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ContrastNet: Unsupervised Feature Learning for EEG Signals and HSI Classification Using DCNN and Autoencoders

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Abstract:

Scientific research on digital images has advanced significantly following their emergence. From earlier times to our current situation, the sizes as well as the quality of the images generated have increased substantially. Nevertheless, there are only so many outcomes that may be achieved when the data in these pictures stays in the band that is visible (RGB band). It has become necessary to obtain photos containing additional broadband information as a result. The Hyperspectral Imaging (HSI) technique was created to address this requirement. A new framework called ContrastNet is intended for unsupervised learning of features in two different domains: ECG readings and HSI. ContrastNet attempts to extract discriminative features from these complicated data types without necessitating labelled data to be trained by utilizing automatic encoders and Deep Convolutional Neural Networks (DCNNs).When it comes to EEG signals, ContrastNet picks up representative features that identify significant patterns connected to various brain activity levels. Comparably, ContrastNet collects features from HSI classification that encode spectral data important for differentiating between various categories of interest. ContrastNet is an adaptable feature learning method that can handle various datasets and applications without requiring a large amount of labelled data by employing DCNNs and automatic encoders in an unsupervised way.

Keywords: Contrastnet, Unsupervised Feature Learning, EEG Signals, HSIry, Deep Convolutional Neural Networks, Autoencoders, Classification.

1. Introduction

Owing to limited advancements in artificial intelligence, a suite of advanced technology for automation must be employed in conjunction with human activities. It is well known that in these human- machine (HM) systems, human operators play a crucial role [1]. In an HM operable setting, tracking human Mental Workload (MW) is crucial for employment involving flight operations, nuclear-powered plants, and operated space exploration, among other hazardous tasks

[2]. Although there isn't a single, agreed-upon definition for MW, it's generally understood to mean the temporary human cognitive resource or ability needed to complete a certain cognitive job [3]. The capacity to manage unforeseen circumstances is indicated by the degree of MW, which is closely correlated with alertness and awareness of the situation.

A high MW level indicates a high-risk operating state for the operator and a significant likelihood of a major HM system malfunction. The essential cognitive resources try to correspond with the level of mental exertion during some mental tasks [4].Due to constrained physiological experiences as well as working memories, an operator's OFS may not always fulfill requirements for the job, unlike those of machinery and/or algorithms.MW evaluation is a crucial component of human-centered HM systems because elevated demands on mental capacity can lead to productivity decrement or even fatal mishaps [5].

The three primary methods used to evaluate MW are physiological assessments human performance, and subjective decisions. Physiological measures were judged appealing in a study that was recently released due to the fact that they can be applied with a minimum of disruption to the primary objective [6]. The EEG has become one of the most frequently employed techniques to monitor brain activity amongst the different physiological measures. Real-time estimation of human cognitive states can be achieved using EEG readings. The machine learning-based method has drawn a lot of interest for its ability to accurately classify EEG signals into milliwatt levels. model's training stability may be weakened by the large dimensionality of EEG features [7].

Nonetheless, there are at least two problems that restrict the deep neural network model's ability to generalize. (1) The beneficial data contained in EEG characteristics is tainted by the noise created by muscle contractions and manoeuvres. (2) The EEG markers' data distribution differs for every individual. For the purpose of more successfully eliminating the noise components in multi-dimensional features [8]. Redesigned the member SDAE's shallow hidden layer into a feature mapping layer that may preserve local information in EEG fluctuations in order to significantly increase classification accuracy. It is anticipated that the individual-specific features in EEG will be more effectively recovered and merged to represent the MW levels, inspired [9]

Accurately interpreting EEG signals to identify motor intents is crucial for enhancing upper limb prosthesis control and giving amputees their sensory input back. Furthermore, using prosthesis is crucial for elevating the quality of life [10]. However, between 6 to 60% more amputees are rejecting them and using them non-functionally. The proximate level of amputation starting at the elbow or transradial to the level of the elbow or shoulder disintegration, respectively, is correlated with this rate. There have been a number of contributing causes to prosthetic rejection [11]. Putting aside the debate over whether prosthesis is best for amputees, the main causes of prosthesis disapproval are feedback from the sensors and loss of control function. With the development of brain-computer interface (BCI) systems, it is now feasible to determine brain activity through the use of a variety of methods as control signal sources [12]. Furthermore, a number of research investigations have demonstrated that people with disabilities who have had their elbows amputated above the elbow still retain the capacity to precisely generate cerebral activity linked to motor function via the brain in order to interpret the goals of limb movements [13]. Therefore, BCI systems are dependable technologies that could interpret the intentions of amputees and convert them into electrical signals for manipulating dexterous hand prosthesis. An unparalleled comprehension of the brain mechanisms controlling the movement of limbs has been made possible by several electrophysiological techniques [14]. Based on their scale of resolution, they are currently divided into three categories: macroscopic, mesoscopic, and microscopic. Single-cell recordings and microelectrode arrays have both been used to capture brain signals with outstanding spatial accuracy at the microscopic level.

By capturing the reflections of hundreds of distinct electromagnetic spectrum bands, a picture with Hyperspectral characteristics can be produced. Reflections in wavelengths known as infrared (IR) and near-infrared (NIR), which are undetectable to man's naked eye, make up a hyperspectral representation [15]. IR reflections are invisible to the human eye; only visible (RGB) band reflections are seen. The whole spectrum of electromagnetic waves is presented in Figure 1.

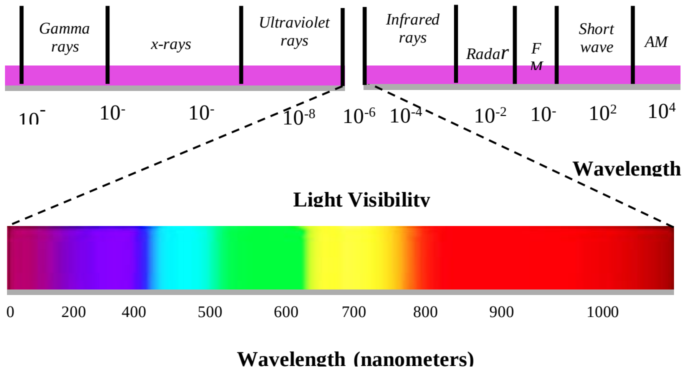

Fig 1. Electromagnetic spectrum

On a comparison HSI has hundreds of subcomponents, whereas a normal RGB image has only three. Following acquisition of the image, a data cube (hypercube) including spectral and spatial information emerges. The measurements of an information cube are determined by the number of bands and the picture's resolution [16]. The 'X' and 'Y' components of the hyperspectral data cube are determined by the image's pixel density, while the image's depth is determined by the total number of bands present. A comparison of RGB and HSIs is shown in Figure 2.

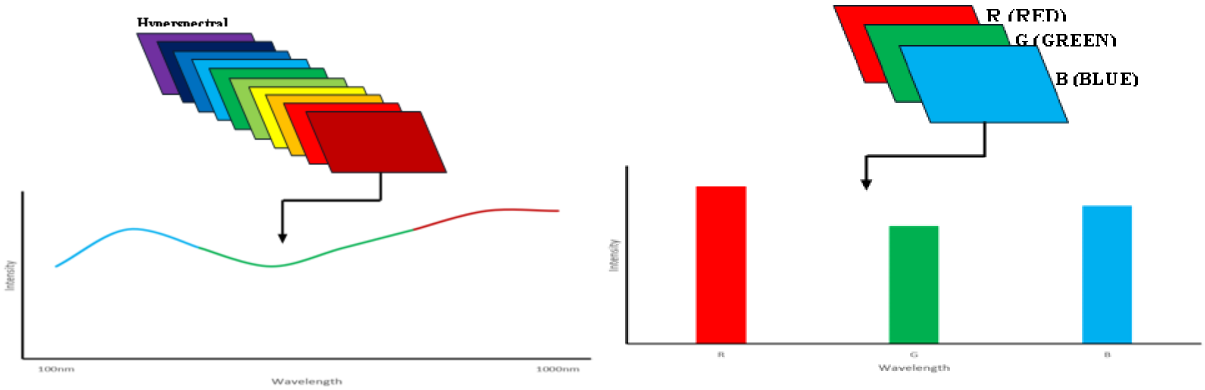

Fig 2. (a) Hyperspectral; (b) RGB image components

2. Related Works

Deep learning in neural networks has proven to be a highly effective method for resolving EEG-based emotion decoding issues and offers a better way to describe and combine the input information deep conceptual characteristics. To perform EEG-based emotion categorization, All of the aforementioned research, however, were supervised learning based, and deep networks in particular required a large number of training samples with emotion labels. For instance, the overfitting issue would prevent the deep network from generalizing effectively with a lesser number of training examples [19]. The performance of the network would be significantly influenced by both the quantity of data collected and the layout of the network.

Unsupervised learning, which requires relevant information from the available samples without any accompanying tutors, would offer a more natural method of decoding EEG signals and is more in line with human learning mechanisms [20]. The concept of unsupervised learning is more in line with human learning mechanisms, which need relevant information from accessible samples without the assistance of teachers, and would offer a more organic method of decoding EEG signals [21], in the lack of label instructions. The relationship structure between the samples may be incorrectly assessed in the event that a feature representation is erroneous. Unfavorably the modeling effectiveness would be severely constrained by conventional and shallow characteristics, which are mostly based on professional expertise, previous learning, and assumptions. Furthermore, from the raw EEG data, conventional features might not be able to effectively extract the complex and non-linear patterns [22].

Introduces the fundamental concepts of a deep encoder-decoder architecture which has greatly aided in the characterization and presentation of features for pictures, videos, and audios. Scientists then demonstrated that it was possible to improve the detection accuracy by using many popular supervised classifiers. In a similar vein, considered the chaotic and non-stationary nature of the high-dimensional EEG data when designing a convolutional automated encoder for EEG learning of properties [23]. Their system demonstrated reliable and precise execution in a computer-assisted medical diagnosis system. Solved a classification challenge by feeding high-dimensional EEG data into a stack autoencoder network after converting it to two-dimensional images using STFT rather than directly utilizing EEG raw signals. In the current study, employ hypergraph theory to tackle the emotion detection issue and present a unique unsupervised EEG feature extraction method [24].

In scenarios where noise distorts input data and the autoencoder's task is to recover the original, undisturbed input, claim that denoising autoencoders offer a reliable foundation for correcting errors. Convolutional autoencoders add to the autoencoder framework. Max pooling and deconvolution layers are used in the encoder, and upscaling and deconvolution layers are used in the decoder. Additionally, to enhance the model's final estimations, deep autoencoders have been utilized to extract features for infrared spectroscopy, such as HSI and point spectroscopy [25].

3. Proposed System

Illustrates a novel framework for unsupervised feature learning in the categorization of HSI and EEG data which are two different domains. Without requiring labeled data for training, the proposed ContrastNet framework uses DCNNs-AE to extract distinguishing characteristics from various complicated data sources. ContrastNet seeks to learn representative features from EEG signals that capture significant patterns linked to various brain functions. Then, these traits can be applied to tasks like emotion identification, brain-computer interfaces, and neurological condition diagnosis.

In a similar vein, ContrastNet aims to extract features from HSI encode spectral data necessary for differentiating across groupings or segments. Applications like precision farming, urban development, monitoring the environment and remote sensing can all benefit from this shown in Figure 3. When DCNNs-AE is used in an unsupervised fashion, ContrastNet can be made to work with a variety of datasets and applications without needing a large amount of labeled data for training. ContrastNet provides an adaptable method for feature learning in both EEG signals and HSIs classification problems by directly learning meaningful representations from the input.

Described how to effectively and unsupervisedly define non-stationary high-dimensional EEG signals using the proposed ContrastNet and its matching architecture and configuration. The gathered raw EEG signals are initially subjected to a comprehensive pre-processing to removing all the noises which include non-physiological artifacts and physiological artifacts. The detailed illustration of the proposed hybrid deep encoder-decoder network design is going to follow. More specifically, present (1) how to build the proposed ContrastNet's fundamental architecture using the DCNN (2) How to use DCNNs-AE to produce features with superior quality, (3) how to build the ContrastNet final architecture by integrating DCNNs-AE based network to more effectively fusing both temporal and spatial information.

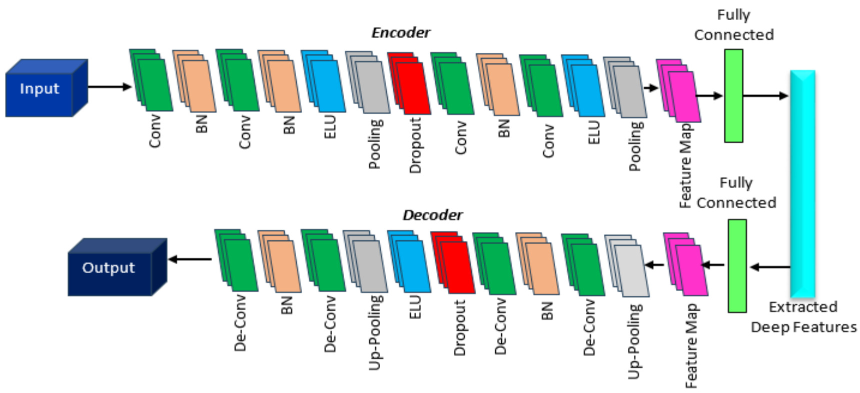

Fig 3. DCNN-AE architecture

A deep encoder-decoder network based on CNN is constructed, as shown in Figure 4 drawing inspiration from the EEG Net topology. For the purpose of creating feature maps that incorporate spatial EEG data at different frequency ranges, a series of two-dimensional layers of convolution is applied sequentially. Batch normalization (BN) is a technique utilized for normalizing every training mini-batch and accelerate the training of networks process by reducing internal covariate shift. For better model fitting, exponential linear units (ELU), the activation function, is introduced to the convolutional and deconvolution layers. The discriminator design in the final version of the planned DCNN-AE is identical to that of the discriminator.

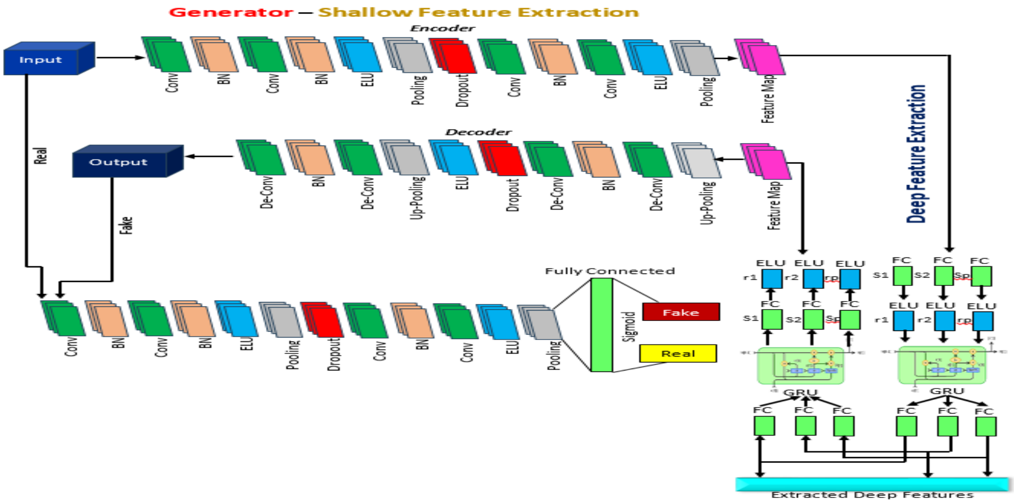

Fig 4. The proposed DCNN-AE architecture makes advantage of Net.

During the training process, the discriminator D(X, G(X)) ∈ [0, 1] calculates the likelihood that the input data (real training sample X or synthesized fake sample G(X) generated by the generator) is either genuine or counterfeit shown in Figure 5. The generator G describes the latent feature representation (o) of the sequential EEG signals X. During the training phase, the goal is to create an excellent D which is able to differentiate between the genuine sample and the counterfeit samples that are produced, and simultaneously trying to create a strong G that can create an invalid sample which resembles as close to the real samples that can be produced (two-player minimax game).

$$L_{GAN}(G, D) = E_I(\log D(I)) + E_I(1 - D(G(I))) \quad (1)$$

In addition to G's objective function,

$$L_1(G, D) = |I - G(I)|_2^2 \quad (2)$$

3.1 Dataset

Table 1 is a hypothetical representation and does not reflect the actual datasets used in the paper.

Table 1. Dataset source

Dataset Name	Data Type	Source	Size	Features	Preprocessing	Purpose
EEG Dataset	EEG signals	Public EEG databases	1000 samples	Electrode readings	Normalization, filtering	Training, Testing
HSI Dataset	Hyperspectral images	Research institution	500 images	Spectral bands	Spectral preprocessing	Training, Validation

3.2 Evaluation

The EEG recordings are regarded as vertices, and the connection between these points in terms of EEG characteristics is used to build a hypergraph. Here, EEG FuseNet's defined characteristics are used to calculate the similarity between the different EEG samples, and the resulting similarity patterns are used to build hyperedges that connect several EEG samples. A hypergraph, as opposed to a basic graph, can connect a few (more than two) vertices that have comparable qualities, showing a wider range of interconnections and exposing more complex hidden frameworks as opposed to simple links. The created hypergraph is divided into a certain number of classes in order to achieve the emotion classification. The computation of the hypergraph Laplacian and solved using an optimal eigenspace. Next, a number of classes are created from the generated hypergraph, and each class represents a single emotion condition.

Gain understanding of the underlying trends that the DCNN-AE model has identified by analyzing the learned features and model predictions.

Analyze the findings in light of the particular application domains, such as remote sensing for hyperspectral imaging and neuroscience for EEG signals.

Loss function of DCNN training: $L_{DCNN} = \frac{1}{N}\sum_{x=1}^{N} j_x \log(\hat{j}_x) + (1 - j_x)\log(1 - \hat{j}_x)$ (3)

where (j_x) is the true label and $(\hat{j}_x)$ is the predicted probability.

Loss function of AE training: $L_{AE} = \frac{1}{N}\sum_{x=1}^{N} |I_x - I'_x|^2,$ (4)

where I_x is the input data and I'_x is the reconstructed output.

Loss function of classifier training: $L_{classifier} = \frac{1}{N}\sum_{x=1}^{N} j_x \log(\hat{j}_x) + (1 - j_x)\log(1 - \hat{j}_x)$
(5)

Similar to the loss function of DCNN training
The main procedures for training a DCNN-AE model for feature learning and classification tasks are described in this algorithmic framework. Real-world implementations could need modifications or extra steps based on those particular needs and features of the data and activities involved

4. Results and Discussions

In order to confirm that the proposed DCNN-AE is successful for classifying MWs, two data partitioning paradigms are created shown in Figure 6.

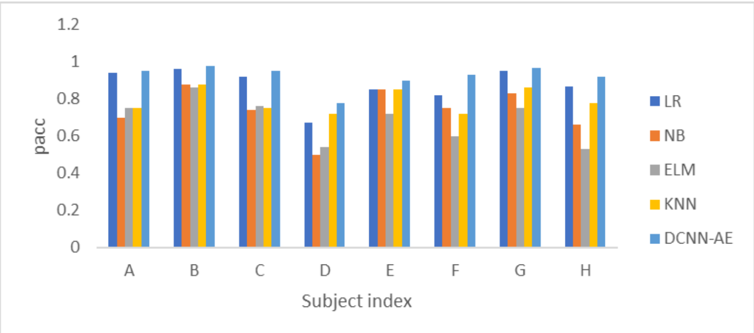

Fig 5. Comparison of the classification accuracy of shallow MW classifiers with DCNN-AE classifiers

The deep model is created and validated by employing approximately 28800 EEG events from the

8 participants, and the best model structure for the DCNN-AE is determined using the subject-generic paradigm. Seven of the nine data points are used for training, and the other two of the nine are used for testing, to provide the outcomes for classification shown in Figure 6. However, in order to assess the performance of classification of the various MW recognition models, utilizing the subject-specific paradigm. For each participant, there are 2800 and 800 samples in the no overlapped training and testing sets, respectively. Each participant's 3600 EEG occurrences are divided equally across the training and assessment sets.

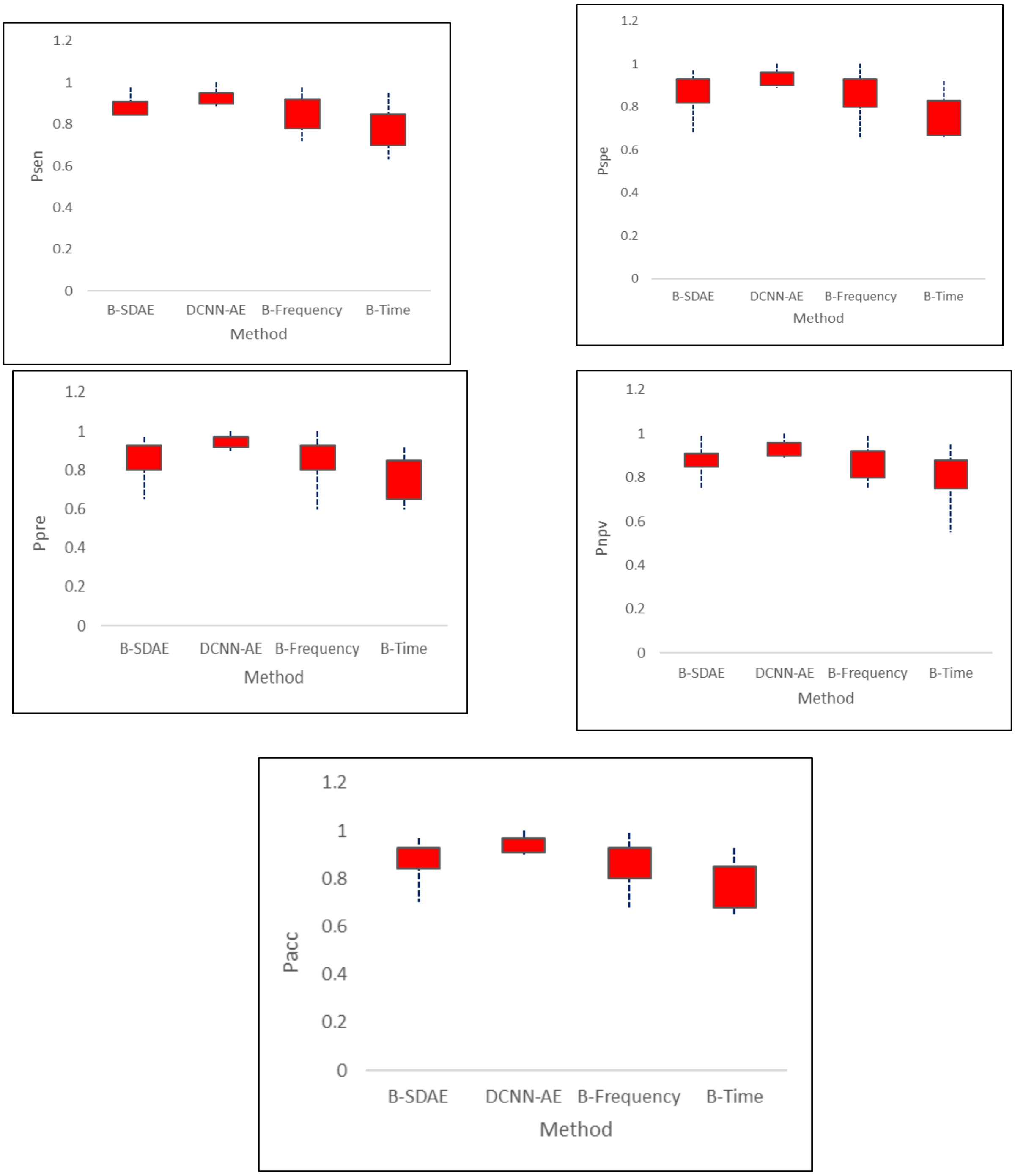

Fig 6. The performance indicators for the MW classification obtained from several ensemble classifiers

The computation of the performance is based on the ideal DCNN-AE structure.A classic binary classifier, the LR model was trained utilizing the maximum likelihood method; it does not require hyperparameter adjustment. Analyse the accuracy of the NB classifier for different combinations of prior probabilities {(0.1, 0.9), (0.2, 0.8),...(0.9, 0.1) }. The optimal values {0.2, 0.8} are those that produce the highest average accuracy.The optimal values {0.2, 0.8} are those that produce the highest average accuracy.The ideal value is 90 when look at its buried neuron size across {10, 20,100}. Moreover, sing KNN, established 100 nearest neighbours for the classification model, an instance-based learning technique. The chart shows that, out of all the classifiers, the DCNN-AE obtains the greatest performance among the 8 subjects shown in Figure 7.

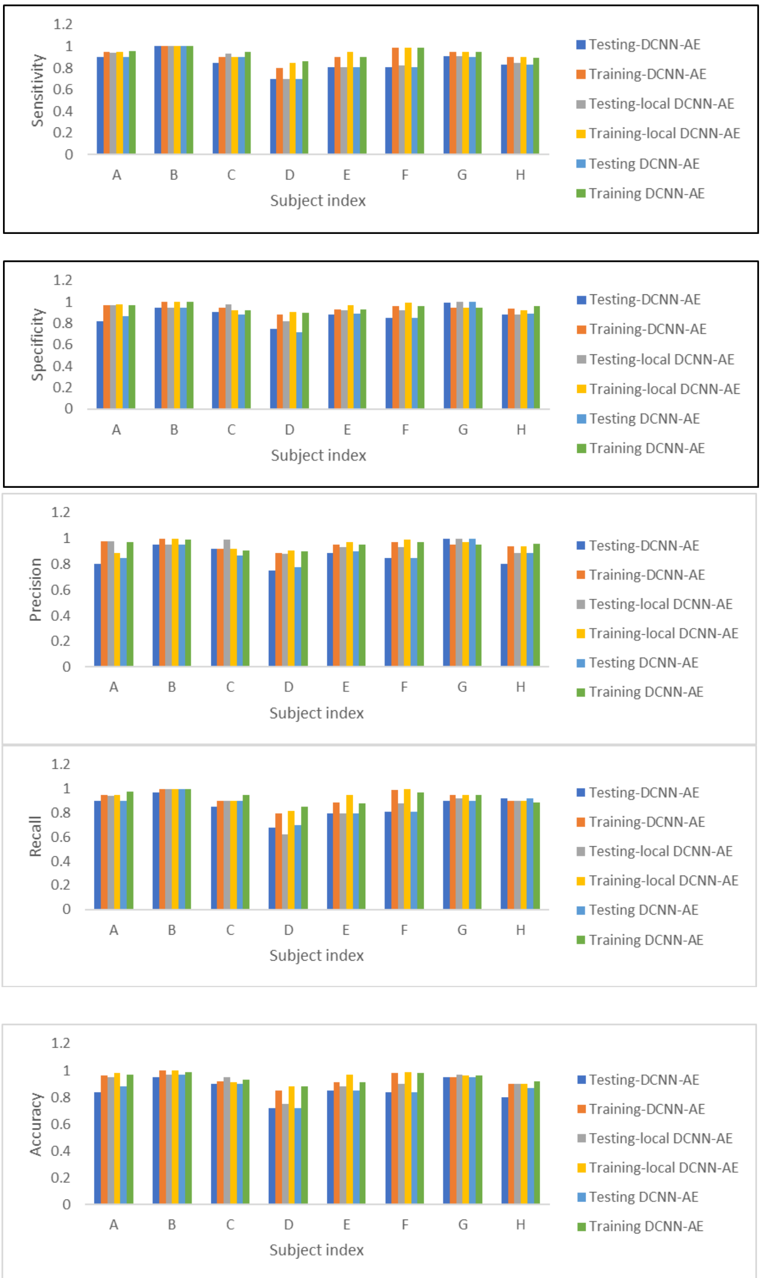

Fig 7. Comparing the DCNN-AE training and testing

Moreover, prominent psycho physiological properties can be acquired by feature representations following the use of the local DCNN-AE model which incorporates an additional hidden layer of linear mapping with local information preservation.

5. Conclusions and Future enhancement

Finally, ContrastNet is a major contribution to the field of unsupervised feature learning, especially in the areas of classification of HSI and EEG signal processing. ContrastNet successfully learns distinguishing characteristics from complicated information without the requirement for labelled samples during training by combining DCNN-AE. The experimental results highlight ContrastNet's efficacy, demonstrating much better classification performance than traditional techniques in both EEG signal analysis and HSI classification tasks. By extracting representative features, ContrastNet can reveal important spectral fingerprints in HSIs and temporal and spectral characteristics in EEG signals, providing knowledge about the fundamental trends present in the data. ContrastNet's adaptability makes it applicable to a wide range of sectors, including neuroscience, science of the environment, the agricultural sector, and remote sensing. This means that it can make a significant contribution to areas where complicated data processing is crucial. Future research endeavors could potentially investigate ContrastNet's capabilities in more detail, particularly with regard to scalability, hyperparameter optimization, and multi-modal data fusion. This would expand on the network's capacity to tackle real-world problems in a variety of disciplines. All things considered, ContrastNet proves to be a powerful instrument that is pushing the boundaries of unsupervised feature learning and ready to spark creative solutions for challenging data analysis and classification problems.

Future directions

Scalability and Efficiency: Explore on ways to make ContrastNet more scalable and computationally efficient, especially for handling bigger datasets and real-time applications. Investigating networked computing frameworks, model compression methods, or hardware acceleration tactics can be part of this.

Robustness and Domain Adaptation: Examine issues with ContrastNet's model resilience and domain adaptability, especially in situations where the distributions of the training and test data differ significantly. Provide methods for extending ContrastNet's functionality while preserving its ability to generalize as well as efficiency in new settings or domains with little to no labeled data.

Real-World Applications: Expand the use of ContrastNet for practical uses and real-world settings in industries including healthcare, agriculture, environmental monitoring, and defense. Work along with subject matter experts to implement ContrastNet in real-world scenarios, assess its functionality, and confirm that it is effective in resolving real-world problems.

By embarking in these new directions, ContrastNet can keep developing into an adaptable and powerful platform for unsupervised feature learning and classification, with a wide range of uses in a variety of fields and real-world situations. To maximize ContrastNet's influence in solving urgent societal problems and to drive innovation, academics, industry professionals, and stakeholders must work together.

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