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# **CAPSTONE PROJECT**

## **PREDICTIVE MAINTENANCE OF INDUSTRIAL MACHINERY**

**Presented By:**  
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and Engineering**

# OUTLINE

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

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# PROBLEM STATEMENT

**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

- **Data Collection:**
  - Gather historical sensor data from the machinery fleet, including Air temperature, Process temperature, Rotational speed, Torque, and Tool wear.
  - Ensure a steady stream of real-time operational data to feed into the predictive model.
- **Data Preprocessing:**
  - Clean and preprocess the collected sensor data to handle any outliers or inconsistencies.
  - Perform feature engineering to identify the most critical data signatures and interactions that signal an impending failure.
- **Machine Learning Algorithm:**
  - Implement a multi-class classification model (e.g., Random Forest, Gradient Boosting, or a Neural Network) using IBM Watson Studio.
  - Train the model to accurately predict the specific Failure Type (e.g., Tool Wear Failure, Heat Dissipation Failure, Power Failure) based on the input sensor data..
- **Deployment:**
  - Deploy the trained model as a real-time API endpoint using the IBM Watson Machine Learning service.
  - This allows for seamless integration with existing factory monitoring systems or a custom-built maintenance dashboard.
- **Evaluation:**
  - Assess the model's performance using classification metrics such as Accuracy, Precision, Recall, and F1-Score.
  - Utilize a Confusion Matrix to analyze the model's effectiveness in distinguishing between different failure types.
- **Result:**
  - The final result is a robust predictive maintenance system that enables proactive repairs, significantly reduces unplanned downtime, and lowers operational costs.

# SYSTEM APPROACH

This section outlines the overall strategy, technical requirements, and methodology for developing and implementing the predictive maintenance system

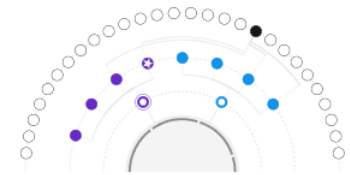
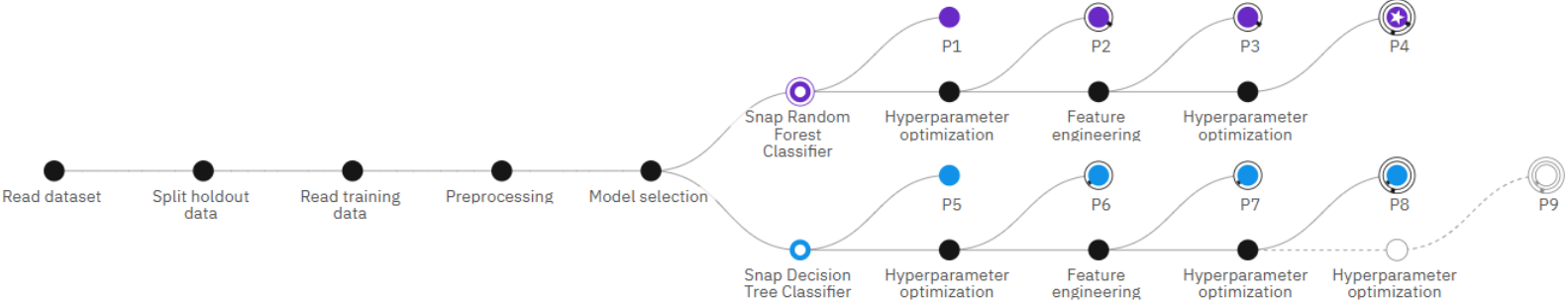
- **System requirements:**
  - **Platform & Services:** An IBM Cloud Lite account with the following provisioned services: Watson Studio, Cloud Object Storage, and Watson Machine Learning
- **Libraries:**
  - **Core Libraries:** Pandas and NumPy for data handling, Matplotlib/Seaborn for visualization, and Scikit-learn for building and evaluating the classification model.

# ALGORITHM & DEPLOYMENT

- **Algorithm Selection:**
  - The Snap Random Forest Classifier was automatically selected by IBM's AutoAI for its high accuracy (99.5%) in identifying complex failure patterns within the sensor data.
- **Data Input:**
  - The model bases its predictions on five key input features: Air Temperature, Process Temperature, Rotational Speed, Torque, and Tool Wear.
- **Training Process:**
  - The model was trained using an automated pipeline that included data preprocessing, automated feature engineering, and hyperparameter optimization to maximize predictive performance.
- **Prediction Process:**
  - The deployed API receives real-time sensor data and returns a JSON response containing the predicted failure type and a confidence score for that prediction.

# RESULT

Projects / Final\_Project / Predictive\_Maintenance



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)<br>Cross Validation | Enhancements   | Build time |
|---|------|---|------------|-------------------------------|----------------|--|----------------|------------|
| ★ | 1    |   | Pipeline 4 | Snap Random Forest Classifier |                | 0.995                                    | HPO-1 FE HPO-2 | 00:00:40   |

|  |   |  |            |                               |  |       |          |          |
|--|---|--|------------|-------------------------------|--|-------|----------|----------|
|  | 2 |  | Pipeline 3 | Snap Random Forest Classifier |  | 0.995 | HPO-1 FE | 00:00:31 |
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# RESULT

Projects / Final\_Project / Predictive\_Maintenance

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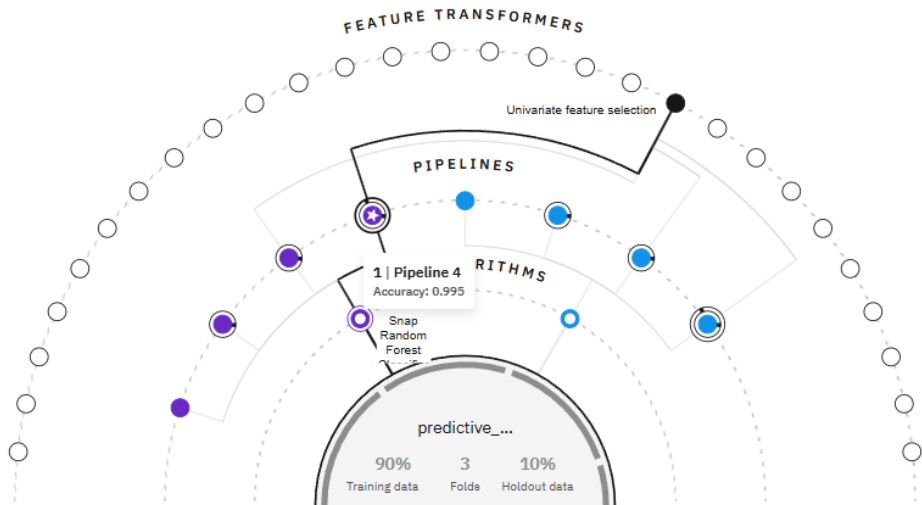
Experiment summary

Pipeline comparison

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

## Relationship map ⓘ

Prediction column: Failure Type



## Progress map

Swap view ↔️



Experiment completed 🟢

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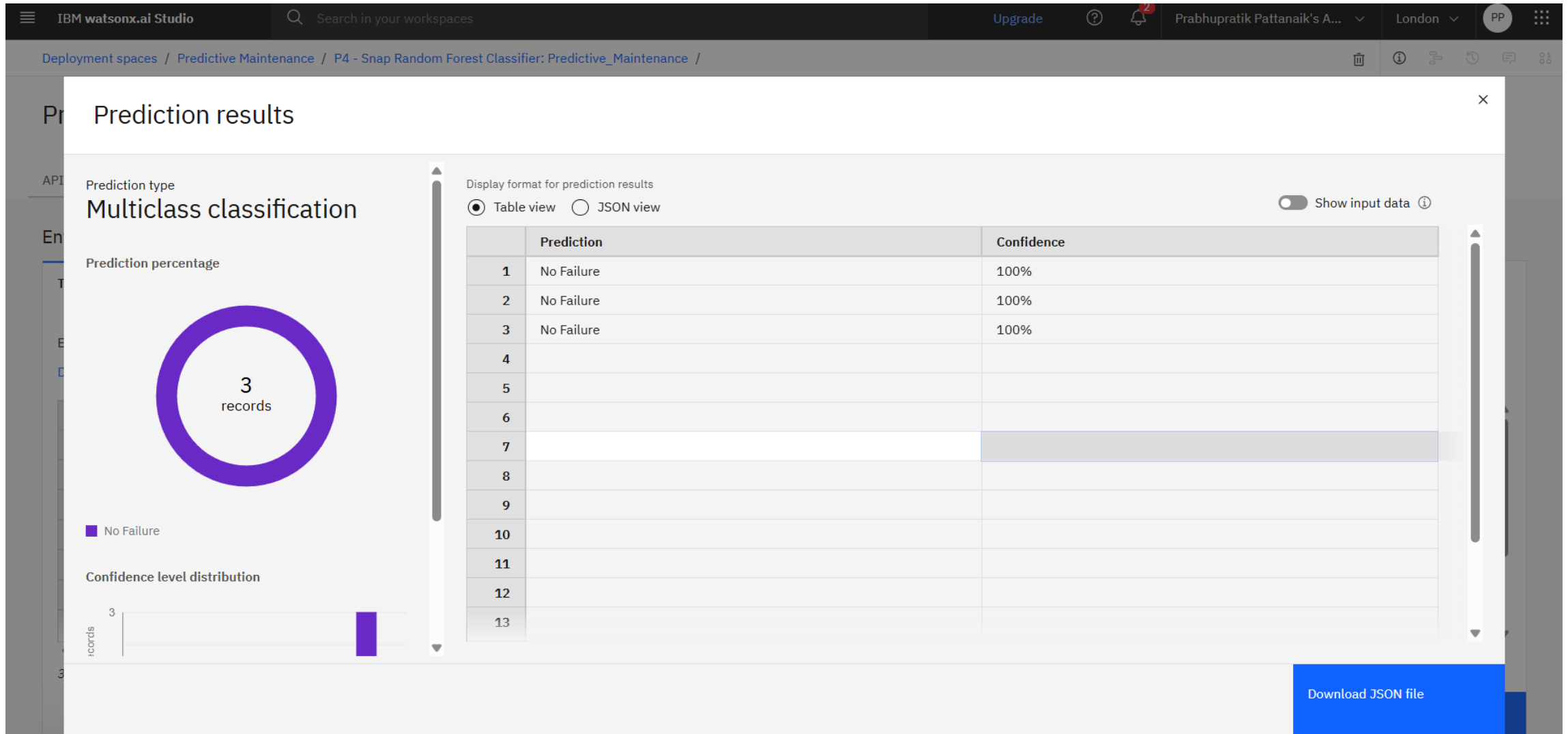
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|   | 2    |   | Pipeline 3 | 🟡 Snap Random Forest Classifier |                | 0.995                                    | HPO-1 FE       | 00:00:31   |



# RESULT



# CONCLUSION

- This project successfully demonstrated the development and deployment of a highly effective predictive maintenance model, achieving 99.5% accuracy in forecasting machine failures using IBM Watson Studio. While interpreting complex sensor data is always a challenge, future improvements could involve integrating a wider variety of machine data and enhancing the user dashboard for maintenance teams. Ultimately, this work underscores the critical importance of data-driven decision-making in modern industry. By enabling a shift from reactive to proactive maintenance, this solution directly contributes to reducing operational downtime, lowering costs, and improving overall plant efficiency and safety.

# FUTURE SCOPE

- The future scope for this project is extensive. The model could be expanded to cover **different types of industrial machinery** or an entire factory floor, creating a plant-wide monitoring system. Future versions could incorporate more diverse data sources, such as **vibration analysis, acoustic data, and historical maintenance logs**, for a more holistic view of machine health. We could also explore advanced **deep learning models like LSTMs** to better capture time-series patterns in the sensor data. Ultimately, the system can evolve from a predictive tool into a complete **prescriptive maintenance platform** that not only forecasts failures but also recommends specific actions and optimal repair schedules.

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# REFERENCES

- **Academic Literature:** Research papers and articles focusing on **Predictive Maintenance (PdM)**, **industrial fault diagnosis**, and **condition-based monitoring** of machinery.
- **Machine Learning:** Technical documentation on **ensemble classification algorithms**, specifically the **Random Forest model**, which was instrumental in building the final solution.
- **Data Science Practices:** Articles and tutorials covering best practices for **preprocessing time-series sensor data** and robust **model evaluation techniques** for classification problems.
- **Dataset Source:** The project utilized the "Machine Predictive Maintenance Classification" dataset, publicly available on the **Kaggle** platform.

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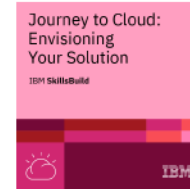
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Completion Certificate



This certificate is presented to  
**Prabhupratik Pattanaik**

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**