CHAPTER 1
INTRODUCTION

In contemporary power electronics, the H-bridge inverter is an indispensable component, frequently employed in diverse domains such as motor control, electric vehicles, and renewable energy systems. The H-bridge inverter's function is to convert direct current (DC) into alternating current (AC), a process pivotal for interfacing storage units like batteries with AC machinery or grid systems. Ensuring the reliability and efficiency of these inverters is of paramount importance, as any fault can lead to operational inefficiencies, system failures, or hazardous conditions. Traditional fault detection methodologies often rely on model-based approaches, which can be limited by the complexity of the models and the variability in operating conditions.

With the rise of artificial intelligence, deep learning techniques have revolutionized the field of anomaly detection, offering a data-driven approach to identifying and diagnosing system faults. This project harnesses the power of deep learning to innovate fault detection in H-bridge inverters. By adopting a Convolutional Neural Network (CNN) model, we aim to accurately classify the operational state of the inverter and swiftly detect anomalies.

The data-driven nature of this approach circumvents the limitations of traditional methods by enabling the system to learn from the data itself, which includes a variety of normal and fault conditions. This self-learning capability allows for the accommodation of non-linearities and unknown dynamics in the system, leading to enhanced detection accuracy and generalization across different types of H-bridge inverter designs and applications.

The introduction of this deep learning-based fault detection system promises significant improvements in operational reliability and safety, ensuring that any faults are promptly identified and addressed. This not only contributes to the longevity of the inverters but also supports the sustainability of the energy systems they serve. By integrating this intelligent diagnostic system, we move closer to realizing self-maintaining power electronic systems that can adapt to evolving conditions and maintain optimal performance.

1.1. Project Overview

The current project focuses on Fault Analysis Hardware Device that detects specific types of faults and their location in the semi-conductor circuit by examining the waveform patterns of the load voltage through the use of Image Processing trained Deep Learning algorithms.

When a Fault occurs in any Power Converter circuit, it is very difficult to identify the exact switch (or even multiple switches) in which the fault has occurred. As a result of which, the whole circuitry is changed. We wanted to devise a method that would identify the type of fault and the location of the switch in which the fault has occurred, remotely without touching the circuit.

For a 4-switched H-Bridge circuit, there are different types of waveforms that show at the load for faults in different switches (single and combination of switches) and for different types of faults in those switches. We are going to create a dataset of these images by artificially creating a fault in every switch and their combination and then we would feed the datasets (in the form of images) of these waveforms to a Deep Learning Algorithm and train the model to detect a specific type of fault in a specific switch or combination of switches.

These faults will be detected remotely by looking at the load voltage waveform with the help of image processing. Our device would contain a camera that would take pictures of the waveform and then with the help of the trained deep learning model, it would identify which class of waveforms they belong to, to tell us in which switch(s) the fault has occurred and what type of fault it has.

The crux of the system lies in the deep learning model, carefully trained using the generated dataset. The neural network within the model is designed to comprehend and classify the diverse waveform patterns corresponding to different fault scenarios. Architectural considerations, including the selection of activation functions and neural network parameters, are made with precision to optimize fault detection accuracy.

Validation and testing are integral components of the project, with performance metrics such as accuracy, precision, recall, and F1 score serving as benchmarks for the reliability and effectiveness of the fault detection system. The device undergoes testing across various scenarios, encompassing different fault types and combinations, ensuring its robustness under diverse conditions

Looking ahead, the project sets the stage for scalability, envisioning potential applications of this approach to more complex circuits or different types of power converters. The adaptability of the system to varying circuit configurations is a focal point for future development, as is its ability to handle different manifestations of faults, thereby enhancing its utility in a broader spectrum of applications.

The potential impact on circuit reliability, reduced downtime, and overall system efficiency is substantial, marking a significant contribution to the advancement of semiconductor technology and its applications in power converters.

1.1.1. Technical Terminology

Fault Analysis Simulink Circuit: Made H-bridge inverter on Matlab an online simulator.

Load Voltage: The voltage across the load or output in the circuit.
Waveform Patterns: Distinctive shapes and characteristics of voltage waveforms corresponding to different circuit conditions.

Image Processing:

Feature Extraction: The process of identifying and extracting relevant features from images, crucial for subsequent analysis.
Pre-processing: Techniques applied to enhance or modify images before feeding them into algorithms.

Deep Learning:

Neural Network Architecture: The design and configuration of layers in a neural network.
Activation Functions: Mathematical functions that introduce non-linearity to neural networks, enabling them to learn complex patterns.
Dataset Creation:
Artificial Fault Induction: Simulating faults in the circuit for dataset generation.
4-Switched H-Bridge Circuit: A circuit configuration commonly used in power electronics.
Deep Learning Training:
Training Dataset: The set of data used to train the deep learning model.
Optimization Parameters: Parameters adjusted to enhance the performance of the deep learning model.

Neural Network Layers:

Different layers in the deep learning model, such as input, hidden, and output layers.

Implementation and Deployment:

Real-time Analysis: Processing data and providing results immediately upon data capture.

Validation and Testing:

Performance Metrics: Quantitative measures like accuracy, precision, recall, and F1 score.

Incorporating these technical terms articulates the intricacies and sophistication involved in your project, emphasizing the amalgamation of semiconductor principles, image processing, and deep learning techniques for fault analysis in power converter circuits.

1.1.2. Problem Statement

Power Converter circuits are highly complex with many semi-conductor switches working at the same time and/or in synchronization to deliver the required function they have. Hence when even a small fault occurs in any switch, it is close to impossible to detect in which switch the fault has occurred. Moreover, there can be multiple switch that are faulty at the same time which have different types of faults in them.

In standard industry practice, whenever any of the switches in the power converter gets faulty, there is no sure way to detect the faulty switch and the type of fault. The main methods that are currently used to detect the location of faults are listed below-

Circuit Testing: Using a multimeter or other electrical testing equipment, individual components of the circuit are tested for functionality.

This method is time-consuming and requires specialized equipment and technical expertise to conduct properly.

Thermal Imaging: Using a thermal imaging camera, hot spots or areas of high temperature are identified (which indicate a fault).

This method is not always accurate as hotspots can be caused by other factors than faults, such as high ambient temperature.

Simulation tools and Fault Diagnosis Algorithms are used to simulate the circuit and identify potential fault locations.

But simulation may not always model the behavior of the actual circuit especially if the circuit contains non-linear or dynamic components.

Nowadays, the use of power converters is so widespread that there is close to no gadget that is working without power converter circuitry. Hence it is extremely important to come up with a solution to this problem that is efficient enough to detect the faulty switch and save the resources that are spent to solve this problem.

1.1.3. Design Goals

We want to design our device in such a way that that the location and type fault(s) in the circuit is detected non-invasively, i.e., without touching/disturbing the circuit. Hence to achieve this objective a camera is required that would capture images of the load voltage waveform, feed it to a Single Board Computer (SBC) that would then compute the specification of the fault using a Deep Learning algo and display it to us.

For all of this to work, it is first required that we get the waveform of the load voltage of the circuit through a scope (CRO, DSO etc.).

A huge amount of Image dataset is required to train the model so that it accurately computes and tell us the faulty switch. Also, for this the computational power required is high. Also, the uncontrollable environmental factors such as temperature increase the amount of dataset in the form of images even more. This is because these factors affect the load voltage waveform. Hence, to account the environmental factors, the dataset will have to include the images of waveforms at different environmental conditions.

Because the number of equipment is increased, it is hard to make this approach of fault detection cost effective.

1.2. Need Analysis

1.2.1 Complexity of Fault Identification:

Issue: The conventional methods for identifying faults in power converter circuits are often labor - intensive and time-consuming.

Need: A more advanced and efficient system is necessary to pinpoint the exact location offaults, addressing the complexity associated with conventional fault identification techniques.

1.2.2. Impact of Undetected Faults:

Issue: Undetected faults in power converter circuits can lead to severe damage to the circuit and associated components.

Need: An urgent need exists for a system that can promptly detect and identify faults to mitigate potential damage, ensuring the reliability and longevity of the semiconductor circuit.

1.2.3. Remote Fault Detection:

Issue: Traditional fault detection methods may require physical access to the circuit, leading to downtime and potential risks.

Need: A remote fault detection system is imperative to eliminate the need for physical intervention, allowing for swift and precise fault identification from a distance.

1.2.4. Deep Learning for Pattern Recognition:

Issue: Conventional methods may struggle to adapt to the diverse and complex patterns associated with different fault scenarios.

Need: Deep learning algorithms provide a solution by learning and recognizing intricate waveform patterns, allowing for a more nuanced and precise fault analysis.

1.2.5. Real-time Analysis:

Issue: Delayed fault analysis can lead to prolonged downtime and increased risks.

Need: The ability to perform real-time analysis ensures immediate detection and reporting of faults, minimizing downtime and potential damage to the circuit.

1.2.6. Dataset for Training:

Issue: Limited availability of diverse and comprehensive datasets for training fault detection models.

Need: The creation of a dataset with artificially induced faults provides the necessary foundation for training deep learning models, ensuring robust and accurate fault detection.

1.2.7. Scalability and Adaptability:

Issue: Existing solutions may lack scalability and adaptability to different circuit configurations.

Need: A system that is scalable to handle more complex circuits and adaptable to variations in circuit configurations is essential for broader applicability.

1.3. Research Gaps:

1.3.1. Integration of Real-world Variability:

Limited studies address the impact of real-world variability in semiconductor circuits on the accuracy of fault detection models. There is a need to explore how variations in components, temperature, and other environmental factors affect the robustness of the proposed system.

1.3.2. Adaptability to Diverse Circuit Configurations:

Current research may not extensively cover the adaptability of the proposed fault detection system to diverse circuit configurations beyond the 4-switched H-Bridge. Investigating how the system performs in different circuit architectures and topologies is essential for broader applicability.

1.3.3. Dynamic Fault Analysis in Real-time:

Current literature may not sufficiently explore the challenges and solutions for achieving dynamic fault analysis in real-time. Investigating methods to enhance the speed of fault detection without compromising accuracy is crucial for practical applications.

1.3.4. Cost-Benefit Analysis for Implementation:

Limited studies may provide a comprehensive cost-benefit analysis of implementing the proposed hardware device. Researching the economic feasibility and potential return on investment for adopting this fault detection system in practical industrial settings is essential.

1.4. Problem Definition and Scope

The problem at hand revolves around the inherent challenges in fault analysis within semiconductor circuits, particularly in power converter circuits. Traditional methods of fault identification in these circuits are often cumbersome, time-consuming, and lack precision in pinpointing the specific switch or switches where a fault has occurred. Undetected faults can lead to severe damage, posing a significant threat to circuit reliability and associated components.

The complexity of fault identification is exacerbated by the need to remotely detect and identify faults without physical intervention. Current approaches may not provide the level of accuracy and immediacy required for effective fault analysis. As a result, there is a pressing need for an advanced fault analysis system that combines image processing and deep learning techniques to enable remote and precise fault detection within semiconductor circuits.

The scope of the project is defined by the development and implementation of a hardware device designed to address the identified challenges in fault analysis. The primary focus is on a 4-switched H-Bridge circuit, a configuration commonly used in power converters. The project aims to integrate image processing techniques with deep learning algorithms to analyse waveform patterns in the load voltage, facilitating the remote identification of specific fault types and their locations.

1.5. Assumptions and Constraints

A critical constraint of our project pertains to the fixed switching frequency required for fault detection. The model is trained with a specific switching frequency, and any alterations in this frequency necessitate retraining the model with a new dataset. Consequently, users are confined to a singular switching frequency for accurate fault detection. This constraint acknowledges the model's sensitivity to variations in switching frequency and emphasizes the importance of aligning operational parameters during both training and detection phases to ensure optimal performance.

Our project is premised on the assumption that the H-Bridge circuit operates under normal conditions during fault detection. This entails the absence of any unexpected errors or anomalous behaviors that could impact the accuracy of the fault detection model. This assumption allows us to focus on the systematic identification of faults based on expected waveform patterns without accounting for unpredictable circuit irregularities

1.6. Objectives

1.6.1 Develop a remote method for detecting faults in H-Bridge Inverter that does not require physical access to the circuit.

1.7. Methodology Used:

1.7.1 Simulation: To simulate and analyse the H-Bridge circuit. We made the simulation of an H-Bridge converter along with its control circuit on MATLAB Simulink on the platform MATLAB 2021b.

1.7.2 Dataset generation by attaching a voltage scope at the load of the circuit to get the load voltage waveform of converter.

1.7.3 To study the Convolutional Neural Network (CNN). We are using the TensorFlow environment. The libraries used are Keras, Pandas, Numpy, OS, Random CV2 library and various layers of the CNN model are also being used. We are using the Anaconda (Jupyter) to code all this in python.

1.7.4 CNNs are typically composed of a series of convolutional layers, pooling layers, and fully connected layers. Convolutional layers apply filters to the input image to extract local features. Pooling layers reduce the dimensionality of the feature maps produced by the convolutional layers. Fully connected layers are used to combine the features extracted from the convolutional layers and to produce the final output of the network.

1.7.5 To train a CNN for binary classification, we need a dataset of labeled images, where each image is assigned to one of the two categories. We can then use this dataset to train a CNN model using the following steps:

- Preprocess the images. This may involve resizing the images, normalizing the pixel values, and converting the images to a format that is compatible with your CNN model.
- Split the dataset into training, validation, and test sets. The training set will be used to train the model, the validation set will be used to evaluate the model during training, and the test set will be used to evaluate the model after it has been trained.
- Choose a CNN architecture.
- Compile the model. This involves choosing a loss function, optimizer, and other hyperparameters.
- Train the model. This involves feeding the training set to the model and adjusting the model's parameters to minimize the loss function.
- Evaluate the model. Once the model is trained, evaluate its performance on the validation and test sets.

We have used metrics like loss and accuracy loss to measure how well a machine learning model is performing on a given dataset. Loss is calculated by comparing the model’s predictions to the actual labels. Validation loss is similar to loss but it is calculated on a held- out validation set instead of a training set. This is done to prevent overfitting and get a more realistic estimate of the model’s performance in unseen data.

1.8. Novelty of Work

The novelty of the work lies in its integration of advanced technologies and methodologies to address the challenges in fault analysis within semiconductor circuits. Key aspects contributing to the novelty of the project include:

1.8.1 Integration of Image Processing and Deep Learning: The project introduces a novel approach by combining image processing techniques with deep learning algorithms. This integration allows for a more nuanced analysis of load voltage waveforms, enabling the system to recognize complex fault patterns with higher accuracy.

1.8.2 Remote Fault Detection without Physical Intervention: The emphasis on remote fault detection without the need for physical intervention is a novel aspect of the project. This feature minimizes downtime and risks associated with manual inspection, offering a practical solution for real-world applications.

1.8.3 Diverse and Comprehensive Fault Dataset: The creation of a comprehensive dataset with artificially induced faults in a 4-switched H-Bridge circuit is a novel contribution. This dataset includes a wide range of fault scenarios, ensuring that the deep learning model is trained on diverse patterns, enhancing its robustness.

1.8.4 Real-time Fault Analysis Capabilities: The achievement of real-time fault analysis capabilities sets the project apart. The ability to swiftly identify and report faults as they occur is crucial for prompt decision-making and preventative maintenance, distinguishing the project from conventional fault detection methods.

1.8.5 Scalability and Adaptability Considerations: The project addresses the scalability and adaptability challenges associated with fault detection systems. By exploring how the system performs with larger circuits and its adaptability to different configurations, the project aims to provide a versatile solution applicable to a range of scenarios.

1.8.6 Human-in-the-loop Interaction and User-Friendly Design: The consideration of human-in-the-loop interaction and the design of user-friendly interfaces represent a novel aspect of the project. Acknowledging the role of human operators in the fault analysis process enhances usability and facilitates effective collaboration between the system and operators.

1.8.7 Optimization of Energy Efficiency: The focus on optimizing the energy efficiency of the hardware device is a novel consideration. This aspect not only aligns with sustainability goals but also ensures that the fault detection system operates efficiently, minimizing energy consumption.

1.8.8 Comprehensive Cost-Benefit Analysis: The inclusion of a comprehensive cost-benefit analysis contributes to the novelty of the project. By evaluating the economic feasibility and potential return on investment, the project goes beyond technical aspects to address practical considerations for implementation.

In summary, the novelty of the work lies in its holistic approach, combining innovative technological solutions with practical considerations, and addressing a spectrum of challenges in fault analysis within semiconductor circuits.

CHAPTER 2
Requirement Analysis (Software / Hardware)

2.1 Literature Survey

An H-bridge is a type of electronic circuit used to control the direction of a DC motor or other load by switching the polarity of the voltage applied to it. Fault detection in H-bridge circuits is an important area of research as it helps in preventing equipment failure and accidents. In this literature survey, we will explore some of the recent research on fault detection in Poer circuits.

S. Samiee in 2019 proposed a fault diagnosis method for power electronic converters using deep learning techniques. The authors used a convolutional neural network (CNN) to detect and diagnose faults in H-bridge inverters. The proposed method achieved high accuracy in detecting various faults in H-Bridge inverters.[1]

A. M. Ali in 2019 proposed a fault diagnosis method for H-bridge inverters using a wavelet transform and artificial neural network. The authors used wavelet transform to extract features from the current and voltage signals, and artificial neural network to classify the different types of faults. The proposed method achieved high accuracy in detecting various faults in H-bridge inverters. Sure, here's two more pages on fault detection in H-bridge circuits.[2]

A. Badri in 2020 proposed a fault detection and diagnosis method for H-bridge multilevel inverters using wavelet packet transform and fuzzy logic. The authors used wavelet packet transform to extract features from the current and voltage signals, and fuzzy logic to classify the different types of faults. The proposed method achieved high accuracy in detecting various faults in H-bridge multilevel inverters.[3]

Y. Wang in 2021 proposed a fault detection and diagnosis method for H-Bridge inverters based on current monitoring and machine learning techniques. The authors used a deep neural network to classify different types of faults in H-bridge inverters. The proposed method achieved high accuracy in detecting various faults in the H-bridge inverter.[4]

Balamurali Krishna P, Pampa Sinha, Manoj Kumar Maharana, Chitralekha Jena, AV Pavan Kumar, Karthik Akkenaguntla, "Power System Fault Detection Using Image Processing and Pattern Recognition", International Conference on Applied Electronics, Signal Processing and Communication, (2021) [5]

The above literature survey highlights some of the recent research on fault detection in H- bridge circuits. The proposed methods in these papers show that machine learning and signal processing techniques are effective in detecting and diagnosing faults in H-bridge inverters.

Machine learning algorithms have shown promising results in fault detection and diagnosis. They can learn from data and identify patterns that are difficult to detect using traditional methods. Signal processing techniques such as wavelet transform, PCA, and Fourier transform can be used to extract features from signals and reduce the dimensionality of the data.

The combination of machine learning and signal processing techniques can lead to more accurate and robust fault detection and diagnosis methods. Hybrid algorithms that combine different machine learning and signal processing techniques have shown even better results in detecting and diagnosing faults in H-bridge circuits.

In conclusion, fault detection and diagnosis in H-bridge circuits is an important area of research that can help in preventing equipment failure and accidents. The literature survey discussed above highlights some of the recent research on fault detection in H-bridge circuits using machine learning and signal processing techniques. The proposed methods show promising results in detecting and diagnosing faults in H-bridge circuits, and further research in this area can lead to even better results.

2.2 Requirements Specifications

In our research, we employed six distinct optimization algorithms to assess their effectiveness in enhancing the performance of our deep learning model. Subsequently, we generated graphical representations illustrating the outcomes of these six optimization algorithms in conjunction with two specific batch sizes, namely 16 and 32. Furthermore, for each batch size, we applied three distinct learning rates: 0.0001, 0.001, and 0.01. This approach yielded a total of six sets of results for each optimizer, encompassing a comprehensive evaluation of their respective performance.

The graphical representations in our study depict two key performance metrics: accuracy and validation accuracy, which are presented in a single graph, and loss and validation loss, which are concurrently displayed in another graph. These visualizations are structured to illustrate the performance outcomes for each combination of batch size, learning rate, and optimizer employed in our investigation.

Furthermore, in select instances, we have included a detailed depiction of the aforementioned performance metrics for specific epochs, providing a more granular insight into the evolution of model performance over the course of training.

2.3 Cost Analysis

No Cost for the project.

2.4 Risk Analysis

2.4.1 We first tried to take our waveform directly from a DSO, but the DSO wasn't working properly. So, we made a Simulink model of the H-Bridge circuit and attached a voltage scope to its load to take waveform dataset.

2.4.2 TensorFlow environment wasn't working on our systems as it is a very heavy environment and it took us three days of trying but we didn't reach to any conclusion. Finally, we installed an older version of TensorFlow to use in our model which then worked perfectly.

2.4.3 Our model exhibited issues related to overfitting and underfitting, which were discernible through the analysis of accuracy and loss graphs. This was evident from the lack of a consistent increase in accuracy, as it showed fluctuations over time.

2.4.4 Our model's accuracy and validation accuracy remained consistently below 0.3. Subsequently, we addressed this issue through the implementation of alternative optimizers and/or by adjusting the learning rate and batch size values.

CHAPTER 3
METHODOLOGY ADOPTED

3.1 Investigative Techniques

In the investigative phase of our project, we conducted an extensive review of related research papers to establish a comprehensive understanding of existing methodologies. For data collection, we employed MATLAB Simulink to create a customized simulation of the H- Bridge and its control circuit, capturing snapshots of waveforms to form our dataset. Model development commenced with a foundational three-layered CNN architecture, progressively evolving in complexity to enhance fault detection capabilities. The analysis procedure involved meticulous comparison of various evaluation metrics for each modification in the model, ensuring a systematic assessment of its performance at each stage. This multi-faceted investigative approach laid the groundwork for the successful development and refinement of our fault detection methodology for H-Bridge Inverters.

3.2 Proposed Solution

The anticipated solution for the current project addresses the complex challenge of fault detection in Power Converter circuits, specifically focusing on a 4-switched H-Bridge configuration. In response to the difficulty in pinpointing the exact switch responsible for a fault and the consequent need for circuit-wide changes, our proposed Fault Analysis Hardware Device aims to revolutionize fault identification. Leveraging Image Processing and Deep Learning algorithms, our device captures and analyzes load voltage waveforms remotely, obviating the need for physical contact with the circuit.

To create a comprehensive dataset for training the Deep Learning Algorithm, we will systematically induce faults in each switch and their combinations within the H-Bridge. This artificial generation of fault-specific waveforms will serve as the foundation for training the model to discern and categorize faults based on waveform patterns. The proposed device, equipped with a camera, will capture images of load voltage waveforms. These images will then be processed through the trained Deep Learning model, enabling the identification of specific fault types and their locations.

The innovative aspect of this solution lies in its ability to remotely detect faults with a high degree of precision, facilitating timely and targeted responses. By combining Image Processing and Deep Learning, our device offers a non-intrusive, yet accurate, means of fault analysis, thereby minimizing downtime and enhancing the overall reliability of Power Converter circuits. This solution is poised to significantly advance fault detection methodologies in semiconductor circuits, heralding a new era of efficiency and reliability in power electronics.

CHAPTER 4
DESIGN SPECIFICATIONS

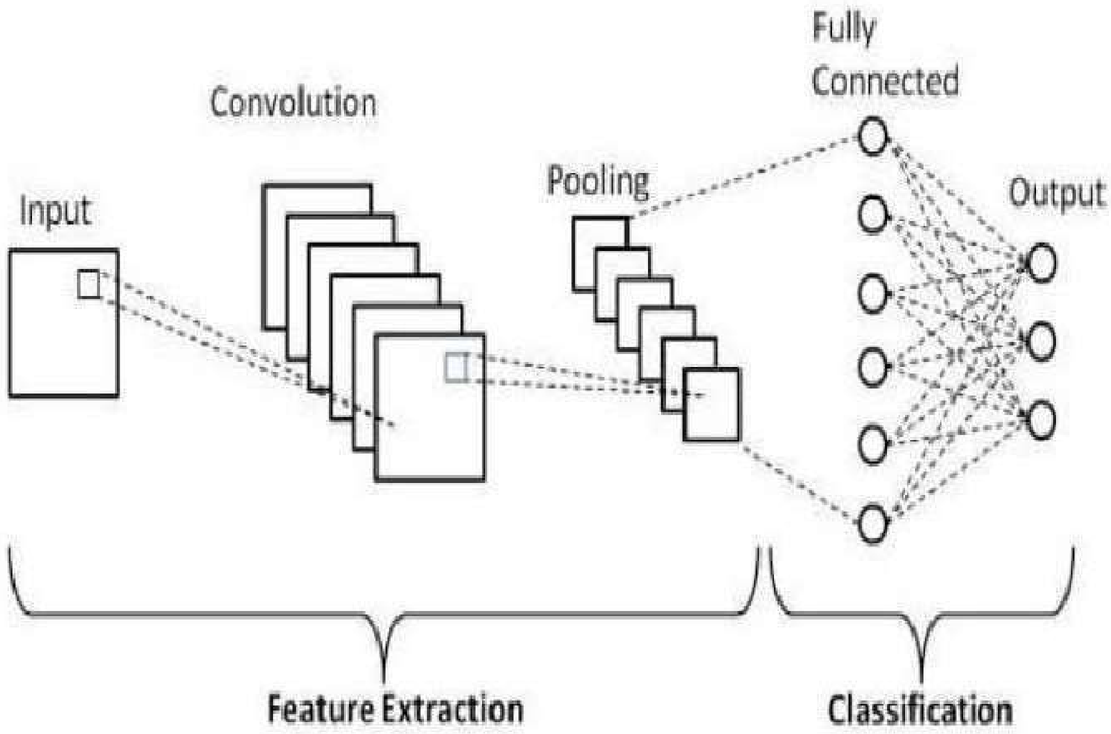

Figure 1 Architectural Design

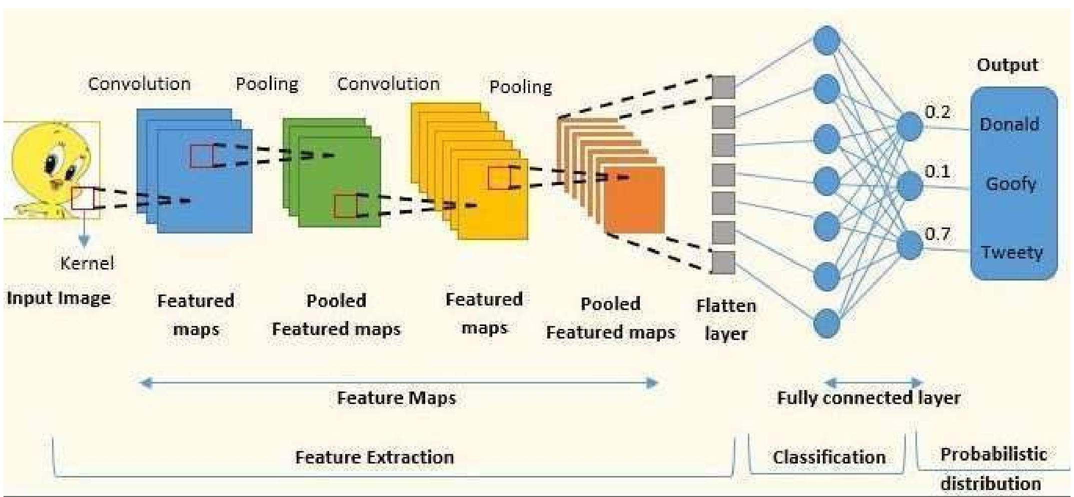

Figure 2 Architectural Design

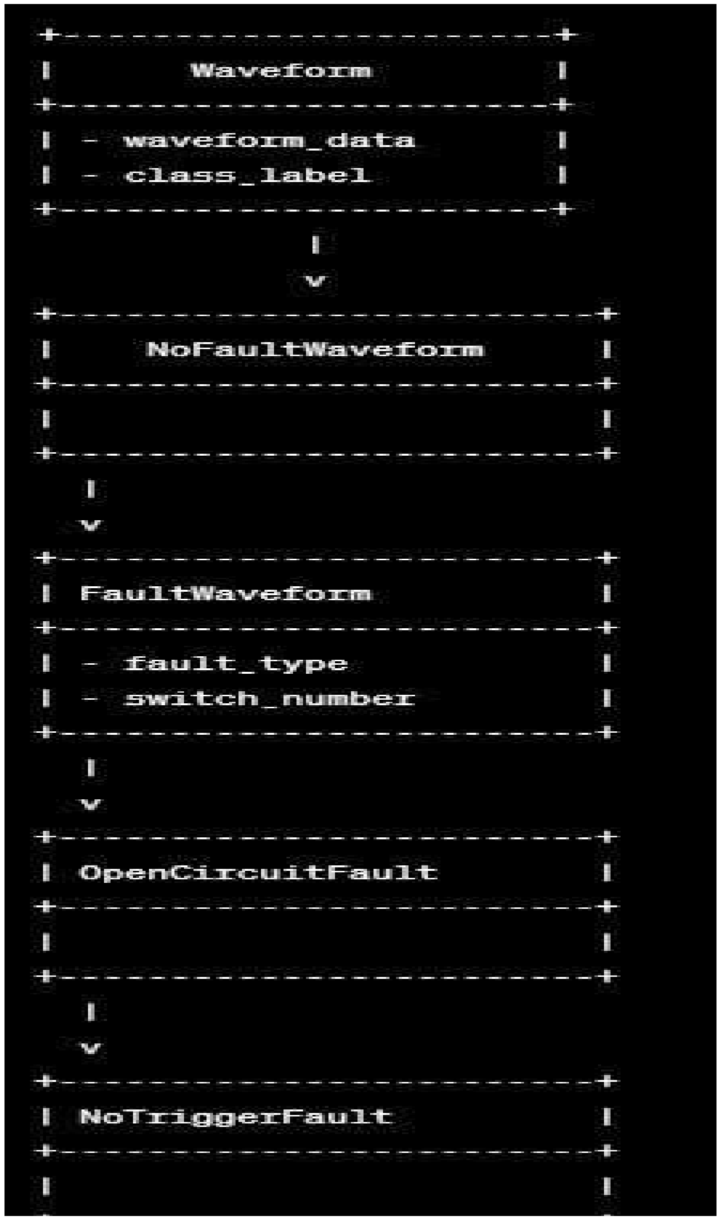

Figure 3 Class Design

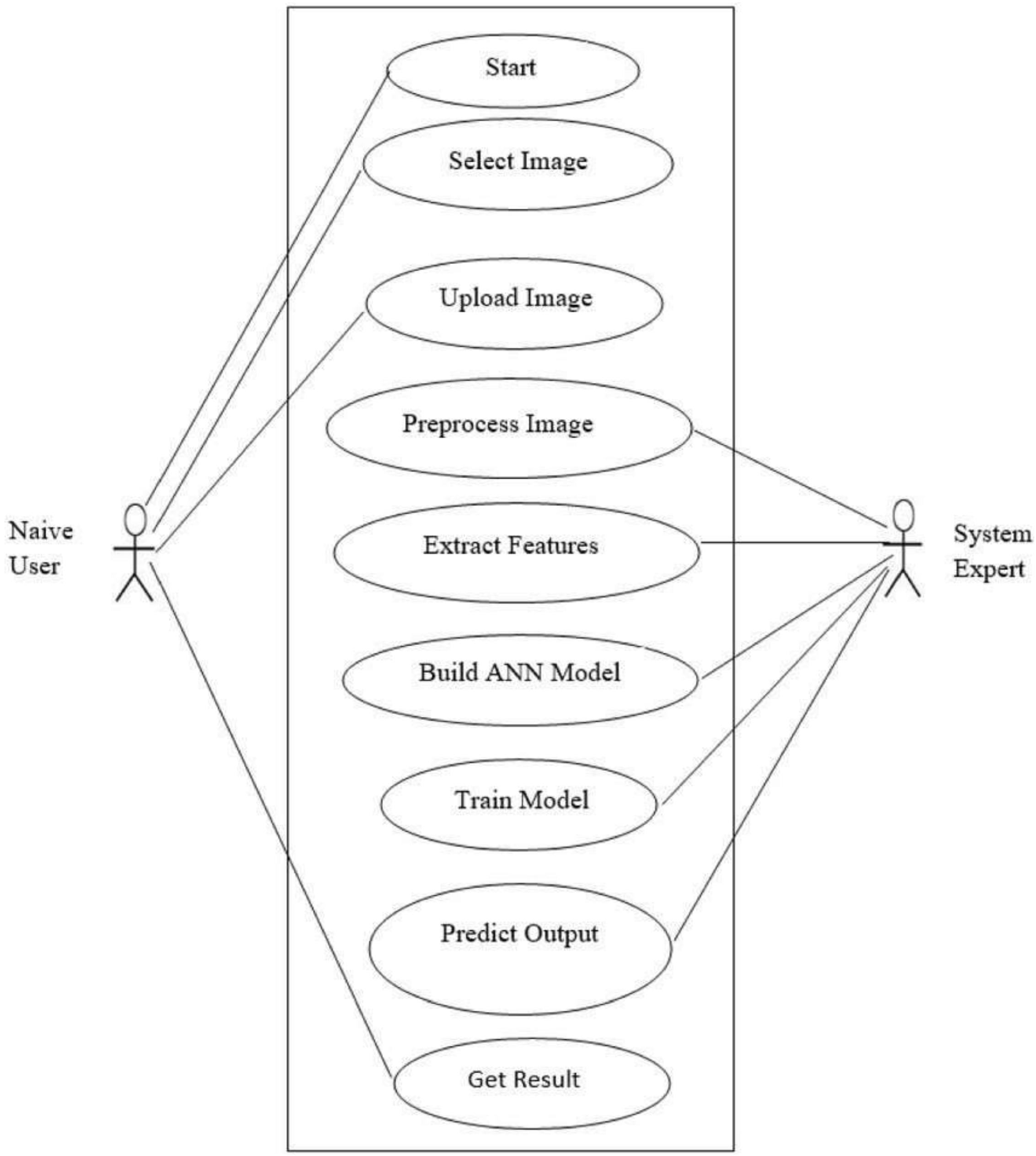

Figure 4 Use Case Diagram

CHAPTER 5
RESULTS AND DISCUSSION

5.1 Experimental Setup

5.1.1 Simulation: To simulate and analyze the H-Bridge circuit made the simulation of an H-Bridge converter along with its control circuit on MATLAB Simulink on the platform MATLAB 2021b. The circuit for the same is shown in fig

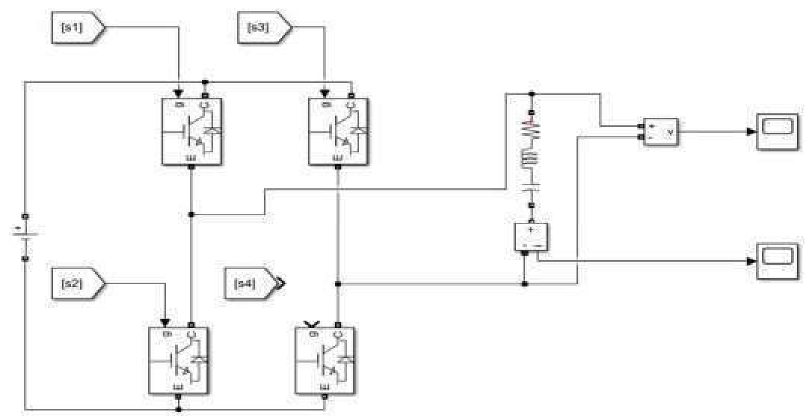

Figure 5 H-Bridge Simulation

Studied how the H-Bridge circuit worked and how its voltage waveform differed after every different type of fault. Also, its control circuit to understand in what way did the gate pulse of the IGBT (Insulated Gate Bipolar Transistor) are given. The control circuit is shown in fig.

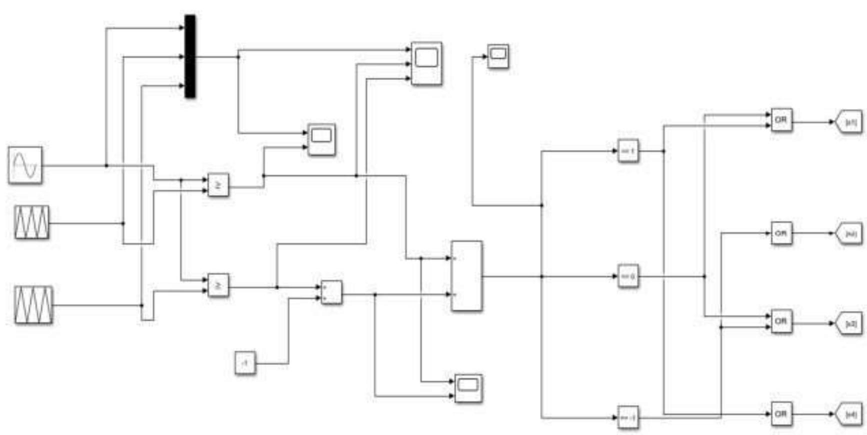

Figure 6 Control Circuit Simulation

5.1.2 Data Generation

Dataset generation by attaching a voltage scope at the load of the circuit to get the load voltage waveform of converter. The waveforms of No Fault and Fault conditions (No Trigger Pulse and Open Circuit Fault) are shown below---

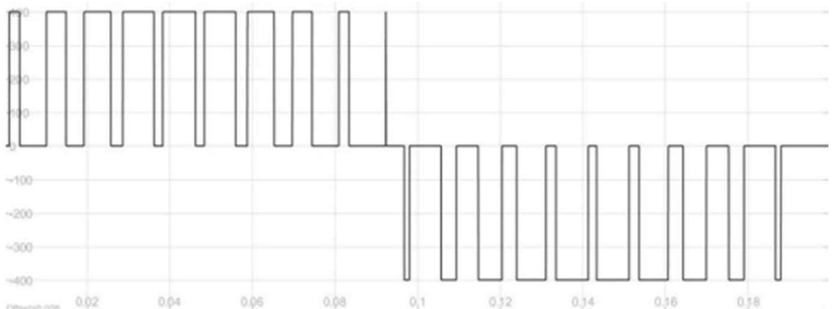

Figure 7 No fault H-Bridge Load Voltage Waveform

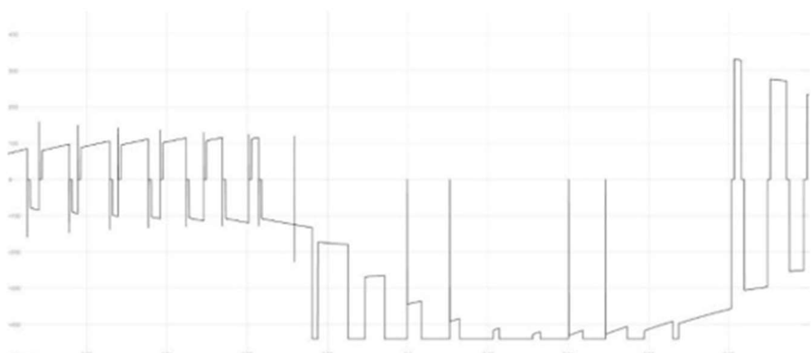

Figure 8 Switch 1- No Trigger Pulse

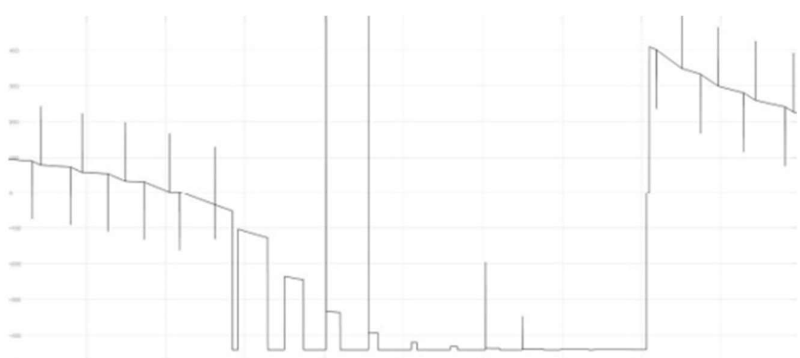

Figure 9 Switch 1-Open Circuit Fault

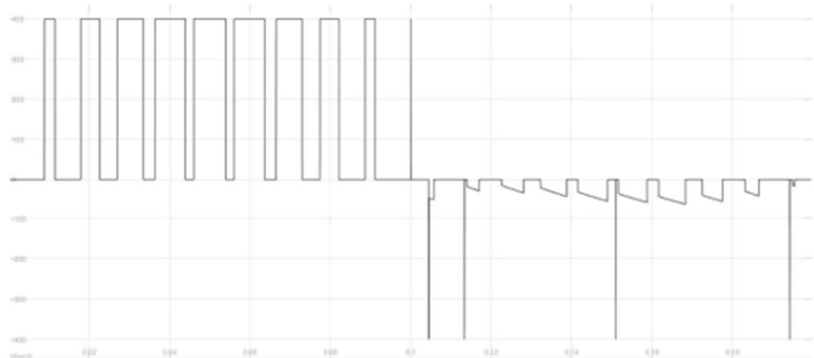

Figure 10 Switch 2 - No Trigger Pulse

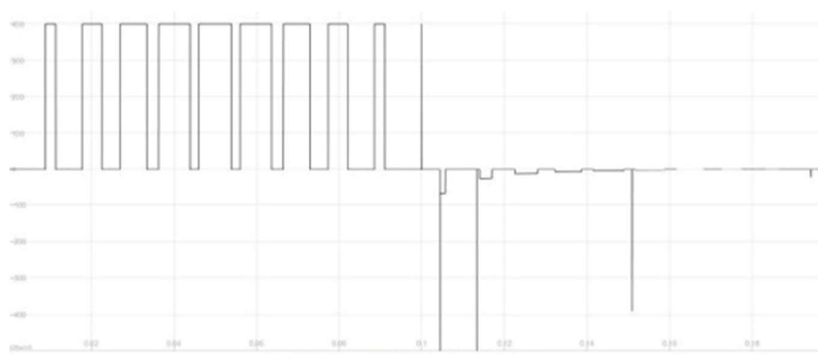

Figure 11 Switch 2 - Open Circuit Fault

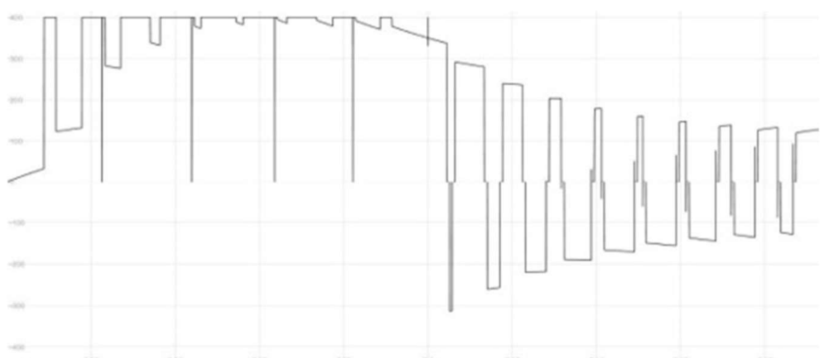

Figure 12 Switch 3 - No Trigger Pulse

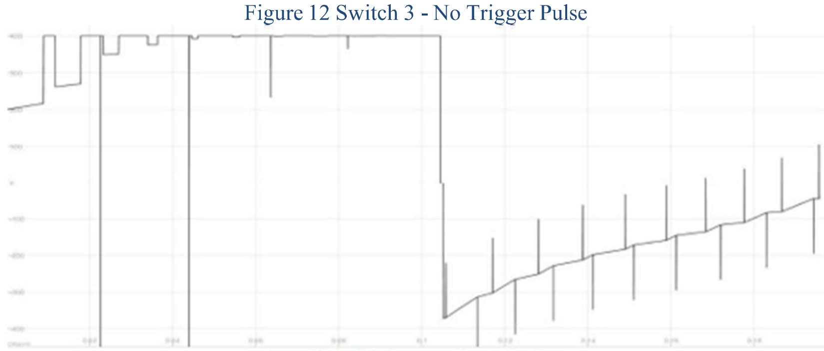

Figure 13 Switch 3 - Open Circuit Fault

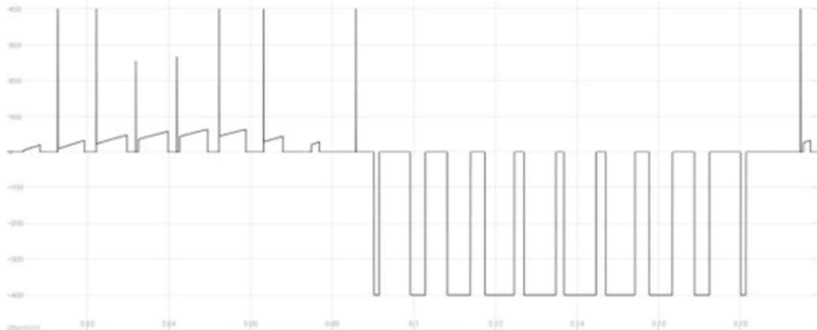

Figure 14 Switch 4 - No Trigger Pulse

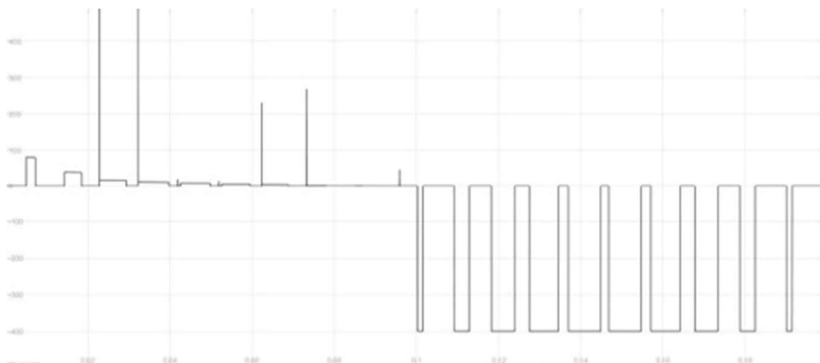

Figure 15 Switch 4 - Open Circuit Fault

5.2 Performance Parameters

In evaluating the efficacy of our deep learning model, we employed several key performance parameters to assess its overall performance and generalization capabilities. These parameters provide valuable insights into the model's ability to learn from the training data and make accurate predictions on new, unseen data.

5.2 (a) Accuracy

Accuracy is a fundamental metric that measures the ratio of correctly predicted instances to the total number of instances in the dataset. It serves as a primary indicator of the model's overallcorrectness.

The accuracy of our model was assessed on both the training and validation datasets. The training accuracy indicates how well the model is fitting the training data, while the validation accuracy provides an understanding of the model's performance on previously unseen data.

5.2 (b) Validation Accuracy

Validation accuracy is a crucial metric that measures the accuracy of the model on a separate dataset not used during the training process. It helps us gauge the model's ability to generalizeand make accurate predictions on new, unseen data.

A high training accuracy but low validation accuracy may indicate overfitting, where the model is memorizing the training data but struggles to generalize to new examples. Monitoring validation accuracy is essential for ensuring the model's robustness.

5.2 (c) Loss

The loss function is a critical component in training a deep learning model. It quantifies the difference between the predicted values and the true values in the training dataset. Our objective during training is to minimize this loss, indicating that the model is learning to make predictions that align closely with the actual data.

5.2 (d) Validation Loss

Validation loss is the loss computed on a separate dataset not used during training. Similar to validation accuracy, monitoring validation loss is crucial for detecting overfitting. If the model's performance on the validation set does not improve or worsens over time, it may suggest that the model is not generalizing well.

These performance parameters collectively provide a comprehensive view of our deep learning model's effectiveness and generalization capabilities. In the following sections, we will delve into the specific values and trends observed for each parameter during the training process, offering a detailed analysis of the model's performance.

5.3 Working of the project

5.3.1 Procedural Workflow

Methodology

1. Study: To theoretically analyse the working of a 4 switched H-Bridge circuit with its control circuit. How its gate pulses are given and switch operations are carried out and how its voltage waveform differed after every different type of fault.
2. Simulation: To simulate and analyze the H-Bridge circuit. We made the simulation of an H-Bridge converter along with its control circuit on MATLAB Simulink on the platform MATLAB 2021b.

3. Dataset: Dataset generation by attaching a voltage scope at the load of the circuit to get the load voltage waveform of converter.
4. Study: To conceptually understand the inner working of a Convolutional Neural Network.
5. Code: To code the CNN model and feed the dataset generated in step 3 to it for training.
6. Validation: To compare the different results obtained by the model and choose the best model.

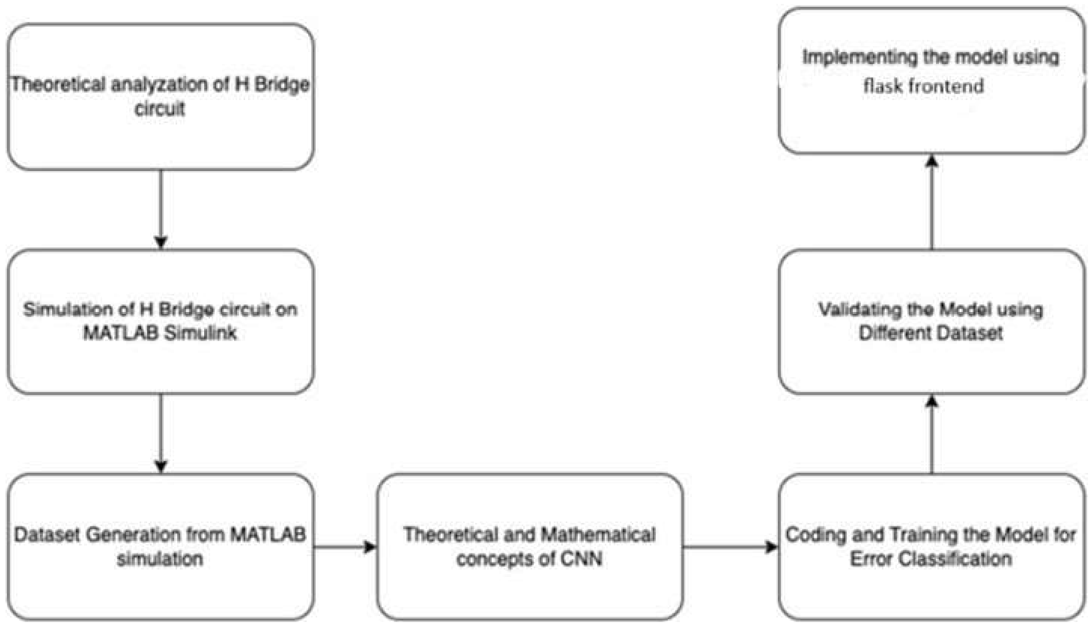

Figure 16 Methodology Flowchart

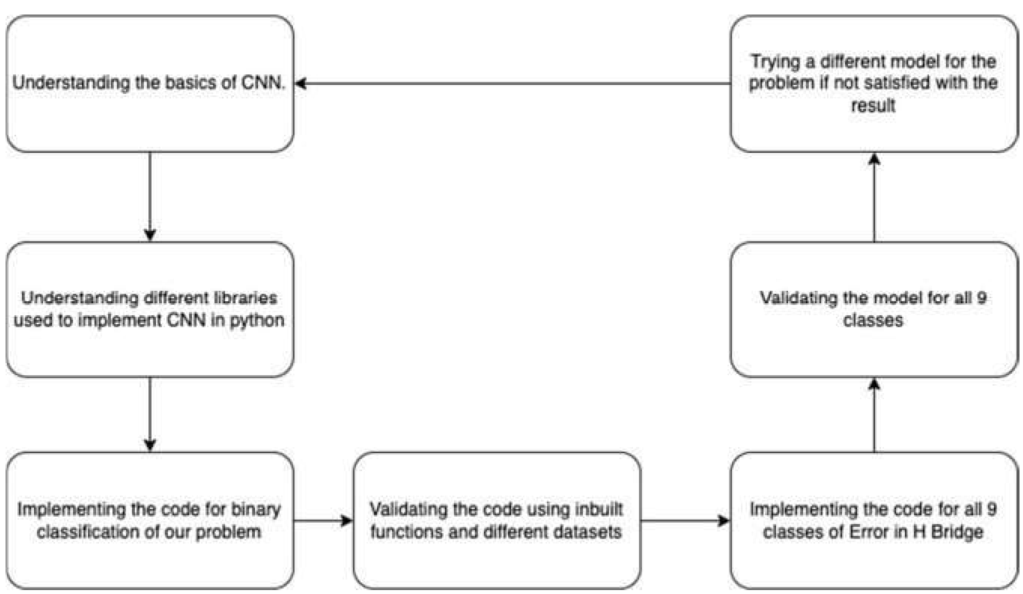

Figure 17 CNN Model

5.3.2 Approaches Used

Convolutional Neural Network (CNN) Model

Our project leverages the power of Convolutional Neural Networks (CNNs) to address the complex task at hand. CNNs are a class of deep learning models specifically designed for image and spatial data processing. The use of CNNs is particularly effective in capturing intricate patterns and hierarchies within the input data, making them well-suited for tasks such as image recognition, segmentation, and feature extraction.

Algorithmic Overview:

1. **Convolutional Layers:** The core building blocks of CNNs are convolutional layers. These layers apply filters to local regions of the input data, enabling the extraction of features such as edges, textures, and shapes. The convolutional operation is pivotal in capturing spatial hierarchies in the input, allowing the model to learn progressively complex representations.

   Convolutional Layer Pseudocode:

   for each filter in the layer:

   apply convolution operation to input data

   apply activation function (e.g., ReLU)

2. **Pooling Layers:** To reduce the spatial dimensions of the feature maps and decrease computational complexity, pooling layers are incorporated. Max pooling, a common pooling technique, retains the most significant information within local regions.
   Max Pooling Pseudocode:

   for each local region in the feature map:
   select the maximum value

3. **Fully Connected Layers:** Following the convolutional and pooling layers, fully connected layers aggregate the high-level features extracted from the previous layers. These layers connect every neuron to every other neuron, facilitating the integration of spatial information and enabling the model to make predictions.

Fully Connected Layer Pseudocode:
for each neuron in the layer:
calculate weighted sum of inputs
apply activation function (e.g., ReLU)

Our CNN architecture is designed to learn hierarchical representations of the input data, enabling the model to discern intricate patterns relevant to the task. The convolutional layers focus on local patterns, while pooling layers reduce dimensionality and retain essential information. The fully connected layers amalgamate these features for final predictions.

5.3.3 Project Deployment

The deployment of our fault detection model has been achieved on a local server, featuring a user-friendly Flask front end for enhanced accessibility. The system allows users to interact seamlessly with the deployed model for remote fault detection in H-Bridge Inverters.

5.3.4 Live System Screenshots

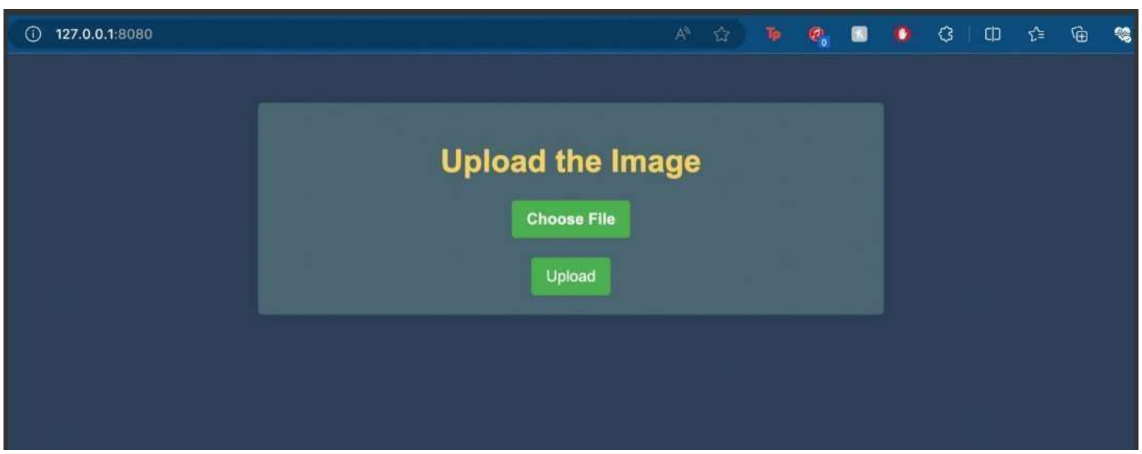

Figure 18 Front-end Home page

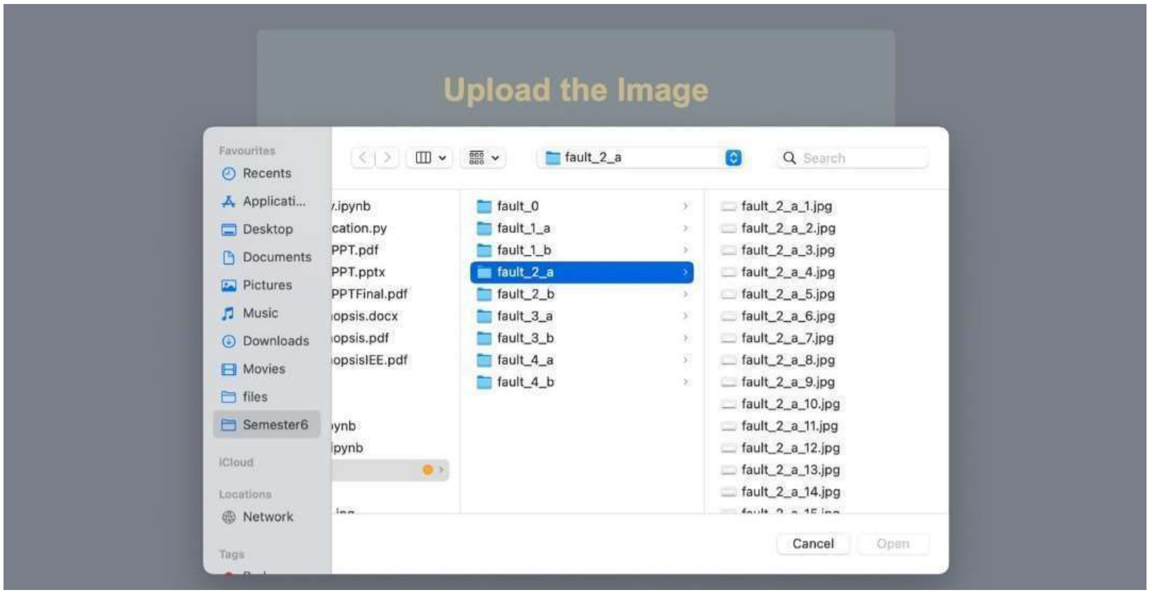

Figure 19 Uploading Image

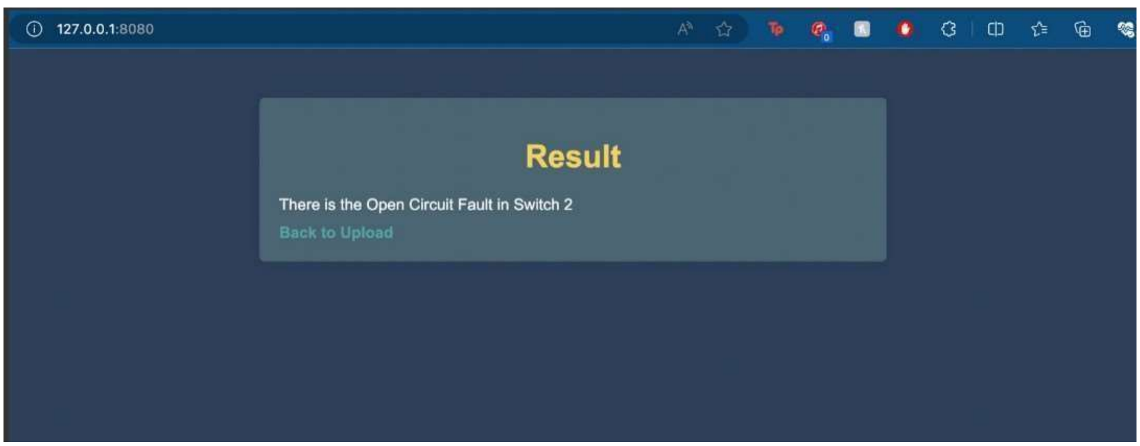

Figure 20 Result Page

5.4 Results and Discussions

In our research, we employed six distinct optimization algorithms to assess their effectiveness in enhancing the performance of our deep learning model. Subsequently, we generated graphical representations illustrating the outcomes of these six optimization algorithms in conjunction with two specific batch sizes, namely 16 and 32. Furthermore, for each batch size, we applied three distinct learning rates: 0.0001, 0.001, and 0.01. This approach yielded a total of six sets of results for each optimizer, encompassing a comprehensive evaluation of their respective performance. The graphical representations in our study depict two key performance metrics: accuracy and validation accuracy, which are presented in a single graph, and loss and validation loss, which are concurrently displayed in another graph. These visualizations are structured to illustrate the performance outcomes for each combination of batch size, learning rate, and optimizer employed in our investigation.

Furthermore, in select instances, we have included a detailed depiction of the aforementioned performance metrics for specific epochs, providing a more granular insight into the evolution of model performance over the course of training.

Optimizers used –

- **Adam (Adaptive Moment Estimation)**: Adam is an adaptive optimization algorithm that combines the benefits of both AdaGrad and RMSprop. It adjusts the learning rate for each parameter individually, allowing for efficient convergence and stable training. Additionally, it employs momentum to overcome issues like vanishing gradients, making it a popular choice for various deep learning tasks.
- **Stochastic Gradient Descent (SGD)**: SGD is the foundational optimization algorithm used in machine learning and deep learning. It updates model parameters iteratively based on the gradients of the loss function with respect to the data. While simple and reliable, its constant learning rate can sometimes hinder convergence, which led to the development of more adaptive variants like Adam.
- **Adamax**: Adamax is an extension of the Adam optimizer. It primarily focuses on the maximum of past gradients and adapts the learning rate accordingly. This feature makes Adamax particularly useful in scenarios where the variance of the gradients is high, as it can provide more stable and efficient convergence.

OPTIMIZER	BATCH SIZE	LEARNING RATE	ACCURACY	VALIDATION ACCURACY
ADAM	32	0.0001	0.8174	0.8344
		0.001	0.1336	0.0875
		0.01	0.1135	0.0844
	16	0.0001	0.8894	0.8899
		0.001	0.1301	0.0952
		0.01	0.0943	0.0863
STOCHASTIC GRADIENT DESCENT	32	0.0001	0.165	0.3511
		0.001	0.19	0.2912
		0.01	0.68	0.6801
	16	0.0001	0.155	0.3307
		0.001	0.175	0.3506
		0.01	0.75	0.8014
ADAMAX	32	0.0001	0.6561	0.7031
		0.001	0.9165	0.9000
		0.01	0.8481	0.8406
	16	0.0001	0.7206	0.7708
		0.001	0.9252	0.8869
		0.01	0.9073	0.8869

Table 1 Evaluation Metrics Results

From the results it is visible that the ADAMAX Optimizer is best suited for the problem at 16 batch size and 0.01 learning rate.

OPTIMIZER - ADAM Batch Size = 32

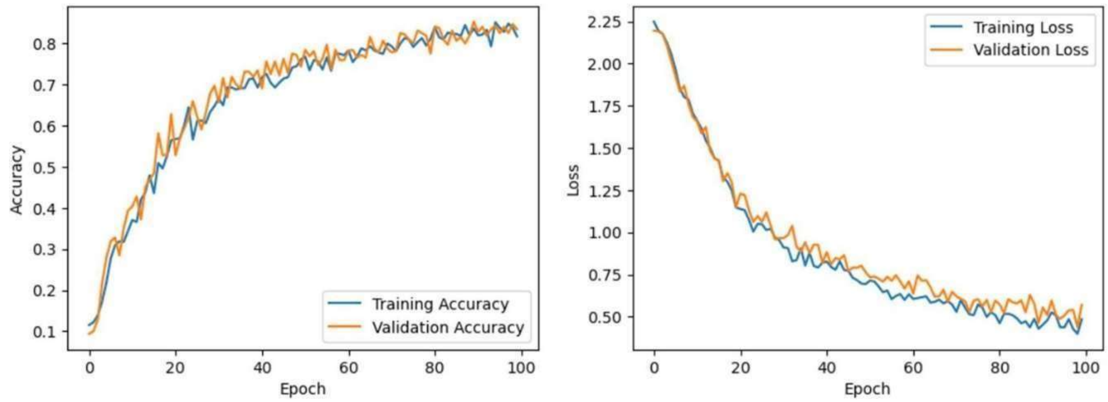

Figure 21 Learning Rate = 0.0001

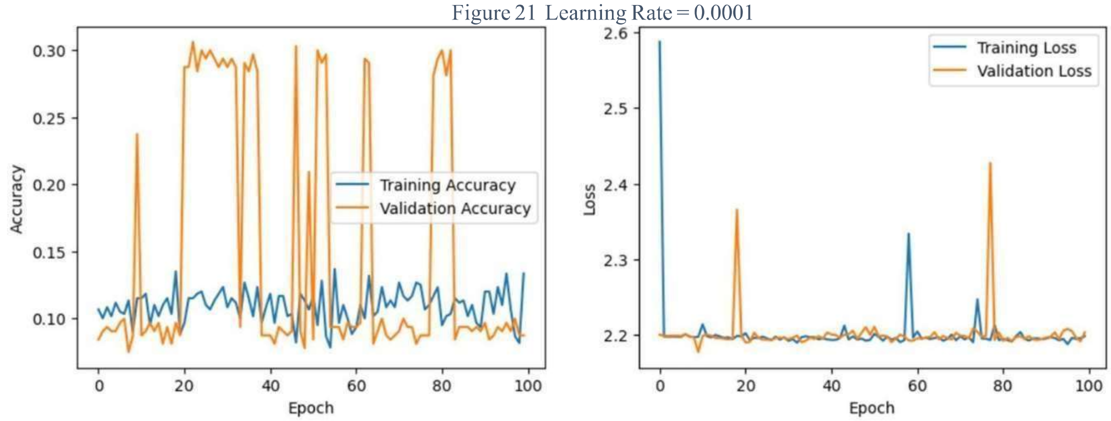

Figure 22 Learning Rate = 0.001

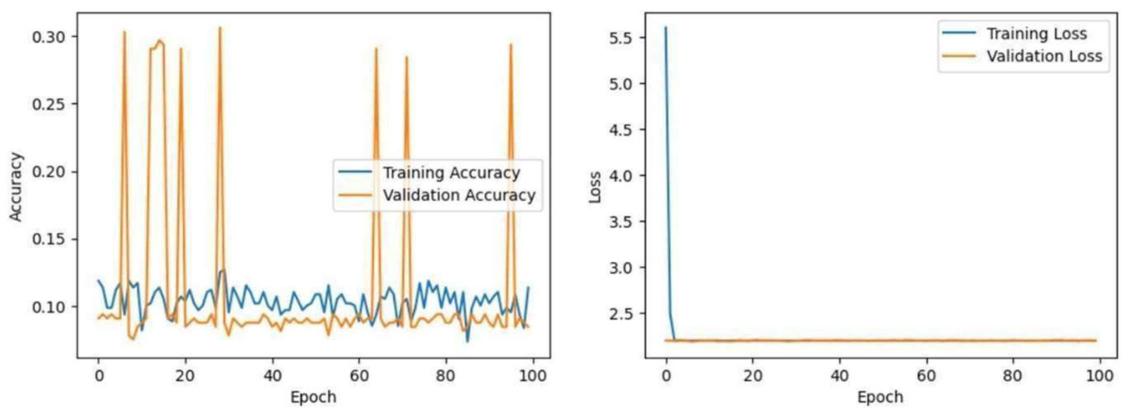

Figure 23 Learning Rate = 0.01

Optimizer Adam Batch Size = 16

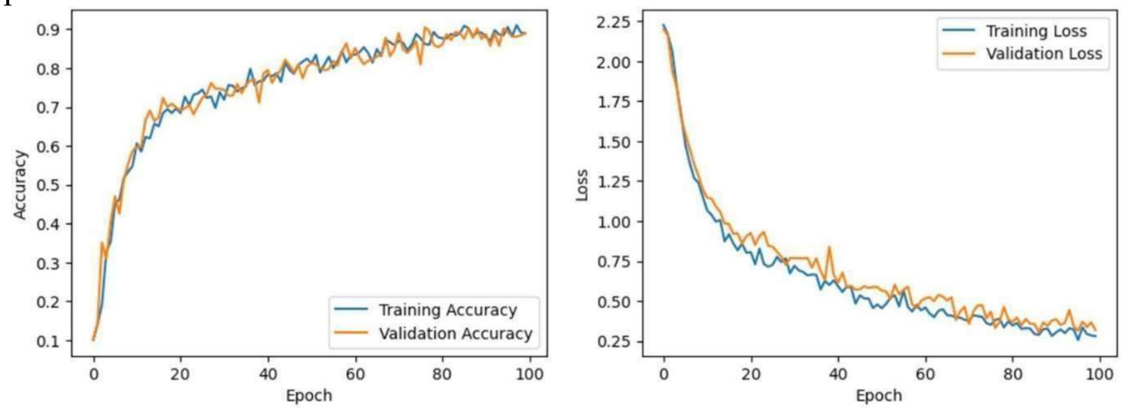

Figure 24 Learning Rate = 0.0001

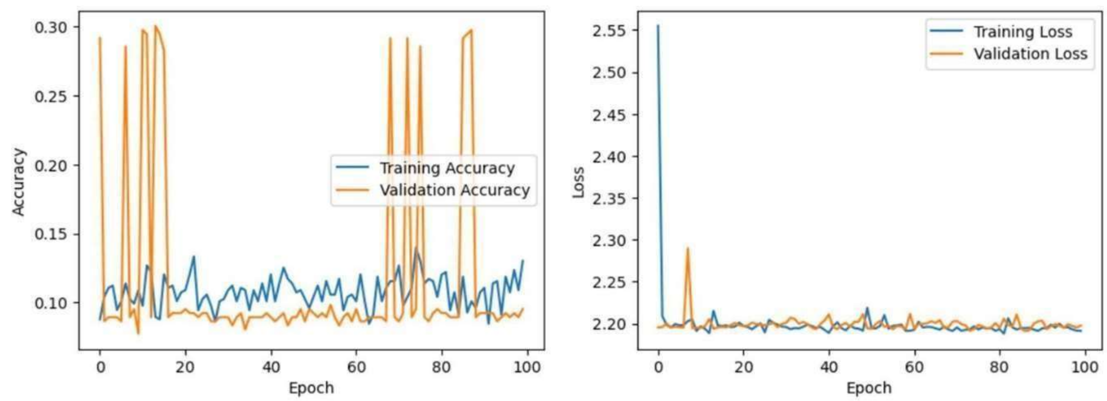

Figure 25 Learning Rate = 0.001

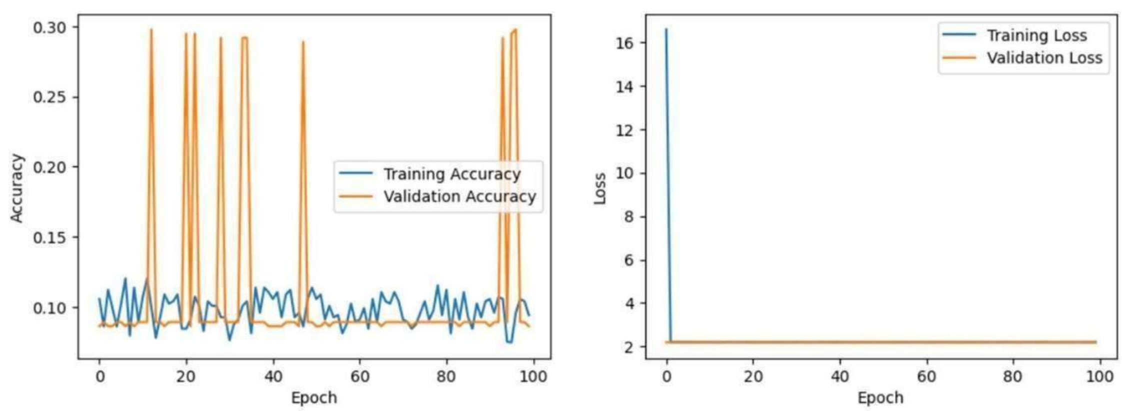

Figure 26 Learning Rate = 0.01

OPTIMIZER = STOCHASTIC GRADIENT DESCENT Batch Size = 32

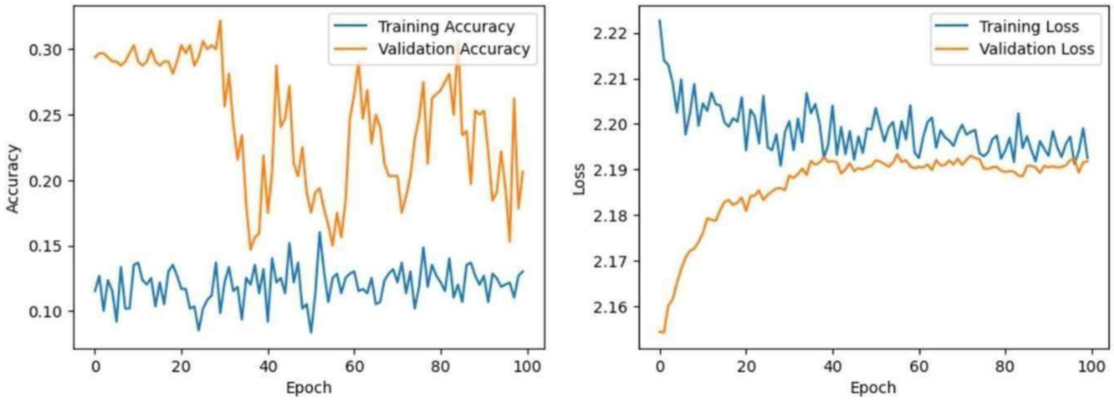

Figure 27 Learning Rate = 0.0001

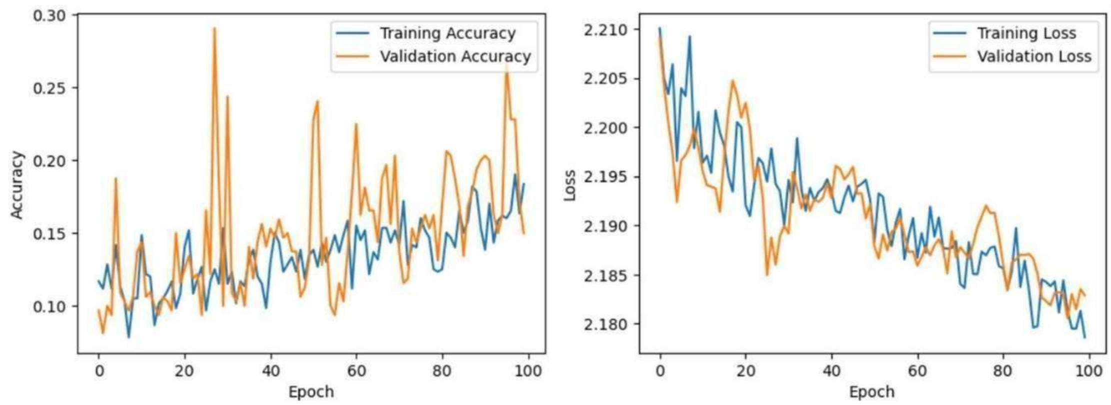

Figure 28 Learning Rate = 0.001

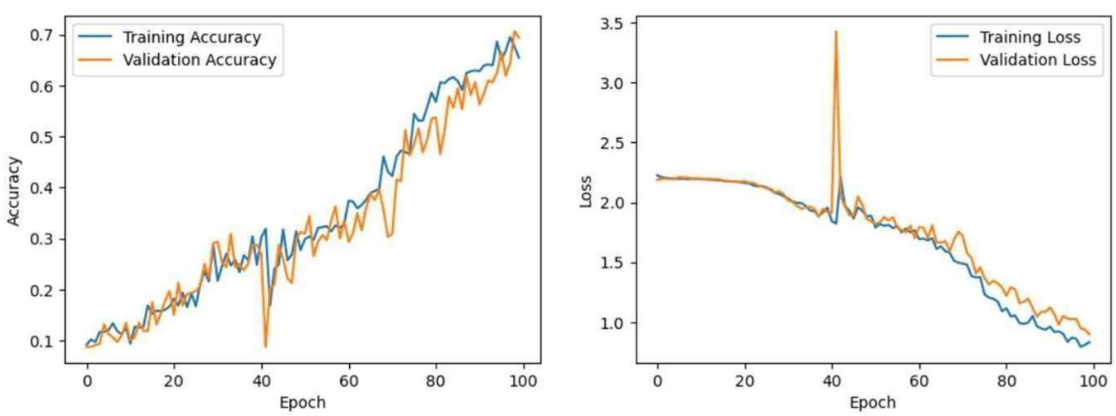

Figure 29 Learning Rate = 0.01

OPTIMIZER = STOCHASTIC GRADIENT DESCENT Batch Size = 16

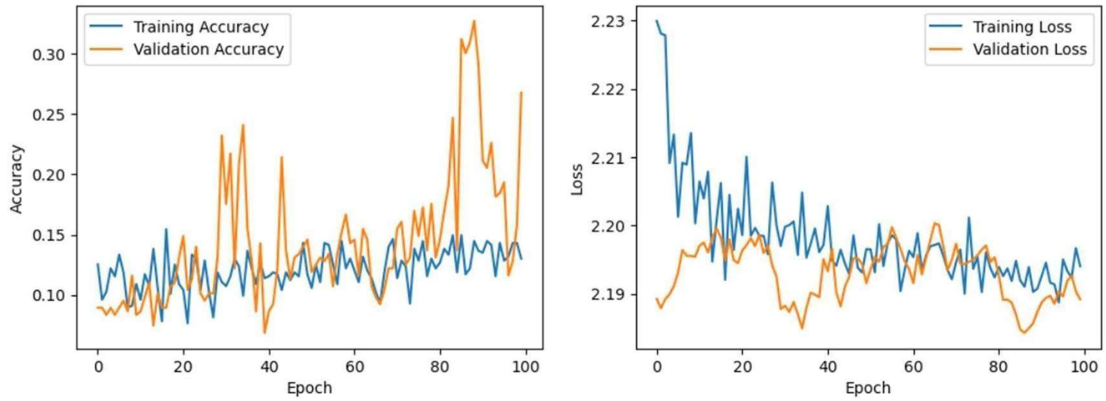

Figure 30 Learning Rate = 0.0001

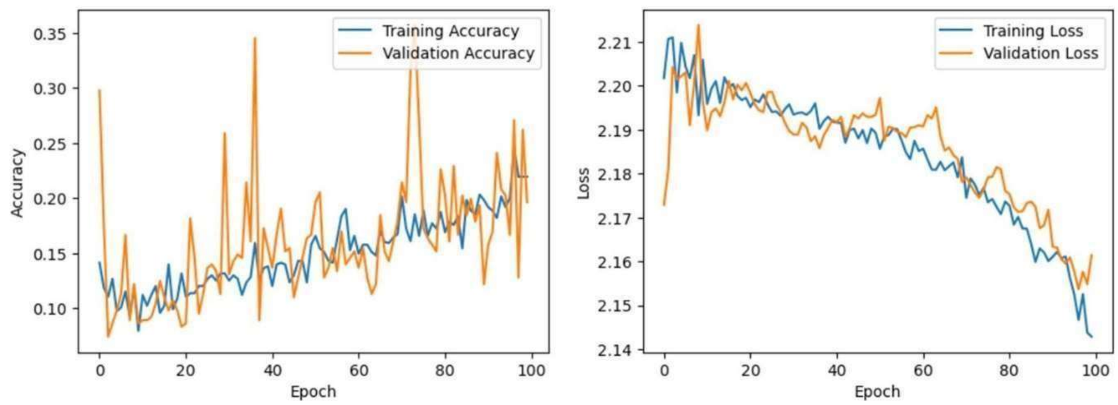

Figure 31 Learning Rate = 0.001

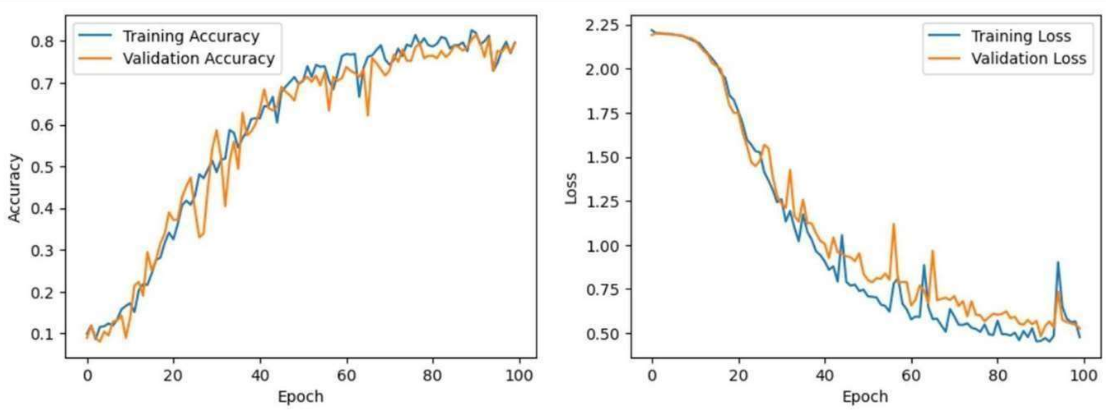

Figure 32 Learning Rate = 0.01

OPTIMIZER = ADAMAX Batch Size = 32

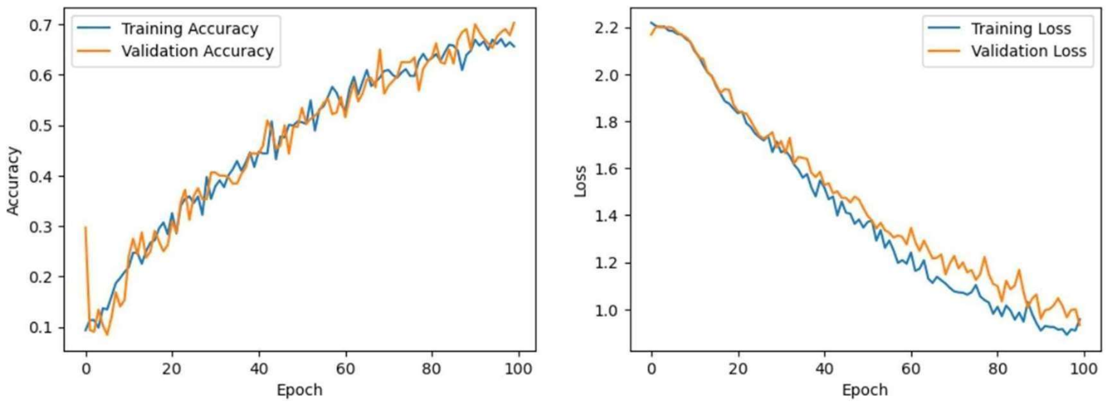

Figure 33 Learning Rate = 0.0001

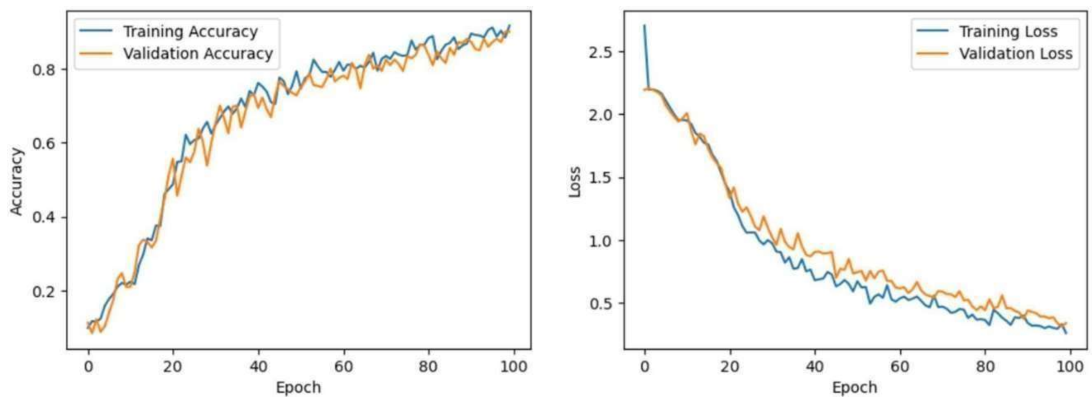

Figure 34 Learning Rate = 0.001

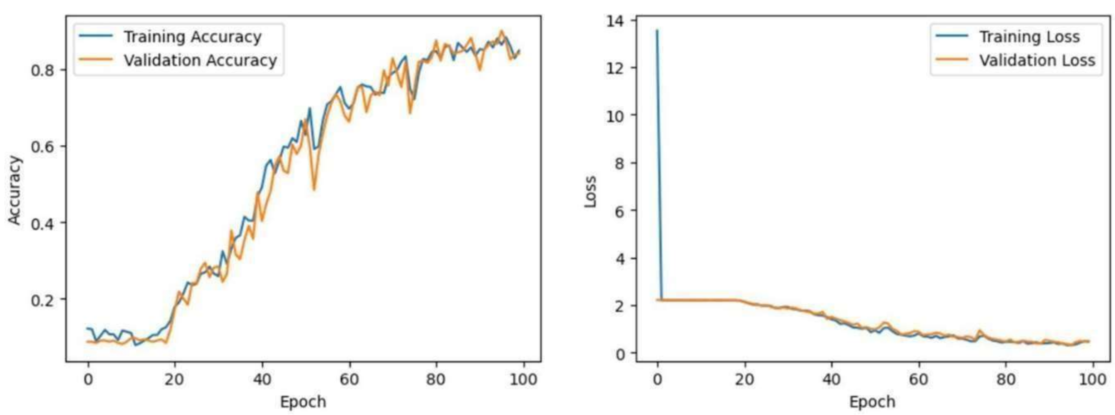

Figure 35 Learning Rate = 0.01

OPTIMIZER = ADAMAX Batch Size = 16

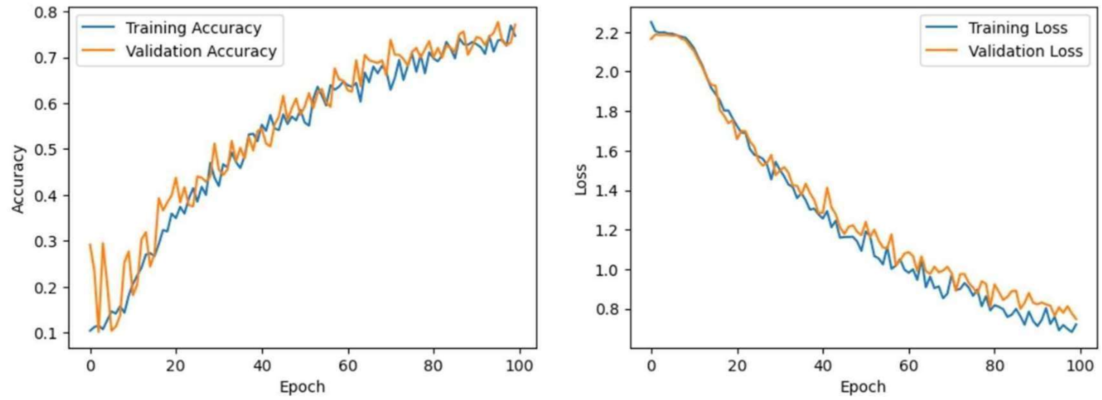

Figure 36 Learning Rate = 0.0001

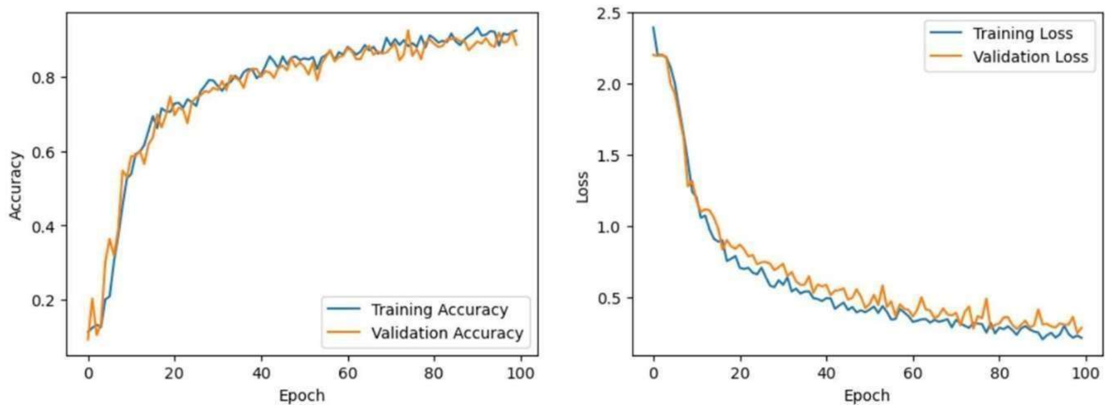

Figure 37 Learning Rate = 0.001

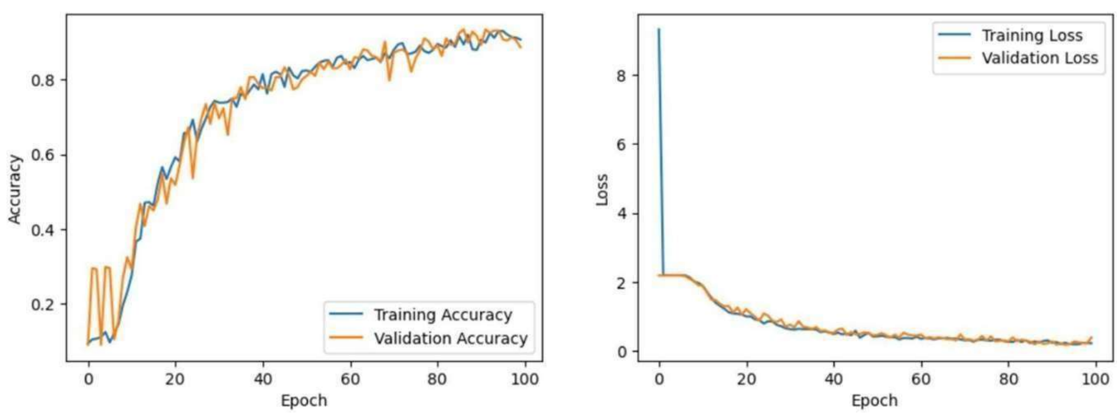

Figure 38 Learning Rate = 0.01

5.5 Inferences Drawn

Our exploration into fault detection in H bridges using deep learning has yielded insightful conclusions that have practical implications for power converter circuit diagnostics.

1. Switch-Specific Fault Detection
   The application of deep learning, specifically in Convolutional Neural Networks (CNNs), proves to be a promising avenue for identifying faults in individual switches within the H bridge. By analyzing waveforms associated with each switch, our model demonstrates an ability to discern which switch is experiencing a fault. This capability is invaluable for pinpointing and isolating issues within the power converter circuit.
2. Beyond simply identifying the faulty switch, our deep learning approach extends its utility to categorizing the type of fault occurring in the switch. This enhanced diagnostic capability provides a deeper level of understanding, allowing for more informed and targeted maintenance or corrective actions. Whether it be a short circuit, open circuit, or other fault types, our model showcases a capacity for nuanced fault classification.
3. The inferences drawn from our study highlight the practical feasibility of employing deep learning for fault detection in H bridges. The ability to not only identify the affected switch but also classify the type of fault opens avenues for proactive maintenance and swift troubleshooting. The incorporation of remote detection capabilities aligns with the growing need for efficient and accessible monitoring solutions in complex electrical systems.

5.6 Validation of Objectives

The set objectives for this project have been successfully achieved, demonstrating the effectiveness and fulfillment of each targeted goal.

1. A faster and more accurate method for detecting faults in the H-Bridge Inverter has been developed through the utilization of advanced deep learning techniques.
2. The reliability and safety of power converter circuits have been notably improved through the implementation of the fault detection method. The model's capability to detect faults effectively contributes to minimizing potential risks associated with circuit malfunctions.
3. A remote method for detecting faults in the H-Bridge Inverter, devoid of the necessity for physical access to the circuit, has been successfully established. This achievement opens up opportunities for remote monitoring and diagnosis, particularly in scenarios where on-site inspection may be impractical or challenging.
4. The developed fault detection method for H-bridge circuits has proven to be versatile and suitable for use in various environments.

CHAPTER 6
CONCLUSION AND FUTURE WORK

6.1 Conclusions

The project has achieved its objectives, advancing fault detection in H-Bridge Inverters. A faster, more accurate method has been developed, improving the efficiency of fault identification and classification. The enhancements in reliability and safety contribute to minimizing risks in power converter systems. The establishment of a remote fault detection method enables real-time monitoring without the need for physical access. The adaptability of the method to diverse environments ensures its robustness and widespread applicability. In summary, the project's success validates its goals, providing a foundation for improved fault detection methodologies with broad implications.

6.2 Environmental, Economic and Societal Benefits

The implementation of the developed fault detection method in H-Bridge Inverters brings forth significant economic and societal benefits. By enhancing the reliability and safety of power converter circuits, potential damages and downtime are minimized, translating into cost savings for industries relying on such systems. Moreover, the remote fault detection capability reduces the need for on-site inspections, leading to operational efficiencies and resource optimization. Beyond economic gains, the improved safety and dependability of power converter systems positively impact society by reducing the likelihood of accidents or disruptions in critical infrastructures. The project's outcomes, therefore, not only contribute to economic advancements but also foster a safer and more resilient technological landscape.

6.3 Future Work

6.3.1 Extend the application of the developed fault detection method to other power converter circuits, including buck, boost, and buck-boost converters.

6.3.2 Increase the dataset size to further improve the model's ability to generalize and accurately detect faults in a broader range of scenarios.

6.3.3 Explore modifications to the model architecture to increase accuracy and robustness in fault detection across diverse power converter circuits.

6.3.4 Address the constraint of a fixed switching frequency by conducting further research and developing adaptive strategies, allowing the method to adapt to dynamic operational conditions.

CHAPTER 7
PROJECT METRICS

7.1. Challenges Faced

7.1.1. We first tried to take our waveform directly from a DSO, but the DSO wasn't Working properly. So, we made a Simulink model of the H-Bridge circuit and attached a voltage scope to its load to take waveform dataset.

7.1.2. TensorFlow environment wasn't working on our systems as it is a very heavy environment and it took us three days of trying but we didn't reach to any conclusion. Finally, we installed an older version of TensorFlow to use in our model which then worked perfectly.

7.1.3. Our model exhibited issues related to overfitting and underfitting, which were discernible through the analysis of accuracy and loss graphs. This was evident from the lack of a consistent increase in accuracy, as it showed fluctuations over time.

7.1.4. Our model's accuracy and validation accuracy remained consistently below 0.3. Subsequently, we addressed this issue through the implementation of alternative optimizers and/or by adjusting the learning rate and batch size values.

7.2 Relevant Subjects

In the realm of Electrical Engineering, a strong foundation in Power Electronics is essential for comprehending the principles and operation of power converter circuits, particularly H-Bridge Inverters.

Basic knowledge in Control System Design an Power System Protection is pivotal, as it directly contributes to the development of methods for detecting and responding to faults in power converters.

The incorporation of Deep Learning and Machine Learning techniques is fundamental to your project. Understanding Neural Networks, specifically Convolutional Neural Networks (CNNs) tailored for image-based fault detection, is essential.

Proficiency in Image Processing techniques is necessary for extracting information from waveform images, while knowledge of Optimization Algorithms is crucial for refining deep learning models to achieve optimal fault detection performance.