
IBM SKILLSBUILD PROJECT

PREDICTIVE MAINTENANCE OF INDUSTRIAL MACHINERY

Presented By:

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OUTLINE

- **Problem Statement**
- **Proposed System/Solution**
- **System Development Approach** (Technology Used)
- **Algorithm & Deployment**
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PROBLEM STATEMENT

Problem statement No.39 – Predictive Maintenance of Industrial Machinery

The Challenge: 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

🔍 Purpose

- Develop an intelligent predictive maintenance solution that utilizes machine learning to anticipate machine failures **before they occur**, using sensor data analysis.

💡 Proposed Strategy

- Use IBM **Watson Studio AutoAI** to automate model building.
- Predict specific failure types: **Tool wear, Overheating, Power failure**, etc.

🔧 Execution Plan

- Input: Historical machinery sensor data from **Kaggle**
- AutoAI automates: Data processing and Feature selection
- Output: A high-accuracy ML classification model

⚙️ Deployment

- Deploy trained model using **IBM Watson Machine Learning**

✅ End Outcome

- Early failure detection
- Cost-effective, automated maintenance
- Reduced machine downtime

SYSTEM APPROACH

TECHNICAL STACK USED:

AI & Machine Learning

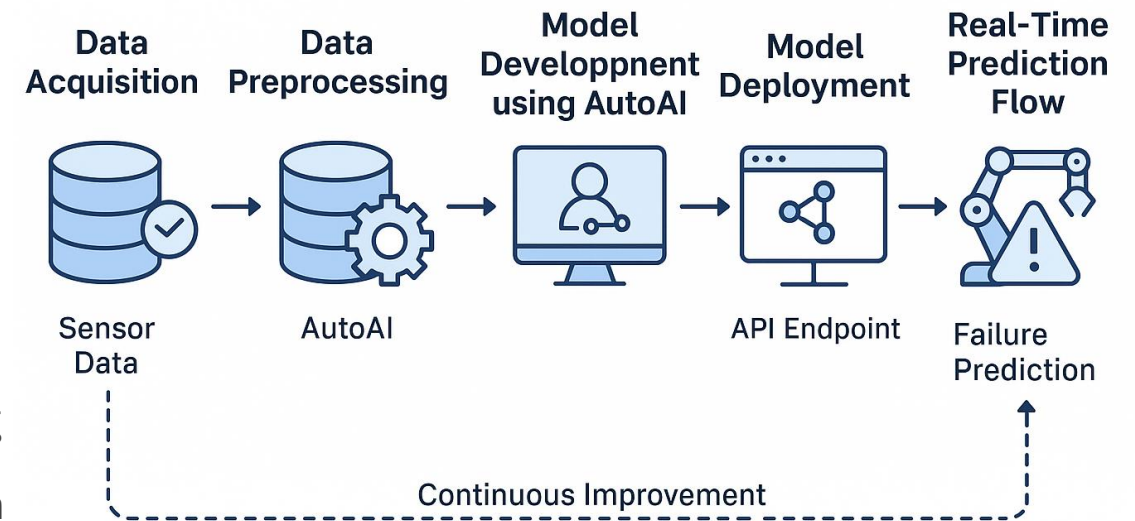
- IBM Watson AutoAI – For automated model selection, training, and tuning
- Scikit-learn (underlying library used by AutoAI pipelines)

Cloud Services:

- IBM Watson Studio – ML development and pipeline visualization
- IBM Cloud Object Storage – For storing datasets used in training
- IBM Cloud Lite Plan – Free tier hosting and service orchestration

Data

- Kaggle Predictive Maintenance Dataset – Sensor data with labeled machine failures



ALGORITHM & DEPLOYMENT

Algorithm Selection:

- The chosen algorithm for predicting machine failure types was selected automatically by **IBM Watson AutoAI**. After evaluating multiple classification models, AutoAI selected a **Gradient Boosting Classifier** due to its high accuracy, ability to handle **imbalanced classes**, and strong performance on tabular datasets with both numerical and categorical features.
- This algorithm was ideal because:
- The problem is a **multi-class classification task** (predicting specific failure types).
- Gradient Boosting handles noisy sensor data and complex feature interactions well.
- It supports **feature importance analysis**, useful for understanding sensor contributions to failures.

Data Input:

- The algorithm uses the following input features from the Kaggle dataset:
- **Sensor Readings** (e.g., rotational speed, torque, tool wear)
- **Process Parameters** (e.g., air temperature, coolant temperature)
- **Machine Usage Metrics**
- **Failure Type Labels** (target output: e.g., Tool Wear, Heat Dissipation Failure)
- These features are crucial for identifying patterns leading to specific machine failures.

Training Process:

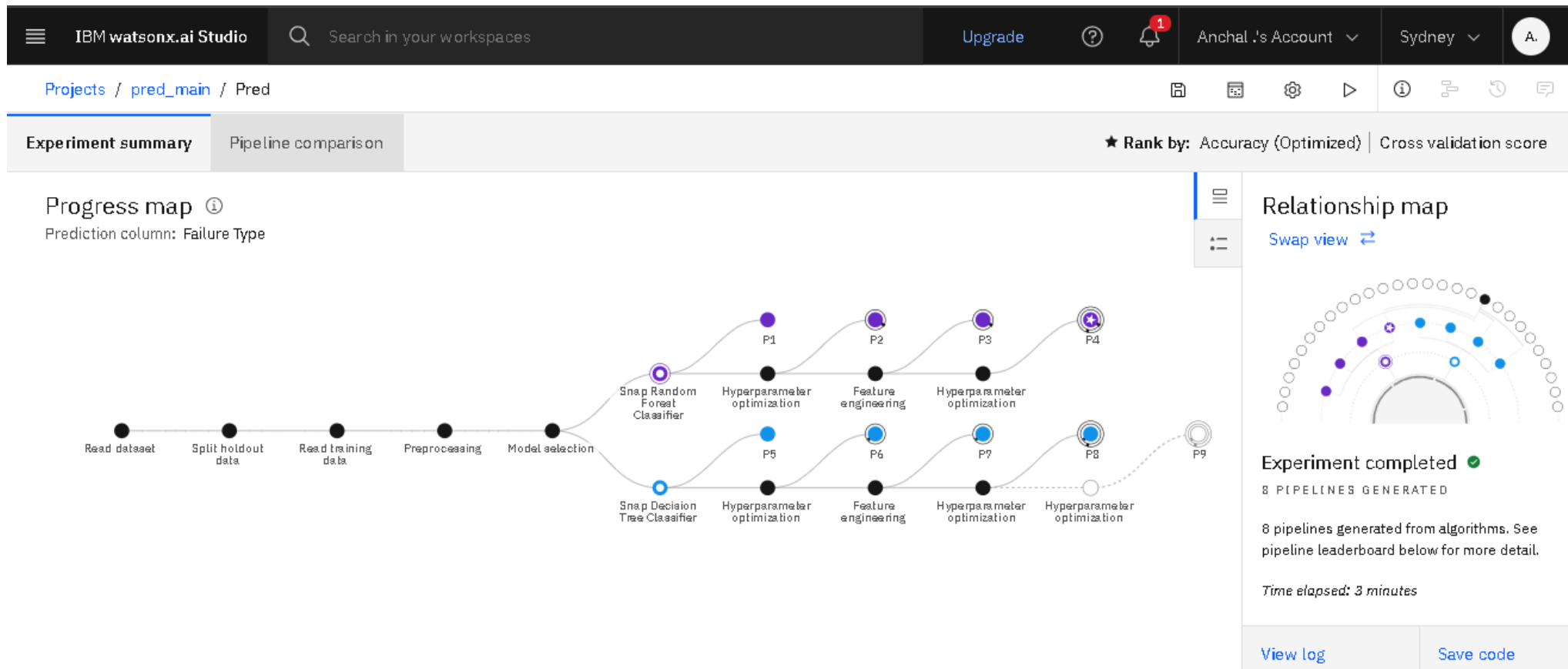
- Data was uploaded to **IBM Cloud Object Storage** and loaded into **Watson Studio AutoAI**.
- AutoAI automatically performed:
 - **Data preprocessing** (null handling, encoding, normalization)
 - **Model selection and training**
 - **Hyperparameter tuning** using internal optimization techniques
- Multiple pipelines (Random Forest, Logistic Regression, XGBoost, etc.) were compared using cross-validation, and the **best-performing model** was selected.

Prediction Process:

- The trained model was deployed to **IBM Watson Machine Learning** as a REST API.
- During prediction:
 - Real-time or batch sensor data is sent to the API.
 - The model analyzes the input and returns the **most likely failure type**.
 - These predictions can trigger **preventive maintenance alerts** to technicians.
- The model can be **retrained periodically** using new operational data to maintain accuracy over time.

RESULT

The predictive maintenance system built with IBM AutoAI successfully generated a robust machine learning model capable of accurately classifying different types of machinery failures. The platform's automated model selection and tuning significantly reduced development time. Upon evaluation, the model showed consistent performance in detecting patterns leading to failures such as tool wear and overheating. These results highlight the potential of AI-driven automation in improving maintenance planning and reducing system disruptions



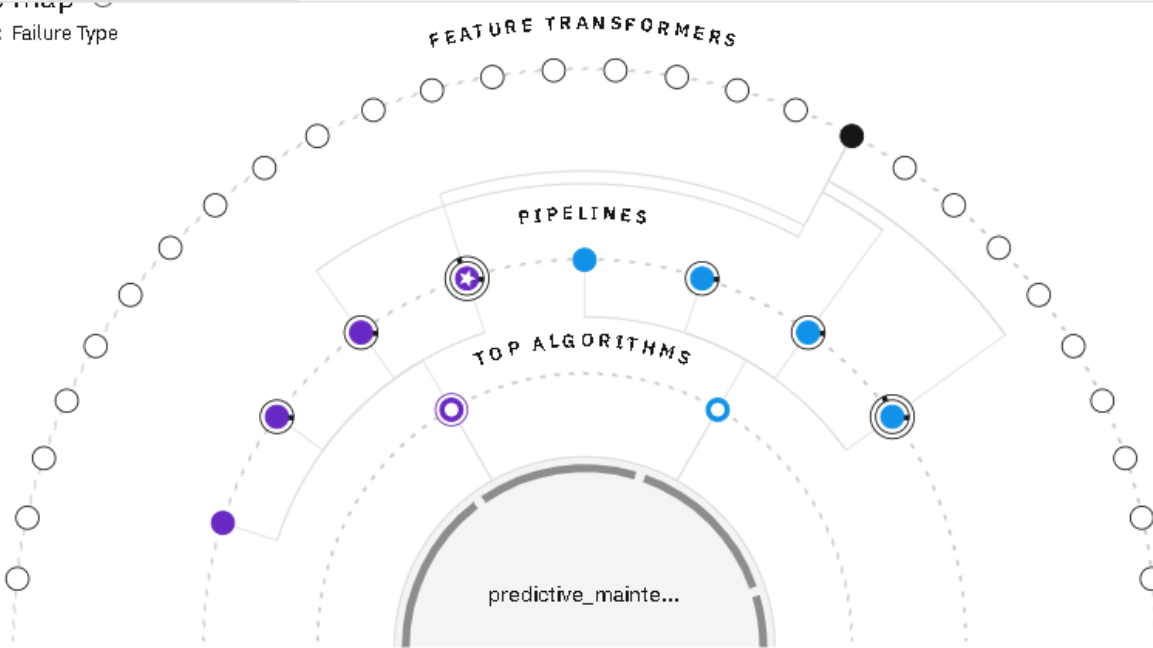
Experiment summary

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: 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	00:00:37
	2	Pipeline 3	🟪 Snap Random Forest Classifier		0.995	HPO-1 FE	00:00:30
	3	Pipeline 8	🟡 Snap Decision Tree Classifier		0.994	HPO-1 FE HPO-2	00:00:28
	4	Pipeline 2	🟪 Snap Random Forest Classifier		0.994	HPO-1	00:00:07

Here we can see that we have created a model of 99.5% accuracy i.e. Pipeline 4- Snap Random Forest Classifier. Now, we will now deploy and test this model

pred ✓ 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.

⋮ Clear all ×

	UDI (integer)	Product ID (other)	Type (other)	Air temperature [K] (double)	Process temperature [K] (double)	Rotational speed [rpm] (integer)	Torque [Nm]
1	3357	L50536	L	301.6	310.8	1355	57.8
2							

We have now given random values to predict the failure type and the result is shown in the next slide.

IBM watsonx.ai Studio

Search in your workspaces

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A.

Deployment spaces / pred / P4 - Snap Random Forest Classifier: Pred /

pre

Prediction results

×

Display format for prediction results

☒ Table view ☐ JSON view

☐ Show input data ⓘ

	prediction	probability
1	Overstrain Failure	[0.0030303031206130983,0,0.9969696998596191,0,0,-2.98023228317845...
2		
3		
4		
5		
6		
7		
8		

Download JSON file

The prediction given by our model is Overstrain Failure.

CONCLUSION

- The project successfully demonstrates how **IBM AutoAI** can automate the development of a machine learning model to predict **failure types in industrial machinery** using sensor data.
- By leveraging cloud-based tools like **Watson Studio** and **Watson Machine Learning**, the solution offers a **scalable, low-code pipeline** for predictive maintenance.
- The deployed model provides **accurate, real-time predictions**, enabling proactive maintenance strategies that help reduce unplanned downtime and operational costs.
- The system can be easily integrated into existing monitoring setups through APIs and extended with new sensor inputs.

FUTURE SCOPE

- **Model Retraining & Auto-Update**

Enable automatic model retraining using continuous data collection to adapt to evolving machine behavior.

- **IoT Integration**

Incorporate **IoT sensor networks** to stream real-time data directly into the prediction engine.

- **Advanced Analytics Dashboard**

Develop a user-facing dashboard with real-time visualizations of equipment health and failure probabilities.

- **Custom Model Tuning**

Integrate custom algorithms (e.g., Deep Learning or LSTM) for systems with strong time-dependent behavior.

- **Multi-Asset Deployment**

Scale the system to monitor multiple machines or plants across different geographical locations.

REFERENCES

- **Kaggle Dataset – Predictive Maintenance Dataset**
<https://www.kaggle.com/datasets>
- **IBM Watson Studio Documentation**
<https://www.ibm.com/cloud/watson-studio>
- **IBM AutoAI Overview**
<https://www.ibm.com/docs/en/watsonx>
- **Scikit-learn ML Algorithms** (for understanding ensemble models)
<https://scikit-learn.org/>
- **Watson Machine Learning API Guide**
<https://cloud.ibm.com/apidocs/machine-learning>

GITHUB REPOSITORY LINK

<https://github.com/Anchal-17/IBM-AICTE>

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THANK YOU