
CAPSTONE PROJECT

PREDICTIVE MAINTENANCE OF INDUSTRIAL MACHINERY

Presented By:

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OUTLINE

- **Problem Statement** (should not include solution)
- **Proposed System/Solution**
- **System Development Approach** (Technology Used)
- **Algorithm & Deployment**
- **Result (Output Image)**
- **Conclusion**
- **Future Scope**
- **References**

PROBLEM STATEMENT

Example: Develop a predictive maintenance model for a fleet of industrial machines to anticipate failures before they occur. The project focuses on analyzing real-time sensor data from machinery to uncover patterns that typically precede different types of failures. The objective is to build a classification model capable of predicting the specific type of failure (e.g., tool wear, heat dissipation issues, or power failure) using operational data. This will support proactive maintenance strategies, minimizing unplanned downtime and reducing overall operational costs..

PROPOSED SOLUTION

The proposed system addresses the challenge of predicting machine failures using historical sensor data, aiming to reduce downtime and maintenance costs through accurate classification of failure types. The solution will consist of the following components:

- **Data Collection:**
 - Use the Kaggle dataset containing machine sensor data and failure types.
 - Optionally integrate real-time telemetry using IBM Cloud IoT for future enhancements.
- **Data Preprocessing:**
 - Clean and prepare the data using IBM Watsonx Data Refinery.
 - Engineer relevant features and format the target variable for classification.
- **Machine Learning Algorithm:**
 - Use Watsonx AutoAI to train a classification model for predicting failure types.
 - Select the best-performing pipeline based on accuracy and F1-score.
- **Deployment:**
 - Deploy the model as a REST API using Watsonx Deployment Spaces.
 - Enable real-time predictions with secure endpoint access.

PROPOSED SOLUTION

- **Evaluation:**
 - Evaluate model performance using metrics like accuracy, precision, and F1-score.
 - Monitor the model using Watson OpenScale for drift and performance tracking.
- **Result:**
 - A predictive maintenance system on IBM Cloud that enables early detection of machine failures, helping reduce operational disruptions and improve equipment reliability.

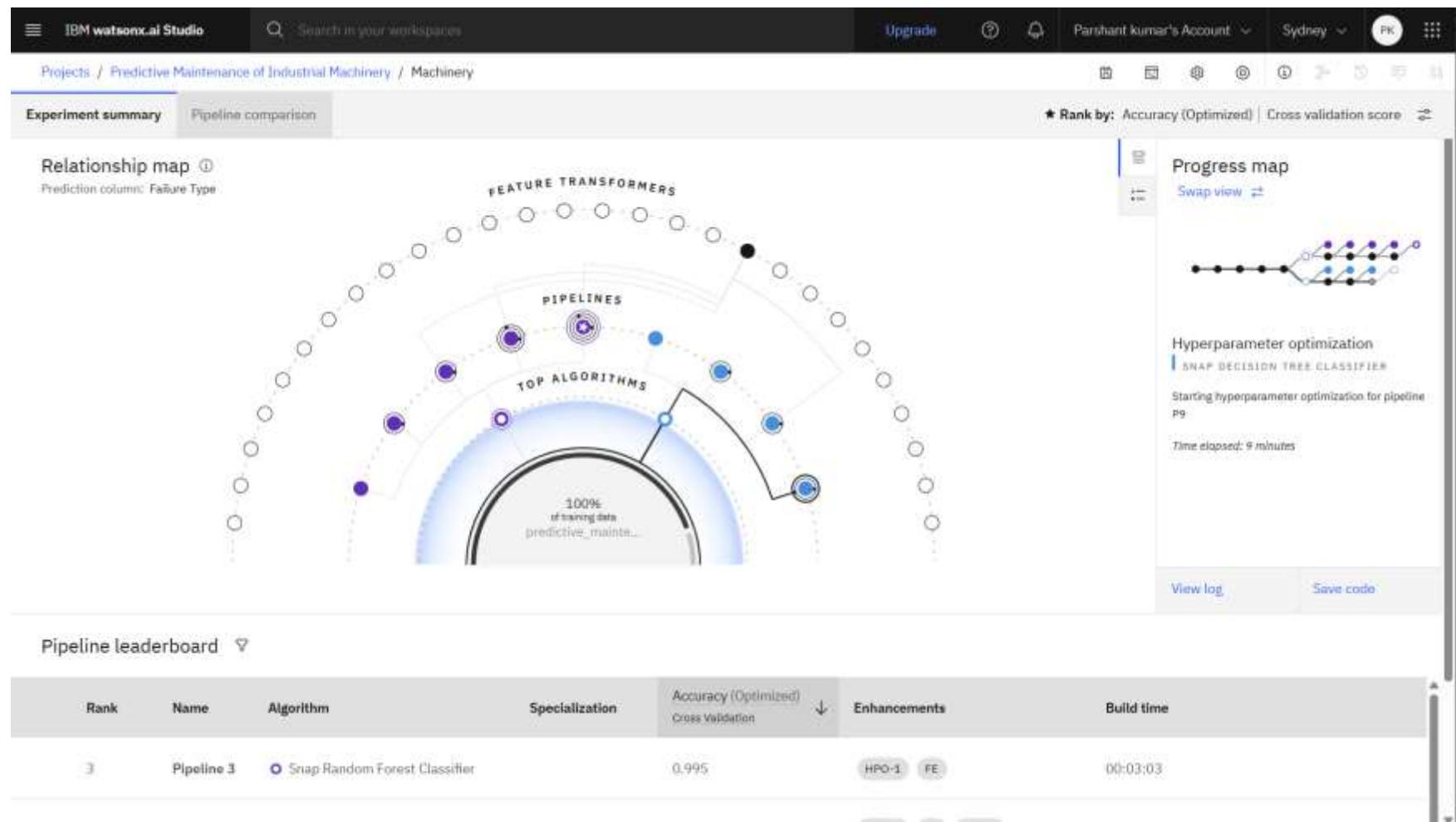
SYSTEM APPROACH

- System Requirements:
- IBM Cloud Account with access to Watsonx.ai, Cloud Object Storage, and AutoAI (Lite/free-tier supported).
- Recommended configuration:
 - Minimum 2 GB RAM (locally, only for file prep/upload; all compute runs in cloud).
 - Stable internet connection and modern web browser (Chrome/Edge recommended).
- Libraries and Tools Used (via Watsonx Platform):
 - Watsonx Data Refinery – for cleaning and transforming the dataset
 - Watsonx AutoAI – for automated model selection, training, and evaluation.
 - Cloud Object Storage (COS) – to securely store datasets and model artifacts.
 - Watsonx Deployment Spaces – for publishing and hosting the trained model as an API.

ALGORITHM & DEPLOYMENT

- **Algorithm**
- This section outlines the classification approach used to predict machine failure types based on sensor data.
- **Algorithm Selection:**
- A classification-based machine learning approach is used to predict the type of machine failure. Algorithms such as Random Forest, Gradient Boosted Trees, and Logistic Regression were considered. Tree-based models were selected due to their robustness with structured data and ability to handle non-linear relationships between sensor readings and failure types.
- **Data Input:**
- Key features include air temperature, process temperature, torque, rotational speed, tool wear, and machine type. The target variable is
- **Training Process:**
- The model was trained on historical machine data using stratified sampling and cross-validation. Hyperparameters were tuned automatically to optimize F1-score.
- **Prediction Process:**
- The trained model takes real-time sensor inputs and predicts the failure category, enabling proactive maintenance before breakdowns occur.

RESULT



RESULT

IBM Watson AI Studio Search in your workspace Upgrade ? Parshant Kumar's Account Sydney PK

Projects / Predictive Maintenance of Industrial Machinery / Machinery

Experiment summary Pipeline comparison ★ Rank by: Accuracy (Optimized) | Cross validation score

Progress map ①
Prediction column: Failure Type

The progress map illustrates the experimental workflow. It starts with 'Read dataset', followed by 'Split holdout data', 'Read training data', 'Preprocessing', and 'Model selection'. From 'Model selection', the flow splits into two parallel paths. The first path leads to 'Snap Random Forest Classifier' (P1), which then branches into 'Hyperparameter optimization' (P6) and 'Feature engineering' (P7). The second path leads to 'Snap Decision Tree Classifier' (P5), which also branches into 'Hyperparameter optimization' (P8) and 'Feature engineering' (P9). Finally, both paths converge at 'Ensemble creation' (P4), which leads to the final 'Ensemble creation' (P5).

Relationship map Swap view

Experiment completed 9 PIPELINES GENERATED
9 pipelines generated from algorithms. See pipeline leaderboard below for more detail.
Time elapsed: 9 minutes

View log Save code

Pipeline leaderboard

Rank	Name	Algorithm	Specialization	Accuracy (Optimized) Cross Validation	Enhancements	Build time
3	Pipeline 3	Snap Random Forest Classifier		0.995	HPO-3, FE	00:03:03
2	Pipeline 4	Snap Random Forest Classifier		0.995	HPO-4, FE, LBN-7	00:03:10

RESULT

The screenshot shows the IBM Watsonx.ai Studio interface. The top navigation bar includes the logo, search bar, upgrade button, notifications (1), user account (Parshant kumar's Account), location (Sydney), and a three-dot menu. Below the header, the breadcrumb path shows 'Deployment spaces / new deployment / PS - Snap Random Forest Classifier; Machinery / machines_failure_identifier'. The main content area displays the 'machines_failure_identifier' endpoint, indicating it is 'Deployed' and 'Online'. There are two tabs: 'API reference' and 'Test' (which is selected). A section titled 'Enter input data' allows for manual entry or CSV file upload. A table is shown with 9 rows and 9 columns of data:

	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)	Target (double)
1	70	L47249	L	296.9	309	1410	65.7	191	1
2	71	M14930	M	298.9	309	1924	22.6	193	0
3	72	L47251	L	298.9	309.1	1452	45.5	196	0
4	73	L47252	L	298.9	309.1	1369	44.4	198	0
5	74	L47253	L	299	309.1	1592	35	200	0
6	75	L47254	L	298.9	309	1601	32.3	202	0
7	76	L47255	L	298.9	308.9	1379	46.7	204	0
8	77	L47256	L	296.9	308.9	1461	47.9	206	0
9	78	L47257	L	298.9	308.9	1455	41.3	208	1
10									

9 rows, 9 columns

RESULT

IBM Watson Studio Search in your workspace Upgrade Pavan Kumar's Account Sydney PK Close X

Deployment spaces / new deployment / PE - Snap Random Forest Classifier: Machinery /

Prediction results

Prediction type: Multiclass classification

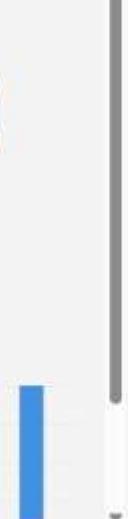
Prediction percentage:



records: 9

Legend: Power Failure (purple), No Failure (blue)

Confidence level distribution:



Number of records

Confidence level distribution

Display format for prediction results:

Table view JSON view

Show input data

	Prediction	Confidence
1	Power Failure	100%
2	No Failure	100%
3	No Failure	100%
4	No Failure	100%
5	No Failure	100%
6	No Failure	100%
7	No Failure	100%
8	No Failure	100%
9	No Failure	100%
10		
11		
12		
13		
14		
15		
16		

Download JSON file

CONCLUSION

- The proposed predictive maintenance solution effectively classifies potential machine failures using sensor data, enabling timely interventions and minimizing unexpected downtime. The model demonstrated strong performance in identifying various failure types, supporting the reliability of the approach. One challenge was ensuring balanced class representation during training, which was addressed through careful sampling techniques. Future improvements could involve integrating live sensor feeds for real-time predictions. Overall, accurate failure prediction plays a critical role in maintaining industrial efficiency, much like accurate bike demand forecasting ensures service availability in urban mobility systems.

FUTURE SCOPE

- Future enhancements could include integrating real-time sensor streams and maintenance logs to enrich model accuracy. Advanced techniques like ensemble learning or deep neural networks can be explored for improved performance. The system can be scaled to monitor machines across multiple sites or regions. Incorporating edge computing would enable on-site predictions with reduced latency, while ongoing model retraining can ensure adaptability to changing machine behavior.

REFERENCES

- **Dataset:**

Machine Predictive Maintenance Classification by Shivam Bansal

[Kaggle Link](#)

- **Platform & Tools:**

IBM Watsonx.ai – AutoAI, Data Refinery, and Deployment Spaces

IBM Cloud Watsonx Documentation

- **General Guide:**

Predictive Maintenance in Manufacturing Using Machine Learning – IBM Blog

IBM Predictive Maintenance Overview

IBM CERTIFICATIONS

Getting Started with Artificial Intelligence

IBM SkillsBuild



IBM

IBM CERTIFICATIONS

Journey to Cloud:
Envisioning
Your Solution

IBM SkillsBuild



IBM CERTIFICATIONS

IBM SkillsBuild

Completion Certificate



This certificate is presented to
Parshant kumar

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