CONFERENCE PROGRAM

2023 IEEE CONFERENCE ON ENERGY CONVERSION

CENCON2023

23rd – 24th October 2023

Imperial Hotel Kuching, Kuching, Sarawak, Malaysia

https://attend.ieee.org/cencon-2023

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MESSAGE FROM THE CHAIRS

With immense pleasure, we extend a warm welcome to Kuching, Sarawak for the 6th IEEE Conference on Energy Conversion (CENCON 2023), taking place at the Imperial Hotel on October 23-24, 2023. Our mission is to be at the forefront of sharing cutting-edge research in electrical energy conversion, spanning power engineering, power electronics and drives, and high voltage engineering. This conference not only facilitates knowledge exchange but also offers the chance to explore the enchanting land of Sarawak, often referred to as the "Land of Hornbills."

CENCON 2023 is jointly organized by the IEEE Malaysia Power Electronics (PELS) Chapter and co-organized by the Power Electronics and Drives Research Group (PEDG), Universiti Teknologi Malaysia (UTM) and the Department of Electrical and Electronics Engineering, Universiti Malaysia Sarawak (UNIMAS). We are delighted to have the technical co-sponsorship of the Korean Institute of Power Electronics (KIPE) and the generous support of the Sarawak Tourism Board and Genetron Sdn Bhd as our Platinum Sponsor.

We are honored to introduce two distinguished keynote speakers, namely Prof Ir Dr Nasrudin Abdul Rahim, a renowned expert in power electronics from the University of Malaya, Malaysia, and Prof Dr Kai Sun from Tsinghua University, China, an authority in hybrid dc/ac microgrid and also the PEL Asia Pacific Regional Vice Chair.

The conference promises a dynamic blend of technical paper presentations and product exhibitions. To date, we have received over 56 submissions from 17 countries. Each paper underwent rigorous peer review by 100 experts in their respective fields, resulting in an acceptance rate of 71.4% for oral presentations.

Once again, we extend a warm invitation to all delegates and their companions to explore the vibrant city of Kuching, Sarawak. We eagerly anticipate engaging in fruitful technical discussions and the exchange of innovative ideas. Following the conference, we encourage you to extend your stay to savor the many captivating attractions in the city and throughout Malaysia.

Selamat Datang!

Shahrin Md Ayob
Ramani Kannan

CENCON 2023 General Chairs

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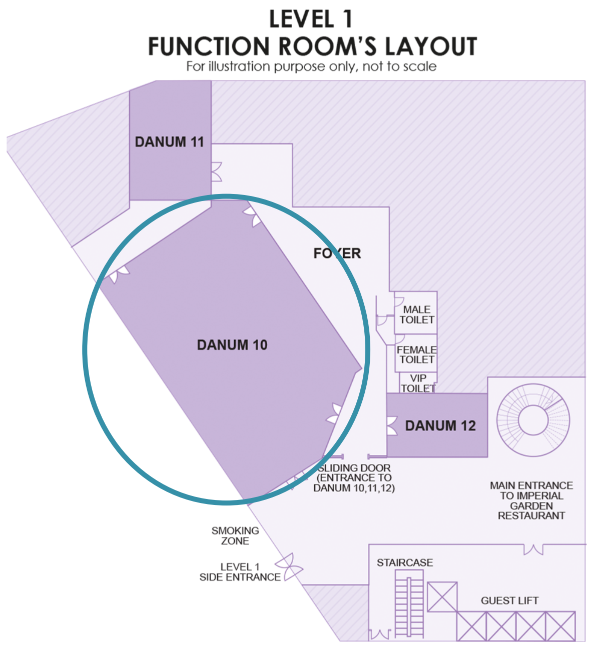

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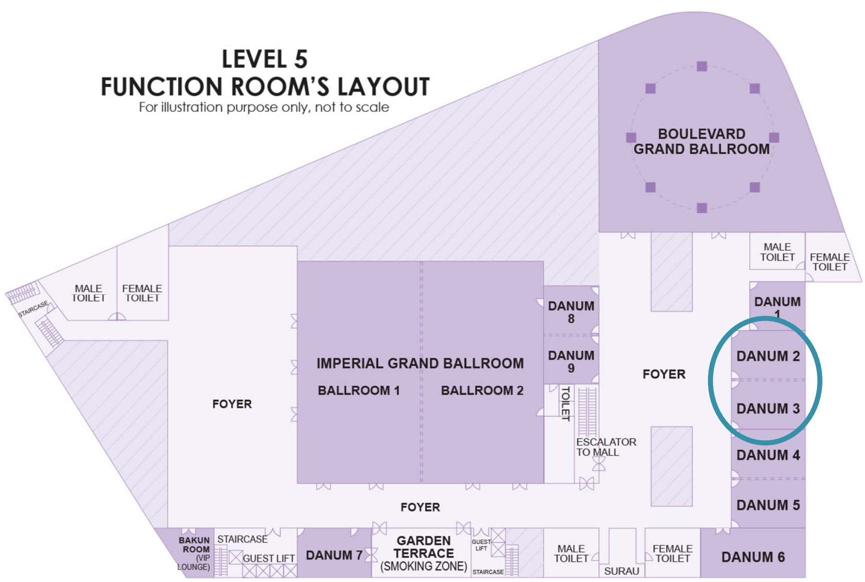

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CENCON 2023

23 OCTOBER 2023, MONDAY

0800-0845	Registration
0845-0900	Opening Ceremony & Speech by General Chair
0900-0950	**Keynote 1 : Professor Dr. Nasrudin Bin Abd Rahim**
0950-1040	**Keynote 2 : Professor Dr. Kai Sun**
1040-1110	Tea Break
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1400-1520	**Session 2A** & **Session 2B**
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:	:
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24 OCTOBER 2023, TUESDAY

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TECHNICAL PROGRAM

23 Oct 2023, Monday

REGISTRATION

Date: **23 Oct 2023, Monday**
Time: **0800-0845**

KEYNOTE SESSION

Keynote Chair: **Dr Norjulia Mohamad Nordin**
Date: **23 Oct 2023, Monday**
Time: **0845-1040**
Venue: **Danum 10, Level 1**

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0900-0945 Keynote Address 1
A New Era of Power Electronics in Malaysia: Research Challenges
Professor Ir. Dr. Nasrudin Bin Abd Rahim (Universiti of Malaya, Malaysia)

0945-1040 Keynote Address 2
Hybrid AC/DC Microgrids: Configuration, Control and Future Development
Professor Dr. Kai Sun (Tsinghua University, China)

SESSION 1A Control of Electrical Drives 1

Session Chairs: **Shahrin Md Ayob & Yanuar Zulardiansyah Arief**
Date: **23 Oct 2023, Monday**
Seminar Room: **Danum 2, Level 5**

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1135-1155 **S1A.2**
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Explainable Machine Learning Method for Open Fault Detection of NPC Inverter Using SHAP and LIME
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SESSION 1B Renewable Energy Systems 1

Session Chairs: **Tan Chee Wei & Jasrul Jamani Jamian**

Date: **23 Oct 2023, Monday**

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Anton Louise P. De Ocampo; Mark Justine Domingo; Melmar Eje; John Miko Malinao

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Session Chairs: **Mohd Junaidi Abdul Aziz & Kyo-Beum Lee**

Date: **23 Oct 2023, Monday**

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24 Oct 2023, Tuesday

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THANK YOU

Insulator Defect Detection in Power Lines Based on Improved Convolution Neural Network

Annie Anak Joseph
Department of Electrical and Electronic Engineering
Universiti Malaysia Sarawak
94300, Kota Samarahan
jannie@unimas.my

Mohd Rahul Bin Mohd Rafiq
Department of Electrical and Electronic Engineering
Universiti Malaysia Sarawak
94300, Kota Samarahan
70497@siswa.unimas.my

Kuryati Bt Kipli
Department of Electrical and Electronic Engineering
Universiti Malaysia Sarawak
94300, Kota Samarahan
kkuryati@unimas.my

Kho Lee Chin
Department of Electrical and Electronic Engineering
Universiti Malaysia Sarawak
94300, Kota Samarahan
lckho@unimas.my

Tengku Mohd Afendi Zulcaffle
Department of Electrical and Electronic Engineering
Universiti Malaysia Sarawak
94300, Kota Samarahan
ztmafendi@unimas.my

Charlie Sia Chin Voon
Faculty of Engineering, Computing and Science
Swinburne University of Technology
Sarawak Campus
93350, Kuching
cvsia@swinburne.edu.my

***Abstract*— In a transmission line architecture, an insulator is essential for preventing the unintended dissipation of electrical current from the conductive elements into the surrounding environment. This purpose is accomplished by effectively isolating the conductors from the supporting framework. A defect in the insulator may cause several malfunctions in the transmission line. It can range from a minor failure to catastrophic damage. Previous studies have investigated some insulator defect detection technologies using image processing methods. In modern research, classifiers are frequently used for this function in widespread detection systems. However, there are still some issues with computational effectiveness and detecting accuracy. This paper introduces an innovative approach by proposing a hybrid system based on You Only Look Once (YOLOv5) and Residual Neural Network (Resnet50) architectures. The proposed methodology achieves an excellent accuracy of 99.0 ± 0.233%. It takes 25 minutes to complete the training process for a dataset containing 1,000 photos of insulators. The suggested method can transform the inspection procedure for high-altitude insulators by smoothly merging the advantages of YOLOv5 and Resnet50 through a carefully thought-out hybrid approach.**

***Keywords*— Convolution Neural Network, Insulator, unmanned aerial vehicle, Resnet50, YOLOv5**

I. Introduction

An insulator is a widely used component of a power transmission line system. Insulator strings are essential because they provide both electrical insulation and mechanical support for the power lines [1]. The transmission system needs to work without issue to serve the customers' continuous power and maintain its safe operation. Therefore, good working insulators are essential in maintaining the reliable operation of a power transmission system. Ensuring that the insulator is working in a good state requires regular inspection and maintenance. This is because insulators, like other power transmission system components, may deteriorate over time. Exposure to the environment for a long time, such that temperature increases due to heavy sunshine, is cultivating the deterioration rate of an insulator. It may experience defects such as self-explosion, breakage, etc [2]. The insulators are also affected by meteorological conditions such as rain, snowfall, and wind. The presence of wildlife, such as birds, also worsened the situation of the insulators by contaminating them. When the insulator fails, it may cause equipment damage, power outages, and even disasters [3]. The traditional method of transmission line inspection is done visually by human and require the inspectors' judgement on the condition of the components. In recent years, one of the most common approaches has been employing manned helicopters flying along the power line corridor and outfitted with various sensors to record the inspection data [1]. However, this method requires demanding human and energy resources apart from having high risk because of the need to fly near the transmission line for better inspection data collection. Therefore, several alternatives involving mobile robotics, such as Unmanned Aerial Vehicle (UAV) [4] and Rolling on Wires (RoW) Robots [5], have emerged to solve the drawbacks of the traditional method. The RoW, however, is prone to the ambiguity of the line's scenario. It must adapt to the high versus medium voltage power lines [1], leaving UAV the most optimum method for modern inspection. Therefore, the images captured from a UAV, such as a drone, have created the realization of an automatic inspection of insulators through images. Inspection through images captured from a UAV has been the prominent method for automated insulator inspection.

The construction of such an autonomous system involves the development of solid insulator defeat detection and diagnosis systems capable of dealing with the high variability in the collected data. Under controlled illumination and background conditions, traditional computer vision algorithm-based methodologies can deliver satisfactory results in structured images. However, most of these systems are based on heuristics, which necessitates a variety of assumptions and constructed criteria that must be manually calibrated and re-adjusted to perform well in previously unanticipated conditions. On the other hand, machine learning algorithms can overcome these restrictions when trained on relevant datasets and deliver a more flexible solution that is more resistant to the ambiguity of illumination and the background.

Various scholars have studied the inspection of insulators through Convolution Neural Network (CNN) methods to improve each method's detection accuracy, precision and speed. A few CNN methods have been developed for insulator detection and defect classification, including single and multiple-stage detection methods. Types of single-stage detection method for insulator includes You Only Look Once (YOLO) [6] [7] [8] and Single Shot Multibox detector (SSD) [9]. In addition, multi-stage detection methods for insulators are Faster Region-based Convolutional Neural Networks (Faster R-CNN) [2] [10] [11] [12] [13] and Region-based Fully Convolutional Networks (R-FCN) [3]. Feng et al. [7] use the YOLOv5 object detection model to propose an automatic insulator detection approach employing contrasting the performance of four distinct versions of YOLOv5. In June 2020, the YOLOv5 model was released with four variants: YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x. The YOLOv5s network has the most minor depth and width of the feature map in the YOLOv5 series. Comparisons were made between four different YOLOv5 versions to show the most effective. Scholars noticed that larger models, like YOLOv5s, require greater training time, such as 1.027 hours for YOLOv5s and 4.156 hours for YOLOv5m. The main attribute of the YOLO method is its fast detection speed, which can be done in real-time. The method's accuracy can, however, still be increased.

Chen et al. [14] suggested combining the YOLOv5 and Spatial Pyramid Pooling (SPP)-Net methods to detect insulator flaws. The authors show how this combination can find insulator faults with great accuracy and computational efficiency. Real-time object detection is possible with YOLOv5. SPP network still makes extracting features at different scales and aspect ratios possible, which is crucial for classifying objects of varied shapes and sizes. This paper's method for discovering insulator faults combines YOLO with SPP-Net and offers outstanding accuracy and real-time object detection. The two methods' diversity enables the quick and accurate detection of insulator defects.

To identify and classify the insulators as being in excellent or flawed condition, Zhang et al. [15] use a UAV to take photographs of insulators, which are then modified using the Faster R-CNN algorithm. The network can extract data from images of various sizes and aspect ratios using the SPP layer, which the authors recommend adding to the Faster R-CNN with the Resnet50 method. The authors find that their method is 97.8% accurate at spotting insulator issues when applied to a set of UAV photos of insulators. Furthermore, they demonstrate that their approach can yield a high identification rate with a low incidence of false positives. The modification of the Faster R-CNN method by adding an SPP layer, which allows the network to extract features at different aspect ratios and sizes, and the use of UAV data for defect recognition in insulators are the primary contributions of this paper. The authors showed that their method could locate insulator faults with high accuracy and a small percentage of false positives.

In [16], the scientists use a collection of photos of insulators to train their Generalized Intersection Over Union (GIOU)-YOLOv3 model, which they subsequently use to recognise insulators in photographs. They demonstrate that their GIOU-YOLOv3 algorithm can reach a high level of accuracy in identifying insulators by evaluating it on a dataset of photos of insulators. The primary contribution of this study is the GIOU-YOLOv3 method, which the authors demonstrate that their technique can precisely identify insulators in photos. In [17], the authors use transfer learning, a prevalent deep learning technique, to leverage pre-trained CNN models. They select a suitable pre-trained model as the backbone network and fine-tune it using the insulator dataset This method lets the model learn pertinent insulator recognition and fault detection features.

In [18], The authors present an improved version of the Faster R-CNN technique for detecting insulator flaws. They modify the original Faster R-CNN architecture to improve its efficacy in identifying and accurately localizing insulator defects. The paper provides a comprehensive overview of the modified Faster R-CNN architecture, focusing on the modifications made to the backbone network, region proposal network, and bounding box regression components. The authors describe how these modifications enhance detection efficacy and computational efficiency. Besides that, Qiu et al. [19] propose a method for insulator flaws detection using an enhanced YOLOv4 algorithm. A sample set of insulator images was created using aerial photos from the power grid, a publicly available dataset from the Internet, and an image augmentation technique based on Graph Cut. The images of insulators were pre-processed using the Laplace refining approach. The YOLOv4 object recognition model's structure was altered using the Mobile Net lightweight convolutional neural network to address to address the issues of having too many parameters and having slow detection performance. Maduako et al. [20] demonstrated that, particularly in developing nations, combining UAV photography and computer vision results in a low-cost solution for a quick and easy inventory of electrical assets. The choice of deep learning architecture, the availability of sufficient training samples across a wide range of fault characteristics, the ramifications of data augmentation, and the balancing of intra-class heterogeneity are other factors to take into account when using this technology,

For identifying insulators, many CNN designs, such as YOLO, SPP-Net, and Resnet50, have been suggested in the literature. The literature indicates that CNNs are a potential tool for finding insulators in photos. The research indicates that CNNs can identify insulators in photos with high accuracy. However, most of the datasets employed in the past researches are relatively small and need more variety, limiting the generalizability of the methodologies. On the other hand, system learning speed is another direction to be considered. In past research, some systems gain high accuracy but slow learning process, and some have higher learning speed but lower learning accuracy. Therefore, further study is required to assess the effectiveness of the approaches by balancing between learning speed and accuracy. Thus, this paper proposes an improved version of CNN based on YOLOv5 and Resnet50, considering the tradeoff between accuracy and learning speed. The remainder of the article is structured as follows. Section II explains the methodology used to achieve the goals. Section III discusses the results, analysis, and discussion data. Section IV is dedicated to the conclusion.

II. METHDOLOGY

In this section, the development of the system is explained and illustrated with a block diagram, as shown in Fig. 1. In this project, i5-9th Gen Central Processing Units (CPU) and GTX 1050 Ti Graphics Processing Units (GPU) are used to train on a dataset consisting of 1000 images of insulators.

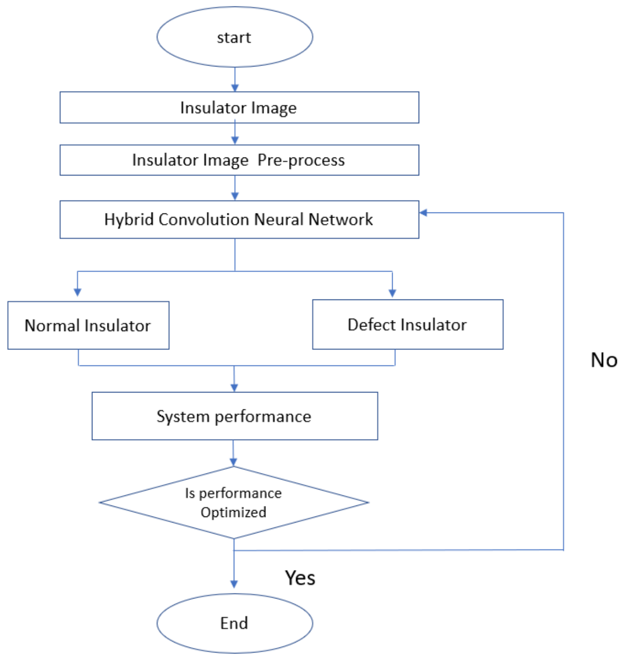

Fig. 1. Flowchart of the System

A. Dataset

The 1000 datasets were obtained from GitHub [21]. These datasets comprise normal and defective insulator images with the same light intensity. The datasets were partitioned into three sections: 80% of the data is used as a training set, 10% as a validation set, and 10% as a testing set..

B. Software

TensorFlow is employed in this study. It is an open-source machine learning software library developed by the Google Brain Team. TensorFlow enables the design and execution of computations represented as directed graphs, known as computational graphs, which consist of a sequence of operations, or "ops," that accept inputs and generate outputs.

C. Proposed Method

The proposed method is developed based on the hybrid between YOLOv5 and Resnet50. The head component of the system is detached from the Resnet50 architecture and integrated into YOLOv5s. This approach enables the system to implement a process for cropping incoming input or images of the insulator, reducing the image's spatial resolution. The Resnet50 layering is imported and integrated into the YOLOv5s Architecture. The parameters in the architecture are modified to meet the requirements of Resnet50, ensuring smooth functionality and preventing any potential errors in the combination of the two systems.

Fig. 2 illustrates the modification of the Hybrid Yolov5s architecture by replacing the backbone of YOLOv5s with the Resnet50 layer. This structure is divided into three main parts. It is labelled as the system's backbone on the left of the images. This backbone is the Resnet50 and hybrid with YOLOv5s. Next, the middle part of the system has a variant color and boxes called the neck of the system. Lastly, the right with orange color is the head of the system. When convolutional and pooling layers, which are meant to extract picture features. Using filters, these layers identify and remove certain visual elements, such as edges and textures.

Each residual block has several convolutional, batch normalization, activation functions layers and a shortcut connection. The shortcut connection enables the input to skip one or more of the block's layers and is added to its output before forwarding it to an activation function. This link helps gradients move more efficiently across the network, hence preventing the issue of disappearing gradients. The output of the residual blocks is then processed through further convolutional, pooling, and normalized layers before the final fully connected layers. The fully connected layers are in charge of creating the final predictions based on the retrieved visual elements. After it passes through the Resnet50, it will be passed on to the SPP-Net. When an image is loaded into a network that employs SPP-Net, it will initially be processed by many convolutional and pooling layers. These layers extract visual characteristics such as edges, textures, and forms. These features are then sent via the SPP layer, where the SPP layer executes various pooling operations with distinct pooling areas to the feature maps created by the convolutional layers. This enables the network to build numerous feature maps from the picture at various sizes. The SPP layer is meant to collect characteristics at several levels of abstraction, which might be crucial. The SPP layers are then concatenated and processed through many further layers of convolutional, pooling, and normalized layers before reaching the final fully connected layers.

Finally, it will go through the last part of the system. When employing YOLO for object recognition, the picture is processed through many convolutional and pooling layers to extract visual properties such as edges, textures, and forms. Then, these characteristics are sent via the YOLO detection layers, which include the “neck” layers. The neck layers oversee processing the extracted visual elements and producing the final predictions. The neck layers of YOLO are made up of a series of convolutional layers that reduce the spatial dimensions of the feature maps while increasing the number of channels.This enables the network to prioritize the most vital characteristics while rejecting less vital data. This is accomplished by employing convolutional layers to extract high-level features from the feature maps created by the first layers and then utilizing pooling or strung convolutions to minimize the spatial dimensions of the feature maps. The decrease in spatial dimensions is significant because it enables the network to process more considerable input pictures without sacrificing computational efficiency. The output of the neck layers is then sent to the detection layers, which provide the final predictions for the image's objects. The detection layers are composed of fully linked layers that predict the class labels, bounding box coordinates, and confidence scores for the objects.

III. Results and Discussions

The system tests datasets ranging from 800 to 1000 insulator images. It is frequently employed in classification assignments when the objective is to forecast the class label of a specific occurrence. The equation to calculate the accuracy of a dataset is

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

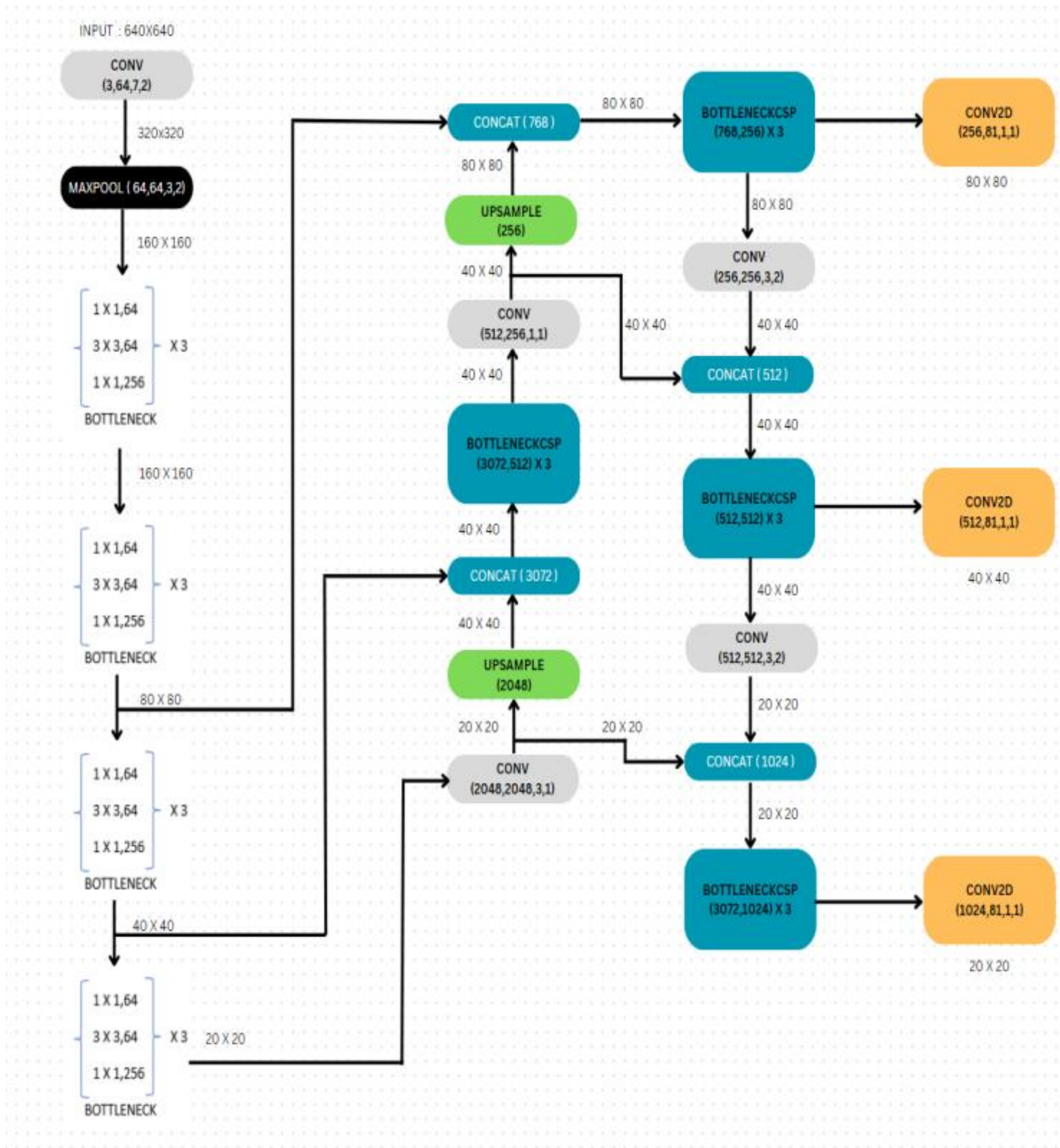

Fig. 2. Conceptional Design of the Hybrid Architecture

The number of incidents accurately classified as positive is called True Positives (TP). The number of situations accurately classified as negative is called True Negatives (TN). The entire number of cases in the data set is Total Prediction.

Accuracy alone is not enough as a performance criterion for a model. In some instances, when the classes are unequally matched, accuracy might be deceiving. Precision provides insight into the model's ability to identify positive cases reliably and may be considered a measure of the model's "score." The model has achieved complete precision if it has a precision value of 1.0, which suggest that it has not produced any false positive predictions. A precision value of 0.0 means that the model made no true positive predictions, which means that all of the predictions it generated were false positives. The intermediate numbers show the proportion of accurate positive predictions made compared to errors. Equation 2 shows the calculation for precision.

$$Precisions = \frac{TP}{(TP+FP)} \tag{2}$$

Where True Positives (TP) represent the correct classification of faulty insulators, and False Positives (FP) represent the wrong classification of non-defective insulators as defective. True Negative (TN) represent the correct classification of non-faulty insulators, while False Negatives (FN) represent the wrong classification of non-faulty insulators.

A. *Training For 800 Images Dataset*

The system processes 800 images in each session of epoch, with the epoch values ranging from 20, 40, 60, 80, and 100, respectively.

TABLE I. RESULTS FOR 800 IMAGES DATASETS

Epoch	Accuracy	Precision	Speed
20	85.6±0.328%	78.1%	4.07 mins
40	96.2±0.348%	95.7%	8.05 mins
60	96.7±0.293%	94.8%	12.03 mins
80	96.3±0.257%	94.5%	14.08 mins
100	97.9±0.236%	95.3%	16.40 mins

Table I shows the results for the 800 images of insulators, and the best result for the 100 epochs tries is 97.9 ± 0.236% with a speed of 16.40 minutes. The accuracy for 800 images per epoch increases when the epoch increases. This is because the proposed method trains with variant types of images when the dataset is increasing. The system demonstrates swift detection capabilities owing to its proficiency in learning from extensive datasets. The simulation result of the detection for the 800 images dataset is shown in Fig. 3, which stated that it predicted an accuracy of 97.9 ± 0.236%.

Fig. 3. Result prediction for 800 images datasets

B. *Training For 1000 Images Dataset*

Next, the system processes 1000 images in each session of the epoch, with the epoch values ranging from 20, 40, 60, 80, and 100, respectively. Table II shows the results for the 1000 images of the insulator, and the best outcome for these 100 epochs is 99.0 ± 0.233% with the speed of 25 minutes. The results show that the proposed method produces high recognition accuracy with considerably fast detection speed. The accuracy for 1000 images per epoch increases because when the dataset increases, the proposed method needs to train with various datasets. Extended learning time results from employing larger datasets, characterized by intricate patterns and variations. Smaller batch sizes are introduced to expedite this process by considering the tradeoff between accuracy and learning time. Despite the lengthened learning period with increasing epochs, it is still considered a fast-training regimen. Quality and diversity of training data, a well-labelled dataset containing a diverse range of insulator images and encompassing a variety of fault categories is essential. The dataset must precisely represent real-world scenarios to teach the model the robust characteristics associated with various faults. It is essential to fine-tune hyperparameters such as learning rate, sample size, optimizer choice, and regularization strength. These modifications can have a substantial effect on accuracy. The paper uses a learning rate 0.01 to increase the model's precision.

Enhanced Generalization, employing a reduced learning rate during training, frequently leads to improved performance in generalization. When the value of the learning rate exceeds an optimal threshold, the neural network tends to rapidly memorize the training examples, resulting in a phenomenon known as overfitting. Decreasing the learning rate facilitates a more comprehensive exploration of the parameter space by the network, thereby promoting the model's ability to capture significant and resilient features. The regularization effect can enhance the network's ability to generalize to unfamiliar examples and improve validation or test set accuracy.

TABLE II. RESULTS FOR 1000 IMAGES DATASETS

Epoch	Accuracy	Precision	Speed
20	92.7±0.335%	88.2%	3.20 mins
40	97.5±0.319%	94.6%	6.20 mins
60	96.3±0.280%	94.5%	12.24 mins
80	93.6±0.254%	95.0%	18.24 mins
100	99.0±0.233%	97.3%	25.00 mins

The dataset simulation result of the detection for 1000 images dataset is shown in Fig. 4, which stated that it predicted an accuracy of 99.0 ± 0.233%.

Fig. 4. Result prediction for 1000 images datasets

IV. CONCLUSIONS

The proposed framework develops a hybrid system between Yolov5s and Resnet50 to detect faulty insulators. The detection of the system achieves an accuracy of 99.0±

0.233% with 1000 datasets and time taken to finish the training within 25 minutes. These consistencies indicate that the model performs well, providing reliable and accurate predictions. Building a good CNN model requires a continuous cycle of experimentation. Apart from that, every dataset has individual properties that set it apart, such as its size, dispersion, noise levels, and class imbalances. These differences can significantly impact the decision-making process regarding the model architecture, hyperparameters, and regularization strategies. For instance, a dataset that has a significant class imbalance may benefit from methods to alleviate the imbalance issue, such as oversampling or class weighting. In contrast, a dataset with different lighting may require a more advanced model strategy regarding color separation. In the future, the availability of computational resources should be considered. GPUs are designed to incorporate finely tuned cores for executing parallel processing operations. This inherent design feature enables GPUs to exhibit exceptional efficiency when handling complex deep-learning computations. CNNs consist of matrix operations, convolutions, and activation functions. These computations can be efficiently executed in parallel across multiple GPU cores. Parallelism enables accelerated computation of both forward and backward passes, leading to notable performance enhancements compared to CPUs. GPUs can concurrently execute numerous operations, effectively handling the inherently parallel computations involved in CNN calculations. To balance between the accuracy and efficiency, the factors as mentioned above must be carefully considered.

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