Biosignals-Based Latent Factor Decoding for emotion detection using a Variational Autoencoder

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***Abstract*—Understanding and recognizing human emotions have been elusive objectives in many fields, including healthcare, education, marketing, and human-computer interaction, for a long time. In this study, we introduce a cutting-edge technique that capitalizes on the power of bio-signal-based latent factor decoding in an effort to revolutionize emotion detection. Our method utilizes unsupervised deep generative models, such as variational autoencoders (VAE) and autoencoders (AE), to explore the complex world of human emotions. To demonstrate the efficacy of our method, we conducted exhaustive experiments on two publicly accessible datasets: the DEAP DATASET and the SEED DATASET. Our novel method was compared to well-established Non-autoencoding models, such as independent component analysis (ICA), principal component analysis (PCA), and restricted Boltzmann machines (RBM), as well as other cutting-edge autoencoder-based methods. The results of our exhaustive evaluation unequivocally demonstrated the superiority of the bio-signal-based latent factor decoding method. This innovative technique not only achieves exceptional precision but also reveals the enigmatic nature of electroencephalogram (EEG) signals that are intricately intertwined with human emotions. The findings of this study represent a significant milestone in the field of emotion detection, providing a glimpse of the vast potential of neural networks, specifically autoencoders, to decode the subtle subtleties of human emotional experiences. By shedding light on the complexities of bio-signals, our research not only improves our comprehension of human emotions, but also paves the way for a vast array of transformative applications in personalized healthcare, virtual environments, and intelligent affective systems.**

***Index Terms*—Autoencoders, EEG, AE, VAE, RBM, ICA, PCA, Emotion Detection, Latent Spaces, DEAP, SEED, Generative Models.**

I. INTRODUCTION

There has been an increased interest in research on affective computing in many different fields, from pattern recognition [1] and signal processing [2] to cognitive neuropsychology [4] and beyond [10]. Using both overt [7] (such as facial expressions and speech cues) and covert [12] (such as biosignals), affective computing seeks to provide revolutionary computer-aided ways for automatically recognizing human emotions. Human-computer interaction and mental health care (where conditions like depression are expected to rise to second place) are two areas where this developing field has enormous potential for use.

Researchers [6] have begun to investigate the significance of other biosignals on emotional states, despite the fact that facial expressions and verbal cues have long dominated the field of emotion recognition. Electrodermal activity (EDA), electrocardiogram (ECG), and temperature changes are only a few examples of biosignals that have emerged as important contributors to generating emotional experiences [24]. Emotion recognition systems benefit from the incorporation of these biosignals because they provide additional physiological insights beyond those provided by conventional modalities.

Due to its ability to record brain oscillations closely associated with emotional processes, multichannel electroencephalography (EEG) has been a main area of study within the field of biosignals. EEG is a promising platform for researching reliable indicators and computational algorithms for EEG-based emotion identification [3] because of its high temporal resolution and extensive monitoring capabilities [8]. Researchers have turned to deep learning architectures, making use of their propensity to learn complicated representations and extract subtle features from raw data, to make the most of EEG and other biosignals.

Multichannel biosignal data analysis and modeling can benefit from the use of deep learning architectures like deep neural networks [1] and deep autoencoders [4]. Deep architectures' ability to learn hierarchical representations opens the door to modeling the complex patterns and nuanced dynamics of human emotions. These deep architectures make it easier to combine data from numerous biosignals, resulting in more precise and reliable emotion recognition systems.

The goal of this study is to overcome obstacles in emotion recognition by utilizing deep architectures and integrating multiple biosignals. This investigation aims to clarify the interplay between innate default characteristics like brain networks, autonomic regulation, and subjective feelings by drawing on existing literature and making educated guesses. Latent factors are extracted from multichannel biosignal data using unsupervised deep neural networks models like deep autoencoders and variational autoencoders. These latent components are useful for estimating participants' emotional states using sophisticated contextual modeling techniques, as they represent the underlying physiological dynamics necessary to comprehend emotional experiences. The issues of generalization across individuals and the extraction of significant features are also addressed in this study, along with the integration of numerous biosignals and the use of deep architectures. Also, because labeled data is so scarce for supervised model training in medical data mining tasks, it is crucial to investigate unsupervised and feature-independent modeling approaches. These techniques allow for the effective usage of constrained data resources, allowing for the improvement of emotion recognition system performance.

This research presents experimental evidence that the suggested unsupervised deep neural network models are effective and feasible for modeling complicated multichannel biosignal data, including EEG, EDA, ECG, and body temperature. The AutoEncoder (AE), the Variational Autoencoder (VAE), and the Restricted Boltzmann Machine (RBM) are the three models used during the preprocessing, feature extraction, and encoding phases to create the latent components. Latent components collected from EEG data are analyzed using these models. These unseen elements are vital inputs for future models that forecast how a person will feel. The encoded latent components are then used in a variety of models for emotional state prediction. The inferred latent components capture subtle but crucial information about emotional states, illuminating the dynamic relationship between the body and the mind. These results help to pave the way for the creation of extremely accurate and comprehensive emotion detection systems that may be used in a wide variety of settings.

II. RELATED WORKS

Complex emotional processes are the result of the interplay of many unseen brain components and networks. Emotional experiences are created by these more complex mental operations. Effective inference of these latent components is a major difficulty in the field of emotion detection, but it is essential for understanding and accurately evaluating emotional status. Electroencephalogram (EEG) analysis is one method for recording these subconscious emotional processes. The EEG monitors neural activity and sheds light on the dynamics of underlying brain components linked to emotions. Inferring the latent components from external multichannel EEG recordings is made possible by the observed internal correlations between EEG signals recorded at various sites on the scalp.

The promise of deep generative models to comprehend and model intricate data distributions has attracted a lot of interest in recent years. Several researchers have investigated the use of deep generative models in the analysis of EEG data for the purpose of biosignal-based emotion identification. To further the limits of standard handmade feature extraction methods, Li et al. [1] implemented long short-term memory (LSTM)-based supervised sequence modeling on decoded latent factor sequences. They did this because traditional feature engineering methods were inadequate for extracting information about how people were feeling. Latent representations of multichannel EEG signals were studied extensively by Arjun et al. [2], who used autoencoder-based architectures to do so. Emotion recognition was one of the many applications of these latent vectors. This method resulted in a more accurate and detailed depiction of the EEG data, which in turn enhanced the accuracy with which emotions could be identified. Li et al. [3] made a significant contribution as well by employing artificial neural networks to predict the unsupervised space of latent variables extracted from multichannel EEGs. They were able to successfully mine emotion-related information from the decoded latent factor sequences by employing recurrent neural network (RNN)-based supervised sequence modeling. Their findings showed promise in identifying mental health issues like depression and dementia.

Deterministic feature learning in EEG representation has also been used in deep learning models. One such work is [4], which sought to find resilient representations in EEG data that are unaffected by inter- and intra-subject variability and experimental noise. They pioneered the use of convolutional neural networks (CNNs) for cognitive load categorization and "EEG movies," which are multi-spectral images that preserve topology. This method proved that deep learning has the potential to extract useful characteristics from raw EEG signals. In addition, Ko et al. [5] suggested a small deep multiscale neural network that could be used for a variety of EEG applications, such as motor imaging, seizure detection, and sleep detection, by learning a temporal and spatial feature concatenated vector format. Their method resulted in a more accurate portrayal of the EEG data, which in turn improved the method's discriminatory capacity when applied to the classification of emotions.

Recent research has incorporated generative models for data augmentation in emotion categorization, including variational autoencoders (VAEs) and generative adversarial networks (GANs). By adding VAE or GAN discoveries into the EEG training datasets, Luo et al. [6] showed enhanced classification performance. However, they used manually-crafted power spectral density parameters as network inputs, which ignored temporal relationships in the input EEG data. Our proposed methodology, on the other hand, takes a holistic, end-to-end approach to analyzing temporal dynamics by starting with raw, multi-channel EEG data.

For downstream task categorization, Ozdenizci et al. [7] offered a CNN, and for EEG data, they suggested a conditional VAE model-based feature encoder. To enable effective decoding of EEG data from unknown users, their method trained a VAE and an adversarial filtering network concurrently to accomplish the generalization of the feature encoder. Emotion identification using EEG has also seen major contributions from other investigations, including those by W.L. Zheng et al. [8], R.-N. Duan et al. [9], K. S. Bano et al. [10], F. Ren et al. [20], Fuji et al., and S. Alhagry et al. [21]. In order to obtain impressive performance in emotion classification tasks, these studies have investigated several deep learning architectures, novel EEG characteristics, and various datasets.

Collectively, these studies results have pushed the boundaries of what is possible with EEG-based emotion identification. Specifically, they have illuminated the efficacy of deep generative models and unsupervised neural network models in identifying and extracting emotion-related latent components from EEG data. Our suggested methodology takes advantage of these developments to improve emotion identification using EEG bio-signals, with the goal of advancing our knowledge of emotional processes and their uses in settings as diverse as healthcare, psychology, and human-computer interaction.

III. METHODOLOGY

The research is investigating the use of deep generative models on EEG signals based on latent factors. Measuring the accuracy of different unsupervised and supervised neural networks by generating latent factors containing emotional data from patients and using them to predict their emotional states.

The study is performed in six main stages. As seen in Figure 1. In this approach, we decided to use latent factors extracted by AE, VAE, and RBM neural networks. Furthermore, we continued estimating the patient's emotional states by developing a recurrent neural network (RNN) supervised learning method with long short-term memory (LSTM) and gated recurrent unit (GRU) extensions. These RNNs helped us estimate how well the reconstructed data performed as well as show how well the models captured emotional information. As a final step, several different visualization methodologies have been applied to better represent the gathering of this research, such as comparing the f1 scores and accuracies of different neural models.

A. *Experimental Dataset*

In this study, we used two public datasets named DEAP and SEED. Detailed information regarding these datasets is mentioned below.

1) DEAP: The DEAP dataset was gathered with the participation of 32 subjects. The subjects watched 40 different music videos, each 60 seconds long. The videos have been rated in terms of arousal, valence, dominance, and familiarity based on dimensional theory of emotion as shown in Figure 2. In this process, the EEG records of the subjects have been recorded simultaneously through 32 channels. Mainly, the signals have been recorded with a sampling rate of 512 Hz, but in order to reduce the noise in the signals, it has been reduced to 128 Hz [24].

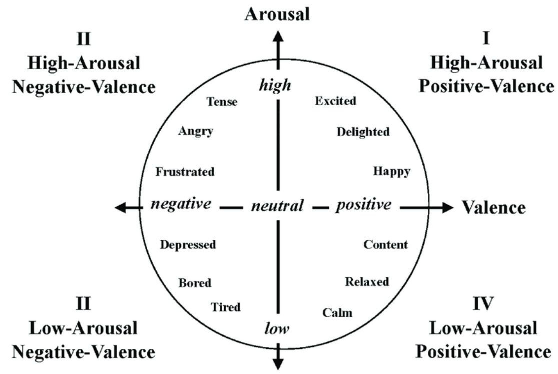

Fig. 2. valence and arousal dimensions of emotion

2) SEED: The SEED dataset has been gathered by recording the brain activities of 15 subjects (7 males and 8 females) who volunteered for this research. The research consisted of three experiments with one-week breaks between each. The volunteer's brainwaves were recorded by 62 channels while watching 15 videos; each video was approximately 4–5 minutes long. In this experiment, the labels have been classified into three main categories: positive (1), neutral (0), and negative (1) [23]. The comparison of these datasets has been represented by table I.

TABLE I
DEAP AND SEED STRUCTURE

	DEAP	**SEED**
Subjects	32	15
Channels	32	62
Trial Number	40	30
Trial Length / session	60 sec	200-240 sec
Video Type	Music	Movie Clips
Sampling Rate	128 hz	200 hz

B. *Pre-processing*

One of the main keys to reaching accurate and reliable data In electroencephalography, these steps can be listed as filtering the noises to prevent and clean electrical interference or physical activities, which might lead to accurate diagnoses; epoching, which helps to shorten the time series of certain activity waves over a long period; and normalization, which involves the EEG signals having a consistent scale and distribution, which can be done by calculating the Z-score or min-max scaling. Some of these steps have been applied to DEAP and SEED datasets, such as clearing artifacts responsible for the noise in EEG signals.

Hence, the sampling rate used to be 512 Hz and was sampled down to 128 Hz and band passed between 4 and 45 Hz in DEAP, and for SEED, the sampling rate recorded at 1000 Hz was sampled down to 200 Hz, and band filtered between 0-75 Hz. The main purpose of this was to clear high-frequency noises and make the data more effective and accurate for analysis. Along with this, all trial lengths in DEAP were standardized to 60 seconds, as some of them were over

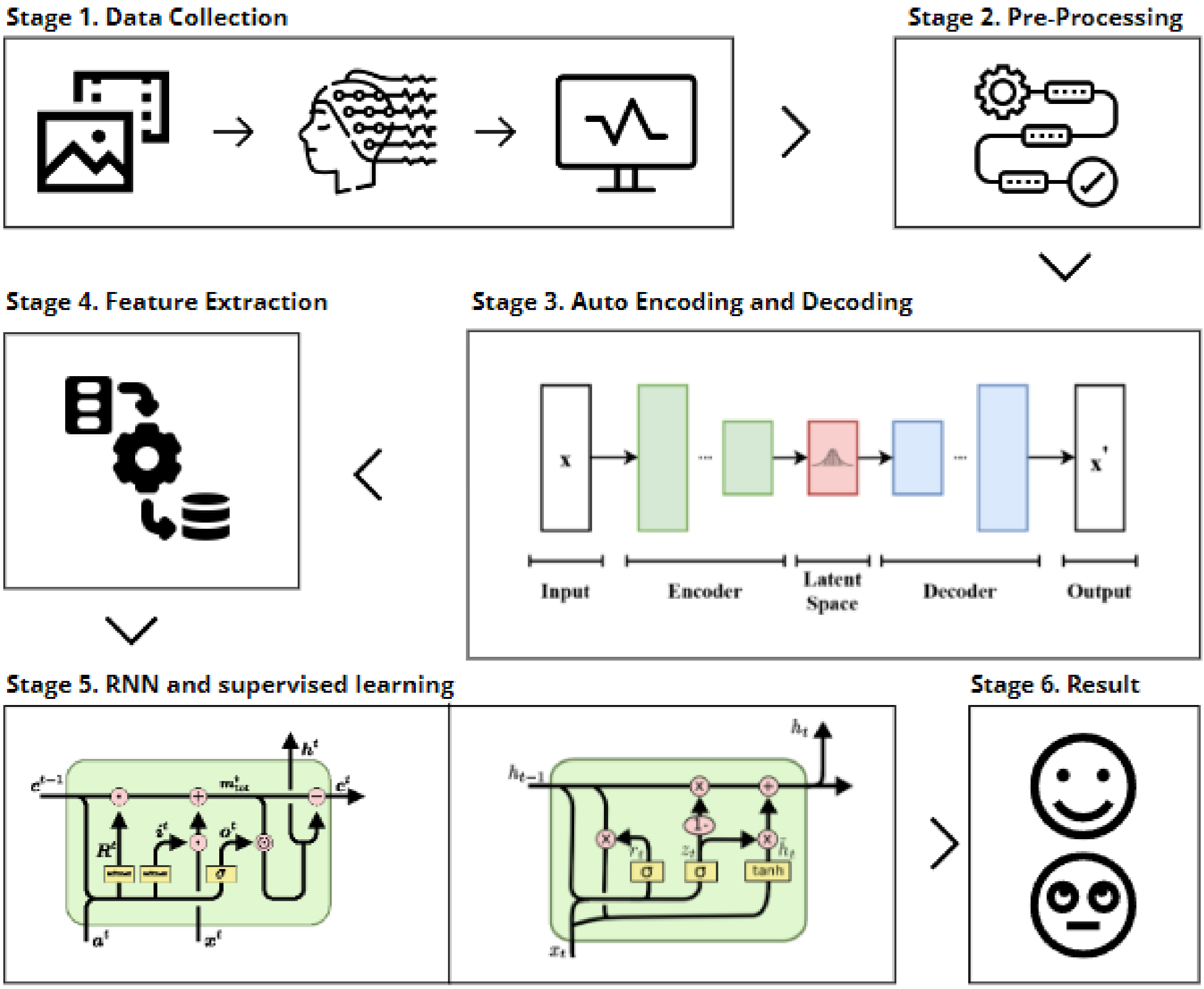

Fig. 1. Methodology Structure

60 seconds. While labeling these data, we have classified data with a rating above 5 as positive and below 5 as negative.

The SEED dataset consisted of three experiments and Feeding the model separately through three experiments is very time-consuming and has the potential to lead to several disadvantages while reaching an acceptable accuracy. Therefore, we've merged all three different experiments. This method helped us work on three experiments at the same time.

In the SEED dataset, the data was originally classified as positive (1), negative (0), and neutral (-1). Following that, the trials labeled neutral were dropped from the dataset to enhance model performance and focus on distinct categories. At this step, 15 neutral trials were detected and dropped from the dataset. After which normalization was applied by calculating the Z-score.

Normalization is scaling the data so it fits inside a standard range or distribution. This method helped us make the data easier to compare, improve the accuracy of statistical analysis, and prepare the data for any machine learning tasks. Normalization was applied on DEAP with a sampling rate of 128 Hz over 32 subjects with 40 trials gathered from 32 channels by calculating their Z-score and saving it as a 2D array. Meanwhile, on SEED, normalization was applied with a sampling rate of 200 Hz over 15 subjects with 30 trials gathered from 62 channels.

C. Latent Space Encoding and Decoding

At this stage of the study, we focused on producing latent factors and then tried to reconstruct the main data from them. For comparison, we have selected RBM, AE, and VAE as autoencoders; moreover, we also compared them with Independent Component Analysis (ICA) and Principal Component Analysis (PCA), as they are widely used for representing EEG source localization and blind source approach problems. In other words, these methods can provide a wide view of underlying neural sources and wave patterns and contribute to recorded signals. ICA and PCA also help with understanding the functionality of the brain by analyzing EEG signals, such as in brain-computer interfaces or cognitive neuroscience. Building upon the previous point, ICA is used for dimensionality reduction, and it can also be used as a preprocessing step for correlation, normalizing data, feature extraction, and reducing noise.

However, PCA is used for dimensionality reduction by identifying the most informative points that capture the maximum amount of information in the data. The projection of the data to a lower-dimensional space defined by the principal components can lead PCA to effectively reduce the dimensionality while keeping most of the relevant information. This dimensionality reduction can be useful for data visualization, computational efficiency, noise reduction, and feature extraction. The five models, including ICA, PCA, RBM, VAE, and AE, are types of unsupervised learning. However, ICA and PCA are used for dimensionality reduction and blind source separation, which makes them worth comparing with autoencoders.

We also analyzed these models to compare and consider the best model with the highest representation accuracy. To perform this, we calculated the correlation between each original signal and the decoded EEG data produced by each different model. This analysis aims to assess the similarity or agreement between the original data and decoded EEG signals. Here, the reconstructed signal with the highest correlation was said to be very close, if not equal, to the original data, and the highest correlation represents the efficiency of decoding the data from the original data. The content below explain the methodologies used while using these five different models.

*1) **Restricted Boltzmann Machine**:*
RBM is a type of unsupervised learning with artificial neural networks, which are widely used to discover hidden structures in the data and draw the probability distribution of the data. In RBM, the process works in two ways: upward and downward. We can look at Figure 2 to understand what the structure of RBM is like.

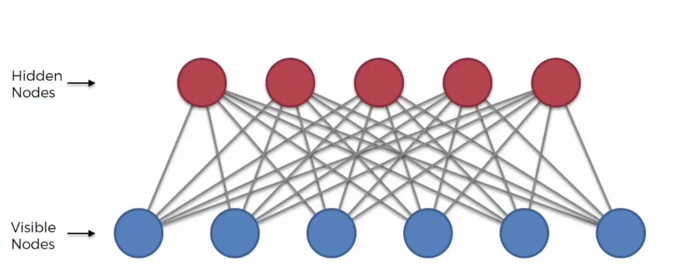

Fig. 3. Restricted Boltzmann Machine

In this method, the experiment was done using an autoencoder named deep belief network (DBN) on both datasets, DEAP and SEED, which consist of RBM layers. The main goal here is also to capture the RBM's efficiency in capturing and reconstructing meaningful representations of both datasets. Therefore, it is encoding the data and reconstructs them back, after which the correlation calculations on the accuracy of the model are done later on.

The RBM is trained using the EEG data, with the aim of learning the underlying patterns and structures. After training, the back propagation algorithm is employed to fine-tune the RBM further, enhancing its ability to reconstruct the input data accurately.

To evaluate the RBM's performance later, both the encoded and decoded EEG signals are obtained. The encoded EEG signals represent compressed representations of the original data, while the decoded EEG signals are the reconstructed versions generated by the RBM layers. These signals provide valuable insights into the RBM's ability to capture and preserve meaningful information during the encoding and decoding processes.

At the next stage, to calculate the correlation between the original and reconstructed data, we loaded both the original preprocessed dataset and the reconstructed dataset. For each channel, the correlation coefficient is calculated using the 'corrcoef' function, which measures the linear relationship between the two sets of signals. The resulting correlation coefficients are stored in the "corr_chs" matrix. Finally, the average correlation across all subjects is computed using the mean function. As a result of this step, we have determined that the similarity correlation of RBM on the DEAP dataset was approximately 100%. And approximately 95% percent on SEED.

*2) **Traditional Autoencoder (AE)**:*
Traditional autoencoders are unsupervised neural networks that mainly consist of two parts: encoders and decoders. Encoders are known as the first step of an autoencoder, which takes the input and learns how to compress and encode that data into latent space representation, which is called a bottleneck. On the other hand, we have decoders, which take the bottleneck as input and try to reconstruct that encoded data representation as close as possible to the original data, as seen in Figure 4.

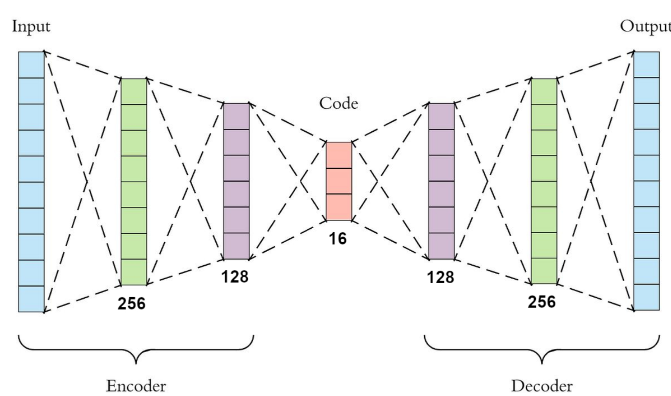

Fig. 4. Traditional Autoencoder

This method's goal is to transform high-dimensional EEG signals into a lower-dimensional latent space without losing important information. So that in the next phases of the study, we can perform accurate estimations on the generated data and consider the best one among them.

The approach for this model is structured as a nested loop that iterates over subject numbers and latent dimensions. For each subject and latent dimension pair for both datasets, we have created an autoencoder model consisting of an encoder and a decoder. The encoder takes the input EEG signals and compresses the data into a lower-dimensional representation. The decoder then reconstructs the original input dimensionality.

During training, the model tries to minimize the reconstruction error between the input and output EEG signals. Once the training is complete, the code uses the trained model to predict the encoded and decoded EEG signals for the training data. The encoded EEG signals represent the lower-dimensional latent space representations, while the decoded EEG signals are the reconstructed versions of the original input data.

Finally, the code saves both encoded and decoded data, which can then be used for further analysis, such as emotion detection or feature extraction methods. Here again, to calculate the efficiency of the autoencoder model, we take the correlation of both encoded and decoded data to compare and measure the similarities.

In this approach, we perform an analysis of the correlation between decoded EEG signals obtained from a deep autoencoder model and the original z-scored EEG signals. It iterates over different latent dimensions and subjects, calculating the correlation coefficient for each channel. The results are stored in an array, allowing the assessment of correlations across multiple dimensions and subjects. Additionally, the code computes the average correlation for each latent dimension, providing insights into the relationship between the decoded and original EEG signals. As the results of this approach for AE show, we have obtained a correlation accuracy of approximately 100% for DEAP and approximately 95% for the SEED dataset.

*3) **Variational Auto Encoder**:*

Variational autoencoders are a type of autoencoder that has the same main structures but different functionalities and methods in several ways. VAE is generative modeling, which can learn to encode and decode complex data types. These models are widely used in generating new samples, which can be used in text generation, data compression, dimensionality reduction, classification, and handling missing data. This model is also mainly made up of two components: the encoder and the decoder. In VAE, we implemented it using the Keras library. As with AE, the purpose of the VAE is also to learn a compressed representation of multi-channel EEG data from DEAP and SEED. The VAE architecture consists of two components: an encoder and a decoder. The encoder part takes the preprocessed EEG data as input and processes it with dense layers. On the other hand, the decoder takes the latent space as input and tries to reconstruct it back to the original EEG data. The decoder aims to reconstruct the input EEG data from the latent space representation.

The VAE model is represented by connecting the encoder and decoder layers. The decoder is connected to the output of the encoder's sampling layer, which helps the model generate reconstructed EEG signals from the latent space factors. Then, to calculate the reconstruction loss, it uses the mean squared error between the input EEG signals and the reconstructed output. Furthermore, the VAE model that was taught has been applied to regenerate the EEG data on the basis of the coded latent factors.

As with previous methods, to measure the correlation between the original EEG signal and the reconstructed data, we performed a correlation analysis between them. The code iterates over different latent dimensions and subjects. For each combination, the decoded EEG data generated by the VAE model and the preprocessed EEG signals are compared. The Pearson correlation coefficient is calculated for each channel, measuring the similarity between the two datasets. This methodology assesses how well the VAE model captures the patterns and features of the EEG data, indicating its effectiveness in reconstructing the original signals.

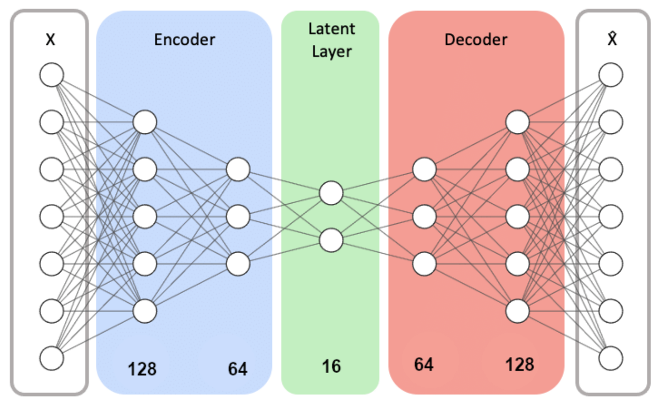

Fig. 5. Variational Autoencoder

D. Emotion Detection From Latent Factors

The emotion detection approach with unsupervised learning models has some main steps. It starts with gathering and preprocessing the data, then training the autoencoder and producing latent factors, which lately will be used as input data for emotion prediction for our supervised models, and then applying dimensionality reduction or any feature extraction methods if required. And as the main part of emotion detection, we select any supervised learning method, feed it with labeled data that is in latent space, and expect it to predict data according to the patterns created in latent space.

There are several different supervised algorithms and libraries for approaches, such as CNN, RNN, support vector machines (SVM), etc. Recurrent Neural Networks (RNN), just as their name suggests, have loops in their architecture that allow them to use previous outputs as inputs to the next time step [4]. RNNs are well-suited for sequential data, including EEG data, due to their inherent ability to capture temporal dependencies and handle variable-length input sequences. LSTM and GRU are variations of RNN, which have been widely used in the fields of signal analysis and emotion detection. This makes it a perfect decision to use LSTM and GRU as architectures for this study.

*1) **Long Short-term Memory**:*
This stage of the study is focusing on predicting the emotional states of subjects from both datasets, specifically defining them as positive or negative in cases of valence or arousal on the DEAP dataset and as negative or positive on the DEAP dataset. The approach uses a LSTM neural network on both datasets.

As the first step, we prepare the data. Trial labels are loaded in the proper order, which ensures that the labels are aligned with the corresponding EEG data. Additionally, Z-score normalization is applied to the EEG data.

After the data preparation step, we focus on the construction of the training and testing datasets. For each test subject, a separate testing set is created, while the remaining subjects contribute to the training set. This ensures that the model is evaluated on unseen data. While creating the model, we also used saved weights to adjust the strength of the connections in the neural model, which played a crucial role in making more accurate predictions and classifications. The layers of LSTM for both datasets is represented by Figure 6.The training and testing sets consist of sequences of EEG data, where each sequence represents a trial. The sequences are obtained by dividing the original EEG data into smaller segments of controlled length.

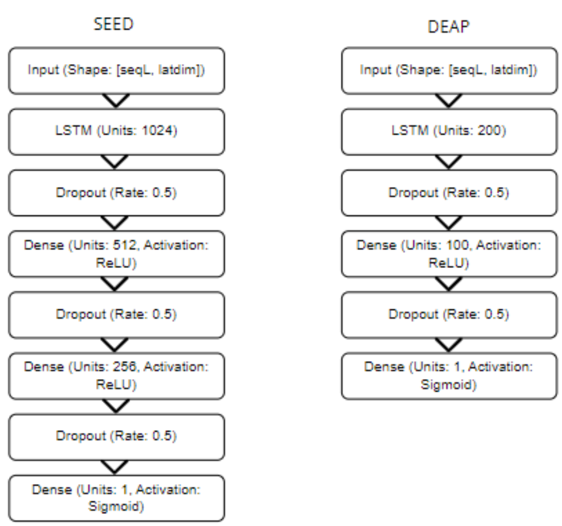

Fig. 6. Long Short-Term Memory Layers

After training the model, predictions are generated for both the training and testing datasets. The predictions are thresholded using a threshold of 0.5 to obtain binary class labels (positive or negative emotional states). Various evaluation metrics, such as F1 score and accuracy, are computed to assess the model's performance on the test and training sets. These metrics provide insights into the model's ability to correctly classify emotional states.

*2) **Gated Recurrent Unit**:*
A gated recurrent unit is a type of recurrent neural network architecture that selectively retains and updates information through gate mechanisms, allowing it to effectively capture long-term dependencies in sequential data. Meanwhile, LSTM is focused on long-term dependency modeling through memory cells and gate mechanisms. The implementation of this neural network is very similar to LSTM. However, some major differences exist.

To begin with, load EEG trial labels and encoded EEG data, which represent emotional states and preprocessed signals, respectively. Z-score normalization is applied to ensure consistency and comparability by standardizing the data with a zero mean and unit standard deviation. While creating the model, we also used saved weights to adjust the strength of the connections in the neural model, which played a crucial role in making more accurate predictions and classifications. Then we divided the data into training and testing sets, with one subject's data reserved for testing and the rest used for training. This cross-validation strategy ensures the evaluation of unseen data.

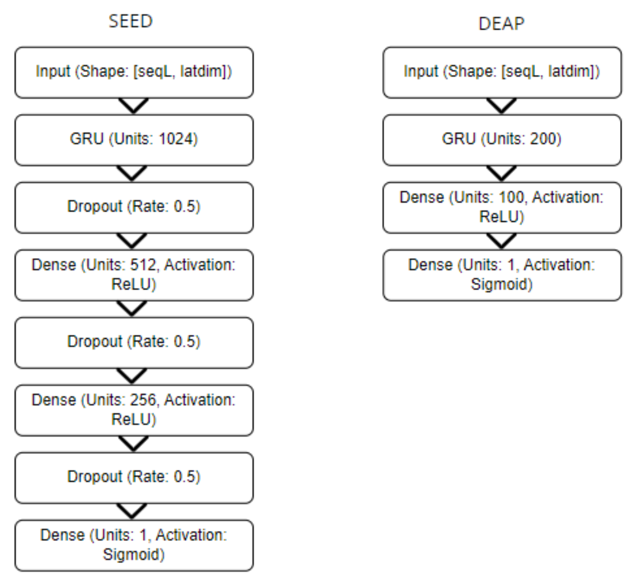

Fig. 7. Gated Recurrent Unit Layers

The EEG trials are grouped into sequences of a specific length, with each sequence further divided into smaller intervals. These intervals, determined by the "step" variable, capture important patterns in the EEG data. The resulting sequences are stored in separate lists for training and testing datasets. The core of the methodology lies in the construction of the RNN model, specifically a GRU model. In this code, the model architecture consists of a GRU layer with 200 units, followed by fully connected dense layers as shown in Figure 7

Once the model is trained, it is evaluated on the testing dataset. We predicted emotional states for the EEG data in the testing dataset. These predictions are then compared to the ground truth labels to compute performance metrics such as accuracy and F1 score. The F1 score provides a measure of the model's balance between precision and recall, considering both false positives and false negatives.

IV. RESULTS

In this part of the study, we would be sharing the results of all comparisons and methods used for comparison between all three Autoencoding methods including RBM, VAE and AE, two dimensionality reduction including ICA and PCA, and finally 2 different RNN Models including GRU and LSTM at emotion recognition based on extracted latent factors. To measure the results, we have used several different metrics on model evaluation. The following paragraph will shed light on all the evaluation metrics used while comparison.

A. Evaluation Metrics

As the first step, to measure the decoder performance, we have decided to use the Pearson correlation coefficient to measure the difference between original signals and reconstructed signals, as shown in the formula 1. In this method, a high R-value represents a higher ability of the model in case of reconstructing the data from the encoded one. Alongside, we tried to represent these similarities by representing after-before signals with all different autoencoding models.

$$r_{x_{\text{in}}\, x_{\text{out}}} = \frac{\sum_{t=1}^{n}\left(x_{\text{in}}^{(t)} - \overline{x_{\text{in}}}\right)\left(x_{\text{out}}^{(t)} - \overline{x_{\text{out}}}\right)}{\sqrt{\sum_{t=1}^{n}\left(x_{\text{in}}^{(t)} - \overline{x_{\text{in}}}\right)^2}\sqrt{\sum_{t=1}^{n}\left(x_{\text{out}}^{(t)} - \overline{x_{\text{out}}}\right)^2}} \tag{1}$$

for measuring the emotion detection performance, we used the 70/30 split of the cross-validation to compare the best working model between GRU and LSTM in this study and with other networks from previous studies. To compare them we have outlined F1-score evaluated on 30% of data (test set).

B. Model's Reconstruction Performances

The reconstruction performance has been measured under a different number of latent factors. The number of latent factors that have been set for both datasets was 16. As previously mentioned, latent factors are dimensions that save hidden information regarding the original data. In other words, more latent factors mean more information regarding to the original data. Hence, as shown in figure 8 for DEAP and figure 9 for SEED, the increasing number of latent factors were positively affecting our model performances. Furthermore, it is noted that these parameters helped RBM, AE, PCA, and VAE to reach a similarity near 100% on DEAP and to achieve scores between 90%-100% for SEED. However, the ICA's performance was significantly low on both datasets. Therefore, it has been proved that ICA-based models are not suitable for encoding and decoding EEG signals.

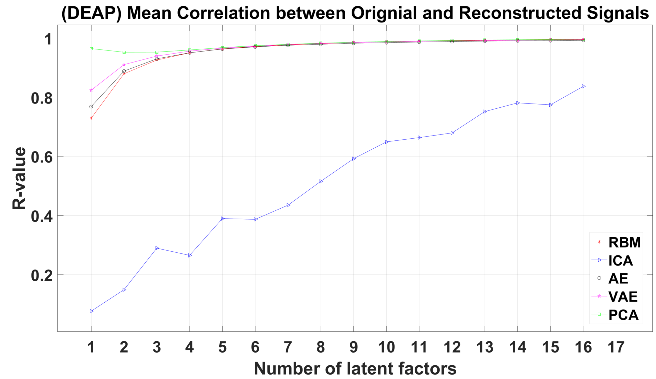

Fig. 8. Models Performance on DEAP

For the remaining models, we can say that PCA has performed well and achieved a mean coefficient correlation near 1.0. As previously mentioned, a PCA is a dimensionality reduction method that is not able to produce a latent factor but it still worth to be examining in emotion recognition. On the other hand, RBM and AE also recorded the highest scores. The mean correlation has been stabilized at around 0.98 on both datasets.
The VAE model was also successful but performed totally differently on both datasets. The first attempts brought us the same results for DEAP and SEED datasets by reaching the mean correlation of 0.95. However, adding more hidden layers paved the way to gain a score of 0.99 on the DEAP dataset. These changes approved that the VAE model has the ability to reach to highest scores and mining important factors.

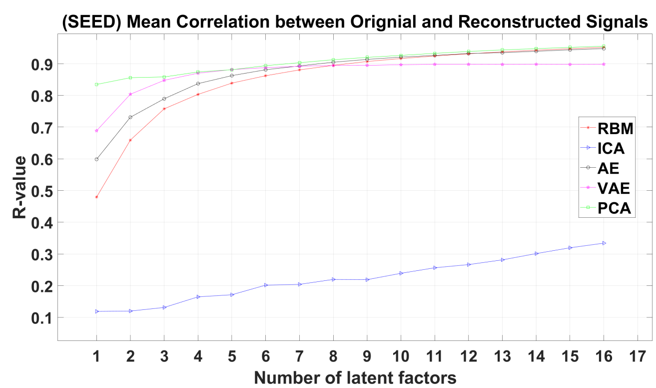

Fig. 9. Models Performance on SEED

Figure 10 and figure 11 represent the Mean correlation between original data and reconstructed data. The results gathered from subjects once more indicate that for each model and subject, the performance increases respectively with increasing latent factors. Alongside this, we can see that after specific points on both datasets, there are no changes in the performance of the model. Hence, It can be proved that number of latent factors does not change the construction performance, In other words, lots of latent spaces do not mean lots of information regarding to the data.

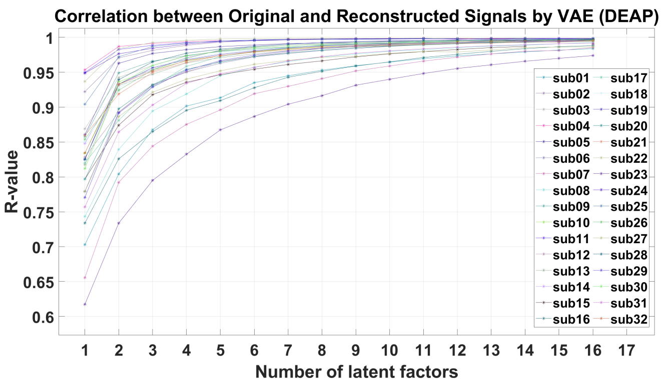

Fig. 10. VAE Subject's Performance on DEAP

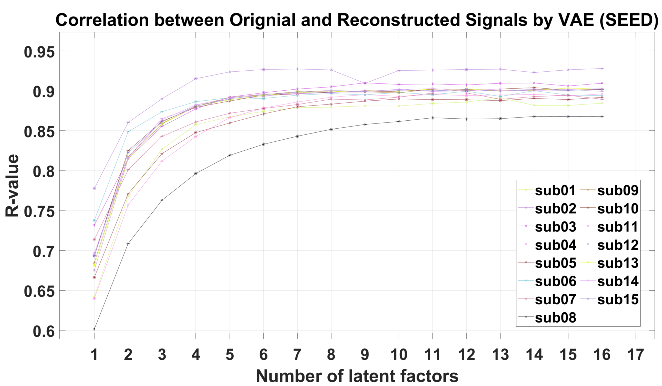

Fig. 11. VAE Subjects Performance on SEED

The scores and values received from these methods have proved that RBM, PCA, AE can be significant methods for generating latent factors and reconstructing the original data back from them. On the other hand, VAE also performed well, however, the efficiency and usability of the model require specific architectural necessities and parameters which must be set according to the data.

Now that we have obtained the results, we can visualize the signals comparing in cases of original data, after visualization form and reconstructed data from each different model to compare and visualize the differences made in this process. To perform it, we selected subject no. 10 and its first channel from the DEAP dataset. As visualized in Figure 12, it represents the signals produced by subject No. 10 on the first trial and first channel.

The chart shows the data from 128 points of signal recordings of specified trial and channel between 10^{th} and 11^{th} seconds. As previously mentioned, the sampling rate for this dataset has been set to 128hz. This means each second 128 values are received by each EEG channel. In the ongoing parts, we will analyze the same example according to different models.

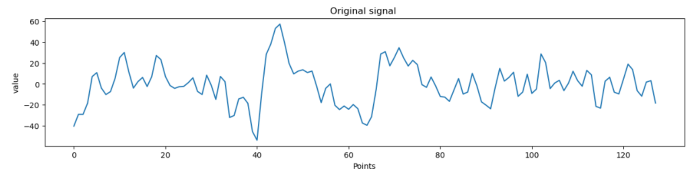

Fig. 12. Original signals

Before feeding the models with data we performed normalization so that the data would fit in a standard range and reduce complexity. The figure 13, represents the subject's data after being normalized. Expectedly, there are no changes in shapes and curves which means the data is still representing itself. Furthermore, we can see that scale has been minimized between 2 and -2.

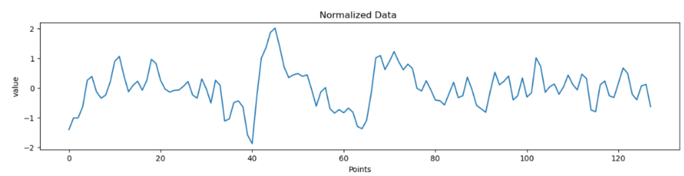

Fig. 13. Normalized signals

Figure 14 represents the signals decoded using extracted latent factors with three different models including RBM, AE, and VAE. After confirming the results with correlation coefficient scores, it approves once more that three of these models had an extremely efficient performance while extracting latent factors and reconstructing the original EEG data. Although, while comparing the results of these models we have noticed some minor changes and deforms in reconstructed data compared to the original one. However, they are not significant enough to create bigger mistakes and mislead our models while creating patterns in emotion recognition.

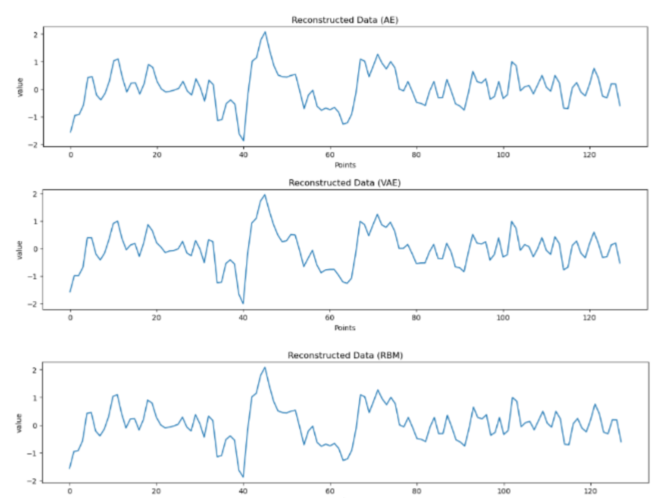

Fig. 14. RBM vs AE vs VAE signals

TABLE II
LSTM DEAP AROUSAL

Subject	PCA+LSTM	ICA+LSTM	RBM+LSTM	AE+LSTM	VAE+LSTM
s1	0.674	0.642	0.676	0.632	0.907
s2	0.633	0.576	0.660	0.666	0.883
s3	0.720	0.591	0.617	0.634	0.891
s4	0.710	0.609	0.526	0.627	0.901
s5	0.644	0.584	0.644	0.644	0.872
s6	0.636	0.584	0.655	0.593	0.883
s7	0.665	0.628	0.620	0.598	0.873
s8	0.680	0.596	0.530	0.615	0.885
s9	0.608	0.566	0.627	0.667	0.884
s10	0.716	0.647	0.652	0.621	0.895
s11	0.524	0.633	0.582	0.632	0.871
s12	0.469	0.571	0.662	0.632	0.872
s13	0.714	0.589	0.666	0.686	0.890
s14	0.590	0.565	0.633	0.645	0.891
s15	0.537	0.611	0.584	0.602	0.863
s16	0.672	0.643	0.562	0.627	0.876
s17	0.686	0.584	0.601	0.641	0.871
s18	0.686	0.542	0.609	0.627	0.888
s19	0.603	0.563	0.594	0.676	0.859
s20	0.669	0.635	0.604	0.633	0.845
s21	0.690	0.629	0.607	0.559	0.868
s22	0.662	0.563	0.572	0.665	0.869
s23	0.596	0.541	0.576	0.590	0.882
s24	0.702	0.607	0.587	0.629	0.887
s25	0.514	0.614	0.635	0.628	0.854
s26	0.710	0.589	0.588	0.625	0.883
s27	0.702	0.572	0.561	0.578	0.860
s28	0.686	0.650	0.555	0.615	0.887
s29	0.620	0.634	0.648	0.620	0.882
s30	0.590	0.531	0.648	0.617	0.913
s31	0.648	0.657	0.666	0.563	0.825
s32	0.633	0.597	0.578	0.625	0.868
$Mean^{f1}$	0.641	0.599	0.614	0.623	0.877

TABLE III
LSTM DEAP VALENCE

Subject	PCA+LSTM	ICA+LSTM	RBM+LSTM	AE+LSTM	VAE+LSTM
s1	0.637	0.641	0.494	0.602	0.846
s2	0.669	0.632	0.489	0.574	0.841
s3	0.635	0.555	0.494	0.600	0.844
s4	0.528	0.539	0.492	0.631	0.835
s5	0.642	0.546	0.510	0.635	0.842
s6	0.532	0.523	0.505	0.607	0.823
s7	0.647	0.616	0.497	0.633	0.864
s8	0.653	0.514	0.515	0.592	0.855
s9	0.508	0.521	0.502	0.616	0.834
s10	0.641	0.538	0.468	0.625	0.822
s11	0.664	0.567	0.510	0.629	0.801
s12	0.635	0.481	0.515	0.622	0.808
s13	0.667	0.590	0.502	0.621	0.788
s14	0.533	0.530	0.471	0.575	0.845
s15	0.522	0.652	0.479	0.639	0.849
s16	0.581	0.551	0.513	0.588	0.825
s17	0.609	0.627	0.486	0.558	0.842
s18	0.620	0.556	0.500	0.626	0.818
s19	0.651	0.594	0.479	0.562	0.814
s20	0.639	0.507	0.486	0.593	0.833
s21	0.614	0.618	0.515	0.535	0.839
s22	0.712	0.632	0.515	0.534	0.838
s23	0.703	0.606	0.473	0.606	0.807
s24	0.587	0.463	0.466	0.587	0.846
s25	0.667	0.522	0.510	0.612	0.815
s26	0.539	0.572	0.497	0.627	0.820
s27	0.682	0.617	0.507	0.604	0.848
s28	0.594	0.526	0.479	0.528	0.842
s29	0.670	0.623	0.479	0.615	0.851
s30	0.591	0.616	0.510	0.566	0.821
s31	0.620	0.570	0.502	0.603	0.840
s32	0.612	0.547	0.494	0.653	0.855
$Mean^{f1}$	0.621	0.569	0.498	0.596	0.834

C. Recognition performance (GRU vs LSTM)

The performance of each model used previously to encode data and reconstruct it back cannot be used as a criterion to judge if the model is successfully able to recognize emotions or not. As previously mentioned in emotion detection steps, we have to recognize patterns in latent factors, so that we can apply a comparison between models. The sequential structure of the data has led us to choose Recurrent Neural Network for the pattern detection method which has been done by applying LSTM and GRU-supervised learning methods. This method helps us with the classification of the reconstructed data with given labels.

While choosing the best methods among ICA, PCA, RBM, AE, or VAE, we have set that to measure and put in the race only those ones with an accurate and high reconstruction performance. Low reconstruction performance means that the reconstructed data is less similar to the original data. Hence, we believe that putting such data in pattern detection models will mislead us to the wrong results.

In this part of the study, we will discuss the efficiency of the models while emotion detection and creating patterns. The comparison will done between two Recurrent Neural Networks models including Long short-Term Memory and Gated Recurrent Unit which are applied on both datasets.

Supervised learning methods for emotion detection has been applied on DEAP dataset to recognize the patterns for emotional dimensions of valence and arousal. In this study for DEAP each emotional dimension (arousal and valence) has been feed to the model to draw the results in aspects of positive and negative. Table II and Table III hand over the results of reconstructed data's emotional dimension (arousal and valence) in DEAP dataset after being patterned through supervised learning methods. Nonetheless, the SEED dataset has been directly sharing the labels of trials as happy or sad which then we change them as positive or negative. For evaluation and comparison of the models we have selected F1 score.

According to Table II, while patterning DEAP dataset in term of arousal with LSTM the ICA got the lowest score. But, in comparison with other models the difference was smaller. Alongside, Restricted Boltzmann Machine had also a good performance among Traditional autoencoder, Restricted Boltzmann Machine and principal Component Analysis. But it is good to mention that the scores were recorded almost the same with each other. The best performance model of this table was Variational Auto encoder which had the highest F1 score from other methods.

TABLE IV
GRU DEAP AROUSAL

Subject	PCA+GRU	ICA+GRU	RBM+GRU	AE+GRU	VAE+GRU
s1	0.613	0.667	0.684	0.642	0.583
s2	0.630	0.671	0.676	0.623	0.636
s3	0.614	0.674	0.634	0.606	0.596
s4	0.615	0.630	0.627	0.647	0.557
s5	0.605	0.648	0.685	0.619	0.623
s6	0.649	0.616	0.664	0.590	0.632
s7	0.597	0.591	0.694	0.545	0.547
s8	0.599	0.657	0.674	0.661	0.584
s9	0.651	0.632	0.639	0.630	0.593
s10	0.699	0.605	0.671	0.609	0.584
s11	0.467	0.550	0.674	0.575	0.589
s12	0.590	0.627	0.662	0.602	0.571
s13	0.596	0.703	0.627	0.604	0.587
s14	0.665	0.550	0.636	0.639	0.630
s15	0.660	0.690	0.648	0.598	0.625
s16	0.694	0.662	0.683	0.631	0.579
s17	0.637	0.659	0.637	0.610	0.657
s18	0.535	0.552	0.665	0.602	0.629
s19	0.487	0.660	0.654	0.644	0.574
s20	0.632	0.644	0.680	0.590	0.646
s21	0.645	0.579	0.687	0.645	0.568
s22	0.529	0.654	0.661	0.653	0.528
s23	0.579	0.686	0.666	0.620	0.640
s24	0.635	0.641	0.700	0.620	0.680
s25	0.537	0.680	0.678	0.638	0.638
s26	0.648	0.640	0.683	0.633	0.618
s27	0.630	0.647	0.645	0.623	0.601
s28	0.600	0.658	0.578	0.575	0.546
s29	0.636	0.601	0.658	0.541	0.516
s30	0.574	0.686	0.623	0.562	0.574
s31	0.625	0.667	0.651	0.655	0.595
s32	0.688	0.637	0.605	0.639	0.561
$Mean^{f1}$	0.616	0.640	0.651	0.618	0.603

TABLE V
DEAP GRU VALENCE

Subject	PCA+GRU	ICA+GRU	RBM+GRU	AE+GRU	VAE+GRU
s1	0.587	0.512	0.538	0.527	0.617
s2	0.564	0.564	0.591	0.570	0.654
s3	0.599	0.590	0.600	0.587	0.632
s4	0.645	0.552	0.582	0.470	0.651
s5	0.667	0.592	0.584	0.614	0.659
s6	0.591	0.426	0.455	0.581	0.626
s7	0.543	0.516	0.560	0.610	0.670
s8	0.569	0.574	0.511	0.600	0.607
s9	0.550	0.585	0.563	0.489	0.619
s10	0.626	0.547	0.568	0.615	0.595
s11	0.510	0.581	0.523	0.595	0.583
s12	0.580	0.538	0.581	0.532	0.653
s13	0.594	0.522	0.632	0.551	0.665
s14	0.514	0.481	0.608	0.593	0.583
s15	0.561	0.425	0.619	0.622	0.649
s16	0.657	0.574	0.599	0.584	0.666
s17	0.563	0.524	0.507	0.613	0.639
s18	0.638	0.546	0.582	0.625	0.658
s19	0.635	0.625	0.594	0.550	0.661
s20	0.614	0.451	0.513	0.616	0.663
s21	0.599	0.526	0.612	0.529	0.596
s22	0.622	0.497	0.592	0.582	00.63
s23	0.530	0.556	0.584	0.547	0.556
s24	0.637	0.613	0.592	0.589	0.605
s25	0.469	0.575	0.529	0.541	0.534
s26	0.667	0.542	0.600	0.622	0.636
s27	0.592	0.581	0.623	0.502	0.553
s28	0.570	0.492	0.501	0.598	0.641
s29	0.557	0.517	0.464	0.565	0.668
s30	0.581	0.526	0.589	0.606	0.641
s31	0.561	0.562	0.568	0.542	0.639
s32	0.670	0.563	0.614	0.566	0.666
$Mean^{f1}$	0.589	0.540	0.568	0.570	0.628

Table III, shows the F1 scores of patterning the DEAP dataset in terms of Valence. The Variational Autoencoder has achieved the highest score in emotion detection far better than all the other models. The instability of the Restricted Boltzmann Machine created a point of concern about deciding if the model is reliable or not so that we can qualify the scores received in case to achieve accurate results.

In Table IV, we present the results gathered from the Gated Recurrent Units. The input data for this model is the same as well as the Long Short-term memory model, After comparing the models, we can see that the Restricted Boltzmann Machine model has achieved the highest score, closely followed by the Independent Component Analysis model with an average score of 0.640. The traditional Autoencoder and Principle Component Analysis models also performed reasonably well, getting a close average F1 score, respectively.

According to these results, it can be concluded that the restricted Boltzmann Machine and Independent Component Analysis models perform well in recognizing arousal levels compared to other models. To approve this idea, it was compared with the results from different models.

The Table V, also presents the performance comparison of models in the DEAP dataset and Gated Recurrent Units model in terms of Valence. To analyze the results, it has been obtained that the Variational Autoencoder model reached the highest average F1 score, in comparison to the other models.

The Restricted Boltzmann Machine model also did a notable performance. The Principle Component Analysis and traditional Autoencoder models did a comparable performance with close F1 score averages as well. On the other hand, the Independent Component model had the lowest average F1 score in this table. As the results of this model, we can say that the Variational Autoencoder and Restricted Boltzmann Machine models did a significant performance in capturing emotions in terms of valence. Meanwhile, the Independent Component Analysis model performance was most unsatisfactory.

So far we have explored the results obtained from the DEAP dataset by applying two Recurrent Neural Network models including Gated Recurrent Neural Networks and Long Short-Term Memory. yet, to approve the results, the SEED dataset has also been put through the same steps. The emotion labels on the SEED dataset basically consist of Happy and Sad. Table VI and Table VII represents the F1 Scores of all subjects after applying pattern recognition methods.

Table VI, Looking at the LSTM results of the SEED dataset, it is shown that Principle Component Analysis consistently exhibits a good performance across all subjects reaching to an average F1 score of 0.898. This indicates that Principle Com-

TABLE VI
LSTM SEED

Subject	PCA+LSTM	ICA+LSTM	RBM+LSTM	AE+LSTM	VAE+LSTM
s1	0.907	0.671	0.811	0.769	0.881
s2	0.911	0.675	0.723	0.776	0.903
s3	0.917	0.648	0.780	0.728	0.888
s4	0.900	0.680	0.782	0.779	0.837
s5	0.903	0.685	0.821	0.774	0.911
s6	0.892	0.694	0.782	0.794	0.933
s7	0.916	0.661	0.780	0.724	0.881
s8	0.901	0.680	0.821	0.774	0.925
s9	0.885	0.657	0.757	0.718	0.874
s10	0.927	0.666	0.805	0.762	0.866
s11	0.869	0.679	0.753	0.774	0.874
s12	0.895	0.694	0.788	0.765	0.807
s13	0.898	0.671	0.808	0.732	0.896
s14	0.879	0.698	0.797	0.744	0.896
s15	0.879	0.684	0.833	0.751	0.874
$Mean^{f1}$	0.898	0.674	0.791	0.754	0.885

TABLE VII
GRU SEED

Subject	PCA+GRU	ICA+GRU	RBM+GRU	AE+GRU	VAE+GRU
s1	0.910	0.624	0.789	0.868	0.917
s2	0.912	0.652	0.810	0.847	0.882
s3	0.890	0.614	0.839	0.882	0.870
s4	0.885	0.676	0.800	0.895	0.915
s5	0.890	0.608	0.776	0.902	0.869
s6	0.902	0.661	0.782	0.871	0.877
s7	0.911	0.618	0.836	0.846	0.920
s8	0.909	0.643	0.782	0.865	0.915
s9	0.910	0.644	0.773	0.878	0.884
s10	0.918	0.657	0.817	0.839	0.867
s11	0.901	0.652	0.794	0.846	0.805
s12	0.916	0.647	0.794	0.872	0.904
s13	0.855	0.662	0.818	0.860	0.914
s14	0.917	0.637	0.810	0.915	0.902
s15	0.921	0.651	0.786	0.855	0.888
$Mean^{f1}$	0.901	0.643	0.800	0.867	0.896

ponent Analysis is successful in capturing relevant features and patterns within the dataset, Variational Autoencoder also reached one of the highest average F1 scores with 0.885. while Restricted Boltzmann Machine and traditional Autoencoder show nearly the same average F1 scores of 0.791 and 0.754 following it came ICA with 0.674.

As a result of these findings, it suggests that models such as VAE and PCA can significantly enhance the performance of catching underlying patterns in such datasets.

Table VII is the results of applying the same models but with the GRU model on the SEED dataset. To analyze the results, Principle Component Analysis once again performs well with the GRU model as well. with an average F1 score of 0.901. Surprisingly, Independent Component Analysis comes next, with an average F1 score of 0.643. Restricted Boltzmann Machine and traditional Autoencoder perform similarly as in the LSTM model, reaching an average F1 scores average of 0.800 for RBM and 0.867 for AE. Variational Autoencoder also shows good results, which makes it the second best after PCA, with an average F1 score of 0.896.

As the result of the usage of the GRU model with the SEED dataset, it approves once more the idea of the underlying hidden patterns and reconstructs from encoded data in a successful way with Principle Component Analysis and Variation Autoencoder models.

Now that we analyzed all unsupervised learning models and applied supervised learning methods to our datasets to recognize patterns to measure the efficiency of Autoencoders from extracted latent factors, We can classify the performances of models. To begin with, Independent Component Analysis performance was below average on both datasets and RNN models, which means the ICA model is not suggested to use with EEG kind of signals. Moreover, Traditional Autoencoder performed well in Gated Recurrent Unit models but the performance was lower in LSTM models.

Similarly, the restricted Boltzmann Machine exhibited a good performance with Gated Recurrent Units, but the performance was lower when it come to the LSTM models. It is good to mention that this ratio was not as lower as traditional Autoencoder results. The principle Component Analysis did the second-best performance in comparison to the other models except for VAE. Finally, the results gathered from Variational Autoencoder were significantly high and accurate in most cases. Thus, the model has proved that Variational Autoencoder can successfully pattern EEG signals,

The table VIII, presents a list of related studies and their performance on the SEED and DEAP datasets with there own methods. For the GRU SEED dataset, various approaches were employed, including dynamical graph CNN, CNN with sparse graph representation, transfer learning methods, generative adversarial network, and spatial-temporal recurrent neural network. Alongside, the VAE-based approach which proposed in our study has also been listed with an achieved highest performance of 0.896.

For the DEAP dataset, different studies utilized ontology-based storage and representation, feature selection, decision tree-based recognition, MRMR-based feature selection, statistical features, band power features, Hjorth parameters, fractal dimension, multi-layer stacking autoencoder, multivariate empirical mode decomposition, and generative adversarial network. Finally, Our VAE-based approach has also listed with the highest average of 0.877.

V. Feature Extraction

In this part to gain a perspective from different views on datasets, we have applied some approaches to analyze brain activities during different emotions and trials. Figure 15 represents the brain activities of subject no. 10, which has been labeled positive in arousal and positive in terms of valence. It is showing the signals between 10^{th} and 11^{th} seconds. The measurement has been done by calculating by scalp electrodes and represents with μV. High amplitudes or red areas show strong activities and lower amplitudes can indicate periods of low activity.

TABLE VIII
COMPARISON WITH PREVIOUS WORKS

Dataset	Study	$Performance^{f1}$
DEAP	Ontology-based storage and representation, feature selection and decision tree based recognition method[11]	0.689
DEAP	Minimum-redundancy-maximum-relevance (MRMR) based feature selection combined with the statistical features, band power features, Hjorth parameters and fractal dimension[12]	0.730
DEAP	Integrated classifier based on multi-layer stacking autoencoder combined with time domain features and PSD features[13]	0.771
DEAP	Multivariate empirical mode decomposition (MEMD) based feature extraction combined with ANN [14]	0.750
DEAP	Generative adversarial network (WGANDA) based transfer learning combined with differential entropy feature [15]	0.668
DEAP	The VAE based approach proposed in this work(LSM arousal)	0.877
SEED	Dynamical graph CNN (DGCNN) learns from the DE, PSD, DASM, RASM and DCAU features based adjacency matrix representation[16]	0.799
SEED	Extracting differential entropy features to construct 2D sparse graph representation, then combining CNN for classification[17]	0.882
SEED	Transfer learning methods combined with differential entropy features and logistic regression based classification[18]	0.724
SEED	Generative adversarial network (WGANDA) based transfer learning combined with differential entropy feature[15]	0.870
SEED	Spatial-temporal recurrent neural network (STRNN) combined with differential entropy feature[19]	0.895
SEED	The VAE based approach proposed in this work(GRU)	0.896

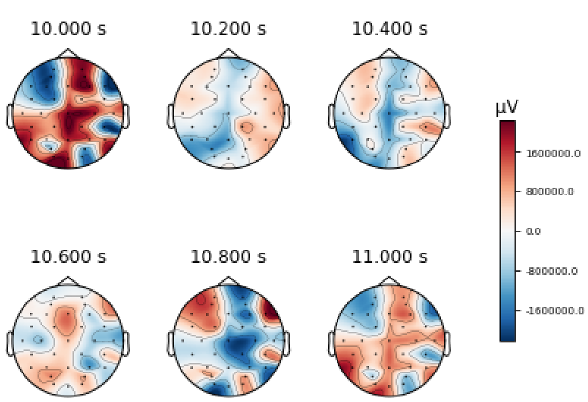

Fig. 15. Brain Activity Between 10-11 seconds

In case to analyze which kind of waves these signals and represent better the activity of the brain, it calculated the Power Spectral Density (PSD) of subject no. 10 using Welch's method. The PSD represents the distribution of power across different frequency components in the signal. While calculating the brain waves the commonly recognized bands are categorized as 0.5 Hz to 4 Hz for delta, 4 Hz to 8 Hz for theta, 8 Hz to 12 Hz for alpha, 12 Hz to 30 Hz for beta, and above 30 Hz for gamma. According to Figure 16 the wave points that the signals are produced with a weighted score on theta waves. These waves are produced generally while imaginative thinking, learning, and relaxing. Hence, gaining such knowledge regarding to the subject's brain activity helps us to draw the invisible journey of the brain.

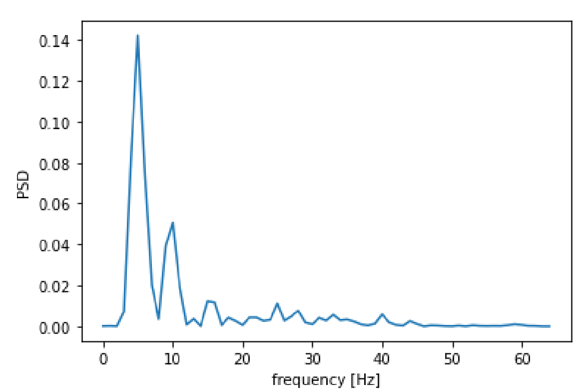

Fig. 16. Brain Waves

VI. CONCLUSION

We have investigated emotion detection with EEG signals using various unsupervised and supervised learning methods. The purpose of the investigation was to evaluate the Variational Autoencoder's ability to detect human emotion. In this method, we began by selecting various deep generative and non-generative autoencoding models, such as RBM and AE, and dimensionality reduction methods, such as ICA and PCA, that are capable of capturing the hidden patterns and important nodes in any given dataset, so that we can compare them to Variational autoencoder.

In addition, to validate the performance of the models, we calculated the correlation coefficient of the original data and compared it to the reconstructed data to determine their similarity. Moreover, to determine if the created patterns are sufficiently significant and if our autoencoders, specifically VAE, effectively patterned the signals and reconstructed data can still represent them, we employed supervised learning, specifically Recurrent Neural Networks. We have decided to implement two distinct RNN models, LSTM and GRU. This method assisted us in validating results obtained through the calculation of correlation coefficients between models.

As a consequence, we have demonstrated that the Variational Autoencoder is effective at capturing and deciphering concealed patterns in EEG signals. After that, PCA, RBM, and traditional AE also performed well, and it was determined that EEG signals are still valuable for further analysis, including emotion detection and medical analysis. In conclusion, the traditional ICA performed poorly in this study. However, it can still be used in a variety of situations, though it may not be the best option for capturing concealed patterns in EEG signals.

VII. DATA AVAILABILITY STATEMENT

The DEAP dataset used for this study can attained from the following link: http://www.eecs.qmul.ac.uk/mmv/datasets/deap/index.html. The SEED dataset used for this study can attained from the following link: https://bcmi.sjtu.edu.cn/ seed/index.html.

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