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, BatchNo
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, accura
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 cnn_model(input_shape=(350, 350, 3), weight_decay=0.001):
    inputs = Input(shape=input_shape, name='input_layer')
    x = Conv2D(32, (3, 3), activation='relu', name='conv2d_layer1')(inputs)
    x = BatchNormalization()(x)
    x = MaxPooling2D((2, 2))(x)
    x = Conv2D(64, (3, 3), activation='relu')(x)
    x = BatchNormalization()(x)
    x = MaxPooling2D((2, 2))(x)
    x = Conv2D(128, (3, 3), activation='relu')(x)
    x = BatchNormalization()(x)
    x = MaxPooling2D((2, 2))(x)
    x = Conv2D(256, (3, 3), activation='relu')(x)
    x = BatchNormalization()(x)
    x = MaxPooling2D((2, 2))(x)
    x = Flatten()(x)
    x = Dense(512, activation='relu', kernel_regularizer=regularizers.l2(weight_decay
    x = Dropout(0.5)(x)
    outputs = Dense(1, activation='sigmoid')(x)

    model = Model(inputs=inputs, outputs=outputs, name='traditional-cnn')
    model.compile(optimizer=Adam(),
                  loss='binary_crossentropy',
                  metrics=['accuracy'])

    return model
```

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

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

Model: "traditional-cnn"

Layer (type)	Output Shape	Param #
input_layer (InputLayer)	(None, 350, 350, 3)	0
conv2d_layer1 (Conv2D)	(None, 348, 348, 32)	896
batch_normalization (BatchNormalization)	(None, 348, 348, 32)	128
max_pooling2d (MaxPooling2D)	(None, 174, 174, 32)	0
conv2d (Conv2D)	(None, 172, 172, 64)	18,496
batch_normalization_1 (BatchNormalization)	(None, 172, 172, 64)	256
max_pooling2d_1 (MaxPooling2D)	(None, 86, 86, 64)	0
conv2d_1 (Conv2D)	(None, 84, 84, 128)	73,856
batch_normalization_2 (BatchNormalization)	(None, 84, 84, 128)	512
max_pooling2d_2 (MaxPooling2D)	(None, 42, 42, 128)	0
conv2d_2 (Conv2D)	(None, 40, 40, 256)	295,168
batch_normalization_3 (BatchNormalization)	(None, 40, 40, 256)	1,024
max_pooling2d_3 (MaxPooling2D)	(None, 20, 20, 256)	0
flatten (Flatten)	(None, 102400)	0
dense (Dense)	(None, 512)	52,429,312
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 1)	513

Total params: 52,820,161 (201.49 MB)

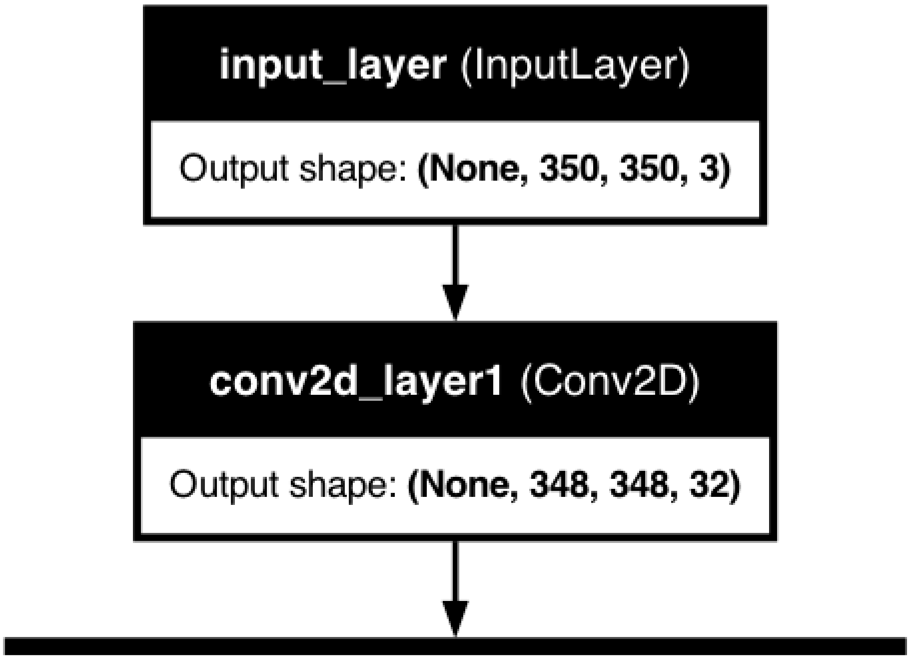
Trainable params: 52,819,201 (201.49 MB)

Non-trainable params: 960 (3.75 KB)

In [12]:

```
plot_model(model, to_file=f'{model.name}_model.png', show_shapes=True, show_layer_name
Image(filename=f'{model.name}_model.png')
```

Out[12]:



In [13]:

```
%%time
checkpointer = ModelCheckpoint(f'{model.name}.weights.h5', verbose=1, save_best_only=
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 852ms/step - accuracy: 0.8741 - loss: 11.0088
Epoch 1: val_loss improved from inf to 1.26682, saving model to traditional-cnn.weig
hts.h5
946/946 ━━━━━━━━━━━━━━━━━━━━ 846s 893ms/step - accuracy: 0.8742 - loss: 11.0032 - va
l_accuracy: 0.9397 - val_loss: 1.2668
Epoch 2/10
946/946 ━━━━━━━━━━━━━━━━━━━━ 0s 904ms/step - accuracy: 0.9106 - loss: 1.3081
Epoch 2: val_loss improved from 1.26682 to 0.36242, saving model to traditional-cnn.
weights.h5
946/946 ━━━━━━━━━━━━━━━━━━━━ 895s 946ms/step - accuracy: 0.9106 - loss: 1.3078 - val
_accuracy: 0.9454 - val_loss: 0.3624
Epoch 3/10
946/946 ━━━━━━━━━━━━━━━━━━━━ 0s 925ms/step - accuracy: 0.9270 - loss: 0.4383
Epoch 3: val_loss did not improve from 0.36242
946/946 ━━━━━━━━━━━━━━━━━━━━ 915s 967ms/step - accuracy: 0.9270 - loss: 0.4383 - val
_accuracy: 0.9151 - val_loss: 0.4674
Epoch 4/10
946/946 ━━━━━━━━━━━━━━━━━━━━ 0s 919ms/step - accuracy: 0.9255 - loss: 0.5784
Epoch 4: val_loss did not improve from 0.36242
946/946 ━━━━━━━━━━━━━━━━━━━━ 907s 959ms/step - accuracy: 0.9255 - loss: 0.5784 - val
_accuracy: 0.9319 - val_loss: 0.4395
Epoch 5/10
946/946 ━━━━━━━━━━━━━━━━━━━━ 0s 881ms/step - accuracy: 0.9331 - loss: 0.5269
Epoch 5: val_loss did not improve from 0.36242
946/946 ━━━━━━━━━━━━━━━━━━━━ 871s 921ms/step - accuracy: 0.9331 - loss: 0.5269 - val
_accuracy: 0.9235 - val_loss: 0.5164
Epoch 6/10
946/946 ━━━━━━━━━━━━━━━━━━━━ 0s 885ms/step - accuracy: 0.9492 - loss: 0.3784
Epoch 6: val_loss improved from 0.36242 to 0.32027, saving model to traditional-cnn.
weights.h5
946/946 ━━━━━━━━━━━━━━━━━━━━ 876s 926ms/step - accuracy: 0.9492 - loss: 0.3783 - val
_accuracy: 0.9303 - val_loss: 0.3203
Epoch 7/10
946/946 ━━━━━━━━━━━━━━━━━━━━ 0s 887ms/step - accuracy: 0.9577 - loss: 0.2928
Epoch 7: val_loss did not improve from 0.32027
946/946 ━━━━━━━━━━━━━━━━━━━━ 877s 927ms/step - accuracy: 0.9577 - loss: 0.2928 - val
_accuracy: 0.9390 - val_loss: 0.3997
Epoch 8/10
946/946 ━━━━━━━━━━━━━━━━━━━━ 0s 906ms/step - accuracy: 0.9614 - loss: 0.3025
Epoch 8: val_loss did not improve from 0.32027
946/946 ━━━━━━━━━━━━━━━━━━━━ 897s 948ms/step - accuracy: 0.9614 - loss: 0.3025 - val
_accuracy: 0.9276 - val_loss: 0.3841
Epoch 9/10
946/946 ━━━━━━━━━━━━━━━━━━━━ 0s 908ms/step - accuracy: 0.9643 - loss: 0.2944
Epoch 9: val_loss did not improve from 0.32027
946/946 ━━━━━━━━━━━━━━━━━━━━ 899s 950ms/step - accuracy: 0.9643 - loss: 0.2944 - val
_accuracy: 0.7702 - val_loss: 0.5111
Epoch 10/10
946/946 ━━━━━━━━━━━━━━━━━━━━ 0s 927ms/step - accuracy: 0.9658 - loss: 0.2586
Epoch 10: val_loss improved from 0.32027 to 0.27882, saving model to traditional-cn
n.weights.h5
946/946 ━━━━━━━━━━━━━━━━━━━━ 917s 969ms/step - accuracy: 0.9658 - loss: 0.2586 - val
_accuracy: 0.9506 - val_loss: 0.2788
CPU times: user 14min 37s, sys: 50min 6s, total: 1h 4min 44s
Wall time: 2h 28min 20s
```

In [14]:
```python
def display_images_with_predictions_from_generator(generator, model, num_wildfire=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_nowi

    selected_images = [wildfire_pool[i][0] for i in selected_wildfire] + [nowildfire_
    selected_labels = [wildfire_pool[i][1] for i in selected_wildfire] + [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()
```

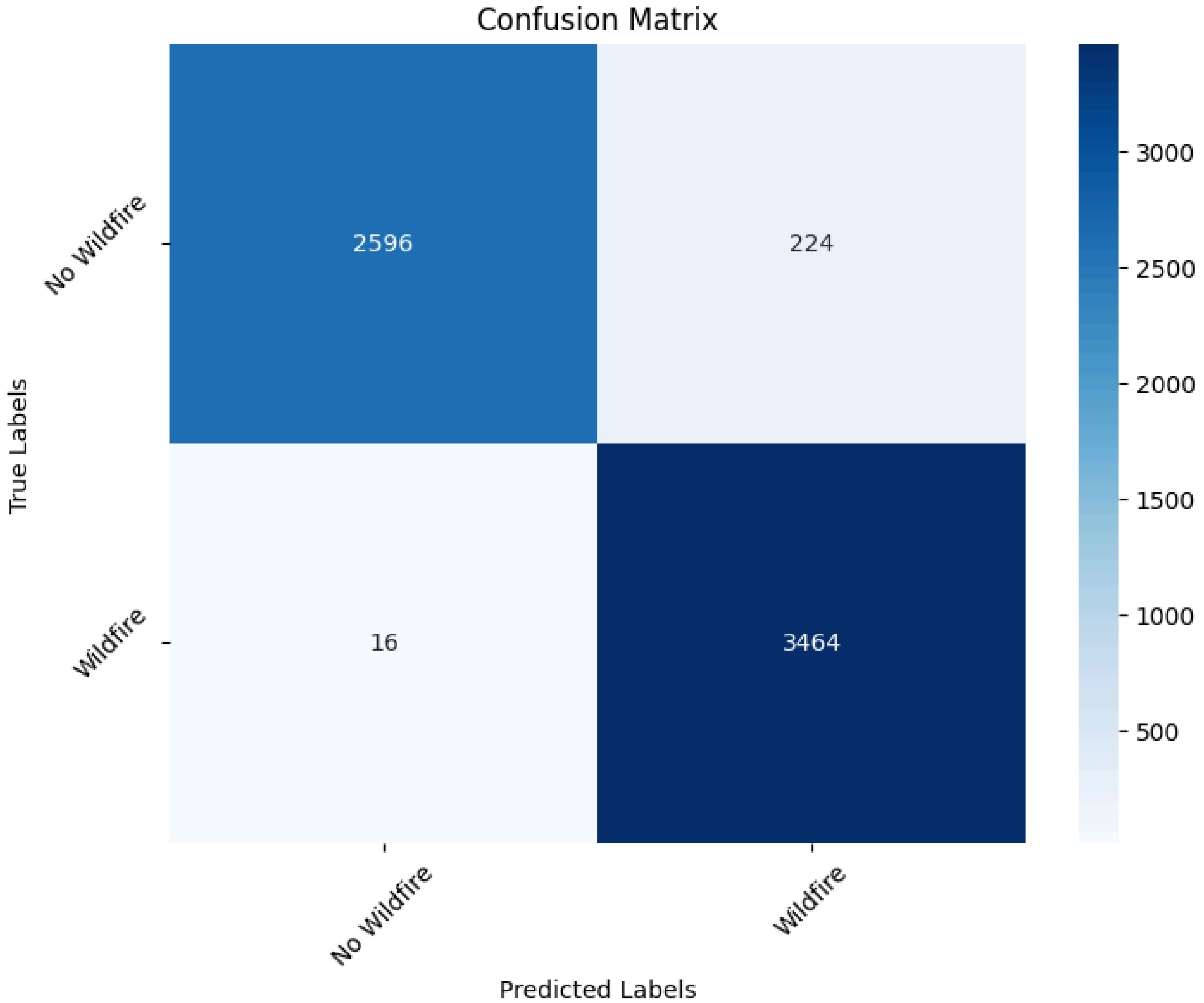
In [15]:
```python
display_images_with_predictions_from_generator(test_generator, model)
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 241ms/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=
    plt.yticks(ticks=np.arange(len(label_names)) + 0.5, labels=label_names, rotation=
    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 ━━━━━━━━━━━━━━━━━━━━ 37s 189ms/step
```




```
              precision    recall  f1-score   support

 No Wildfire       0.99      0.92      0.96      2820
    Wildfire       0.94      1.00      0.97      3480

    accuracy                           0.96      6300
   macro avg       0.97      0.96      0.96      6300
weighted avg       0.96      0.96      0.96      6300

F1 Score: 0.97
Accuracy: 96.19%
```

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', mar
    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)
```