Raspberry Pi-based IoT Application Enhanced By Machine Learning

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Abstract—To minimize delays and allow real-time automation, IoT data processing is moving from centralized cloud servers to smart edge devices capable of local decision-making. This is a systematic review of the feasibility and performance of the Raspberry Pi 4 Model B as an inexpensive system-on-chip regarding lightweight ML models and cluster system architectures in edge-based AI. Results showed that Pi 4B ML was extremely practical and energy-efficient in time-consuming applications, such as industrial predictive maintenance and remote medical supervision. More importantly, although Pi clusters can provide the cheap computation foundation, its scalable performance of Distributed Deep Learning is hindered by immaturity from existing frameworks. Benchmarks show that small neural networks can perform at very high speed by a single Pi 4B model compared to other general-purpose hardware of the same size. The paper does confirm that Pi 4B plays an essential role in facilitating cost-effective, decentralized intelligence; therefore, optimized algorithms and enhanced distributed architectures should be developed in order to unlock the complete scale potential of the Pi clusters for next-generation Distributed AI Systems.

Index Terms—IoT, Machine Learning, Raspberry Pi 4 Model B, Edge Computing, Distributed AI, TinyML, Low Power

I. INTRODUCTION

The advanced network of connected objects— the Internet of Things— today, is the world's largest data generator. Machine learning is necessary to assist real time automated decision making. For the timeand computation-intensive training and inference processes, embedded systems advances now allow improved on-device ML capabilities, thus narrowing the gap with remote dead servers and embedded systems. Raspberry Pi 4 Model B, which has a memory capacity of 8 GB, has become the first tile to build AI and DL edge applications. The low-cost, high performance single board computer is invaluable today. Even as latency issues mount, centralized cloud computing is increasingly unsustainable and costly because of the high-volume, high bandwidth, and continuous cloud- IoT sink data streams, particularly under industrial controls, real time arms of the service latency issue the fog- cloud- IoT paradigm. The choke point demands on the edge paradigm computing— data processing and analysis is moved to the point of sensing to the edge of the network. The concept of Edge Intelligence is essential to interconnected devices. The Pi 4 can execute local decision- making processes making it a smart device.

Edge Computing is data processing and analysis that are transferred efficiently to the source. At this point, the idea of Edge Intelligence becomes fundamental to making connected devices smarter, local decision-makers, and the Pi 4B can be of great interest in the context of supporting the approach of a distributed AI ecosystem by facilitating the local execution of energy-efficient, cost-effective ML algorithms. Local inference significantly decreases response times, lowers power usage, and decreases the need to have constant cloud connectivity. Resource-scheduling techniques such as TinyML are invaluable in such resource-restricted settings. The present paper represents a systematic review concerning the current state-of- the-art of ML implementation on Raspberry Pi 4 to implement Distributed AI, taking into consideration a certain number of objectives. These include research regarding the Performance Feasibility, by examining the resource requirements, accuracy, speed, and power consumption in running ML/DL algorithms on the Pi 4B, while comparing the performance of Distributed Architectures—namely, using Pi 4B clusters for parallel processing and inference scalability in order to analyze optimal trade-offs. Application Domains is another survey we conduct to point toward transformative and low-latency edge ML solutions in fields such as Industrial IoT (IIoT), remote healthcare, smart cities, and network security. Finally, the review discusses such critical barriers as hardware limitations, constraints of distributed DL models, and further research on more efficient hardware and highly optimized deep learning models.

II. TECHNICAL SPECIFICATION

The below Specifications are of the latest Raspberry Pi 4 Model B.

- **Processor:** Broadcom BCM2711, Quad core Cortex-A72 64-bit SoC @ 1.5GHz
- **RAM:** 8GB LPDDR4-3200 SDRAM
- **Bluetooth:** Bluetooth 5.0, BLE
- **Wi-Fi:** 2.4 GHz and 5.0 GHz IEEE 802.11ac wireless
- **USB:** 2 USB 3.0 ports; 2 USB 2.0 ports
- **Ethernet:** Gigabit Ethernet
- **HDMI:** 2 × micro-HDMI ports
- **Storage:** MicroSD Card Slot
- **Power Supply:** 5.1V 3A USB Type C Power
- **Dimensions:** 85.6mm × 56.5mm

The Raspberry Pi 4 Model B is a small but powerful computer that can handle a wide range of tasks, making it one of the most versatile single-board computers available today. It is built using the Broadcom BCM2711 system-on-chip (SoC) and comes with a quad-core ARM Cortex-A72 processor running at 1.5 GHz. This gives it much better speed, performance, and connectivity compared to older versions of the Raspberry Pi. It can be used for both simple projects like home automation and more advanced ones such as machine learning and data analysis. The Pi 4 Model B supports up to 8 GB of LPDDR4 RAM, which allows it to smoothly handle memory-intensive applications. It also includes a gigabit Ethernet port for high-speed networking, two USB 3.0 ports for faster data transfer, and micro-HDMI ports that can connect to dual 4K displays. For heavy tasks like compiling or running deep learning models, at least 2 GB of RAM is recommended. The Raspberry Pi 4 usually runs on Raspberry Pi OS, a version of Debian Linux made especially for it, but it can also run other operating systems such as Ubuntu and Arch Linux ARM, giving users great flexibility and customization options.
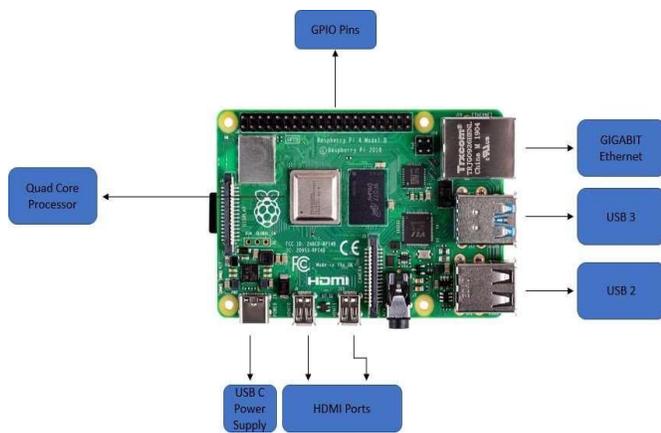

Fig. 1: Diagram of the Raspberry Pi 4 Model B components.

III. BACKGROUND

The convergence of low-cost yet high-performance embedded computer systems, the ubiquity of connectivity, and the value of machine learning algorithms all point towards a necessary shift for edge computing, where data processing closer to the source than ever before occurs. This type of decentralized model is critical to the management of massive, high-speed flows of data from the Internet of Things. In this section, it is stated that the primary technologies that drive this trend are SBCs such as Raspberry Pi platform, IoT ecosystem, and some key ML techniques.

A. Raspberry Pi: Hardware Capabilities and Advantages

The Raspberry Pi, which originally began as an educational tool for learning programming and electronics, has now evolved into a powerful single-board computer (SBC) widely used in edge AI systems. Its biggest advantages lie in being cost-effective and energy-efficient, consuming only about 3.8 to 4 watts, which is far lower than traditional cloud data processing setups. Compact and easy to integrate, it fits perfectly into space-constrained embedded systems, while its large global community continuously supports development, making innovation, troubleshooting, and project expansion remarkably simple and accessible.

A. Internet of Things: Concepts and Edge Enhancement

IoT refers to the collection of devices used in collecting and transmitting data. Traditional IoT was centered on centralized cloud computing. Today, there are issues such as high latencies, congested bandwidth, and increased cost of the large amount of data in centralized cloud computing. Edge Computing resolves these challenges because it is capable of processing and analyzing data on the device like Pi 4B. It enables real-time responses and makes devices connected smart ones. Edge Enhanced IIoT applications are disruptive in sectors like Industrial IoT for predictive maintenance, Healthcare to track patients' status in real-time, Smart Homes for energy consumption automation, and Security Systems for network intrusion detection.

IV. METHODOLOGY

A. Raspberry Pi for IoT Application

• *Overview of Suitability of Raspberry Pi for IoT:* The Raspberry Pi is an affordable, credit card-sized, single-board computer (SBC), which is highly prevalent in the Internet of Things ecosystem and is rapidly becoming a dominant hardware platform upon which edge computing and embedded intelligence-based applications are developed. Hardware and Features Raspberry Pi is chosen because of its affordability, functionality, and compact size, providing a full-fledged Linux server in miniature form.

1) **Processing Power:** Design the Pi 4B is powered by the Broadcom BCM2711 SoC, boasting a Quad-core ARM Cortex-A72 processor with a typical clock of 1.5 GHz. This substantial increase in processing power, combined with its VideoCore VI GPU, is the primary reason that the Pi 4B can be considered a potential edge processor in computation-intensive ML and DL applications.

2) **Memory and Storage:** Raspberry Pi 4B supports a maximum memory of 8 GB. RAM, which is ideal for use in AI and Deep Learning (DL) applications. But at least 2GB of RAM would be needed even with the Pi 4B just to build and train higher-level models such as Convolutional Neural Networks (CNNs). The latest Pi models all use a pluggable micro SD card as their primary storage. The Pi 4B has USB 3.0 ports that can be used to access external SSD or HDD storage much faster.

3) **Connectivity and I/O:** Ethernet, Wi-Fi, and Bluetooth connectivity will be supported by the platform. It also contains GPIO pins, UART, I2C, and SPI and can be interfaced with without much hassle, that supports various sensors and peripherals. Operating System: The operating system of choice is the Raspberry Pi OS, formerly known as Raspbian, a custom Debian-based operating system, optimized to run on the SBC.

• **Role in Edge Computing and AI**: This architecture puts Pi in the best position for Edge Computing, processing the data and analyzing near the source. It is free from high latency, high bandwidth consumption, and high expense incurred during

the process of shuffling raw streams of data all the way to centralized cloud servers. Technological improvement in chips have now enabled embedded machine learning to perform on device inferences, and the Raspberry Pi, among others, can leverage that capability to respond to inputs on-device and make its connected devices into more intelligent systems. One of the most important factors in the applications that require speed is having edge processing to provide quick response.

• *Common IoT Applications Using Raspberry Pi:* In many IoT application areas, Raspberry Pi SBCs are utilized as trustworthy edge nodes or gateways.

• *Advantages and Limitation*: Using the Raspberry Pi for IoT applications offers both unique advantages and real-world hardware limitations and operational issues.

a) Advantages (Benefits): The Raspberry Pi offers a number of key advantages for ML-enabled IoT applications, including:

1) **Affordability and Cost-Effectiveness:** Raspberry Pi devices are very inexpensive - costs range from approximately $3, 551 to $7, 102 making ML-powered IoT solutions affordable for prototyping, educational use, small to medium enterprises (SMEs) and researchers.

2) **Low Power Consumption:** Pi makes extremely low power consumption, e.g., Pi 3 Model B has a power usage of 1.5 Watts, and Pi 4B has **3.8-4 W**. Power usage of the Pi during operation of ML applications is less than that of regular high-performance machines, evidence that operating ML inference is energy-efficient and possible for IoT edge devices.

3) **Versatility and Flexibility:** It is extremely flexible as the OS is an open-source Linux variant and accommodates numerous various software packages like Python, Docker, Node-RED, and InfluxDB, which facilitates custom solutions, integration of sensor data, and protocols like Modbus/MQTT Gateway.

4) **Portability and Compactness:** The compact system fits well within enclosures that are constrained in nature and embedded systems.

5) **Community and Ecosystem:** The massive, vibrant scientific and industrial community offers strong support with rich resources.

b) Limitation:

1) **Performance and Computational Limitations:** While the Pi 4B models have been upgraded, the systems are computationally and memory-limited relative to more industrial-grade or specialized computing hardware like the NVIDIA Jetson. Extremely computationally resource-intensive or complex tasks like training Deep Learning models are impractical or take interminably long, for instance, a CNN training script took 2.7 hours for an epoch on a Pi 4B.

2) **Scalability Challenges:** Although Pi's may be grouped together for distributed workloads, employing frameworks for the execution of distributed DL inference, like Spark TensorFlow Distributor, tends to reveal a

Fig. 2: Cost comparison for 1 year between Cloud function, Cloud VM and Distributed Raspberry Pi's.

scarcity of performance scalability or no appreciable speedup compared to a single upgraded Pi. This reflects framework immaturity and high overhead.

3) **Software and Real-Time Constraints:** Official Raspbian, the OS for Raspberry Pi, is **not hard real time compliant**, thus restricting its use in safety-critical industrial applications.

4) **Environmental and Security Vulnerability:** IoT devices are vulnerable to cyber threats, requiring robust security protocols such as encryption of communication protocols (e.g., MQTT). Furthermore, standard Pi boards are **not industrially hardened** and are less resilient to high-level vibration or harsh temperatures compared to dedicated industrial platforms.

5) **I/O Limitations:** GPIO numbers ranging from **26 to 40** become greatly limiting for large-scale I/O projects without special hardware add-ons referred to as HATs.

B. Machine Learning On Raspberry Pi Platform

Raspberry Pi depends more on resource management and optimization of software or algorithms, for example, Random Forest over SVM due to its higher accuracy or SVM due to its greater speed and efficiency. Support Vector Machines have been found to be slightly faster and consume less power, while Random Forest is generally best at classification accuracy. Normal task inference times can be below one second, and the Pi is more energy-efficient than average laptops since it matters when incorporated into an IoT with a battery.

• *Optimization Techniques:*

1. **Tiny ML:** It involves the domain of applying ML/DL models to very constrained underlying hardware and hence enables energy-efficient local computation.

2. **Model Compression:** Model compression methods such as pruning or quantization lower memory usage along with model execution time with negligible loss in the accuracy of the model.

TABLE I: Common IoT Applications Using Raspberry Pi

Application Domain	Specific Tasks and Functionalities	Key ML/DL Relevance
Industrial IoT (IIoT) & Smart Manufacturing	Predictive maintenance using vibration and temperature sensors	Light-weight ML models (e.g., TensorFlow Lite) detect equipment faults locally.
Healthcare Monitoring	Real-time patient monitoring and anomaly detection	ML classifies bio signals and triggers alerts
Smart Environments & Building Automation	Adaptive lighting and HVAC control	ML models analyze occupancy and environmental data
Security and Intrusion Detection (IDS)	Network anomaly detection for IoT devices	Decision trees and gradient boosting detect cyberattacks
Agriculture and Smart Farming	Crop health and irrigation management	Random Forest predicts crop and soil conditions
Transportation and Autonomous Systems	Object detection in traffic systems	Edge ML models recognize obstacles and improve safety

3. **Lighter Architectures:** Networks like MobileNets can reduce latency and resource usage, bridging the performance gap between networks and desktops.

4. **Hardware Augmentation:** AI accelerators like Intel Neural Compute Stick 2 or Coral Edge TPU are external hardware that can significantly boost DL. There has been one instance where adding an accelerator to a Pi 3B led to image recognition work that was boosted in performance by as much as 38 times.

Raspberry Pi 4B will be a competent edge inference chip capable of handling ML using suitable algorithm selection, software optimization, and optional hardware augmentation; thus, its applicability in numerous applications in IoT and IIoT.

V. IMPLEMENTATION

A. ML Raspberry Pi IoT Integration Applications

Raspberry Pi offers a low-cost and multifaceted platform that can be used to implement machine learning (ML) features at the edge to provide solutions in a variety of areas where resourcefulness, real-time decisions, and latency are critical.

1) Smart Home Automation: The use of machine Learning in smart homes focuses on ensuring better resource utilization and enhancing automation through predictive capabilities. Specifically, as shown in table below, systems like the one using the Raspberry Pi 3 for Occupancy Recognition and HVAC Control employ video-based ML to achieve high accuracy (80–90%) in real-time, resulting in significant energy savings (over 30%). Furthermore, ML models such as Support Vector Machines (SVMs) are applied to analyze energy consumption and environmental data (temperature, humidity) for more efficient Energy Management. Beyond efficiency, machine learning also contributes to Safety and Surveillance features, including systems for gas leakage and fire detection.

The combination of the low cost and enhanced processing power of the Raspberry Pi makes it a viable platform for conducting computationally sophisticated tasks in building automation systems that traditionally relied on oversimplified models.

Feature	Details and Implementation	Algorithms & Performance
Occupancy Recognition & HVAC Control	Pi-based system analyzes camera feeds for occupancy prediction	30% reduction in energy use
Energy Management	Smart meters with ML-based prediction of consumption trends	Better forecasting and load balancing
Safety and Surveillance	Gas leak and fire detection using ML models	Faster and more reliable alerts

2) Environmental monitoring and prediction using machine learning on Raspberry Pi devices enable efficient processing of large, diverse environmental data streams. These systems support sustainable development and smart city management by

transforming sensor data into actionable insights for air quality analysis, waste tracking, and climate forecasting.

Feature	Details and Implementation	Algorithms & Performance
Urban Waste Management	Indoor/outdoor air and noise measurement using low-cost sensors	Deep Learning models like SSD MobileNetV2 are used for garbage identification.
Air Quality Monitoring	Supervised ML classification	Supervised ML techniques are deployed for data classification.
Infrastructure Monitoring	Image-based waste recognition	Lightweight CNN (e.g,MobileNet)
General Monitoring	Leak detection in pipelines.	Real time analysis using Tiny ML

3) Agriculture and precision farming benefit greatly from integrating machine learning and IoT technologies. These systems analyze real-time data from soil, weather, and crop sensors to optimize irrigation, fertilizer use, and pest control, improving farm efficiency, productivity, and overall food security.

Feature	Details and Implementation	Algorithms &Performance
Crop/Farm Management	Track soil moisture, temperature, and weather data	The use of Random Forest models is cited practices.
Disease Detection	Analyze plant images and sensor data	CNN-based early warning system
Irrigation Management	Optimize water use.	Regression models predict irrigation needs

4) Healthcare and Medical Applications: ML on the Raspberry Pi enables critical, low-latency health monitoring, particularly for remote patients, improving preventative and diagnostic care.

Feature	Details and Implementation	Algorithms & Performance
Remote Patient Monitoring	Pi collects vitals (heart rate, SpO₂, temperature) local doctors.	Random Forest detects anomalies
Anomaly and Condition Detection	EEG and ECG analysis for mental state classification	Rule-based or ANN classifiers.
Rural Telemedicine	Edge-based data collection and forwarding	ML ensures low-latency triage support

5) Security and Surveillance Systems: ML is extensively used on the Raspberry Pi to enhance IoT network security through anomaly detection and provide real-time surveillance capabilities via computer vision.

Feature	Details and Implementation	Algorithms & Performance
Intrusion Detection (IDS)	Network traffic anomaly detection	Decision Tree or XGBoost classifiers
Computer Vision/Surveillance	Real-time face or sign recognition	CNN achieves high recognition accuracy
Benefits & Challenges	Edge ML identifies tampering or malware	Local ML reduces dependence on cloud systems

VI. CHALLENGES

It is seen that the usage of the Machine Learning capabilities on the Raspberry Pi (RasPi) platform to exploit the Internet of Things (IoT) has a big plus point, namely to reduce latency and less bandwidth demand. However, the use of the hot computationally heavy ML algorithms, especially Deep Learning (DL), on such low-end devices carries some troublesome challenges with hardware space, power consumption, safety, and scalability issues, which must be challenging to solve.

A. Hardware Limitations and Performance Constraints

While the number of resources that RasPi devices have access to continues to grow (e.g., the specifications upgrades in the Pi 4B), they are devices with limited resources, energy budget, memory, and computational capacity.

- **Processing Deficit:** The Raspberry Pi contains a low-end System-on-a-Chip (SoC) designed to be not intended for big processing burdens such as ML model training. Consequently, it is generally considered not very practicable or time-consuming that DL models might be trained on the Pi. At least 2 GB of RAM is required to finish more sophisticated tasks such as the compilation and training of more complex Convolutional Neural Networks (CNNs).
- **Performance Gap:** Comparative analysis has identified the gap in performance between the Pi 4B and an average desktop in inference tasks to be in the range of 6-15 times, depending on the variability in the complexity of the used DL model. The Pi 4B was not competing well with other devices such as the Jetson Nano and TX2 mainly because it did not have the integrated AI acceleration.
- **I/O Constraints:** The RasPi I/O is constrained, offering only 26 to 40 GPIO ports so it may not support largescale interface without the addition of other hardware (HATs). Additionally, to be connected with generic industrial communication protocols (e.g., RS-485 or CAN) some external hardware interfaces are necessary.

B. Power and Energy Consumption

IoT devices have very small power and energy limitations, and the power supplies of the device are heavily burdened by the complexity of the computations and memory of the ML algorithms.

- **Task Isolation:** A popular standard hybrid mitigation technique is to transfer the computation-intensive tasks of machine learning (i.e., training the model) to remote high-power hardware (e.g., the cloud) and transfer only the time limiting low-power inference task to the less powerful RasPi.
- **Feasibility Insight:** It has been discovered that ML inference may be run on RasPi at low energy usage. Executing a handful of classifiers on a Raspberry Pi 3 implied an additional power consumption of less than **15 amps per second**, which was very realistic in comparison with normal web surfing activity (18 amps or more).
- **Choice of the ML algorithm:** The choice of ML algorithm has

direct correlation on the energy used, with SVM being marginally more power efficient compared to the Random Forest algorithm.

- **Latency:** Local processing (TinyML) reduces the need to transmit data continuously and at high bandwidth that is essential in extending the life of the device in operation.

C. Data Privacy and Security Issues

The IoT is extremely susceptible to cyberattacks because of the decentralized structure that leaves the edge devices open to numerous threats.

- **Lack of Standards and Vulnerability:** The security challenges include the issue of encryption, privacy, and information security issues, and a lack of international authentication and authorization standards.
- **Device Inflexibility:** The central issue is that most IoT devices do not have proper security features or an inherent solution that can be updated further post-manufacturing because of the limitations of the hardware.
- **Resource-Constrained Cryptography:** Given the limited memory and processing power of the Pi, there are few security algorithms at all, leading to a conundrum of balancing diminished ability and enhanced security needs.
- **Mitigation Strategies:** Intense security measures must be deployed at all levels, including encryption and utilization of secure communication protocols (e.g., deploying the TLS/SSL on the MQTT brokers). Edge deployment of TinyML also facilitates enablement of improved privacy due to limited transmission of the raw data.

D. Scalability Issues

The enormous number of the data generated by an immense number of inter-linked devices is a threat to the ability of the system to handle them and is a serious scaling challenge.

- **Clustering Limitations:** RasPi clusters may offer a lowcost and energy-efficient computing platform of enormous size, but currently it is not that scalable for scenarios where lots of processing are required. There were no noticeable differences in the performance of the experimental tests of distributed inference on a 2-node Pi 4B Spark cluster compared to one enhanced Pi 4B.
- **Framework Immaturity:** Distributed Deep Learning (DL) frameworks like the immaturity of Spark TensorFlow Distributor is the main reason for this deficiency of scaling performance, as they are not distribution-ready to conduct inference, and scale with nodes.
- **Volume and Complexity of Data:** Sophisticated DL models like InceptionV3 can take 3 GB of memory, which would quickly exhaust the memory of the Pi at inference.
- **Mitigation Strategies:** Researchers should utilize distributed architectures and employ lightweight algorithms. Enhanced neural networks with enhanced CPU optimization such as MobileNetV3 can improve the gap in performance to enable low-end devices such as the Pi 4B to conduct lightweight internet-DL inference tasks on a competitively comparable basis with more capable solutions.

VII. CONCLUSION

In conclusion, the Raspberry Pi 4 Model B is a convenient and affordable device for running simple Machine Learning tasks directly on Internet of Things (IoT) devices. It is the perfect choice for edge computing, which means data processing occurs locally instead of in a far-off cloud. This shift is crucial because it reduces delays and enables real-time automation in various applications. Raspberry Pi 4B strengths for Edge AI:

- **Power and Efficiency**: With its quad-core processor and up to 8 GB of RAM, the Pi 4B can easily handle simple machine learning tasks like predicting when a machine needs maintenance or remotely monitoring a patient's health. It does this while being incredibly energy-efficient.

- **Speed and Value**: For small neural networks, the Pi 4B offers high speed for its size and price. This makes it an ideal fit for quick-response systems in smart homes, healthcare care, and security devices.

Key Challenges and the Path Forward:

However, the Pi 4B has limitations when dealing with massive, distributed AI systems:

- **Scaling Issues:** While grouping many Raspberry Pis (clusters) is cheap, they don't scale well for complex jobs because the software frameworks for Distributed Deep Learning are still immature and inefficient.

- **Training Power:** The Pi's hardware simply isn't robust enough to train large, complicated machine learning models from scratch, especially when compared to specialized hardware like the NVIDIA Jetson series.

At the end, the future use of Raspberry Pi in advanced AI depends on software breakthroughs. Researchers need to develop better optimization algorithms and more efficient distributed system designs. Techniques like TinyML, model compression, and the use of lightweight network designs (such as MobileNet) will make it easier and faster to deploy AI models on these devices.

The Raspberry Pi 4 Model B series is capable and cost-effective to develop the smart systems of tomorrow. As distributed learning technology keeps evolving, the Pi's role in autonomous systems is only going to grow.

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