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Towards Green Edge Intelligence

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***Abstract*—This study presents our ongoing activities, along with a demonstration that showcases the integration of these endeavours into a real-world application. We demonstrate the integration of IoT devices with energy harvesting systems, as well as the incorporation of deep learning techniques into IoT devices. Finally, we consider the utilization of radio frequency (RF) technology for gesture detection and classification, based on deep learning algorithms.**

***Index Terms*—Internet of Things, Cloud computing, Edge intelligence, Wireless power transfer, E-Health, Smart Cities**

I. Introduction

The Internet of Things (IoT) encompasses a vast network of interconnected physical devices embedded with sensors, software, and connectivity capabilities. As a result, IOT has revolutionized various aspects of our lives, ushering in an era of enhanced efficiency, connectivity, and convenience. Its exponential growth has resulted in the generation of vast amounts of data, which poses challenges for traditional cloud computing models in terms of scalability. To overcome these challenges, new layers such as fog and edge computing have been introduced.

Recognizing the growing design productivity gap[1], wherein electronic advancements outpaces developers' ability to cope, industries and organizations offer open source software stacks to expedite development processes. For instance, Amazon's acquisition of freeRTOS [2] provided a popular framework with associated libraries. This trend extended to the Linux Foundation, which provided comprehensive and business-friendly IOT solutions [3]. Also other ecosystems like NUTTX, sponsored by companies such as SONY [4] and Samsung [5] have emerged. Collectively, these developments contributed to the rise of edge computing, enabling signal processing at the edge device itself.

However, the shift towards edge computing introduced new challenges, particularly in power consumption. Unlike standard IoT devices that spend significant time in deep sleep, edge devices consume more power due to their active processing. The integration of environmental considerations in the design, development, and implementation of IoT solutions is crucial to mitigate the extensive energy consumption and carbon footprint associated with IoT devices and infrastructure.

The emergence within the IoT landscape has been transformative; it empowered the processing and analysis of massive datasets in real-time, facilitating intelligent decision-making and enabling automation at an unprecedented scale. Techniques such as quantization, have reduced the size of the models significantly without sacrificing accuracy, and given rise to edge intelligence.

The evolution of IoT has witnessed a transformation from minimal processing at end devices to edge devices capable of deploying machine learning models and making inferences. Edge intelligence leverages the computational power and data processing closer to the data source, reducing excessive data transmission to centralized cloud servers. This approach minimizes latency and optimizes bandwidth usage.

This paper explores the integration of edge intelligence in developing sustainable IoT systems. By combining the power of machine learning algorithms with edge computing capabilities, we can create intelligent, energy-efficient solutions that minimize environmental impact without compromising performance or functionality.

II. Sustainable Power Generation

Battery-powered IoT devices face limitations in terms of energy storage capacity, leading to frequent replacements that can be costly, cumbersome, or even impossible in certain scenarios. One approach to extend the lifespan of traditional wireless systems is through energy harvesting.

Our focus lies on three prominent sources of energy harvesting: solar power, radio frequency (RF) wireless power transfer, and inductive wireless power transfer.

A. RF wireless power transfer

RF wireless power transfer is a method to convert energy from the electromagnetic field into electrical energy, offering the potential to serve as an additional source of ambient energy. These systems typically consist of a receiving antenna to capture RF signals, an impedance matching network, and a rectifier circuit to generate DC power [7].

RF harvesters operate within license-free ISM bands [8], such as 900/2.4 GHz, and can be classified as either omnidirectional or unidirectional radiation depending on the direction of the the emitted energy.

In addition to RF wireless power transfer, other ambient energy harvesting technologies can be used. Our current research efforts are focused on developing a hybrid energy solution

[1]T. Dillinger, An update on the Design Productivity Gap, Mars 2018, https://semiwiki.com/eda/cadence/7622-an-update-on-the-design-productivity-gap
[2]FreeRTOS, https://aws.amazon.com/freertos
[3]Zephyrproject, https://www.zephyrproject.org
[4]Spresense Nuttx, https://github.com/sonydevworld/spresense-nuttx
[5]TizenRT, https://github.com/Samsung/TizenRT

that integrates solar power with RF wireless power transfer. By combining these two energy sources, we aim to maximize power availability and sustainability. This hybrid approach takes advantage of the consistent energy supply provided by solar power and the flexibility of RF wireless power transfer, resulting in a robust and efficient energy harvesting system.

B. Inductive wireless power transfer

The concept of inductive wireless power transfer, particularly with high-frequency currents has gained significant attention in recent years, notably following a successful demonstration of mid-range power transfer [9]. Another group developed a proof of concept by powering a drone without a battery that can hover freely in proximity to an Inductive power transmitter [10].

Importantly, inductive power transfer in the 13MHz range has been deemed safe for human health when adhering to the established safety standards set by the International Commission on Non-Ionizing Radiation Protection (ICNIRP) [11].

Despite significant advancements in energy harvesting techniques, the widespread adoption of these technologies in industrial settings remains relatively low [7].

III. Green Edge Intelligence

Another area of investigation involves the realization of efficient and environmentally friendly end-to-end solutions based on edge intelligence. Notable is the ability to conduct real-time data analysis. Furthermore, edge intelligence enables context-aware data processing, wherein data is analyzed within its environmental context.

We target a comprehensive solution that integrates cloud, fog, and edge intelligence, which will be powered by a hybrid solar and RF energy harvester. We will consider one of the following use cases. The first involves predictive maintenance in the manufacturing sector, where continuous monitoring of equipment can detect potential failures before they occur, thereby preventing costly downtime and repairs. The second use case pertains to smart homes, where machine learning algorithms analyze sensor data to make context-based decisions, such as adjusting temperature based on the time of day or turning off lights in unoccupied rooms. The third use case is related to healthcare, particularly real-time patient monitoring, which enables healthcare providers to respond promptly to critical situations [12].

Production environments deal with the complexities of working with messy and potentially biased data, necessitating careful deliberation in the design, development, and selection of models to meet the diverse and sometimes conflicting requirements of stakeholders. Additionally, in production settings, rigorous testing and versioning of both code and data assume paramount importance, setting it apart from the conventions of traditional software engineering [13].

To streamline the development, various platforms, such as SensiML and Edge Impulse, have emerged, providing developers with abstraction layers that hide complex mathematics and programming details, thereby simplifying the workflows

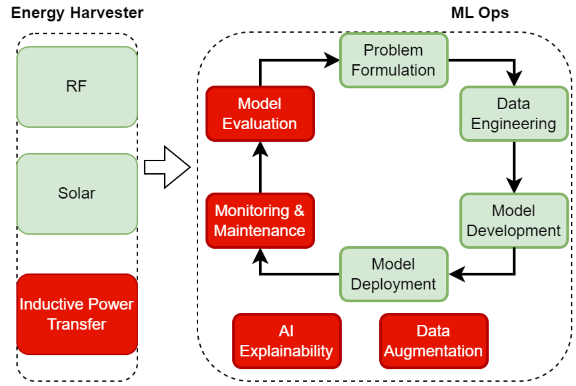

Fig. 1. End to End system

IV. Gesture Classification

We will address the utilization of RF signals for gesture detection, with a specific emphasis on two scenarios: omnidirectional transmission and unidirectional radiation. Our approach evolves around utilizing Deep learning models to extract significant features from the raw RF signal data by harnessing the spatial and temporal patterns indicative of specific gestures. By training the neural network on labeled RF signal data that includes a variety of gestures, the models can learn distinctive features that capture the specific characteristics of each gesture. This allows the deep learning models to accurately classify gestures and gain the ability to make real-time inference.

We will be using Transfer Learning to replicate and validate prior results [6]. Additionally, we explore Data Augmentation [14] to increase the diversity and richness of our dataset.

V. Demo

The demo showcases the technological capabilities of integrating the pieces discussed in the previous sections into a real-world application. It encompasses both a tangible component, represented by the physical product, as well as an intangible component that emphasizes the underlying process involved in building the demo.

The content for the demonstration is illustrated in Fig. 1. These components are specifically applicable to three areas of investigation: inductive power transfer utilizing high-frequency current, AI explainability to enhance consumer confidence, and the utilization of data augmentation techniques to enable inference with minimal data.

There is a hybrid energy harvester system that combines solar and RF energy sources. The harvester will power an end-to-end edge intelligence system. A clear separation of concerns will be followed to allow for the independent development of each subsystem.

The intangible part of the demo lies in the systematic process employed to develop machine learning (ML) systems. We embraced practices from the domain of DevOps [15], such as automation, continuous integration, and continuous delivery. The adoption of these practices, commonly referred to as

MLOps [16], takes critical importance due to the consequential risks associated with deploying models without proper MLOps considerations [13].

VI. Conclusion

The exploration of energy harvesting techniques holds promise for sustainable development. While solar energy has long been recognized as a renewable power source, our investigation into RF energy opens up new possibilities, such as gesture recognition, and presents a novel approach that could revolutionize human-computer interaction.

In addition to the hybrid solution, we also recognize the importance of exploring non-radiative inductive wireless power transfer for future applications. This alternative method eliminates the need for radio frequency waves, addressing potential concerns regarding electromagnetic radiation.

Furthermore, by taking a holistic perspective of the entire edge-to-cloud architecture and actively constructing and evaluating a comprehensive solution, we can gain a better understanding of the feasibility of transforming existing edge computing into sustainable edge intelligence. This transformation has the potential to significantly impact various domains, including industrial automation, smart cities, healthcare, and transportation.

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