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Boosting Telemedicine Healthcare Assessment Using Internet of Things and Artificial Intelligence for Transforming Alzheimer's Detection

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Abstract

The emergence of Internet-of-Things (IoT)-based telemedicine platforms has initiated a new technological age that enables early detection and treatment for remote patients. This is especially vital for serious conditions like Alzheimer's Disease (AD), which involves decreased memory and cognitive impairment that greatly disrupts everyday functioning, requiring prompt medical intervention. The influx of information from automated systems, originating from many sources, has increased complexity and reduced diagnostic precision. This study enhances Telemedicine Healthcare Assessment by integrating IoT and Artificial Intelligence to advance Alzheimer's Detection (THA-AI-AD). The paper outlines the fundamental principles and key elements of multifaceted sensing data acquisition, the design and execution of medical tracking using an AI platform, robotics-driven multifaceted data sensing and gathering, and the long-term acquisition of physiological signals with high comfort through smart clothing. The study presents an innovative technique for the automated identification of AD using Convolutional Neural Networks (CNN). Consisting of two subsystems, one focused on AD detection with an accuracy of 97.12% using CNN and another for AI-based telemedicine therapy, yielding exceptional outcomes.

Keywords: Telemedicine, Alzheimer's Detection, Healthcare, Convolutional Neural Networks, Artificial Intelligence, Sensing Data Acquisition.

1 INTRODUCTION AND RELATED WORKS

AD is a devastating neurological disorder that impacts millions globally. With the aging global population, the incidence of Alzheimer's Disease is anticipated to rise, imposing a considerable strain on medical systems, caretakers, and society at large. A significant problem for caretakers of AD patients is to offer continuous support and assistance to their family members while preserving their well-being. As AD advances, individuals afflicted by the condition become unwilling to independently manage everyday tasks independently, necessitating heightened care and assistance in the latter stages of the illness (Jadhav et al., 2019).

Friends and family members now provide around 17.9 billion hours of assistance to relatives with AD, leading to a substantial caregiving burden. Caregivers may encounter both emotional and physical challenges, including anxiety, dejection, and exhaustion, which may negatively impact their physical and mental wellness. Consequently, caregivers of individuals with AD need continuous assistance, starting at the point of diagnosis and extending into the latter stages of the illness (Qureshi et al., 2023).

The electronic healthcare system for AD care comprises several interrelated ideas. Telemedicine enables physicians to evaluate and manage patients via remote technological means. E-health uses applications and websites to monitor patients' illnesses and to facilitate communication with healthcare practitioners (Lindauer et al., 2021). Transitioning from online healthcare to physical environments, intelligent technologies allow the creation of houses that adjust to patients' needs. Simultaneously, the IoT (Chokri et al., 2022) collects real-time data from interconnected devices, maintaining continuous surveillance.

The Internet of Medical Things (IoMT) also integrates medical equipment and sensors for ongoing monitoring. To enhance treatment precision, Customized Accessibility Solutions (Le Xin et al., 2021) employs diverse sensor technologies to address the specific requirements of AD patients. These developments together foster development in AD care in distinct and significant ways. All the above models use various sensor technologies to collect patient information. These developments include wearable and ambient detectors, audio monitoring, video detecting, and digital platform functionalities.

Telemedicine services amalgamate medical capabilities to enhance the reach of medical associations, functioning as a telemedicine electronic system for families, neighborhoods, and rehabilitation facilities, with services aimed at nearly the entire population (Chakraborty et al., 2020). Injured individuals in emergencies, maternity cases, infants, older people, disabled individuals, chronic disease sufferers, victims of emergencies, and those in suboptimal health may all serve as desires for service. The application domains encompass examining individual physiological states under critical circumstances, advancing emergency medical care, and enhancing medical standards in remote regions and family healthcare for numerous households, thereby disrupting the current medical service paradigm (Shei et al., 2022).

As technology matures and the need for applications grows, IoT garners heightened interest in the healthcare sector. Recently, the proliferation of portable communication devices has generated significant market potential for the healthcare industry. Nonetheless, there are few effective implementations of IoT technologies that provide health amenities for families and people and offer tailored health care. Health IoT is a significant sector within IoT applications, and the transformation of the medical care model it facilitates will not only advantage the majority of consumers but also advance the healthcare service business (Zhang et al., 2024).

2 PROPOSED METHOD

In recent times, extensive study in sensor technology has propelled the growth of residential health tracking systems (HTS) and facilitated the creation of diverse health tracking gadgets (HTG) that can properly measure and analyze human physiological information for detecting AD in THA. Nonetheless, tension persists among the device's convenience and durability, the nature of physiological information obtained, and the longevity of its battery. This paper presents a typical structure for constructing a cloud-integrated HTS, as illustrated in Figure 1. It emphasizes delivering high Quality of Service (QoS) and Quality of Experience (QoE) through an autonomous robot that gathers ecological facts and people's health data while incorporating cloud computing (CC) technology. HRS has been defined by substantial data volume, diverse data kinds, elevated complexity, and rapid fluctuations. Conventional storage technologies are insufficient to satisfy the requirements for rapid access and effective information processing in HRS for AD. The rapidly advancing CC and big data technologies may address the data management and processing challenges HRS encounters for AD.

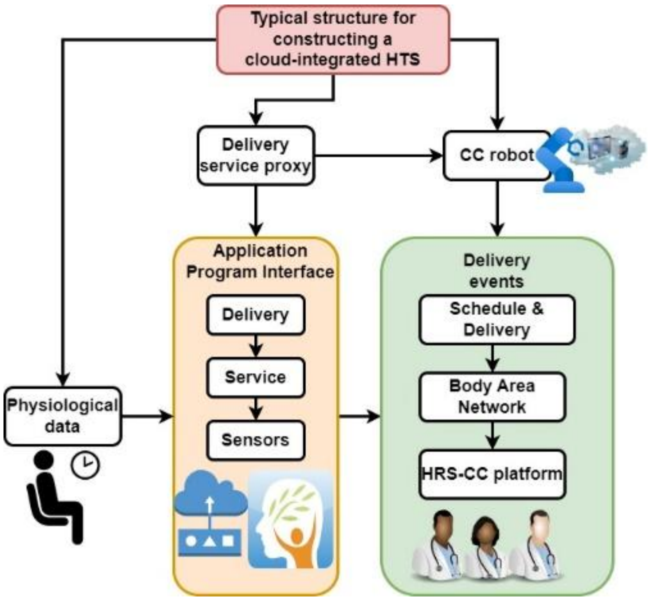

Figure 1: Typical Structure for Constructing a Cloud-Integrated HTS for Detecting AD Using AI in THA

The amalgamation of portable computation, robotics, AI, and CC techniques with HTS would significantly enhance the standard and reliability of HTG. This work proposes an HTS that includes four components: the end-user, portable smart garments, a robot, and a medical cloud service. Human physiological data is gathered using wearable health sensors, which then transmit the obtained information to a distant CC platform via a robot or HTG. The robot's function inside the framework includes ecological sensing, data storage, and transmission, facilitating interaction between people and machines, and incorporating mobile communication components. The CC facilitates the storage of extensive medical information, the development of health designs, and the provision of tailored medical treatments via the examination and forecasting of medical big data, among other tasks.

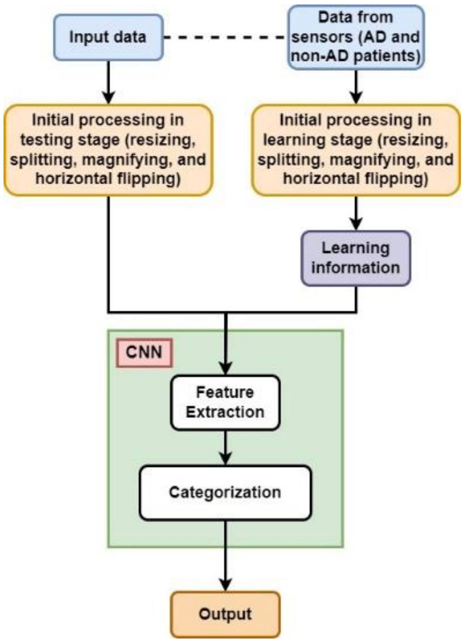

Figure 2: Block Diagram Representing AD Detection Method Using CNN

The method consists of two primary phases: (I) an initial processing and test stage and (II) a simultaneous learning and testing stage. Figure 2 depicts a block diagram that represents the AD detection method.

Initial Processing

During this stage, the image input undergoes resizing via the following preliminary processing stages: resizing by 1/155, splitting by 0.25, magnifying by 0.25, and horizontal flipping. Ultimately, the pre-processed image dimensions were diminished to 152 x 152 x 4 before the learning and testing stages were implemented.

Learning and Evaluation Stage

This stage is accountable for the learning and evaluation of data. It comprises processing data for learning, learning data, and a CNN. The MRI images of 705 mildly AD patients and 4150 non-AD individuals are sourced from different places, as previously stated.

- ***Learning Pre-processing***

This unit performs resizing, trimming, zooming, and horizontal flips with the same parameters as during the preliminary testing step. This information will be used and trained inside a CNN framework.

- ***Learning Resources***

The supervised learning principle using the backward propagation (BP) algorithm was implemented in this phase for training objectives.

The initially processed picture inputs are the primary data source inputted into the CNN for training. During the feature extraction phase, the system identifies appropriate characteristics and minimizes the size of inputs before training in the predictor. The data extraction and classification components work similarly to encoding processes and decoding devices, with the specifics of the CNN architecture to be discussed in the next step. The fully-connected CNN classifier leverages the BP technique for learning and feature extraction.

CNN Architecture

The structure of the proposed CNN consists of two primary elements: extraction of features and a classification algorithm. In this hierarchical progressive model for MRI categorization in AD, every level in the feature mining component utilizes the output from the previous layer as its input, and the resultant output is then sent to the following levels.

This model has four convolutional layers (CL) using 32, 64, 64, and 128 filters. The initial stages of the proposed network incrementally include more filters when they identify concealed patterns during learning and recognize characteristics within smaller parts of the picture. As the network extends, the structure of the CNN layers deepens, and the quantity of features extracted at each level directly correlates with the variety of filters used. The dimensions of the characteristic mapping may be established using the equation that follows:

$$characteristic\ mapping\ dimension = 1 + (I - F + 2W)/S \tag{1}$$

In this context, I denotes input size, F represents filter size, S indicates stride, and W signifies buffering. The standard kernel size of 3 x 3 and a nonlinear rectified linear unit (ReLU) activation algorithm have been employed. Utilizing ReLU, neurons with low input values remain inactive and assume a value of zero, hence enhancing processing and learning efficiency.

3 RESULTS AND DISCUSSION

The conceptual framework focuses on accurately recognizing each sensor to enable the aggregation of diverse sensing information using suitable techniques according to sensor types. An 8-bit microprocessor and a streamlined, integrated operating system have minimized overall energy use while managing the microcontroller's operations. A standardized collection of APIs is developed and executed primarily on the embedded control architecture, with all interactions with the hardware conducted over this public API. The primary robot controller employs a 32-bit ARM processor with 1 TB of RAM and operates on the Android platform. Its functions include conveying sensory data over a wireless network, delivering a user interface, and facilitating human interaction.

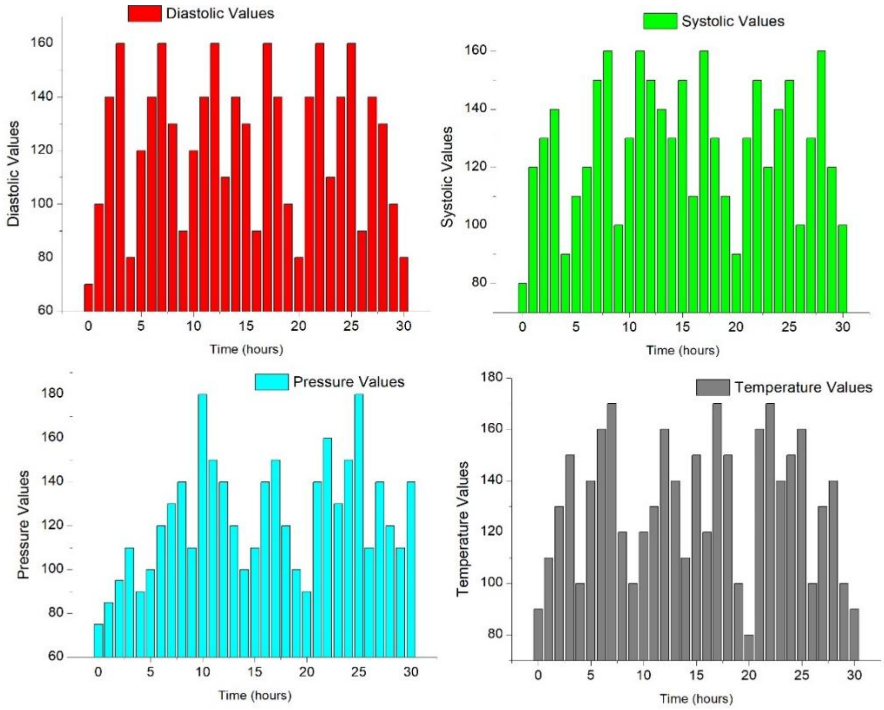

Figure 3: Key Elements of Multifaceted Sensing Data Acquisition From AD Patients for THA

Figure 3 depicts the key elements of multifaceted sensing data acquisition from AD patients for THA. The diastolic and systolic readings exhibit considerable oscillations, indicating typical variations in blood pressure over time. The pressure measurements demonstrate significant fluctuation, suggesting potential external factors or physiological reactions. The temperature measurements vary significantly due to differing ambient or metabolic factors. Although IoT-based HTS have been previously examined, the research explicitly focuses on incorporating IoT technology to identify and prevent AD. Integrating IoT devices improves telemedicine availability, facilitating early detection and mitigation for remote AD patients.

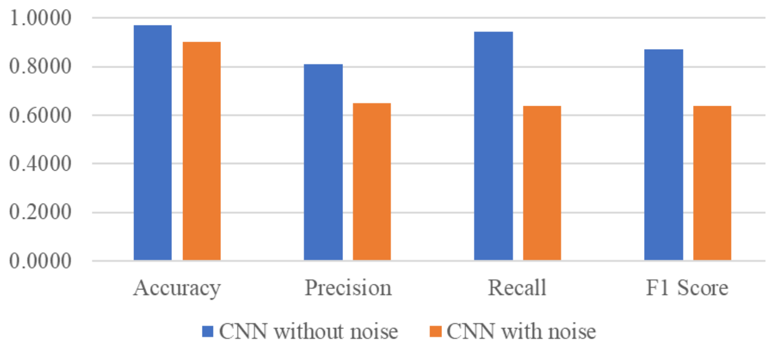

Figure 4: Performance Analysis of CNN for THA Using AI and IoT

Figure 4 presents the performance analysis of CNN for AD detection in THA using AI and IoT. The CNN devoid of noise surpasses the CNN with noise across all criteria, demonstrating that noise adversely impacts classification performance. The accuracy decreases from 97.12% to 90.13% when noise is present. The precision, recall, and F1-score exhibit a notable reduction, indicating diminished reliability and efficacy of the model under noisy environments.

4 CONCLUSION

This research improves Telemedicine Healthcare Assessment by incorporating IoT and Artificial Intelligence to enhance Alzheimer's Detection (THA-AI-AD). The document delineates the essential principles and critical components of multifaceted sensing data acquisition, designing and implementing a medical tracking system utilizing an AI platform, robotics-driven multifaceted data sensing and collection, and the prolonged acquisition of physiological signals with enhanced comfort via smart apparel. The research introduces a novel method for automated AD detection via CNN. Comprising two subsystems, one dedicated to AD detection with an accuracy of 97.12% using CNN and another for AI-driven telemedicine treatment, producing outstanding results.

REFERENCES

[1] Jadhav, R. P., Kengar, M. D., Narule, O. V., Koli, V. W., & Kumbhar, S. B. (2019). A review on Alzheimer's Disease (AD) and its herbal treatment of Alzheimer's Disease. *Asian Journal of Research in Pharmaceutical Science*, *9*(2), 112-122. http://dx.doi.org/10.5958/2231-5659.2019.00017.1

[2] Qureshi, R., Irfan, M., Ali, H., Khan, A., Nittala, A. S., Ali, S., ... & Alam, T. (2023). Artificial intelligence and biosensors in healthcare and its clinical relevance: A review. *IEEE Access*, *11*, 61600-61620. https://doi.org/10.1109/ACCESS.2023.3285596

[3] Lindauer, A., Messecar, D., McKenzie, G., Gibson, A., Wharton, W., Bianchi, A., ... & Dodge, H. H. (2021). The Tele-STELLA protocol: Telehealth-based support for families living with later-stage Alzheimer's disease. *Journal of advanced nursing*, *77*(10), 4254-4267. https://doi.org/10.1111/jan.14980

[4] Chokri, R., Hanini, W., Daoud, W. B., Chelloug, S. A., & Makhlouf, A. M. (2022). Secure IoT assistant-based system for Alzheimer's disease. *IEEE Access*, *10*, 44305-44314. https://doi.org/10.1109/ACCESS.2022.3168311

[5] Le Xin, T., Arshad, A., & bin Abdul Salam, Z. A. (2021, December). AlzBot-Mobile App Chatbot for Alzheimer's Patient to be Active with Their Minds. In *2021 14th International Conference on Developments in eSystems Engineering (DeSE)* (pp. 124-129). IEEE. https://doi.org/10.1109/DeSE54285.2021.9719410

[6] Chakraborty, S., Bhatt, V., & Chakravorty, T. (2020). Big-data, iot wearable and mhealth cloud platform integration triads-a logical way to patient-health monitoring. *International Journal of Engineering and Advanced Technology*, *9*(3), 388-394.

[7] Shei, R. J., Holder, I. G., Oumsang, A. S., Paris, B. A., & Paris, H. L. (2022). Wearable activity trackers–advanced technology or advanced marketing?. *European Journal of Applied Physiology*, *122*(9), 1975-1990. https://doi.org/10.1007/s00421-022-04951-1

[8] Zhang, C., Yu, Z., Wang, X., Chen, Z. J., Deng, C., & Xie, S. Q. (2024). Exploration of deep learning-driven multimodal information fusion frameworks and their application in lower limb motion recognition. *Biomedical Signal Processing and Control*, *96*, 106551. https://doi.org/10.1016/j.bspc.2024.106551