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Exploring the Landscape of Deep Learning Techniques for IoT Data: A Systematic Literature Review

Ansarullah Lawi [a], Aulia Agung Dermawan [b], Dwi Ely Kurniawan [c,*] Ivan Muhammad Reza [d], Feberlian Elisabeth Gulo [b], Zainal Arifin Hasibuan [e]

[a] Department of Industrial Engineering , Institut Teknologi Batam, Indonesia
[b] Department of Engineering Management, Institut Teknologi Batam, Indonesia
[c] Department of Informatic Engineering, Politeknik Negeri Batam, Indonesia
[d] Faculty of Computer Science, Universitas Dian Nuswantoro, Semarang, Indonesia
[e] Faculty of Engineering and Computer Science, Universitas Komputer Indonesia, Bandung, Indonesia
Corresponding author: [*]dwialikhs@polibatam.ac.id

Abstract*—The rapid evolution of software, hardware, and internet technology has enabled the proliferation of internet-connected sensor tools that gather information and observations from the physical world. The IoT comprises billions of intelligent devices, extending physical and virtual boundaries. However, traditional data processing methods face significant challenges in handling the vast volume and variety of IoT data. This paper systematically reviews. These devices generate vast amounts of data daily, with diverse applications crucial for generating new knowledge, identifying future trends, and making informed decisions. This underscores IoT's value and enhances technology. Deep learning (DL) has significantly enhanced IoT and mobile applications, demonstrating promising outcomes. Its data-driven, anomaly-based approach for detecting emerging threats positions it well for IoT intrusion detection. This paper proposes a comprehensive framework leveraging DL techniques to address data processing challenges in IoT environments and enhance intelligence and application capabilities. Furthermore, this study systematically reviews and categorizes existing deep learning techniques applied in IoT, identifies critical challenges in IoT data processing, and provides actionable insights to inspire further research in this domain. It discusses the introduction of IoT and its data processing challenges and explores various DL approaches applied to IoT data. Significant DL efforts in IoT are surveyed and summarized, focusing on datasets, features, applications, and challenges to inspire further advancements in this field.

***Keywords*— IoT; deep learning; data processing; anomaly detection; literature review.**

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I. INTRODUCTION

Smartphone, sensor, and actuator technologies have improved application intelligence, enabling devices to communicate and perform complex tasks. However, the exponential growth of IoT data hpas surpassed traditional processing capabilities, requiring innovative approaches like deep learning to address challenges such as scalability and real-time analytics. Current machine learning approaches often fail to address the challenges of data volume, variety, and velocity inherent in Internet of Things (IoT) systems, leading to inefficiencies in processing and analysis. Furthermore, there is a lack of integrated frameworks that combine deep learning techniques to unlock the full potential of IoT data in diverse applications. Be that as it may, in 2008, the number of devices connected to networks exceeded the total number of people on the planet. Since then, it has been growing exponentially [1]. In the present age of the IoT, a wide range of devices—including smartphones, integrated systems, wireless sensors, and almost every other sort of device—are linked together via local networks or the internet [2]. The rapid use of IoT technology, such as smartphones, sensor networks, unmanned aerial vehicles (UAVs), cognitive smart systems, and other related breakthroughs, has fueled the creation of various unique mobile and remote applications [3], [4]. New technologies are being created to analyze this data, providing actionable insights and informed decision-making. However, efficiently processing and analyzing the ever-increasing amount of IoT data remains a significant challenge. Existing solutions often struggle with the complexities of data heterogeneity, real-time processing, and scalability, which are critical for IoT systems. Addressing these challenges is essential to enable IoT applications to meet current and future demands across various sectors. This is taking place as the quantity of data collected by those gadgets and the sheer amount of devices continue to grow. The implementation of artificial intelligence ("AI") strategies, such as Machine Learning (ML), and Deep Learning (DL), has been made possible as a consequence of this breakthrough. However, the lack of comprehensive approaches to integrating deep learning techniques into IoT applications limits the ability to address the challenges of big data processing, scalability, and real-time analysis challenges. This study aims to bridge this gap by proposing an integrated framework leveraging deep learning techniques to address these pressing challenges. This study makes several significant contributions to IoT and deep learning. First, it systematically reviews and categorizes state-of-the-art deep learning techniques applied in IoT environments, providing a structured overview for researchers and practitioners. Second, it identifies critical challenges in IoT data processing, such as heterogeneity, scalability, and real-time analytics, and highlights potential solutions leveraging deep learning. Third, this paper proposes a novel framework that integrates deep learning to address these challenges effectively, offering a practical approach to enhance IoT application performance. Lastly, it provides actionable insights and identifies promising research directions to advance the intersection of IoT and deep learning

Our method uses a comprehensive workflow model that covers data acquisition, processing, display, and assessments, as shown in Figure 1 [5].

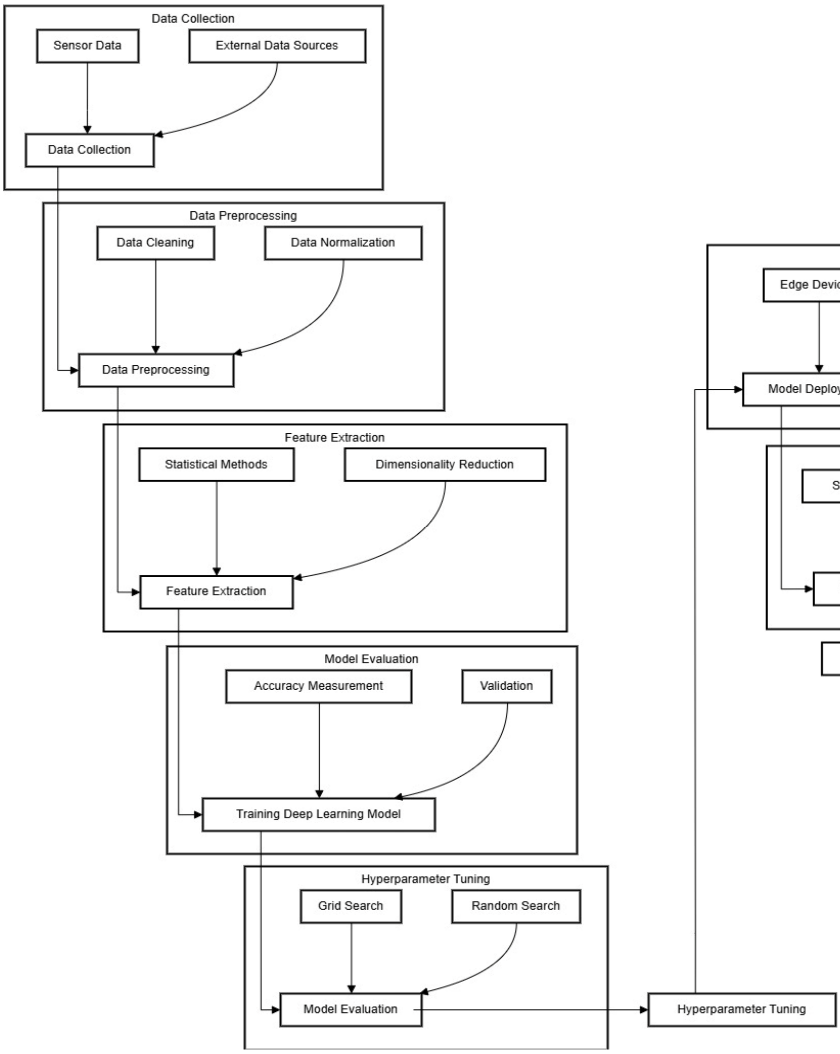

Fig. 1 Workflow Model for Deep Learning in IoT Data Analysis

Utilising this methodology allows for developing Internet of Things apps that are both effective and efficient. Data analysis has typically depended on technical knowledge and machine learning methods such as logistical regression, support vector regression, and random forests for tasks including traffic forecasting [6], tracking of vehicles [7], and shipment time estimate [8]. These approaches have been used for a variety of applications. This is because data analysis is a crucial component that requires a significant amount of computational power. On the other hand, traditional methods often fail to handle the enormous amounts of volatile and unpredictable data created from various Internet of Things databases in this era of "big data." Traditional techniques often emphasize the fundamental characteristics of the subject matter and rely significantly on previous expertise in specific areas. Therefore, advanced methodologies are needed to manage IoT data efficiently. This research identifies a critical gap in integrating deep learning techniques with IoT applications, particularly in addressing data heterogeneity, real-time processing, and scalability. By addressing these issues, this study aims to provide a comprehensive framework that enhances the intelligence and efficiency of IoT applications. Most learning algorithms in these systems use shallow structures, severely restricting their modeling and representational capacities.

The ability to accurately explain and comprehend data is of the highest significance due to this consideration. For this purpose, there is a pressing requirement for statistical instruments that are more successful to fully utilize the possibilities of the initial information that is provided by a broad range of applications that are connected to the Internet of Things. According to a study that McKinsey carried out on the subject of the international economic consequences of the IoT, it is anticipated that the IoT would have an impact on the global economy that is likely to range around \$2.7 trillion and the amount of \$6.2 trillion by 2025, according to the study. [9]. Following the industrial sector, which is forecast to contribute 33% of the overall effect, and the oil industry, which is anticipated to contribute 7% of the total impact, the healthcare sector will likely be the most major contributor, accounting for 41% of the entire impact. Furthermore, transportation, irrigation, public infrastructure, security, and commerce combined account for more than fifteen percent of the Internet of Things business [10].

According to these forecasts, the Internet of Things ecosystem will undergo significant and fast expansion, particularly regarding the services, data creation, and associated demand related to the ecosystem. Machine learning is the automated process by which computers amass knowledge to execute complex analyses, make accurate evaluations, and design novel problem-solving solutions [11]. In addition, the paper by McKinsey dives into the economic repercussions of machine learning. Within this paper, the primary factors that are responsible for these technical developments are investigated. Particularly noteworthy is the fact that developments in machine learning, such as deep learning and neural networks, have made it possible to automate the processing of large data sets. The use of this automation is essential for the production of significant insights and the improvement of decision-making procedures.

Machine-to-machine (M2M) interactions are made possible by various communication technologies essential to deploying Internet of Things devices. Systems like Wi-Fi, Bluetooth, and ZigBee are technologies that make communicating easier across shorter distances. Conversely, long-range communication may be performed by many mobile networks, including Sigfox, LoRa, M1 CAT, GSM, 4G, LTE, and eventually 5G networks [12]. These various communication methods are essential to ensure that Internet of Things devices can function without interruption and remain connected across various applications and settings.

To keep the Internet of Things devices affordable, it is essential to accomplish key features like data gathering and machine-to-machine (M2M) interactions. Because of the continual acquisition and distribution of vast quantities of information by IoT devices, there is a significant link between the notion of "big data" and the IoT [13]. This is because they both collect and distribute information. One of the most important aspects of Internet of Things design is the ability to effectively manage, organize, and analyze these vast data streams [14]. AMQP, MQTT, CoAP, and HTTP are some protocols that have made it easier for machines to communicate. This has enabled Internet of Things platforms such as Thingsboard, Thingspeak, DeviceHive, and Mainflux to be integrated into Internet of Things infrastructures [15], [16].

Edge computing is essential to the IoT since it entails data processing directly on Internet of Things devices under certain circumstances. However, because of the limits of low-end Internet of Things devices, it is necessary to use intermediate nodes, sometimes known as "fog nodes," to undertake complicated processing jobs closer to the network's edge. This strategy considerably reduces the burden of moving data to other cloud nodes for additional processing. After some time, the data is saved in cloud storage and submitted to more complex analyses employing machine learning (ML) and deep learning techniques. Through this approach, intelligent apps with expanded capabilities that can be distributed across many devices may be developed. [17], [18], [19].

Since deep learning solves the constraints of standard machine learning approaches in terms of satisfying the requirements of IoT systems, it has received a large amount of interest due to its considerable analytical capabilities. Even though there have been significant developments in the IoT, the use of deep learning technologies in IoT settings is still in its early phases. Several researchers have performed reviews on a variety of topics, including the application of deep learning techniques in the IoT for the analysis of big and streaming data [20], the use of machine learning techniques in sensor networks with wireless connections (WSN) [21], the application of deep learning in the medical field [22], and the use of deep learning (DL) algorithms for intelligent advancement [23], [24]. Although there is a noticeable absence of comprehensive evaluations that extensively analyze the wide variety of Internet of Things devices that use deep learning, there is an apparent absence of such assessments.

This publication thoroughly reviews the most recent research achievements and underlying ideas in using deep learning methods to improve the Internet of Things or IoT programs. Deep learning has a wide range of applications, which are shown in a variety of fields. These fields include safety monitoring, illness analysis, urban localization, intelligent control, traffic estimation, domestic robots, drive automation, defect assessment, and factory inspection. In addition, this paper investigates the difficulties and problems that arise when implementing deep learning software for Internet of Things applications and suggests possible research avenues that should be pursued to progress this promising topic. The organization of this document's structure may be summarised as follows: In the second section, a comprehensive examination of effective architectures for deep learning and cutting-edge deep learning approaches is presented. This section also provides an extended overview of various deep learning neural network (DNN) architectures with various applications. In the third section, we investigate the use of deep learning in the IoT across various industries, such as intelligent towns and cities, education, manufacturing, medicine, transportation information systems (ITS), and agriculture. We also discuss the unique issues connected with these types of industries. The text's conclusion is presented in

Section 4, which summarises the most important results and suggests topics that should be investigated further.

The purpose of this document is to provide a comprehensive and in-depth review of the most current developments in research and underlying concepts. This text's primary emphasis is on using deep learning methods to improve the efficiency and capabilities of IoT systems. The practical applications of deep learning have been proven in a wide variety of fields, including but not limited to the following: safety monitoring, illness analysis, indoor localization, synthetic control, traffic estimation, domestic robots, drive automation, defect assessment, and factory inspection. In addition, this article goes into the many difficulties and problems that occur when deep learning is used in Internet of Things contexts and suggests prospective research avenues that should be pursued to progress this promising topic further. The following makes up the document's structure: This section thoroughly reviews several deep neural networks, also called structures with broader applications. It assesses efficient deep learning designs and the most recent deep learning approaches. In the third section, we study the use of deep learning in the IoT across a range of industries, such as cities that are smart, education, manufacturing, medical care, intelligent transport systems (ITS), and agriculture. With this investigation, we address the distinct issues that are present in each of these fields. In the last section of the publication, Section 4, a summary of the most important results and some suggestions for areas that may be the subject of further study are presented. This study proposes a systematic workflow model integrating deep learning architectures to address critical challenges in IoT data processing, including anomaly detection, big data management, and efficient distributed training

The application of deep learning (DL) techniques in IoT has gained significant attention due to their ability to efficiently process and analyze large volumes of data. Previous studies have focused on various aspects of IoT and DL integration:

A. DL in IoT for Healthcare

Researchers have explored DL for health monitoring and diagnosis. For example, Bordoloi et al. [22] highlighted using DL in healthcare to enhance service quality, specifically focusing on patient monitoring systems. However, their work does not address real-time analytics, a critical requirement for healthcare applications.

B. DL in Smart Cities

Smart city applications extensively utilize IoT and DL. Studies by Tanwar et al. [23] examined streaming data analytics for smart cities. While their methods are promising, the scalability of these solutions remains a challenge in large-scale implementations.

C. Big Data Analytics in IoT

Mohammadi et al. [20] surveyed DL techniques for big data and streaming analytics in IoT, identifying key challenges such as data heterogeneity and processing latency. Their review, however, lacks a structured framework to address these challenges.

D. DL Techniques for IoT in Agriculture

Gupta et al. [25] proposed IoT-enabled smart farming systems utilizing DL for soil quality monitoring. While this approach shows potential, it is constrained by limited computational resources in rural areas. Despite these advances, there is a noticeable lack of comprehensive frameworks integrating DL techniques to address IoT challenges, such as scalability, real-time processing, and data heterogeneity. This study addresses these gaps by proposing an integrated framework that leverages state-of-the-art DL techniques.

II. Material and Method

A. Deep Learning Techniques

It is of the utmost importance that stakeholders maintain a complete grasp of the IoT and the enormous amounts of data that it creates. This understanding should include the relevance of the IoT, as well as its essential components, possibilities, and problems. There are two aspects to the link between the IoT and big data: first, the IoT makes a substantial contribution to the creation of enormous amounts of data; second, the goal of considerable data research is to improve the services and processes that are associated with the Internet of Things [25]. Because research has proved the significance of the Internet of Things big data to society, it is vital to investigate the distinctive characteristics of IoT data and how they vary from conventional big data to properly establish the needs for IoT data analytics [26], [27].

At present, there is an ongoing discussion over the superiority of deep learning (DL) over traditional machine learning (ML) methodologies, especially concerning the advantages that DL provides in IoT applications [28], [29]. Deep learning has an extraordinary potential of extracting detailed patterns from vast amounts of unprocessed data spread across various Internet of Things applications [30]. This is in contrast to the classic machine learning approaches that are currently in use. The ability to analyze data is highly impacted by the complexity and variety of structures that learning models, particularly convolutional architectures, possess. Therefore, it is predicted that deep learning models would display improved performance in situations involving significant volumes of data. Still, standard learning models may have difficulties managing the large amount of data being presented to them. Because of its end-to-end approach, deep learning can autonomously gather and extract useful features from raw data. This is made possible by eliminating the requirement for manually produced applications requiring much time and effort to construct. The rise in popularity of deep learning models over the last several years may be attributed to the autonomous feature extraction that has been taking place.

Deep learning is a sophisticated approach for training multi-layered neural networks that has broadened the bounds of artificial intelligence and increased the quality of interaction between people and computers. One of the most significant changes that deep learning has brought about in the field of machine learning is the profound transformation that it has brought about. Deep belief networks (DBNs) and convolutional neural networks (CNNs) have both been shown to have a high level of accuracy in tests that were conducted using the MNIST and real-life handwritten character databases [31]. A semi-white box scenario, in which just the structure and parameters of the system model are known but not the user data, has been demonstrated to offer significant hazards [32]. The effect of membership inference attacks (MIA) on deep-learning-based face recognition systems has been shown to pose significant dangers.

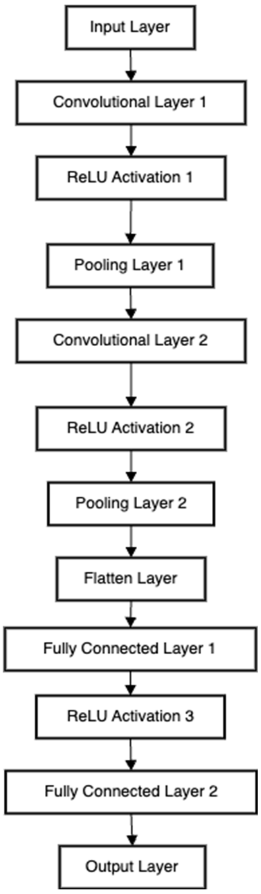

Fig. 2 Neural Network Structure in Deep Learning

Deep learning methods are used extensively in various fields, including predicting time series, managing large datasets, and completing computationally tricky tasks such as detecting picture patterns and identifying speech [33], [34]. Although it needs skilled computer skills and much work for model training, deep learning has gained favor as a data processing and modeling approach in this age of big data. Additionally, it has gained popularity in recent years. Thankfully, these issues have been overcome by the advent of powerful graphics processing units (GPUs), making it possible to train deep learning models effectively. Functionality estimate may be automated by using dense layer configurations in DL approaches, which eliminates the requirement for human feature computation and extraction. These approaches have been used by researchers to measure and analyze EEG characteristics to get a better understanding of the neurological abnormalities that are brought on by strokes [35]. Additionally, biomarkers have been utilized to differentiate between people who have had an ischemic stroke and those who are in good condition [36], [37].

Deep learning models provide considerable gains over traditional machine learning techniques during either the learning or forecast stages. These benefits include reducing the requirement for human guidance and the autonomous extraction of less noticeable elements [38], [39]. Supervisory learning, in which models are trained on data that has been labeled, and unsupervised learning, in which models are trained on data that has not been labeled, are the two primary categories used in machine learning.

B. Learning Through Supervision

The process of constructing a system model using a labeled training set is known as supervised learning. The backpropagation approach is the most common strategy used in supervised learning. This method modifies the weights of the model depending on the amount of inaccuracy it produces in its predictions [40].

C. RNNs, which stand for recurrent neural networks

Recurrent neural networks, often known as RNNs, have been conceptualized to handle sequential and time series data efficiently. Recurrent neural networks (RNNs) are suited for applications that are reliant on input sequences because they take into account prior inputs in their calculations. Every neuron that makes up an RNN has an innate memory function responsible for storing and maintaining prior data estimations. Backpropagation across Time (BPTT) is a method of training recurrent neural networks (RNNs) that differs from regular backpropagation in that it involves unrolling the network across time to compute gradients [41], [42]. Recurrent units with gates (GRUs) and LSTM networks, which stand for Long Short-Term Memory, are two examples of creative techniques that have been developed to solve the limitations of recurrent neural networks (RNNs) [43], [44]. These constraints are caused by gradient diffusion and a longer-term dependence.

D. Memory for the Long-Term and Short-Term (LSTM)

A form of recurrent neural network (RNN) known as LSTM networks is beneficial for managing data that is time-stamped, sequential, and reliant on the long term [46]. To govern the flow of facts, LSTMs make use of unit gates [47]. This enables them to recall pertinent material while simultaneously dismissing inputs that are irrelevant. Feedback chains, recall gates, read gates, and writing gates are all components of this architecture that are responsible for managing data access and memory maintenance. In tasks that require a sustained temporal dependence, LSTMs perform better than typical RNNs [48]. Additionally, LSTMs have been effectively used to anticipate sequences and labeling tasks according to Song et al. [49], Safaei et al. [50], Gers and Schmidhuber [51], and Han et al. [52].

E. CNNs (Convolutional Neural Networks)

The primary applications of CNNs are in the areas of recognition of images and classification. Some hidden layers, including layers of convolution, layers of pooling, and fully connected layers, are included in their composition. Additionally, they include an input layer and an output layer. While extracting high-quality features from the input data, the convolutional layers apply filters to the data, while the pooling layers lower the dimensionality of the data. Conventional neural networks (CNNs) are able to effectively analyze two-dimensional input data and overcome the issues that highly connected neural networks encounter while performing vision-based tasks [53], [54], [55].

Deep neural networks are based on transformers, which are sequence-to-sequence neural network designs that rely on self-attention processes to capture global relationships in data [56]. Transformers are used to understand and analyze data [57]. NLP, natural language processing, and computer vision are two areas in which they have become more prominent [58]. The transformer-based model known as BERT has shown state-of-the-art performance in various natural language processing applications. Transformers have recently been used in the process of picture classification and object recognition, which has resulted in the simplification of these jobs by removing the need for components that were developed by Wang et al. [59], Özçift et al. [60], Sánchez et al. [61], and Zhang et al. [62].

F. *Learning Without Supervision*

Unsupervised learning is a very useful when dealing with large volumes of unlabeled data. Methods such as stacked restricted Boltzmann devices (RBMs) and autoencoders with stacks are used for training. These methods enable initialization, reverse propagation, and global adjustments. Without the need for labeled outputs, these strategies make it possible for models to learn the underlying data structures [63], [64].

G. *Autoencoders, often known as AEs*

Neural networks intended to transfer input information for output data are called autoencoders. This allows for the successful extraction of features and the reduction of the amount of the data. Specifically, they are made up of an encoder that converts the data entered into an unnoticed image and a device called a decoder that restores the data input from the disguised representation. As a result of their ability to reconstruct the input at the output stage, autoencoders are used widely in diagnostics and defect diagnosis. This is because they provide valuable insights into the structure of the data that lies under the surface [65], [66], [67].

H. *Machines created by Boltzmann (RBMs)*

Feature extraction, dimensionality reduction, and data categorization are all aspects that may be accomplished using RBMs, which are generative models. These probabilistic graphical models have a bipartite structure, allowing them to link visible versus hidden neurons without requiring connections between internal layers. In deep belief networks (DBNs), recurrent neural networks (RBMs) are trained to optimize the probability of products belonging to visible units. They serve as the backbone of DBNs. RBMs are comparable to autoencoders' ability to measure latent parameters for data reconstruction [68].

I. *Deep Belief Networks, often known as DBNs*

An example of a generative approach is the DBN, which combines fundamental unsupervised networks such as RBMs and AEs. Layer by layer, they are taught, with each hidden layer acting as the visible layer for the subsequent layer in the training process. Deep neural networks (DBNs) are a relatively quick and effective method for deep learning. They combine supervised and unsupervised training to produce robust models. The first phase is centered on the processing of data with unidentified information. At the same time, the following step is concerned with bringing DBN and labeled data into harmony to achieve optimum solutions. Done by both Wang et al. [69] and Zhang et al. [70].

The purpose of this in-depth analysis is to emphasize the relevance of deep learning methods in improving Internet of Things applications, to illustrate their potential across a variety of sectors, and to emphasize the need for continuing development and research in this promising subject

III. Result and Discussion

A. IoT *Applications* and Challenges

Data analysis is an essential component of the IoT. This section explores the distinctive qualities of IoT data, investigates its many uses, and examines the most critical concerns and obstacles associated with advancing IoT data analysis, with a specific focus on deep learning.

B. *Indicators of Internet of Things Data*

Data is the foundation upon which knowledge extraction is built, highlighting the importance of access to high-quality information. IoT, which stands for the Internet of Things, is a complicated paradigm with properties that vary from one area to another [71].

One of the most important aspects of the Internet of Things is connectivity, which makes it possible for everyday devices to be included in a linked network. By integrating smart devices and apps into a single network, this connection makes it easier for devices to communicate with one another, which in turn helps to cultivate collective intelligence within the Internet of Things ecosystem and generates new business prospects.

C. *Dynamic Data Collection*

The Internet of Things entails collecting data from the physical environment, necessitating several devices undergoing complicated transitions. These devices possess characteristics that allow them to constantly transition among states, including sleep, wake-up, connection, and separation. Furthermore, they can adapt to diverse conditions such as temperature, speed, place, and user interactions.

Sensors are critical in the IoT since they can detect and measure changes in the surrounding environment [72]. They provide rich data that offers real-time insights into various systems and how those systems interact with themselves and their environment. Integrating IoT sensors with machine learning algorithms has revolutionized health informatics systems. This combination has enabled the identification of problems such as heart failure, lung infections, and brain activity [73].

D. *Applications in a Wide Range of Domains*

Sensors have applications in a wide range of domains, including actions that people do daily. Multiple sensors, for example, perform essential tasks in an Automatic Aircraft Control System. These tasks include controlling the aircraft's speed, monitoring its height, tracking its location, checking the state of its doors, avoiding obstacles, monitoring its fuel level, and managing navigation. Computers analyze these sensors' data to arrive at judgments based on set values.

E. Considerations Regarding Security

It is of the utmost importance to guarantee the safety of endpoints, networks, and data moving across the Internet of Things network, which calls for a strong security architecture. IoT intelligence is accomplished by combining smart computing methodologies, software, and hardware. IoT intelligence primarily emphasizes device interactions instead of conventional input methods and visual user interfaces that cater to human-system interactions.

A few qualities have been characterized from some angles concerning big data in the IoT [74]. These characteristics include volume, velocity, and diversity. Specifically, the 6V characteristics may be characterized when applied to the context of big data in the IoT [75]. The data flood is caused by the IoT, which creates a vast quantity of data, with billions of devices contributing to it.

1) Velocity: To keep up with the rapid development of Internet of Things data, it is vital to have access to both efficient and real-time data. The IoT data comprises a wide range of forms, such as text, video, audio, and sensor data, which may be composed of organized or unstructured information. To get exact analytics and trustworthy insights, the data collected by the IoT must be accurate, consistent, and reliable. Data flow rates in the IoT fluctuate depending on the applications being used, resulting in the generation of data components that may alter with time, location, and user interactions.

2) Value: Transforming IoT big data into usable information provides organizations with several benefits, including the ability to make informed choices and increase operational efficiency.

F. Utilising Internet of Things Devices for Deep Learning

An explosion in the number of IoT datasets has occurred due to the growing availability of powerful IoT frameworks and open-source libraries [76]. These datasets include various data kinds, including text, tabular data, audio, and video. These datasets are produced by various hardware devices that function in multiple locations, such as sensors in smart cities, organizational fields, and augmented reality and virtual reality practice centers. A distributed training system that can quickly expand across millions of IoT devices while optimizing hardware resources is required to effectively train high-quality, extensive datasets of the IoT that have been gathered over time [77]. Effectively training these datasets presents considerable obstacles.

A unique strategy that involves distributed training on various Internet of Things devices has been suggested by researchers as an alternative to established approaches that entail the centralization of big datasets where a GPU cluster or data center is located [78]. A significant amount of medium-sized Network of Things gadgets spread throughout the infrastructure is used in this technique to train a deep neural network (DL) model based on the electronic components of the devices. Through this technique, essential problems such as model convergence and system scalability are addressed, guaranteeing that the training process makes efficient use of the global Internet of Things infrastructure.

On the other hand, training deep learning models on a dispersed Internet of Things infrastructure presents some significant issues that call for further attention. The fact that every Internet of Things device is involved in the training process raises privacy issues and makes it necessary to have secure measures to safeguard data. Additionally, loading datasets from various devices may be time-consuming, resulting in a decrease in the training pace. The sluggish exchange of model gradients during training and heavy computing activities makes the intricate process even more complicated. These problems call for in-depth research to develop a reliable and effective system for training and constructing deep learning models using the global IoT infrastructure. The potential of distributed training on IoT devices will be unlocked if these obstacles are effectively addressed. This will enable solving problems in real-time using efficient methods and deep learning models that can handle and analyze the enormous amounts of data created by the growing Internet of Things ecosystem. Achieving the full advantages of distributed IoT-based DL training and its transformational effect across various fields will need the discovery of creative solutions to these difficulties, which will become more critical as Internet of Things technologies continue to improve.

G. IoT Applications, Section C

Key qualities and characteristics are considered when categorizing Internet of Things apps. There are a few obstacles that need to be taken into consideration to guarantee efficient Internet of Things data analysis. It is possible to divide applications for the Internet of Things into several different categories:

1) "Smart Home": The pioneering application of IoT is the smart home, which has garnered substantial customer interest and investments from big corporations. Internet connectivity enables smart home equipment like washing machines, refrigerators, lamps, fans, TVs, and smart doors to connect to the Internet, enabling improved monitoring, administration, and optimization of energy use.

2) "Smart City": The goal of smart cities is to optimize several elements, including traffic management, water and waste management, security, water and waste management, climate monitoring, and traffic management. IoT applications improve quality of life by addressing concerns such as the availability of clean drinking water, the quality of the air, and the density of metropolitan areas.

3) The IoT is revolutionizing medical research by providing real-time field data and test findings [79]. Devices connected to the Internet of Things, such as sensors, can monitor vital indicators of patients, such as their heart rate, blood pressure, and body temperature, without the continual presence of medical practitioners. This results in improved patient care and health outcomes [80].

4) Security: IoT-powered smart cameras improve worldwide security by recognizing images in real time, identifying perpetrators of illegal acts, and averting potentially hazardous situations. However, there is still a massive problem with security in the IoT industry [81].

5) "Smart Retail": IoT applications in the retail sector concentrate on monitoring items, sharing information about inventories, and using technology such as GPS and RFID to enhance inventory management, expedite logistics, and cut costs [82].

6) The IoT revolutionizes agricultural operations by enabling remote monitoring of soil quality, weather conditions, crop management, and resource optimization [25], [83]. Intelligent agrarian systems have the potential to boost output and decrease waste [84].

7) Wearable technology is a prominent IoT application that influences human health and well-being. Wearable technology analyzes various factors, including heart rate, blood pressure, sleep habits, and more.

8) Industrial Automation: The Industrial Internet of Things (IIoT) enables remote access, control, and data extraction from various sources, ultimately resulting in considerable gains in workforce efficiency. IIoT solutions provide automation that is both cost-effective and efficient, hence improving customer service and optimizing supply chain operations.

The many Internet of Things applications show that IoT technology can be used in various fields. By leveraging the IoT's potential, groundbreaking breakthroughs and efficiency in various industries can be accomplished, eventually altering how we live, work, and interact with the world.

H. Obstacles in the Internet of Things and Deep Learning

The success of DL approaches is closely tied to the data sources used. The absence of big datasets, which are essential for improving DL accuracy, is a barrier to applying deep learning to the IoT. In addition, IoT applications have challenges in generating raw data that can be efficiently fed into deep learning models [85].

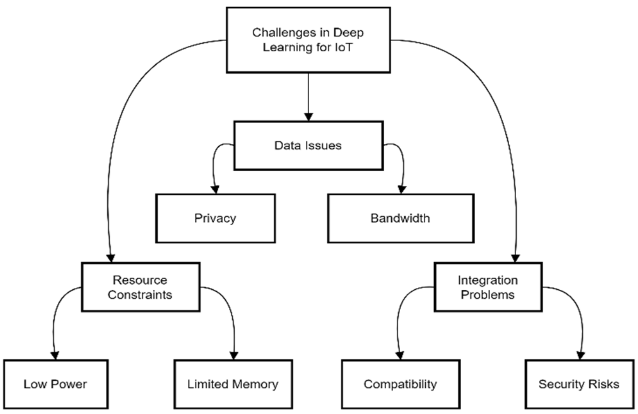

Fig. 3 Challenges in Implementing Deep Learning in IoT

As a result of the IoT, preprocessing data becomes more complicated since it requires managing heterogeneous data from various sources, each with a distinct format, distribution, and instances of missing data. Research on data-collecting methods is essential to guarantee the quality of the data, particularly when considering the quantity and placement of sensors that directly influence the model's effectiveness.

Given the large amount of data gathered from various sources, cyber security stands out as the most serious concern in the world of the IoT. Maintaining data safety and confidentiality is essential, mainly when Internet of Things data is transmitted and viewed worldwide. Approaches to anonymization may be used in several applications to solve the issue of data privacy; nevertheless, these approaches may be vulnerable to exploitation, which might result in the re-identification of data that has been anonymized. Specific strategies must be used to identify and manage irregular or incorrect data streams, hence enhancing the dependability of data and the efficiency of models in IoT applications. This is necessary to guarantee the integrity of deep learning models. To successfully integrate deep learning in the ever-expanding environment of the IoT, it is still essential to establish confidence in the data gathering and security procedures.

System designers have substantial hurdles when designing deep learning for IoT systems, particularly when managing devices with limited resources. It is becoming more challenging to fulfill system requirements as datasets grow and new deep-learning algorithms are included in IoT solutions [86]. Despite its promise, deep learning has certain drawbacks, such as an excessive dependence on pictures recognizable to humans and an overemphasis on categorization, which neglects regression analysis, an essential component of other IoT applications. Many academics have tried to overcome this issue by including regression skills in deep neural networks (DNNs). One such attempt is the ensemble of DBN and Support Vector Regression (SVR) that was suggested in [87]. IoT sensor technologies are complex and expensive, making it difficult to monitor off-road vehicles using these technologies. Edge devices, such as smartphones, offer a viable solution for restricted network connections, cloud and fog computing, and a dependence on the professional expertise of specialists. Regarding monitoring and diagnosing the health of off-road vehicles (HM&D systems), researchers have devised an artificial intelligence system enabled by edge devices [88]. This system uses low-cost microphones as sensors

IV. CONCLUSION

The purpose of this article was to provide a comprehensive analysis of the potential uses of deep learning (DL) and IoT methods across various areas, including intelligent homes, smart cities, public transportation, energy, translation, healthcare, safety, and agriculture. This study highlights the transformative impact of deep learning and IoT integration in addressing key challenges such as data heterogeneity, real-time analytics, and scalability in IoT systems. The proposed framework leverages distributed training approaches to optimize IoT applications in critical domains like healthcare, smart cities, and agriculture. Additionally, practical guidelines for deploying scalable IoT systems were provided, aligning with the primary objective of integrating deep learning to achieve actionable insights and optimized performance.

However, several challenges remain, including data privacy concerns, computational complexity, and the time-consuming nature of specific processes. The study also reviewed the latest advancements in deep learning models for IoT applications, covering supervised models like Recurrent

Neural Networks (RNNs), Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNNs), and Transformer-based architectures, as well as unsupervised models such as Autoencoders (AE), Restricted Boltzmann Machines (RBM), and Deep Belief Networks (DBN).

The combination of IoT and deep learning has driven significant advancements across diverse sectors by minimizing the reliance on manual feature engineering and enabling scalable, data-driven solutions. This study contributes to the IoT and DL intersection by presenting a structured review of state-of-the-art techniques, identifying critical challenges, and proposing a framework that addresses these issues effectively. The findings aim to serve as a foundational resource for researchers and practitioners looking to enhance IoT applications through profound learning innovations.

Looking ahead, developing highly accurate and resource-efficient systems will remain a critical focus. Further research and innovation are essential to overcome the inherent difficulties associated with distributed training, data privacy, and resource management. Continued advancements in deep learning and IoT frameworks are expected to unlock transformative possibilities across various industries, paving the way for exciting and impactful innovations.

In conclusion, this study highlights the potential of deep learning techniques in addressing critical IoT challenges, such as data heterogeneity, real-time processing, and scalability. Proposing a structured framework offers actionable solutions for enhancing IoT applications in domains such as healthcare, smart cities, and agriculture. This study is a resource for researchers and practitioners aiming to leverage deep learning to unlock IoT's full potential.

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