# Deep Neural Network beyond just prediction: quantitative fracture characterization of core images.

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## Summary

In this work, we examined the use of Deep Neural Network for quantitative fracture characterization. Our approach consists of using a modified and pre-trained VGG19 neural network to identify and perform quantitative fracture characterization. The dataset used for this application is available in the public domain. The partial use of the calibrated weights of VGG19, previously trained on the large dataset of ImageNet, served as a learning transfer scheme to accelerate the training and reduce the computational cost. Additionally, the examination of the DNN attention illustrated the benefit of using Deep Neural Networks beyond just prediction and labeling. It was demonstrated that DNN attention, reconstructed from the final convolutional layer of the network, strongly correlate with fracture width in the case of single fracture and fracture density in the case of multiple fractures. Despite the benefit of using a deeper Neural Network in performing accurate prediction and classification, the information that could be extracted from the model attention deteriorates with increasing depth. Therefore, a tradeoff between the Network depth and the resolution of the input data is required to ensure the effective use of DNN attention for quantitative attribute analysis.

## Introduction

Deep learning – a potent approach to machine learning, involving many layers of brain-inspired neural networks has proved highly adept at tasks as diverse as translation and object detection. The latest development in the field of image recognition provided more sophisticated and robust models and algorithms for image and attribute analysis. In this paper, we present an oil and gas application of using Deep Neural Network for quantitative fracture characterization using core images. To achieve this objective, we propose the use of transfer learning, a method to reuse and fine-tune the network weights of multiple layers previously trained, between different datasets and the integration of model attention into performing quantitative anomaly characterization.

In this paper, we first present the architecture of the VGG19 Deep Neural Network. Then, we present the methodology of using "pre-trained weights" as a weight initialization scheme for our problem of fracture detection. Furthermore, we examine the relationship between the Neural Network attention, extracted from the last convolutional layer of the network, and the fracture geometry/density. To illustrate this, we present simple application examples of fracture identification. Finally, we compare the performance of VGG19 relative to other deeper neural networks and examine their attention to fracture identification and characterization.

## Methodology

Our work here is based on using VGG19 as a neural network for fracture detection. Figure 1 presents the architecture and dimensions of the DNN. The network encompasses 5 main blocks. Each block contains multiple Convolutional layers with a ReLu activation function and a MaxPooling layer.

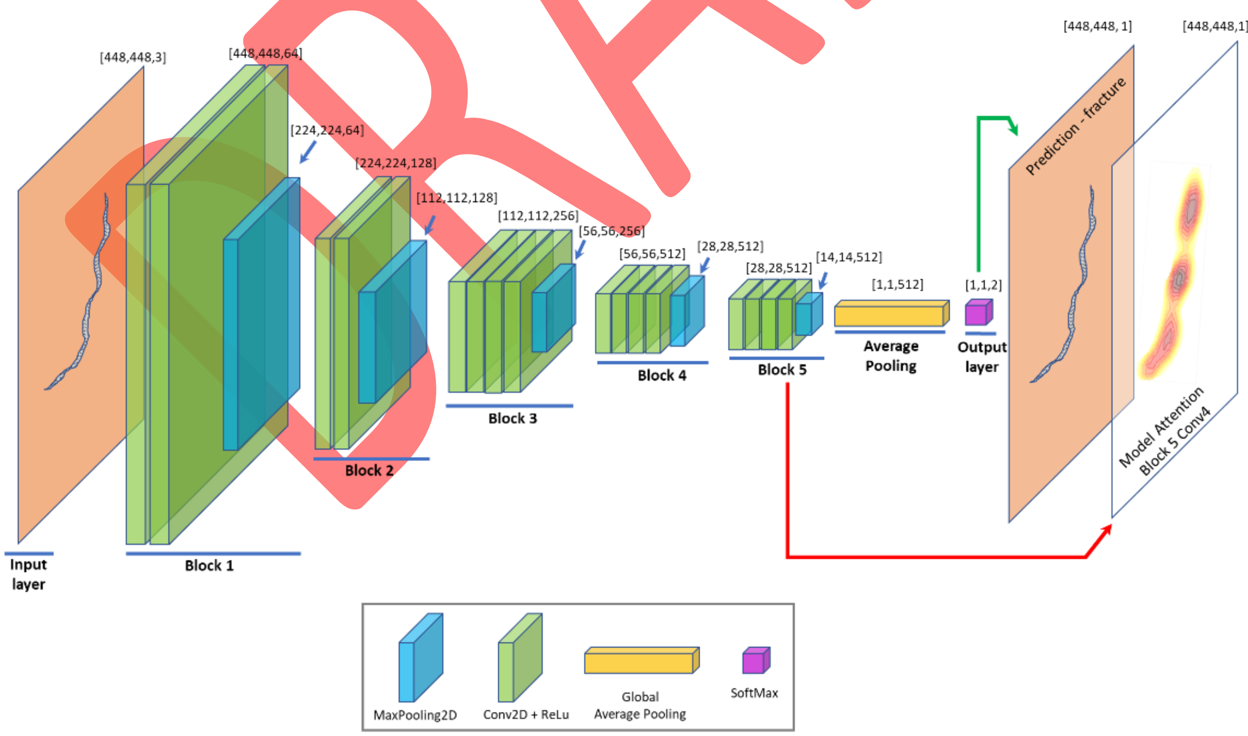


Figure 1: Deep Neural Network Architecture to perform fracture identification. DNN attention reconstructed from the last convolutional layer of block 5 of the network.

To implement the learning transfer, we propose the partial use of the calibrated weights of VGG19 previously trained on the large dataset of ImageNet, which contains 3.2 million images of 1000 different classes. This serves as a weight initialization scheme to re-train an altered version of VGG19 to identify fractures from a smaller dataset of fracture images. The variable appearances and positions of the objects in the ImageNet dataset provide a unique calibration to the DNN weights to focus on feature detection (Deng et al., 2009).

To achieve this goal, first, we preserve the pre-trained weights of the first 10 layers learned from the large dataset of ImageNet. Then, we re-train the last 8 layers using the new dataset of fracture images. To adapt the network to our application, we add a Global Averaging Pooling layer and we modify the output layer to account for two classes (fracture and no fracture) with a SoftMax activation function (figure 1). We compile the DNN using “categorical-cross-entropy” as a loss function and “Stochastic-Gradient-Descent” as an optimizer with a learning rate of 0.0001 and momentum of 0.9. Here we apply data augmentation and scaling to enhance the training and validation accuracy. Additionally, we challenge the model prediction and the learning process by introducing ‘fracture-lookalike’ features to the training dataset.
The input dataset used in this application is from the public domain. It consists of 1142 images as a training set and 286 images as a test set. Initially, we load and resize the images to 448 x 448 x 3 (3 channels). Then, we pass the images into the DNN for training and validation. We run the model for 30 epochs with a batch size of 32.



**Application: More than just classification**

In this section, we summarize the results from the training stage and the model prediction using the test dataset. Accuracy and loss are the metrics for model evaluation during the training stage. As illustrated in figure 2A, the loss function decreases with each epoch. However, the accuracy increases and reaches 89% after 30 epochs. Figure 2B shows the confusion matrix for the True and the Predicted labels. Among all the models tested, we selected the model with the highest F1 – score of 88%. The recall for predicting “fracture” is 93%, the false-positive and false-negative predictions are only 16% and 7% respectively.


Figure 2: A) Loss and Accuracy with Epochs. B) confusion matrix highlighting precision and recalls

In this work, we extend the findings of the Deep Neural Network beyond just predictions. For this, we examine the model attentions at different stages of the network and their relationship to the fracture geometry. After reconstructing and reshaping the attention matrixes from the last convolutional layer of DNN - Block 5, we overlay the resulting maps on top of the fracture images. Figure 3A illustrates examples of DNN attention for different fractures. For each of the fracture cases, the reconstructed DNN attention was able to identify the fracture location as well as its orientation.

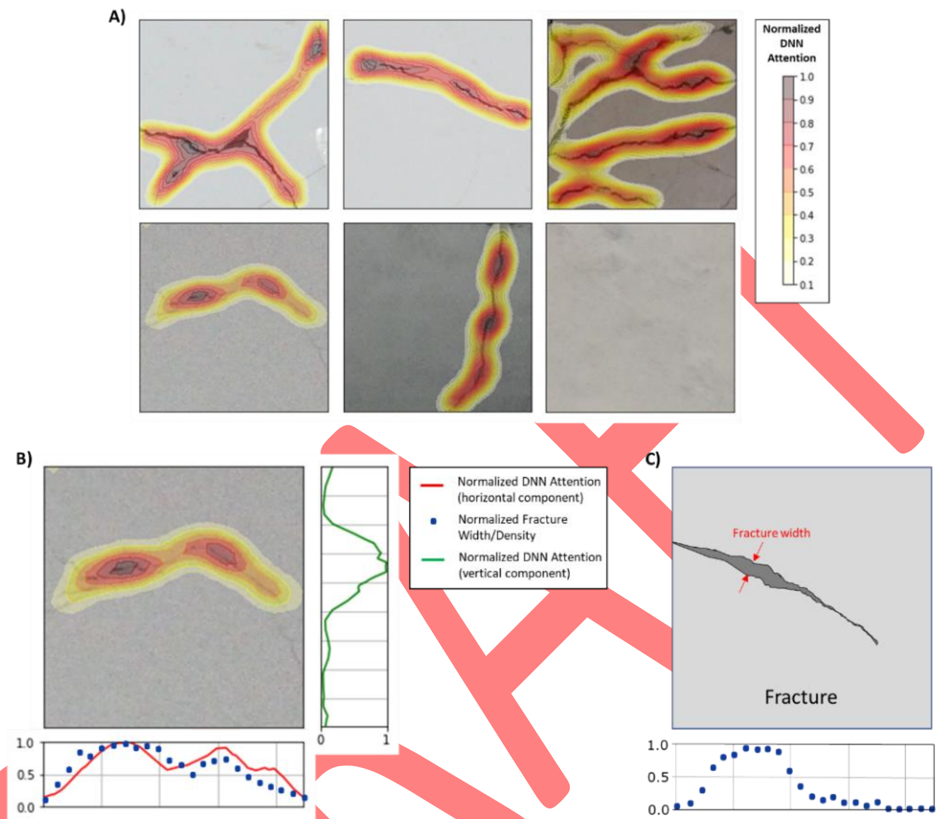


Figure 3: A) Clear examples of fractures identified by the DNN. Model attention overlaid on top of the images to highlight the location and the orientation of the fractures. - B) Example illustrating the strong correlation between the DNN attention (red curve) and measured fracture width. C) shows a schematic illustration of the fracture width definition.

In Figure 3B we examine the intensity of the DNN attention with respect to the fracture geometry. The horizontal and the vertical components of the normalized DNN attention are shown in red and green curves respectively. On a separate task, we compute the normalized fracture width/density by measuring the fracture width weighted by the number of existing fractures. when plotted on top of the horizontal component of the DNN attention (blue dots) we observed a strong correlation between the two attributes. The model showed similar observations for all the cases of true-positive predictions. These results illustrate clear examples of using deep neural network attention to characterize fracture geometry. To examine the performance of VGG19 against other Deep Neural networks, we generate predictive models using ResNet50 (He et al. 2015) and MobileNet (Howard et al. 2017). A comparison between the results from the three Deep Neural Networks is presented in Figure 4.

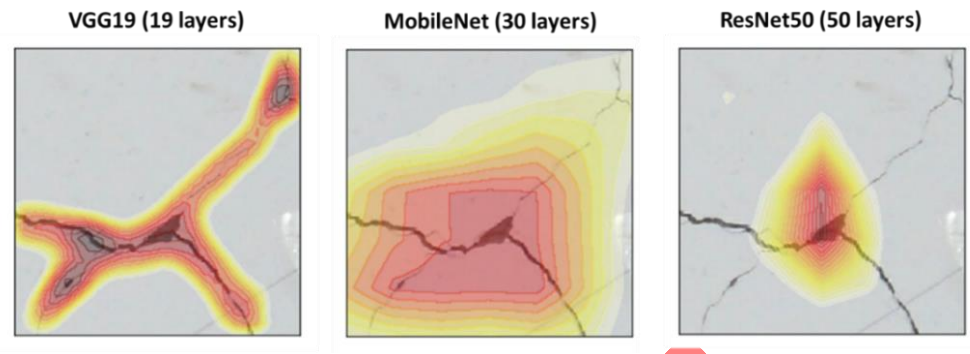


Figure 4: Comparison of DNN attentions from different Networks (VGG19, MobileNet, ResNet50).

While all the three networks scored accuracies above 85% for label predictions (fracture / no fracture), by far, VGG19 presented the best model attention to highlight the existing fractures. Further examination of these findings suggests that, as the depth of the network (number of layers) increases the reconstruction of the DNN attention becomes harder and hence the quality of the embedded information diminishes. It is important to note that VGG16, an older version of the VGGs with only 16 layers, scored comparable results to those using 19 layers. Our sensitivity analysis suggests that, for deeper neural networks, high-resolution input images are required in order to reconstruct a meaningful DNN attention. These findings agree with those of Howard et al. from his work on datasets and weak models published in 2019.

**Conclusions**

In this work, we presented an example of how to use Deep Neural Network VGG19 beyond just solving a classification/prediction problem. We applied VGG19, with prior training, to perform quantitative fracture characterization using fracture images. It was demonstrated that the DNN attention, extracted from the late stages of the network, strongly correlates with the width/density of the identified fractures. Additionally, the implementation of learning transfer from prior training has proven to be beneficial in reducing the computational cost during the training process. Furthermore, by comparing several DNNs with different depths we learned that deeper neural networks such as ResNet50, Incpetion_ResNetV2 require higher resolution input images in order to reconstruct a meaningful DNN attention. Our results on using DNN attention for quantitative interpretation yet again highlights the benefits of using Neural Networks beyond just predictions.

**References**

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