International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-12 Issue-2, July 2023

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

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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 vibrations 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 built-in accelerometer. The acquired 1-D vibration signals are transformed to 2-D scalograms using continuous wavelet transform. Scalograms are then used to train a deep learning model to predict the strength class. Preliminary findings show that the model is capable of classifying the strength of concrete to low, high, or medium. The developed model achieved a high accuracy of 91.67%. The promising results of this work shed light into 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 pertaining to durability of concrete. Nevertheless, concrete that does not meet strength requirements probably will not meet durability requirements either. Evaluating the quality of concrete is based mostly on its compressive strength, which is tested using compression test on cylindrical samples or cubic samples of varying dimensions depending on the building and design codes used.

Manuscript received on 18 May 2023 | Revised Manuscript received on 29 May 2023 | Manuscript Accepted on 15 July 2023 | Manuscript published on 30 July 2023.
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The compressive strength of concrete ranges from low-strength that is used for plain concrete, to high-strength concrete that 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. Compression test is a destructive test for evaluating the strength of concrete, however, non-destructive tests exist that aid in the evaluation of concrete's properties. For instance, there are surface hardness techniques, which use empirical correlations between strength of concrete and its surface hardness. The most widely used surface hardness-based method is the rebound hammer test. Further, the elastic modulus of concrete is another very important factor for 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 via resonance frequency test and ultrasonic pulse velocity test in accordance with ASTM C215 and ASTM C597, respectively. Although a useful correlation exists be-tween 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 mod-ulus, Poisson's ratio, density, etc. ASTM provides a guide to calculating the longitudinal and transverse elastic moduli incorporating several parameters such as the sample dimen-sions and mass, as well as the resonant frequency obtained via the resonance frequency test. Many non-destructive tests are limited to lab environment and/or require testing equip-ment that is costly in addition to requiring training. In recent years, machine learning and deep learning techniques have been widely used to improve the prediction accuracy of the mechanical properties of concrete. Some of these techniques have been implemented to work out civil engineering problems including 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 modeled 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 strength of concrete can be evaluated in a lab or a filed environment where destructive tests can be performed, where 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 such equipment. 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.

II. MATERIALS AND METHODS

To predict the strength class of concrete, this work proposes hitting the concrete cylinders 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. Thus, obtaining unique acceleration signals from concrete samples of different compressive strengths. The resulting vibration signals are then transformed into images which can be then used to train a deep learning model that maps the vibration to the strength class. This approach is illustrated in Figure 1 and is further explained in the following sections.

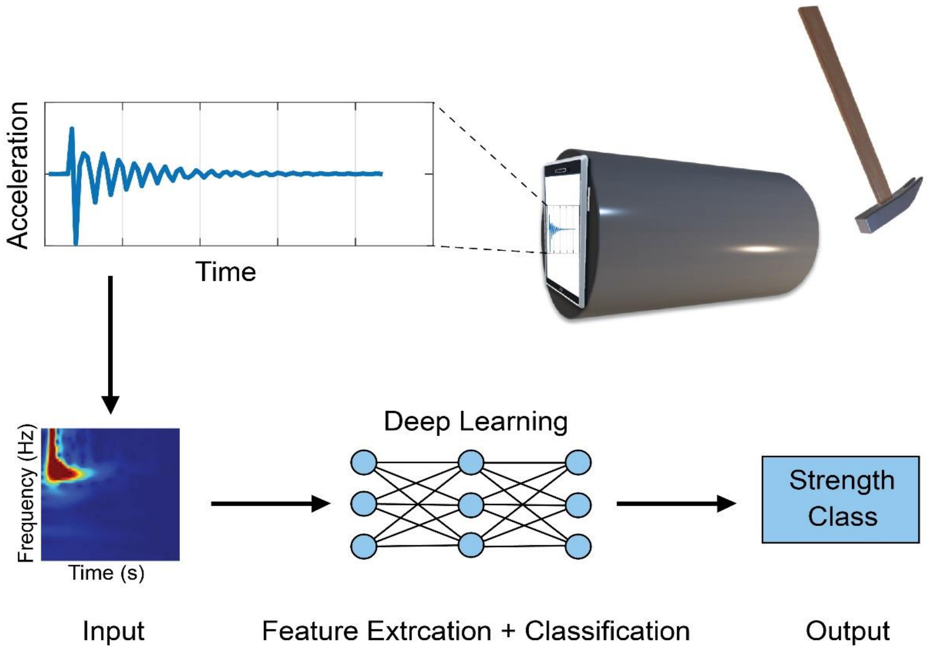

Figure 1. A schematic of the workflow of the proposed method.

Lab experiments are required for the training and validation of the deep learning model. In this regard, cylindrical concrete specimens were made having different compressive strengths. Each sample is cured for 28 days in a water bath, and extracted roughly a day before it is tested. Two tests were conducted on each sample, first the vibration test and then the compression strength test. As mentioned above, to acquire the vibration signals, a small 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. Prior to hitting the concrete sample, each sample is placed on two wooden blocks having 5-cm side square cross sections. In addition, the two supporting blocks were roughly five centimeters apart. These wooden blocks were used to support the weight of the concrete cylinders but not constrain them completely, which will prevent free vibration of the concrete cylinders. For these conditions to be achieved, the supports were situated near the longitudinal center of the cylinder, see 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 a duct tape. The smartphone used was an iPhone Xs (Model Number: MT9H2AH/A). This model is equipped with a three-axes 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 have 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 grouped according to their strength level. 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 medium, and lastly samples that showed compressive strengths higher than 40 MPa were labelled high. Each category contained two samples, and a total of 20 vibration signals were acquired from each category, as shown in Table 1.

Retrieval Number: 100.1/ijrte.B77380712223
DOI: 10.35940/ijrte.B7738.0712223
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Table 1. Training data

Number of vibration signals	Strength range (MPa)	Strength class
20	<30	Low
20	30-40	Medium
20	>40	High

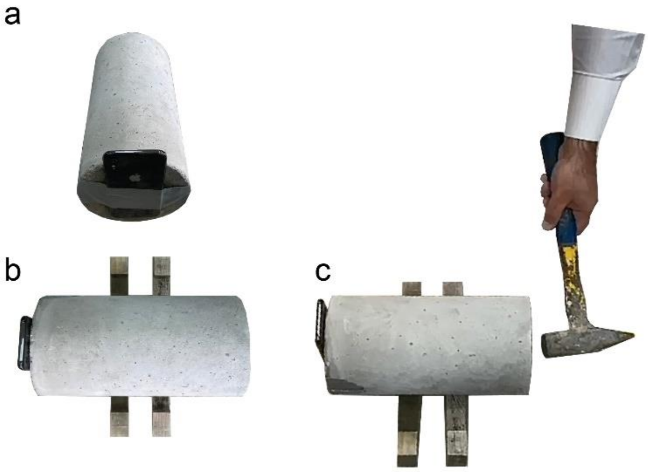

Figure 2. Illustrations of the proposed method of acquiring vibration data via hitting the concrete sample and registering the vibration signal by a taped-in-place smartphone.

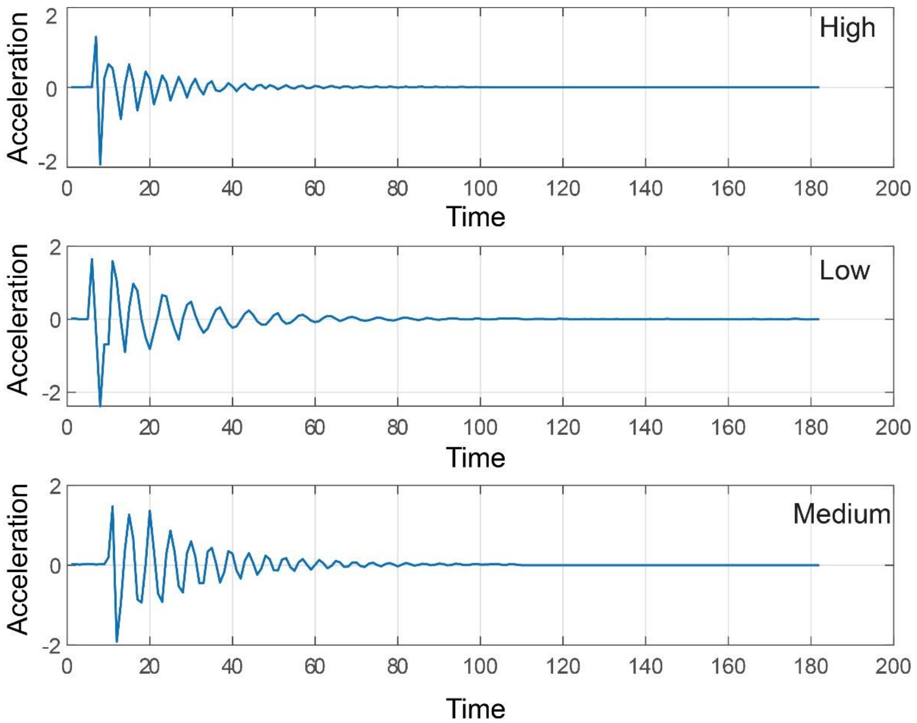

Figure 3. Representative acquired vibration signals of high, low, and medium strength classes.

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

The deep learning model used in this work requires images as input, hence, all 1-D vibrations 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 ψ(t), a function x(t) is transformed via CWT using the following formula:

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

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 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 vibrations signals for high, low, and medium strength classes.

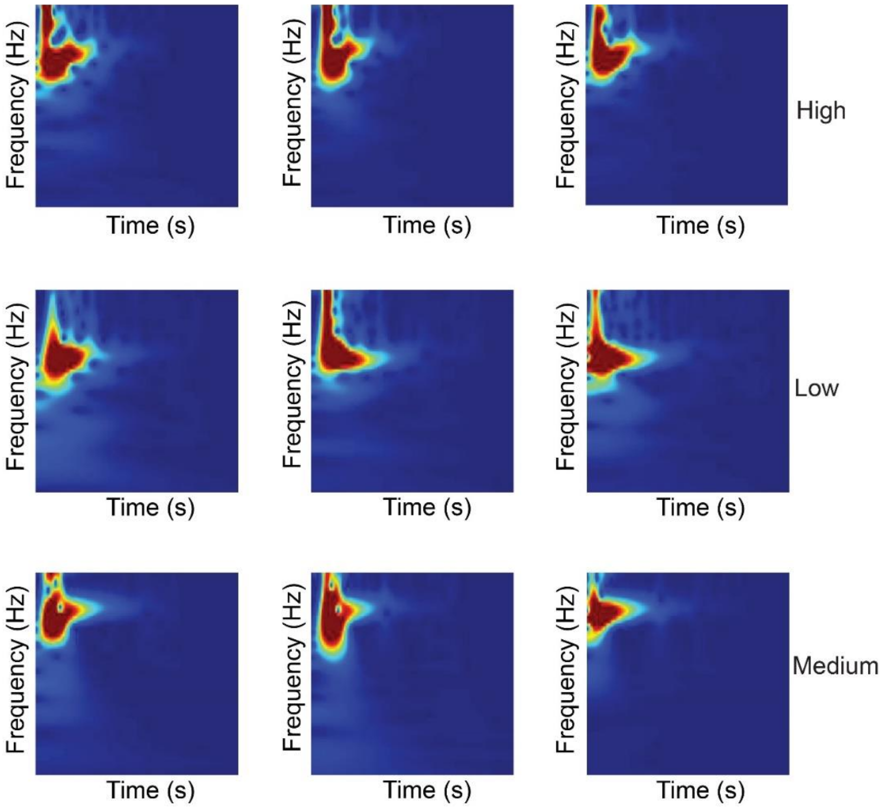

Figure 4. Scalograms of vibration signals of high, low, and medium strength classes.

Before feeding the obtained 2D images to the deep learning model to classify strength classes, each image is resized to a 224x 224x3. The deep learning model used in this work is Convolutional Neural Networks (CNN), which is a deep learning model that makes use of 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 usually consists of many layers, including convolution layers which extract features through filters. In addition to convolutions layers, there are activation layers such as the rectified linear unit (ReLU) for learning nonlinearity, batch normalization layer which uses normalization to reduce training time and increase stability. Further, there are pooling layers which are used for dimensionality reduction of features by obtaining the maximum convolution features of previous convolution 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 increases the training time and accuracy and reduces the fine-tuning time of the model. In particular, we use, and fine-tune Goog Le Net [19], which is a deep convolutional neural network that was originally trained on over a million images and can accurately perform classification of images to up to 1000 object categories (such as animals, office supplies, coffee mug, etc.). The power of transfer learning is through the use of the previously learned rich feature representations acquired by training the network on wide variety of images. Input of Goog Le Net 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, 'loss3-classifier' was replaced with a new fully connected layer, and 'output' layer was replaced with a new classification layer. The full architecture of the modified network used in this work is shown in Figure 5.

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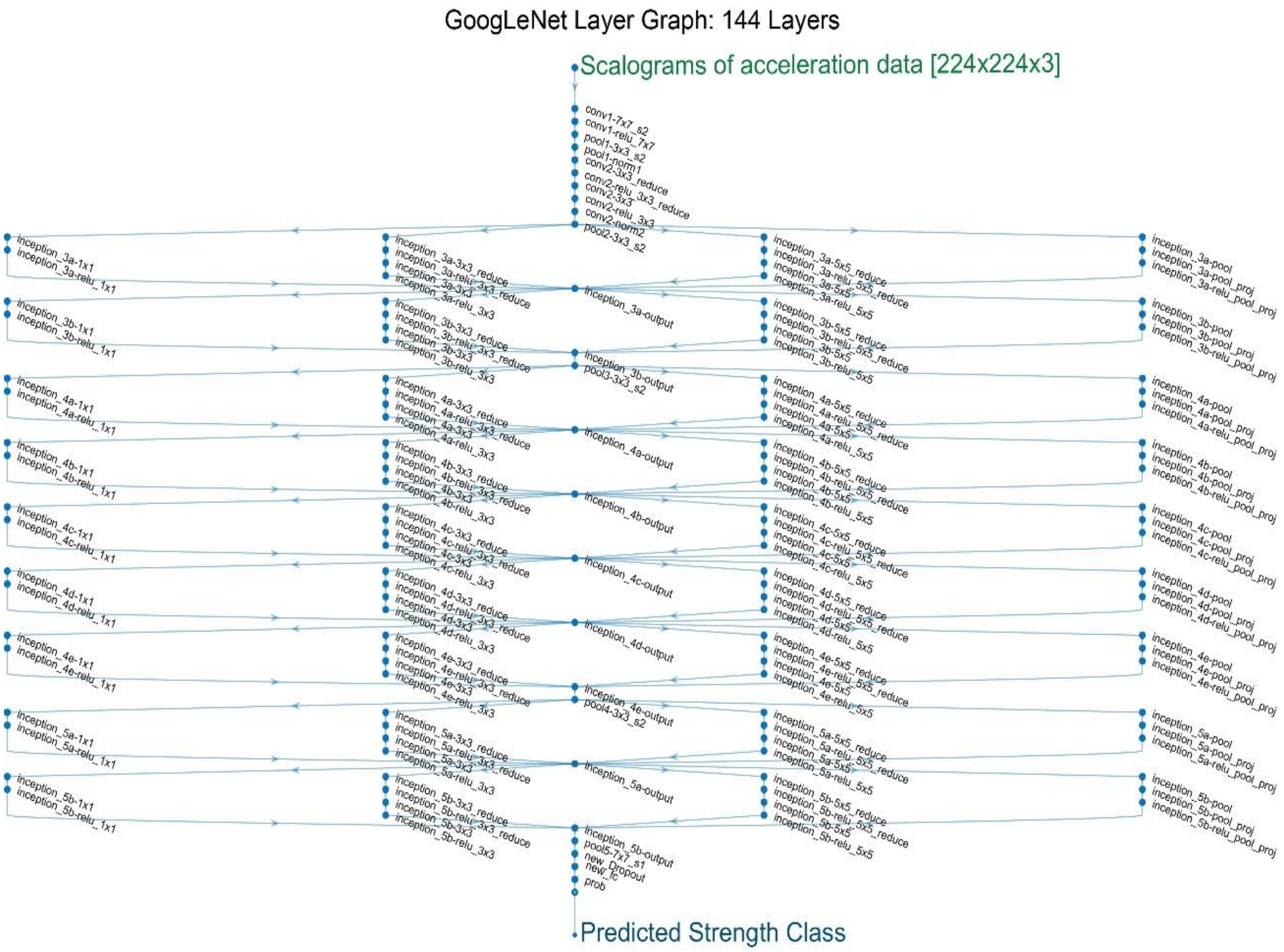

Figure 5. Architecture of the modified Goog Le Net

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

Table 2. Training parameters

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 leaning neural network, accuracy measure was used, which is defined as:

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

In addition to accuracy, confusion matrix was also used to evaluate the deep learning model even 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 off-diagonal cells correspond to the incorrectly classified instances.

III. RESULTS AND DISCUSSION

Upon training the deep learning model on the 80% of the vibration data, it was tested using the remaining 20%. After 30 epochs of training, the resulting trained model achieved a 100% training accuracy and an accuracy of 91.67 % when tested using the previously unseen testing data. In addition, the training stopped after the model has reached a consistently low loss value, see Figure 6.

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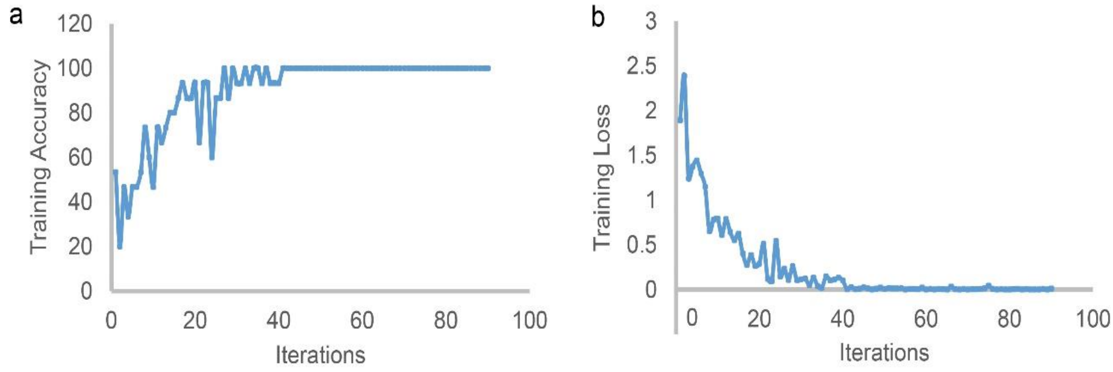

Figure 6. (a) Training accuracy and (b) Training loss

To fully examine the trained deep learning classifier, 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 instances. Cells located on the diagonal of the matrix (colored light green) show the instances that the model classified correctly, three out of four in 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 (colored light red) show the instances that the model classified incorrectly, only one in this case, where the model predicted that the strength class was low while it was actually 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 models' accuracy.

It can be seen from the confusion matrix that the deep learning model is performing properly reaching 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%.

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

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 into the sea of possibilities the proposed method promises. More comprehensive experimental and modeling efforts are needed to establish a robust method and model.

IV. CONCLUSIONS

In this work, we proposed 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 through vibrations signals that were 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. Findings show that the model successfully classified the strength of concrete to low, high, or medium. The developed model achieved a high accuracy of 91.67%. The promising results of this work shed light into the sea of possibilities of smartphone-based measurements of construction materials' properties. Nonetheless, more comprehensive experimental and modeling 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/ Competing Interests	No conflicts of interest to the best of our knowledge.
Ethical Approval and Consent to Participate	No, the article does not require ethical approval and consent to participate with evidence.
Availability of Data and Material/ Data Access Statement	Yes, it relevant to Availability of Data and Material. Data can be provided upon a rea-sonable request.
Authors Contributions	I am only the sole author of the article.

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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 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 Uni-versity of Vermont, Dr. Alghamdi is currently conducting research on different subjects pertaining to civil engineering materials. His research experience as a civil engineer, therefore, has aided him in gaining skills in conducting experiments, computer simulation, characterization, and analytical methods, as well as programming platforms. Dr. Alghamdi's background has thus resulted in publication of his work in high im-pact-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 many college-level as well as university-level administrative missions.