CAPSTONE PROJECT

PREDICTIVE MAINTENANCE OF INDUSTRIAL MACHINERY

Presented By:

1. Rosemary Benny - Fr. C. Rodrigues Institute Of Technology - Computer Engineering Department



OUTLINE

- Problem Statement
- Proposed System/Solution
- System Development Approach
- Algorithm & Deployment
- Result (Output Image)
- Conclusion
- Future Scope
- References



PROBLEM STATEMENT

Develop a predictive maintenance model for a fleet of industrial machines to anticipate failures before they occur. This project will involve analyzing sensor data from machinery to identify patterns that precede a failure. The goal is to create a classification model that can predict the type of failure (e.g., tool wear, heat dissipation, power failure) based on real-time operational data. This will enable proactive maintenance, reducing downtime and operational costs.



PROPOSED SOLUTION

The proposed system aims to address the challenge of predicting machine failures in a fleet of industrial machines before they occur. This involves leveraging sensor data analytics and machine learning techniques to anticipate potential failures and ensure uninterrupted machine operation. The solution will consist of the following components:

Data Collection:

- Gather historical data from industrial machines, including operational parameters such as temperature, pressure, load, and speed.
- Utilize real-time sensor data streams to enhance the prediction of failure events

Data Preprocessing:

- Clean and preprocess the collected data to handle missing values, outliers, and inconsistencies.
- Perform feature engineering to extract and select relevant features that may influence machine failures (e.g., duration of operation, type of machine).

Machine Learning Algorithm:

The following algorithms were tried:

- Snap Random Forest Classifier
- Snap Decision Tree Classifier

The best-performing ensemble model (P5), built through automated hyperparameter tuning and feature engineering, was selected for accurately predicting machine failure types.

Deployment:

- Develop a user-friendly interface or application that allows operators to input real-time sensor data and receive predictions of possible failure types.
- Deploy the solution on IBM Cloud using Watsonx.ai for scalability, reliability, and easy access.

Evaluation:

- Assess the model's performance using classification metrics such as Accuracy, Precision, Recall, and F1-Score.
- Fine-tune the model based on continuous feedback and real-time monitoring of prediction results.

Result:

- The trained model will accurately classify the failure type based on real-time operational data, enabling proactive maintenance actions.
- This will help reduce machine downtime, optimize maintenance schedules, and lower operational costs.



SYSTEM APPROACH

This section outlines the overall strategy and methodology for developing and implementing the machine failure prediction system.

System Requirements

- Operating System: Windows 10 / Ubuntu 20.04+
- **RAM**: Minimum 4 GB (8 GB recommended)
- Browser: Chrome or Firefox (for IBM Cloud access)
- IBM Cloud Lite Account with Watsonx.ai Studio enabled

Libraries / Tools Used

- IBM Watsonx.ai (AutoAl for model building and deployment)
- pandas (for initial data formatting before upload)
- scikit-learn (used internally by AutoAl pipelines)
- numpy (data transformation within preprocessing)
- matplotlib / seaborn (for optional visualization)



ALGORITHM & DEPLOYMENT

Algorithm Selection:

The model selection process in IBM Watsonx.ai tested multiple algorithms including:

Snap Random Forest Classifier

Snap Decision Tree Classifier

The final model was an ensemble pipeline (P5), chosen for its high accuracy in predicting different failure types such as tool wear and overstrain.

- Data Input: The input features included:
 - Machine type (categorical: L, M)
 - Dimensional values (e.g., 302, 311.2)
 - Operational metrics like speed, load, temperature, pressure
 - Label: Failure Type (e.g., No Failure, Tool Wear Failure, etc.)

Training Process:

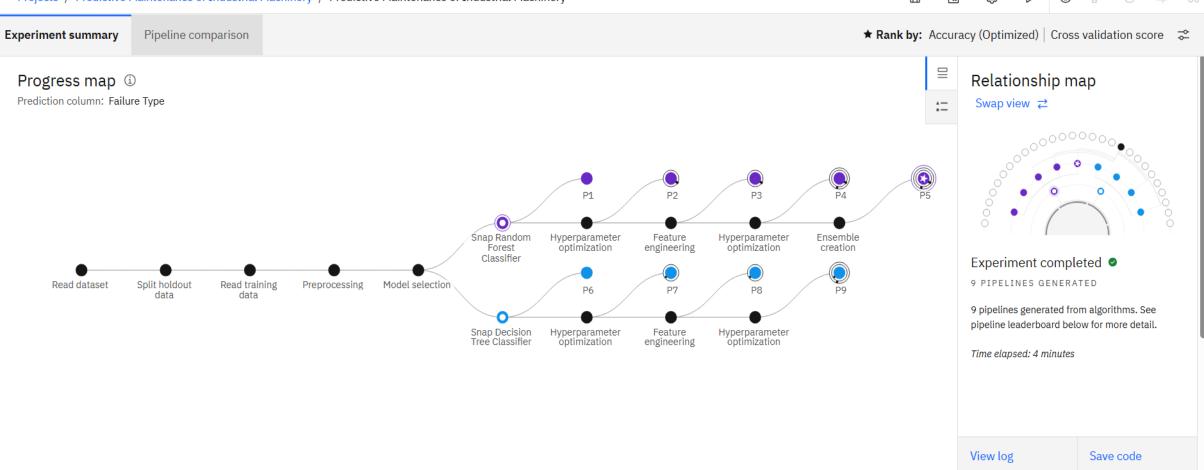
- The model was trained on historical sensor data using IBM Watson AutoAl, which automatically handled:
- Data preprocessing and cleaning
- Feature engineering
- Hyperparameter tuning
- Ensemble creation for best performance

Prediction Process:

• Once trained, the model predicts the type of failure based on live or batch sensor input. It takes real-time parameters and outputs the likely failure class along with a confidence score, enabling proactive maintenance.

RESULT

Projects / Predictive Maintenance of Industrial Machinery / Predictive Maintenance of Industrial Machinery





predictive Maintenance Openhoyed Online

API reference

Test

Enter input data

Text

JSON

Enter data manually or use a CSV file to populate the spreadsheet. Max file size is 50 MB.

Download CSV template ★ Browse local files ↗

Search in space 7

	UDI (double)	Product ID (other)	Type (other)	Air temperature [K] (double)	Process temperature [K] (double)	Rotational speed [rpm] (double)	Torque [Nm] (double)	Tool wear [min] (double)
1	51	L47230	L	298.9	309.1	2861	4.6	143
2	52	L47231	L	298.9	309.1	1383	54.9	145
3	53	H29466	Н	298.8	309	1497	43.8	147
4								





Prediction results

	nat for prediction results view	Show input data ①
	prediction	probability
1	Power Failure	[0,0,0,1,0,0]
2	No Failure	[0,0.9997901439666749,0,0
3	No Failure	[0,1,0,0,0,0]
4		
5		
6		
7		
8		
9		



CONCLUSION

• The predictive maintenance model developed in this project effectively utilizes machine learning techniques to anticipate potential failures in industrial machinery. By analyzing real-time operational data, the system can accurately classify failure types such as tool wear and overstrain, enabling timely and proactive maintenance. Leveraging IBM Watsonx.ai's AutoAl capabilities ensured an automated, scalable, and optimized approach to model development and deployment. This solution not only minimizes unplanned downtime but also enhances operational efficiency and reduces maintenance costs, making it a valuable asset in industrial settings.



FUTURE SCOPE

•Integration with IoT Devices:

Real-time sensor data from IoT-enabled machinery can be continuously fed into the model to make live predictions and trigger automated maintenance alerts.

•Failure Severity Prediction:

Extend the model to not just classify the type of failure, but also predict the severity or remaining useful life (RUL) of machine components.

•Support for More Failure Modes:

Incorporate additional failure types such as power failure, overheating, or mechanical imbalance as more labeled data becomes available.

•Self-Learning Model:

Implement a feedback loop where the model retrains periodically using newly collected data to adapt to evolving machine behavior.

•Cloud-to-Edge Deployment:

Deploy the model on edge devices to enable on-site, low-latency failure prediction without relying entirely on cloud infrastructure.



REFERENCES

- ☐ Shivamb, "Machine Predictive Maintenance Classification Dataset," Kaggle.
 - https://www.kaggle.com/datasets/shivamb/machine-predictive-maintenance-classification
- ☐ IBM Watsonx.ai Documentation, IBM Cloud.

https://www.ibm.com/cloud/watsonx-ai



IBM CERTIFICATIONS

In recognition of the commitment to achieve professional excellence



Rosemary Benny

Has successfully satisfied the requirements for:

Getting Started with Artificial Intelligence



Issued on: Jul 16, 2025 Issued by: IBM SkillsBuild

Verify: https://www.credly.com/badges/4b91240c-b98e-4416-b364-8dd33d9d8d39





IBM CERTIFICATIONS

In recognition of the commitment to achieve professional excellence



Rosemary Benny

Has successfully satisfied the requirements for:

Journey to Cloud: Envisioning Your Solution



Issued on: Jul 20, 2025 Issued by: IBM SkillsBuild

Verify: https://www.credly.com/badges/f1ab2558-c3a2-4749-a714-f7fe7e77deea





IBM CERTIFICATIONS

7/24/25, 8:52 PM

Completion Certificate | SkillsBuild

IBM SkillsBuild

Completion Certificate



This certificate is presented to

Rosemary Pulikkotil

for the completion of

Lab: Retrieval Augmented Generation with LangChain

(ALM-COURSE_3824998)

According to the Adobe Learning Manager system of record

Completion date: 24 Jul 2025 (GMT)

Learning hours: 20 mins



THANK YOU

