Two Models (Extra Work)

December 16, 2023

```
[1]: import os
     import keras
     from keras import layers
     import numpy as np
     import matplotlib.pyplot as plt
     # If you need ops from TensorFlow, import it like this:
     from tensorflow.python.ops import math_ops # You can adjust the path based on_
      →your TensorFlow version
     import numpy as np
     import pandas as pd
     import tensorflow as tf
     import tensorflow.keras.layers as L
     import tensorflow_addons as tfa
     import glob, random, os, warnings
     import matplotlib.pyplot as plt
     from sklearn.metrics import confusion_matrix, classification_report
     import seaborn as sns
```

C:\Users\nehag\anaconda3\lib\sitepackages\tensorflow_addons\utils\tfa_eol_msg.py:23: UserWarning:

TensorFlow Addons (TFA) has ended development and introduction of new features. TFA has entered a minimal maintenance and release mode until a planned end of life in May 2024.

Please modify downstream libraries to take dependencies from other repositories in our TensorFlow community (e.g. Keras, Keras-CV, and Keras-NLP).

For more information see: https://github.com/tensorflow/addons/issues/2807

```
warnings.warn(
C:\Users\nehag\anaconda3\lib\site-
packages\tensorflow_addons\utils\ensure_tf_install.py:53: UserWarning:
Tensorflow Addons supports using Python ops for all Tensorflow versions above or
equal to 2.12.0 and strictly below 2.15.0 (nightly versions are not supported).
The versions of TensorFlow you are currently using is 2.10.0 and is not
supported.
```

```
Some things might work, some things might not.

If you were to encounter a bug, do not file an issue.

If you want to make sure you're using a tested and supported configuration, either change the TensorFlow version or the TensorFlow Addons's version.

You can find the compatibility matrix in TensorFlow Addon's readme: https://github.com/tensorflow/addons warnings.warn(

import os import cv2 import numpy as no
```

```
[3]: import os
     import numpy as np
     import re
     def load_images_from_folder(folder):
         images = []
         labels = []
         for filename in os.listdir(folder):
             img_path = os.path.join(folder, filename)
             if os.path.isfile(img_path):
                 img = cv2.imread(img_path)
                 if img is not None:
                     images.append(img)
                     # Extract the label from the filename using a regular expression
                     match = re.search(r'\d{4}-\d{2}-\d{2}', filename)
                     if match:
                         label = match.group(0)
                         labels.append(label)
         return np.array(images), np.array(labels)
     # Replace 'YourDatasetFolder' with the actual path to your dataset folder
     dataset_folder = 'images'
     x_train, y_train = load_images_from_folder(dataset_folder)
     # Print the size of the loaded data
     print("Size of X_train:", len(x_train))
     print("Size of y_train:", len(y_train))
```

Size of X_train: 744 Size of y_train: 744

C:\Users\nehag\AppData\Local\Temp\ipykernel_3824\3386135084.py:20:
VisibleDeprecationWarning: Creating an ndarray from ragged nested sequences
(which is a list-or-tuple of lists-or-tuples-or ndarrays with different lengths
or shapes) is deprecated. If you meant to do this, you must specify
'dtype=object' when creating the ndarray.

return np.array(images), np.array(labels)

```
[4]: def data_augment(image):
        p_spatial = tf.random.uniform([], 0, 1.0, dtype = tf.float32)
        p_rotate = tf.random.uniform([], 0, 1.0, dtype = tf.float32)
        image = tf.image.random_flip_left_right(image)
        image = tf.image.random_flip_up_down(image)
        if p_spatial > .75:
            image = tf.image.transpose(image)
        # Rotates
        if p rotate > .75:
            image = tf.image.rot90(image, k = 3) # rotate 270°
        elif p_rotate > .5:
            image = tf.image.rot90(image, k = 2) # rotate 1800
        elif p_rotate > .25:
            image = tf.image.rot90(image, k = 1) # rotate 90°
        return image
[5]: from sklearn.model_selection import train_test_split
    from sklearn.preprocessing import LabelEncoder
    # Convert date labels to numerical values
    label encoder = LabelEncoder()
    y_train_encoded = label_encoder.fit_transform(y_train)
     # Split the data into training and testing sets
    X_train, X_test, y_train_encoded, y_test_encoded = train_test_split(x_train, u
      # Print the shapes of training and testing sets
    print("Shape of X train:", X train.shape)
    print("Shape of X_test:", X_test.shape)
    print("Shape of y_train:", y_train_encoded.shape)
    print("Shape of y_test:", y_test_encoded.shape)
    Shape of X_train: (595,)
    Shape of X_test: (149,)
    Shape of y_train: (595,)
    Shape of y_test: (149,)
[6]: import numpy as np
     # Print the size and shape of X_train
    print("Size of X_train:", X_train.shape)
```

```
# Print the unique labels in y_train
     print("Unique labels in y_train:", np.unique(y_train))
     # Print the number of unique labels in y train
     print("Number of unique labels in y_train:", len(np.unique(y_train)))
    Size of X_train: (595,)
    Unique labels in y_train: ['2020-01-01' '2020-01-02' '2020-01-03' '2020-01-04'
    '2020-01-05'
     '2020-01-06' '2020-01-07' '2020-01-08' '2020-01-09' '2020-01-10'
     '2020-01-11' '2020-01-12' '2020-01-13' '2020-01-14' '2020-01-15'
     '2020-01-16' '2020-01-17' '2020-01-18' '2020-01-19' '2020-01-20'
     '2020-01-21' '2020-01-22' '2020-01-23' '2020-01-24' '2020-01-25'
     '2020-01-26' '2020-01-27' '2020-01-28' '2020-01-29' '2020-01-30'
     '2020-01-31']
    Number of unique labels in y_train: 31
[7]: from sklearn.preprocessing import LabelEncoder
     # Convert date strings to numeric labels
     label_encoder = LabelEncoder()
     y train encoded = label encoder.fit transform(y train encoded)
     # Print the unique encoded labels in y_train
     print("Unique encoded labels in y_train:", np.unique(y_train_encoded))
     # Print the number of unique encoded labels in y_train
     print("Number of unique encoded labels in y_train:", len(np.

unique(y_train_encoded)))
    Unique encoded labels in y_train: [ 0 1 2 3 4 5 6 7 8 9 10 11 12 13 14
    15 16 17 18 19 20 21 22 23
     24 25 26 27 28 29 30]
    Number of unique encoded labels in y_train: 31
[8]: import cv2
     # Resize images to (224, 224, 3)
     X_train_resized = [cv2.resize(img, (224, 224)) for img in X_train]
     # Convert the list to a NumPy array
     X_train_resized = np.array(X_train_resized)
     # Verify the new shape
     print("New shape of X_train:", X_train_resized.shape)
    New shape of X_train: (595, 224, 224, 3)
```

```
[9]: import cv2
      # Resize images to (224, 224, 3)
      X_test_resized = [cv2.resize(img, (224, 224)) for img in X_test]
      # Convert the list to a NumPy array
      X_test_resized = np.array(X_test_resized)
      # Verify the new shape
      print("New shape of X_train:", X_test_resized.shape)
     New shape of X_train: (149, 224, 224, 3)
[10]: print(f"x_train_shape: {X_train_resized.shape} - y_train_shape:__
       →{y_train_encoded.shape}")
      print(f"x test shape: {X_test_resized.shape} - y_test_shape: {y_test_encoded.
       ⇔shape}")
     x_train shape: (595, 224, 224, 3) - y_train shape: (595,)
     x_test shape: (149, 224, 224, 3) - y_test shape: (149,)
[11]: import numpy as np
      import pandas as pd
      # Assuming you have an array of image IDs
      image_ids = y_train_encoded
      # Reshape the 4D array into a 2D array
      reshaped_array = X_train_resized.reshape(X_train_resized.shape[0], -1)
      # Create a DataFrame with the reshaped array
      df = pd.DataFrame(reshaped_array, columns=[f'pixel_{i}' for i in_
       →range(reshaped_array.shape[1])])
      # Add image IDs to the DataFrame
      df['image_id'] = image_ids
[12]: x_train=X_train_resized
      x_test=X_test_resized
      y_train=y_train_encoded
      y_test=y_test_encoded
[13]: import keras
      import tensorflow as tf
      import tensorflow.keras
      from tensorflow.keras.models import Sequential
```

```
from tensorflow.keras.layers import Dense, Activation, Dropout, Flatten, Gonv2D, MaxPooling2D

from tensorflow.keras.layers import Input, Add, Dense, Activation, MaxPooling2D, BatchNormalization, Flatten, Conv2D, AveragePooling2D, MaxPooling2D, GlobalMaxPooling2D, MaxPool2D

from tensorflow.keras.initializers import glorot_uniform

from tensorflow.keras import layers

from tensorflow.keras.models import Model, load_model

from tensorflow.keras.preprocessing import image

from keras.callbacks import ReduceLROnPlateau
```

1 Implementation of the AlexNet architecture

```
[14]: model = Sequential()
      # 1st Convolutional Layer
      model.add(Conv2D(filters = 96, input_shape = (224, 224, 3),
                  kernel_size = (11, 11), strides = (4, 4),
                  padding = 'valid'))
      model.add(Activation('relu'))
      # Max-Pooling
      model.add(MaxPooling2D(pool_size = (3, 3),
                  strides = (2, 2), padding = 'valid'))
      # Batch Normalisation
      model.add(BatchNormalization())
      # 2nd Convolutional Layer
      model.add(Conv2D(filters = 256, kernel_size = (5, 5),
                  strides = (1, 1), padding = 'same'))
      model.add(Activation('relu'))
      # Max-Pooling
      model.add(MaxPooling2D(pool_size = (2, 2), strides = (2, 2),
                  padding = 'valid'))
      # Batch Normalisation
      model.add(BatchNormalization())
      # 3rd Convolutional Layer
      model.add(Conv2D(filters = 384, kernel_size = (3, 3),
                  strides = (1, 1), padding = 'same'))
      model.add(Activation('relu'))
      # Batch Normalisation
      model.add(BatchNormalization())
      # 4th Convolutional Layer
      model.add(Conv2D(filters = 384, kernel_size = (3, 3),
                  strides = (1, 1), padding = 'same'))
```

```
model.add(Activation('relu'))
      # Batch Normalisation
      model.add(BatchNormalization())
      # 5th Convolutional Layer
      model.add(Conv2D(filters = 256, kernel_size = (3, 3),
                  strides = (1, 1), padding = 'same'))
      model.add(Activation('relu'))
      # Max-Pooling
      model.add(MaxPooling2D(pool_size = (2, 2), strides = (2, 2),
                  padding = 'valid'))
      # Batch Normalisation
      model.add(BatchNormalization())
      model.add(Dropout(0.5))
      # Flattening
      model.add(Flatten())
      # 1st Dense Layer
      model.add(Dense(4096, input_shape = (227*227*3, )))
      model.add(Activation('relu'))
      # Add Dropout to prevent overfitting
      model.add(Dropout(0.5))
      # Batch Normalisation
      model.add(BatchNormalization())
      # 2nd Dense Layer
      model.add(Dense(4096))
      model.add(Activation('relu'))
      # Add Dropout
      model.add(Dropout(0.5))
      # Batch Normalisation
      model.add(BatchNormalization())
      # Output Softmax Layer
      model.add(Dense(31))
      model.add(Activation('softmax'))
[15]: model.compile(
          loss='sparse_categorical_crossentropy',
          optimizer=tf.optimizers.Adam(learning_rate=0.001),
          metrics=['accuracy']
      model.summary()
     Model: "sequential"
      Layer (type)
                                 Output Shape
                                                            Param #
```

| conv2d (Conv2D) | (None, 54, 54, 96) | 34944 |
|--|---|-------------------------------------|
| activation (Activation) | (None, 54, 54, 96) | 0 |
| <pre>max_pooling2d (MaxPooling2D)</pre> | (None, 26, 26, 96) | 0 |
| <pre>batch_normalization (BatchN ormalization)</pre> | (None, 26, 26, 96) | 384 |
| conv2d_1 (Conv2D) | (None, 26, 26, 256) | 614656 |
| <pre>activation_1 (Activation)</pre> | (None, 26, 26, 256) | 0 |
| <pre>max_pooling2d_1 (MaxPooling 2D)</pre> | (None, 13, 13, 256) | 0 |
| <pre>batch_normalization_1 (Batc hNormalization)</pre> | (None, 13, 13, 256) | 1024 |
| conv2d_2 (Conv2D) | (None, 13, 13, 384) | 885120 |
| activation_2 (Activation) | (None, 13, 13, 384) | 0 |
| | | |
| <pre>batch_normalization_2 (Batc hNormalization)</pre> | (None, 13, 13, 384) | 1536 |
| | (None, 13, 13, 384) (None, 13, 13, 384) | 1536 1327488 |
| hNormalization) | (None, 13, 13, 384) | |
| hNormalization) conv2d_3 (Conv2D) | (None, 13, 13, 384) (None, 13, 13, 384) | 1327488 |
| hNormalization) conv2d_3 (Conv2D) activation_3 (Activation) batch_normalization_3 (Batc | (None, 13, 13, 384) (None, 13, 13, 384) | 1327488 |
| hNormalization) conv2d_3 (Conv2D) activation_3 (Activation) batch_normalization_3 (BatchNormalization) | (None, 13, 13, 384) (None, 13, 13, 384) (None, 13, 13, 384) (None, 13, 13, 256) | 1327488 0 1536 |
| hNormalization) conv2d_3 (Conv2D) activation_3 (Activation) batch_normalization_3 (BatchNormalization) conv2d_4 (Conv2D) | (None, 13, 13, 384) (None, 13, 13, 384) (None, 13, 13, 384) (None, 13, 13, 256) (None, 13, 13, 256) | 1327488 0 1536 884992 |
| hNormalization) conv2d_3 (Conv2D) activation_3 (Activation) batch_normalization_3 (BatchNormalization) conv2d_4 (Conv2D) activation_4 (Activation) max_pooling2d_2 (MaxPooling) | (None, 13, 13, 384) (None, 13, 13, 384) (None, 13, 13, 384) (None, 13, 13, 256) (None, 13, 13, 256) (None, 6, 6, 256) | 1327488 0 1536 884992 |
| hNormalization) conv2d_3 (Conv2D) activation_3 (Activation) batch_normalization_3 (BatchNormalization) conv2d_4 (Conv2D) activation_4 (Activation) max_pooling2d_2 (MaxPooling 2D) batch_normalization_4 (Batch | (None, 13, 13, 384) (None, 13, 13, 384) (None, 13, 13, 384) (None, 13, 13, 256) (None, 13, 13, 256) (None, 6, 6, 256) | 1327488 0 1536 884992 0 |

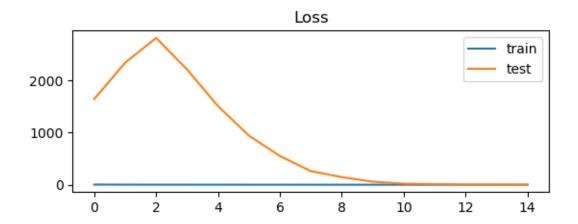
```
(None, 4096)
      dense (Dense)
                                                         37752832
      activation_5 (Activation)
                                (None, 4096)
      dropout_1 (Dropout)
                                (None, 4096)
                                                         0
      batch normalization 5 (Batc (None, 4096)
                                                         16384
      hNormalization)
      dense_1 (Dense)
                                (None, 4096)
                                                         16781312
      activation_6 (Activation)
                                (None, 4096)
                                                         0
      dropout_2 (Dropout)
                                (None, 4096)
      batch_normalization_6 (Batc (None, 4096)
                                                         16384
      hNormalization)
      dense_2 (Dense)
                                (None, 31)
                                                         127007
      activation_7 (Activation)
                                (None, 31)
     ______
     Total params: 58,446,623
     Trainable params: 58,427,487
     Non-trainable params: 19,136
[16]: print(x_train.shape)
     print(x_test.shape)
     print(y_train.shape)
     print(y_test.shape)
     (595, 224, 224, 3)
     (149, 224, 224, 3)
     (595,)
     (149,)
[17]: from tensorflow.keras.callbacks import ReduceLROnPlateau
     rlp = ReduceLROnPlateau(factor=0.5, patience=3) # Adjust parameters as needed
     history = model.fit(
         x_train, y_train,
         epochs=15,
         callbacks=[rlp],
         validation_split=0.10
```

Epoch 1/15

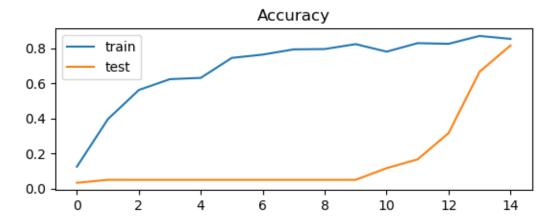
```
0.1252 - val_loss: 1642.8438 - val_accuracy: 0.0333 - lr: 0.0010
  Epoch 2/15
  0.3963 - val_loss: 2340.1904 - val_accuracy: 0.0500 - lr: 0.0010
  Epoch 3/15
  0.5626 - val_loss: 2814.7026 - val_accuracy: 0.0500 - lr: 0.0010
  Epoch 4/15
  0.6243 - val_loss: 2210.3086 - val_accuracy: 0.0500 - lr: 0.0010
  0.6318 - val_loss: 1507.5922 - val_accuracy: 0.0500 - lr: 5.0000e-04
  0.7458 - val_loss: 942.3228 - val_accuracy: 0.0500 - lr: 5.0000e-04
  Epoch 7/15
  0.7645 - val_loss: 551.7170 - val_accuracy: 0.0500 - lr: 5.0000e-04
  0.7944 - val_loss: 261.7301 - val_accuracy: 0.0500 - lr: 5.0000e-04
  Epoch 9/15
  0.7963 - val loss: 146.6189 - val accuracy: 0.0500 - lr: 5.0000e-04
  Epoch 10/15
  0.8243 - val_loss: 58.5519 - val_accuracy: 0.0500 - lr: 5.0000e-04
  Epoch 11/15
  0.7813 - val_loss: 20.5472 - val_accuracy: 0.1167 - lr: 5.0000e-04
  Epoch 12/15
  0.8299 - val_loss: 12.6105 - val_accuracy: 0.1667 - lr: 5.0000e-04
  Epoch 13/15
  0.8262 - val_loss: 2.5669 - val_accuracy: 0.3167 - lr: 5.0000e-04
  Epoch 14/15
  0.8710 - val_loss: 1.2419 - val_accuracy: 0.6667 - lr: 5.0000e-04
  Epoch 15/15
  0.8542 - val_loss: 0.5125 - val_accuracy: 0.8167 - lr: 5.0000e-04
[18]: plt.subplot(211)
  plt.title('Loss')
```

```
plt.plot(history.history['loss'], label='train')
plt.plot(history.history['val_loss']
         , label='test')
plt.legend()
```

[18]: <matplotlib.legend.Legend at 0x2a4c49c4d30>



```
[19]: plt.subplot(212)
    plt.title('Accuracy')
    plt.plot(history.history['accuracy'], label='train')
    plt.plot(history.history['val_accuracy'], label='test')
    plt.legend()
    plt.show()
```



```
[20]: x_test.shape
```

```
[20]: (149, 224, 224, 3)
[21]: y_test.shape
[21]: (149,)
[22]: import tensorflow as tf
     from sklearn.metrics import classification report, confusion matrix
     import numpy as np
     # Assuming you have your model defined, data loaded (x test, y test), and model
      \hookrightarrow trained
     # Evaluate the model on the test set
     test_loss, test_accuracy = model.evaluate(x_test, y_test)
     print(f'Test Loss: {test_loss:.4f}')
     print(f'Test Accuracy: {test_accuracy:.4f}')
     # Make predictions on the test set
     y_pred_probs = model.predict(x_test)
     y_pred = np.argmax(y_pred_probs, axis=1)
     # Convert true labels to class indices if needed
     y_true = np.argmax(y_test, axis=1) if len(y_test.shape) > 1 else y_test
     # Print classification report
     print("Classification Report:")
     print(classification_report(y_true, y_pred))
     # Calculate and print confusion matrix
     conf_mat = confusion_matrix(y_true, y_pred)
     print("Confusion Matrix:")
     print(conf_mat)
     0.8523
     Test Loss: 0.3943
     Test Accuracy: 0.8523
     5/5 [=======] - 3s 378ms/step
     Classification Report:
                  precision recall f1-score
                                                support
               0
                      1.00
                                1.00
                                         1.00
                                                      3
                                                      5
               1
                      1.00
                                1.00
                                         1.00
                      1.00
                                0.75
                                         0.86
                                                      8
               3
                      0.82
                               1.00
                                         0.90
                                                      9
               4
                      0.80
                                1.00
                                         0.89
                                                      4
               5
                      1.00
                                0.67
                                         0.80
                                                      3
```

| | 6 | 1.00 | 0.60 | 0.75 | 5 |
|----------|------|------|------|------|-----|
| | 7 | 0.40 | 1.00 | 0.57 | 2 |
| | 8 | 1.00 | 0.62 | 0.77 | 8 |
| | 9 | 0.67 | 1.00 | 0.80 | 4 |
| | 10 | 0.86 | 1.00 | 0.92 | 6 |
| | 11 | 1.00 | 0.50 | 0.67 | 2 |
| | 12 | 1.00 | 1.00 | 1.00 | 5 |
| | 13 | 1.00 | 0.71 | 0.83 | 7 |
| | 14 | 0.00 | 0.00 | 0.00 | 4 |
| | 15 | 0.50 | 0.71 | 0.59 | 7 |
| | 16 | 0.67 | 1.00 | 0.80 | 6 |
| | 17 | 1.00 | 1.00 | 1.00 | 9 |
| | 18 | 0.86 | 1.00 | 0.92 | 6 |
| | 19 | 1.00 | 0.50 | 0.67 | 2 |
| | 20 | 1.00 | 0.75 | 0.86 | 4 |
| | 21 | 0.80 | 1.00 | 0.89 | 4 |
| | 22 | 0.80 | 1.00 | 0.89 | 4 |
| | 23 | 1.00 | 0.67 | 0.80 | 3 |
| | 24 | 1.00 | 0.60 | 0.75 | 5 |
| | 25 | 0.75 | 1.00 | 0.86 | 6 |
| | 26 | 1.00 | 1.00 | 1.00 | 3 |
| | 27 | 1.00 | 1.00 | 1.00 | 3 |
| | 28 | 1.00 | 1.00 | 1.00 | 4 |
| | 29 | 1.00 | 1.00 | 1.00 | 3 |
| | 30 | 1.00 | 1.00 | 1.00 | 5 |
| accur | racy | | | 0.85 | 149 |
| macro | v | 0.87 | 0.84 | | 149 |
| weighted | _ | 0.87 | 0.85 | | 149 |
| | | | | | |

Confusion Matrix:

```
C:\Users\nehag\anaconda3\lib\site-
packages\sklearn\metrics\ classification.py:1471: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
 _warn_prf(average, modifier, msg_start, len(result))
C:\Users\nehag\anaconda3\lib\site-
packages\sklearn\metrics\_classification.py:1471: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
 warn prf(average, modifier, msg start, len(result))
C:\Users\nehag\anaconda3\lib\site-
packages\sklearn\metrics\ classification.py:1471: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
```

_warn_prf(average, modifier, msg_start, len(result))

```
# Convert true labels to class indices if needed
y_true = np.argmax(y_test, axis=1) if len(y_test.shape) > 1 else y_test
# Print classification report
print("Classification Report:")
print(classification_report(y_true, y_pred))
# Calculate and print confusion matrix
conf_mat = confusion_matrix(y_true, y_pred)
print("Confusion Matrix:")
print(conf_mat)
# Extract precision, recall, and F1-score from the classification report
precision = classification_report(y_true, y_pred, output_dict=True)['weighted_|
 →avg']['precision']
recall = classification_report(y_true, y_pred, output_dict=True)['weightedu
 →avg']['recall']
f1_score = classification_report(y_true, y_pred, output_dict=True)['weighted_\_
 →avg']['f1-score']
# Calculate accuracy and sensibility
accuracy = np.sum(y true == y pred) / len(y true)
sensibility = recall # Sensibility is the same as recall in binary_
 \hookrightarrow classification
# Print accuracy, sensibility, precision, recall, and F1-score
print(f'Accuracy: {accuracy:.4f}')
print(f'Sensibility: {sensibility:.4f}')
print(f'Precision: {precision:.4f}')
print(f'Recall: {recall:.4f}')
print(f'F1 Score: {f1_score:.4f}')
0.8523
Test Loss: 0.3943
Test Accuracy: 0.8523
5/5 [======== ] - 2s 388ms/step
Classification Report:
             precision recall f1-score
                                           support
          0
                  1.00
                           1.00
                                     1.00
                                                 3
          1
                 1.00
                           1.00
                                     1.00
                                                 5
          2
                  1.00
                           0.75
                                     0.86
                                                 8
          3
                 0.82
                          1.00
                                     0.90
                                                 9
          4
                 0.80
                           1.00
                                     0.89
                                                 4
          5
                 1.00
                           0.67
                                     0.80
```

| | 6 | 1.00 | 0.60 | 0.75 | 5 |
|----------|------|------|------|------|-----|
| | 7 | 0.40 | 1.00 | 0.57 | 2 |
| | 8 | 1.00 | 0.62 | 0.77 | 8 |
| | 9 | 0.67 | 1.00 | 0.80 | 4 |
| | 10 | 0.86 | 1.00 | 0.92 | 6 |
| | 11 | 1.00 | 0.50 | 0.67 | 2 |
| | 12 | 1.00 | 1.00 | 1.00 | 5 |
| | 13 | 1.00 | 0.71 | 0.83 | 7 |
| | 14 | 0.00 | 0.00 | 0.00 | 4 |
| | 15 | 0.50 | 0.71 | 0.59 | 7 |
| | 16 | 0.67 | 1.00 | 0.80 | 6 |
| | 17 | 1.00 | 1.00 | 1.00 | 9 |
| | 18 | 0.86 | 1.00 | 0.92 | 6 |
| | 19 | 1.00 | 0.50 | 0.67 | 2 |
| | 20 | 1.00 | 0.75 | 0.86 | 4 |
| | 21 | 0.80 | 1.00 | 0.89 | 4 |
| | 22 | 0.80 | 1.00 | 0.89 | 4 |
| | 23 | 1.00 | 0.67 | 0.80 | 3 |
| | 24 | 1.00 | 0.60 | 0.75 | 5 |
| | 25 | 0.75 | 1.00 | 0.86 | 6 |
| | 26 | 1.00 | 1.00 | 1.00 | 3 |
| | 27 | 1.00 | 1.00 | 1.00 | 3 |
| | 28 | 1.00 | 1.00 | 1.00 | 4 |
| | 29 | 1.00 | 1.00 | 1.00 | 3 |
| | 30 | 1.00 | 1.00 | 1.00 | 5 |
| accur | racy | | | 0.85 | 149 |
| macro | v | 0.87 | 0.84 | | 149 |
| weighted | _ | 0.87 | 0.85 | | 149 |
| | | | | | |

Confusion Matrix:

```
Accuracy: 0.8523
Sensibility: 0.8523
Precision: 0.8706
Recall: 0.8523
F1 Score: 0.8422
C:\Users\nehag\anaconda3\lib\site-
packages\sklearn\metrics\_classification.py:1471: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
 warn prf(average, modifier, msg start, len(result))
C:\Users\nehag\anaconda3\lib\site-
packages\sklearn\metrics\_classification.py:1471: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero division` parameter to control this behavior.
 _warn_prf(average, modifier, msg_start, len(result))
C:\Users\nehag\anaconda3\lib\site-
packages\sklearn\metrics\ classification.py:1471: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
 _warn_prf(average, modifier, msg_start, len(result))
C:\Users\nehag\anaconda3\lib\site-
packages\sklearn\metrics\_classification.py:1471: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
 warn prf(average, modifier, msg start, len(result))
C:\Users\nehag\anaconda3\lib\site-
packages\sklearn\metrics\_classification.py:1471: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
 _warn_prf(average, modifier, msg_start, len(result))
C:\Users\nehag\anaconda3\lib\site-
packages\sklearn\metrics\_classification.py:1471: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
```

```
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\nehag\anaconda3\lib\site-
packages\sklearn\metrics\_classification.py:1471: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  warn prf(average, modifier, msg start, len(result))
C:\Users\nehag\anaconda3\lib\site-
packages\sklearn\metrics\_classification.py:1471: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\nehag\anaconda3\lib\site-
packages\sklearn\metrics\_classification.py:1471: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\nehag\anaconda3\lib\site-
packages\sklearn\metrics\_classification.py:1471: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\nehag\anaconda3\lib\site-
packages\sklearn\metrics\_classification.py:1471: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\nehag\anaconda3\lib\site-
packages\sklearn\metrics\_classification.py:1471: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

2 InceptionV3 models

```
[26]: print(x_train.shape)
    print(x_test.shape)
    print(y_train.shape)
    print(y_test.shape)

    (595, 224, 224, 3)
    (149, 224, 224, 3)
    (595,)
    (149,)
[34]: import time
    from tensorflow.keras.models import Model
```

```
from tensorflow.keras.layers import Input, Dense, Flatten, _
 →GlobalAveragePooling2D
from tensorflow.keras.applications.inception_v3 import InceptionV3, __
→preprocess_input
from tensorflow.keras.optimizers import SGD
# Load the InceptionV3 model without the top layers
base_model = InceptionV3(weights='imagenet', include_top=False)
# Add new layers on top of the base model
x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dense(1024, activation='relu')(x)
x = Dense(512, activation='relu')(x)
x = Flatten(name='flatten')(x) # Rename the flatten layer with input shape_
\hookrightarrow specified
predictions = Dense(31, activation='softmax')(x)
# Define the new model
inceptionv3_model = Model(inputs=base_model.input, outputs=predictions)
# Freeze the layers in the base model
for layer in base model.layers:
    layer.trainable = False
# Compile the model with a learning rate and optimizer
opt = SGD(1r=0.001, momentum=0.9)
# Train the model with specified number of epochs, batch size, and validation
 \hookrightarrowsplit
#epochs = 15
batch_size = 32
validation_split = 0.2
start time = time.time()
inceptionv3_history = inceptionv3_model.compile(
    loss='sparse categorical crossentropy',
    optimizer=tf.optimizers.Adam(learning_rate=0.001),
    metrics=['accuracy']
model.summary()
```

```
Model: "sequential"
```

| activation (Activation) | (None, 54, 54, 96) | 0 |
|--|---------------------|----------|
| <pre>max_pooling2d (MaxPooling2D)</pre> | (None, 26, 26, 96) | 0 |
| <pre>batch_normalization (BatchN ormalization)</pre> | (None, 26, 26, 96) | 384 |
| conv2d_1 (Conv2D) | (None, 26, 26, 256) | 614656 |
| activation_1 (Activation) | (None, 26, 26, 256) | 0 |
| <pre>max_pooling2d_1 (MaxPooling 2D)</pre> | (None, 13, 13, 256) | 0 |
| <pre>batch_normalization_1 (Batc hNormalization)</pre> | (None, 13, 13, 256) | 1024 |
| conv2d_2 (Conv2D) | (None, 13, 13, 384) | 885120 |
| activation_2 (Activation) | (None, 13, 13, 384) | 0 |
| <pre>batch_normalization_2 (Batc hNormalization)</pre> | (None, 13, 13, 384) | 1536 |
| conv2d_3 (Conv2D) | (None, 13, 13, 384) | 1327488 |
| activation_3 (Activation) | (None, 13, 13, 384) | 0 |
| <pre>batch_normalization_3 (Batc hNormalization)</pre> | (None, 13, 13, 384) | 1536 |
| conv2d_4 (Conv2D) | (None, 13, 13, 256) | 884992 |
| activation_4 (Activation) | (None, 13, 13, 256) | 0 |
| <pre>max_pooling2d_2 (MaxPooling 2D)</pre> | (None, 6, 6, 256) | 0 |
| <pre>batch_normalization_4 (Batc hNormalization)</pre> | (None, 6, 6, 256) | 1024 |
| dropout (Dropout) | (None, 6, 6, 256) | 0 |
| flatten (Flatten) | (None, 9216) | 0 |
| dense (Dense) | (None, 4096) | 37752832 |

```
activation_5 (Activation) (None, 4096)
    dropout_1 (Dropout)
                       (None, 4096)
    batch_normalization_5 (Batc (None, 4096)
                                           16384
    hNormalization)
    dense_1 (Dense)
                 (None, 4096)
                                           16781312
    activation_6 (Activation) (None, 4096)
    dropout_2 (Dropout)
                        (None, 4096)
    batch_normalization_6 (Batc (None, 4096)
                                           16384
    hNormalization)
    dense_2 (Dense)
                        (None, 31)
                                           127007
    activation_7 (Activation)
                                           0
                        (None, 31)
   Total params: 58,446,623
   Trainable params: 58,427,487
   Non-trainable params: 19,136
   -----
[35]: from tensorflow.keras.callbacks import ReduceLROnPlateau
    rlp = ReduceLROnPlateau(factor=0.5, patience=3) # Adjust parameters as needed
    history = model.fit(
       x_train, y_train,
       epochs=15,
       callbacks=[rlp],
       validation_split=0.10
    )
   Epoch 1/15
   0.8486 - val_loss: 0.9378 - val_accuracy: 0.7833 - lr: 5.0000e-04
   Epoch 2/15
   0.8636 - val_loss: 0.7117 - val_accuracy: 0.8000 - lr: 5.0000e-04
   Epoch 3/15
   0.8411 - val_loss: 3.4740 - val_accuracy: 0.4167 - lr: 5.0000e-04
   Epoch 4/15
   0.8467 - val_loss: 10.7585 - val_accuracy: 0.1667 - lr: 5.0000e-04
```

```
0.8336 - val_loss: 20.0754 - val_accuracy: 0.1167 - lr: 5.0000e-04
   0.8598 - val_loss: 11.9999 - val_accuracy: 0.1500 - lr: 2.5000e-04
   Epoch 7/15
   0.8897 - val_loss: 3.4485 - val_accuracy: 0.4000 - lr: 2.5000e-04
   Epoch 8/15
   0.8860 - val_loss: 0.5659 - val_accuracy: 0.8667 - lr: 2.5000e-04
   Epoch 9/15
   0.9009 - val_loss: 0.4898 - val_accuracy: 0.9167 - lr: 2.5000e-04
   Epoch 10/15
   0.9065 - val_loss: 0.4284 - val_accuracy: 0.8333 - 1r: 2.5000e-04
   Epoch 11/15
   0.8935 - val_loss: 0.6951 - val_accuracy: 0.8000 - lr: 2.5000e-04
   Epoch 12/15
   0.8991 - val_loss: 0.6130 - val_accuracy: 0.8333 - lr: 2.5000e-04
   Epoch 13/15
   0.9028 - val_loss: 1.0599 - val_accuracy: 0.7667 - lr: 2.5000e-04
   Epoch 14/15
   0.9234 - val_loss: 0.3587 - val_accuracy: 0.8833 - lr: 1.2500e-04
   Epoch 15/15
   0.9047 - val_loss: 0.3510 - val_accuracy: 0.8667 - lr: 1.2500e-04
[36]: import os
   import matplotlib.pyplot as plt
   import tensorflow as tf
   from sklearn.metrics import accuracy_score, precision_score, recall_score,

¬f1_score, classification_report, confusion_matrix
   import numpy as np
   # Assuming you have your model defined, data loaded (x_{test}, y_{test}), and model
    \hookrightarrow trained
   # Evaluate the model on the test set
   test_loss, test_accuracy = model.evaluate(x_test, y_test)
   print(f'Test Loss: {test_loss:.4f}')
```

Epoch 5/15

```
print(f'Test Accuracy: {test_accuracy:.4f}')
# Make predictions on the test set
y_pred_probs = model.predict(x_test)
y_pred = np.argmax(y_pred_probs, axis=1)
# Convert true labels to class indices if needed
y_true = np.argmax(y_test, axis=1) if len(y_test.shape) > 1 else y_test
# Print classification report
print("Classification Report:")
print(classification_report(y_true, y_pred))
# Calculate and print confusion matrix
conf_mat = confusion_matrix(y_true, y_pred)
print("Confusion Matrix:")
print(conf_mat)
# Extract precision, recall, and F1-score from the classification report
precision = classification_report(y_true, y_pred, output_dict=True)['weightedu
 →avg']['precision']
recall = classification_report(y_true, y_pred, output_dict=True)['weightedu
 →avg']['recall']
f1_score = classification_report(y_true, y_pred, output_dict=True)['weightedu
 →avg']['f1-score']
# Calculate accuracy and sensibility
accuracy = accuracy_score(y_true, y_pred)
sensibility = recall # Sensibility is the same as recall in binary_
 \hookrightarrow classification
# Print accuracy, sensibility, precision, recall, and F1-score
print(f'Accuracy: {accuracy:.4f}')
print(f'Sensibility: {sensibility:.4f}')
print(f'Precision: {precision:.4f}')
print(f'Recall: {recall:.4f}')
print(f'F1 Score: {f1_score:.4f}')
0.9060
Test Loss: 0.3288
Test Accuracy: 0.9060
5/5 [=======] - 2s 388ms/step
Classification Report:
             precision recall f1-score
                                           support
          0
                 1.00
                           0.67
                                    0.80
```

| 1 | 0.83 | 1.00 | 0.91 | 5 |
|------|--|---|------|-----|
| 2 | 0.89 | 1.00 | 0.94 | 8 |
| 3 | 1.00 | 0.89 | 0.94 | 9 |
| 4 | 1.00 | 1.00 | 1.00 | 4 |
| 5 | 1.00 | 1.00 | 1.00 | 3 |
| 6 | 1.00 | 1.00 | 1.00 | 5 |
| 7 | 1.00 | 1.00 | 1.00 | 2 |
| 8 | 1.00 | 0.75 | 0.86 | 8 |
| 9 | 0.67 | 1.00 | 0.80 | 4 |
| 10 | 0.86 | 1.00 | 0.92 | 6 |
| 11 | 1.00 | 0.50 | 0.67 | 2 |
| 12 | 1.00 | 1.00 | 1.00 | 5 |
| 13 | 1.00 | 0.86 | 0.92 | 7 |
| 14 | 0.50 | 1.00 | 0.67 | 4 |
| 15 | 1.00 | 0.43 | 0.60 | 7 |
| 16 | 0.86 | 1.00 | 0.92 | 6 |
| 17 | 0.82 | 1.00 | 0.90 | 9 |
| 18 | 0.80 | 0.67 | 0.73 | 6 |
| 19 | 1.00 | 0.50 | 0.67 | 2 |
| 20 | 1.00 | 1.00 | 1.00 | 4 |
| 21 | 1.00 | 1.00 | 1.00 | 4 |
| 22 | 1.00 | 0.75 | 0.86 | 4 |
| 23 | 0.75 | 1.00 | 0.86 | 3 |
| 24 | 1.00 | 1.00 | 1.00 | 5 |
| 25 | 1.00 | 1.00 | 1.00 | 6 |
| 26 | 1.00 | 1.00 | 1.00 | 3 |
| 27 | 1.00 | 1.00 | 1.00 | 3 |
| 28 | 1.00 | 1.00 | 1.00 | 4 |
| 29 | 1.00 | 1.00 | 1.00 | 3 |
| 30 | 1.00 | 1.00 | 1.00 | 5 |
| racv | | | 0.91 | 149 |
| v | 0.93 | 0.90 | | 149 |
| avg | 0.93 | 0.91 | 0.90 | 149 |
| avg | 0.93 | 0.91 | 0.90 | |
| | 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 | 2 0.89 3 1.00 4 1.00 5 1.00 6 1.00 7 1.00 8 1.00 9 0.67 10 0.86 11 1.00 12 1.00 13 1.00 14 0.50 15 1.00 16 0.86 17 0.82 18 0.80 19 1.00 20 1.00 21 1.00 22 1.00 23 0.75 24 1.00 23 0.75 24 1.00 25 1.00 26 1.00 27 1.00 28 1.00 29 1.00 30 1.00 | 2 | 2 |

Confusion Matrix:

Accuracy: 0.9060 Sensibility: 0.9060 Precision: 0.9305 Recall: 0.9060 F1 Score: 0.9029

[]: