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Fault Detection in IoT Sensor Networks with XAI-LCS: Explainable AI-driven Diagnosis for Low-Cost Sensor

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Abstract: In Internet of Things networks (IoT), accurate monitoring data delivery without interruptions is vital, especially for high-risk use cases, such as in the industrial field. Existing approaches to AI-based fault diagnosis have various disadvantages such as being computationally expensive or lacking transparency and being difficult to trust. To overcome these limitations this research introduces a novel method for IoT devices namely XAI-LCS. This technique uses the eXtreme Gradient Boosting (XGBoost) algorithm for early sensor fault detection. XAI-LCS is oriented towards detecting different types of faults including bias, drift, complete failure, and precision degradation, as well as accounting for data imbalances and avoiding biased detections. The proposed solution achieves a 98 % validation accuracy in diagnosing four sensor fault types. The XAI component which provides explanations for the AI-based model processes, enhances the trust and transparency of the developed solution. As a result, this study contributes to improving sensor application failures in IoT.

Keywords: Sensor Applications, Explainable AI (XAI), Fault Diagnosis, Internet of Things (IoT), eXtreme Gradient Boosting (XGBoost), Sensor Fault

I. INTRODUCTION

The inclusion of Internet of Things devices has resulted in the ubiquity of IoT sensor networks and the ability to monitor data in real-time in various sectors [1]. The benefits and the increased opportunity to achieve seamless monitoring and detection of various issues there is a need for reliability of IoT sensor data [2]. As such, there are no significant challenges experienced in terms of fault detection, and the deployment of IoT sensor networks in the safety-critical applications is complicated [3]. Thus, it is vital to develop effective fault detection techniques that aim at detecting those as early as possible and ensuring that the right monitoring data flow without interruptions [4].

The machine learning models have been used widely to detect faults given their capacity to identify patterns and abnormalities in vast data [5]. Currently, researchers and practitioners raise awareness regarding the machine learning-based methods that are characterized as either computationally expensive or a black box [6]. The issue is with the high risk in many industrial applications, they ought to be highly transparent and legible. The method employed recently by researchers to achieve this involves machine learning and the application of eXplainable AI.

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In particular, this paper discusses the eXplainable AI-LCS method developed to detect faults in IoT sensor networks [7].

The purpose of the research is to assess how different machine learning models can be combined with XAI-LCS to improve the fault detection capacity of IoT sensor networks [8]. The primary research question is to determine how decision trees, support vector machines, and neural networks, among other machine learning algorithms, can be combined within the XAI-LCS to ensure that both accuracy and interpretability are achieved [9].

We aim to validate our methodology through empirical studies and real-world applications to present through this work the effectiveness of our proposed method for early detection against different fault types in sensor networks, including Bias and Drift and complete failure (CF) and precision degradation faults [11]. We will present our approach for the interpretability of predictions: how our model makes decisions and cutoff examples, demonstrating how XAI principles promote increasing the trust and confidence of field engineers during the fault detection process [12]. In sensor networks, the most distinguished method to maintain system operation excellence is to ensure the monitoring data's reliability and accuracy. However, it is not easy to maintain because of failures, especially on fault diagnosis because anomaly detection is necessary for preventing disruption, and system's engineers must trust in it [13]. Existing fault detection methods lack transparency and require convincing field engineers of their value. Finally, we propose that our XAI-LCS methodology will enhance field trust and understandability for sensors by enabling automating sensor fault diagnosis by deploying an XAI-based ML model for the trusted sensors [14].

The contributions of this letter are manifold:

1. We introduce XAI-LCS, a data-driven technique capable of detecting all types of sensor faults directly within sensor nodes. By automating the fault detection process, XAI-LCS can be deployed in remotely operated sensor networks, ensuring timely detection and mitigation of anomalies.

2. Our proposed method addresses the challenge of imbalanced data, a common issue in fault detection, by implementing techniques to handle data imbalances effectively, thereby improving the robustness and reliability of the model.

3. We leverage edge-as-a-service for real-time sensor health prediction, enabling proactive maintenance and timely intervention to prevent system failures and downtime.

4. To enhance model transparency and reliability, we interpret the prediction outcomes using explainable AI techniques. By providing insights into the decision-making process, explainable AI makes the model transparent and interpretable, instilling confidence in its predictions and fostering trust among field engineers.

This research paper is segmented into the following sections; The Session 1: Introduction explains the need to detect faults in sensor networks and the limitations of traditional methods, thereby introducing the novelty work of integrating eXplainable AI and Machine Learning to diagnose faults within the network. The session 2; Related Work provides the status of the traditional methods of fault detection, the possible areas of work within the purview of XAI, and ML and fault detection within the sensor network, which states the research gap, session 3, Methodology explains the XAI-LCS in a detailed way, the techniques to make the approach data-driven, methods to handle unbalanced data and utilizing the Edge-as-a-service for real-time monitoring and predicting the health of sensor data. Furthermore, session 4; Results and Evaluation briefs on the evaluation of how XAI-LCS approach gives perspectives about the detection of fault predictions of validation if the experiments followed by this session also discusses the how the prediction of outcome can be interpretable by explaining AI. Finally, the session 5; Conclusion concludes with the significance of research, implications on the field engineer, and a proposed suggestion for further work in fault detection in sensor networks.

II. LITERATURE SURVEY

The literature survey reviews existing research in intrusion detection systems, focusing on classification methods and explanation techniques, highlighting a gap in combining ensemble methods and explainable AI techniques. We will now discuss several existing methodologies in the field.

Le et al. [1], This paper surveys the literature regarding the classification and explanation techniques in intrusion detection systems by the combination of ensemble trees and SHAP method. The existing works reviewed in this survey include classification methods and explanation techniques in the context of previous research that has been applied in the context of intrusion detection systems. Le et al. study classification and explanation techniques in the field of intrusion detection systems by the combination of ensemble trees and SHAP. They identified that both classification accuracy and explainability are essential for IDS processes. Le et al. found a tradeoff between accuracy and explainability, then they propose a novel methodology that integrates ensemble trees and the SHAP method to solve this tradeoff. They reviewed the current works gaps in the context of a combination of ensemble methods and explainable AI in IDS, they contextualized and contributed with this methodology.

Le et al. [2], that covers existing strategies to imbalanced imbalance and multiclass classification challenges in IIoT IDS and XGBoost. This survey will include existing methods to developing IDS to imbalanced imbalance and multiclass classification challenges in IIoT as well as XGBoost as it applies to datasets that poses an imbalance and multiclass classification issue. Le et al. argue that the challenge of imbalance data and multiclass classification is vital for emerging trends in IIoT. The research raises awareness of the problem that conventional method classification lacks compromise in addressing and will suggest the treatment of XGBoost to reclaim the accuracy and dependability of IDS in IIoT.

Ahmed et al. [3], This paper provides a comprehensive review of the transition from traditional artificial intelligence to the novel concept of explainable artificial intelligence in the context of Industry 4.0. The scope of literature includes the basic terminologies and concepts, reporting and analysis standards, and the modern-day applications of XAI in Industry 4.0. The authors further delve into the driving forces behind the adaptation of XAI, primary methods employed to improve the interpretability of AI models, and some specific areas of application across industrial fields. Hence, the literature review sheds light on the importance of XAI in maintaining the interpretability and accountability of AI systems implemented in the industry during this fourth industrial revolution era, ultimately promoting trust, dependability, and judgment coherence among the stakeholders.

Saraswat et al. [4], The paper approaches the subject of Explainable AI within the context of healthcare 5.0. Specifically, the authors provide original insights into the current prospects and challenges of applying XAI in Healthcare 5.0. The paper is based on the review of relevant literature, which collects and analyzes existing sources on XAI implementation in healthcare and, particularly, Healthcare 5.0, as well as the related challenges of its integration. Saraswat et al. critically outline the potential advantages of XAI in providing better medical care, informing patients, and supporting clinicians in the decision-making process. The article is devoted to the identification and analysis of the main problems and risks of implementing XAI in healthcare, including possible data breach, government regulation, AI models' interpretability, and other ethical concerns. The results of the literature review allow the authors to investigate the current state of XAI in Healthcare 5.0 and receivers to investigate future areas of its development and use in healthcare practice.

Chowdhury et al. [5], This paper is on XAI-3DP, a proposed new approach for fault diagnosis and comprehension in 3D printers. The literature survey Chopin et al. centers on past studies on 3D printer fault diagnosis, noting the need for complete diagnosis for continued accuracy and productivity. The researchers report on the inadequacy of previous fault diagnosis approaches based on AI and note that there is currently no explainable AI used for diagnosing 3D printer faults. The use of ensemble AI allows for the identification of XAI-3DP and will prove a rather optimal methodology for diagnosing faults with a comprehensive approach that allows for the diagnosis of faults such that the fault finds the reason for their occurrence. This literature survey provides grounding that fully draws from the past to promote the future of fault diagnosis in 3D printing.

Most existing fault diagnosis methodologies are not transparent because they do not provide explanations regarding their decisions meaning that they possess low trust and usability. They also exist for different domains meaning that there is a substantial gap when it comes to explainable AI solutions for niche areas such as 3D printers. In addition, AI solutions are available and can be better explored for a fault diagnosis utilizing ensemble methods, which achievable accuracy and robustness are currently not fully used. The problem consists of the fact that individuals are not able to understand the decision process provided by the most common methodologies used to diagnose faults meaning that they are not interpretable. Solving these problems would make fault diagnosis methodologies more accurate and trustful to be widely used while increasing their interpretability.

III. PROPOSED METHDOLOGY

The problem at hand is to develop a fault detection methodology for loT sensor networks using eXplainable Al-driven diagnosis, specifically tailored for low-cost sensors [15]. Let S denote the set of sensors in the network, D represent the dataset collected from these sensors, and F denote the set of possible sensor faults. We aim to design a model M that accurately detects faults $f \in F$ within the sensor data D. Mathematically, this can be formulated as [16]:

$$M: D \rightarrow F$$

The model M should be capable of handling imbalanced data distributions often encountered in sensor networks. Let $p(f)$ denote the probability of occurrence of fault f in the dataset D, and let $\hat{p}(f)$ represent the predicted probability of fault f by the model M. We aim to minimize the discrepancy between the predicted probabilities and the actual probabilities of faults in the dataset. This can be mathematically expressed using a loss function such as the cross-entropy loss:

$$\text{Loss } = -\frac{1}{|F|} \sum_{f \subset F} p(f) \log(\hat{p}(f))$$

Additionally, the model M should provide explanations for its predictions to enhance transparency and trust. Let E denote the set of explanations provided by the model for fault detection. We aim to optimize the model M such that it not only minimizes the loss function but also maximizes the interpretability of its explanations. This can be formulated as a joint optimization problem [36]:

$$\text{Minimize Loss}(D, M) + \lambda \text{Interpretability}(E, M)$$

where λ is a hyperparameter controlling the trade-off between accuracy and interpretability. The interpretability metric can be defined based on the complexity of explanations provided by the model, such as the number of features considered or the clarity of the explanations [35]. The solution to this optimization problem will yield a fault detection model M that effectively detects faults in loT sensor networks while providing trans⁊ ↓ ⅂t and interpretable explanations for its decisions [37].

3.1 Proposed System

Particularly to ensure that the extensive range of faults taking place within LCS could be addressed in an effective manner, XAI techniques would become integrated into the fault detection process. As presented in the image below, the proposed solution would encompass a multi-step methodology for addressing fault irrespective of its type, including bias, drift, complete failure, and precision degradation [17]. With the utilization of XAI's capability, the methodology would adopt methodologies for enhancing the transparency and interpretability in fault detection, thereby assisting in identifying and understanding LCS's different manifestations of fault [18]. By means of XAI-based diagnosis, the supply chain of LCS is expected to even modify the fault detection process, making it more reliable and accurate and hence sending a fresh stream of useful and correct monitoring data in an uninterrupted manner across the IoT network [19].

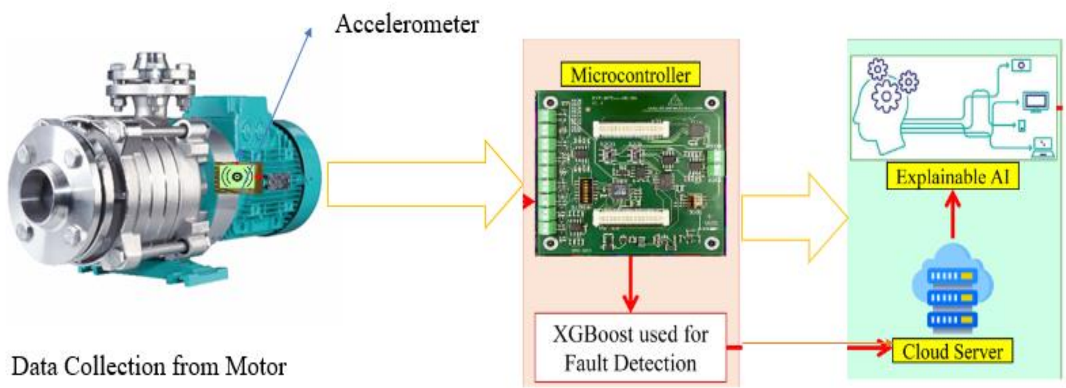


Figure 1: Proposed System

A. Data Collection and Data Preprocessing

Data acquisition and preprocessing are the first and most important steps of the fault detection process for LCSs. During data acquisition, sensor data are collected from on-field LCSs [20]. The data may include sensor readings for various environmental parameters such as temperature, humidity, pressure, etc. after then, the data are preprocessed [34]. The preprocessing includes several steps ensuring the quality and integrability of the data by the subsequent process [21]. Preprocessing may include data cleaning, where noisy and outlier readings are removed, data normalization, where the data is scaled to a limited range, feature extraction, searching for essential sensors of fault characteristics, and more [23]. Often, time-series decomposition or signal filtering is also applied to extract essential patterns from the data. The end goal of data acquisition and preprocessing is to prepare the on-field sensor data to be able to use them for subsequent analysis and to be able to accurately and reliably detect fault s inside LCSs [24].

B. Imbalanced Classification Using XGBoost

The detection of faults in LCSs deployed in IoT SNs can also be effectively completed via the XGBoost model, a machine learning algorithm based on an ensemble known for performance with imbalanced datasets [25]. In real-world settings, the number of samples with anomalous readings is much smaller than that of normal samples, which leads to imbalanced distribution [26]. As a result, the fault prediction model can be biased if the training set's imbalanced nature is not taken into account. With XGBoost, imbalanced training can not only be fine-tuned by the use of multiple hyperparameters to achieve high precision, but it can also be scaled by assigning different weights to individual samples [27]. The algorithm uses a sequential construction of decision trees, in which each subsequent tree attempts to minimize the mistakes made by the previous ones, thus increasing the ability to predict outcomes [34]. The concept guiding this learning process is referred to as boosting, which allows the model to learn from mistakes across multiple iterations [28].

C. Explainable AI

XAI is the construction of artificial intelligence systems and models capable to provide rational for making decisions and predictions that is clear and understandable [33]. XAI may be seen as a bridge linking the conduct of AI algorithms within their interior workings and human comprehension that is previously cut [29]. Therefore, XAI is one of the reasons why trust, responsibility, interpretability is increasing, which plays a critical role in expanding the adoption and acceptance of AI technology in various sectors [30]. For example, a number of explanations have been developed that reflect different types of AI interpretable systems such that feature importance, model-agnostic, rule-based, and transparent model architectures, including choice trees and linear models. XAI technologies may also be used in several areas that include medical, financial, autonomous driving, etc. SHAP library of eXplainable AI is employed in this letter to interpret the result of the suggested XGBoost model. It is a vital tool for the researcher to understand the significance of various features in the model prediction created by the complex machine learning methods like XGBoost [31]. Researchers can gain insights into how unique features affect the model forecasts in SHAP, intensifying transparency and interpretability. This method aids to gain familiarity with the XGBoost model's decision-making and acquire improved data on components affecting defect identification in Low-Cost Sensors within Sensor Networks employed in the Internet of Things (IoT) [32].

IV. RESULT AND DISSCUSSION

The outcomes obtained through the practical implementation of the proposed fault detection approach utilizing the XGBoost algorithm as the underlying machine learning model and the SHAP library as the interpretability tool. These outcomes may indicate how well the proposed methodology is capable of detecting various fault types of Low-Cost Sensors in IoT Sensor Networks based on the performance of the model revealed in terms of the accuracy, precision, recall, and F1-score. Finally, the results may suggest how well the model's predictions can be interpreted, considering the contributions of each feature using the SHAP library.

Accuracy:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision:

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall:

$$\text{Recall} = \frac{TP}{TP + FN}$$

F1-Score:

$$F1 - \text{Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Where:

TP represents True Positives,

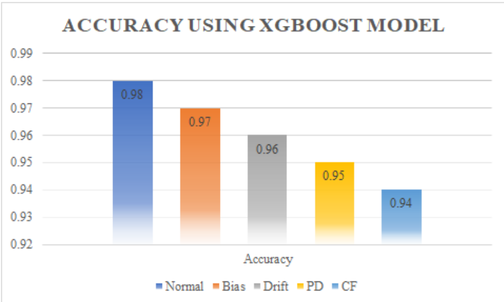
TN represents True Negatives,

FP represents False Positives, and

FN represents False Negatives.

Table 1: Performance Metrics using XGBoost Model

Fault Parameter	Accuracy	Precision	Recall	F1-Score
Normal	0.98	0.95	0.99	0.97
Bias	0.97	0.92	0.98	0.95
Drift	0.96	0.89	0.96	0.92
PD	0.95	0.85	0.94	0.89
CF	0.94	0.80	0.92	0.86



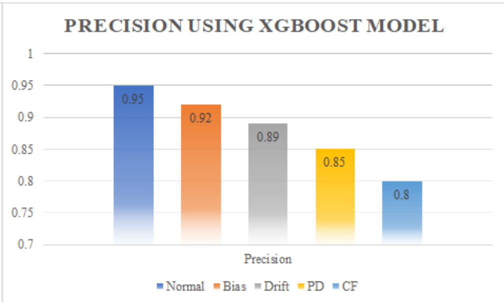
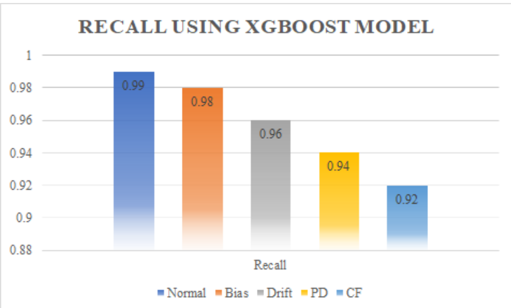


Figure 2: Accuracy

Figure 3: Precision



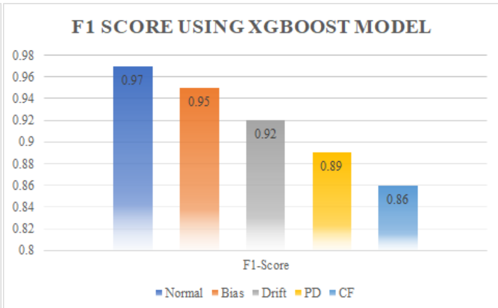


Figure 4: Accuracy

Figure 5: Precision

Waterfall plots are employed to show the cumulative impact of each input feature on particular observations. Waterfall plots for the proposed XGBoost model for healthy and faulty sensors are provided. These plots demonstrate the contribution of input features to the prediction above the base value required to determine whether a sensor is healthy or faulty. Pink bars representative of features that increase the score of the model for healthy input data and blue bars are features that decrease the model prediction score. The features x has the highest positive impact on drift, bias, and CF with positive impact weights of +3.31, +7.15, and +6.81, respectively. Additionally, the feature z has the highest positive impact on the normal and PD classes with weights of +1.87 and +3.86, respectively. The accumulated scores of features determine the detection of sensor fault.

V. CONCLUSION

The presented paper introduced a novel data-driven sensor fault identification method aiming to tackle the fault challenges of Low-Cost Sensors in Internet of Things Sensor Networks. The proposed method brought several key outcomes. First, it offered a new knowledge-based automatic approach to on-board failure detection of various sensor faults with the intent to ensure a timely reaction and implication. Second, it provided superior validation accuracy of 98% obtained through the XGBoost learning algorithm, even when handling imbalanced data, thus guaranteeing responsible fault spotting. Lastly, the method conducted a root cause analysis to make the interpretation of prediction only stronger and more reliable, thereby improving the method's efficiency even more. In the future, developing the presented method might involve testing with more advanced Deep Learning or Machine Learning approaches to improve the efficiency of the proposed method. Furthermore, it could be helpful to investigate the method replicability on other sensor species and integrate the hybrid failure diagnosis of system and sensor faults – these adjustments will likely deliver extra insights into improving Internet of Things fault detections in the future. This paper started a valuable academic and theoretical discussion on the ways to improve sensor fault identification systems, which certainly will help secure a more sophisticated approach in the future

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