Hybrid Algorithm Based on Machine Learning and Deep Learning to Identify Ceramic Insulators and Detect Physical Damages

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***Abstract*—This work proposes a hybrid algorithm that is based on machine and deep learning algorithms. The paper studied and implemented an Aggregate Channel Feature and Semantic Segmentation to identify the existence of a ceramic insulator in an image, then pass a cropped image to a deep learning classifier to diagnose the insulators' health status. The Artificial Intelligence networks were developed via a reliable database that consisted of thousands of images. The work concludes with a comparison and evaluation of the performance between the developed object detection techniques.**

Keywords—transfer learning, object detection, classification, ceramic insulator

I. Introduction

Overhead power lines are widely used at both the transmission and distribution level. These lines are basically composed of conductors, insulators, towers, and accessories. The roles of the insulators are primarily to provide electrical insulation between the tower and the conductors as well as to provide mechanical support to the structures. There are two types of insulators: ceramic and polymer insulators. While polymer insulators are relatively new in the power system grid, ceramic insulators have been used in the past 100 years.

From an asset management point of view, detecting defects in outdoor insulators in a smart, safe and cost-effective scheme is becoming a crucial requirement. Currently, there is a special interest in the detection of defects in ceramic insulators. This is due to the fact that there are 150 million ceramic insulators within the grid in North America, while 60% of these are about to exceed their expected life expectancy [1-2]. Duration of service is not the only factor that impacts the health conditions of insulators. Environmental conditions, gunshots, mechanical, electrical and thermal stresses all play a vital role in the insulator's overall health condition [3]. As a result, these factors will result in defects in the insulator which eventually cause electrical failure. The impact of this electric failure can vary from momentary interruption, to up to days of downtime in the power system operation. Complete and/or routine changeover of the ceramic insulators is not cost effective due to their high numbers, consequently, a smart, reliable, robust, fast and cost-effective monitoring of the insulators must be developed.

The current technology examines the physical structure by visual inspection that can be completed by human inspection or by camera capture. The traditional practice of insulator inspection is performed by foot patrol inspection sometimes involving cranes or manned aerial vehicles such as a helicopter. In both approaches, the human involvement is a necessity which may create fatal hazards. In addition, the associated costs to perform the inspection are high. Additionally, the completion rate and time requirements are not efficient [3-8].

Using Unmanned Aerial Vehicles (UAV) such as drones provides an optimum solution to overcome the cons of the current practices because they are cost effective, minimize human fatalities and are relatively fast. Further, it is possible to provide reliable data and measurements when equipped with proper cameras [4-7]. Processing the captured images through Artificial Intelligence (AI) techniques optimizes the inspections means in terms of cost and the time requirements.

II. Utilized Artificial Intelligence Techniques

A. *Machine Learning: Object Detection:*

Machine learning is a category of Artificial Intelligence algorithms that use a set of input data to make an adaptive decisions without referring to a priori known models of the system. Typically, machine learning can be trained using one of two techniques: supervised and unsupervised learning. The choice of selection for best the learning technique is dependent on the application where the developed classifier is intendent to be used. In the case of object detection and recognition, supervised learning is the most popular approach.

Under the supervised learning strategy, Aggregate Channel Feature (ACF) is a well-established algorithm; it is fully adopted by MATLAB and it is available as a toolbox to be applied on different training data sets. ACF is based on computing several channels of an input image. After that the channels are aggregated by summing all the pixels in each block in the computed channels. The resulted channels of low resolution images are then smoothed for the next step. The features are extracted from the channels per pixel and the extracted features are vectorized. Finally, the training is launched using a boosting technique where a tree decision approach is used. The target in the training process is to detect the object from the rest of the background by distinguishing the related pixels in the aggregated channels [9].

B. *Deep Learning: Object Detection:*

An alternative approach to ACF is to use Semantic Segmentation to train a neural network to classify every pixel based on a range of object types. Typically, the networks are made up of several convolutional layers that extract various features about the image, which are then used to make pixel-wise predictions about the content of each pixel. These networks are trained by using images where each pixel has

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been manually classified by object type and then the network is trained using supervised learning to predict the content of a pixel. It is quite common to retrain existing networks with transfer learning. Many pre-trained networks exist and can easily be retrained using a library such as TensorFlow in Python [10].

C. *Deep learning and Transfer Learning: Classification Task*

Unlike machine learning, deep learning has the ability to extract features from input data without user intervention. Deep learning can be achieved through transfer learning where initially, a pretrained network is used and then adjusted to classify objects as a new task. Using transfer learning is time efficient because it requires a smaller number of images in the training set compared to training a network completely from scratch. Further, reducing the amount of the required data in the training set will not need a high computational power computer unlike training a network from scratch. In MATLAB, there are several options for pretrained networks. AlexNet is one of the most popular networks as it has 8 deep layers and it was trained to classify 1000 different objects. This provides an optimal option because it balances the performance as well as the training duration requirements.

Transfer learning is implemented in MATLAB by loading a pre-trained network (this work used AlexNet). After that the number of nodes in the final classification layers, is adjusted to be equal to the number of classes that the classifier is intended to categorize the input images into. In the next step, the database that is used to complete the training and testing is loaded as “imagedatastore”. The images are assigned into three sets: training, validating, and testing. The validating set is optional yet recommended because it helps to enhance the system performance and increase the classification accuracy. The dimensions of the images are then preprocessed to make them suitable for training as per the requirement of the network. For instance, AlexNet requires the size of the image to be 227 by 227 pixels. Finally, the solver is assigned, and the training properties are set. MATLAB offers different type of solvers and allows the user to select different training properties such as: initial learning rate, batch size, number of epochs, and the execution environment.

III. METHODOLOGY

This paper proposes a hybrid algorithm that detects and diagnoses the physical damages in ceramic insulators through AI techniques for unprocessed images captured by a drone. The algorithm can be divided into two main stages: insulator identification and health diagnoses. Fig 1 demonstrates a block diagram for the developed algorithm processes.

In the first stage, insulator identification, two AI techniques are compared for identification of the existence of a ceramic insulator in the captured image. The first is a detector that is trained by Aggregated Channel Feature (ACF) to identify if the image has a ceramic insulator or not. If the image has a ceramic insulator, the developed ACF detector will identify it by tracing a box around it. Then the algorithm will crop the image to include only the ceramic insulator. Alternatively, a Semantic Segmentation network which has been trained to identify insulators in the image by assigning each pixel a confidence that it contains an insulator. This can then be used to crop by selecting the smallest bounding box containing most of the high-confidence pixels. Since the neural network takes in square inputs the original image must be resized to be square for the sake of generating the boxes. This transformation is then reversed once a bounding box is identified.

In the second stage, the cropped image is examined by a classifier that is developed using deep learning via the transfer learning process. The classifier will diagnose the status of the insulator to be either healthy or broken.

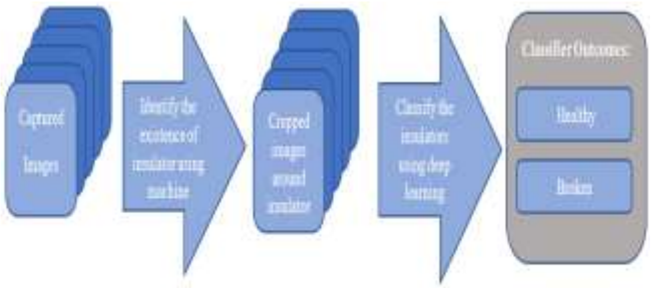


Fig 1. Block diagram of the algorithm process

IV. DATABASE CONSTRUCTION

A. *Database for Object Detection:*

In order to develop an object detector an appropriate database should be constructed. In this work, 1350 images of pictures that have a string of insulators were captured as a training database. The captured strings included two types of data sets: complete healthy insulators strings and strings with at least one broken disc. The images were captured and equally distributed under the following conditions:

1. One meter away from the insulator string and in indoor condition with grey background
2. One meter away from the insulator string and in indoor condition with white background
3. One meter away from the insulator string and in indoor condition with mixed items in the background
4. One meter away from the insulator string and in outdoor condition
5. Four meters away from the insulator string and in indoor condition with grey background
6. Four meters away from the insulator string and in indoor condition with white background
7. Four meters away from the insulator string and in indoor condition with mixed items in the background
8. Four meters away from the insulator string and in outdoor condition

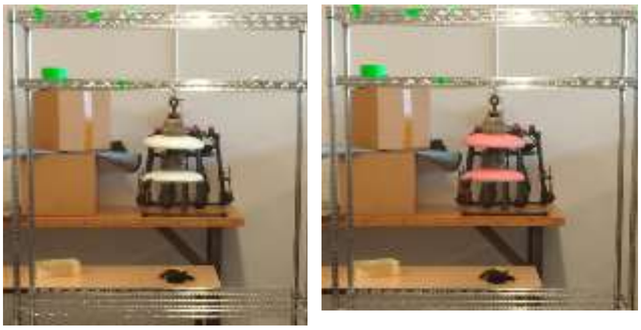
Furthermore, the strings mostly included three insulator discs of either the same or different colors. The colors of the captured insulators are white, grey, and brown. Fig 2 shows a sample of healthy and broken strings that were used in the training process.

(a) (b)

Fig 2. Sample images in the database that include healthy and broken insulator strings taken at a distance of 1 meter: (a) broken (b) healthy

The final step in building the ACF training database is defining the region of interest (ROI) in the training set. This step is completed manually where a region described by a rectangle box is drawn around the insulator in the training images. At the end of last step, a ground truth table is generated which is used directly in the training process.

For the Semantic Segmentation, 225 of the above images were selected and the regions of the image that contain an insulator were manually highlighted. This associates every pixel in the original image with a binary value specifying if it contains an insulator. Figure 3 demonstrates a sample of a labelled insulator.



(a) (b)

Fig 3: An image from the segmentation network's dataset labelled using Labelbox software: (a) Un-labelled (b) Manually highlighted insulator

B. *Database for Insulator Status Classification:*

In order to develop a deep learning network through transfer learning, a database with sufficient training samples shall be constructed. In this paper, 1411 images were captured to construct the database and it was divided into two classes: Healthy Class which is composed of 634 images, and Broken Class that included 777 images. The images were captured under the following conditions:

1. To have the string of three discs
2. To have the string with complete same and/ or mixed color discs
3. The camera lens is perpendicular to the side surface of the string
4. The background is clear and/ or with distractions in the background
5. Images are taken 1 meter away from the string without modifying lens or filters

After capturing the images under the aforementioned conditions, additional images are added to the database by rotating the original images by 90, 180, and 270 degrees.

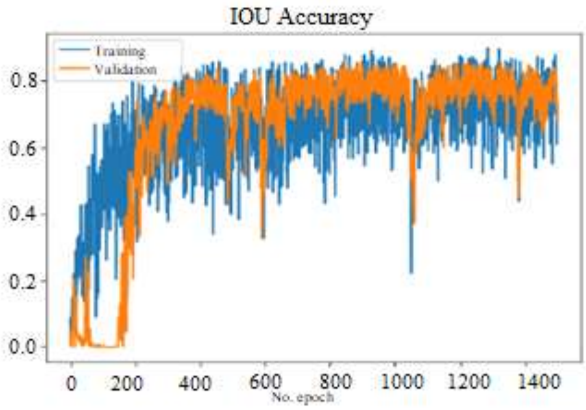
In order to complete the training process, the database is divided into two sets: training and testing sets. The training and testing sets are assigned as 80% and 20% respectively of the original database on random basis.

V. TRAINING SIMULATIONS AND RESULTS

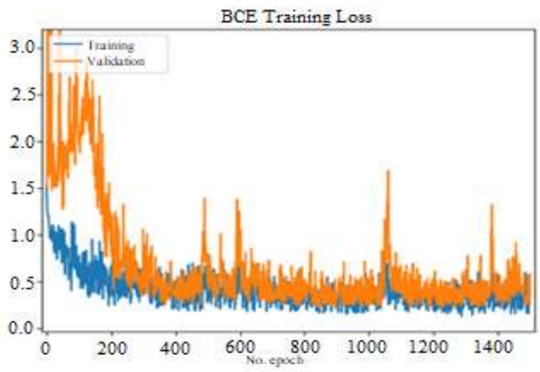
A. *Object Detection:*

The ACF training was completed in MATLAB using the assigned database for object detection. The training was completed in 200 stages where around 96% of the database was assigned as a training set. The performance was assessed through a testing set of 50 images and it achieved an accuracy rate around 90%. The undetected cases resulted primarily from cases where the lens was out of the focus completely.

The Segmentation training was completed several times in TensorFlow using the assigned database of 225 images with 10% of images randomly selected each time for validation showing consistent results across multiple random seeds. In the training process, the Intersection Over Union accuracy of the network predictions as well as the BCE Loss for both the training and validation sets were measured and recorded as depicted in Figure 4. In addition to the quantitative metrics, a qualitative output sample is used as shown in Figure 5. Such qualitative samples show the segmentation output as well as the resulting automatically cropped image.

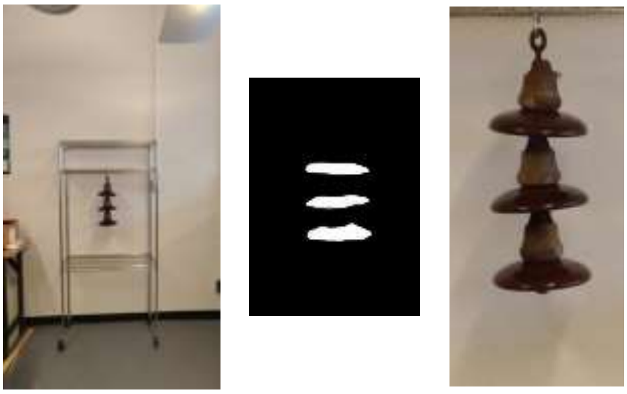


(a)



(b)

Fig 4: The training results for the Segmentation Training



(a) (b) (c)

Fig 5: An input image (a) was put through the segmentation network which generated (b) which was then used to crop and result in (c)

B. Deep Learning Training:

The transfer learning was completed using AlexNet in MATLAB. A dedicated database, as explained earlier, was used in the training process to develop a classifier that diagnoses the status of the insulator as either healthy or broken. The training set was assigned to be 80% from the constructed database while the testing set was assigned as the remaining 20% of the database.

The training required 10,900 iterations in 100 epochs. The solver that was used to train the network was a Stochastic Gradient Descent with Momentum (SGDM) with an initial learning rate of 0.0001 which was dropped by a factor of 0.1 every 50 epochs. The training batch sizes were 16. In order to avoid any biasing in the training, the images were shuffled before the training. After assigning the previous properties, the network training was completed.

After the training completion, the network was examined, and an accuracy of 97.52% was found over the training set. The confusion matrix of the trained network is depicted in Figure 6. Analysis of the results shows that only 0.645% and 4.72% of the testing set were misclassified as healthy or broken respectively.

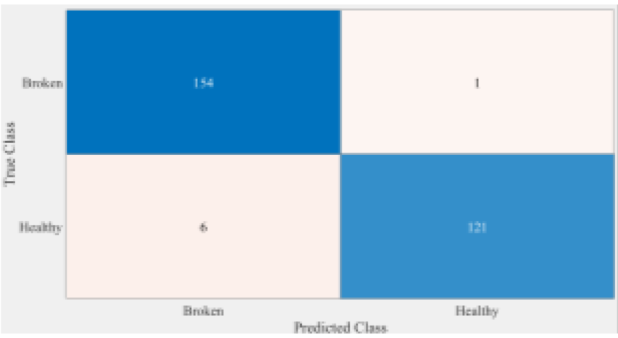


Fig 6. Confusion matrix of the trained network through transfer learning

CONCLUSION

This work proposes and validates the utilization of ACF as well as Semantic Segmentation to identify the existence and location of an insulator in an image. Furthermore, the work develops a classifier that is based on deep learning to diagnose the health status of the detected insulator. Within the scope of this paper, the prime benefits and drawbacks of each object detection approach has been explored. With the ACF method, the dataset which needs to be used is simpler to prepare, and it directly yields the information that a user is interested in. With semantic segmentation on the other hand, the data must be painstakingly prepared, however, the method yields more precise information about every pixel as opposed to just yielding a region of interest layout. In this work, the pixel information is used to crop a box surrounding the insulators. This information can also be used in other paradigms such as individually cropping specific insulators out of the string, which is not possible with ACF, thus this method has the added benefit of being more general, as it allows for a flexible number of insulators in the string since it will simply highlight all of the insulators in the image.

After detecting an insulator in a picture, a deep learning developed classifier is used to diagnose the health status of the detected insulator. Using the deep learning classifier resulted in a superior classification rate that reached a 97.52% success rate. In addition to the high classification rate on the testing set (unseen data), deep learning provides an easier, more efficient and more reliable means to develop a classifier with respect to classical machine learning techniques.

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