

```
In [1]: import os
import tensorflow as tf
import numpy as np
from keras.applications import ResNet50
from efficientnet.tfkeras import EfficientNetB4
from keras.models import Sequential, Model
from keras.layers import Input, Conv2D, MaxPooling2D, Dropout, Flatten, Dense, BatchNorm
from keras import regularizers
from keras.optimizers import Adam
from keras.callbacks import ModelCheckpoint, EarlyStopping
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from keras.utils import plot_model
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, f1_score, classification_report, accuracy_score
import seaborn as sns
from IPython.display import Image
import warnings
os.environ['TF_CPP_MIN_LOG_LEVEL'] = '2'
warnings.filterwarnings('ignore', category=UserWarning)
```

```
In [2]: from PIL import ImageFile
ImageFile.LOAD_TRUNCATED_IMAGES = True
```

```
In [3]: train_path = "./wildfire-dataset/train"
valid_path = "./wildfire-dataset/valid"
test_path = "./wildfire-dataset/test"
```

```
In [4]: train_datagen = ImageDataGenerator(rescale=1./255)
valid_datagen = ImageDataGenerator(rescale=1./255)
test_datagen = ImageDataGenerator(rescale=1./255)

train_generator = train_datagen.flow_from_directory(
    train_path,
    target_size=(350, 350),
    batch_size=32,
    class_mode='binary',
    shuffle=True)

valid_generator = valid_datagen.flow_from_directory(
    valid_path,
    target_size=(350, 350),
    batch_size=32,
    class_mode='binary',
    shuffle=True)

test_generator = test_datagen.flow_from_directory(
    test_path,
    target_size=(350, 350),
    batch_size=32,
    class_mode='binary',
    shuffle=False)
```

```
Found 30250 images belonging to 2 classes.
Found 6300 images belonging to 2 classes.
Found 6300 images belonging to 2 classes.
```

```
In [5]: def display_images_from_generator(generator, num_images=5):
    x_batch, y_batch = next(generator)

    plt.figure(figsize=(num_images * 3, 3))
    for i in range(num_images):
        plt.subplot(1, num_images, i+1)
        plt.imshow(x_batch[i])
        label = "1: wildfire" if y_batch[i] > 0.5 else "0: nowildfire"
        plt.title(label, fontsize=12)
        plt.axis('off')
    plt.tight_layout()
    plt.show()
```

```
In [6]: display_images_from_generator(train_generator)
```



```
In [7]: display_images_from_generator(valid_generator)
```



```
In [8]: display_images_from_generator(test_generator)
```



```
In [9]: def resnet50(input_shape=(350, 350, 3), num_classes=1):
    base_model = ResNet50(weights='imagenet', include_top=False, input_shape=input_shape)

    for layer in base_model.layers[:-4]:
        layer.trainable = False

    x = base_model.output
    x = GlobalAveragePooling2D()(x)
    x = Dense(1024, activation='relu')(x)
    predictions = Dense(num_classes, activation='sigmoid')(x)

    model = Model(inputs=base_model.input, outputs=predictions)
    model.compile(optimizer=Adam(), loss='binary_crossentropy', metrics=['accuracy'])
    model.name = 'ResNet50'

    return model
```

```
In [10]: model=resnet50()
```

```
In [11]: model.summary()
```

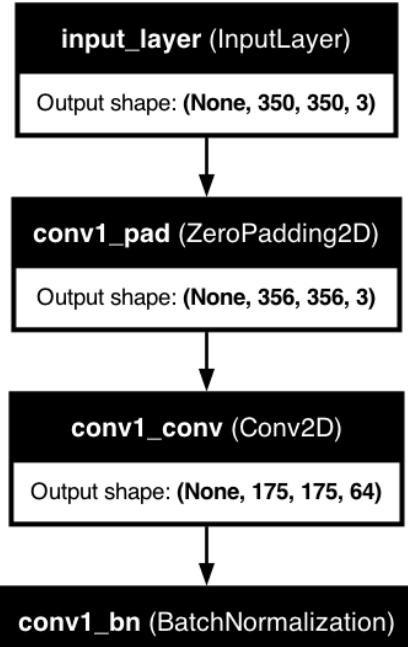
(BatchNormalization)	2048		- - -
conv5_block3_add (Add)	(None, 11, 11, 2048)	0	conv5_block2_out... conv5_block3_3_b...
conv5_block3_out (Activation)	(None, 11, 11, 2048)	0	conv5_block3_add...
global_average_poo... (GlobalAveragePool...)	(None, 2048)	0	conv5_block3_out...
dense (Dense)	(None, 1024)	2,098,176	global_average_p...
dense_1 (Dense)	(None, 1)	1,025	dense[0][0]

Total params: 25,686,913 (97.99 MB)

Trainable params: 3,153,921 (12.03 MB)

```
In [12]: plot_model(model, to_file=f'{model.name}_model.png', show_shapes=True, show_layer_names=True)
Image(filename=f'{model.name}_model.png')
```

Out[12]:



```
In [13]: %%time
checkpointer = ModelCheckpoint(f'{model.name}.weights.h5', verbose=1, save_best_only=True)
early_stopping = EarlyStopping(monitor='val_loss', patience=10)

history = model.fit(
    train_generator,
    epochs=10,
    verbose=1,
    validation_data=valid_generator,
    callbacks=[checkpointer, early_stopping]
)
```

Epoch 1/10
946/946 0s 684ms/step - accuracy: 0.8574 - loss: 0.3748
Epoch 1: val_loss improved from inf to 0.54970, saving model to ResNet50.weights.h5
946/946 787s 826ms/step - accuracy: 0.8574 - loss: 0.3747 - val_accuracy: 0.7324 - val_loss: 0.5497
Epoch 2/10
946/946 0s 708ms/step - accuracy: 0.9038 - loss: 0.2473
Epoch 2: val_loss did not improve from 0.54970
946/946 808s 853ms/step - accuracy: 0.9038 - loss: 0.2473 - val_accuracy: 0.4484 - val_loss: 1.5135
Epoch 3/10
946/946 0s 735ms/step - accuracy: 0.9118 - loss: 0.2269
Epoch 3: val_loss improved from 0.54970 to 0.20246, saving model to ResNet50.weights.h5
946/946 837s 885ms/step - accuracy: 0.9118 - loss: 0.2269 - val_accuracy: 0.9241 - val_loss: 0.2025
Epoch 4/10
946/946 0s 738ms/step - accuracy: 0.9159 - loss: 0.2237
Epoch 4: val_loss did not improve from 0.20246
946/946 837s 885ms/step - accuracy: 0.9159 - loss: 0.2237 - val_accuracy: 0.8813 - val_loss: 0.2568
Epoch 5/10
946/946 0s 744ms/step - accuracy: 0.9154 - loss: 0.2148
Epoch 5: val_loss did not improve from 0.20246
946/946 845s 893ms/step - accuracy: 0.9155 - loss: 0.2148 - val_accuracy: 0.5030 - val_loss: 1.2729
Epoch 6/10
946/946 0s 754ms/step - accuracy: 0.9173 - loss: 0.2116
Epoch 6: val_loss did not improve from 0.20246
946/946 858s 907ms/step - accuracy: 0.9173 - loss: 0.2116 - val_accuracy: 0.8570 - val_loss: 0.3427
Epoch 7/10
946/946 0s 769ms/step - accuracy: 0.9223 - loss: 0.2043
Epoch 7: val_loss did not improve from 0.20246
946/946 862s 910ms/step - accuracy: 0.9223 - loss: 0.2043 - val_accuracy: 0.8851 - val_loss: 0.2585
Epoch 8/10
946/946 0s 734ms/step - accuracy: 0.9258 - loss: 0.1938
Epoch 8: val_loss improved from 0.20246 to 0.19862, saving model to ResNet50.weights.h5
946/946 838s 885ms/step - accuracy: 0.9258 - loss: 0.1938 - val_accuracy: 0.9273 - val_loss: 0.1986
Epoch 9/10
946/946 0s 733ms/step - accuracy: 0.9286 - loss: 0.1873
Epoch 9: val_loss did not improve from 0.19862
946/946 843s 891ms/step - accuracy: 0.9286 - loss: 0.1873 - val_accuracy: 0.6222 - val_loss: 0.8002
Epoch 10/10
946/946 0s 742ms/step - accuracy: 0.9269 - loss: 0.1841
Epoch 10: val_loss did not improve from 0.19862
946/946 841s 889ms/step - accuracy: 0.9269 - loss: 0.1841 - val_accuracy: 0.9111 - val_loss: 0.2393
CPU times: user 15min 22s, sys: 13min 52s, total: 29min 14s
Wall time: 2h 19min 16s

```
In [14]: def display_images_with_predictions_from_generator(generator, model, num_wildfire=2, num_nowildfire=2):
    wildfire_pool = []
    nowildfire_pool = []

    while len(wildfire_pool) < num_wildfire or len(nowildfire_pool) < num_nowildfire:
        x_batch, y_batch = next(generator)
        for i in range(len(y_batch)):
            if y_batch[i] > 0.5: # Wildfire
                wildfire_pool.append((x_batch[i], y_batch[i]))
            else: # No Wildfire
                nowildfire_pool.append((x_batch[i], y_batch[i]))

    np.random.seed(10)
    selected_wildfire = np.random.choice(range(len(wildfire_pool)), size=num_wildfire)
    selected_nowildfire = np.random.choice(range(len(nowildfire_pool)), size=num_nowildfire)

    selected_images = [wildfire_pool[i][0] for i in selected_wildfire] + [nowildfire_pool[i][0] for i in selected_nowildfire]
    selected_labels = [wildfire_pool[i][1] for i in selected_wildfire] + [nowildfire_pool[i][1] for i in selected_nowildfire]

    predictions = model.predict(np.array(selected_images)).flatten()

    plt.figure(figsize=(len(selected_images) * 3, 3))
    for i in range(len(selected_images)):
        plt.subplot(1, len(selected_images), i + 1)
        plt.imshow(selected_images[i])
        true_label = "Wildfire" if selected_labels[i] > 0.5 else "No Wildfire"
        predicted_label = "Wildfire" if predictions[i] > 0.5 else "No Wildfire"
        plt.title(f"True: {true_label}\nPred: {predicted_label}")
        plt.axis('off')
    plt.tight_layout()
    plt.show()
```

```
In [15]: display_images_with_predictions_from_generator(test_generator, model)
```

1/1 ————— 2s 2s/step



```
In [16]: def plot_confusion_matrix_and_metrics(generator, model):
    label_names = ['No Wildfire', 'Wildfire']
    # Step 1: Calculate metrics and prepare the data
    y_true = generator.classes
    y_pred = model.predict(generator)
    y_pred = (y_pred > 0.5).astype(int)

    # Confusion matrix visualization
    conf_mat = confusion_matrix(y_true, y_pred)
    plt.figure(figsize=(8, 6))
    sns.heatmap(conf_mat, annot=True, fmt='d', cmap='Blues')
    plt.title('Confusion Matrix')
    plt.xlabel('Predicted Labels')
    plt.ylabel('True Labels')
    plt.xticks(ticks=np.arange(len(label_names)) + 0.5, labels=label_names, rotation=45)
    plt.yticks(ticks=np.arange(len(label_names)) + 0.5, labels=label_names, rotation=45)
    plt.show()

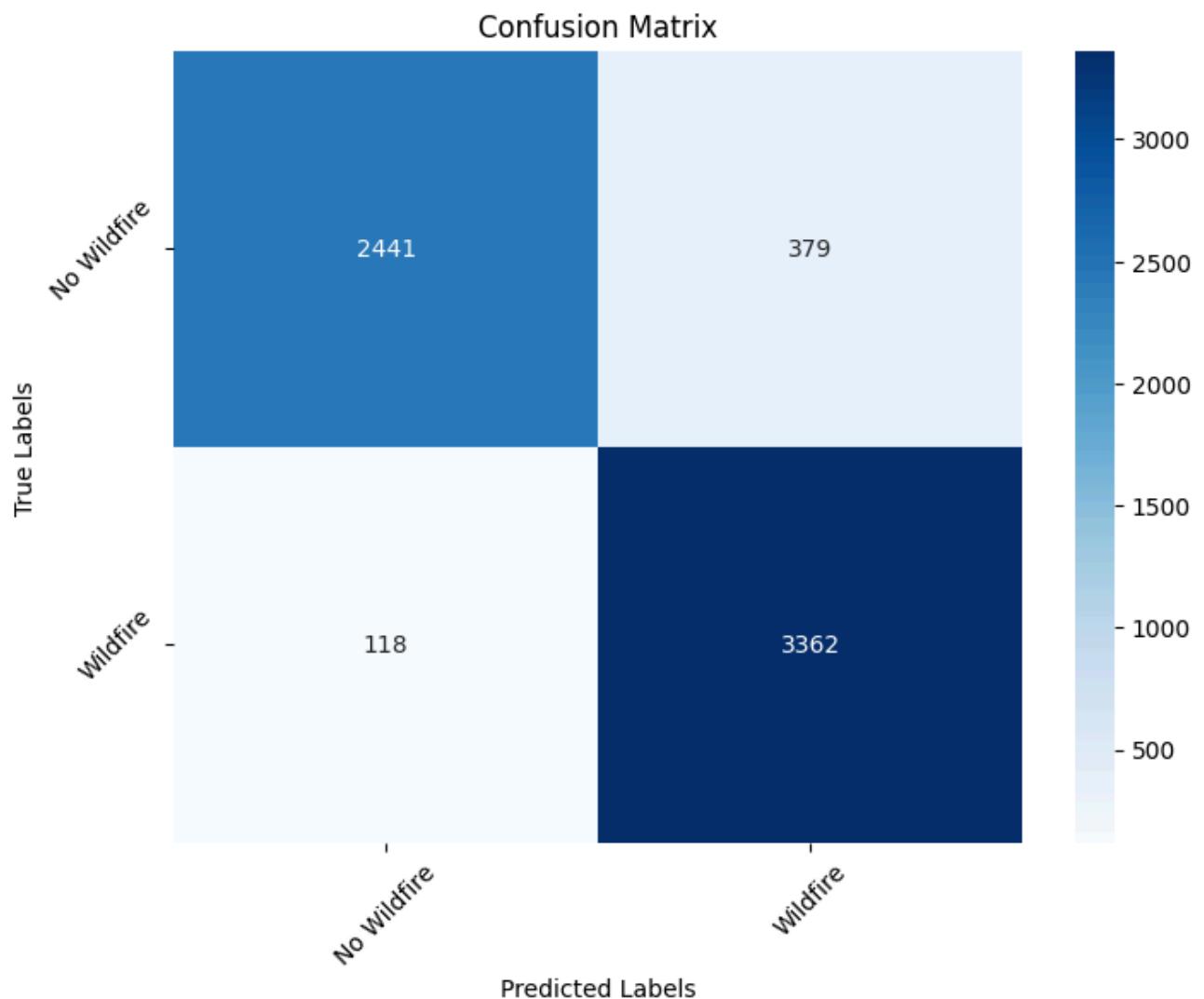
    # Classification Report in text
    report_text = classification_report(y_true, y_pred, target_names=label_names)
    print(report_text)

    # Print F1 score
    f1 = f1_score(y_true, y_pred)
    print(f"F1 Score: {f1:.2f}")

    # Print accuracy in percentage
    accuracy = accuracy_score(y_true, y_pred)
    print(f"Accuracy: {accuracy * 100:.2f}%")
```

```
In [17]: plot_confusion_matrix_and_metrics(test_generator, model)
```

197/197 ━━━━━━ 137s 685ms/step



	precision	recall	f1-score	support
No Wildfire	0.95	0.87	0.91	2820
Wildfire	0.90	0.97	0.93	3480
accuracy			0.92	6300
macro avg	0.93	0.92	0.92	6300
weighted avg	0.92	0.92	0.92	6300

F1 Score: 0.93

Accuracy: 92.11%

```
In [18]: def plot_training_history(history):
    plt.figure(figsize=(16, 6))

    epochs = range(1, len(history.history['accuracy']) + 1)

    plt.subplot(1, 2, 1)
    plt.plot(epochs, history.history['accuracy'], label='Train Accuracy', marker='o')
    plt.plot(epochs, history.history['val_accuracy'], label='Validation Accuracy', marker='o')
    plt.title('Model Training and Validation Accuracy')
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.xticks(epochs)
    plt.legend()

    plt.subplot(1, 2, 2)
    plt.plot(epochs, history.history['loss'], label='Train Loss', marker='o')
    plt.plot(epochs, history.history['val_loss'], label='Validation Loss', marker='o')
    plt.title('Model Training and Validation Loss')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.xticks(epochs)
    plt.legend()

    plt.tight_layout()
    plt.savefig(f'{model.name}_training_history.png', dpi=300)
    plt.show()
```

```
In [19]: plot_training_history(history)
```

