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A Deep Learning Based Non-Destructive Method for Estimating Concrete Strength using Continuous Wavelet Transform of Vibration Signals Acquired using A Smartphone's Accelerometer



Abstract: Most non-destructive tests of concrete require sophisticated equipment and training; in this work, we aim to develop a simple method to estimate the strength class of cylindrical concrete samples based on vibration signals that are collected after striking a concrete cylinder with a hammer. The vibration signals were collected by attaching a smartphone to the concrete cylinder and logging the vibrations registered via the smartphone's builtin accelerometer. The acquired 1-D vibration signals are transformed to 2-D scalograms using the continuous wavelet transform. Scalograms are then used to train a deep learning model to predict the strength class. Preliminary findings indicate that the model is capable of classifying the strength of concrete as low, medium, or high. The developed model achieved a high accuracy of 91.67%. The promising results of this work shed light on the future of smartphone-based measurements of construction materials' properties.

Keywords: Concrete; Compressive Strength; Deep Learning; Nondestructive Tests

I. INTRODUCTION

Concrete's compressive strength is one of the most important properties to be considered during the construction and design stages of concrete structures. It is a result of the types and amounts of ingredients used to make the concrete mix, as well as the curing process. Other mechanical properties of concrete are also important, such as flexural and shear strength. Compressive strength, however, remains the basis for acceptance of concrete. In addition to strength, other properties of concrete are also of high importance, such as those related to the durability of concrete. Nevertheless, concrete that does not meet strength requirements is unlikely to meet durability requirements as well. Evaluating the quality of concrete is primarily based on its compressive strength, which is determined through a compression test on cylindrical or cubic samples of varying dimensions, as specified by the building and design codes in use.

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Dr. Saleh J. Alghamdi*, Department of Civil Engineering, College of Engineering, Taif University, P.O. Box 11099, Taif 21944, Saudi Arabia. E-mail: sjalghamdi@tu.edu.sa, ORCID ID: 0000-0003-1020-4704

© The Authors. Published by Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP). This is an <u>open access</u> article under the CC-BY-NC-ND license <u>http://creativecommons.org/licenses/by-nc-nd/4.0/</u> strength, which is used for plain concrete, to high-strength concrete, which is used in megastructures, such as high-rise buildings. Moreover, the ACI 318 requires a minimum specified compressive strength of 17 MPa for structural concrete. A compression test is a destructive test for evaluating the strength of concrete; however, non-destructive tests also exist that aid in assessing concrete's properties. For instance, there are surface hardness techniques that use empirical correlations between the strength of concrete and its surface hardness. The most widely used surface hardness-based method is the rebound hammer test. Furthermore, the elastic modulus of concrete is another crucial factor in the design and construction of structures. The static elastic modulus of concrete is computed from the stress-strain curve according to ASTM C469. However, specimens must be destroyed to obtain this property, and a large number of samples are needed. Alternatively, the elastic modulus can be obtained through a resonance frequency test and an ultrasonic pulse velocity test, as specified in ASTM C215 and ASTM C597, respectively. Although a beneficial correlation exists between the dynamic modulus and compressive strength of concrete, it can be challenging to obtain consistent data due to the presence of voids, moisture, among others. In addition, the resonance frequency test relies on the assumption that concrete has homogeneous properties, such as elastic modulus, Poisson's ratio, density, etc. ASTM provides a guide to calculating the longitudinal and transverse elastic moduli, incorporating several parameters such as sample dimensions and mass, as well as the resonant frequency obtained via the resonance frequency test. Many non-destructive tests are limited to a lab environment and/or require costly testing equipment, in addition to requiring specialised training. In recent years, machine learning and deep learning techniques have been widely applied to enhance the prediction accuracy of concrete's mechanical properties. Some of these techniques have been implemented to work out civil engineering problems, including the prediction of normal and high-strength concrete's 7, 14 and 28-day mechanical properties [1-7]. Additionally, many other types of concrete have been modelled using artificial intelligence. For instance, high-performance and ultra-high-performance concrete [8-11], bacterial concrete [12], green concrete [13], structural lightweight concrete [14], self-consolidating concrete [15] and recycled aggregate concrete [16].

The compressive strength of concrete ranges from low-

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The strength of concrete can be evaluated in a laboratory or field environment, where destructive tests can be performed. However, it is difficult to measure the strength without crushing the samples. Alternatively, non-destructive testing methods are employed, which usually require sophisticated equipment and training on their use. Therefore, in this work, we propose a deep learning-based non-destructive method for estimating concrete strength. The proposed method is inexpensive, accurate and can be performed in any environment. The proposed method relies on a deep learning model that is trained on scalograms of smartphone-acquired vibration signals generated after concrete is impacted with a hammer. To predict the strength class of concrete, this work proposes striking the concrete cylinders with a regular hammer on one of their flat faces while recording the induced vibrations at the other flat face using a cellphone's built-in accelerometer. Thus, obtaining unique acceleration signals from concrete samples of different compressive strengths. The resulting vibration signals are then transformed into images, which can be used to train a deep learning model that maps the vibration to the corresponding strength class. This approach is illustrated in Figure 1 and is further explained in the following sections.



II. MATERIALS AND METHODS

Lab experiments are required for the training and validation of the deep learning model. In this regard, cylindrical concrete specimens were made with different compressive strengths. Each sample is cured for 28 days in a water bath and extracted approximately a day before testing. Two tests were conducted on each sample: the vibration test and the compression strength test. As mentioned above, to acquire the vibration signals, a negligible impact was performed on each sample. The hammer used for impact is commonly called a blacksmith's hammer, weighing about 1.33 kg. This hammer was chosen because it is typically found in local construction sites. Each sample was hit 10 times, waiting at least five seconds between hits. Before hitting the concrete sample, each sample is placed on two wooden blocks with 5-cm square cross-sections. In addition, the two supporting blocks were roughly five centimetres apart. These wooden blocks were used to support the weight of the concrete cylinders, but not to constrain them completely, which prevents the free vibration of the concrete cylinders. For these conditions to be achieved, the supports were positioned near the longitudinal centre of the cylinder, as shown in Figure 2. To induce vibration, each concrete cylinder was impacted with a regular hammer on one of its flat faces while recording the induced vibrations at the other flat face by a cellphone built-in accelerometer. The vibration signals were recorded via a cellphone that was taped in place on the flat face of the concrete cylinder using duct tape. The smartphone used was an iPhone XS (Model Number: MT9H2AH/A). This model is equipped with a three-axis accelerometer. The z-axis, which passes through the screen, was used as the primary acceleration axis. Acquiring the vibration signals was conducted by using the freely available application iDynamics, v2020-6 (University of Kaiserslautern) [17] with a sampling rate of about 100 Hz. Representative vibration signals of high, low, and medium strength classes are shown in Figure 3. After all vibration tests on all samples had been carried out, concrete cylinders were tested under compression according to ASTM C39 using an automatic compression testing machine (ELE International LLC, United Kingdom) at a loading rate of 4 kN/sec. Specimens were loaded until failure, and the resulting strengths were categorised according to their level of strength. Namely, samples that showed compressive strengths of less than 30 MPa were labelled low, while samples that showed compressive strengths ranging from 30 to 40 MPa were labelled me-

dium, and lastly, samples that showed compressive strengths higher than 40 MPa were labelled high. Each category contained two samples, and a

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total of 20 vibration signals were acquired from each category, as shown in <u>Table 1.</u>



Figure 2. Illustrations of the proposed method of acquiring vibration data via hitting the concrete sample and registering the vibration signal by a taped-in-place smartphone.



Figure 3. Representative acquired vibration signals of high, low, and medium strength classes.

The acquired vibration signals were used as training and testing data for the deep learning model. Before they could be used in the deep learning model, the vibration signals were adjusted so that they all had the same length. This was achieved by zero-padding. The total number of signals was 60, each lasting 1.89 seconds, with a total of more than ten thousand data points. The data was split into training and testing sets, with the training set constituting 80% of the total dataset and the testing set comprising 20% of the total dataset.

Retrieval Number: 100.1/ijrte.B77380712223 DOI: <u>10.35940/ijrte.B7738.0712223</u> Journal Website: <u>www.ijrte.org</u> The deep learning model used in this work requires images as input; hence, all 1-D vibration signals were converted to 2-D matrices containing information about time and frequency. This conversion was accomplished through the continuous wavelet transform (CWT), which transforms the vibration

signals to 2D images, known as scalograms. Given a mother wavelet $\psi(t)$, a function x(t) is

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converted via CWT using the following formula:

$$X(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} \psi\left(\frac{t-b}{a}\right) x(t) dt$$

Where a is the scale which corresponds to frequency information, and b is the shifting parameter which corresponds to the time information. As a is the scale, changing it alters the size of the wavelet, while changing b shifts the wavelet over the signal being transformed. Each vibration signal is transformed using CWT by creating a continuous wavelet transform (CWT) filter bank. The wavelet used in the filter bank is the analytic Morse (3,60) wavelet. The filter bank uses 12 wavelet bandpass filters per octave (12 voices per octave). Figure 4 shows the scalograms of the vibration signals for high, low, and medium strength classes.

(1)



Before feeding the obtained 2D images to the deep learning model for classification of strength classes, each image is resized to 224x224x3. The deep learning model used in this work is a Convolutional Neural Network (CNN), which is a type of deep learning model that utilises convolution operations in deep neural networks. It can efficiently extract features through the training process. CNN has been extensively used in literature recently for purposes such as classification and image recognition [18]. CNN typically consists of multiple layers, including convolutional layers that extract features through filters. In addition to convolutional layers, there are activation layers, such as the rectified linear unit (ReLU), for learning nonlinearity, and a batch normalisation layer that uses normalisation to reduce training time and increase stability. Furthermore, there are pooling layers that are used for dimensionality reduction of features by extracting the maximum convolutional features from the previous convolutional layer. Usually, the last layer of a typical CNN is the fully-connected layer for calculating the outputs of classes. The backpropagation algorithm is used for training the network by minimizing errors and adjusting weights accordingly. In this work, we use the transfer learning technique. Transfer learning improves both training time and accuracy while reducing the fine-tuning time required for the model. In particular, we utilise and fine-tune Google LeNet [19], a deep convolutional neural network trained initially on over a million images. It can accurately classify images into up to 1000 object categories (such as animals, office supplies, and coffee mugs). The power of transfer learning lies in the use of previously learned, rich feature representations acquired by training the network on a wide variety of images. The input of Google LeNet is in the form of images, and the output is a label for the object in the image, as well as its probability. In this paper, we slightly changed the architecture of the GoogLeNet before it was trained on the vibration data. Specifically, in the last layers of Goog Le Net, three layers were replaced, namely, 'pool5-drop 7x7 s1' layer was replaced with a new dropout layer, also, 'loss3classifier' was replaced with a new fully connected layer, and 'output' layer was replaced with a

new classifier was replaced with a new fully connected layer, and output layer was replaced with a new classification layer. The whole architecture of the modified network used in this work is shown in Figure 5.

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GoogLeNet Layer Graph: 144 Layers

Scalograms of acceleration data [224x224x3]



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Training a deep learning model requires fine-tuning and choosing the correct parameters and properties of the model's network. The training parameters used for training the modified GoogLeNet are shown in Table 2.

Table 2.	Training	parameters
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Parameter	Value	
Feature extraction network	GoogLeNet	
Input Size	224x224x3	
Number of layers	144	
Optimizer	SGDM	
Max epochs	30	
Initial learning rate	0.001	
Batch size	15	

The software environment used for this research was MATLAB R2021b. In particular, Signal Processing Toolbox, Wavelet Toolbox and Deep Learning Toolbox were used.

To measure the performance of the trained deep learning neural network, an accuracy measure was used, which is defined as:

$$Accuracy = \frac{Number of correct predictions}{Total number of predictions}$$
(2)

In addition to accuracy, a confusion matrix was also used to evaluate the deep learning model further. The confusion matrix's rows correspond to the predicted class (predicted strength class), while the columns correspond to the true class (actual strength class). The diagonal of the confusion matrix shows the instances that were correctly classified, and the offdiagonal cells correspond to the incorrectly classified instances.

#### **III. RESULTS AND DISCUSSION**

Upon training the deep learning model on 80% of the vibration data, it was tested using the remaining 20%. After 30 epochs of training, the resulting model achieved 100% training accuracy and a test accuracy of 91.67% on previously unseen data. Additionally, the training ceased after the model achieved a consistently low loss value, as illustrated in Figure <u>6.</u>



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To thoroughly examine the trained deep learning classifier, a confusion matrix was used. Each cell in the confusion matrix shown in Figure 7 contains the total number of instances along with the percentage of the number of cases. Cells located on the diagonal of the matrix (colored light green) show the cases that the model classified correctly, three out of four in the high strength class, four out of four in the low strength class and four out of four in the medium strength class. On the other hand, cells located off-diagonal in the confusion matrix (coloured light red) indicate instances where the model classified incorrectly, in this case, only one, where the model predicted that the strength class was low while it was high. The rightmost column of the matrix (light blue) shows the percentages of all the instances predicted to belong to each class (low, high, or medium) that were correctly classified (precision) and incorrectly classified (false discovery rate). The bottom row of the confusion matrix (colored light blue) shows the percentages of all the instances that belong to each class that were correctly classified (recall) and incorrectly classified (false negative rate). The cell in the bottom right corner of the confusion matrix (colored grey) shows the overall model's accuracy.

As shown in the confusion matrix, the deep learning model is performing effectively, achieving an accuracy of 91.67%. In addition, the model's precision is no less than 80% and the model's recall is no less than 75%.

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Output Class ⊠ ⊓	1 8.3%	4 33.3%	0 0.0%	80.0% 20.0%
	0 0.0%	0 0.0%	4 33.3%	100% 0.0%
	75.0% 25.0%	100% 0.0%	100% 0.0%	91.7% 8.3%
H L M Target Class				

Figure 7. Confusion matrix of the performance of the CNN-based classifier.

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It can be argued that the type of hammer and its physical features, the hitting location, as well as the supports and the material of which they are made, and how far apart the supports are -among other variables- will influence the vibration signal characteristics, and in turn, the outcome of the model will change. Nonetheless, this work aims to present preliminary findings and sheds light on the sea of possibilities the proposed method promises. More comprehensive experimental and modelling efforts are needed to establish a robust method and model.



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### **IV. CONCLUSIONS**

In this work, we propose a promising deep learning-based, non-destructive, inexpensive, and accurate method for estimating concrete's compressive strength. The method estimated the strength class of cylindrical concrete samples by analysing vibration signals collected after striking a concrete cylinder with a hammer. The vibration signals were collected by attaching a smartphone to the concrete cylinder and logging the vibrations that were registered via the smartphone's built-in accelerometer. The acquired 1-D vibration signals were transformed to 2-D images using continuous wavelet transform, which were then used to train a deep learning model to predict the strength class. The findings demonstrate that the model accurately classified the strength of concrete as low, medium, or high. The developed model achieved a high accuracy of 91.67%. The promising results of this work shed light on the sea of possibilities of smartphone-based measurements of construction materials' properties. Nonetheless, more comprehensive experimental and modelling efforts are needed to establish a robust method and model for estimating concrete strength, following the steps presented in this work.

#### DECLARATION

Funding/ Grants/ Financial Support	No, we did not receive.	
Conflicts of Interest/	No conflicts of interest to the	
Competing Interests	best of our knowledge.	
Ethical Approval and Consent to Participate	No, the article does not require ethical approval or consent to participate, as it presents evi- dence that is not subject to inter- pretation.	
Availability of Data and Material/ Data Access Statement	Yes, it is relevant to the Availa- bility of Data and Materials. Data can be provided upon a reasonable request.	
Authors Contributions	I am the sole author of the article.	

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#### **AUTHOR PROFILE**



**Dr. Saleh J. Alghamdi** obtained his undergraduate degree in civil engineering from Al Baha University and received his master's in civil and environmental engineering from the University of Vermont. After he completed his Ph.D. at the University of Vermont, he was appointed to the College of Engineering at Taif University in 2019 as an assistant professor. In addition to conducting graduate-level research at the University of

Vermont, Dr. Alghamdi is currently investigating various subjects related to civil engineering materials. His research experience as a civil engineer has therefore aided him in gaining skills in conducting experiments, computer simulation, characterisation, and analytical methods, as well as programming platforms. Dr. Alghamdi's background has thus resulted in the publication of his work in high-impact-factor journals such as ACS Nano Letters (IF: 11.2), Composites Part B: Engineering (IF: 7.6) and Scientific Reports (IF: 3.99), among others. Dr. Alghamdi is involved in numerous administrative roles at the college and university levels.

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