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EXPLAINABLE ARTIFICIAL INTELLIGENCE MODEL FOR PREDICTIVE MAINTENANCE IN SMART AGRICULTURAL FACILITIES

[1] Mohammad Abdul Waheed Farooqui, [2] Raamagi Vinod Kumar,[3] Santhosh Kumar Adla, [4] Ambore Madhuri

[1,2,3] Assistant Professors,Department of Computer Science and Engineering, Brilliant Grammar School Educational Society's Group Of Institutions, Abdullapur (V), Abdullapurmet(M), Rangareddy (D), Hyderabad - 501 505

[4]student,Department of Computer Science and Engineering, Brilliant Grammar School Educational Society's Group Of Institutions, Abdullapur (V), Abdullapurmet(M), Rangareddy (D), Hyderabad - 501 505

ABSTRACT

When it comes to explainability, AI applications in SAF often encounter problems, which prevent farmers from making full use of their potential. This research fills that need by suggesting a paradigm that combines PdM with eXplainable Artificial Intelligence (XAI). The data, model, result, and end-user aspects are the focus of the model's predicted insights and explanations. By changing the way these technologies are understood and used, this method signifies a sea change in agricultural AI. There are clear performance gains with the suggested model compared to previous methods. Classifiers eXtreme Gradient Boosting (XGBoost) and Long-Short-Term Memory (LSTM) both improve accuracy by 5.81% and 7.09%, respectively, while XGBoost also improves accuracy by 10.66% and ROC-AUC by 4.29%. Based on these findings, it seems that the model has the potential to improve maintenance prediction in practical agricultural contexts. In the context of PdM for SAF, this research also provides helpful insights on data purity, local and global explanations, and counterfactual possibilities. The work contributes to the advancement of AI applications in agriculture by highlighting the importance of explainability in addition to standard performance indicators. As an added bonus, it promotes further study into topics like HITL systems and multi-modal data integration, both of which have the potential to enhance AI performance while tackling ethical concerns like FAT in agricultural AI.

I.INTRODUCTION

Artificial intelligence (AI) has the ability to optimise operations, improve resource management, and enhance production in Smart Agricultural Facilities (SAF), which might lead to a revolution in the agricultural business. In this regard, one of the most encouraging uses of AI is in predictive maintenance (PdM), which allows for the early diagnosis of equipment faults and the subsequent reduction of maintenance costs and downtime. Nevertheless, a major obstacle, the lack of explainability, often prevents AI-based PdM systems from being widely used in agriculture, despite their efficiency. Because they may lack in-depth technical understanding, farmers and operators have a hard time trusting and making good use of AI systems because they can't comprehend how these systems make decisions.

An important new area of study, eXplainable Artificial Intelligence (XAI) seeks to solve this problem by making AI models easier to understand and work with. The ability to explain anything to users is crucial in predictive maintenance since it clarifies why specific

they are provided with maintenance action recommendations that empower them to make educated choices. Specifically for PdM in Smart Agricultural Facilities, this paper presents an explainable AI model that combines explanations with predictive insights. Ensuring that stakeholders can appreciate the logic behind AI-driven predictions, the model delivers clarity across four critical dimensions: data, model, result, and end-user.

Bridging the gap between complicated AI algorithms and the practical demands of farmers, this concept intends to boost user trust and engagement by integrating explainability with predictive maintenance. The research shows that this approach enhances predictive performance, providing quantifiable gains in accuracy, F1 score, and other assessment criteria, while also making AI models more interpretable. Additionally, the study emphasises the significance of integrating ethical factors, such FAT (Fairness, Accountability, and Transparency), into the use of AI in farming.

This paper continues by detailing the explainable AI model's development and deployment, comparing its results to those of other methods, and concluding with an examination of potential future work towards improving AI-based predictive maintenance in SAFs through the integration of multi-modal data and Human-in-the-Loop (HITL) systems. Our goal in doing this study is to make AI more widely used in farming by making sure that farmers can rely on these technologies and that they are easy to use.

II.LITERATURE REVIEW

In order to analyse eXplainable Artificial Intelligence (XAI) models—a subset of sophisticated AI-driven Predictive Maintenance (PdM) techniques—this research reviewed the literature extensively. We set out to determine if XAI might improve maintenance methods by shedding light on model decision-making with more precision. In order to provide a thorough picture of where things are and where they're headed in terms of integrating XAI into agricultural PdM systems, this study sought to emphasise the benefits, drawbacks, and practical use of different XAI techniques in PdM.

A. Predictive Maintenance Approaches

First, prognostics; second, diagnostics; and third, anomaly detection were the three main PdM methods uncovered by the evaluation [21]. While prognostics try to foretell how well a system will do in the future, anomaly detection looks for out-of-the-ordinary patterns in data. Performance analysis is the basis for diagnostics, which seek to uncover present difficulties. Eleven investigations centred on prognostics [30, [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], three on anomaly detection [41, [42], [43], and two on combined prognostics and diagnostics [40], [44] (among the research examined). An important omission in the current research is that no study focused only on diagnosis. To improve the overall efficiency and resilience of PdM systems in Smart Agricultural Facilities (SAF), future research should investigate how integrating anomaly detection with prognostics might enhance diagnostic capabilities.

B. Deep Learning and Machine Learning in Predictive Maintenance

Astonishingly, methods like Long-Short-Term Memory (LSTM) networks and Recurrent Neural Networks (RNNs) achieved an accuracy of 90.07% when used to prognostics [33]. More sophisticated models, such as Bidirectional Recurrent Neural Networks (Bi-RNNs) and Long Short-Term Memory (LSTMs), achieved an unprecedented 96.15% accuracy in forecasting Remaining Useful Life (RUL) [30]. Anomaly detection tasks have been very fruitful for LSTMs, especially when combined with One-Class Support Vector Machines (OC-SVM) to drastically cut down on false alarms [38]. Unfortunately, OC-SVMs have a hard time handling supervised difficulties and may not work in every situation.

Using AutoML, another research that used Random Forest (RF) for prognostics showed how versatile it is, especially when it comes to component-level analysis [32], [36]. Even while AutoML has made machine learning accessible to more people by automating model selection, optimising individual models for specific applications is still challenging due to its generalist approach [45]. The field of prognostics, and the industrial sector in particular, found success using Ensemble Learning (EL) approaches [36]. Alternatives to PdM exist, and they aren't as complicated, such as Balanced K-Star, Multi-Layer Perceptron (MLP), Extreme Learning Machine (ELM), and Transfer Learning (TL). Another area that has been investigated for possible predictive maintenance applications is Deep Convolutional Autoencoders [34], [35], [40], [46]. The diagnostic potential of PdM has not been well investigated, however what little research there is indicates that this is an area that need further investigation [40].

C. Explainable Artificial Intelligence

Complex models have proliferated in sectors including healthcare, banking, and agriculture as a result of the fast developing domains of deep learning (DL) and machine learning (ML). There are serious worries about the models' openness and interpretability due to the complexity that obscures their decision-making processes [23]. This haziness has prompted the search for explainable AI (XAI), an idea that transcends basic transparency to make DL and ML model decision-making comprehensible to humans and machines alike. To build confidence in AI systems, it is important to make their inner workings as transparent as possible. This will allow users to understand how choices are made and will aid in explainability. The need for explainability is multi-faceted, yet it is essential for improving the trustworthiness and comprehension of DL models.

1) Explainability Factors

According to a literature search, there are four main aspects of explainability: data, model, result, and end-user. Problems and opportunities with the data used by

AI algorithms are the emphasis of the data dimension [22]. Further study on the data capabilities in predictive maintenance for Smart Agricultural Facilities (SAF) is needed, since many studies did not evaluate whether the data was enough to provide the insights sought. This highlights the relevance of this topic. Examining the impact of input data on model predictions is the responsibility of the model dimension [22]. A common source of bias is the assumption of feature independence. There were a few of research that looked at both the model and outcome aspects [30, [31], [32], [36], [39], but the majority didn't. A lack of study into the logic underlying individual AI model predictions is shown by the fact that only two studies[34,37] focused on result explainability. Closing this gap might improve AI systems' decision-making and transparency. Research that makes AI systems more accessible to a larger audience is needed, since the end-user dimension, which modifies explanations for non-technical users [47], was mostly ignored in the literature.

2) Ways to Make Things Easy to Understand

After analysing all of the research, six main schools of thought on explainability stood out: (1) local explainability, (2) global explainability, (3) model-specific, (4) model-agnostic, (5) model-centric, and (6) data-centric. Both local and global explainability are important, although the former seeks to shed light on specific predictions and the latter on the model's general behaviour. Despite the fact that two studies investigated both local and global explainability, there is a notable lack of research that just addresses global explainability [33], [41]. On its own, local explainability was the focus of thirteen investigations [30, [31], [32], [34], [35], [36], [37], [38], [39], [40], [42], [43], [44].

While model-agnostic techniques are applicable to several kinds of AI models, model-specific approaches are customised to specific models. While three research concentrated on model-specific strategies, ten employed model-agnostic approaches [30, [31], [32], [34], [36], [40], [42], [43], [44]. No more than two studies have ever used a hybrid strategy [39], [41]. techniques that focus on models examine the input-output linkages inside models, while data-centric techniques place an emphasis on data quality and relevance [47]. There has to be more investigation into data-centric tactics, because all of the studies in the study relied on model-centric techniques.

D. Explainable Artificial Intelligence for Predictive Maintenance

The capacity of SHapley Additive exPlanations (SHAP) to elucidate the effect of characteristics on predictions has made it stand out among the XAI methods used for predictive maintenance, especially in the areas of false alarm reduction [38] and diagnostic interpretation improvement [40], [44]. Although SHAP has many practical uses, its complexity often prevents it from being widely used. Anomaly detection in transportation systems is one area where Local Interpretable Model-agnostic Explanations (LIME) have proven useful in providing localised explanations for predictions [41]. While LIME does a great job of breaking down specific predictions, it doesn't do a very good job of describing the overall model since it just looks at local reasons.

In-depth understanding of the factors that impact predictions is provided by Layer-wise Relevance Propagation (LRP), which is often used in deep learning models [33]. However, LRP is rather model-specific, even if it has proven beneficial in several contexts. Each of the three methods—LIME, SHAP, and ELI5—was shown to have different levels of efficiency and feature attribution [39]. ELI5 offered more understandable explanations, but it was not flexible enough to operate with other models, in contrast to LIME, which was determined to be efficient. One prominent strategy for increasing the generalisability of AI systems, particularly among those without specialised training, is the use of Counterfactual Explanations (CFE), which focus on creating "what-if" scenarios [34], [36].

III.SYSTEM ARCHITECTURE

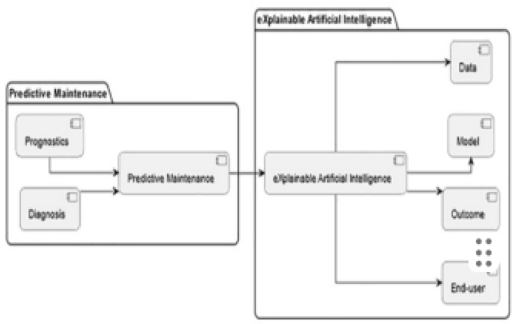

Fig1.System Architecture

Efficient data flow, trustworthy predictive capabilities, and transparent insights for stakeholders are key components of the proposed Explainable Artificial Intelligence (XAI) paradigm for Predictive Maintenance (PdM) in Smart Agricultural Facilities (SAF). Each of the many levels that make up this architecture—artificial intelligence (AI), data processing, and human interaction—

contributes to the system's overall transparency and usefulness.

IV.METHODOLOGY

Data Collection Layer

Collecting data in real-time from the agricultural facility's many sources is the job of the Data Collection Layer. Factors including soil moisture, temperature, and humidity as well as data collected by equipment health sensors are all part of this Internet of Things (IoT) data set. Essential data for predictive maintenance activities is provided by these sensors, which continually monitor vital facility conditions. To reduce latency and ensure that only relevant data is delivered for further analysis, edge devices analyse the data before transmitting it to the cloud. To further enhance the predictions, the system also incorporates data from other sources, such weather forecasts and maintenance records from the past.

Data Preprocessing Layer

The Data Preprocessing Layer is responsible for cleaning, normalising, and extracting features from gathered data. Predictive models are vulnerable to noise, missing values, and errors in raw data. In order to address these challenges, this layer standardises data units, fills in missing values, and extracts important characteristics, such as patterns that indicate equipment wear or possible failures. Machine learning models are trained using preprocessed data to guarantee high-quality input for accurate predictions.

Predictive Maintenance Model Layer

In order to anticipate possible faults and plan maintenance, the system relies on the Predictive Maintenance Model Layer, which applies machine learning and deep learning techniques. This layer makes use of state-of-the-art models such as LSTM networks for sensor data time-series analysis and XGBoost for feature-based predictions. The system is able to anticipate mechanical breakdowns, make suggestions for maintenance tasks, and calculate the remaining useful life (RUL). Within this layer, anomaly detection algorithms aid in the identification of out-of-the-ordinary patterns that may suggest impending breakdown or inefficiency.

Explainability Layer

The predictive maintenance models are made clear and easy to comprehend via the Explainability Layer. Layers like SHAP (SHapley Additive exPlanations), LIME (Local Interpretable Model-agnostic Explanations), and CFE

(Counterfactual Explanations) give light on the model's prediction process. To illustrate the point, SHAP details the factors that had the greatest impact on the failure prediction, such as environmental factors or machine performance measurements. While CFE provides "what-if" scenarios for users to investigate potential outcomes, LIME aids in comprehending specific projections. This layer guarantees that the AI system's predictions are understandable and trustworthy for people with and without technical backgrounds.

Decision Support Layer

The Decision Support Layer is the point of contact between the system and its end users. This layer offers practical insights, such maintenance warnings and suggestions, based on the AI forecasts and their explanations. In the case of impending maintenance requirements, for instance, customers may get warnings based on prediction models and the logic behind them. In addition, the system gives precise maintenance suggestions that include what has to be done and when to do it in order to minimise the likelihood of failure. Furthermore, the layer has a feedback loop that allows users to provide insights that might gradually enhance the model's accuracy.

User Interface Layer

Interacting with the predictive maintenance system is made easy and straightforward with the help of the User Interface (UI) Layer. In a graphical user interface (GUI), dashboards provide data from sensors in real time, insights from predictive analytics, and suggestions for preventative maintenance. Users may also get explanations of specific forecasts, examine the significance of features, and investigate model predictions using the interactive capabilities provided by these dashboards. Stakeholders may access vital information from any location in the building thanks to the system's architecture that works across PCs, tablets, and mobile devices.

V.CONCLUSION

The model for Predictive Maintenance (PdM) in Smart Agricultural Facilities (SAF) using Explainable Artificial Intelligence (XAI) offers a new and strong way to deal with the problems that contemporary farming is having. This approach guarantees openness and confidence in AI-driven judgements while also accurately predicting future failures and maintenance requirements using a combination of sophisticated machine learning algorithms and explainability methodologies. The system's decisions are made accessible and understandable to non-expert users through the integration of technologies like LSTM networks and XGBoost, which provide precise predictions of RUL and anomaly detection. SHAP, LIME, and Counterfactual Explanations (CFE) are examples of explainability methods.

Integrating the system into agricultural facilities is a breeze because to its architecture, which can manage real-time data collecting, preprocessing, and predictive modelling. This boosts operational efficiency and minimises downtime. Timely forecasts and maintenance notifications are also provided via the Cloud/Edge Computing paradigm, which guarantees scalability and low-latency processing. Stakeholders are able to engage with the system and act upon insights produced by AI more easily via the User Interface Layer, which ultimately improves decision-making.

By proving how crucial explainability is for AI systems, this effort has a substantial impact on agricultural AI. It paves the door for more sustainable, efficient, and open agricultural operations by promoting data-driven maintenance methods in SAF. Additional capabilities of the system may be investigated in future studies by integrating data from other modalities, improving explainability methodologies, and enhancing decision-making using Human-in-the-Loop (HITL) systems. This technique revolutionises AI applications in agriculture by tackling important challenges like Fairness, Accountability, and Transparency (FAT).

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