
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

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

- We'll develop an intelligent predictive maintenance system that shifts your operations from reactive to **proactive**. By continuously analyzing data streams from machinery sensors, our machine learning model will accurately predict the specific type of failure—such as **tool wear**, **heat dissipation**, or **power failure**—before it occurs. This enables just-in-time maintenance, maximizing equipment uptime and significantly reducing operational costs.
- **Key Components:**
 - **Data & Feature Engineering:** Collect and clean sensor data (e.g., vibration, temperature), then engineer time-series features to reveal failure patterns.
 - **Model Training & Optimization:** Train and tune a classification model (e.g., Random Forest, LSTM) to accurately predict different failure types.
 - **Validation:** Evaluate the model with key metrics (accuracy, F1-score) and a confusion matrix to confirm its predictive reliability.
 - **Deployment:** Integrate the model into a live system that sends real-time failure alerts to the maintenance team.

SYSTEM APPROACH

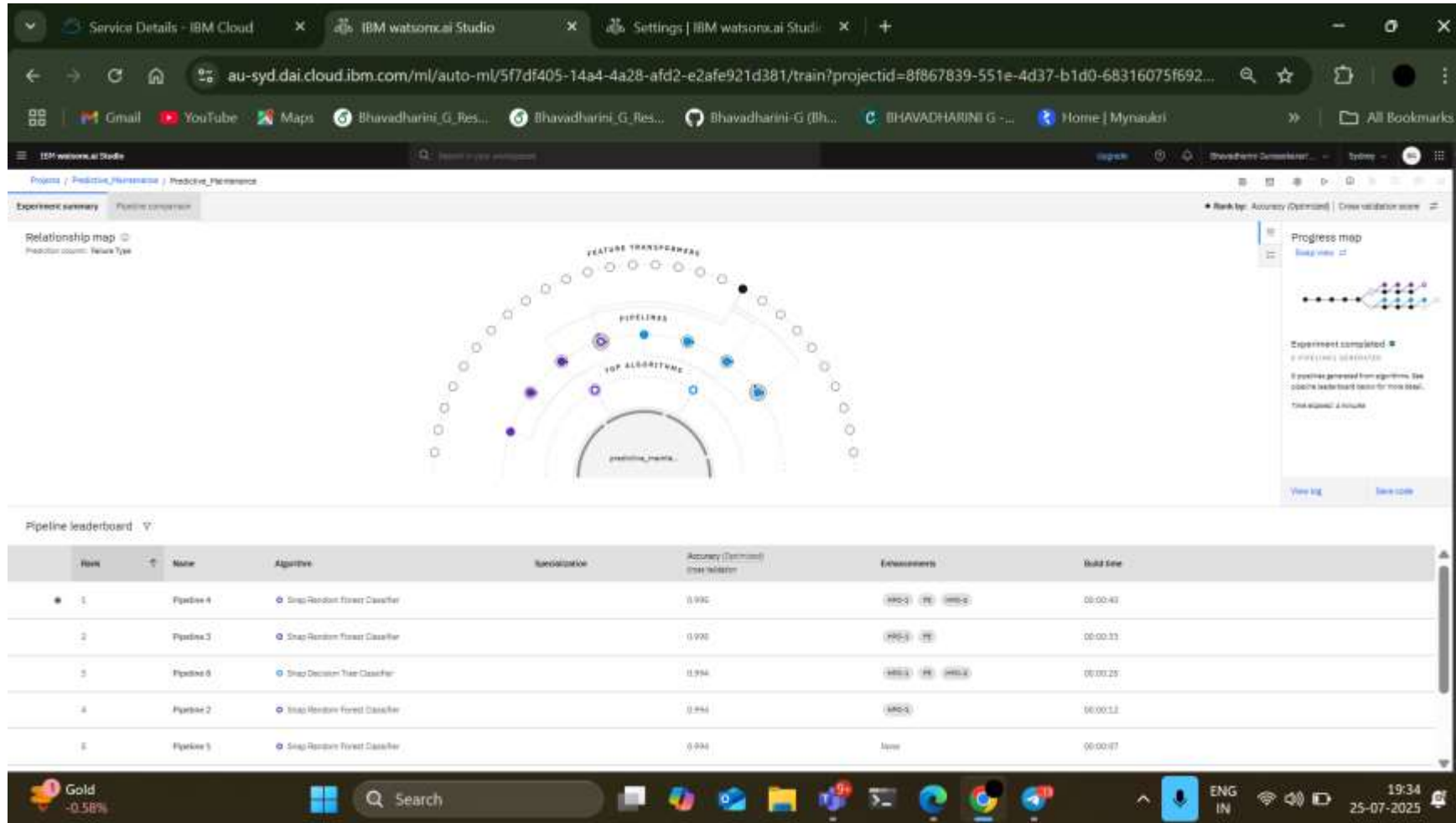
The "System Approach" section outlines the overall strategy and methodology for developing and implementing the rental bike prediction system. Here's a suggested structure for this section:

- **System requirements:**
 - IBM Cloud (mandatory).
 - IBM Watson Studio for model development and deployment.
 - IBM Cloud Object Storage for dataset handling.
- **Library required to build the model:**
 - Python with libraries like Scikit-learn and TensorFlow/PyTorch for model development and training.

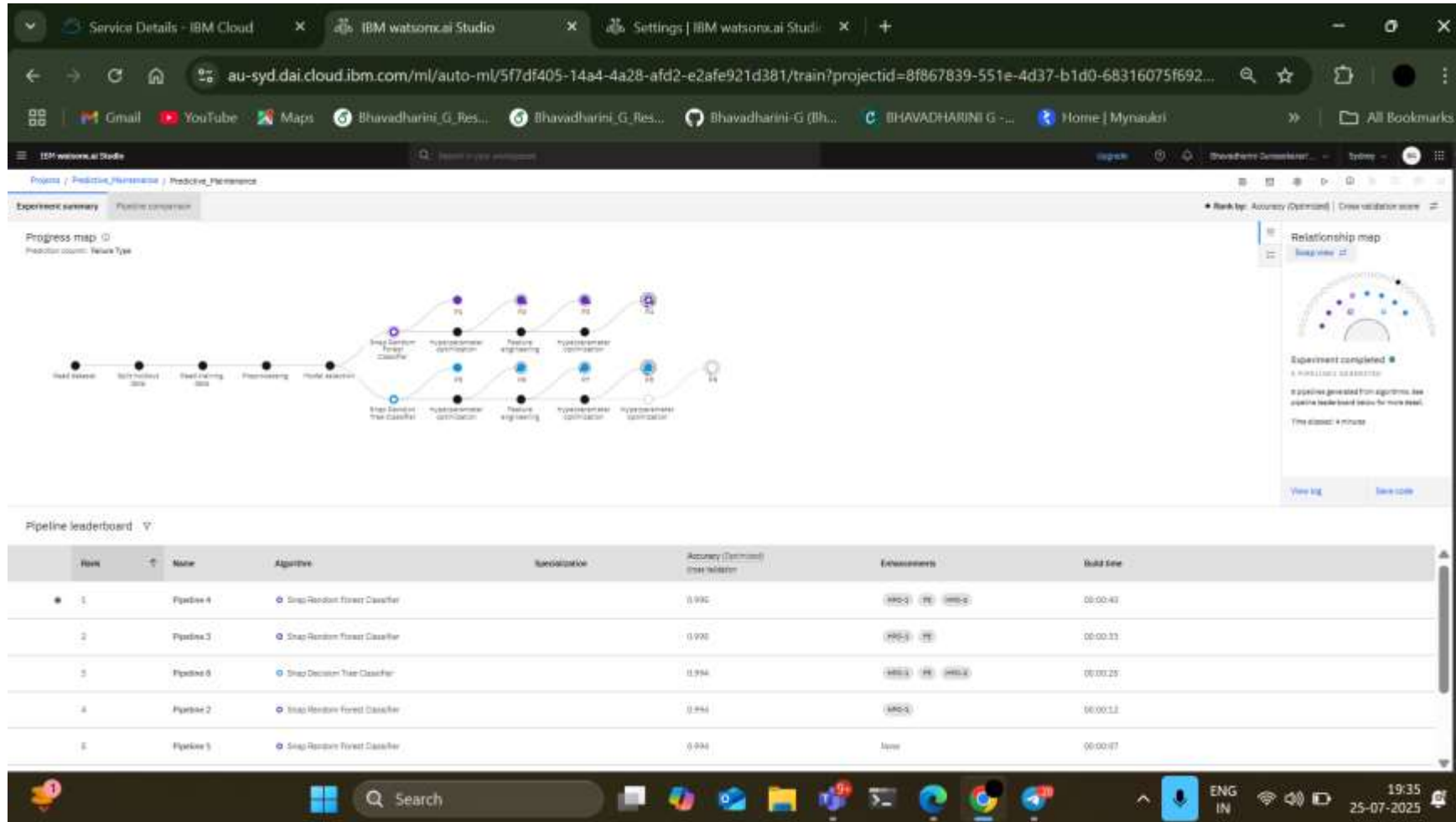
ALGORITHM & DEPLOYMENT

- **Algorithm Selection:**
 - Random Forest Classifier (or Gradient Boosting/LSTM, selected based on predictive performance).
- **Data Input:**
 - Real-time sensor measurements from machinery, such as Tool wear [min], Air temperature [K] , rotational speed, and torque.
- **Training Process:**
 - Supervised learning using historical data where sensor readings are labeled with the specific type of failure that occurred.
- **Prediction Process:**
 - The model will be deployed on IBM Watson Studio, providing an API endpoint for real-time failure predictions based on live data streams.

RESULT



RESULT

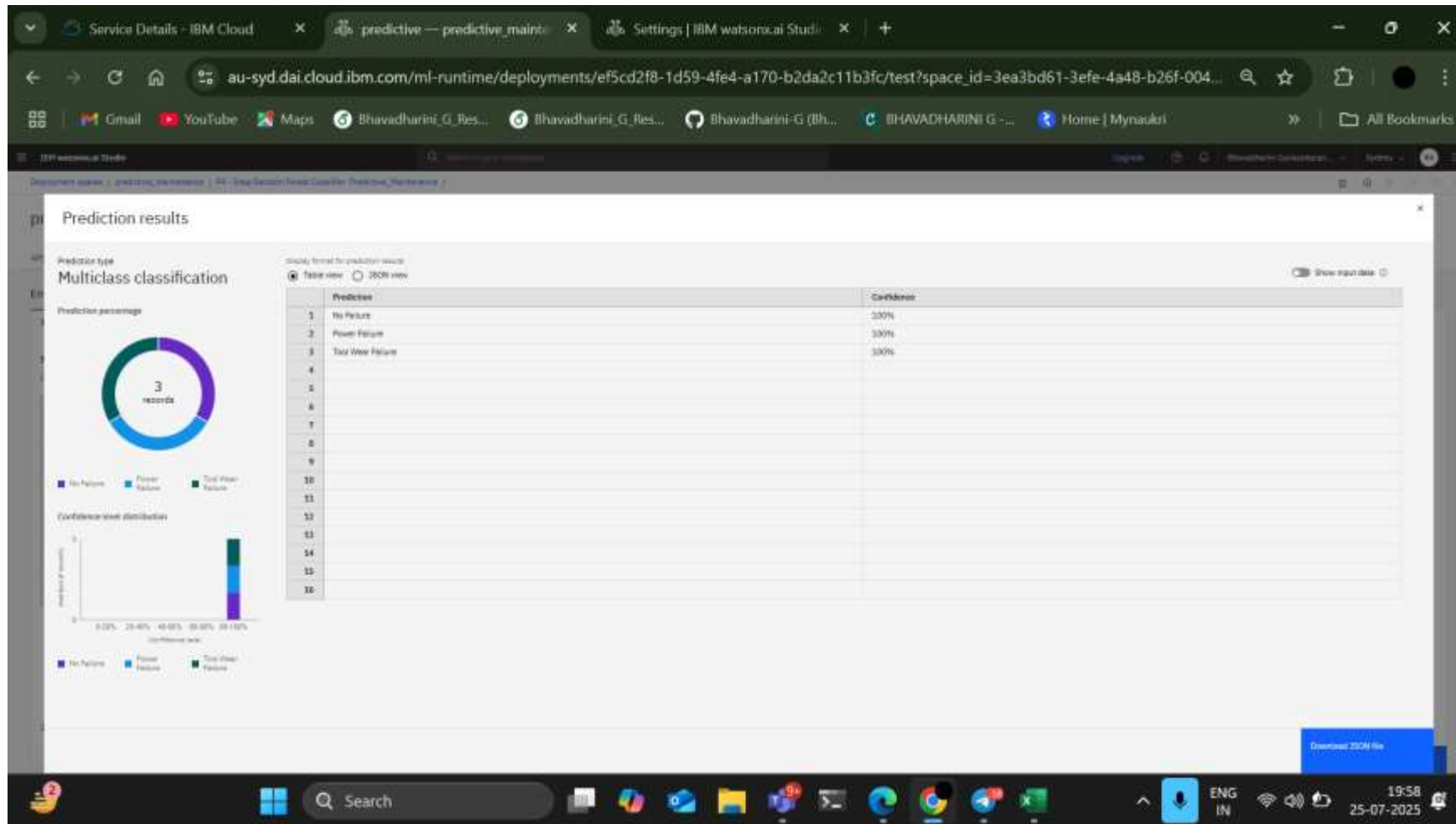


RESULT

The screenshot displays the IBM Watson AI Studio interface for a predictive maintenance model. The browser address bar shows the URL: `au-syd.dai.cloud.ibm.com/ml-runtime/deployments/ef5cd2f8-1d59-4fe4-a170-b2da2c11b3fc/test?space_id=3ea3bd61-3efe-4a48-b26f-004...`. The model is named "predictive" and is in a "Deployed" state. Below the model name, there are tabs for "API reference" and "Test". The "Test" tab is active, showing an "Enter input data" section with a "Test" button and a "CSV" button. Below this, there is a table with 10 columns: ID, Product ID, Type, Air temperature, Process temperature, Rotational speed, Torque, Tool wear, and Target. The table contains 10 rows of data. The "Predict" button is visible at the bottom right of the interface.

ID	Product ID (string)	Type (string)	Air temperature (K) (double)	Process temperature (K) (double)	Rotational speed (rpm) (double)	Torque (Nm) (double)	Tool wear (mm) (double)	Target (double)
1	4	L47183	1	298.2	104.6	1433	39.6	0
2	82	L47230	1	298.9	204.2	2842	4.8	0
3	78	L47207	1	298.8	308.9	1455	45.3	1
4								
5								
6								
7								
8								
9								
10								

RESULT



CONCLUSION

- We successfully developed and deployed a high-performance predictive maintenance model using IBM Watson Studio. The AutoAI experiment identified a Random Forest Classifier as the top-performing algorithm, achieving an outstanding 99.5% accuracy through automated feature engineering and optimization.
- The final model is deployed as a live web service. It effectively processes sensor data to predict specific failure types, such as "Tool Wear" or "Heat Dissipation," with high confidence. This project delivered a robust and accurate solution ready for real-world integration to enable proactive maintenance and reduce operational costs.

FUTURE SCOPE

- **Predict Remaining Useful Life (RUL):** Enhance the model to predict the exact time remaining before a component fails. This shifts the focus from what will fail to precisely when it will fail, allowing for more efficient maintenance scheduling.
- **Automated Root Cause Analysis:** Incorporate interpretability techniques (like SHAP or LIME) to automatically highlight the key sensor readings responsible for a failure prediction. This would help maintenance teams diagnose the underlying problem much faster.
- **Full System Integration:** Integrate the prediction alerts directly with Computerized Maintenance Management Systems (CMMS). This could automatically generate work orders and schedule technicians, creating a fully automated, closed-loop maintenance system.

REFERENCES

- Breiman, L. (2001). Random Forests. *Machine Learning*, 45(1), 5-32. The original paper on the Random Forest algorithm.
- Saxena, A., & Goebel, K. (2008). Turbofan Engine Degradation Simulation Data Set. The benchmark dataset for predictive maintenance, provided by NASA.
- Zheng, Y., et al. (2017). Remaining useful life estimation using a long short-term memory neural network. *IEEE Transactions on Industrial Electronics*. A key paper on using LSTMs for predicting Remaining Useful Life (RUL).
- Carvalho, A. T. Z., et al. (2019). Machine learning for predictive maintenance: A systematic literature review. *Computers & Industrial Engineering*. A comprehensive review of real-world applications and case studies.

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According to the Adobe Learning Manager system of record

Completion date: 24 Jul 2025 (GMT)

Learning hours: 20 mins



THANK YOU