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SMART HEALTH CARE FOR MONITORING ELDERLY PEOPLE USING IoMT AND ML

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ABSTRACT:
With the help of the Internet of Things, the wearable and smart device industries are making big strides in healthcare, products like hearing aids that work with Bluetooth and robotic caregivers. In recent years, there has been a dramatic shift from a centralized care delivery system based mostly on hospitals toward a more decentralized healthcare system that puts the patient first. Healthcare has undergone a rapid transformation as a result of several technological advances. Innovative healthcare services and apps now use 4G and other connectivity technologies. As the healthcare sector expands, more and more applications are likely to generate vast quantities of data of varying shapes and sizes. Currently, the Internet of Things (IoT) and Artificial Intelligence (AI) are causing a revolution in the healthcare business regarding detecting, diagnosing, and treating several diseases. Artificial intelligence increasingly realizes the revolutionary character of IoT technologies, which promote innovation in the creation of linked medical equipment because of their widespread presence in the sector, from smart phones to robots. The Internet of Medical Things (IoMT) refers to the interconnectivity of devices used in healthcare. The practice of using internet-enabled medical devices like smart watches, fitness trackers, and various sensors to collect and share health data. IoMT aims to enhance healthcare quality by facilitating real-time monitoring of a patient's health state to enhance the effectiveness and efficiency of treatment. In addition to facilitating better patient outcomes and industry-wide research and development, IoMT allows for collecting and analyzing massive volumes of data.
The goal of the IoMT and Machine Learning (ML) in "smart healthcare" is to expand access to healthcare and enhance senior citizens' quality of life and efficiency of healthcare delivery. The IoMT enables continuous tracking of a senior citizen's health thanks to a network of connected wearable's, sensors, and other medical devices. In this way, machine learning algorithms can monitor patients' vitals and accurately predict the onset of severe health problems. Health care practitioners may be more proactive in their responses and provide more prompt medical intervention, leading to better patient outcomes and lower healthcare costs. While long short-term memory (LSTM) excels at time-series data like heart rate and blood pressure values, which are often gathered in geriatric care, the author presents a hybrid method that combines LSTM with Random Forest. Random Forest and Boosted Decision Trees rely on many decision trees to conclude. It is possible to categorize patients based on their health condition and identify potential dangers.
Keywords : Internet of Medical Things, Monitoring Patients, LSTM, Random Forest.

1. INTRODUCTION:

Smart healthcare paves the way for state-of-the-art diagnostic tools, which in turn allow for modern medicine and cutting-edge healthcare devices, improving healthcare quality by delivering indicators of life force status continuously. Efficient medical treatment systems are designed to help people by providing them with information about medical problems and possible treatments. With the help of smart health care, people are better equipped to handle emergencies [1]. It paves the way for remote check-up services, which decrease treatment costs and help healthcare providers extend their reach beyond traditional geographic boundaries. As the number of "smart cities" grows, so does the need for a reliable smart healthcare system to ensure the residents' health. Healthcare cost reduction is a significant improvement from catching problems early on. For example, by 2022, the Internet of Things (IoT) market for "smart" healthcare forecasts a value of $158.1 billion. [2].

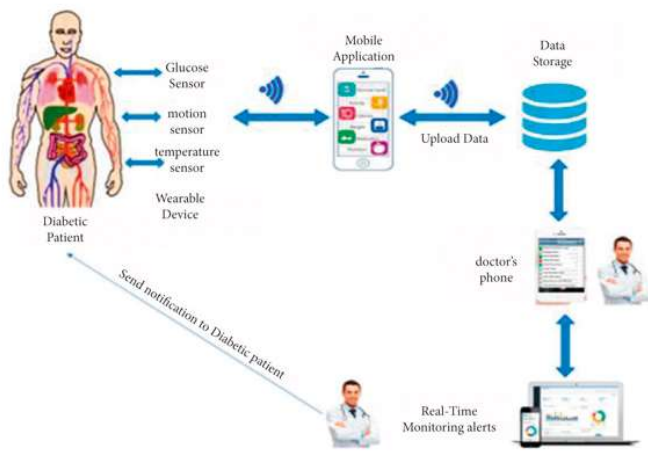

Figure 1.1: IoMT Health Care Monitoring System [28]

In smart healthcare, IoT may enhance a variety of applications, such as hospital asset management, monitoring of behavioral changes, remote monitoring. Monitoring of the use of technology in healthcare has led to advancements in areas such as patient adherence, supported living, smarter medicines [5]. The medical industry of the future will rely heavily on these applications. Healthcare IoT will drive the industry to about $200 billion by 2020 [6]. Several use cases are offered for connecting mobile devices, internet health care, and other services. The authors of [7] propose a mobile health app for checking for pressure sores and electronically collecting health information. The goal of the smart health application proposed in [8] is to do evaluations and monitor dietary intake. In [9], the author offers a fresh approach to developing health-related apps for mobile devices. As an example of a solution for the home setting [10], suggests wearable's that aid in movement. In [11], a mobile gateway-based Internet of Things application is shown to provide smart support in mobile healthcare settings. According to [12], The IoT, or Internet of Things, is a crucial component of any e-health platform with potential medical applications.

Integrating healthcare with IoMT raises standards of living, provides better care management, and can lead to more cost-efficient systems. IoMT relies on a sustaining system that allows sensors, users, and communication modules to deliver health services safely and effectively. Self-care and early diagnostic capabilities via remote monitoring are examples of how IoMT technology improves healthcare. As medical technology improves, people become more proactive about their health and conscious of the need to make good decisions for themselves. The importance of telemedicine in this setting cannot be overstated. However, the current healthcare systems need technology to improve patient care by giving clinicians access to real-time patient data and inspiring them to take actionable measures in treatment [13].

Despite having top-notch infrastructure and modern equipment, healthcare still needs to be within reach for many people. Smart healthcare (SHC) is intended to help people make resources available for their health and medical issues. Because of SHC, people can tackle some crises on their own. SHC uses cutting-edge IT technologies such as Big Data, Cloud, AI, and the Internet of Things (AI) to revolutionize healthcare [14].

An LSTM (Long Short-Term Memory) and Random Forest based IoMT Internet of Medical Things (IoMT) patient monitoring system is a healthcare system that utilizes two machine learning algorithms to monitor patients remotely. The LSTM algorithm processes time-series data such as vital signs and analyzes the patient's health status based on their historical health data. The Random Forest algorithm is used for predictive modeling and classifying the patient's health status. This combination of algorithms provides

- a robust and effective solution for monitoring patients,
- improving healthcare outcomes, and
- reducing the costs associated with traditional in-person monitoring.

2. RELATED STUDY:

As a result of IoMT, digital devices may now collect, computing cloud to infer and disseminate medical information. Many reasons contribute to the IoMT's meteoric rise, including the increasing accessibility of wearable's and the falling prices of sensor-based technologies. With an increasing number of seniors and a longer average lifespan comes a greater need for cost-effective healthcare services, innovative technologies, and policy reforms. IoMT, when combined with ML algorithms, has the potential to revolutionize the medical field by improving the quality of care provided to the elderly. Tests conducted using IoMT datasets revealed that the SHC model successfully kept tabs on the older population. Accuracy, ROC, F-score, Precision, and Recall are some metrics that may be calculated for assessment. The purpose of this study was to assess the SHC model's output. The authors compare it to that produced by several other, more traditional ML techniques, such as the SVM, K-nearest-neighbor (KNN), and the decision tree (DT) [15].

Keeping tabs on the health of its patients, especially those with chronic illnesses or who are getting on in years, presents several difficulties for the healthcare system and the NHS. Using smart IoT and AI, care in the home is the future for healthcare providers and the NHS. Incorrect or forgotten medicine is a significant cause of harm to public health worldwide. Medication errors and non adherence can be mitigated using wireless health technologies. This research proposed a method to address this problem by monitoring patients' vitals in real-time using wireless sensor network equipment already in their homes to send data radio-free to the appropriate authorities (medical staff, primary care physicians, hospitals, and specialists). The suggested solution uses algorithms to give patients rapid and accurate health advice at home. The program then utilizes the results of the data processing performed by the database web server. Everything from a patient's blood pressure and glucose levels to their heart rates and temperatures is recorded by the devices and stored in a database along with the patient's medical history. Using a machine learning system, we can monitor user health information and alert them if we see any significant changes. By analyzing patient medical information for trends, ML can alert doctors to any irregularities they may have missed [16].

Global mortality and morbidity rates are affected by individual choices in lifestyle. The possibility of developing type 2 diabetes and subsequent complications, including cardiovascular disease, can be lowered by engaging in preventative health behaviors, including regular exercise, a balanced diet, and regular weight maintenance are all essential for good health, Nutritious diet. The onset of chronic diseases and their associated consequences can be slowed or avoided by adopting a healthy lifestyle, but only a minority of individuals actually heed this advice. This study aims to further our understanding of the variables that have a role in a person's ability to self-manage and avoid the onset of type 2 diabetes through behavioral modifications. An Android app for managing diabetes independently is the subject of this study. Using the app, authors could monitor eating habits and health statistics. It is possible to monitor carbohydrate consumption, blood sugar levels, medication compliance, and exercise progress using Bluetooth-enabled insole devices. Two different ML models were developed to identify seated and standing individuals. For these jobs, the SVM and decision tree models achieved an accuracy of 86%. A live software system for categorizing activities uses the decision tree approach. It is encouraging to see people using self-management applications for their mobile health to combat chronic conditions [17].

Diabetic patient monitoring is a methodical approach that helps us learn more about the individual with diabetes. Items connected to the Internet of Things (IoT) include those used in diabetic patient monitoring systems, which are crucial in keeping tabs on patients' well-being. The primary function of diabetic patient monitoring systems is to keep track of a person with diabetes and record relevant data, such as their current blood glucose level, temperature, and whereabouts. In addition to monitoring patients, this system can categorize data with ML techniques. Analytics for diabetes prognosis is crucial because it facilitates data-driven treatment decisions for patients, their loved ones, healthcare providers, and researchers. This research presents a novel method for keeping tabs on people with diabetes and addresses predictive analytics based on four distinct machine-learning algorithms. The algorithms used and their relative performance and accuracy are compared and contrasted to select the best one based on several criteria [18].

As a result of medicine's rising importance in people's daily lives, the volume of data collected on medicine has exploded. With the help of the Internet of Things (IoT), wearable technology is becoming increasingly popular in the healthcare industry to improve efficiency in evaluation and care. Internet usage has increased dramatically during the past several years has enabled the connection of countless sensors, devices, and automobiles in the billions. Remote patient monitoring is a widespread tool in the medical industry. While these technologies have the potential to improve many aspects of our lives significantly, they also present serious hazards to our privacy and security concerning the transmission and recording of sensitive information. Delays in treatment due to concerns over the confidentiality of medical information might jeopardize the patient's life. Authors propose a blockchain-based system to safely store, transfer, and analyze extensive medical data. However, blockchains are resource-intensive, making them inappropriate for most IoT devices designed for smart cities due to their limited processing power, bandwidth, and storage capacity. This paper addresses these and other problems associated with integrating blockchain technology with the Internet of Things. Based on the distributed nature of blockchains and other network privacy and security features, a unique framework of modified blockchain models is well-suited for IoT devices. The model's supplementary privacy and security features are derived from state-of-the-art cryptographic primitives. Data and transactions made using Internet of Things applications may now be made more anonymously and securely across a blockchain-based network with the help of the solutions provided here [19].

2.2 RESEARCH CHALLENGES:

Monitoring elderly people using Internet of Medical Things (IoMT) and Machine Learning (ML) poses several research challenges, some of which are:

Data collection and privacy: Collecting and managing personal health data from the elderly securely and ethically is a significant challenge. There is a need to ensure that the collected *data is appropriately de-identified, protected, and complies with privacy regulations.*

Data quality and variability: The data collected from the elderly may be highly variable and noisy, affecting the accuracy and robustness of the ML models. There is a need to develop methods for missing data, inconsistencies, and variability.

Model interpretability and transparency: The ML models used for monitoring elderly people should be transparent and interpretable so that clinicians can understand the reasoning behind the predictions made by the model. This is particularly important for decision-making in healthcare.

Human-centric design: The design of the IoMT devices and systems should be centered around the needs and preferences of the elderly. The devices should be easy to use, non-invasive, and provide real-time feedback to the user.

Generalizability and scalability: The ML models developed for monitoring elderly people should be generalizable to different populations and scalable to handle large volumes of data. There is a need to develop methods to transfer models across different domains and populations.

3. METHODOLOGY:

Smart healthcare using the Internet of Medical Things (IoMT) methodology is a system that uses connected devices and technologies to monitor and manage the health of elderly people. This includes wearable devices, sensors, and medical devices that collect and transmit real-time data to healthcare providers and family members. The data collected can be used to monitor vital signs, detect changes in health conditions, and provide timely interventions. Here we use a hybrid algorithm that combines LSTM and Random forest, which can handle time series data and categorize the patients based on their health conditions. So finally, this leads to improved patient care and outcomes, increased efficiency in the healthcare system and better quality of life for elderly people.

3.1 Hardware Used:

There are some wearable devices that must be used to monitor the patients, and these devices will have connections with sensors that return the live values generated from the patient's body. And the proposed algorithm will be deployed on the board where the devices are connected.

3.1.1 Raspberry Pi 3 Board:

Raspberry Pi boards can be used to implement machine learning algorithms. Raspberry Pi is a low-cost, single-board computer that has enough computing power and memory to run basic machine learning models. Additionally, Raspberry Pi supports various programming languages such as Python, which is a popular language for machine learning.

Figure 3.1: Raspberry pi 3board

Here are various libraries available for machine learning on Raspberry Pi, including TensorFlow, Keras, and PyTorch, which can be used to build, train, and deploy machine learning models. Raspberry Pi can also be used to develop and test machine learning algorithms and then deploy them to more powerful hardware for production use.

3.1.2 Blood Pressure sensor:

A blood pressure sensor module with IoT refers to a device that measures blood pressure and integrates with the Internet of Things (IoT) to transmit the data over the internet. The device typically includes a blood pressure sensor, an IoT module for connectivity, and a microcontroller for processing the data and controlling the device.

Figure 3.2: Blood Pressure sensor

With IoT integration, the data from the blood pressure sensor can be transmitted to cloud-based platforms, allowing for remote monitoring and tracking of blood pressure readings. This can be especially useful for elderly patients or individuals with chronic health conditions, as it allows for continuous monitoring and timely alerting of any changes or concerns.

3.1.3 Heart Beat sensor

CMS 50 Plus is a portable pulse oximeter device used to measure blood oxygen saturation levels (SpO2) and pulse rate. The device is designed for non-invasive and continuous monitoring of blood oxygen levels, making it suitable for various healthcare applications, such as monitoring patients with respiratory conditions or sleep disorders.

Figure 3.3: Heart Beat Sensor CMS50 plus

The CMS 50 Plus device is compact and easy to use, allowing for convenient monitoring at home or on the go. The device typically includes a display screen that shows the current SpO2 and pulse rate readings, and some models may have additional features such as an alarm, data storage, and connectivity options.

3.1.4 Wearable Blood Glucose Monitoring Device:

A wearable blood glucose monitor is a device that is worn on the body to continuously measure and monitor blood glucose levels in real time. This type of device is typically used by individuals with diabetes to manage their condition and maintain proper blood glucose levels.

Figure 3.4: Wearable Blood Glucose monitoring device

Wearable blood glucose monitors typically use a small sensor that is inserted under the skin to measure glucose levels. The sensor is connected to a wearable device, such as a watch or patch, that displays the glucose readings and sends the data to a mobile app or cloud-based platform. Some wearable blood glucose monitors also have additional features, such as alerts for high or low glucose levels, data storage and analysis, and integration with insulin pumps and other medical devices.

3.2 Data-Pre Processing:

Data pre-processing is an important step in building a machine learning model, including a Long Short-Term Memory (LSTM) model. It involves cleaning, transforming, and normalizing the input data so that it can be fed into the model effectively. The specific pre-processing steps used in LSTM may vary based on the type and nature of the data.

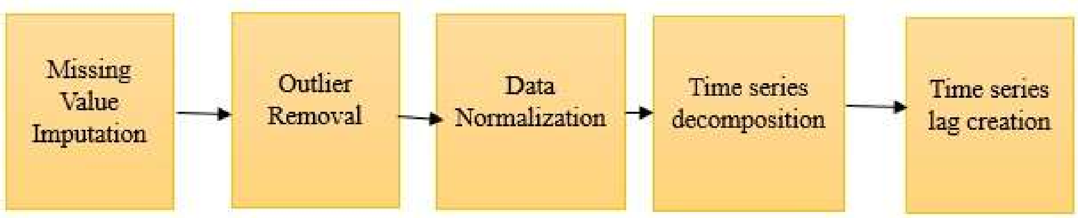

Figure 3.5: Data Pre-Processing

Missing value imputation: Handling missing values in the data, such as by replacing them with the mean or median of the column, interpolating the values, or using machine learning algorithms.

Outlier detection and removal: Identifying and removing extreme values in the data that may skew the results of the model.

Data normalization: Scaling the values in the data to a common range, such as between 0 and 1, so that all features are on the same scale and do not influence the model differently.

Time series decomposition: Breaking down time series data into the trend, seasonality, and residual components to better understand the underlying patterns and trends in the data.

Time series lag creation: Creating lagged features from the time series data, where each new feature is a shifted version of the original data, to capture the dependencies between time steps.

3.3 System Architecture:

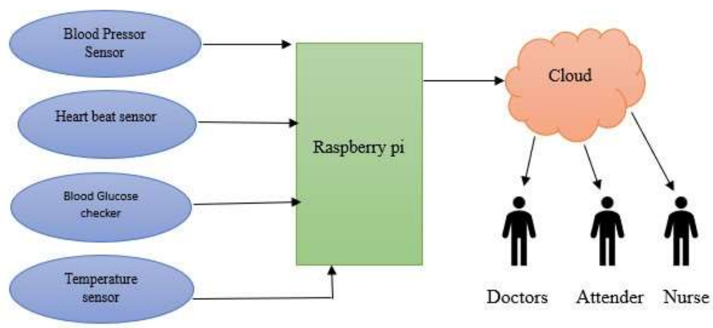

Figure 3.6: Proposed Architecture

Based on this proposed methodology Raspberry pi board will act as a mini computer, here it is connected with different sensors to get the values taken from the elderly patients and those data will be pre processed and those data will be analysed using the proposed hybrid algorithm which is deployed in raspberry pi board. And whenever a patient's condition is abnormal this microcontroller will communicate with the Doctors, Attenders and Nurses regarding the patient's emergency condition.

$$D = min(N, O), Dataset3(2 + TOS) - (1)$$

It is possible to employ Shannon's theorem for the capacity of a network, which states that the maximum capacity of a communication link is a given number of bits per second, as a guiding principle in the pursuit of higher data rates.

$$Miss\ Rate = \frac{\sum True\ Positive}{\sum Condition\ Negative} \text{ - (2)}$$

3.4 Proposed Hybrid Algorithm:

L- DataGen(2^{γ})

1. Records the data from the sensor L.
2. Set L = (l,L_f)
3. Generate $l_{Er}||I(l, JE_r)$

4. Generate $l_{Er}, 2, JE_r$ = I($l_{Er}||2$) $and\ l_{Er,3} = I(l_{Er}||3)$.
5. Compare sensor data with threshold value $i_{JEr} = I(k_{Er}, 2, JE_r)$
6. If $\gamma_r = I_{JEr}$) in L, sends message.
7. Else
8. Generate $l_{Er}||I(l, JE_r)$
9. Return f_r, k.

4. RESULTS AND DISCUSSION:

Medical database systems based on patient's electronic health information are typically built using machine learning (ML) techniques. There are a variety of approaches that have been employed up to this point to keep tabs on medical data and emergency alert systems for patients. However, researchers find that various methods yield varying degrees of precision. Therefore, we take such approaches and evaluate them against the suggested technique.

Table 1: Existing Algorithms compression with accuracy and disease

S.NO	Algorithm	Accuracy	Disease
1.	Support Vector Machine	94.99%	Heart Failure
2.	Rule-Based grammar approach	90%	Breast Cancer
3.	Natural Language Processing	98.9%	Asthma
4.	Data Mining	95.1%	Hyper Kalema
5.	Proposed Method	99.10%	Diabetics

As per the research methods, the plotted graph shows the readings generated from the elderly patient's body with different sensors. In this graph, three sensor data are displayed where the green line shows the Heartbeat rate, the Orange line shows the patient's body temperature, and the yellow line shows the Blood glucose level. And here, the threshold level is set with respective to the sensors because each sensors values different state to alert. Here once the sensor value reaches the threshold it sends the alert to the Doctor, Attender and Nurse.

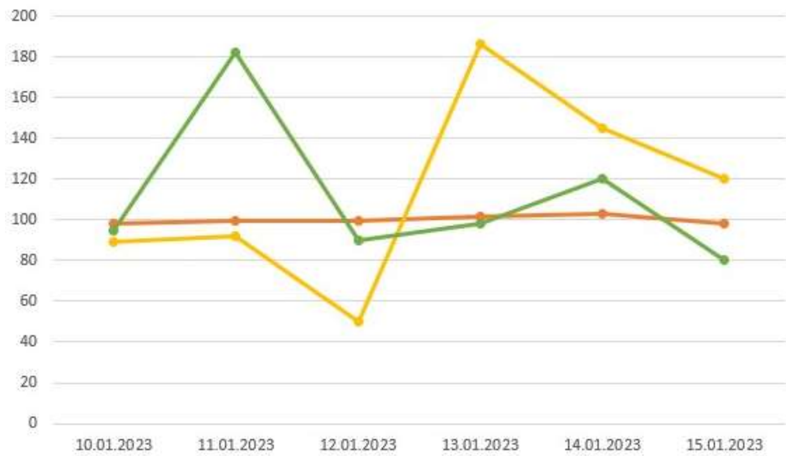

Figure 4.1: Combined sensor data of an elderly patient

Accuracy can vary based on the task, the dataset, and the performance metrics being used. In general, some of the most accurate algorithms include Long Short-Term Memory (LSTM) networks for sequence prediction, and Random Forests or Gradient Boosted Trees for many structured data problems. However, our proposed algorithm for a given task shows the highest accuracy when compared with the existing.

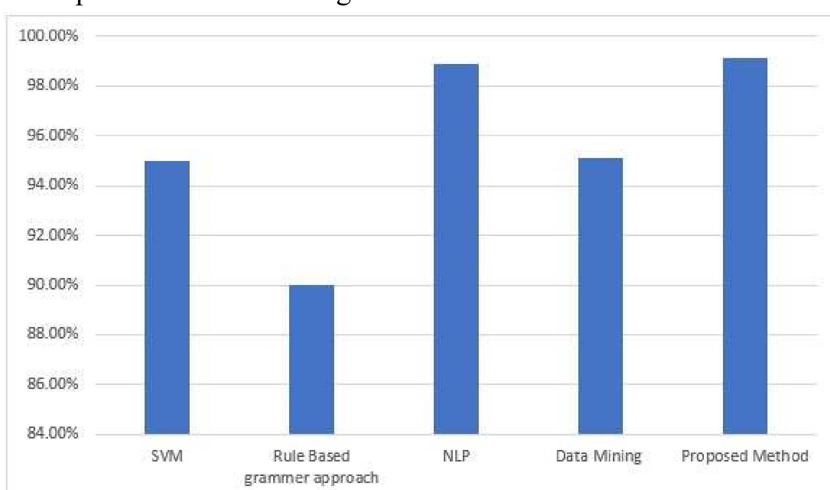

Figure 4.2: Accuracy compression graph

5. CONCLUSION AND FUTURE WORK:

The Hybrid algorithm with the combination of Both Long Short-Term Memory (LSTM) networks and Random Forest algorithms have shown promising results for predicting health outcomes in elderly people in various health monitoring tasks. LSTMs are well-suited for sequential data, such as time-series health measurements, and have the ability to capture long-term dependencies in the data. Random Forest algorithms, on the other hand, can effectively handle high-dimensional data and can provide feature importance, which can help understand the contribution of different variables to the predicted outcome.

However, the combination of LSTM and Random Forest algorithms should be based on the specific requirements of the task and the available data. In some cases, LSTMs may be more

appropriate, while in others Random Forest algorithms may perform better. Hence the proposed hybrid algorithm shows the highest accuracy when compared with existing algorithms.
In future for monitoring elderly people using IoMT and ML could emphasis on the following areas; Research could focus on developing ML models that can handle noisy and variable data, and that can provide accurate predictions of health outcomes. This could involve using more advanced ML techniques, such as deep learning, and incorporating additional data sources, such as environmental sensors or social media data. The design of IoMT devices and systems could be improved to provide a more user-friendly experience for the elderly. This could involve developing devices that are more intuitive to use, reducing the need for manual input of data, and providing real-time feedback to the user. Researchers develop methods to improve transparency and interpretability of machine learning models, enabling clinicians to understand how the models predict. This could involve developing visualizations or other methods for presenting the output of the model in an understandable way. As with any technology, there is a need to ensure that IoMT and ML systems are used ethically and responsibly. Future work will be on developing guidelines and best practices for the use of these systems, and on addressing any potential ethical concerns or unintended consequences that may arise.

REFERENCES:

1. Sundaravadivel, P.; Kougianos, E.; Mohanty, S.P.; Ganapathiraju, M.K. Everything you wanted to knowabout smart health care: Evaluating the different technologies and components of the Internet of Things for better health. IEEE Consum. Electron. Mag. 2017, 7, 18–28.
2. 2019 Global Health Care Outlook Shaping the Future—Deloitte. Available online: https: //www2.deloitte.com/content/dam/Deloitte/global/Documents/Life-Sciences-Health-Care/gxlshc-hc-outlook-2019.pdf (accessed on 10 June 2020).
3. Liu, X.; Jia, M.; Zhang, X.; Lu, W. A novel multichannel Internet of things based on dynamic spectrum sharing in 5G communication. IEEE Internet Things J. 2018, 6, 5962–5970.
4. Li, D. 5G and intelligence medicine—How the next generation of wireless technology will reconstruct healthcare? Precis. Clin. Med. 2019, 2, 205–208.
5. Brito, J.M. Technological Trends for 5G Networks Influence of E-Health and IoT Applications. Int. J. Health Med Commun. (IJEHMC) 2018, 9, 1–22.
6. McCue, T.J. $117 billion market for the internet of things in healthcare by 2020. Forbes Tech. 2015. Available online: https://www.forbes.com/sites/tjmccue/2015/04/22/117-billion-market-for-internet-of-things in-healthcare-by-2020 (accessed on 10 June 2020).
7. Rodrigues, J.J.; Pedro, L.M.; Vardasca, T.; de la Torre-Díez, I.; Martins, H.M. Mobile health platform for pressure ulcer monitoring with electronic health record integration. Health Informatics J. 2013, 19, 300–311.
8. Rodrigues, J.J.; Lopes, I.M.; Silva, B.M.; Torre, I.D. A new mobile ubiquitous computing application to control obesity: SapoFit. Informatics Health Soc. Care 2013, 38, 37–53.
9. Silva, B.M.; Rodrigues, J.J.; Lopes, I.M.; Machado, T.M.; Zhou, L. A novel cooperation strategy for mobile health applications. IEEE J. Sel. Areas Commun. 2013, 31, 28–36.
10. Yang, G.; Urke, A.R.; Øvsthus, K. Mobility Support of IoT Solution in Home Care Wireless Sensor Network. In Proceedings of the 2018 Ubiquitous Positioning, Indoor Navigation and Location-Based Services (UPINLBS), Wuhan, China, 22–23 March 2018; pp. 475–480.

11. Santos, J.; Rodrigues, J.J.; Silva, B.M.; Casal, J.; Saleem, K.; Denisov, V. An IoT-based mobile gateway for intelligent personal assistants on mobile health environments. J. Netw. Comput. Appl. 2016, 71, 194–204.
12. Vilela, P.H.; Rodrigues, J.J.; Solic, P.; Saleem, K.; Furtado, V. Performance evaluation of a Fog-assisted IoT solution for e-Health applications. Future Gener. Comput. Syst. 2019, 97, 379–386.
13 K. Sultan, I. Naseer, R. Majeed et al., “Supervised machine learning-based prediction of covid-19,” Computers, Materials & Continua, vol. 69, no. 1, pp. 21–34, 2021.
14 Q.-T.-A. Khan, S. Abbas, M. Adnan Khan, A. Fatima,S. Alanazi, and N. Sabri Elmitwally, “Modelling intelligent driving behaviour using machine learning,” Computers,Materials & Continua, vol. 68, no. 3, pp. 3061–3077, 2021.
15. Khan, Muhammad Farrukh et al. “An IoMT-Enabled Smart Healthcare Model to Monitor Elderly People Using Machine Learning Technique.” Computational Intelligence and Neuroscience 2021 (2021):
16. Elsaadi, Riyad and Mahmoud Shafik. “Intelligent Healthcare Platform Solution and Medication Management System for Elderly People with Long Term Health Conditions.” Advances in Transdisciplinary Engineering (2021):
17. Malik Bader Alazzam, Hoda Mansour, Fawaz Alassery, Ahmed Almulihi, Machine Learning Implementation of a Diabetic Patient Monitoring System Using Interactive E-App, Computational Intelligence and Neuroscience, vol. 2021, Article ID 5759184, 7 pages, 2021. https://doi.org/10.1155/2021/5759184
18. Rghioui, Amine et al. An IoT Based diabetic patient Monitoring System Using Machine Learning and Node MCU. Journal of Physics: Conference Series 1743 (2021)
19. Dwivedi AD, Srivastava G, Dhar S, Singh R. A Decentralized Privacy-Preserving Healthcare Blockchain for IoT. *Sensors*. 2019; 19(2):326. https://doi.org/10.3390/s19020326:
20. Khozeimeh, Fahime et al. Importance of Wearable Health Monitoring Systems Using IoMT; Requirements, Advantages, Disadvantages and Challenges. 2022 IEEE 22nd International Symposium on Computational Intelligence and Informatics and 8th IEEE International Conference on Recent Achievements in Mechatronics, Automation, Computer Science and Robotics (CINTI-MACRo) (2022): 000245-000250.
21. Kabilan, V et al. Design and Development of Cardiopulmonary Health Monitoring System using IoMT. 2022 IEEE 3rd Global Conference for Advancement in Technology (GCAT) (2022): 1-5.
22. Chakraborty, Chinmay and Amit Kishor. “Real-Time Cloud-Based Patient-Centric Monitoring Using Computational Health Systems.” IEEE Transactions on Computational Social Systems 9 (2022): 1613-1623.
23. Moni, Shafika Showkat and Deepti Gupta. “Secure and Efficient Privacy-preserving Authentication Scheme using Cuckoo Filter in Remote Patient Monitoring Network.” ArXiv abs/2211.01270 (2022): n. pag.
24. Alegría, Brandon et al. “Model for Implementing a IoMT Architecture with ISO/IEC 27001 Security Controls for Remote Patient Monitoring.” 2022 32nd Conference of Open Innovations Association (FRUCT) (2022): 38-48.

25. Salem, Osman and Ahmed Mehaoua. “A Secure Framework for Remote Healthcare Monitoring using the Internet of Medical Things.” ICC 2022 - IEEE International Conference on Communications (2022): 1233-1238.
26. Abdel-Gawad, Menatalla et al. “Remote Healthcare Monitoring using Wearable IoT Devices and Cloud Services.” 2022 5th Conference on Cloud and Internet of Things (CIoT) (2022): 108-113.
27. Raj, K. Perumal and Srinivas Bodapati. “FPGA Based Light Weight Encryption of Medical Data for IoMT Devices using ASCON Cipher.” 2022 IEEE International Symposium on Smart Electronic Systems (iSES) (2022): 196-201.
28. Srivastava, Jyoti et al. “Internet of Medical Things (IoMT)-Based Smart Healthcare System: Trends and Progress.” *Computational Intelligence and Neuroscience* 2022 (2022):