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Pretrained Configuration of Power Quality Grayscale Image Dataset for Sensor Improvement in Smart Grid Transmission

Abstract

Since real-time data exchange via a network of various sensors demands a small file size without adversely affecting information quality, one measure of power quality monitoring in a smart grid is restricted by the vast volume of data collection. In order to provide dependable and bandwidth-friendly data transfer, the data processing techniques' effectiveness is evaluated for precise power quality monitoring in wireless sensor networks (WSNs) using Grayscale PQD Image data and employing pretrained PQD data with deep learning techniques such as Resnet50, MobileNet, and EficientNetB0. The suggested layers, added between the pretrained base model and the classifier, modify the pretrained approaches. The results show that EfficientNetB0 outperforms the other pretraining methods evaluated generally, outperforming them with the accuracy of 99.10%, training accuracy of 99.55%, and validation accuracy of 98.58%. This is a good fit model, as evidenced by training and validation loss that diminishes to the point of stability with a negligible disparity between the two final loss values. The preprocessed data's output is anticipated to allow for reliable and bandwidth-friendly data packet transmission in WSNs.

Keywords: Pretrained methods, PQDs, sensor network

1. Introduction

The process of developing and delivering power to end users has remained fairly stable over the years. In a traditional grid, Figure 1, power systems are built on a few controlled and massive power sources, primarily hydroelectric or fossil fuel-based energy production systems, with a vast transmission network supplying power to customers through a distribution system. The electricity supplier creates a consumption plan based on historical data from their customers and orders electricity from the power plant based on that plan. This is possible because fluctuations in energy use were low in the past, and the transmission system was generally reliable. This is significantly different from today when large fluctuations in electricity usage make the transmission system more unreliable. As a result, a technological upgrade from the conventional grid is required to change the existing grid into a high-performance grid with huge potential.

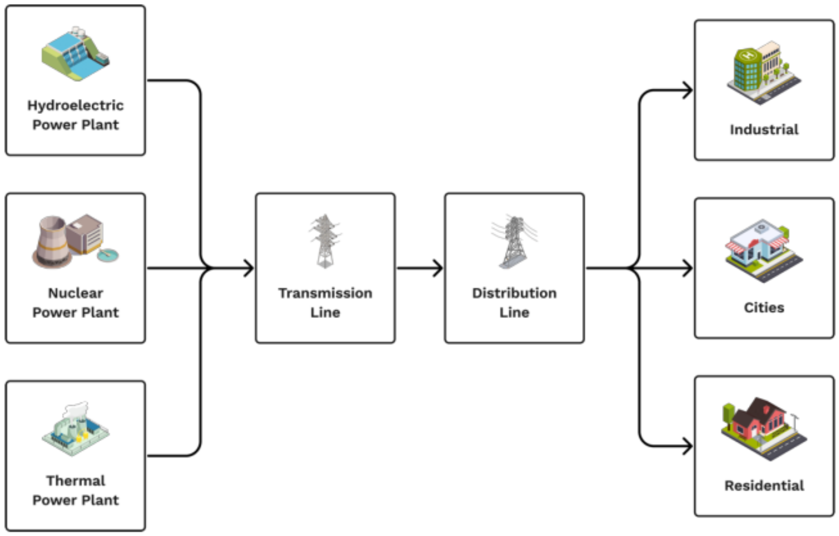


Figure 1. Traditional grid system [1]

Due to this transition, the smart grid has attracted much research interest in the past ten years. The emergence of smart grids becomes a solution when traditional networks are no longer adequate for implementation in the power system. Since traditional electricity systems are inactive due to directional power and communication transfer, the integration and contribution of every distributed energy resource in the smart grid environment makes it a dynamic grid due to two-way electricity and data flows [1]. Smart networks use the information other than historical data. It constantly monitors what is going on in the network and handles the flow of electricity directly. The software that collects, analyzes, and independently decides how energy will be distributed is at the heart of the smart grid. The information gathered by energy suppliers from many sources is thereby processed in a single location, making the power grid far more predictable, adaptable, and trustworthy. The smart grid collects information from smart meters and other intelligent sensors, including IoT devices (IoT - Internet of Things).

Since the traditional power system is being transformed into a more efficient and reliable smart grid, this shift places increased strain on a couple of centuries of power grid infrastructure, necessitating further expenditure to guarantee safe and consistent electricity delivery to consumers. The smart grid is made up of a vast number of sensors, gadgets, measurement units, and computers that are linked by a pervasive network, which is the ultimate source of various Power Quality Disturbances (PQDs) concerns. International standards for categorizing electrical disturbances that affect the grid or the user have been developed because PQ is a crucial prerequisite for smart grids. The methods and threshold values that define an electrical disturbance, such as an overvoltage, undervoltage (sag or dip), fluctuation, harmonic distortion, etc., are laid forth in the PQ definition provided by the standards IEEE-1159 [2] and EN-50160 [3].

Among the available methods to monitor the above disturbances, data acquisition with traditional wired systems may certainly result in considerable repercussions concerning the operator's safety [4]. On the other hand, using a Wireless Sensor Network (WSNs) eliminates these shortcomings and makes the data acquisition much safer [5]. Remote monitoring of multiple machines can be achieved through one receiving station. Moreover, most wired sensor networks use lengthy cables to deliver the acquired data to the central computer. These cables are subjected to wear and tear, leading to channel losses. Thus, the use of a WSNs in data acquisition does not only contributes to its safety but also to its economy.

A WSNs is a system made up of several computational and sensor units dispersed throughout a monitored environment. WSNs have been used to automate the usage of computer, sensor, and wireless communication equipment for both academic and commercial applications throughout the past few decades. ZebraNet, for instance, was created to track wildlife. The purpose of CitySense is to provide weather and air quality reports. The Sensormap portal was created to provide services for genetic monitoring. Designing specialized systems like the one above has received more research focus to meet application-dependent service needs [6].

WSNs are employed for a wide range of purposes, which frequently need real-time data transfer. A well-known obstacle to WSNs implementation is bandwidth restriction, which results in the sample rate and sensor number limitations. This can be resolved by decreasing extra using compression techniques and an occurrence communication method [7].

Some computations must be performed by the smart meter online to identify PQ, while others need an off-line strategy like disturbance propagation. As a result, the smart sensor network must perform some computations while relying on a big-data post processor for others. A general smart sensor in a smart grid system is shown in Figure 2.

Smart sensors can be discreetly installed inside several structures, including private residences, commercial buildings, and public buildings. This smart sensor incorporates a wireless Bluetooth communication module, a large storage device, and a data gathering module. A microprocessor, real-time clock, internal data bus, universal serial bus (USB), and various soft-cores for signal processing are also included. The network of smart sensors is integrated into the system using a mobile device, such as a smartphone or tablet, to integrate and remotely monitor them. The system generates a significant amount of data, which is then processed further in a big-data center. The system does not need to be powered off to connect the smart sensors because they are not obtrusive. This makes the system very simple to use. It is also incredibly adaptable because it supports a wide range of current and voltage levels and a variety of programmable soft-core-based processing capabilities.

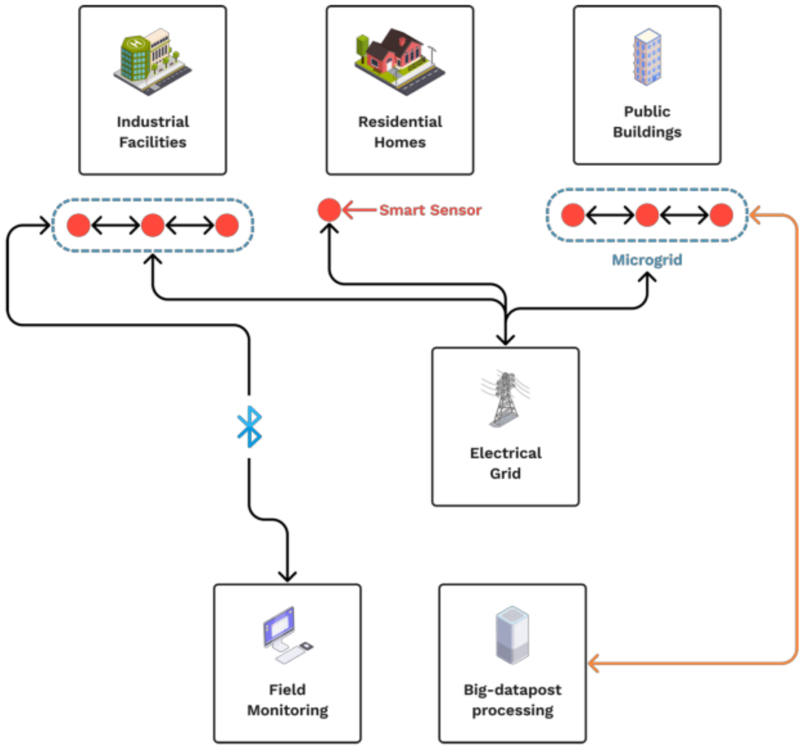


Figure 2. Smart sensor in smart grid system [8]

One measure of power quality monitoring is constrained by the enormous volume of data collection since real-time data sharing over a network of numerous sensors requires a small file size without compromising information quality. Delivering power quality monitoring services is difficult as a result. This problem is addressed by evaluating the effectiveness of data processing techniques for precise power quality monitoring in WSNs using 2D Regulated Grayscale PQD Image data from recent research findings and providing pretrained PQD data using deep learning techniques such as Resnet50, MobileNet and EficientNetB0 in order to provide dependable and bandwidth-friendly data transfer.

The following are the primary contributions of this work:

- An experimental evaluation of dataset pre-training methodologies has been conducted for online PQD classification on WSN nodes with constrained computing capabilities, constrained internal storage, and low energy consumption. To the extent of our knowledge, earlier PQD research only provided ResNet data for pre-training. While this is occurring, it is still difficult or challenging to locate references to the implementation of MobileNet, and EfficientNetB0 pre-training on PQD.
- Investigates how responsive response-based 2D depth CNN power quality classifiers are to substantive improvements in field power quality. Because the PQD data utilized for the power quality classifier was synthetic, PQD was developed using a mathematical model

with parameter changes in line with IEEE Std. 1159, earlier research had difficulty identifying real disturbances because the model was an abstraction from reality.

The following are the contents of this study. Section 1: Introduction, section 2 describes the prior works that provide the background for the current topic. Section 3 proposes data and solutions for addressing the presented situation. Section 4 describes data-driven validation and discusses the results. Finally, section 5 concludes the paper and presents future work.

2. Related Work

It has been determined that categorization and abnormality detection are crucial methods for preserving power quality. The computational speed of the algorithm for classifying and detecting disturbances is the most critical aspect to take into account in the context of the smart grid, intending to send information on consumption and disruptions to utilities via a two-way communication infrastructure. In other words, the computational speed must be compatible with the bandwidth and data transfer speed.

One-dimensional (1-D) and two-dimensional (2-D) datasets are two novel dataset-based methodologies for finding and classifying PQD. In past research, the main goal was to improve PQD classification performance in 1-D Convolutional neural networks (CNNs). The most effective methods, CNNs, are frequently used in PQD classification research [9]. The current technique uses a 1-D CNN algorithm and principal component analysis (PCA) to categorize data using 1-D PQDs. The wind-grid distribution system, a wind-energy-based renewable energy system conceived and developed to distribute electricity to the grid, uses this technology [10]. However, past research on the problem of training time was limited because of the vast data volume. Large data files are generated in PQ monitoring as a result of the high sample rate and amount of measurement points [11].

A data compression approach is necessary to shorten the amount of time calculations take during the training stage [12]. Signal compression algorithms have been proposed to reduce the amount of data that needs to be saved. Recently, there has been some scientific interest in CNN compression. In order to save storage costs and enable Fast Fourier Transform to speed up computing, this work [13] suggests replacing traditional linear projection on the completely linked layer with circular projection. A different study [14] aims to reduce the network's total number of parameters and operations. The computing workload and parameter size can be significantly reduced using the pruning approach. However, significant PQD data would be lost as a result of the compression process.

Since 2-D images can include more PQD information than 1-D signals, an image conversion approach has been developed in recent years to make it easier to use CNN for PQD classification. PQD signals are 1-D signals that require data pre-processing to transform into 2-D images. In the study in [15], the PQD classifier is immediately trained using the signal-waveform picture, and in [16], the sag signal is converted into the PQD image using the space phasor diagram. While prior studies used a three-channel format comprising data for red, green, and blue hues (RGB), [17] displays an image transformation matrix where the PQD signal's sample points are rearranged in the matrix before being turned into a grayscale image. Nevertheless, as [18] transition, certain crucial elements are utterly lost. According to Karasu's method in [17] and [19], when the fundamental frequency deviates from its nominal value, rearranging the picture transformation matrix leads to classification error. Because the fundamental frequency varies, the time locations of PQD would decrease. The approach has a training accuracy of 98.69%, while Zheng's method [20] has a training accuracy of 97.98%.

The fundamental frequency variation was detected, and the image matrix was controlled by the IEC-based synchronizer to enhance classification performance. The controlled 2D grayscale image can maintain the signal's information and waveform characteristics. The results of the testing and field measurements showed that the suggested strategy was more effective than the previously used approaches and could boost the PQD classification's effectiveness with an accuracy of greater than 99.79 percent [21].

The optimum PQD classification method is still being researched in order to enhance system reliability in a power system. Many researchers use enhanced CNN architecture, specifically Residual Neural Network (ResNet), to perform multiple PQD analyses. According to research [22], ResNet-18 outperforms other CNN designs in terms of accuracy (95.77 percent) when compared to other Classifiers such as basic CNN, Deep CNN (DCNN), and GoogLeNet. In comparison, the MobileNetV2 classifier is built and tested to classify the quality of surface water. The testing findings reveal that the classifier performs admirably and can be easily implemented on edge devices [23]. The foundational EfficientNet-B0 network is built on the inverted bottleneck residual blocks of MobileNetV2, as well as squeeze-and-excite blocks. With an order of magnitude fewer parameters, EfficientNets transfer well and reach state-of-the-art accuracy on CIFAR-100 (91.7 percent), Flowers (98.8 percent), and three other transfer learning datasets [24].

3. Research Methodology

3.1. Transfer Learning

DCNN is extremely good at identifying low, medium, and high-level features in images and stacking additional layers, resulting in higher accuracy overall. Because deep neural network architecture is comprehensive and design complex, a valuable technique known as transfer learning can be employed for a specific type of task. Transfer learning (TL) is a strategy for solving other similar problems by employing a pretrained model on a dataset as a starting point and adjusting and updating its parameters to fit the new dataset. When performing the model training process, the TL model will assist reduce the amount of data utilized, the calculation procedure, and the calculation time [25].

3.2. Pretrained Deep Learning Network

With fixed weights for the specific application, a pretrained network has already learned to retrieve powerful and valuable features from natural photos. When the dataset is small, and the application domain is related, pretrained networks can be deployed. Moreover, it takes time and computing power to train CNN from the beginning. According to the study [26], employing weights from a distant task may improve performance compared to randomly initialized weights.

There are currently a ton of pretrained CNN, such as ResNet, MobileNet, EfficientNet, et cetera. In some cases, several pretrained networks deliver exceptional performance. The current study looks into the ideal CNN network configuration for PQD classification in light of the excellent performance. The pre-training network was chosen based on its ease of use and its most excellent performance in prior iterations of the ILSVRC (Imagenet Large Scale Visual Recognition Challenge) competition. Other factors considered include the network's time and space complexity, error rate displayed in the ILSFRC challenge, and more.

Table 1. Summary of ImageNet performance

Model	Size (MB)	Top-1 Accuracy	Top-5 Accuracy	Parameters	Depth	Time [27] per inference step (CPU)	Time [27] per inference step (GPU)
ResNet-50	98	74.9%	92.1%	25.6M	107	58.2	4.6
MobileNet	16	70.4%	89.5%	4.3M	55	22.6	3.4
EfficientNetB0	29	77.1%	93.3%	5.3M	132	46.0	4.9

Table 1 highlights the ImageNet performance, an images database arranged according to the WordNet hierarchy, with hundreds of millions of images representing each node of the hierarchy. The data demonstrates that the EfficientNets-B0 outperforms other pretrained models significantly. EfficientNetB0, in particular, use 5.3M parameters; has a running time of 4.9 ms for each inference step (GPU) and achieves 93.3 percent in the top 5 accuracy. In comparison to MobileNet, which computes 4.3M parameters in 3.4 ms per inference step (GPU) but only achieves 89.5 percent top-5 accuracy. The widely used ResNet-50 has a top-5 accuracy of 92.1 percent using 25.6M, 4.6 ms per inference step (GPU). With a 99.62% accuracy rate, improved EfficientNet outperformed a number of the well-known DCNNs that had been previously released, including ResNet [28] and MobileNet [29].

4. Experiment and Result

The experiments are carried out to evaluate the performance of the three different pretrained CNNs, ResNet-50, MobileNet, and EfficientNetB0, when PQD classification is applied to the photos from the signal power quality dataset of the Amrita Honeywell Hackathon 2021.

4.1. Data and Hardware

The dataset used in this study consists of signals divided into the following five power quality categories: normal, third harmonic wave, fifth harmonic wave, voltage dip, and transient. A nominal fundamental frequency (*f*) in the range of 59.5 and 60.5 Hz, two sampling cycles (*Nc*), and 128 sample data points (N_s) are used to describe each signal. With a total of 11,998 raw data, the following power quality conditions are described in relation to the output class value: normal (1,998), third harmonic wave (2,000), fifth harmonic wave (3,000), voltage dip (2,000), and transient (3,000).

The used hardware is a MacBook Air with the following features: 8 GB of RAM, a 16-core Neural Engine on the M1 chip, a 7-core GPU, and an 8-core CPU with four performance cores and four efficiency cores. The learning model was implemented utilizing a Google Colab-accelerated GPU and a Wi-Fi 802.11ax Wi-Fi 6 connection to the internet.

4.2. Data Pre-processing

Pre-processing data is essential in preparation and modification before being utilized in model training. When the range of the data samples fluctuates, normalization is a frequent data processing technique where numerical column values are changed to have a uniform scale. Before using the data to reconstruct the dataset into two dimensions, the data must be scaled into a value range of -1 to 1 as part of the normalization process since the power quality distribution of one-dimensional dataset value has a wide range, especially between -7,185 and 11,997. The raw power quality distribution data in this study were handled in the data pre-processing phase, which includes the two steps of signal synchronization (SS) and image regulation (IR), as shown in Figure 3.

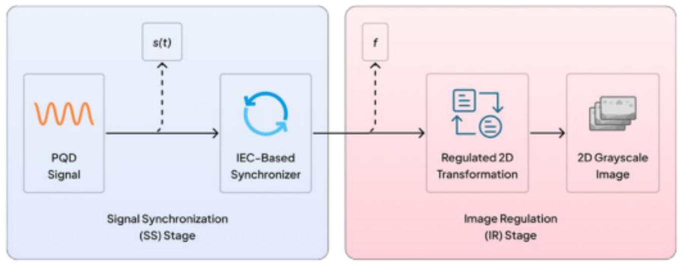
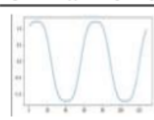
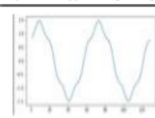
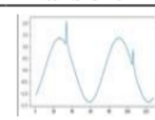


Figure 3. The stage of data preparation

In the SS stage, the fundamental frequency obtained from the IEC (Standard 61000-4-7) based synchronizer is used to calculate the regulated cycle duration in accordance with the fundamental frequency variation. After the PQD signal has been properly separated using the acquired fundamental frequency, the 2D grayscale picture matrix will be controlled in the IR stage. The crucial step in data preparation is determining the submatrix dimension. The square submatrix has precisely as many columns (N_{col}) chosen as rows (N_{row}). The PQD signal should then be divided into several cycles. The f value determines the N_c cycles of the PQD signal. Third, take the divided cycles and generate submatrices. Step four should merge the submatrices to produce a controlled matrix. Finally, take the controlled matrix and turn it into a 2D grayscale image. The matrix's components are converted to the grayscale color space to create the grayscale image (0–255). N_{row} x N_{col} pixels are the size of the final image [21]. The output of a controlled 2D grayscale image produced using the previously mentioned technique is shown in Table 2.

Table 2. Power quality disturbances signal form and 2D grayscale image

	Normal	**3rd Harmonic**	**5th Harmonic**	**Voltage Dip**	**Transient**
PQD 1-D Signal					
PQD 2-D Image					

The disturbance classification stage would then process the regulated feature image to complete the PQD identification.

4.3. Method

According to Figure 4, the research process for this study was divided into six parts. Create a CSV file first containing the power quality signal dataset for the first five classes. In the data preprocessing stage, the signal dataset is initially normalized. Third, the normalized dataset produces an image format with a metric resolution of 64 x 64. In the fourth step, model training data accounted for 80% of the dataset used for model learning, while model validation data made up 20% of the dataset. In many areas, splitting information into ratios is a common practice when utilizing machine learning or deep learning models to solve problems. Additionally, 200 test results were given to each category, totaling 1,000 test results divided among five classes.

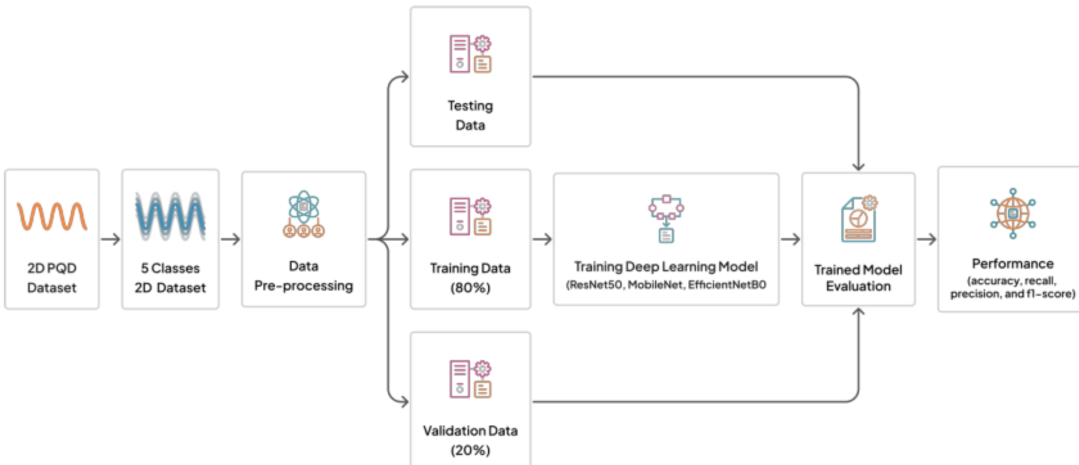


Figure 4. Stages of research method

The model training stage is the fifth stage. Resnet50, MobileNet, NASNetMobile, and EficientNetB0 transfer learning models (trained models) for PQD classification were employed in this work because they are among the best-performing transfer learning models (trained models) commonly utilized by researchers for image classification. The performance of the 2D deep CNN model in recognizing PQDs was evaluated based on the training model in the sixth stage. Figure 5 illustrates the model structure of the applied 2D deep CNN, which consists of four convolutional layers, two maxpooling layers, and one dropout layer before two fully connected layers. Therefore, the model's performance outcomes were assessed using the accuracy, recall, precision, and f1-score [30].

4.4. Proposed Layers

This study modified pretrained methods to dig more information from the PQDs dataset. The proposed layers are placed between the based model of pretrained and classifier. Figure 5 illustrates proposed layers for EfficientNetB0, MobileNet, and ResNet50 composed of a Global Average Pooling 2D (GAP2D), Dropout layer, and Batch Normalization. To avoid cases of extreme overfitting caused by the advanced feature management, a pooling layer was introduced. By rescaling the height, width, and depth of the incoming tensor from the base model, the GAP2D layer could significantly reduce the number of parameters. By switching to the dense layer at this stage, which can overwhelm the classifier, the massive influx of characteristics is controlled. The feature maps were not entirely diminished by the GAP2D. Instead, it averaged the entire spatial data set and retained the most complex patterns necessary to identify the image [31].

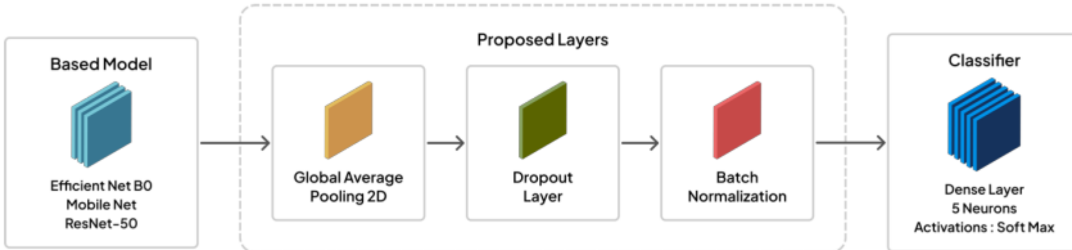


Figure 5. Proposed layers for advanced pretrained model

The feature sets from the GAP2D are directed to a dropout layer and batch normalization layer. Furthermore, the model connected the classifier with SoftMax activation and five neurons representing five given labels.

4.5. Hyper-Parameters Value

The hyper-parameter settings and loss function used for the task to yield effective results are described in this section.

A DL model's performance is measured not solely in terms of accuracy but also in terms of loss. [32]. The model seeks to achieve its lowest rate of mistakes since a model with a smaller computed loss is more effective [33]. The cross-entropy [34] loss function is used in this work to obtain the average measure of the difference between the expected and forecast value. The loss measurement for binary classification is shown in Equation (1), where y represents the binary values of 0 or 1, and p is the probability [35].

$$CE = -(y\log(p) + (1-y)\log(1-p)) \quad (1)$$

The Adam optimizer was used in this work to provide optimal loss reduction during training. This optimization approach works as an adaptive gradient descent function, allowing for faster weight loss towards local minima [36]. When compared to alternative optimizers such as Stochastic Gradient Descent (SGD) [37] or RMSProp [38], the Adam optimizer was chosen because of its ease of implementation, efficient memory usage, and speedier learning phase.

Table 3 displays the hyper-parameter settings. A low learning rate (LR) works well with the other hyper-parameters specified. The 32-batch size provided enough load to transport data across the network without using all the computing memory. Furthermore, we chose durations within 50 epochs to train each model incrementally to see how it would perform.

Table 3. Hyper-parameters specified for training

Hyper-parameters	**Value**
Learning Rate	0.0004
Batch Size	32
Optimizer	Adam
Dropout	0.5
Epoch	50

4.6. Results

This section reviewed the results gained from the prepared dataset throughout the validation and training stages. The outcomes of evaluating the deep learning networks EfficientNetB0, MobileNet, and ResNet50 in the PQD classification task on the actual PQD images dataset are presented in Table 4.

Table 4. Performance of pretrained deep learning network for 2D grayscale images PQDs dataset

Network	**Accuracy (%)**	
	Training	**Validation**
EfficientNetB0	99.55	98.58
MobileNet	98.90	97.46
ResNet50	99.03	96.85

Training learning is calculated from the training dataset. It provides information about how well the model is learning, whereas validation learning is calculated from a hold-out validation dataset and how well the model generalizes. Compared to MobileNet and ResNet50, the data from the table shows that EfficientNetB0 produces very accurate deep learning solutions for identifying 2D grayscale images from the PQD dataset with a training accuracy of 99.55% and validation accuracy of 98.58%.

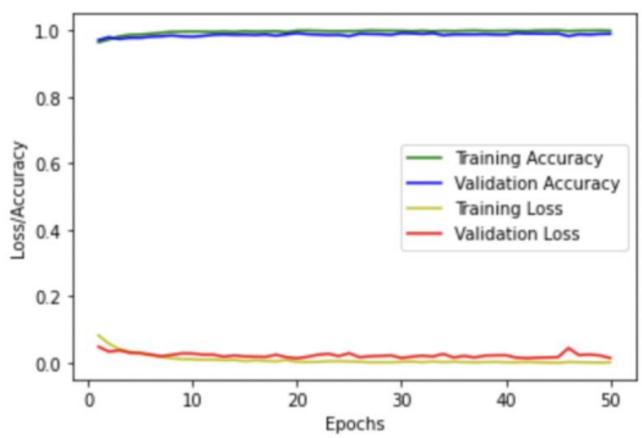


Figure 6. Training and validation progress of EfficientNetB0

Figure 6 depicts that the EfficientNetB0 training process is a good fit model, as indicated by a training and validation loss that decreases to the point of stability with a minimal gap between the two final loss values.

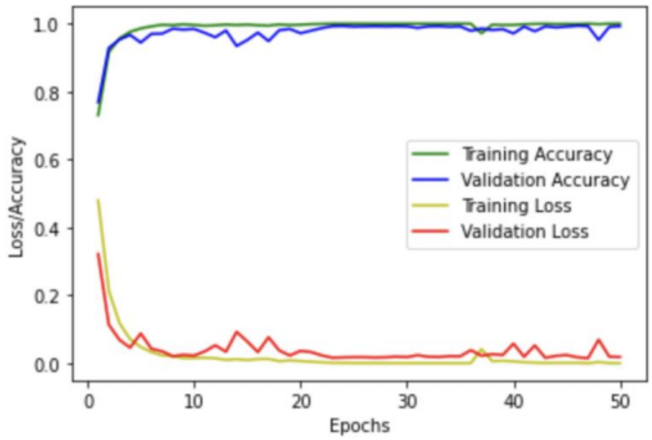


Figure 7. Training and validation progress of MobileNet

Figure 7 depicts an example of MobileNet overfitting. It may arise if the model is trained for an inordinately extended period. The 30th epoch may be the inflection point in validation loss, as experience after that point illustrates the dynamics of overfitting.

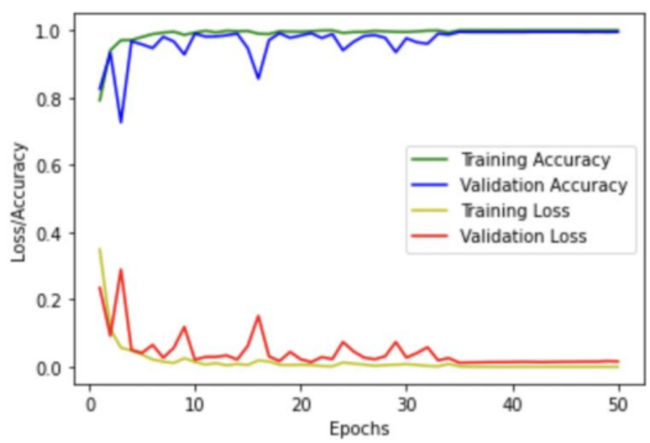


Figure 8. Training and validation progress of ResNet50

Figure 8 shows that the training and validation learning curves of ResNet50 demonstrate a training dataset that may be too small compared to the validation dataset. Both learning curves can identify this situation for training loss and validation loss showing improvement, but after the 35th epoch, a slight gap remains between both curves.

A specialized metric called the Confusion Matrix (CM) shows how well a trained model can forecast from a given validation dataset. A 3rdHarmonic, 5thHarmonic, Normal, Transient, and Voltage Dip are the true class and ground truth labels shown by the CM's corresponding rows and columns. The projected results provide the proportion of accurate and inaccurate predictions or classifications for each validation sample. Following the values, the accuracy, precision, recall, and F1 score of each model are computed. The recall value indicates how many times the model was able to detect a specific category. Precision is the frequency with which a model correctly predicts an actual class. The total number of accurate predictions made from all available samples is the accuracy. The F1 score is also the weighted average of the recall and precision values [39].

Table 5. Comparison of classification performance

Network	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
EfficientNetB0	99.10	98.60	99.00	98.80
MobileNet	99.32	99.00	99.20	99.20
ResNet50	99.55	99.20	99.40	99.40
Basic CNN	98.99	98.60	98.80	98.80

Table 5 computes the total performance of the classification using pretrained model based on its accuracy, precision, recall, and F1-score using the CM matrix. From the examined finding, Resnet50 achieved the highest accuracy of 99.55%, followed by MobileNet with 99.32% and EfficientNetB0 with 99.10%. However, in the training performance of EfficientNetB0, its accuracy is better than ResNet50, while the accuracy of MobileNet is improved for lea smaller number of epochs rather than the training performance of ResNet50. As shown in the architecture and way of implementing all the models ResNet-50 has more parameters, 25.6 MB, to be used, so it is obvious that it will show better performance compared to the EfficientNetB0 and MobileNet. ResNet50, on the other hand, requires a more extensive data capacity of 98 MB.

The most severe resource limitation on WSNs during implementation for smart grid objectives is restricted battery energy. Transmission power control and data packet size optimization are effective strategies for increasing network lifetime and lowering energy consumption [40]. As a result, this study suggests that MobileNet and EfficientNetB0 pretraining models be used for 2D grayscale images PQD data classification. The MobileNet basic model requires only 16 MB of data size. The EfficientNetB0 base model requires 29 MB of data size. Furthermore, the compute times for both models are 22.6 ms and 46.00 ms, respectively, comparing the ResNet50 compute time of 58.2 ms per inference step (CPU) and the base model requiring 98 MB of data size. At the same time, three models' accuracy differs slightly.

5. Conclusions and Future Work

Previously, an experimental evaluation of ResNet dataset pre-training approaches for online PQD classification on WSN nodes with limited processing capabilities, internal storage, and low energy consumption was carried out. However, references to the implementation of MobileNet and EfficientNetB0 pre-training on PQD are still challenging to find. As a result, this work took the initiative to examine contemporary CNNs for classifying and detecting PQDs utilizing MobileNet and EfficientNetB0 data pretrained approaches. Pretrained techniques are modified by the proposed layers, which are inserted between the pretrained base model and the classifier. This research also looks into how responsive response-based 2D depth CNNs power quality classifiers can lead to significant improvements in field power quality.

Since ResNet-50 has a greater number of parameters, 25.6 MB, upon evaluation with 11,998 raw data images, CNNs classifier utilizing Resnet50 achieved the highest accuracy of 99.55%, followed by MobileNet with 99.32% and EfficientNetB0 with 99.10%. However, in the training performance, the accuracy of EfficientNetB0 is better than other pretrained methods, with a training accuracy of 99.55% and validation accuracy of 98.58%, which is a good fit, as indicated by a training and validation loss that decreases to the point of stability with a minimal gap between the two final loss values.

As a result, compared to the basic deep CNN classification technique, the transfer learning-based EfficientNetB0, MobileNet, and ResNet50 could efficiently improve classify 2D deep CNN using regulated 2D grayscale images. EfficientNetB0 surpasses the other pre-training methods evaluated in general. The outcome of the preprocessed data is assumed to enable reliable and bandwidth-friendly data packet transmission in WSNs. The modest number of data samples obtained during the training procedure limits research with real data. As a result, we advocate doing more studies that include collecting additional data from other smart grids using various sensor devices.

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