# Multimodal Fusion of EEG and Eye Data for Attention Classification using Machine Learning

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***Abstract*—The cognitive process of attention can be classified into two broad categories: Internally Directed Cognition (IDC) and Externally Directed Cognition (EDC). Classification of attention state based on goal-oriented tasks can assist in the diagnosis of mental disorders, such as attention deficit hyperactivity disorder (ADHD), schizophrenia or obsessive-compulsive disorder (OCD). Certain time-sensitive neurophysiological characteristics such as electroencephalogram (EEG) and eye movement can serve as the basis for differentiating between the two attention states. This paper introduces an efficient binary classification model for distinguishing between IDC and EDC. After preprocessing and analysis of captured data, a multimodal machine learning model is employed for classification of attention. The model achieved an accuracy of 74.64% outperforming the state-of-the-art model.**

***Index Terms*—multimodal data, binary classification, eye data, EEG data**

## I. Introduction

Attention is defined as the selective suppression and focus on a certain stream of oncoming stimuli for further processing of information for a given task [1]. Several studies have shown the use of attention study to detect mental disorders in patients [2]. Externally Directed Cognition (EDC) [3], refers to the processing of stimuli from external sources or the outside world (eg., talking to a friend). Internally Directed Cognition (IDC) [4] refers to processing information and attention directed towards internal processes and information, often retrieving information stored in long-time memory. The most common feature to measure human alertness has been Electroencephalogram (EEG) signals [5]. Internal attention has been associated with increased EEG alpha power in different brain regions [5]. Visual indicators have also been considered to be a reliable parameter of attention classification [6]. Visual disengagement has been associated with the change from Externally Directed Cognition to Internally Directed Cognition.

In our study, the aim was to classify internal and external focus of attention by fusing two physiological indicators– EEG and eye behaviour movements. IDC is generally indicated by reduced visual scanning, higher spontaneous eye activity and fewer but longer fixations, forming the experimental work's basis.

Section II of the paper details the dataset details, the preprocessing method and the classifier employed. Section III details the classification results while Section IV concludes the paper and discusses the future scope of the project.

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## II. Proposed Method

This paper proposes a machine learning method that classifies attention states using a multimodal approach. Our study integrates EEG and eye behavior data through feature fusion to classify attention states. Before that, we perform preprocessing for artifact removal, followed by dimensionality reduction for feature extraction and model training.

### *A. Data*

The data used in this study was acquired from the dataset created by [7]. In this dataset, the experiment for collecting the data comprises 17 healthy participants, both male and female whose EEG and eye parameters were analysed for the classification of attention states. The eye parameters used for this study include pupil diameter, gaze position of the eyes along $x$ and $y$ coordinates and blinks. The EEG data used for attention classification comprised multi-trial data recorded in 20 channels with 3 additional Electrooculography (EOG) electrodes for better analysis of eye-related artifacts captured during experiments. The data for the two attention states were obtained through the experimentally induced attention demands. Both EEG and eye data were originally sampled at 1000 Hz and then were downsampled to 100 Hz by averaging across 10 data points (10 ms). More details about the dataset and capture methodology is available in [7].

### *B. Preprocessing*

*1) Eye-tracking Data:* The raw data, recorded using Eyelink eye-tracker (SR Research Ltd.), consisted of pupil diameter data, gaze position data (both for the $X$ and $Y$ axis) and blinks. The raw eye data variables, which included gaze position on both axes (recorded in pixels) and pupil diameter were cleaned by applying a Savitzky-Golay filter. The filter uses the least square approximation approach to smooth noisy data while preserving the data peaks which contain relevant information for further classification and analysis of the data. Gaze position data for both eyes along the $x$ and $y$ coordinates were averaged and measured in millimetres (mm), and subsequently converted to degrees. The saccadic eye velocity was calculated after downsampling and setting a velocity threshold for the obtained radial velocity in deg/ms.

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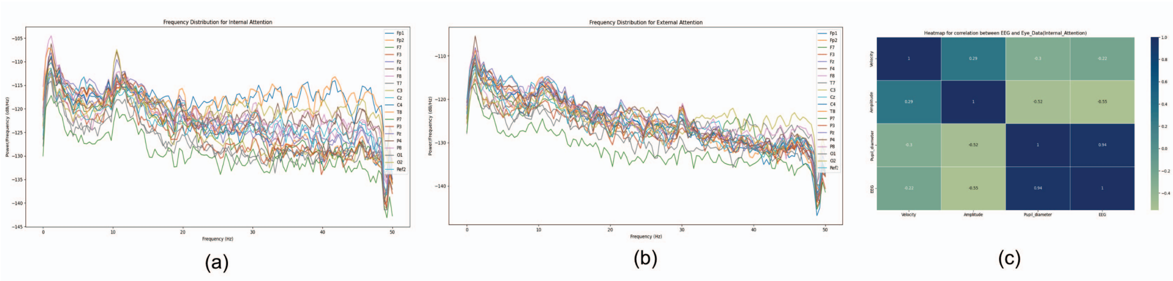


Fig. 1. $EEG_{\alpha}$ Behaviour for (a) internal and (b) external attention. Heatmap of correlation between EEG and eye data is shown in (c).

*2) EEG Data:* There were 19 active electrodes positioned accordingly, with a reference electrode (A2) and three EOG channels placed around the left and right of the eyes, adjacent to the radix nasi. The raw EEG data (which was recorded in $\mu$V) was contaminated by eye and muscle artifacts. Eye artifacts comprised of eye blinks and eye movements (both horizontal and vertical). To remove artifacts, Independent Component Analysis (ICA) was used for source separation. EEG signals were studied only for the activation window phase of 19.5 seconds and 20 seconds respectively. Fig. 1 shows power spectral density (PSD) plot for the two classes of attention and shows that the alpha band activation ($EEG_{\alpha}$) is significantly higher for internal attention.

### C. Exploratory Data Analysis

The alpha power activity of EEG signals was determined by frequency extraction that was obtained through Welch's method for power spectra estimation. There was a peak observed in the alpha band region (8-13 Hz) [6] for internal attention activities. In our study, a strong positive correlation has been observed between EEG alpha power and pupil diameter (See Fig. 1 (c)), suggesting that pupil diameter is an indicator for the classification of attention. Principal Component Analysis was performed separately for both raw EEG and eye data to reduce it to 4 principal components each.

### D. Classification

The dataset consisting of fused EEG and eye data features was used to train a binary classification machine learning model, where the target labels consisted of the two classes of attention– IDC and EDC.

## III. Results

The final dataset consisted of 16 subjects with 22 experimental trials, each for internal and external attention. A Random Forest classifier was used for the initial classification of attention and obtained an accuracy of 55%. However, the K-Nearest Neighbour (KNN) classification method outperformed it by having a classification accuracy of 74.64%. The results of KNN classifier is shown in Table 1. Our model performs better in comparison to the state-of-the-art model for attention classification with a classification accuracy of 71% accuracy in [8].

| Attention_Class | precision | recall | Fscore |
|---|---|---|---|
| External | 0.71 | 0.76 | 0.74 |
| Internal | 0.78 | 0.74 | 0.76 |

TABLE I
CLASSIFICATION RESULTS OF KNN CLASSIFICATION ALGORITHM.

## IV. Conclusion

In this work, we used a multimodal machine learning approach for classification of the attention states where the correlation between EEG and eye features is utilized which showed promising results. In future research, to further enhance classification accuracy, we could explore the integration of additional metrics such as the angle of eye vergence, along with the adoption of more advanced machine learning models such as neural networks.

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