Transformer Diagnostics Model Report

---

1. Data Generation: High-Fidelity Synthetic Approach

The foundation of this diagnostic system is a **synthetic dataset** meticulously generated to emulate the complex impedance signatures of power transformers under various fault conditions. This approach was necessary to overcome the challenge of collecting sufficient, diverse, and well-labeled real-world fault data.

A. Simulation Core

- **Data Basis:** The synthetic data generation was informed by industry standards for FRA, specifically **IEC 60076-18** and **IEEE C57.149**.
- **Scale:** The final, robust dataset contained **1,350 unique transformer samples** (traces), resulting in **270,000 total frequency measurements** across the 10 Hz to 1 MHz spectrum.

B. Fault Scenarios & Variation

- **Fault Types:** The dataset includes simulation modules for three critical mechanical and electrical faults: **Radial Deformation**, **Axial Displacement**, and **Short Circuits**.
- **Granularity:** The model trained on a wide range of fault severity levels, typically **10 discrete levels per fault type**, in addition to various healthy baseline conditions.
- **Robustness:** To mitigate overfitting and improve generalization, **stochastic variations** and increased **measurement noise** were deliberately introduced during the simulation of both the healthy baselines and fault effects.

---

2. Model Methodology: Feature Engineering & Dual Random Forest

The raw frequency data was not fed directly to the models. Instead, a critical **Feature Engineering** step was employed to extract informative features, which were then used to train a **dual Random Forest pipeline**.

A. Feature Engineering

The core strategy involved creating features based on the **Difference Trace** (subtracting a healthy baseline trace from the sample trace) to isolate the fault signature.

- **Spectral Features:** Calculated the **Area Under the Curve (AUC)** within defined **Low-**, **Medium-**, and **High-Frequency Bands**.
- **Statistical Features:** The final refined feature set contained **18 features**, including the original spectral features augmented by **statistical moments** (mean, standard deviation, skewness, and kurtosis) of the difference traces across the entire spectrum and within the three bands.

B. Dual Model Architecture

Two distinct Random Forest models were chosen for their efficiency and handling of complex, non-linear relationships:

1. **Random Forest Classifier:** Trained to predict the **discrete fault type** (e.g., 'Axial Displacement_0.1', 'Short Circuit_1.0').
2. **Random Forest Regressor:** Trained to predict the **continuous severity level** (a float value representing the magnitude of the fault).

---

3. Model Training and Evaluation Metrics

The training pipeline was designed to maximize robustness and prevent the overfitting observed in early experiments on smaller datasets.

A. Training Strategy

- **Data Splitting:** The large dataset was partitioned using a **stratified split** into 60% Training, 20% Validation, and 20% Test sets.
- **Overfitting Mitigation: 5-Fold Cross-Validation (CV)** was implemented across the training data to provide a **robust and consistent estimate of model performance**, successfully addressing the initial suspicion of overfitting (where models achieved 100% accuracy on the original, small validation set).
- **Hyperparameter Tuning: Grid Search** was used to tune the hyperparameters for both models (e.g., n_estimators, max_depth) on the training data.

B. Evaluation Metrics and Results

The final performance was assessed using the mean scores from the 5-Fold Cross-Validation on the refined feature set.

Task	Model	Primary Metric	Final Mean CV Score	Interpretation

Classification (Fault Type)	Random Forest Classifier	**Accuracy**	**73.41%**	The model consistently classifies the correct fault type and severity level from 30 possible classes.
Regression (Severity)	Random Forest Regressor	**RMSE** (Root Mean Squared Error)	**0.0110**	The model accurately predicts the continuous severity level, with an average prediction error of ≈1.1%.

The low standard deviation (≈0.0108 for accuracy and ≈0.0007 for RMSE) in the CV scores confirms that the final models are **robust** and **generalize consistently** across diverse fault conditions.