

readme

Training The Model

Installing the dependencies

```
conda create -n cifar10
```

```
pip install tensorflow tensorflow-gpu opencv-python os matplotlib seaborn
```

```
jupyter notebook
```

The classes are:

Label	Description
0	airplane
1	automobile
2	bird
3	cat
4	deer
5	dog
6	frog
7	horse
8	ship
9	truck

Returns:

Tuple of NumPy arrays: `(x_train, y_train), (x_test, y_test)`.

x_train: uint8 NumPy array of grayscale image data with shapes `(50000, 32, 32, 3)`, containing the training data. Pixel values range from 0 to 255.

y_train: uint8 NumPy array of labels (integers in range 0-9) with shape `(50000, 1)` for the training data.

x_test: uint8 NumPy array of grayscale image data with shapes `(10000, 32, 32, 3)`, containing the test data. Pixel values range from 0 to 255.

y_test: uint8 NumPy array of labels (integers in range 0-9) with shape `(10000, 1)` for the test data.

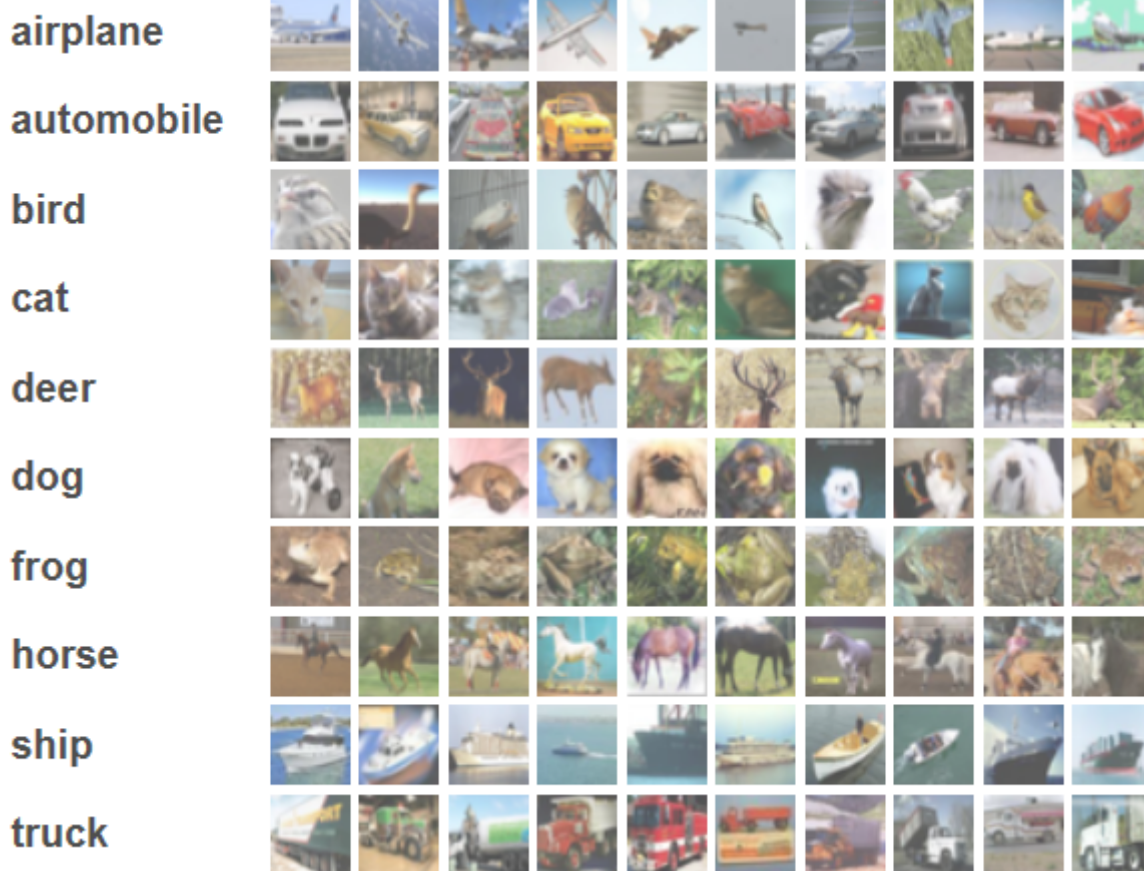
Cifar10 is a dataset of 50,000 32x32 color training images and 10,000 test images, labeled over 10 categories. See more info at the

[CIFAR homepage](#)

Turns out that the images are already splitted

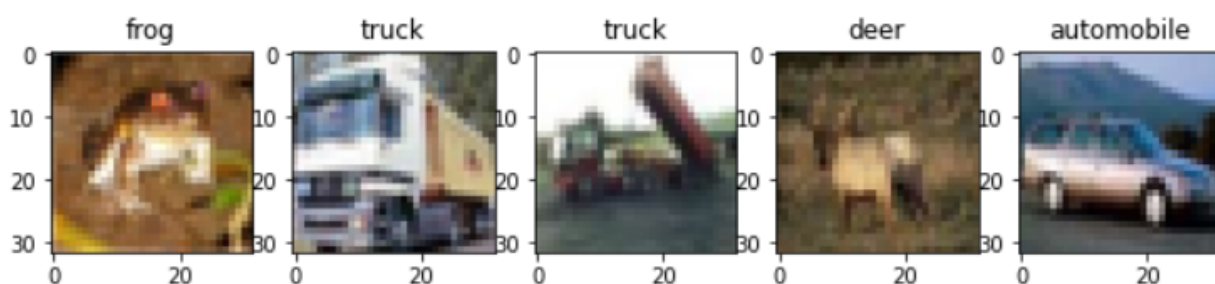
The classes of the datasets are

```
classes =  
["airplane", "automobile", "bird", "cat", "deer", "dog", "frog", "horse", "ship", "truck"]
```



Plotting the image

Image can be plotted with `matplotlib` library



The weird part is the image looks like Japanese video 🤔🤔🤔

Pre-processing the data

1. Normalizing The Image's Arra
2. Reshaping the y to fit into the model

Architecture

The most important part of the project is CNN Model

- The efficiency is tested with three different models

Model 0

- This is the first model which has
 1. Convolutional Layer with 16 filters of size (3,3)
 2. MaxPooling
 3. Convolution Layer with 32 filters of (3,3) size with stride = 1
 4. MaxPooling
 5. Flatten
 6. Fully Connected Layer with neurons =256
 7. Final Output Layer with sigmoid activation

```
In [9]: 1 model.summary()

Model: "sequential_8"
-----
Layer (type)                Output Shape                Param #
-----
conv2d_23 (Conv2D)          (None, 30, 30, 16)         448
max_pooling2d_21 (MaxPoolin (None, 15, 15, 16)         0
g2D)
conv2d_24 (Conv2D)          (None, 13, 13, 32)         4640
max_pooling2d_22 (MaxPoolin (None, 6, 6, 32)           0
g2D)
conv2d_25 (Conv2D)          (None, 4, 4, 64)           18496
max_pooling2d_23 (MaxPoolin (None, 2, 2, 64)           0
g2D)
flatten_7 (Flatten)         (None, 256)                 0
dense_17 (Dense)            (None, 256)                 65792
dense_18 (Dense)            (None, 10)                  2570
-----
Total params: 91,946
Trainable params: 91,946
Non-trainable params: 0
-----

model.add(Conv2D(16, (3,3), 1, activation='relu', input_shape=(32,32,3)))
```

•
$$\lfloor \frac{n - f + 2p}{s} + 1 \rfloor$$

- Here $n = 32, f = 3, p = 0, s = 1$

- $$\lfloor \frac{32 - 3}{1} + 1 \rfloor$$

- 30 is the width of the output layer of the first convolutional layer

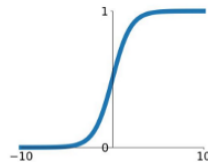
- `activation = 'relu'` is the rectified linear unit which

- $$f(x) = \max(0, x)$$

Activation Functions

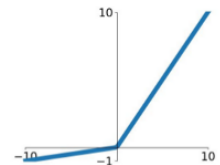
Sigmoid

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$



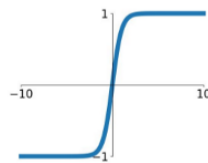
Leaky ReLU

$$\max(0.1x, x)$$



tanh

$$\tanh(x)$$

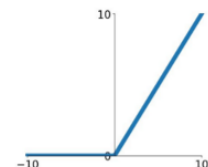


Maxout

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

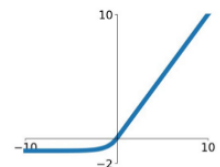
ReLU

$$\max(0, x)$$



ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



•

Parameters

- First parameter = $\$((333)+1)*16 = 448\$$

```
MaxPooling2D(
    pool_size=(2, 2),
    strides=None,
    padding='valid',
    data_format=None,
    **kwargs,
)
```

- For maxpooling

- $$\lfloor \frac{254}{2} \rfloor = 127$$

- There wont be parameter for the max pooling.

For second conv2D

```
model.add(Conv2D(32, (3, 3), 1, activation='relu'))
```

means that **32** 3*3 filters of RGB(3) channels have stride =1

- $$\lfloor \frac{n - f + 2p}{s} + 1 \rfloor$$

- Here $n = 127, f = 3, p = 0, s = 1$

- $$\lfloor \frac{127 - 3}{1} + 1 \rfloor$$

- 125 is the width and height of its output layer
- The channels would be 32
- Hence, the output shape = (None, 125, 125, 32)

Parameters

$$((f_H * f_W * n^{[C-1]} + 1) * n^{[C]})$$

$$((3 * 3 * 16) + 1) * 32 = 4640$$

For max pooling

- $$\lfloor \frac{125}{2} \rfloor = 62$$

For third conv2D

```
model.add(Conv2D(64, (3, 3), 1, activation='relu'))
```

means that **64** 3*3 filters of RGB(3) channels have stride = 1

- $$\lfloor \frac{n - f + 2p}{s} + 1 \rfloor$$

- Here $n = 62, f = 3, p = 0, s = 1$

- $$\lfloor \frac{62 - 3}{1} + 1 \rfloor$$

- 60 is the width and height of its output layer
- The channels would be 64
- Hence, the output shape = (None, 60, 60, 64)

Parameters

$$((f_H * f_W * n^{[C-1]} + 1) * n^{[C]})$$

$$((3 * 3 * 32) + 1) * 64 = 18496$$

```
dense_17
```

$$Parameters = 256 * 256 + 256 * 1 = 65792$$

```
dense_18
```

$$Parameters = 256 * 10 + 10 * 1 = 2570$$

```
model.compile('adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])
```

Adaptive Moment Estimation Algorithm optimizer is used with loss = sparse_categorical_crossentropy

$$\text{Loss} = -\frac{1}{\text{output size}} \sum_{i=1}^{\text{output size}} y_i \cdot \log \hat{y}_i + (1 - y_i) \cdot \log (1 - \hat{y}_i)$$

model 1 and model 2 have same architecture but they differ on the architecture only

Model 1

```
In [10]: 1 model1.summary()
```

Model: "sequential_11"

Layer (type)	Output Shape	Param #
conv2d_32 (Conv2D)	(None, 30, 30, 8)	224
max_pooling2d_30 (MaxPooling2D)	(None, 15, 15, 8)	0
conv2d_33 (Conv2D)	(None, 13, 13, 16)	1168
max_pooling2d_31 (MaxPooling2D)	(None, 6, 6, 16)	0
conv2d_34 (Conv2D)	(None, 4, 4, 32)	4640
max_pooling2d_32 (MaxPooling2D)	(None, 2, 2, 32)	0
flatten_10 (Flatten)	(None, 128)	0
dense_25 (Dense)	(None, 3000)	387000
dense_26 (Dense)	(None, 1000)	3001000
dense_27 (Dense)	(None, 10)	10010

```
=====
Total params: 3,404,042
Trainable params: 3,404,042
Non-trainable params: 0
=====
```

Model 2




Model: "sequential_12"

Layer (type)	Output Shape	Param #
conv2d_35 (Conv2D)	(None, 30, 30, 8)	224
max_pooling2d_33 (MaxPooling2D)	(None, 15, 15, 8)	0
conv2d_36 (Conv2D)	(None, 13, 13, 16)	1168
max_pooling2d_34 (MaxPooling2D)	(None, 6, 6, 16)	0
conv2d_37 (Conv2D)	(None, 4, 4, 32)	4640
max_pooling2d_35 (MaxPooling2D)	(None, 2, 2, 32)	0
flatten_11 (Flatten)	(None, 128)	0
dense_28 (Dense)	(None, 3000)	387000
dense_29 (Dense)	(None, 1000)	3001000
dense_30 (Dense)	(None, 10)	10010
Total params: 3,404,042		
Trainable params: 3,404,042		
Non-trainable params: 0		

```
model_name.add(MaxPooling2D())
model_name.add(Conv2D(16, (3,3),1,activation='relu'))
model_name.add(MaxPooling2D())
model_name.add(Conv2D(32, (3,3),1,activation='relu'))
model_name.add(MaxPooling2D())
model_name.add(Flatten())
model_name.add(Dense(3000,activation='relu'))
model_name.add(Dense(1000,activation='relu'))
model_name.add(Dense(10,activation='softmax'))
```

Model is saved and loaded to/from the disk

```
model.save(os.path.join('models', 'model.h5'))
model = load_model(os.path.join('models', 'model.h5'))**strong text**
```

 model.h5	1/29/2023 10:45 PM	H5 File	1,131 KB
 model1.h5	1/29/2023 10:45 PM	H5 File	39,952 KB
 model2.h5	1/29/2023 10:45 PM	H5 File	13,333 KB

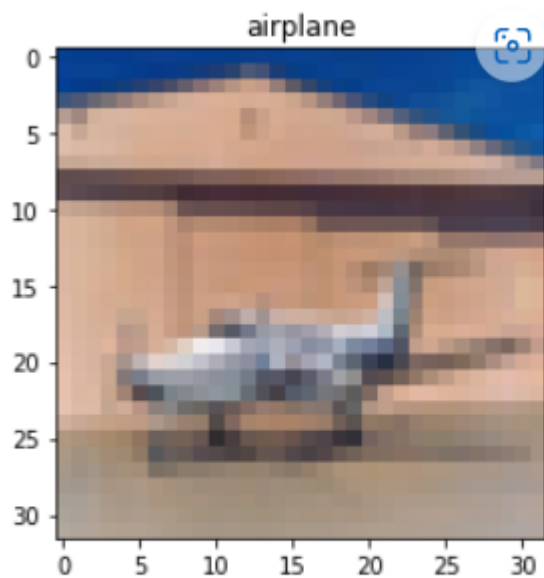
GitHub allows upto 100 MB files so the h5 files cant be included but please let me know if you need this

Testing the result 😊😊

Parameter	Model 0	Model 1	Model 2
Accuracy After 10th	0.7955	0.7925	0.5813
Loss After 10th epoch	0.5730	0.5719	1.1919
Parameters	91,946	3,404,042	3,404,042

Randomly testing with test-images

Actual image is airplane 742 index

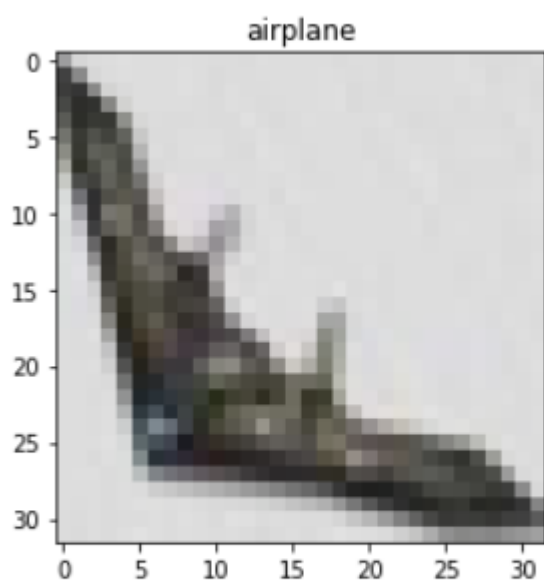


Model 0 predicted airplane

Model 1 predicted airplane

Model 2 predicted truck

Actual image is airplane 180 index



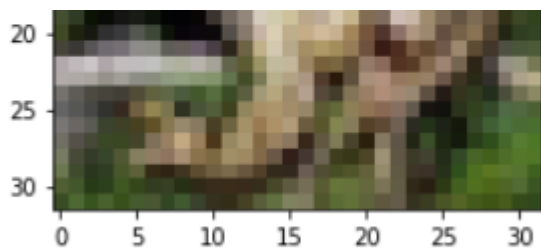
Model 0 predicted airplane

Model 1 predicted airplane

Model 2 predicted airplane

Actual image is frog 379 index



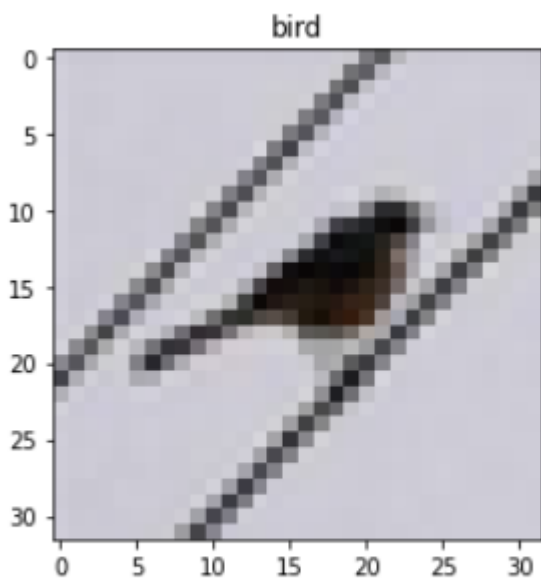


Model 0 predicted frog

Model 1 predicted frog

Model 2 predicted frog

Actual image is bird 731 index



Model 0 predicted airplane

Model 1 predicted bird

Model 2 predicted bird

Actual image is truck 609 index

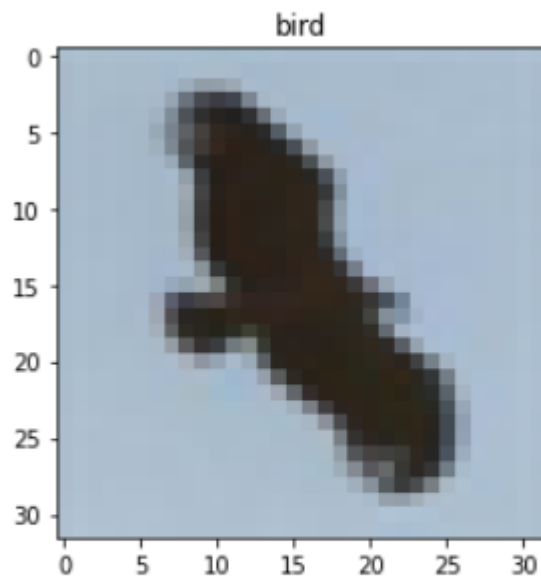


Model 0 predicted truck

Model 1 predicted truck

Model 2 predicted truck

Actual image is bird 160 index

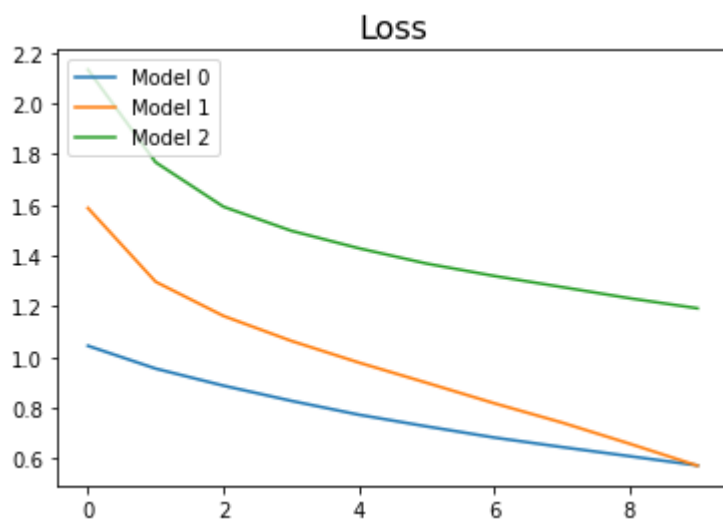


Model 0 predicted bird

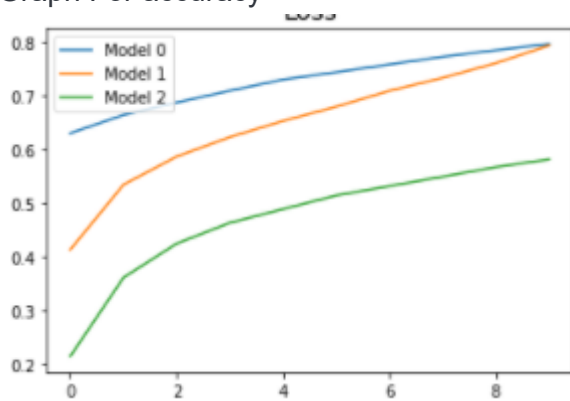
Model 1 predicted bird

Model 2 predicted airplane

Graph of accuracy and loss

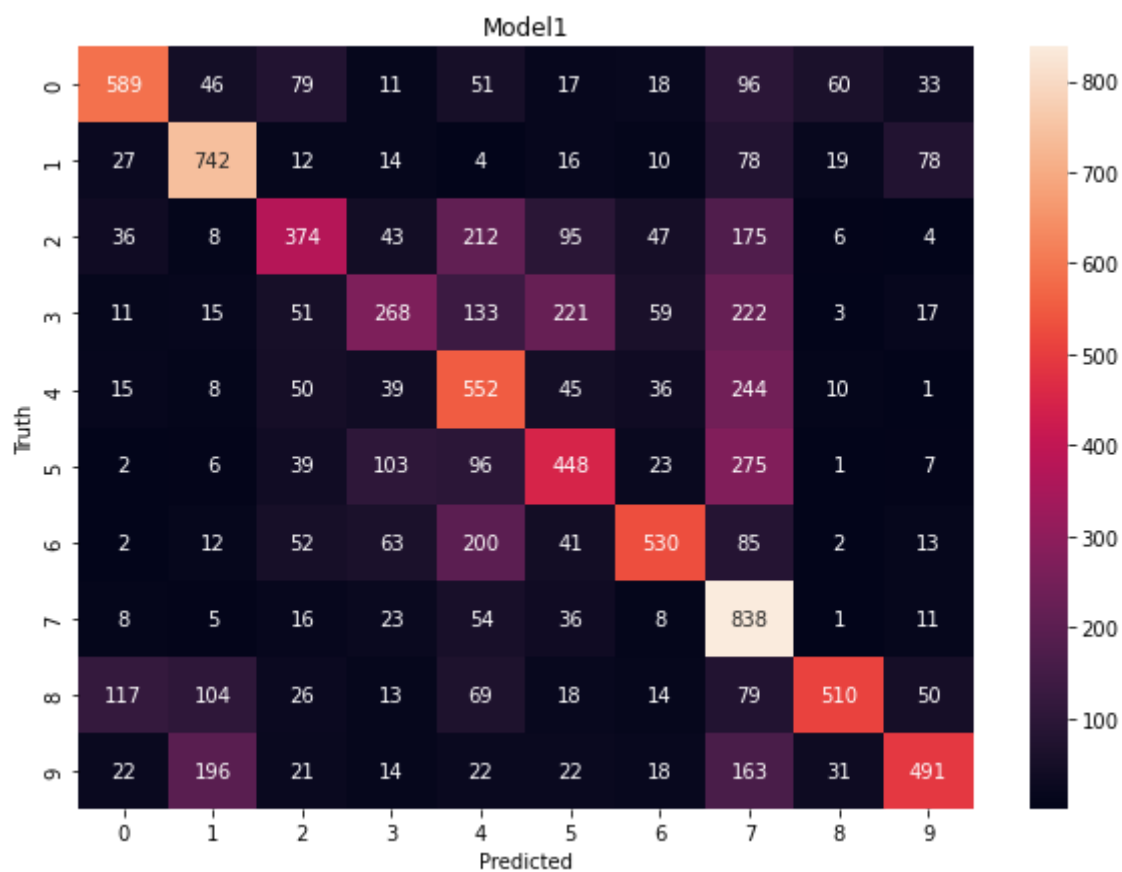
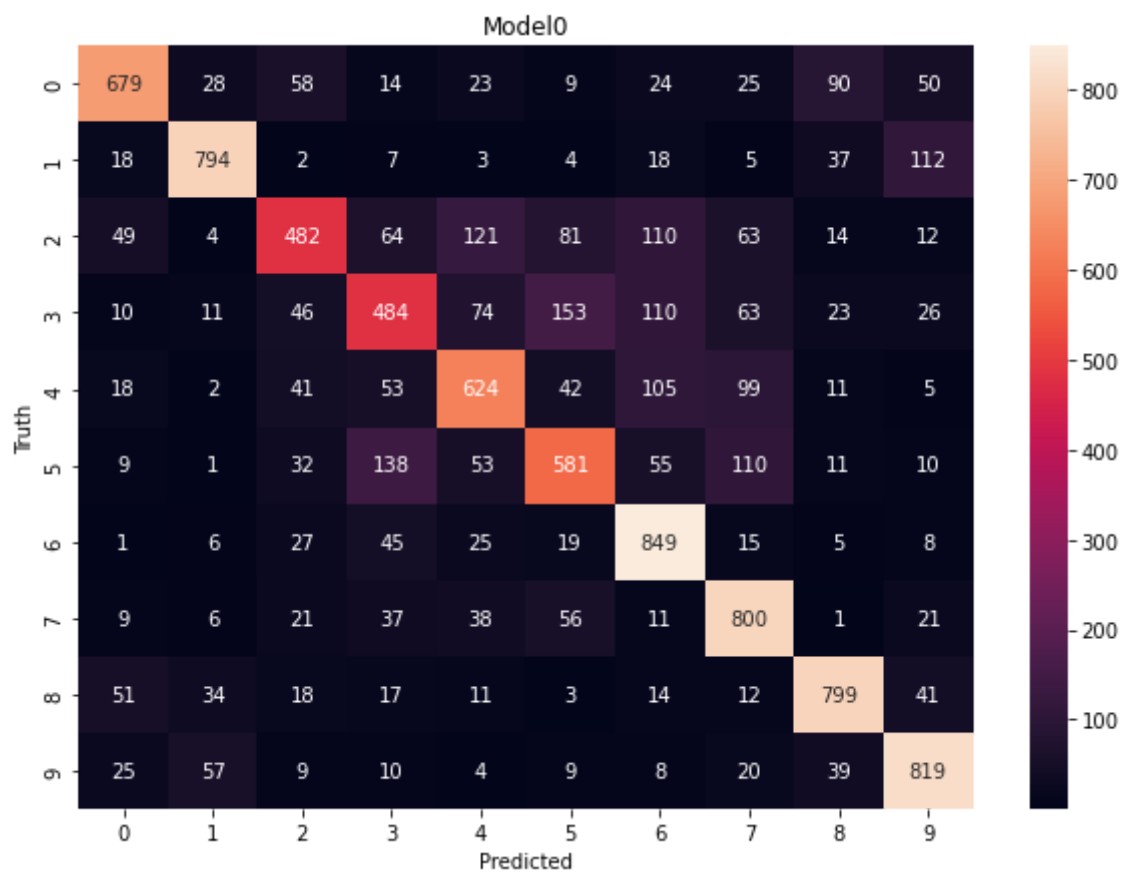


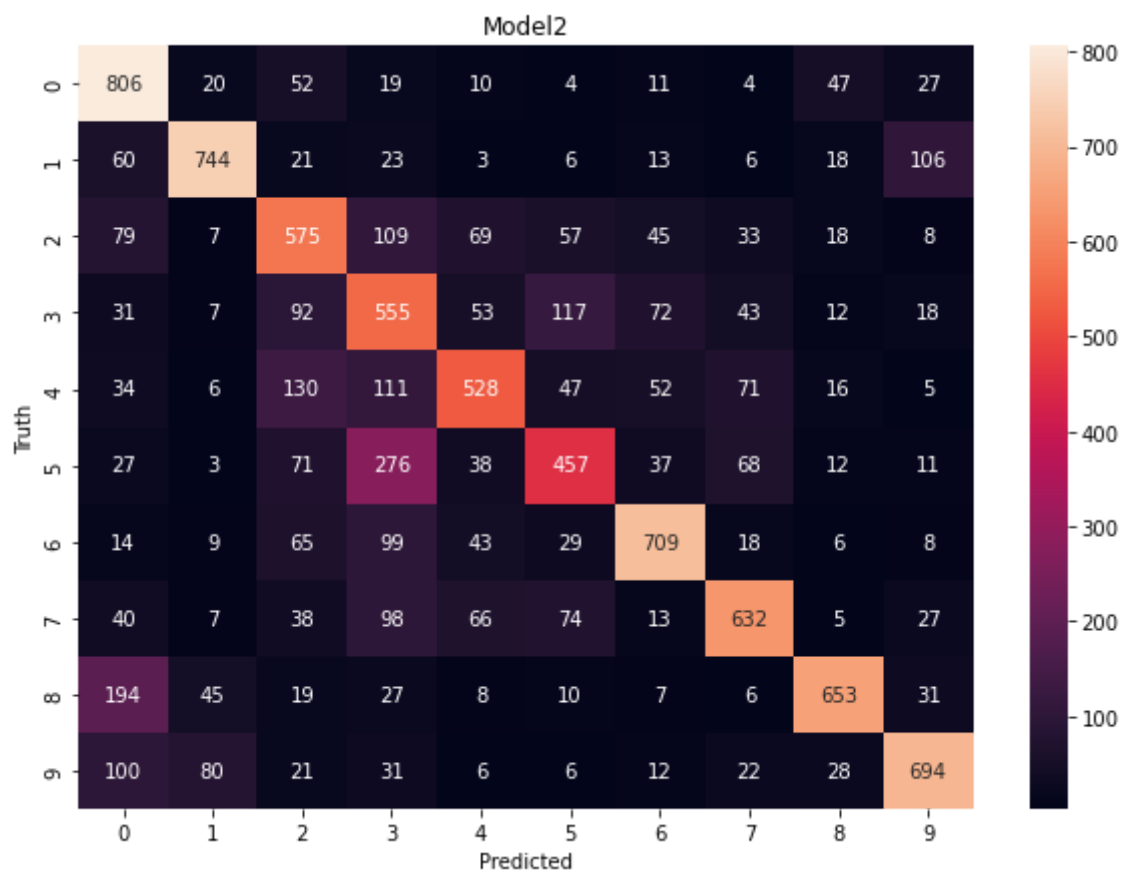
Graph For accuracy



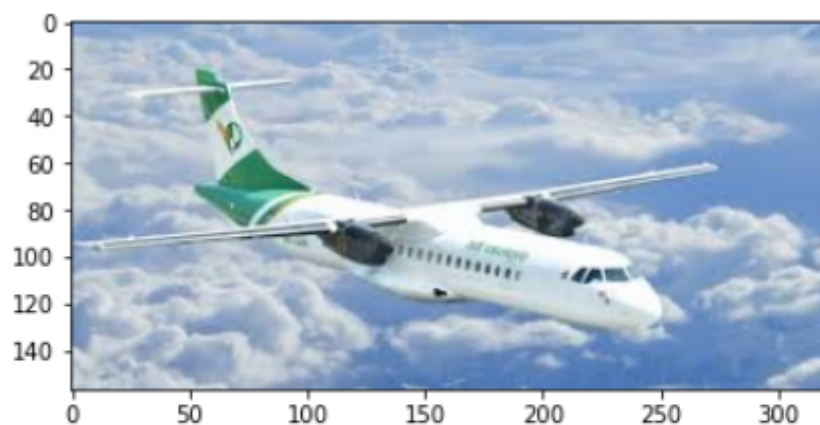
Model 0 seems to be appropriate one

Confusion Matrix

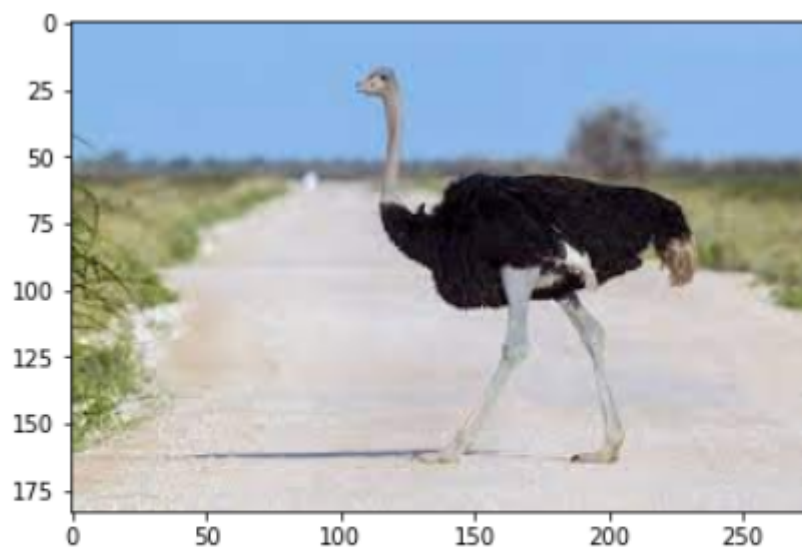




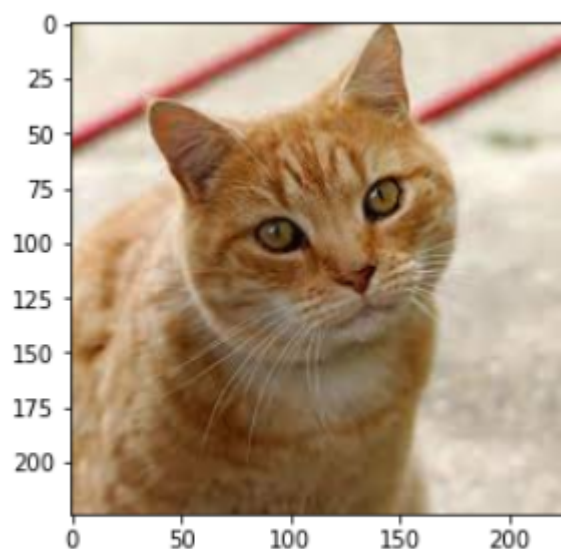
My favourite part is testing with new images typically



1/1 [=====] - 0s 24ms/step
airplane



1/1 [=====] - 0s 16ms/step
bird



1/1 [=====] - 0s 16ms/step
cat

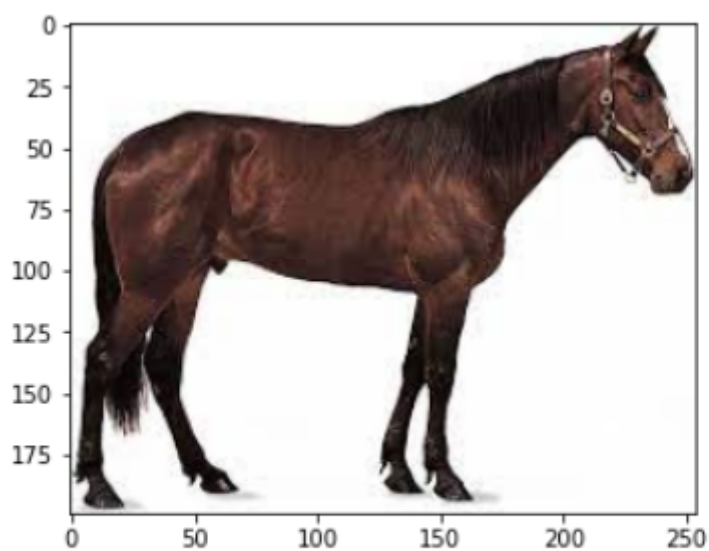




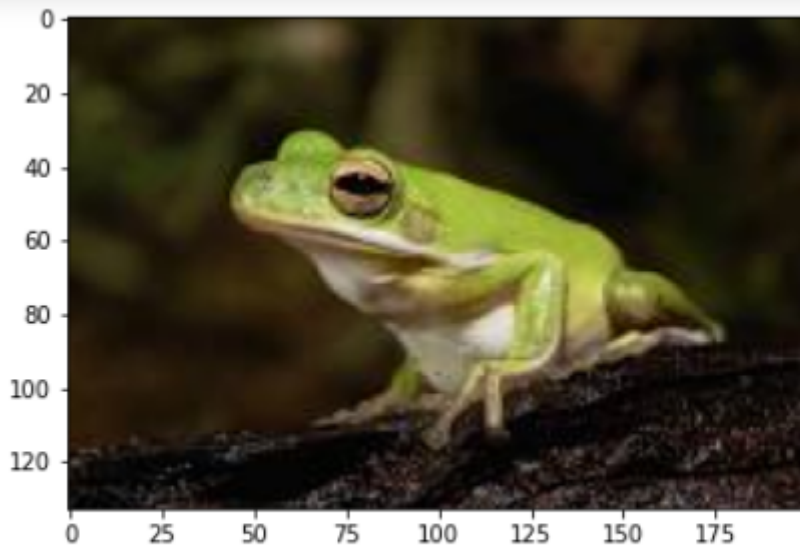
1/1 [=====] - 0s 16ms/step
airplane



1/1 [=====] - 0s 16ms/step
truck



1/1 [=====] - 0s 16ms/step
horse



1/1 [=====] - 0s 16ms/step
frog



1/1 [=====] - 0s 27ms/step
horse

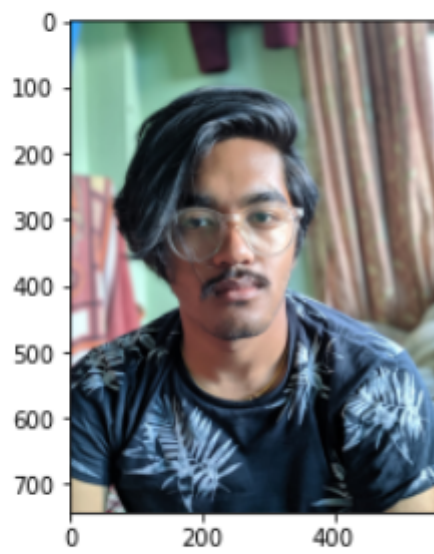
The model does have error

Fun Thing I did was even though there is not class for a human I wanted to know how it will classify my image



In [9]:

```
1  
2 image_test('images/10.jpg')
```



```
1/1 [=====] - 0s 16ms/step  
truck
```

TURNS OUT I'M A TRUCK 🚚 🚚