Mechanical Features Extraction of Microstructures Using Deep Learning Models

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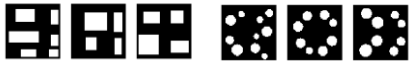
Background Introduction

Computational analysis of material properties is important in the field of mechanical engineering. However for most cases, high computational power and long computational time are required. This is especially true for the analysis of material properties for microstructure. Due to the fact that there are vast variety of microstructural topology, the analysis process is difficult. Therefore, we proposed to replace the traditional computational methods in calculation of material properties such as Finite Element Analysis (FEM) with deep learning methods. With the application of deep learning methods, the computational efficiency is expected to be able to improve in terms of time and power requirement.

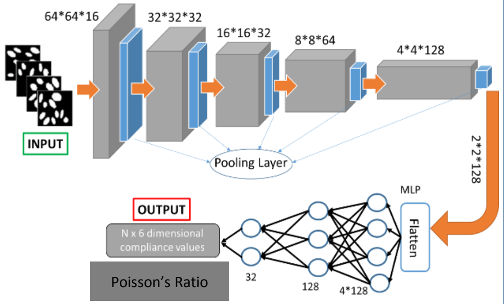
Proposed Method

In this work, we will demonstrate and study the application of deep learning methods to the calculation of mechanical properties (Poisson's ratio in this case) from microstructural images. Samples of microstructural images that will be considered in this work are shown in the figure below. The images are shown in black and white color to represents the solid and holes part of a microstructure topology respectively. To successfully apply deep learning methods to replace traditional methods, a supervised training is firstly carried out on the deep learning model. The microstructural images are passed through the traditional methods such as FEM for the calculation of Poisson's ratio to be used as the label for the supervised training. The deep learning model will be trained to maps the microstructural images (inputs) to the Poisson's ratio (outputs). After the deep learning models are trained, the microstructural images are passed through the models for feature extraction. The extracted features are visualized for some other aspects that are directly related to the microstructural images. The extracted features are analysed for the categorisation in Poisson's ratio, volume fraction, count of holes, and rectangle or circle holes. Further classification can be done by performing LDA on the extracted features.



Deep Learning Models Architectures

Convolutional Neural Network (CNN)

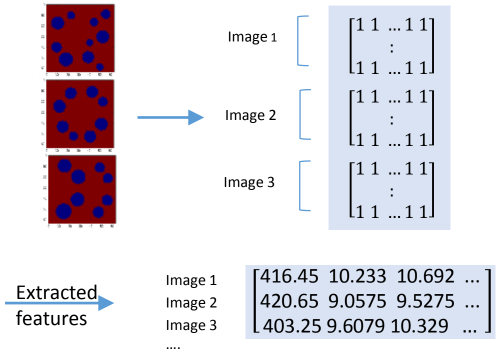


As can be seen from the architecture of CNN above, the extracted features will be obtained from the last layer of convolutional layers, which is a dimension of 2x2x128=512. Principal Component Analysis (PCA) is then performed on the extracted features to reduce the dimensionality of the features to 2, which is then visualized on 2-dimensional graph.

Scattering Net

A wavelet scattering network computes a translation invariant image representation, which is stable to deformations and preserves high frequency information for classification.

For each microstructure's image, a Scattering Net is performed to extract that structure's feature. And these features would preserve some important information while the dimensionality can be greatly reduced.

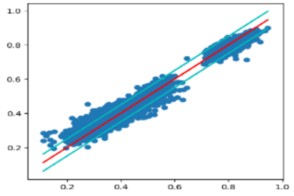


Results & Analysis

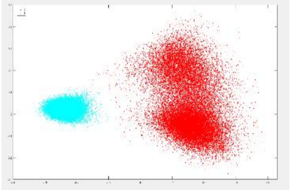
Principal Component Analysis is a dimension-reduction tool that can be used to reduce a large set of variables to a small set that still preserves most of the information in the large set. Here PCA is adopted to reduce the dimension of features extracted from CNN/scattering Net to two ,which are then plotted out to see if they can be used to visually classify different categories

Visualization of features extracted by CNN

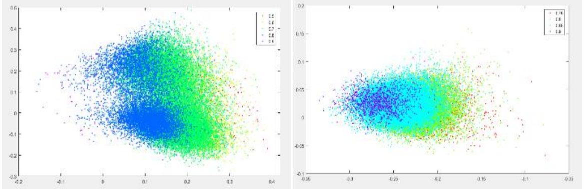
The accuracy of the trained CNN is shown in the graph below, where the predicted value (y axis) is plotted against ground truth (x axis) Poisson's ratio. Features are extracted from the CNN and PCA is then performed on the extracted features to reduce them to 2 dimensional. The features are visualized in the figures below for different categories of labels.



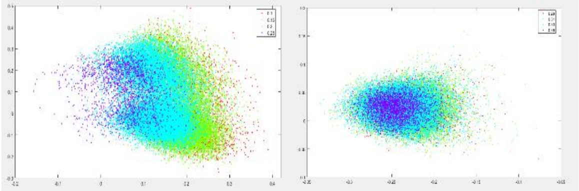
(i) Plot of prediction vs ground truth



(ii) Classification according to the shape of holes (rectangle or circle)



(iii) Classification according to the different categories of volume fraction for rectangle (left) and circle (right)



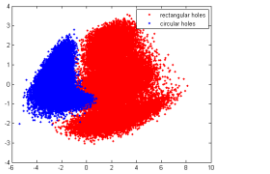
(iv) Classification according to the different categories of Poisson's ratio for rectangle (left) and circle (right)

Deep Learning Model	Circle/ Rectangle Holes	Volume Fraction rectangle	Volume Fraction Circle	Poisson's Ratio rectangle	Poisson's Ratio Circle
Accuracy of CNN	0.9999	0.8435	0.8368	0.8165	0.7310

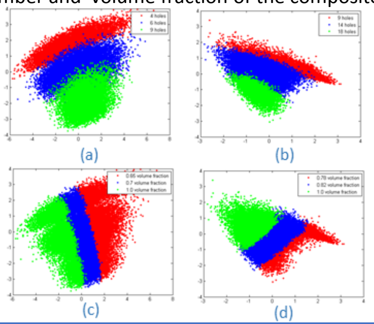
Results & Analysis

Visualization of features extracted by scattering Net

Features extracted from scattering Net are reduced to 2 dimensional using PCA and then plotted out. As we can see, the reduced features are easy to visually distinguish the hole types of different porous composite material. It can also distinguish the hole number and volume fraction of the composite structure.



Classification according to the shape of holes (rectangle or circle)



Visualization of Scattering Net extracted features using PCA: Number of holes in structures with (a) rectangle holes; (b) circle holes. Volume fraction of solid material in structures with (c) rectangle holes (d) circular holes

The extracted features from CNN and Scatter Net are then passed through LDA for classification. The accuracy of classification is shown in the table below.

Deep Learning Model	Circular/ rectangle Holes	Volume Fraction of structures with rectangle holes	Volume Fraction of structures with circle holes	Number of rectangle holes	Number of circle holes
Accuracy of Scatter Net	1.000	1.0000	0.91825	0.99975	0.9555

Discussion and future work

From the visualization results of the extracted features, it can be observed that both CNN and Scatter Net performed well in the feature extraction of microstructural images. This is especially true for the case of CNN as supervised pretraining process is performed on the model before feature extraction is carried out. From the visualization of CNN extracted features, it can be found that CNN model performs particularly well in the extraction of features which have strong correlation with geometry structure. This can be shown in the categorization of rectangle and circle holes. However for the volume fraction and Poisson's ratio categorization, the separation is not that clear comparably. Besides we can also observe that the categorization and classification of labels in rectangle are generally better than circles. We postulate that this might be due to the data distribution in rectangle has a lower variance compared to that of circle.

As the images are very simple binary images with clear differences, the scattering net achieves quite good performance in feature extraction. When reduced to 2 dimensional and plotted out, these features can be used to easily distinguish the physical/geometrical patterns of the real images.

until present only simple binary images are used to represent the microstructure. However, in real application, composite material can be more complex containing various components. They can also form some irregular interfaces. So in the future, we may try some more complicated images with multiple pixel values and irregular interfaces.

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