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Segmentation of fatigue cracks in ancillary steel structures using deep learning convolutional neural networks

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Abstract— **Regular structural inspections to detect cracks in ancillary structures are necessary to prevent fatigue cracks from compromising a structure's safety and durability. As the most common inspection, visual methods for ancillary structures are limited because they are time-consuming, costly, and require a great deal of experience. The inspection can benefit greatly from automation through implementation of deep learning. However, there is no comprehensive annotated dataset for deep learning to detect cracks in ancillary structures. In this work, a dataset containing 250 images were collected from previous studies and 30 images were collected of in-service ancillary structures. This dataset was annotated by labeling image tiles and bounding box for AlexNet, and Faster RCNN (FRCNN), respectively. Data augmentation, such as change in color and crack orientation, were performed to increase the size of training dataset to 1400 images. Moreover, an image of a fatigue crack was superimposed on images of intact and in-service ancillary structures to increase the dataset size to 1500 sub-images. The image labeler mode was trained in fully trained, transfer learning, and classifier modes. Additionally, bounding box annotation was used to label fatigue crack as an object in 200 images with cracks. Next, FRCNN as an object detection algorithm was used to determine the location of cracks in ancillary structures. FRCNN and AlexNet with transfer learning can be used to determine the location of cracks in ancillary structures with an accuracy rate higher than 90% and 93%.**

Keyword: fatigue crack, ancillary structure, deep learning, faster RCNN, data augmentation, structural condition assessment.

I. Introduction

Different types of tall and large steel structures such as ancillary structures, signal mast arm connections are subjected to frequent cyclic loads in service, which makes them susceptible to fatigue cracking on the structure. Therefore, inspection and monitoring structures to control fatigue crack initiation and growth play a significant role in maintaining steel structural safety [1]. In some studies[1-3], manned visual inspection is used to detect fatigue cracks in ancillary structures. Several researchers have been investigating on deep learning to detect the location, growth, and initiation of fatigue. Raw images or motion videos were used to create a dataset for fatigue crack and deep learning [3]. For motion videos, the crack is recognized based on the form of the fatigue crack formation. Fatigue cracks are propagated in the steel structure by cyclic loads. Therefore, video motion can be used to predict the patch and tip of fatigue cracks. The other method to detect fatigue crack is image based, i.e. the picture with cracks are used to detect the fatigue cracks [3]. Dong et al. used the pixel level crack segmentation approach to detect fatigue crack(s) in images of large-scale n steel structures [4]. The result showed the accuracy rate of suggested approach achieved an Intersection over Union (IOU) higher than 65% to detect fatigue cracks. They generated a big dataset for fatigue cracks of steel structures with using laboratory images [4]. Quqa et al [5], generated a novel technique to detect fatigue crack by using digital images, CNNs and image processing approaches. The dataset of this study contained images of high-resolution digital cameras from the welding joints of a long-span steel bridge [5]. Pixels representing the cracks, together with the crack's width and length, were used for training and validating the model. The result indicated that the model had a high accuracy rate, about 80% to determine the location and size of cracks [5]. Mohamed et al. used artificial intelligence and images with cracks from steel structures to detect fatigue cracks in steel structures. The authors of this study mentioned that the number of images in training and evaluation datasets was insufficient to demonstrate network performance [6]. Visual inspection is the most common approach to monitor fatigue cracks in ancillary structures [7-8]. However, the result of previous studies about steel structures and vision inspection shows crack detection is sometimes inaccurate because it is based solely on the inspector's precision [9-10]. Training a sufficient number of inspectors to detect and monitor fatigue cracks occurring at different places on the structure is time consuming and costly [9]. Applying vision inspection for ancillary structures and monitoring them in terms of the start and propagation of the crack(s) could be challenging for tall ancillary structures.

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Therefore, implementation of deep learning models for autonomous defect detection has the potential to improve the practice of manned visual inspections for ancillary structures. The previous scientific research for deep learning and fatigue crack is based on raw images as a train dataset. However, there is a limited published dataset on fatigue cracks and steel structures [6]. Moreover, there is no comprehensive annotated dataset for deep learning to detect fatigue cracks in ancillary structures as a type of the structure. Deep learning models can be used to label the images with crack or alternatively to find a region of interest containing fatigue cracks in visual images. In this study, AlexNet and Faster RCNN (FRCNN) as deep learning models have been used to detect fatigue cracks in ancillary steel structures for the first time. The annotated dataset for ancillary structures was developed based on previous studies and images were taken of in-service structures. Data augmentation and random under sampling approach have been employed to create a balanced and generalized training dataset, respectively. Finally, the dataset has been annotated based on labeling and bounding box approaches for training set of AlexNet and FRCNN, respectively.

II. METHOD

Fatigue cracks are a rare occurrence in ancillary steel structures [9-10]. To ensure the longevity of these types of structures, engineers are often required to look into their causes and carry out suitable repairs and remedial measures. Various approaches based on machine vision have been used to help inspectors identify fatigue cracks in steel structures. Among them, edge detector algorithms and deep learning are more common to detect fatigue crack, which will be discussed in this section.

A. Image processing using edge detection.

Canny, an edge detection algorithm, was used to detect cracks on ancillary structures in this study. Canny works based on the gradients of neighboring pixels to find "edge" or "edge-shaped" objects, i.e. crack, in images. Crack detection often includes gray-scale conversion and extracting morphological features of the crack in the image. Ultimately, the exact location has a difference in terms of gray or morphological features compared to the sound part (pixel without crack) [13].

B. Deep learning

Deep learning was generated based on the CNNs architecture, which was introduced by Fukushima (Fukushima 1980) for the first time, and improved by LeCun et al. (1998), which is wildly used as the most common version of CNN today [14]. The pixels from all images in both datasets (sound or crack) were transformed to a set of features to operate a series of mathematical processes for crack detection based on the deep learning approach. Several layers have been employed to generate a network based on feature selection and predict cracks in the images [15]. A complex nonlinear function was developed based on merging several layers, which can be used to predict image labeling. AlexNet and FRCNN as two deep learning networks were used to detect cracks in this study. In deep learning, convolution layers and pooling layers were used to detect edge, crack, object feature extraction, and texture in images in both algorithms [15].

C. AlexNet

Alex Krizhevsky in 2012 proposed the first version of AlexNet as a convolutional neural network (CNN), which has been widely used for object detection, including structural defect detections [16]. Three networks were employed to generate deep learning on the training dataset. The first network is to fully train the network from scratch on the training dataset. In this network, all the weights are assigned with random numbers and different ways [17]. It is possible to use previously trained models using ‘‘domain adaptation" in the deep learning literature [17-18]. One can use a previously trained DCNN on the ImageNet dataset as a classifier for new images. This type of domain adaptation is referred to as classifier (CL mode). In the CL mode, only the last fully connected layer (last layer in Fig. 2) needs to be altered to match with the target labels in the dataset. Another studied domain adoption method is to partially retrain a pre-trained network and modify the layers according to a new dataset. This approach is called fine-tuning or transfer learning (TL mode). In the TL mode, the network must be re-trained, since both classifier and weights should be generated regarding to the new dataset. The AlexNet DCNN architecture was illustrated in Table I and Fig. 1.

Table I parameters in model

Parameter	**Input Layer**	**Convolution Layer**	**Channel Normalization**
Values	1	5	5
Parameter	Max Pooling	Convolution	Fully Connected
Values (Layer)	3	4*3	3
Parameter	Dropout Layer	Mini Batch Size	Max Epochs
Values	2	10	30

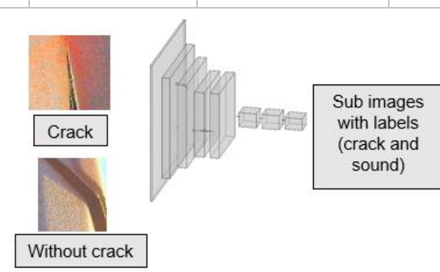

Fig. 1. AlexNet architecture.

D. Faster FRCNN

FRCNN is a deep convolutional network, was considered as a member of the family of deep learning models to detect objects in images, as opposed to labeling images what contained that object (Fig. 2). FRCNN was employed to produce a set of bounding boxes as output, where each bounding box contains an object and the category [19]. In this study, the crack in the images was in the region (box), the

FRCNN model was generated, and cracks in the images were predicted.

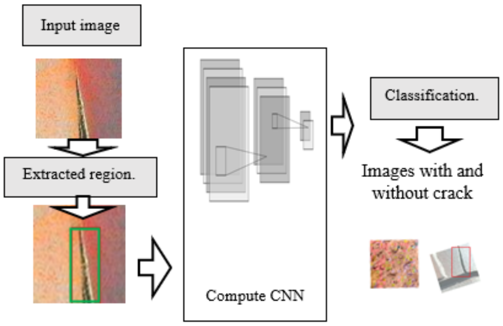

Fig. 2. Region with CNN features

E. Dataset for AlexNet

In this work, a dataset containing 250 images collected from previous [4] studies and 30 images collected of in-service ancillary structures were used. The dataset has been made of all the available images in previous research and all images taken from in field structure for making the data set. This has resulted in a complete dataset for investigating cracks in all parts of the structure. This dataset was divided into two annotated sets based on the type of detection done by the deep convolutional neural networks (DCNN). The annotated dataset of AlexNet contained 200 images with fatigue cracks and 250 sub-images without fatigue cracks, both 256 by 256 pixels. Data augmentation, such as a change in color, brightness, and crack orientation, was performed to increase the training size to 1400 sub-images. Moreover, realistic fatigue crack images were superimposed on images of intact and in-service ancillary structures to increase the dataset size to 1500 sub-images. A random under sampling approach and data augmentation was used to increase crack subsets.

III. Data Augmentation

A. Color

The ancillary structures are often painted with silver or blue anticorrosion paint in addition to the red color in this study. To create a generalized training dataset, the color of some images has been altered to silver and blue. Moreover, corrosion is a common phenomenon in the steel structures. The color of some images was changed by applying the color of the images taken from the corroded plate or galvanized steel plate to create a more generalized dataset for ancillary structure. To do this, the color of the steel surfaces was changed (color augmentation) to target color (color of silver plate or corroded plate) by applying the approach established in Reference [14]. To do this, the color of galvanized steel plates with and without corrosion were considered as a target object (Fig. 3b and Fig. 3e). The images from in-field structures were considered as an input object (Fig. 3a and Fig. 3d). By applying the method in Reference [22], the color of raw images was changed to the color of images in the target dataset (Fig. 3b and Fig. 3e) to increase the size of the train set. Fig. 5 shows the input, target images, and color transform algorithm's result (Fig. 3c and Fig. 3f).

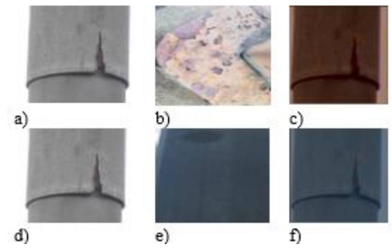

Fig.3. Data augmentation a) raw images, b) raw image with corrosion c) fused image, d) raw images, e) galvanized steel, f) fused images

B. Superimposed crack

Finding structures without cracks (sound image) was not challenging, however, taking images from structures with cracks can be challenging since this type of structure is repaired quickly to prevent structural collapse hazards. A limited number of images of ancillary structures with and without fatigue cracks was provided by the North Dakota Department of Transportation (Fig. 4a) and previous studies (Fig. 4d, and Fig. 4g) were fused on images of sound ancillary structures (Fig. 4b, Fig. 4e, Fig. 4h). We used Photoshop [14] and transfer color algorithm [15] to fuse images with and without crack using a multi-data augmentation approach. To generate realistic images of ancillary structures with fatigue cracks as seen in Fig. 4c, Fig. 4f, and Fig. 4i; The fused images were generated to increase the effectiveness of both deep learning algorithms by introducing more images to the training dataset [4] By implementation of augmentation, the size of dataset was increased to 1500 sub-images.

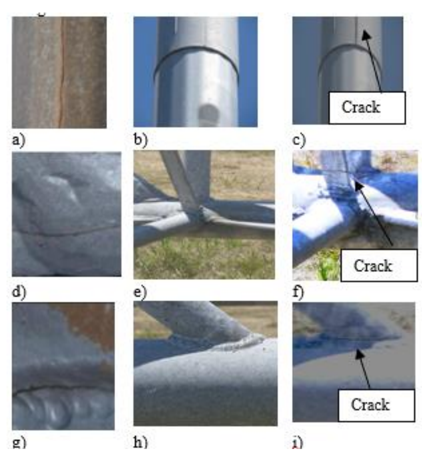

Fig.4. Data augmentation, a) the raw sub-images with a crack, b) raw sub-images without crack, c) a superimposed crack at the junction, d) extracted raw sub-image from Reference [4], e) raw sub-images without crack, f) superimposed crack, g) extracted raw sub-image from Reference [4], h) raw sub-images without, i) a superimposed crack at structure's arm.

C. Rotation

The rotation approach has been used to increase the size of crack dataset since it has shown to be as a successful data augmentation approach in previous research [8]. The approach was used to increase training size. Fig. 5a shows the raw images, in Fig. 5b and Fig. 5c, the images are rotated uniformly at 45° and 135° angles.

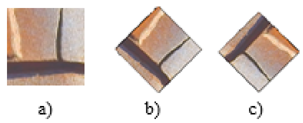

Fig. 5. Data augmentation, a) raw image, b) rotated by 45, c) rotated by 90.

D. Random under sampling

A balanced dataset is essential for developing a machine learning network that can detect defects in a test set [15]. In the training dataset, the ratio of cracked to not cracked images was 0.02 after splitting the images and creating sub images. Several studies have shown that deep learning algorithms are unable to predict accurately due to severe imbalances in classification in the training dataset [15,16]. Instead of using all images, under sampling involves randomly selecting examples from the majority class of the training dataset instead of using all images, which has been commonly used in previous studies [23-25]. The following three balanced data sets shown in Table II were created with using random under sampling strategy and data augmentation for AlexNet.

DEVELOPED CNNS

In this study, three models were developed for fatigue crack datasets by using AlexNet, AlexNet (TL), and AlexNet (CL) algorithms. For each model, trainset 1, trainset 2, and trainset 3 were used as training datasets. Therefore, nine networks were developed to classify fatigue crack in this study.

Trainset -1: A total number of 100 original images were used for making the network. The images were split into 120 sub images. After splitting the images, totally, 5700 images were produced. The images taken from the surface of the structure include the edges of the structure, too. The made network was more robust since it could detect and differentiate cracks from the edges of the structures by placing these images (images taken from structure's edges) in the dataset without cracks. For balancing the dataset, the under-sampling approach was used to decrease the size of images without cracking. To do this, form 5700 sub-images, 162 without cracks were randomly selected. Table II shows the training dataset which has been created after using the under-sampling approach.

Trainset -2: Data augmentation approach was used to increase the size of images with crack. Table II shows the number of images with and without using the data augmentation and under sampling approaches in training datasets.

Trainset -3: To make a generalized dataset, a total number of 30 images taken from real structures with superimpose approach were added to the datasets.

Table II Train dataset.

	Crack	Uncrack	Approach name
Train dataset 1	162	162	Under sampling
Train dataset 2	668	668	Augmentation
Train dataset 3	791	791	Augmentation and fusion

A. Train dataset for FRCNN

The dataset of FRCNN contained 75 images from ancillary structures and laboratory images. Therefore, data augmentation and superimposed approach was used to increase training size to 200 images. Bounding box annotation was used to label fatigue crack as an object in 200 images with cracks.

B. Test dataset for all deep learning approach

All models were tested by using 74 sub-images with cracks and 74 sub-images without cracks. The images were taken from ancillary structures in the street, laboratory images from previous studies [4], and images taken from NDDOT for all networks.

C. Evaluating a machine learning model

To compare the real and predicted classifications, a set of performance metrics were used. True positive is a sub image or pixel with crack and true negative is sub image or pixel without crack. True positives rate (TPR), false negatives rate (FNR), false positives, and true negative rate (TNR), and Intersection over Union (IoU) are used to check deep learning performance. IoU is a more meaningful performance metric for fatigue crack detection using FRCNN while the rest of the metrics are more common for labeling images with cracks using AlexNet [10].

Workstation

A desktop computer was used to create all deep learning models. It has a 64-bit operating system, 24 GB memory, Intel® CoreTM i7 CPU, and 15.8 GPU. MATLAB 2021 and python were used to create networks.

IV. RESULTS

A. Canny

Fig. 6a and Fig. 6c shows two raw images with fatigue cracks of ancillary structures. Then, Canny was used to detect fatigue cracks. Canny failed to find a crack for image one. For image two, Fig 6.c shows the edge detection approach accurately identified cracks in the ancillary structure; however, the algorithm generated residual noise in the final output especially near the edge of the structure. Moreover, the result of binary images after applying Canny algorithm shows that images taken from ancillary structures contained multiple edges with crack (Refer to Fig. 6d and Fig. 6b). Therefore, the edge detection algorithm cannot help inspectors to detect cracks from the structure's edge in the ancillary structures.

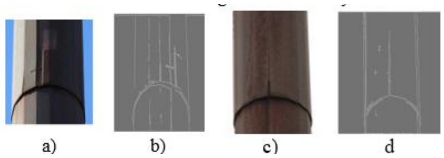

Fig.6. Edge detection algorithm output, a) Image from fatigue crack, b) edge detection algorithm output b) Raw images, b) edge detection algorithm output.

B. AlexNet

Fig. 7 depicts the loss for training and validation for AlexNet (TL). The validation criterion was reached for trainset1, trainset2, and trainset3 after 1500, 3000, and 3500 iterations, respectively. The loss values for all models were near zero based on the graphs. To avoid overfitting, the validation graph should be close to the training graph. The result of this study showed that increasing the number of images in the training dataset reduces the distance between two graphs (validation loss and training loss). For all crack datasets, the distance was also reduced by using AlexNet (TL) rather than AlexNet or AlexNet(CL) as well.

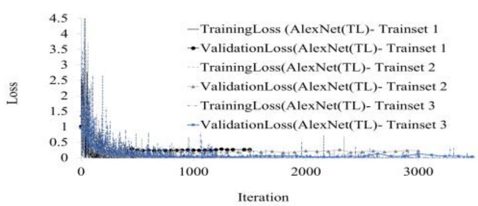

Fig.7. Training and validation loss for AlexNet (TL)

The validation accuracies for all models were also extracted after training all models. AlexNet's validation accuracy was 74.19%, 85%, and 87% for trainsets 1, 2, and 3, respectively. The validation accuracy of AlexNet (TL) for trainsets 1, 2, and 3 was 93%, 94%, and 95%, respectively. The validation accuracy of AlexNet(CL) for trainset 1, trainset 2, and trainset 3 was 92%, 95%, and 94%, respectively. For all datasets, AlexNet (TL) had the highest accuracy rate and the lowest loss values. It is expected that the accuracy rate of deep learning models to increase as the size of the training dataset is increased using data augmentation. In total, three networks were trained on three data sets where the table II presents the number of images in trainset (cracked and un-cracked), and the method applied for creating each dataset. Also, three deep learning models were utilized for crack estimation. As Table III depicts, the accuracy of all three approaches exceeded 85% by increasing the size of the dataset, which shows using data augmentation was effective to improve the model's performance. Moreover, the accuracy of AlexNet (TL) and AlexNet were higher than 87% by increasing size of training dataset. However, the AlexNet (CL) network had TNR higher than 99%, which was the best model to detect sub images without crack among all models in this study, while AlexNet produced only 81%, and 83% for train set 2 and 3, respectively. The AlexNet (TL) network had the highest TPR=90%, among all the studied approaches, which was the best algorithm to detect sub images with cracking. The most tangible increment had been seen in TPR, TNR, and ACC rate among all models because of using data augmentation and adding data from structures in the field (Trainset 3 and Trainset 1). Accuracy rates had improved by 16%, 3%, and 6%, for AlexNet , AlexNet (TL) , and AlexNet(CL) respectively after using data augmentation. By adding images from real structures and data augmentation, this improvement was increased by 25%, 10%, and 7%, respectively. Moreover, The TPR value was improved by 82%, 16%, and 17% for AlexNet, AlexNet (TL), and AlexNet(CL) respectively after using data augmentation. This improvement was 72%, 12%, and 20% with using data augmentation and real images with crack from ancillary structures. Models trained on the trainset -3 were more accurate in labeling crack images.

Table III Metric parameters.

	Train set (1)			Train set (3)		
Metric parameter	TPR	TNR	ACC	TPR	TNR	ACC
AlexNet	50%	80%	72%	86%	90%	90%
AlexNet (TL)	77%	80%	79%	87%	93%	87%
AlexNet (CL)	69%	89%	83%	83%	99%	89%
	Train set (2)					
Metric parameter	TPR	TNR	ACC			
AlexNet	91%	72%	84%			
AlexNet (TL)	90%	71%	82%			
AlexNet (CL)	81%	99%	88%			

C. FRCNN result

The FRCNN algorithm was also applied to detect cracks in this study. In the test dataset, the coordinate of a bonding box containing a fatigue crack in the images were predicted using FRCNN. A test dataset of 30 new images was used to verify the model's performance. Fig. 8 shows the performance of FRCNN by using the bonding box in the crack test dataset. IOU, TPR and TNR were used to determine the performance of FRCNN for crack detection and were summarized in Table III. The purpose of using four deep learning algorithms was to find the best approach to determine the location of the crack. Fig. 8 shows the FRCNN output. In all images, the green boxes were ground trough, while the red boxes were considered a predicted location of the cracks. According to the result, FRCNN was an efficient approach to determine the exact location of crack in the specified location of structures with TNR=90% and TPR=90%. However; AlexNet could be used to predict the cracked sub image's label without identifying the specified location of crack in the sub images. A TPR of 87% and a TNR of 93% were obtained with AlexNet(TL) as one of the best labeling approaches.

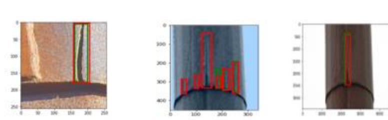

Fig.8. FRCNN result for identifying location of crack.

Table IV FRCNN result

	TPR	TNR	Average IOU
FRCNN	90%	90%	86 %

The result indicated that the proposed model can efficiently provide a higher level of metric parameters in detecting cracks by using AlexNet (TL). These models can predict the location of cracks in different places of structures with a general dataset which was obtained from data augmentation and superimposed approach. Moreover, the AlexNet's performance as a deep learning technique in different training dataset were compared with each other to obtain the highest accuracy rate, TPR and TNR. Data augmentation helped the research team to reach maximum number of images and improved AlexNet training accuracy consistently. FRCNN, however, is capable of detecting cracks within special parts of structures with good performance with fewer images. Moreover, raw images were split into sub images for creating datasets like those in previous studies [9]. The FRCNN algorithm, however, uses raw images since it detects objects in special parts of ancillary structure.

V. Conclusion

Deep CNN for labeling images with fatigue cracks and FRCNN for detection of fatigue cracks in images were used on this data under different modes of training. The result of this research showed:

- The developed methodology in this investigation increased the number of crack images by 50%.
- The results show that the AlexNet (TL) is capable of crack estimation indicated high accuracy in the structure's crack detection because the values of TPR, TNR and ACC are higher than 87% for AlexNet (TL) with data augmentation.
- The results showed that FRCNN could accurately detect the pixels that contain cracks in ancillary structures with IoU higher than 85%.

VI. Acknowledgment

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