

Damage detection of Bridge using Improved region based Convolutional Neural Networks

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Abstract- Autonomous structural health monitoring (SHM) of a large number of bridges became a topic of paramount importance for maintenance purposes and safety reasons. Concrete bridge crack detection is critical to guaranteeing transportation safety. The introduction of deep learning technology makes it possible to automatically and accurately detect cracks in bridges. This article proposes a set of machine learning (ML) tools to perform automatic detection of anomalies in a bridge structure from vibrational data. As a case study, we considered the Z-24 bridge for which an extensive database of accelerometric data is available. The features extracted are then fed to a one-class classification (OCC) combined with Region Based Convolutional Neural Network (RCNN) algorithm to perform anomaly detection. The proposed RCNN solution presents increased accuracy and F1 score over conventional algorithms, without the need to set critical parameters. We proposed an end-to-end crack detection model based on the convolutional neural network (RCNN), taking the advantage of atrous convolution, Atrous Spatial Pyramid Pooling (ASPP) module and depth wise separable convolution. The atrous convolution obtains a larger receptive field without reducing the resolution. The ASPP module enables the network to extract multi-scale context information, while the depthwise separable convolution reduces computational complexity. The proposed model achieved a detection accuracy of 96.37% without pre-training. Experiments showed that, compared with traditional classification models, the proposed model has a better performance. Besides, the proposed model can be embedded in any convolutional network as an effective feature extraction structure.

Keywords — *image processing, region based convolutional neural networks, deep learning, Atrous Spatial Pyramid Pooling.*

I. INTRODUCTION

Bridges play a significant role in daily life. Regular bridge checks are important for maintaining the structural health and reliability of bridges. Bridge crack is one of the main damages of bridges, and its detection is an important task for bridge maintenance. Traditional bridge detection methods rely on human visual inspection, so the detection efficiency and accuracy cannot be guaranteed. In recent years, machine learning and computer vision were applied to the field of crack detection [1–5], and achieved good results.

The modern convolutional neural network (CNN) was first proposed by LeCun et al. [6] in 1989. Due to its effectiveness in feature extraction, it is widely used in computer vision tasks such as image classification [7–10], object recognition [11–13], and action recognition [14–16]. Inspired by these achievements, recent studies have applied convolutional neural networks to the area of crack detection.

In this article, We proposed an region based convolutional neural network to detect bridge cracks automatically/.

We used a region based CNN trained with images detect cracks, using only images and image label as input. Our region based CNN model achieved a 99% accuracy in detecting cracks without pre-training and fine-tuning on other datasets.

II. LITERATURE SURVEY

Sampaio et al. proposed a damage index in terms of variations in the operational deformed shapes, which is derived from frequency response functions. Dilena et al. further implemented the interpolation damage detection method to the case of a reinforced concrete single span bridge in Dogna, Italy. Wang et al. demonstrated damage detection and localization on a simulated four span bridge model by exploiting strain operating deflection shapes, along with an extraction method using frequency and spatial domain decomposition is proposed.

Tondreau and Deraemaeker introduced an automated data based unsupervised technique for damage localization, adopting in service dynamic strain measurements in place of accelerations; a feature extraction process is implemented by means of the so called “modal filters,” which bears the additional advantage of low computational cost. On the other hand, Sun et al. investigated applicability of dynamic displacement signals extracted from beam type bridge structures under moving vehicle loads, for damage detection; a closed form solution of dynamic displacements is offered, decomposed into a quasi static and a dynamic component; the second derivative of this expression, that is, the dynamic curvature is then used for localizing and quantifying damage; the method is verified on simulated data of a single span beam type steel bridge.

Schommer et al used experimentally derived modal characteristics (frequencies, shapes, and modal masses) to calculate the so called flexibility matrix. Although easier to extract from dynamic measurements, the flexibility matrix may not be linked to damage quantification and localization in a manner that is as straightforward as the stiffness.

III. PROPOSED SYSTEM

This study presents the framework processing chain capable of monitoring the structural health of bridges by means of output-only system identification based on the accelerometric data. The proposed strategy is capable of automatically processing the OMA results to detect the presence of damages in a bridge. In particular, we found that, combining clustering of the stabilization diagram with a proper time-domain tracking algorithm for the extracted natural frequencies, we obtain a feature space capable of revealing the presence of anomalies when processed by ML tools. We then proposed the algorithm, Region-based Convolutional Neural Network for anomaly detection, that exhibit very good performance.

A. Dataset Preapration

The original dataset is composed of 2068 bridge crack images collected by the Phantom 4 Pro’s CMOS surface array camera with a resolution of 1024×1024 . The bridge crack dataset we used was generated by the original dataset through the following operations:

Data preprocessing : Since the pictures in the original dataset all contain cracks, which were not conducive to the differentiation of positive and negative samples during network training, we cropped a 1024×1024 resolution image into four 512×512 resolution images. Then, the obtained 8272 pictures were filtered to remove the blurred pictures, and a crack dataset containing 6069 images was obtained. The dataset included 4058 crack images and 2011 background images. At last, we randomly selected 4856 images as the training set and 1213 images as the testing set.

Data Augmentation : In order to meet the input requirements of the network, we cropped the picture size to 224×224 through the random center crop operation. Then, we randomly flipped the training set images to further augment the dataset.

B. Feature Extraction module

The network contains a total of 28 layers, including 16 convolutional layers and 3 maxpooling layers, while the Atrous Spatial Pyramid Pooling (ASPP) module contains 10 convolutional layers. In the structure the first three convolutional layers are used to extract image features, and the output feature maps are then input into the ASPP module, whose structure will be described to extract the multi-scale crack feature information. Furthermore, the depthwise separable convolution contained in the ASPP module reduces the computational complexity of the model, thus making the network easier to optimize. In the last three convolutional layers of the network, we apply atrous convolution to replace the maxpooling layers, thus avoiding the degradation of the image resolution while increasing the receptive field. At last, the network uses Softmax to classify the input pictures (cracks or backgrounds).

C. Classification and Performance analysis module

Image classification is done upon analyzing the properties of various features from the images and organizes this data into two categories : Positive and Negative. The overall results obtained from the crack detection experiments and perform comparative evaluations against several competing techniques. The performance of the proposed solution is investigated on a real data set from Z-24 bridge.

V. RESULT ANALYSIS AND DISCUSSION

```

from torch.utils.data import DataLoader
import torchvision.transforms as transforms

#from src.model import CrackClassifier
#from src.dataloader import CrackDataset
from tqdm import tqdm
import os
from tensorboardX import SummaryWriter

device = ("cuda" if torch.cuda.is_available() else "cpu")

transform = transforms.Compose(
    [
        transforms.Resize((64, 64)),
        transforms.ToTensor(),
        transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5)),
    ]
)

num_epochs = 20
num_classes = 2
learning_rate = 0.001
batch_size = 2
shuffle = True
pin_memory = True
num_workers = 1
data_path = "/content/drive/MyDrive/data"
  
```

Fig.1.Preprocessing

The dataset is loaded into the detection model and its datatypes are explored and displayed as output.

```

train_data = CrackDataset(data_path, 'train', transform=transform)
test_data = CrackDataset(data_path, 'test', transform=transform)

train_data_loader = DataLoader(dataset=train_data, batch_size=batch_size, shuffle=True)
test_data_loader = DataLoader(dataset=test_data, batch_size=batch_size, shuffle=True)

def write_scalars(logger, epoch, loss):
    logger.add_scalars('train/loss', {'loss':loss}, epoch)

def write_test_scalars(logger, epoch, accuracy):
    # logger.add_scalars('test/loss', {'loss':loss}, epoch)
    logger.add_scalars('test/accuracy', {'accuracy':accuracy}, epoch)
  
```

Fig.2. Training of images

Input images are categorized into training and testing data. The trained images are tested and the results are evaluated in terms of accuracy .

```

0% | 0/400 [00:00<7.717s] | checking accuracy on validation data
Epoch [1/10]: 100% | 400/400 [00:14:00:20, 29.917s, loss=0]
0% | 0/400 [00:00<7.717s] | checking accuracy on validation data
Epoch [2/10]: 100% | 400/400 [00:14:00:20, 29.917s, loss=0.002286]
0% | 0/400 [00:00<7.717s] | checking accuracy on validation data
Epoch [3/10]: 100% | 400/400 [00:14:00:24, 31.291s, loss=0.0061] | accuracy : 89.0
-----
0% | 0/400 [00:00<7.717s] | checking accuracy on validation data
Epoch [4/10]: 100% | 400/400 [00:14:00:20, 29.917s, loss=0.0029]
0% | 0/400 [00:00<7.717s] | checking accuracy on validation data
Epoch [5/10]: 100% | 400/400 [00:14:00:20, 29.917s, loss=0.002721]
0% | 0/400 [00:00<7.717s] | checking accuracy on validation data
Epoch [6/10]: 100% | 400/400 [00:14:00:20, 29.917s, loss=0]
0% | 0/400 [00:00<7.717s] | checking accuracy on validation data
Epoch [7/10]: 100% | 400/400 [00:14:00:24, 31.291s, loss=1.09] | accuracy : 98.0
-----
0% | 0/400 [00:00<7.717s] | checking accuracy on validation data
Epoch [8/10]: 100% | 400/400 [00:14:00:20, 29.917s, loss=3.22e-6]
0% | 0/400 [00:00<7.717s] | checking accuracy on validation data
Epoch [9/10]: 100% | 400/400 [00:14:00:20, 29.917s, loss=1.07e-7] | accuracy : 98.0
-----
0% | 0/400 [00:00<7.717s] | checking accuracy on validation data
Epoch [10/10]: 100% | 400/400 [00:13:00:00, 36.711s, loss=0]
  
```

The loss and accuracy of trained images is predicted by the trained model.

Fig. 3.Training of iterations

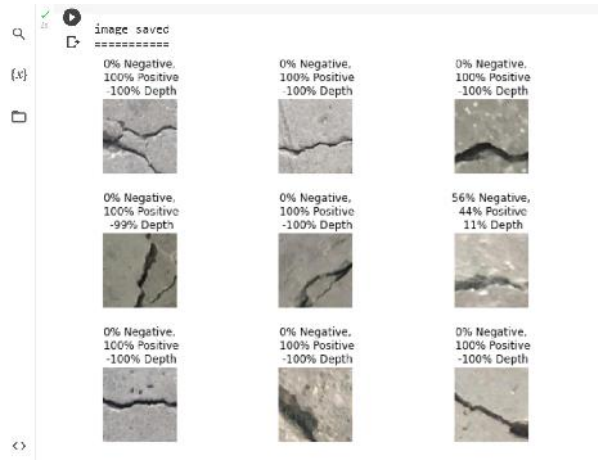


Fig. 4. Performance Metrics

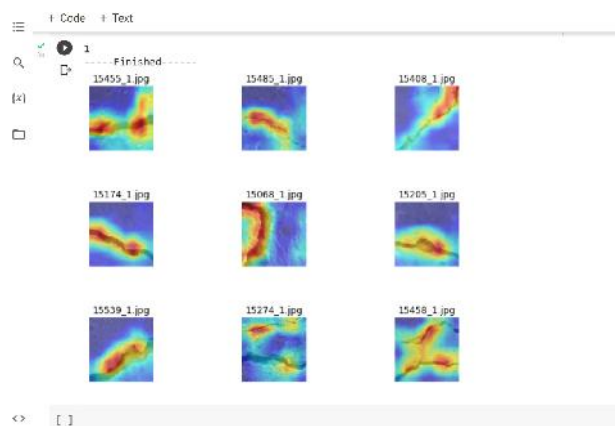


Fig. 5. Converting into grayscale images

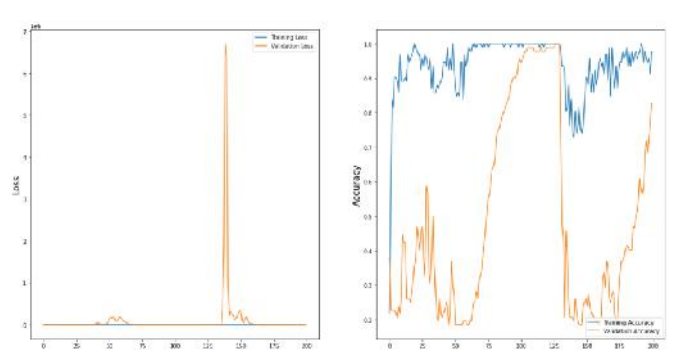


Fig. 6. Result Analysis and Matplot Graph

The graph is plotted for loss and validation loss, accuracy and validation accuracy.

VI. CONCLUSION

A complete processing chain capable of monitoring the structural health of bridges by means of output-only system identification based on the accelerometric data is proposed.

The proposed framework on data collected from the Z-24 bridge to assess its effectiveness and perform anomaly detection technique: RCNN. The RCNN solution presents considerable accuracy and an F1 score higher than algorithms without the need to set critical parameters.

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