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Impact of Data Quality on EEG-Based Biomedical Systems

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Abstract—With the widespread use of biomedical signal acquisition systems, particularly for EEG signals, some probes do not capture information optimally. Poor skin contact and the influence of external electrical signals explain this phenomenon. In this study, we analyze the impact of data quality on the overall performance of the system in terms of analysis quality but also power consumption. To do this, we use an epileptic seizure detection algorithm that we have already analyzed, and we simulate data loss on the one hand, and signal disturbances on the other, in order to determine their impacts. We also propose the best way to compensate for missing data as well as tolerance thresholds that may allow us to change the algorithm.

Index Terms—Bio-medical signal, System performance, EEG signal, Neural network

I. INTRODUCTION

In recent years, the intersection of artificial intelligence, biomedical signal processing, and advanced hardware platforms has emerged as an essential domain with profound implications for healthcare care such as apnea [1], narcolepsy [2], isomnia [3] and scientific research such as the study of cognitive processes [4], memory [5], attention [6]. The combination of these disciplines provides a unique avenue to enhance understanding and interpretation of complex biological signals, such as those inherent in electroencephalogram (EEG) recordings, in a high efficiency and low cost way. Electroencephalography, a non-invasive technique for monitoring electrical brain activity, holds unparalleled importance in the diagnosis and understanding of neurological disorders, particularly epilepsy. In healthcare field, it is widely used for clinical diagnosis and monitoring like to diagnose and monitor epilepsy by detecting abnormal brain activity [7]. And EEG is also used to assist in diagnosing and monitoring conditions such as Alzheimer's disease [8] and Parkinson's disease [9]. And to help assess brain function after traumatic brain injuries [10]. However, the integration of EEG into wearable technology introduces distinct challenges, especially concerning power consumption and signal processing. Given that these devices operate within resource-limited environments, optimizing both hardware and algorithms for minimal power usage is imperative. Concurrently, ensuring the acquisition of high-quality data in dynamic, real-world environments presents a considerable challenge. The growing reliance on EEG in wearable technology underscores the urgent need to overcome these obstacles, thereby facilitating reliable and

efficient functionality across a diverse range of applications [11].

Power consumption is a critical factor in the design and operation of intelligent wearable devices, as it directly affects battery life and, consequently, the usability and practicality of such systems in real-world applications. Wearable devices are often designed for extended use in resource-constrained environments where frequent recharging is not feasible. For instance, EEG-based wearable systems used for continuous health monitoring must strike a balance between processing power and energy efficiency to maintain user convenience and reliability [12]. The detailed workflow of the EEG recording system [13], as depicted in the accompanying figure 1 This

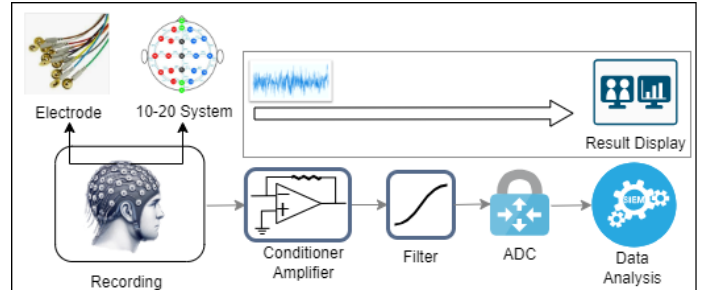


Fig. 1. Diagram of the EEG recording system

paper focuses on the challenges associated with data quality in medical research, particularly addressing issues related to noise, errors, and data loss. The variability in data collection methods and the heterogeneity of data sources frequently give rise to significant data quality concerns. Such uncertainties cast doubt on the validity of research findings derived from compromised data. The aim of this paper is to examine the impact of data quality fluctuations on system performance. By doing so, we intend to explore potential avenues for optimizing system performance, enabling adaptive adjustments in response to environmental changes, and ensuring the reliability and accuracy of applications in diverse settings.

II. USE CASE DESCRIPTION

We give a setting in which the quality of the collected data will change with the changes in the environment or application scenario. The database and algorithm used are the same as in [14], an open source seizure one-channel

classification database from Bonn University [15] and an 1D six-convolutional layers CNN structure (referenced in [16] and [17]).

A. Definition of system performance

When measuring the performance of AI-based biomedical systems, three core metrics are usually considered: accuracy, execution time, and power consumption. Together, these metrics describe the efficiency and usability of the system in a real-world medical setting. Accuracy is a key metric for evaluating the correctness of an AI system's predictions in diagnosis, treatment recommendations, or other medical tasks. High accuracy ensures the reliability of medical decisions, which is critical to patient safety. Execution time refers to the length of time it takes a system to complete a specific task. In emergency medical situations, shorter execution times can speed up the decision-making process, potentially saving lives. Power consumption measures the energy required to run a system. Especially for wearable medical devices and mobile health monitoring devices, low-power designs mean longer battery life and greater device usability. The three performance metrics of accuracy, execution time, and power consumption not only affect the technical design of the system, but are also directly related to the application value and patient experience of the system in a clinical setting.

B. Definition and Simulation of Data Variation

Data noise refers to noise or signal interference caused by external sources. This noise is mixed into valid data during the data collection process, reducing the quality of the data. It is usually caused by electromagnetic noise in the environment, interference between devices, or physical factors. EEG signals, which collect weak electrical activities occurring on the scalp, are extremely susceptible to such noise, including electromagnetic interference and interference from other signals, thereby affecting the quality and availability of the data. This noise increases the randomness and unpredictability of the data, making it difficult for previously trained models to recognize patterns in new data, resulting in a decrease in system accuracy. Data noise is quantified by the signal-to-noise ratio (SNR), expressed in decibels (dB). The lower the SNR, the stronger the interference.

To simulate the interference of the signal, we consider adding Gaussian white noise to the original signal to simulate the signal under different SNRs conditions. Referring to [18], we set 10 different SNRs at +4dB, +2dB, 0dB, -2dB, -4dB, -6dB, -8dB, -10dB, -12dB, -14dB as shown in the code and formula (1).

```

1 for SNR = SNRs
2     signal_power = rms(x)^2;
3     noise_power=signal_power/10^((SNR)/10);
4     lambda = sqrt(noise_power);
5     n = lambda * randn(size(x));
6     y = x + n;
7 end

```

$$\text{SNR (dB)} = 10 \log_{10} \left(\frac{P_{\text{signal}}}{P_{\text{noise}}} \right) \quad (1)$$

Data error refers to the data being recorded or modified incorrectly during the collection, storage or transmission process. It may be caused by hardware failure, software defects, operational errors or external interference, resulting in the data content not matching the actual value. Data errors can be measured by error rate (%), such as an error rate of 5% means that among all data items, 5% of the data does not match the original value due to errors.

Another possible situation is data loss, which refers to the unavailability of some data during data collection, transmission or processing. Data loss often occurs in the case of communication failure, storage error or processing interruption. Data loss is usually measured as a percentage (%), describing how much of the data in the entire dataset is lost. For example, the missing data rate can range from 0% (no loss) to 100% (all lost).

When simulating missing data, we use Rubin [19]'s MCAR (Missing Completely at Random) method, that means randomly delete values from the dataset, ensuring no systematic pattern to the missing data. Using 5% intervals, from 0% to 100% to make the data randomly missing, in order to ensure that the size of the model interface is not changed, we replace the missing part with 0. Similarly, we randomly dropped data from the dataset and replaced the original values with random numbers to simulate wrong data. Using an intervals of 5%, from 0% to 100% to the data randomly wrong.

C. Experimental platform

We use PyCharm as an integrated development environment and TensorFlow as a neural network framework to develop and test deep learning models. The experiment was conducted on a computing platform with the following hardware configuration:

- GPU: NVIDIA GeForce GTX 1650.

During the experiment, the program's running platform (GPU or not) is determined by setting the environment variable `os.environ["CUDA_VISIBLE_DEVICES"]` to "0" (using GPU) or "-1" (don't use GPU).

```
os.environ["CUDA_VISIBLE_DEVICES"] = "-1" # "0"
```

In addition, in order to monitor and record hardware usage, the experiment simultaneously opened two command line windows and ran the following commands in administrator mode:

```

for /l %x in (1, 1, 3600) do @(echo %time% &
↪ nvidia-smi --query-gpu=power.draw --
↪ format=csv,noheader,nounits | find /v "
↪ ") >> D:\pyCharm_work\
↪ CNN_training_data_interference\GPU_usage
↪ \gpu_usage.txt
nvidia-smi -l 1 >D:\pyCharm_work\
↪ createCNN_training\GPU_usage\gpu_log.txt

```

III. RESULTS

A. Accuracy Results

The accuracy results for noise-corrupted data across different SNR levels are shown in Figure 2. The highest accuracy is observed for the original noise-free data ("Orig_data"). Accuracy gradually decreases as SNR reduces from +4 dB to 0 dB. However, for negative SNR values (0 dB to -14 dB), the decline becomes steeper, indicating a greater impact of noise at this stage. Around -10 dB and beyond, accuracy degradation tends to plateau, suggesting a threshold beyond which noise has a diminishing additional effect.

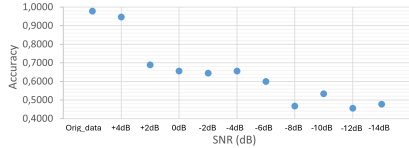


Fig. 2. Accuracy result of noise with different SNR value

The impact of data loss (orange dots) and data errors (blue dots) on system accuracy is illustrated in Figure 3. Accuracy declines linearly with increasing data loss, with a more pronounced drop beyond 20% loss. In contrast, the effect of data errors on accuracy is more gradual compared to data loss, particularly below 40%. However, beyond a 60% error rate, accuracy degradation accelerates, indicating the system's reduced ability to handle excessive erroneous data.

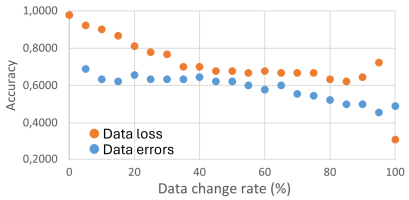


Fig. 3. Accuracy results for different losses and errors, at a 5% change rate

B. Power consumption results

The GPU power consumption results under different SNR values are shown in Figure 4. The figure illustrates temporal variations in GPU power usage across different noise levels. At higher SNR values (e.g., org_Data, +4dB, and +2dB), GPU power consumption remains relatively stable, with peak power levels of 30.51W, 26.92W, and 27.20W, respectively. These correspond to 61%, 53.84%, and 54.4% of the GPU's maximum power capacity (50W). For moderate SNR values (0dB to -6dB), power consumption shows slight variations, with the peak power at -6dB reaching 31.13W. As the SNR decreases further to -8dB and beyond, GPU power consumption declines, with the peak power at -14dB dropping to 23.32W, representing 46.64% of the maximum capacity. Additionally, power consumption fluctuations increase at lower SNR values.

The results of GPU power consumption in the data error case illustrate the temporal variations in GPU power consumption under different data error rates, ranging from error-0 (no errors) to error-100 (100% of data points altered). The

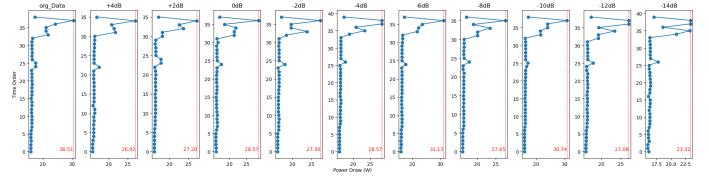


Fig. 4. GPU power results for different SNR values

results show that peak power consumption fluctuates between approximately 27W and 31W across different error rates. At low error rates (error-0 and error-10), power consumption remains relatively stable, with minimal variations. When the error rate increases to a moderate level (error-30 to error-60), fluctuations in power consumption become more noticeable, indicating variations in computational workload. At the highest error rates (error-100), power consumption stabilizes again at around 30W. Figure 5 highlights selected cases, showing representative power consumption trends at different error levels.

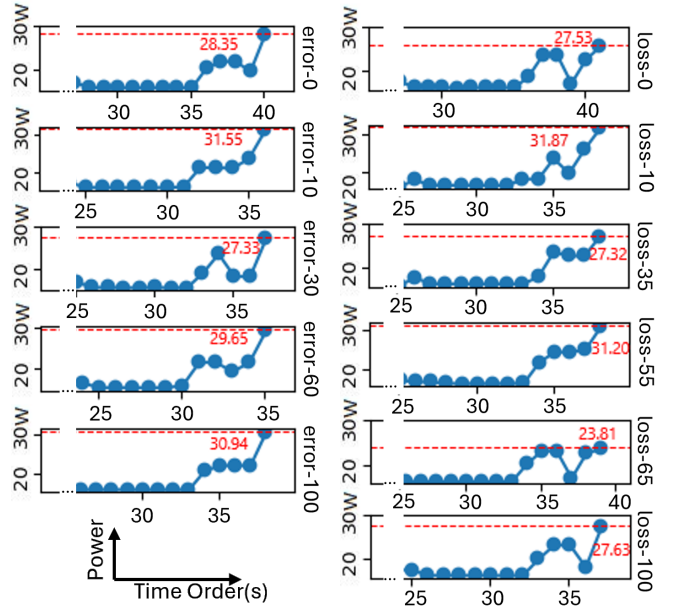


Fig. 5. Representative power consumption trends at different error and loss levels

The results of GPU power consumption in the data error case illustrates the temporal variations in GPU power consumption under varying data loss rates, ranging from loss-0 (no data loss) to loss-100 (complete data loss). The results show that at low data loss rates (loss-0 to loss-25), GPU power consumption remains stable, with peak power draw fluctuating between 30.81W and 31.87W. As data loss increases to moderate levels (loss-30 to loss-60), the peak power draw shows a decreasing trend, with values ranging from 27.32W (loss-35) to 31.20W (loss-55). At high data loss rates (loss-65 to loss-100), GPU power consumption remains relatively stable at a lower range, between 27.61W and 30.72W. Figure 5 highlights selected

cases, showing representative power consumption trends at different loss levels. We calculated the energy consumption under different noise conditions. The analysis begins from the time point where power draw values show significant fluctuations, indicating the start of computational activity, and continues until the computational task concludes. For each recorded power consumption value (Power.draw) and its corresponding time interval, the energy consumption for that interval is obtained by multiplying power consumption and time. This calculation is repeated for each SNR level, ranging from original data (Orig_data) to different noise levels (+4dB to -14dB), producing Figure 6. The figure shows that the total energy consumption varies across different SNR levels, with the highest recorded value around 18,000 mJ and the lowest around 12,000 mJ, representing a difference of approximately 6,000 mJ, or 50% of the lowest energy consumption. High SNR levels (Orig_data, +4dB, +2dB) correspond to higher energy consumption. The energy consumption decreases slightly at mid-range SNR levels (0dB to -6dB) and stabilizes at lower SNR levels (-8dB to -14dB), with a minor increase at the lowest SNR levels.

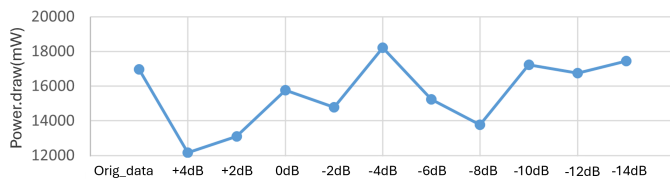


Fig. 6. GPU energy consumption results for different SNR values

IV. DISCUSSION AND CONCLUSION

The study highlights the critical role of data quality in determining the performance of biomedical systems. While modern neural network-based systems exhibit some resilience to fluctuations in data quality, their performance is significantly affected by severe noise, errors, or data loss. Impact of missing data on classification result: Clearly missing data presents a more fundamental impact than noise or errors, as the accuracy drop rapidly from 100%. Impact of missing data on power: In this case also, replacing the missing data by 0 permits to optimize power consumption as multiplications, ReLU function and softmax will be less energy-intensive, depending on data, fig 7 shown the power consumption varies of 25% depending on data values. Impact of noise on classification result: Obviously presence of noise decreases the accuracy of the classification. Fig 2 shows that this deterioration is not linear and occurs by steps. Impact of noise on power consumption: There are no tendency concerning the impact of noise on power consumption as shown in fig 3. The algorithm is resilient to small data losses and small noise. Adding a pre-analysis of signal which permits to detect data losses permits to prevent the user, in order to change the algorithm. At least replacing some incoherent data by a 0 signal permits to save 25% of power. These findings emphasize the importance of designing adaptive AI-driven biomedical systems that dynamically adjust

computing strategies based on real-time data quality assessments. Optimizations in noise handling, error correction, and data recovery are essential for maintaining system reliability while minimizing energy consumption and execution time.

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