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Iot Technologies and Deep Learning to Support the Smart Building Development: Review, Opportunities, and Challenges

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ABSTRACT
The Internet of Things (IoT) and artificial intelligence offer everyone new types of services to improve daily life in our buildings. The integration of these two technologies allows for the improvement of old services and the innovation of new systems. Smart buildings rely on the use of smart sensors and IoT systems to retrieve many data (temperature, humidity, presence or not of people in a given space...). This data must be analyzed to obtain valuable information that contributes to improving the quality of life of users. Deep Learning (DL), a subfield of artificial intelligence (AI), based on mathematical approaches, recently demonstrated its ability to model data and increase the efficiency and performance of IoT big data analysis. In this paper, we present a literature review of smart building development using IoT and DL. We start with define the IoT and liste the characteristics of big data from IoT. We then introduce the key computing technologies needed to analyzeIoT big data, including cloud, and edge computing. We then examine common DL models and review recent studies that leverage both IoT and DL to develop smart solutions and tools for smart buildings. Finally, we describe current issues and problems encountered when deploying services for smart buildings.

Keywords: Internet of Think, Smart building, Deep Learning, Artificial Intelligence.

1 INTRODUCTION

Rapid population growth around the world is leading to new challenges in the daily lives of citizens (United Nation, 2020), including energy consumption, space management, safety and comfort of occupants, etc. Recently, new technologies have been proposed to manage this rapid growth by developing smarter cities. Smart cities are conceived as a complex and layered interconnection of various systems to make the urban environment smarter. Smart cities offer smart home, industry 4.0, smart healthcare, intelligent transportation, smart environment, among others (L .U. Khan, 2020) (D. Wu, 2020), (S. Musa, 2018). In this scenario, smart buildings are essential components of smart cities.

Intelligent buildings are buildings in the tertiary sector or residential buildings for which high-tech tools and a sophisticated control system make it possible to adapt the settings according to the needs of the occupants.

Different types of buildings have recently acquired the ability to use smart technologies and actions. These types include (Figure 1):

Smart home: housing composed of sophisticated equipment connected to the Internet. These smart devices, including curtains, lights, and doors, communicate with each other and broadcast information to users. The implementation of smart homes aims to optimize the management of appliances and improve energy consumption (D. Marikyan, 2019).

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Smart schools: In smart buildings, there is a strong trend for information technology to be used extensively in the teaching and learning process. Smart schools will bring students and teachers closer together through connected devices that can lead to more relevant interactions and also enhance or extend training programs.

Today's teachers have a variety of technology tools at their disposal. From smartboards to tablets, teaching tools to digital textbooks, educators have access to multiple tools to teach their students. However, the IoT allows all of these resources to be connected to better track students' abilities and develop new teaching methods.

A "smart hospital" is a new concept born out of the accelerated digitization of healthcare sectors through the implementation of key technologies, including the Internet of Things (IoT), data analytics and artificial intelligence (AI). IoT is an ever-evolving technology that features the use of distributed computing and the ability to modify data to make rapid choices for system requirements within a massive distributed network. This technology connects everyday objects (smartphone, smart watch, smart lamp, etc.) such as sensors, actuators and things to the internet via already existing networks with the aim of simplifying diagnosis and treatment of patients while improving the performance of medical services.

For example, in the COVID-19 pandemic, the Internet of Things, robots, and smart technologies are helping healthcare personnel to limit the spread of the virus (S.Senhaji, 2021).

Smart office: The current trend is to make offices and workplaces smarter. Smart office technology provides a range of benefits at the institutional and individual level. It offers institutions the opportunity to minimize their energy expenditures, and thus costs, as well as reduce their environmental footprint and support positive climate action. At the individual level, this technology allows employees to adjust their workspaces in terms of temperature and lighting, which can make them more independent and productive.

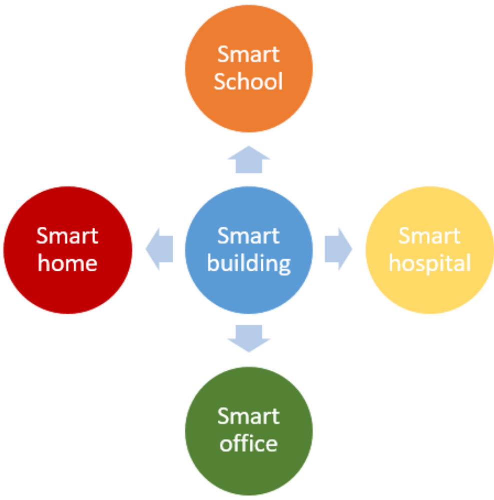

Figure 1: Smart building use cases considered in this research.

In recent years, with significant advances in computing and communication technologies, which constitute new great leaps in the digital world, the terms called "Internet of Things" (IoT) and artificial intelligence have gained strong acceptance.

Artificial intelligence (AI) (R. Mitchell, 2013) and the Internet of Things (IoT) [9, 7] seem to be charting the future of the world, a world of connected, intelligent objects that require little human intervention. The integration of these advanced technologies into buildings has given rise to the concept of smart buildings, which indicates the ability to understand the environment and react

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accordingly. Subsequently, AI and machine learning (such as the deep reinforcement learning algorithm adopted in this article) have the potential to enhance user comfort and energy consumption in buildings, and thus the quality of life of individuals.

AI is the skill of computers to perform tasks that traditionally require human intelligence, including image recognition, speech-to-text translation, and migration between languages. . The performance of AI has increased greatly in recent years and ML, a subset of AI, provides computer programs with the ability to learn and optimize their behaviors by training them with a given set of knowledge. The trained program then acquires the ability to make decisions without being explicitly programmed.

IoT is the combination and interconnection of millions or even billions of various objects over the Internet to build an intelligent environment (A. Whitmore, 2015) Based on standardized communication protocols, these devices share and exchange information across heterogeneous platforms. As a result, IoT improves the interactivity and efficiency of critical infrastructures such as those used in the safety, education, and healthcare sectors.

In this research, we choose the smart building as an IoT application domain. This is because smart buildings involve a large number of IoT use cases.

The remainder of this paper is organized as follows. In Section 2IoT application for smart buildings , in section 3, a review on deep learning for future smart building, section 4 applications of deep learning in the smart Building, and we ended with conclusion.

2 IOT APPLICATIONS FOR SMART BUILDINGS

IoT is part of the interconnection and connections between billions of different types of objects on the internet to build a smart space (Gubbi.al, 2013).

Based on standardized communication prototypes, these devices can share and send information across heterogeneous platforms. Subsequently, IoT increases the responsiveness and productivity of critical infrastructures such as those used in security, education, and healthcare.

IoT collects data in different forms and from different sources; for this reason, it is referred to as heterogeneous data [R. Mital, 2014]. IoT can collect data from healthcare, smart building, smart traffic management, automotive systems, agricultural sensors, and many other activities, as shown in Figure 2

Figure 2: Data sources for IoT

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2.1 IoT architecture

The IoT structure consists of four levels: Automatic system (hardware), control and data acquisition system, data Mining platform, and IoT applications. This architecture is summarized in Figure 3. For example, the hardware tier contains a variety of smart devices, particularly transducers and actuators that have the ability to sense and process signals. Transducers collect data from the environment, and actuators transform it into hardware actions. Information is collected in real time, which facilitates interconnection between devices and networks.

2.1.1 Automatic system

This level is composed of two intelligent devices, sensors and actuators that can generate and process signals. Sensor as an input device which provides an output (signal) with respect to a specific physical quantity (input), sensors collect data and information from the environment while actuators translate electrical signals into physical actions. Sensors collect data in real time, which allows the interconnection between physical devices and digital networks (S. Mukhopadhyay, 2015).

2.1.2 Control and data acquisition system

Connectivity and communication middleware.

In general, the data from the sensors is savedin the cloud.

Connectivity and communication middleware are responsible for the process of transmitting the collected data. These types of middleware act as a transport medium to move data from the hardware level to the storage and analysis tools. Some of the examples of middleware include WIFI, RFID, and Ethernet (Lincoln David, 2012).

2.1.3 Big data storage and analysis.

Data is currently becoming increasingly important and available in daily operations. With data also comes analysis, and in order to make more effective decisions, we need to think about various analytical solutions to identify what will help us get the most out of this information.

The data acquired by the IoT is stored and evaluated to extract useful information that can support decision-making (P.Gulia 2020). Data analysis is the process of converting raw data into relevant actions and information.

There are three main types of data analysis [25,26]:

Descriptive Analytics, predictive, and prescriptive.

Descriptive Analytics*: "What does our past look like and what does it tell us?",i*s typically used to evaluate historical data and attempt to extract the most important trends, occurrences, and areas for improvement. This allows them to discover not only what happened, but also the factor(s) that may have influenced, and how that may affect another measure in the future

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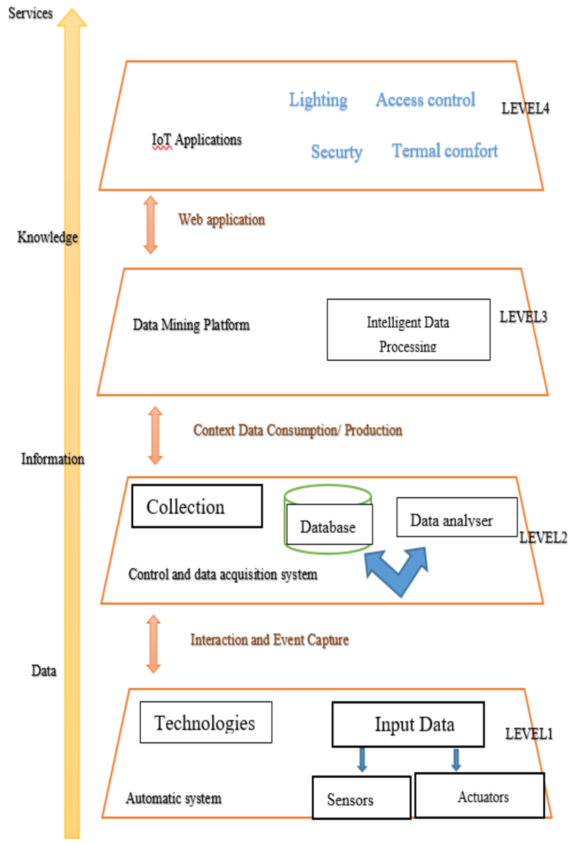

Figure 3: IoT architecture for smart building

Predictive Analytics: *"What is possible in the future and how can we think proactively?"*

The analysis in this step does what is directly stated in the name - it predicts. Using the information provided by descriptive analysis can lead us to effective predictive analysis to better understand the future. They take past trends and data distributions and use them to predict future outcomes so that they can in turn manage expectations, restructure strategies and set new goals.

Prescriptive Analytics: "*What is advised for us to do and what decisions should we make?"*.Prescriptive analysis goes beyond the historical knowledge of descriptive analysis and the possible future outcomes of predictive analysis to provide recommendations on next steps. With prescriptive analysis, we can evaluate and decide on a number of options based on the simulation results of various potential scenarios.

2.1.4 IoT applications.

The last level of IoT architecture is IoT applications.

IoT can be leveraged in a variety of applications in different fields of activity, including monitoring, healthcare, education, smart buildings and energy management. These applications make the environment capable of intelligent attitudes and actions in real time.

2.2 IoT big data characteristics

Many works have described the general properties of big data in various aspects (M.Hilbert,2016) with respect to volume, velocity and variety. However, we have adopted the general definition of big data to characterize IoT big data based on the following "6V" characteristics:

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- Volume: The volume of data is a key criterion for classifying a dataset as "big data" or as traditional massive/very large data. The mass of data produced using IoT devices is much larger than before and fits this characteristic perfectly.
- Velocity: The rate of IoT big data production and processing is so high that it supports the disposition of big data in real time. This justifies the need for advanced analytics tools and technologies to operate efficiently given this high rate of data production.
- Variety: Big data often manifests itself in many forms and types. It can refer to structured, semi-structured and unstructured data. unstructured data.
- Veracity: Veracity refers to the good quality, consistency and reliability of data, which leads to relevant and accurate information resulting in reliable analysis. This property requires special attention for IoT applications, especially those that use data.
- Variability: This quality appeals to the various data flow rates. Depending on the IoT application used, different components producing data are likely to have incompatible data streams. Indeed, it is also possible for the same data source to have different data loading rates depending on some specific. For example, a parking application that uses IoT sensors may experience a peak in data loading during peak hours.
- Value: Value is the conversion of big data into useful information that provides a competitive advantage to organizations. The quality of the data is based on the underlying processes/services and how the data is handled. For example, a certain application (e.g., medical monitoring of vital signs) may need to collect all sensor data, process it and update it. whereas a weather forecasting service may only need random samples of data from its sensorsThe rapid progression of Big Data with IoT has been encouraged by the creation of many software and hardware platforms. These platforms have been able to meet the expectations of users within a reasonable time frame. Different researches have reviewed the existing platforms on the horizontal and vertical site (D. Singh, 2015)Horizontal scaling platforms provide users with the power to boost the efficiency and performance of their programs in small increments. The most popular platforms are Apache Hadoop, 3 Spark4 and H2O5.Vertical scaling platforms, on the other hand, present the various components capable of adding power or complementary capabilities.For example, increasing computing capacity by installing more processors and faster memories. Graphics processing units (GPUs), and field-programmable gate arrays (FPGAs)

2.3 IT infrastructure for IoT big data analysis

Recently, predictive analytics for IoT big data have significantly improved performance and accuracy, especially using DL techniques.

However, these improvements have high computational and memory requirements, although these requirements can be addressed with more advanced specific computing platforms.

In addition to cloud computing, fog computing and edge computing are proposed.

2.3.1. Cloud computing

Cloud computing is a technology that provides wide access to information from anywhere at any time. It consists of different servers and data centers that are accessible over the Internet for a large number of users around the world.

Cloud computing is considered an attractive solution for analyzingIoT big data. Yet it may not be the best option for IoT data that is subject to security, policy, or time restrictions. Furthermore, high-level data abstraction for some analytical needs must be acquired by aggregating different IoT

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data sources; therefore, there is no need to develop analytical solutions on particular IoT nodes in these cases.

2.3.2. Fog computing

Fog computing refers to an infrastructure responsible for storing and processing data from connected objects. Whether it is a direct competitor, an alternative or an additional solution to cloud computing, fog computing has the particularity of managing data via equipment located at the edge of the network. It therefore allows both actions to be carried out locally, without having to call on a datacenter located several hundred kilometers away or on a cloud. In this area of data storage and processing and IoT, fog computing provides a complementary interface that can be found between Edge Computing and Cloud Computing.

2.3.3. Edge computing

Fog computing and edge computing are two quite similar infrastructures. Both are based on the processing of data produced by connected objects at the edge of the network. This proximity leads to a significant decrease in latency.

The difference between fog computing and edge computing lies in the computing devices involved: Edge refers to the processing terminals, while fog computing involves the computer architecture, according to the OpenFog Consortium.

3. A REVIEW ON DEEP LEARNING FOR FUTURE SMART BUILDING

Deep Learning, an advanced Machine Learning technique, has also attracted great interest in smart buildings in recent years.

Deep learning is a new type of artificial intelligence (R. Mitchell, 2013) stemming from machine learning where the machine is likely to learn by itself, unlike programming where it is limited to interpreting predetermined rules to the letter, it is based on an artificial neural network inspired by the human brain (B.Bostami, 2019) (S.Senhaji, 2020). This network is made up of dozens, even hundreds of "layers" of neurons, each one receiving and analyzing information from the layer before it. For example, the system will learn to distinguish letters before moving on to the words in a text, or to determine whether there is a face in a photo before knowing who it is.

It is classified into three categories:

supervised learning, unsupervised learning, semi-supervised learning and reintegration learning, as shown in Figure 4 and figure 5

Supervised learning is a machine learning task consisting in learning a prediction function from annotated examples, The two most common applications of supervised learning are classification and regression.

Unsupervised learning is part of machine learning where data is not labeled. Its goal is to detect the underlying structures of these unlabeleddata.unsupervised learning is used to find the hidden, interesting structure in data

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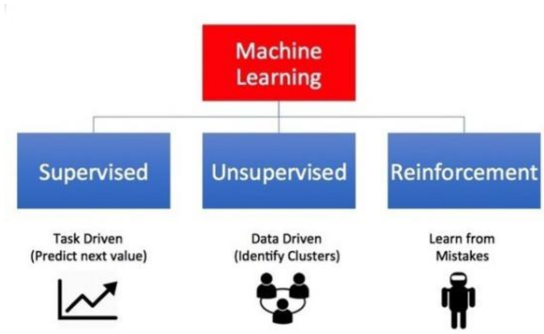

Figure. 4. Different types of learning techniques

Reinforcement learning problems involve learning what to do-how to match situations to actions-in order to maximize the numerical reward signal. In an essential way, they are closed-loop problems because the actions of the learning system influence its subsequent inputs (H.Hasselet, 2016).

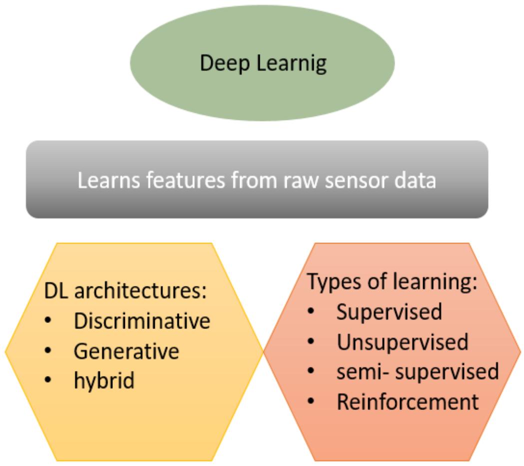

Figure. 5. Different types of learning techniques

3.1 Applications of deep learning in the smart Building

Adopting DL techniques to analyzeIoT data has had considerable results in several areas of the building (R. Rashid, 2019). This technology improves the quality of life of intelligent building inhabitants and shows excellent performance especially when working with massive data.

Many sectors of the building industry have recently been equipped with the ability to adopt smart strategies and technologies. These areas are summarized in Figure 6.

Figure. 6. Different types of smart Building applications

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3.2 Some examples of open source DL tools

Tensor-Flow: With TensorFlow, it's easier to create machine learning models for desktops, mobile devices, the web, or the cloud for both beginners and experts. With TensorFlow, one has access to a set of workflows to develop and train models in Python or JavaScript, be able to easily deploy these models in the cloud, in the browser or on devices, regardless of the language used.

TensorFlow is the second machine learning environment created by Google and used to develop, create and train deep learning models. We can use the TensorFlow library to perform numerical computations, these computations are performed with data flow graphs. In these graphs, the nodes are mathematical operations, while the edges correspond to the data, which are usually multidimensional data arrays or tensors, which are passed between these edges (V. Athira 2018).

One of the most powerful and easy-to-handle Python libraries for developing and evaluating deep learning models is Keras(K.Yan, 2019); it combines the powerful numerical computation libraries Theano and TensorFlow. The main advantage of Keras is that you can learn about neural networks in an easy and pleasant way.

4. IOT CHALLENGES FOR DEEP LEARNING, AND FUTURE DIRECTIONS

In this section, we review several challenges that are critical, from a machine learning perspective, to the implementation and deployment of IoT analytics.

Next, we indicate ongoing research on machine learning in the context of IoT analytics implementation and development. We then indicate research directions that can address the shortcomings of IoT analytics based on machine learning approaches.

4.1 Challenges

4.1.1 Secure and confidential deep learning:

Data security and privacy are a primary concern in many IoT applications, because IoT big data is carried over the Internet for analysis, and thus can be tracked anywhere in the world.

While anonymization is used in many applications, these techniques are susceptible to being hacked and re-identified as anonymous data.

4.1.2 Challenges of 6V's

Recent advances in DL for big data do not prevent important challenges to be met for this technology to mature.

The large volume of data presents a great challenge for DL, especially for temporal and structural complexity (X.-W. Chen, 2014).

The diversity of IoT data formats, which come from a variety of sources, poses the challenge of coordinating conflicts between different data formats.

By avoiding data source conflicts, DL has the ability to efficiently manage heterogeneous data.

However, more research is needed to increase LD with online learning andsequential learning techniques.

The veracity of IoT big data also poses challenges to DL analytics. IoT big data analysis cannot be useful if IoT big data analysis will not be useful if the input data is not from a reliable source. The validation and reliability of the data should be checked at (M. M. Najafabadi).

Varying IoT data rates pose challenges for online analytics. In the case of massive data flows, DL technologies handle this, especially those over the Internet. Data sampling techniques can be useful in these scenarios.

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5. DEEP LEARNING LIMITATIONS:

Although the results are convincing in various applications, DL models still possess some limitations. Nguyen et al (A. Nguyen, 2015) mentioned the false confidence of NMS for simulating non-human recognizable images. By producing misleading examples.

The other limitation is the focus of DL models on classification, whereas many IoT applications (electrical load prediction, temperature prediction) require some form of regression at the core of their analysis. A few works have attempted to enrich DNNs with regression capabilities.

Several researches have tried to enhance DNNs with regression capabilities, (X. Qiu,2014) which presents a set of DBNs and support vector regression (SVR) for regression tasks.

For regression-related tasks. However, further research is needed to clarify many points of regression with DNNs.

6 OUR PROPOSAL CONTRIBUTION

6.1 Data acquisition platform

Our main objective is to obtain correlations between certain emerging diseases prevalent in the building (temperature, humidity and air quality). To obtain indicators, we used cards based on microcontrollers equipped with sensors and fixed in several places of the building (M. Hamlich 1, 2012). The data is sent over the Internet to a web server (figure 7).

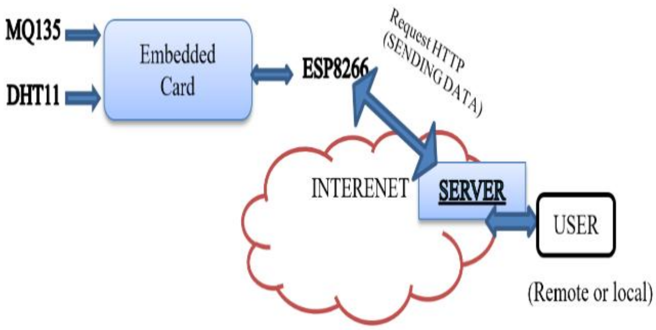

Figure 7 : Structure of the data acquisition system

The sensors: DHT11 provides us with the temperature and humidity values. The MQ135 can detect several gases: NH3, NOx, alcohol, benzene, smoke, CO2 ... etc. From these gases, we arrive at the level of pollution in ppm (parts per million).

Before using the MQ135 sensor, it must be calibrated and adapted to the atmosphere and the environment in which it will be mounted.

To send this data to a web server, we use the ESP8266 wifi module

6.2 Analysis of data collected using machine learning methods

We used the ant colony-based learning methods (M. Hamlich 1, 2012, M. Hamlich 2020) to hope to find correlations between certain diseases and the air quality of the building.

Fuzzy Ant Miner is a supervised machine learning algorithm based on ant colonies which from training data generates decision rules in the form: If attr1 = V1 AND attr2 = V2, then Class = C1 . It will be used initially on static data chosen by the user.

The data will be divided into test data (10%) and training data (90%) using a 10 cross validation.

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6.3 Perspectives:

The data is massive, arrives in streaming and it is heterogeneous, hence the need to analyze it in a Big Data environment. The Fuzzy Ant Miner algorithm must therefore be deployed in a parallel and distributed environment.

The data will be sampled or compressed and distributed over several nodes for analysis.

7 CONCLUSIONS

DL and IoT have attracted considerable attention from researchers in recent years, these two cutting-edge technologies have the potential for great impact on people's lifestyles, buildings, cities and the world at large. IoT and DL create a chain of data producers, in which IoT products are raw data that are analyzed by DL models produce high-level abstraction and insight that are fed to IoT systems for fine-tuning and service development.

In this investigation, we examined the characteristics of DL and big data IoT analytics in the development and improvement of smart buildings. We then defined IoT technology and described the IT infrastructure used to leverage IoT data, including cloud, fog, and edge computing. Next, we reviewed DL architectures, their uses and benefits. Thus, we present the most important open-source platforms developed to support DL research.

Finally, we concluded by our proposal contribution to obtain correlations between certain emerging diseases prevalent in the building

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