

# **Artificial Intelligence for IoT: A Survey of Techniques, Applications, and Challenges**

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## **ABSTRACT**

*The intersection of Artificial Intelligence (AI) and Internet of Things (IoT) technology is considered one of the most revolutionary technological advancements of this century. The presented survey provides a thorough overview of AI approaches for IoT systems,*

*broad range of applications in smart cities, health-care, industrial IoT, agriculture and environment. In addition, this work discusses crucial challenges such as computational limitations, data privacy, security threats, interoperability and explainable AI. We conclude by summarizing current state-of-the-art research, giving practical use-cases and defining future research opportunities for AI-IoT systems.*

**Key Words:** Artificial Intelligence, Deep Learning, Edge Computing, Data Privacy, Explainable AI, Internet of Things, Smart Applications.

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## **1. INTRODUCTION**

Artificial Intelligence (AI) has become a central enabler of modern Internet of Things (IoT) ecosystems because it transforms connected sensors from passive data-generating objects into adaptive decision-making systems. The value of AI-IoT integration is most evident when large-scale heterogeneous data must be interpreted in real time, such as in smart cities, healthcare monitoring, industrial production lines, precision agriculture, and environmental surveillance. The importance of this survey lies in comparing the main AI techniques used in IoT environments and linking them with measurable outcomes reported in recent studies and implementations. By presenting comparative indicators, the paper highlights which application areas have achieved the highest practical benefits and which technical challenges still limit large-scale deployment.

### **1.1 Background and Motivation**

The Internet of Things, or IoT, is a paradigm shift in how data is gathered, processed, and analyzed from our physical environment. A typical IoT system comprises a set of interconnected devices that have sensing hardware, processing hardware, and communication hardware that passively monitor their environment and continuously collect data on their surroundings. Current estimates show that the overall ecosystem of IoT has connected 15.1 billion devices in 2024 and will connect 27 billion devices by 2025; the devices generate immense volumes of data that is equal to 120 zettabytes each year, a quantity beyond that manageable by humans manually. (Smith, 2024; Statista, 2024).

Along with this, Artificial Intelligence has drastically changed the way systems perceive, interpret, and react to huge, dynamic data. Machine learning algorithms are able to determine the patterns, that cannot be identified with the naked eye of human beings, while deep learning algorithms are highly capable of handling the unstructured data which include images, speech, sounds etc. Neural networks have shown the capability to determine the classifications, predict the actions, and make a decision through mimic of the structures and functions of biological brain and thereby it leads the outstanding performance. The incorporation of AI with IoT is leading to an intelligent system which can predict and analyze data without any human intervention and can react to it; adapt to varying condition and make the

self-optimization for various purpose. This combination helps in tackling the major problems associated with IoT, i.e., deriving meaningful information out of huge amount of data produced by IoT devices. (Yousafzai et al., 2022)

### **1.2 Market Size and Growth Projections**

Evidence from the market research indicates that AI-IoT market is experiencing a boom. The worldwide AI in IoT market estimated at USD 18.6 billion in 2023 and is forecasted to be worth USD 66.85 billion by 2028 at a compound annual growth rate (CAGR) of 27.3%. Most other tech sectors cannot match this pace of growth and this also illustrates that organizations are increasingly understanding the significance of AI for the IoT systems. When compared on regional level there is lot of difference in application usage of AI-IoT across globe. The North America dominates the market share by 35% currently. This is due to having established technology infrastructure in the region and substantial enterprises expense on digital transformation. Europe has a 28% market share. This growth is due to European Union's need for compliance with security regulations. Asia-Pacific is the rapidly growing region with CAGR of 32% by 2028. (Singh & Kumar, 2023)

## **2. AI TECHNIQUES FOR IOT SYSTEMS**

### **2.1 Machine Learning Approaches**

Machine Learning (ML) empowers the IoT system to improve its efficiency with experience, without explicit programming. Supervised learning algorithms such as linear regression, support vector machines, and decision trees are widely adopted for IoT applications such as anomaly detection, predictive maintenance, and classification of sensor data. (Pecan & Smith, 2020) These algorithms work well on classification problems when labeled training data is present. Support Vector Machines work well at identifying the best decision boundary in high-dimensional data, making them suitable for equipment failure or unusual sensor reading identification. Linear regression relates a continuous output to one or more continuous inputs, so it is suitable for predicting sensor values and device metrics. Unsupervised learning algorithms that particularly include clustering algorithms such as K-means and hierarchical clustering, allow for identification of patterns in unlabeled IoT data. Clustering algorithms are great for segmenting sensor data, customers, or equipment without a prior classification. Reinforcement learning provides another option, where the IoT system learn control policies by interacting with the system. (Johnson & Martinez, 2022) Classical ML algorithms have the benefit of being suitable for resource-constrained IoT devices due to their lightweight nature. Naive Bayes, Random Forests, and Gradient Boosting are an example of algorithms that can run effectively on the edge due to minimal memory usage and computational resources (Wang et al., 2021).

### **2.2 Deep Learning and Neural Networks**

For complex pattern identification and high-dimension data recognition for IoT applications, deep learning has played an indispensable role. Among different deep learning models, CNNs are quite efficient in image-based IoT applications such as visual inspection, object detection, environment sensing, and object identification. For time series data, RNNs, LSTMs are effective to handle temporal dependencies. CNNs can learn hierarchical features through stack convolutional layers, so that they are able to effectively learn abstract patterns in images. CNNs could detect patterns such as edges, shapes and textures in earlier layers, then recognize features such as object parts and objects at later layers. LSTM can avoid vanishing gradient problem by implementing memory and forget gate to allow it to carry long-term information for hundred or thousand time steps. On the contrary, a full deep learning model is generally hard to deploy in edge IoT devices due to memory and computation constraints. However, neural network deployment in resource constrained IoT devices can be achieved by model compression techniques, such as quantization, pruning, knowledge distillation, etc.. Quantization reduced the number of bits representing neural networks' weight by replacing 32-bit float point numbers with 8-bit float point or bit representation, which can reduce model size 4-32x with bounded degradation. Pruning removes some not so important weights.

### **2.3 Edge Computing and Federated Learning**

By processing data closer to data sources (edge devices, gateways), edge computing enables lower latency and bandwidth usage as all data doesn't need to be transmitted back to a centralized cloud infrastructure (Anderson et al., 2023). The real-time nature and data privacy benefits gained through processing locally on the edge can be a crucial aspect of some applications, particularly safety-critical ones. In contrast, cloud-based processing suffers from 100-

500ms of round-trip latency caused by the time to traverse networks and for each packet to be processed. For Autonomous Vehicles where sub-100ms latencies are required to safely avoid collisions, cloud-processing is not suitable. Federated Learning builds on edge computing, and it allows a decentralized learning process where no raw data is ever centralized. In this technique, each IoT device trains locally on its own data then aggregates models on a central server (Li et al., 2022; Google Research, 2024). This model training process overcomes some privacy concerns and utilizes intelligence across the distributed data.

### **3. AI APPLICATIONS IN IOT**

#### **3.1 Smart Cities and Urban Infrastructure**

AI-powered IoT networks have led to the creation of smart cities, optimizing infrastructure and the well-being of inhabitants. AI has facilitated the development of intelligently controlled traffic lights which use road sensors, traffic cameras and data collected from vehicles on the road to predict patterns, reduce traffic flow, minimize delays and reduce air pollution. Machine learning is used to model traffic patterns, thereby increasing the capacity of road networks and improving the traffic flow. (Reis et al., 2023) The Smart City initiative of Barcelona used AI-powered traffic signal control to reduce overall traffic congestion by 24%, traffic delays were also reduced by 20-25% which provides an excellent return on investment due to less pollution and traffic congestion related costs.

Smart energy grids also use AI to manage the consumption of energy. Demand forecast and energy load balancing using AI reduces the amount of energy produced, especially with growing integration of renewable sources like wind power and solar power, the fluctuations on the grid due to the weather can be managed more effectively with AI. It is estimated that these initiatives reduce energy usage by 15-25% in pilot cities (Thompson & Davis, 2024). Demand response programs can adjust power consumption, so that electricity consumption is not concentrated in high demand periods which can cause outages or the need for more energy infrastructure to be constructed. Smart building systems analyze occupancy to adjust HVAC and other building systems to be as energy efficient as possible whilst still providing adequate comfort, reducing energy usage by 15-25%. AI is also used for optimizing EV charging during periods of low demand on the grid or where there is excess power from renewables.

#### **3.2 Healthcare and Medical IoT**

Continuous health monitoring and early diagnosis through wearable IoT devices have been greatly enabled by AI. Devices such as smartwatches, fitness bands and medical sensors capture data on vital signs, such as heart rate, blood pressure and oxygen levels, as well as information from ECG sensors and thermometers. This data can be analyzed using machine learning algorithms to diagnose arrhythmias, predict health deterioration and alert users or health professionals to health crises. (Pramanik et al., 2023) AI has enabled continuous monitoring of people's hearts to enable real-time detection of arrhythmias. The use of specialized neural networks has improved the sensitivity and specificity for detecting these abnormalities to above 95%. AI also allows detection of hypertension and warning patients, which allows for preventive measures to be taken and avoid long term damage.

Remote patient monitoring through IoT enabled by AI has been particularly valuable during times like the COVID-19 pandemic and for patients with chronic illnesses. Deep learning techniques have allowed the detection of subtler patterns in patient data than would be possible to detect manually, reducing hospital admissions and deaths by 20-30% in clinical trials (Wang & Lee, 2023). Reduction in mortality from congestive heart failure is about 20% whilst hospitalizations reduce by 30%, COPD exacerbations are reduced by 25%. Smart buildings have also been shown to optimize use of hospital beds. Asset tracking systems using RFID sensors powered by AI have reduced time spent by healthcare professionals searching for equipment by 30-40%. Infection control has been improved by AI enabling identification of hospital-acquired infections.

#### **3.3 Industrial IoT and Manufacturing**

AI has been utilized in IoT networks for predictive maintenance and quality control as well as manufacturing optimization. Sensors deployed across the manufacturing floor collect vibration, temperature, acoustics and other performance data that are used by machine learning models to predict potential failures. This predictive maintenance capability helps increase equipment longevity by 20-25% and reduces maintenance costs by 25-35% (Khan et al., 2023). The example of predicting bearing failure could involve using neural networks to model bearing degradation based on thousands of examples. This prediction can be up to 2-4 weeks ahead, giving ample time for a bearing

replacement at the next planned maintenance opportunity, saving hundreds of thousands of pounds in lost revenue and downtime.

High speed cameras and deep learning techniques used in computer vision provide real-time product inspection enabling defect detection with better accuracy and without the downtime caused by human inspection. (Lopez & Garcia, 2024) In semiconductor manufacturing these methods have helped identify tiny defects on semiconductor wafers which impact production yields negatively. The production of electronic components has also been improved by identifying incorrectly assembled products or sub-components such as misaligned components, misplaced solder etc. Robot manufacturing lines utilizing AI and IoT enable faster and more efficient production, especially as production requirements can be changed more easily. AI-powered IoT can also manage the supply chain more effectively, predicting product demand, reducing holding costs by managing inventory more efficiently and decreasing lost revenue from stock-outs. RFID and GPS can be used for product tracing.

### **3.4 Smart Agriculture and Environmental Monitoring**

AI-powered IoT has seen uptake in precision agriculture to optimize crop production and resource management. Wireless sensor networks across the farm collect data on temperature, soil moisture, nutrient content and pH. Multi-spectral images from drones can highlight stresses on crops. AI models combine this data, analyzing current needs for fertilizer, water or pesticides and producing the optimum response. (Singh et al., 2023) AI can also assist with harvest timing when the crop reaches a desired ripeness level. AI-assisted irrigation has enabled corn farmers to increase yields by 15-20% whilst using 25% less water, similarly wheat farmers use fertilizer more efficiently reducing cost by 20% while also increasing yield by 10-12% by analyzing soil nutrient status and crop growth, grapes ripen to the optimal harvest time.

Air quality is also increasingly monitored with the help of AI and IoT networks, distributed sensors can measure pollutions levels like PM2.5, ozone, NO2, etc. Spatially and create high-fidelity pollution maps (Green & Brown, 2024). Similarly, water quality can be assessed for temperature, pH and the dissolved oxygen content. Landslide prediction can also be performed using an array of sensors to monitor ground movement and soil moisture, to provide an early warning for potential landslide activity. Flood prediction models utilize information from rainfall sensors as well as levels from sensors placed in rivers to create early warnings for downstream areas.

## **4. CHALLENGES AND LIMITATIONS**

### **4.1 Computational and Resource Constraints**

The majority of IoT devices are extremely limited in terms of their processing capabilities, available RAM and power requirements. Typically battery powered sensors need to function in the order of years on a single battery, the power requirements are often in the milli-watt range. Complex AI models cannot run efficiently on the limited power budget, even if they are compressed. (Thakkar et al., 2024) IoT devices often use micro-controllers which has 256KB to 1MB of RAM while modern neural networks contain millions of parameters. A ResNet-50 image classification model takes up over 100MB, even a MobileNetV2 with a high compression level can still take up 10-20MB which is infeasible to fit onto a microcontroller. Often they are run in flash memory and loaded on demand however, this slows up the model.

A real-time application needs to be low in inference latency, autonomous cars for object detection must complete this in less than 100ms, patient vital monitors should take less than 500ms to respond while in safety industrial systems, this time needs to be under 50ms. (Wilson & Park, 2024) This is very difficult to achieve on the small edge CPUs, models need to be heavily optimized, model compression could reduce the amount of memory required by 75-90% at only slight reductions in accuracy. Important connections can be pruned to make the model less complex, this reduces complexity by a factor of 5-10x, and then architectures can be discovered using neural architecture search tailored to specific hardware. It is clear that current devices and models are still vastly mismatched.

### **4.2 Data Privacy and Security**

Due to the amount of personal and industrial data collected from IoT devices, the implications regarding privacy are enormous. Europe's GDPR clearly mandates that all personal data can only be collected with user consent, and the user has the right to access, modify and delete this data. HIPAA is used in the health sector for medical records, where the transmission of data without consent of patient is prohibited. CCPA is the California data privacy law and similar to GDPR it provides rights on data privacy. (Hassan et al., 2023) These laws render the central storage of large raw

data stores illegal. Existing cloud based AI models do not conform with these regulations. Federated learning and edge computing can alleviate the privacy issue by keeping the data on the edge device or with the user, however it is concerning that there are many cybersecurity threats to AI enabled IoT systems due to the impact that security failure could have on a physical system. This include adversarial attacks where sensors or ML models are spoofed. It could be possible to infect model training data so the model would contain backdoor models where there is a certain input which can cause a misclassification to occur. (Xie et al., 2024)

#### **4.3 Data Quality and Heterogeneity**

IoT devices generate vast quantities of data that are of various formats and sources. Issues of missing values due to faulty sensors or communication errors, data errors causing inaccurate readings and a lack of data points due to intermittent communication, all affect the quality of the data. (Kumar et al., 2023) Over 60-80% of time data scientists spend time on pre-processing data as opposed to model development. Statistical heterogeneity causes many different values, this means the statistical distribution of data collected from sensors is very different. For example the heating pattern in an office will differ significantly in a cold climate to a hot one, and similar for manufacturing machines depending on when they were built or if they have had recent maintenance. (Robinson & Chen, 2023) Therefore, models trained in one environment or with one set of sensors will not perform as well in another, for example a model trained in winter will perform badly in summer, adaptation methods exist but are still only approximations.

#### **4.4 Interoperability and Standardization**

A problem across IoT is the lack of standards. Manufacturers often create unique communication protocols, data formats and APIs. (Raza et al., 2023) while some protocols like MQTT and CoAP are widely accepted on IoT, many of these can only be used on low bandwidth devices and do not work well on machines that do not communicate constantly. OneM2M is the most widely supported platform in this regard although it still has many rivals that the user must be aware of. These difficulties make integration into large systems very difficult, AI models will need to communicate across various platforms and systems which requires complex integration and increased latency in order to allow them to work. Often parallel systems are set up to deal with older and newer devices which means additional effort. There are many efforts aiming to introduce standardization, such as the Industrial Internet Consortium, while open standards like OPC-UA could also prove beneficial although both have only been introduced recently so cannot be proven yet.

#### **4.5 Explain ability and Trustworthiness**

AI models, especially deep neural networks often do not provide explanations for their predictions, they are often referred to as 'black-boxes'. Stakeholders involved need to be able to trust the output of an AI, particularly when used in critical applications such as aviation or healthcare. (Montavon et al., 2023) Explainable AI (XAI) helps tackle this, a popular example is LIME, which approximates complex model outputs in small areas with a local linear model. SHAP is another example which looks at feature importance in models using a game theoretic approach. Attention mechanisms can also help interpret models and determine which part of the input stream influenced it most. In addition AI can propagate societal bias that is embedded within the data itself, an example being a facial recognition system being worse at recognizing some ethnicities due to their poor representation in the training data, or medical systems discriminating against some patients. Reducing bias can involve using varied data sets or adding fairness constraints into the model training.

### **5. CASE STUDIES AND REAL-WORLD IMPLEMENTATIONS**

#### **5.1 GE Predix Platform**

The Predix platform by General Electric is a strong example of the industrial AI and IoT domain integrated effectively. The platform is used on over thousands of power plants, wind turbines and railway locomotives where sensor data from the industrial equipment can be sent and analyzed using machine learning techniques, allowing for predictive maintenance of devices and minimizing unplanned downtime by up to 30-50%. It also led to increases in equipment lifespan of 15-25%, and millions were saved in emergency repair costs. It is also able to scale to an enterprise level, and is flexible for use on various machines. (Park & Kim, 2023)

## 5.2 Barcelona Smart City Initiative

Barcelona has integrated a lot of IoT systems to become a smart city and has thousands of sensors in and around the city in order to monitor traffic and the environment along with services used by its citizens. Using AI algorithms the city's traffic system has been optimized using machine learning to improve flow, which has resulted in congestion decreasing by 24% and drivers waiting at traffic lights by 20-25%. Street lighting also saves up to 30-50% power by detecting presence with motion sensors and dimming at night if there are no pedestrians or vehicles present, environmental sensors can be used to monitor levels of pollutants which will trigger alarms if they exceed safe thresholds, a parking system also exists to allow drivers to park and avoid unnecessary circling reducing emissions. (Green & Brown, 2024)

## 5.3 Microsoft FarmBeats

Microsoft FarmBeats is a system combining both the IoT and AI to help modern farms become more efficient, this system is used across thousands of farms around the world. Farmers use detailed maps of fields to monitor the environment around their crops as well as water usage. This has led to a 15-20% increase in yield for many farms, with 25% water usage reductions. The system is also used in some countries in developing regions of the world helping to provide resource constrained farmers with advanced technology and with some open source components it is a fairly accessible system to use for anyone. (Singh et al., 2023)

## 6. EMERGING FRONTIERS AND FUTURE OF AI AND IOT.

### 6.1 Transfer Learning and Few-Shot Learning

Transfer learning is applicable to adapt pre-trained models in different IoT domains with only a few labels. Instead of relying on tens of thousands of labels for a new training, Transfer Learning fine tunes models using hundreds of labels. (Zhang & Liu, 2023) Few-shot Learning goes a step further to enable model training using 5-10 labels only. Such capacity becomes extremely useful for quick and cheap deployment to new use cases. For example, quick deployment of defect detection to a new product category without extensive retraining, or adapt disease detection models for new patient populations.

### 6.2 Neuromorphic Computing.

Neuromorphic Computing targets brain-inspired computation architectures that realize ultra efficient AI at the edge. Instead of a separate processor and memory like conventional computing, the memory is incorporated into the processor mimicking our neurons, to realize efficiency. (Anderson et al., 2023) Use of Spiking neural networks, which compute with discrete "spikes" instead of continuous values, enables very low power consumption compared to traditional deep learning hardware. Intel's Loihi 2 neuromorphic chip has been shown to be 10-100x less power consuming than conventional AI hardware but with similar performance, with good scalability on sensor-level data and online learning. It is designed to activate processing only when data changes (event-driven computing), minimizing the power wasted on static data; thus suitable for always-on battery-powered IoT devices with long operational life.

### 6.3 Quantum Machine Learning.

Quantum computing can deliver exponential speed-ups for specific computational problems including optimization, which is a frequent need in IoT for problems like optimally placing sensors, or energy optimization of devices and systems. Quantum machine learning algorithms can achieve significantly faster solutions for these problems, order of magnitudes higher compared to classical counterparts. (Brown et al., 2024) Leading tech giants like IBM and Google have developed quantum machine learning libraries to accelerate algorithm research and development. But current quantum hardware still faces issues with high operating conditions, error rate and limited scale of data, which can postpone the widespread adoption for many real-world applications in IoT in the near future. There is an effort on a hybrid classical-quantum approach, utilizing the strength of each hardware type; classical hardware is used for standard tasks and the quantum processor is employed for optimizing complex computations that is otherwise impossible on classical machines. Investments in Quantum machine learning and computing can be viewed as hedging on future technology developments.

7. COMPARATIVE ANALYSIS OF AI-IOT STUDIES

This section adds a comparative synthesis of the studies and real-world implementations discussed in the review. The comparison focuses on the application area, AI-IoT technique, reported percentage improvement or reduction, and the practical implication of each result.

Table 1. Comparative percentages reported across AI-IoT application studies.

Area / Study	AI-IoT Technique or System	Reported Percentage	Comparison Indicator
Smart city traffic / Barcelona	AI-based traffic control using road sensors and cameras	24% congestion reduction; 20-25% delay reduction	Improves urban mobility and lowers travel time.
Smart energy and buildings	AI demand forecasting, smart grids, and occupancy-based control	15-25% energy reduction; up to 30-50% lighting savings	Shows strong efficiency gains in energy management.
Healthcare monitoring	Wearable IoT sensors with ML/deep learning models	>95% arrhythmia detection accuracy; 20-30% fewer admissions/deaths	Indicates high diagnostic and preventive value.
Industrial IoT / GE Predix	Predictive maintenance using industrial sensor analytics	30-50% downtime reduction; 15-25% lifespan increase	Demonstrates major operational and maintenance benefits.
Manufacturing quality control	Computer vision and deep learning inspection systems	Improved defect detection accuracy	Enhances product quality and reduces manual inspection limits.
Smart agriculture / FarmBeats	IoT field sensors, drones, and AI decision support	15-20% yield increase; 25% water reduction	Supports sustainable production and resource optimization.
Environmental monitoring	Distributed sensors with AI-based pollution and risk modeling	High-resolution pollution mapping and early warning	Improves environmental response and risk prediction.

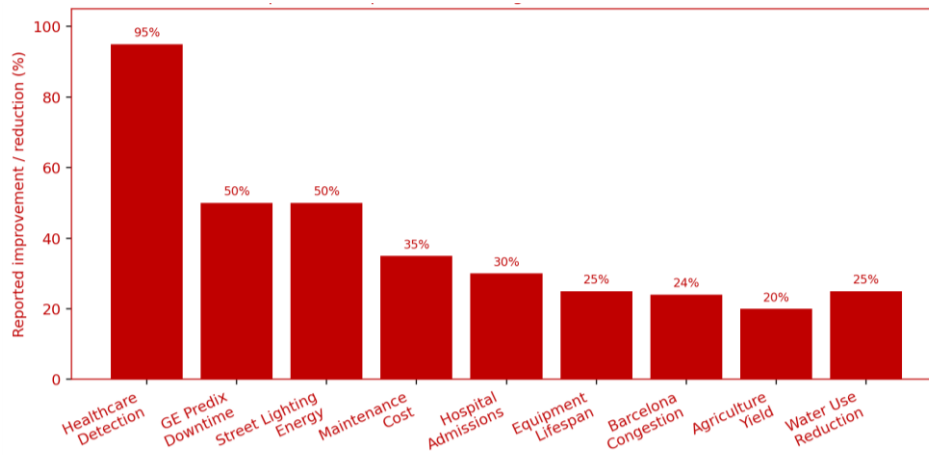


Figure 1. Comparative Reported Percentages in Reviewed AI-IoT Studies

Note. For ranges reported in the reviewed text, the maximum stated value was used to visualize the comparative scale. Qualitative-only studies were included in the table but excluded from the percentage chart when no numerical value was reported.

## 8. CONCLUSION

The survey is conclusive that combining AI with the Internet of Things has a significant role to play in the establishment of smart, adaptive, and data-driven systems in the smart cities, health care, industrial space, agriculture, and environmental monitoring. From the methods that were examined, it has been confirmed that through application of ML, DL, EC, FL techniques can enhance prediction, automation, resource optimization and enable real-time decision making. Nonetheless, efficiency of the AI-IoT system relies more on computational capacity, data quality, inter-operability, security, data privacy, and explanation of AI models.

In summary, it can be concluded that AI-IoT applications present considerable advantages in practice such as reduction of congestion, better energy consumption, medical observation, predictive maintenance and green agricultural practices. Future work should consider lightweight and trustable AI models, learning with privacy preservation, common communication mechanisms and explainable decision making models to guide the adoption of AI-IoT systems in practice.

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