CRACKED CONCRETE SURFACE IMAGE CLASSIFICATION ON LOW-DIMENSIONAL IMAGE USING ARTIFICIAL INTELLIGENCE ALGORITHMS

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DEDICATION

First and foremost, I would like to praise and thank Allah, the almighty, who has granted countless blessings, knowledge, and opportunities to the writer, so that I have finally been able to accomplish the thesis.

This thesis is also dedicated to ministry of higher education in Iraq, Al-Iraqia university, collage of Arts. And, to University Technology Malaysia (UTM), school of electrical engineering, computer and micro electronic systems.

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ABSTRACT

The project aims to create a Convolutional neural network (CNN) to detect and classify building cracks. Cracks are a key factor in determining how well-built a concrete structure is since they affect its sturdiness, utility, and safety. Due to its superior image processing capabilities, CNN is rapidly gaining traction as a credible option to replace manual crack detection. Cracks on the concrete surface are one of the earliest signs of structural damage, which is important for maintenance and can cause significant environmental harm. The first step in a manual examination is to sketch the crack and note the conditions. The manual approach is dependent on the specialist's expertise and experience, resulting in a lack of impartiality in quantitative analysis. As an alternative, automated image-based crack detection is suggested where a variety of detection methods are available, such as k-nearest neighbors (KNN), support vector machines (SVM), decision trees (DT), artificial neural networks (ANN), and convolutional neural networks (CNN). These techniques will be used in this project. Positive crack and negative crack are two classes that make up the dataset that will be used with the mentioned strategies, and there are 20,000 photos per class. The images are resized into five different sizes (50×50, 35×35, 25×25, 10×10, and 5×5), and then the results are analyzed based on the performance of the techniques used in the project. It is concluded that the performance with low-resolution images is at par with that of high-resolution images. In addition, for the 50×50 sample image, the accuracy score of the classifiers (KNN, SVM, DT, ANN, and CNN) was (89, 98, 97, 94, and 99) % respectively, while for the 5×5 sample image, the value of the accuracy was (91, 90, 89, 92 and 95) % respectively.

ABSTRAK

Projek ini bertujuan untuk mencipta Convolutional Neural Network (CNN) untuk mengesan dan mengklasifikasikan keretakan bangunan. Keretakan adalah faktor penting dalam menentukan sejauh mana kekukuhan struktur konkrit tersebut kerana ianya mampu menjejaskan kekukuhan, utiliti dan keselamatannya. Disebabkan keupayaan pemprosesan imejnya yang unggul, CNN menjadi pilihan yang boleh dipercayai untuk menggantikan pengesanan keretakan secara manual. Keretakan pada permukaan konkrit adalah salah satu tanda awal kerosakan struktur dan penting untuk penyelenggaraan kerana ianya boleh menyebabkan kemudaratan alam sekitar yang ketara. Langkah pertama dalam pemeriksaan manual ialah melakar keretakan dan memeriksa keadaannya. Pendekatan manual bergantung kepada kepakaran dan pengalaman pakar, menjadikan ketidakpastian dalam analisis kuantitatif. Sebagai alternatif, pengesanan retak berasaskan imej automatik dicadangkan di mana pelbagai kaedah pengesanan tersedia, seperti k-nearest neighbours (KNN), support vector machines (SVM), decision trees (DT), artificial neural network (ANN), dan convolutional neural network (CNN). Teknik-teknik ini akan digunakan dalam projek ini. Keretakan positif dan keretakan negatif ialah dua kelas berbeza yang membentuk set data yang akan digunakan dengan strategi yang dinyatakan, dan terdapat 20,000 foto setiap kelas. Imej diubah saiz kepada lima saiz berbeza (50×50, 35×35, 25×25, 10×10, dan 5×5), dan kemudian keputusan akan dianalisis berdasarkan prestasi teknik yang digunakan didalam projek ini. Kesimpulannya menunujukkan bahawa prestasi dengan imej resolusi rendah adalah setanding dengan imej resolusi tinggi. Tambahan pula, untuk imej sampel 50×50, skor ketepatan pengelas (KNN, SVM, DT, ANN dan CNN) masing-masing ialah (89, 98, 97, 94 dan 99) %, manakala untuk 5× 5 sampel imej, nilai ketepatan adalah (91, 90, 89, 92 dan 95) %.

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LIST OF ABBREVIATIONS

AI	-	Artificial Intelligence
ML	-	Machine Learning
NN	-	Neural Network
CML	-	Conventional Machine Learning
DL	-	Deep Learning
KNN	-	K-Nearest Neighbors
SVM	-	Support Vector Machine
DT	-	Decision Tree
ANN	-	Artificial Neural Network
CNN	-	Convolutional Neural Network
HP	-	Hyperplane
MMH	-	Maximum Marginal Hyperplane
SV	-	Support Vector
SHM	-	Structural Health Monitoring System
FCN	-	Fully Convolutional Network

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CHAPTER 1

INTRODUCTION

1.1 Overview

In recent years, a surge in interest in research on structural health monitoring has been witnessed. Cracking can occur in a diversity of constructions, including pavements, buildings, and bridges. It is essential to emphasise that cracking may accelerate the degradation process. Therefore, the presence and severity are crucial signs of the need for maintenance. As a result, crack examination is crucial for public safety [1].

Traditionally, the human visual examination was the most prevalent and frequently utilized technique for monitoring cracks in concrete buildings. However, Manual visual inspection has a number of problems, including the fact that it is time consuming, costly, labour intensive, and not as exact as it might be since the inquiry relies on the inspector’s expertise. Thus, many research efforts have been made to create automated techniques for detecting building cracks with minimum human involvement in order to circumvent this disadvantage and enhance the accuracy and efficiency of crack detection in buildings [2].

Machine learning (ML) is a kind of algorithm that develops itself automatically based on experience rather than via the intervention of a programmer who writes a better algorithm. The algorithm acquires experience by processing increasing amounts of data and then changing itself in response to the data’s characteristics [3].

ML has become a prominent method in nearly every area due to its ability to execute various tasks with exceptional performance. By giving enough data, ML algorithms may automatically digest the data’s inherent information, such as hidden structures or connections. Traditionally used ML methods need a specified feature extraction step to decrease the data's complexity and enhance the visibility of patterns to ML algorithms. Nevertheless, even with more data, this restricts the models' performance. The term "deep learning" refers to a subset of ML techniques that makes use of neural networks (NNs) with several layers and has grown in popularity in recent years. Compared to conventional machine learning (CML), DL methods are more intelligent since the data's characteristics are automatically learnt throughout the training process. DL does not need a predetermined feature extraction step. By providing more data, it is possible to train a more general and robust model [4].

1.2 Problem Statement

Classification is a supervised learning technique that utilizes a discrete target variable (or categorical). Various machine learning techniques are used to identify numerous patterns and trends. Not all data sets or use cases respond best to one method. You must run several tests, evaluate the machine learning algorithms, and fine-tune their hyperparameters to get the optimal outcome.

The process of identifying the set of inputs for an objective function that yields the highest or minimum value is called optimization. It is a significant challenge that underlies many machine learning methods. There are several optimization algorithms and many algorithms available in popular scientific code libraries. When faced with an optimization challenge, it could be hard to decide which algorithms to test.

There is a need to create an automated technique, for detecting building cracks with minimum human involvement. Researchers are developing models that will operate on previously unknown data. As a result, a comprehensive and flexible assessment is needed to develop a viable model.

The evaluation and optimization of the classification algorithms using very low-size images are significantly critical for creating a robust model over time. This can be done by covering a variety of different metrics and their associated benefits and disadvantages

1.3 Research Objectives

The project's primary aims are as follows:

1. To evaluate machine learning models in detecting cracked concrete surfaces using a small dimensional image.

2. To optimize the hyperparameters of the machine learning models to achieve the best scenario.

1.4 Scope of Research

This project used KNN, SVM, DT, ANN, and CNN classifiers to evaluate and optimize the cracked concrete surface of the structure. The primary programming language utilized throughout the project was Python. A dataset of cracked concrete surface images divided into two classes, negative and positive, has been used for the classification. Then, the data is stored with class labelling. Following that, the data is partitioned into test and train. KNN, DT, SVM, ANN, and CNN classifiers are applied for matching with the test and train data, and the performance of these classifiers is determined based on the accuracy of the classifications.

1.5 Significant of Research

Edge computing is the process of gathering, processing, and analyzing data near to its source. Edge devices must assess the data they collect and take appropriate action when necessary to be considered intelligent. Edge computing is the study of having devices at the edge of a network do this job without sending the data to another server environment. Edge processing will become less complex and faster in computations if small-dimensional images are fed to machine learning algorithms.

1.6 Report Outline

Chapter 2 summarizes relevant research suggested or presented by other researchers. The chapter discusses the background research for this project. Chapter 3 presents the methodology and the project's approach. Software-related methods and processes are described in detail. Chapter 4 depicts the results of the classifiers before and after optimizing their hyperparameters. Finally, in chapter 5, a summary of findings, conclusions, and a list of recommendations have been described.

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