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Research Paper

Deep convolutional neural network-based transfer learning method for health condition identification of cable in cable-stayed bridge

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The cables are extremely important and vulnerable components in the cable-stayed bridges. Because cable tension is one of the most crucial structural health indicators, therefore, assessing the cable condition based on the cable tension is a major interest in the structural health monitoring (SHM) of the cable-stayed bridges. This paper aims to develop a deep convolutional neural network (DCNN)-based transfer learning method that is integrated with a continuous wavelet transform (CWT) for the health condition identification of the cables in a cable-stayed bridge using the one-dimensional time series cable tension data. For this purpose, the CWT is adopted to convert the cable tension to the images of a time-frequency representation. The last three new layers emerged in the pre-trained DCNN model, which is called AlexNet, as a new learning framework to use for the identification of the cable condition. The performance of the proposed DCNN model is examined using several statistical measures that include accuracy, sensitivity, specificity, precision, recall, and the F-measure. The results show that the proposed DCNN model gives superior accuracy (100%) for the identification of the undamaged cables and the damaged cables based on the cable tension data.

1 Introduction

Cable-stayed bridges are widely used to pass over rivers due to their long-span capacity, good stability, and aesthetic design [1]. In the cable-stayed bridges, the cables are the major structural components, which primarily suffer from various effects of the dead load, the vehicle loads, the environmental actions, and natural disasters. The influences of these effects are adverse, and they prone to accelerate the collapse of the bridge. The sudden rupture of the cables can threaten the safety of the bridge, which causes severe vibrations on the bridge due to the loss of the cables and many changes in the internal forces of all the structural members [2]. The cable tension can be directly estimated using the load sensors, or it can be calculated indirectly using the different parameters of a cable, such as stress, strain, or the natural frequencies [3]. Several vibration based cable tension identification methods have been proposed for time-varying cable tension identification [4-6].

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Evidently, the consistency of the cable tension over time is considered as one of the health indicators for the cable bridges. Thus, it is necessary to recognize the cable condition timely to ensure the safety of the cable-stayed bridges.

Monitoring the structural damage is critically important to sustain and preserve the service life of civil structures. Structural health monitoring (SHM) is a broad research field that involves experimental testing, system identification, data acquisition, data management, and the long-term measurement of the environmental conditions [7-10]. SHM has been implemented in mechanical, aerospace, and civil engineering applications [11-13] for both the theoretical and the experimental methods for an early warning against structural damage or any type of anomaly [14, 15]. A considerable amount of effort has been put into the vibration-based methods, which utilize the vibration response in order to assess the condition of the structures as well as identify the damage to the structures [16]. In the past, machine learning (ML) algorithms have become more feasible and extensively used in SHM systems with elegant performances and often with rigorous accuracy [17]. The basic ML algorithms require a fixed number of features. Therefore, it is pertinent to pre-process a data sample in order to extract certain features that represent the most characteristic pieces of information [18], before applying the algorithm. This means that these algorithms significantly rely on the choice of the extracted features [19]. Nevertheless, it is not very easy to manually select a good group of features to train the ML system [20] for many cases. To avoid the hand-crafted features, the deep learning (DL) methods were introduced. The DLs have networks that are capable of learning unsupervised from the unstructured data. In addition, the DL algorithms can learn not only to correlate the features to the desired output, but they can also carry out the feature extraction process itself [21]. A DL is then able to explain the high-level and abstract features as a hierarchy of the simple and low-level learned features. This ability allows the DL algorithms to deal with complex tasks by breaking them down into a large number of simple problems [16]. Recently, a deep convolutional neural network (DCNN) has demonstrated a state-of-the-art performance with image classification, object detection, and image segmentation [22]. For the image classification, many excellent DCNN models, such as AlexNet [23], GoogLeNet [24], VGG Net [25], and ResNet [26], have been developed using 1.4 million images. Generally, these DCNNs take the images as the input directly for the classification process, which avoids the high complexity of the pre-processing and the feature extractions. Instead using manual feature extractions, they offer automatic feature extractions using the concept of a deep neural network.

In signal processing, the signal can be transformed into a time-frequency representation using a time-frequency distribution, which can be used as the input on a DCNN for diagnosis, classification, and identification. Wang et al. [27] used a series of wavelet scalograms as the input for a DCNN without manual feature extractions in order to diagnose the fault detection. Verstraete et al. [28] employed a spectrogram, which involved using the HilbertHuang Transform (HHT) and a wavelet scalogram as the input in a DCNN for the fault detection. Duan et al. [29] proposed a DCNN-based approach to detect the damages in a tied-arch bridge by using the acceleration responses. A numerical analysis with different damage conditions was conducted to generate the datasets. The acceleration responses and the generated Fourier spectra were used to transform the datasets, and the performances of the damage detection were compared. Tang et al. [30] proposed a five-layer CNN to detect and classify the anomalous monitoring data from an SHM system. The acceleration data from a cable-stayed bridge was utilized and divided into training sets with different sizes for the performance evaluation.

Even though the DCNN models have achieved good results, the hyper parameters optimization that is performed by the intelligent optimization algorithms for the complex DCNN models may consume a lot of computational time. Therefore, when a small number of samples is available, the transfer learning offers huge advantages in terms of the accuracy and time consumption. The purpose of a transfer learning is to fine-tune a pre-trained DCNN that will be used to perform the classifications on a new problem. Transfer learning provides an approach that can transfer knowledge from one domain to other domains when the latter has a small amount of high-quality training data [31, 32]. Therefore, it is generally faster than having to train a network from the beginning with an arbitrary initialisation of weights. Dung et al. [33] compared three deep learning-based methods, which included a shallow CNN trained from scratch, a pre-trained VGG-16 with a fine-tuned classifier, and a pre-trained VGG-16 with a fine-tuned convolution layer and classifier to detect the cracks at the welded joints of the gusset plates. The performances of these models were compared using the accuracy rate, the precision rate, and the recall rate. Feng et al. [34] proposed a highly accurate damage detection method using a DCNN with transfer learning to detect the crack on concrete surfaces. The accuracy of the proposed damage detection method is 96.8%, which is considerably higher than the accuracy of a support vector machine. Gong et al. [35] proposed a deep transfer learning model in order to accurately extract the features for the inclusion of the defects in the X-ray images of aeronautics composite materials. The results showed that the model can reach a 96% classification accuracy (F1-measure) with satisfactory detection results.

This paper aims to investigate the performance of a pre-trained DCNN, which is called AlexNet, through transfer learning that is integrated with the continuous wavelet transform (CWT) for the health condition identification of the cables in a cable-stayed bridge using the time series cable tension data. In this regard, the CWT is used to convert the time series data to the time-frequency representations, which is called scalograms. A scalogram is the absolute value of the CWT coefficients of a signal. Subsequently, these scalograms are given as the inputs to the pre-trained DCNN model to train and test for the classification of the cable conditions. The proposed method is evaluated using a publicly available structural health monitoring (SHM) dataset. The evaluation results show that the proposed method can achieve superior accuracy for the undamaged and the damaged cables using a cable tension indicator.

2 Methodology

2.1 Continuous wavelet transformation

Wavelet transformation (WT) [36] is known as a mathematical tool that converts a signal in the time domain into a different form, which is a series of wavelet coefficients. A WT is effectively used for the time-frequency decomposition of nonstationary signals because of the excellent local zooming property of the wavelet. Traditionally, the wavelet transform can be categorized as the discrete wavelet transform (DWT), the wavelet packets transform (WPT), and the continuous wavelet transform (CWT) [37]. Among them, the CWT provides smoother and specific time-frequency resolution throughout the signals over the other two methods. The CWT, which is $\omega(s,\tau)$ of a continuous-time signal $x(t)$, is defined by comparing the signal $x(t)$ to the probing function $\Psi_{s,\tau(t)}$, which is expressed as

$$\omega(s,\tau) = \int_{-\infty}^{+\infty} x(t)\Psi_{s,\tau}(t)dt \tag{1}$$

This equation represents the convolution between the signal (t) and a filter with impulse response $\Psi(-t/s)/\sqrt{s}$, the CWT can be viewed as a linear filter.

As the CWT decomposes the waveform into coefficients of two variables s and τ, a double integration is needed to be performed to reconstruct the original waveform from the wavelet coefficients

$$x(t) = \frac{1}{C_\Psi}\int_{-\infty}^{\infty}\int_{0}^{\infty} \omega(s,\tau)\Psi_{s,\tau}(t)\frac{d\tau ds}{s^2} \tag{2}$$

$$C_\Psi = \int_{0}^{\infty} \frac{|\Psi(f)|^2}{|f|}df < \infty \tag{3}$$

where $\Psi(f)$ represents the Fourier Transform (FT) of $\Psi(t)$.

The wavelet transform coefficients are obtained by correlating the normalized wavelet function at selected scales and shifting along the signal at each instant of time. This study uses a scalogram that is represented by the absolute values of the CWT of the signal, which can be plotted as a function of both the frequency and the time [38].

2.2 Deep convolutional neural network

A deep convolutional neural network (DCNN) is a multiple layer feedforward neural network [39]. It takes an input as an image, assigns learnable weights and biases to various objects in the image, and capable of differentiating each object from another object. The DCNN is mostly used to identify images, cluster them by their similarities, and implement object recognition within the scenes. The DCNN includes different types of layers, which are input layers, convolution layers, ReLU layers, pooling layers, and fully connected output layers. The architecture of the DCNN and its terminology are fully given in [23].

2.2.1 Input layer

The input layer takes the image as an input in normalized raw pixel values. For an image input layer, this is where the type of network is specified, and the choices regarding the image size and the data augmentation are made.

2.2.2 Convolutional layer

The convolution layer is the place where the image processing starts. It consists of two parts that include a feature detector and a feature map. A feature detector is a matrix that can transform an image into a feature map through a convolution operation. During the forward pass, the feature detector moves along the width and the height of the image, which produces the image representation of the receptive region. This two-dimensional representation is known as an activation map that shows the response of the feature detector at each spatial position of the image, which is shown in Fig. 1.

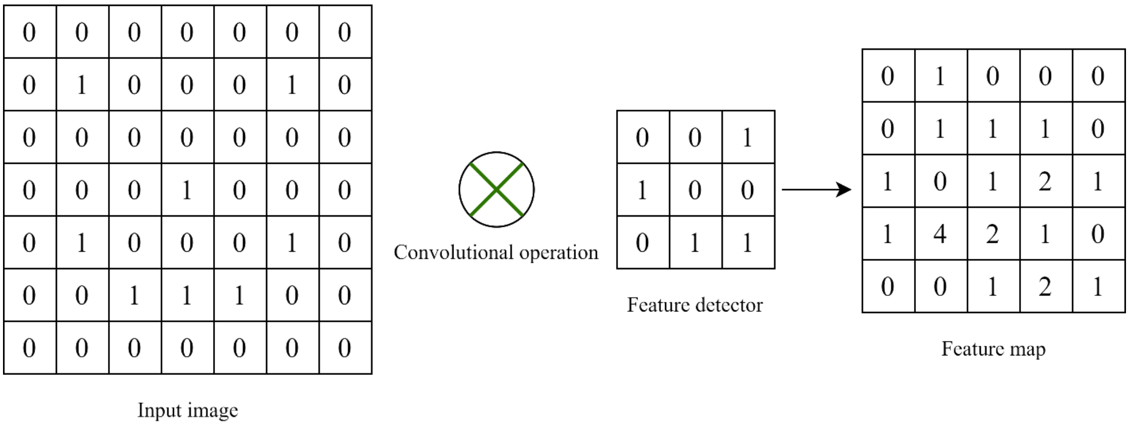


Fig. 1 – Convolution processing.

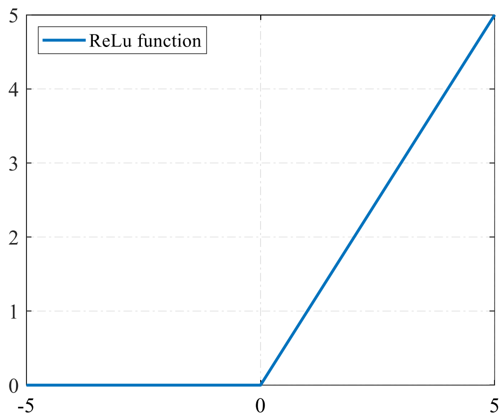


Fig. 2 - The ReLu activation function.

The feature detector slides across the input image with a step that is called a stride. If L is the actual convolution layer, f_L is the size of the filter, p_L is its padding, s_L is its stride, and c_L is the number of filters. For an image that has a size of $(n_{L-1}, m_{L-1}, c_{L-1})$, where n is the height of the image, m is the width, and c is the number of channels, the output of the layer would be a two-dimensional representation of the image that has the following size (n_L, m_L, c_L), where n_L and m_L are computed by

$$n_L = \frac{n_{L-1} + 2 \times p_L - f_L}{s_L} + 1 \qquad (4)$$

$$m_L = \frac{m_{L-1} + 2 \times p_L - f_L}{s_L} + 1 \tag{5}$$

2.2.3 *Activation function*

In general, a nonlinear activation function is used after the convolutional layer. The most common and the most effective activation function used in a DCNN is the rectified linear unit (ReLU) function [40], which is shown in Fig. 2.

The gradients of the ReLU function are always zeros and ones. The ReLU function not only solves the disappearing gradient problem that can occur during training, but it also executes much quicker and achieves better accuracy than other functions, which includes the sigmoidal function. Therefore, when the ReLU function is used as the activation function of the hidden layers, the errors can propagate back through the hidden layers properly.

2.2.4 *Pooling layer*

The pooling layer can be used to ignore the less important data in the image, and it reduces the image further, which all occurs while preserving its important features [39]. In this method, the feature map derived from the convolution layer is passed through a pooling layer to further reduce the image. The pooling layer consists of functions, such as max pooling, min pooling, and average pooling. Each feature map is subjected to region-wise pooling, such as the maximum non-overlapping pixels or the average of the non-overlapping pixels. The output of this layer will lead to a dimensional reduction depending on the chosen stride, which is shown in Fig. 3.

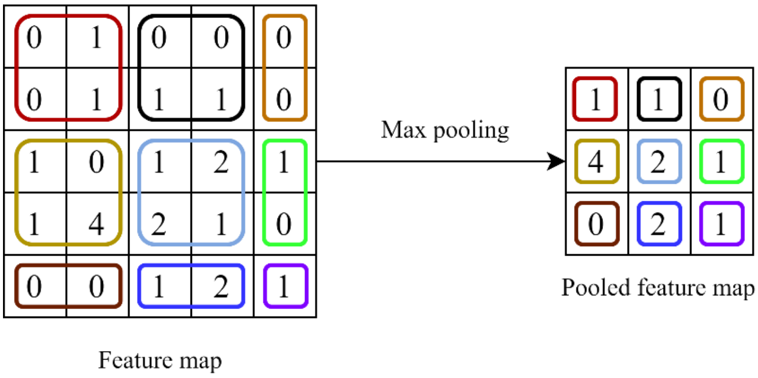


Fig. 3 - Pooling processing.

In a pooling operation, for an activation map, which has a size $n \times m \times c$, a pooling filter of a size f and stride s would lead to a reduction in the spatial size of the output layer, which follows the two-formula listed below

$$n_{output} = \frac{n - f}{s} + 1 \tag{6}$$

$$m_{output} = \frac{m - f}{s} + 1 \tag{7}$$

where the output consists of a volume of size $(n_{output}, m_{output}, c)$ with n being computed by Equation (4), and m is calculated by Equation (5).

2.2.5 *Fully connected output layers*

A fully connected layer then connects all the previous layers. In this layer, the pooled image is flattened and converted into a single column. Each row is made into a column, and they are stacked on top of each other, which is shown in Fig. 4.

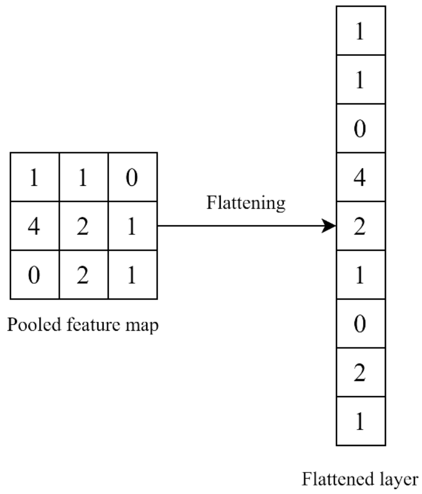


Fig. 4 - Flattening processing.

It then computes the class scores by using the softmax activation function [9] to classify the images into the corresponding classes from the features extracted. The softmax layer is used just before the output layer of the DCNN. It outputs a probability distribution where the sum of the output values is equal to one. The softmax function is given by $P\left(y^{(i)} = n \middle| x^{(i)}; W\right)$, which is computed by Equation (8), where i varies from 1 to m: number of training examples, j is the class out of n classes, W is the adopted weights, and finally $W_n^T x^{(i)}$ serves as the layer input. The function returns the probability per each class of the input.

$$P\left(y^{(i)} = n \middle| x^{(i)}; W\right) = \begin{bmatrix} P(y^{(i)} = 1|x^{(i)}; W) \\ P(y^{(i)} = 2|x^{(i)}; W) \\ \dots \\ P(y^{(i)} = n|x^{(i)}; W) \end{bmatrix} = \frac{1}{\sum_{j=1}^{n} e^{W_j^T x^{(i)}}} \times \begin{bmatrix} e^{W_1^T x^{(i)}} \\ e^{W_2^T x^{(i)}} \\ \dots \\ e^{W_n^T x^{(i)}} \end{bmatrix} \tag{8}$$

The adopted n (number of classes) in this study is equal to two ($n = 2$), which presents the undamaged classes and the damged classes.

2.3 Transfer learning

Transfer learning is a solution to the problem of too little training data by reusing the models of trained similar problems in order to map the existing and the original problems to the same feature space [31, 41]. Transfer learning is often referred to as the fine-tuning an existing network, which is generally faster than having to train a network from the beginning with an arbitrary initialisation of weights. Using the transfer learning method, a better classification rate can be achieved even with a limited amount of data. A common practice is to use a pre-trained model, which is trained on large dataset, such as ImageNet and use these pre-trained weights for the problem at hand. It is also possible to reduce the total number of classification classes for the DCNN to learn compared to the number of output classification classes of the initial network.

The process of using a pre-trained network for transfer learning is shown in Fig. 5. In this process, the first step is to select a relevant pre-trained network that has been trained. After that, the classification layers are replaced for the new task. One can also choose to fine-tune the weights depending on the new task and the data that is available. Generally, the more data you have, the more layers you can chose to fine-tune. Finally, train the network on the data for the new task and test the accuracy of the new network.

Fig. 6 shows the network performance for the models with transfer learning and the models that are trained from scratch. Evidently, it is possible to achieve a higher model accuracy in a shorter time with transfer learning.

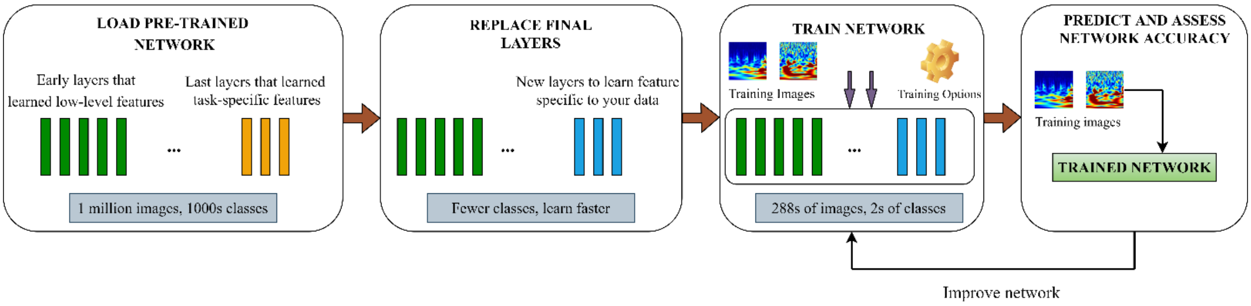


Fig. 5 - Transfer learning process.

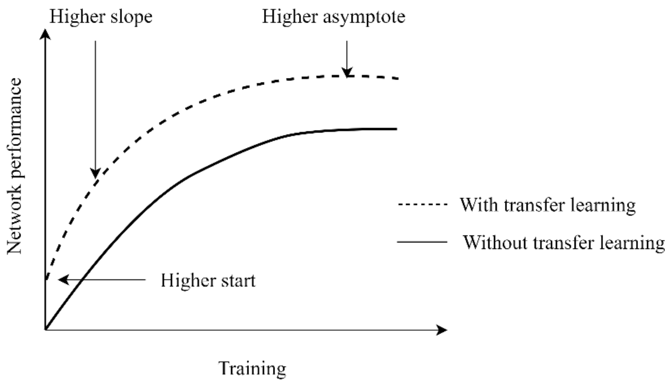


Fig. 6 - Comparison of accuracy and time between model with and without transfer learning.

3 Data acquisition

In this paper, the dataset from a long-span cable-stayed bridge in China is used. This bridge is a double-tower and double-cable-plane cable-stayed bridge that consists of 168 stay cables, which contains steel wires that are 7 mm in diameter, that are distributed in the double cable planes. The main span of the bridge is 648 m, and two side spans are 320 m each. The height of the two towers is approximately 215 m from the base level to the top of the tower. The bridge was opened to public traffic in October 2005 [5]. The configuration of the cable-stayed bridge is shown in Fig. 7.

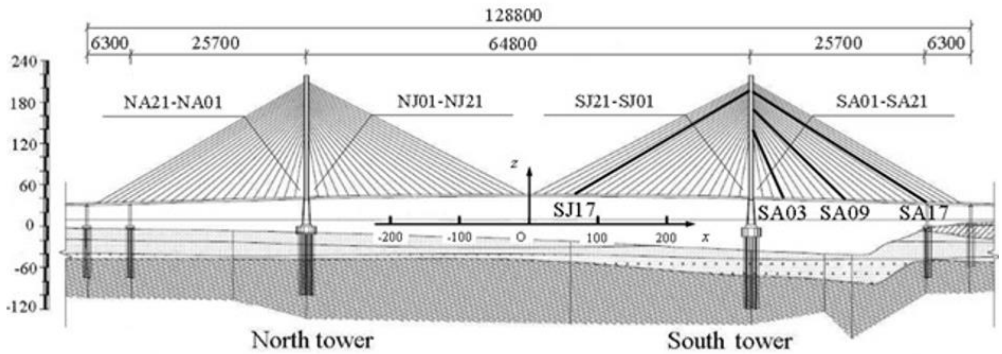


Fig. 7 - The investigated the long-span cable-stayed bridge [7].

The tension force of the stay cables was monitored using a load cell incorporated into the anchorage end of the stay cable [5]. The dataset contains the monitored cable tension data of a cable in an undamaged state in the year 2005 and a cable in a damaged state, which included ruptured wires in the year 2011. For the undamaged and the damaged level, 24 hour long time series cable tension data was collected at a 2 Hz sampling rate with 172800 data points. Fig. 8 illustrates the time-varying tension of the cable with the undamaged and the damaged states.

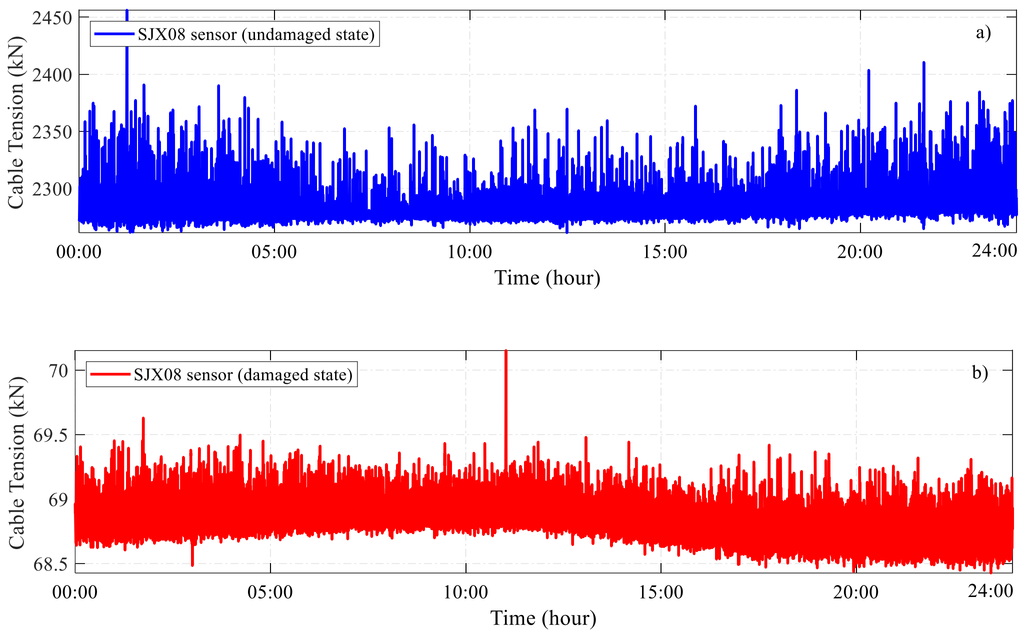
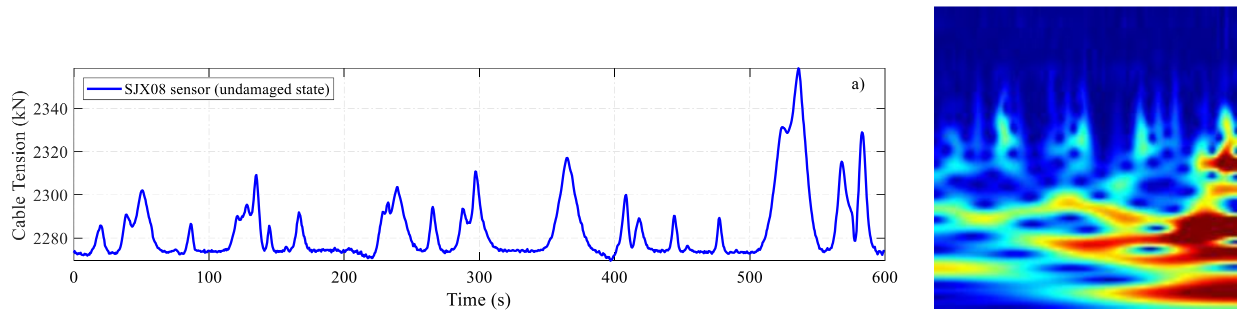
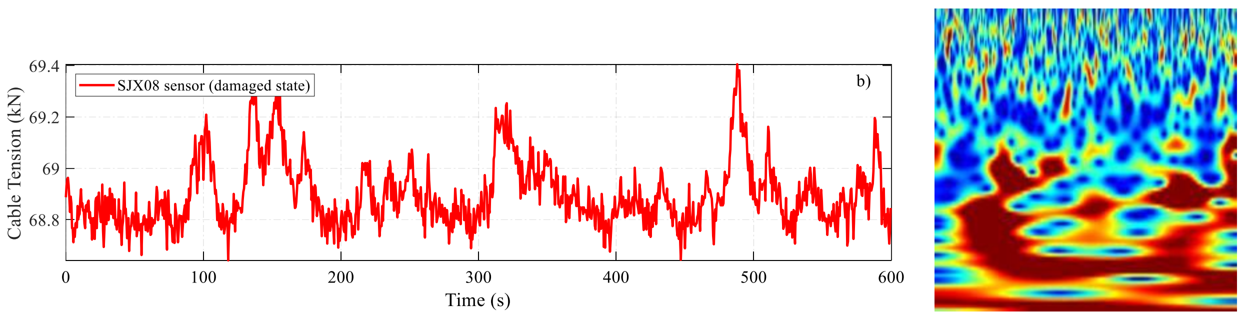


Fig. 8 - Cable tension of SJX08 sensor (a) in 2005 and (b) in 2011.



a) 10 minutes data series of undamaged cable.



b) 10 minutes data series of damaged cable

Fig. 9. Cable tension and respective scalogram.

4 CWT and DCNN-based classification

4.1 Data processing

Evidently, the signal data can be represented in the time-domain, frequency-domain, and time-frequency-domain. Generally, Short-Time Fourier Transform (STFT) and Wavelet Transform (WT) can be used to represent information in both the time and the frequency-domain. The previous studies [42, 43] showed that when the dataset is not big data, the wavelet function can already be determined, since it follows the shape of the excitation signal. Therefore, the CWT is used in this study to transform the cable tension signal to the time-frequency domain. Herein, the 24 hours dataset is divided in to 144 segments that represent each 10 minutes datasets. Fig. 9 shows one 10 minutes data series, which is 1200 data points, and they are converted to a one time-frequency spectra image, which is the scalograms with 227x227x3 pixels, using the CWT. As a result, 144 images are generated for each class, and there are 288 images in total for the undamaged and the damaged states. The datasets are divided in such a way that 80% is used as a training set and 20% as a validation set for the DCNN model.

4.2 Transfer AlexNet DCNN model

AlexNet [23] is a classic DCNN that is trained on more than a million images from the ImageNet database, and it was widely used as a reference model. Fig. 10 shows the original architecture of AlexNet. It is a relatively simple layout compared to the other modern architectures.

The AlexNet network is 8 layers deep, which is comprised of five convolutional layers and 3 fully connected layers. The series of convolutional and max pool layers, which includes layers 1–5, extract features from the input scalogram images. The three fully connected layers, which include layers 6–8, along with the output classification layer performs the task of the classification.

Based on the pre-trained AlexNet model, a transfer learning framework for classification in this study is established in Fig. 11. In this framework, the last three layers with a fully connected layer, a softmax layer, and a classification output layer of the pre-trained AlexNet are replaced. These three layers must be fine-tuned for the new classification problem. The options of the new fully connected layer are specified according to the new data.

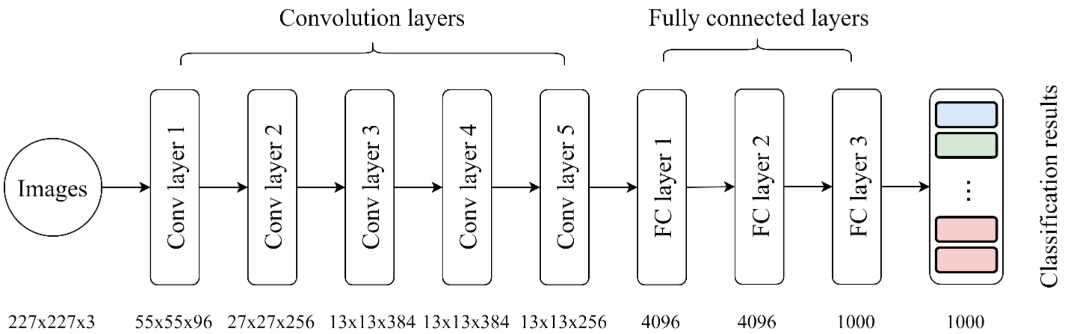


Fig. 10. Original architecture of AlexNet.

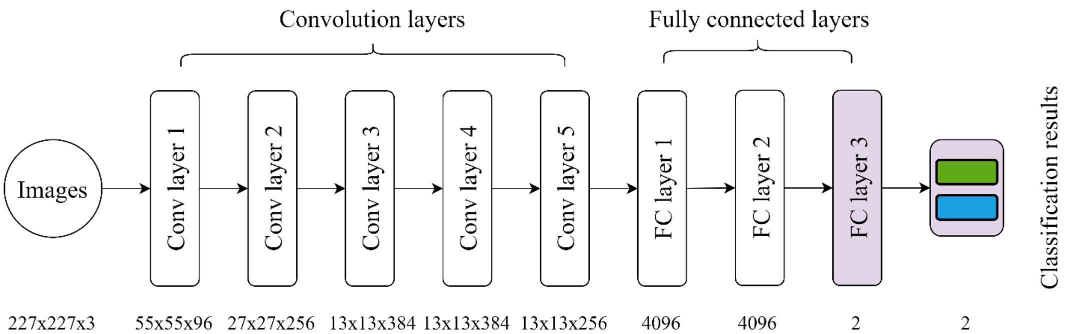


Fig. 11. The proposed transfer framework based on AlexNet.

5 Performance evaluation metrics

The confusion matrix, which is shown in Fig. 12, is used to evaluate the performance of the proposed DCNN model. Herein, the TP, TN, FP, and FN represent the True Positive, True Negative, False Positive, and False Negative, respectively.

The Positive or Negative refers to the class labels predicted by the model, and True and False refers to the accuracy of the prediction.

Based on the confusion matrix, the performance metrics, such as the accuracy, sensitivity, specificity, precision, recall, and the F1-measure are evaluated. The accuracy is given as the ratio of the correctly classified instances to all the instances, which is expressed as

$$Accuracy\ (Acc) = \frac{TP + TN}{TP + FP + FN + TN} \tag{9}$$

Sensitivity is the ratio of the instances correctly classified as positive to all the positive instances, which is expressed as

$$Sensitivity\ (Se) = \frac{TP}{TP + FN} \tag{10}$$

Specificity is represented as the ratio of instances incorrectly classified as positive to all the negative instances, which is expressed as

$$FPR = \frac{TN}{FP + TN} \tag{11}$$

Precision is the ratio of instances correctly classified as positive to all the instances classified as positive, which is expressed as

$$Precision = \frac{TP}{TP + FP} \tag{12}$$

A relation between the properly classified instances, which are the true positives, and the misclassified instances, which are the false negatives, is called recall, which is expressed as

$$Recall = \frac{TP}{TP + FN} \tag{13}$$

F-measure is defined as the harmonic mean of the precision and the recall indicators, which is expressed as

$$F1 - measure = 2 \times \frac{Precision \times Recall}{Precision + Recall} = \frac{2 \times TP}{2 \times TP + FP + FN} \tag{14}$$

	PREDICTED CLASS		
ACTUAL CLASS		Positives	Negatives
	Positives	(TP)	(FN)
	Negatives	(FP)	(TN)

Fig. 12. Representation of confusion matrix.

6 Results and discussions

The main parameter settings for modelling the proposed DCNN architecture are listed in the Table 1. The other parameters are set according to the default values of the original AlexNet architecture.

The training progress of the proposed DCNN model is illustrated by the accuracy and the loss for both the training and the validation, which is shown in Fig. 13. It can be seen that the proposed DCNN model reaches a high accuracy after 6 iteration. It means that the proposed DCNN model can get the convergence with short-time training. The loss value is almost equal zero indicated that the proposed DCNN model works perfectly.

Table 1. The main parameters of the proposed DCNN model.

No.	Hyperparameters	Values
1	Momentum	0.9
2	Initial learning rate	0.0001
3	Learning rate drop factor	0.2
4	Learning rate drop period	5
5	Number of epochs	15
6	Batch size	10
7	Optimizer	SGDM

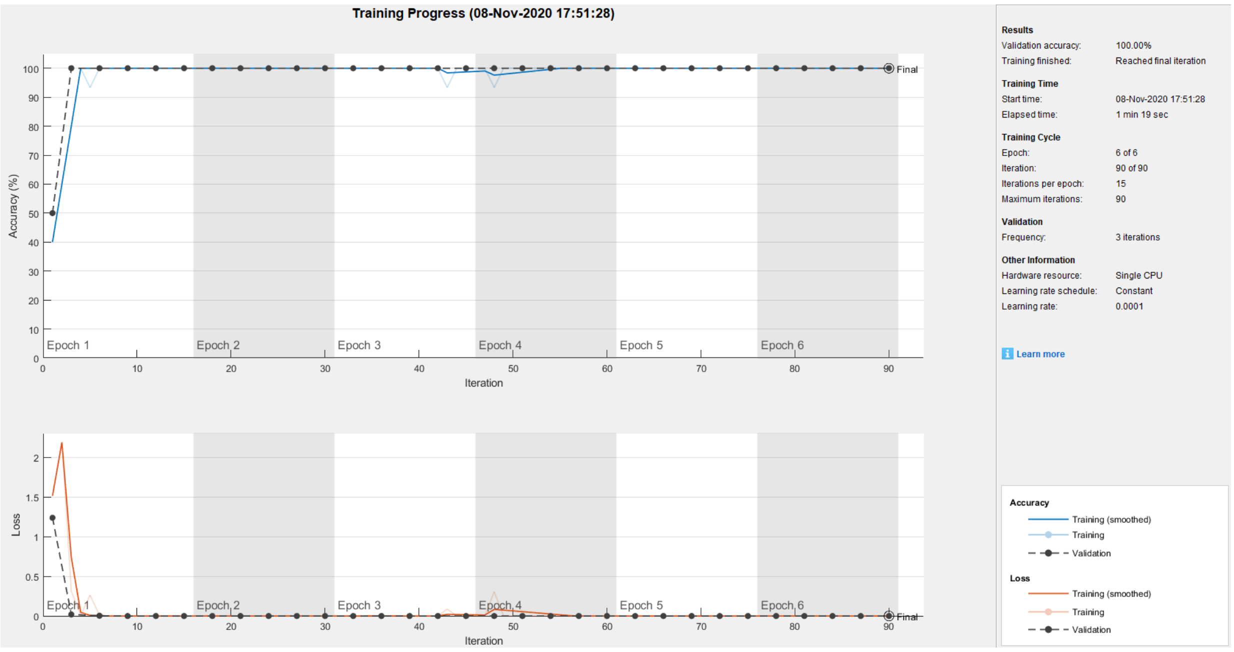


Fig. 13. Training progression of the DCNN model.

Table 2. The result for the different metrics.

Class/label	Acc	Se	FPR	Precision	Recall	F1-measure
Undamaged	1.0	1.0	1.0	1.0	1.0	1.0
Damaged	1.0	1.0	1.0	1.0	1.0	1.0

The confusion matrices of the training and the testing of the proposed DCNN model are illustrated in Fig. 14. In addition, Table 2 and Fig. 15 show the results of the training and validation phases of the proposed DCNN with the performance metrics of sensitivity, specificity, precision, recall, and the F1-measure. The results show that the proposed DCNN model utilized the pre-trained Alexnet CNN performs perfectly with the classification of the cable damage. Evidently, the proposed DCNN model successfully achieves two important targets, which do not only work with small feature numbers but also achieve a high accuracy. Furthermore, using a few hundred images to build and then train the DCNN model is considerable challenging, because the deep neural networks need large amounts of images to work efficiently and produce efficient features. However, the proposed DCNN model achieves superior results using the transfer learning approach. One of the main disadvantages is that the proposed DCNN model is built basically within two different classes of undamaged and damaged states due to the limitation of the damage levels. For further study, it is recommended to apply this approach for a dataset that has many damage severities, so the same approach can be extended to propose a DCNN model for an SHM system of other structures with different indicators.

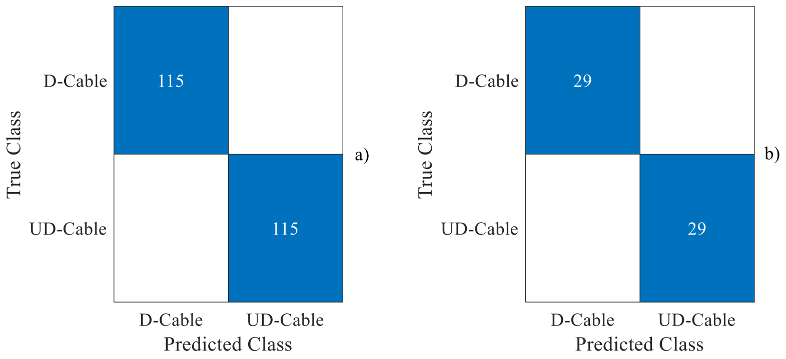


Fig. 14. Confusion matrix of training and validation datasets.

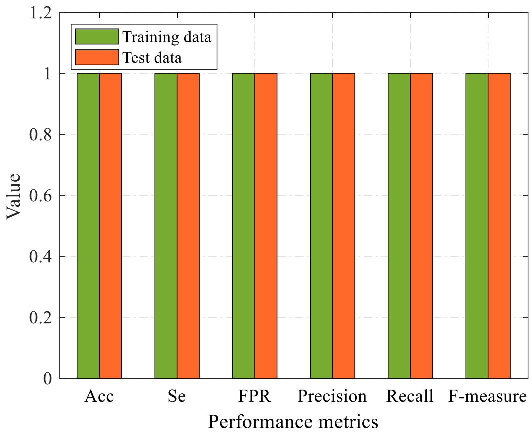


Fig. 15. Performance evaluation metrics.

7 Conclusions

Monitoring cable tension to access the cable condition or to detect a damaged cable is a necessary task in the structural health monitoring (SHM) system of cable-stayed bridges to ensure the safety, serviceability, durability, and sustainability. In this paper, a hybrid health monitoring approach, which is based on the integration of a continuous wavelet transform (CWT) and a deep convolutional neural network (DCNN), is proposed to identify the undamaged and the damaged cables. One-dimensional time series cable tension signals are transformed into time-scale images through the CWT. These images are then classified by the DCNN through a transfer learning technique, which is able extract the underlying features and the deep features embedded in the images. The results indicate that the proposed approach achieved a 100% classification accuracy for the health condition identification of the cables in a cable-stayed bridge. The promising results of the proposed DCNN model, which combines the DCNN-based transfer learning and the CWT transformation, could be useful and might be successful in being applied to other classification tasks.

Conflicts of interest

The authors declare that they have no potential conflicts of interest in this paper.

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