Original Article

SURVEY ON VARIOUS IOT HEALTHCARE MONITORING AND PREDICTION SYSTEM USING MACHINE LEARNING CONCEPTS

C. Veeraprakashkumar[1], Dr. T. S. Baskaran[2]

[1]Research Scholar, Research & PG Department of Computer Science, A.Veeraiya Vandayar Memorial Sri Pushpam College, Poondi. Thanjavur.

Affiliated to Bharathidasan University.

[2]Associate Professor & Research Supervisor, Research & PG Department of Computer Science, A.Veeriya Vandayar Memorial Sri Pushpam college, Poondi. Thanjavur.

Affiliated to Bharathidasan University.

Email: cvprakash3@gmail.com

DOI: 10.47750/pnr.2022.13.S09.332

Abstract

The IoT is a network of networks that makes it possible for whole new network topologies to emerge. IoT pervasive web connectivity has opened up paths for business growth in fields as diverse as industry, agriculture, economics, and healthcare. Providing high-quality medical services is a crucial economic and social challenge for any nation. In this paper, we provide a complete survey on various IoT healthcare applications that involves monitoring and predictions in healthcare system using machine learning models and algorithms. The study provides a complete survey on the models available to improve the accuracy of IoT monitoring and prediction systems. Further the study presents the limitations and provides possible directions for the researchers.

Keywords: IoT, Healthcare, Prediction, Monitoring, Machine Learning

1. INTRODUCTION

The field of artificial intelligence (AI) is quite broad, including many subfields such as machine learning. Due to the digitization of medical data, machine learning is now an integral part of the diagnostic process for many diseases, including cancer. In the last decade, researchers in the healthcare industry have been exploring a wide range of machine learning techniques. These techniques first discover abnormalities by segmenting them, and then classify them as malignant. The first step can be thought of as a supervised classification task in which semantic information is provided by labelling each pixel or voxel as belonging to a suspicious lesion or not, and the second step permits further analysis or quantification of the detected or segmented abnormalities and final labelling as dangerous or not. In the first stage, semantic information is provided by identifying each pixel or voxel as either belonging to a suspicious lesion or not [1].

Human services administrators, doctors, analysts, and others in the health care industry are increasingly being pressed to adjust their methods to accommodate the needs of both the public and private sectors. because an ever-increasing percentage of the population, including the elderly, the disabled, and those with long-term medical conditions, must confine their daily lives to their homes or other isolated locations. Because of this, telemedicine and remote patient monitoring are quickly becoming the norm in the medical world. Right now, researchers are trying to figure out how to provide high-quality medical care in non-hospital settings [2].

It is essential that state-of-the-art electronic medical service administrations be accessible to all people, at all times, from any place. Therefore, the IoT has been proposed as a platform for repairing the infrastructure required for proper sensor correlation. By making adjustments from a distance, this system will ensure that medical staff is always up-to-date on a patient status. On the market there are a variety of Internet of Things (IoT) devices that, at the user touch, may detect and transmit information about vital signs including heart rate, blood pressure, breath, and alcohol level. The IoT will soon make it possible to continuously monitor a patient health condition and control their treatment from otherwise unreachable locations with the use of interconnected sensors and mobile devices. Therefore, it appears likely that the Internet of Things will play a significant role in the delivery of state-of-the-art medical care in the not-too-distant future [3].

There are several obstacles that must be overcome in order to design and execute a mobile-friendly healthcare system, such as the need for massive data storage and management, interoperability, the availability of diverse assets, security and protection, data anomalies, and so on. Cloud computing provides users with streamlined and customizable access to pooled resources and basic infrastructure. The system ability to fulfill requests for services whenever they are needed makes this a reality [4].

Internet of Health Things (IoHT) is a part of the IoT-based healthcare monitoring architecture. The potential flood of data from such devices would be too much for a doctor to handle. The doctor first concern is with the patient well-being; hence it is essential that he be able to separate individual patient details from the deluge of generalized statistics. This means that a health data IoT operator will be used to transmit information to the cloud, where it can be monitored and managed to benefit big data analytics. Data mining and analysis allow for the continuous tracking of a patient health status.

Many sensor nodes are implanted in or on the patient to gather data (such as blood pressure, temperature, blood glucose, etc.). In addition, agents in the IoT and mobile devices with access to the cloud network carry the collected data. In the cloud computing environment, data processing and storage are fine-tuned for maximum effectiveness. Through remote data analysis and cloud storage, clinicians can take action without physically being present. Improving the accuracy with which diseases are diagnosed and the efficacy with which patients are treated should be the starting points for any healthcare improvement initiative. Diagnosis is a difficult yet necessary process that requires precision. To a large extent, doctors conduct medicine by making predictions based on their knowledge and experience, which can have unexpected outcomes [5].

For this reason, it is crucial to develop an automated medical analysis system that can make use of existing data and infrastructure to aid in making decisions. This method can help doctors make more precise diagnoses earlier and with fewer costly diagnostic procedures, often before the patient shows any noticeable symptoms. The authors utilize hospital-run heath information systems to meet this demand. Massive datasets were amassed for the purposes of disease diagnosis using a disease database and disease risk prediction for the future. By compiling this information, they were able to foresee the spread of diseases. For this reason, the e-healthcare network employs machine learning methods to sift through mountains of patient data and unearth previously unknown yet crucial information.

2. IoT

Behavioral and physiological monitoring systems, like an IoT-based student healthcare monitoring system, have advanced rapidly in recent years because to advancements in sensor technologies. As the number of students living off-campus grows, it becomes more important than ever to monitor their well-being, despite the challenges posed by their widespread distribution. This research presents an IoT-based method for tracking student well-being. This approach seeks to examine biometric data in order to detect changes in behavior as they occur. A key component of this framework is the use of machine learning to information gathered from IoT devices with the goal of identifying dangers to student well-being. The experimental results show that the proposed technique is both quick and accurate in determining the student health status. Our evaluation of the proposed model revealed that the support vector machine achieved a maximum accuracy of 99.1%. Decision trees, random forests, and multilayer perceptron neural networks all produced findings that were vast improvements over previous methods [6].

The IoT has the ability to serve as a reliable foundation upon which state-of-the-art healthcare facilities can be built. It can swiftly link students and persons with disabilities who may have trouble retaining their independence with medical services that can aid them. As a direct result, student health is rapidly deteriorating, compelling us to prioritize the development of online health monitoring systems for the early detection and treatment of the most common fatal illnesses, such as cancer. Cutting-edge technologies like wireless sensor networks (WSN) and the IoT have been instrumental in the recent development of smart healthcare monitoring systems (IoT). There have been major advancements in the sector thanks to both of these technologies. Applications that facilitate the exchange of health data with the end objective of providing reliable analytical information to medical professionals and healthcare institutions have also profited from these technological advancements. Noncommunicable diseases like cancer and mental problems will benefit from these analyses since they will allow for earlier diagnosis. Medical IoT devices allow for remote monitoring of student health from anywhere, including their homes, classrooms, hospitals, and more. When patients use Internet-connected medical devices, they may send doctors and nurses vital health information instantly and from anywhere [7].

Fast progress in IoT and sensor technology has led to the commercialization of numerous state-of-the-art healthcare and medical monitoring systems. The majority of recent studies have been on general well-being and chronic conditions like diabetes, kidney disease, and heart disease. Checking the pupil activity levels and behavioral models is just as important as checking their vital signs like heart rate, blood sugar, and blood pressure so that medical help can be given quickly if needed. It is crucial to keep an eye on the kid vitals, such as their heart rates, blood sugar levels, and blood pressure. Furthermore, most already deployed systems still have severe shortcomings, such as a lack of real-time data collection, processing, and analysis, and a singular concentration on the detection of chronic diseases like cardiovascular disease and diabetes without any form of prediction methodology. Based on student health-function status, we present a methodology for health surveillance. This model runs on a platform accessible via the IoT, which keeps track of physiological and behavioral parameters in real time. The intent of this approach is to fill in those spaces. In order to keep track of student health data, the proposed building employs biological sensors and other health-related technology. After collecting this information, machine learning algorithms are used to calculate an individual fitness level [8].

The following are the most pressing issues that this research addresses:

- The use of IoT and ML to the healthcare industry, resulting in a paradigm shift.
- Checking in on the student well-being by keeping an eye on both behavioral and physical indicators of illness.
- Classifying kids according to their physical and mental health to make better forecasts.

3. IoT with ML in Healthcare

Various different networks allow for the existence of the IoT. Utilizing low-cost wireless connections for sensors, along with computers and storage devices, IoTs can link otherwise distant and immobile things or equipment. The potential for advancement in many disciplines has been increased by the Internet of Thing ability to link previously disconnected devices and systems together on the web. As the backbone of an IoT-based healthcare monitoring system, networked medical sensors are a must. Because of the volume of information it includes, keeping up with it might be challenging for the doctor. To make reliable prognoses about their patient future health, doctors, however, need access to such records. In the last few decades, machine learning methodologies have been used by a wide range of medical applications. However, there is a problem with how parameter adjustment is handled in conventional machine learning methods. These parameters, when twisted appropriately, have the potential to increase the efficacy of existing machine learning algorithms for making medical predictions across a wide range of applications. Cancer, diabetes, brain tumors, and similar disorders are just a few potential targets for such therapies. Data mining, the practice of examining large amounts of information in search of hidden patterns and insights, has a rich and storied history. The authors hope to draw on these three domains to create a framework for electronic remote health monitoring that is powered by cloud computing and founded on the IoT. Since these prerequisites already exist, it stands to reason that the cloud, where the healthcare database resides, would someday reap the benefits of machine learning. The ultimate aim of this work is to give real-time tracking of user health and treatment progress [9].

A cloud-based decision-support architecture and a suite of additional machine-learning techniques well-suited to work with cloud data are presented, with contributions from a number of authors. There are two main types of patients: those who live in large cities with ready access to any and all medical care they might need, and those who live in more remote areas with limited or no medical facilities at all. A third group of people in need of help are those who go to clinics or laboratories that don't employ doctors but do have the required medical equipment and employees to help patients and function as mediators. Information collected by the sensors is uploaded to the cloud where doctors can access it and act upon it. For the time being, the sensor network will update the mobile devices with all the latest health data [10].

The sensor network can be established by a variety of connectivity methods, including Bluetooth, Wi-Fi, and even a USB connector. Medical records can be uploaded to the cloud using a cell phone, which acts as an IoT operator. As the amount of health data continues to grow, cloud computing would be able to store it, disseminate it in novel ways across different social insurance systems, and lay the groundwork for information mining, a crucial and important process for getting things done.

Even the rising quantity of social security claims might be processed with cloud computing. Breast cancer, diabetes, heart disease, spect heart, thyroid, surgery data, dermatology, and a liver disorder were just some of the disease datasets employed in this investigation, along with other important machine learning techniques like K-NN, Linear-SVM, Decision Tree, Random Forest, and MLP. Besides the aforementioned MLP, other significant machine learning approaches have been implemented thus far in this investigation [11].

One branch of AI is called machine learning, and its primary goal is to develop automatic processes that computers can utilize to better themselves, but that are difficult to design with more traditional kinds of computer programming. Machine learning algorithms have been used in many different contexts before they were implemented in the medical field. These contexts include the recognition of objects, the study of consumer behavior, the detection of credit card fraud, search engines, and many more.

It getting harder for doctors to collect the data they need to correctly diagnose patients based on symptoms, and it also harder for them to systematize the hypothetico-deductive reasoning that would help them distinguish between diseases that present identical symptoms. Reason being, there is always more being learned in the field of medicine. Automated systems that aid in diagnostic or treatment decisions have been developed, and ML characteristics have emerged as a potential answer to this problem.

4. Patient Monitoring

Remote health monitoring systems that leverage the IoT can be extremely helpful for people who need ongoing monitoring, such as the elderly, people with impairments, and people with chronic conditions. People with chronic illnesses such as diabetes and cardiovascular disease fall into this category. Patients can receive round-the-clock care without having to move from their homes because to these technologies. By doing so, they can identify developing health problems earlier and get treatment without delay. In the following paragraphs, we'll discuss how the IoT might benefit long-term patients, the elderly, and those in need during times of crisis.

Chronic Patients Healthcare Monitoring

There has been a lot of time and energy put into researching the viability of in-home monitoring devices for patients with chronic diseases. By allowing for the early detection of abnormalities and the subsequent quick therapy of abnormalities, continuous monitoring can help reduce readmissions. Other systems then utilised this information to make a diagnosis and, if necessary, call for medical help. Some of these devices were able to take electrocardiography (ECG) readings and send them to a medical database over the Internet or via wireless communications. The ECGaaS system can keep tabs on the ECG data of several people simultaneously. The foundation of this technology is the marriage of cloud PaaS infrastructure and networks of sensors implanted in the human body. Several studies have been conducted to collect data from sensors to aid in the early detection of high and low blood pressure or to trigger alerts if anything out of the norm was observed [12].

The systems not only analyze vital signs, but also have patients fill out questionnaires to learn more about their health. Those who participated in a field trial for the Care@Distance project considered the technology to be helpful and easy to operate; however, some people complained about the intrusiveness of the blood pressure monitor. Heart failure patient vital indicators (such as weight and level of activity) and symptoms (using a questionnaire) can be monitored and used to alert clinicians to significant changes [13].

A health monitoring system for patients with CHF that makes use of Web servers, databases, and sensors. The number of people whose weight or blood pressure was outside the normal range decreased dramatically when this monitoring device was utilized with them. When compared to models that only used average daily weight, these are more accurate by more than 20%.

A smartphone-based telemonitoring tool to keep tabs on patients with heart failure and spot any unusual patterns of behavior. When configured in this fashion, a smartphone serves not just as a node but also as a sensor, processor, and transmitter.

Aged Care Monitoring

Improved independence and security can be had by the elderly without them having to leave the comfort of their own homes, thanks to telecare services. The smart home and telemedicine are two examples of technological interventions that can aid seniors in doing their daily activities [14].

SilverLink is a system that uses human and non-human sensors to track a user activities and health. Sensor data processing enables the detection of out-of-the-ordinary patterns of activity. The technology triggers alarms and informs the proper authorities whenever it finds a deviation from the norm. Extensive in-house testing in Taiwan showed that the prototype passed with 70-80% accuracy using sensors but failed with under 60% accuracy when evaluated by humans. (The success rate can be determined by dividing the number of times an occurrence was reported by the number of times it actually took place.)

Help to You (H2U) healthcare system was developed to improve medical care for the elderly. The system utilizes biosensors, wireless sensor networks, and wearable devices to support real-time activity and monitor the health of seniors. The proposed system has the potential to do numerous tasks, such as alerting medical professionals to emergencies, reminding users to take their medications, and recognizing symptoms. In the event of a medical emergency, this system is meant to alert the appropriate people (caregivers, doctors) immediately. The technique allowed for the addition of additional sensors and real-time modifications to existing alert criteria, all with zero impact on system availability. Several studies have examined various methods of prompting patients to take their prescriptions as directed and keeping their records current to account for any developments in their treatment. The potential exists for each of these strategies to improve adherence to medication regimens among the elderly [15].

Both a radio-frequency identification reader and a camera are used in the drug-tracking system described by Parida et al. [16]. Those who need medicine reminders at the right times would appreciate the smart pill box exhibited. Interventions like this can help seniors at risk for dementia.

Emergency Applications

Critical applications can now detect anomalies at the right time and alert the proper authorities. It is probable to pursue the strategy of having medical equipment monitor the state of patients, followed by the use of individual mobile devices to analyze the data in order to identify potential hazards and the transmission of this information to bigger medical databases. All patients are within reach of the ambulatory staff in the event of an emergency. So, in order to get the clinic ready for the clinical therapy, the doctors and nurses go over any situation-specific first aid instructions with the patients.

Telemedicine diagnostics and telecare for emergency conditions were reported by the authors of [19]. The distinction between emergency telecare and telemedicine diagnostics is that the former informs the user about diseases, medical information, and therapies, while the latter reveals the user position, emergency information, and directions for how to help the user.

In the [17] provided several case studies illustrating the utility of a digital assistance service in times of crisis in their article. Emergency applications that target fall prevention and fall detection are crucial because falls are such a severe problem for a certain age group. There are primarily three categories of fall detection systems: vision-based systems, ambient sensors, and wearable devices.

Using wearable sensors to monitor the wearer motion and location, [18] presented a system that can detect falls in real time. Fall detection was a primary design goal of the system. Ten planned slips and five routine actions were used to test the proposed method. For each activity, 30 repetitions were decided upon as the optimal number of trials. According to the results of the tests, the total accuracy of the suggested system for detecting falls is 96.4%. Another method for detecting falls is to observe the motion of human objects in depth frames [19]-[20], such as those captured by the Microsoft Kinect depth sensor.

Medical Diagnosis

HealthFog was first introduced by Tuli et al. [21] with the goal of automating the detection of heart conditions. HealthFog uses deep learning and the IoT to achieve this. Patients with cardiac problems can benefit from HealthFog lightweight and effective data handling thanks to the information gathered from a wide variety of IoT devices. Low-latency solutions for data processing and energy savings are only two of the many advantages offered by recent advancements in computing, such as fog and edge computing. Quality of Service (QoS) challenges in real-time fog environments have been identified as one of the drawbacks of fog computing for medical applications.

Automated EEG disease diagnosis and detection systems have advanced greatly with the use of deep learning algorithms, as stated by Sarraft et al. [22]. One of the many merits of this investigation is the potential for robotic feature extraction. As a result, the standard of EEG decoding performance can be raised to new heights with the use of this capability. The EEG can also be used to diagnose certain diseases. While there are a few accessible EEG pathology datasets, the great majority are too small to be useful for many deep learning models.

When certain regions of the brain become inoperable due to ischemia or bleeding, medical professionals refer to this as a cerebral vascular accident (commonly abbreviated as CVA). It almost always has fatal consequences. This problem can only be fixed by getting a proper diagnosis as soon as possible so that therapy can begin. Stroke diagnostics usually involve imaging tests like computed tomography (CT) and magnetic resonance imaging (MRI).

It has been possible to classify CT scans for strokes using Convolutional Neural Networks (CNN) within an IoT framework. Because of this, we can tell if the brain is healthy, if the stroke was brought on by ischemia, or if it was brought on by bleeding. One reason why the IoT is useful in the healthcare industry is that it reduces dependency on humans, which in turn reduces the likelihood of human error. Unfortunately, expanding the system to include additional sorts of medical images is outside the scope of our current capabilities.

Using long short-term memory, Faust et al. [23] created a deep learning model for identifying episodes of atrial fibrillation (LSTM). An analysis of HR signals was used to create the model. The LSTM-based deep learning system was tested using labeled HR signal data from the Physio Net Atrial Fibrillation Database and 20 subjects (AFDB). The possibilities for this deep learning model success are greater than those offered by machine learning approaches. Moreover, in some cases, results from a small sample size can be extrapolated to a much larger data set. One of the major flaws of this study is that it pays no attention whatsoever to the topic of training.

Traditional Chinese medicine approach to infectious fever relies heavily on a correct diagnosis of the underlying cause. When it comes to infectious fevers, traditional Chinese medicine has a hard time telling them apart due to the complexity of the symptoms associated with each. Despite the difficulty of the task, deep learning offers hope as a potential way for integrating computer-aided diagnosis of infectious fever syndrome. As part of the modification, an adaptive dropout function will be added to the stacked auto-encoder. A positive outcome of this study is that it can reduce the prevalence of overfitting and boost classification precision. It might be challenging for clinicians to determine the etiology of a fever when no specific culture is available. You could say that this is a flaw in the examination.

In their review of deep reinforcement learning models, Bray et al. [24] talk about using computers to help in lung cancer diagnosis and treatment. Worldwide, lung cancer is a major health concern right now. Both benign and malignant lung tumors are extremely common. We have strong faith in the results from deep reinforcement learning models used to diagnose lung cancer. However, using deep reinforcement learning models to treat lung cancer is challenging because of the need to devise an effective method of updating the Q-value associated with each action.

Melanomas are among the worst types of skin cancer because they are so prone to metastasis, or spread to other parts of the body. Typical nevi, atypical nevi, and melanomas are the three forms of melanocytic lesions. The most typical variety of nevus is the conventional variety. In this study, we use an IoT-based system to classify the various types of skin lesions that have been seen. CNN models were applied to the ImageNet database to get the images. The flexibility and ease of use of this technology are two of its greatest advantages. The participants in this study will not have access to the internet, which is a limitation of the research. Sending pictures and connecting to LINDA API both necessitate a reliable and constant internet connection.

Schirrmeister [25] presented new perspectives on the features and highlighted how ConvNets may detect the use of variable alpha, beta, and high gamma powers. Furthermore, the task used in the study is metaphorical for the way of building ConvNets, which are used in the process of interpreting information, and the study itself is an analogy for the conventional EEG, which contains no man-made components. Two of these benefits are their scalability to large datasets and their ability to facilitate end-to-end learning. Their major challenges are the necessity of using training data and the potential for inaccurate prediction.

Personal Healthcare Applications

Below, we discuss some accessible medical applications for use in private settings or at home. Many other settings, case studies, benefits and drawbacks, and outcomes are examined and evaluated in this study as well.

Fonseca et al. [26] proposed creating smart homes as a means to allow patients with a wide range of chronic diseases to get treatment in the comfort of their own homes. Knowledge Acquisition Bottleneck describes the current state of the healthcare industry inability to provide reliable measures of medical expertise. Supervised learning, often known as predictive analytics, is a sort of machine learning that we employ for our inquiry. In this technique, systems are taught to map inputs to outputs by being exposed to a training set, which is a labeled collection of input-output pairs. The term training set is used to refer to this group of input/output data. This approach encourages the creation of a new breed of care facilities that can improve the quality of life for people with multiple chronic conditions while keeping costs down. There are no supporting numbers for the model claimed usefulness and effectiveness, which is problematic.

Cloud services like IBM IoT and Emotion Sense, enable smartphone users to share the sensor data collected by their devices. It is clear that the smartphone has had a major impact on the fields of ambulatory evaluation, behavior monitoring, and understanding and prediction. In terms of one health, data collected by a smartphone sensor can be connected using a technique called deep learning. At the outset, deep-stacked auto encoders (SAE) segment the information. In the next step, the features are extracted from the data and the SoftMax layer is labelled independently by each subset. Subsets of sensor data are then analyzed to establish a quantifiable relevance between the data and the patient health. Finally, a simulation is built to verify the effectiveness of the proposed approach. The SAE format is intuitive, the approach doesn't require a specialized GPU, and the efficiency is high (regularizing weight and sparsity). However, it would be beneficial to examine more forms of sensor data from mobile phones and wearable devices in a future study.

Tooth diseases are a widespread problem that affect people of all ages and backgrounds everywhere. A startlingly high percentage of the Chinese population (94%) has experienced dental problems of some kind, according to the results of a recent evaluation of the state of oral health in China. A system based on smart technology, deep learning, and a portable terminal for tracking dental health could potentially resolve the issue. A variety of dental problems were identified and categorized with the use of this approach. A decision was made to install both the dentist app and the patient app. The main benefit is that it works equally well on small and large lips. Its 5.5 mm width and 4 mm thickness allow for this, in contrast to the 3 mm breadth and 1 mm thickness of conventional mouth endoscopes. One to six and a half centimeters in length, this extract has programmable lighting and a mouthpiece. Additionally, low-cost equipment makes home deployment much simpler. Larger teeth can't be covered up by regular glasses, which is a drawback for some people.

The difficult topic of precise physiological monitoring in healthcare was explored by the author [27]. A monitoring system built on the Body Sensor Network was created to ensure the safe delivery of medical care. Users of the IoT who employ a system to track their physiological data may one day be able to foresee their own health problems, such as persistent fever, heart attacks, and the need for care for the elderly. In order to learn from patient physiological signs, it has been recommended that a Deep Neural Network (DNN) be utilized to elicit parts of the signal in multiple sensors. Thus, the indications may be taught. The high level of accuracy and affordable price of this prototype model are both advantages. DNN insatiable appetite for data is one of their primary drawbacks in comparison to alternative approaches.

A highly accurate detection model that can be applied in inexpensive equipment is the most crucial part of fall detection. Some researchers have proposed using sensors that are attached to the subject torso as a way to improve the reliability of detection; nevertheless, the vast majority of the elderly are uncomfortable with and uninterested in trying out such devices. Traditional and non-traditional methods are used to build fall detection models with the Smartwatch, Notch, and Farseeing datasets, respectively.

Malasingh et al. [28] state that the use of smart patches and chips embedded with IoT sensors to track people health is in its infancy in the context of multimedia technology. Thin, flexible arrays of patches are used to track vitals including body temperature and heart rate. Cloud computing is used by the aforementioned patches in the field of smart healthcare to track user motion at several locations. Use of multimedia technologies improves the performance of both these patches and the access points themselves. The data from IoT devices is elicited and processed in the cloud using deep learning, machine learning, and convolutional neural networks, and CCT enables the transfer of this data across the internet.

Smart Log Patch, an environment tailored to computing with a Bayesian deep learning network, has shown promising results in terms of accuracy, efficiency, mean residual error, time to solution, and energy usage. Soon, suggestions for innovative multimedia solutions that can aid with privacy and cost will be required.

One of the main objectives of device development in the field of intelligent healthcare is tracking caloric intake and expenditure. Connecting sensor data with cloud-based analytics is made possible by the IoT. The IoT is a network of devices that can be accessed and recognized individually. When a smart sensor board is combined with a mobile app, the resulting device is called a smart-log, which can also be used to describe the device itself. The sensor board features a food-weight detecting sensor. With the help of a microprocessor housed in a wireless module, weighing data may be transmitted wirelessly and uploaded to the cloud, where it can be analyzed. As such, the suggested system will be adapted to function as a thing within the context of the IoT. Use the smartphone camera and an app to learn about the food nutritional value.

Most sporting events, as stated by [29], The unforeseen consequences of a prolonged diagnostic procedure could be inconvenient. Due to this, studies are being conducted on the IoT potential for treating sports-related injuries. To assess if muscles have been harmed, it is necessary to utilize a portable terminal, evaluate and detect the collected data over the ZigBee network, make the data explicit via the gateway that monitors circumstances, and show and transmit the final result via the LED screen. This research is superior to others in terms of accuracy and low packet loss. However, there are other restrictions on this approach, such as the limited scope of the feedback experiment.

5. Summary

Using deep learning technologies, this study shows how to better the IoT in healthcare. The study goal is to examine the many components of deep learning-based IoT healthcare technologies and to suggest new healthcare frameworks, architectures, platforms, and algorithms that can be used to enhance medical treatment. Extensive research endeavors related to the potential applications of deep learning in the fields of tele-health, ambient supported living, machine health monitoring, human activity detection, vital sign collection, and data fusion are also included in this paper. The paper discusses each of these areas in detail. To provide readers with a deeper understanding of the healthcare system, we do this.

REFERENCES

1. Zaouiat, C. A., & Latif, A. (2017, November). Internet of things and machine learning convergence: The e-healthcare revolution. In Proceedings of the 2nd International Conference on Computing and Wireless Communication Systems (pp. 1-5).
2. Abdulkareem, K. H., Mohammed, M. A., Gunasekaran, S. S., Al-Mhiqani, M. N., Mutlag, A. A., Mostafa, S. A., ... & Ibrahim, D. A. (2019). A review of fog computing and machine learning: concepts, applications, challenges, and open issues. IEEE Access, 7, 153123-153140.
3. Atitallah, S. B., Driss, M., Boulila, W., & Ghézala, H. B. (2020). Leveraging Deep Learning and IoT big data analytics to support the smart cities development: Review and future directions. Computer Science Review, 38, 100303.
4. Nashif, S., Raihan, M. R., Islam, M. R., & Imam, M. H. (2018). Heart disease detection by using machine learning algorithms and a real-time cardiovascular health monitoring system. World Journal of Engineering and Technology, 6(4), 854-873.
5. Alshamrani, M. (2021). IoT and artificial intelligence implementations for remote healthcare monitoring systems: A survey. Journal of King Saud University-Computer and Information Sciences.
6. Bharadwaj, H. K., Agarwal, A., Chamola, V., Lakkaniga, N. R., Hassija, V., Guizani, M., & Sikdar, B. (2021). A review on the role of machine learning in enabling IoT based healthcare applications. IEEE Access, 9, 38859-38890.
7. Ullah, Z., Al-Turjman, F., Mostarda, L., & Gagliardi, R. (2020). Applications of artificial intelligence and machine learning in smart cities. Computer Communications, 154, 313-323.
8. Kondaka, L. S., Thenmozhi, M., Vijayakumar, K., & Kohli, R. (2021). An intensive healthcare monitoring paradigm by using IoT based machine learning strategies. Multimedia Tools and Applications, 1-15.
9. Supriya, M., & Deepa, A. J. (2020). Machine learning approach on healthcare big data: a review. Big Data and Information Analytics, 5(1), 58-75.
10. Mohana, J., Yakkala, B., Vimalnath, S., Benson Mansingh, P. M., Yuvaraj, N., Srihari, K., ... & Sundramurthy, V. P. (2022). Application of internet of things on the healthcare field using convolutional neural network processing. Journal of Healthcare Engineering, 2022.
11. Durga, S., Nag, R., & Daniel, E. (2019, March). Survey on machine learning and deep learning algorithms used in internet of things (IoT) healthcare. In 2019 3rd international conference on computing methodologies and communication (ICCMC) (pp. 1018-1022). IEEE.
12. Ramkumar, M., Basker, N., Pradeep, D., Prajapati, R., Yuvaraj, N., Arshath Raja, R., ... & Alene, A. (2022). Healthcare Biclustering-Based Prediction on Gene Expression Dataset. BioMed Research International, 2022.
13. Gupta, A., & Katarya, R. (2020). Social media based surveillance systems for healthcare using machine learning: a systematic review. Journal of biomedical informatics, 108, 103500.
14. Sandhiya, S., & Palani, U. (2020). An effective disease prediction system using incremental feature selection and temporal convolutional neural network. Journal of Ambient Intelligence and Humanized Computing, 11(11), 5547-5560.
15. Salman, O. H., Taha, Z., Alsabah, M. Q., Hussein, Y. S., Mohammed, A. S., & Aal-Nouman, M. (2021). A review on utilizing machine learning

technology in the fields of electronic emergency triage and patient priority systems in telemedicine: Coherent taxonomy, motivations, open research challenges and recommendations for intelligent future work. Computer Methods and Programs in Biomedicine, 209, 106357.
16. Parida, M., Yang, H. C., Jheng, S. W., & Kuo, C. J. (2012, September). Application of RFID technology for in-house drug management system. In 2012 15th international conference on network-based information systems (pp. 577-581). IEEE.
17. Darshan, K. R., & Anandakumar, K. R. (2015, December). A comprehensive review on usage of Internet of Things (IoT) in healthcare system. In 2015 International Conference on Emerging Research in Electronics, Computer Science and Technology (ICERECT) (pp. 132-136). IEEE.
18. Nguyen, H. H., Mirza, F., Naeem, M. A., & Nguyen, M. (2017, April). A review on IoT healthcare monitoring applications and a vision for transforming sensor data into real-time clinical feedback. In 2017 IEEE 21st International conference on computer supported cooperative work in design (CSCWD) (pp. 257-262). IEEE.
19. Cheng, Y., Jiang, C., & Shi, J. (2016, March). A Fall detection system based on SensorTag and Windows 10 IoT core. In 2015 international conference on mechanical science and engineering (pp. 238-244). Atlantis Press.
20. Gasparrini, S., Cippitelli, E., Spinsante, S., & Gambi, E. (2014). A depth-based fall detection system using a Kinect® sensor. Sensors, 14(2), 2756-2775.
21. Tuli, S., Basumatary, N., Gill, S. S., Kahani, M., Arya, R. C., Wander, G. S., & Buyya, R. (2020). HealthFog: An ensemble deep learning based Smart Healthcare System for Automatic Diagnosis of Heart Diseases in integrated IoT and fog computing environments. Future Generation Computer Systems, 104, 187-200.
22. Sarraf, S., & Tofighi, G. (2016). Classification of alzheimer's disease using fmri data and deep learning convolutional neural networks. arXiv preprint arXiv:1603.08631.
23. Faust, O., Shenfield, A., Kareem, M., San, T. R., Fujita, H., & Acharya, U. R. (2018). Automated detection of atrial fibrillation using long short-term memory network with RR interval signals. Computers in biology and medicine, 102, 327-335.
24. Bray, F., Ferlay, J., Soerjomataram, I., Siegel, R. L., Torre, L. A., & Jemal, A. (2018). Global cancer statistics 2018: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. CA: a cancer journal for clinicians, 68(6), 394-424.
25. Schirrmeister, R. T., Springenberg, J. T., Fiederer, L. D. J., Glasstetter, M., Eggensperger, K., Tangermann, M., ... & Ball, T. (2017). Deep learning with convolutional neural networks for EEG decoding and visualization. Human brain mapping, 38(11), 5391-5420.
26. Mendes, D., Lopes, M., Parreira, P., & Fonseca, C. (2017). Deep learning and IoT to assist multimorbidity home based healthcare. https://dspace.uevora.pt/rdpc/handle/10174/22965
27. Sandstrom, G. M., Lathia, N., Mascolo, C., & Rentfrow, P. J. (2016). Opportunities for smartphones in clinical care: the future of mobile mood monitoring. The Journal of clinical psychiatry, 77(2), 13476.
28. Malasinghe, L. P., Ramzan, N., & Dahal, K. (2019). Remote patient monitoring: a comprehensive study. Journal of Ambient Intelligence and Humanized Computing, 10(1), 57-76.
29. Sharma, S., Chen, K., & Sheth, A. (2018). Toward practical privacy-preserving analytics for IoT and cloud-based healthcare systems. IEEE Internet Computing, 22(2), 42-51.