

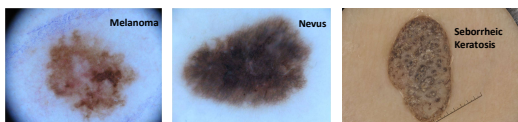
Optimizing a Convolutional Neural Network to Detect Melanoma in Images

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Goal: Implement machine learning knowledge to tune a model that detects melanoma in images

The Problem

Melanoma is a rare form of skin cancer that accounts for most skin-cancer-related deaths. Given a set of approximately 2700 images of benign and malicious skin lesions, can we develop a convolutional neural network to detect melanoma with 70% accuracy?



Machine Learning in a Nutshell

Given:

- A random input X in n dimensions
- A random output Y
- Loss (error) function $L(Y, f(X))$, where $f(X)$ is the model's output

Want:

- A mapping from $X \rightarrow Y$ minimizing the expected value of the loss function

$$\hat{g} = \arg \min E[L(Y, g(X))]$$

CNNs: Convolutional Layers

- Foundation of Convolutional Neural Networks
 - What separates CNNs from other Machine Learning models
- Purpose: extract high-level features from an image
- Method:
 - Iterate a small 'window' over our image
 - Window (a.k.a. 'filter', 'kernel') has a (random) decimal value at each pixel
 - Each pixel multiplied with kernel value corresponding, add all products
 - Window shifts to next pixel

Image

0.604	0.545	0.553	0.62	0.601	0.522
0.639	0.573	0.541	0.573	0.616	0.6
0.659	0.631	0.573	0.541	0.589	0.635
0.651	0.675	0.643	0.561	0.537	0.584
0.639	0.675	0.678	0.616	0.545	0.541
0.627	0.639	0.659	0.655	0.612	0.561

Kernel

0.202	-0.757	-0.667
-0.118	-0.995	-0.482
-0.51	0.132	-0.492

Result

1.87122	-1.9	-1.971	-1.912
-1.954	-1.888	-1.927	-1.974
-2.085	-1.958	-1.888	-1.936
-2.172	-2.066	-1.912	-1.87

$$(0.604 * 0.202) + (0.545 * -0.757) + (0.553 * -0.667) + (0.62 * -0.118) + (0.601 * -0.995) + (0.522 * -0.482) + (0.639 * 0.202) + (0.573 * -0.757) + (0.541 * -0.667) + (0.573 * -0.118) + (0.616 * -0.995) + (0.6 * -0.482) + (0.659 * 0.202) + (0.631 * -0.757) + (0.573 * -0.667) + (0.541 * -0.118) + (0.589 * -0.995) + (0.635 * -0.482) + (0.651 * 0.202) + (0.675 * -0.757) + (0.643 * -0.667) + (0.561 * -0.118) + (0.537 * -0.995) + (0.584 * -0.482) + (0.639 * 0.202) + (0.675 * -0.757) + (0.678 * -0.667) + (0.616 * -0.118) + (0.545 * -0.995) + (0.541 * -0.482) + (0.627 * 0.202) + (0.639 * -0.757) + (0.659 * -0.667) + (0.655 * -0.118) + (0.612 * -0.995) + (0.561 * -0.482) = 1.87122$$

Values in the kernel are determined with the Xavier Glorot initialization

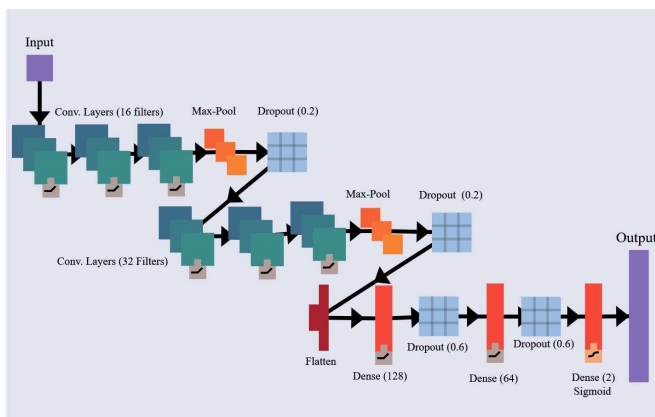
- Random distribution dependent on the size of multiple layers in the network

$$W_{i,j} \sim U\left[-\frac{\sqrt{6}}{\sqrt{n_j + n_{j+1}}}, \frac{\sqrt{6}}{\sqrt{n_j + n_{j+1}}}\right]$$

CNNs: Other Layers

- Input Layer:** Image represented as 256 x 256 x 3 image
- Convolution Layers:** Extract patterns and important features
- Max-pool Layers:** Retain most impactful features
- Dropout Layers:** Randomly deactivate neurons (reduce overfitting)
- Flatten Layers:** Reduces dimensionality from 3 to 1
- Dense Layers:** traditional neural network structure
- Sigmoid Dense Layer:** calculate probability of match for each class
 - Transforms data to interval [0, 1] and select corresponding class
 - Ex. [0.01, 0.99] would select class 1 (melanoma) as the prediction for the input
- Output Layer:** Vector containing predicted class of image
 - Ex. [0, 1]

Final Model Structure

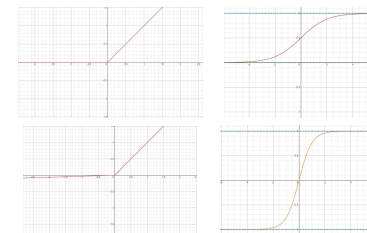


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CNNs: Parameters

- Optimizer Learning Rate:** Extremity of weight adjustments per iteration
- Batch Size:** How many images are fed to the model simultaneously
- Activation Function:** Functions that find nonlinear patterns in data
- Epochs:** Number of training iterations
- Sample Size:** Number of images in training dataset



Activation Functions: ReLU, LeakyReLU, Sigmoid, Tanh

Results

Summary:

- Achieved 60 – 65% accuracy consistently**
- Was not able to develop model to reliably detect melanoma in an image**
- Was able to develop model to classify between melanoma and non-melanoma images with 60 – 65% accuracy**

Final Model Specs:

- Total Layers: 16**
- Conv Layers: 6**
- Dense Layers: 3**
- Activation Function: LeakyReLU (0.03)**
- Dropouts: 4**
- Optimizer LR: ??????**
- Batch Size: ??????????**