**IEEE SPMB 2021: Review Results**

**Submission Type:** Paper

**Paper No. P035:** Low Latency Real-Time Seizure Detection Using Transfer Deep Learning

**Score:** 8 / 10 (Rank: 7/36)

**Summary:**The paper presents a deep learning approach to fast seizure detection using noninvasive EEG signal features, with comparable but improved performance over the authors’ previous best, and improved ROC curve results over the existing state of the art. The existing literature is surveyed well, and the approach and results are clearly communicated. One area for consideration raised by the reviewers is the balance between sensitivity and specificity, especially in a clinical setting: for example, how does a sensitivity of 42% translate to the number of missed events per 24 hours?

Some typographical and grammatical errors should be remedied, for example: “We demonstrate the efficacy of this approach We have achieved…” in the abstract.

**Reviewer #1:**

In their paper, the authors present their real-time, low-latency seizure detection algorithm. The authors discuss that they were able to achieve results comparable to other seizure detection schemes. Their scheme leverages grayscale images based on multi-channel EEG data, which require only light-weight processing to achieve seizure detection.

The paper does a great job with the following items:

The authors present a detailed introduction section that shows extended coverage of state of the art. They also make good comparisons to the Neureka 2020 Epilepsy Challenge and also show why they didn’t want to follow channel limitations set by the competition.

The use of grayscale images make is very easy to see the difference between the background and seizure events. It is an excellent way of visualizing the two types of events they are attempting to detect/differentiate.

The paper is easy to read and is well organized

Authors could further improve their paper based on the following points:

While the authors defined that their solution is low-latency and close to real-time, there is no concrete reason given for why their solution is needed. It seems like the other solutions discussed in the paper provide similar or sometimes better results. Therefore, the strength of the proposed solution lies with the fact that it can provide results quickly even when only lightweight processing is available. I think the paper would benefit greatly if there were quantifiable comparisons of how much processing power is saved and how fast the seizure detection is compared to the other schemes.

As mentioned above, the paper lacks the clear answer to “Why was this needed?”. Although the authors seem to potentially answer this inherently by presenting their solution.

In section II, the authors mention “Neurologists are capable of manually interpreting EEGs with accuracies…”. Have they consulted with a neurologist to see how a human reads and detects the seizure? If so, is it possible to detect a seizure before it starts? Visually looking at the grayscale images that the paper presents, background event vs seizure event is like night and day. Perhaps a discussion could be added to talk about the transition period. Although, it is possible this discussion is a bigger item that is reserved for a future study.

In Section IV, the authors introduce the 3 parameters they use for post processing. While the results are presented in terms of Detection Delay (which consists of BDmin and SDmin), there is no mention of what the ratio between BDmin and SDmin are. Are they equal?

Throughout the paper and specifically in Section V, the results are presented in terms of how low their false alarm rates are. How does this compare to missed detection rate? In a critical-care environment, I would expect to not miss any events that should have been caught even though I might receive an increased number of false alarms. Could you elaborate on the connection between false alarm vs. missed detection rates with your algorithm?

Figure 1 might have originally been a powerpoint slide and it seems to have writing but is impossible to read. In fact, most figures in the paper are hard to read as the font on them are too small. Use of color in graphs might also cause issues for readers that use a black-and-white printer.

Table 3 might have a wrong label (mentions Background twice under “Detected”)

Paper seems to have minor grammatical errors and typos. It also seems to be missing keywords in the abstract (if needed)

Overall, the paper does a good job summarizing the authors’ research.

**Reviewer #2:**

This paper presents a method for real-time seizure detection using a CNN and transfer learning. The paper reads well and flows logically. The introduction sufficiently motivates the problem and the presented experiments show good results.

The method of using a weighted loss function to reduce bias is a logical one, but I feel somewhat dangerous in a clinical setting. Does this loss improve both sensitivity and specificity?

The grayscale images used for classification is stretched from 20x256 to a 256x256 to fit into a ResNet model. I would suggest that the authors try a custom CNN for this problem. Not only do the pretrained weights of ImageNet not transfer well, they also were trained on a set of images with very different structure and statistical properties. I think you will find a simple 3 layer CNN trained from scratch could achieve as good, if not better results than the ResNet 18 pretrained model.

Minor typo – Table 3, one of the backgrounds should be labeled seizure.

**Reviewer #3:**

Compliments

I liked that they focus on jointly modeling temporal and spatial information and think that is a novel approach as some CV architectures do the same like Wide & Deep Models and Deep & Cross Networks.

That being said, I think they contradict that when they mention the hybrid CNN/LSTM in Evaluation Results since a CNN captures spatial info and LSTM captures temporal info; thus, are they truly the first to focus on jointly modeling both?

They do a thorough job of explaining existing work and the benefits and flaws of that work to distinguish their own work

I also appreciate the emphasis of low latency and how their chosen architecture is simpler and allows for the low latency required in this environment.

Improvements

I think it would be helpful for a few citations as this is SPMB and not ICCV or something more with ML;  moreover, they mention dropout and batch normalization and actually use batch normalization but never formally define it so it would be helpful to include a citation to some of those regularization methods.

In the same vein, I think it would be helpful for citations to the scaling or normalization techniques such as moving average filters and local scaling.

I am curious as they randomly selected 1/5 of the background patterns to rebalance the dataset and was unsure if 1/5 was chosen empirically or for some other reason on page 3 in the second paragraph.

Typos

I noticed a typo in their abstract "The system can run easily run in real-time using single core CPU"

Also, in the last paragraph of Evaluation Results they write "resnet" and the second paragraph of Evaluation Results they write "Resnet18" and in the methodology Application of Transfer Learning they write "ResNet18". Overall, they are not as focused on consistency in their naming.

Overall, I think they provide a significant contribution to the field and are very novel in training simultaneously both temporal and spatial information at the same time to learn better correlations between the two. However, I think there are just a few places for consistency remarks and to include more citations so the average reader could understand why one technique is better than another.