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AN APPROACH FOR DETECTING BUILDING DEFECTS USING DEEP LEARNING CONVOLUTION NEURAL NETWORKS

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Abstract -
Customers are increasingly looking for fast and efficient ways to frequently check and inspect the condition of their buildings so essential repairs and maintenance can be done in a timely manner. Act quickly before they become too dangerous and costly. Traditional methods for this type of work commonly comprise engaging inspection officers to undertake a condition assessment which involves a lengthy site inspection to produce a systematic recording of the building defects, including cost estimates of immediate and project the long-term costs of renewal, repair and maintenance of the building. Current asset condition assessment procedures are extensively time-consuming and expensive and pose health and safety threats to inspection officers, particularly at height and roof levels which are difficult to access. This project aims toward an automated detection and localization of key building defects, e.g., moss, cracks, deterioration and stains, from images using Convolution Neural Networks. The proposed model was built on a pre-trained CNN classifier of VGG-16, with class activation mapping (CAM) using a squeeze net for object localization. The challenges and limitations of the model in real-life applications have been identified. The proposed neural network model has proved that it can accurately detect and localize building defects.

Key Words: Object Detection, Convolutional Neural Network, Deep Learning, VGG16

1.INTRODUCTION

Construction defects are a major concern in the construction industry. Differently constructed buildings can generate different types of defects and demands at different levels in a construction project and the types of quality depend on the function, system, methods and materials used. Various systems have been designed to eliminate the defects during the construction process. To fix the defects more working hours are required as well as costs extra resources. Various factors like time, materials and equipment are considered to fix the defects. Precious time is lost while fixing the defects. The defective construction may also lead to the complete failure of the structure. All around the world the construction industry is becoming modern, and advanced & growing day by day with the help of development in technology.

Image processing is the process of converting an image to a digital aspect and performing functions on it, in order to get an enhanced image or extract other useful information from it. It has a large number of applications in various business sectors. Image processing became the core of the research space within the engineering and computer science industry as well. Image processing is a technique for applying operations on an image in order to improve it or extract relevant information from it. Image processing is similar to signal processing in which an image is taken as input and output may be an image or characteristics associated with that image. Nowadays, image processing is a well-known growing technology.

A convolutional neural network, or CNN, is a deep learning neural network designed for processing structured arrays of data such as images. Convolution neural networks are widely used in computer vision and have become the state of the art for many visual applications such as image classification, and have also found success in natural language processing for text classification. Convolution neural networks are very good at picking up on patterns in the input image, such as lines, gradients, circles, or even eyes and faces. This property makes convolutional neural networks so powerful for computer vision. Unlike earlier computer vision algorithms, convolutional neural networks can operate directly on a raw image and do not need any pre-processing.

2.LITERATURE SURVEY

1. NHAT-DUC HOANG - During the construction and maintenance of high-rise buildings, it is very crucial to attain the good surface quality of structures due to safety and aesthetic aspects.

Because of the combined effects of ageing, weather conditions, and human activities, the condition of building structures deteriorates over time Detection of defects including cracks and spalls on the wall surfaces in high-rise buildings is a crucial task of building maintenance. If these defects are left unnoticed, then these defects can significantly affect the structural integrity of the building. Timely and cost-effective methods of building condition survey are of practicing need for the building owners and maintenance agencies to replace the time and labor-consuming approaches and construct an image processing approach for frequently evaluating the condition of wall structures.

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2. WOORAM CHOI – Periodical inspection is the dominant form of structural health monitoring (SHM). However, civil engineering societies in North America have expressed common consent that the current inspection practice is not sufficient to ensure infrastructure safety. With the increasing number of ageing infrastructures, an approach for inspecting building defects is needed. A computer vision algorithm can be employed for identifying damage, as image processing algorithms (IPAs) are also similar to human inspections because both use visual information to recognize and classify the defects. The outcomes of computer vision methods are much simpler to a common man than systems with traditional contact sensors. So, researchers have proposed a variety of different methods.

3. EXISTING METHOD

Surface Crack Estimation Using Gaussian Regression, Support Vector Machines and Neural Networks:

This previous paper focuses on a computer vision-based inspection approach capable of relating surface damage observations to quantitative damage and load levels in structures. This approach is based on image processing and machine learning techniques which are used to build predictive models capable of estimating internal loads (i.e., shear and moment) and damage states in RC beams and slabs derived from surface cracks. The proposed models have been trained and tested using image data sets obtained from the earlier published studies, which provided about 900 crack patterns from 130 RC beams and slabs both with and without web reinforcement across a range of load and damage levels. These earlier studies focused on investigating different phenomena and parameters such as size effect, aggregate size, and concrete strength, longitudinal and transverse steel ratio on shear strength of reinforced concrete beams. The datasets were divided into two categories: (i) beams with web reinforcement; and (ii) beams without web reinforcement (i.e., beams intended to be shear-critical). By using these datasets, the proposed regression model is trained and fine-tuned to get more accurate predictions. In this project, simple crack datasets are used to train and test the robustness of the model but in reality, cracks have distinct properties that may not fall under the category of the cracks provided in the dataset. In general terms, the results support the potential ability to detect the cracks, with future applications for in-field inspection and post-disaster assessments.

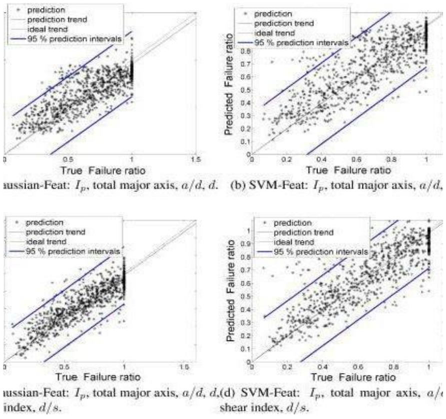

Fig-1: Gaussian Regression Model

4. PROPOSED METHOD

In our proposed method, we detect building defects using the VGG16 network. The building defects dataset containing around 300 images is used in the pre-trained network. In this dataset, 70 per cent of images are used for training and 30 per cent are used for testing.

In this proposed system, we used VGG16 neural network as a backbone of the project. It contains 13 convolutional + ReLu layers, 5 pooling layers and 3 fully connected layers.

Convolution and Pooling layers extract the features, while fully connected layers are used to classify the input image.

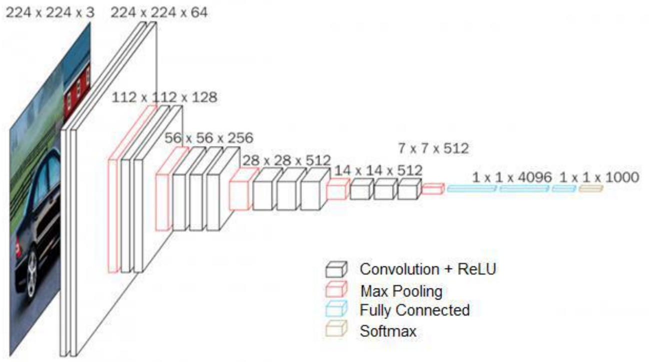

Fig-2: Architectural view of VGG16 network

5. NUMBER OF MODULES

Pre-processing: In this technique, the input images are scaled, transposed and flipped using the image augmentation technique. All the training images are resized to 247x247x3 since the VGG16 network input size is 247x247x3.

Feature extraction: After preprocessing, the features are extracted from the given input image at the convolution layers in the neural network. Each class has different features such as edges, color, etc; so that the objects are identified precisely.

Image classification: After extracting the features from the images, all the extracted features are fed as input to the fully connected layers. This fully connected layer learns the features of each class by assigning weights to each neuron. While testing the network, features extracted from the test image are compared to the features learned in the training session and classified the test image accordingly.

6. RESULTS

The simulation results our project will be discussed in this section. The learning rate of the model is set to 0.0003 and we have trained our model with different epochs to compare the confusion matrix obtained and evaluate the accuracy of the model. For testing the model, four images will be taken randomly from the validation dataset and predict the defect with

its confidence score of the prediction. Predicted label and the confidence score of the image is given as their title respectively. To test the CAM model for localizing the defect, a random image from validation dataset is taken as a test image and run through the CAM model to represent the localized defect.
Outputs obtained by simulating our model are as follows,
With 75 Epochs: On simulating the modified VGG16 model with a learning rate of 0.003 and 75 Epochs, we have obtained an accuracy of 89.99%.

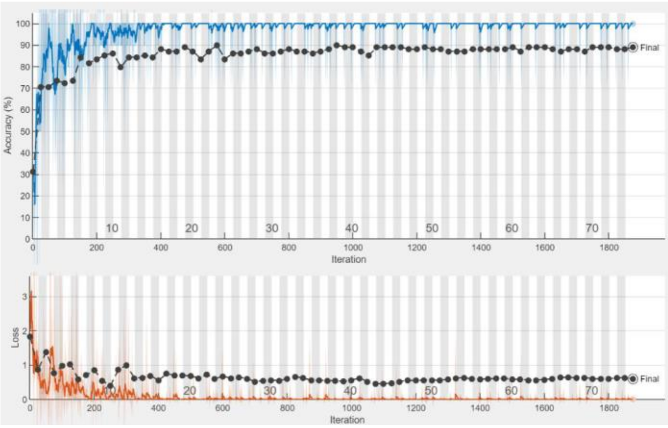

Fig-1: Accuracy & Loss Curves for 75 Epochs

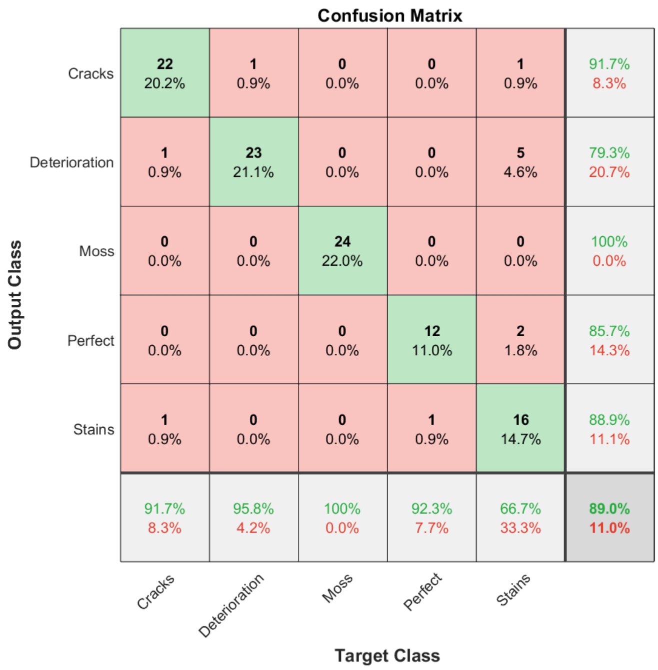

Fig-2: Confusion Matrix for 75 Epochs

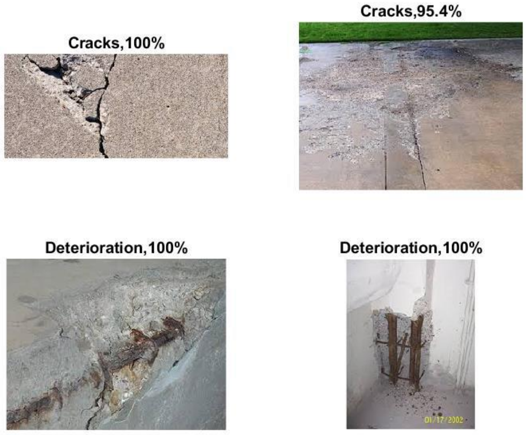

Fig-3: Predicting Validation Images with 75 Epochs

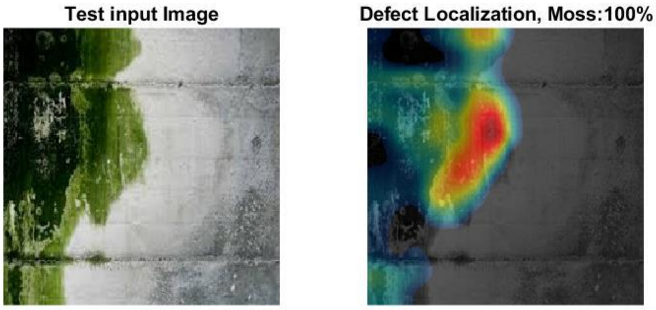

Fig-4: Defect Localization with 75 Epochs

Comparing the Accuracies of the Model

S.No	No. of Epochs	Accuracy
1	25	86.7%
2	50	88.1%
3	75	89.99%

Table 1: Comparing Accuracies of the model with different Epochs

We can clearly observe that the accuracy of the model increases as the number of epochs increases.

7. CONCLUSION

An approach for detecting building defects using the VGG16 model has been presented and the accuracies of the model trained with different epoch values have been tabulated for comparison. The training period is proportional to the number of epochs used for the training of the model. Even though this model consumes time to get trained for detecting the defects when a trained model is loaded it is very simple to implement and can be used in real-time applications. MATLAB code has been provided for quick implementation of the proposed. Computer vision toolbox, VGG16, SqueezeNet, Deep learning toolbox, Image processing toolbox and Parallel computing toolbox are implemented in MATLAB 2021a of our PC having Operating system Windows 11. The building defects dataset images having cracks, stains, deteriorations, moss and perfect walls are given as input to the network.

Detecting building defects early will save many lives as well as properties. This approach can be implemented in high-risk areas like outside of a skyscraper, radioactive buildings like nuclear power plants and where ever humans can't reach and do a repetitive task. This model not only detects the building defects but also localizes the defect so that respective measures will be taken for that particular defect.

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