Effectiveness of Cross-Model Learning Through View-Model Ensemble on Detection of Spatiotemporal EEG Patterns

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Keywords: Autoencoder, Biometric, Brain, Convolutional Neural Network, Electroencephalograph, Spatiotemporal, Transfer Learning.

Abstract: Understanding the neural dynamics of human intelligence is one of the top research topics over the decades. Advances in the computational technologies elevated the level of solving the complex problems by means of the computational neuroscience approaches. The patterns extracted from neural responses can be utilized as a biometric for authentication. In this study, we aim to explore cross-model transfer learning approach for extraction of distinct features from Electroencephalography (EEG) neural signals. The discriminative features generated by the deep convolutional neural network and the autoencoder machine learning models. In addition, a 3D spatiotemporal View-matrix is proposed to search distinct patterns over multiple EEG channels, time, and window segments. We proposed a View-model approach to obtain intermediate predictions. At the final stage, these intermediate scores are ensembled through a majority-voting scheme to reach the final decision. The initial results show that the proposed cross-model learning approach can outperform the regular classification-based approaches.

1 INTRODUCTION

Machine learning has been utilized in different electroencephalography-related research including brain computer interface (Aggarwal, 2021), diagnosis of neurological disorders (Oh, 2020), human computer interaction (Zhao, 2020), development of authentication systems (Fidas and Lyras, 2023) and many others (Khosla, 2020). As non-invasively collected data, EEG recordings exhibits both spatial and temporal features for comprehensive analysis of human brain characteristics.

Intra-subject characteristics of EEG signals demonstrate similar patterns extracted over various trials while they differ significantly among the subjects (Mueller, 2013). This distinctiveness property allows EEG patterns to be utilized as a biometric for personal authentication. Various advantages of identification based on brain signals have been emphasized compared to traditional personal verification methods (Bidgoly, 2020). For example, fingerprint, retinal scan, voice recognition and facial recognition systems may have vulnerabilities in terms of data security and deception attempts against these systems (Bharadwaj, 2014). However, brain signals can provide a more secure personal verification method against such threats (Riera, 2007).

The fusion of multi-view predictions can improve classification performance (Xu, 2013). Among various fusion strategies, (Kuncheva, 2014) and (Atrey, 2010) showed that the majority-voting scheme performed better than single-view decision making.

In this study, we explored effectiveness of cross-model based learners that generate feature patterns from proposed spatiotemporal View-matrix utilizing a multi-view ensemble classifier system. The proposed approach is unique in terms of introducing 1) a cross-model transfer learning framework that employs the DCNN and the AE with widely used regular classifiers and 2) testing the performance of the proposed system using cross-session datasets. The rest of the report is organized as follows: The method section starts with describing the data acquisition and preparation procedure. The section flows with presenting the proposed View-Matrix data structure, View-Model, and ensemble of these models. The result section is discussing the effectiveness of the proposed framework and hyperparameter scheme.

Soysal, Ö. M., Kelvin, I. E. and Oztemel, M. E.
Effectiveness of Cross-Model Learning Through View-Model Ensemble on Detection of Spatiotemporal EEG Patterns.
DOI: 10.5220/0013265300003912

In *Proceedings of the 20th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP 2025) - Volume 2: VISAPP*, pages 942-949
ISBN: 978-989-758-728-3; ISSN: 2184-4321

The conclusion summarizes outcomes and points to limitations that can be improved.

1.1 Previous Work

Machine learning techniques are widely used for verification of individuals based on EEG patterns. Fidas et al. discussed the role of machine learning techniques in personal verification applications. In summary, wavelet transform, power spectral density, autoregressive modelling and fast Fourier transform are the main techniques used for feature extraction. Support vector machine, hidden Markov models, multilayer perceptron, recurrent neural networks (RNN) and convolutional neural networks (CNN) were used in the classification of the data obtained from these features.

Autoencoders have been studied for different purposes in analysis of brain signals (Weng, 2024). As an example, AE mechanism can be used to remove eye blink artifacts from EEG signals (Acharjee, 2024), to identify sleep stages (Dutt, 2022). (Abdelhameed, 2018) utilized an AE network to predict epileptic seizures. (Bandana, 2024) employed a spatial AE network for personal verification. Latent features obtained from the AE network trained a CNN model. Ari et al. pointed out that AEs provide an ideal solution for artificial data generation to increase the amount of training data (Ari, 2022). Tian et al. operated two encoders simultaneously (Tian, 2023). Zhou and Wang utilize spatiotemporal AE, with adaptive diffusion method, to obtain high resolution EEG data from low-resolution data (Zhou, 2024).

Yao and Motani stated that the vital signs of the patients contain both temporal and spatial information. Therefore, they proposed a hybrid learning mechanism for classification purposes. Their system first extracts spatial features, and then temporal patterns to determine if an individual is an alcoholic or not. Support vector machine, gradient boosting, random forest and decision tree algorithms were applied for classification. Among these classification techniques, SVM achieved the most successful results (Yao, 2018).

On the other hand, multi-view fusion models provide improved performance over single view-based classification. Mane et al. examined multi-view features obtained from different frequency bands to train a CNN (Mane, 2020). Spyrou et al. applied multi-view tensor factorization for detection of epilepsy by means of a linear regression method (Spyrou, 2015). (Gao, 2022) compared the multi-view and single-view classification for emotion recognition; it was found that the multi-view classification is superior to single-view. (Emanet, 2024) employed multi-view hierarchical learning model with 3D-CNN for classification of a stimulus type. Jia et al. aimed to classify sleep stages utilizing spatial-temporal graph convolutional network through multiple views that are consisted of functional connections and distance-based connections (Jia, 2021).

Transfer learning techniques have been successfully used in various EEG-related studies such as motor imagery and evoked potential applications (Wu, 2020). Waytowich et al. focused on unsupervised spectral transfer learning and geometry-based knowledge training for brain-computer interface study examining subject independence (Waytowich, 2016). Qi et al. used inter-subject transfer learning to reduce the calibration time. A small number of epochs for target subject is taken as references and the Riemann distance metric was calculated and applied to the most similar target subject (Qi, 2018). Transfer learning can be applied across devices as well as across subjects. Wu et al. investigates how to improve the performance of brain-computer interfaces (BCIs) by reducing the amount of time needed to calibrate them for use with different EEG headsets. The authors propose a new method called active weighted adaptation regularization (AwAR), which combines transfer learning and active learning to facilitate the calibration process. AwAR leverages data from previously used EEG headsets to train a classifier for a new headset, selecting only the most informative data points for labelling. This significantly reduces the amount of data required for calibration, ultimately making BCI technology more user-friendly and accessible (Wu, 2016). Additionally, Cimtay et al. used a previously trained CNN model based on Inception-ResNet in emotion recognition systems by transferring its weights between subjects and datasets (Cimtay, 2020).

2 METHOD

In this section, we describe the framework for extraction of distinct patterns from spatio-temporal EEG neural responses. The framework is composed of the following main modules: 1) Preprocessing, 2) feature extraction, 3) generating view-models, 4) building fusion-model as illustrated in Figure 1.

Preprocessing is responsible for filtering artifacts from the raw signal such as mean-line harmonics, extraction of the spectrum of interest. The Laplacian of Gaussian (LoG) is used as a signal conditioning operator to enhance the signal. The View-Matrix Generator formats the original 2D (channel, time) data into a 3D spatiotemporal matrix. The View-models are composed of the base learners, deep convolutional neural network (DCNN) and AE, and four regular classifiers namely k-nearest neighbours (KNN), random forest (RF), support vector machines (SVM), and artificial neural network to identify participants. At the final stage, the fusion unit ensembles View-model predictions to reach the final decision.

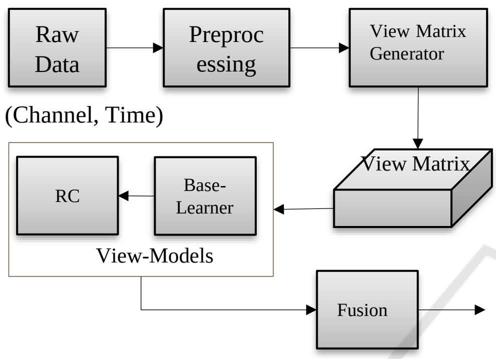

Figure 1: Workflow.

The proposed method has been tested on EEG data, which is composed of 7 subjects in 2 sessions, 10 days apart. We utilized the mBrain Smarting PRO amplifier equipped with a 24-channel head cap. The electrode locations on the head cap were designed according to the 10-20 system. The amplifier was configured at a sampling frequency of 500 Hz. We designed and implemented several protocols using the Presentation software: 1) Baseline, 2) inner voice-audio, 3) shape-trace-audio, and 4) motion. Each protocol is repeated for a total of 10 trials. In this study, we presented results for the stimuli associated with the resting state while eyes were open.

The EEG signal undergoes initial filtering with a notch filter during the preprocessing stage. Next, a band-pass filter is applied to focus on the 0.5 – 32 Hz spectrum. The LoG operator described in (Oztemel, 2024) is then applied to enhance the signal. We focused on trials with time duration of 0.5 seconds for several stimuli. The EEG signal of a length L is partitioned into different k segments of a length $W = L/(p\ k)$ with an overlap p.

2.2 3D Spatiotemporal Views

The proposed 3D Spatiotemporal View, named View-Matrix, presented in Figure 3 combines the neural dynamics over time for all EEG channels together with cross-segment interactions. The neural activity patterns are extracted from three views. View-1 is composed of stacking the (channel, time) frames over window segments. Similarly, View-2 enables extraction of patterns in the stack of channel-window frames over several periods and View-3 provides a perspective from (window, time) frames across the stack of channels.

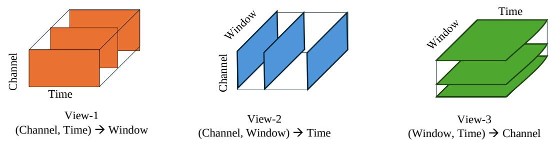

Figure 2: 3D Spatiotemporal Views.

The descriptive feature patterns are generated through a cross-model learning strategy. We explored the effectiveness of the cross-model based transfer learning over the regular classifiers (RC) ANN, KNN, SVM, and RF. We utilized the DCNN and the AE as base-learners. A View-model is generated by employing an RC or combination of a base-learner with an RC. Each View-model is constructed using its designated View-matrix. When the training is completed, the FC unit is dropped from the DCNN model. Similarly, the decoder unit is discarded from the AE model. The output of these models is utilized to generate features passing through the flattening unit F to train the regular classifiers. Figure 4 illustrates the training process flow. In the feature extraction stage, a transfer-learning network model generates features from the spatio-temporal set of signals, named View-matrix. The fusion-model combines predictions from multiple views to reach the final decision.

2.3 Ensemble of View-Models

In the ensemble of intermediate predictions, we utilized the idea of a voting classifier that produces the final prediction from multiple opinions by majority vote, i.e., the class with the highest probability of being predicted by each classifier. The fusion module yields the most frequently voted class label together with the corresponding prediction score. The mean prediction score is calculated when more than one View-model predicts the same class. When all three View-models disagree with each other, a simple random selection determines the final decision. Figure 5 illustrates the View-Model fusion process.

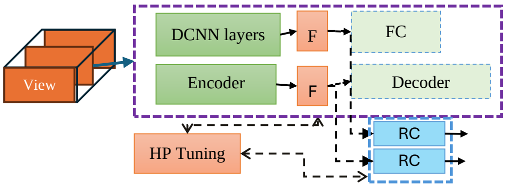

Figure 3: Training Process of View-Models.

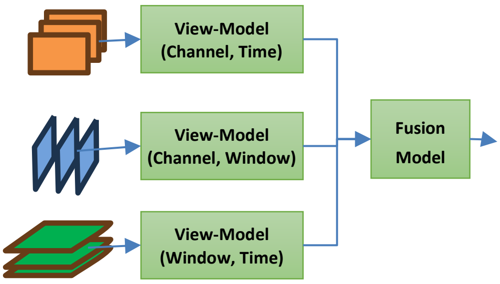

Figure 4: View-Model Fusion Process.

3 RESULTS

In this section, we present our findings on the effectiveness of the proposed framework. Two performance measures, the accuracy (ACC) and the area under the curve (AUC), were utilized for evaluation of the proposed framework. We compared the regular learning models with the cross-model learning networks, DCNN and AE. We employed a 5-fold cross-validation strategy to measure the stability of the proposed framework against the uncertainty of the data distribution. At each fold, we split the data into 80% for training and 20% for validation. For the assessment of permanence, the session-1 EEG recordings were utilized to generate the models, and the session-2 recordings were used for testing. Hyperparameter tuning was conducted at each fold. The duration of a segment of Interest (SoI) was 0.5 seconds. The EEG amplifier operated at a sampling frequency of 500 Hz. The session-1 and session-2 included 514 SoIs, making 1028 SoIs in total. The size of the View-matrix per subject was 24×16×32 (channel, time, window).

3.1 Effectiveness of Cross-Model Learning

Figure 6 presents the effect of each learning scheme for extraction of distinct patterns from the 3D View-matrix. The regular classifiers ANN, KNN, and SVM trained by the features directly flattening of a View-Matrix performed poorly compared to the RF as Figure 6a shows. In addition, the RF classifier did not show a stable performance as its distribution was quite wide.

On the other hand, the DCNN and AE-based cross-learner models outperformed the regular classifiers as shown in Figure 6b and Figure 6c. The distribution of the average prediction scores elevated significantly. It should be noted that the predictions' stability requires attention to improve the proposed approach.

The analysis of Figure 7 clearly shows that the proposed cross-model approach significantly improved the learning performance. Overall, the DCNN base learner showed slightly higher prediction scores on average than the AE's predictions. As a remark, there is room to conduct research on the stability of the base learners.

3.2 Identifiability of Individuals

In this study, we present outcomes from our in-house dataset of EEG recordings from 7 individuals. It is expected that individuals can be distinguished from one another due to the unique characteristics of their brain's anatomical and functional differences. In Figure 8, we presented AUC performance values of the classification algorithms for each subject. The performances of the KNN and SVM models provided very similar results. However, the random forest and ANN models showed performance improvement in some cases, depending on the utilized learning approach. These findings show that the cross-learner model with DCNN and RF combination can be more successful for certain subjects.

3.3 Comparison with the State of the Art

Arnau pointed out a common mistake in EEG-based biometric studies (Arnau, 2021). Surprisingly, few studies have focused on the effects of time-dependent changes in brain signals. In most studies, systems developed for high-accuracy detection of subjects were typically trained and tested on data collected in the same session. Alternatively, data collected from different sessions were combined; and then split into learning and testing datasets. As a result, their performance scores were reported as high. Being aware of this situation, some studies performed the learning and testing phases using data collected from completely different sessions. Nakamura et al. analysed two different scenarios in their study focusing on this issue. In the first scenario, learning and testing data were collected from the same session, while in the second scenario, data were obtained from different sessions. In the second scenario, the time difference between the sessions varied from 5 to 15 days (Nakamura, 2017). As Arnau emphasized, it has been proven that performance was higher when data from the same session were used. It is worths mentioning that one of the recent rare studies (Plucińska, 2023), a spectral-based biometric verification experiment, resulted in 75 to 96% ACC depending on whether the cross-session data were used for training and testing. A simple ANN classifier was utilized to extract distinct features.

In this study, we used data from one session to train the models and data from another session for testing. The data collection sessions were completed with a 10-day interval. Therefore, this study provides one of the unique reports in the literature in terms of isolating training and testing datasets. To the best of our knowledge, this study is the first to propose a multi-view cross-session framework for EEG-based authentication utilizing a cross-session test dataset.

3.4 Hyperparameter Tuning

Table 1 and Table 2 provide insight into the hyperparameters of each model. We utilized Bayesian optimization in Keras Tuner to identify the best parameters for our models. The KNN's neighbour parameter reduced from 11 to 4 (3) when trained by the base-learner AE (DCNN). The SVM changed its kernel type from polynomial to linear when used with both base learners. The RF's max_depth parameter dropped from 14 to 5 and 11 when trained by the DCNN and AE, respectively. The number of layers remained the same when the AE was used while it decreased from 5 to 3 when the DCNN was the base trainer. The number of units at each layer showed a variation. The DCNN's number of layers remained the same across RCs while the AE utilized 2 layers with the same number of units at each layer for all RCs.

Table 1: Best Parameters for RC and AE+RC models.

KNN	{'n_neighbors': 11, 'leaf_size': 26, 'weights': 'uniform', 'metric': 'cityblock'}	AE+KNN	{'activation': 'elu', 'dropout': 0.6, 'optimizer': 'adamW', 'kernel_initializer': 'he_uniform', 'kernel': 3, 'cnnlayers': 2, 'conv_0': 150, 'conv_1': 20, 'batch_size': 32, 'epochs': 100}{'n_neighbors': 4, 'leaf_size': 20, 'weights': 'distance', 'metric': 'cityblock'}
SVM	{'C': 10.0, 'gamma': 1.0, 'kernel': 'poly'}	AE+SVM	{'activation': 'elu', 'dropout': 0.6, 'optimizer': 'adamW', 'kernel_initializer': 'he_uniform', 'kernel': 3, 'cnnlayers': 2, 'conv_0': 150, 'conv_1': 20, 'batch_size': 32, 'epochs': 100}{'C': 10.0, 'gamma': 1.0, 'kernel': 'linear'}
RF	{'max_depth': 14, 'min_samples_split': 2, 'criterion': 'gini', 'n_estimators': 200}	AE+RF	{'activation': 'elu', 'dropout': 0.6, 'optimizer': 'adamW', 'kernel_initializer': 'he_uniform', 'kernel': 3, 'cnnlayers': 2, 'conv_0': 150, 'conv_1': 20, 'batch_size': 32, 'epochs': 100}{'max_depth': 11, 'min_samples_split': 3, 'criterion': 'gini', 'n_estimators': 300}
ANN	{'activation': 'elu', 'dropout': 0.2, 'optimizer': 'adam', 'kernel_initializer': 'he_uniform', 'ann_layers': 5, 'units_0': 75, 'units_1': 200, 'units_2': 50, 'batch_size': 32, 'epochs': 100, 'units_3': 50, 'units_4': 50}	AE+ANN	{'activation': 'elu', 'dropout': 0.6, 'optimizer': 'adamW', 'kernel_initializer': 'he_uniform', 'kernel': 3, 'cnnlayers': 2, 'conv_0': 150, 'conv_1': 20, 'batch_size': 32, 'epochs': 100}{'activation': 'elu', 'dropout': 0.6, 'optimizer': 'adamW', 'kernel_initializer': 'glorot_uniform', 'ann_layers': 5, 'units_0': 200, 'units_1': 50, 'units_2': 200, 'batch_size': 32, 'epochs': 100, 'units_3': 50, 'units_4': 50}

Table 2: Best Parameters for RC and DCNN+RC models.

KNN	{'n_neighbors': 11, 'leaf_size': 26, 'weights': 'uniform', 'metric': 'cityblock'}	DCNN+KNN	{'activation': 'elu', 'dropout': 0.6, 'optimizer': 'adam', 'kernel_initializer': 'glorot_uniform', 'pooling': 2, 'kernel': 3, 'cnn_layers': 3, 'conv0': 150, 'conv1': 40, 'batch_size': 32, 'epochs': 100, 'conv2': 10}{'n_neighbors': 3, 'leaf_size': 27, 'weights': 'uniform', 'metric': 'cityblock'}
SVM	{'C': 10.0, 'gamma': 1.0, 'kernel': 'poly'}	DCNN+SVM	{'activation': 'elu', 'dropout': 0.6, 'optimizer': 'adam', 'kernel_initializer': 'glorot_uniform', 'pooling': 2, 'kernel': 3, 'cnn_layers': 3, 'conv0': 150, 'conv1': 40, 'batch_size': 32, 'epochs': 100, 'conv2': 10}{'C': 1.0, 'gamma': 1.0, 'kernel': 'linear'}
RF	{'max_depth': 14, 'min_samples_split': 2, 'criterion': 'gini', 'n_estimators': 200}	DCNN+RF	{'activation': 'selu', 'dropout': 0.2, 'optimizer': 'adam', 'kernel_initializer': 'glorot_uniform', 'pooling': 2, 'kernel': 3, 'cnn_layers': 3, 'conv0': 10, 'conv1': 100, 'batch_size': 32, 'epochs': 100, 'conv2': 10}{'max_depth': 5, 'min_samples_split': 4, 'criterion': 'gini', 'n_estimators': 300}
ANN	{'activation': 'elu', 'dropout': 0.2, 'optimizer': 'adam', 'kernel_initializer': 'he_uniform', 'ann_layers': 5, 'units_0': 75, 'units_1': 200, 'units_2': 50, 'batch_size': 32, 'epochs': 100, 'units_3': 50, 'units_4': 50}	DCNN+ANN	{'activation': 'elu', 'dropout': 0.4, 'optimizer': 'adamW', 'kernel_initializer': 'he_uniform', 'pooling': 2, 'kernel': 3, 'cnn_layers': 3, 'conv0': 10, 'conv1': 130'batch_size': 32, 'epochs': 100, 'conv2': 10}{'activation': 'elu', 'dropout': 0.6, 'optimizer': 'adamW', 'kernel_initializer': 'glorot_uniform', 'ann_layers': 3, 'units_0': 125, 'units_1': 175, 'units_2': 100, 'batch_size': 32, 'epochs': 100}

4 CONCLUSIONS

In this research, we introduced our proposed 3D spatiotemporal multi-view cross-learning framework for the identification of individuals using EEG based neural responses. We explored the effectiveness of cross-model machine learning approaches compared to regular classifiers. In addition, we investigated individuals' identifiability using the proposed framework. The results indicate that the proposed approach is promising, although more detailed exploration is needed to achieve stable learning.

As an extension of this research, attention mechanisms could be employed to enhance stability. Furthermore, a longitudinal study involving data collection over an extended period would help us better understand the stability of EEG neural responses.

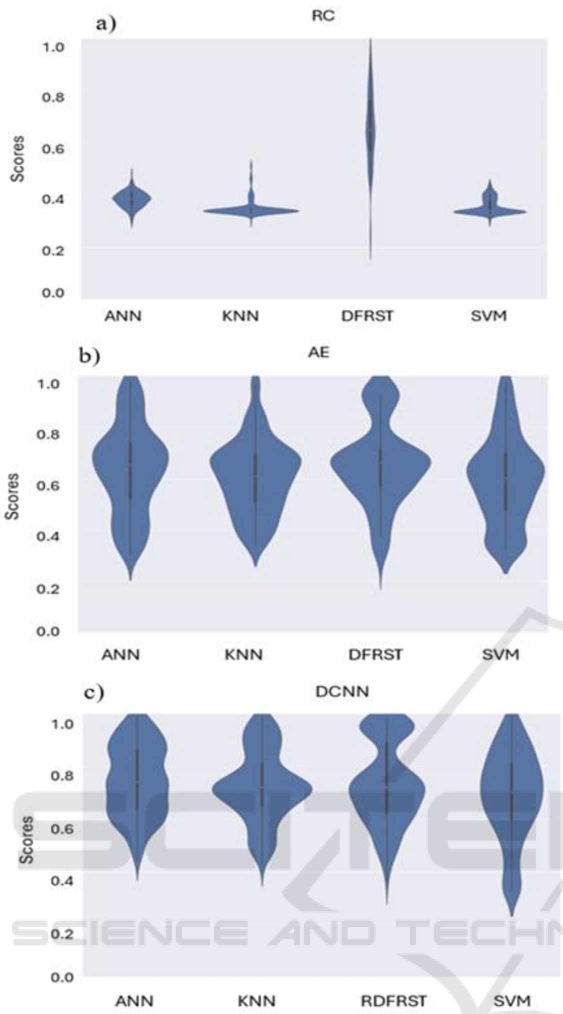

Figure 6: Comparison of RCs when trained by base learners, a) Regular classifiers, b) AE, c) DCNN (ACC scores).

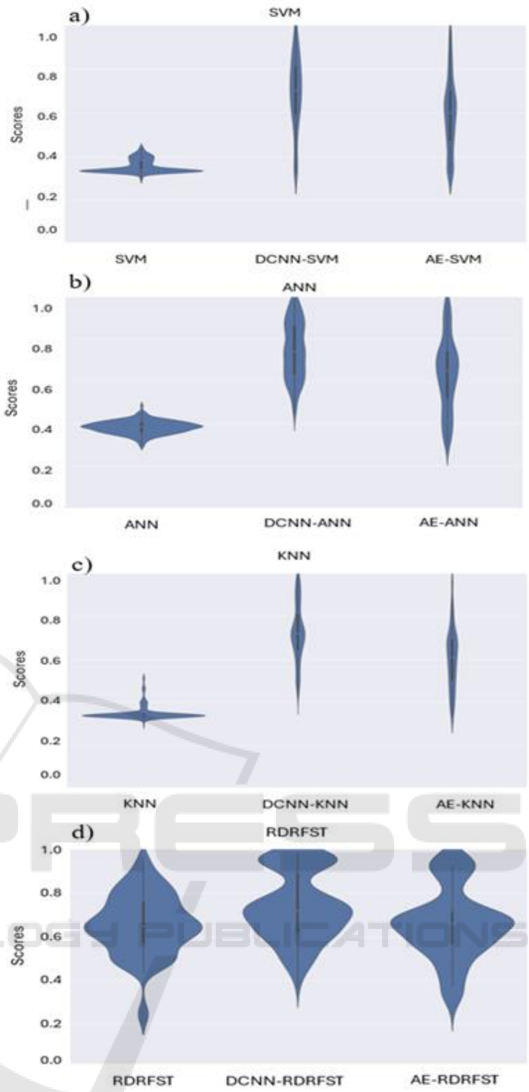

Figure 7: Effectiveness of cross-model learners across RCs (ACC scores).

ACKNOWLEDGEMENTS

Research reported in this publication was supported by an Institutional Development Award (IDeA) from the National Institute of General Medical Sciences of the National Institutes of Health under grant number P20GM103424-20 via Louisiana Biomedical Research Network.

Author Contribution Statement:

All authors discussed the methods, results, and commented on the manuscript. Major individual contributions are as in the following.

Ömer M. Soysal: Supervising the project, conceptualization, pipeline design, supervising the data collection, implementing the pipeline, leading the preparation of the manuscript.

Iphy E. Kelvin: Pipeline implementation, debugging, testing the code, data structure design, running the code, assisting in the data collection and writing the method section.

Esad M. Oztemel: Implementation of the autoencoder and signal conditioning functions, assisting in conceptualization, writing the introduction, and results section.

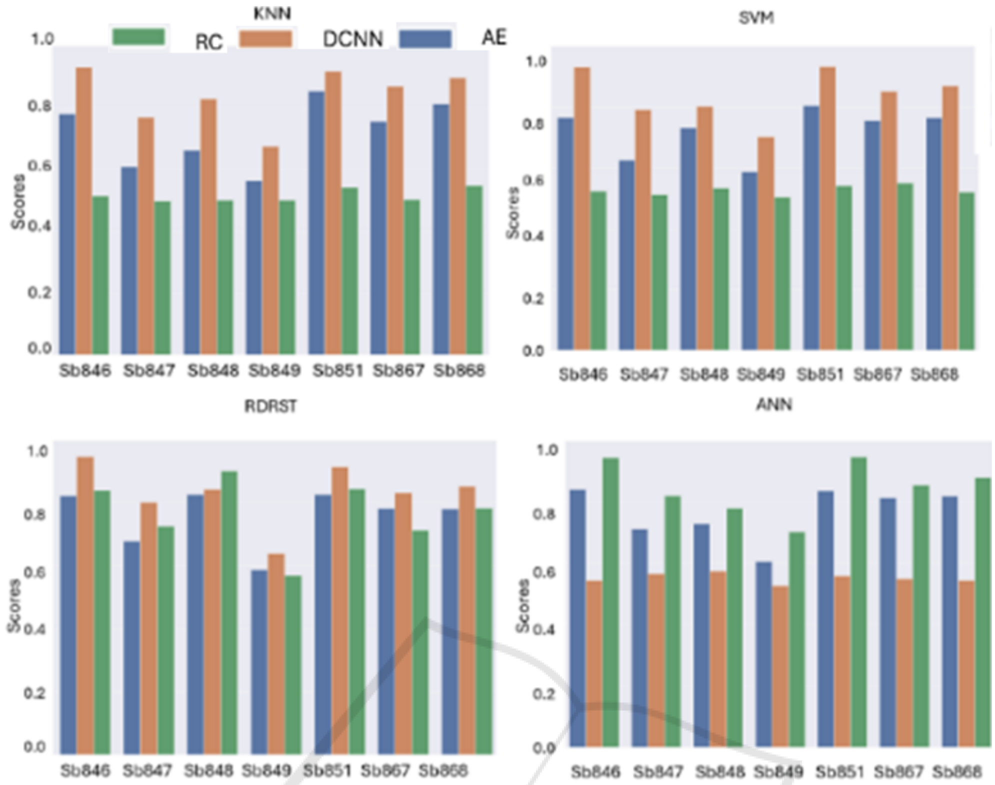

Figure 8: Identifiability of individuals (AUC scores).

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