure, including convolution kernels of different sizes, such as 1 * 1 convolutional layer, 3 * 3 convolutional layer, 5 * 5 convolutional layer, * 3 Pooling layer, which is equivalent to the model being able to make a certain selection of the network structure. Through automatic parameter optimization, the network structure is more reasonable.

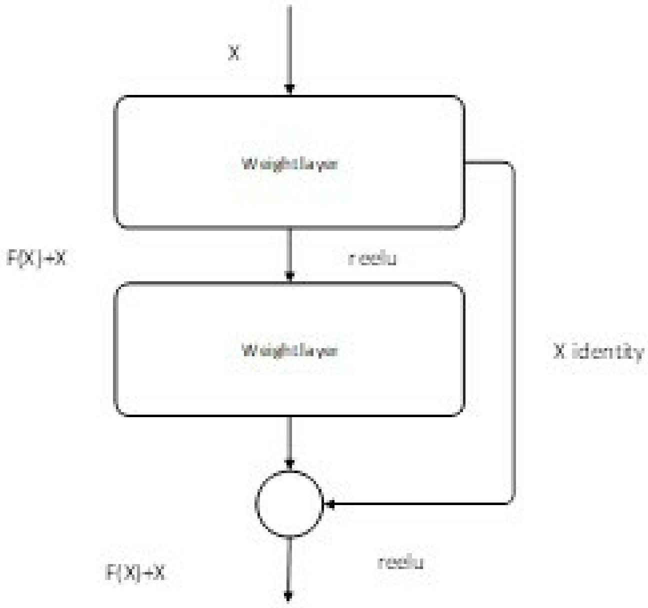

Figure 4

Cross-layer connection structure□Resnet's cross-layer link structure, through learning the weights of F (x) and x, can avoid model degradation caused by gradient attenuation, because the x model can be forwarded losslessly. At the same time, the relu activation function is used to make the model richer in nonlinear expression.

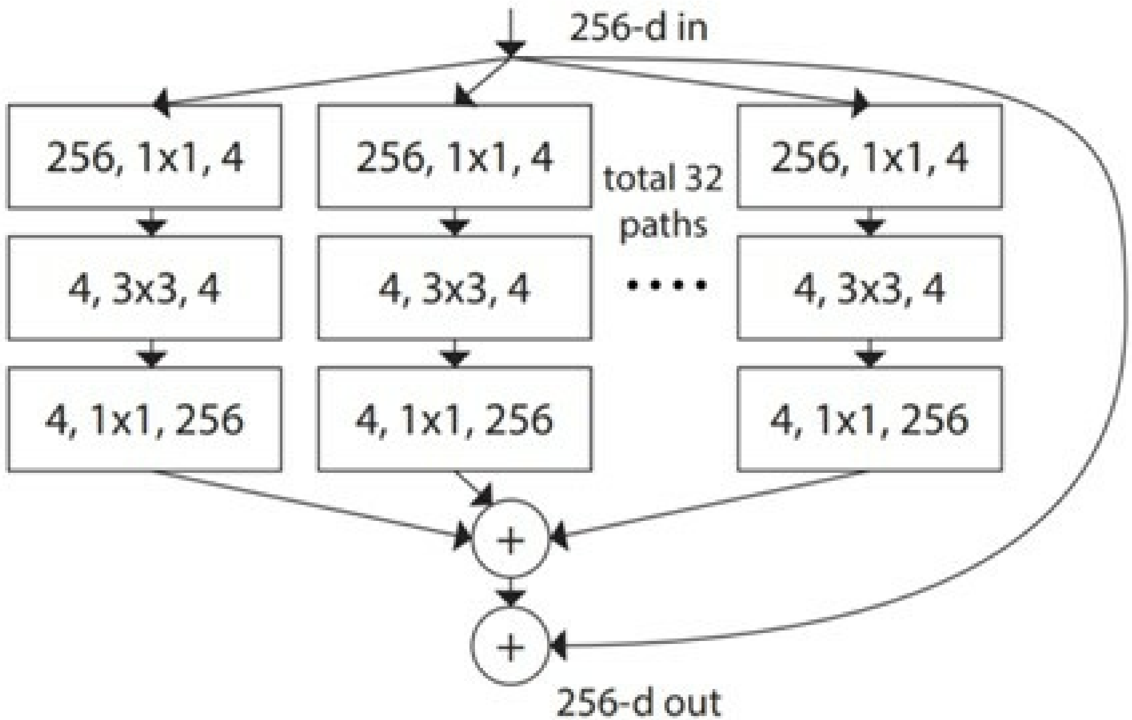

Figure 5

Transform Set Structure：Resnext's topological network structural unit. The structural unit contains 32 convolutional neural network paths. Each path is first a 1 * 1 convolution kernel, which changes the number of input data channels from 256 to 4 without changing the data information. Secondly, the feature is extracted by 3 * 3 convolution, and the number of channels is still 4. Finally, the 1 * 1 convolution kernel is used to restore the number of channels from 4 to 256. Finally, the data obtained from the 32 paths are summed to obtain the output of the unit.

ResNeXt-50 (32×4d)	
7×7, 64, stride 2	
3×3 max pool, stride 2	
$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128, C{=}32 \\ 1\times1, 256 \end{bmatrix}$	×3
$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256, C{=}32 \\ 1\times1, 512 \end{bmatrix}$	×4
$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512, C{=}32 \\ 1\times1, 1024 \end{bmatrix}$	×6
$\begin{bmatrix} 1\times1, 1024 \\ 3\times3, 1024, C{=}32 \\ 1\times1, 2048 \end{bmatrix}$	×3
global average pool 1000-d fc, softmax	

Figure 6

ResNeXt-50 module: A typical network structure of Resnext has three phases. In the first stage, the resolution of the image is reduced mainly through the 7 * 7 convolutional layer and the 3 * 3 maximum pooling, and the detailed features are extracted to a certain extent. Then there are four different resnext convolution operation units. There are a total of 19 layers and 32 paths in each layer. The function is mainly feature extraction. The field of view of the convolution kernel becomes larger as the network level deepens, so that it can perform more global information. Finally, the extracted features are input to the global pooling to change the data shape and extract the global information. On the one hand, it avoids some complex operations of the fully connected layer, and secondly, it can automatically adapt to the input of picture data of different sizes. Finally, the probability information is output through the fully connected layer and the activation function.

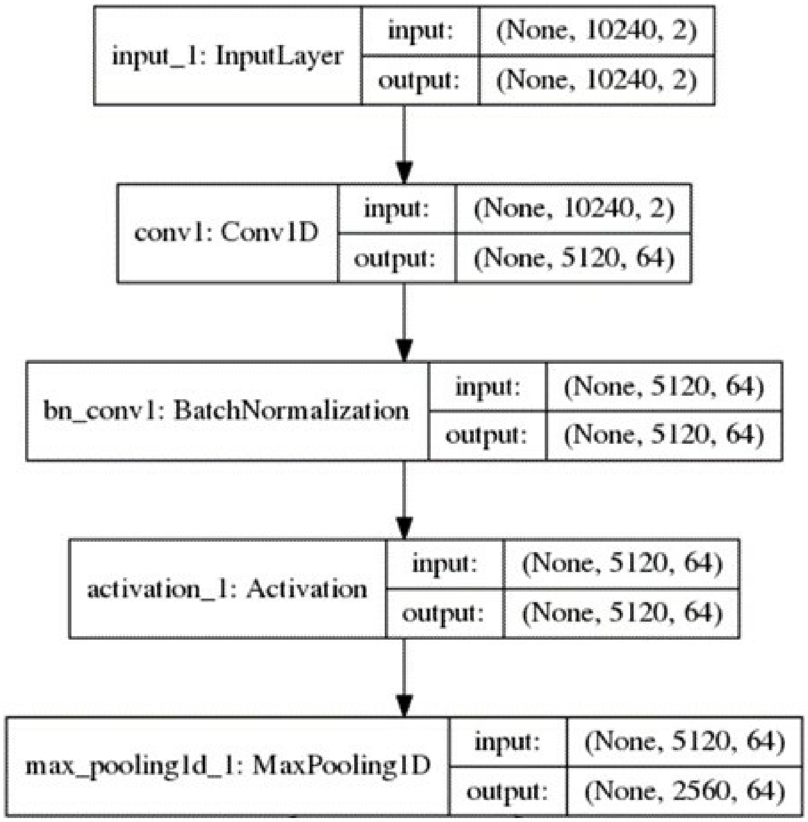

Figure 7

Detailed Network Structure of Time-ResNeXt Phase I: The first stage of the Time-resnext network structure for time series classification obtained after optimization is to first extract features by using a convolution kernel with a convolution kernel size of 2 * 2 and a number of 64 channels, and then batch normalize the data The calculation operation makes the data distribution more logical, avoids the phenomenon of neuron death in the lower activation layer, and finally extracts more overall information through the 2 times the maximum pooling layer.

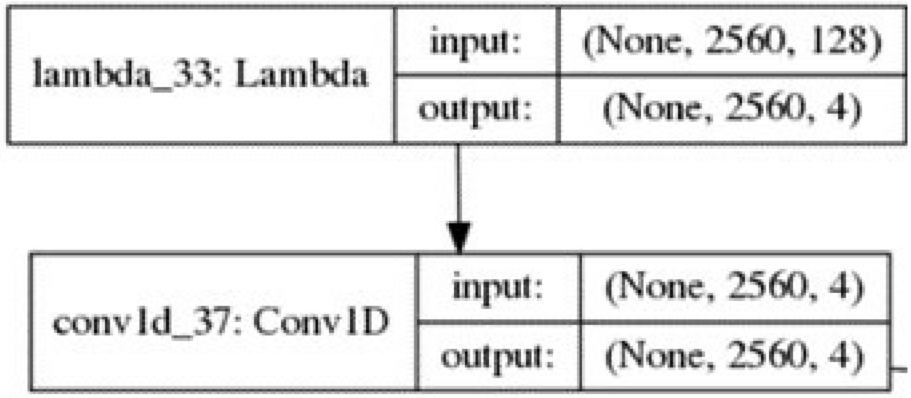

Figure 8

Time-ResNeXt detailed network structure in the second phase:The structure of a single path in the second stage of the time-resnext network structure. The original 1 * 1 convolution kernel is not applicable to change the channel. Instead, the data is directly divided through the lambad layer, and the 128 channels are divided into 32 4-channel data. Secondly, each piece of data is subjected to a 3 * 3 convolution operation. After adding the sum, you can get the output of the arithmetic unit.

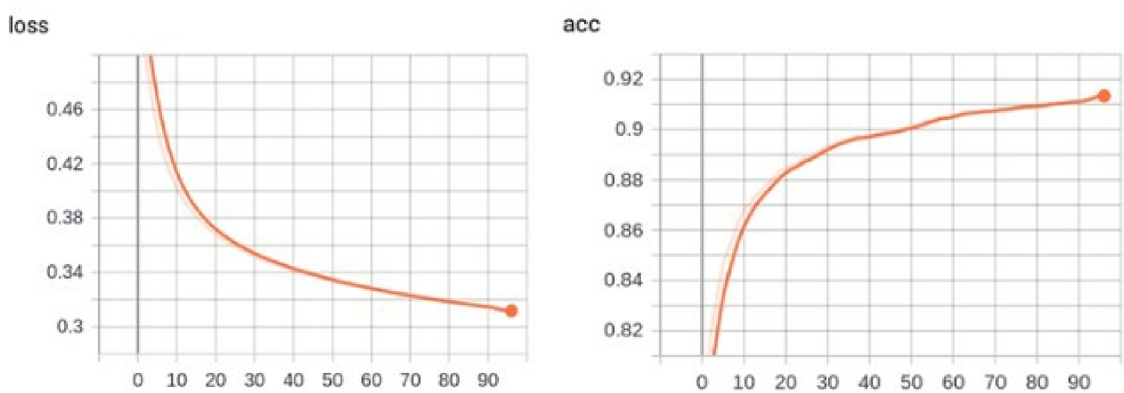

Figure 9

Training set results: The results of the training set are shown in this, the X-axis is the training algebra, and the Y-axis is the training evaluation index.

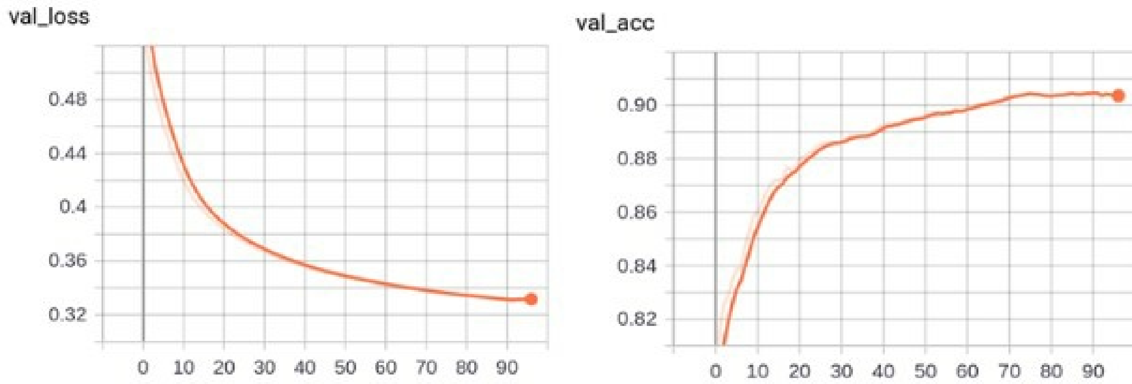

Figure 10

Validation set results: The results show that at 74th generation, the model performs best on the validation data, with a correct rate of 0.9150.