Unknowingly after convolution operation we increase the chance of linearity in the data which may yield inferior results. So, to break this linearity and increase non-linearity we use Rectified Linear Unit (ReLU) operation on data.

Pooling operation involves reducing the size of the image while introducing spatial invariance, and still preserving the features in the image. Reducing the size make the processing faster. This step also prevents overfitting which is a common problem faced while training a network. There are several types of pooling. Max-Pooling operation has been used in this study. The Flattening step involves putting these pooled feature maps into a column vector so that it can be called as input in the ANN structure.

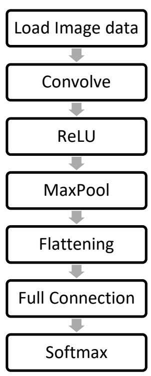


Figure 4: Various layers in a CNN. Some operations can be used many times depending upon the tuning requirement.

### 2.5 Choosing activation function and Batch Size

There are different types of activation functions such as Sigmoid, Tanh, Softmax, ReLU, Leaky ReLU, Exponential Linear Unit (ELU), and Self-Normalizing ELU (SELU). Each of these activation functions have their pros and cons. We have utilized ReLU activation function for all hidden units and Softmax function in output layer. The advantage of Softmax function in the final layer is that the output pore types can be predicted and shown as probabilities.
Nitish et. al. (2017) demonstrate in their paper on the choice of batch size. Common choice of batch size is 32, 64, 128 etc. However, choosing the large batch size degrades the quality of model and a low batch size i.e. 4 or 8 training time goes up before convergence. There is a sweet spot between low and high batch size. We have used 32 batch size in this study. The large networks with high batch size requires more computational power of the machine. Large networks require more time on a CPU machine. The benefit of using a small batch size is that it can be trained on a CPU.

## 3. Result & Discussion

This section deals with giving a meaning to the abstract features produced in convolution and max-pool layers and visualize them.
An image can be thought of as an array of numbers stored in pixels. Each pixel value ranges between 0 to 255. Grayscale image has a single whereas a colored image has 3 channels Red, Green and Blue (RGB). Each channel is filled with pixel values depending upon the image. When a CNN network takes an image as input it identifies the features in the image with their pixel values. The convolution and max-pool operations pick different characteristics present in the image. In this way with multiple feature detectors the signature of either a vuggy pore or channel pore remains preserved by the network. The abstract looking features have been shown in Fig 5.

Carbonate reservoirs are extremely heterogeneous hence they display a complex porosity owing to their environment of formation and undergo a lot of diagenetic porosity modifications. These modifications can result in different types of micro-porosities and may enhance or suppress the interconnectivity of pores. Each pore type has a fixed hydrocarbon holding capacity. For example, a fracture in carbonate reservoir may enhance the interconnectivity between different pore types.

Identifying the correct porosity is extremely crucial for correct estimation of reserve potential. In manual classification there is always a chance of misinterpreting the pore-type which can result in incorrect estimation of hydrocarbon potential in the reservoir. This study aims to automate the process which will save time and cost of geoscientists.

## 4. Conclusion

## Classification of pore types using Deep Neural Network

A six-layered neural network architecture was used in the study. There are two main issues that affect the model. First, the quality of dataset should be of high resolution so that different pore types can be distinguished with ease. Second, the network architecture which is an experimental parameter can be improved with training. The proposed classifier is very accurate and swiftly produces results in a moment on a standard computing system. However, the model is as good as the data we feed in the network and sometimes it can classify sample washed images or images containing bubbles incorrectly. Thus, it is important to ensure that high resolution and accurate data is acquired and quality check is performed before fed to the network.

The classifier designed has oust our expectations. At present the model is correctly identifying 2 types of pores i.e. Channel and Vuggy pores. We would take this study forward to classify all important pore types described by Lucia (1995). We aim to achieve a higher accuracy and exhaustive experimentation with hyper-parameter tuning of the model.

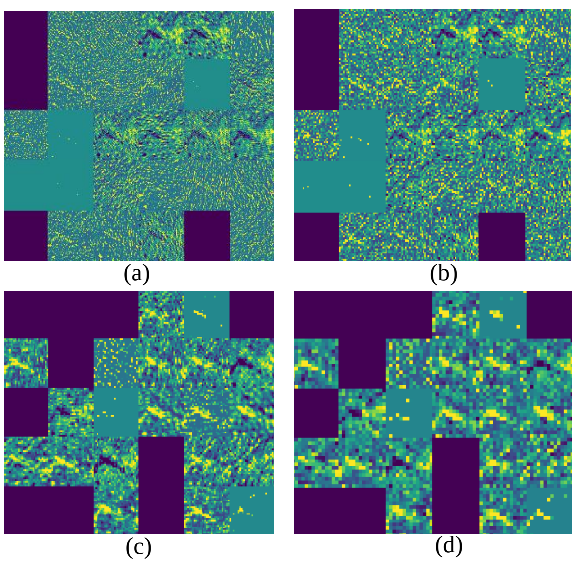


Figure 5: Visualization of the intermediate CNN layers. The input image is a channel which can be seen in each 5x6 tile in the above images. The algorithm is learning about the sinuosity which is a characteristic feature of a channel type porosity. Image after: (a) first convolution operation (b) first max-pooling (c) second convolution operation (d) second max-pooling operation

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