# INDUCTION MOTOR FAULT ANALYSIS USING MULTI-INPUT CONVOLUTIONAL NEURAL NETWORKS ON EXPERIMENTAL MEASUREMENT DATA

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## What ?

We develop a 1D-CNN model that fuses vibration and current signals to diagnose induction motor faults:

- We use experimental data with various fault types and severities for training and evaluation.
- Signal features are analyzed in time and frequency domains to improve accuracy.
- Model performance is assessed by accuracy, F1-score, and confusion matrix.

## Why ?

- Induction motors are critical in industry, but existing fault monitoring methods mostly rely on single-signal analysis, limiting accuracy under complex or noisy conditions.
- Combining multiple signal sources with deep learning enables more reliable detection and classification of faults.
- This supports better predictive **maintenance** and reduces industrial **downtime**.

## Overview

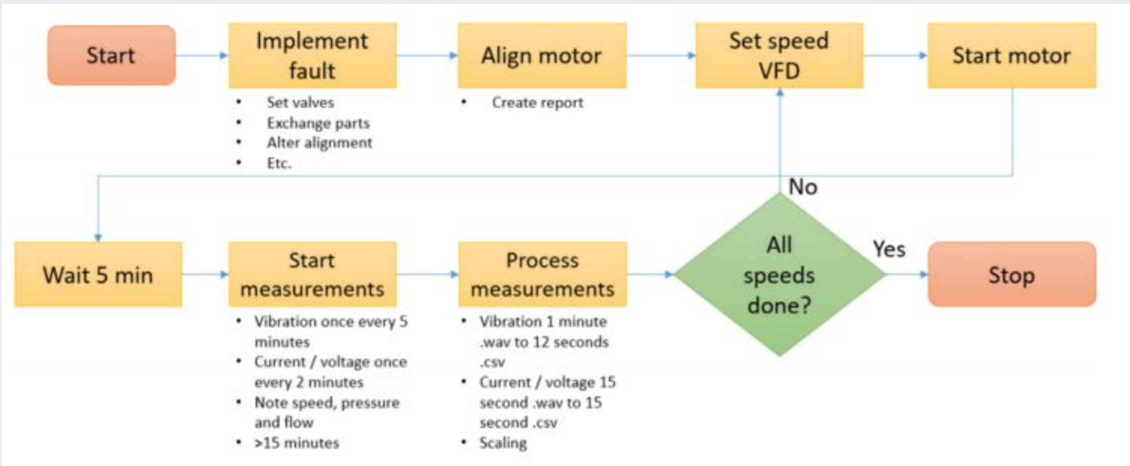


Figure 1: Flowchart measurement acquisition.

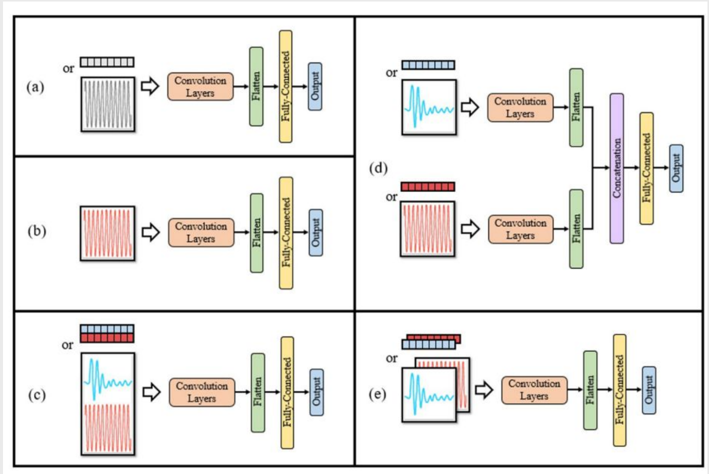

Figure 2: Model architecture

## Description

Parallel Processing → Feature Fusion → Fault Classification

**Branch 1: Vibration Signal**

- Input: Vibration signal (5 channels), normalized to [-1, 1], size [batch_size, 5, sequence_length].
- Structure: Conv1D (32 filters, kernel=3) → BatchNorm → ReLU → MaxPooling, repeated 2-3 times.
- Output: Local features reflecting mechanical faults (bearing, misalignment).

**Branch 2: Current Signal**

- Input: Current signal (3 channels), normalized, size [batch_size, 3, sequence_length].
- Structure: Conv1D → BatchNorm → ReLU → MaxPooling, parameters adjusted.
- Output: Features for electrical faults (stator, imbalance).

- **Flatten**: Transform each branch's output from the final MaxPooling layer into a 1D vector for further use.
- **Concatenation**: Combine the 1D vectors from vibration and current branches (e.g., 512 + 512 → 1024), uniting key features.
- **Fully Connected Layer**: Feed into fully connected layers (1024 → 256 → fault classes), applying BatchNorm for stability and ReLU for non-linearity.
- **Purpose**: Blend vibration and current signals to enhance fault detection accuracy.

- **Output**: Use the final fully connected layer to map the fused feature vector to probabilities for over 20 fault types, like bearing failure, shaft misalignment, and stator issues.
- **Loss Function**: Apply Cross-Entropy Loss to compare predicted probabilities with true labels, guiding model improvement.
- **Optimization**: Employ Adam optimizer with a dynamic learning rate via scheduler to update weights efficiently.
- **Target**: Target >95% accuracy and F1-score >0.9 on test set for robust, reliable fault detection.

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