A Study on Vision Based Method for Damage Detection in Structures

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A Study on Vision Based Method for Damage Detection in Structures

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Abstract. To ensure the safety and the usefulness of civil structures, it is fundamental to visually inspect and survey its physical and functional condition. Current techniques in condition and safety assessment of large concrete structures are performed physically promoting to subjective and unreliable outcomes, costly and time-consuming data collection, and safety issues. This paper presents a study on less time consuming and less expensive alternative to the present methods of preliminary assessment for the detection of damages in structures. Henceforth, the focus is set on various vision-based methods for different parameters like cracks, corrosion and spalling which cause damage and deterioration of structures. Thus, a study is made on the current achievements and drawbacks of existing methods as well as open research difficulties are outlined to help both the structural engineers and the computer science researchers in setting a motivation for future research.

Keywords: Damage detection · Vision based methods · Computer based techniques · Structural health assessment

1 Introduction

Even though the use of concrete has started centuries back, larger light was shed in the 19th century. Many experiments were carried to combine concrete and Iron, later replaced steel in the place of Iron producing effective and economical structures [1]. From the beginning of its use, reinforcement concrete as a construction material has been accepted worldwide and usage is exponential. The amount of Concrete used in last two centuries is equivalent to concrete used in last two decades. As perspective of global development, concrete is highly preferred for various structures, but the major challenge is maintenance throughout their design life for the civil engineer community [2]. Severity of deterioration in structures depends on geographical location and its functional utility like structures nearer to the sea-shore are more prone to corrosion and spalling e.g. harbors, shipyards and bridges [3], whereas structures which undergo cyclic loading or subjected to fatigue stress lead to microscopic to structural cracks e.g.

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beams, girders and tall buildings [4]. Initiation of internal distress is generally projected on the external surface of the concrete structure in terms of cracks and spalling. If these kind of damages are detected early, can prevent further deterioration and also enhances structural design life [5]. Maintenance of structures in countries like India with huge infrastructure commonly depends on Human visual inspection, which requires subject expertise in structural health assessment, types and severity of damages. At the same time this procedure has limitations related to human error, climatic conditions, time, accessibility and visibility. Computer's vision in the form of Artificial Intelligence (AI) is playing a vital role to address the mentioned limitations. This study is motivated to find solutions through images using AI for robust and faster visual inspection techniques.

2 Related Work

Computer vision based techniques have evolved drastically in last two decades along with the higher degree of improvements, especially as an effective tool in the field of structural health assessment and monitoring. Currently, human visual inspectors are replaced by self-navigating robots with the help of AI to assess all kinds of damages in structures [6]. Hutchison and Chen [7] worked on automatic detection of concrete surface damages like cracks and spalling from images using a statistical based method and relied on a Bayesian method. Lee et al., [8] proposed a model for accurate detection of cracks through integrating different image processing techniques, apart from that, class labels of the cracks were classified using a neural network based model. Kim et al., [9] surveyed on identification of cracks in concrete structures through various image binarisation algorithms. Silva and Lucena [10] demonstrated the capability of deep learning approach for concrete crack detection. Choi and Kim [11] carried research to identify the corrosion type based on the morphology of the corroded surface and for training and testing the classifier, 150 to 200 images were taken under optical microscope considering the features like color, texture and shape. Medeiros et al. [12] demonstrated the segregation of corroded and non-corroded surfaces using texture descriptors obtained from GLCM (grey level co-occurrence matrix) and color. Itzhak et al., [13] was the first to carry out research on pitting corrosion using digital image processing. Kim et al., [14] presented on Terrestrial laser scanner(TLS) for the detection of surface damages on concrete using laser and simultaneously locate and quantify the spalling defects. Similarly, Dawood et al., [15] developed a model to detect and quantify spalling by image data processing and machine learning techniques. Author was successful in getting the results about 89 to 90% accurate, with only limitation of not providing exact shape of damaged region. Hoang et al., [16] proposed a model using hybridization of image texture analysis and machine learning techniques to characterize the condition of concrete wall surface. In line with that many researchers have attempted to develop a model which can classify all types of damages seen on a single structure. Lin et al., [17] studied on different types of damages caused during the natural disasters like earthquake, tsunami and debris flows. Damages can vary in its scale from collapsing of structures, breaking of bridges and cracks on roads, author also discussed the role of computer vision based technique in the prevention of structural damages. Spencer et al., [18] did a detail review on recent advances in computer vision techniques applied to various civil infrastructure for structural health assessment considering visual defects like cracks in concrete, concrete spalling, fatigue cracks in steel, steel corrosion and Asphalt damages. Authors also detailed damage detection methods like heuristic feature-extraction, deep learning-based damage detection, and change detection. Apart from the damage detection techniques vision based methods are also currently used in calculation of compressive strength of concrete, which is taken as a video or set of image frames during the lab experiment [19–21].

3 Methodology

To understand damages in various locations of a structure, we have experimented with the latest technological advancements by using algorithms in Machine Learning (ML) and Artificial Neural networks (ANN). Considering Images as samples we can define ML as the "Area of study that enables Systems to learn without being explicitly programmed". At its most fundamental it is the act of utilizing algorithms to tokenize data, learn from it, and afterward estimate or predict something. So instead of hand-coding the programming schedules with a particular set of instructions to achieve a specific task, the machine is "trained" utilizing huge amounts of data that gives to the machine the ability to figure out how to learn to perform the task. The challenge is, ML models need to be input with relevant features and it might be complex to find the right combination of features to correctly identify and classify the objects in the images. To overcome the aforementioned problem, Deep Learning (DL), a special discipline in ML is required for classification purposes. Neural Networks are inspired by our understanding of the biology of our brains. In the current work the image processing is carried out in order to automatically crop out the object of interest from the whole images. The crops will feed the DL classification tool and they will be classified into three classes as Crack or No Crack, Corrosion or No Corrosion and Spalling or No Spalling. To train a network from scratch requires hundreds of thousands of labelled images. In order to deal with the availability of a smaller dataset (200 each of crack, corrosion and spalling), pre-trained networks are adopted for the purpose. That process is called Transfer Learning and it is commonly used in deep learning applications. Fine-tuning a network with transfer learning is much faster and easier than constructing and training a new network. The advantage of transfer learning is that the pre-trained network has already learned a rich set of features. These features can be applied to the broad range of other similar tasks. To use that networks for the purpose of damage detection in structures, only the fully connected last layers need to be changed introducing the desired labels. To experiment, we have chosen AlexNet architecture which measures the performances in terms of precision and accuracy as well as in terms of time consumed for training and testing.

3.1 Dataset Building

Images used to build the dataset for this study are collected during the visual inspections of various structures carried in the last four years. Even though images have been captured from different devices, they are standardized into the resolution of $227 \times 227 \times 3$ RGB before importing into the model. Majority of the images related to crack are obtained from the visual inspection carried out for four hundred national highway bridges and residential buildings, as they have single crack to multiple cracks on the surfaces. Concrete Bridges nearer to sea-shore had high corrosion and spalling when compared to the bridges which are in other part of the country or 300 to 400 km away from the shores. Spalling was also seen in the bridges which were very old and had less maintenance. Figure 1 depicts various damages captured during site investigations for concrete and steel infrastructure. Figure 1(a) shows minor hairline cracks to structural cracks, Fig. 1(b) shows quantity of corrosion increasing from left to right and largely calculated on surface area rather than depth of the corrosion and Fig. 1(c) shows minor spalling to major spalling, this is also calculated on surface area exposure. Figure 1(a–c) are arranged in such way that the severity of damage is increasing from left to right.

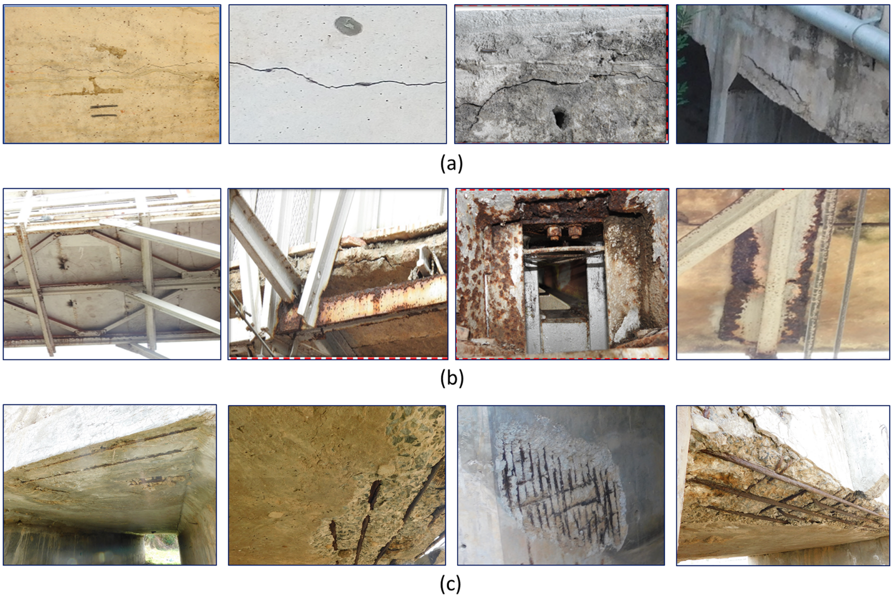

Fig. 1. Images captured during the bridge visual Inspections (a) Cracks (b) Corrosion (c) Spalling, images are arranged in the increasing severity of the damage from left to right.

Figure 1 shows images capture from bridge inspection, similarly large database is also created from the visual assessment of residential and historical structures too. Images were added from every perspective and not necessarily taken perpendicular to the damage. So that the code can more robust and implemented directly on live project site investigations.

3.2 Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNN) are special kind of multi-layer neural networks, designed to recognize visual patterns directly from pixel images with minimal pre-processing. To implement these CNN's we require complex computational power, so it is easily accessible via software programs or architectures like LeNet, AlexNet, ResNet etc. Among which we have experimented using AlexNet. Figure 2 represents proposed architecture for this research work. Dataset comprises of 600 images in total undergoes training individually and images are filtered based on its noise. Few images with greater noise get rejected and accepted images are taken to next step for feature extraction and feature learning. As a next step AlexNet architecture is proposed to classify the dataset further. Firstly, it goes through a large convolutional layer and max pooling layer and process is repeated twice to detect the object (crack, corrosion and spalling) in the images. Then the images go through three smaller convolutional layers followed by a maxpooling layer. In pipeline images are flattened and connected with the several fully-connected layers. The activation functions are all Rectified Linear Units (ReLU) which is mostly preferred for accurate predictions.

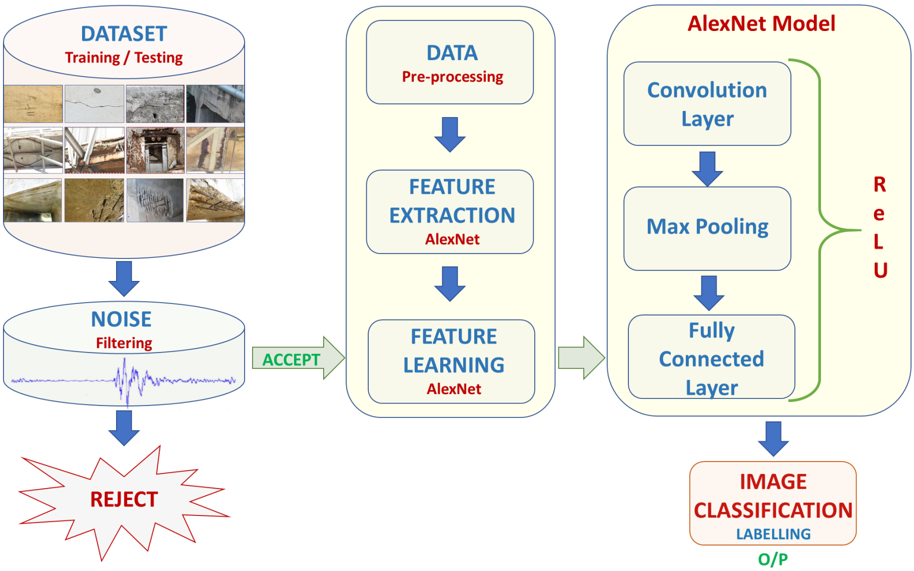

Fig. 2. Proposed architecture

Model built using such small dataset, the training time is around 60 s using a GPU and around 90 min using only the CPU for AlexNet architecture. The training and testing ratio considered in this study is 9:1 for good accuracy, if the ratio is 8:2 or 7:3 the accuracy of the results will be decreased as the trained images are less.

4 Results and Discussion

The proposed methodology has resulted in good accuracies even though the dataset is small. As described experiments were carried on three classes of images i.e. crack, corrosion and spalling.

4.1 Crack Detection

Identification of crack at early stage is important as it effects the strength and stiffness of the structure.

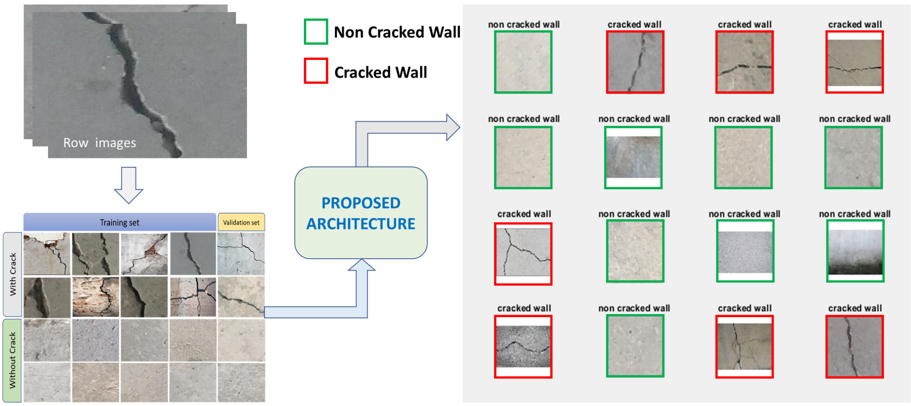

Fig. 3. Model for crack detection

Figure 3 demonstrates the outcome of the proposed architecture using AlexNet which was successful in identifying hairline crack to the severe structural cracks. The model was also able to classify single and multiple cracks with different contrasts.

Figure 4 shows the results of the model which is trained using 200 images with 9:1 training and testing ratio which has taken 6 epochs and 204 iterations with the learning rate of 0.0001 by achieving 98% accuracy for image classification in labelling cracks and no cracks. The accuracies can increase or decrease based on the size of the dataset, varieties of the images in the dataset and the ratio of training and testing. So, in this case achieved accuracy is considered to be good.

Similar observations were made related to the accuracies while experimenting other two classes of images.

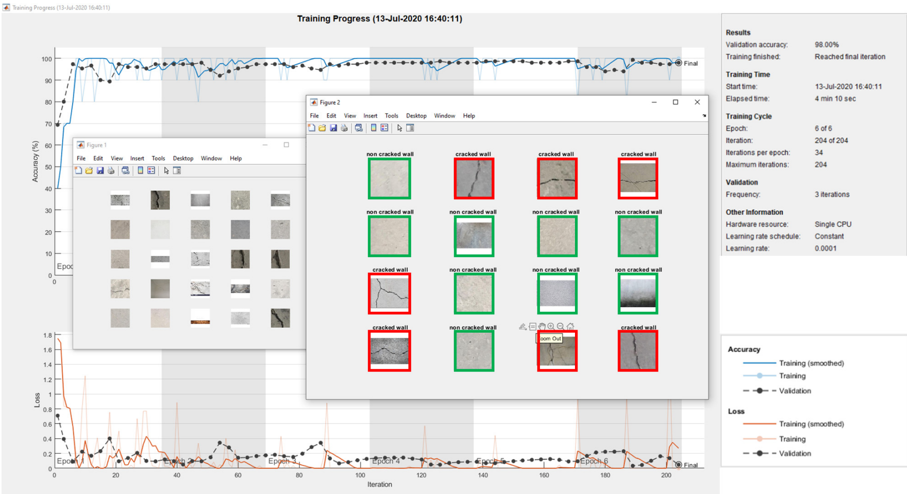

Fig. 4. Training and validation of results for crack dataset with accuracy and loss while training images.

4.2 Corrosion Detection

Corrosion detection at early stages in steel structures plays a vital role and automatic detection could be one of the most needed solution for the current scenarios considering the scale of infrastructure.

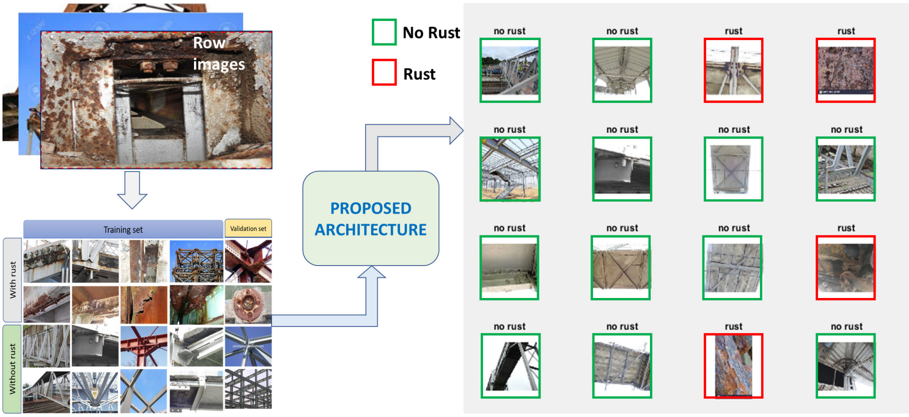

Fig. 5. Model for corrosion detection

Figure 5 demonstrates the outcome of the proposed architecture using AlexNet which was successful in identifying rust and no rust for various given scenarios.

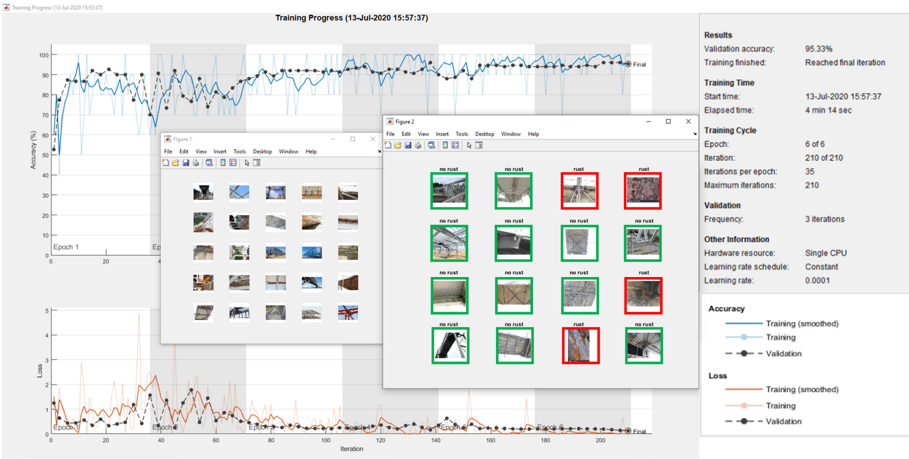

Fig. 6. Training and validation of results for corrosion dataset with accuracy and loss while training images.

Figure 6 shows the results of the model which is trained using 200 images with 9:1 training and testing ratio which has taken 6 epochs and 210 iterations with the learning rate of 0.0001 by achieving 95.33% accuracy for image classification in labelling rust and no rust.

4.3 Spalling Detection

Detecting spalling at the initial stage can arrest the further deterioration, largely spalling is observed at the seashore or in the old structures.

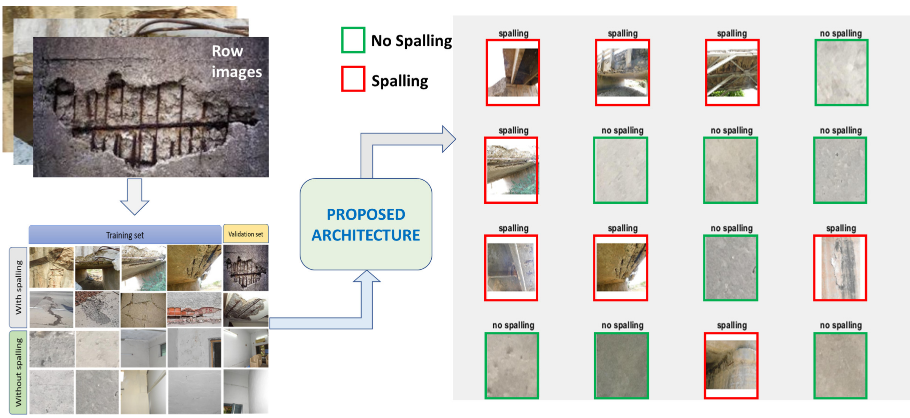

Fig. 7. Model for spalling detection

Figure 7 demonstrates the outcome of the proposed architecture using AlexNet which was successful in identifying spalling and no spalling for various given scenarios.

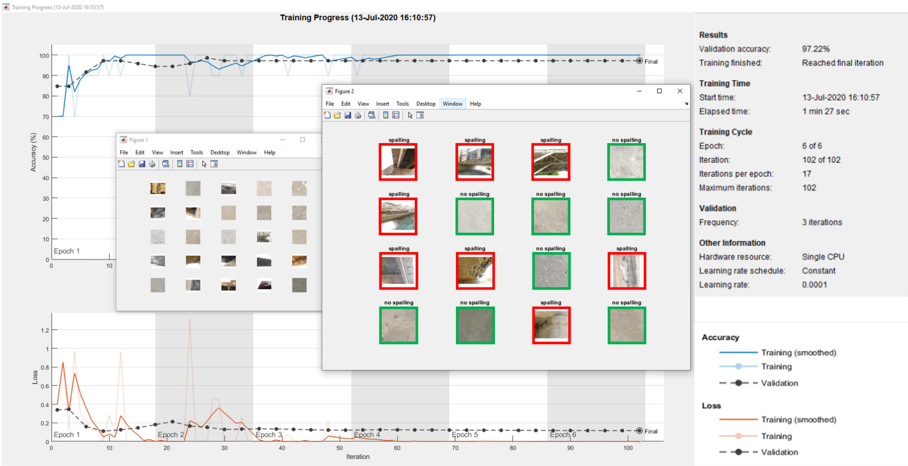

Fig. 8. Training and validation of results for spalling dataset with accuracy and loss while training images.

Figure 8 shows the results of the model which is trained using 200 images with 9:1 training and testing ratio which has taken 6 epochs and 102 iterations with the learning rate of 0.0001 by achieving 97.22% accuracy for image classification in labelling spalling and no spalling.

5 Conclusions

The proposed architecture in the study is easy, faster and robust as the obtained results for all the three classes resulted in higher accuracies. Dataset created had varied variety of images and it shows that this method is capable of identifying three categories of damages crack, corrosion and spalling. Increased dataset can lead to higher accuracy and more types of damages can be detected. Can attempt in using different software architectures to observe the accuracies. Faster development in this line of integrating Artificial Neural Networks to structural health assessment problems can provide robust solutions and save man-hours and also economy of any country apart from sudden failures.

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