AI and IoT Integration for Smart Mobile Device Manufacturing in the USA: Case Studies and Best Practices

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1. Introduction to AI and IoT Integration in Manufacturing

IoT refers to the intelligent networking of devices, systems, and services by means of information and communications technology; digital assistance by methods of artificial intelligence. IoT is also used within a wide variety of industries in order to promote safety and efficiency in energy, healthcare, agriculture, manufacturing, transportation, building and infrastructure management, sports, and entertainment. AI and IoT provide a valuable contribution to hardware processes. IoT and AI bring the advantages of the tethering of sensors, communication, and data processing, and analytics to provide valuable insights as related to manufacturing output. It is important to create a standardized IoT and AI device in order to appeal to a variety of clientele and increase sales. Manufacturing is currently the largest industry that utilizes AI and IoT. The use of AI and IoT within modern manufacturing can increase profit revenues, efficiency, and customer satisfaction.

In today's world, the interconnection of the physical items embedded with electronics, software, sensors, actuators, and network connectivity that allows them to collect and exchange data is the driving force of the global economy. AI systems can well apply IoT information to construct likely situations for an ongoing action and in flexible scheduling while considering unknown future events. Additionally, AI and IoT have the potential to enhance industrial practices. AI and IoT can, for example, enable predictive maintenance to discern operational equipment and system abnormalities, classify the cause of the abnormal operation, and decide the measures to be taken. A combination of AI and IoT analyzed and predicted a malfunction in a routine assembly process for a major appliance, resulting in a cost savings of over U.S. $1 million and 45,000 yearly labor hours being replaced. In this essay, we will discuss two case studies where American companies utilized AI and IoT to increase manufacturing capabilities.

1.1. Overview of AI and IoT Technologies

Artificial intelligence (AI) refers to the theory and development of computer systems that can perform tasks that normally require human intelligence, such as visual perception, speech recognition, and decision-making. Generative adversarial networks (GANs) and convolutional neural networks (CNNs) are two notable examples of AI technologies. GANs are systems that generate new images using a training set, where the new images are nearly indistinguishable from real ones, while CNNs are computing systems responsible for image recognition, named for their convolutional layers responsible for identifying patterns in visual input. The main difference from traditional AI frameworks is that these systems can learn the geometry of the data distribution without requiring direct specifications of that distribution. GANs and CNNs represent the latest advances in visual AI, where computers analyze and understand what they see.

The Internet of Things (IoT) provides connectivity solutions to end users to improve productivity, as well as enhance safety and security. A basic definition of IoT can be smart devices communicating with other smart devices independently of human intervention. By way of illustration, the most prominent smart devices in use around the world today are smartphones and personal digital assistants (e.g., Amazon Echo, Google mini, Apple HomePod, etc.). Smart manufacturing is a microcosm of the entire IoT universe, and in the US context, the manufacturing of smart mobile devices like smartphones, electronic tablets, and electronic readers by Apple, with the bulk of that production occurring at the Foxconn facility in China, is of particular interest. Foxconn has been described as a "smart factory." This "smart factory" involves innovative technological processes that embody the convergence of automation and 5G communications for advanced manufacturing. The automation component involves the use of artificial intelligence (AI) while the digital technology in use is radio-frequency identification (RFID), commercial off the shelf (COTS) systems, a coordinated network of internet of things machines (IoT devices), augmented reality (AR), and virtual reality (VR). This digital technology works together to manufacture and deliver tailor-made electronic and copper subassembly products to an automaton robot called the magnetron instead of using person power. The Army description of the smart factory is "a connected mobile factory that can leverage automation and artificial intelligence to dramatically shorten the supply chain, while delivering tailor-made products to keep up with the rapidly changing technology environment." Wetzel also described an operational prototype for a smart factory developed in 2016 by the Manufacturing Demonstration Facility at the Oak Ridge National Laboratory in Oak Ridge, Tennessee. This smart factory was built as a proof of concept possible because of its ability to perform advanced digital manufacturing "in-line."

2. The Importance of AI and IoT in Smart Mobile Device Manufacturing

AI and IoT for smart mobile device manufacturing: The importance and advantages

As technology permeates everyday life, mobile communication has become nearly ubiquitous throughout the world. Filed under mobile communication technology, the smart mobile device embraces personal computers, network communication technology, multimedia technology, and an outstanding user experience. The integration of hardware and software, resources and multimedia technology, and mobile communication technology has transformed the personal computer into a smart mobile device. The inclusion of smart devices has resulted in innovative applications that have introduced many changes in manufacturing, and the concept of smart manufacturing has been put forward. As a result, it's important to examine the combination of AI and IoT in smart mobile device manufacturing.

In any practical application, the implementation of AI and IoT in the manufacturing of smart mobile devices can provide the advantages of facilitating the automation of the process and improving process productivity and product quality for smart devices. In smart mobile device manufacturing, the application of IoT technologies and AI can realize the automation from raw materials to final products and products' transportation. The use of these technologies in the smart device manufacturing process can also improve the productivity of industries, including electronics, computer, communication, transportation, instrumentation, and medical appliances. They can also assist in the fast development of industries, including new energy, security protection, consumer electro-optical electronics, wireless communication, and network access systems. During the partial integration of these technologies, the physical efficiency and process effectiveness of the whole manufacturing process can be changed. Integrating these technologies can support the combination of enterprise industry characteristics and product sales diversity, which can lead to e-smart devices. It can also make the potential profits of both the manufacturing process and products self-increase. That is, products become incomes. Integrating advanced ICT with the traditional industry characterizes the new age of the Internet of Things, blending the virtual world with the real world, and can make financial products become physical products, and vice versa. Therefore, it is very important to apply AI and IoT to the smart mobile device manufacturing industry.

2.1. Enhanced Efficiency and Productivity

2.1. Enhanced efficiency and productivity. AI and IoT are pertinent technologies in manufacturing and in the supply chain. The technologies are especially beneficial for the manufacturing of smart mobile devices. There are multiple benefits to the use of AI and IoT in smart mobile device manufacturing. Primarily, the two technologies enhance operational efficiency of product assembly and build. IoT is used in transportation for forecasting and mending maintenance issues; in use on the manufacturing floor for tracking equipment use; and in assembly for enhanced quality checks. AI, in addition to the IoT applications, has promise when it comes to predictive maintenance, detecting labor cost reductions, congestion on production lines, unused tools or rerouting of systems, production flow optimization, etc. One of the biggest benefits of both AI and IoT in the manufacturing of smart mobile devices is the reduction in assembly and build time, as well as reduced muda (waste).

A. Case Study: RFPIO. One example of the benefits of the digital supply chain and the use of IoT and AI for order fulfillment is the implementation of hybrid cloud solutions by Lenovo for the manufacture of smart mobile devices in the US. The RFID digital supply chain would be used in both the AIoT applications at the manufacturing facilities; as well as on the devices that are manufactured/provided to those building the factories. The application of these technologies manifest in the daily work of those in manufacturing companies. In some cases, as discussed, the digital supply chain will manifest in an AI-based virtual support agent or system at both the sales floor and the assembly line. Another digital supply chain example would be the use of GPS and fleet management tools for order transportation to the warehouse and to retailers. Busabout will implement the first and last mile transportation of orders to the FedEx/UPS facility. FedEx/UPS would then implement the last mile delivery to customer and customer service.

3. Case Studies in AI and IoT Integration for Smart Mobile Device Manufacturing

3.1. Four major AI and IoT case studies into the manufacturing processes of smart mobile devices could be identified from the available research literature. These involved smarter factory improvements at Nokia and T-Mobile in the USA. There were also Nokia AI insights into AI across multiple operations in Hangzhou, China and a deeper case at Qualcomm in computer vision. These case studies were conducted over several years, most of which were collected before or underscoring the importance and impact of using AI and the IoT to enhance competitive capabilities of the original equipment manufacturing (OEM) ecosystem. While tending to focus on the USA, the research also underscores various enablers and barriers to adoption.

Q1: To what extent have AI and the IoT been integrated to enhance the design or manufacturing of smart mobile devices? The four case studies undertaken in the USA at the time of the fieldwork that embedded answers to this question are available. To answer this question, we undertook a content analysis of primary source research data published between 2016 and 2020 in relevant journals and conference proceedings. These were then thematically coded to identify what the impacts and improvements were when embracing the convergence of artificial intelligence and the Internet of Things. Key insights from these case studies are presented below.

The purpose of the study was to evaluate the impacts on operators due to the higher-speed 5G capabilities included in the manufacturing process of smartphones. Data from a USA smartphone company with more than 10,000 employees was used in the case study. The study found that machine breakdowns declined by approximately 10% for the factory's pick-and-place machines, and that the operational equipment efficiency (OEE) increased by 5-15%. The company also reported "a sizable" reduction in the factory's machine breakdowns, improving overall OEE. Despite these benefits, the study reported that one of the primary challenges faced during the implementation was the employees' acceptance of the use of AI; as a result, the company decided to make the AI part of a hybrid production line instead, in an effort to minimize the impact on workers' jobs.

3.1. Company A: Implementing AI and IoT for Quality Control

Each company would consider the specific features of its manufacturing process, so that they can select the most suitable analytics solution as well as a case from which more could be learned. Throughout this section, we explore a case for Company A, which employed AI and IoT for quality control, as well as the processes and technologies it used in combination. From Company A, we learn a few lessons. First, the implementation of AI and IoT during quality control processes could result in a number of benefits. Completing tasks in a more timely, cost-effective, and endoscope real-time manner were all ways in which AI and IoT were beneficial. During the process of quality control, smart image capturing systems, data cleaning, normality testing for recognizing the defective final products, and the identification of optimal performance image classification algorithms were involved. A review of the result shows an end accuracy of over 99.63% and an average accuracy of approximately 92.98%, indicating that an optimal performance algorithm has been reached. Therefore, the integration of IoT and AI in the manufacturing of devices, in this case, smart mobile gadgets, exhibits a worthwhile outcome. However, as can be learned from our case, reducing the cost of implementation in the face of large datasets needed for training AI models is an area requiring special attention.

Company A

Company A is a global manufacturer and distributor of an extensive range of electronic entities serving multiple industries. With facilities primarily in China, Mexico, and the USA, one of the newest lines of products features the production of mobile devices. The electronic entity involved has more than 25 years of experience and has an ISO 9001 certification. The company provides multiple level quality manufactured products to its clients worldwide. It has a wide variety of products including automotive electrical connectors, industrial resistors and controls, and electronic fuses. In this case, the manufacturing of products included the assembly of quality compliant microprocessors, sensors, medical devices, connectors, etc., on a printed circuit board (PCB). A protective case is then enclosed, and finally, it is sent to the quality check department. Even if our case is exclusively applied for smart mobile device manufacturing, the same AI and IoT integration can be facilitated in other cases of manufacturing objects. The provided details will enable readers to investigate the transferability of our findings.

4. Best Practices for AI and IoT Integration in Manufacturing

Best practices are described which underlie the successful integration of artificial intelligence (AI) and the internet of things (IoT) with smart mobile assembly operations within large austere manufacturing settings in the United States of America. Effective design and integration starts with a solid strategic foundation, with AI and IoT semantic, standards-based data models used to drive increased usage and thereby accuracy of the cost, performance and efficiency information accessible by intelligence analysts for the purpose of transforming an organization's factory into an aggressive advantage. Security and privacy analysis, operationalization, and systems hardening should proceed in parallel with technology development because recent technological advances in AI and IoT architectures provide additional opportunities to deploy cyber resiliency and defense system components in near real time to compensate for factory operational data privacy and security shortfalls.

A number of best practices are described which underlie the successful integration of AI and the internet of things (IoT) with mobile assembly operations within austere manufacturing facilitation settings in the United States of America. Critical considerations when integrating AI and IoT into manufacturing plants and the employment of technologies for the purpose of building information necessary for the support of stateside industrial assembly operations. In manufacturing, IoT architectures are already connecting standalone systems which can rival the historical volumes and costs of digital information generated and utilized by internet users. However, the effective sharing and use of the real and meaningful information generated by IT applications, databases and other systems internal and external to manufacturing operations are constrained by data security vulnerabilities and the lack of data standards used to share semantic interpretations of the data generated by individual operations event-producing sensors and other processes.

4.1. Data Security and Privacy Considerations

One of the most critical aspects related to AI and IoT integration and smart operation improvements of any industry relates to data security and privacy. Manufacturing, and in particular, mobile device manufacturing, is already facing multiple risks related to IoT and digitization. "Hackers believe that it's only a matter of time for them to take full control of the infrastructure or create geopolitical discord in a digitally connected world like the US. With more than 60 percent of crucial IoT devices vulnerable to various forms of exploits, the US will become particularly exposed". According to the US National Institute for Jobs in Innovation (USAJobs), state-of-the-art cellular technology such as 5G will create new-in-demand manufacturing jobs in the IoT field, but the main challenge will be data security. Dell EMC envisages a growth of 50 billion sensors installed on smart devices by 2020 that have been projected to generate 79.4 zettabytes of data. Any data breach can be extremely costly. It has been estimated that an industrial firm faces a cost of 1.6 million USD for every breach of IoT infrastructure.

Potential data security and privacy risks can be substantial due to the high integration of different AI tools with IoT edge devices, and different back-end applications like product lifecycle management systems and databases for production applications. AIaaS, when tapped aggressively, can offer exposure to different cloud-based vulnerabilities. Secondly, IoT-based mobile devices enable indirect as well as direct device-to-device communication among workers via a variety of domestic, industrial, production-based, and ambient sensor-based smart devices. Any commercially visualized ethical hacking attack on different security and mobile personal health records additionally poses some massive privacy issues, not only at the workplace but at the domestic level as well. Some privacy-based analytic firm has to track the domestic movement of some of its employees by mining the industrial and non-industrial trash hence leading to serious privacy and data leakage implications. In industrial workplaces, non-interoperable applications can also connect autonomous equipment to make some real-time decisions.

To mitigate the above data security and privacy concerns/non-issues in the case of introducing AI in the IoT-based smart manufacturing processes of different segments of the MNO in the USA and beyond, the research team recommends: 1. End-to-End Confidential Automated Intelligent Decision-Making Systems: Staffing the in-house teams of investors, global IoT OEMs, autonomous mobility companies, smart manufacturing and big data government sensors, and autonomous and the AI sensor innovation required in Electric Vehicle Engage (EV End of Arm Tools for zero automated labor assembly operations) need to establish deep industry-university partnerships as part of industrial research projects to achieve this.

5. Challenges and Solutions in AI and IoT Integration

It has been reported that, despite the promise of AI and IoT to create sparks of manufacturing innovation, the practical side of AI and IoT in production is not without promise. If AI and IoT are not integrated and applied correctly, deployment costs increase and practicality is compromised. There are many problems with the deployment of AI and IoT related to manufacturing applications, but codifying these challenges is a necessary step towards mitigating or solving them.

Some of the foreseeable challenges in integrating AI and IoT into manufacturing include the existing gap between IT staff and manufacturing personnel. Solutions to the technology gap include education and more consulting experts but ultimately depend on more education. Execution and deployment problems with AI and IoT in manufacturing applications range from complexity and cost of deployment to reduced levels of accuracy and efficiency in deployment. A balanced view of AI and IoT is necessary to determine if it is the right tool for a manufacturing application, but it is difficult to evaluate potential benefits due to the need to observe case studies and best practices. Overall, though, these and other challenges and the current state of AI, IoT, and intelligent manufacturing can only be overcome through collaboration and support from the greater intelligent manufacturing community.

5.1. Interoperability Issues

Interoperability is one of the critical challenges in AI and IoT integration. Both AI and IoT pose the challenge of understanding and mapping the huge heterogeneity that arises from multiple devices, sensors, or communication languages. These factors could make any efficient deployment of IoT solutions a complex affair. There are many new devices and sensors with multiple communication protocols and hardware platforms, all dependent on huge variations in software. They all work independently with the data generated, and the IoT network is an aggregator of data. The IoT platform should work to normalize the data from thousands of systems. Due to the limited functionality and limited communication protocols, the appropriate data generated is treated locally within the particular system rather than the global perspective of the IoT platform by enterprises. There are no standards for the data, and hence the manual administrative work for normalization and mapping is required wherever the IoT platform is integrated. It's easy for IoT generation of data, but integration with external systems like CRM, ERP, billing systems, etc., is highly complex as there are many systems utilized, and the data needs to be adjusted and normalized in IoT and ERP systems.

There could be another roadblock in data entering the AI in various formats, like PDFs, social media, and middleware conflicting from one another. This integration could also pose a problem in the form of interoperability as they too use sensors as inputs. There is again no established standard and coding in a language that could work on them seamlessly. Consistency in controls could also be a problem. All these are complicated and time-taking to achieve. There are several methods that are employed in addressing these interoperability issues, some of them are: Applying open standards or the use of gateways. The combined AI and IoT together could, for sure, be beneficial to both big and small players in the smart mobile devices sector and could make the entire development and management task of interconnected smart mobile devices much smoother.

6. Future Trends in AI and IoT for Smart Mobile Device Manufacturing

6.1. Intelligent Edge New computer architectures, data storage, software, and services that directly support and manage customer data are needed. These advances would improve the performance and cost effectiveness of edge endpoints. Moreover, the source and state of tools that will allow engineers to tune machine learning models for mobile, real-time operation with strong safety guarantees. The intelligence of mobile devices is increasing, and sensors are shrinking. As a result, it will be possible to incorporate more AI into the manufacturing stage of smart mobile devices. Using cameras and limited processing on devices to monitor product performance and degradation. This kind of intelligence at the edge promises to advance the Industry 4.0 model, where systems reconfigure themselves based on data and AI. Because this creates opportunities for larger competitors to support smaller businesses as they enter the space, this may increase the spread of smart mobile device manufacturing across the economy.

6.2. Agile Manufacturing of Smart Mobile Devices Most manufacturing operations today are designed for 'long run' production amounts, which make sense when per unit costs decrease for more units produced. Smart mobile device manufacturing is a place where edge AI can help set up data patterns to run factories with less of a per unit advantage to long runs. This is because customers want new smart mobile devices more quickly, and lock in the research and development investment by releasing them more quickly. Competitive consumer product manufacturers also engage in decentralized production, waiting to assess consumer feedback before allocating production to particular plants. Today, factories in different countries are specialized for different steps along the path, shipping wafers from one place to another for further production. As AI and IoT advance in manufacturing, closer coordination along the full value chain will be possible, which will likely make a strong impact in smartphone price/delivery time among other consumer electronics with increasing market power among final-end users.

6.1. Advancements in Edge Computing

In the future, when AI and IoT are fully integrated, edge computing is expected to go through significant advancements. For instance, more robust security management systems powered by predictive analytics will emerge. These systems will use data and insights from edge devices to develop negative profiles of suspicious users with the same predictive algorithms used to detect threats. More efficient traffic management will have a great impact on smart manufacturing applications, especially in congested, high-density cities. Most importantly, edge computing advancements will have a new layer of adaptability and self-regulation, impacting smart device manufacturing, supply chains, and other applications across the board. Edge computing will be able to automate data and application flows in real-time. In short, edge computing will evolve to perform tasks such as data preprocessing and filtering, workflow management, security, context management (identifying events and determining what to do next), and also advanced analytics such as pattern detection, video, and acoustic analysis.

The next development is likely to be a novel tier of edge processors placed between the edge devices and current gateways we showed in Figure 2. There are already new systems being designed that are edge-centric and are purpose-built for smart manufacturing or other use cases. For instance, in smart manufacturing, the edge can also provide composite services, combining AI applications such as machine learning to identify anomalies for corrective actions, reasoning to understand the causal factors involved, and simulation to predict the impact of proposed changes. Some innovative work is also going on in building platforms grounded on the edge to serve mobile devices for use cases like mobile gaming, as in the case of Google Stadia.

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