Gaussian-Enhanced CNN Auto encoder for Efficient EEG Signal Compression

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***Abstract*— Compressing electroencephalography (EEG) signals is crucial for reducing data storage and transmission costs in real-time healthcare monitoring and brain-computer interface systems. This study proposes an optimized EEG signal compression process based on a convolutional automatic encoder (CNN-AE) with integrated preprocessing. Unlike traditional approaches, this deep learning-based framework systematically investigates the impact of preprocessing strategies on compression model performance. Specifically, we introduce a Gaussian filtering stage to enhance signal quality prior to encoding.. The suggested approach involves normalization, segmentation, and then extraction of features, followed by the application of a CNN-based auto encoder for processing dimensionality reduction on EEG signals which is constructed in layers. Various learning rates, segment lengths, and training epochs were conducted for the process' overall framework robustness evaluation of the model. Mean Squared Error (MSE), Percentage Root Mean Square Difference (PRD), and Peak Signal-to-Noise Ratio (PSNR) are used for the model's evaluation on reconstruction performance. There's an undeniable proof in the experiments result stating the accuracy of the suggested Gaussian Filter + CNN-AE model framework in contrast to the baseline CNN-AE model with bandpass filtering. With a compression rate of 8:1, the suggested method has the ability for a reduction of reconstruction error to less than 1.7 × 10^{-5} MSE, a minimized relative measure of Distortion (PRD) below 1%, and superior reconstruction quality (PSNR over 47dB). This also proves to the evaluation that the Gaussian smoothing method is superior and that the compression is superior in overall and representation stability. The proposed method can be considered a computationally efficient and effective solution for compressing EEG signals and can be extended to include real-world biomedical signal processing applications.**

Keywords*— EEG Compression, CNN Auto encoder, Gaussian Filter, Reconstruction Quality, Deep Learning for Biomedical Signals, Efficient Data Compression , Signal Reconstruction

I. Introduction

Electroencephalography (EEG) is a widely used non-invasive physiological technique that measures the brain's electrical activity. Electrodes are placed on the patient's scalp, playing a crucial role in diagnosis. Due to its affordability, portability, and quick performance, EEG has become an essential tool for monitoring brain conditions. It is widely used in clinical settings, including sleep stage analysis, epilepsy detection, anesthesia monitoring, and neurological rehabilitation. Modern businesses and research projects are beginning to realize the growing importance of efficient compression methods to address challenges presented by EEG compression. Effective compression reduces the size of the data while retaining information that is clinically important to facilitate diagnostic testing. Predictive coding and statistical modeling over the years have been used with various degrees of success. EEG signals are described as non-stationary and are often contaminated with artifacts, and the variability from one person to the next can make the non-stationary nature of the EEG signals and artifacts challenging. The variability between subjects presents problems to the conventional compression techniques EEG's high compression and the low distortion difficult to achieve. In the last few years, various methods have been used to try and to improve the compression of EEG signals. Techniques that focus on sparse coding, deep neural networks, adaptive coding, and hybrid coding have been used to obtain better results. The focus is to obtain the best balance in trade-offs between the compression, quality of the reconstruction, the cost of the processing, and the level of complexity of real-time and real-time systems that have limited resources. Despite this progress, challenges remain in ensuring signal recovery after compression, reducing computational complexities, and addressing inter-individual variability [1] .With the rapid development and growth in the use of electroencephalography (EEG) applications in clinical diagnosis, computer-aided diagnostics, brain-brain interfaces, and remote health monitoring, the volume of data has increased. This has led to a significant increase in research focused on developing electroencephalography (EEG) signal compression techniques to preserve information, reduce power consumption, and lower storage and transmission bandwidth requirements. Recent EEG compression research has also focused on transformation-based methods, particularly wavelet transformations, due to their ability to efficiently represent unstable medical signals and concentrate signal energy into a few key parameters. Wavelet-based compression relies on multi-resolution analysis, effectively reducing data while maintaining high signal retrieval quality.[2]. Khalifa and colleagues demonstrated that wavelet displacement compression can achieve reasonable compression ratios while maintaining the accuracy of the recovered signal. Although this method is computationally efficient, its performance is highly dependent on the choice of wavelet basis and threshold strategy. To improve compression efficiency, compressed sensing (CS) has been proposed as a promising framework for acquiring and compressing electroencephalography (EEG) signals. This approach enables the use of sampling rates lower than the Nyquist rate, since the EEG signal spacing is used within a suitable transformation range, significantly reducing data transmission and storage costs. However, traditional compressed sensing algorithms, such as convex or greedy optimization methods, are computationally expensive and require long signal reconstruction times. More recent studies have addressed these issues by integrating deep learning techniques with compressed sensing.. Du et al. proposed a newer deep learning-based reconstruction framework that reconstructs iterative CS signals using a non-recurrent neural network model. This results in faster signal reconstruction and higher accuracy. By learning the nonlinear relationship between the compressed measurements and the original EEG signal, these methods significantly reduce signal reconstruction time. This makes it more suitable for real-time systems; however, deep learning methods typically require a massive set of training data and significant computing resources during the training phase [3][4]. In addition to the methods mentioned above, more adaptive and hybrid compression frameworks have been discovered, aiming to balance signal compression and reconstruction, as well as reduce system complexity. This model combines signal preprocessing, robustness enhancement, and displacement techniques under varying conditions. Despite these approaches, the challenge remains in balancing compression efficiency, computational cost, and signal distortion. [5]. Other multi-mode compression frameworks have been discovered to reduce computational and transmission burdens in wearable healthcare systems. Dasan and Ganaraj proposed a model combining electrocardiogram (ECG), electroencephalogram (EEG), and electromyography (EMG) signals. In this model, a multi-mode convolutional encoder was used to remove deep noise. The results showed that combined compression achieves higher compression efficiency and less computation time compared to compressing each signal separately[6]. In addition to multi-mode learning, another signal processing model emerged that is graph-based. This model was considered an effective tool for compressing electrical brain signals. Fujiashi and Koike Akino presented a graph-based EEG signal compression scheme using the Graph Fourier Transform (GFT) with quantization and entropy coding. This method achieved higher signal reconstruction quality compared to other traditional methods, highlighting the effectiveness of utilizing spatial correlations between channels[7]. However, Sisutu and colleagues proposed hvEEGNet, a hierarchical differential auto encoder specifically designed for multichannel signal reconstruction. This model (hvEEGNet) demonstrated consistent and high-accuracy reconstruction across all individuals, compared to previous auto encoder-based models that either failed to preserve frequencies or were limited to single-channel signals. Lerogeron and colleagues also discovered a convolutional autoencoder using a neural network-based approximation of dynamic time-matching (DTW) technology, which preserves task-relevant EEG signal characteristics more effectively than the traditional mean squared error (MSE)Especially when assessed using subsequent tasks such as classifying sleep stages [8][9]. Mohsen Nia et al. presented a study analyzing the feasibility of continuous monitoring systems incorporating electroencephalography (EEG) sensors. This study demonstrated that conventional sensing and transmission schemes are inadequate for long-term operation. This study achieved a significant reduction in power and storage requirements by integrating compact sensing and transmission technologies based on anomaly detection, thus providing a strong impetus for integrating effective compact technologies into practical, wearable, and remote healthcare platforms [10]

The contributions of this paper are threefold:

- This study proposes an improved EEG signal compression framework based on a convolutional automatic encoder (CNN-AE) designed to learn concise and efficient representations of EEG signals while preserving temporal characteristics.
- A pre-processing stage based on Gaussian filtering is used to improve signal quality before compression. This step effectively suppresses high-frequency noise and enhances the stability of the extracted representations.

- The proposed Gaussian filter + CNN-AE This framework achieves better performance than the configurations, exhibiting less reconstruction error (MSE), less distortion (PRD), and higher signal quality (PSNR) compared to traditional methods, while maintaining an effective compression ratio of 8:1.
- It provides a comprehensive assessment of the model's robustness and generalizability because it performs intensive experimental analysis under varying learning rates, segment lengths, and training periods, which.

II. METHODOLOGY

A. Overview of the Proposed Framework

In the proposed study, an effective method for compressing electroencephalography (EEG) signals was demonstrated. This framework utilizes a Gaussian filtering stage followed by a self-contrast convolutional neural network (CNN-AE). The goal is to reduce the dimensions of EEG signals while preserving the essential temporal characteristics necessary for accurate reconstruction. Four main stages were followed in this proposed study:

1- Generating or acquiring an EEG signal
2- Passing the signal through a Gaussian filter to smooth it
3- Compressing features using a self-encoding convolutional neural network
4- Reconstructing the signal and evaluating the performance.

In the first stage, the raw (EEG) signals are pre-processed using a Gaussian filter to reduce some of the noise and high-frequency distortions that negatively affect the neural network's learning process. After this processing, the signals are printed and divided into fixed-length windows to facilitate the training process with high efficiency. After that, a self-encoding convolutional neural network (CNN) is used to learn a compressed latent representation of the EEG signal. This process significantly reduces the data size while preserving the structural information of the signal. At the end of the process, the reconstructed signals are compared with the original signals using several metrics, including the peak signal-to-noise ratio (PSNR), the root mean square difference ratio (PRD), and the mean squared error (MSE).

B. Gaussian Filtering

Because EEG recordings often contain various sources of noise, including measurement impurities and environmental interference, which can impair compression performance and reconstruction accuracy, a pre-compression filter was used. The EEG signals were preprocessed using a Gaussian filter for smoothing. The Gaussian filter performs a weighted averaging process, and the proximity of the samples contributes to smoothing the signal according to a Gaussian distribution. The filtered signal y(t) is obtained as:

$$y(t) = \sum_{k=-\infty}^{\infty} x(t-k)G(k) \qquad (1)$$

where x(t) represents the original EEG signal and G(k) denotes the Gaussian kernel defined as:

$$G(\boldsymbol{K}) = \frac{\mathbf{1}}{\sqrt{\mathbf{2}\pi\sigma\text{^}\mathbf{2}}}\; \boldsymbol{e}^{-\frac{\boldsymbol{k}^{\mathbf{2}}}{2\sigma^{2}}} \qquad (2)$$

In this work, a value of **σ = 2** was selected as it provides a good balance between noise reduction and signal preservation **, σ** is considered a control factor for the smoothing level . Applying a Gaussian filter enhanced the neural network's ability to learn during the compression phase and improved the quality of the electroencephalography (EEG) signal.

C. EEG Segmentation and Normalization

After the filtering process, the electroencephalogram (EEG) signals are divided into fixed-length segments to facilitate model training. Each segment contains 256 samples, allowing the neural network to efficiently capture the temporal characteristics of the EEG signals. The signal amplitudes are then normalized using minimum and maximum normalization to ensure the stability of the training process, which transforms the signal values into the following range[0,1]:

$$Xnorm = \frac{x - xmin}{xmax - xmin} \qquad (3)$$

The normalization step prevents numerical instability during training and improves the convergence speed of the neural network.

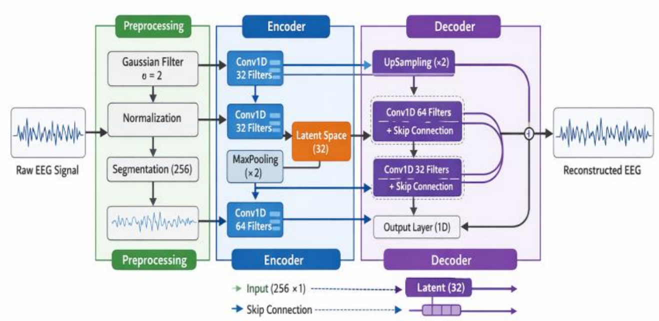


Fig.1: Proposed EEG compression framework built with Gaussian pre-processing, and CNN auto-encoder with skip connections. The encoder compresses an input signal into a dense latent representation, and the decoder reconstructs the signal while preserving high fidelity.

D. CNN Autoencoder Architecture:

An architecture called Convolutional Auto encoders (CNN-AEs) is used for the compression of EEG signals. For the compression of data, the Auto encoders do not involve an explicit process of feature selection, and therefore, it is faster and easier to process data. CNN-AEs are divided into two parts:

- Encoder

The encoder extracts and compresses the EEG signal into a set of lower features, and therefore, reduces the dimensionality of the set. The encoder consists of a number of 1-D Convolutional Layers, and these are followed by Max Pooling Layers. The result of these combination of set of layers is to lower the number of constituent temporal features to a number of constituent features. The encoder takes the original EEG signal and produces as a result a latent representation with a dimension of 32.

- Decoder

The reconstructed version of the latent EEG signal is produced by the decoder. There are Up Sampling Layers and Convolutional layers which are used to restore the original temporal features of the signal. There are a set of layers called Skip Connection which span across the layers of the encoder and decoder and are used for retaining and enhancing the quality of the reconstruction of the original signal features.

E. Compression Strategy

The encoder performs a compression process using dimensionality reduction. For example, an input EEG segment that is 256 samples in length is compressed by the encoder to a latent representation of size 32. This gives us a compression ratio defined as:

$$CR = \frac{256}{32} = 8$$

This shows that the proposed method compresses the original signal to an 1/8 of its size, and the decoder reconstructs the signal with little distortion. The neural network is trained with the Mean Squared Error (MSE) loss function, which computes the difference between the original signal, and the reconstructed signal. The parameters of the model are optimized using the Adam optimizer with a learning rate of 10^{-3}

III. Experimental Setup

A. Dataset

A dataset containing EEG-like signals was used to perform the proposed EEG compression framework. The dataset used signals that were designed to mimic the Spectral characteristics typical of EEG recordings. Every signal was modeled to mimic the different oscillatory components that brain signals are made of and was separated into frequency bands that correspond to the commonly recorded EEG frequency bands comprising of: low frequency rhythms (1 – 4 Hz), middle frequency components (4 – 8 Hz) and higher frequency oscillations (8 – 13 Hz). To simulate natural variability of the brain signals, random variations were made to the frequency parameters. To approximate real-life conditions of brain recordings, additive Gaussian noise was artificially incorporated into the signals to simulate Delta waves which are brain waves that have a frequency of 0 – 4 Hz and are found in the EEG recordings of patients who are asleep or in a very relaxed state. Additionally, a Gaussian smoothing filter was used to block Delta waves and to prepare the signals. A collection of 800 segments of signals was made in the dataset and each segment was made to contain 256 samples, which is the average number of samples recorded in a short interval of time from the activity of brain signals. To prepare the signals for training, the signals were normalized through Min-Max normalization, which is a method of scaling of the amplitude of the neural signals to fall within the range of [0,1]. This method improves the speed of training for the neural network model and provides numerical N stability for the model. For the dataset, it was decided that the dataset be divided into working samples and validation samples, wherein 80% of the dataset would go to the construction of the working samples and the remaining 20 % would be used for the evaluation of the compression framework model.

B. Training Configuration

In the proposed model, the convolutional auto encoder was trained to learn a condensed representation of EEG signals while preserving the temporal characteristics for accurate reconstruction. The Adam optimizer was used to improve the model parameters. Training was conducted over 60 training cycles using a batch size of 32 with a segment length of 256 samples. In addition, the proposed study was implemented using Python with several scientific computing libraries. A deep learning model was applied using Tensor Flow and Keras, which provide effective tools for building and training convolutional neural networks. The encoder compresses each segment of the EEG signals into a 32-fold compressed latent representation, resulting in a compression ratio of 1:8. The decompression process reconstructs the signal from this latent representation. All experiments were conducted using the same training mechanism to ensure a consistent and fair compression framework.

C. Performance Evaluation Metrics

The compression of EEG signals was assessed using three common measures of signal reconstruction: mean squared error (MSE), mean squared difference ratio (PRD), and peak signal-to-noise ratio (PSNR).

- Mean Squared Error (MSE)

It measures the difference between the original signal and the reconstructed signal:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(x_i - x_s)^2 \quad (4)$$

Where , x_i represents the original EEG signal and x_s denotes the reconstructed signal

- Percentage Root Mean Square Difference (PRD)

PRD is used to determine the amount of reconstructive distortion and is a commonly used measure in biomedical signal compression:

$$PRD = \sqrt{\frac{\sum(x_i - x_s)^2}{\sum x_i^2}} * 100 \quad (5)$$

Lower PRD values indicate better signal reconstruction quality.

- Peak Signal-to-Noise Ratio (PSNR)

The PSNR index is a measure of the quality of the reconstructed signal in decibels (dB) and is defined as follows:

$$PSNR = 10\log_{10}(\frac{MAX^2}{MSE}) \quad (6)$$

Where, MAX represents the maximum possible value of the signal, The higher the PSNR values, the more accurate the reconstruction.

IV. Result and Discussion :

In this study, the performance of EEG signal compression was evaluated using three preprocessing configurations: a basic convolutional neural network-based auto encoder without filtering, a bandpass filter combined with a convolutional neural network-based auto encoder, and a Gaussian filter followed by a convolutional neural network-based auto encoder. Reconstruction quality was assessed using three metrics: mean squared error (MSE), peak signal-to-noise ratio (PSNR), and root mean squared ratio (PRD), under different learning rate settings, different epochs, and different segment lengths.

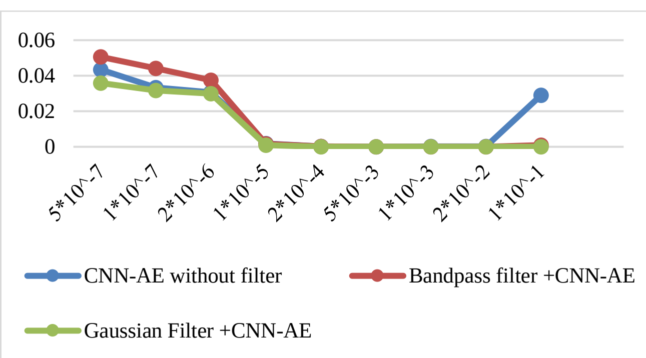


Fig.2: PSNR performance versus EEG segment length for CNN-AE without filtering, Bandpass filter + CNN-AE, and Gaussian filter + CNN-AE.

The experimental results indicate that preprocessing significantly enhances the stability and accuracy of the neural compression model. In most cases, the CNN-AE without filtering has high reconstruction errors, even at very small learning rates, with MSE exceeding 4.34*10^{-2}. A bandpass filter reconstructs more successfully because it allows some range of frequency components to pass through unrestricted, but consistently, the best results come from applying Gaussian filtering before the compression stage. For example, at a learning rate of 1*10^{-3}, the Gaussian-filtered model has an MSE of 1.7*10^{-5}, which is better than band pass filtering (3.9×10^{-5}) and worse than the baseline CNN-AE (1.91×10^{-4})

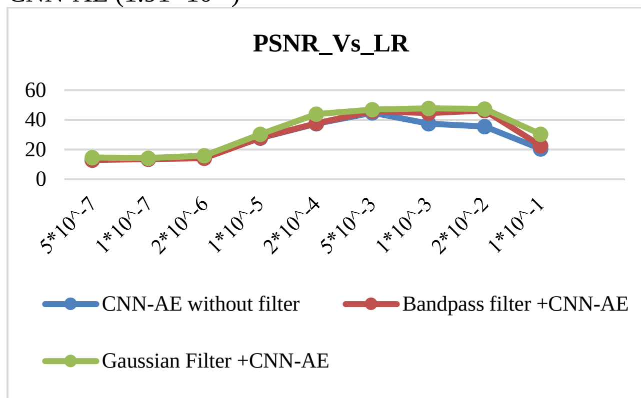


Fig.3: PRD comparison versus EEG segment length for the three evaluated configurations: CNN-AE without filter, Band pass filter + CNN-AE, and Gaussian filter + CNN-AE.

Here we observe similar improvements when evaluating signal reconstruction quality using the PSNR metric. At the same learning rate (10^{-3}), the Gaussian filtered configuration achieves a PSNR of 47.75 dB, surpassing both the bandpass filtering configuration (44.53 dB) and the basic CNN-AE model (37.47 dB). This improvement of over 10 dB compared to the model without preprocessing highlights the significant contribution of Gaussian filtering to signal reconstruction quality.

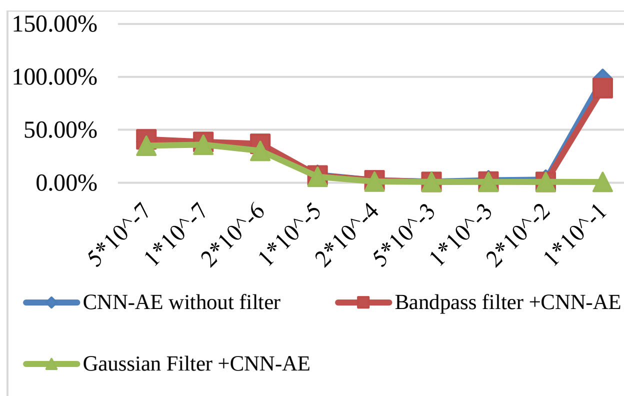


Fig.4: PSNR variation with respect to training epochs for CNN-AE without filter, Bandpass filter + CNN-AE, and Gaussian filter + CNN-AE.

The PRD metric confirms the effectiveness of the proposed approach, achieving the lowest possible distortion across most learning rates. With Gaussian filtering at a learning rate of 10^{-3}, the PRD drops to 0.79%, compared to 1.12% using a bandpass filter and 2.48% for the unpreprocessed CNN-AE model. Experiments conducted at varying signal lengths further confirm the robustness of the method, with

Gaussian filtering consistently achieving the lowest PRD values. For instance, at a signal length of 512 samples, the PRD reaches 0.69%, outperforming the bandpass filter (0.74%) and the baseline CNN-AE model (0.86%)

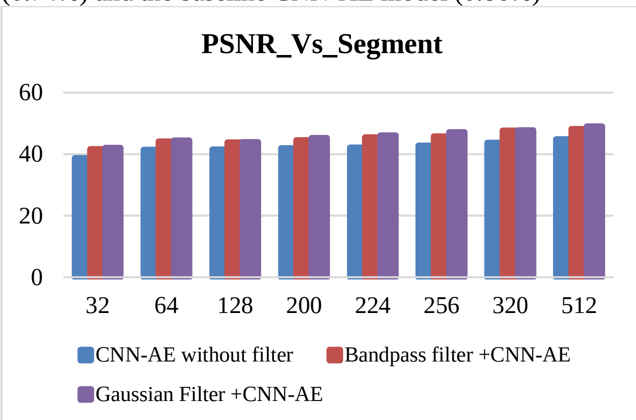


Fig.5: PSNR performance comparison versus EEG segment length for CNN-AE without filtering, Bandpass filter + CNN-AE, and the proposed Gaussian filter + CNN-AE framework.

The figure displays the PSNR performance for various EEG segment lengths and the three configurations of CNN-auto encoder (CNN-AE) without preprocessing, Bandpass filter + CNN-AE, and Gaussian filter + CNN-AE. It can be seen that as segment length increases, the PSNR also increases. This is primarily the result of longer segments containing more temporal information available for the auto encoder. A notable trend is that CNN-AE + Gaussian filter consistently achieves the highest PSNR values for all segment lengths, out-performing the baseline method of CNN-AE as well as bandpass filtering. For instance, a segment length of 512 samples achieves nearly 50 dB for the proposed method, compared to 48 dB for bandpass filtering and 45 dB for the model without filtering. This data shows how the Gaussian preprocessing method first reduces the noise to increase the quality of the data to be reconstructed.

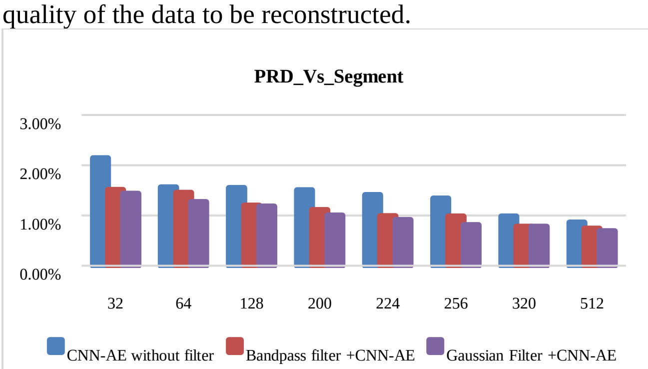
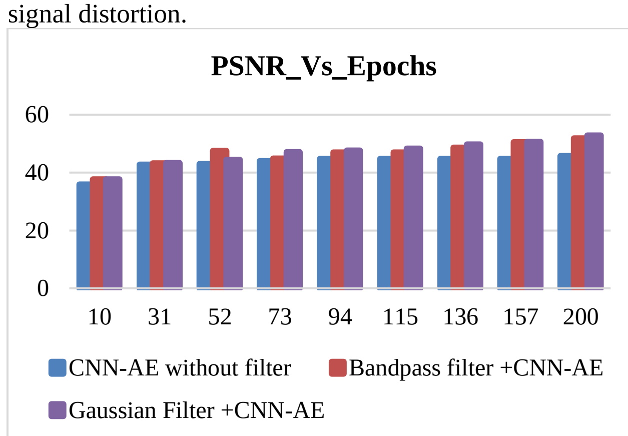


Fig.6: PRD versus Segment Length

Figure 6 illustrates how the Percentage Root Mean Square Difference (PRD) changes in relation to the length of the EEG segments for the three configurations under consideration. PRD values demonstrate a gradual decrease with increasing length of the segments, suggesting a greater accuracy of reconstruction as the length of the signal segments is increased. Out of all the methods, the combination of Gaussian filter and CNN-AE method consistently provides the lowest PRD values for all segment lengths. This shows that it has a greater performance in the reconstruction of the signal in comparison to the bandpass filtering method and the CNN-AE method without preprocessing. Thus, these findings show that Gaussian filtering before the compression stage is capable of reducing signal distortion.



Fig,7 : PSNR versus Training Epochs

The figure above shows the signal-to-noise ratio (PSNR) performance as the number of training cycles increases for the three evaluated configurations. The PSNR values gradually improve with increasing cycle counts, indicating better reconstruction quality with extended training. Furthermore, among the three configurations, the Gaussian filter combined with CNN-AE consistently achieves the highest PSNR values, demonstrating superior reconstruction performance compared to both the bandwidth-filtering configuration and CNN-AE without preprocessing.

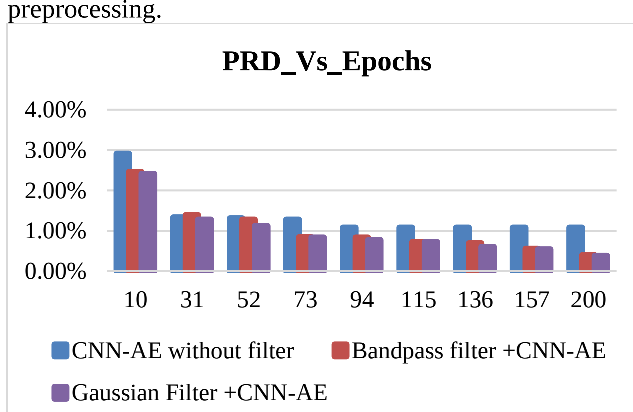


Fig.8 PRD versus Training Epochs

From the figure above, we observe the evolution of the reconstruction distortion, measured by the PRD index, with increasing training cycles. The results show a significant decrease in PRD values during the initial training phases, followed by gradual stabilization as the model approaches convergence. This behavior indicates that the auto encoder is gradually learning a more accurate latent representation of the electroencephalogram (EEG) signal. The Gaussian filter combined with the convolutional neural network auto encoder (CNN-AE) consistently achieves the lowest PRD values throughout the training process. This improvement suggests that Gaussian smoothing enhances the robustness of the extracted features by reducing noise components prior to the compression phase. Therefore, the proposed Gaussian filter + CNN-AE framework achieves a more accurate signal reconstruction compared to all other configurations.

V. Conclusion :

In the proposed study, a framework for compressing electroencephalography (EEG) signals was developed using an automatic convolutional encoder preceded by signal processing. Evaluation was performed using three configurations: an automatic convolutional encoder without filtering, a bandpass encoder with an automatic convolutional encoder, and a Gaussian encoder with an automatic convolutional encoder. The experimental results showed that preprocessing improved signal reconstruction quality. The Gaussian encoder achieved the best results in terms of mean squared error (MSE), relative variance ratio (PRD), and signal-to-noise ratio (PSNR), regardless of the learning rate, segment length, or number of training cycles. The results confirmed that Gaussian smoothing, among all other filters, was the best at improving the stability of learned representations and reducing noise, leading to improved signal reconstruction. It also achieved the best tested technique for achieving the goal of EEG signal compression with an acceptable level of reconstruction quality. The next phase of this study is expected to involve applying this technique to real EEG datasets and integrating the latest deep learning techniques to better address the compression problem.

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