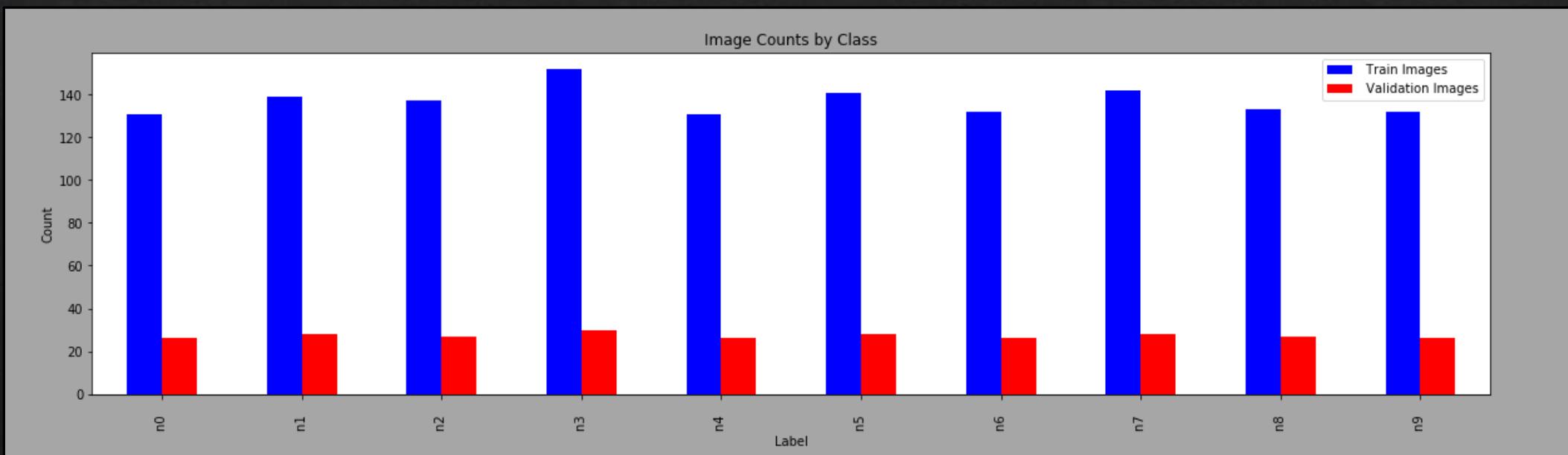


# Final Capstone: Image Classification of 10 Monkey Species

By Jacob Knopping

# About the Data

- ❖ “10 Monkey Species” image dataset ([Kaggle](#))
- ❖ Images  $\geq 400 \times 300$  px, JPEG
- ❖ Consists of two folders: training and validation
  - ❖ Each folder contains 10 subfolders, each corresponding to a monkey species



n0



n1



n2



n3



n4



n5



n6



n7



n8



n9



	Label	Latin Name	Common Name	Train Images	Validation Images
0	n0	<i>alouatta_palliata</i> t	mantled_howler	131	26
1	n1	<i>erythrocebus_patas</i> t	patas_monkey	139	28
2	n2	<i>cacajao_calvus</i> t	bald_uakari	137	27
3	n3	<i>macaca_fuscata</i> t	japanese_macaque	152	30
4	n4	<i>cebuella_pygmea</i> t	pygmy_marmoset	131	26
5	n5	<i>cebus_capucinus</i> t	white_headed_capuchin	141	28
6	n6	<i>mico_argentatus</i> t	silvery_marmoset	132	26
7	n7	<i>saimiri_sciureus</i> t	common_squirrel_monkey	142	28
8	n8	<i>aotus_nigriceps</i> t	black_headed_night_monkey	133	27
9	n9	<i>trachypithecus_johnii</i>	nilgiri_langur	132	26

# Project Goal

- ❖ Build a high-performance convolutional neural network (CNN) model for image classification of 10 monkey species
- ❖ In order to accomplish this goal, multiple models will be trained and evaluated
  - ❖ Build a CNN without using pre-trained models
  - ❖ Pre-trained models (Keras Applications)
    - ❖ Xception
    - ❖ InceptionResNetV2



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# Project Significance

- ❖ Image classification can be invaluable for wildlife conservation efforts
- ❖ Using imagery data with motion sensitive cameras = minimally invasive approach to estimation population trends in animals over time
- ❖ Drawback: human labor is currently primary means to recognize and count images
  - ❖ Impractical, impedes progress of ecological studies
- ❖ From Scientific Reports: “Deep-learning methods have revolutionized our ability to train digital computers to recognize all kinds of objects from imagery data including...wildlife species. [Deep learning/image recognition techniques] **may significantly increase the efficiency of associated ecological studies**”



<https://www.google.com/url?sa=i&url=https%3A%2F%2Ftheconversation.com%2Fcamera-traps-designed-for-animals-are-now-invading-human-privacy-105327&psig=AOvVaw2XRa23392F2MRnTCVVWSsh&ust=1587837170835000&source=images&cd=vfe&ved=0CA4QjhxqFwoTCOCm5MrOgekCEQAAAAdAAZABAI>

- ❖ Keras Image Preprocessing makes this easy
    - ❖ `ImageDataGenerator, flow_from_directory`
  - ❖ Generate training and validation data → usable format for building CNN models

# First CNN Model

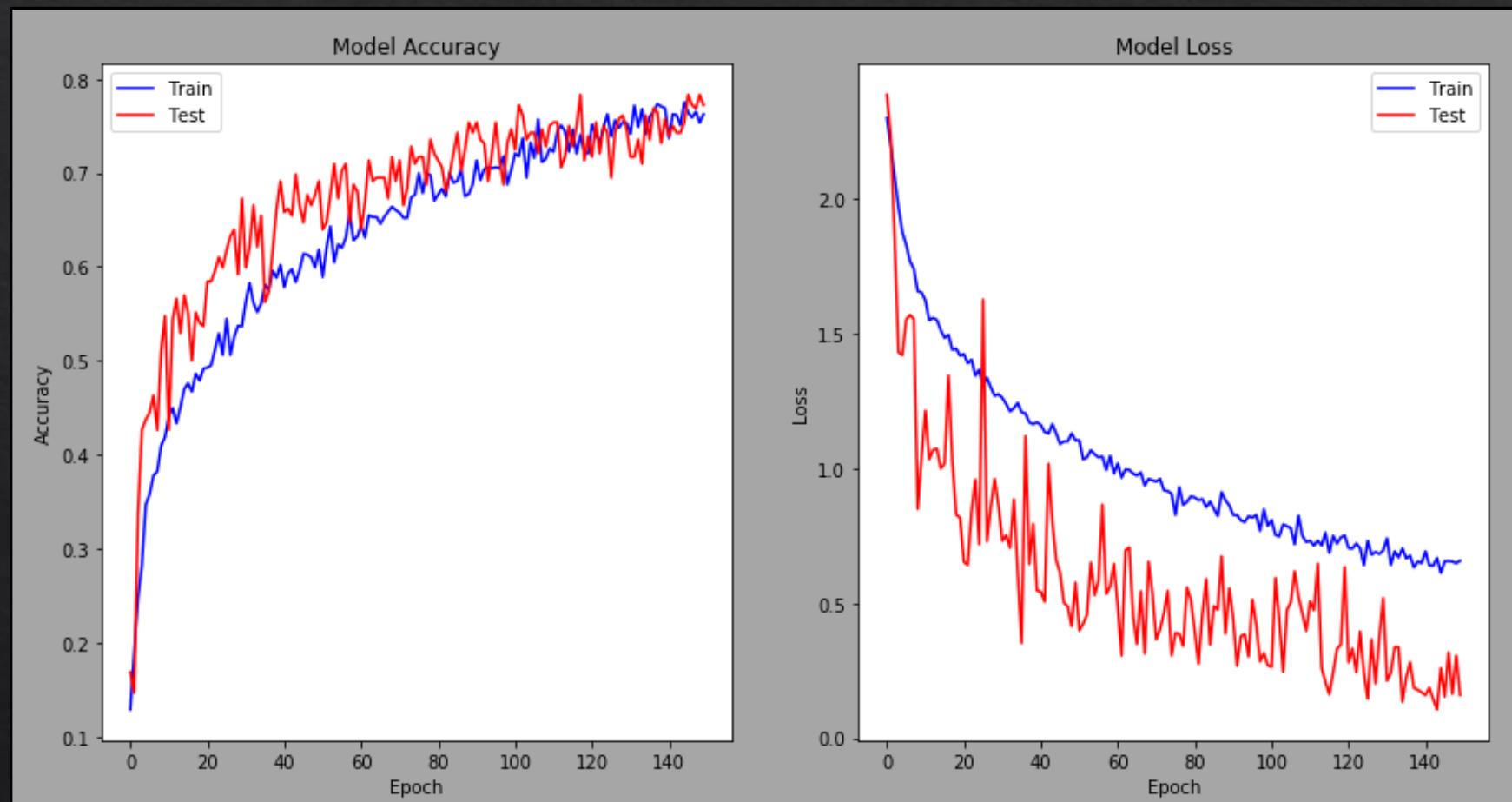
- ❖ Built with simplicity in mind: less parameters, will train quickly
  - ❖ Multiple Conv2D/MaxPooling2D layers to reduce complexity
- ❖ 462, 314 parameters (approx. 22 million, 55 million for next two)
- ❖ ~ 90 sec/epoch, 150 epochs

```
# Compile
cnn_model.compile(loss=keras.losses.categorical_crossentropy,
                    optimizer=Adam(lr=0.0001),
                    metrics=['accuracy'])
```

Model: "sequential_2"		
Layer (type)	Output Shape	Param #
conv2d_5 (Conv2D)	(None, 222, 222, 32)	896
max_pooling2d_3 (MaxPooling2D)	(None, 111, 111, 32)	0
conv2d_6 (Conv2D)	(None, 109, 109, 64)	18496
max_pooling2d_4 (MaxPooling2D)	(None, 54, 54, 64)	0
conv2d_7 (Conv2D)	(None, 52, 52, 128)	73856
max_pooling2d_5 (MaxPooling2D)	(None, 26, 26, 128)	0
conv2d_8 (Conv2D)	(None, 24, 24, 64)	73792
max_pooling2d_6 (MaxPooling2D)	(None, 12, 12, 64)	0
dropout_3 (Dropout)	(None, 12, 12, 64)	0
flatten_2 (Flatten)	(None, 9216)	0
dense_3 (Dense)	(None, 32)	294944
dropout_4 (Dropout)	(None, 32)	0
dense_4 (Dense)	(None, 10)	330
Total params: 462,314		
Trainable params: 462,314		
Non-trainable params: 0		

# First CNN Model Results

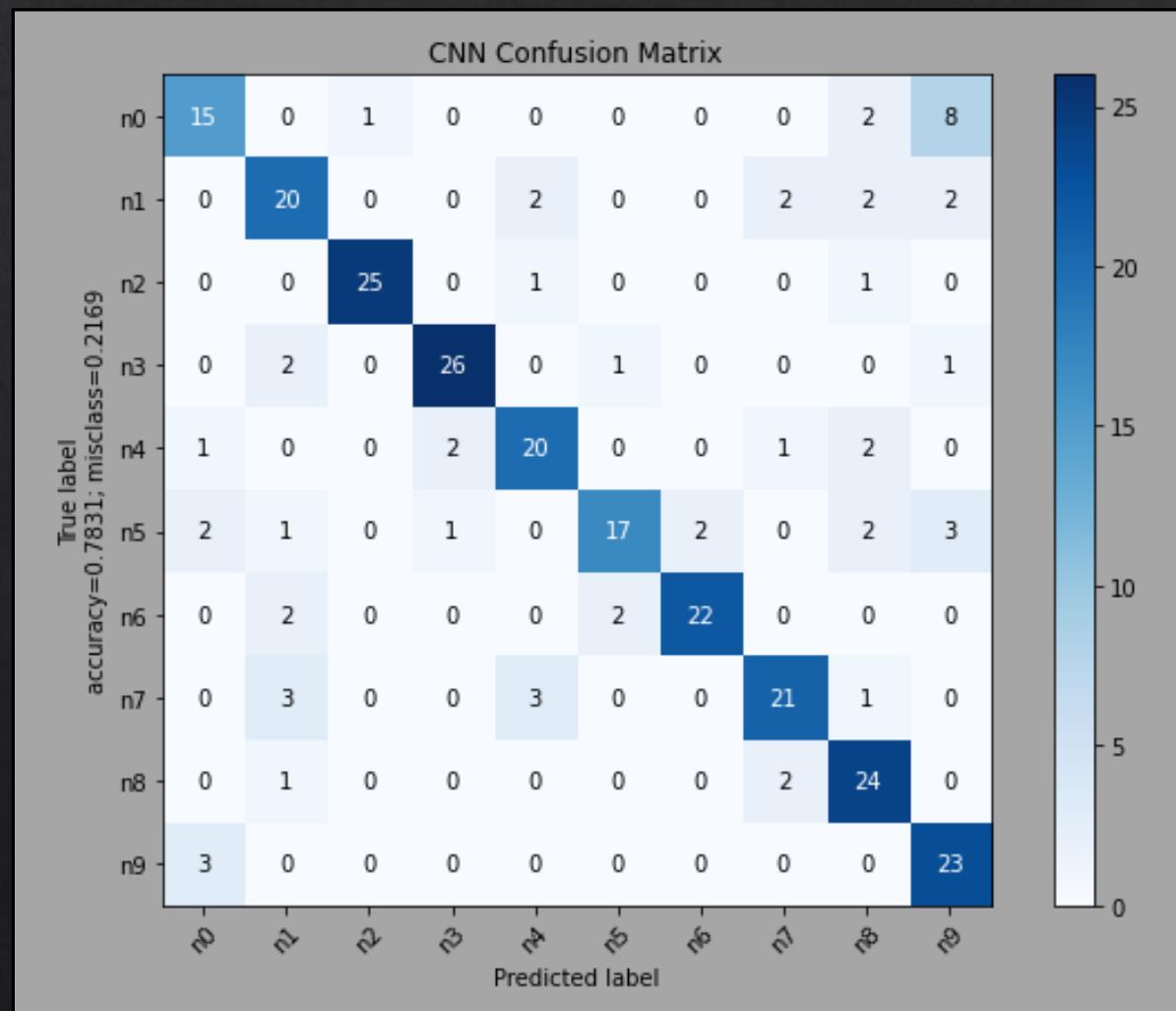
- ❖ Accuracy: 78.3%, Loss: 0.330



# First CNN Model Results

- ❖ Predicting class ‘n9’ for ‘n0’ 8 times
    - ❖ Low recall
  - ❖ Uneven performance overall

	precision	recall	f1-score	support
n0	0.71	0.58	0.64	26
n1	0.69	0.71	0.70	28
n2	0.96	0.93	0.94	27
n3	0.90	0.87	0.88	30
n4	0.77	0.77	0.77	26
n5	0.85	0.61	0.71	28
n6	0.92	0.85	0.88	26
n7	0.81	0.75	0.78	28
n8	0.71	0.89	0.79	27
n9	0.62	0.88	0.73	26
accuracy			0.78	272
macro avg	0.79	0.78	0.78	272
weighted avg	0.79	0.78	0.78	272



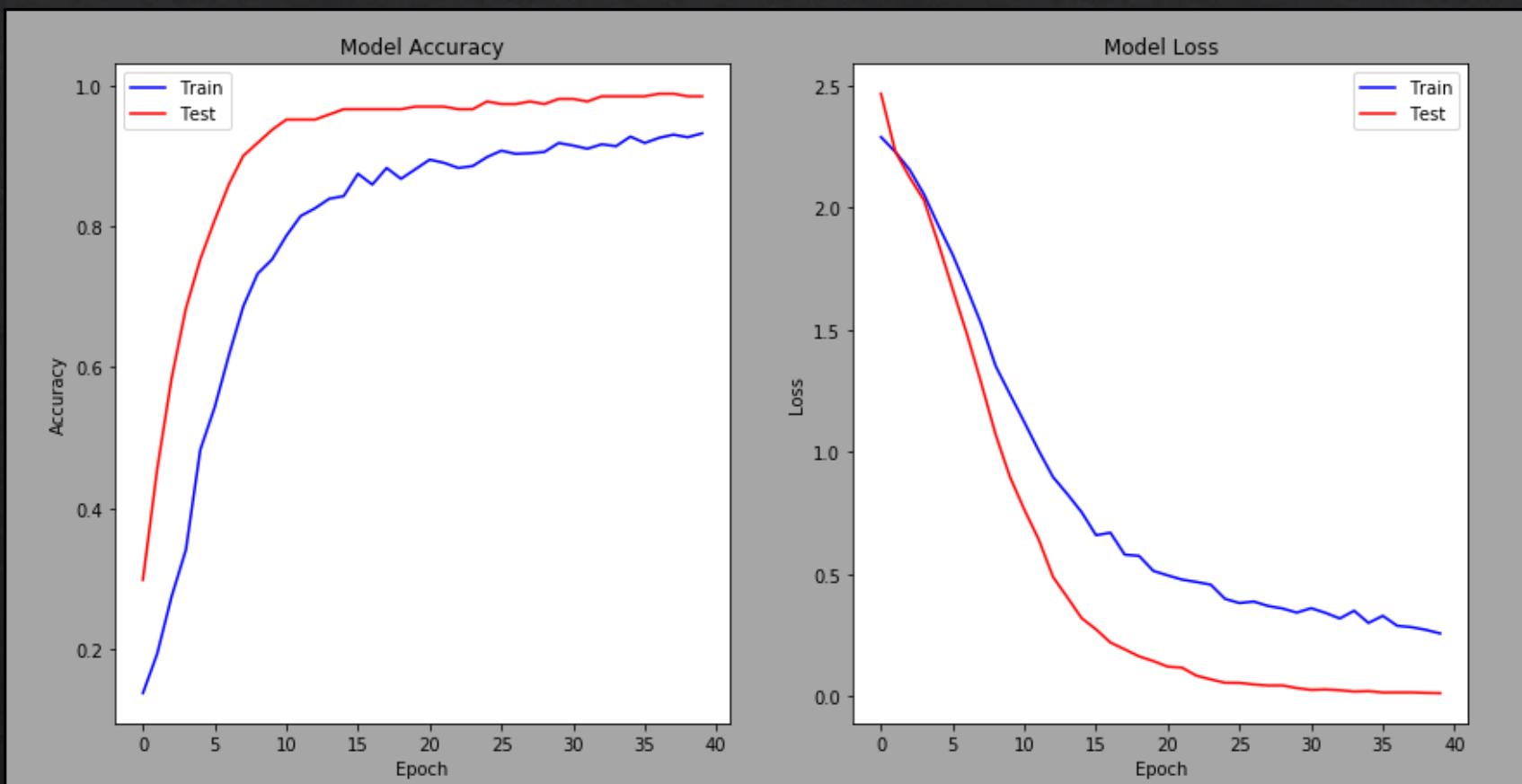
# Xception Model

- ❖ High-performer on ImageNet, comparatively low # parameters
- ❖ `applications.Xception(weights='imagenet', include_top=False)`
  - ❖ Keras Applications
  - ❖ Used pre-trained weights, did not include top layer
- ❖ ~20.9 million parameters
- ❖ ~600 sec/epoch, 40 epochs

```
# Compile
Xception_model.compile(loss='categorical_crossentropy',
                        optimizer=SGD(lr=.0001, momentum=0.9),
                        metrics=['accuracy'])
```

# Xception Model Results

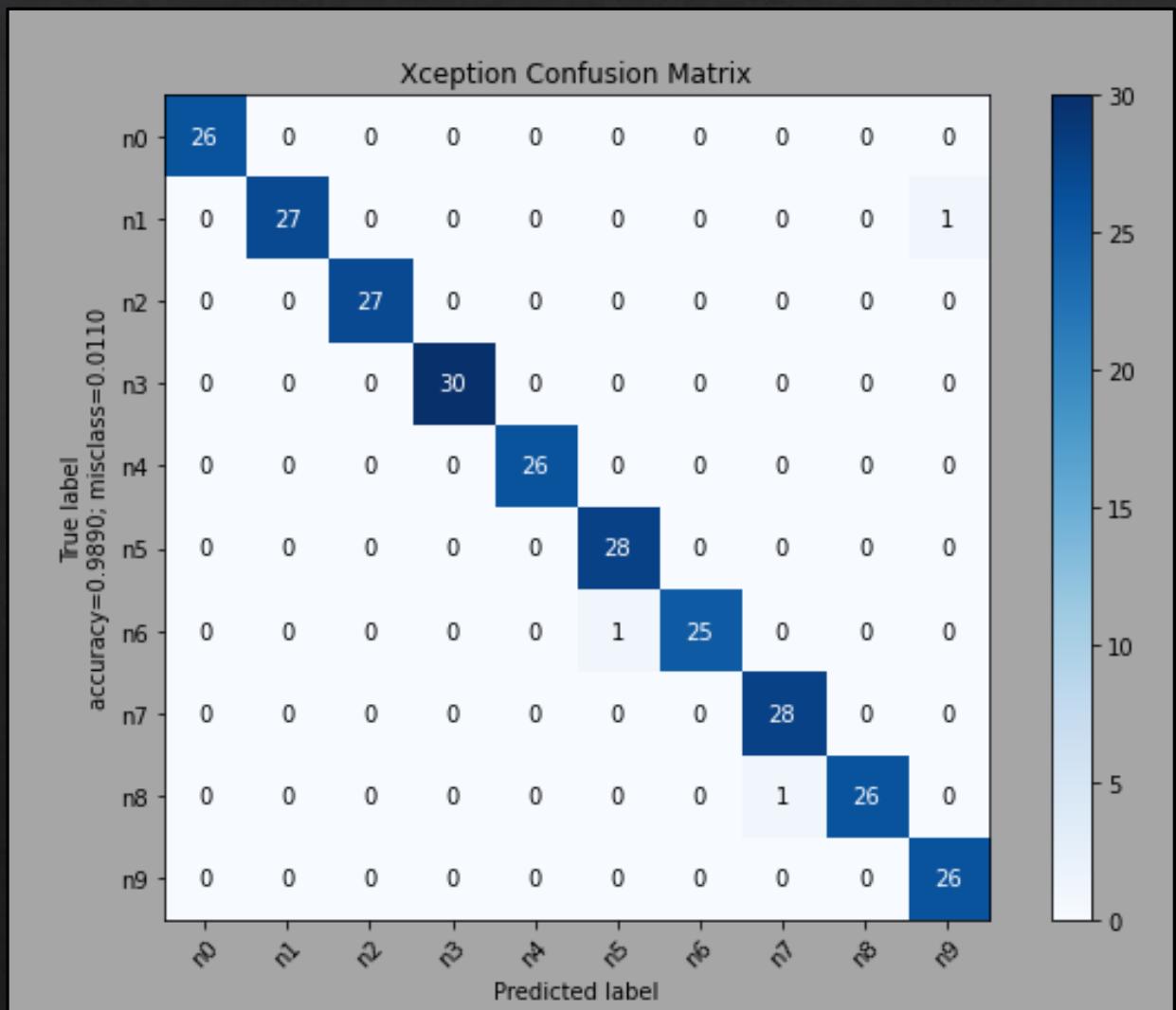
- ❖ Accuracy: 98.9%, Loss: 0.014



# Xception Model Results

- ❖ Only three mislabeled classes
  - ❖ Each error for a separate class
- ❖ Recall/precision consistent

	precision	recall	f1-score	support
n0	1.00	1.00	1.00	26
n1	1.00	0.96	0.98	28
n2	1.00	1.00	1.00	27
n3	1.00	1.00	1.00	30
n4	1.00	1.00	1.00	26
n5	0.97	1.00	0.98	28
n6	1.00	0.96	0.98	26
n7	0.97	1.00	0.98	28
n8	1.00	0.96	0.98	27
n9	0.96	1.00	0.98	26
accuracy			0.99	272
macro avg	0.99	0.99	0.99	272
weighted avg	0.99	0.99	0.99	272



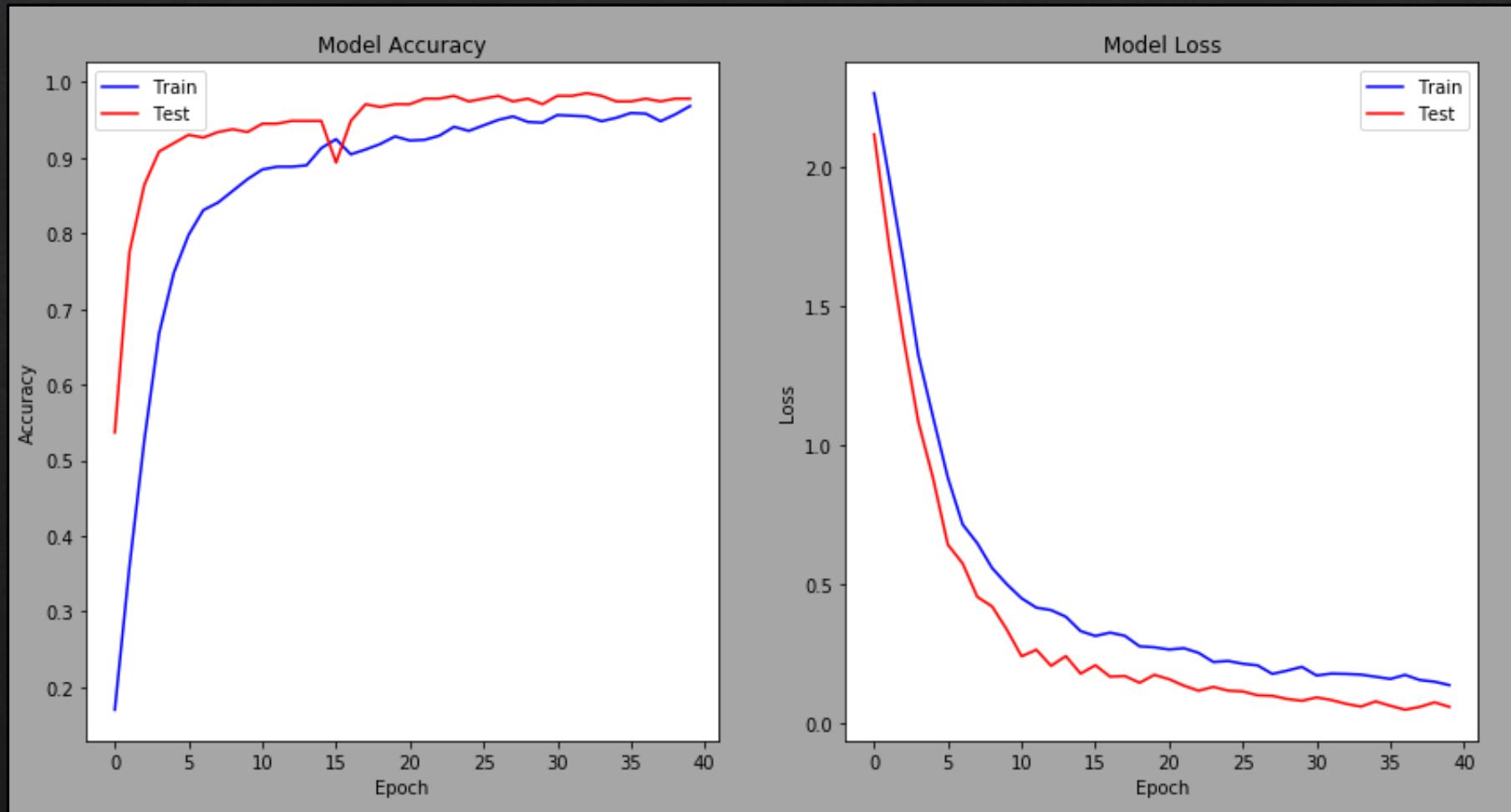
# InceptionResNetV2 Model

- ❖ Slightly higher performance on ImageNet than Xception, although with a greater number of parameters
- ❖ `applications.InceptionResNetV2(weights='imagenet', include_top=False)`
  - ❖ Keras Applications
  - ❖ Used pre-trained weights, did not include top layer
- ❖ ~54.4 million parameters
- ❖ ~1040 secs epoch, 40 epochs

```
# Compile
resNet_model.compile(loss='categorical_crossentropy',
                      optimizer=SGD(lr=.0001, momentum=0.9),
                      metrics=[ 'accuracy' ])
```

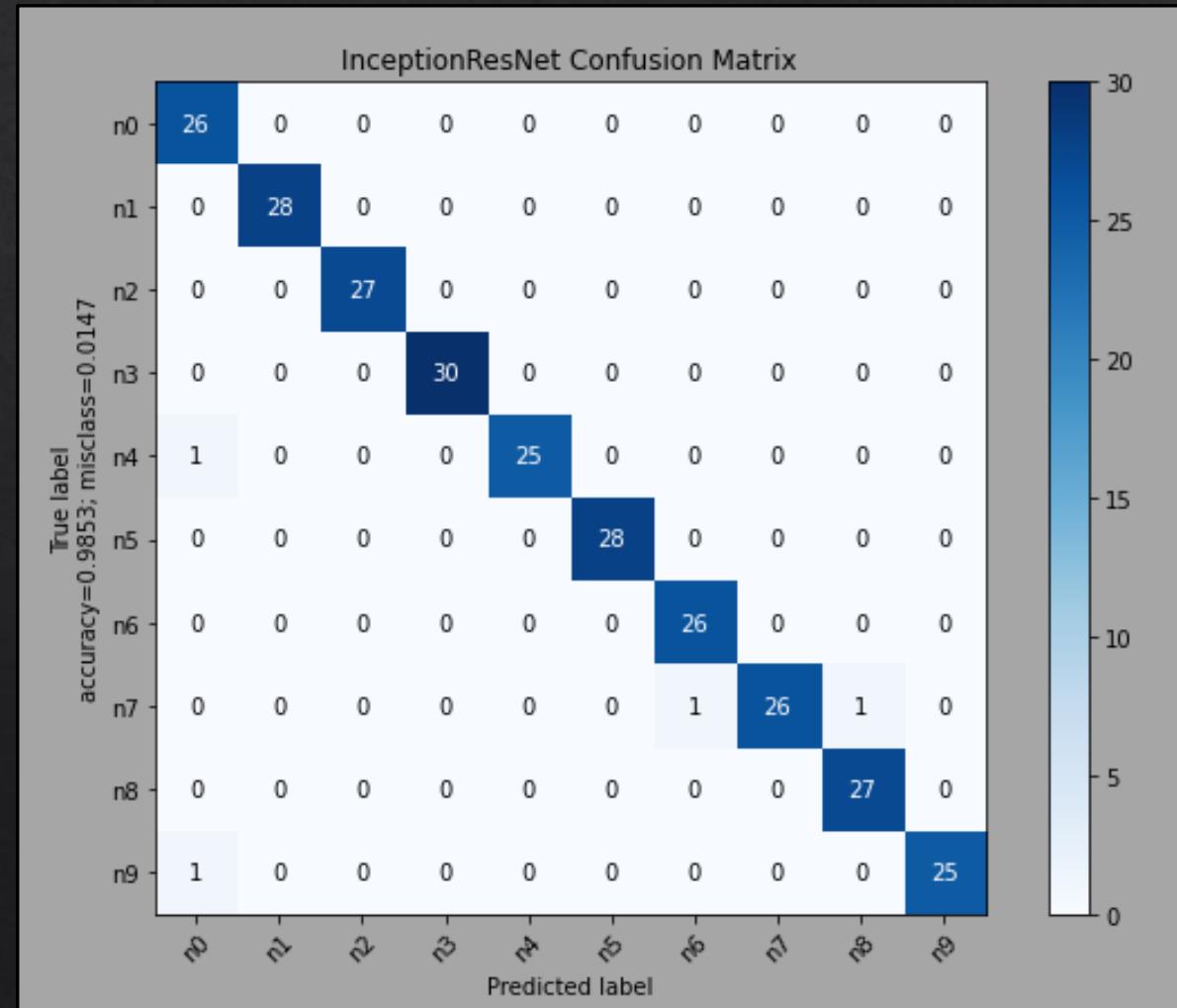
# InceptionResNetV2 Model Results

- ❖ Accuracy: 98.5%, Loss: 0.067



- ❖ Only four mislabeled classes
  - ❖ Precision and recall marginally less even across classes
  - ❖ Comparable to Xception results

	precision	recall	f1-score	support
n0	0.93	1.00	0.96	26
n1	1.00	1.00	1.00	28
n2	1.00	1.00	1.00	27
n3	1.00	1.00	1.00	30
n4	1.00	0.96	0.98	26
n5	1.00	1.00	1.00	28
n6	0.96	1.00	0.98	26
n7	1.00	0.93	0.96	28
n8	0.96	1.00	0.98	27
n9	1.00	0.96	0.98	26
accuracy			0.99	272
macro avg	0.99	0.99	0.98	272
weighted avg	0.99	0.99	0.99	272



# Conclusions

- ❖ Goal was accomplished:
  - ❖ Achieved two high performance CNN models for image classification of monkey species
  - ❖ Pre-trained models both achieved 99% accuracy
  - ❖ CNN model without pre-trained data (weights from ImageNet) yielded 78% accuracy on validation data
  - ❖ Time cost of using more complex models proved worthwhile on this dataset
  - ❖ Model could have use in ecological studies, estimating animal populations

# Further Work

- ❖ InceptionResNetV2 model had higher accuracy on training data than the Xception model (~97%, vs. ~93%)
- ❖ Examining which model performs better on another dataset of the same monkey species, and whether or not this difference has any significance
- ❖ Motion capture dataset, with actual field images



# QUESTIONS?

