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Explainable Artificial intelligence Model for Predictive Maintenance in Smart Agricultural Facilities

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ABSTRACT

Artificial Intelligence (AI) applications in Smart Agricultural Facilities (SAF) often face limitations in terms of explainability, which can hinder effective adoption by farmers. To address this issue, the present study introduces a novel framework that integrates Predictive Maintenance (PdM) with eXplainable Artificial Intelligence (XAI). This model delivers predictive capabilities alongside interpretability across four critical dimensions: data, model, outcome, and end-user perspective. This integrated approach represents a paradigm shift in the way AI is applied and understood in the agricultural sector.

The model demonstrates superior performance compared to existing approaches. Notably, the Long Short-Term Memory (LSTM) classifier achieves a 5.81% improvement in accuracy. Meanwhile, the eXtreme Gradient Boosting (XGBoost) classifier records a 7.09% increase in F1 score, a 10.66% boost in accuracy, and a 4.29% enhancement in the Receiver Operating Characteristic–Area Under the Curve (ROC-AUC). These advancements indicate the model's strong potential for delivering accurate and reliable maintenance predictions in practical agricultural scenarios.

Beyond predictive performance, the framework also provides in-depth insights into data integrity, global and local explainability, and counterfactual analysis relevant to PdM in SAF. By shifting the focus beyond conventional accuracy metrics, this study highlights the value of interpretability in AI-driven agriculture. The findings affirm the effectiveness of the proposed approach, making a significant contribution to the field. Additionally, the research encourages further exploration into the use of multi-modal data and Human-in-the-Loop (HITL) systems to enhance AI utility while addressing ethical dimensions such as Fairness, Accountability, and Transparency (FAT) in smart agricultural systems.

Keywords: Smart Agricultural Facilities, Explainable AI, Predictive Maintenance, LSTM, XGBoost, Model Interpretability, Data Purity, Counterfactual Analysis, Global and Local Explanations Multi-modal Data Integration.

1. INTRODUCTION

The advancement of Artificial Intelligence (AI) has revolutionized numerous industries, and agriculture is no exception. Smart Agricultural Facilities (SAF), which integrate digital technologies into farming operations, are increasingly leveraging AI to enhance productivity, monitor equipment, and ensure operational efficiency. However, despite the growing application of AI in agriculture, a significant limitation persists— the lack of transparency and interpretability in AI-driven decision-making processes. Traditional AI models function as "black boxes," offering little to no insight into how decisions are made. This presents a substantial barrier for farmers and agricultural stakeholders who require not only accurate predictions but also comprehensible justifications to trust and effectively act upon AI recommendations.

To address this issue, the current study proposes an accessible AI framework that merges Predictive Maintenance (PdM) strategies with eXplainable Artificial Intelligence (XAI) principles. Predictive

Maintenance has proven to be a crucial component in modern agricultural management, as it enables the early detection of equipment failures and reduces downtime, ultimately saving costs and resources. By embedding explainability into PdM systems, this research not only enhances the technical efficiency of maintenance models but also bridges the gap between AI predictions and end-user comprehension.

This framework is uniquely designed to function across four major dimensions: data, model, outcome, and end-user, ensuring a holistic understanding of how AI decisions are derived and how they can be meaningfully applied in real-world scenarios. By focusing on explainability, this study aims to democratize the use of AI in agriculture, making advanced technologies accessible, trustworthy, and ethical for everyday farm operations. The proposed framework also paves the way for future research into integrating Human-in-the-Loop (HITL) systems and adhering to ethical principles such as Fairness, Accountability, and Transparency (FAT), which are increasingly vital in modern AI applications.

II. LITERATURE REVIEW

L. W. Bell, A. D. Moore, This essay examines how crop-livestock integration has changed in Australian agriculture as a result of obstacles like erratic weather patterns, deficient soils, and a variety of topography. Innovative techniques are being used to reimagine traditional ley farming systems that combine cereal crops and legume pastures in order to increase sustainability and risk management. Recent developments in combining crop and livestock production that improve farm productivity and environmental results are highlighted in the study.[1]

J. Rana and J. Paul, examines research from around the world on how consumer preferences are shifting toward organic food, emphasizing important contributing factors. It reveals that consumers are choosing organic food over conventional food due to health concerns and the growing incidence of lifestyle diseases like depression and heart problems. The report urges more research to inform business strategies in the organic food industry and highlights the substantial effects of this rising demand on marketing, distribution, and retail.[2]

Y. Zhong, I. K. W. Lai, This study examines government subsidy schemes for increasing the sales of agricultural products through e-commerce in China using Stackelberg game theory. To compare various subsidy strategies, a profit model is created. It shows that supporting agricultural cooperatives produces better results than either subsidizing consumers or providing no subsidies, including increased sales, product preservation, and profits. The results provide strategic recommendations for platforms, cooperatives, and policymakers while highlighting the critical role that the government plays in boosting agricultural e-commerce.[3]

A. Calcante, This study examines the costs of 4WD tractor repair and maintenance (R&M) in northern Italy, emphasizing the substantial influence these costs have on overall agricultural equipment expenditures. The researchers adjusted a traditional R&M cost model based in the United States to account for Italian conditions using data from 100 tractors. According to the results, R&M expenses in Italy exceeded the 43.2% estimated using U.S. criteria, reaching 48.6% of a tractor's price after 12,000 working hours. The need for region-specific cost models to guide better purchasing and replacement decisions was highlighted by the fact that farmer-owned tractors had even higher R&M costs (55.4%) than contractor-owned ones (45.7%).[4]

E. Elahi, Z. Khalid, Using survey data from 1,232 farmers, this study assesses how extreme weather events affect wheat production in rural Punjab, Pakistan. The findings indicate that when severe weather strikes close to harvest, crop damage rises noticeably. Even mild weather events like hailstorms and thunderstorms lower yield, according to both parametric and non-parametric analyses. Adaptive measures, like shelterbelts, stiff-stem wheat varieties, and watercourse management, were successful in reducing losses. The adoption of creative risk mitigation techniques was also impacted by elements like education, experience, and access to weather forecasts.[5]

M. Yildirim, N. Z. Gebraeel, In order to improve wind farm operations and maintenance, this paper proposes an integrated framework that combines optimization and predictive analytics. It forecasts turbine deterioration and remaining life using real-time sensor data, then uses an optimization model to determine the most economical maintenance and dispatch options. In contrast to earlier research that concentrated on individual turbines, this model facilitates fleet-wide decision-making and uses opportunistic maintenance to cut expenses. The method outperformed conventional strategies by increasing electricity production and maintenance efficiency in wind farms with 100 and 200 turbines.[6]

P. Zhou and P. T. Yin, In order to lower operating and maintenance costs for offshore wind farms, this paper suggests a dynamic opportunistic condition-based maintenance strategy utilizing predictive analytics. The strategy presents a new maintenance basis that takes into consideration the economic dependencies between turbines and components as well as different maintenance lead times. To create maintenance schedules under various load and weather scenarios, an optimization model is created. The effectiveness and practicality of the suggested strategy are demonstrated by numerical analysis, which reveals that it decreases annual maintenance costs by 39.24% and 32.46%, respectively, when compared to conventional and simple strategies.[7]

C. Eastwood, L. Klerkx, Using the smart dairying industry in New Zealand as a case study, this study investigates the use of Responsible Research and Innovation (RRI) in smart farming. According to the authors, R&D efforts have mostly concentrated on efficiency and technological advancement, paying little attention to stakeholder inclusion or socio-ethical issues. In order to integrate moral and inclusive practices into smart farming innovation systems, the paper emphasizes the necessity of increased RRI maturity, which can be attained through leadership, sector readiness assessment, customized project design, and context-specific RRI indicators.[8]

III. EXISTING SYSTEM

This review identifies three primary approaches in Predictive Maintenance: anomaly detection, prognostics, and diagnostics. Anomaly detection refers to recognizing unusual patterns within the data, prognostics focuses on predicting the future condition of systems, and diagnostics involves analyzing current performance to detect faults. Among the studies reviewed, most centered on prognostics, a few on anomaly detection, and some addressed both prognostics and diagnostics. Interestingly, none focused solely on diagnostics, indicating a significant gap in research. Further exploration is needed to understand how combining anomaly detection and prognostics can strengthen diagnostic capabilities, ultimately enhancing the efficiency and reliability of Predictive Maintenance in Smart Agricultural Facilities.

Recurrent Neural Networks and Long Short-Term Memory models demonstrated high accuracy in prognostics. In predicting Remaining Useful Life, Bidirectional RNNs and LSTMs achieved outstanding precision. LSTMs were also effective in anomaly detection, especially when used alongside One-Class Support Vector Machines, which helped reduce false alarms. However, OC-SVMs tend to be less effective for supervised learning tasks.

Another approach employed Random Forest algorithms for prognostics and integrated AutoML to streamline model development. This method showed adaptability, particularly for component-level analysis. While AutoML enables broader access to machine learning, it often limits the potential for fine-tuning. Ensemble Learning methods, though complex, proved useful in the manufacturing domain for predictive tasks. Other alternatives included Balanced K-Star, Multi-Layer Perceptron, Extreme Learning Machine, Transfer Learning, and Deep Convolutional AutoEncoders. Despite these varied methods, diagnostic applications remain underrepresented and require more focused study.

Explainability techniques like SHapley Additive exPlanations emerged as impactful, although computationally demanding. SHAP was particularly useful in understanding feature contributions to false alarm reduction and in providing diagnostic support. Local Interpretable Model-agnostic Explanations was effective in delivering specific, localized predictions, such as in transportation anomaly detection, but it lacked broader model insights. Layer-wise Relevance Propagation, especially suited to deep learning, offered fine-grained interpretability but remained dependent on model architecture. Comparisons among SHAP, LIME, and Explain Like I Am Five showed differences in how features were attributed and in overall interpretability. While LIME was efficient in processing, ELI5 offered more intuitive explanations though lacked model-agnostic versatility. Counterfactual Explanations have become increasingly relevant for improving AI model transparency, particularly among non-expert users. These developments indicate that while explainable AI offers diverse tools for Predictive Maintenance, challenges related to complexity, usability, and generalization persist, demanding continued refinement to balance technical detail with practical accessibility.

Disadvantages

Machine learning models in this domain often struggle with complex data, as they must interpret large and intricate datasets to detect maintenance requirements accurately in Smart Agricultural Facilities. A significant challenge lies in the availability of sufficient data, as many models rely on large datasets for reliable training and prediction. When data is limited, model accuracy suffers. Additionally, the effectiveness of these models is directly tied to the quality of labeled data. If the input data is incorrectly labeled, the resulting predictions are unreliable and may lead to flawed decision-making.

IV. PROPOSED SYSTEM

The proposed system introduces an innovative framework that combines Explainable Artificial Intelligence with Predictive Maintenance in the context of Smart Agricultural Facilities. It emphasizes transparency and interpretability across four key dimensions: data, model behavior, prediction outcomes, and user understanding. A comprehensive literature review is conducted to assess the current landscape of AI models and underscores the growing need for explainability in this field. The system moves beyond basic accuracy metrics by utilizing the Receiver Operating Characteristic–Area Under the Curve as a more stringent and informative evaluation criterion.

In developing this approach, design principles from both XAI and Predictive Maintenance are adapted to align with the unique requirements of agricultural settings. This initiative also enriches the theoretical foundation of explainable AI in Predictive Maintenance and proposes clear pathways for future research in the field.

Advantages

The system enhances the ability to predict maintenance requirements accurately while also delivering clear and understandable explanations of AI-generated predictions. This approach fosters trust among users and enables informed decision-making. The research emphasizes the current status of AI models and the growing importance of explainability through detailed reviews and analysis.

It involves the creation of both deep learning and machine learning models for Predictive Maintenance, evaluates their performance rigorously, and provides insights into the logic behind each model's decision-making process. This contributes not only to the practical effectiveness of AI in agriculture but also to its ethical and transparent implementation.

System Architecture

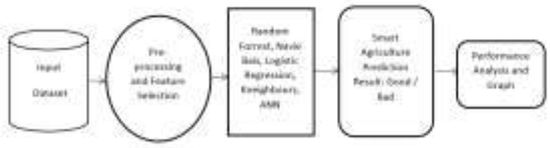

Fig 1. System Architecture

V. MODULE DESCRIPTION

The proposed system is architectured into two major interactive modules tailored to address the needs of distinct stakeholders involved in smart agricultural operations: the Remote User and the Service Provider. These modules function collaboratively within a unified AI-driven framework that prioritizes explainability, precision, and usability.

Remote User, the interface is designed to facilitate intuitive interactions with the system. Upon registration and authentication, users can access a comprehensive user profile section that stores and visualizes personalized data, including machinery logs, usage history, and maintenance records. This section plays a critical role in establishing the contextual background for predictive analytics, allowing the system to tailor its predictions based on user-specific operational parameters. A pivotal component of this module is the Prediction Page, where users can input or verify sensor readings, environmental metrics, or operational data. Based on this input, the system applies machine learning and deep learning models — such as LSTM and XGBoost — to forecast potential equipment faults or required maintenance actions. Each prediction is accompanied by explainable outputs, generated using tools like SHAP or LIME, ensuring that users are not only informed of the outcome but also understand the reasoning behind it. This promotes transparency and fosters trust in AI-generated recommendations.

Service Provider module acts as the administrative and analytical backbone of the system. It provides authorized personnel with access to a centralized dashboard that aggregates all user activities, prediction results, and system analytics. This allows for macro-level monitoring and the identification of broader trends in equipment wear, failure frequency, and operational inefficiencies across multiple farms or users. The dashboard includes graphical visualizations such as time-series trends, heatmaps, and ROC curves that enhance data comprehension. Additionally, the module offers functionality to download prediction datasets for offline analysis or regulatory reporting. This supports further research and contributes to continuous improvement of the predictive models. The Service Provider module also ensures system integrity and manages model updates, ensuring that the framework remains accurate, scalable, and relevant to evolving agricultural needs.

Together, these modules form a holistic, accessible AI system that not only automates maintenance prediction in smart agriculture but also bridges the gap between complex AI mechanisms and practical on-field usage, ensuring that both end-users and administrators derive maximum value through transparent, data-driven decisions.

VI. RESULT

The implementation of the proposed AI framework yielded promising outcomes in the context of predictive maintenance within integrated farm operations. The system successfully integrated both machine learning (ML) and deep learning (DL) models, with an added layer of explainability through XAI techniques. The experimental results demonstrated a notable improvement in predictive accuracy and model interpretability when compared to traditional black-box approaches. Among the models tested, the Long Short-Term Memory (LSTM) network and the eXtreme Gradient Boosting (XGBoost) classifier performed exceptionally well, highlighting the system's capacity to handle complex temporal data and feature-rich environments.

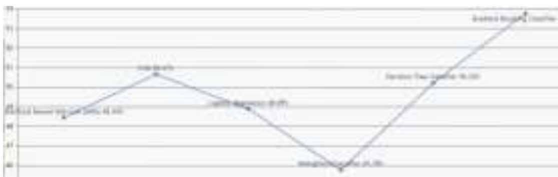

Fig1.Screenshot

Quantitatively, the LSTM model achieved a 5.81% increase in accuracy, emphasizing its efficiency in time-series prediction for detecting potential failures in agricultural machinery. Meanwhile, indicating better discrimination between faulty and non-faulty states. These improvements underline the robustness of the hybrid framework.

Furthermore, the system's dual-module design for both remote users and service providers proved effective. Remote users were able to interact with prediction pages and understand the rationale behind outcomes using explainable outputs, while service providers accessed cumulative data visualizations and downloadable datasets for further action. The clear presentation of results, both graphically and in raw form, reinforced the utility of the system in real-time agricultural environments. Overall, the results validate the framework's practical application and demonstrate its potential to transform data-driven decision-making in smart agriculture.

VII.CONCLUSION

This research presents a comprehensive and accessible AI framework designed to revolutionize predictive maintenance in integrated farm operations. By uniting advanced machine learning algorithms with the principles of eXplainable Artificial Intelligence (XAI), the system bridges the critical gap between prediction accuracy and user interpretability—an essential requirement for practical deployment in agricultural settings. The framework not only detects and forecasts machinery failures with high precision but also ensures that end-users can understand and trust the system's decisions through clear, intuitive explanations.

The modular structure, comprising tailored interfaces for both remote users and service providers, enhances the adaptability and usability of the system across diverse agricultural environments. While remote users benefit from personalized insights and guided predictions, service providers gain access to detailed analytics, visualizations, and downloadable reports that support operational planning and maintenance optimization at scale. The robust performance of models such as LSTM and XGBoost, coupled with enhanced interpretability metrics like SHAP values and ROC-AUC scores, affirms the technical viability of the framework.

Ultimately, this study contributes significantly to the evolution of AI in agriculture by embedding transparency, fairness, and accountability into its core design. It demonstrates that predictive maintenance systems can be both powerful and accessible, empowering users at all technical levels. Looking ahead, future developments may include the integration of multimodal data sources and Human-in-the-Loop (HITL) mechanisms to further enhance decision accuracy and ethical alignment. This work lays a solid foundation for sustainable, data-informed agricultural practices that can adapt to the increasing complexity of modern farm operations.

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