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RMSProp Optimization Convolutional Neural Network based Islanding detection in a Grid connected PV Inverter

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ABSTRACT
An islanding event, which occurs when a utility is integrated with an electrical system and is cut off from the rest of the distributed system, is a more serious concern for electrical utilities. This is especially true when renewable energy sources are present. In this work, we provide a unique approach to islanding detection, based on a deep learning model of a convolutional neural network (CNN) improved using the RMSProp (Root Mean Square Propagation) algorithm to reduce the loss function of the model. The recommended technique is based on time frequency wavelet analysis to generate the dataset for the model, the scalogram image (RGB picture) that is collected from the time series data of voltage signal at the point of common coupling in the proposed system. Finally based on the data and model will predict the islanding and non-islanding event.
Keywords- *Convolutional Neural Network, machine Learning, RMSProp, Scalogram.*

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I. INTRODUCTION

A circumstance known as "ISLANDING" occurs when a portion of the distribution network is powered by one or more distributed generation (DG) units that are linked to it but is not connected to the grid[1]. Three primary groups of islanding detection strategies exist: communication-based approaches [17], [18], passive [12]– [17], and active [2]–[11]. A little noise signal is introduced into the system via active means.

In most circumstances, this signal won't significantly alter the system's properties. This signal will, however, be increased during islanding, making islanding detection easier.

Simple techniques for passive islanding detection rely on quantifiable values at the point of common coupling (PCC), such as voltage, frequency, etc., to identify islanding. While communication-based techniques are the most-costly for detecting islanding, they are also the most accurate.

A variety of islanding detection techniques have been put out in recent years, all with the general goal of reducing the non-detection zone (NDZ). The islanding detection techniques that have been previously suggested in the literature are DG dependent, or put another way, they have been tried and tested on a certain kind of DG interface. Inverter-based DG, for instance, has shown to have small or even negligible NDZ for islanding detection techniques such as Sandia frequency shift (SFS) [3], [4], positive-feedback-based active islanding detection [7], frequency drift anti-islanding [8], high-frequency signal injection [21], and Bayesian passive islanding detection [22]. When used with synchronous-based DG, these techniques would either not work correctly or could not be incorporated in the same way. Conversely, islanding detection techniques like the decision tree (DT)-based technique [23], the fuzzy rule-based approach [24], the pattern recognition approach [25], [26], and the synchronous distributed generation islanding protection using intelligent relays [27] have been specifically developed for synchronous-based distributed generation. Similarly, similar solutions may not work well for synchronous-based and inverter-based distributed generation (DG) due to their differing responses to an islanding state.

Passive islanding detection techniques that may be regarded as universal as they can be used with both kinds of DGs include rate of change of frequency (ROCOF) [16] and over/under frequency and over/under voltage protection (OFP/UFP and OVP/UVP) [15, 16]. These techniques have a significant NDZ, particularly for DG that uses inverters. Although it is a more expensive option than other approaches, communication-based islanding detection is nevertheless regarded as a universal strategy.

II. RELATED WORK

Artificial intelligence (AI) methods for islanding detection have been presented recently. The primary benefit of AI approaches is their capacity to identify the best feature/parameter combinations and threshold settings that may drastically lower the non-detection zone of islanding detection methods.

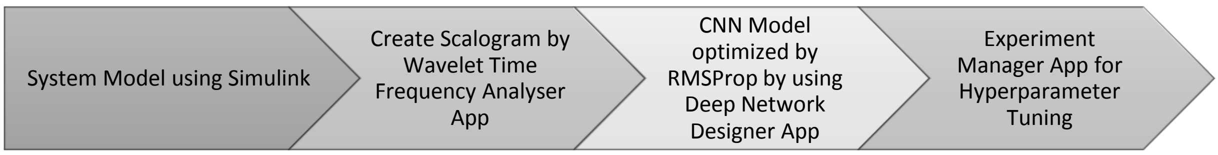
An intelligent islanding detection method was described in [23] that extracts threshold values for eleven system characteristics using decision trees. A fuzzy rule-based technique was created in [24] as a result of the method's inability to capture all potential islanding occurrences. This approach produced extremely accurate results for islanding identification.

In [22], a different passive islanding detection method was put out. This method employed a Bayesian classifier to identify islanding based on 64 characteristics determined by ESPRIT. The suggested method created features by using voltage and frequency waveforms, which were then input into a naïve Bayesian classifier to identify islanding instances. A pattern recognition method was used in [25] and [26] to detect islanding. To extract features, discrete wavelet processing was used to discretize transient voltage and current waveforms. Based on the energy content in the wavelet coefficients, a decision tree model was created to distinguish between islanding and non-islanding occurrences [26].

When appropriate characteristics were collected and an appropriate classifier was employed, AI approaches demonstrated highly accurate results in identifying islanding for all of the aforementioned methodologies [22], [26]. However, each solution was evaluated and put into practice using a single kind of DG (synchronous or inverter).

This paper proposes a smart method to determine islanding detection by using convolutional neural network analyzing the voltage signal in terms of time frequency analysis, which is called scalogram and generating dataset by varying the load values of real and reactive power. The voltage signal is converted into the time series data and by using this time series data is converted into scalograms. These scalograms are fed to CNN model and further it was optimized by using RMSProp algorithm, which results the lowest value of loss function of the model and it also provides accuracy of the model performance.Again, the model is further experimented by hyperparameter tuning with the 3 initial learning rates and obtained the loss and accuracy plots along with the confusion matrix for training data and validation data.

III. PROPOSED METHODOLOGY



3.1 System model description

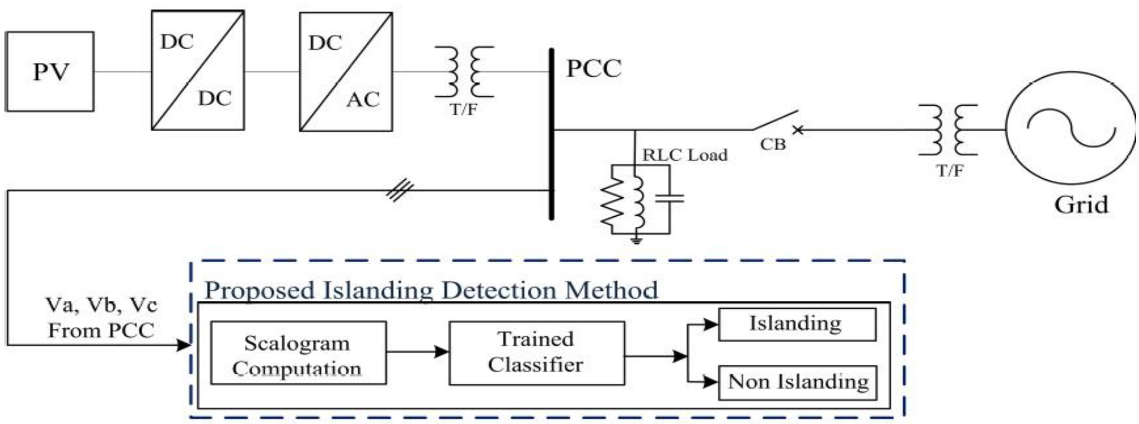


Figure 1 Proposed Test system

From the above figure 1, PV source 2MW is connected to the DC-DC converter to stable the voltage and it is further converted into DC to AC voltage and is feed the PCC bus, at this bus grid, load is connected. By varying load values, the voltage signal is converted time series data and from their-on, the signal is converted into scalogram and by this way generated the dataset, tabled below in table 1.

3.2 Dataset Generation

Table 1 Total islanding and non-islanding events

Total Observations	$[\boldsymbol{V_{abc}}]$	**1107**
Islanding Cases	$[V_{iabc}]$	548
Non-Islanding Cases	$[V_{gabc}]$	559

3.3 Scalogram

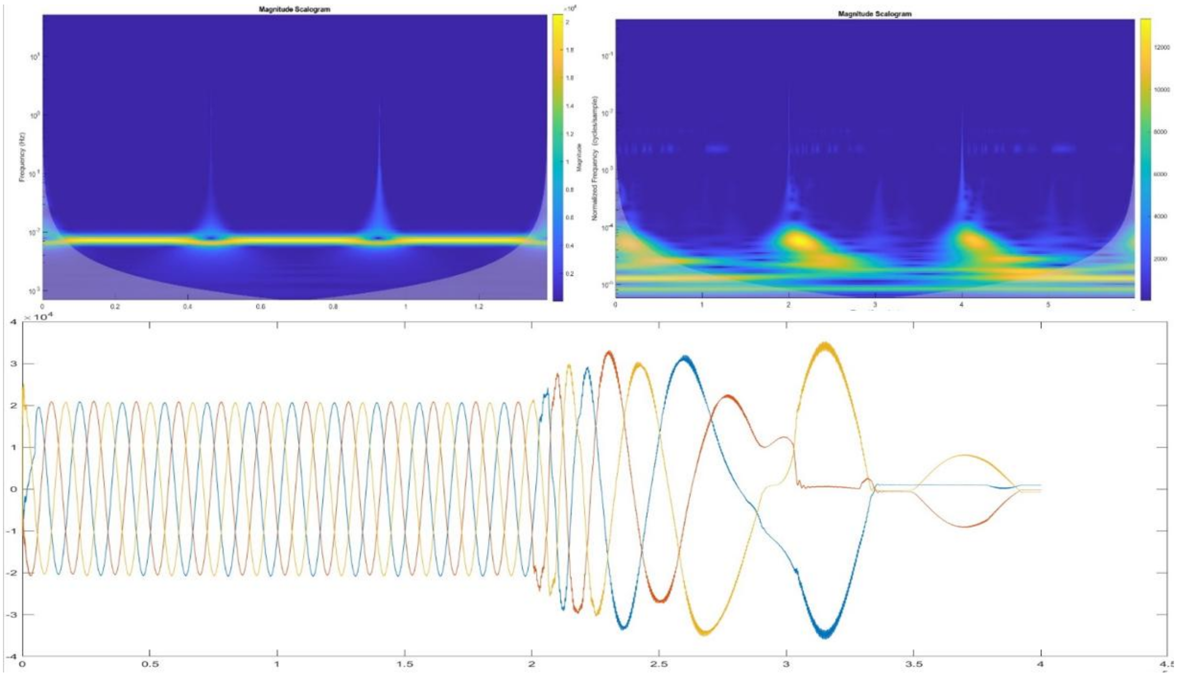


Figure 2 Scalogram

From the above figure 2, the voltage is represented in the form of scalogram, which further represents as islanding and non-islanding events.

3.4 Load Training Data

For Training 80% of data

Figure 3 Data loaded to the model

From the above figure 3, the data is loaded into the model in the ratio of eighty percent with respect to total data.

For Validation 20%

Figure 4 Data loaded to the model for validation

3.5 CNN model

A. CNN DESIGN

- Convolution layer

$g_j^l = x_j^{l-1}(s,t) \times w_{ij}^l = \sum_{\sigma=-n1}^{n1} \sum_{\sigma=-n2}^{n2} x_j^{l-i}(s-\sigma, t-v) w_{ij}^l(\sigma, v)$(4)

- Activation or ReLu (Rectified linear unit) layer (it introduces non linearity)

$x_j^l = \max(0, \sum_{i\epsilon M_j} g_j^l + b_j^l)$(5)

- Max pooling (MP) layer (it picks max values from sub matrix, it performs down sampling of the features that are extracted in the convolution layer, i.e. feature maps)

$x_j^{l+1} = f_p(b_j^{l+1}(x_j^l) + b_j^{l+1})$- (6)

- Fully Connected layer (FC)(fully developed model)

$x^{L-1} = f_c(\beta^{L-1} x^{L-2} + b^{L-1})$ (7)

- SoftMax layer (n-dimensional vector of real numbers and converts them into probabilities for each class and finalizes the loss function)

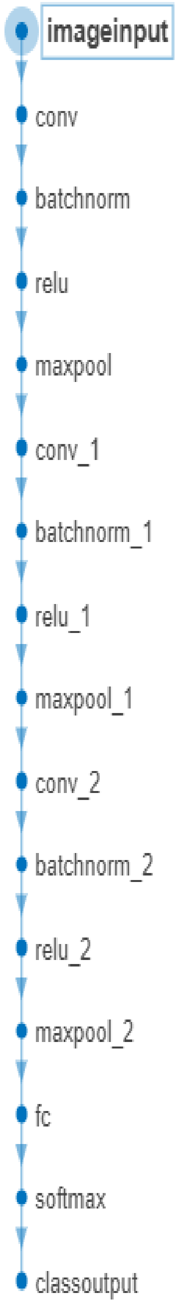
$z_d = \frac{e^{od}}{\sum_{C=1}^{C} e^{o_c}} \rightarrow \frac{e^{x_d^{L-1}}}{\sum_{C=1}^{C} e^{x_C^{L-1}}}$ (8)

CNN model

No of layers 16

No of connections 15

Total learnable parameters 3.3 million



Type/Layers	Activations	Learnable parameters
Image Input	227*227*3*1	
2-D Convolution	227*227*8*1	Weights 3*3*3 Bias 1*1*8
Batch Normalization	227*227*8*1	Offset 1*1*8 Scale 1*1*8
ReLu	227*227*8*1	
2-D Max Pooling	227*227*8*1	
2-D Convolution	227*227*16*1	Weights 3*3*8 Bias 1*1*16
Batch Normalization	227*227*16*1	Offset 1*1*16 Scale 1*1*16
ReLu	227*227*16*1	
2-D Max Pooling	227*227*16*1	
2-D Convolution	227*227*32*1	Weights 3*3*16 Bias 1*1*32
Batch Normalization	227*227*32*1	Offset 1*1*32 Scale 1*1*32
ReLu	227*227*32*1	
2-D Max Pooling	227*227*32*1	
Fully Connected	1*1*10*1	Weight 10*1648 Bias 10*1
Softmax	1*1*10*1	
Classification Output	1*1*10*1	

3.6 RMSProp algorithm

- Root Mean Square Propagation (RMSProp), it keeps a moving average of the element-wise squares of the parameter gradient

$$v_l = v_{l-1} - (1-\beta_2)[\nabla J(w_l)]^2 - - - \text{eq}$$

β_2= squared gradient decay factor of moving average.
Common values of the decay rate are 0.9, 0.99, and 0.999.

- Average lengths of the squared gradient=$\frac{1}{1-\beta_2}$ =10,100,1000 parameters update respectively.
- The RMSProp algorithm uses this moving average to normalize the updates of each parameter individually,

$$w_{l+1} = w_l - \frac{\alpha\nabla J\,(w_l)}{\sqrt{v_l}+\epsilon}\text{-----eq}$$

where the division is performed element-wise. Using RMSProp effectively decreases the learning rates of parameters with large gradients and increases the learning rates of parameters with small gradients. ε is a small constant added to avoid division by zero.

Figure 5 CNN Architecture

in

loss

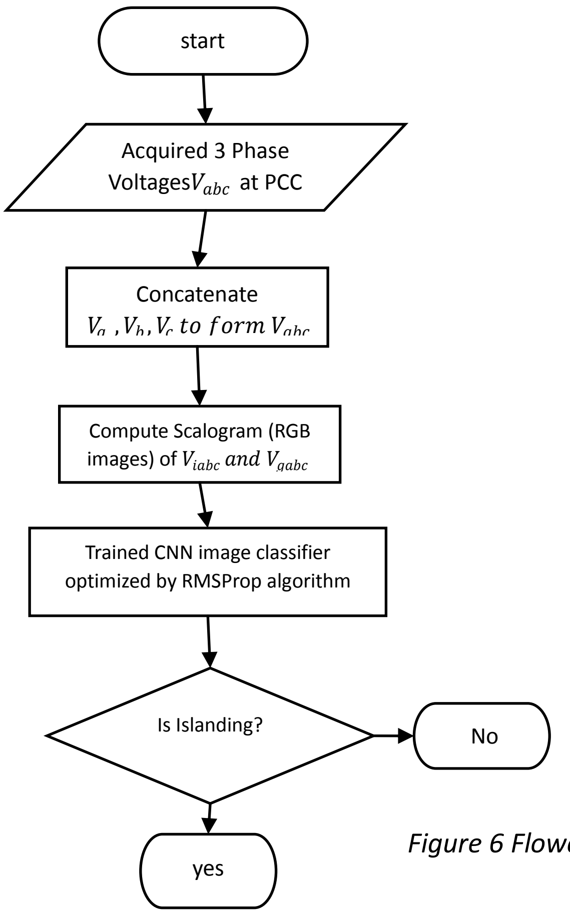


Figure 6 Flowchart

- ➢ Step 1 Initialize weights and biases convolutional and fully connected layers
- ➢ Step 2 Initialize β = 0.9
- ➢ Step 3 compute the gradient of the function with respect to the model's weights.
- ➢ Step 4 if gradient $\nabla J(w)$ received

$$v_l = v_{l-1} - (1-\beta_2)[\nabla J(w_l)]^2$$

$$w_{l+1} = w_l - \frac{\alpha \nabla J\,(w_l)}{\sqrt{v_l + \epsilon}}$$ //RMSProp Weight update

- ➢ Step 5 repeat the step 3 and 4 until converges the loss function

Table 2 Training Options

Frequently used options	
Solver	RMSProp
InitialLearnRate	0.01
MiniBatchSize	128
MaxEpochs	30
ValidationFrequency	50

IV. RESULTS AND DISCUSSIONS

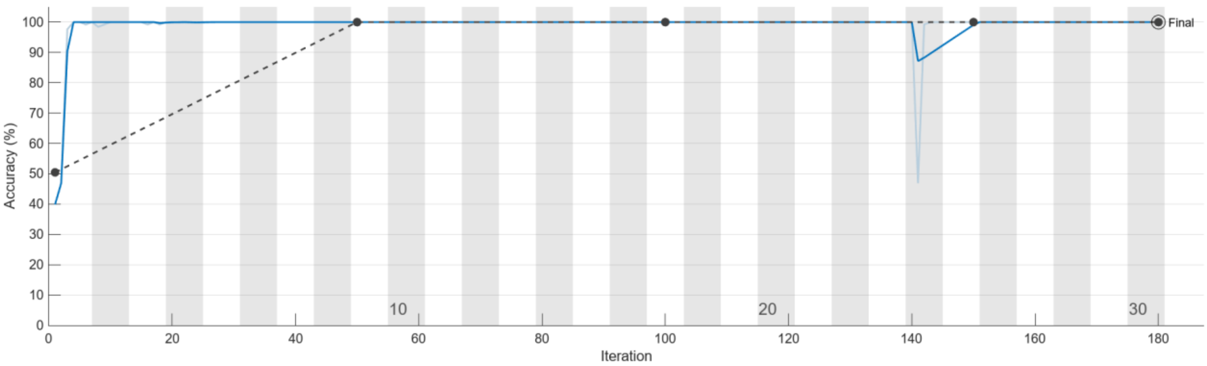


Figure 7 Accuracy Vs Iterations Plot

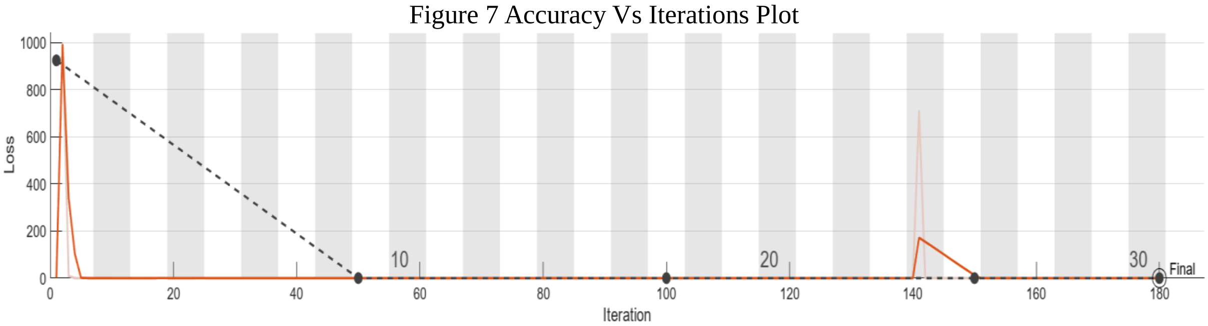
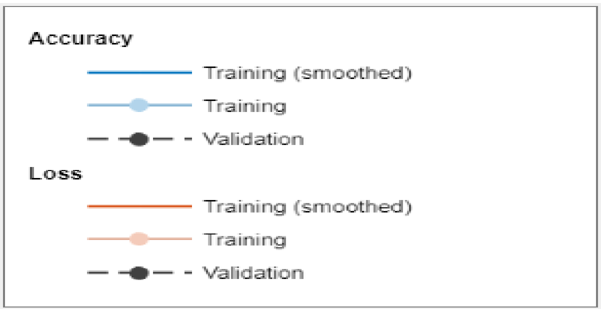


Figure 8 Loss Vs Iterations plot

From the above plot 7, 8, represents the accuracy versus iterations, the model performance is measured in terms of accuracy and loss function, from plot 7, the accuracy of the model, initiated from the 50 percent in the first epoch and reached almost 99 percent in its first epoch. The loss function value is almost zero first its first epoch.



Trial 1 initial learning rate = 0.0001

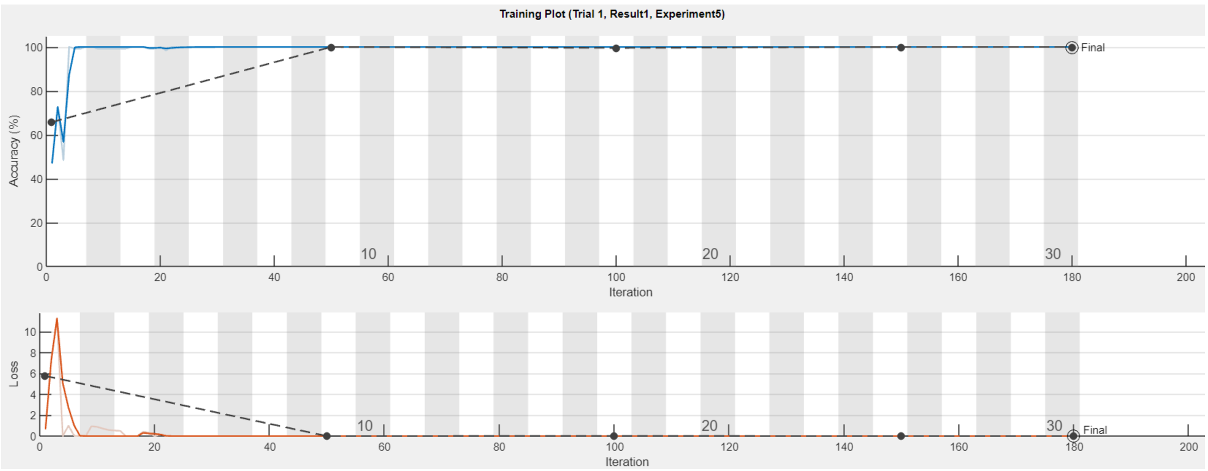
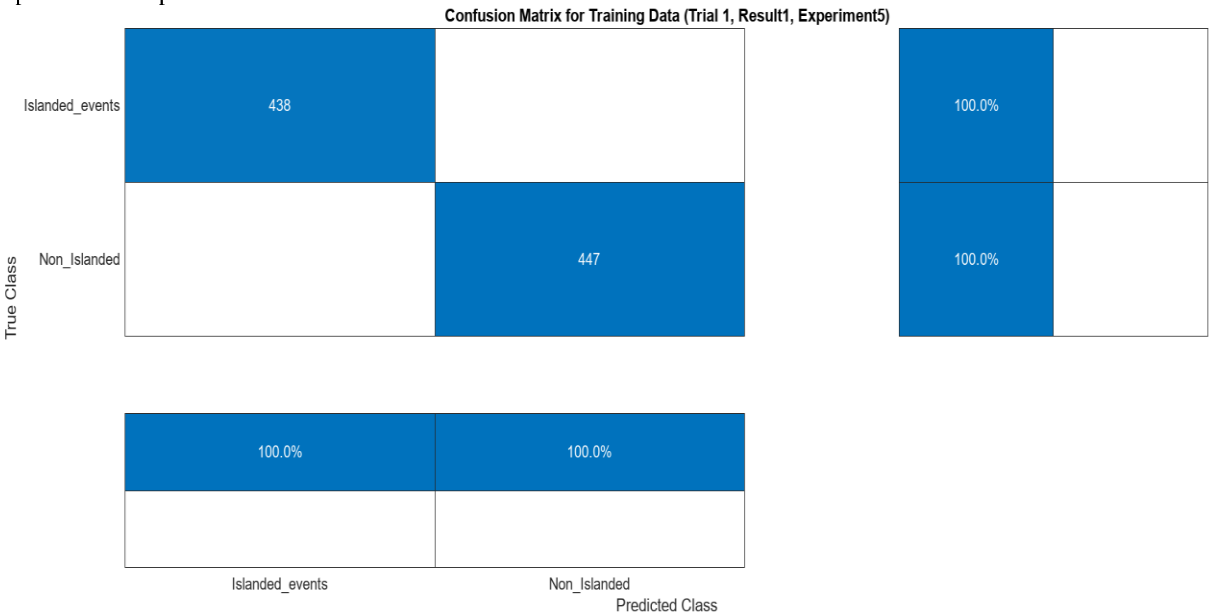
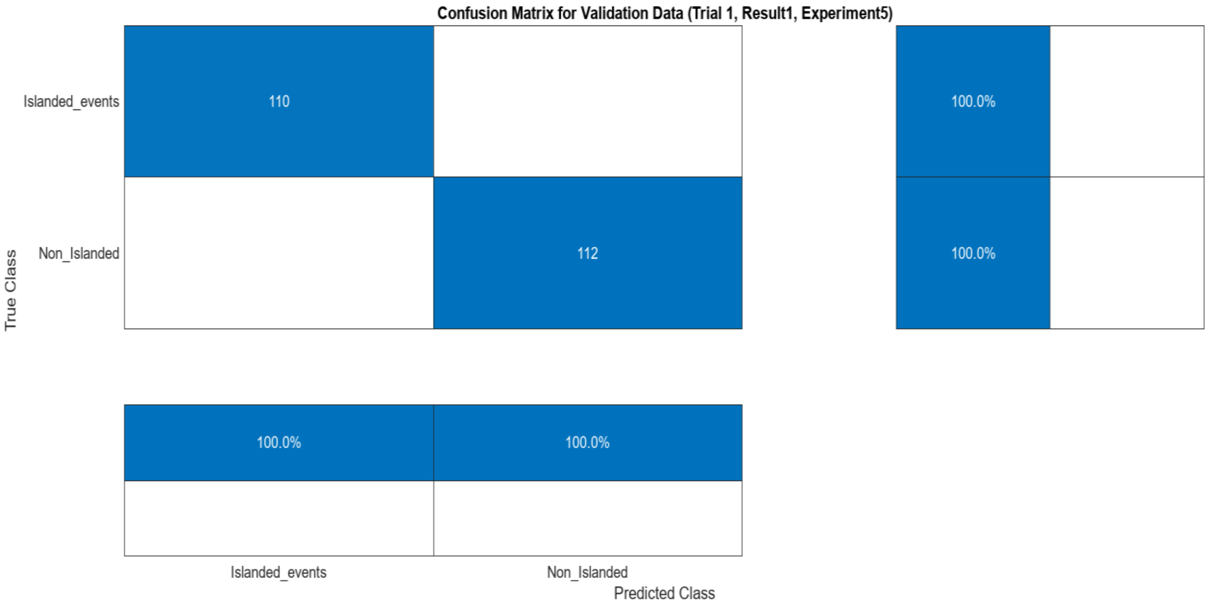


Figure 9 Accuracy and Loss function Vs Iterations

From the above plots, under trial 1 initial learning rate is 0.0001, the accuracy curve is started from 50 percent and reached almost 99 percent in its first epoch, while the loss function is almost becoming zero in its first epoch with respect to iterations.



Matrix 1 Confusion Matrix for Training Data



Matrix 2 Confusion Matrix for Validation Data

From the above results in terms of matrix, under training data matrix, 438 events were islanded as true class and 447 events were non islanded as true class with respect to predicted class. No events were misclassified. Under confusion matrix for validating data, 110 events were classified as islanded events under true class and 112 events were classified as non-islanded, no events were misclassified under predicted class.

Trial 2 initial Learning Rate = 0.001

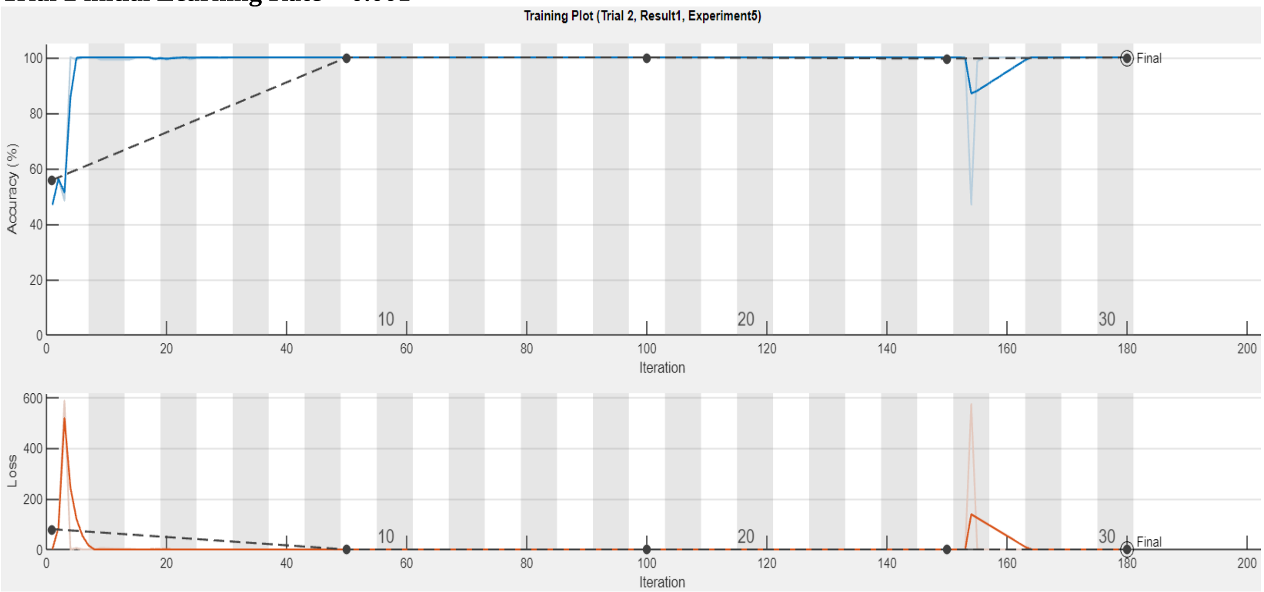
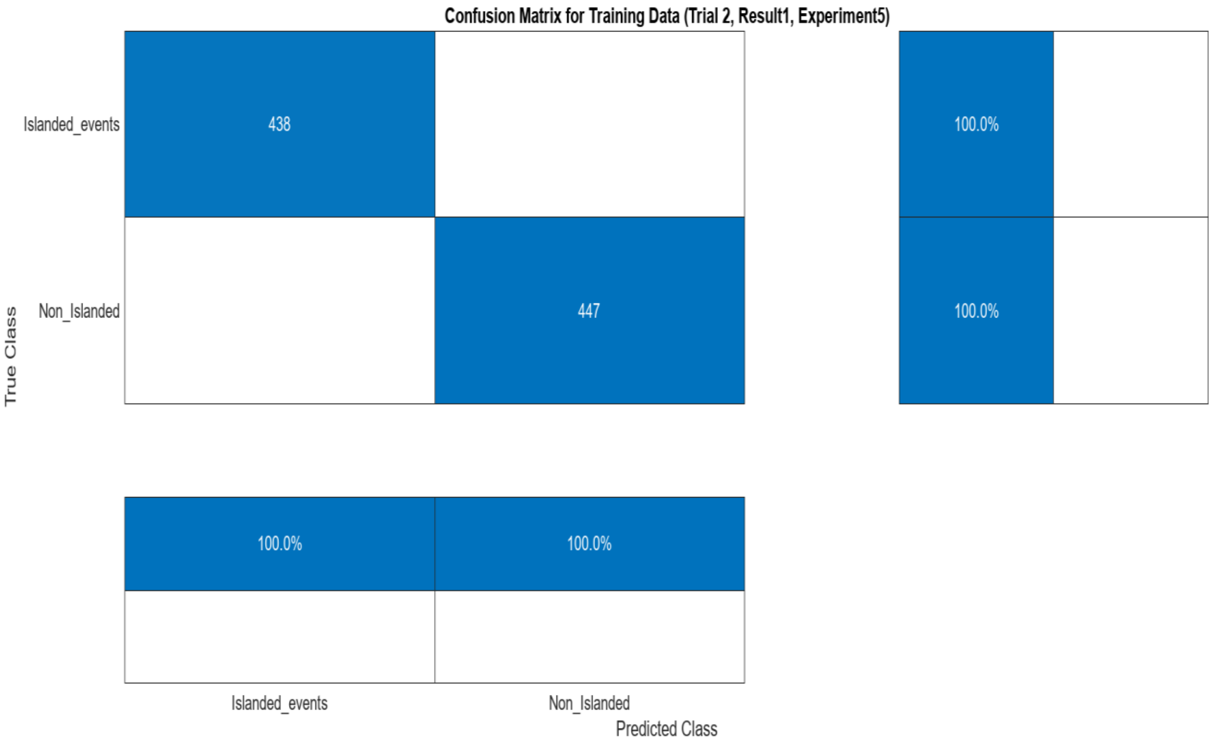
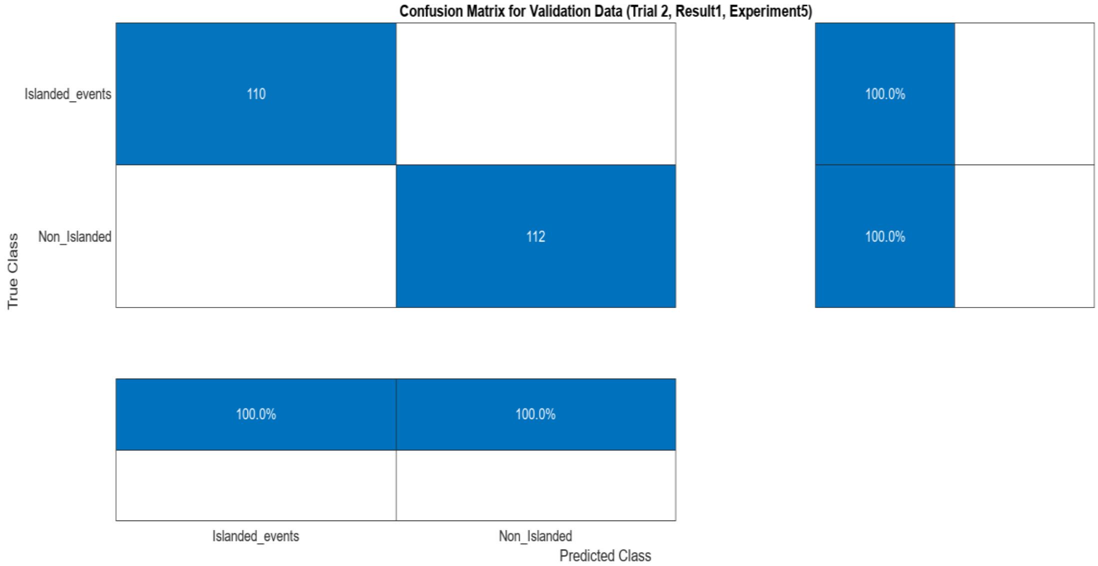


Figure 10 Accuracy and Loss Function Vs Iterations

From the above result, the learning rate is 0.001 and optimized the model accuracy improved and loss value is decreased.



Matrix 3 Confusion Matrix for Training Data



Matrix 4 Confusion Matrix for Validation Data

From the above matrix, under trial 2, the initial learning rate is 0.001 true class versus predicted matrix is same as for learning rate 0.0001.

Trial 3 Initial Learning rate = 0.01

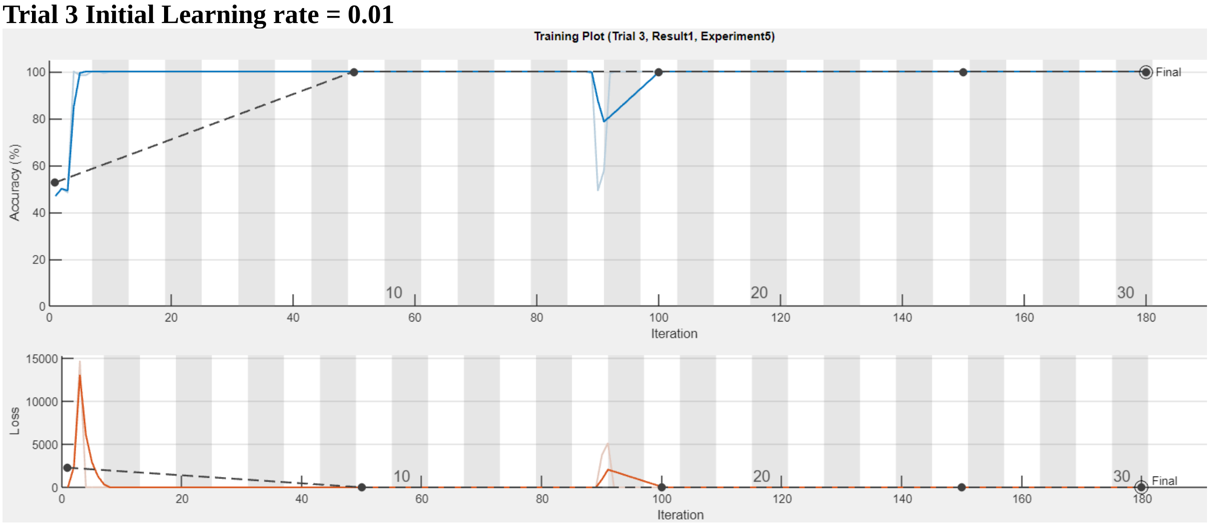
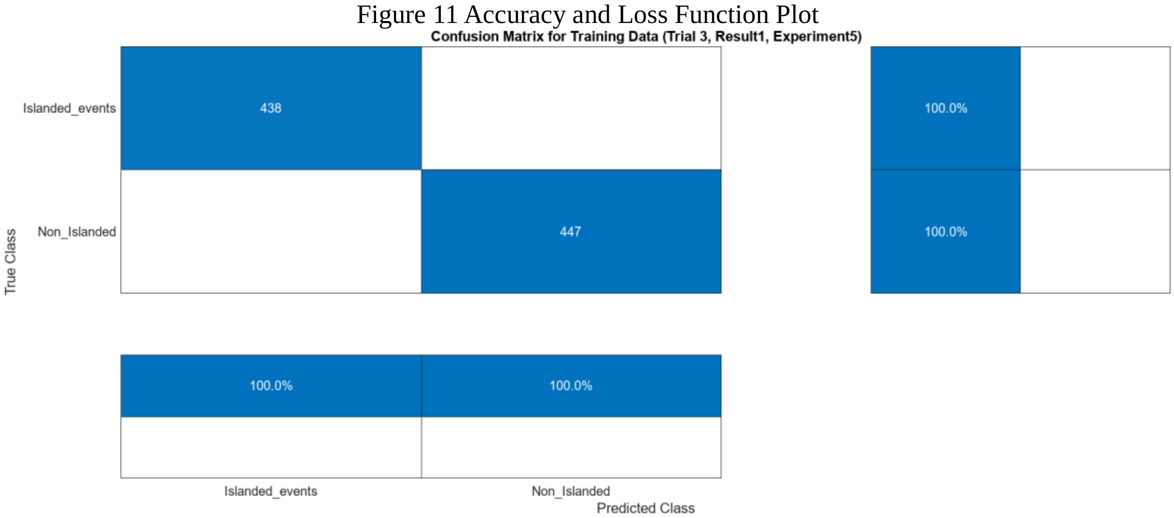
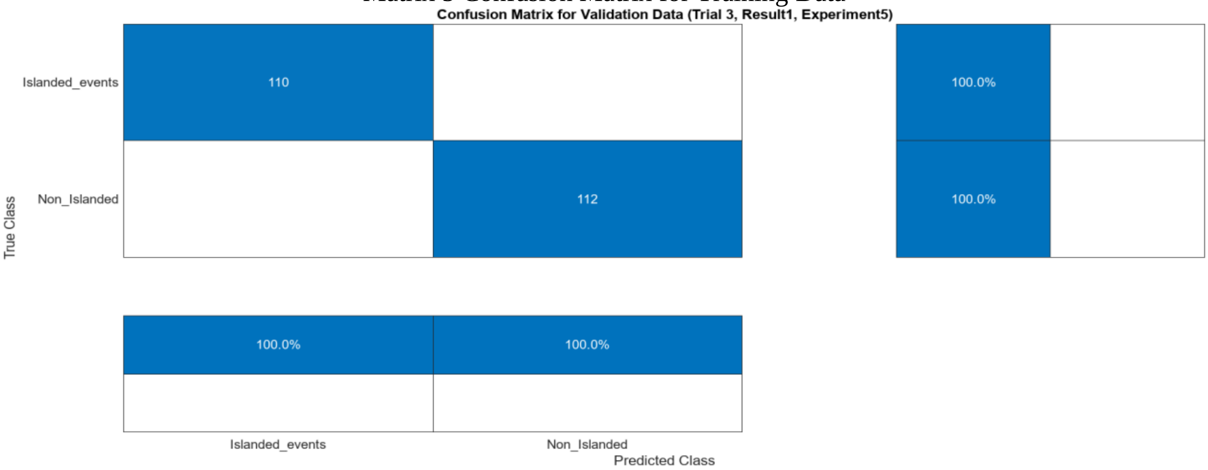


Figure 11 Accuracy and Loss Function Plot



Matrix 5 Confusion Matrix for Training Data



Matrix 6 Confusion Matrix for Validation Data

From the above matrix, under trial 3, the initial learning rate is 0.01 true class versus predicted matrix is same as for learning rate 0.00001.

V. CONCLUSIONS

A new islanding detection method is obtained for the DG system is having CNN model is optimized by using Root mean square propagation algorithm for the reduction of the loss value of the function and model performance is improved in terms of accuracy with respect to the iterations under 3 different learning values, the validation accuracy is obtained over 99 percent. It is extremely fast in detecting islanding, which is a very important factor in

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