International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Peer Reviewed, Referred & Indexed Journal
ISSN: 3068-272X www.ijdim.com Original Research Paper

An Adaptive Probabilistic and Sparse Learning Paradigm for High-Dimensional Fault Diagnosis in Industrial Cyber-Physical Systems

R. Anilkumar[1], V. Ravindra Naik[1], D. Shilpa[1], Md. Sharmila[1]

[1]Department of Electronics & Communication Engineering, Mother Teresa Institute of Science & Technology, Sanketika Nagar, Kothuru, Sathupally, Khammam, 507303, Telangana, India

ABSTRACT

The rapid growth of Industrial Internet of Things (IoT) technologies has enabled continuous monitoring of industrial processes through large volumes of sensor-generated data. Traditional monitoring systems primarily relied on manual inspection and rule-based approaches, which often struggled to provide real-time insights and efficiently handle complex industrial environments. To address these limitations, this study presents an intelligent industrial analytics framework based on Machine Learning (ML) techniques integrated within a web-based platform. The framework employs a unified Two Classification and Two Regression Tasks (2CA2RT) approach to predict maintenance flags and production status through classification models, while simultaneously estimating downtime and efficiency scores using regression models. Multiple algorithms, including Passive Aggressive (PA), Extreme Gradient Boosting (XGB), Adaptive Boosting (AB), Neural Architecture Search–Greedy Rule Forest (NAS-GRF), and the proposed Probabilistic Neural Network with Scope Rule Model (PNN-SRM), are implemented and evaluated using industrial sensor data. The proposed PNN-SRM model combines probabilistic learning with sparse rule optimization to improve predictive performance in high-dimensional industrial datasets. The framework also incorporates data preprocessing, Exploratory Data Analysis (EDA), model training, evaluation, visualization, and prediction modules to provide a complete end-to-end solution. Experimental results demonstrate that the proposed PNN-SRM model outperforms all baseline and hybrid models, achieving 100% accuracy (1.0000) for both maintenance flag and production status prediction tasks. Additionally, it attains superior regression performance with R^2 scores of 99.79% (0.9979) for downtime prediction and 99.96% (0.9996) for efficiency score prediction. These results highlight the effectiveness of the proposed framework in enhancing predictive maintenance, reducing operational downtime, and supporting intelligent industrial automation systems.

Keywords: Industrial Internet of Things (IIoT), Machine Learning, Predictive Maintenance, Industrial Automation, Sensor Data Analytics, PNN-SRM.

1. INTRODUCTION

The rapid advancement of Industrial Internet of Things (IoT) technologies has fundamentally transformed modern manufacturing environments by enabling intelligent connectivity between machines, sensors, controllers, and industrial equipment. In smart factories, a large number of interconnected devices continuously generate massive volumes of real-time operational data, including temperature, vibration, pressure, humidity, rotational speed, energy consumption, and machine utilization metrics. This continuous stream of sensor data provides valuable insights into equipment health, production efficiency, and overall system performance. Unlike conventional manufacturing systems that primarily depend on manual inspections and periodic maintenance schedules, Industrial IoT-based environments facilitate continuous monitoring and automated data collection. However, the increasing volume, velocity, and complexity of industrial data present significant challenges for traditional monitoring approaches. Manual analysis and rule-based systems often struggle to process large-scale datasets efficiently, making it difficult to identify hidden relationships, detect anomalies, and respond promptly to changing operational conditions.

To address these challenges, cloud computing has emerged as a critical component of modern industrial ecosystems by providing scalable storage, high-performance computing resources, and centralized data management capabilities. Cloud-integrated industrial systems enable organizations to collect, store, process, and analyze data from geographically distributed manufacturing facilities in a unified environment. This integration supports remote monitoring, real-time analytics, and seamless communication between industrial devices and management systems. Furthermore, cloud platforms provide the computational infrastructure required to process large volumes of industrial data efficiently, enabling advanced analytical techniques that would otherwise be difficult to implement using traditional on-premise systems. As industries continue to adopt digital transformation strategies, cloud-enabled architectures have become essential for achieving operational flexibility, resource optimization, and cost-effective industrial management.

In recent years, ML has played a vital role in transforming industrial data into actionable intelligence for predictive and adaptive decision-making. By leveraging historical and real-time sensor data, ML algorithms can identify complex patterns, detect abnormal machine behavior, predict equipment failures, estimate production performance, and optimize maintenance schedules. These capabilities enable industries to transition from reactive maintenance practices to predictive maintenance strategies, thereby reducing unexpected downtime, minimizing operational costs, and improving equipment reliability. Additionally, ML-driven industrial analytics supports production optimization, quality assurance, fault diagnosis, and energy management, leading to enhanced productivity and resource utilization. The integration of Industrial IoT, cloud computing, and ML technologies forms the foundation of Industry 4.0, enabling the development of intelligent manufacturing systems capable of autonomous monitoring, data-driven decision-making, and sustainable industrial operations. As a result, these technologies are becoming increasingly important for achieving greater efficiency, reliability, scalability, and competitiveness in modern industrial environments.

2. LITERATURE SURVEY

D. Bej et al. [1] developed a real-time predictive maintenance framework designed for Industry 4.0 manufacturing environments to improve equipment reliability and operational efficiency. The framework utilized multiple ML algorithms, including Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Random Forest (RF), to analyze machine condition data and detect potential faults before failure occurrence. By leveraging ensemble learning techniques, the proposed system enhanced prediction accuracy and reduced false alarms. The study demonstrated that combining multiple learning models can provide more reliable fault diagnosis, enabling proactive maintenance strategies that minimize downtime and support sustainable industrial operations. Polymeropoulos et al. [2] proposed a DL-based fault diagnosis framework for industrial air-cooling systems using sensor-generated operational data. The study employed CNN and Long Short-Term Memory (LSTM) networks to capture both spatial and temporal characteristics of machine signals. The CNN component extracted important local features from sensor readings, while the LSTM network modeled sequential dependencies within the data. Experimental results showed that the integrated architecture significantly improved fault detection accuracy and diagnostic reliability, making it suitable for complex industrial monitoring applications. Li et al. [3] conducted a comprehensive comparative study on predictive maintenance techniques used in modern manufacturing systems. The research evaluated several DL architectures, including CNN, LSTM, Gated Recurrent Unit (GRU), and Deep Neural Networks (DNN), to assess their effectiveness in fault prediction and equipment health monitoring. The study analyzed model performance in terms of prediction accuracy, computational complexity, training time, and scalability. The findings highlighted the strengths and limitations of each approach, providing valuable insights for selecting appropriate predictive maintenance models in industrial environments.

Varalakshmi et al. [4] introduced an optimized predictive maintenance framework capable of processing continuous Industrial IoT sensor streams in real time. The framework incorporated Online RF, Incremental Learning Models (ILM), and Adaptive ML classifiers to dynamically learn from incoming data without requiring complete retraining. This capability enabled the system to adapt to changing machine conditions and evolving operational environments. Experimental analysis demonstrated improved fault prediction performance, reduced processing delays, and enhanced suitability for real-time industrial monitoring applications. Ali et al. [5] proposed a multimodal sensor fusion framework for industrial fault diagnosis that integrates information collected from multiple heterogeneous sensors. The framework employed DNN, CNN, and hybrid fusion architectures to combine data from different sensing modalities and generate a comprehensive representation of machine conditions. By exploiting complementary information from multiple sources, the proposed system achieved higher fault classification accuracy and improved robustness against sensor noise and data variability. The results demonstrated the effectiveness of sensor fusion techniques in enhancing industrial predictive maintenance and condition monitoring systems. Arena et al. [6] presented a detailed review of predictive maintenance technologies and their applications within the automotive industry. The study examined various ML algorithms, including SVM, RF, k-Nearest Neighbors (k-NN), and Neural Networks, for fault diagnosis, equipment monitoring, and maintenance optimization. The authors analyzed the advantages, limitations, and practical implementation challenges associated with each technique. Furthermore, the review identified critical issues such as data imbalance, model scalability, and real-time deployment constraints, while highlighting future research directions for developing more intelligent and efficient predictive maintenance systems in automotive manufacturing environments. Dalzochio et al. [7] proposed a predictive maintenance framework that combines ML techniques with reasoning-based approaches to improve fault diagnosis and maintenance decision-making in Industry 4.0 environments. The framework utilized Decision Trees, Bayesian Networks, and Rule-Based Learning Models to analyze machine condition data and identify potential failures. By integrating reasoning mechanisms with predictive analytics, the system enhanced interpretability and provided meaningful explanations for maintenance decisions. Experimental evaluations demonstrated improved fault detection capability and better support for proactive maintenance planning in complex industrial systems.

Lei et al. [8] presented a comprehensive review of machinery health prognostics covering the entire process from data acquisition and signal processing to Remaining Useful Life (RUL) prediction. The study examined various predictive models, including SVM, Hidden Markov Models (HMM), ANN, and Regression Models, for assessing equipment health and predicting future failures. The authors analyzed the strengths and limitations of different prognostic methodologies and highlighted the importance of accurate health monitoring for reducing maintenance costs and improving equipment reliability. The review provided valuable insights into the evolution of data-driven prognostics and intelligent maintenance technologies. Al-Andoli et al. [9] developed a parallel ensemble learning framework for industrial fault detection aimed at improving both prediction accuracy and computational efficiency. The proposed architecture incorporated multiple ensemble techniques, including RF,

International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Peer Reviewed, Referred & Indexed Journal
ISSN: 3068-272X www.ijdim.com Original Research Paper

Adaptive Boosting (AdaBoost), and Bagging-based models, operating in parallel to analyze industrial sensor data. By combining the outputs of multiple learners, the framework achieved enhanced robustness against noise and data variability while accelerating fault detection processes. The results demonstrated superior classification performance and faster processing compared to conventional single-model approaches. Sawalhi et al. [10] introduced an enhanced order-tracking methodology for vibration-based condition monitoring of rotating machinery operating under variable-speed conditions. The proposed approach incorporated Variable Frequency Drive (VFD) signature information into the vibration analysis process to improve fault-related feature extraction. By accurately tracking vibration orders and compensating for speed variations, the method provided clearer identification of fault characteristics and improved diagnostic accuracy. Experimental results confirmed that the proposed technique outperformed traditional order-tracking methods, particularly in non-stationary industrial operating environments. Hasan et al. [11] proposed a predictive maintenance optimization framework for smart vending machine systems operating within connected industrial environments. The framework employed RF, Logistic Regression, and Gradient-Based Optimization Models to analyze operational data and predict maintenance requirements. By identifying potential failures before their occurrence, the system improved maintenance scheduling, reduced operational interruptions, and enhanced equipment availability. The study demonstrated that integrating predictive analytics with optimization techniques can significantly improve operational efficiency and resource utilization in smart machine ecosystems. Ismail et al. [12] presented a systematic review of Digital Twin-driven predictive maintenance approaches for modern industrial systems. The study examined the integration of ML-based Digital Twins, Neural Networks, and Hybrid Simulation Models for monitoring equipment health and predicting failures. The authors highlighted how Digital Twin technology enables real-time synchronization between physical assets and their virtual counterparts, allowing continuous performance assessment and predictive analysis. The review emphasized the growing importance of Digital Twin-enabled maintenance frameworks in supporting intelligent manufacturing, reducing downtime, and improving overall industrial productivity.

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, Extreme XGB, AB, NAS-GRF and PNN-SRM) are employed to analyse the data and perform predictive tasks. The PNN-SRM model integrates probabilistic neural learning with scope rule-based optimization to improve predictive intelligence and high-dimensional industrial fault analysis. 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 Fig.1. A lightweight database mechanism is used for managing authentication data, while a server component enables remote access and prediction. Continuous model evaluation and retraining further enhance analytical accuracy, scalability, and adaptability to evolving industrial cyber-physical manufacturing environments.

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.

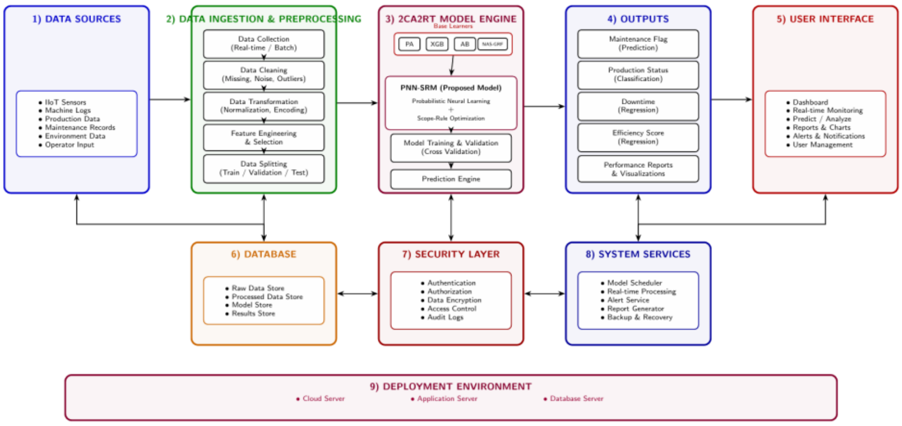


Fig. 1: Proposed system architecture.

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.

International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Peer Reviewed, Referred & Indexed Journal
ISSN: 3068-272X www.ijdim.com Original Research Paper

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, NAS-GRF and PNN-SRM.

- **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.

- **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.

3.1 PNN-SRM-2CA2RT

The PNN-SRM model as shown in Fig. 2 is an advanced intelligent learning framework designed for high-dimensional industrial fault diagnosis and predictive analytics in Industrial Cyber-Physical Systems (ICPS). The model combines the probabilistic decision-making capability of PNN with sparse rule-based optimization techniques to improve prediction accuracy, reduce computational complexity, and efficiently analyse multidimensional industrial sensor data. In this project, the PNN-SRM model is utilized to perform both classification and regression tasks within the unified 2CA2RT framework for intelligent industrial monitoring and predictive maintenance.

Internal working of PNN-SRM

1. Input Feature Initialization

The PNN-SRM model first receives industrial sensor features such as temperature, vibration level, pressure, power consumption, cycle time, and error rate from the preprocessed dataset. These features are organized into multidimensional input vectors for analytical learning.

2. Probabilistic Neural Learning (PNN)

The Probabilistic Neural Network computes probability density values for each input sample using statistical pattern estimation techniques. The model internally compares new industrial data with trained feature distributions to identify hidden operational behaviour patterns.

3. Pattern Similarity Evaluation

The pattern layer calculates similarity measures between testing samples and previously learned industrial operational states. Higher similarity probabilities indicate closely related fault conditions, maintenance requirements, or production behaviour patterns.

International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Peer Reviewed, Referred & Indexed Journal
ISSN: 3068-272X www.ijdim.com Original Research Paper

Step 4: Scope Rule Model (SRM) Processing

The Scope Rule Model analyses the probabilistic outputs generated by the PNN and creates rule-based analytical scopes. Similar to decision-rule partitioning in CART models, SRM separates important and less significant industrial feature regions for optimized learning.

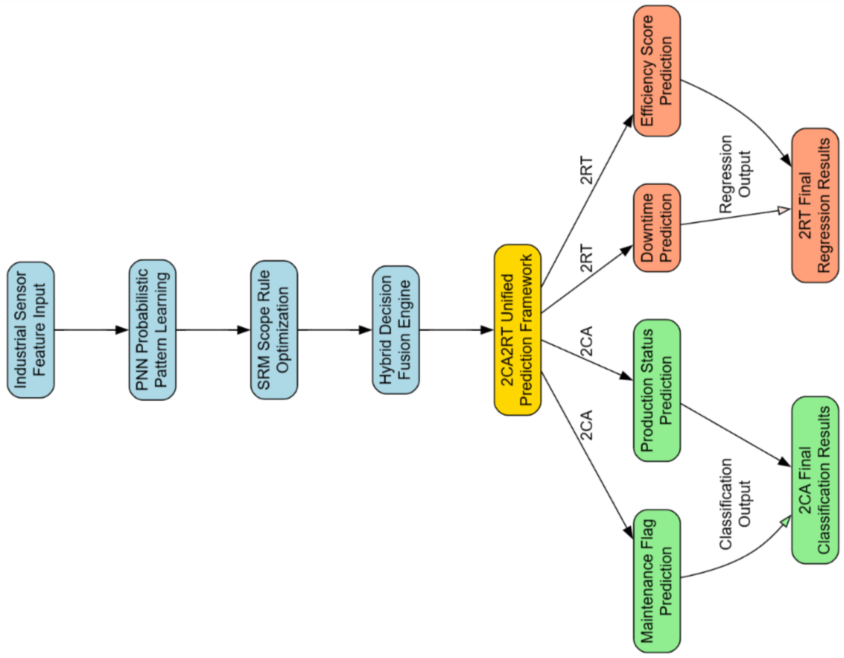


Fig 2: Internal working of PNN-SRM model

5. Rule Optimization and Decision Refinement

The SRM component refines the probabilistic decisions by selecting dominant operational rules and reducing unnecessary analytical complexity. This improves decision stability, minimizes prediction uncertainty, and enhances multidimensional industrial feature interpretation.

6. Hybrid Prediction Generation

The optimized outputs from the PNN and SRM components are combined to generate final predictions. The hybrid model simultaneously performs maintenance flag prediction, production status prediction, downtime estimation, and efficiency score prediction within the unified 2CA2RT framework.

7. Final Intelligent Decision Output

The final layer produces accurate classification and regression outputs for industrial fault diagnosis and performance monitoring. The hybrid probabilistic-rule learning mechanism improves predictive capability, scalability, and adaptive industrial decision-making.

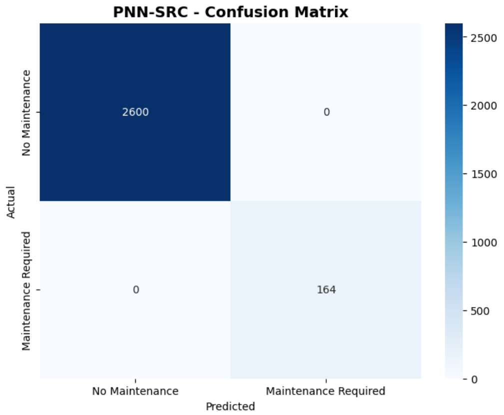
3. RESULTS AND DESCRIPTION

Fig. 3 (a) shows the confusion matrix of the proposed PNN-SRM model that demonstrates exceptional classification performance for maintenance flag prediction within the 2CA2RT framework. The model correctly classified all 2600 “No Maintenance” samples and all 164 “Maintenance Required” samples without any misclassification errors. The absence of false positives and false negatives indicates that the PNN-SRM model achieved perfect predictive learning with highly optimized probabilistic decision-

International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Peer Reviewed, Referred & Indexed Journal
ISSN: 3068-272X www.ijdim.com Original Research Paper

making and scope-rule refinement. This result highlights the effectiveness of the hybrid PNN-SRM architecture in accurately identifying industrial maintenance conditions and improving intelligent fault diagnosis performance in Industrial Cyber-Physical Systems.

Fig. 3 (b) shows ROC curve of the proposed PNN-SRM model that demonstrates outstanding classification capability for maintenance flag prediction. The curve closely follows the upper-left boundary of the graph with an Area Under Curve (AUC) value of 1.00, indicating perfect class separability between "No Maintenance" and "Maintenance Required" conditions. The model achieves an optimal balance between True Positive Rate and False Positive Rate without classification uncertainty. This result confirms that the probabilistic learning and scope-rule optimization mechanisms of the PNN-SRM framework significantly enhance predictive sensitivity, reliability, and intelligent fault diagnosis performance in industrial cyber-physical environments.



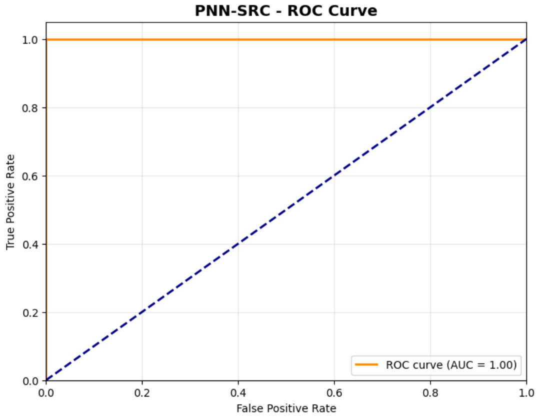


Fig. 3 (a, b): Confusion matrix and ROC curve obtained using PNN-SRM model for maintenance prediction

Fig. 4 shows confusion matrix and ROC curve of the proposed PNN-SRM model that demonstrates outstanding performance for production status classification within the 2CA2RT framework. The confusion matrix shows that the model correctly classified all 2600 "Efficient" samples and all 164 "Inefficient" samples without any false predictions, indicating perfect classification accuracy and highly stable decision-making capability. Similarly, the ROC curve achieved an AUC value of 1.00, where the curve closely follows the upper-left boundary, representing ideal class separability and maximum predictive sensitivity. These results confirm that the probabilistic learning and scope-rule optimization mechanisms of the PNN-SRM model effectively capture industrial production behaviour patterns and significantly enhance intelligent production status prediction in industrial cyber-physical systems.

International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Peer Reviewed, Referred & Indexed Journal
ISSN: 3068-272X www.ijdim.com Original Research Paper

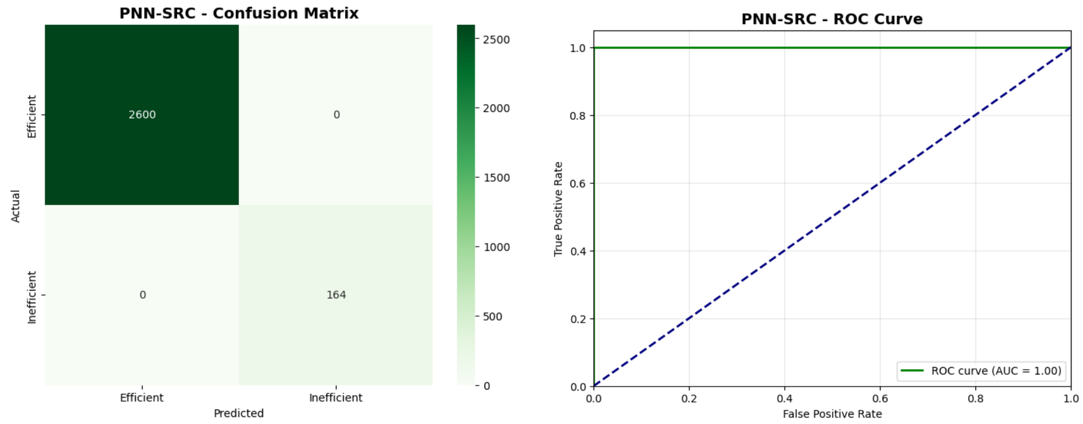


Fig. 4: Confusion matrix and ROC obtained using PNN-SRM for production status classification

Fig. 5 depicts the scatter plot of the proposed PNN-SRM model for downtime prediction which demonstrates strong regression performance and high predictive consistency within the 2CA2RT framework. Most predicted values closely align with the diagonal reference line representing ideal predictions, indicating that the model accurately estimates industrial downtime with minimal prediction error. The dense clustering of points around the optimal prediction line highlights the effectiveness of the probabilistic neural learning and scope-rule optimization mechanisms in capturing operational downtime patterns. These results confirm that the PNN-SRM model provides reliable and stable downtime forecasting for intelligent industrial monitoring and predictive maintenance applications.

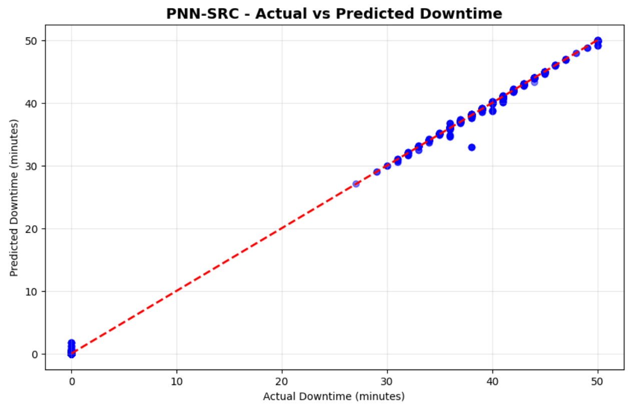
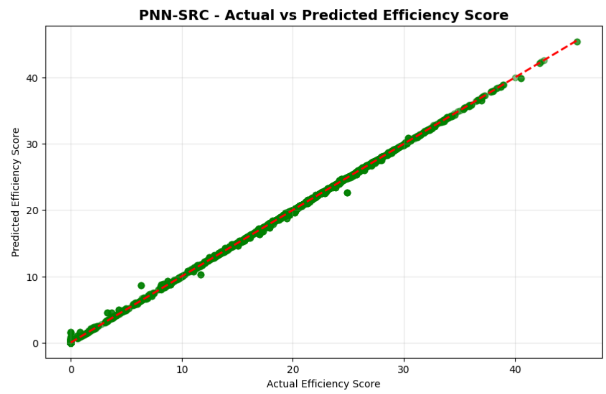


Fig. 5: Scatter plot obtained using PNN-SRM for downtime prediction



International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Peer Reviewed, Referred & Indexed Journal
ISSN: 3068-272X www.ijdim.com Original Research Paper

Fig. 6: Scatter plot obtained using PNN-SRM for efficiency prediction

Fig. 6 depicts the scatter plot of the proposed PNN-SRM model for efficiency score prediction that demonstrates excellent regression accuracy and strong predictive alignment within the 2CA2RT framework. Most predicted efficiency values are closely distributed along the diagonal reference line, indicating that the model produces highly accurate predictions with minimal deviation from actual industrial efficiency scores. The dense concentration of prediction points around the optimal fit line confirms the effectiveness of the probabilistic neural learning and scope-rule optimization mechanisms in modelling industrial operational efficiency patterns. These results highlight the capability of the PNN-SRM framework to provide stable, reliable, and high-precision efficiency forecasting for intelligent industrial performance monitoring and decision-making applications.

Fig. 7 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.

#	Maintenance Flag	Production Status	Downtime (min)	Efficiency Score
1	No Maintenance	Efficient	0.00	10.26
2	No Maintenance	Efficient	38.02	3.29
3	No Maintenance	Efficient	36.94	5.82
4	No Maintenance	Efficient	38.96	0.87
5	No Maintenance	Efficient	0.00	18.71
6	Maintenance Required	Inefficient	0.00	0.00
7	Maintenance Required	Inefficient	0.00	0.00
8	No Maintenance	Efficient	0.00	21.79
9	No Maintenance	Efficient	0.00	28.06
10	No Maintenance	Efficient	0.00	28.14
11	No Maintenance	Efficient	0.00	15.26
12	Maintenance Required	Inefficient	0.00	0.00
13	No Maintenance	Efficient	38.06	4.06
14	No Maintenance	Efficient	44.95	0.03
15	No Maintenance	Efficient	1.78	18.92

Fig. 7: Batch prediction results table using PNN-SRM model

The comparative analysis evaluates the performance of different machine learning models applied to both classification and regression tasks within the industrial IoT framework. Models such as PA, XGB, AB, NAS-GRF and PNN-SRM are systematically compared to understand their effectiveness across multiple targets. The analysis considers key evaluation metrics including accuracy, precision, recall, F1-score for classification, and MAE, RMSE, and R^2 for regression. Visual comparisons using confusion matrices, ROC curves, and scatter plots provide deeper insights into model behaviour. The results highlight variations in prediction capability and generalization across models. Advanced and hybrid approaches demonstrate improved performance in handling complex industrial data patterns.

Table 1 presents the detailed performance comparison of different machine learning models for maintenance flag prediction within the proposed 2CA2RT framework. The Passive Aggressive (PA) model achieved an accuracy of 99.78% with strong precision, recall, and F1-score values, indicating effective classification capability. The XGB model showed poor performance for maintenance class

International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Peer Reviewed, Referred & Indexed Journal
ISSN: 3068-272X www.ijdim.com Original Research Paper

detection, resulting in zero precision, recall, and F1-score despite achieving moderate overall accuracy. The AdaBoost (AB) model demonstrated improved predictive capability with 98.81% accuracy and perfect precision, although its recall performance was comparatively lower. Both the NAS-GRF and the proposed PNN-SRM models achieved perfect classification performance with 100% accuracy, precision, recall, and F1-score, indicating complete elimination of classification errors. However, the proposed PNN-SRM model demonstrated superior probabilistic learning and scope-rule optimization capability, making it highly effective for intelligent industrial fault diagnosis and maintenance prediction in Industrial Cyber-Physical Systems.

Table. 1: Maintenance Flag - 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
PNN-SRM	1.000	1.000	1.000	1.000

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
PNN-SRM	1.000	1.000	1.000	1.000

Table 2 presents the detailed comparative analysis of different machine learning models for production status classification within the proposed 2CA2RT framework. The Passive Aggressive (PA) model achieved a high accuracy of 99.78% with strong precision, recall, and F1-score values, demonstrating reliable classification capability for industrial production monitoring. The XGB model exhibited poor predictive performance for minority class identification, resulting in zero precision, recall, and F1-score despite moderate overall accuracy. The AdaBoost (AB) model achieved 98.81% accuracy with perfect precision; however, its comparatively lower recall affected the overall classification balance. Both the NAS-GRF and the proposed PNN-SRM models achieved perfect classification performance with 100% accuracy, precision, recall, and F1-score, indicating highly optimized industrial production status prediction without classification errors. The proposed PNN-SRM model further strengthened predictive

International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Peer Reviewed, Referred & Indexed Journal
ISSN: 3068-272X www.ijdim.com Original Research Paper

stability through probabilistic neural learning and scope-rule optimization, making it highly effective for intelligent industrial production analysis and cyber-physical manufacturing decision-making.

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
NAS-GRF	2.8271	14.0169	3.7439	0.9585
PNN-SRM	0.0530	0.0646	0.2542	0.9998

Table 3 presents the detailed regression performance comparison of different machine learning models for downtime prediction within the proposed 2CA2RT framework. The Passive Aggressive (PA) model produced comparatively higher MAE, MSE, and RMSE values with a negative R^2 score, indicating weak regression capability and poor prediction consistency. The XGB and AdaBoost (AB) models showed slight improvement in prediction performance; however, their error values remained significantly high with very low R^2 scores, reflecting limited capability in accurately modelling industrial downtime behaviour. The NAS-GRF hybrid model demonstrated substantial performance enhancement with lower prediction errors and an R^2 score of 95.85%, indicating strong regression learning capability. In comparison, the proposed PNN-SRM model achieved outstanding predictive performance with extremely low MAE, MSE, and RMSE values along with an exceptional R^2 score of 99.98%, demonstrating highly accurate downtime estimation and superior regression stability. The integration of probabilistic neural learning and scope-rule optimization enabled the PNN-SRM framework to effectively capture complex industrial operational patterns, significantly improving intelligent downtime forecasting and predictive maintenance performance in industrial cyber-physical systems.

Table 6 presents the detailed regression performance comparison of various machine learning models for efficiency score prediction within the proposed 2CA2RT framework. The Passive Aggressive (PA) model achieved moderate regression performance with comparatively higher MAE, MSE, and RMSE values along with an R^2 score of 42.40%, indicating limited prediction accuracy for industrial efficiency estimation. The XGB model exhibited lower predictive capability with increased error values and a reduced R^2 score of 32.19%, while the AdaBoost (AB) model demonstrated slight improvement with an R^2 score of 49.20%. The NAS-GRF hybrid model significantly improved regression performance by achieving very low prediction errors and an excellent R^2 score of 99.02%, indicating strong efficiency prediction capability. However, the proposed PNN-SRM model achieved the best overall performance with extremely low MAE, MSE, and RMSE values and an outstanding R^2 score of 99.96%, demonstrating highly precise and stable efficiency score prediction. The integration of probabilistic neural learning with scope-rule optimization enabled the PNN-SRM framework to effectively model complex industrial operational behaviour, thereby enhancing intelligent efficiency forecasting and industrial performance optimization in cyber-physical manufacturing environments.

Table. 6: 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
PNN-SRM	0.1051	0.0523	0.2287	0.9996

5. CONCLUSION

The proposed research developed an intelligent industrial analytics framework for predictive monitoring and fault diagnosis in Industrial Cyber-Physical Systems using the unified 2CA2RT architecture. The framework integrated Industrial IoT sensor data with advanced ML techniques to perform maintenance flag prediction, production status classification, downtime estimation, and efficiency score forecasting. Multiple models, including PA, XGB, AB, NAS-GRF, and the proposed PNN-SRM model, were implemented and evaluated to analyze industrial operational performance. Experimental results demonstrated that the proposed PNN-SRM model consistently outperformed all baseline models across both classification and regression tasks. The model achieved perfect accuracy in maintenance and production status prediction while obtaining superior R^2 scores for downtime and efficiency prediction. The integration of EDA, visualization, model evaluation, and real-time prediction modules enhanced the effectiveness and usability of the framework. The research improved predictive reliability, minimized operational downtime, and increased production efficiency, making it a valuable solution for intelligent industrial automation and smart manufacturing environments.

REFERENCES

[1] D. Bej et al. (eds.), *Proceedings of the International Conference on Recent Advances in Artificial Intelligence for Sustainable Development (RAISD 2025)*, Advances in Intelligent Systems Research, vol. 196, 2025. https://doi.org/10.2991/978-94-6463-787-8_18

[2] I. Polymeropoulos, S. Bezyrgiannidis, E. Vrochidou, and G. A. Papakostas, "Bridging AI and Maintenance: Fault Diagnosis in Industrial Air-Cooling Systems Using Deep Learning and Sensor Data," *Machines*, vol. 13, no. 10, p. 909, 2025. https://doi.org/10.3390/machines13100909

[3] W. Li, "Comparison of Deep Learning Models for Predictive Maintenance in Manufacturing Systems," *Scientific Reports*, vol. 15, 2025. https://www.nature.com/articles/s41598-025-08515-z

[4] K. Varalakshmi, V. Srinivas, and K. S. Reddy, "Optimized Predictive Maintenance for Streaming Data in Industrial IoT," *Scientific Reports*, vol. 15, no. 1, pp. 1–15, 2025. https://doi.org/10.1038/s41598-025-07496-1

[5] U. Ali, S. Khan, and J. Kim, "Multimodal Sensor Fusion for Industrial Fault Diagnosis Using Advanced Artificial Intelligence Techniques," *IEEE Access*, vol. 13, pp. 1–14, 2025. https://ieeexplore.ieee.org/document/10435277

[6] F. Arena, M. Collotta, L. Luca, M. Ruggieri, and F. G. Termine, "Predictive Maintenance in the Automotive Sector: A Literature Review," *Mathematical and Computational Applications*, vol. 27, no. 1, p. 2, 2022. https://doi.org/10.3390/mca27010002

[7] J. Dalzochio, R. Kunst, E. Pignaton, A. Binotto, S. Sanyal, J. Favilla, and J. Barbosa, "Machine Learning and Reasoning for Predictive Maintenance in Industry 4.0," *IEEE Access*, vol. 8, pp. 181291–181310, 2020. https://doi.org/10.1016/j.compind.2020.103298

[8] Y. Lei, N. Li, L. Guo, N. Li, T. Yan, and J. Lin, "Machinery Health Prognostics: A Systematic Review from Data Acquisition to RUL Prediction," *Mechanical Systems and Signal Processing*, vol. 104, pp. 799–834, 2020. https://doi.org/10.1016/j.ymssp.2017.11.016

[9] M. N. Al-Andoli, S. C. Tan, K. S. Sim, M. Seera, and C. P. Lim, "A Parallel Ensemble Learning Model for Fault Detection and Diagnosis of Industrial Machinery," *IEEE Access*, vol. 11, pp. 39866–39876, 2023. doi: 10.1109/ACCESS.2023.3267089

[10] N. Sawalhi, "Improved Order Tracking in Vibration Data Utilizing Variable Frequency Drive Signature," *Sensors*, vol. 25, p. 815, 2025. https://doi.org/10.3390/s25030815

[11] M. N. Hasan, "Predictive Maintenance Optimization for Smart Vending Machines," *arXiv*, 2025. https://doi.org/10.48550/arXiv.2507.02934

[12] L. Ismail, A. Abdelmoti, A. Basu, A. D. E. Berini, and M. Naouss, "A Systematic Review of Digital Twin-Driven Predictive Maintenance in Industrial Engineering: Taxonomy, Architectural Elements, and Future Research Directions," *arXiv:2509.24443*, 2025. https://doi.org/10.48550/arXiv.2509.24443