
CAPSTONE PROJECT

PREDICTIVE MAINTENANCE OF INDUSTRIAL MACHINERY

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OUTLINE

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

PROBLEM STATEMENT

- Traditional maintenance is reactive → leads to **unexpected failures, downtime, and costly repairs**
- Objective: Develop a **predictive classification model** to anticipate failure types before they occur
- Use **sensor-based data** to forecast failures like:
 - Tool wear
 - Power failure
 - Heat dissipation issues

PROPOSED SOLUTION

- The proposed system aims to address the challenge of predicting potential industrial machinery failures before they occur, thereby enabling proactive maintenance and minimizing unexpected downtime. The solution leverages data analytics and machine learning techniques through IBM Watsonx.ai to classify different types of machine failures accurately. The solution will consist of the following components:
- **Data Collection:**
 - Gather historical operational data from industrial machines, including sensor readings such as temperature, torque, tool wear, vibration, and power consumption.
 - Include failure labels like tool wear failure, heat dissipation failure, power failure, etc., to train the classification model.
- **Data Preprocessing:**
 - Clean and preprocess the data to address missing values, outliers, and inconsistencies.
 - Use automatic feature engineering and transformation pipelines provided by IBM Watsonx.ai AutoAI.
 - Normalize and encode features for compatibility with machine learning algorithms.
- **Machine Learning Algorithm:**
 - Utilize IBM Watsonx.ai's AutoAI to explore multiple model architectures automatically.
 - AutoAI selects the best-performing algorithm—**SNAP Random Forest** in this case—with hyperparameter optimization and feature selection.
 - The classifier is trained to predict one of several failure types (multi-class classification).
- **Deployment:**
 - Deploy the final model using IBM Watsonx.ai's deployment capabilities.
 - The model is exposed as a **REST API** endpoint that can be integrated with dashboards or alert systems.
 - Allows real-time inferencing using live sensor inputs from the machine network.
- **Evaluation:**
 - Evaluate the model using accuracy, confusion matrix, precision, recall, and F1-score.
 - Achieved a maximum accuracy of **99.5%**, indicating highly reliable failure prediction.
 - Ongoing performance monitoring and feedback loop enable model fine-tuning for long-term effectiveness.

SYSTEM APPROACH

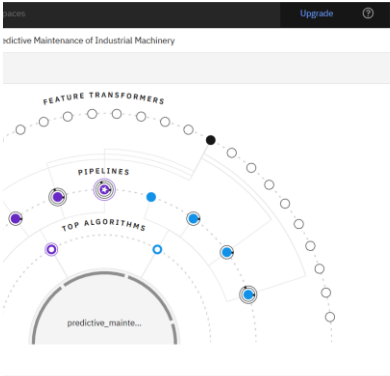
- **Step 1:** Data acquisition from Kaggle
- **Step 2:** Preprocessing via AutoAI (feature scaling, encoding)
- **Step 3:** Model training using AutoAI-generated pipelines
- **Step 4:** Evaluation using accuracy, precision, recall, F1-score
- **Step 5:** Model deployment (Watsonx Studio Deployment → optional API)

ALGORITHM & DEPLOYMENT

- **Algorithm Selection:**
 - Chosen by IBM Watsonx.ai AutoAI: **SNAP Random Forest**
 - Justification: High accuracy (99.5%), handles multiclass classification, robust to noise and overfitting
- **Data Input:**
 - Sensor data: Temperature, Torque, Tool Wear, Rotational Speed
 - Metadata: Machine Type, Product ID
 - Target: Failure types (Tool Wear, Power, Overstrain, etc.)
- **Training Process:**
 - AutoAI performed:
 - Feature engineering & preprocessing
 - Cross-validation & hyperparameter tuning
 - Model selected based on best F1-score & accuracy
- **Prediction Process:**
 - Real-time sensor inputs → model predicts failure type
 - Supports proactive maintenance before breakdowns occur

RESULT

Pipeline Comparison



Pipeline Leaderboard

Specialization	Accuracy (Optimized) Cross Validation	Enhancement
CR	0.995	HPO-1
	0.995	HPO-1
	0.995	HPO-1
	0.994	HPO-1

Result

Display format for prediction results

☒ Table view ☐ JSON view

	Prediction	Confidence
1	No Failure	100%
2	Power Failure	100%
3		
4		
5		
6		
7		
8		
9		

Input Data

trial Machinery Deployed Online

sheet. Max file size is 50 MB.
[arch in space](#) ²¹

Process temperature [K] (double)	Rotational speed [rpm] (double)	Torque [Nm] (double)
308	1551	42
309	2861	4.6

CONCLUSION

- Developed a high-performing predictive maintenance system
- Model can proactively alert teams to upcoming machine failures
- Reduces:
 - Unplanned downtime
 - Repair costs
 - Operational delays

FUTURE SCOPE

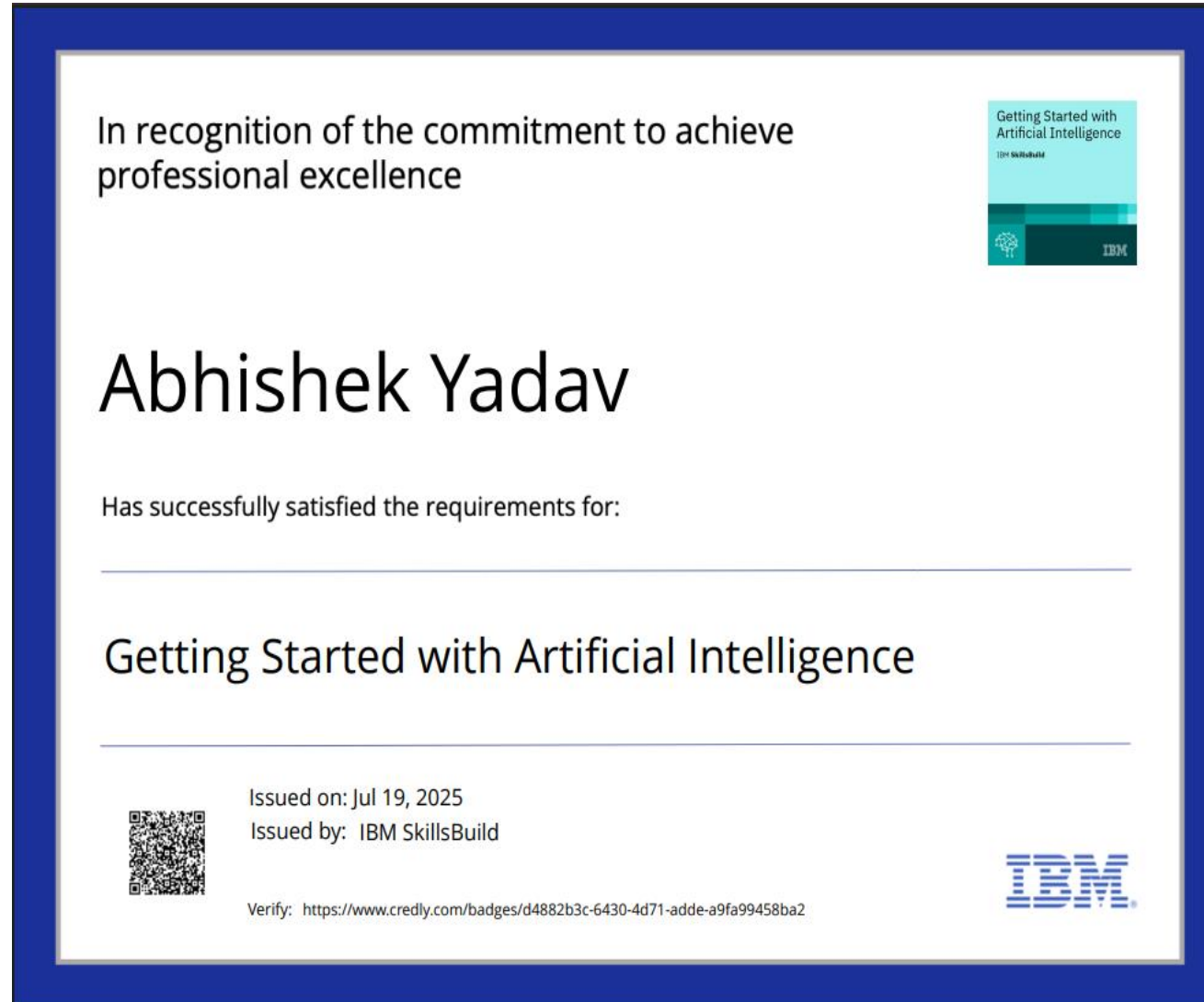
- Integrate with **real-time IoT sensors** via edge devices
- Build a **dashboard** for maintenance teams
- Implement **continuous learning** to adapt to new patterns
- Expand failure prediction to other industries: automotive, energy, etc.

REFERENCES

- Kaggle Dataset: <https://www.kaggle.com/datasets/shivamb/machinepredictive-maintenance-classification>
- IBM Watsonx.ai Documentation: <https://dataplatform.cloud.ibm.com/>

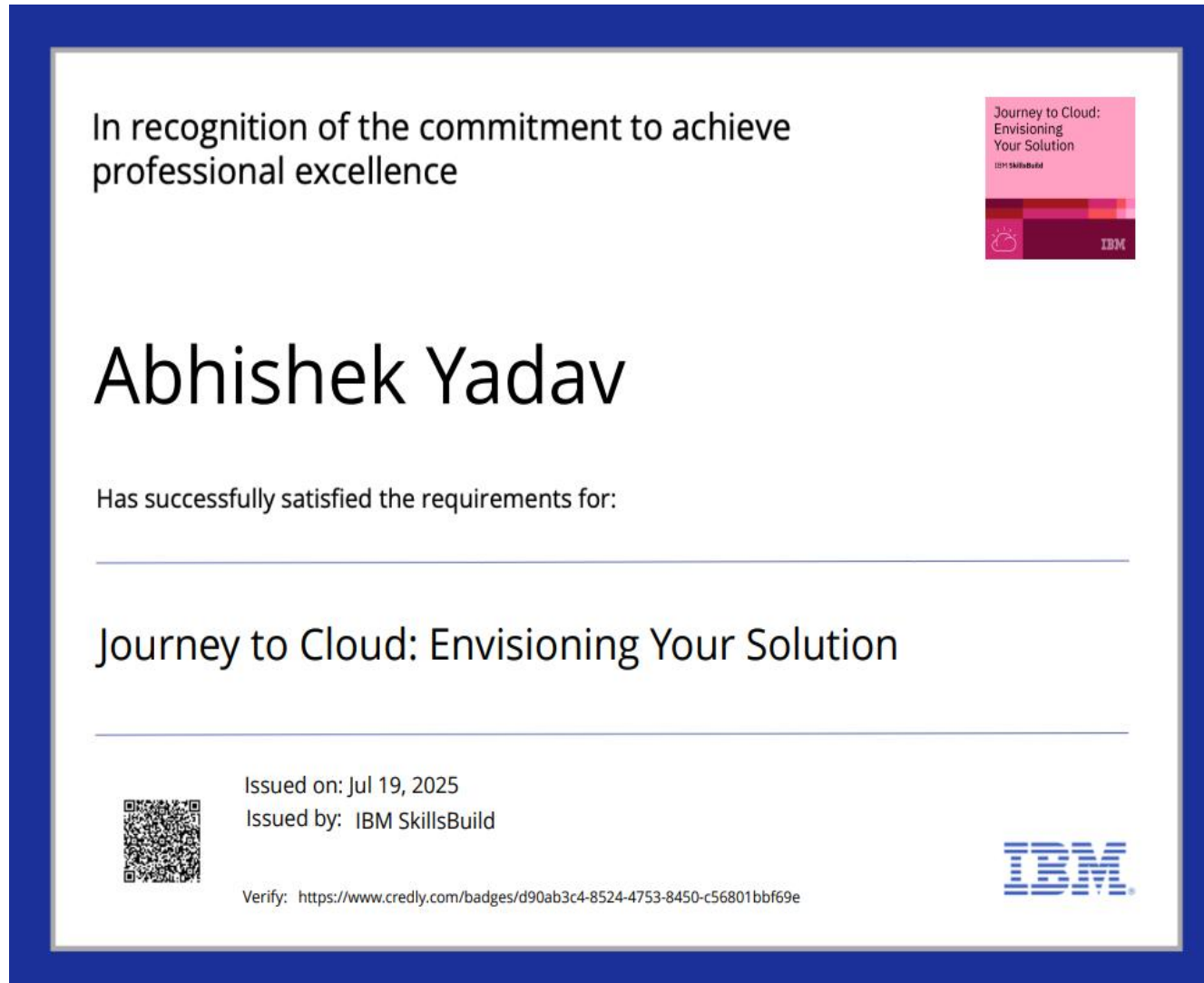
IBM CERTIFICATIONS

- Screenshot/ credly certificate(getting started with AI)



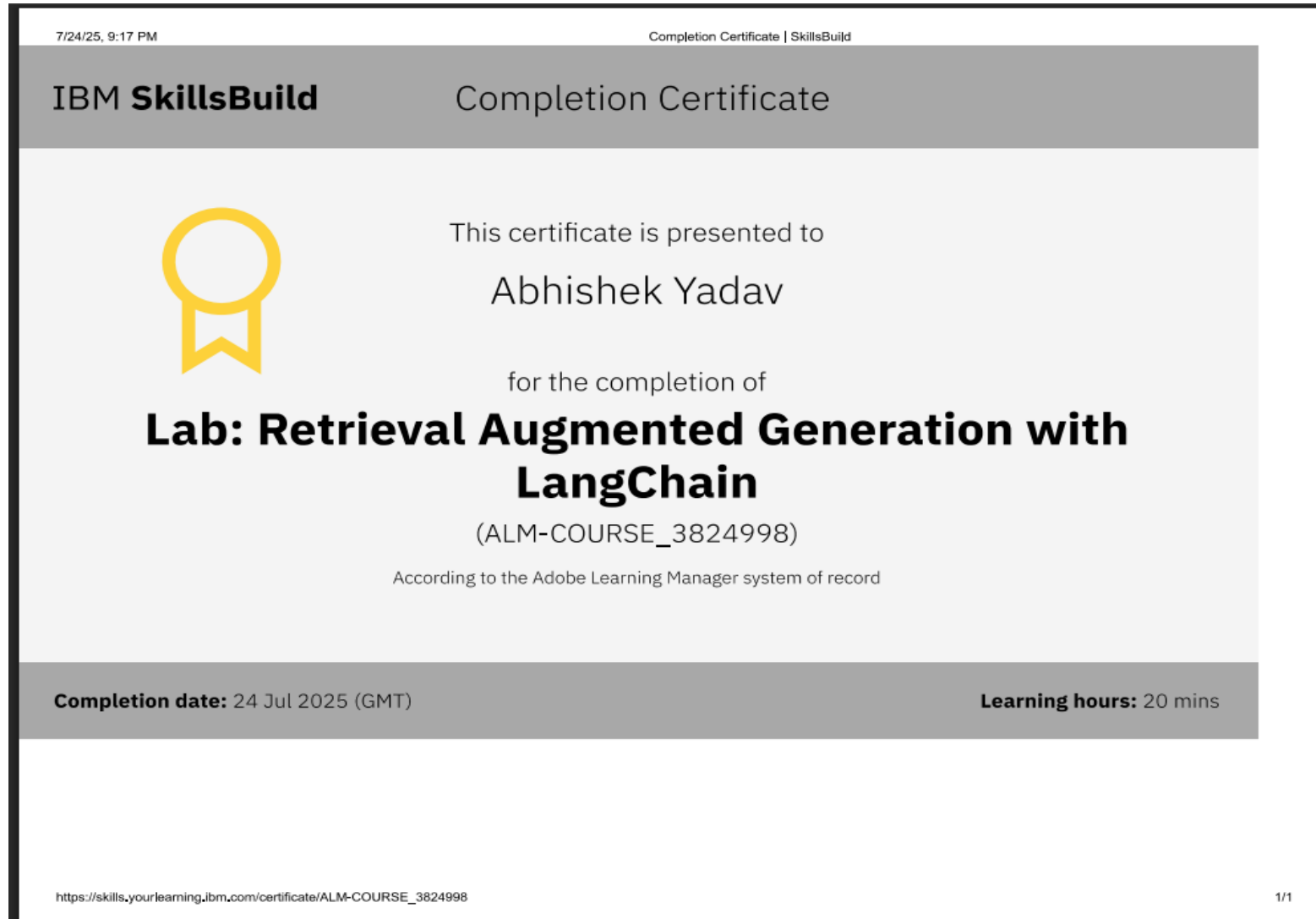
IBM CERTIFICATIONS

- Screenshot/ credly certificate(Journey to Cloud)



IBM CERTIFICATIONS

- Screenshot/ credly certificate(RAG Lab)





THANK YOU