CAPSTONE PROJECT

PREDICTIVE MAINTENANCE OF INDUSTRIAL MACHINERY

Presented By:

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PROBLEM STATEMENT

- In industrial settings, the unexpected failure of machinery is a primary cause of operational disruption.
- These failures lead to costly, unplanned downtime, increased maintenance expenses, and significant reductions in production output.
- The current maintenance approach is often reactive, meaning action is taken only after a failure has already occurred.
- The crucial challenge is to anticipate these failures before they happen and to understand the specific type of fault that is developing.

PROPOSED SOLUTION

- The proposed system aims to develop a predictive maintenance model to anticipate and classify machine failures before they occur. The solution will consist of the following components:
- **Data Collection:**
  - Utilize the "Machine Predictive Maintenance Classification" dataset from Kaggle, containing sensor data from industrial machinery.
- **Data Preprocessing:**
  - Clean the collected sensor data to handle any inconsistencies or missing values.
  - Perform feature engineering to extract the most relevant operational parameters that influence machine failure.
- **Machine Learning Algorithm:**
  - Develop a multi-class classification model capable of predicting the specific type of failure (e.g., tool wear, heat dissipation, power failure, overstrain).
  - The model will be trained on historical sensor data to learn the patterns that precede a failure and predict what type of failure is going to occur.
  - **We will use Hyperparameter optimization to increase the accuracy of the model.**
- **Deployment:**
  - **Develop a user-friendly interface or application that provides real-time predictions for bike counts at different hours.**
  - **Deploy the solution on a scalable and reliable platform, considering factors like server infrastructure, response time, and user accessibility.**
- **Evaluation:**
  - Assess the model's performance using standard classification metrics such as Accuracy, Precision, Recall, and F1-Score.
  - **Fine-tune the model based on feedback and continuous monitoring of prediction accuracy.**

SYSTEM APPROACH

- **System requirements:**
  - **Language**: Python 3.11.
  - **Platform**: IBM Cloud Lite Services, specifically leveraging **IBM Watson Studio** with the **watsonx.ai** client for model development and deployment.
- **Library required to build the model:**
  - **Core: AI/ML**:
    - IBM watsonx.ai Studio (for platform interaction)
    - IBM watsonx ai Runtime service (for building the model)
    - IBM Cloud Object Storage (for storing and working on model and deployment)
    - autoai-libs, scikit-learn (for modelling and metrics)
    - snapml, and lale (for pipeline optimization)
  - **Data Visualization:**
    - matplotlib for plotting the learning curve.

ALGORITHM & DEPLOYMENT

- **Algorithm Selection:**
  - The model is an optimized pipeline (Pipeline_5) generated by IBM's AutoAI feature.
  - The core algorithm is a **Snap Random Forest Classifier**, a high-performance version of the standard Random Forest algorithm.
  - It's a multi-class classification model trained to predict the specific failure type from six possible classes: **'Heat Dissipation Failure', 'No Failure', 'Overstrain Failure', 'Power Failure', 'Random Failures', and 'Tool Wear Failure'**.
- **Data Input:**
  - The input features used by the algorithm are: **UDI, Product ID, Type, Air temperature [K], Process temperature [K], Rotational speed [rpm], Torque [Nm], Tool wear [min], Target to predict the type of failure that can occur.**
- **Training and Prediction Process:**
  - The model is trained using an incremental learning approach with the partial_fit method, which allows the model to continue learning as new data arrives without retraining from scratch.
  - Training data is processed in batches of 10,000 rows to simulate a real-world data stream.
- **Deployment:**
  - The final trained pipeline is stored as a model asset in the IBM WatsonX repository.
  - The model is deployed as a real-time online web service, which allows for making live predictions by sending new sensor data to an API endpoint.

RESULT

Pipeline 5	Batched Tree Ensemble Classifier (Snap Random Forest Classifier)	INCR	0.995	HPO-1	FE	HPO-2	BATCH

- The model achieved a training accuracy of 99.5%.
- The Prediction Results are:

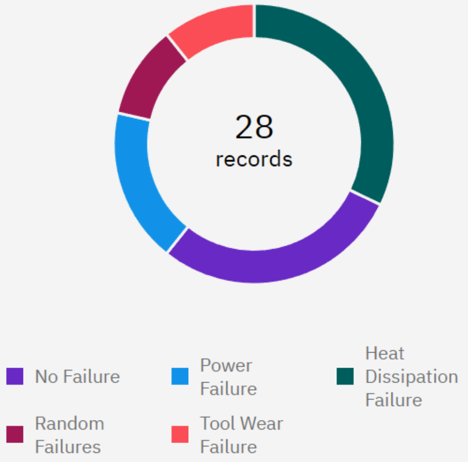
Prediction results

×

Prediction type

Multiclass classification

Prediction percentage

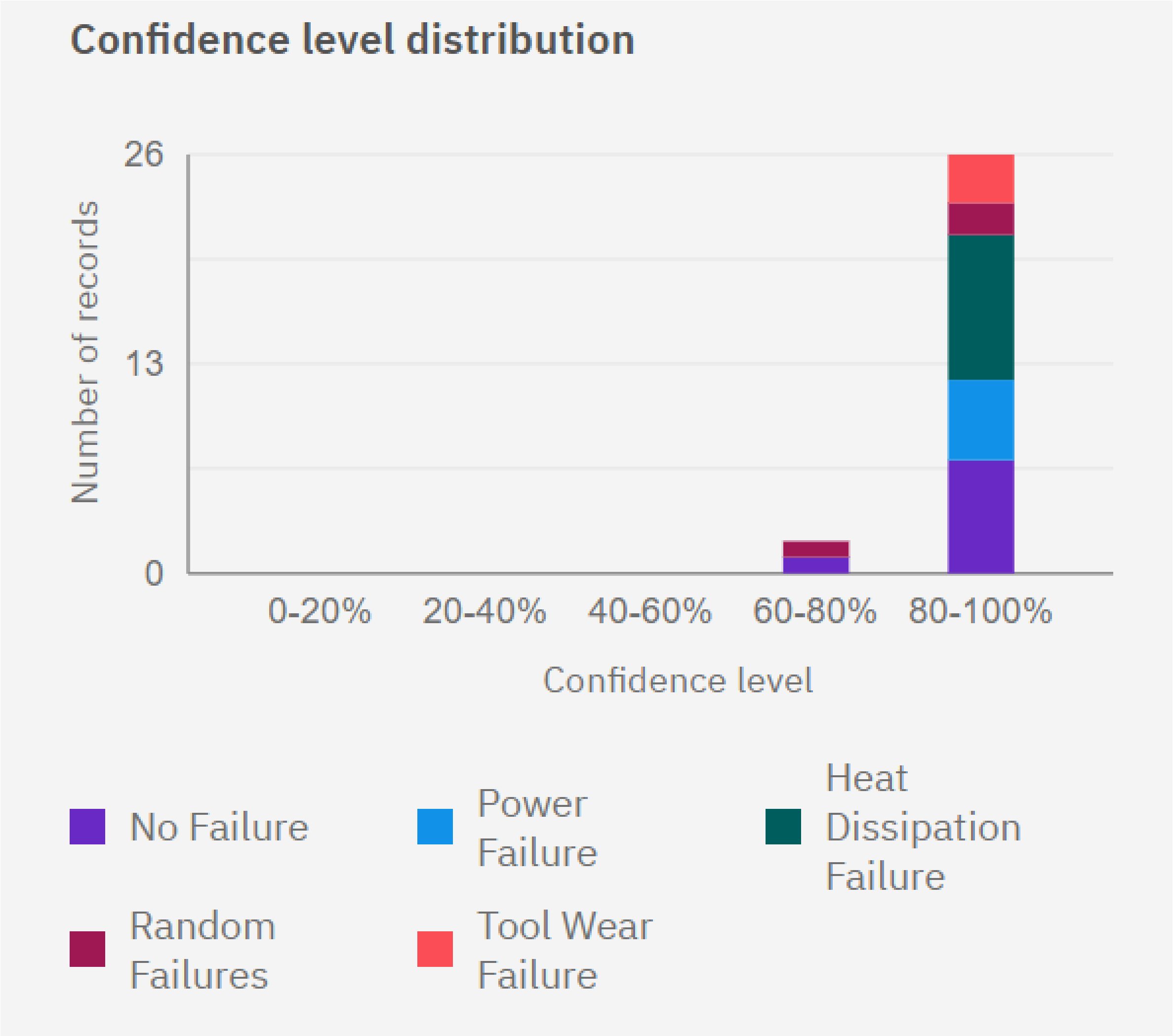


Display format for prediction results

Table view   JSON view   Show input data

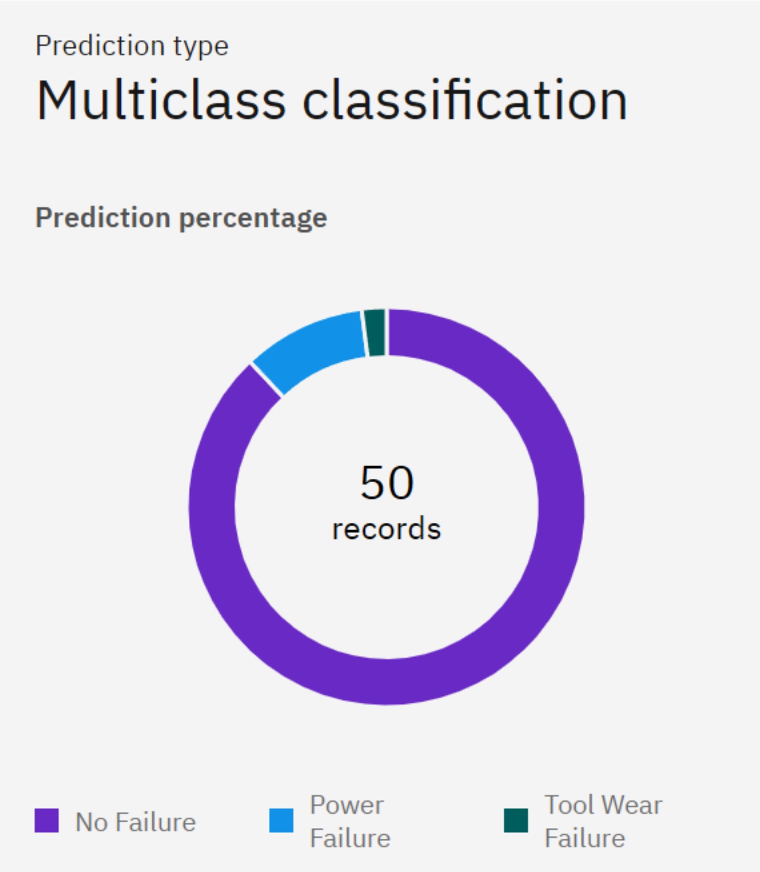
	Prediction	Confidence	UDI	Product ID	Type	Ai
1	No Failure	100%		H29581	H	29
2	Power Failure	100%	848	L48027	L	29
3	Power Failure	100%	208	M15067	M	29
4	Power Failure	100%	260	M15119	M	29
5	Power Failure	100%	381	L47560	L	29
6	Power Failure	90%	443	L47622	L	29
7	Heat Dissipation Failure	90%	3807	M18666	M	30
8	Heat Dissipation Failure	100%	3815	M18674	M	30
9	Heat Dissipation Failure	100%	3830	H33243	H	30
10	Heat Dissipation Failure	90%	4079	H33492	H	30
11	Heat Dissipation Failure	90%	3807	M18666	M	30
12	Heat Dissipation Failure	100%	3815	M18674	M	30

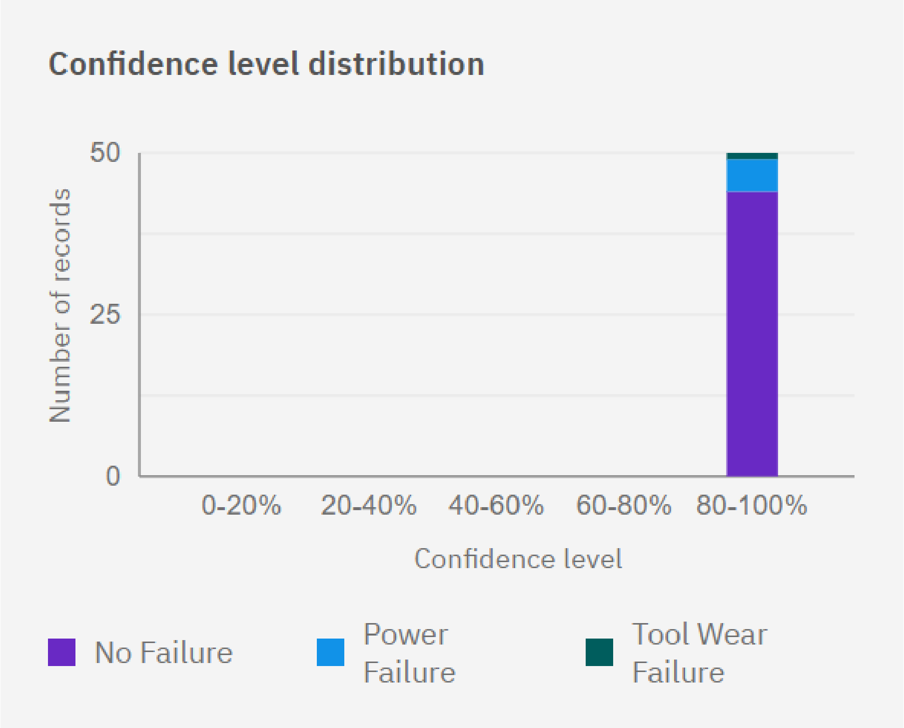
RESULT


Confidence level distribution
26
13
0
Number of records
0-20%
20-40%
40-60%
60-80%
80-100%
Confidence level
No Failure
Power Failure
Heat Dissipation Failure
Random Failures
Tool Wear Failure

RESULT

- This model predicted all the data with 100% accuracy with an average confidence score of 96%.
- The model was also able to accurately predict the type of failure on unknown synthetic data.





CONCLUSION

- This project successfully utilized IBM's AutoAI to select and build an efficient classifier (Snap Random Forest) for predicting industrial machinery failures.
- The use of incremental learning (partial_fit) demonstrates a practical approach for updating the model in dynamic environments where data is continuously generated.
- The model was successfully deployed as a scalable online web service on the IBM Cloud platform, making it ready for integration into a real-world predictive maintenance application.
- The outcome is a functional, deployable system that enables a proactive maintenance strategy, directly addressing the core problem of reducing costly downtime.

FUTURE SCOPE

- Real-World Pilot: Integrate the deployed web service with live sensor data from a pilot group of machines to validate its real-world performance and business impact.
- Concept Drift Monitoring: Implement mechanisms to monitor the model's performance over time to detect "concept drift" (when real-world data patterns change) and trigger retraining.
- Predict Remaining Useful Life (RUL): Develop a companion regression model to predict the exact time remaining until a predicted failure occurs.
- Refine Incremental Strategy: Experiment with different batch sizes and sampling strategies to further optimize the incremental learning process.

REFERENCES

- Project & Dataset Sources:
  - Dataset:
    - Shivam, B. (2020). Machine Predictive Maintenance Classification. Kaggle. Retrieved from: https://www.kaggle.com/datasets/shivamb/machine-predictive-maintenance-classification
  - Problem Statement Source:
    - Edunet Foundation & IBM. (2024). Problem Statements on ML by using AI_KOSH data sets. SB4Academia_Problem Statements_2025 (1).pdf.
  - Notebook & Methodology:
    - IBM. (2025). P5 - Snap Random Forest Classifier_ Model Builder.ipynb. AutoAI Generated Notebook, IBM Watson Studio.
- Academic & Technical Literature:
  - On the Core Algorithm (Random Forest):
    - Breiman, L. (2001). Random Forests. Machine Learning, 45(1), 5-32.
    - This is the original, seminal paper by Leo Breiman that introduced the Random Forest algorithm. Citing this shows you're referencing the foundational theory behind your chosen model.
  - On Predictive Maintenance using Machine Learning:
    - Carvalho, T. P., Soares, F. A., Vita, R., Francisco, R. d. P., Basto, J. P., & Alcalá, S. G. (2019). A systematic literature review of machine learning methods applied to predictive maintenance. Computers & Industrial Engineering, 137, 106024.
    - This academic review provides a comprehensive overview of different machine learning methods used for predictive maintenance. It helps contextualize your work and justifies the use of a classification approach.

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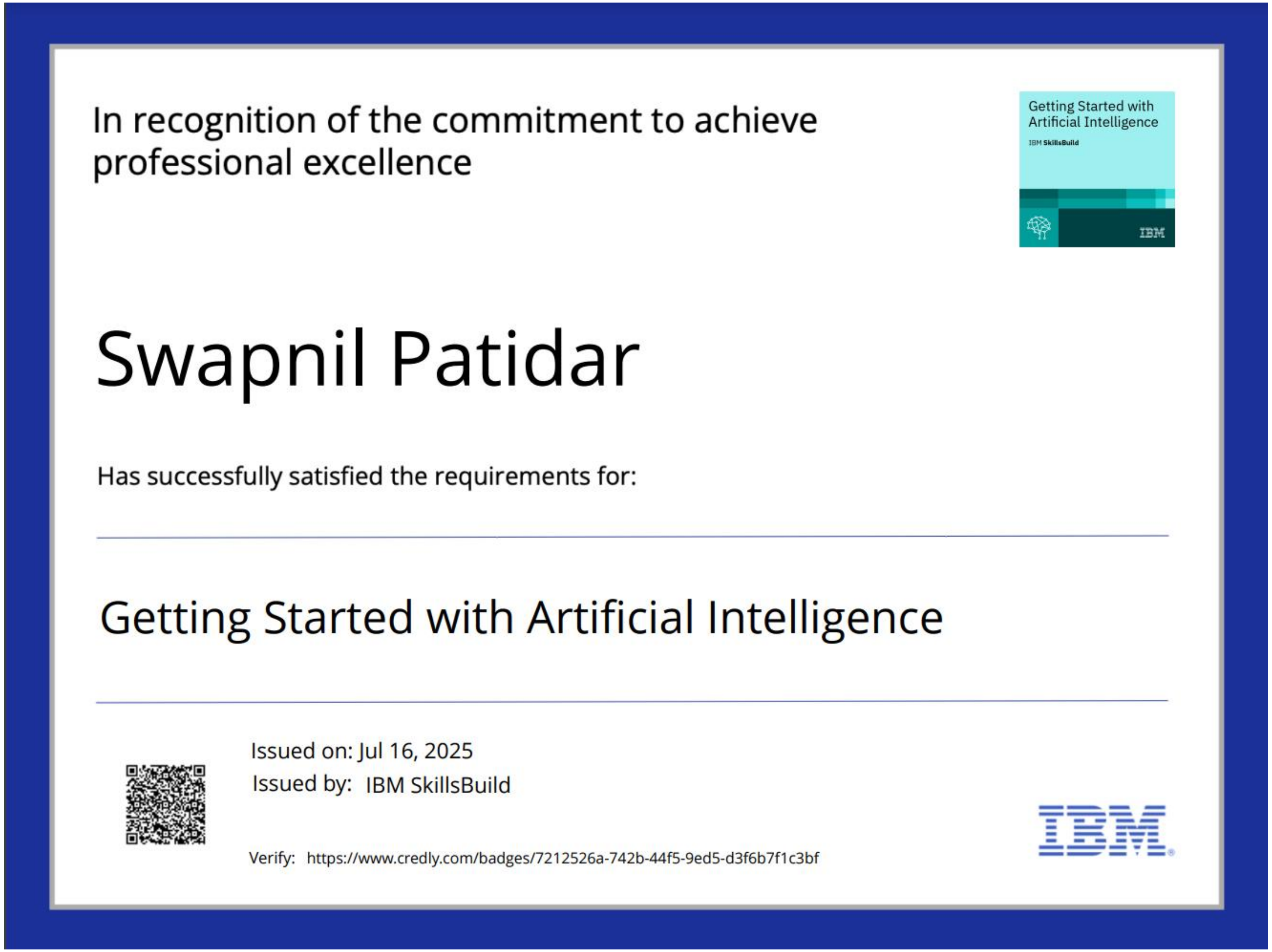
IBM CERTIFICATIONS



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