Artificial Intelligence of Things: AIoT in Various Markets of IoT Deployments

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Abstract: **With AIoT, AI is embedded into infrastructure components, such as programs, chipsets and edge computing, all interconnected with IoT networks. APIs are then used to extend interoperability between components at the device level, software level and platform level. These units will focus primarily on optimizing system and network operations as well as extracting value from data. While the concept of AIoT is still relatively new, many possibilities exist to improve industry verticals, such as enterprise, industrial and consumer product and service sectors, and will continue to arise with its growth. AIoT could be a viable solution to solve existing operational problems, such as the expense associated with effective human capital management (HCM) or the complexity of supply chains and delivery models.**

***Keywords*: Artificial Intelligence, Artificial Intelligence of Things, Internet of Things, IoT Data as a Service**

I. INTRODUCTION

The Artificial Intelligence of Things (AIoT) is the combination of artificial intelligence (AI) technologies with the Internet of Things (IoT) infrastructure to achieve more efficient IoT operations, improve human-machine interactions and enhance data management and analytics. AI can be used to transform IoT data into useful information for improved decision making processes, thus creating a foundation for newer technology such as IoT Data as a Service (IoTDaaS) [1].

AIoT is transformational and mutually beneficial for both types of technology as AI adds value to IoT through machine learning capabilities and IoT adds value to AI through connectivity, signaling and data exchange. As IoT networks spread throughout major industries, there will be an increasingly large amount of human-oriented and machine-generated unstructured data. AIoT can provide support for data analytics solutions that can create value out of this IoT-generated data [2].

Applications of AIoT

Many AIoT applications are currently retail product oriented and often focus on the implementation of cognitive computing in consumer appliances. For example, smart home technology would be considered a part of AIoT as smart appliances learn through human interaction and response [3]. In terms of data analytics, AIoT technology combines machine learning with IoT networks and systems in order to create data "learning machines." This can then be applied to enterprise and industrial data use cases to harness IoT data, such as at the edge of networks, to automate tasks in a connected workplace. Real time data is a key value of all AIoT use cases and solutions [4].

In one specific use case example, AIoT solutions could also be integrated with social media and human resources-related platforms to create an AI Decision as a Service function for HR professionals [5].

Using AI to create thinking, learning things

The next generation of internet of things platforms could be one that allows things to become thinking, learning objects. Imagine that your smartwatch could not only predict when you might be ripe for a heart attack, it could also sense when a hacker was trying to access your personal data. The way to augment things with a “brain” is to enhance them with artificial intelligence (AI). Let’s call this AIoT, the artificial intelligence of things [6]. This year has shown peak investment in AI, with startups in the U.S. alone having raised $1.5 billion, and I’m sure we will see the fruits of those investments in our daily lives very soon. To imagine where AI will play a role we need to understand what AI is — and what it is not. AI is an algorithm powered by statistical models allowing the AI to “learn” through feedback loops. So rather than deterministic models where an algorithm uses predefined rules upon which to base its decisions, other models are applied [7].

For example, Google makes use of a technique that’s called deep learning; much of the work in this area is inspired by how the human brain works. Those models are no longer deterministic and, as such, could mean that how an AI comes to a certain decision might become opaque. This could give rise to unforeseen situations; witness Microsoft’s AI chatbot that learned to be racist within hours through analyzing twitter feeds. Will AI become all-knowing? The current AI’s will certainly not, they are trained on specific domains and will not be able to apply that knowledge in other contexts. For example, a recent botnet attack crashed several high-profile websites by infiltrating things such as connected DVRs and cameras. Had they been augmented by AI, the things could have sensed a traffic overload and shut them down [8].

So where will AI augment IoT? The most likely area will be in manufacturing, an industry that is already spending heavily on IoT [85]. The use case that manufacturing is attacking with AI is predominantly predictive maintenance. The form of AI they are doing this with is called machine learning [9]. Manufacturers are chasing predictive maintenance because there are some real and tangible benefits; the low-hanging fruit is increased uptime and less unplanned downtime, allowing organizations to lower the cost of maintenance and repair [10].

But there is more at stake. Having those capabilities will allow manufacturers to adopt new business models to better compete in the marketplace [84]. For example, in some areas there is a need to move from capital intensive investment to more operational investments, from Capex to Opex. So instead of offering a machine for a fixed price, a machine is rented and paid for only when it is used. IoT will allow the monitoring of usage [11].

A side effect to this is that the manufacturer would not be paid when the machine breaks down, so uptime is in his direct interest, likewise is the lifetime of the goods. If the lifetime can be extended then the margin on the rent will go up. Having predictive maintenance capabilities are essential to reaching those goals [12]. If predictive maintenance is so important, why isn't there a full adoption going on yet? Well, there are some steep hurdles [83]. The lack of reliable sensors for monitoring performance and behavior of machines is one, the challenges of getting reliable connectivity into shop floor operations another. Both are prerequisites to collecting the data that is necessary to test the statistical models [13].

Then there is a lack of statistical models that can predict behavior, largely because of a shortage of data scientists that can build and test those models. And the real world is complex; machines are shipped all over and work under different conditions. For example, the vibration of a machine will be influenced based on the type of floor it stands on; a wooden floor will influence the measurements differently than concrete [14]. Manufacturers often make many different machines, in different versions and models [82]. Those machines often are constructed on parts that were ordered through different vendors and suppliers. Although designers tend to set the quality to certain standards, spare parts delivered by third-party vendors might behave slightly differently, undercutting the models in unseen ways [15]. We are certain that deterministic models will be insufficient to deal with the above situations effectively and that the only way forward to tackle these challenges will be AI-inspired, real-time analysis approaches [16].

II. WHY AIOT IS IMPORTANT?

Use of Artificial Intelligence can improve the overall outcome of most of the the tools or process out there, if not all, given than it is used in the correct context. Internet of things, being a relatively new technology can make rapid advancements by using the benefits of machine learning and AI. AIoT enabled devices will be able to be **proactive rather than reactive** using AI [17]. Normally IoT enabled devices will act as sensors which are connected to a cloud computing platform. The role of the device will be to capture all the available data as per the configuration and send it back to the cloud for processing [81]. The task of processing the data and providing meaning full insight will be limited to cloud computing platform in this type of an environment. More or less, IoT devices will act as passive sensors which can be deployed in numbers so that we can get data, to do analysis or processing [18].

With the introduction of AI chips the IoT devices can be more active rather than passive. For example, an AI enabled smart speaker can process the trigger word using a Natural Language Processing (NLP) model locally rather than sending all the voice capture to the cloud for processing [19]. This essentially means that an AI enabled IoT system will be more **robust**, more **secure**, and even more **scalable** [79]. On the other hand, most of the Machine Learning and AI models depends on data to perform inference. IoT enabled devices can provide AI algorithms with enough amount of data to do prediction, so that the algorithms can run effectively in a local environment [80]. For instance, if we have a self driving car using an AI model, the model can use the input from the radar system of the car in case the camera input is obstructed for some reason [20].

These systems, using the power of AI, can perform **auto correction** and be decisive in terms of deciding to shutdown a system in case of malfunctioning. Such as, it the model for a self-driving car detects discrepancies in the data from different sensors it can decide to disengage and force the human driver to take control [21]. Ranging from home automation to climate prediction, the use-cases for AIoT is wide and varied [78]. This scope is ensuring that major players in the field like Amazon and Nvidia is investing heavily on AIoT [22]. AWS IoT integrates with AI services, so that we can make devices smarter, even without Internet connectivity. Amazon says that, AWS IoT provides broad and deep functionality, spanning the edge to the cloud, so that we can build IoT solutions for virtually any use case across a wide range of devices [23].

In addition to this, chip manufactures like Arm and XMoS is coming up with new and cheap AI enabled chips that can extensively improve the uses cases for AIoT by empowering engineers to come up with intelligent applications, which costs as low as a single dollar [24].

III. FROM IOT TO AIOT – SMART IOT POWERED BY AI

While IoT allows enterprises to turn device data into actionable insights to optimize business processes and prevent problems, the ability to handle data in a timely, effective manner will determine whether an enterprise can fully enjoy the benefits of IoT [77]. With numerous flows of data streamed from connected sensors and devices that are increasing by billion per year, it is only a matter of time that the enterprise clouds, growing slowly at an annual rate of thousands, will eventually be overwhelmed by enormous volumes of datasets which are beyond their capacity to digest [25].

Also, in applications like autonomous machine operation, security surveillance, and manufacturing process monitoring, local devices need to act instantly in response to time-critical events [76]. Waiting for feedback from the cloud can result in a response delay and make devices less likely to accomplish the tasks in real time. To resolve the issues of data overload and response lag, a growing number of companies are now seeking to incorporate edge computing and AI solutions into their IoT systems [26].

Edge computing: processing data where it is needed

Edge computing is a distributed computing technology which brings computation to the edge of an IoT network, where local devices are able to process time-sensitive data as close to its source as possible, rather than having to send the data to a centralized control server for analysis [27]. The primary benefit of bringing data processing back to the edge is that it allows sensor data to be processed right on the spot where it is generated, which eliminates latency and enables local devices and applications to respond instantaneously [75]. Meanwhile, by filtering raw data near the source, edge computing can significantly reduce the amount of data to be sent to the enterprise cloud, alleviating both bandwidth usage and analytical burden [28].

AIoT: when IoT meets artificial intelligence

Although some IoT systems are built for simple event control where a sensor signal triggers a corresponding reaction, such as switching on/off light based on ambient lighting changes, many events are far more complex, requiring applications to interpret the event using analytical techniques in order to initiate proper actions [74]. To make this work, a new IoT structure known as the Artificial Intelligence of Things (AIoT) comes into play [29]. It applies intelligence to the edge and gives devices the ability to understand the data, observe the environment around them, and decide what to do best – all can be done with minimum human intervention. With the power of AI, AIoT devices are not just messengers feeding information to the control center, but have evolved into intelligent machines capable of performing self-driven analytics and acting independently [30].

Deep Learning – Machines Learn Like Humans

Deep learning is an advanced branch of artificial intelligence algorithms increasingly deployed at the edge for analyzing visual imagery. A key technology behind computer vision, self-driving vehicles, robots, and many other vision-enabled autonomous machines, deep learning teaches computers to learn complex patterns from image data in order to detect and identify objects in photos and videos – in a similar way that the human brain does [31].

Deep learning allows a computer to recognize intricate patterns much faster and with greater accuracy, in many cases surpassing human-level performance. It is also a highly data-driven technology because a deep neural network must take in tremendous amounts of training data in order to increase inference accuracy [72]. This makes IoT a perfect environment for deep learning, where interconnected machines and sensors constantly feed tons of data from which deep learning models can learn and improve their performance [73]. Deploying AI at the edge of an IoT network also gives deep learning models the ability to observe their surroundings more closely than they ever could before, allowing them to deliver better inference results [32].

IV. AI KEY TO UNLOCK IoT POTENTIAL

Artificial intelligence plays a growing role in IoT applications and deployments. Both investments and acquisitions in startups that merge AI and IoT have climbed over the past two years. Major vendors of IoT platform software now offer integrated AI capabilities such as machine learning-based analytics [32]. The value of AI in this context is its ability to quickly wring insights from data [70]. Machine learning, an AI technology, brings the ability to automatically identify patterns and detect anomalies in the data that smart sensors and devices generate—information such as temperature, pressure, humidity, air quality, vibration, and sound [71]. Compared to traditional business intelligence tools—which usually monitor for numeric thresholds to be crossed—machine learning approaches can make operational predictions up to 20 times earlier and with greater accuracy [33]. Other AI technologies such as speech recognition and computer vision can help extract insight from data that used to require human review. AI applications for IoT enable companies to avoid unplanned downtime, increase operating efficiency, spawn new products and services, and enhance risk management [34].

AVOIDING COSTLY UNPLANNED DOWNTIME

In a number of sectors—industrial manufacturing or offshore oil and gas, to name two— unplanned downtime resulting from equipment breakdown can cost big money [69].

Predictive maintenance—using analytics to predict equipment failure ahead of time in order to schedule orderly maintenance procedures—can mitigate the damaging economics of unplanned downtime. Machine learning makes it possible to identify patterns in the constant streams of data from today's machinery to predict equipment failure. In manufacturing, Deloitte finds predictive maintenance can reduce the time required to plan maintenance by 20–50 percent, increase equipment uptime and availability by 10–20 percent, and reduce overall maintenance costs by 5–10 percent [35].

INCREASING OPERATIONAL EFFICIENCY

AI-powered IoT can also help improve operational efficiency. Just as machine learning can predict equipment failure, it can predict operating conditions and identify parameters to be adjusted on the fly to maintain ideal outcomes, by crunching constant streams of data to detect patterns invisible to the human eye and not apparent on simple gauges. Machine learning often finds counterintuitive insights [68]: A shipping fleet operator's machine learning tools determined that cleaning their ships' hulls more often—an expensive, downtime-causing process—actually increased the fleet's overall profitability. The math went against shipping industry instincts: Hulls kept smooth through frequent cleaning improve fuel efficiency enough to vastly outweigh the increased cleaning costs [36].

ENABLING NEW AND IMPROVED PRODUCTS AND SERVICES

Enhancing IoT with AI can also directly create new products and services. Natural language processing (NLP) is getting better and better at letting people speak with machines, rather than requiring a human operator. AI-controlled drones and robots—which can go where humans can't—bring all-new opportunities for monitoring and inspection that simply didn't exist before [37]. Fleet management for commercial vehicles is being reinvented through AI, which can monitor every measurable data point in a fleet of planes, trains, trucks or automobiles to find more efficient routing and scheduling, and reduce unplanned downtime. Cloudera claims its fleet management AI has cut downtime for fleet vehicles monitored by Navistar devices up to 40 percent [38].

ENHANCING RISK MANAGEMENT

A number of applications pairing IoT with AI are helping organizations better understand and predict a variety of risks as well as automate for rapid response, enabling them to better manage worker safety, financial loss, and cyber threats.

Applications already in use include detecting fraudulent behavior at bank ATMs, predicting auto driver insurance premiums based on their driving patterns, identifying potentially hazardous stress conditions for factory workers, and monitoring law enforcement surveillance data to identify likely crime scenes ahead of time [39].

IMPLICATIONS FOR ENTERPRISES

For enterprises across industries, AI is a natural complement to IoT deployments, enabling better offerings and operations to give a competitive edge in business performance. Machine learning for predictive capabilities is now integrated with most major general-purpose and industrial IoT platforms, such as Microsoft Azure IoT, IBM Watson IoT, Amazon AWS IoT, GE Predix, and PTC ThingWorx [40].

A growing number of turnkey, bundled, or vertical IoT solutions take advantage of AI technologies, especially machine learning. It is often possible to use AI technology to wring more value from IoT deployments that were not designed with the use of AI in mind. IoT deployments generate huge, constant streams of data, which machine learning excels at examining to identify patterns that lead to greater value [67].

V. HOW AI HELPS BUSINESSES MAKE THE MOST OF IOT DEPLOYMENTS.

According to Gartner, the number of enterprise IoT endpoints could reach 5.8 billion units by the end of this year (up from 4.8 billion in 2019). All these devices produce terabytes of data that could help businesses discover and eliminate inefficiencies in their workflows. Yet 73% of enterprise data goes unused for analytics [41]. Most companies fail to collect and process data coming from IoT devices because of the excessive amount of that data, obsolete or unreliable data acquisition tools, and flawed data analytics practices [66].

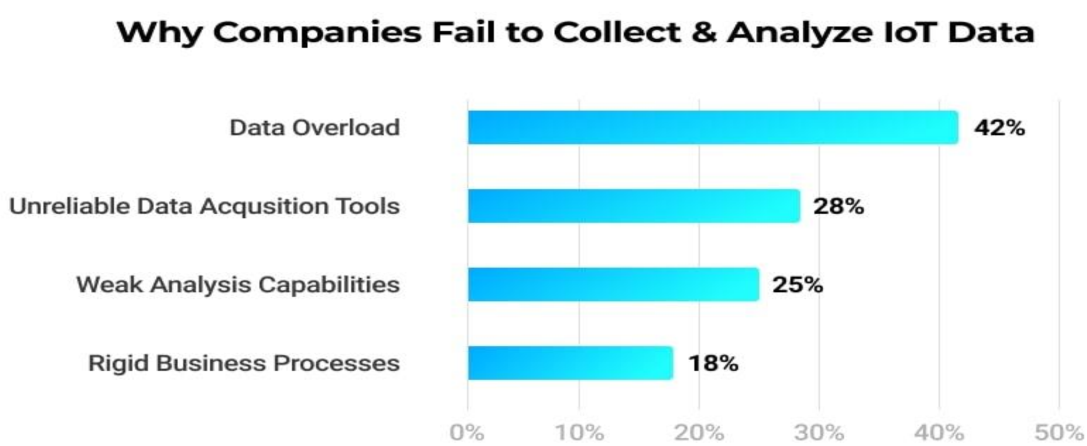

Figure 1 IoT Data

With the introduction of edge computing and cloud platforms with AI capabilities, businesses get an opportunity to uncover additional insights in IoT data that would otherwise get lost, and thus drive more value from existing IoT deployments [65]. Here's what you need to know about the Artificial Intelligence of Things (AIoT)—a powerful combination of connected devices and intelligent data processing algorithms.

Understanding the Artificial Intelligence of Things

The Internet of Things (IoT) is a multi-level system where devices and non-electronic objects collect telemetry data using sensors. The *things* then transmit the data to the cloud over wireless communication protocols.

Artificial Intelligence (AI) is an umbrella term that describes miscellaneous IT systems where algorithms interpret information and make smart predictions [42]. When we merge AI with IoT, we get connected devices that gather, analyze, and act on sensor data with little to no human involvement, and adapt to the current environment around them [64].

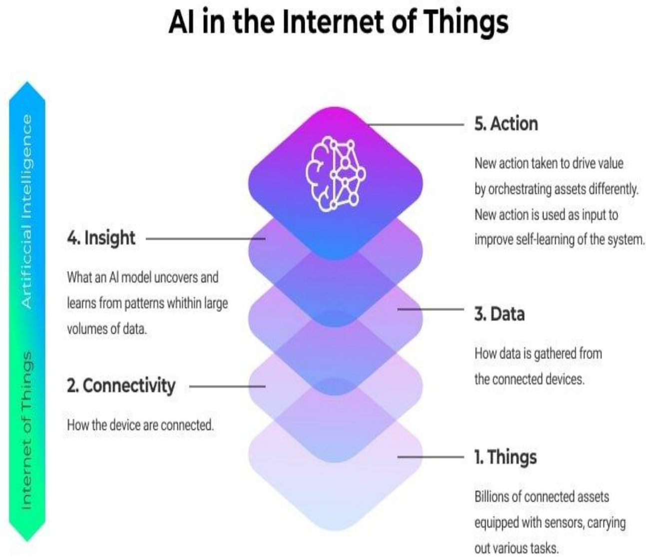

Figure 2 AI into IoT

The Artificial Intelligence of Things exists in two forms:

- Data analytics platforms, such as Microsoft Azure IoT, Amazon AWS IoT, and PTC ThingWorx. These platforms allow IoT developers to set up a complete infrastructure supporting cyber-physical systems' logic and merge them with AI services via APIs [63].
- Intelligent edge devices like surveillance cameras and autonomous vehicles. Such devices incorporate powerful processors that filter out the so-called status data, process critical data locally, and bulk-upload sensor readings to the cloud at present intervals [43].

Choosing an AIoT implementation strategy depends on the gadget's performance requirements.

An IoT gateway that captures information from soil moisture sensors, for example, doesn't have to relay data to the cloud every minute. On the contrary, a smart heart monitor cannot possibly wait for a command from the cloud server to realize that a patient's condition is deteriorating; instead, the gadget needs to make instant decisions based on real-time heart rate data [62].

Until recently, the CPUs capable of performing data analysis closer to the network's edge were scarce. But the chip industry has made an enormous step forward and is now cutting down CPU costs while maintaining their high performance. The only issue hardware manufacturers have yet to solve is CPU versatility [44].

The Artificial Intelligence of Things solutions may vary in forms and applications, and therefore have different performance requirements. To deploy AIoT solutions at scale, we need integrated circuits that support multiple combinations of computing tasks, including AI-driven data analysis, digital signal processing, and remote device control among others [45].

Why AI is the Internet of Things' Missing Element

- In 2019, IoT Analytics published a comprehensive overview of the IoT startup landscape. Seven out of ten companies that topped the IoT startup list specialize in AI, data science, and analytics.
- 70% of companies that use Artificial Intelligence obtain AI capabilities through cloud platforms—and that's where IoT data dwells anyway [46].
- Thanks to 5G rollouts, the number of IoT devices could reach 41 billion units by 2027 (up from just 8 billion in 2019).
- Compared to traditional business intelligence (BI) tools, AI algorithms make operational predictions 20 times faster and with greater accuracy.

In the IoT context, the value of Artificial Intelligence lies in its ability to quickly parse and discern insights from mountains of data that has been previously reviewed by humans [47].

How AIoT is Changing the World around Us

- **Voice assistants.** Operating devices via voice commands is the most natural form of human-machine interaction. To integrate natural language processing (NLP) capabilities into IoT systems, developers use pre-trained AI services like Siri, Google Assistant, and Alexa. In terms of device interoperability, the latter is clearly winning the voice assistant race [61]. Last year, Amazon added Alexa Voice Service (AVS) to the AWS IoT Core platform, thus enabling developers to create voice interfaces for any connected device regardless of its form, size, and processing power. Besides consumer electronics, voice assistants are gradually infiltrating industrial equipment and driver assistance systems [48].
- **Security systems.** Before AIoT, CCTV cameras had been passive, meaning security officers had to watch live footage 24/7 to prevent accidents and deter crime. By teaching Machine Learning models to recognize objects and humans in video data, IT companies take this burden

off state agencies, businesses, and property owners [60]. Some examples of AI-based security systems include the Ella video platform, which processes video data obtained from IC Realtime security cameras, smart video doorbells that use face recognition to identify homeowners, and surveillance drones monitoring the US-Mexico border.

- **Automated inspection solutions.** Speaking of drones, it is estimated that 60% of the total drone market revenue comes from enterprises—in particular, manufacturing, construction, and energy companies. The industrial sector uses drones to automate equipment and infrastructure checkups in remote and hazardous locations, thus reducing inspection costs by up to 50%. Advanced drone models rely on Computer Vision (CV), which is a form of Artificial Intelligence, to maneuver around objects and detect equipment failures. Companies further implement AI-driven image analysis tools to review and annotate photos taken by inspection drones. With this data, it is possible to create more accurate Machine Learning models and boost drones' cognitive abilities [49].
- **Self-driving vehicles.** Self-driving cars are a primary example of AIoT solutions where smart algorithms interpret real-time data coming from in-vehicle cameras, lidar and radar sensors, and cloud services. Although we're still a few years away from fully autonomous vehicles that can navigate their way from one point to another, Artificial Intelligence is finding a home in advanced driver assistance systems (ADASs) [50]. AI's scope of application here ranges from reducing the fish-eye effect in videos recorded by onboard cameras to monitoring driver behavior.
- **Predictive equipment maintenance.** Across heavy industries like industrial manufacturing and oil and gas, an hour of unplanned equipment downtime may cost up to $260,000. AI-based Predictive Maintenance systems help companies boil raw industrial sensor data down to actionable insights and predict equipment failures. According to Deloitte, Predictive Maintenance solutions could reduce overall equipment maintenance costs by 5-10% while boosting equipment availability by 10-20% [51].
- **Remote patient monitoring (RPM) solutions.** Amid the COVID-19 pandemic, more healthcare providers are turning to technology to free up space for critically ill patients, protect hospital staff from the coronavirus, and keep operational expenses down. Besides telehealth systems, which could become a $175 billion market in 2026, it is AI-powered heart rate monitors, oximeters, medication trackers, and fall detection systems that help physicians accomplish these goals. By feeding patient data to AI algorithms deployed in the cloud or directly on a device, the AIoT solutions can flag health incidents before they occur [52].

IoT Merely Connects "Dumb" Devices to the Internet; It is AI that Gives Them Brains

Without a mobile app, there's no way you could view your body composition data from a Bluetooth smart scale. Alexa is good at shuffling playlists on Spotify; if you need to book a flight though, you'd better double-check the information from a PC or smartphone [53]. The Internet of Things and Artificial Intelligence are a perfect example of technologies that complement each other. When combined, they help businesses maximize ROI on their IoT investments in multiple ways [54] because they can:

- Automate time-consuming tasks that were previously carried out by humans
- Detect inefficiencies in their workflows
- Monitor equipment performance to prevent failures
- Improve employee safety [59]
- And increase profitability by up to 38%

By 2022, 80% of enterprise IoT deployments will have an AI component. If you're thinking of developing an IoT solution today, make sure it works with AI. In case you're training a custom Machine Learning model, think about how it could benefit from IoT data and connectivity [55].

VI. CONCLUSION AND FUTURE WORK

The convergence of AI and IoT is inevitable at the point. AIoT as a platform is all set to improve several business use-cases out there [56]. With billions of smart devices out there, the use of Artificial Intelligence to construct secure and robust solutions will be a necessity rather than a choice [57]. It is more likely that we will see more advanced AI processors coming to edge computing which are economic enough for practical use, which will in turn ensure that AIoT will be leading the way in Smart homes, industrial automation, self driving and transportation, hospitality and almost any other field. AIoT will be inevitable [58].

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