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PREDICTION OF MECHANICAL PROPERTIES OF COMPOSITE MATERIALS BASED ON CONVOLUTIONAL NEURAL NETWORK--LONG AND SHORT-TERM MEMORY NEURAL NETWORK

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Convolutional neural networks (CNNs) have the advantage of processing complex images and extracting feature information from the images, while long and short term memory networks (LSTMs) are good at processing data with sequential features. In this paper, based on the deep material network, we propose to apply the CNN-LSTM neural network model to the prediction of mechanical properties of carbon fibre composites. Then the experimental results are compared with the model prediction results, and the results show that the CNN-LSTM prediction of the mechanical properties of carbon fibre composites is within 5% of the corresponding tensile mechanical experimental results, which proves the accuracy of the CNN-LSTM neural network model in the prediction of the mechanical properties of carbon fibre composites.

Keywords: Artificial neural networks; Deep learning; Performance prediction

INTRODUCTION

With the development of advanced machine learning and deep learning, artificial neural networks play an important role in many fields (unmanned vehicles, natural language processing, etc.), which are capable of constructing complex input-output model relationships, but their application in the field of material mechanics is still limited[1-3]. In this paper, we propose to apply deep learning to the prediction of mechanical properties of carbon fibre composites based on the deep material network model[4]. It can achieve fast and accurate prediction of mechanical properties of carbon fibre composites with different phase properties, volume fractions and layup angles, avoiding the large amount of manpower and material resources consumed in material performance experiments, and at the same time, improving the rate of composite material design and reducing the development cycle[5-8]. In this paper, a CNN-LSTM network model connecting convolutional neural network and short-term and long-term memory neural network is improved to predict the mechanical properties of carbon fibre composites. In this chapter, the proposed model is introduced in detail, and then the CNN-LSTM model is trained and the training and testing results are analysed.

CNN-LSTM NETWORK MODEL CONSTRUCTION

Convolutional neural network (CNN) model is the main application is to extract the feature information in the image data, but when the data show sequential features between them, it is not enough, and the long short-term memory neural network (LSTM) model can make up for the shortcomings of the CNN network model, which is particularly good at recognising data with sequential features, and will affect the terminal output by combining the historical input with the input of the current time step. The former is particularly good at recognising data information with sequential features, and will affect the terminal output by combining the historical input information with the current time step. Therefore, this paper chooses to link the two models together, firstly using the convolutional neural network (CNN) model to extract the feature information in the image sequence, and then passing it to the long short-term memory network (LSTM) model, so as to make it analyse and identify the image features with sequential characteristics to achieve the final regression output. The CNN-LSTM network model is built by linking the CNN model and LSTM model back and forth. Its specific structure is shown in Figure 1, which contains a convolutional neural network for feature extraction and two layers of short-term and long-term memory neural networks for temporal information processing.

In the CNN-LSTM network, each image in the sample is extracted to the corresponding features by a CNN neural network, and then input to the subsequent LSTM neural network as a time sequence for recognition. In this paper, VGG16 and ResNet-101 networks are used as the feature extraction network of CNN module respectively, whose role is no longer image classification but image feature extraction, so the two network layers at the end of the network (fully-connected layer and

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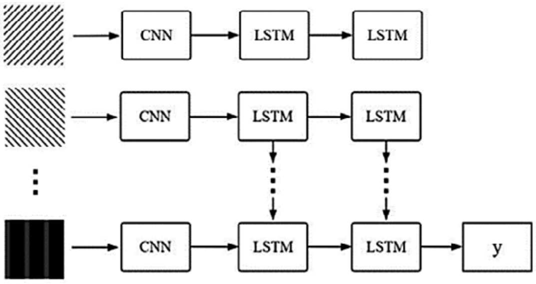

Figure 1 Schematic diagram of CNN-LSTM model architecture

softmax layer) are removed, and only the convolutional layer and pooling layer are retained, so that each image sample will get a feature map of 7×7×512.

CNN-LSTM NETWORK MODEL TRAINING

The hardware and software platforms used in this test are listed in Table 1.

Table 1 **Hardware and software platform**

Projects	Parametric
System	Ubuntu16.04
GPU	NVIDA RTX4080 16GB
CPU	Intel® Core™ i9 processor 14,900K
RAM	48 GB
Deep learning frameworks	Pytorch

The paper focuses on the prediction of mechanical properties of carbon fibre reinforced nylon 6 composites, where the required input data are the flexibility matrices of each phase of the material and the final output is the homogenised flexibility matrix of the composite. The mechanical constants of the composite are obtained through the flexibility matrix along with the intrinsic properties of the composite. Therefore the material parameter space of the constituent phases is to be generated. For the purpose of data generation, carbon fibres are considered as transverse isotropic materials and nylon 6 as isotropic materials. Thus, only five sets of parameters need to be generated for carbon fibre and two sets for nylon 6. In order to better simulate the properties of the two-phase material and to allow for some mobility in the model, the elastic constants of the carbon fibre and nylon 6 are given an interval of values, as shown in Table 2.

Table 2 **Range of values for carbon fibre and nylon 6 material properties**

Causality	Carbon fibre	Nylon 6
Axial young's modulus/Mpa	200,000-400,000	2,000-4,000
In-plane young's modulus/Mpa	15,000-40,000	/
Plane poisson's ratio	0,20-0,4	/
Transverse poisson's ratio	0,2-0,4	0,3~0,4
Transverse shear modulus/Mpa	15,000-40,000	/

The space of values of the elastic constants of the constituent phases of the carbon fibre reinforced nylon 6 composites was determined and based on this table,

Table 3 **Summary of data**

Projects	Number
Carbon fibre	200
Nylon 6	200
Bedding angle	6
Combined sample size	1,200
Tabs	1,200

Latin hypercube sampling was used to generate the 200-group input sample space required for this paper. The training dataset is summarised below Table 3.

The dataset validation set and test set are divided according to 6:2:2.

The purpose of the deep material network-based mechanical property prediction algorithm for carbon fibre composites is to predict the intrinsic properties of laminates made from different batches of carbon fibre composites with different layup structures. In this paper, a CNN-LSTM model is used to predict the mechanical properties of carbon fibre composites, and VGG-16 or ResNet-101 is used as the feature extraction module of the network model, which is pre-trained on ImageNet dataset beforehand, and then the final BN layer and fully connected layer of the feature extraction network are removed, and a Max-pooling layer is added to obtain the extracted properties, because the ReLU function produces a lot of 0 values. Because the ReLU function produces many zeros, a max-pooling layer is added to obtain the extracted feature maps. Then the image converted from the flexibility matrix of the constituent phases of the material and the image representing the pavement information are used as inputs to the CNN-LSTM network, and after the convolutional neural network (CNN) module, the features in the input sequence of images are extracted and processed into sequence information, and then sequentially fed into the long and short-term memory network (LSTM) for analysis, and the network is fitted to output the homogenised flexibility matrix of the carbon fibre composite. The network will fit the output of the homogenised carbon fibre composites flexibility matrix.

TEST RESULTS

The performance of the trained CNN-LSTM model is tested on the test set. Firstly, the curve of the loss function with the number of iterations is given, as shown in Figure 2, the feature extraction network used

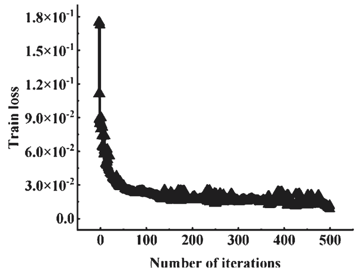

Figure2 Loss function curve

in the model training is the VGGNet-16 model, and after 500 iterations, the curve of the Train Loss of the CNN-LSTM network tends to be stable. The parameters of the network gradually converge, and the model basically reaches the expected goal.

The feature extraction module of the CNN-LSTM model can also use Inception V2, ResNet-101 and other models, and the test results show that the accuracy of ResNet-101 for feature extraction is somewhat higher than that of VGGNet-16. Table 4 shows the validation results of CNN-LSTM model using different CNN models for feature extraction.

Table 4 **Evaluation metrics of CNN-LSTM**

Model	Method	MSE	RMSE	MAE	R^2
VGGNet-16	CNN-LSTM	0.0011	0.032	0.0179	0.941
ResNet-101	CNN-LSTM	0.0012	0.035	0.0196	0.976

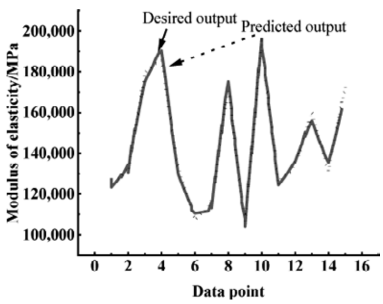

Figure 3 Comparison curve between desired and predicted outputs of modulus of elasticity

The R^2-squared values in Table 4 show that both models achieve high accuracy, which shows that the prediction accuracy of the mechanical properties of carbon fibre composites based on the deep material network CNN-LSTM network model training basically meets the requirements. When the ResNet-101 network is used for extraction, the accuracy is 3,5% higher than that of VGGNet-16, which achieves the desired result. Next, 15 independent samples from the test set are taken to compare the prediction results.

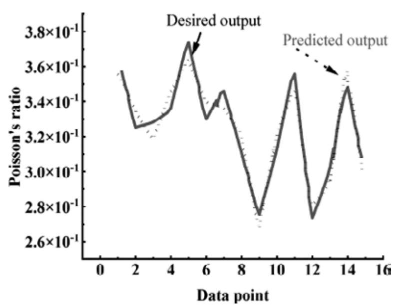

Figure 4 Expected versus predicted output curves for Poisson's ratio

Figure 3 shows the comparison between the expected results of the elastic modulus of the homogenised composites and the prediction results of the CNN-LSTM model. Figure4 shows the comparison between the expected results of the Poisson's ratio of the homogenised composites and the prediction results of the CNN-LSTM model after the modelling simulation on the Digimat platform. By comparing the output results of the deep material network with the simulation results of Digimat, it can be seen that the maximum error is 4,13%, and the error of the prediction results is within a reasonable range, which basically meets the requirements.

CONCLUSION

In this paper, we constructed a CNN-LSTM model based on the feature extraction networks VGGNet-16 and ResNet-101, as well as the short- and long-term memory neural networks, and completed the training and testing process based on the homemade training set, and finally achieved a prediction accuracy of 97.6%. The following problems were solved:

The division of the dataset. In view of the small sample size of the homemade dataset, the data set is divided into training sets according to the ratio of 6:2:2 during model training. The dataset is divided into training set, validation set, and test set. 2.

The accuracy of the CNN-LSTM model is compared with different feature extraction networks, and it is concluded that using ResNet-101 as the CNN-LSTM model is the best way to improve the accuracy of the CNN-LSTM model. ResNet-101 is used as the feature extraction network of CNN-LSTM, which can improve the accuracy of the model, and the accuracy is 0,976, which meets the expected results.

Supporting projects

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Note: The responsible translator for English language is P. HUANG, Xinjiang University, China.