CAPSTONE PROJECT

Predictive Maintenance of Industrial Machinery

(Problem statement No. 39)

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OUTLINE

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PROBLEM STATEMENT

In modern industrial sectors, unplanned equipment failures can lead to costly downtime and decreased productivity. To address this, many facilities have started integrating real-time sensor technologies in machines to monitor their health. However, identifying the exact moment and type of potential machine failure remains a major challenge. Predicting failures in advance allows for timely maintenance scheduling and uninterrupted operations. The critical task is to develop a model that can predict the failure type (e.g., tool wear, power failure, heat dissipation issues) using real-time sensor data from the machinery. This ensures proactive maintenance, reduces unexpected downtimes, and optimizes operational efficiency.

PROPOSED SOLUTION

The proposed system aims to address the challenge of predicting the type of machinery failure in advance to enable timely and proactive maintenance actions. This involves leveraging sensor data and machine learning techniques to classify failure types accurately. The solution will consist of the following components:

Data Collection:

- Gather historical and real-time sensor data from various industrial machines, including attributes such as rotational speed, torque, tool wear, and vibration levels.
- Use the publicly available dataset from Kaggle: Machine Predictive Maintenance Classification, which contains labeled failure types like heat dissipation, power failure, and tool wear.

Data Preprocessing:

- Clean and preprocess the dataset to address missing values, outliers, and data imbalance issues.
- Perform normalization or standardization of sensor readings to ensure consistency.
- Engineer relevant features from the time-series data that reflect underlying machine behavior and degradation patterns.

Machine Learning Algorithm:

- Implement a classification algorithm (e.g., Snap Random Forest Classifier, XGBoost, or Support Vector Machine) to predict the type of failure based on sensor input.
- Optionally explore deep learning models such as LSTM or GRU if temporal dependencies in the data are significant.
- Perform hyperparameter tuning and cross-validation to ensure robust model performance.

Deployment:

- The selected model was deployed using IBM Watson Studio's AutoML deployment feature.
- The system supports: Input via manual CSV or JSON, Instant predictions through the deployed API interface.

Evaluation:

- Evaluate the model using metrics such as Accuracy, Precision, Recall, F1-score, and Confusion Matrix to measure classification performance.
- Perform real-world simulation or testing in a controlled environment to assess model responsiveness and reliability.
- Continuously monitor the model in production and retrain it periodically with new data to maintain high accuracy.

Result:

- The proposed system enables early detection of machinery faults, helping industries schedule maintenance activities proactively. This reduces unexpected breakdowns, minimizes production losses, lowers maintenance costs, and extends machine life. By providing actionable insights in real-time, the system supports data-driven maintenance decisions for industrial efficiency.

SYSTEM APPROACH

This section outlines the methodology and tools employed to develop and deploy the predictive maintenance model, aimed at forecasting equipment failures in industrial machinery using real-time sensor data.

System Requirements

Component	Specification
Platform	IBM Watsonx.ai Studio (Cloud-based)
Dataset Source	Kaggle: Predictive Maintenance Classification
Processor	Cloud-based, managed by IBM infrastructure
Storage	IBM Object Storage / Watson Studio Asset Storage
Interface	Web-based User Interface (via Watson Studio Deployment)
File Formats	CSV for input; JSON supported for prediction API
Max Input File Size	50 MB

Libraries and Tools Used

Tool / Library	Purpose
IBM Watson Studio	Model development, training, AutoAI pipelines
AutoAI	Automated model building, evaluation, and optimization
Scikit-learn (backend)	Classification algorithms (e.g., Random Forest)
Pandas & NumPy	Data preprocessing, feature extraction
Matplotlib / Seaborn	Visualization of training/evaluation metrics
Watson Machine Learning	Deployment of final model as a web service
REST API (auto-generated)	Used for integrating with front-end applications

ALGORITHM & DEPLOYMENT

This section outlines the machine learning algorithm used to predict the type of machinery failure based on real-time sensor inputs. The algorithm was selected and optimized using IBM Watson AutoAI, which automatically compares multiple models and pipelines to identify the best-performing solution.

Algorithm Selection

The chosen algorithm for this project is the **Batched Tree Ensemble Classifier**, implemented as a Snap Random Forest Classifier within IBM Watson AutoAI. This algorithm was selected after evaluating multiple pipelines, including Decision Tree Classifiers and standalone Random Forest models.

Random Forest is well-suited for this classification problem because it:

- Handles high-dimensional, mixed-type input data (numerical + categorical)
- Is robust to outliers and noise
- Offers high interpretability and generalization performance
  It achieved an optimized accuracy of 99.5% during cross-validation, outperforming other contenders in precision, recall, and F1-score.

Data Input

Feature Name	Description
UDI	Unique identifier for each data row
Product ID	Unique ID of the machine model
Type	Machine type (H, M, L)
Air Temperature [K]	Environmental temperature
Process Temperature [K]	Machine internal temperature
Rotational Speed [rpm]	Motor RPM
Torque [Nm]	Rotational force applied
Tool Wear [min]	Tool usage duration

Training Process

- The dataset was split into training and holdout sets using **AutoAI's automatic data partitioning**.
- Preprocessing steps included normalization, encoding categorical variables, and feature selection.
- **Hyperparameter optimization (HPO)** was performed to fine-tune the Random Forest model parameters, such as:
    - Number of estimators
    - Max tree depth
    - Feature sampling method
- **Cross-validation** was applied to ensure that the model generalizes well to unseen data.
- Multiple pipelines (P1–P9) were evaluated, and the best-performing one (P5) was selected based on overall accuracy and log loss.

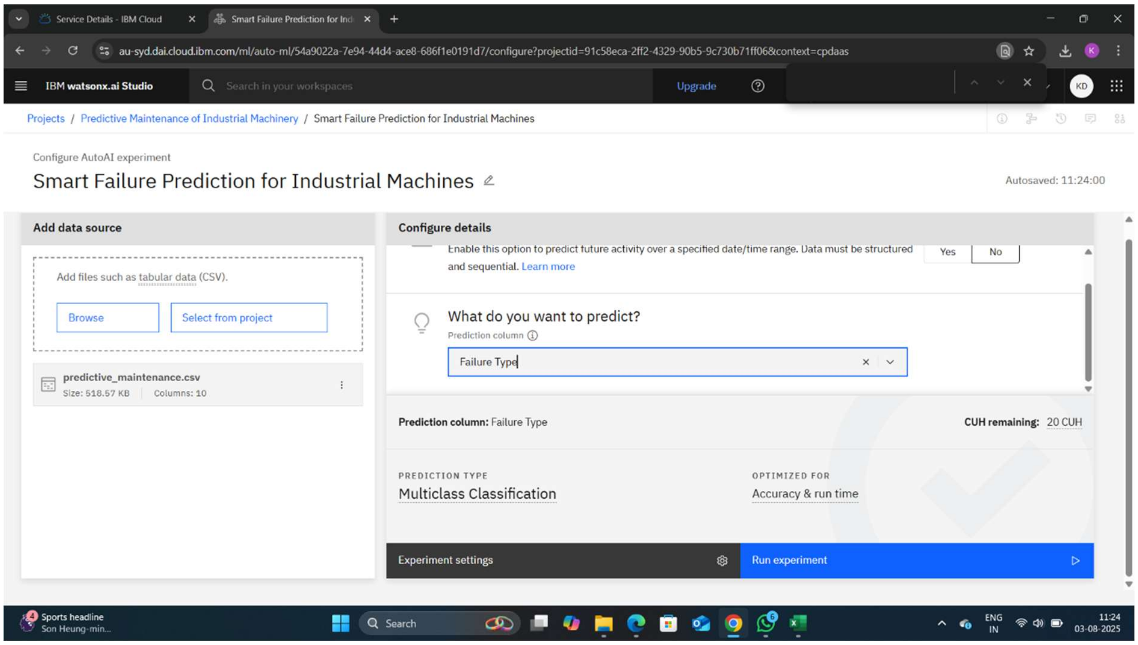
Prediction Process

Once deployed, the model accepts **real-time or batch input** via CSV or JSON format through a web interface or API. The model processes the input features and predicts the **failure type**, which may include:

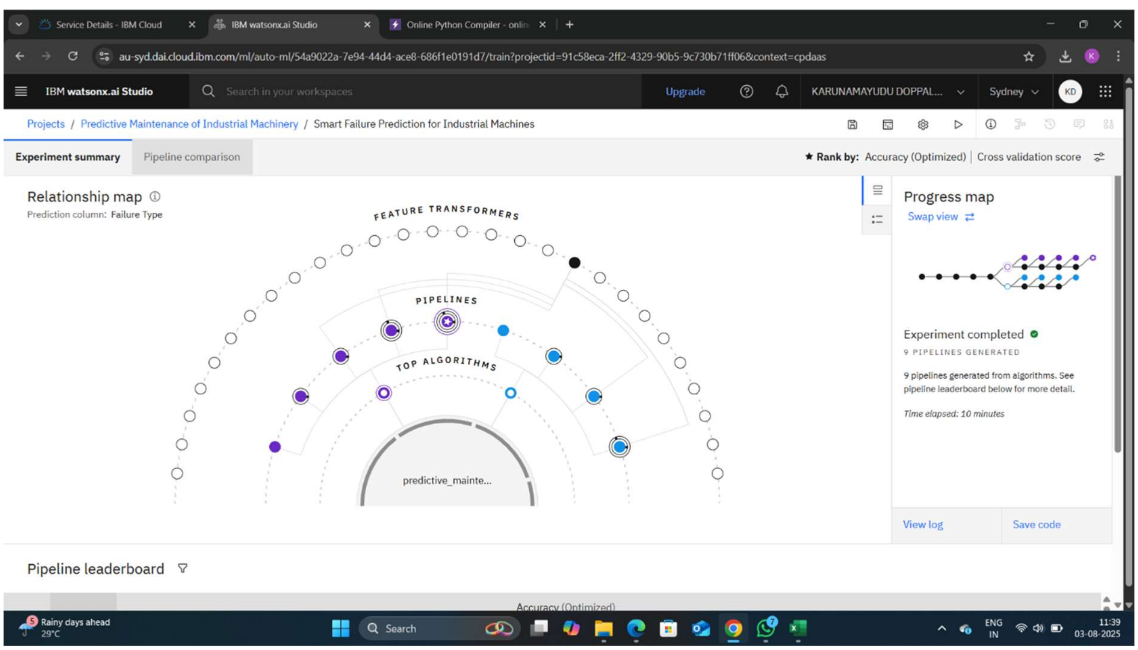
- Heat Dissipation Failure
- Tool Wear Failure
- Power Failure
- Overstrain Failure
- No Failure (Normal operation)

The real-time system can be integrated into industrial monitoring dashboards, enabling instant alerts for preventive maintenance actions based on the predicted failure category.

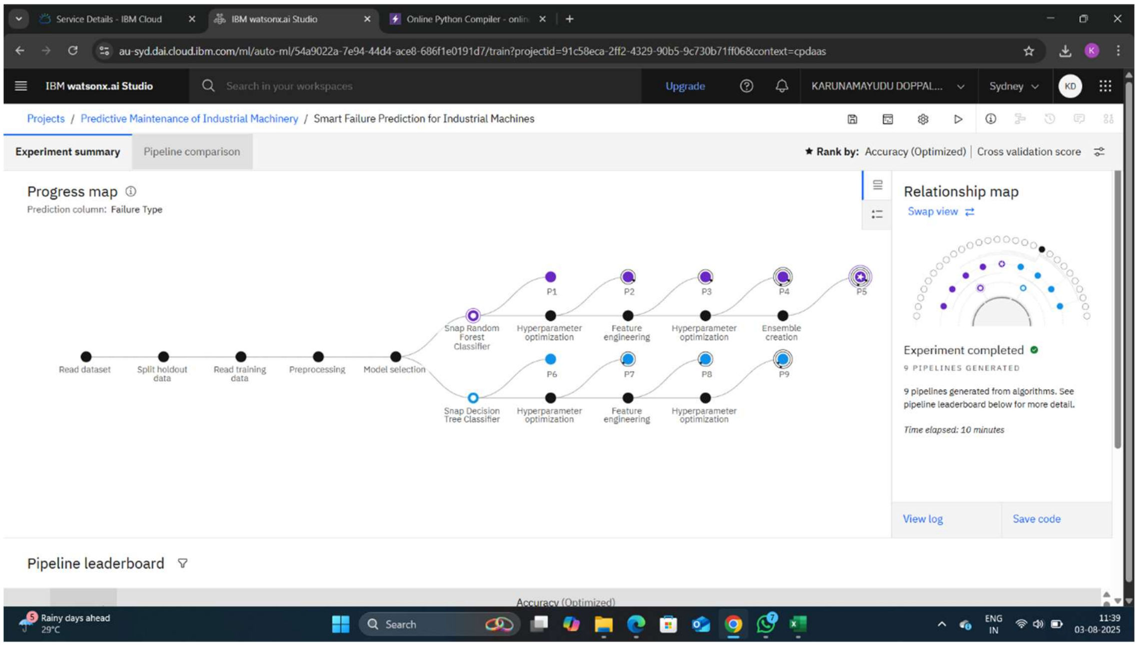
RESULT

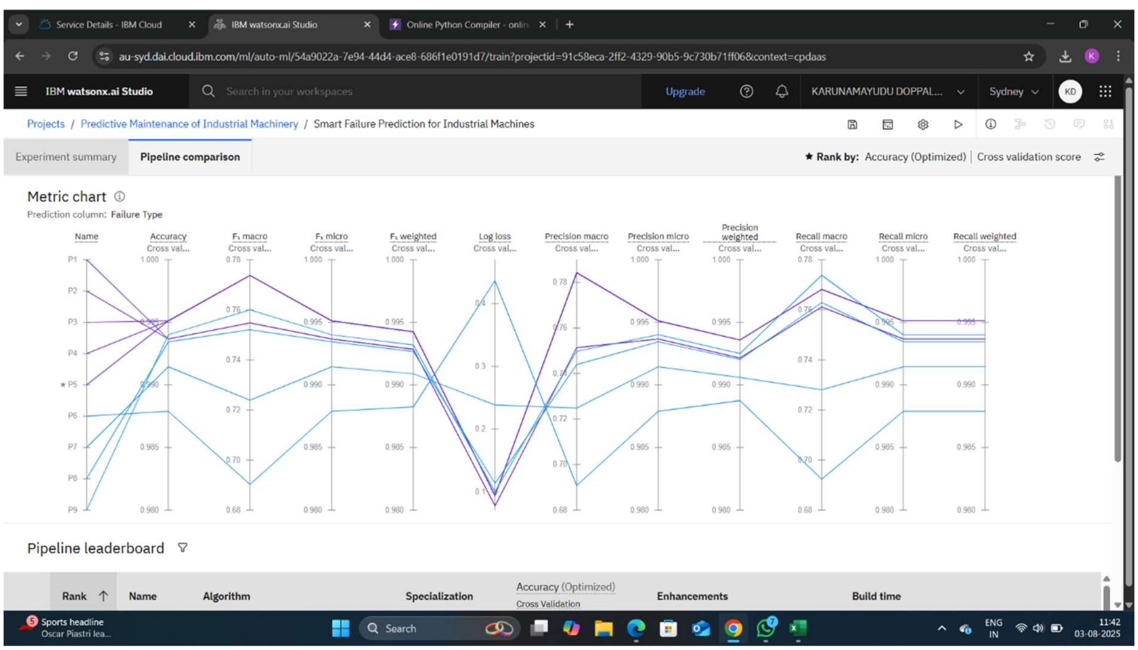


Smart Failure Prediction for Industrial Machines
IBM watsonx.ai Studio
Projects / Predictive Maintenance of Industrial Machinery / Smart Failure Prediction for Industrial Machines
Configure AutoAI experiment
Smart Failure Prediction for Industrial Machines
Autosaved: 11:24:00
Add data source
Add files such as tabular data (CSV).
Browse
Select from project
predictive_maintenance.csv
Size: 518.57 KB
Columns: 10
Configure details
Enable this option to predict future activity over a specified date/time range. Data must be structured and sequential. Learn more
Yes
No
What do you want to predict?
Prediction column
Failure Type
Prediction column: Failure Type
CUH remaining: 20 CUH
PREDICTION TYPE
Multiclass Classification
OPTIMIZED FOR
Accuracy & run time
Experiment settings
Run experiment

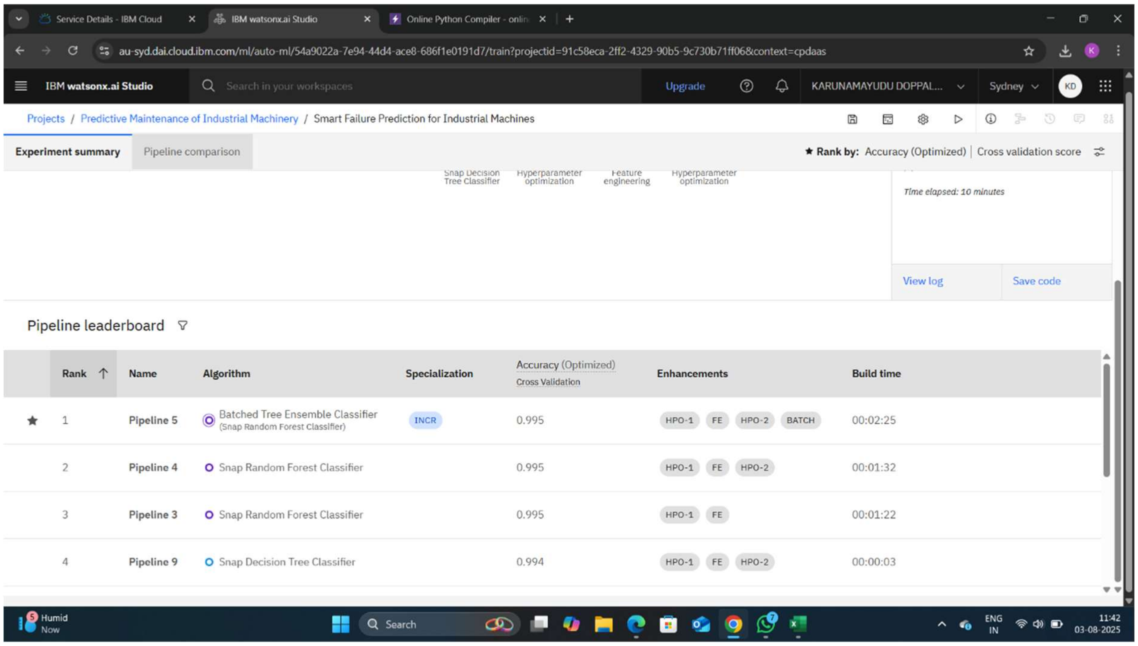


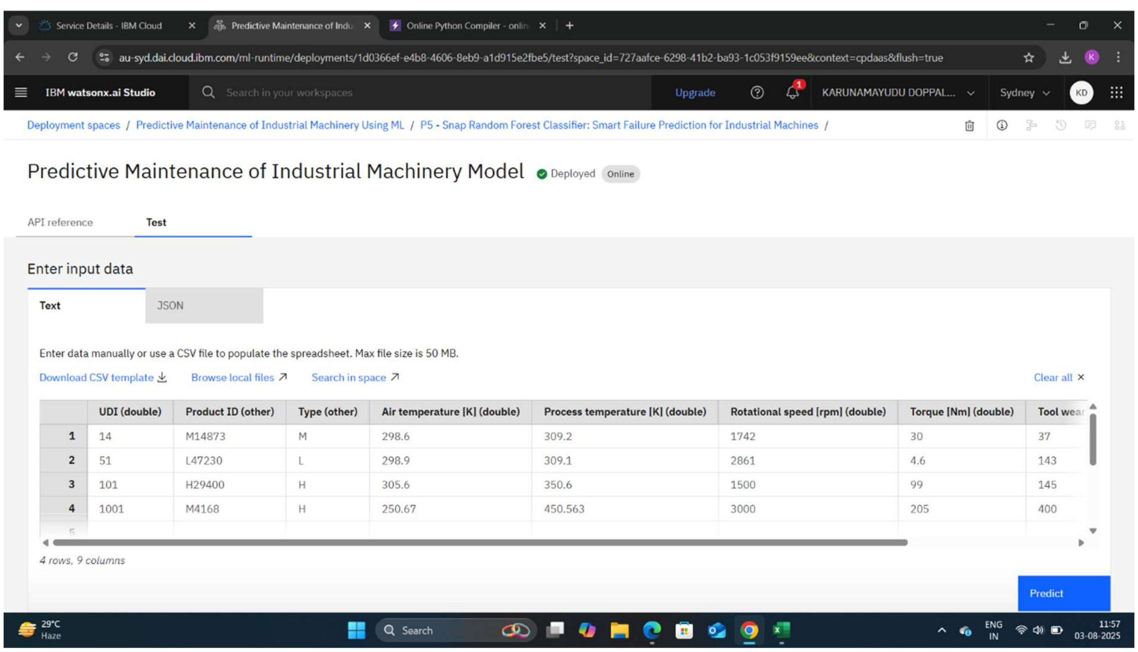
IBM watsonx.ai Studio
Projects / Predictive Maintenance of Industrial Machinery / Smart Failure Prediction for Industrial Machines
Experiment summary
Pipeline comparison
Rank by: Accuracy (Optimized) | Cross validation score
Relationship map
Prediction column: Failure Type
FEATURE TRANSFORMERS
PIPELINES
TOP ALGORITHMS
predictive_mainte...
Progress map
Swap view
Experiment completed
9 PIPELINES GENERATED
9 pipelines generated from algorithms. See pipeline leaderboard below for more detail.
Time elapsed: 10 minutes
View log
Save code
Pipeline leaderboard





edunet foundation





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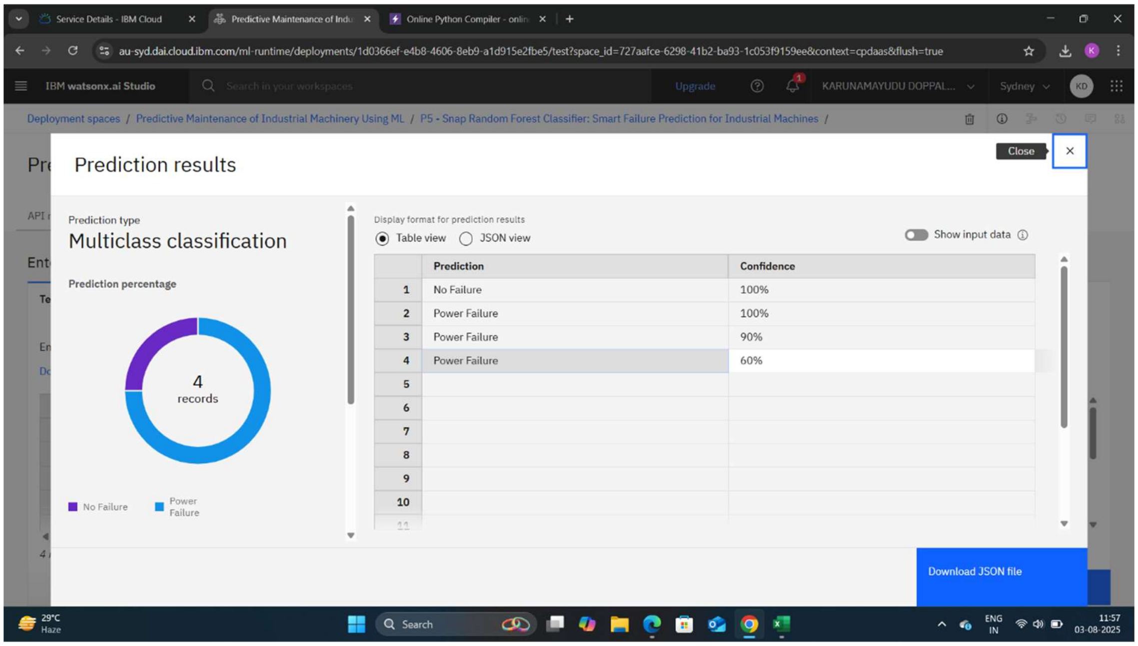
IBM watsonx.ai Studio
Deployment spaces / Predictive Maintenance of Industrial Machinery Using ML / P5 - Snap Random Forest Classifier: Smart Failure Prediction for Industrial Machines /
Prediction results
Close
Prediction type
Multiclass classification
Prediction percentage
4
records
No Failure
Power Failure
Display format for prediction results
Table view
JSON view
Show input data
Prediction
Confidence
1 No Failure 100%
2 Power Failure 100%
3 Power Failure 90%
4 Power Failure 60%
Download JSON file

CONCLUSION

This project successfully developed and deployed a machine learning-based predictive maintenance system for industrial machinery using real-time sensor data. Leveraging IBM Watson's AutoAI capabilities, the most optimal model—a Batched Tree Ensemble Classifier—was identified, achieving a high classification accuracy of **99.5%**. The model effectively predicts potential failure types such as tool wear, heat dissipation, and power failure, enabling timely and proactive maintenance decisions.

Throughout the implementation, challenges included managing data preprocessing, handling imbalanced failure classes, and optimizing hyperparameters for best performance. These were effectively addressed using AutoAI's automated pipeline generation and cross-validation techniques.

While the current system performs exceptionally well, future improvements could include integrating real-time streaming data, adaptive learning for continuous updates, and enhanced visualization dashboards for industrial teams.

Accurate failure prediction plays a crucial role in reducing machinery downtime, optimizing maintenance schedules, and cutting operational costs—similar in impact to how accurate bike count predictions support urban mobility planning. Just as stability in bike supply ensures rider satisfaction and citywide efficiency, early fault detection in machines ensures smoother industrial operations and higher productivity.

FUTURE SCOPE

In the future, the predictive maintenance system can be enhanced by incorporating additional sensor data such as vibration analysis, humidity, voltage fluctuations, and machine-specific operational logs. Integrating real-time data streams from IoT-enabled industrial devices can improve prediction accuracy and help detect failures even earlier. The model can also be continuously retrained using live data to adapt to changing machine behaviors, ensuring its relevance and accuracy over time.

Further improvements may include the use of advanced machine learning techniques such as deep neural networks (e.g., LSTM, CNN) or ensemble hybrid models to capture complex patterns in time-series sensor data. The system can be extended to support edge computing, allowing predictions to happen directly on local industrial devices, reducing latency and enhancing reliability. In large-scale applications, this solution can also be scaled to monitor multiple factories or industrial units across different regions, offering centralized control with decentralized intelligence.

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(ALM-COURSE_3824998)

According to the Adobe Learning Manager system of record

Completion date: 24 Jul 2025 (GMT) **Learning hours:** 20 mins

THANK YOU