Abstract—The process of recording Electroencephalography (EEG) signals is onerous, limiting the amount of training data available for downstream machine learning tasks, especially when using deep learning methods. Some previous works applied data augmentation techniques that slightly improve the performance, but there is no data like more data. In this work, we propose the Event-Related Potential Encoder Network (ERPENet); a semi-supervised autoencoder-based model, that can be applied to any ERP-related tasks. The strength of ERPENet lies in its capability to handle various datasets across multiple recording setups, enabling joint training across datasets, thereby increasing the amount of training data. ERPENet incorporates Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM), in an unsupervised autoencoder setup, which tries to compress the input EEG signal into a latent vector. The network also includes the classification part, consisting of a one-layer fully connected, for attended and unattended events classification. ERPENet significantly outperforms Xdawn, achieving 79.37% - 88.52% accuracy, depending on the dataset.

Index Terms—EEG, P300, Deep learning, Pre-trained model, BCI, Semi-supervised autoencoder

I. INTRODUCTION

Brain informatics-based large-scale architecture and its applications have been introduced in the recent years [1]. The pipeline of brain informatics comprises data acquisition (physical layer), brain data center (storage and computational layer) and service objects (application layer). The tools used to acquire data on the physical layer are wearable devices, non-contact sensing, high cognitive measurements (such as brain activity) and questionnaires. Then, the data is transferred to the storage and computational layer. In this layer, data management, mining, clustering, and computing (including machine learning and deep learning algorithms) are performed. At the end of the pipeline, the application layer provides a service for various groups of users such as researchers, physicians, healthcare-related businesses, etc. In this study, we focus on the large scale non-invasive brain signal data called electroencephalography (EEG), which is stored inside the computational layer. As a consequence of focusing on EEG management and computation, a large volume of data is exploited from EEG-related research such as brain-computer interface (BCI) and cognitive neuroscience to obtain a pre-trained deep neural network model for EEG which can handle various downstream tasks.

This work was supported by The Thailand Research Fund under Grant MRG6180028.

A. Dithaporn is with the Computer Department, Worcester Polytechnic Institute, Worcester, MA, USA.
E. Chuangswanich is with the Computer Engineering Department, Chulalongkorn University, Bangkok, Thailand.
T. Wilaiprasitporn, N. Banluesombatkul and S. Ketrat are with Bio-inspired Robotics and Neural Engineering Lab, School of Information Science and Technology, Vidyasirimedhi Institute of Science & Technology, Rayong, Thailand (e-mail: theerawit.w@vistec.ac.th).

To prove the concept of brain informatics on large-scale EEG data, EEG responses known as event-related potentials (ERPs) are examined. ERPs are widely known EEG responses from brain activity related to human perceptual and cognitive processes [2], [3]. Furthermore, the major ERP components are narrowed down, namely P300 using simple experimental tasks or paradigms across BCIs and cognitive neurosciences (the oddball paradigm). A fundamental experimental design is then adopted to study P300 responses from both attended and unattended events according to the human perceptual and cognitive processes [4]. The attended event is one where a human is waiting to perceive the target information with a low probability of occurrence. In contrast, an unattended event perceives non-targeted information with a higher probability of appearances. Here, six P300 databases (large-scale EEG data) are examined from various studied events including Documenting, Modelling and Exploiting P300 Amplitude in Donchin’s Speller [5], BCI Competition III - Dataset II [6], Auditory Multi-Class BCI [7], BCI-Spelling using Rapid Serial Visual Presentation (RSVP) [8], Examining EEG-Alcoholism Correlation (control group) [9] and Decoding Auditory Attention [10]. These six databases are combined to develop attended and unattended events P300 classification systems. The aggregated P300 data is used to train a universal feature extractor (pre-trained model) that can be easily adapted to new tasks or applications using minimal training data.

Due to the potentially large volume of data, an effective way is required to compress and store the collected data. Several studies have attempted to reduce the amount of data by decreasing the length of each sample. One popular procedures for achieving this is compressed sensing (CS). It projects a portion of the input signal onto a random matrix like Gaussian, sparse binary, or binomial such that the size of the projected data is smaller than the length of original samples. Prior to data analysis, we needed to reconstruct the projected data using certain variants of CS techniques such as sparse Bayesian learning [11]–[14], or reconstruction-based inter-channel and intra-channel correlations [15]–[19]. However, the reconstruction of CS involves the solution of optimization problems which can be time-consuming, so is impractical for use in real-time applications such as online BCI for electrical appliances controls [20].

Recently, a CS method based on deep learning (DL), namely the Autoencoder (AE), for body area networks and tele-monitoring systems was proposed [21]. The authors reported the advantages of AE over the classical CS technique in both computation time and accuracy for bio-signal data reconstruction. The goal of their work was not only to find the optimal data compression procedure but also to classify the event type. To combine the data compression feature of AE to address classification problems, a semi-supervised AE was applied, since it could also learn a linear mapping to label each class of data along with reconstruction (The concept of a semi-supervised AE is described further in the methodology section of this paper). Epileptic, eyes-closed and eyes-opened EEGs from five subjects and five classes in total, [22], were used in their proposed model evaluation. Unlike their semi-supervised AE which was simply formed by two fully connected (FC) layers, we propose our own semi-
The data in each dataset was preprocessed (as described in Section III) and partitioned according to attended and unattended events, labeled in one-second lengths. Only samples measuring from 0.2 to 0.6 seconds were selected, such that each was reduced from 250 to 100 (250 Hz × 0.4 s) points (as described in Section III). Each sample was subsequently selected only midline and occipital parts of the scalp, as indicated by the orange circles in the figure and mapped into a 5 × 9 x 100 matrix. Finally, these were used as inputs for the semi-supervised AE, composed of two main parts. The first part is the unsupervised AE. The inputs were brought into an encoder of the AE, including two blocks of CNNs followed by an LSTM (many-to-one) layer. From the LSTM output, a latent vector of the AE was obtained. At ⋆, the latent vector was then repeated 100 times to bring it into the decoder of the AE. The decoder has symmetrical CNN blocks and LSTM sizes, but the number of filters in each layers is different, as shown in the figure. Moreover, unlike LSTM (many-to-one), LSTM (many-to-many) is set to return the full sequence. In the aforementioned structure of this unsupervised AE, the output represents reconstruction of an input signal. The second part of our model is the supervised classifier. The latent vector from the first part was brought into a single FC layer using sigmoid activation in order to classify the data into two classes: attended and unattended events.

In this section, we first introduce Deep Neural Networks (DNNs) for constructing the semi-supervised autoencoder in Section A. Then, the architecture of our proposed AE model is described in Section B.

A. Convolutional neural network and recurrent neural network

The 10-20 system has become a common standard in scalp electrodes placement [24]. In higher resolution EEG, a modified combinatorial nomenclature (MCN) was developed by adding 10% divisions to increase the EEG channels. However, in a practical experiment setups, the positioning and number of electrodes differ depending on the applications. In this work, six public datasets were recorded using different electrodes positionings. To overcome the inconsistent positioning of electrodes across multiple datasets, 2D-CNNs were included at the beginning to extract the spatial information in our proposed model.

EEG channels were mapped to a 2D-grid topography representing the 2D scalp-map. To reduce the number of training parameters, we supervised AE, using stacks of two-dimensional convolutional neural networks (2D-CNNs) and long short-term memory units (LSTMs) in order to capture both spatial and temporal information.

The previous work also lacks the ability to handle and exploit information shared across different recording steps, whereas the proposed semi-supervised AE in this study is trained and validated across six datasets, obtained from various experimental studies with different numbers of EEG channels and sampling frequencies. This is achieved through mapping the CNN layers. However, all have common EEG features such as P300 responses from either the attended or unattended events. Two kinds of experiments were conducted to verify the academic merits and novelty of our work. Firstly, our experiments were conducted to demonstrate performance on large-scale EEG data compression using our semi-supervised AE compared to recently reported semi-supervised AE on biomedical signals including EEG [21]. The same AE was then applied to the attended and unattended event P300 classification systems. The results are compared to the state-of-the-art P300 dimensionality reduction algorithm named Xdawn with Bayesian LDA classification [23]. We strongly believe that the outcomes from this research will inspire not only EEG-related research but also other research on physiological data for the study and formation of pre-trained models in future engineering applications.

The remainder of this paper includes a section on the methodology section used to introduce the proposed model. Section III presents the datasets used in the experimental studies, with experimental protocols are described in Section IV. Finally, the results, discussion and conclusion are contained in Sections V, VI and VII, respectively.

II. METHODOLOGY

In this section, we first introduce Deep Neural Networks (DNNs) for constructing the semi-supervised autoencoder in Section A. Then, the architecture of our proposed AE model is described in Section B.

A. Convolutional neural network and recurrent neural network

The 10-20 system has become a common standard in scalp electrodes placement [24]. In higher resolution EEG, a modified combinatorial nomenclature (MCN) was developed by adding 10% divisions to increase the EEG channels. However, in a practical experiment setups, the positioning and number of electrodes differ depending on the applications. In this work, six public datasets were recorded using different electrodes positionings. To overcome the inconsistent positioning of electrodes across multiple datasets, 2D-CNNs were included at the beginning to extract the spatial information in our proposed model.

CNN is a grid-like topology neural network with a convolution operation at its core. It is widely used to extract spatial information, resulting in a dramatic reduction in the number of hidden nodes. CNN is the basis of many state-of-the-art DNNs in various vision models such as Resnet [25], Alexnet [26], R-CNN [27]. CNN also provides the properties of parameters sharing and equivariant representations, overall benefiting the encoder network [28]. In this work, CNN was adopted inside the time-distributed wrapper to extract spatial the features across all temporal slice with shared weights.

EEG channels were mapped to a 2D-grid topography representing the 2D scalp-map. To reduce the number of training parameters, we
selected EEG channels only between midline and occipital, which previously were considered as the optimized set of channels in BCI P300 [6]. However, CNN was known to lack the ability to capture the long-term relationships within time series. Only data points within the CNN filters are used for information extraction. To combat this problem, the Recurrent Neural Network (RNN), was incorporated into our proposed model.

RNN is another kind of DNN with the capability of sequence prediction from self-feedback. Each RNN node has its own internal memory which can produce arbitrary sequences, but RNN is known for vanishing and exploding gradient problems. To alleviate these problems, long short-term memory (LSTM) was developed [29] by adding 3 gates inside the RNN cell. The three gates are the input gate ($g_i^{(t)}$), the forget gate ($f_i^{(t)}$) and the output gate ($o_i^{(t)}$). Intuitively, the input gate controls the flow of new information entering the cell. The forget gate then makes a decision on which information should be kept in the cell, and the output gate decides when to generate the output. Every gate is based on the state unit($s_i^{(t)}$). Mathematically, it can be represented using the following equations:

$$f_i^{(t)} = \sigma(b_i^f + \sum_j U_{i,j}^f x_j^{(t)} + \sum_j W_i^f h_j^{(t-1)}),$$  
$$g_i^{(t)} = \sigma(b_i^g + \sum_j U_{i,j}^g x_j^{(t)} + \sum_j W_i^g h_j^{(t-1)}),$$  
$$o_i^{(t)} = \sigma(b_i^o + \sum_j U_{i,j}^o x_j^{(t)} + \sum_j W_i^o h_j^{(t-1)}),$$

where $U$ is the weight matrix connecting the inputs to the current hidden layer, $W$ is the weight matrix connecting the previous hidden layer and current hidden layer, $b$ is the bias matrix. $x(t)$ is the current input vector and $h_i^{(t)}$ is the current hidden layer vector. $i$ denotes a dependent cell, and $t$ denotes the time step in each cell. $\sigma$ is the sigmoid function acting as a gate in the LSTM unit.

B. semi-supervised autoencoder

Autoencoders (AEs) were first introduced in the 1980s for unsupervised feature extraction [30], dimensionality reduction [31] and data compression [32], which were previously used in EEG features extraction and compression [21]. AEs have two main components: the encoder and the decoder. The encoder network $E$ maps an input signal $s$ to a latent representation $h$, and the decoder network $D$ is a reconstruction that maps $h$ to an output layer. Ideally, there should be fewer nodes in the latent representation than in the input, resulting in the creation of a bottleneck effect, limiting the information passed to the decoder network. The decoder network reproduces the input in

| TABLE I: Semi-supervised Autoencoder Architecture |
|-----------------------------------------------|
| Encoder(ERPENet) | Decoder | Latent Supervised Classifier |
| Layer | Parameters* | Output | Layer | Parameters** | Output | Layer | Parameters | Output |
|-------|-------------|--------|-------|-------------|--------|-------|------------|--------|
| Input | - | (100,5,9,1) | Latent | - | 512 | Latent | - | (512) |
| CNN2D | (16,2,2) | (100,5,9,16) | Repeat | 100 | (100,512) | FC | 1 | (1) |
| BN | - | (100,3,5,16) | LSTM | 96 | (100,96) | Sigmoid | - | 1 |
| LReLU | 0.10 | (100,3,5,16) | Reshape | - | (100,2,3,16) |
| Dropout | 0.20 | (100,3,5,16) | Upsampling | (2,2) | (100,4,6,16) |
| CNN2D | (8,1,1) | (100,3,5,8) | ZeroPadding | (1,1) | (100,5,7,16) |
| BN | - | (100,3,5,32) | CNN2D | (32, True) | (100,3,5,32) |
| LReLU | 0.10 | (100,3,5,8) | BN | - | (100,3,5,32) |
| Dropout | 0.20 | (100,3,5,8) | LReLU | 0.10 | (100,3,5,32) |
| CNN2D | (8,1,1) | (100,3,5,8) | Dropout | 0.20 | (100,3,5,32) |
| BN | - | (100,3,5,8) | CNN2D | (16, False) | (100,3,5,16) |
| LReLU | 0.10 | (100,3,5,8) | BN | - | (100,3,5,16) |
| Dropout | 0.20 | (100,3,5,8) | LReLU | 0.10 | (100,3,5,16) |
| CNN2D | (32,2,2) | (100,2,3,32) | Dropout | 0.20 | (100,3,5,16) |
| BN | - | (100,2,3,32) | CNN2D | (16, False) | (100,3,5,16) |
| LReLU | 0.10 | (100,2,3,32) | BN | - | (100,3,5,16) |
| Dropout | 0.20 | (100,2,3,32) | LReLU | 0.10 | (100,3,5,16) |
| CNN2D | (16,1,1) | (100,2,3,16) | Dropout | 0.20 | (100,3,5,16) |
| BN | - | (100,2,3,16) | Upsampling | (2,2) | (100,5,10,16) |
| LReLU | 0.10 | (100,2,3,16) | ZeroPadding | (1,1) | (100,7,11,16) |
| Dropout | 0.20 | (100,2,3,16) | CNN2D | (16, True) | (100,5,9,16) |
| CNN2D | (16,1,1) | (100,2,3,16) | BN | - | (100,5,9,16) |
| BN | - | (100,2,3,16) | LReLU | 0.10 | (100,5,9,16) |
| LReLU | 0.10 | (100,2,3,16) | Dropout | 0.20 | (100,5,9,16) |
| Dropout | 0.20 | (100,2,3,16) | CNN2D | (8, False) | (100,5,9,8) |
| Flatten | - | (100,96) | BN | - | (100,5,9,8) |
| LSTM | (512,0.20) | Latent(512) | LReLU | 0.10 | (100,5,9,8) |
| Dropout | 0.20 | (100,2,3,16) | CNN2D | (8, False) | (100,5,9,8) |
| LReLU | 0.10 | (100,2,3,16) | BN | - | (100,5,9,8) |
| Dropout | 0.20 | (100,2,3,16) | Dropout | 0.20 | (100,5,9,8) |
| Flatten | - | (100,96) | BN | - | (100,5,9,8) |
| LSTM | (512,0.20) | Latent(512) | LReLU | 0.10 | (100,5,9,8) |

*Parameters format in encoder: CNN(number of filters,vertical stride,horizontal stride) with filter size of (3,3), LReLU(alpha), Dropout(Dropout Rate), LSTM(filter size,Dropout Rate)

**Parameters format in decoder: CNN(number of filters,zero padding) with filter size of (3,3), LReLU(alpha), Dropout(Dropout Rate), LSTM(filter size,Dropout Rate) with full sequence output, Upsampling(vertical scale,horizontal scale), ZeroPadding(vertical padding, horizontal padding)
the output layer; the networks are trained to minimize reconstruction loss, defined as $L(s, D(E(s)))$.

In the recent years, modern AEs have become more complex due to the integration of various kinds of DNN into $f$ and $g$. To prevent the AE from over-compressing the EEG, a supervised network was added - extended from the latent vector. Thus, the model is capable of learning to classify the input signal along with that of the reconstruction, namely a semi-supervised AE. The encoder is a transferable model called ERP Encoder Network(ERPENet). Here, we proposed a semi-supervised AE with CNN and LSTM model to reconstruct and classify EEG signals (Figure 1).

ERPENet is composed of 2 CNN blocks, each with three time-distributed CNNs, followed by a Batch Normalization(BN) layer, a Leaky Rectified Linear Unit(LReLU) [33] and a dropout layer. The final CNN is connected to a many-to-one LSTM as illustrated in Table I. The input has a dimension format of ((100,5,9,1)) (time, vertical coordinate, horizontal coordinate, data). The first CNN layer in each CNN block has a stride of 2, behaving behaving in a similar way to max pooling and reducing the size of the model. Max pooling was avoided in this study because there was a report of checkerboard artifact being generated in the reconstruction output [34]. The latter two CNNs extract the informations without any additional compressions. After every CNN layers, dropout regularization with a 0.20 dropout rate was applied prior to feeding into the next CNN layer to avoid overfitting. Output of the last CNN layer has a shape of (100,96), which is fed into a LSTM layer, composed of 512 LSTM units with a recurrent dropout. The LSTM layer is located after the CNN to compress the data in the temporal domain. Intuitively, the output of the LSTM at the final time step is considered as the latent vector, encapsulating the compressed information. As a result, the EEG signal is compressed in the spatial and temporal domains into a single vector of size 512.

In the decoder network, all layers are aligned symmetrically with the encoder network. The latent vector is repeated for 100 times to construct the data in a temporal format, matching the input format required for the many-to-many LSTM. In the CNN blocks of the decoder network, upsampling and zero-padding layers are added to each block. In similarity to the encoder network, it was decided not to use deconvolution, because of the reported checkerboard artifact generated [34]. After two blocks of CNN, the input EEG signal is reconstructed.

The layers parameters and complete model architecture are listed in Table I. The parameters were optimized from the larger values, and gradually decreasing the size of the model until degradation in performance is observed.

To further extend and improve the latent subspace, a basic supervised classifier was added, composed only of a single FC unit and sigmoid activation after the latent vector ($h$), which could be considered as an auxiliary input to the model. The extended supervised network creates a constraint for the latent vector to become interpretable as well as a compression of EEG.

C. Loss Function

Our proposed semi-supervised AE model was trained for two different tasks: reconstruction and binary classification. Two loss functions were incorporated and implemented into TensorFlow, providing reverse-mode auto differentiation [35]. For the reconstruction, the Mean Square Error (MSE) metric was computed from the difference between the reconstruction and the input. Due to the fact that most channel mapping is blank, the MSE function needs to be modified to compute the reconstruction loss only on the feature ($x_j$) not filled with zero as in Eq. 6:

$$ L_{MSE}(s) = \|s_j - D(E(s))_j\|^2, s_j \neq 0. \quad (6) $$

$s_j$ is the input signal where $j$ denotes the channel containing blanks on 2D mapping. This prevents the reconstruction preferring to output zeros in the early training stage. In the latent supervised classifier, attended and unattended events are classified by the sigmoid binary cross-entropy as shown in Eq. 7:

$$ L_{Binary}(y, y') = -\frac{1}{n} \sum_{i=1}^{n} y_i \ln(y_i'), \quad (7)$$

where $n$ denotes the total number of the input signals($s$). The prediction ($y'$) was predicted straight from the sigmoid attached to the $f(x)$ while $y$ is a true label. Binary class weights ($W_{c,i}$), where $c$ denotes class of sample $i$, was optimized to penalize the imbalances classes and weight between binary loss and reconstruction loss. In the cases that classes were balanced, the model worked best with $W_{d,i} = 0.667$. Finally, the total loss function was a summation of both objective loss functions weighted by dataset weights ($W_{d,i}$) as in Eq. 8:

$$ L_{Total}(s, y, y') = W_{(d,i)}[W_{(c,i)}L_{Binary}(y, y') + L_{MSE}(s)], \quad (8)$$

where $d$ denotes the sample of dataset $i$.

III. DATASET AND PREPROCESSING

The following six datasets were exploited in this study. All were from the P300-BCI experimental tasks based on the oddball paradigm, including visual and auditory stimuli, each of which has their own specific attended and unattended events. Moreover, these datasets were chosen in order to represent the strength of the model in which the neural networks, especially the CNN, are still able to capture the essential features from the input signals even though they were derived from various montage systems, sampled at different sampling rates, collected with diverse hardware filtering methods, and recorded in an unequal number of channels. Descriptions of the datasets are shown in Table III as follows:

- Exploiting P300 Amplitude changes [5]: this dataset resulted from a visual stimuli experiment. The study aimed at identifying the factors limiting the performance of BCIs based on ERPs, in order to improve the transfer rate and usability of these interfaces. In every run, each subject was asked to look at a 6x6 matrix, including 36 different characters. The rows and columns of the matrix were randomly highlighted one at a time for a short period, specifying a target character before each run. Each subject was then asked to mentally count the number of times any row or column, including the target character, intensified. During the experiment, EEG signals were collected using a BioSemi ActiveTwo EEG system. Subsequently, the signals were bandpass filtered in the band 0.15-5 Hz.
- BCI Competition III - Dataset II [6]: this study used a visual stimuli experiment with an intra-subject classifier proposed to predict the desired character from EEG signals. The experiments were similar to those in the above dataset. They also used the 6x6 matrix and attended events also occurred when any row or column with the target character was flashed. Instead of focusing on one character for each run, participants in this experiment were asked to focus on a single word containing a sequence of five characters. For each character epoch, rows and columns were randomly highlighted 180 times (6 rows x 15 times and 6 columns x 15 times), 30 of which included the target character specified as an attended event. For every run, each subject had to monitor five characters per epoch. Signals from the subjects
were collected using a montage system not specified in the paper. Finally, they were bandpass filtered from 0.1-60 Hz.

- auditory multi-class BCI [7]: this dataset was collected from a study using auditory experiments. They tried to propose a multi-class auditory-BCI classification using spatially distributed, auditory cues. In the experiment, each participant was surrounded by eight speakers, only five of which were used. These speakers were programmed to turn on at random, one at a time. In each run, a subject was instructed to mentally keep track of the extent to which the target direction (target speaker) was stimulated. The EEG was recorded using a number of Ag/AgCl electrodes, amplified using a 128-channel amplifier from Brain Products, filtered by an analogue bandpass filter between 0.1 and 250 Hz.

- BCI-Spelling using Rapid Serial Visual Presentation (RSVP) [8]: the aim of this study was to develop a visual speller that did not require eye movements to overcome the limitations of conventional BCIs. Each subject participated in two experiments: In the first experiment, geometric shapes were randomly flashed on the screen. Each geometric contained a unique set of five characters and had a unique shape and color. In the second experiment, each shape was changed to contain only a single character. In each run, a subject was asked to mentally keep track of the extent to which the target character was shown on the screen. The signals were recorded using an actiCAP active electrode system from Brain Products (Munich, Germany). All skin electrode impedances were kept below 20 kΩ. The bandpass of the hardware filter was 0.016–250 Hz.

A. Data preprocessing

Before using these datasets to evaluate our method, power line noise (50 Hz) was manually checked, and a Notch filter was applied if a noise was found. A low pass second order Butterworth filter of 30 Hz and high pass second order Butterworth filter of 0.5 Hz were then applied to normalize the datasets. We used a low order filter because some of the datasets had already been preprocessed. For consistency, they were resampled from the original sampling rates to 250 Hz.

From previous works [36]–[37], the P300 interest period was shown to be between 0.2 and 0.6 seconds after the stimulus. Therefore, we reduced the length of the EEG signal to 0.4 seconds.

IV. EXPERIMENTAL EVALUATION

In this section, the evaluation methods are designed to examine our proposed semi-supervised AE model for two different uses. The first (Experiment A) measures the reconstruction error and classification accuracy of various P300 datasets. In Experiment B, trained encoder networks from Experiment A were treated as pre-trained to retrain and benchmark the classification accuracy of a different dataset.

A. Experiment A: Semi-supervised AE reconstruction error

In this experiment, the compression performance of the proposed semi-supervised AE is measured by reconstruction error, attended, and unattended events classification accuracy. The encoder network encodes an input, 0.4 seconds of 35 EEG channels, into a latent vector with a dimension of 512. Hence, the compression ratio of our proposed AE model is $6.84(0.4s \times 250Hz \times 35/512)$. 

| Table II: Datasets used to train ERPNet |
|---------------------------------|---------------------------------|
| dataset                         | stimuli type | no. of subjects | no. of samples | sampling rate (Hz) | no. of channels |
| Exposing P300 amplitude changes (P300-Amplitude) | visual | 12 | 26182 | 2048 | 64 |
| BCI Competition III - Dataset II (BCI-COMP) | visual | 2 | 8295 | 240 | 64 |
| Auditory multi-class BCI (Auditory-BCI) | auditory | 10 | 40161 | 250 | 60 |
| BCI-spelling using RSVP (BCI-Spell) | visual | 13 | 84360 | 250 | 63 |
| Examining EEG-Alcoholism Correlation - control group (EEG-Alcohol) | visual | 122 | 10962 | 256 | 61 |
| Decoding auditory attention (Decode-Audi) | auditory | 11 | 24560 | 200 | 63 |
This evaluation method is designed to test the robustness of our proposed model over multiple datasets. One dataset was held back from AE training and used as a testing dataset to evaluate the trained AE with the reconstruction error, attended, and unattended event classification accuracy. Five datasets, excluding the testing dataset, were aggregated, stratified, and randomly split into two sets: training and validation. Here, one dataset was held back from AE training to underline the robustness of our proposed AE model across multiple datasets, and recorded from different fields of EEG study. After the AE training, the MSE metric was measured on the dataset held back from AE training.

In the semi-supervised AE training, the optimization algorithm and learning rate were chosen by grid searching between RMSprop [38] and vanilla SGD [39], with the initial learning rate between $[2^{-10}, 2^{-5}]$ in the decreasing power of 2, and the decay rate between $[10^{-7}, 10^{-4}]$ in the decreasing power of 10. After grid searching all six permutations, vanilla SGD with a learning rate of $2^{-8}(0.002)$ and a decay rate of $10^{-5}$ achieved the lowest validation loss. The AE was trained until there was no improvement in the validation loss for 100 epochs.

For baseline comparison, the Semi-supervised Stacked Label Consistent Autoencoder (SSLc-AE) [21] proposed by Hoffmann et al. was implemented. The baseline model also has a semi-supervised part, identical to that in our proposed semi-supervised AE. However, the reconstruction and classification losses in the SSLC-AE model were not combined into a single loss but kept separate and applied alternatively with the Split Bregman technique, instead of the reverse-mode auto differentation used in our model. Moreover, the model architecture was different. The baseline model was implemented with only two FC layers in the encoder and decoder networks. FC is known to be sensitive to the training data and may easily overfit, limiting the model to shallow networks. In that paper, EEG was augmented to avoid the overfitting problem. Since our proposed model was trained using aggregating EEG, and CNN with LSTM tends to be more robust to overfitting than FC, a complex model with deeper architecture was introduced.

In the original SSLC-AE, the encoder network is composed of 2 FC layers, 125 nodes and 63 nodes, with a symmetrical decoder and supervised classification on the latent vector. However, for a fair comparison with our proposed model, we increased the number of nodes in FC layers to 500 and 250, respectively. As such, the latent vector in SSLC-AE was comparable to that in our proposed AE model. The 2D-grid map was flattened to a single vector and used as the input of SSLC-AE. The reconstruction error of SSLC-AE was also modified to compute only on the non-blank inputs. Prior to the training of SSLC-AR, optimization in the SSLC-AE model was tuned with the same grid search as our proposed model. The RMSprop optimizer with a $2^{-5}$ learning rate and a decay rate of $10^{-5}$ yielded the lowest loss in all dataset permutations. The AE was trained until there was no improvement in validation loss for 100 epochs.

Another objective of our proposed model was to use the latent vector to predict ERP attended and unattended events directly without any additional neural network layers besides the sigmoid. For each test dataset, the classification network (a single FC node) was retrained with 10-fold cross-validation on the held back dataset. In the results, only attended and unattended event classes were predicted from the supervised network.

B. Experiment B: Adoption of pre-trained model (ERPENet)

The drawback of DL is that it requires a substantial amount of data in the training process, as mentioned in Experiment A. For a small single dataset, DL performance is often poorer than a traditional machine learning algorithm. To overcome this obstacle, AEs have been used to pre-train various kinds of DL model [40]. Our proposed semi-supervised AE was trained with a variety of large EEG datasets, which partially solved the problem.

General representations of EEG have been learnt in a semi-supervised fashion, thereby minimising the overfitting problem. In this section, the trained weights of CNN blocks and LSTM in the encoder network have been adapted and extended using a supervised classifier as shown in Figure 2.

First, we compared the training losses of an adapted pre-trained model and the same model with Xavier [41] initialized weights. In the adapted model, a concave-down triangular learning rate technique was applied as shown in Figure 2 [42]. The model with Xavier initialized weights was trained using the SGD with learning rate of $2^{-8}(0.002)$ and the decay rate of $10^{-5}$ as in the Experiment A.

To further validate our model using a state-of-the-art P300 feature extraction method, we compared our ERPENet against the Xdawn algorithm [43]. Xdawn is widely adopted in many dimensional reduction works to enhance the features of ERP-based EEG. Bayesian LDA classification was applied in the pipeline to classify the attended and unattended event classes [23], with 10-fold cross-validation used to cross-validate the Xdawn-LDA. Eight folds were used in training one as a validation set to tune the number of components in Xdawn. The last fold was used to test the algorithm as reported in the next section. A comparison with the pre-trained, fine-tuned SSLc-AE was also carried out using the same technique as in ERPENet.

V. RESULTS

In this section, the results of Experiments A and B are shown and statistically analyzed to evaluate our proposed Semi-supervised AE model.

A. Experiment A: Semi-supervised AE reconstruction error

Our proposed semi-supervised AE was trained on six datasets using permutation testing and evaluated by reconstruction error (MSE), and classification errors (accuracy and area under the curve).

In table IV, the mean of reconstruction error and its standard error are in bold text. With the Wilcoxon signed-rank test, a two-sided $p$-value for the null hypothesis where the mean difference of zero is less than 0.01 indicates that the MSEs of the proposed semi-supervised AE are competitive against SSLC-AE.
TABLE IV: Reconstruction error of the proposed semi-supervised AE and SSLC-AE on six different datasets trained by holding out the testing dataset.

| Dataset          | Proposed Semi-Supervised AE | SSLC-AE |
|------------------|----------------------------|---------|
|                  | MSE                        | MSE     |
| P300-Amplitude   | 0.1447 ± 0.0326             | 0.3224 ± 0.0142 |
| BCI-COMP         | 0.1325 ± 0.0184             | 0.3821 ± 0.0117 |
| Auditory-BCI     | 0.2572 ± 0.0226             | 0.4206 ± 0.0193 |
| BCI-Spell        | 0.2622 ± 0.0214             | 0.4399 ± 0.0184 |
| EEG-Alcohol      | 0.1494 ± 0.0162             | 0.3436 ± 0.0102 |
| Decode-Audi      | 0.2761 ± 0.0196             | 0.4635 ± 0.0095 |

TABLE V: Attended and unattended event classification ACC and AUC of the ERPENet and SSLC-AE on six different datasets trained by holding out the testing dataset.

| Dataset          | ERPENet | SSLC-AE |
|------------------|---------|---------|
|                  | ACC     | AUC     | ACC     | AUC     |
| P300-Amplitude   | 88.32 ± 2.74 | 80.60 ± 0.48 | 81.20 ± 0.87 | 73.72 ± 1.33 |
| BCI-COMP         | 83.54 ± 1.53 | 69.15 ± 0.83 | 86.02 ± 1.4 | 70.97 ± 3.28 |
| Auditory-BCI     | 72.56 ± 1.02 | 54.28 ± 2.53 | 72.43 ± 1.31 | 50.11 ± 0.08 |
| BCI-Spell        | 73.29 ± 0.58 | 51.55 ± 1.42 | 76.37 ± 1.85 | 58.47 ± 0.63 |
| EEG-Alcohol      | 63.02 ± 2.87 | 67.40 ± 2.83 | 78.38 ± 3.47 | 74.32 ± 1.08 |
| Decode-Audi      | 54.76 ± 1.62 | 50.01 ± 0.07 | 56.14 ± 1.45 | 53.82 ± 0.12 |

In classification evaluation, the area under the curve (AUC) of the receiver operating characteristic (ROC) is reported in addition to classification accuracy (ACC), to test the discriminability of the models. ACC is also known to be insensitive to imbalance classes, validating the binary classification model better than the accuracy metric.

In Table IV, the features representing latent vector quality were evaluated through ACC and AUC classification from a single classifier node. Statistically, we cannot reject the null hypothesis that the ACC and AUC are equal to the Wilcoxon signed-rank test in every dataset. Only one dataset, namely ERPENet, outperformed the SSLC-AE, while SSLC-AE outperformed the ERPENET in two datasets. SSLC-AE performed slightly better than our proposed model, from which we conclude that fine-tuning was required for efficient use of the ERPENet.

B. Experiment B

The validation losses of both models were plotted in Figure 3. In the Xavier weight initialized model, overfitting started appearing at epoch 25th. Overfitting problem appears in Xavier initialized model, overfitting started appearing at epoch 25th. Overfitting problem appears in Xavier initialized model, overfitting started appearing at epoch 25th. Overfitting problem appears in Xavier initialized model, overfitting started appearing at epoch 25th.

Among all datasets, BCI-COMP, EEG-Alcohol, and P300-Amplitude have the smallest number of samples, with ERPENet obtaining a higher ACC and AUC than the Xdawn algorithm on all three datasets. It could be inferred that the pre-trained model would improve the training of DL models on held-out datasets with a small number of samples.

In ERPENet training, multiple P300 datasets from various sources and tasks were combined together to improve the model. There was some incompatibility in recording standards and protocols across the datasets, increasing the bias of the model. Before implementing the supervised classifier part, experiments were conducted on variational AE, but higher diversity between P300 tasks prevented the models reaching the optimal points, resulting in overfitting on the dominated dataset.

In this work, comparison across all datasets was possible since the EEG was normalized prior to the training. From Table IV, the ACC of auditory-BCI, BCI-Spell, and Decode-Audi datasets were below 70 using all methods. Auditory-BCI, BCI-COMP, and P300-Amplitude have the smallest number of samples, with ERPENet obtaining a higher ACC and AUC than the Xdawn algorithm on all three datasets. It could be inferred that the pre-trained model would improve the training of DL models on held-out datasets with a small number of samples.

VI. DISCUSSION

In Experiment A, the SSLC-AE is much shallower than our proposed model, converging in only 295 epochs. Whereas, our proposed semi-supervised AE was trained for 833 epochs without any improvement in validation loss. The training epochs required to train our model were about three times greater, representing a trade-off on the complex model.

TABLE III: Attended and unattended event classification ACC and AUC of fine-tuned ERPENet and SSLC-AE in comparison with XdawnLDA on six different datasets.

| Dataset          | ERPENet | SSLC-AE | XdawnLDA |
|------------------|---------|---------|----------|
|                  | ACC     | AUC     | ACC      | AUC     |
| P300-Amplitude   | 88.52 ± 2.42 | 84.25 ± 0.98 | 83.43 ± 1.87 | 78.29 ± 1.14 | 76.25 ± 0.71 | 77.22 ± 2.11 |
| BCI-COMP         | 86.39 ± 1.13 | 80.11 ± 6.35 | 68.60 ± 5.53 | 74.58 ± 0.85 | 63.17 ± 0.01 | 73.33 ± 2.85 |
| Auditory-BCI     | 83.43 ± 4.52 | 50.00 ± 0.00 | 83.43 ± 5.53 | 52.86 ± 2.92 | 60.56 ± 1.28 | 61.16 ± 10.5 |
| BCI-Spell        | 83.33 ± 4.62 | 50.00 ± 0.00 | 83.58 ± 4.72 | 49.26 ± 1.97 | 83.33 ± 4.62 | 50.00 ± 0.00 |
| EEG-Alcohol      | 79.37 ± 2.41 | 87.39 ± 1.42 | 76.56 ± 2.36 | 83.83 ± 1.63 | 75.79 ± 0.75 | 83.28 ± 0.85 |
| Decode-Audi      | 54.68 ± 1.83 | 52.52 ± 0.03 | 51.43 ± 4.26 | 50.36 ± 1.63 | 50.10 ± 0.31 | 50.16 ± 0.31 |
In conclusion, we have shown that our proposed semi-supervised AE, incorporating CNN and LSTM, has the capability for better compression than the previously proposed semi-supervised AE (SSLIC) composed of FCs, while maintaining high accuracy in the prediction of attended and unattended events on single trials of P300 EEG. Moreover, the encoder part of our proposed model can be extended as a pre-trained network, namely ERPENet, for other P300 tasks thereby reducing overfitting during training and hastening the training of complex models.

REFERENCES

[1] N. Zhong, S. S. Yau, J. Ma, S. Shimono, M. Just, B. Hu, G. Wang, K. Oiwa, and Y. Anzai, “Braininformatics-based big data and the wisdom web of things,” IEEE Intelligent Systems, vol. 30, no. 5, pp. 2–7, Sept 2015.

[2] S. J. Luck, An Introduction to the Event-Related Potential Technique. MIT Press, 2014.

[3] T. W. Picton, “The P300 wave of the human event-related potential.” Journal of clinical neurophysiology, vol. 9, no. 4, pp. 456–479, 1992.

[4] N. K. Squires, K. C. Squires, and S. A. Hillyard, “Two varieties of long-latency positive waves evoked by unpredictable auditory stimuli in man,” Electroencephalography and clinical neurophysiology, vol. 38, no. 4, pp. 387–401, 1975.

[5] L. Cui, R. Poli, and C. Cinel, “Documenting, modelling and exploiting P300 amplitude changes due to variable target delays in donchin’s speller,” Journal of Neural Engineering, vol. 7, no. 5, p. 056006, 2010.

[6] A. Rakotomamonjy and V. Guigue, “BCI competition iii: dataset ii-ensemble of SVMs for BCI P300 speller; IEEE transactions on biomedical engineering, vol. 55, no. 3, pp. 1147–1154, 2008.

[7] M. Schreuder, B. Blankertz, and M. Tangermann, “A new auditory multi-class brain-computer interface paradigm: spatial hearing as an informative cue,” PloS one, vol. 5, no. 4, p. e9813, 2010.

[8] L. Acqualagna and B. Blankertz, “Gaze-independent BCI-spelling using rapid serial visual presentation (RSVP);” Clinical Neurophysiology, vol. 124, no. 5, pp. 901–908, 2013.

[9] “EEG correlates of genetic predisposition to alcoholism.” https://archive.ics.uci.edu/ml/datasets/eeg+database.

[10] M. S. Treder, H. Purwins, D. Miklody, I. Sturm, and B. Blankertz, “Decoding auditory attention to instruments in polyphonic music using single-trial EEG classification;” Journal of Neural Engineering, vol. 11, no. 2, p. 026009, 2014. [Online]. Available: http://stacks.iop.org/1741-2552/11/i=2/a=026009

[11] Z. Zhang, T.-P. Jung, S. Makeig, and B. D. Rao, “Compressed sensing for energy-efficient wireless telemonitoring of noninvasive fetal ecg via block sparse bayesian learning;” IEEE Transactions on Biomedical Engineering, vol. 60, no. 2, pp. 300–309, 2013.

[12] Z. Zhang, T.-P. Jung, S. Makeig, and B. D. Rao, “Compressed sensing of EEG for wireless telemonitoring with low energy consumption and inexpensive hardware;” IEEE Transactions on Biomedical Engineering, vol. 60, no. 1, pp. 221–224, 2013.

[13] Z. Zhang and B. D. Rao, “Extension of SBL algorithms for the recovery of block sparse signals with intra-block correlation;” IEEE Transactions on Signal Processing, vol. 61, no. 8, pp. 2009–2015, 2013.

[14] Z. Zhang, T.-P. Jung, S. Makeig, Z. Pi, and B. D. Rao, “Spatiotemporal sparse bayesian learning with applications to compressed sensing of multichannel physiological signals;” IEEE transactions on neural systems and rehabilitation engineering, vol. 22, no. 6, pp. 1186–1197, 2014.

[15] A. Majumdar, A. Gogna, and R. Ward, “A low-rank matrix recovery approach for energy efficient EEG acquisition for a wireless body area network;” Sensors, vol. 14, no. 9, pp. 15729–15748, 2014.

[16] A. Majumdar and R. K. Ward, “Non-convex row-sparse multiple measurement vector analysis prior formulation for EEG signal reconstruction;” Biomedical Signal Processing and Control, vol. 13, pp. 142–147, 2014.

[17] A. Shukla and A. Majumdar, “Row-sparse blind compressed sensing for reconstructing multi-channel EEG signals,” Biomedical Signal Processing and Control, vol. 18, pp. 174–178, 2015.

[18] A. Majumdar and R. K. Ward, “Energy efficient EEG sensing and transmission for wireless body area networks: A blind compressed sensing approach,” Biomedical Signal Processing and Control, vol. 20, pp. 1–9, 2015.
deep network with a local denoising criterion,” *Journal of machine learning research*, vol. 11, no. Dec, pp. 3371–3408, 2010.

[41] X. Glorot and Y. Bengio, “Understanding the difficulty of training deep feedforward neural networks,” in *Proceedings of the thirteenth international conference on artificial intelligence and statistics*, 2010, pp. 249–256.

[42] L. N. Smith, “Cyclical learning rates for training neural networks,” in *Applications of Computer Vision (WACV)*, 2017 IEEE Winter Conference on. IEEE, 2017, pp. 464–472.

[43] B. Rivet, A. Souloumiac, V. Attina, and G. Gibert, “x’dawn algorithm to enhance evoked potentials: application to brain–computer interface,” *IEEE Transactions on Biomedical Engineering*, vol. 56, no. 8, pp. 2035–2043, 2009.

---

*Apiwat Ditthapron* is currently pursuing B.S. degree from the department of computer science, Worcester Polytechnic Institute, MA, USA. His current research interests include Computer Vision, Machine learning, Deep learning, and Data Visualization.

*Nannapas Banluesombatkul* received the B.Sc. degree in Computer Science from Thammasat University, Thailand in 2017. She is currently a Research Assistant with Bio-inspired Robotics and Neural engineering (BRAIN) lab, School of Information Science and Technology at Vidyasirimedhi Institute of Science and Technology (VISTEC), Thailand. Her current research interests include biomedical signal processing and clinical diagnosis support system.

*Sombat Ketrat* received the Ph.D. degree in Chemistry from Kasetsart University, Thailand in 2018. He is currently a post-doctoral researcher at School of Information Science and Technology, Vidyasirimedhi Institute of Science and Technology (VISTEC), Thailand. His current research interests are the areas of A machine learning based computer-aided molecular design.

*Ekapol Chuangsuwanich* received the B.S. and S.M. degree in Electrical and Computer Engineering from Carnegie Mellon University in 2008 and 2009. He then joined the Spoken Language Systems Group at MIT Computer Science and Artificial Intelligence Laboratory. He received his Ph.D. degree in 2016 from MIT. He is currently a Faculty Member of the Department of Computer Engineering at Chulalongkorn University. His research interests include machine learning approaches applied to speech processing, assistive technology, and health applications.

*Theerawit Wiaiprasitporn* received the Ph.D. Degree in Engineering from Graduate School of Information Science and Engineering, Tokyo Institute of Technology, Japan, in 2017. As a Ph.D. student, he obtained own research funding from Japan Society for the Promotion of Science (JSPS). While pursuing his Degree, he did short-term research at NASA Ames Research Center in USA. Now, he is working as lecturer position at School of Information Science and Technology at Vidyasirimedhi Institute of Science and Technology (VISTEC), Thailand. His current research are Neural Engineering (BCI), Bio-Potential Applications, Biomedical and Health Informatics and Smart Living.