Title

Predictive Maintenance Using Neural Networks.

Introduction

Predictive maintenance refers to the practice of using data-driven insights to predict when equipment will fail or require maintenance, enabling proactive actions to reduce downtime and costs. This case study aims to apply machine learning techniques, specifically artificial neural networks (ANN), to predict the **Remaining Useful Life (RUL)** of machinery. By accurately forecasting when a machine will fail, organizations can plan maintenance more effectively, minimizing disruptions and optimizing resources.

Data Overview

The dataset used in this case study includes various operational features of machines, such as **voltage**, **rotation speed**, **pressure**, and **vibration**, along with **failure indicators** and the **failure datetime**. These features were collected over time, with the objective of predicting the RUL for each machine.

Key features in the dataset:

- **datetime**: Timestamp of machine readings.
- **machineID**: Identifier for the machine.
- **volt, rotate, pressure, vibration**: Operational features capturing the machine's condition.
- **Model**: Model name
- **Error_count**: Numbers of error occurred in a particular machinery
- **failure**: Indicator of whether the machine failed (1) or not (0).
- **failure_datetime**: The timestamp when the machine failed.
- **rul**: Remaining Useful Life (RUL) of the machine in hours.

Methodology

Feature Extraction and Pre-processing:

1. **Datetime Conversion**: The datetime column was converted to extract useful features like the **year**, **month**, **day**, and **hour**.
2. **Merging Datasets**: Five of the given datasets were merged to further facilitate analysis and model building to predict RUL(remaining useful life) .
3. **Handling Missing Values**: Missing values in the failure_datetime column were filled with the maximum datetime value for rows where failure did not occur.
4. **Feature Scaling**: The features were scaled using **StandardScaler** to ensure uniformity in input ranges for the neural network, improving model performance.

Model Architecture:

The model used for this case study is a simple **Artificial Neural Network (ANN)** with the following layers:

- **Input Layer**: Consists of the preprocessed features (scaled).
- **Hidden Layer**: Two hidden layer with 15 neurons and ReLU activation function.
- **Output Layer**: A single neuron that predicts the **RUL**.

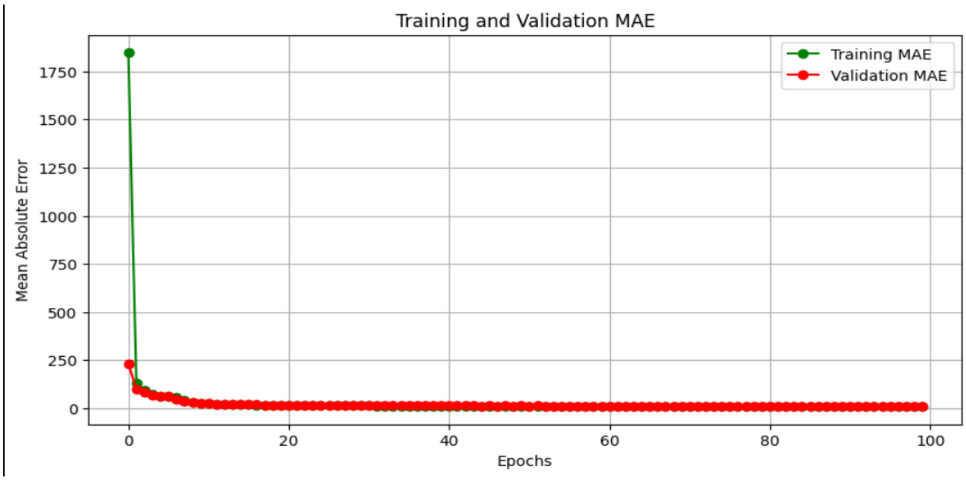
The model uses **Mean Squared Error (MSE)** as the loss function and **Adam optimizer** for training.

Results

Model Performance:

- **Training Loss**: The model's training loss was evaluated after each epoch, showing gradual convergence.
- **Test Loss**: The model's performance on the test set was evaluated, showing reasonable accuracy for predicting RUL for both failing and non-failing machines.

Visualization of Training ,Validation MAE and MSE :



Visualization

1. **Heat Maps:** Understanding the correlation between each features.
2. **Bar plots**: analyse the general shape of distribution in the data**.**
3. **Line Plot:** Used to understand the trend of few features against the date time

Insights from Visualization:

- There are 100 unique machines each with unique **machineID.**
- These machines has 4 unique model types.
- The oldest among all the machine model is model2 (avg age 13 years) followed by model 3, model 1 and model 4.
- Each of the machinery has 4 components named comp1, comp2, comp3 and comp4.
- **RUL (remaining useful life)** has strong negative correlation with **Datetime** feature (-0.96) indicating that as the machines get older they have less remaining useful life.
- The moderate correlation between **failure** and **error_count** suggests that as the error increases, failure are more likely to occur.
- **Failure** correlates negatively with rul**(remaining useful life)** , indicating that as machines approach the end of their useful life, the likelihood of failure increases.
- Weak correlations between **maint_comp_*** and other features suggest that maintenance events might not always align with predictive indicators like sensor readings or age.

- There is a general downward trend in failures shown in all the components as time progresses. This could indicate improved maintenance practices, component replacements, or reduced operational stress over time.
- Component 2 (orange) exhibits a significant peak around **mid-2015**, suggesting a potential design flaw, operational stress, or external factors affecting its performance during this period.
- Some overlapping trends in failure timings (e.g., mid-2015 for all components) suggest shared external factors, such as environmental conditions or operational intensity, might influence multiple components simultaneously.

Conclusion

This case study demonstrates the application of an artificial neural network for predicting the Remaining Useful Life (RUL) of machinery, an essential task in predictive maintenance. By leveraging operational data, we can forecast equipment failure, enabling better planning and reducing unplanned downtime. Future work could focus on improving model accuracy through advanced techniques like ensemble methods or adding more features related to machine health.

Future Scope

Future improvements in this case study could include:

- **Data Augmentation**: Using synthetic data to balance the classes.
- **Model Tuning**: Further hyperparameter tuning to optimize the ANN's performance.
- **Advanced Techniques**: Exploring more sophisticated models like LSTM (Long Short-Term Memory) networks for time-series data to capture temporal dependencies better.
- **Real-Time Prediction**: Deploying the model in a production environment for real-time monitoring and maintenance prediction.