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Energy-Efficient Neural Architecture Search for Joint Production Status and Predictive Maintenance Classification

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ABSTRACT

Unexpected machine breakdowns are a major contributor to productivity loss in modern manufacturing, accounting for nearly 20–30% of total downtime in smart industrial environments. Although Industry 4.0 enables continuous monitoring through interconnected sensors, transforming large volumes of operational data into actionable insights for fault detection remains challenging. Conventional fault analysis methods rely heavily on manual inspections and expert intervention, often resulting in delayed fault identification and inconsistent maintenance decisions. In this study, a comprehensive dataset is utilized, consisting of parameters such as timestamp, machine ID, temperature, vibration intensity, 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 reduction, normalization, missing-value handling, and feature alignment, followed by Exploratory Data Analysis to uncover operational patterns, feature relationships, and key fault indicators. Baseline models such as Adaptive Boosting (AdaBoost)-Classification and Regression Trees (CART), Extreme Gradient Boosting (XGBoost)-CART, and Passive-Aggressive (PA)-CART are implemented for performance comparison. To address the limitations of manual feature engineering, a hybrid framework combining Neural Architecture Search (NAS) with Greedy Rule Forest (GRF)-CART is proposed, where NAS automatically learns optimal feature representations from complex sensor interactions and GRF-CART enhances interpretability and decision robustness. The framework performs classification tasks to predict downtime occurrence, maintenance requirement, and production status, along with regression-based estimation of efficiency score, and experimental results demonstrate improved prediction accuracy, reduced false maintenance alerts, and reliable efficiency assessment.

Keywords: Industrial Fault Diagnosis, Intelligent Maintenance Systems, Hybrid ML Framework,

Rule-Based Learning, Neural Architecture Optimization

1. INTRODUCTION

Modern manufacturing industries are steadily transitioning from conventional production approaches toward highly automated and digitally integrated environments. This transformation is primarily driven by the widespread deployment of smart sensors, programmable controllers, and interconnected machinery that continuously capture real-time operational parameters such as temperature, vibration, pressure, and rotational speed. These technologies enable continuous monitoring of equipment health and process conditions, allowing industries to shift from reactive maintenance practices to predictive and condition-based maintenance strategies. As a result, organizations now generate and manage massive volumes of machine-generated data, fundamentally reshaping how industrial systems are supervised, optimized, and maintained. This data-centric approach not only improves operational efficiency but also reduces unexpected failures, enhances product quality, and supports informed decision-making.

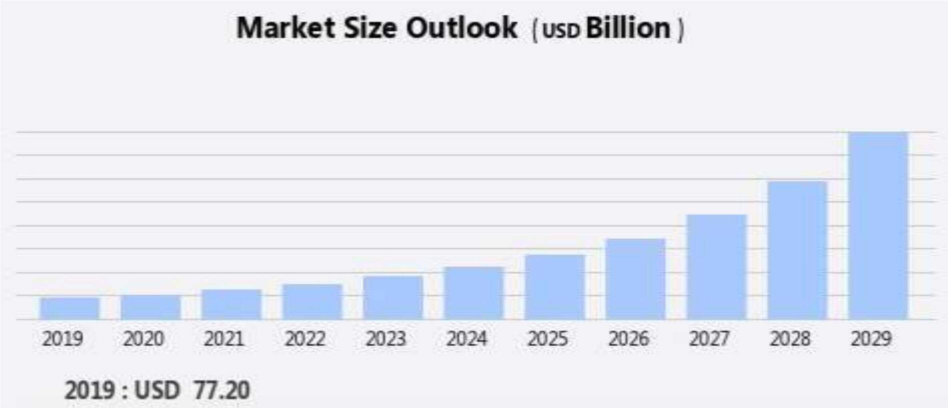

Fig. 1: Size of industry 4.0 market

Figure 1 illustrates the projected market growth, highlighting a consistent upward trend from 2019 to 2029. Beginning at approximately USD 77.20 billion in 2019, the market demonstrates steady year-over-year expansion, reflecting increasing adoption of smart manufacturing technologies across various sectors. In the initial years, growth progresses at a moderate pace, driven by gradual digital adoption and infrastructure development. However, from the mid-period onward, the growth rate accelerates significantly, indicating a surge in demand for advanced automation, intelligent monitoring systems, and data-driven industrial solutions. This rapid expansion is further supported by advancements in artificial intelligence, machine learning, and industrial analytics, which are becoming integral to modern production systems. Overall, the trend emphasizes a strong global shift toward intelligent, connected, and highly efficient manufacturing ecosystems.

2. LITERATURE SURVEY

Alsaif et al. [1] proposed a multimodal large language model–based fault diagnosis system for Industry 4.0. Algorithms such as LLMs integrated with deep neural networks were used. The approach enables intelligent reasoning but raises explainability concerns. Kullu et al. [2] proposed a deep learning–based multimodal sensor fusion model for equipment fault detection. Algorithms such as CNN, LSTM, and multimodal deep networks were employed. The system improves fault detection under complex operating conditions. Ali et al. [3] proposed a deep learning–based time-to-fault prediction framework for automated manufacturing systems. Algorithms such as LSTM, GRU, and temporal neural networks were used. The framework supports proactive maintenance decisions. Liu et al. [4] proposed a fault-tolerant soft sensor algorithm for uneven batch processes. LSTM networks were employed. The model improves process monitoring by handling nonlinear batch variations. Angelopoulos et al. [5] presented a comprehensive survey of ML solutions for Industry 4.0 fault handling. Algorithms such as SVM, RF, ANN, deep learning, and ensemble models were reviewed. The survey highlights the need for hybrid and interpretable models.

Leija et al. [6] proposed a comparative analysis to evaluate the performance of different ML algorithms for fault diagnosis in manufacturing systems. The study applied SVM, k-NN, decision trees, RF, and ANN to industrial datasets. The results showed that ensemble-based models achieved higher diagnostic accuracy, while simpler models offered faster computation. Illeri et al. [7] presented an efficient automatic fault classification approach that addressed data imbalance using one-dimensional deep learning. The method employed 1D-CNN combined with data balancing techniques to improve fault classification performance. The results demonstrated enhanced accuracy, particularly for minority fault classes. Tancredi et al. [8] described the integration of digital twin technology with ML methods for anomaly detection in an Industry 4.0 food processing plant. The study utilized RF and SVM to analyze real-time sensor data generated through the digital twin. The approach enabled early anomaly detection and improved operational monitoring. Megdadi et al. [9] designed an ML-driven predictive maintenance framework based on the best–worst method. The study applied RF and SVM to support maintenance decision-making and prioritize critical maintenance factors. The results indicated improved maintenance planning in Industry 4.0 environments.

Ryalat et al. [10] reviewed the integration of advanced mechatronic systems into Industry 4.0 for smart manufacturing. The paper discussed the use of ANN and SVM for monitoring, fault diagnosis, and control of mechatronic systems. The review highlighted the importance of intelligent data-driven techniques for system reliability. Goodarzi et al. [11] presented a robust distribution-aware ensemble learning approach for fault diagnosis in multi-sensor systems. The framework employed ensemble models that combined multiple base learners to handle variations in sensor data distributions. The results demonstrated improved fault classification accuracy and robustness in industrial multi-sensor applications. Yoo et al. [12] presented an induction motor fault diagnosis framework using low-cost MEMS acoustic sensors combined with MLNN. The study focused on capturing acoustic signals generated by motor operation and using neural network–based classification to identify different fault conditions. The results showed reliable fault detection performance while reducing sensing and hardware costs. Çınar et al. [13] reviewed the application of ML techniques for predictive maintenance in sustainable smart manufacturing under Industry 4.0. The study discussed algorithms such as SVM, ANN, k-NN, decision trees, and RF for fault diagnosis and maintenance prediction. The review emphasized the role of data-driven models in improving equipment reliability and reducing downtime. Kim et al. [14] presented a data-driven fault diagnosis approach for robot drive systems based on dynamics learning models. The study utilized ML techniques to learn system dynamics directly from operational data and identify deviations caused by faults. The method demonstrated effective fault detection and isolation under varying operating conditions without relying on explicit physical modeling. Koteleva et al. [15] described the use of the industrial metaverse concept for technical diagnosis of electric drive systems. The study integrated virtual environments with data-driven diagnostic methods, employing ML-based diagnostic models to analyze operational data. The results highlighted improved visualization, monitoring, and fault diagnosis capabilities within smart industrial systems.

3. PROPOSED SYSTEM

The proposed system presents a multi-stage intelligent pipeline for industrial fault detection, prediction, and decision support by integrating advanced ML and DL models. It begins with continuous acquisition of real-time and historical sensor data, which is preprocessed to ensure quality and consistency. The architecture then applies EDA to identify significant patterns and fault-related indicators. An adaptive feature extraction mechanism is employed to learn high-level representations from sensor data, followed by GRF to refine interpretable decision rules. These refined features are integrated into a hybrid NAS-GRF CART model that combines automated architecture search, rule optimization, and tree-based decision making. As depicted in Fig. 2, the system further benchmarks performance against models such as AB-CART, XGBoost-CART, GB-ART, and PA-CART to validate superiority. Finally, the unified framework performs both classification and regression tasks simultaneously, predicting downtime, maintenance needs, and production efficiency with high accuracy and robustness.

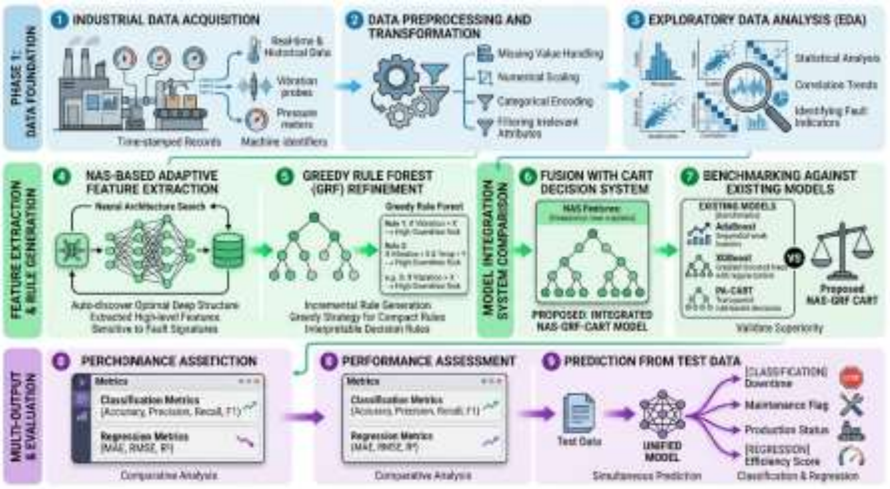

Fig. 2: Proposed system Architecture

1. Industrial Data Acquisition and Preprocessing: The system collects time-stamped data from multiple industrial sensors including vibration, pressure, and machine operation logs. Preprocessing techniques such as missing value handling, normalization, and categorical encoding are applied to standardize the dataset. Noise and irrelevant features are removed to enhance data quality. This step ensures that the input is reliable and suitable for ML and DL model training.

2. Exploratory Data Analysis and Fault Indicator Identification: EDA is performed using statistical analysis and visualization to understand data distribution, correlations, and trends. It helps in identifying key fault-related indicators and relationships between variables. Techniques such as correlation matrices and distribution plots support feature understanding. This step improves feature relevance and guides model learning.

3. NAS-Based Adaptive Feature Extraction: An NAS-based mechanism is used to automatically discover optimal neural architectures for feature extraction. It learns high-level representations from sensor data by exploring different network configurations. This approach captures complex patterns and reduces dimensionality. The extracted features significantly enhance the performance of downstream models.

4. GRF-Based Rule Refinement: GRF is applied to refine and optimize decision rules derived from extracted features. It incrementally simplifies complex rule sets into more interpretable and compact forms. This step ensures that important feature interactions are preserved while reducing redundancy. The refined rules improve both interpretability and decision-making efficiency.

5. Hybrid Decision Model with NAS-GRF CART: The system integrates NAS, GRF, and CART into a unified hybrid model. CART is used as the core decision-making algorithm, leveraging refined features and rules for accurate predictions. The hybrid approach combines deep feature learning with rule-based interpretability. It supports both classification and regression tasks simultaneously, improving overall system performance.

6. Benchmarking, Performance Evaluation, and Prediction: The proposed model is evaluated against baseline models such as AB-CART, XGBoost-CART, GB-ART, and PA-CART. Performance metrics including accuracy, precision, recall, F1-score, MAE, RMSE, and R² are used for comprehensive evaluation. Comparative analysis demonstrates the effectiveness of the hybrid model. The final system generates predictions for downtime, maintenance requirements, and production status, enabling data-driven decision-making in industrial environments.

4. RESULTS AND DISCUSSIONS

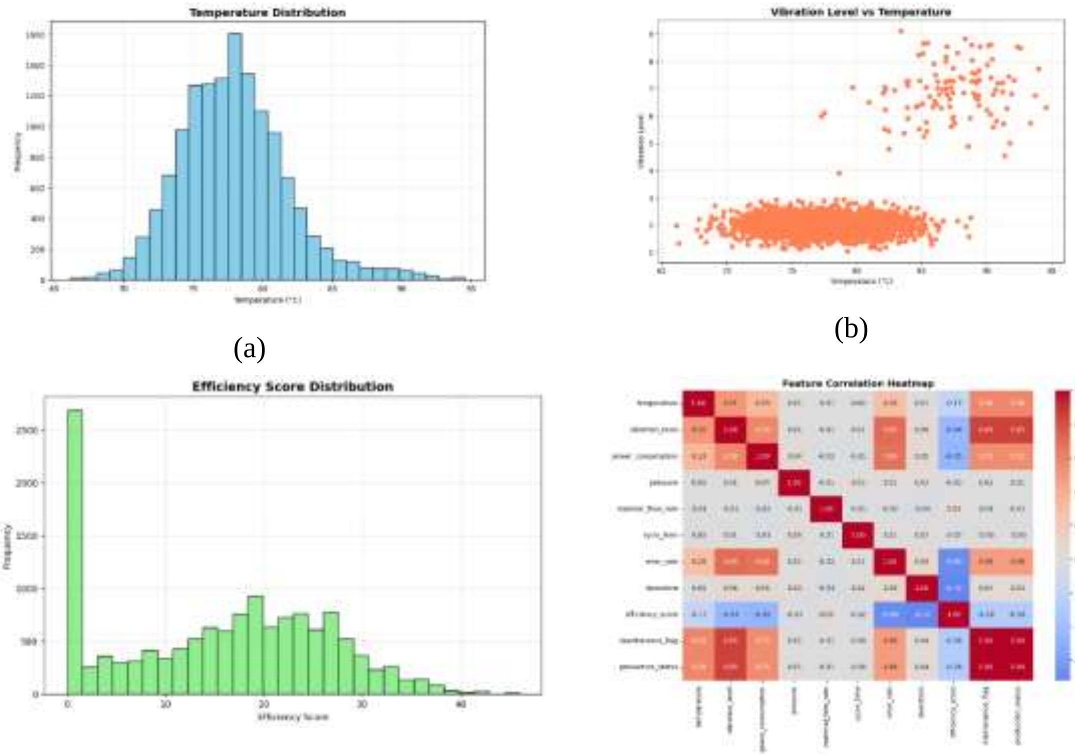

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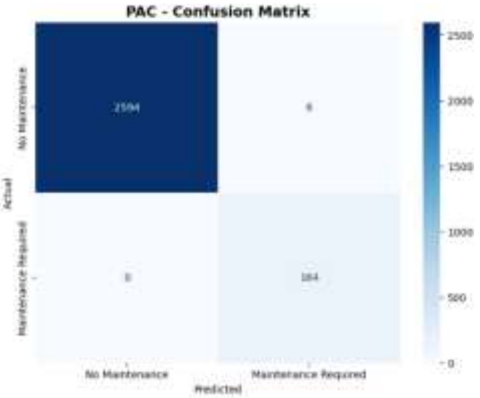
Fig. 3: Data analysis. (a) histogram, (b) scatter plot, (c) histogram, (d) correlation heatmap.

Fig. 3 presents the exploratory data analysis of the dataset used in the research.

- (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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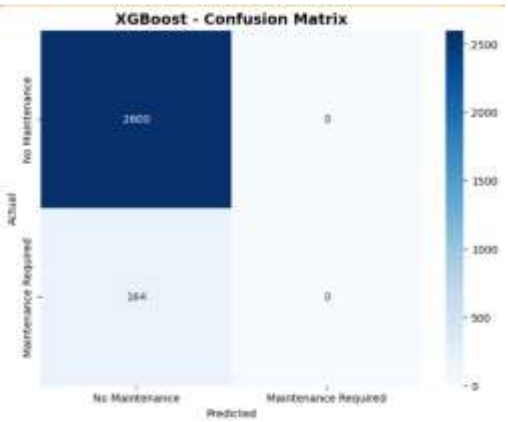

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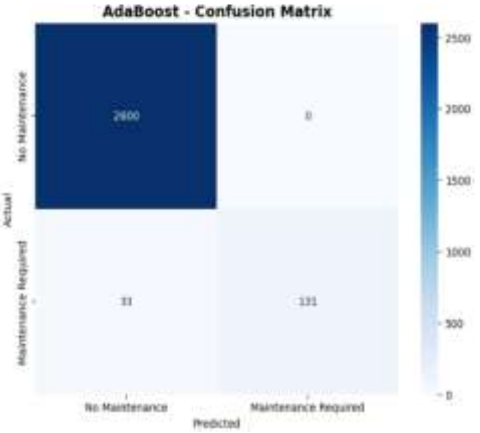

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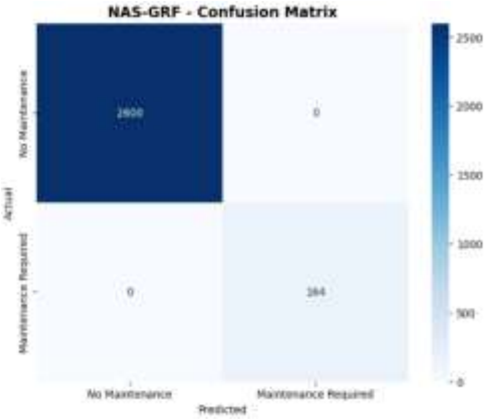

(d)

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

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.

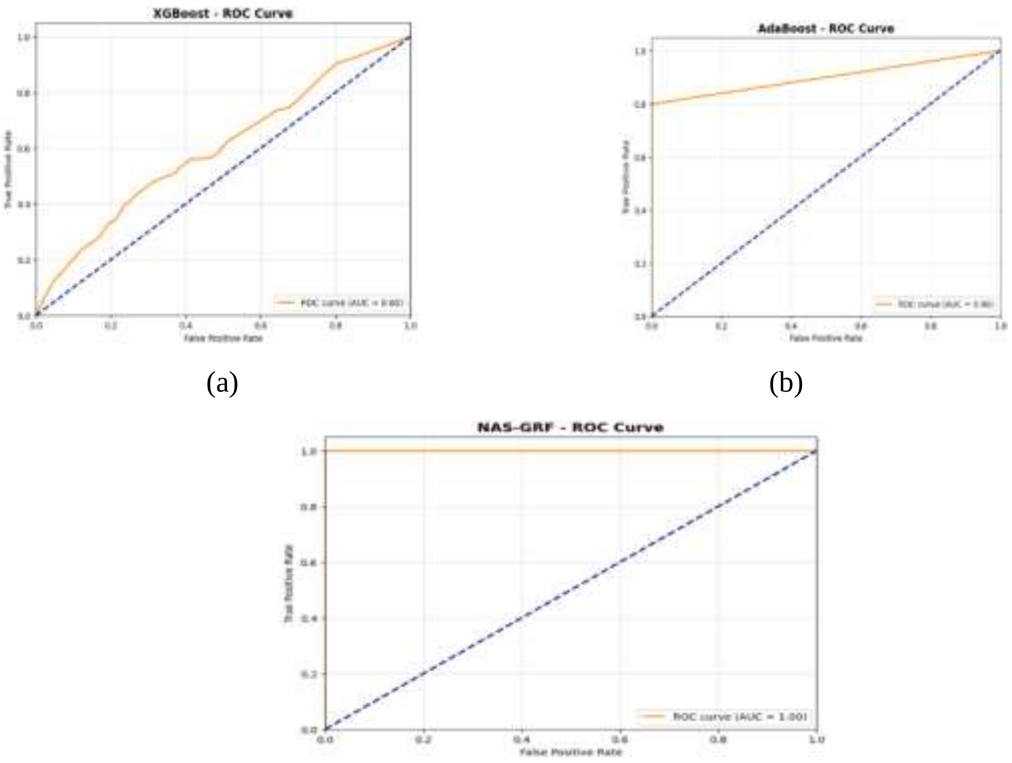

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Fig. 5: ROC Curves of Maintenance output (a) XG BOOST. (b)ADA BOOST. (c) proposed NAS-GRF.

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.

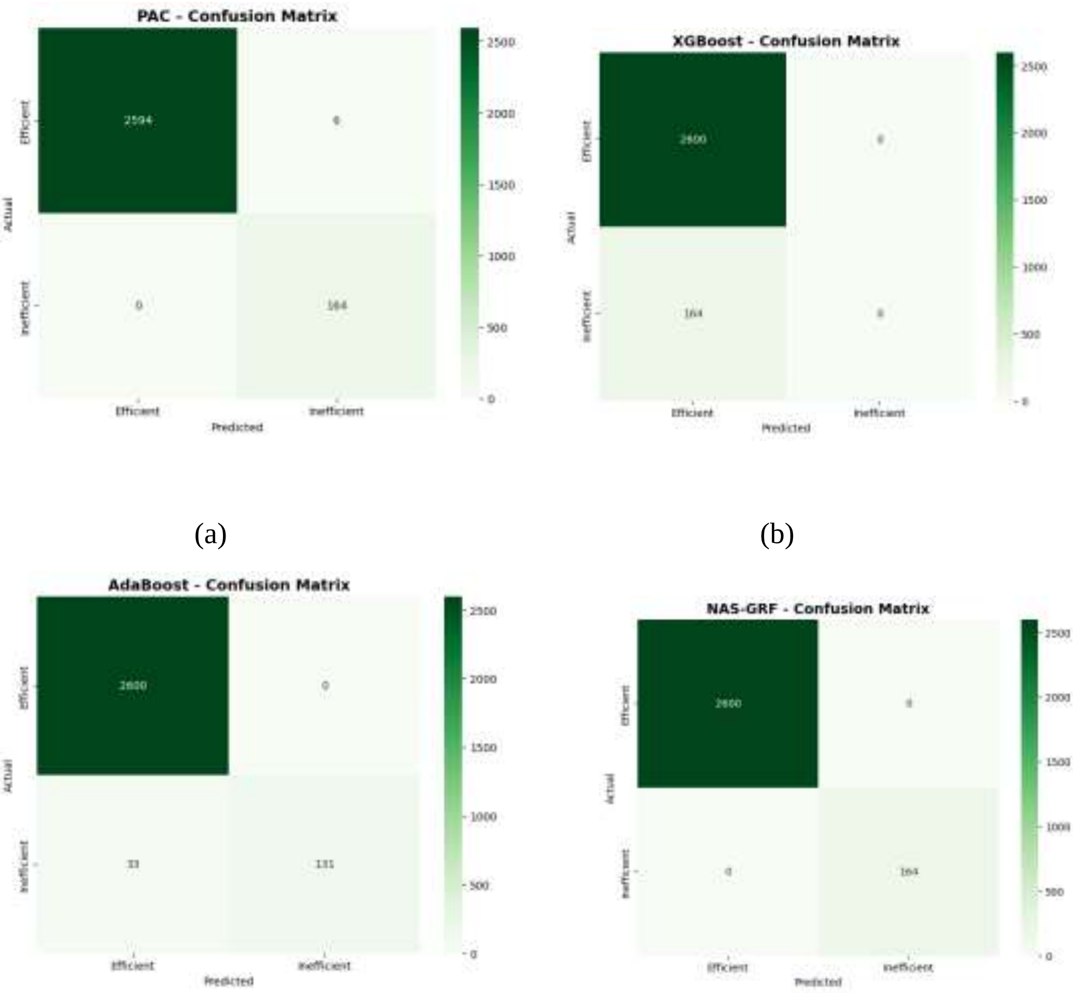

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Fig. 6: Confusion Matrix of Production Output (a)PAC. (b)XGBOOST. (c)ADA BOOST. (d) proposed NAS-GRF.

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.

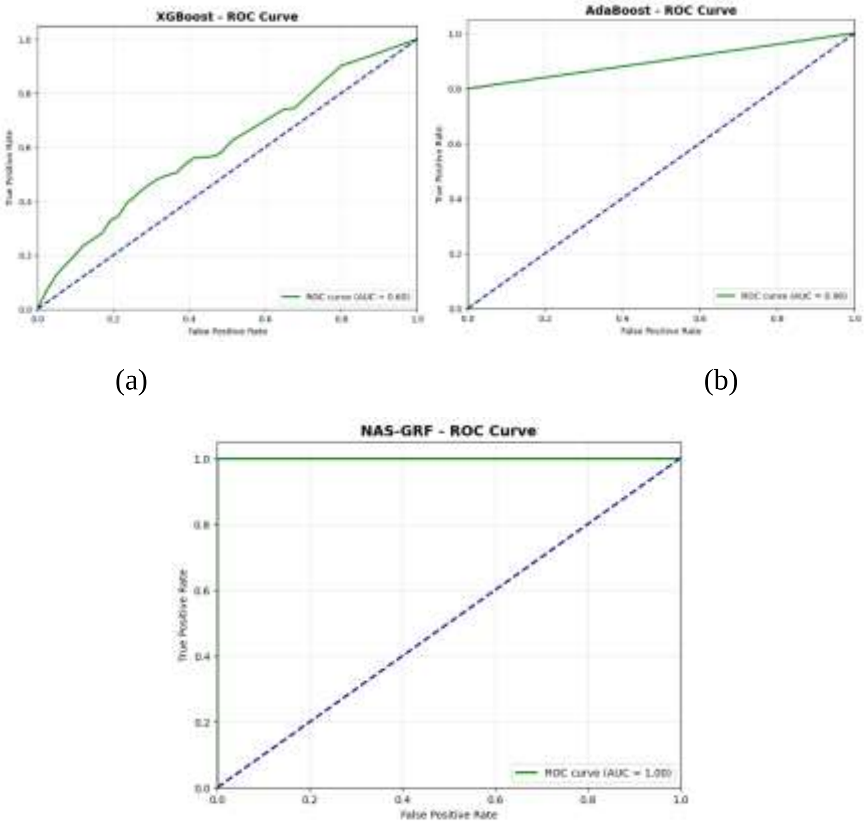

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Fig. 7: ROC Curves of Production output (a) XG BOOST. (b)ADA BOOST. (c) proposed NAS-GRF.

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.

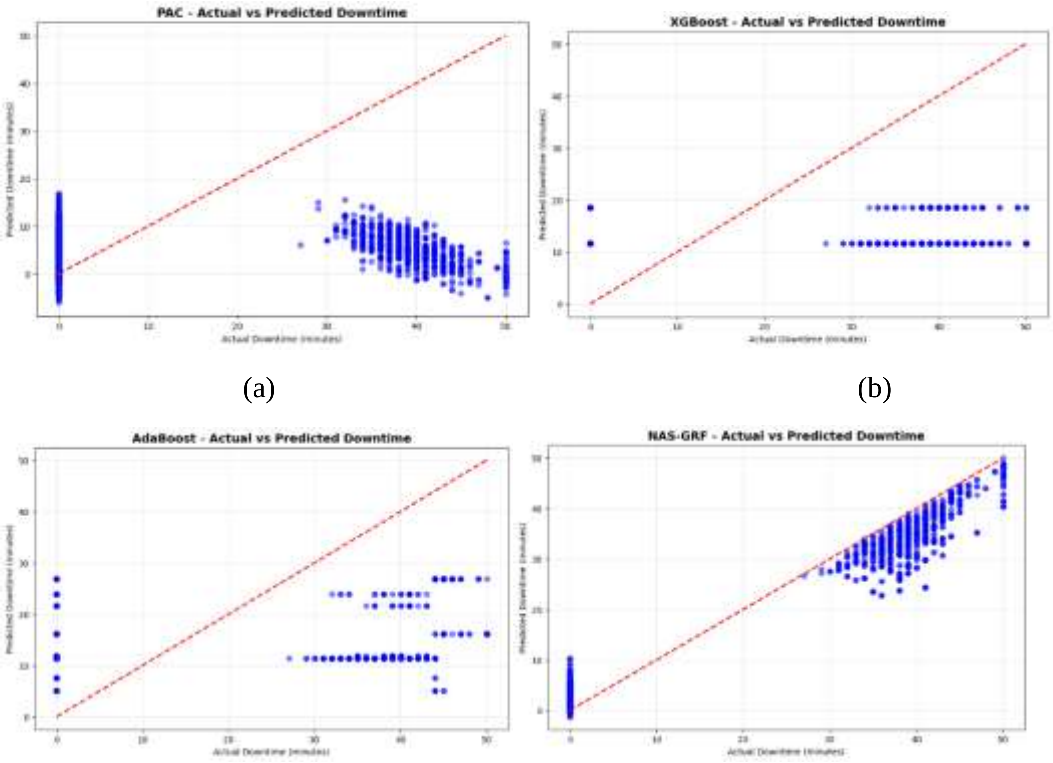

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Fig. 8: ROC Curves of Downtime Output(a) PAC. (b) XG BOST. (c) ADA BOOST. (d) Proposed NAS-GRF.

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.

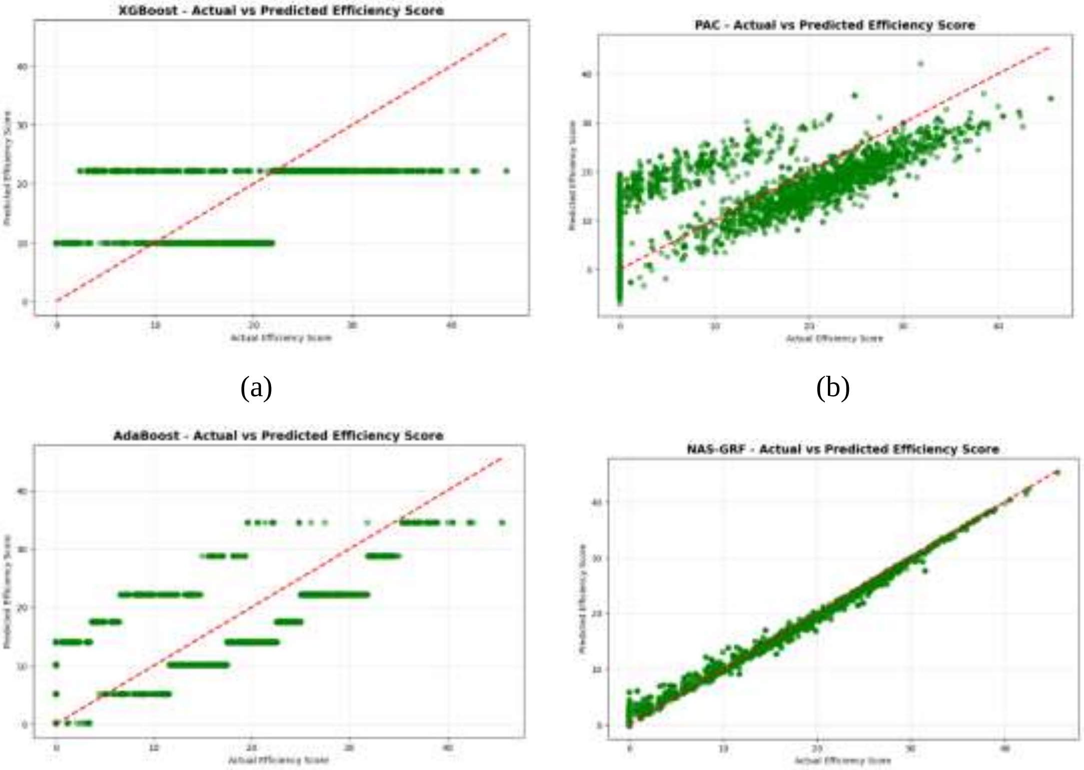

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Fig. 9: ROC Curves of Efficiency Score output (a) XG BOOST. (b)ADA BOOST. (c) proposed NAS-GRF.

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

The table 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

The table 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 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.

☑ **Prediction Results**

Single Prediction Results

Maintenance Flag
No Maintenance

Production Status
Efficient

Downtime (minutes)
16.17

Efficiency Score
1.67

Fig. 10: Prediction on sample test inputs.

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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