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Title of the Paper:

NeuroSense: Smartwatch based Early Detection Framework for Alzheimer's Disease (AD)

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Motivation

- AD is a global health crisis, that is currently affecting over 55 million people worldwide, with numbers projected to rise to 152 million by 2050 [1].

- The economic burden of AD is immense, with global costs exceeding 1.3 trillion annually, including healthcare expenses and lost productivity [2,3].

- Early detection of AD is critical for effective intervention and management; however, current diagnostic methods are plagued with significant challenges. Traditional diagnostic techniques, such as CSF analysis and neuroimaging, although clinically validated, are invasive, expensive, and often inaccessible for routine screening [4,5].

- Late diagnosis exacerbates cognitive decline, leading to increased care needs and substantial emotional and financial strain on families. Moreover, delayed intervention diminishes the effectiveness of treatments aimed at slowing disease progression.

Abstract

- Alzheimer's disease (AD) is a progressive neurodegenerative disorder.
- The early diagnosis is crucial to mitigate disease progression, yet current detection methodologies lack consistency and accuracy in delineating disease stages.
- To address these challenges, we introduce NeuroSense, a novel smartwatch based early detection framework for AD.
- NeuroSense employs advanced activity recognition algorithms to passively monitor ambulatory patterns, behaviors, and sleep cycles via Inertial Measurement Unit (IMU) and photoplethysmogram (PPG) sensors from smartwatches (i.e., Apple Watch and Fitbit), including metrics like walking speed, sleep posture, and heart rate variability.
- To validate its efficacy, NeuroSense was tested on AI-generated datasets, achieving a detection accuracy of 94.4%, substantially higher than existing approaches.
- This novel framework provides a robust, scalable, and non-invasive solution for continuous AD monitoring, representing a significant advancement in the early detection and management of neurodegenerative disorders.

Introduction

- We propose a NeuroSense framework, depicted in Fig. 1, encapsulates the end-to-end process from data collection using smartwatch sensors, data preprocessing to handle missing values and time-based data segmentation, and application of advanced deep learning algorithms for AD prediction.
- NeuroSense leverages consumer-grade smartwatches to continuously capture and analyze extensive physiological and behavioral data, including gait patterns, sleep metrics, and cardiovascular signals, all in a user-friendly, non-intrusive manner.
- NeuroSense's novelty is rooted in its multi-tiered data processing pipeline that begins with the extraction of raw data from smartwatches and preprocessing techniques to ensure quality and relevance.

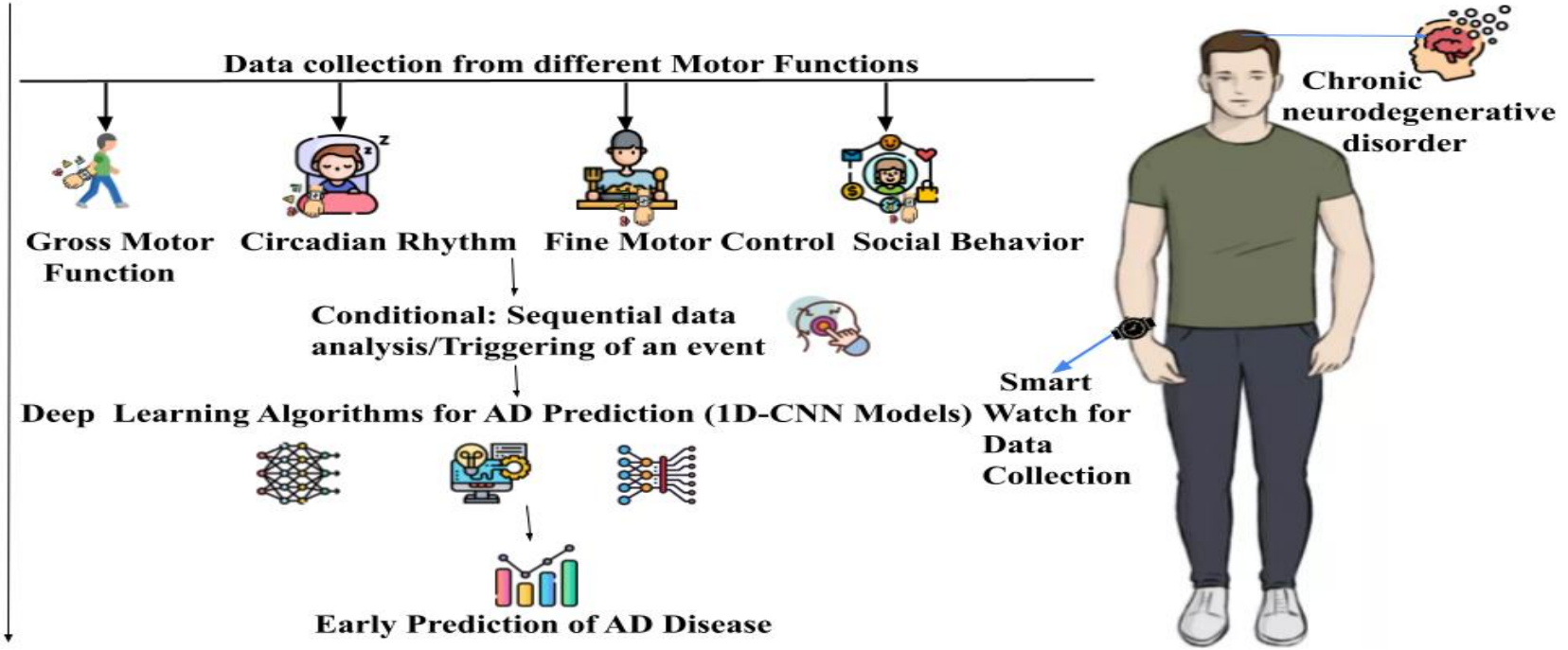


Fig. 1: Activities required during the data collection

Background Information of Alzheimer's Disease on different Biological Structure

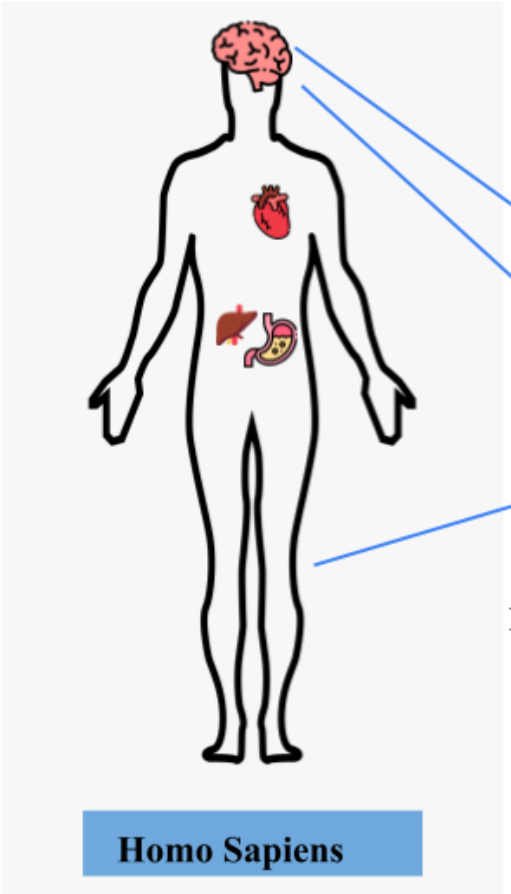
- **Gross Motor Function:** This includes activities involving large muscles, such as walking, running, and climbing stairs. AD patients show significant impairments in these movements compared to healthy individuals [9].

- **Fine Motor Control:** This involves small muscle movements, hand-eye coordination, eating and writing. Studies have shown that AD patients struggle with fine motor tasks, notably during activities like eating [10].

- **Circadian Rhythm:** Disruptions in circadian rhythm, regulating the sleep-wake cycle, are among the earliest symptoms of AD. Patients typically experience irregular sleep patterns, difficulty falling asleep, and frequent awakenings.

- **Social Behavior:** AD affects social behavior, with patients showing changes in social interactions and usage of social networking applications. They tend to rely more on clock applications due to cognitive and attention difficulties and often avoid social networking platforms.

Background Information of Alzheimer's Disease on different Biological Structure (Cont.)



Disease Name: Alzheimer (Dementia) (Chronic Neurodegenerative disorder)

Cause: Environmental, Genetic health, Lifestyle factor, Ageing

Alzheimer Detection Process Factors:

1. A gradual decline in memory, thinking, behavior and social skills : Cognitive Decline, Neurodegeneration
2. Memory and brain cells: Entorhinal cortex and hippocampus
3. Loss of Balance and Coordination : Ataxia and Cerebellar Dysfunction

Symptoms :

1) Brain

1. Amyloid Plaques
2. Neurofibrillary Tangles
3. Synaptic Dysfunction
4. Neuronal Loss
5. Cholinergic Dysfunction

2) Limbs

1. Ataxia
2. Apraxia
3. Muscle Weakness
4. Tremors
5. Bradykinesia

3) Ingestion

1. Dysphagia
2. Anorexia
3. Choking and Aspiration

Fig. 2: Onset and progressive organs altered by AD progression

Contributions of the Paper

The key contributions are as follows

- This research introduces a novel application of cross-sectional entropy that dynamically adjusts feature weights, improving sensitivity to subtle variations in AD biomarkers and increasing detection reliability.
- The framework optimizes the loss function by incorporating entropy-driven feature extraction and fusion techniques are the true and predicted labels.
- The SqueezeNet model introduces deeper fire modules and expanding filter sizes. These enhancements enable high-resolution feature extraction while maintaining computational efficiency, making the model suitable for deployment on resource-constrained wearable devices
- We incorporate advanced signal processing techniques, including adaptive filtering and time-frequency analysis, to preprocess and enhance the quality of physiological signals captured by smart watches.
- These techniques improve the signal-to-noise ratio, facilitating more accurate feature extraction and subsequent AD detection.

Related work

This section reviews prior research on AD detection and mobile health systems, emphasizing the increasing interest in leveraging mobile sensing and deep learning (DL) technologies for early diagnosis.

- The research developed BodyScope, a wearable sensor that records throat sounds to classify user activities such as walking, talking, and laughing. Utilizing support vector machines (SVM), they achieved a detection accuracy of 79.5% [13].

- This research suggests that sensors could detect vocal biomarkers associated with AD, identifying vocal patterns indicative of cognitive decline. Expanding on mobile sensing principles, recent studies have demonstrated the utility of digital tools in cognitive assessment [11].

- Authors introduced a digital variant of the attention metrics test using a digital pen to detect dementia. The authors highlights the role of smartphones in health data collection and analysis, demonstrating their potential in detecting health patterns and conditions, including AD [8].

- An intelligent system to monitor positions and identify risks, specifically targeting AD detection in individuals prone to wandering. This underscores the importance of continuous monitoring in managing AD symptoms. Another significant contribution in presented a prototype wireless-sensing intelligent wearable device designed as a multi-functional solution for AD [7, 8].

- This device utilizes GPS to track patient locations and provide biomedical assistance, illustrating the integration of location-based services in AD care. Further, authors proposed TATC, a solution leveraging altimeter data for AD prediction [4].

Various steps related to the Implementation of the Proposed Framework

- **Data Collection:** The AD dataset is synthetically generated using artificial intelligence (AI) techniques, incorporating features indicative of AD, including fine motor control (eating), circadian rhythm disruptions (sleep cycle abnormalities), social behaviour patterns (mobile application usage), and gross motor functions (walking speed, navigating stairs). These features are monitored using Apple Watch and Fitbit devices.

- **Data Pre-processing:** This phase involves encoding data, handling missing values, and performing time filtering to segregate relevant time-based data segments. Incorrect records are removed to ensure data quality.

- **Model Training and Evaluation:** The dataset is split into training (80%) and testing (20%) subsets. A confusion matrix is utilized to evaluate the performance of the classification model.

- **Advanced Deep Learning Classification Algorithms:** Multiple DL algorithms, including modified Shallow Neural Network and SqueezeNet, are employed for early AD detection. These algorithms leverage feature fusion and entropy-driven feature extraction to improve detection accuracy.

- **Model Evaluation and Results:** The proposed model is evaluated across five AD severity stages: demented (ADD), not demented (ND), early-stage demented (ESD), moderately cognitively impaired (MCI), and partially demented (PD).

Various steps related to the Implementation the Proposed Framework (Cont.)

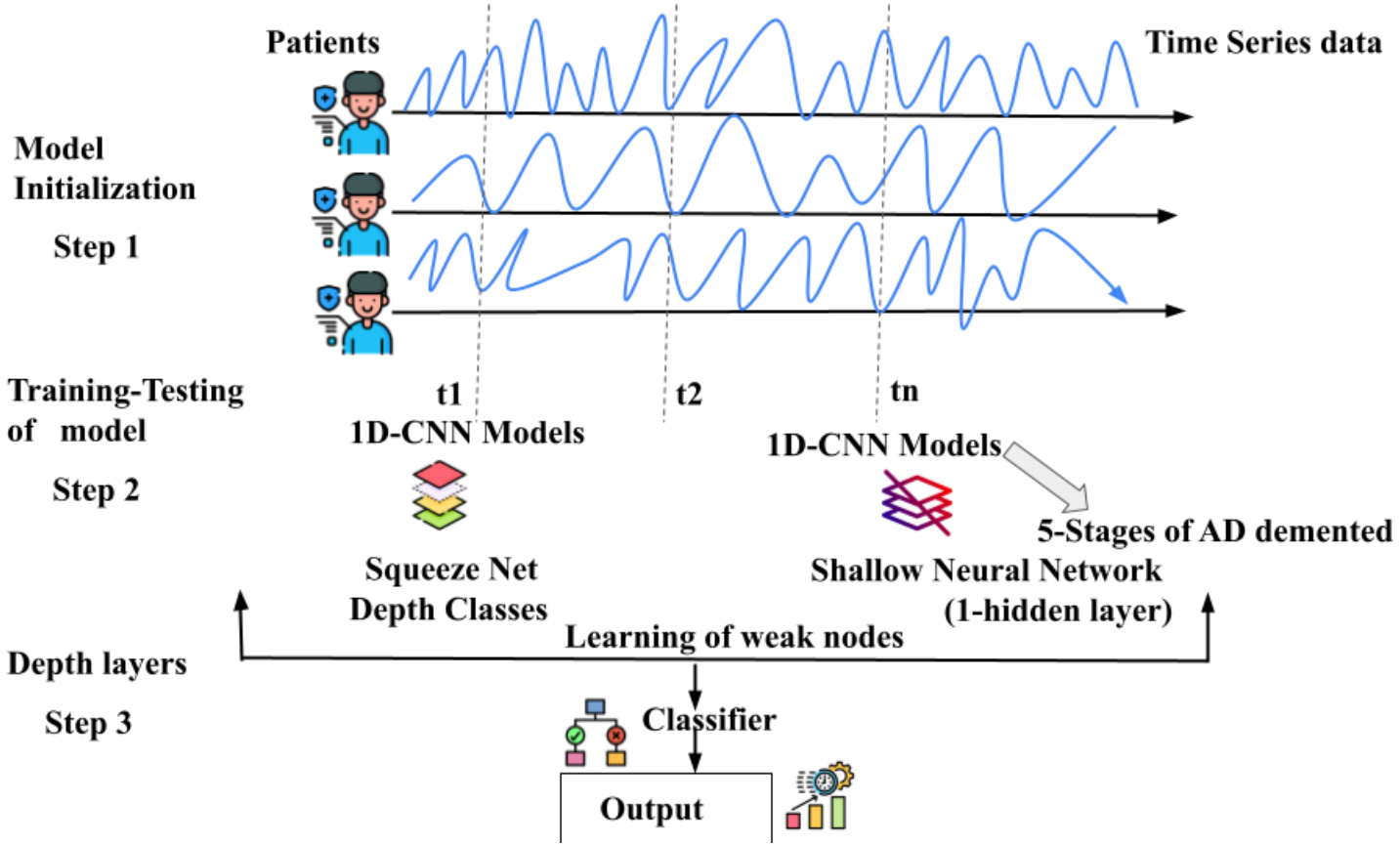


Fig. 3: Framework of the proposed AD detection model

NeuroSense's Modified Advanced Shallow Neural Network with Cross-Sectional Entropy

- A modified advanced shallow neural network with cross-sectional entropy offers a promising approach for early diagnosis and monitoring of AD.

- This neural network leverages DL methodologies to process complex biomedical data, ensuring accurate and reliable detection of AD-related biomarkers.

- The modified shallow neural network, comprising one hidden layer, is well-suited for the dataset used in this research. It efficiently processes input features derived from patient data, including neuroimaging, genetic markers, and cognitive assessments.

- It outlines the modified advanced shallow neural network for AD detection. The network is trained to distinguish between ADD, PD, ESD, ND, and MCI cases, with labels y= {0, 1, 2, 3, 4} indicating the five AD variations.

- Cross-sectional entropy is utilized to identify the most relevant features for AD detection, enhancing the network's ability to detect subtle patterns indicative of the disease.

NeuroSense Modified Shallow Neural Network and SqueezeNet Algorithm

Algorithm 1 NeuroSense Shallow Neural Network with Cross-Sectional Entropy

Require: $X \in \mathbb{R}^{n \times m}$ (input data), $y \in \{0, 1, 2, 3, 4\}^n$ (labels), learning rate α, epochs E, batch size B

Ensure: Trained model parameters θ

Initialize θ randomly
for epoch = 1 to E **do**
  Shuffle training data
  for batch = 1 to $\lceil \frac{n}{B} \rceil$ **do**
    $X_{\text{batch}}, y_{\text{batch}} \leftarrow$ next batch of size B
    Forward pass:
      $z = X_{\text{batch}} \cdot \theta$
      $\hat{y} = \sigma(z)$ ▷ Sigmoid function
    Compute cross-sectional entropy:
      $H = -\sum_{j=1}^{m} p_j \log(p_j)$ ▷ Probability distribution of features
    Enhance features:
      $X'_{\text{batch}} = X_{\text{batch}} \cdot H$
    Recompute forward pass:
      $z' = X'_{\text{batch}} \cdot \theta$
      $\hat{y}' = \sigma(z')$
    Compute loss:
      $L = -\frac{1}{B} \sum_{i=1}^{B} [y_i \log(\hat{y}'_i) + (1 - y_i) \log(1 - \hat{y}'_i)]$
    Backward pass:
      $g = \frac{1}{B} X'^{\top}_{\text{batch}} (\hat{y}' - y_{\text{batch}})$
    Update θ:
      $\theta \leftarrow \theta - \alpha g$
  end for
end for
return θ

Algorithm 2 NeuroSense Modified SqueezeNet Algorithm

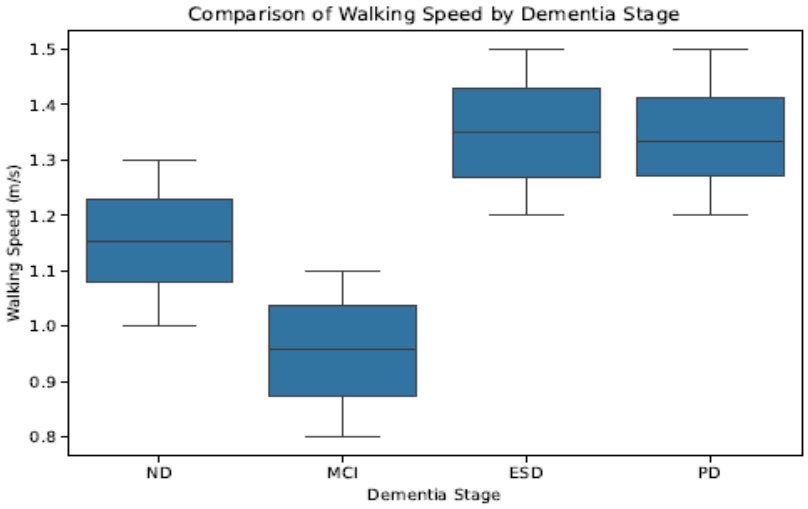
Require: Input data $X \in \mathbb{R}^{n \times m}$ (features), labels $y \in \{0, 1, 2, 3, 4\}^n$ (AD stages), learning rate α, epochs E, batch size B

Ensure: Trained model parameters θ

Initialize θ randomly
for epoch = 1 to E **do**
  Shuffle training data
  for batch = 1 to $\frac{n}{B}$ **do**
    $X_{\text{batch}}, y_{\text{batch}} \leftarrow$ next batch of size B
    Forward pass: $z = \text{SqueezeNet}(X_{\text{batch}}, \theta)$
    $\hat{y} = \sigma(z)$ ▷ Softmax function
    Compute loss: $L = -\frac{1}{B} \sum_{i=1}^{B} [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)]$
    Backward pass: $g = \nabla_\theta L$
    Update parameters: $\theta \leftarrow \theta - \alpha g$
  end for
end for
return θ

Results

- Walking speed is a significant biomarker in AD detection and progression monitoring. Research indicates that gait analysis, particularly walking speed, can reflect underlying changes in brain structure and function indicative of cognitive decline.
- It elucidates how walking speed varies across different dementia stages, supported by a box plot for visual representation, and explains the underlying mechanisms linking gait abnormalities to AD. Fig. 4 a) suggests that ND individuals exhibit the highest walking speed, with a median of approximately 1.2 m/s. Individuals with MCI show a noticeable decrease in walking speed, with a median below 1.0 m/s. ESD, DM, and PD stages display similar median walking speeds, around 1.3 to 1.4 m/s, with slight variations.



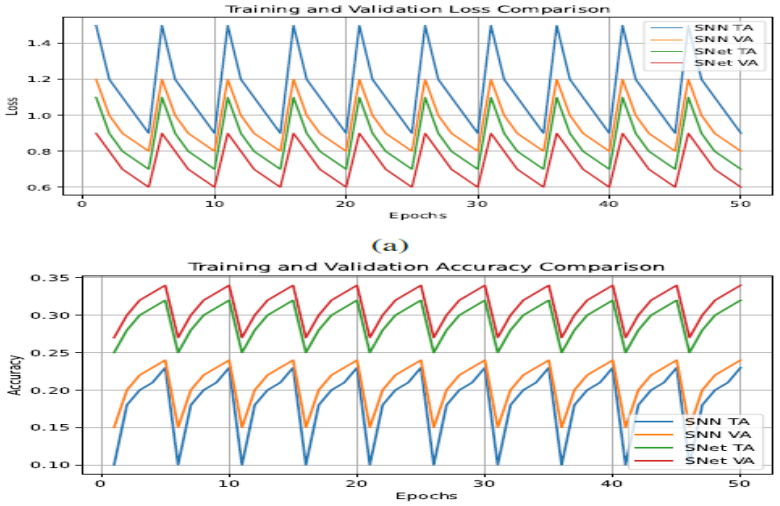


Fig. 4 a) Walking Speed responsible for AD
b) Training and validation loss (TA, VA) of the modified shallow neural network (SNN) and squeeze (SNet) models c) Traning and validation accuracy (TA, VA) of the modified shallow neural network (SNN) and squeeze (SNet) models

Results for Sleep Duration and Sleep Posture Distribution by Dementia Stage (Cont.)

- The first subplot, Fig. 5a), illustrates the distribution of sleep duration across different dementia stages. The x-axis represents sleep duration in hours, ranging from 5 to 9 hours, while the y-axis represents the frequency of individuals. Each color in the histogram corresponds to a different dementia stage: Not Demented (ND), Mildly Cognitive Impaired (MCI), Early Stage Demented (ESD), Demented (DM), and Partially Demented (PD).

- The second subplot, Fig. 5b), illustrates the distribution of sleep postures encoded as 1 to 4, with the x-axis representing sleep posture categories and the y-axis representing the frequency of individuals. The colors in the histogram correspond to different dementia stages. Sleep posture for an individual can be encoded

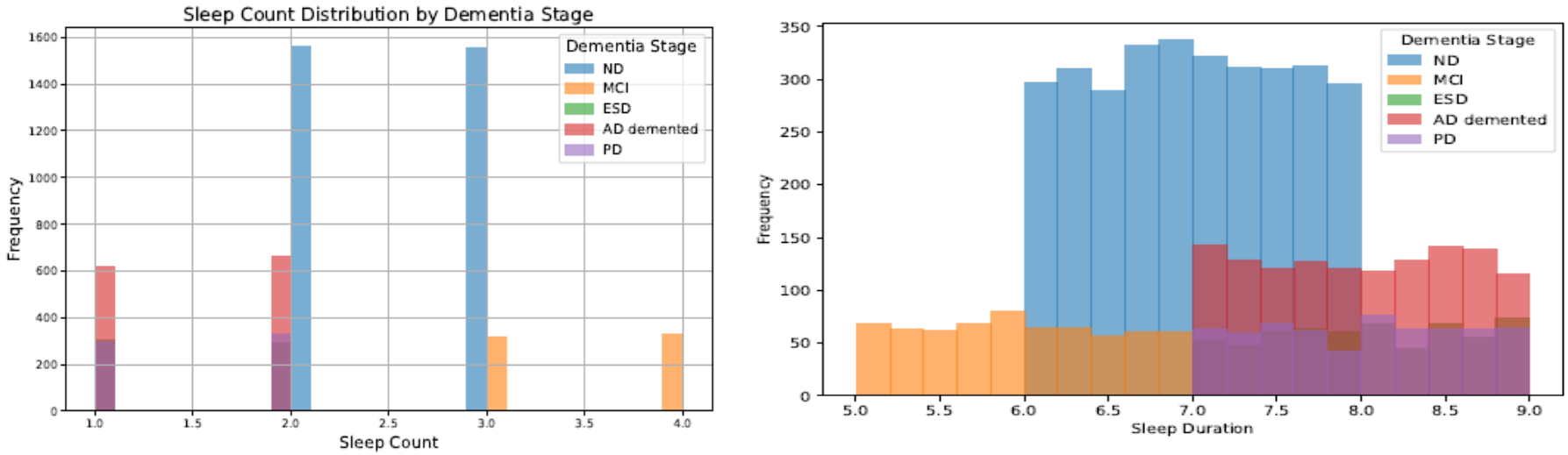


Fig. 5 a) A person's sleep duration responsible for AD detection b) A person's sleep count responsible for AD detection

Comparison methods that are used in the various state-of-the-art

TABLE I: Comparison of Various Approaches for Early AD Detection

Approach	Accuracy in different stages	Biomarkers	Sensors	Subjects	TIme-taken
TATC approach [20]	42.3% MCI	1	Acti-graph	729 (185 AD, 103 MCI, 441 NC)	7 days
ADReSS orientation [26]	60.8% AD	6	Audio	156 (78 AD, 78 non-AD)	10 mins (in lab)
Bayat et al. [27]	82% AD	14	Vehicle GPS	139 (64 AD, 75 non-AD)	1 year
Alberdi et al. [28]	Not any results	Num of 5 features events	PIR motion sensor	29 (6 AD, 10 MCI, 12 NC)	2 years
Ouyang et al. [29]	88.9% MCI	Numb of 22 activities	Audio, Depth, Radar	91 (31 AD, 30 MCI, 30 NC)	4 weeks
Our Study	94.4%	Multiple (Steps, Heart Rate, Distance, etc.)	Apple Watch, Fitbit Watch	6264 (ND: 3117, AD demented (DM): 1281, MCI: 647, PD: 624 ESD: 595)	21 days

Conclusion

- This paper introduces a NeuroSense framework, which leverages digital smartwatches to recognize AD biomarkers through passive monitoring of daily activities.
- The NeuroSense framework is designed to detect early signs of AD without user interaction, making it a practical tool for real world application. By integrating multiple functionalities such as gross motor, fine motor, social-behavioral, and circadian rhythm monitoring.
- NeuroSense enhances the accuracy of AD detection using various modified advanced DL algorithms. Looking forward, we plan to integrate additional physiological and environmental sensors, such as electrodermal activity (EDA) and ambient light sensors, to further enhance the accuracy of AD detection.
- Moreover, we are exploring federated learning approaches to ensure data privacy and security while enabling collaborative model training across multiple devices.
- This advancement will allow for a more comprehensive and secure detection process, paving the way for widespread adoption of smartwatches in the early diagnosis and management of AD.

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Thank You !