An Intelligent System Using Deep Learning for Healthcare Monitoring in Light of the COVID-19 and Future Pandemics Based on IoT

Assist. Lect. Sara Salman Qasim(1)

Assist. Lect. Rajaa J.khanjar(2)

Assist. Prof. Dr. Jamal Nasir Hasoon(3)

Lect. Dr. Baesher Abdullateff Abad(4)

Lect. Ali Hussein Fadil(5)

Assist. Lect. Shajan M. Alsowaidi(6)

(1) Department of Information Technology, College Science, Al-Esraa University, Baghdad, Iraq
(2) Department of Computer Science, College of Science, Baghdad University, Baghdad, Iraq
(3) Department of Computer Science, College of Science, Mustansiriyah University, Baghdad, Iraq
(4) Department of Biology, College Science, Al-Esraa University, Baghdad, Iraq
(5) Presidency University, University of Diyala, Diyala, Iraq
(6) Al-Mustansiriya University, College of Education, Computer Department

Corresponding author: sarah@esraa.edu.iq

نظام ذكي يستخدم التعلم العميق لمراقبة الرعاية الصحية في ظل فيروس كورونا (COVID-19) والأوبئة المستقبلية بناءً على إنترنت الأشياء

م. م. سارة سلمان قاسم[1]
م. م. رجاء جبارخنجر [2]
ا. م . د. جمال ناصر حسون[3]
م. د. بشائر عبد اللطيف عباد[4]
ا. م. علي حسين فاضل[5]
م. م. شجن محمد السويدي[6]

(1) قسم تكنولوجيا المعلومات، كلية العلوم، جامعة الإسراء، بغداد\العراق
(2) مديرية الرصافة الثانية، بغداد، العراق
(3) قسم علوم الحاسوب، كلية العلوم، الجامعة المستنصرية، بغداد\ العراق
(4) قسم علوم الحياة، كلية العلوم، جامعة الإسراء، بغداد\ العراق
(5) رئاسة الجامعة، جامعة ديالى، ديالى\ العراق
(6) الجامعة المستنصرية كلية التربية قسم الحاسوب , بغداد\العراق

Abstract

Recently, the Internet of Things has become a compelling research field as a new topic of research in various disciplines, particularly in the field of healthcare, because the Internet of Things is rebuilding modern healthcare systems by integrating technology, economics, and social perspectives. The development of healthcare systems from traditional to more personalized systems in which patients can be easily diagnosed, monitored and treated and many people can be helped. People are treated and cared for remotely and this is what some people need in the crisis the world has been through like COVID-19. This epidemic is caused by the new severe acute respiratory syndrome, and is considered the largest global health crisis since the outbreak of the influenza pandemic. As the number of new cases of coronavirus around the world has reached more than thirty-one million that marks the beginning of the epidemic, there have been rapid efforts in the various research communities to exploit a wide range of technologies to combat this global threat, moreover, the Internet of Things technology represents One of the pioneers in this field especially regarding COVID-19. IoT-enabled devices/applications are used to reduce the potential spread of this epidemic to others through rapid patient diagnosis, monitoring, and practice protocols, specifically, after recovery, and case classification by introducing machine learning to know the type of infection especially that the epidemic is starting to develop and is Similar to the cases of the normal flu, and the infection process is similar, and the process of caring for the patient requires meticulous work, because the treating doctor will give the appropriate treatment according to the case.

Keywords: Deep Learning , WBAN, COVID-19, IoT.

المستخلص

في الآونة الأخيرة، أصبح إنترنت الأشياء مجالًا بحثيًا مقنعًا كموضوع جديد للبحث في مختلف التخصصات، وخاصة في مجال الرعاية الصحية، لأن إنترنت الأشياء يعيد بناء أنظمة الرعاية الصحية الحديثة من خلال دمج التكنولوجيا والاقتصاد ووجهات النظر الاجتماعية. . تطوير أنظمة الرعاية الصحية من الأنظمة التقليدية إلى الأنظمة الأكثر تخصيصًا والتي يمكن من خلالها تشخيص المرضى ومراقبتهم وعلاجهم بسهولة ويمكن مساعدة العديد من الأشخاص. يتم علاج الناس ورعايتهم عن بعد وهذا ما يحتاجه بعض الناس في الأزمة التي مر بها العالم مثل كوفيد19-. وينجم هذا الوباء عن المتلازمة التنفسية الحادة الوخيمة الجديدة، ويعتبر أكبر أزمة صحية عالمية منذ تفشي جائحة الأنفلونزا. ومع وصول عدد حالات الإصابة بفيروس كورونا المستجد حول العالم إلى أكثر من واحد وثلاثين مليونا، وهو ما يمثل بداية تفشي الوباء، فقد بذلت جهود سريعة في مختلف الأوساط البحثية لاستغلال مجموعة واسعة من التقنيات لمكافحة هذا التهديد العالمي، علاوة على ذلك، تمثل تقنية إنترنت الأشياء إحدى الشركات الرائدة في هذا المجال خاصة فيما يتعلق بفيروس كورونا (كوفيد19-). تُستخدم الأجهزة/التطبيقات التي تدعم إنترنت الأشياء للحد من الانتشار المحتمل لهذا الوباء للآخرين من خلال التشخيص السريع للمريض ومراقبته وبروتوكولات الممارسة، وتحديداً بعد الشفاء، وتصنيف الحالات من خلال إدخال التعلم الآلي لمعرفة نوع العدوى خاصة أن فالوباء بدأ يتطور ويشبه حالات الأنفلونزا العادية، وعملية العدوى متشابهة، وعملية رعاية المريض تتطلب عملاً دقيقاً، لأن الطبيب المعالج سيعطي العلاج المناسب حسب الحالة.

الكلمات المفتاحية: التعلم العميق، WBAN، كوفيد19-، إنترنت الأشياء.

1. Introduction

After the successful global connection of people through the Internet, it is now the time for the objects in our surroundings to also join the international information network known as "the Internet" [1]. The Internet of Things (IoT) refers to a collection of interconnected devices or cabins that can communicate with each other (machine-to-machine) or with humans (machine-to-human) on a daily basis.

The initial stages of a singular ring with a designated set of activities are quite challenging. The term "Internet of Things" was first coined in 1999 by British scientist Kevin Ashton. Ashton's idea was to connect various devices, such as electrical and home appliances, in order to gather accurate information about their status without the need for constant monitoring [2]. However, this approach rapidly waned in appeal among developing multinational organizations in this industry, such as Gartner, a company that conducts research in this domain: Redefine the concept of the Internet of Things to encompass both individuals and all internet-connected gadgets. The Internet of Things offers numerous benefits, both at the individual and business levels. The effect on human lives will be significant [3]. Below are many examples of applications of the Internet of Things:

Enhancing homes with automation to enhance livability, defend against risks, save expenses, and enhance overall quality.

By autonomously regulating the levels of lighting, temperature, and humidity within the household, and remotely managing a variety of equipment. In addition to monitoring human health by observing health signs and predicting potential diseases, particularly those that may result in severe health complications. Furthermore, in the industrial sector, this technology has many uses such as monitoring devices and equipment in factories, forecasting potential defects, minimizing losses, and facilitating timely availability of spare parts [4].

The medical industry has had advantageous outcomes from the implementation of digital transformation and current communication technologies, and it is expected that their adoption will continue to increase. The Internet of Smart Things is expected to experience significant growth in the next years, thanks to advancements in communication technologies and artificial intelligence. These developments have led to the emergence of novel features that support healthcare services [5].

The Internet of Things has emerged as a crucial tool in healthcare monitoring due to its ability to offer cost savings, enhanced user experiences, and superior service quality [6]. Due of its extensive capabilities in data collection, identification, tracking, and authentication. The Internet of Things in healthcare is expected to grow rapidly, with its market size projected to climb from $72 billion in 2020 to $188 billion in 2025 [7].

COVID-19 is the most significant global health disaster since the emergence of the pandemic influenza in 1918 [8]. According to the most recent data from the World Health Organization (WHO) in September 2020, there have been over 31 million confirmed cases of COVID-19 and more than 960,000 deaths [9]. The current pandemic exhibits flu-like symptoms, including cough, tiredness, and fever, which are crucial for early diagnosis [10]. The COVID-19 incubation period ranges from 1 to 14 days. Surprisingly, those who do not display any signs of COVID-19 have the capacity to spread the disease to uninfected individuals. Therefore, it is crucial to segregate those who are afflicted [11]. Moreover, the duration of COVID-19 recovery is variable and contingent upon factors such as underlying diseases, patient age, and so on. Typically, it has a duration ranging from 6 to 41 days [12]. Nevertheless, COVID-19 exhibits a higher propensity for transmission when compared to other comparable illnesses.

Significant endeavors are currently being made and extensive research is being conducted to mitigate the transmission of COVID-19. In this regard, the Internet of Things technology has demonstrated its efficacy and safety in addressing this pathogen [13].

The primary objective of this study is to determine the role of IoT-based technologies in monitoring and managing COVID-19. It also involves examining the most recent IoT-based platforms, infrastructures, industrial solutions, and applications used to combat this pandemic in three key stages: early diagnosis, quarantine period, and post-recovery. Early identification and detection can result in reduced infection rates and improved healthcare services for individuals who are infected [14].

Implementing quarantines for those who are suspected or confirmed to have a contagious disease, as well as enforcing lockdown measures, can effectively decrease the spread of infection by physically isolating sick individuals from the general population. Monitoring the recovered individuals for potential infection and symptoms is a valuable technique in following their progress [15]. Figure 1 is displayed. IoT healthcare monitoring survey chart

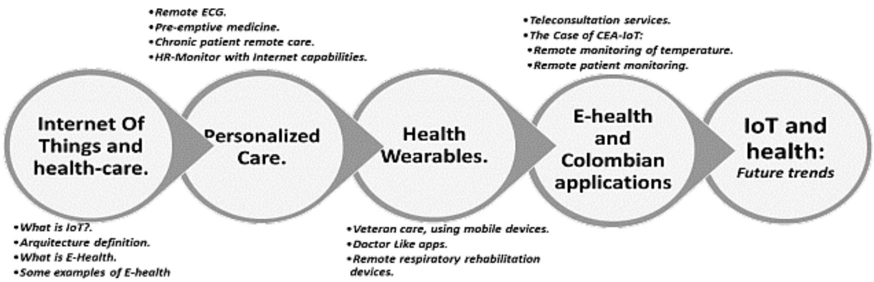

Figure (1) IoT of healthcare monitoring.

2. Theory of Wireless Body Area Networks (WBAN) or Wireless Body Area Sensor Networks (WBASN)

A coordinator (Crd) and a number of low-power sensors that can be implanted or connected to the human body make up the localized network known as WBAN/WBASN. Wireless Body Area Networks, or WBANs, have a wide range of uses in industries such as consumer electronics, healthcare, sports, and the military. They allow for real-time patient monitoring. Over the past ten years, WBAN has had a major technological expansion due to developments in MEMS and wireless communication technologies. When it comes to Wireless Body Area Networks, there are several crucial factors to take into account. Rather than employing a wireless sensor configuration, the WBAN monitoring scenario is restricted to the human body, heterogeneous information rate, the need for biocompatible sensor devices, and changeable network geography owing to body movement. Two types of correspondence exist inside the Body sensor network: While the On-body correspondence refers to communication between wearable sensor hubs, the RF correspondence describes communication between intrusive sensor hubs implanted inside the human body. For communication within the human body, the 402-405 MHz frequency range, also known as the MICS (Medical Implantable Communication Service) band, should be utilized. It is possible to communicate with the human body using ISM or UWB[16].

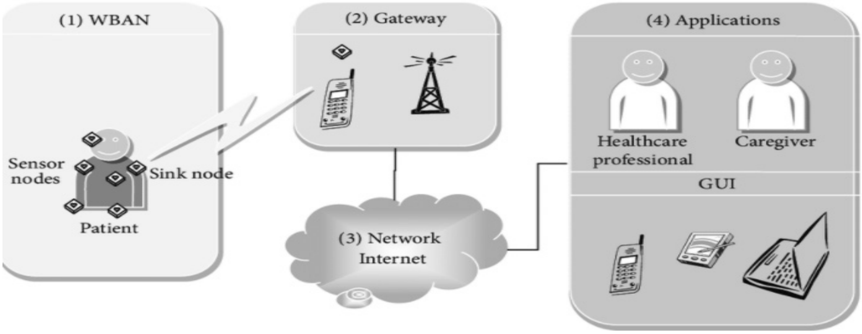

Figure (2) Wireless Body Area Network

2.1 Theory of Requirements WBAN

Since WBAN is essential to daily life, it will be able to meet a variety of needs. The following lists the numerous prerequisites that a Wireless Body Area Network (WBAN) must meet:

- **Low power consumption** – Because the WBAN device is worn or implanted within the human body, it should use as little electricity as possible. The gadgets must function continuously without requiring battery replacement when integrated. As such, maintaining WBAN's lifetime necessitates a significant level of energy efficiency.
- **Self-healing**: The mobile, subcutaneous devices are positioned beneath the human body. WBANs that provide QoS management features to prioritize services should be robust against frequent variations. Transmission latency and packet loss are the primary quality of service (QoS) issues in regard to clinical data.
- **Interoperability**: To improve data interchange, connectivity, and device interaction, WBAN frameworks must provide smooth data transfer across multiple standards, including Bluetooth, ZigBee, etc.

- **Deployment**: In the end, the innovation should be invisible to the user, carrying out its monitoring functions without drawing their attention to itself.
- **Data Aggregation**: A BAN produces a lot of data, which needs to be combined into a small structure without compromising the original data's integrity.
- **Security**: To guarantee the accurate and safe transfer of personal medical data, a great deal of work is required. Ensuring that a patient's private information is only accessed through their designated Body Area Network (BAN) system and isn't combined with that of other patients is crucial. Furthermore, access to the data produced by WBAN should be restricted.
- **Easy to understand** The length of time and end-to-end delay of the entire network are determined by the media access control (MAC) and network layer. As a result, it's critical that these calculations be simple.
- **Fewer false alarms**: It's critical to put the appropriate safety measures in place to lessen the frequency of false alarms. While faults in wireless transmission from several sensors can be difficult to detect, they can still be found even in erratic scenarios.
- **Low Latency**: Clinical data that discloses anomalous conditions like heart failure or long-term disease must be provided right away.
- The maximum necessary communication bandwidth impacts the maximum delay for data transmissions and is the necessary threshold for the occurrence of urgent notifications.

- The battery's mass, size, and type are determined by the Maximum Power Supply Current. Transmissions of data frequently need the maximum amount of current.
- **Communication setup**: This is the amount of time needed to connect a device to a network or to another device.

2.2 Theory of IEEE 802.15.6 Standard

To standardize WBAN (Wireless Body Area Network), IEEE 802 has formed a Task Group called IEEE 802.15.6. A Medium Access Control layer, as defined by IEEE 802.15.6, enables many physical layers, including as Narrowband, Ultra-wideband, and Human Body Communications levels. DQPSK, DBPSK, and GMSK are some of the suggested correction systems. One major obstacle to the development of WBANs is the continued accuracy of PHY or frequency band identification. Most nations' communication agencies control how frequencies are allotted for WBANs. [17].

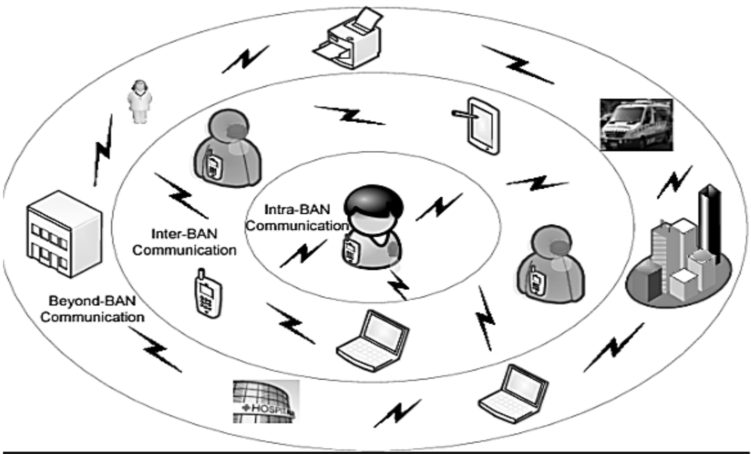

Figure (3) IEEE 802.15.6 Standard

2.3 Theory of WBAN Challenges

A Body Sensor Network (BSN) is made up of a number of smart Sensor Nodes that can gather information from the body, process it, and send it wirelessly to a Base Station that is located nearby. Underbody sensor networks provide a number of difficulties and necessitate carefully selecting the best models.

- **Scalable Data Rate**: Because the applications are so varied, the data rates differ greatly, from a few kilobits per second for low-speed data transfer to several megabits per second for high-speed video streaming. The testing rate, measurement precision required, and range are taken into consideration while determining the data rates for various applications. The data rate fluctuated when using the program, suggesting that it ought to be customizable. Thus, one of the biggest challenges in WBSN is striking a compromise between consistency and power consumption. With little power consumption and a potential data throughput of up to 1Gbps, short-range wireless communication is made possible by the newly developed ultra wideband technology.
- **Real-Time Computing**: A variety of steering protocols are intended for scenarios in which timely message transmission is critical. There are many uses for real-time sensor frameworks, particularly in the fields of medical diagnostics, fire safety, medical detection, and intrusion detection. Since obsolete information can have disastrous implications, it is imperative to ensure the timely and accurate distribution of data in order to achieve beneficial outcomes. In its most basic applications, the real-time architecture

provides a number of significant qualities, including as timeliness, support for large loads, consistency, resistance to non-critical errors, pragmatism, and flexibility.

- **Energy efficiency is the capacity to reduce energy usage in several system components**. It may be broken down into three distinct categories when it comes to energy consumption: data preparation, wireless transmission, and detection. It is anticipated that wireless communication would use the most energy. There are often limitations on the power that may be accessed via the hubs. One of the most important factors in increasing the length is energy efficiency. For embedded devices in particular, the longevity is critical. For instance, a diabetic monitor or a pacemaker must continue to work for at least five years. Since the handset sector consumes most of the energy, an exceptionally energy-efficient communication protocol must be used to get around this energy limitation. The phone uses less energy while it is in its many operating stages, which include transmit, receive, idle, and sleep. The MAC Layer manages the booking process and is also in charge of lowering energy usage. Different types of sensors are grouped to minimize power usage. While some sensors are utilized for sensing applications, others are employed for communication. The best way to achieve autonomous wireless body area networks in WBANs seems to be to use energy scavenging from on-body sources, such as body vibration and body heat. Electronic gadgets produce heat during communication, which is absorbed by the surrounding tissue and causes an increase in body temperature.

The quantity of power used by the tissue is expressed in terms of the Specific Absorption Rate (SAR). The body's permitted SAR (Specific Absorption Rate) must be regulated and adhere to local and international SAR laws.

- **Protecting and maintaining the privacy of information**: To protect patient privacy, health-related data that is sent between sensors in a Wireless Body Area Network (WBAN) and over the Internet to servers should be encrypted. This information is extremely secret and classified. There are security flaws in the wireless channel by nature. The wireless nature of the communication route opens up a wide range of potential security vulnerabilities. Both the network layer and the application layer need to have security. While data privacy refers to an individual's right to control the acquisition and use of their personal information, data security refers to safeguarding data from unauthorized users during transit and storage. Systems for security and privacy insurance should be lightweight and energy-efficient as they use a large amount of the energy that is available. The creation, transport, storage, and processing of data inside data systems gives rise to security and privacy issues. The ensuing security mechanisms need to be available.

Data hoarding Dependability, Integrity affirmation, and Secrecy Access management, accountability, revocability, and non-denial of data access Additional: Verification and Accessibility

- **Mobility: Customers of BANs may travel. It is not appropriate to think about the network as static**. Movement of the body (such as walking, sprinting, bending, and so on) can cause effects such as channel blurring and shadowing. As a result, unlike WSN hubs, which are typically thought of as stationary, BAN hubs have a comparable mobility architecture. Mobility makes the convention plan's requirements rigorous. This causes changes in visitation geography. A visit configuration of guiding conventions is necessary for this. Because of the characteristics of the medium, the particularly designated directing convention is inappropriate in this situation. The information should be uploaded to the internet for thorough verification. As a result, guiding convention needs to be modified to facilitate internet access and mobility.

2.4 Theory of WBAN Architecture

Three separate components make to the design of WBAN communication [18]:

- **Communications within BAN**: WBAN level is the first level. Each operator in Tier 1 has unique sensor axes that are purposefully placed on the human body. The core functions of these sensor hubs are to analyze the necessary signals and send the relevant data to a single server using a single low-power, low-speed wireless network that is implemented using a single IEEE 802.15.6-described wireless network. Because there is a direct connection between the body sensors and the Body Area Network (BAN), the communications architecture inside the BAN is important.

Additionally, the cost-effectiveness and special battery-powered features of the existing body sensor devices make it an attractive topic for energy-efficient MAC control.

- **Inter-BAN Communications**: The subsequent phase involves a single server that oversees the WBAN sensor hubs, offers the graphical user interface (GUI), and facilitates communication with the top-tier services. This includes information passing between the local server and one or more designated lanes. It might be excellent in foundation or spontaneous design. Wireless innovations for communication between BANs have matured, unlike communications within BANs; these include WLAN, Bluetooth, ZigBee, mobile, 3G, and more.
- **The clinical server, which is the third layer of Beyond-BAN Communications**, offers a range of services to clients and medical professionals in addition to storing electronic clinical information for registered users. Beyond-BAN's communication strategy is customized for each application and needs to adhere to customer-specific service standards. Through the Internet, the doctor may remotely access the patient's data and review it to make sure the patient's health parameters—such as heart rate, blood pressure, and physical activity—are within normal bounds. The doctor can also assess if the patient is following instructions or reacting to a particular treatment.

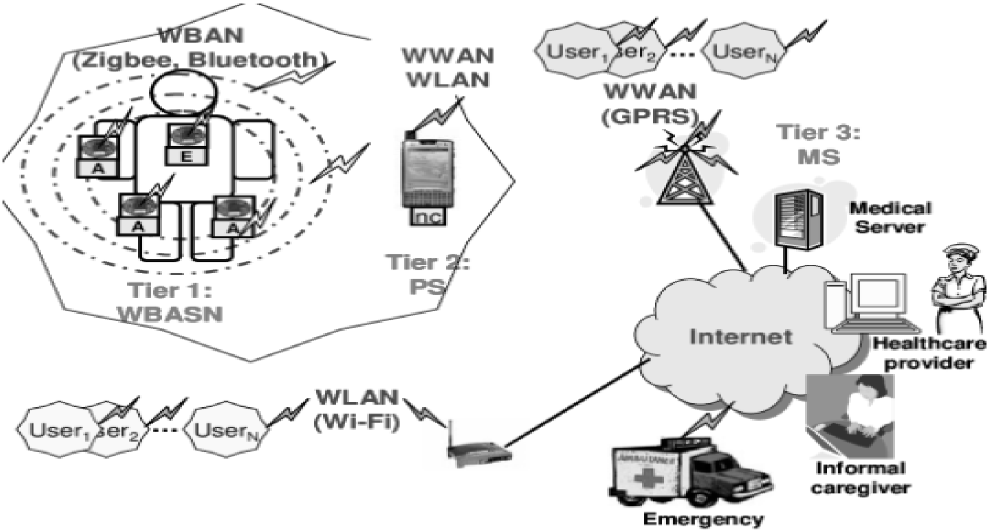

Figure (4) WBAN Architecture

Table 1: IoT-Based Healthcare Monitoring

Ref.	Independent.	Dependent.	Method
B. Thaduangta *et al.*[19]	Device sensor	The individual relied on routine health exams, which included frequently monitoring bodily parameters and sharing the collected data with medical professionals. The data is acquired using a web application.	Technology Acceptance Model
D. Kajaree *et al.*, [20]	Device sensor	used Body wireless sensor Network (BWSN) transmit the parameters of patients' health collected through the microcontroller "Raspberry Pi" to the caretaker and physicians wirelessly.	BWSN, caretaker wirelessly,

Ref.	Independent.	Dependent.	Method
Trivedi *et al.* [21]	to utilize a Bluetooth device that doesn't cover a big region and to avoid using other devices for the transmission procedure..	The analog values are translated into digital data based on the collected measurements. The physical characteristics were transferred to the constructed gadget via Bluetooth.	a mobile device regulated Arduino-based health parameter surveillance
Kumar *et al.* [22]	Not use other devices for many sensors cannot be treated properly.	In the control segment, a DS18B20 sensor was utilized for measuring the temperature of the body, furthermore, a pulse sensor was utilized for measuring the pulse. The Arduino was used to load data into the cloud via the module of the Ethernet shield and Wi-Fi on the transport layer.	Arduino, Ethernet, and Wi-Fi
Tamilselvi *et al.* [23]	No specific performance measures are described for any patient.	used Heartbeat, SpO2, Temperature, and Eyeblink sensors as capturing elements and "Arduino-UNO" as a device of processing.	ARDUINO-UNO board as a microcontroller and Cloud computing
Prajoona Valsalan *et al.*[24]	----	This system is worked on monitoring the pulse rate, the temperature of the body, and room temperature and humidity utilizing sensors. These sensor values are displayed on LCD as well. Then, these values are transmitted to a medical server utilizing wireless communication.	WLAN, LCD, wireless communication.
Acharya *et al.* [25]	The major drawback of the system is that no interfaces for data visualization are developed.	Pulse sensor, BP sensor, temperature sensor, ECG sensor, and the microcontroller "raspberry pi" were utilized. These sensors could collect data and transmit them to the raspberry pi for processing and again sent to the IoT network.	BP sensor, ECG sensor, and raspberry pi.

2.3 Deep Learning Classification

In recent decades, deep learning has achieved significant success mostly due to its capacity to efficiently process vast quantities of data. In addition to conventional methods, hidden layer approaches have attracted attention, especially in the field of pattern recognition. Convolutional neural networks are often used as one of the most common forms of deep neural networks.

Since the 1950s, when artificial intelligence first surfaced, scientists have faced challenges in developing a system capable of comprehending visual input. Subsequently, this discipline was designated as computer vision. In 2012, a team of academics from the University of Toronto created an artificial intelligence model that outperformed the leading picture identification algorithms, representing a significant breakthrough in computer vision.

The artificial intelligence system called AlexNet achieved a remarkable 85% accuracy rate and emerged as the winner of the 2012 ImageNet computer vision competition. The name Alex Krizhevsky is given to it as a tribute to the main designer. The runner-up test taker achieved a commendable score of 74 percent.AlexNet was built around convolutional neural networks, which are a specific kind of neural networks that closely mimic human vision. Convolutional Neural Networks (CNNs) have become an essential component of online computer vision training courses due to their growing significance in many computer vision applications. Now, let's examine the functioning of convolutional neural networks (CNNs).Artificial neural networks (ANN) are computational models that mimic the structure and functions of the human brain. They use a kind of machine learning known as deep learning to derive insights from vast quantities of data. The term used to describe the period in which robots are capable of doing tasks that have historically required human skills is referred to as artificial intelligence. Machine learning is a component of this system that enables computers to acquire knowledge from previous experiences and acquire new abilities without human involvement. Similar to its ability for experiential learning, a deep learning algorithm repetitively executes an activity, making small adjustments to the outcome each time in order to enhance it. The term "deep learning" is used due to the fact that neural networks include several layers, which enable the process of learning. Deep learning may be used to address any issue that requires cognitive processing. Deep learning utilizes a vast, disorganized, and interconnected dataset to enable computers to effectively tackle complex issues. According to Figure 5, there is a positive correlation between the complexity of learning algorithms and their performance [18].

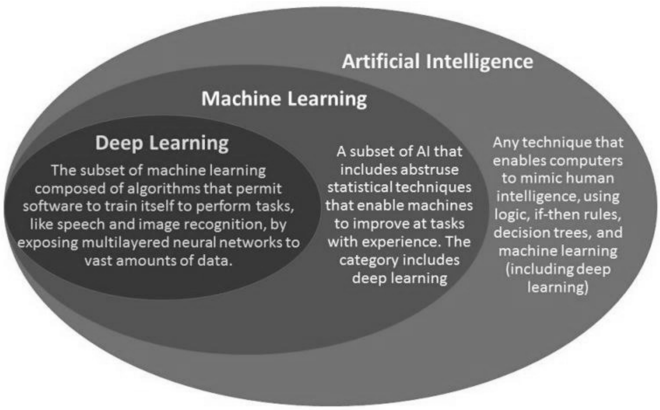

Figure (5) AI self-learning .

2.3.1 Convolutional Neural Network (CNN)

One kind of deep learning technique that is particularly useful for handling the processing of picture and video data is the convolutional neural network. It does this by taking important features out of the data and building a neural network that gives these features weights. After that, the network filters the data in order to modify it before classifying and selecting an image.

When it comes to handling image or video processing data, data scientists choose CNN. Using our layers, you can easily modify the transfer learning model. Convolutional neural networks, or CNNs, are widely used in computer vision. CNN is a particular kind of neural network that successfully solves a number of AI and computer vision problems. Since the convolution process is a crucial component in at least one of its layers, the term "convolutional neural networks" is employed. The input and output layers of a convolutional neural network (CNN) are joined by a number of hidden layers. Examples of layers are pooling layers, convolutional layers, and fully connected layers. Depending on the particular use case, different CNN designs utilize different numbers and combinations of layers. Text from the user is "[19]." CNN layers can have several filters, from few to many, that evaluate each channel and examine the input in a methodical manner.

Convolutional neural networks (CNNs) may extract characteristics that are more and more complicated and abstract as they go through layers. Starting with the farthest corners and edges in the first layers and moving forward to full faces and objects in the levels that follow. In the course of training, the network determines on its own which particular characteristics must be retrieved in order to solve the given issue. CNN's versatility stems from its ability to tackle a wide range of computer vision problems without requiring specific knowledge or human involvement in feature creation [27]. The architecture of a convolutional neural network (CNN) is shown in Figure 6.

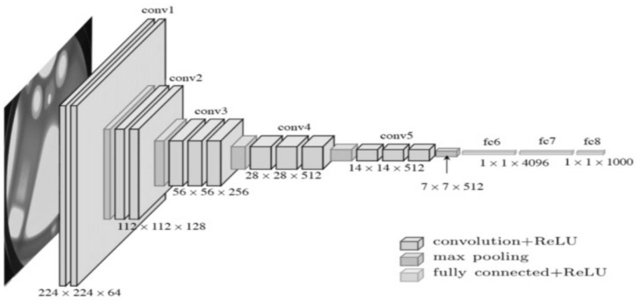

Figure (6) Architecture of CNN

The subsections below provide explanations for several of the terminology and terminologies related with CNN.

I. Input layer of CNN

The input layer serves as the first input for the whole Convolutional Neural Network (CNN). In an image processing neural network, the input typically consists of the pixel matrix of an image. The dimensions of the grayscale image can be utilized to determine the size of the input image[20]

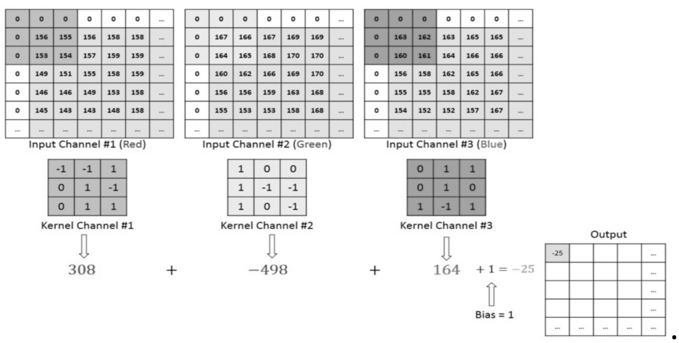

Figure (7) input layer RGB Image of CNN

II. Convolution Operation and Filter

The convolutional layer is employed to extract the salient characteristics of the image. The convolutional layer at the lower level extracts rudimentary characteristics, such as edges, lines, and corners. The high-level convolutional layer acquires abstract characteristics by incorporating low-level features. The convolutional layer generates numerous feature activation maps by performing a correlation operation between a convolution kernel of a certain size and the previous layer, as depicted in equation (1).

$$X_j^l = f\left[\sum_{\in M_j} (X_i^{l-1} * K_{ij}^l + b_j^l)\right], \qquad (1)$$

The kernel consists of a limited number of actual values. The size of the photo is reduced compared to the original. The filter sizes typically range from 1 x 1 to 7 x 7 in neural networks, and these filters determine the weights of the network. They are established during the training phase. Convolution, mathematically speaking, refers to the act of merging two functions described by an integral that demonstrates how one function's shape is altered by the other. Figure 8 illustrates the Convolution process.

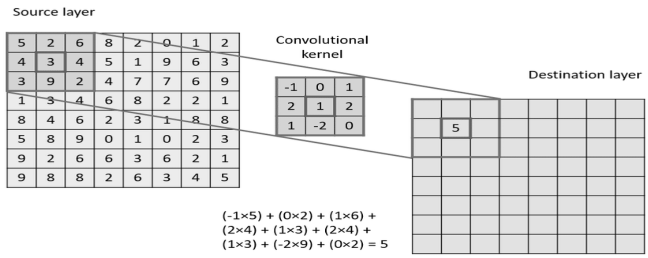

Figure (8) Convolution operation

From the top-left corner of the image, the convolutional process begins, and the kernel moves horizontally from the left side to the right side.

The kernel moves left to right again after shifting one object downward in the top-right corner of the picture. Until the kernel reaches the lower-right corner of the input picture, this procedure is repeated. The outcome of this process is the feature map [29].The stride value controls how the filter moves across the picture. For example, the filter will only move across the image by one pixel at a time when the stride is set to 1.

III. Image Features

Points of interest, edges, and lines in photographs offer diverse information about the content of an image. Localities in an image are described and utilized in several image analysis applications, including reconstruction, recognition, matching, and more [21].

IV. Zero Padding

No matter whatever convolution phase it goes through, the picture will get smaller. To keep the original input size, zero padding is the process of adding zeros to the input picture matrix. Cushioning comes in two different types. "Valid" is the first option; it signifies that no padding is used and that the convolutional layer is never padded. The input size is not maintained as a result. The term "same" denotes the second kind, which means that before to convolution, the input picture is padded. This means that the output's size is equal to the input's size. The zero padding notion is seen in Figure 9. In conclusion, padding is evident in our input volume as it's required to make sure our kernels can handle the input matrices. Sometimes we fill matrices with zeros with an extra row or column. This is known as zero padding. As an alternative, eliminate the unfitting area of the image using a method known as legitimate padding [22].

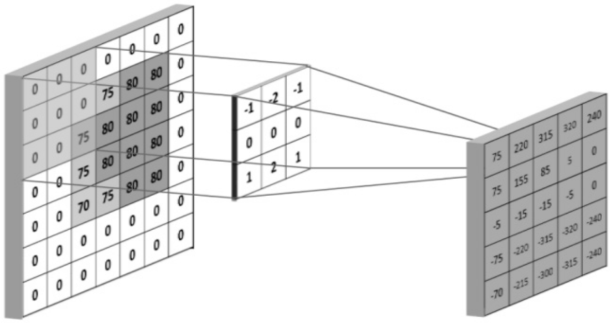

Figure (9) Zero Pegging.

V., Batch Size, Iterations and Epoch

In machine learning, large datasets are frequently handled, therefore batch sizes, iterations, and epochs are crucial. To solve this problem, the data must be divided into smaller chunks and entered into our model one after the other. At the end of each phase, the neural network weights must be adjusted to better match the data. An epoch is a predetermined window of time that a network uses to process data. When a network is trained, its whole data set is used for a single network iteration, a process known as an epoch. The batch size in each session determines how many I/O pairs are shown on the network. The total number of batches needed to finish a single period is referred to as the iterations. Square brackets [23] encompass the number 23.

VI. Cost Function

The network's performance is assessed using the cost function. It is the outcome of deep learning and reflects the goal that the network seeks to reduce. An optimizer is needed in order to minimize the cost function. In this situation, a popular option is the ADAM Optimizer, which stands for Adaptive Moment Estimation Optimizer. ADAM is an optimization technique that iteratively adjusts the network weights based on the training data, in contrast to the traditional random gradient descent approach [24].

2.5.2 Layers of CNN

Layers of CNN There are many layers in a convolution neural network. The most important layers are explained in the subsections below:

a) **Convolution Layer**

Extracting features from an input picture while maintaining the spatial connection between pixels is the main objective of the convolution process. This is accomplished by teaching a filter (kernel) about the characteristics of the picture. An essential part of a convolutional neural network is the convolution layer, which wraps the input picture in order to extract its characteristics. While later layers extract higher-level characteristics, the initial convolution layer concentrates on extracting low-level features like lines, corners, and edges. The equation for these layers is given in equation (2) [25].

$$a^{1} = \sigma\left(b + w * a^{0}\right) \tag{2}$$

a1 indicates the collection of activations that are output from the feature map, while a0 denotes the input activations. σ stands for the activation function, w for weight, b for bias, and * for the convolution process. The height and breadth of the input picture are greater than those of the kernel. The kernel convolves with the picture by sliding across it to build a feature map. The product of the kernel element and its matching element in the original picture is the convolution.

b) Pooling Layers

Neural networks (NN) employ pooling as a way to reduce computational complexity and variance. A lot of times, inexperienced people use the assembly method without realizing why they should. Three basic assembly techniques that are often used are compared here.

Aggregating activities come in three different flavors:

Choosing the largest value inside a certain window is how max pooling, a deep learning approach, downsamples the input data. The value specified denotes the batch's maximum pixel value.

Min pooling: Identifies the batch's lowest pixel value.

In computer vision and image processing, average pooling is a technique that downsamples an input picture by splitting it into non-overlapping sections and replacing each region with the average value of the pixels inside that It computes the average value of each pixel in the batch.

The term "batch" here refers to a group of pixels the same size as the filter, which is based on the image's dimensions. Here, a 9x9 filter was selected. The aggregation approach's outcome varies according to the particular filter size setting. Consequently, the convolutional layers' spatial dimensions, which provide the feature maps. The accuracy of the features is reduced by the pooling layer. Maximum and average pooling ideas are shown in Figure 10. Not all of the info is removed when we aggregate a picture. Rather, we extract an overview of all the values that are there.

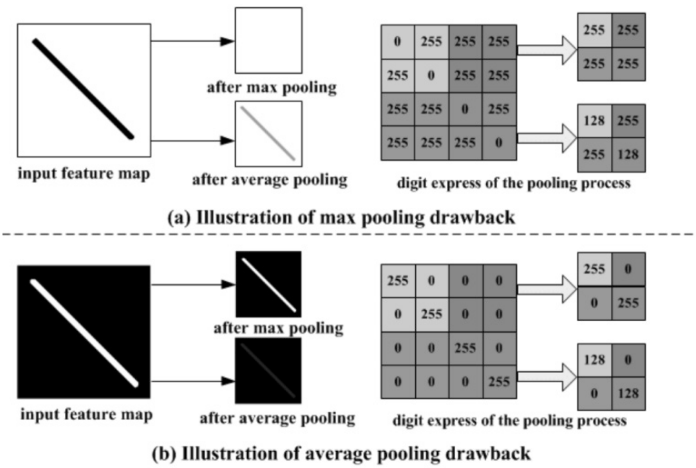

Figure (10) max or average pooling

c) Fully Connected Layer (FC)

In addition to neurons, the FC layer, which links neurons between layers, also contains weights and biases. These layers comprise the final few levels of the CNN architecture, before the output layer. By doing this, the input picture from the layers above is fed into the FC layer, flattening it. Arithmetic function operations are carried out by applying additional FC layers on top of the flat vector. At this moment, the categorization process starts.

d) Dropout

Weights, biases, and neurons make up the FC layer, also referred to as the fully connected layer, which creates connections between neurons in various layers. These layers make up the last few levels of the CNN architecture before the output layer. The fully connected (FC) layer is compressed throughout this process, and the input picture from the layers above is sent to it. The flattened vector is further extended with completely linked layers to perform arithmetic function operations. This is the point where the classification process starts.

$$r^{(-1)} \sim Bernolli\,(p)$$ **……………………………(3)**

$$x_j^l = f[\sum_{i \in M_j} (r^{(l-1)} * x_i^{l-1}) * W_{ij}^l + b_j^l]$$ **…………………(4)**

When every feature in the training dataset has a strong connection to the fully connected (FC) layer, overfitting can occasionally happen. After performing well on training data, the model suddenly exhibits poor performance on fresh data. According to equation (3), every value in vector (1) lr− has a probability of p and hence follows a Bernoulli distribution, producing values that are either 0 or 1. Starting from the first layer l and moving through the vector (1) lr−, each layer of the model blocks is a component of the 1lix− input vector. As a result, the model can roughly represent the subnetwork model that was taken out of the network model as a whole. Forward propagation is used to acquire the lth layer's output.

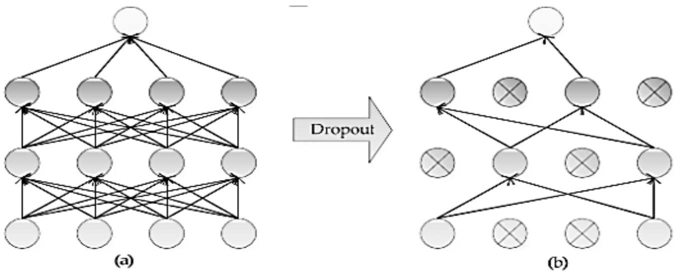

Figure (11) Neural network utilizing Dropout

e) Activation Function Layer

Even though neurons have activating activities, not all neurons have them, as Figure (12) illustrates. While the input layer lacks activation functions, the output layer has hidden neurons.

To guarantee that the output values are maintained within a range that is convenient to deal with, activation functions are utilized to perform a mathematical action on the input data. It is not necessary to alter input layer data because they are usually centered around zero and have already been appropriately scaled. Nevertheless, these numbers frequently go beyond the bounds of their original scale when multiplied by weights and summed collectively. Activation functions are important in this situation since they are activated to bring the numbers back into an acceptable range.

Activation functions need to be continuous differentiable and non-linear in order to be successful. Because of its nonlinearity, the neural network may be used as a global approximation. Gradient-based optimization techniques need the existence of a continuously differentiable function in order to effectively backpropagate errors across the Connectivity infrastructure.

Within the neuron:

- The activation function is given to an individual neuron or to the whole layer of neurons.
- The input values are combined using a weighted sum.
- The resulting sum is then sent through an activation function, causing a transformation to occur.

The output to the subsequent layer is represented by the converted value [36].

$$\text{sigmoid:} \qquad f(x) = \frac{1}{1+e^{-z}},$$

$$\text{tanh:} \qquad f(x) = \frac{e^{z}-e^{-z}}{e^{z}+e^{-z}},$$

$$\text{ReLU:} \qquad f(x) = \max(0,x),$$

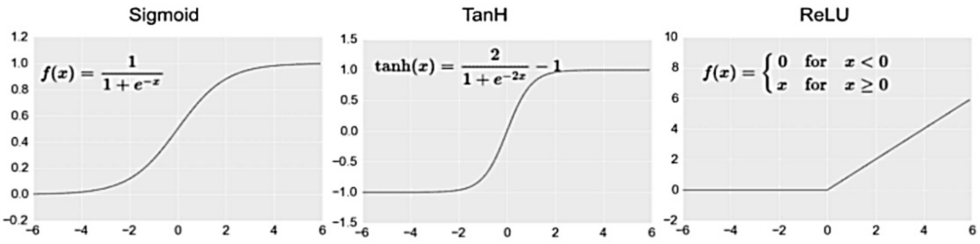

Figure (12) activation function

3 Research methodology

The proposed approach entails developing an intelligent system that leverages the Internet of Things (IoT) for healthcare in response to the COVID-19 pandemic. The system aims to address the challenges faced by a significant number of infected individuals who were unable to access medical facilities or healthcare professionals. Ensuring the implementation of this care system is highly crucial. The research technique comprises four fundamental stages:

1. **Data gathering stage**: The researcher gathers and examines data either by adhering to established medical guidelines or by utilizing intelligent technology like mobile phones.
2. **During the design and analysis stage**, servers are utilized to connect gadgets and utilize fundamental information to create an automated model that represents the healthcare process.
3. **The proposed development model**: The health care monitoring model can function independently of the Internet of Things that it was originally built upon.

4. **Validation of the suggested model**: Researchers assess the efficacy, user-friendliness, and utility of the presented model by conducting interviews with Internet specialists. Figure 6 illustrates the proposed system.

3.1. Data collection

A. Wearable devices

We may use a variety of gadgets, such as wearable technology and smart sensors, to detect blood pressure, oxygen saturation, temperature, accelerometers, weight scales, and smartwatches. To track the patient's physiological indicators, including heart rate, blood pressure, blood sugar, stress level, oxygen saturation level, temperature, and weight, the body's signals will be recorded in real-time in each of these situations. In our system, portable gadgets are widely used to track physiological functions. The mobile device's sensors allow for the exact collecting of data on a number of human bodily features. Therefore, in addition to collecting personal data like age, gender, height, and other pertinent information, smartphones are used to collect data on food, exercise, and other types of physical activity. This information is very beneficial for healthcare and illness prevention, especially in light of the coronavirus epidemic. Nevertheless, smartphone data is very erratic and easily corruptible. Therefore, it is difficult to use smartphone data to obtain accurate health information and extract relevant data. To efficiently process sensor data and extract relevant information for healthcare applications, we have used ontology-based data extraction and semantic knowledge approaches.

Multiple access ports are incorporated into the distinctive architecture to enable the body sensors' information to be sent more easily. As a result, the service coverage is greater than that of buildings based on infrastructure. During situations, like the coronavirus pandemic, when the Body Area Network (BAN)'s range is limited to around two meters, these devices enable users to migrate to any area or building in order to seek safety. The system's range may be increased to about 100 meters using an ad hoc linking architecture, allowing for both temporary and permanent deployments. There are two types of nodes that may be used in this architectural arrangement: sensor nodes that are located within or near the human body, and router nodes that are placed near the body area network (BAN). In Wireless Sensor Networks (WSNs), each node performs the dual roles of a router and a sensor. The ad hoc architectural configuration connects to the outside world through a traditional gateway that resembles a Wireless Sensor Network (WSN). Every infrastructure typically uses one radio, which means that bandwidth is shared. Therefore, when there is a high density of router nodes and sensor/actuator nodes in a certain location, there is a chance that a collision may occur. In order to resolve these conflicts, an asynchronous MAC technique might be used. The network architecture provides access to the system and has the following unique characteristics:

- Wide-ranging radio coverage made possible by data being sent across several hops. As a result, it is possible to provide improved support for patient mobility, especially for those infected with the coronavirus, because of the reduced bandwidth when data is sent over many hops.
- Rapid progress has been made in the timely and flexible wireless deployment of emergency response systems.

By adding more access points or other required components, the network's flexibility may be readily increased without interfering with the operation of the entire network.

B. Medical Records

In this instance, data is gathered from patients' medical records regarding the therapies they received. We gather patient medical records that encompass the patient's medical history, including details on therapies, laboratory testing, and drug administration. Analyzing these records can yield valuable information that can offer ideas for enhancing medical guidance. Nevertheless, medical records typically have a substantial volume, with each record containing data that has scattered variables and high dimensions. Additionally, those with diabetes and high blood pressure may experience several symptoms, including kidney and cardiovascular disease, neuropathy, and skin and eye problems. Their weakened immune systems make them more susceptible to contracting the Karuna virus and experiencing related diseases. It is crucial to have appropriate information regarding these matters. Hence, it is imperative to scrutinize medical records in order to identify individuals who have been impacted by the aforementioned issues and closely follow their condition through more specialized tests.

3.2. WBAN

Wireless Body Area Network (WBAN) is a subset of Wireless Sensor Network (WSN), a burgeoning technology used in healthcare applications. A Wireless Body Area Network (WBAN) is a network of small, low-power wireless nodes that are strategically positioned on or around the human body to constantly monitor a patient's essential health indications. These sensors have the capability to transmit data on physiological parameters obtained from the human body to other devices for the purpose of diagnostic procedures and prescribing treatments. WBAN offers healthcare services globally and facilitates unrestricted mobility by allowing medical professionals to monitor a patient's health using data transmitted through wireless networks. This study presents a healthcare monitoring system utilizing Wireless Body Area Network (WBAN) technology. The system is capable of collecting data on electrocardiogram (ECG), heart rate, and human body temperature. This is precisely what we require, particularly during the COVID-19 pandemic. It is feasible to enhance this by considering or presenting other instances in the event of a novel virus. This particular type of virus undergoes self-development approximately every twenty or ten years, as per the research conducted by the World Health Organization. During this period, a significant number of individuals are uncertain whether they are dealing with a virus or a common flu. The inability to access a hospital or a doctor has left patients feeling disheartened. Consequently, this type of network has experienced substantial advancements. The data obtained from the human body is wirelessly transmitted via the IEEE802.15.6 MAC protocol on NS-3. The physiological data will be transmitted to a distant medical server where it will be stored and evaluated. If a patient is diagnosed with any disease, the medical team is capable of promptly providing aid.

3.3 Deep Learning in IoT

An exceptionally efficient deep learning compression approach, known as DeepIoT, has the capability to compress frequently utilized deep neural network architectures. This procedure facilitates the doctor's acquisition of information through the utilization of medical devices. The obtained data is then subjected to a classification stage in order to determine the presence of any infection or disease, such as the Corona virus or potential future epileptic episodes. This enables the doctor to prescribe the appropriate medication for the patient.

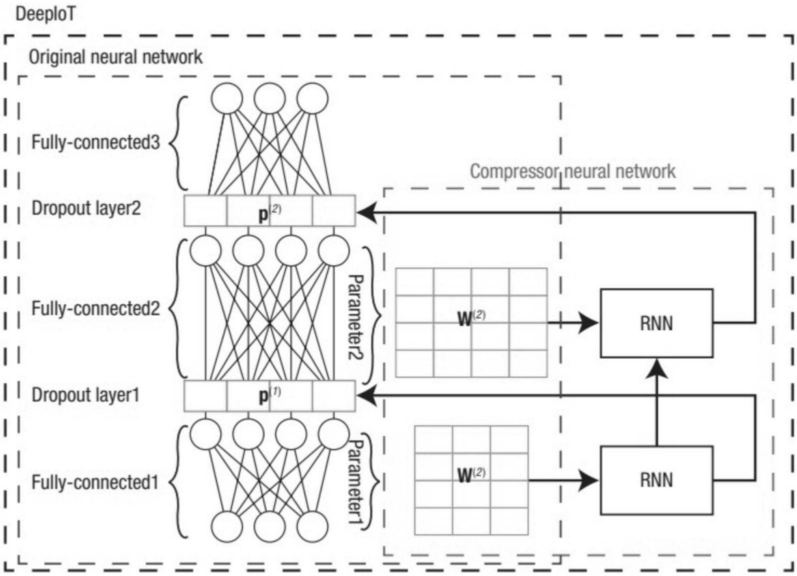

Figure (13) deep learning of IoT

4.Conclusion

Extracting meaningful information from unprocessed IoT data is a highly intricate undertaking that surpasses the capabilities of conventional data analysis methods. This paper presents a thorough examination of Deep Learning, a sophisticated machine learning technology that has proven to be particularly effective in evaluating complicated data produced by IoT applications. Deep Learning models surpass conventional machine learning paradigms in the following aspects. Firstly, they eliminate the need for supervised feature sets to be used for training. As a result, Deep Learning models may effectively extract features that may not be easily identifiable by a human. Furthermore, Deep Learning models produce more precise prediction outcomes. Moreover, Deep learning models are suitable for representing complex patterns in diverse datasets. This proposal offers an in-depth analysis of different Deep Learning architectures. This text presents a comprehensive overview of the research endeavors that have utilized Deep Learning models for data analysis in Internet of Things (IoT) scenarios. Finally, this paper discusses the problems and future research directions that need to be addressed in order to support continued study in this field. It is important to note that the use of deep learning for analyzing IoT data is still in its early stages. Further study is necessary to fully utilize the capabilities of deep learning models for IoT data analysis.

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