ISSN:2791-1322(Online) JNCBAE Volume1, Issue2 (April-June 2022)
ISSN:2791-1314(Print)

An IoMT enabled smart healthcare model to monitor elderly people using Explainable Artificial Intelligence (EAI)

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Abstract- Disease forecast and control via several healthcare gadgets and services have recently recognized a lot of attention, especially with the fast transition to an ageing people and increased attention in healthcare. In this age of advanced technology, advances in the Internet of Medical Things (IoMT), wearable sensors, and telecommunication technologies have made human life smarter, enabling smart healthcare services. The Internet of Things (IoT) can revolutionize the healthcare sector. By utilizing Wireless Body Sensor Networks (WBSNs) and Implantable Medical Devices based IoMT, smart healthcare systems (SHSs) are delivering quick and effective disease medication. This paper describes an IoMT-based intelligent healthcare model that uses explainable artificial intelligence (EAI) to keep track of the health of elderly people. EAI can be used to overcome the explainability and reliability limitations of Machine Learning (ML) and Deep Learning (DL) models, resulting in more accurate results.

Keywords: Smart healthcare model, IoMT, EAI, healthcare monitoring system

1 Introduction

The IoT is a network of interconnected computing gadgets with Unique Identifiers (UIDs) and the capability to send and receive information without making a human-to-human or human-to-computer interface. IoMT is a practical use of IoT gadgets with medical technology employed in the health industry. IoT allows data from healthcare devices and applications to be transferred to medical IT servers for remote evaluation. Healthcare staff can access patients' clinical data in real-time via a web platform or any mobile application, allowing them to trade with clinical issues and assist them in preventing serious situations in the future. This expertise in interrelated medical devices permits patients to monitor their health situations and follow doctors' treatment recommendations using smart devices and applications while also making it easier for doctors to learn about patients' medical history before the checkup by collecting real-time data using IoMT.[1]

In brief, combining healthcare and IoMT improves people's lives, enhances care, and allows for more cost-effective frameworks. IoMT is also known as Healthcare IoT. IoMT's services involve remote patient monitoring for people with persistent or long-term illnesses. These services maintain patients' medical prescribed medications, hospital admission locations, and wearable health gadgets that can send every patient's health data to a designated caretaker. Infusion pumps which interact with analytics dashboards and hospital beds equipped with sensors which calculate patients' vital indications are examples of medical gadgets that have been transferred to or implemented as IoMT technology. IoMTs realize their maximum ability by utilizing objects, or "smart" objects that use multiple sensing devices to measure fully prepared data in their specific situation and communicate with every available alternative via integral networking capabilities. These gadgets use open supply network services and can move around in real life. It not only connects them globally but also strengthens and comforts them. Patients and doctors benefit from the network of gadgets within the area of interest, providing comfort and presence of mind. It comprises a structure that communicates among networked systems, apps, and gadgets, making it easier for patients and doctors to monitor and record vital medical information. Positive metric tracking, wearable health bands, fitness shoes, RFID-based watches, and high-end video cameras are just a few available devices. Smartphone apps also make it easier to keep track of cases and receive periodic alerts and emergency services.[2]

IoMT has undoubtedly changed aspects as a result of its expanded online network. IoMT-based medical wearable gadgets have facilitated the widespread adoption of virtual healthcare transformation systems. Furthermore, teleoperation, a technology that can be controlled remotely, has emerged as a feasible apparatus for wireless healthcare technologies. The new healthcare policies can make clinical methods more efficient and convenient, allowing them to be used even in remote areas. Many efforts have gone into designing and developing a user-friendly and dependable framework for IoMT-based medical monitoring systems. These medical systems are gradually shaping with the increase of smart, convenient wearable gadgets in the biomedical industry. The enormous majority of these devices are used in primary clinical examinations to collect ECG, EEG, blood pressure, fever, breathing rate, motion activity, and glucose recognition information that are mainly anxious at the protection of health by offering early checkups to differentiate the awareness of other difficulties.[3]

A smart healthcare system (SHC) is a framework for medical systems that use wearable devices, the IoT, and remote communication to traverse health data easily, connect individuals, sources, and institutions, and intelligently manage and respond to the healthy environment needs. Clinicians, patients, clinics, and academic institutions are part of the smart healthcare ecosystem. Disease handling and detection, assessment and care, healthcare management, patient decision-making, and clinical science are all part of this complex system. Smart healthcare is built on digital systems like IoT and sensors, fast internet, edge and cloud networking, big data, next-generation wireless communication, ML, artificial intelligence (AI), and developing biotechnologies.[4]

The following are the key features of the SHC. One of the most important features of privacy demands is data security. For access control, data authentication is a critical parameter. The operational requirement for connectivity is low latency. Finally, the platform's accuracy is improved by the data sharing capability. At the very least, these key parameters must be included in the smart healthcare monitoring platform developed.

A Wearable Sensor (WS) provides technical assistance and remote patient monitoring in the healthcare system. The sensor is worn on the patient's body and identifies their movements at different periods. The collected data is sent to the healthcare service providers for treatment recommendations for the remotely patient. Information is distributed and evaluated to a predefined dataset on the heterogeneous platform. A predefined set of clinical data and patient information makes up the dataset. According to the information provided, the patient has a record of interaction with healthcare service providers and rehabilitation. Consequently, clinical information is responsive and confidential, and it must be protected from illegal access, which could threaten a patient's health. At predetermined intervals, the WS monitors and stores bodily function-related interests. There can be faults and dormancy when collecting data, which must be focused on immediately. In the health industry, WS information is a critical component of secure information transfer and early monitoring of the health of the elderly. [5]

An aged population is progressively prevalent in both advanced and growing countries. Elderly people with a weakened resistant system need daily examinations to stay healthy. They must travel to hospitals or clinics for this purpose, which is a major issue due to the mobility issues that elderly people face. More elderly people live alone at home than are living with family members who can care for them. As a result, in this era of human-centred artificial intelligence, assisted living (AL) and healthcare monitoring (HM) can be critical issues (AI). The concept of EAI is introduced in this scenario. Explainable Artificial Intelligence (EAI) was invented to address this need. It is defined as follows: "Given an audience, an explainable Artificial Intelligence produces details or reasons to make its functioning clear or easy to understand." The deficiency of explainability of certain prediction models in the medical context must be addressed, as clinicians find it difficult to trust complex ML methods due to their high technical knowledge requirements. As a result, XAI would enable healthcare specialists to make more informed and data-driven decisions about the health of the elderly, resulting in more personalized and reliable treatments and diagnoses.[6]

2 Related work

Most researchers have been working on emerging technology (IoMT) in the health care sector. Some of their works are highlighted in this section.

The multi-approach model for human being health care was suggested by Siddiqui et al. Using a backpropagation system; the automated model suggested Diagnosis of cardiovascular disease (DCD), which involves fuzzy logic (DCD-MFIS), Artificial neural network (DCD-ANN), and Deep extreme machine learning (DCD-DEML). These frameworks aid in the attainment of greater precision and accuracy.[7]

The researchers used the accelerometer and gyroscope sensors on smartphones to store information among the elderly and their caregiver counterparts. Three machine learning algorithms, namely SVM (Support Vector Machine), ANNs (Artificial Neural Networks), and a hybrid of HMM (Hidden Markov Models) and SVM, were used to infer six activities (sitting, walking, laying, standing, descending and ascending the stairs) (SVM-HMM).[8]

This research investigated IoT-enabled systems for remote monitoring of elderly people and proposed a hierarchical four-tiered model. The Application Layer takes care of elderly needs like daily activity monitoring and fall detection. Health, safety, nutrition monitoring, social network, navigation, and localization are all monitored by the Domain Layer, which is the second tier. The third tier, the Objective Layer, organizes high-level goals and challenges for remote monitoring of elderly people. The System Layer's fourth tier connects to a comprehensive elderly monitoring system.

The authors in this research presented that In aspects of consultation accuracy and cost reduction related to human labour, SHS based on IoMT is a game-changer for the medical field. Researchers can work on numerical analyses of diseases and prescription patterns using vast medical data. As a result of the beginning of IoMT in the medical field, more focus has been placed on improving ubiquitous information retrieving solutions for acquiring and processing information from distributed data sources. Due to the lack of processing capabilities of medical sensors and implantable medical devices, data is sent to a remote server for analysis and control decisions in the IoMT network (IMDs).[9]

In this research [10], The General Medical Council of the United Kingdom suggested a well clinical practice guideline updated in 2019. In all clinical situations, offer a prescription based on the best available testimony and take all promising steps to relieve pain and anguish. Consult colleagues and respect the patient's right to a second view when necessary. Investigate the prescription list for interactions with other medications, comorbidity, and over-the-counter medications. Treating yourself and patients you know is not a good idea. In older patients, a new medication prescription requires a crucial reading of rules and understanding their consequences and segregation criteria. Adapting treatment for older adults entails extrapolating the effects of medication treatment in middle-aged people to the aged population. Based on the incorporation of functionality in older patients and the detection of aged syndromes for their prominent impact on prediction, it is essential to synchronize Diagnosis, prognosis, and medication.

This research looked into the health-related quality of life (HRQOL) of the empty-nest elderly people in rural China to raise social awareness about their HRQOL. HRQOL was measured using the five-dimensional European health standard scale (EQ-5D) and the 12-point Short Form Health Survey (SF-12). The Spearman correlation coefficient, the logistic regressions model, organized probity regression and logistic retraction multinomial, and the Structural Equation Model are all used to test the relationship (SEM).[11]

The authors present that the Proficient demand for tools that make AI more accessible is growing in the healthcare domain, as AI solutions typically require expert knowledge of ML algorithms. It is essential in precision medicine, where disease diagnosis necessitates interpretable and transparent information. EAI solutions to provide healthcare professionals with global explanations of prediction models have been used for over a decade. Transparent models such as logistic and linear regression, nave Bayes, decision trees, and k-nearest neighbours were used in urology, cardiology, toxicology, endocrinology, neurology, psychiatry, occupational diseases, knee osteoarthritis, breast cancer, prostate cancer, Alzheimer's disease severity, diabetes, and CVD mortality rates, among other clinical fields (e.g. myocardial infarction or perinatal stroke). Other model-agnostic explainability solutions, such as SHAP (Shapley Additive explanations) or MUSE (Model Understanding through Subspace Explanations), have been used to diagnose depression and prevent hypoxemia during surgery and image detection of acute intracranial haemorrhage in complex AI solutions based on deep learning.

In this research, the authors explain that Explainable AI (EAI), which provides apparatus to show AI decisions, has emerged as a means of looking deeper into the AI black box. The demand for AI model transparency is extreme in medicine, where uncertainty, ambiguity, and the unknown are all part of the job. Understanding refers to understanding the inner mechanisms of an AI model; explaining and revealing "why" a machine technically decided on an outcome based on a collection of features that contributed to the AI decision, and interpreting and mapping the abstract (and technical) EAI concepts to a human-understandable format are some of the taxonomies that EAI distinguishes. While humans often cannot explain the reasoning behind a decision, understanding the decision-making process of an AI model will increase trust and acceptance of the machine.[12]

The authors [13] explain that The aim of using explainable AI techniques in conjunction with the deployed model is to point out how the prediction results are generated. The data is fed into the explainable AI module and the trained model. It is possible to provide explanations alongside prediction results using explainable AI techniques. Medical professionals can use the explanation to validate the AI models' predictions. Clinical records can generate more in-depth insights and recommendations in conjunction with explanations.

In this research, the authors present that EAI is a technique that allows humans to comprehend the reasoning behind artificial intelligence models' decisions. Its main purpose is to improve the consistency of machine learning results. A misinterpretation of EAI is caused by low machine learning accuracy. The EAI technique identifies the importance of features and explains how they influence model decisions.[14]

3 Methodology

In recent decades, accurate monitoring of elderly people's health issues has become a significant challenge. People face multiple medical problems due to the environmental situation and their living habits, so early detection of health issues is becoming a significant task. Explainable Artificial Intelligence (EAI) is an emerging technique that plays a critical role in overcoming this challenge while monitoring elderly people's health issues, as discussed in this paper. This research aims to develop an EAI model that can effectively monitor the health of elderly people based on the signs they exhibit. Fig. 1 illustrates the proposed model.

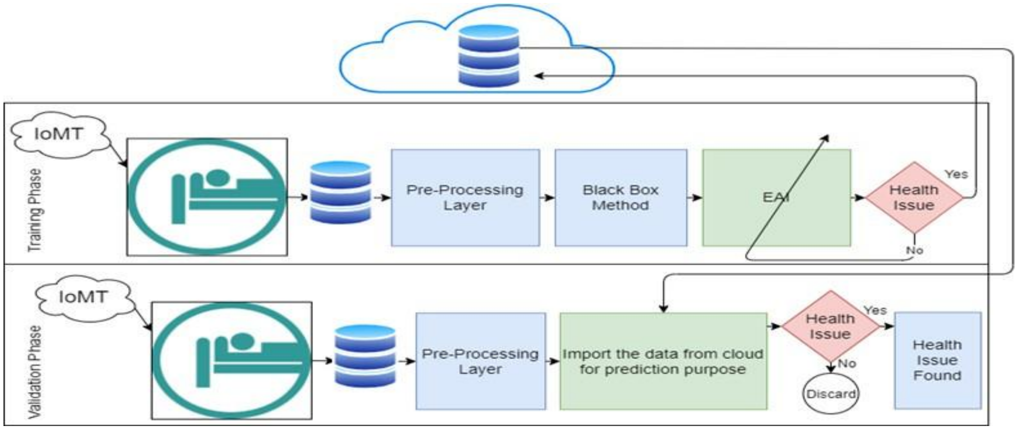

Fig.1. Proposed Methodology

The proposed model is integrated with the training and validation phases, as shown in Figure 1. The patient provides the samples, which are then entered into a database known as raw data. Because the communication channel is wireless, the data stored in the database may be noisy. Because the data in the database may be noisy or raw, it must be preprocessed to reduce the amount of noise. The processed data is then forwarded to the black box method and EAI model via the data preprocessing layer. In the prediction layer, the data is trained using an EAI approach. The end-user and other stakeholders can understand algorithmic decisions thanks to EAI. The predicted understandable outcome of the EAI process will be checked to see if the health issue was discovered or not.

If no health issues were discovered, the EAI would be updated, and so on. On the other hand, it also stores the output in the cloud.

The cloud-based trained data will be imported for prediction purposes using the EAI approach in the validation phase. It is determined whether or not a health problem exists. If the answer is no, the operation will be discarded; if the answer is yes, the notification will state that a health problem has been found.

Most researchers have previously worked on different methods by using the EAI approach. Their performance is highlighted in the table1 in terms of accuracy and miss rate.

Table 1: EAI-based Methods and their performance

Author Names	References	Methods	Accuracy	Miss-Rate
(Angelov & Soares, 2020)	[15]	xDNN	94.31	5.69%
(Simonyan & Zisserman, 2014)	[16]	VGG-16	90.32%	9.68%
(He et al., 2016)	[17]	ResNet-50	90.39%	9.61%
(Breiman, 2001)	[18]	Random forest	87.12%	12.88%
(Hearst et al., 1998)	[19]	SVM	86.64%	13.34%
(Peterson, 2009)	[20]	KNN	85.65%	14.35%
(Quinlan, 1996)	[21]	Decision Tree	86.42%	13.58%
(Rish, 2001)	[22]	Naïve Bayes	54.84%	45.16%

Table 1 shows different EAI-based methods and their accuracy and miss rate results. By comparing all these methods, xDNN method shows maximum accuracy of 94.31% and a minimum miss-rate of 5.69%. And Naïve Bayes method shows minimum accuracy of 54.84% and a maximum miss-rate of 45.16%.

4 Conclusion

Portable tools and methods to analyze healthcare risks in elderly people daily, rather than demanding a specialized hospital setting, are urgently needed. The physical Activity Recognition and Monitoring (PARM) system has been regarded as a key concept for smart healthcare because of its significant and beneficial impacts on physical and mental health and its strong involvement with many therapy programs. EAI is a cutting-edge technology that allows end-users and stakeholders to understand algorithmic decisions. Based on wireless body sensors, this study proposes an explainable artificial intelligence approach to assist in diagnosing health issues in elderly people. This EAI-based approach has the potential to outperform the xDNN method. [15]

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