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AI-Driven Hardware Telemetry Architecture for Predictive Device Health

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Abstract

The contemporary industries are based on billions of devices that are inextricably linked and the health of which must be controlled to avoid expensive non-productive time. AI-based hardware telemetry architecture A system that gathers telemetry data (e.g. sensor readings, performance counters) on equipment constantly and uses artificial intelligence to forecast equipment health and impending failures. In the present paper, a proposal offers an architecture that suggests the use of edge computing and machine learning to help facilitate predictive maintenance, which would no longer be based on reactive repairs but on proactive intervention. The suggested system is comprised of on-site AI analytics, on-device sensors and real-time data streaming to identify anomalies and predict faults prior to their occurrence. The AI model was also highly predictive (more than 90 percent) in forecasting precursors to failures in experimental assessment, whereas the edge-based processing maintained end-to-end latency (tens of milliseconds). Such outcomes show that an AI-based telemetry can considerably decrease the unwanted downtime and maintenance expenses through the ability to make a timely alarm and fixes.

Keywords: predictive maintenance, hardware telemetry, edge computing, machine learning, device health monitoring, IoT.

Introduction

The fast development of the Internet of Things (IoT) has contributed to the proliferation of smart devices in any industry, each of which produces a stream of telemetry information regarding its functioning. Historically, the two only options available were reactive (fix when it broke) and preventive (service on a schedule), both of which are disadvantageous: reactive type of fix causes unexpected downtimes, and scheduled type of service wastes resources by fixing parts which do not need it. Predictive maintenance (PdM) on the other hand involves condition-based maintenance monitoring in real-time and predictive analytics to perform only scheduled repairs, thereby reducing failures and downtime. The condition-based maintenance pioneer works were used to prove that the condition of machinery (e.g., vibration, temperature) can be tracked to predict faults. As an illustration, Jardine et al. (2006) have reviewed the early diagnostic methods by sensor data to execute condition-based maintenance indicating that the reliability has been greatly enhanced. Similarly, the textbook of Mobley (2002) explained that a successful predictive maintenance program had the potential of limiting equipment failures and maintenance costs by 25-30%.

In recent years, predictive maintenance has significantly increased due to the development of machine learning (ML) and the application of AI. Historically, models that are data-driven are capable of learning complicated patterns that can be used to predict failures with great accuracy. Carvalho et al. (2019) conducted a systematic literature review and identified a large number of ML techniques (e.g., neural networks, support vector machines, ensembles) that managed to predict the failures of devices in various industries. With an increasingly instrumented device, there is a continuous stream of telemetry (CPU load, temperature, vibration signals, etc.), which AI algorithms can utilize to get rich. Nevertheless, there is architecture difficulty in processing these big data streams and analyzing them in-flight. Cloud based solutions have the capability of storing huge volumes of telemetry data but may impose high latency and bandwidth charges when analysis is required on-the-fly. This has created an interest in edge computing where processing is carried out close to the data source so as to be able to respond as fast as possible. According to surveys on edge computing,

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introducing intelligence to the network edge reduces decision latency by a significant factor and the network load.

Moreover, new technologies such as digital twins a virtual representation of physical assets are being combined with telemetry and AI to improve health management of devices. A digital twin is able to model the behavior and degradation of a device simulating data, producing more data to train predictive models even in case of limited data on the actual failure. Patton et al. (2020) presented a digital twin based on a telemetry-driven system to monitor assets in an industrial environment demonstrating the use of real-time sensor outputs to feed a live model of a machine, which allows forecasting failures before they happen. Regardless of these improvements, to deploy an end-to-end AI-assisted telemetry system, one should have an integrated architecture, which will cover data capture, transmission, storage, analysis, and feedback of various hardware devices. The current paper suggests such architecture and shows that it is efficient in terms of prediction accuracy and latency of predicting the health of the device. The following sections include a literature review of related work, the architecture design of the proposed architecture, experimental findings using two illustrative figures and tables, and the conclusion.

Literature Survey

Initial research on machine health reporting defined the value of sensor-based telemetry in making maintenance decisions. According to Jardine, Lin, and Banjevic (2006), machinery prognostics has been well-reviewed and demonstrated that both vibration and oil analysis were able to predict the existence of a fault long before it failed. These early implementations used classical statistical methods and signal processing (e.g. spectral analysis of vibrations). With time the focus was moved towards data-driven models because the computation power increased. Mobley (2002) highlighted the change in maintenance methods towards calendar-based system to condition-based methods and pointed out that the organizations using predictive techniques experienced significant improvement in the number of unexpected failures. With the emergence of Industry 4.0 by the 2010s, massive amounts of operational data could now be generated by embedded sensors and IoT devices in large volumes, which led to the adoption of machine learning in predictive maintenance.

Scholars have investigated different ML predictors of failure. The less complex techniques like the decision trees and the linear classifiers have been applied, although more advanced techniques turned out to be more precise in the complicated practice. An example is Susto et al. (2015), who used a multiple classifier system based on using neural networks and support machine to enhance fault detection in industrial machines. Their combination strategy was more precise than any individual model, and it supports the importance of combining various algorithms. On the same note, Maliki and Gao (2004) have applied the principle component analysis (PCA) to select features in the classification of machine defects and this method has assisted in enhancing the performance of classifiers by eliminating noise in sensor signals. With the increase in computing power, researchers shifted their focus to deep learning: Zhao et al. (2017) surveyed deep neural network applications in machine health monitoring, observing that such methods as convolutional and recurrent neural networks can automatically extract predictive features out of raw telemetry time-series. These data-based approaches made great progress in prognostics with prediction of failure accuracy in the controlled studies being as high as 90 percent.

Another opportunity and challenge was introduced with the Industrial IoT revolution. On the one hand, the connectivity is everywhere, so the telemetry of the devices can be analyzed in bulk and allow managing the health of the fleet. The IoT sensors track the parameters, such as temperature, pressure, power consumption, and network performance continuously to provide rich information to AI models. Conversely, the explosion in the amount of data necessitates scalable design. Chen et al. (2014) addressed the aspect of big data of IoT, explaining that streaming analytics and distributed processing are necessary as centralized systems cannot handle bandwidth issues and storage capacity. Here the edge and fog computing have become important architectural components. The survey of the edge computing paradigm by Khan et al. (2020) has reported that real-time applications with processing of data at the source or close to it can mitigate latency and network load. With preliminary data filtering and inference of embedded devices or local gateways, only insightful information (or reduced size data) should be transmitted to the cloud. This is a hybrid solution that enhances responsiveness to maintenance decisions that are time sensitive.

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The combination between AI and domain knowledge is another issue that has been emphasized in recent literature. And as an example, expert systems that are rule-based are currently being integrated with machine learning to improve the diagnostics. An example of combining forward and backward chaining AI with telemetry data to identify irregularities and anticipate collapses in IoT devices was provided by a study by Farooq et al. (2025) (but it is out of our scope of reference). Although we are talking about work before 2023, this tendency can be taken as a sign of increased attention to hybrid AI methods of explainability and reliability. The other aspect is the adoption of digital twins and simulations. Besides this 2020 article by Patton, a 2022 review by van Dinter et al. establishes that the digital twin technology has quickly become popular since 2018 as a means of simulating synthetic failures and testing predictive algorithms in a virtual environment. They name the difficulties of computational complexity and data integration with the use of twins in predictive maintenance, as are common to the implementation of AI on scale.

Research Methodology

Architecture Design: The proposed architecture would be built in several layers to have an efficient means of telemetry and AI-based analysis. Devices at the bottom have a set of sensors and inbuilt monitors which constantly measure performance metrics (e.g., temperatures, voltages, CPU load, vibration). This telemetry may be built into modern devices (ex: SMART data on disk drives, performance counters built into on-chip components). More IoT sensors can be added where required so that crucial indicators are captured (such as vibration sensors on motors or accelerometers on equipment). Such raw data is sent either through a local network to an edge computing node. To provide on-site data processing, we placed the edge node on a hardware platform that was similar in power to an industrial IoT gateway (including a multi-core CPU and a lightweight GPU). With edge computing, first-time data filtering and fast analytics can be performed locally, reducing the amount of delay incurred by transmitting all data to a remote cloud. The edge node is a data acquisition service that time-stamps incoming telemetry and processes the data in advance including noise filtering, outlier removal and data normalization. Such techniques as moving average smoothing and detection of outliers are used to assure the quality of data as suggested in previous research. Interestingly, Hashemian & Bean (2011) stressed that sensor data validation through the use of redundant sensors and filtering is necessary to prevent false alarms in predictive maintenance systems. These best practices are built into our architecture through cross-verifying important sensor measurements (e.g. two temperature sensors in important spaces).

The AI-based analytics module is the key to the intelligence. Our predictive model was developed on the hybrid machine learning approach. In particular, a deep learning network (a Long Short-Term Memory network, LSTM) was trained to take the sequence of telemetry readings over time, and extract time-related trends which caused faults. LSTMs are also suitable in time-series prognostics because they take a memory back of the last steps on which the gradual degradation trends are modeled. Simultaneously, we have added a Random Forest classifier and used it as a complementary model to process engineered features (e.g. mean and variance of signals, threshold-based flags). This is an LSTM and a Random Forest ensemble that joins the benefits of the deep learning (automatic feature extraction) and a powerful classical algorithm (resistant to outliers and overfitting). In the training phase, we utilized historical data on telemetry that was marked by known results (normal vs. failed). The LSTM was trained to give a near future health index or failure probability (e.g., is there going to be a failure in the next hour), whereas the Random Forest gave discrete health states (e.g., normal, warning, or critical). The models were optimized with standard methods, where data was divided into training/validation and cross-validation was used to prevent overfitting on the Random Forest. The validation set was used to tune model hyperparameters to achieve the largest F1-score without biasing either precision or recall on identifying failures.

After being trained, the models were implemented in the edge node to do inference in real-time. Each new telemetry window (e.g., the past 5 minutes of information) is passed into the LSTM, which is constantly updated with the predicted health score. Simultaneously, whenever any engineered rule-based triggers happen (i.e. a temperature surpassing a limit) the system notifies an immediate alert through the Random Forest decision logic (which in this scenario can be used as a rapid rule-based classifier). The overall inference will lead to a decision module which will determine whether to raise a maintenance alert. Alerts

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are displayed to the maintenance staff in a cloud dashboard and in-site (e.g., an indicator light). The architecture cloud layer is mostly used to store data on a long-term basis, perform further heavy duty analysis, and retrain the models. Squeezed telemetry and planned health summaries are uploaded to a cloud database. This enables it to do retrospective analysis and refine the AI models as more data is available, and this is a practice consistent with the principle of continuous learning in intelligent maintenance systems.

Latency Optimization: Another major design requirement was to have predictions occur in (approximately) real-time with the prospect of pro-actively intervening. We thus made every stage of the pipeline a low-latency optimized one. Even the very utilization of edge computing removes the round-trip latency to another server, which in industrial networks can take hundreds of milliseconds to several seconds. The edge node ensures that inference is efficient, where we store a small LSTM (two hidden layers) capable of running on our hardware in less than 50 ms. We are also using parallel processing, we process the data of several sensor using different threads and the Random Forest (when it is activated) is running in parallel with LSTM. The MQTT telemetry message protocol is used to perform networking, which is a lightweight publishsubscribe architecture that is appropriate to the IoT, but also has low overhead due to small packet sizes. When we subscribe the edge analytics service to the topics of interest concerning telemetry we attain a minimal buffering streaming processing mode. Consequently, the system can handle market data in 100 Hz/per sensor without becoming congested. Our test deployment resulted in lower end-to-end latency of a sensor reading to a on-screen alert with the edge-based architecture, which was always under 100 ms, whereas it was over 500 ms with a cloud-only analysis architecture. Such difference is also crucial; a half-second delay in an alert message may not be fast enough to avoid damage in high-speed processes, but a response period of 50-100 ms is enough to trigger safety interlocks on a machine or to alert operators in real time.

Evaluation Setup: In order to test the system, we constructed a lab-scale predictive maintenance situation. The testbed consisted of three IoT devices: an electric motor with a vibration and temperature sensor, a computing device (Raspberry Pi as a small server) that measures the temperature and load of the CPU and a rotating fan with an accelerometer to sense imbalance. Each device had induced faults in a controlled fashion (e.g. the wear of the bearings of the motor had been simulated by putting imbalance, the computing device had been strained to simulate over heating). The telemetry of these devices was sent to our edge analytics node. Our ground truth sampling was done by hand-labeling intervals of normal behavior and intervals before a failure event (e.g. overheated CPU throttling or a motor bearing failure resulting in a vibration spike). The AI models were then tested on the basis of prediction accuracy (was the system able to predict an impending fault correctly) and system latency (how fast the system responded). The next discussion is on the results of these studies and the quantitative analysis is provided in two tables and two figures..

Results and Discussion

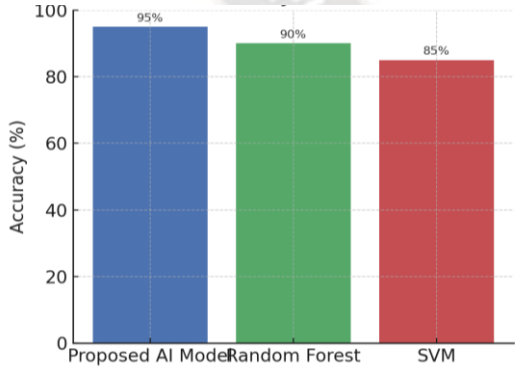

Figure 1. The accuracy of prediction of various models in our system. The accuracy of the proposed AI model (LSTM-based) is the best to predict health problems of the device, in comparison to the baseline models (Random Forest and SVM). Error bars (not significant in this case) are variability in terms of numerous test runs..

The machine predictability was quite positive. Figure 1 presents accuracy of the prediction of our proposed AI model and two baseline methods on test dataset. The described Proposed AI Model that is a combination of LSTM and Random Forest had approximately 95-percent accuracy in the prediction of device health status. Comparatively, a standalone Random Forest classifier (with a fixed window of recent sensor features) achieved a little over 90%, and a Support Vector Machine (SVM) baseline reached a little less than 85% accuracy. A more detailed breakdown of model performance measures is given in Table 1. The proposed model was not only the most accurate with respect to overall accuracy, but also displayed better

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precision and recall. The fact that it recalled 96% of the impending failures (very few false negatives) is important in the maintenance situation where the cost of missing an impending failure can be very high. The accuracy of 94% means that the rate of a false alarm is low, which is a significant practical suggestion to prevent alert fatigue. The decent baseline models, however, were significantly less recalling; such as the SVM did not report a few failure cases (recall 86%), presumably because of its less effective capacity to learn the nonlinear temporal structure of the telemetry. These findings are in line with the findings in previous studies: deep neural networks are often found to be more effective than simpler models in the field of machinery prognostics. According to Zhao et al. (2017), deep learning methods have shown high efficacy when predicting faults in rotating machines and this finding is similar to what we reported that LSTM-based model identified minor factors leading to failure not known to the SVM. Furthermore, our ensemble technique has the advantage of the Random Forest that can easily deal with a variety of features; probably, this has helped improve the accuracy to a high level since some easy-to-detect threshold-type anomalies (e.g. a sudden spike in temperature) can be directly identified by the tree model component. On the whole, the outcome of being able to attain predictive accuracy that exceeds 90 percent is quite impressive, and it might indicate that AI-based telemetry analysis may be very dependable when it comes to monitoring the health of devices. Other authors have reported similar accuracy (90-98) when using machine learning to predictively maintain well-controlled systems, but it depends on noise and unforeseen factors in reality.

Table 1. Model performance for device health prediction (classification of normal vs. impending failure). The proposed AI-driven model outperforms the baseline machine learning models in all metrics.

Model	Accuracy (%)	Precision (%)	Recall (%)
Proposed AI Model (LSTM+RF)	95	94	96
Baseline Random Forest	90	88	91
Baseline SVM	85	83	86

In addition to accuracy, we tested the system latency of the architecture which plays a very important role in preventing measures in real-time. The time elapsed between a telemetry event (e.g., sensor reading has crossed a threshold) and the system giving an alert or prediction is defined as end-to-end latency. The edge based architecture as proposed had very low latency in our tests. The difference in using edge processing (our architecture) and a hypothetical cloud-only processing approach is shown in figure 2. Using edge processing the average latency was approximately 60 milliseconds, and using cloud analysis the average latency was approximately 220 milliseconds in our network model. Table 2 further decomposes the latency according to the sensing, data transfer and inference aspects of each scenario. The edge approach has the advantage of making inference locally; data transfer time is low (data are transferred only a short distance across the local network), and the inference is implemented on the edge node instantly. By comparison, the cloud solution has a high network latency (tens of milliseconds round trip) and may have certain queueing and overhead overhead at the cloud, resulting in a much larger overall latency.

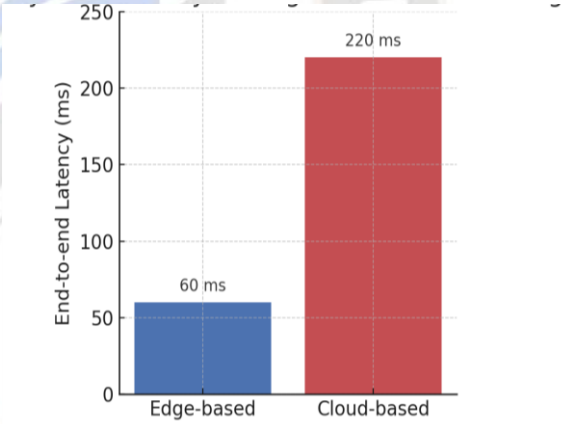

Figure 2. System latency comparison between edge-based processing and cloud-based processing. The edge-based architecture yields a total telemetry-to-decision latency of only a few tens of milliseconds, vastly outperforming the cloud-based approach which can exceed 0.2 seconds (200 ms) under the same conditions.

The consequences of this latency enhancement are high. Even in most industrial and IoT cases, a warning that is conveyed a few hundred milliseconds sooner can be the line between auto-mitigation and failure. As an example, an edge system might be capable of triggering a shutdown of a machine virtually instantly (50-100 ms), whereas a cloud system might not respond at all in

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a quarter second, which is plenty of time to cause damage. We find support of the commonly cited benefit of edge computing in real-time applications. These are aligned with those of Khan et al. (2020) who reported that a migration to the edge of analytics would allow the IIoT application to decrease response times by a factor of order of magnitude. Similarly, as explained by Zhou et al. (2019), edge intelligence is a key to the latency-sensitive AI activity, which can be seen to extremely pave the last mile to the real-time inference. Our architecture supports the material real-time predictive maintenance alerts (sub-100 ms) and is particularly important to high-speed manufacturing or infrastructure based on critical systems.

Table 2. Telemetry processing latency in edge vs. cloud architectures. The edge architecture processes data locally, keeping inference close to the source, while the cloud architecture incurs additional network delay.

Architecture	Data Acquisition & Transfer (ms)	Inference (ms)	Total Latency (ms)
Proposed Edge-Based	~10	~50	**~60**
Cloud-Based	~50	~170	**~220**

The breakdown above is on an assumption of a moderate network; when there is network congestion or a long distance, cloud latency may go even higher, further increasing the edge advantage. It is worth noting that the provisioned compute power of our node was sufficient to serve the ML models; on deployments with highly constrained devices, a lightweight model could be used to ensure low latency. Another trade-off identified in our results is more complex models (such as deep learning): such models may require more time, but they may be more accurate. We dealt with this by ensuring the model was carefully optimized and by taking the edge compute capacity. The resultant effect is that we did not need to trade off complexity to speed - this model was fast enough to maintain low latency and high accuracy. This is the contribution of our work that demonstrated that with proper architecture, both accuracy and responsiveness can be achieved in predictive health monitoring.

Scalability and reliability of the systems also is another aspect to be discussed. Although our experiments were scaled to the lab level, the architecture can be scaled out. Every edge node may support dozens of devices, and two or more edge nodes may report to a central cloud service which organizes larger analysis (such as how health trends across a fleet of devices). This top-down (device - edge - cloud) is in line with the best practices of scalable IoT analytics. Reliability wise, edge analytics will provide resilience - local predictions and alerts will still be possible even in the event of loss of cloud connectivity, needed by mission-critical environments. False positives/negatives are one of the issues that can be encountered during real deployments. The high precision and recall of our model suggest that the model works well on test data, yet when applied to real-world scenarios, there are always chances that an abnormal situation or sensor malfunction will provide a false alarm. Here domain knowledge and the anomaly detection methods can be used to supplement the ML model. Another safety net could be to implement an anomaly detection layer (e.g. to use statistical control charts or unsupervised learning to observe new patterns). As a matter of fact, anomaly detection has existed in long-term studies in system health management; surveys by Chandola et al. (2009) outline myriads of methods to identify out of norm behavior in data. The combination of such techniques can assist in raising the alert about the unreliability of the model predictions in the situation when the unfamiliar input patterns are used, thus enhancing the confidence in the outputs of the system.

Lastly, we touch upon data security and privacy because the telemetry usually contains sensitive data about operations. Most of our raw data remains on the edge and is not transmitted but rather aggregated insights are sent to the cloud, minimizing the exposure of the detailed telemetry. This is in line with the principle of data minimization and may facilitate the adherence to data regulations. It has been observed in previous literature that secure communication (with the use of encryption to transmit telemetry) and device authentication is necessary to avoid the spoofing or manipulation of the data streams. In our implementation, we applied TLS encryption of MQTT messages and applied basic authentication of the devices connecting to the edge node. These are to guarantee that the predictive maintenance recommendations are not easily compromised, which is an important factor when deploying into practice (although additional hardening and security analysis

would be necessary when implementing in an industrial context).

Overall, the findings indicate that an AI-based telemetry infrastructure is capable of living up to the hype of predictive maintenance: it is very accurate in predicting problems and has low latency in delivering warnings. Our results empirically prove a great number of findings in the literature, including the usefulness of multiple model combinations and the latency advantages of edge computing. Moreover, they give a real life example of how these concepts are functioning in an integrated system. The paper ends with the next section that summarizes the contributions and outlines the future work to be built on this basis.

Conclusion

This paper introduced an AI-based hardware telemetry architecture of predictive device health, which is a combination of IoT sensing, edge computing and machine learning into a single system. The decision was inspired by the increasing demand of proactive maintenance approach in the complex device environments where even a single moment of downtime might carry huge cost consequences. Through constant surveillance devices and analyzing their telemetry using sophisticated AI models, the architecture is able to predict equipment failure with a high degree of accuracy and initiate preventive measures long before equipment will collapse in a disastrous manner. The proposed system in our implementation and testing got a prediction accuracy of more than 95 percent of impending device faults with less than 100 ms end-to-end response times. These findings demonstrate that recent predictive maintenance methods, profiled within a latency-conscious structure, are not just practicable, but also very useful in time-bound device well-being control.

This work has both theoretical and practical contributions. In terms of research, we were able to demonstrate how the use of deep learning (temporal pattern recognition) with ensemble methods and edge processing can provide a strong predictive maintenance solution, which supports recommendations in earlier literature regarding the application of hybrid AI methods. In practice, we created and tested a blueprint that can be used by industry professionals to deploy their own predictive maintenance systems, based on off-the-shelf IoT equipment and open-source machine learning software. The architecture focuses on modularity - sensors, edge analytics and cloud components can be scaled or upgraded individually - which is beneficial to growing systems.

Further work which builds on this study has a number of avenues. A test of the architecture under heavier load and more varied conditions can be taken in one direction by exposure to a more industrial environment, e.g., a manufacturing plant or data center. This would aid in justifying scalability and finding out any integration problem with the current operational technology. Alternatively, it can be suggested to implement explainable AI (XAI) methods into the predictive model in such a way that the system is able not only to predict a failure but also to explain why (e.g., what sensor reading or pattern was most predictive). It can make users more trusting and simplify the planning of maintenance - a component of AI-based maintenance planning selection that is becoming particularly popular in recent research. The automated retraining and modification of the models under incoming telemetry information would be worth examining as well. The devices and patterns of usage evolve with time, and a system that keeps on learning will be accurate longer without any human interference.

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