Article

A Survey of AI Techniques in IoT Applications with Use Case Investigations in the Smart Environmental Monitoring and Analytics in Real-Time IoT Platform

Yohanes Yohanie Fridelin Panduman [1], Nobuo Funabiki [1,*], Evianita Dewi Fajrianti [1], Shihao Fang [1] and Sritrusta Sukaridhoto [2]

[1] Graduate School of Natural Science and Technology, Okayama University, Okayama 700-8530, Japan; p8f01q6f@s.okayama-u.ac.jp (Y.Y.F.P.); p2mu1tom@s.okayama-u.ac.jp (E.D.F.); pkpb8c9q@s.okayama-u.ac.jp (S.F.)

[2] Department of Informatic and Computer, Politeknik Elektronika Negeri Surabaya, Surabaya 60111, Indonesia; dhoto@pens.ac.id

* Correspondence: funabiki@okayama-u.ac.jp

Abstract: In this paper, we have developed the *SEMAR (Smart Environmental Monitoring and Analytics in Real-Time)* IoT application server platform for fast deployments of IoT application systems. It provides various integration capabilities for the collection, display, and analysis of sensor data on a single platform. Recently, *Artificial Intelligence (AI)* has become very popular and widely used in various applications including IoT. To support this growth, the integration of AI into *SEMAR* is essential to enhance its capabilities after identifying the current trends of applicable AI technologies in IoT applications. In this paper, we first provide a comprehensive review of IoT applications using AI techniques in the literature. They cover predictive analytics, image classification, object detection, text spotting, auditory perception, *Natural Language Processing (NLP)*, and collaborative AI. Next, we identify the characteristics of each technique by considering the key parameters, such as software requirements, input/output (I/O) data types, processing methods, and computations. Third, we design the integration of AI techniques into *SEMAR* based on the findings. Finally, we discuss use cases of *SEMAR* for IoT applications with AI techniques. The implementation of the proposed design in *SEMAR* and its use to IoT applications will be in future works.

Keywords: Internet of Things; AI; integration; survey; application server platform; *SEMAR*

check for updates

Citation: Panduman, Y.Y.F.; Funabiki, N.; Fajrianti, E.D.; Fang, S.; Sukaridhoto, S. A Survey of AI Techniques in IoT Applications with Use Case Investigations in the Smart Environmental Monitoring and Analytics in Real-Time IoT Platform. *Information* **2024**, *15*, 153. https://doi.org/10.3390/info15030153

Academic Editors: Vasco N. G. J. Soares, João M. L. P. Caldeira, Bruno Bogaz Zarpelão and Jaime Galán-Jiménez

Received: 23 February 2024
Accepted: 7 March 2024
Published: 9 March 2024

1. Introduction

Nowadays, the *Internet of Things (IoT)* has attracted significant interest from both industrial and academic communities as an emerging technology designed to connect cyberspace with physical devices using Internet infrastructure [1]. As IoT infrastructures become common, an IoT application system can consist of various sensor devices and network connections across multiple domains [2]. In this context, developers need to efficiently design and implement the system adopting standards for heterogeneous device management and interoperability with other systems [3].

In this paper, we have developed the IoT application server platform called *SEMAR (Smart Environmental Monitoring and Analytics in Real-Time)*. It can serve as a cloud server for integrating various IoT application systems. It offers various integration capabilities for the collection, display, and analysis of sensor data on a single platform [4], by providing *built-in* functions for data communications, aggregations, synchronizations, and classifications using machine learning algorithms in *Big Data* environments. It also supports the implementation of *plug-in* functions by allowing other systems to access data through the *Representational State Transfer Application Programming Interface (REST API)*. Although

SEMAR has been efficiently used in several IoT applications, improvements to the platform will be expected to address the demands of IoT applications that may require more advanced data processing algorithms.

Recently, *Artificial Intelligence (AI)* has become very popular as a data processing algorithm. AI has been inspired by the thinking of the human brain [5]. It can create intelligent systems that may learn, operate, and respond intelligently like human behaviors [6,7]. In fact, AI is a field of intelligence systems that covers not only algorithms for data processing but also offers a wide range of tools and techniques that help computers perform specific tasks [8]. Machine learning, *Natural Language Processing (NLP)*, deep learning, pattern recognition, optimization, robotics, and computer vision can be included as subfields of AI. Due to its ability to solve a lot of complex problems, AI is now widely used in various applications including IoT.

The integration of AI plays a critical role in the evolution of IoT technology. It enables advanced sensor data analysis by identifying data patterns, extracting valuable information, and making rapid decisions based on it [9]. Furthermore, the utilization of *Big Data* technologies enhances this integration by providing huge data sets for training AI models. This significantly increases the potential of AI implementations in various IoT applications. To support this growth, the integration of AI into *SEMAR* becomes essential to enhance its capabilities as an effective IoT application server platform.

The current AI studies are concerned with selecting appropriate techniques for specific cases of IoT applications. Each technique has its own characteristics and requirements. For instance, deep learning models require more computational resources, which increase with the computational complexity of the model. Therefore, it is important to identify the current trends of applicable AI techniques and their characteristics for effective integration.

In this paper, we present an overview of current AI techniques and their use cases in IoT applications. Our methodology explores the potential of AI integrations and how they can be implemented in IoT applications. First, we provide a comprehensive review of current studies on IoT applications using AI techniques. They include predictive analytics, image classification, object recognition, text spotting, auditory perception, *NLP*, and collaborative AI. Then, we identify the characteristics of each technique by considering the key parameters that play a critical role in integrations. These parameters include software requirements, *input/output (I/O)* data types, processing methods, and computations. Based on our findings, we design the seamless integration of AI capabilities into the *SEMAR* platform. Finally, we discuss use cases of IoT applications with AI techniques to illustrate how *SEMAR* can be used to support their developments.

This study contributes to the field of AI integration in the IoT domain. First, we present a comprehensive review of recent studies on AI technologies applied in various IoT application use cases. Second, we provide a detailed analysis of an AI algorithm with key parameters that are critical for effective AI integrations in IoT application developments. Third, we present the design of an IoT platform service with seamlessly integrated AI-driven capabilities that include both cloud and edge components. Through three IoT application use cases, we illustrate how our designed platform supports and enhances IoT application development with AI processes.

The rest of the paper is organized as follows: Section 2 briefly reviews our previous development of *SEMAR*. Section 3 presents the comprehensive literature review of AI techniques in IoT applications and highlights their use cases. Section 4 presents the design of AI techniques integrations in *SEMAR*. Section 5 describes the use cases of *SEMAR* in IoT applications. Finally, Section 6 concludes this paper with future works.

2. Review of *SEMAR* IoT Application Server Platform

In this section, we review the *SEMAR* IoT application server platform to facilitate the development of IoT applications in the cloud. In our previous studies [4], we presented the design and implementation of *SEMAR* with several IoT application systems. Currently, *SEMAR* provides integrated capabilities functions to collect, display, process, and analyze sensor data. It provides *built-in* functions for data communication, aggregation, synchronization, and classification using machine learning algorithms that can be used without implementation or modification of the original source code. It also allows users to add *plug-in* functions by providing data access through the *REST API*. Furthermore, it was integrated with the edge device framework [10] that allows users to seamlessly create, update, and delete the edge configuration file for edge devices through the user interface of *SEMAR*. Figure 1 shows the system overview of *SEMAR*.

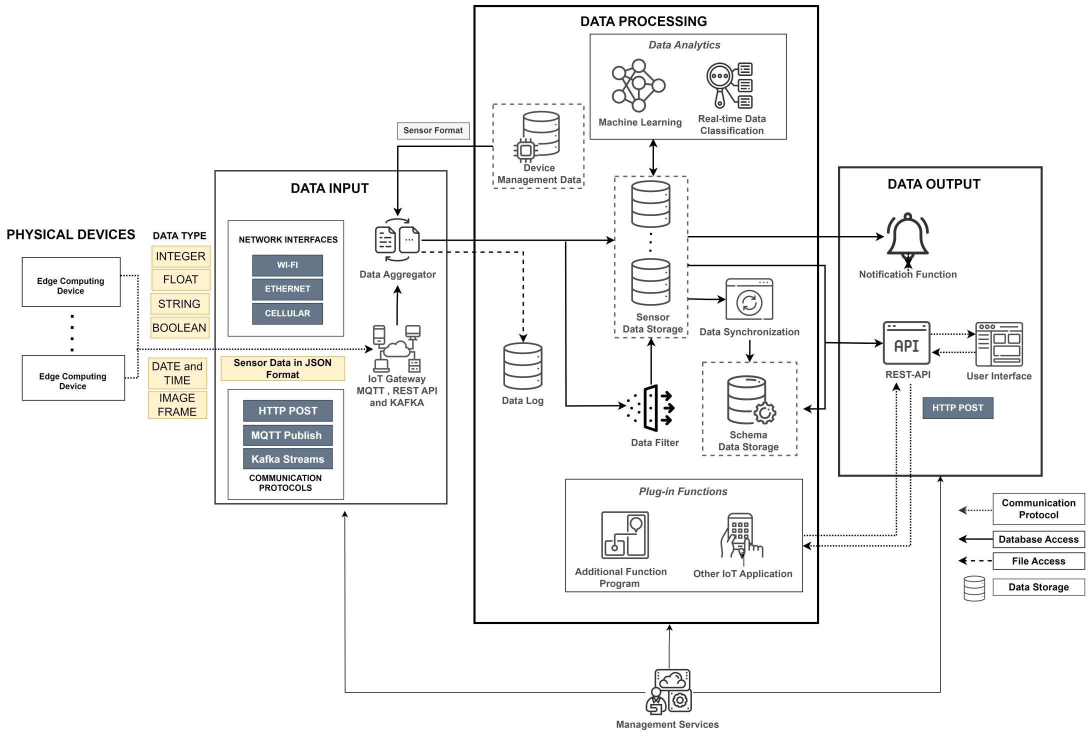


Figure 1. Design overview of *SEMAR* IoT application server platform.

The *built-in* functions can be divided into several components for *data input*, *data processing*, and *data output*. All the components are managed by the *management* system.

Collecting data from various IoT devices using network interfaces and communication protocols in *SEMAR* is handled by the *data input* components. They include the *IoT cloud gateway*, which provides services for data communications through *MQTT*, *HTTP POST* and *KAFKA* communication protocols, and the *data aggregator*, which collects raw sensor data and converts them to the consumable form according to the sensor format defined in the device management data. The *data aggregator* transmits the sensor data to the *data processing* components and stores them in the data storage. *MongoDB* [11] is implemented for the data storage service. The *SEMAR* platform allows for receiving various types of sensor data from devices in *JavaScript Object Notation (JSON)* format, as illustrated in Figure 1. They include image frames and common data types such as integer, float, string, boolean, date, and time.

The *data processing* components provide the functions for processing and analyzing the obtained data. The *data filter* allows to use several digital filtering techniques to reduce noise and inaccuracies in the data. The *data synchronization* allows the data from different resources to be synchronized into a single data record. It stores the result data in the *schema data storage*. The machine learning techniques can be used to provide real-time data classification services in the *data analytics* component. The current implementation covers the decision tree and *Support Vector Machines (SVM)* classification techniques.

According to the current trend of IoT applications, it is necessary to use several AI techniques in the *data analytics* component. In this paper, we first conducted a study of AI integration in IoT applications to identify the characteristics of each AI technique. Then, based on the findings, we design the integration of AI techniques in *SEMAR*. In future works, we will implement the proposed design to improve the *data analytics* component.

The *data output* components provide the functions to visualize the obtained data and allow users to access them. A web-based *user interface* is prepared to visualize the data. The *data export* function is implemented in the user interface to allow the user to download the data at a specific time in a TEXT, Excel, JSON, or CSV format. The *notification* function sends the message when the sensor value matches the user-defined threshold. The last component utilizes the *REST API* service for data sharing and integrations with the *plug-in* functions or other systems through *HTTP POST* communications in the JSON format.

In terms of the user model, the *SEMAR* platform is designed to support multi-user usage. In order to manage devices, user authorizations, communication protocols, and data in *SEMAR*, the *management service* is implemented. This service facilitates data sharing and access control among users through the user interface. First, the user is required to register a device on the platform, specifying the types of sensor data to be collected. Then, the user can send invitations to other registered users to grant them permission to access the sensor data. Once the invitation is accepted by the target user, access to the shared device data is granted. Finally, the user is able to view and download the data from the user interface of *SEMAR*.

In Ref. [10], we designed and built the *edge device framework* to optimize device utilizations by configuring it remotely through the *SEMAR* as the feature for device management. It allows users to create, update, and delete the edge configuration file by accessing the functions through the *user interface*.

The real-time system in the *SEMAR* platform processes data collected from devices and generates responses within a specified timeframe. This implies that the system is expected to meet deadlines to ensure time for data processing and response. For this purpose, the soft deadline approach has been implemented as the deadline constraint in our system. The *soft deadline* implies that completing a task within a certain time frame is preferable, but not mandatory. If a data processing task misses its soft deadline, it will trigger the timeout mechanism to avoid waiting indefinitely. However, this may result in data loss. To address this issue, we have implemented the data log function to store all the data sent by IoT devices as it is received by the IoT gateway. In addition, we have utilized the *Network Time Protocol (NTP)* to synchronize clocks between functions in the *SEMAR* platform.

3. Literature Review on Use Cases of AI Techniques in IoT Applications

In this section, we present a review of use cases of AI techniques in IoT applications as comprehensively as possible.

3.1. Methodology

The main purpose of this literature review section is to identify AI techniques that have been frequently used in IoT applications, including algorithms, characteristics, and how they can be implemented in IoT application use cases. For this purpose, we followed a structured research methodology. It consists of identifying the trends of applied AI techniques, finding the related literature, investigating characteristics, and analyzing necessary requirements for seamless integrations.

First, we identify the trends of applied AI techniques in the development of IoT application systems. For this purpose, we explored the surveyed papers that discuss applied AI techniques in IoT application systems with their potential. According to the findings in several studies [12–16], we selected predictive analytics, image classification, object detection, text spotting, auditory perception, NLP, and collaborative AI as the typical AI techniques to be explored in this paper.

In the next step, we systematically selected relevant papers for reviews from popular scientific databases, including *Scopus*, *Elsevier*, and *IEEE*. To capture the current state of each AI technique, we limited our literature review to publications that have been published between 2019 and 2023. Our literature selection was based on a combination of keywords representing each AI technique identified in the previous step, as well as the domains of IoT application use cases. They included smart environments, smart manufacturing, smart cities, smart homes, smart buildings, smart healthcare, smart agriculture, smart farming, and smart laboratories.

For investigating the characteristics of each technique and its application use cases, we considered critical features such as software requirements, *I/O* data types, processing methods, and computations. Finally, we analyzed the unique strengths and requirements of each AI technique with the specific purpose of designing seamless integration. Following this insight, we designed the AI integration into the *SEMAR* platform.

3.2. Predictive Analytics

This subsection provides an overview of the current state of the art for integrating predictive analytics into IoT systems by reviewing papers with considering application use cases.

3.2.1. Overview

The integration of AI into an IoT application has changed the way how data is collected, processed, and visualized. As an IoT application requires the ability to rapidly extract meaningful information from data, a function or a system that enables the identification of data patterns and trends in a real-time manner becomes a critical issue. Predictive analytics is one of the AI techniques often used to solve this issue. It finds knowledge in current and past data to generate predictions of future events by using machine learning, statistics, and data mining techniques [17].

In the context of IoT, predictive analytics analyzes historical sensor data saved in the database to predict future events or data trends. It is often used to perform anomaly detection, predictive maintenance, optimization, and decision-making in a real-time or near-real-time manner.

3.2.2. Use Cases in IoT Applications and Characteristics Overview

Several papers discussed use cases that provide the potential for using predictive analytics techniques to improve IoT application systems. They include applications in smart environments [18–22], smart manufacturing [23,24], smart home [25], smart building [26], smart healthcare [27,28], smart farming [29], and smart agriculture [30].

Forecasting future environmental conditions based on historical data that were collected by sensors is one of the goals of smart environments. As a direction toward this goal, in [18], Imran et al. proposed an IoT-based simulation system that predicts fire spread and burned areas in mountainous areas. In Ref. [19], Hussain et al. used predictive analytics techniques to forecast the level of *carbon monoxide (CO)* concentration in the area around a garbage bin. Mumtaz et al. in [20] provided a system that can predict the concentration level of air pollutants in an indoor environment. Barthwal et al. in [21] proposed an IoT application to predict the *air quality index (AQI)* based on collected mobile sensor data. Jin et al. in [22] proposed a novel approach for predicting *particulate matter (PM)* 2.5 concentrations using a *Bayesian* network. This study introduced a *Bayesian*-based algorithm that provides a potential robust prediction for time-series data.

In Ref. [23], Bampoula et al. developed a system for predicting the remaining useful life of machinery in the steel industry. Teoh et al. in [24] developed an application focused on the predictive maintenance of manufacturing equipment. These use cases illustrate the effectiveness of integrating predictive analytics into IoT application systems to improve industrial asset management by accurately estimating machine or equipment conditions.

Predictive analytics techniques have also been applied to predict energy consumption in smart homes and smart building applications. In Ref. [25], Shorfuzzaman et al. presented the practical implementation for minimizing energy consumption of home appliances in a smart home context using predictive analytics. Then, Guo et al. in [26] provided a system for predicting building electricity consumption based on a small-scale data set collected by sensors.

In Ref. [27], Nancy et al. offered the application of predictive analytics techniques into IoT cloud-based systems to forecast the risk of heart disease based on the medical history data of patients in the context of smart healthcare. Subahi et al. in [28] introduced a self-adaptive *Bayesian* algorithm for predicting heart disease based on medical data collected from patients. The medical data include several parameters related to the patient's vital signs, such as blood pressure and heart rate.

In Ref. [29], Patrizi et al. demonstrated the implementation of a virtual-based soil moisture sensor in the context of smart farming applications. This can be achieved by estimating soil moisture using collected sensor data using predictive analytics techniques. Kocian et al. in [30] introduced an IoT system for smart agriculture. This system facilitated crop coefficient modeling and crop *evapotranspiration (ET)* prediction in a soilless substrate using a dynamic *Bayesian* approach. It utilized data collected from multiple sensors, including crop weight, global radiation, and temperature, to predict crop *ET*.

Table 1 summarizes the characteristics of predictive analytics techniques that were adopted in the papers discussed in this subsection. *Long Short-Term Memory (LSTM)* is the widely used algorithm for predicting future events. It belongs to the variant of *Recurrent Neural Network (RNN)* architecture, which effectively learns and retains information over a long period using cell states [31]. The works by Barthwal et al. in [21], Shorfuzzaman et al. in [25], and Guo et al. in [26] utilized the capabilities of the *Autoregressive Integrated Moving Average (ARIMA)* algorithm [32] to construct robust data models for predicting future values in time series data. Taking it one step further, Guoh et al. in [26] combined *Support Vector Regression (SVR)* with *ARIMA* to predict energy consumption. Then, Imran et al. in [18] integrated *Principal Component Regression (PCR)* and *Artificial Neural Network (ANN)* for an effective predictive model in their application system.

Table 1. Key characteristics of predictive analytics technique in current studies.

Ref.	**Algorithms**	**Software Requirements**	**Data Types**		**Processing Methods**	**Computations**
			Input	**Output**		
[18]	ANN with PCR and Kalman filter	Python	Time-series data	Predicted area	Filtering and real-time data processing	Raspberry PI with 3.00 GB RAM
[19]	LSTM	Python, TensorFlow	Time-series data	Predicted CO level	Real-time data processing	Google Cloud Server
[20]	LSTM	-	Time-series data	Predicted air pollutants level	Real-time data processing	-
[21]	ARIMA	-	Time-series data	Predicted AQI	Real-time data processing	IBM Cloud
[22]	Bayesian Network	Python	Time-series data	Predicted PM2.5 level	Missing data handling, data normalization, and data correlations	AMD R7-5800 processor 4.0 GHz with 16GB of RAM
[23]	LSTM	Python, TensorFlow	Time-series data	Predicted machine states	Data transformation and real-time data processing	Intel CoreTM i7 CPU with 8.00 GB RAM
[24]	Logistic Regression	Azure Machine Learning *REST API* services	Time-series data	Predicted equipment health states	Real-time data processing	Azure Machine Learning
[25]	LSTM and ARIMA	Python, TensorFlow	Time-series data	Predicted energy consumption	Missing data handling, outlier detection, data transformation	Intel CoreTM i7 CPU with 8.00 GB RAM

Table 1. *Cont.*

Ref.	Algorithms	Software Requirements	Data Types		Processing Methods	Computations
			Input	Output		
[26]	ARIMA and SVR	Python	Time-series data	Predicted electric consumption	Missing data handling, data normalization, and data correlations	Intel Core i5 CPU with 8.00 GB RAM
[27]	Bidirectional LSTM	Python, TensorFlow	Time-series data	Predicted diagnosis of heart disease	Data Filtering	i2k2 Cloud platform
[28]	Self-Adaptive Bayesian	-	Time-series data	Predicted diagnosis of heart disease	Data normalization	-
[29]	LSTM	Python, TensorFlow	Time-series data	Predicted soil moisture	Data correlations and data synchronization	-
[30]	Dynamic Bayesian	MATLAB™	Time-series data	Predicted ET value	Real-time data processing	-

In addition, the works by Kocian et al. in [30], Jin et al. in [22], and Subahi et al. in [28] used *Bayesian*-based approaches. While *ARIMA* focuses on constructing models of the time-series data, *Bayesian* approaches take a different approach by generating prior knowledge in the form of a probability distribution for predicting the data. This prior knowledge represents initial beliefs. It is then updated with observed data using *Bayes' theorem*, allowing for more flexible and robust modeling. Moreover, *Bayesian* approaches can be implemented in scenarios with limited datasets, as mentioned in the work by Kocian et al. in [30].

Predictive analytics is essential to estimate future values or labels in real-time scenarios of IoT applications. The effective implementation of this technique requires consideration of several key elements. First, a database system that can handle time-series data is critical for efficient data storage and retrieval. Second, the pre-processing capabilities must be implemented to prevent potential error data in the collected data and improve reliability. Third, the IoT system must have real-time data processing capabilities to perform immediate analysis for rapid forecasting and decision-making. Fourth, *Python*, with its extensive support for algorithms for predictive analytics such as *LSTM*, *ARIMA* and *Bayesian*, becomes the suitable option for the software environment. As shown in Table 1, the predictive analytics can be deployed on either servers or edge devices such as *Raspberry Pi*.

3.3. Image Classification

In this subsection, we review papers emphasizing IoT application use cases for image classifications.

3.3.1. Introduction

Computer vision is the field of AI that mimics human intelligence to understand image data. It enables machines to see and recognize objects from visual images to facilitate decision-making [33]. Techniques such as image classification and object detection are part of the fields in computer vision, where image classification refers to the ability to identify categories of images. In the IoT domain, image classification plays an important role in recognizing visual data using a classification model. Typically, the data model is trained using labeled image datasets, where each image is assigned to a specific category.

3.3.2. Use Cases in IoT Applications and Characteristics Overview

The implementation of an image classification in an IoT application has been explored in numerous papers. Each paper demonstrated the effectiveness of image classification algorithms in addressing vision-based use cases in a variety of applications.

For IoT applications in agriculture, image classification is a valuable technique for monitoring crops and detecting plant diseases. In Ref. [34], Chouhan et al. introduced a system for detecting galls, a plant disease that affects leaves, using captured images. This technique is also suitable for drone-based IoT applications in environmental monitoring systems. In a separate study [35], Munawar et al. developed a system to detect flooding from aerial images captured by drones using image classifications.

Image classification is a proven AI technique for supporting diagnostic processes through visual data analysis. In Ref. [36], Abd Elaziz et al. proposed a deep learning model incorporating *MobileNet* and *DenseNet* architectures for medical image classifications to achieve rapid diagnostic results. In Ref. [37], Saleh et al. employed a hybrid approach of combining *Convolutional Neural Network (CNN)* and SVM to classify lung cancers based on *computed tomography (CT)* scan images. These studies demonstrated the effectiveness of image classifications in improving diagnostic capabilities within smart healthcare use cases.

In Ref. [38], Iyer et al. explored the application of image classifications in transportation monitoring. This study demonstrated the detection of rail fractures by analyzing images captured by a mobile robot. Similarly, Medus et al. in [39] introduced a vision-based system for detecting leakage in food tray seals on the production line, using a similar concept of image classifications with the *CNN* algorithm. These use cases demonstrated the versatility of image classifications and extended its benefits to diverse areas beyond healthcare, such as transportation infrastructure and quality control in food production.

Table 2 shows the overview of the characteristics of image classification techniques in the literature discussed in this paper. The CNN algorithm [39] has been widely used for image classifications in various applications. The architecture of the CNN algorithm allows it to be integrated with other algorithms, such as SVM. In Ref. [37], Saleh et al. presented a hybrid algorithm with CNN and SVM to achieve robust performance. SVM is used to generate the classification result using features extracted by CNN. This approach leverages the strengths of both models and enhances accuracy in classification tasks.

Several researchers have proposed alternative approaches to classifying images instead of the CNN algorithm. Abd Elaziz et al. in [36] have developed a deep learning model that combines *MobileNet* and *DenseNet* architectures to extract medical image representation. This model is able to extract complex features from medical images, making it useful for better understanding and diagnosing medical conditions. Medus et al. in [39] presented the implementation of the *Fuzzy-Based Functional Network (FBFN)* algorithm that integrates fuzzy logic with function network capabilities. This approach allows the user to apply the image classification process in real time.

There are several key elements to be considered for implementing image classification algorithms. As the programming language, Python is often used. Then, libraries such as *TensorFlow*, *Keras*, and *OpenCV* are installed to implement various deep learning-based image processing algorithms. Since the input data includes image files, storage capacity becomes necessary. To achieve high performance, additional functions such as noise reductions in images are applied. Hyperparameter optimization is also applied to optimize the performance of the model under different input data. Finally, for the computation device, researchers often use GPU-integrated and memory-optimized approaches. For example, Saleh et al. in [37] improved the performance by adding GPUs, accelerating the training phase, and reducing the processing time during the detection phase.

Table 2. Key characteristics of image classification techniques.

Ref.	Algorithms	Software Requirements	Data Types		Processing Methods	Computations
			Input	Output		
[34]	FBFN	Python and OpenCV	Captured images	Leaf gall detection (Boolean)	Image pre-processing, feature extraction, hyperparameters optimization, and real-time data processing	-
[35]	CNN	Python, OpenCV, and TensorFlow	Captured images	Flooded detection (Boolean)	Image pre-processing	Intel Core i7 CPU
[36]	Deep learning (MobileNetV2 and DenseNet169)	Python, OpenCV, and TensorFlow	Medical images	Medical diagnostic classes	Feature extraction, feature selection, and *REST API* services	-
[37]	The hybrid of CNN and SVM	Python, OpenCV, and TensorFlow	Medical images	Lung cancer classes	Hyperparameters optimization	Intel Core i5 CPU with 16.00 GB of RAM and NVIDIA GeForce RTX 2060 GPU
[38]	CNN	Python, OpenCV, and TensorFlow	Captured images	Fracture detection (Boolean)	Image pre-processing and feature extraction	Raspberry Pi 3
[39]	CNN	Python, OpenCV, TensorFlow, and Keras	Captured images	Failure detection (Boolean)	Hyperparameters optimization	Intel Core i7 CPU with 8.00 GB of RAM

3.4. Object Detection

In this subsection, we provide an overview of integrating object detection techniques into IoT applications.

3.4.1. Introduction

Object detection is one of the AI techniques in the field of computer vision. While image classification focuses on categorizing entire images, object detection goes a step further by recognizing both the categories and the precise locations of specific objects within the images. This technique is often used as the first step to perform other tasks, including recognizing faces, estimating poses, and analyzing human activity.

In the context of IoT, object detection plays a critical role in various applications, such as autonomous video surveillance, smart cities, and manufacturing. Its integration into IoT devices facilitates real-time analysis of video sequences, which is essential for ensuring safety and efficiency in various environments. However, this integration brings new challenges in detecting moving objects and rapidly extracting their features. Addressing these challenges requires consideration of computational resources to efficiently manage the huge amount of IoT data, especially in use cases of intelligent surveillance systems.

3.4.2. Use Cases in IoT Applications and Characteristics Overview

In this section, we explore the papers that discuss the integration of object detection in the IoT domain. They presented how object detection algorithms are applied in various application scenarios, such as smart cities with drones, smart manufacturing, smart buildings, and smart laboratories. In the context of smart cities, object detection helps to improve urban management. It allows the detection and localization of various entities in urban environments, such as vehicles, pedestrians, and objects, for intelligent transportation, intelligent surveillance, and drone monitoring.

In Ref. [40], Zhou et al. presented a multi-target detection system for real-time surveillance using IoT sensors. By following this concept, Abdellatif et al. in [41] advanced the implementation of object detection by developing a server framework that uses a flying drone and data stream communication to detect multiple objects. They used the *You Only Look Once (YOLO)* algorithm for this purpose. To address a similar use case, Lee et al. in [42] proposed a cloud computing service for detecting multiple objects in drone-captured images by using the *Faster Region-based CNN (Faster R-CNN)* algorithm. In another study, Meivel et al. in [43] presented a mask detection and social distance measurement system using drones. These literature studies highlight the effectiveness of integrating object detection and IoT devices, such as drones, to enhance urban surveillance and security management.

The concept of *Industry 4.0* brings manufacturing processes to be monitored and controlled virtually. Recent research in this area has focused on the detection of intelligent small objects to build a digital twin environment. As an example, Yao et al. in [44] proposed a small object detection model in a manufacturing workshop use case using *YOLOX*.

In the context of smart laboratories, object detection contributes to efficient equipment monitoring and helps ensure compliance with safety protocols. Ali et al. in [45] introduced an IoT-based monitoring system for detecting compliance with *personal protective equipment (PPE)* guidelines to improve laboratory safety.

With the growth of communication protocol technology, object detection can be seamlessly performed on cloud servers in real-time scenarios. Baretto et al. in [46] demonstrated an application for person detections with CCTV cameras on cloud servers using *WebRTC* technology [47]. As the technology continues to evolve, the integration of real-time object detection on cloud servers opens up new possibilities for improved monitoring and decision-making.

Table 3 summarizes the characteristics of the object detection techniques used in the papers discussed in this subsection.

YOLO and *Faster R-CNN* are popular algorithms for their computation speed and accuracy in detecting objects in image data. The architecture of *YOLO* processes entire images in a single forward pass through the neural network to enable real-time object detection. On the other hand, *Faster R-CNN* uses a two-stage process, where the first stage proposes regions of interest, and the second stage classifies these regions and refines the bounding boxes to achieve better accuracy. This difference in concepts contributes to the different characteristics of the two algorithms, with *YOLO* being highly efficient for real-time processing, while *Faster R-CNN* focuses on improving accuracy by using a two-stage approach.

Implementing *YOLO* and *Faster R-CNN* typically involves using deep learning frameworks such as *TensorFlow* and *PyTorch*. These frameworks are commonly employed within Python environments that seamlessly integrate with *CUDA* for GPU acceleration and supporting libraries such as *Keras* and *OpenCV*. In order to accommodate the high demand for computing resources, a physical server is deployed along with GPUs. This hardware setup ensures more efficient processing and optimization of the algorithms.

According to use cases of IoT applications, object detection processes a captured image to obtain the detected objects in an image file. The detected objects are annotated with bounding boxes, class labels, and confidence scores. Similar to image classification, these techniques require a significant storage capacity for dataset storage. In addition, the data management approach is a critical aspect. The users need to carefully consider whether the results will be stored on temporary or permanent storage mechanisms.

Table 3. Key characteristics of object recognition techniques.

Ref.	Algorithms	Software Requirements	Data Types		Processing Methods	Computations
			Input	Output		
[40]	Integration of YOLOv3 and *Multitask CNN (MTCNN)*	Python, TensorFlow, CUDA, and OpenCV	Captured images	Images with bounding box, class labels, and confidence scores	Real-time data processing	Jetson TX1 with 6.00 GB RAM and NVIDIA Maxwell GPU
[41]	YOLOv5	Python with PyTorch, Apache Kafka, Apache Flink and CUDA	Captured images	Images with bounding box, class labels, and confidence scores	Real-time data processing, batch processing, and dynamic model deployment	Intel Core i7 CPU with 8.00 GB RAM
[42]	Faster R-CNN	Python with PyTorch and OpenCV	Captured images	Images with bounding box, class labels, and confidence scores	Real-time data processing	Intel Xeon E5-2680 v3 with 128.00 GB and Nvidia Tesla K40 GPU
[43]	Faster R-CNN and YOLOv3	Python with PyTorch, TensorFlow, CUDA, Keras, and OpenCV	Captured images	Images with bounding box, class labels, and confidence scores	Image pre-processing	-
[44]	YOLOX	Python with PyTorch, CUDA, and OpenCV	Captured images	Images with bounding box, class labels, and confidence scores	Image enhancement and feature enhancement	Intel Core i9 CPU with16.00 GB RAM and NVIDIA RTX A4000 GPU
[45]	YOLOv5	Python, TensorFlow, CUDA, and OpenCV	Captured images	Images with bounding box, class labels, and confidence scores	Real-time data processing	Intel XEON E5-2698 v4 with NVIDIA DGX-1 GPU
[46]	YOLOv3	Python, OpenCV, CUDA, and WebRTC	Captured images	Images with bounding box, class labels, and confidence scores	Real-time data processing	Intel Core i7 CPU with Nvidia GTX 1050 GPU

3.5. Text Spotting

This subsection presents an overview of the papers that focus on application use cases of text-spotting techniques in IoT systems.

3.5.1. Introduction

In AI, text spotting refers to the ability to detect and recognize texts within an image [12]. This technique is closely related to object detection, as it includes the recognition and localization of the text regions within images. However, text spotting extends beyond object detection by further extracting the textual content presented in the identified regions. The objective of this technique is to automate the extraction of meaningful information from images containing texts. This is particularly important for real-world applications such as mapping, document analysis, and augmented reality.

Text spotting has a significant role in IoT by enabling the extraction of valuable information in texts from visual data collected by sensors. This capability is particularly valuable for the tasks such as recognizing street signs, license plates, and product labels. By effectively identifying and extracting texts from images, text spotting enhances the intelligence of IoT systems, enabling them to derive meaningful insights and support diverse application use cases. Nevertheless, the implementation of text spotting involves numerous challenges. The wide variety of text appearances, including variations in sizes, lengths, widths, and orientations, poses a significant challenge to the development of effective text-spotting techniques.

3.5.2. Use Cases in IoT Applications and Characteristics Overview

The implementation of text spotting in IoT has been thoroughly explored in numerous literature studies. They illustrated the effectiveness of text-spotting algorithms in detecting and recognizing textual information from images for various application use cases.

The seamless integrations of IoT and text-spotting techniques in smart cities play a critical role in improving the efficiency, safety, and functionality of urban environments. The integrations are able to optimize parking management, ensure city safety, and improve public services.

In Ref. [48], Bassam et al. presented an IoT system designed to detect available parking spaces in urban areas. Following this concept, Wu et al. in [49] proposed a vehicle localization system to detect parking space numbers in real time. Both studies employed cameras placed in parking lots and implemented an *Optical Character Recognition (OCR)* model to extract the textual information about available parking spaces. This innovative approach highlights the effectiveness of integrating IoT and text-spotting techniques for efficient parking management in urban environments.

The works of Glasenapp et al. in [50] and Tham et al. in [51] proposed innovative systems to improve public safety. Their works focus on the development of IoT solutions for license plate recognitions from video streams. In another study, Ktari et al. in [52] presented an IoT-based system for monitoring water consumption. This helps staff to efficiently recognize water meters and improve smart city services, especially in the area of water consumption management.

This technique has also been applied to assist in recognizing medicine labels in smart healthcare applications. In Ref. [53], Abdullah et al. presented an IoT device for recognizing medicine names to manage the medicine consumption of elderly people by using the OCR model and *Bidirectional LSTM (BiLSTM)* algorithm. Chang et al. in [54] demonstrated the implementation of the OCR model in an intelligent medicine dispensing system to detect medicine bag information. These applications collectively highlighted the significant role of text recognition research in advancing healthcare applications.

In Ref. [55], Dilshad et al. applied an OCR model to determine the location of a UAV by analyzing visual data from its surroundings. Meanwhile, Promsuk et al. in [56] implemented a neural network to recognize numbers in seven-segment displays of industrial instruments. Extending this concept, Meng et al. in [57] developed early warning systems for cold chain logistics using text spotting to detect labels on goods. In addition, Cao et al. in [58] demonstrated the application of an OCR model in an infrastructure management scenario. They proposed systems for identifying irregular components on terminal blocks of electrical power equipment cabinets. These studies clearly demonstrate the versatility and practicality of text spotting in various domains.

Table 4 presents the characteristics overview of text-spotting techniques applied in the literature studies discussed in this paper.

Among the applied text-spotting algorithms, OCR models have proven their effectiveness in extracting textual information from vision-based data. First, these models identify regions within the image where text exists. Then, characters within each identified region are recognized and converted to machine-readable texts. Finally, they output the recognized texts and the image with the bounding boxes indicating the text locations.

Currently, a variety of OCR models are available to address different use cases, such as *TesseractOCR*, *EasyOCR*, *PaddleOCR*, and *PaddlePaddle OCR (PP-OCR)*. These models offer different capabilities and should be selected based on characteristics such as performance, ease of use, and suitability for specific applications. In addition, OCR models can be effectively combined with other algorithms to improve the accuracy. In Ref. [53], Abdullah et al. demonstrated the integration of *EasyOCR* models with the *BiLSTM* algorithm to improve text recognition results. These integrations implement the adaptability of OCR models and the ability to benefit from complementary algorithms in specialized use cases.

Table 4. Key characteristics of text-spotting techniques.

Ref.	Algorithms	Software Requirements	Data Types		Processing Methods	Computations
			Input	Output		
[48]	OCR model	LabView	Captured images	Recognized text	Image pre-processing, segmentation, and morphology filters	-
[49]	ABCNet OCR	Python, PyTorch, and OpenCV	Captured images	Recognized text	Object detection, anomaly filter module, and real-time data processing	-
[50]	OCR model by OpenALPR API	Python, OpenCV, and OpenALPR API	Captured images	Recognized text	Object Detection, Image pre-processing, feature extraction, segmentation, and real-time data processing	Intel Core i5 CPU with 20.00 GB of RAM and Nvidia GTX 1050 GPU
[51]	Tesseract OCR	Python, OpenCV, CUDA, and TensorFlow	Captured images	Recognized text	Object Detection, Image pre-processing, geofencing, segmentation, and real-time data processing	UP Squared AI Edge X Intel Atom CPU with Intel Movidius Myriad VPU
[52]	Tesseract OCR	Python, OpenCV, CUDA, and TensorFlow	Captured images	Recognized text	Object detection and real-time data processing	-
[53]	EasyOCR with BiLSTM	Python, OpenCV, and TensorFlow	Captured images	Recognized text	Image pre-processing and real-time data processing	AMD Ryzen 5900x CPU with 64.00 GB of RAM and NVIDIA RTX 3080 GPU
[54]	PP-OCR	Python and OpenCV	Captured images	Recognized text	Image pre-processing and parameters optimization	Intel Xeon i5 CPU with 16.00 GB of RAM
[55]	EasyOCR	Python, OpenCV, and PyTorch	Captured images	Recognized text	Object detection, image pre-processing, and real-time data processing	Intel Core i7 CPU with 32.00 GB of RAM and Nvidia RTX 2060 Super GPU
[56]	Neural Network	Python	Captured images	Recognized text	Image pre-processing, feature extraction, and real-time data processing	Intel Core i5 CPU with 8.00 GB of RAM
[57]	OCR model	Python and OpenCV	Captured images	Recognized text	Video pre-processing and real-time data processing	-
[58]	Paddle OCR	Python, PyTorch, and OpenCV	Captured images	Recognized text	Object detection, feature extraction, and segmentation	AMD Ryzen 9 with 32.00 GB of RAM and NVIDIA GeForce RTX 3080

Although existing OCR models are still the leading algorithm for text spotting, researchers have also explored alternative approaches. For instance, Promsuk et al. introduced a novel neural network algorithm in [56]. The algorithm was designed to recognize numbers in seven-segment displays.

Several aspects should be considered for effective implementations of text spotting. First, an appropriate software environment is required. Python environments are commonly used because of the key libraries such as *OpenCV*, *CUDA*, and *TensorFlow*. To achieve optimal performance, object recognition techniques often require a lot of computational resources. The addition of hardware accelerations is one solution to meet this demand. While the algorithms can be adapted for deployments on edge devices, it is noteworthy that additional GPUs will be required to achieve better performances, as shown in the studies of Glasenapp et al. in [50], Tham et al. in [51], Abdullah et al. in [53], Dilshad et al. in [55] and Cao et al. in [58].

On the data storage aspect, an effective data management system becomes critical. Due to the possibility of storing the input data, it is necessary to have a system for handling and organizing the image data. In addition, the implementation of additional processing methods in the algorithm is essential to improve accuracy and prevent errors in text recognition.

3.6. Auditory Perception

In this subsection, we provide an overview of the integration of auditory perception techniques into IoT through a review of the current literature studies that include application use cases.

3.6.1. Introduction

The motivation behind the development of auditory perception in AI is to mimic the human ability to understand and interpret sound. While computer vision enables machines to "see" by recognizing objects from visual information, auditory perception enables machines to "hear" and understand auditory information [33]. This capability expands AI applications to perform tasks that involve processing and extracting meaningful information from audio signals. Speech recognition, speaker recognition, sound classification, and environmental sound analysis are integral components of auditory perception. By applying these techniques, AI systems are able to extract and identify the auditory environment. This enables the development of more immersive and interactive applications.

In the IoT context, auditory perception is essential for extracting valuable information from the audio data gathered by IoT devices. In general, this technology allows the devices to analyze the sounds in their environments to identify certain patterns, events, and irregularities. This feature enhances the cognitive capabilities of IoT devices, where the IoT systems are able to trigger automated responses and actions based on the results of this auditory analysis.

3.6.2. Use Cases in IoT Applications and Characteristics Overview

In this section, we review the literature studies that presented how algorithms in auditory perception are applied in various application scenarios, such as smart cities [59–61], smart homes [62], and smart environments [63].

The application of auditory perception techniques in smart cities refers to the implementation of audio analysis algorithms for urban security. In this case, IoT devices were used to collect audio data in the urban environment. In Ref. [59], Balia et al. introduced an IoT system designed to enhance urban security by identifying potential threats through audio-based analysis on roads. They used the *Short-Time Fourier Transform (STFT)* algorithm to extract spectrograms as features of audio data. Following this approach, Yan et al. in [60] developed a sound detection system to identify traffic accidents in tunnels by using *Deep Neural Network (DNN)* for classifier and *Mel-Frequency Cepstral Coefficients (MFCCs)* for feature extraction. In another use case, Ciaburro et al. in [61] proposed a UAV presence detection system using sound analysis. This system addresses the increasing use of UAVs in urban areas.

The auditory perception has been employed to monitor environmental sounds in homes and buildings. Polo et al. in [62] combined MFCCs with CNN to detect activities of daily living based on sound cues. This research demonstrates the effectiveness of the integrated approach in identifying various activities of daily living through auditory analysis. Chhaglani et al. in [63] presented the application of auditory perception techniques in an intelligent environment. This study focused on predicting the airflow rate in a building by analyzing the sounds associated with air flowing through a duct in a building.

Table 5 summarizes the characteristics of the auditory perception techniques applied in the literature studies discussed in this subsection.

Table 5. Key characteristics of auditory perception techniques.

Ref.	Algorithms	Software Requirements	Data Types		Processing Methods	Computations
			Input	Output		
[59]	STFT, CNN, FCNN, and Bi-LSTM	Python, TensorFlow, and Keras	Audio spectrograms	Dangerous event classes	Audio pre-processing, feature extraction, and hyperparameter optimization	32.00 GB RAM with Nvidia GeForce GTX 1060 Max
[60]	MFCCs and DNN	Python, TensorFlow and Keras	Audio spectrograms	Accident event classes	Audio pre-processing and feature extraction	Intel Core i5 CPU with 16.00 GB RAM
[61]	CNN	Python and TensorFlow	Audio spectrograms	UAV state classes (Boolean)	Feature extraction	-
[62]	MFCCs and CNN	Python and Keras	Audio spectrograms	Daily living activities classes	Feature extraction and real-time processing	Raspberry Pi
[63]	XGBoost Regressions	Python and Java	Audio in frequency domain	Predicted Air Flow Rate	Filtering and data transformation	Android Mobile Phone

In the field of auditory perception, neural network-based algorithms are commonly used. In computer vision applications, features extracted from an image are typically used as the input. However, to process audio data, CNN analyzes spectrograms of audio data as features. Spectrograms refer to visual representations of the frequency variations of a sound signal over time. They consist of coefficients that capture the spectral characteristics of an audio signal. To obtain spectrograms of audio data, feature extraction algorithms such as *MFCCs* [64] and *STFT* [65] algorithms are integrated. The effectiveness of this integration was demonstrated in works by Balia et al. in [59] and Polo et al. in [62]. In addition, similar to the CNN algorithm, other approaches such as *DNN*, *Fully Connected Neural Network (FCNN)*, and *Bi-LSTM* algorithms also require spectrograms of audio data as the input. The selection among these algorithms depends on several factors, such as the complexity of the auditory task, the size and nature of the dataset, and the desired level of abstraction for feature extraction.

Currently, auditory perception algorithms are implemented using deep learning frameworks along with Python programming environments. Through integration with supporting libraries such as *Keras*, the process of building, training, and deploying algorithms based on neural networks can be simplified. As a result, algorithms for auditory perception have lower computational requirements compared to computer vision applications. Researchers are potentially using edge computing devices such as the *Raspberry Pi* to implement the algorithms.

As we explore the characteristics of auditory perception, the implementation requires specific pre-processing steps before audio data can be analyzed. The steps include filtering, data transformation, and feature extraction, because algorithms cannot directly handle raw sensor data. They need transformed representations of audio data, such as spectrograms, to perform auditory perception effectively. Thus, we highlight that selecting feature extraction approaches offers the potential for significantly improving IoT applications in the auditory perception field.

3.7. Natural Language Processing

This subsection provides an overview of papers on implementations of NLP techniques in IoT systems considering application use cases.

3.7.1. Introduction

In the field of AI, *NLP* refers to the ability of computers to understand and interact with human language [66]. The objective of this technique is to enhance the efficiency of communications between humans and computers. This involves computers not only understanding human language but also recognizing the contextual details involved in human communication. Through this process, computers are able to perform actions and generate responses that are associated with human language and communication patterns. *NLP* techniques are mainly divided into *Natural Language Understanding (NLU)* and *Natural Language Generation (NLG)*. *NLU* is concerned with understanding and recognizing the linguistic aspects of natural language, while *NLG* is concerned with generating clear responses in the form of words or sentences to facilitate efficient communication. *NLP* integrates speech recognition, particularly in specific scenarios such as voice control systems, to extend its functionality and potential.

Currently, *NLP* has attracted widespread attention from researchers due to its capabilities. In the IoT context, *NLP* plays an important role in enabling users to control and interact with IoT systems using human language. The integration of *NLP* into IoT applications enables more instinctive and interactive connections between humans and computers. It facilitates voice control, text data analysis, and intelligent assistants in IoT environments.

3.7.2. Use Cases in IoT Applications and Characteristics Overview

The implementation of *NLP* in IoT applications has been thoroughly explored by several researchers. They demonstrated the effectiveness of *NLP* approaches in improving communications and interactions between humans and IoT systems.

In smart home applications, ongoing developments use *NLP* techniques to recognize and understand natural language commands spoken by humans accurately. In Ref. [67], Ismail et al. developed an IoT system that provides speech recognition to control home appliances. This system enables users, especially elderly patients and people with disabilities, to effortlessly control home appliances using voice commands. They adopted a robust combination of the *SVM* algorithm and *Dynamic Time Warping (DTW)* to accurately interpret commands from users' voice audio. Following this work, Froiz et al. in [68] incorporated advanced technologies such as *Wav2vec2* and *Whisper* models for speech recognition and the *Bidirectional Encoder Representations from Transformers (BERT)* model for *NLP* to enable seamless control of IoT devices through voice commands. Furthermore, Ali et al. in [69] combined the *Google Speech API*, *NLP* model, and logistic regression to enable the recognition and execution of both structured and unstructured voice commands.

In the context of smart buildings, Dweik et al. in [70] presented a significant step forward by introducing a voice control system designed to manage devices in buildings autonomously. These smart home and smart building use cases demonstrate the benefits of *NLP* techniques in diverse domains.

Table 6 presents the characteristics overview of the *NLP* techniques applied in the literature studies discussed in this paper.

The main purpose of NLP is to extract information from transcribed spoken sentences. To achieve this task, researchers often employ *NLP* models, as illustrated in the works of Ali et al. in [69] and Dweik et al. in [70]. Typically, an *NLP* model executes multiple steps, such as sentence segmentation, word tokenization, prediction of parts of speech, lemmatization, identification of stop words, definition of relationships between tokens, and recognition of named entities. Nevertheless, it is necessary to emphasize that different *NLP* models, such as *BERT* and *BoW* models, may contain different procedures. For instance, a *BoW* model involves steps including tokenization, stop word removal, token normalization, and vocabulary generation [71].

According to the use cases of IoT applications, the effective implementation of this technology requires the consideration of several key elements. Firstly, the software requirements should be considered. Currently, Python programming provides *Natural Language Toolkit (NLTK)* libraries to perform algorithms in *NLP* techniques. The *NLTK* libraries work together with *TensorFlow* to produce the desired results.

Table 6. Key characteristics of NLP techniques.

Ref.	Algorithms	Software Requirements	Data Types		Processing Methods	Computations
			Input	Output		
[67]	SVM with a Dynamic Time Warping (DTW) algorithm	Python and Java	User's speech audio	Command recognized (string)	Speech recognition and device control	Raspberry Pi
[68]	Wav2vec2, Whisper, and BERT models	Python and TensorFlow	User's speech audio	Command recognized (string)	Speech recognition, device control, model optimization	Raspberry Pi 4 with 2 GB of RAM
[69]	Google Speech API, NLP model, and Logistic Regression	Python, NLTK, and TensorFlow	User's speech audio	Command recognized (string)	Speech recognition and device control	Intel Core i5 CPU with 16.00 GB of RAM and NVIDIA GeForce 830 GPU
[70]	Google Speech API and NLP model using Bag-of-Words (BoW) approach	Python, NLTK, and TensorFlow	User's speech audio	Command recognized (string)	Speaker verification, speech recognition, and device control.	-

As we explore the characteristics of *NLP* in IoT systems, implementing the related processes will significantly contribute to achieving optimal results. A speech recognition algorithm becomes an important process. For this purpose, researchers can use existing models or third-party platforms such as *Whisper* models and the *Google Speech API*. Then, a device control process is required to allow an IoT application to perform the control systems. Finally, the model optimization is able to enhance the trained models. For computational hardware, Table 6 shows that *NLP* models can be deployed and executed on either servers or edge devices such as *Raspberry Pi*.

3.8. Collaborative AI

In this subsection, we provide an overview of the practical use cases of the collaborative AI approach in IoT systems in existing literature studies.

3.8.1. Introduction

The development of collaborative AI in IoT systems is driven by the demand to address challenges associated with traditional cloud-based processing. In the traditional model, AI algorithms are executed on centralized cloud servers. As a result, cloud servers require high computational resources to cover all the AI processes. This raises many issues related to latency, communication, connectivity, and privacy concerns [12]. To address these challenges, collaborative AI aims to distribute computational tasks effectively by using both edge computing and cloud resources.

In the IoT context, collaborative AI extends data processing at the edge to reduce latency and bandwidth consumption. The purpose of this technique is not only to optimize resources but also to enable real-time or near-real-time analysis of IoT data. This is important in applications where rapid decision-making is required. This paradigm emphasizes the balanced and efficient use of local and cloud resources. Local processing involves the execution of lightweight AI algorithms for fast analysis, addressing the need for reduced latency. At the same time, the centralized cloud servers handle heavier data processing tasks, ensuring a comprehensive and robust approach to AI computation. The implementation of this collaborative approach indicates improvements towards an AI application in IoT systems, which is more adaptable and efficient.

3.8.2. Use Cases in IoT Applications and Characteristics Overview

In this section, we conducted a thorough review of the literature studies that explored applications of collaborative AI in IoT systems. They demonstrated the effectiveness of collaborative AI in improving system performance across various application use cases. By leveraging the processing capabilities of both the edge and the cloud, collaborative AI has become a powerful paradigm for improving the efficiency and effectiveness of IoT systems.

In Ref. [72], Song et al. presented the implementation of collaborative AI in a monitoring system using *Unmanned Aerial Vehicles (UAVs)* as edge computing and cloud servers. The UAV used a faster *R-CNN* model to detect insulator strings. Then, the images of the insulator strings were transmitted to the cloud server. Finally, the cloud-based system identified defects in the insulator strings using the *Up-Net* model. This collaborative approach effectively optimizes the resources of the UAV and the cloud, which improves the efficiency of the monitoring system.

In Ref. [73], Li et al. introduced an edge/cloud collaborative architecture designed for efficient image recognition in the smart agriculture use case. The system employs a lightweight DNN model for object detection at the edge. If the object is not successfully recognized, the image is then transmitted to a server for further processing using more powerful DNNs.

In addition, this technique has been developed for further distributed AI architectures. In Ref. [74], Chen et al. introduced a distributed real-time object detection framework for video surveillance systems. This approach allows edge nodes to perform object detection using a *YOLO* model. Then, images of the detected objects are sent to the server to be used to generate a new model. Once the model is generated, it is sent back to the edge nodes. Following this concept, in [75], Loseto et al. proposed edge intelligence components that allow edge devices to perform data training using local data to generate models for early prediction. Using data collected from multiple edge devices, the cloud performs more advanced data training to generate highly accurate models and sends them to the edge devices. These scenarios illustrate the use of collaborative AI to continuously improve AI capabilities at the edge.

Table 7 presents the characteristics overview of the collaborative AI applied in the literature studies discussed in this paper.

Table 7. Key characteristics of collaborative AI techniques.

Ref.	Algorithms	Software Requirements	Data Types		Processing Methods	Computations
			Input	Output		
[72]	Faster RCNN (UAV), Up-Net Model (cloud)	Python, TensorFlow, Keras, OpenCV and Caffe	Captured images (UAV and cloud)	Images with bounding box (UAV and cloud)	Image pre-processing, image rotation and segmentation on the cloud, image detection on UAVs, and real-time data processing	PC Server with NVIDIA GeForce RTX 2080 Ti (Server)
[73]	DNN	Python and PyTorch	Captured images	Image classes	Image difficulty prediction and model optimizations	-
[74]	YOLOv3	Python, PyTorch, and OpenCV	Captured images	Images with bounding box, class labels, and confidence scores	Real-time data processing and model update capabilities	NVIDIA Jetson Xavier NX (Edge) and Intel Core i7 CPU with 32.00 GB of RAM and Nvidia RTX 2080 GPU (Cloud)
[72]	Multi-layer perceptron regressor	Python, Apache Kafka, TensorFlow and Keras	Time-series data	Predicted amount of silica	Real-time data processing and model update capabilities	Raspberry Pi 4 Model B with 4.00 GB of RAM (Edge) and Intel Xeon CPU E5-2673 with 32.00 GB of RAM (Cloud)

The effective integration of collaborative AI into IoT applications involves several elements. First, the software requirement plays an important role in designing lightweight algorithms specifically for resource-constrained edge devices. Due to its integration capabilities with popular AI frameworks and supporting libraries, Python is often preferred for this application.

The integration architecture between the edge and the cloud is also necessary, as highlighted in the work of Chen et al. in [74] and Loseto et al. in [72]. The proposed distributed AI architecture allows local data training and model updates directly from the cloud server. To achieve this, well-designed communication methods with an emphasis on efficient protocols are required.

3.9. Integration of AI in IoT Platforms

This section presents a comparison between the *SEMAR* platform and the current state-of-the-art research on the integration of AI in IoT platforms to highlight our proposed ideas. We identified eight literature studies that have similar approaches to our design. In Ref. [76], Bu et al. proposed a platform for integrating AI with *Industrial Internet of Things (IIoT)* technologies to monitor and optimize manufacturing processes. In Ref. [77], Seshan et al. demonstrated the integration of the *FIWARE* framework [78] with AI capabilities, specifically for anomaly detection in wastewater monitoring applications. The *FIWARE* framework was chosen for device management and data collection processes. In another study presented in [79], Ramallo-Gonzalez et al. proposed an IoT platform for smart healthcare that leverages the *FIWARE* framework, big data technologies, and AI-based data analysis support. Both studies demonstrate the use of existing open-source frameworks to build an IoT platform service.

In Ref. [80], Raj et al. developed a framework called *EdgeMLOps* to deploy AI models directly at the edge. In Ref. [81], Li et al. introduced an *Artificial IoT (AIoT)* platform for smart agriculture applications that supports the addition of AI models on the edge device. In another study by Rong et al. in [82], the *Sophon Edge* platform was designed for collaborative computing between the cloud and edge devices. This platform enables the updating of AI models. In Ref. [83], Liang et al. developed an AIoT platform that facilitates the implementation of various AI models. Utilizing a micro-service architecture, each AI model runs concurrently. It allows the platform to support the combination of multiple AI models into a single dataflow process. Then, in [84], Stavropoulos et al. introduced the integration of machine learning into the IoT platform to create virtual sensors to replace physical sensors.

Table 8 shows the comparison of our proposed idea with the eight literature studies. Several parameters are considered, as follows:

- *IoT applications*: represents the use cases of the IoT applications that are implemented in each work.
- *Device management*: represents the ability to allow users to dynamically manage devices connected to the platform (Yes or No).
- *Model management*: represents the ability to manage multiple AI models, including adding and updating models (Yes or No).
- *Support various AI techniques*: indicates that the platform supports AI-driven capabilities across several techniques (Yes or No).
- *Edge device integration*: refers to the ability to deploy AI models to edge device systems (Yes or No).
- *Data types*: represents the specific types of data that can be handled by the platform.

Table 8. State-of-the-art comparison between the existing related studies and the proposed solution.

Ref.	**IoT Application**	**Device Management**	**Model Management**	**Support Various AI Techniques**	**Edge Devices Integration**	**Data Types**
[76]	Smart Manufacturing	✓	✗	✓	✗	Common data types
[78]	Smart Environments	✓	✗	✗	✗	Common data types
[79]	Smart Healthcare	✓	✗	✓	✗	Common data types
[80]	Various IoT applications	✓	✓	✗	✓	Common data types
[81]	Smart Agriculture	✓	✓	✗	✓	Common data types and image
[82]	Various IoT Applications	✓	✓	✗	✓	Common data types and image
[83]	Various IoT Applications	✓	✓	✓	✗	Common data types, image and audio
[84]	Smart Homes and Environments	✓	✗	✗	✗	Common data types
Our Work	Various IoT applications	✓	✓	✓	✓	Common data types, image and audio

Regarding the covered IoT application use cases, the works of Raj et al. in [80], Rong et al. in [82], and Liang et al. in [83] have the potential to be used in various IoT applications. This is similar to our *SEMAR* platform, which has been implemented and integrated into various IoT application use cases.

All of the mentioned works, including our IoT platform, provide device management capabilities for adding and removing connected IoT devices. These works also allow for receiving common data types from sensors, such as integer, float, string, boolean, date, and time. However, since IoT devices have a variety of data types, an IoT platform should be able to handle media file data types, including images and audio. The works by Li et al. in [81] and Rong et al. in [82] have demonstrated the ability to receive image frame data. Furthermore, the work of Liang et al. in [83] extends this capability by providing a system that can process both image and audio data. Our proposed design for the *SEMAR* platform addresses these concerns by facilitating the collection of both image and audio data types.

An IoT platform may require the ability to manage a large number of AI models and flexibly deploy different models across its processes. For this purpose, robust AI model management capabilities are used to enable users to handle AI models in order to achieve optimal results. The works of Raj et al. in [80], Li et al. in [81], Rong et al. in [82], and Liang et al. in [83] exemplify these capabilities in managing AI models within the flow of IoT data processes. The AI integration in the *SEMAR* platform follows this approach. We develop the functionalities that enable users to manage the versioning of AI models, store them in data storage, and deploy them in the flow of data processing.

Several works have emphasized the importance of AI techniques in IoT platforms by designing systems that support multiple AI capabilities. The works of Bu et al. in [76], Ramallo-Gonzalez et al. in [79], and Liang et al. in [83] have demonstrated that their proposed platform is able to accommodate different types of AI techniques. By supporting multiple AI techniques, an *AIoT* platform can effectively handle the variety of data generated by IoT devices. In line with this concept, the AI capabilities in the *SEMAR* platform are designed to facilitate the seamless integration of multiple AI techniques. With these capabilities, our platform is able to process different types of data.

In the field of IoT, the current approach involves the utilization of edge computing to perform data processing close to the device. The work by Raj et al. in [80], Li et al. in [81], and Rong et al. in [82] introduced a platform that facilitates the implementation of AI models on edge devices. This approach involves utilizing AI models that are designed to be lightweight in order to accommodate the limited computational resources available on the edge device. Following this idea, we also provide the capability to allow users to deploy their AI model to the edge device through the cloud environment.

4. Design of AI Techniques Integration in *SEMAR*

In this section, we present the design of integrating AI techniques in the *SEMAR* IoT server platform.

4.1. System Overview

The section presents the design for the seamless integration of AI techniques into *SEMAR* with considering the key characteristics and analysis of each AI technique described in Section 3. Figure 2 shows the design overview of integrating AI techniques in *SEMAR*. It consists of *AI Model Management*, *Real-Time AI*, and *Batch AI* services. The *AI Model Management* feature is responsible for managing AI models. It allows users to generate models from datasets stored in the sensor data storage and to upload existing models from other machines. The *Real-Time AI* feature performs data processing using AI in real-time scenarios. The *Batch AI* feature enables users to apply AI models to process existing data in the data storage. Furthermore, we show how to implement AI on edge computing devices by integrating the *Edge Device Framework* [10] with *SEMAR*.

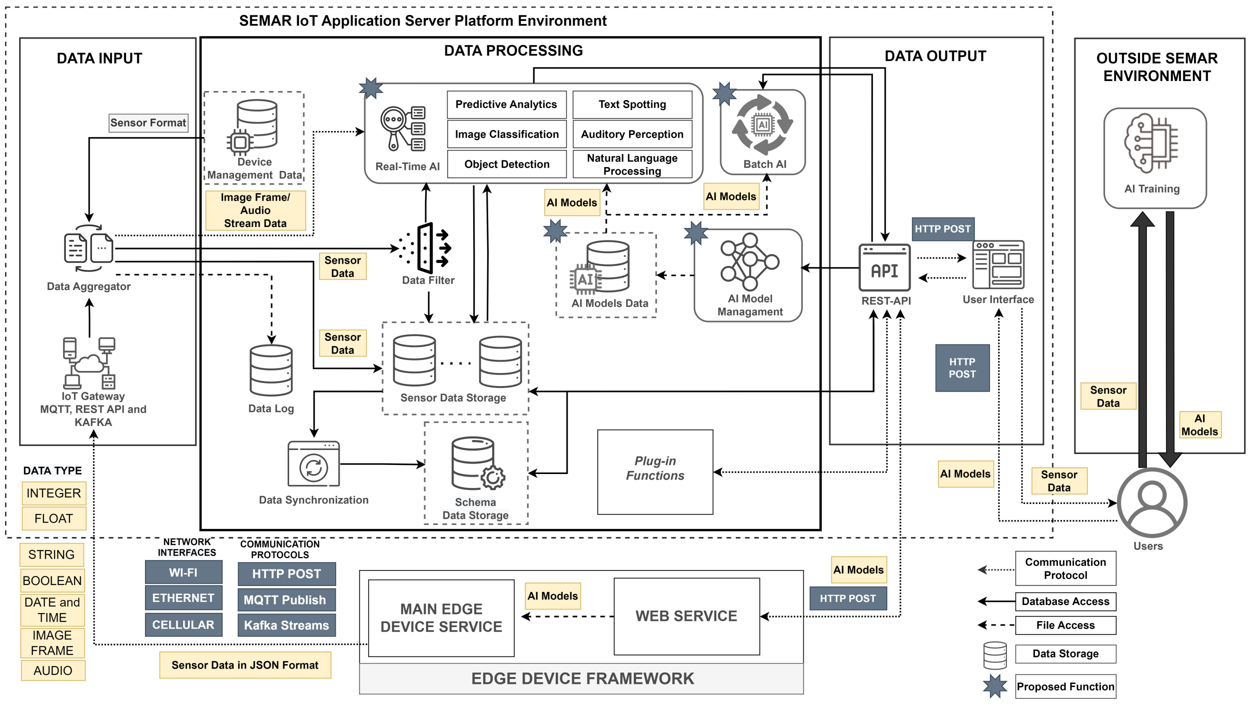


Figure 2. Design overview of AI techniques in *SEMAR* IoT application server platform.

The limitation of our proposed approach arises from the fact that the training of the AI model occurs in an environment external to the *SEMAR* platform. This implies that our platform is not able to directly influence or control the performance of the model. As a result, there may be variations in the performance of the model. To mitigate this limitation, the *AI Model Management* feature allows seamless versioning of AI models for deployments, enabling users to effectively track and manage different AI models. Another limitation is related to the compatibility of AI models supported by the *SEMAR* platform. Our approach restricts the platform's support to Python-based models only.

4.2. AI Model Management

The implementation of AI requires a systematic approach to defining objectives, collecting data, building models, and deploying them for real-world applications. As an IoT development tool, *SEMAR* should perform the functions that allow users to implement AI techniques in the applications easily. The current implementation of *SEMAR* provides the ability to collect sensor data. To help the integration of AI models, we design the implementation of the *AI Model Management* feature in *SEMAR*. It allows users to manage, add, remove, and deploy models through the user interfaces of *SEMAR*.

In this design, *SEMAR* enables users to utilize models generated on other machines. First, users can grab sensor data stored in the data storage of *SEMAR*. This provides easy access to relevant data sets and simplifies the data preparation process. Then, users engage in the data training process to generate an AI model. After obtaining a trained model, users upload it through user interfaces of *SEMAR*. Next, users define the properties of the model, including its name, version, inputs, outputs, and the type of AI techniques employed. Inputs represent the list of data to be processed, while outputs represent the list of results obtained after AI processing. The system simplifies the deployment process by automatically specifying the data types of inputs and outputs for image classification, object detection, text spotting, and NLP techniques, although users are still able to customize these settings. For predictive analytics, users manually define input and output elements. Once a user registers a new model, the system stores it in the AI model data store through file access. This ensures that the model can be easily accessed for future use. Finally, to bring the models into applications, users are allowed to deploy the models for *Real-Time AI* or *Batch AI* processing.

According to the software requirement characteristics identified in the literature review, we select Python to build the features. Then, we build new features in user interfaces and *REST API* services of the *SEMAR* that focus on seamlessly guiding users in managing AI models.

4.3. Real-Time and Batch AI Processing

This section introduces two features, namely *Real-Time AI* and *Batch AI* services, for applying AI models in *SEMAR*. The *Real-Time AI* service is specifically designed for scenarios that require immediate AI processing. As shown in Figure 2, this service is seamlessly integrated with *IoT cloud gateway* and the *data aggregator* to perform the data stream processing.

In object detection, image classification, text spotting, audio recognition, and *NLP* techniques, the *IoT cloud gateway* receives image frames or audio data. The *data aggregator* verifies the format of the data in following standards such as *JPEG* and *WAV*. The verified data are sent to the *Real-Time AI* service through established communication protocols for further processing by AI models. For this purpose, we utilize the *Kafka* communication protocols. Once the system receives the results, it stores them in the data storage. In the predictive analytics scenario, the data aggregator forwards the data to the data filter before reaching the *Real-Time AI* services, which perform data pre-processing. These services predict the future events of data using an AI model and the historical data collected from the data storage.

The *Batch AI* service provides a service designed for AI processing on existing data saved in the data storage. This service is particularly useful for dealing with large data sets that cannot be processed in real-time scenarios. Unlike the *Real-Time AI* services that process data automatically, users should first select specific data that will be processed through the user interface of *SEMAR*. Then, users select a suitable AI model from the storage. The system systematically applies the AI processes to all of the selected data, collects the results, and saves them back to the data storage. The implementation of *Real-Time AI* and *Batch AI* services in *SEMAR* enhances system flexibility by handling both immediate processing tasks and post-processing analysis requirements.

4.4. AI Implementation in Edge Devices

Previously, we introduced the *edge device framework* as one feature of *SEMAR* [10]. This framework allows users to optimize the functionality of IoT devices by allowing them to be configured remotely from the server. It provides the functions for connecting to multiple IoT sensors, processing data in standard formats, and using the collected data through multiple output components. These functions are organized into the *input*, *processing*, and *output* components. As the insights from collaborative AI techniques in the literature review, we design a strategic extension by implementing AI models on edge devices. Figure 3 illustrates the design overview of the AI implementation in the edge device framework. We add the *Real-Time AI* function within the processing components to facilitate the immediate processing of sensor data using AI models.

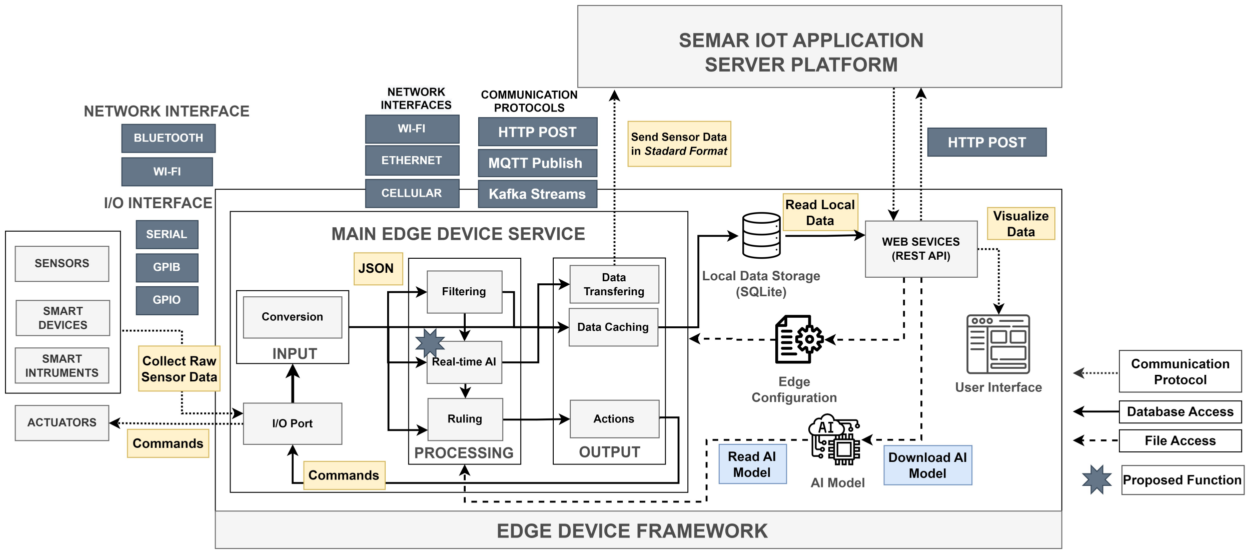


Figure 3. Design overview of AI model implementation in edge device framework.

For the installation process, users need to select the appropriate AI model and define field output to store the result. Then, web services download the AI models from the *SEMAR* server through the *HTTP-POST* communication. After the download process is completed, the *main service* on the framework reads the AI model and runs the service to collect sensor data. Finally, once the *Real-Time AI* function receives sensor data from input components or the *filtering* function, it processes the data using this AI model. The generated results are forwarded to the output components or serve as the input to the *ruling* function. This interconnected workflow enables dynamic and responsive integration of AI models at the edge.

5. Use Cases of Integration AI and IoT Applications in *SEMAR*

In this section, we discuss IoT application use cases that are integrated with the AI-driven capabilities in *SEMAR*. Each use case presents the application overview, requirements, the AI algorithms being employed, and how *SEMAR* can be utilized to support them. They include the drone-based building monitoring system, the *Indoor Navigation System Using Unity and Smartphone (INSUS)*, and the *air-conditioning guidance system (AC-Guide)*.

5.1. Drone-Based Building Monitoring System

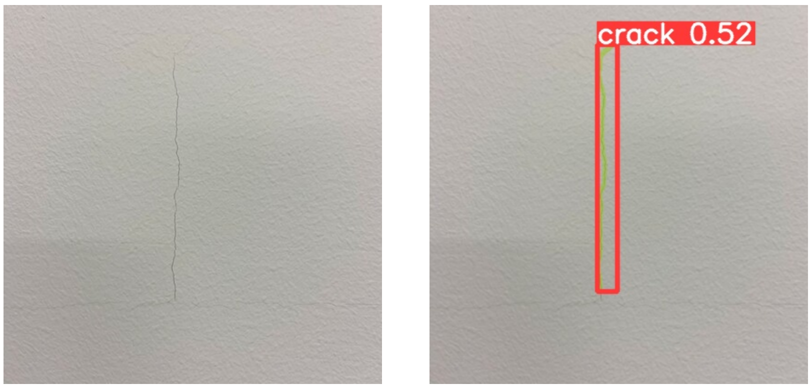
As the first application use case, we discuss the implementation of AI within a drone-based surveillance system. In the building inspection use case, drones emerge as powerful tools for rapid surveillance systems with the ability to navigate autonomously based on missions defined by the programs or to be operated under human control. Their versatility is advantageous for expanding the coverage areas of monitoring systems. By seamlessly integrating drones with AI technologies and an IoT system, drones are able to automatically detect defects in buildings such as cracks.

In the previous research, we introduced the concept of a drone-based building crack detection system [85]. This system consists of flying drones and edge devices connected to the *SEMAR* server. The flying drones capture the image data around the building, while the edge devices are placed in a specific area of the building to control the drones and facilitate the transfer of image data to the *SEMAR* server through a communication protocol service. Once the *SEMAR* server receives the image data, it processes the data using object detection models to detect cracks in the images. Finally, the user interface visualizes the crack detection results.

Several services are required to build this application, such as the communication protocol, object detection, data storage, and user interface services. The communication protocol service should be responsible for transmitting image data. Then, the object detection service provides the capability to identify the crack objects in the image.

To achieve an efficient implementation of this use case, we will use *Confluent Kafka* as the communication protocol service between *SEMAR* and edge devices. As mentioned in Section 3, the *YOLO* algorithm has gained popularity for its efficiency in real-time scenarios. Thus, the *AI Model Training* service generates a *YOLO* model using the open-source crack datasets available on the Internet in [86]. We then deploy the *YOLO* model to the *Real-Time AI* service to perform crack detections. This deployment step places the crack-detecting capabilities derived from the *YOLO* algorithm into the flow of data streams in *SEMAR*. Once the system detects crack objects in an image, it stores them in the data storage. Finally, the user interface visualizes the detected cracks for users by accessing the *REST API* service.

Figure 4 shows the preliminary implementation results of crack detections using the *YOLOv7* algorithm. The crack images were captured using the *Ryze Tello* drone. The model was built using 3717 crack images. Then, we utilized an additional 200 images to validate the model with the *Intersection over Union (IoU)* threshold of 50%. The validation results show that the average model accuracy is up to 73% and the *mean average precision (mAP)* is up to 82%.



(**a**) Crack image captured by drone. (**b**) Crack detection result.

Figure 4. Drone-based crack detection result.

5.2. *Indoor Navigation System Using Unity and Smartphone*

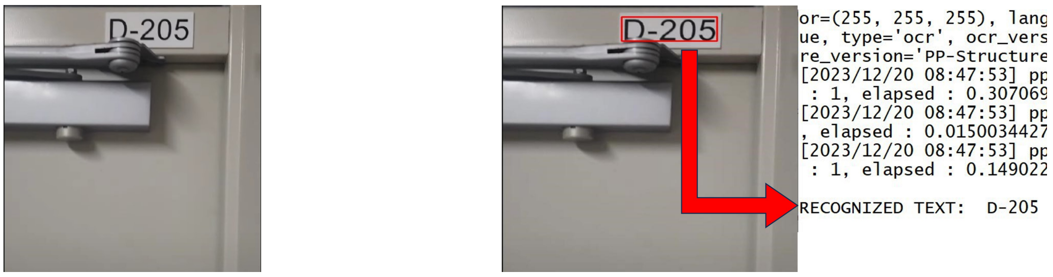
For the second application use case, we introduce the integration of the *SEMAR* server with the *Indoor Navigation System Using Unity and Smartphone (INSUS)*. In this scenario, the primary requirement for the navigation system is to accurately determine the current position of the user. While *Global Positioning System (GPS)* is a commonly used technology in outdoor scenarios, its accuracy decreases in the indoor environment due to the difficulty of obtaining a stable signal. To address this limitation, indoor navigation systems use alternative approaches to determine the current position of the user.

In Ref. [87], the INSUS application introduced *Augmented Reality (AR)* technology for user guidance. This system utilizes the *Simultaneous Localization and Mapping (SLAM)* technique, which combines a 3D map of the building with a camera and *inertial measurement unit (IMU)* sensors of the smartphone. This system works by identifying the users' initial position using the *QR* code technology. It then guides users from their starting position to their destination using the 3D arrows in the real view. However, a drawback of this method is the requirement of the QR code sheet in every room of the target building to achieve accurate initial positions. In order to solve this challenge, the current implementation of INSUS proposes a novel approach to identify the user's position by recognizing room-specific information that appears at the door, including floor levels, the number of rooms, and resident names.

Text spotting becomes a viable solution for this use case. It can extract room-specific information from the image captured by the smartphone through the INSUS system. In contrast to the first use case, where the application does not need any feedback from the *SEMAR* server after sending the image frame, this use case requires real-time communication that is able to send the image to the *SEMAR* server and receive the corresponding room information in real time.

For this purpose, the combination of *HTTP-POST* for the communication protocol and an OCR model for the text recognition can be a solution to achieve the efficient implementation of this use case. The process consists of several steps. First, we build the OCR model within *AI Model Training Service*. Next, the generated model is deployed to the *Real-Time AI* service. When the system receives input from the INSUS application, it employs the OCR model to recognize the room information in the image. Finally, the result is sent back to INSUS through the *REST API* services in *JSON* format to complete the real-time communication loop.

Figure 5 demonstrates the preliminary results of the text recognition using the *PaddleOCR* model. The results show that the room label was successfully identified from the image captured by the camera in the INSUS application.



```
or=(255, 255, 255), lang
ue, type='ocr', ocr_vers
re_version='PP-Structure
[2023/12/20 08:47:53] pp
 : 1, elapsed : 0.307069
[2023/12/20 08:47:53] pp
, elapsed : 0.0150034427
[2023/12/20 08:47:53] pp
 : 1, elapsed : 0.149022

RECOGNIZED TEXT:  D-205
```

(**a**) Door image captured by camera in INSUS. (**b**) Recognized text result.

Figure 5. Result of text recognition algorithm using OCR model.

5.3. Air-Conditioning Guidance System

As the last use case of IoT applications, we introduce the integration of AI in the air conditioning guidance system, namely *AC-Guide*. Recently, the development of smart homes has gained significant popularity and attention from both academia and industry. It focuses on technologies that enhance the convenience, efficiency, and comfort of users' daily lives. In this use case, the environmental condition data are essential for the system to recognize the comfort or discomfort state of the specific area. Therefore, a smart home system utilizes IoT sensors to measure environmental conditions in order to fulfill this important requirement.

Previously, we integrated *AC-Guide*, an IoT system, to guide the use of AC by identifying the discomfort state of the room, with the *SEMAR* IoT application platform [4]. This system consists of a *Raspberry Pi* with attached sensors to measure the temperature and humidity of the room and a camera to collect images of the AC control panel. It accesses the *OpenWeatherMap API* [88] to collect the standard outdoor weather data. Then, it calculates the indoor and outdoor *discomfort index (DI)* to identify whether the current state conditions are *comfort* or *discomfort*. By considering the on/off state of AC, indoor DI and outdoor DI, it sends the proper guidance to users to *turn on* or *turn off* the AC through a message. Finally, it sends data to the server through *MQTT* communication and stores the data in the local log file.

Our implementation results demonstrate that the system has successfully identified the current state of DI. However, this system can be improved by using advanced analysis techniques to identify data patterns for predicting future events. This improvement is useful in preventing discomfort states.

One AI technique that can be applied to this application is predictive analytics. As mentioned in Section 3, predictive analytics allows the system to estimate future values and use the results to support decision-making. Therefore, we propose the application of predictive analytics techniques to perform early guidance systems for the use of AC by considering the prediction data.

For this purpose, we use the *LSTM* algorithm to generate AI models for predicting indoor temperature and humidity using collected sensor data. This process is performed by the *AI Model Training* service. After the models are generated, the system deploys them to the *Real-Time* AI service. Once it receives the sensor data, it predicts the future value by using the AI models and the stored data from the data storage. Then, it stores the data in the data storage. Finally, we build the *plug-in* function to calculate the DI state based on the predicted sensor values.

In this paper, we present the preliminary system to predict the humidity and temperature data collected by the AC-Guide system. We trained a model based on the *LSTM* algorithm for 100 epochs. The data sets contain 132 data for training and 68 data for validation. The validation results indicate that the model can predict the values with a *root mean square error (RMSE)* of 0.08 for humidity and 0.04 for temperature. Figure 6 shows the results of the predicted values compared to the real value.

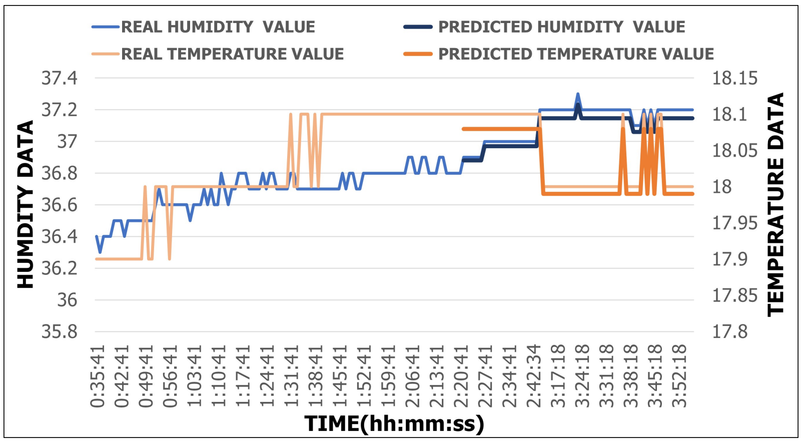


Figure 6. Predictive analytics results using LSTM algorithm in AC-Guide system.

6. Conclusions

This paper presents the study of AI techniques and their implementation use cases for designing AI integrations in the *SEMAR* IoT application server platform. This study provides a comprehensive review of current research on implementing AI techniques in IoT applications, covering predictive analytics, image classification, object detection, text spotting, auditory perception, *NLP*, and collaborative AI. Software requirements, *input/output (I/O)* data types, processing methods, and computations are parameters used to identify the characteristics of each technique.

Based on the findings, we have designed the implementation for the seamless integration of AI techniques into *SEMAR* by incorporating new features such as *AI Model Training*, *Real-Time AI*, and *Batch AI* services. The paper also outlines the design of AI implementations in edge devices by utilizing the *SEMAR* and the edge device framework. Through the integration design with three IoT application use cases, the advantages of the proposed system are described.

In future works, we will continue to implement AI technologies in *SEMAR* to complete the proposed design in Figure 2, and will proceed with evaluations through integrations with other IoT application use cases.

Author Contributions: Conceptualization, Y.Y.F.P., N.F. and S.S.; Methodology, Y.Y.F.P., E.D.F. and S.F.; Software, Y.Y.F.P., E.D.F. and S.F.; Writing—Original Draft Preparation, Y.Y.F.P.; Writing—Review and Editing, N.F.; Validation, S.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Dataset used in this work is available based on the request.

Acknowledgments: The authors thank the reviewers for their thorough reading and helpful comments.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Gubbi, J.; Buyya, R.; Marusic, S.; Palaniswami, M. Internet of things (IoT): A Vision, Architectural Elements, and Future Directions. *Future Gener. Comput. Syst.* **2013**, *29*, 1645–1660. [CrossRef]
2. Stankovic, J.A. Research Directions for the Internet of Things. *IEEE Internet Things J.* **2014**, *1*, 3–9. [CrossRef]
3. Noura, M.; Atiquzzaman, M.; Gaedke, M. Interoperability in Internet of Things: Taxonomies and Open Challenges. *Mob. Netw. Appl.* **2018**, *24*, 796–809. [CrossRef]
4. Panduman, Y.Y.F.; Funabiki, N.; Puspitaningayu, P.; Kuribayashi, M.; Sukaridhoto, S.; Kao, W.-C. Design and Implementation of SEMAR IoT Server Platform with Applications. *Sensors* **2022**, *22*, 6436. [CrossRef] [PubMed]
5. Hassabis, D.; Kumaran, D.; Summerfield, C.; Botvinick, M. Neuroscience-inspired Artificial Intelligence. *Neuron* **2017**, *95*, 245–258. [CrossRef] [PubMed]
6. Duan, Y.; Edwards, J.S.; Dwivedi, Y.K. Artificial Intelligence for Decision Making in the Era of Big Data—Evolution, Challenges and Research Agenda. *Int. J. Inf. Manag.* **2019**, *48*, 63–71. [CrossRef]
7. Belgaum, M.R.; Alansari, Z.; Musa, S.; Mansoor Alam, M.; Mazliham, M.S. Role of Artificial Intelligence in Cloud Computing, IoT and SDN: Reliability and Scalability Issues. *Int. J. Electr. Comput. Eng. (IJECE)* **2021**, *11*, 4458. [CrossRef]
8. Janbi, N.; Katib, I.; Mehmood, R. Distributed Artificial Intelligence: Taxonomy, Review, Framework, and Reference Architecture. *Intell. Syst. Appl.* **2023**, *18*, 200231. [CrossRef]
9. Saleem, T.J.; Chishti, M.A. Deep Learning for the Internet of Things: Potential Benefits and Use-cases. *Digit. Commun. Netw.* **2021**, *7*, 526–542. [CrossRef]
10. Panduman, Y.Y.F.; Funabiki, N.; Ito, S.; Husna, R.; Kuribayashi, M.; Okayasu, M.; Shimazu, J.; Sukaridhoto, S. An Edge Device Framework in SEMAR IoT Application Server Platform. *Information* **2023**, *14*, 312. [CrossRef]
11. MongoDB, Mongodb: The Application Data Platform. Available online: https://www.mongodb.com/ (accessed on 22 February 2024).
12. Zhang, J.; Tao, D. Empowering Things with Intelligence: A Survey of the Progress, Challenges, and Opportunities in Artificial Intelligence of Things. *IEEE Internet Things J.* **2021**, *8*, 7789–7817. [CrossRef]
13. Talib, M.A.; Majzoub, S.; Nasir, Q.; Jamal, D. A Systematic Literature Review on Hardware Implementation of Artificial Intelligence Algorithms. *J. Supercomput.* **2020**, *77*, 1897–1938. [CrossRef]
14. Abioye, S.O.; Oyedele, L.O.; Akanbi, L.; Ajayi, A.; Davila Delgado, J.M.; Bilal, M.; Akinade, O.O.; Ahmed, A. Artificial Intelligence in the Construction Industry: A Review of Present Status, Opportunities and Future Challenges. *J. Build. Eng.* **2021**, *44*, 103299. [CrossRef]
15. Sarker, I.H. Machine Learning: Algorithms, Real-world Applications and Research Directions. *SN Comput. Sci.* **2021**, *2*, 160. [CrossRef]
16. Alahi, M.E.; Sukkuea, A.; Tina, F.W.; Nag, A.; Kurdthongmee, W.; Suwannarat, K.; Mukhopadhyay, S.C. Integration of IoT-enabled Technologies and Artificial Intelligence (AI) for Smart City Scenario: Recent Advancements and Future Trends. *Sensors* **2023**, *23*, 5206. [CrossRef] [PubMed]
17. Kumar, V. Predictive Analytics: A Review of Trends and Techniques. *Int. J. Comput. Appl.* **2018**, *182*, 31–37. [CrossRef]
18. Imran; Iqbal, N.; Ahmad, S.; Kim, D.H. Towards Mountain Fire Safety Using Fire Spread Predictive Analytics and Mountain Fire Containment in IoT Environment. *Sustainability* **2021**, *13*, 2461. [CrossRef]
19. Hussain, A.; Draz, U.; Ali, T.; Tariq, S.; Irfan, M.; Glowacz, A.; Antonino Daviu, J.A.; Yasin, S.; Rahman, S. Waste Management and Prediction of Air Pollutants Using IoT and Machine Learning Approach. *Energies* **2020**, *13*, 3930. [CrossRef]
20. Mumtaz, R.; Zaidi, S.M.; Shakir, M.Z.; Shafi, U.; Malik, M.M.; Haque, A.; Mumtaz, S.; Zaidi, S.A. Internet of Things (IoT) Based Indoor Air Quality Sensing and Predictive Analytic—A COVID-19 Perspective. *Electronics* **2021**, *10*, 184. [CrossRef]
21. Barthwal, A.; Acharya, D. An IoT Based Sensing System for Modeling and Forecasting Urban Air Quality. *Wirel. Pers. Commun.* **2021**,*116*, 3503–3526. [CrossRef]
22. Jin, X.B.; Gong, W.T.; Kong, J.L.; Bai, Y.T.; Su, T.L. A Variational Bayesian Deep Network with Data Self-screening Layer for Massive Time-series Data Forecasting. *Entropy* **2022**, *24*, 355. [CrossRef]

23. Bampoula, X.; Siaterlis, G.; Nikolakis, N.; Alexopoulos, K. A Deep Learning Model for Predictive Maintenance in Cyber-Physical Production Systems Using LSTM Autoencoders. *Sensors* **2021**, *21*, 972. [CrossRef] [PubMed]
24. Teoh, Y.K.; Gill, S.S.; Parlikad, A.K. IoT and Fog-computing-based Predictive Maintenance Model for Effective Asset Management in Industry 4.0 Using Machine Learning. *IEEE Internet Things J.* **2023**, *10*, 2087–2094. [CrossRef]
25. Shorfuzzaman, M.; Hossain, M.S. Predictive Analytics of Energy Usage by IoT-based Smart Home Appliances for Green Urban Development. *ACM Trans. Internet Technol.* **2021**, 22, 1–26. [CrossRef]
26. Guo, N.; Chen, W.; Wang, M.; Tian, Z.; Jin, H. Appling an Improved Method Based on ARIMA Model to Predict the Short-term Electricity Consumption Transmitted by the Internet of Things (IoT). *Wirel. Commun. Mob. Comput.* **2021**, *2021*, 6610273. [CrossRef]
27. Nancy, A.A.; Ravindran, D.; Raj Vincent, P.M.; Srinivasan, K.; Gutierrez Reina, D. IoT-cloud-based Smart Healthcare Monitoring System for Heart Disease Prediction via Deep Learning. *Electronics* **2022**, *11*, 2292. [CrossRef]
28. Subahi, A.F.; Khalaf, O.I.; Alotaibi, Y.; Natarajan, R.; Mahadev, N.; Ramesh, T. Modified Self-Adaptive Bayesian Algorithm for Smart Heart Disease Prediction in IoT System. *Sustainability* **2022**, *14*, 14208. [CrossRef]
29. Patrizi, G.; Bartolini, A.; Ciani, L.; Gallo, V.; Sommella, P.; Carratu, M. A Virtual Soil Moisture Sensor for Smart Farming Using Deep Learning. *IEEE Trans. Instrum. Meas.* **2022**, *71*, 1–11.
30. Kocian, A.; Carmassi, G.; Cela, F.; Chessa, S.; Milazzo, P.; Incrocci, L. IoT Based Dynamic Bayesian Prediction of Crop Evapotranspiration in Soilless Cultivations. *Comput. Electron. Agric.* **2023**, *205*, 107608. [CrossRef]
31. Yu, Y.; Si, X.; Hu, C.; Zhang, J. A Review of Recurrent Neural Networks: LSTM Cells and Network Architectures. *Neural Comput.* **2019**, *31*, 1235–1270. [CrossRef]
32. Schaffer, A.L.; Dobbins, T.A.; Pearson, S.-A. Interrupted Time Series Analysis Using Autoregressive Integrated Moving Average (ARIMA) Models: A Guide for Evaluating Large-scale Health Interventions. *BMC Med. Res. Methodol.* **2021**, *21*, 58. [CrossRef]
33. Xu, Y.; Liu, X.; Cao, X.; Huang, C.; Liu, E.; Qian, S.; Liu, X.; Wu, Y.; Dong, F.; Qiu, C.W.; et al. Artificial intelligence: A powerful paradigm for scientific research. *Innovation* **2021**, *2*, 100179. [CrossRef] [PubMed]
34. Chouhan, S.S.; Singh, U.P.; Jain, S. Automated Plant Leaf Disease Detection and Classification Using Fuzzy Based Function Network. *Wirel. Pers. Commun.* **2021**, *121*, 1757–1779. [CrossRef]
35. Munawar, H.S.; Ullah, F.; Qayyum, S.; Heravi, A. Application of Deep Learning on UAV-based Aerial Images for Flood Detection. *Smart Cities* **2021**, *4*, 1220–1243. [CrossRef]
36. Abd Elaziz, M.; Mabrouk, A.; Dahou, A.; Chelloug, S.A. Medical Image Classification Utilizing Ensemble Learning and Levy Flight-based Honey Badger Algorithm on 6g-enabled Internet of Things. *Comput. Intell. Neurosci.* **2022**, *2022*, 5830766.
37. Saleh, A.Y.; Chin, C.K.; Penshie, V.; Al-Absi, H.R. Lung Cancer Medical Images Classification Using Hybrid CNN-SVM. *Int. J. Adv. Intell. Inform.* **2021**, *7*, 151. [CrossRef]
38. Iyer, S.; Velmurugan, T.; Gandomi, A.H.; Noor Mohammed, V.; Saravanan, K.; Nandakumar, S. Structural Health Monitoring of Railway Tracks Using IoT-based Multi-robot System. *Neural Comput. Appl.* **2020**, *33*, 5897–5915. [CrossRef]
39. Medus, L.D.; Saban, M.; Francés-Víllora, J.V.; Bataller-Mompeán, M.; Rosado-Muñoz, A. Hyperspectral Image Classification Using CNN: Application to Industrial Food Packaging. *Food Control* **2021**, *125*, 107962. [CrossRef]
40. Zhou, X.; Xu, X.; Liang, W.; Zeng, Z.; Yan, Z. Deep-Learning-Enhanced Multitarget Detection for End–Edge–Cloud Surveillance in Smart IoT. *IEEE Internet Things J.* **2021**, *8*, 12588–12596. [CrossRef]
41. Abdellatif, T.; Sedrine, M.A.; Gacha, Y. DroMOD: A Drone-Based Multi-Scope Object Detection System. *IEEE Access* **2023**, *11*, 26652–26666. [CrossRef]
42. Lee, J.; Wang, J.; Crandall, D.; Šabanović, S.; Fox, G. Real-time, cloud-based object detection for unmanned aerial vehicles. In Proceedings of the 2017 First IEEE International Conference on Robotic Computing (IRC), Taichung, Taiwan, 10–12 April 2017; pp. 36–43.
43. Meivel, S.; Sindhwani, N.; Anand, R.; Pandey, D.; Alnuaim, A.A.; Altheneyan, A.S.; Jabarulla, M.Y.; Lelisho, M.E. Mask Detection and Social Distance Identification Using Internet of Things and Faster R-CNN Algorithm. *Comput. Intell. Neurosci.* **2022**, *2022*, 2103975. [CrossRef] [PubMed]
44. Yao, R.; Qi, P.; Hua, D.; Zhang, X.; Lu, H.; Liu, X. A Foreign Object Detection Method for Belt Conveyors Based on an Improved YOLOX Model. *Technologies* **2023**, *11*, 114. [CrossRef]
45. Ali, L.; Alnajjar, F.; Parambil, M.M.; Younes, M.I.; Abdelhalim, Z.I.; Aljassmi, H. Development of YOLOv5-Based Real-Time Smart Monitoring System for Increasing Lab Safety Awareness in Educational Institutions. *Sensors* **2022**, *22*, 8820. [CrossRef] [PubMed]
46. Baretto, A.; Pudussery, N.; Subramaniam, V.; Siddiqui, A. Real-Time WebRTC based Mobile Surveillance System. *Int. J. Eng. Manag. Res.* **2021**, *11*, 30–35. [CrossRef]
47. Sredojev, B.; Samardzija, D.; Posarac, D. WebRTC technology overview and signaling solution design and implementation. In Proceedings of the 2015 38th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO), Opatija, Croatia, 25–29 May 2015; pp. 1006–1009. [CrossRef]
48. Bassam, R.; Samann, F. Smart Parking System based on Improved OCR Model. *IOP Conf. Ser. Mater. Sci. Eng.* **2020**, *978*, 012007. [CrossRef]
49. Wu, Z.; Chen, X.; Wang, J.; Wang, X.; Gan, Y.; Fang, M.; Xu, T. OCR-RTPS: An OCR-Based Real-time Positioning System for the Valet Parking. *Appl. Intell.* **2023**, *53*, 17920–17934. [CrossRef]
50. Glasenapp, L.A.; Hoppe, A.F.; Wisintainer, M.A.; Sartori, A.; Stefenon, S.F. OCR Applied for Identification of Vehicles with Irregular Documentation Using IoT. *Electronics* **2023**, *12*, 1083. [CrossRef]

51. Tham, M.L.; Tan, W.K. IoT Based License Plate Recognition System Using Deep Learning and OpenVINO. In Proceedings of the 2021 4th International Conference on Sensors, Signal and Image Processing, Nanjing, China, 15–17 October 2021; pp. 7–14.
52. Ktari, J.; Frikha, T.; Hamdi, M.; Elmannai, H.; Hmam, H. Lightweight AI Framework for Industry 4.0 Case Study: Water Meter Recognition. *Big Data Cogn. Comput.* **2022**, *6*, 72. [CrossRef]
53. Abdullah, R.; Ahmed, R.; Jamal, L. A Novel IoT-Based Medicine Consumption System for Elders. *SN Comput. Sci.* **2022**, *3*, 471. [CrossRef]
54. Chang, J.; Ong, H.; Wang, T.; Chen, H.-H. A Fully Automated Intelligent Medicine Dispensary System Based on AIoT. *IEEE Internet Things J.* **2022**, *9*, 23954–23966. [CrossRef]
55. Dilshad, N.; Ullah, A.; Kim, J.; Seo, J. LocateUAV: Unmanned Aerial Vehicle Location Estimation via Contextual Analysis in an IoT Environment. *IEEE Internet Things J.* **2023**, *10*, 4021–4033. [CrossRef]
56. Promsuk, N.; Taparugssanagorn, A. Numerical Reader System for Digital Measurement Instruments Embedded Industrial Internet of Things. *J. Commun.* **2021**, *16*, 132–142. [CrossRef]
57. Meng, J. Research on the Early Warning System of Cold Chain Cargo Based on OCR Technology. *World J. Eng. Technol.* **2022**, *10*, 527–538. [CrossRef]
58. Cao, W.; Chen, Z.; Deng, X.; Wu, C.; Li, T. An Identification Method for Irregular Components Related to Terminal Blocks in Equipment Cabinet of Power Substation. *Sensors* **2023**, *23*, 7739. [CrossRef]
59. Balia, R.; Giuliani, A.; Piano, L.; Pisu, A.; Saia, R.; Sansoni, N. A Comparison of Audio-Based Deep Learning Methods for Detecting Anomalous Road Events. *Procedia Comput. Sci.* **2022**, *210*, 198–203. [CrossRef]
60. Yan, L.; Ko, S.-W. In-tunnel Accident Detection System based on the Learning of Accident Sound. *Open Transp. J.* **2021**, *15*, 81–92. [CrossRef]
61. Ciaburro, G.; Iannace, G. Improving Smart Cities Safety Using Sound Events Detection Based on Deep Neural Network Algorithms. *Informatics* **2020**, *7*, 23. [CrossRef]
62. Polo-Rodriguez, A.; Vilchez Chiachio, J.M.; Paggetti, C.; Medina-Quero, J. Ambient Sound Recognition of Daily Events by Means of Convolutional Neural Networks and Fuzzy Temporal Restrictions. *Appl. Sci.* **2021**, *11*, 6978. [CrossRef]
63. Chhaglani, B.; Zakaria, C.; Lechowicz, A.; Gummeson, J.; Shenoy, P. FlowSense: Monitoring Airflow in Building Ventilation Systems Using Audio Sensing. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* **2022**, *6*, 1–26. [CrossRef]
64. Tiwari, V. MFCC and Its Applications in Speaker Recognition. *Int. J. Emerg. Technol.* **2010**, *1*, 19–22.
65. Giv, H.H. Directional Short-time Fourier Transform. *J. Math. Anal. Appl.* **2013**, *399*, 100–107. [CrossRef]
66. Otter, D.W.; Medina, J.R.; Kalita, J.K. A Survey of the Usages of Deep Learning for Natural Language Processing. *IEEE Trans. Neural Netw. Learn. Syst.* **2021**, *32*, 604–624. [CrossRef] [PubMed]
67. Ismail, A.; Abdlerazek, S.; El-Henawy, I.M. Development of Smart Healthcare System Based on Speech Recognition Using Support Vector Machine and Dynamic Time Warping. *Sustainability* **2020**, *12*, 2403. [CrossRef]
68. Froiz-Míguez, I.; Fraga-Lamas, P.; Fernández-CaraméS, T.M. Design, Implementation, and Practical Evaluation of a Voice Recognition Based IoT Home Automation System for Low-Resource Languages and Resource-Constrained Edge IoT Devices: A System for Galician and Mobile Opportunistic Scenarios. *IEEE Access* **2023**, *11*, 63623–63649. [CrossRef]
69. Ali, A.A.; Mashhour, M.; Salama, A.S.; Shoitan, R.; Shaban, H. Development of an Intelligent Personal Assistant System Based on IoT for People with Disabilities. *Sustainability* **2023**, *15*, 5166. [CrossRef]
70. Dweik, W.; Abdalla, M.; AlHroob, Y.; AlMajali, A.; Mustafa, S.A.; Abdel-Majeed, M. Skeleton of Implementing Voice Control for Building Automation Systems. *Sci. Program.* **2022**, *2022*, 6886086. [CrossRef]
71. Juluru, K.; Shih, H.-H.; Keshava Murthy, K.N.; Elnajjar, P. Bag-of-Words Technique in Natural Language Processing: A Primer for Radiologists. *RadioGraphics* **2021**, *41*, 1420–1426. [CrossRef]
72. Song, C.; Xu, W.; Han, G.; Zeng, P.; Wang, Z.; Yu, S. A Cloud Edge Collaborative Intelligence Method of Insulator String Defect Detection for Power IIoT. *IEEE Internet Things J.* **2021**, *8*, 7510–7520. [CrossRef]
73. Li, M.; Li, Y.; Tian, Y.; Jiang, L.; Xu, Q. AppealNet: An Efficient and Highly Accurate Edge/Cloud Collaborative Architecture for DNN Inference. In Proceedings of the 2021 58th ACM/IEEE Design Automation Conference (DAC), San Francisco, CA, USA, 5–9 December 2021; pp. 409–414. [CrossRef]
74. Chen, Y.-Y.; Lin, Y.-H.; Hu, Y.-C.; Hsia, C.-H.; Lian, Y.-A.; Jhong, S.-Y. Distributed Real-Time Object Detection Based on Edge-Cloud Collaboration for Smart Video Surveillance Applications. *IEEE Access* **2022**, *S10*, 93745–93759. [CrossRef]
75. Loseto, G.; Scioscia, F.; Ruta, M.; Gramegna, F.; Ieva, S.; Fasciano, C.; Bilenchi, I.; Loconte, D. Osmotic Cloud-Edge Intelligence for IoT-Based Cyber-Physical Systems. *Sensors* **2022**, *22*, 2166. [CrossRef]
76. Bu, L.; Zhang, Y.; Liu, H.; Yuan, X.; Guo, J.; Han, S. An IIoT-Driven and AI-Enabled Framework for Smart Manufacturing System Based on Three-Terminal Collaborative Platform. *Adv. Eng. Inform.* **2021**, *50*, 101370. [CrossRef]
77. Seshan, S.; Vries, D.; van Duren, M.; van Helm, A.; Poinapen, J. AI-Based Validation of Wastewater Treatment Plant Sensor Data Using an Open Data Exchange Architecture. *IOP Conf. Ser. Earth Environ. Sci.* **2023**, *1136*, 012055. [CrossRef]
78. Cirillo, F.; Solmaz, G.; Berz, E.L.; Bauer, M.; Cheng, B.; Kovacs, E. A Standard-Based Open Source IoT Platform: FIWARE. *IEEE Internet Things Mag.* **2019**, *2*, 12–18. [CrossRef]
79. Ramallo-Gonzalez, A.P.; Gonzalez-Vidal, A.; Skarmeta, A.F. CIoTVID: Towards an Open IoT-Platform for Infective Pandemic Diseases such as COVID-19. *Sensors* **2021**, *21*, 484. [CrossRef] [PubMed]

80. Raj, E.; Buffoni, D.; Westerlund, M.; Ahola, K. Edge MLOps: An Automation Framework for AIoT Applications. In Proceedings of the 2021 IEEE International Conference on Cloud Engineering (IC2E), San Francisco, CA, USA, 4–8 October 2021; pp. 191–200. [CrossRef]
81. Li, H.; Li, S.; Yu, J.; Han, Y.; Dong, A. AIoT Platform Design Based on Front and Rear End Separation Architecture for Smart Agricultural. In Proceedings of the 2022 4th Asia Pacific Information Technology Conference (APIT 2022), Virtual Event, Thailand, 14–16 January 2022; ACM: New York, NY, USA, 2022; pp. 208–214. [CrossRef]
82. Rong, G.; Xu, Y.; Tong, X.; Fan, H. An edge-cloud collaborative computing platform for building AIoT applications efficiently. *J. Cloud Comput.* **2021**, *10*, 36. [CrossRef]
83. Liang, Y.-C.; Wu, K.-R.; Tong, K.-L.; Ren, Y.; Tseng, Y.-C. An Exchange-based AIoT Platform for Fast AI Application Development. In Proceedings of the 19th ACM International Symposium on QoS and Security for Wireless and Mobile Networks, Montreal, QC, Canada, 30 October–3 November 2023; pp. 105–114. [CrossRef]
84. Stavropoulos, G.; Violos, J.; Tsanakas, S.; Leivadeas, A. Enabling Artificial Intelligent Virtual Sensors in an IoT Environment. *Sensors* **2023**, *23*, 1328. [CrossRef]
85. Panduman, Y.Y.F.; Funabiki, N.; Sukaridhoto, S. An Idea of Drone-Based Building Crack Detection System in SEMAR IoT Server Platform. In Proceedings of the 2023 IEEE 12th Global Conference on Consumer Electronics (GCCE) 2023, Nara, Japan, 10–13 October 2023. [CrossRef]
86. University, "Crack Instance Segmentation Dataset (V2) by University," Roboflow. Available online: https://universe.roboflow.com/university-bswxt/crack-bphdr/dataset/2 (accessed on 22 February 2024).
87. Fajrianti, E.D.; Funabiki, N.; Sukaridhoto, S.; Panduman, Y.Y.F.; Dezheng, K.; Shihao, F.; Surya Pradhana, A.A. INSUS: Indoor Navigation System Using Unity and Smartphone for User Ambulation Assistance. *Information* **2023**, *14*, 359. [CrossRef]
88. OpenWeatherMap. Current Weather and Forecast—OpenWeatherMap. Available online: https://openweathermap.org/ (accessed on 22 February 2024).