Real-Time Structural Damage Detection Using Kolmogorov-Arnolds Neural Networks and Cepstral Features

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Motivation & Goal

The Problem: Civil infrastructures undergo continuous stress, and early detection of damage is critical to prevent catastrophic failures.

Tool: Vibration-based Structural Health Monitoring is the process of implementing a damage detection strategy where structural damage can be detected from changes in the damage-sensitive features extracted from vibration measurements.

Can AI Help Detect Structural Damage Before It's Too Late?

Machine learning models can process vast amounts of vibration data, learning patterns that indicate damage with improved adaptability and accuracy. These models enhance real-time monitoring capabilities, making structural assessment more **efficient, robust, and scalable**.

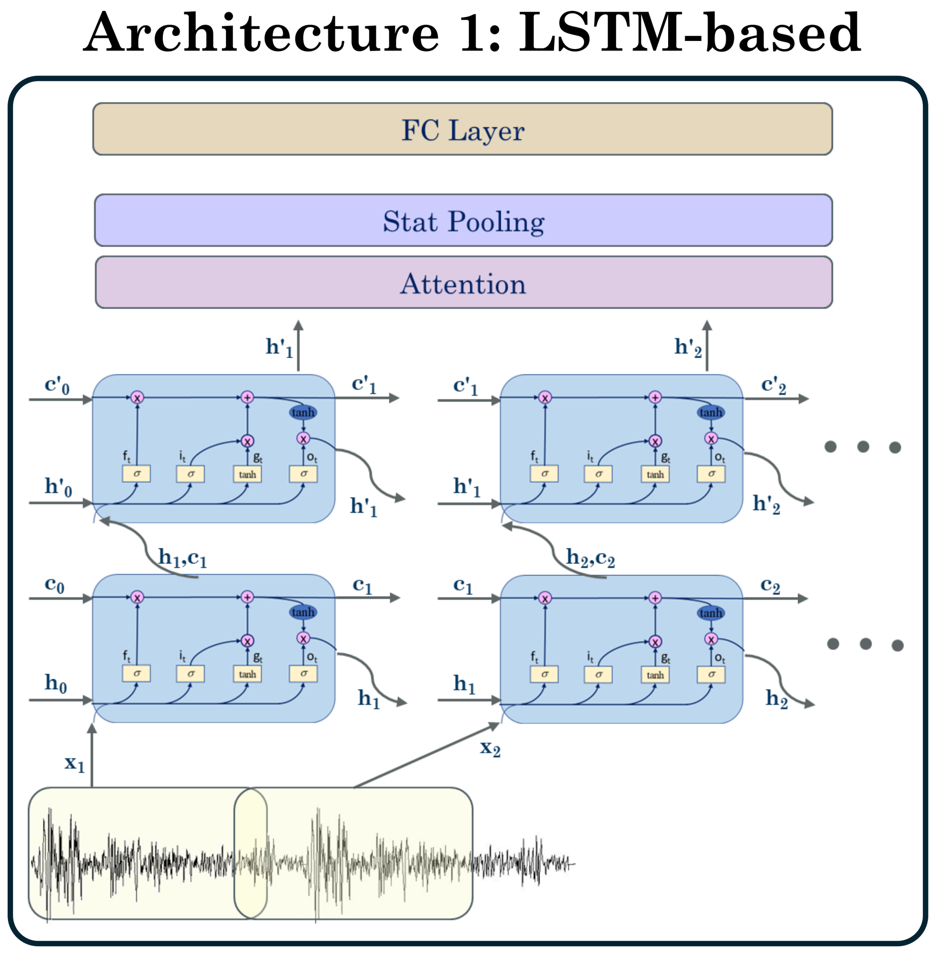
Approach: We propose an AI-driven framework that combines cepstral feature extraction with a Neural Network to classify structural states as damaged or undamaged.

Vibration Data → Cepstral Features → Neural Networks → Damage Prediction

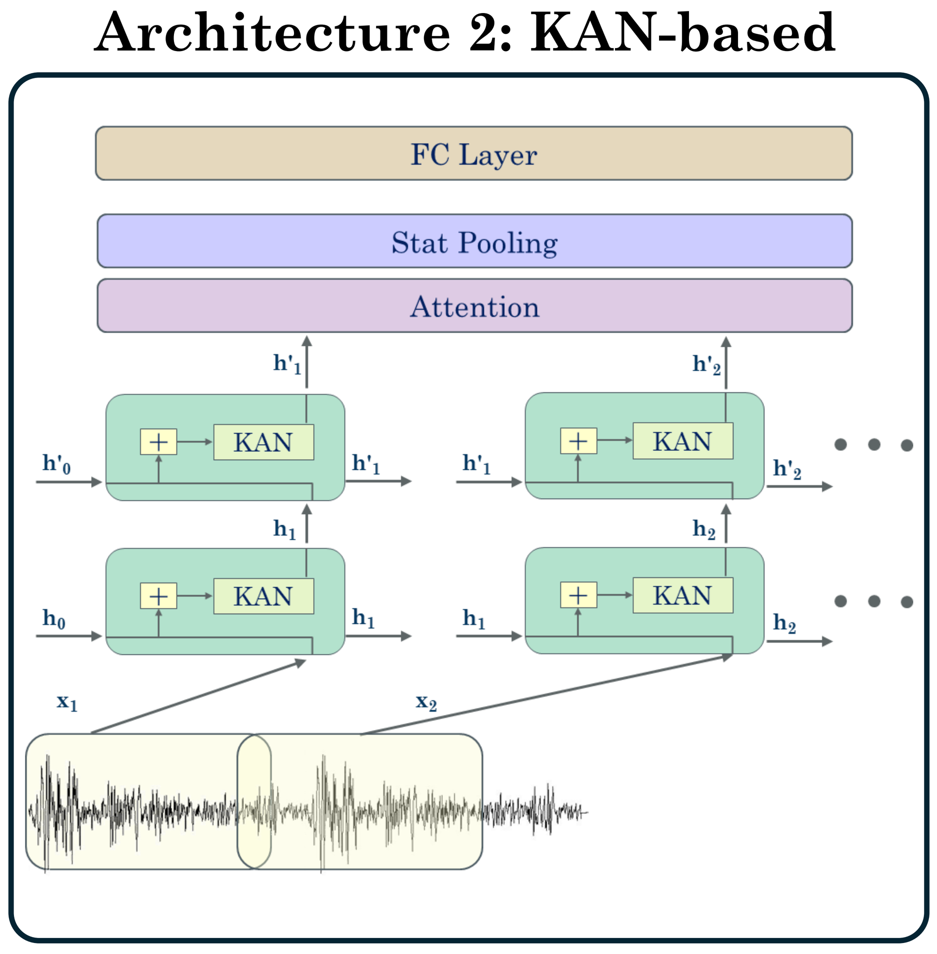
Methodology

Feature Extraction: **Cepstral Analysis** captures frequency-domain characteristics of vibration signals, aiding in damage identification.

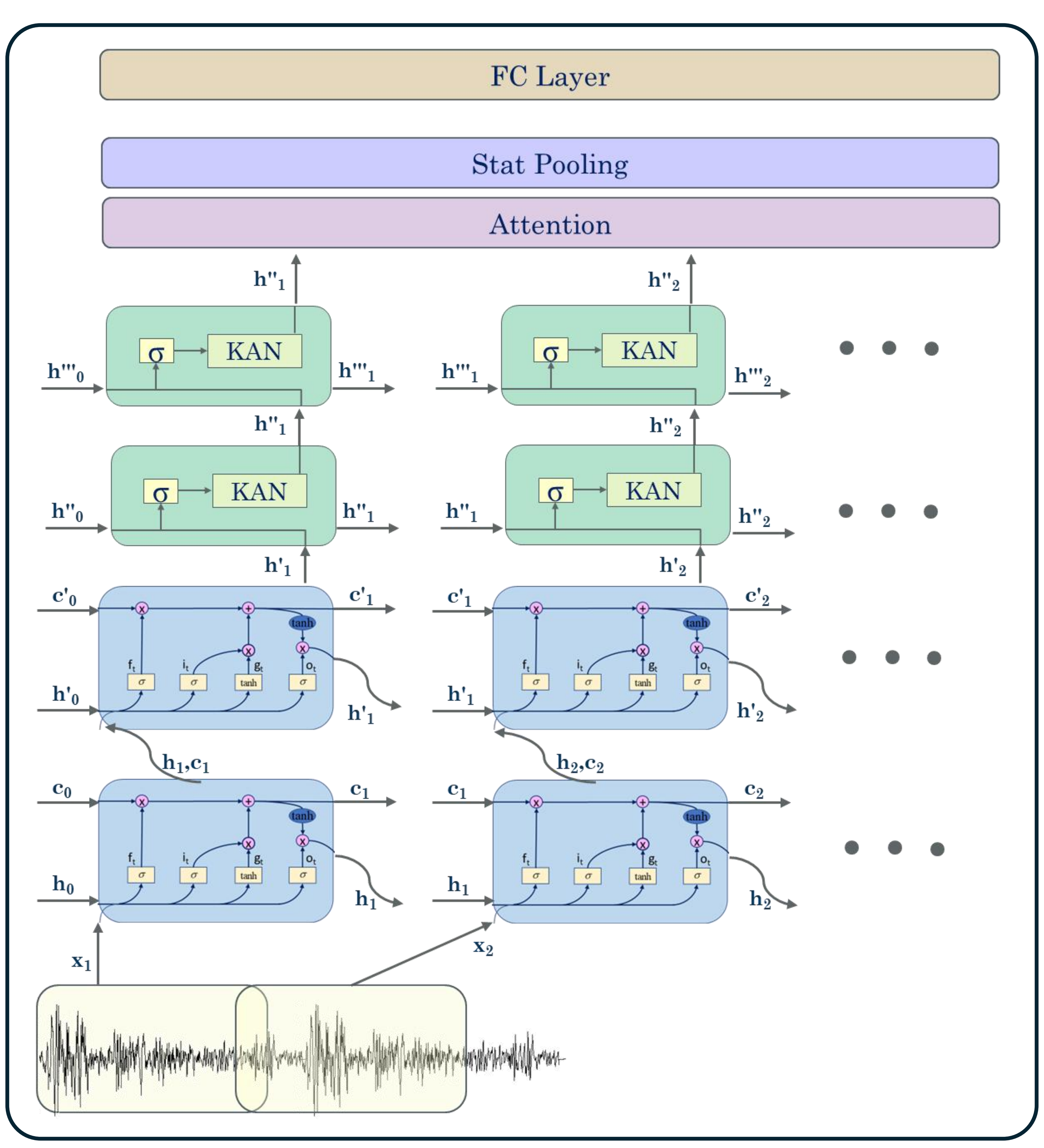
Architecture 1: LSTM-based



Architecture 2: KAN-based



Next Step 2: Hybrid KAN-LSTM

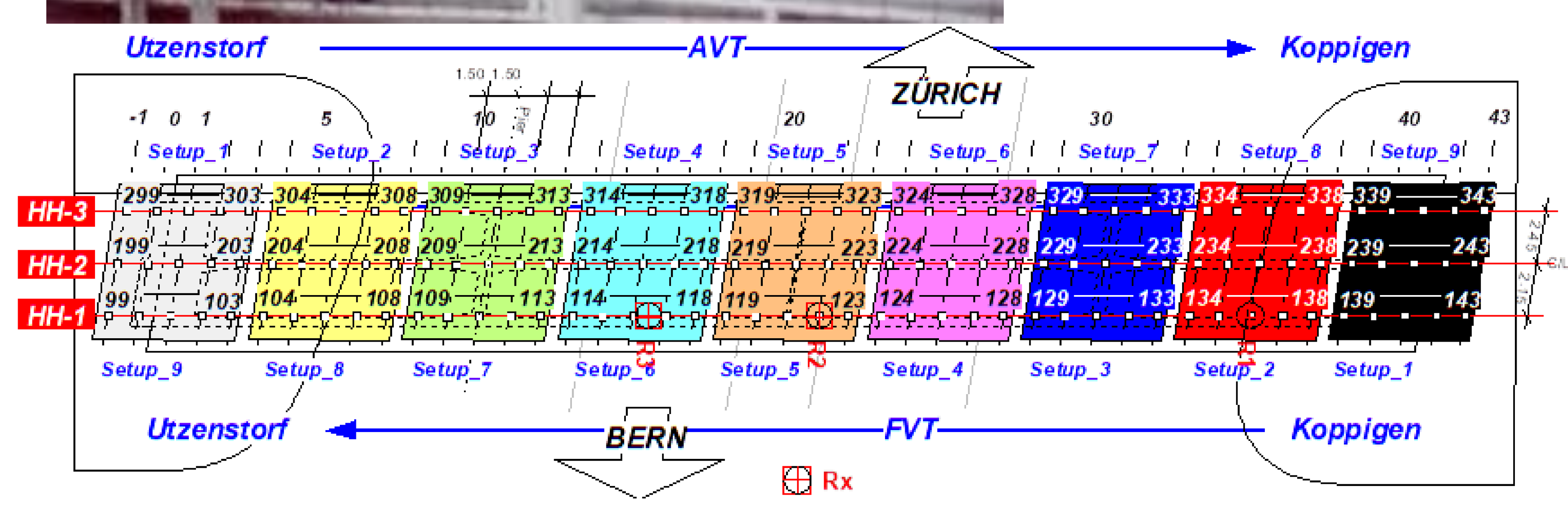


Data

Swiss Z24 bridge: Built in **1963**, this three-span bridge spans ~60 meters and was used for **controlled damage experiments**.

Data was recorded in nine setups using five reference channels due to limitations in available accelerometers.

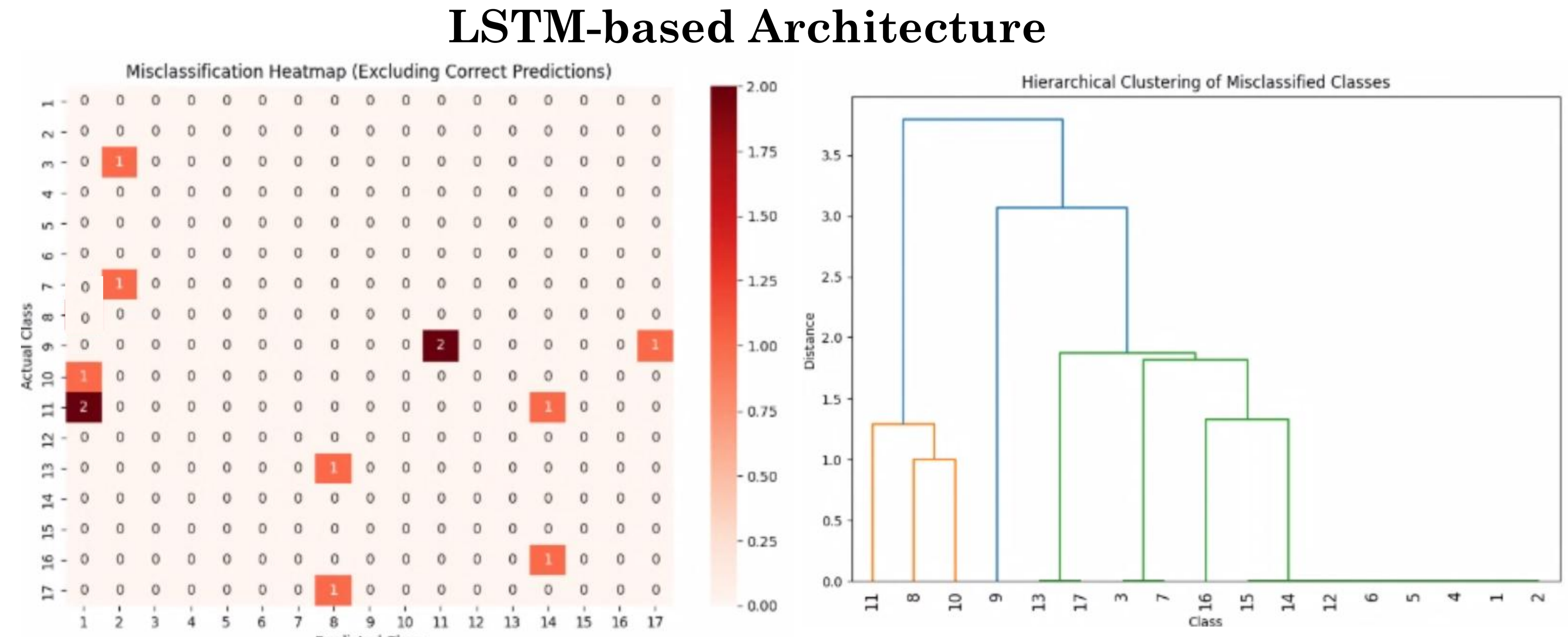
Sampling Rate: **100 Hz**



Installation of pier settlement system	Lowering pier 20 mm	Lowering pier 40 mm	Lowering pier 90 mm
Lowering pier 95 mm	Lifting of pier, tilt of foundation	New reference condition	Spalling of concrete at soffit, 12 m²
Spalling of concrete at soffit, 24 m²	Landslide of 1 m at abutment	Failure of concrete hinge	Failure of 2 anchor heads
Failure of 4 anchor heads	Rupture of 2 out of 16 tendons	Rupture of 4 out of 16 tendons	Rupture of 6 out of 16 tendons

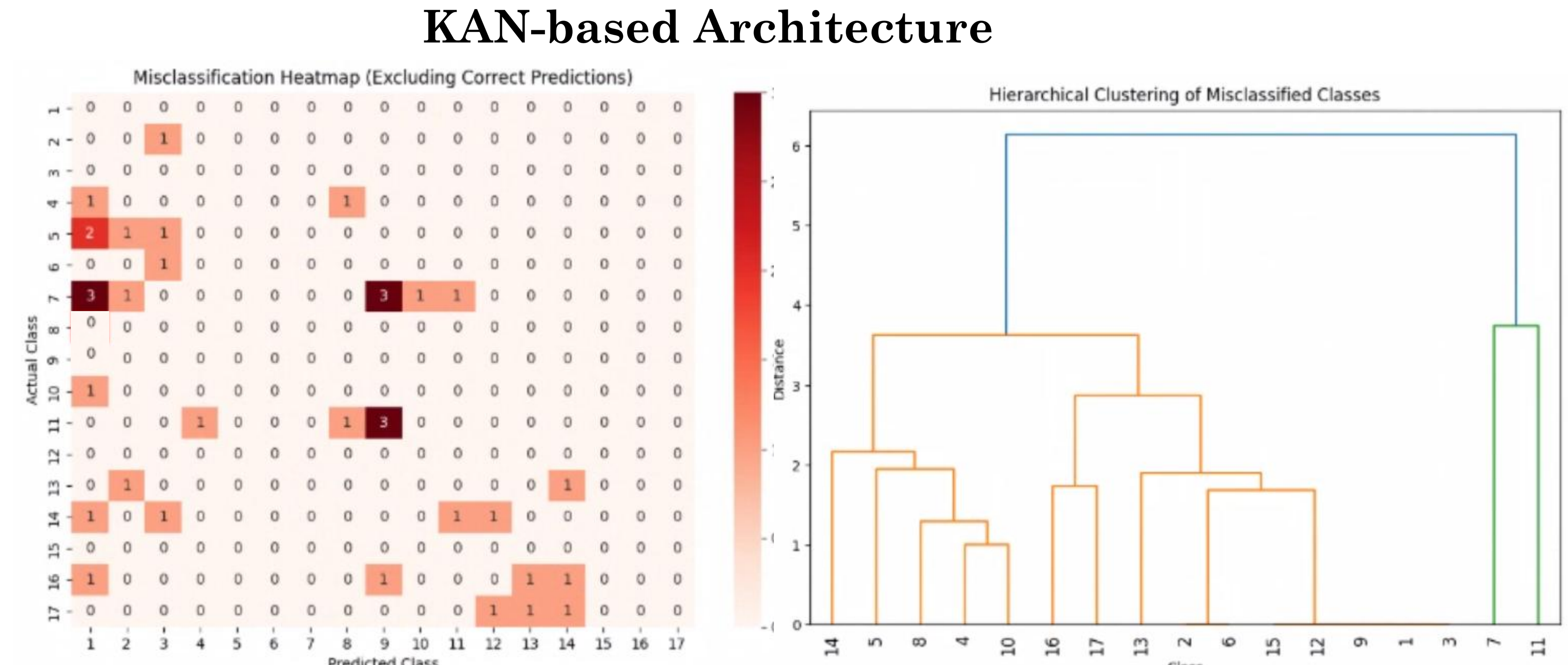
Results

LSTM-based Architecture



Higher accuracy 0.94, Lower Parameter Count 73,041, Better Class Separation

KAN-based Architecture



Lower accuracy 0.84, Higher Parameter Count 186,705, Worse Class Separation

Research Directions: Optimize KAN Architecture, Investigate Hybrid Model Performance, Combine Structurally Similar Classes

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