```
In []:
```

Prepare libraries, import and check dataset

```
In [6]: import tensorflow as tf
         import tensorflow datasets as tfds
         import matplotlib.pyplot as plt
         import numpy as np
         from tensorflow.keras.optimizers import Adam
         from tensorflow.keras.layers import Dense, Flatten, Conv2D, MaxPooling2D, Dr
         from tensorflow.keras.models import Sequential
         from tensorflow.keras.callbacks import ReduceLROnPlateau
         from tensorflow.keras.callbacks import EarlyStopping
 In [7]: print(tf.__version__)
         print(tfds.__version__)
         2.9.2
         4.6.0
 In [8]: # Specify the directory to download the dataset
         data_dir = './malaria_datasets'
 In [9]:
         # Download the dataset to the specified directory
         builder = tfds.builder('malaria', data_dir=data_dir)
         builder.download and prepare()
In [10]: # Load the dataset
         dataset, info = tfds.load('malaria', data_dir=data_dir, with_info=True, as_s
         full_dataset = dataset['train']
In [11]: # Function to inspect a few samples from the dataset
         def inspect dataset(dataset, num samples=5):
             for image, label in dataset.take(num samples):
                 print("Label: ", label.numpy())
                 print("Image shape: ", image.numpy().shape)
                 print()
```

```
In [12]: # Function to inspect and display a few samples from the dataset
         def display dataset(dataset, num samples=9):
             plt.figure(figsize=(10, 10))
             for i, (image, label) in enumerate(dataset.take(num samples)):
                 ax = plt.subplot(1, num samples, i + 1)
                 plt.imshow(image.numpy().astype("uint8"))
                 plt.title(f"Label: {label.numpy()}")
                 plt.axis("off")
             plt.show()
In [13]: # Print dataset information
         print(info)
         tfds.core.DatasetInfo(
             name='malaria',
             full name='malaria/1.0.0',
             description="""
             The Malaria dataset contains a total of 27,558 cell images
             with equal instances of parasitized and uninfected cells from the thin b
         lood
             smear slide images of segmented cells.
             homepage='https://lhncbc.nlm.nih.gov/publication/pub9932',
             data path='./malaria datasets/malaria/1.0.0',
             file format=tfrecord,
             download size=337.08 MiB,
             dataset size=317.62 MiB,
             features=FeaturesDict({
                  'image': Image(shape=(None, None, 3), dtype=tf.uint8),
                  'label': ClassLabel(shape=(), dtype=tf.int64, num classes=2),
             }),
             supervised keys=('image', 'label'),
             disable shuffling=False,
             splits={
                  'train': <SplitInfo num_examples=27558, num_shards=4>,
             citation=""@article{rajaraman2018pre,
               title={Pre-trained convolutional neural networks as feature extractors
         toward
               improved malaria parasite detection in thin blood smear images },
               author={Rajaraman, Sivaramakrishnan and Antani, Sameer K and Poostchi,
         Mahdieh
               and Silamut, Kamolrat and Hossain, Md A and Maude, Richard J and Jaege
         r,
               Stefan and Thoma, George R},
               journal={PeerJ},
               volume={6},
               pages={e4568},
               year={2018},
               publisher={PeerJ Inc.}
             }""",
         )
```

```
In [14]: # Inspect a few samples from the dataset
         inspect dataset(full dataset)
         Label: 1
         Image shape: (103, 103, 3)
         Label: 1
         Image shape: (106, 121, 3)
         Label: 0
         Image shape: (139, 142, 3)
         Label: 1
         Image shape: (130, 118, 3)
         Label: 1
         Image shape: (121, 109, 3)
In [15]: # Display a few samples from the dataset
         display_dataset(full_dataset)
                                           Label: 1 Label: 0 Label: 1
                                   Label: 1
                                                                     Label: 1
          Label: 1
                          Label: 0
                                                                             Label: 0
                 Label: 1
         Preprocessing dataset
In [16]: # Calculate the number of examples
         num examples = info.splits['train'].num examples
In [17]: | # Define the split sizes
         train size = int(0.7 * num examples)
         val size = int(0.2 * num examples)
         test size = num examples - train size - val size
In [18]: # Shuffle and split the dataset
         full dataset = full dataset.shuffle(num examples)
         train_dataset = full_dataset.take(train_size)
         remaining_dataset = full_dataset.skip(train_size)
         val dataset = remaining dataset.take(val size)
         test dataset = remaining dataset.skip(val size)
In [19]: # Define the image size to uniform size of images
         image size = (130, 130)
```

```
In [20]: # Function to preprocess the images, resize and uniform
def preprocess(image, label):
    image = tf.image.resize(image, image_size)
    image = image / 255.0 # Normalize the image
    return image, label
```

```
In [21]: # Apply the preprocessing function to the datasets and batch them
    train_dataset = train_dataset.map(preprocess).batch(16).prefetch(tf.data.exp
    val_dataset = val_dataset.map(preprocess).batch(16).prefetch(tf.data.experim
    test_dataset = test_dataset.map(preprocess).batch(16).prefetch(tf.data.experim
```

Model and training

```
In [22]: # Function to create and compile the model

def create_model():
    model = Sequential()
    model.add(Conv2D(32, (3, 3), activation='relu', input_shape=image_size +
    model.add(MaxPooling2D((2, 2)))
    model.add(Conv2D(64, (3, 3), activation='relu'))
    model.add(MaxPooling2D((2, 2)))
    model.add(Conv2D(64, (3, 3), activation='relu'))
    model.add(MaxPooling2D((2, 2)))
    model.add(MaxPooling2D((2, 2)))
    model.add(Flatten())
    model.add(Dense(128, activation='relu'))
    model.add(Dropout(0.5))
    model.add(Dense(1, activation='sigmoid'))
    model.compile(optimizer=Adam(learning_rate=0.0001), loss='binary_crossen return model
```

```
In [23]: # Function to plot training progress and save the figure
         def plot training history(history, model name):
             acc = history.history['accuracy']
             val acc = history.history['val accuracy']
             loss = history.history['loss']
             val loss = history.history['val loss']
             epochs = range(len(acc))
             plt.figure(figsize=(12, 6))
             plt.subplot(1, 2, 1)
             plt.plot(epochs, acc, 'r', label='Training accuracy')
             plt.plot(epochs, val_acc, 'b', label='Validation accuracy')
             plt.title('Training and validation accuracy')
             plt.ylim(0.7, 1.005)
             plt.legend()
             plt.subplot(1, 2, 2)
             plt.plot(epochs, loss, 'r', label='Training loss')
             plt.plot(epochs, val_loss, 'b', label='Validation loss')
             plt.title('Training and validation loss')
             plt.ylim(-0.01, 0.6)
             plt.legend()
             # Save the figure
             if not os.path.exists('figures'):
                 os.makedirs('figures')
             plt.savefig(f'figures/{model name} training history.png')
             plt.show()
```

```
In [24]: # Create the model
  model = create_model()
  model.summary()
```

8/3/24, 12:10 PM Final_one_node

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 128, 128, 32)	
<pre>max_pooling2d (MaxPooling2D)</pre>	(None, 64, 64, 32)	0
conv2d_1 (Conv2D)	(None, 62, 62, 64)	18496
<pre>max_pooling2d_1 (MaxPooling 2D)</pre>	(None, 31, 31, 64)	0
conv2d_2 (Conv2D)	(None, 29, 29, 64)	36928
<pre>max_pooling2d_2 (MaxPooling 2D)</pre>	(None, 14, 14, 64)	0
flatten (Flatten)	(None, 12544)	0
dense (Dense)	(None, 128)	1605760
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 1)	129
Cotal params: 1,662,209 Crainable params: 1,662,209 Jon-trainable params: 0		

```
In [25]:
```

```
history = model.fit(
    train_dataset,
    epochs=80,
    validation_data=val_dataset
)
Epoch 1/80
```

```
1206/1206 [============== ] - 29s 22ms/step - loss: 0.5763 -
accuracy: 0.7039 - val loss: 0.3725 - val accuracy: 0.8684
Epoch 2/80
accuracy: 0.9016 - val_loss: 0.2001 - val_accuracy: 0.9227
Epoch 3/80
accuracy: 0.9346 - val_loss: 0.1632 - val_accuracy: 0.9445
Epoch 4/80
1206/1206 [=============== ] - 27s 22ms/step - loss: 0.1717 -
accuracy: 0.9405 - val_loss: 0.1557 - val_accuracy: 0.9467
Epoch 5/80
```

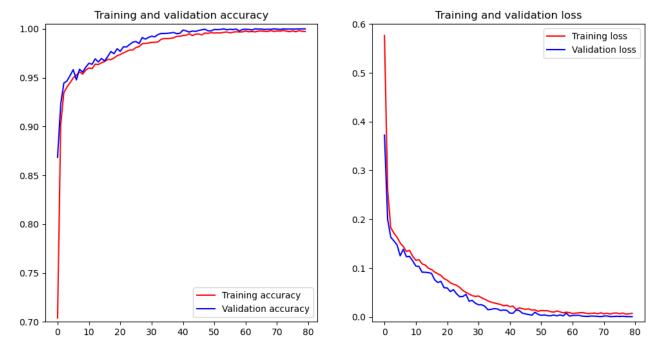
```
accuracy: 0.9449 - val loss: 0.1476 - val accuracy: 0.9523
Epoch 6/80
1206/1206 [============== ] - 27s 22ms/step - loss: 0.1515 -
accuracy: 0.9498 - val_loss: 0.1251 - val_accuracy: 0.9583
Epoch 7/80
accuracy: 0.9527 - val loss: 0.1384 - val accuracy: 0.9477
Epoch 8/80
1206/1206 [============== ] - 26s 22ms/step - loss: 0.1340 -
accuracy: 0.9559 - val loss: 0.1232 - val accuracy: 0.9586
Epoch 9/80
accuracy: 0.9537 - val loss: 0.1239 - val accuracy: 0.9557
Epoch 10/80
accuracy: 0.9578 - val loss: 0.1148 - val accuracy: 0.9608
1206/1206 [============== ] - 27s 22ms/step - loss: 0.1160 -
accuracy: 0.9600 - val loss: 0.1041 - val accuracy: 0.9648
Epoch 12/80
accuracy: 0.9593 - val loss: 0.1033 - val accuracy: 0.9637
Epoch 13/80
accuracy: 0.9639 - val loss: 0.0915 - val accuracy: 0.9693
Epoch 14/80
accuracy: 0.9636 - val loss: 0.0914 - val accuracy: 0.9661
Epoch 15/80
accuracy: 0.9653 - val loss: 0.0908 - val accuracy: 0.9697
accuracy: 0.9666 - val loss: 0.0891 - val accuracy: 0.9672
Epoch 17/80
accuracy: 0.9688 - val_loss: 0.0761 - val_accuracy: 0.9717
Epoch 18/80
accuracy: 0.9685 - val loss: 0.0705 - val accuracy: 0.9768
Epoch 19/80
accuracy: 0.9703 - val loss: 0.0728 - val accuracy: 0.9746
Epoch 20/80
accuracy: 0.9725 - val_loss: 0.0597 - val_accuracy: 0.9797
Epoch 21/80
accuracy: 0.9738 - val_loss: 0.0593 - val_accuracy: 0.9770
Epoch 22/80
accuracy: 0.9754 - val_loss: 0.0518 - val_accuracy: 0.9817
```

```
Epoch 23/80
accuracy: 0.9769 - val_loss: 0.0558 - val_accuracy: 0.9815
Epoch 24/80
accuracy: 0.9783 - val_loss: 0.0472 - val_accuracy: 0.9840
Epoch 25/80
accuracy: 0.9784 - val loss: 0.0414 - val accuracy: 0.9864
Epoch 26/80
accuracy: 0.9809 - val loss: 0.0418 - val accuracy: 0.9871
accuracy: 0.9819 - val loss: 0.0461 - val accuracy: 0.9849
Epoch 28/80
accuracy: 0.9849 - val_loss: 0.0321 - val_accuracy: 0.9911
Epoch 29/80
accuracy: 0.9851 - val_loss: 0.0338 - val_accuracy: 0.9895
Epoch 30/80
accuracy: 0.9855 - val_loss: 0.0279 - val_accuracy: 0.9913
Epoch 31/80
accuracy: 0.9862 - val loss: 0.0248 - val accuracy: 0.9926
Epoch 32/80
accuracy: 0.9863 - val loss: 0.0249 - val accuracy: 0.9918
Epoch 33/80
accuracy: 0.9866 - val_loss: 0.0218 - val_accuracy: 0.9942
Epoch 34/80
accuracy: 0.9893 - val_loss: 0.0146 - val_accuracy: 0.9953
Epoch 35/80
1206/1206 [============= ] - 26s 22ms/step - loss: 0.0302 -
accuracy: 0.9902 - val_loss: 0.0154 - val_accuracy: 0.9953
Epoch 36/80
1206/1206 [=============== ] - 26s 21ms/step - loss: 0.0286 -
accuracy: 0.9900 - val loss: 0.0170 - val accuracy: 0.9955
Epoch 37/80
accuracy: 0.9903 - val loss: 0.0162 - val accuracy: 0.9958
accuracy: 0.9909 - val loss: 0.0132 - val accuracy: 0.9964
Epoch 39/80
1206/1206 [============== ] - 26s 21ms/step - loss: 0.0227 -
accuracy: 0.9923 - val loss: 0.0140 - val accuracy: 0.9951
Epoch 40/80
```

```
accuracy: 0.9924 - val loss: 0.0135 - val accuracy: 0.9955
Epoch 41/80
accuracy: 0.9933 - val_loss: 0.0078 - val_accuracy: 0.9987
Epoch 42/80
accuracy: 0.9935 - val_loss: 0.0074 - val_accuracy: 0.9980
Epoch 43/80
accuracy: 0.9951 - val_loss: 0.0143 - val_accuracy: 0.9967
Epoch 44/80
accuracy: 0.9932 - val loss: 0.0130 - val accuracy: 0.9978
Epoch 45/80
accuracy: 0.9946 - val loss: 0.0075 - val accuracy: 0.9975
Epoch 46/80
accuracy: 0.9948 - val_loss: 0.0061 - val_accuracy: 0.9984
Epoch 47/80
accuracy: 0.9938 - val_loss: 0.0048 - val_accuracy: 0.9991
Epoch 48/80
accuracy: 0.9958 - val_loss: 0.0034 - val_accuracy: 0.9996
Epoch 49/80
accuracy: 0.9954 - val loss: 0.0095 - val accuracy: 0.9980
Epoch 50/80
accuracy: 0.9962 - val_loss: 0.0052 - val_accuracy: 0.9980
Epoch 51/80
accuracy: 0.9957 - val_loss: 0.0032 - val_accuracy: 0.9995
Epoch 52/80
accuracy: 0.9960 - val_loss: 0.0040 - val_accuracy: 0.9993
Epoch 53/80
accuracy: 0.9959 - val_loss: 0.0026 - val_accuracy: 0.9995
Epoch 54/80
accuracy: 0.9965 - val loss: 0.0022 - val accuracy: 1.0000
Epoch 55/80
accuracy: 0.9968 - val loss: 0.0039 - val accuracy: 0.9991
Epoch 56/80
1206/1206 [============= ] - 27s 22ms/step - loss: 0.0121 -
accuracy: 0.9959 - val_loss: 0.0021 - val_accuracy: 0.9996
Epoch 57/80
1206/1206 [============= ] - 27s 22ms/step - loss: 0.0103 -
accuracy: 0.9967 - val_loss: 0.0040 - val_accuracy: 0.9993
Epoch 58/80
```

```
accuracy: 0.9970 - val loss: 0.0021 - val accuracy: 0.9998
Epoch 59/80
1206/1206 [============== ] - 27s 22ms/step - loss: 0.0097 -
accuracy: 0.9968 - val_loss: 0.0076 - val_accuracy: 0.9978
Epoch 60/80
accuracy: 0.9969 - val loss: 0.0016 - val accuracy: 0.9995
Epoch 61/80
1206/1206 [============== ] - 27s 22ms/step - loss: 0.0068 -
accuracy: 0.9978 - val loss: 0.0028 - val accuracy: 0.9996
Epoch 62/80
accuracy: 0.9970 - val loss: 0.0031 - val accuracy: 0.9995
Epoch 63/80
accuracy: 0.9974 - val loss: 0.0033 - val accuracy: 0.9989
Epoch 64/80
1206/1206 [============== ] - 27s 22ms/step - loss: 0.0088 -
accuracy: 0.9969 - val loss: 0.0016 - val accuracy: 1.0000
Epoch 65/80
accuracy: 0.9977 - val loss: 0.0011 - val accuracy: 0.9998
Epoch 66/80
accuracy: 0.9978 - val loss: 9.2736e-04 - val accuracy: 0.9998
Epoch 67/80
accuracy: 0.9976 - val loss: 0.0018 - val accuracy: 0.9995
Epoch 68/80
accuracy: 0.9974 - val loss: 0.0015 - val accuracy: 0.9996
accuracy: 0.9982 - val loss: 9.8334e-04 - val accuracy: 0.9996
Epoch 70/80
accuracy: 0.9975 - val_loss: 4.8609e-04 - val_accuracy: 1.0000
Epoch 71/80
accuracy: 0.9979 - val loss: 0.0017 - val accuracy: 0.9998
Epoch 72/80
accuracy: 0.9977 - val loss: 0.0018 - val accuracy: 0.9995
Epoch 73/80
accuracy: 0.9983 - val_loss: 5.9385e-04 - val_accuracy: 1.0000
Epoch 74/80
accuracy: 0.9978 - val_loss: 7.2975e-04 - val_accuracy: 0.9998
Epoch 75/80
accuracy: 0.9971 - val_loss: 0.0012 - val_accuracy: 0.9998
```

In [26]: # Plot training history and save the figure plot_training_history(history, 'basic_model')



```
In [27]: # Evaluate the model using the test data
loss, accuracy = model.evaluate(test_dataset)
print(f"Test Loss: {loss}")
print(f"Test Accuracy: {accuracy}")
```

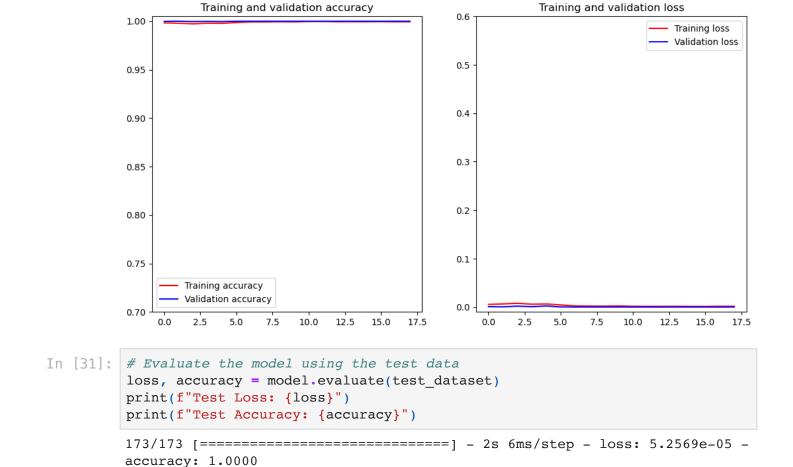
Test Loss: 0.000574044301174581

Test Accuracy: 1.0

Introduce Learning Rate Scheduling and Early Stopping

```
In [28]: reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.2, patience=3, mi
     early stopping = EarlyStopping(monitor='val loss', patience=5, restore best
In [29]: history = model.fit(
        train dataset,
        epochs=80,
        validation data=val dataset,
        callbacks=[reduce_lr, early_stopping]
     Epoch 1/80
     accuracy: 0.9983 - val_loss: 8.7567e-04 - val_accuracy: 0.9998 - lr: 1.0000e
     -04
     Epoch 2/80
     accuracy: 0.9979 - val loss: 4.5340e-04 - val accuracy: 1.0000 - lr: 1.0000e
     -04
     Epoch 3/80
     accuracy: 0.9973 - val loss: 0.0020 - val accuracy: 0.9996 - lr: 1.0000e-04
     Epoch 4/80
     accuracy: 0.9980 - val loss: 7.8061e-04 - val accuracy: 0.9998 - lr: 1.0000e
     -04
     Epoch 5/80
     accuracy: 0.9978 - val_loss: 0.0023 - val_accuracy: 0.9996 - lr: 1.0000e-04
     accuracy: 0.9987 - val_loss: 2.9758e-04 - val_accuracy: 1.0000 - lr: 2.0000e
     -05
     Epoch 7/80
     accuracy: 0.9993 - val_loss: 1.2412e-04 - val_accuracy: 1.0000 - lr: 2.0000e
     -05
     Epoch 8/80
     accuracy: 0.9993 - val loss: 1.0557e-04 - val accuracy: 1.0000 - lr: 2.0000e
     -05
     Epoch 9/80
     accuracy: 0.9995 - val_loss: 1.6534e-04 - val_accuracy: 1.0000 - lr: 2.0000e
     -05
     Epoch 10/80
```

```
accuracy: 0.9994 - val loss: 9.3571e-05 - val accuracy: 1.0000 - lr: 2.0000e
     -05
     Epoch 11/80
     accuracy: 0.9997 - val loss: 8.0285e-05 - val accuracy: 1.0000 - lr: 1.0000e
     -05
     Epoch 12/80
     accuracy: 0.9997 - val loss: 7.3930e-05 - val accuracy: 1.0000 - lr: 1.0000e
     -05
     Epoch 13/80
     accuracy: 0.9995 - val loss: 4.2267e-05 - val accuracy: 1.0000 - lr: 1.0000e
     -05
     Epoch 14/80
     accuracy: 0.9995 - val loss: 1.0627e-04 - val accuracy: 1.0000 - lr: 1.0000e
     -05
     Epoch 15/80
     accuracy: 0.9995 - val_loss: 5.8789e-05 - val_accuracy: 1.0000 - lr: 1.0000e
     -05
     Epoch 16/80
     accuracy: 0.9996 - val_loss: 6.3728e-05 - val_accuracy: 1.0000 - lr: 1.0000e
     -05
     Epoch 17/80
     accuracy: 0.9994 - val_loss: 4.9783e-05 - val_accuracy: 1.0000 - lr: 1.0000e
     -0.5
     Epoch 18/80
     accuracy: 0.9995 - val_loss: 1.1664e-04 - val_accuracy: 1.0000 - lr: 1.0000e
     -05
In [30]: # Plot training history and save the figure
     plot_training_history(history, 'basic_model_with_LRS_ES')
```



Deeper model

Test Accuracy: 1.0

Test Loss: 5.256887379800901e-05

```
In [32]: # Function to create and compile the deeper model
         def create deeper model():
             model = Sequential()
             model.add(Conv2D(32, (3, 3), activation='relu', input shape=image size +
             model.add(MaxPooling2D((2, 2)))
             model.add(Conv2D(64, (3, 3), activation='relu'))
             model.add(MaxPooling2D((2, 2)))
             model.add(Conv2D(128, (3, 3), activation='relu'))
             model.add(MaxPooling2D((2, 2)))
             model.add(Conv2D(128, (3, 3), activation='relu'))
             model.add(MaxPooling2D((2, 2)))
             model.add(Flatten())
             model.add(Dense(256, activation='relu'))
             model.add(Dropout(0.5))
             model.add(Dense(128, activation='relu'))
             model.add(Dropout(0.5))
             model.add(Dense(1, activation='sigmoid'))
             model.compile(optimizer=Adam(learning rate=0.0001), loss='binary crossen
             return model
In [33]: # Create the deeper model
         model = create deeper model()
         model.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d_3 (Conv2D)	(None, 128, 128, 32)	896
<pre>max_pooling2d_3 (MaxPooling 2D)</pre>	(None, 64, 64, 32)	0
conv2d_4 (Conv2D)	(None, 62, 62, 64)	18496
<pre>max_pooling2d_4 (MaxPooling 2D)</pre>	(None, 31, 31, 64)	0
conv2d_5 (Conv2D)	(None, 29, 29, 128)	73856
<pre>max_pooling2d_5 (MaxPooling 2D)</pre>	(None, 14, 14, 128)	0
conv2d_6 (Conv2D)	(None, 12, 12, 128)	147584
<pre>max_pooling2d_6 (MaxPooling 2D)</pre>	(None, 6, 6, 128)	0
flatten_1 (Flatten)	(None, 4608)	0
dense_2 (Dense)	(None, 256)	1179904
dropout_1 (Dropout)	(None, 256)	0
dense_3 (Dense)	(None, 128)	32896
dropout_2 (Dropout)	(None, 128)	0
dense_4 (Dense)	(None, 1)	129

```
In [34]: # Train the deeper model
         history = model.fit(
             train_dataset,
             epochs=80,
             validation_data=val_dataset
```

```
Epoch 1/80
accuracy: 0.7405 - val_loss: 0.1872 - val_accuracy: 0.9216
Epoch 2/80
```

```
accuracy: 0.9445 - val loss: 0.1316 - val accuracy: 0.9597
Epoch 3/80
1206/1206 [============== ] - 32s 26ms/step - loss: 0.1511 -
accuracy: 0.9536 - val_loss: 0.1314 - val_accuracy: 0.9555
Epoch 4/80
accuracy: 0.9573 - val loss: 0.1303 - val accuracy: 0.9595
Epoch 5/80
1206/1206 [============== ] - 32s 26ms/step - loss: 0.1294 -
accuracy: 0.9579 - val loss: 0.1247 - val accuracy: 0.9581
Epoch 6/80
accuracy: 0.9584 - val loss: 0.1121 - val accuracy: 0.9608
Epoch 7/80
accuracy: 0.9626 - val loss: 0.0990 - val accuracy: 0.9650
1206/1206 [============== ] - 32s 26ms/step - loss: 0.1152 -
accuracy: 0.9606 - val loss: 0.1077 - val accuracy: 0.9621
Epoch 9/80
accuracy: 0.9631 - val loss: 0.1034 - val accuracy: 0.9628
Epoch 10/80
accuracy: 0.9646 - val loss: 0.0879 - val accuracy: 0.9675
Epoch 11/80
1206/1206 [=============== ] - 32s 26ms/step - loss: 0.0996 -
accuracy: 0.9660 - val loss: 0.0878 - val accuracy: 0.9692
Epoch 12/80
accuracy: 0.9653 - val loss: 0.0857 - val accuracy: 0.9717
accuracy: 0.9668 - val loss: 0.0801 - val accuracy: 0.9737
Epoch 14/80
accuracy: 0.9692 - val_loss: 0.0675 - val_accuracy: 0.9764
Epoch 15/80
accuracy: 0.9700 - val loss: 0.0788 - val accuracy: 0.9770
Epoch 16/80
accuracy: 0.9715 - val loss: 0.0637 - val accuracy: 0.9771
Epoch 17/80
accuracy: 0.9747 - val_loss: 0.0553 - val_accuracy: 0.9793
Epoch 18/80
accuracy: 0.9765 - val_loss: 0.0652 - val_accuracy: 0.9773
Epoch 19/80
accuracy: 0.9766 - val_loss: 0.0486 - val_accuracy: 0.9822
```

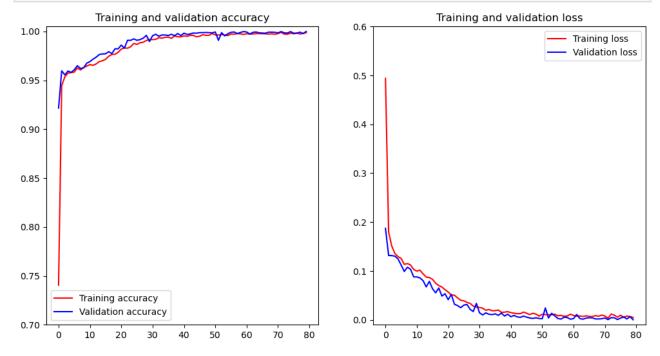
```
Epoch 20/80
accuracy: 0.9786 - val_loss: 0.0534 - val_accuracy: 0.9822
Epoch 21/80
accuracy: 0.9820 - val_loss: 0.0413 - val_accuracy: 0.9860
Epoch 22/80
accuracy: 0.9832 - val loss: 0.0520 - val accuracy: 0.9829
Epoch 23/80
accuracy: 0.9828 - val loss: 0.0319 - val accuracy: 0.9909
accuracy: 0.9843 - val loss: 0.0292 - val accuracy: 0.9909
Epoch 25/80
accuracy: 0.9877 - val_loss: 0.0248 - val_accuracy: 0.9924
Epoch 26/80
accuracy: 0.9867 - val_loss: 0.0302 - val_accuracy: 0.9909
Epoch 27/80
1206/1206 [============= ] - 32s 26ms/step - loss: 0.0357 -
accuracy: 0.9884 - val_loss: 0.0314 - val_accuracy: 0.9917
Epoch 28/80
accuracy: 0.9890 - val loss: 0.0215 - val accuracy: 0.9931
accuracy: 0.9907 - val loss: 0.0170 - val accuracy: 0.9960
Epoch 30/80
accuracy: 0.9918 - val_loss: 0.0338 - val_accuracy: 0.9897
Epoch 31/80
accuracy: 0.9917 - val_loss: 0.0144 - val_accuracy: 0.9956
Epoch 32/80
1206/1206 [============= ] - 32s 26ms/step - loss: 0.0239 -
accuracy: 0.9919 - val_loss: 0.0100 - val_accuracy: 0.9971
Epoch 33/80
1206/1206 [=============== ] - 32s 26ms/step - loss: 0.0196 -
accuracy: 0.9937 - val loss: 0.0143 - val accuracy: 0.9951
Epoch 34/80
accuracy: 0.9931 - val loss: 0.0115 - val accuracy: 0.9964
accuracy: 0.9940 - val loss: 0.0107 - val accuracy: 0.9964
Epoch 36/80
1206/1206 [============== ] - 32s 26ms/step - loss: 0.0188 -
accuracy: 0.9942 - val loss: 0.0123 - val accuracy: 0.9958
Epoch 37/80
```

```
accuracy: 0.9929 - val loss: 0.0093 - val accuracy: 0.9971
Epoch 38/80
accuracy: 0.9954 - val_loss: 0.0138 - val_accuracy: 0.9956
Epoch 39/80
accuracy: 0.9946 - val_loss: 0.0078 - val_accuracy: 0.9978
Epoch 40/80
accuracy: 0.9944 - val_loss: 0.0116 - val_accuracy: 0.9958
Epoch 41/80
accuracy: 0.9955 - val loss: 0.0063 - val accuracy: 0.9982
Epoch 42/80
accuracy: 0.9950 - val loss: 0.0090 - val accuracy: 0.9969
Epoch 43/80
accuracy: 0.9961 - val_loss: 0.0062 - val_accuracy: 0.9975
Epoch 44/80
accuracy: 0.9960 - val_loss: 0.0051 - val_accuracy: 0.9984
Epoch 45/80
accuracy: 0.9945 - val_loss: 0.0076 - val_accuracy: 0.9982
Epoch 46/80
accuracy: 0.9951 - val loss: 0.0056 - val accuracy: 0.9987
Epoch 47/80
accuracy: 0.9966 - val_loss: 0.0038 - val_accuracy: 0.9987
Epoch 48/80
accuracy: 0.9960 - val_loss: 0.0029 - val_accuracy: 0.9989
Epoch 49/80
accuracy: 0.9961 - val_loss: 0.0041 - val_accuracy: 0.9987
Epoch 50/80
accuracy: 0.9978 - val_loss: 0.0028 - val_accuracy: 0.9985
Epoch 51/80
accuracy: 0.9965 - val loss: 0.0022 - val accuracy: 0.9995
Epoch 52/80
accuracy: 0.9963 - val loss: 0.0244 - val accuracy: 0.9909
Epoch 53/80
1206/1206 [============= ] - 32s 26ms/step - loss: 0.0104 -
accuracy: 0.9969 - val_loss: 0.0038 - val_accuracy: 0.9987
Epoch 54/80
1206/1206 [============= ] - 32s 26ms/step - loss: 0.0104 -
accuracy: 0.9963 - val_loss: 0.0133 - val_accuracy: 0.9955
Epoch 55/80
```

```
accuracy: 0.9958 - val loss: 0.0081 - val accuracy: 0.9976
Epoch 56/80
1206/1206 [============== ] - 32s 26ms/step - loss: 0.0083 -
accuracy: 0.9973 - val_loss: 0.0028 - val_accuracy: 0.9991
Epoch 57/80
accuracy: 0.9972 - val loss: 0.0016 - val accuracy: 0.9995
Epoch 58/80
1206/1206 [============== ] - 32s 26ms/step - loss: 0.0075 -
accuracy: 0.9978 - val loss: 0.0056 - val accuracy: 0.9978
Epoch 59/80
accuracy: 0.9975 - val loss: 0.0046 - val accuracy: 0.9989
Epoch 60/80
accuracy: 0.9969 - val loss: 0.0014 - val accuracy: 0.9998
Epoch 61/80
1206/1206 [============== ] - 32s 26ms/step - loss: 0.0089 -
accuracy: 0.9977 - val loss: 0.0026 - val accuracy: 0.9995
Epoch 62/80
accuracy: 0.9974 - val loss: 0.0110 - val accuracy: 0.9973
Epoch 63/80
accuracy: 0.9974 - val loss: 0.0026 - val accuracy: 0.9991
Epoch 64/80
1206/1206 [=============== ] - 32s 26ms/step - loss: 0.0068 -
accuracy: 0.9978 - val loss: 0.0013 - val accuracy: 0.9995
Epoch 65/80
accuracy: 0.9978 - val loss: 0.0036 - val accuracy: 0.9985
accuracy: 0.9977 - val loss: 0.0043 - val accuracy: 0.9984
Epoch 67/80
accuracy: 0.9976 - val_loss: 0.0040 - val_accuracy: 0.9982
Epoch 68/80
accuracy: 0.9973 - val loss: 0.0018 - val accuracy: 0.9993
Epoch 69/80
accuracy: 0.9976 - val loss: 0.0018 - val accuracy: 0.9993
Epoch 70/80
accuracy: 0.9971 - val_loss: 0.0023 - val_accuracy: 0.9991
Epoch 71/80
accuracy: 0.9978 - val_loss: 0.0038 - val_accuracy: 0.9985
Epoch 72/80
accuracy: 0.9991 - val_loss: 4.3958e-04 - val_accuracy: 0.9998
```

```
Epoch 73/80
accuracy: 0.9973 - val loss: 0.0045 - val accuracy: 0.9985
Epoch 74/80
accuracy: 0.9971 - val_loss: 0.0042 - val_accuracy: 0.9984
Epoch 75/80
accuracy: 0.9982 - val loss: 6.0558e-04 - val accuracy: 0.9998
Epoch 76/80
accuracy: 0.9976 - val loss: 0.0036 - val accuracy: 0.9982
accuracy: 0.9985 - val loss: 0.0059 - val accuracy: 0.9982
Epoch 78/80
accuracy: 0.9973 - val loss: 0.0018 - val accuracy: 0.9993
Epoch 79/80
accuracy: 0.9980 - val_loss: 0.0065 - val_accuracy: 0.9978
Epoch 80/80
accuracy: 0.9987 - val_loss: 1.9709e-04 - val_accuracy: 1.0000
```

In [35]: # Plot training history and save the figure plot_training_history(history, 'deeper_model')



```
In [36]: # Evaluate the deeper model using the test data
loss, accuracy = model.evaluate(test_dataset)
print(f"Test Loss: {loss}")
print(f"Test Accuracy: {accuracy}")
```

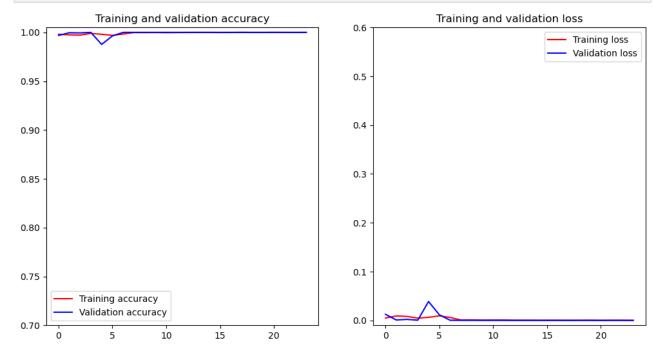
Introduce Learning Rate Scheduling and Early Stopping for deeper model

```
In [37]: history = model.fit(
       train_dataset,
       epochs=80,
       validation data=val dataset,
       callbacks=[reduce_lr, early_stopping]
     Epoch 1/80
     accuracy: 0.9981 - val_loss: 0.0124 - val_accuracy: 0.9969 - lr: 1.0000e-04
     Epoch 2/80
     accuracy: 0.9975 - val loss: 8.7114e-04 - val accuracy: 0.9996 - lr: 1.0000e
     Epoch 3/80
     accuracy: 0.9972 - val loss: 0.0021 - val accuracy: 0.9995 - lr: 1.0000e-04
     Epoch 4/80
     accuracy: 0.9990 - val_loss: 4.1087e-04 - val_accuracy: 1.0000 - lr: 1.0000e
     -04
     Epoch 5/80
     accuracy: 0.9980 - val_loss: 0.0387 - val_accuracy: 0.9877 - lr: 1.0000e-04
     Epoch 6/80
     accuracy: 0.9969 - val loss: 0.0114 - val accuracy: 0.9964 - lr: 1.0000e-04
     Epoch 7/80
     accuracy: 0.9983 - val loss: 3.3159e-04 - val accuracy: 1.0000 - lr: 1.0000e
     -04
     Epoch 8/80
     4 - accuracy: 0.9998 - val_loss: 1.4918e-04 - val_accuracy: 1.0000 - lr: 2.0
     000e-05
     Epoch 9/80
     accuracy: 0.9998 - val loss: 1.1557e-04 - val accuracy: 1.0000 - lr: 2.0000e
     -05
     Epoch 10/80
```

4 - accuracy: 0.9999 - val loss: 8.9402e-05 - val accuracy: 1.0000 - lr: 2.0

```
000e-05
Epoch 11/80
4 - accuracy: 0.9997 - val_loss: 5.3075e-05 - val_accuracy: 1.0000 - lr: 2.0
000e-05
Epoch 12/80
4 - accuracy: 0.9998 - val loss: 3.8047e-05 - val accuracy: 1.0000 - lr: 1.0
000e - 05
Epoch 13/80
4 - accuracy: 0.9999 - val loss: 2.6674e-05 - val accuracy: 1.0000 - lr: 1.0
000e-05
Epoch 14/80
4 - accuracy: 0.9999 - val loss: 3.0078e-05 - val accuracy: 1.0000 - lr: 1.0
000e-05
Epoch 15/80
4 - accuracy: 0.9999 - val loss: 4.9924e-05 - val accuracy: 1.0000 - lr: 1.0
000e-05
Epoch 16/80
4 - accuracy: 0.9998 - val_loss: 4.0461e-05 - val_accuracy: 1.0000 - lr: 1.0
000e-05
Epoch 17/80
4 - accuracy: 0.9999 - val loss: 2.8247e-05 - val accuracy: 1.0000 - lr: 1.0
000e-05
Epoch 18/80
4 - accuracy: 1.0000 - val loss: 2.0468e-05 - val accuracy: 1.0000 - lr: 1.0
000e-05
Epoch 19/80
1206/1206 [==============] - 32s 26ms/step - loss: 2.7635e-0
4 - accuracy: 0.9999 - val loss: 9.2260e-06 - val accuracy: 1.0000 - lr: 1.0
000e - 05
Epoch 20/80
1206/1206 [============== ] - 32s 26ms/step - loss: 3.9879e-0
4 - accuracy: 0.9999 - val_loss: 1.4197e-05 - val_accuracy: 1.0000 - lr: 1.0
000e-05
Epoch 21/80
5 - accuracy: 1.0000 - val loss: 1.1735e-05 - val accuracy: 1.0000 - lr: 1.0
000e-05
Epoch 22/80
1206/1206 [============== ] - 32s 26ms/step - loss: 3.1754e-0
4 - accuracy: 0.9999 - val loss: 1.7731e-05 - val accuracy: 1.0000 - lr: 1.0
000e-05
Epoch 23/80
4 - accuracy: 0.9999 - val_loss: 1.1800e-05 - val_accuracy: 1.0000 - lr: 1.0
000e-05
```

```
In [38]: # Plot training history and save the figure
plot_training_history(history, 'deeper_model_with_LRS_ES')
```



```
In [39]: # Evaluate the model using the test data
loss, accuracy = model.evaluate(test_dataset)
print(f"Test Loss: {loss}")
print(f"Test Accuracy: {accuracy}")
```

Test Loss: 1.0464496881468222e-05

Test Accuracy: 1.0

In []: