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Autonomous Industrial Intelligence via Multi-Modal Learning in Cloud-Connected Manufacturing Ecosystems

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ABSTRACT

The rapid evolution of Industrial Internet of Things (IoT) has transformed modern manufacturing by enabling continuous monitoring of machines through sensor-generated data. Traditionally, industrial systems relied on manual inspection and rule-based monitoring, where operators analyzed parameters such as temperature, vibration, and pressure to make decisions. However, these approaches often lacked real-time analytical capability and were unable to handle large-scale data effectively. As industrial environments became more complex, the need for intelligent data-driven systems emerged. Existing traditional systems suffer from limitations such as delayed fault detection, reactive maintenance strategies, poor scalability, and inability to capture hidden patterns in multidimensional data. To address these challenges, this study presents an advanced industrial analytics framework based on machine learning techniques integrated within a web-based environment. The proposed system utilizes a unified Two Classification and Two Regression Tasks (2CA2RT) framework to perform maintenance flag and production status prediction (classification), along with downtime and efficiency score prediction (regression). Multiple models including Passive Aggressive (PA), Extreme Gradient Boosting (XGB), Adaptive Boosting (AB), and a hybrid Neural Architecture Search–Greedy Rule Forest (NAS-GRF) are implemented to analyses industrial sensor data. The system incorporates data preprocessing, Exploratory Data Analysis (EDA), model training, evaluation, and prediction modules to ensure end-to-end functionality. Experimental results demonstrate that the proposed NAS-GRF model achieves superior performance across all four target variables. For classification tasks, it achieves 100% accuracy (1.0000) in maintenance flag prediction and 100% accuracy (1.0000) in production status prediction.

Key words: Multidimensional Sensor Data Analysis, Exploratory Data Analysis (EDA), Internet of things, Machine learning.

1. INTRODUCTION

The rapid evolution of Industrial Internet of Things (IIoT) technologies has revolutionized modern manufacturing by enabling continuous monitoring and intelligent control of industrial operations. Advanced smart sensors embedded within machinery continuously capture high-frequency data related to critical parameters such as temperature, vibration, pressure, and energy usage. This real-time data provides valuable insights into system behavior, facilitating improved efficiency, predictive maintenance, and optimized resource utilization. However, conventional manufacturing environments still depend heavily on manual supervision and rule-based systems, which are not well-suited to process large-scale, high-dimensional data or adapt to dynamic industrial conditions. As a result, these traditional approaches often lead to delayed responses, reduced accuracy, and suboptimal decision-making.

With the ongoing shift toward Industry 4.0 and digital transformation, there is an increasing demand for intelligent, data-driven systems capable of analyzing complex industrial data in real time. Machine

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learning and advanced analytics techniques are being integrated to extract meaningful patterns, detect anomalies, and support automated decision-making processes. Furthermore, the incorporation of cloud computing technologies significantly enhances system capabilities by providing scalable storage, high-performance processing, and seamless remote access to industrial data across geographically distributed environments. This integration enables centralized monitoring, collaborative analysis, and efficient management of industrial operations, thereby improving reliability, productivity, and overall system performance, as illustrated in Figure 1

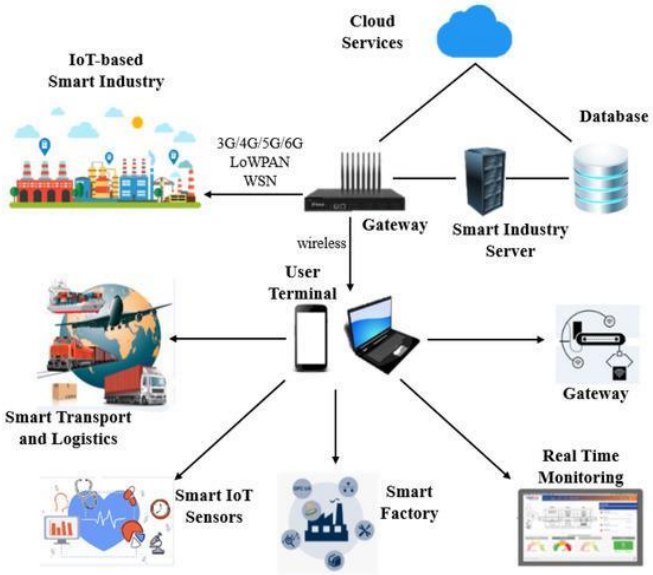


Figure 1. IoT-Based Smart Industry System Integrating

By leveraging cloud-integrated architectures, manufacturing systems can perform advanced analytics, predictive maintenance, and performance optimization in a scalable and efficient manner. Machine learning models can identify hidden patterns, predict failures, and optimize production processes based on historical and real-time data. This approach not only reduces downtime and operational costs but also enhances overall productivity and reliability. The combination of Industrial IoT, cloud computing, and machine learning enables the development of intelligent manufacturing frameworks that support data-driven decision-making. Such systems play a vital role in achieving sustainable and efficient industrial operations in the era of Industry 4.0.

2. LITERATURE SURVEY

2.1 Machine Learning-Based Predictive Maintenance

Machine learning (ML) techniques have been extensively applied for predictive maintenance in industrial environments. D. Bej et al. [1] proposed a real-time predictive maintenance framework using ANN, SVM, and RF, demonstrating improved fault detection through ensemble learning. Similarly, Varalakshmi et al. [4] introduced an optimized framework for continuous Industrial IoT data streams using Online RF and incremental learning models, enabling real-time fault prediction. Hasan et al. [11] developed a predictive maintenance system using RF and logistic regression to enhance maintenance scheduling and operational efficiency. Additionally, Khalil et al. [14] applied ML classifiers such as SVM, Decision Tree, k-NN, and RF for reliable fault classification in rotating machinery systems.

2.2 Deep Learning Approaches for Fault Diagnosis

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Deep learning (DL) models have shown significant advantages in capturing complex patterns from industrial sensor data. Polymeropoulos et al. [2] utilized CNN and LSTM models to analyze spatial–temporal patterns in air-cooling systems, improving diagnostic accuracy. Li et al. [3] conducted a comparative study involving CNN, LSTM, GRU, and DNN models, highlighting trade-offs between accuracy and computational cost. Furthermore, Lai et al. [13] proposed a residual attention-based Vision Transformer model, demonstrating its ability to extract complex vibration features for accurate fault diagnosis.

2.3 Ensemble and Hybrid Learning Techniques

To enhance robustness and prediction accuracy, several studies have explored ensemble and hybrid learning approaches. Ali et al. [5] proposed a multimodal sensor fusion framework combining CNN, DNN, and hybrid models to integrate heterogeneous sensor data for improved fault classification. Al-Andoli et al. [9] introduced a parallel ensemble architecture using Random Forest, AdaBoost, and Bagging, improving both detection speed and robustness. Similarly, Dalzochio et al. [7] combined ML models with reasoning techniques such as Bayesian Networks and rule-based learning to enhance interpretability and decision-making.

2.4 Signal Processing and Feature Engineering Techniques

Feature extraction and signal analysis play a crucial role in improving fault detection performance. Sawalhi et al. [10] proposed an improved vibration analysis method using Variable Frequency Drive (VFD) signatures to enhance order tracking and fault feature identification under non-stationary conditions. Lei et al. [8] emphasized the importance of feature extraction and degradation modeling in machinery health prediction, analyzing techniques such as HMM, ANN, and regression models.

2.5 Reviews and Challenges in Predictive Maintenance

Several studies have provided comprehensive reviews highlighting existing challenges and research gaps. Arena et al. [6] analyzed various ML algorithms including SVM, RF, k-NN, and Neural Networks, identifying issues such as scalability and data imbalance. Ismail et al. [12] explored digital twin–driven predictive maintenance systems, discussing integration challenges between physical and virtual environments. Seid Ahmed et al. [15] reviewed ML and DL-based fault detection techniques, emphasizing the need for real-time adaptability in automated manufacturing systems.

3. PROPOSED SYSTEM

The proposed analytical framework establishes a structured approach for analysing industrial IoT data to enhance manufacturing efficiency using artificial intelligence techniques. The analytical pipeline begins with sensor data acquisition and dataset organization, followed by data preprocessing and feature scaling. Industrial parameters such as temperature, vibration level, pressure, and power consumption are processed to remove inconsistencies and prepare the data for learning. The processed data is then transformed into standardized feature representations suitable for machine learning models. Multiple models including PA, XGB, AB, and NAS-GRF are employed to analyse the data and perform predictive tasks. A unified 2CA2RT framework is incorporated to simultaneously handle classification and regression tasks, enabling comprehensive evaluation of industrial performance. A graphical interface allows user interaction for data handling, model training, performance visualization, and prediction processes, as shown in figure 2. A lightweight database mechanism is used for managing authentication data, while a server component enables remote access and prediction. Continuous model

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evaluation and retraining further enhance analytical accuracy and adaptability to evolving industrial conditions.

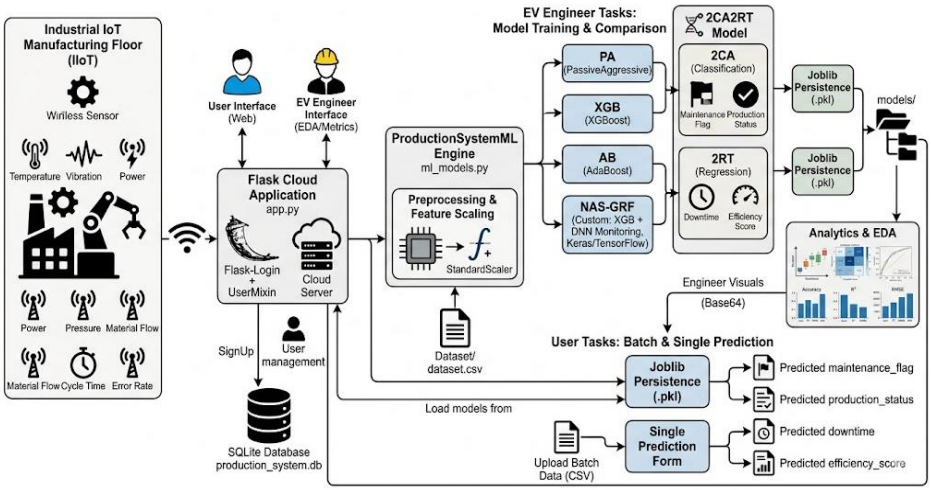


Figure 2: Proposed system architecture of IoT manufacturing with cloud.

1. User Interface (Client Application): The system serves as a bridge between industrial operators and the analytical backend via a modern web interface.

- **Functionality:** Provides dedicated modules for secure login, dataset uploading, and real-time prediction.
- **Interaction:** Captures manual parameter inputs or bulk CSV uploads, forwarding them to the Flask backend.
- **Visualization:** Renders performance graphs and prediction results for immediate interpretation by the user.

2. Flask Application Server: The Flask server functions as the central orchestration layer for the entire framework.

- **Request Routing:** Manages the communication flow between the web UI and the machine learning modules.
- **Execution Engine:** Handles the logic for data processing, triggering model training, and coordinating inference.
- **Concurrency:** Supports multiple simultaneous user sessions, enabling distributed industrial monitoring.

3. SQLite Database (Authentication Storage): A lightweight storage solution is implemented to manage the security perimeter.

- **Security:** Stores usernames and encrypted password hashes to prevent unauthorized access.
- **Management:** Maintains user roles and session data with a simple, high-performance architecture that requires minimal overhead.

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4. Industrial Dataset (Sensor Data Collection): The framework is powered by high-fidelity industrial sensor data reflecting real-time operations.

- **Parameters:** Includes critical metrics such as vibration levels, pressure, power consumption, and error rates.
- **Utility:** Acts as the ground truth for both training the 2CA2RT models and evaluating their predictive reliability.

5. Data Preprocessing & Feature Scaling: Before analysis, raw sensor inputs are refined to enhance mathematical stability.

- **Refinement:** Involves the removal of missing values and noise reduction to ensure data integrity.
- **Standardization:** Applies feature scaling to transform various sensor units into a uniform distribution, preventing any single parameter from biasing the models.

6. ML Models (2CA2RT Framework): The core intelligence of the system is organized into a specialized four-task structure utilizing models like PA, XGB, AB, and NAS-GRF.

- **2CA (Two Classification Tasks):**
  - **maintenance_flag:** Predicts if a machine requires immediate technical attention.
  - **production_status:** Classifies the current state of production efficiency.
- **2RT (Two Regression Tasks):**
  - **downtime:** Estimates the duration of potential machine inactivity.
  - **efficiency_score:** Calculates a numerical value representing operational performance.

7. Prediction & Inference Module: The inference engine processes the vectorized data to output actionable industrial insights.

- **Multi-Task Output:** Delivers simultaneous classification labels and regression values.
- **Interpretation:** Converts complex model outputs into readable formats displayed directly on the user dashboard.

8. Performance Visualization & Evaluation: The framework includes a diagnostic layer to verify the precision of the 2CA2RT models.

- **Metrics:** Utilizes F1-score and Recall for classification tasks, and RMSE and R^2 score for regression tasks.
- **Visual Analytics:** Generates confusion matrices and ROC curves to provide a transparent view of model strengths and weaknesses.

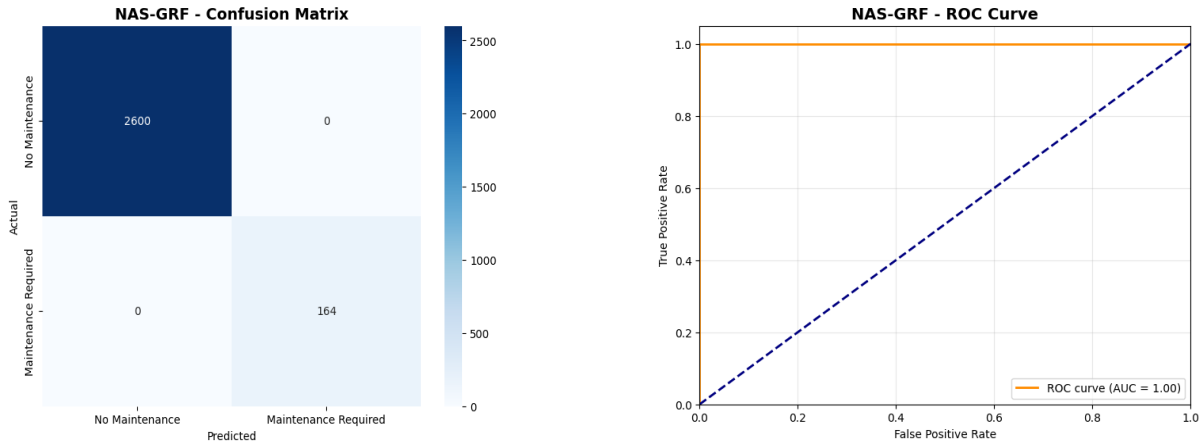
9. Remote Prediction & Model Evolution: The system is designed for scalability and long-term industrial deployment.

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- **Remote Workflow:** Enables users to send sensor data from remote factory floors to a centralized server for real-time analysis.
- **Adaptive Learning:** Supports model retraining with new industrial data patterns, ensuring the framework remains accurate as machine behaviour evolves over time.

4. RESULTS AND DISCUSSION

The results obtained from the analytical framework demonstrate the effectiveness of machine learning models in predicting industrial performance parameters. The evaluation is carried out using both classification and regression metrics to assess the accuracy and reliability of the system. Models such as PA, XGB, AB, and NAS-GRF are compared to determine their performance across different tasks under the 2CA2RT framework. Classification results are analysed using metrics like accuracy, precision, recall, F1-score, and ROC curves, while regression results are evaluated using MAE, RMSE, and R^2 scores. Visual representations such as confusion matrices, scatter plots, and performance graphs provide deeper insights into model behaviour. The results indicate that ensemble and hybrid models perform better in capturing complex relationships within industrial data. The analysis confirms that the system can deliver accurate and consistent predictions in real-time industrial environments.



(a) (b)

Figure 3 (a, b): Confusion matrix and ROC of NAS-GRF model for maintenance prediction.

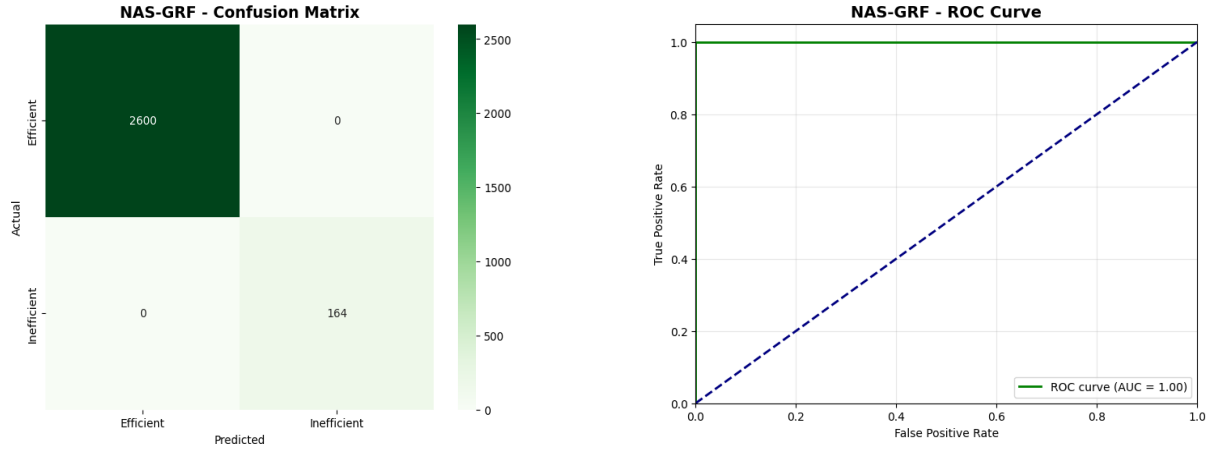
Figure 3(a) illustrates the confusion matrix generated by the NAS-GRF classification model for maintenance prediction. The matrix shows a perfect classification outcome where all instances are correctly identified without any misclassification. It indicates that the model accurately distinguishes between maintenance and non-maintenance conditions across all observations. The absence of false positives and false negatives reflects the model's strong learning capability. This result demonstrates the effectiveness of the hybrid approach in capturing complex patterns within industrial data

Figure 3(b) depicts the ROC curve of the NAS-GRF model, illustrating its classification performance across different threshold values. The curve reaches the top-left corner, indicating an ideal balance

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between true positive rate and false positive rate. The AUC value of 1.00 reflects perfect discrimination between classes. This suggests that the model can reliably distinguish maintenance requirements without error. The visualization confirms the robustness and consistency of the model's predictions.

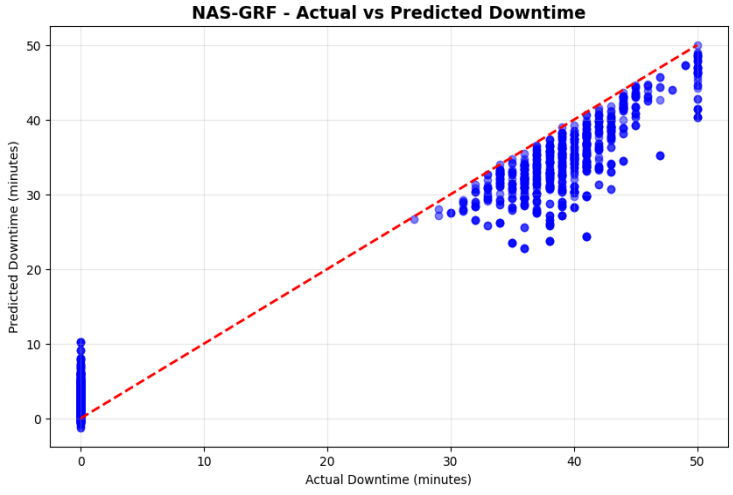
Figure 4(a) illustrates the confusion matrix generated by the NAS-GRF model for production status classification. The matrix shows that all instances are correctly classified into their respective categories without any misclassification. This indicates that the model achieves perfect prediction for both efficient and inefficient production states. The absence of false positives and false negatives reflects the model's strong capability in capturing complex patterns within the dataset. The visualization highlights the robustness and precision of the hybrid model.



(a) (b)

Figure 4 (a, b): Confusion matrix and ROC of NAS-GRF model for production status classification.

Figure 4(b) depicts the ROC curve of the NAS-GRF model for production status classification. The curve reaches the ideal top-left region, indicating maximum true positive rate with minimal false positive rate. The AUC value of 1.00 confirms perfect discriminative ability between classes. This suggests that the model consistently produces accurate predictions across all threshold values. The visualization provides strong evidence of the model's reliability and effectiveness.



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Figure 5: Actual vs Predicted downtime using NAS-GRF model.

Figure 5 illustrates the scatter plot of actual versus predicted downtime generated by the NAS-GRF regression model. The points are closely aligned along the reference line, indicating strong agreement between predicted and actual values. This alignment demonstrates the model's ability to accurately capture underlying patterns in downtime data. The reduced spread of points reflects high prediction precision and consistency. The visualization highlights the effectiveness of the hybrid model in regression tasks.

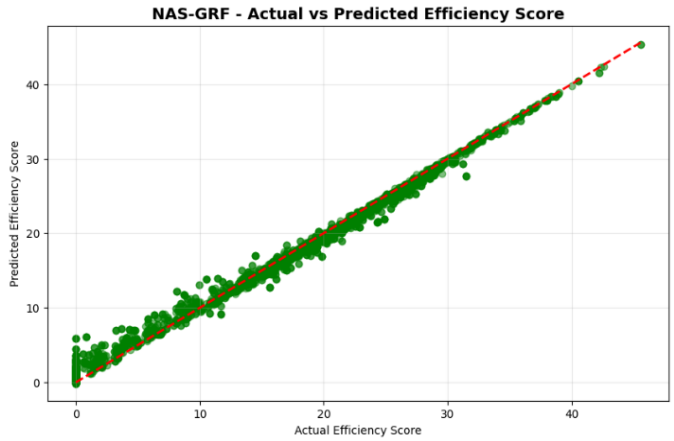


Figure 6: Actual vs Predicted efficiency score using NAS-GRF model.

Figure 6 illustrates the scatter plot comparing actual and predicted efficiency scores using the NAS-GRF regression model. The points are closely aligned along the reference line, indicating strong agreement between predicted and actual values. This alignment demonstrates the model's ability to accurately capture underlying efficiency patterns. The minimal deviation reflects high precision and consistency in predictions. The visualization highlights the superiority of the hybrid model in regression tasks.

The table 1 presents a comparative evaluation of classification models used for maintenance prediction within the industrial IoT system. It highlights key performance metrics including accuracy, precision, recall, and F1-score for models such as PA, XGB, AB, and NAS-GRF. The PA model achieves a high accuracy of 0.9978, indicating strong classification capability with perfect recall. AB also performs effectively with an accuracy of 0.9881, demonstrating balanced precision and recall. In contrast, the XGB model records a lower accuracy of 0.9407 and fails to capture minority class instances, resulting in zero precision and recall. The NAS-GRF model achieves perfect performance with an accuracy of 1.0000, along with ideal precision, recall, and F1-score.

Table. 1: Maintenance Flag - Detailed Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
PA	0.9978	0.9647	1.0000	0.9820

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XGB	0.9407	0.0000	0.0000	0.0000
AB	0.9881	1.0000	0.7988	0.8881
NAS-GRF	1.0000	1.0000	1.0000	1.0000

The table 2 presents a comparative evaluation of classification models using percentage-based performance metrics within the industrial IoT system. It includes accuracy, precision, recall, and F1-score for models such as PA, XGB, AB, and NAS-GRF. The PA model achieves an accuracy of 99.78%, demonstrating strong performance with high recall. AB also performs effectively with an accuracy of 98.81%, showing balanced predictive capability across metrics. The XGB model records an accuracy of 94.07%, but fails to identify minority class instances, resulting in zero precision and recall. The NAS-GRF model achieves perfect performance with 100% accuracy, precision, recall, and F1-score.

Table. 2: Production Status - Detailed Comparison

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1 Score (%)**
PA	0.9978	0.9647	1.0000	0.9820
XGB	0.9407	0.0000	0.0000	0.0000
AB	0.9881	1.0000	0.7988	0.8881
NAS-GRF	1.0000	1.0000	1.0000	1.0000

The table 3 presents a comparative evaluation of regression models used for predicting industrial parameters such as downtime and efficiency score. It includes performance metrics such as MAE, MSE, RMSE, and R^2 score for models including PA, XGB, AB, and NAS-GRF. The PA model shows higher error values with an MAE of 14.34% and a negative R^2 score of -0.2070, indicating poor predictive performance. The XGB and AB models demonstrate slight improvement with lower error values and marginally positive R^2 scores. However, their predictive capability remains limited in capturing complex data patterns. In contrast, the NAS-GRF model significantly outperforms all others with a low MAE of 2.82% and a high R^2 score of 95.85%.

Table 3: Downtime - Detailed Comparison

Model	**MAE (%)**	**MSE (%)**	**RMSE (%)**	**R^2 Score (%)**
PA	14.3494	407.2436	20.1803	-0.2070
XGB	16.7114	336.7798	18.3516	0.0019
AB	16.4930	328.1668	18.1154	0.0274

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NAS-GRF	2.8271	14.0169	3.7439	0.9585

The table 4 presents a comparative evaluation of regression models for efficiency score prediction using percentage-based metrics. It includes MAE, MSE, RMSE, and R^2 score for models such as PA, XGB, AB, and NAS-GRF. The PA model achieves moderate performance with an MAE of 6.71% and an R^2 score of 42.40%. The XGB model shows slightly lower performance with higher error values and an R^2 score of 32.19%. AB performs better among traditional models with an MAE of 6.75% and an improved R^2 score of 49.20%. The NAS-GRF model significantly outperforms all others with a very low MAE of 0.72% and a high R^2 score of 99.02%.

Table. 4: Efficiency Score - Detailed Comparison

Model	**MAE (%)**	**MSE (%)**	**RMSE (%)**	**R^2 Score (%)**
PA	6.7189	67.1581	8.1950	0.4240
XGB	7.7351	79.0615	8.8917	0.3219
AB	6.7519	59.2232	7.6957	0.4920
NAS-GRF	0.7279	1.1438	1.0695	0.9902

Figure 7 illustrates the prediction configuration interface of the industrial IoT production system, where users can define input parameters and select models for generating predictions. The interface allows users to choose a specific machine learning model and prediction type, supporting both single and batch prediction modes. It provides input fields for entering machine-related parameters such as temperature, vibration level, power consumption, pressure, material flow rate, cycle time, and error rate. These inputs are processed by the selected model to generate outputs related to maintenance, production status, downtime, and efficiency. The configuration module ensures flexibility and control over the prediction process.

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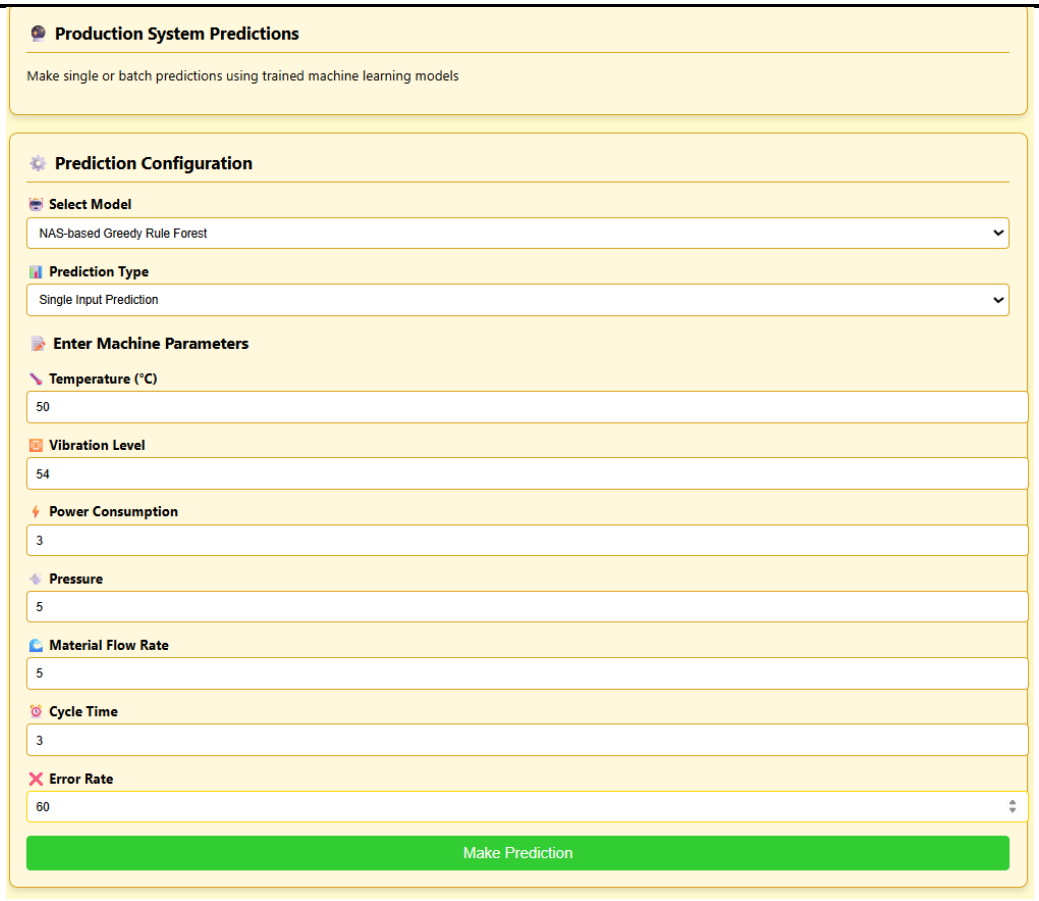


Figure 7: Prediction configuration interface

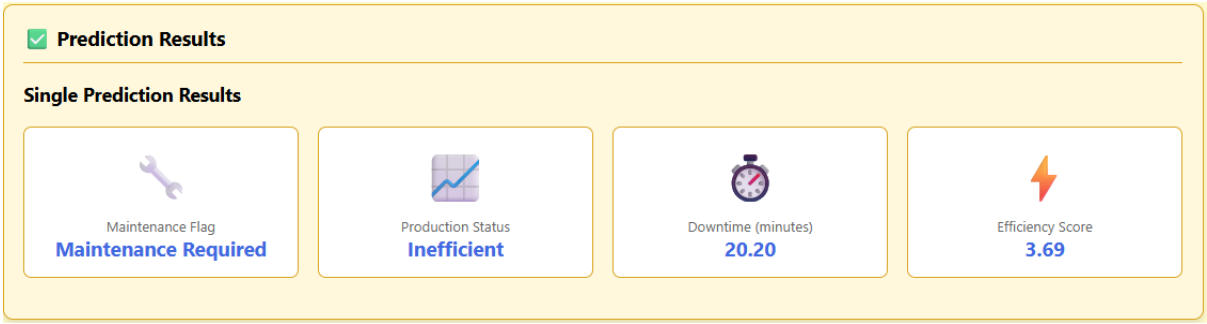


Figure 8: Single prediction results display

Figure 8 illustrates the prediction results interface of the industrial IoT production system, which displays the outcomes generated by the selected machine learning model. The interface presents results for multiple target variables, including maintenance requirement, production status, downtime, and efficiency score. It provides a clear and structured representation of predictions, enabling users to interpret system performance easily. The output reflects the analytical capability of the 2CA2RT framework in handling both classification and regression tasks simultaneously. This component plays a crucial role in supporting decision-making by providing actionable insights.

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Prediction Results

Batch Prediction Results (27 records)

#	Maintenance Flag	Production Status	Downtime (min)	Efficiency Score
1	No Maintenance	Efficient	10.28	9.19
2	No Maintenance	Efficient	33.36	4.07
3	No Maintenance	Efficient	36.52	5.77
4	No Maintenance	Efficient	35.08	2.50
5	No Maintenance	Efficient	1.26	18.58
6	Maintenance Required	Inefficient	0.26	0.16
7	Maintenance Required	Inefficient	1.42	-0.04
8	No Maintenance	Efficient	0.57	21.83
9	No Maintenance	Efficient	0.28	27.64
10	No Maintenance	Efficient	2.49	27.61
11	No Maintenance	Efficient	3.75	14.66
12	Maintenance Required	Inefficient	1.24	0.05
13	No Maintenance	Efficient	28.80	5.99
14	No Maintenance	Efficient	39.27	1.70
15	No Maintenance	Efficient	0.33	18.80
16	No Maintenance	Efficient	35.41	1.40
17	No Maintenance	Efficient	4.08	23.80
18	No Maintenance	Efficient	3.29	13.71

Figure 9: Batch prediction results table

Figure 9 illustrates the batch prediction results generated by the industrial IoT production system, displaying outputs for multiple input records simultaneously. The interface presents predictions for maintenance status, production performance, downtime, and efficiency score in a tabular format. It enables users to analyse large volumes of data efficiently by providing structured and organized results. The table format facilitates easy comparison across different records and helps identify patterns or anomalies in predictions. This component demonstrates the capability of the system to handle bulk data processing under the 2CA2RT framework.

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5. CONCLUSION

The study successfully demonstrates the effectiveness of an industrial IoT analytics framework for predicting maintenance requirements, production status, downtime, and efficiency using machine learning techniques. The integration of multiple models such as PA, XGB, AB, and NAS-GRF under the 2CA2RT framework enables comprehensive analysis of both classification and regression tasks. Experimental results indicate that traditional models provide moderate performance, while advanced ensemble approaches significantly improve prediction accuracy. In particular, the NAS-GRF model achieves superior performance with near-perfect classification accuracy and high R^2 scores in regression tasks. The system effectively handles industrial sensor data, providing reliable insights for decision-making and performance optimization. Visualization techniques further enhance interpretability and understanding of model behaviour. The implementation ensures scalability, efficiency, and secure user interaction through a web-based interface. Compared to conventional approaches, the proposed framework demonstrates clear performance improvements in accuracy, error reduction, and consistency. The system contributes to intelligent manufacturing by enabling data-driven optimization and predictive maintenance strategies.

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