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1 Branch 0 Tags Go to file t Go to file + Add file Code

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71aee52 · 1 hour ago

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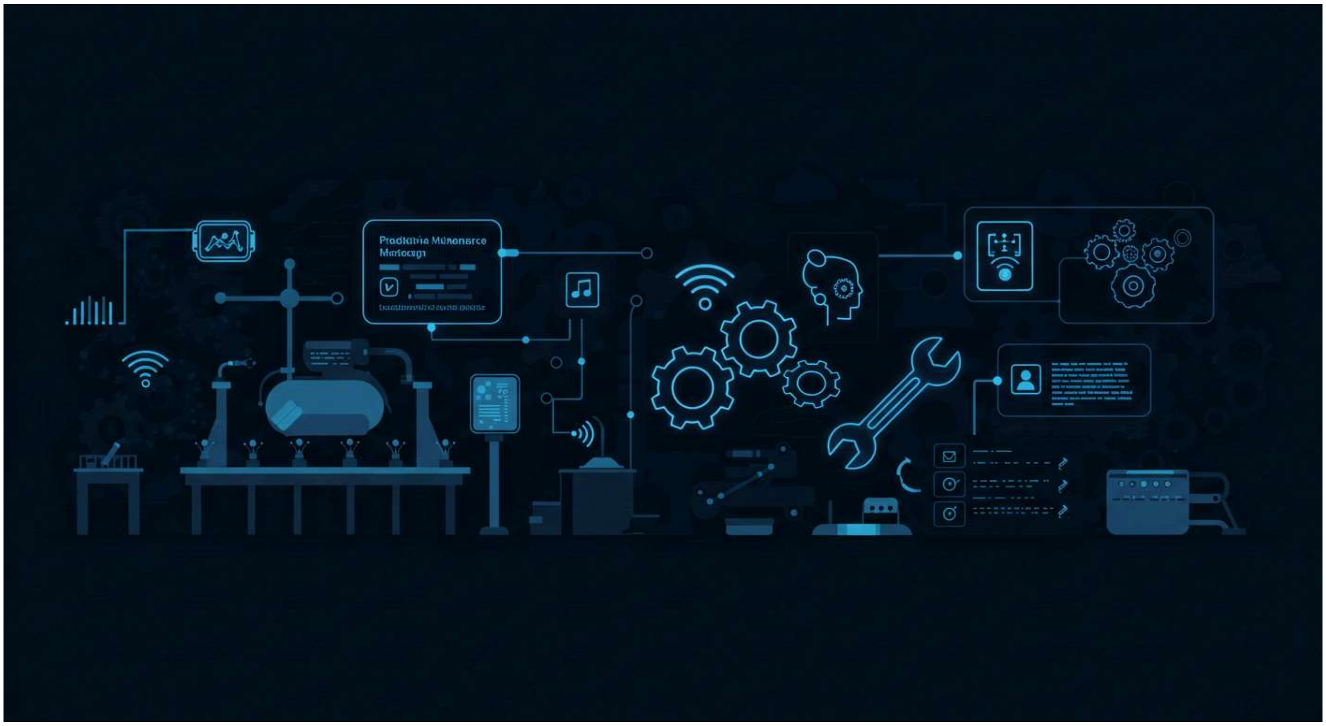
|---|---|---|
| .ipynb_checkpoints | Finished the notebook and the REA... | 5 hours ago |
| images | Added the slides | 1 hour ago |
| Predictive maintenance.pdf | Added the slides | 1 hour ago |
| README.md | Update README.md | 5 hours ago |
| industrial_iot_data.zip | Initialized the project | 4 days ago |
| notebook.ipynb | Finished the notebook and the REA... | 5 hours ago |

README

# Predictive Maintenance - Classifying whether a machine will fail within the next 7 days

### Author : Kelvin Kipkorir



## Business Problem

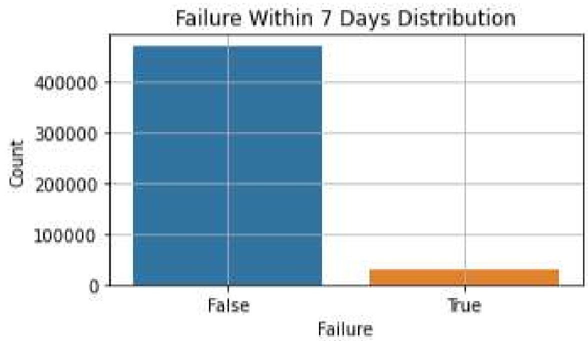
Techline Industries is a growing manufacturing company that has numerous machines in its manufacturing plants. As part of its digital transformation strategy, the company is investing in predictive maintenance to reduce operational costs, minimize unplanned downtime, and improve equipment reliability. However, with complex sensor data being generated across various machine types, the company lacks a robust system to anticipate failures before they occur.

To address this challenge, historical sensor data will be used to develop a machine learning model that can predict equipment failures up to one week in advance. This will empower maintenance teams to take timely, corrective actions — helping the company avoid costly downtimes typically associated with traditional maintenance strategies.

## Data Understanding

The dataset used in this project, sourced from Kaggle and titled **"Industrial IoT"**, contains **500,000 entries** representing various operational conditions of industrial machines. It includes **22 columns** capturing both sensor readings and metadata, such as temperature, vibration, pressure, coolant flow, and installation year. These features simulate real-world telemetry data from Industrial IoT systems, providing a good foundation for developing predictive maintenance models.

A visualization of the target feature distribution




## Data Preprocessing

To ensure the dataset was suitable for machine learning models, several preprocessing steps were carried out:

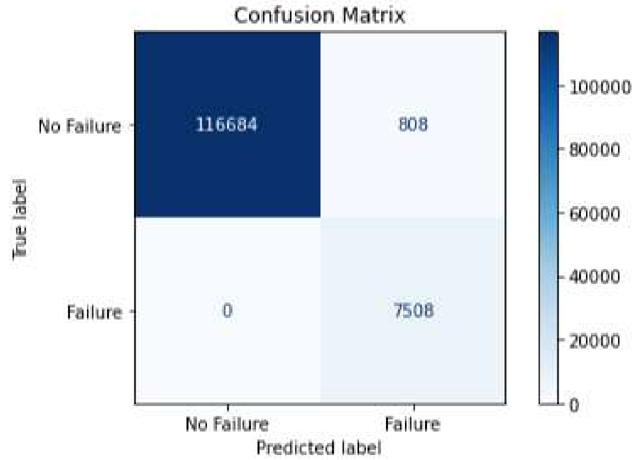
- **Handling Missing Values**: Numerical columns with missing values were imputed using `SimpleImputer`. Additionally, `MissingIndicator` was used to flag the presence of missing values as separate features, preserving any potential signal from missingness patterns.
- **Categorical Encoding**: The `machine_type` feature, which contains 33 unique categories, was transformed using `OneHotEncoder` to allow models to interpret the categorical data numerically.
- **Feature Scaling**: Numerical features were standardized to have zero mean and unit variance using `StandardScaler`, which is especially beneficial for models like Logistic Regression.
- **Class Imbalance Handling**: The target variable was highly imbalanced, with far fewer failure instances. To address this, **SMOTE (Synthetic Minority Over-sampling Technique)** was applied to the training data to generate synthetic samples for the minority class, helping models learn more balanced decision boundaries.

## Model Evaluation

Two machine learning models were trained and evaluated: **Logistic Regression** and **Decision Tree Classifier**.

**Logistic Regression:**

```
Accuracy : 0.9935
Precision: 0.9028
Recall   : 1.0000
F1 Score : 0.9489
```




**Decision Tree:**

```
Accuracy : 1.0000
Precision: 1.0000
Recall   : 1.0000
F1 Score : 1.0000
```


## Observations

Both models demonstrated strong performance but he decion tree gave a model with higher perfomance achieving an AUC of **~1.0** and near-perfect accuracy and recall, especially for the failure class.

> **Business Implication**: A high-performing Decision Tree model like this can significantly improve failure detection, especially for rare but critical failure events.

> **Caveat**: The perfect score may indicate **overfitting** on synthetic or oversampled data. Careful real-world testing and monitoring will be essential post-deployment.

An added advantage of Decision Trees is their **transparency**. Maintenance teams can visualize decision paths

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- **Jupyter Notebook** 100.0%