

**DETECTION WITH K-NEAREST NEIGHBOUR ALGORITHM
FOR CRACKED CONCRETE**



UNIVERSITI TEKNIKAL MALAYSIA MELAKA

**DETECTION WITH K-NEAREST NEIGHBOUR ALGORITHM FOR CRACKED
CONCRETE**

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**This report submitted
in fulfillment of the requirements for the degree of
Bachelor of Mechanical Engineering**

Faculty of Mechanical Engineering

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

2022

DECLARATION

I declare that this project report entitled “Detection With K-Nearest Neighbour Algorithm for Cracked Concrete” is the result of my own work except as cited in the references

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APPROVAL

I hereby declare that I have read this project report and in my opinion this report is sufficient in terms of scope and quality for the award of the degree of Bachelor of Mechanical Engineering.

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DEDICATION

To my beloved parent and family.



ABSTRACT

Nowadays, the construction sector plays a vital role in country development. Many high and unique buildings were made to show how the economic status and progress of the country developed. Thus, solid and high efficiency materials such as concrete are needed to construct modern and robust buildings. Even though concrete has high material durability compared to other materials, that specialty cannot deny that the concrete has one main problem if not well maintained. The problem is the cracked wall surface structure. Generally, three types of cracks can be found at the concrete surface, there is a minor crack, moderate crack, and severe crack. This will make the building safety low. The current method nowadays to perform structural health monitoring (SHM) for the concrete wall is by using manual inspection that is visual inspection. The reason why SHM is performed is to detect concrete surfaces and monitor the current structure condition. Several problems have been carried out in this study when the manual inspection is applied to inspect the presence of cracks toward the concrete surface. The first problem is that manual inspection consumes more time to inspect the presence of cracks at the surface since the inspection is done visually and can be done by an experienced inspector only. Next is, hazardous environment to perform inspection increase the safety risk toward the inspector since the presence of crack indicates that the building is not in good condition. Lastly, a limited number of experienced inspectors has become one of the problems for current crack building condition inspection. Thus, the main objective of this study is to produce a technique that can detect the present crack at the concrete surface by using the K-Nearest Neighbor (KNN) algorithm, which can reduce the crack inspection time, reduce the number of inspectors at the hazardous area and lastly required fewer experiences manpower for crack inspection. This technique can detect the presence of crack by using crack concrete surface images. The highest crack classification accuracy obtained in this work was 94.40% correct class classification. The suitable number of greyscale intensity level that had been used is 0.4 for features extraction and the K value is 3. The best number of training datasets that had been used to archive 94.40% accuracy level is 800 crack datasets and 100 non-crack datasets that use 90.00% training and 10.00% testing from the datasets. In conclusion, the crack detection method was able to detect the crack dataset with high correct classification accuracy.

ABSTRAK

Pada masa kini, sektor pembinaan memainkan peranan penting dalam pembangunan sesebuah negara. Banyak bangunan tinggi dan unik dibuat untuk menunjukkan bagaimana taraf ekonomi dan kemajuan negara tersebut berkembang. Oleh itu, bahan kukuh dan tinggi kecekapan seperti konkrit diperlukan untuk membina bangunan moden dan kukuh. Walaupun konkrit mempunyai ketahanan bahan yang tinggi berbanding bahan lain, keistimewaan itu tidak dapat menafikan bahawa konkrit mempunyai satu masalah utama jika tidak diselenggara dengan baik. Masalahnya ialah struktur permukaan dinding yang retak. Secara amnya, tiga jenis rekahan boleh didapati pada permukaan konkrit iaitu retak kecil, retak sederhana dan retak teruk. Ini akan menjadikan keselamatan bangunan tersebut rendah. Kaedah pada masa kini yang digunakan untuk melaksanakan pemantauan kesihatan struktur (SHM) bagi dinding konkrit adalah dengan menggunakan pemeriksaan manual iaitu pemeriksaan visual. Tujuan SHM dilakukan adalah untuk mengesan keretakan pada permukaan konkrit dan memantau keadaan semasa struktur konkrit. Beberapa masalah telah ditemui dalam kajian ini apabila pemeriksaan manual digunakan untuk memeriksa kehadiran retakan pada permukaan konkrit. Masalah pertama ialah pemeriksaan manual memerlukan lebih banyak masa untuk memeriksa kehadiran retakan pada permukaan konkrit memandangkan pemeriksaan dilakukan secara visual dan boleh dilakukan oleh pemeriksa yang berpengalaman sahaja. Seterusnya, persekitaran berbahaya untuk melakukan pemeriksaan meningkatkan risiko keselamatan terhadap pemeriksa kerana kehadiran keretakan menunjukkan bangunan itu tidak dalam keadaan baik. Akhir sekali, bilangan pemeriksa berpengalaman yang terhad telah menjadi salah satu masalah untuk memeriksa kehadiran retakan pada permukaan. Justeru, objektif utama kajian ini adalah untuk menghasilkan satu teknik yang dapat mengesan rekahan yang ada pada permukaan konkrit dengan menggunakan algoritma K-Nearest Neighbor (KNN), yang dapat mengurangkan masa pemeriksaan retak, mengurangkan bilangan pemeriksa pada kawasan berbahaya dan akhirnya memerlukan lebih sedikit tenaga kerja pengalaman untuk pemeriksaan retak. Teknik ini boleh mengesan kehadiran retak dengan menggunakan imej permukaan konkrit yang retak. Ketepatan pengelasan retak tertinggi yang diperoleh dalam kajian ini ialah 94.40% pengelasan kelas betul. Bilangan tahap keamatan skala kelabu yang sesuai yang telah digunakan ialah 0.4 untuk pengekstrakan ciri dan nilai K ialah 3. Bilangan set data untuk latihan yang terbaik telah digunakan untuk mendapatkan 94.40% tahap ketepatan pengelasan ialah 800 set data retak dan 100 set data tidak retak yang menggunakan 90.00% latihan dan 10.00% ujian daripada set data. Kesimpulannya, kaedah ini dapat mengesan dataset retak dengan ketepatan pengelasan betul yang tinggi.

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TABLE OF CONTENTS

	PAGE
DECLARATION	i
APPROVAL	ii
DEDICATION	iii
ABSTRACT	iv
ABSTRAK	v
ACKNOWLEDGEMENTS	vi
TABLE OF CONTENTS	vii
LIST OF FIGURES	x
LIST OF TABLES	xiv
LIST OF ABBEREVATIONS	xvi
CHAPTER	
1. INTRODUCTION	1
1.1 Background Study	2
1.2 Problem Statement	4
1.3 Objectives	5
1.4 Scope of Project	6
2. LITERATURE REVIEW	7
2.1 Introduction	7
2.2 Factor of Cracking Concrete	8
2.3 Crack Classification	9
2.4 Types of Images for Images Processing	12
2.5 Architecture Process	14
2.6 Image Processing Method	16
2.6.1 Feature Extraction	18
2.7 Classification Algorithm	21
2.7.1 K Nearest Neighbour (KNN) Algorithm	21
2.8 Classification Analysis	27
2.8.1 Confusion Matrix	27

3.	METHODOLOGY	31
3.1	Introduction	31
3.2	General Methodology	32
3.3	Image Preparation	37
3.3.1	Images Quantity	38
3.3.2	Images Specification	42
3.3.3	Type of Crack	42
3.4	Image Processing	45
3.4.1	Greyscale Image Conversion	45
3.4.2	Image Binarizing Process	46
3.5	Feature Extraction	47
3.6	Images Classification with K Nearest Neighbour (KNN) Algorithm	52
3.6.1	Dataset for Training and Testing Quantity	52
3.6.2	K Value for KNN Crack Detection	54
3.6.3	KNN Testing Visualisation Result	54
3.6.4	KNN Visualisation Description	56
3.7	Result Evaluation	58
3.7.1	Confusion Matrix	58
3.8	Random Images Testing	62
4.	RESULT AND DISCUSSION	63
4.1	Introduction	63
4.2	Images Processing and Features Extraction	63
4.3	K-Nearest Neighbor (KNN) Image Classification Result	68
4.3.1	The Testing Result For 80% Training And 20% Testing	69
4.3.2	The Testing Result For 90% Training And 10% Testing	75
4.3.3	Crack Detection Testing by Using Different Value Training Dataset	82
4.3.4	K- Nearest Neighbor (KNN) Visualization Discussion	89
4.4	Classification Accuracy with Different K- Nearest Neighbor (KNN) Value Analysis	92
4.5	Testing with Different Number of Training Datasets Analysis	94
4.6	Confusion Matrix Testing Result	97

4.7	Random Images Testing Result	100
5.	CONCLUSION AND RECOMMENDATION	108
5.1	Conclusion	108
5.2	Recommendation for Future Work	109
	REFERENCES	110
	APPENDICES	115



LIST OF FIGURES

FIGURE	TITLE	PAGE
2.1	Shrinkage cracking sample toward concrete structure from the source (Larosche, 2009).	9
2.2	Minor crack sample from the source (Kaish et al., 2018).	10
2.3	Moderate crack sample from the source (Kaish et al., 2018).	11
2.4	Severe crack sample from the source (Kaish et al., 2018).	12
2.5	Binary image sample from the source (Amlan and Devdas, 2000).	13
2.6	Greyscale image sample from the source (Varsha et al., 2019).	13
2.7	RGB image sample source from (Maurits, 2020).	14
2.8	Crack image feature extraction source from (Varsha et.al 2019).	18
2.9	Feature extraction by using Sobel method from sources (Ali & Clausi, 2001).	20
2.10	Feature extraction by using Canny method from sources (Ali & Clausi, 2001).	20
2.11	KNN algorithm classification concept from the source (Imandoust & Bolandraftar, (2013).	21
2.12	Classification accuracy different value of K source from (Chih et al., 2014).	24
2.13	KNN classification accuracy and time taken image processing from source (Zhang et al.2018).	26
2.14	Effect of K value toward running cost from source (Zhang et al.2018).	26
2.15	Confusion Matrix plot from the source (Jason, 2020).	28
2.16	Accuracy formula for confusion matrix from the source (Ajay et al., 2020).	30

3.1	Flowchart for general methodology.	34
3.2	Flow work of the images processing and crack detection test process.	36
3.3	Sample images of crack concrete surface.	37
3.4	Sample images of crack concrete surface.	37
3.5	Sample images of non- crack concrete surface.	38
3.6	Sample images of non- crack concrete surface.	38
3.7	Crack image dataset folder.	39
3.8	Training and testing crack image datasets.	40
3.9	Training and testing non-crack image datasets.	41
3.10	Minor crack image.	42
3.11	Moderate crack image.	43
3.12	Severe crack image.	43
3.13	Non-crack image has hole on surface.	44
3.14	Non-crack image has rough surface.	44
3.15	Non-crack image has small object on it.	44
3.16	KNN visualisation graph.	55
3.17	Table of 2x2 confusion matrix from the source (Shin, 2020).	58
3.18	Formula for precision, recall and accuracy source from (DataQ, 2013).	59
3.19	Table of Confusion Matrix.	60
3.20	Random crack and non-crack dataset for classification test.	62
4.1	0.2 Greyscale intensity level result.	65
4.2	0.4 Greyscale intensity level result.	66
4.3	0.6 Greyscale intensity level result.	66
4.4	0.4 Greyscale intensity level result for non-crack image.	67
4.5	Crack length measurement for training dataset. 68	68
4.6	Confusion Matrix accuracy data result for K value 3.	69
4.7	KNN classification visualization result for K value 3.	70
4.8	Confusion Matrix accuracy data result for K value 5.	71
4.9	KNN classification visualization result for K value 5.	72
4.10	Confusion Matrix accuracy data result for K value 7.	73
4.11	KNN classification visualization result for K value 7.	74

4.12	Confusion Matrix accuracy data result for K value 3.	76
4.13	KNN classification visualization result for K value 3.	77
4.14	Confusion Matrix accuracy data result for K value 5.	78
4.15	KNN classification visualization result for K value 5.	79
4.16	Confusion Matrix accuracy data result for K value 7.	80
4.17	KNN classification visualization result for K value 7.	81
4.18	Confusion Matrix accuracy data result for high crack image dataset.	84
4.19	KNN classification visualization result for high crack image dataset.	85
4.20	Confusion Matrix accuracy data result for low crack image dataset.	87
4.21	KNN classification visualization result for low crack image dataset.	88
4.22	KNN classification visualisation for balance training dataset.	89
4.23	KNN classification visualisation for crack training dataset is high.	90
4.24	Graph of accuracy against the number of K value.	92
4.25	KNN clustering concept source from (Band, 2020).	93
4.26	Graph of accuracy comparison for different number of datasets for training process.	95
4.27	Confusion Matrix accuracy result for K value 3.	98
4.28	Formula for precision, recall and accuracy calculation source from (DataQ, 2013).	99
4.29	Correct severe crack dataset class prediction.	101
4.30	Correct minor crack dataset class prediction.	101
4.31	Correct moderate crack dataset class prediction.	101
4.32	Correct blur crack dataset class prediction.	102
4.33	Correct moderate crack dataset class prediction.	102
4.34	Correct blur crack dataset class prediction.	102
4.35	Correct obstacle crack dataset class prediction.	103
4.36	Correct moderate crack dataset class prediction.	103
4.37	Correct severe crack dataset class prediction.	103
4.38	Correct obstacle crack dataset class prediction.	104

4.39	Correct class prediction for obstacle non-crack dataset.	104
4.40	Correct class prediction for non-crack dataset.	104
4.41	Correct class prediction for obstacle non-crack dataset.	105
4.42	Correct class prediction for rough surface non-crack dataset.	105
4.43	Correct class prediction for smooth surface non-crack dataset.	105
4.44	Correct class prediction for smooth surface non-crack dataset.	106
4.45	Correct class prediction for rough surface non-crack dataset.	106
4.46	Correct class prediction for smooth surface non-crack dataset.	106
4.47	Correct class prediction for rough surface non-crack dataset.	107
4.48	Correct class prediction for obstacle non-crack dataset.	107



LIST OF TABLES

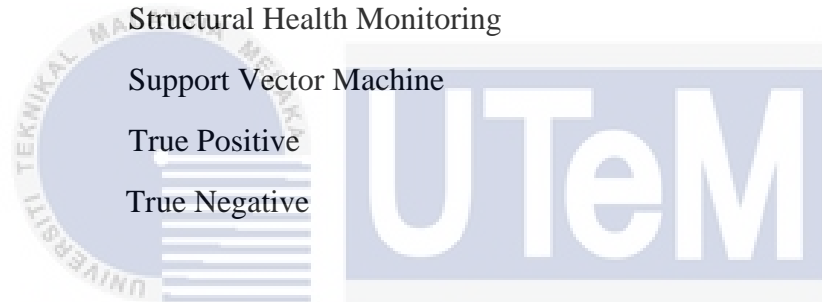
TABLE	TITTLE	PAGE
2.1	Average performance of KNN classification from the source (Jinho et al., 2012).	22
2.2	Accuracy result for medical images classification from the source (Rakesh & Khachane, 2012).	23
3.1	Images specification.	42
3.2	MATLAB command for image processing.	45
3.3	Crack greyscale image output after undergoes colour conversion process.	46
3.4	MATLAB Command for image binarizing.	47
3.5	MATLAB command for feature extraction.	49
3.6	The crack image binarizing and features extraction process output.	49
3.7	Crack length measurement for horizontal and vertical position.	51
3.8	Table for 80% training and 20% testing dataset.	53
3.9	Table for 90% training and 10% testing dataset.	53
3.10	MATLAB command for KNN algorithm.	54
3.11	MATLAB command for KNN visualisation.	57
3.12	MATLAB command for Confusion Matrix data tabulation.	60
3.13	Confusion Matrix calculation formula.	61
4.1	KNN classification accuracy data result for K value 3.	69
4.2	KNN classification accuracy data result for K value 5.	71
4.3	KNN classification accuracy data result for K value 7.	73
4.4	KNN classification accuracy data result for K value 3.	75
4.5	KNN classification accuracy data result for K value 5.	78
4.6	Table 4.6: KNN classification accuracy data result for K value 7.	80

4.7	Classification result for 800 crack dataset and 100 non-crack dataset.	83
4.8	Classification result for 100 crack dataset and 800 non-crack dataset.	86
4.9	Accuracy result when number of crack dataset is higher for training process.	94
4.10	Accuracy result data when too high crack dataset is used for training process.	96
4.11	Data of precision, recall and accuracy.	99



LIST OF ABBEREVATIONS

FP	False Positive
FN	False Negative
KNN	K- Nearest Neighbor
RGB	Red, Green and Blue
SHM	Structural Health Monitoring
SVM	Support Vector Machine
TP	True Positive
TN	True Negative



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CHAPTER 1

INTRODUCTION

In this era of modernisation, the construction sector plays an essential role in country development. The necessary element that completed the construction sector is the concrete element which is the concrete structural part. Due to the rapid growth of superhigh buildings, larger sizes, and longer spans, the best concrete performance is now needed. The importance of the concrete construction necessitates an initial structural health monitoring examination toward the concrete surface. Concrete, according to Amlan and Devdas (2000), is a composite material made up mainly of a binding medium, such as a mixture of Portland cement and water, and embedded particles or pieces of aggregate, generally a mix of fine and coarse aggregate.

In comparison to others construction mediums such as natural stone or steel that had previously been used, concrete was employed in construction because it satisfied a broad range of performance criteria. Since the use of concrete in the construction industry is critical, inspecting the concrete's physical condition has become a top priority in order to ensure the best structure efficiency. The physical surface state of the concrete is used to determine whether or not cracks are present on the surface. If the sign was present, it meant that the structure needed to do a repairing process. The maintenance of concrete structures necessitates the presence of concrete surface cracks. Furthermore, seemingly insignificant cracks can develop and eventually trigger multiple structural failures.

The stability of a structure is an important consideration not only in the construction phase but also in the conservation phase. Visual inspection, which lacks detailed examination, is the current approach for inspecting the surface quality of concrete nowadays. As a result, a more effective crack classification method is required in order to determine whether any cracks have formed on the surface utilising computerised techniques. Thus, this report will present the technique for cracked concrete image detection and classification using the k-nearest neighbour algorithm method.

1.1 Background Study

In comparison to other materials, concrete now makes up the majority of infrastructure. One of the techniques used to determine the structural health of these structures is to look at a crack on the concrete's surface. Since the condition of a solid structure is generally quickly and directly determined by inspecting the surface crack, the inspection should be performed regularly to ensure sturdiness and protection over its life cycle. A concrete crack is a flaw in the surface of the concrete that shows up as a crack. One of the most common and significant forms of asphalt concrete crack is cracking. Cracking distress is generally categorised into three types: longitudinal, alligator, and transverse cracking.

Concrete structural maintenance is described as work done to maintain or prolong the service life of concrete before major restoration or full reconstruction is completed. It is graded as routine or preventive based on its purpose. Cracks are a significant source of concern for a structure's stability, longevity and serviceability. The reason for this is because when cracks develop and spread, they diminish the effective loading area, increasing stress and ultimately causing the concrete or other structures to collapse.

Cracking is unavoidable in all sorts of constructions, including concrete walls, since reinforced concrete constructions are still restricted and buildings degrade with time. Cracks in the concrete surface will allow another material to enter the structure, compromising the structure's integrity and efficiency. Surface cracks are vital signs of structural damage and stability in almost all forms of structures. Visual inspection of the structural elements is critical for detecting cracks and assessing the physical and functional conditions. However, many developing countries using manual crack detection methods to inspect building's structures by referring to Nhat.(2018). As a consequence, crack measurements and gathering or processing pertinent data would take longer and need more work.

In addition, manual inspection necessitates subjective judgements by inspectors and in terms of cost and reliability of the analysis, manual visual examination is inefficient. The appearance of cracks on the concrete surface indicates severe problems inside the structures. As a result, structure health monitoring (SHM) systems are needed to ensure the primary stability and execution of the structure for an extended period in order to avoid ruinous disappointment in the early stages. SHM is a technique for identifying cracks in building systems as well as a methodology for crack detection.

Therefore, a more efficient semi-automated fracture categorization analysis method is required. Hence the application of the k-nearest neighbour algorithm was explored in order to evaluate the surface condition of the cracked concrete such as cracked width and length. The K-Nearest Neighbour (KNN) algorithm was proposed in this report to identify the presence of cracks on the surface focused on building concrete structures. According to Zhang.(2016), this classifier method was chosen because it is straightforward, requires little data, and has been documented to be highly efficient and successful in solving classification problems.

1.2 Problem Statement

This project focus on crack detection and classification method toward the surface condition images of the concrete building structure. Since the safety of concrete condition become the priority toward the building structure, it is necessary to do a safety inspection toward the concrete structure for maintenance purpose. The current method for concrete maintenance inspection nowadays is manual inspection. Manual inspection consuming more time to analyse the concrete surface condition since the procedure is done by observation toward the concrete surface manually and need to be done by an experienced inspector.

Besides, the area that has a crack at the concrete surface might affect the building structure condition. This will make the inspection environment hazardous for an inspector to do measurements of cracks and record the data at the inspection site. Thus, we need a method that reduces the interaction of inspector and cracks area to classify the surface is crack or not.

Next, to do structural health inspection need many inspectors since most buildings nowadays have significant structures. Thus, limited numbers of experienced inspectors become one of the problems to perform the manual inspection. When the number of inspectors less compared to the inspection area, this will be affected the subjective judgment of inspectors since they cannot spend more time for analysis at a specific site.

Based on the problem statement, it is vital to do an alternative way for concrete crack detection and classification in order to reduce time consumption during the concrete surface inspection, to decrease the hazardous risk toward the inspector during the analysis process and finally to overcome the limited number of experienced inspectors to do maintenance inspection.

1.3 Objective

The objective in this study would be:

1. To study the suitable method for crack image processing process that can enhanced the present of crack clearly.
2. To develop a technique that detect and classify cracked and non-crack concrete image using K-Nearest Neighbour (KNN) algorithm method.
3. To evaluate the result of classifier and determine the crack image classification accuracy.



1.4 Scope of Project

The main scope of this research is to develop a technique that can detect crack at the concrete surface from images and categorised the image which is crack or non-crack categories through the implementation of the K-Nearest Neighbour (KNN) Algorithm method. The sources of crack concrete images were obtained from SDNET2018 only and the images sample are from building concrete wall structure. The project scopes are as follow.

1. Prepared and study the image data set for non-crack concrete and crack from SDNET 2018 for the proposed method.
2. Enhanced the images by using image processing program.
3. Develop the K-Nearest Neighbour (KNN) algorithm for crack detection and classification test by using MATLAB software. The detection process uses 80% training and 20% testing, and 90% training and 10% testing of datasets.
4. Analyse the accuracy of crack image classification result for different value of K which is 3,5,7 by using confusion matrix.