Proceedings of Machine Learning Research 319:278–292, 2026 IndabaX Nigeria 2026

Benchmarking Classification Performance for Binary-Class Fault Detection Under Real-World Imbalanced Data Conditions

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Editor: Sakinat Folorunso, Roseline Ogundokun, and Francisca Oladipo

Abstract

Predictive Maintenance (PdM) has emerged as a critical strategy for improving operational efficiency in Nigeria's manufacturing sector by enabling early detection of equipment faults before failures occur. Traditional reactive maintenance results in high operational costs and unplanned breakdowns. Additionally, real-world industrial datasets are often characterised by significant class imbalance, where fault conditions are far less frequent than normal operating states, posing a major challenge to machine learning classifiers. This study addresses the gap in predictive maintenance implementation by comparing machine learning algorithms and proposing an ensemble architecture for fault prediction in rotating electromechanical machinery, specifically turbines, pumps, and compressors. Utilizing a dataset of 7,672 real-time sensor measurements, four models are benchmarked: Logistic Regression, Random Forest, Support Vector Machines (SVM), and XGBoost. Beyond standard benchmarking, this study proposes a stacking ensemble architecture that combines SVM, Random Forest, and XGBoost as heterogeneous base learners under a Logistic Regression meta-learner. Our results demonstrate that AI-driven maintenance is highly effective, with the stacked ensemble learner emerging as the superior model, achieving an accuracy of 98.37% and an F1-score of 91.35%. These findings establish an empirical foundation for adopting intelligent, data-driven operations aligned with Industry 4.0 principles in Nigerian industrial settings.

Keywords: Predictive Maintenance, Machine Learning, Industry 4.0, Fault Detection, Rotating Machinery, Nigeria Manufacturing

1. Introduction

In Nigeria's competitive manufacturing sector, maintenance management efficiency directly impacts production rates and operational profitability, as equipment uptime directly determines production capacity and cost efficiency (Pech et al., 2021). Traditional reactive maintenance, repairs conducted only after failures occur, results in high operational costs, increased downtime, extravagant resource utilisation, production inefficiencies, and unplanned breakdowns (Ayeni, 2025). This reactive approach is economically unsustainable for competitive manufacturers (Okpala et al., 2025). Planned preventive maintenance emerged to address these limitations, utilizing scheduled servicing and inspections to prevent failures (Erbiyik, 2022). Despite reduced failure rates, preventive maintenance has a critical flaw; fixed schedules often require maintenance before equipment actually needs it, wasting resources.

Predictive Maintenance (PdM) uses sensors present in the industrial equipment to collect real-time data on set parameters. This data is analyzed to identify patterns to predict failures in the equipment before they occur (Akinbolajo, 2021). The integration of PdM into the industrial sector continues to offer numerous benefits which have proven useful for long-term production and operational planning (Achouch et al., 2022). Firstly, it increases the reliability of these machines by extending their lifespan and enhancing overall efficiency (Patel, 2021). Unplanned downtime and costs are also reduced through the application of PdM. Additionally, maintenance schedules are optimized to ensure equipment reliability, staff safety, and regulatory compliance (Chowdhury et al., 2021). However, traditional PdM faces a critical limitation: manual analysis of sensor data becomes impractical at scale. While PdM proves to be beneficial compared to traditional maintenance methods, the human analysis of high-volume sensor data is time-consuming, error-prone, and impractical for facilities operating thousands of machines simultaneously (Kumar, 2024). The emergence of Artificial Intelligence (AI)-driven PdM fused with Internet of Things (IoT) proffers a solution through real-time data analysis.

Artificial Intelligence (AI), with the integration of IoT for data collection, improves predictive maintenance strategies by leveraging the power of processing big data. IoT interfaces machines and sensors to create an interconnected system that extensively collects data on parameters like temperature and vibration for real-time monitoring of equipment conditions (Abbas, 2024). AI algorithms process real-time sensor data without human intervention, detecting patterns and anomalies that manual analysis would miss, thereby drastically reducing the time-consuming and often inaccurate process involved in manual data interpretation (Bidollahkhani and Kunkel, 2024). Simultaneous analysis of multi-source sensor data yields insights with high accuracy and precision. The data-driven insights enable intelligent decision-making in Nigerian industries as the transition yields fewer errors. This AI-driven maintenance reduces operational waste and downtime while improving production output. This approach enables Nigerian manufacturers to adopt Industry 4.0 practices and improve overall equipment effectiveness (Ogbu et al., 2023). An important example of machinery that requires this regular and accurate maintenance is the rotating electromechanical machinery.

Electromechanical rotating machinery, particularly the turbines, pumps, and compressors, constitutes critical infrastructure in core national sectors, including national power generation, oil and gas, and the manufacturing sector (Das et al., 2023). These devices operate under measurable physical conditions such as temperature, pressure, vibration, and humidity that exhibit detectable degradation patterns before failure (Das et al., 2023; Forbicini et al., 2025). Despite the economic importance of equipment reliability in Nigeria, predictive maintenance implementation remains limited. Additionally, several studies have benchmarked ML classifiers for predictive maintenance; most treat model selection as the final output, reporting accuracy comparisons without proposing a unified architecture that leverages the complementary strengths of multiple learners.

This study addresses this gap by developing and comparing machine learning algorithms for fault prediction in turbines, pumps, and compressors by utilizing a dataset of real-time sensor measurements with corresponding fault annotations. It evaluates four models: Logistic Regression, Random Forest, Support Vector Machines, and XGBoost to determine the optimal performance for equipment fault classification. Critically, this study moves beyond model selection; rather than identifying a single best classifier, a stacking ensemble is proposed that treats the complementary strengths of SVM, Random Forest, and XGBoost as a design resource, combining their structurally diverse decision boundaries through a learned meta-learner that allocates trust to each base classifier based on the reliability of its probability estimates. The research proposes, as a novelty, the stacking architecture, which has not been previously applied to industrial fault detection in the Nigerian manufacturing context, where the combination of real-world sensor noise, class imbalance, and multi-equipment operation creates a classification problem that no single model paradigm fully addresses.

2. Related Works

Predictive maintenance is a key technology that has risen amongst others in the 4th industrial revolution, and it plays a major role in promoting sustainable manufacturing amongst industries (Zonta et al., 2020; Çınar et al., 2020). However, PdM relies on a large amount of real-time and historical data to predict anomalies in the equipment, which is a challenge faced in its implementation (Dalzochio et al., 2020). The inclusion of AI and IoT has provided more solutions for industrial equipment through the use of sensors to collect real-time data and store historical data (Calabrese et al., 2020), also with the integration of AI to predict the future health states of the systems and potential future failures (Achouch et al., 2022). This suggests that the use of AI maintenance plans to improve the health of these systems can mitigate the impact of predicted failures (Bousdekis et al., 2019).

Kamgba (2024) underscore the use of several state-of-the-art AI techniques within critical industrial systems with the use of real-time data obtained through IoT sensors, enabling continuous monitoring and timely predictions (Baptista et al., 2018). From classification and regression techniques of supervised learning (Ferreira et al., 2022), clustering approach of unsupervised learning (Nota et al., 2024), reinforcement learning (Siraskar et al., 2023), and neural networks (Khan et al., 2019) have been applied to scrutinize available data. The model technique applied is dependent on the dataset available, the industrial equipment, and the specific problems being addressed (Çınar et al., 2020).

Akinbolajo (2021) outlines different supervised learning approaches, such as Random Forest (Ouadah et al., 2022), Support Vector Machines (Shamayleh et al., 2020), and Ensemble Learning (Gadde, 2021). The learning uses a combination of multiple base models to output an optimized predictive model with multiple training runs to reduce the variance and bias of the predicted values and actual values. Aziz et al. (2020) used different ensemble techniques, such as Light GBM, Gradient Boost Machine, and XGBoost, for the prediction of machine failures, which had high output accuracy and confidence levels for monitoring (Theissler et al., 2021). The ensemble technique is known for allowing the identification of complex patterns and anomalies in equipment behavior while also highlighting limitations related to data quality (Serin et al., 2020). Ensemble technique can also achieve high accuracy, even with missing data, showcasing its robustness (Jain et al., 2019).

The Random Forest (RF) model is also developed through the ensemble learning method, through a technique known as bagging (Stetco et al., 2019). In the bagging technique, trees are constructed from the dataset, and then forest prediction is done through a majority vote of the individual trees (Kaparthi and Bumblauskas, 2020). The randomness value used changes the tree's construction and is popularly used for classification purposes; prediction is usually based on these trees (Bampoula et al., 2021). Prihatno et al. (2021) implemented the RF algorithm to predict Relative Humidity in a smart factory with the aid of IoT devices based on the M2M standard platform. The study had an accuracy value of 82.49%, depicting the high accuracy and precision standard of RF; in addition to its low computation time, it efficiently works with high-dimensional data (Kusumaningrum et al., 2021).

Support Vector Machines (SVMs) are popularly used in PdM to identify equipment status (Tama et al., 2023). This process is achieved by applying a linearized model with an optimal partition. SVM is popularly used for the conditional monitoring of electrical and mechanical machines based on the acquired signal and is a powerful application of the ensemble methods, likewise, Gradient Boosting Machine (GBM) (Theissler et al., 2021). SVM can be used to capture the decision-making boundaries of linear models, while GBM implements loss functions to improve model performance (Paolanti et al., 2018).

Gradient Boosting Machines (GBM) is an ensemble technique popularly used for regression and classification problems by fitting a weak learner to a residual learner, and this process improves model performance over increasing iterations (Theissler et al., 2021). It has also been implemented to increase the efficiency of machines and reduce maintenance costs (Farooq et al., 2024). Real-time data was collected from a vending machine and used to validate the proposed framework using GBM, RF, and SVM. The obtained results show 80% accuracy with the GBM model for the diagnosis and prognostics of that vending machine. Despite the breadth of ML applications in predictive maintenance, two gaps remain underexplored. First, most studies evaluate individual classifiers independently rather than designing ensemble architectures that explicitly exploit the complementary decision boundaries of heterogeneous learners. While stacking has been explored in other domains, its application to industrial IoT fault detection, particularly under class imbalance, has received limited attention. This study addresses this gap.

3. Methodology

3.1. System Overview

The objectives of this study are achieved by using four machine learning approaches to perform a thorough forecast of the relationship between measured circumstances and the faultiness of three major industry equipment: turbines, compressors, and pumps. The predictive capabilities of Logistic Regression, Random Forest, Support Vector Machine (SVM), and XGBoost are benchmarked. To move beyond individual model benchmarking, this study proposes a stacking ensemble architecture that leverages the complementary strengths of the highest-performing base classifiers.

3.2. Machine Learning Techniques

The models are trained independently on the preprocessed dataset.

a) Logistic Regression

Logistic regression serves as a baseline to understand the linear relationships between the sensor measurements and the fault probability. Modelling the probability of fault occurrence based on input features (temperature, humidity, and pressure) serves to predict if the equipment is faulty (1) or not (0). The predicted probability is given by:

$$P(y = 1 \mid x) = \frac{1}{1 + e^{-(w \cdot x + b)}} \tag{1}$$

where w is the weight vector, x is the input feature vector, and b is the bias term.

b) Random Forest

Random Forest uses an ensemble method to construct multiple decision trees during training, combining their output through a majority vote to improve predictive performance and reduce overfitting. Mathematically, if there are B decision trees, the prediction $\hat{y}$ is given by:

$$\hat{y} = \frac{1}{B} \sum_{t=1}^{B} \hat{y}_t \tag{2}$$

where $\hat{y}_t$ represents the prediction from the t-th decision tree.

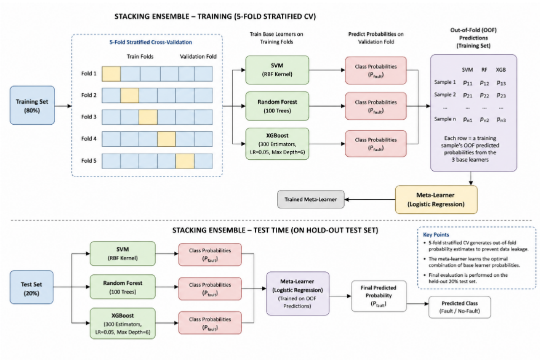
c) Support Vector Machine (SVM)

SVM separates different classes by finding the optimal decision boundary, known as a hyperplane. It identifies the complex decision boundaries that best separate two classes by maximizing the margin (the distance from the hyperplane to the nearest data points, or support vectors) on each side.

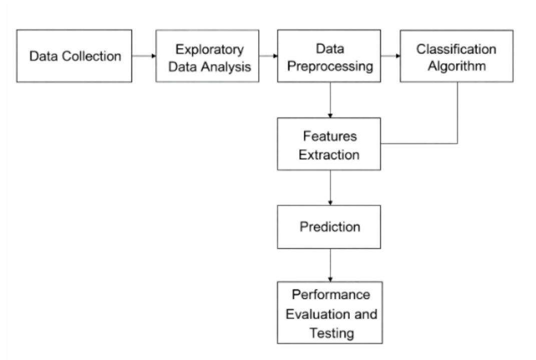
d) XGBoost (Extreme Gradient Boosting)

XGBoost was employed to capture complex patterns and interactions on tabular datasets using sequential gradient boosting to iteratively correct residual errors. The model can be mathematically represented as:

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i) \tag{3}$$



(a) Stacking ensemble architecture flowchart.



(b) Model Development Pipeline.

Figure 1: Stacking ensemble architecture flowchart (left) and Model Development Pipeline (right).

3.3. Stacking Ensemble Architecture and Pipeline

To exploit the decision boundaries of the best-performing base classifiers, a stacking ensemble was developed. The base learners selected were SVM (RBF kernel), Random Forest (100 trees), and XGBoost (300 estimators, learning rate 0.05, max depth 6). Logistic Regression was selected as the meta-learner to produce calibrated, interpretable probability outputs.

To prevent data leakage, out-of-fold probability estimates were generated using 5-fold stratified cross-validation on the training set, preserving the minority fault class ratio. The meta-learner was subsequently trained on these predictions and evaluated on the held-out 20% test set.

3.4. Data Preparation and Pre-processing

The Equipment Anomaly Dataset (**?**) was utilized. Initial Exploratory Data Analysis (EDA) confirmed the dataset comprises 7,672 rows with no missing values, duplicated data, or nulls requiring imputation.

The “Equipment Type” categorical feature was removed from the dataset to prevent the model from associating fault likelihood with equipment labels rather than learning patterns from the underlying sensor behaviour.

Because SVM and Logistic Regression are highly sensitive to feature scale differences, a Standard Scaler was applied to normalise the numeric input features to zero mean and unit variance. To address significant class imbalance, algorithm-level corrections were applied. For Logistic Regression, Random Forest, and SVM, the `class_weight=‘balanced’` parameter was utilized, which rescales the misclassification penalty for each class inversely proportional to its frequency. The data was then split into 80% training and 20% testing sets.

Table 1: Equipment types covered are rotating machinery: Turbine, Compressor, and Pump.

Feature	Description	Unit	Data Type
Temperature	Sensor reading of equipment temperature	°C	Continuous
Humidity	Environmental humidity level	%	Continuous
Pressure	Pressure reading at the time of observation	Bar	Continuous
Vibration	Vibration level reading	Normalized	Continuous
Fault Type	Binary target (0 = No Fault, 1 = Fault)	N/A	Binary
Equipment Type	Rotating machinery monitored	N/A	Categorical

3.5. Model Evaluation Metrics

The models were evaluated using key performance metrics to assess their predictive capability.

A. Accuracy Accuracy measures how often the model is correct overall through the proportion of all correct classifications.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

B. Recall (True Positive Rate) Recall is the proportion of actual positive instances (faults) that were successfully identified, which is critical for minimizing missed machinery failures.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{5}$$

C. Precision Precision measures how many of the positive predictions made by the model are actually correct, which is useful when the cost of false positives (unnecessary maintenance) is high.

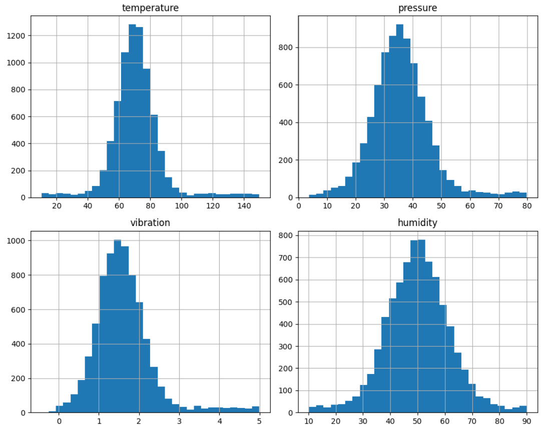
$$\text{Precision} = \frac{TP}{TP + FP} \tag{6}$$

D. Confusion Matrix & McNemar's Test A 2×2 confusion matrix was utilized to visualize the true vs. predicted classifications. To determine if there is a statistically significant difference in proportions between the models' error rates, McNemar's test was applied to the paired nominal data.

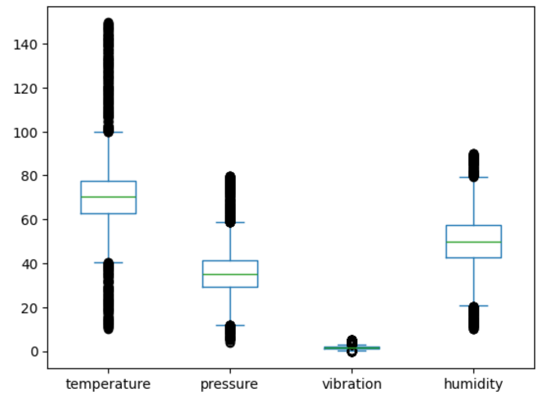
E. SHAP-Based Interpretability Analysis To reveal which sensor parameters drove individual predictions, SHAP (Shapley Additive exPlanations) analysis was applied to the XGBoost and Random Forest models. A positive SHAP value indicates a feature pushed the prediction toward the faulty class.

4. Results

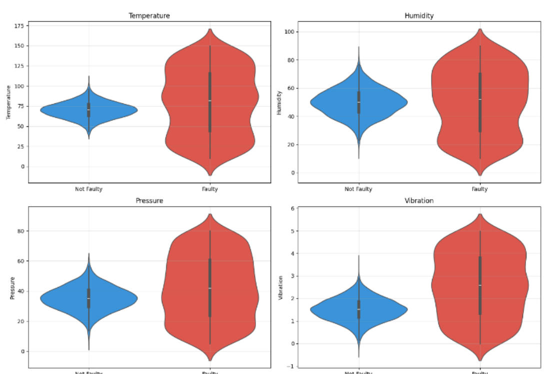
This section evaluates the predictive accuracy of the four base classification models (Logistic Regression, Support Vector Machine, XGBoost, and Random Forest) alongside the



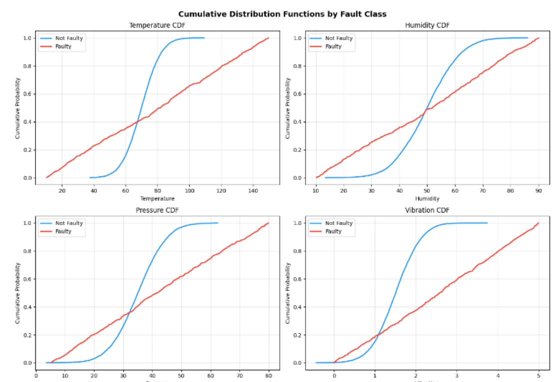
(*a*) Sensor distributions.



(*b*) Box plots of features.



(*c*) Violin plots.



(*d*) Cumulative distributions.

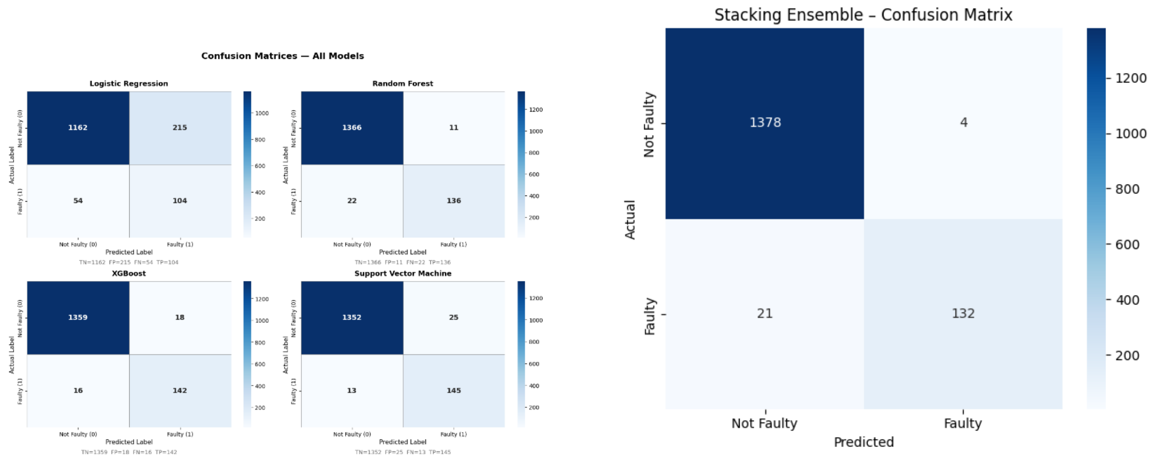
Figure 2: Comprehensive Exploratory Data Analysis of sensor readings.

proposed stacking ensemble architecture. The results highlight the comparative strengths of the individual algorithms and their suitability for deployment in industrial predictive maintenance.

4.1. Exploratory Data Analysis

Initial Exploratory Data Analysis (EDA) was conducted to characterize the sensor distributions and their relationship with the target variable. As illustrated in Figure 2, normal operating conditions cluster tightly around central values, whereas faulty systems exhibit significantly greater variability, broader ranges, and numerous extreme outliers across all four features (temperature, pressure, vibration, and humidity).

Notably, scatter and pair plots indicate that fault cases are not distinctly clustered in any single feature space. No single sensor variable is sufficient to predict faults, confirming that the classification problem is highly non-linear and necessitates a multivariate machine learning approach.



(a) (b)

Figure 3: Confusion Matrices for base models and the proposed Stacking Ensemble.

4.2. Model Performance Evaluation

Model predictions were evaluated against actual outcomes using confusion matrices (Figure 3). Out of 1,535 test instances, the stacking ensemble correctly classified 1,378 of 1,382 non-faulty observations (only 4 false positives). Of the 153 actual fault instances, 132 were correctly identified. The 21 false negatives represent the ensemble's primary limitation: borderline observations where sensor readings remained within normal operating bounds despite an underlying fault condition. Overall, this low false alarm rate ensures maintenance teams are not unduly burdened with unnecessary interventions.

Table 2 presents the comparative performance of all classifiers. Logistic Regression provided the weakest performance (Accuracy: 94.20%, F1-Score: 0.5936), struggling with false positives and missing more than half of the actual faults, confirming its inability to map the non-linear sensor relationships. Conversely, the tree-based models and SVM demonstrated excellent reliability. SVM achieved a perfect precision score (1.0000), while Random Forest and XGBoost balanced precision and recall effectively.

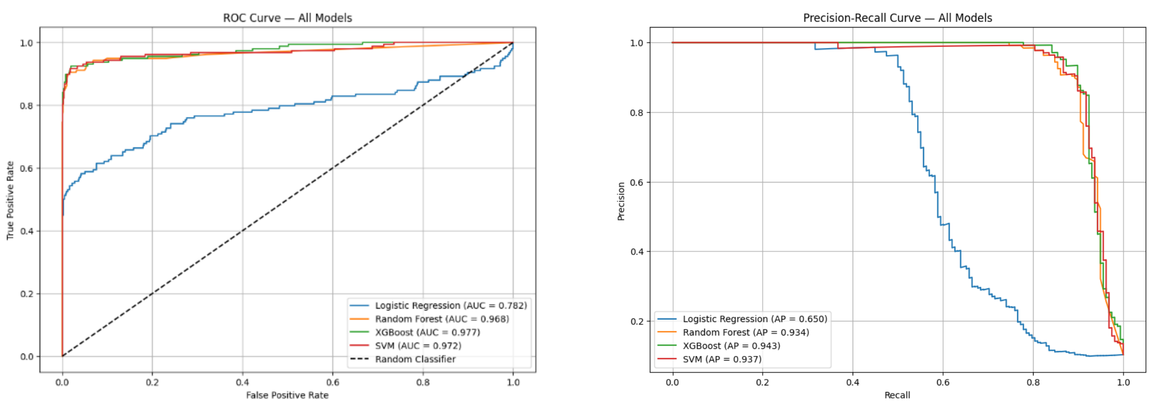
Ultimately, the Stacking Ensemble achieved the highest accuracy (98.37%) and F1-score (0.9135). By yielding a Matthews Correlation Coefficient (MCC) of 0.9065, the ensemble demonstrates genuine discriminative ability across both the majority and minority classes, proving resilient to the dataset's class imbalance.

Figure 4 illustrates the ROC and Precision-Recall (PR) curves. The Stacking Ensemble achieved an AUC of 0.987, indicating near-perfect discriminative ability across all classification thresholds. XGBoost (AUC: 0.977), SVM (AUC: 0.972), and Random Forest (AUC: 0.968) cluster tightly together, while Logistic Regression trails significantly (AUC: 0.782). Average Precision (AP) scores above 0.93 for the top models confirm they have learned meaningful fault patterns rather than simply predicting the majority class.

To determine the statistical significance of these performance differences, McNemar's test was applied (Table 3). Logistic Regression is unambiguously the weakest classifier,

Table 2: Comparative Results of Classification Models

Model	Accuracy	Precision	Recall	F1-Score	MCC
Logistic Regression	0.9420	0.9848	0.4248	0.5936	0.4023
Random Forest	0.9831	0.9635	**0.8627**	0.9103	0.8801
XGBoost	0.9798	0.9552	0.8366	0.8920	0.8720
SVM	0.9779	**1.0000**	0.7778	0.8750	0.8800
Stacking Ensemble	**0.9837**	**0.9706**	**0.8627**	**0.9135**	**0.9065**



(a) ROC curve comparing models.

(b) Precision-Recall curves.

Figure 4: Performance tradeoff curves for the classification models.

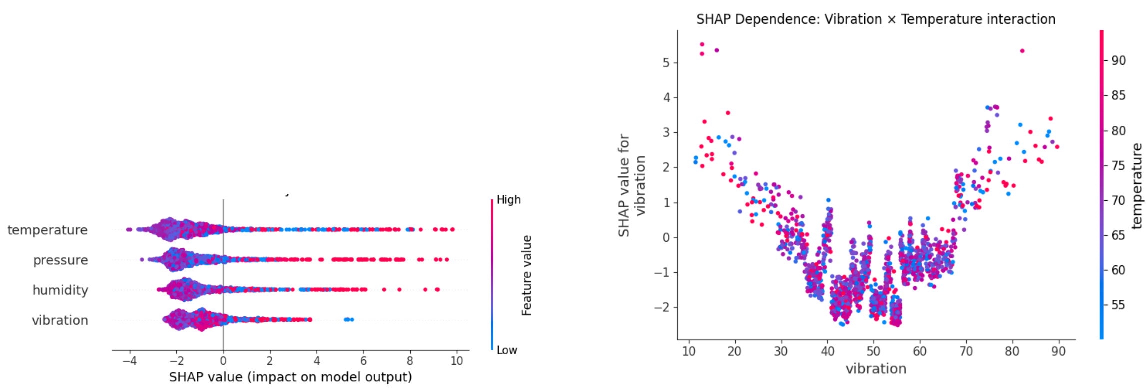
significantly outperformed by all other models ($p < 0.0001$). While the differences among the top four models are statistically significant due to the test's high power, the Stacking Ensemble conclusively demonstrates that the meta-learner successfully combined the base classifiers' complementary strengths—adopting SVM's precision discipline and XGBoost's fault-hunting aggressiveness.

4.3. SHAP-Based Interpretability Analysis

SHAP (Shapley Additive exPlanations) analysis was applied to provide sensor-level interpretability. The SHAP beeswarm summary reveals that thermal and pressure anomalies are more diagnostically decisive than mechanical vibration, a finding with direct implications for sensor prioritization in monitored industrial environments. Furthermore, SHAP dependence plots illustrate a U-shaped relationship between vibration magnitude and fault contribution, confirming that the co-occurrence of vibration anomalies and elevated temperatures produces a substantially stronger fault signal, representing a compounding mechanical and thermal failure.

Table 3: McNemar's Test pairwise comparisons at significance level $\alpha = 0.05$

Model A	Model B	A✓B×	A×B✓	Statistic	p-value	Significant
Logistic Regression	Random Forest	98122	10863	69862.4450	0.0000	YES
Logistic Regression	XGBoost	93976	10404	66910.4430	0.0000	YES
Logistic Regression	SVM	83991	18854	41253.3278	0.0000	YES
Logistic Regression	Stacking Ensemble	96740	10710	68878.4443	0.0000	YES
Random Forest	XGBoost	11204	14891	520.6590	0.0000	YES
Random Forest	SVM	2754	24876	17710.4105	0.0000	YES
Random Forest	Stacking Ensemble	3223	4452	196.4800	0.0000	YES
XGBoost	SVM	9970	28405	8855.0451	0.0000	YES
XGBoost	Stacking Ensemble	10439	7981	327.7334	0.0000	YES
SVM	Stacking Ensemble	23494	2601	16726.4098	0.0000	YES



(a) SHAP beeswarm summary plot for XGBoost.

(b) SHAP dependence plot for vibration and temperature.

Figure 5: SHAP interpretability analysis.

5. Conclusion

This study investigated the application of AI-driven maintenance for industrial electromechanical equipment, specifically turbines, pumps, and compressors, within the Nigerian manufacturing context. Four machine learning models—Logistic Regression, Random Forest Classifier, XGBoost, and Support Vector Machine (SVM)—were developed and evaluated with real-time sensor measurements to classify equipment fault conditions. Additionally, a stacking ensemble architecture is proposed that combines SVM, Random Forest, and XGBoost as heterogeneous base learners under a Logistic Regression meta-learner, demonstrating that ensemble design yields better performance over individual classifiers.

The stacking ensemble emerged as the superior model achieving an accuracy of 98.37%, precision of 97.06%, recall of 86.27%, F1-score of 91.35%, and an MCC of 0.9065. An AUC of 0.987 confirmed near-perfect discriminative ability between faulty and non-faulty equipment across all classification thresholds.

The findings of this research affirm that AI-driven predictive maintenance is a viable and effective approach for Nigerian industries seeking to transition from reactive and preventive maintenance strategies towards intelligent, data-driven operations aligned with Industry 4.0 principles. The study provides a comparative analysis of ensemble machine learning techniques in the context of Nigerian industrial infrastructure, an area that has received limited research attention.

Data Availability Statement

The dataset used in this study is publicly available and accessible at:
https://www.kaggle.com/datasets/glorybagai/equipment-anomaly-dataset.

The complete source code, trained model implementations, and supplementary figures supporting the findings of this study are openly available in the corresponding GitHub repository at:
https://github.com/Kuzay3t/Industrial-Predictive-Maintenance.

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