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Deep learning applications for IoT in health care: A systematic review

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A R T I C L E I N F O

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A B S T R A C T

In machine learning, deep learning is the most popular topic having a wide range of applications such as computer vision, natural language processing, speech recognition, visual object detection, disease prediction, drug discovery, bioinformatics, biomedicine, etc. Of these applications, health care and medical science-related applications are dramatically on the rise. The tremendous big data growth, the Internet of Things (IoT), connected devices, and high-performance computers utilizing GPUs and TPUs are the main reasons why deep learning is so popular. Based on their specific tasks, medical IoT, digital images, electronic health record (EHR) data, genomic data, and central medical databases are the primary data sources for deep learning systems. Several potential issues such as privacy, QoS optimization, and deployment indicate the pivotal part of deep learning. In this paper, deep learning for IoT applications in health care systems is reviewed based on the Systematic Literature Review (SLR). This paper investigates the related researches, selected from among 44 published research papers, conducted within a period of ten years – 2010 to 2020. Firstly, theoretical concepts and ideas of deep learning and technical taxonomy are proposed. Afterwards, major deep learning applications for IoT in health care and medical sciences are presented through analyzing the related works. Later, the main idea, advantages, disadvantages, and limitations of each study are discussed, preceding suggestions for further research.

1. Introduction

In machine learning, deep learning is considered a new area and, consequently, an essential subset of artificial intelligence (AI). Several definitions are offered for deep learning, but the following definition is the most comprehensive of all. Deep learning is a series of algorithms founded on artificial neural networks having multiple layers [1].

Artificial neural networks were first proposed in the 1940s by McCulloch and Pitts [2]. Biological neural systems inspired the main idea of neural networks for information processing [3].

A biological neuron consists of several entities, but investigating the role of the following elements is substantial in studying the functionality of artificial neural networks:

- Synapse: Input signals receiver.
- Dendrite: Weight assignments.
- Cell body: Summation and integration.
- Axon: Signal transportation.
- Axon terminal: Output result.

As Fig. 1 shows, deep neural networks are artificial neural networks with several layers. Each layer is responsible for extracting some information represented by a score times weight, and forwarding them to the next layer. The sum of all the values related to a specific input makes the output. The input layer collects the input data, hidden layers are in charge of storing the corresponding weights, and the output layer yields the output results [4].

IoT connects the physical world to the digital world [5]. There are numerous ways to explain IoT, some of them are as follows: "3A concept: anytime, anywhere and any media, resulting into sustained ratio between radio and man around 1:1" (Srivastava, 2006) [6].

A universal network includes connected objects, which are communicating distinctively through communication protocols [7].

> "A dynamic global network infrastructure with self-configuring capabilities based on standard and interoperable communication protocols where physical and virtual 'Things' have identities, physical attributes, and virtual personalities and use intelligent interfaces,

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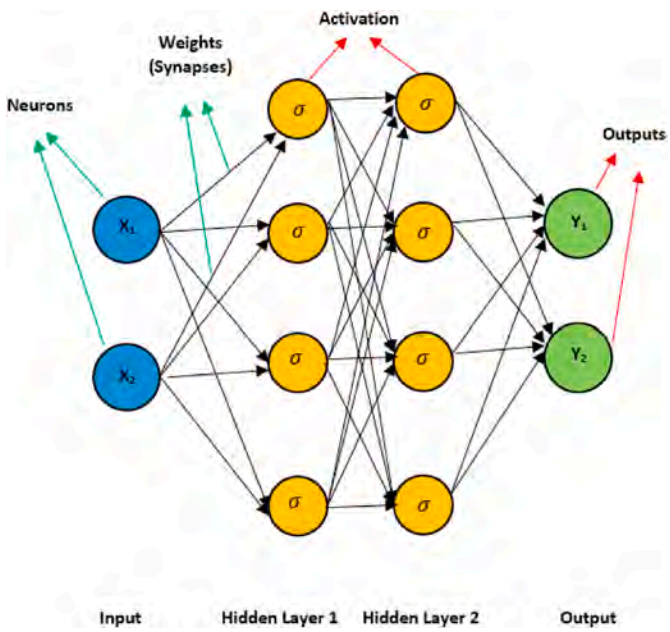

Fig. 1. Architecture of deep neural network [9].

and are seamlessly integrated into the information network" (Kranenburg, 2008) [8].

Broadband Internet and applications of electronics have turned out to be essential elements of healthcare; therefore, Medical Internet of Things (MIoT) plays a pivotal part in people's lives [10]. MIoT refers to the use of wearable sensors and connected medical devices for delivering novel medical services to hospitals, patients, and physicians.

At present, a big part of data is being generated by IoT devices, used as "big data" and input feed by deep learning algorithms to yield meaningful information. Deep learning has numerous implications and is almost available in every aspect of our life. Medical uses and healthcare are among the most popular ones, and are still growing. EHRs, integrated administrative and medical data bases, digital images (radiography, mammography, and histology), data taken from mobile applications, medical devices IoT, genes data, and data coming from search engines are main sources of deep learning algorithms that can predict, diagnose, help decide clinically, etc. some others are used in biomedical and pharmaceutical fields such as molecular diagnostics, pharmacogenomics, identification of pathogenic variants, DNA Sequencing, gene splicing, personalized cancer care, and drug discovery [11].

This paper aims to study the latest research and reviews on different deep learning applications and IoT in medical sciences and health care services. The significant applications investigated in this review include disease prediction, diagnosis, treatment, biomedicine, and health informatics. What makes this research outstanding compared to similar works is that it especially covers the application of deep learning, IoT, and a combination of them both, while related works just focused on one of these areas. This survey presents a systematic literature review (SLR) and discusses with the following:

- Illustrating technical taxonomy for diverse uses of IoT deep learning in medical services
- Inspecting challenges of utilizing related applications
- Considering open problems and potential opportunities in the future

The following indicate the organization of this survey: such works: Section 2. Research method: Section3. Applications of deep learning and IoT in health care: Section 4. A technical taxonomy of related applications also appears in this section. Present issues and opportunities: Section 5. An overall review of the contents of this paper: Section 6.

2. Review of related studies

This section intends to review the studies conducted on deep learning applications for IoT in healthcare.

Zhao et al. [12] provided a systematic overview of deep learning research on monitoring health by machine. The purpose of the systems that monitor health through deep learning-based machine (MHMS) is extracting hierarchical indications from input data through creating deep neural networks with different layers of nonlinear changes. The suggested DL-based MHMS are made shown based on four aspects of DL architecture, as reported by Auto-encoder models, Restricted Boltzmann Machines models, Convolutional Neural Networks, and Recurrent Neural Networks. The focus in this study include the following: DL-based MHMS does not need considerable practice and expert information. The problem with this study is that the scale of datasets limits the depth of the DL model.

Friday Nweke et al. [13] discussed varied deep learning techniques in mobile and human activities, which are sensor-based and wearable in a way that automatically extracts features. Deep learning methods are mainly divided into a generative model, discriminative models, and hybrid models. For generative categories, Restricted Boltzmann Machines, auto-encoder, deep mixture models, as well as sparse coding are mentioned; the methods to discriminate are the convolutional neural network, recurrent neural network, deep neural model, and hydrocarbon. A generative and discriminative model is stated as a hybrid approach that can improve feature learning. The merit of extracting effective vectors from mobile sensor data saves some time in computing and provides precise recognition performance. However, fields such as DL-based decision fusion that use deep learning onboard mobiles and transfer learning, and problems in class imbalance are open research challenges.

Pasluosta et al. [14] studied the concept of the Internet of Health Things (IoHT). Switching objects leads to control patients' physical conditions by congregating and merging data on significantly crucial signs in hospitals. IoHT includes four stages: collecting, storing, processing, and presenting. The positive features of IoHT are twofold: it can reduce service downtimes and allot limited resources efficiently. The primary defects of this survey are related to the volume and complexity of collected data, which interprets an arduous task for caregivers.

Data fusion for IoT that focuses on computational and mathematical techniques such as methods in probability, AI, the theory of belief, and specified IoT ambiances, including disseminated, nonlinear, non-homogeneous, and environments where objects are tracked was reviewed by Alam et al. [15]. Data fusion, which is the fusion of varied kinds of data, would be a crucial factor in ubiquitous environments since it improves the data quality and decision-making. Some of the data fusion drawbacks are related to ambiguities and inconsistencies and are inconsistent with the nature of data that may yield to outcomes which are conversely intuitive.

Riazul Islam et al. [16] surveyed various features of IoT-based technologies in healthcare area and suggested varied medical network structures and platforms that provide the IoT foundation available and aid transferring and collecting data in medicine. Merits of IoT-based medical services are reducing expenses and enhancing life quality. In contrast, IoT healthcare tools are placed within with slow processors. Moreover, these devices cannot perform computationally expensive

Table 1
Researches conducted in deep learning uses for IoT in healthcare.

Reference	Main topic	Publication year
Zhao et al. [12]	MHMS	2015
Friday Nweke et al. [13]	human activity recognition	2018
Pasluosta et al. [14]	IoHT	2018
Alam et al. [15]	Data fusion	2017
Riazul Islam et al. [16]	IoT-based healthcare technologies	2015

operations.

Table 1 indicates a brief account of the mentioned researches conducted and reviewed on deep learning uses for IoT in healthcare.

3. Research method

This part discusses the SLR method as an evaluation method of research study for the classification of deep learning applications for IoT in healthcare is provided [17–19].

This paper answers the following Research Questions concerning the targets of the study:

RQ1: Which categories have been classified as deep learning applications for IoT in healthcare?
RQ2: Which major contexts are mentioned for deep learning applications for IoT in healthcare?
RQ3: What appraisal environments are inspected in deep learning applications for IoT in the healthcare domain?

Fig. 2 shows how evaluation chart and criteria for research surveys were selected. The section which has been excluded contains chapters of books, imperfect studies, and non-peer-reviewed surveys. The principles considered to include principles are:

- The researches published from 2010 to 2020
- The studies with more than 20 citations

The principles of exclusion are:

- The researches not found in WoS (ISI-indexed)
- The researches which are not in English

The mentioned principles used to select eventual research based on assessing journal show up after analytical questions. Ultimately, we approved 44 peer-reviewed research studies to evaluate and answer the analytical questions, elaborated in Section 4.

Fig. 3 represents the dissemination of the research surveys accomplished by the supreme publishers regarding citation and review methods, such as IEEE, ACM, Elsevier, and Springer. Moreover, in this arrangement, we applied electronic databases.

4. Organization of deep learning applications for IoT in healthcare

This part presents a review of selected deep learning applications for IoT in healthcare for the available surveys according to the systematic literature review. Fig. 4 indicates a comprehensive classification of the deep learning applications for IoT in healthcare domains consisting of medical diagnosis and differentiation applications, home-based and personal healthcare applications, disease prediction applications, and human behavior recognition applications. We review papers that tackle problems related to deep learning applications in healthcare. For example, major topics on smartphone sensor data, multi-morbidity chronic patients, learning patient physiological signal, smart dental Health-IoT system, fall detection models, sport injury, and nutrition monitoring system were stipulated in the section on personal healthcare and home-based applications.

This paper focuses on the different deep learning applications as related to challenges IOT in healthcare faces, and also on the significant factors mentioned in some papers.

Different techniques in deep learning applications are demonstrated in the subsequent subsections. Furthermore, we compare and contrast the main part, case studies, privileges, weaknesses, and innovative achievements in those papers.

4.1. Medical diagnosis and differentiation applications

Tuli et al. [20] proposed HealthFog for automatic diagnosis of heart diseases utilizing deep learning and IoT. A lightweight fog service and effective data management related to patients suffering heart diseases from various IoT devices are provided through HealthFog. The advantages of a new pattern of fog and edge computing are included as solutions to save energy and those which are low latency solutions for data processing. As for fog computing weaknesses in medical applications, it is concluded that it is important to know the response and latency time it is and hard to make an optimum use of parameters of Quality of Service (QoS) in real-time fog ambiances [21].

Sarraft et al. [22] stated that neoteric technological breakthroughs in automated EEG disease diagnosis and detection systems have occurred due to deep learning methods. Some positive points of this survey are enhanced EEG decoding performance because of the automated feature extraction facility. Moreover, the detection of unusual health conditions is possible through assessing their EEG. However, the availability of EEG pathology datasets will lead to a challenge as some of these can be accessed online, but a vast majority is small and unsuitable for some deep learning models [23–26].

Cerebral Vascular Accidents (CVA) [27,28] i.e. stroke, is an illness where some brain parts stop functioning because of ischemic or bleeding. In most cases it can cause death. Prompt diagnosis can tackle this issue. CT and MRI imaging are normally used to diagnose strokes.

IoT framework can be utilized to classify stroke through CT images deploying Convolutional Neural Networks (CNN) to recognize if the brain is healthy, the stroke is ischemic, or a stroke happened because of bleeding. The advantages of employing IoT in healthcare are less human-dependent areas, leading to fewer human errors. Limitation of this study: we cannot use the proposed structure in other medical images, yet the expansion of this system is required.

Faust et al. [29] developed a deep learning model on the basis on Long Short-Term Memory (LSTM) by using Heart Rate (HR) signals to detect Atrial Fibrillation (AF) episodes. The deep learning LSTM based

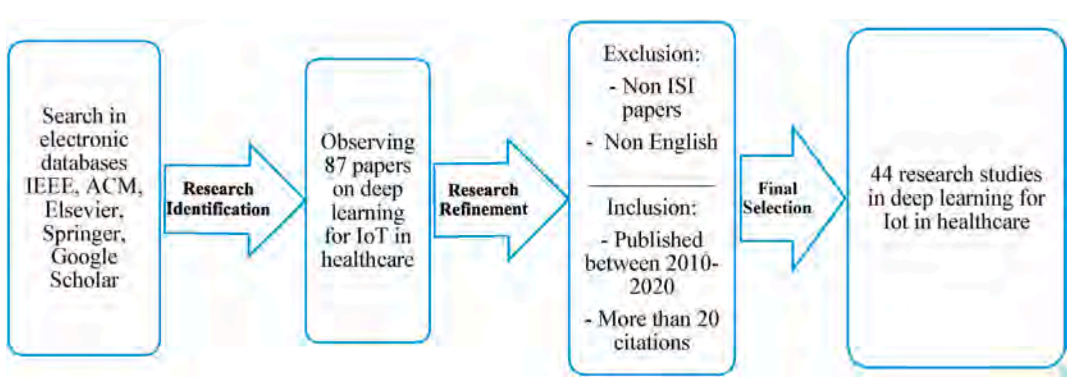

Fig. 2. The criteria for selection, and the chart on evaluating research findings.

Fig. 3. Publishers' research papers Distribution.

system was piloted on 20 subjects with labeled HR signal data sourced from Physio Net's Atrial Fibrillation Database (AFDB). As compared to machine learning approaches, achievements of this deep learning model are less limited. Moreover, information elicited from a small dataset may be generalized to a larger dataset. The problem with this survey is that the critical concept of training is not addressed.

The fundamental part of Chinese medication used to cure infectious fever is syndrome differentiation [30]. It is onerous for old classical Chinese medication to make a difference between the infectious fever syndromes due to its complication. Deep learning is a promising model for differentiating computer-assisted syndrome of infectious fever by integration. The suggestion is an adaptive dropout function into the stacked auto-encoder. To reduce over-fitting as well as to enhance the classification accuracy are considered the strengths of this study. Deficiency: it cannot differentiate infectious fever in many clinical cases.

Bray et al. [31] explored the deep reinforcement learning models for computer-assisted diagnosis and the treatment for lung cancer. Currently, lung cancer poses a severe threat to the humans. Numerous people suffer two types of tumors in their lungs: benign and malignant. Deep reinforcement learning models can spot lung tumors and yield valid outcome. However, defining a good function to update each action's Q-value is the biggest challenge in using deep reinforcement learning models to cure lung cancer.

Melanoma [32] is a serious skin cancer, since it is more likely to cause metastasis. Melanocytic lesions are of three types: common nevi, atypical nevi, and melanomas. In this survey, an IoT technology based system is used to categorize lesions of skin. The proposed method applied CNN models for ImageNet dataset to get images. Merits of this method are accessible usage in different areas and convenience. The downside of this study is related to internet access. Connection to API (Application Programming Interface) in LINDA and sending images requires a good connection.

Schirrmeister [33] offered innovative methods to visualize the features and denoted that ConvNets learn to use a variation of power in the alpha, beta, and high gamma frequencies.

Moreover, the study represents the process of designing ConvNets which is used to decode information, and is related to the task taken from the bland EEG having no handmade features. Being suitable for end-to-end learning well and satisfactory scalability for huge datasets are among the privileges. The weakness of ConvNets is that they may show false predictions and require training data.

4.1.1. Analysis of the reviewed medical diagnosis and differentiation applications

Table 2 represents the above papers' classification and their crucial features to assess medical diagnosis and differentiation for IoT in healthcare.

4.2. Home-based and personal healthcare applications

In this section, home-based and personal healthcare applications are illustrated. Moreover, this paper compares and assesses several studies from different aspects such as the primary context, case studies, benefits and drawbacks, and their outputs.

Fonseca et al. [34] offered to work on intelligent living spaces for home-based healthcare in multimorbidity chronic patients. "Knowledge Acquisition Bottleneck" is the main barrier in developing sufficient indications of medical knowledge, i.e., ontologies in the healthcare area. The supervised or predictive machine learning method is used in this survey. In this technique, mappings from an input to another output are a part of the systems, and they are provided a training set, which is a labeled set of input-output pairs. This method contributes to a new wave of caregiving amenities since it provides a better quality of life for patients who suffer from comorbidities and controlling costs. The problem is that there are no data to confirm the effectiveness and functioning of the presented model.

Sandstrom et al. [35] stated that smartphone users could transfer their sensor data to other people in the cloud, such as that of the IBM for IoT and Emotion Sense. Smartphone affects three areas greatly: ambulatory assessment, behavior monitoring, understanding, and foreseeing outcome. A deep learning method can build a correlation between smartphone sensor data and personal health. Initially, data is classified into sections by Deep-stacked Auto Encoders (SAE) in order to elicit their features and categorize their softmax layer. Then, the quantitative relevance is created between divided sensor data and health. Finally, to approve of the performance of the suggested technique, simulation is devised. Positive points of this method: SAE holds a plain format, small computation (without forced GPU), and very good performance (regularizing weight and sparsity). However, as a future assessment, more sensor data genres from smartphones and wearable devices should be studied.

Dental diseases of various types are widespread globally. According to the latest oral health survey, a shocking 94% of the Chinese nation suffers from varied dental problems [36]. Accordingly, Smart system for Health-IoT of teeth, founded on smart hardware, deep learning, and mobile terminal, may solve this issue. The trained model was utilized to detect and classify teeth disorders. A respective application (Apps) was deployed for both the dentist and the client. Its main advantage over the available endoscopy of mouth is it is 5.5 mm wide and 4 mm thick for the betterment of adults or children's mouths. This concentrate ranging from 1 cm to 6.5 cm and can make automatic changes in the light and the mouth. Moreover, cheap hardware makes home usage easier. The

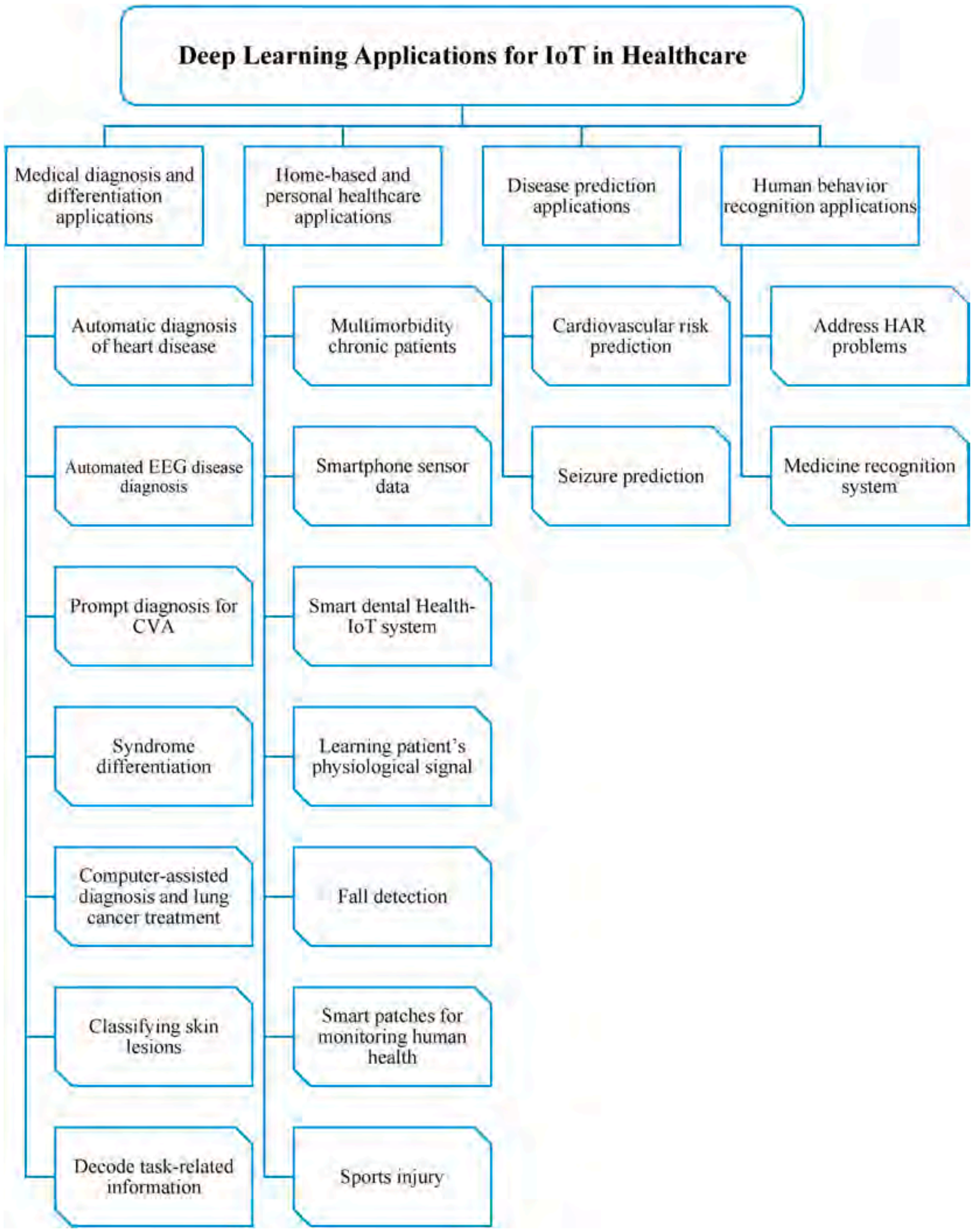

Fig. 4. The taxonomy of deep learning applications for IoT in healthcare.

drawback is the bigger teeth cannot be detected and covered by lenses.

Sagar et al. [37] addressed the challenging issue of reliable physiological monitoring in the healthcare system. To have a secure healthcare, a monitoring system was developed which was founded on Body Sensor Network (BSN). Through a system to monitor physiological signals, it is possible for IoT users to predict their own conditions like chronic fever, heart attacks, and care for the elderly [38–40]. A Deep Neural Network (DNN) has been proposed to elicit qualities of the signal in various sensors for learning the physiological signs received from patients. The merits of the designed prototype model are high accuracy as well as cost effectiveness. One major limitation of DNNs is that in order to perform better than other techniques, much information is required.

The most significant aspect of fall detection is constructing a highly precise detection model in cheap devices. Although sensors connected to the monitored subject's torso have represented the ability to attain higher detection accuracy, a majority of old people do not care for these sensors because they cannot convince themselves to use them. classical (Support Vector Machine and Naive Bayes) and non-classical (Deep Learning) algorithms used to build fall detection models use three different fall sets of data (Smartwatch, Notch, Farseeing) [41–43]. This study aims at finding out whether the Deep Learning Model utilizes raw data to make patterns for generalization purposes, while the weakness of this method is concluded to be the problems of Deep Learning model on activities of daily living (ADLs).

Malasinghe et al. [44] claimed smart patches or chips that can monitor human health conditions employing IoT sensors have just begun in the multimedia technology domain. such patches use very thin

Table 2
Categories of recent researches conducted in medical diagnosis and differentiation applications.

Research	Main context	Advantage	Weakness	New finding
Tuli et al. [20] Mutlag [21]	- A lightweight fog service and effective management of data to diagnose heart diseases automatically - Optimization of QoS parameters in real-time fog environments	- Low latency - Energy-efficient solutions to process data	Latency and response time are hard for optimization of Quality of Service (QoS) parameters in real-time fog environments	Framework
Sarraft et al. [22] Kamnitsas et al. [23] Hossain et al. [24] Acharya et al. [25] Zhang et al. [26]	- Breakthroughs in detecting diagnosing EEG disease automatically - Detecting abnormal medical conditions	Enhanced EEG decoding	Most of the EEGs are small and unsuitable for models which are based on deep learning	A cloud-based framework
Filho et al. [27] Masoumi et al. [28]	- Prompt diagnosis can tackle CVA. - Salient devices to diagnose strokes are CT imaging and MRI. - IoT framework can be utilized to categorize stroke through CT images	- Less human dependent area - Fewer human errors	We cannot use the proposed structure in other medical images	An IoT framework
Faust et al. [29]	- The LSTM based deep learning system was piloted with labeled HR signal	- Less limited as against machine learning approaches - Information elicited from a small training dataset may be generalized to a bigger dataset	Training during the job is not addressed	A creation of Deep Learning model to detect AF using HR
Jiang et al. [30]	- Differentiating Syndromes is the core of Chinese medication - Differentiating syndromes of infectious fever assisted computers	- Reduce over-fitting - Enhance the classification accuracy	- Cannot differentiate numerous cases of fever which are infectious and were observed cases in clinics	An adaptive Deep Learning model
Bray et al. [31]	- The deep reinforcement learning models for computer assisted diagnosis and cure of lung cancer	Problem of localizing cancer of lungs shall be solved	Q-value shall be updated in every action	A number of models to represent deep reinforcement learning
Ma et al. [32]	- Melanoma is a serious skin cancer. - A system based on IoT technology is used to classify skin lesions	- Accessible usage in different regions - easy to handle manner	Requires a good connection	utilizing Deep Learning and Transfer Learning in an IoT system
Schirrmeister et al. [33]	- Methods of visualizing the learned features were presented - Represents the process of ConvNets for decoding data related to tasks	- ConvNets suit end-to-end learning - Their scalability for huge datasets is satisfactory	- They may show false predictions - Need a huge body of data for training purposes	Architecture

patch array which is not stiff and can screen the skin temperature and check if the heart is well [45]. The mentioned patches [46] in the smart healthcare field of the system to monitor body with several access points benefiting from multimedia technology are working in the cloud to observe physical activities. The cloud computing technology (CCT) helps send the information which is elicited and processed by IoT devices via internet utilizing different deep learning, machine learning, and convolutional neural network which are used in the cloud environment [47].

Auspicious upshots of smart log patch with a Bayesian deep learning network; a platform designed for computation are precision, efficiency, mean residual error, delay, and use of energy. In the future, advanced multimedia methods should be suggested to reduce cost factors and privacy.

The purpose of designing wearable or devices for screening in smart healthcare is tracking calorie input and calorie output [48]. For creating a connection between the data which is taken from sensors, and analytics taken from the cloud, the IoT is used. The IoT is a body of tools where tools are identifiable in that body [49]. Smart-log can be considered an outcome that contains a smart sensor board, along with a smartphone application. A food weighing sensor is located on the sensor board. A wireless connection sends the weight of food or ingredient to the cloud using the Internet helped by a microcontroller which is placed inside a wireless module. Therefore, in an IoT network, the proposed system will be converted to a “thing”. Using a smartphone camera via smartphone application, the corresponding nutritional fact is obtained. The advantages of the implemented design are cost effectiveness and high accuracy in diet morning; while, it will be more favorable if smart-log integrates with a mechanism to screen the body to screen every activity of the user to predict the diet.

Kinnison et al. [50] asserted most of the sports events are at distant regions. If the process to diagnose the treatment time is delayed, this may cause unpleasant outcomes. Thus, current research focuses on applying IoT to the field of sports injury [51]. It is requisite to employ a handheld terminal to check if muscles are injured, assess and detect the gathered data through the ZigBee network, explicit data through gateway that screens the conditions, and ultimately show the outcome and send it through the LED screen, where the data is processed through mobile terminals, LED screens, and the voice links. The strengths of this survey are its superior performance in packet loss rate and accuracy. There are still some limitations in this article, such as the small size of the system’s experiment on feedback population.

4.2.1. Analysis of the reviewed home-based and personal healthcare applications

Table 3 describes the above papers’ classification and their significant features to assess home-based and personal healthcare applications. Case studies done based on this approach include multimorbidity chronic patients, personal health assistance, smart dental Health-IoT system, patient monitoring system, fall detection, multi-access physical monitoring system, nutrition monitoring, and sports injury.

4.3. Disease prediction applications

Using sensors that indicate heart rate graded by users in a medical circumstance suggests various challenges: 1. Sensors themselves are

Table 3
A Classification of newly conducted researches in home-based and personal healthcare applications.

Research	Main context	Case study	Advantage	Weakness	New finding
Fonseca et al. [34]	Make smart living conditions for home-based healthcare in the multimorbidity chronic patients	Multimorbidity chronic patients	- A new wave of caregiving amenities - Controlling costs	- There are no statistics to prove the effectiveness	- Algorithm - Framework
Sandstrom et al. [35]	Build a connection between smartphone sensor data and individuals' health through a deep learning method	Personal health assistance	- Simple structure - Low computation load - High performance	More genres of sensor data should be researched.	- Architecture - Framework
Liu et al. [36]	Smart dental Health-IoT system founded on smart hardware, deep learning, and mobile terminal	Smart dental Health-IoT system	– 5.5 mm wide and 4 mm thick for the betterment of adults and children's mouth - its coverage ranges from 1 cm to 6.5 cm and may change the light to fit the ambiance. - the cheap cost of hardware	Incomplete coverage of larger teeth	- Prototype - Implementation
Sagar et al. [37]	A DNN proposed to find qualities of the signal in the sensor array to understand the body conditions of the patients	Patient monitoring system	- High accuracy - Low cost	Require a large amount of data	- Algorithm - Architecture
Klenk et al. [43]	classical (Support Vector Machine and Naive Bayes) and non-classical (Deep Learning) algorithms to make models to detect fall	Fall detection	Learn formats that can help in generalization	The DL model is not very flawless on ADLs	- Algorithm - Architecture
Malasinghe et al. [44]	Smart patches or chips that can monitor human health conditions employing IoT sensors	The multi-access physical monitoring system	- Auspicious upshots based on: - Precision - Efficiency - Mean residual error -Delay - Using Energy	Advanced multimedia methods should be suggested cutting expenses and privacy	A novel optimized neural network
Wei et al. [48]	A new system to screen nutrition which is totally automatic (Smart-Log)	Nutrition monitoring	- Cost-efficient - high accuracy	Another method should be suggested for more accurate diet prediction	Algorithm
Kinnison et al. [50]	using IoT in the area of sports injuries	Sports injury	Working better in packet loss rate and accuracy	- small size of system experiment feedback population	Framework

sources of errors 2. In order to preserve battery life, they vary the rate of measurement 3. As wearable are applied in an ambulatory setting, daily activities may confuse simple heuristics. A semi-supervised sequence learning in the experiment was deployed. At first, DeepHeart, as a sequence auto encoder, has pertained to use the encoder weights as the start point of a second, supervised phase. This attitude yields an important enhancement of high cholesterol, high blood pressure, and sleep apnea. Some deficiencies of this study are the problem of using and the need for interpretability [52].

Epilepsy can be controlled through a brain-computer interface (BCI) to predict seizure. Three principal phases constitute an automatic BCI system, including gathering and processing data using a computer, and electronic devices to implement the necessary action. The EEG illustrates the brain's spontaneous electrical activity recorded utilizing several electrodes available all over the scalp [53,54]. Techniques for signal processing, machine learning, and electrographic brain-state prediction in huge datasets collected from users in real-time are needed for a practical BCI system. In order to do calculations in real-time for incoming data, computations made through cloud provides an easy way to avail databases and sources to make computation with, via the Internet. The suggested BCI centers' key merit is learning made possible from huge data which is not supervised, making it a productive way to build a real-time patient-based seizure prediction and localization system.

4.3.1. *Analysis of the reviewed disease prediction applications*

Table 4 depicts the categories of the above papers and their main features to assess disease prediction applications. The main contexts in the disease prediction approach comprise a supervised learning process and is used for predicting cardiovascular risk, a deep learning model, including LSTM neural network for predicting air quality in smart cities, and Seizure prediction BCI.

4.4. *Human behavior recognition applications*

Human activity recognition (HAR) is a vital concept in both theory and practice. It may be applied in many fields, such as health monitoring [55,56], smart homes [57,58], and human-computer interactions [59,60]. Zhao et al. [61] proposed a novel deep residual bidirectional long short-term memory LSTM (Res-Bidir-LSTM) network to address HAR problems. Although precision requires plenty of time to take place, it represents high precision in the beginning stages of training. When sensor fusion is needed, this technique can be deployed in complex, large-scale HAR problems. The HAR's input should include time series,

Table 4
Classification of recent studies in disease prediction applications.

Research	Main context	Advantage	Weakness	New finding
Ballinger et al. [52]	Deployed a learning process which is somehow supervised and is used for predicting cardiovascular risk	- Significant enhancement on: - High cholesterol - High blood pressure - Sleep apnea	- Difficulty of deployment - The necessity of interpretability	Architecture
He et al. [53]	Seizure prediction BCI	- learning made possible from huge data which is not supervised - Productive method for real-time patient-based seizure prediction and localization system	- Trap at local minima - Lower performance - High computational time	- Platform - Algorithm - Framework

and preserving characteristics based on the temporal features is yielded through the fundamental structure of LSTM. The beneficial point of this method is preventing the gradient vanishing problem effectively. However, the suggested deep LSTM neural network is limited on the number of available data points.

Chang et al. [62] offered a smart system to recognize medication based on deep learning methods, called ST-Med-Box, which may aid patients with chronic diseases take various medicine precisely and make sure they take the medication. The steps patients should take in this method are straightforward. In the beginning, they should download the offered application for Android and scan QR codes on their drug packages to store the related medication information. Afterwards, they can have reminders to take their medicine. The issues including medicines counter effect are mitigated by utilizing this method. Some strengths of this survey are: they can record the entire process, recognize with high accuracy, and operate easily: whereas, there is still room for improvement in the recognition accuracy of this system in future work.

4.4.1. Analysis of the reviewed human behavior recognition applications

Table 5 illustrates the categories of the mentioned research papers and their crucial features to assess human behavior recognition applications. Researchers conducted in human behavior recognition approach include human activity recognition using wearable sensors and chronic patients.

5. Discussion and comparison

Deep learning applications for IoT in healthcare were elaborated in the preceding sections. In this part, statistical assessment of indicated deep learning applications for IoT in the healthcare domain is suggested. Moreover, a few write ups for analysis purposes concerning the mentioned research questions in section 3 are as follows:

RQ1: Which categories are classified in deep learning applications for IoT in healthcare?

Fig. 5 illustrates the percentage of varied deep learning applications for IoT in healthcare based on the suggested taxonomy in section 4. Four deep learning application fields for IoT in healthcare are considered, including medical diagnosis and differentiation applications, home-based and personal healthcare applications, disease prediction applications, and human behavior recognition applications. The highest percentage of the application domains belongs to medical diagnosis by 52% usage. As for personal healthcare, 30% of applications are related to this sector. Furthermore, disease prediction and human behavior recognition possess the least amount of application accounting for 11% and 7%, respectively.

RQ2: Which major contexts are taken into account in deep learning applications for IoT in healthcare?

The leading contexts of deep learning applications for IoT in the healthcare zone are represented in Fig. 6. CNN approaches have the most deployment with 11 types of research, followed by DNN methods utilized in 8 studies. The automatic process of detecting significant

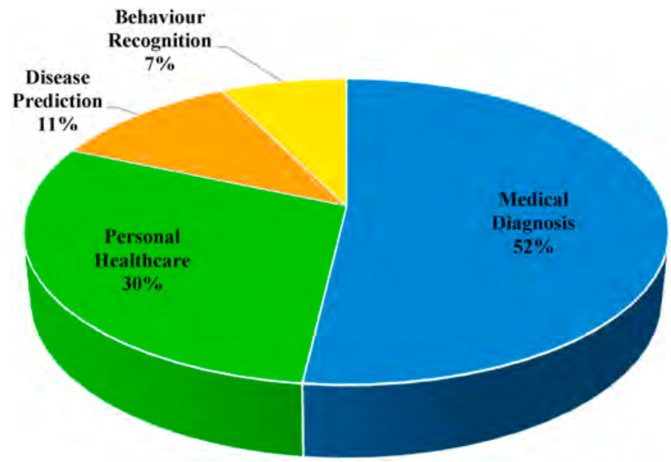

Fig. 5. Percentage of presented deep learning applications for IoT in healthcare.

features through pre-processing done by CNN has attracted the researchers. Their implications are growing rapidly. CNN based methods are in most cases faster and more efficient than other methods.

RQ3: What appraisal environments are inspected in deep learning applications for IoT in the healthcare domain?

As shown in Fig. 7, the most utilized evaluation environment is the dataset, which consists of 62% of research studies. Moreover, we noticed that a quarter of this pie chart is related to implementing the suggested approach to develop deep learning applications for IoT in healthcare. Eventually, it is worth mentioning that 13% of the surveys deployed simulation equipment to assess the presented case studies in the deep learning platform applied for IoT in the healthcare area.

6. Conclusion

This paper elaborated on several technical methods in order to boost IoT in the healthcare area through deep learning applications. This paper intends to find out various aspects of deep learning-based IoT healthcare technologies and proposed different healthcare frameworks, architecture, platform, and algorithms to the deep learning foundation and facilitate medical treatments. Furthermore, this paper presents comprehensive research activities about how deep learning can address tele-health and ambient assisted living systems, machine health monitoring systems, human activity recognition, collecting vital signs of patients, and data fusion. For more profound perceptions into the healthcare domain, the survey organizes deep learning applications for IoT in healthcare into four categories: medical diagnosis and differentiation applications, home-based and personal healthcare applications, disease prediction applications, and human behavior recognition applications. In this survey, we intended to scrutinize deep learning for IoT applications in healthcare based on a Systematic Literature Review. We reviewed more than 50 published research papers written in a decade from 2010 to 2020. In order to understand deep learning applications in

Table 5
Aclassification of newly conducted researches in human behavior recognition applications.

Research	Main context	Case study	Advantage	Weakness	New finding
Zhao et al. [61]	A novel Res-Bidir-LSTM network to address HAR problems	Human activity recognition using wearable sensors	Avoids the gradient vanishing problem	Limitation in numbers of data points that can be accessed	-Architecture -Framework
Chang et al. [62]	A smart system to recognize medication based on deep learning methods (ST-Med-Box)	Chronic patients	- Perfect recording - High-precision Recognition - Simple operation	The recognition accuracy should be improved	-Platform -Prototype

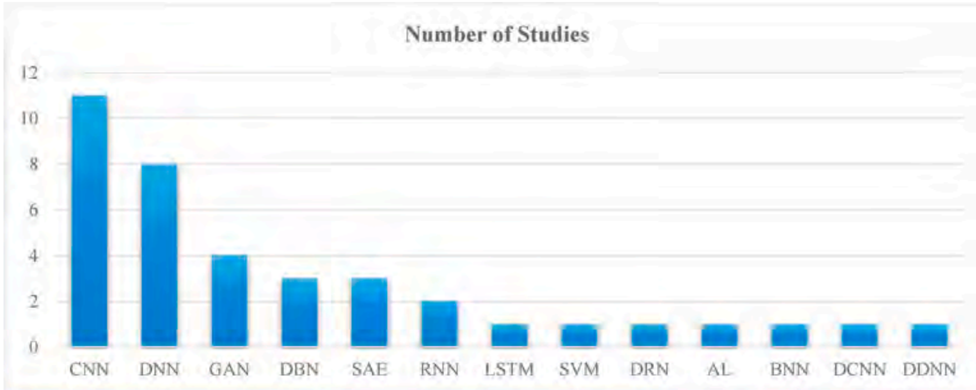

Fig. 6. The number of studies related to the main context of deep learning applications for IoT in healthcare.

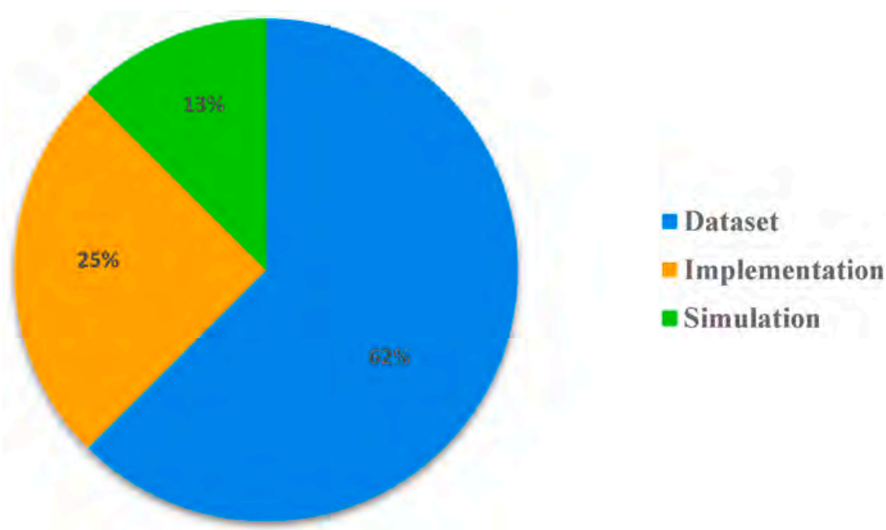

Fig. 7. Percentage of the suggested evaluation environments in the investigated studies.

the healthcare zone better, this study considers varying challenges and alleviates them in different aspects such as feature extraction, recognition, cost, latency, computation load, etc. However, there are still some potentials for optimizing QoS parameters, privacy, and deployment, which can be addressed in future works. Overall, this paper's results are anticipated to be practical for scholars, engineers, healthcare professionals, and policymakers who work in the field of IoT in healthcare.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Abbreviations

IoT	Internet of Things
EHR	Electronic Health Record
SLR	Systematic Literature Review
AI	Artificial Intelligence
MIoT	Medical Internet of Things
MHMS	Machine Health Monitoring System
IoHT	Internet of Health Things
QoS	Quality of Services
CVA	Cerebral Vascular Accident
CT	Computed Tomography
MRI	Magnetic Resonance Imaging
CNN	Convolutional Neural Network
DNN	Deep Neural Network
DBN	Deep Belief Network
BNN	Bayesian Belief Networks
DCNN	Deep Convolutional Neural Networks
DDNN	Deep Deconvolutional Neural Networks
GAN	Generative Adversarial Network
LSTM	Long Short Term Memory
HR	Heart Rate
AF	Atrial Fibrillation
AFDB	Atrial Fibrillation Database
API	Application Programming Interface
SAE	Stacked Auto Encoder
GPU	Graphics Processing Unit
BSN	Body Sensor Network
SVM	Support Vector Machine
ADL	Activities of Daily Living
AQI	Air Quality Index
BCI	Brain-Computer Interface
EEG	Electroencephalogram

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