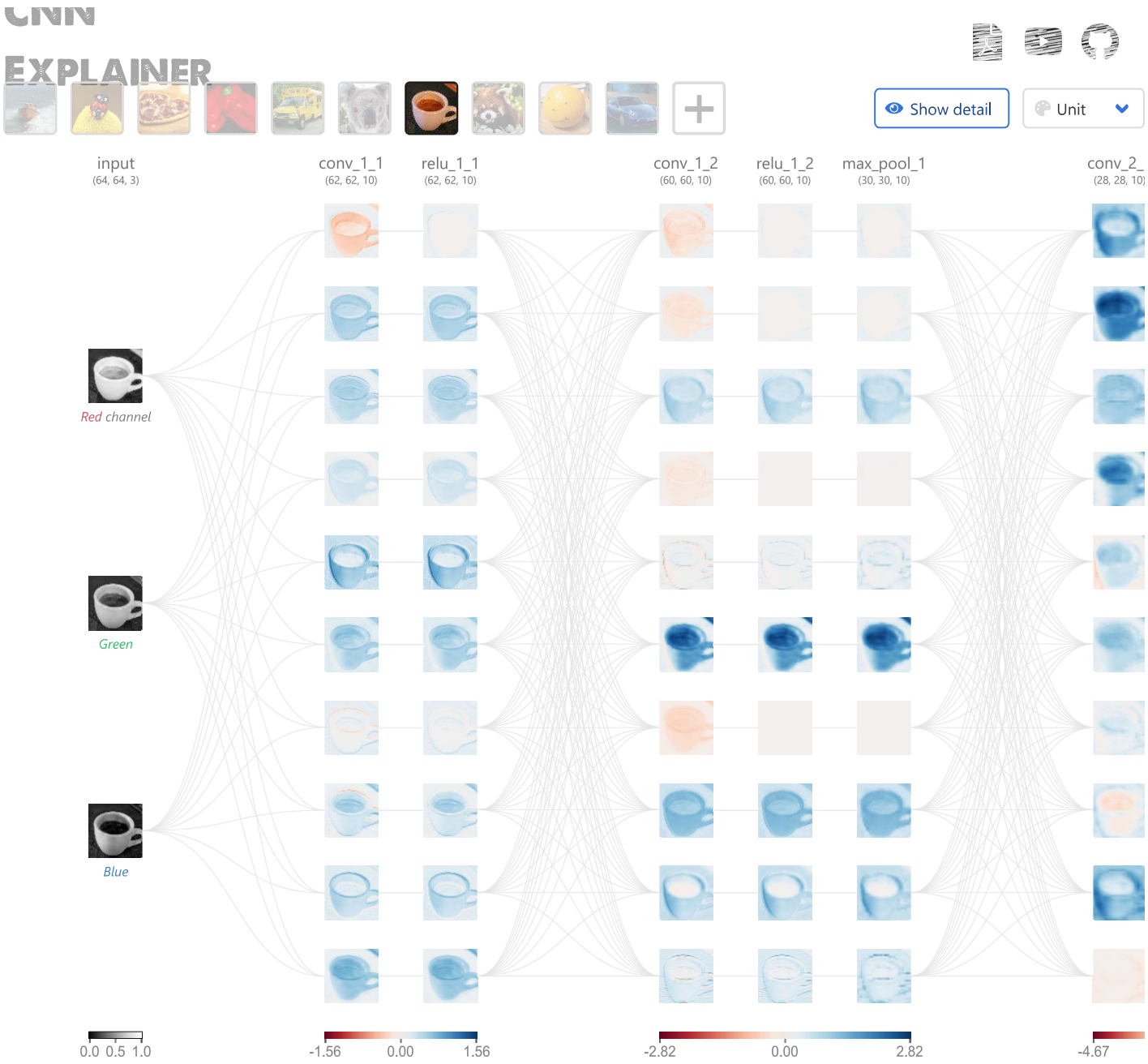

What is a Convolutional Neural Network?

In machine learning, a classifier assigns a class label to a data point. For example, an *image classifier* produces a class label (e.g, bird, plane) for what objects exist within an image. A *convolutional neural network*, or CNN for short, is a type of classifier, which excels at solving this problem!

A CNN is a neural network: an algorithm used to recognize patterns in data. Neural Networks in general are composed of a collection of neurons that are organized in layers, each with their own learnable weights and biases. Let's break down a CNN into its basic building blocks.

1. A **tensor** can be thought of as an n-dimensional matrix. In the CNN above, tensors will be 3-dimensional with the exception of the output layer.
   a function that takes in multiple inputs and yields a urons are represented above as the red → blue
   neurons with the same operation, including the
   le unique to each neuron, are tuned during the training phase, and allow the classifier to adapt to the problem and dataset provided. They are encoded in the visualization with a yellow → green diverging colorscale. The specific values can be viewed in the *Interactive Formula View* by clicking a neuron or by hovering over the kernel/bias in the *Convolutional Elastic Explanation View*.
5. A CNN conveys a **differentiable score function**, which is represented as **class scores** in the visualization on the output layer.

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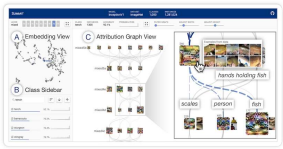

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If you have studied neural networks before, these terms may sound familiar to you. So what makes a CNN different? CNNs utilize a special type of layer, aptly named a convolutional layer, that makes them well-positioned to learn from image and image-like data. Regarding image data, CNNs can be used for many different computer vision tasks, such as image processing, classification, segmentation, and object detection.

In CNN Explainer, you can see how a simple CNN can be used for image classification. Because of the network's simplicity, its performance isn't perfect, but that's okay! The network architecture, Tiny VGG, used in CNN Explainer contains many of the same layers and operations used in state-of-the-art CNNs today, but on a smaller scale. This way, it will be easier to understand getting started.

What does each layer of the network do?

Let's walk through each layer in the network. Feel free to interact with the visualization above by clicking and hovering over various parts of it as you read.

Input Layer

The input layer (leftmost layer) represents the input image into the CNN. Because we use RGB images as input, the input layer has three channels, corresponding to the red, green, and blue channels, respectively, which are shown in this layer. Use the color scale when you click on the Show detail icon above to display detailed information (on this layer, and others).

Convolutional Layers

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dation of CNN, as they contain the learned kernels distinguish different images from one another—this you interact with the convolutional layer, you will ers and the convolutional layers. Each link represents convolution operation to produce the current convolutional neuron's output or activation map.

The convolutional neuron performs an elementwise dot product with a unique kernel and the output of the previous layer's corresponding neuron. This will yield as many intermediate results as there are unique kernels. The convolutional neuron is the result of all of the intermediate results summed together with the learned bias.

For example, let's look at the first convolutional layer in the Tiny VGG architecture above. Notice that there are 10 neurons in this layer, but only 3 neurons in the previous layer. In the Tiny VGG architecture, convolutional layers are fully-connected, meaning each neuron is connected to every other neuron in the previous layer. Focusing on the output of the topmost convolutional neuron from the first convolutional layer, we see that there are 3 unique kernels when we hover over the activation map.

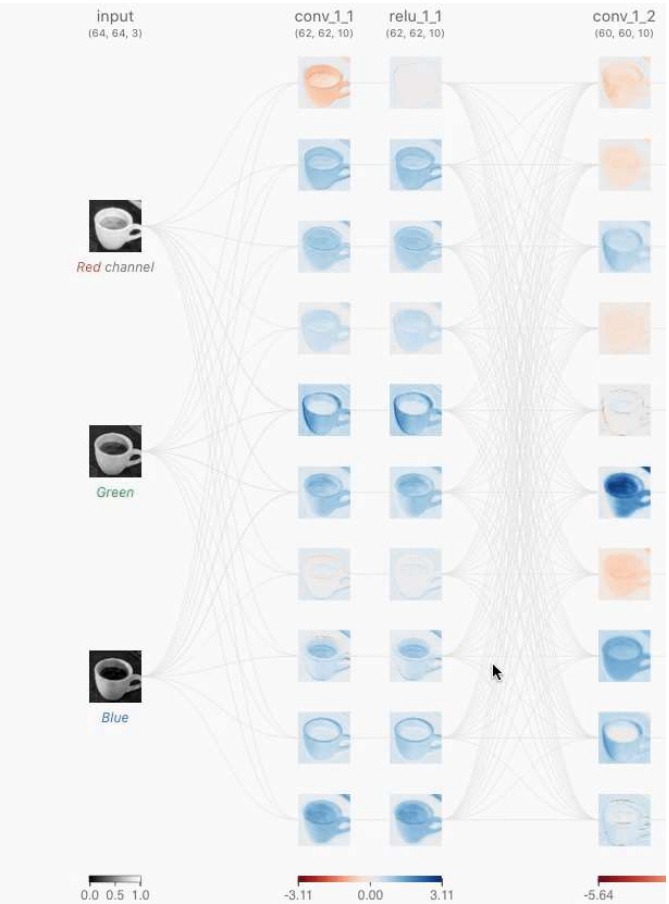

Figure 1. As you hover over the activation map of the topmost node from the first convolutional layer, you can see that 3 kernels were applied to yield this activation map. After clicking this activation map, you can see the convolution operation occuring with each unique kernel.

The size of these kernels is a hyper-parameter specified by the designers of the network architecture. In order to produce the output of the convolutional neuron (activation map), we must perform an elementwise dot product with the output of the previous layer and

the unique kernel learned by the network. In TinyVGG, the dot product operation uses a stride of 1, which means that the kernel is shifted over 1 pixel per dot product, but this is chitecture designer can adjust to better fit their nels, which will yield 3 intermediate results.

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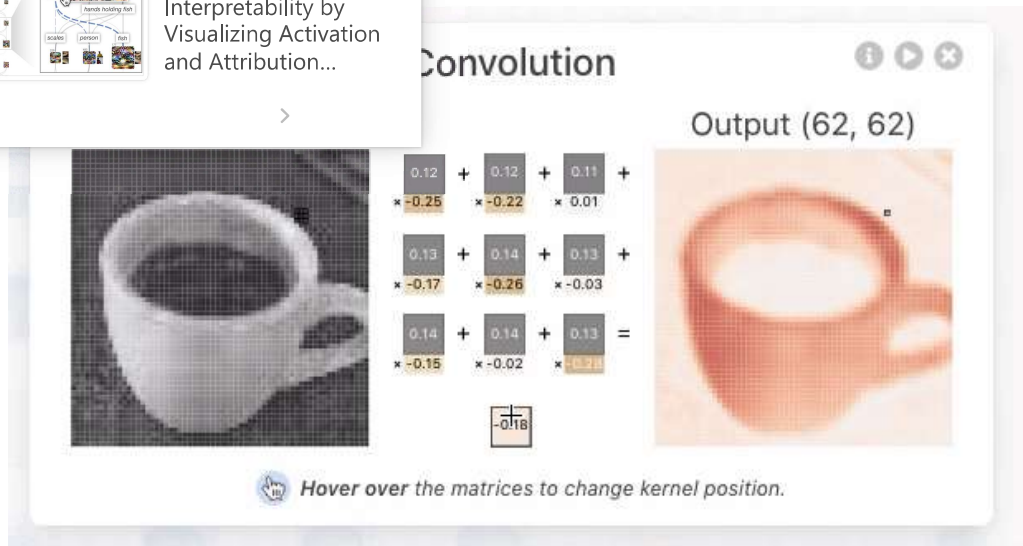
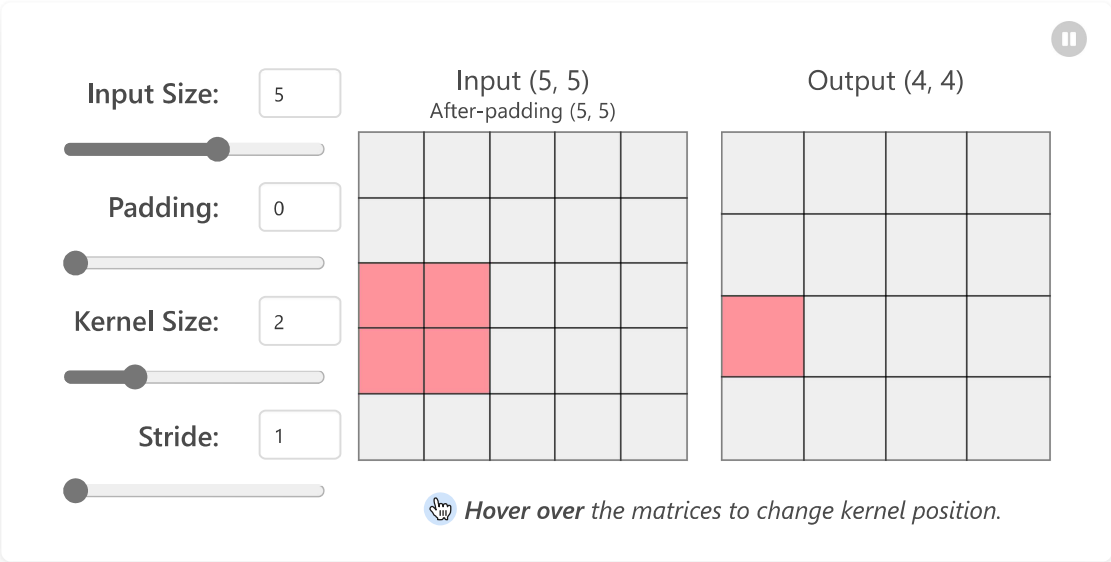


Figure 2. The kernel being applied to yield the topmost intermediate result for the discussed activation map.

Then, an elementwise sum is performed containing all 3 intermediate results along with the bias the network has learned. After this, the resulting 2-dimensional tensor will be the activation map viewable on the interface above for the topmost neuron in the first convolutional layer. This same operation must be applied to produce each neuron's activation map.

With some simple math, we are able to deduce that there are 3 x 10 = 30 unique kernels, each of size 3x3, applied in the first convolutional layer. The connectivity between the convolutional layer and the previous layer is a design decision when building a network architecture, which will affect the number of kernels per convolutional layer. Click around the visualization to better understand the operations behind the convolutional layer. See if you can follow the example above!

Understanding Hyperparameters



1. **Padding** is often necessary when the kernel extends beyond the activation map. Padding conserves data at the borders of activation maps, which leads to better eserve the input's spatial size, which allows an eeper, higher performing networks. There exist many st commonly used approach is zero-padding olicity, and computational efficiency. The technique cally around the edges of an input. This approach is ng CNNs such as AlexNet.

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2. **Kernel size**, often also referred to as filter size, refers to the dimensions of the sliding window over the input. Choosing this hyperparameter has a massive impact on the image classification task. For example, small kernel sizes are able to extract a much larger amount of information containing highly local features from the input. As you can see on the visualization above, a smaller kernel size also leads to a smaller reduction in layer dimensions, which allows for a deeper architecture. Conversely, a large kernel size extracts less information, which leads to a faster reduction in layer dimensions, often leading to worse performance. Large kernels are better suited to extract features that are larger. At the end of the day, choosing an appropriate kernel size will be dependent on your task and dataset, but generally, smaller kernel sizes lead to better performance for the image classification task because an architecture designer is able to stack more and more layers together to learn more and more complex features!
3. **Stride** indicates how many pixels the kernel should be shifted over at a time. For example, as described in the convolutional layer example above, Tiny VGG uses a stride of 1 for its convolutional layers, which means that the dot product is performed on a 3x3 window of the input to yield an output value, then is shifted to the right by one pixel for every subsequent operation. The impact stride has on a CNN is similar to kernel size. As stride is decreased, more features are learned because more data is extracted, which also leads to larger output layers. On the contrary, as stride is increased, this leads to more limited feature extraction and smaller output layer dimensions. One responsibility of the architecture designer is to ensure that the kernel slides across the input symmetrically when implementing a CNN. Use the hyperparameter visualization above to alter stride on various input/kernel dimensions to understand this constraint!

Activation Functions

ReLU

Neural networks are extremely prevalent in modern technology—because they are so accurate! The highest performing CNNs today consist of an absurd amount of layers, which are able to learn more and more features. Part of the reason these groundbreaking CNNs are able to achieve such tremendous accuracies is because of their non-linearity. ReLU applies much-needed non-linearity into the model. Non-linearity is necessary to produce non-linear decision boundaries, so that the output cannot be written as a linear

combination of the inputs. If a non-linear activation function was not present, deep CNN architectures would devolve into a single, equivalent convolutional layer, which would not

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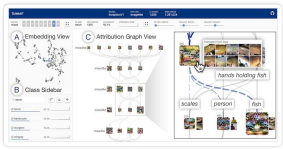

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vation function is specifically used as a non-linear

her non-linear functions such as *Sigmoid* because it

NNs using ReLU are faster to train than their

-to-one mathematical operation:

$$\mathrm{ReLU}(x) = \max(0, x)$$

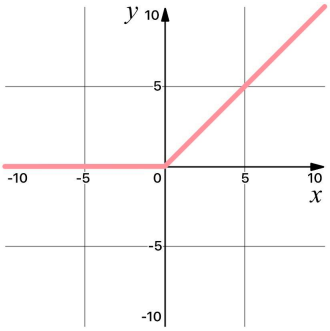


Figure 3. The ReLU activation function graphed, which disregards all negative data.

This activation function is applied elementwise on every value from the input tensor. For example, if applied ReLU on the value 2.24, the result would be 2.24, since 2.24 is larger than 0. You can observe how this activation function is applied by clicking a ReLU neuron in the network above. The Rectified Linear Activation function (ReLU) is performed after every convolutional layer in the network architecture outlined above. Notice the impact this layer has on the activation map of various neurons throughout the network!

Softmax

$$\mathrm{Softmax}(x_i) = \frac{\exp(x_i)}{\sum_j \exp(x_j)}$$

A softmax operation serves a key purpose: making sure the CNN outputs sum to 1. Because of this, softmax operations are useful to scale model outputs into probabilities. Clicking on the last layer reveals the softmax operation in the network. Notice how the logits after flatten aren't scaled between zero to one. For a visual indication of the impact of each logit (unscaled scalar value), they are encoded using a light orange → dark orange color scale. After passing through the softmax function, each class now corresponds to an appropriate probability!

You might be thinking what the difference between standard normalization and softmax is—after all, both rescale the logits between 0 and 1. Remember that backpropagation is a key aspect of training neural networks—we want the correct answer to have the largest "signal." By using softmax, we are effectively "approximating" argmax while gaining differentiability. Rescaling doesn't weigh the max significantly higher than other logits, whereas softmax does. Simply put, softmax is a "softer" argmax—see what we did there?

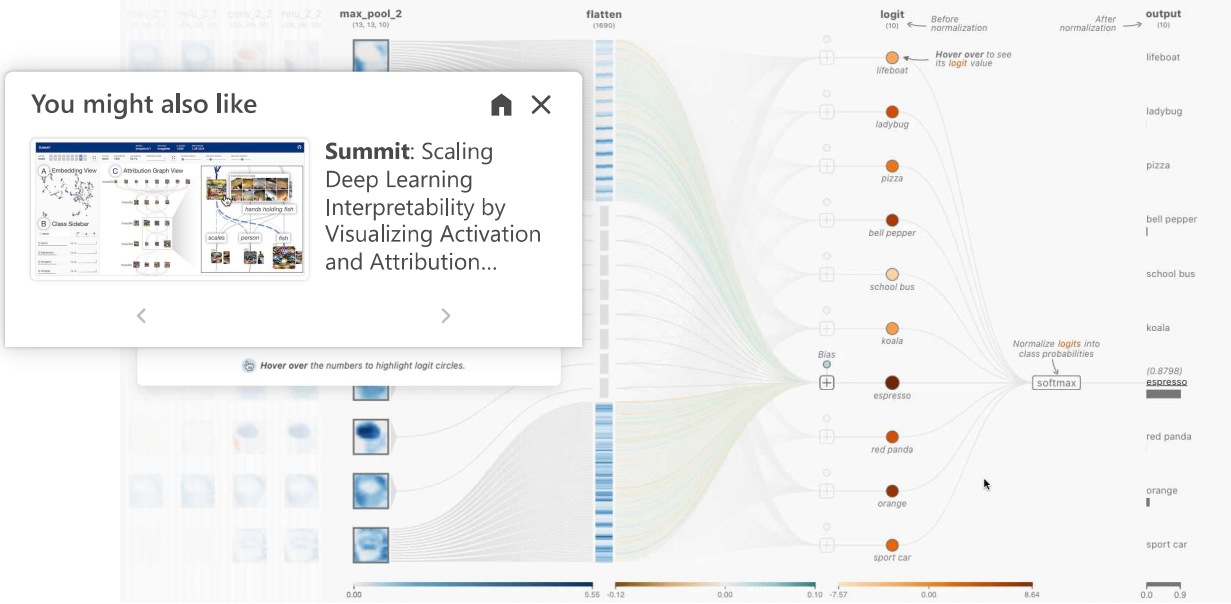


Figure 4. The *Softmax Interactive Formula View* allows a user to interact with both the color encoded logits and formula to understand how the prediction scores after the flatten layer are normalized to yield classification scores.

Pooling Layers

There are many types of pooling layers in different CNN architectures, but they all have the purpose of gradually decreasing the spatial extent of the network, which reduces the parameters and overall computation of the network. The type of pooling used in the Tiny VGG architecture above is Max-Pooling.

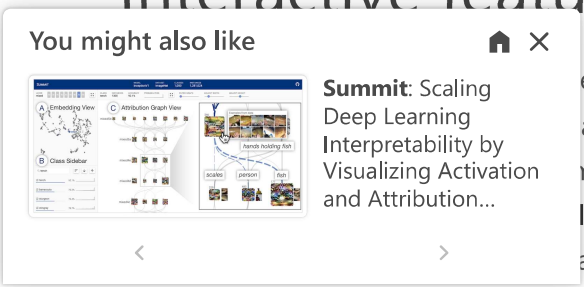
The Max-Pooling operation requires selecting a kernel size and a stride length during architecture design. Once selected, the operation slides the kernel with the specified stride over the input while only selecting the largest value at each kernel slice from the input to yield a value for the output. This process can be viewed by clicking a pooling neuron in the network above.

In the Tiny VGG architecture above, the pooling layers use a 2x2 kernel and a stride of 2. This operation with these specifications results in the discarding of 75% of activations. By discarding so many values, Tiny VGG is more computationally efficient and avoids overfitting.

Flatten Layer

This layer converts a three-dimensional layer in the network into a one-dimensional vector to fit the input of a fully-connected layer for classification. For example, a 5x5x2 tensor would be converted into a vector of size 50. The previous convolutional layers of the network extracted the features from the input image, but now it is time to classify the features. We use the softmax function to classify these features, which requires a 1-dimensional input. This is why the flatten layer is necessary. This layer can be viewed by clicking any output class.

Interactive features

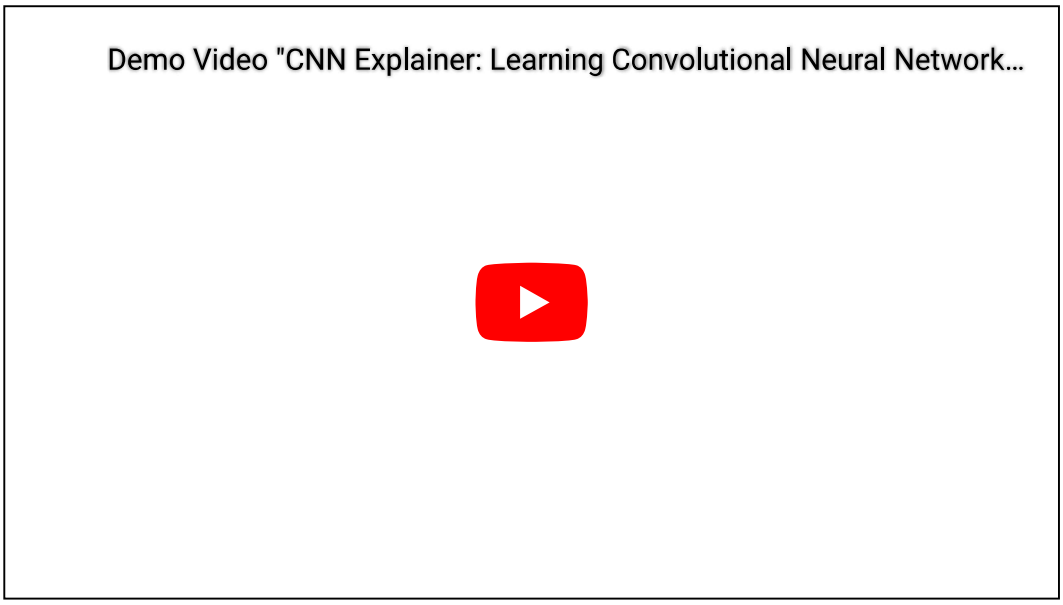


ecting + to understand how your image is
analyzing the neurons throughout the network, you
naps and extracted features.
lorscale to better understand the impact of
abstraction by adjusting Unit.

3. **Understand network details** such as layer dimensions and colorscales by clicking the Show detail icon.
4. **Simulate network operations** by clicking the button or interact with the layer slice in the *Interactive Formula View* by hovering over portions of the input or output to understand the mappings and underlying operations.
5. **Learn layer functions** by clicking from the *Interactive Formula View* to read layer details from the article.

Video Tutorial

- CNN Explainer Introduction (0:00-0:22)
- *Overview* (0:27-0:37)
- Convolutional *Elastic Explanation View* (0:37-0:46)
- Convolutional, ReLU, and Pooling *Interactive Formula Views* (0:46-1:21)
- Flatten *Elastic Explanation View* (1:22-1:41)
- Softmax *Interactive Formula View* (1:41-2:02)
- Engaging Learning Experience: Understanding Classification (2:06-2:28)
- Interactive Tutorial Article (2:29-2:54)



How is CNN Explainer implemented?

CNN Explainer uses *TensorFlow.js*, an in-browser GPU-accelerated deep learning library to load the pretrained model for visualization. The entire interactive system is written in k and *D3.js* for visualizations. You only need a web today!

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Who developed CNN Explainer?

CNN Explainer was created by Jay Wang, Robert Turko, Omar Shaikh, Haekyu Park, Nilaksh Das, Fred Hohman, Minsuk Kahng, and Polo Chau, which was the result of a research collaboration between Georgia Tech and Oregon State. We thank Anmol Chhabria, Kaan Sancak, Kantwon Rogers, and the Georgia Tech Visualization Lab for their support and constructive feedback. This work was supported in part by NSF grants IIS-1563816, CNS-1704701, NASA NSTRF, DARPA GARD, gifts from Intel, NVIDIA, Google, Amazon.