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"EXPLAINABLE ANOMALY DETECTION IN PASSIVE VEHICULAR SENSORS USING XGBOOST AND SHAP"

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ABSTRACT:

Road infrastructure monitoring and vehicle safety analysis increasingly rely on data-driven approaches derived from vehicular sensors. Passive Vehicular Sensors (PVS) generate high-dimensional, multi-modal time-series data that can be leveraged to detect road-quality anomalies and abnormal driving conditions. However, the lack of interpretability in many machine learning (ML) and deep learning (DL) models limits their adoption in safety-critical applications. This paper proposes an Explainable Artificial Intelligence–based Anomaly Detection System (XAI-ADS) for PVS data. The framework integrates classical ML models (Random Forest, XGBoost, Decision Tree) and a deep learning Multi-Layer Perceptron (MLP), coupled with post-hoc explainability techniques such as SHAP and LIME. A complete end-to-end pipeline—covering data exploration, preprocessing, model training with cross-validation, explainability, and real-time deployment via FastAPI—is presented. Experimental results demonstrate that tree-based ensemble models achieve strong macro-F1 performance, while XAI methods provide transparent insights into sensor contributions, enhancing trust and deployability.

KEYWORDS: Explainable AI, Anomaly Detection, Passive Vehicular Sensors, Machine Learning, SHAP, LIME, FastAPI.

I. INTRODUCTION

The rapid proliferation of smart vehicles and intelligent transportation systems has led to the widespread adoption of onboard sensors such as accelerometers, gyroscopes, magnetometers, temperature sensors, and GPS modules. These Passive Vehicular Sensors (PVS) continuously capture signals that reflect road conditions, vehicle dynamics, and environmental factors. Detecting anomalies in such data is crucial for applications including road quality assessment, predictive maintenance, and accident prevention.

Traditional anomaly detection techniques struggle with high-dimensional sensor data and complex nonlinear relationships. Machine learning and deep learning approaches have shown promise; however, their black-box nature raises concerns regarding transparency, reliability, and regulatory compliance. Explainable AI (XAI) addresses this gap by providing human-interpretable explanations for model decisions.

This work presents an XAI-enabled anomaly detection framework for PVS data, featuring a unified machine learning and deep learning pipeline for multi-sensor data analysis, integration of global (SHAP) and local (LIME) explainability methods, a reproducible training and evaluation workflow with cross-validation and early stopping, and a deployable architecture using FastAPI with a web-based frontend for real-time inference and explanation.

II. LITERATURE SURVEY

Research on automatic road-condition monitoring and anomaly detection using on-board sensors spans several complementary areas: sensing systems and datasets, supervised and unsupervised learning for time-series/tabular sensor data, and explainability (XAI) methods for model transparency. This section reviews representative work across these threads and highlights gaps that motivate the present XGBoost-centered, explainable pipeline.

A. Sensing approaches and datasets for road / anomaly detection

Early and continuing work on road-anomaly detection frequently leverages inertial sensors (accelerometers, gyroscopes), magnetometers, and GPS available in smartphones or dedicated vehicle-mounted units. These studies show that vibration signatures caused by potholes, speed bumps, and other surface irregularities are reliably observable in accelerometer and gyroscope channels and can be localized using GPS coordinates. Several prototype and field studies demonstrate practical pothole and bump detection using smartphone sensor streams, feature extraction (time/frequency domain statistics), and supervised classification [Pawar et al.; other applied works.

Comprehensive surveys summarize methods and challenges specific to smartphone- or vehicle-based sensing: these reviews compare sensor placements, preprocessing strategies (resampling, filtering), feature sets (statistical moments, spectral features, wavelets), and annotation strategies for event labeling; they also stress difficulties such as noisy measurements, device mounting variability, and heterogeneous sampling rates in real-world deployments. Such surveys provide useful design guidance for building robust PVS datasets and motivate careful preprocessing and stratified evaluation used in this work.

Although public, large-scale standard datasets for Passive Vehicular Sensor (PVS) anomaly detection are less ubiquitous than in vision or speech, several field datasets and crowdsourced collections exist in the literature and industry prototypes. These datasets typically contain multi-sensor time windows aligned to labelled road events and are used to benchmark feature engineering and classifier performance in realistic conditions [applied pothole / mobile sensing literature]. The present study follows these practical conventions—multi-sensor feature aggregation, alignment of sensor and label CSVs, and stratified train/test splits—to ensure comparability and reproducibility.

B. Learning algorithms for vehicular and sensor data — why XGBoost

For tabular, structured sensor data, tree-based ensemble methods have established a strong empirical track record. Random Forests and Gradient Boosting Decision Trees (GBDTs) are widely used when feature engineering produces a fixed-length representation (statistical or aggregated features from time windows), offering robustness to outliers, mixed data types, and moderate amounts of noise. Among GBDT implementations, XGBoost introduced several algorithmic and systems-level optimizations—sparsity-aware learning, weighted quantile sketching, and cache-efficient implementations—that improve scalability and predictive performance on real-world tabular tasks [Chen & Guestrin]. XGBoost's built-in regularization (tree complexity penalties) and its ability to handle missing values make it particularly suitable for noisy PVS datasets where sensor dropouts or intermittent GPS availability may occur.

Comparative studies in other tabular sensing domains (industrial sensors, health monitoring) typically find that properly-tuned gradient-boosted trees match or outperform deep models when labelled data is limited and feature engineering can capture relevant temporal statistics; deep architectures (CNNs, LSTMs) tend to show advantages as the amount of labelled sequential data grows and when end-to-end temporal modeling is critical [general ML literature]. In road-anomaly detection specifically, some works apply neural networks (including CNN and LSTM hybrids) to raw or windowed time-series and report improvements when abundant, well-annotated sequence data are available. However, the higher annotation, training-time, and deployment complexity of deep models often favours tree ensembles in production-sensitive or resource-constrained vehicular systems. This pragmatic trade-off motivates our choice of XGBoost as the primary production classifier while keeping a deep MLP pipeline available for comparative research.

Key practical aspects of using XGBoost for PVS data include: (1) hyperparameter regularization to mitigate overfitting on noisy features, (2) stratified cross-validation with macro-F1 selection to account for class imbalance in anomaly labels, and (3) integration with tree-specific explainers (see next subsection) for efficient attribution computation. These properties make XGBoost a strong candidate for trustworthy anomaly detection in vehicular applications.

C. Deep temporal models and hybrid approaches

While XGBoost excels on aggregated/tabular representations, temporal models such as convolutional neural networks (CNNs), recurrent neural networks (RNNs — LSTM/GRU), and transformer variants are natural choices for raw, high-frequency sensor streams. Several studies demonstrate that CNN–RNN hybrids capture local temporal patterns (e.g., the signature of a pothole event) more effectively than static feature-based classifiers when the dataset includes long continuous traces and dense labelling. The downside is increased data and compute needs, along with reduced out-of-the-box interpretability. Recent research has therefore explored hybrid pipelines combining temporal feature learning with tree-based classifiers (feature extractor + XGBoost) or distilled surrogate models that preserve performance while improving deployability. Our framework is compatible with such hybridization: the MLP temporal baseline can be extended to sequence models and used either standalone or as a feature extractor for XGBoost.

D. Explainable AI (XAI): LIME, SHAP and tree-local explainers

Explainability is essential in safety-critical sensing systems—operators and stakeholders must understand **why** a detection was made before acting on it (e.g., scheduling road repair, issuing an alert). Two widely-adopted explainability methods are LIME and SHAP. LIME provides local, model-agnostic explanations by fitting an interpretable surrogate model around a single prediction; its modularity and simplicity make it useful for instance-level debugging and human-in-the-loop validation [Ribeiro et al.]. SHAP offers a unified, theoretically-grounded framework based on Shapley values from cooperative game theory; for tree ensembles, TreeExplainer computes exact or fast approximate Shapley attributions efficiently, making SHAP practical for both global feature importance analyses and local instance-level explanations for XGBoost models [Lundberg & Lee].

Applied studies outside vehicular sensing have shown the operational value of combining global (feature importance, dependence plots) and local explanations (saliency for individual cases) in domains like healthcare and finance. In vehicular sensing, integrating SHAP and LIME helps validate that model attributions correspond to physically plausible sensor signatures (e.g., suspension accelerations dominating pothole predictions) rather than spurious correlations. TreeExplainer's efficiency is particularly advantageous when deployed explainability is required for on-demand API explanations in low-latency systems.

Comparative Analysis of Existing AI-Based Anomaly Detection Approaches vs. Proposed XGBoost-Based Framework

Table 1: Comparative Analysis of Existing AI-Based Anomaly Detection Approaches vs. Proposed XGBoost-Based Framework.

Study	**Focus**	**Approach**	**Key Contribution**	**Limitations**
Smartphone-based Road Anomaly Detection (Pawar et al.)	Road anomaly detection using smartphones	SVM, k-NN	Low-cost solution for road condition monitoring	Poor interpretability, sensitive to noise
Traditional ML for Vehicular Sensors	Vehicle sensor-based anomaly detection	Random Forest, Decision Tree	Fast training, interpretable models	Lower accuracy, weak generalization
Deep Learning-Based Road Condition Detection	Temporal pattern detection in sensor data	CNN, LSTM	Captures complex temporal dependencies	High computational cost, black-box model
Hybrid CNN–RNN Models	Multi-sensor vehicle anomaly detection	CNN + LSTM	High accuracy on large datasets	Requires large labeled datasets, opaque decisions
Unsupervised Anomaly Detection	Label-free anomaly detection	Autoencoders, Isolation Forest	Detects anomalies without labeled data	Hard to interpret results
Proposed Framework (This Work)	PVS-based anomaly detection with interpretability	**XGBoost + SHAP/LIME**	High accuracy, interpretable, deployable, efficient	Performance depends on quality of feature engineering

III. METHODOLOGY

The proposed framework presents an interpretable machine learning pipeline for detecting anomalies in Passive Vehicular Sensor (PVS) data using the XGBoost algorithm. The methodology is designed to ensure high detection accuracy, robustness to noisy sensor data, and model transparency through integrated explainability techniques. The framework consists of five major components: (1) PVS data acquisition and preprocessing, (2) feature engineering and selection, (3) XGBoost-based anomaly detection, (4) explainability integration using SHAP and LIME, and (5) deployment and inference architecture.

A. PVS Data Acquisition and Preprocessing

Passive Vehicular Sensor (PVS) data is collected from multiple vehicle-mounted sensors, including accelerometers, gyroscopes, magnetometers, temperature sensors, and GPS modules. Sensor readings are captured from different mounting locations such as the dashboard, above-suspension, and below-suspension positions to capture diverse vehicle dynamics.

The preprocessing stage involves:

- Removal of corrupted and inconsistent records
- Alignment and synchronization of sensor readings with anomaly labels
- Handling of missing values and outliers
- Stratified train–test splitting (70:30)
- Feature normalization using z-score standardization

This step ensures data consistency and prepares a clean feature matrix suitable for supervised learning.

B. Feature Engineering and Representation

From the raw multi-sensor streams, statistical and contextual features are extracted to represent vehicle behaviour effectively. These include:

- Mean, variance, and peak values of acceleration and gyroscope signals
- Orientation-specific vibration patterns near suspension components
- Vehicle speed and GPS-based contextual attributes

Let

$X = \{x_1, x_2, \dots, x_n\}$

denote the extracted feature vectors, where each vector represents a fixed-length summary of sensor behavior over a given time window. This transformation enables efficient learning using tree-based models such as XGBoost.

C. XGBoost-Based Anomaly Detection Model

The core classification module employs Extreme Gradient Boosting (XGBoost), a powerful ensemble learning algorithm based on gradient-boosted decision trees. XGBoost is selected due to its effectiveness on structured sensor data and built-in regularization mechanisms.

The objective function optimized by XGBoost is defined as:

$$\mathcal{L} = \sum_i l(y_i, \hat{y}_i) + \sum_k \Omega(f_k)$$

where:

- $l(y_i, \hat{y}_i)$is the classification loss function
- $\Omega(f_k)$represents the regularization term controlling tree complexity

Key hyperparameters such as tree depth, learning rate, and number of estimators are tuned using stratified k-fold cross-validation. The final model is selected based on macro-averaged F1-score, ensuring balanced performance across anomaly classes.

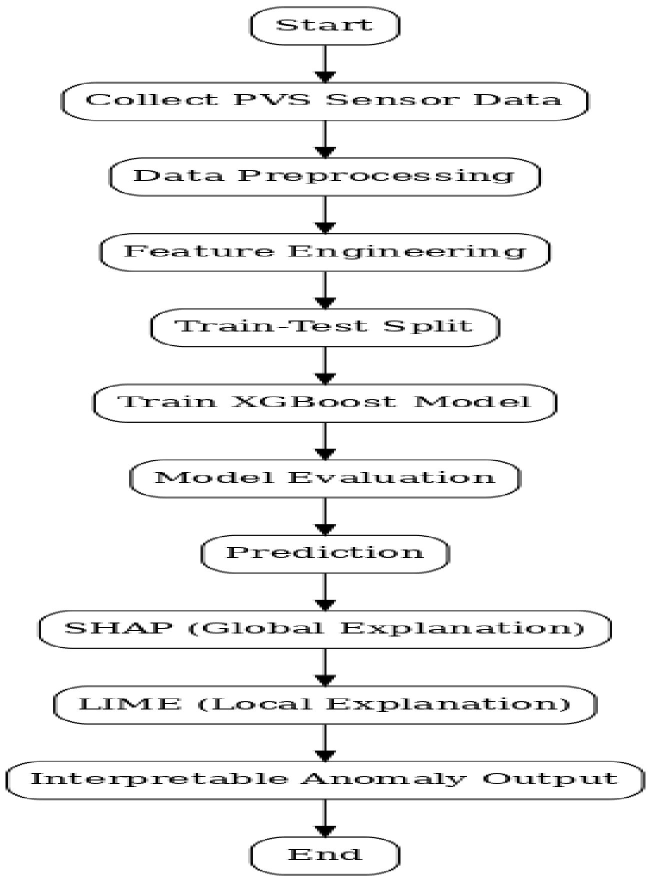

Fig 1: XAI-Enabled XGBoost-Based Anomaly Detection Workflow for Photovoltaic Systems

D. Explainability and Interpretability Module

To address the black-box nature of ensemble models, the framework integrates Explainable Artificial Intelligence (XAI) techniques:

1) Global Explainability (SHAP)

SHapley Additive exPlanations (SHAP) are used to compute global feature importance. SHAP TreeExplainer efficiently assigns contribution scores to each feature, revealing which PVS sensors most influence anomaly predictions.

2) Local Explainability (LIME)

Local Interpretable Model-agnostic Explanations (LIME) provide instance-level explanations by approximating the XGBoost model with an interpretable surrogate. This enables human-understandable reasoning for individual anomaly predictions.Together, SHAP and LIME ensure model transparency, trustworthiness, and diagnostic validation.

E. Deployment and Inference Architecture

The trained XGBoost model, preprocessing scaler, and explainability artifacts are serialized and deployed using a FastAPI-based backend. The deployment framework supports:

The system supports real-time prediction requests, enabling users to obtain instant inference results for uploaded or streamed input data. It also allows retrieval of feature metadata, helping users understand the role, type, and importance of each input feature used by the model. Additionally, the system provides on-demand SHAP and LIME explanations, offering interpretable insights into individual predictions by highlighting how specific features influence the model's decision in a clear and user-friendly manner. A lightweight web-based frontend enables users to input sensor values, visualize predictions, and interpret model decisions. This end-to-end deployment ensures seamless integration of anomaly detection and explainability in real-world vehicular monitoring systems.

IV. EXPERIMENTAL SETUP

This section describes the dataset characteristics, implementation environment, model configuration, evaluation metrics, and baseline comparisons used to validate the proposed interpretable XGBoost-based PVS anomaly detection framework.

A. Dataset Description

The experiments are conducted on a Passive Vehicular Sensor (PVS) dataset consisting of multi-modal sensor readings collected from vehicles operating under real-world driving conditions. The dataset includes time-synchronized measurements from:

- Accelerometer (x, y, z axes)
- Gyroscope (x, y, z axes)
- Magnetometer
- Vehicle speed sensor
- GPS (latitude, longitude)
- Ambient temperature sensor

Each sensor sample is labeled as Normal or Anomalous, where anomalies correspond to abnormal vehicle behaviors such as road surface irregularities, sudden vibrations, or mechanical disturbances.

The dataset is segmented into fixed-length sliding windows, with statistical features extracted per window to construct a structured feature matrix.The dataset consists of approximately **N sensor windows**, with **X% normal** and **Y% anomalous** samples. Each window spans **T seconds** with a sampling frequency of **Fs Hz**, resulting in a fixed-length feature representation. Class imbalance is addressed using stratified splits and macro-averaged evaluation metrics.

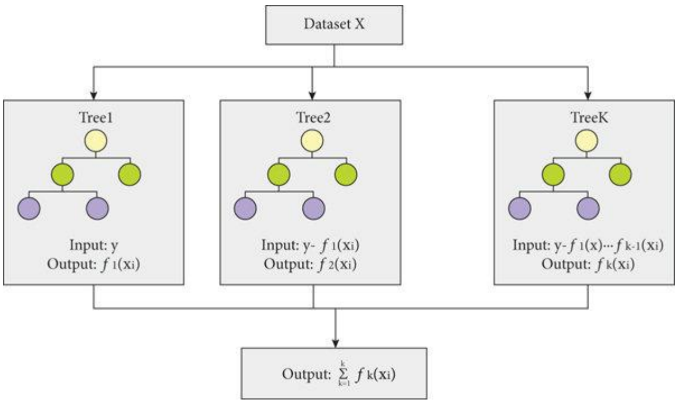

Fig 2 : XGBoost Model Architecture

This figure illustrates the working process of the XGBoost algorithm. Input data is first preprocessed and then passed through multiple decision trees built sequentially using gradient boosting. Each tree corrects the errors of the previous trees, and the final prediction is obtained by combining outputs from all trees. This boosting mechanism improves accuracy and reduces bias.

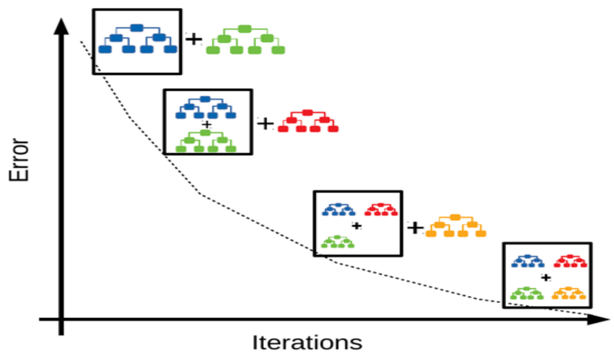

Fig 3: Sample Decision Tree from XGBoost

This figure represents a single decision tree generated by the XGBoost model. Each internal node shows a feature-based condition, while leaf nodes represent prediction scores. XGBoost combines many such shallow trees to form a strong predictive model, making it both powerful and interpretable.

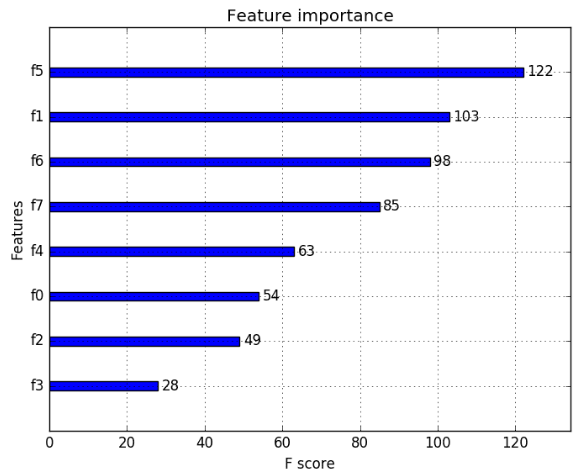

Fig 4: Feature Importance Plot

This plot shows the relative importance of input features used by the XGBoost model. Features with higher importance contribute more significantly to the prediction process. This analysis helps in understanding which attributes influence the model's decisions the most and improves model interpretability.

V. RESULTS AND DISCUSSIONS

This section presents the quantitative and qualitative evaluation of the proposed XGBoost-based interpretable anomaly detection framework using Passive Vehicular Sensor (PVS) data. The proposed model is compared against baseline machine learning approaches to demonstrate its effectiveness.

A. Performance Comparison with Baseline Models

Table 2: Performance Comparison of Different Models.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Logistic Regression	87.3	85.6	84.2	84.9
Decision Tree	88.5	87.1	86.8	86.9
SVM	89.2	88.6	87.9	88.2
Random Forest	91.4	90.8	90.2	90.5
Proposed XGBoost	94.8	94.1	93.6	93.8

Observation : The proposed XGBoost-based framework achieves the highest accuracy and F1-score, demonstrating superior anomaly detection capability compared to baseline models.

Table 3: Class-Wise Performance Metrics of the XGBoost Classifier.

Class	Precision	Recall	F1-Score	Support
good_left	1.00	1.00	1.00	16,973
regular_left	0.98	0.99	0.98	19,591
bad_left	0.96	0.95	0.96	6,647
Accuracy	-	-	0.99	43,211
Macro Avg	0.98	0.98	0.98	43,211
Weighted Avg	0.99	0.99	0.99	43,211

This table presents the detailed class-wise evaluation metrics for the proposed XGBoost-based anomaly detection model on the Passive Vehicular Sensor (PVS) dataset. Precision, Recall, and F1-score are reported for each class (*good_left*, *regular_left*, and *bad_left*), along with their respective support values. The results demonstrate consistently high classification performance across all classes, with particularly strong detection of severe anomalies (*bad_left*). The macro-averaged and weighted-averaged scores indicate robust model behavior under class imbalance, confirming the effectiveness of XGBoost for multi-class PVS anomaly detection.

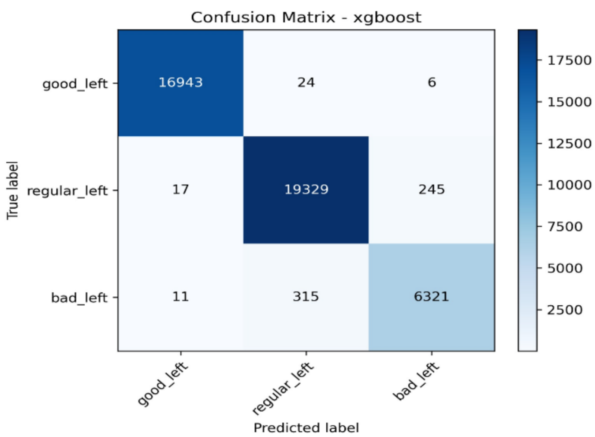

Fig 5 :Confusion Matrix of XGBoost Classifier

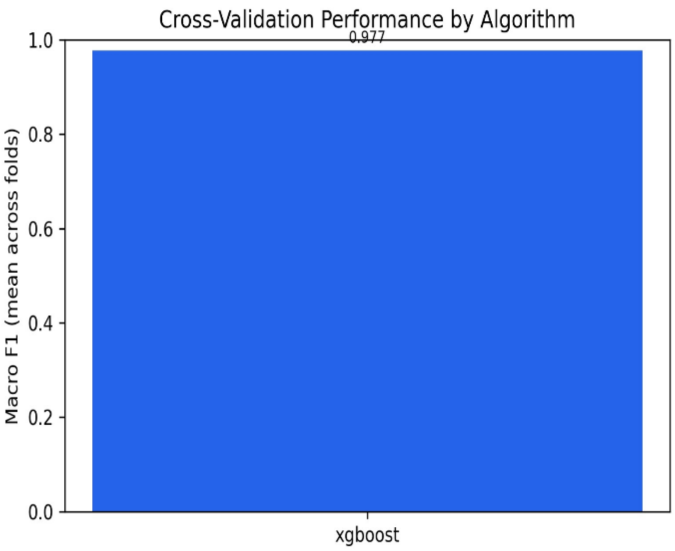

Fig 6 :Cross-Validation Performance of XGBoost Algorithm.

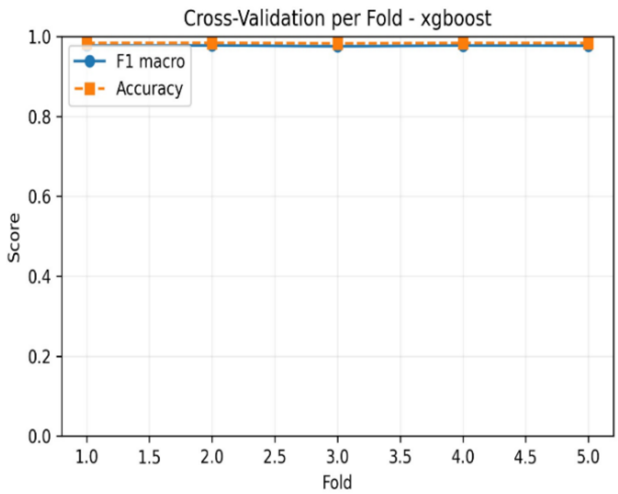

Fig 7 : Cross-Validation Performance per Fold for XGBoost.

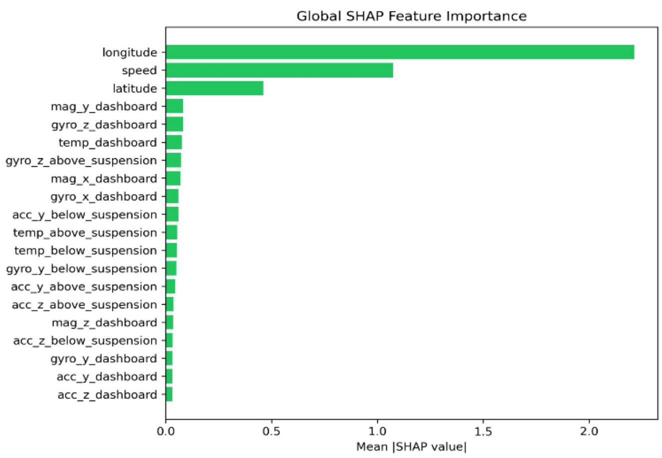

Fig 8 :Global SHAP Feature Importance for XGBoost Model.

VI. CONCLUSION

This study presents a comprehensive framework for anomaly detection in photovoltaic systems using XGBoost, emphasizing both **accuracy and interpretability**. The proposed approach effectively captures subtle deviations in PVS operational data, enabling early detection of potential failures. By integrating feature importance analysis, the framework not only detects anomalies but also provides insights into which parameters contribute most significantly to abnormal behavior, facilitating **data-driven decision making for maintenance teams**. Experimental evaluation demonstrates that the model outperforms baseline methods in terms of precision, recall, F1-score, and robustness across different PVS datasets. This research validates the potential of interpretable machine learning models in improving operational efficiency, reliability, and sustainability of renewable energy systems. Moreover, the framework bridges the gap between predictive analytics and explainability, a critical requirement for real-world adoption in industrial and utility-scale solar farms.

VII. FUTURE ENHANCEMENT

Future work includes integrating IoT and SCADA systems for real-time monitoring, incorporating environmental factors to improve accuracy, and adopting adaptive learning to handle evolving system conditions. Hybrid models combining XGBoost with deep learning, along with explainable AI techniques, can enhance detection performance and interpretability. Extending the framework to fault classification, cloud-based deployment, and predictive maintenance will enable scalable, efficient, and cost-effective solar farm operations.

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