A Multi-View Ensemble Approach to Epileptic Seizure Recognition Using Deep Neural Networks

Extended Abstract: Epileptic seizure recognition plays a critical role in **neurological diagnostics**, so far manual interpretation of EEG signals is both time-consuming and prone to bias. This study introduces a **novel deep meta-learning framework** for automated seizure detection using the Epileptic Seizure Recognition dataset, comprising 11,500 EEG samples across five classes, each represented by 178 features. To simplify the task and enable early testing, we initially express it as a binary classification problem—distinguishing between seizure and non-seizure activity. Addressing class imbalance, we apply a blending of **NearMiss** (under sampling) and **SMOTE** (oversampling) techniques to produce a **balanced dataset**, followed by scaling to normalize feature distributions.

Three complementary base learners are established: a deep neural network (**DNN**) with fully connected layers, a 1D convolutional neural network (**CNN**), and a custom-designed 2D CNN inspired by **ResNet** architecture. In the 2D model, we identify and remove 9 features showing high pairwise correlation ($|\rho| > 0.945$), retaining 169 features which are reshaped into 13×13 pseudo-images. This spatial mapping enables the CNN to extract structural outlines from the EEG signal, providing enhanced interpretability. All models are trained independently for only 20 epochs, highlighting **computational efficiency**. However, individual models show trade-offs between false positives and false negatives. The DNN and CNN models showed tendency toward false positives (**Type I error**) and false negatives (**Type II error**) which could lead to severe consequences in clinical decision-making.

To support decision-making, we collect the output probabilities from each base model and **create a set of meta-features** that summarize inter-model agreement and doubt. These include the probabilities, their mean, standard deviation, minimum, maximum, entropy, and pairwise differences. This meta-representation is then used as input to a **Support Vector Machine (SVM)** with an **RBF** kernel, which acts as a next-stage decision maker and learns from the shared behaviour of the base learners.

This ordered ensemble model achieves strong performance, reporting an **accuracy of 99.9%, F1 score of 0.99**, and **ROC AUC of 0.99** on the test set. The improvement over individual base models, which has accuracy of **98.0%, 98.5% and 99.0%** respectively, highlight the efficiency of our meta-learning strategy. The flexible design also allows future development for multiclass problem, so that is becomes versatile framework for generalized seizure classification.

Our approach has several innovations: (1) **combining** various deep learning architectures to capture complementary signal features, (2) **transforming** 1D feature vectors into 2D grids for spatial learning, (3) creating useful **meta-level features** from model predictions, and (4) using a **SVM** for final classification. The model's low training cost and high accuracy make it suitable in real-time clinical environments and wearable EEG devices.

In summary, this work establishes that merging deep learning with structured meta-learning offers a powerful, generalizable solution for EEG-based epileptic seizure detection, with promising implications for both binary and multiclass medical classification tasks.