

SELF PROJECT

Gear Fault Diagnosis Comparing Machine Learning vs. Deep Learning for Predictive Maintenance



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Project Goal & Methodology

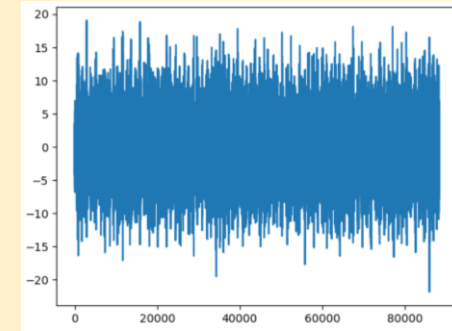
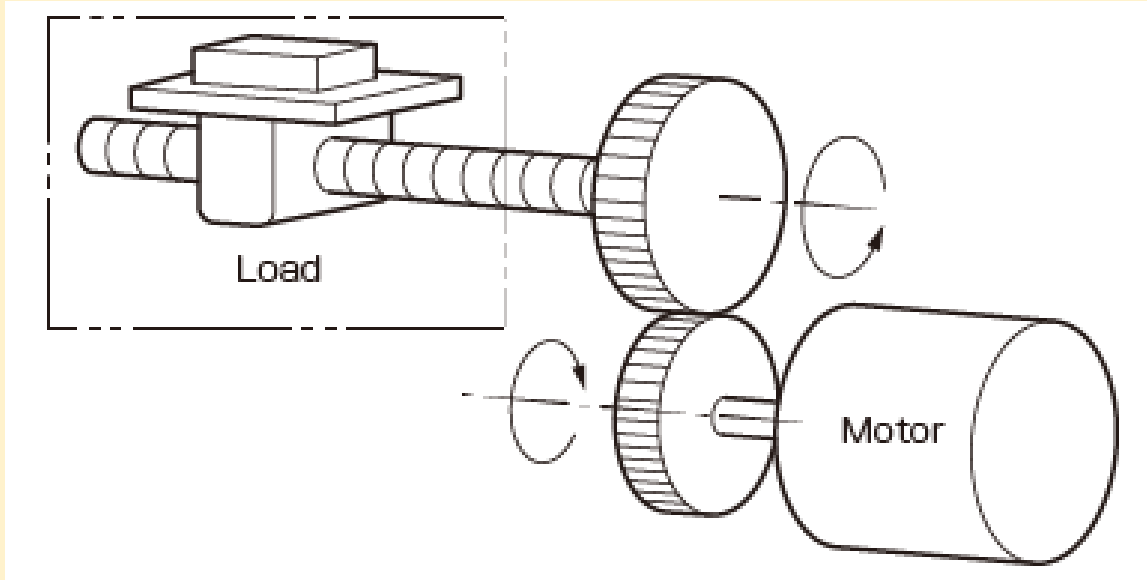
- **Objective:** To develop a robust model that can accurately diagnose a "broken tooth" fault in a gear using vibration sensor data

Methodology:

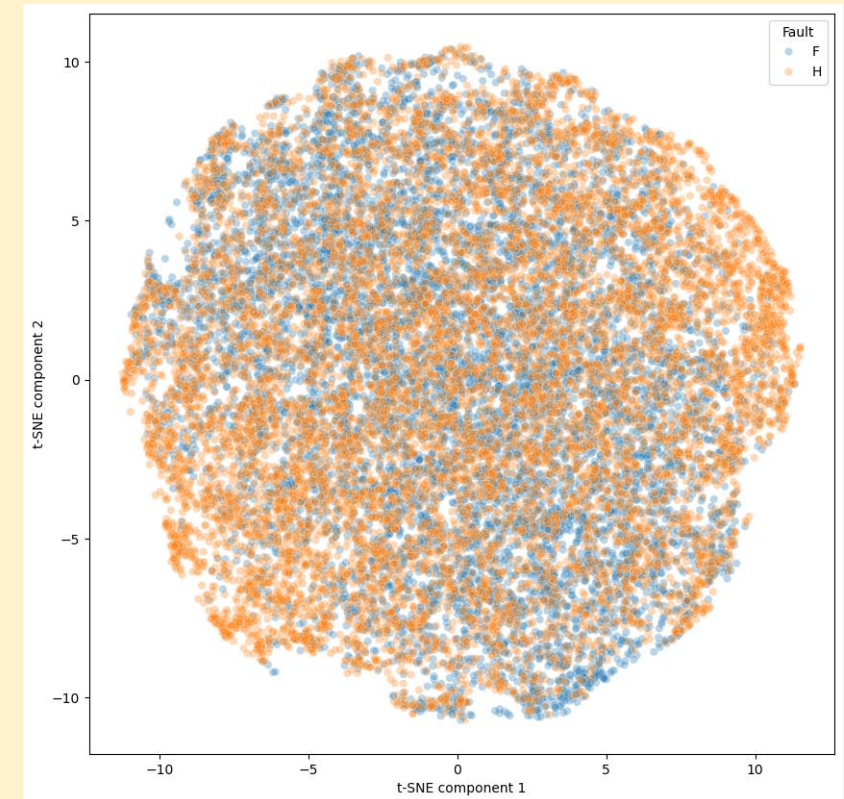
- **Collect Data:** Use vibration data from healthy and faulty gears.
- **Build Two Models:**
 - A traditional Machine Learning model (**Random Forest**).
 - A Deep Learning model (**Convolutional Neural Network - CNN**).
- **Compare Performance:** Evaluate which model provides a reliable and accurate diagnosis on unseen data.

The Dataset

(Source: <https://www.kaggle.com/brjapon/gearbox-fault-diagnosis>)



- **Source:** Vibration data from a test rig.
- **Classes:** 2 conditions - 'Healthy' and 'Faulty' (Broken Tooth).
- **Sensors:** 4 vibration sensors (a1, a2, a3, a4).
- **Operating Conditions:** Data recorded under loads from 0% to 90%.

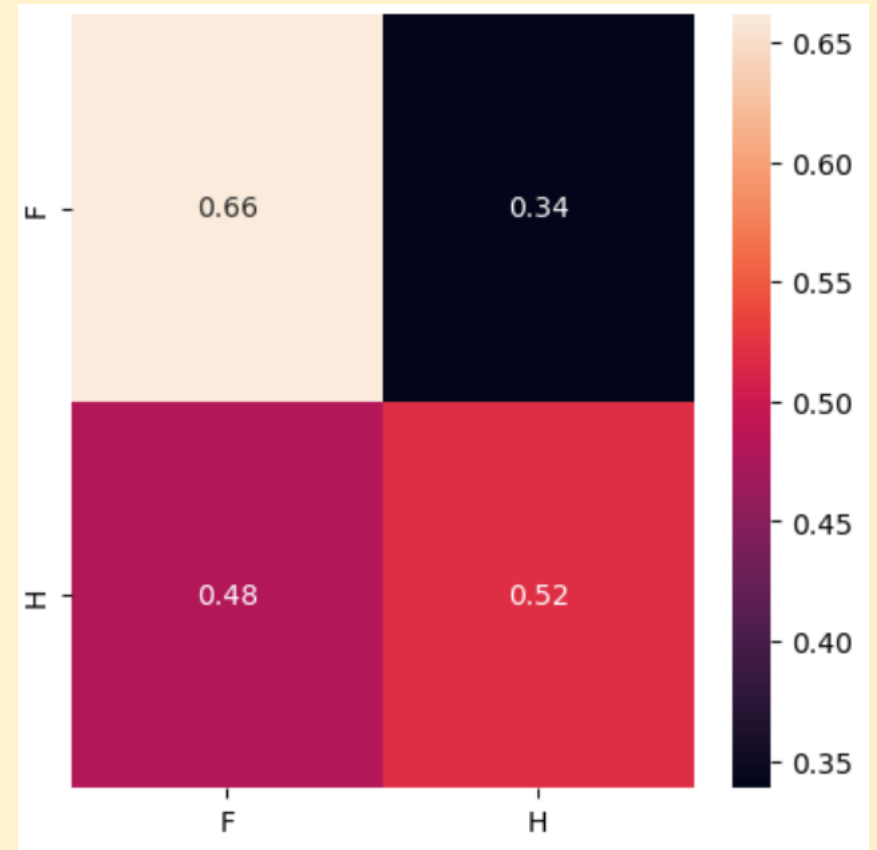


Random Forest

- Problem: Severe Overfitting
- The model learned the training data perfectly but failed to generalize to new, unseen data.
- **Training Accuracy: 100%**
- **Test Accuracy: 59.06%**
- **Result:** The model was no better than a coin toss for real-world diagnosis.

Random Forest - The Evidence of Failure

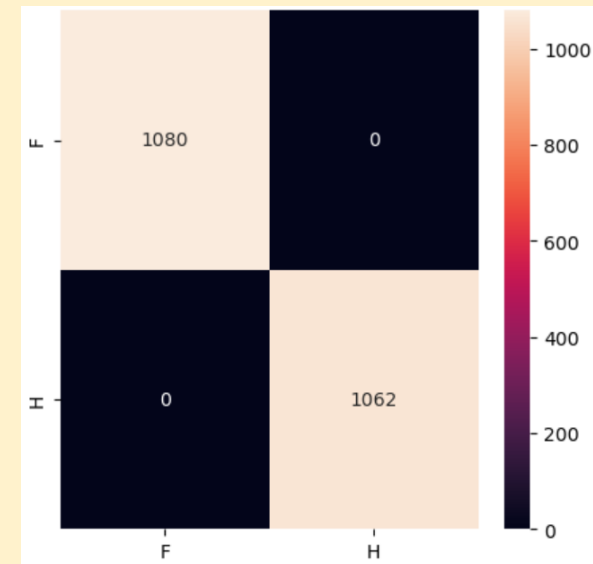
- **Interpretation of the Confusion Matrix:**
- The model was only able to correctly identify about half of the healthy and faulty gears.
- The large numbers in the off-diagonal cells show a high rate of misclassification.
- This visually confirms the model's inability to distinguish between the two classes on test data.



Convolutional Neural Network (CNN)

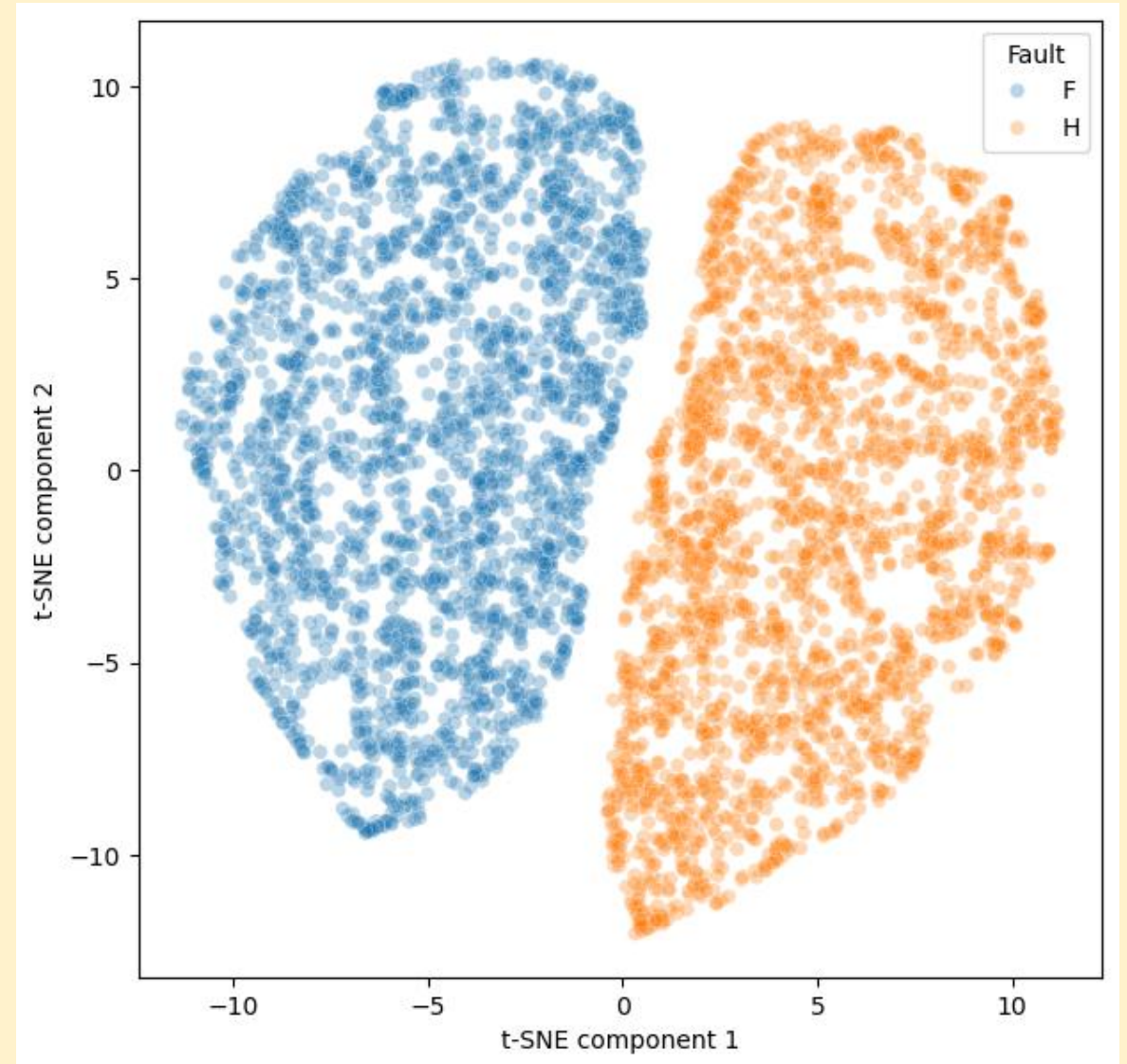
- **Why It Worked:** The CNN learned the underlying patterns and features of the vibration signals, allowing it to generalize effectively.
- **Training Process:** Within 5 epochs, the model's performance on the validation (test) data rapidly improved.
- **Final Validation Accuracy:** Reached ~100%, demonstrating that it learned patterns applicable to both seen and unseen data

```
Epoch 1/5
40/40 ————— 3s 25ms/step - accuracy: 0.9045 - loss: 0.2310 - val_accuracy: 1.0000 - val_loss: 9.4038e-04
Epoch 2/5
40/40 ————— 1s 18ms/step - accuracy: 1.0000 - loss: 3.9347e-04 - val_accuracy: 1.0000 - val_loss: 2.7098e-04
Epoch 3/5
40/40 ————— 1s 20ms/step - accuracy: 1.0000 - loss: 1.5741e-04 - val_accuracy: 1.0000 - val_loss: 1.8334e-04
Epoch 4/5
40/40 ————— 1s 20ms/step - accuracy: 1.0000 - loss: 1.2387e-04 - val_accuracy: 1.0000 - val_loss: 1.8848e-04
Epoch 5/5
40/40 ————— 1s 19ms/step - accuracy: 1.0000 - loss: 8.5131e-05 - val_accuracy: 1.0000 - val_loss: 1.0494e-04
```



CNN – Visualization (t-SNE)

- **Interpretation of the t-SNE Plot:**
- This plot visualizes the features learned by the CNN.
- The **Healthy (blue)** and **Faulty (orange)** classes form two distinct, widely separated clusters.
- This is clear visual proof that the CNN learned to effectively differentiate between the two gear conditions.



Conclusion

- For complex time-series data like vibrations, **Deep Learning models like CNNs are significantly more effective** than traditional Machine Learning models like Random Forest.
- The Random Forest model **overfit** the data, making it useless for practical application.
- The **CNN successfully generalized**, learning the essential features to accurately diagnose gear faults with near-perfect accuracy on unseen data.

Future Work & Recommendations

- **Model Optimization:** Fine-tune the CNN's architecture (hyperparameters) to ensure maximum robustness.
- **Expand Fault Types:** Train the model on data from other fault types (e.g., gear wear, cracks) to create a comprehensive diagnostic system.
- **Explore Other Architectures:** Investigate other Deep Learning models like LSTMs or Transformers, which are also powerful for sequence data.
- **Deployment:** Plan for deploying the trained CNN model for real-time monitoring on industrial equipment.