FINAL REPORT

Transmission line segmentation using Deep Learning

By:
Anishkumar SS - 2017A7PS0069P

Study Oriented Project,
Under the mentorship of

Dr. J Jennifer Ranjani
Dr. Sanjay Singh Yadav

TABLE OF CONTENT

ACKNOWLEDGEMENT

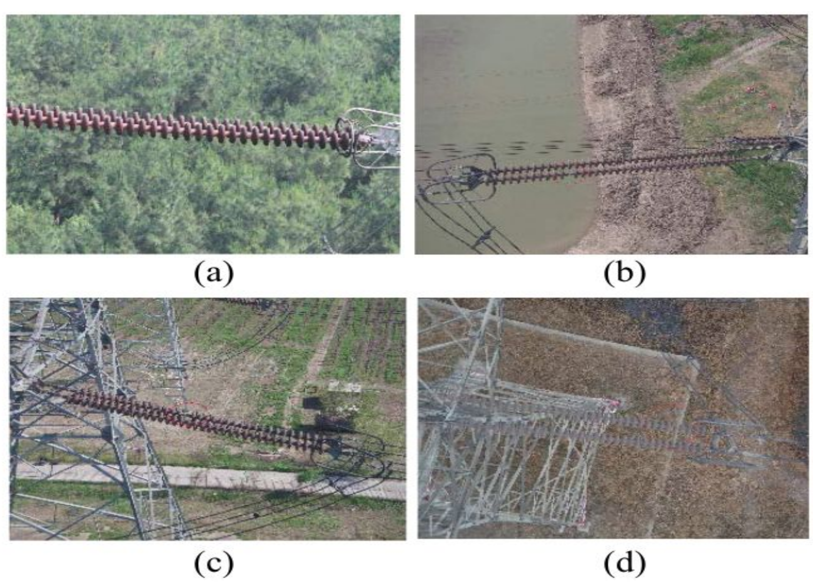
I would like to extend my gratitude to the Department of Computer Science, BITS PILANI, for giving me this opportunity to pursue this project. I wish to express my sincere regards to Dr.Jennifer Ranjani of the Computer Science Department, BITS PILANI and Dr.Sanjay Singh of CEERI, Pilani, for providing me the opportunity to work on this project and assisting me in the same for the duration of the semester.

ABSTRACT

Insulators are essential equipment used to electrically isolate and mechanically secure wires in high voltage power transmission systems. Insulator failure is a direct threat to the stability and safety of power transmission lines. Owing to this reason an insulator inspection based on an aerial platform with the aid of Unmanned Aerial Vehicles (UAV) is being employed. The images captured by such aerial vehicles are processed using Deep learning techniques to detect issues. Shallow learning techniques, can only localize insulators and detect faults under specific detection conditions, such as when sufficient prior knowledge is available, with low background interference, at certain object scales, or under specific illumination conditions. In this project we try to develop a deep learning model that could detect and draw bounding boxes around the insulator in the given image. We attempt at using different CNN networks to provide a study of comparative results.

INTRODUCTION

Insulator failure is a direct threat to the stability and safety of power transmission lines. Statistically, accidents caused by insulator defects account for the highest proportion of power system failures. Therefore, intelligent and timely detection of insulator defects is particularly important. Helicopters and UAVs are extensively used to collect images for study and analysis. Images captured by aerial inspection platforms often include cluttered backgrounds resulting from the presence of towers, mountains, rivers, grasslands, and farmland. This causes complication as most of the existing proposed model will not be able to produce a satisfactory result for the images of study. Usually defect detection of transmission line encompass defect detections in insulators, pylons and transmission lines. We shall be focussing more towards defect detection in insulators. The method implemented usually locates the object of interest (insulator), and then proceeds to extract its feature and with a classifier to determine its status. The image below gives an idea of the diversity of possible backgrounds.



(a) (b) (c) (d)

LITERATURE SURVEY:

In order to find a relevant approach to the problem at hand, a number of papers were referred. Despite segmentation in aerial images captured by Unmanned Aerial Vehicles(UAV) being a very popular field in computer vision, most of the method proposed are restrictive since one must have prior knowledge of the insulator shape, and it can only function under certain scenarios, e.g., with untextured backgrounds or with a camera facing the sky. The methods which could handle a complex aerial background were mostly related to pure image processing, which could not be employed for the purpose of error detection and classification. The method as suggested by Li *et al* [1] used Otsu thresholding algorithm, which only functions effectively for high contrast images which was not the case in the given problem statement. Liao and An[2] proposed an insulator detection method based on local feature and spatial orders in aerial images, this technique would not lead to the required result as the fraction of insulator in the image is too small. The final paper, which was found most relevant was "*Detection of Power Line Insulator Defects Using Aerial Images Analyzed With Convolutional Neural Networks*" by Xian Tao, De Xu. The paper of interest also additionally specifies methods of employing semantic segmentation using U-Net architecture in data augmentation to compensate for the scarcity in test images.

OBJECTIVE:

The complete scope of the project is to develop a learning model which could analyze image captured by Aerial vehicles and detect the presence of a defect in the subject image. However I have worked on designing the initial localization network (ILN) that detects the presence of an insulator in the given aerial image and draws a bounding box around it. This initially processed image is further put through a cropping module and fed into the consecutive defect detection network (DDN) which works on the more specific cropped image.

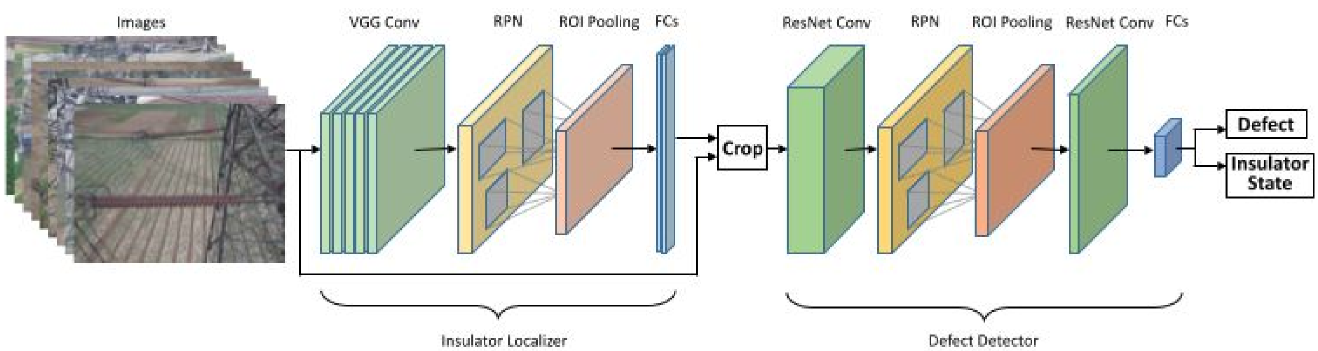
The proposed method should work despite the constraints of limited dataset, complex and largely distinct backgrounds. The image below highlights what we are trying to accomplish.

The first image shows a red bounding box around the defective insulator and also another smaller box around the area of defect. The image on the right has been declared as detected as defect free.

PROPOSED METHOD

(i) Architecture:

The proposed model transforms problem to a two-level detection problem, directly uses object detection to locate insulator position, and then uses the object detection method again to locate the defect position on the insulator. This makes full use of the strong representation and regression performance of CNN.



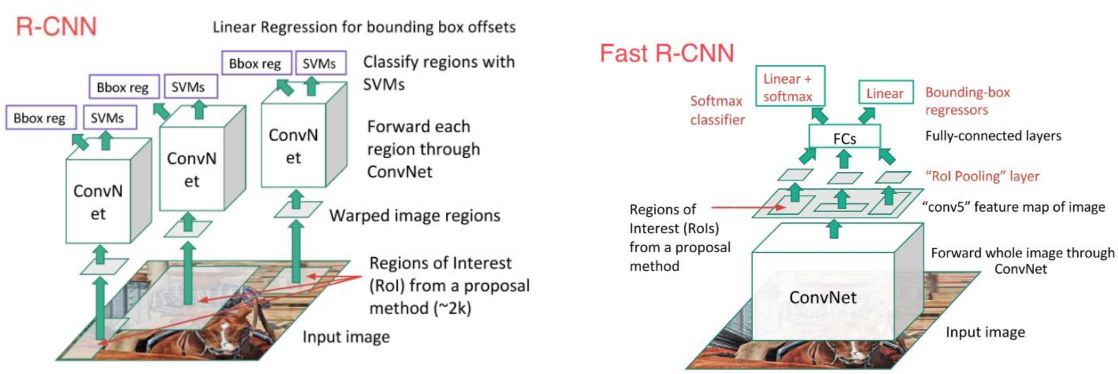
Overall Expected architecture proposed in the base paper

The proposed cascading model includes two networks. The first network ILN detects all the insulators in the images. Insulators in the form of rectangular boxes are cropped from the original image, while other parts are discarded. The second network DDN detects all the missing caps from the cropped images.

I worked towards creating and optimising the initial ILN using a modified Faster RCNN deep learning architecture with reference to the paper [3] Ren *et al*. The general working of the architecture will be explained below.

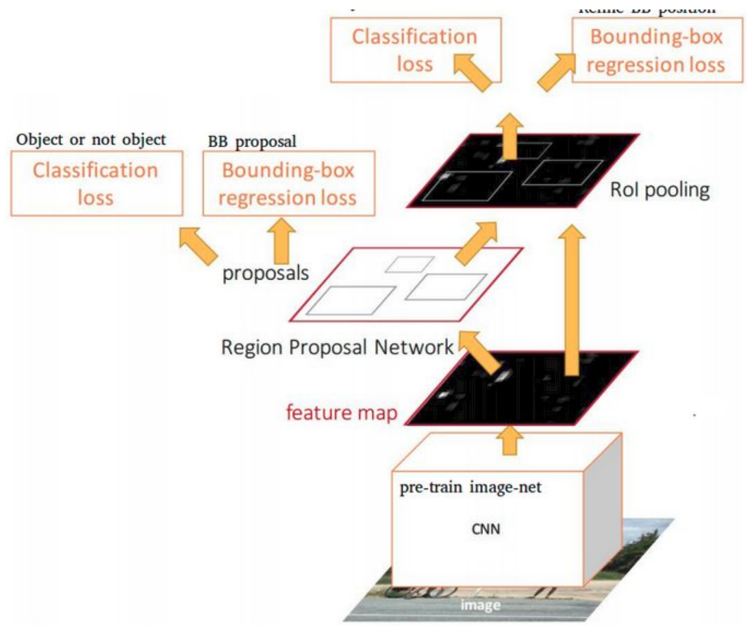
Faster RCNN

R-CNN is the first step for Faster R-CNN. It uses search selective to find out the regions of interests and passes them to a ConvNet. It tries to find out the areas that might be an object by combining similar pixels and textures into several rectangular boxes. The R-CNN paper uses 2,000 proposed areas (from search selective. Then, these 2,000 areas are passed to a pre-trained CNN model. Finally, the outputs (feature maps) are passed to a SVM for classification. The regression between predicted bounding boxes (bboxes) and ground-truth boxes are computed.



Fast R-CNN moves one step forward. Instead of applying 2,000 times CNN to proposed areas, it only passes the original image to a pre-trained CNN model once. Search selective algorithm is computed based on the output feature map of the previous step. Then, ROI pooling layer is used to ensure the standard and pre-defined output size. These valid outputs are passed to a fully connected layer as inputs.

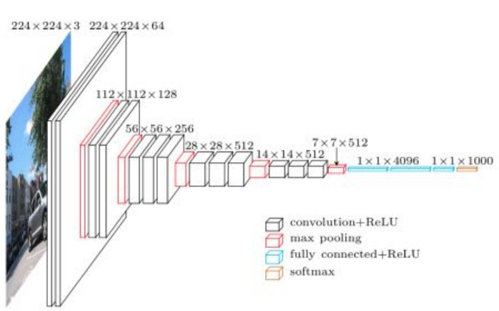
Faster R-CNN (frcnn) makes further progress than Fast R-CNN. Search selective process is replaced by Region Proposal Network (RPN). Faster R-CNN achieved much better speeds and a state-of-the-art accuracy.

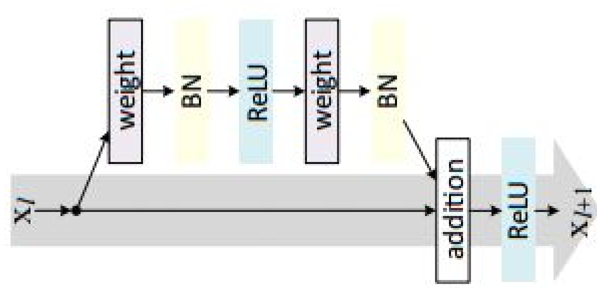


Faster RCNN

A Region Proposal Network (RPN) takes an image as input and outputs a set of rectangular object proposals, each with an objectness score. To be more precise, RPN predicts the possibility of an anchor being background or foreground, and refine the anchor.

The initial CNN layer processes the input image to generate a more simplified feature map which is further sent as input towards RPN and ROI networks. In this project, I had experimented with trying different CNN network to check the relative performance of the network. For this experiment, I had run the FRCNN network with [4]Resnet50 and [5]VGG16.



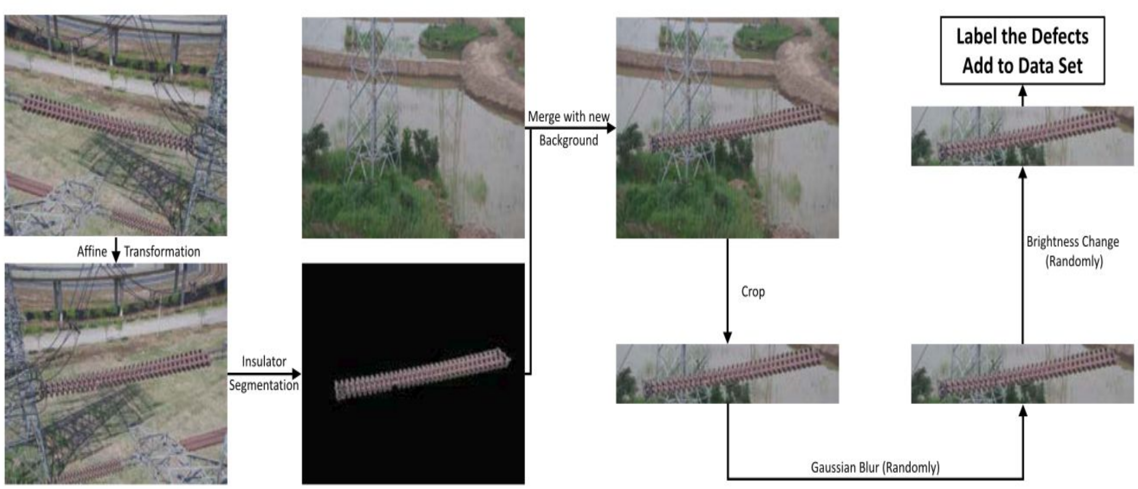


VGG16 *RESNET50*

(ii) Dataset

At present I am working with the Chinese power line insulator dataset (CPLID), which was also used in the paper. The dataset consists of images of 600 normal insulators and 250 odd defective insulators created by data augmentation.Each of the images present are labelled using an xml file, which contains the coordinates of the bounding boxes of the insulator and the defect area. Further scope to create augmented data has also been specified in the base paper. The paper proposes a method of segmenting a faulty insulator and superimposing them on images with varied background along with Gaussian blur, brightness transformation etc. The method has been illustrated in the image below, which could be utilized under the circumstance of needing more dataset.

The images were all labelled as .xml file, so a script had to be written to extract the data and provide them in a csv/text file. The code snippet for that has also been attached.



EXPERIMENTAL RESULTS

After the implementation of both the CNN networks and training them on 600 odd images for 100 epochs each. The following losses have been evaluated for the mean case situation. The net losses of Resnet50 and VGG16 are respectively 0.526 and 0.69 on average during insulator detection.

Model	**Classifier Accuracy**	**RPN classifier Loss**	**RPN regression Loss**	**Loss detector classifier**	**Loss detector regression**
Resnet50	0.925	0.13	0.103	0.194	0.099
VGG16	0.832	0.185	0.145	0.231	0.130

Table 1

The accuracy with respect to test set, is as follows:

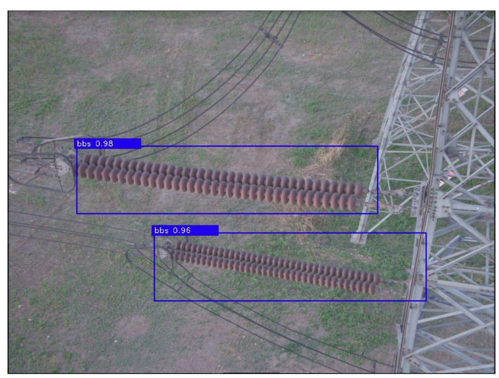
Model	**Mean predicting Accuracy**
1. Resnet50	68%
2. VGG16	57%

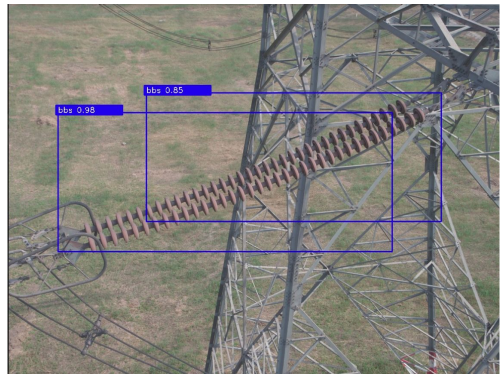
Table 2

The above accuracy measures the fraction of the given input images are being processed to give any output. The accuracy of the predicted bounding boxes with respect to the ground truth is depicted in table 1

CONCLUSION

In the duration of the semester, I have done extensive literature survey to narrow down a research papers that could cater to the specific nature of the presented problem. Worked towards acquiring and changing the dataset to the required format for processing. Post preprocessing of data and acquiring an idea of what needs to be done, I worked on implementing a faster Regional-CNN for the object detection of insulators from the given images. After frcnn implementation, I tried to incorporate transfer learning by modifying the initial CNN network of the architecture and evaluated the relative performance with respect to the CNN used. Post object detection I have also made the cropping module, which specifically extracts the cropped image and stores it as a separate image .
The below listed images are example output images acquired post image detection.

Cases	Output Image
1. Accurate Detection	
2. No detection	

3. Redundant multiple detections	

REFERENCES:

[1] B. Li, D. Wu, Y. Cong, Y. Xia, and Y. Tang, “A method of insulator detection from video sequence,”

[2] S. Liao and J. An, “A robust insulator detection algorithm based on local features and spatial orders for aerial images,”

[3] S. Ren, Kaiming He,Ross Girshick and Jian Sun, “Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks”

[4] Kaiming He, Xiangyu Zhang, Shaoqing Ren and Jian Sun, “Deep Residual Learning for Image Recognition”

[5] Karen Simonyan and Andrew Zisserman, “Very Deep convolutional networks for large-scale image recognition”