Machine Learning-based Classification of Cognitive Workload via In-ear EEG

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***Abstract*—In-ear EEG has recently emerged as a promising avenue to assess cognitive workload using minimally obtrusive sensors, thus promoting continuous and ubiquitous health monitoring. However, concerns around the quality and representativeness of data collected with this new technology need further investigations. In this work, we utilize a dataset related to a participant engaged in various mathematical tasks while wearing an in-ear EEG device. We apply signal processing techniques and feature extraction methodologies to analyze the EEG data. Feature vectors were constructed from each data segment, and subsequently used to train various machine learning classifiers to discriminate between different levels of cognitive workload. Moreover, we investigate the effectiveness of feature selection methods, to reduce the dimensionality of the feature space and potentially improve classifier performance. The results indicate that in-ear EEG, together with proper processing in terms of feature selection and machine learning, can adequately differentiate cognitive workload levels. Our findings proved the convenience of carrying on the investigation of this new kind of technology to promote a healthcare service closer to patients.**

***Index Terms*—In-ear EEG, BCI, Data quality, Machine learning, Neural networks.**

I. Introduction

Electroencephalography (EEG) captures the brain's electrical activity, which arises from the simultaneous activation of a large number of nearby neurons in different areas of the brain, depending on the task to be accomplished by the individual [1]. EEG offers several advantages over alternative brain function assessment techniques in terms of reduced hardware costs, elimination of exposure to radiation or the need for injections [2], [3], and faster acquisition times, making it an exceptionally safe investigation modality. Furthermore, EEG provides superior temporal resolution, capturing changes on the millisecond scale.

The EEG signal is subdivided into distinct frequency bands: delta (0.5–4 Hz), theta (4–7.5 Hz), alpha (7.5–14 Hz), beta (14–30 Hz), and gamma (above 30 Hz) [4]. These frequency bands are indicative of various cognitive states, and deviations from normative EEG patterns can assist clinicians in diagnosing neurological disorders [5].

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In this spirit, the unprecedented advancements of machine learning and automated reasoning techniques have led to conceive many applications of human activity or brain condition classifications from EEG-related signals [6]–[10], broadly expanding the horizons for possible automated real-time detection of brain function anomalies.

However, in traditional scalp-measurement systems, an EEG cap embedded with several sensors has to be worn, which represents a source of discomfort for the individual. This has motivated the development of in-ear EEG devices, designed to capture neural signals through electrodes placed within the ear canal [11], [12]. This offers a promising avenue to advance Brain-Computer Interfaces (BCIs) by improving user comfort and easing the widespread adoption [13], [14] of this technique.

In this paper, we utilize a dataset by *IDUN Technologies* involving a participant engaged in three phases of mathematical tasks with varying difficulty levels, while wearing an in-ear EEG device [15]. A range of signal processing techniques and feature extraction methodologies were applied, including Welch's periodogram method for power spectral density estimation, to analyze the EEG data [16]. The feature vectors were then constructed from each data segment, encompassing the statistical, temporal, and frequency domain features.

This was then used to train various machine learning classifiers [17]–[20], including random forest (RF), perceptron, and support vector machine (SVM), to discriminate between different levels of cognitive workload. Moreover, our study investigates the effectiveness of feature selection methods, such as SelectKBest [21], to reduce the dimensionality of the feature space and potentially improve the performance of the classifier.

Our results show that in-ear EEG recordings, combined with appropriate feature selection and machine learning models, can adequately classify distinct cognitive workload levels. At the same time, in-ear EEG is confirmed as a cost-effective and comfortable alternative to assess cognitive workload remotely, which is key in various fields such as human-computer interaction, neuroergonomics, cognitive science, and, more general, in the continuous and ubiquitous health monitoring [22], [23].

The rest of this paper is organized as follows. In Section II, we review the related literature. Section III presents our analysis, detailing preprocessing and filtering, as well as classification inputs. In Section III-D, we introduce the different classifiers that we designed. Section IV shows numerical results, and we conclude in Section V.

II. Related Work

One line of application for in-ear EEG with the contextual implementation of ML techniques is the recognition of emotions, where multiple authors have been advocating for the better practicality of an easy to wear device versus scalp-based EEG sensors. A preliminary work in this sense is [11], where mismatch negativity is used as the signal of interest, and the results are discriminated through an SVM classifier, so as to detect four classes of emotions, relative to the two categories of positive/negative and high/low arousal. Also, the paper is one of the first describing a generic in-ear EEG device based on a silicone structure.

More recent evaluations were proposed by the authors of [24], further expanded upon in [7], considering only two classes of emotions, positive and negative, but replacing the signal of interest with the PSD and considering a deep neural network methodology that allows for considerable improvements in the classification accuracy, despite the presence of some limitations, e.g., the relatively small size of the dataset.

Fatigue and stress detection is also another relevant potential application of in-ear EEG, which can find useful application in monitoring drowsiness of personnel working in hazard-prone environments such as transportation, healthcare, or precision industry, to reduce the risk of accidents [8]. A first paper proposing to leverage in-ear EEG measurements from an absolute standpoint, and specifically towards automated mechanisms for drowsiness detection is [12]. In [9], in-ear measurements were more specifically exploited for monitoring attention level, with similar purposes of increasing safety and efficiency under complex task. Also, an advanced machine learning mechanism based on echo state network was used, obtaining improved accuracy.

For the specific task of cognitive workload assessment, which we tackle in this paper, a close reference is [25], whose main focus is the application of SpO_2-based tracking. However, this study also explores in-ear EEG as a complementary modality for the classification of mental fatigue. Similarly, [10] studies in-ear EEG for measuring cognitive fatigue using mental arithmetic tasks and compares the performance of different EEG methodologies, such as in- and around-ear EEG as well as traditional cap EEG. In [26], in-ear EEG is considered to explicitly address the problem of classifying the cognitive workload of construction workers. Also, [27] discusses the problem for control room operators, highlighting how the power spectral density of theta waves in the EEG signal has the potential to identify excessive cognitive workloads. In [28], two experimental protocols were employed to evaluate data quality of in-ear EEG recordings as compared to a conventional 64-channel EEG system. The authors showed that in-ear and scalp EEG signals exhibited similar spectral power and fluctuations (especially in the α band), with comparable RMS values and a slightly lower signal-to-noise ratio (SNR).

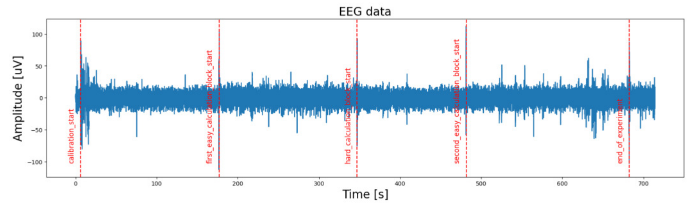

Fig. 1. Filtered EEG recording of the entire experiment.

However, mismatches between the two types of signals were observed, leaving significant room for hardware improvements.

Thus, in our work, we align to the above lines of investigation while focusing on the exploration of different traditional machine learning models. In a first phase, we decided not to include deep learning models, to evaluate the effectiveness of a very simple and portable solution that includes an in-ear EEG device and a simple computational module that can implement standard ML. This represents a viable way to realistically bring a minimally obtrusive technology closer to users while providing reliable results with a small computation need.

III. System model

A dataset from a study executed by *IDUN Technologies* [15] was taken into analysis, where only the ear-centric EEG signal was acquired. The investigation involved a single participant engaged in solving mathematical tasks while equipped with the *IDUN Guardian earbud*, a single channel EEG apparatus with the reference electrode located in the left ear canal. The experimental protocol was segmented into three phases: an initial series of simple arithmetic tasks, followed by more challenging problems, and concluding with another sequence of simple tasks.

The EEG data for the cognitive workload assessment were recorded over a duration of approximately 8 minutes at a sampling rate of 250 Hz.

A. Pre-processing and data cleaning

The dataset employed included both unprocessed (raw) and filtered signals. Typically, the raw signal would undergo processing through a filter bank to eliminate artifacts such as power grid noise, followed by various procedures such as independent component analysis (ICA). However, for this study, it was chosen to employ the already preprocessed signal. Given that preprocessing was performed by *IDUN Technologies*, we determined that this represented the optimal filtering approach available, and any additional attempts at processing on our part would probably have been inferior. The entire filtered EEG recording is plotted in Fig. 1. The preprocessed dataset was provided in a comma-separated values (CSV) format, with each sample containing a timestamp, the instantaneous EEG value, and a label. This last field indicated one of five distinct conditions: calibration, initial easy calculation phase, challenging calculation phase, second easy calculation phase, and end of experiment. For the purpose of this analysis, the timestamp field was removed from each sample and all samples labeled as calibration or end of experiment were discarded because they provided negligible information with respect to our classification problem.

To visually explore potential features within the frequency domain, power spectral density (PSD) plots were generated for the three aforementioned experimental sections. To compute the spectral density of the signals across the three tasks, we initially computed the Fast Fourier Transform (FFT) on all samples within each dataset. Subsequently, Welch's algorithm [29] was applied to each of the phases of brain workload to further refine our analysis. Welch's method enhances PSD estimation by segmenting the input signal into overlapping parts, each subjected to a window function to reduce spectral leakage. For each windowed segment, the FFT is computed. The periodogram, obtained by squaring the normalized FFT magnitude, is averaged across segments for the PSD estimate.

This averaging action reduces the variance compared to the single-periodogram methods. Mathematically, such a PSD can be expressed as:

$$P(f) = \frac{1}{K}\sum_{k=1}^{K}\left|\sum_{n=0}^{L-1} x_k[n]w[n]e^{-j2\pi fn/N}\right|^2$$

Welch's technique balances frequency resolution and variance, making it widely used in applications like EEG analysis, as suggested by [30], to identify frequency components related to cognitive states. In the analysis presented, the recorded EEG activity was segmented with a Hanning window of 500 samples, allowing 250 samples of overlap at the extremes, and using 1024 points for acceptable FFT frequency resolution.

Fig. 2 depicts the PSD of the EEG signal during the three distinct phases of the experiment. As expected, discerning salient characteristics in the frequency domain through visual inspection proved challenging; however, a subtle similarity between the PSD plots of the two easy calculation phases was observed.

B. Segmentation

To prepare the data for classification, we followed a well-established approach [4], [6]: Each of the three experimental recordings was segmented into 1-second epochs and any residual sample that did not align with the epoch length was discarded. This segmentation process facilitated the extraction and selection of features from different segments that could be associated with either "easy" or "hard" computational tasks.

Note that the dataset showed a moderate imbalance between the two classes: the "easy" class included 370 samples, while the "hard" class only 134. However, we decided not to apply any augmentation or subsampling technique, as we verified that this imbalance did not lead to significant biases in the classification. This is also confirmed by results obtained in the 3-class classification problem.

C. Feature Extraction

From every 1-second segment, we extracted both temporal and frequency domain features.

In particular, the following temporal domain features were extracted employing the `SciPy` and `NumPy` libraries:

- mean, variance and standard deviation;
- peak-to-peak, absolute minimum and maximum values, with their corresponding indexes;
- mean square and root mean square (RMS) values;
- absolute discrete difference between adjacent datapoints;
- skewness and kurtosis.

In the frequency domain, the measured power within the delta, theta, alpha, beta and gamma bands was the main object of study. The `bandpower()` function of *MATLAB* was used to this scope, with further processing in Python.

D. Classification Methods

Three different machine learning classifiers were employed to differentiate between task conditions (2 classes, "easy" vs "hard") based on all extracted features. For all models, we adopted a standard 80%-20% split for training and test, respectively, and the same training and test sets were used by all different models to ensure fair comparison of the results. We evaluated the performance of the selected models with all available features. Later, we also explored the performance with a reduced set of features, selected by using different criteria.

Perceptron

The Perceptron [31], a simple linear classifier, effectively identified linear decision boundaries, but its performance was somewhat limited due to the complexity of EEG signals, as illustrated in the confusion matrix presented in Fig. 3(a). Nonetheless, it served as a useful baseline, allowing for comparison with more sophisticated techniques. The training loss for the perceptron was 0.09, the test loss was 0.14, and the accuracy on the test set was 86.14%.

Random Forest

A Random Forest (RF) can offer a robust predictive performance with an accuracy that highlighted its ability to handle the complexity and variability in EEG data [18]. The ensemble approach of this classifier combines the predictions of multiple decision trees, proving to be effective in capturing nonlinear relationships within the data, ensuring greater flexibility, and improving generalization over single models such as decision trees. The RF model achieved notable accuracy in identifying task conditions, underscoring its suitability for EEG-based cognitive load classification. The training loss for the RF was almost zero, while the test loss was 0.04. Correspondingly, we obtained the confusion matrix reported in Fig. 3(b) and the accuracy was 96% on the test set.

Support Vector Machine

The Support Vector Machine (SVM), particularly with a linear kernel, was explored due to its effectiveness in high-dimensional spaces like those formed by EEG features [17]. SVM excels in binary classification tasks where the classes are somewhat separable and provides high accuracy by maximizing

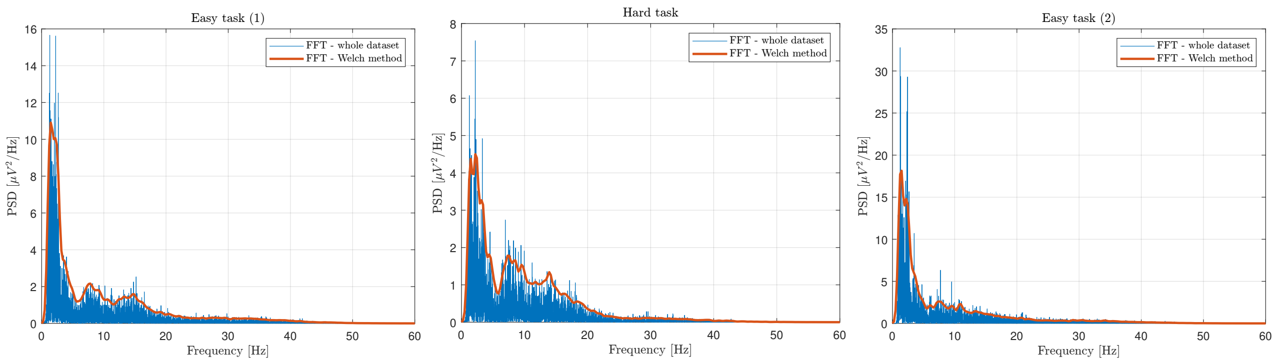

Fig. 2. (a) PSD of EEG during the initial phase (easy calculations). (b) PSD of EEG during the second task (more complex problems). (c) PSD of EEG during the third task (easy arithmetics, again).

the margin between the two classes. Here, SVM achieved a very satisfactory classification, as evidenced by the confusion matrix in Fig. 3(c). The training loss for the SVM was 0.04, the test loss was 0.05, and the accuracy on the test set was 95%.

IV. Results and Discussion

To potentially enhance model efficiency and improve performance, a feature selection process was undertaken to reduce the dimensionality of the feature space [32]. After that, a second round of classification was conducted using SVM to assess any improvements in the results.

A. *Frequency-domain features*

In previous literature [33], cognitive workload was proven to be associated with the power of theta, alpha, and beta bands. In particular, the power in the theta band was shown to serve as a robust indicator of cognitive workload, while alpha and beta powers exhibited significant influence. Thus, we tested the performance of an SVM model trained on frequency-domain features, only. However, the results of this choice were clearly suboptimal, with a training loss of 0.12, a test loss of 0.14. The confusion matrix is reported in Fig. 4(a) and the model reached an accuracy of 86.13%. These values are notably worse than those obtained without any form of feature selection.

B. *SelectKBest method*

As the manual selection of the features, based on previous literature, was found to be limited, we decided to employ the popular SelectKBest method. The latter automatically selects the most discriminative features based on the mutual information criterion. This approach focused on identifying the most significant features, effectively reducing computational complexity and improving model performance without compromising accuracy. Setting $k = 5$ resulted in the selection of the following features: mean, index of minimum value, mean square, root mean square, and beta power band. We chose to keep k to a very low value to assess the classification performance when the number of features is drastically reduced. Both training and test losses exhibited promising results, with values of 0.05 and 0.08, respectively, indicating superior performance compared to the previous feature selection method. Correspondingly, the confusion matrix is reported in Fig. 4(b), and the model achieved an accuracy of 92.07%.

C. *Augmented SelectKBest method*

As a third experiment, we explored the classification performance in the case where the SelectKBest method is augmented by the integration of the features in the alpha and beta bands. The confusion matrix is reported in Fig. 4(c). Augmenting the feature space with this strategy yielded a notable improvement, with the training loss decreased to 0.06 and the test loss to 0.04. Correspondingly, the model achieved an accuracy of 96%, as can be computed from the confusion matrix. This result exceeds previous outcomes from similar articles (e.g., 69% accuracy using in-ear EEG for an arithmetic task [10]).

D. *3-class classification*

To investigate potential changes in cerebral activity associated with habituation to mathematical tasks or increased relaxation over the course of the experiment, a multi-class classification was conducted. This involved distinguishing not only between “hard” and “easy” tasks (with the two "easy" task phases aggregated), but also between the two different easy task phases. For the classification, we trained two different RF models, the second using the augmented SelectKBest method described above. Figs. 5 and 6 report the confusion matrices obtained in the two cases. The models achieved accuracy of 68.3% and 70.7%, respectively, which is consistently higher than the chance level of 33.3% for this classification problem. On the other hand, both classifiers failed to differentiate between the first and second easy tasks, as clearly seen from the number of misclassified "easy" task-related samples (labels 0 and 1).

Nevertheless, this can be interpreted as the fact that the individual can easily recover cognitive energies to perform an "easy" task, even though he/she has just accomplished a "hard" task. More interestingly, we can conclude that a simple machine learning model can easily classify in-ear EEG recordings, as

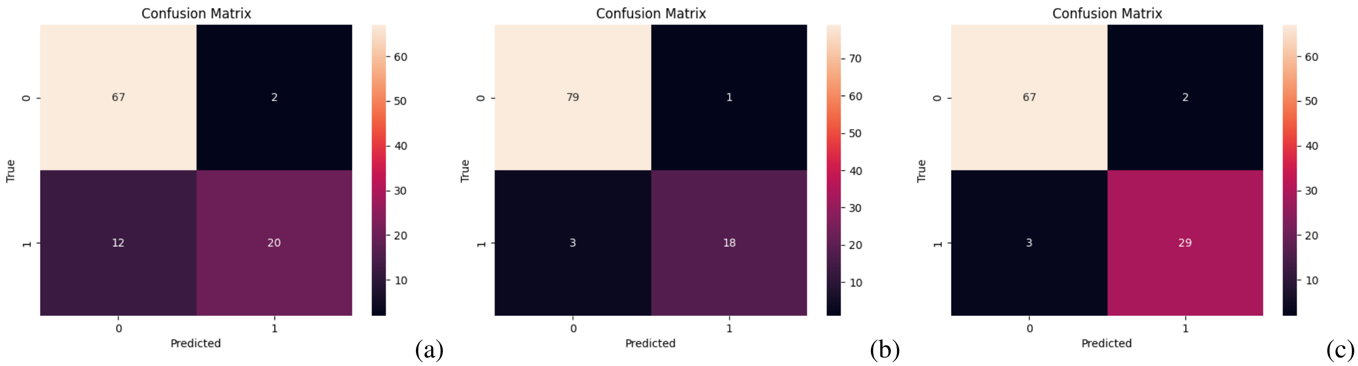

Fig. 3. Confusion Matrices of binary classification using (a) Perceptron, (b) RF, (c) linear SVM.

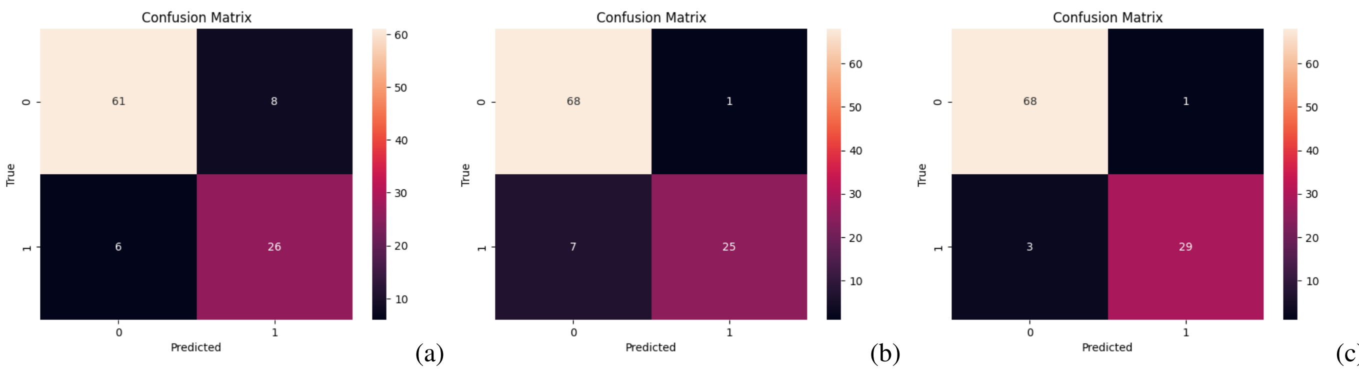

Fig. 4. Confusion Matrices of binary classification with feature selection using (a) frequency domain features only, (b) SelectKBest, (c) Augmented SelectKBest.

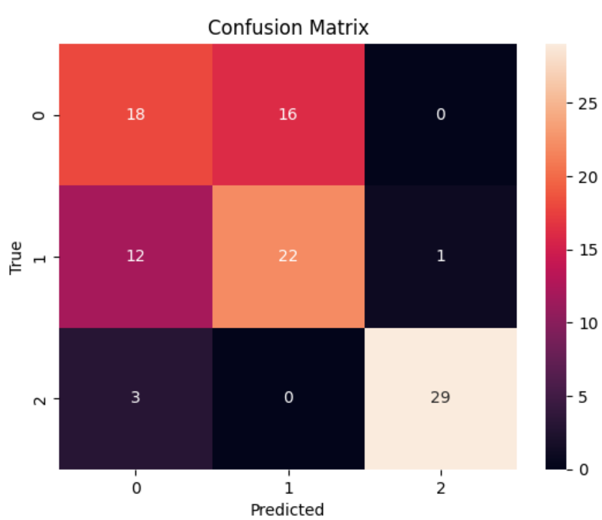

Fig. 5. Confusion Matrix of the 3-class classification using RF model (all features). Labels 0 and 1 are for the "easy" task, while 2 is for the "hard" task.

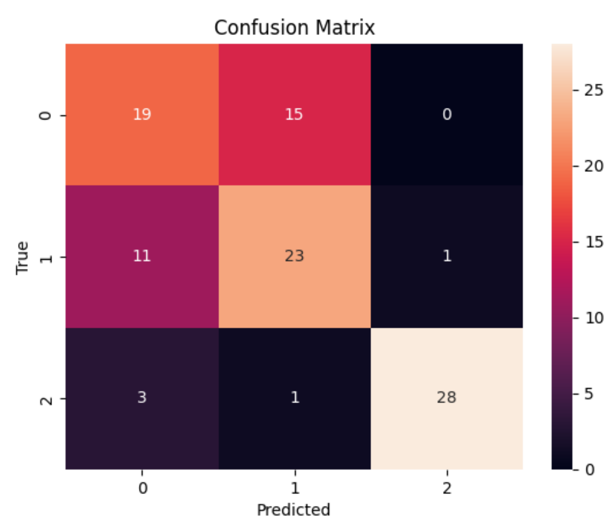

Fig. 6. Confusion Matrix of the 3-class classification using RF model with feature selection (augmented SelectKBest method). Labels 0 and 1 are for the "easy" task, while 2 is for the "hard" task.

expected: samples associated with an "easy" task are clearly distinguished from those related to a "hard" task.

V. Conclusions

The study showed how combining statistical, temporal, and frequency domain features from EEG data allows for a robust classification of cognitive load levels. Machine learning models effectively separated the conditions, with feature selection critically enhancing model performance.

The results of this investigation highlight the significant potential of classification over in-ear EEG signals for cognitive tasks, demonstrating its viability for practical BCI applications. This finding aligns with prior research [14], which underscores the remarkable potential of in-ear EEG data for clinical monitoring. This technology positions itself as a valuable resource for researchers, clinicians, and engineers actively contributing to the field of neural engineering.

As a continuation of the current investigation, the methodologies outlined herein could be applied to the raw signal without any supplementary filtering. The resulting outcomes could then be juxtaposed with those obtained from the present analysis, aiming to identify concordant findings. Should similar results be observed, this would prove beneficial, as it could potentially eliminate the initial signal pre-processing phase.

Additionally, a larger dataset with a larger number of features could be considered to confirm our findings, and to enable further exploration using diverse deep neural network architectures, which yielded valuable insights such as in the work by [34]. The objective would be to identify the minimal complexity solution capable of generating predictions with sufficient accuracy while being embedded in the wearable device itself.

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