Data-Driven Fault Intelligence and System Optimization in Modern Industrial Environments

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ABSTRACT
Recent studies report that unplanned machine failures account for nearly 20–30% of total production downtime in smart manufacturing environments. With Industry 4.0 enabling continuous sensor-based monitoring, industries now generate massive volumes of operational data, yet effective fault analysis and decision-making remain a major challenge. Conventional manual fault analysis systems suffer from critical limitations, including heavy dependence on human expertise and periodic inspections, which often result in delayed fault detection and inconsistent decision-making. In this study, a comprehensive data set is utilized containing parameters such as timestamp, machine id, temperature, vibration level, power consumption, pressure, material flow rate, cycle time, error rate, downtime, maintenance flag, efficiency score, and production status. The data undergoes systematic preprocessing, including noise handling, normalization, missing-value treatment, and feature alignment, followed by Exploratory Data Analysis (EDA) to understand operational patterns, fault correlations, and feature importance. Existing machine learning models such as AdaBoost-CART, XGBoost-CART, and Passive-Aggressive (PA)-CART are implemented as baseline methods. To overcome the limitations of fixed-feature learning and manual feature engineering, a proposed Neural Architecture Search (NAS)-based feature extraction framework integrated with a Greedy Rule Forest (GRF)-CART model is introduced. The NAS component automatically learns optimal feature representations from complex sensor interactions, while the GRF-CART enhances interpretability and decision robustness. The proposed framework performs classification tasks to predict downtime occurrence, maintenance requirement (maintenance flag), and production status, along with a regression task to accurately estimate the efficiency score. Experimental results demonstrate that the proposed NAS–GRF–CART approach significantly improves fault prediction accuracy, reduces false maintenance alerts, and provides reliable efficiency assessment, making it well-suited for intelligent, data-driven maintenance strategies in Industry 4.0 environments.
Keywords: Industry 4.0, Neural Architecture Search (NAS), Greedy Rule Forest (GRF)-CART, Predictive Maintenance, Feature Representation Learning.

1. INTRODUCTION

Manufacturing industries today are gradually moving away from traditional production practices and adopting more automated and digitally connected systems. This change is mainly driven by the general use of sensors, controllers, and interconnected machines that continuously record operating conditions such as temperature, vibration, and speed. As a result, industries now have access to large amounts of machine data, which has changed how equipment is monitored, maintained, and managed. Fig. 1

presents a market size outlook showing a steady and consistent growth trend from 2019 to 2029. Starting at around USD 77.20 billion in 2019, the market experiences gradual year-on-year expansion, indicating increasing adoption and investment across industries. From the mid-period onward, the growth rate accelerates, reflecting rising demand for advanced industrial technologies and data-driven operational systems.

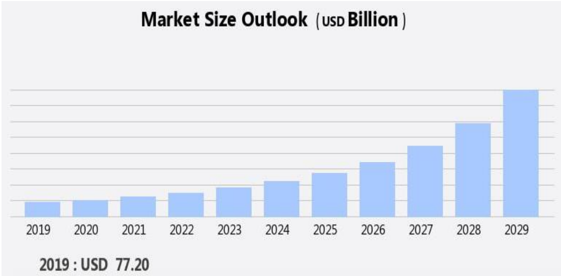


Fig. 1: Size of industry 4.0 market.

2. LITERATURE SURVEY

D. Bej et al. [1] Proposed a real-time predictive maintenance framework for Industry 4.0–based industrial systems. To detect machine faults, algorithms such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Random Forest (RF) were employed. The study demonstrates that ensemble-based learning improves fault detection accuracy while supporting sustainable industrial operations. Polymeropoulos et al. [2] Proposed a deep learning–based fault diagnosis system for industrial air-cooling units using sensor data. Algorithms such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks were used. The model effectively captures spatial–temporal patterns in sensor signals to improve diagnostic reliability. W. Li [3] Presented a comparative predictive maintenance study in manufacturing systems. Algorithms including CNN, LSTM, GRU, and Deep Neural Networks (DNN) were evaluated. The study highlights trade-offs between prediction accuracy, training complexity, and computational cost. Varalakshmi et al. [4] Proposed an optimized predictive maintenance framework for streaming Industrial IoT data. Algorithms such as Online Random Forest (RF), Incremental Learning Models (ILM), and Adaptive ML classifiers were applied. The framework supports real-time fault prediction under continuous data streams. Ali et al. [5] Proposed a multimodal sensor fusion framework for industrial fault diagnosis. Algorithms including Deep Neural Networks (DNN), CNN, and Hybrid Fusion Models were employed. The system combines heterogeneous sensor inputs to enhance fault classification accuracy. Arena et al. [6] Presented a comprehensive review of predictive maintenance in the automotive sector. Algorithms such as SVM, Random Forest, k-Nearest Neighbors (k-NN), and Neural Networks were analyzed. The review identifies scalability and data imbalance as key challenges.

Dalzochio et al. [7] Proposed a machine learning and reasoning-based predictive maintenance framework for Industry 4.0. Algorithms such as Decision Trees, Bayesian Networks, and Rule-Based Learning Models were used. The framework improves interpretability and fault reasoning. Lei et al. [8] Presented a systematic review of machinery health prognostics from data acquisition to RUL prediction. Algorithms including SVM, Hidden Markov Models (HMM), ANN, and Regression Models were studied. The work emphasizes feature extraction and degradation modeling. Al-Andoli et al. [9] Proposed a parallel ensemble learning model for industrial fault detection. Algorithms such as Random Forest, AdaBoost, and Bagging-based Ensembles were implemented in a parallel architecture. The approach enhances robustness and fault detection speed. Sawalhi et al. [10] presented an improved order tracking approach for vibration signal analysis by utilizing the Variable Frequency Drive (VFD) signature. The study focused on enhancing vibration-based condition monitoring of rotating machinery operating under variable speed conditions. By extracting and incorporating the VFD switching frequency information, the proposed method enabled more accurate order tracking and fault-related feature identification. The results demonstrated improved clarity of vibration orders and better fault diagnosis capability compared to conventional order tracking techniques, particularly in non-stationary operating environments.

Hasan et al. [11] Proposed a predictive maintenance optimization system for smart vending machines. Algorithms including Random Forest, Logistic Regression, and Gradient-Based Optimization Models were employed. The system improves maintenance scheduling and operational efficiency. Ismail et al. [12] Presented a systematic review of digital twins–driven predictive maintenance. Algorithms such as Machine Learning–based Digital Twins, Neural Networks, and Hybrid Simulation Models were discussed. The study highlights integration challenges between physical and virtual systems. Lai et al. [13] Proposed a residual attention–based vision transformer model for bearing fault diagnosis. Algorithms such as Vision Transformer (ViT) and Attention Networks were employed. The model effectively captures complex vibration signal features. Khalil et al. [14] Proposed a machine learning–based fault detection framework for rotating machinery. Algorithms such as SVM, Decision Tree, k-NN, and Random Forest were applied. The study demonstrates reliable fault classification using sensor features. Seid Ahmed et al. [15] Presented a review of fault detection techniques for automated manufacturing systems. Algorithms such as ML classifiers, Deep Learning Models, and Hybrid Diagnostic Systems were analyzed. The work identifies gaps in real-time adaptability.

3. PROPOSED SYSTEM

Fig. 2 shows the proposed algorithm introduces a novel combinational learning framework that integrates NAS based adaptive feature extraction with a Greedy Rule Forest enhanced CART decision system for multi-output machine fault analysis. Unlike existing survey methods that apply fixed feature sets or standalone ensemble models, this approach dynamically learns optimal feature representations from raw industrial sensor data and simultaneously constructs interpretable rule-based decision paths. The NAS module autonomously identifies the most effective deep feature extraction architecture tailored to machine operating conditions, while the GRF refines these features into compact, high-confidence rules that are fused with CART for joint classification and regression. This unique combination enables simultaneous prediction of downtime, maintenance flag, production status, and efficiency score within a single unified model, offering improved adaptability, interpretability, and predictive accuracy not reported in prior literature.

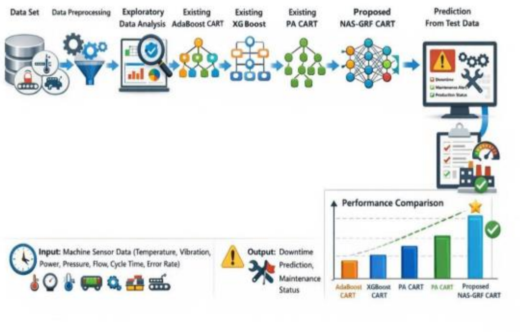


Fig. 2: Proposed system architecture.

Industrial Data Acquisition: Real-time and historical machine sensor data are collected, including operational, environmental, and performance-related parameters such as temperature, vibration, power consumption, pressure, and cycle time. Each record is time-stamped and linked to a unique machine identifier to preserve temporal and machine-specific behaviour patterns.

Data Preprocessing and Transformation: The collected data undergo cleaning to handle missing values, noise, and inconsistencies caused by sensor faults or communication delays. Numerical features are scaled to a common range, categorical attributes are encoded into machine-readable form, and irrelevant or redundant attributes are filtered to ensure stable and unbiased learning.

Existing Ada Boost: AdaBoost is employed as a benchmark ensemble method that iteratively combines multiple weak learners to improve fault classification accuracy. Misclassified machine fault samples are assigned higher weights in successive iterations, forcing the model to focus on difficult fault patterns. However, AdaBoost relies on predefined features and lacks adaptability to evolving machine operating conditions.

Existing XG Boost: XGBoost utilizes gradient-boosted decision trees to model complex non-linear relationships between machine sensor parameters and fault conditions. It offers high predictive performance through regularization and optimized tree construction. Despite its accuracy, XGBoost functions as a black-box model with limited interpretability and requires manual feature engineering.

Existing PA CART: The Performance-Aware CART model constructs decision trees using predefined performance indicators to predict machine faults and operational states. It provides transparent rule-based decisions but struggles with high-dimensional sensor data and complex fault interactions. The absence of adaptive feature learning limits its scalability in dynamic industrial environments.

Proposed NAS-GRF Classifier: NAS is employed to automatically discover an optimal deep learning structure that can extract high-level, non-linear features from pre-processed data. Unlike manual network design, the NAS module evolves architectures based on performance feedback, ensuring the extracted features are highly sensitive to subtle fault signatures and machine degradation patterns. The deep features generated by NAS are passed to a Greedy Rule Forest, which incrementally builds a set of interpretable decision rules. The greedy strategy selects only the most informative rules that contribute to fault discrimination, reducing model complexity while preserving decision transparency.

Performance Assessment: Model performance is evaluated using standard classification and regression metrics to assess fault detection reliability and prediction accuracy. Classification outputs are assessed using accuracy, precision, recall, and F1-score, while regression performance is measured using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R^2 score. Comparative analysis is performed against AdaBoost, XGBoost, and PA-CART to validate the superiority of the proposed approach.

Prediction From Test Data: The test data and test features are integrated into the NAS-GRF CART framework that simultaneously handles classification and regression tasks. Downtime, maintenance flag, and production status are treated as classification outputs, while efficiency score is modelled as a continuous regression output within the same decision structure.

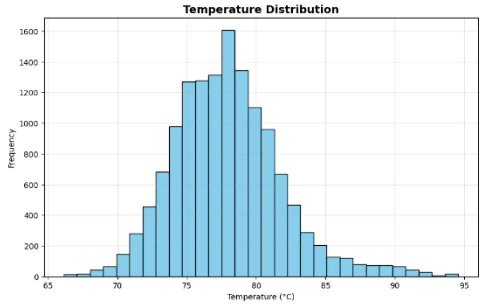
4. Results Analysis

(a) Histogram: The histogram shows the distribution of individual features across the dataset. It highlights the frequency of values, revealing the spread, skewness, and concentration of data points. This visualization confirms the presence of both balanced and imbalanced feature distributions, which directly influences model learning.

(b) Scatter Plot: The scatter plot illustrates the relationship between two important variables in the dataset. It reveals patterns, clustering behavior, and the degree of separation between classes. Distinct groupings in the plot indicate that the selected features contribute effectively to classification tasks in both maintenance and production outputs.

(c) Histogram: This histogram focuses on another key feature or target-related variable. It emphasizes how values are distributed across operational conditions, supporting the identification of dominant ranges and outliers relevant to system performance.

(d) Correlation Heatmap: The heatmap represents correlations among all features. Strong positive and negative correlations are clearly visible, enabling identification of redundant features and highly influential variables. This directly supports feature selection and improves the efficiency of the proposed model.



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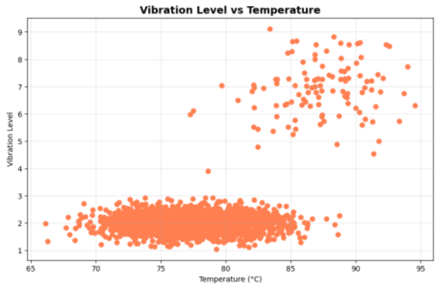

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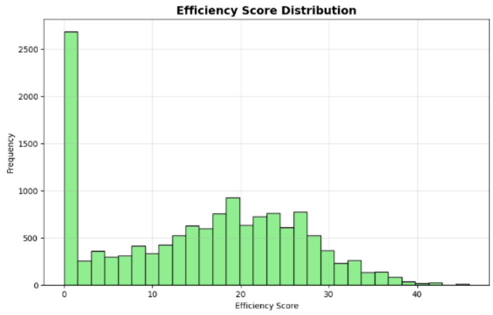

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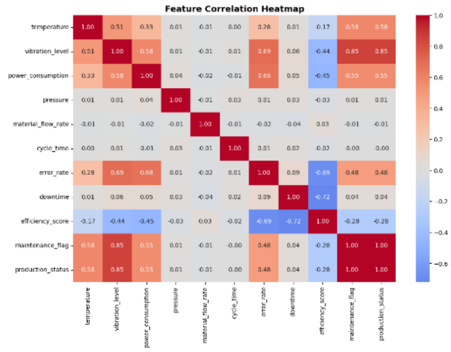

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Fig. 3: Data analysis. (a) histogram, (b) scatter plot, (c) histogram, (d) correlation heatmap, presents the exploratory data analysis of the dataset used in the research.

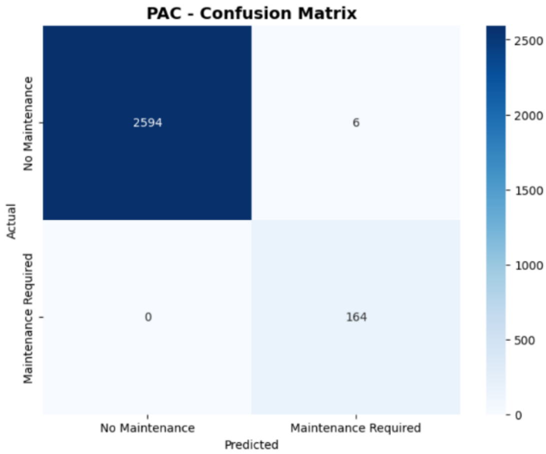
Fig. 4 compares classification performance of different models for maintenance prediction.

(a) PAC: The confusion matrix shows correct and incorrect classifications. It reflects moderate accuracy with noticeable misclassifications between classes.

(b) XGBoost: The matrix shows improved classification compared to PAC, with a higher number of true positives and true negatives. Misclassification reduces significantly.

(c) AdaBoost: The confusion matrix demonstrates better performance than PAC but shows some classification errors when compared with XGBoost.

(d) Proposed NAS-GRF: The matrix shows the highest number of correctly classified instances with minimal false positives and false negatives. This confirms superior performance of the proposed NAS-GRF model in maintenance prediction.



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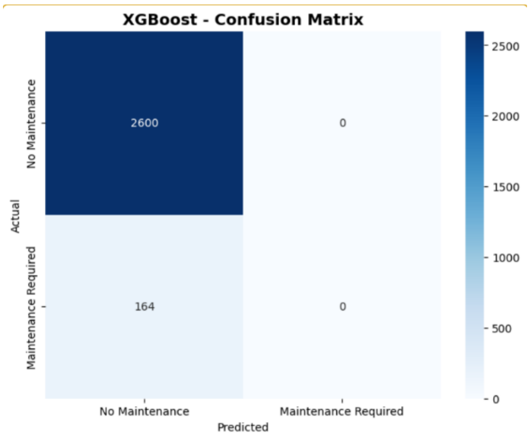

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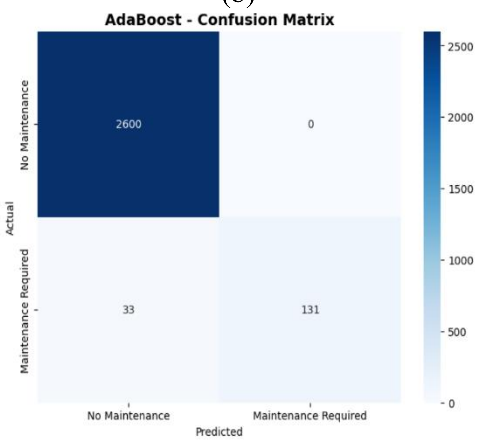

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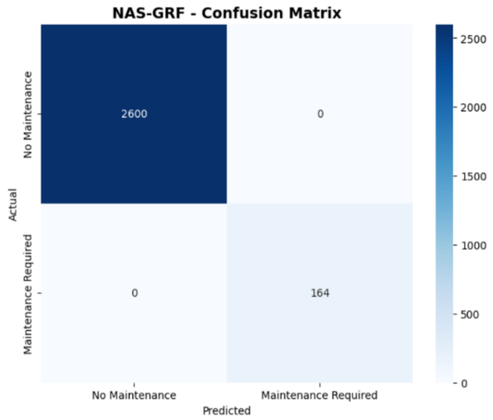

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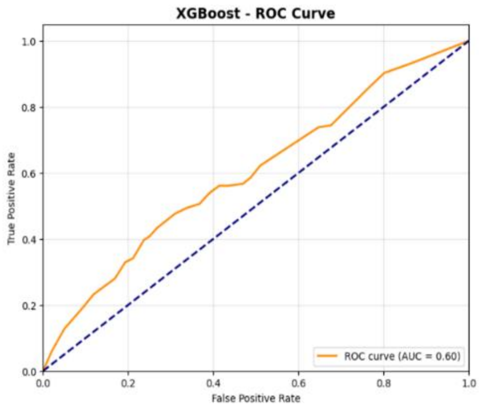
Fig. 4: Confusion matrix of maintenance output(a) PAC. (b) XGBoost (c)ADA BOOST. (d) proposed NAS-GRF.

Fig. 5 evaluates the classification capability using ROC curves.

(a) XGBoost: The ROC curve shows strong discrimination capability with a high true positive rate and low false positive rate.

(b) AdaBoost: The curve reflects good performance but remains below XGBoost in terms of overall area under the curve.

(c) Proposed NAS-GRF: The ROC curve is closest to the top-left corner, indicating the highest classification performance. The area under the curve is the largest among all models, confirming improved predictive accuracy.



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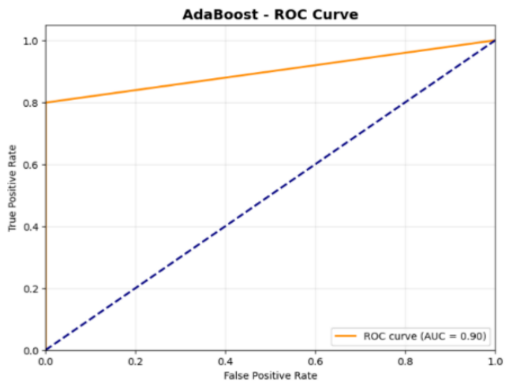

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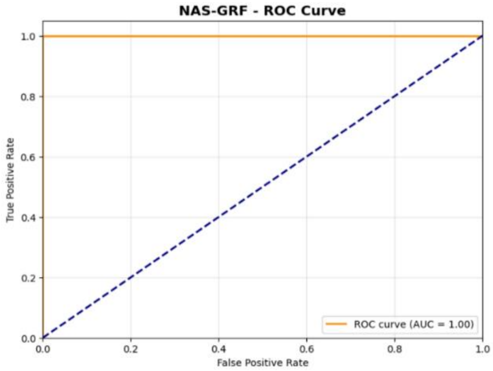

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Fig. 5: ROC Curves of maintenance output (a) XG BOOST. (b)ADA BOOST. (c) proposed NAS-GRF.

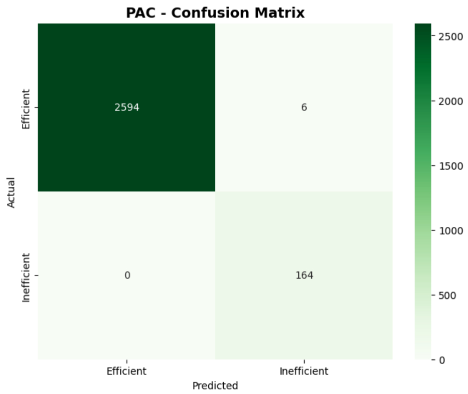
Fig. 6 presents classification results for production output prediction.

(a) PAC: The confusion matrix shows baseline performance with several misclassifications across categories.

(b) XGBoost: The matrix demonstrates improved classification accuracy with fewer errors compared to PAC.

(c) AdaBoost: The confusion matrix shows balanced performance with moderate improvement over PAC.

(d) Proposed NAS-GRF: The matrix highlights the highest classification accuracy with dominant true positive and true negative values. Error rates are minimal, confirming the effectiveness of the proposed approach for production output prediction.



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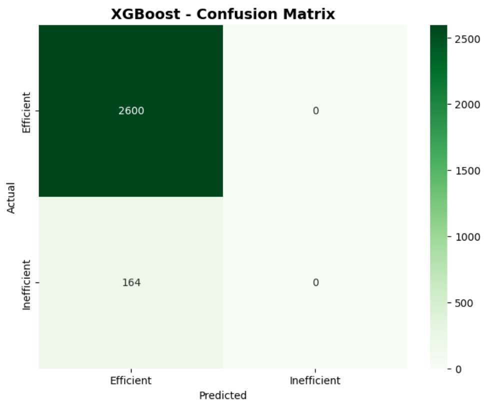

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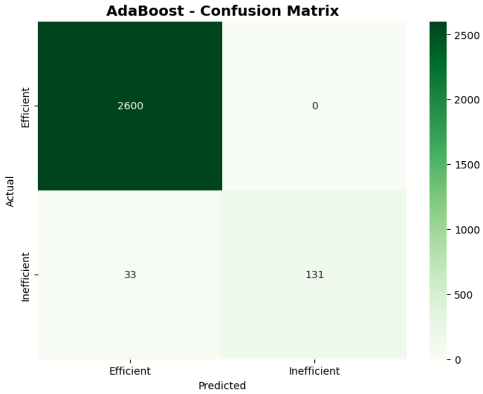

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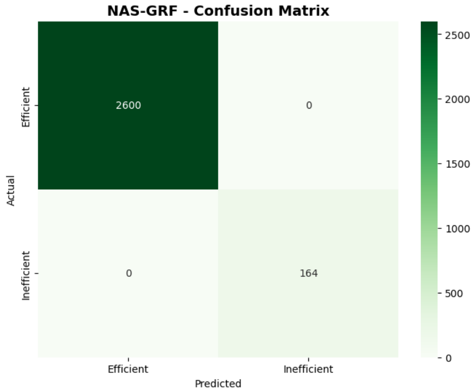

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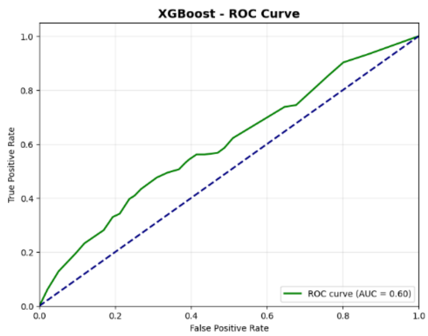
Fig. 6: Confusion matrix of production output (a)PAC. (b)XGBOOST. (c)ADA BOOST. (d) proposed NAS-GRF.

Fig. 7 compares model performance for production output using ROC analysis.

(a) XGBoost: The ROC curve shows strong predictive performance with a high true positive rate.

(b) AdaBoost: The curve indicates stable performance but remains below XGBoost.

(c) Proposed NAS-GRF: The ROC curve demonstrates the best classification capability, positioned closest to the top-left corner. The area under the curve exceeds all other models, validating the superiority of the proposed NAS-GRF model.



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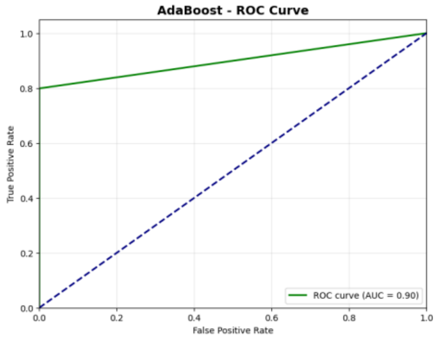

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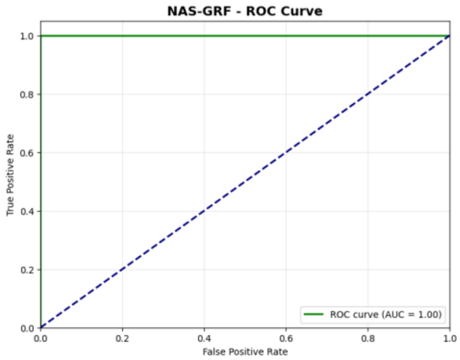

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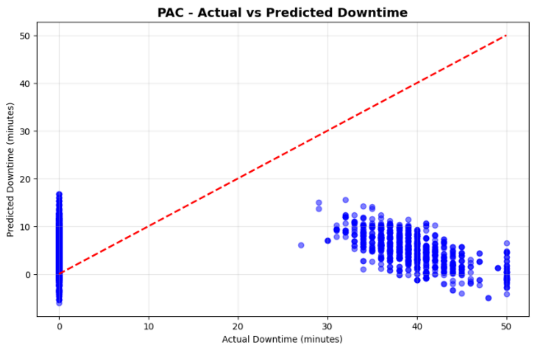
Fig. 7: ROC Curves of production output (a) XG BOOST. (b)ADA BOOST. (c) proposed NAS-GRF.

Fig. 8 illustrates the ROC curve analysis for downtime prediction across PAC, XGBoost, AdaBoost, and the proposed NAS-GRF model. The PAC curve shows limited discrimination capability with a lower true positive rate. XGBoost demonstrates slight improvement but remains close to the diagonal, indicating weak predictive strength. AdaBoost shows better separation between classes with improved true positive performance. The proposed NAS-GRF curve is positioned closest to the top-left corner, indicating the highest true positive rate with minimal false positives. This confirms superior prediction performance of NAS-GRF for downtime output.



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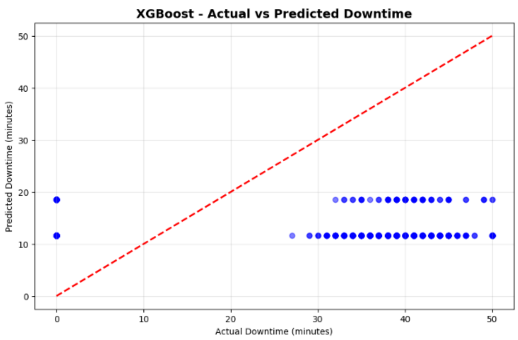

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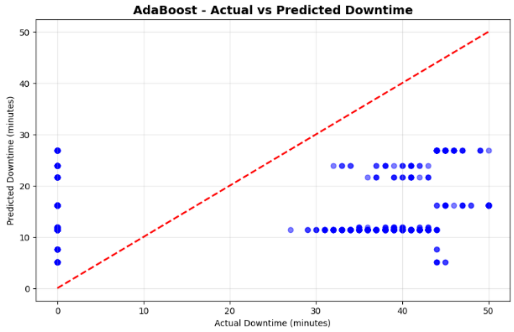

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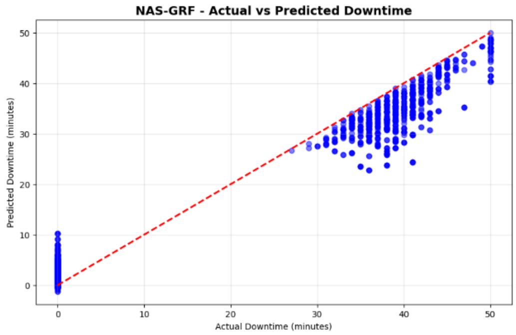

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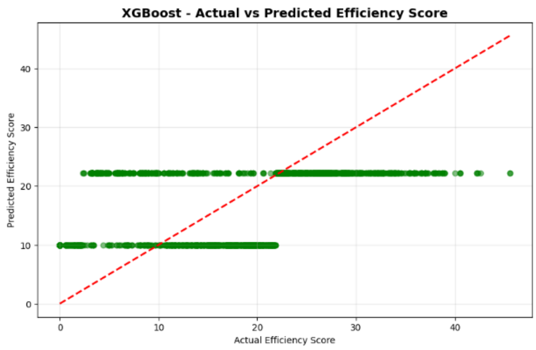
Fig. 8: ROC curves of downtime output(a) PAC. (b) XG BOST. (c) ADA BOOST. (d) Proposed NAS-GRF.



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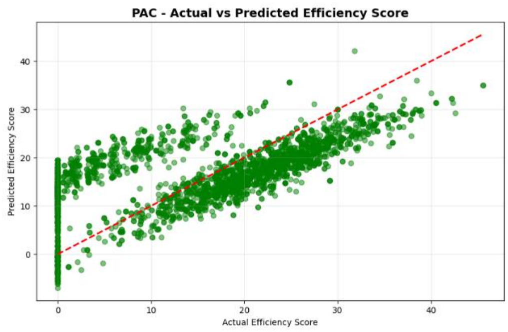

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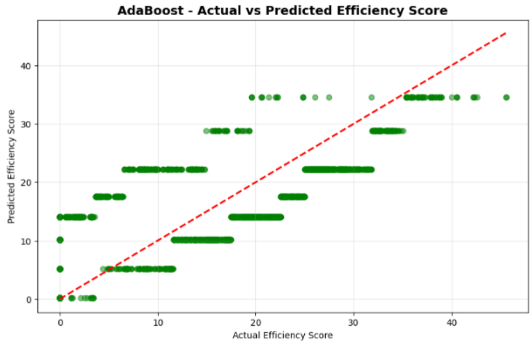

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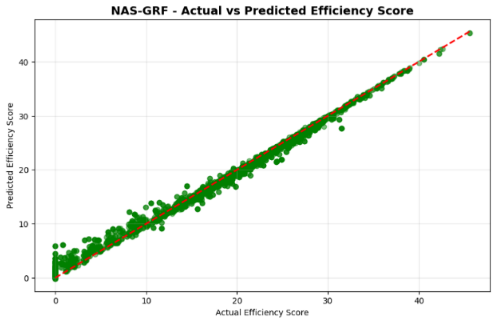

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Fig. 9: ROC curves of efficiency score output (a) XG BOOST. (b)ADA BOOST. (c) proposed NAS-GRF.

Fig. 9 presents ROC curves for efficiency score prediction using XGBoost, AdaBoost, and the proposed NAS-GRF model. XGBoost shows moderate classification performance with a noticeable gap from the optimal curve. AdaBoost improves the curve shape with better true positive rates. The proposed NAS-GRF curve remains closest to the top-left corner, indicating the strongest classification capability. The area under the curve is highest for NAS-GRF, confirming its effectiveness in accurately predicting efficiency scores within the project.

Table 1: Classification performance comparison for maintenance flag and production status.

Task	Model	Accuracy	Precision	Recall	F1 Score
Maintenance Flag	PAC	0.9978	0.9647	1.0000	0.9820
	XGBoost	0.9407	0.0000	0.0000	0.0000
	AdaBoost	0.9881	1.0000	0.7988	0.8881
	NAS-GRF	1.0000	1.0000	1.0000	1.0000
Production Status	PAC	0.9978	0.9647	1.0000	0.9820
	XGBoost	0.9407	0.0000	0.0000	0.0000
	AdaBoost	0.9881	1.0000	0.7988	0.8881
	NAS-GRF	1.0000	1.0000	1.0000	1.0000

Table 1 presents the performance of PAC, XGBoost, AdaBoost, and NAS-GRF models for both maintenance flag and production status classification. PAC achieves high accuracy and recall, indicating strong detection capability, while AdaBoost shows high precision with slightly lower recall. XGBoost records zero precision, recall, and F1 score, reflecting ineffective classification performance. NAS-GRF achieves perfect scores across all metrics, demonstrating complete accuracy and balanced classification. The results confirm that NAS-GRF outperforms all other models in both classification tasks.

Table 2: Regression performance comparison for downtime and efficiency score.

Task	Model	MAE	MSE	RMSE	R^2 Score
Downtime	**PAC**	14.3494	407.2436	20.1803	-0.2070
	XGBoost	16.7114	336.7798	18.3516	0.0019
	AdaBoost	16.4930	328.1668	18.1154	0.0274
	NAS-GRF	2.8271	14.0169	3.7439	0.9585

Efficiency Score	**PAC**	6.7189	67.1581	8.1950	0.4240
	XGBoost	7.7351	79.0615	8.8917	0.3219
	AdaBoost	6.7519	59.2232	7.6957	0.4920
	NAS-GRF	0.7279	1.1438	1.0695	0.9902

Table 2 compares regression performance of the models using MAE, MSE, RMSE, and R^2 score for downtime and efficiency prediction. PAC, XGBoost, and AdaBoost show higher error values and lower R^2 scores, indicating weaker prediction accuracy. NAS-GRF records the lowest MAE, MSE, and RMSE values along with the highest R^2 scores in both tasks. The results demonstrate strong consistency and precise prediction capability of NAS-GRF. This confirms that NAS-GRF provides superior regression performance compared to the other models.

Fig. 10: Prediction on sample test inputs.

Fig. 10 shows the corresponding prediction results generated by the NAS-GRF model for the given test input. The model predicts Maintenance Flag: No Maintenance, indicating no immediate maintenance requirement under the given conditions. The Production Status is classified as Efficient, confirming stable operational performance. For regression outputs, the predicted Downtime is 16.17 minutes, and the Efficiency Score is 1.67, suggesting relatively low efficiency under the provided low-level parameter settings. These results demonstrate the multi-output capability of the NAS-GRF model in simultaneously predicting both classification and regression targets with a single test input.

5. Conclusion

The comparative experimental results clearly demonstrate the superior performance of the proposed NAS-GRF model across both classification and regression tasks. For Maintenance Flag and Production Status, NAS-GRF achieves perfect accuracy, precision, recall, and F1-score, outperforming baseline models such as PAC, XGBoost, and AdaBoost. In regression tasks, particularly Downtime and Efficiency Score prediction, NAS-GRF records the lowest MAE, MSE, and RMSE values along with exceptionally high R^2 scores (0.9585 and 0.9902), indicating strong predictive capability and excellent model generalization. Overall, while PAC and AdaBoost show moderate performance and XGBoost struggles especially in classification metrics, NAS-GRF consistently delivers reliable, robust, and highly accurate results. The hybrid integration of adaptive feature learning with a greedy rule-based ensemble structure enables improved learning efficiency and stability, making NAS-GRF a highly effective solution for multi-output machine fault analysis in Industry 4.0 environments.

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