AI-Powered IoT for Intelligent Systems

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Abstract

In recent years, intelligent systems (ISs) have been developed to implement tasks requiring physical and mental effort. These systems are pervasive and useful in virtually all aspects of life, from routine tasks to professional activities. The convergence of artificial intelligence (AI) and the internet of things (IoT) delivers the intelligence and real-time decision-making required for optimal IS performance. The current study reviewed recent literature to document AI approaches compatible with IoT, especially over the cloud-edge architecture. The main identified options were deep learning, machine learning, genetic algorithms, reinforcement learning, generative models, and distributed AI. These methods can rapidly process IoT data in the edge cloud, allowing ISs to obtain practical interpretations for real-time, autonomous decision-making and responses to their environments.

Introduction

Scientific progress has led to the development and uptake of powerful and sophisticated tools. Conventionally, these provisions were created as machines that automated activities requiring physical human effort. However, the current digital age focuses on computer-based systems for automating tasks requiring physical and mental effort. Over time, the capabilities of these technologies have proliferated to include tasks requiring increased intelligence. These developments led to the advent of intelligent systems (IS), essentially progressive computer systems capable of gathering, assessing, and reacting to data collected from the environment. ISs are not only useful for specialized professional tasks, such as airport management and medical diagnosis, but also for tedious routine activities, such as housekeeping and driving. The development of these systems is contingent on the availability of effective intelligence methods and tools.

Artificial intelligence (AI)-powered Internet of Things (IoT) is among the most effective supportive tools for ISs. AI essentially refers to the ability of a computerized system to perform tasks that typically need human intelligence. Contrarily, the IoT is the rapidly growing network of objects, devices, and machines that can amass and share data in real-time using embedded sensors. According to Whelan (2022), the optimal functionality of IoT and AI lies at the intersection between the said two technologies. AI and IoT have a mutually beneficial relationship that facilitates several disruptive innovations in ISs. Specifically, the integration of the two technologies allows these systems to be autonomous, prescriptive, and predictive. These capabilities should positively impact all industries, including transportation, telecommunication, healthcare, retail, and manufacturing. Specifically, IoT devices will support the collection of large data volumes, while AI will help develop intelligence for creating smarter applications based on the amassed data.

AI Applications in IoT

IoT devices result in a pool of vast amounts of data. Kapoor (2019) states that only about 10% of the collected data is captured for analysis. Furthermore, the data is extremely time-dependent and can lose value if not handled in real-time. Manual assessment cannot meet this objective, necessitating the use of AI to derive meaningful insights from the data promptly. This approach is the only guaranteed way of ensuring the optimal performance of ISs. Several AI methods and models can be implemented on IoT to enable the functionality of ISs, including deep learning, machine learning, genetic algorithms, reinforcement learning, and generative models.

Machine Learning for IoT

Machine learning is an AI subset that aims to develop computer systems capable of automatically learning from experience without explicit reprogramming. This capability is vital for improving IS experiences by leveraging Big Data accumulated using IoT. Besides automation and managing large data volumes, machine learning enables prescient investigation. Specifically, it allows systems to identify the right input to deliver the expected output. Previous actions are exploited to recognize and build patterns that support more efficient future behavior. Thus, amalgamating AI and IoT can produce smart ISs that can deliver informed decisions and tasks with minimal or no human input.

These capabilities reveal the capacity of embedding machine learning algorithms in IoT systems to deliver efficient ISs. These algorithms are typically categorized based on the adopted method: supervised or unsupervised, optimization or modeling, and probabilistic or non-probabilistic (Kapoor, 2019). Despite the functional differences, the outputs are generally similar.

Regardless of the employed method, the main machine learning algorithms include decision trees, Naïve Bayes, support vector machines, logistic regression, and linear regression (Kapoor, 20190). However, several potential risks, such as overfitting, must be addressed for these techniques to provide accurate insights into IS functionality. When adequately designed, the algorithms accommodate IoT data monitoring, processing, and smart use.

Deep Learning for IoT

Deep learning is a type of machine learning comprising neural networks based on multiple layered models. Kapoor (2019) reports three commonly used deep learning techniques: recurrent neural network (RNN), convolutional neural network (CNN), and multilayered perceptron (MLP). The application of these models is contingent on the availability of extensive high-quality datasets and parallel computing capabilities based on one graphical processing unit. Furthermore, the algorithms help overcome the Big Data issue introduced by IoT. Specifically, deep learning can capture unsupervised information and high-level, dynamic data structures amassed using IoT. These capabilities are particularly vital in IS recognition and perception tasks. Thus, combining deep learning with IoT is a feasible strategy to achieve smart ISs.

Deep learning models generally use an artificial neuron as the key component. According to Kapoor (2019), this unit is based on the functionality of biological neurons. It comprises several inputs linked using synaptic connections. The weighted sum of these inputs undergoes an activation function to produce a non-linear output. Three essential parameters must be specified to model one artificial neuron: the loss function, activation functions, and learning rate parameter (Kapoor, 2019). However, single neurons are inferior to linear regression and unsuitable for ISs. Thus, multiple layers of separate neurons are commonly used to define the MLP. Alternatively, CNNs and RNNs can be used. Therefore, deep learning is adequately scalable for all possible IS typologies.

Genetic Algorithms for IoT

Like deep learning, genetic algorithms are inspired by nature. Specifically, these techniques are based on the natural evolution process described by Charles Darwin (Kapoor, 2019). Genetic algorithms are uniquely suited for optimization problems in IoT and ISs. In principle, optimization is finding the best solution to make something better. This process alludes to multiple solutions, and variable inputs, processes, or parameters are adjusted until the desirable maximum or minimum solution is found. IS functionality mainly comprises optimization of tasks. For example, ISs for factory automation should autonomously select the most feasible production route of all available options. Genetic algorithms leverage IoT data to facilitate accurate optimization in such applications.

A genetic algorithm implements sequential steps that mimic the selection of traits in living organisms. Two activities must be fulfilled before implementing the technique. Firstly, the problem variables are encoded into genes representing potential solutions (Kapoor, 2019). Each gene can be a string of binary bits or real numbers. Secondly, the fitness function is determined to compute the score of each possible solution (Kapoor, 2019). Consequently, the genetic algorithm follows five steps to arrive at a feasible choice: population initialization, parent selection, reproduction, evaluation, and termination (Kapoor, 2019). Initialization involves creating an initial population, where the full spectrum of potential solutions is produced using randomly-generated chromosomes. Parent selection encompasses choosing a proportion of the existing population using the fitness function or randomly, which is then employed to breed a new generation. After that, genetic operators produce the successive generation in the reproduction phase. Evaluation involves assessing the produced offspring based on the fitness function. The algorithm terminates when an offspring meets the objective fitness score or the peak number of generations is achieved. These processes are implemented in real-time for efficacious optimization.

Reinforcement Learning for IoT

Unlike both supervised and unsupervised learning, reinforcement learning mimics the learning process of most living organisms, particularly humans. For example, infants' learning can either be based on goals, trial, and error, or interaction with the environment (Kapoor, 2019). Reinforcement learning is fundamentally goal-oriented and founded on interactions with the environment. The agent typically has a specific objective and can sense the environment's state to inform the consequent action. Integrating AI facilitates the optimal and accurate data-based perception of the environment. The agent can then implement precise well-defined actions on the environment. In the context of ISs, actioning can instigate one of two possibilities: a reward or a change in the environment's state (Kapoor, 2019). Therefore, the fusion of reinforcement learning and IoT allows ISs to learn from their environment for optimal task implementation without human input.

Reinforcement learning algorithms are functionally categorized as either value or policy-based, depending on what they iterate. The former are methods that select the action that achieves the maximum value function (Kapoor, 2019). In an IS, the agent learns and approximates the goodness of a particular activity or state. Q-learning is arguably the most commonly used value-based technique. Conversely, policy-based algorithms determine the best policy that attains the optimal value function (Kapoor, 2019). Policy gradients are excellent examples of these methods. Specifically, they estimate the policy function, enabling the mapping of every state to the best conforming action. Notably, neural networks can be integrated to approximate the value or policy, achieving deep reinforcement learning. This approach offers a faster and more accurate method of goal-oriented learning in ISs.

Generative Models for IoT

Generative models are novel deep learning approaches based on unsupervised learning. They are classified as either generative adversarial networks (GANs) or variational autoencoders (VAEs) (Kapoor, 2019). The latter are explicit in that the probability density function is defined and computed explicitly. Contrarily, GANs are implicit since the network learns to produce samples from the probability density function without any explicit definitions. Nonetheless, the central idea is common: generating new samples with similar distribution to the training data. These functionalities are optimized when the generative models are combined with IoT. For example, the models can enable simulation and planning using time series data. Moreover, they can reveal and elucidate the latent representation of collected data. These capabilities can benefit several ISs functions, including platform monitoring, anomaly detection, and network traffic protection.

Distributed AI for IoT

Distributed AI (DAI) also offers a feasible solution to handling and analyzing data from IoT networks to support IS functions. Although there are multiple ways to implement DAI, H2O and the Apache machine learning library (MLlib) are the most reliable for IoT and ISs (Kapoor, 2019). The former offers a distributed, large-scale architecture, allowing machine learning models to run more efficiently and quickly. It also provides a scalable implementation for commonly used decomposition, clustering, collaborative filtering, regression, and classification algorithms. Similarly, H2O is a rapid, scalable deep learning framework that employs in-memory compression (Kapoor, 2019). Thus, it can manage large data volumes in memory regardless of the size of machine clusters. The conforming algorithms include gradient boosting, random forest, Naïve Bayes, and generalized linear modeling. In brief, DAI allows ISs to maximize deep learning and machine learning for exploiting data from IoT systems and networks.

AI for Edge Computing

The advent of cloud computing offers a crucial platform to deploy AI for the benefit of ISs. IoT devices are primarily based on cloud computing to overcome storage and computation limitations (Wu, 2021). However, conventional remote cloud computing introduces communication delays between IoT devices and ISs. The edge cloud was introduced to increase the proximity between IoT devices and the cloud. The reduced distance allows real-time data analysis to inform IS functionalities. Notably, AI offers a robust tool for the intelligent orchestration of cloud-edge architecture. The AI models and methods presented in the previous sections can be deployed on the cloud to rapidly derive meaningful insights for ISs. This setup provides users, especially industries, the maximum benefit of AI-IoT integration without necessarily introducing extra resource costs.

AI for IIoT and Smart Cities

In the context of ISs, the industrial IoT (IIoT) and smart cities are the biggest benefactors of the convergence of AI and IoT. The availability of robust edge infrastructure, cloud platforms, and low-cost IoT sensors enables the IIoT, which features elaborate ISs that optimize the provision of products and services to customers and the underlying interactions (Kapoor, 2019). For example, IoT and AI-enabled ISs can predict future errors and anomalies using collected data and implement preventive mechanisms autonomously. Successful smart cities also depend on the availability and use of AI-powered and IoT-enabled ISs, including smart parking, transportation, farming, traffic management, waste management, and building systems (Kapoor, 2019). These applications result in healthier environments, safer cities, optimized consumption of natural resources, and minimize energy costs. Thus, integrating AI and IoT should enable the anticipated advancements in future society.

Over the past few decades, the population of people in cities has increased significantly. It is estimated that 4.1 billion people live in cities today, and this number is expected to increase significantly in the near future. The ballooning population increases the pressure on social amenities and services such as transportation. As the number of cars increases on the road, the problem of traffic congestion becomes apparent. In most cities, traffic management is a leading critical infrastructure problem. Besides traffic congestion, other challenges associated with traffic management include accidents and pollution. Traffic congestion can be costly from a financial perspective as they lead to the loss of valuable time that could have been spent doing productive activities. Therefore, it is essential to increase urban mobility, especially in the context of traffic congestion, by promoting infrastructure development facilitated by technology.

Leveraging Data in AI Systems

Luckey et al. presented a platform for intelligent transportation based on the internet of things approach (2020, 1). The platform was able to acquire data using coordinated devices in linked automobiles and roadside units. In their test, they employed the resistive multi-objective-based data set compelled ideal method calculation, which provides dynamic street protection from the weight of each segment, computes the ideal path from the starting point to the goal, and variably records the data by street (Luckey et al. 1). This study demonstrates the process of collecting data and using it to comprehend the traffic situation of the road network based on the directed framework and then select the optimal route to the destination (Luckey et al. 1). The effectiveness of this framework is based on the ability to collect timely, accurate, and relevant data.

Installing sensors in critical areas of buildings makes it possible to collect social event data on energy use and to predict how people are likely to act. Data from the AI system can enhance consistency and keep track of daily, weekly, and occasional changes. Using traffic signals and data congestion, crisis administrations can reach their objections more quickly and safely. Cities may collect accident data or measure several indicators to help them plan for the future and make more effective safety measures.

Short-, medium-, and long-range communications can be integrated into vehicle communication systems to support intelligent vehicular interchanges. According to Al-Sakran, continuous control and management are possible if the framework includes IoT (37). Still, several security and framework security concerns and risks must be addressed. The combination of artificial intelligence (AI) and the internet of things (IoT) is called the AI-controlled internet-of-things (AIoT). This combination can solve the complicated problems that arise from using various devices. By adding artificial intelligence into their IoT-based road infrastructure, cities can make their street networks work better.

Smart urban lighting is the foundation upon which smart cities are developed. Lights play an integral role in directing traffic, which means that they must be intelligent to enhance effectiveness and efficiency. Accordingly, IoT devices can be installed to collect, send, and process data about traffic and pedestrian flows environmental parameters like air quality, temperature, wind speed, and humidity, and acoustic data like gunfire detection and urban noise. Having a system for collecting diverse types of data is particularly important as the accuracy and effectiveness of machine learning algorithms depend on the quality and quantity of data used.

Experiments and Outcomes

Using remote sensor monitoring and internet of things (IoT) technologies is a practical framework for evaluating traffic volume and vehicle arrangement. Xiao and Wang conducted a study on the integration of artificial intelligence (AI) and internet-of-things (IoT), also known as AI-driven Internet-of-Things (AIoT), into an automated traffic management system (887). Taking into consideration vast volumes of data collected by a large number of devices, their research demonstrated that this combination could solve complex problems. As a result, they devised a system that could utilize this combination to manage traffic lights. The method can increase the effectiveness of the smart city's road system. Using distributed multi-agent Q-learning and many surveillance cameras, they provided real-time data for intelligent traffic signal control systems to monitor motorized and non-motorized traffic scenarios (Xiao and Wang 887). The data-driven approach adopted in this study improved prediction outcomes.

Another experiment is based on the concept of using functional radio-frequency identification (RFID), remote sensor improvements, systems administration, and Internet-based data frameworks to allow labeled traffic objects to be addressed, tracked, and questioned across an organization. Al-Sakran presented an intelligent traffic information system based on the internet of things and specific integration of AI intelligence data (37). The study offered a framework for collecting and monitoring real-time traffic data using the internet of things and wireless communications. Active radio-frequency identification (RFID), wireless sensor technologies, object ad hoc networking, and Internet-based information systems were utilized to represent, track automatically, and query tagged traffic issues within a network. They presented a solution that ensures the uniqueness of license plates by using an EPC code and an RFID code to receive radio frequency signals from traffic tools. They demonstrated that the RIFD-based monitoring system is not hindered by darkness or adverse weather.

With the help of IoT and an AI-powered data approach, Kong et al. concluded that urban environments could be improved, and some of the most critical transportation problems in cities may be fixed or minimized (97). Smart City environments can make it easier to get to public stopping areas by using sensors that can, for example, indicate to the driver where the closest parking space is. This way, the driver does not have to move around randomly. Kong et al. used data obtained from RFID to reduce the number of stops which eventually helped to minimize traffic and air pollution (97). With the city's data available through the network of IoT, city planners can make informed and valuable decisions. Suppose this information is combined with other pieces of data provided by the city's networked infrastructure. The overall value of the informational assets increases considerably. Smart city amenities may include smart seats, smart traffic lights, and smart road lighting. The idea is to implement systems to collect vast quantities of data to support the artificial intelligence system in automating traffic and other elements of the smart city.

Future Recommendations

Artificial intelligence, which entails making machines with human-like abilities, continues to find applications in many areas of life. At the heart of artificial intelligence is the field of machine learning that encompasses using statistical approaches to make machines learn without explicit programming. In cities around the world, inhabitants face a myriad of problems, including traffic congestion, accidents, and pollution. Using artificial intelligence, combined with an extensive network of sensors, can help minimize such issues. Rather than focusing on machine learning models, there is a need to develop data-driven systems as they are likely to produce better outcomes. It is also critical to address challenges associated with intelligent systems, such as data security and privacy issues. In particular, mechanisms for protecting the confidentiality of private data collected through sensors are key. More importantly, there is a need to address the issue of the digital divide and algorithmic bias. The data used and the models created should be made deliberately objective to ensure fairness and transparency.

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