```
! # ls Datasets/scrapped/All
from google.colab import drive
drive.mount('/content/drive')
Mounted at /content/drive
!ls "/content/drive/My Drive/Training Dataset"
Fire NoFire
import os
import cv2
import numpy as np
from tgdm import tgdm
DATADIR = '/content/drive/My Drive/Training Dataset'
CATEGORIES = ['Fire', 'NoFire']
IMG SIZE = 64
def create training data():
    training data = []
    for category in CATEGORIES:
        path = os.path.join(DATADIR,category)
        class num = CATEGORIES.index(category) # get the
classification (0 or a 1). 0=C 1=0
        for img in tqdm(os.listdir(path)): # iterate over each image
                img array = cv2.imread(os.path.join(path,img)) #
convert to array
                new_array = cv2.resize(img_array, (IMG_SIZE,
IMG SIZE)) # resize to normalize data size
                training_data.append([new_array, class num]) # add
this to our training data
            except Exception as e: # in the interest in keeping the
output clean...
                pass
    return training data
training data = create training data()
               | 1124/1124 [00:45<00:00, 24.72it/s]
100%|
100%||
               | 1301/1301 [00:51<00:00, 25.49it/s]
import random
print(len(training data))
random.shuffle(training_data)
```

```
for sample in training data[:10]:
    print(sample[1])
2423
1
0
0
1
1
1
1
1
1
1
X = []
Y = []
for features, label in training data:
    X.append(features)
    Y.append(label)
X = np.array(X).reshape(-1, IMG_SIZE, IMG_SIZE, 3)
X = X/255.0
X.shape[1:]
Y = np.array(Y)
# # set up image augmentation
# from keras.preprocessing.image import ImageDataGenerator
# datagen = ImageDataGenerator(
      rotation range=15,
      horizontal flip=True,
      width_shift_range=0.1,
#
      height shift range=0.1
#
      #zoom range=0.3
# datagen.fit(X)
import tensorflow as tf
from tensorflow.keras.datasets import cifar10
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Activation,
Flatten
from tensorflow.keras.layers import Conv2D, AveragePooling2D
model = Sequential()
```

```
model.add(Conv2D(filters=16, kernel size=(3, 3), activation='relu',
input shape=X.shape[1:]))
model.add(AveragePooling2D())
model.add(Dropout(0.5))
model.add(Conv2D(filters=32, kernel size=(3, 3), activation='relu'))
model.add(AveragePooling2D())
model.add(Dropout(0.5))
model.add(Conv2D(filters=64, kernel size=(3, 3), activation='relu'))
model.add(AveragePooling2D())
model.add(Dropout(0.5))
model.add(Flatten())
model.add(Dense(units=256, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(units=128, activation='relu'))
model.add(Dense(units=2, activation = 'softmax'))
model.compile(loss='sparse categorical crossentropy',
           optimizer='adam',
          metrics=['accuracy'])
history = model.fit(X, Y, batch size=32,
epochs=100, validation split=0.3)
# model.fit generator(datagen.flow(X, Y, batch size=32),
                 epochs=100,
#
                 verbose=1)
Epoch 1/100
accuracy: 0.6745 - val loss: 0.5569 - val accuracy: 0.7276
Epoch 2/100
53/53 [============== ] - 5s 93ms/step - loss: 0.5263 -
accuracy: 0.7500 - val loss: 0.4774 - val accuracy: 0.7730
Epoch 3/100
accuracy: 0.7801 - val loss: 0.5205 - val accuracy: 0.7469
Epoch 4/100
accuracy: 0.7930 - val loss: 0.4921 - val_accuracy: 0.7620
Epoch 5/100
accuracy: 0.8113 - val loss: 0.4527 - val_accuracy: 0.7758
Epoch 6/100
```

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accuracy: 0.8237 - val loss: 0.4093 - val accuracy: 0.8033
Epoch 7/100
53/53 [============= ] - 3s 63ms/step - loss: 0.4153 -
accuracy: 0.8184 - val loss: 0.4842 - val accuracy: 0.7524
Epoch 8/100
53/53 [============== ] - 3s 63ms/step - loss: 0.4092 -
accuracy: 0.8137 - val loss: 0.3926 - val accuracy: 0.8171
Epoch 9/100
accuracy: 0.8432 - val loss: 0.3961 - val accuracy: 0.8061
Epoch 10/100
accuracy: 0.8520 - val loss: 0.3592 - val accuracy: 0.8514
Epoch 11/100
accuracy: 0.8567 - val loss: 0.3303 - val accuracy: 0.8514
Epoch 12/100
accuracy: 0.8738 - val loss: 0.3000 - val accuracy: 0.8721
Epoch 13/100
accuracy: 0.8550 - val loss: 0.3006 - val accuracy: 0.8652
Epoch 14/100
accuracy: 0.8791 - val loss: 0.2990 - val accuracy: 0.8638
Epoch 15/100
accuracy: 0.8945 - val loss: 0.2633 - val accuracy: 0.8996
Epoch 16/100
accuracy: 0.9027 - val_loss: 0.3124 - val_accuracy: 0.8721
Epoch 17/100
accuracy: 0.8998 - val loss: 0.2643 - val accuracy: 0.8858
Epoch 18/100
accuracy: 0.8974 - val loss: 0.2785 - val accuracy: 0.8872
Epoch 19/100
accuracy: 0.9163 - val loss: 0.2619 - val accuracy: 0.8913
Epoch 20/100
- accuracy: 0.9092 - val_loss: 0.2212 - val_accuracy: 0.9037
Epoch 21/100
accuracy: 0.9228 - val_loss: 0.2172 - val_accuracy: 0.9216
Epoch 22/100
accuracy: 0.9328 - val loss: 0.2363 - val accuracy: 0.9120
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Epoch 23/100
accuracy: 0.9334 - val loss: 0.2162 - val accuracy: 0.9216
Epoch 24/100
accuracy: 0.9292 - val loss: 0.2106 - val accuracy: 0.9216
Epoch 25/100
accuracy: 0.9387 - val loss: 0.2440 - val accuracy: 0.9051
Epoch 26/100
accuracy: 0.9399 - val loss: 0.2279 - val accuracy: 0.9188
Epoch 27/100
accuracy: 0.9440 - val loss: 0.2385 - val accuracy: 0.9188
Epoch 28/100
accuracy: 0.9428 - val loss: 0.2255 - val accuracy: 0.9367
Epoch 29/100
accuracy: 0.9322 - val loss: 0.2552 - val accuracy: 0.9051
Epoch 30/100
accuracy: 0.9475 - val loss: 0.2171 - val accuracy: 0.9285
Epoch 31/100
accuracy: 0.9499 - val_loss: 0.2159 - val_accuracy: 0.9257
Epoch 32/100
accuracy: 0.9640 - val loss: 0.2510 - val accuracy: 0.9257
Epoch 33/100
accuracy: 0.9587 - val loss: 0.2576 - val accuracy: 0.9161
Epoch 34/100
accuracy: 0.9581 - val loss: 0.2632 - val accuracy: 0.9298
Epoch 35/100
53/53 [============== ] - 4s 74ms/step - loss: 0.1023 -
accuracy: 0.9676 - val loss: 0.2452 - val accuracy: 0.9175
Epoch 36/100
accuracy: 0.9682 - val loss: 0.2433 - val accuracy: 0.9312
Epoch 37/100
accuracy: 0.9676 - val loss: 0.2400 - val accuracy: 0.9381
Epoch 38/100
accuracy: 0.9599 - val loss: 0.2557 - val accuracy: 0.9092
Epoch 39/100
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accuracy: 0.9658 - val loss: 0.2123 - val accuracy: 0.9422
Epoch 40/100
accuracy: 0.9788 - val loss: 0.2252 - val accuracy: 0.9367
Epoch 41/100
accuracy: 0.9717 - val loss: 0.2851 - val accuracy: 0.9188
Epoch 42/100
accuracy: 0.9705 - val loss: 0.2303 - val accuracy: 0.9312
Epoch 43/100
53/53 [============== ] - 5s 88ms/step - loss: 0.0832 -
accuracy: 0.9670 - val loss: 0.2414 - val accuracy: 0.9381
Epoch 44/100
accuracy: 0.9735 - val loss: 0.2414 - val accuracy: 0.9271
Epoch 45/100
accuracy: 0.9723 - val loss: 0.2193 - val accuracy: 0.9257
Epoch 46/100
accuracy: 0.9794 - val_loss: 0.2870 - val_accuracy: 0.9285
Epoch 47/100
accuracy: 0.9841 - val loss: 0.2724 - val accuracy: 0.9312
Epoch 48/100
accuracy: 0.9699 - val loss: 0.2204 - val accuracy: 0.9367
Epoch 49/100
accuracy: 0.9794 - val loss: 0.2331 - val accuracy: 0.9354
Epoch 50/100
accuracy: 0.9758 - val loss: 0.2270 - val accuracy: 0.9354
Epoch 51/100
accuracy: 0.9841 - val loss: 0.2621 - val accuracy: 0.9326
Epoch 52/100
accuracy: 0.9858 - val loss: 0.3039 - val accuracy: 0.9340
Epoch 53/100
53/53 [============== ] - 3s 64ms/step - loss: 0.0550 -
accuracy: 0.9811 - val loss: 0.2597 - val accuracy: 0.9381
Epoch 54/100
accuracy: 0.9811 - val loss: 0.2627 - val accuracy: 0.9422
Epoch 55/100
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accuracy: 0.9741 - val loss: 0.2836 - val accuracy: 0.9312
Epoch 56/100
accuracy: 0.9829 - val loss: 0.2414 - val accuracy: 0.9395
Epoch 57/100
accuracy: 0.9764 - val loss: 0.2526 - val accuracy: 0.9354
Epoch 58/100
accuracy: 0.9823 - val loss: 0.2414 - val accuracy: 0.9340
Epoch 59/100
accuracy: 0.9764 - val loss: 0.2476 - val accuracy: 0.9395
Epoch 60/100
accuracy: 0.9841 - val loss: 0.2638 - val accuracy: 0.9312
Epoch 61/100
accuracy: 0.9876 - val loss: 0.2621 - val accuracy: 0.9464
Epoch 62/100
accuracy: 0.9894 - val loss: 0.2823 - val accuracy: 0.9381
Epoch 63/100
accuracy: 0.9711 - val loss: 0.3099 - val accuracy: 0.9092
Epoch 64/100
accuracy: 0.9782 - val loss: 0.2430 - val accuracy: 0.9409
Epoch 65/100
accuracy: 0.9888 - val loss: 0.3146 - val_accuracy: 0.9271
Epoch 66/100
- accuracy: 0.9894 - val loss: 0.2818 - val accuracy: 0.9298
Epoch 67/100
accuracy: 0.9776 - val loss: 0.2336 - val accuracy: 0.9395
Epoch 68/100
accuracy: 0.9811 - val loss: 0.2474 - val accuracy: 0.9326
Epoch 69/100
accuracy: 0.9870 - val loss: 0.2842 - val accuracy: 0.9340
Epoch 70/100
accuracy: 0.9935 - val_loss: 0.2884 - val_accuracy: 0.9243
Epoch 71/100
accuracy: 0.9900 - val loss: 0.2835 - val accuracy: 0.9409
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Epoch 72/100
accuracy: 0.9929 - val loss: 0.2844 - val accuracy: 0.9436
Epoch 73/100
accuracy: 0.9917 - val loss: 0.3423 - val accuracy: 0.9312
Epoch 74/100
53/53 [============= ] - 5s 105ms/step - loss: 0.0339
- accuracy: 0.9917 - val loss: 0.2765 - val accuracy: 0.9257
Epoch 75/100
accuracy: 0.9805 - val loss: 0.2673 - val accuracy: 0.9326
Epoch 76/100
accuracy: 0.9876 - val loss: 0.2602 - val accuracy: 0.9243
Epoch 77/100
accuracy: 0.9858 - val loss: 0.2750 - val accuracy: 0.9436
Epoch 78/100
accuracy: 0.9847 - val loss: 0.2459 - val accuracy: 0.9312
Epoch 79/100
accuracy: 0.9882 - val loss: 0.2938 - val accuracy: 0.9312
Epoch 80/100
accuracy: 0.9888 - val loss: 0.3093 - val accuracy: 0.9340
Epoch 81/100
accuracy: 0.9894 - val loss: 0.3359 - val accuracy: 0.9216
Epoch 82/100
accuracy: 0.9870 - val loss: 0.2877 - val accuracy: 0.9381
Epoch 83/100
accuracy: 0.9864 - val loss: 0.2839 - val accuracy: 0.9395
Epoch 84/100
53/53 [============= ] - 3s 64ms/step - loss: 0.0175 -
accuracy: 0.9941 - val loss: 0.4221 - val accuracy: 0.9354
Epoch 85/100
accuracy: 0.9870 - val loss: 0.2818 - val accuracy: 0.9326
Epoch 86/100
accuracy: 0.9935 - val loss: 0.3306 - val accuracy: 0.9395
Epoch 87/100
accuracy: 0.9953 - val loss: 0.3130 - val accuracy: 0.9381
Epoch 88/100
```

```
accuracy: 0.9870 - val loss: 0.3054 - val accuracy: 0.9326
Epoch 89/100
accuracy: 0.9858 - val loss: 0.3173 - val accuracy: 0.9409
Epoch 90/100
accuracy: 0.9805 - val loss: 0.2885 - val accuracy: 0.9285
Epoch 91/100
accuracy: 0.9741 - val loss: 0.2638 - val accuracy: 0.9326
Epoch 92/100
accuracy: 0.9965 - val loss: 0.3029 - val accuracy: 0.9312
Epoch 93/100
accuracy: 0.9923 - val loss: 0.2999 - val accuracy: 0.9340
Epoch 94/100
53/53 [============== ] - 4s 67ms/step - loss: 0.0288 -
accuracy: 0.9917 - val loss: 0.3103 - val accuracy: 0.9326
Epoch 95/100
accuracy: 0.9941 - val_loss: 0.3299 - val_accuracy: 0.9340
Epoch 96/100
accuracy: 0.9912 - val loss: 0.3725 - val accuracy: 0.9285
Epoch 97/100
accuracy: 0.9882 - val loss: 0.2543 - val accuracy: 0.9298
Epoch 98/100
accuracy: 0.9882 - val loss: 0.2769 - val accuracy: 0.9422
Epoch 99/100
accuracy: 0.9929 - val loss: 0.3085 - val accuracy: 0.9367
Epoch 100/100
accuracy: 0.9971 - val loss: 0.2737 - val accuracy: 0.9409
model.save('TrainedModels/Fire-64x64-color-v7.1-soft.h5')
/usr/local/lib/python3.10/dist-packages/keras/src/engine/
training.py:3079: UserWarning: You are saving your model as an HDF5
file via `model.save()`. This file format is considered legacy. We
recommend using instead the native Keras format, e.g.
`model.save('my model.keras')`.
 saving api.save model(
from matplotlib import pyplot as plt
plt.plot(history.history['accuracy']) # since tensorflow 2.x version,
```

```
acc -> accuracy
plt.plot(history.history['val_accuracy']) # val_acc -> val_accuracy
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper left')
plt.show()
```

## model accuracy 1.00 train validation 0.95 0.90 accuracy 0.85 0.80 0.75 0.70 0 20 40 80 60 100 epoch

```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper left')
plt.show()
```

