### **CAPSTONE PROJECT**

# PREDICTIVE MAINTENANCE OF INDUSTRIAL MACHINERY

### **Presented By:**

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### **OUTLINE**

- Problem Statement
- Proposed System/Solution
- System Development Approach
- Algorithm & Deployment
- Result
- Conclusion
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# 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 will utilize IBM's AutoAl on the watsonx.ai platform to build a high-accuracy predictive maintenance model. AutoAl automates the end-to-end process of machine learning model development, allowing for the rapid creation and deployment of a solution.

The solution will consist of the following components:

#### Data Collection:

 The project will use the "Machine Predictive Maintenance Classification" dataset from Kaggle. This dataset contains historical operational data and failure records for industrial machinery.

### Data Preprocessing (Automated by AutoAI):

 The AutoAl tool will automatically handle essential data preparation steps, including cleaning the data, handling any missing values, and encoding features for optimal model performance

### Automated Model Building (AutoAl):

- AutoAl will streamline the model creation process through:
  - Algorithm Selection: It will test and evaluate multiple classification algorithms to find the most suitable one for predicting machine failures.
  - Feature Engineering: It will automatically create new, insightful features from the raw sensor data to improve the model's predictive power.
  - Hyperparameter Optimization: It will fine-tune the selected algorithms to achieve the highest possible accuracy.



### PROPOSED SOLUTION

#### Deployment:

 The best-performing model pipeline discovered by AutoAl will be deployed as a web service on IBM Cloud. This creates a scalable and reliable API endpoint for making real-time failure predictions.

#### Evaluation:

- The model's ability to predict failures will be rigorously evaluated using key classification metrics:
  - Accuracy: The overall percentage of correct predictions.
  - Precision and Recall: To measure the model's performance for specific failure types.
  - **F1-Score:** The harmonic mean of precision and recall, providing a single score for model quality.
  - Confusion Matrix: To visualize the model's accuracy across different failure classes.



# SYSTEM APPROACH

#### SYSTEM APPROACH

 The development strategy for the predictive maintenance system is centered around the integrated and automated environment of IBM's cloud services.

#### System Requirements:

- An active IBM Cloud Lite account.
- Provisioned instances of the following core services:
  - watsonx.ai Studio
  - Watson Machine Learning

### Libraries and Frameworks Utilized by AutoAl:

- While AutoAl provides a no-code interface, it leverages a powerful stack of open-source machine learning libraries in the background, including:
  - Scikit-learn: For a comprehensive suite of data preprocessing tools and classification models.
  - XGBoost & LightGBM: For state-of-the-art gradient boosting algorithms known for their high performance.



# **ALGORITHM & DEPLOYMENT**

### Algorithm Selection (Automated by AutoAl):

AutoAl will run a competition among various classification algorithms such as Logistic Regression, Decision Trees, Random Forests, and
Gradient Boosting Machines. It will automatically select and present the top-performing algorithms based on their predictive accuracy on
the dataset.

#### Data Input:

The model will be trained on the Kaggle "Machine Predictive Maintenance Classification" dataset. The input features include sensor readings like air temperature, process temperature, rotational speed, torque, and tool wear, along with the corresponding failure type.

#### Training Process (Automated by AutoAI):

The training process is fully automated. AutoAl ingests the dataset, splits it for training and validation, and then systematically applies a wide range of data transformations, feature engineering techniques, and model training routines. It performs hyperparameter optimization to ensure the final model is highly tuned for this specific task.

#### Prediction Process:

Once deployed, the model will function via an API. A system can send a set of current sensor readings from a machine to this API. The
model will then return a prediction, indicating whether the machine is operating normally or is likely to experience a specific type of
failure soon.

#### Deployment:

The final, optimized model pipeline from AutoAI will be promoted to a deployment space within the Watson Machine Learning service. An online (real-time) deployment will be created, which provides a REST API endpoint for integration with other applications.



Projects / Predictive Maintenance of Industrial Machinery / predictive\_maintenance.csv

Feature group B

Visualization

Preview asset

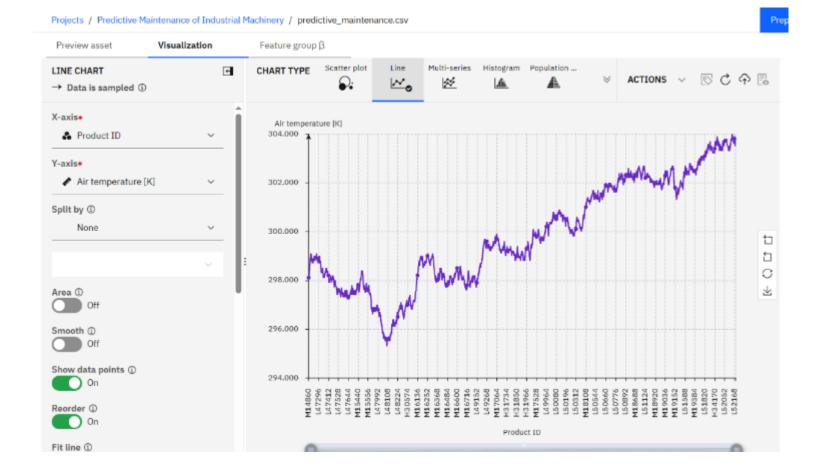
| n., |  |
|-----|--|
|     |  |
|     |  |
|     |  |

| Columns: 10   Sample rows: 1000 |            |      |                     |                         |                        |  |  |
|---------------------------------|------------|------|---------------------|-------------------------|------------------------|--|--|
| UDI                             | Product ID | Туре | Air temperature [K] | Process temperature [K] | Rotational speed [rpm] |  |  |
| 1                               | M14860     | М    | 298.1               | 308.6                   | 1551                   |  |  |
| 2                               | L47181     | L    | 298.2               | 308.7                   | 1408                   |  |  |
| 3                               | L47182     | L    | 298.1               | 308.5                   | 1498                   |  |  |
| 4                               | L47183     | L    | 298.2               | 308.6                   | 1433                   |  |  |
| 5                               | L47184     | L    | 298.2               | 308.7                   | 1408                   |  |  |
| 6                               | M14865     | М    | 298.1               | 308.6                   | 1425                   |  |  |
| 7                               | L47186     | L    | 298.1               | 308.6                   | 1558                   |  |  |
| 8                               | L47187     | L    | 298.1               | 308.6                   | 1527                   |  |  |
| 9                               | M14868     | М    | 298.3               | 308.7                   | 1667                   |  |  |
| 10                              | M14869     | М    | 298.5               | 309                     | 1741                   |  |  |
| 11                              | H29424     | Н    | 298.4               | 308.9                   | 1782                   |  |  |
| 12                              | H29425     | Н    | 298.6               | 309.1                   | 1423                   |  |  |
| 13                              | M14872     | М    | 298.6               | 309.1                   | 1339                   |  |  |
| 14                              | M14873     | М    | 298.6               | 309.2                   | 1742                   |  |  |
| 15                              | L47194     | L    | 298.6               | 309.2                   | 2035                   |  |  |

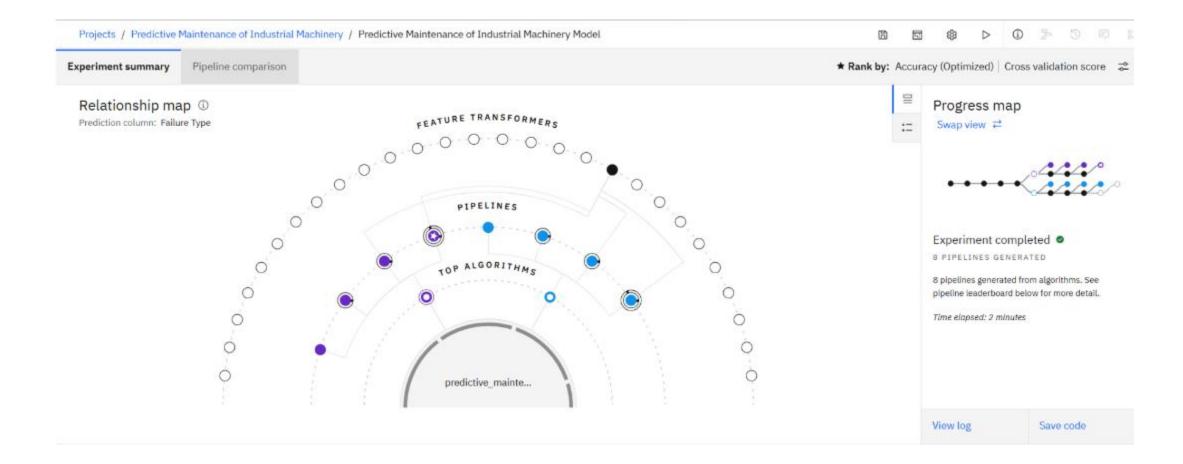
### DataSet:



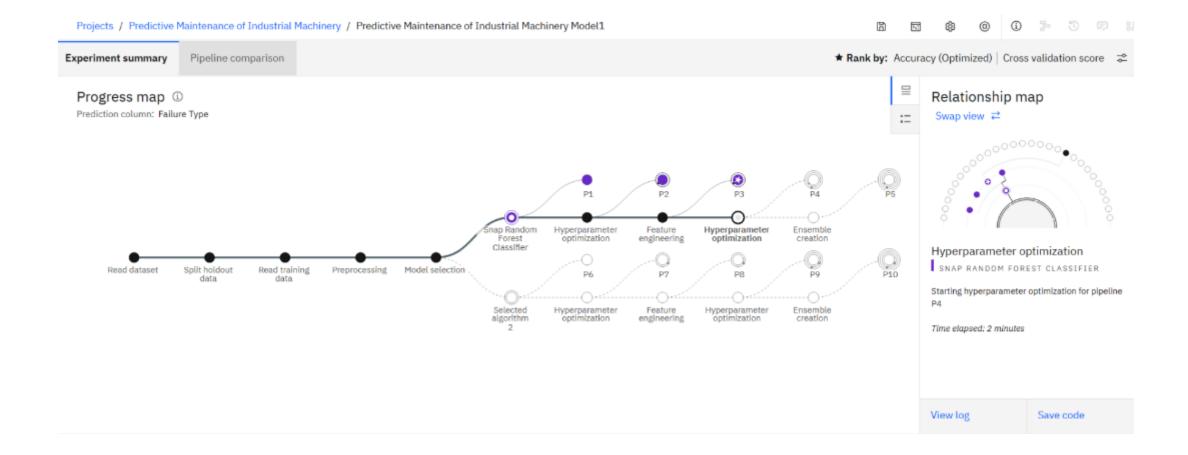
DATASET ANALYSIS:









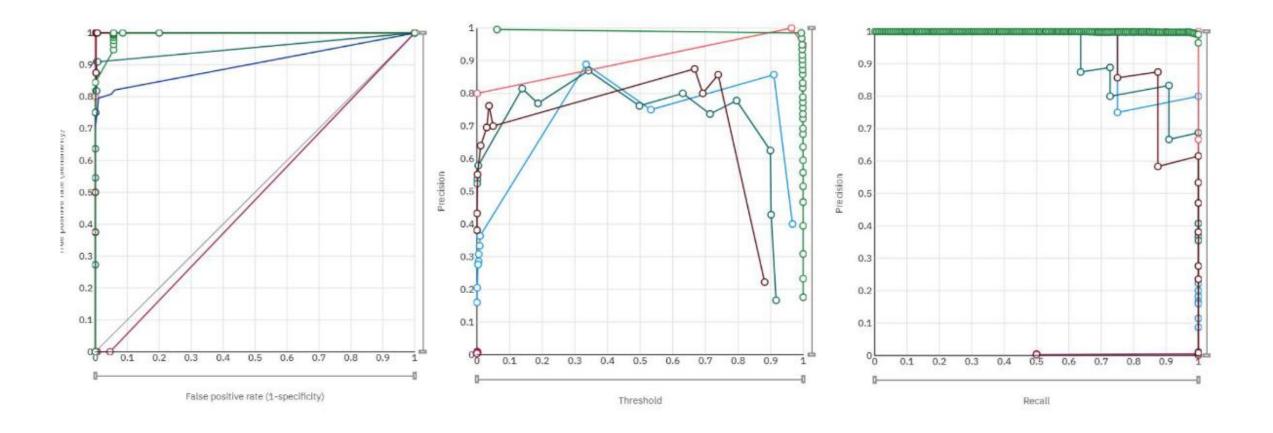




### Pipeline leaderboard $\ \, \nabla$

|   | Rank ↑ | Name       | Algorithm   | Specialization | Accuracy (Optimized) Cross Validation | Enhancements   | Build time       |
|---|--------|------------|---|----------------|---------------------------------------|----------------|------------------|
| * | 1      | Pipeline 4 | O Snap Random Forest Classifier                   |                | 0.995                                 | HPO-1 FE HPO-2 | 00:00:41 Save as |
|   | 2      | Pipeline 3 | O Snap Random Forest Classifier                   |                | 0.995                                 | HPO-1 FE       | 00:00:32         |
|   | 3      | Pipeline 8 | <ul> <li>Snap Decision Tree Classifier</li> </ul> |                | 0.994                                 | HPO-1 FE HPO-2 | 00:00:27         |







### TESTING:

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 A Search in space A

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 | 5            | L47184             | L            | 298.2                        | 308.7                            | 1408                            | 40                   | 9                        | 0               |
| 2 | 626          | L47805             | L            | 298.3                        | 310.1                            | 1545                            | 36.3                 | 90                       | 0               |



### Final Results





# CONCLUSION

This project successfully demonstrates the development of a predictive maintenance system using IBM's AutoAl on watsonx.ai. The use of an automated platform like AutoAl proves to be highly effective in tackling complex industrial challenges, drastically reducing the time and expertise required to build and deploy a high-performance machine learning model. The resulting solution provides a clear pathway for businesses to minimize operational downtime, reduce maintenance costs, and improve overall industrial efficiency.



### **FUTURE SCOPE**

- The current system provides a strong foundation that can be expanded upon in several ways:
- Real-time Data Streaming: Integrate the deployed model with live data streams from IoT sensors on actual factory floor machinery for immediate, real-time failure prediction.
- Remaining Useful Life (RUL) Prediction: Develop a regression model to predict the remaining time before a component is expected to fail, allowing for even more precise maintenance scheduling.
- Root Cause Analysis Integration: Enhance the system to not only predict a failure but also to suggest the most likely contributing factors based on sensor data patterns.
- Edge Deployment: Deploy the trained model onto edge computing devices located near the machinery. This would reduce latency and allow for predictions even without a constant internet connection.



# REFERENCES

- REFERENCES
- B, S. (2020). Predictive Maintenance Dataset. Kaggle. Retrieved
   from <a href="https://www.kaggle.com/datasets/shivamb/machine-predictive-maintenance-classification">https://www.kaggle.com/datasets/shivamb/machine-predictive-maintenance-classification</a>
- IBM. (n.d.). AutoAI. IBM. Retrieved from <a href="https://www.ibm.com/watson/ai-and-data/autoai">https://www.ibm.com/watson/ai-and-data/autoai</a>
- IBM. (n.d.). Watson Machine Learning. IBM. Retrieved from <a href="https://www.ibm.com/cloud/watson-machine-learning">https://www.ibm.com/cloud/watson-machine-learning</a>
- GeeksforGeeks. (2024). Predictive Maintenance using Machine Learning.
- Towards Data Science. (2020). A practical guide for Predictive Maintenance.



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IBM **SkillsBuild** Completion Certificate



This certificate is presented to

Rahul Paul

for the completion of

# Lab: Retrieval Augmented Generation with LangChain

(ALM-COURSE\_3824998)

According to the Adobe Learning Manager system of record

Completion date: 25 Jul 2025 (GMT)

Learning hours: 20 mins



# **THANK YOU**

