
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

- Industrial facilities suffer significant losses due to unexpected machine failures, which lead to unplanned downtime, costly repairs, and safety hazards. Traditional maintenance strategies such as reactive or scheduled maintenance often fail to anticipate imminent failures, resulting in inefficiencies.

PROPOSED SOLUTION

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.

Key Components:.

- **Data Collection:**

- The dataset used for this predictive maintenance project is sourced from the Kaggle website. The dataset includes features such as Product ID, Type, Air Temperature , Process Temperature , Rotational Speed , Torque , Tool Wear , Target , Type of Failure.
- Link : <https://www.kaggle.com/datasets/shivamb/machine-predictive-maintenance-classification>

- **Data Preprocessing:**

- Real-world data is often incomplete, inconsistent, or noisy. The raw data is cleaned by removing duplicates, handling missing values, correcting data entry errors.
- Followed by data transformation(scaling and normalization) , data integration (combining data from multiple sources, if needed), data organization.

- **Machine Learning Algorithm:**

- Trained a classification model and algorithm such as XG-Boost and Random Forest are very useful.

- **Evaluation:**

- Validate the model using accuracy and precision , despite the variation of confidence level of the ML. The more the machine learns by repeated inputs it will gain higher confidence.

SYSTEM APPROACH

The "System Approach" section outlines the overall strategy and methodology for developing and implementing the rental bike prediction system. Here's a suggested structure for this section:

- **System requirements**

- IBM CLOUD
- IBM WATSON STUDIO
- IBM Cloud Object Storage

ALGORITHM & DEPLOYMENT

- In the Algorithm section, describe the machine learning algorithm chosen for predicting bike counts. Here's an example structure for this section:
- **Algorithm Selection:**
 - Random Forest or XG-Boost as your main classification algorithm
- **Data Input:**
 - Product ID, Type, Air Temperature , Process Temperature , Rotational Speed , Torque , Tool Wear and Target from the dataset
- **Training Process:**
 - The algorithm is trained by the Failure Types from the dataset.
- **Prediction Process:**
 - Prediction is developed through a model deployed on IBM Watson Studio with API endpoint.

RESULT

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

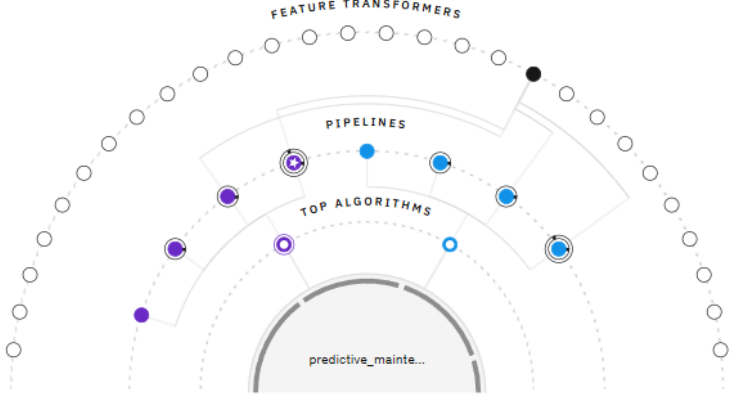
Experiment summary

Pipeline comparison

★ Rank by: Accuracy (Optimized) | Cross validation score

Relationship map

Prediction column: Failure Type



Progress map

Swap view



Experiment completed

8 PIPELINES GENERATED

8 pipelines generated from algorithms. See pipeline leaderboard below for more detail.

Time elapsed: 2 minutes

View log

Save code

Pipeline leaderboard

	Rank		Name	Algorithm	Specialization	Accuracy (Optimized) Cross Validation	Enhancements	Build time
★	1		Pipeline 4	● Snap Random Forest Classifier		0.995	HPO-1 FE HPO-2	00:00:46
	2		Pipeline 3	● Snap Random Forest Classifier		0.995	HPO-1 FE	00:00:35
	3		Pipeline 8	● Snap Decision Tree Classifier		0.994	HPO-1 FE HPO-2	00:00:29
	4		Pipeline 2	● Snap Random Forest Classifier		0.994	HPO-1	00:00:10
	5		Pipeline 1	● Snap Random Forest Classifier		0.994	None	00:00:04

RESULT

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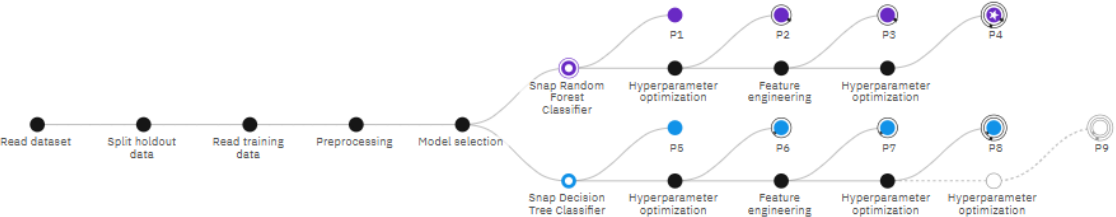
Experiment summary

Pipeline comparison

★ Rank by: Accuracy (Optimized) | Cross validation score

Progress map ⓘ

Prediction column: Failure Type



Relationship map

Swap view ↗



Experiment completed ✓

8 PIPELINES GENERATED

8 pipelines generated from algorithms. See pipeline leaderboard below for more detail.

Time elapsed: 3 minutes

View log

Save code

Pipeline leaderboard ▾

	Rank	↑	Name	Algorithm	Specialization	Accuracy (Optimized) Cross Validation	Enhancements	Build time
★	1		Pipeline 4	🟡 Snap Random Forest Classifier		0.995	HPO-1 FE HPO-2	00:00:45
	2		Pipeline 3	🟡 Snap Random Forest Classifier		0.995	HPO-1 FE	00:00:35
	3		Pipeline 8	🟢 Snap Decision Tree Classifier		0.994	HPO-1 FE HPO-2	00:00:30
	4		Pipeline 2	🟡 Snap Random Forest Classifier		0.994	HPO-1	00:00:09
	5		Pipeline 1	🟡 Snap Random Forest Classifier		0.994	None	00:00:02

RESULT (INPUT DATA)

[Deployment spaces](#) / [Predictive_Maintenance_Deploy](#) / [P4 - Snap Random Forest Classifier: Predictive Maintenance of Industrial Machinery](#) /

Maintenance_Deployment ✔ Deployed 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](#) 

[Clear all](#) ×

	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	4	L47183	L	298.2	308.6	1433	39.5	7	0
2	51	L47230	L	298.9	309.1	2861	4.6	143	1
3	78	L47257	L	298.8	308.9	1455	41.3	208	1
4	161	L47340	L	298.4	308.2	1282	60.7	216	1
5	1088	H30501	H	296.9	307.8	1549	35.8	206	1
6	1222	M16081	M	297	308.3	1399	46.4	132	0
7									
8									

6 rows, 9 columns

Predict

RESULT

Prediction results

Close

×

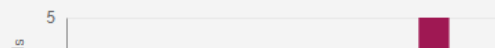
Prediction type

Multiclass classification

Prediction percentage



Confidence level distribution



Display format for prediction results

☒ Table view ☐ JSON view

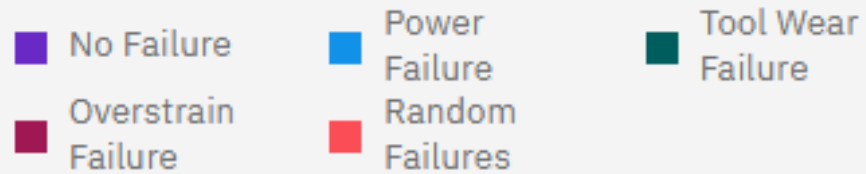
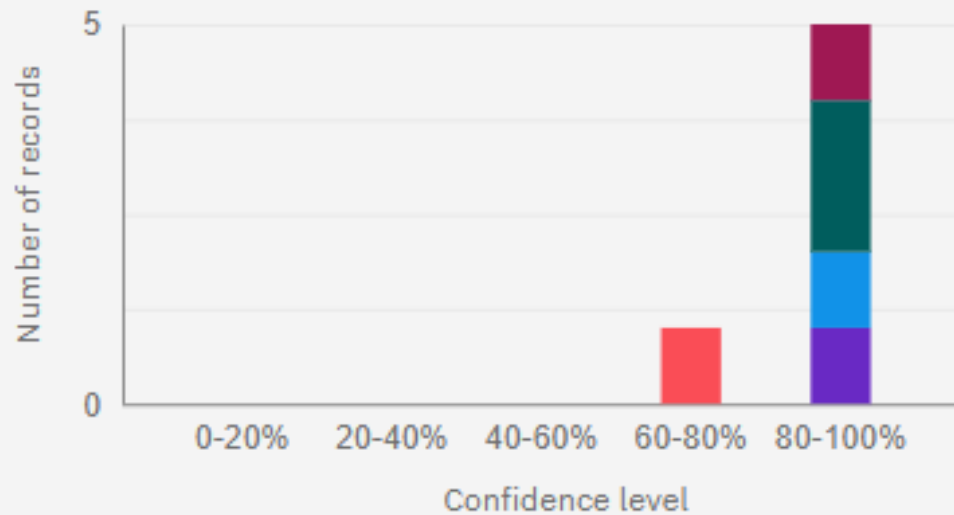
☐ Show input data ⓘ

	Prediction	Confidence
1	No Failure	100%
2	Power Failure	100%
3	Tool Wear Failure	100%
4	Overstrain Failure	96%
5	Tool Wear Failure	100%
6	Random Failures	60%
7		
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9		
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11		
12		
13		
14		

Download JSON file

RESULT (CHARTS)

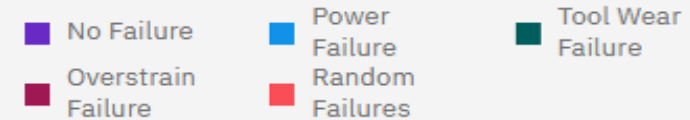
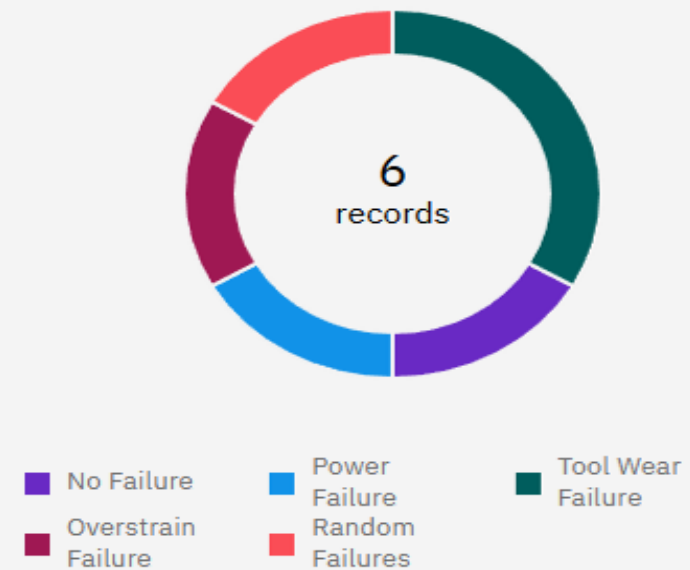
Confidence level distribution



Prediction type

Multiclass classification

Prediction percentage



CONCLUSION

- This project successfully developed a predictive maintenance model using machine learning techniques to anticipate industrial machine failures based on real-time sensor data. By leveraging algorithms such as Random Forest and XG-Boost, the model was able to classify failure types—such as tool wear, heat dissipation issues, and power failures—with a high degree of accuracy. Through effective data preprocessing, feature engineering, and model tuning, the system demonstrated strong potential to reduce unplanned downtime, maintenance costs, and operational risks. The continuous feedback loop and periodic retraining strategy ensure that the model adapts to evolving machine behavior, maintaining its accuracy over time.

FUTURE SCOPE

- Predictive maintenance model opens up several promising avenues for future development, both in terms of technological advancement and practical application. As industries increasingly adopt data-driven decision-making, the future scope of this system is broad and impactful. With ongoing advancements in AI, IoT, and edge computing, the predictive maintenance system has the potential to evolve into a real-time, autonomous, and intelligent platform. Its future scope includes transforming not just industrial efficiency but also contributing to sustainability goals, resource optimization, and public safety.

REFERENCES

- Resources used for the development of this project are:
 - IBM cloud(accessing and storage of the development of the project)
 - IBM Watsonx ai Studio(Service offered by IBM cloud to implement and obtain result from the project)
 - Edunet Foundation's GLE Modules (for understanding the working and functions to implement onto the problem statement)

IBM CERTIFICATIONS




IBM CERTIFICATIONS



IBM CERTIFICATIONS

IBM SkillsBuild

Completion Certificate



This certificate is presented to

Mahidhar Balaji

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