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# **CAPSTONE PROJECT**

## **PREDICTIVE MAINTENANCE OF INDUSTRIAL MACHINERY**

**Presented By:**

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# OUTLINE

- **Problem Statement**
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# PROBLEM STATEMENT

Example: In industrial settings, unexpected machinery failures can lead to significant downtime, increased maintenance costs, and loss of productivity. Traditional maintenance practices such as reactive or scheduled maintenance are either too late or inefficient. This project aims to address the challenge of implementing a predictive maintenance system for industrial machinery by leveraging real-time sensor data. The primary goal is to develop a machine learning classification model capable of predicting the type of failure—such as tool wear, heat dissipation issues, or power failure—before it occurs. By anticipating failures in advance, industries can schedule timely maintenance, minimize machine downtime, improve operational efficiency, and reduce maintenance costs. The project uses a real-world dataset available on Kaggle and employs IBM Cloud services for model development, training, and deployment..

# PROPOSED SOLUTION

- ❑ To address the problem of unexpected industrial machine failures, we propose a predictive maintenance system powered by machine learning. The solution involves analyzing historical and real-time sensor data from machines to identify patterns that precede specific types of failures. A supervised classification model is developed to predict potential issues like tool wear, power failure, and overheating before they happen.
- ❑ **Data Collection:**
  - ❑ Utilize the Kaggle dataset containing machine operational and failure history data.
- ❑ **Data Preprocessing:**
  - ❑ Clean, normalize, and structure the data for model training.
- ❑ **Machine Learning Algorithm:**
  - ❑ Use machine learning algorithms like Random Forest, Logistic Regression, or XGBoost to classify failure types.
- ❑ **Deployment:**
  - ❑ Deploy the trained model on IBM Watson Machine Learning and integrate it with IBM Cloud Object Storage and Watson Studio.
- ❑ **Evaluation:**
  - ❑ The performance of the predictive maintenance model was evaluated using standard classification metrics such as accuracy, precision, recall, and F1-score.

# SYSTEM APPROACH

The effectively analyze the MIS 78th Round dataset and deploy the solution using IBM Cloud Lite, the system is designed with the following development tools, environments, and supporting libraries.

- **System requirements:**

  - Operating System:** Windows 10 / Ubuntu 20.04 or higher

  - Processor:** Intel Core i5 or higher (or equivalent)

  - Internet:** Stable connection for accessing IBM Cloud Lite services

- **Library required to build the model:**

- **IBM Cloud Services:**

  - IBM Watson Studio – for running Jupyter notebooks in the cloud

  - IBM Cloud Object Storage – for uploading and accessing datasets

- **Machine Learning & Analysis:**

  - scikit-learn – for correlation analysis, clustering, or classification models,statsmodels,scipy

# ALGORITHM & DEPLOYMENT

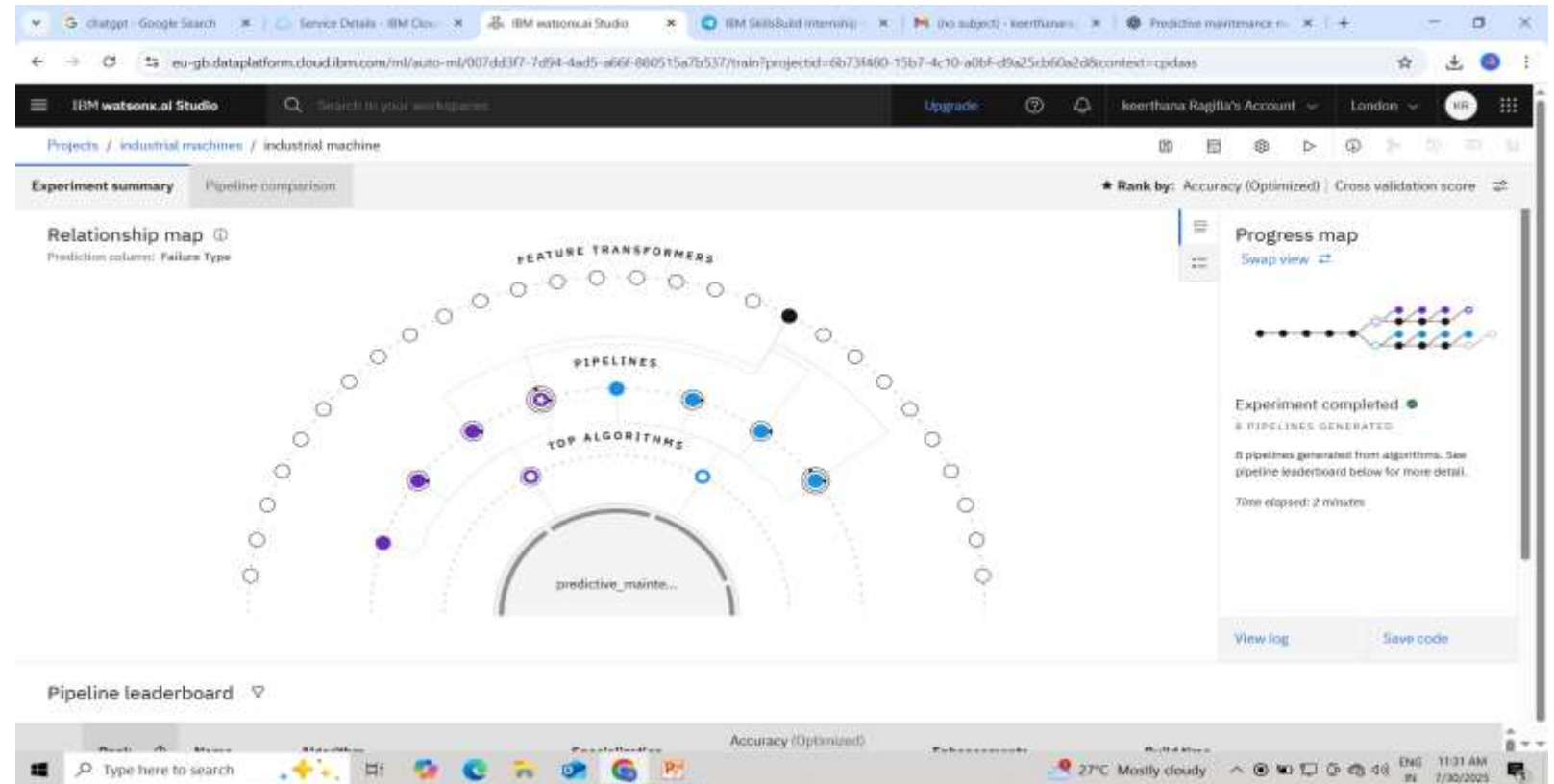
- ❑ The system uses descriptive analytics and exploratory data analysis (EDA) techniques to extract patterns and correlations from the predictive maintenance dataset.
- ❑ **Algorithm Selection:**
  - ❑ Random Forest Classifier is selected as the primary algorithm to predict failure types such as tool wear, power failure, heat dissipation failure, etc. It is ideal due to its robustness, ability to handle feature importance, and suitability for classification tasks on sensor-based datasets.
- ❑ **Data Input:**
  - ❑ The model uses features such as: Torque, Air temperature, Rotational speed etc
- ❑ **Training Process:**
  - ❑ Preprocessing and standardizing the input features, Splitting the dataset into training and testing sets Fitting the model using labeled sensor data..
- ❑ **Prediction Process:**
  - ❑ After training, the model classifies each machine instance into a specific failure category. This enables early detection of potential issues and helps industries take proactive maintenance actions before actual breakdowns occur.

# RESULT

The predictive maintenance model successfully classified various types of machinery failures such as tool wear, power failure, and heat dissipation issues with high accuracy. Using the Random Forest algorithm, the model achieved strong performance metrics, including a high F1-score and precision across all failure categories. The application of exploratory data analysis revealed key sensor features contributing to failure prediction, and the deployed model on IBM Cloud enables real-time monitoring and proactive maintenance decisions. This significantly reduces unplanned downtime and improves overall operational efficiency..

# RESULT

Processing the  
Data set with the  
suitable Algorithms  
and progress map





# RESULT

We can Enter manually to predict the output

The screenshot displays the IBM Watson AI Studio interface for a deployed model named 'industrial machine'. The interface includes a navigation bar with the IBM logo and 'watson.ai Studio' text. Below the navigation bar, the deployment status is shown as 'Deployed' and 'Online'. The 'Test' tab is active, showing an 'Enter input data' section with a 'Text' input mode selected. A table with 8 columns and 5 rows is visible, containing input data for prediction. The columns are: Type (other), Air temperature [K] (double), Process temperature [K] (double), Rotational speed [rpm] (double), Torque [Nm] (double), Tool wear [min] (double), and Target (double). The rows contain data for 5 different samples. A 'Predict' button is located at the bottom right of the table.

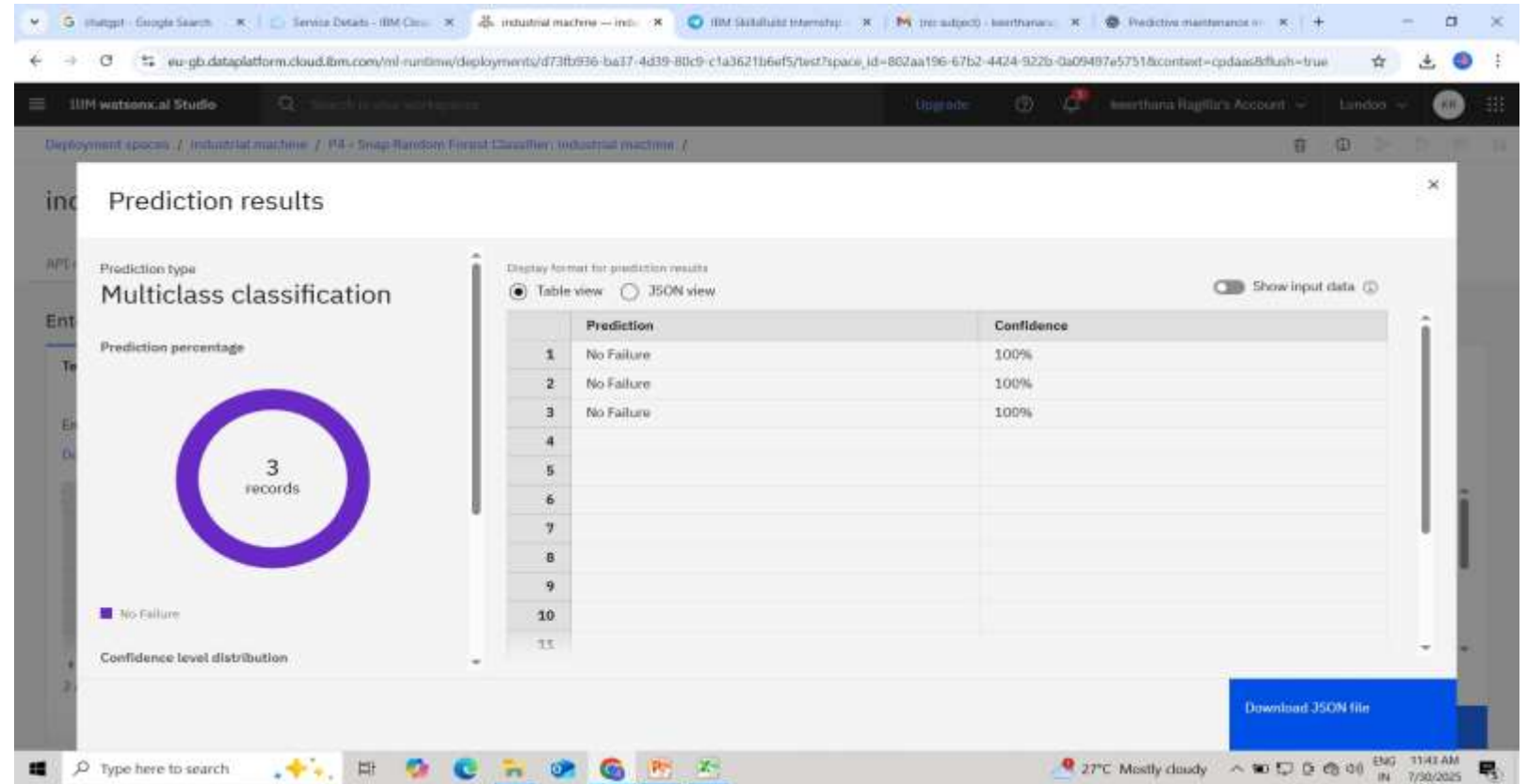
	Type (other)	Air temperature [K] (double)	Process temperature [K] (double)	Rotational speed [rpm] (double)	Torque [Nm] (double)	Tool wear [min] (double)	Target (double)
1	M	298.1	308.6	1551	42.8	0	0
2	L	298.2	308.7	1408	46.3	3	0
3	L	298.1	308.5	1498	49.4	5	0
4							
5							

3 rows, 9 columns

Predict

# RESULT

This is the final prediction to our data and its prediction distribution



# CONCLUSION

- The study highlights the existing disparities in access to improved drinking water across various regions and social groups in India. By analyzing data from the 78th Round of the Multiple Indicator Survey, important patterns and correlations were identified, particularly between water access and factors such as clean cooking fuel usage, sanitation, and migration. The use of clustering and visualization techniques on IBM Cloud Lite enabled clear identification of high-risk areas that require immediate policy attention. Overall, the project provides valuable, data-driven insights to support targeted interventions, ensuring that efforts toward achieving Sustainable Development Goal 6—clean water and sanitation for all—are both effective and inclusive.

# FUTURE SCOPE

- This project can be further extended by integrating **real-time data sources** such as water quality monitoring systems, satellite-based rainfall data, and IoT-enabled water supply tracking to enhance the accuracy and timeliness of insights. Future versions can also incorporate **predictive models** to forecast potential shortages or emerging risk zones based on seasonal trends and migration patterns. Additionally, expanding the scope to include **district-level and village-level data** will enable more granular analysis for local policymaking. The solution can also be adapted into an interactive **web-based dashboard or mobile app** for use by government officials, NGOs, and public health agencies to monitor and address disparities proactively.

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# IBM CERTIFICATIONS

Getting Started  
with AI



# IBM CERTIFICATIONS

Journey to Cloud



# IBM CERTIFICATIONS

RAG



[https://skills.yourlearning.ibm.com/certificate/ALM-COURSE\\_3824998](https://skills.yourlearning.ibm.com/certificate/ALM-COURSE_3824998)

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**THANK YOU**