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Identification of Mind Awareness from EDA signals using Wavelet based ResNet50 model

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Abstract: The analysis of spontaneous mind wandering is crucial for comprehending an individual mental state and holds the potential to enhance performance and productivity. This paper proposes a framework using Continuous Wavelet Transform (CWT) based ResNet model to analyze Electrodermal Activity (EDA) signals for mind wandering detection. In this analysis, EDA signals are sourced from an openly accessible database and preprocessed for artifact and noise removal. Time-frequency analysis generates CWT spectrogram images, which are classified using a modified ResNet50 model that is custom built to classify the spectrogram images corresponding the mind wandering and awareness. Hyperparameter tuning is carried to obtain the optimal network parameters that provides the best accuracy. Results indicate that batch size of 32, learning rate 1e-5 provides better results. This hyperparameter tuned model achieved an accuracy of 64% in differentiating between the two classes. This paper proposes an adapted ResNet50 model that could be employed in wearable devices as a potential application of knowing the mind awareness of an individual.

Keywords: Mind Wandering, Electrodermal Activity, Continuous Wavelet Transform, ResNet50.

1 Introduction

Mind Wandering (MW) is a cognitive state marked by the spontaneous shift of attention from external stimuli to self-generated thoughts unrelated to the immediate task or environment, often leading to a lapse in focused attention [1]. This analysis aids in comprehending the neural and psychological foundations of mind wandering, providing valuable insights for psychology, neuroscience, and education. Existing techniques to detect and analyse MW encompass a range of approaches, from self-report measures to advanced neuroimaging technologies [2][3][4]. Video-based techniques may encounter challenges in accurately interpreting behavioural cues due to subjective and context-dependent expressions. Image-based methods may struggle to capture subtle internal mental states linked to MW. Although eye-tracking provides valuable gaze data, it may not fully reveal the cognitive content of wandering thoughts [5].

Physiological signals, particularly electrodermal activity (EDA), offer advantages in MW detection [6][7]. EDA measures changes in skin conductance, reflecting sympathetic nervous system activity influenced by emotional and cognitive processes [8]. It reflects emotional arousal, like anxiety or excitement, causing fluctuations in skin conductance. MW can also stem from emotional states. If individuals mentally drift towards emotionally charged subjects, it could influence their EDA. EDA provides continuous, real-time data with high temporal resolution, making it a reliable indicator of cognitive states [9].

Current research on MW using EDA focuses on extracting features from both time and frequency domains to correlate with mind wandering states. However, solely relying on features from one domain can result in information loss. To overcome this limitation, spectrogram-based approaches, such as Fourier analysis, Short-Time Fourier Transform, wavelet analysis, and decomposition techniques, are being employed [10][11][12]. These methods offer high-frequency resolution, enabling better visualization of inter-frequency changes and understanding of how EDA frequencies evolve in response to stimuli. Continuous Wavelet Transform (CWT) is a time-frequency analysis method that is beneficial for examining the temporal evolution of signals, making it well-suited for the analysis of time-varying signals like EDA [11]. Unlike traditional Fourier analysis, which provides a fixed resolution in the frequency domain, CWT offers a dynamic resolution.

Deep learning plays a crucial role in capturing intricate patterns present in spectrograms, leveraging the hierarchical representations learned through successive layers to distinguish subtle variations and patterns within the data. ResNet's residual connections facilitate the training of deep neural networks, enabling effective capture of complex temporal patterns in signals like EDA. Thus, this paper proposes a CWT spectrogram-based deep learning model for mind wandering analysis and classification.

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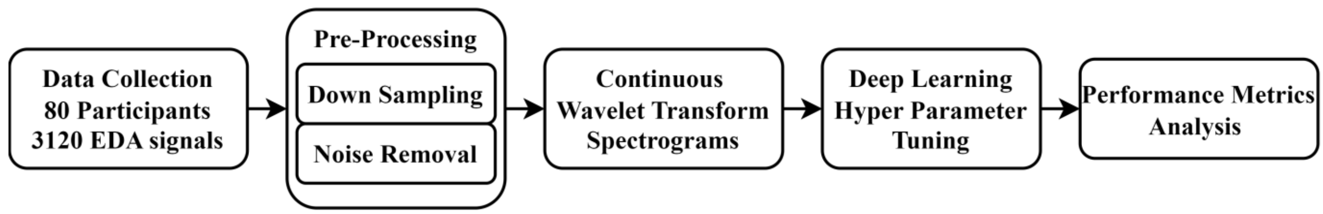


Figure 1: Workflow Schematic

2 Methodology

2.1 Dataset

For this study, EDA signals are considered from the Multi-modal Sustained Attention to Response Task (MM-SART) database [8] which is a public database focusing on detecting Mind Wandering with different modalities using the experiment design used in SART [13]. Out of 82 participants in the dataset, 80 were included due to inconsistencies in the data of two participants. Each participant contributed 39 signals, resulting in a total of 3120 samples based on the probe timestamps. The participants were asked to subjectively assess their state of attention on a scale of 1 (completely wandering) to 7 (very focused) just before they come across the probe. In this context, a MW rating of 4 and above is categorized as indicative of mind awareness, while a rating below 4 is considered to signify mind wandering.

2.2 Pre-Processing

In preprocessing, down sampled EDA signals from the database were utilized, followed by noise reduction using the Neurokit2 library's 'clean' function, implementing a 4th-order Butterworth filter with a 3 Hz cut-off frequency [14]. This low-pass filter effectively smoothened the signals, providing a noise-free EDA signal for subsequent analysis. The original data, sampled at 256 Hz, resulted in variable signal lengths ranging from 14,000 to 50,000 samples. Spectral analysis revealed primary frequency components concentrated within the 0.05 Hz to 1 Hz range, with some peak frequencies reaching up to 3 Hz. To ensure signal analysis uniformity, signals were down sampled to an average of 3000 samples.

2.3 Time Frequency Analysis – Continuous Wavelet Transform

Continuous Wavelet Transform is the process of convolving the input signal with a set of functions generated by the mother wavelet. The CWT of a real-valued signal $x(t)$ is given by (1), where $\Psi(t)$ is called the mother wavelet which is a continuous function in both the time domain and the frequency domain. It is also a function of scale $(a > 0)$ and position (b) [15]. $X_w(a, b)$ is the wavelet transform of the signal x(t) at scale a and translation b. In this work, spectrograms are generated by considering the EDA signals as input and 'Morlet' wavelet with a mu value of 2 with log scales [16].

$$\boldsymbol{X_w(a,b)} = \frac{\mathbf{1}}{|\boldsymbol{a}|^{\mathbf{1/2}}}\int_{-\infty}^{\infty} \boldsymbol{x(t)}\overline{\boldsymbol{\psi}}\left(\frac{\boldsymbol{t-b}}{\boldsymbol{a}}\right)\,\boldsymbol{dt} \qquad (1)$$

The time-frequency distribution from CWT spectra in EDA analysis represents the evolution of frequency content over time. Peaks and variations signify specific frequencies during different intervals, aiding in identifying transient events and patterns like those linked to mind wandering. This distribution captures dynamic signal changes, offers insights into temporal physiological responses and highlighting dominant frequencies.

2.4 Deep Neural Network

The spectrogram images generated by the Continuous Wavelet Transform (CWT) are fed as input to a modified ResNet-50 model for classifying spectrograms associated with signals indicating mind wandering or mind awareness. ResNet-50 is a deep neural network with 50 layers, including 48 convolutional, a pooling, and a fully connected layers, featuring residual connections to facilitate gradient flow and feature extraction. The output of model is connected to a global average pooling layer, followed by dense layers, culminating in a final sigmoid layer for binary classification. Initially, the model is pre-trained on a large dataset of labelled images to acquire generalized features. Pre-trained layer weights are frozen to update only modified layers. The dataset is split into training, validation, and testing sets with a ratio of 70-15-15. Training involves 100 epochs with various hyperparameters, including different learning rates (1e-5, 1e-4, 1e-3), batch sizes (8, 16, 32, 64), dropout probabilities (0.2, 0.3, 0.4), and binary cross-entropy loss function. Model performance is evaluated using accuracy and loss metrics.

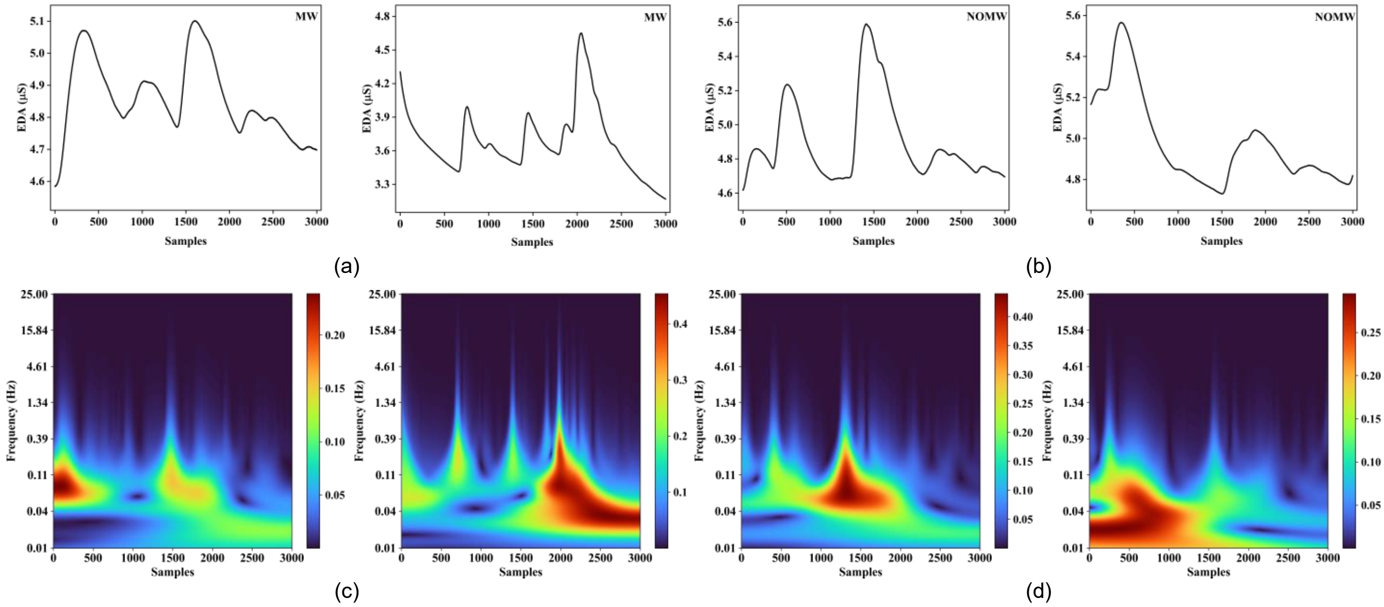


Figure 2: Representative EDA signal of (a) MW and (b) NOMW and their corresponding spectrograms (c) and (d)

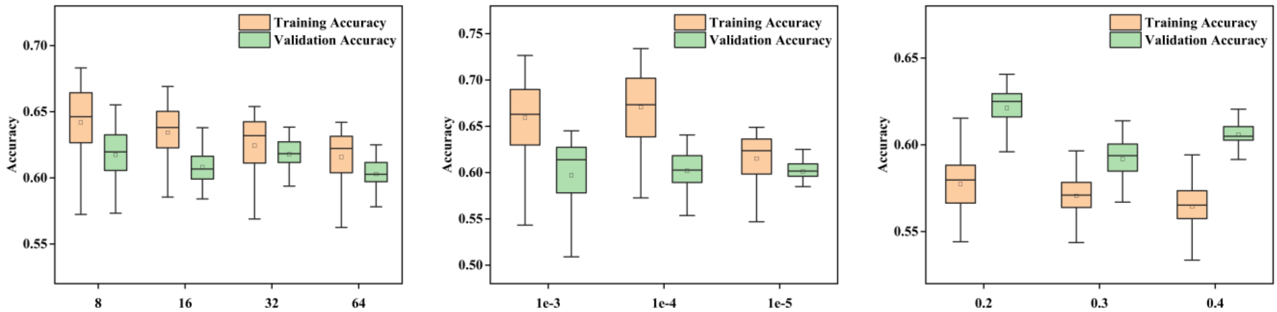
3 Results and Discussion

The representative signals of MW and NOMW from the EDA are presented in Figure 2(a) and 2(b). From observation, it is seen that a higher peak count is present in the MW signal when compared to the NOMW signal. Analysing CWT spectra of EDA signals reveals specific frequencies over time, aiding in identifying periodic patterns, event-related responses, and dominant frequencies. The corresponding CWT spectrograms are depicted below the respective signals in Figure 2(c) and 2(d) respectively. The intensities at each point (time, frequency) indicate the presence and strength of that frequency component at that specific time, providing a visual representation of the frequency dynamics. The frequency is scaled logarithmically, revealing that most frequency components lie in the range of 0.1 to 3 Hz. The choice of the 'Morlet' wavelet with a mu of 2 was based on experimentation with various other wavelets. The 'Morlet' wavelet is particularly well-suited for analysing physiological signals, offering a better representation of signal variation and its intensities. The selected mu value is justified as lower values capture lower frequencies with higher time resolution, and vice versa.

Figure 3(a), 3(b), and 3(c) present box plots illustrating the distribution of training and validation accuracies while varying different hyperparameters in the deep learning model. To keep uniform overall training times, the models were trained for 100 epochs each. For training for different batch sizes, parameters such as learning rate and dropout layers are kept constant. For all the batches the training and validation are similar which indicates that the models are not overfitting. A batch size of 32 gave the best validation accuracy with less variations which can be seen in Figure 3(a). Different learning rates have been tested which is illustrated in the Figure 3(b). The learning rate of 1e-5 is observed to perform best given it narrow distribution for both training and validations accuracies. And finally, while varying different dropout probabilities, it is seen in the Figure 3(c) that the model overfits the data as the validation accuracies are higher than the training accuracies. Hence dropout layers are not preferred for the model. The variance of the box plots shows the variability of the accuracies, a low variance suggests a smoother learning curves.

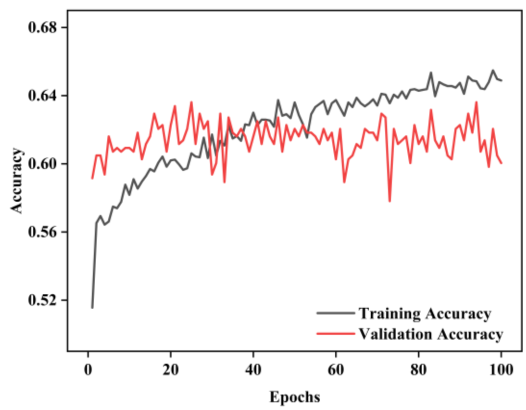
The curves for accuracy vs epochs and the loss curves to the training and validation datasets for the deep learning model are shown in Figure 4(a) and 4(b) that gave the best performance during hyperparameter tuning. The loss of the model shows a decreasing trend as the number of epochs increases. As the model is trained for more epochs, the model learns and recognizes the patterns in the spectrograms, resulting in a decrease in the loss and an improvement in the accuracy (64%).

The utilization of CWT spectra in EDA analysis proved instrumental in distinguishing between MW and NOMW states. This approach visually illustrated the evolution of frequency content over time, providing crucial insights into the underlying patterns. Optimal representation of signal variation and intensities was achieved by employing the 'Morlet' wavelet with a mu of 2. Moreover, ResNet50 effectively captured intricate signal patterns, facilitating classification between MW and NOMW states.

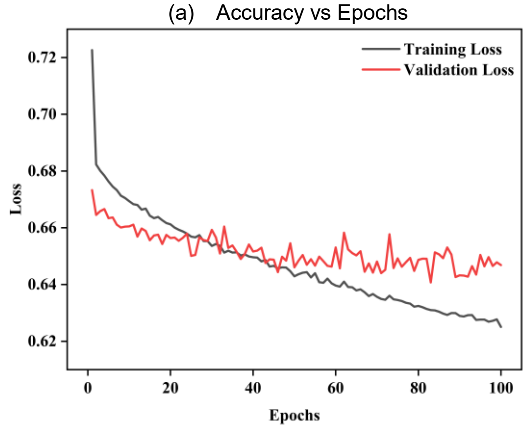


(a) (b) (c)

Figure 3: Influence of (a) batch size, (b) learning rate and (c) dropout probability on the performance of the ResNet50 Model



(a) Accuracy vs Epochs



(b) Loss vs Epochs

Figure 4: Performance curves of the model

4 Conclusion

In this study, Continuous Wavelet Transform and deep learning methods are combined to explore mind-wandering detection. EDA signals from an open-sourced database undergo preprocessing and are analysed using CWT to generate spectrograms as images. These images are then fed into a modified ResNet50 deep learning model, tuned for classifying mind wandering and mind awareness. Various hyperparameters are tested, and the best parameters are selected for final training, resulting in a 64% accuracy post-tuning. ResNet50 aided in capturing intricate patterns present in the signal, contributing to the classification process. Thus, this proposed framework helps to detect mind awareness based on the spectrograms the signals generate. Beyond the lab settings, the application of this model in wearable devices holds promise for real-world mindfulness monitoring.

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