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Detection and Classification of Power Quality Issues Using Neural Network

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Abstract— In today's scenario, power quality issues have turned into a serious matter for both electric power utilities and for power system engineers. Power distribution equipment is highly sensitive to supply system disturbances. Moreover, this equipment is connected in the supply system and in industries for the purpose of manufacturing. As a result, the effect of any issue on the equipment will affect the machine. Usually, some of the power system equipment generates disruptions, which consecutively affect the other equipment's, and are supposed to cause harmonic distortion. These distortions result in inefficient use of power and are the major cause of abrupt failure of the equipment. It affects the production process in industries, which causes financial instability. It reduces the generation of power and affects data processing activities. This project focuses on detecting and classifying power quality issues using neural networks algorithms and solving those issues. Neural networks have the inherent capability to automatically learn optimal features from raw input data and thus eliminates the need of domain expertise. The MATLAB software is used for electrical simulation to generate faults and disturbances, and its output data is given to MATLAB with an efficient neural network model for the analysis procedure**.**

Keywords: Power Quality Disturbances (PQDs); Deep Learning; Stacked Autoencoder; Feature Extraction; Particle Swarm Optimization (PSO); Signal Variance; Classification; Cross-Validation

I.INTRODUCTION

In today's world, power systems are becoming more complex, and the equipment used in both utilities and industries is getting increasingly sensitive, especially with the rise of electronics that rely on clean and stable power. Even small disturbances in voltage, current, or frequency, what we commonly refer to as power quality issues can have a noticeable impact, sometimes even causing damage to equipment or disrupting operations [8]. These issues can take many forms, such as voltage sags and swells, notches, transients, and harmonic distortions. For example, when a large motor starts up, it tends to draw a high initial current, which can cause a voltage sag. Similarly, switching on a large capacitor bank can lead to a voltage swell. With so many potential causes, identifying and understanding these disturbances is the first step toward fixing them.

As renewable energy sources like solar and wind become more common, and with the growing shift toward Smart Grids, the need for better power quality management is more important than ever. These changes introduce new challenges to the stability of the grid [9], making it essential to have systems that can detect and respond to problems in real-time. This is where machine learning comes in. Thanks to its ability to find patterns and make fast, accurate decisions, machine learning especially techniques like Convolutional Neural Networks (CNNs) offers a promising way to tackle power quality problems.

The goal of this project is to build a system that can automatically detect and classify different power quality events using machine learning. To do this, we start by collecting real-time data from PQubes, which are devices that monitor power quality in detail. Then, we extract meaningful features from that data and organize it into a dataset representing different types of disturbances. Using that dataset, we train machine learning models to recognize and classify the events. The hope is that this kind of system will help prevent equipment failures, lower maintenance costs, and improve overall safety and reliability in electrical networks especially as our power infrastructure continues to evolve.

II.LITERATURE SURVEY

Over the years, researchers have explored various methods to detect and classify power quality disturbances (PQDs), as these short-duration, non-stationary events can significantly impact the performance and lifespan of sensitive electrical equipment. Power systems today are evolving with the integration of renewable energy and smart grid technologies, which makes accurate and timely detection of such disturbances even more crucial. A common challenge with analyzing PQDs lies in the need for both time and frequency domain information.

As highlighted in paper [1], while the Fourier Transform is widely used for spectral analysis, it lacks the ability to localize events in time, an essential feature when dealing with transient or short-lived disturbances. To overcome this limitation, researchers have turned to more advanced techniques that combine time-frequency analysis with intelligent classification systems. In this regard, machine learning has emerged as a particularly effective tool. Paper [2] discusses the application of Support Vector Machine (SVM) algorithms, which offer a more refined approach to classifying PQDs by achieving improved time–frequency resolution. The study also introduces optimization indices that help the algorithm adapt better to the input data, ensuring higher accuracy and efficiency. Compared to other models such as Back Propagation Neural Networks (BPNN) and Extreme Learning Machines (ELM), SVM stands out for its faster training time, simpler architecture, and better precision, factors that are especially important in real-time applications. Building on this, paper [3] evaluates a machine learning framework using SVMs on both simulated and real-time data. The results show that the proposed architecture performs well across different types of disturbances, including both single and combined events, confirming its suitability for real-world smart grid environments. Paper [4] presents a hybrid framework using Wavelet Transform and SVM to enhance classification by improving time-frequency resolution. Feature optimization methods such as those discussed in paper [5] highlight the importance of selecting optimal time-frequency coefficients using MODWT and least SVM when combined with deep architectures like stacked autoencoders improve PQD classification [6]. From these studies, it's evident that incorporating machine learning not only enhances the detection and classification of power quality events but also offers scalability and adaptability to changing grid conditions. The use of synthetic datasets that mimic real disturbances further strengthens the robustness of these models. These insights directly inform the current project, which seeks to implement an intelligent, machine learning-based solution for PQD classification. By using real-time data from PQubes and extracting meaningful features, the project builds upon this foundation to develop a practical and effective system capable of supporting the reliability and safety of modern electrical networks.

III.BACKGROUND AND THEORETICAL FOUNDATIONS

In electrical power systems, the term Power Quality (PQ) refers to the extent to which the delivered electrical power conforms to the standard requirements in terms of voltage magnitude, waveform shape, frequency, and continuity. Ideally, voltage and current waveforms should be pure sinusoids at constant frequency and magnitude. However, due to various electrical faults, switching operations, or the integration of nonlinear loads and renewable energy sources, the power supply can experience disturbances that degrade its quality.

These Power Quality Disturbances (PQDs) have become more prevalent with the increasing use of sensitive electronic devices and the emergence of Smart Grids. Even short-lived deviations in power quality can cause equipment malfunction, reduced lifespan, unexpected downtime, and in industrial contexts, costly production interruptions. The most common types of PQDs include voltage sag, voltage swell, voltage interruption, and voltage unbalance, each with unique characteristics and implications.

1. **Voltage Sag** refers to a short duration drop in voltage, typically ranging between 0.1 and 0.9 per unit (pu), and lasting from half a cycle to several seconds. Common causes include short circuits, motor startups, and sudden load switching. These events can affect motors, relays, and sensitive control systems, often leading to process interruptions (see Figure 1).

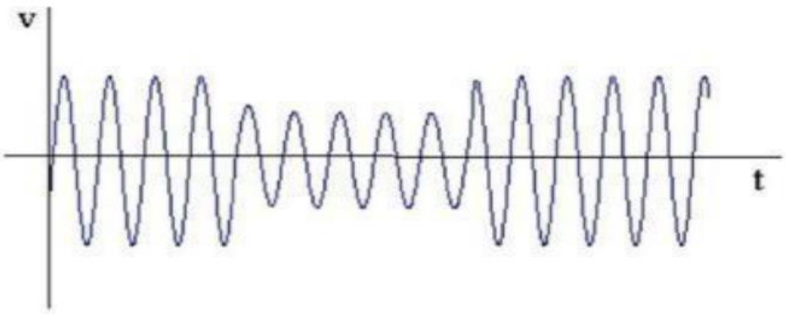

Fig. 1. Voltage Sag

2. **Voltage Swell** is the opposite phenomenon, an increase in voltage magnitude, generally between 1.1 and 1.8 pu, for a similar duration. It usually results from sudden disconnection of heavy loads or energization of capacitor banks, which can damage sensitive electronics and reduce the efficiency of power delivery (see Figure 2).

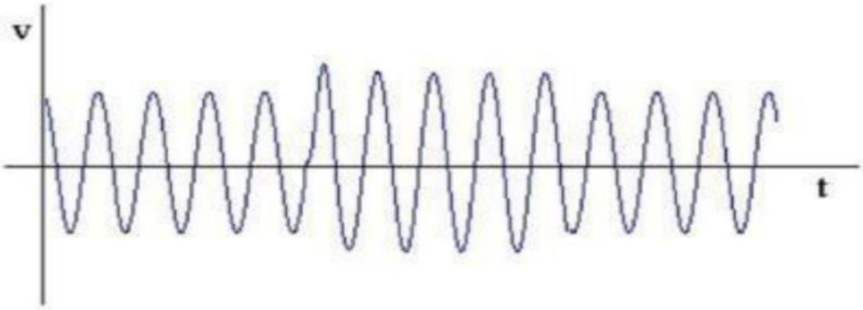

Fig. 2. Voltage Swell

3. **Voltage Interruption** refers to the complete loss of voltage (<0.1 pu) for durations ranging from a few cycles to several minutes. These can occur due to tripping of breakers, accidental faults, or scheduled maintenance (see Figure 3).

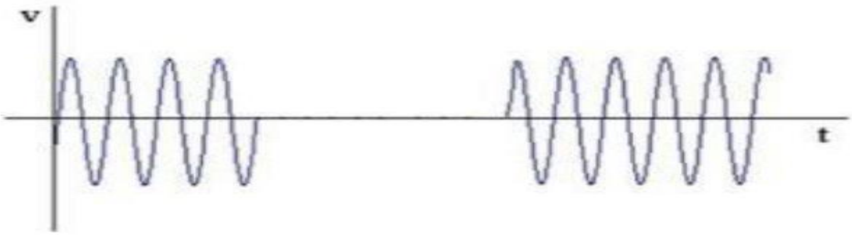

Fig. 3. Voltage Interruption

4. **Voltage Unbalance** occurs in three-phase systems when the phase voltages differ significantly in magnitude or phase angle. Unbalance is often caused by uneven single-phase loads, damaged components, or faults in one or two phases, and can result in overheating, inefficiency, and reduced lifespan of motors (see Figure 4).

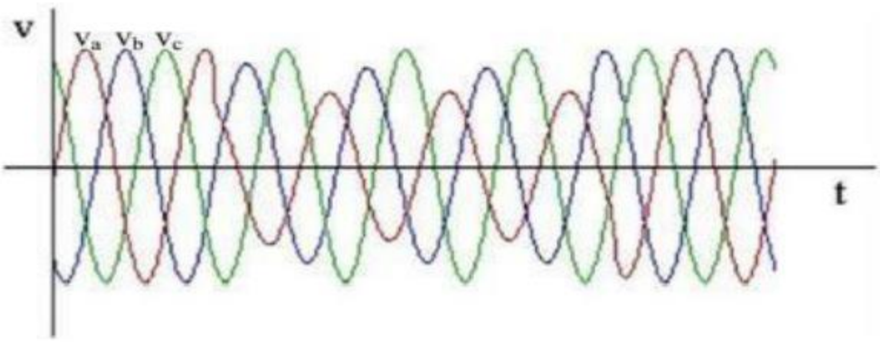

Fig. 4. Voltage Unbalance

Monitoring these disturbances manually or using traditional signal analysis methods can be time-consuming and often lacks the precision needed for real-time applications. This is where Machine Learning (ML) and Neural Network (NN) based approaches offer a transformative advantage due to their nonlinear decision boundaries and learning capacity [7].

A typical ML pipeline includes data collection, feature extraction or preprocessing, model training, testing, and evaluation. Among supervised ML techniques illustrated in Figure 5, the Support Vector Machine (SVM) algorithm has been extensively used in power quality studies due to its robustness and accuracy [13], methods such as decision trees and k-NN have been used for automated PQ classification [10].

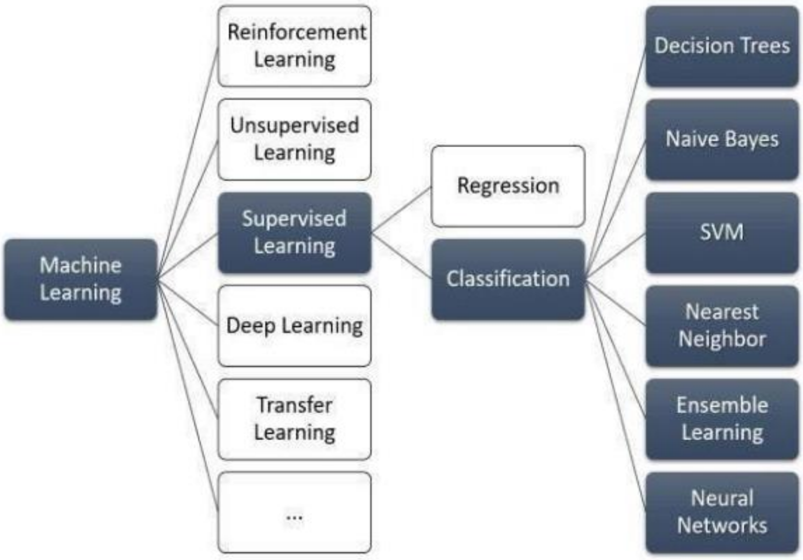

Fig. 5. Framework of ML Algorithms

While traditional ML models require manual feature engineering, recent advancements in Deep Learning, particularly in Neural Networks, allow models to automatically learn feature hierarchies directly from raw input data. In contrast to SVM, neural networks as in paper [6] can automatically learn features and capture nonlinear patterns without manual selection. The basic architecture includes an input layer that receives the data, one or more hidden layers that transform it through nonlinear operations, and an output layer that generates the final prediction (see Figure 6).

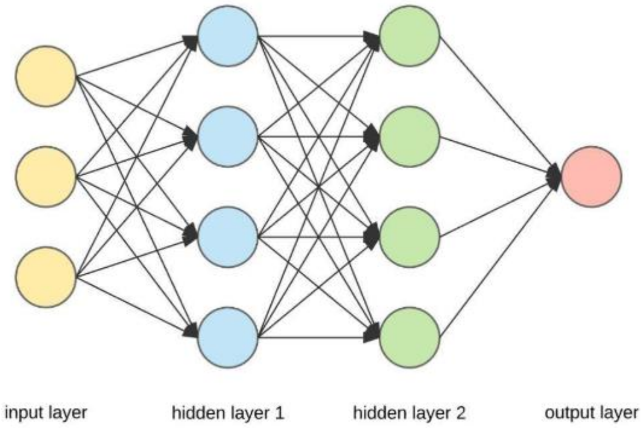

Fig. 6. Layers of neural network

Among various types of neural networks, Convolutional Neural Networks (CNNs) have shown great promise in power quality applications. Originally designed for image recognition, CNNs are now widely used for time-series classification due to their ability to capture local patterns in structured data. A CNN typically consists of convolutional layers that apply filters to extract features, pooling layers to reduce dimensionality, and fully connected layers that perform final classification. These models are trained using backpropagation algorithms such as the Polak-Ribiere Conjugate Gradient method, as demonstrated in the MATLAB Neural Network Training Toolbox (see Figure 7).

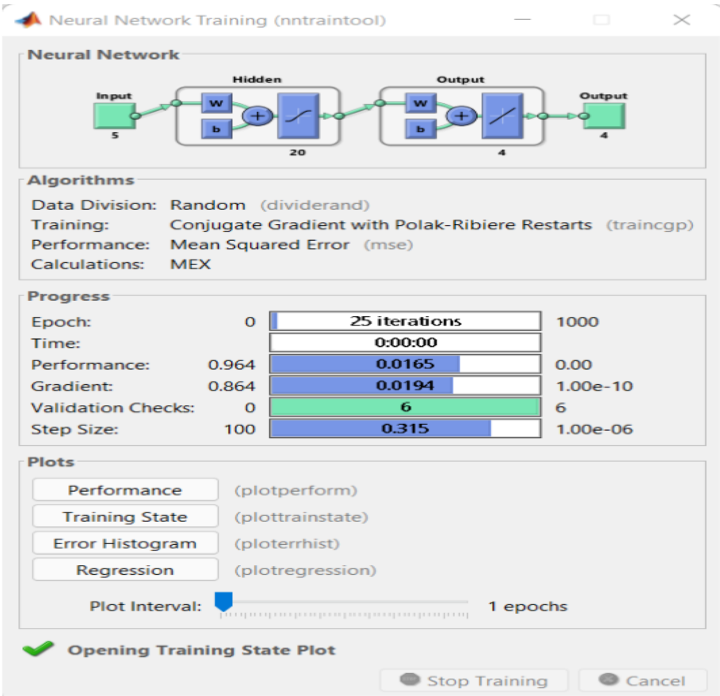

Fig. 7. Neural Network Training Toolbox

In summary, understanding power quality disturbances and equipping systems with intelligent classifiers like ML and deep learning models form the core foundation for developing robust detection systems. This background provides the necessary context for the proposed methodology, which integrates simulation, data acquisition, neural network training, and classification of PQ events in a unified framework.

IV.PROPOSED DESIGN

To address the growing challenges in detecting and classifying power quality disturbances (PQDs), this work presents a machine learning based solution leveraging simulation, real-time data generation, feature extraction, and neural network-based classification. The entire framework was designed and implemented using MATLAB Simulink and Python, with the goal of developing a robust, scalable, and accurate detection model for key PQ events such as voltage sag, swell, interruption, and unbalance.
As illustrated in Figure 8, the starting point of the proposed solution is the simulation environment, where various power quality events were modelled using MATLAB Simulink. A detailed circuit was constructed consisting of a 33kV voltage source, stepped down to 11kV, and connected to a distribution line via a circuit breaker. The line was terminated using a 11/0.433kV distribution transformer that supplied a typical industrial load of 190 kW and 140 kVAR. This helps to isolate temporal features of voltage fluctuations more effectively [11]. Initially, the model was run without any disturbances to establish a baseline RMS voltage at the point of common coupling (PCC), which served as the reference for subsequent simulations. The circuit was then modified to simulate PQDs including voltage sags (caused by three-phase ground faults), swells (from capacitor bank switching), interruptions (from opening the circuit breaker), and unbalance (due to asymmetric faults). These scenarios were executed over a defined simulation time to capture realistic transient and steady-state behavior.

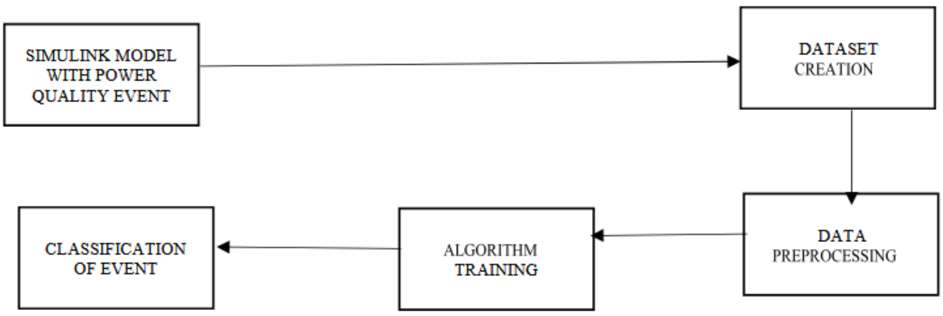

Fig. 8. Block diagram of proposed work

The root-mean-square (RMS) voltage at the PCC was sampled at a frequency of 6 kHz for the entire simulation period. This raw waveform data was exported to Excel format to form the foundation of the dataset. Each segment of the dataset corresponds to a specific event class like SAG, SWELL, INTERRUPTION, UNBALANCE, or NOPQ (No Power Quality issue). These were labeled accordingly to allow for supervised learning. A Python script in Jupyter Notebook was used to automate the classification of raw waveform segments based on their voltage magnitude, enabling efficient dataset diversification.
Once the dataset was established, preprocessing was done to enhance its suitability for training machine learning models. Attributes included the one-phase RMS voltage and corresponding class labels. The class distribution was visualized using Matplotlib to

ensure dataset balance and representativeness. Following this, the dataset was split into training and test subsets using Scikit-learn, with 70% of the data used for training and 15% reserved for model validation and testing.

The classification model was built using a Convolutional Neural Network (CNN), chosen for its ability to automatically learn and extract features from time-series data. CNNs, as validated in paper [7], are especially effective in classifying PQDs due to their spatial pattern learning from waveform input. In this case, the CNN was structured into multiple layers: an input layer to accept the signal features, hidden layers to learn complex patterns, and an output layer that classifies the signal into one of the predefined PQD categories. Each connection between neurons carries a weight, and during training, these weights are adjusted using a backpropagation algorithm to minimize the Mean Squared Error (MSE) between the predicted and actual outputs. This iterative process continues until the network converges on an optimal configuration.

After training, the model was evaluated using the reserved test data. Each test instance was passed through the network, which then classified the signal based on the learned weights. The model was able to accurately identify the type of disturbance like voltage sag, swell, unbalance, or interruption based on the test condition's fault resistances. The classification results validated the effectiveness of the approach in capturing and distinguishing between different PQ events, laying the groundwork for real-time deployment in monitoring systems.

V.RESULTS AND ANALYSIS

To evaluate the effectiveness of the proposed classification framework, simulations were conducted in MATLAB Simulink to generate realistic power quality disturbance (PQD) scenarios. The simulation circuit, as shown in Figure 9, was designed to replicate a typical medium-voltage power distribution system. It includes a 33kV voltage source, which is stepped down to 11kV and supplied through a circuit breaker to a feeder line. This line is connected to a 190kW, 140kVAR load through a distribution transformer rated at 11/0.433kV. To observe and analyse PQ disturbances, voltage and current measurement scopes were positioned across key points in the system, especially around the point of common coupling (PCC).

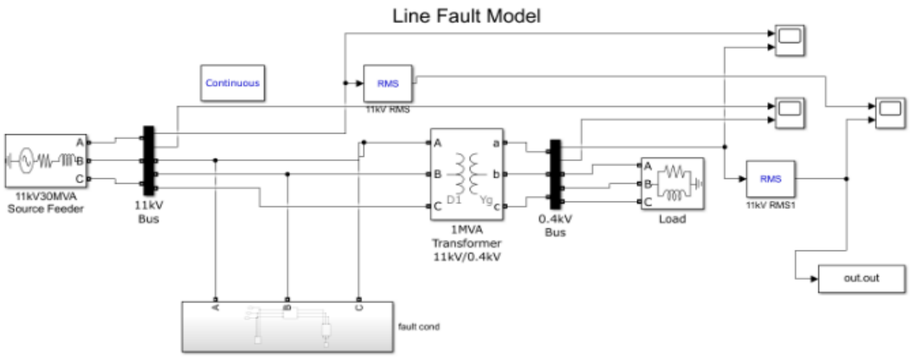

Fig. 9. Simulation Model

Faults were injected into this system to simulate various PQDs including voltage sag, swell, interruption, and unbalance. The fault condition circuit, illustrated in Figure 10, is connected between the transformer and the 0.4kV bus. It utilizes different combinations of fault types and resistances to produce disturbances reflective of real-world events. To induce specific PQD patterns, faults such as three-phase to ground were triggered by specifying a fault resistance of 100 ohms and a ground resistance of 1 ohm.

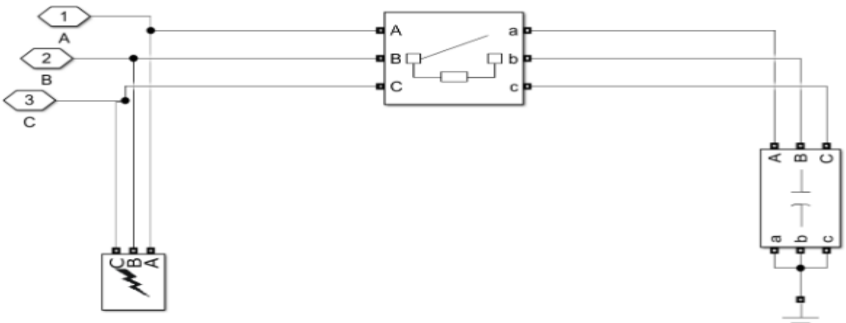

Fig. 10. Fault condition model

The simulation environment was designed to allow easy modification of fault conditions, as shown in Figure 11, providing flexibility to simulate a wide range of scenarios.

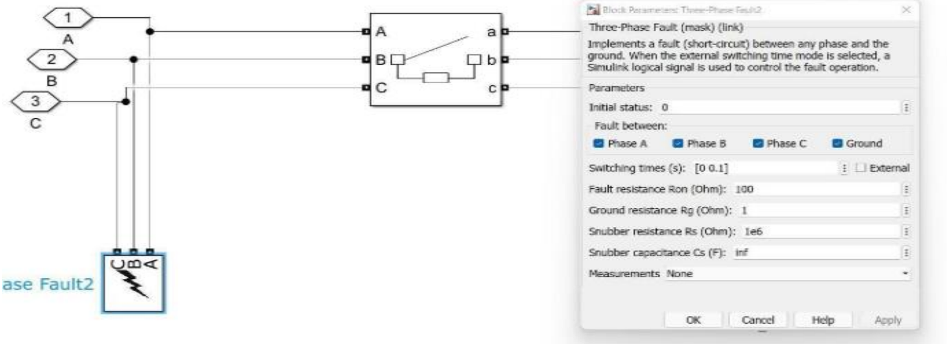

Fig. 11. Fault Injection

As each disturbance event unfolded, the RMS voltage waveform at the PCC was recorded using Simulink's data logging features. These waveforms were sampled at a rate of 6 kHz and stored in Excel format. The data was then pre-processed and labelled according to the type of event, such as SAG, SWELL, INTERRUPTION, UNBALANCE, or NOPQ and used to train and validate the classification models. When the trained model was tested, it successfully classified the given input data, producing accurate labels that reflect the fault conditions simulated. For instance, in a test case involving a voltage interruption scenario, the model returned the correct output label "Voltage Interruption," as depicted in Figure 12.

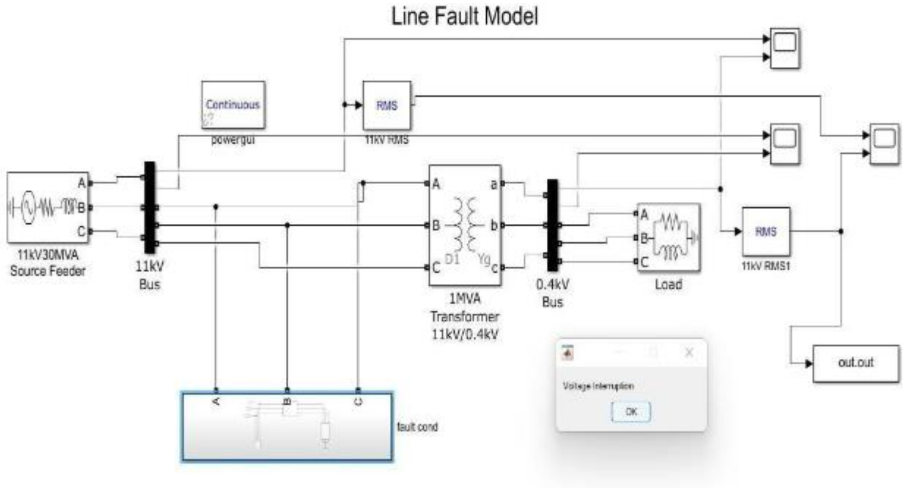

Fig. 12. Output label for the given fault condition

To evaluate the training process of the model, performance metrics were plotted across training, validation, and testing phases. The mean squared error (MSE) values at each iteration were tracked, with the best model performance observed at the 25th iteration, as illustrated in Figure 13. This figure reflects how the model minimized error over time, indicating effective learning and convergence.

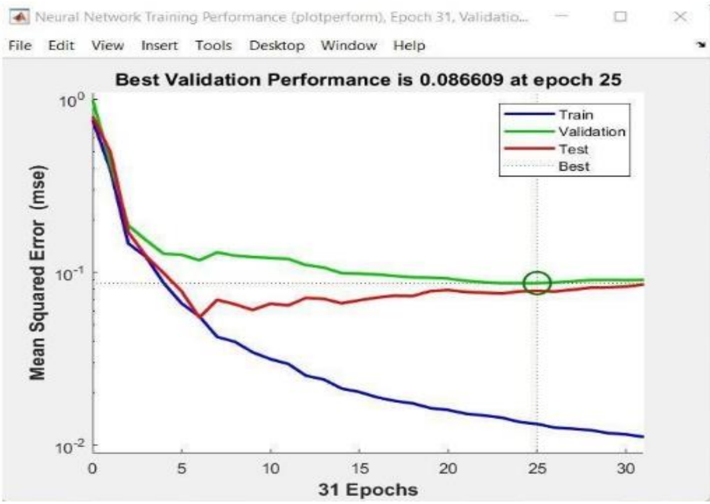

Fig. 13. Training Performance Plot

Further insight into the model's behaviour was provided by the regression analysis plot in **Figure 14**, which visualizes the correlation between predicted and actual values across different datasets. These regression hyperplanes help assess the model's generalization ability and validate its performance consistency.

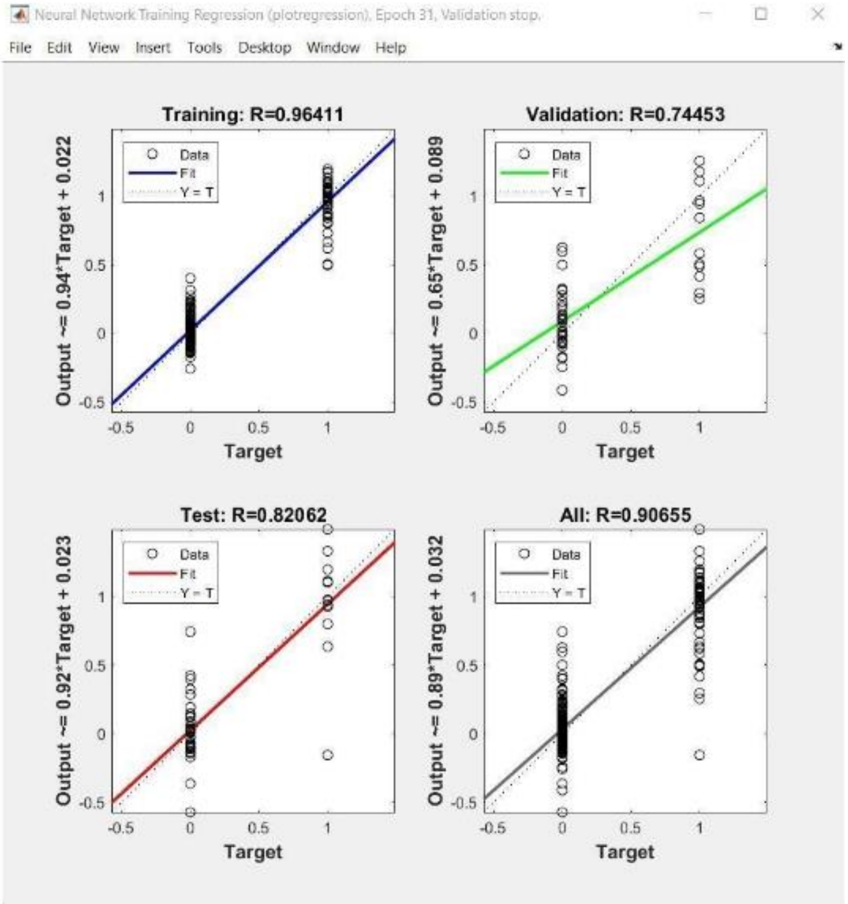

Fig. 14. Training Regression Plot

Overall, the simulation and training results demonstrate that the proposed neural network-based classification system is capable of accurately detecting and labelling various power quality disturbances under different fault conditions. This confirms the feasibility of integrating such intelligent systems into real-time PQ monitoring frameworks.

VI.CONCLUSION AND FUTURE SCOPE

As power quality is becoming the utmost important factor today, identifying and mitigating should be very fast and accurate to protect the equipment. This presents different data mining algorithms like Support Vector Machine, K-Nearest Neighbor tools for classification of various power quality issues such as voltage sag, swell, interruption, and unbalance. With the information set obtained from the sampled rms voltage waveforms generated in MATLAB Simulink, the algorithms are trained and checked. The accuracy depends on the type of data collected and amount of data used for training the model and the training time. So, the best performing algorithm can be decided based on the trade-off between accuracy and training time. This work can be extended to accurately classify different harmonics present in the power system and hence necessary mitigation methods can be implemented to safeguard the system.
There are several challenging issues in the automatic classification of PQ disturbances such as detection of the underlying causes of disturbances, detection of the single and multiple disturbances. The most suitable feature extraction technique should be applied because the classification algorithms are highly dependent on the input feature vectors. A lot of research has been focused on the synthetic data for training and testing the classifiers. The real-time data must be applied. De-noising is still a challenge for the classification of noise riding PQ signals researchers because the feature extraction and classification algorithms poorly perform for the noise riding PQ signals. Most of the PQ disturbances classification techniques are based on the single-phase data. In actual practice, power system is a three-phase system. Therefore, more research must be focused on real-time three-phase power system disturbances.

REFERENCES

[1] Abdullah Asuhaimi Mohdzin, "MATLAB/Simulink Based Modeling and Simulation of Power Quality Disturbances", IEEE Conference paper (2018).

[2] Akinola, S., & Oyabugbe, O. (2015), "Accuracies and training times of data mining classification algorithms: An empirical comparative study", Journal of Software Engineering and Applications, 8, 470–477.

[3] Avdakovic.S , A. Nuhanovic, M. Kusljugic, E. Becirovic, "Applications of wavelets and neural networks for classification of power system power quality events", Turkish Journal in Electrical Engineering Computer Science 22 (2014) 327–340

[4] De Yong. D , S. Bhowmik, F. Magnago, "An effective power quality classifier using Wavelet Transform and Support Vector Machines", Expert System Application 42 (2015).

[5] Eris ti.H , Ö. Yıldırım, B. Eris ti, Y. Demir, "Optimal feature selection for classification of the power quality events using wavelet transform and least support vector machines", International Journal of Electrical Power Energy System 49 (2013)95–103.37.

[6] JIan Ma, Jun Zhang, Luxin Xiao, "Classification of power quality disturbances via deep learning", IETE technical review,2016, pp.743-752.

[7] Khokhar. S, A.A.B. Mohd Zin, A.S.B. Mokhtar, M. Pesaran, "A comprehensive overview on electric power quality and artificial neural networks techniques in classification of power quality disturbances", Renewable and Sustainable Energy Reviews 51 (2015) 1650–1663.

[8] [2] Ma. J, J. Zhang, L. Xiao, K. Chen, and J. Wu, "Classification of power quality disturbances via deep learning," *Electric Power Components and Systems*, vol. 44, no. 4, pp. 408–415, 2016. [Online].

[9] Mohd Izhwan Muhamad, Norman Mariun, Mohd Amran Mohd Radzi, "The Effects of Power Quality to The Industries", IEEE 5th Student Conference on Research and Development, Scored., 2007.

[10] Pandit, N., & Chakrasali, R. L. (2017), "Powerquality issues in Indian power distribution utilities and feasible solutions", International Journal of Scientific & Technology Research, 6(5), 23–25.

[11] Sharmila, M., Sundarabalan, C. K., & Selvi, K. (2017), "Power quality disturbances classification using data mining technique", International Journal of Research in Science & Engineering,3(3), 77–90.

[12] Upadhyaya, S., & Mohanty, S. (2016), "Localization and classification of power quality disturbances using maximal overlap discrete wavelet transform and data mining-based classifiers", IFAC-Papers Online, 49(1), 437–442.

[13] Zhang. S, P. Li, L. Zhang, H. Li, W. Jiang, and Y. Hu, "Modified S transform and ELM algorithms and their applications in power quality analysis," *Neurocomputing*, vol. 185, pp. 231–241, Apr. 2016. [Online]. Available: https://doi.org/10.1016/j.neucom.2015.12.050.