TOWARD SENSOR-BASED EARLY DIAGNOSIS OF COGNITIVE IMPAIRMENT OF ELDERLY ADULTS IN SMART-HOME ENVIRONMENTS USING POISSON PROCESS MODELS

A Thesis

By

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ABSTRACT

Emerging sensor-based assessment in combination with machine learning methodologies provide the potential to revolutionize current practices of (early) diagnosis of dementia. The goal of this research is to detect cognitive impairment in elderly adults using sensor-based measures. Longitudinal time-series data of sensor signals are analyzed with advanced computational models and supervised machine learning algorithms to identify individuals with cognitive impairment. This research further designs novel computational models using Poisson Processes that can model subtle temporal changes in sensor-based measurements, therefore have the potential to provide more reliable descriptors of cognitive impairments compared to aggregate time-series measures. Our results indicate that the proposed approach can effectively distinguish between dementia and MCI based on the sensor features yielded by the Poisson Process. Sensor-based assessment that relies on the non-homogeneous Poisson Process is further found to be effective in differentiating between adults with dementia and healthy adults, and depicts better performance compared to expert-based assessment. Findings from this research have the potential to help detect the early onset of cognitive impairment for elderly adults, and demonstrate the ability of advanced computational models and machine learning techniques to predict one's cognitive health, thus, contributing toward advancing aging-in-place.

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Contributors

The thesis committee for this work include Dr. Theodora Chaspari (Chair) from the Department of Computer Science, Dr. Ryan Changbum Ahn (Co-Chair) of the Department of Construction Science and Dr. Tracy Hammond (Member) of the Department of Computer Science at Texas A&M University.

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NOMENCLATURE

MCI	Mild Cognitive Impairment
AD	Alzheimer’s Disease
ADL	Activities of Daily Living
AI	Artificial Intelligence
CASAS	Center for Advanced Studies in Adaptive Systems
PP	Poisson’s Process
HPP	Homogeneous Poisson’s Process
NHPP	Non-Homogeneous Poisson’s Process
PCA	Principal Component Analysis
ML	Machine Learning

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1. INTRODUCTION

Individuals with mild cognitive impairment (MCI), a noticeable decline in cognitive abilities that does not interfere with daily functioning, are at increased risk of developing Alzheimer's disease (AD) or other dementia [1]. The prevalence of dementia is expected to increase dramatically in future years as life expectancy continues to increase. Research shows that 75% of patients with dementia remain undetected at an early stage [2], and are not diagnosed until they have progressed to a moderate or advanced stage [3]. The Alzheimer’s Association reported an estimate of more than 5 million Americans living with dementia as of 2020, of which 83% patients are of age 75 or older [4]. The number of people in the United States aged 65 and older suffering from AD may reach 13.8 million by 2050 [4]. Being the 6th leading cause of mortality in United States, deaths of patients with AD have increased by 146% between 2000 and 2018 [4]. In addition to the high emotional and mental strain of MCI-related conditions to the patient and his/her family, the cost is equally high: caregivers provide an estimated 18.6 billion hours of care to patients that is valued at nearly $244 billion [4].

These cognitive diseases are of slow progressive nature, which severely impact the mental and physical functioning of patients showing symptoms of memory problems, forgetfulness, and poor judgement and thinking. A meta-analysis found that 38% patients with MCI developed dementia over a period of five years [5]. A practical approach to the diagnosis of dementia involves an assessment related to progressive decline in memory, decrease in the patient's ability to perform activities of daily living, psychiatric problems, personality changes and problem behaviors. Clinical assessment of dementia involves the assessment of cognitive domains, including speech, motor memory, sensory recognition, and executive functioning. The Mini-Mental State Examination (MMSE), although not a diagnostic of dementia, is a test for assessing cognitive function and documenting subsequent decline. Yet, degradation of cognitive functioning is not always easy to diagnose, especially in elderly adults who live alone. Access to clinical diagnosis is limited for many adults due to cost and practical issues (e.g., lack of transportation to the healthcare provider).

MCI assessment is traditionally performed by collecting surveys reported by the individuals and caretakers, or closely monitoring occupant's activities in a controlled environment. These assessments for tracking the progression of diseases are conducted once every few months, thus providing measures of an individual's health status at a low temporal resolution. Due to lack of awareness about the disease and ignorance of symptoms, these self-reported observations tend to be erroneous and generally biased [6]. Hence, the longitudinal continuous monitoring of an individual's behavior has the potential to detect cognitive impairment at an early stage. Today, longitudinal continuous data can be collected with modern advancements in smart home technologies with high temporal specificity by leveraging smart devices, such as motion capture devices, audio, video, and wearable sensors [7, 8, 9, 10]. This enables monitoring the behavior and longitudinal health of individuals, thereby, providing insightful information on the onset, progression, and aggravation of cognitive diseases.

Emerging ambulatory measurement in combination with machine learning methodologies provide the potential to revolutionize current practices of (early) diagnosis of dementia in a smart home by relying on sensor-based measurements of the activities of daily living [11], [12], [13]. Prior work has demonstrated the ability of machine learning techniques in predicting participant's cognitive health that can help understand an individual's everyday health using automated task assessment [14]. This involved assessing the activity quality and tracking the activities performed by individuals in smart homes to correlate sensor features with automated scores obtained from direct performance observations.

The sensors used in smart homes are categorized as obtrusive and non-obtrusive/ unobtrusive sensors based on their prominence. Obtrusive sensors are noticeable in an intrusive manner and include cameras, microphones, and wearable sensors providing wide range of rich physiological and audiovisual data. These highly sophisticated sensors are useful in modeling activities of daily living, however, can cause individual discomfort and privacy issues. These obtrusive sensors have a lower adoption rate for elderly adults, since it might be difficult for them to have the wearable sensors. Thus, as a potential solution to this challenge, we are utilizing the unobtrusive sensors in our research. These unobtrusive sensors, such as binary sensors, wireless motion sensors and passive infrared sensors, are not burdensome and have the potential to be widely used in smart home environments and allow the collection of rich temporal information about individuals' health states.

2. PRIOR WORK

Clinical activity assessment of dementia and MCI is traditionally performed by monitoring an individual's activities through survey data from the caregiver and the patient [15], [16]. These self-reported observations are time-consuming [18] and can be subjective and biased [19]. Pavel *et al.* found that changes in mobility patterns directly relate to the decline in cognitive ability [20]. Mobility was measured by assessing the instantaneous walking speed and response time to a telephone ring. Other work has instructed elderly adults a set of predefined activities, for which the quality and correctness was assessed through expert observation [21].

Clinical review criteria for diagnosis of MCI involve cognitive testing of changes in memory, language, visuospatial function, and attention/executive function [36] [37] [38]. Some of the clinical characteristics indicating MCI due to Alzheimer's disease include longitudinal decline in cognitive function, lack of prominent behavioral or language disorders, and lack of parkinsonism, vascular risk factors, visual hallucinations and extensive cerebrovascular brain imaging disease [39]. The approach for diagnosing and managing MCI as adopted in [36] registers history of changes in functional status, prescription and medications, neurological symptoms such as speech, vision, hearing, and numbness, and psychiatric symptoms including anxiety, depression and behavioral changes. This study performed physical and neurological examination, and conducted laboratory testing of biomarkers such as blood cell count, electrolytes, thyroid function, glucose, and calcium. Widely used cognitive screening tests include the Mini-Cognitive Assessment Instrument (Mini-Cog) [40] and the Montreal Cognitive Assessment (MoCA) screening tool for detecting MCI [41]. The Mini-Cog test combines the clock drawing test with a 3-word recall that can be performed in 3 minutes or less, whereas MoCA is a tool developed specifically for MCI detection which usually takes 10 minutes to administer. MoCA examines the patient's orientation, short-term memory, executive function, language abilities, abstraction, and attention.

As part of another line of work, detection of early-stage dementia has been conducted using speech-based protocols that collect and analyze patients' conversational speech [43] [44] [45]. Some methods to assess dementia of Alzheimer type (DAT) in older adults include structured interviews aimed at capturing the suffered deficits [42], since the capacity for functional communication and the linguistic skills are most significantly affected by the DAT. The lexical approach introduced in [42] provides the ability of diagnosing patients through spontaneous speech analysis. This approach relies on character n-grams that model the linguistic consistency of the speaker. N-grams comprised the input of a naive rule-based classifier, which achieved an accuracy of 70% in recognizing dementia, and 50% accuracy in classifying between severe, moderate, mild, and normal dementia. The study conducted in [43] involved recording an individual's audio data by extracting vocal features related to pause timing, sentence duration, and verbal reaction time yielding 20% equal error rate between dementia and MCI detection. The speech analysis system presented in [44] supports dementia assessment using speech processing techniques. A comprehensive statistical analysis is done on the language-independent vocal features, thereby, revealing the importance of spoken tasks for automatic assessment of early dementia. Further work in this area involves detecting dementia using manual pipeline transcriptions and the fully automatic pipeline transcriptions to transcribe speech [45]. This approach utilized an automatic speech recognition (ASR) system with acoustic and linguistic features extracted from audio and automatic transcriptions, and language models for modeling the word sequence probability.

Other works have performed sensor-based assessment through signal processing and machine learning methodologies [14] [29]. Urwyler *et al.* estimated the degree of routineness using Poincare plots by performing activity recognition with a CAR classifier [12] [22]. This used a rule base ad-hoc classifier proposed in [12] to detect and classify activities of daily living (ADL). The Poincare plot is used to represent activities of consecutive days. The degree of routineness is estimated by detecting similar activities on two consecutive days which are paired and then plotted on a two-dimensional plot. A

Markov chain implemented by Shirin *et al.* is used for detecting unusual sensor patterns of dementia patients [25]. Finally, autoencoders have been used by Sharma and Ghose for reducing dimensionality of data and representing routines as encodings of fixed length [26]. Covinsky *et al.* measured the degree to which the ADL's are performed adequately by older adults, and found that variations in ADL patterns are indicative of one's mental health status [27] [28]. Despite the promising results, the aforementioned work does not consider contextual information (e.g., type of task) when designing or learning the corresponding features. In addition, many of the proposed feature learning algorithms, such as the autoencoder and Markov chain, require a large number of data in order to yield accurate descriptors of the signals of interest.

AI-based algorithms used for cognitive assessment include the Gestalt Sequence Matching algorithm [23] used by Alberdi *et al.* [24] for computing the similarity between routines. This Gestalt Sequence Matching algorithm computes the similarity between two sequences using longest common sub-sequences (LCS). An activity recognition algorithm [17] was further used to recognize the activities, which are then represented as routine sequence in comparison to the sequence of next day. The challenges involved in these routine based assessments through recognized activities include lack of annotated activity-based data, and the requirement of large amounts of training data for every subject.

Prior work has further performed activity assessment by real-time activity recognition using CASAS smart home [31]. This used a support vector machine to analyze the resident behavior using the smart home data. The limitation to their work of not performing longitudinal study assessment is overcome in this thesis by continuous monitoring of individuals using moment-to-moment sensor measures. Other works have performed automated assessment of task quality using machine learning algorithms on the basis of sensor data collected during the performance of task [14]. The participants completed a neuropsychological test which provided a ground truth activity score and an experimenter rates the performance of activities performed by individuals in a smart home. This study only focused on one complex activity of DOT tasks or the Day Out Tasks. This approach used raw sensor data on which an activity recognition algorithm was implemented and feature extraction was performed on the collected annotated sensor data to predict activity quality scores. The smart home data was analyzed to classify cognitive health. Results from this work provided a foundation toward automating the longitudinal assessment of well-being in home environments.

The limitation to the cognitive assessment study conducted in [14] that it relies on participants completing the scripted activities can cause unnatural performance due to factors such as unfamiliar environment, awareness of being monitored and the manner of scripted activities. It was observed from their study that only limited cognitive assessments can be automated using algorithms and smart home sensors. Direct observation scores were used for training the machine learning models and derived features required human annotation of the sensor data. Since the direct observation score can't capture natural activity performance, the limitation to their work being the coarse granularity of home-based sensors is overcome in this thesis. Thus, the cognitive assessment study in our research allows to provide sensor-based assessment as well as the automated/expert-based assessment, and contrasts the performance between the two using advanced computational models and supervised learning algorithms.

More detailed information about the automatic assessment of cognitive impairment can be found in previous systematic review studies [46], in which the use of multimodal sensing is emphasized for effectively capturing the diversity of behaviors indicative of cognitive impairment. There have been studies in the systematic review which do not use behavioral or clinical assessment tools to detect dementia [47] [48] [49] [50] [51]. Some of the previous work [49] [50] has described the design of system architectures and sensor platforms, which have been validated with small-scale study protocols, rather than clinical studies. On the contrary, other work included clinical studies using data analysis techniques [52], [53] or sensing [54] [55] [56] [57]. These studies indicated the correlation between various sensor-based measures and dementia outcomes.

Poisson Processes (PPs) have been used to model the occurrence of events of interest in various applications [29]. Prior work has used PP to model earthquake series and characterize seismic activity [30]. This study utilized a stationary PP and hypothesized that the deviation of the data from the model is indicative of seismic events of interest. Another study employed a non-homogeneous PP to quantify physiological reactivity patterns occurring as part of an interpersonal interaction in a therapeutic setting for children with Autism Spectrum Disorders [29]. The authors used a non-homogeneous PP to model the occurrence of skin conductance responses in the electrodermal activity signal. The rate function of the PP model was further dependent on the observable events that occurred during the therapy session. The promising results yielding from prior work have led us to exploring the use of homogeneous and non-homogeneous PP models in association to sensor-based events for detecting cognitive degradation.

In contrast to prior work, this thesis proposes a new methodology to accurately model sensor-based signals based on a PP framework that assumes an event sequence in these signals. We anticipate that this will provide a more efficient modeling of time-series in a fine-grained scale through this process, essentially leaning towards the early detection of dementia cases. Thus, the application of PP models on sensor-based time-series for the task of identifying cognitively impaired adults is novel in this field.

3. PROPOSED WORK AND CONTRIBUTIONS

This research aims to leverage moment-to-moment sensor-based measures collected from non-intrusive devices to detect cognitive impairment in elderly adults. The unobtrusive measures used in our research study consist of sensor-based measurements, where sensors are not installed on the person's body, instead substituted as environmental sensors. We aim to address computational challenges involved with its endeavor for reliably modeling fine-grain variations in the longitudinal sensor-based time-series data. For this reason, we design and formulate a Poisson's Process (PP) framework, which models time arrival of events. We argue that this is a particularly attractive framework for modeling the considered sensor-based time-series, since we assume that a sensor being ON represents an arrival or occurrence of a certain event. PP models can model subtle temporal changes, therefore have the potential to provide more reliable descriptors of cognitive impairments compared to aggregate time-series measures. We further incorporate contextual information by separately estimating the arrival rate of the PP based on the start and end of a given task through a non-homogeneous PP model. The proposed PP measures are used as an input to supervised machine learning algorithms for classifying between participants with MCI/dementia and healthy participants, and are compared to expert-driven assessment of activity scores for the same task.

4. RESEARCH OBJECTIVES

4.1. Research Aims:

This thesis aims to answer the following research questions:

1. Can sensor-based measures modeled with Poisson's Process (PP) and combined with machine learning methodologies detect cognitive impairment, specifically dementia and MCI?

   We model the time-series sensor data using homogeneous and non-homogeneous PP models and implement a supervised machine learning algorithm to classify between cognitively impaired (i.e., Dementia, MCI) and healthy adults. In doing so, different groups of classes are combined together to perform the binary classification experiments. Our results indicate that homogeneous and non-homogeneous PP models can reliably model fine-grain variations in the longitudinal sensor-based time series data. Incorporating contextual information related to the start and end of each task through a non-homogeneous PP model increases the ability to differentiate between healthy and cognitively impaired adults.
2. Does the order of subtasks within a given task affects the estimation of cognitive impairment?

   We investigate the extent to which the order of subtasks within a given task affects the ability of the PP models to classify between cognitively impaired and health adults. For this reason, we compute the proposed homogeneous and non-homogeneous PP features for three types of tasks that include uncued, cued and interwoven subtasks. Our results indicate that the order of subtasks appears to have a small effect on the classification accuracy between healthy and cognitively impaired adults with interwoven uncued tasks providing the lowest accuracy.
3. Can the proposed PP models complement expert-based assessment of activity scores for the task of cognitive impairment recognition?

   We compare the sensor-based assessment from homogeneous and non-homogeneous PP with the expert-based assessment obtained from a human observer/experimenter. Our results indicate that the proposed PP models can complement and provide better results than the expert-based assessment for detecting cognitive impairment. The combination of sensor and expert-based features further yielded an improved performance in certain cases.

5. RESEARCH WORK

5.1. Data Description:

The data used in this research is collected by the Washington-State University (WSU) through the study of “Activities of Daily Living and Memory in Older Adulthood and Dementia”. This study included data from CASAS smart home testbed [31], such as motion sensors, door sensors, temperature sensors, item sensors for selected items in the kitchen, burner sensors, hot and cold water sensors, and apartment’s electricity usage. A total of 400 study participants performed a set of activities generating sensor events for each activity, recording the date, time, sensor identifier, and a sensor message of each sensor event (Figure 5.1).

```
10:21:34.033448 T002 27
10:21:35.074953 M013 OFF 12-end
10:21:36.002809 M008 ON
10:21:37.047284 M007 ON
10:21:37.074832 M014 OFF
10:21:37.088788 M001 ON 13-start,13.1
10:21:38.009194 M023 ON 13.1
10:21:38.050637 D012 OPEN 13.2
10:21:39.015485 M007 OFF
10:21:40.053918 M023 OFF
10:21:40.079851 M008 OFF
10:21:41.046711 M001 OFF
10:21:44.037702 D012 CLOSE 13.2
10:21:44.086852 M023 ON
10:21:45.010648 M001 ON
10:21:45.063821 M008 ON 13.3
10:21:45.080669 M007 ON 13.4
10:21:46.083838 M006 ON 13.4
10:21:47.000777 M001 OFF
```

Figure 5.1: Example of raw data that include the time that each sensor turned on or off.

A list of 24 activities is provided and divided in: (1) 8 uncued tasks whose subtasks are not performed in a predefined sequence; (2) 8 cued tasks whose subtasks are performed in a predefined sequence; and (3) 8 interwoven uncued tasks which are performed by interchanging subtasks that focus on planning a day out of the house (i.e., also referred to as the ‘Day Out Tasks’ or DOT). More details about these can be found in [32-35] and some examples of subtasks are shown in Figure 5.2. The subtasks within an activity are further denoted by sensor events, start time of an activity, end time of an activity, and an activity label index. Participant diagnosis is also provided as shown in Figure 5.3 and includes dementia (*N* = 36), MCI (*N* = 59), middle age adults between 45-59 years (*N* = 37), young-old age adults between 60-74 years (*N* = 83), old-old age adults older than 75 years ($N = 44$), and younger adults ($N = 78$). Each individual participated in the user study for 3 hours.

* Uncued Tasks

1) Sweep the kitchen and dust the living room.
    1) Participant retrieves broom from supply closet
    2) Participant retrieves duster from supply closet
    3) Participant retrieves dust pan and brush from closet
    4) Participant sweeps kitchen floor
    5) Participant uses dust pan and brush
    6) Participant dusts living room
    7) Participant dusts dining room
    8) Participant returns broom to supply closet
    9) Participant returns duster to supply closet
    10) Participants returns dust pan and brush to supply closet

2) Obtain a set of medicines and a weekly medicine dispenser, fill as per directions.
    1) Participant retrieves materials from cupboard "A"
    2) Participant reads instructions
    3) Participant fills dispenser with medication

* Cued Tasks

9) Check the wattage of a desk lamp and replace the bulb.
    1) Participant checks wattage
    2) Participant moves to the kitchen
    3) Participant retrieves light bulbs from cabinet "B"
    4) Participant moves to the dining room
    5) Participant removes old light bulb
    6) Participant throws away old light bulb
    7) Participant replaces the bulb

10) Wash hands with soap at the kitchen sink.
    1) Participant moves to the kitchen
    2) Participant turns on water
    3) Participant uses hand soap
    4) Participant washes hands
    5) Participant dries hands

11) Wash and dry all kitchen countertop surfaces.
    1) Participant locates the sponge
    2) Participant locates the dish detergent

* Interwoven Uncued Tasks

17) Examine a bus schedule; plan a trip including length of time and when to leave.
18) Microwave a comfort heat-pack for the bus ride.
19) Select a magazine to read during the trip.
20) Count out appropriate change for bus fare.
21) Take a dose of an anti-motion sickness medication.
22) Find a recipe book, gather ingredients cited as necessary for a picnic meal.
23) Obtain a picnic basket from the hall closet and fill with all items for the trip.
24) Take the filled picnic basket toward the apartment exit, as though leaving as planned.

Figure 5.2: Examples of subtasks within uncued, cued and interwoven uncued tasks [31].

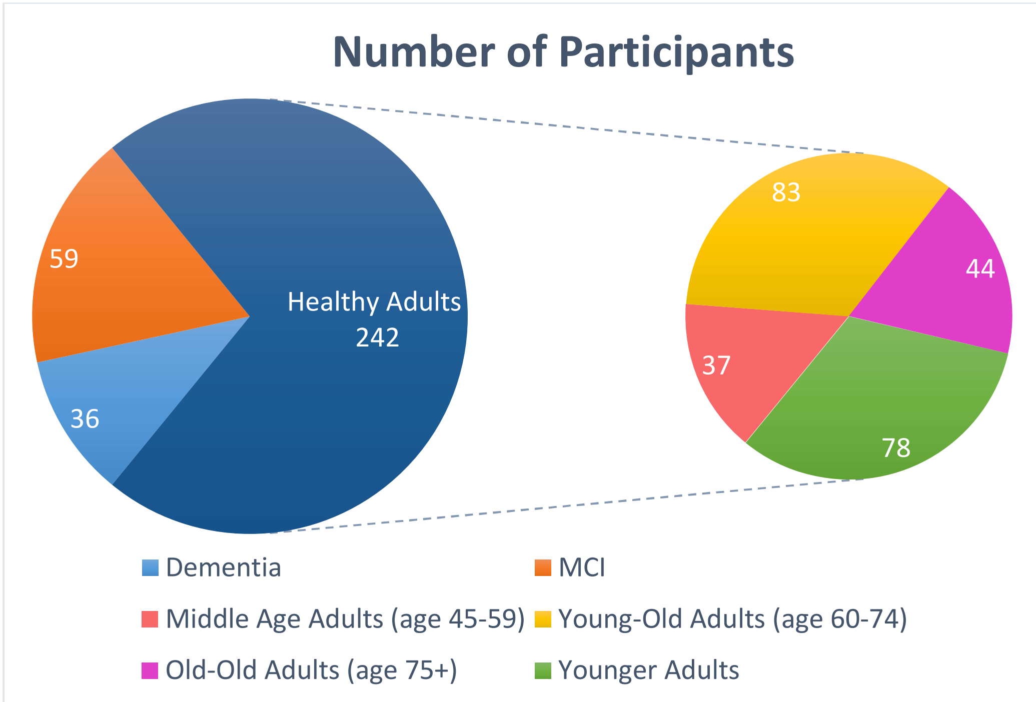

Figure 5.3: Number of participants per each category.

5.2. Proposed Approach and Methodology:

5.2.1. Sensor-based feature design with homogeneous Poisson Process (HPP)

A homogeneous PP (HPP) is used to model the time arrival of sensor events, where arrival is defined as every time a sensor installed in the home environment is turned on. The homogeneous PP assumes a constant arrival rate $\lambda(t) = \lambda$ for the entire 3-hour duration of the user study. The arrival rate λ is defined for each sensor and is computed as the number of times each sensor turns ON, divided by the total 3-hour duration of the experiment. Since there are 52 sensors installed in the home environment, a total of 52 features are extracted for each participant based on this homogeneous PP model.

The raw sensor data is preprocessed for missing and noisy values. The duration of tasks for which the sensors never turned OFF was replaced by the average ON duration of all sensors. Values of missing sensors were replaced with NaN. Thus, same sequence of sensors was created for all the participants' data. If a sensor had missing values in the start of the data collection, then these were replaced by the first recorded value for the corresponding sensor. Similarly, if missing values were found at the end of the recording, these were replaced with the last recorded value of the corresponding sensor.

Hence, the longitudinal time series data concentrated within the dataset is visualized (Figure 5.4), and the final features are obtained after cleaning the noisy data. The HPP rate is then computed for each sensor stream, therefore resulting in 52 arrival rates per participant, resulting in a $52 \times N$ feature matrix, where N is the number of participants.

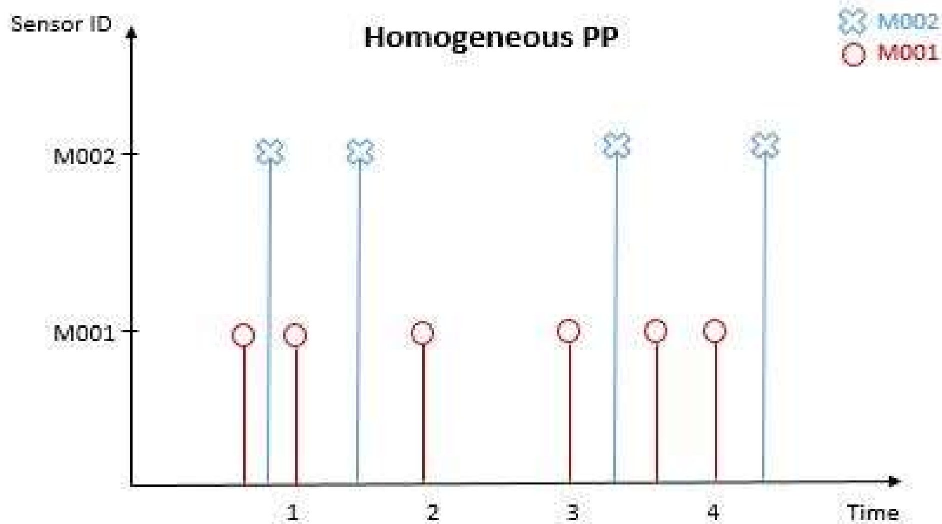

Figure 5.4: Schematic representation of homogeneous Poisson process (HPP) based on the time that each sensor turned on or off.

These features resulting by the HPP model comprise the input to a machine learning algorithm that conducts two sets of binary classification experiments. The first set of experiments focuses on classifying between 5 different classes: dementia, MCI, middle age, young-old, old-old, and younger adult, resulting in 15 binary classification experiments. The second set of experiments focuses on classifying between patients with dementia and healthy adults (i.e., middle age, young-old, old-old, and younger adult), as well as patients with MCI and healthy adults (i.e., middle age, young-old, old-old, and younger adult). A logistic regression classifier is used and a K-fold cross-validation (K = 5) is carried out for evaluating the machine learning models. Since each participant corresponds to only one sample of data, there is no leakage of information from the same participant between training and testing. The results obtained from the machine learning model with the 52 HPP features are evaluated by computing the imbalanced accuracy, balanced accuracy, and F1-scores for each class.

Imbalanced Accuracy = No. of classified individuals/ No. of samples

Balanced Accuracy = No. of accurately classified individuals/ No. of samples

Further, the sensor-based features extracted from HPP and the score-based features obtained from expert assessment are combined, and 15 binary classification tasks are combined in a total set of 63 features. This combined feature set is evaluated using a logistic regression classifier and a K-fold cross-validation, similarly as above.

5.2.2. Sensor-based feature design with non-homogeneous Poisson Process (NHPP)

A non-homogenous PP (NHPP) is used to model the time arrival of sensor events with an arrival rate $\lambda(t)$ which varies with time t. We assume that each of the tasks that participants are instructed to conduct during the data collection depicts distinct patterns in the way sensors are turned ON, therefore the sequence of sensor ON events will depict different arrival rates across tasks (Figure 5.5). For this reason, the overall arrival rate $\lambda(t)$ of the NHPP changes across each task and is defined as follows:

$$\lambda(t) = \begin{cases} \lambda_1, & \text{for Task 1} \\ \lambda_2, & \text{for Task 2} \\ \lambda_3, & \text{for Task 3} \\ & \quad \cdots \\ \lambda_{24}, & \text{for Task 24} \end{cases}$$

Arrival rates for 24 tasks:

$$\lambda(t_1) = \text{Count (Sensor turns ON)}/\ t_1$$

……….

$$\lambda(t_{24}) = \text{Count (Sensor turns ON)}/\ t_{24}$$

Since we have a total of 52 sensors, the above formulation will yield a total of $52 \times 24 = 1248$ arrival rate features per participant. The arrival rate for each sensor and task is calculated by computing the mean of sensor arrival occurrences for a sensor being ON per each sensor, divided by the duration of sensor data collection for each activity performed by a participant. The features derived by the NHPP model are further evaluated through a binary classification experiment that differentiates between: (1) cognitively impaired adults, including patients with MCI or dementia; and (2) healthy adults, including middle age, young-old, old-old, and younger adults.

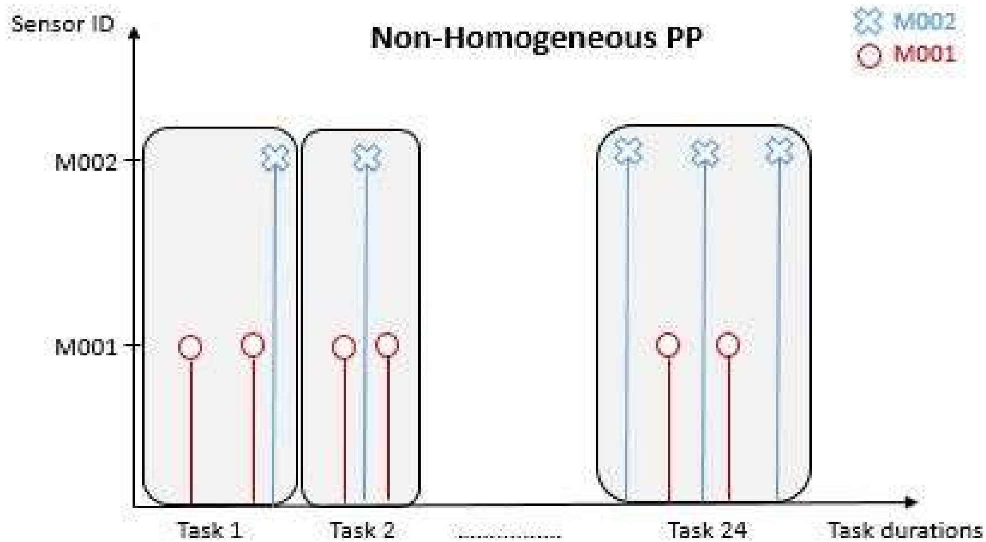

Figure 5.5: Schematic representation of non-homogeneous Poisson process (NHPP) based on the time that each sensor turned on or off.

5.2.3. Reducing data dimensionality using PCA

Due to the large dimensionality of NHPP features, PCA is implemented to reduce their dimensionality to 50 features (Figure 5.6), a number which was found to preserve a large portion of the data variability and also provide good performance. Binary classification experiments are performed with these features by utilizing a supervised logistic regression classifier and a K-fold cross validation (K = 5) to evaluate the machine learning models. The results of these sensor-based assessments from 50 features are evaluated by computing the imbalanced and balanced accuracies, and F1-scores for each class.

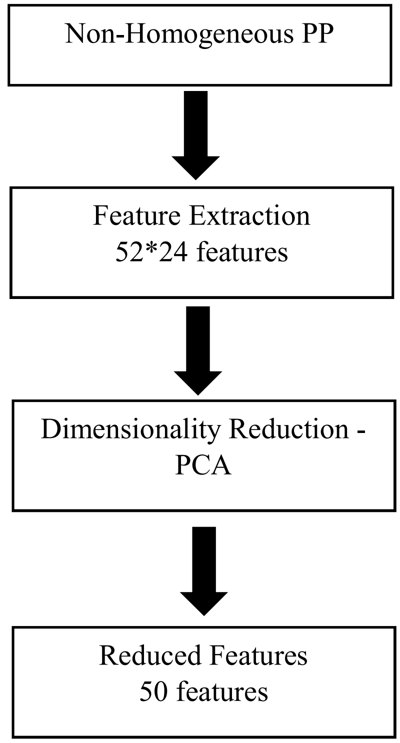

Figure 5.6: Feature engineering process with a non-homogeneous PP

5.2.4. Features from expert-based assessment

Beyond the sensor-based assessments, we further conduct the classification experiments on human-based scores obtained by third-party assessments from annotators. Human-based scores represent ratings of the completeness and correctness of each subtask performed by the participants, including the accuracy score for the day out task (DOT) and the sequencing score based on whether participants sequenced the subtasks correctly in the DOT. These resulted in 11 features extracted from the human score-based assessment data, which comprised the input of binary classification tasks for classifying between healthy and cognitively impaired adults, as well as between all participant categories separately. The results of these score-based assessments are evaluated similarly to the previous experiment by computing the imbalanced and balanced accuracies, as well as the F1-scores per class.

6. RESULTS

In answering the first research question in regards to the ability of the proposed PP models to differentiate between healthy adults and adults with cognitive impairment, we present the results of the corresponding binary classification experiments using the HPP and NHPP features (Tables 1, 2, 3, 4; Figure 6.1). We observe that the overall feasibility of recognizing dementia from healthy adults based on the HPP (Table 3) and NHPP (Table 4) features is higher than the corresponding accuracy of classifying between MCI and healthy adults. This might be due to the fact that MCI is more related to early stages of cognitive impairment compared to dementia, therefore the corresponding activity patterns of patients with MCI might not be significantly different compared to the ones from healthy adults. We further note that the proposed approach performs well in differentiating between dementia and MCI for HPP, achieving 73% balanced classification accuracy between the two classes (Table 1). This result is significantly higher than the chance balanced accuracy (50%) for the same binary classification task, and indicates the feasibility of differentiating between these two populations based on the sensor-based features. On the contrary, the classifier classifies MCI and old-old with a balanced accuracy of 54% which is closer to the 50% chance balanced accuracy, thereby indicating a probably less distinction between these two classes with sensor features. This means that the classes MCI and old-old have similar sensor patterns, making it difficult for the classifier to distinguish between the two.

We also observe that the NHPP features provide on average improved performance compared to the HPP features (Tables 1, 2), signifying the usefulness of incorporating additional contextual information of the tasks' start and end times in modeling the sensor-based data. We further see similar results when the classes of healthy adults are combined and differentiated from the patients with dementia or MCI (Tables 3, 4; Figure 6.1). Since dementia is more severe than MCI, its behavior as registered in the sensor measurements will depict larger differences from the healthy group, compared to the differences between healthy adults and adults with MCI, thus, giving better results (i.e. higher balanced accuracies for individual dementia classifications as compared to individual MCI classifications in both HPP and NHPPs) (Tables 1, 2). The chance accuracy as shown in all the tables reflects the percentage of majority classifier of the states.

Table 1. Binary classification results with sensor-based features using homogeneous Poisson process (HPP).

Class 1	Class 2	Chance Accuracy	Imbalanced Accuracy	Balanced Accuracy	F1-Score of Class1	F1-Score of Class 2
Dementia	MCI	0.62	0.79	0.73	0.65	0.83
	Younger Adult	0.68	0.75	0.75	0.63	0.81
	Middle Age	0.51	0.77	0.76	0.76	0.76
	Young-Old	0.69	0.82	0.78	0.70	0.88
	Old-Old	0.55	0.76	0.76	0.71	0.80
MCI	Younger Adult	0.57	0.70	0.70	0.61	0.76
	Middle Age	0.61	0.71	0.70	0.76	0.60
	Young-Old	0.58	0.62	0.59	0.48	0.70
	Old-Old	0.57	0.55	0.54	0.62	0.44

Table 2. Binary classification results with sensor-based features using non-homogeneous Poisson process (NHPP).

Class 1	Class 2	Chance Accuracy	Imbalanced Accuracy	Balanced Accuracy	F1-Score of Class1	F1-Score of Class 2
Dementia	MCI	0.62	0.78	0.76	0.68	0.82
	Younger Adult	0.68	0.80	0.82	0.69	0.83
	Middle Age	0.51	0.82	0.82	0.83	0.80
	Young-Old	0.69	0.87	0.86	0.79	0.91
	Old-Old	0.55	0.84	0.84	0.81	0.85
MCI	Younger Adult	0.57	0.73	0.71	0.65	0.77
	Middle Age	0.61	0.62	0.64	0.68	0.53
	Young-Old	0.58	0.56	0.57	0.48	0.62
	Old-Old	0.57	0.53	0.52	0.62	0.40

Table 3. Binary classification results with sensor-based features using Homogeneous Poisson Process (HPP) when combining all healthy adults.

Class 1	Class 2	Chance Accuracy	Imbalanced Accuracy	Balanced Accuracy	F1-Score of Class1	F1-Score of Class 2
Dementia	Healthy Adults	0.87	0.87	0.54	0.15	0.93
MCI	Healthy Adults	0.80	0.80	0.51	0.06	0.89

Table 4. Binary classification results with sensor-based features using Non-Homogeneous Poisson Process (NHPP) when combining all healthy adults.

Class 1	Class 2	Chance Accuracy	Imbalanced Accuracy	Balanced Accuracy	F1-Score of Class1	F1-Score of Class 2
Dementia	Healthy Adults	0.87	0.90	0.69	0.43	0.94
MCI	Healthy Adults	0.80	0.76	0.60	0.24	0.85

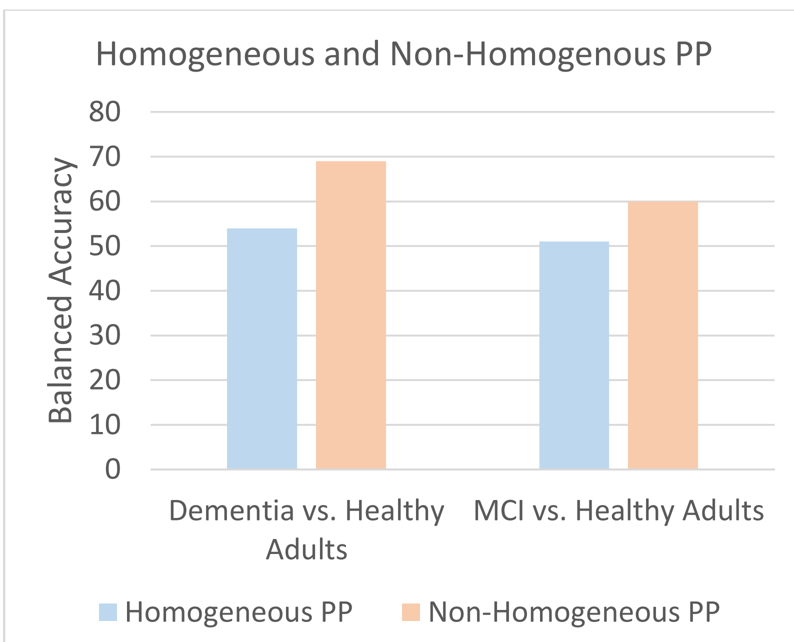

Figure 6.1: Comparing the binary classification results with sensor-based features using Homogeneous Poisson Process (HPP) features when combining all healthy adults.

We further attempt to answer the second research question on whether the order of subtasks within a given task affects the estimation of cognitive impairment. Our results indicate that the order of tasks affects the cognitive impairment recognition in certain cases. For example, the classification accuracy between healthy and cognitively impaired adults decreases for the interwoven uncued tasks compared to the cued and uncued tasks (Tables 5, 6, 7; Figure 6.2). This can be potentially attributed to the unstructured nature of the interwoven uncued tasks, which are part of participants' activities to plan a day out of the house (i.e., DOT task).

Table 5. Binary classification results with sensor-based features using non-homogeneous Poisson process (NHPP) on uncued tasks

Class 1	Class 2	Chance Accuracy	Imbalanced Accuracy	Balanced Accuracy	F1-Score of Class1	F1-Score of Class 2
Dementia	Healthy Adults	0.87	0.90	0.66	0.43	0.95
MCI	Healthy Adults	0.80	0.76	0.57	0.29	0.86

Table 6. Binary classification results with sensor-based features using non-homogeneous Poisson process (NHPP) on cued tasks

Class 1	Class 2	Chance Accuracy	Imbalanced Accuracy	Balanced Accuracy	F1-Score of Class1	F1-Score of Class 2
Dementia	Healthy Adults	0.87	0.88	0.63	0.33	0.93
MCI	Healthy Adults	0.80	0.75	0.55	0.21	0.85

Table 7. Binary classification results with sensor-based features using non-homogeneous Poisson process (NHPP) on interwoven uncued tasks

Class 1	Class 2	Chance Accuracy	Imbalanced Accuracy	Balanced Accuracy	F1-Score of Class1	F1-Score of Class 2
Dementia	Healthy Adults	0.87	0.87	0.50	0.00	0.93
MCI	Healthy Adults	0.80	0.78	0.53	0.18	0.87

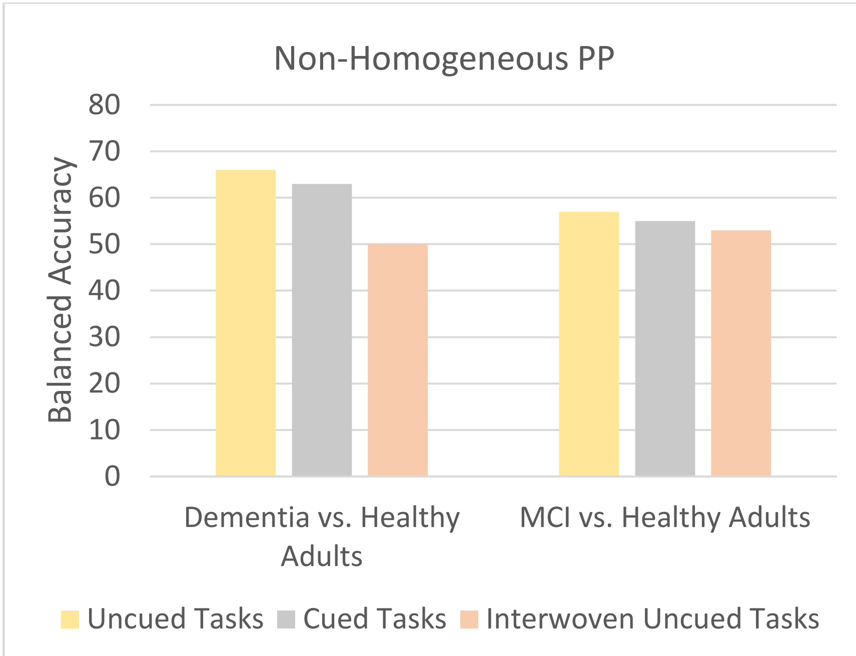

Figure 6.2: Comparing the classification results on activities with non-homogeneous PP.

Finally, in answering the third research question on whether the expert-based assessment can complement the sensor-based measures, we report the results of the classification models whose input is each of the two modalities separately, as well as their combination. We observe that in the majority of cases, the classification between dementia and healthy adults is better using the sensor-based measures, when compared to human-based scores assessment (Tables 1, 8). However, the classification task between adults with dementia and middle age adults (Tables 1, 8), as well as between adults with MCI and healthy adults (Tables 3, 4), was more successful when human/expert-based scores were used. The combination of sensor-based scores and expert scores more accurately classifies dementia vs healthy adults as compared to the individual assessments, except dementia vs middle age which has still efficient results with human-based assessment (Table 9). Similarly, we observe that when the sensor-based assessment using the NHPP features provides improved performance compared to the expert-based assessment measures when the classes of healthy adults are combined altogether (Tables 3, 4, 10; Figure 6.3).

Table 8. Binary classification results with expert-based features using homogeneous PP (HPP).

Class 1	Class 2	Chance Accuracy	Imbalanced Accuracy	Balanced Accuracy	F1-Score of Class1	F1-Score of Class 2
Dementia	MCI	0.62	0.62	0.56	0.32	0.73
	Younger Adult	0.68	0.80	0.74	0.59	0.86
	Middle Age	0.51	0.88	0.87	0.88	0.86
	Young-Old	0.69	0.79	0.68	0.52	0.86
	Old-Old	0.55	0.66	0.66	0.55	0.73
MCI	Younger Adult	0.57	0.82	0.80	0.76	0.85
	Middle Age	0.61	0.70	0.66	0.77	0.54
	Young-Old	0.58	0.64	0.62	0.47	0.72
	Old-Old	0.57	0.66	0.63	0.74	0.50

Table 9. Binary classification results with combined sensor-based using homogeneous Poisson process (HPP) and expert-based features.

Class 1	Class 2	Chance Accuracy	Imbalanced Accuracy	Balanced Accuracy	F1-Score of Class1	F1-Score of Class 2
Dementia	MCI	0.62	0.82	0.79	0.73	0.86
	Younger Adult	0.68	0.82	0.77	0.69	0.86
	Middle Age	0.51	0.74	0.75	0.72	0.73
	Young-Old	0.69	0.84	0.77	0.69	0.89
	Old-Old	0.55	0.75	0.74	0.70	0.79
MCI	Younger Adult	0.57	0.72	0.71	0.61	0.77
	Middle Age	0.61	0.70	0.68	0.75	0.59
	Young-Old	0.58	0.60	0.58	0.47	0.67
	Old-Old	0.57	0.58	0.56	0.68	0.41

Table 10. Binary classification results with combined sensor-based using homogeneous Poisson process (HPP) and expert-based features when combining all healthy adults

Class 1	Class 2	Chance Accuracy	Imbalanced Accuracy	Balanced Accuracy	F1-Score of Class1	F1-Score of Class 2
Dementia	Healthy Adults	0.87	0.87	0.50	0.00	0.93
MCI	Healthy Adults	0.80	0.81	0.56	0.18	0.89

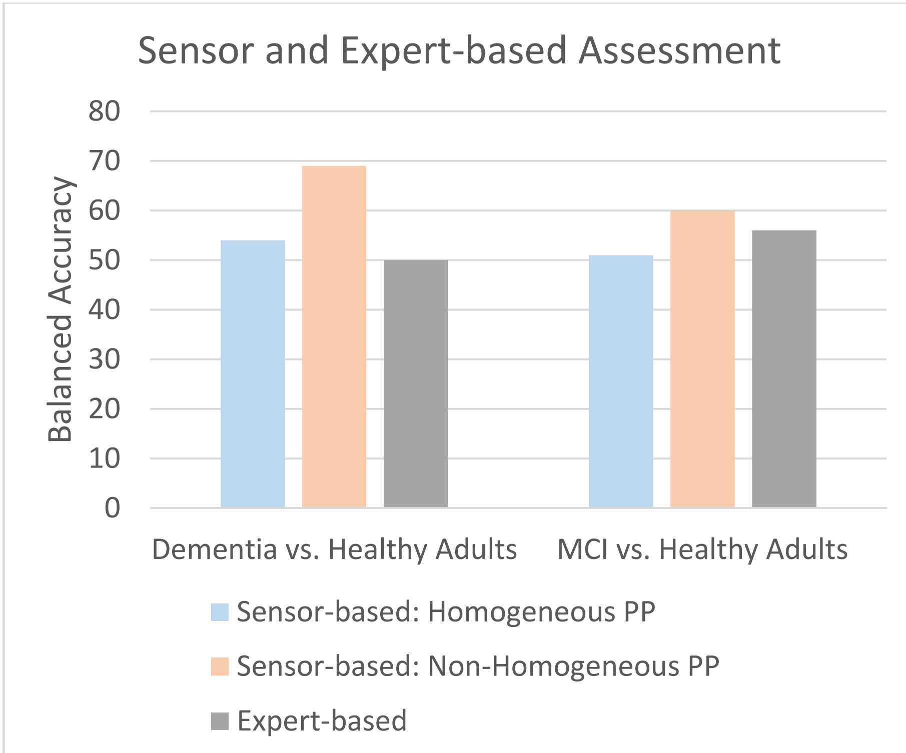

Figure 6.3: Comparing the classification results of sensor assessment vs. expert-based assessment

A decision tree classifier is used for feature selection to compute the most informative features in the classification experiments of dementia vs. healthy adults (Figure 6.4) and MCI vs. healthy adults (Figure 6.5). The classification accuracy of the two decision trees using a decision tree classifier for the classification experiments is reported in Table 11. The data description of the sensor layout as available in the dataset is provided in Figure 6.6. It is observed (Figure 6.4) that the sensors M017, M018, and M003 were selected as part of the first levels of the tree in a decision tree for classifying between dementia and healthy adults. The motion sensors M017 and M018 belonging to the set of kitchen sensors, and M003 sensor which belongs to a living room provide the most informative feature values. Since various function- and leisure-related activities are conducted in the kitchen and in the living room, this finding potentially suggests that sensor-based patterns of the activities conducted in these locations of the house (e.g., meal preparation) might be indicative of cognitive decline. For classification between MCI and healthy adults as observed in Figure 6.5, the features M012, M039, and M008 are the descriptive features among the root and first levels of the decision tree. The motion sensor M012 in the balcony imbibed near the door sensor D002, the sensor M039 near the bathroom, and M008 sensor in the living room are examined as part of first levels of the tree, and provide information regarding the descriptiveness of certain features. This can be justified by the fact that sensors near the bathroom might capture personal hygiene activities, which are activities of daily living deemed highly relevant to independent aging [12].

Table 11. Binary classification results with a decision tree classifier

Class 1	Class 2	Chance Accuracy	Imbalanced Accuracy	Balanced Accuracy	F1-Score of Class1	F1-Score of Class 2
Dementia	Healthy Adults	0.87	0.83	0.64	0.31	0.90
MCI	Healthy Adults	0.80	0.80	0.56	0.22	0.88

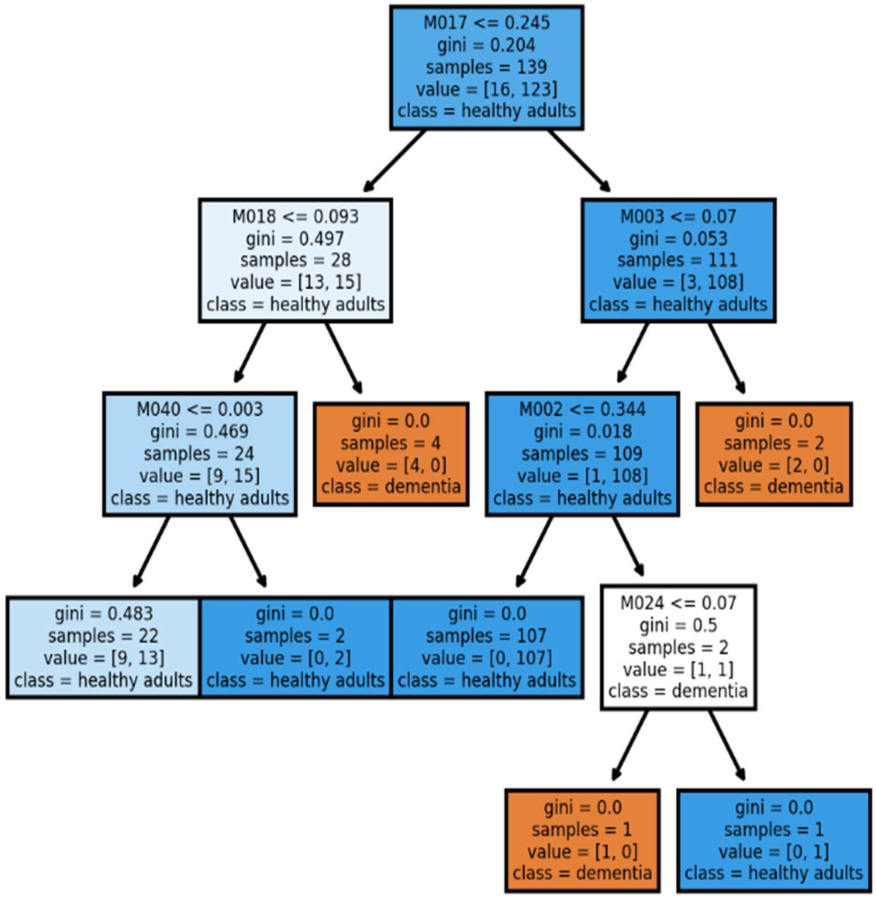

Figure 6.4: Decision Tree for classifying between dementia and healthy adults.

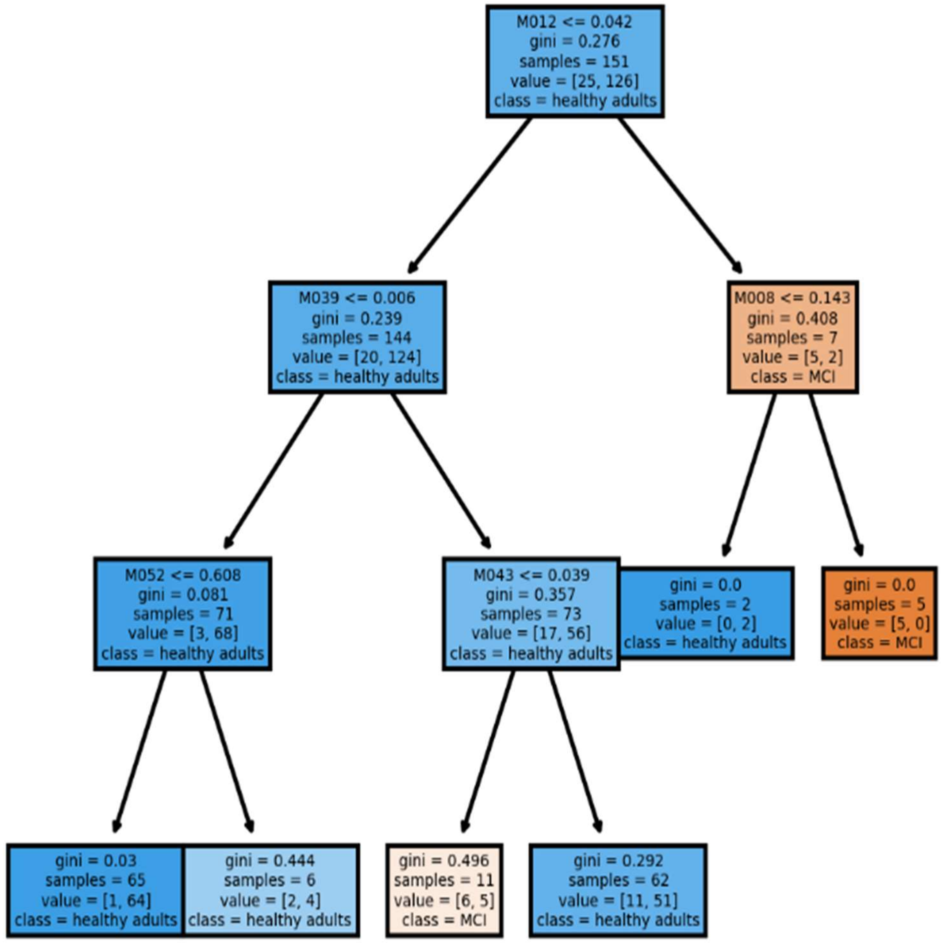

Figure 6.5: Decision tree for classifying between MCI and healthy adults.

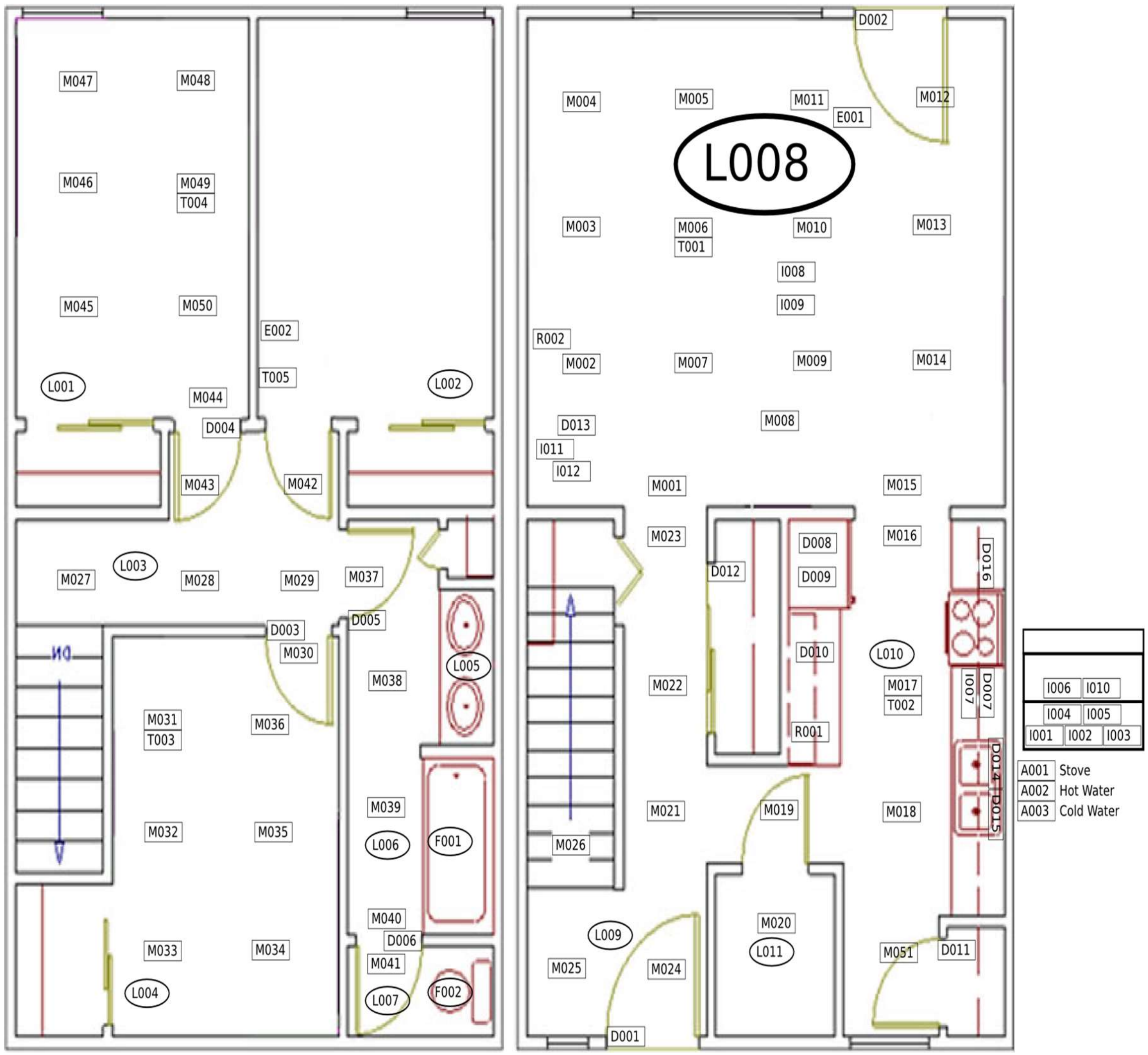

Figure 6.6: Sensor Layout of the cognitive assessment dataset [31].

7. DISCUSSION

The proposed work used a PP for modeling sensor events, which comprises a novel approach of sensor-based assessment. We implemented and compared both HPP and NHPP models, with the NHPP integrating contextual information for the task of interest.

To summarize our findings, our research was able to leverage moment-to-moment sensor-based measures to detect cognitive impairment, thus, answering our research question of PP models having the ability to model subtle temporal changes within sensor data. The non-homogeneous PP measures provide more accurate detection of cognitive impairment compared to homogeneous PP. Our findings further concluded that the order of the task can also affect the ability of the models to detect cognitive impairment with the proposed algorithm performing worse in unstructured compared to structured tasks. It was observed that PP models complement expert-based assessment and provide better classification results for the purpose of detecting cognitive impairment.

Previous works [14] have indicated the ability of using ubiquitous computing technologies in smart homes to monitor complex everyday functions for automating assessment of daily activities. This work measured the performance of machine learning classifiers such as support vector machines (SVMs), neural networks, and the naive Bayes classifier on the supervised classification of assessing the quality of a target task. In this work, the authors focused on a single complex activity (i.e. DOT) and found the correlation between aggregate sensor-based features and task accuracy scores, as provided by human experts, to be statistically significant. Similar works [14] that have tried to classify between healthy and cognitively impaired individuals have used SVMs and neural networks which provide classification accuracies of 80.45 and 79.33, which is slightly better as compared to our results since these rely on more advanced machine learning models and are considering more features, such as the DOT activity features, sequencing features, interruption, and parallelism measures. However, these measurements in the prior works do not consider ambulatory measurements or the moment-to-moment sensor-based signals which can be indicative of an individual's cognitive decline patterns. We are overcoming this by using these moment-to-moment based measures in our PPs. Thus, the feasibility of our work in real-life application of cognitive impairment recognition at early stages is high and can be further explored.

The limitations to our research include data not being captured from completely unconstrained activities of daily living. We are using longitudinal sensor-based time series data for continuous measurement across the time duration of the experiment. However, our data does not include a longitudinal component to measure the month-to-month evolution of cognitive impairment. The rate of the PP within each task is still considered constant, and healthy adults include adults from all ages for classification experiments. The non-homogeneous PP modeled by combining different activity sets being a limitation to our work can be worked upon to improve the classification accuracies of the models. Another limitation being the imbalanced set of classes having different number of samples can be reduced by selecting only the subset of classes including participants who have completed the activities. Since incomplete activities cause a lot of noise in the data, this can be handled to improve the model performance.

8. CONCLUSION AND FUTURE WORK

The proposed approach leverages moment-to-moment sensor-based measures to detect cognitive impairment. PP models can model subtle temporal changes in homogeneous and non-homogeneous PPs. Non-homogeneous PP sensor assessment performs better than expert driven assessment to classify between dementia and MCI vs. healthy adults. PP provide reliable descriptors of cognitive impairments compared to aggregate time series, and reliably models fine-grain variations in time-series data. Sensor-based assessment complements expert-based assessment by providing better classification results. Thus, by designing and formulating a PP model, this research study shows the potential of revolutionizing the way traditional clinical assessment is performed and models subtle temporal changes by leveraging moment-to-moment sensor data. This allows to use the granularities of data on a sensor-based time series, and reliably model the variations in data and patterns observed by integrating machine learning methodologies with PPs. Thus, this research has the potential to detect the early onset of cognitive impairment in elderly adults.

As part of the future work, additional sensor modalities of data can further be added to the experiments on different activities, such as appliance usage. The PP models can be designed with time-dependent arrival rate within each task, this more advanced models can be used in which the shape of rate of PP is learned by the data. The data can be modeled using further advanced computational models and other machine learning methodologies, such as hidden Markov models and support vector machines, and combined with the PPs to compare and contrast the various learning algorithms. The incomplete and complete activity sets can further be considered to reduce class imbalance and providing more descriptive data by only considering the individuals who complete their day-to-day activities as instructed. The activity sets of uncued, cued, and interwoven uncued can be further modeled for the complete and incomplete activities, and their differences in the sequence of activities performed. In order to translate findings from this work in practical applications, it is also necessary to explore the feasibility of the proposed PP measures between healthy adults of older age and adults with cognitive impairment.

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