CAPSTONE PROJECT

PROJECT TITLE

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OUTLINE

- Problem Statement
- Proposed System/Solution
- System Development Approach
- Algorithm & Deployment
- Result
- Conclusion
- Future Scope
- References



PROBLEM STATEMENT

Maintenance of Industrial Machines is crucial for a Manufacturing Company. Machine Failure can be predicted by certain parameters like tool wear, rotational speed, heat dissipation and torque. Machines can be fitted with sensors which collect data for these parameters. This sensor data must be analysed to identify patters that precede a failure. The crucial part is to create a classification model that can predict the type of failure is (e.g., tool wear, heat dissipation, power failure). This will enable proactive maintenance, reducing downtime and operational costs.



PROPOSED SOLUTION

- The proposed system aims to address the challenge of predicting machine failures to minimise unplanned downtimes and improve operational efficiency. This involves leveraging data analytics and machine learning techniques to forecast failure patterns accurately. The solution will consist of the following components:
- Data Collection:
 - Gather historical data on machine failures, including air temperature, process temperature, rotational speed, torque, tool wear and other relevant factors.
 - Utilize real-time data sources to enhance prediction accuracy.
- Data Preprocessing:
 - Clean and preprocess the collected data to handle missing values, outliers, and inconsistencies.
 - Feature engineering to extract relevant features from the data that might cause machine failure.
- Machine Learning Algorithm:
 - Implement a machine learning algorithm, either manually or IBM AutoAl (e.g. Random Forest, XGBoost, Support Vector Machine (SVM)), to predict machine failures based on historical patterns.
 - Train the model on labelled historical data.
- Deployment:
 - Create a deployment space in IBM Watson Studio.
 - Deploy the most efficient ML algorithm on the deployment space created.
- Evaluation:
 - Assess the model's performance using appropriate metrics such as Accuracy, Precision, Confusion matrix or other relevant metrics.
 - Fine-tune the model based on feedback and continuous monitoring of prediction accuracy.
 - Result: A reliable machine failure prediction is obtained, facilitating predictive maintenance.



SYSTEM APPROACH

System requirements

Hardware Requirements:

- A system with a minimum of 8 GB RAM
- 2. Internet connectivity

Software Requirements:

Operating System: Windows 10/Linux/macOS

IBM Cloud Services:

- 1. IBM Watson Studio
- IBM Watson Machine Learning
- 3. IBM Cloud Object Storage

Library required to build the model

- pandas Data preprocessing
- 2. numpy Numerical computations
- scikit-learn Machine learning models & evaluation
- matplotlib, seaborn Data visualization
- 5. imblearn Handling imbalanced datasets (e.g., SMOTE)
- 6. xgboost / lightgbm Advanced classifiers
- 7. requests API interaction
- 8. joblib / pickle Model saving & loading



ALGORITHM & DEPLOYMENT

Algorithm Selection:

Random Forest Classifier is best suited for this project because it can handle high-dimensional sensor data. It reduces overfitting
by averaging multiple decision trees. It is highly accurate, thus facilitating predictive maintenance of complex machines.

Data Input:

Inputs used by the algorithm: Air temperature, Process temperature, Rotational speed, Torque and Tool wear.

Training Process:

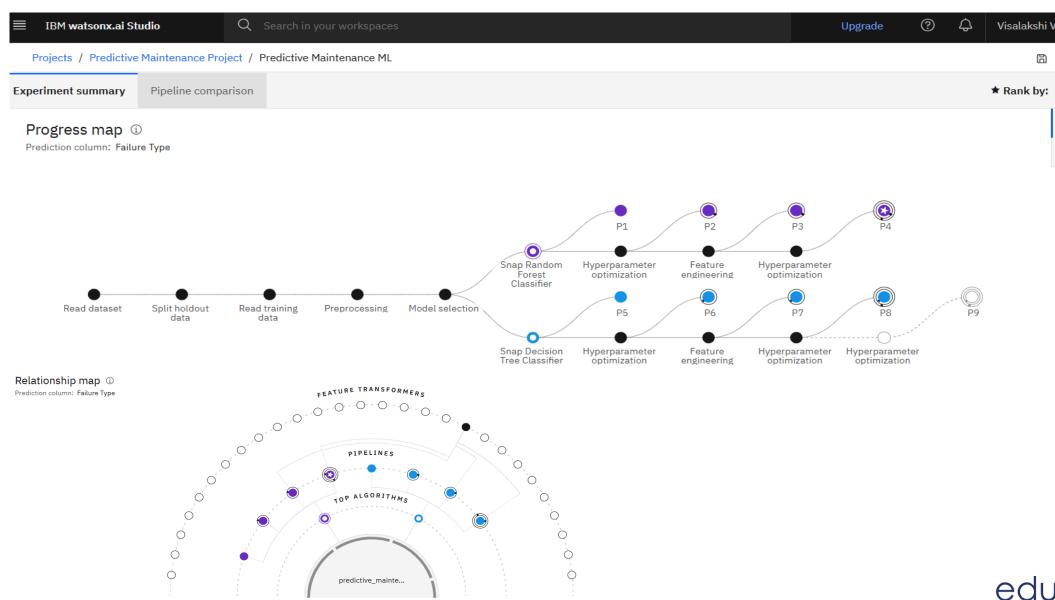
- Data from Kaggle is uploaded to IBM Watson Studio.
- IBM AutoAl generates Pipelines using different algorithms and tunes hyperparameters using grid search and cross-validation.
- The various models are ranked based on accuracy and the model with the best performance is selected and deployed.

Prediction Process:

- Detail how the trained algorithm makes predictions for future bike counts. Discuss any real-time data inputs considered during the prediction phase.
- The input file structured exactly like the original dataset used in training excluding the label column (Failure type) is uploaded in the test module.
- Predictions are run by IBM cloud and the results obtained are in percentage and also in downloadable JSON file format.



AUTO AI MACHINE LEARNING PIPELINE



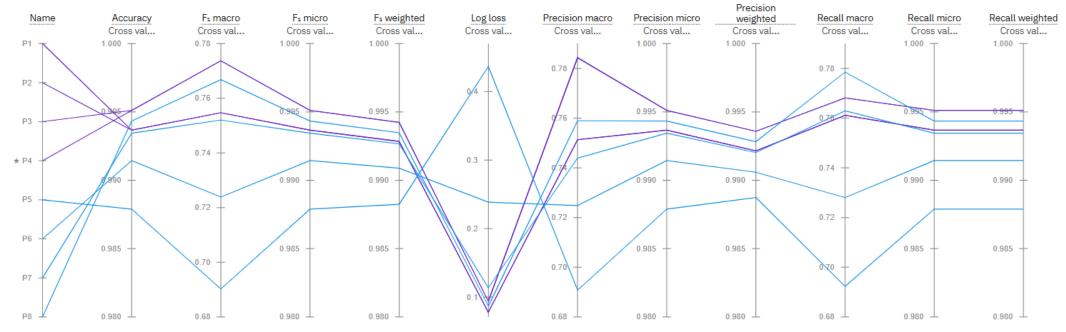
	Rank ↑	Name	Algorithm	Specialization	Accuracy (Optimized) Cross Validation	Enhancements	Build time
*	1	Pipeline 4	O Snap Random Forest Classifier		0.995	HPO-1 FE HPO-2	00:00:47
	2	Pipeline 3	O Snap Random Forest Classifier		0.995	HPO-1 FE	00:00:37
	3	Pipeline 8	O Snap Decision Tree Classifier		0.994	HPO-1 FE HPO-2	00:00:29
	4	Pipeline 2	O Snap Random Forest Classifier		0.994	HPO-1	00:00:09
	5	Pipeline 1	O Snap Random Forest Classifier		0.994	None	00:00:03
	6	Pipeline 7	O Snap Decision Tree Classifier		0.993	HPO-1 FE	00:00:25
	7	Pipeline 6	O Snap Decision Tree Classifier		0.991	HPO-1	00:00:04
	8	Pipeline 5	O Snap Decision Tree Classifier		0.988	None	00:00:02



PIPELINE COMPARISON

Metric chart ①

Prediction column: Failure Type





RESULT

Present the results of the machine learning model in terms of its accuracy and effectiveness in predicting bike counts. Include visualizations and comparisons between predicted and actual counts to highlight the model's performance.

Prediction results

isplay format for prediction results

Table view	\circ	JSON v
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	prediction	probability	UDI	Product ID	Туре	Air temperature [K]	Process temperature [K]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]	Target
1	No Failure	[0,1,0,0,0,0]	1	M14860	М	298.1	308.6	1551	42.8	0	0
2	Tool Wear Failure	[0,0,0,0,0,1]	0	L47257	L	298.8	308.9	1455	41.3	208	1
3	No Failure	[0,1,0,0,0,0]	2	L47181	L	298.2	308.7	1408	46.3	3	0
4	No Failure	[0,1,0,0,0,0]	3	L47182	L	298.1	308.5	1498	49.4	5	0
5	No Failure	[0,1,0,0,0,0]	4	L47183	L	298.2	308.6	1433	39.5	7	0
6	No Failure	[0,1,0,0,0,0]	5	L47184	L	298.2	308.7	1408	40	9	0
7	No Failure	[0,1,0,0,0,0]	6	M14865	М	298.1	308.6	1425	41.9	11	0
8	No Failure	[0,1,0,0,0,0]	7	L47186	L	298.1	308.6	1558	42.4	14	0
9	No Failure	[0,1,0,0,0,0]	8	L47187	L	298.1	308.6	1527	40.2	16	0
10	No Failure	[0,1,0,0,0,0]	9	M14868	М	298.3	308.7	1667	28.6	18	0
11	No Failure	[0,1,0,0,0,0]	10	M14869	М	298.5	309	1741	28	21	0
12	No Failure	[0,1,0,0,0,0]	11	H29424	Н	298.4	308.9	1782	23.9	24	0
	prediction	probability	UDI	Product ID	Туре	Air temperature [K]	Process temperature [K]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]	Target
71	prediction Power Failure	probability [0,0,0,1,0,0]	UDI 70	Product ID	Type L	Air temperature [K]	Process temperature [K]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]	Target
71 72			_								
	Power Failure	[0,0,0,1,0,0]	70	L47249	L	298.9	309	1410	65.7	191	1
72	Power Failure No Failure	[0,0,0,1,0,0]	70 71	L47249 M14930	L M	298.9 298.9	309	1410 1924	65.7	191 193	1 0
72 73	Power Failure No Failure No Failure	[0,0,0,1,0,0] [0,0.99988 [0,1,0,0,0,0]	70 71 72	L47249 M14930 L47251	L M L	298.9 298.9 298.9	309 309 309.1	1410 1924 1452	65.7 22.6 45.5	191 193 196	1 0 0
72 73 74	Power Failure No Failure No Failure No Failure	[0,0,0,1,0,0] [0,0.99988 [0,1,0,0,0] [0,0.99887	70 71 72 73	L47249 M14930 L47251 L47252	L M L	298.9 298.9 298.9 298.9	309 309 309.1 309.1	1410 1924 1452 1369	65.7 22.6 45.5 44.4	191 193 196 198	1 0 0 0
72 73 74 75	Power Failure No Failure No Failure No Failure No Failure	[0,0,0,1,0,0] [0,0.99988 [0,1,0,0,0,0] [0,0.99887 [0,0.99988	70 71 72 73 74	L47249 M14930 L47251 L47252 L47253	L M L L	298.9 298.9 298.9 298.9 299.9	309 309 309.1 309.1 309.1	1410 1924 1452 1369 1592	65.7 22.6 45.5 44.4 35	191 193 196 198 200	1 0 0 0
72 73 74 75 76	Power Failure No Failure No Failure No Failure No Failure No Failure	[0,0,0,1,0,0] [0,0,9988 [0,1,0,0,0,0] [0,0,99887 [0,0,9988	70 71 72 73 74 75	L47249 M14930 L47251 L47252 L47253 L47254	L M L L	298.9 298.9 298.9 298.9 299 298.9	309 309 309.1 309.1 309.1 309	1410 1924 1452 1369 1592 1601	65.7 22.6 45.5 44.4 35 32.3	191 193 196 198 200 202	1 0 0 0 0
72 73 74 75 76 77	Power Failure No Failure No Failure No Failure No Failure No Failure No Failure	[0,0,0,1,0,0] [0,0,99988 [0,1,0,0,0,0] [0,0,99887 [0,0,99988 [0,1,0,0,0,0]	70 71 72 73 74 75	L47249 M14930 L47251 L47252 L47253 L47254 L47255	L M L L L L	298.9 298.9 298.9 298.9 299 298.9 298.8	309 309 309.1 309.1 309.1 309 308.9	1410 1924 1452 1369 1592 1601	65.7 22.6 45.5 44.4 35 32.3 46.7	191 193 196 198 200 202 204	1 0 0 0 0 0
72 73 74 75 76 77	Power Failure No Failure	[0,0,0,1,0,0] [0,0.99988 [0,1,0,0,0,0] [0,0.99887 [0,1,0,0,0,0] [0,1,0,0,0,0] [0,1,0,0,0,0]	70 71 72 73 74 75 76	L47249 M14930 L47251 L47252 L47253 L47254 L47255 L47256	L M L L L L L	298.9 298.9 298.9 298.9 299 298.9 298.8 298.8	309 309 309.1 309.1 309.1 309 308.9	1410 1924 1452 1369 1592 1601 1379	65.7 22.6 45.5 44.4 35 32.3 46.7 47.9	191 193 196 198 200 202 204 206	1 0 0 0 0 0 0
72 73 74 75 76 77 78	Power Failure No Failure Tool Wear Failure	[0,0,0,1,0,0] [0,0,9988 [0,1,0,0,0,0] [0,0,99887 [0,1,0,0,0,0] [0,1,0,0,0,0] [0,1,0,0,0,0] [0,0,99979	70 71 72 73 74 75 76 77	L47249 M14930 L47251 L47252 L47253 L47254 L47255 L47256 L47257		298.9 298.9 298.9 298.9 299 298.9 298.8 298.8	309 309 309.1 309.1 309.1 309 308.9 308.9	1410 1924 1452 1369 1592 1601 1379 1461	65.7 22.6 45.5 44.4 35 32.3 46.7 47.9 41.3	191 193 196 198 200 202 204 206 208	1 0 0 0 0 0 0



CONCLUSION

• Machine Failures like tool wear, power failure, overstrain failure, and random failures are predicted accurately using this Predictive Maintenance Machine Learning model developed using IBM AutoAI services. Challenges encountered during the implementation of this project were proper formatting of the input data, selecting the most accurate Machine learning algorithm and API configuration errors. These challenges were overcome to produce a precise predictive maintenance model.



FUTURE SCOPE

- Advancements in Artificial intelligence can be integrated with Internet of things (IoT), Edge computing,
 Cloud computing, Computerized Maintenance Management System (CMMS), Human-Machine
 Interfaces (HMI) and Automation Systems to actually perform the predictive maintenance in real time.
- Prescriptive maintenance can be executed using machine data, Artificial intelligence, and Machine learning to predict equipment failures and recommend specific actions to prevent them. Instead of simply predicting when a failure might occur, it offers instructions on what maintenance tasks to perform and when, thus improving performance and minimizing downtime.



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Completion Certificate



Completion date: 25 Jul 2025 (GMT)

This certificate is presented to

Visalakshi V

for the completion of

Lab: Retrieval Augmented Generation with LangChain

(ALM-COURSE_3824998)

According to the Adobe Learning Manager system of record

Learning hours: 20 mins

THANK YOU

