A digital twin framework with MobileNetV2 for damage detection in slab structures

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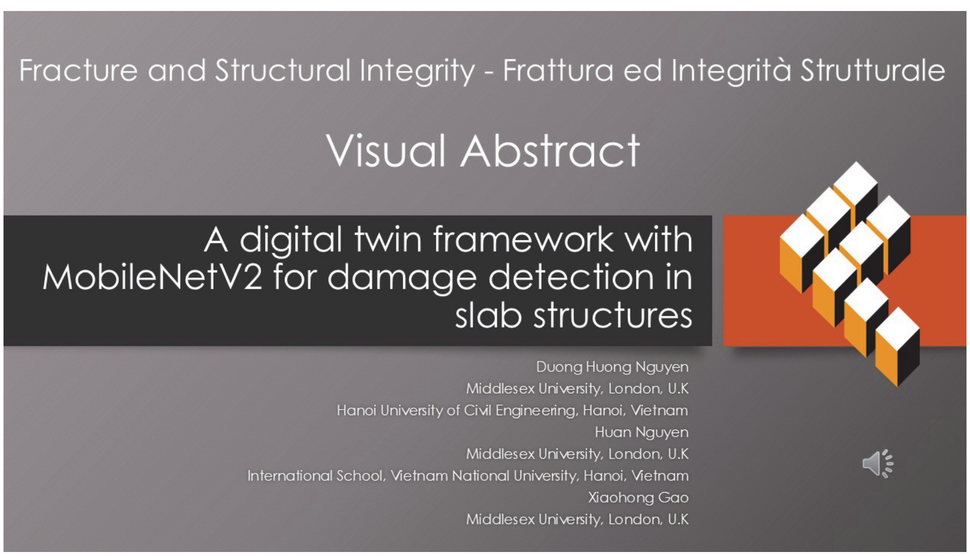

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INTRODUCTION

The Structural Health Monitoring (SHM) of civil structures is one of the most popular subjects in structural engineering. SHM can be defined as the process of monitoring and measuring the structural response in real-time to detect anomalies in the early stages of damage in structures based on data from instrumentation installed in the structure [5]. This process can be divided into four different phases: instrumentation, monitoring, analysis, and management. The most popular employed sensors in structural are accelerometers, strain gauges, LVDTs. All these sensors and data acquisition systems correspond to the measurement of the physical parameters. The set of techniques is employed to analysis structural measurement response to understand structural behaviour and detect damage. Finally, this real-time information is transferred to the right people for decision-making in the management phases. The recent advanced SHM technology involved the development of machine learning, digital twin, internet of things, sensor networks, etc [3]. Digital twin concepts use a digital reconstruction of a real-life structure which can automatically update identified uncertainties parameters based on data produced by sensors. The digital twin is more than a FE model because it is updated and calibrated with data measured from the physical model.

The potential of Digital twin integration into SHM through deep learning is becoming increasingly significant. Applying deep learning in machine health monitoring systems is discussed in [24]. A digital twin based SHM framework based on cloud computing and deep learning is proposed and demonstrated via case studies with high accuracy in damage detection [6]. The pros of implementing Digital Twin are functionalities for updates, an overview history of a structure, timely interceptions of damage, and decision-making support. Whereas, the cons are technological immaturity, lack of standards and guidelines, and the operation cost [3]. Moreover, the outlook of digital-based SHM, applications related is highlighted in [20]. Nowadays, the combination of machine learning and digital twin is becoming the core of SHM [13].

Vibration-based monitoring is on destructive method that tracks the dynamic response of the structure [2]. Digital twin coupling with machine learning will analyse vibration data extracted from monitoring techniques such as acceleration, deflection, strain, etc. Moreover, many research works targeted the evaluation of modal parameters such as natural frequency, mode shape, and damping ratio. Some identified uncertainties parameters of the structure will be updated in the virtual model if the difference between measured and calculated values is significant [23]. From measured, simulated data obtained from the updated virtual model, the appropriate deep learning models will be developed for SHM applications. Hielscher et al. [8] propose a method that uses Fibre Bragg Grating (FBG) sensors to measure the strain and temperature at discrete locations along the bridge. A deep neural network is then developed to convert the strain data into an interactive digital twin visualization and is used to predict the reinforced concrete bridge health. The digital twin of a bridge is calibrated using data collected from sensors and the support vector machine algorithms used to ensure the safety of the bridge are proposed [1]. A decision tree framework is proposed to perform anomaly detection multiclass classification of acceleration data collected from a real-life bridge [21]. Modern monitoring technologies include, among others, smart sensors, wireless sensors, Global Positioning Systems (GPS), Fiber Sensors (OFS), radars, Micro Electro Mechanical Systems (MEMS) are the evidence of the potential of this monitoring tool for SHM applications [3].

This paper uses deflection data collected from measurement as the input data set. Wavelet transform is then used to analysis the response data. Only the response of the damaged structure is required to detect damage in a structure [7]. The review and discussion of using wavelet-based method applied to various civil and mechanical structures are presented in the articles [12]. The authors pointed out that the measurement of damage severity is still a concern. For slab structure, a two-dimensional wavelet transform extracted from deflection data needs to be composed. Therefore, in this research, a two-dimensional continuous wavelet transform for the slab will be converted into a picture and used to train the convolutional neural networks for damage location and severity. The training data set is created by using the digital twin model. The classification in this study is provided with deep learning algorithms through image classification methods: traditional CNN and MobileNetV2.

The contributions of this work are as follows:

- We utilise defection data to facilitate the Wavelet transform based analysis where only the response is required to detect damage. This technique does not require the response data of intact structure which is hard to collect in many cases.
- We develop a signal processing algorithm to prepare for the digital twin model based on the dynamic characteristics of the physical model of a slab in the laboratory. In this algorithm, natural frequencies are used as the objective function while GWO and Cuckoo search methods are used for optimization.
- We create a digital twin framework to help train the convolutional neural networks for the detection of damage location and severity, employing a two-dimensional continuous wavelet transform for the slab converting into a picture. The classification is conducted with deep learning algorithms through image classification methods: traditional CNN and MobileNetV2. We found that the accuracy of the framework to detect damage location is more than 80% and the

severity is more than 90%. The traditional CNN provides higher accuracy however the number of training parameters is more than the MobileNetV2 and requires more time and effort to train.

– We successfully use MobileNetV2 as a deep learning base model and transfer learning. This is the first step of further implementation on mobile devices. With the help of transfer learning, the digital twin framework can be built with less training data set and high accuracy.

METHODOLOGY

Wavelet theory

Wavelet was first introduced by Mallat in 1989 [14] . The basic function of wavelet analysis is two parameters: scale and translation. Wavelets can be real or complex functions. The basic function of mother wavelet analysis can be the function of time t or space x. In this paper, the independent variable x will be considered. The discrete wavelet transform (DWT) uses a discrete set of the wavelet scale and translation and must satisfy some rules. The basic function of a wavelet at level j of order N can be represented as [4]:

$$\Psi(n)= \sum_{j=0}^{N-1} (-1)^{j}\, c_j\, (2n+j-N+1) \tag{1}$$

where: c_j is the coefficient.
Two following conditions should be satisfied:

$$\int_{-\infty}^{\infty} \Psi(t)\, d(t)=0 \tag{2}$$

$$\int_{-\infty}^{\infty} |\Psi(t)|^{2}\, d(t)<\infty \tag{3}$$

The condition presented in Eqn.(2) is to suggest that the basic function is oscillatory or wave shape. Whereas Eqn. (3) implies that most of the energy in the basis function is confined to a finite duration. The two important properties of a basic function are 'orthogonality' and 'biorthogonality', which make it possible to calculate the coefficient very efficiently.
In DWT, the signals can be presented by approximations and details. At level j, the details can be expressed as below:

$$D_j(t)=\sum_{k\in Z} D_{j,k}\, \Psi_{j,k}(t) \tag{4}$$

where $D_{j,k}$ is the wavelet coefficients at level j and Z is a set of positive integers. The approximation at level j is presented as:

$$A_J=\sum_{j>J} D_j \tag{5}$$

Finally, the signal $f(t)$ can be presented as:

$$f(t)=A_J+\sum_{j<J} D_j \tag{6}$$

The wavelet transform can be extended to any dimension. In slab structures, a two-dimensional wavelet transform is analysed to localize the damage. Two-dimensional scaling function $\Phi(x,y)$, and three two-dimensional wavelet $\Psi^{H}(x,y)$, $\Psi^{V}(x,y)$, $\Psi^{D}(x,y)$ are presented as the product of one-dimensional as below:

$$\Phi(x,y)=\Phi(x).\Phi(y) \tag{7}$$

$$\Psi^{H}(x,y)= \Psi(x).\Phi(y) \tag{8}$$

$$\Psi^{V}(x,y)= \Phi(x).\Psi(y) \tag{9}$$

$$\Psi^D(x,y) = \Psi(x).\Psi(y) \tag{10}$$

The first scale input is two-dimensional signal *f(x,y)*, the output is four quarter-sized sub-images (W_Φ is an approximation sub-image, and W_Ψ^H, W_Ψ^V, W_Ψ^D are the horizontal, vertical, and diagonal direction sub-image, respectively).
Some of the most well-known wavelets that are available in Matlab toolbox are: the Gaussian Mexican Hat, Morlet, and Shannon, the Meyer, the Haar [17]. In this work, the defection signal of the damaged slab structure is analysed with DWT. The input is the two-dimensional signal, and the diagonal direction sub-image output is then used to detect damage in the slab.

Transfer learning

Transfer learning used in machine learning is the reuse of a pre-train model on a new problem. Transfer learning is very useful when it can complete a new task by transferring knowledge from a related task that has been trained. Therefore, instead of training from the start, the trained model has learned with many available labelled training data and is transferred to a new but related task that doesn't have much data (Fig. 1). In transfer learning, only the lateral layer is retrained to classify the input to the newly defined task. Transfer learning is widely used because the network can provide high accuracy with less data. As much as possible knowledge from the previous task is tried to transfer to the new task within various forms depending on the problem and the data. The main advantages of transfer learning are saving processing time, not needing a lot of data, and in most cases having better performance.
Transfer learning techniques can be categorized into three sub settings: inductive transfer learning, transductive transfer learning, and unsupervised transfer learning [19]. In inductive transfer learning, the learning task in the target domain is different from the target task in the source domain. If many labelled data in the source domain are available, inductive learning is like a multitasking learning setting, if not is like self-taught learning. In the transductive transfer learning setting, the learning tasks are the same in both domains, while the source and target domains are different. The unlabelled data in the target domains will be available at training time, and the new data will be classified with existing data. In unsupervised learning, the data in the source and target domain is not labelled. It is similar to inductive transfer learning; the target task is different from the source task.
Transfer learning applications are varied. Several data sets for transfer learning have been developed such as text, email, image, and WiFi. There is some pre-trained network availability for example MobileNetV2, Inception-v3 model which were trained for the ImageNet. The network after training can be saved and used as a pre-train for new tasks. In this paper, this network will be retrained and applied to detect damage in slab structures.

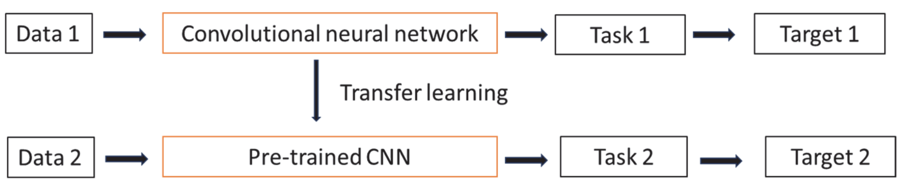


Figure 1: The transfer learning setup

Convolutional neural network

CNN is a deep neural network used to process images, they can also be adapted to work with audio and other signal data. CNNs use several layers to detect different features of an input image. The number of layers depends on the complexity of the task. Typically, CNN consists of several layers and can be categorized into three groups: convolution layer, pooling layers, and fully connected layers. CNN plays a role as a function f in the equation $y = f(x)$, where x is the input data set and y is the output data set.
The convolution layer is the layer in which the majority of computations occur. A small matrix of weights known as a kernel is used to reduce the number of computations while still finding out the presence of specific features in the input image. The pooling layer follows the convolutional layer to reduce the dimensionality, keeping the main feature. There are two kinds of pooling layers: average and max pooling. In some networks, the dropping layer is added to protect from overfitting. Some of the trained weights will be dropped and set to zero and be trained from the beginning of the next process. The fully connected layer is responsible for classifying images based on the features extracted in the previous layers. CNN makes a final classification decision based on each input from the previous layers connected to the fully connected layers. The fully connected layer is the last layer before the output layer.

CNN is very useful for computer vision tasks such as image recognition and classification. Transfer learning applications for CNN are very popular. The pre-trained model is fine-tuned for new tasks, benefits when the number of data is limited, and helps to minimize computational costs.

MobileNetV2 Network

MobileNetV2 Network is a Convolutional neural network developed for use with mobile devices or low-cost devices. The MobileNetV2 is pre-trained model based on its previous version MobileNetV1. Depthwise Separable Convolutions are used in both MobileNetV2 and MobileNetV1. Depthwise Separable Convolutions used for image classification were first introduced by Sifre [22]. The computation of depthwise separable convolution has two layers: depthwise convolution which refers to convolution that does not cross channels and reduces cost compared which traditional convolution; and pointwise convolution for feature merging and dimension alternating. Depthwise separable convolution is a set of convolutions obtained by combining a depthwise convolution and a pointwise convolution; two hyper-parameters are the width multiplier and resolution multiplier. The computation in MobileNetV1 using depthwise separable convolution can be almost 8 or 9 times smaller than traditional CNN. The MobileNetV1 has promising performance however it still has some problems such as the vanishing gradient problem. MobileNet V2 is improved to solve this problem. Besides Depthwise Separable Convolutions, MobileNetV2 introduces Linear Bottlenecks and Inverted residual structures to perverse the information. Linear bottleneck layers were inserted into the convolutional blocks assuming the manifold of interest I slow-dimensional. When an activation function (Relu) collapses the channel, the information in that channel will be lost. Using linear layers prevents non-linearities from destroying too much information. The bottlenecks layer contains all the necessary information; therefore, shortcuts are added between different bottlenecks to increase the gradient propagate ability. Compared to the traditional structure, an inverted design is considerably more memory efficient.
The MobileNetV2 architecture has 32 filter convolution layers and 19 residual bottlenecks. ReLU6 is used as an activation function on convolutional layers because of fast computation, SoftMax function is used as a classifier at the last layer. Kernel size 3 x 3 is always used to utilize dropout and batch normalization during training. The input size of the MobileNetV2 is 224 x 224 pixels. In this study, MobileNetV2 is used as a pre-trained model, and the structure is shown in Tab. 1 and Tab. 2.

Input	Operator	Output
$h \times w \times k$	1x1 Conv2D, ReLU6	$h \times w \times (tk)$
$h \times w \times (tk)$	3x3 dwise s=s, ReLU6	$\frac{h}{s} \times \frac{w}{s} \times (tk)$
$\frac{h}{s} \times \frac{w}{s} \times (tk)$	Linear 1x1 conc2d	$\frac{h}{s} \times \frac{w}{s} \times k'$

Table 1: Bottle neck residual block transforming from k to k' channels, with stride s, and expansion factor t.

Input	Operator
224x224x3	Conv2D
112x112x32	bottleneck
112x112x16	bottleneck
56x56x24	bottleneck
28x28x32	bottleneck
14x14x64	bottleneck
14x14x96	bottleneck
7x7x160	bottleneck
7x7x320	conv2d
7x7x1280	avgpool 7x7
1x1x1280	conv2d 1x1

Table 2: MobileNetV2 layers.

DIGITAL TWIN FRAMEWORK

A proposed digital twin concept for damage detection

A digital twin is a virtual model developed to represent the physical object. In civil structure, a digital twin is more than a Finite Element Model (FEM). It is a FEM that analyses uncertainty parameters to calibrate with data measured from its physical twin. Inside the digital twin framework are some areas such as FEM, neural networks, model updating, structural health monitoring, and digital signal processing. The base of digital twin is physical model, virtual model and the communication between them. Dynamic characteristic of a structure is one of the most popular communication factor and can be extracted from vibration measurements. Mihai et al. [15] refer to digital twin as a self-adapting, self-regulating, self monitoring and self-diagnosing system-of-systems.

The framework of the digital twin is displayed in Fig. 2. The two systems (physical and digital) exist side by side, sharing all the inputs and operations using information transfer and real-time data signals. Sensors are attached to a physical twin model to collect vibration data. These data are used to calibrate the digital twin model. Optimization algorithms are used to do this task. Uncertainty parameters such as the geometry of the model, material properties, and boundary conditions are some popular updated parameters. The target is the behaviour of the physical model and digital twin are identical. For example, the differences between natural frequencies, the MAC value of the mode shape, and the defection of the structures are minimized. Different damage scenarios are simulated in the digital twin model. The resulting significant amount of data is employed to train a neural network. The main goals of a digital twin model and a machine learning system are locating and evaluating the severity of the damage. Considering the connection between a virtual to a physical model, data collected from the physical model will be analysed and trained to predict the damage in the physical model.

The procedure to identify damage locations and its severity in a structure using digital twin framework is summarised below:

Step 1: Sensors are attached to the slab to monitor the slab's vibration and deflection.

Step 2: A digital twin of the structure is created as the finite element model. Measured data from Step 1 will be used to calibrate the digital model.

Step 3: Damages are introduced in the slab structure digital twin and the deflection data set of the damaged structure is restored.

Step 4: Using DWT analyse the defection data and create an input dataset.

Step 5: Training CNN using the input dataset and its labelled target.

Step 6: The trained CNN is saved for future use, saved as a pre-trained model for MobileNetV2.

Step 7: Predict the location and severity of the damage for new cases.

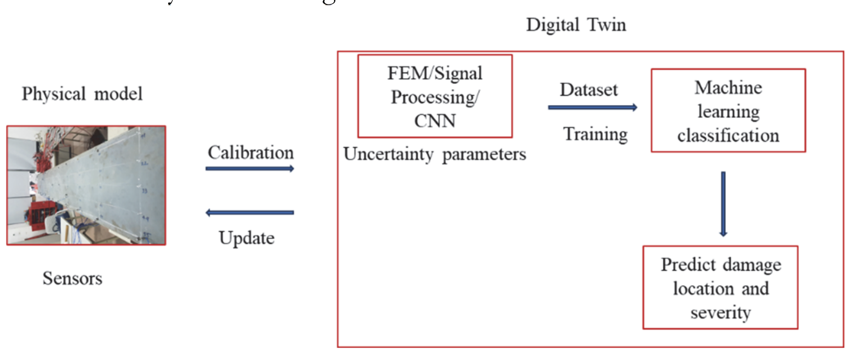


Figure 2: The digital twin framework.

Case study: Slab structure

– The physical model of the slab

The slab model in this research length is 3.5 m, wide 0.5 m, and height 0.0433 m. The slab is made from Ultra-High-Performance Concrete (UHPC). The boundary condition is simply supported, one bearing is fixed and the other is rolled. 55 discrete locations are marked to measure the acceleration. Fig. 3 shows the prototype and experiment setup in the laboratory. 15 accelerometers (S1 to S15), 5 setups, and 5 reference points are used.

Tab. 3 presents the location of each accelerometer marked in the slab. Five setups containing 55 discrete locations are shown in detail. The sensitivity of an accelerometer from 10.13 − 10.50 mV/m/s2, and weight 7.8 g. The accelerometer weight was considered to not affect the slab vibration behaviour.

The slab is excited by a hammer, the sampling frequency and time were 2560 Hz and 300 seconds. The slab vibration almost stops during the measurement time. The vibration data was analysed by the SSI method which set the criterion of 1% error in frequency, 5% error in damping, and 98% confidence in mode shape vectors. The stabilisation diagram is presented in Fig. 4. The characteristics of the physical model are identified by using the first four natural frequencies extracted from vibration data. The natural frequencies of mode 1, mode 2, mode 3, and mode 4 are 9.49 Hz, 41.46 Hz, 86.83 Hz, and 141.41 Hz, respectively.

Figure 3: The physical model of the UHPC slab.

Setup	Accelerometer label														
	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15
1	1	2	3	4	5	6	7	8	9	10	11	41	28	14	49
2	12	13	15	4	16	17	18	19	20	21	22	41	28	14	49
3	23	24	25	4	26	27	29	30	31	32	33	41	28	14	49
4	34	35	36	4	37	38	39	40	42	43	44	41	28	14	49
5	45	46	47	4	48	50	51	52	53	54	55	41	28	14	49

Table 3: Measurement setup.

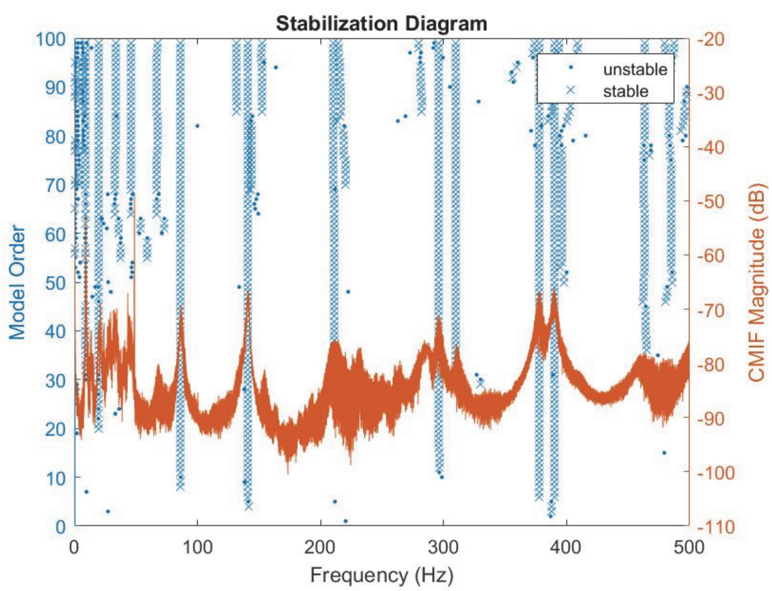


Figure 4: The stabilization diagram.

– Digital twin model of the slab

The FE model of the slab was created by using Sap2000 software. The area section is used to model the slab. Fig. 5 illustrates the FE model of the slab. The slab is high 0.0432m, width 0.5m, and length 3.5m. The boundary conditions are set to simple supported where the distance between two supports is 3m. The FE model is meshed with 10000 area elements. This model contains information on the structures and will be updated using optimization algorithms. The Grey Wolf Optimization (GWO) and Cuckoo Search algorithms are adopted to update the physical model of the bridge. The objective function is the first four natural frequencies of the physical model and FE model.

$$Objective\ function = \sum_{i=1}^{4}\left[100\times\frac{f_{Exp}f_{FE}}{f_{Exp}}\right]^2 \tag{11}$$

where: f_{FE}, f_{Exp}: the natural frequencies of the numerical model and experimental model, respectively.

GWO mimics the leadership hierarchy and hunting mechanism of grey wolves (Canis lupus) in nature. Cuckoo search algorithms mimic the brood parasitism of some cuckoo species . Many works are successful in using these optimizations to update the civil structures model based on dynamic characteristics [10,16]. FE model combined with machine learning algorithms and sensor networks can be used as a digital reconstruction of a real-life structure which can integrate the sensor data to get the structural health information.

Sap Matlab toolbox is responsible for evaluating objective functions based on the FE results and updating the uncertainty parameters [11]. Two linear parameters considered to update are the UHPC material characteristics: modulus of elasticity (E) and density (ρ). Fig. 6 presents that the value of objective functions reduces when the number of iterations increases. After 20 iterations, the objective functions calculated by Cuckoo algorithms don't change. Whereas the GWO optimization algorithm needs 50 interactions before the value of the objective function becomes stable. The values of E and ρ are shown in Tab. 4. The upper and lower boundary of E and ρ used in both algorithms are the same. The difference between GWO and Cuckoo search is small. After updating, the difference between the natural frequencies of the digital twin and the physical model is below 10% (Tab. 5). The FE model of the slab is successfully updated. Fig. 7 presents the mode shape of the FE model of the UHPC slab. This FE model is then used as the digital twin model to induce damages, creating a training data set for neural networks.

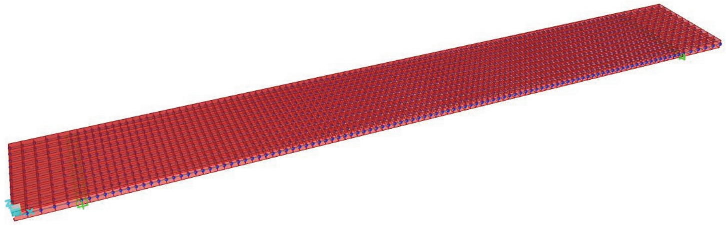


Figure 5: The FE model of the UHPC slab

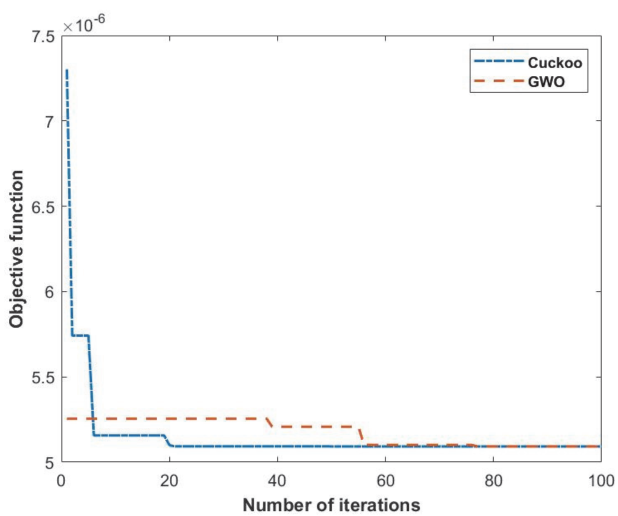


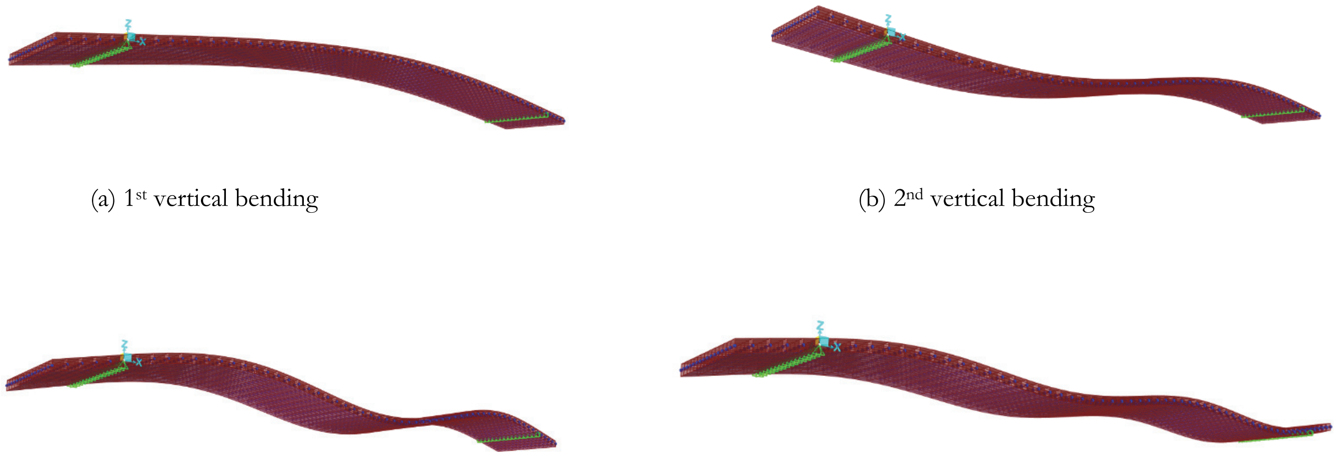
Figure 6: The value of objective function versus number of iterations

	Upper boundary		Lower boundary		Updated value	
	E (GPa)	(kg/m^3)	E (GPa)	(kg/m^3)	E (GPa)	(kg/m^3)
Cuckoo	45	2350	50	2450	47.58	2428
GWO	45	2350	50	2450	47.62	2430
Differences	-	-	-	-	0.08%	0.08%

Table 4: Uncertainty parameters.

No	Mode	Frequency			Relative error	
		Experimental data	Model updating - Cuckoo	Model updating - GWO	Cuckoo (%)	GWO (%)
1	1st vertical bending	9.49	9.53	9.53	0.42	0.42
2	2nd vertical bending	41.46	37.76	37.76	-8.92	-8.92
3	3rd vertical bending	86.83	83.35	83.34	-4.01	-4.02
4	4th vertical bending	141.41	143.07	143.06	1.17	1.17

Table 5: Natural frequencies based on numerical and experimental models.



(a) 1st vertical bending

(b) 2nd vertical bending

(c) 3rd vertical bending

(d) 4th vertical bending

Figure 7: The four first mode shapes of the UHPC slab.

– Proposed digital twin method for damage detection

To predict the location of damage and its severity in slab structures, the neural networks are trained using TensorFlow. The details of the input Dataset will be discussed below. After training, both traditional CNN and MobileNetV2 can predict the damage location and severity with high accuracy. However, after training, the MobileNetV2 is fine-tuned, and the weights are saved for use as a pre-trained model.

The digital twin model of the slab is used to create the dataset for training. The slab is divided into 20 locations, each location subdivided into 50 finite elements (Fig. 8). Damages are introduced in each location, varying from 2% to 10%. Three levels of severity are introduced in this work. Level 1, the severity of the damage in each location is below 4%. Level 2, and Level 3 the severity is below 6% and 10%, respectively.

The slab is subjected to concentrated static loads. The location and magnitude are varied on the slab and randomly. Details of each load case are shown in Fig. 9. The defection shape of the slab under the static forces (load case 3) with and without damage is shown in Fig. 10. The deflection differences between damaged and intact slab can't be identified. To create the data training set, two-dimensional DWT is applied to the response defection for each load case, and the diagonal wavelets are extracted (Fig. 11). Combining the diagonal wavelets of 8 load cases into one image, Fig. 12 are plotted. Fig. 12 a, b, c are the input images of damage severity at Levels 1, 2, 3, respectively. 1000 images of damage severity at Level 1 are used to train the network for identify the location. Then the network is saved and used as a pre-trained network to predict the location of damage at Level 2 and 3. 1200 images of damage at Level 1, 2, 3 are used to train the network for damage severity. Each image in the dataset is a 224x224x3 RGB image. Tab. 6 details the dataset used in the research.

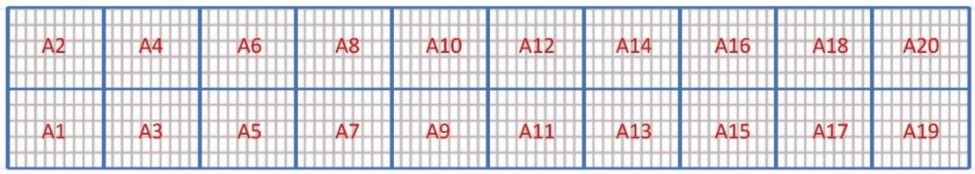


Figure 8: The mesh model of the slab

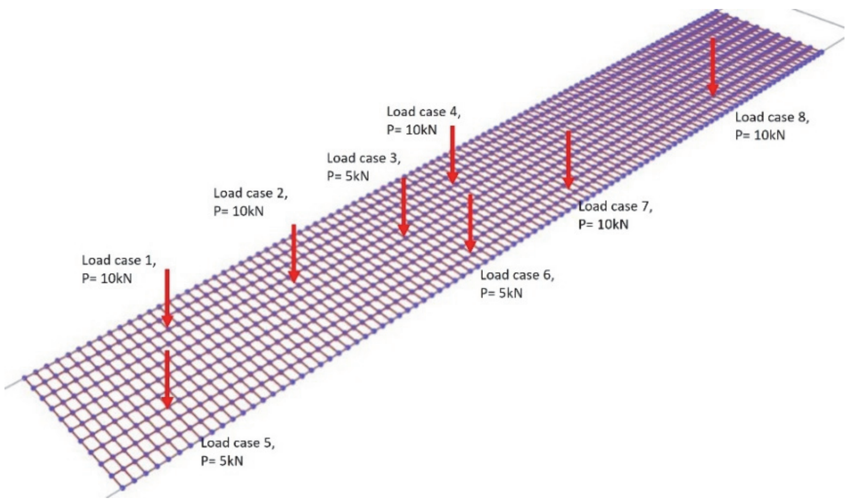


Figure 9: The location of static load cases

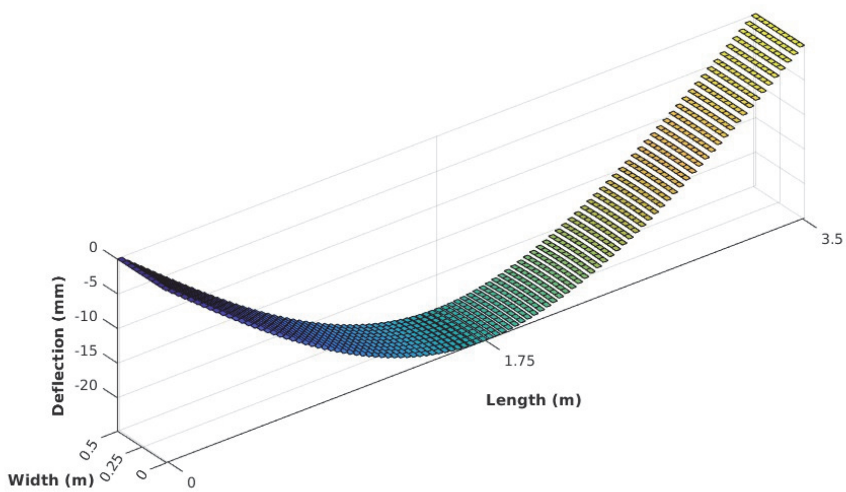


Figure 10: The damaged slab defection due to static load (load case 3).

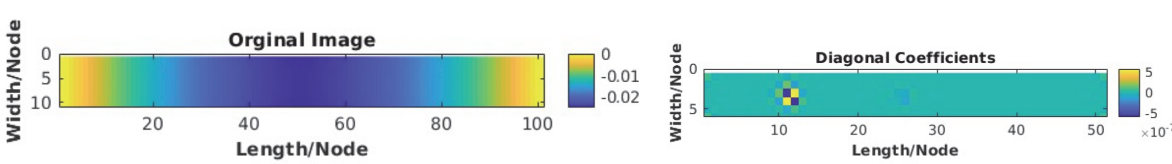
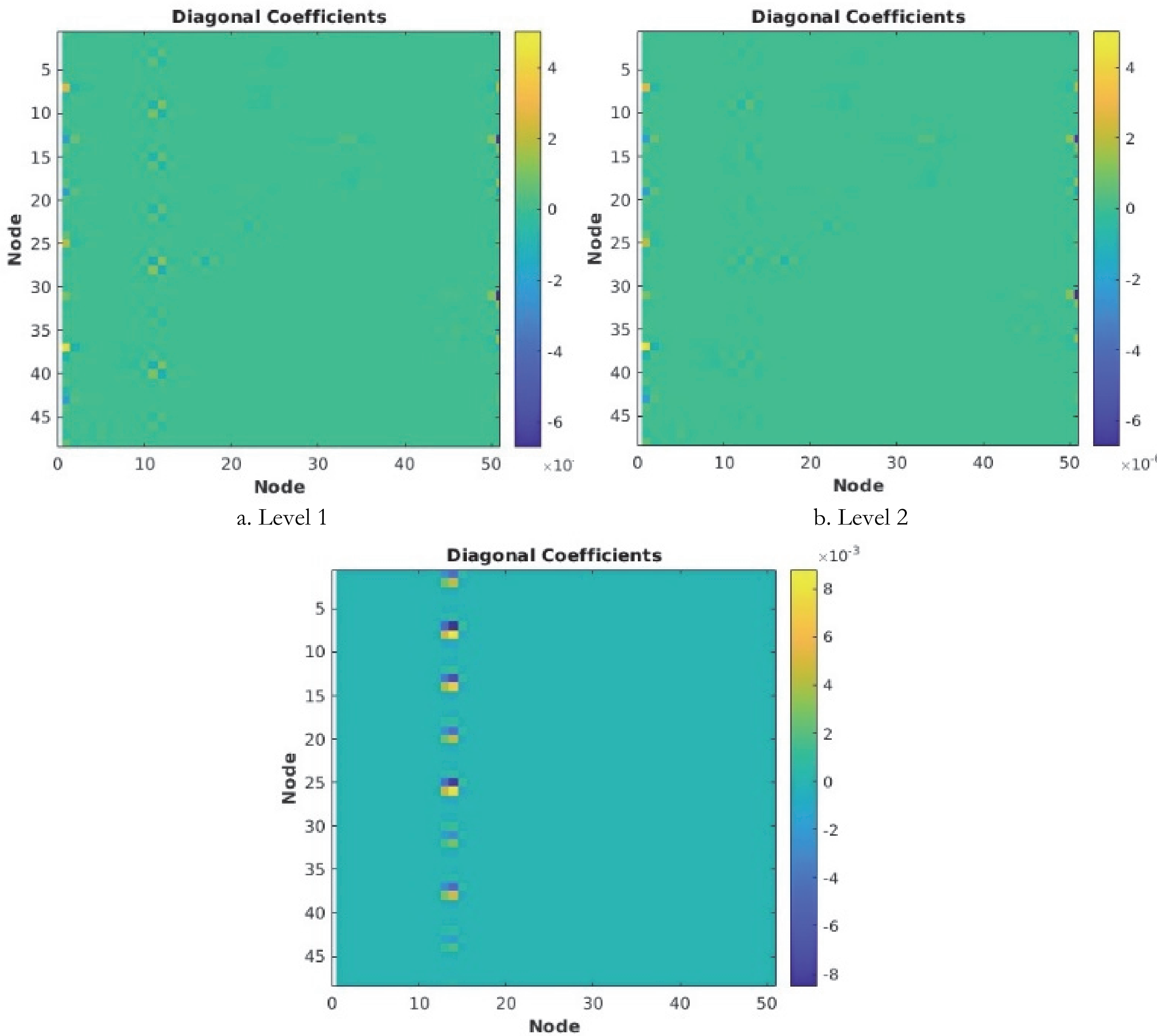


Figure 11: The damaged slab defection analyzed with wavelet transform (load case 3).



a. Level 1 b. Level 2

c. Level 3

Figure 12: The input dataset for all load cases (Damaged at A6).

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Name	Samples	Classes	Size
Location	1000	20	224x224x3
Severity	1200	3	224x224x3

Table 6: The datasets used in the research.

In this research, we propose to use both CNN with a traditional structure built manually and MobileNetV2 for classification. The structure of CNN and MobileNetV2 are shown in Fig. 13, and Fig. 14, respectively. Traditional CNN was built with three convolution layers, a pooling layer, and a dropout layer to avoid overfitting. The number of features extracted in the first, second, and third layers is 16, 32, and 64, respectively. The pooling layers summarise the features using the average, and the last layer helps to fully connect layers of neurons.
MobileNetV2 is used as a pre-trained neural network. At the end of the MobileNetV2 stage, the feature map matrix is flattened and fed into fully connected layers, called the classified stage. Finally, the SoftMax activation function is applied to classify output such as damage location or severity (Fig. 14). Tab. 7 summarizes the total number of parameters and trained parameters in traditional CNN and MobileNetV2. The MobileNetV2 has fewer parameters than traditional CNN for both tasks.

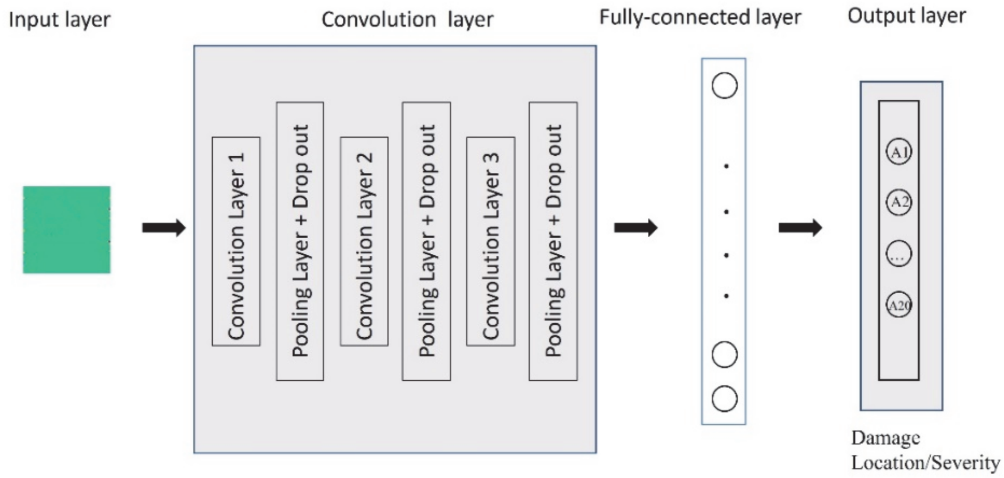


Figure 13: The proposed traditional CNN architecture

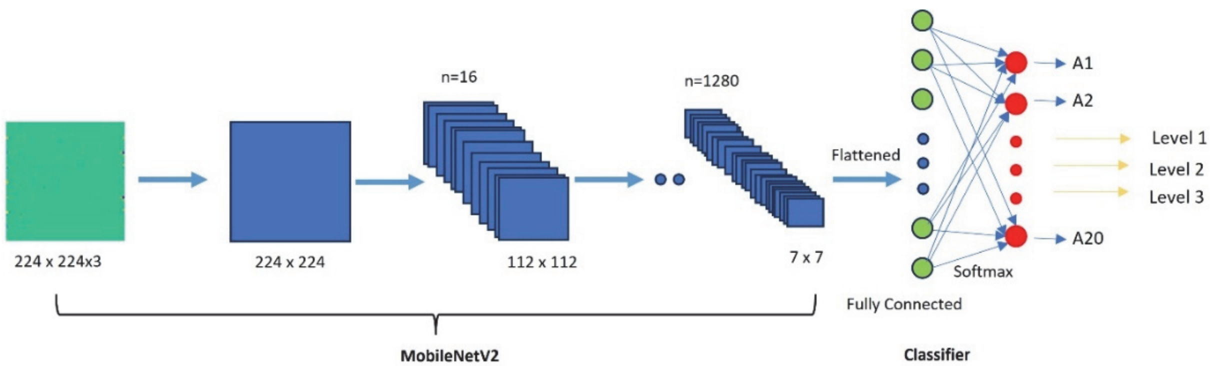


Figure 14: The proposed MobileNetV2 network architecture

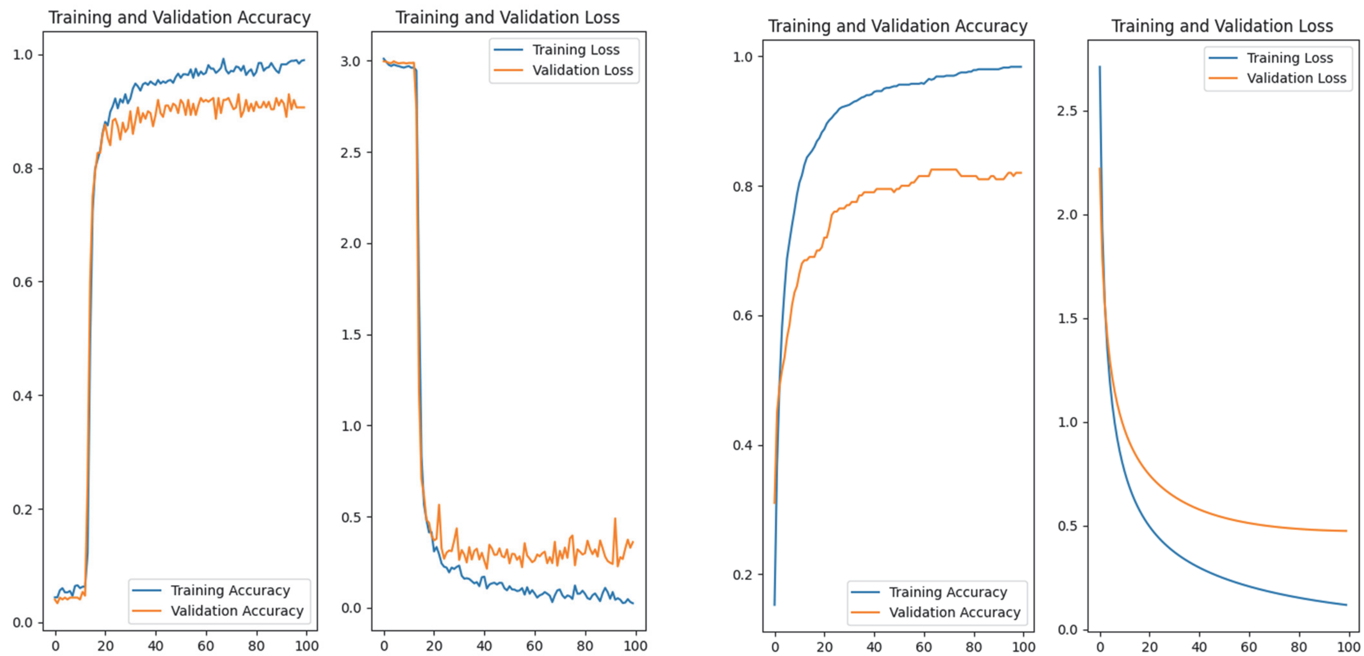
	Name	Total parameters	Trainable parameter	Epoch
Location	Traditional CNN	3311412	3311412	100
	MobileNetV2	2283604	25620	100
Severity	Traditional CNN	3309219	3309219	30
	MobileNetV2	2261827	3843	30

Table 7: Information of the proposed neural network architecture

– Results
  ✓ Damage location

The model is trained using Tensorflow, 16GPU, and 16 batch sizes are used. The dataset contains 1000 images analysed from 1000 damage scenarios in which severity 2% is used. 80% of the dataset is used for training and 20% is used for validating. After training, the network is tested with different damage severity locations. Fig. 15 presents the performance of traditional CNN and MobileNetV2. Both neural networks have an accuracy of more than 90% for the training dataset and more than 80 % for the validation test. Fig. 16 presents some examples of model predictions.

Based on the input image, the model can predict the damage locations. Traditional CNN failed to adjust weights for the first 20 epochs, however, MobileNetV2 was successful from the very beginning. After 100 epochs, the accuracy of both CNNs reaches more than 90%, traditional CNN training and validation accuracy are higher than MobileNetV2, however, the trainable parameter in traditional CNN is very large and requires more time and effort to train. This proves that traditional CNN is suitable for cases with large training datasets. MobileNetV2 is suitable for the tasks that have fewer data and is a lightweight CNN.



a. Traditional CNN b. MobileNetV2

Figure 15: Performance of the training CNN for damage location based on proposed method.

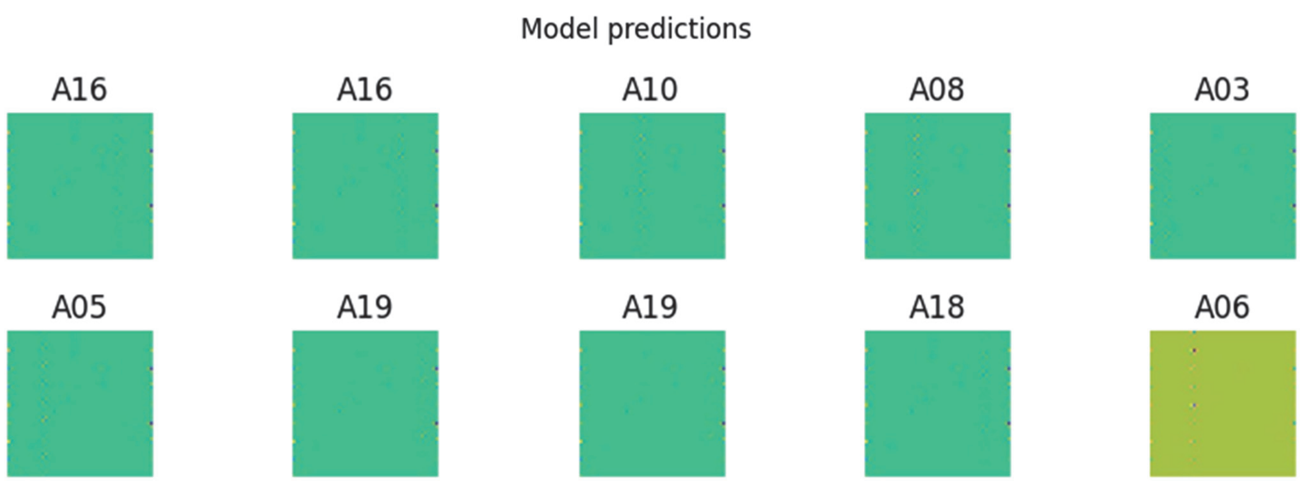
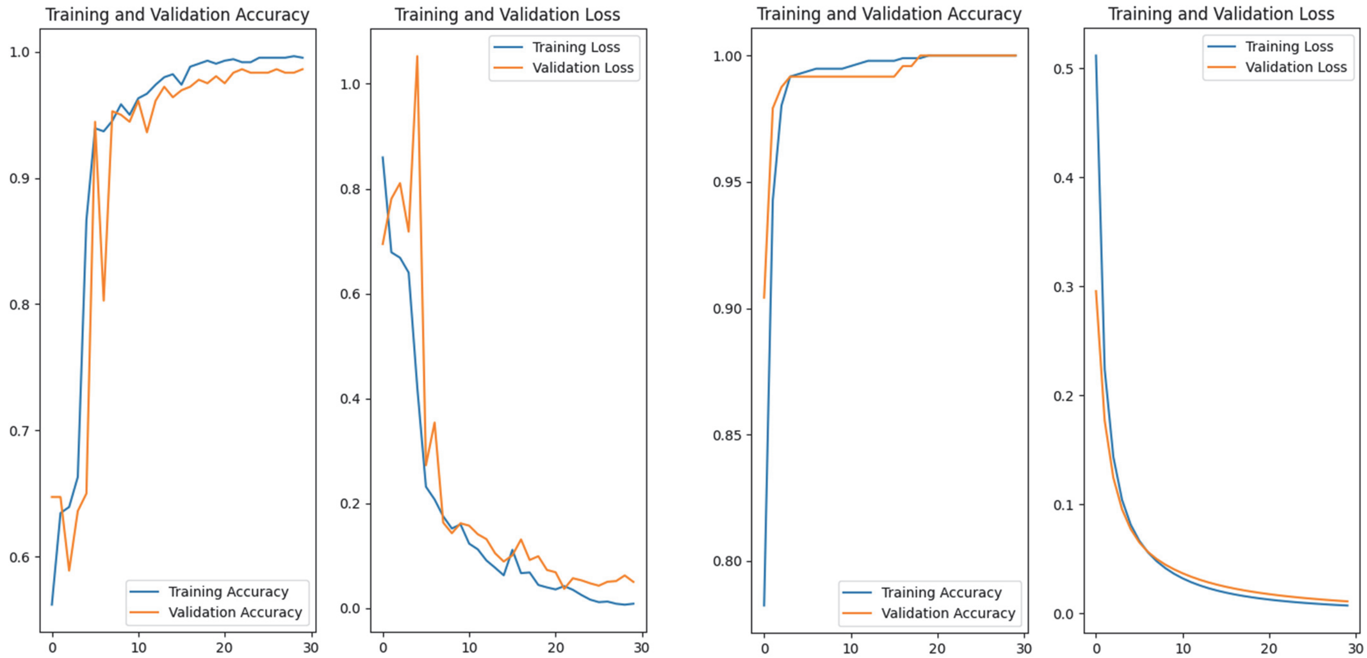


Figure 16: Example of damage location classification results

✓ Damage severity

1200 images were used to train the damage severity. Three level of damage with stiffness reduces less than 10% is considered. Level 1, Level 2, and Level 3 the severity is below 4%, 6% and 10%, respectively. Fig. 17 provides the training and validation accuracy and loss when using CNN to predict the damage severity. Both simple CNN and MobileNetV2 have high accuracy, almost reaching 100%. However, MobileNetV2 needs fewer epochs to reach high accuracy and reduce loss than traditional CNN. At the first 10 epochs, the accuracy of traditional CNN is not steady, while MobileNetV2 need only 5 epochs to reach the accuracy of 90% and loss function is reduced when the number of epochs increases. Fig. 18 shows some prediction results from the neural network model. The accuracy of training and validation are high, proves that CNNs are successful in predicting.



a. Traditional CNN b. MobileNetV2

Figure 17: Example of damage location classification results.

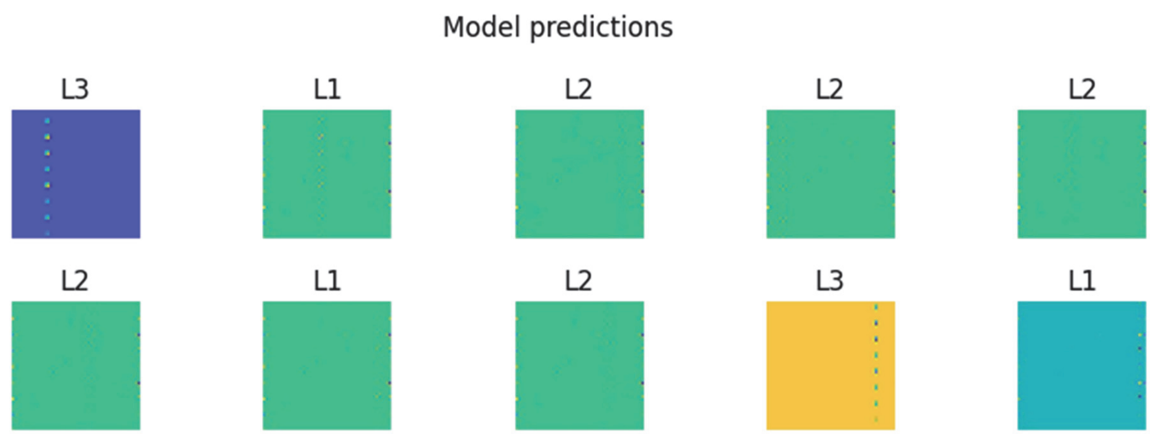


Figure 18: Example of damage severity classification results.

Conclusion

The present work proposes a damage detection method based on digital twin and deep learning algorithms. A slab structure length 3.5m is used to verify the methods. The dynamic characteristics of the slab are identified by analysing vibration data collected from accelerometers. Optimization algorithms then help to calibrate the FE model and create the digital twin model. Different damage scenarios are created in the digital twin model, and the slab structure deflection is decomposed by two-dimensional discrete wavelet analysis. Both traditional CNN and MobileNetV2 are trained with the training images created by deflection data composed from a digital twin model. This method deals with damage scenarios with a severity of less than 10%, which is a limitation in some research [18]. The results show that the proposed method can give high accuracy, which is more than 80% for location and 90% for severity.

The wavelet transforms (DWT) are applied to the defection data of the slab in this work. The formulation of the two-dimensional wavelet transform for a slab structure is presented. The diagonal direction sub-image output is then used as input data to train the convolutional neural networks in the digital twin framework. The study on wavelet analysis and deep

learning applied to damage detection shows some advantages of this method such as not requiring the data from intact structures, and success with minor severity damage.
The success of using MobileNetV2 as a deep learning base model and transfer learning gives this method the potential to be implemented further on mobile devices. Moreover, with the development of technology, sensors pairing with IoT devices can provide valuable information for validating and updating the digital twin [9]. The deep learning and digital twin model introduced within this work demonstrates the application of the SHM strategy. Damage can be detected and localized from changes in structural deflection before visual inspection. This SHM approach provides an automated way to automatically, and continuously assess structure health, prevent structure from serious failure, and help with maintenance.

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