AUTOMATED DEFECTS DETECTION MODEL FOR IBS ELEMENTS CONSIDERING IR 4.0 APPLICATION ENVIRONMENT

ASHWYEIN A/L KUPUSAMY

CIVIL ENGINEERING

UNIVERSITI TEKNOLOGI PETRONAS

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by

Ashwyein A/L Kupusamy

16003361

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Universiti Teknologi PETRONAS

Bandar Seri Iskandar

32610

Perak Darul Ridzuan

CERTIFICATION OF APPROVAL

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16003361

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Approved by,

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(Dr Wesam Salah Alaloul)

UNIVERSITI TEKNOLOGI PETRONAS

SERI ISKANDAR, PERAK

January 2022

CERTIFICATION OF ORIGINALITY

This is to certify that I am responsible for the work submitted in this project, that the original work is my own except as specified in the references and acknowledgements, and that the original work contained herein have not been undertaken or done by unspecified sources or persons.

ASHWYEIN A/L KUPUSAMY

ABSTRACT

One of the most important jobs in construction industry is the quality inspection of the concrete elements. It is important to inspect the defects and plan a solution to tackle it before it can lead to time, and cost overrun. Quality and defect inspections are now mostly reliant on daily manual inspections. This approach has several drawbacks, including tediousness and mistake during the examination. As the implementation of IR 4.0 applications in other industries are improving, it should be widely used in construction industry too. Its goal is to change how we live, work, and communicate, as well as what we value and how we value it in the future. IR 4.0 is mainly used to automate procedures as it is related to artificial intelligence. In this study, it is planned to make the defects detection process automated considering IR 4.0 environment. Defect detection with automated technologies, on the other hand, is quick and accurate. By making this improvement and implementation, engineers can easily find out the defects present on IBS elements. The main goal of this project is to minimize the dependency on engineers to spot the defects on IBS elements. This can bring the construction industry to another level due to the automation applied.

ACKNOWLEDGEMENTS

First and foremost, I want to convey my thanks to Universiti Teknologi PETRONAS (UTP), for nurturing me over the last five years. The information and skills I gained during these years improved my research and writing abilities, allowing me to complete a research project that I thought may benefit the construction industry.

In addition, I would like to thank Dr. Wesam, my Final Year Project supervisor, for mentoring me and providing important advice throughout my FYP journey. Moreover, I would also want to express my gratitude to Mr. Abdul Hannan for always assisting me in the FYP whenever I had an issue or difficulty.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

1.1 Background Study

Defect detection is important in construction industry. In construction sector, works will be inspected as it progresses to ensure that it complies with the contract documents' criteria. On major projects, separate site inspectors for mechanical and electrical services, structural work, and architectural work may be necessary.

The construction industry is always expanding to better serve consumers. Ways to improve the building business at a lower cost and with higher quality are always being discovered. In research from (Alaloul et al., 2018), it is known that the construction sector has lagged in terms of technological innovation when compared to a range of other industries. As a result, technological developments have been insufficient and unimproved.

Conventionally, most of the construction organization uses manual inspection method. For example, the QAQC engineers will visually inspect the concrete elements and record the defects such as cracks, blisters, honeycomb, pinholes and many more. Then, the design engineers and workers will work to fix the defects. However, this method has several limitations such as time-consuming and less accuracy (Bartel, 2001).

Moreover, manual defect inspection is based on the experience of the inspectors (Yang et al., 2015). Construction workers rely substantially on specific skills, practise, technical preparation, and judgement based on experience, all of which are exceedingly difficult to automate. This can cause the design engineers to wrongly interpret the data collected and plan a wrong solution to solve the defects. Thus, this will increase the time and resources of the company.

Certain construction processes can be automated. As technology progresses, jobs with these three traits are more likely to be automated. Those traits are the jobs must be repetitive, based on rules and require physicality that is confined or well-defined. According to these traits, the IBS elements defects detection can be automated because it is based on rules.

In the 21st century, cyber-physical systems are being tried in a variety of areas. Combining digital and physical systems to automate and artificially intelligent things is what a cyber-physical system is all about. With the development of information technology and the consistent advancement of technology, a significant improvement in the construction industry has developed, and that invention is automated defect detection considering IR 4.0 environment. In 2011, the concept of the Fourth Industrial Revolution (4IR) or Industrial Revolution 4.0 (IR 4.0) was born (Alaloul et al., 2018).

Automated defect detection is a process that uses data collecting technologies, computer software, and algorithms to detect the defects present in concrete. Several researchers have begun the process of automating traditional defect detection method, which has significant limitations. This method was created to increase the accuracy of defect detection while reducing human participation.

1.2 Problem Statement

In this research, IR 4.0 application is used to detect the defects on the IBS elements. When compared to other industries, the construction industry is sluggish to implement current technology into its current methods, despite other industries' quick advancements (Alaloul et al., 2018).

The construction sectors' previous approach for detecting defects was time-consuming and energy intensive (Bartel, 2001). To achieve the desired outcome, the procedure demands the collaboration of several parties. If the person is busy or preoccupied with other tasks, it may cause a delay.

By visually inspecting the IBS elements, the engineers manually check for defects. After the production engineers have completed the IBS elements, the QAQC engineers will inspect the IBS elements that have been built by comparing them to the manufacturing drawing. So, manual inspection has restrictions because it mainly relies on the inspector's personal experience and knowledge to understand evaluation criteria, it frequently leads to a subjective judgement (Yu et al. 2007). Human error occurs because of human limits or negligence. QAQC engineers may miss small fracture lines and other minor faults during the quality and defect inspection of IBS panels.

1.3 Research Objective

There are 3 objectives in this research, which are:

- To reduce human errors of defects detection for IBS elements.
- To conduct faster detection of defects in IBS elements.
- To develop a data recording tool for defects in IBS elements.

1.4 Scope of Work

The goal of this research is to use IR 4.0 environment to make defect detection automated. Thus, minimizing the dependency on engineers to spot the defects on IBS elements. This study will focus on IBS elements. Technologies such as video-based, audio-based, laser-based methods are compared to find out the factors affecting the defect detection method.

CHAPTER 2

LITERATURE REVIEW

This chapter summarizes the research on automated defect detection approaches and processes. Between 2014 and 2022, a total of 50 papers were gathered. Scopus, Web of Science, and Science Direct were the three research databases used to find the papers. In the search, the terms ‘automatic defect detection,’ ‘concrete cracks,’ and ‘types of cracks’ were utilised.

2.1 Shapes of Cracks in IBS Elements

In research from Ying et al. (2020), based on their shape and direction, concrete cracks are classified into four types. Those are corner cracks, transverse cracks, longitudinal cracks, and crushing plates. There are two types of crushing plates, which are cross crack and parallel crack.

- Corner Crack

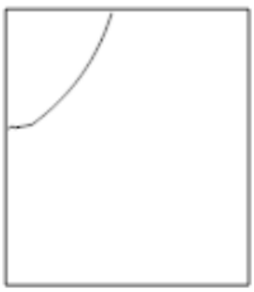


FIGURE 2.1: Corner Crack

The figure 2.1 above shows the corner crack. The crack appears at the corner of the cement slab, and it is less than half the length of the slab where it intersects the edge.

- Transverse Crack

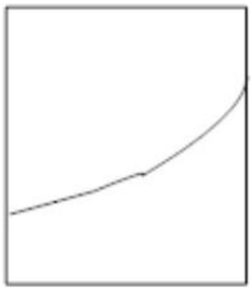


FIGURE 2.2: Transverse Crack

The figure 2.2 shows transverse crack. This narrow crack travels across the cement panel.

- Longitudinal Crack

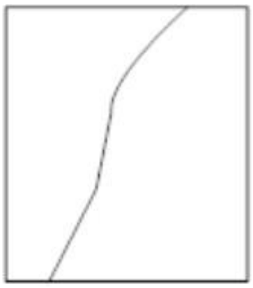


FIGURE 2.3: Longitudinal Crack

The figure 2.3 shows longitudinal crack. This single crack run through the cement panel.

- Crushing Plates

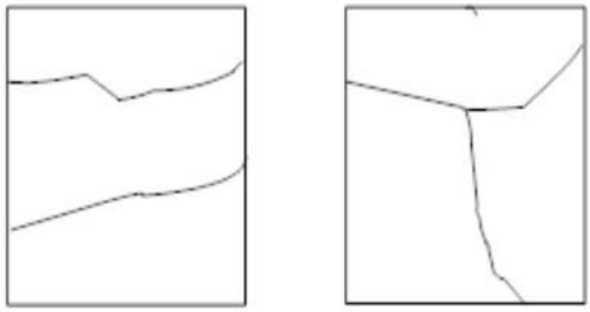


FIGURE 2.4: Crushing Plates

The figure 2.4 shows crushing plates. On the same cement panel, there are two or more cracks. There are two basic types of cracks: one is the intersection of the cracks, and the other is the approximately parallel cracks. The more complicated scenario is when there are both parallel and cross cracks.

2.2 Types and Causes of Cracks in Concrete Cracks

Concrete cracks develop for a variety of reasons, and their performance varies greatly depending on the structure. Figure 2.5 below shows a crack and its width. In this research, based on the article by (Pan & Pi, 2018) it is believed that that temperature cracks, shrinkage cracks, settlement cracks, load fractures, and construction cracks are the most common types of cracks in concrete structures.

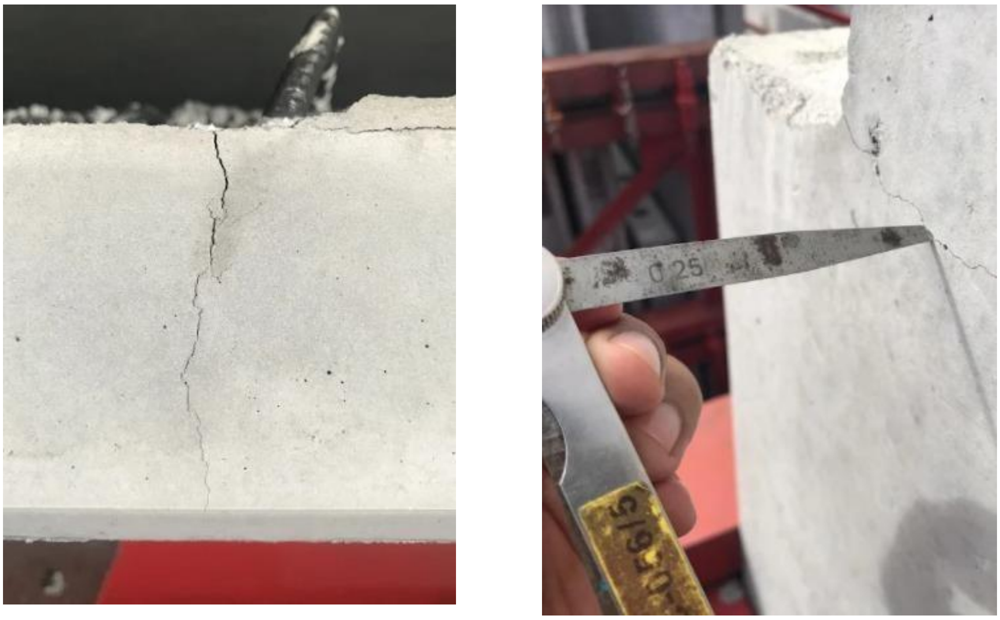


FIGURE 2.5: Images Showing a Crack and Width

- Shrinkage cracks

Dry shrinkage cracks and plastic shrinkage cracks are the two forms of shrinkage cracks. The variable degree of evaporation of water inside and outside the concrete create dry shrinkage cracks (Pan & Pi, 2018). They're frequently shaped by hairline fractures on the component's surface or cracks that are thin at both end and wide in the middle (often between two bars and parallel to the bars). Shrinkage stress surpassing concrete's ultimate tensile strength owing to high temperature or high wind force causes plastic shrinkage cracks.

- Temperature Cracks

Temperature cracks are more visible in mass concrete constructions, and they are often deeper or even penetrating, causing significant structural damage. The crack direction is mainly perpendicular to the long side for a member whose dimension in one direction is much larger than that in the other two directions, and the cracks appear along the full-length section, with the middle dense; for a large-volume (three-dimensional) structure, there is no obvious law of cracks (Pan & Pi, 2018). Along the whole length of the crack, the crack width does not alter substantially. Temperature changes have a greater impact on crack width. For example, cracks are broader in the winter and narrower in the summer.

- Load Cracks

This type of crack is more complicated and complex. Load cracks have different characteristics depending on the loads they are subjected to. All types of stress forms, including tension, compression, bending, shear, and torsion, can theoretically cause equivalent crack forms (Pan & Pi, 2018). However, load cracks tend to emerge more in the tension zone, eccentric compression zone (bending zone), shear zone, or regions with higher cyclic load. For example, central tension cracks penetrate the cross section of the member and are perpendicular to the stress direction; the bending area or large eccentric compression area generally appears cracks perpendicular to the tension direction starting from the edge near the maximum bending moment section and gradually develop to the neutral direction; the shear area may develop oblique compression failure. When the centre compression is excessively large, short, and thick cracks parallel to the stress direction may form.

- Construction Cracks

Construction cracks are cracks in concrete structures produced by improper construction technique, incorrect sequencing, or poor building quality during the pouring, fabrication, formwork support, transporting, lifting, and other construction processes (Pan & Pi, 2018). Surface or shallow cracks easily caused by improper early curing of concrete. Cracks perpendicular to the stressed steel bar may be formed by surface pollution, too small or too large protective layer. Moreover, lack of stiffness of the formwork during construction causes deformation, which is easy to form cracks consistent with the deformation of the formwork.

- Settlement Cracks

This type of cracks is caused by the foundation's uneven settlement. It comes in a variety of shapes, some of which are continually changing, and the crack width is often different, ranging from a few centimetres to several metres. According to their stress shapes, fractures are classified as shear cracks or flexural cracks (Pan & Pi, 2018). The eight-character form fractures and oblique cracks on the wall are the most common cracks. Settlement cracks are more common in the lower portion of the structure, and the fractures on the bottom are larger than those on the top.

2.3 Crack Detection Using Vision – Based Method

Cracks in the concrete surface are one of the first signs of mechanical damage, which is important for maintenance and will cause severe environmental damage if left unattended. The most often used approach for crack inspection is manual inspection. In a manual examination, a sketch of the crack is drawn by hand, and the irregularities' conditions are noted. The manual approach lacks impartiality in quantitative analysis because it is entirely dependent on the specialist's expertise and experience. In this research by Mohan and Poobal (2018), an alternative is proposed: automatic image-based fracture detection. Using image processing techniques, numerous techniques are presented in the literature to automatically identify the fracture and its depth.

The figure 2.6 below shows a crack detection system based on digital image processing technology, which has been proposed by Yiyang et al. They were able to gather information about the crack image using pre-processing, image segmentation, and feature extraction. After smoothing the acceptable input image, the threshold approach of segmentation was utilized. They estimated the size and perimeter of the roundness index to rate their image. They then assessed the presence of the crack in the image using the comparison.

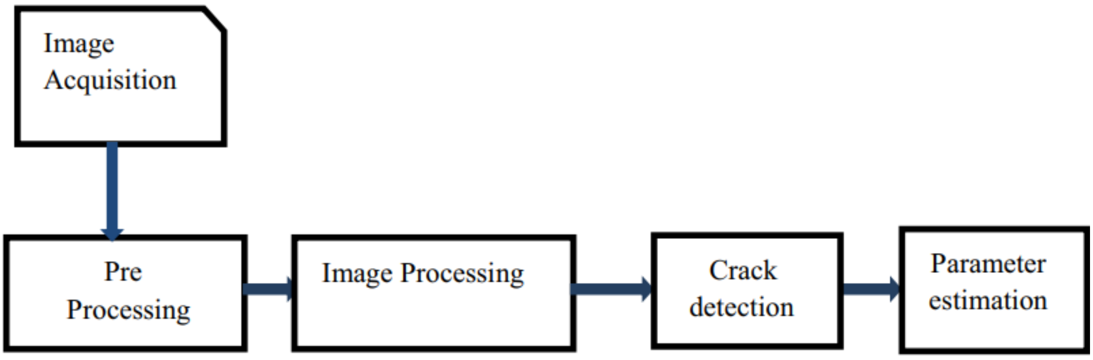


FIGURE 2.6: The process of crack detection using vision-based method

For crack detection using high contrast images, Iyer et al. (2005) devised a three-step technique. Using curvature evaluation and mathematical morphology techniques, the suggested method recognises a crack-like structure in a noisy environment. It recognises crack-like features in a noisy environment using mathematical morphology and curvature evaluation. Segmentation is done in their work by defining the crack-like pattern in relation to a precise geometric model. After evaluating cross curvature, linear filtering was used to separate them from a similar background pattern. They used geometry-based recognition crack features to progressively identify the abnormality.

The image processing scheme's filtering Procedures have an impact on the overall efficiency of the operation. Based on the Gabor filtering, Salman et al. (2013) suggested a way to automatically distinguish fractures in digital photographs. A high potential Gabor filter may identify cracks in multiple directions. The Gabor filter is a promising approach for detecting multidirectional cracks. The manual visual perception was directly tied to the image processing of the Gabor filter function. Following the completion of the filtering, the cracks aligned in opposite orientations are recognised. They claim that their proposed approach has a detection precision of 95%.

Talab et al. (2016) developed an innovative image processing method for detecting cracks in concrete structure pictures. There are three steps to this methodology: To detect fractures, first convert the image to grayscale using the image's edge, and then apply Sobel's approach to generate an image using Sobel's filter. The pixels are then classified into foreground and background images using a suitable threshold binary image of the pixel. Sobel's filtering was employed to remove remaining noise once the photos had been classified. Cracks were found utilising the otsu's method after a thorough picture filtering operation. In some circumstances, the sober filter has been replaced by multiple median filtering. A percolation-based crack detecting technique has been developed by Yamaguchi et al. (2010). They were able to achieve their reduced computation time by modifying the termination and skip add techniques. They feature a fast percolation technique that uses surrounding pixels based on the circularity of the pixel requirements. Because matching in percolation images was straightforward to examine, the template matching technique was crucial to their percolation proposal.

2.4 Crack Detection Using Audio – Based Method

This section looks at how ultrasonic image processing can be used to locate cracks in engineering constructions. Ultrasonic sound can also be utilised to identify surface cracks with conceptual crack feature extraction, in addition to the ultrasonic imaging system.

Shirahata et al. (2014) suggested a methodology for using an ultrasonic non-destructive test to distinguish between fatigue cracks. They've created ultrasonic testing systems with a tandem array that can identify incomplete penetration. The reflected wave at the partial penetration and the bottom of the asymmetry structure was detected by the transducer utilised in the tandem array (Crack origin). The multi synthetic aperture focusing approach image reconstruction system was created to study the crack tip closure and opening, which are particularly noticeable for longer cracks.

Wolf et al. (2015) have introduced a detection system that uses the ability of integrated ultrasonic sensors to locate propagating cracks within a concrete structure before they become present on the exterior. Due to the sensors' continual connection to the medium, they used extremely complex data processing techniques, such as the correlation between signals and their attenuation, to detect changes in the signal caused by propagating fractures. The implanted ultrasonic sensor was utilised to track the development of large cracks in concrete elements near the transmitted ultrasonic waves. Non-destructive testing methods such as acoustic emission and Digital Image Correlation were used to assess the accuracy of the identified crack initiation.

Iliopoulos et al. (2015) suggested a crack detection system that uses Digital Image Correlation, Acoustic Emission, and Ultrasonic Pulse Velocity techniques all at the same time. The findings of the procedures used reveal the crack's timing and location. Using the AE analysis, they have highlighted the severity of the cracks. Since it can cross over the grey image with the initial picture, the image processing was done utilising the matrix detection approach. Based on the GLCM texture analysis technique and an ANN classifier, Kabir et al. suggested a detection system. Using an ANN classifier, they were able to gather exterior damage report such as total amount of surface cracking, breadth, and length. Thermographic, visual colour, and grey scale photographs of concrete blocks were used to test these approaches.

Ganpatye et al. (2006) have created a detection matrix for ultrasonic testing detection. The ultrasonic data was initially collected over the specimen. The data was then compared to results acquired using more traditional methods such as optical microscopy. Their findings demonstrate a strong link between the comparisons. They discovered matrix fractures using the ultrasonic back scattering method, which are grey-scale representations rather than optical pictures as in photography.

2.5 Crack Detection Using Laser – Based Method

This section discusses the approach for detecting fractures in buildings utilising a laser image in conjunction with an image processing technique.

Mostafa Rabah et al. (2013) suggested a crack recognition system with a high-level three-dimensional resolution imaging capabilities and a great capability for measuring three-dimensional space using laser scanning. Due to the combined action of data collecting and data synthesis, the suggested design has a higher potential. Three stages were taken to accomplish the task of fracture identification and mapping: shading correction, crack detection, and crack mapping. They defined the fracture in terms of a pixel coordinate system. After completing the definition, reverse engineering was used to remap the crack into the referenced coordinate system. This was accomplished by combining terrestrial laser-scanner point clouds with the associated camera picture, such as converting the pixel coordinate system to the terrestrial laser-scanner or global coordinate system.

Sun et al. (2012) have developed a laser-based three-dimensional fracture detecting system. The sparse description was created to breakdown the profile signal into the sum of the cracks and the main profile (MP). Once the flaws were identified, they developed a mixed dictionary. A mixed dictionary was developed using an exponential function and a trapezoidal membership function that are both overcomplete. They used a matching pursuit technique to compare the sparse representation. The wavelet and median filtering methods were used to verify the comparison’s efficacy. To demonstrate the method’s efficiency, they created a simulation signal with the principal profile. The usage of the laser as a source, on the other hand, may get implicated in the crack discrimination.

Nazaryan et al. (2013) used a measuring approach to create a novel method for crack identification on completed surfaces. They calculated the fracture features using the centroid approach as a mathematical procedure. Their findings indicated a high degree of correlation between computed values. Their inquiry produced an enticing outcome thanks to the use of CCD technology and a modified laser beam.

2.6 Summary

There are many shapes of cracks in IBS elements such as corner cracks, transverse cracks, longitudinal cracks, and crushing plates. Besides that, there are also many types of cracks such as temperature cracks, shrinkage cracks, settlement cracks, load fractures, and construction cracks. Over these years, there are some researchers that proposed some methods to detect defects in concrete structures. In this study, 3 main methods are chosen, which are vision-based, audio-based, and laser-based method.

CHAPTER 3

METHODOLOGY

This chapter discusses the methodology used for this research. Brainstorming was done to choose the suitable methodology to accomplish the objectives of this research. The methodologies planned have three stages.

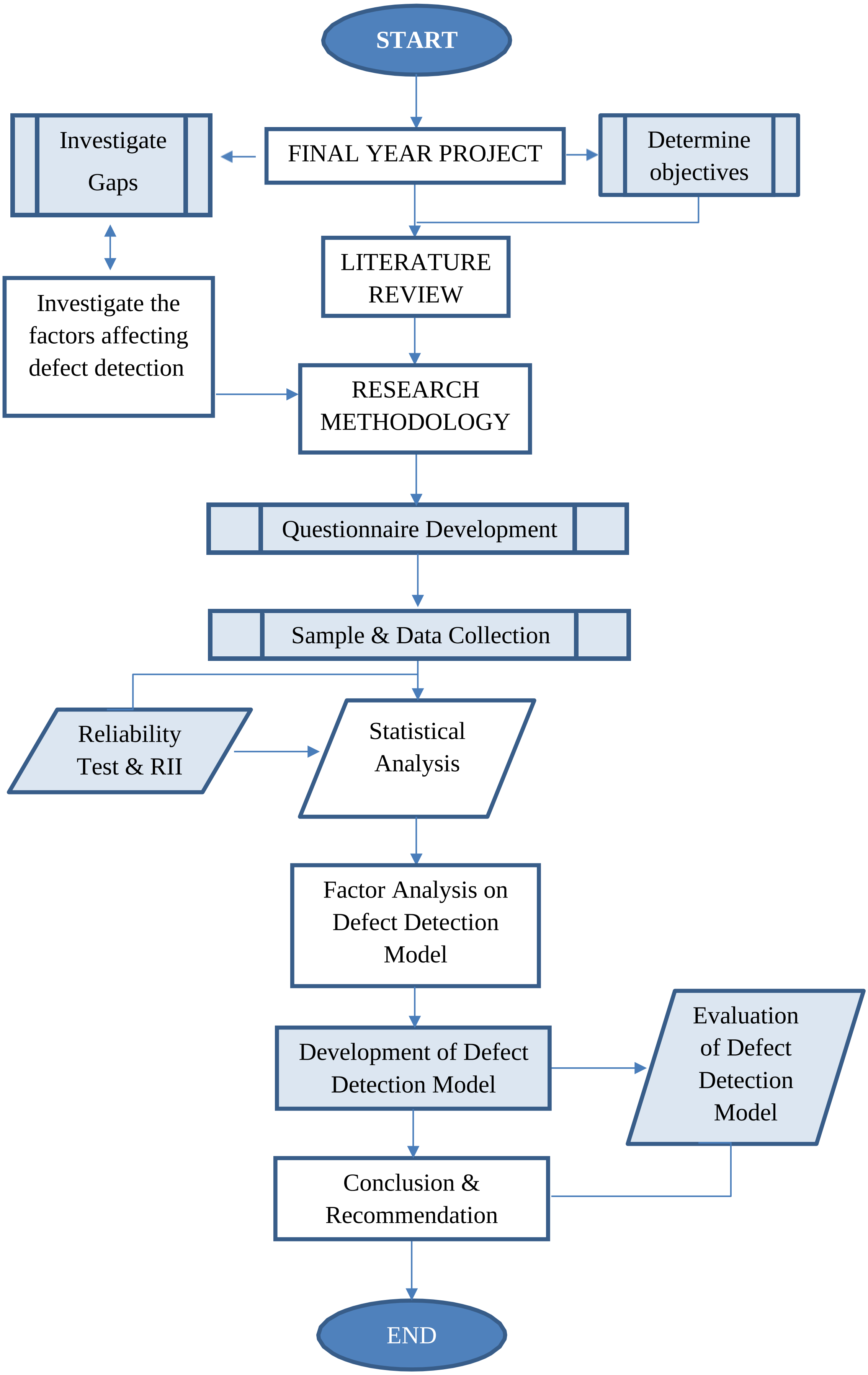
3.1 Description of Methodology

To accomplish the objectives of this project, the process is separated into three steps: the first and second stages involved data collection and analysis. The last stage involved the research output. Each stage is detailed in depth below:

- 1st stage: Detailed literature review
- 2nd stage: Quantitative survey
- 3rd stage: Defect detection model

Additionally, the Figure 3.1 below illustrates the study approach using a flowchart.

FIGURE 3.1: Project Work Flowchart



3.2 Detailed Literature Review

A comprehensive study of the literature on automated defect detection in concrete structures was done, which aid in the comprehension of the research. In the past, exploratory study has been conducted in the literature. Many papers were discovered to be connected in the main three research databases: “Web of Science,” “Scopus,” and “Science Direct”. After a thorough screening, the number of linked research was decreased to 50 articles, and a total of 14 factors affecting automated defects detection were identified in the prior literature.

3.3 Quantitative Survey

On the analysis of earlier efforts, a questionnaire survey was built based on the content analysis outcomes. The survey was broken into three parts, which are shown below.

- Section A: Demographic profile
- Section B: Basic questions about cracks
- Section C: Factors affecting vision, audio, and laser – based method

The section A in this questionnaire survey discuss about the background of the respondents. The survey respondents represent all participants in the construction sector, including contractors, consultants, developers, government agencies, non-government organisations, and institutions. The section B discuss about common questions about cracks in IBS elements and suggested automated defect detection method. In the section C, a Likert scale of 1 to 5 was used to discuss about the factors affecting those automated defect detection methods.

3.3.1 Sampling

The respondents for this survey were contractors and staff registered with the Construction Industry Development Board (CIDB). According to the CIDB website, there are total of 130635 of contractors were registered. Thus, the following equation (1) was used to determine the sample size for a population of 130635 with an accuracy level of 10% (Israel,2003).

$$n = \frac{N}{1 + N(e)^2} \tag{1}$$

where "N" represents the population size, "e" represents the level of accuracy, and "n" is the sample size. The minimum sample size required by the equation was 100, and this study generated a total sample size of 104, which meets the minimal sample size requirement.

3.3.2 Statistical Analysis

Cronbach alpha analysis

IBM SPSS Statistics 28 was used to evaluate the outcomes gathered from the quantitative survey. The Cronbach alpha was calculated to find out the reliability of the data collected.

Relative Importance Index (RII)

The quantitative survey results were analysed using IBM SPSS 26. Following that, statistical evaluation was done on the acquired outcomes to determine the data's consistency, descriptive analysis was performed, and the Relative Importance Index (RII) for each aspect was generated. The following equation (2) was used to calculate the importance index (El-Sawalhi & Hammad, 2015).

$$\textbf{Relative Importance Index (RII)} = \frac{\Sigma W}{AN} = \frac{5n_1+4n_2+3n_3+2n_4+1n_5}{5N} \qquad (2)$$

3.4 Development of Defect Detection Model

To develop the defect detection model, PyCharm and Anaconda3 environment were used. These applications were used to code the detection model. PyCharm is a computer programming integrated development environment that focuses on the Python programming language. Anaconda3 is a collection of over 7,500 open-source programmes that includes a package manager, an environment manager, a Python/R data science distribution, and a package manager.

CHAPTER 4

RESULTS AND DISCUSSION

In this chapter, the result of the statistical analysis from the quantitative survey will be analysed and discussed. Then, the result of defect detection model will be presented.

4.1 Demographic Details

The questionnaire survey was performed with the construction related individuals in Malaysia. There were nearly 950 emails delivered to all the listed Construction Industry Development Board (CIDB) members in the CIDB online page. There were 104 comebacks, which was sufficient according to the sampling calculation. Figure below shows the demographic profile of those participants.

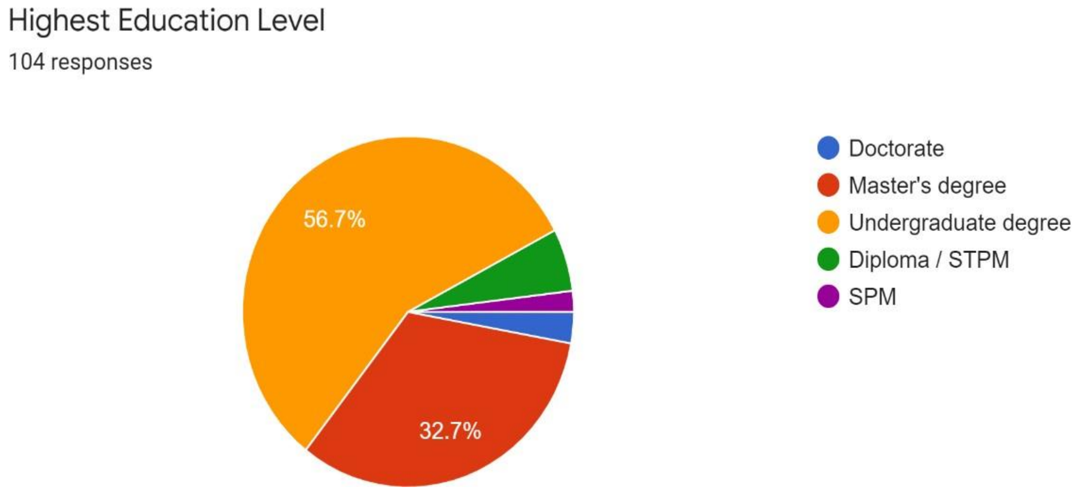


FIGURE 4.1: Highest Education Level of the respondents

The Figure 4.1 above shows highest education level of the respondents. Among the 104 respondents, the most respondents have undergraduate degree. 56.7% (59 out of 104) have undergraduate degree. Then, 32.7% (34 out of 104) obtained master's degree and 5.8% (6 out of 104) obtained diploma or STPM. 2.9% (3 out of 104) obtained the highest education, which is Doctorate, PhD. Finally, 1.9% (2 out of 104) have SPM certificate only.

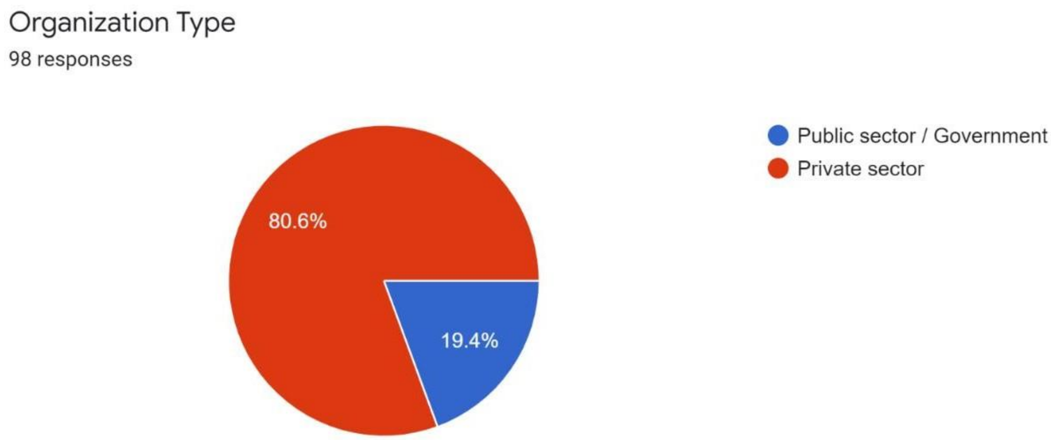


FIGURE 4.2: Organization Type of the respondents

The Figure 4.2 above shows the type of organization of the respondents of the questionnaire survey. Only 94 respondents have answerred this because some of the respondents are academician and some of them prefer not to mention about their workplace. 80.6% (79 out of 94) are working in private sectors such as Sunway, Gamuda, IJM, Guocoland and other organizations. 19.4% (19 out of 94) are working in public sector such as Jabatan Kerja Raya (JKR).

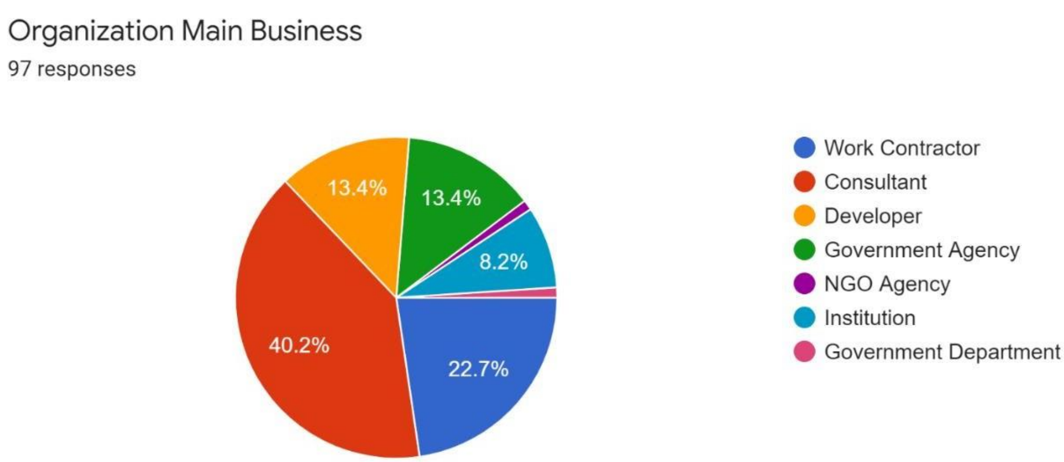


FIGURE 4.3: Organization Main Business of the respondents

The Figure 4.3 above shows the main business of the organization of the respondents. Most of the respondents' organization main business is consultant. 40.4% (39 out of 97) are from consultant companies. A building consultant is a specialist who assists, in both general and specialised activities, to secure a desirable outcome for the management of a building. Besides that, there are 22.7% (22 out of 97) respondents' organization main business is work contractor. 13.4% (13 out of 97) are from developer and government agency organization. 8.2% (8 out of 97) respondents are working at institution.

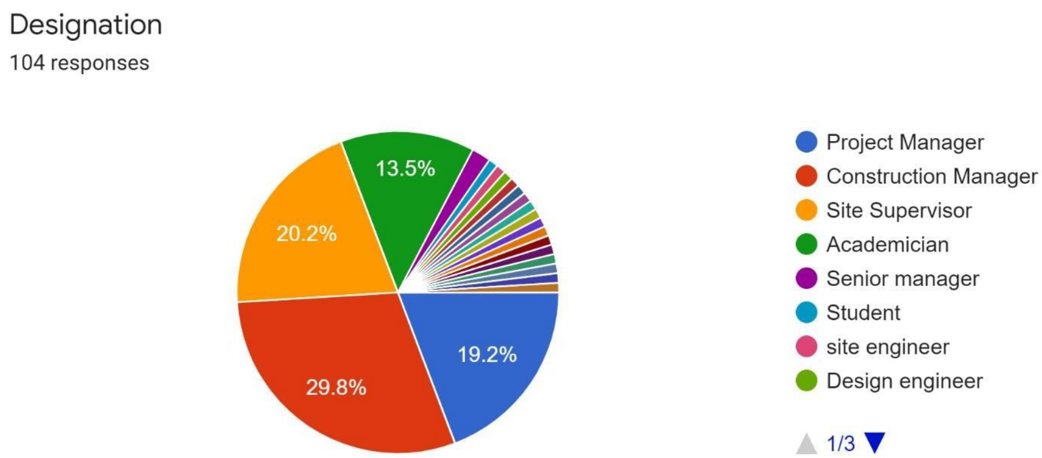


FIGURE 4.4: Designation of the respondents

The Figure 4.4 above shows the designation of the respondents. Most of the respondents are working as construction manager. 29.8% (31 out of 104) are working as construction manager in their company and 20.2% (21 out of 104) are working as site supervisor. Moreover, 19.2% (20 out of 104) are working as project manager and 13.5% (14 out of 104) are academician. There is also other designation filled up by the respondents such as design engineers, QAQC, lecturer and structural engineers.

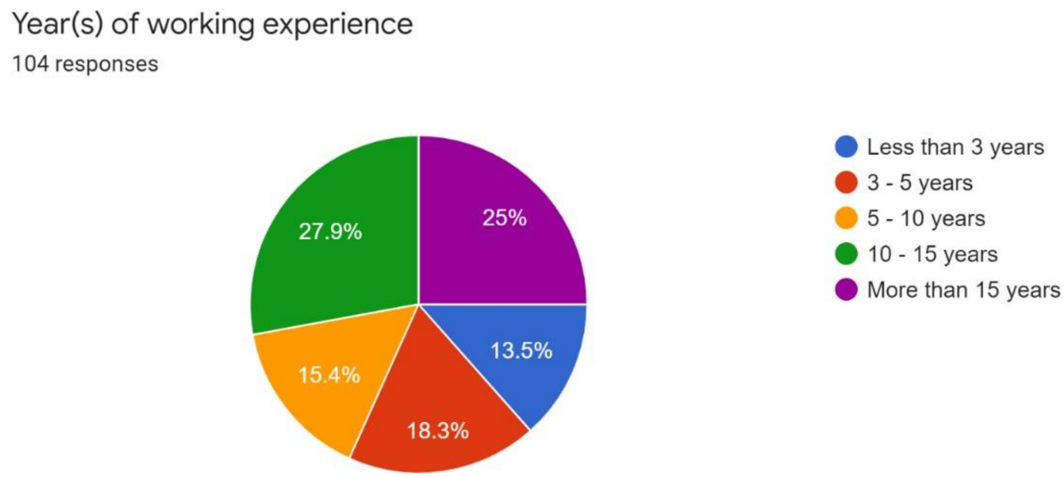


FIGURE 4.5: Years of Working Experience of the respondents

The Figure 4.5 above shows the working experience of the respondents. Most of the respondents have a working experience from 10 to 15 years. 27.9% (29 out of 104) have working experience of 10 to 15 years. 25% (26 out of 104) have more than 15 years working experience and 18.3% (19 out of 104) have 3 to 5 years of working experience. 15.4% (16 out of 104) have 5 to 10 years of experience while, 13.5% (14 out of 104) have less than 3 years of experience.

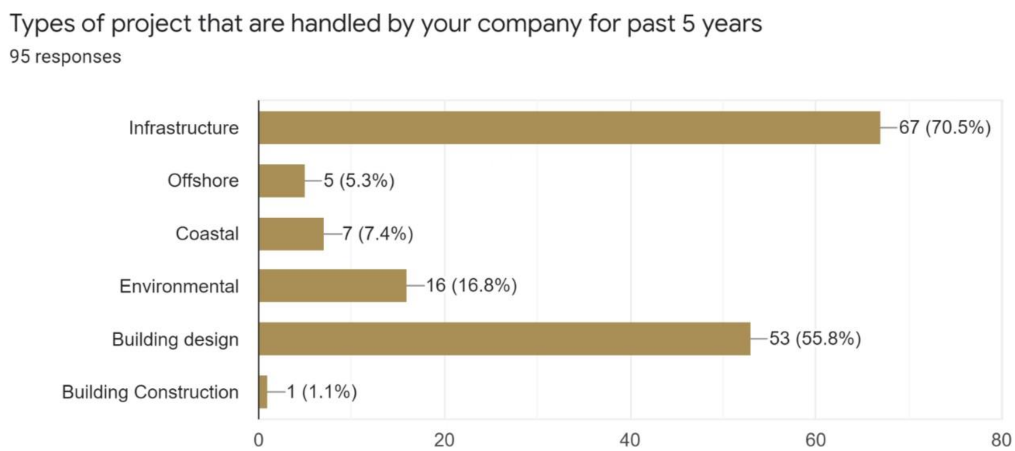


FIGURE 4.6: Types of the projects handled by the company of the respondents

The Figure 4.6 above shows the types of the projects handled by the respondents' company. Some of the respondents' company handles multiple projects. Most of the company handles infrastructure and building design projects. There are also some companies handling offshore, coastal, and environmental projects.

4.2 General Crack Inquiry Report

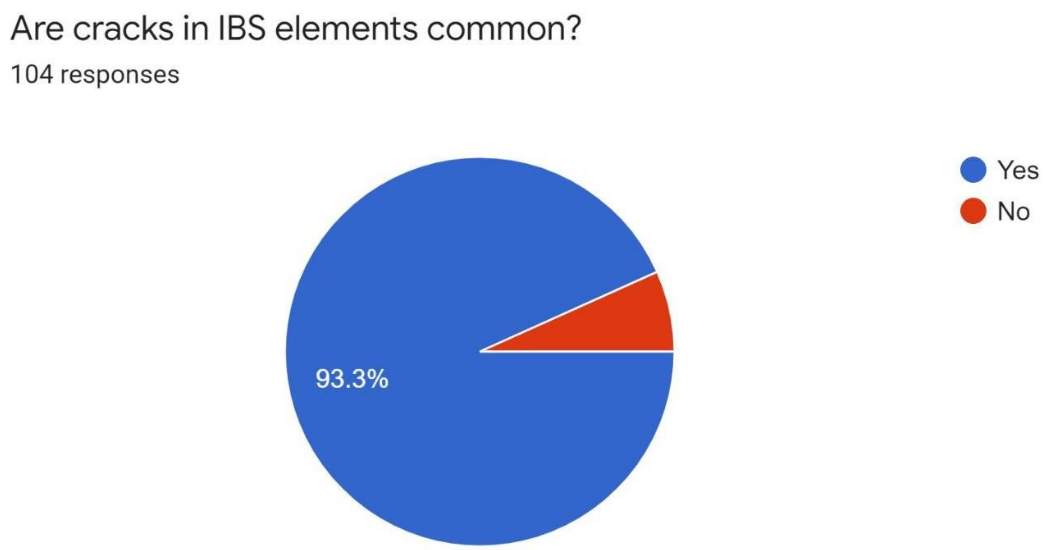


FIGURE 4.7: The frequentness of cracks in IBS elements

The Figure 4.7 above shows the commonness of cracks in IBS elements. 93.3% (97 out of 104) respondents agree that cracks are common in concrete while, 6.7% (7 out of 104) respondents chose cracks are not common in concrete.

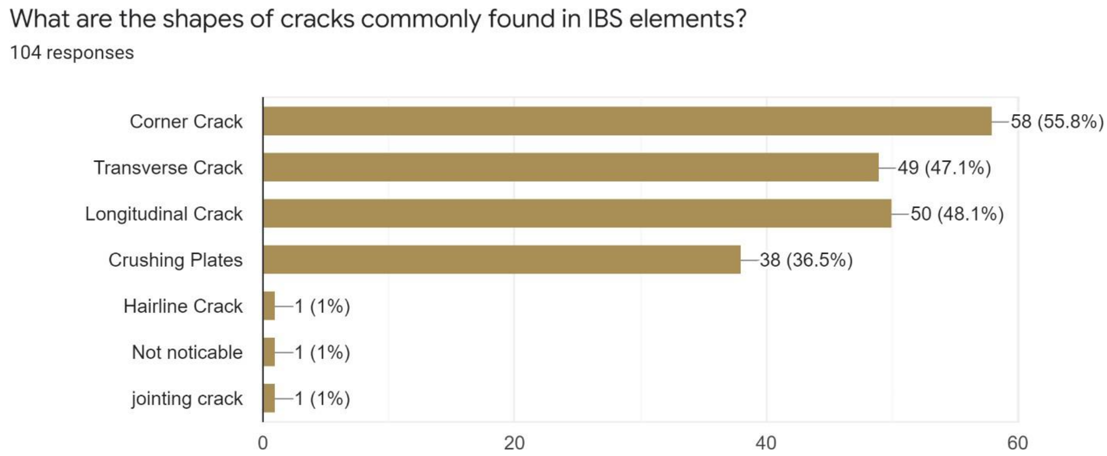


FIGURE 4.8: The shapes of cracks commonly found in IBS elements

The Figure 4.8 above shows the shapes of cracks mostly present in IBS elements. 4 multiple choices are given in this question. Most of the defects found in IBS elements is corner cracks (Figure 2.1). Then, the second most cracks found in IBS elements is longitudinal cracks (Figure 2.3) followed by transverse cracks (Figure 2.2). Crushing plates (Figure 2.4) are the shapes of cracks that are rarely found in IBS elements. Some respondents also filled up hairline crack, jointing cracks and not noticeable shapes.

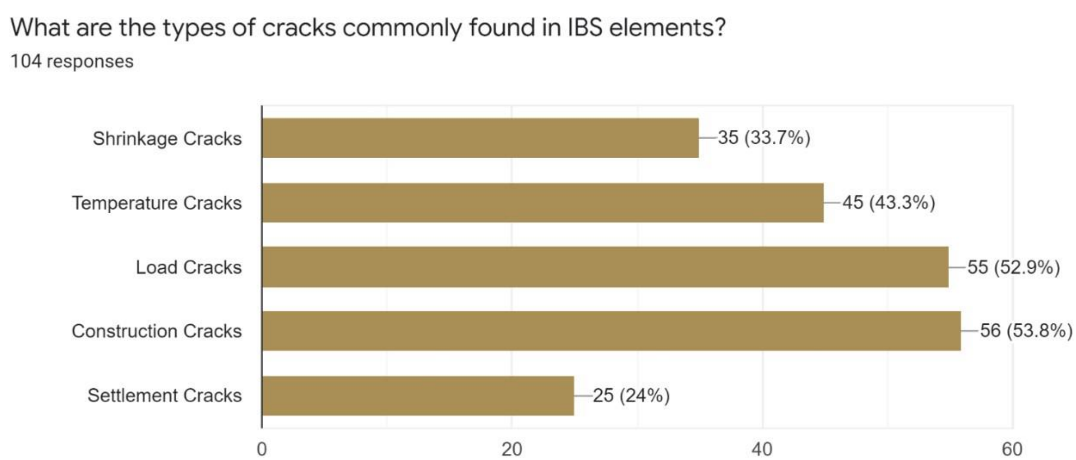


FIGURE 4.9: The types of cracks commonly found in IBS elements

The Figure 4.9 above shows the types of cracks found in IBS elements. Construction cracks is the most common type in IBS elements based on the responses collected. Construction cracks have recorded 56 responses. Load cracks can be also considered as most common type, as 55 respondents have chosen that. Temperature cracks and shrinkage cracks are slightly common to be found in IBS elements. Settlement cracks are rarely found in IBS elements.

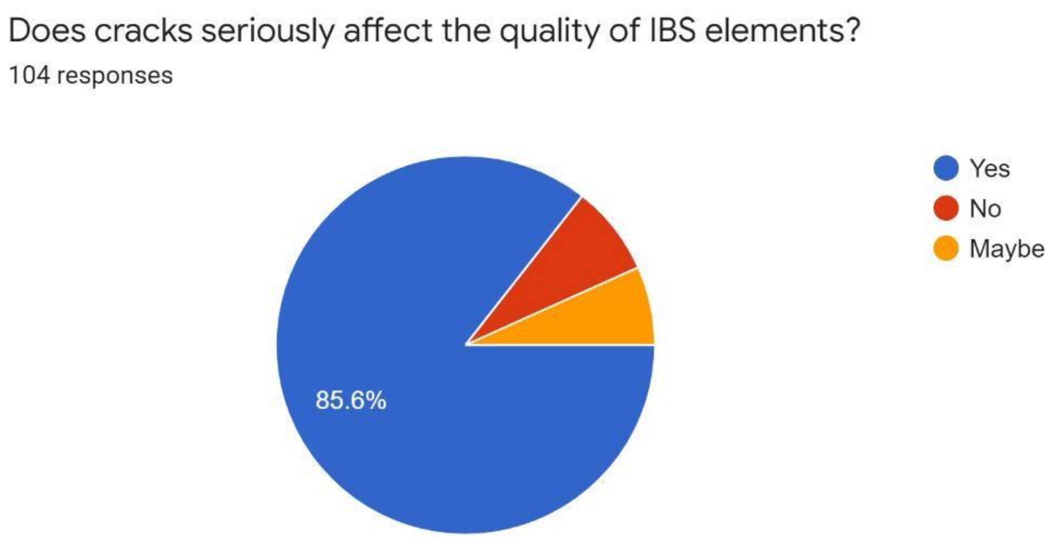


FIGURE 4.10: The quality of IBS elements affected by the cracks

The Figure 4.10 above shows the thoughts of respondents on the effect of cracks on IBS elements. 85.6% (89 out of 104) respondents feel that cracks really affect the quality of the IBS elements. 7.7% (8 out of the 104) respondents said that cracks do not affect the quality of the IBS elements. 6.7% (7 out of the 104) respondents were not sure whether cracks affect the quality of the IBS elements.

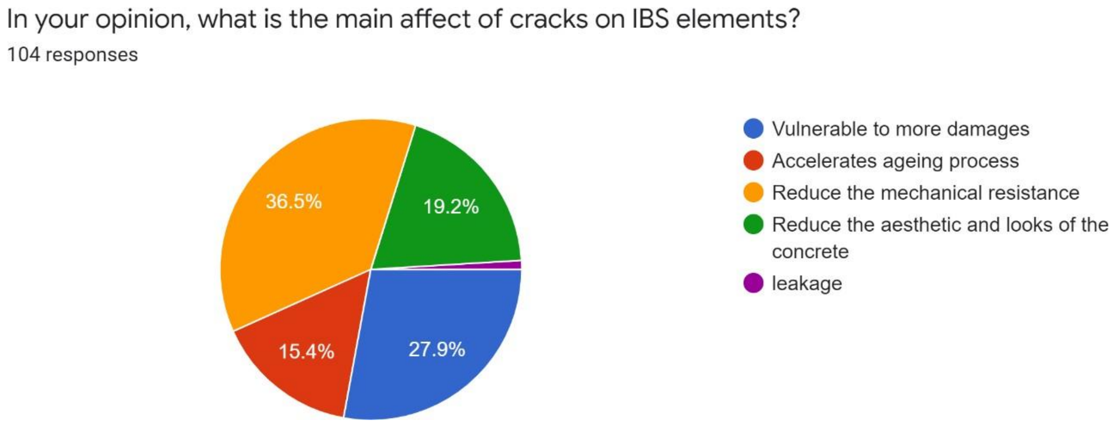


FIGURE 4.11: The main effect of cracks on IBS elements

The Figure 4.11 above shows the main effect of cracks on IBS elements. According to the data collected, the main effect of the cracks is cracks will reduce the mechanical resistance of the IBS elements, as 36.5% (38 out of 104) respondents chose that. Moreover, 27.9% (29 out of 104) responded with vulnerable to more damages and 19.2% (20 out of 104) said that cracks will reduce the aesthetic and looks of concrete. 15.4% (16 out of 104) respondents said that cracks accelerate aging process of the IBS elements. There is 1 respondent said that cracks will cause leakage, which is acceptable as it can be a major problem in future for a building.

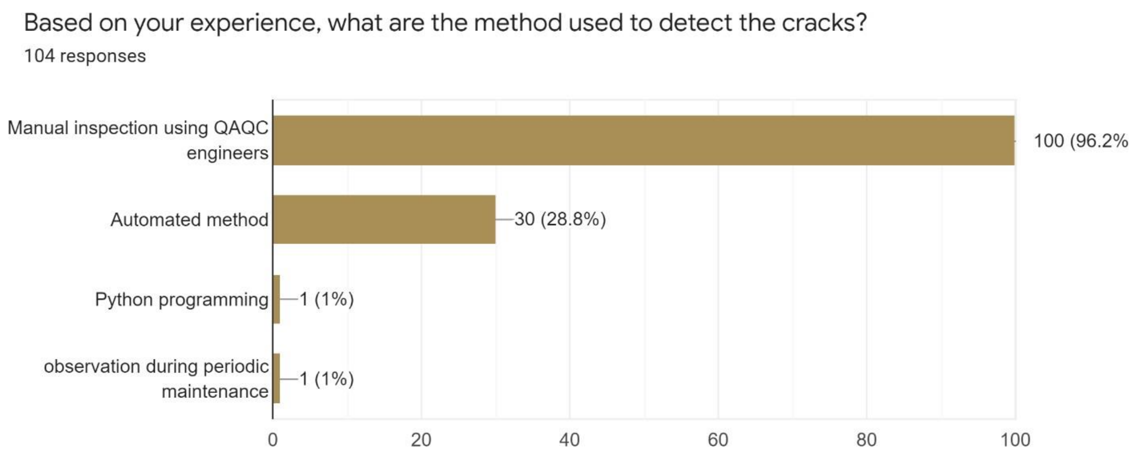


FIGURE 4.12: The methods known to detect the cracks

The Figure 4.12 above shows the method widely used to detect the cracks. Manual inspection using QAQC engineers are the widely used method in construction sector, as 100 respondents have chosen it. There are also 30 responses for automated method as some of the companies might be using this technique. There are responses such as python programming and observation during periodic maintenance.

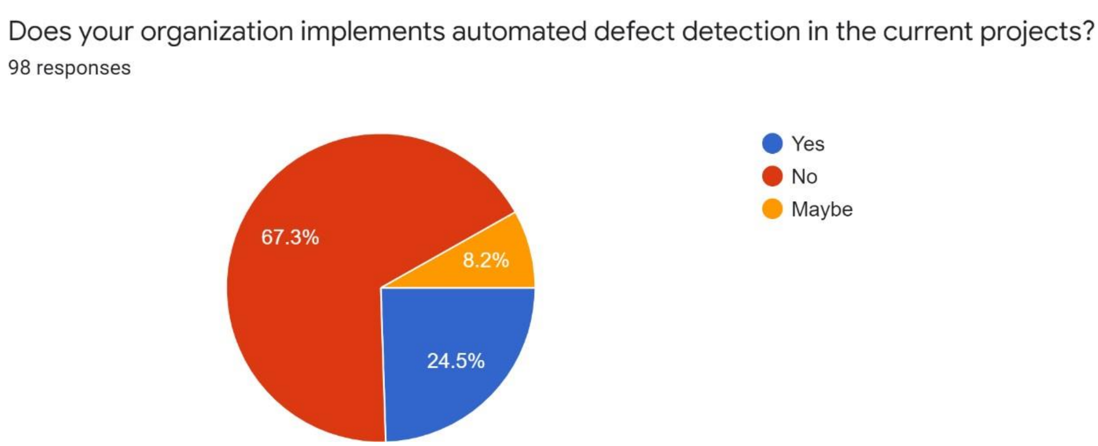


FIGURE 4.13: The implementation of automated defect detection in the organizations

The Figure 4.13 above shows the implementation of automated defect detection in the respondents' organization. 67.3% (66 out of 98) respondents' organizations do not implement automated defect detection in their current project. 24.5% (24 out of 98) respondents' organization implements automated defect detection in their current project while, 8.2% (8 out of 98) respondents are not sure about it.

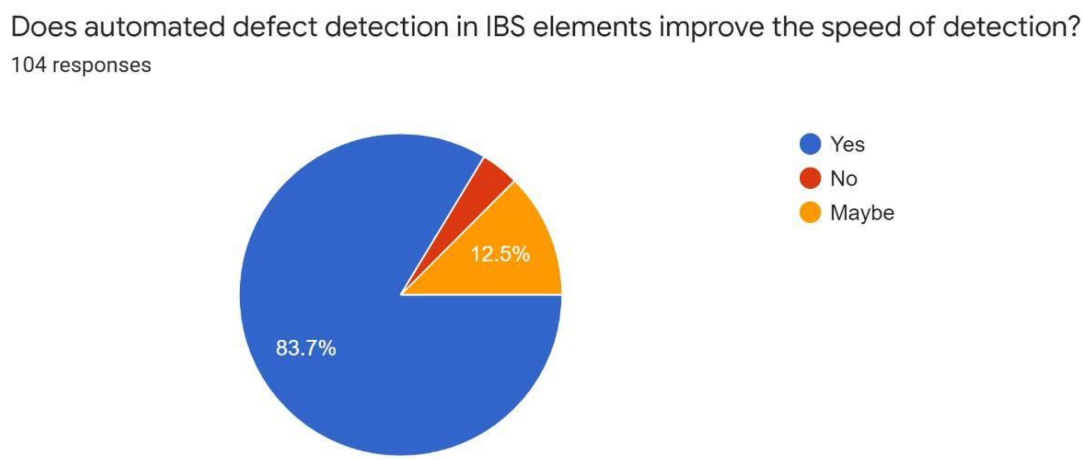


FIGURE 4.14: The ability for the defect detection to improve the speed of detection

The Figure 4.14 above shows the ability for the defect detection to improve speed of detection compared to traditional method. 83.7% (87 out of 104) respondents agreed that automated defect detection can improve the speed of detection. 12.5% (13 out of 104) respondents were not sure whether it can improve the speed or not. Besides that, 3.8% (4 out of the 104) respondents said that automated defect detection cannot improve the speed of detection compared to traditional method.

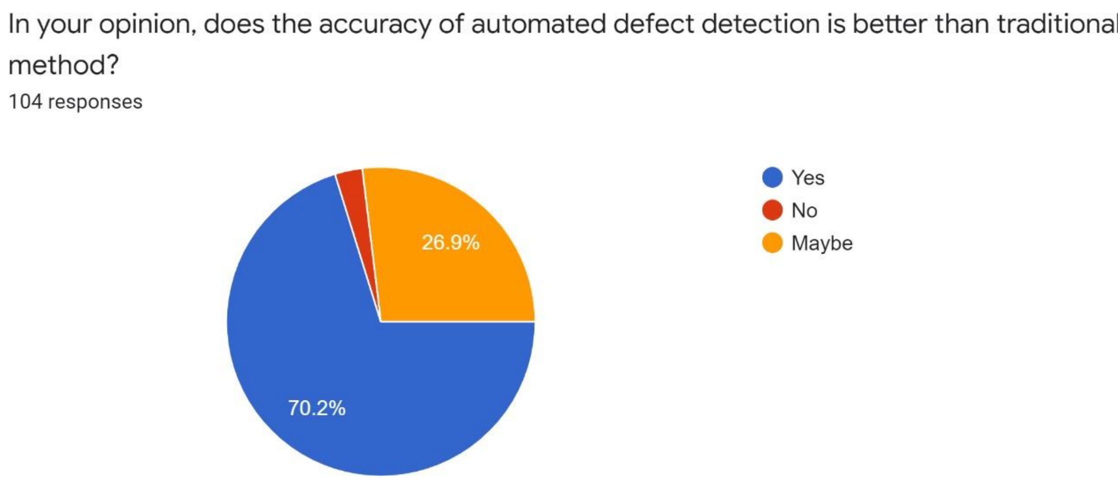


FIGURE 4.15: The ability for the defect detection to improve the accuracy of detection

The Figure 4.15 shows the ability for the defect detection to improve the accuracy of detection compared to the traditional method. 70.2% (73 out of 104) respondents agreed that automated defect detection can improve the accuracy of detection. 26.9% (28 out of 104) respondents were not sure with the statement and 2.9% (3 out of 104) respondents disagree with the statement.

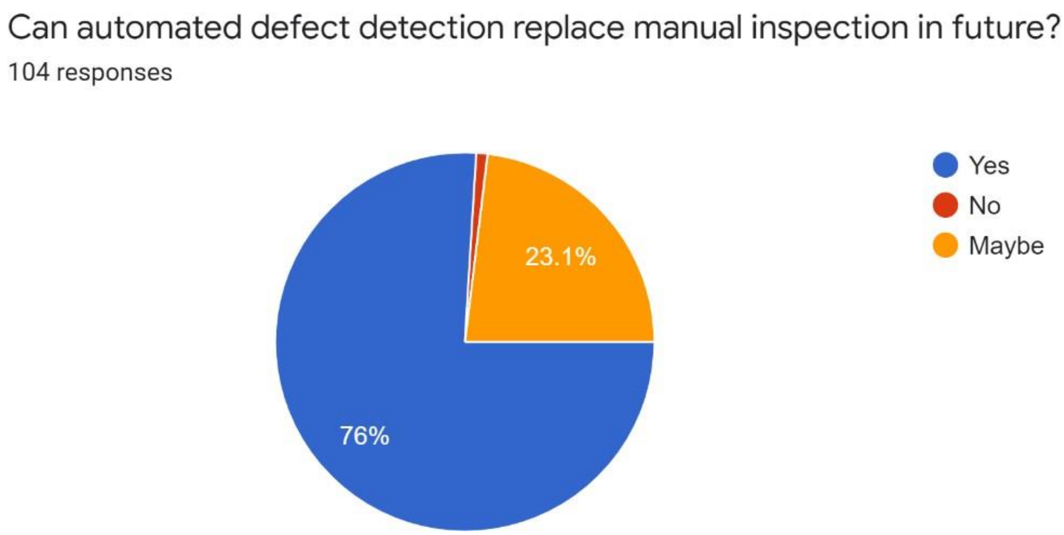


FIGURE 4.16: Chances for automated defect detection to replace manual inspection

The Figure 4.16 above shows the chances for the automated defect detection to replace manual inspection in future. 76% (79 out of 104) respondents feels that automated defect detection can replace manual detection in future. 23.1% (24 out of 104) were not sure whether automated defects detection can be better than manual inspection. 1% (1 out of 104) respondent thought that manual inspection cannot be replaced.

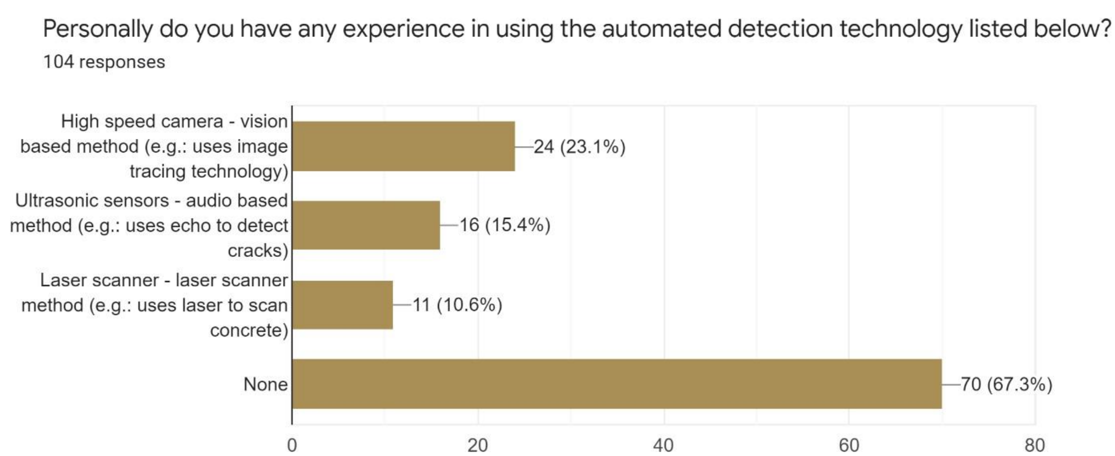


FIGURE 4.17: The experience of respondents with automated defect detection

The Figure 4.17 above shows the experience of respondents with automated defect detection. Most of the respondents do not have experience in automated defect detection as their organization uses traditional method. 67.3% of the respondents do not have experience with automated defect detection. 23.1% of the respondents have experience with high-speed camera method while, 15.4% of respondents have experience with ultrasonic method. Moreover, 10.6% of respondents have experience with laser scanning method.

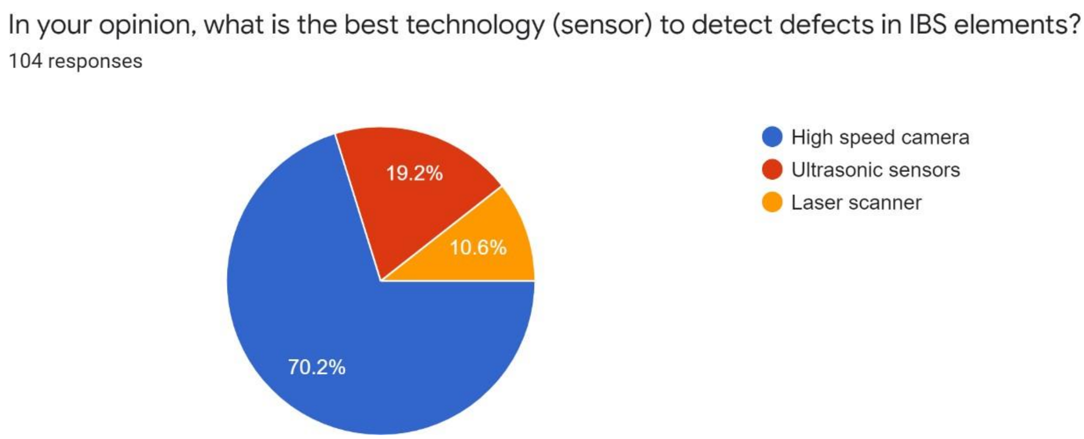


FIGURE 4.18: The best sensor to detect defects based on respondents' opinion

The Figure 4.18 above shows the best technology (sensor) to detect defects in IBS elements based on respondents' opinion. 70.2% (73 out of 104) of respondents chose high-speed camera. 19.2% (20 out of 104) respondents chose ultrasonic sensors while, 10.6% (11 out of 104) respondents chose laser scanner method. In this study, the methodology used is something close to high-speed camera method. Images are taken using camera and inserted in the algorithm.

4.3 Reliability of the Quantitative Data

The information gathered from the quantitative survey were analysed. The analysis carried out was Cronbach's alpha using IBM SPSS Statistics 28. This analysis was carried out to know the reliability of the data collected. The value of Cronbach's alpha will be between 0 to 1. Cronbach's alpha should not be less than 0.5. Any value above 0.7 is considered very reliable (Al-yafei, 2018). The results for vision, audio and laser-based method are 0.665 (Table 4.1), 0.654 (Table 4.2) and 0.662 (Table 4.3) respectively. All these values are more than 0.5 and closer to 0.7. Hence, the data is acceptable. The overall Cronbach's alpha (Table 4.4) of the survey is 0.823. This shows that the results obtained are reliable.

TABLE 4.1: Cronbach's alpha for vision-based method

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.665	0.663	6

TABLE 4.2: Cronbach's alpha for audio-based method

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.654	0.659	4

TABLE 4.3: Cronbach's alpha for laser-based method

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.662	0.657	4

TABLE 4.4: Overall Cronbach’s alpha

Reliability Statistics		
Cronbach’s Alpha	Cronbach’s Alpha Based on Standardized Items	N of Items
0.823	0.822	14

4.4 Relative Importance Index (RII)

The ranking results for the important factors are shown in Table 4.5. As proposed by (Akadiri, 2011), the importance degree of each factor can be classified as follows: (1) High, H ($0.8 \leq RII \leq 1$), (2) High to Medium, H-M ($0.6 \leq RII \leq 0.8$), (3) Medium, M ($0.4 \leq RII \leq 0.6$), (4) Medium to Low, M-L ($0.2 \leq RII \leq 0.4$), and (5) Low, L ($0 \leq RII \leq 0.2$). The maximum RII value is 0.9038, which corresponds to a "High" importance level for a factor affecting vision-based method, and the lowest RII value is 0.8308, which corresponds to a "High" importance level also, but the value is smaller than other factors. All factors have high importance as only important factors are discussed in this study.

TABLE 4.5: Relative Importance Index (RII) Ranking

Technique	Question ID	Factors	RII	Rank
Vision-based method	V1	Workers or objects such as machineries blocking the view of IBS elements during inspection	0.9038	1
	V2	The lighting condition might affect the inspection process	0.8673	6
	V3	The weather condition (e.g.: rain, dust, fog) affect the inspection process	0.8404	11
	V4	The camera resolution can affect the results produced	0.8615	7
	V5	The distance between camera and IBS elements can affect the results	0.8346	12
	V6	The angle and position of camera towards the IBS elements can affect the results	0.8500	8
Audio-based method	A7	Workers or objects such as machineries blocking the IBS elements during inspection	0.8308	13
	A8	The number of microphones used to receive the ultrasonic echo affects the results	0.8750	3
	A9	The weather condition (e.g.: rain, dust, fog) affect the inspection process	0.8308	14
	A10	Noisy background can affect the result of audio-method for the crack inspection	0.8827	2
Laser-based method	L11	Workers or objects such as machineries blocking the IBS elements during inspection	0.8750	4
	L12	The lighting condition might affect the inspection process	0.8692	5
	L13	The weather condition (e.g.: rain, dust, fog) affect the inspection process	0.8423	10
	L14	The distance between laser scanner and objects affects the inspection process	0.8481	9

4.4.1 Important Factors for Vision-Based Method

For vision-based method, the factor that got the highest rank is “Workers or objects such as machineries blocking the view of IBS elements during inspection”. This shows that the respondents found out that workers or objects such as machineries, formwork and tower crane would cause disruptions when capturing image to process it. This factor also can be related to findings from (Braun et al., 2015). Moreover, the factor that got the second highest rank is “The lighting condition might affect the inspection process”. As camera is used, the lighting condition is also important for clearer view and detection of the cracks.

4.4.2 Important Factors for Audio-Based Method

For audio-based method, “Noisy background can affect the result of audio-method for the crack inspection” is highly ranked. Noisy background can interrupt the travelling ultrasonic sound towards the concrete need to be tested. It can also affect once the ultrasonic waves are bounced off the concrete. Besides, “The number of microphones used to receive the ultrasonic echo” is ranked as second important factor in audio-based method. The more the number of microphones, the more accurate the results will be.

4.4.3 Important Factor for Laser-Based Method

For laser-based method, “Workers or objects such as machineries blocking the IBS elements during inspection” and “The lighting condition might affect the inspection process” are the two highest ranked factors in laser-based method. These two factors have similar rankings as in vision-based method. This shows that these factors play an important role in automated defect detection model.

4.5 Outcomes of the Defect Detection Model

The defect detection model was built using the methods and ideas proposed in the literature review. The defect detection model is developed in PyCharm. An innovative image processing method were developed by Talab et al. (2016) for detecting cracks in concrete structure pictures. An idea similar to it was used to design this defect detection model. In this methodology, there are three steps to design a simple detection model. First, the image inserted for detection will be converted to grayscale. Then, the image is generated using OpenCV and Bilateral filter. Then, the canny edge detection is used. The pixels are then classified into foreground and background images using a suitable threshold binary image of the pixel. Then, the output images are saved to a folder for the reference of the stakeholders. The Figure 4.19 below shows the flowchart of the defect detection model.

The Table 4.6 below shows the original image and the outcome after the defect detection process. The defect detection model can detect the cracks on the concrete surface. If high-speed camera is added to the process, the whole process can be automated. Thus, stakeholders can detect the cracks present without depending on inspectors.

FIGURE 4.19: The flowchart of the defect detection coding

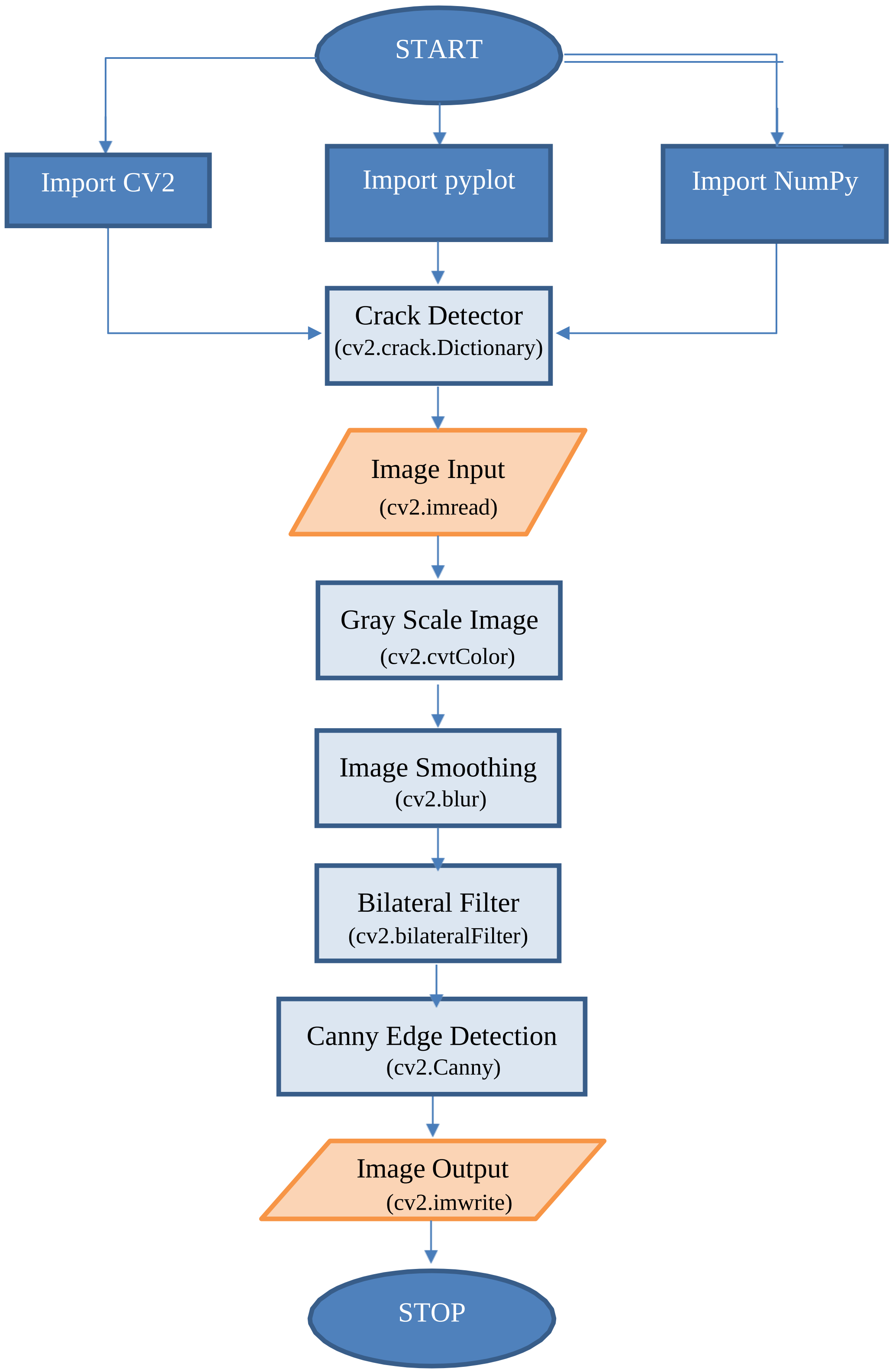
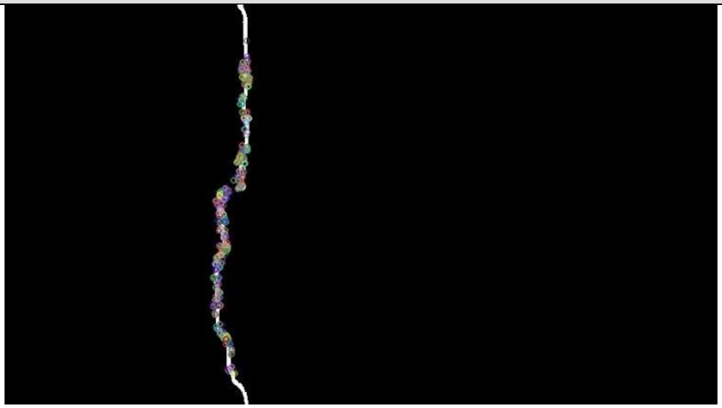
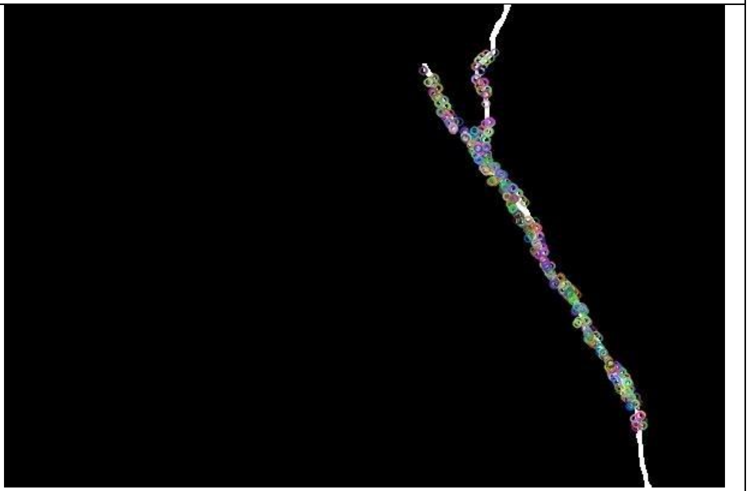
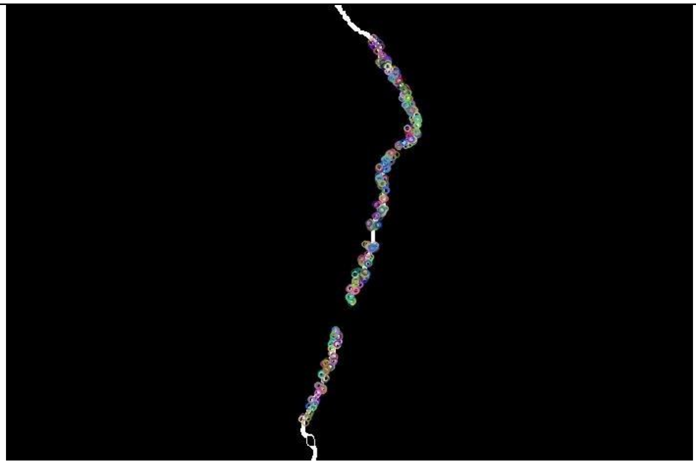
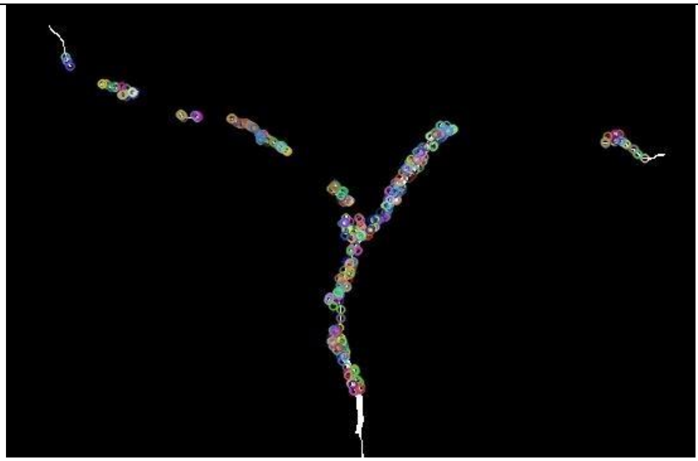
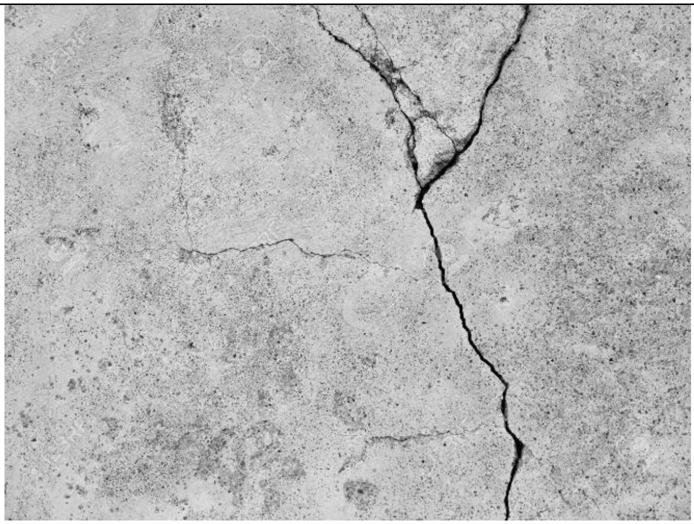
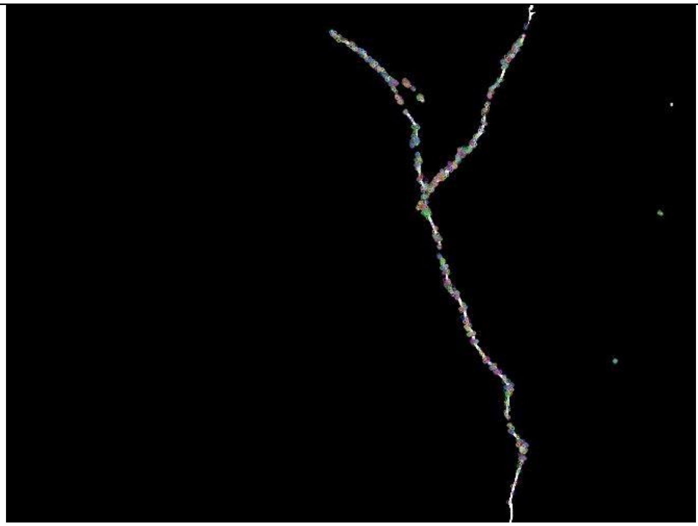
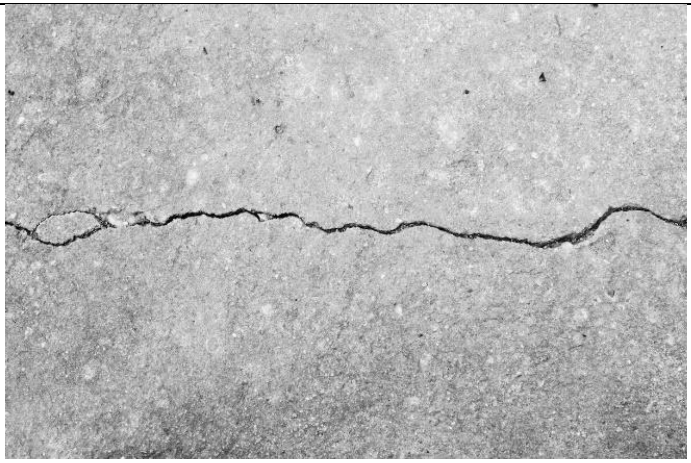
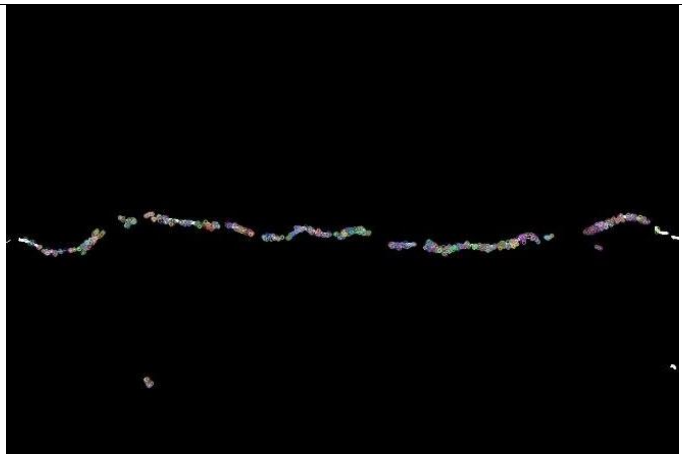
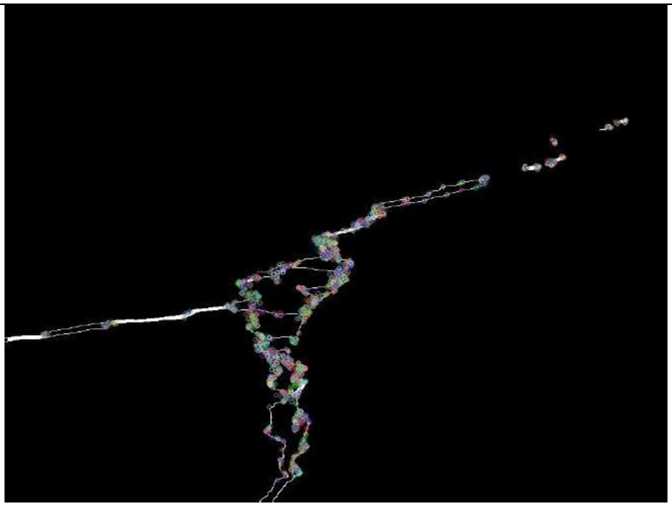
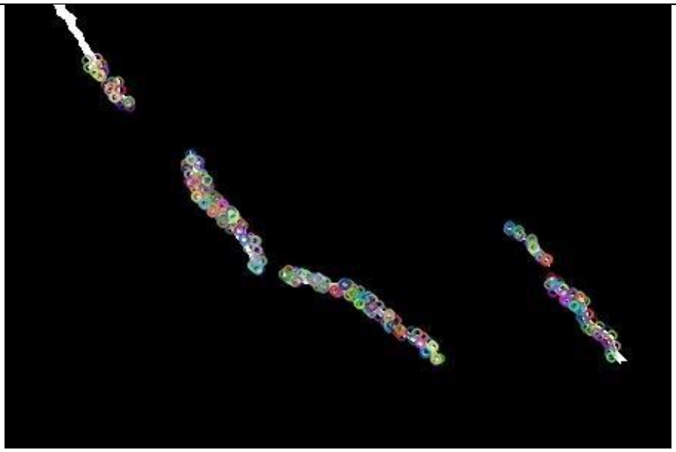


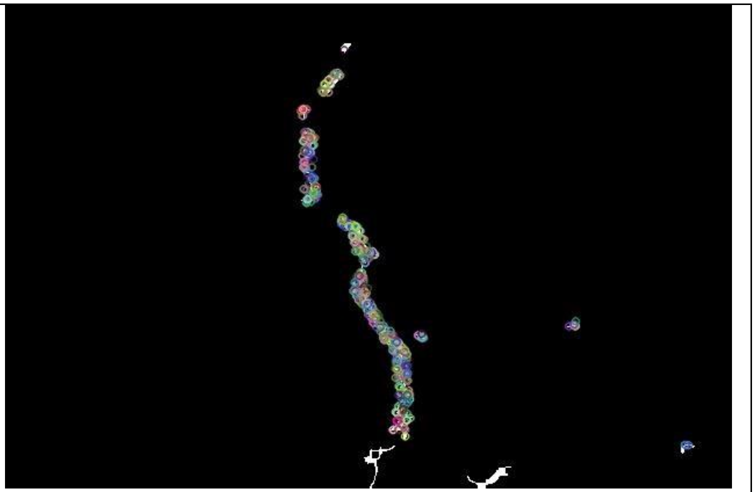
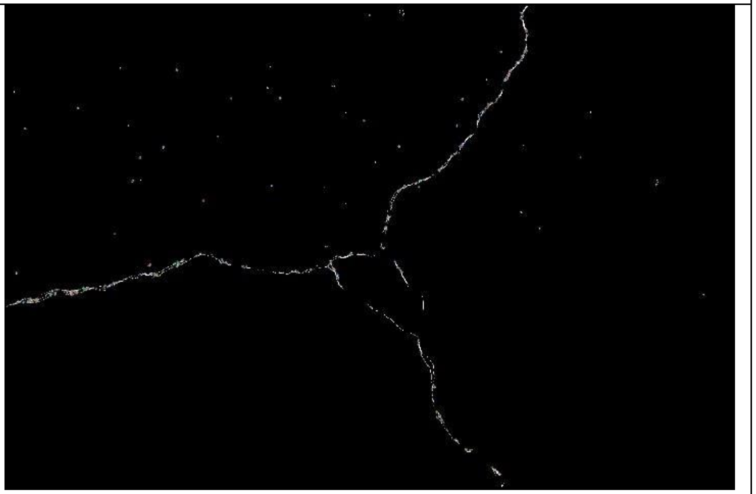
TABLE 4.6: Original and Processed Image

Image No.	Original Image	Outcome
1		
2		

3		
4		

5		
6		

7		
8		

9		
10		

4.6 Performance Evaluation of Defect Detection Model

F1 method was used to evaluate the images for algorithm performance. In statistics, the F1 score method is used to measure the accuracy of the defect detection model. Both the precision (P) and the recall (R) are considered to compute the score. Precision (P) is the number of correct results divided by the number of all returned results. The precision formula (3) is shown below:

$$P = \frac{TP}{TP + FP} \tag{3}$$

Recall (R) is the number of the correct results divided by number of results that should have returned. The recall formula (4) is shown below:

$$R = \frac{TP}{TP + FN} \tag{4}$$

TP (True Positive) = True positive test result is one that detects the condition when the condition is present.

FP (False Positive) = False positive test result is one that detects the condition when the condition is absent.

FN (False Negative) = False negative test result is one that does not detect the condition when the condition is present.

$$F1\ Score = 2 \quad \frac{P \times R}{P + R} \tag{5}$$

The F1 score is the weighted average of the precision and recall as shown in the formula (5) above. F1 score ranges from 0 to 1. The closer the F1 score to 1, the more accurate the defect detection model. F1 score for the images (Table 4.6) against defect detection of IBS elements by using an algorithm is shown below in Table 4.7.

TABLE 4.7: F1 Score for Processed Image by the Defect Detection Model

Image No.	TP	FP	FN	P	R	F1 Score
1	9	0	0	1	1	1
2	17	0	2	0.95	0.89	0.92
3	14	0	1	0.94	0.93	0.94
4	18	0	9	0.96	0.67	0.79
5	21	0	3	0.96	0.88	0.92
6	15	0	4	0.95	0.79	0.86
7	28	0	3	0.97	0.90	0.93
8	17	0	6	0.96	0.74	0.83
9	12	2	2	0.93	0.86	0.89
10	22	1	2	0.96	0.92	0.94

The results shows that the highest F1 score have been recorded for the image 1, which has F1 score of 1. The F1 score is high because the defect on the concrete elements is detected accurately. There are no false positive or false negative detection. The lowest F1 score is from image 4, which has F1 score of 0.79. The score is low because there is false negative, where the algorithm did not detect the crack on the concrete.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

In conclusion, concrete defects are common in construction industry. It is also common in IBS elements. These defects jeopardise the structural strength of the concrete. Moreover, it also affects the aesthetic appeal of the IBS elements. This causes a company to form an inspecting team to ensure the materials' grade and quality level. Most of the company are still using manual inspection, although the inspection results might be unreliable in some cases.

Besides that, it also takes a long time and a significant amount of effort. Automated defects detection by using vision-based inspection is a method to overcome the shortcomings of manual inspection. To identify defects from the concrete IBS elements, most of the previous research focused on using image processing methods such as thresholding, edge detection, and image segmentation.

This study presents an automated inspection method for detecting and analysing defects on IBS elements. The common concrete surface problem is cracking. It is specifically discussed in this research.

Users can access the quality of the IBS elements surface, such as cracking using the methods presented in this study. QAQC engineers, for example, can save time by simply imaging the under-inspection surfaces during a site walk or visit, allowing them to concentrate on improving the concrete surface quality. Managers or general contractors may save money by utilising less professional and low-cost workers to use this automated defect detection instead of hiring experienced workers for manual inspection.

The methods presented in this study were implemented using Phyton programming. The proposed methods were put to the test on a database of IBS element images with cracks. The findings indicated that the solutions offered were reliable. The evaluation of concrete surface images using detection results will be the subject of future study. There will be more photographs assessed, and more exact evaluation criteria will be developed.

5.2 Recommendation

The objectives of the study were met. There were certain limitations due to this pandemic despite the best efforts given out in the study. As a result, more work to improve and refine the research is advised. First, the sample data size was insufficient for factor analysis; nonetheless, it is thought that a larger sample size will considerably improve the model's efficiency. Second, the data collected were insufficient. An interview with some construction industry experts should be done. As a result, the findings of this study are projected to be advantageous to the building project in terms of cost, time, and quality. More research can be done in future to improve this study and make defect detection fully automated without any human interactions.

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