

# 1 Image Based Inspection and Monitoring of Buildings

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11 **Abstract.** The rapid evolution of cameras and drones in the past few years has  
12 paved a way for image-based inspection and monitoring of buildings and other  
13 structures. This study presents a framework for the development of an automated  
14 image-based building inspection and monitoring system. Images acquired from  
15 multiple locations of the building can be used to construct a 3D model or a 2D  
16 elevation view which is then matched to its BIM (Building Information  
17 Modeling) model. The image of each structural member and its dimensions  
18 obtained from the matched model is fed to an image processing algorithm which  
19 detects cracks in concrete surfaces and measures crack parameters. A machine  
20 learning algorithm trained on several synthetic crack scenarios automatically  
21 predicts severity of each crack and the corrective action to be taken for  
22 maintenance. The detected cracks are color coded and the severity is mapped  
23 back to the BIM model so that the current structural state can be effectively  
24 visualized. Using several images of real structural members, it is demonstrated  
25 that the crack analysis system shows fairly accurate results. Apart from being a  
26 smart and convenient tool for structural inspection, the developed framework also  
27 results in better operations, planning and facility management.

28 **Keywords:** Structural Inspection and Monitoring, Drones, Image Processing,  
29 Building Information Modeling, Machine Learning.

## 30 1 Introduction

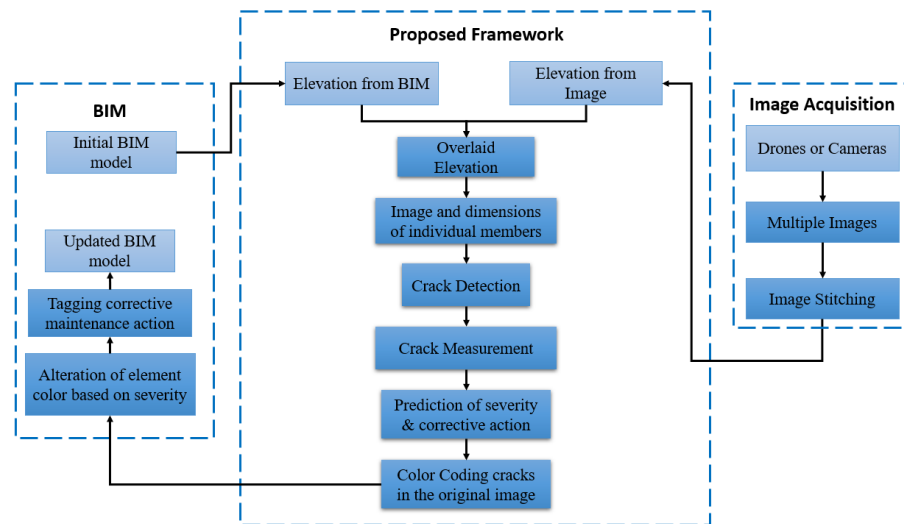
31 Infrastructures need periodic inspection to ensure that they are performing as intended  
32 and do not pose risks to public health and safety. They are liable to deterioration due to  
33 environmental factors, overloading, excessive usage or aging [1]. Cracks appear as an  
34 earliest sign of deterioration in structures. These cracks may cause material  
35 discontinuities and decrease in local stiffness. An early detection of these cracks allows  
36 for intervention to be taken to avoid further damage.

37 Manual visual inspection is the most commonly used crack inspection method in the  
38 present scenario. This method however, has poor efficiency as it is time-consuming,

39 uneconomic, may require use of expensive monitoring means for inaccessible regions  
 40 and might even pose safety risks to the inspectors.

41 Fortunately, the rapid evolution of cameras and drones in the past few years have  
 42 paved a way for image-based inspection of tall buildings. For crack monitoring in  
 43 concrete, drone images combined with digital image processing has shown promising  
 44 prospect for overcoming the shortcomings of manual visual inspection [2].

45 This study presents a framework for the development of a fully automated image-  
 46 based structural inspection and monitoring system. In addition to detecting and  
 47 measuring cracks in concrete surfaces, the developed system also assigns a severity  
 48 index to each cracks and suggests corrective action to be taken for the maintenance.  
 49 Figure 1 provides an overview of the proposed framework.



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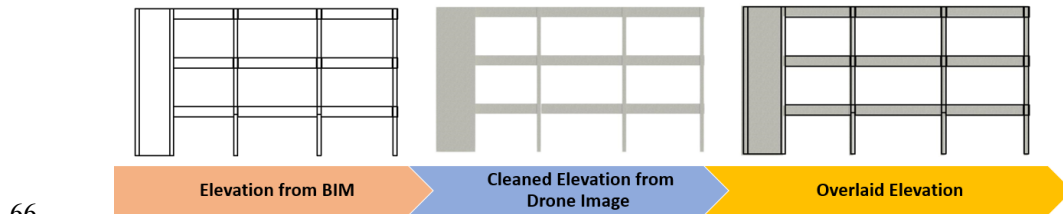
Fig. 1. An overview of the proposed framework

## 52 2 System for Image-Based Building Monitoring

### 53 2.1 Pre-Processing:

54 The images can be acquired by flying a drone vertically along the elevation of the  
 55 building. Images obtained from multiple locations can then be stitched together so that  
 56 an entire elevation appears as a single image. Furthermore, this elevation can be  
 57 manually cleaned to remove unwanted materials in the background. An algorithm can  
 58 also be developed for automatic cleaning. This elevation is then overlaid to its  
 59 corresponding elevation in the BIM model. The BIM model contains informations such  
 60 as the unique Element ID for each element along with its coordinate and dimensions.  
 61 With the help of these coordinates, element level image of each structural member  
 62 is extracted from the overlaid elevation. This image along with the dimensions and type  
 63 of structural member is stored for each structural member under its unique element ID.

64 This information and images will then be read by the crack analysis algorithm. Figure  
 65 2 illustrates an example of the process.



66  
 67 **Fig. 2.** An example of overlaying elevation from BIM to the elevation from Drone Image

## 68 2.2 Crack Analysis:

69 The crack analysis framework can be divided into three major parts: crack detection,  
 70 crack measurement and severity analysis. The crack detection module takes the image  
 71 of each structural member as an input. Using bilateral filtering followed by binary  
 72 thresholding a potential crack map is created. Utilizing the slenderness of potential  
 73 cracks compared to potential non-cracks [3], a module is developed that successfully  
 74 isolates all cracks in the images and creates a binary crack map.

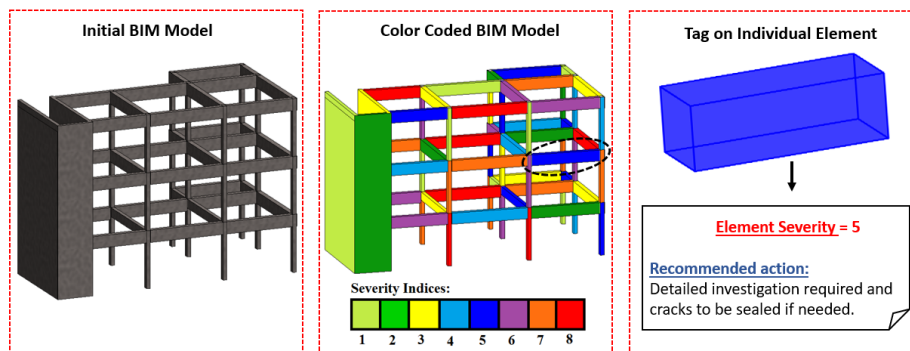
75 This binary crack map is taken by the crack measurement algorithm which draws  
 76 rectangular bounding boxes around each crack shape to measure its length, orientation  
 77 [4] and co-ordinates of end points. For measurement of crack width, distance  
 78 transformation is used. Likewise, for determining the generalized position of the crack  
 79 with respect to the structural member, it is transformed to a generalized local scale.

80 Severity indexes are usually predicted solely based on crack width and/or density,  
 81 examples of which can be seen in [5], [6] and [7]. A new severity index was created  
 82 based on these guidelines and by combining engineering judgement and understanding  
 83 of concrete mechanics about the effect of crack position and crack type on structural  
 84 members. Based on the new index, several crack scenarios were created to train the  
 85 machine learning algorithm. 1080, 1008 and 936 datasets were used for beams, columns  
 86 and walls respectively with 80% data used for training and 20% data used for testing.  
 87 Decision tree algorithm was found to give the best accuracy for the datasets. After the  
 88 decision tree predicts the severity of each crack, a report file is automatically generated  
 89 that contains the parameters of each individual cracks along with its severity and the  
 90 corrective action to be taken for the maintenance of that structural element. The  
 91 framework was built entirely on Python.

## 92 2.3 Post-Processing:

93 For post-processing, the cracks are color coded in the original image of the structural  
 94 element based on their severity value. A color coding plugin reads the severity level of  
 95 the element from an external CSV (Comma Separated Value) file by matching the  
 96 element ID of the BIM element and the CSV file. It then transforms this severity value  
 97 into its corresponding RGB (Red, Green, Blue) value. A function is created which takes

98 this RGB value and overrides the color of the element so that the final output is the  
 99 element with its color coded based on its severity. As a result, the current state of the  
 100 structural member can be easily visualized. Figure 3 shows an example of the initial  
 101 model and the model automatically color coded based on its severity. Each element  
 102 is tagged with a report that contains the number of cracks, their measurements, severity  
 103 and the corrective action to be taken for the maintenance of that element.



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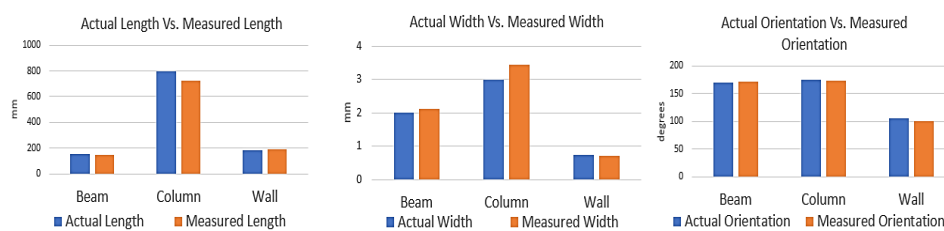
105

Fig. 3. Initial Model and Color Coded Model with tag on individual elements

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### 3 Monitoring of Some Case Study Structural Members

107 The presented approach of structural inspection and monitoring is applied to 35 sample  
 108 images taken around the AIT campus. The images of the structural members were taken  
 109 and manual measurements of the cracks were carried out on site. The comparison  
 110 between the actual values measured on site and the values measured automatically by  
 111 the algorithm was carried out. Figure 4 shows the comparison of these values for a  
 112 sample beam, column and wall taken for the case study.



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Fig. 4. Comparison of Actual Crack Parameters Vs. Parameters Measured by the System

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Based on the 35 samples of structural members, the measurement accuracies for length, width and orientation were found to be 94.16%, 90.57% and 95.92% respectively.

## 118 **4 Discussion**

119 The developed system functions as a novel method of using image processing and  
120 machine learning techniques for inspection and monitoring of structures. It presents a  
121 framework for matching elevation from drone image with the elevation from BIM  
122 model and then identifying the properties of each structural member. While past studies  
123 use image processing for crack detection or measurement, the developed framework  
124 goes a step forward and also predicts the severity of the cracks and recommends the  
125 corrective action to be taken.

126 The algorithms used for image-processing are simple, have fast execution speed  
127 and are fairly accurate. The algorithm transforms all the structural elements to a local  
128 scale so that all the elements are generalized and comparison among them is easier and  
129 more logical. For selecting the machine learning algorithm, eight different algorithms  
130 were evaluated and it was found that decision tree performs the best as the dataset was  
131 based on a set of predefined rules about crack severity. After the decision tree predicts  
132 the severity, a report was automatically generated with all information including the  
133 severity and the corrective action to be taken based on this severity.

134 Then the cracks were color coded in the original image as well as back into the  
135 BIM model based on their severity. A tag added to each element in the BIM model  
136 helps provide additional information about the damage and the corrective action to be  
137 taken for the maintenance of that element. The final output helps even a person with  
138 limited understanding of structural engineering or the behavioral mechanics of concrete  
139 easily visualize the current state of the structure. As each operation in the overall  
140 framework is written as a separate module, additional features can be easily upgraded  
141 to it. The overall system is expected to act as a state-of-the-art tool for automated  
142 building monitoring.

## 143 **5 Conclusions**

144 This paper presents a framework for the development of a fully automated image-based  
145 building inspection and monitoring system. It aims at overcoming the shortcomings of  
146 the traditional way of manual visual inspection. The main limitation of the system is  
147 that sometimes it may falsely detect marks or other disturbances as cracks. This could  
148 be overcome in the future by identifying and filtering those false detections using deep  
149 learning. The developed system is mostly suitable for buildings without glass façade or  
150 cladding on its surface. With inclusion of crack scenarios to account for other types of  
151 structures, the developed system can be modified to inspect cracks in structures other  
152 than buildings. Moreover, the same principle can be applied with slight modification to  
153 detect water leakage or for other forensic engineering applications. Using several case  
154 study images, it is demonstrated that the measurements done by the developed system  
155 is close to the actual field measurements. The system not only acts as a smart and  
156 convenient tool for structural inspection but also results in better operations, planning  
157 and facility management.

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