Faculty of Engineering

STRUCTURAL DAMAGE DETECTION USING DEEP LEARNING AND IMAGE PROCESSING

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STRUCTURAL DAMAGE DETECTION USING DEEP LEARNING AND IMAGE PROCESSING

Structural Damage Detection Using Deep Learning And Image Processing

MOHD FARIS BIN HARDJI

A dissertation submitted in partial fulfilment
of the requirement for the degree of
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ABSTRACT

This study focuses on the development and evaluation of deep learning image classification models for detecting different types of building damage, with a specific emphasis on efflorescence damage. The objectives of this research are threefold: (1) to propose a deep learning image classification model capable of accurately classifying various types of building damage, (2) to build a dedicated deep learning image classification model specifically for efflorescence damage classification, and (3) to assess the performance of the image classification models in detecting efflorescence damage. In this study, the performance of various popular deep learning architectures is compared, namely EfficientNet, ResNet, Inception Network, VGGNet, MobileNet, and DenseNet. Our evaluation metrics include average training loss, validation loss, and test loss, as well as average training accuracy, validation accuracy, and test accuracy. The results indicate that EfficientNet outperforms the other architectures, demonstrating the lowest values for average training loss (17%), validation loss (36%), and test loss (41%). Additionally, EfficientNet achieves the highest values for average training accuracy (96%), validation accuracy (92%), and test accuracy (93%). These findings suggest that EfficientNet is the ideal image classification model for accurately detecting and classifying different types of building damage, particularly efflorescence damage. The superior performance of EfficientNet in terms of both loss minimization and accuracy maximization highlights its effectiveness in addressing the challenges associated with building damage classification. The outcomes of this research have significant implications for the development of automated systems for building damage assessment and maintenance, enabling timely and accurate identification of specific damage types, including efflorescence damage, for effective remedial actions.

Keyword: deep learning, image classification, building damage, efflorescence damage, EfficientNet, ResNet, Inception Network, VGGNet, MobileNet, DenseNet, average training loss, validation loss, test loss, average training accuracy, validation accuracy, test accuracy, evaluation, performance assessment.

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CHAPTER 1

INTRODUCTION

1.1 Background

It takes a lot of time and effort to identify and evaluate superficial building damage using vision-based manual inspection techniques[1]. This is where the application of computer vision and deep learning take place. Computer vision is a branch of artificial intelligence (AI) that enables computers and systems to extract useful information from digital photos, videos, and other visual inputs and to execute actions or make recommendations based on that information. AI makes it possible for computers to think, while computer vision makes it possible for them to see, hear, and comprehend [2] while deep learning is a group of machine learning algorithms that: (1) extract and transform features via a cascade of numerous layers of nonlinear processing units. Each new layer learns many layers of representations that correspond to various levels of abstraction, forming a hierarchy of concepts. Each new layer utilises the output from the preceding layer as input [3].

1.2 Problem Statement

Buildings, bridges, roads, and dams are all necessary components of contemporary society. Even though they are built to be utilized in a variety of settings, major unforeseen occurrences such as earthquakes and hurricanes, as well as deterioration due to ageing, can raise serious concerns about the buildings' safety and usefulness. As a result, the health of the buildings must be monitored throughout their existence [4].

Structural health monitoring refers to the process of establishing a damage identification method for aeronautical, civil, and mechanical engineering infrastructure (SHM). Damage is defined in this context as changes to the material and/or geometric qualities of these systems, including changes to the boundary conditions and system connectivity, that have a negative impact on the system's performance. For such monitoring, a large range of extremely effective local non-destructive examination methods are available. However, the majority of SHM research over the last 30 years has sought to discover structural damage on a more global scale. The quantity of study on SHM has increased dramatically over the last ten years, as seen by the large rise in articles published on the subject [3].

Due to the differences in the structures, each structure must have a different monitoring technique. When there is a lot of construction, it gets challenging. Analyzing each structure separately is a laborious process that can have errors. Standard regulations for the use of monitoring techniques can thereby reduce measurement error and save time and money on capital expenses. The SHM approach in use is influenced by variations in the shapes, sizes, and ages of the structures. Establishing a uniform methodology for all structures, which might further reduce time and effort, is challenging due to the variances. The kind of SHM system used on any given structure depends on several variables, including the object's size and shape [5].

Due to the increase research on the structural damage detection tool for the convenience of everyone, deep learning application can be a standard technique for structural health monitoring because of its capabilities to detect different kind of building damages for any kind of building structures. Therefore, deep learning is implemented in the detection of structural damage.

1.3 Research Questions

1. What is the problem in current structural health monitoring?
2. What are the tools and limitations of damage detection in structural health monitoring?
3. How deep learning helps in improving current damage detection in structural health monitoring?

1.4 Research Hypothesis

1. There is no monitoring technique for efflorescence damage.
2. There are only a few classifications model for efflorescence damage currently in the structural health monitoring field.
3. Deep learning can help improving current damage detection in structural health monitoring by using Convolutional Neural Network (CNN) models to detect various types of building structure damage.

1.5 Objectives

The objectives for this project:

i. To propose deep learning image classification model to classify different building damage.

ii. To build a deep-learning image classification model to classify efflorescence damage.

iii. To evaluate the performance of the image classification model for the detection of efflorescence damage.

Chapter 2

LITERATURE REVIEW

2.1 Overview

This review is mainly to provide an overview on existing structural health monitoring (SHM) by using the application of computer vision and deep learning model, and to compare existing work in terms of their performances and the accuracy of the damage detection. This includes comparing the working scheme, the types of damage detected, software and hardware that are used, the parameters measured in the study, the type of classification technique, Image size, number and format, and image acquisition tool of all the previous and existing study. In the following sections, we will also briefly discuss the use of computer vision in today detection technology, the significance of deep learning, and the importance of convolutional neural network (CNN).

2.2 Computer Vision

Computer vision focuses on gathering details about a situation from images of that scene. It has numerous uses, including in the processing of documents, robotic guiding, radiography, microscopy, industrial inspection, and remote sensing.

Only visible-light images are discussed here; assuming that the scene is lighted by one or more light sources, either natural or artificial, and that the sensor includes an optical system that generates an image of the scene on an image plane. The brightness and color of this image at a given place are determined by the light received by the sensor from a certain direction, and so correlates to the brightness and color of a spot on the surface of an item in the scene located in that direction. (If translucent objects are disregarded, only the nearest object surface will be visible along a given direction.).

To process a picture using a (digital) computer, it must first be converted into a digital image, which is a discrete array of numbers indicating brightness or color values at a discrete grid of points in the image plane—or, more specifically, average values in the neighborhoods of these points. The array's members are commonly referred to as pixels (short for "picture elements"). In many applications, only one value is measured at each sample point, representing the image brightness at (or near) that place; this value is referred to as the pixel's grey level. In color applications, many values are measured at each sample point, indicating brightness measurements in a set of k spectral bands; hence, each pixel has a k-tuple of values.

The input in computer vision is a picture (or several images), and the output is information about the scenario that led directly to the image(s); for example, the result could be some type of scene description. The technique of extracting scene descriptions from photographs is often known as image analysis, "image understanding," or pictorial pattern recognition [6].

2.3 Deep Learning

A branch of machine learning and artificial intelligence called "deep learning" (DL) is now regarded as a key technology of the Fourth Industrial Revolution (4IR or Industry 4.0). A hot issue in computing due to its data-driven learning capabilities, deep learning (DL) technology, which is derived from artificial neural networks (ANN), is used extensively in a variety of fields, including healthcare, visual identification, text analytics, cybersecurity, and many more. However, because real-world problems and data are dynamic and variable, creating an acceptable DL model is a difficult undertaking [7].

Due to its ability to learn from the provided data, DL technology is currently regarded as one of the hottest subjects in the fields of machine learning, artificial intelligence, data science, and analytics. Numerous businesses, like Google, Microsoft, Nokia, etc., actively research it since it can produce noteworthy results in various classification and regression issues and datasets [8]. DL can be thought of as an AI function that mimics the way the human brain processes data because it is a subset of ML and AI in terms of working domain. To develop computational models, DL technology represents data abstractions using several layers. Due to the large number of parameters, deep learning requires more time to train a model than other machine learning algorithms, but it runs faster during testing [9].

DL technology, which was derived from ANN, has emerged as one of the core technologies to accomplish the goal, even though the Fourth Industrial Revolution (also known as Industry 4.0) of today typically focuses on technology-driven "automation, smart, and intelligent systems" [10], [11]. A typical neural network is primarily made up of numerous small, interconnected processing units, or "neurons," each of which produces a string of real-valued activations for the desired result. The mathematical model of an artificial neuron, or processing element, is schematically depicted in Figure 1 with input (Xi), weight (w), bias (b), summation function (), activation function (f), and associated output signal highlighted (y). In numerous industries and disciplines of study, including healthcare, sentiment analysis, natural language processing, image recognition, business intelligence, cybersecurity, and many others, neural network-based deep learning technology is increasingly widely used.

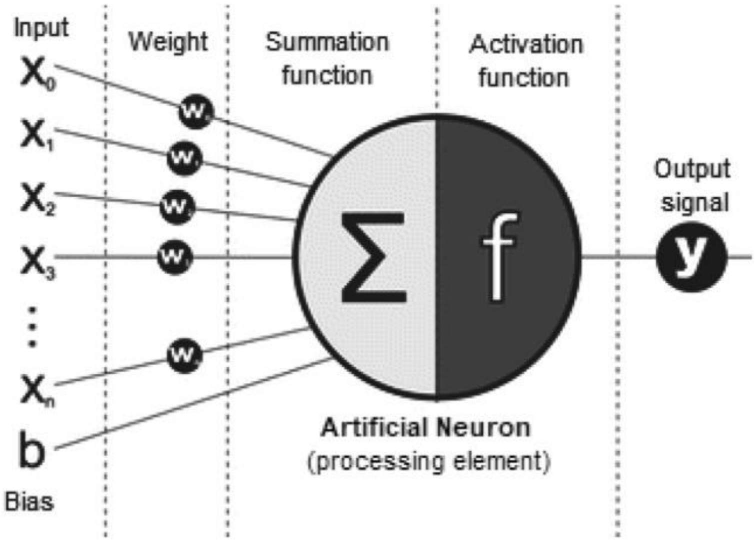

Figure 2.1 Artificial Neuron.

The Fourth Industrial Revolution (Industry 4.0) of today is primarily focused on technology-driven automation, smart and intelligent systems, across a variety of application domains, including smart healthcare, business intelligence, smart cities, cybersecurity intelligence, and many others [12]. Deep learning techniques have significantly improved in terms of performance across a wide range of applications, especially when it comes to security technologies as a great way to reveal complex architecture in high-dimensional data. Because of their excellent learning capabilities from historical data, DL techniques can thus play a crucial role in developing intelligent data-driven systems that meet today's needs. So, DL has the power to automate and learn from experience, which can change the world and people's everyday lives. So, DL technology is useful for artificial intelligence [10], machine learning [13], and data science with advanced analytics [12], which are all well-known areas of computer science, especially today's intelligent computing.

2.4 Structural Health Monitoring

Infrastructure safety and integrity have always been a top priority for those in charge of making decisions. The failure of structures because of wear and tear and dangerous events has caused not only deaths but also direct and indirect economic losses, which threatens the well-being of societies on a massive scale. For the past few decades, performance evaluation methods with structural analysis and local material sampling frameworks have been the main way to figure out how existing structures react to natural and man-made forces. But these methods rely a lot on simulations, which may not match up with reality due to the high level of uncertainty in infrastructure systems [14].

Recent improvements in sensor and information technology have given together a data-driven way to use vibration-based SHM methods to include actual global structural behavior [15]. Sensor data from structures can be used to evaluate their dynamic properties, update mathematical models with field data, find out if there is any damage, and predict any future threats based on projections of system properties based on current trends or expected extreme events. In other words, SHM provides frameworks for how to interpret the structural status of buildings and bridges using the most up-to-date algorithms, inverse dynamics theories, and real observations from sensors in buildings and bridges [14].

In the context of structural health monitoring (SHM), deep learning can be used to analyze sensor data collected from structures (such as bridges or buildings) to detect signs of damage or deterioration. One example of this application is the use of deep learning to analyze vibration data from structures. A neural network can be trained on "normal" vibration data collected from a healthy structure, and then used to analyze real-time vibration data to detect any abnormal patterns that may indicate damage[16].

Even though SHM has a lot of benefits, it hasn't been used much in the infrastructure industry because the tools and labor are expensive and it's hard to set up. Sensing equipment that is fragile can break in harsh field conditions, so it needs to be carefully maintained. In the same way, installing traditional systems with cabling and set positions takes a lot of time and work. In addition to all of these, scalability has been a big problem because infrastructure is so different and there aren't enough observations [14].

2.5 Efflorescence Damage

Efflorescence is a whitish powdery deposit that forms on the surface of masonry, concrete, and other building materials because of the migration of soluble salts to the surface. The salt deposits are formed due to the presence of moisture that dissolves the salt, and then evaporates leaving the salt behind. Efflorescence damage can occur when the salt deposits accumulate to the point that they damage the surface of the building material. This can cause discoloration, staining, and can even lead to spalling or cracking of the surface. Efflorescence can also lead to corrosion of embedded metal elements such as reinforcement bars in concrete structures[17]. Efflorescence damage can be caused by a variety of factors such as:

1. High water table
2. Poor drainage
3. Leaking pipes
4. Improperly sealed surfaces
5. Use of salt-containing materials

Figure 2.2 Efflorescence damage on concrete wall.

Figure 2.3 Efflorescence damage on brick wall.

Figure 2.4 Efflorescence damage on brick wall.

2.6 Convolutional Neural Network (CNN)

Recently, convolutional neural networks, often known as CNNs, have been able to execute tasks that were formerly thought to be something that could only be done by people. In this chapter, we will talk about CNNs, and we will start by explaining ordinary neural networks and the training process for them. After that, we will go more into the idea of convolution and how it relates to CNNs in the following section. CNNs are constructed in the same way that classic neural networks are, with the exception that the weights of the neurons in CNNs are able to be adjusted. However, CNNs take into account the organized character of inputs such as images by employing shared weights for each place in the image and limiting neuron response to particular parts of the image. [18].

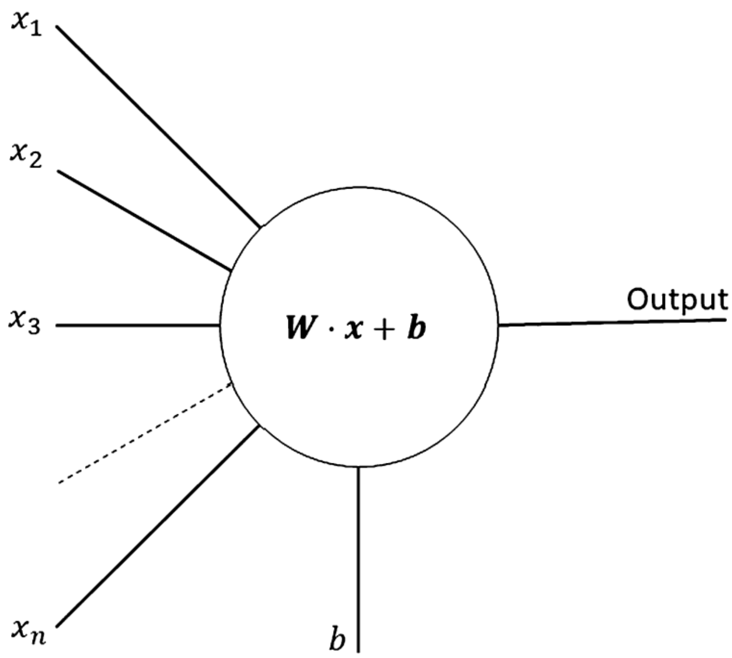

Figure 2.5: Schematic Version of Neuron.

CNNs, as opposed to typical neural networks, have neurons that are structured in channels, breadth, height, and the number of filters in their most basic, two-dimensional form. A CNN, much like an MLP, is made up of numerous layers, each of which affects the output of the layer below it by applying a differentiable function. These layers are connected in a cascade fashion. CNNs make use of a wide variety of layers. However, the convolution layer, the pooling layer, and the fully linked layers are the CNN architecture building blocks that are most frequently encountered. These layers perform the duties of data classification, feature extraction, and dimension reduction respectively. CNNs build a whole convolutional layer by stacking these layers one on top of the other. The input to