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Deep Learning in IoT systems: A Review

Shavan Askar, Chnar Mustafa Mohammed, Shahab Wahhab Kareem

Abstract

The expansion of the internet, along with its interconnection of devices has made it possible to increase the world's interconnectedness in these days, with the growth in internet connectivity capabilities and quality, a lot of items are interconnected, which means they communicate with each other using new and powerful techniques. Innovative sensor systems are spreading their consumers are strongly connected to the internet. The growth of linked sensors and systems has an incremental impact on the quantity of data. Regardless of its purpose, it is accumulating whole data. The Internet of Things (IoT) has a practical use for industries such as obtaining field data, tracking it and keeping them, all connected. To imitate the human intelligence level, the machine or software is made smarter by using advanced deep learning. In the paper, several diverse types of IoT technologies will be referenced, including intelligent cities, smart health care, mobility networks, and educational systems, among others. In addition, a range of novel deep learning algorithms that were implemented to simplify the intelligent usage of the machines without involving human control has been reviewed and good results of each algorithm in different categories are demonstrated as a table of comparison. This paper gives an overview of the applications that need to combine deep learning to serve IoT applications in an efficient and automated manner.

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About Author (s)

Shavan Askar (Corresponding Author), Assistant Professor, CEO of Arcella Telecom, College of Engineering, Erbil Polytechnic University, Erbil, Iraq.
Email: shavan.askar@epu.edu.iq

Chnar Mustaf Mohammed, Information System Engineering, Erbil Polytechnic University, Erbil, Iraq.

Shahab Wahhab Kareem, Lecturer, Erbil Polytechnic University, Erbil, Iraq.

1. Introduction

The IoT is a system of artifacts, that are mostly devices but also include any kind of machine, instrument, car, or building that have built-in electronics, sensors and network connections and allow these to capture and share data (Shafique et al., 2020). It enables things to be detected and monitored remotely, increasing clear penetration of the real environment with digital devices, through increased reliability and precision (Mohammed and Askar, 2021; Qadir & Askar, 2021). With the emergence of IoT, existing concepts and technologies are being modernized, including massive data mining and machine intelligence (Tiwari et al., 2019). The Internet of Things connects billions of integrated systems to specific consumers' identities to handle daily lives with very little human intervention (Al-Garadi et al., 2020). IoT can carry out actions without the involvement of humans. More use cases of the Internet of Things have been implemented in the healthcare, transportations and industrial sectors, but they are only at the initial stages of growth (Ahmed & Askar, 2021; Mohammed & Askar, 2021).

Though several innovations have occurred most of these inventions are still in the initial stages, the fields of connecting the Internet to all things, the IoTs are rapidly emerging many facets of its creation that must be considered before they can begin, including architecture, connectivity, platform specifications and policies (Ahmed and Askar, 2021, Thakkar and Lohiya, 2020). When IoT apps on smart devices use complex and large datasets that need more sophisticated models, customized and effective approaches to deal with such aspects, deep models can be developed and can be effective in use (Ma et al., 2019). Innovative algorithms, such as deep learning, have shown tremendous promise in understanding and simplifying massive, complicated datasets, making them better analytical and transformational for humans (Hatcher and Yu, 2018, Zantalis et al., 2019). Deep learning's potential to capture high-level, dynamic data structures and unsupervised information from massive data sets allows it an appealing big data analytics resource. Semantic indexing, labeling, accelerated knowledge processing and deep learning all have important solutions to Big Data issues (Najafabadi et al., 2015). Deep learning approaches have shown positive results in various areas, including perception and recognition tasks for devices. Likewise, IoT is increasingly growing in terms of deep learning methods (Mohammadi et al., 2018; (Ali & Askar, 2021; Hamad & Askar, 2021).

This paper presents how DL could be combined with IoT systems and what would be its outcomes in various fields such as healthcare, smart cities, education, and intelligent recognition systems in different gestures. The article is ordered as follows: 2.1 Background Theory and Concepts of IoTs. 2.2 IoT Applications. 2.3 Challenges. 2.4 Incorporating deep learning algorithms in IoT including several units (2.4.1. DL common methods, 2.4.2 DL Benefits and 2.4.3. DL applications and Platforms). Section 3 is the use cases of using deep learning with IoT. Section 4 Discussing and Comparisons, and lastly in section 5 is the conclusion of the work. Fig.1. Provides standard architecture for IoT in concern to how things, insights with actions are working and their shows the interconnections.

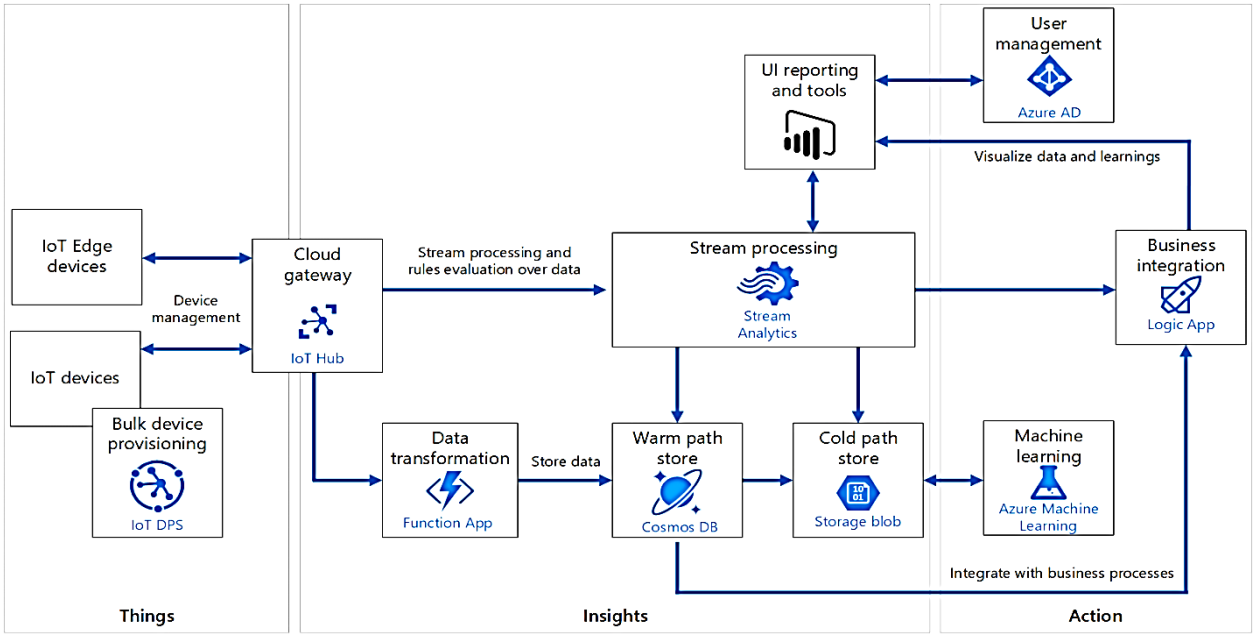

Figure 1. IoT Architecture System (Al-Garadi et al., 2020).

2. Background Theory

2.1 Overview and Concept of IoT systems

Today, more and more items are related to the internet to integrate the perceptions of the IoT in a variety of fields such as intelligent buildings, public transport, medical facilities, industry, agriculture, etc. The IoT model converts entities in these domains from conventional to intelligent to provide consumers with IoT-system features and attributes to take account of environmental adjustments, certain structures must be modified during operations (Husain & Askar; Samann & Askar, 2021; Husain & Askar, 2021). IoT refers to all the objects that are linked and continuously associate such as an electronic device comprises sensors, actuators and a microprocessor-embedded module. Since things have to be in touch, requiring Machine-to-Machine (M2M) communication for short-range wireless technology such as WiFi, Bluetooth, and ZigBee, the contact range is either limited or broad, concerning the air and mobile networks for long-distance including WiMAX, LoRa, Sigfox, CAT M1, NB-IoT, GPRS, and GSM, and LTE (Zantalis et al., 2019). The Internet of Things is intended to offer items digital identities such that they can connect and share knowledge and access different resources. The notion of digital identity of a wide number of devices contributes to the advancement of modern Radio Frequency Identification technologies (RFID). Due to being resource-limited, these networks were set up as low-powered machines, which motivated resource-constrained Wireless Sensor Networks (WSNs) (Ali and Askar, 2021, Hamad and Askar, 2021). An illustration of an IoT-enabled environment is a highly interconnected device that can be reconfigured when required. The usage of IoT has been employed to maintain patient rehabilitation by following specific criteria, as well as to monitor the parameters that pertain to the patient. Additionally, the results obtained can be applied to studies comparing patient exposures to diverse care contexts on a global scale (Ali and Askar, 2021).

As seen in Fig.2. The Internet of Things is capable of monitoring and controlling energy use, as well as being used for entertainment. In agriculture and food development. It is capable of measuring and managing variables such as weather, sociopolitical, climatic, agriculture, food, animal disease variables as the number of individuals with physical disorders and life- and long-limiting illnesses increases, there is an increased need for IoT facilities and products (Uviase and Kotonya, 2018).

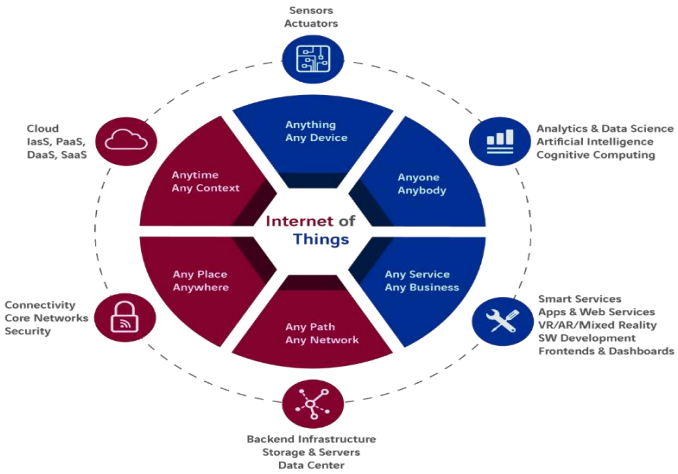

Figure 2. IoT Concepts (Zeinab and Elmustafa, 2017).

2.2 Applications of IoT

The internet of things offers many practical benefits for people, including making life simpler, plus ensuring safety and performance. It has several possible uses, including healthcare devices, city buildings, home applications, vehicle design, electricity distribution, and the smart world. With the advent of ultra-rapid and advanced technologies, there are a thousand applications in every aspect of existence (Rehman et al., 2017).

2.2.1 Health system:

New methods have been developed to increase the well-being of patients. Wounds can be tracked wirelessly to display details without any skin touch. Other sensors can record a variety of information including the heart rate, blood oxygenation, sugar levels, or temperature (Jeong et al., 2016).

2.2.2 Smart Home:

This community includes traditional home use, such as refrigerators, washing machines, and led lights, developed with access to the internet, to help track and control devices, and to optimize energy usage with each other or to registered users. Besides conventional electronics, modern innovations are also spreading, offering clever home helpers, sophisticated door locks, etc. (Rehman et al., 2017).

2.2.3 Smart Transportation:

As sensors built into cars or attached to the city devices can allow smarter route guidance, reserved parking, communications regarding traffic conditions, telematics, and accident avoidance, it is feasible to provide personal assistance, save money, and reduce carbon emissions (Kök et al., 2017).

2.2.4 Environmental Conditions Monitoring:

Any wireless sensor placed in the city will handle a broad range of conditions. Other types of barometers, as well as humidity sensors, allow for the production of advanced weather stations. Smart sensors are particularly useful at measuring air quality and water emission levels in the city because they can track pollution both at a distance and on the molecular level (Zantalis et al., 2019).

2.2.5 Logistics and Supply Chain Management:

Using RFID tags, the product's availability in the manufacturing and the store is greatly reduced, minimizing the total expense and time required. Additionally, intelligent packaging features such as product authentication, customer quality assurance, client relation, and customization are essential (Tiwari et al., 2019).

2.2.6 Security and Surveillance Systems:

High-capacity video cameras can take the input over long distances. Rapidly identifying objects using various sensor technologies is possible, allowing for intelligent protection systems to protect users from danger (Askar et al., 2011; Reddy et al., 2018).
Figure 6 shows the variety of IoT applications in multiple life zones.

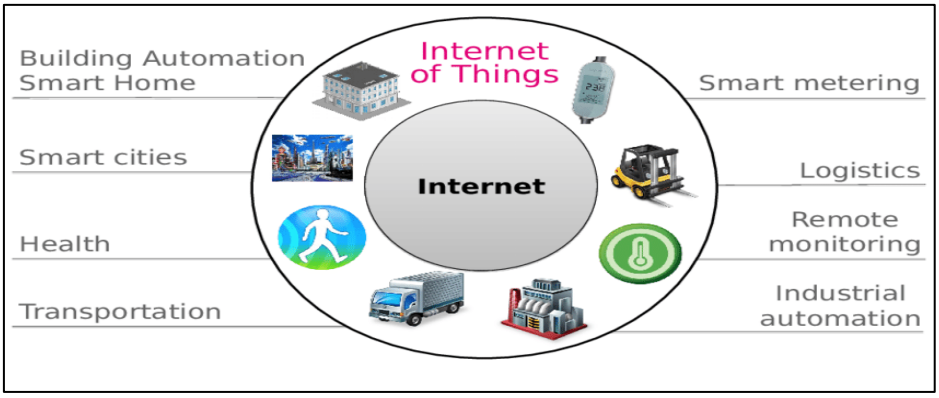

Figure 3. IoT applications (Jeong et al., 2016)

2.3 Challenges of IoT

Surely, all transitions offer not only advantages but difficulties that need to be resolved. These difficulties could be to resolve issues relating to protection, safety, etc. This segment summarizes the different potential problems in consideration of the IoT system identification (Firouzi et al., 2020). Other obstacle includes the limitation of the current network structure that are incapable to handle real-time sensitive applications using IoT, therefore Software Defined Networking is expected to be a suitable network infrastructure for such applications (Askar, 2017; Fizi & Askar, 2016; Askar, 2016; Keti & Askar, 2015; Qadir & Askar, 2021).
The most important issues facing IoT specified in Table 1 (Kumar and Mallick, 2018, Qiu et al., 2020):

Table 1. Challenges in IoT systems.

Challenges	Descriptions
Scale	Increasing the number of linked devices presents huge difficulties, and networking technologies including frameworks must adapt to handle that in this scenario, new technologies such as distributed IoT networks (such as P2P), and blockchain are beneficial (Abdulkahleq & Askar, 2021; Khalid & Askar, 2021; Kumar and Mallick, 2018, Qiu et al., 2020).
Heterogeneity	The truth of IoT is that it has an incredibly complex variety of various interfaces and protocols, which necessitates a standardized approach to encapsulate the inherent heterogeneity.
Privacy	When the information is required to remain anonymous, it must be kept hidden and safe.
Data ownership	Manufactured data were provided by machines to the person that owns the IoT machine.
Cybersecurity	It is important to overcome attackers who want to dominate, steal or mislead (Sulaiman & Askar, 2015; Fares & Askar, 2016).
Legal liability	If something goes incorrect with algorithms and decisions, who takes responsibility?
Sensors	The features that make for an effective sensor are lower cost, accuracy, and energy efficiency
Networks	Despite working in an atmosphere with several errors and threats, make the transfer both safe and reliable (capable of arriving on time, accurate and robust)
Big data	To handle a high volume of various types of data and with continuous connectivity and contributions to new sources, and allow resource- and cost-allocation.
Analysis	The information should be understood and evaluated with integrity and close attention to detail if artificial acts are involved, particularly if false results are allowed to happen.
Interoperability	This is an area of emerging competitiveness where all stakeholders must work together to act and secure investments, and this must take place in an equal and integral manner.

2.4 Deep Learning Algorithms in IoTs

DL is a method of algorithm used on a cascade of several layers, each with a non-linear transformation. Artificial intelligence involves using a multiplicity of algorithms, such as regression, classification, clustering, auto-encryption, and so on. in computation, the single basic logistical node is the sigma neuron (Ghosh and Grolinger, 2019). Deep learning has demonstrated a very high capacity for mapping massive, complicated datasets into informative and actionable intelligence, dramatically aiding the development of personalized systems (Hatcher and Yu, 2018). As shown in Fig.2. DL is classified into two categories: uncontrolled learning (models with unlabeled data) and controlled learning in compliance with traditional computer instruction (models trained with labeled data) (Ma et al., 2019). The Two unregulated learning structures are the Boltzmann Restricted Machines (BRMs) and Autoencoders. The supervised learning models are Neural Networks (CNNs) and (RNNs) (Ma et al., 2019).

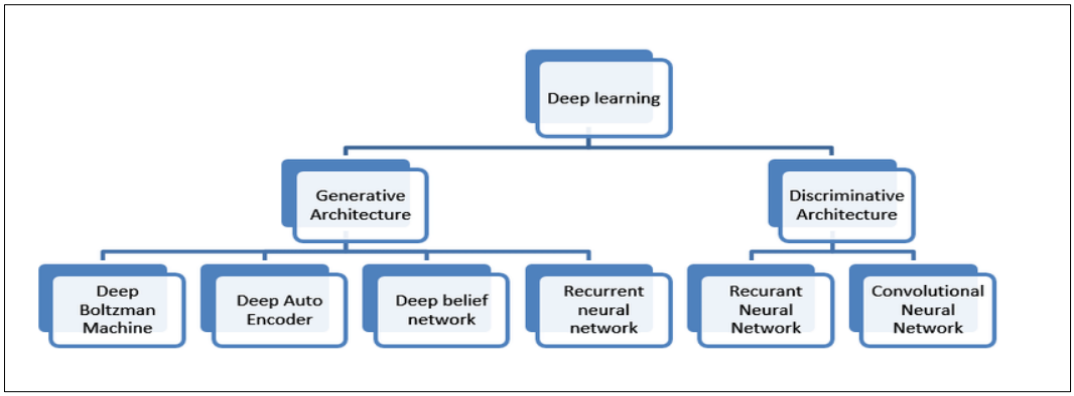

Figure 4. DL Algorithms (Srinivas et al., 2016).

2.4.1 Deep Learning Common Algorithms

1. Convolutional Neural Network (CNN): It is an Artificial Neural Network (ANN) deep feed-forward collection used for analyzing visual imaging (not recurrent). These networks consist of neurons with weights and perceptions that can be learned. Each neuron has those inputs, and then they carry out a dot product. A CNN embraces the two-dimensional entrance as a picture or a voice sign and creates features via a secret layer chain. The structure consists of the compressed and grouped layers for extraction and the two related layers serve as classification. In agricultural areas such as detection of cropping and plant leaf diseases, field covers, plant identification, weed identification, and fruit count, CNN may also be implemented (Thompson and Talley, 2019).

2. Recurrent Neural Networks (RNN): Are a neuron-like node network is made up of subsequent layers. In the following sequential sheet of each node, the soil cover designation, the estimate of crop production, the climate forecast, the calculation of soil humidity, animal science, in addition to others, are all linked with a single side-linking node in several agricultural regions. RNN is good at processing data from time series (Garg and Alam, 2020).

3. Generative Adversarial Networks (GAN): Are compose fundamentally of two contesting models of neural networks. These models may be used to inspect the training dataset, analyze it, and imitate it. GAN was sometimes used to improve databases. One of these two neural networks is generational and the second one is discriminatory, both function together to generate high-quality results. Both networks work together. GAN is yet another sorting of the ANN; it has been seen as very helpful in image processing (Tiwari et al., 2019).

4. Long- Short Term Memory (LSTM): This is the most effective method of various algorithms. This can handle individual data sources (for instance the picture) as well as entire data sequences (for example, voice or video) (Al Majeed et al, 2014). This can be classified and

predicted based on time series results. It is utilized for product classification, crop yield prediction, and weather forecast in agricultural applications. LSTM often refers to the identification of handwriting, expression acknowledgment, and others (Kök et al., 2017). Fig.5. demonstrated the general unique process for working algorithms of DL.

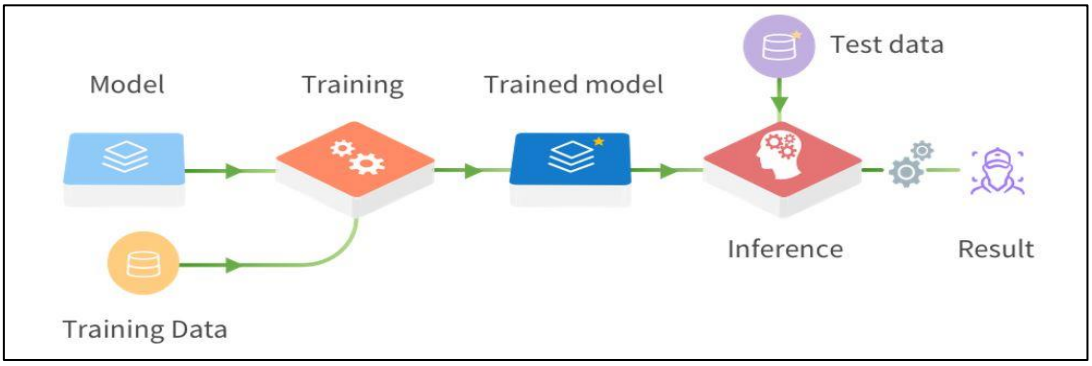

Figure 5. Typical DL process (Akhil et al., 2018).

2.4.2 Advantages of applying Deep learning in IoT systems

Utilizing the DL in IoT systems illustrates a few of the potential good results that can be accomplished by using DL algorithms when designing intelligent systems, particularly for this part of the IoT sector:

1. DL involves more deep neural network frameworks and can remove and characterize more complicated, unknown features (e.g., temporary and/or spatial boundaries). Except for those standard straightforward methods of research, deep learning can generalize the complex connection of huge raw data in different IoT applications (Ma et al., 2019).
2. Deep learning can allow optimal use of vast and priceless data tools. Usually, the capacity to process data is dependent on the depth and structure of experimental research, like coevolutionary architectures. DL models may be achieved using large databases, while simpler learning models can be easily assisted by a range of content (Venkataramani et al., 2016).
3. Data-driven learning is a type of end-to-end learning technique that robotically identifies important aspects of the data without the time-consuming and labor-intensive construction of certain functions (Venkataramani et al., 2016).

2.4.3 Deep Learning Applications and Platforms

Table 2.DL Apps. and Frameworks

DL Applications	
1	Recognize and classify images and videos.
2	Audio post-production.
3	Analyze document.
4	Speech Recognition Handling.
5	Engineering and Autonomous Systems.
6	Medication assessment.
7	Bioinformatics and Biochemical Engineering.
8	Physical Sciences
9	Banking, Economics, and Market Analysis.
Platforms	
1	TensorFlow.
2	Microsoft Cognitive Toolkit (CNTK).
3	Caffe and Caffe2.
4	MXNet.
5	Keras.
6	Deep Learning for Java (DL4J).
7	Theano, and Torch.

Deep learning algorithms derive abstract concepts by progressively, gaining information at higher levels via hierarchical learning. Having understood basic concepts at an earlier stage, each stage, complicated ones at the next then only analyzed at a less detailed and generalized level that were derived from first (Rehman et al., 2017). Huge volumes of raw data have often translated into useful use in regulated processing, rendering DL a vital asset in unsupervised analysis, which gets a lot of raw data and extracts little insights (Venkataramani et al., 2016). Running such developed algorithms will have a positive impact on developing applications through frameworks to execute these methods. There are several examples of developed applications of DL in big data performed through various platforms as indicated in Table 2.

3. Deep Learning in IoT, Use Cases (Related Works)

The IoT is used in different areas of daily life, involving hospitals, smart cities, education, connected technology, and the surrounding world. In this section, additional details are reviewed from other prior researches in different fields by using DL algorithms in IoT systems and their impact for each category.

3.1 Health systems

Chiuchisan et al. (2014) presented the design of healthcare infrastructure for Intensive Care Units (ICU), using Kinect, along with several environmental sensors, which have new capabilities and methods that recently become available, utilizing the IoTs concept and a tracking approach such as video recording environmental data and varied sensor devices to examine individual health danger. The key goal of the scheme is to increase the number of individuals who are getting long-term support or surveillance and reduce obstacles, but only to the required number of people, and to eliminate unneeded expenses and cost savings measures.

In (Woo et al., 2018) study, two models are proposed. First, a stable IoT-based one Machine to Machine (oneM2M) framework for Personal Health Device (PHDs) is suggested. Access points (MN-CSEs) are used to connect PHDs to the PHD server. As the number of protocol steps rises, efficiency doesn't decline. This is something that is proven by the analysis, which concludes in the report because the device does not undergo significant deterioration from protocol conversion. Based on the experiments, the procedure conversion, it seems that the solution is stable and does not negatively impact results. Furthermore, they suggested a fault-tolerant algorithm for the method, in which the devices are bound in a chain by their location in the system, and the backup of the previous computer is stored directly ahead of the latter.Both data from the daisy-chained bus/daisy-wheeled modules are processed in the upper-layered gateway. This may happen concurrently: two different gateway failures can be detected and sorted out, which significantly expands the range of gateways that can be fixed. In tests, the resource trees of the oneM2M-based IoT framework, the tree of daisy-chained resources were added to keep track of backup copies, and system equality. In the tests, they found that the proposed algorithm could deal with faults in the gateways of the oneM2M IoT scheme. Harerimana et al. (2019) and Xiao et al. (2018) by conducting this analysis, the authors included explanations about how to obtain useful knowledge from Electronic Health Records (EHRs) using innovative methods, including deep learning. Dealt with the hard and expansive technical challenges in applying deep learning models to the fields of healthcare research by working with large healthcare data sets that include electronic records. There is still much to be done for other purposes with other systems of artificial intelligence, but deep learning has demonstrated enormous potential in hospital EHR data applications like billing and patient management. Although there have been a number of successes, this is still something that calls for expert medical supervision. Chhowa et al. (2019) suggested some analytical techniques to complement the IoT medical data using deep learning. The paper evaluated various DL

methods for large data handling, and their ideas for use of Internet of Things-based health tracking, applicability and efficiency. As the project progressed, they explored methods for health monitoring IoT tools that use deep learning to gain essential medical expertise for healthcare professionals in IoT design. The online-based health tracking method can provide a solution for those researchers to collect large datasets sustainably. Through doing this study, medical experts would also be allowed to meet the diverse health care needs of the majority of the population in the future. Chuma et al., (2020) proposed a novel Internet of Things, privacy-protected Doppler Radar-Based, consisting of Google Net, Alex Net, and VGG. With Google Net, the device had a drop-finding precision of 99,9%, Alex Net 94,29%, VGG-19 and CNN 91,43%. It was an optically focused device and obtained no details that could be used to classify specific people. This camera is superior to conventional cameras because it uses a radar sensor instead of a reflective detector that is unable to work in dark or bright conditions and is not only normal for regular ones. Furthermore, the proposed device is capable of monitoring other kinds of movement such as instances of COVID-19 and even has the capacity to identify symptoms such as COVID-19 through cough movement(Gadekallu et al., 2020). The Principal Component Analysis (PCA) approach, known as a "firefly deep neural network," was used in this study to categorize the diabetic retinopathy dataset. When they first collected the dataset, it has redundant and irrelevant attributes. The key purpose of the analysis was to explore the need for comprehensive pre-processing while establishing a three-stage pre-processing system. Standardization was used for the initial data set normalization, and PCA was then used to select the feature. In addition, the Firefly algorithm used the dimensionality reduction technique. The input data is used to feed into the Deep Neural Network (DNN), contributing to higher precision classifications. Interestingly, in terms of precision, specificity, recall, and sensitivity, these findings have been defended for model results. The additional benefit of the model is: almost any data collection in other fields will use this model. However, if a model has small proportions, it would override the data.

3.2 Smart Cities System Services

Kök et al. (2017) suggested a deep learning model to help cities combat emissions issues in the article on smart cities. They set the hyperparameters according to the experimental findings and later fine-tuned the network parameters to get the best results. After the model has been developed, it is trained and tested with the commonly accepted RMSE and MAE metrics. After that, the software is configured and the parameters are evaluated with the Precision, Recall, F1, and Accuracy scores are then evaluated to provide an estimate of the model's results. The findings support the notion that LSTM based models have higher accuracy and responsiveness than SVR-based models. Thus, the use of an LSTM dependent model on IoT data proves to be highly successful and very encouraging. Zhao et al. (2019) suggested a new and intelligent utility routing algorithm for multiple deliveries of the crowd, also known as Deep Reinforcement-Learning-based Smart (DRLS), to deal with the challenges of the smart city administration. Huge populations in smart cities could be handled by efficient facilities, as huge amounts of technologies may be needed for day-to-day operations, and efficiency is needed while large crowds are present. An alternative analysis procedure, using separate test results on output for well-connected service providers and testing all randomly selected aggregation locations, proved that DRLS is efficient in both cases. The experimental findings demonstrated that, relative to both the standard Open Shortest Path First (OSPF) and EOSPF, the DRLS technique outperformed both of them. Zhang et al. (2019b) suggested an advanced deep-learning-driven method for the short-aided-neural-based prediction that could go a long way toward predicting spatial and temporal heterogeneities between intersections. Using a layered convolution-based model, this method of predicting traffic variance through road networks, the extension then maximizes the return on additional road resources by extending the

network solution to several layers, such as both intersection and network segments. Neural levels are fused by a mixture of two nodes that are fully linked. To provide continuous, neural spatiotemporal tuning to the most important periodical traffic detail, the system utilizes Spatio-temporal mechanisms. Real-world test results were obtained in the city of Hangzhou, China, and the new strategy was tested. Experiments indicated that the approach could be scalable and confirmed that it provides realistic strategies for defining the efficiency and the congestion of signal patterns on signalized roadways. Zhang et al. (2019a) proposed a scheme to consider transportation approaches, making life more comfortable and simpler for individuals as well as a whole. It was suggested to use a Multi-Scale function learning with an autoencoder for deep modeling and visualization. This was the final classification achieved by integrating the features. The data collection system used a new ImageNet data structure called DenseNet, along with attention process and regularization to obtain the image classification network. This model accounted for spatial features while still building on long-upon-duration Moreover, the network structure is often reduced to a minimal. The DM-LS model has been validated on two real-world datasets. In test precision, recall, and f1-score, the model's findings illustrate the power of existing province models. If the mobility in the model could be better understood, the effects from the classifications could be significantly beneficial. An and Wu (2020) defined a new method of vehicular communications, known as the Big Data Assisted Communication scheme (BDAC) made and used vast amounts of data to make predictions. The core portion of the current strategy comprises two key elements. The first element, known as traffic density and velocity prediction, uses a large volume of traffic data to forecast traffic density and traffic velocity. The second aspect of the system is a data forwarding strategy based on the forecast outcomes. They followed the scheme and built upon it in a receiver-transmission mode and began to research a receiver-dependent broadcasting scheme that employs a multi-hop algorithm that allowed the use of prediction knowledge. When the broadcast algorithm used vehicle density to make a packet forwarding decision, it could obtain a large ratio of forwarding while keeping the packet load low. They run computer simulations to demonstrate the best output over multiple baseline receiver approaches.

3.3 Smart IoT System Recognition

Hatori and Kobayashi (2017) covered the experiment's work in gesture recognition that was in regards to its first stages of progress, which was begun with an experimental study of acceleration. For simplicity, they grouped four distinct motions into different classes: round, expansive, interjecting, indexing, spreading and intensifying smartphone motion sensors in addition to the compasses and tilt sensors to collect and report data on the position of the users to get features via Singular Value Decomposition (SVD). Through using the Vector Machine algorithms, recognition is created. One participant had an 82.5% identification score. What findings emerged from this experiment show is the influence of motion on vision. Next, they doubled the number of subjects to enable the device to be scalable across a wider range of users. The authors (Alanwar et al., 2017) identified and contrasted the recently established SeleCon IoT control methodologies. SeleCons has an easy-to-use, unremarkable menu-based interface to manage various smart devices using hand gestures. Any system needs to be UWB-enabled, but the consumer just needed to wear an inertial sensor and UWB transceiver. Both smartwatches and their physical prototypes were produced. SeleCon's numerous computer classifiers are used to reliably target the chosen devices from UWB measurements. SeleCon also supported 11 separate movements to monitor the chosen unit. Moreover, they suggested an energy-convertible method that uses low-power inertial instruments to wake up UWB about 92% of the time. SeleCon achieved 84% precision even with a high unit density. And the device had a precision of 97% for hand motion identification. (Jafari et al., 2018) this study used deep learning to develop physical authentication methods to authenticate Radio Frequency (RF)

applications. Channel estimation can be handled with a maximum number of RF expansion over a minimum SNR expansion technique for effective modeling of DNN, CNN, and a long-based LSTM as best practices for maximum throughput channel durability in the proposed models. As well as conventional ways of looking at traditional data are now dependent on large data and cutting-powerful machine learning techniques, the latest developments in wireless fingerprinting are useful for distinguishing between adversaries that might or approved RF devices that may be using similar technologies. Experiments conducted in an RF bed using real USRP and ZigBee devices have shown that deep learning models are effective for the sequence dataset of RF trace analysis. Jangamreddy et al. (2019) provided a web-based gesture and deep learning recognition to provide further input capabilities to IoT devices for user interaction. The controllers here used a variety of movements to monitor numerous IoT gadgets. Concerning the methodology, supervised learning includes two distinct phases: training and testing. During the training phase, different motions of the patient are used to aid the classifier in becoming accustomed to IoT operations. In the testing process, the motion is recognized by the web user interface and a request is sent from the web browser to the targeted IoT system. The architecture showed the various hardware can be linked together in a single Internet of Things (IoT) environment to perform tasks that are best served by disparate hardware. in (Gupta et al., 2019) paper, effective lessons, such as expressing your emotions and listening attentiveness in training, are modeled by Max-Margin Face Detection (MMFD) and M-Inception-3, which applied to the student's facial expressions. The approach was for differentiating the effect on all students based on the projections with the total school average participation results from this method yields a final enhanced perspective of the respective effect in the classroom. The findings of this classroom engagement review will be utilized to support the teachers develop their teaching or learning strategies. The suggested performance of the affective examination using the classroom data showed a precision of 99.56% for the face recognition and 87.65% for the state classification. Furthermore, it has been noted that the proposed effective states have a major effect as opposed to simple and learning feelings since the effect is found to be permanent in temporal dynamics. Pampattiwar et al. (2019) the study used CNN as a means of training models and received a successful outcome, culminating in a success rate of 66%. A visualization was created which depicts the affective data set relative to what system considered the data to be influencing the impact that was received by the effect of the systems. While attempted to extrapolate the expected sad or fearful data from the sample, several typical errors arose, such as coming up with "sad" instead of "fear" and arriving at "angry" instead of "disgust. several emotional reasons may be accepted to be the fact that led the majority of the population to assume that this was an ordinary type of energy. One may be easily deceived as to assume that a frown expressed on someone's face when they are upset means they hate someone or are frustrated with the other individual. The CNN learned to associate specific traits with such emotions such as the grin, the teeth, the eyebrows, and the expansion of the eyes with expanded possibilities.

4. Comparisons and Analysis of Algorithms

This section demonstrates the previous study of IoT systems that use a deep learning algorithm and categorizing them. As shown in Table 1 a summary provided regarding the used methodology, IoT applied fields, the aims and the effective results for each utilized algorithm in the reviewed prior studies.

Table 1. Comparison of the Previous Studies.

Author(s)	Objectives	Methodology/Algorithms	Applied Fields/ Systems	Significant Results
(Chiuchisan et al., 2014)	Tracking patients at risk in the Smart Intensive Care Unit (ICU)	Kinect sensors	Health system-ICU	The system notifies the physicians and staff on adjustments in important issues or on new patients that join or exit, allowing them to take precautionary steps.
(Woo et al., 2018)	Personal Healthcare IoT device with high reliability proposed for health systems using two models (one M2M and Fault Tolerance)	OneM2M & Fault Tolerance	Health system-Personal Health Devices (PHDs)	In the oneM2M system experiments, daisy-chained resources are used to hold copies of resources. The suggested algorithm is found to be capable of dealing with faults in the oneM2 IoT scheme's gateways.
(Harerimana et al., 2019, Xiao et al., 2018)	New approaches have been developed for electronic health records algorithms.	(CNN) & (RNNs)	Electronic Health Record	The informatics practitioners identify process and data requirements for carrying out each clinical task to achieve specific outcomes with blueprints.
(Chhowa et al., 2019)	As an analysis method for health screening, significant learning techniques are used.	ANN, CNN& DNN	Medical big data Applications	Results often help in identifying potential medical centers that serve the large numbers of individuals with a need of this and guarantee good quality of healthcare for all.
(Chuma et al.)2020	Radar tracker monitoring device for the elderly.	CNN	Novel fall-detection system-health	The proposed device is capable of monitoring other kinds of movement such as instances of COVID-19 through movements.
(Gadekallu et al., 2020)	Early diabetic retinopathy detecting using PCA-Firefly	(PCA)-Firefly & DNN	Detecting System-Diabetic Retinopathy	This model can be used on nearly any dataset in other areas.
(Kök et al., 2017)	To forecast potential pollution levels in an intelligent city	LSTM &RNN	Intelligent Air pollution system	The findings demonstrate that using an LSTM-based model on the IoT data results in success and satisfaction.
(Zhao et al., 2019)	A modern and intelligent route has been developed for multiple crowd generation	DRLS, OSPF & EOSPF	Smart Cities-Smart Routes	This solution can significantly improve the efficiency of the daily use of networks while also helping to avoid network congestion.
(Zhang et al., 2019b)	Estimated link-based traffic speed prediction through deep learning	RNN & The graph convolution network model (GCN)	Smart Cities-Traffic Speed Forecasting	Evaluations of the method show that it is flexible and useful for forecasting short-term traffic speeds
(Zhang et al., 2019a)	Deep multi-scale modeling of trajectories, and discoveries of moving objects	Deep Multi-Scale Learning Model& DNN	Transport Mode and Speed.	The classification findings obtained from the models will further assist in assessing mobility.
(An and Wu, 2020)	Large data traffic has enabled V2X smart transportation connectivity	Temporal Convolutional Network (TCN)& BDAC	Smart Transportation V2X	The model can achieve a strong load to throughput ratio. they perform computer models to help work out the most effective solutions

(Hatori and Kobayashi, 2017)	Body movement recognition	SVM & Singular Value Decomposition (SVD)	Gestures Recognition	The result of this experiment was that motion has an impact on visual perception
(Alanwar et al., 2017)	Propose a pointer approach to system interaction	SVM& ultra-wideband (UWB)	SeleCon-Hand Gestures	Display that SeleCon can function even though the user's wrist is stable
(Jafari et al., 2018)	The DNN, CNN, and LSTM models are tested for wireless ZigBee interface suitability with the dataset	DNN, RNN& CNN	Radio Frequency Fingerprinting-ZigBee	Deep learning models were used to show that RF devices can be separated based on their data sets
(Jangamreddy et al., 2019)	IoT devices can allow communication with users through movements	MobileNet & K-nearest neighbors (KNN)	IoT web device recognition	demonstrated the various IoT devices may be managed using a common web interface
(Gupta et al., 2019)	A novel approach focused on the max-margin face recognition for facial expressions of students	Max-Margin Face Detection (MMFD)& a modified version of inception-v3	Facial Expression (mood) detector	The suggested grouping of states seems to have a major influence on state classifying the impact of temporal dynamics as well.
(Pampattiwar et al.) 2019	the study used CNN as a means of training models for detecting student mood	CNN	Facil Expression	The CNN learned to associate specific traits with such emotions such as the grin, the teeth, the eyebrows, and the expansion of the eyes with expanded possibilities.

5. Conclusion

Today, the Internet of Things model focuses on data which is obtained from heterogeneous sensors. combinatorial extraction and collection of this kind of IoT data are difficult. These abilities are essential to success: modeling and simulation require good models that accomplish these tasks quickly and precisely. Deep learning is a continuously growing technique that has been implemented with considerable success in a multiplicity of applications and domains. Although deep learning technologies are being implemented in full in industry, it is important to take measures to ensure the proper usage of deep learning, as a subversion of deep learning trends can in severe cases lead to a serious loss of currency value, confidence, and even of existence. This paper presents different use cases for using deep learning algorithms in IoT systems in fields of smart Health, industry, environment, buildings, and transportation, smart systems in recognition gestures, etc. Then the challenges demonstrated in IoT devices as well as an overview on Deep Learning algorithms and their benefit on IoT discussed applications and platforms that are used through deep learning mentioned. In conclusion, utilizing DL algorithms in IoT smart systems make daily works and life easier also reduces human intervention, the smart devices support people in various areas of life to implement all tasks autonomously and more accurately as well as recording a large amount of data another positive point in this approach by using DL algorithms.

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