A Review of Intelligent IoT Devices at The Edge

Kevin Afachao[1]
[1] Department of Electrical, Electronic and Computer Engineering
University of Pretoria
Hatfield, Pretoria, South Africa u22851217@tuks.co.za

Adnan M. Abu-Mahfouz[1,2]
[2]Council for Scientific and Industrial Research (CSIR)
Pretoria, 0083, South Africa
a. abumahfouz@ieee.org

***Abstract*— The Internet of Things is fast expanding with paradigms to describe its new frontiers. A more closely tied term to the Internet of Things is Edge Computing, which describes empowering devices at the edge with intelligence. One characteristic of these edge devices is the improved latency provided against Cloud computing. The network edge is an under-utilized area and by merging intelligence with edge computing devices, we can effectively exploit it with novel approaches. This paper seeks to bring to light several "Internet of Things" devices at the edge and their capability in bringing intelligence to the network edge. A novel approach is introduced by comparing devices concerning the processing capability, memory capacity and applications. It is then clear, that there are many devices today on par with smartphones equally capable of deploying intelligence at the edge.**

Keywords- Internet of Things, edge devices, artificial intelligence, deep learning, processing unit

I. INTRODUCTION

Massachusetts Institute of Technology (MIT), Executive director of Auto-ID Center, Kevin Ashton came up with the term "Internet of Things", today the term is gaining popularity although to different people it carries to each person its own meaning. In simple words, the Internet of Things, no matter the definition seems to carry these key concepts, Computing devices, the Internet, Smart services and Information [3]. With the accretion of computation power and cyber-physical devices to match, the IoT infrastructure has grown enormously, and the number of connected devices today would soon overwhelm the network bandwidth, as recorded by Cisco [4] and IDC [5]. However, there is a need to introduce strong standards to enhance device interoperability.

Artificial intelligence came on the scene in 1956 and has since been a trending term[6]. A machine or device is said to possess artificial intelligence (AI) when it can interpret data, learn from the data to suit a situation and eventually adapt as the situation demands change whiles achieving a set of goals. Today, there are many applications of AI, for example, personalized shopping recommendations, personalized advertisements, smart video surveillance, and also smart digital assistants[6], [7]. AI is now commonplace mainly due to the rise in device computation power, and memory capacity, without this AI, would lose much of its potential.

In recent years, several computing models have been generated to describe various outcomes of using smart devices with the Internet of Things (IoT). At least three of these models are most notable; Cloud, Edge and Fog. Characteristically, Edge is an evolution of the Cloud. Although the Edge computing model advocates for localized data processing and data storage at the edge server, devices at the edge are capable of carrying out intelligent data processing and task execution. It is significant to know that, unlike the Cloud where data is solely processed within its system on the Edge, data gets processed by several nodes, in this case developing a software architecture, flexible enough to adapt to the increasing number of different devices is a challenge.

Integration of Artificial Intelligence (AI) with the Edge has led to the term Intelligence Edge (IE). The idea of bringing AI to the edge environment is currently in its novice phase. There are still more opportunities for research in this area nonetheless, the lack of standard definitions and architecture leads to research dwelling on the most convenient cases and scenarios. Current research considers a limited number of edge devices, the smartphone being the most prominent. Nevertheless, the advent of IE means real-time applications running at the edge of the network would be cost-efficient i.e. the network bandwidth, device memory, computation power, energy demand, and communication latency would be preserved since the AI application would not need to depend on the Cloud for deployment.

The study of hardware in the edge environment has progressed beyond the study of just a single device or just processing units. In [1], the study of multiple edge devices covers the various parameters which make a significant difference between the devices and hence grouping them into categories. The paper [2] describes what current techniques allow for some machine learning methods in current high-end IoT edge devices, thus paving the way for more research in the area of IE.

This paper aims to state other least-known platforms and hardware equally capable of being empowered with AI, thus improving device flexibility and the quality of service (QoS) delivery.

The paper is outlined as follows. In the next section, we discuss the applications of the intelligent edge. In the following section, we describe the IoT devices at the edge and then we continue by elaborating on open research issues and concerns. Finally, the paper ends with a conclusion.

II. APPLICATIONS OF THE INTELLIGENT EDGE

In this section, we consider specific scenarios of how intelligence at the Edge creates better outcomes for otherwise unsatisfactory situations and events.

A. *Smart Home*

Things at the edge should not be classified as smart by having just a Wi-Fi module, instead, in environments such as the home, the inclusion of the floors, walls, and the ceiling as things with wireless sensors, controllers and intelligence is necessary for an all-inclusive smart home[12]. For example, the provision of distributed deep RL methods, on edge devices means power distribution and load scheduling in the home can be optimized without having to send data to the internet for processing.

B. *Smart Industry*

In the manufacturing industry, AI at the edge has not been left out, industrial robots occasioned to a limited scope, can extend their functions considerably with the aid of AI [7]. For example, in autonomous manufacturing inspection, DeepIns [3] an application of edge computing and DL is used to improve inspection efficiency. In another example, an intelligent manufacturing framework [6] was designed to meet real-time application needs by facilitating event learning.

C. *Smart Transportation*

Smart transportation serves to help as many traffic users as possible, with the advent of AI, we can equip cars, and other edge devices with intelligence thus creating autonomous self-driving cars. The edge computation provides us with low latency, fast response time and effective use of network bandwidth, this would be advantageous for autonomous vehicles. Integrating AI into autonomous vehicles creates an optimized and holistic system. For example, DRL enables the optimum task offloading for vehicle edge computing [7].

D. *Video Analytics*

Today, video analytics is aided by the increased use of smartphones and developed cameras. The popularity of video analytics is evident in smart security systems, automatic piloting, VR and AR. Smart security is viewed as a means to protect physical or cyber products with the help of AI. One application of smart security is in the detection and recognition of people using human-centric perceiving, this recognition system can be deployed on the edge, and a lightweight model [7] has since been deployed and is yielding good results. Also, it has been discovered that once a domain-aware adaptation model is trained together with the help of the domain-constrained deep model good results can also be attained [6]. However, edge devices cannot carry the full load of the DL model hence a trade-off is proposed in some instances, between video compression and device metrics, the excess load can then be directed to edge nodes. If multiple DL tasks have to run on edge devices independently, parallel analytics would have to be used, supported by a multi-capacity model like NestDNN [3]

E. *Smart Healthcare*

Smart Healthcare at the edge, means coupling healthcare and its related edge devices with AI capability, it's no news that wearable devices like smartwatches have sensors that track human data points, and activities such as heartbeat rate and motion equipped with a lightweight recognition module to provide the hospital with meaningful data to monitor and treat patients accordingly [7].

III. IOT DEVICES AT THE EDGE

A. *Criteria for Devices*

Before enumerating the devices and how they compare with each other, we must first describe the specifications associated with devices, various descriptions and examples [1], [13].

1) Processing: The main backbone of the IoT system is the processing power since the processor runs all the tasks and ensures the efficient and reliable performance of the device. In light of the constraints at the edge of the network, processors are made to handle these limitations to still deliver services. For processing units, key factors to consider are the demands of the application on the processor, the instruction architecture and the energy efficiency of the processor.

2) Memory: Memory defined on an IoT device is limited by the computational capacity of the device, the cost and the application of the device. The device memory can be found as flash memory and Random-Access Memory (RAM). Flash Memory, the NAND flash and the NOR flash play crucial roles in wearable devices due to the data consumption of these devices. Embedded flash memory is also contending for space on IoT devices, due to its high computation performance. It can be found on microcontrollers. Types of flash memory are External Flash Memory and Internal Flash Memory. On the other hand, there are also types of RAM: Static RAM (SRAM), Synchronous Dynamic RAM (SDRAM), Double Data Rate (DDR), and Embedded Multimedia Card.

3) Size and Cost: The development of smaller boards has made a direct impact on the cost of the boards, this is due to the minimized area Silicon covers on the board as well as the smaller embedded components. IoT devices in a quest to become ubiquitous, have taken advantage of Moore's Law to be smaller and yet capable of processing complex tasks. The cost of the boards is largely influenced by processing and memory features. Much consideration is given to protecting the boards against harsh environmental conditions. They are now being made to withstand, water, dust, and shock

4) Security: Security, privacy and ethics are major concerns when it comes to IoT. The IoT edge device, due to its constrained resource presents itself as a vulnerability in the network since it cannot be updated as with normal devices considering its limited memory constraint. For example, connected devices are very susceptible to Denial of Service (DoS) attacks which could have huge implications for the network. Solutions are being proposed to meet these problems, for example, the TinyOS has TinySec Library to provide secure message authentication and integrity on the OS. For hardware security, ARM TrustZone provides robust security for ARM processors by embedding in the processors a feature that allows secure boot.

B. Classification of Devices

Below are edge devices and how they compare with each other, we must describe the specifications associated with devices, various descriptions and examples.

1) Low-end edge devices: Low-end edge devices are simply devices at the edge considered to have the least computing resources. They are connected to actuators and sensors. Due to the constraint on resources, they don't run any local OS and are programmed using low-level firmware. Devices like the OpenMote-B have been involved in several IoT applications [14]. Motes are simply wireless sensor nodes found at the edge of the network. In Table I, we consider some common Low-edge devices found in IoT implementations.

2) Middle-end edge devices: Middle-end IoT devices as the name suggests are supposed to lie between low-edge devices and high-edge devices, due to their clear tradeoff between computing resources and low power consumption. They feature more communication technologies than low-edge devices and have memory capacities greater than 250kB, yet they are not able to run heavy computation tasks like high-edge devices. With Central Processing Unit (CPU) clock speeds of about 100MHz, middle-end devices which have single-core processors can handle multisensory interfacing and basic mathematical operations, however, for more complex matrix computations they fall short in that area. Examples are Arduino Yun and Net Duino devices which have also been deployed in several IoT projects [1]. Table II illustrates some common middle-end edge devices.

In AI deployments, middle-end edge devices fall behind in many metrics such as low memory capacity and low computing power. However, there are currently many researchers trying to utilize optimized AI models to run on these resource-constrained devices. The following are some popular middle-end IoT edge devices:

a) Arduino Yun: Arduino Yun uses the ATmega32u4 and the Atheros AR9331. The MCU has Ethernet and Wi-Fi, a USB-A port, a micro-SD card clot, 20 digital pins, a micro-USB connection and an ICSP header.

b) ESP8266: ESP8266 utilizes a 32-bit CPU with a speed of 80MHz and comes with 1MB of flash memory. It functions in four states, an on state, a deep sleep state, a sleep state, and an off state. It includes an extended 16-pin GPIO, SPI control, Digital IO Pads, I2C, UART, ADC and Wi-Fi support.

c) STM32F401 RE: The STM32F401 RE uses an ARM Cortex-M4 32-bit CPU. The CPU uses a Floating-Point Unit with SRAM and Flash memory. It comes along with ADC, UART, I2C and SPI communications.

3) High-end edge devices: High-end IoT edge devices stand out as Single Board Computers (SBC), with a lot more resources. They are used as IoT Gateways clearly because they accommodate a lot more computing resources and hence have the added advantage of being able to carry out demanding machine learning algorithms at the edge of the network.

TABLE I. A COMPARISON OF LOW-END EDGE DEVICES

Edge device	Processing unit	Clock speed	RAM	Flash memory
Arduino Yun	ATmega32u4 and Atheros AR9331	16MHz	64MB DDR2	16MB & micro-SD
Netduino N3	ARM Cortex-M4	168MHZ	164KB	384KB
ESP8266	L106 32-bit RISC	80MHz	160KB	16MB
Carabola 2	Atheros AR9331	400MHz	64DDr2	16MB
Intel Galileo Gen 2	Intel Quark X1000 x86 Quark	400MHz	256MB DDr3	8MB & micro-SD
Arduino Uno	Intel Edison	400MHz	2KB	32KB
STM32 F401 RE	ARMCortex- M4	84MHz	96KB	512 KB

One clear feature than makes high-end edge devices stand apart is the possession of a GPU, Fast Ethernet/Giga Ethernet interface, USB ports, WIFI chipset and sometimes a Camera Serial Interface and Display Serial Interface. They are the most used in IoT deployments [15], [16]. Table III illustrates some high-end edge devices.

The significant increase in the number of high-end IoT edge devices is partly due to the decrease in the size and cost of devices. It is common for networks to be left vulnerable due to IoT devices lacking strong security, this is also the case with high-end IoT edge devices which act as edge gateways for the network. Preliminary research has led to introduced embedded hardware security and Operating System (OS) security features. With some optimization, devices run Deep Learning inference tasks, such as image processing, pattern recognition, distributed computing and video analysis. They come equipped with multicore processors and thus have the capability of carrying out more complex mathematical operations than middle-end devices. Google and other industry partners are developing SBCs with special chips to process AI tasks [2]. The following are some popular and more common high-end IoT edge devices:

a) Raspberry Pi 3 Model B+: Pi 3 Model B+, was released in 2016. It uses a 64-bit Cortex- A53 CPU with 1GB SDRAM. It comes along with 4 USB ports, a Gigabit Ethernet port, Bluetooth and a 40-pin GPIO port for connectivity. It has a full-size HDMI port, a MIPI CSI camera port, a MIPI DSI display port, a 4-pole stereo, an output video port, and a micro-SD port.

TABLE II. A COMPARISON OF MIDDLE-END EDGE DEVICE

Edge device	Processing Unit	Clock Speed	RAM	Flash Memory
Arduino Zero	Cortex-M0	32MHz	32KB	256KB
Neutrino	Cortex-M0	48MHz	32KB	256KB
Node MCU ESP8266	Xtensa LX106	80MHz	64KB	4MB
LSN50	Cortex-M0+ / STM32L072CZ T6	32MHz	20KB	192KB
Wemos D1 Mini	Xtensa Diamond	80MHz	64KB	4MB

Waspmote PRO	AtmelATmega 1281	14.7MHz	8KB	128KB
Raspberry Pi Zero WH	Cortex-M0	1GHz	512 MB	256KB
Raspberry Pi Pico	Cortex-M0	133MHz	2MB	264KB
TelosB	T1MSP430F16 11	8MHz	10KB	48KB
Arduino MKR 1000	Cortex-M0	48MHz	32KB	256KB
Adafruit Feather M0	Cortex-M0	48MHz	32KB	256KB
Micro Wonder Gecko STK	Cortex-M4	48MHz	32KB	256KB
Pinoccio	Atmega256RF 2	16MHz	32KB	256KB
SODAQ Autonomo	ATSAMD21J18 Cortex M0+	48MHz	32KB	256KB

b) Samsung ARTIK 710: Samsung ARTIK was released in 2015, and it is the integrated IoT platform bringing secure, interoperable, and intelligent IoT products and services to consumers. It enables any of their devices to interact with 3rd party devices, apps or services. For accessibility, it utilizes GPIO pins, SPI, UART, I2C and USB 2.0. It uses a 64-bit ARM Cortex A-53 CPU with 1GB RAM and 4GB flash memory. For connectivity, it uses Wi-Fi, Bluetooth, and ZigBee [1].

c) Odroid – XU4: A single-board computer (SBC) released in 2015, is used to deploy several IoT applications even in healthcare. Odroid- XU4 is an SBC with a Samsung Exynos 5422 CPU, and an improved Mali GPU. The Samsung Exynos has two types of Cortex processors, first, a Cortex-A15 quad-core CPU and a Cortex-A7 quad-core CPU. The XU4 comes with GPIO pins that run at 1.8V hence incompatible with 3.3V devices in the market. This can be solved by adding a shifter shield to give the Odroid access to a high voltage. Odroid allows users to experience fast data transfer speeds to support high processing power on ARM devices. For connectivity and access, it uses an HDMI port, an Ethernet port, GPIO ports and a USB port.

IV. OPEN RESEARCH ISSUES

A. *Data privacy*

The relevant stakeholders involved in bringing intelligence to the Edge include but are not limited to: platform providers (e.g. Amazon and Google), AI software providers (e.g., SenseTime), edge device providers (e.g., Hikvision), network operators (e.g., AT&T), data generators (e.g., mobile device owners) and service consumers (i.e., users) do not have an official supervisory body ensuring data concerns of the end-users are monitored and protected. User private data needs to be ensured it is kept at the Edge or masked to prevent data leakages. For example, the European Union (EU) General Data Protection and Regulation (GDPR) came to ensure that the personal data of users lies in the hands of the owners in deciding what is done with their data. However, privacy-focused design needs to be made available to users, to enhance their competency in handling their data since user privacy awareness is still poor. The author in [12] indicates that taking 439 million households, 49% of Wi-Fi networks are unsecured, and 80% of households still have their routers set on default passwords. Public Wi-Fi hotspots also show 89% of them being unsecured, this is a vulnerability to user privacy at the edge. Also, with intelligence at the edge, the use of AI methods like federated learning across heterogeneous devices to prevent leakage of user data needs to be given further research. With cooperation amongst these stakeholders, there would be no need for fear of data monopoly.

TABLE III. A COMPARISON OF HIGH-END DEVICES

Edge Device	**Processing Unit**	**Clock Speed**	**RAM**	**Application**
Samsung ARTIK 710	Octa-core ARM Cortex-A53	1.4GHz	1GB DDR3	Data processing (PCA) [42]
Odroid- XU4	Samsung Exynos542 2 octa core	2GHz	2GB LPDDR 3	Image detection [43]
Banana Pi M2 Berry	AllWinner V40 quad- core ARM Cortex-A7	1.2GHz	1GB DDR3	Image processing [44]
CubieBoar d 5	AllWinner SOC H8, octa core ARM Cortex-A7	2GHz	2GB DDR3	N/A
Radxa Rock Pro	Quad-core ARM-A9	1.6GHz	2GB DDR3	N/A
Raspberry Pi 3 Model B+	Broadcom BCM2837B 0, quad- core ARM Cortex-A53	1.4GHz	1GB LPDDR 2	Image recognition , Distributed computing, video analysis [45]-[47]
PcDuino4 Nano	AllWinner H3 quad core ARM Cortex-A7	1.2GHz	1GB DDR3	N/A
PandaBoar d ES	OMAP4430 dual-core ARM Cortex-A9	1.2GHz	1GB DDR3	Image processing [48]
BeagleBoar d-X15	TI AM5728 Dual ARM Cortex-A15 + Dual ARM Cortex-M4 + Quad PRU	1.5GHz	2GB DDR3	N/A
Orange Pi PC Plus	AllWinner H3 quad- core Arm Cortex-A7	1.536G Hz	1GB DDR3	Image recognition [49]
ESP32	Xtensa Dual Core	600MH z	448KB ROM, 520 KB SRAM	Human activity recognition [51], [52]

B. *Optimization and Task offloading*

Across the “end-edge-cloud” architecture, there are present heterogeneous devices which vary in computational strength, to run AI models, we need to consider computational scheduling, memory resources and communication technologies being used. Cooperation among heterogeneous devices is to be considered, however, a design needs to be made to accommodate synchronization and dynamic task scheduling across the devices, the varying computation and the harsh nature of the environment present themselves as equal challenges left unexploited. The author in [6] proposes blockchain (e.g., Ethereum) for the devices across the "end-edge-cloud" platform.

C. *Smart Resource and Service Management*

At the Edge OS, smart service management needs to find a suitable design to deal with cases where the edge application malfunctions, and causes the applications to fail, an edge device is taken from the network and replaced in a plug-and-play manner, the device should not delay in syncing with the network. DRL is being leveraged to provide dynamic resource scheduling and allocation in a self-learning way.

D. *Programmability*

Programming of edge devices requires either of these languages (e.g., TensorFlow Lite, Caffe2, CoreMI, and MXNet) whiles AI programming has the following frameworks available (TensorFlow, Torch and Caffe), however, there is no seamless service across these devices for users. The user has to connect and disconnect across devices. We need to bring this seamless and smooth service to users by creating an open platform to allow for this.

V. CONCLUSION

The IoT architecture is only possible once it is coupled with devices and computing resources. This article brought to light the many edge devices currently in use, from the least computing power to the most advanced in computing resources and their integration with AI in various IoT applications. Recognition goes to the fact, that the list of devices stated is not extensive, however, as compared to papers concerning the subject more devices are compared. The limitation on the use of other devices in AI implementation has to do with the community, for example, the wider community of Raspberry Pi users have easier discussions and applications in novel areas. Also, popular devices, such as the Raspberry Pi offer a lot of peripherals, for communication and connectivity whereas other devices do not offer such features. Besides this, the OS and AI libraries also cause a handicap to some devices, since AI libraries have not yet been developed to suit their OS. Generally, this paper indicates that once attention is given to other devices, it is very possible to run AI applications and also come up with suitable applications for the devices. Open research areas and the possible future direction of intelligent IoT devices at the edge are stated. Finally, in this paper, interest and attention should also be given to more recent and upcoming devices to enable a holistic understanding and application of devices at the edge.

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