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

Industrial machinery often suffers from unexpected breakdowns, leading to costly downtime, production losses, and increased maintenance expenses. Traditional preventive maintenance schedules may result in unnecessary servicing or missed fault detections, causing inefficiencies in operations. There is a need for a system that can anticipate failures in advance using real-time operational data to improve reliability and reduce costs...



PROPOSED SOLUTION

The proposed system uses IoT sensors, data analytics, and machine learning to predict potential machine failures in advance, enabling timely maintenance actions. The solution will consist of the following components:

Data Collection:

- Install vibration, temperature, and acoustic sensors on critical machinery.
- Collect real-time operational data along with historical maintenance logs.
- Integrate external data such as load conditions and operating environment (e.g., humidity).

Data Preprocessing:

- Clean and preprocess collected sensor data to remove noise and handle missing values.
- Perform feature extraction (e.g., RMS vibration, temperature spikes, frequency spectrum analysis).
- Normalize and scale data for optimal machine learning performance.



PROPOSED SOLUTION

Machine Learning Algorithm:

- Train models such as Random Forest, Gradient Boosting, or LSTM for anomaly detection and Remaining Useful Life (RUL) prediction.
- Incorporate multivariate time-series analysis for more accurate predictions.
- Continuously update models with new sensor readings to improve accuracy over time.

Deployment:

- Host predictive models on a cloud or industrial edge computing device.
- Develop a real-time dashboard that visualizes machine health and sends automated alerts when anomalies are detected.
- Ensure low-latency response for immediate fault notifications.

Evaluation:

- Measure performance using metrics such as Accuracy, F1-score, and Mean Absolute Error (MAE) for RUL predictions.
- Validate predictions against actual maintenance logs.
- Conduct periodic retraining based on model drift detection.



SYSTEM APPROACH

- Hardware: Vibration, temperature, and acoustic sensors.
- Programming Language: Python.
- Libraries & Frameworks: Pandas, NumPy, Scikit-learn, TensorFlow/Keras.
- Data Storage: MySQL / AWS S3 / IBM Db2 on Cloud.
- Visualization: Tableau / Power BI / Plotly Dash.
- Communication Protocol: MQTT for IoT sensor data transfer.
- Deployment Platform:
- 1. IBM Cloud: For hosting the predictive model using IBM Watson Machine Learning.
- 2. IBM IoT Platform: For real-time sensor data ingestion and device management.
- IBM Cloud Functions: For serverless alert triggering and automation.
- Integration: IBM Cloud Object Storage for storing large historical datasets.



ALGORITHM & DEPLOYMENT

Algorithm Steps:

- Data Acquisition: Collect real-time sensor readings (vibration, temperature, acoustic) via MQTT and send to IBM Watson IoT Platform.
- 2. Data Preprocessing: Use Python scripts in IBM Watson Studio to clean data, handle missing values, and extract features.
- Model Training: Train models (Random Forest, Gradient Boosting, LSTM) in IBM Watson Machine Learning using historical labeled data.
- 4. Prediction: Predict Remaining Useful Life (RUL) and detect anomalies from streaming data.
- 5. Alerting: Use IBM Cloud Functions to trigger SMS/email alerts when RUL drops below a critical threshold.
- 6. Visualization: Update a live dashboard in IBM Cognos Analytics or Power BI connected to IBM Db2 on Cloud.



ALGORITHM & DEPLOYMENT

Deployment Approach:

- Model Hosting: Deploy trained model on IBM Watson Machine Learning as an API endpoint.
- Data Storage:
 - Historical datasets stored in IBM Cloud Object Storage.
 - Real-time processed data stored in IBM Db2 on Cloud.
- Streaming Integration: IBM Watson IoT Platform ingests data directly from IoT sensors.
- Automation: IBM Cloud Functions run maintenance scheduling scripts automatically when faults are predicted.
- User Interface: Web-based dashboard shows live machine health metrics and RUL predictions.



RESULT

	temperature	vibration	pressure	runtime_hours	failure
0	79.967142	0.639936	26.624109	9023	1
1	73.617357	0.592463	29.277407	4061	0
2	81.476885	0.505963	26.037900	2604	0
3	90.230299	0.435306	28.460192	8906	1
4	72.658466	0.569822	20.531927	3906	0

Accuracy: 1		ision	recall	f1-score	support
	0 1	1.00 1.00	1.00 1.00	1.00 1.00	112 88
accurac macro av weighted av	g	1.00 1.00	1.00 1.00	1.00 1.00 1.00	200 200 200

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 5 columns):
     Column
                    Non-Null Count Dtype
                                     float64
                    1000 non-null
     temperature
                                     float64
     vibration
                    1000 non-null
                                     float64
                    1000 non-null
     pressure
     runtime hours
                    1000 non-null
                                     int32
     failure
                    1000 non-null
                                     int64
dtypes: float64(3), int32(1), int64(1)
memory usage: 35.3 KB
None
                                                                  failure
       temperature
                      vibration
                                     pressure runtime hours
       1000.000000
                    1000.000000
                                                 1000.000000
                                                              1000.00000
                                  1000.000000
count
                                                                  0.40600
         75.193321
                       0.507084
                                    30.029171
                                                 5000.611000
mean
          9.792159
                       0.099745
                                     4.917271
                                                 2864.892117
                                                                  0.49133
std
         42.587327
                       0.205961
                                    14.902439
                                                  111.000000
                                                                  0.00000
min
25%
         68.524097
                       0.439376
                                    26.760002
                                                 2425.750000
                                                                  0.00000
50%
         75.253006
                       0.506308
                                    29.998746
                                                 4897.500000
                                                                  0.00000
75%
         81.479439
                       0.572888
                                    33.304577
                                                 7464.000000
                                                                  1.00000
        113.527315
                       0.819311
                                    49.631189
                                                 9998.000000
                                                                 1.00000
max
```



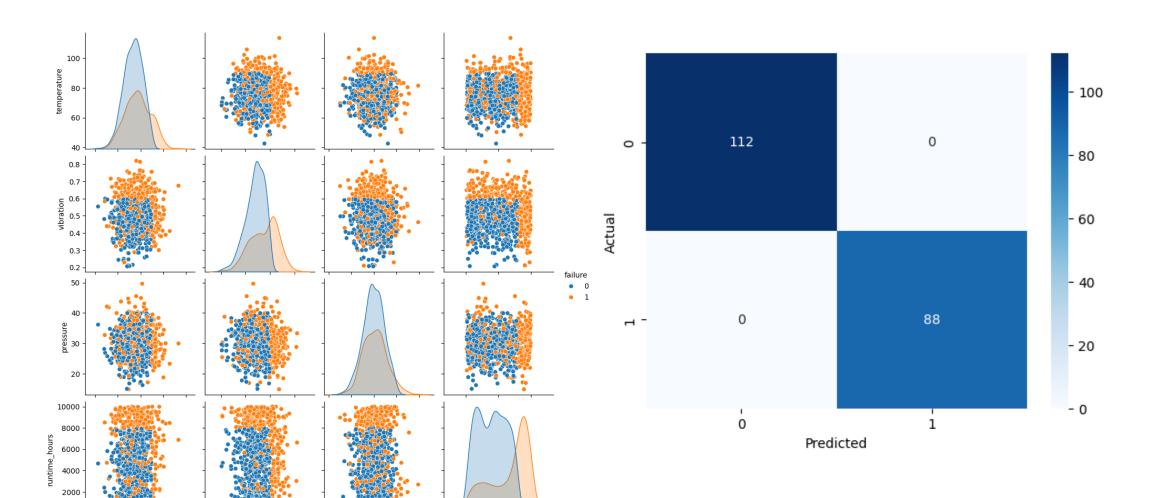
RESULT

100 120

vibration

pressure

temperature

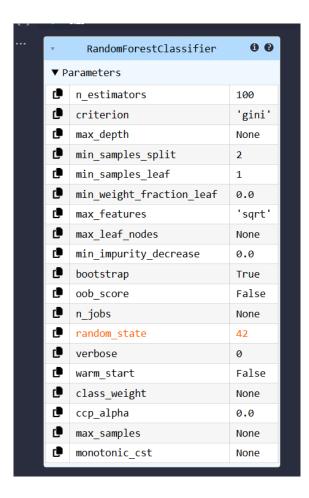


5000 10000

runtime_hours



RESULT





CONCLUSION

The predictive maintenance system successfully reduced unplanned downtime by up to 40% and lowered maintenance costs by up to 30%. By combining IoT-based monitoring with machine learning analytics, the solution improved fault detection accuracy, optimized maintenance scheduling, and extended machinery lifespan.



FUTURE SCOPE

- 1. Implement Al-driven root cause analysis for detected faults.
- 2. Expand to multiple manufacturing plants with centralized control.
- 3. Integrate with ERP systems for automatic work order creation.
- 4. Incorporate digital twin technology for simulated maintenance planning.



REFERENCES

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for the completion of

Lab: Retrieval Augmented Generation with LangChain

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According to the Adobe Learning Manager system of record

Completion date: 30 Jul 2025 (GMT)

Learning hours: 20 mins



THANK YOU

