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Deep Smart Cities: A Review of Smart Cities Applications-Based an Inference of Deep Learning Upon IoT Devices

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ABSTRACT

Recent years have witnessed an increase in the use of IoT devices in Smart Cities (SC). With the remarkable success of integrating deep learning (DL) in various fields of SC such as smart environment, smart agriculture, and more. There is an emerging field to deploy DL into IoT devices to meet the requirement of SC applications as real-time applications and lightweight computation. However, the limited resource of IoT devices poses a challenge to fulfilling the DL models that demand large storage and massive computation. The aim of this paper is focused on the integration of DL with IoT in SC and conducts up-to-date state-of-the-art studies on the SC applications. First, a present overview of SC, IoT and DL. Second, we review studies that integrate DL and IoT into four SC applications (smart environment, smart transportation, smart agriculture, and smart home). It covers a series of crucial applications in SC such as Air pollution, water pollution, autonomous driving, activity recognition and detection, indoor localization, and more. Third, present the main challenges once integrate DL on IoT devices in SC. Lastly, we introduced open issues for the future direction obtained when integrate DL models with IoT devices in SC applications to inspire further research in this area.

1. Introduction

In the context of the increase in population and accelerated growth of cities. Since the world population residing in cities will increase to 50% in the year 2050 [1]. According to World Population Data Sheet in 2020, the world population will reach 9.9 billion by 2050 and rise to 25% from the current 2021 population of 7.8 billion [2]. The enormous world population, rising urbanization, digital revolution, and the demands of citizens for more efficient and sustainable services and the enhancement of quality of life imposed several challenges. Therefore, the development of SC should be including solutions that enable more appropriate responses to these challenges [3,4]. On another side, the growth of the Internet of Things (IoT) devices is often considered the main factor in the development and execution of SC services. Recently, IoT field and SC gained intensive global attention as in Figure 1. Since the IoT term refers to interconnecting billions of intelligent devices with each

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other. It plays a vital role in SC, where enable access and interaction to a wide variety of devices e.g., monitoring sensors, CCTV cameras, vehicles, etc. which in turn leads to support the improvement and innovations in multiple sectors of SC including transportation, health, environment, etc. For instance, IoT allows monitoring of the city in real-time and uses the live status report to respond more intelligently to emerging situations. Adopting IoT devices in SC gives it the ability to overcome challenges and it can handle urbanization problems which leads to providing high quality of life for the population [5,6].

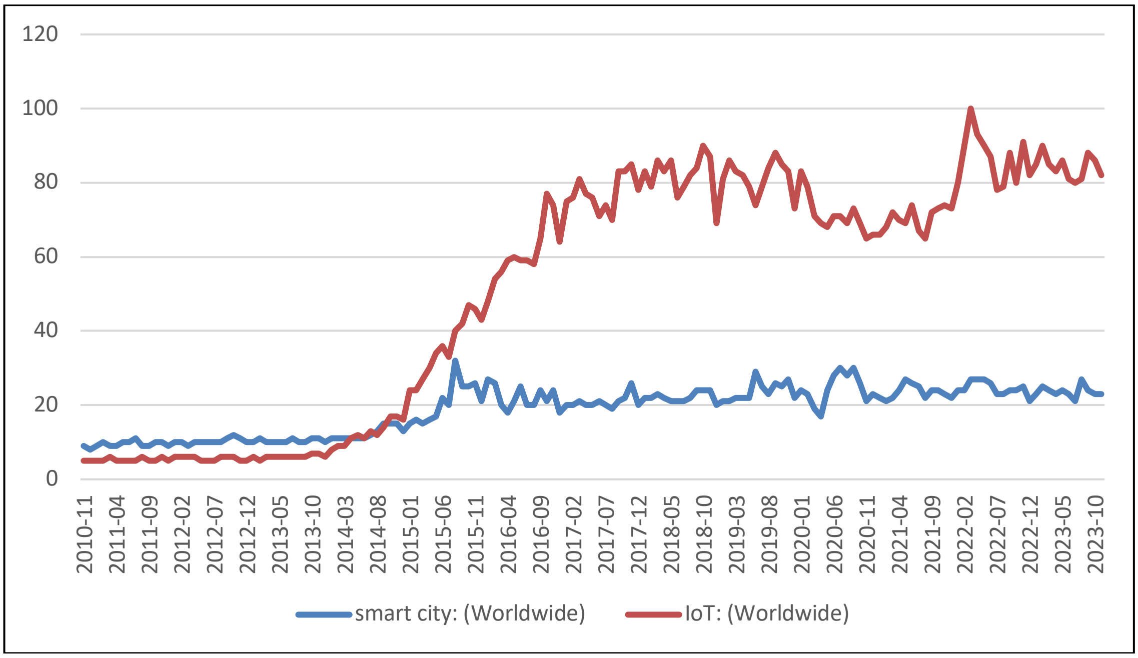

Fig. 1. The number of Google searches for the terms “Smart city ‘‘and “IoT” from 2010 to 2023, according to the Google trend. The X-axis represents years from 2010 to 2023 and the y-axis represents the number of searches

It Nowadays, the recent growth of IoT devices in SC such as sensors and actuators led to generating a myriad of valuable data. The growth of the data led to integrated IoT devices with cloud computing to store the da-ta, besides applied real-time analytics using Machine Learning (ML) and Deep Learning (DL) algorithms. The data generated by IoT devices are transmitted to the cloud to store the data and implement different DL algorithms to conduct real-time analytic [1,4].

DL achieved remarkable breakthroughs in recent years in processing and analysing data of IoT devices in SC. Due to powerful perception capability, but has many challenges once integrated with IoT devices. The major challenge in deploying DL in IoT devices in SC is dense computation which in turn consume a substantial volume of resource in IoT devices. As well, DL models have heavy-weight that demand large storage which is not affordable for IoT devices that have small memory. Another challenge is the long delay due to complicated architecture for DL that takes long time through the inference phase due to limited computation power in IoT devices. Which, is not appropriate to SC where time is critical in taking decisions e.g., alerting fire outbreaks, and accidents to the related authority, and also intima of crime to security agencies. Where the delay may lead to loss of life [7-9].

To fulfil this gap, the contribution of this paper is focused on the integration of DL with IoT in SC and conducts up-to-date state-of-the-art studies on the applications of SC. The main contributions of this paper are:

i. This paper present, an overview of the role of DL and IoT devices to develop smart cities. On the other side, we define the architecture of Integrate DL with IoT devices in SC applications.
ii. Review the studies that integrate DL models with IoT devices in four fields of smart cities including smart environment, smart transportation, smart agriculture, and smart home. In each application, we review two do-mains.
iii. Analysis and findings from previous studies are provided for the main three items used in TinyML (Dataset, DL Models, and Devices).
iv. Discuss the main challenges when Integrating DL with IoT devices in SC applications.
v. Shed light on the most relevant open issues concerning of the integration DL models with IoT devices in SC, which will provide the directions for future research.

The rest of this paper is organized as follows; we present an overview of the main concepts such as SC, IoT and deep learning in Section 2. After that, we introduce the research methodology in Section 3. Review up-to-date studies that integrate DL with IoT in various fields of SC in Section 4. We highlight the key challenges when integrating DL with IoT devices in Section 5. We provide the open issues for future research directions in Section 6. Lastly, conclude this paper in Section 7.

2. Overview of Smart Cities, IoT and Deep learning

This section, presents an overview and the role of IoT and DL in SC. First, it introduces an overview of SC. Next, it shows the role and the values delivered of IoT in SC. Afterward, an outline of DL and the ad-vantages of DL in SC.

2.1 What are Smart Cities?

Smart cities are referred as digital cities but recently gradually changed by SC. The digital cities point to a connected community that collected the broadband communications service; a flexible, service-oriented computing service based on the open industry standards [8]. Lately many of definitions to SC are appear. Authors in Ref [10] refer to many definitions of SC one of them was for Harrison, who defined SC is connected, instrumented and intelligent city. Another definition for Giffinger and Gudrun that propose the SC has six intelligent features which are environment, governance, economy, life, people, and mobility. Whereas Silve referred to a city that optimizes access to public services through Information Communication Technologies (ICTs) as a “Smart city”. Therefore, there is consensus for innovation technologies including ICT, Cloud computing, IoT, and Artificial Intelligence (AI) which are critical items that provide essential support for building an SC as sustainability, effort, and survivability. The SC takes care of the conditions of the basic services and facilitates e.g., communication, airports, roads, bridges, tunnels, subways, and buildings to improve its security and resources [8,11].

2.2 What is the Role of IoT in Smart Cities?

IoT is the core of smart cities and considers the main driver of the emergence of the notion of SC. IoT acts enable technology that is available ubiquitous digitalization in SC. The role of IoT devices in SC is valuable and has many benefits, that will optimize the services in SC within various fields as environment, transportation, agriculture, home, and more, it will enhance the level of living for the society. Shahzad Ashraf [12] studies the role of IoT in SC and the impact of smart service as smart agriculture, transportation, energy, health, infrastructure, and recreation on society. In addition, make a comparison between living in smart cities and traditional cities. They conduct the Analytic Hierarchy Process. questionnaire to collect data from various sources. The results showed 98% of local communities are satisfied with the smart services. However, people living in traditional cities are also satisfied. Since most of them live in villages or the suburbs and do not have experience of the services in smart cities. Further, they have a limited approach and neutral opinion, since they think lives in their vicinity are better.

Mathias Valcke [13] defined the role of IoT in SC in two components that enable the delivered of the specific values of IoT to SC. The first component is the communication of the IoT devices, which enables to conduct of real-time changes in the processes and makes the system interoperable. The second component is the data generation of IoT devices of various fields in SC. The data permit the measurement of certain systems and processes. Moreover, conducting a deep analysis of the data allows us to reach valuable insight from the data. The IoT devices generate massive of data from SC, as a result of interconnected devices, the data is generated from various fields as smart environment, smart transportation, smart agriculture, and smart home. Data is various such as text, image, video, and signals, which enable of measure special system and processes. After performing analysis on the data allows us to turn up valuable insights which in turn have many benefits to the SC [8]. The results of data analytics can serve a government, society, and business e.g., new revenues or create business models using IoT [13]. However, it can be useful for many fields in SC e.g., in smart environment IoT devices such as air water and temperature sensors gather data from the environment, then used software and tools to perform analysis. Consequently, help us to monitor the environment and prevent disasters and substantial contamination of our resources [14]. Furthermore, the data generated by IoT devices in the transportation field is important and valuable to manage transportation in SC. Using IoT in transportation e.g., sensors can help people to avoid waiting long time and time wastage [15]. On the other end, using IoT plays a vital role in building a smart home. Since its possible to control home devices remotely through the internet. It offers comfort and convenience for people. In addition, help to reduce the consumption of energy and provide high security [14].

2.3 Deep Learning in Smart Cities?

In this section, a brief background about DL for more details of DL in Ref [16]. DL models consist of many layers, wherein the input data passes out of each layer in sequences. Each layer applied matrix multi-plications over the data. After that, the result of each layer is input to the next layer. After the data is processed, passed to the final layer, which is play role in classifying the results, since the output is either a classification, regression, clustering, and more. Once the model has the number of layers in sequence, the neural network is called a deep neural network (DNN). However, there are many types of DNN that are designed for the special purpose of data analysis. For instance, to analyse the images and videos usually used the convolutional neural networks (CNNs) models that contain the convolutional filter operations in matrix multiplications. CNNs consist of convolutional layers, pooling layers, and fully connected layers. Common models of CNNs namely VGG, GoogleNet, AlexNet, LeNet and ResNet. However, there is another type of DNN which is designed for prediction time series known as recurrent neural networks (RNNs). RNNs have loops in the inner layers connections to retain state and enable the predictions on sequential inputs [7,8]. RNN showed promising in process audio processing and Natural Language Processing (NLP) applications. The most common model used of RNN is Long Short-Term Memory (LSTM) model which consists of three gates namely forget gates, input gates, and output gates [7].

Recently, DL has gained popularity in SC due to its ability to handle massive of data and process complex operations with successful performance and achieve high accuracy. Since the data generated from IoT devices in SC is big and complex. Particularly, the data generated by the devices come in different forms as structured, semi-structured, and unstructured. Besides, it has different types as image, video, speech, and text. Consequently, DL has capabilities to perform analysis to huge of data, along with applied to any type of data analysis as classification, regression, and clustering [8] With the deep penetration of IoT devices, there are strongly derived to use DL in SC applications. Since DL provides solution for security and surveillance. For instance, ensure the safety of human life through road surveillance and provides real-time information for the drivers on the roads. In [17] proposed system based on the CNN and LSTM to detect the accident from video footage obtained from CCTV cameras and Raspberry Pi 3 (RPi3) as remote computer installed on the highway. Dwivedi *et al.,* [18] proposed a model to detect and classify the drowsy state of a driver as drowsy and non-drowsy using CNN models. CNN model consists of a number of layers that have the ability to extract the facial features from the images. Furthermore, DL has a strong footprint in the detection of humans in images and videos.

2.4 Architecture of Integration Deep Learning with IoT in Smart cities

The architecture of integrating DL with IoT in SC involves four layers; Sensing Layer, Connectivity and communication middleware layer, Storage and analytics data layer and the Application layer. This architecture is depicted in Figure 2 and its layers are briefly described in the following subsections.

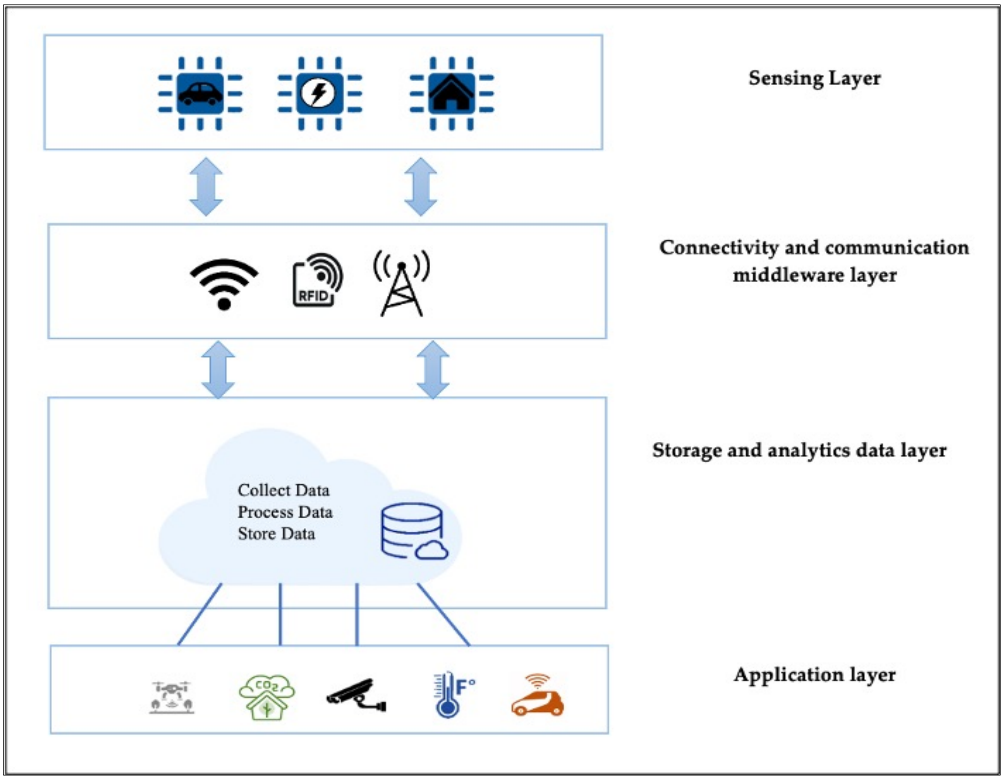

Fig. 2. Architecture of integration IoT with DL in smart cities

2.4.1 Sensing layer

The first layer sensing layer which is also known as the Perception layer consists of different IoT devices e.g., sensors, actuators, mobile phones and Radio Frequency Identifications (RFIDs). The IoT devices install in every object in SC and connect with each other [20]. The role of the devices is to collect different forms of data such as (images, videos, text) and signals from the different fields of the SC. The data read from the sensing layer is passed onward to the Middleware layer [21]. For instance, the wearable devices employed to collect human activities data, further satellite capture images for the land, and different IoT devices e.g., temperatures, air quality, and air monitoring are installed to monitor the weather.

2.4.2 Connectivity and communication middleware layer

The connectivity and communication layer comprise heterogeneous technologies (e.g., wireless, satellite) that are responsible to delivered gathered data from IoT devices in the environment to storage layer. Its middleware level acts as transportation channel to transfer data from the sensing layer to storage centre and to different external servers e.g., the cloud and perform analysis [12,22].

2.4.3 Storage and analytics data layer

The large data was collected from IoT devices from various fields in SC. It needs to large storage for processing and analysis of data, wherein the IoT devices do not have capability to store and make data analysis in most cases. For instance, cloud computing platforms provide large storage space, high computing power, and high communication bandwidth to store and analyse data. Cloud computing enhances IoT devices by providing efficacious online management to control, manage, store, and analysis the data [23]. DL has been used to analysis of IoT data in SC which has the capability to transform the large raw data and extract the knowledge, in turn enabling the stockholder e.g., citizens, government to make decisions. DL models deployed on cloud computing to process and analysis the data and back the result to the devices in real-time. Although DL achieved great success and outperformed other methods, it is not a versatile solution for the ap-plications in SC due to many challenges, that will be explained in the next section [12,20].

2.4.4 Application layer

The last layer is IoT applications. These applications enable the smart real-time behaviours and actions in the SC environment. IoT can be used in diverse applications leveraged across several fields in SC such as agriculture, transportation, smart buildings, surveillance, and energy [12].

3. Research Methodology

This section presents the methodology to locating, selecting, and critically assessing papers that address all topics related to Integrating DL with IoT devices in smart city applications. The objective of the paper was to import all the papers related to integrating deep learning with IoT devices in smart cities applications and impart details review of the research works performed in this domain and their key contributions. Along with mentioning details for datasets, models, and devices. This paper was carried out following the guidelines in PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses). The method process is de-scribed in the following subsections.

3.1 Core Questions?

The selection of the studies is based on whether or not the study answering research questions, the focused research questions in this study are:

i. What are the main applications of a smart city ecosystem?
ii. What are the devices, datasets, DL models and performance that are used in smart cities applications?
iii. What are the existing challenges facing integrating DL models with IoT devices to develop SC applications?
iv. What are the existing open issues when integrating DL models with IoT devices for future researchers?

3.2 Search Strategy

The web-based resources (Google Scholar) and Clarivate's Web of Science (WoS) which is powerful and trusted database contains various academic disciplines are based databases for searching about Integrating DL with IoT in smart cities. In addition to other databases as complementary sources: Science direct, IEEE, MDPI, and Springe. The keyword used for searching are listed in Table 1.

Table 1
Search plan/approach

Source	Criteria
Database	web-based resources and Web of Science
Keywords	Deep Learning Internet of Things IoT devices Smart cities applications Smart Environment Smart Transportation Smart Agriculture Smart Home Deep learning AND IoT devices Deep Learning AND IoT devices AND smart cities Challenges of Integrate Deep learning with IoT devices
Language	English
Type of publication	Conference Proceedings Journals Book Research Article
Inclusion criteria	Integrating deep learning with IoT devices Develop Framework Challenges and directions papers Review and Survey papers
Exclusion criteria	Studies that the abstracts or content not directly have relevance to our field. Studies with missing full text Studies that are not written in English

3.3 Eligibility Criteria

The published studies with dataset, models and the type of devices were included. The published studies must include the experiment with purely outcomes.

3.4 Inclusion and Exclusion Criteria

The Inclusion Criteria were select studies that aimed to; Integrating DL with IoT devices on various smart city applications as smart environment, smart transportation, smart agriculture, smart home. Further survey and review studies that discusses their challenges. Excluded Criteria were the articles have irrelevant results based on information and keywords found in paper abstracts or content. Studies with missing full text and the Studies that are not written in English language.

3.5 Data Extraction and Synthesis

After selecting study for review, next carry out an in-depth study of each selected paper. To extract the main contribution, implementation including datasets, models, devices, and the evaluation criteria for models and devices results of each paper. The purpose of the data synthesis approach is to answer research questions. The information extracted from studies are described in sections 4.

3.6 Data Selection

A total of 101 relevant published papers/articles were retrieved using search engines from the electronic data source. Using Mendeley Desktop software to import papers and filtered a duplication. The paper included and excluded in this study according to the preferred reporting items for systematic reviews and meta-analyses (PRISMA) Statement.

At the beginning the main strategy was conducting an exploratory reading based on the titles and reading abstract. In addition to reading the challenges of integrating DL with IoT. In order to exclude all articles that did not have some evidence or information on the issues addressed. After that, we conducted a selective reading for the articles. Articles whose abstracts were selected underwent a full read, except for those that had no primary information relevant to the research questions. We finished once we were no finding new paper with relevant information. Thus, we identified 101 articles from various databases for instance ACM, Elsevier, IEEE, MDPI, etc. Figure 3 summarizes the process for selecting papers using the PRISMA flowchart. Whilst, Figure 4 obtained the depicts the distribution of selected papers by publishers.

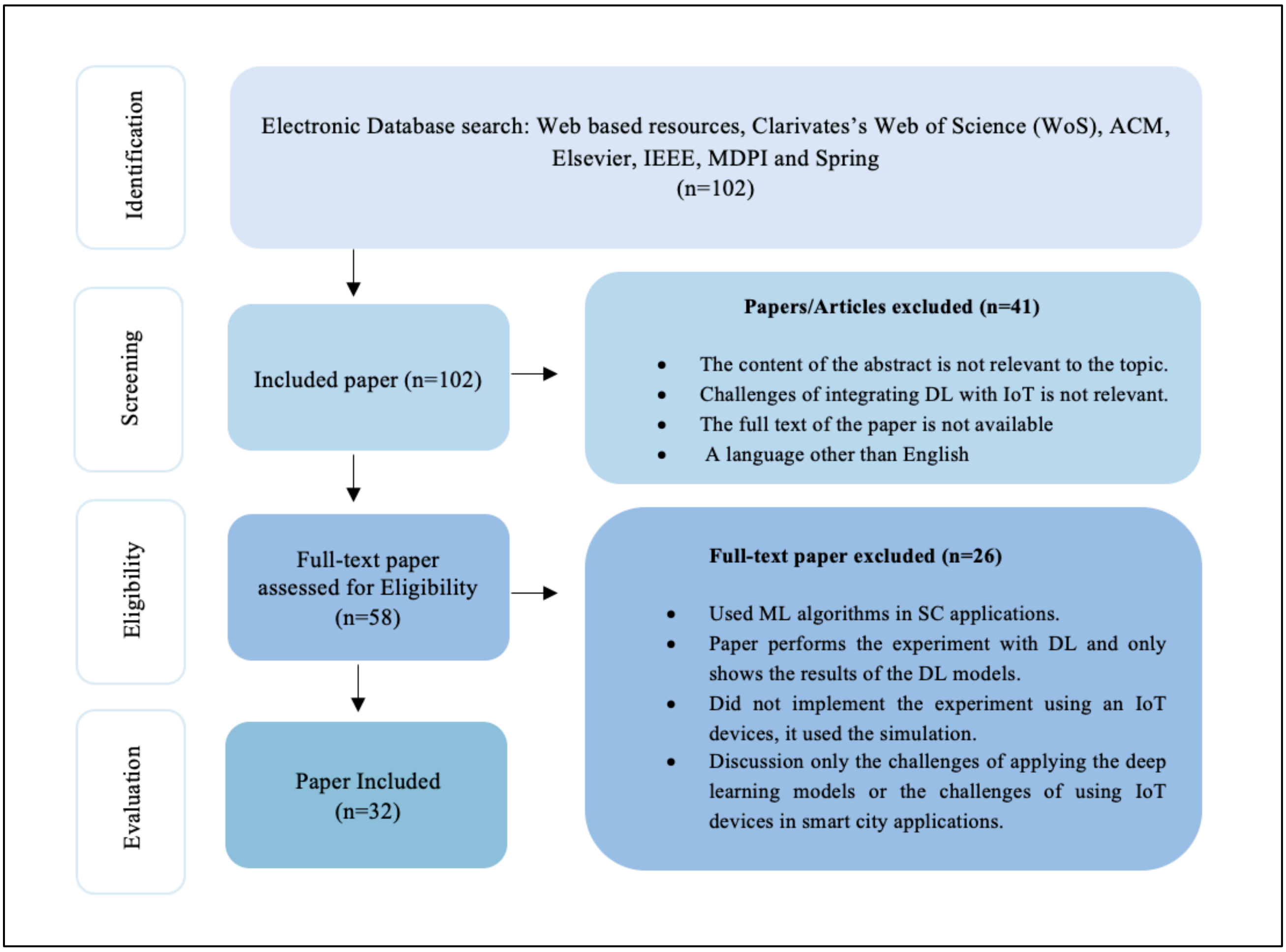

Fig. 3. PRISMA flowchart for the study

Based on the preliminary reading of the titles and abstracts as well as to the challenges, we ignored 41 articles. The abstracts that did not meet the inclusion criteria were those that lacked clarity in terms of their relevance to our study or failed to adequately convey this relation in their content. Articles published in journals that do not provide full text, as well as studies performed using languages other than English.

We conducted a thorough examination of the complete text of the remaining 58 publications to validate the extent to which our initial assessment of their research contribution based on the abstracts was substantiated. As a result, 26 papers were excluded. The exclusion criteria, first the study not applied DL algorithms with IoT devices, wherein they used one of ML algorithms in SC applications. Second, the study performs the experiment with DL and only shows the results of the DL models. Third, the study did not implement the experiment using an IoT device, it used the simulation. Fourth, for the articles related to challenges of integrating DL with IoT devices, we ignored studies that only discussed the challenges of applying the DL model or the challenges of using IoT devices in smart city applications.

The remaining 32 articles were effectively used and analysed in detail. These articles including the most relevant sections that are included to provide support and address the research questions.

4. The Integration of Deep Learning with IoT in Smart Cities

Recently, SC witnessed rapid growth in technologies and achieved major success of IoT applications. However, the massive amount of generated and collected data from IoT devices required more intelligent processing. In order to fully unleash to potentials and satisfy the demands increasing of different applications. Lately, DL applications shed a light on IoT applications in SC and achieved great accomplishments. DL provides efficiently processing of data, decision making, data management and the ability to information perception accurately. The convergence between these two technologies promotes creating more new opportunities in SC. Further, pave the way to develop many novel applications in many fields that serve SC [19].

4.1 Studies of Integrating Deep Learning with IoT in Smart Cities Applications

In this section, we conduct an overview of state-of-the-art studies that work on IoT applications with DL in several fields in SC including smart environment, smart transportation, smart agriculture, and smart home. Figure 4 depicts the road map of smart cities applications

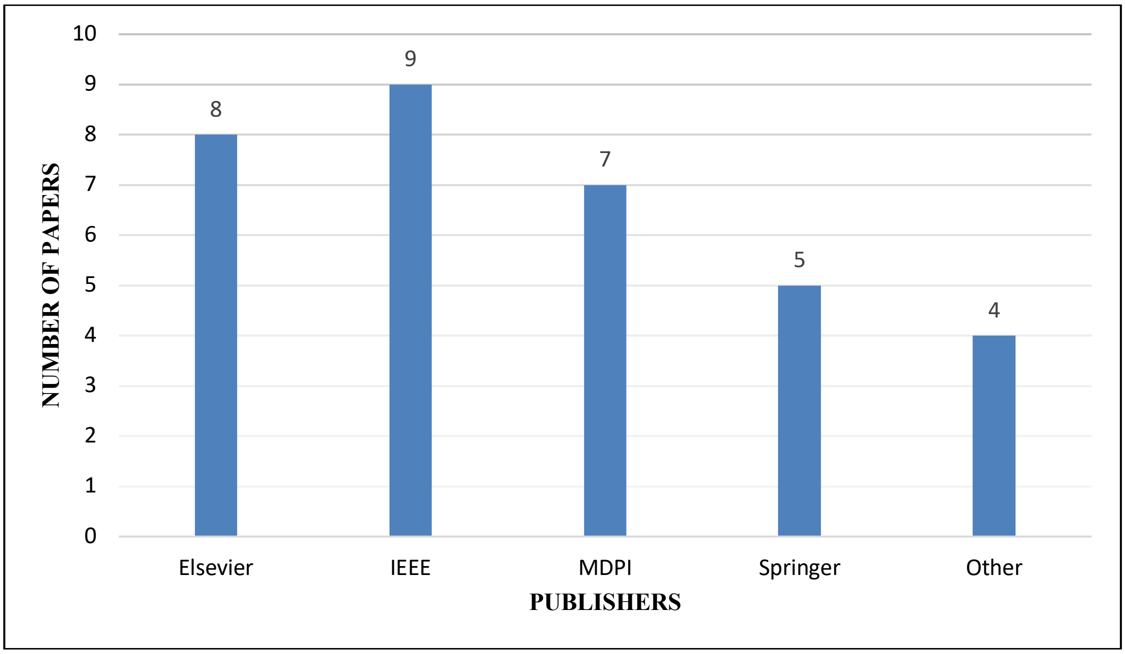

Fig. 4. Distributed of Papers

4.2.1 Smart environment (SE)

The term environment refers to the surroundings which deal with air pollution, air quality water pollution, weather changes, and more. With the more recent advance in IoT (sensors, actuators) and machine learning especially with DL, the environment becomes a smart environment system (SE) [24,25]. These IoT devices connected through wireless networks and were employed to collect the data like images, videos, or signals from the environment and then send it to a cloud database to store it and perform the processing and analysis using DL [26]. SE was implemented in diverse applications in order to serve certain purposes such as air pollution, water pollution, monitor water quality and monitor the pollution, in addition, and other many fields [27].

i. Air Pollution
Air pollution is considered the main pollution effect on the environment and human health. Wherein the air pollution is controlled by a circuit that contains sensors and devices that detect the pollution level and control of pollution [28]. There are many studies proposed and developed models using DL to predict air pollution and monitoring

air quality using IoT devices in different cities e.g., Study in Ref [29] predicts the PM2.5 pollution in Beijing using a hybrid model which consists of CNN and LSTM algorithms. After that applied four quantization techniques (Dynamic range, full integer quantization integer with float fallback, full. Integer quantization- integer only and float16) using TensorFlow Lite (TF Lite) to deploy models on RPi3 and Raspberry Pi4 (RPi4) devices. As in Table 1, they used a dataset from an Irvine (UCI) Machine Learning Repository page that was collected from 12 websites. The dataset consists of Pollutant data (PM2.5, PM10, NO2, SO2 and O3) and meteorological data (air pressure, temperature, dew point, wind speed and wind direction). The results obtained from the proposed model outperform other DL models with a Root mean squared error (RMSE) of 15.268 and MAE 8.778 for PM2.5 values. Besides, the dynamic range and full integer quantization outperform others in size of models with 41kb and 42 respectively. And full integer quantization achieved better latency with 4.73s for RPiB3+ and 2.19 s for RPi4. On the other hand, study in [28] proposed a system that integrates DL with cloud-centric IoT middleware architecture, which is used to receive data from statistical air pollution and existing weather sensors. The dataset contains data of daily weather and air pollution data from 2018 to 2019 which was collected from [30,31]. The author used ANN algorithm to predict the level of Sulfur dioxide (SO2) and Particular Matter (PM2.5). As a result, the experiments reflecting the proposed system are reliable and helpful with the RMSE of SO2 is 0.0128 and 0.0001 for PM2.5.

ii. Water Pollution

With the accelerated urbanization and rapid development of the economy in SC. Water ecosystems as seas, rivers and lakes face many threats and pollution problems become more serious. Therefore, the development of systems using integration of DL and IoT to control and monitor water pollution is of great significance. Where DL algorithms enable the researchers to understand relevant data under the environment of IoT. Hence, can develop systems to instantly monitor and control water pollution to protect water ecosystems [32,33].

Nguyen Thai-Nghe *et al.,* [34] proposed a system consisting of IoT and DL to monitor and predict water quality in aquaculture and fisheries. Water Quality indicators data such as (salinity, temperature, pH, and dissolved oxygen (DO)) have been collected every day by sensors. Then, transferred data to the cloud to per-form analysis and forecasting, then visualization data using mobile or PC. The proposed model was LSTM which was used to forecast models. Six datasets were used which include different indicators. The results obtained LSTM outperform the performance in most indicators where salinity achieved 0.36, pH 0.19, temperature 0.31, and DO 4.1 of RMSE respectively. Another study aims to propose a system to monitor water pollution in real-time and solve the challenges of similarity in clean and polluted water images in oceans, rivers, lakes, etc. Authors in [33], proposed Attention Neural Network model based on the VGG-16 network to solve the challenge of classification of (clean, polluted) water images. They used a dataset that was introduced by [35], which contains 10000 images of clean and polluted. To evaluate the performance of the model, authors conducted a comparison among proposed models with and without attention modules, besides with [36]. The results showed the proposed model exceeds the accuracy of other models with 66.4% of accuracy for clean water and 73.6% of accuracy for polluted water.

Smart environment field includes many of categories for research, we selected this research due to the importance since these categories can help to develop and design of the environment which in turn help to achieve the sustainability and provides health environment. SE variety based on the type of sensors involved, type of IoT devices were used, and DL models applied. Hence, constitute challenges due to different type of data captured from different types of sensors. In addition, suffer from huge computational complexity. Table 2 provides a summary of smart environment related studies and their applications. Including the device name, datasets, DL models, and the purpose of DL models, and presents the main results of performance.

Table 2
Integrating of DL into IoT devices with Smart Environment Applications

Application	Work	Devices	Dataset	DNN	Purpose of DNN	Performance Results
Air Pollution	[29]	Raspberry Pi3 and Raspberry Pi4	Pollutant and meteorological data	CNN and LSTM.	Predict $PM_{2.5 \text{ values}}$	RMSE: 15.268. MAE: 8.778
Air Pollution	[28]	Sensors and Cloud platform	Daily weather and air pollution data	ANN	Predict the level of Sulphur dioxide (SO_2) and $PM_{2.5}$.	RMSE: 0.0128 SO2. RMSE: 0.0001 PM2.5.
Water Pollution	[34]	Sensors with cloud	salinity, temperature, pH, and dissolved oxygen	LSTM	Forecasting values for indicators	RMSE: Salinity 0.36, temperature 0.31, ph 0.19, dissolved oxygen 4.1.
Water Pollution	[33]	-	Clean water Polluted water	Attention Neural Network model +VGG16	Classifying water images	Accuracy: 66.4% Accuracy: 73.6%

4.2.2 Smart transportation (ST)

Smart transportation (ST) is a very popular area of research, and it is the next intelligent information. Particularly integrating the transportation devices with DL technique will enable the IoT devices installed in the city to be more intelligent [37]. For instance, embedded devices such as sensors that are embedded in vehicles, streetlights, and cameras. Hence leads to optimizing the transportation field in a city such as autonomous vehicles, route suggestions, easy parking reservations, economic street lighting and accident prevention [38]. Implementation of DL in IoT devices has a huge footprint on ST in SC. Many studies in ST applied DL on IoT devices in many fields using various techniques as CNN, GNN, etc. and deployed it into IoT devices e.g., Raspberry Pi, Smart camera with the aim to automatically make decisions. This section presents the studies related to autonomous vehicles and smart parking.

i. Autonomous Vehicles
IoT has a broad range of effects on vehicles and optimized the application e.g., used to predict congested routes, detect the obstacles, and recognize pedestrians automatically. In addition, IoT can improve the safety of vehicles through the ability to monitor the driving of other vehicles [6]. For example, the authors in previous study [39] developed mobility vehicles by applying CV techniques and DL methods in order to be auto vehicles. Auto vehicles refer to the vehicle that has the ability to avoid obstacles and recognize pedestrians. Authors used RPi3 as controller on the mobility scooter through attached

Ultrasonic sensors and Cameras to be fully autonomous. Two CV techniques were used to recognize pedestrians, namely histogram of oriented gradients (HOG) descriptors and Haar-classifiers. In addition, they used the DL algorithm to compare the results. Two datasets were used; first Pretrained Natasha Seo training dataset for the HOG and Haar classifier. Second, COCO and VOCO712 datasets. The performance of the experiment demonstrates the HOG achieved higher accuracy than HAAR with 83% and 53% respectively. On the contrary, DL outperforms other CV techniques with 88% of accuracy. Another approach to auto vehicles was introduced by Donghwoon Kwon *et al.,* [40], developing a system for an autonomous vehicle to detect objects. They developed a safe and lightweight blind spot detection system based on the camera. Processing of data using a HOG and fully Connected Network (FCN) to detect objects. The FCN model achieved 98.99% of accuracy. Subsequently, deploy the model to an off-the-shelf embedded board for real testing on a road with connecting to the cloud platform. the system achieved 93.75% average of accuracy.

ii. Smart Parking
Recently, Smart Parking applications have grown widely e.g., tracking of availability of parking, presenting reservations to the users also to detect and notification mechanisms in parking. IoT devices are used in parking such as cameras or other sensors like wireless or IR sensors. Deploying DL models into IoT devices leads to be Smarter wherein the services are done automatically. For example, deploy DL models in smart cameras to detect the availability of parking [38].

Giuseppe Amato *et al.,* [41], presented a decentralized and effective method for visual detection of the parking status; occupied or vacant. With the aim to run the detection software completely on smart cameras with Raspberry Pi2 (RPi2) as a controller in the parking. Since the camera has the ability to process the images acquired and transfer the result to the server. Two datasets were used PKLot and CNRPark-EXT datasets consisting of occupied or vacant parking images from 9 cameras and with different situations of the weather. They proposed the mAlexNet model based on the DL algorithm and used the Alexnet model. The experiment showed the accuracy of the PKLot dataset was 98.81% and 98.07% from Alexnet and mAlexNet models. The CNRPark-EXT dataset achieved 98% and 97.71% accuracy from Alexnet and mAlexNet models respectively. Another smart parking approach is suggested in [42], a proposed method based on attentional Graphical Neural Network (GNN) algorithm to detect the slot detection of parking in around-view images. Two datasets were used namely Ps2.0 dataset contains vision-based parking-slot detection images in various conditions and DMPR-PS. The experiment was implemented using Pytorch software and on the Nvidia Titan Xp GPU and. The results showed of GNN in Ps2.0 dataset achieved 99.56% of precision and 99.42% of Recall. Whilst on DMPR-PS dataset achieved 97.05% of precision and 90.70% of recall.

The summary of application in ST of SC introduced to used various of DL models to perform detection well and obtained high accuracy. After that deploy on the IoT devices that have large resources to process the complex images. Due to the images collected in ST depended on time factors as nighttime, daytime and based on climate conditions. Pose a challenge once integrate DL with IoT devices, thus we selected this category of applications to perform further research. Table 3, present the studies of ST applications including Autonomous vehicles and Smart parking that discussed above, including the IoT devices used, datasets, type of DL models and the purpose of each one utilizes. Along with showed the major results with different metrices.

Table 3
Integrating DL with IoT devices in Smart Transportation Applications

Application	Work	Devices	Dataset	DNN	Purpose of DNN	Performance Result
Autonomous Vehicles	[39]	Raspberry Pi 3	-Pretrained Natasha Seo training -COCO and VOCO712 datasets	HOG descriptors, Haar-classifiers -Deep learning.	Detect and recognize pedestrian	Accuracy: 83% Accuracy: 88%.
Autonomous Vehicles	[40]	Embedded board	Real testing on the road	HOG and FCN	Detect the objects.	Accuracy: 93.75%.
Smart Parking	[41]	Smart cameras with Raspberry Pi 2	-CNRPar k-EXT dataset -PKLot dataset	mAlexNet and Alexnet models.	Detection and classification of parking	Accuracy: 98% AUC: 0.997 Accuracy: 98.81% AUC: 0.998
Smart Parking	[42]	Nvidia Titan Xp GPU	-Ps2.0 dataset training. -DMPR-PS dataset	Attention Graphical Neural Network.	Detect the slot parking.	Precision 99.56% Recall: 99.42%. Precision: 97.05%. Recall: 90.70%

4.2.3 Smart agriculture (SA)

Smart Agriculture (SA) is a combination of harnessing a set of various Information and Communication Technologies (ICTs) to increase the productivity of farms and ensure food sustainability. The Food and Agri-culture Organization of the United Nations estimated the prevalence of global undernourishment in 2019 is slightly below 11% [43]. The new approach of Smart agriculture benefits from converging the new emerging technologies including remote sensing, automatic control, mobile computing, geographical system, and tele-communications. All these technologies are unified under the umbrella of IoT, and cloud computing enables the effective deployment of technologies to the agrarian world [44]. IoT devices offer many benefits to the farmer in main agriculture applications including Farmer and Monitoring Fields, Greenhouse, and Livestock [45,46]. Recently, DL achieved great improvement in IoT-based agriculture. Various DL algorithms have been used for the classification or recognition of plant diseases, animals, and images, or using videos and data [47]. State-of-the-art studies are presented in the section of inference of DL in IoT devices in Precision Agriculture and Livestock Monitoring fields.

i. Precision Agriculture
Precision farming is a subset of agriculture fields the term of Precision Agriculture is related to many fields in agriculture such as monitoring Pets and Crop diseases, Soil Patterns, and Farming Management systems [45]. To enhance the crop production inference of DL into IoT devices and connect with IoT platforms-based cloud computing has been developed. In order to collect the data of crops in real-time and classify it accurately. Authors in [48] used DL on an unmanned aerial vehicle (UAV) with ASUS Tinker

Board S embedded system to classify the crops (rice or corn) in real-time. They gather images of crops (225 images of rice and corn) using semantic segmentation model (SegNet model) on the cloud server and using 4Nvidia Tesla V100 SMX2 GPUs accelerator. The SegNet model achieved 89.44% of classification accuracy, where the speed of the inference model was 0.7seconds. Likewise, authors in Olsen *et al.,* [49], develop models for the classification of Weeds. The DeepWeeds dataset including images for the eight Weed that has nationally significant in north-ern Australia. They attempt to infer CNN and ResNet models on the Nvidia Jetson TX2. Since the best classification accuracy was achieved by the ResNet model with 95.7%, for inferencing time achieved 18.7 FPS on the TensorRT platform. On the other side, the authors developed DL model and inference it on a low-power embedded system to detect pests in plants. Where in [50], developed CNN model on a low-power embedded system in order to detect cotton pests. Using National Bureau of Agricultural Insect Resources (NBAIR) dataset that contains 50 classes of cotton pets. The CNN model has been used to extract the features from images, then implemented on a PYNQ-Z2 development board which comprises an Advanced RISC Machine and FPGA. The testing accuracy was obtained above 95% with the inference runtime 2FPS. Detect the whitefly and thrips for improvement of greenhouse monitoring fields in agriculture. Victor *et al.,* [51], constructed models to detect the whitefly and thrips from sticky trap images obtained in greenhouse conditions. They developed a model namely "TPest-RCNN" that is based on the Faster Regional-Convolutional Neural Network (R-CNN) to enhance the detection accuracy of tiny pests. They construct two datasets over time intervals with (low, medium and high density). Rpi4 has been used to implement a graphical interface. The performance of the model was 0.944 of F1 score and 0.952 for average precision.

ii. Livestock monitoring;
Livestock monitoring is considered a critical element in the agriculture field. Maintaining livestock is a costly process that requires labour and brings huge costs. Integration of IoT and DL in livestock fields has many advantages; it will reduce costs on farms, provide an optimal livestock environment and improve livestock conditions. Attaching the IoT sensors to the animals helps the farmers to monitor the log performance, activities, monitor the animal's health and temperatures [45,52]. DL plays a major role in improved livestock, wherein it can infer on IoT devices or used in IoT platforms cloud-based. Where in Ref [53], develop CNN model in RPi3 device for detection and classify an animal from images. RPi3 device has been used with CPU (Quad-core 1.2 GHz Broadcom BCM2837 64bit) and 1 GB for RAM. They collect for 4 classes (Horse, Dog, Cow and Cat). As a result, the performance of the model was extended between 84.29% to 90.19% of accuracy to identify the Horse, Dog, Cow and Cat. In Table 4, we summarize the studies of the smart agriculture field dis-cussed above, which have included applications for Precision agriculture and Livestock Monitoring.

Overall, using DL models in SA has an effective contribution to detect the disease and improving the greenhouse, pits in plants and livestock as well, such as monitoring, classification, and detection the animals. They can benefit of integrate DL with IoT in many ways as checking weather conditions, soil quality, and more. SA suffered from challenges when integrate DL with IoT devices in term of robustness of sensors, energy efficiency, and cost-effectiveness. Table 4, we summarize the studies of the smart agriculture field dis-cussed above, which have included applications for Precision agriculture and Livestock Monitoring.

Table 4
Integrating of DL with IoT devices in Smart Agriculture Applications

Application	Work	Devices	Dataset	DNN	Purpose of DNN	Performance Result
Precision Agriculture	[48]	Unmanned Aerial Vehicle (UAV) with ASUS Tinker Board S embedded system	Custom dataset of rice and corn	Semantic Segmentation	Classify crops.	Accuracy: 89.44%. inference model: 0.7 s
Precision Agriculture	[49]	Nvidia Jetson TX2 device	DeepWeeds dataset	CNN and ResNet	Classify the weeds	Accuracy: 95.7%, Inference time: 18.7 FPS
Precision Agriculture	[50]	PYNQ-Z2 device	NBAIR dataset	CNN	Detecting the pests of cotton.	Accuracy: 95%. Inference time: 2FPS.
Green House	[51]	Raspberry Pi 4	Custom thrips dataset	TPest-RCNN	Detect the whitefly and thrips from sticky trap images	F1: 0.944 Precision: 0.952
Livestock Monitoring	[53]	Raspberry Pi 3	Custom animals' dataset	CNN	Classify the animals.	Accuracy: 90.19%.

4.2.4 Smart home (SH)

Smart Home (SH) is one of the applications which has ubiquitous computing, it considers a subset of everyday computing. It is an application domain that combines home automation and ambient intelligence. It includes smart technology to offer comfort, health, security, and energy reduction. To enhance the quality of the life of dwellers and optimize services [54,55]. SH enables the interconnection between a set of IoT devices via the internet, that collects and process the data to monitor and control functions in the home. Such as controlling air conditioning, lights and activity recognition [54]. In recent years, DL has conspicuous prosperity in processing intricate data in many fields in SH. The following section presents the studies that used DL and IoT in Human Activity Recognition and Indoor Localization.

i. Human Activity Recognition (HAR) and Anomaly Detection (AD):
Intelligent IoT devices in SH can be used to recognize and monitor Human Activity inside the home such as sitting, standing, walking, sleeping, and more of activities. The data for activity can be collected from sensors, actuators, images, and video frames [56]. Thereafter, processing of data using DL techniques. The activities for humans can be categorized into two physical and complex general activities. Physical activities, such as jogging, running, etc., can be recognized via the accelerometer and mobile or gyroscope wearable. Where-as complex general activity, such as drinking, eating, and taking medication can be recognized via ambient switch state sensors. Another aspect is anomaly detection. Anomaly detection refers to recognition of rare and unexpected deviations activities, which can be detected by the deviated patterns from activities standard pat-terns. The recognition of human activities and related anomalies can derive many benefits, particularly for the elderly [57]. Recently studies sprung up the role of DL

in HAR field [58] Xile Gao *et al.,* [55] performed HAR for learning the most crucial features that are required based on Stacking Denoising Autoencoder (SDAE) and LightGBM (LGB) on the four datasets. Four datasets were used as in Table 4, dataset contains different scenarios for human activities. The experiment results were 95.73% accuracy on HMMwithPre, HMMwithoutPre 93.70%, HDBD 96.31% and HSBD 98.22%. Another study applied DL approach to recognize HAR and detect AD inside the home. In Ref. [57], deployed a sensor in various locations in a home. A probabilistic neural network (PNN) has been applied to the pre-segment of data from sensors. Besides H2O autoencoder identifies the anomaly activities from the normal activities. Two datasets are used which are Aruba and Milan that include a variety of human activities. The results of the Aruba dataset showed the model achieved 90% of over-all accuracy. While the Milan dataset achieved 80% of overall accuracy. On the other side, for anomaly detection, the performance of the H2O autoencoder achieved more than 90% of accuracy in 9 out of 11 activities. Fangxin Wang *et al.,* [59], proposed a framework that combined the CNN and LSTM algorithms. In order to process and analyse the human activity data in spatial and temporal zone. Commercial WiFi cards were used to collect data and construct the dataset of human activities e.g., (Walking, Running, Falling, and Sitting). The authors applied models in the real word, where the performance of the model was an average of 96% of accuracy.

ii. Indoor Localization (IL)

Recently, Indoor Localization (IL) has become an essential part of daily activity for people with the proliferation of IoT devices. IL aims to locate the person inside the home by enabling many services. Several technologies were applied in IL to collect the data [60]. Newly, integrating DL with IL applications led to growing it rapidly. Using DL can predict the target indoor location in real-time accurately. Mingyang Zhang *et al.,* [61] introduce a novel framework based on indoor magnetic location using an android smartphone. Authors pro-posed LSTM to address the problems that occurred in existing approaches such as time-consuming prediction. In addition, it used the double sliding window-based dimension scheme. To evaluate the model, they conduct a set of real experimental scenarios on both PC and smartphones. The performance of the proposed model was 0.53 m which reduced 58% of the average error in comparison with DTW. Furthermore, authors [62], pro-posed a model to track a person moving in a complex indoor environment using BLE signals. The proposed novel methods use CNN positioning models based on the 2D image. It composed of the received number of signal indicators from both x-axes and y-axes. Besides used the Particle Swarm Optimization (PSO) algorithm to optimize the weight layers of CNN. The performance of the experiment showed the optimized CNN model achieved high performance in comparison with other ML algorithms on thirteen beacons. The accuracy of the model was 97.92% and a 2.8% of error rate for tracking the person’s location inside a complex building.

Generally, used the IoT and deep learning in SH application provides solution to home service particularly in two field that we mentioned above, such as assistance in daily tasks and health care monitoring. SH suffer from pattern identification especially in extract the features from complex activities and time series classification. Table 5 shows the summary of the main results for the performance of previous studies in smart home field. Along with demonstrating the IoT devices, datasets, deep learning models, and purpose of deep learning models used.

Table 5
Integrating DL with IoT devices in Smart Home Applications

Applications	Work	Devices	Dataset	DNN	Purpose of DNN	Performance Result
HAR	[55]	-	-HMMwithPre dataset HMMwithoutPre dataset -HDBD dataset -HSBD dataset	SDAE and LGB algorithms	Recognition of human activities	Accuracy:95.73% Accuracy:93.70% Accuracy:96.31% Accuracy:98.22%.
HAR	[57]	Sensors	-Aruba dataset -Milan dataset	PNN and H2O autoencoder	Identify the normal and anomaly of human activities	HAR: Overall Accuracy: 90%. Anomaly detection: Accuracy: 90%.
HAR	[59]	WiFi cards	Real-Time	CNN and LSTM	Recognition of human activities	Average Accuracy: 96%.
IL	[61]	Android-Smartphone	Real-time	LSTMs	Locate a location in indoor	Response time: 0.53 m. Average Error: 58%
IL	[62]	BLE sensors	Real-Time.	CNN and PSO	Tracking persons in indoor	Accuracy: 97.92% Error rate: 2.8%

5. Challenges of Integrating DL with IoT devices in Smart Cities

Recently, deep learning achieved remarkable breakthroughs in recent years in processing and analysing IoT devices data in smart cities. As well, it outperforms the performance of other algorithms as computer vision in many SC applications. DL models achieved high accuracy and low rates of error in prediction. How-ever, Due to the powerful perception capability of integrating deep learning with IoT devices but has many challenges. Wherein, in some SC applications, DL models cannot be achieved adequate solutions. Based on the previous studies we derived, there are some challenges in integrating deep learning with IoT devices in smart city applications as depicted in both Figure 5 and the following subsections:

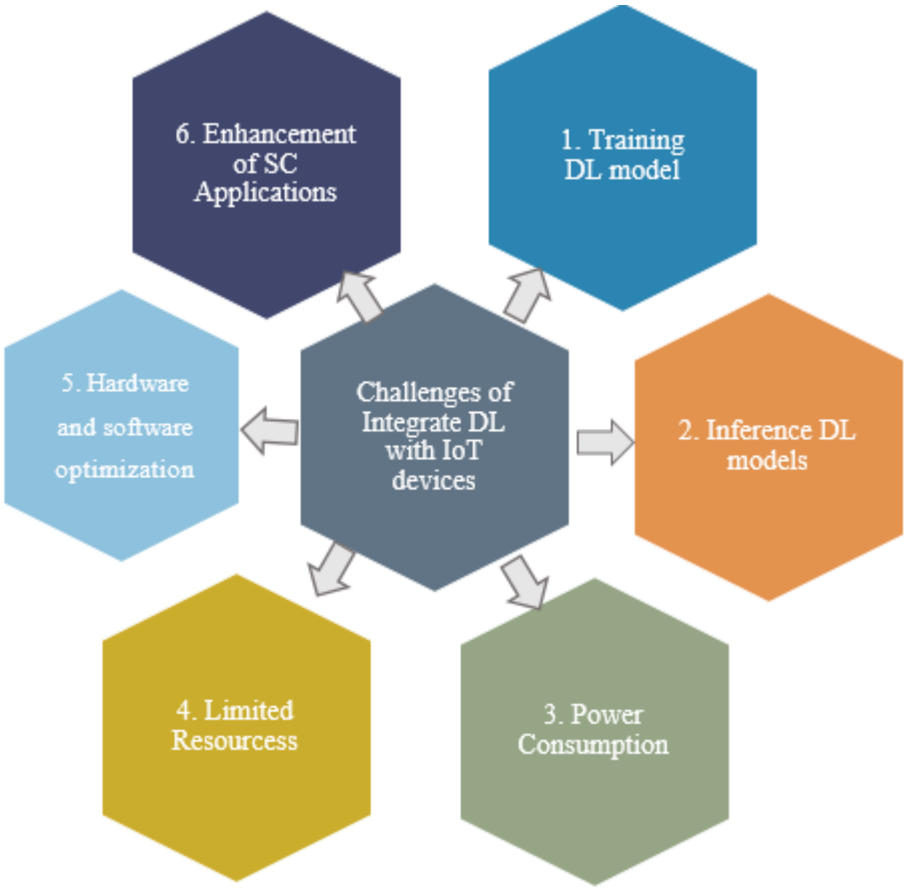

Fig. 5. Challenges of Integrating DL with IoT devices in smart cities

5.1 Training Deep Learning Models

Training DL models is one of the big issues for IoT devices in SC. Training DL models means extracting the key features that in turn required heavy-weighted DL models. It is often a complicated task and computationally expensive, consuming massive CPU and GPU resources, time, memory, and energy. While IoT de-vices usually have limited resources as limited computation power, memory and battery life which are not cost-efficient, to solely take the model training tasks [4,64,65]. For instance, in [66] present the training DL model is the main challenge of integrating DL with industries internet of things (IIoT). Numbered surveys and review studies discuss the training DL model is a major challenge in integrating DL with IoT. In the previous studies [7, 64-69] present the complexity of training DL model which required extra effort and consumed resources as considerable storage that effect the performance of DL. In addition, IoT servers at least are not cost-efficient, to just take the model training task. In addition to required large datasets.

Most of the studies in smart city applications used CNN models or hyper of DL models or used CV algorithms with DL models. In order to, process data from IoT devices and obtain high performance. For instance, in the previous studies [29,49-51,53,59,62] used CNN model which hierarchical structure and complex computation. Hyper models pose also significant challenge once integrate with IoT devices due to heavy-weight.

5.2 Inference of Deep Learning Models

Due to complicated architectures of DL model which are not suitable for IoT devices. Therefore, perhaps occurs the delay of long inference DL models. DL models are often deployed in a centralized cloud to process raw input data from IoT devices that are distributed in different regions in SC. Which causes the lateness in response time that may not be suitable to real-time applications in SC, especially to critical application as emergencies [54,65]. The authors on study [7] presented state-of-the-art studies of the challenges of learning on mobile and embedded devices. They explained that running DL models on them poses a significant challenge, whereas the mobile and embedded devices have constrained resources. As well in studies [36,64] surveyed the deploying DL on IoT devices in various applications in SC.

They showed most of the applications in SC deployed DL models in the cloud and received the raw input data from the distributed IoT devices. As we mentioned in SC applications the smart environments and smart homes fields used IoT devices to sense data then transfer data to DL models that deployed in cloud computing to perform processes on raw input data from distributed IoT devices in SC. On other hands, other studies [29,39,41,51,53] deploys DL models completely on the devices but as used IoT devices that have large resources such as smart camera with RPi4, RPi3, PYNQ-Z2 Board, Raspberry pi2, and so on.

5.3 Power Consumption

Power consumption is one of the significant challenges in deploying DL models on IoT devices in SC. Since running DL models on devices consumed a lot of power. While the energy capacity of IoT devices is limited and they have a short lifetime. Therefore, taking into consideration the performance of IoT devices is far less powerful compared to servers in data centres [20]. For instance, [70] discovered that power is a challenge for accident detection systems based on IoT for smart vehicles in SC. They suggest introducing mechanisms to IoT devices that will consume less power. However, some devices can’t be charged so they must be replaced after some time [65].

5.4 Limited Resources

IoT devices have limited resources including battery power, small memory, and computation unit. The massive computation of DL will consume a substantial quantity of resources. Due to DL models consists of dozens of convolution layers, that in turn prohibitive energy consumption and considerable storage space that are not affordable for IoT devices. Thus, poses challenges for deployed DL on IoT devices in SC [54]. However, in previous studies address this challenge twofold: first, make the IoT devices as data collector. Second, try to reduce the complexity of DL architectures to let IoT devices execute some of the learning tasks [65].

5.5 Hardware and Software Optimization

Deploying DL on the IoT devices in SC has a challenge in terms of hardware, software and programming abstraction constraints. Most of the existing software platforms are designed for special hardware architecture. In addition, most of them were designed for the cloud-based computing paradigm [65]. Since the performance of DL on IoT devices is different compared to the performance of cloud computing. Due to the hardware and software constraints. Du *et al.,* [71] proposed the streaming hardware accelerator for Cortex-M micro-controllers, in order to better performance of CNN on the end devices. On another end, for the software constraints many corporations proposed their software platforms or services to support the learning on the end IoT devices e.g., Amazon, Microsoft’s Azure IoT Edge, and Greengrass. For the programming abstraction, recently some of the frameworks are designed to support the deploying DL on IoT devices e.g., CoreML, and Tensorflow Lite. Although with existing software platforms and frameworks, none of the existing solutions support the offload of DL on IoT devices with low consumption of resources. there is still a need to IoT of effort to integrate DL with IoT devices. In order to achieve high performance on applications in SC [65].

5.5 Enhancement of SC Applications

Integration of DL with IoT devices achieved remarkable improvement in many SC application scenarios. Most SC applications are still designed based on cloud computing, which poses challenges, particularly for critical applications which need low delay and rapid response time. Most of these applications need real breakthroughs. Autonomous driving and Real-time VR gaming are the two most representative applications [65].

IoT studies have been carried out over the course of the past few years for the IoT and DL in SC. Using integrated DL with IoT in SC has opened several new studies avenues and challenges for SC. Table 6 provides challenges that were previously detailed in integrating DL with IoT in SC in a number of recent studies reviews and survey studies.

Table 6
Challenges of integrating DL with IoT in smart cities

References	Training DL models	Inference of DL	Power Consumption	Limited Resources	Hardware and software optimization	Enhancement of SC applications
[8]	√	-	-	√	-	-
[7]	√	√	-	√	-	-
[72]	√	-	√	√	-	-
[20]	√	-	√	-	-	-
[65]	√	√	-	-	√	√
[54]	√	-	-	√	-	-
[4]	√	√	-	√	-	-
[64]	√	-	-	-	-	-
[66]	√	√	-	√	-	-
[67]	√	√	√	√	-	-
[68]	√	-	-	-	-	-
[73]	-	-	-	√	-	-
[74]	√	√	-	-	-	-
[69]	√	-	-	-	-	-

6. Future Research Directions

The challenges of integrating IoT with deep learning in SC discussed in the aforementioned section, revealed great plenty of opportunities and promising fertile ground for future research directions. This section indicates the future research directions of DL models when integrate with IoT devices in SC:

i. Recently, DL models tended to be deeper and deeper making the learning processes extremely hard. Transfer learning is promising direction in which the model learned the features from the previous model. Thus, many ameliorations are provided once using transfer learning. Boost the performance accuracy of the models. As well as decrease the training cost of DL models since the training data are already collected from many sources.

Which in turn, provides high performance along with decrease in latency response time in SC applications. Specially in health applications as elderly care applications.

ii. At present, most DL models deploying in IoT devices in SC are supervised, which required high volume of training data, which is poses a challenge, once these data are limited size or not available. Therefore, there is a need to design semi-supervised or unsupervised DL models.
iii. Design lightweight DL models that achieve accurate performance, to enable inferencing into IoT devices in SC that have limited resources.
iv. Enable off-line training DL modelling on devices that have limited resources, as few kilobytes of memory, computational power, and have a long battery life to enable processing data near devices, which is the main demand for SC applications.
v. There is a need to develop general environment platform software for enabling deploying DL models into different hardware from different corporations.
vi. Improve SC applications not based on Cloud computing, especially for critical applications that need low delay and rapid response time.
vii. Develop and enhance SC applications in new recent areas as: water quality and distribution [75-77], smart factory lighting and electromechanical impedance damage solutions [78,79], artificial intelligence with IoT technologies [80-83], energy efficiency [84-86], sustainable power generation [87-89], and drone monitoring [90].

7. Conclusion

The evolution of IoT along with DL technologies has had a great impact on the development of SC applications. Which turned the idea of an SC into reality. Although the advantages of integrating IoT with DL in SC pose challenges. To that end, this paper presents an overview of the main terms; smart cities, the role of IoT in smart cities, and deep learning. Next, we shed light on the integration of deep learning with IoT and their impact on developing smart cities applications. Followed by reviewing state-of-the-art studies on the integration of IoT with DL in various smart city applications fields including smart environment, smart transportation, smart agriculture, and smart home. We summarize the finding of each study including the IoT devices used in the studies, datasets, deep learning models, and the results of the performance based on the different metrics. More specifically, based on previous studies we highlight the challenges faced integrate DL with IoT in smart city applications. Finally, we indicate the future research directions of integrating DL with IoT in smart cities. Since an urgent need for solutions that enable the integration of DL with the IoT easily for optimized the quality of life in SC. We hope this paper is able to present more discussion and inspiration for the integration of IoT and DL in SC applications to facilitate the deployment of DL models on IoT devices in SC. As well, we anticipate that this paper will present the points for the other researchers that investigate the field of integrating DL with IoT in SC.

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