Deep learning for defect detection and characterization in composite laminates inspected by pulsed thermography

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Currently, pulsed thermography is widely used for defect detection as a non-destructive testing technique that allows the remote examination of materials and systems. This work presents a complete procedure for the non-destructive analysis of composite laminates by taking advantage of deep neural networks for the classification of one-Dimensional (1D) temperature vs. time profiles captured via pulse thermography.

Laureti et.al [4] investigated the use of pulse-compression thermography for detecting defects in paintings. This paper describes a pulse-compression infrared thermography for defect detection in painting with focusing on two goals as optimizing defect detection while minimising the rise in temperature for the purpose of painting conservation. In [3] the defect detection in composite products based on sparse moving window principal component thermography (SMWPCT) has been investigated. The basic idea of the SMWPCT technique is extracting both cross-correlations from the temporal and spatial scales. For this purpose, the moving window strategy is utilized to cover several adjacent temporal thermal images within a period of time. In the next step, the principal features of these moving windows are further extracted for defect detection. Using the moving window, the time series correlations among the thermal images can be effectively extracted, and it is applied for the distinguishing the defect region and the normal region.

Qiang et.al [2] investigated defects segmentation and Identification by Mask Region based Convolutional Neural Networks. In [2], synthetic data from the standard Finite Element Models are combined with experimental data to build repositories with Mask Region based Convolutional Neural Networks (Mask-RCNN) to strengthen the neural network, for the purpose of learning the essential features of objects of interest and achieving defect segmentation automatically. By getting the main idea of Generative adversarial nets (GAN) [1] as learning the distribution of the given training data and then generating similarly distributed data, in [5] generative adversarial network is introduced to the thermography field as an image augmentation approach to improve its defect detection performance.

Convolutional neural networks comprised of convolution layers as feature extractors have proven to be an efficient models for time series classification problems. On the other hand, stacked LSTMs architecture, which consists of more that one layer of LSTM have been widely used for different sequence learning problems. In this paper, for the purpose of defected and sound pixel classification and defect type characterization, in which the profile of each pixel is a time-series based format, we applied a network architecture comprised of CNNs and stacked LSTM architectures as shown in Figure 1. In the following, I will discuss the details of each component architecture with details.

The applied stacked LSTM based architecture is comprised of three general LSTM blocks including, 50, 40, and 20 units receptively. In the first LSTM block we used ReLU activatation function, while in the rest two other LSTM blocks tanh activation function has been applied. Furthermore, We have set up the dropout rate as 0.1 for regularization purpose in each LSTM block.

The CNN architecture applied in the overall network architecture, includes four convectional layers. The data from previous layer enters parallelly in each layer in each filter and is processed by convolutions having kernels of size 1*64. In the proposed network, number of 1D convolutional filters at each layer is 32. Each convolution block also applies a batch normalization, for the purpose of normalizing the outputs of the convolutions to keep the numerical values comparable, followed by a ReLU activation function. Only in the first three convolutional layers, a pooling layer based on max-pooling technique with pooing size 2, has been applied as a way the network groups the representations coming from the convolutional filters to create new ones of lower size.

The outputs of the last LSTM and convolutional blocks is concatenated and passed onto a fully connected neural network, made of N_c parallel neurons, in which N_c is the number of target classes, followed by a softmax activation function. The softmax layer receives the N_c values and transforms it into N_c probabilities. For defected and sound pixels classification as a binary classification problem we set the N_c as 2, while for defect-type classification (as multi-class classification problem) N_c was initialized with 5.

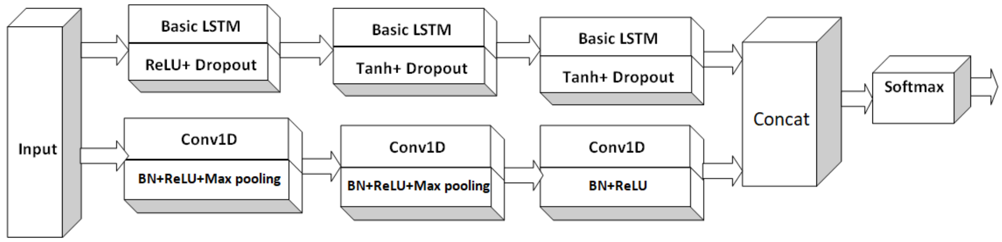
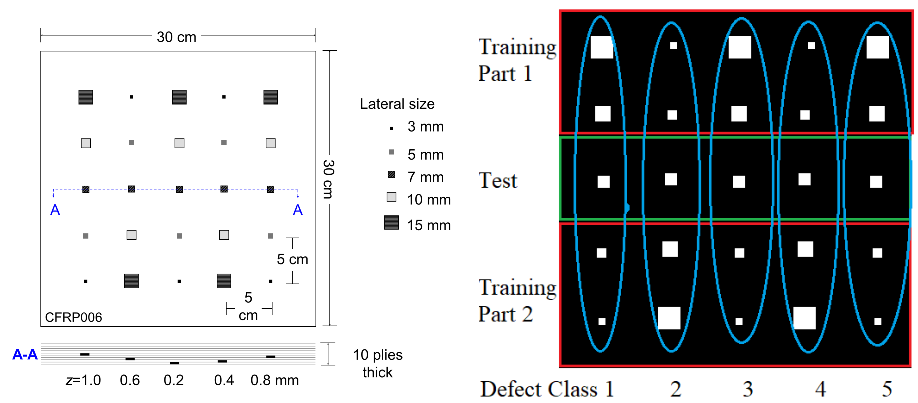


Figure 1: The applied deep learning network comprised of CNNs and stacked LSTM architectures

Experimental validation is performed on a laminate including 25 square-shaped holes arranged in 5*5 rows and columns, representing a set of holes in different depths and sizes. For the purpose of defect-type characterization, we assumed five groups of holes/columns representing five class of holes differing in terms of defect depth. As the first step in the experiments, after region of interest selection from frames, we obtained the thermal profile of all pixels. Considering that each frame has the resolution of 414×409, a $2D$ matrix with size $(169326, 993)$ was obtained indicating the thermal profile of all pixels during 993 frames. Since, the total number of the sound pixels is much higher than the defected pixels, resulting the original dataset to be considered as imbalanced datasets, we used the randomly down-sampling the number of the sound pixels.

As illustrated in Figure 2, the specimen region as the original dataset was split horizontally into train and test datasets for performance measurement of the proposed model, guaranteeing the existence of all defect-type classes in both train and test datasets, equally. Furthermore, Table 1 shows the population of train and test datasets in details.

In Tables 2 and 3, we showed the performance of propose model in terms of sound-defected pixels classification and defect-type characterization, respectively, based on four criteria precision, recall, F1-score and accuracy. Our experimental results showed that the proposed deep learning network model achieves the average accuracy 92%, precision 91%, recall 91% and F1-score 91% in detecting of defective and sound pixels. Furthermore, our experiments illustrated for the purpose of characterization of defect-type in terms of defect depth, the proposed deep learning model reached the average accuracy 91%, precision 88%, recall 81%, and F1-score 84%. In Figure 3, we illustrated the specimen template prediction in terms of predicting all pixels labels, included in both train and test datasets, for both binary-class and multi-class classification scenarios.



(a) (b)

Figure 2: (a) Scheme of the specimen used for the experiments and the specification of the holes, (b) Train and test split.

Table 1: Population of train and test datasets

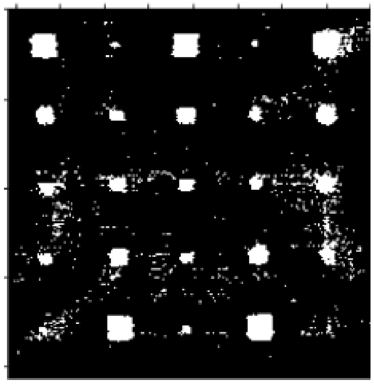
	size of defected pixels per class	size of defected pixels	sizer of sound pixels	size of sound pixels after balancing
Train	1,184	5,740	126,771	6,524
Test	195	1,155	35,650	2,379

Table 2: Sound-Defected pixels classification performance report

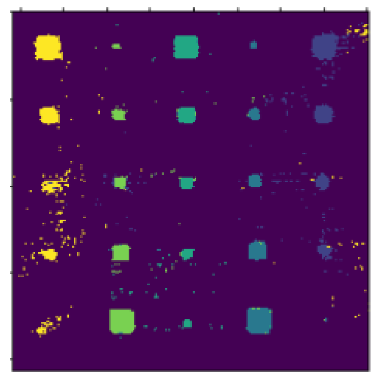
	Precision	Recall	F1-score	Accuracy
Sound	0.94	0.94	0.94	0.92
Defected	0.88	0.88	0.88	

Table 3: Defect-type classification performance report

	Precision	Recall	F1-score	Accuracy
Sound	0.92	0.97	0.94	0.91
Defected Type 1	0.71	0.88	0.78	
Defected Type 2	0.94	0.89	0.92	
Defected Type 3	0.99	0.84	0.91	
Defected Type 4	0.98	0.69	0.81	
Defected Type 5	0.76	0.61	0.68	



(a) Sound-defect classification



(b) Defect-depth classification

Figure 3: The specimen template prediction as predicting all pixels labels

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