Embedded intelligence and the data-driven future of application-specific Internet of Things for smart environments

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Abstract
The advances and convergence in sensor technology, information and communication technology, and intelligent analytics have given rise to the Internet of Things or also known as the Internet of Everything or the Industrial Internet. The research and development works for the Internet of Things can be seen to have progressed in two main phases: (1) In the first phase, the earlier works for the Internet of Things focused on developing the building blocks and enabling technologies such as the sensors and RFID technologies, communications and wireless protocols, machine-to-machine interfaces, energy efficiency of nodes, and energy harvesting technologies, and (2) in the second phase, the latter and recent works focused on the addition of, and embedding value to application-specific Internet of Things using technologies for smart environments and applications such as intelligent analytics and machine learning, embedded vision and image processing, augmented reality, and autonomous systems. We associate the term of embedded intelligence and analytics with the data-driven future for application-specific Internet of Things. In this article, we give an introduction and review recent developments of embedded intelligence for the Internet of Things; the various embedded intelligence computational frameworks such as edge, fog, and cloud for the application-specific Internet of Things; and highlight the techniques, challenges, and opportunities for effective deployment of application-specific Internet of Things technology to address complex problems for various smart environments and applications.

Keywords
Artificial intelligence, deep learning, embedded analytics, Internet of Things, smart environments

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Introduction
The advances and convergence in sensing technologies, information and communication technologies (ICT) and in combination with intelligent analytics and edge artificial intelligence (AI), have shaped the Internet of Things (IoT) of today, which is termed as the Internet of Everything1 or the Industrial Internet.2 The IoT objective has been to provide a framework to connect hundreds of thousands of sensors and networks using computational and communication technologies, enabling the tracking of multiple IoT devices, and

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harvesting valuable information for intelligent applications. The 2020 Gartner's Hype Cycle Special Report demonstrates the strong impact of IoT in the hype cycle for AI, ranging from producing small sensing devices and Things, to embedding intelligence in smart robots and insight engines as shown in Figure 1.

The research and development work in IoT can be seen to have progressed through two main phases. In the first phase, the focus has been on developing the building blocks of an IoT infrastructure by deploying multi-sensor platforms, proximity sensing (e.g. Bluetooth Low Energy (BLE) beacons), indoor localization (e.g. RFID), and WiFi positioning systems. This earlier phase is responsible for the emergence of new communications, networking and wireless protocols, machine-to-machine interfaces, energy efficiency of nodes, and energy harvesting technologies. Many prototypes and commercial products have progressed and matured over the past years, and they can be purchased off-the-shelf and offer a turnkey solution for IoT applications.

In the second phase, the focus has been on the addition of, and embedding value into application-specific Internet of Things (ASIoTs), a term proposed by Ang and Seng to conceptualize the development of IoTs targeted toward specific domains, communications mediums, and industry sectors, leading to a taxonomy for ASIoTs that consists of three levels: (1) user domain-driven; (2) communications medium-driven; and (3) technology constraint-driven. The domain-driven ASIoTs are designed and deployed for specific applications such as Internet of Battlefield Things, Internet of Medical Things, Internet of Animal Things, Internet of Mobile Things, Internet of Underwater Things, and Internet of Waste Things.

From the perspective of communications medium-driven ASIoTs, the design is dominated by the characteristics of the network communications since they play an important role in supporting efficient and optimal machine learning (ML) models, which ensure the processing of a variety of tasks required by any ASIoT. Continuous and accumulated data streams need to be analyzed as they are being transported through many different sensors at the far-edge, edge, and fog resources of ASIoT networks.

For example, short-range network characteristics such as latency, QoS, data rate, network management power ratio, and protocols used for the Internet of

Figure 1. Cycle for artificial intelligence.
Underwater Things\textsuperscript{19} are significantly different from the Internet of Underground Things.\textsuperscript{20} The third perspective is the technology constraint-driven ASIoTs. The Internet of Nano Things\textsuperscript{21} and the Internet of Mobile Things\textsuperscript{16} are examples where the design can be constrained by the communications and information processing capabilities, and the unpredictability and an increased number of faults and disruptions for data stream ingestion. Machine learning can be used to automatically infer information about data being transported and ingested without the need for relying on human intervention. However, to achieve fast analysis and early detection for actionable insights in ASIoT applications and services, the current trend is to move the sensing and intelligent information capabilities from centralized processing to the on-node information processing and computational resources of the ASIoT nodes. However, there are significant challenges that remain to be addressed for practical realizations. For example, techniques such as deep neural networks (DNN) require very large amounts of computational resources (e.g. GPU clusters) for training and classification, making them very challenging for implementation in resource-constrained platforms such as ASIoT nodes.

In addition, the use of edge devices streamlines the data analysis process by performing it in real time and in situ to ensure as much useful information is garnered from the ASIoT devices as possible. Edge devices are designed to contain their own processing and analytical capabilities to this end. Real-time feedback within the device itself ensures immediate and appropriate use of the data it is gathering, circumventing the need to send the data elsewhere for outside consideration. Part of the workload is decentralized and distributed among the IoT nodes, turning these devices from simple sensors into more powerful and smart embedded systems, capable of several new features. Fog computing (or fogging) is an architecture that uses edge devices to carry out a substantial amount of computation, storage, communication locally and routed over the Internet.

In this article, we associate the ASIoTs with a process in which objects are equipped with sensors, actuators, and processors that collectively build up a distributed computing paradigm of embedded systems. The term of embedded intelligence (EI) characterizes the ability of ASIoTs to include technologies such as real-time data analytics and machine learning models, embedded vision and image processing, augmented reality and autonomous systems, and computational frameworks such as edge, fog, and cloud computing. The mature development of edge computing\textsuperscript{22-24} and fog computing\textsuperscript{25,26} devices afford the development of a portable, reduced computational complexity hardware platform to serve as an analytics engine for on-node ASIoT deployments.

This article is organized into the following sections. The “EI and enabling technologies for ASIoT” section gives discussions on EI and enabling technologies for the ASIoT. The section “EI and application requirements for ASIoT” gives discussions on EI and application requirements for the ASIoT. The “EI and smart environments for ASIoT” section discusses EI for various smart environments such as smart oceans,\textsuperscript{27} smart forests,\textsuperscript{28} smart cities,\textsuperscript{29,30} smart mobility, and smart grid. The section “Challenges and future directions for EI deployment in ASIoTs” highlights some challenges and opportunities for effective deployment of ASIoT technology to address complex problems, and the “Conclusion” section gives some final concluding remarks. Table 1 shows a summary and framework for ASIoTs in data-driven and smart environments, which also serves as a concise summary for the article.

### EI and enabling technologies for ASIoT

This section gives discussions on EI and enabling technologies for the ASIoT from five emerging perspectives: (1) machine learning in ASIoTs; (2) nature-inspired algorithms for ASIoTs; (3) edge, fog, and cloud computing for ASIoTs; (4) coding approaches for ASIoTs; and (5) Nano Things for ASIoTs.

#### Machine learning in ASIoTs

Data streams are constantly transported across a network of distributed ASIoT devices, edge nodes, and cloud environments, to optimize learning strategies where training is usually performed by global and centralized ML models in the cloud, whereas inferences are enabled at edge nodes. However, there is a paradigm shift of advancing local distributed ML models that can perform both training and inference at the edge, leading to learning architectures such as incremental learning\textsuperscript{31} and federated learning.\textsuperscript{32} In contrast to the current vertical application silos in ASIoT, these learning architectures introduce horizontal connectivity and interoperability between contributing ASIoT devices, edge nodes, and cloud environments. Table 2 provides an overview of the main characteristics of both learning architectures. Note that incremental learning techniques can be applied on single-agent or multi-agent machine learning. In the context of ASIoT, we have focused the discussion more toward decentralized learning and approaches.

Masana et al.\textsuperscript{86} define incremental learning as a continual or lifelong learning strategy, which aims to develop artificially intelligent systems that can continuously learn to address new tasks from new data streams while preserving knowledge learned from previously learned tasks. Concept drift plays a crucial role in incremental learning due to its impact on the accuracy and robustness of local ML models.\textsuperscript{33,34} Incremental
ML modeling consists of capturing continuous data streams using a sliding time window model, and then, different local ML models available at many edge nodes start their training and inference tasks as soon as a new data stream arrives from an ASIoT device. Gama et al.35 have shown that sliding time windows have the advantage to promptly recover from concept drift in comparison with the landmark and hierarchical time window models. After the stream data are not needed at the edge nodes, it is transported and accumulated in the cloud, where an embedded global ML model will ensure learning integrity. One important advantage of embedded global ML models is their potential to be integrated with drift detection algorithms and incorporate dynamic updates due to (a) gradual changes, when there are (relatively) smooth changes in the underlying distributions; (b) abrupt changes, when there is a sudden change in the underlying distributions; and (c) systematic trends or recurrent environments, when the concept will reoccur.87 Bottom-up methods such as voting and stacking are used to take into account the outputs of the local ML models and their combination.

Table 1. Summary and framework for application-specific Internet of Things (ASIoTs) in data-driven and smart environments.

| Focus area                                      | Characteristic(s) and reference(s) |
|------------------------------------------------|------------------------------------|
| Embedded intelligence and enabling technologies for the ASIoT | Machine learning in ASIoTs Incremental learning,31 federated learning,32 concept drifting in incremental learning,23,34 sliding time windows,35 federated learning for edge nodes,36 Singh37 |
| Nature-inspired algorithms for ASIoTs           | Taxonomy for nature-inspired algorithms,38 FPsOC evolutionary computing39 |
| Coding approaches for ASIoTs                    | IoT coding approaches,40 Huffman coding,41 JPEG/DCT coding,42 wavelet coding43 |
| Edge, fog, and cloud computing for ASIoTs       | IoT edge, fog, cloud platforms,44,45 workload allocation policy for delay-sensitive IoT using GA,46 Analytics Everywhere framework47 IoNT architecture,21,48 nanonetwork transmission policy for human circulatory system,49 routing protocol for nanoscale networks50 |
| Nano things for ASIoTs                          |                                    |
| Embedded intelligence and application requirements for ASIoT | Embedded vision and image processing for ASIoTs Multimedia IoT,51,52 coding standards,53 compressive sensing,54 multimedia traffic streams in ASIoTs,55 IoT platforms and cloud infrastructures,56 large-scale M-IoT,57 split and combine approach,58 cooperative M-IoT edge computing framework,59 IoT augmented reality environments,60,61 AR IoT interactions,62 framework for visualization and authoring of IoT virtual sensors63 |
| Augmented reality and ASIoT                     | IoT architecture and features for IoT,64 behaviors of human vehicle drivers in presence of autonomous vehicles,65 real-time IoT in smart traffic control66 |
| Internet of autonomous vehicle systems          | Architecture and features for IoT,64 architecture and features for IoT,64 behaviors of human vehicle drivers in presence of autonomous vehicles,65 real-time IoT in smart traffic control66 |
| Embedded intelligence and ASIoT for smart environments | Smart cities and ASIoT Early smart city IoT architecture,67 smart city IoT architecture with deep learning, SDN, and blockchain,68 swarm intelligence for smart city IoT69 Two-stage approach to detect fires using IoT,70 smart forestry and IoT (FloFT) architecture,70 forestry IoT and UAV,71 IoT and forestry robots72 MAC protocols for water-based networking,73 Underwater IoT (UloT) architecture74 Smart oceans and ASIoT ASIoTs for smart energy systems,74,75 IoT framework for smart building environments,76 IoT and Big data analytics energy management system for smart homes,7 Smart grid IoT (SGIoT) architecture77 |
| Smart energy systems and ASIoT                  |                                    |
| Smart forestry and ASIoT                        | Two-stage approach to detect fires using IoT,70 smart forestry and IoT (FloFT) architecture,70 forestry IoT and UAV,71 IoT and forestry robots72 |
| Smart oceans and ASIoT                          | MAC protocols for water-based networking,73 Underwater IoT (UloT) architecture74 |
| Smart energy systems and ASIoT                  | ASIoTs for smart energy systems,74,75 IoT framework for smart building environments,76 IoT and Big data analytics energy management system for smart homes,7 Smart grid IoT (SGIoT) architecture77 |
| Challenges and future directions for embedded intelligence deployment in ASIoTs | Interoperability among ASIoTs Taxonomy of IoT interoperability challenges,78 future challenges for semantic interoperability,79 interoperability as a service,80 interoperability in IoT81 |
| Software tools and EI frameworks for ASIoTs     | Challenges for IoT software development and EI frameworks,82 IoT Composer83 |
| Benchmarks for EI ASIoTs                        | IoMT benchmark suite,84 IoT RDSP benchmark85 |

AR: augmented reality; SDN: software-defined network; EI: embedded intelligence.
In contrast, federated learning is based on an aggregate learning strategy where edge nodes can collaborate in training the same local ML model under the coordination of a central cloud service, relying on transporting only focused updates to achieve a learning objective. Kairouz et al. define focused updates as containing the minimum information necessary for the specific learning task at hand. Note that there is no longer any training of a global ML model, since the learning process is designed in such a way that each local ML runs a copy of the global ML model on its own data streams. The cloud receives the focused updates from every edge node and computes and updates weights until they converge. Singh et al. show that increasing the number of training data being gathered by the edge nodes as well as the complexity of local ML models make federated learning architectures more communication efficient. It is still premature to know which learning architecture will prevail in the future. Human-oriented design and experimental ML models are the main paths to be explored to identify the challenges and the potential benefits for developing new ASIoT applications.

A final point to note is that new emerging topics within machine learning are constantly being developed to meet application-specific requirements. For example, a machine learning approach termed as assisted learning has been recently reported to be suitable for applications requiring confidentiality which enables collaborations between multiple entities without revealing any details for the entity’s algorithm or data. Another example to meet the specific requirements for an untrusted central server can be found in Chen et al. which utilizes blockchain techniques to achieve decentralized privacy-preserving and secure machine learning systems.

**Nature-inspired algorithms for ASIoTs**

An approach for machine learning is based on nature-inspired algorithms or evolutionary computing (EC).

| Table 2. Characteristics of learning architectures for ASIoT. |
|---------------------------------------------------------------|
| **Incremental learning**                                      | **Federated learning**                                      |
| **Network Connectivity**                                      | Continuous data streams are generated and exchanged or transferred to/from multiple edge nodes and the cloud. |
| Training Settings                                            | Accumulated data streams are generated and stored at multiple edge nodes, never exchanged or transported to the cloud. |
| Orchestration                                                | Top-down coordination from a central cloud service.         |
| Learning Process                                             | Focus on centralized learning.                              |
|                                                               | Combine a set of different local ML models to obtain an enhanced composite for a global ML model. |

ML: machine learning.

**Figure 2.** Overview of nature-inspired algorithms.

**Nature-inspired algorithms**

- **Biology Inspired Algorithms**
  - Genetic algorithm (GA)
  - Artificial immune systems algorithm
  - Bacterial foraging algorithm

- **Swarm Intelligence Algorithms**
  - Particle swarm optimization algorithm
  - Ant colony optimization algorithm
  - Firefly algorithm

- **Chemistry/Physics-based Algorithms**
  - Simulated annealing algorithm
  - Harmony search algorithm
  - Gravitational search algorithm

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**Nature-inspired algorithms for ASIoTs**

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components and systems such as (1) wireless network communications; (2) IoT node computation; and (3) application-specific platforms. An example of using EC for IoT node computation can be found in the work by Molanes et al.\textsuperscript{39} which proposed an approach using field programmable system-on-chip (FSPoC) for implementing evolutionary computing (EC) architectures in resource-constrained IoT environments. The authors showed that their FPSoC approach had the advantage of the availability of embedded hard processors to implement the fit functions, capability for floating-point calculations and efficient execution of the algorithm in software. The authors showed that a similar performance as a desktop computer implementation could be achieved with a FPSoC at a much lower size, cost, and power consumption.

**Coding approaches for ASIoTs**

The sensors for ASIoT devices can range from simple scalar sensors to more complex sensing modalities such as image and video streams. These data (streams) would need to be transmitted from the IoT-sensing devices to a central collector for information processing. A popular approach to reduce the data requirements and bandwidth for the amount of data to be transmitted through the IoT network is to utilize data, image, video coding or compression techniques and approaches. Hamdan et al.\textsuperscript{40} give a comparative discussion of coding approaches for IoT applications and devices. The techniques can be categorized into two approaches: (1) Lossless compression techniques where no information is lost in the coding processing (e.g. Huffman coding approaches\textsuperscript{41}), and (2) lossy compression techniques where some information may be lost to gain higher coding efficiency (e.g. JPEG/DCT-based coding approaches\textsuperscript{42} and wavelet-based coding approaches\textsuperscript{43}). The challenges are to develop low-complexity approaches for efficient implementation of the coding algorithms or approaches on the memory and resource-constrained IoT devices or nodes.

**Edge, fog, and cloud computing for ASIoTs**

The designer of the ASIoT has several options and decisions to make for the platform architecture(s) to be utilized to meet the computational and storage requirements. Some popular platform architectures, which are currently available to the designer, are edge, fog, and cloud architectures.\textsuperscript{44} Ang and Seng\textsuperscript{45} remarked that the optimal combination of frameworks and platform architectures such as edge, fog, and cloud for IoT systems deployment remain open research issues to be resolved. An important issue to be considered in this area is the workload allocation and distribution among the various platform architectures and devices to achieve the overall performance efficiency and requirements for the ASIoT application. Abbasi et al.\textsuperscript{46} proposed an evolutionary computing approach using genetic algorithms to reduce delay and power consumption for delay-sensitive IoT applications. Cao and Wachowicz\textsuperscript{47} proposed an approach termed as “Analytics Everywhere” and demonstrated an IoT architecture which combines edge, fog, and cloud resources for a smart city parking application in Canada.

**Nano things for ASIoTs**

A characteristic IoT would have three main components: (1) sensors to collect data from the real-world environment; (2) computing nodes/devices for information processing for specific tasks; and (3) communication transceivers to collect and transmit data to other nodes and/or central data collectors. The Internet of Nano Things (IoNT)\textsuperscript{21,48} aims to realize the IoT components with nano-technology approaches and nanomachines with dimensions ranging from 1 to 100 nm.\textsuperscript{90} The realization of the IoNT would require significant redesigning efforts. Some recent examples can be found in the works by Canovas-Carrasco et al.\textsuperscript{49} and Al-Turjman.\textsuperscript{50} The work by Canovas-Carrasco et al.\textsuperscript{49} proposed a nanonetwork transmission policy for the human circulatory system and performed a detailed analysis on the communication budget, power consumption, and energy harvesting for nanonodes within a flow-guided environment.

The authors proposed an approach using Markov decision processes (MDP) to resolve the challenges when the nanonode devices encounter long out-of-coverage periods and the energy harvesting management, and showed that their proposed transmission policy could perform as well as other alternative policies with 34.6% to 150% fewer nanorouters. The work by Al-Turjman\textsuperscript{50} proposed a novel routing protocol for nanoscale networks such as collecting data from numerous wireless sensors distributed on a human body. The authors’ investigation considered the performance of the nanonetwork when the size of the nanocomponents decreases to the nanoscale, and proposed a novel routing technique termed E3A which increased the network lifetime and gave high efficiency for transmission and energy consumption for nanonetworks in IoNT.

**EI and application requirements for ASIoT**

This section gives discussions on EI and application requirement for enabling technologies for the ASIoT from three emerging perspectives: (1) embedded vision and image processing for ASIoTs; (2) augmented reality and ASIoTs; and (3) autonomous vehicle systems for ASIoTs.
Embedded vision and image processing for ASIoTs

Image and video multimedia streams pose a significant challenge for AI/ML implementation in ASIoTs. On one hand, scalar data from simple IoT sensors (e.g., temperature and humidity) have the characteristics of low data rates which can be implemented in IoT devices with a few kilobytes of memory storage and limited computational processing power at a low energy consumption. On the other hand, multimedia data streams (e.g., for surveillance for a smart city) have the characteristics of high data rates and require significant memory storage and computational processing. For image sensors, these challenges can be met to some extent using coding approaches as discussed in the section on EI enabling technologies. However, real-time video streaming from ASIoT nodes/devices still pose significant challenges. This is particularly the case for the implementation of complex processing EI-based algorithms on M-IoT edge devices. This is related to the 3 V’s (volume, variety, and velocity) characteristics and information processing requirements for multimedia Big data streams in sensor network-based environments. These ASIoTs which may also include audio and speech data streams are termed as multimedia IoT,51 IoT-based multimedia (IoTMM)52 and need to overcome similar challenges encountered by wireless multimedia sensor networks (WMSNs).91

Nauman et al.51 presented a comprehensive survey of the current state-of-the-art for the multimedia IoT (M-IoT). Their work identified six critical areas and challenges to be addressed for the M-IoT computational paradigm for practical deployment (multimedia coding and compression, event processing, cloud computing, fog computing, edge computing, and software-defined network (SDN)). In M-IoT applications when some parts of the multimedia data need to be sent to the central cloud for information processing, it is advantageous to perform coding and compression (e.g., using traditional HEVC video coding standards53 or more recent techniques like compressive sensing54 for the multimedia data for the transmission through the network. SDN architectures can also be used to provide increased flexibility and reconfigurability to manage the traffic streams for the multimedia data in ASIoTs.55

A major design factor for ASIoTs is to determine which parts of the information processing are required to be performed on the IoT device itself and which parts can be offloaded to the central cloud server to meet the delay and latency requirements. Ahmed et al.56 performed a comparative study between IoT platforms and cloud infrastructures for a real-time face recognition application. In their study, the face recognition task was divided into two sub-tasks (face detection and face classification). The face detection sub-tasks were implemented on the IoT (edge) devices (Raspberry Pi), and the face classification learning sub-tasks were implemented on the backend cloud servers. The Message Queue Telemetry Transport (MQTT) protocol was used for the data transfer between the edge device and the cloud server. In this work, the authors deployed two IoT platforms (Mosquito IoT broker and Kaa IoT middleware) to implement for comparisons. Their experimental results showed that the processing time for the Mosquito broker which used a light-weight MQTT protocol gave improved performance over the Kaa IoT platform.

In the work by Cuzzocrea and Mumolo,57 some other aspects for the M-IoT are considered for deployment in large-scale smart environments. Figure 3 shows their proposed platform architecture for IoT Big multimedia data for a surveillance application. Their approach is illustrative of the various challenges to be addressed to integrate the various smart sensors, devices, and objects to enable large-scale collaborative information processing and for supporting the deployment of machine learning and intelligent algorithms in the M-IoT ecosystem. The target environment continuously monitors the application scenarios for smart environments (e.g., intelligent traffic management systems, smart surveillance and monitoring, real-time crowd management) to gather the Big data from multimedia-based sensors. The gathered M-IoT data are processed by the IoT edge devices to extract the relevant information (e.g., segmenting moving objects from the video streams) and perform pre-processing such as feature extraction. Novel approaches and techniques can be deployed to efficiently compute the large-scale multimedia data. Seng and Ang58 proposed a split-and-combine approach to perform the LDA (linear discriminant analysis) on large multimedia datasets for integration toward data analytics with decision-making. Long et al.59 proposed an approach for human
detection from video streams in a cooperative M-IoT edge computing framework. The authors proposed cooperative video processing techniques and demonstrated that their approach was suitable for delay-sensitive multimedia IoT tasks. The Big Multimedia Data Fusion module combines the data streams for various multimedia sensing devices and modalities which is then processed by the Big Multimedia Data Correlation module to extract the value from the gathered data streams.

**Augmented reality and ASIoT**

Srimathi et al.⁶⁰ and Jo and Kim⁶¹,⁶² discussed the combination of the IoT with augmented reality (AR) for realizing smart and interactive environments. In Jo and Kim,⁶² the authors identified three components, namely distributed and object-centric data management, IoT object-guided tracking, and seamless interaction and content interoperability which can be used to realize the AR IoT integration. The AR IoT system enables user interaction with real-world IoT objects using augmented reality as shown in the figure in Jo and Kim.⁶² The figure shows three potential AR user interactions or scenarios among the real-world, computing devices and the IoT objects.

Jeong et al.⁶³ proposed a framework for the visualization and authoring of IoT virtual sensors and actuators in indoor environments. The concept of virtual sensors is to detect non-trivial events which is of interest by the combination and/or fusion from physical sensors. As an example, a virtual fire event could be created to be activated when the physical smoke sensor has an output of “ON” and the physical temperature sensor has an output of “VERY HIGH.” The activation of the virtual fire event could also trigger a virtual action event to unlock all doors and windows, and communicate the necessary commands to the physical actuators controlling the locking mechanisms in the environment. Along with the framework, the authors also developed an interactive IoT authoring tool which had the capabilities for creating virtual nodes, behavior definition, event handling, and visual debugging.

**Autonomous vehicle systems for ASIoT**

Jameel et al.⁶⁴ discussed the architecture, features, and challenges for the Internet of Autonomous Vehicles (IoAV). The authors proposed an architecture for the IoAV consisting of three layers (physical layer, virtual layer, and management layer) to enable a platform for real-time information communications. The focus of the physical layer is to enable low-latency and high data rate communications. The focus of the virtual layer is to enable flexible management of resources (e.g. edge and fog devices), and the focus of the management layer is to enable a trustworthy communication ecosystem. Other than technical challenges, the IoAV also raises new social challenges for traffic flow dynamics. One challenge is the modeling of behaviors of human vehicle drivers in the presence of autonomous vehicles.⁶⁵ The work in Rahmati et al.⁶⁵ investigated the differences between human to human and human to AV interactions. Their work showed that there was a significant difference between human driver behavior in human AV scenarios where human drivers put less concern on the crash risk and drove closer to the AV.

Other social challenges for the IoAV include the development of legal models to assign responsibility to different stakeholders, defining the boundaries for public and private data, and incentivized cooperation among vehicles. Some technical challenges for the IoAV include energy management of resource-constrained devices, efficient and intelligent routing techniques, and hardware impairments of wireless devices. Philip et al.⁶⁶ considered the challenges for real-time IoT applications in smart traffic control. The authors considered and proposed a solution for a smart traffic scenario where a group of autonomous vehicles independently decide on their lane velocity in collaboration with road side units.

**EI and smart environments for ASIoT**

This section gives discussions on EI for several types of smart environments: (1) smart cities; (2) smart oceans; (3) smart forestry; and (4) smart energy systems.

**Smart cities and ASIoTs**

Some examples of ASIoT applications for smart city and urban environments include monitoring the structural health of buildings, air quality, noise, energy consumption, monitoring, optimizing traffic flow and reducing congestion, smart parking, and smart lighting systems. An early work by Zanella et al.⁶⁷ proposed a prototype smart city and IoT architecture for the city of Padova in Italy. In this work, IoT sensors were deployed on streetlights and used to gather environmental data such as air quality (CO levels), noise levels, temperature, humidity, and lighting. However, this work did not report on using advanced analytics such as machine learning to derive further value from the gathered data streams. Recent and advanced works which deployed EI for smart cities and ASIoTs can be found in the works by Singh et al.⁶⁸ and Zedadra et al.⁶⁹ Singh et al.⁶⁸ proposed a novel smart city IoT architecture combining deep learning, SDN, and blockchain technologies. The figure in Singh et al.⁶⁸ shows a schematic of their smart city and IoT architecture.

The architecture proposed by Singh et al.⁶⁸ consists of three layers: (1) connection layer—gathers the data
from sensors and IoT devices at the edge of the smart city network; (2) conversion layer—sends the collected data to the fog nodes for data analysis and format conversion; and (3) application layer—contains a deep learning cloud architecture with data centers to provide application services to the smart city for self-management, self-configuration, self-distribution, and self-decision support. The conversion layer uses a blockchain distributed network and SDN on the fog nodes to overcome the security and privacy challenges in the architecture. The authors showed that their proposed architecture satisfies the properties of anonymity, fairness, confidentiality, and repudiation. Zedadra et al. proposed approaches utilizing swarm intelligence for a scalable and reliable smart city IoT architecture. In their architecture, a smart city system is composed of several interacting sub-systems. Each sub-system is composed of applications, where each application is modeled as a swarm of entities (sensors and actuators). The authors identified two types of interactions in their smart city architecture: (1) co-work interactions—sensors and actuators from in the same application exchange information to realize the global objectives, and (2) social interactions—sensor and actuators from different applications exchange information to realize their individual objectives.

**Smart oceans and ASIoTs**

An important smart environment for the deployment of ASIoTs which have not been intensively investigated is for smart oceans and underwater environments. These ASIoTs would need to take into consideration the characteristics and capabilities for acoustics communications and information processing sensor-based EI systems in oceans and underwater environments. For example, MAC protocols for water-based networking environments need to take into account various factors (e.g. limited communication bandwidth, high propagation delay, Doppler spread, and multipath effects), which are different for terrestrial-based communications. Qiu et al. proposed the extension of the traditional IoT to encompass the Underwater Internet of Things (UIoT). The figure in Qiu et al. shows a schematic of their smart ocean and IoT architecture.

The proposed UIoT architecture consists of five layers: (1) sensing layer—gathers the data from IoT-sensing devices, monitoring devices (terrestrial, UAV, satellite, etc.), and forestry robots; (2) network layer—contains the wireless communications technologies (e.g. industrial gateways and routers) and edge storage/analytics components for data communications from the sensing devices to the data analytics and information processing components; (3) data analytics layer—consists of forest data analytics, machine learning algorithms, historical and streaming data analytics; and (4) application layer—contains the service elements for users and stakeholders (forest department authority, augmented/mixed reality, web and database servers, cloud data centers, and storage). In this work, the authors utilized dynamic window configuration recommendation techniques based on the data characteristics, workload and resource constraints to handle the IoT variable data streams. Their experimental results demonstrated significant improvements and reduced latency to deliver the timing alerts for the detection of potential fire events.

**Smart energy systems and ASIoTs**

A practical application of ASIoTs can be found in smart energy systems and its various sub-systems for generation, transmission, and distribution of electrical energy. The objective is to meet the energy and services requirements for different industries and stakeholders while reducing the energy loss. Some examples of ASIoTs for smart energy systems and smart grids can be found in Al-Ali et al., Khan et al., Tushar et al.,
Pan et al.\textsuperscript{76} and Reka and Dragicevic.\textsuperscript{77} Pan et al.\textsuperscript{76} proposed an IoT framework to monitor and improve the energy efficiency for smart building environments. Their work involved the construction of a testbed for collecting the energy usage data. In this work, smartphones were used as the devices to monitor and manage the building energy systems following control policies. The control policies were established at three levels (the building-level, user-level, and organizational-level). The smart energy system then consolidated the various requirements for determining the optimal usage based on the energy proportionality.

A further work was proposed by Al-Ali et al.\textsuperscript{7} for an energy management system for smart homes using IoT and Big data analytics. Their approach used the MQTT protocol for scalability advantages and utilized business intelligence techniques to derive meaningful value from the data. A general architecture for a smart grid and IoT architecture can be found in Reka and Dragicevic.\textsuperscript{77} The figure in Reka and Dragicevic\textsuperscript{77} shows a schematic of their smart grid (SG) and IoT architecture. The proposed SGIoT architecture consists of four layers: (1) sensors connectivity and network layer—gathers the data from IoT-sensing devices in the SGIoT and energy system; (2) gateway and network layer—contains the network and wireless communications technologies; (3) management service layer—provides services to the IoT (e.g. device data and flow management of load data, system and power consumption data, market data, customer profiling); and (4) application layer—provides the energy management and smart grid applications (e.g. smart buildings, electric vehicles, demand side modeling and management, integration of renewable energy sources, and faults monitoring).

The various ASIoTs and smart environments which have been discussed in this section show similar layers and components. It would be useful to have a generic IoT architecture, which can be used for many ASIoT applications. Figure 3 shows a generic ASIoT architecture with seven layers: (1) identification layer; (2) object layer; (3) communication layer; (4) middleware layer; (5) cloud and computation Layer; (6) decision-making and multimodal layer; and (7) application layer. Compared with the types of smart environments which were discussed in this section, the generic ASIoT architecture contains a middleware layer for interoperability, and a decision-making and multimodal layer\textsuperscript{92} to cater for different data sources. The ASIoT architecture also contains a security and privacy layer, which feeds into the other layers.

**Challenges and future directions for EI deployment in ASIoTs**

Several critical challenges remain to be addressed to realize the usefulness and potential of ASIoTs for effective EI deployment in smart environments. As discussed throughout this article, although several use cases and projects have demonstrated some success, the technology has not yet seen widespread deployment, and several issues and requirements remain to be overcome. This section discusses some challenges and future directions for designing and building ASIoTs: (1) Interoperability among EI ASIoTs; (2) Software tools and EI frameworks for ASIoTs; and (3) Benchmarks for EI ASIoTs.

**Interoperability among EI ASIoTs**

A critical challenge to be addressed is the issue of interoperability among EI ASIoTs. This is particularly important to deal with the large-scale and heterogeneous data streams, which are generated from different types of ASIoTs. Larger scale and more complex ASIoTs can be achieved by successfully addressing interoperability issues. Noura et al.\textsuperscript{78} discussed a useful taxonomy of IoT interoperability issues and challenges from five perspectives: (1) device interoperability—enables the heterogeneous devices on IoT networks to communicate using various communication protocols and standards; (2) network interoperability—enables the exchange of messages through different networks for seamless end-to-end communication; (3) syntactical interoperability—enables the message sender and message receiver to encode data in a defined message format using syntactic rules (e.g. XML, JSON) among IoT entities; (4) semantic interoperability—enables the different IoT agents, services, and applications to exchange information, data and knowledge in a meaningful way; and (5) platform interoperability—enables the development and deployment of cross-platform and cross-domain IoT systems with diverse operating systems, programming languages, data structures, and access mechanisms.

Rahman and Hussain\textsuperscript{79} discussed future challenges for semantic interoperability for heterogeneous and resource-constrained IoT networks including the need for light-weight and dynamic semantic models, fast and scalable response based on incorporating edge computing models into IoT networks and generic ontologies to support different IoT applications. Cimmino et al.\textsuperscript{80} proposed an approach termed as VICINITY to address the challenges for semantic interoperability in IoT networks. This work proposed the concept of “interoperability as a service” for large-scale and heterogeneous IoT networks. Poltronieri et al.\textsuperscript{81} discussed challenges to be overcome for IoT interoperability in the context of battlefield scenarios (e.g. Internet of Battlefield Things—IoBT). The authors proposed an approach using a device-agnostic philosophy where the IoT devices were identified by its capabilities and information, and not its specific type.
Software tools and EI frameworks for ASIoTs

A second critical challenge to be addressed is the requirement for software tools and frameworks for the development of ASIoTs. Taivalsaari and Mikkonen remarked that software tools, methods, and languages which are currently available are not well suited for the emergence of millions of programmable things such as for large-scale IoT systems. Their work discussed the differences between software development frameworks for IoT when compared with web-based and mobile software development. The authors identified several characteristics of IoT systems and challenges which need to be considered for the development of IoT software development and frameworks (e.g. highly heterogeneous, weak connectivity, dynamic topologies). Several frameworks and tools for deep learning such as TensorFlow, Theano, and Keras are currently available. However, the challenge remains to integrate these powerful EI tools and platforms into resource-constrained IoT objects and devices. Krishna et al. proposed a software tool termed as IoT Composer which supports the various stages for building an IoT application from the design, composition, and deployment to the configuration and binding of the available smart objects. The IoT composer tools use behavioral modeling languages and automated verification for developers to build compositions of IoT smart objects and devices and check for correctness (e.g. defined composition bindings for objects can be deployed; composition is free of deadlocks).

Benchmarks for EI ASIoTs

A third critical challenge to be addressed is benchmarks for fairer and objective comparisons among different ASIoT deployment approaches. Associated with the need for software tools are the requirements for IoT industry benchmarks for applications and domains. Limaye and Adegbija proposed a benchmark suite for the Internet of Medical Things (IoMT) termed as HERMIT. The HERMIT benchmark suite comprises of eight medical-related applications (e.g. physical activity estimation, sleep apnea, heart rate variability, blood pressure monitoring) and two applications for security and compression (advanced encryption standard and Lempel–Ziv compression). The authors demonstrated the usefulness of the benchmarks for measurement of low-level hardware characteristics (e.g. instruction count, cache references, and branch instructions) for different IoMT applications. Another usage of the benchmark suite is to enable performance comparisons on different hardware platforms (e.g. ASIC, FPGA, GPU). Shukla et al. proposed an IoT benchmark suite for real-time distributed stream processing platforms termed as RIoTbench. Their benchmark suite contains stream profiles with 3 million sensors which are comparable to large-scale ASIoT deployments from four real-world domains (smart grid, smart transportation, urban sensing, and personal fitness).

Conclusion

In the future, large-scale networked sensor systems and ASIoTs are expected to continually produce high data volumes and increasing complexity of data streams. The current centralized approaches for IoT information processing remain inadequate and result in bottlenecks and inefficiencies to realize the business values contained in the data. A promising solution to deal with the data deluge is by the practical deployment of embedded intelligence (EI) and machine learning techniques, which are implemented on the sensor and edge nodes. This article has given an overview of the current landscape of EI for ASIoTs and highlighted the challenges, opportunities, and future directions for practical deployment of the technologies for various smart environments.

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