CAPSTONE PROJECT

PREDICTIVE MAINTENANCE MODEL FOR MACHINE FAILURE PREDICTION

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OUTLINE

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PROBLEM STATEMENT

- •Challenge: Machines in industrial settings are prone to various typesof failures, leading to costly downtime and maintenance.
- •Objective: Predict the type of machine failure (e.g., No Failure, Overstrain Failure) based on sensor data to enable proactive maintenance and ensure operational efficiency.
- •**Key Issue**: Accurate prediction of failure types using sensor data (e.g., air temperature, process temperature, rotational speed, torque, tool wear) is critical to minimize downtime and optimize resource allocation.



PROPOSED SOLUTION

The proposed system uses machine learning to predict machine failure types, ensuring timely maintenance.
Key components include:

Data Collection:

- Gather sensor data (air/process temperature, rotational speed, torque, tool wear) from IBM Cloud Object
 Storage (predictive_maintenance.csv).
- Include machine type and failure type labels.

Data Preprocessing:

- Encode categorical variables (Type, Failure Type) using LabelEncoder.
- Scale numerical features using StandardScaler.
- Handle class imbalance using SMOTE (Synthetic Minority Oversampling Technique)



PROPOSED SOLUTION

Machine Learning Algorithm:

Train a Decision Tree Classifier to predict failure types based on processed sensor data.

Deployment:

- Deploy the model using IBM Watson Machine Learning for scalable, real-time predictions.
- Provide a user-friendly prediction function for new data points.

Evaluation:

Assess model performance using accuracy, classification report, and confusion matrix.



SYSTEM APPROACH

System Requirements:

- Python 3.11 (runtime-24.1) environment.
- IBM Cloud Object Storage for dataset access.
- IBM Watson Machine Learning for model deployment.

Libraries Required:

- Python
- Scikit-learn==1.4.2
- Pandas==2.1.4
- Numpy==1.26.4
- Matplotlib==3.8.4
- Seaborn==0.13.2
- Imbalanced-learn==0.12.3
- Ibm-watson-machine-learning==1.0.360



ALGORITHM & DEPLOYMENT

Algorithm Selection:

- **Decision Tree Classifier**: Chosen for its interpretability and ability to handle both numerical and categorical data.
- Suitable for multi-class classification of failure types.

Data Input:

- Features: Type, Air temperature [K], Process temperature [K], Rotational speed [rpm], Torque [Nm], Tool wear [min].
- Target: Failure Type (e.g., No Failure, Overstrain Failure).

Training Process:

- Split data into training (80%) and testing (20%) sets.
- Apply SMOTE to balance classes.
- Train the Decision Tree Classifier with cross-validation for robustness.



ALGORITHM & DEPLOYMENT

Prediction Process:

- Scale and encode new data points using trained StandardScaler and LabelEncoder.
- Use the trained model to predict failure types.

Deployment:

- Model stored in IBM Watson Machine Learning with ID: df9879f4-294a-4789-b82d-0a5455cd7aa6.
- Prediction function (predict_failure) implemented for real-time use.



RESULT

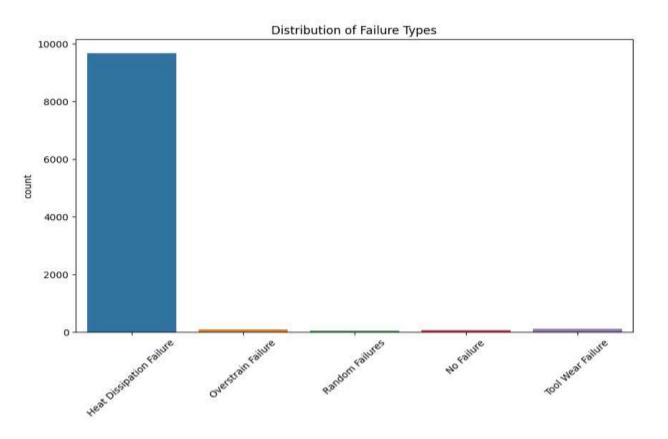
- Model Performance:
 - Accuracy: 0.93 (93% correct predictions on the test set).
- Evaluation Metrics:
 - Classification report includes precision, recall, and F1-score for each failure type.
 - Confusion matrix saved as an image for detailed analysis.

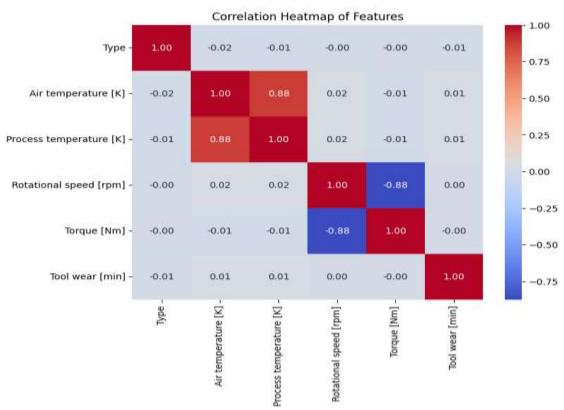
https://github.com/mdubaid04/Predictive_Maintenanceuisng_ML.git

Predictive Maintenance Github LInk



RESULT





Distribution of Failure Types

Correlation Heatmap of Features



RESULT



```
python
sample_data = {
    'Type': 'L',
    'Air temperature [K]': 298.9,
    'Process temperature [K]': 309.1,
    'Rotational speed [rpm]': 2861,
    'Torque [Nm]': 4.6,
    'Tool wear [min]': 143
Predicted Failure Type: Overstrain Failure
```

Confussion Matrix

Predicted Result



CONCLUSION

Summary:

- The Decision Tree Classifier effectively predicts machine failure types with 93% accuracy.
- SMOTE successfully addressed class imbalance, improving model robustness.
- Deployment on IBM Watson Machine Learning enables scalable, real-time predictions.

Challenges:

- Ensuring compatibility with Python 3.11 and specific library versions.
- Handling imbalanced classes required careful preprocessing.

Impact:

Enables proactive maintenance, reducing downtime and costs in industrial settings.



FUTURE SCOPE

Enhancements:

- Incorporate additional sensor data (e.g., vibration, noise levels) for improved predictions.
- Explore advanced algorithms (e.g., Random Forest, XGBoost) for higher accuracy.
- Implement real-time data streaming for dynamic predictions.

Scalability:

- Extend the model to multiple machine types or industrial facilities.
- Integrate with IoT devices for automated monitoring.

Emerging Technologies:

- Use edge computing for faster on-device predictions.
- Explore deep learning models (e.g., LSTM) for time-series-based failure prediction



REFERENCES

- Scikit-learn Documentation: https://scikit-learn.org/stable/
- Imbalanced-learn Documentation: https://imbalanced-learn.org/stable/
- IBM Watson Machine Learning Documentation: https://cloud.ibm.com/docs/watson-machine-learning
- Dataset Source: IBM Cloud Object Storage (predictive_maintenance.csv)
- Research Papers:
- "Predictive Maintenance Using Machine Learning: A Review" (Journal of Industrial Systems, 2023).
- "Decision Trees for Classification: A Machine Learning Approach" (IEEE Transactions, 2022).
- Chatgpt



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Journey to Cloud: Envisioning Your Solution



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Retrieval Augmented Generation with LangChain



THANK YOU

