

# face-detection

May 19, 2024

```
[36]: import tensorflow as tf
      from tensorflow.keras.preprocessing.image import ImageDataGenerator
      from tensorflow.keras import layers, models
      import matplotlib.pyplot as plt
      import numpy as np
      import os
```

```
[37]: from google.colab import drive
      drive.mount('/content/drive')
```

Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force\_remount=True).

```
[38]: # Directory paths
      train_dir = '/content/drive/MyDrive/Face_Dataset/train'
      validation_dir = '/content/drive/MyDrive/Face_Dataset/validation'
      test_dir = '/content/drive/MyDrive/Face_Dataset/test'
```

```
[39]: # Parameters
      img_height, img_width = 150, 150
      batch_size = 32
```

```
[40]: # Create ImageDataGenerators
      train_datagen = ImageDataGenerator(rescale=1./255)
      validation_datagen = ImageDataGenerator(rescale=1./255)
      test_datagen = ImageDataGenerator(rescale=1./255)

      train_generator = train_datagen.flow_from_directory(
          train_dir,
          target_size=(img_height, img_width),
          batch_size=batch_size,
          class_mode='binary' # Use 'categorical' if you have more than two classes
      )

      validation_generator = validation_datagen.flow_from_directory(
          validation_dir,
          target_size=(img_height, img_width),
          batch_size=batch_size,
```

```

        class_mode='binary' # Use 'categorical' if you have more than two classes
    )

    test_generator = test_datagen.flow_from_directory(
        test_dir,
        target_size=(img_height, img_width),
        batch_size=batch_size,
        class_mode='binary', # Use 'categorical' if you have more than two classes
        shuffle=False
    )

```

Found 27 images belonging to 2 classes.  
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```

[41]: # Debugging statements
print(f'Training samples: {train_generator.samples}')
print(f'Validation samples: {validation_generator.samples}')

```

Training samples: 27  
 Validation samples: 27

```

[42]: # Calculate steps per epoch
steps_per_epoch = max(1, train_generator.samples // batch_size)
validation_steps = max(1, validation_generator.samples // batch_size)

```

```

[43]: # Define the CNN model
model = models.Sequential([
    layers.Conv2D(32, (3, 3), activation='relu', input_shape=(img_height,
↪img_width, 3)),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(128, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(128, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Flatten(),
    layers.Dense(512, activation='relu'),
    layers.Dense(1, activation='sigmoid') # Use softmax for more than two
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```

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```

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```

```

[45]: # Compile the model
model.compile(optimizer='adam',
              loss='binary_crossentropy', # Use 'categorical_crossentropy' for
↳ more than two classes
              metrics=['accuracy'])

```

```

[46]: # Train the model
history = model.fit(
    train_generator,
    steps_per_epoch=steps_per_epoch,
    epochs=15,
    validation_data=validation_generator,
    validation_steps=validation_steps
)

```

```

Epoch 1/15
1/1 [=====] - 3s 3s/step - loss: 0.6893 - accuracy:
0.6296 - val_loss: 1.0221 - val_accuracy: 0.6667
Epoch 2/15
1/1 [=====] - 1s 725ms/step - loss: 1.0221 - accuracy:
0.6667 - val_loss: 0.6219 - val_accuracy: 0.6667
Epoch 3/15
1/1 [=====] - 1s 1s/step - loss: 0.6219 - accuracy:
0.6667 - val_loss: 0.6575 - val_accuracy: 0.6667
Epoch 4/15
1/1 [=====] - 1s 756ms/step - loss: 0.6575 - accuracy:
0.6667 - val_loss: 0.6535 - val_accuracy: 0.6667
Epoch 5/15
1/1 [=====] - 1s 605ms/step - loss: 0.6535 - accuracy:
0.6667 - val_loss: 0.6220 - val_accuracy: 0.6667
Epoch 6/15
1/1 [=====] - 1s 579ms/step - loss: 0.6220 - accuracy:
0.6667 - val_loss: 0.6138 - val_accuracy: 0.6667
Epoch 7/15

```

```

1/1 [=====] - 1s 594ms/step - loss: 0.6138 - accuracy:
0.6667 - val_loss: 0.5949 - val_accuracy: 0.6667
Epoch 8/15
1/1 [=====] - 1s 591ms/step - loss: 0.5949 - accuracy:
0.6667 - val_loss: 0.5659 - val_accuracy: 0.6667
Epoch 9/15
1/1 [=====] - 1s 603ms/step - loss: 0.5659 - accuracy:
0.6667 - val_loss: 0.5418 - val_accuracy: 0.6667
Epoch 10/15
1/1 [=====] - 1s 563ms/step - loss: 0.5418 - accuracy:
0.6667 - val_loss: 0.5205 - val_accuracy: 0.6667
Epoch 11/15
1/1 [=====] - 1s 581ms/step - loss: 0.5205 - accuracy:
0.6667 - val_loss: 0.4933 - val_accuracy: 0.6667
Epoch 12/15
1/1 [=====] - 1s 570ms/step - loss: 0.4933 - accuracy:
0.6667 - val_loss: 0.4641 - val_accuracy: 0.6667
Epoch 13/15
1/1 [=====] - 1s 566ms/step - loss: 0.4641 - accuracy:
0.6667 - val_loss: 0.4352 - val_accuracy: 0.6667
Epoch 14/15
1/1 [=====] - 1s 574ms/step - loss: 0.4352 - accuracy:
0.6667 - val_loss: 0.4074 - val_accuracy: 0.7778
Epoch 15/15
1/1 [=====] - 1s 593ms/step - loss: 0.4074 - accuracy:
0.7778 - val_loss: 0.3604 - val_accuracy: 0.8148

```

```

[47]: # Evaluate the model
test_loss, test_acc = model.evaluate(test_generator, verbose=2)
print(f'\nTest accuracy: {test_acc}')

```

```

1/1 - 0s - loss: 0.3604 - accuracy: 0.8148 - 305ms/epoch - 305ms/step

```

```

Test accuracy: 0.8148148059844971

```

```

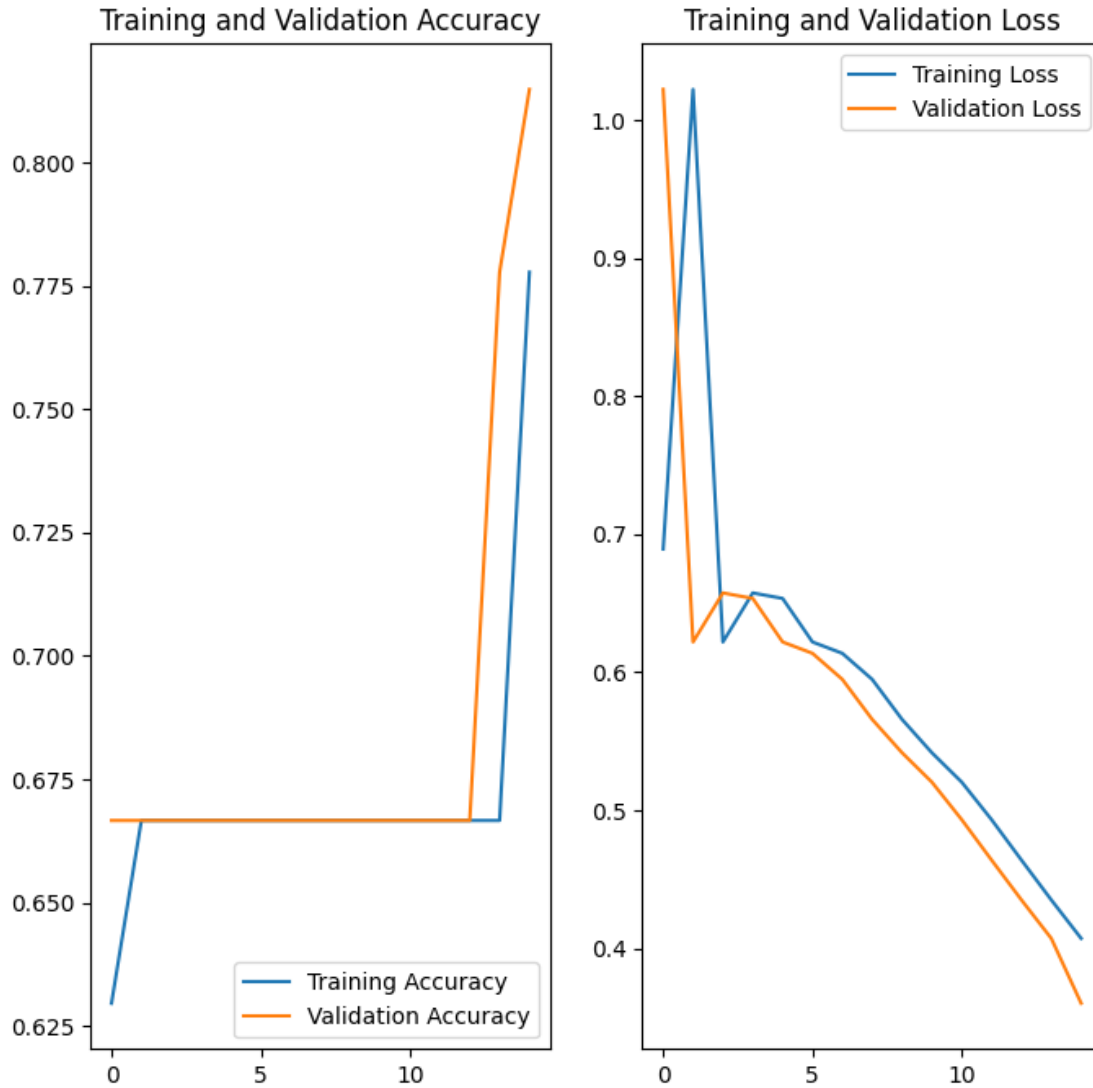
[48]: # Plot training and validation accuracy and loss
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']
loss = history.history['loss']
val_loss = history.history['val_loss']
epochs_range = range(15)

plt.figure(figsize=(8, 8))
plt.subplot(1, 2, 1)
plt.plot(epochs_range, acc, label='Training Accuracy')
plt.plot(epochs_range, val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')

```

```
plt.title('Training and Validation Accuracy')

plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss, label='Training Loss')
plt.plot(epochs_range, val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
```



```
[49]: model.save('my_cnn_model.h5')
```

```
[50]: # Load the saved model
model = tf.keras.models.load_model('my_cnn_model.h5')
```

```
[51]: # Function to make a prediction on new images
def predict_images(images, model, class_indices):
    predictions = model.predict(images)
    predicted_classes = [class_indices[np.argmax(prediction)] for prediction in
↪ predictions]
    return predicted_classes
```

```
[52]: # Making predictions on test set
test_generator.reset()
pred = model.predict(test_generator, steps=test_generator.samples // batch_size
↪ + 1, verbose=1)
```

1/1 [=====] - 0s 333ms/step

```
[53]: # Get the predicted class indices
predicted_class_indices = np.argmax(pred, axis=1)
```

```
[54]: # Get the class labels
labels = (train_generator.class_indices)
labels = dict((v,k) for k,v in labels.items())
predicted_labels = [labels[k] for k in predicted_class_indices]
```

```
[55]: # Display the images with predicted and actual labels
plt.figure(figsize=(20, 20))
for i in range(10): # Display first 10 images
    plt.subplot(5, 5, i + 1)
    plt.xticks([])
    plt.yticks([])
    plt.grid(False)
    plt.imshow(test_generator[0][0][i])
    actual_class = labels[np.argmax(test_generator[0][1][i])]
    predicted_class = predicted_labels[i]
    plt.xlabel(f'Actual: {actual_class}\nPredicted: {predicted_class}')
plt.show()
```



