JOIV : Int. J. Inform. Visualization, 8(3-2): IT for Global Goals: Building a Sustainable Tomorrow - November 2024 1528-1535

INTERNATIONAL JOURNAL ON INFORMATICS VISUALIZATION

journal homepage : www.joiv.org/index.php/joiv

Classification of Defect Photovoltaic Panel Images Using Matrox Imaging Library for Machine Vision Application

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***Abstract*—The maintenance of large-scale photovoltaic (PV) power plants has long been a challenging task. Currently, monitoring is carried out using electrical performance measurements or image processing, which have limited ability to detect faults, are time-consuming and costly, and cannot pinpoint the defect's precise location quickly. To address these challenges, this research focused on using deep learning techniques to classify defect and non-defect PV panels. The application provided deep learning algorithms capable of image classification in various classifiers. The image dataset was carefully curated and split into training and development datasets during the training model to ensure the highest accuracy for the prediction of the presence or absence of defects on the PV panel. Statistical measures, which are the average accuracy for the training model and average prediction, were employed to evaluate the classification performance of the defect PV panel model. The results demonstrated a remarkable total accuracy of model 99.9% for each class, and prediction results showed that almost 70% of defect PV panels were detected from the testing dataset. Furthermore, a comparative analysis was conducted to benchmark the findings against other algorithms. The practical implications of this research are significant, showcasing the effectiveness of deep learning algorithms and their compatibility with machine vision applications for the classification of defect PV panel images. By leveraging these techniques, solar farm operators can significantly improve maintenance management, thereby enhancing the efficiency and reliability of solar power generation and potentially saving significant costs.**

***Keywords*—Artificial intelligence; photovoltaic panel; deep learning; matrox imaging library; machine vision applications.**

Manuscript received 3 Oct. 2023; revised 31 Jan. 2024; accepted 13 Jul. 2024. Date of publication 30 Nov. 2024.

I. INTRODUCTION

Over the past decade, solar PV energy, a clean and sustainable energy source, has garnered significant attention and experienced substantial global development, driven by escalating environmental pollution and the energy crisis. [1]. As stated in [2], in many nations, photovoltaic power generation has rapidly advanced to become a clean, low-carbon energy source with excellent price competitiveness. Ensuring the reliability of PV panels is essential for optimizing energy output and reducing maintenance costs. [3]. The intensity of the incoming solar radiation, surrounding temperatures, the PV panel's tilt, wind speed, the panel's mounting configuration, partial shading, dust buildup, and fault situations in the panels all affect the condition of the PV Panel. [4]

However, manual visual inspection of PV panels is time-consuming and prone to inaccuracy. According to the International Energy Agency (IEA), the capacity of all renewable energy sources will increase by 50% globally between 2019 and 2024, with solar PV making up 60% of the capacity. To solve this issue, machine vision and deep learning algorithms have gained importance in automating the detection and categorization of defects in PV panel images [5]. This study aims to investigate the classification of defect PV panel images using advanced technology deep learning algorithms, thereby leading to more efficient and accurate inspection processes [6]. By that, defects can be spotted early using machine vision and intelligent models.

Two primary approaches are utilized to detect the invisible defect types. They consist of manual electrical testing, which includes current-voltage (IV) curve analysis at the module and string levels, and aerial and ground-based infrared thermography (IRT) imaging examinations [7]. Photovoltaic modules may acquire faults that, if found in time, can be corrected; however, this can significantly reduce energy production and occasionally even safety concerns. Localization, online issue detection, and fault diagnosis during field operations are significant challenges, particularly for large-scale systems [8].

Photovoltaic panels (PV) may have several defects which could affect their effectiveness and durability. The formation of cracks and fractures in the PV panel's cells or modules, which can be caused by mechanical stress, temperature cycles, or external impacts, is one frequent problem [9]. Another problem with PV panels is delamination, which happens when layers inside the module separate and hurt electrical performance [9]. There were also defect PV panels when they got hot spots. The localized areas with higher temperatures inside the solar cells often come on by shading or cell mismatch, and they can result in cell deterioration and decreased overall panel performance [10]. There are several reports in the literature regarding the severe environmental conditions that can severely affect the PV modules' performance. Among all the environmental conditions, humidity, heat, extreme weather, dust, and cloud shading affect the PV modules' performance drastically and may degrade their lifetime [10,11,12,13]. It is also reported that snail trails due to water vapor [14] can be the cause of discolorations on solar cells and indicators of cell cracks. Another issue with PV panels is potential-induced degradation (PID), which develops because of voltage stress between the solar cells and the ground and results in performance degradation over time [12].

Another defect that affects PV panels is back sheet degradation since it shields the modules from the elements. Its deterioration may result in moisture infiltration and subsequent cell deterioration [13]. When solar cells are first exposed to sunlight, they experience light-induced degradation (LID), which temporarily affects their performance but recovers over time. It results from boron-oxygen-related flaws [14]. Both defects may affect the performance of PV panels.

Cracking on PV panels may also affect their performance in power consumption and thermal effects, destructing their module and reducing their life reliability [15]. In addition, as seen in [16], defect detection is made by using Ghost convolution with Bottleneck CSP module as the hot spot is one of the common defects and got a higher percentage, followed by scratch, black border, broken and no electricity. Referring to most of the defects in PV panel images, this paper focuses on crack and scratch defects as they concern the most common defects and affect the functionality of PV panels.

Besides all the types of defect PV panels, many ways have been used to classify defect or non-defect ones. One of them is convolutional neural networks (CNNs), which have emerged as powerful algorithms for distinguishing defect and undamaged photovoltaic (PV) panels [17]. By learning hierarchical patterns and features directly from images, CNNs excel at image classification tasks. A CNN is trained on a sizable dataset of labeled images to classify PV panels, including defect and non-defect panels.

Next, an efficient Real-Time Multi Variant Deep Learning Model (RMVDM) to address the issue of detecting the faulty PV Panel is introduced [18]. The approach detects and localizes faults, including spotlights, cracks, dust, and micro-cracks. The preprocessed images are then used with the Grey Scale Quantization Algorithm (GSQA) to extract features. In contrast, the extracted characteristics are learned using a Multi Variant Deep Learning model, which consists of multiple layers from various neural classes. Each class neuron is designed to assess Defect Class Support (DCS).

The network gains the ability to distinguish between the visual characteristics of defects and non-defects, enabling it to categorize PV panels as either defect or non-defect. This automated approach has benefits, such as improved productivity, scalability for industrial applications, and flexibility for various defect kinds and image changes [19]. This approach is based on deep learning, specifically CNNs, and has been used to classify defects in PV panels, documented in scientific literature.

One intriguing method for pretraining CNNs without the need for human annotations is self-supervised learning. Based on [20]. It includes contrastive learning, rotation prediction, and pretext tasks based on spatial context prediction. Self-supervised learning techniques such as SimCLR++ and SwAV-ResNet showed remarkable improvements in classification accuracy by utilizing large-scale unlabeled datasets, even outperforming supervised methods in some cases.

Another detection of PV defect is done by [21] based on a multi-spectral deep convolutional neural network (CNN). The light spectrum properties of the solar cell color image are analyzed, and the best CNN model structure is chosen. In various spectral bands, it was discovered that a range of flaws displayed distinctive traits that could be distinguished. Therefore, a multi-spectral CNN model was created to improve the model's ability to differentiate between complicated texture background features and fault features.

As seen by [22], it includes two methods for automatically detecting these defects in a single image of a PV cell. The hardware requirements of the techniques differ, as determined by their different application contexts, so the more hardware-efficient approach is based on hand-crafted features that are classified in a Support Vector Machine (SVM), and the more hardware-demanding approach uses an end-to-end deep CNN that runs on a Graphics Processing Unit (GPU). Both methods were trained using 1968 cells from high-resolution EL-intensity pictures of monocrystalline and polycrystalline PV modules.

Despite using the real image of the PV Panel, in [23], an Electroluminescence Image (EL) was used. It created a channel attention system and integrated both attention networks into a modified U-net architecture we call the multi-attention U-net (MAU-net). As seen in [24], the EL image-generating method blends GAN features with conventional image processing technology, and it can generate a sizable number of high-resolution EL picture samples. Then, a model based on a convolution neural network (CNN) for automatically classifying flaws in an EL image is explained.

CNN has also been used in various research, especially for classification purposes. According to [25], it is used to automatically detect saw-mark defects in multi-crystalline solar wafers. A saw-mark defect is a serious fault in solar cell wafers that contains cutting tension that could lead to cracks in a thin silicon wafer. It also lowers the efficiency of power transmission, and as a result, early detection of saw-mark faults in sliced solar wafers is critical in solar wafer manufacturing.

Furthermore, reviewing the numerous leather flaws, their impact on leather quality, and advancements in visual inspection-based leather quality evaluation are other findings. It examines the most modern image analysis-based techniques for automatically identifying leather defects and weighs their advantages and disadvantages. This offers comprehensive advice for designing and implementing a machine vision-based leather flaw detection system. On top of that, these recommendations were motivated by the success of recent deep learning-based systems for autonomous visual inspection in similar applications [26].

Next, according to [27], it presents a resource-constrained convolutional neural network (CNN) implementation in OpenMV Cam H7 Plus as an image detector that performs real-time plant disease classification. The images were trained on two distinct datasets for plant disease detection: the ESCA and Plant Village-augmented datasets. It was built with a Python-programmable machine vision camera for actual-time image acquisition and classification. It features an LCD to show the user the real-time classification response.

As shown by Zhang *et al*. [28], hybrid convolutional neural networks (CNNs) are recommended to monitor the powder-bed fusion (PBF) process. Based on the strengths of the CNN architecture, the suggested approach can automatically learn the spatial and temporal representative features from the raw images. The outcomes show that the recommended technique performs better than conventional methods with handcrafted features.

Within deep learning, data augmentation is an important role that aims to improve model performance and generalization by generating enriched copies of the training data. Several modifications, such as flipping, rotation, zooming, and color alterations, are used to increase the adequate size of the dataset and create diversity. This procedure increases the model's robustness to real-world fluctuations while decreasing the risk of overfitting. While often utilized in computer vision applications, this technique can also be used for other data sources, such as audio and text [29].

As time passed and technology grew, deep learning was implemented in machine vision applications, which provided more benefits, especially in the industrial sector. Computer vision, often known as machine vision, has advanced significantly over the past five years, opening up a wide range of applications. Machine vision is widely utilized in industrial automation and quality control, where automated inspection and product assurance are two examples of such applications. Deep learning techniques have been applied in industrial inspection, stressing their efficiency in defect detection and improving production processes [30].

In [31], it seeks to offer a generalized technique for automatic material identification utilizing machine learning and vision technologies to improve the cognitive capabilities of industrial robots and machine tools. 4.0. It is created and processed to separate the red, green, and blue color components of the RGB color model from a dataset of the surfaces of four materials (aluminum, copper, medium-density fiberboard, and mild steel) that need to be identified and categorized. The machine learning method is trained using these color components as characteristics. In addition to using a Support Vector Machine as a classifier, the generated data set also uses other classification methods like Decision Trees, Random Forests, Logistic Regression, and k-nearest Neighbor.

Imaging machines can examine, recognize, and interpret images that resemble people with the help of a technique called machine vision [32]. Machine vision application to industrial processes is frequently driven by a desire to save costs by boosting productivity and efficiency, reducing errors to improve quality, or collecting data. Additionally, and maybe more importantly, technology might compensate for a lack of trained personnel or free people from hazardous, taxing, or exhausting industrial tasks [33].

Two types of machine vision applications exist within a Learning Factory in Brazil: a solution for quality control and a station for sorting [34]. The outcomes encompass heightened awareness of machine vision among students and industry members and the development of a solution that can extend beyond the Learning Factory into industrial applications.

Medical image analysis has also been used extensively in machine vision, which helps with disease detection and diagnosis. Analyzing MRI scans showed the promise of machine vision in medicine [35] by demonstrating how combining deep learning models with other measures can improve the diagnosis of moderate cognitive impairment. Real-time monitoring and detection of suspicious actions also play a vital part in security and surveillance systems. Their study on using deep learning approaches for moving object detection and tracking emphasized the significance of machine vision in surveillance applications [36].

Finally, machine vision has also been widely applied in agriculture for disease diagnosis, yield assessment, and crop monitoring. To highlight its function in precision agriculture, it concentrated on deep learning-based crop identification from remote sensing photos [37]. These examples highlight the extensive use of machine vision across many industries, made possible by ongoing developments in deep learning and computer vision research.

Even so, CNN methods are used to classify PV panel defects; this paper will use the deep learning algorithm, CNN, in MIL software that consists of various classifier contexts. Plus, the model that has been generated will be utilized in machine vision applications in the future as machine vision is one of the primary technologies used in intelligent manufacturing and has effectively replaced artificial visual inspection [38].

II. Materials and Method

A. Pre-trained Dataset for Machine Vision Application

Figure 1 explains the whole process of classifying PV panel images. These activities involving various mediums and sources are also advisable and consulted by experts. It goes through until data training takes place in the MIL workspace. It focuses on using deep learning algorithms that build up together inside MIL. It is essential to have pre-trained model data before applying it to the prediction dataset. Pre-trained models provide an efficient solution in the field of deep learning, where the extraction of essential insights from images is crucial. Activity 1 makes a great start in the preliminary studies in this paper. Many research and findings are found in various techniques and methods to achieve their objectives. Despite that, this paper is coming up with another finding. Based on that, the next activity was conducted.

Based on the preliminary study, a few characteristics were counted to define the images to be put respectively in the categories for training purposes. Dataset images of PV Panels are collected thoroughly in defect and non-defect categories. In Activity 2, the data acquisition involving data collection and cleaning are involved in this work. The image is collected from online sources to get the suitable part of the PV panel to meet the defect detection accuracy and maximize the compatibility with MIL software. Data cleaning took part by choosing an image of the PV panel's defect, which likely looks like a crack and scratch effect.

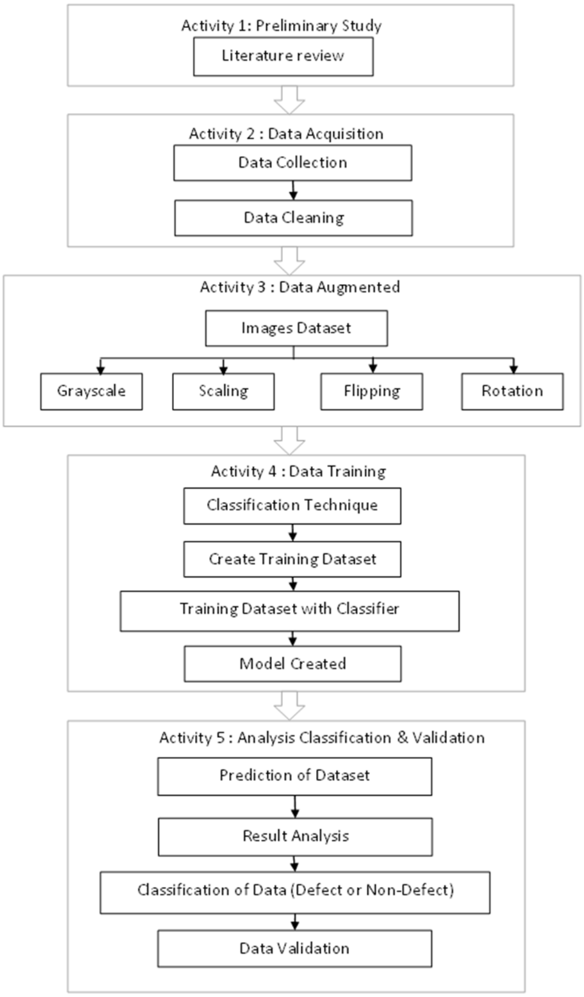

Fig. 1 Steps On Classifying Defect and Non-Defect PV Panels

Moving to Activity 3, every image undergoes an augmentation process consisting of converting it into a grayscale image, scaling, flipping, and rotating it to ensure it is fit to be trained in the MIL environment. To get the best result, all the dataset images are taken from various angles to show possibilities in real situations, which implements rotating and flipping the images. All the images' datasets have also been prepared in grayscale color and have the same size and image type file. The dimensions set are 190x150 and in JPEG format. These specifications are essential for succession in a created model and for the accuracy of prediction results in classifying the PV panels.

Figure 2 and Figure 3 show the example for both classes of PV panels. The non-defect PV panel images are constant to strengthen the photos in good condition. In comparison, defect PV panel images are messing up with scratching and cracking effects. Moving to the next step in Activity 4, MIL uses deep learning as the classification technique. It involves a few layers of neural networks connected by neurons to help learn the features of the images. By that, MIL had prepared the corresponding environment, yet it is still revisable to meet any project requirement.

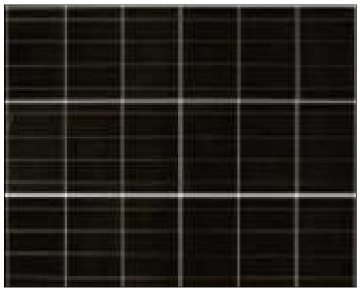

Fig. 2 Image dataset for non-defect PV panel

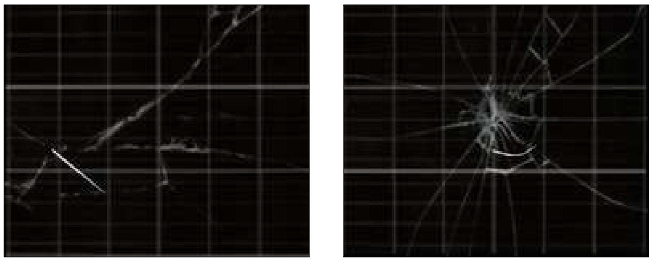

Fig. 3 Training dataset image for defect PV panels

The training dataset is split into the development and training datasets. The Training Dataset is used to train the classifier context, while the Development Dataset, also known as the Dev Dataset, is used to verify the classifier context during the training. In this paper, 700 images are used in the training dataset for both categories. Then, MIL automatically divides it into two datasets by referring to the conditions that have been assigned.

TABLE I
ICNET CLASSIFIER CONTEXT

Type	Classifier Context
ICNET	Small
	Medium
	XL
	Mono XL
	Color XL

Table 1 represents in MIL there are many classifiers to train the image dataset and created a model for classification. The classifier is using CNN, that is well known in giving a satisfactory in recognizing design in the input image, such as lines, gradient and circle. Only two classifiers had been chosen to find the best fit to classify defect and non-defect PV panels, ICNET Small and ICNET Medium. Both are designed specifically in MIL for deep learning process together with image dataset specifications especially on pixels range.

Referring to Activity 3, the pixels stated are in the range that is suitable with ICNET Small and ICNET Medium, which need minimum receptive pixels of 43 and 83 pixels, respectively. Besides, the compatibility is for grayscale images, which made it a strong reason to compare these two classifiers. ICNET XL had a higher minimum receptive pixel, which may concern the time constraint in the training dataset. ICNET Mono and ICNET Color XL were made for color images with the purpose of transfer learning.

Both classifiers, ICNET Small and ICNET Medium, used the same dataset to see differences in the percentage of the average training model. In addition, it took different estimated times to finish the training depending on factors such as the number of images, the size of each image dataset, and the complexity of the image dataset.

TABLE II
PERCENTAGE FOR AVERAGE TRAINED MODEL

Classifier (ICNET)	PV Panel Class	Avg Trained Model (%)
Small	Class 1 (Defect)	99.75
	Class 0 (Non-Defect)	83.45
Medium	Class 1 (Defect)	99.31
	Class 0 (Non-Defect)	63.46

Table 2 showing the percentage for average trained model which showing the accuracy on training the image dataset to be known in their category. In the average trained model, both classifier showing the success of training in higher percentage for class 1 which are detected as defect PV panel images. Whereas, for class 0, non-defect PV panel, the classifier ICNET Small shows a higher percentage of success training compared to ICNET Medium. Based on this percentage of success training, it may affect the result on testing data while using this model.

The model is produced after the process of training image dataset with relative classifier. It will be compiled and saved in MIL library class known as *MClass*. By having this model, prediction testing can be done to see how well the model can work to classify the PV panels. Another testing image dataset will be used in this model by mixing all the images with an indicator of defect and non-defect PV panels. All these processes will be executed in Activity 5 and briefly explained in the results and discussion section

B. Matrox Imaging Library (MIL)

Machine vision technology for automated visual inspection is becoming more capable and practical through the development of artificial intelligence. This is particularly true of machine learning through deep learning, as this technology imitates how the human brain interprets visual data. Still, it does it quickly and robustly as a computerized system. By limiting production costs and raising consumer satisfaction, technology helps manufacturing companies maintain quality.

In situations where there are complicated and varied imaging settings, deep learning technology excels at applications such as identification and defect detection. The system still benefits from traditional image processing and analysis to identify regions of interest inside images to speed up the total process and make it even more robust. These evolving technologies were so welcoming to make good use of a better experience in many sectors.

Matrox Imaging Library acts as a machine vision application in this research. It is a machine vision and image analysis software development kit with an interactive MIL CoPilot environment. For training, MIL CoPilot offers dedicated workspaces for classification, one of the deep learning neural networks techniques. These workstations include a condensed user interface that only displays the tools required to complete the training assignment, such as an image label mask editor, image annotation, image editing region, and many more functions specifically designed for deep learning purposes. An additional specialized workspace is offered to batch-process photos from an input folder to an output folder. Once an operation sequence is defined, it can be translated into executable programmed code in any language that MIL X supports. The programmed code may be presented as a command-line executable or dynamic link library (DLL) and it may be bundled as a Visual Studio project, which may thus be built without leaving MIL CoPilot.

MIL provides several advantages which is why it had been highlighted in this research. It eliminates the need for starting coding from scratch, especially for deep learning algorithms, while also offering an efficient, consistent, and easily understandable user interface. Moreover, the models created using the library are compatible with commonly used programming languages such as Java, C#, C++, and Visual Basic, ensuring broader applicability. The library further simplifies coding by generating code with the appropriate functions directly from the MIL workspace, enhancing workflow efficiency and ease of use.

The workspace that contains all the work completed during a session is preserved for future use and collaboration with colleagues. This application was always sought for improvements to meet the latest technological requirements. Besides, there was great team support to assist all users in getting to know more and making full use of this application.

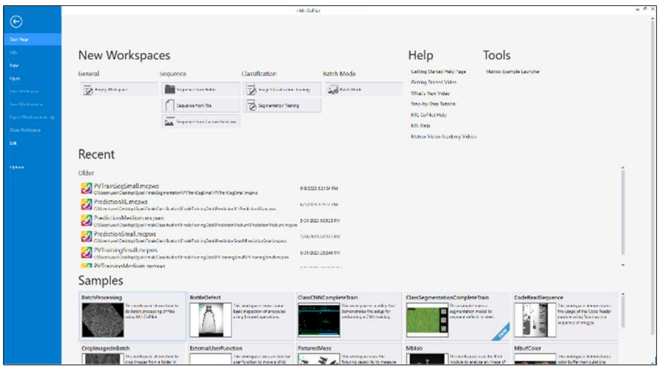

Fig. 4 Matrox Imaging Library environment

Figure 4 shows the user interface for starting up the application. Deep learning techniques were used with machine vision applications, which gained interest and became one of the best tools and technologies available today. They never make humans less but add more help to daily tasks.

III. Results and Discussion

This section assesses the model's effectiveness developed from the training dataset using several classifier contexts. The training dataset for this study consists of PV panel images that reflect the defect and non-defect categories. The numerical results demonstrate the suggested model's precision and the PV panels' classification result. A few images of PV panels consisting of both defect and non-defect PV panels were set in one dataset to see how the model would help classify the PV panel images. The testing image dataset will be tested in another workspace, and some steps will be assigned until the result is achieved. Predictions on the class of PV panels are expected to be accurate based on the trained model.

There are some class libraries available in the MIL workspace. When importing the test dataset image into the new workspace, the class library for prediction, MClassPredict, must be recalled together with another predefined class. This is one of the necessary steps to differentiate the workspace into a prediction environment, and every class has an important function to ensure the trained model progresses well.

The model created will be restored in the current workspace to run the prediction test together with the new testing image dataset. In conjunction with that, some of the class libraries have also been set up to be prepared before the testing by referring to guidance from MIL experts and the suitability of achieving the objective of this research. Everything must be set up in sequence. Then, the prediction test is good to go.

The model is created in another workspace; it must be saved as a MIL-type file to be implemented in the MIL workspace. The prediction dataset is tested using the training model developed to ensure the PV panel images can be classified accurately into defect and non-defect PV panels. The testing image dataset thoroughly reviews the training model and predicts that it will be placed in its class. This result focuses on the value of accuracy in prediction testing when comparing training models from different classifiers. The result of the testing image dataset will be explained in the next paragraph.

TABLE III
Result of an Average Test Model

Classifier (ICNET)	PV Panel Class	Avg Trained Model (%)	Avg Test Model (%)
Small	Class 1 (Defect)	99.75	99.75
	Class 0 (Non-Defect)	83.45	83.46
Medium	Class 1 (Defect)	99.31	99.20
	Class 0 (Non-Defect)	63.46	63.47

Table 3 shows the result of an average test model for 100 images of testing dataset. Classifier ICNET Small for defect PV panel has same percentage for trained and test model while non-defect PV panel have a very slight difference value. Compared with ICNET Medium, both shown differences between the trained and test model. Figure 5 shows chart for the result after testing image dataset is running through the model created. The most critical part in this work is to classify the defect or non-defect PV panel.

Thus, classifier ICNET Small has shown higher accuracy based on the trained model and the testing model from 100 images testing dataset in classifying the PV panels into Class 1 (Defect) and Class 0 (non-defect). This strengthens the result on the reliability of the trained model in classifying the PV panels into their respective class. Varying characteristics and factors of the classifier itself, as well as the type of images that have been used in this research, may influence the results. Thus, future work can be done in many other ways.

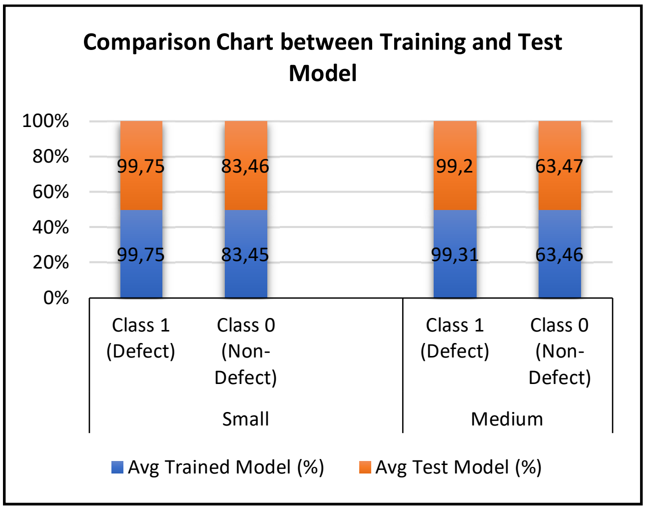

Fig. 5 Comparison Chart Model

IV. Conclusion

In this paper, an algorithm from machine vision application for classifying PV panel image with respective image dataset was proposed. First, it was determined that the images dataset was suitable for use in the MIL environment by performing a prescribed data acquisition and specific data augmentation. Then, a trained model was created using a classification strategy that utilized a deep learning classifier that was built into MIL. Using the ICNET Small classifier's training model, a higher degree of accuracy is attained when identifying photos of PV panels without defects. Multiple perspectives are used to evaluate the model's performances, mentioning the type of classifiers and the total of dataset images help in demonstrating the model's effectiveness.

Future work will consider a range of research routes, many of which will require more study and development work. First, MIL specializes in image classification with five types of ICNET classifiers, while this current research compares just two. Another classifier test can be done concerning the minimum requirement of pixels, coloring images, number of datasets, and type of learning, complete or transfer. Then, the image dataset can be tested to predict the classification of PV panel images.

All the models created can be used on another platform or machine that is compatible with it. Also, the model can be trained again to improve its classification performance based on the learning and training dataset. These advantages are wisely helpful in concerning the quality of PV panels, which are best before deploying them for their primary purpose as a renewable source.

ACKNOWLEDGMENT

We thank the Computer Science Department of the Faculty of Science and Technology, National Defense University of Malaysia, for allowing me to use the Artificial Intelligence and Robotic (AIR) Laboratory and Control Easy Technology Sdn Bhd for assisting me in running the Matrox Imaging Library software.

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