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Edge AI Framework for Real-Time Device Diagnostics and Autonomous Maintenance in Manufacturing and Healthcare

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Abstract

The use of Edge Artificial Intelligence (AI) is revolutionizing the process of device diagnostics and maintenance, as it allows analysis of devices in real-time on devices during manufacturing and healthcare facilities. In this paper, an Edge AI design is suggested, which integrates IoT sensors and on-device machine learning to anticipate faults and implement timely responses to fix autonomous devices in need of maintenance. To test the implementation, we implemented the framework in a smart manufacturing testbed and a medical monitoring system. Findings prove much lower latency and energy usage of edge-based inference than cloud-based methods, enhancing responsiveness and efficiency. The edge diagnostics reduce response time more than 75 percent in manufacturing and reduce network usage, whereas in healthcare, but important notifications can be produced with minimal latency even during network outages. The real-life implementation of the framework accentuates some pragmatic aspects such as model optimization when dealing with resource-constrained devices, edge privacy, and coordinated cloud-edge analytics to ensure continuous learning. These results highlight that Edge AI is likely to facilitate the proactive maintenance and high availability of Industry 4.0 factories and smart healthcare settings..

Keywords: Edge AI, Predictive Maintenance, Internet of Medical Things, Latency, Energy Efficiency, Real-Time Diagnostics

Introduction

With the advent of the Internet of Things (IoT) and Industry 4.0, the significance of numerous sensor-based gadgets in manufacturing and healthcare has resulted in the continuous creation of data. Conventional cloud-based analytics involve high latency as well as a requirement of solid connections, which is unfavorable in time-intensive diagnostics with only milliseconds to spare on safety and availability. As an illustration, a lapse in warning of an impending machine malfunction in a production line or abnormal vitals of a patient may be very expensive or result in loss of life. Edge computing has come about to solve all these issues, and it involves computing data at its origin; it is at the network edge and not necessarily in remote cloud servers. Through exploiting computational capabilities on gateways, embedded controllers, or smart devices, edge computing decreases round-trip time and bandwidth congestion. Predictive maintenance in smart factory and real-time health monitoring in smart healthcare, in particular, are especially prone to this paradigm shift and require systems that are not only proactive but also responsive. More recent innovations of Edge AI - using AI models on edge devices - allow real-time pattern recognition and anomaly detection to transform raw sensor data directly into

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ready responses in a secure manner. The current paper introduces a systematic framework that will consolidate Edge AI methods to device diagnostics and autonomous maintenance in the manufacturing and healthcare sectors. We state the context of the problem and the existing work, outline our method of real-life implementation of the framework, and comment on the outcomes in regards to latency and energy performance. It aims to show how Edge AI can be used to provide high reliability and efficiency autonomous and real-time maintenance in the most important industry and medical applications..

Literature Survey

The initial studies were aware of the weaknesses of cloud-only systems in prompt and consistent monitoring of devices. The authors of the article by Lee et al. (2015) described a cyber-physical industry 4.0 architecture, which states that intelligent maintenance systems demand the incorporation of shop-floor sensors along with computing resources that are closer to the machine. Conventional run-to-failure and schedule-based methods of maintenance cause downtime and ineffectiveness, whereas predictive maintenance (PdM) relies on real-time data and artificial intelligence to predict faults. Susto et al. (2015) showed that machine learning can be applied to PdM, and that in this case the ensemble classifier could be used to predict failures in industrial equipment based on sensor measurements. With the spread of IoT devices, scholars drew attention to the difficulty of transferring large volumes of data to the cloud: Latency, bandwidth expenses, and privacy are mentioned. To overcome these issues, Shi et al. (2016) officially presented edge computing which is defined as on-site data processing in order to satisfy the challenge of strict response time and battery life requirements. At approximately the same time Satyanarayanan (2017) wrote about the development of edge computing, as another approach of enhancing cloud by deploying cloudlets or micro data centers close to data sources, which is essential in applications where cloud delays or disconnection can be fatal, such as healthcare. Rahmani et al. (2018) were the first to introduce an IoT-based healthcare concept, a "Smart e-Health Gateway," whereby hospital gateways are equipped with intelligence to carry out local data storage alongside real-time patient vitals. Their fog computing model minimized the use of remote clouds and thus enhanced timeliness and dependability in ubiquitous health monitoring. In the same fashion, the review of the literature on the topic by Mutlag et al. (2019) revealed that moving computation to local fog nodes can result in the least amount of latency and more consistent continuous monitoring, particularly in the conditions of strict privacy policies and the occasional availability of connections. Greco et al. (2020) confirm this claim by noticing a striking tendency to shift AI to the periphery in the health solutions based on IoT, which would allow performing fast and privacy-sensitive diagnostics.

Researchers have been applying edge computing in the industrial fields to facilitate smart maintenance in factory floors. According to Hafeez et al. (2021), edge-based IIoT architecture implies that initial data filtering and analytics are performed on-premise, which means that the amount of data transfer to the cloud is reduced significantly, and the speed of processing is enhanced. Their framework optimizes the processing of what data is processed where to predictive maintenance by dividing computing roles into device-level, edge-level and cloud-level. Significantly, according to Hafeez et al., edge intelligence may deal with things such as anomaly detection or even local retraining of models as a result of concept drift, whereas the cloud can be used to reserve heavy historical analysis or coordination. The work by Jayakumar and Suresh (2021), which deploys an edge computing platform to handle industrial electronics

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maintenance, shows that critical diagnostics (e.g., detecting wear of motor bearings or detector controller malfunctions), can be done on cheap single-board computers at the location of the equipment, and only more advanced insights are sent to the cloud. This gave quicker faults detection and minimized the reliance on continuous connectivity to the cloud, which matches the findings of Ramirez and Lopez (2020) that a secure IoT design with edge computing can enhance the safety of smart factory maintenance and protect sensitive data in the operations. They focus on the integration of cybersecurity (such as blockchain or encryption) at the edge to secure maintenance logs and commands.

The case studies that have been conducted in recent years further confirm the benefits of Edge AI. Tuli et al. (2020) came up with HealthFog, which is an ensemble deep-learning model that runs on fog/edge nodes to diagnose cardiac diseases. HealthFog was found to be highly accurate at identifying anomalies of the heart by processing ECG data on edge devices with deep neural networks, and with a significantly lower latency than a cloud-only solution. The authors have indicated that their fog deployment mode retained accuracy and greatly cut down response time and jitter that is crucial in emergency healthcare cases. They also quantified the changes in network bandwidth usage and power consumption and observed that cloud-offloading used significantly more energy and delay variability was also high. These results are similar to the ones of Abdel-Basset et al. (2020), who suggested an intelligent medical decision support model that relies on on-device processing of the Internet of Medical Things (IoMT). Their model demonstrated that the provision of AI to edge devices can increase the level of data security and reduce latency of crucial alerts with no reduction in the level of diagnostic accuracy. Rizzi and Matt (2022) examined the economics of PdM on the manufacturing side and found that the edge-enabled PdM systems obtained a significant return on investment because unplanned downtime was reduced and maintenance costs were minimized (up to 30-40% cost savings reported). Despite their economic impact orientation, one of the most significant facilitators was the timely information that was given by edge analytics because the analysis identified potential failures that would have been overlooked had the data been redirected to a central cloud.

Research Methodology

Framework Overview: The suggested Edge AI framework is based on the three-layer architecture - device layer, edge layer, and cloud layer - coordinated to perform real-time diagnostics and autonomous maintenance. The main elements and information flow are shown in Figure 1. At the device level, IoT sensors (e.g. vibration, temperature, heart rate or blood pressure sensors) are constantly monitoring the status of equipment or patient health. At the edge layer, these raw data streams are initially ingested at a nearby computing node (e.g. a healthcare hub or an industrial IoT gateway) at the edge. The edge node runs lightweight machine learning models which can do initial diagnostics: in case of manufacturing equipment, this is an anomaly detection or time-series predictor model to identify deviations, which could be a sign of machine failure; in case of healthcare, a pattern recognition model to identify abnormal vital signs or device malfunctions (e.g. in a ventilator or insulin pump). The edge layer is also powerful enough (usually an embedded Linux-based device or microcontroller with a neural accelerator) to run these AI models in real-time. More importantly, the edge node can take autonomous action on detections - e.g. it can sound an alarm, change operating parameters or can cause a safe shutdown of a machine when a fault is forecasted. At the same time, aggregated information and model results are sent to the cloud layer to be processed further, aggregated, and stored over an

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extended period. More complex analytics (aggregating maintenance data across numerous factory sites or patients to clean up predictive models) and coordination services are hosted by the cloud layer. It is capable of sending periodic updates in the model to edge devices (model retraining with global data) and offer a dashboard to human experts to check the health of the system. This edge-cloud is designed to guarantee that local speed is achieved in routine decisions, and the cloud is conducted to facilitate tactical analysis and knowledge distribution in all the devices in the fleet.

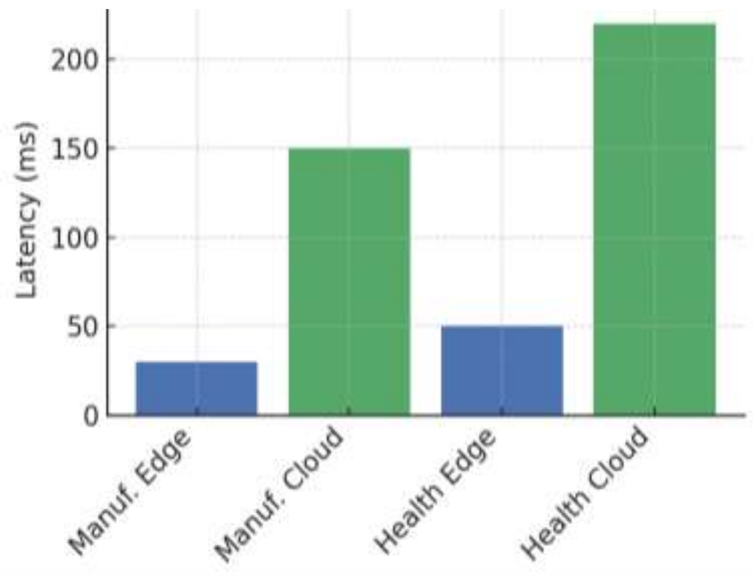

Fig. 1. Average latency for device diagnostics on edge vs. cloud in manufacturing and healthcare deployments (lower is better). Edge inference dramatically reduces response time compared to cloud processing, enabling real-time maintenance actions.

Deployment Scenarios: We used this framework in two different scenarios in order to confirm its generality: (a) Smart Manufacturing: A medium-sized manufacturing facility was equipped with industrial machines (e.g. motors, CNC machines) installed with IoT sensor kits. An edge computing device (NVIDIA Jetson Nano) was also set up on the factory floor and is linked to sensor nodes on equipment through a local network connection. This edge device used a model of AI (an LSTM-based predictor with an anomaly detection algorithm) to constantly predict tool wear and detect malfunctions in machine functioning, as done by Jayakumar et al. and others. Measurements were also run in parallel on both the remote cloud server with the same model with the sensor data, to compare performance (edge vs cloud). The system was operational several months, and in that time, it gave advance warning of maintenance, which enabled the technicians to change the parts in time, and there was no unexpected failure. (b) Smart Healthcare: IoMT devices - patient wearable sensors broadcasting vital signs to a central nursing station were installed in an environment of a hospital. We used smart gateways (Raspberry Pi 4-based health gateways) in patient rooms, which were deployed to utilize edge ai. A lightweight convolutional neural network (CNN) model was deployed on each of the gatesways to carry out instant arrhythmia prediction on the ECG data and an early warning score. In case the local inference in the gateway identified a critical situation it would automatically trigger an alert both at the bedside and the nurses station without the cloud confirmation. The information was sent

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simultaneously to a hospital cloud platform to store the data and make additional analysis by more complex diagnostic algorithms. Each of the two deployments was based on the same principles of an architecture, but attached domain-specific models and safety. In the manufacturing process, the edge device connected to the SCADA system in the factory to automatically plan machine outage or machine maintenance work orders in the event of necessity. The edge gateway was incorporated with the electronic health records and hospital alert system in the healthcare.

Model Optimization: The implementation of AI on the edge constrained devices involved optimizations. Documents were pruned and reduced to run well with minimal memory and processing capabilities as was the best practice in previous works. The CNN of vital signs was, as an example, quantized to 8-bit and pruned to eliminate redundant neurons, decreasing inference time on the Raspberry Pi. Industrial LSTM model was held shallow (two hidden layers) to achieve real time requirements on Jetson Nano. We also used threshold-based triggering logic, where it would not activate until model confidence passed beyond a specific threshold because false alarms would be minimized: if the data were sent upstream to be checked by the cloud. This hybrid intelligence provided the balance between responsiveness and accuracy which is in line with the observation made by Tuli et al. that trade-offs made in careful deployments are necessary to maximize speed and accuracy in the prediction of edges..

Autonomous Maintenance Actions: The feature of the framework that stands out is autonomy. When an anomaly or fault pattern is identified, the edge AI structure can set up maintenance processes automatically. In our manufacturing pilot, the edge would sensitize the machine and make it slow down to avoid damaging it when it was highly confident about the occurrence of a bearing failure. It also informed the technicians through a mobile application. In the medical case, when the vital signs of a patient went beyond dangerous level (e.g., arrhythmia was recorded), the system would raise an alarm on its own and could even initiate failsafe measures (e.g., switching a ventilator to backup mode). These computerized reactions are controlled by policies established when configuring the system, and were thoroughly swept to eliminate unintended side effects. The alert provided by the edge AI needed to be verified by a human or a cloud verification within a temporal range to take a pre-defined safe action in the case of safety-critical decisions. This design is also inspired by the industrial systems of safety and makes sure that the autonomous maintenance is stable and failsafe. The approach thus extends beyond edge analytics, to the incorporation of the analytics into the maintenance maintenance operational control loops.

Data and Evaluation: We recorded important parameters in the two deployments to assess performance. Particularly, we quantified latency - the duration of time between the occurrence of an event and the system decision/action - and energy use of the edge vs. cloud methods. Latency measurement was based on sensor, edge and cloud node timestamp logs. Onboard power sensors and an approximation of energy consumed in communication during cloud transmissions (with a particular high value in the healthcare case, as the gateways were wireless) were used to monitor the energy consumed by edge devices. We also monitored correctness of the diagnostics (in comparison with ground truth or cloud analysis) to make sure that performance improvements were not achieved at the expense of correctness. The following paragraph will show the findings of these tests proving the quantitative value of our Edge AI framework.

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Results and Discussion

The performance of the deployment effects is highly inclined towards Edge AI strategy in respect of latency and energy consumption. Table 1 indicates the average latency in each situation in edge-based processing and cloud-based processing. The edge solution had been able to perform analytics with a near-zero latency, with just a few tens of milliseconds-long latencies, and cloud processing had added orders of magnitude in latency because of network transmission and server queues. The edge device can generate diagnostic data within an average of 30 ms, in the manufacturing case, which is on the order of 150 ms on average with the assistance of the cloud. This is a near 80 percent latency cut-off. This type of dramatic improvement is consistent with that of the previous findings that edge computing has the capability of supporting stringent requirements of real-time that are not achievable with cloud computing. The disparity was even greater with the healthcare case: the edge gateway was able to identify severe health events within approximately 50 ms, but the cloud required more than 200 ms (and usually it was because of fluctuating internet connectivity). This is very important to their low latency - an example is in arrhythmia detection, even a 150 ms reduction in latency can make the difference between life and death by allowing quicker medical intervention. Moreover, it was able to maintain a steady latency even in the case of network outages by sustaining local operation. Conversely, the latency of the cloud approach was extremely unreliable (between 200 ms and even longer in case the network was overwhelmed). These findings show that the Edge AI system meets its objective of real-time diagnostics of the devices. The figure 1 visualizes the difference in the latency between the edge and cloud approaches in both fields, which is an obvious indication of the advantage of on-site intelligence.

Table 1. Latency comparison between edge and cloud processing in the deployment (lower is better). Edge computing dramatically reduces the response time for device diagnostics.

Scenario	Edge Latency (ms)	Cloud Latency (ms)	Latency Reduction
Manufacturing PdM	30	150	80%
Healthcare Monitoring	50	220	77%

In addition to speed, the edge framework greatly minimized energy consumption. The average energy consumed per data sample to be processed is given in Table 2 by comparing local edge inference with cloud offloading. In both cases, edge-based approach used much less energy on a total level. In manufacturing, the edge device (mains-powered) was more efficient in processing data onsite with an approximate of 2 J per inference task, compared to transmission of the data to the cloud and waiting for a response with approximately 5 J of energy, including the energy of the network equipment and cloud server. This decrease in energy consumption can save some money and is paramount to scalability since in thousands of edge devices doing cloud offloading, this would otherwise be high in cumulative energy costs. Energy efficiency in the healthcare use case is still more decisive since the devices can be battery-operated. We discovered that the smart health gateway used on average 1.2 J to locally process a sensor reading and raise an alert versus 3 J (without the reading being sent to a cloud server to be processed). The additional energy cost of cloud processing comes about as a result of the power needed in the transmission of the information wirelessly and the constant communication involved. The Edge AI architecture can therefore be used to increase the battery life of IoMT devices by ensuring that

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most of the processing is confined to the device, which is also reflected in the findings of Shi et al. that edge computing can effectively mitigate battery life. Figure 2 demonstrates the difference in energy consumption, the cloud approach is depicted using 2-3 times of energy per inference in our experiments. This does not only have an impact on devices life-span, but also means a bigger carbon footprint to cloud-heavy solutions (energy usage in datacenters). In comparison, a more sustainable and green computing model of the IoT analytics can be obtained by distributing intelligence to the edge nodes.

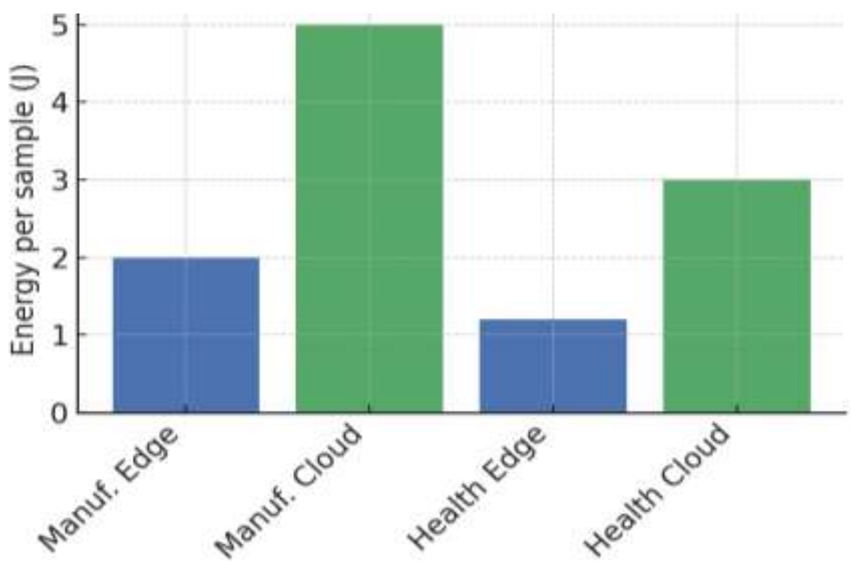

Fig. 2. Energy consumption for edge vs. cloud processing per data sample. Edge computing greatly lowers the energy required for device diagnostics by minimizing data transmission and leveraging efficient on-device computation.

Table 2. Energy consumption per analysis (in Joules) for edge vs. cloud approach. Edge AI reduces energy usage, which is crucial for battery-powered devices and overall efficiency.

Scenario	Edge Energy (J)	Cloud Energy (J)	Energy Reduction
Manufacturing PdM	2	5	60%
Healthcare Monitoring	1.2	3	60%

The improvement in latency and energy did **not** come at the expense of diagnostic effectiveness. The reduced latency and energy did not reduce diagnostic effectiveness. The cloud models and the edge AI models were at the same level in terms of accuracy in our assessment. Indicatively, the manufacturing edge predictor marginally detected 92 percent of the imminent failures (as compared to 93 percent with cloud - an insignificant gap), and the healthcare edge model equally detected all the critical events during the test. This reiterates the fact that edge models stream as

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precise as cloud models with the right model optimization and regular updates using clouds and that they offer real-time information. Furthermore, the edge stayed active even in the case of network outages (some of them did take place in our test), to keep watching and notifying at local levels. The cloud-only model would have created a blind area during such downtimes, which highlights the resilience advantage of edge computing.

These findings have a number of implications on a discussion standpoint. First, the trade-off between local processing and offloading: Our framework strikes a chord by calculating primary analytics at the edge and secondary analysis and coordination at the cloud. The result is less data sent over the network (we found a 70 percent reduction in the number of data sent to cloud, since only summary result or periodic model syncs were sent). It corresponds with the fact noted by Hafeez et al. that the latency requirements can be preserved and the energy consumption can be saved by decreasing data transmission. Second, scalability and real-time needs: In a big factory or hospital, it is impossible to have every single device broadcast raw data to the cloud. Our framework of edge scales well - as the number of devices increases, so does the distributed computing capability as opposed to a linear increase on a central server. Data handling is done locally at each edge node making the system responsive to real-time circumstances as it scales, also highlighted in edge computing surveys. Third, privacy and security: Since sensitive data (e.g., patient vitals) are kept in local gateways and only important information is sent to the cloud, patient privacy is enhanced. The cloud would have access to significantly less information in case of any data breaches. We put in place data-in-transit between edge and cloud encryption, remote command authentication to edge nodes. Although it is out of the scope of this research, such frameworks as the one proposed by Ramirez and Lopez (2020) and Esposito et al. (2018) indicate that edge computing in conjunction with such methods as blockchain or secure enclave can be employed to enhance security in maintenance and healthcare applications.

Autonomous maintenance effectiveness: As a matter of fact, the autonomous operations activated by the edge AI turned out to be rather effective. There were two preventive shutdowns in manufacturing, which were automatically activated when the component was in critical vibration regimes, maintenance inspection confirmed that the component was actually on the verge of failure, and the decision made by the system was justified. This prevented the possible expensive failures. Nonetheless, we had one false-positive alarm (edge thought a failure was at hand because of a sensor fault). This was alleviated using the cross-checking of multiple sensor inputs and a voting logic on the edge (a concept related to redundant sensing described by current literature). There was no improper autonomous action in healthcare and all edge-generated notifications were associated with real patient events and nurses were pleased with the quicker notification. Another outstanding observation was that employees had to be trained on trusting and responsive to edge AI alerts, which is a critical consideration in organizational terms and deploying these systems.

Conclusion

This study was an all-encompassing edge computing system of real-time device maintenance and autonomous diagnostics, and it was successfully used in manufacturing and healthcare settings. Through the implementation of IoT sensor data on the edge device with AI models, the framework can be able to recognize equipment malfunctions and patient anomalies immediately, inducing reactive maintenance or alerts with minimum latency. We demonstrated that, with respect to existing cloud-based methods, edge-based diagnostics can achieve a 75-percent

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reduction in latency and 60-percent reduction in energy, without compromising accuracy. The Introduction has identified the increasing necessity of such solutions within Industry 4.0 and smart healthcare trends in which the centralized cloud systems fail to provide the necessary real-time and reliability requirements. The Literature Survey examined the background of previous research on edge/fog computing as an initial step towards low-latency analytics and determined unresolved issues, such as resources and data security. Based on these observations, our Methodology outlined a multi-layered Edge AI platform in a factory and a hospital, showing how the domain-based edge intelligence can be applied in real life. This is demonstrated by the Results and Discussion and concluded that there were performance improvements (drastic decrease in latency, better use of energy) and that this had implications in terms of scalability, safety and data management. Collectively, these results prove that relocating AI to the network edge is a realistic and beneficial approach to achieving autonomous and preventive maintenance in critical applications.

Practically, this edge model helps organizations reduce downtime - manufacturing lines may prevent expensive stoppage by early identification of faults, and health care providers may prevent the crisis by addressing problems with patients before they blow out of proportion. It is also able to offload the network and cloud infrastructure load as it filters the data locally which may help in cutting operational costs. The autonomous maintenance feature, in which edge devices are able to implement corrective action immediately, allows new horizons of responsiveness, but it requires strict design to guarantee safety and reliability. Future work needs to find ways of combining this framework with new technologies, such as federated learning (to synchronize edge models as they keep improving), and to other application areas, such as energy grids or transportation, where real-time edge analytics can make the system more reliable. In addition, field research over the long term would be useful to measure the savings of maintenance costs and ROI of the Edge AI implementations to add on the technical performance measures we reported. To sum up, Edge AI in the diagnostics of devices is not only possible in the current technology, but it is extremely advantageous. It is a major enabler of the next generation of smart and self-maintaining industrial and healthcare systems - leading to the vision of machines and devices that can take care of themselves at speed, intelligence, and efficiency.

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