Facial Recognition of Identical Twins using Convolutional Neural Networks

Springboard Capstone #2

Anthony Johnson

Outline

- Motivation
- Model
- Data
- Training
- Interpretation
- Conclusions

My brother

Me

Motivation

- Facial recognition software has come a long way in the last few years, thanks to **convolutional neural networks** (CNNs)
  - iPhone X uses your face to unlock your phone
- How good exactly are CNNs?
- On a number of occasions I've been able to unlock my identical twin brother's iPhone with my face.
- Anything less than 100% accuracy is a major security concern

Model

- **VGG-Face** model [1]
  - Open-source CNN
  - Pre-trained on hundreds of thousands of faces
- Use **transfer learning** to build on this

[1] https://gist.github.com/EncodeTS/6bbe8cb8bebad7a672f0d872561782d9

Model Adaptation

- Define function **instantiate_model(num_dense, num_trainable)**
  - Creates same architecture as VGG-Face
  - Load pre-trained weights, **vgg_face_weights.h5**
  - Remove final layer
  - Add a Dense layer with **num_dense = 100 nodes**
  - Add a Dense Activation('softmax') layer with 2 nodes
  - Set all but the last **num_trainable = 5 layers** as untrainable
  - Input hyperparameters **num_dense** and **num_trainable**

Model Architecture

- 145M parameters
  - 11M trainable
  - 134M untrainable

	Layer (type)	Output Shape	Param #
1)	zero_padding2d_131_input (In	(None, 224, 224, 3)	0
2)	zero_padding2d_131 (ZeroPadd	(None, 226, 226, 3)	0
3)	conv2d_161 (Conv2D)	(None, 224, 224, 64)	1792
4)	zero_padding2d_132 (ZeroPadd	(None, 226, 226, 64)	0
5)	conv2d_162 (Conv2D)	(None, 224, 224, 64)	36928
6)	max_pooling2d_51 (MaxPooling	(None, 112, 112, 64)	0
7)	zero_padding2d_133 (ZeroPadd	(None, 114, 114, 64)	0
8)	conv2d_163 (Conv2D)	(None, 112, 112, 128)	73856
9)	zero_padding2d_134 (ZeroPadd	(None, 114, 114, 128)	0
10)	conv2d_164 (Conv2D)	(None, 112, 112, 128)	147584
11)	max_pooling2d_52 (MaxPooling	(None, 56, 56, 128)	0
12)	zero_padding2d_135 (ZeroPadd	(None, 58, 58, 128)	0
13)	conv2d_165 (Conv2D)	(None, 56, 56, 256)	295168
14)	zero_padding2d_136 (ZeroPadd	(None, 58, 58, 256)	0
15)	conv2d_166 (Conv2D)	(None, 56, 56, 256)	590080
16)	zero_padding2d_137 (ZeroPadd	(None, 58, 58, 256)	0
17)	conv2d_167 (Conv2D)	(None, 56, 56, 256)	590080
18)	max_pooling2d_53 (MaxPooling	(None, 28, 28, 256)	0
19)	zero_padding2d_138 (ZeroPadd	(None, 30, 30, 256)	0
20)	conv2d_168 (Conv2D)	(None, 28, 28, 512)	1180160
21)	zero_padding2d_139 (ZeroPadd	(None, 30, 30, 512)	0
22)	conv2d_169 (Conv2D)	(None, 28, 28, 512)	2359808
23)	zero_padding2d_140 (ZeroPadd	(None, 30, 30, 512)	0
24)	conv2d_170 (Conv2D)	(None, 28, 28, 512)	2359808
25)	max_pooling2d_54 (MaxPooling	(None, 14, 14, 512)	0
26)	zero_padding2d_141 (ZeroPadd	(None, 16, 16, 512)	0
27)	conv2d_171 (Conv2D)	(None, 14, 14, 512)	2359808
28)	zero_padding2d_142 (ZeroPadd	(None, 16, 16, 512)	0
29)	conv2d_172 (Conv2D)	(None, 14, 14, 512)	2359808
30)	zero_padding2d_143 (ZeroPadd	(None, 16, 16, 512)	0
31)	conv2d_173 (Conv2D)	(None, 14, 14, 512)	2359808
32)	max_pooling2d_55 (MaxPooling	(None, 7, 7, 512)	0
33)	conv2d_174 (Conv2D)	(None, 1, 1, 4096)	102764544
34)	dropout_21 (Dropout)	(None, 1, 1, 4096)	0
35)	conv2d_175 (Conv2D)	(None, 1, 1, 4096)	16781312
36)	dropout_22 (Dropout)	(None, 1, 1, 4096)	0
37)	conv2d_176 (Conv2D)	(None, 1, 1, 2622)	10742334
38)	flatten_11 (Flatten)	(None, 2622)	0
39)	dense_21 (Dense)	(None, 100)	262300
40)	dense_22 (Dense)	(None, 2)	202

Total params: 145,265,380
Trainable params: 11,004,836
Non-trainable params: 134,260,544

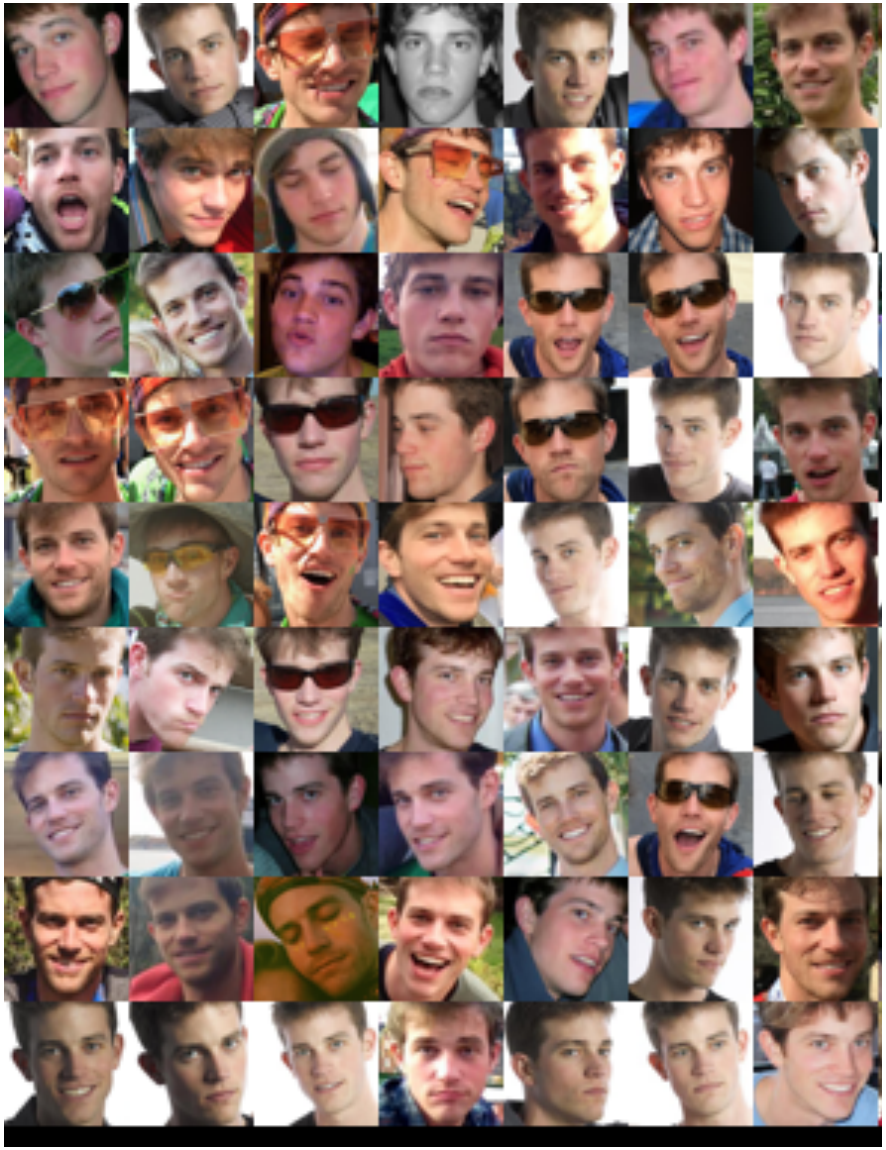
Data

- I gathered digital photographs of me and my brother
- Square cropped each image
- Split into 3 datasets
  - Training = 118 images per twin
  - Validation = 27 images each per twin
  - Testing = 33 images each per twin
- Define **getXY**() function
  - Resizes images to 224x224
  - Stacks them together into trainX, valX, testX
  - Categorical dependent variable trainY, valY, testY

Sample Training Images

Anthony

Paul

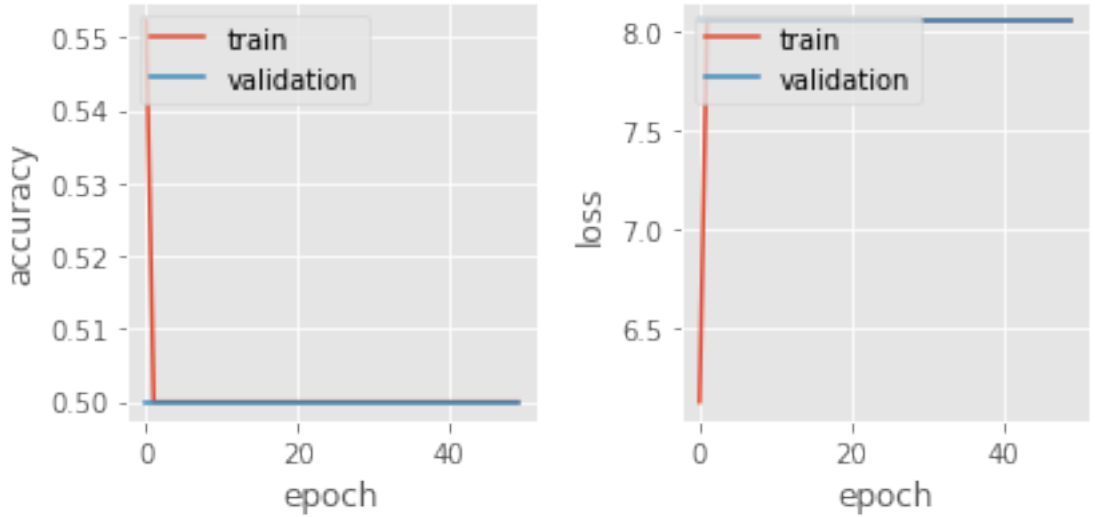


Training

- Hyperparameters/settings to tune:
  - The number of layers that are trainable, **num_trainable**
  - The learning rate, **lr**
  - The number of nodes, **num_dense**, in the penultimate layer
  - The decay rate, **decay**, of the learning rate
  - The optimizer: SGD vs. Adam

Training – Iteration #1

- Varied **num_trainable** = [3, 4, 5, 6, 7, 8, 9]
- 120 nodes in the penultimate layer
- SGD optimizer with
  - Learning rate = 0.1 (Decay = 0)
  - Loss = ‘categorical_crossentropy’
  - Metrics = ‘accuracy’
- These runs suffered from overfitting and thus did not converge.



Training – Iteration #2

- Varied:
  - **num_trainable** = [3, 4, 5, 6, 7, 8, 9]
  - Learning rate **lr** = [0.001, .005, .01, .05, .1, 1]
  - **num_dense** = [10, 50, 100, 200]
- EarlyStopping condition
  - Patience of 4
  - Monitoring **val_loss**
- These runs converged!
  - Training accuracies 90%-100%
  - Validation accuracies 85%-95%

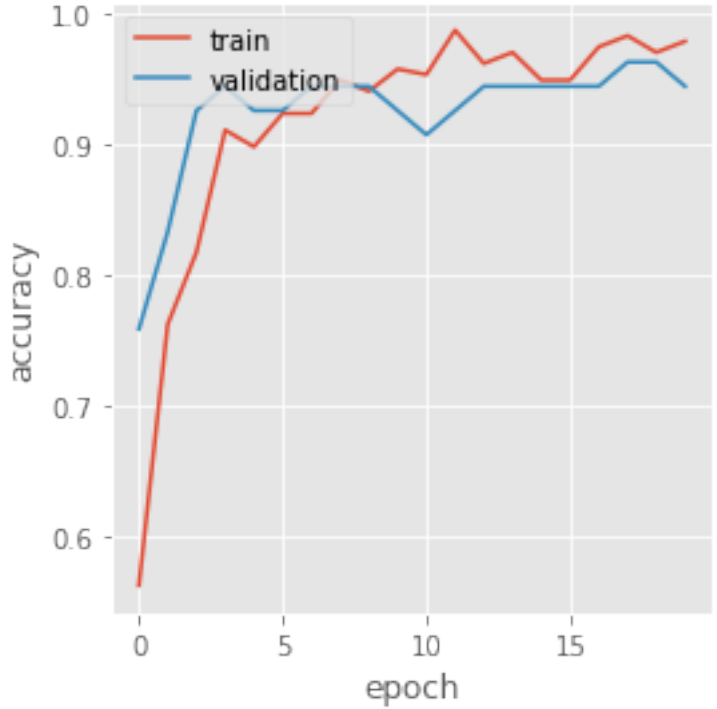
Training – Iteration #3

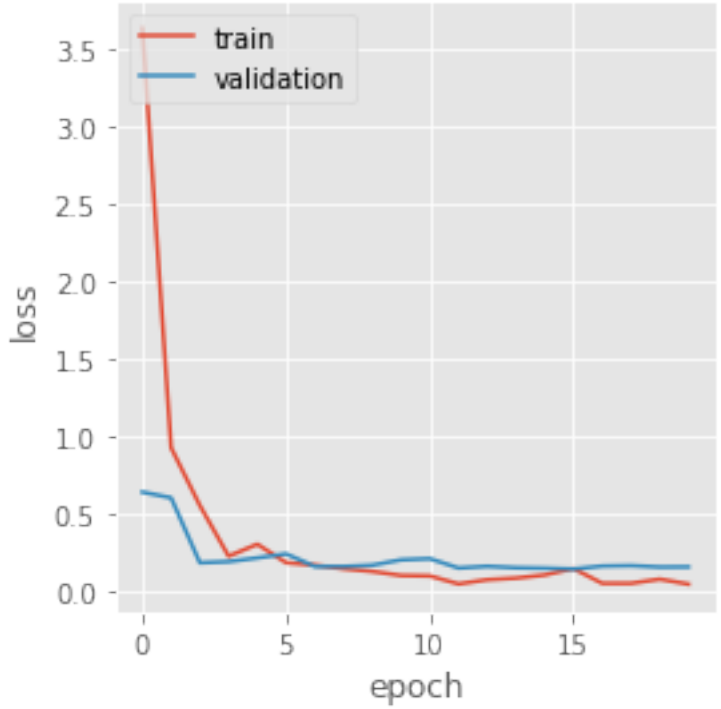
- Varied: Same as previous but varied decay
  - **Decay** = [.000005,.00001,.00002,.00004]
- EarlyStopping condition
  - Increased patience to 6
  - Monitoring **val_loss**
- These runs also converged!
  - Training accuracies 90%-100%
  - Validation accuracies 85%-95%

Best Model

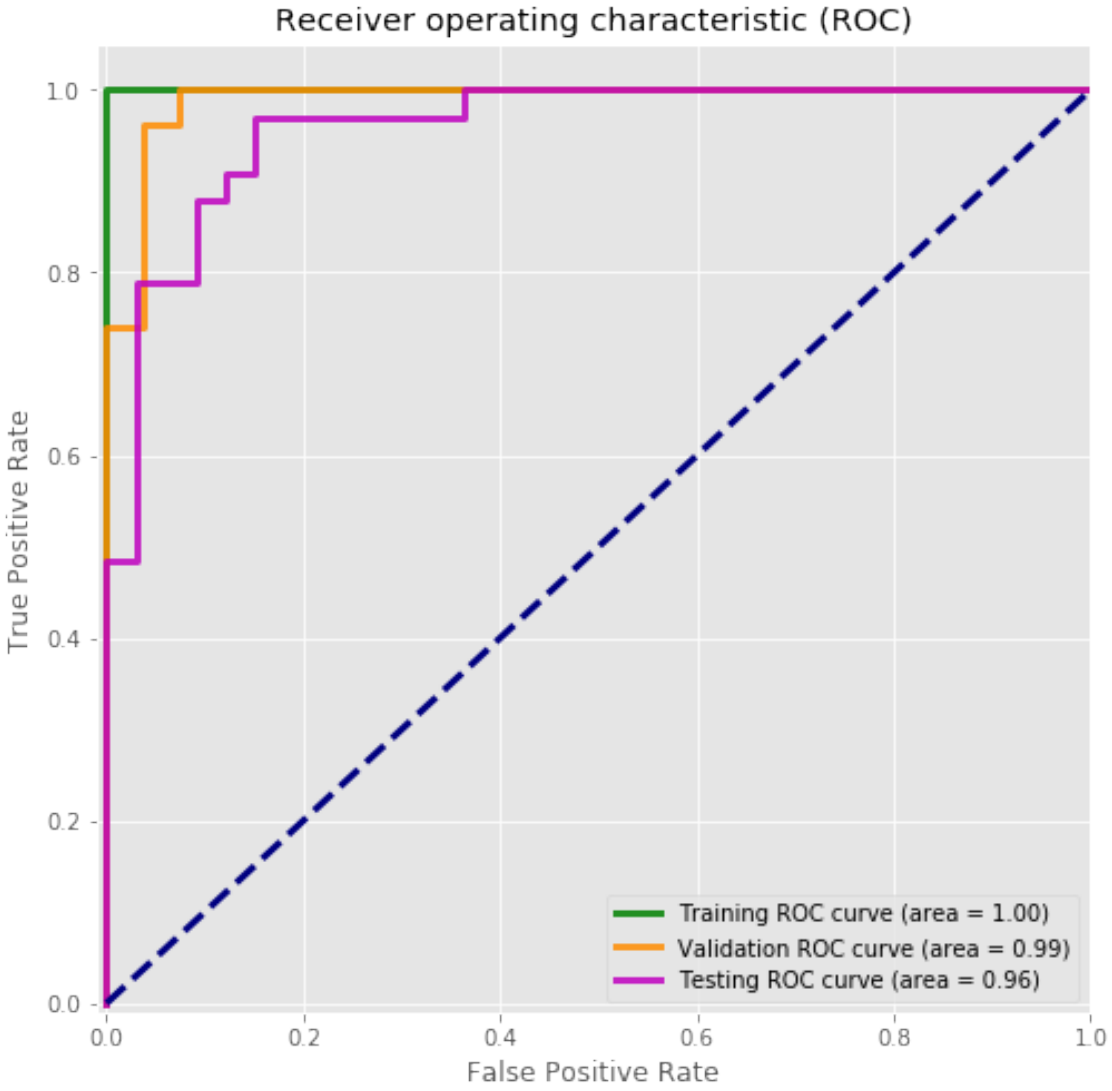
- Parameters:
  - Num_dense = 100
  - Num_trainable = 5
  - Learning rate = 0.001
  - Decay = 0
  - Optimizer = SGD
  - EarlyStopping patience of 6 epochs

- Model accuracy:
  - Training: 100%
  - Validation: 94%
  - Testing: 88%





Best Model – ROC Curve

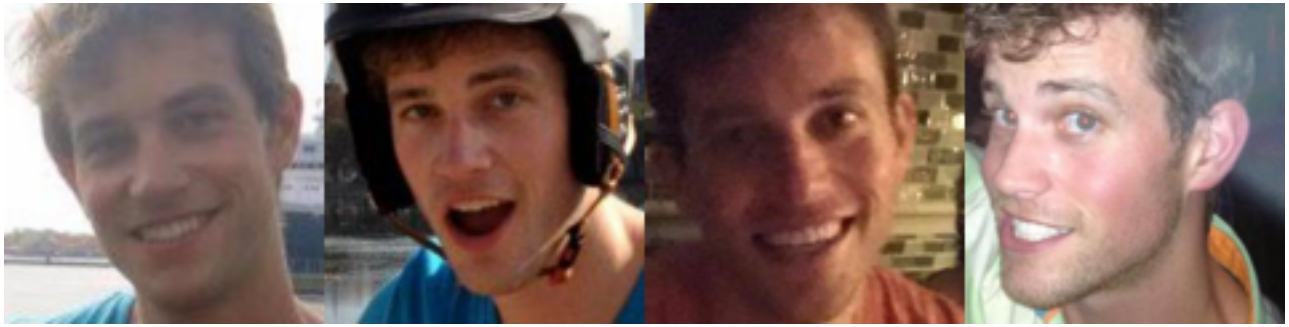


Best Model – Testing Results

TESTING SET	PREDICTED - AJ	PREDICTED - PJ
ACTUAL - AJ	29	4
ACTUAL - PJ	4	29

Actual = AJ, Predicted = PJ

Actual = PJ, Predicted = AJ



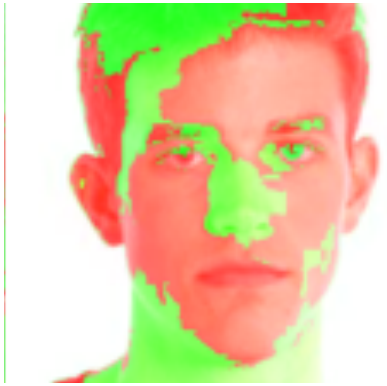
Potential causes of these misclassifications:

- Bad Lighting
- Sunglasses
- Unusual facial tilt or expressions

Interpretation

- **LIME** = Local Interpretable Model-Agnostic Explanations [2]
  - *LimeImageExplainer*() identifies features in an image that increase the probability (green) or decrease the probability (red) of a certain class
  - Red patches indicate a higher probability of Paul and green patches indicate a higher probability of Anthony

Paul

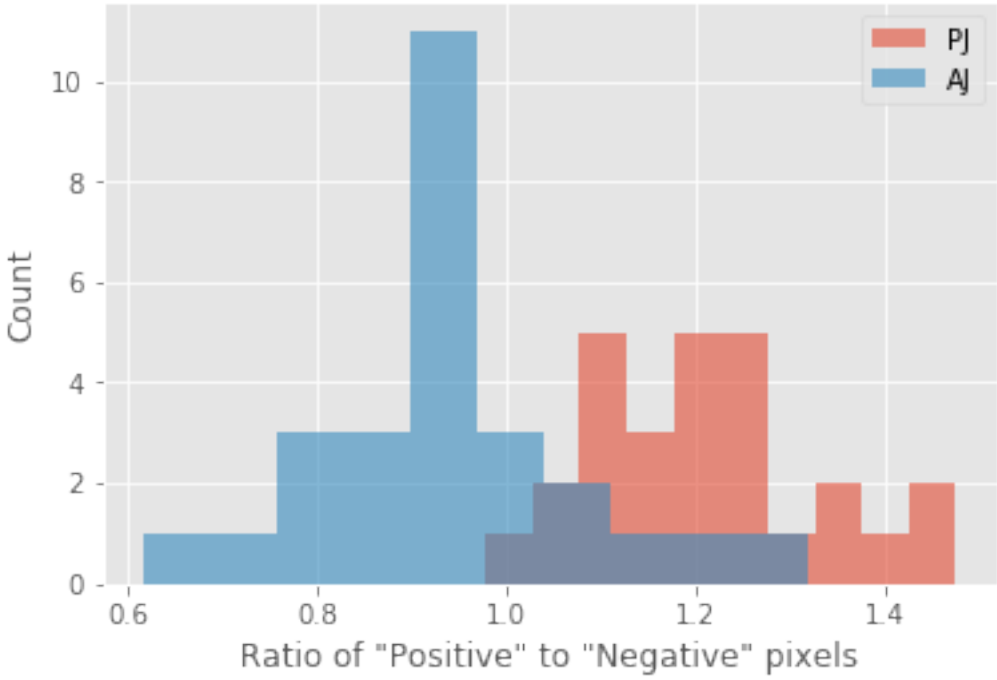


Anthony

[2] https://github.com/marcotcr/lime

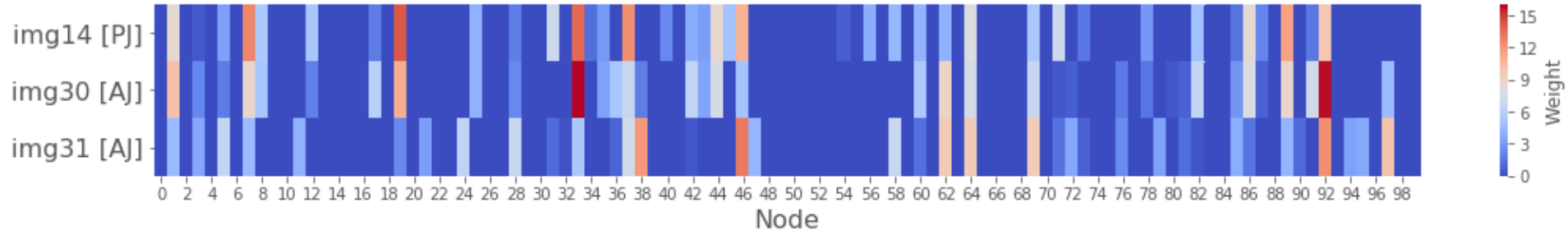
Interpretation

- Analysis:
  - Sum the total number of green and red pixels for both AJ and PJ
  - Divide total “positive” pixels by total “negative” pixels
  - Create histogram (right)
- In PJ images, the ratio of red to green pixels was between 1.0 and 1.5, averaged to 1.21.
- In AJ images, the equivalent ratio varied much more widely, between 0.6 and 1.3.



Direct Face Comparison

- Penultimate layer node weights
  - Middle row is misclassified



Img14 [PJ]

Img30 [AJ]
[thinks it is PJ]

Img31 [AJ]

Conclusions

- The final convolutional neural network:
  - Optimized the learning rate (.001), number of trainable layers (5), and number of nodes in the final layers (100)
  - Converged in <5 epochs
  - Final testing accuracy = 88%
  - Final testing ROC AUC = 0.96
- Overall, the model failed in cases with bad or inconsistent lighting or sometimes when we were wearing sunglasses
- Model seems to have slightly easier time recognizing PJ than AJ
  - Maybe PJ images are "better" or more unique by chance

Future Work

- While decent for identical twins, this model would be unacceptable in a security application
- To improve the model:
  - Train more images (the more the better)
  - Further optimize the hyperparameters
  - Optimize the optimizer
- I would like to dig deeper into interpreting and visualizing CNNs
  - With millions of parameters, CNNs are difficult to interpret
  - But this is still a new field, and anything is possible