Geriatric Care Management System Powered by the IoT

Subjects: Nursing
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The digitalisation of geriatric care refers to the use of emerging technologies to manage and provide person-centered care to the elderly by collecting patients' data electronically and using them to streamline the care process, which improves the overall quality, accuracy, and efficiency of healthcare. In many countries, healthcare providers still rely on the manual measurement of bioparameters, inconsistent monitoring, and paper-based care plans to manage and deliver care to elderly patients. This can lead to a number of problems, including incomplete and inaccurate record-keeping, errors, and delays in identifying and resolving health problems.

Keywords: geriatric care ; IoT ; vital parameters ; posture recognition

1. Introduction

Geriatric care is a field of healthcare that focuses on the physical, mental, and social needs of older adults. As people age, they may experience physical, cognitive, and social changes that require special care and support. Geriatric care is based on the specific needs of older adults and aims to improve their health and well-being as well as manage age-related diseases and conditions so that they can maintain their independence, quality of life, and overall comfort. Such care often involves a multidisciplinary approach with care provided by a team of health care professionals, including physicians, nurses, therapists, and social workers, who are trained in gerontology and geriatrics [1][2]. The estimated number of dependent people in need of some form of long-term care in Europe is 30.8 million, and this is expected to increase to 38 million by 2050. Furthermore, the expected shortage of nurses will reach 2.3 million in 2030. By 2080, the population aged over 80 years and older in Europe will have multiplied by 2.5. It should be noted that the majority of dependent patients suffer from Alzheimer's and chronic diseases, such as past myocardial infarction, congestive heart failure, cardiac arrhythmia, renal failure, and chronic pulmonary disease, have an increased risk of mortality in nursing homes [3].

Currently, the main problems are caused by the absence of tools to design automated care plans. The problems identified are related to the lack of digital evidence-based protocols for different situations and the nonadherence to existing protocols by nursing staff. Typically, an individualised nursing care plan is developed for the elderly patient upon admission to meet their needs. This plan is developed based on a thorough assessment of the person's medical history and evidence-based care practices. As elderly individuals reside in nursing homes, it is common for their health to decline, which makes it crucial to monitor their health status while they are there. Thus, caregivers must regularly check important biometric data, such as blood pressure, heart rate, body temperature, and respiratory rate. Collecting and documenting patient vital signs data manually is a relatively slow and therefore inefficient process. Depending on the types of vital signs, it usually takes up to five minutes to assess three to six vital signs [4]. Moreover, this information is usually documented in paper form separately from the nursing care plans, and therefore, the whole process takes up to 13 min per patient [5]. Furthermore, care plans have to be regularly re-evaluated by comparing current and historical health records to look for abnormalities and changes that could have clinical significance. However, biometric data are documented separately from nursing care plans and records of doctors. With such fragmented data sources, the process is human-dependent, highly inefficient, and cumbersome and can take up to 37 min per patient [5][6]. Moreover, in the absence of a systematic approach in geriatric care management, it becomes challenging to quickly capture monitoring data and act on them. This can cause caregivers to miss any unusual changes in the biometric data, leading to delays in administering treatment.

2. The Use of Wearable Devices

Recently, wearable technology has benefited from technological progress, as the size of devices has significantly reduced, while the efficiency of energy consumption has improved simultaneously [7]. In particular, wearable technology can be used for a variety of purposes, ranging from keeping track of physical activity to monitoring clinically important health and safety data. Wearable devices provide real-time monitoring of the wearer's walking speed, respiratory rate, measuring sleep, energy expenditure, blood oxygen and pressure, and other related parameters [8]. Such devices can also be useful tools for people living with heart failure to facilitate exercise and recovery [9][10]. Comparatively, a study demonstrated the strong potential for improvement in healthcare through the use of wearable activity monitors in oncology trials [11]. The use of wearable technology to identify gait characteristics is another intriguing example [12], where lower limb joint angles and stride length were measured simultaneously with a prototype wearable sensor system. The study [13] investigated how a wearable device could help physicians to optimize antiepileptic treatment and prevent patients from sudden unexpected death due to epilepsy. For particular groups of individuals that suffer from chronic disease such as diabetes mellitus, cardiac disease, or chronic obstructive pulmonary disease, wearables may be used to monitor changes in health symptoms during treatment and may contribute to the personalisation of healthcare [14][15][16]. The use of wearables within a group of elderly population brings additional challenges. For example, it is very important to detect falls, which has already become a topic of particular importance in this field. For example, in [17], a framework was proposed for edge computing to detect individual's falls using real-time monitoring by cost-effective wearable sensors. For this purpose, an IoT-based system that makes the use of big data, cloud computing, wireless sensor networks, and smart devices was developed and integrated with an LSTM model, showing very promising results for the detection of falls by elderly people in indoor circumstances. The validity and reliability of wearables have been addressed by many studies focusing on different classes of devices used to measure activity or biometric data [18][19][20][21]. Apparently, there is no consensus among researchers, as findings depend on the manufacturer, device type, and the purpose for which it was used. This is also true because devices are constantly being upgraded to new models, which suggests that their validity and reliability will improve with time.

3. Contactless Measurement of Vital Signs

There are still some concerns regarding the reliability and accuracy of wearables to detect physical activity and evaluate health-related outcomes within elderly individuals, as they are generally designed primarily to collect biometric information during activities of daily living in the general population [22][23][24][25]. First, the ability of older people to recognise the need for wearables and properly use them poses new challenges. Second, the high prevalence of different diseases in this population and the heterogeneity associated with their lifestyle, needs, preferences, and health point to the need for wearable devices that are valid and reliable and that can accurately measure and monitor important signals. Additionally, taking into account the problems associated with time-inefficient work in care homes, contactless monitoring of vital signs may be beneficial for healthcare [26][27][28]. In particular, contactless measurement techniques can be applied to measure the respiratory rate and monitor the heart rate variability, which is one of the fourth most important vital parameters [29]. Monitoring the respiratory rate is useful for the recognition of psychophysiological conditions, the treatment of chronic diseases of the respiratory system, and the recognition of dangerous conditions [30][31]. Combining respiratory rate and heart rate data provides even more useful information on the condition of the cardiovascular system [32][33]. The most promising method of noncontact monitoring of the respiratory process is through infrared and near-infrared cameras [34][35]. An infrared camera is a device that can capture small temperature changes on the surface of an object and/or in the environment. This device can record the temperature fluctuations of airflow from the mouth or nose. Infrared cameras can successfully measure the respiration rate if advanced computer vision algorithms that are insensitive to constantly varying lighting and temperature conditions are applied.

4. Benefits of Computer Vision Techniques

Image recognition is one of the main methods used to determine an individual's pose and activity. The use of pose estimation technology in geriatric care offers several advantages, including the continuous monitoring of patients, early detection of potential health problems, essential data on the patient's movements, and, in particular, the detection of extra situations (e.g., the person is lying on the ground and not moving) [36]. Pose estimation algorithms vary in complexity and accuracy, ranging from simple rule-based algorithms to more complex deep-learning-based algorithms. Simple algorithms may be faster and easier to implement but typically they are not as accurate as more complex ones. Deep-learning-based algorithms, on the other hand, may provide more accurate results but may be more computationally intensive and require large amounts of training data. Comparatively, deep-learning-based methods have shown great potential for improving the accuracy of human posture recognition, for both single individuals [37][38] and multiple individuals [39][40] in images or videos. In particular, methods such as the multisource deep model [41], the position refinement model [42][43], and the stacked hourglass network [44] have demonstrated the effectiveness of deep learning in human posture recognition. These methods use convolutional neural networks to extract features from input images and estimate the positions of human joints. However, the early detection of falls [45][46][47] is one of the most important functions of the geriatric care system as it allows prompt medical assistance to be provided and can prevent further injuries. Human fall detection systems can help to identify when a fall has occurred and alert caregivers or emergency services immediately. Therefore, various types of fall detection and prediction systems suggested in the field not only rely on image recognition techniques [34][48][49] but also employ other information sources, for example, biological factors or signals obtained by wearable devices that are more commonly used for fall risk assessments [50][51]. Although computer vision techniques have been used widely and very successfully in medicine, the monitoring and identification of patients in nursing homes should take into account the fact that image capture devices cannot always be used to track patients (e.g., hygiene rooms) according to privacy and ethical requirements [52][53]. In addition, capturing certain information with cameras may not always be possible due to changes in the environment or, for instance, in cases when the person reappears or is partially obscured by other objects, which poses the additional challenge of re-identifying the same individual. Therefore, it is important to determine which factors may be automatically recorded and tracked over time utilising image processing technology. It is also crucial that the solution is quick. As such, it is essential to carefully assess the trade-off between precision and speed in order to choose a solution that meets the specific requirements of the application.

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