Stage 1 Report on

**”DRONES FOR INFRASTRUCTURE CRACK DETECTION”**

Submitted in partial fulfilment of the requirements of the degree of

Bachelor of Technology

(Information Technology)

By


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**CERTIFICATE**

This is to certify that Mr. Aditya Shenoy (161080036), Mr. Rahul Bhoir (161080063), Ms. Kalyani Borkar (171081990), and Ms. Rani Deore (171081993), students of Bachelor of Technology in Information Technology has successfully completed the report, entitled ”Drones for Infrastructure Crack Detection” to our satisfaction.

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**Date:** ____________________

**Place: VJTI, Mumbai**

## DECLARATION OF THE STUDENT

I declare that this written submission represents my ideas in my own words and where other's ideas or words have been included, I have adequately cited and referenced the original sources. I also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in my submission. I understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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## APPROVAL SHEET

The report entitled, **"Drones for Infrastructure Crack Detection"** submitted by Mr. Aditya Shenoy (161080036), Mr. Rahul Bhoir (161080063), Ms. Kalyani Borkar (171081990), and Ms. Rani Deore (171081993), is found to be satisfactory and is approved for the Degree of Bachelor of Technology in Information Technology.

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| **Project Guide** | **Examiner 1** | **Examiner 2** |

**Date:** ____________________

**Place: VJTI, Mumbai**

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## Abstract

Conventional crack detecting inspections of structures have been mainly based on visual investigation methods. Huge and tall structures such as cable bridges, high-rising towers, dams and industrial power plants are known to have their inaccessible areas and limitations in field inspection due to their geometry. In some cases, inspection of critical structural members is not possible due to their spatial constraints. With rapid technical development of Unmanned Aerial Vehicle (UAV), the limitation of conventional visual inspection could be overcome with advanced digital image processing technique. In this study, the crack detecting system using UAV and digital image processing techniques is developed for structural inspection.

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# 1 Introduction

Cracks are of major concern for ensuring the safety, durability, and serviceability of structures. This is because when cracks are developed and propagate, they tend to cause the reduction in the effective loading area which brings about the increase of stress and subsequently failure of the concrete or other structures. Since there always exists constraints in reinforced concrete structures and buildings being deteriorated overtime, cracking seems unavoidable and appears in all types of structures, for example, concrete wall, beam, slab, and brick walls. Particularly for concrete elements, cracks create access to harmful and corrosive chemicals to penetrate into the structure, which consequently damage their integrity as well as aesthetics.

Structural cracks in building can occur for various reasons, including repetitive loading, chemical reactions, faulty construction, structural factors such as design mistakes, and environmental factors. Such structural cracks greatly affect the load transfer capacity and durability of a structure, posing a substantial risk to its safety. It is therefore crucial to ensure the stability of a structure by detecting defects, analyzing their causes, and providing appropriate remedies. In general, regular safety inspection and maintenance/repair of structures are required by law, given their importance and associated risks.

Massive disaster and safety-accident have frequently occurred all over the world. Accordingly, interest in the safety inspection and maintenance of infrastructure facilities has soared. However, structure inspection and maintenance techniques applied until the present are time-consuming and expensive and there is a limit to that as the objectivity of the results can fall due to the subjective judgment of the inspector. The need for a system capable of inspecting and investigating the structure more efficiently and preventing a disaster promptly and obviously has emerged. This study presents the potential of technology used in the inspection and investigation of the structure by combining the drone (UAV) technology in progress of a recent breakthrough and study and digital image analysis techniques.

## 1.1 Conventional Method for Crack Detection

The main purpose of crack detection is to carry out the condition assessment of buildings before taking up repair and upgrading work. This will determine whether or not a distressed building should be demolished to build back better or whether it will be cost-effective to either repair or retrofit it, in the context of overall safety. Factors causing building distress are corrosion, cracking, and extreme loading conditions due to natural calamities.

### 1.1.1 Need of Crack Detection

- To record the damage if any, and find out the causes for distress
- To assess the extent of distress and to eliminate the residual strengths of structural components and the system including the foundation
- To plan the rehabilitation and retrofitting/strengthening of the building
- Identify the cause of building and infrastructure damage through comprehensive damage assessment
- Assess the most cost-effective solution with expert repair recommendations

### 1.1.2 Categories of Building according to Crack Detection

- The building has not shown any signs of distress and it satisfies all the safety and serviceability requirements according to relevant codes of practice, hence no action is needed towards retrofitting
- The building is seen to be deficient (or distressed) but it can be repaired and strengthened to satisfy the safety requirements or performance criteria set by the user
- The building is badly damaged. It is to be demolished and a new and better building may be built

For crack detection there are many methods. The methods depend on the type of material of the surface. Method for detecting crack in concrete is not applicable on iron crack and vice-versa. Below is a method for crack detection.

### 1.1.3 Rapid (Visual) Investigation

There are mainly three components and steps:

1. Collection of information and details about the building design, construction, utilization, and maintenance in the past
2. Visual inspection of condition at site and recording details of distress
3. Evaluation of safety against the provisions in building codes or specified performance criteria

### 1.1.4 Different testing used in this method

1. **Penetrant Testing:** Penetrant solution is applied to the surface of a pre-cleared component. The liquid is pulled into surface-breaking defects by capillary action.
2. **Magnetic Particle Testing:** A magnetic field is established in a component made from ferromagnetic material. The magnetic lines of force travel through the material, and exit and reenter the material at the poles. Defects such as crack or voids cannot support as much flux, and force some of the flux outside of the part. Magnetic particles distributed over the component will be attracted to areas of flux leakage and produce a visible indication.
3. **Ultrasonic Testing:** High frequency sound waves are sent into a material by use of a transducer. The sound waves travel through the material and are received by the same transducer or a second transducer. The amount of energy transmitted or received and the time the energy is received are analyzed to determine the presence of flaws. Changes in material thickness, and changes in material properties can also be measured.

## 1.2 Background

Here we provide a background summary of the technologies used in brief.

### 1.2.1 Machine Learning

Machine learning is an application of artificial intelligence (AI) that provides systems the ability to automatically learn and improve from experience without being explicitly programmed. Machine learning focuses on the development of computer programs that can access data and use it to learn themselves. The process of learning begins with observations or data, such as examples, direct experience, or instruction, in order to look for patterns in data and make better decisions in the future based on the examples that we provide. The primary aim is to allow the computers learn automatically without human intervention or assistance and adjust actions accordingly.

**Machine Learning Methods** Machine learning algorithms are often categorized as supervised or unsupervised.

- **Supervised machine learning algorithms** can apply what has been learned in the past to new data using labeled examples to predict future events. Starting from the analysis of a known training dataset, the learning algorithm produces an inferred function to make predictions about the output values. The system is able to provide targets for any new input after sufficient training. The learning algorithm can also compare its output with the correct, intended output and find errors in order to modify the model accordingly.
- In contrast, **unsupervised machine learning algorithms** are used when the information used to train is neither classified nor labeled. Unsupervised learning studies how systems can infer a function to describe a hidden structure from unlabeled data. The system does not figure out the right output, but it explores the data and can draw inferences from datasets to describe hidden structures from unlabeled data.
- **Semi-supervised machine learning algorithms** fall somewhere in between supervised and unsupervised learning, since they use both labeled and unlabeled data for training – typically a small amount of labeled data and a large amount of unlabeled data. The systems that use this method are able to considerably improve learning accuracy. Usually, semi-supervised learning is chosen when the acquired labeled data requires skilled and relevant resources in order to train it / learn from it. Otherwise, acquiring unlabeled data generally doesn't require additional resources.
- **Reinforcement machine learning algorithms** is a learning method that interacts with its environment by producing actions and discovers errors or rewards. Trial and error search and delayed reward are the most relevant characteristics of reinforcement learning.

This method allows machines and software agents to automatically determine the ideal behavior within a specific context in order to maximize its performance. Simple reward feedback is required for the agent to learn which action is best; this is known as the reinforcement signal.

#### 1.2.2 Drone Technology

A drone, in technological terms, is an unmanned aircraft. Drones are more formally known as unmanned aerial vehicles (UAVs) or unmanned aircraft systems (UASes). Essentially, a drone is a flying robot that can be remotely controlled or fly autonomously through software-controlled flight plans in their embedded systems, working in conjunction with onboard sensors and GPS. In the recent past, UAVs were most often associated with the military, where they were used initially for anti-aircraft target practice, intelligence gathering and then, more controversially, as weapons platforms. Drones are now also used in a wide range of civilian roles ranging from search and rescue, surveillance, traffic monitoring, weather monitoring and firefighting, to personal drones and business drone-based photography, as well as videography, agriculture and even delivery services.

## 1.3 Problems Faced by Conventional Method

**Human Error:** As the conventional process requires a human to go to the buildings and check the crack. Sometime it may happen that the entries made by the human are incorrect and may led to incorrect retrofitting and repair analysis.

**Height and geometry of the infrastructure:** Huge and tall structures such as cable bridges, high-rising towers, dams and industrial power plants are known to have their inaccessible areas and limitations in field inspection due to its geometry. Due to these limitations humans cannot reach each and every part of the infrastructure and detect crack in that part of the infrastructure.

## 1.4 Motivation

Massive disaster and safety-accident have frequently occurred all over the world. To prevent large scale damage on the infrastructures, preventive measures need to be taken by carrying out regular structural audit to check the strength of the infrastructures. This auditing is also required post disaster when assessment of the infrastructure damage is being done. We are helping in the automation of manual and error prone crack detection and crack width measurement process.

## 1.5 Problem Statement

The proposed system should be able to capture images of buildings using drones, which can be further processed for crack detection and crack width measurement, which are crucial components of structural audit and disaster assessment which will be useful in maintenance and rescue planning

## 1.6 Objective

- Regular infrastructure monitoring to find any damages in infrastructure
- Infrastructure damage scaling using crack detection on infrastructure
- Providing input to rescue team after disaster occurs so that they can plan the rescue mission
- Automatic testing methods to improve the testing efficiency
- Reduction of cost by using drones and machine learning models

## 1.7 Goals

- Reliable infrastructure monitoring and structural auditing
- Proper metrics to detect and measure cracks on infrastructure

- Helping post disaster rescue team by providing inputs
- Building better automation system for testing

# 2 Literature Review

## 2.1 Image-Based Crack Detection Using Crack Width Transform (CWT) Algorithm [1]

This paper proposed an algorithmic approach to detect cracks and measure its width. It has 5 steps: Crack Width Transform (CWT), Aspect Ratio Filtering, Crack Region Search, Hole Filling, and Relative Thresholding. In the Crack Width Transform, the pixels on the opposing edges of the cracks are found which satisfy the minimum width and contrast with background criteria. The Aspect Ratio Filtering step filters out those crack candidates which have lower aspect ratio as the length of the crack is generally much larger than its width. Crack Region Search step, then finds the inner region of the crack with the help of the identified crack edges. The Hole Filling step is applied so that irregular crack edges and regions can be made of regular shape. The final step of Relative Thresholding is used to reduce the number of False Positives that is caused due to Hole Filling step. The methodology used for crack width measurement can be used as a pre-processing step on the images of our data set so that the accuracy of our model can be increased and the width of the cracks can be accurately measured.

## 2.2 DeepCrack: Learning Hierarchical Convolutional Features for Crack Detection [2]

This paper proposed a machine learning approach to detect cracks in the images. It uses Seg-Net, which is a Convolutional Neural Network (CNN), with encoding and decoding network. The architecture used in this work is different than other Deep Convolutional Neural Network (DCNN) as it allows skip through edges which connects outputs of previous layers to further layers skipping some of the middle layers. Thus it combines the outputs of the low level features and high level features of the model to identify the crack in the image. We can look at the architecture idea presented in this work and deploy similar architecture in our machine learning model. We can also use convolution concept in the pre-processing stage.

## 2.3 Gap Analysis

The paper ”Image-Based Crack Detection Using Crack Width Transform (CWT) Algorithm” presented an approach to detect cracks and measure their width. But the width measured in this work is in the units of pixels and not actual physical unit of length like meters. Thus, we are trying to map this pixel scale of the image to the actual scale of physical unit by taking a reference point in the image with known physical length so that relative mapping of the crack width can be done.

The paper ”DeepCrack: Learning Hierarchical Convolutional Features for Crack Detection” uses modified Convolutional Neural Network (CNN). This work does not measure the crack width but only detects them. Hence we are making a neural network that can identify the cracks and measure the crack width as well. Our current plan does not require pure Convolutional Neural Network but only standard Neural Network.

# 3 Proposed System

The proposed system should be able to capture images of buildings using drones, which can be further processed for crack detection and crack width measurement, which are crucial components of structural audit and disaster assessment which will be useful in maintenance and rescue planning

## 3.1 Functions

- Drone would take images of the infrastructure.
- Cracks on these images would be detected using machine learning model.
- Position of the cracks would be reported.
- Crack width in actual physical measurement would also be reported.

## 3.2 Technology Stack/ Technology to be Used

### 3.2.1 DJI Mavic Mini

We have selected this drone as it is very light in weight (250 g). Its maximum flight time is 30 minutes which is very good for longer operation time. It can capture and transmit HD videos to receivers 4 km away from the drone. The GPS sensor installed in the drone is also sensitive and is reliable for operations in our project. The drone also has 3 axis gimbal 2.7K camera. It also has other supported features such as recording and editing.

### 3.2.2 Python

Python is an interpreted, high-level, general-purpose programming language. Created by Guido van Rossum and first released in 1991, Python's design philosophy emphasizes code readability with its notable use of significant whitespace. Its language constructs and object-oriented approach aim to help programmers write clear, logical code for small and large-scale projects. We will be using Python for communicating with drone interface, pre processing and machine learning modules available in Python.

#### 3.2.3 TensorFlow

TensorFlow is an end-to-end open source platform for machine learning. It has a comprehensive, flexible ecosystem of tools, libraries and community resources that lets researchers push the state-of-the-art in ML and developers easily build and deploy ML powered applications. We will be using TensorFlow to build our Neural Network architecture and train the model using its API.

### 3.3 General Schematics

#### 3.3.1 Block Diagram

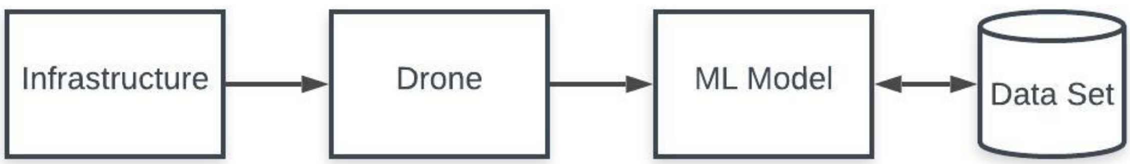



Figure 1: Block Diagram

The proposed system consists of 3 entities and data set. Figure 1 consists of a block diagram depicting those 3 entities and data set. The infrastructure is the building on which we are detecting and measuring cracks. The drone is used to capture images of the building and transmit it to the server. The ML model resides on the server which classifies the crack. This ML model is trained using data set, SDNET2018 Data Set [3] and Mendeley Data Set [4], containing crack images. The server also measures the width of the crack and locates its position.

### 3.3.2 Architecture

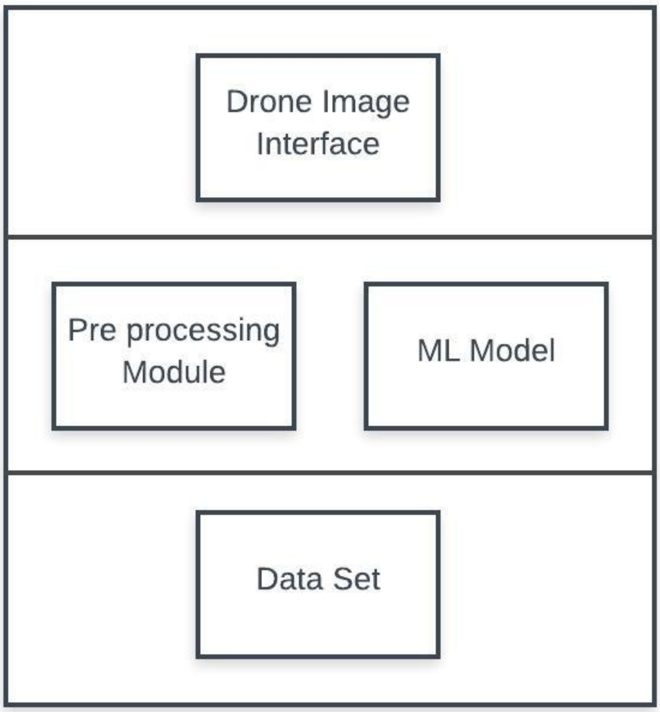



Figure 2: Architecture

The proposed system consists of 3 tiers in its architecture as shown in Figure 2. The upper tier is the interface layer which is responsible to communicate with the drone and collect captured images of infrastructure from it. The middle tier is where the processing will occur. It consists of pre-processing modules and ML model used for crack detection and measurement. The last tier consists of the data layer consisting of the data set with the help of which the ML model is trained.

### 3.3.3 Flow Chart

The working of our proposed system is illustrated in the Figure 3. At the beginning, human surveyor, who will be controlling the drone as well, will make a mark, whose physical length is known, on the wall of the infrastructure. This mark would be later used to map the crack width in pixels to actual physical dimensions. The drone will be flied around the infrastructure and its images would be captured in such a way that the crack and the human mark are in the same image. Then the captured images would be sent to the server.

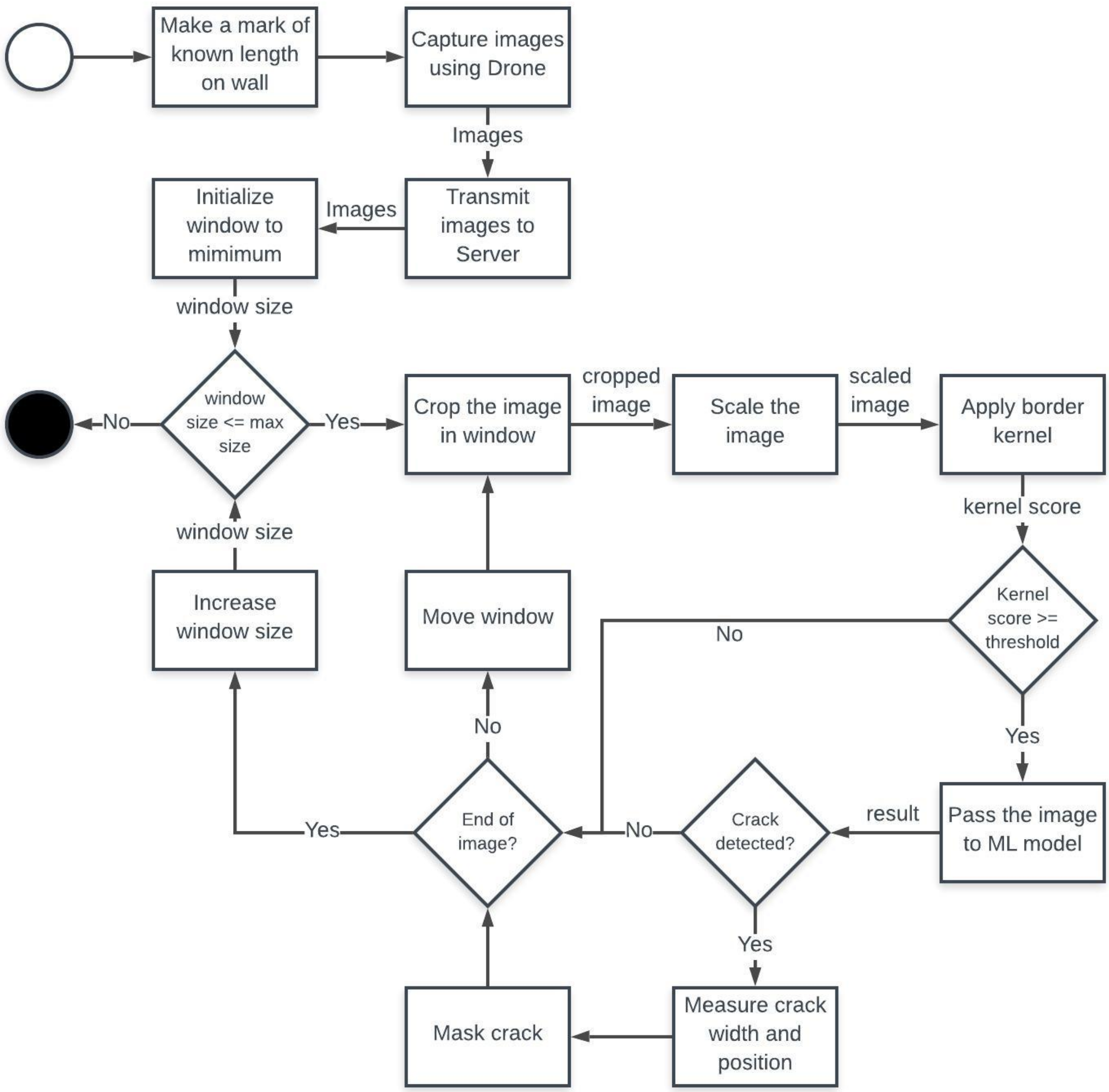



Figure 3: Flow Chart

The server will then initialize the window size to minimum. This minimum size would be defined by the minimum length of the crack that is worth being considered. This length would be mapped to the pixels by making use of the human mark as a relative scale. After this, a loop would be run until the maximum window size is being reached. This maximum window size can be the entire image. The window would start checking from top left corner. Then it will move left to right and top to bottom pixel by pixel. The image in the window would be cropped and scaled to match the dimensions that can be fed into the Neural Network.

The image would then be multiplied element wise to a kernel. This step is required to avoid parts of the bigger cracks being detected in the smaller window. This problem is illustrated in Figure 4a. The kernel is a simple kernel with 0's filled in the middle and a constant number filled in the border (say 1), refer Figure 4b. Then the kernel score would be calculated by summing the elements of the matrix that came as a result of the multiplication with the kernel. This kernel score would be high if there is no dark pixel in the border, i.e. the crack is not located on the border constraining it to be fully contained in the window. If the kernel score is greater than a threshold, then it is further processed else window is moved further.

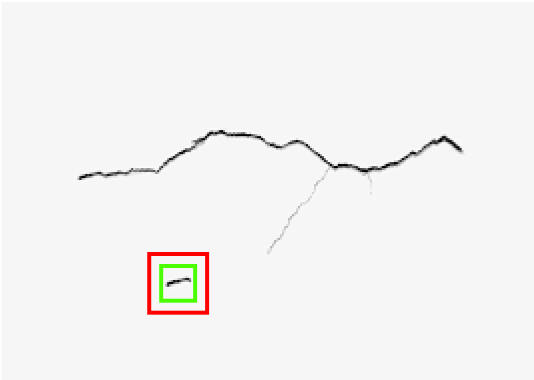
(a) Part of a big crack being detected in the smaller window

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |

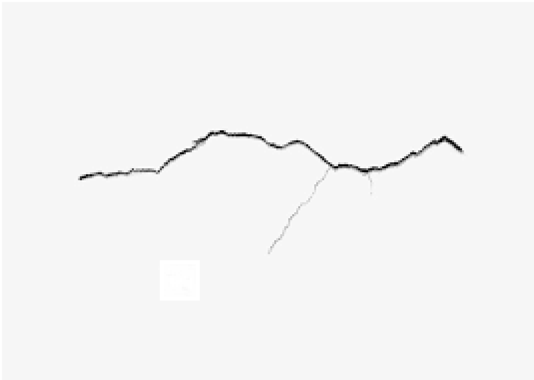
(b) Kernel with border constraints

Figure 4: Using kernel to avoid detection of parts of big crack

Then the original cropped and scaled image would be passed into the ML model. This ML model would already be trained using data set to detect whether the given image contains a crack or not. If the crack is detected, then the crack width and crack position on the wall would be reported in actual physical dimensions, by again making use of the human mark for relative scaling. This crack is then masked by pasting a white region, shown in Figure 5b. This step is necessary because, the same crack should not be detected in the bigger window frame in the next pass. This problem is illustrated in Figure 5a. Once the complete image has been traversed, the window size is increased and the image is traversed again until maximum window size, or image size whichever is smaller, is not reached.



(a) Small crack being detected multiple times



(b) Image after masking detected crack

Figure 5: Using masks to avoid detection of smaller cracks in larger window

After all this processing, a report would be generated which will contain the position of the cracks along with its width. This report can then be used in structural audit. The number of cracks in an infrastructure can be used to prioritize the buildings that needs precaution notice or post disaster recovery.

# 4 Future Aspects

1. To train and test the machine learning model
2. Configuration of drones for operation
3. Creating reports of infrastructure cracks
4. Creating user interface for accessing the report

# 5 Conclusion

By proposing the above system, we demonstrated an innovative approach of using Unmanned Aerial Vehicles (UAVs) and Machine Learning models to detect and locate the cracks on the infrastructure which can replace the current manual and error prone structural auditing process. We look forward to implement this system in the above proposed manner.

# References

[1] Hyunwoo Cho, Hyuk-Jin Yoon, and Ju-Yeong Jung, (2018), ”Image-Based Crack Detection Using Crack Width Transform (CWT) Algorithm”, Digital Object Identifier 10.1109/ACCESS.2018.2875889

[2] Qin Zou, Zheng Zhang, Qingquan Li, Xianbiao Qi, Qian Wang, and Song Wang, (2018), ”DeepCrack: Learning Hierarchical Convolutional Features for Crack Detection”, JOURNAL OF LATEX CLASS FILES, VOL. X, NO. X, FEB. 2018

[3] Maguire, Marc; Dorafshan, Sattar; and Thomas, Robert J., (2018), ”SDNET2018: A concrete crack image dataset for machine learning applications”.Browse all Datasets.Paper 48.

[4] Özgenel, Çağlar Fırat, (2019), “Concrete Crack Images for Classification”, Mendeley Data,v2