Journal of Modern Technology
https://journal.krrishpub.com/index.php/jmt/index

RESEARCH ARTICLE

A Light Weight Mobile Net SSD Algorithm based Identification and Detection of Multiple Defects in Ceramic Insulators

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Abstract

Presently, transmission lines play a major role for transferring electricity from generating stations to consumer premises. As the components are exposed to environmental conditions, damage to these components is more severe. Among those components insulators area accountable for 81.3% of line interruptions. In this paper, a drone-based transmission line inspection using mobile net single shot detection (SSD) is proposed that aims to detect the potential defects of insulators. The proposed system employs a regression-based algorithm using mobile net uses an upgraded compact mobile net SSD to identify targets network, allowing for precise categorization and placement of electrical equipment. Simulation is performed by loading the datasets that are collected. There are totally 800 images of ceramic insulators these are sub divided into 3 classes train class has images with 590 test class with 130 and validation (Val) class with 80. In this methodology, mobile net SSD can identify and detect the ceramic insulators with pollution flashover, corroded and broken. Precision, recall, F1 Score are calculated. Analysis is carried out on the variation of batch parameters, size etc. to ascertain the effectiveness of the proposed method.

Keywords: Environmental Conditions, Transmission line inspection, Potential defects, Mobile Net SSD.

Article information:
Published by: **Krrish Scientific Publications Pvt. Ltd.**
DOI: https://doi.org/10.71426/jmt.v1.i1.pp59-74
Received: *01 Jun. 2024* | Revised: *20 Jun. 2024* | Accepted: *25 Jun. 2024* | Published: *08 Sep. 2024*

1. Introduction

Presently, transporting electricity from the point of generation to the main centres of consumption is the responsibility of the transmission lines. These devices are typically installed outdoors in hard-to-reach places. Prior to shutdowns, transmission system checks are carried out to identify issues and guarantee the supply of electricity [1]- [4]. Failures can occur in a variety of ways, such as the accumulation of pollutants within the network or the absence or breakage of insulators, which are extremely dangerous for maintaining network isolation. Patrol inspections of overhead transmission wires have evolved through four phases: manual, robotic, helicopter-based, and unmanned aerial vehicle-based. Because of its efficacy, safety, affordability, and additional benefits, inspections have progressively emerged as the most effective method for monitoring the state of transmission lines. Unmanned aerial vehicles (UAVs) can currently be used in using a sliding window to collect features from the image, which is then used to two primary methods to photograph insulators in order to detect defects [15]- [17]. The first is the traditional approach to image processing, while the second is deep learning convolutional in neural network (CNN) technique. The process of images sing method trains a classifier to identify errors. Failures in networks might include contamination and missing insulators, posing a significant threat to network isolation shown in Figure 1.

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Figure 1: The overhead electrical line inspection procedure.

In literature, several studies have been conducted for insulator fault identification and detection. Wang et al.[1] presented A method for determining the transmission line thickness of ice that combines an SSD detecting model with a compact extracted feature network. Zhao et al.[2] used to locate defective bolt elements, the automatic vision shape cluster network (AVSCNet), a computer-based detection of defects model. Davari et al. [3] utilized better Region based convolutional neural network (RCNN) to identify corona discharges along lines of distribution in every shot of ultraviolet visible video. Coloured thresholding was then utilized to detect the faults, and the severe of the problem was described by the comparison of spot region to defect region. Rong et al. [4] investigated vegetation encroachment on electricity transmission cables. Improved RCNN speed, Hough transform, and state-of-the-art stereo. Accurate identification and localization were achieved by converting 2D photos of the vegetation and electricity transmission wires into 3D height and position data. In accordance with an automated approach for identifying insulator defects. Feng et. al. [5] suggested a you only look once (YOLO) v5 targeted identification model. The k-mean clustering-based YOLOv5x models can detect and pinpoint insulator problems in transmission lines, unlike the four separate versions of the YOLOv5 model. However, accuracy drops to 86.8% at its best. Using a multiple-scale detection head with multiple scales featured fusion structure, the YOLO network model suggested by Liu et al. [6] increases the model's detection accuracy. The one exception however is insulator flaws.

Wu et al. [7] presented a centre net-based insulator defects detection method to improve network detection accuracy. This method includes a reduction in back bone network complexity and attention mechanism to limit extraneous information in the model. Centre Net's detection performance is slow, and it can only recognize one kind of defect when two different fault classes share a centroid. Qiu et al. [8] developed a YOLOv4-based method that is more effective in detecting insulator defects. In order to build a new dataset, the photographs were sharpened utilizing the graph cut image enhancement method. A mobile net lightweight network is fused with the YOLOv4 model framework. For the goal of defect localization and insulator identification, Tao et al. [9] introduced a unique cascade model of convolutional neural networks. Using a convolutional neural network (CNN) built on an area suggestion network, this network transforms the detection of defects into the two-level object identification problem.

A method for detecting insulator defects was introduced by Wang et al. [10] which relies on the region proposal network (RPN) and the upgraded residual neural network (ResNet). The updated network first used the improved RPN for featured extraction to improve the detection of tiny insulator problems. Initially, the ResNet framework was used to develop this new network. Using double insulator strings, Cheng et al. [11] sought to address the problem of defect detection. Because the leading insulator string acts as an umbrella, protecting the rear insulator string from the elements. Using characteristics in the picture space, they suggested approaches for insulator self-burst fault identification. Additionally, this approach is often restricted due to variations in lighting, distance shot, and angle of view. Computer hardware has greatly improved, leading to better progress in machine learning. Zuo et al. [12] have suggested a technique for pictures with complicated backgrounds. It used a number of methods for processing digital images to extract features, after which the insulators were segmented. In the end, it checked the insulator pixels for defects like missing caps to see if the string was defective. Machine learning-based solutions require more expensive computing resources and more intricate network structures. Recent studies on the detection of insulator defects have focused on the use of deep algorithm of learning for automated gathering and evaluation of aerial pictures [13]- [17]. When it comes to pascal visual object classes (VOC) object detection R-CNN is initial learning the deep model to reach a more detection accuracy. By reusing the convolution model for both applicant zone generation and feature extraction, Faster R-CNN drastically cuts down on R-CNN computation. In contrast to the wasteful two-stage approaches, by treating the location data as a prospective object and skipping the candidate box creation stage, one-stage algorithms can directly forecast both the location and the category of a target. Some algorithms, like the YOLO and SSD, are one-stage. Taking into account a better balance between accuracy and speed, these strategies take real-time performance into account.

Several researchers have been focused on insulator identifications using some algorithm techniques with only single fault. The key purpose of this paper is to identify and detect the multiple defects of insulator at a time with one image using the machine learning and learning the deep algorithms. Many of them have been focused on YOLO techniques and by improving the versions of YOLO the insulator defects have been identified. The main reason of taking this proposed methodology is due to the advantages of methodology contains the improved efficiency and light weight design, enhanced performance in real world applications include robotics, health care, agriculture, smart cities etc.

The primary Contributions of this study include,

- The mobile net SSD outperforms existing dataset-based models for insulators identification and detection, yielding better evaluation metrics. The usage of datasets plays a vital part in the process of detecting insulators.
- The recommended mobile net SSD is the hybrid approach it combines the mobile net and SSD to build on the ResNet-18 classification showed to better for multiple classification challenge, as it could recognise diverse circumstances by altering the classifier, resulting in higher F1_score outcomes than traditional models. Identifying defective insulating substances throughout electrical system inspections is challenging due to similarities among functioning and defective components.
- The proposed approach is computationally efficient, making it suitable for embedded devices and online applications with UAVs. This benefit is inherent in the technology, as mobile net SSD recognises items in a single shot, which makes it is better than traditional sliding window-based models.

In this paper, multiple defects of Insulators overhead transmission lines are being identified and detected using the mobile net SSD algorithms which is based on the datasets, there are totally 800 images of ceramic insulators. These are sub divided into 3 classes train class has images with 590 test class with 130 and Val class with 80. The study provides a quick and effective insulator identification model using the lightweight mobile net-SSD network. This concept allows for the quick and precise detection of insulators through the use of a lightweight network that can be installed into a UAV. The application procedure trains the network model with collected images (from UAVs or other sources) on a ground workstation. Subsequently, the UAV algorithms incorporate the learned model for identification and detection purposes. This study focuses on developing, testing, and assessing network models.

2. Mathematical modelling

The lightweight deep neural network is built using a simplified architecture and deeply separable convolution. Firstly, set the global hyper parameters breadth and resolution to achieve a compromise between the accuracy and efficiency. Both variables make it possible to choose the right model by considering the real-world challenges 1×1 point-by-point convolution mixes the results, depth wise convolution utilizes kernels of convolution for each channel for drastically decreasing model size, this method accomplishes the same results as conventional convolution. Two comparisons of conventional and depth-wise separable convolutions are shown in Figures 2 and Figure 3.

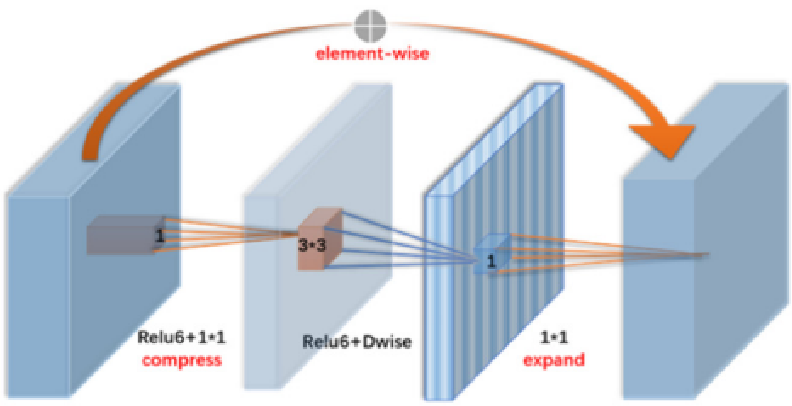

Figure 2: Origin residual block.

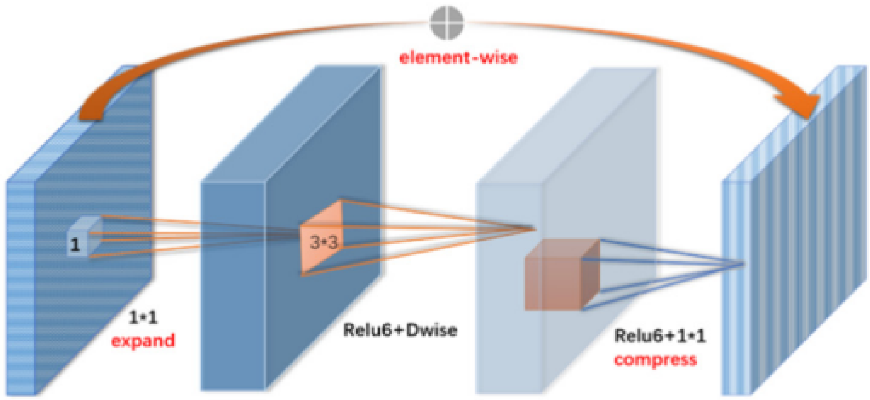

Figure 3: Invert residual block.

Depth wise Convolution differs from typical convolution by performing a distinct convolution for each channel, using a single convolution matrix. Following depth convolution, the total quantity of feature mappings is directly proportional to the input layer's channel and more features can't be added to the feature maps. For using feature information from many channels in an identical spatial location, this approach won't work since it needs separate convolution for each input layer channel. The merging of these feature maps into a new one requires pointwise convolution. This separation approach computes the calculating proportion (CCR = DW Conv Cost / Std Conv Cost) and saves computation time.

$$\mathrm{CCR} = \frac{G_k^2 * M * G_f^2 + M * N * G_f^2}{G_k^2 * M * N * G_f^2} \tag{1}$$

$$\mathrm{CCR} = \frac{1}{N} + \frac{1}{G_k^2} \tag{2}$$

N is the number of feature maps, and it's usually more than 10. The ratio is less than one, and the sized of the convolutions kernel, G_k^2, is usually 3×3. Consequently, computing is reduced while using convolution compared to standard convolution. Following the addition of two hyper-parameters, the following is the formula for computing the network:

$$G_k^2 * \alpha * M * \rho G_f^2 + \alpha * M * \alpha * N * \rho G_f^2 \tag{3}$$

The width parameter (α) reduces the multiple features of maps by changing the input and output channels. The resolution parameter (ρ) adjusts the input layer's resolution. Combining the two can further reduce the amount of calculation required.

3. Methologoly

In order to better the expressive capacity of image information features and complement object contour, it executes fusion operations on the features layer. This process can lower the missed detection rate and improve detection capability. SSD use multi-scale feature detection to identify objects. The dimensions of the input picture might range from 300×300 to 512×512, and so on. The initial SSD basic network relies on VGG16 as its backbone network. A multiple scales pyramid feature map is generated by augmenting the basic network with an increasing number of convolution layers: To begin, VGG16 no longer has any dropout levels or FC8 layers; instead, the FC7 layer is replaced with the convolutional layer Conv7. Secondly, new feature layers Conv8, Conv9, Conv10, and Conv11 are added. In order to make predictions, the SSD network first consults the vgg16 Conv4_3 layer, and then it moves on to the featured maps acquired of the Conv7, Conv8_2, Conv9_2, Conv10_2, and Conv11_2 layers. Six prediction feature maps of varying sizes are therefore produced. As an example, with an input picture size of 300×300, the feature extraction network would provide six projected featured maps with sizes of 38×38, 19×19, 10×10, 5×5, 3×3, and 1×1 as shown in Figure 4.

3.1. Base network

Mobile net SSD as with all the others algorithms are built on neural networks. Features for detection or classification at a high level are provided by the base network. Ending these networks with a fully linked layer is a good idea. The Fig. 4 shows the base network of mobile net SSD.

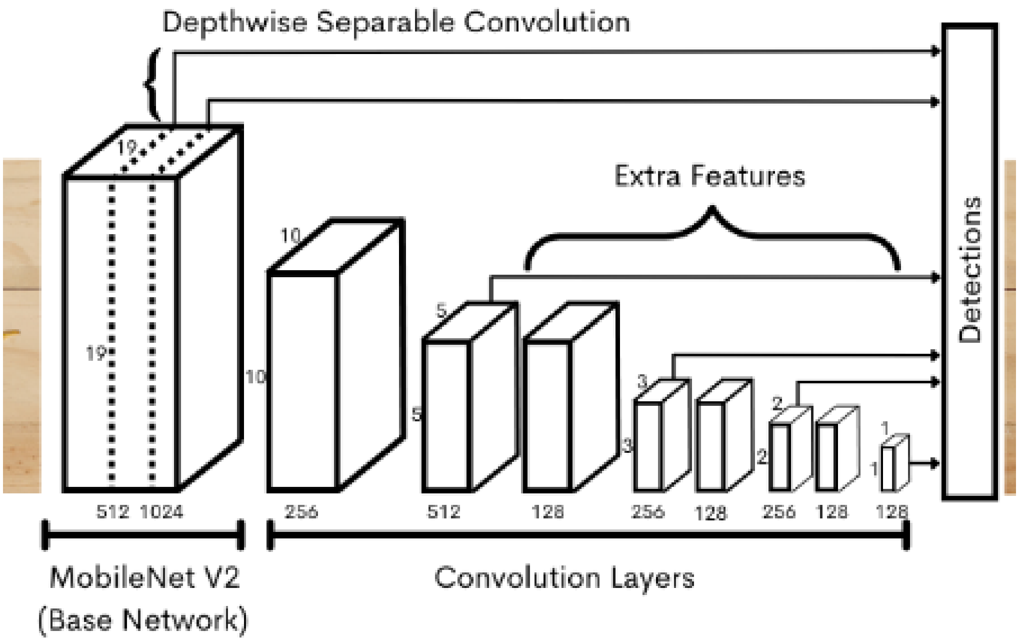

Figure 4: Base network of mobile net SSD.

SSD to accomplish object detection however exclude the completely connected layers and substitute detection networks such as SSD and Faster R-CNN for the construction of mobile net SSD.

3.2. Network for detection

Two of the most popular detection networks are RPN (Regional Proposal Network) and SSD (Single Shot Detection). One single shot is all it takes to use SSD to identify several items in a picture. However, methods that rely on regional proposal networks (RPNs), like the R-CNN series, need a second shot—one to generate region suggestions and another to identify the target of each proposal. For this reason, SSD outperforms RPN-based methods in terms of speed, although it often compromises accuracy for the sake of real-time processing speed. Additionally, they often struggle to discern items that are either too large or too little. One single shot is all it takes to use SSD to identify several items in a picture. However, methods that rely on regional proposal networks (RPNs), like the R-CNN series, need a second shot—one to generate region suggestions and another to identify the target of each proposal. Consequently, SSD outperforms RPN-based methods in terms of speed but it often compromises accuracy for the sake of real-time processing speed. Additionally, they often struggle to discern items that are either too large or too little.

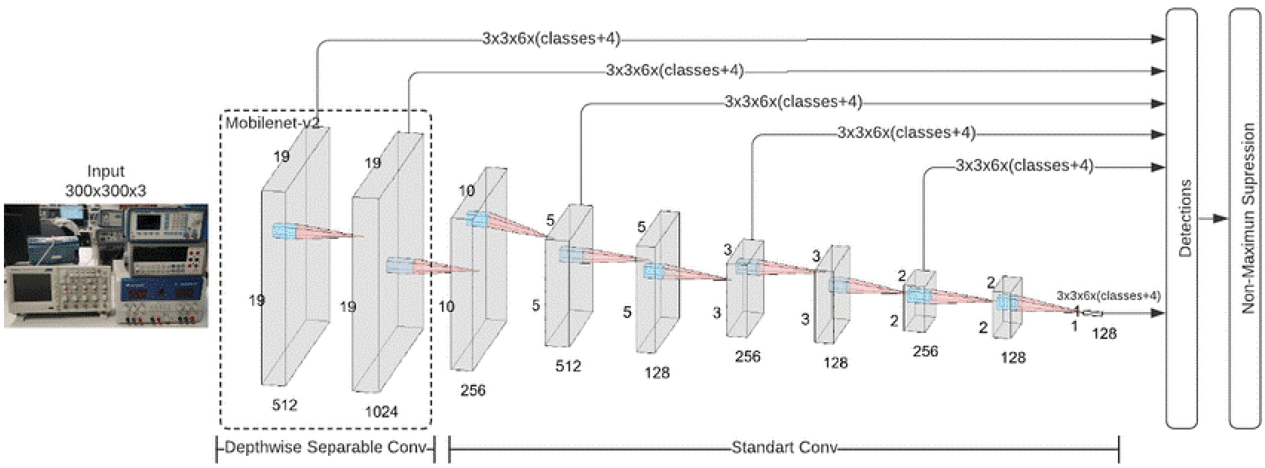

Figure 5: Network for detection of mobile net SSD.

The Figure 5 shows the network for detecting the images of insulator using mobile net SSD by verifying the layers the image detection takes place.

3.3. Feature pyramid network

It is quite difficult to detect items of varying sizes, especially very minute ones. One feature extractor that uses the feature pyramid idea to boost speed and accuracy is the Feature Pyramid Network (FPN) as shown in Figure 6.

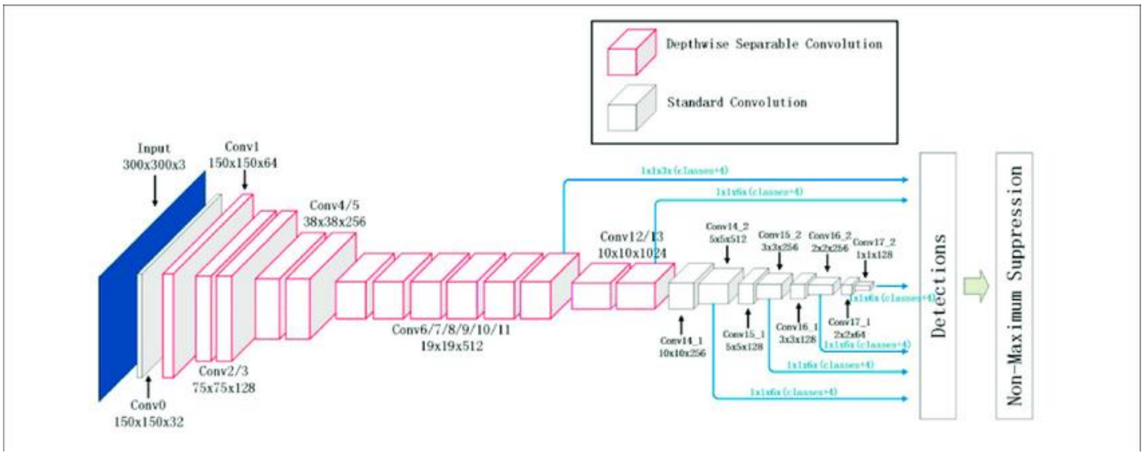

Figure 6: Feature pyramid network.

3.4. Applications from the previous version

In accordance with Dewi et al., YOLOv4 obtains a precision of in an application that utilizes the identification of traffic signals when compared to more recent versioned with YOLO, regarding YOLOv3, established object identification algorithms perform better. When compared to other models, YOLOv3 performed better than Retina Net, Faster R-CNN, DSSD513, and featured pyramid networks with Faster R-CNN. The YOLOv3 outperformed the other models in terms of speed and mean average precision (mAP) outcomes, according to the study. For the purpose of electrical system inspection using UAVs, Sadykova et al. used YOLO. Based on his findings, data augmentation should be considered to avoid overfitting in small datasets.

3.5. Datasets

Datasets may get from the sources, which includes high-resolution images of insulator strands with broken components. ceramic, and other insulators in a rainbow of hues and recorded at all sorts of angles and against all kinds of picture backdrops make up this database's insulators. This dataset consists of three subclasses: insulator, broken, and insulator damaged by flashover. Among the 800 images are ceramic insulators these are sub divided into 3 classes train class has images with 590 test class with 130 and Val class. The dimensions (height, breadth, and vertical and horizontal orientations of the enclosing boxes) are used to identify the parts. The way of approach to detect the insulator defects is process of Identification and Detection shown in Figure 7.

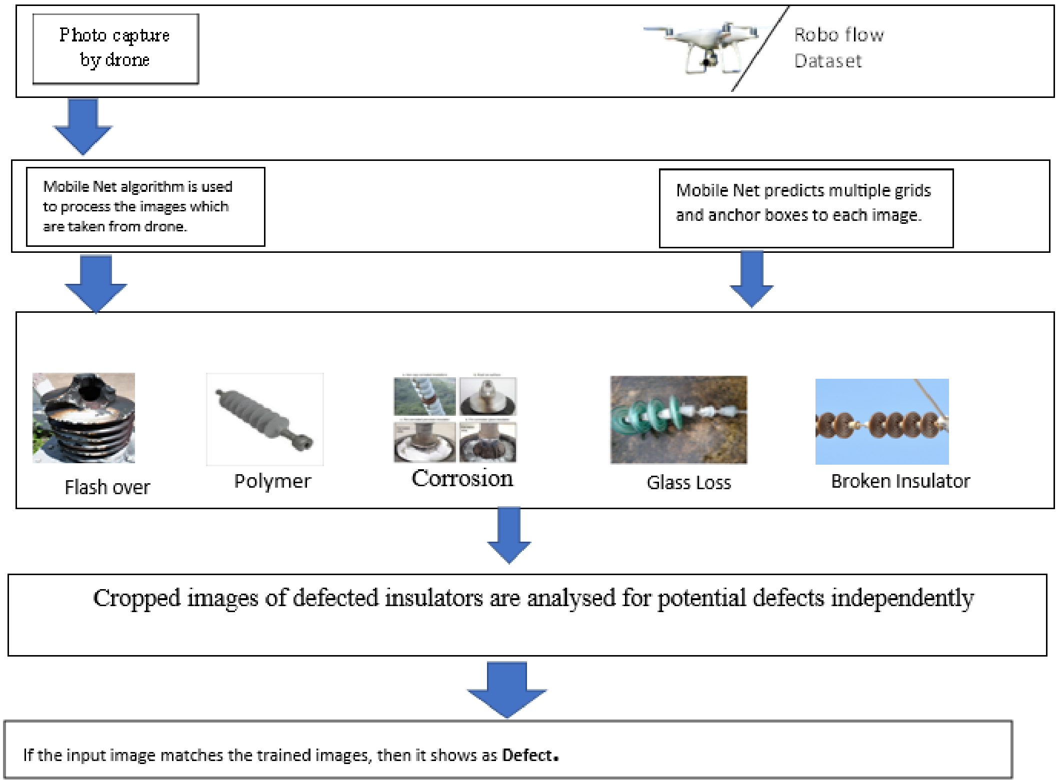

Figure 7: Process of recognition.

3.6. Mobile net SSD algorithm

There are two parts to the simulation. one deals with insulator detection and the other with insulator categorization. Method used 590 training photos and 130 validation images from the dataset to train the mobile net SSD versions for insulator detection. The categorization process made use of 800 cuts. The number of photos used to assess the model remained constant. The Figure 8 shows the algorithm for mobile net SSD.

From Figure 9, insulator preprocessing techniques, deep learning techniques were used to build the algorithms that are being examined in this study. A computer vision algorithm may be measured in several ways, with the metrics being based on data acquired from the confusion matrices. Further evaluation of precision, recall, and accuracy is provided by Precision = Positive Trues / (Positives Trues + Positives False)

$$\text{Precision} = \frac{t_p}{t_p + f_p} \tag{4}$$

Recall = Positive Trues / (Positive Trues + Negatives False)

$$\text{Recall} = \frac{t_p}{t_p + f_n} \tag{5}$$

$$F1 \text{ score} = \frac{2 \times \text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \tag{6}$$

where t_p is the positive true, f_n is the negative false, and f_p is the positive false.

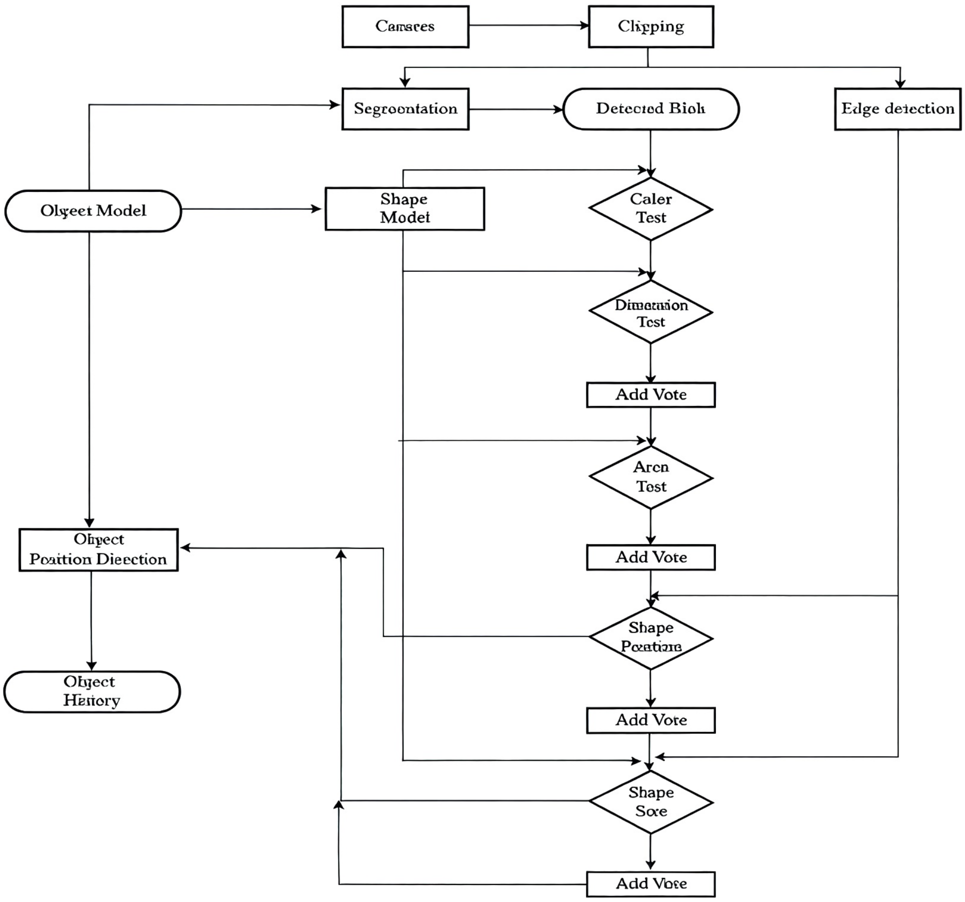

Figure 8: Mobile net SSD algorithm for insulator detection.

3.7. Mobile Net SSD Algorithm

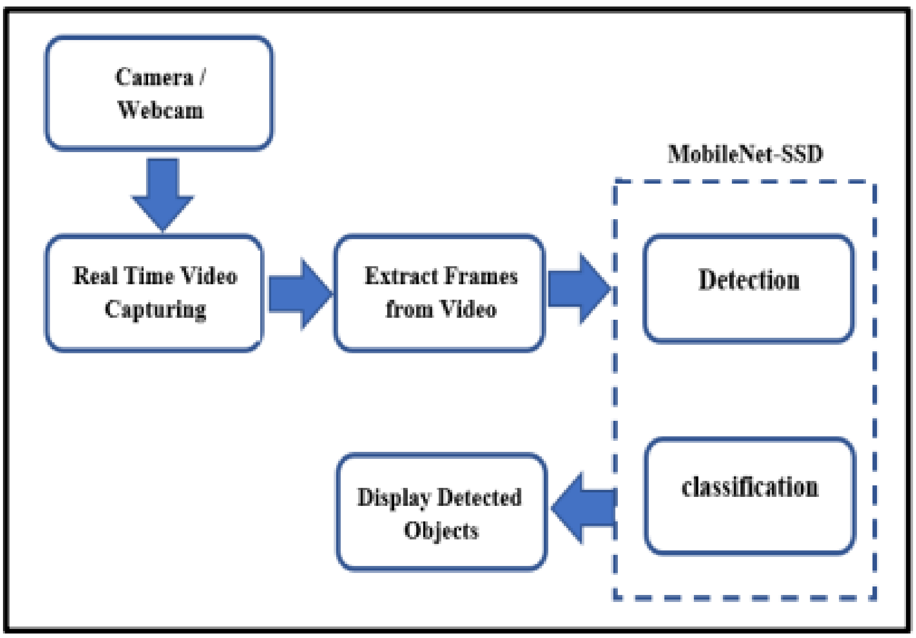

Figure 9: Mobile Net SSD flow chart for insulator detection.

In image detection, an intersectional over union (IoU) criteria compares identified and real objects to determine their similarity. The intersection area is calculated by dividing it by the union of the image and recognised areas. A t_p identification is definition as IoU $> T$, when T is a preset threshold. This paper evaluates T at 0.5. The standard deviation of average precision summarises a precision recall curve by calculating the amount average of precision at every thresholder, as follows:

$$\text{Average Precision} = \sum_{\eta} (\text{recall}_{\eta} - \text{recall}_{\eta-1})\, \text{precision}_{\eta} \tag{7}$$

4. Results

Choosing the optimum model for fault diagnosis might be challenging due to the numerous variants of existing models. The distinction in this parameter is selection based Depending on the available data, utilizing networks with multiple layers may not be efficient for analysis. Choosing the right model requires balancing available resources, database size and computing speed. This work aims to produce optimal object identification and classification results while minimizing training time due to offline training. To improve mAP performance, ideal structures are defined and fine-tuned based on the results.

4.1. The framework specification for recognizing objects

Table displays the outcomes for the particular object identification job using the YOLOv2, YOLOv3, YOLOv4, YOLOv5, and Mobile net SSD models with different batch sizes. It is to be expected that bigger models, with more parameters, take longer to converge. Computing effort was not seen as a constraint due to the resources used in the trials, since the moto of this study is to identify the version that yields the best classified output. Models converge quicker with larger batches, but it takes a GPU with greater memory with loaded data, which means have to weigh needs for processing time against the hardware that is currently available. The simulation reproducibility was ensured by choosing an unlimited batch size of 16. With mAP@ [0.5] =0.99262, the mobile net SSD produced the best result among the YOLO variants, according to the preliminary analysis. The objective of this stage is to assess object detection using this metric, hence the initial choice for image detection was the mobile net SSD algorithm with a maximum number of batches of 8. Generally speaking, for mAP@ [0.5], models with less variables had worse results (sometimes below 0.99) as shown in Table 1.

Table 1: Detection of Object evaluation by changing parameters.

Type	**Size of Batch**	**Precision values**	**Recall values**	**F1 score**	**mAP**	**Time (hr)**
YOLO V7	2	0.93454	0.94356	0.95678	0.95987	7.93
	4	0.93567	0.95678	0.95892	0.96786	8.95
	8	0.94523	0.95987	0.96345	0.96987	10.54
	16	0.95678	0.96789	0.97452	0.9758	20.56
	64	0.96789	0.97865	0.98675	0.9876	25.98
Mobile Net SSD	2	0.94563	0.95644	0.96543	0.96789	2.5
	4	0.95634	0.96734	0.97896	0.97654	4.29
	8	0.95987	0.96789	0.97896	0.97890	7.90
	16	0.96345	0.97653	0.98654	0.98120	10.1
	64	0.96723	0.98765	0.98987	0.9123	15.1

4.2. Comprehensive evaluation with mobilenet SSD

In this paper part presents the findings of a research study utilizing mobile net SSD for insulator detection. Comparative studies on the detection of various insulator faults under various background conditions are studied confirmed efficacy of the advanced approach suggested in the paper. The mobile net SSD algorithm serves as the baseline in each simulation. Recall, precision, and mAP are the main metrics used in this simulation to assess the effect because the main objective work is to increase detection of fault accuracy. The results to be trained model is shown in Figure 10.

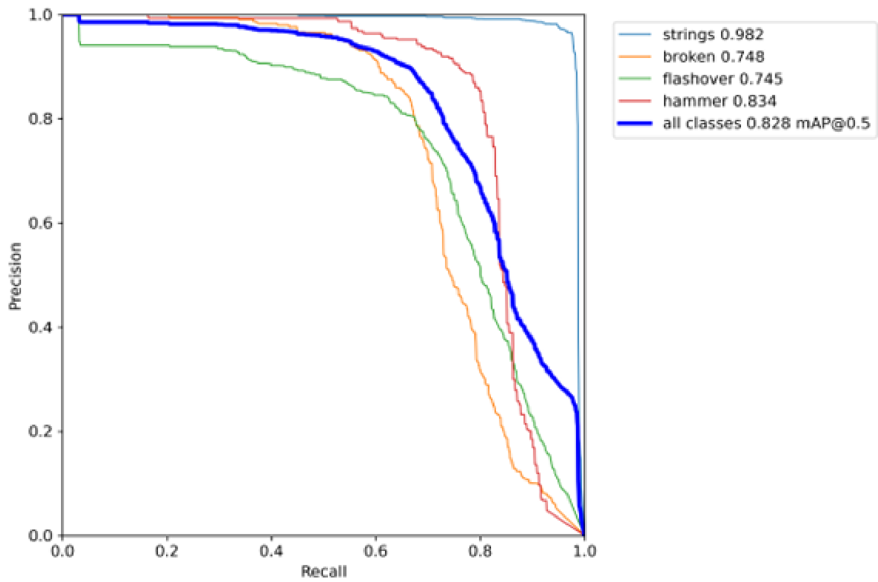

Figure 10: Precision–recall curve of mobile net SSD.

4.3. Evaluation

After training the model, visualize its detection. The displayed detection model displays the information in which the network model is interested. In addition, investigate whether the model helped to detect flaws when two problems occurred in the same insulator. Figure depicts the output of the discovered insulators. Figure 11 is broken /damaged, Figure 12 has pollution flashover faults, Figure 13 shows ceramic Insulator with percentage of defect. Some of the ceramic insulators that are found defects are the following.

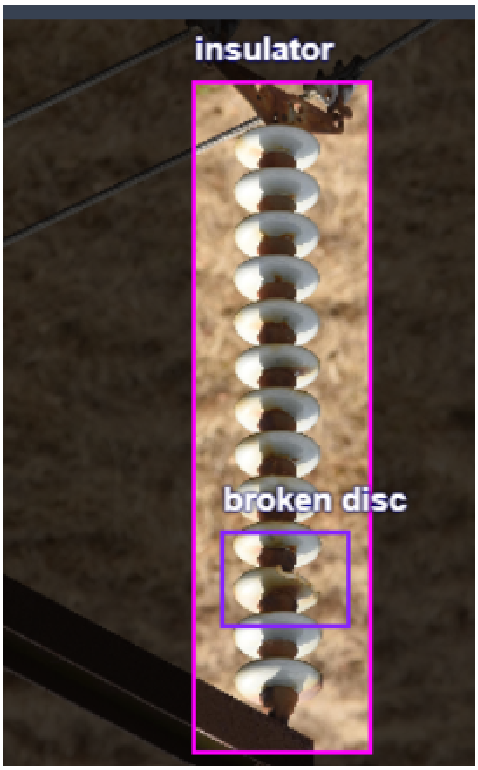

Figure 11: Ceramic insulator with broken disc.

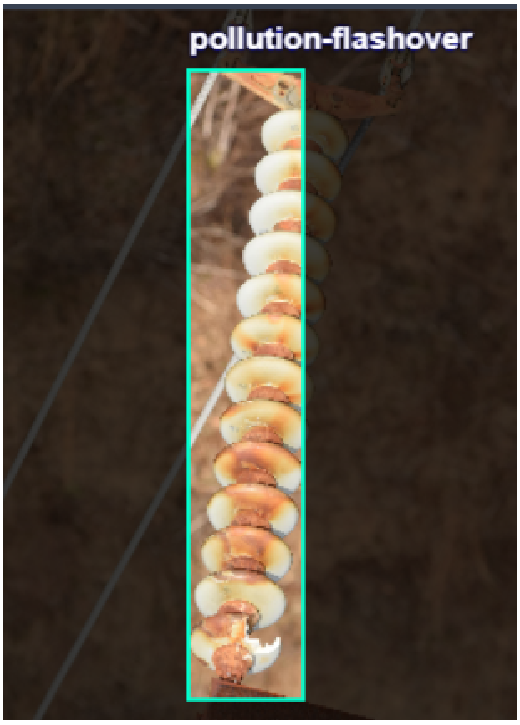

Figure 12: Ceramic insulator with pollution flashover.

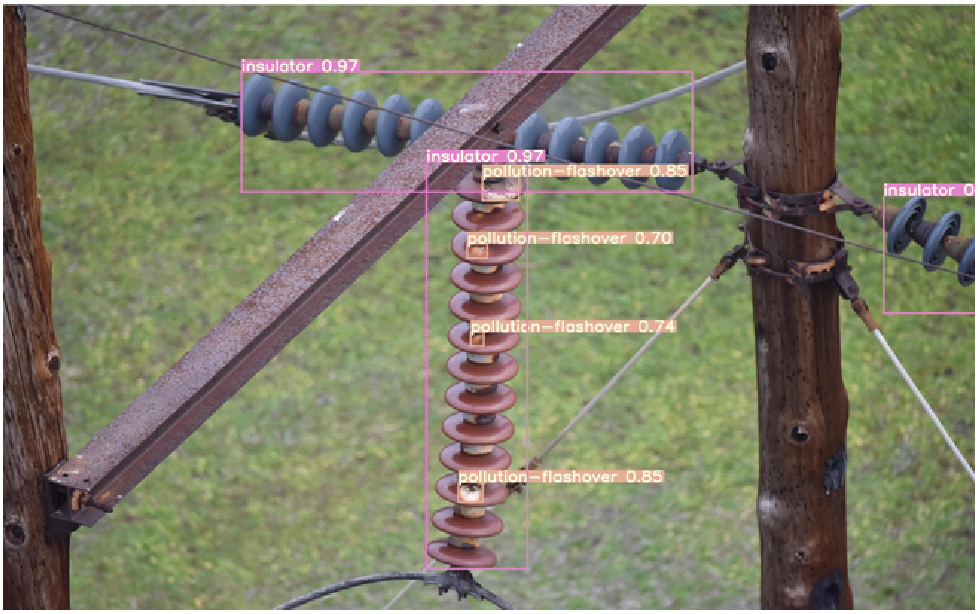

Figure 13: Ceramic insulator with percentage of defect.

The recognition networks were evaluated once following two hundred training cycles. The decrease in curve and exactness were mean values acquired after between forty and fifty iterations of the testing set. The mobile net-SSD detection method clearly outperformed the other two networks that had fewer network parameters.

Table 2: Model Parameters Comparisons of YOLO V7 and mobile Net SSD.

Model	**Precision**	**Recall**	**Accuracy**	**F1 score**
YOLO V7	0.825	0.855	0.812	0.839
Mobile Net SSD	0.8566	0.9311	0.95	0.892

The Figure 14 describes the comparison of algorithms regarding the precision, recall, accuracy and F1 score. By

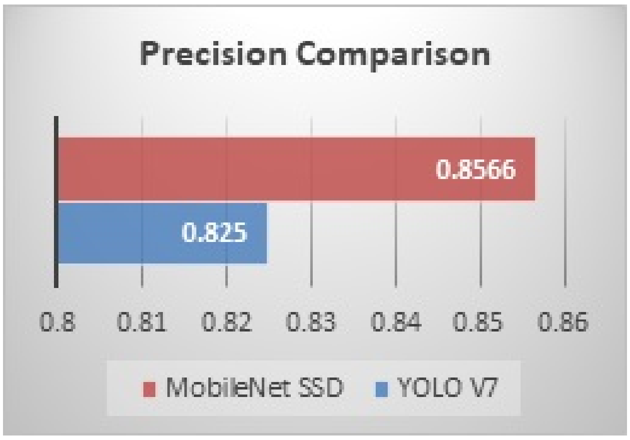

Figure 15a: Comparison of precision values.

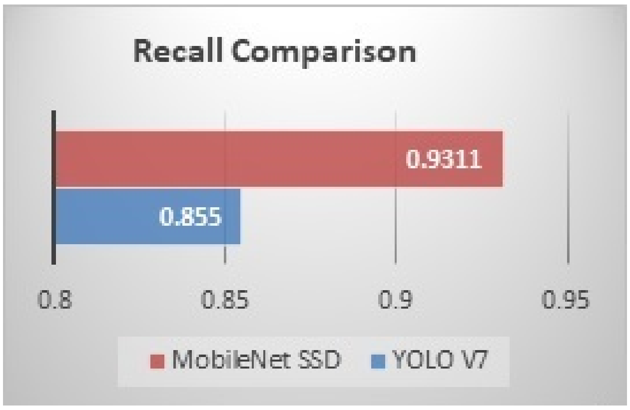

Figure 15b: Comparison of recall values.

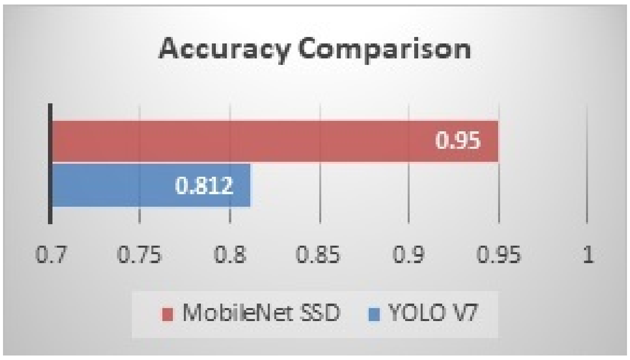

Figure 15c: Comparison of accuracy values.

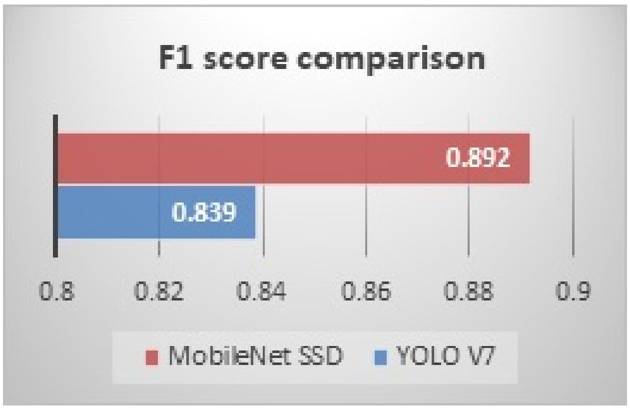

Figure 15d: Comparison of F1-score values.

Figure 15: Performance comparison of the proposed MobileNet SSD and YOLO V7 models using precision, recall, accuracy, and F1-score metrics.

comparing Table 2, can infer that accuracy of mobile net SSD is more as it has 0.95 when compare to YOLO V7 and relatively precision and recall is also more. The best method to use is mobile net SSD from the results.

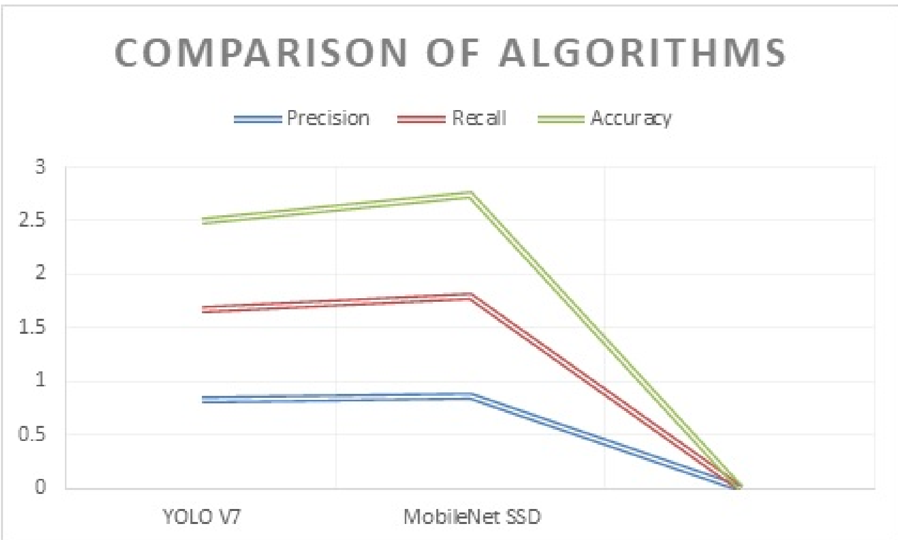

Figure 14: Comparison of algorithms.

The Figures 15 a, b, c, d shows the comparison results of Yolov7 and mobile net SSD algorithms. By comparing different algorithms, the image accuracy and MAC (Multiply Accumulate) performs the best among the latest image processing techniques are shown in Figure 16.

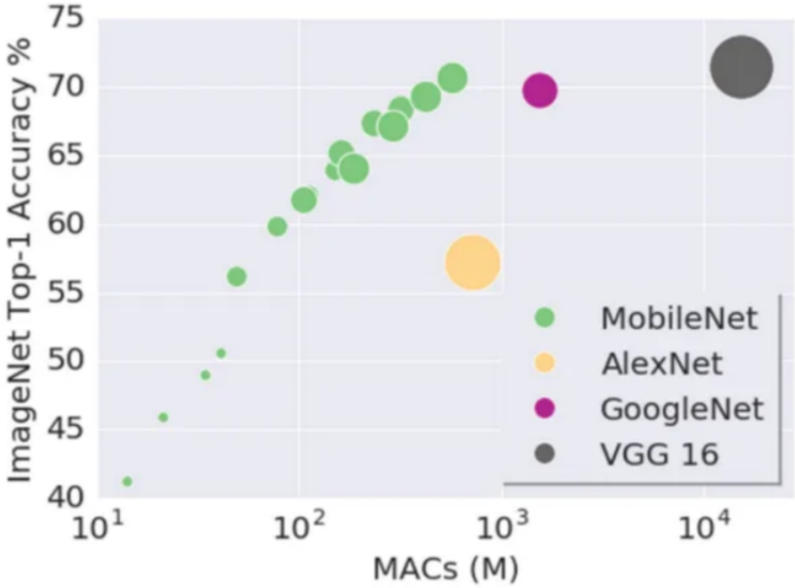

Figure 16: Accuracy Vs MAC.

By analysing the accuracy and threshold to the previous version of YOLO V7 Accumulate Operations shown in Figure 17, Mobile Net and present mobile net SSD, mobile net SSD preformation is very good accuracy reaches to 90% nearly which gives the results accurately.

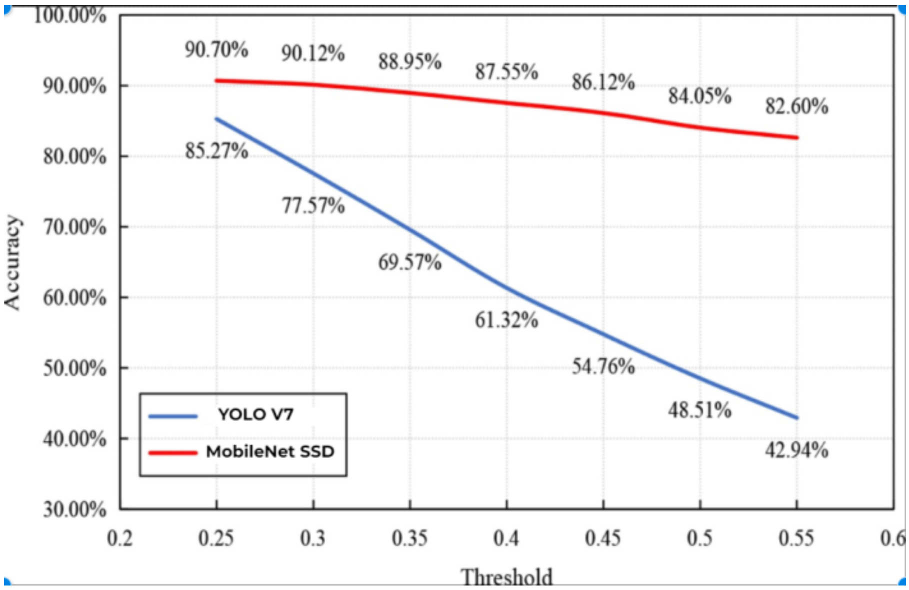

Figure 17: Accuracy Vs Threshold.

Comparison of Insulator Image detection performance with algorithm and without algorithm is shown in Figure 18, with the use of algorithm, the improvement of image detection has improved more with accurate.

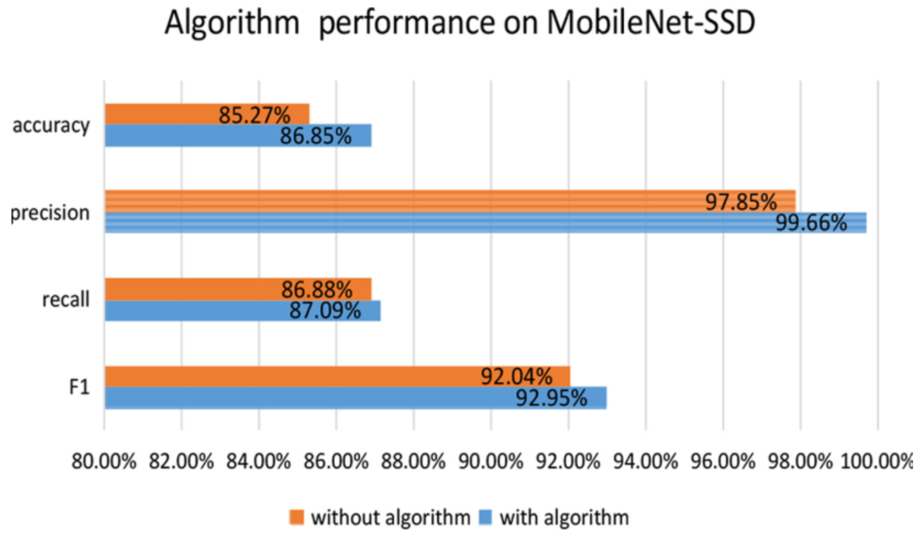

Figure 18: Algorithm performance on mobile net SSD.

The confusion matrix comparison for YOLO V7 and mobile net SSD algorithm.

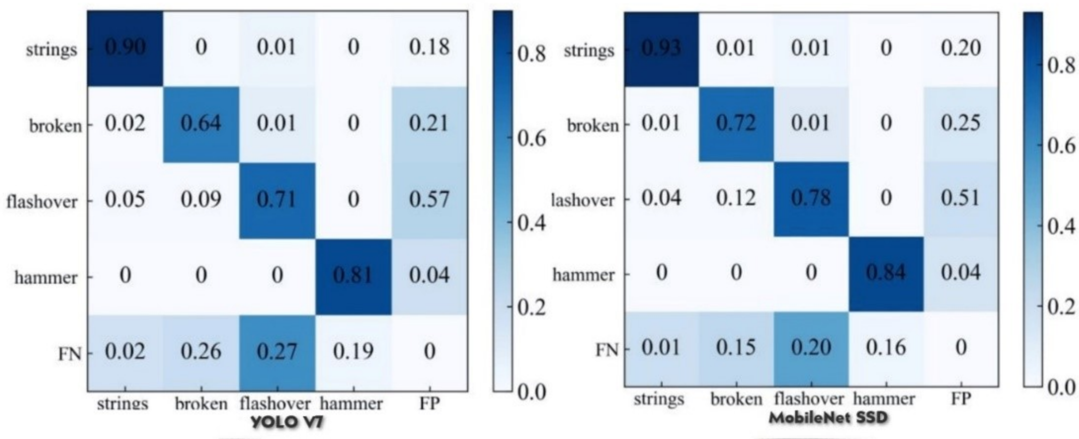

Figure 19: Confusion matrix comparison.

The matrix of Fig 19 shows the confusion matrix of YOLO V7, the improved technique suggested in this paper increases the opportunities for small target detection, such as insulator flaws. Here, 0 indicates what is wrong of pollution flashover, while 1 indicates the defect of damage. 2m indicates the insulator, whereas 3 depicts the background. In the graphic, the row direction is shown, and the column direction reflects the projected category. Based on the data in each line, the proper detection rates for damage and pollutant flash over are ninety-five % and 91 percent, respectively. The confusion matrix summarises the prediction results for classification challenges. It is apparent that the grouping of insulator faults is accurate.

4.4. Classifier

Models performed poorly in comparison to other CNN architectures, with the model achieving the best F1_score of 0.89238. Model convergence time increased with the multiple parameters. The DenseNet-61 model outperformed all VGG structures in classification, with F1 score of 0.95384. ResNet-18 outperformed other classifiers with an F1 score of 0.96216, making it the default method in this paper. While the duration of processing was not a factor in determining the best model for classification, ResNet-18 performed faster. Using bigger models may not yield optimal outcomes for specific issues. Benchmarking is conducted utilising ResNet-18 as the fundamental classification versus standard mobile net SSD versions.

5. Conclusion

Images have grown more popular because to advancements in aircraft control technology and affordable tiny equipment. Inspection of the electric system to be significantly better. This model is utilised when installing electrical power grids in difficult-to-access locations. The suggested technology uses UAV photos to inspect power grids more readily and at a reduced cost, leading to increased life span of the electrical power system.

- Depending on the mobile net SSD network, this research proposes a model for recognizing normal, damaged, and flash over insulators in transmission lines for power. After training on 800 photos, the model achieved a 95% precision and 91% recall in its detection accuracy and with accuracy 80%, leading to improved performance. This gives the intelligent maintenance of power systems a theoretical foundation.
- Its superior performance in comparison to other technologies is due to its ability to expertly balance detection speed with engineering precision, resulting in faster and exact from beginning to last recognition on the datasets. The analysis findings depending with the insulator's datasets show that the proposed technique successfully detects insulator target with their locations. Even in complex and loud settings, it manages to accurately identify insulator defects.
- In future work, the methodology study based on calculating the aging of insulators using the image processing algorithms.

Declarations and ethical statements

Conflict of interest: The authors declare that there is no conflict of interest.
Funding statement: This research received no external funding.
Artificial Intelligence usage statement: During the preparation of this manuscript, the authors utilized ChatGPT solely for language refinement and grammatical corrections. The authors carefully reviewed and revised the generated content and take full responsibility for the accuracy, integrity, and originality of the final manuscript.
Availability of data and materials: The data and/or materials that support the findings of this study are available from the corresponding author upon reasonable request.

CRediT authorship contribution statement

P. Bhavya Sree: Conceptualization, Data curation, Methodology, Investigation, Visualization, Writing–Original draft, Review & Editing. **K. Balaji**: Conceptualization, Methodology, Writing–Review & Editing. **Naveen Banoth**: Data curation, Formal analysis & Visualization. **Mohammad Parhamfar**: Validation & Formal analysis.

Publisher's note

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