
CAPSTONE PROJECT

PREDICTIVE MAINTENANCE OF INDUSTRIAL MACHINERY

Presented By:

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OUTLINE

- **Problem Statement**
- **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

- The proposed system aims to build a Predictive Maintenance model using machine learning and real-time sensor analytics to identify industrial machine failures such as tool wear, heat dissipation, and power failures. The solution will be implemented and deployed on IBM Cloud for scalability, reliability, and enterprise-grade performance.
- **Data Collection**
Collect historical and real-time sensor data from industrial machines, including parameters like temperature, vibration, voltage, RPM, and load. IBM Watson IoT Platform will be used to stream real-time sensor data. Maintenance logs and historical failure records will also be collected and labeled for training the model.
- **Data Preprocessing**
IBM Watson Studio will be used to clean and preprocess the data. This includes handling missing values, filtering out noise, and engineering relevant features such as rolling averages, rate of change, and machine usage duration. Data will be normalized to ensure consistency across different sensor types.
- **Machine Learning Model**
Using IBM Watson Studio, machine learning models such as Random Forest or LSTM (for time-series analysis) will be trained to classify different failure types. Models will be evaluated and fine-tuned using cross-validation and hyperparameter tuning techniques.
- **Deployment**
The trained model will be deployed using IBM Watson Machine Learning. An API endpoint will be created to allow real-time predictions. A dashboard or alert system will be developed using IBM Cloud Functions or Node-RED to notify maintenance teams about predicted failures and their types.
- **.Evaluation**
Model performance will be assessed using accuracy, precision, recall, F1-score, and confusion matrix. The system will also be monitored for drift and retrained periodically using new data to maintain prediction accuracy.

SYSTEM APPROACH

- **System Requirements**
- **Hardware Requirements (Environment):**
 - RAM: 8GB
 - Storage: 25 GB of free service
 - Internet connection: Required for accessing IBM Cloud services
- **IBM Cloud Services Used:**
 - Watsonx.ai Studio – For building, training, and deploying ML models
 - IBM Cloud Object Storage – To store historical sensor data and datasets

ALGORITHM & DEPLOYMENT

- **Algorithm Selection**

- The Random Forest classifier was chosen due to its strong performance on tabular data and ability to handle complex feature interactions. It reduces overfitting by combining multiple decision trees and works well with labeled historical data stored in CSV format.

- **Data Input**

- The model uses features from the CSV file such as temperature, vibration, pressure, voltage, RPM, and the failure type label. These features represent machine operating conditions recorded over time.

- **Training Process**

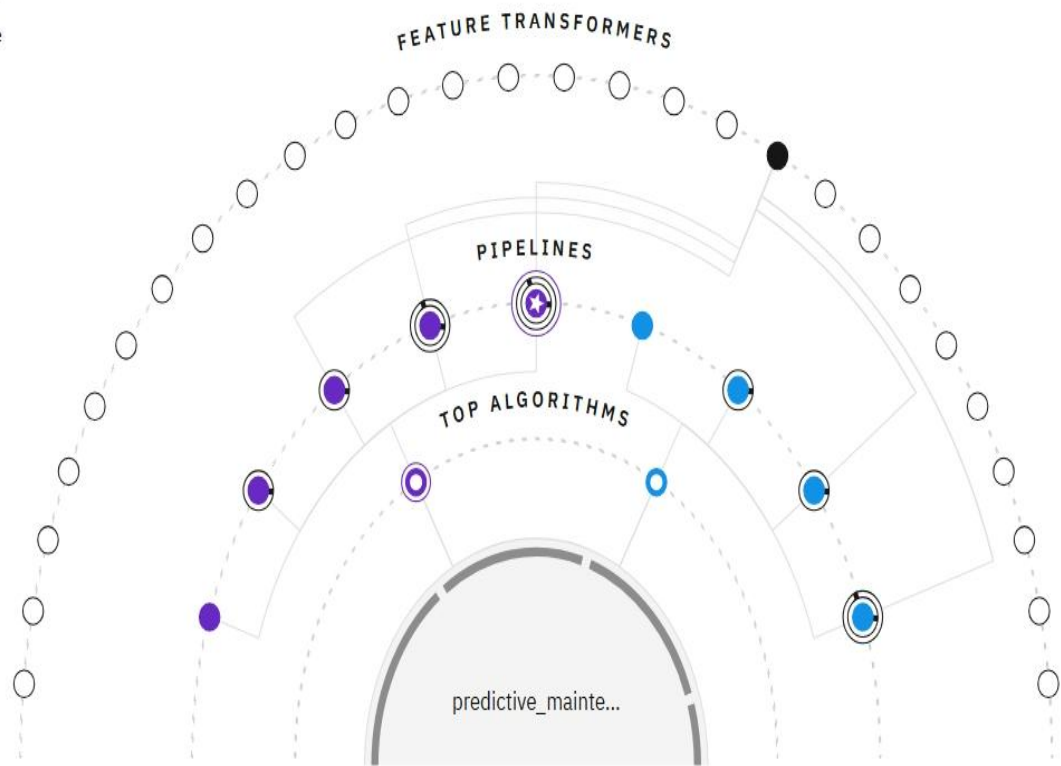
- The CSV data is preprocessed to handle missing values and split into training and testing sets. The Random Forest model is trained with tuned hyperparameters and evaluated using accuracy, precision, recall, and F1-score to ensure reliable predictions.

- **Prediction Process**

- Once trained, the model predicts failure types on new data formatted like the CSV input, helping to identify potential machine issues early and enabling timely maintenance actions.

ALGORITHMS IMAGES

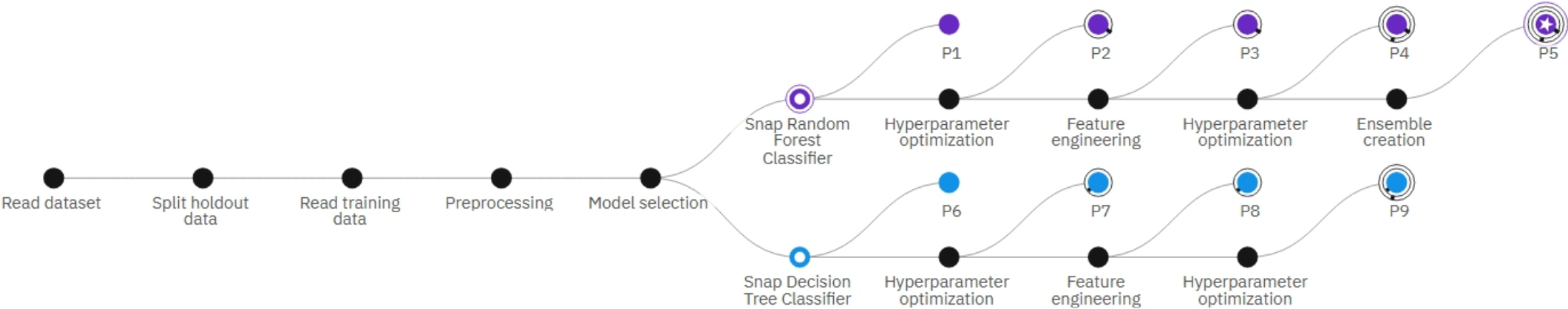
Relationship map ⓘ
Prediction column: Failure Type



ALGORITHM IMAGE

Progress map ⓘ

Prediction column: Failure Type



RESULT

Prediction results


Display format for prediction results






☒ Table view ☐ JSON view

☐ Show input data ⓘ

	prediction	probability
1	No Failure	[0,1,0,0,0,0]
2	Power Failure	[0,0,0,1,0,0]
3	No Failure	[0,0.9997901439666749,0,0,0.00020986357703804971,-7.543712987612139e-9]
4	Power Failure	[0,0,0,1,0,0]
5	Tool Wear Failure	[0,0,0,0,0,1]
6	Overstrain Failure	[0.0030303031206130983,0,0.9969696998596191,0,0,-2.9802322831784522e-9]
7		
8		

ACCURACY

Pipeline leaderboard 

	Rank 	Name	Algorithm	Specialization	Accuracy (Optimized) <u>Cross Validation</u>	Enhancements	Build time
★	1	Pipeline 5	 Batched Tree Ensemble Classifier (Snap Random Forest Classifier)	INCR	0.995	HPO-1 FE HPO-2 BATCH	00:02:22
	2	Pipeline 4	 Snap Random Forest Classifier		0.995	HPO-1 FE HPO-2	00:02:19
	3	Pipeline 3	 Snap Random Forest Classifier		0.995	HPO-1 FE	00:01:20
	4	Pipeline 9	 Snap Decision Tree Classifier		0.994	HPO-1 FE HPO-2	00:00:03

CONCLUSION

- The predictive maintenance system developed using a Random Forest classification algorithm and historical CSV data proved to be highly effective in identifying machine failure types with a high degree of accuracy (99.5%). By leveraging key operational features such as temperature, vibration, and RPM, the model was able to recognize patterns associated with common failure modes like tool wear, heat dissipation issues, and power failures.
- The high performance of the model, combined with its ability to generalize well across unseen data, demonstrates its reliability for real-world deployment. This solution enables industries to transition from reactive to proactive maintenance strategies, reducing unexpected downtimes, extending machine life, and lowering operational costs.
- Overall, the project showcases the potential of machine learning in optimizing industrial maintenance operations and improving asset management through data-driven decision-making.

FUTURE SCOPE

The predictive maintenance system can be enhanced by integrating real-time data sensor using IoT platforms like IBM Watson .IoT, enabling live monitoring and quicker fault detection. Expanding the system to support multiple machines across different locations would improve scalability. Future improvements could also include advanced models like LightGBM or LSTM for better accuracy. Deploying the model on edge devices would enable real-time predictions without internet dependency. Automated retraining and the use of explainable AI techniques like SHAP can improve adaptability and trust. Finally, integration with maintenance management systems can automate repair scheduling and enhance operational efficiency..

REFERENCES

- **IBM Corporation.** *Building and deploying machine learning models with Watsonx.ai Studio.* IBM Cloud Documentation. Retrieved from <https://www.ibm.com/docs/en/watsonx>
- **IBM Developer.** *Build and deploy a machine learning model with Watson Studio and Watson Machine Learning.* Retrieved from <https://developer.ibm.com/tutorials/build-and-deploy-a-machine-learning-model-with-watson-machine-learning-and-watson-studio/>
- **IBM Corporation.** *Watsonx.ai: Next-Generation Enterprise Studio for AI Builders.* IBM Blog. Retrieved from <https://www.ibm.com/blogs/watsonx/>

IBM CERTIFICATIONS

In recognition of the commitment to achieve
professional excellence



Vaishnavi Neeli

Has successfully satisfied the requirements for:

Getting Started with Artificial Intelligence

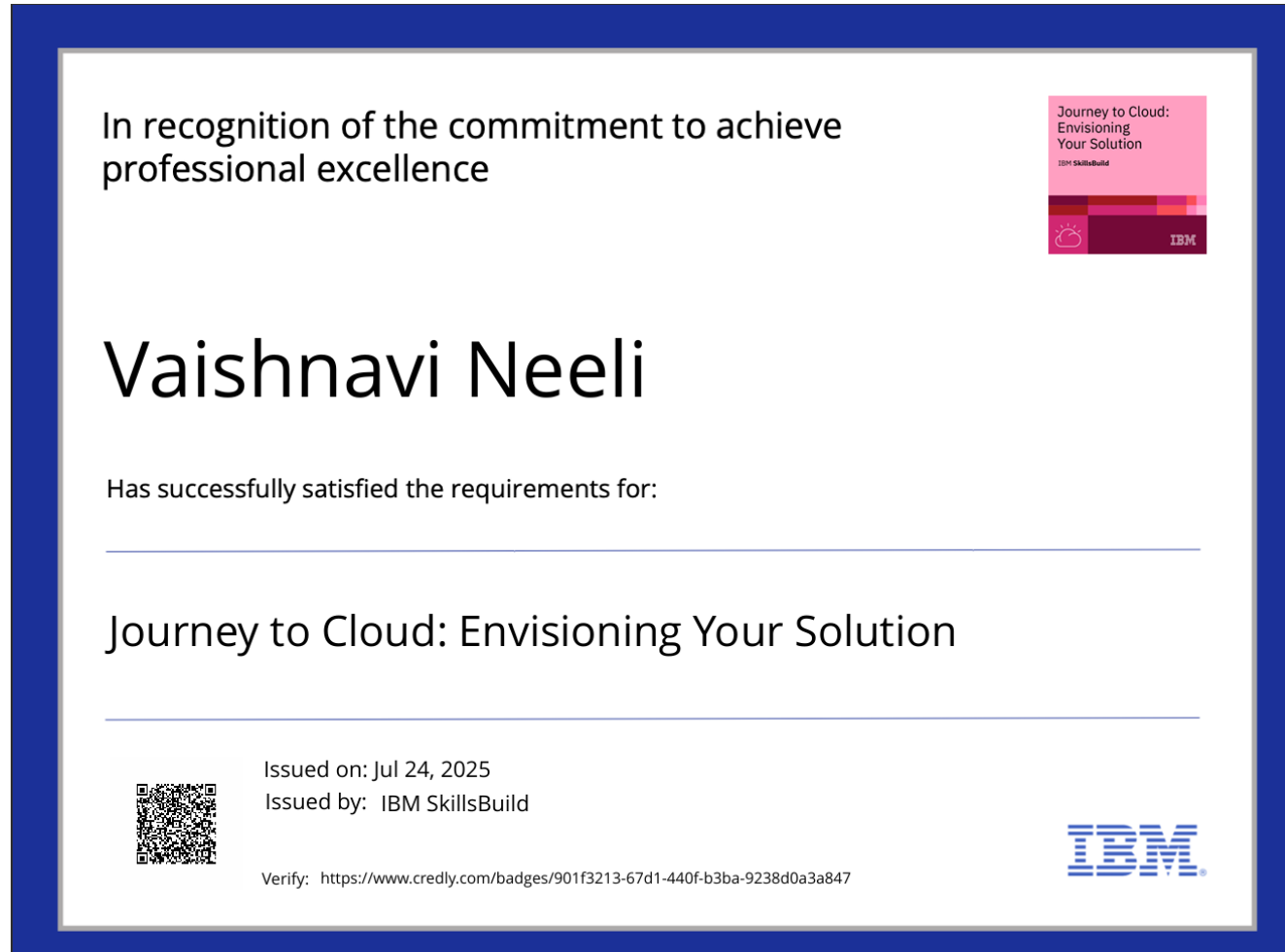


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THANK YOU