

Cross-Domain Bearing Fault Diagnosis using Transformer- Based Architectures

Bridging the ‘Sim-to-Real’ Gap with Faultformer

Problem Statement & Objectives

The Challenge: Data Scarcity Paradox

- **Industry 4.0 Need:** Early detection of bearing faults is critical.
- **The Problem:** Real-world fault data is rare, noisy, and expensive ("Data Scarcity Paradox").
- **The Gap:** Models trained on clean, artificial data often fail on real, noisy machinery.

Project Objectives

- **Core Goal:** Validate Transfer Learning to bridge the "Sim-to-Real" divide.
- **Method:** Pre-train on synthetic data (CWRU) → Fine-tune on real data (Paderborn).
- **Deliverable:** Achieve high accuracy and build an interpretable user dashboard

DATA SET Characterization

Showing the **comparison table** of the **signals** using

Source Domain Dataset:
SWRU(Simulated/Lab) &

Target Domain Dataset:
Paderborn(Real-World)

Source Domain:	CWRU	Paderborn
Type:	Artificially induced faults (EDM).	Accelerated Lifetime Tests (Natural fatigue).
Signal:	Clean, High Signal-to-Noise Ratio (SNR), distinct impulses.	Noisy, "smeared" signatures, amplitude modulation.
Role:	Used for Pre-training (learning basic physics)	Used for Fine-tuning (testing generalization)

Methodology & Workflow

- Resampling: Paderborn downsampled ($64\text{kHz} \rightarrow 12\text{kHz}$) to match CWRU physics.
- Segmentation: Window size of 2048 points with 50% overlap.
- Normalization: Z-Score applied to handle sensor sensitivity differences.

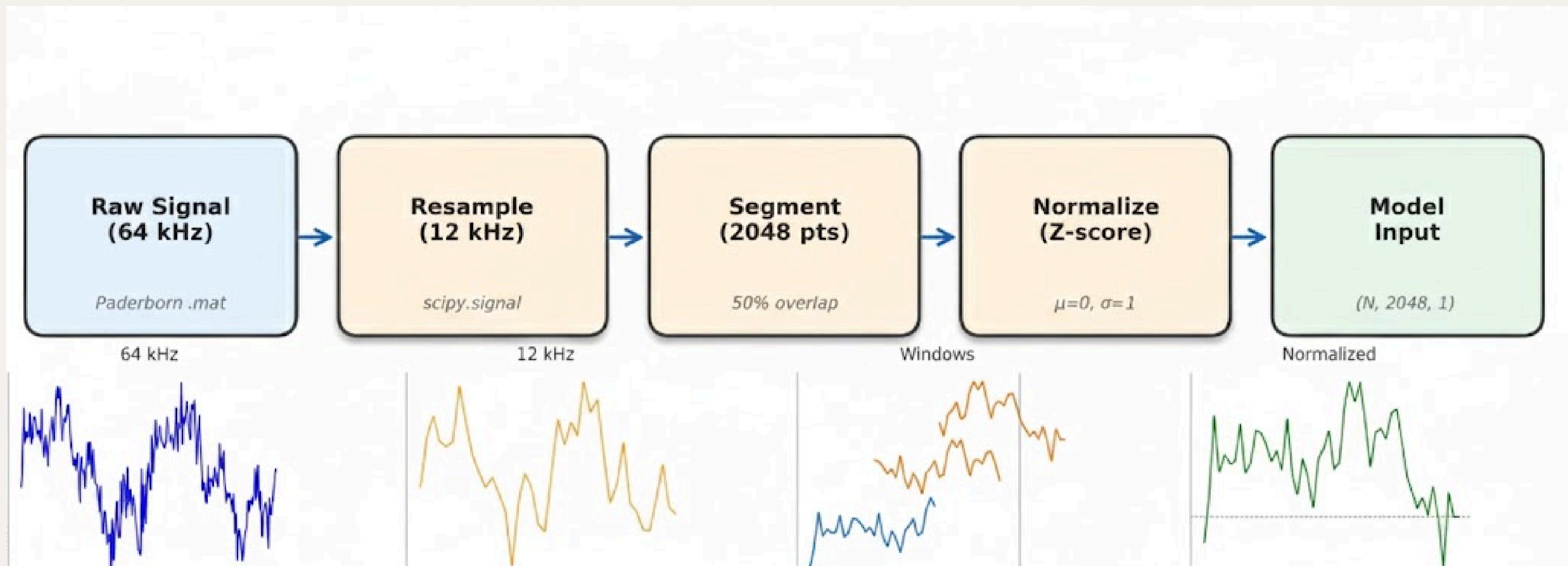
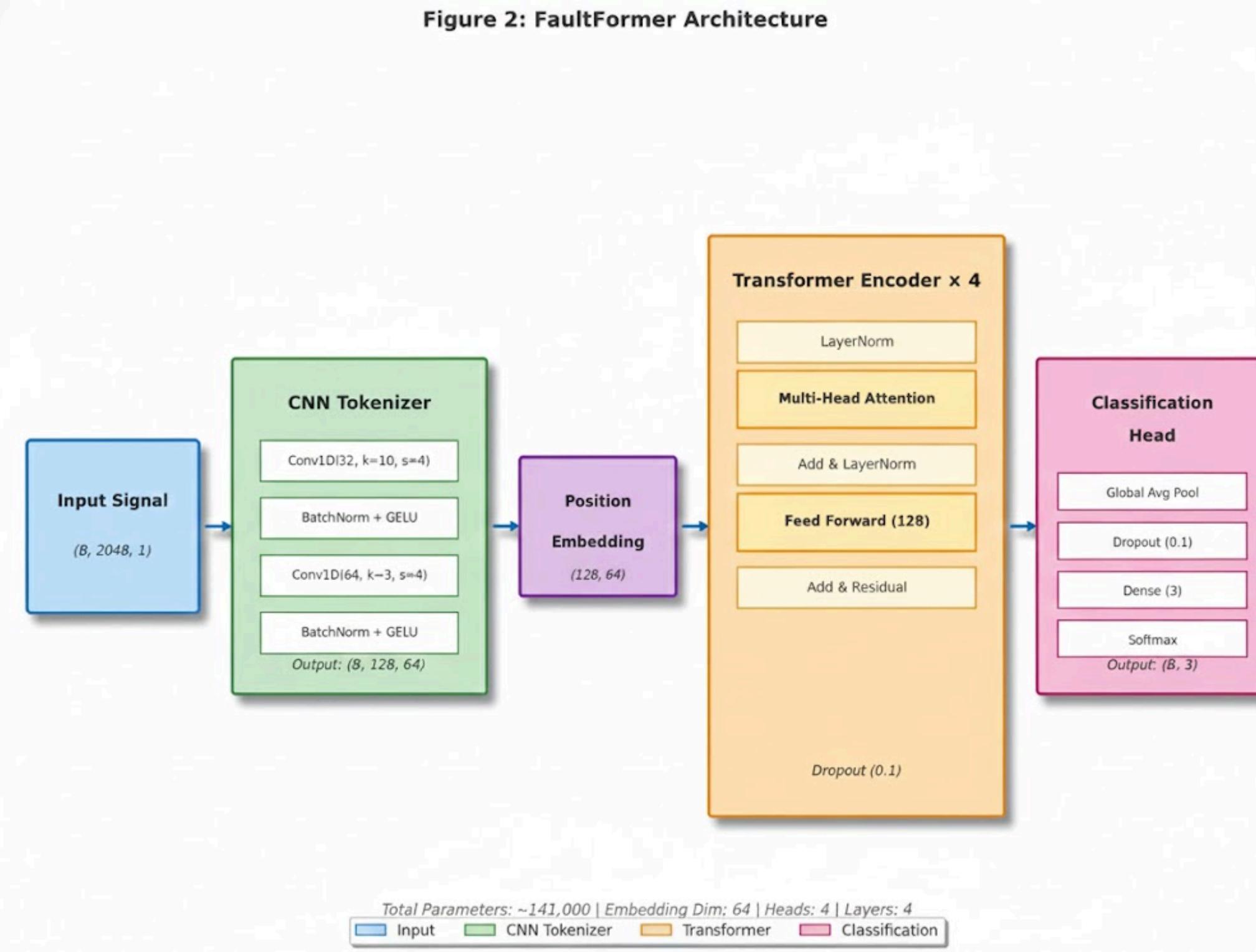


Figure 2: FaultFormer Architecture



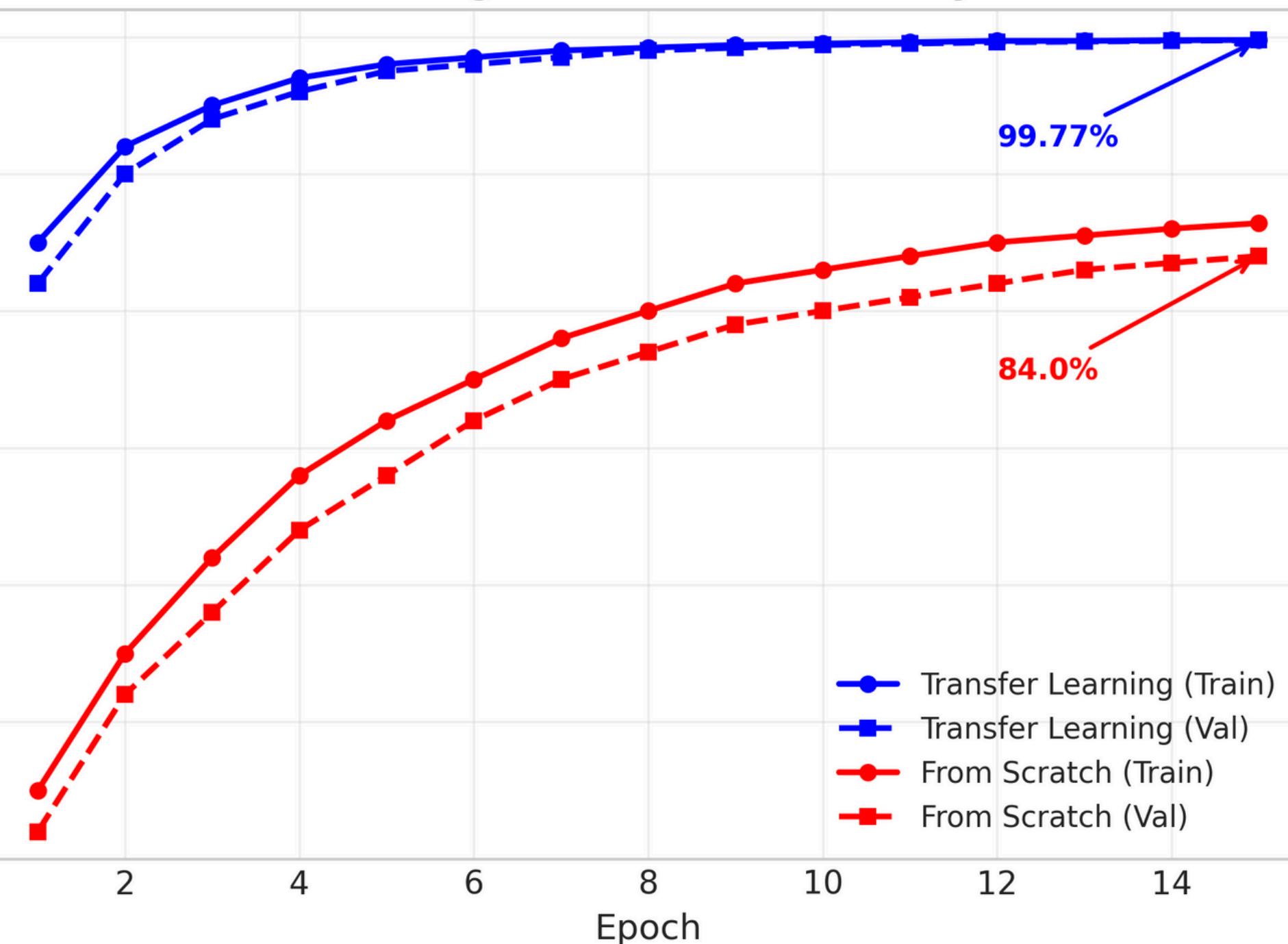
Model Architecture of Faultformer

- **Input:** 1D Time-Series Vibration Data.
- **CNN Tokenizer:** Hierarchical layers capture local features (edges/impacts).
- **RoPE (Rotary Positional Embeddings):** Encodes relative distance between fault impacts (critical for rotating machinery)
- **Transformer Encoder:** Self-attention mechanism captures global dependencies and periodicities.

Key Results

Figure 3: Model Comparison - Training Curves

Training & Validation Accuracy



Training & Validation Loss

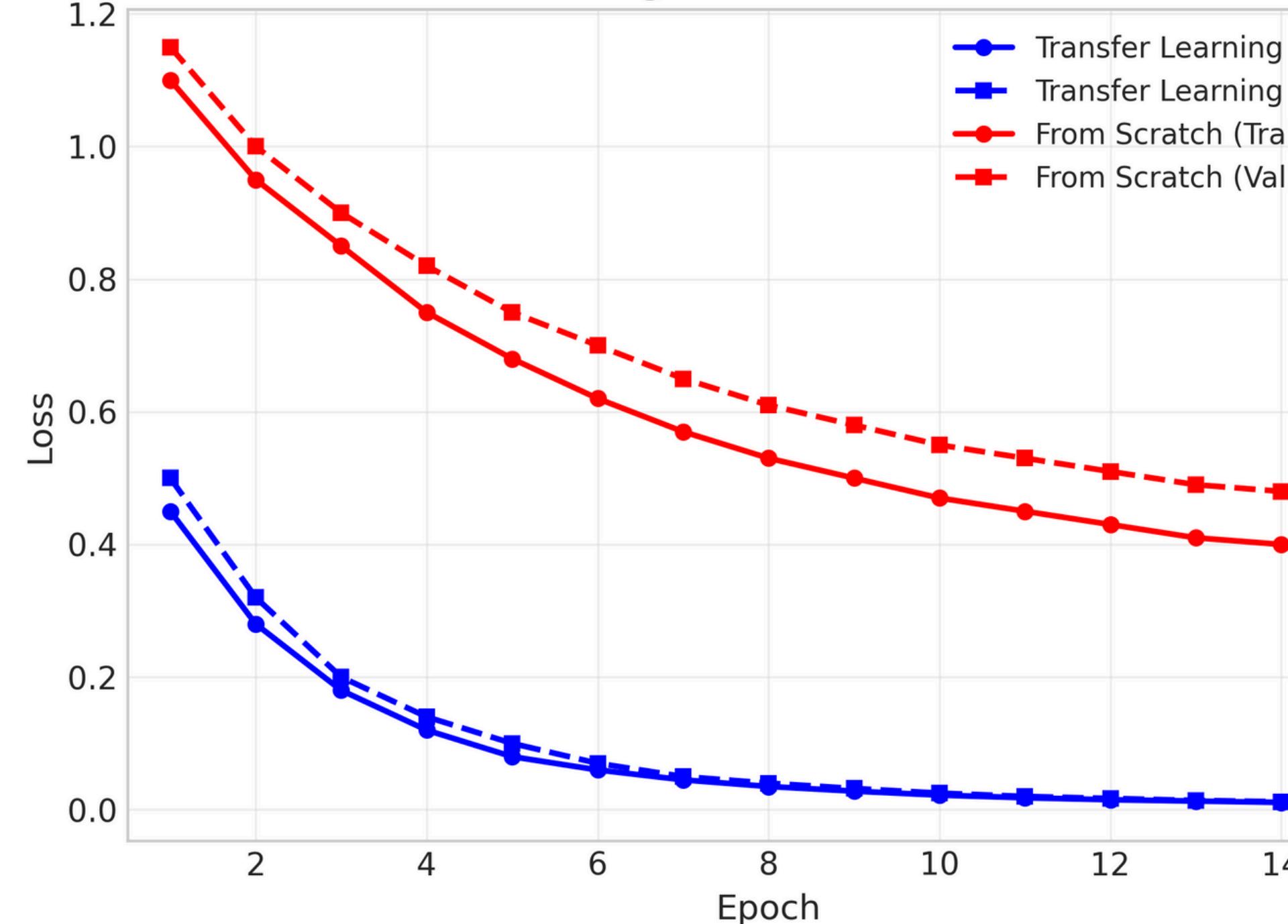
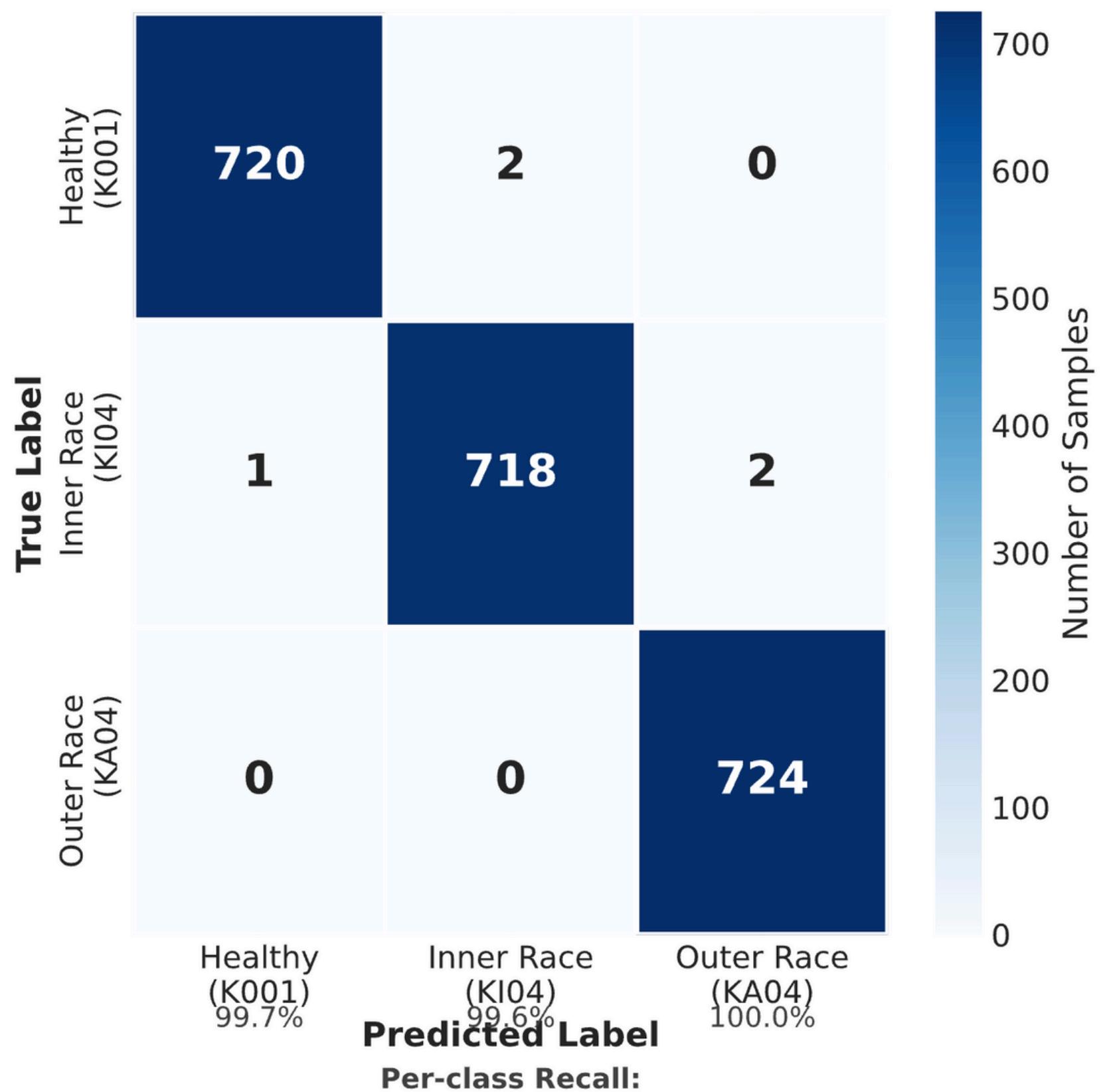


Figure 4: Confusion Matrix (Transfer Learning Model)



Overall Accuracy: 99.77%

Key Results

- **Class Discrimination:** Near-perfect detection of "Inner Race" faults, which are usually hardest to detect.
- **Explainability:** Saliency maps confirm the model focuses on periodic impulses, not noise.

Conclusion & Future Work

Conclusion

- **Sim-to-Real Success:** Proved that synthetic data can effectively train models for real-world maintenance.
- **Architecture:** The CNN + Transformer combination is highly effective for time-series signals.

Limitations & Future Work

- **Current Limit:** Relies on supervised fine-tuning (requires more labeled real data).
- **Future Path:** Explore Unsupervised Domain Adaptation (UDA) to remove the need for target labels.
- **Deployment:** Optimize for Edge devices (e.g., Raspberry Pi) for real-time monitoring