

Roll No	21BCP376	Practical No:	6
Division	6	Date:	

### Part 1

Understand the project available on following link

Project Link: [https://github.com/aharley/nn\\_vis](https://github.com/aharley/nn_vis)

Project by: <https://adamharley.com/>

Reference in case needed: <https://www.youtube.com/watch?v=pj9-rr1wDhM>

### Part 2

Populate the table below to summarize your understanding of the project mentioned in part 1

Layer	Task	Rationale
Input Layer	Receives input data	In CNN, input will be an image or a sequence of images. This layer holds the raw input of the image with width 32, height 32, and depth 3.
Convolution layer 1	It applies filters to the input image to extract features.	Kernel is used to slide across the whole image, as a result of which we will get another image with different widths, heights, and depths.
Downsampling layer 1	It downsamples the input image i.e. reduce the dimensionality of the features.	It reducing the number of parameters by using layer such as max pooling layer or averaging layer.
Convolution layer 2	It applies filters to the input image to extract more complex features, horizontal and vertical edges and shapes.	More complex kernels are incorporated that detect shape and objects.
Downsampling layer 2	Reduces the dimensions of the image.	Reduces the number of parameters for detecting the simple features to build more complex features.
Fully-connected layer 1	It takes the inputs from the feature analysis and applies weights to predict the correct label.	Takes the output of the previous layers, "flattens" them and turns them into a single vector that can be an input for the next stage.
Fully-connected layer 2	It takes the output of previous Fully-connected layer as acts as classifier.	It classifies the features into the output.

Output layer	It gives output of given input.	It transform the output into the number of classes as desired by the network.
How does the following hyper-parameters affect the network performance		
Hyper-Parameter	One Line Definition	Effect on the CNN
Stride	It refers to the number of pixels by which we move the filter across the input image.	Stride is used to control the size of the receptive field, which is the area of the input feature map that is used in calculation by sliding the filter over the input map by a certain number of pixels.
Dilation Rate	It indicates how much the kernel is widened. There are usually spaces inserted between kernel elements.	This process enlarges the receptive field of the filters without increasing the number of parameters. The dilation rate determines how many pixels are skipped between each step of the convolution.
Type of pooling layer	<p>Max = Max pooling is a pooling operation that selects the maximum element from the region of the feature map covered by the filter.</p> <p>Min = Min pooling is a pooling operation that selects the minimum element from the region of the feature map covered by the filter.</p> <p>Average = Average pooling computes the average of the elements present in the region of feature map covered by the filter.</p> <p>GAP=Global pooling reduces each channel in the feature map to a single value.</p>	Pooling layers are used to reduce the dimensions of the feature maps. Thus, it reduces the number of parameters to learn and the amount of computation performed in the network.
Kernel size	It refers to the dimensions of the filter applied to the input data during the convolution operation.	It is a crucial hyperparameter that influences the network's ability to capture relevant features from the input data, its computational efficiency, and its generalization performance.
padding	It is the technique of adding extra pixels around the input image or feature map to maintain spatial dimensions during the convolution operation.	It preserves the spatial dimensions of the input volume. Padding allows the output size to match the input size or at least maintain more information about the spatial dimensions.

References:

[An Intuitive Explanation of Convolutional Neural Networks – the data science blog \(ujjwalkarn.me\)](https://ujjwalkarn.me/2016/09/04/intuitive-explanation-convnets/)

[Gentle Dive into Math Behind Convolutional Neural Networks | by Piotr Skalski | Towards Data Science](#)

[Intuitively Understanding Convolutions for Deep Learning | by Irhum Shafkat | Towards Data Science](#)

[An Introduction to different Types of Convolutions in Deep Learning | by Paul-Louis Pröve | Towards Data Science](#)

Rubrics:

Part 1 (Indirect)

Part 2 Layer Task – 5 points

Hyper Parameter Task – 5 points