Remote Monitor System for Alzheimer Disease

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Abstract. Health Remote Monitoring Systems (HRMS) offer the ability to address health-care human resource concerns. In developing nations, where pervasive mobile networks and device access are linking people like never before, HRMS are of special relevance. A fundamental aim of this research work is the realization of technological-based solution to triage and follow-up people living with dementias so as to reduce pressure on busy staff while doing this from home so as to avoid all unnecessary visits to hospital facilities, increasingly perceived as dangerous due to COVID-19 but also raising nosocomial infections, raising alerts for abnormal values. Sensing approaches are complemented by advanced predictive models based on Machine Learning (ML) and Artificial Intelligence (AI), thus being able to explore novel ways of demonstrating patient-centered predictive measures. Low-cost IoT devices composing a network of sensors and actuators aggregated to create a digital experience that will be used and exposure to people to simultaneously conduct several tests and obtain health data that can allow screening of early onset dementia and to aid in the follow-up of selected cases. The best ML for predicting AD was logistic regression with an accuracy of 86.9%. This application as demonstrated to be essential for caregivers once they can monitor multiple patients in real-time and actuate when abnormal values occur.

Keywords: Alzheimer Disease, Dementia, Prevention, Machine Learning, Artificial Intelligence, Health Remote Monitoring Systems, Data Analytics, IoT.

1 Introduction

Dementia is an increasing problem in modern aging societies worldwide, and particularly in medium income countries like Portugal with a frailer social and health care systems, with a high burden of disease and scoring as the fastest aging society in Europe [1]. Dementia poses multiple challenges such as the optimization of current processes for triaging, evaluating, and monitoring. Specialist skills and resources are limited and cannot scale to meet demand. Alzheimer disease (AD) is the most common type of dementia and therefore most of previous studies in the last years were performed in an AD context [2].

The costs of healthcare and long-term care for individuals with dementia are substantial [3]. The number of people living with dementia in the EU27 is estimated to be

7,853,705 and it is one major cost [4]. Even more, on 18th of February 2020, Alzheimer Europe presented a new compelling report at the European Parliament with findings on the raising prevalence rates for dementia in Europe, as one significant cause of health costs and struggling with staff storage [4].

The number of people living with the condition is set to double by 2050 according to the new Alzheimer Europe report [4], which will only place greater pressure on care and support services unless better ways of treating and preventing dementia are identified. Dementia is a major social and health concern, with increasing prevalence [5]. Having said this, this topic becomes relevant as the HRMS allow the collection of parameters on the patients in order to understand the evolution and generating alerts for atypical behaviors requiring intervention, thus saving on staff costs, which, as said before, are high. Care processes digitalization, holistic sensing supported by the Internet of Things (IoT) system and Artificial Intelligent (AI) tools are being actively applied to the health sector giving rise to the smart health paradigm [6]. This emerging market was evaluated in USD for 143.6 billion in 2019, and it has an estimated annual growth rate of 16.2% between 2020 and 2027 [7]. A Scopus search showed that were 1066 publications between 2010 and 2020 regarding Smart Health, and by **Erro! A origem da referência não foi encontrada.** we can see its exponential growth.

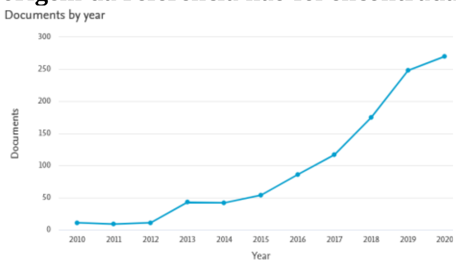

Fig. 1. Number of Studies per Year

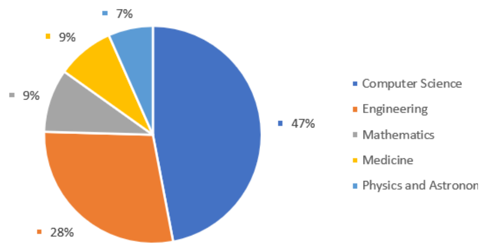

Fig. 2. Topics by Subject Area

On **Fig. 2** we can see the top 5 subject areas of study where it is noticeable that the area with more impact is Computer Science.

In this transformative process, the Health Remote Monitoring Systems (HRMS) are recognized as an emerging technology, using sensors and wearable devices to collect patient's data. However, to present clinical value these systems have to be associated with clear clinical processes and therapeutics, so the measurements could be linked with actual patient care.

The implementation of HRMS is based on a health related IoT system that incorporates, stores and communicates the information gathered by a set of wearable devices and sensors. The computer senses and records the daily physiological data of the patient by means of a data processing device, data transition, data archive, data analytics and AI [8]. The HRMS developed is based on two main pillars and aims to: (1) develop a system to identify disease development and disease prevention through the use of remote sensors (2) develop prediction models built by Artificial Intelligence implemented on top of the processed data, which would allow the classification of patients, discovering behavioral patterns. Through this process, alerts by email are generated when an abnormality is registered in order to help with disease prevention. Therefore, HRMS enables a data-intensive approach, in which a large amount of health data is generated, stored and available for data mining, allowing for the generation of useful knowledge.

A quite recent review [9] emphasizes the relevance of taking comorbidity burden into account when investigating dementia progression. Therefore, this research work takes inspiration from the ICOPE guidelines [10] to offer an integrated and person-centered approach to AD. This research work demonstrates that simple tasks with a small IoT device can be interpreted by a trained Artificial Intelligence tool, in order to automatically and remotely determine health and disease related aspects, the progress of dementia, and make outcome predictions, in order to support health practitioners and reducing their workload.

2 Literature Review

A systematic literature review was made by following PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analysis) Methodology [11], and with the research question "What is the state of the art on Healthcare Remote Monitoring Systems usage in the prevention of patients suffering from Alzheimer's disease?".

Databases searched were *Scopus* and *Web of Science Core Collection* (WoSCC) and the research was conducted through October 26th, 2021; all the results had to be articles, published between 2011-2021 and written in English. The documents collected were only about Computer Science, Medicine, Engineering and Health Professions. The search strategy was based on one query made with different focuses of research. This method allowed for the observation of the number of articles existing in both databases, considering the concept and context, and population under study.

This method allowed for the observation of the number of articles existing in both databases, considering the concept and context, and population under study. It is important to note that the values corresponding to the queries still have duplicate articles.

For this review only articles were considered. Grey literature, reviews, conference papers, workshops, books, and editorials were excluded, as well as works not related to the domain. All the databases were searched systematically regarding the published work related with the concept "*Health Remote Monitoring Systems*" or "*Smart Health*", the target population "*Alzheimer's Disease*" and within a "*Prevention*" context of the study. After performing a manual process, towards the identification of significant subjects on their research questions, identifying the outcomes and removing the duplicates, 17 documents were obtained.

Considering the goals of this article is to identify the use of HRMS on Alzheimer, a list of the main topics discussed on each of the reviewed articles are described on **Fig. 3**, where it is noticeable the focus on the prevention of Alzheimer by resorting to the use of wearables.

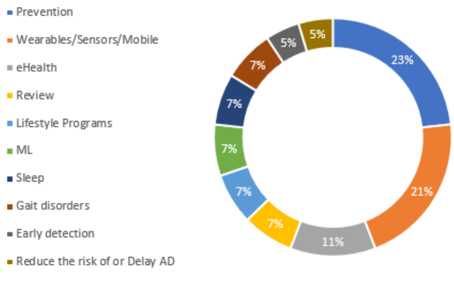

Fig. 3. Main Topics from the Literature review

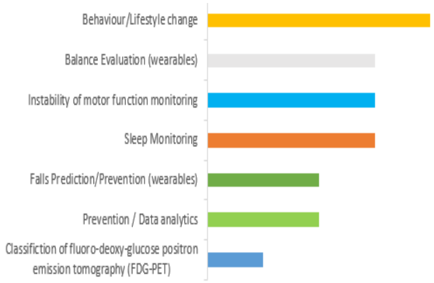

Fig. 4. Main objectives of the reviewed

After assessing all the included studies, it was possible to acknowledge the growing of the remote monitoring systems across the globe in the recent years. Considering the goals of this article is to identify the use of HRMS, a list of the main objectives of each system described in the reviewed articles was performed (**Erro! A origem da referência não foi encontrada.**).

From the most popular topic, authors from [12] acknowledge the growing number of studies on this matter. Brid, M. et al [13] present us that e-health tools to improve dietary behavior lacks credibility. From [14] authors don't present any results, nevertheless, on study [15] arrive to the conclusion that there is no positive association between physical activity and working memory. On study [16] no results about the impact of the Web-mobile application are presented, allowing only that users know the risks if they continue with the same lifestyle habits.

Regarding HRMS, it is secure to merge the topics that are from wearables and from monitoring devices (Balance Evaluation, Instability of motor function monitoring, Sleep Monitoring and Falls Prediction and Prevention). On study [17], the authors by sleep monitoring can track cognitive changes cognitive changes related to pre-clinical Alzheimer Disease, recurring only to wearable biosensor devices. Author of study [18] review the last fifteen years of wireless sensors on neurological disorders, arriving to the conclusion that this devices have been greatly used on the assessment of this disorders, retrieving valuable data. On [19], a device is placed under the patient mattress, to monitor his sleep parameters, in order to characterize sleep disturbances in patients with AD, and arriving to the conclusion that frequent bed leaving is a highly correlated predictor of the duration of dementia. Researchers on [20] describe a noninvasive sensor for patient movement monitoring, identifying patterns that would lead to a fall and predicting them. On [21] the sleep is evaluated using wearables, and this data has been revealed as a significant predictor on identifying AD and the patient's health status. Lastly, on study [22], by using home-based technologies combined with teleassistance service in elderly persons with Alzheimer's disease the number of incidents has suffered a considerable reduction.

3 Methods and Materials

Recent recommendations for health and care workers point out that it is dramatically necessary to develop and carry out a person-centered integrated care for older people

(ICOPE) in which an integrated and person-centered approach is required as declines in intrinsic capacity are interrelated.

Considering current state of art, this research work handles several technical challenges to creating an AI based solution for this challenge in computer science: 1) Fusion of different data sources in a big data for dementia; 2) Successfully training ML algorithm to classify the risk; and 3) Present meaningful and useful data to decision makers to support improved interventions.

Our method is complemented by advanced predictive models based on ML and AI, thus being able to explore novel ways of demonstrating person-centered predictive measures. AI provides a better decision-making in the adjustment of the parameters of each evaluation process of the disease so that we achieve a user-centered approach but also a generalization to other patients. Our proposed method bases on different technological advancements to complement and to reorient current early diagnosis, prevention, and intervention of AD, including the advantage to be prepared for evaluating the progression of the AD condition through time. These technological advancements have a significant impact in terms of: Personalized early-risk diagnosis, prevention, and evaluation of AD through (1) estimating the probability of suffering AD, (2) achieving an earlier and better intervention, and (3) improving the quality of life of the citizens.

Creation of pathways to manage cognitive (and related) decline by (1) getting early warning signs of likely deterioration for citizens and professionals, and (2) increasing health literacy in the interpretation of symptoms and effects.

3.1 Data collected

For the analysis purpose, it was collected data from different sensors, where a prototype was developed joining different sensos in just one device (see **Fig. 5**).

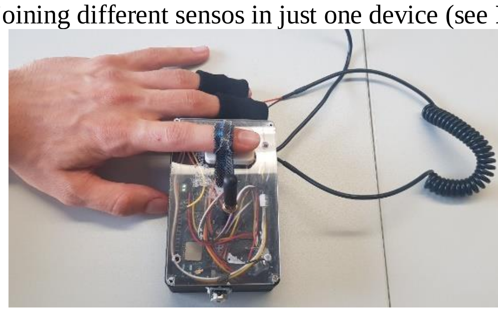

Fig. 5. Prototype of the IoT sensor with 4 types of health measurements

This device is a sensor prototype developed for the collection of health data from the test subjects, collecting 4 biometric parameters, including heart rate, arterial oxygen, body temperature and Galvanic Skin Response (GSR) The sensor prototype consists of two components: the microcontroller with wireless communication and sensors for biometric data collection.

3.2 Big Data Analytics and Machine Learning

The multiple types of data within this research work are gathered, stored, and processed. The data was collected in the time frame between 2 and 3 weeks per test subject and with an average of over 3 measurements per day, preferably between the morning, afternoon, and evening before bedtime. The prototype used not only sends raw data, but instead sends the data already structured and pre-processed, this is the same to say, that if a given value appears to be complete nonsense the microcontroller won't send that value. For this reason, we will make our data immediately available in our database, avoiding unnecessary operations of ETL and data treatments.
In addition to the IoT sensor, a cloud server is part of the intelligent system for automatic data processing functions and standardizing the collected data and storing it in a MariaDB database. This server has Node RED [23] mechanism that will analyze all the sensor data, processing it and applying the machine learning algorithms, generating the dashboards and respective alerts when necessary, as depicted on **Fig. 7**. With the data stored (without personal information) of the test subjects, it can be used to develop solutions using AI and obtain relevant information to improve the quality of life and care of patients with Alzheimer's disease.

For the predictive analysis, we have implemented a Logistic Regression Algorithm on top of the data collected for 6 months from a group of 15 patients where 6 of these patients suffer from AD. The data was collected from the sensor depicted on **Fig. 5**, retrieving the data from sensors of the heart rate, oximeter, body temperature and GSR measurement. A dataset from the last 6 months was compiled with a classification (dependent) variable (where 1 means the patient suffers from AD and 0 means the patient does not suffer from AD). We have applied different ML algorithms, where Logistic Regression as given better results, achieving 86,89% of accuracy when compared to K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Naïve Bayes, Decision Trees amd Random Forest, as depicted on **Fig. 6**.

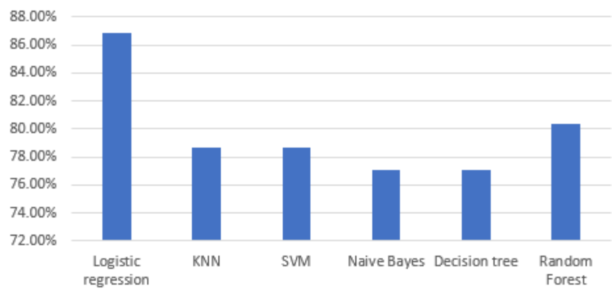

Fig. 6. Algorithm performance

To test our model, we have used the data from for different patients selected, where in Table 1 we have a summary of the data collected by using the prototype sensor.

3.3 Decision Support & Visualization

The vast data acquired from all the sensors is analyzed and organized visually so health literacy can be increased by providing manageable and understandable personal data to the patient and giving advances in professionals' proficiency in interpretation.

The definition of Key Performance Indicators (KPIs) for dementia follow-up we have defined the data stated previously, being the variables used on this research work: heart rate, arterial oxygen, arterial oxygen, temperature, GSR.

To increase the health literacy, dashboards were designed and implemented, recurring to the set of KPIs extracted from the values produced by the sensors, being this presented to the different users in an understandable way that aids in their tasks and decisions. In this sense, two separate sets of dashboards were implemented. The first set of dashboards implemented focus on improving the proficiency of clinicians in early-risk diagnosis dashboards. The second set of dashboards focus on health literacy dashboards, aiming to understand existing risk factors and the conditions of patients in order to improve health-related decisions. To this aim, this task includes the output of predictive systems that aid in the diagnosis based on data collected in the past. The design and implementation of dashboards for advancing proficiency in data-oriented health services will use the KPIs already identified, being this presented to the different users in an understandable way, complemented with additional information that aids in their tasks and decisions.

Table 1. Summary of biometric data collected per test subject.

	Test subject 1	Test subject 2	Test subject 3	Test subject 4
Age Rate	~65	~70	~55	~45
Heart Rate -max/min (bpm)	132/75	128/70	140/83	149/90
daily average (bpm)	100	84	93	88
Arterial Oxygen				
daily average (%)	95	89	98	98
Temperature				
daily average (ºC)	35.7	36.5	36.9	37.2
GSR daily average (ohm)	512	889	684	856
Feeling	Happiness	Grief	Normal	Anxiety

As can be seen in **Fig. 7**, **Fig. 8** and **Fig. 9**, the user dashboard shows the history of the data collected over the test periods, as well as the individual sensor measurements and an alert system.

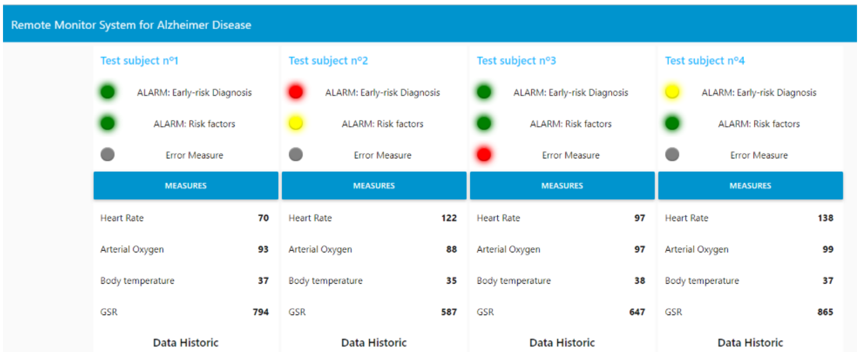

Fig. 7. User Dashboard implemented with data collected by the sensor and alarms

The alarm system consists of three prompts, Error Measure, Risk factors and Early-risk Diagnosis. When the system detects a failure of the sensor to collect the data or an invalid value it gives the Error Measure alert and turns red. In the case of Risk factor the alarm information and color indicates if the collected values present risk factors for the health of the test subject, where green means "low risk", yellow means "some risk" and red alerts for health risks. In the Early-risk diagnosis alarm, the result of the analysis of the data collected from the test subject is indicated and where the system informs that it has detected a probability of diagnosis of Alzheimer's disease. The Early-risk Diagnosis comes from the ML algorithm, where: 1) Green represents "low risk" (probability of developing AD from 0-49); 2) yellow represents "some risk" (probability of developing AD from 50-70); 3) red represents "high risk" of developing AD. The caregiver, on the dashboard can select the Risks Factors and a Dashboard is presented to him, showing which warning the visaed patient has, see **Fig. 7** and **Fig. 8**.

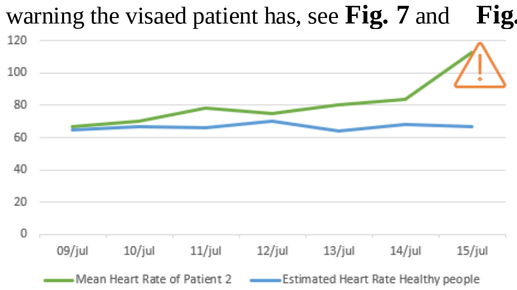

Fig. 8. Dashboard with the KPI requiring attention

When a certain value requires attention, an alert is sent to the caregiver as depicted in **Fig. 9**.

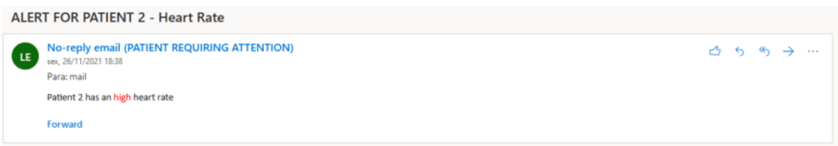

Fig. 9. Notification alert

4 Conclusions

The literature review showed that the topic studied is not yet exhausted, returning 35 papers, and of these 35, only 17 papers met the inclusion criteria. Throughout the literature, we can perceive the wide use of wearables in Alzheimer's prevention, and the most common objective of the eligible studies is lifestyle change. This topic has not proved to be the most relevant in the scientific community, being considered not very credible and is also notable for the lack of results in the studied papers. The use of HRMS is the one that prevails in quantitative terms in the cluster of the different topics. Of these, those within the HRMS are quite concise and with interesting results and impact on patients suffering from AD. From the data, and after the application of ML algorithms, it was realized that the best algorithm to deal with this type of data is the Logistic Regression. With this application, caregivers can keep better track of the patient, also receiving real-time notifications when a certain value to be monitored goes out of the standard. This way, patients are safer, since each caregiver can monitor different patients simultaneously.

Regarding visualizations, we implemented different dashboards adapted according to: (i) the tasks and responsibility assigned to each actor (i.e. the relevant information they should be aware of), (ii) their particular perspective of the ecosystem (i.e. what are they interested in), and (iii) which other actors they interact with (i.e. people with dementia, informal careers, etc.). We intend to complement our solution with wearables and process their signal to extract psychological and physiological information (using edge computing), including IMU (accelerometer/gyroscope), electrodermal activity (EDA) and photoplethysmography (PPG) sensors, among others to be studied. This includes the challenging denoising of the EDA and PPG signals by filtering out the effect of motion artifacts and the ambient variations (light, temperature, humidity). Environmental IoT signal processing using edge computing that communicate with the IoT devices, are able to acquire the streams of raw data that these devices produce to quantify the ambient parameters (lighting, color, temperature, humidity, sound). With this new data, we will enlarge our dataset, therefore the use of dimensionality reduction algorithms can become necessary. Dimensionality reduction seeks and exploits the inherent structure in the data, describing the data using less information, therefore avoiding data (and model) complexity.

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