🗎 Weekly Progress Report

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Domain: Predictive Maintenance using ML
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Week Ending: 02

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1. **Overview:**
   This week focused on advancing from data preprocessing and EDA into model building and evaluation for the three predictive maintenance projects. The primary objectives were to create baseline machine learning/deep learning models, perform hyperparameter tuning, and start integrating advanced signal processing techniques for feature improvement.

II. Achievements:

1. Project 6 – Turbofan Engine RUL Prediction

- Implemented LSTM and GRU models for Remaining Useful Life estimation using the FD001 dataset.
- Conducted hyperparameter tuning (epochs, batch size, hidden units) to improve performance.
- Achieved an initial RMSE of **18.4 cycles** (GRU performed better than LSTM in this iteration).
- Added rolling average smoothing to sensor data for noise reduction.
- Started building visualization scripts for predicted vs actual RUL.

2. Project 7 – Bearing Lifetime Prediction

- Completed feature engineering with additional features like spectral entropy, RMS frequency, and wavelet energy.
- Implemented Random Forest and Gradient Boosting models for classification of bearing health states (healthy, degraded, imminent failure).
- Achieved **F1-score: 0.86** with Random Forest as the baseline.
- Visualized bearing health trends over time for early fault detection.

3. Project 8 – Gearbox Fault Diagnosis Using Vibration Sensors

- Implemented FFT-based CNN model for binary classification (Healthy vs Broken Tooth).
- Achieved **Accuracy: 93%** on test data.
- Integrated short-time Fourier transform (STFT) visualizations for better interpretability.
- Explored transfer learning possibilities with pre-trained CNN architectures.

4. Python & ML Learning Enhancement

- Learned and applied advanced techniques like Bayesian optimization for hyperparameter tuning.
- Practiced PyTorch basics for future deep learning model experiments.
- Worked with SciPy's signal module for more robust preprocessing.

III. Challenges:

1. **Overfitting in LSTM models** – Required adding dropout layers and reducing network depth.
2. **FFT and STFT computation time** – Optimized using NumPy's vectorized operations and caching.
3. **Class imbalance in bearing dataset** – Applied SMOTE oversampling to balance health state classes.

IV. Lessons Learned:

- Data preprocessing for vibration signals benefits significantly from combining time-domain and frequency-domain features.
- GRU models can outperform LSTM in smaller, more structured datasets.
- Hyperparameter tuning is crucial but should be coupled with regularization to avoid overfitting.
- Visual interpretability (plots, heatmaps) helps in explaining model predictions to non-technical stakeholders.

V. Learning Resources:

- "Practical Time Series Analysis" – Apress Publication.
- Kaggle notebooks on predictive maintenance with LSTM/GRU.
- Signal processing courses (MIT OpenCourseWare) – Wavelets & Fourier Transform.
- Documentation for Optuna and Scikit-learn's model_selection module.

VI. Next Week's Goals:

- Improve RUL prediction accuracy with ensemble deep learning models.
- Conduct SHAP analysis for model explainability in bearing and gearbox projects.

- Start integrating dashboards using Plotly/Dash for interactive result viewing.
- Prepare initial draft of a consolidated project report combining all three projects.

Additional_Comments:

Week 2 was a shift from pure preprocessing into hands-on model building and performance evaluation. The results are promising, especially in bearing and gearbox fault detection. The focus now will be on refining models, enhancing interpretability, and preparing for project presentation.