# FOREST FIRE CLASSIFICATION

## **Importing Libraries**

```
import os, random
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
from keras.api.models import Sequential
from tensorflow.keras.layers import Input, Convolution2D, MaxPooling2D, Flatten, De
```

# **Importing Dataset**

```
In [2]: # Get list of file names
_, _, forest_fire_images = next(os.walk('data/train/fire'))
_, _, forest_non_fire_images = next(os.walk('data/train/non_fire'))
```

# **List of 9 Best Forest Fire Random Images**

## Plotting the images

```
In [4]: # List of image file names
    random_image_files = random.sample(forest_fire_images, 9)
    image_files = best9_random_fire_imgs
    # Create a figure and get the axes objects
    fig = plt.figure(figsize=(10, 10))
    axes = [fig.add_subplot(3, 3, i+1) for i in range(9)]

# Loop through the images and display them
    for i, ax in enumerate(axes):
        if i < len(image_files):
            img = mpimg.imread('data/train/fire/'+image_files[i])
            ax.imshow(img)
            ax.axis('off')
    else:
        ax.set_visible(False)</pre>
```

```
plt.suptitle('9 Random Forest Fire Images', fontsize=14, fontweight='bold')
plt.tight_layout()
plt.show()
```

#### 9 Random Forest Fire Images

















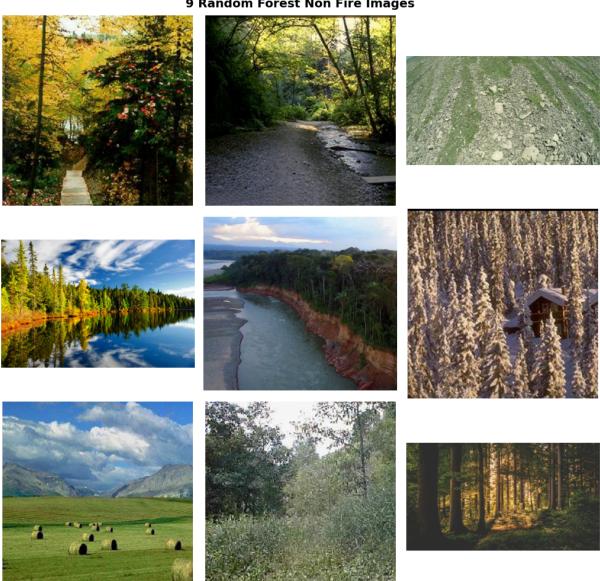


# 9 Best Forest Non-Fire Random Images

# Plotting the images

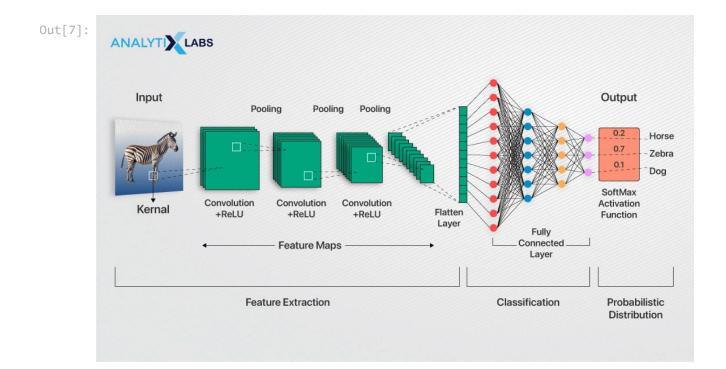
```
In [6]: # List of image file names
        random_image_files = random.sample(forest_non_fire_images, 9)
        image_files = best9_random_non_fire_imgs
        # image_files = best9_random_fire_imgs
        # Create a figure and get the axes objects
        fig = plt.figure(figsize=(10, 10))
        axes = [fig.add_subplot(3, 3, i+1) for i in range(9)]
        # Loop through the images and display them
        for i, ax in enumerate(axes):
            if i < len(image_files):</pre>
                img = mpimg.imread('data/train/non_fire/'+image_files[i])
                ax.imshow(img)
                ax.axis('off')
            else:
                ax.set_visible(False)
        plt.suptitle('9 Random Forest Non Fire Images', fontsize=14, fontweight='bold')
        plt.tight_layout()
        plt.show()
```

#### 9 Random Forest Non Fire Images



### **CNN Model**

```
In [7]: import requests
        from IPython.display import Image
        url = 'https://www.analytixlabs.co.in/blog/wp-content/uploads/2024/01/7.jpg'
        response = requests.get(url)
        image_data = response.content
        Image(data=image_data)
```



# **Constructing CNN Model**

```
classifier = Sequential(name='ForestFireClassifierCNN')
In [8]:
        classifier.add(Input(shape=(32,32,3)))
                                                   # 1st Layer: Input
        classifier.add(Convolution2D(filters=32, kernel_size=(3,3), strides=2, padding='sam
        classifier.add(MaxPooling2D(pool_size = (2,2))) # 3rd Layer: MaxPooling2D
        classifier.add(Convolution2D(filters=32, kernel_size=(3,3), strides=2, padding='sam
        classifier.add(MaxPooling2D(pool_size = (2,2)))
                                                         # 5th Layer: MaxPooling2D
                                      # 6th Layer: Flatten
        classifier.add(Flatten())
        classifier.add(Dense(units = 128, activation = 'relu'))
                                                                   # 7th Layer: Dense
        classifier.add(Dropout(0.5)) # 8th Layer: Dropout
        classifier.add(Dense(units = 1, activation = 'sigmoid')) # 9th Layer: Output
        classifier.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['ad
        classifier.summary()
```

Model: "ForestFireClassifierCNN"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 16, 16, 32)	896
max_pooling2d (MaxPooling2D)	(None, 8, 8, 32)	0
conv2d_1 (Conv2D)	(None, 4, 4, 32)	9,248
max_pooling2d_1 (MaxPooling2D)	(None, 2, 2, 32)	0
flatten (Flatten)	(None, 128)	0
dense (Dense)	(None, 128)	16,512
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 1)	129

Total params: 26,785 (104.63 KB)

Trainable params: 26,785 (104.63 KB)

Non-trainable params: 0 (0.00 B)

## **Generating Image Data for Train & Test**

```
In [9]: from tensorflow.keras.preprocessing.image import ImageDataGenerator
        training_data_generator = ImageDataGenerator(rescale=1./255, shear_range=0.2, zoom_
        test data generator = ImageDataGenerator(rescale=1./255)
        train_set = training_data_generator.flow_from_directory('data/train', target_size=(
        test_set = test_data_generator.flow_from_directory('data/test', target_size=(32, 32
        classifier fit(train_set, steps_per_epoch=4609//16, epochs=20, validation_data=test
       Found 4609 images belonging to 2 classes.
       Found 50 images belonging to 2 classes.
       Epoch 1/20
       D:\anaconda3\Lib\site-packages\keras\src\trainers\data adapters\py dataset adapter.p
       y:121: UserWarning: Your `PyDataset` class should call `super().__init__(**kwargs)`
       in its constructor. `**kwargs` can include `workers`, `use_multiprocessing`, `max_qu
       eue_size`. Do not pass these arguments to `fit()`, as they will be ignored.
         self._warn_if_super_not_called()
                                  - 74s 242ms/step - accuracy: 0.8057 - loss: 0.4464 - val_
       accuracy: 0.8125 - val_loss: 0.4997
       Epoch 2/20
       288/288 -
                               —— 0s 396us/step - accuracy: 0.9375 - loss: 0.2028 - val_a
       ccuracy: 1.0000 - val_loss: 0.0627
       Epoch 3/20
       D:\anaconda3\Lib\contextlib.py:158: UserWarning: Your input ran out of data; interru
       pting training. Make sure that your dataset or generator can generate at least `step
       s_per_epoch * epochs` batches. You may need to use the `.repeat()` function when bui
       lding your dataset.
         self.gen.throw(typ, value, traceback)
```

```
32s 108ms/step - accuracy: 0.9013 - loss: 0.2411 - val_
accuracy: 0.8125 - val_loss: 0.4366
Epoch 4/20
                   Os 160us/step - accuracy: 0.8125 - loss: 0.2910 - val_a
288/288 -
ccuracy: 1.0000 - val_loss: 0.0181
Epoch 5/20
                    31s 103ms/step - accuracy: 0.9208 - loss: 0.2110 - val_
288/288 ----
accuracy: 0.8125 - val_loss: 0.5744
Epoch 6/20
                  Os 198us/step - accuracy: 0.8750 - loss: 0.3212 - val_a
288/288 -
ccuracy: 1.0000 - val_loss: 0.2354
Epoch 7/20
288/288 — 30s 101ms/step - accuracy: 0.9262 - loss: 0.1977 - val
accuracy: 0.8750 - val loss: 0.3885
Epoch 8/20
                      ---- 0s 222us/step - accuracy: 0.9375 - loss: 0.1572 - val a
288/288 -
ccuracy: 1.0000 - val_loss: 0.0021
Epoch 9/20
                       --- 30s 99ms/step - accuracy: 0.9292 - loss: 0.1868 - val a
ccuracy: 0.8750 - val_loss: 0.4014
Epoch 10/20
                     Os 188us/step - accuracy: 1.0000 - loss: 0.0181 - val a
288/288 ----
ccuracy: 1.0000 - val_loss: 0.0283
Epoch 11/20
288/288 ----
                     33s 112ms/step - accuracy: 0.9390 - loss: 0.1617 - val
accuracy: 0.8750 - val loss: 0.4098
Epoch 12/20
288/288 _____
            0s 281us/step - accuracy: 0.9375 - loss: 0.1752 - val_a
ccuracy: 1.0000 - val_loss: 0.1590
Epoch 13/20
                   31s 106ms/step - accuracy: 0.9384 - loss: 0.1765 - val_
288/288 -----
accuracy: 0.8958 - val_loss: 0.3991
Epoch 14/20
                       --- 0s 160us/step - accuracy: 1.0000 - loss: 0.0944 - val a
ccuracy: 1.0000 - val_loss: 0.5490
Epoch 15/20
                   ______ 31s 105ms/step - accuracy: 0.9410 - loss: 0.1634 - val_
288/288 -
accuracy: 0.7917 - val_loss: 0.4984
Epoch 16/20
                  Os 139us/step - accuracy: 1.0000 - loss: 0.0389 - val_a
288/288 -
ccuracy: 1.0000 - val_loss: 8.3962e-04
Epoch 17/20
                    31s 105ms/step - accuracy: 0.9463 - loss: 0.1444 - val_
288/288 ----
accuracy: 0.9375 - val_loss: 0.3267
Epoch 18/20
                  Os 149us/step - accuracy: 0.9375 - loss: 0.1810 - val_a
288/288 -----
ccuracy: 0.5000 - val_loss: 2.7899
Epoch 19/20
                 ______ 31s 103ms/step - accuracy: 0.9394 - loss: 0.1587 - val_
accuracy: 0.8542 - val loss: 0.5386
Epoch 20/20
                  0s 254us/step - accuracy: 0.9375 - loss: 0.0977 - val_a
288/288 -----
ccuracy: 1.0000 - val_loss: 0.0198
```

Out[9]: <keras.src.callbacks.history.History at 0x288e5a43e10>

#### **Metrics Evaluation**

```
In [10]: score = classifier.evaluate(test_set, steps=len(test_set))
for idx, metric in enumerate(classifier.metrics_names):
    print("{}: {}".format(metric, score[idx]))

4/4 _______ 1s 166ms/step - accuracy: 0.8773 - loss: 0.5130
loss: 0.5499006509780884
compile_metrics: 0.8600000143051147
```

# **Transfer Learning using VGG16**

```
In [11]: url = 'https://storage.googleapis.com/lds-media/images/vgg16-architecture.width-120
    response = requests.get(url)
    image_data = response.content
    Image(data=image_data)
Out[11]:
```

# OUTPUT ARCHITECTURE ACCHING CONV 2: 2 CONV

In [12]: from tensorflow.keras.applications.vgg16 import VGG16

```
In [13]: INPUT_SIZE = 128 # Change this to 48 if the code takes too long to run
   vgg16 = VGG16(include_top=False, weights='imagenet', input_shape=(INPUT_SIZE,INPUT_
```

Note that we used `include\_top=False when we created a new VGG16 model. This

LAYER

argument tells Keras not to import the fully connected layers at the end of the VGG16 network.

We're now going to freeze the rest of the layers in the VGG16 model, since we're not going to retrain them from scratch

Next, we're going to add a fully connected layer with 1 node right at the end of the neural network. The syntax to do this is slightly different, since the VGG16 model is not a Keras Sequential model that we're used to. In any case, we can add the layers by running the following code:

```
In [15]: from keras.api.models import Model
  input_ = vgg16.input
  output_ = vgg16(input_)
```

```
last_layer = Flatten(name='flatten')(output_)
last_layer = Dense(1, activation='sigmoid')(last_layer)
# model = Model(input=input_, output=last_layer)
model = Model()

In [16]: vgg16.output

Out[16]: <KerasTensor shape=(None, 4, 4, 512), dtype=float32, sparse=False, name=keras_tens or_55>

In [16]:
```