# Enhancing Fault Detection & Classification in Wind Farm Power Generation Using Convolutional Neural Networks (CNN)

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## ABSTRACT

Real time fault detection and classification is important for power system stability and resilience of power grid to minimize the downtime and preventing cascading failures. Numerical relays (NRs) are used to detect fault in power system network and isolate the power to prevent the grid instability in the time of any fault. Faults may occur due to many factors such as lightning strikes, weather events (heavy rain, snow, and wind), accidents or power surges. However, integrating renewable energy sources, particularly wind farms introduces more complex and unpredictable fault conditions due to weather patterns that traditional numerical relays struggle to handle effectively. In addition micro grids impose more complex types of faults which may vary challenges to NRs to deal with and necessitate a "smart grid" where communication can happen between the Power Company and devices on the grid for either non-false response or fast responses. In this paper, a sliding window based continuous online monitoring Convolutional Neural Network (CNN) technique is proposed by leveraging the LVRT code to detect the type of faults on power generation system in wind farm.

To evaluate the performance of the proposed model, extensive simulations on different fault condition are conducted using MATLAB/Simulink. Electrical fault data are converted to the visualized images, which are fed to the neural network. To validate our model, a detailed analysis was performed with a different number of hidden layers. The proposed model is well performed in fault detection and classification.

## OBJECTIVES

•Develop a robust AI based model using CNN for quickly and precisely fault detection in Wind farm power generation.
•Design & Implement a prototype of an "Artificial Intelligence-based Smart Power System Relay" that improves the reliability and efficiency of fault detection in renewable energy system

## METHODS

The Convolutional Neural Network (CNN) model in Fig 1 is designed to detect and classify the fault from time-series data by automatically extracting meaningful features. The model takes images from time-series data as input. Before feeding the data into the model, preprocessing steps such as segmentation has been applied to enhance learning efficiency, which will consider as sliding window in real time.
The initial stage involves feature extraction. The primary Convolutional layer applies a set of filters to detect basic patterns within the time-series data. The output of this layer is passed through a pooling layer, which reduces the dimensionality while preserving critical information. The process is repeated in further 2nd and 3rd Convolutional layers, where higher-level features are learned. Each Convolutional layer captures progressively more details features, allowing the model to understand complex temporal dependencies.
The final stage focuses on classification. After the final pooling layer, the extracted feature maps are flattened into a one-dimensional vector. This vector is passed through fully connected layers, where neurons learn relationships between the extracted features. The final output layer produces the classification result.

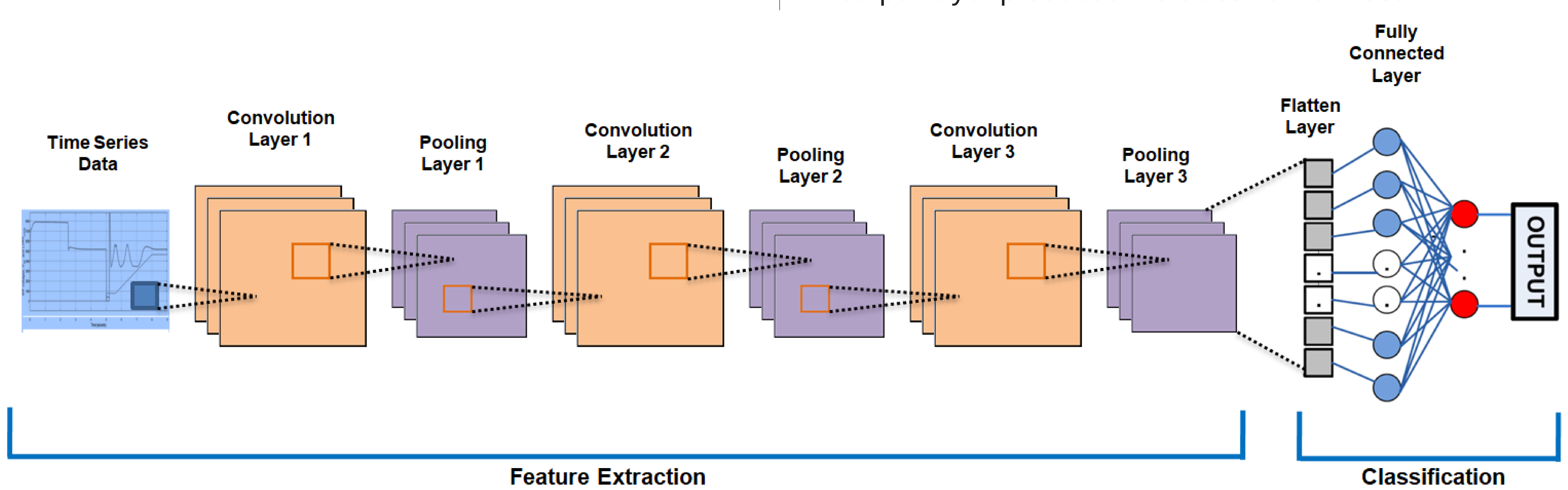


*Fig 1: Architecture of CNN Model*

**MATLAB/SIMULINK model of the studied system**

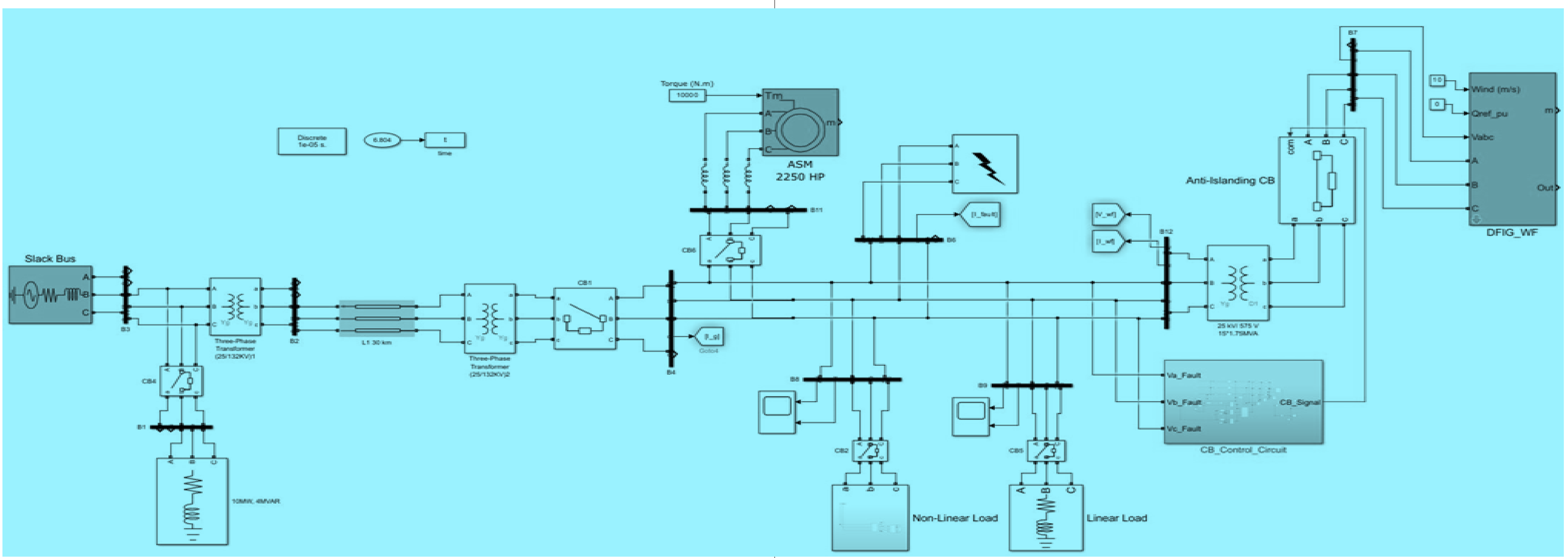


*Fig 2: MATLAB/Simulink Model for Data Collection*

## DATA COLLECTION & PROCESSING

To assess the effectiveness of the proposed CNN-based fault detection model during a grid fault and to determine the most effective LVRT has been used, the power system shown in Figure 2 is simulated using Matlab/Simulink for various fault types and locations. A 25 kV, 60 Hz power plant with a 25/132 kV step-up transformer powers the power system. A 20 MVA wind farm is then connected to the grid using a 13.8 kV transmission line and a 132/13.8 kV transformer. The grid and WF, which has a 0.575/13.8 kV step-up transformer, are providing 30 MVA loads which are located at the 13.8 kV level. In figure 3 a Line to Ground fault curve has been shown.

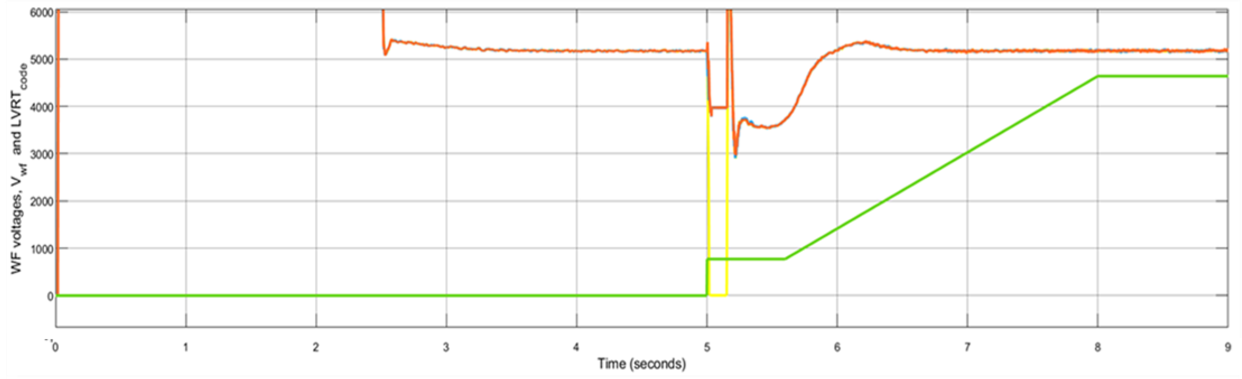


*Fig 3: A Typical Line Ground Fault Curve*

The first step of data processing is data windowing, where the fault data are split into different windows. In the proposed model, the data is partitioned into non overlapping sliding windows for fault detection in power system. This method ensures the whole dataset into different discrete segments where each window is processed independently. Window Partitioning Process: The input data is selected from a range of rows, with the total number of rows denoted as, R = End Row – Start Row +1. The total number of windows, N, is defined, and the size of each window, W, is calculated as: W= N/R. Each window is treated as a self-contained unit with the RMS values of each phase voltage. In single simulation, the number of divided windows is 100 with 40,000 of data points for offline analysis and data processing. Transitioning this methodology to real-time applications introduces critical considerations, particularly in terms of fault detection accuracy and computational efficiency.

## RESULTS

The training and validation performance of the CNN model for time-series fault detection and classification is evaluated using accuracy and loss metrics as fig 4.
With the number of epochs, the training accuracy reaches 98% while validation accuracy stabilizes slightly below it, suggesting a strong learning trend with some fluctuations. The minimum gap between training and validation accuracy indicates that the model works well with minimal overfitting.

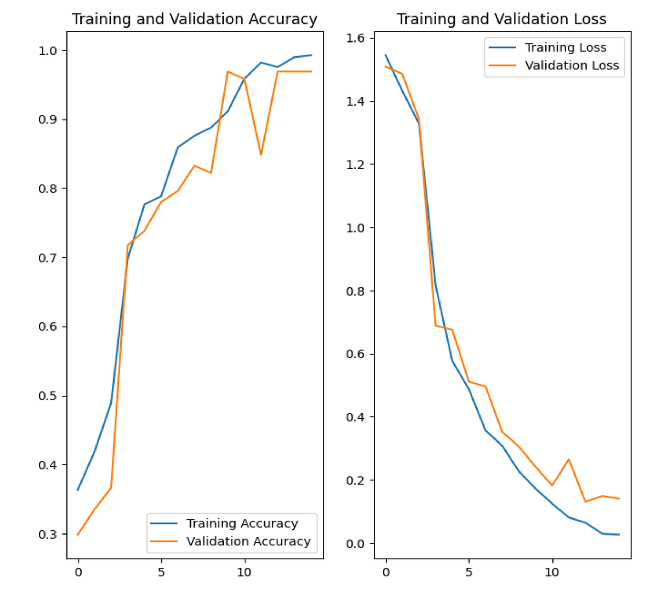


*Fig 4: Accuracy & Loss Curve*

## CONCLUSIONS AND RECOMMENDATION

In this research a novel CNN model for fault detection and classification has been developed in the application of Wind farm power generation. The proposed CNN model utilizes the three phase voltage and LVRT voltage level code for detection and classification task. The significant improvement of our model is leveraging the LVRT code for protection grid from destabilization under faulty condition of wind farm
As a part of further work we will work on the following improvement:
•Generate more fault data in different fault class to train the model.
•Improve the efficiency by utilizing optimization technique.
•Design and implement a smart device to run our model in real time situation.

### References

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