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A Comprehensive Review of Ml and Iot in Current Technologies for Remote Healthcare

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Abstract:-The present review analyzes the impact of new advanced technologies in the medical field. The study reveals an understanding of the fundamentals of H-IoT. Machine learning (ML) and the Internet of Things (IoT) have been effectively utilized in healthcare recently. The technology development, especially in remote healthcare, is more significant. In this work of art, review the most recent technical paradigms and cutting-edge research in the newest technologies, which are crucial for the future advancement of remote medical services and facilitated living. Initially, a quick explanation of the requirement for employing the most recent technical advancements in the field of remote health care is presented. The most significant technological advancements and concepts are then highlighted as being essential to enable remote medical care and supported living. The methods between the sensing nodes and the processors are among the fundamental enabling technologies, as are the processing algorithms used to provide an output from the sensor data. However, A number of new technologies are currently supporting these enabling technologies. Artificial intelligence (AI) utilization has significantly changed H-IoT systems on practically every level. Hereafter, a thorough analysis of current technology and potential issues with those technologies is provided.

Keywords*:* Healthcare, H-IoT, Internet of Things (IoT),Remote medical care , patient monitoring, mobile-health, machine learning(ML).

1. Introduction

Worldwide development toward distant monitoring, actual and rapid illness credentials, and the remote healthcare is a growing research area. The numerous subdivisions of remote healthcare (such as tele-health and mobile-health), which all state about employing technology to keep track of patients away from hospitals.The advantages of remote patient monitoring involve the capability to consistently track patients, the capacity to notice diseases rapidly and in instantaneously, a reduction of expenses related to hospitals and hospitalizations as much , the ability to get readings that are more precise yet permitting patients to continue going about living their lives as usual, the enhancement of the effectiveness of healthcare services by using technologies for communication, as well as the ability to deliver immediate medical treatment and support for patients with it[1].

Patients with persistent ailments, those with mobility issues or some disabilities, those who have recently undergone surgery, neonates, and elderly patients are just a few of the patient subgroups that are the focus of remote patient monitoring. All of these patient types have problems that benefit from ongoing observation. The ability to support daily living for all patients as comfortable as possible is the goal of good healthcare. The majority of studies adopt the philosophy that patients benefit more from having freedom of movement and activity at home or in other private settings than from being confined to an expensive hospital room. As a result, complete systems are being constructed to support this idea using various technologies. The new remote health monitoring applications allow older people to carry out daily tasks independently of a caregiver. Therefore, with the least amount of user inconvenience, these programs supporting actions including viewing television, learning, sleeping, standing up, and using the restroom. Even if there are wearable sensors, their impact on the activities is minimal. One such instance is sensor-based smart watches.

The core elements of a remote monitoring system are the data collection system, information processing system, healthcare end-terminal, and the network of communications. Various sensors, or gadgets that incorporate sensors that have wireless data transmission capacity make up a data acquisition system. As technology develops, sensors might not just be used in medical applications; they might also be found in cameras or cell phones[2]. Humans are more susceptible to diseases because they engage in less physical activity. The Internet of Things (IoT) is essential to the health care industry. It is now possible to track a person's medical state using a variety of sensors, and a message can be sent to hospitals in the area to assist the patients[3]. Machine learning can be used to construct algorithms that are based on data trends and associations to extract the necessary information from a vast amount of data. IoT and machine learning have been applied into healthcare for automated devices to create patient files and monitor patients in real time. Several Machine Learning techniques must be learned in order to manage IoT data in the healthcare industry. Machine learning has the potential to be useful in a variety of fields, including intrusion detection, bioinformatics, healthcare, marketing, and gaming. It enables machines and robots to make decisions based on data rather than being explicitly programmed to carry out a certain task. These programs or algorithms are designed to learn and get better over time as they are exposed to new or unknown data[4].

The organization of the paper: The organization of the paper is mentioned here. A quick contrast with the relevant effort is provided in Segment I and II. The foundations of H-IoT systems are discussed in Section III. The application-based frameworks utilized in H-IoT systems are covered in Segment IV. The effects of ML, blockchain on H-IoT are covered in Segment V through VI, respectively. the conclusion is given in Segment VII. The illustration shows how the paper is organized in Figure1.

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Figure1. Our Survey Structure

2.Distant Carers

The primary causes of the recently observed increase in life expectancy are contemporary medical systems and innovations, better overall wellness, and increased personal hygiene. However, the population’s expanding average age is increasing the volume of work (i.e., expenditures and manpower) relating to health, on the one hand and diminishing current principles of senior citizens’ welfare on the other side disturbs the socioeconomic makeup of numerous nations [5]. Ageing specifically causes a number of chronic illnesses and ailments, including dementia, cancer, diabetes, heart disease, and stroke [6]. The elderly need regular and urgent medical attention due to these disorders, as well as assistance with daily tasks because failure to do so could have grave repercussions [7].

Notably, some diseases grow and get worse as people age. One of the most common medical disorders that require appropriate care is dementia, which serves as a good illustration. Common signs of dementia in elders include amnesia, diminished ability to solve problems, communication problems, and difficulty in performing daily tasks like bathing and dressing. Alzheimer's disease is one of the greatest common dementia-causing factors. Because Alzheimer is a degenerative brain disease, it deteriorates over time. Alzheimer's patients encounter a variety of signs, some of which evolve with time. Formal and informal carers can generally be divided into two categories. Individuals who provide formal care are typically compensated professionals who work for institutions that include nurses, personal assistants, rehabilitation experts as well as doctors, etc. [8,9]. Examples of informal carers include family members and relatives who look after an individual they love who needs help. The need for formal and informal carers is rising daily as a result of the significant increase in the world's ageing population.

Both sorts of caregiving are becoming more expensive. In formal caregiving, the process of providing care carries a significant financial burden. For instance, the global economic According to estimates, the cost of dementia alone (including formal and informal care) exceeds $1 trillion USD [10]. In addition, informal carers invest a lot of time, money, and effort in helping the elderly with daily duties. On the positive side, staying at residence, receiving assistance from relatives and friends allows for saving money for the medical system and may stop an elder individual from being transferred to a care facility [10]. On the down side, not many unofficial carers have the necessary training to deliver care services in a competent manner. The necessary resource gap that prevents professional carers from providing the required care remotely can be filled by technological solutions. Most care givers believe that technology is already aiding them significantly in their roles as carers. Believe technology can assist them in providing care in a more effective, efficient, safe, and stress-free manner [11]. In addition to assisting in the monitoring and care for patients and close relatives, technological solutions, such as telehealth and remote activity monitoring, also make it possible for effective and seamless interaction with medical personnel and other healthcare providers [11,12].

3. Healthcare IoT

The sector of healthcare is one among the main areas where IoT is being used. As a result, the IoT system utilized for healthcare applications is known as the H-IoT. A Universal IoT system includes the H-IoT as a subset[13]. WSNs and BSNs are the primary underpinning IoT and H-IoT technologies respectively. Their underlying technology can be used to distinguish between IoT and H-IoT. A synopsis of the distinctions between IoT and H-IoT is provided in Table 1. The key differences between the two systems are outlined in Table 1 [14]. IoT adoption in healthcare is a relatively new development. In the past few years, the use of fitness detecting gadgets or smart watches has dramatically increased & the market data supports this given the anticipated rise in usage of these in the future [15]. IoThNet, a system focused on healthcare, was created as a result of the development of health detecting gadgets and enhanced access to the IoT infrastructure for communication [45]. These IoT solutions have enormous promise for tracking users' health improvements.. In order to provide accurate diagnoses and high levels medical care, the individuals who are linked to the network will be monitored for variations in their health metrics, such as indicators of health and biographical data [17,18]. It highlights the requirement for the creation of a standardised architecture to simplify information flow between the many participating organisations.

A noteworthy factor of H-IoT would be a standard or reference design. For the deployment of diverse IoT applications, numerous consortiums and commercial companies are developing multiple standard designs [19]. A Team of experts for the standardisation of service-oriented distributed Point-of-Service medical equipment’s has been created by the IEEE Standards Association. Along with the Quality of Service characteristics, it determines node creation, exploration, and H-IoT scenario communication [20].

Generic IoT

- The generic IoT typically covers a broad geographic area and a single purposeoth sun and wind energy are potential energy sources. If the nodes are stationary, they might be continuously powered.
- Both sun and wind energy are potential energy sources. If the nodes are stationary, they might be continuously powered.
- Environment monitoring, a tool for defense applications, and industrial monitoring
- Nodes should be as tiny as possible, although size varies depending on surroundings and its utilization
- Typically immobile.
- Sensor deployment is rather simple.
- Data integrity is attempted to be maintained. Errors are mitigated by redundancy.

H-IoT

- Typically used inside and within the human body or in a medical facility, both of which are enclosed or tiny geographic areas.
- Additionally, H-IoT nodes can use heat, stress, and motion to obtain energy from the body of an individual.
- Used to keep an eye on a person's health
- Each of the nodes are reduced in size to minimize obtrusion.
- When referring to the body of a person, it is essentially movable.
- Deployment is challenging, especially with implants, which typically necessitate surgery.
- The data must be protected and sent with the greatest care.

Table 1. Generic IoT and H-IoT Characteristic Features [14,21]

4.ArchitectureandFramework of H-IoT

The normal architecture used in H-IoT systems is a three-tier structure made up of the Transmission layer, the application or processing layer, and the Device or objects layer, That refers to the network's open end. [13]The common three-tier design used in H-IoT is depicted in Figure 2. The H-IoT devices are system of sensors that, depending on the application, record various indices. The service provider or an actuators that delivers the result to users next the examination are further examples of "things" that can be used. Prior to being sent to the Application layer at the edge nodes, the data may occasionally be pre-processed.

The Network system makes sure that the observed information is sent to the application layer, in which large data analysis takes place. Yin et al. [22]discussed IoT-based tele rehabilitative systems, their enabling technologies, and deployment. By isolating sensing systems from end-users such as hospitals, ambulances, and medicine distribution networks, a fourth layer can sometimes be developed [23]. Additionally, H-IoT systems can forecast impending health difficulties, enhance the standard of living for seniors in supported living services, and support healthcare services in ERs and hospitals [24] [25]. As an example, consider a cardiac monitoring system, we may comprehend how an H-IoT system functions on a fundamental level [26].

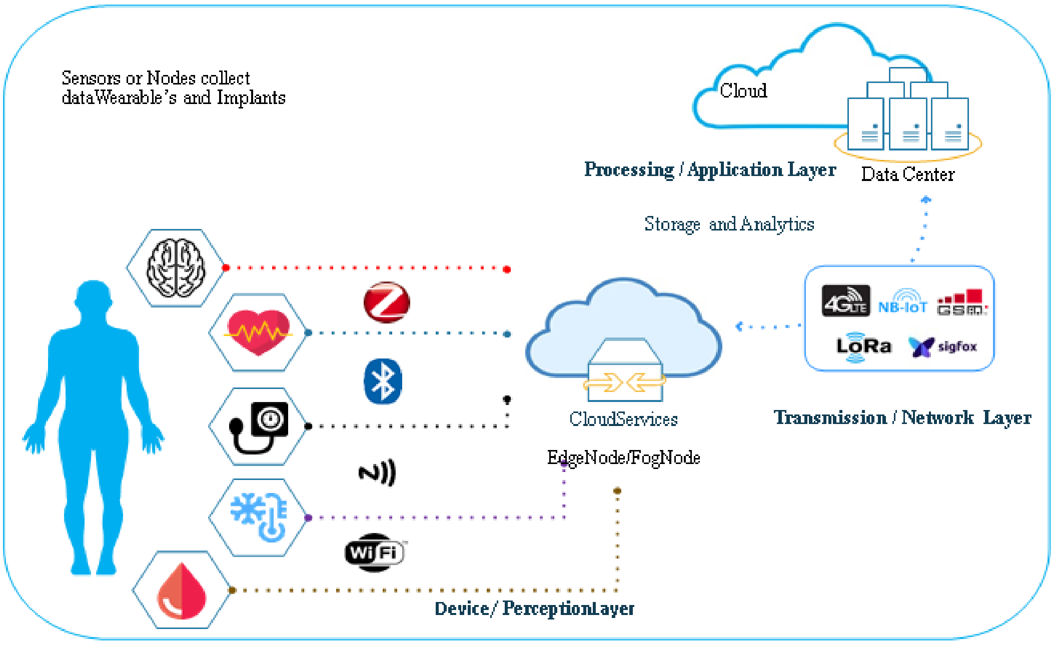

Figure2. The H-IoT systems' 3-tier architectures. The various tiers' communication technology are identified. The interactions between the various layers are shown.

In order to create a new class of multi-physiological parameter medical monitoring devices with a distant data transmission capability, this research integrates embedding and cell phone technologies. This device collects and displays numerous physiological indicators such as blood pressure, heart rate, saturation of oxygen in the blood, and temperature of the body in real time in order to aid in early identification and prompt cure for disorders [27].The Health Monitoring and Predicting Framework Using IOT portrays the collection and interoperability of Patient information gathered from the sensors. The collected sensor data will be incorporated through microcontroller Arduino board for processing and the processed data is sent to remote server Thing Speak using ESP8266 Wi-Fi module. An IoT analytics platform called Thing Speak Server enables us to visualize and explore real-time data streams in the cloud. And the machine learning technique is used to forecast it with the highest degree of accuracy[28].

5. H-IoT MachineLearning

In all scientific areas as well as the industry, ML application is dominating. Artificial intelligence (AI) was described as the next stage in the evolution of human beings during 2019 Show for Consumer Electronics, an yearly event which provides a preview of the upcoming year's technological developments [29]. A significant amount of customer electronics, particularly in the medical industry, have been introduced, the bulk of which are AI-powered. medical equipment and diagnostic tools, and rehabilitation are becoming more widespread among the wearable's, lifestyle, and assistive categories [30]. We examine the use of machine learning in H-IoT in this part. Artificial intelligence gives robots intelligence akin to that of humans. ML falls under the umbrella of AI. AI is capable of processing natural language, seeing, and decision-making based on knowledge. ML gives computers being able to learn on their own without being explicitly programmed.

To make predictions, the Machine learning algorithms could develop models from labelled or unlabelled datasets. Without using any prior datasets, the machine learning algorithms can also learn from themselves. This distinction between supervised, unsupervised, and Reinforcement Learning (RL) methods is helpful. Support vector machines (SVM), Nave Bayes, Linear Regression, Random Forest, Classification & Regression Trees and K-Means are a few ML algorithm examples. Semi-supervised learning methods are a sort of machine learning that fall somewhere between having small portion of data is labelled and lots of data is unlabelled. Another branch of machine learning is called deep learning that makes an effort to replicate how the brain of a person makes decisions. Deep learning is a class of machine learning algorithms that uses several layers with more capabilities. Deep belief networks (DBN) and CNN are examples of common deep learning algorithms.

The advantages of both approaches are combined by the working Deep learning and Reinforcement Learning methods, producing high-efficient methods like Deep Reinforcement Learning [31]. The interplay of AI, ML, and DL is depicted in Figure 3.[32]

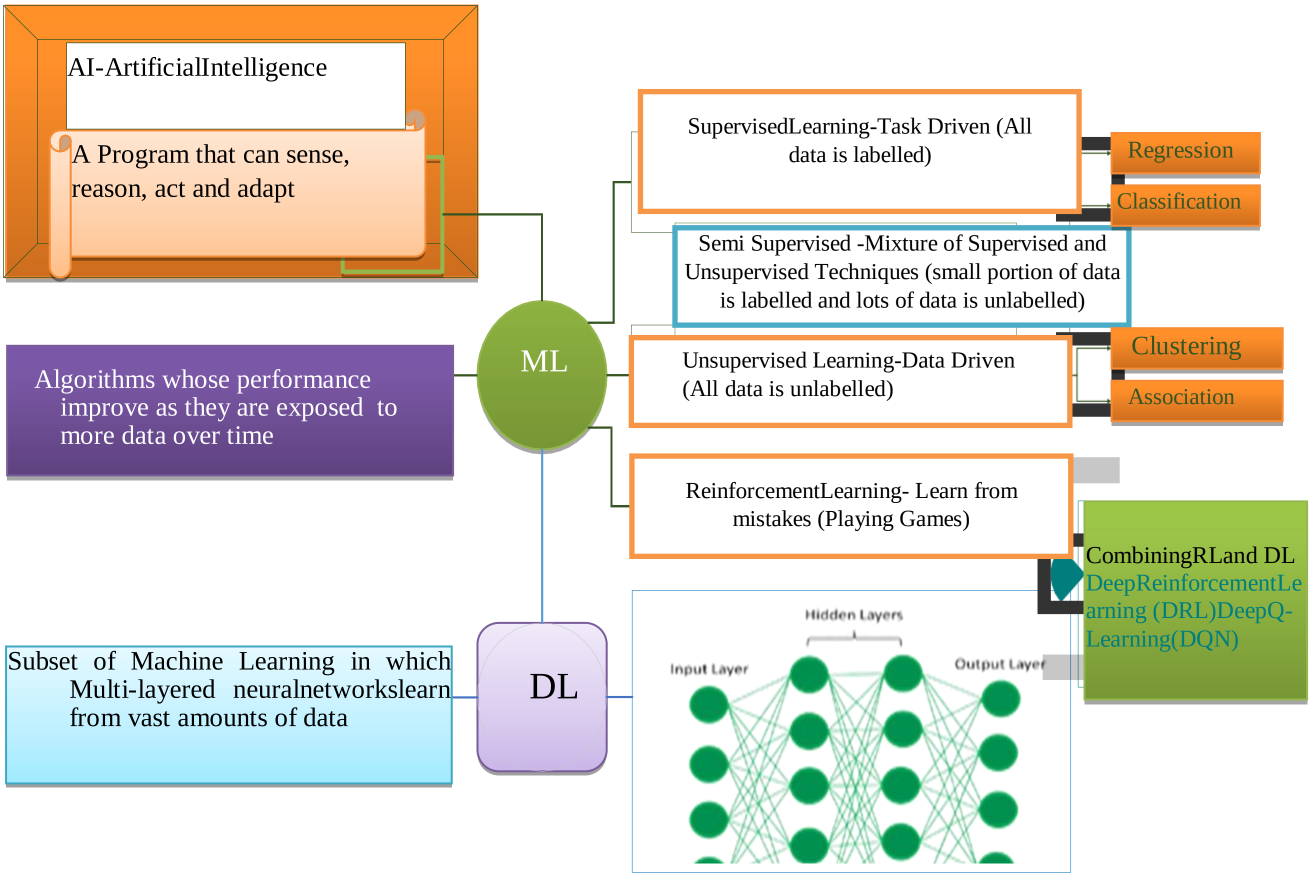

Figure3. The interplay of AI, ML, and DL

IoT is only one of the many scientific fields where ML is having a transformative impact. IoT applications for healthcare are changing thanks to AI. AI has had a substantial impact on the discovery and prognosis of illnesses that called for difficult medical investigations. Real-time disorder diagnosis and individualized healthcare can both be provided with the usage of ML. [33] Machine Learning uses in the IoT for personalized healthcare can be found in 3 primary domains: monitoring, alarm, and assistive systems for patients.ML can help with both the distant and quick diagnosis of illnesses when there are no established healthcare services. Assistive systems aid in the recovery of patients following trauma or medical operations. As was covered in the part above, monitoring systems for old and immobile patients promote AAL. But it is clear that using H-IoT for CVD diagnosis and therapy is a very feasible strategy. In [34], the idea of employing IoT devices to anticipate cardiac arrest before it occurs is put forth. The loud noise elements in the recorded ECG data are eliminated during processing. The predication method is applied in a pair of phases, the first of which comparing threshold values to the characteristics of temperature of the person and heartbeat. The changes in heart activity are anticipated if the thresholds are crossed, and the proper warning is generated. [35] Lio is regarded as an all-in-one platform appropriate for personal care assistance and human-robot interaction. For safe navigation and environment comprehension, a combination of mechanical, optical, laser, ultrasonic, and auditory sensors is used. Researchers may access raw sensor data and have full control over the robot with to the ROS-enabled setup. Since Lio has a kind appearance, both patients and medical staff have embraced the robot. A configurable decision engine, autonomous navigation, and automatic recharge enable fully autonomous operation.[36] A lightweight and inexpensive IoT node, a smartphone app, and fog-based Machine Learning (ML) tools for data analysis and diagnosis make up the proposed platform. The IoT node monitors health indicators like body temperature, respiration rate, cough rate, and blood oxygen saturation, and subsequently updates the mobile app to show the user's health statuses.[37] We conducted a study on BP estimate based solely on photoplethysmography (PPG) signal in order to show a promising use of our suggested Medical Edges. With a publicly accessible data set termed Multiparameter Intelligent Monitoring in Intensive Care II (MIMIC II), we propose a hybrid neural network architecture and put it to use. Five 1-D convolutional neural networks (CNNs), three bi-directional long short-term memory networks, and four fully linked layers make up the model.

[38] Personalized Lifestyle Recommendations for Blood Pressure Improvement Using Wearables and Machine Learning. Utilizing feature engineering techniques to address time-series data and improve interpretability, automated data collection is done utilizing wearable activity trackers and home blood pressure monitors. To provide individualized BP modeling and top lifestyle factor detection, Random Forest is combined with Shapley-Value-based Feature Selection.[39] Since parents' top worry is that their parents might become ill, this study places a strong emphasis on geriatric healthcare. They were always in danger of losing their senior citizens. The next step is to develop and build an experimental setup that can keep track of the patient's health. In this analysis, a commercial device was found. Data like heart rate, oxygen levels, ECG, and other variables are continuously monitored by sensors.[40]The proposed solution has been created to help non-tech users around the world become acclimated to smart health care in a user-friendly way.[41]An IoT-based noninvasive automated patient distress monitoring and surveillance system is designed and developed in this work using a deep learning-based methodology. Without the use of any smart wearables, the system uses an IP camera to monitor the participant's strength and mobility. The Mask-RCNN method is used to retrieve a number of significant spots on the patient's body.[42] With the least amount of resources available from low-powered medical devices, this research intends to propose a novel architecture for safeguarding medical information from outside threats. The ML-based biometric security framework is proposed in this paper, and for the training phase, features are used from Electrocardiogram (ECG) data.[43]The IoT module collects essential data in this concept, and data assessment is done using neural network models to analyze the data to estimate the possible hazards to kids' physiological and behavioral changes. According to the results of the experiments, the proposed model is effective and accurate in determining the state of the pupils.

The HRV value can be obtained from the wearables' continuous ECG monitoring. In turn, arrhythmias can be predicted using the HRV. The real-time detection of heart arrhythmia has a high accuracy of 97% when utilizing the classifier k-Nearest Neighbors (kNN) [44].The electronic health records (EHR) can be used to save the data in the proposed technique in [44] for future references. It is noteworthy that body movements and interference cause noise and aberrations in the ECG waveforms. It is therefore vital to eliminate these artifacts and process only real ECG readings. As a result, [45] offers a solution for the ML-based identification of CVDs that takes signal quality into account. The suggested method employs a Signal Quality Assessment (SQA) algorithm based on machine learning to rate the signal's effectiveness. Depending on the results of this evaluation, the signal will either be processed for further investigation or not. The information is provided for storage and processing unless the signal quality is deemed inadequate. By eliminating the processing and transmission of noisy, poor-quality data, this ML-based technique improves the system's sustainability through preserving inputs. Additionally, because the system has been tested in a variety of settings, it helps to provide the user with greater accessibility and freedom of actions with no compromising the system's efficiency and precision. One of the most prevalent CVDs that frequently causes limb paralysis is stroke.

For this, a surface EMG signal detecting armband containing sensors has been developed. The data gathered by these variables is processed using principal component analysis & ML-based classification complexity estimating algorithms (CCEAs). With a 97% accuracy rate, using this system recognize the sEMG signals' hand movements. A controllable robotic hand made using 3D printing in real-time using the sEMG signals that have been analyzed serves as proof of the findings [46].H-IoT has a huge impact on AAL applications. Numerous applications in the AAL sector are made possible using ML. Architecture based on the cloud and the edge is used to implement the application of ML in the detection of patient falls. The ML-based method for analysing a camera's video stream in a smart home scenario yields an astounding result of over 99 per cent accuracy in identifying a patient falling. This strategy also functions well in non-edge architecture [47]. Combining fall detection with the risk variables can be used to improve the Ambient Assisted Living scenario for identifying falls. The research in [48] suggests an algorithm based on ML algorithms to predict risk factors and detect falls. However, the input for this system is data produced by gyroscopes. The suggested approach employs four

Machine learning methods, using kNN producing maximum precision of 82.2 % when risk variables are added, the peak accuracy rises to 84.1%. The findings vary depending on where the gyro sensor is worn, with waist-mounted sensors performing worse than wrist-worn sensors in terms of outcomes. One of the crucial parts of AAL is the observation of sleep patterns. Since sleep has a direct impact on human health, Examining sleep patterns might help you build good sleeping habits.

To determine sleep patterns, heterogeneous input such as electroculogram (EOG), which measures eye movement, electrocardiogram (ECG) and electroencephalogram(EEG) can be used. [49]Analyzes a multimodal input by classifying sleep patterns using DL algorithms. Using a three-layer process, the signals received from a smart mattress that detects the aforementioned health are first classified using a DBN. Classification is improved by using Long Short-Term Memory, which aids in learning the long-term relationships in time-related information. Using a k-medoid technique, the obtained data for the various sleep patterns is then aggregated into groups that define the sleep patterns as normal or pathological classifications. the eye activities also have to be taken into account It involves identifying different patterns of sleep, including Rapid Eye Movements (REM). The ability to recognize posture while sleeping is critical for studying sleep patterns. Typically, a pressure-sensing mattress that keeps track of the pressure on various regions of the mattress is used to determine the posture of the sleeper. The clustering of data is done using the SVM, a machine learning technique. PCA is used as a pre-processing method to make feature extractions using the sensor data. In order to determine how well a person sleeps, the features are finally separated into three postures using SVM[50]. In a smart environment, activity recognition is one of the AAL systems' features.

The ability to track user activity can aid in tailoring improving the user experience and health services. Activity recognition performance can be greatly improved by ML implementation. The method suggested in [51] is unique in that it employs a covert method to detect user activity. The suggested method involves detecting the connectivity among the various nodes placed close to the individual. To determine a channel link quality, the route loss between the nodes is calculated. The information is then exposed to determine the user's actions, ML-based classifiers are used. The exchange of data between nodes may be connected to or disconnected from the subject.According to the performance examination of many cases, SVM results are correct but come with a latency penalty. Although the Linear Discriminant (LD) analysis produces quick outcomes, the most accurate classifier is the Random Forest (RF) classifier. The user's activities can be identified with outstanding accuracy by the evaluated classification algorithms, but the best use of those data depends on QoS criteria like computing efficiency and latency.The developments in brain-computer interfacing (BCI) systems have a direct bearing on the advancements in prosthetics technology. By implementing what are known as Assistive Systems, interfacing (BCI) systems are steadily enhancing the standard of Living for those suffering from impairments and debilitating conditions. Using text-to-speech capabilities, a system for learning EEG patterns can help paraplegic patients enjoy normal lives by enabling them to produce speech from their brain waves [52]. The analytics algorithms included into the Intel cloud allow for the analysis of emotions from EEG readings. The sensors gather key physiological signals from patients in order to track patients' health.

The authors of [53] have developed a method to recognize eye blinking motions as input to operate gadgets, allowing individuals with disabilities to live independent lives. The technology proposed in [54] extends the use of brain–computer interface for creating typing systems using EEG signals. The control of robots for domestic assistance is the other use that is being tested. People who are deaf or hard of hearing are supported by this method. The analysis and categorization of EEG patterns utilized as the input rely heavily on the application of RL.In this work, SAM (Selective Attention Mechanism) and LSTM (Long Short-Term Memory) are combined to develop a system that learns by itself that gets customized to the individual using it and adapts to their needs. For that specific user, the fundamental properties of the individuals EEG can be established through the application of deep learning algorithms. This trait has broad implications for identifying illnesses of the CNS (central nervous system). The prediction and localization of epileptic seizures using DL are suggested [90]. The authors developed a system for predicting seizures and epilepsy localization as two sequential processes employing a combination of Machine Learning and Deep Learning systems for extracting features from EEG along with ECoG (Electrocardiogram signal) inputs.

The SVM divides the characteristics into normal and abnormal groups. A hybrid approach-based optimization technique is used to improve the outcomes. The creation of an approach enabling the distribution of inhibiting signals for epilepsy control is one of the unspecified future tasks. The suggested systems must meet the quality of service standards for their intended usage. Every one of these systems are Internet of Things-based, therefore it is crucial ensure the proposed solutions are appropriate for locations with limited resources. The goal of the study in [55] is to use sparse representation techniques to compress the data by 50%. Nearly 90% of the compressed data can be accurately reconstructed. The suggested system is implemented by FPGA (Field-Programmable Gate Array) with an ARM (Advanced RISC Machine) processor.The Multi-Layer Perceptron (MLP) is the foundation for the method, which uses many cascaded layers for input signal reduction and reconstruction. The system's energy efficiency, which comes along with the less transmissions and data storage, is an additional benefit of compression. The usage of ML and BCI methods for implementation in the area of BCI for controlling prostheses has been described in numerous publications, some of which have been cited in [56].

Many researchers are interested in the creation for real-time illness surveillance systems. Many scholars have put up internet-based frameworks that uses System-on-Chip (SoC) based Internet of Things platforms to detect prevalent illnesses in this direction.[57]Suggests an example of an analysis of a programmable device using microfluidics for the detection of breast cancer. An implant or wearable device can be used to analyze bodily fluids at the Point-of-Care. ML-based data analytic techniques can be used to analyze the outcomes. The prerequisites and justification for such online systems are laid out in this essay. [58] Describes the method to handle health care information for diabetic patients in an Internet of Things setting using machine learning. The proposed system integrates big data, IoT, ML, and cloud technologies to support caretakers in offering individualized care of diabetes patients depending on health information gathered in time.

Authors in [59] provide an approach for categorizing observed health indicators in an Internet of Things setting using machine learning-based classifier to evaluate the severity of a health issues in order to prevent diseases proactively. To detect violations of the critical parameter threshold limit, the classifiers examine patient records and compare them to previous records. An alert or feedback is produced in the event of a breach. However, the effectiveness of this approach depends on the classifier ability to group the data accurately, which is dependent on the calibre of the data that has been labelled provided to the classifier during learning.An unsupervised learning method called a Generative Adversarial Network (GAN) which enhances the classification process by enhancing the quality of the labeled data [60]. In essence, the GAN form of unsupervised learning technique it is used to produce synthetic data to be evenly distributed each type of data across datasets. To enhance the effectiveness of traditional classifiers like Support Vector Machines (SVM) and k-Nearest Neighbour (kNN), this data is utilized to train them. So, the technique as a whole can be defined as semi-supervised.Outcomes compared to cerebral stroke datasets confirm the effectiveness of this strategy in supporting physicians to make knowledgeable actions regarding their patients' care. ML's applications can be expanded to real-time decision-making for carers. It is possible to build robust feedback systems in Ambient Assisted Living as well as self-care contexts using data mining and machine learning techniques [61].

In many everyday items we use every day, there are several sensors built in. In particular, The Internet of Things (IoT) can benefit greatly from ML deployment [62]. The addition of artificial intelligence at the equipment level can aid increase flexibility by creating them more intelligent, individualized & precise[63]. Authors in [64] have constructed a DL-based approach that reduces the number of neural networks that have layers that are hidden to accommodate for low resources so as to demonstrate the significance of the on-node ability to process. The observed findings show that mobile device implementation of this technique is feasible. The actual issue is the adaption to low power sensor, which are the most constrained. Two of the most significant problems with the installation of internet of things are both privacy and security. Whenever information provided by patients is processed on a cloud platform, this problem became critical. It became essential should the information be secured in opposition to all intrusions. Misuse of data may result in dangerous repercussions for users and in extreme circumstances it could be fatal. When an algorithm is being trained, biases can be produced by any manipulation of labeled data. As a result, measures for protecting the system throughout all levels are necessary. Machine Learning is a potent technology getting utilized to increase H-IoT systems' security. The writers of [65] presented a solution that makes use of DL to safeguard user confidentiality in Ambient Assisted Living context. The recommended method encrypts as well as decrypts information using long short-term memory(LSTM). According to authorization to view data, encoding and decoding are carried out. Having the appropriately matched decoder according to authorization allows the relevant authorization owner to view the information.

Because LSTM's can distinguish between different data kinds, it may provide access based on the users' authorized levels. The H-IoT system's performance can be distorted by illicit data manipulation or sensors operating in suboptimal conditions. To establish the limits of realistic number a sensor can detect, the proposed technique [66] combines the Otsu's thresholding method with statistical method. The data is divided into true and modified classes using supervised machine learning approach and a liner kernel SVM. When using blood glucose sensor in an Internet of Things (IoT) setting, the system showed remarkable categorization accuracy. It is commonly known that an Internet of Things (IoT) Intrusion Detection System (IDS) uses algorithms that draw inspiration from nature. The uses of bio-algorithms in H-IoT could provide autonomous control. Additionally, Swarm Intelligence-based IDS [67] has been explored previously when it comes to protecting sensitive health data. However, the location of a users' through a smart environment using Machine Learning can be accomplished using the same approaches. The suggested method [68] uses information from several sensors, including a MEMS-based gyroscope, magnetometer, and accelerometer, to pinpoint the user's location. To collect information on the actions, a number of nodes of this sensor combination are deployed.

Depending on the activity, the performance of various classifiers varied. [69] Makes the case for using cellular data to identify activities. The suggested system takes advantage of CSQ (cellular signal quality) for establishing the user's location and, essentially, the actions they took based on changes in CSQ. By differentiating between the movements of the body and the surrounding environment, Classifiers based on supervised learning may pinpoint the activities made. With 90% accuracy, both the LSTM and the decision tree (DT) classifiers perform similarly. Machine learning algorithms aided in improving H-IoT systems' overall performance. The wearable sensor battery life in an H-IoT system utilizing Machine learning is a notable metric that can be improved [70]. Typically, the sensors use energy resources by sending all of the processing units with the raw data. The proposed method combines embedded ML with SVM optimization to pre-process and classify data onboard. The battery's lifetime has increased astonishingly between 13 and 997 days, according to the results.

The IEEE standard IEEE 802.15.6 was created with the intention of monitoring wireless body area networks (WBAN) health metrics in real-time. Since,for such applications, the QoS comprises high fault tolerance and low latency in WBANs, the choice of frequency channels is a crucial process [71], [72]. To satisfy the H-IoT's QoS requirements, the study described in [73] suggests an RL-based channel selection algorithm. The suggested method is an RL Channel Assignment Algorithm (RL-CAA). It makes use of channel loads to discover channel traffic patterns. The suggested channel allocation mechanism performs better than static methods.

The IoT systems' suggested routing algorithms geared toward the healthcare industry should maximize not simply the routing choices as well as the energy effectiveness and lifetime of networks. The majority energy-efficient routing algorithms are effective for extending the network's life [74]. However, achieving the other QoS requirements are also crucial. In the suggested research, RL is used for the first time in WBAN routing decisions [75]. The usage of clustering aids in lowering the power consumption of the network with limited power. Finding the best paths from the source to the sinks while also reducing energy use is done using a RL learning technique known as Q-Learning. Clustering techniques help to improve energy efficiency by distributing a load among all nodes and selecting the cluster head with the highest load. By taking into account the possibility that sensors at a location may gather redundant data, this theory can be put into practice. Data aggregation techniques based on machine learning may be used to aggregate data which is more valuable and has a greater importance. The authors of [76] suggest aggregating data depending on priority and data type using an Support vector machine (SVM) based categorization method. With this strategy, the distribution of load is improved, and as a result is energy conservation. This may help the method of routing in a crucial IoT system make better routing decisions. An overview of machine learning use cases in the IoT is provided in Table 2.

Authors Contributions	Results	Reference and Year
Mobile robot platform with a multi-functional arm	Lio work continuously throughout the day, with a battery life of up to 8 hours	**Justinas Miseikis et al. [35][2020]**
COVID-SAFE architecture	Reduce the danger of exposure to the corona virus	**Seyed S. Vedaei et al. [36][2020]**
PPG-Based Blood Pressure Estimation in IoT-Based Medical Edge Devices	MAE and STD for DBP and SBP, respectively, were 0.95 and 1.44 millimeters of mercury (mmHg) and 1.38 and 2.13 mmHg.	**Denis Bernard et al. [37][2022]**
Personalized Lifestyle Recommendations Using Wearables and Machine Learning	Reduced their systolic and diastolic BPs by 3.8 and 2.3 respectively.	**Po-hanchiang et al. [38][2021]**
Monitoring the patient's health is conceived and built.	Information will be supplied to the smartphone app.	**Naga Swathi Tallapaneni et al. [39][2021]**
patients receive non-contact care and remote healthcare	LightGBM is a machine learning model with a 91.12% prediction accuracy	**Tasnim Hossain Orpa et al. [40][2022]**
monitoring and surveillance system for patient distress that is automated	Constant observation of a person's posture and physical position	**Aashat Gehlot et al. [41][2022]**
the Machine Learning-based architecture for biometric security	The scientific and economic significance of framework	**Sandeep Pirbhulal et al. [42][2019]**
An IoT-based management strategy for improving student health	Maximum performance for the support vector machine was 99.1%.	**M. Pradeepa et al. [43][2022]**
HRV value determination using ECG data	kNN Classifier has a 97% classification accuracy rate.	**Walinjker et al. [44] [2017]**
A system that classifies ECG signals based on IoT signal quality	97% High reliability was attained.	**Satija*etal.*[45][2017]**
a system for stroke recovery that uses EMG data to recognize gestures on Artificial devices	The classification accuracy with PCA was 99.87%.	**Yang *etal.* [46][2018]**
a fall detection system for smart houses with sensors	A 99 % chance of success rate was attained.	**Hsu *etal.* [47][2017]**
Utilizing wearable motion sensors for fall detection while accounting for risk variables	The accuracy of the kNN classifier is 84.1%.	**Anupama*etal.*[48][2018]**
Classification of sleep patterns using an AAL setting	Deep Belief Network (DBN)- Long Short–Term Memory (LSTM) has a 91% classification accuracy rate.	**Hong*etal.* [49][2017]**
Analysis of sleep patterns using posture recognition	High accuracy was observed with a Cohen's Kappa value of 0.866.	**Matar*etal.* [50][2016]**

Activity detection using ML based on path loss data in WBANs using two techniques (M1 & M2)	Random Forest's mean accuracy in M1 is 98.77, and in M2 it is 49.6%.	**Negra*etal.* [51][2018]**
BCI's categorization of EEG data for quadriplegics	Model for enabling disabled people to live independently	**Kanagasabai*etal.*[52][2016]**
ML-based BCI system for smart house control	The typical recognition accuracy is 95.2%	**Jagdish*etal.*[53][2017]**
Automated speech generation system using EEG signal analysis	The accuracy of the suggested method is 93.63%.	**Zhang *etal.* [54][2019]**
ML-based compression method for Internet of Things data	With an MLP, a 50% compression ratio and 89.85% reconstruction accuracy are achieved.	**Shrivastava*et al.*[55][2018]**
machine learning (ML) solution for managing diabetes	Diabetes patients are tested using a machine learning and cloud-based approach..	**Ara *etal.* [58][2018]**
Utilizing Machine Learning techniques to categorize the incoming datathen use the wearable to map the disorder.	Creation of a warning based on the information	**Asthana *etal.*[59][2017]**
A decision assistance system using machine learning and GAN-based data labelling	Semi-supervised learning and a high accuracy stroke judgment method for labelling training data	**Yang *etal.* [60][2019]**
An analysis of the H-IoT's underpinning technologies	Real-time feedback generation using machine learning techniques	**Nguyen *etal.*[61][2017]**
Review of Machine Learning (ML) applications for IoT	Review of the ML sensor level implementation tools	**Shanthamallu*etal.*[62][2017]**
the hybridization of IoT and AI technologies	laying the groundwork for the design of proof-of-concept identifying illnesses monitoring sensors	**Knickerbocker*etal.*[63][2018]**
Activity recognition combining wearable sensors and deep learning	System for recognizing humanoid activities with 95%–99% accuracy in various situations	**Ravi*etal.*[64][2017]**
Utilizing the long short-term memory(LSTM)Encoder Decoder to improve privacy	Permissioned data access in an AAL context	**Psychoula*etal.*[65][2018]**
Data categorization method based on machine learning to identify data manipulation in WBANs	SVM-based classification with 99.22% recall and 100% accuracy	**Verner*etal.* [66][2017]**
cellular signal quality analysis using machine learning for activity recognition	Using a decision tree and LSTM, body movement can be detected with an accuracy of 90%.	**Savazzi*etal.*[69][2018]**
utilizing ML to extend the sensors' battery life	The sensor's life is increased by the SVM data classifier's ability to distinguish between critical and superfluous transmission data.	**Fafoutis*etal.*[70][2018]**
Using clustering to route the data in WBAN	Base Q-Learning A low latency system was created by QL-CLUSTER.	**Kiani[75][2017]**

Table 2. An overview of Machine Learning use cases in the IoT

6. BlockchaininH-IoT

The top technical developments for the near future include blockchain. Although blockchains have uses in many sectors, they are typically most closely connected with cryptocurrencies. [77]A block chain is “a distributed, fully decentralized peer-to-peer database that maintains a continuously growing list of ordered records, called blocks. It gets its name from the fact that information is stored as a chain of immutable data blocks.

Satoshi Nakamoto first described block chain as a peer to peer money transfer system via a white paper he wrote in 2008; eventually, in 2009, it developed into what is now known as bit coins [78]. The essence of a block on a block chain is a grouping of data that is by cryptography signed with a private key which serves as the input for a unique hash. Every time the data in a block is changed, this hash, which is unique to the block, is updated. Using this hash, the block's provenance or chain is preserved. The block is made available to every user on the network. The validity of the block is confirmed by successfully performing a proof of work, which is essentially a challenging mathematics task. On the block chain, A group of users known as miners seeks out the proof of work necessary to verify the chain's block in exchange for a pay-out.This strategy makes the block chain safe, transparent, and resistant to unauthorized alterations [79]. Figure 4 provides an illustration of how blockchain functions.

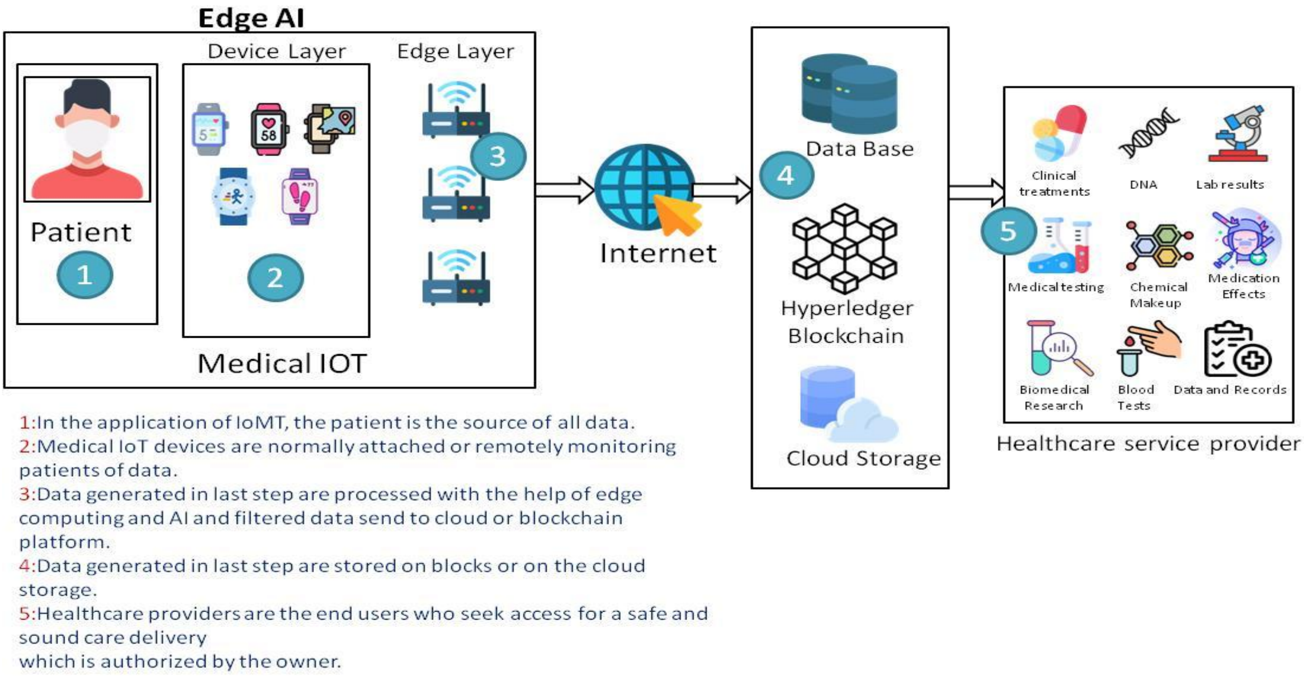

Figure4.Developing a Blockchain for Sharing H-IoT Data

Security, integrity, and privacy are needed for H-IoT systems, but the blockchain is built to provide decentralized, trustworthy, and anonymous features [80,81]. The use-cases and performance of IoT system are improved by integrating block chain with them. Blockchain technology is helpful in the implementation of services in the healthcare, smart grid and smart city sectors, but there are still significant challenges with storage, security, scalability, and consensus [82,83,84]. The storage and restriction of access to the gathered medical data are the primary applications of block chain in healthcare [83].The H-IoT paradigm has yet to fully utilize blockchain's promise.

To enhance the system's overall performance, a simulation-optimization strategy is suggested in [85].To check the integrity of the entire system and assess the performance metrics of the blockchain network, use the JaamSim and JSImgraph Simulators 1.2. JSImgraph simulations to examine the internal features of blockchain-based smart healthcare, including the efficiency of block miners, the capacity of block transactions, and the storage capabilities of blocks. The blockchain is used in the Ethereum network together with related programming languages, tools, and methodologies like robustness, web3.js, Athena, etc.

An architecture for continually monitoring the patients' health is presented in the work in [86]. Blockchain technology is utilized to support the architecture and maintain anonymity. A suggested patient-centric agent (PCA) is in charge of the customized blockchain that the remote monitoring system uses. The patient-centric agent (PCA) is responsible for choosing the miners, classifying stored data according to its criticality, and in some cases standing in for a miner if none is available. by controlling the RPM blockchain's authentication keys ,the PCA is in charge of maintaining security. The majority of blockchain applications in healthcare, however, are primarily concerned with data management and security. According to the authors of [87], big data and blockchain are applied in the management of health care information in the Internet of things scenario. The researchers conclude that adopting blockchain increases the robustness and security of sensor node data.

According to the IEEE 802.15.6 standard, the research described in [88] suggests a methodology for sharing the collected data across sensor nodes that collect health data or pervasive social network (PSN) nodes. With proposed blockchain-enabled key verification, consumers can get medical care remotely without worrying about their privacy. An overview of blockchain use cases in the IoT is provided in Table 3. With the help of smart contracts, the authors of [89] developed the four-layer MedShare structure, which regulates who has access to the data kept on the blockchain. To determine whether a suggested procedure is valid, it is put to an experimental test.

Authors Contributions	Performance	**Reference** and Year
Industry 4.0, blockchain technology, and the healthcare system are all combined to create healthcare 4.0.	Block utilization is above 80%, making the suggested system operational. Execution time for automated smart contracts is under 20 seconds.	**Adarsh Kumar et all.[85][2020]**
Blockchain-supported infrastructure for continuous monitoring	a PCA agent that protects privacy and chooses miners depending on the importance of the data	**Uddinet al.[86][2018]**
Blockchain is used for handling medical data gathered through Internet of things.	Increased security and resilience provided by H-IoT use of the blockchain.	**Simicet al.[87][2019]**
Healthcare WSN IEEE 802.15.6 security protocol	Remote data access system using a key-based datasecurity scheme	**Zhangetal.[88][2016]**
A smart contract-based, four-layer MedShare architecture	proving the effectiveness of smart contracts for data access	**Xiaetal.[89][2017]**

Table 3. An overview of blockchain use cases in the IoT

7. Conclusion

The review analyzed the significance and need of ML and IoT in current remote healthcare. Remote health care has long been an important component of the health-care ecosystem. The Internet of Things (H-IoT) is a system of sensors that collects essential health data everywhere and shares it via a secure network. An alert is sent if irregularities are discovered after the collected data is analyzed to look for them. This study examines a few of the cutting-edge technologies driving the H-IoT systems. In the H-IoT, a variety of architectures utilizing various computing paradigms are employed. These architectures are fuelled by machine learning, edge computing, and emerging technologies such as SDN blockchains. The capabilities of ML are being used in a variety of H-IoT use cases, including network maintenance and assisting in achieving optimal network and service performance. The blockchain introduces a transparent and secure way of information and distribution, improving the capacity for data storage. Explained are actual technologies, upcoming technical concepts, and ongoing study efforts. In conclusion, this essay clarifies new and existing technologies for remote health care in order to enhance the welfare of our society.

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