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Supporting Independent Prayer in Alzheimer's Patients with an EEG-Enabled BCI System

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Abstract

Alzheimer's disease (AD) significantly impairs cognitive functions, making independent activities, including Muslim prayers, challenging for patients. This study introduces an innovative Brain-Computer Interface (BCI) system leveraging Electroencephalography (EEG) signals to facilitate prayer practices for individuals with AD. Utilizing a 5-channel EEG headset to monitor attention levels, our system detects alpha and beta wave patterns to assess user focus. When attention diminishes, the system provides guidance to the next prayer step, ensuring continuity and support. Additionally, motion detection technology captures physical movements associated with prayer, enabling the classifier to learn and recognize different prayer postures from a dataset of two individuals. This approach aids AD patients in maintaining religious practices independently while significantly enhancing their psychological well-being by fostering autonomy and spiritual fulfillment. Our findings suggest that integrating EEG-based BCI systems with motion detection offers a promising avenue for supporting daily activities and improving quality of life for individuals with cognitive impairments.

Keywords: Alzheimer's Disease (AD), Brain-Computer Interface (BCI), EEG Signal Processing, Islamic Prayer (Salat), Machine Learning, Classification.

1. INTRODUCTION

Alzheimer's disease (AD), the foremost cause of dementia, currently affects over 55 million people globally, with projections indicating a rise to 78 million by 2030 and 139 million by 2050 [1][2]. This alarming increase underscores the urgency for innovative solutions to mitigate AD's effects on patients and their ability to engage in meaningful daily activities. Among these, the performance of the five daily prayers (Salat), a fundamental aspect of life in the Islamic community, becomes particularly challenging due to AD's progressive cognitive and memory impairments. The early stages of the disease, while allowing for some degree of functional independence, present subtle yet impactful difficulties in memory and cognitive tasks, escalating to a total dependence on caregivers in the disease's advanced stages.

Contemporary neurotechnology has demonstrated significant progress in utilizing electroencephalography (EEG) for both diagnostic and therapeutic applications, particularly in Alzheimer's disease diagnosis and movement intention classification [3]–[5]. Recent advances in brain-computer interface (BCI) technology have shown remarkable potential in addressing neurological conditions, with studies demonstrating successful applications in motor disabilities, speech impairments, and cognitive dysfunction[6]. Furthermore, research has highlighted the transformative impact of BCI systems in providing innovative solutions for managing neurological disorders and motor impairments, significantly improving quality of life for affected individuals [7]. The integration of assistive technologies with neurological rehabilitation has proven effective in supporting daily living activities and enhancing independence for individuals with disabilities [8]. Additionally, emerging evidence suggests that BCI-based cognitive training interventions can contribute to maintaining brain network organization in cognitively normal aging populations [9]. However, despite these technological advances, current research predominantly focuses on diagnostic and classification capabilities, with limited exploration of direct applications that enhance daily living experiences for patients with neurodegenerative diseases like Alzheimer's. This represents a critical gap in translating sophisticated neurotechnology into practical, life-improving interventions for vulnerable populations.

This paper introduces a Brain-Computer Interface system using an EMOTIV 5-channel EEG headset to support Alzheimer's patients during prayers. The system monitors attention through EEG signals and tracks prayer postures via motion detection, providing guidance to help patients pray independently and demonstrating technology's potential to enhance quality of life for those with neurodegenerative diseases

Addressing this issue presents significant challenges, notably in acquiring accurate motion signals and selecting the appropriate motion channels essential for the system's classifier to correctly identify each prayer movement. Additionally, accurately discerning attention levels from raw EEG data necessitates meticulous selection of features, frequencies, and EEG channels, given that the headset employed generates raw EEG values. Overcoming these hurdles, classifying movements into distinct classes and calculating attention levels to differentiate between low and high attention, is crucial for the system's ability to autonomously guide patients through their prayers.

In the subsequent sections of this paper, we outline the organization as follows: the background of the problem, along with an overview of related works, will be presented in Section 2. Section 3 will illustrate and analyze the system functionalities. Section 4 will detail the design and implementation of the entire system, accompanied by supporting experiments and discussion. Finally, the conclusion and future work will be discussed in Section 5.

2. RELATED WORKS

This section has been divided into 2 subsection: Background and Related Works.

2.1. Background

2.1.1 Brain Computer Interaction (BCI)

BCI encompasses hardware and software enabling direct communication between the human brain and external devices, facilitating interaction with various machines and applications through brain signal interpretation. BCI technology primarily aids disabled individuals, enhancing their ability to engage with their surroundings [10][11]. There are three main types of BCI: invasive, which requires surgery to place sensors directly on or in the brain, offering high-quality signals but posing significant risks; non-invasive, the most common form, which uses wearable devices like caps to detect brain signals without surgery, offering ease of use and safety despite potential signal interference from the skull; and partially invasive, a middle ground that involves less risky surgery to place electrodes on the brain's surface, providing better signal accuracy than non-invasive BCIs but with fewer risks than fully invasive systems [10][12]. This study utilized the Emotiv 5-channels EEG insight [13], a non-invasive BCI, equipped with multiple channels and motion sensors for detailed brain signal and movement analysis.

2.1.2 Emotiv 5-channels EEG insight

One of the most productive companies at creating non-invasive BCIs is Emotiv. So, in this study experiment insight headset produced from Emotiv has been used. This headset has 5 different channels around the head to get different EEG values for several features. As shown in Figure 1, the five channels are: AF3, T7, T8 and AF4 [13]. These channels are used to get the required values to calculate the attention. In addition to these channels, there exist 9 axis motion sensors: ACCX, ACCY, ACCZ, GYROX, GYROY, GYROZ, MAGX, MAGY and MAGZ. Those motion sensors are required to get the wave of each movement in order to get them into the system's classifier.

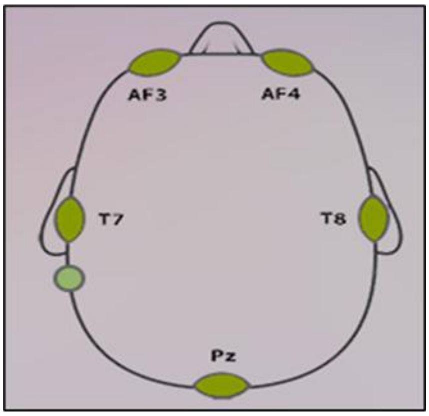

Figure 1. Emotiv 5-Channels EEG insight 1.

2.2. Related Work

2.2.1 Movements intention detection using BCI

Studies [5], and [14] developed methods for identifying upper limb movement intentions using EEG signals. Study [5] tested SVM, KNN, and Naïve Bayes classifiers on six participants performing mouse movements, with SVM achieving 72% accuracy. Study [14] examined six participants interacting with a robotic arm through observation, mimicking, and kinesthetic imagery, finding that observation significantly impacted detection rates for two subjects (53-97%).

Recent research has increasingly focused on leveraging deep learning architectures to improve the accuracy and robustness of motor imagery classification. A significant advancement in this area is the use of hierarchical attention-enhanced deep learning models. A study by Chen et al. introduced a novel attention-enhanced convolutional-recurrent framework that achieved a state-of-the-art accuracy of 97.24% on a four-class motor imagery dataset. Their approach, which integrates convolutional layers for spatial feature extraction, Long Short-Term Memory (LSTM) networks for temporal dynamics modeling, and selective attention mechanisms, demonstrates the power of biomimetic architectures that mirror the brain's own processing strategies [15].

Transformer-based models have also emerged as a powerful tool for EEG signal classification. Liao et al. developed EEG Encoder, a deep learning framework that employs modified transformers and Temporal Convolutional Networks (TCNs) to overcome the challenges of manual feature extraction and noise susceptibility. Their proposed Dual-Stream Temporal-Spatial Block (DSTS) architecture effectively captures both temporal and spatial features, achieving an 86.46% accuracy for subject-dependent classification on the BCI Competition IV-2a dataset [16].

Further expanding the scope of BCI applications, recent studies have explored more complex movement intentions. Khan et al. evaluated various classification and regression algorithms for detecting motion intentions for robotic rehabilitation, comparing deep learning with conventional machine learning techniques for upper limb movements [17].

A study by Ganesan et al.[3] analyzed EEG signals for arm movements, highlighting the parietal region's role. Using FFT, wavelet transforms, and a Levenberg-Marquardt Algorithm, they achieved 97.2% accuracy, with a PatternNet deep learning model enhancing performance for neuro-prosthetic applications. Another study [18], used a BCI to differentiate between slow and fast upper limb movements. By applying Filter Bank Common Spatial Pattern (FBCSP) and a Convolutional Neural Network (CNN), they achieved a 90% accuracy rate in classifying movement speed from EEG signals during shoulder tasks.

2.2.2 EEG in Muslims' prayer

A study [19] on alpha wave activity during Muslim prayer found increased alpha wave power at parietal and occipital sites during prostration, suggesting relaxation effects similar to meditation. The acted prayer session, without recitation, showed even higher alpha wave power, emphasizing the posture's role in relaxation. Another study [20] recorded brain activity during a four-rakah Salat, analyzing connectivity across different frequency bands. It found the most significant changes in the delta band, achieving a 73.8% classification accuracy for different prayer postures and highlighting how ritualistic movements alter neural connectivity.

2.2.3 EEG features of Alzheimer's studies

The work in [5] analysed EEG data from Alzheimer's patients and healthy controls using a single dry electrode. They found that AD patients had lower beta band powers and higher theta and delta band powers. While achieving results comparable to studies using more complex equipment, this work did not monitor patient focus levels in real-time.

Consistent with earlier findings, recent studies have confirmed that AD is associated with a slowing of EEG rhythms. A comprehensive analysis by Chetty et al. [21] found that spectral power ratios, particularly the theta/alpha and theta/beta ratios, are robust biomarkers for distinguishing AD from healthy controls. Their study revealed higher theta power in AD patients, indicative of slowing neural oscillations, and a strong negative correlation between the theta/alpha ratio and Mini-Mental State Examination (MMSE) scores. The study achieved classification accuracies of up to 79.19% using an artificial neural network. A review by Yuan and Zhao [22] further highlighted the role of quantitative EEG (qEEG) biomarkers in AD research. They emphasized the value of various qEEG measures, including power spectrum analysis, connectivity, microstates, and non-linear analyses like entropy.

The application of machine learning has been instrumental in advancing the use of EEG for AD diagnosis. A scoping review by Qi et al. [23] analyzed 86 AI models for AD digital biomarkers, including those based on EEG. The review found that classical machine learning models are prevalent, with an average Area Under the Curve (AUC) of 0.887 for AD-focused models. Other studies, like [24], and [25], also highlight EEG's potential for AD diagnosis. reviews how EEG signals, combined with machine learning, can detect AD early. introduces a method using EEG and ERP signals with a Convolutional Neural Network (CNN) to diagnose mild AD, demonstrating superior performance.

3. ORIGINALITY

The system assists Alzheimer's patients during prayers based on research involving AD associations, caregivers, and 44 survey respondents (see Figure 2 and 3). Key findings revealed that 38.6% of caregivers provide pre-emptive verbal guidance and 29.5% intervene during delays. Importantly, 63.6% of AD patients need prayer guidance, with over half requiring assistance more than six times per prayer, informing the system's time-based attention monitoring approach.

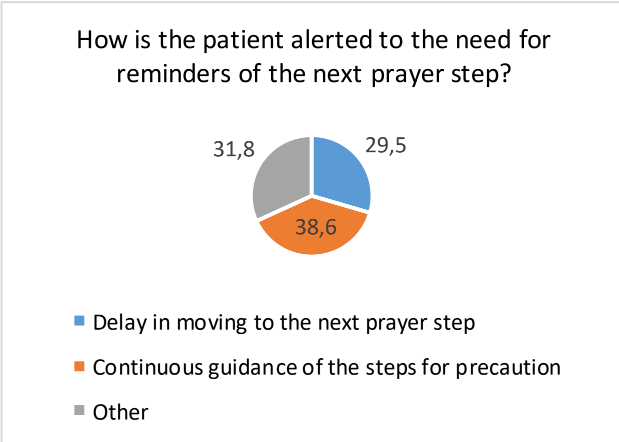

Figure 2. Survey 1 – patient's need of guidance.

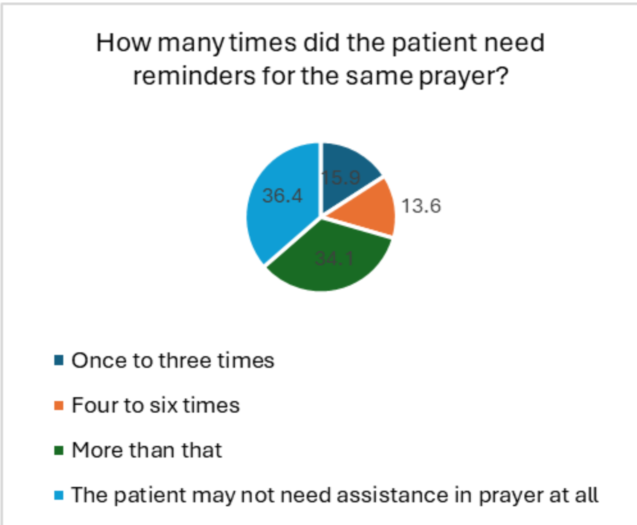

Figure 3. Survey 2 - times of guidance per prayer

3.1 Scenario description

Initially, the user is required to do the insight headset and correctly position the sensors, facilitated by instructional figures provided by the system. Subsequently, to enable recognition of the user's movements, the system undergoes training using a dataset of two individuals' prayer movements. Upon selecting the start option, the system guides the user through the prayer, monitoring their position and attention every 5 seconds. If a decline in attention is detected, the system provides vocal guidance for the next movement. This guidance specifically covers the dawn prayer, consisting of two bows, after which the system automatically ceases guidance. Additionally, a stop function is available should the user desire to halt or restart the prayer.

4. SYSTEM DESIGN

The proposed system comprises two phases: the learning phase and the real-time phase, illustrated in Figure 4. One fundamental aspect of machine learning involves preparing data in a format understandable to the classifier. Thus, the initial step in this learning phase involves capturing motion signals from the headset and importing them into the system. Subsequently, by plotting the motion signals acquired from motion sensors, it has been observed that each prayer movement typically lasts a maximum of 500 units of time (equivalent to 3.7 seconds). Consequently, these prayer movements have been segmented into 500-unit intervals to eliminate irrelevant data from the classification process. As a result, the dataset for this project will be divided into several attributes, as outlined in Table A1. in the Appendix.

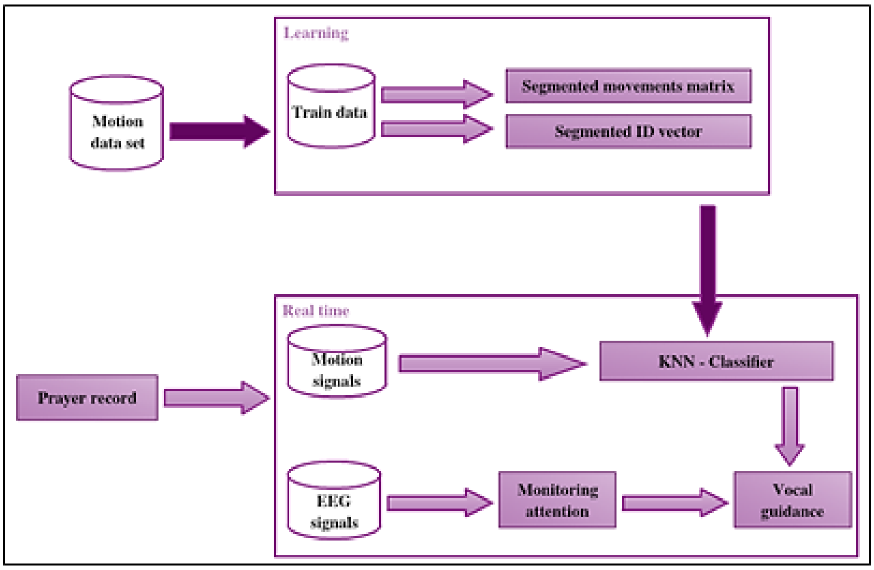

Figure 4. System Architecture.

The dataset utilized consisted of 120 movement records, derived from two individuals performing prayer movements ten times each. Prior to the classification session, preparatory steps were taken. Initially, values in the RQ_ch10, SQ_ch10, and SJ_ch10 channels were segmented into 500-unit intervals, assigned to the Training_matrix. Each segmented value was then used to generate a row representing a single prayer movement, added to the Training_matrix. Finally, the Training_ID was appended to the last column of the matrix, with each row of this vector containing the corresponding movement class. These classes serve as labels for each prayer movement.

To engage the user's attention during prayer, EEG signals are obtained from the headset. Subsequently, the power of each frequency is determined through power spectral density calculation. This process yields a vector R, derived from spectral analysis to capture alpha and beta waves. By obtaining the latest values and dividing alpha waves by beta waves, attention levels can be calculated [26].

In real-time, the system processes a continuous data stream in 500-unit segments. A standard deviation threshold of 220 distinguishes rest from active movements. Active segments are classified to identify the current movement and predict the next, enabling proactive vocal guidance. If no movement is detected for 7.5 seconds, the system checks attention levels and provides vocal prompts if a lapse is detected. This iterative process continues until the prayer concludes. Figure 5 illustrates the flow chart of the system.

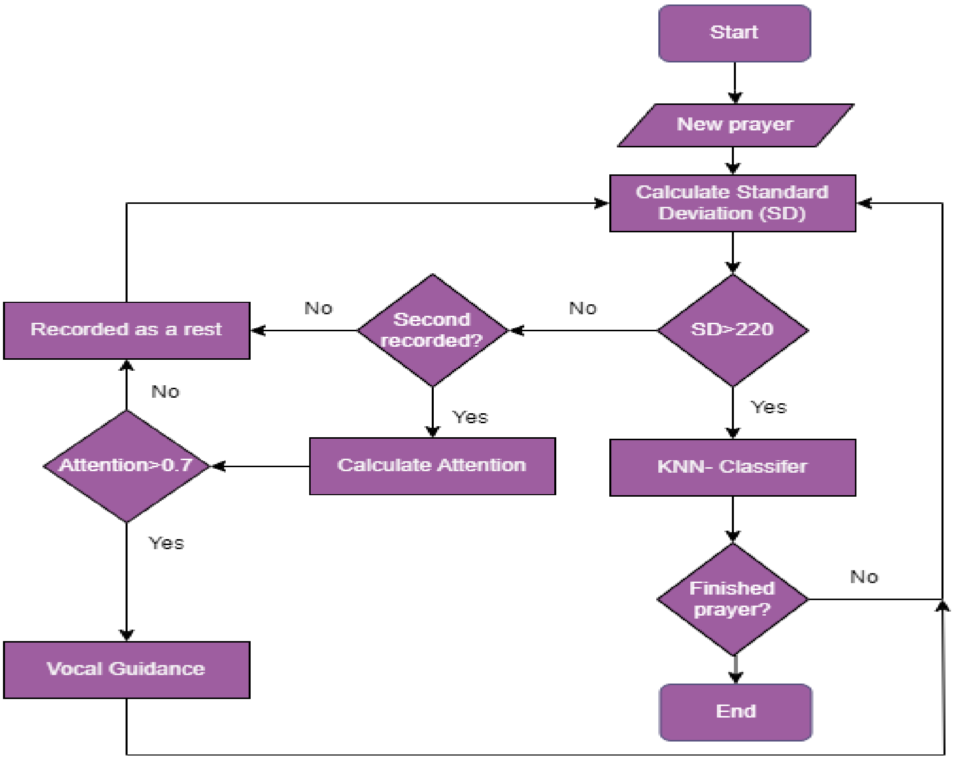

Figure 5. System flowchart.

5. EXPERIMENT AND ANALYSIS

5.1 Implantation

For implementation details, the system's hardware requirements include the Emotiv 5-channels EEG insight headset [13], which captures EEG and motion signals, and a personal computer (PC) with a Windows operating system connected to the internet. The system also utilizes a USB Receiver universal model for wireless headset connection.

In terms of software, MATLAB is employed as the programming language due to its ease of use and extensive signal processing functionality. MATLAB R2015b (32-bit) serves as the programming environment, with GUIDE toolbox utilized for creating graphical user interfaces (GUIs). Emotiv software development kit (SDK) is utilized for real-time logging of EEG and motion signals, while the Emotiv Xavier pure. EEG application is used to create the dataset. Challenges include the SDK's compatibility constraints with newer MATLAB versions and the limited daily records allowed by Emotiv for dataset creation.

5.2 Graphical user interface description

The system features a simple, clear interface designed for Alzheimer's patients using a light purple theme that aligns with Alzheimer's awareness colors. The logo in Figure 6 "ETMAM" (meaning completion/perfection) incorporates tree leaves and half a brain, symbolizing partial memory loss in AD patients. The interface prioritizes accessibility with Arabic language support, minimal auditory elements, and consistent layouts to reduce cognitive strain and confusion for users with dementia (see Figure A1. and Figure A2. in the Appendix).

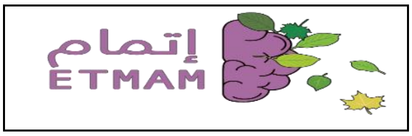

Figure 6. System's Logo.

5.3 Datasets for Movement Classification

To capture prayer movements, two datasets (dataset1 and dataset2) were created from two individuals, each performing the movements ten times. Initially, the data was segmented into six classes (including bowing, rising from bow, prostration, sitting between two prostrations, and the subsequent rising from prostration), but this led to low accuracy with SVM and KNN classifiers. To address this, we consolidated the datasets into four classes by grouping the two prostration movements into one category, similarly consolidating the rising movements. To further enhance classification accuracy, we refined our approach to three classes: one for bowing, a combined class for both prostration movements, and a single class for the actions of sitting and all forms of rising.

The "rest state" was initially a separate class but negatively impacted accuracy. Researchers found that rest periods had a consistently low standard deviation (below 220). Consequently, the rest state was removed from the classification model and is now identified by its standard deviation before the data is processed, ensuring more accurate movement classification.

5.4 Results and Discussion for Movement Classification

Optimizing the performance of our system necessitated conducting various experiments across its functionalities, focusing primarily on monitoring attention and classifying movements. For attention monitoring, we explored two methodologies[26]. Initially, we calculated the spectral power density across frequencies, summing up alpha, beta, delta, and theta waves within the 1 to 30 Hz range, achieving an accuracy of 90 to 93%. Despite its effectiveness, a second approach—calculating spectral power density to derive a ratio of alpha to beta waves for attention levels—proved superior, with accuracy rates soaring to 95 to 96.6%.

In terms of movement classification, extensive testing was undertaken to select the most effective classifier. We began with offline classification of prayer movements, gradually refining our approach by adjusting the number of classes based on the specificity of movements, such as bowing or prostration. Our experiments, detailed in Table 1, initially explored multiple classes but eventually found that reducing the number of classes improved accuracy.

The term "1 dataset" refers to a dataset from a single individual, while "2 datasets" signifies the combination of dataset1 and dataset2. The SVM classifier did not yield satisfactory results when applied to combined datasets or when classifying a single person's dataset into six classes, leading to the absence of reported results for these scenarios. In contrast, the KNN classifier outperformed the SVM, demonstrating superior accuracy. Notably, the system achieved a 100% accuracy rate with three classes. However, when this approach was extended to full prayer recordings, it became necessary to generate a training set for each user to personalize the classifier's learning process and guidance. The data indicates that expanding the number of datasets tends to diminish classification accuracy. Specifically, applying this classification method to entire prayers resulted in an accuracy rate below 55%. A two-class system, distinguishing between bowing/prostration and other movements, emerged as the most accurate, achieving 96 to 100% accuracy in offline, full prayer, and real-time classifications.

Table 1. Movement Classification Results

Classifier	Dataset	Number of classes	Accuracy
SVM classifier	1 dataset	4	38%
	1 dataset	3	61%
	1 dataset	2	38%
KNN classifier	2 datasets	4	72%
	2 datasets	2	100%
	1 dataset	6	50%
	1 dataset	4	85%
	1 dataset	3	100%
	1 dataset	2	100%

In conclusion, the rigorous testing and refinement of our system's functionalities have led to a highly accurate and efficient system. By tailoring our methods and continually adjusting our approach based on experimental outcomes, we have achieved remarkable accuracy rates exceeding 90% across the system's applications, demonstrating the effectiveness of our techniques and the system's potential in real-world scenarios.

5.5 Attention level detection for Alzheimofer's patients

One important part of our system is detect if the attention level of AD patients is low to start the pryer guidnes. Attention states were categorized into high and low attention levels for EEG-based classification[27]. To classify attention levels as either high or low, two distinct attention metrics were calculated based on the power spectral densities of theta (θ), alpha (α), and beta (β) EEG frequency bands. The first metric, termed Pure Attention, was defined a ratio of alpha to beta:

$$Attention\_pure = alpha/beta \quad ,beta \neq 0 \tag{1}$$

The second metric, referred to as Alzheimer Attention, was formulated to capture attention dynamics potentially altered in Alzheimer's disease, using the ratio of beta power to the sum of theta and alpha powers:

$$Attention\_\ Alzheimer = beta/(theta+alpha) \quad ,theta+alpha \neq 0 \tag{2}$$

5.6 Dataset for Attention level detection for Alzheimofer's patients

For this experiment we utilized the OpenNeuro dataset ds004504, a publicly available collection of EEG recordings from individuals diagnosed with Alzheimer's disease (AD), Frontotemporal Dementia (FTD), and healthy control (CN) subjects [28]. For the purpose of this research, only data from the Alzheimer's disease and healthy control groups were included. The dataset comprises EEG recordings from a total of 88 participants. Specifically, it includes 36 subjects with Alzheimer's disease and 29 healthy control subjects. The mean age for the AD group was 66.4 years. The healthy control group had a mean age of 67.9 years. Furthermore, the data underwent standard preprocessing steps, including a high-pass filter at 0.3 Hz and a low-pass filter at 70 Hz, to remove drift and high-frequency noise.

EEG spectral features vary significantly across datasets due to differences in recording equipment, preprocessing methods, and participant characteristics. Therefore, many EEG studies determine attention states using dataset-dependent labeling strategies rather than fixed universal thresholds. In this study, a median split was used to separate high- and low-attention states [29][30].

5.7 Experimental Settings for Attention level detection

The Pure Attention, where lower values indicate higher attention levels, and the Alzheimer Attention, where higher values correspond to increased attention. For each attention metric, subjects were categorized into 'High Attention' or 'Low Attention' based on the median of the calculated attention scores across the entire dataset. Specifically, for Pure Attention, scores below the median were classified as 'High Attention', while for Alzheimer Attention, scores at or above the median were classified as 'High Attention'.

Two distinct machine learning models were employed for the classification of attention levels. The SVM was configured with a Radial Basis Function (RBF) kernel, utilizing default parameters for regularization (C=1.0) and kernel coefficient (gamma='scale'). To mitigate potential class imbalances, the class_weight parameter was set to 'balanced'. KNN classifier was implemented with n_neighbors set to 5, employing the default Minkowski distance (p=2, equivalent to Euclidean distance) for proximity calculations. Prior to classification, all features were standardized using StandardScaler to ensure consistent scaling across the dataset.

5.8 Results and Discussion for Attention level detection

This section presents the classification performance for attention levels (high or low) based on two EEG-derived attention metrics: Pure Attention (alpha/beta) and Alzheimer Attention (beta/(theta+alpha)). The results are categorized into three distinct groups: All Subjects, Healthy Controls, and Alzheimer's patients.

Table 2 summarizes the performance for the entire dataset, while Table 3 and Table 4 present the results for the Healthy and Alzheimer groups, respectively. KNN model consistently demonstrated superior performance over the Support SVM for both attention metrics for all subjects from Table 2. The Healthy group, in Table 3, showed the highest classification accuracy, with the KNN model achieving a perfect score using the Pure Attention metric. Meanwhile, for the Alzheimer's group, in Table 4, the Pure Attention metric maintained strong classification performance, while the Alzheimer-specific metric showed a significant decline in efficacy.

Table 2. The classification performance for attention level for all groups in OpenNeuro dataset.

Attention Metric	**Model**	**Weighted Precision**	**Weighted Recall**	**Weighted F1-Score**
Alpha/Beta (Pure)	SVM	25%	50%	33%
	KNN	86%	85%	85%
Beta/(Theta+Alpha)	SVM	61%	58%	54%
	KNN	78%	77%	77%

Table 3. The attention classification the results for the Healthy group

Attention Metric	**Model**	**Weighted Precision**	**Weighted Recall**	**Weighted F1-Score**
Alpha/Beta (Pure)	SVM	55%	67%	60%
	KNN	100%	100%	100%
Beta/(Theta+Alpha)	SVM	61%	58%	56%
	KNN	76%	75%	75%

Table 4: The attention classification the results for the Alzheimer group

Attention Metric	Model	Weighted Precision	Weighted Recall	Weighted F1-Score
Alpha/Beta (Pure)	SVM	81%	73%	67%
	KNN	89%	87%	86%
Beta/(Theta+Alpha)	SVM	27%	47%	34%
	KNN	55%	53%	52%

The Pure Attention (alpha/beta) metric consistently outperformed the Alzheimer-specific formula across both models, achieving a superior weighted F1-score of 86% with the KNN classifier. This suggests that the simpler alpha/beta ratio is a more robust and reliable indicator of attention states in clinical populations, as the more complex Alzheimer-specific metric appeared to introduce noise that hindered classification accuracy.

6. CONCLUSION

Witnessing the challenges faced by Alzheimer's patients and their families underscores the urgent need for innovative solutions that can ease their daily struggles. Our proposed system addresses the challenges faced by Alzheimer's patients by using motion and EEG signal analysis. It classifies prayer movements and monitors attention, fostering independence and enhancing the user's spiritual and physical well-being by providing tailored support during daily routines.

Our research culminated in a system enabling Alzheimer's patients to pray with minimal help, achieving 93-96.6% overall accuracy. The classification process demonstrated high efficacy, with an attention ratio of 90-96.66%. Further validating these capabilities, an independent analysis using the OpenNeuro ds004504 dataset specifically showed that for Alzheimer's patients, the Pure Attention method, when combined with a KNN classifier, yielded highly accurate and reliable results for identifying attention states, achieving a weighted F1-score of 86%. These combined results strongly validate the system's potential to effectively support Alzheimer's disease patients by accurately assessing and classifying their attention levels.

Future plans include developing a mobile app, integrating comfortable headsets, and ensuring cross-platform compatibility to improve accessibility and usability. This will further enhance the independence of AD patients and provide greater support for their families.

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Appendix A

A.1. Appendix A.1

Figure A1. Interface 1.

Figure A2. Interface 2 (help).

Table A1. System Attributions.

Attributes	Value type	Description
RQ_ch10	double vector	Holds motion signals for bow and rising movement from 10th channel GYROY
SQ_ch10	double vector	Holds motion signals for prostration and rising movement from 10th channel GYROY
SJ_ch10	double vector	Holds motion signals for prostration and sitting movement from 10th channel GYROY
Training_set	double matrix	Holds the motion signals dataset
Training_ID	Integer vector	Holds the classes of each movement for the dataset
EEG_Motion	matrix - double	Signals stream read from the headset
prayer_mov	Integer vector	Holds the expected movement of the prayer
Motion_segment	double vector	Holds the segment of motion signals
EEG_segment	double vector	Holds the segment of EEG signals
sys_classifier	integer vector	Holds the classification result from classifier
SPD	double vector	The resultant spectral power density
R	Double vector	Holds the calculation of attention results