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Original Article

An Optimized Deep Learning Model Based PV Fault Classification for Reliable Power Generation

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Abstract *- Solar energy is considered important renewable energy due to its cleanliness and low-cost power generation. In hard-working conditions, various types of faults affect the performance of the Photovoltaic (PV) system. Detection and classification of PV faults are critical to assure a reliable power generation operation. Many fault detection schemes have been proposed based on visual and embedded approaches. However, the image processing-based fault detection technique achieved great attention by offering higher detection accuracy. This work proposes the metaheuristic optimized deep learning model for solar fault detection. The learning model of MobileNetV2 is developed with hyperparameter optimization. The performance of the proposed model is analyzed in terms of accuracy, precision, recall and F-Score rates.*

Keywords *- PV, Deep learning, Fault and MobileNetV2.*

1. Introduction

Solar energy is the fastest growing and inexpensive source of new electricity worldwide. In a PV array, the cells are serially connected to convert the sunlight into power. A fault in the cell affects the entire system's performance. The performance or efficiency of the PV system can be measured as the product of the efficiency of thermodynamics, reflectance, charge carrier separation, and conductive efficiency. To get a reliable operation, the faults in a PV system should be detected and rectified.

The fault in the PV panel is categorized into three main types: permanent, intermittent and incipient. The permanent fault of PV can be solved only by fault-tolerant and redundant techniques such as line to line, bridging and shorting. The intermittent fault may include partial shading, leaf and dust particles. The incipient faults include partial damage and performance degradation etc.

Generally, fault detection techniques are introduced to improve the generation system's performance and increase the lifetime of a PV system. Fault detection techniques are grouped into different types based on the strategy followed: visual approach, sensor-based approach, ARC fault detector and artificial intelligence techniques. Compared to other approaches, image processing-based solution receives great attention due to their accuracy and low-cost solution. It allows using machine and deep learning algorithms for automated detection and classification. Three common imaging techniques are fault detection: Ultrasonic inspection, Lock Thermography, Electro-luminescence Imaging and Thermal imaging.

Deep learning (DL) is the most popular method for image classification problems. DL models are a sub-category of artificial intelligence that aim to extract different levels of the distributed representations from the input image. Compared to machine learning, the DL algorithms achieve higher classification accuracy and support early predictions. This work proposed a new DL model for solar crack detection and classification. The main objective of this work is as follows:

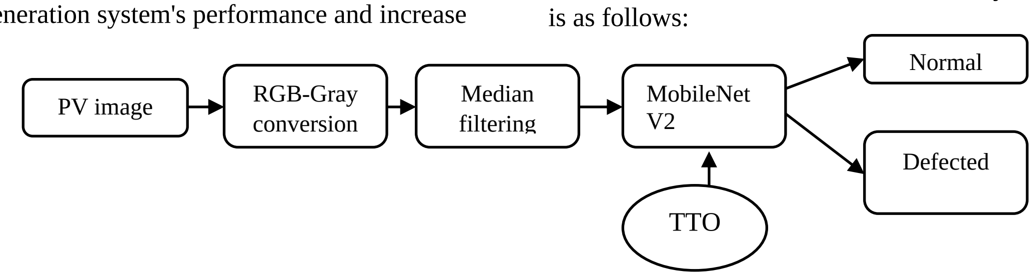


Fig. 1 Proposed detection method

- To propose an accurate DL model for crack detection
- To propose an efficient parameter tuning method for model enhancement
- The proposed model is compared with conventional models and studies

This paper is structured in this fashion: In 2, the existing works related to fault detection techniques are discussed. 3 describes the proposed deep learning-based fault detection approach. 4 presents results & discussion part. 5 concludes the work.

2. Related work

Many researchers have proposed fault detection methods to improve the reliability of PV-based power generation. Alsafasfeh et al. 2017 proposed a Simple Linear Iterative Clustering for PV fault detection using thermal images. The hot spots on the solar surface are identified by applying iterative clustering. Initially, the images are grouped into small regions. Then, k means clustering is processed to locate a faulty region.

The machine learning algorithm of the Support Vector Machine (SVM) based fault classification system is proposed by Serfa Juan et al. 2020. Electroluminescence (EL) imaging is applied to detect faults in a PV array. The performance of SVM depends on the choice of hyperplane to separate a data boundary. The optimum selection of hyperplane supports the classifier to increase the detection performance. Seung Heon Han et al. 2021 introduced a deep learning model of YOLOv3 for solar array crack detection. YOLOv3 is the convolutional neural network that classifies the object based on pattern recognition. To detect a faulty region, the concept of intersection over union (IOU) is applied between normal and abnormal images.

Mohammad Haider et al. 2020 proposed a thresholding-based fault detection technique to overcome the drawback of edge detection approaches. The severity of cracks in the surface is analyzed using Linear Discriminant Analysis (LDA). The features extracted from segmentation are used to train the LDA model. The hybrid method proposed by Bharath et al. 2019 combines edge detection and hough transform for accurate fault detection. Adding a hough transform improves the feature extraction capability of a classifier. Implementation results show that the proposed hybrid model achieved an accuracy of around 96.85, higher than other approaches.

Anwar Jarndal et al. 2020 analyzed the performance of image processing-based fault detection approaches for different deep learning models such as ResNet, GoogleNet and MobileNet. Finally, the hybrid model is newly developed to increase the performance of detection accuracy. Zhendong Huang et al. 2021 developed a CNN-based fault detection model for infrared images. Different augmentations like flipping and rotating are carried out to train the model. For preprocessing, the bilateral filter is applied. Results show that the CNN models increase the accuracy of the individual techniques in fault detection.

The concept of multi-wavelength composite is proposed by Anne GerdImenes et al. 2020 for fault detection using thermal images. Also, the new fusion algorithm is proposed to combine the features extracted from different wavelengths. The proposed fusion technique achieved the highest accuracy of 9456 %, which exceeds thresholding model accuracy by 4.25%.

Ye Zhao et al. investigated the detection accuracy of data mining techniques for fault detection in solar panels. The data mining algorithm of a decision tree is applied for fault classification with the attributes of voltage, current and temperature. Compared to the image processing technique, the data mining concepts show less accuracy for classification. Alajmi et al. developed a hot spot detection algorithm.

For IR Thermal Image Analysis. The proposed hot spot localization includes three steps: median filtering, hue, saturation and value (HSV) conversion and classification. In classification, the XOR operation is performed in a sequence of images to identify the hot spots. The fault's severity is categorized into soft, hard and healthy conditions.

Venkata Siva Prasad Machina et al. proposed an InceptionNet-based fault locating algorithm for solar panels. The layers of InceptionNet are modified to reduce the training complexity of the model. Experimental results indicate that the proposed model can achieve an accuracy of 96.2 %, a sensitivity of 94.56 % and an F-score of 94.2% in different crack image databases.

The combined model of neural network and SVM is proposed by David Prince Winston et al. 2020 for micro crack classification in PV systems. SVM determines the number of hidden layers in the neural network to increase overall classification accuracy. The classification results include healthy and cracked panels.

Kurukuru et al. 2019 proposed a texture analysis-based fault diagnosis model combined with a machine learning algorithm. The features of contrast, entropy and homogeneity are used for classification. The proposed model is analyzed in terms of mean squared error (MSE) and accuracy rates. Nian et al. 2020 developed a crack severity classification algorithm using the AdaBoost classifier. The weak classifier results combined to produce a final classification result. The dyadic transform is applied in preprocessing stage to improve the classification performance.

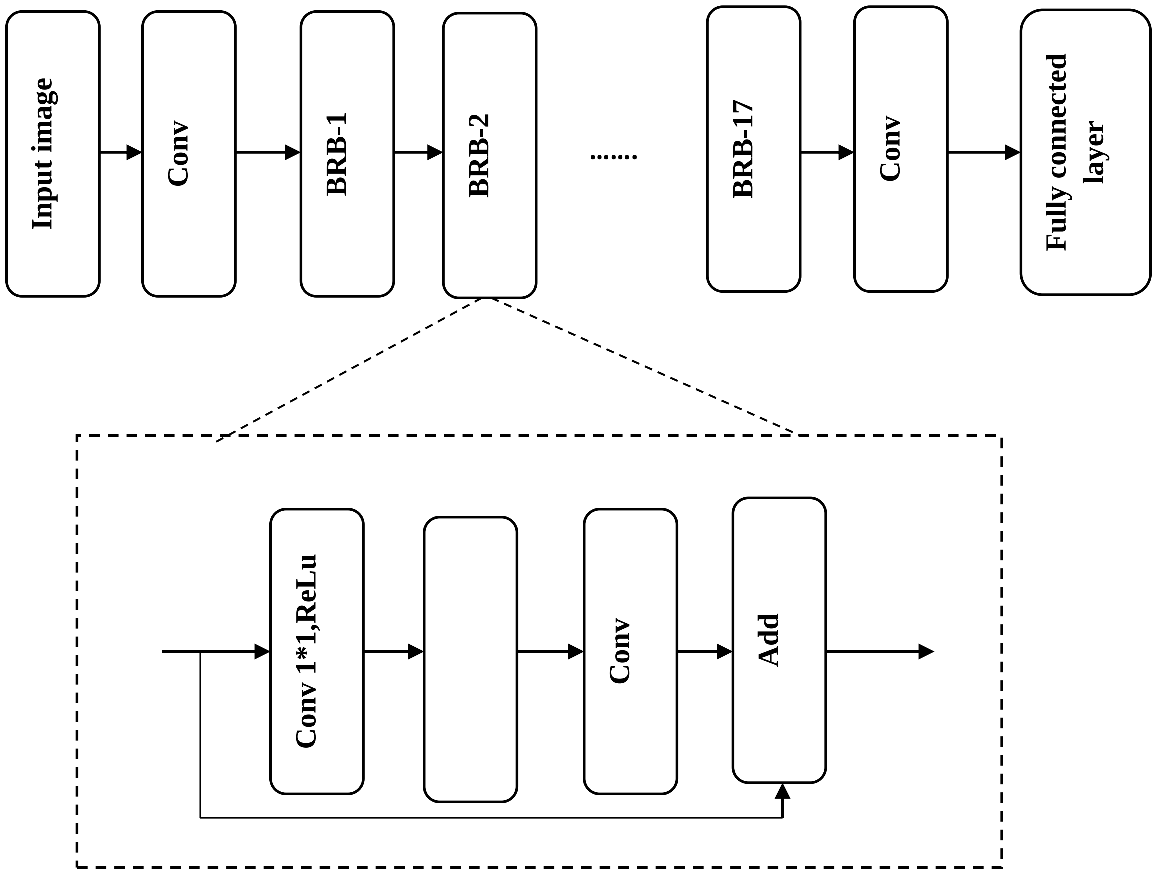


Fig. 2 The modified MobileNetV2

3. Proposed optimized MobileNetV2 Model For Crack Detection and Classification

The block diagram of the proposed classification model is shown in Figure 1. It includes four steps: preprocessing, median filter, MobileNetV2 classifier and performance analysis. These blocks are explained in the following subsections.

3.1. Preprocessing

In preprocessing stage, the RGB images are converted into grey images and resized into the required dimensions. Different filters are available to remove noise from an image. This work median filter is used for filtering by replacing each pixel with the median of neighbouring pixel values.

3.2. The modified MobileNetV2

The proposed modified MobileNetV2 model is faster than conventional MobileNetV1 & modified MobileNetV1 architectures with the requirements of minimum network parameters. Also, the accuracy for segmentation and classification is higher than in other deep learning models. The proposed model consists of 19 basic blocks or elements called bottleneck residual blocks(BRB). BRB is opposite to existing convolutional layers by the inversion, which uses expanded representations in the input. It also uses minimum overhead depth-wise convolutions to process the features in the intermediate expansion layer. In addition, it includes a 1×1 convolution layer, average pooling layer and classification layers. The architecture proposed model is shown in figure 2.

3.3. Tiki-taka optimization (TTO)

Metaheuristic algorithms are developed to solve real-world problems and used to identify the best solutions in search space. TTO is a newly proposed optimization algorithm inspired by the nature of identifying the best player positioning to defeat an opponent in the game. In a football game, the player positioning strategy is followed to defeat the opponent and update the player position to the key player position and ball position. Also, a short passing tactic is adopted to overcome opponents. The main aim of developing new optimization is to achieve a better balance between exploration and exploitation throughout the optimization. TTO offers a superior balance between exploration and exploitation capabilities. TTO includes three stages: initialization, ball position updating and key player location updating.

3.3.1. Initialization

Consider a football game with k number of players. A minimum of 3 players are nominated as key players. The number of layers in the game is modelled as some possible solutions for the problem in a search space. The position ball and players are mathematically formulated as follows:

$$P=\begin{bmatrix} p_{1,1} & . & . & p_{1,j} & . & . & p_{1,d} \\ . & . & . & . & . & . & . \\ . & . & . & . & . & . & . \\ p_{i,1} & . & . & p_{i,j} & . & . & p_{i,d} \\ . & . & . & . & . & . & . \\ . & . & . & . & . & . & . \\ p_{k,1} & . & . & p_{k,j} & . & . & p_{k,d} \end{bmatrix} \quad (1)$$

$$B=\begin{bmatrix} b_{1,1} & . & . & b_{1,j} & . & . & b_{1,d} \\ . & . & . & . & . & . & . \\ . & . & . & . & . & . & . \\ b_{i,1} & . & . & b_{i,j} & . & . & b_{i,d} \\ . & . & . & . & . & . & . \\ . & . & . & . & . & . & . \\ b_{k,1} & . & . & b_{k,j} & . & . & b_{k,d} \end{bmatrix} \quad (2)$$

Where d dimensions are in the bound limit.

3.3.2. Ball position updating

The strategy of passing the ball to the nearest player is modelled as follows:

$$b_{i,j}^{new} = \begin{cases} r * (b_i - b_{i+1}) + b_i, & s_p > l_p; \\ b_i - (r +* a_1)(b_i - b_{i+1}), & s_p < l_p \end{cases} \quad (3)$$

. $b_{\mathrm{i}}^{new}$is the ball's current position, and r is the random number that varies between zero and one.$s_p$is a successful pass and l_p is the ball loss probability

3.3.3. Player location updating

The position of players is changed or updated as a function of ball position, and key player position is formulated as follows:

$$p_{\mathrm{i}}^{new} = p_i + r * a_2 * (b_i^{new} - p_i) + \mathrm{r} * a_3 * (\mathrm{kp} - p_i) \quad (4)$$

Where kp is the key player position.$p_{\mathrm{i}}^{new}$is the position of the player for the new ball position. a_2 and $a_3$are coefficients for balancing position between the key player and ball position. r is the random number that varies between zero to one.

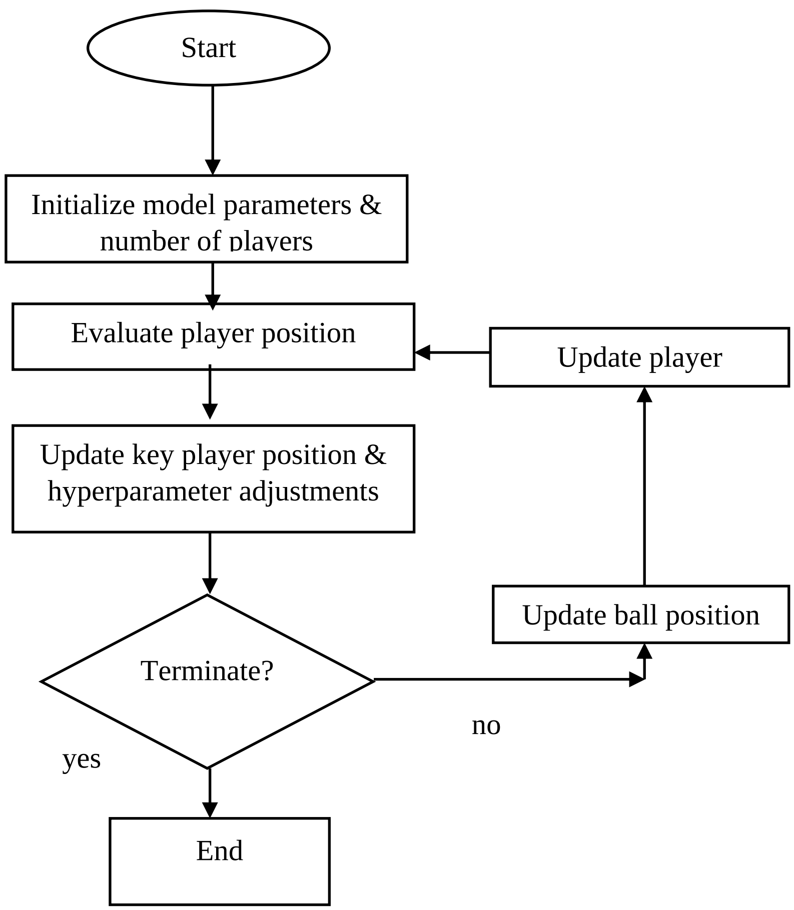


Fig. 3 The workflow of hyperparameter tuning

3.4. Hyperparameter tuning in MobileNetV2

The performance of the learning model depends on the values of the hyperparameter. MobileNetV2 consist of two types of hyperparameters: network structure-based hyperparameters and learning parameter-based hyperparameters. This work learning parameter of epochs, learning rate and batch size is adjusted based on TTO. The optimal parameters are identified through the use of TTO for achieving higher accuracy.

The steps involved in tuning are given below:

Step 1. Initialize model parameters.
Step 2. Initialize TTO parameters like the number of players and key players.
Step 3. Set s_p, l_p and c1,c2 and c3 parameters of optimization.
Step 4. Use the initial population to create the MobileNetV2 model.
Step 5. Calculate the error rate for the fitness function.
Step 6. Get the best solution having the least fitness in the population.
Step 7. Go to last when the criteria are satisfied; go to step 8.
Step 8. Increment the number of iterations and update the population; go to step 4.
Step 9. Return the best values hyperparameters.

Fig. 3 shows the proposed hyperparameter adjustment using TTO. The iterations are continued until they reach the best solution.

4. Experimental results

The proposed model is coded in python and verified in the KAGGLE website data set (https://www.kaggle.com/datasets/lakshaymiddha/crack-segmentation-dataset). The data set consist of different solar panel cracked images with different crack levels.

This Dataset comprises around 12400 images combined from 12 available crack segmentation datasets. They are categorized into normal, minor and severe cracked images.

Of the total, 70% of images were used for training, and the remaining 30% of images were used for testing. The proposed hyperparameter tuned MobileNetV2 model is compared with other classifiers in terms of Accuracy (ACC), Specificity (SPC), Recall (REC) and Precision rate (PRE) as follows:

$$\mathrm{ACC} = \frac{\mathrm{TP+TN}}{(\mathrm{TP + TN+FP +FN'})} \quad (5)$$

$$\mathrm{SPC} = \frac{\mathrm{TN}}{(\mathrm{TN + FP'})} \quad (6)$$

$$\mathrm{REC} = \frac{\mathrm{TP}}{(\mathrm{TP + FN'})} \quad (7)$$

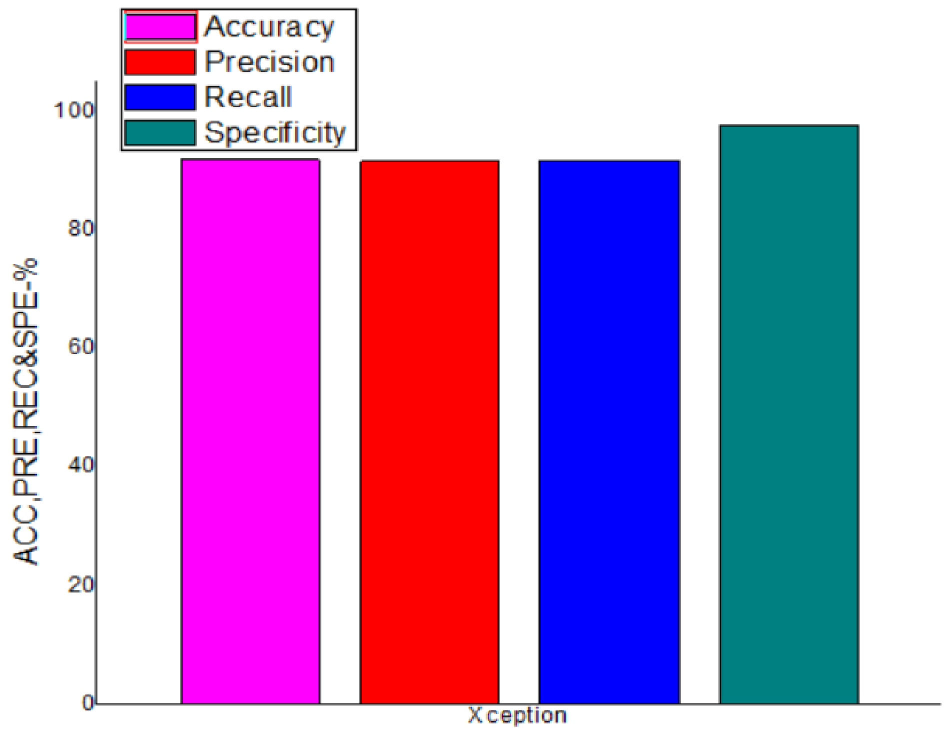
$$\mathrm{PRE} = \frac{\mathrm{TP}}{(\mathrm{TP + FP'})} \quad (8)$$

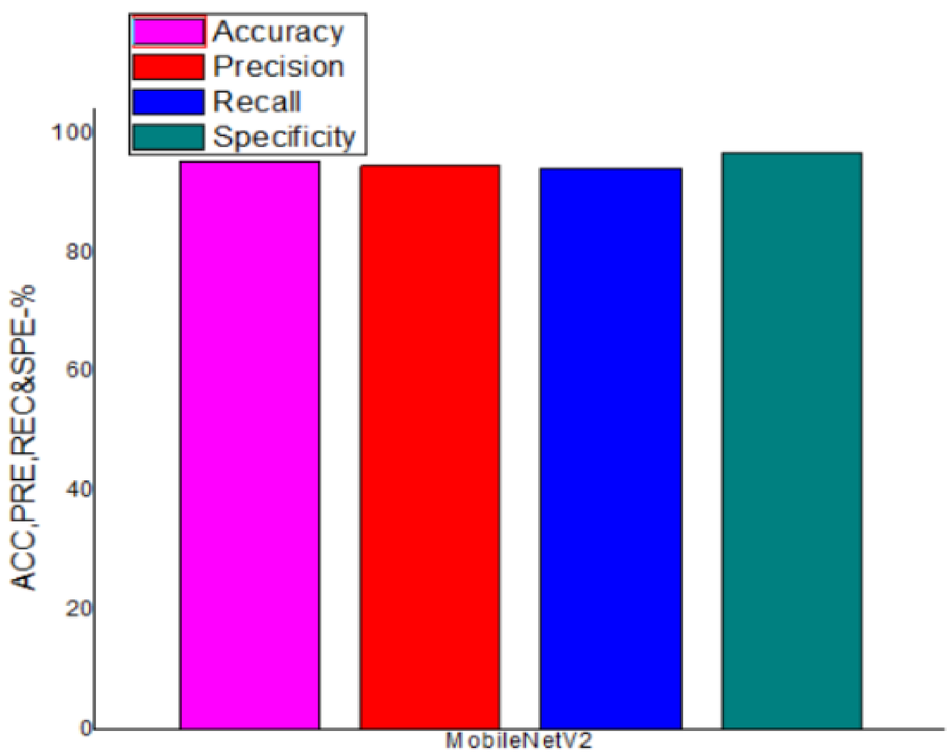
Where FP is the false positive, FN is the false negative; TP is the true positive, and TN is the true negative of the samples.

Table 1 shows the performance of the classifier model after applying 15 iterations. The TTO- MobileNetV2 achieved a better result in all iterations for ACC, PRE, REC and SPC 98.85%, 97.89%, 97.98 % and 99.5 % respectively.

Table 1. Classification of performance of proposed and existing models.

Method	Accuracy	Precision	Recall	Specificity
EfficientNetB0	91.82	91.5	89.36	96.5
Xception	91.9	91.6	91.75	97.56
MobileNetV2	95.45	94.68	94.23	96.72
TTO- MobileNetV2	98.85	97.89	97.98	99.5


Accuracy
Precision
Recall
Specificity
100
80
60
40
20
0
ACC,PRE,REC&SPE-%
Xception


Accuracy
Precision
Recall
Specificity
100
80
60
40
20
0
ACC,PRE,REC&SPE-%
MobileNetV2

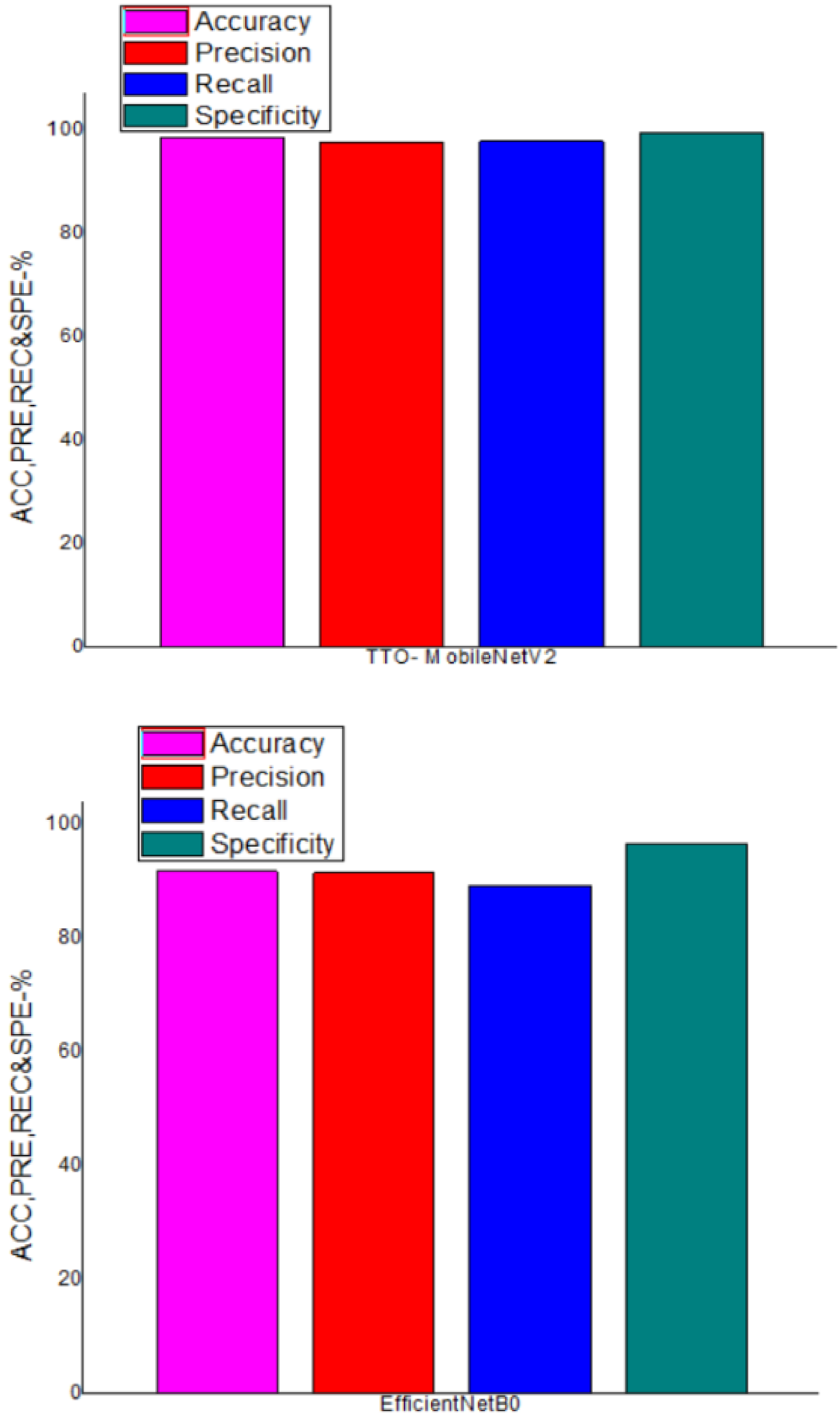


Fig. 4 Performance analysis

The EfficientNetB0 model achieved a result in all iterations for ACC, PRE, REC and SPC are91.82%, 91.5%, 89.36 % and 96.5% respectively. The Xception model achieved a result in all iterations for ACC, PRE, REC, and SPC are 91.9%, 91.6%, 91.75 % and 97.56 %, respectively. The MobileNetV2 model without tuning attained a result in all iterations for ACC, PRE, REC, and SPC is 95.45%, 94.68%, 94.23% and 96.72 %, respectively. Compared to all the models, the TTO- MobileNetV2 model shows superior performance in all the performance parameters. The performance of the proposed model is graphically shown in Figure 4.

5. Conclusion

Automatic detection of faults in the PV system increases power generation efficiency and reduces the maintenance time of solar farms. A novel automated deep learning-based PV fault detection system is presented. The fault classification algorithm based on mobileNetV2 with hyperparameter tuning show's highest fault detection and classification accuracy compared to other learning models. The proposed model is suitable for solar farms without additional hardware overhead and cost.

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