Microwave Imaging-Based Stroke Classification Using a Spatio-Temporal Convolutional Neural Network

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Abstract: Microwave imaging is gaining prominence as a diagnostic method for brain stroke owing to its non-invasive, non-ionizing, reliable, and wearable characteristics. Deep learning has demonstrated significant potential for abnormality detection in comparison to conventional and intricate techniques. However, deep learning systems necessitate considerable quantities of labelled RF data for training, which are frequently constrained in brain stroke diagnostic tasks, including detection, localization, and size classification. The dataset containing S-parameters from CST head model is collected by a microwave set up with two antennas. Then the collected S-parameters are applied as input to Spatial-Temporal Convolutional Neural Network (ST-CNN) model in the form scalogram images. It captures both spatial information and temporal interdependence. This study significantly improves diagnosis and continuous monitoring of brain stroke with an accuracy of 94.6%.

Keywords: Deep Learning; Brain stroke Detection; S-Parameters; ST-CNN

Introduction

Brain stroke is a leading cause of death around the world. This is caused by the rupture of blood vessels within the brain. It harms the brain's key tissues and eventually leads to death. It endangers human life, has a fatal prognosis, and significantly reduces quality of life. Research on the biological effects of electromagnetic field has been steadily rising from the initial years of the previous century. This significance has made substantial contributions to the fields of biophysics, resulting in a rapid expansion of various biomedical applications and electromagnetic characterization techniques. Non-ionizing electromagnetic signals are capable of penetrating through human tissues without inducing any adverse effects. Head imaging using electromagnetic scattering plays a major role in detecting brain stroke using a portable set up. This portable scanning device is suitable for onsite diagnosis and real-time imaging. The integration of Artificial intelligence (AI) with healthcare has enabled more advancements in medical imaging and therapy. Microwave Imaging is a cost-effective technique with promising applications in biomedical imaging. The combination of Microwave Imaging and AI has revolutionized biological imaging research. This collaboration is transforming healthcare diagnostics by enabling non-invasive, real-time evaluation of many medical disorders. Integrating AI algorithms and techniques with microwaves allows for enhanced data processing, image construction, and categorization of abnormality. machine learning and deep learning methods are the common approaches utilized to detect stroke based on features extracted from the microwave scattering parameters during the classification process. Image classification has recently emerged as a critical component of medical image analysis, with deep convolutional neural networks (DCNNs) being employed for recent years. CNN can handle image classification task efficiently. Deep learning algorithms extract the features of image data via a cascade of numerous layers to provide an accurate output. The CNN consists of convolutional layers for feature extraction and densely linked layer(s) for classification. So, the detection of stroke from scattering parameters are possible without reconstructing an actual head image.

Related work

The objective of this study is to develop a portable microwave imaging device that can detect hemorrhagic brain clots by analyzing electrical properties of healthy and abnormal tissues. Microwave imaging is a suggested option for diagnosing breast cancer [1], brain tumor and brain stroke [2], and to obtain a detailed view of the biological tissues. It is critical to consider physical compatibility with human body while designing microwave imaging devices. This involves the creation of a prototype comprised of appropriate sensing devices as well as a method of target detection [3]. The microwave signals are radiated towards the human body and then the scattered signals are collected, which extract both structural and functional information from tissues. The physical quantities observed in microwave medical imaging are the dielectric properties of human tissues (Permittivity and Conductivity) [4]. The significant dielectric difference between the target tissue of the human body and the surrounding tissue is the fundamental basis of microwave imaging techniques. The imaging system uses two antipodal Vivaldi antennas with parasitic patch positioned around the head at an angle of (0◦ and 180◦). The antennas were located 10 mm apart from the head [5]. Dataset was acquired using CST microwave studio antenna simulation software. The antenna generates four S-parameters [S_{11}, S_{12}, S_{21}, S_{22}] of 1001 values which are exported to MATLAB. Three layers of recurrent neural networks (RNNs) are trained using extracted information to detect hemorrhaging strokes. This allows clinicians to provide prompt treatment to patients [6].

ST-CNN effectively captures intra slice and interslice interactions by treating MRI slice sequences as spatial temporal data, similar to video frames [7]. Accurate diagnoses are frequently required. This architecture uses spatial-temporal convolution decomposition, which improves feature extraction while reducing parameter count compared to typical 3D CNN models.

Key Contribution

The major contribution of this work contains:

- Design of ST-CNN for the prediction of brain stroke from raw scattering parameters obtained from antenna configuration.
- Performance examination in the presence of simulation environment
- Fine-tuning of ST-CNN model for noisy data and their performance evaluation for real-world scenarios.

Method, Experiments and Results

The proposed Spatio-Temporal Convolutional Neural Network (ST-CNN) design is illustrated in Figure 1 which includes convolutional layer, batch normalization, activation, max pooling, and addition layer to efficiently learn scalogram spatio-temporal features at the same time minimizing vanishing gradients. The convolution block is intended to extract fundamental spatiotemporal patterns from raw data. The pooling method decreases dimensionality even more by picking the most important information in both spatial and temporal dimensions. The architecture also includes another Convolution block with Batch Normalization and activation layer. This inner convolutional stage is concerned with capturing higher-level temporal correlations and more complicated structural patterns that may not be evident in the earlier layers. These convolutional layers allow the network to learn robust and discriminatory feature maps by gradually improving the model's representational capacity. Following convolutional feature extraction, the output is routed via a flatten layer, which converts the multi-dimensional feature tensors into a one-dimensional vector and prepares it for fully connected classification. The model's last stage is a dense layer with batch normalization that combines and refines the extracted features prior to classification

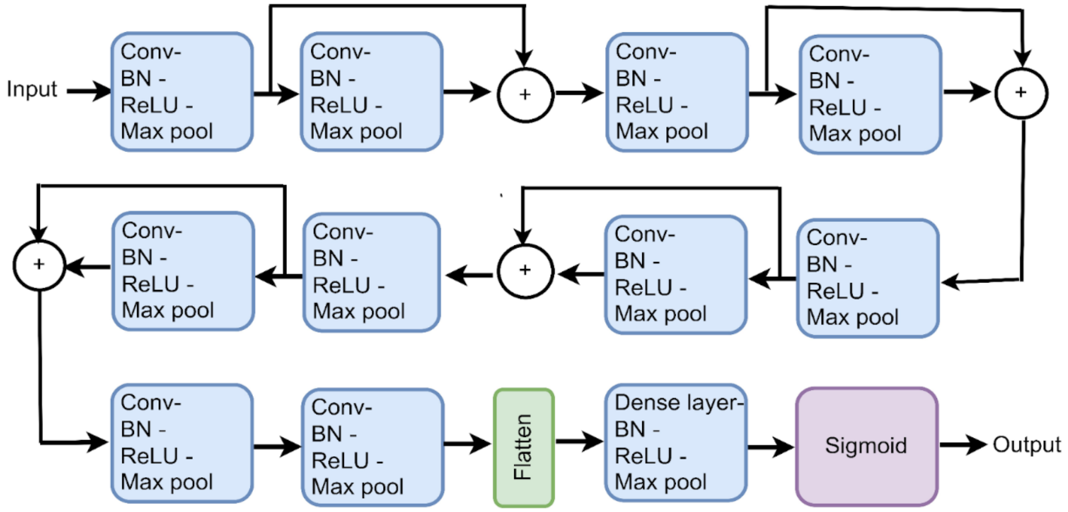
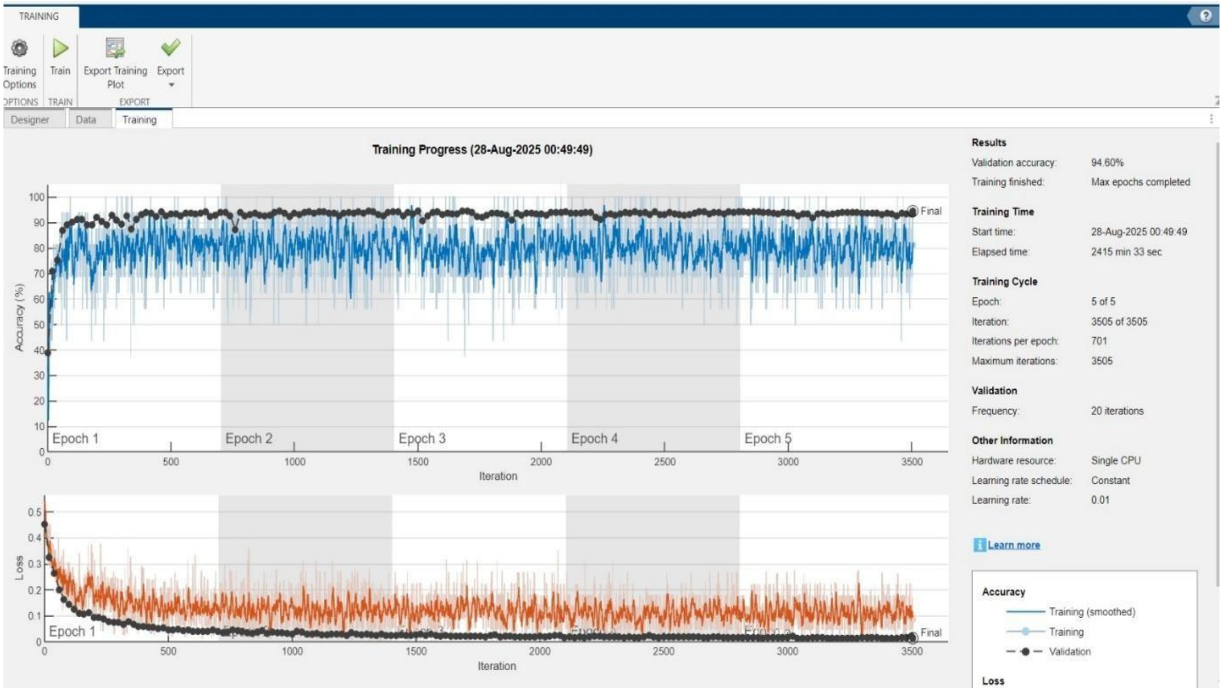


Figure 1. Layer representation of 8-layer ST-CNN

Discussions



Results
Validation accuracy: 94.60%
Training finished: Max epochs completed

Training Time
Start time: 28-Aug-2025 00:49:49
Elapsed time: 2415 min 33 sec

Training Cycle
Epoch: 5 of 5
Iteration: 3505 of 3505
Iterations per epoch: 701
Maximum iterations: 3505

Validation
Frequency: 20 iterations

Other Information
Hardware resource: Single CPU
Learning rate schedule: Constant
Learning rate: 0.01

Accuracy
Training (smoothed)
Training
Validation

Loss

Figure 2. Training progress for 8-layer ST- CNN

The 8-layer deep learning model's training process depicted in Figure 2 enables steady convergence and excellent generalization performance. The accuracy curve reveals that the smoothed training accuracy goes up quickly during the first few iterations of Epoch 1, reaching over 85%. After that, it stays around 90% for the rest of the training. The validation accuracy stays high throughout all epochs, reaching 94.60% in the end. This means that the network learned how to tell the difference between things without overfitting. Even while the raw accuracy scores show normal batch-to-batch changes, the smoothed trend shows that the learning path is stable. The loss curve also shows a sharp drop in the early part of Epoch 1, going from above 0.5 to below 0.1. After that, it stays in a low-loss region for the rest of the epochs, which shows that the optimization was done well and the difference between forecasts and ground truth was kept to a minimum.

Conclusions

This study illustrates the efficacy of microwave imaging for stroke classification utilizing a spatio-temporal convolutional neural network (ST-CNN) as a viable non-invasive and expeditious diagnostic method. The proposed ST-CNN architecture does a better job of categorizing different types of strokes compared to traditional image-only approaches by using both spatial features from reconstructed microwave images and temporal dynamics from multi-antenna signal measurements. The result from the simulation data with extra noise demonstrates that the model can correctly classify the stroke 94.6% of the time.

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