BRAIN TUMOR DETECTION WITH TENSORFLOW (COMPARISION BETWEEN FNN AND CNN)

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CSE - A

FEED FORWARD NEURAL NETWORK

```
from zipfile import ZipFile
file_name = "brain-tumor .zip"

with  ZipFile(file_name, 'r') as zip:
  zip.extractall()
  print('Done')
```

+ Code + Text

```
#Load libraries
import os
import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt
from tensorflow.keras.preprocessing.image import ImageDataGenerator
import torch
import glob
import pathlib


#checking for device
device=torch.device('cuda' if torch.cuda.is_available() else 'cpu')


print(device)
```

```
cuda
```

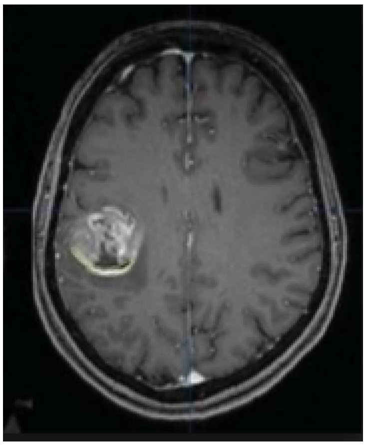
```
import pathlib
import numpy as np
data_dir = pathlib.Path("/content/brain-tumor /train")
class_names = np.array(sorted([item.name for item in data_dir.glob('*')]))
class_names = class_names[1:]
print(class_names)
```

```
['Brain Tumor' 'Healthy']
```

```
# Let's visuvalize our images
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
import random

def view_random_image(target_dir, target_class):
  # Setup the target directory
  target_folder = target_dir+target_class

  # Get a random image path
  random_image = random.sample(os.listdir(target_folder), 1)


  img = mpimg.imread(target_folder + "/" + random_image[0])
  plt.imshow(img)
  plt.title(target_class)
  plt.axis("off");

  print(f"Image shape: {img.shape}") # show the shape  of the img

  return img


img = view_random_image(target_dir="brain-tumor /train/",
                        target_class="Brain Tumor")
```

```
Image shape: (359, 297, 3)
```

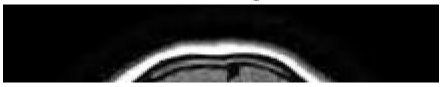
Brain Tumor



```
img = view_random_image(target_dir="brain-tumor /train/",
                        target_class="Healthy")
```

```
Image shape: (225, 225, 3)
```

Healthy



```
img
```

```
array([[[0, 0, 0],
        [0, 0, 0],
        [0, 0, 0],
        ...,
        [0, 0, 0],
        [0, 0, 0],
        [0, 0, 0]],

       [[0, 0, 0],
        [0, 0, 0],
        [0, 0, 0],
        ...,
        [0, 0, 0],
        [0, 0, 0],
        [0, 0, 0]],

       [[0, 0, 0],
        [0, 0, 0],
        [0, 0, 0],
        ...,
        [0, 0, 0],
        [0, 0, 0],
        [0, 0, 0]],

       ...,

       [[0, 0, 0],
        [0, 0, 0],
        [0, 0, 0],
        ...,
        [0, 0, 0],
        [0, 0, 0],
        [0, 0, 0]],

       [[0, 0, 0],
        [0, 0, 0],
        [0, 0, 0],
        ...,
        [0, 0, 0],
        [0, 0, 0],
        [0, 0, 0]],

       [[0, 0, 0],
        [0, 0, 0],
        [0, 0, 0],
        ...,
        [0, 0, 0],
        [0, 0, 0],
        [0, 0, 0]]], dtype=uint8)
```

```
img.shape
```

```
(225, 225, 3)
```

```
import tensorflow as tf
import matplotlib.pyplot as plt
from tensorflow.keras.preprocessing.image import ImageDataGenerator
```

```
# Create ImageDataGenerator training instance with data augmentation (horizontal fl
train_datagen = ImageDataGenerator(rescale=1/255.,
                                   horizontal_flip=True)

# Create ImageDataGenerator test instance without data augmentation
test_datagen = ImageDataGenerator(rescale=1/255.)
```

```
import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator

# Set the seed
tf.random.set_seed(42)

# Preprocess data (get all of the pixel values between 1 and 0, also called scaling
```

```
train_dir = "brain-tumor /train/"
test_dir = "brain-tumor /test/"

# Import data from directories and turn it into batches
train_data = train_datagen.flow_from_directory(train_dir,
                                               batch_size=32, # number of images to
                                               target_size=(150, 150), # convert al
                                               class_mode="binary", # type of probl
                                               seed=42)

valid_data= test_datagen.flow_from_directory(test_dir,
                                               batch_size=32,
                                               target_size=(150, 150),
                                               class_mode="binary",
                                               seed=42)
```

```
Found 4350 images belonging to 2 classes.
Found 242 images belonging to 2 classes.
```

TRYING DIFFERENT OPTIMIZER

SGD

```
tf.random.set_seed(42)


model_a = tf.keras.Sequential([
  tf.keras.layers.Flatten(input_shape=(150, 150, 3)),
  tf.keras.layers.Dense(4, activation='relu'),
  tf.keras.layers.Dense(4, activation='relu'),
  tf.keras.layers.Dense(1, activation='sigmoid')
])

# Compile the model
model_a.compile(loss='binary_crossentropy',
              optimizer=tf.keras.optimizers.SGD(),
              metrics=["accuracy"])

# Fit the model
history_a = model_a.fit(train_data, # use same training data created above
                        epochs=5,
                        steps_per_epoch=len(train_data),
                        validation_data=valid_data, # use same validation data crea
                        validation_steps=len(valid_data))
```

```
Epoch 1/5
136/136 [==============================] - 14s 101ms/step - loss: 0.6958 - acc
Epoch 2/5
136/136 [==============================] - 14s 99ms/step - loss: 0.6904 - accu
Epoch 3/5
136/136 [==============================] - 13s 98ms/step - loss: 0.6895 - accu
Epoch 4/5
136/136 [==============================] - 14s 100ms/step - loss: 0.6890 - acc
Epoch 5/5
136/136 [==============================] - 13s 99ms/step - loss: 0.6888 - accu
```

ADAM

```
tf.random.set_seed(42)


model_b = tf.keras.Sequential([
  tf.keras.layers.Flatten(input_shape=(150, 150, 3)),
  tf.keras.layers.Dense(4, activation='relu'),
  tf.keras.layers.Dense(4, activation='relu'),
  tf.keras.layers.Dense(1, activation='sigmoid')
])


model_b.compile(loss='binary_crossentropy',
              optimizer=tf.keras.optimizers.Adam(),
```

```
             metrics=["accuracy"])
```

```
history_b = model_b.fit(train_data,
                        epochs=5,
                        steps_per_epoch=len(train_data),
                        validation_data=valid_data,
                        validation_steps=len(valid_data))
```

```
    Epoch 1/5
    136/136 [==============================] - 14s 101ms/step - loss: 0.6989 - acc
    Epoch 2/5
    136/136 [==============================] - 13s 99ms/step - loss: 0.6888 - accu
    Epoch 3/5
    136/136 [==============================] - 13s 99ms/step - loss: 0.6883 - accu
    Epoch 4/5
    136/136 [==============================] - 13s 98ms/step - loss: 0.6896 - accu
    Epoch 5/5
    136/136 [==============================] - 13s 99ms/step - loss: 0.6885 - accu
```

INCREASING THE HIDDEN LAYER

```
tf.random.set_seed(42)
```

```
model_c = tf.keras.Sequential([
  tf.keras.layers.Flatten(input_shape=(150 , 150, 3)),
  tf.keras.layers.Dense(4, activation='relu'),
  tf.keras.layers.Dense(4, activation='relu'),
  tf.keras.layers.Dense(4, activation='relu'),
  tf.keras.layers.Dense(4, activation='relu'),
  tf.keras.layers.Dense(1, activation='sigmoid')
])
```

```
model_c.compile(loss='binary_crossentropy',
             optimizer=tf.keras.optimizers.Adam(),
             metrics=["accuracy"])
```

```
history_c = model_c.fit(train_data,
                        epochs=5,
                        steps_per_epoch=len(train_data),
                        validation_data=valid_data,
                        validation_steps=len(valid_data))
```

```
    Epoch 1/5
    136/136 [==============================] - 14s 101ms/step - loss: 0.6412 - acc
    Epoch 2/5
    136/136 [==============================] - 13s 99ms/step - loss: 0.5308 - accu
    Epoch 3/5
    136/136 [==============================] - 14s 100ms/step - loss: 0.4460 - acc
```

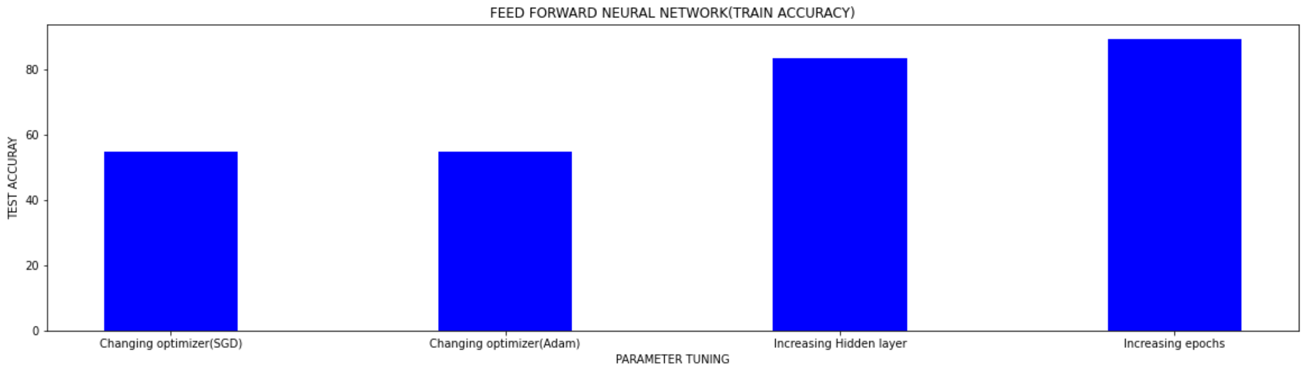
```
Epoch 4/5
136/136 [==============================] - 14s 99ms/step - loss: 0.4077 - accu
Epoch 5/5
136/136 [==============================] - 13s 99ms/step - loss: 0.4028 - accu
```

Increasing epoch

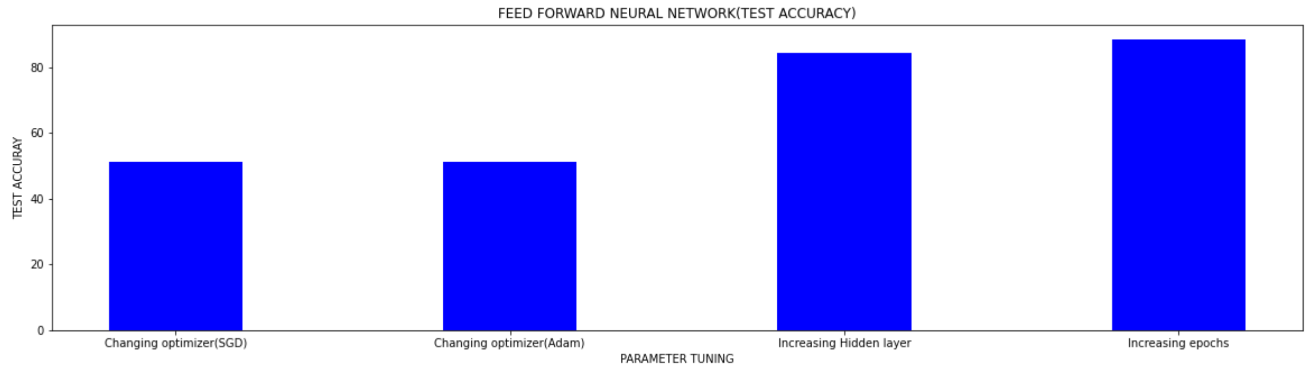
```
tf.random.set_seed(42)

model_d = tf.keras.Sequential([
  tf.keras.layers.Flatten(input_shape=(150, 150, 3)),
  tf.keras.layers.Dense(4, activation='relu'),
  tf.keras.layers.Dense(4, activation='relu'),
  tf.keras.layers.Dense(4, activation='relu'),
  tf.keras.layers.Dense(4, activation='relu'),
  tf.keras.layers.Dense(1, activation='sigmoid')
])

model_d.compile(loss='binary_crossentropy',
              optimizer=tf.keras.optimizers.Adam(),
              metrics=["accuracy"])

history_d = model_d.fit(train_data,
                        epochs=10,
                        steps_per_epoch=len(train_data),
                        validation_data=valid_data,
                        validation_steps=len(valid_data))
```

```
Epoch 1/10
136/136 [==============================] - 14s 100ms/step - loss: 0.6558 - acc
Epoch 2/10
136/136 [==============================] - 13s 99ms/step - loss: 0.5737 - accu
Epoch 3/10
136/136 [==============================] - 13s 99ms/step - loss: 0.5861 - accu
Epoch 4/10
136/136 [==============================] - 13s 99ms/step - loss: 0.4819 - accu
Epoch 5/10
136/136 [==============================] - 13s 99ms/step - loss: 0.4339 - accu
Epoch 6/10
136/136 [==============================] - 13s 99ms/step - loss: 0.4267 - accu
Epoch 7/10
136/136 [==============================] - 14s 99ms/step - loss: 0.4284 - accu
Epoch 8/10
136/136 [==============================] - 14s 99ms/step - loss: 0.3620 - accu
Epoch 9/10
136/136 [==============================] - 14s 100ms/step - loss: 0.3257 - acc
Epoch 10/10
136/136 [==============================] - 14s 100ms/step - loss: 0.3041 - acc
```

```
# creating the dataset
data = {'Changing optimizer(SGD)':54.83, 'Changing optimizer(Adam)':54.83, 'Increas
        'Increasing epochs':89.33}
courses = list(data.keys())
values = list(data.values())

fig = plt.figure(figsize = (20,5))

# creating the bar plot
plt.bar(courses, values, color ='blue',
        width = 0.4)

plt.xlabel("PARAMETER TUNING")
plt.ylabel("TEST ACCURAY")
plt.title("FEED FORWARD NEURAL NETWORK(TRAIN ACCURACY)")
plt.show()
```

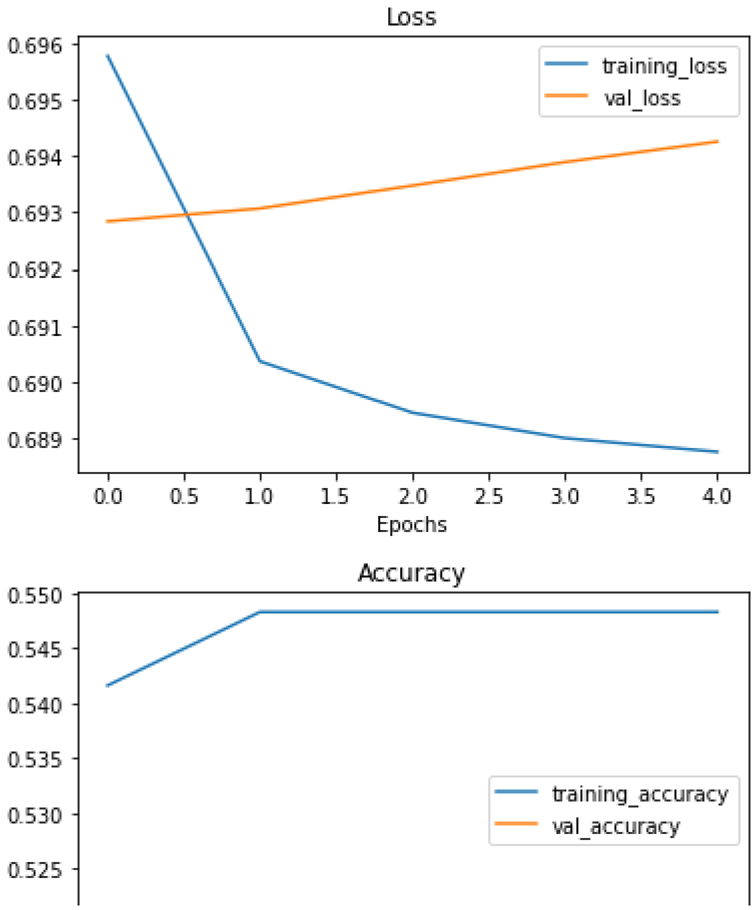



```
# creating the dataset
data = {'Changing optimizer(SGD)':51.24, 'Changing optimizer(Adam)':51.24, 'Increas
        'Increasing epochs':88.43}
courses = list(data.keys())
values = list(data.values())

fig = plt.figure(figsize = (20,5))

# creating the bar plot
plt.bar(courses, values, color ='blue',
        width = 0.4)

plt.xlabel("PARAMETER TUNING")
plt.ylabel("TEST ACCURAY")
plt.title("FEED FORWARD NEURAL NETWORK(TEST ACCURACY)")
plt.show()
```



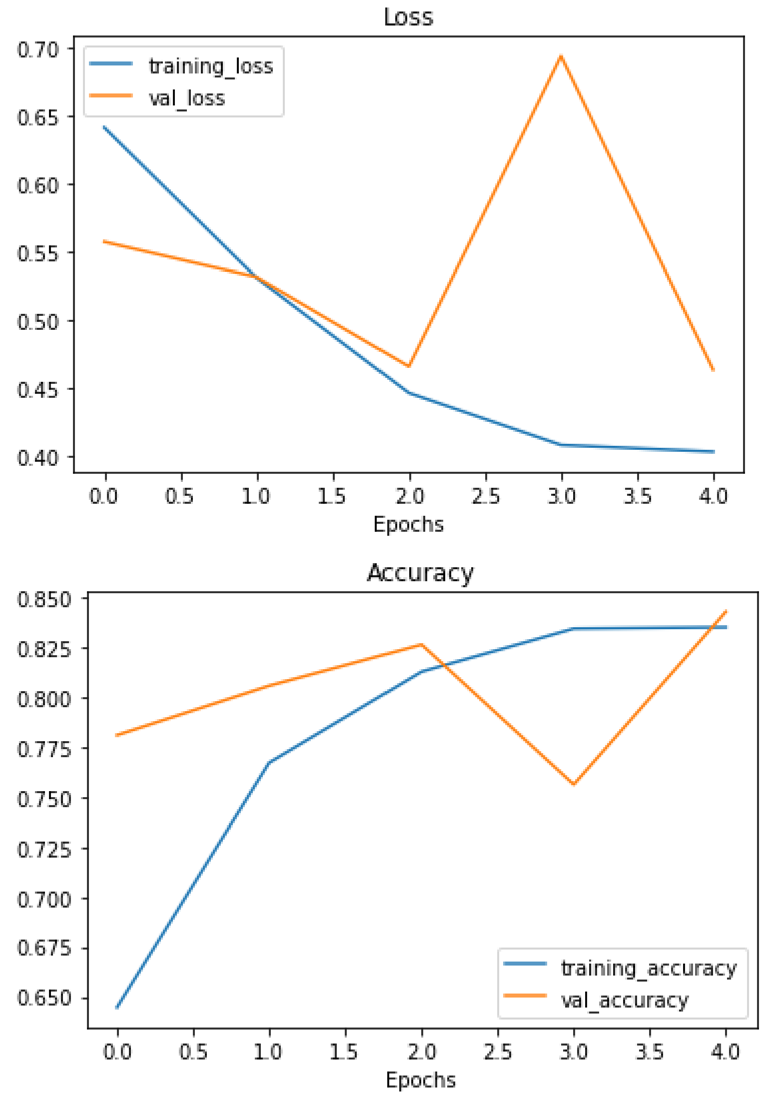

```
# Plot the validation and training data separately
def plot_loss_curves(history):
  """
  Returns separate loss curves for training and validation metrics.
  """
  loss = history.history['loss']
  val_loss = history.history['val_loss']

  accuracy = history.history['accuracy']
  val_accuracy = history.history['val_accuracy']

  epochs = range(len(history.history['loss']))

  # Plot loss
  plt.plot(epochs, loss, label='training_loss')
  plt.plot(epochs, val_loss, label='val_loss')
  plt.title('Loss')
  plt.xlabel('Epochs')
  plt.legend()

  # Plot accuracy
  plt.figure()
  plt.plot(epochs, accuracy, label='training_accuracy')
  plt.plot(epochs, val_accuracy, label='val_accuracy')
  plt.title('Accuracy')
  plt.xlabel('Epochs')
  plt.legend();
```

```
plot_loss_curves(history_a)
```




```
plot_loss_curves(history_b)
```


```
plot_loss_curves(history_c)
```




```
plot_loss_curves(history_d)
```

Increasing Hidden layer and epochs seems like it shown promising results - Test Accuracy of ~ 88%

Changing the optimizer only gave an test accuracy around ~54%

But let's look for CNN

CNN

```
model_1 = tf.keras.models.Sequential([
  tf.keras.layers.Conv2D(filters=10,
                         kernel_size=3, # can also be (3, 3)
                         activation="relu",
                         input_shape=(150, 150, 3)), # first layer specifies input


  tf.keras.layers.Conv2D(10, 3, activation="relu"),
  tf.keras.layers.MaxPool2D(pool_size=2, # pool_size can also be (2, 2)
                            padding="valid"),
  tf.keras.layers.Conv2D(10, 3, activation="relu"),
  tf.keras.layers.Conv2D(10, 3, activation="relu"),

  tf.keras.layers.MaxPool2D(2),






  tf.keras.layers.Flatten(),
```

```
  tf.keras.layers.Dense(1, activation="sigmoid") # binary activation output
])

# Compile the model
model_1.compile(loss="binary_crossentropy",
              optimizer=tf.keras.optimizers.Adam(),
              metrics=["accuracy"])

# Fit the model
history_1 = model_1.fit(train_data,
                        epochs=10,
                        steps_per_epoch=len(train_data),
                        validation_data=valid_data,
                        validation_steps=len(valid_data))
```

```
Found 4350 images belonging to 2 classes.
Found 242 images belonging to 2 classes.
Epoch 1/10
136/136 [==============================] - 17s 120ms/step - loss: 0.4986 - acc
Epoch 2/10
136/136 [==============================] - 16s 119ms/step - loss: 0.3139 - acc
Epoch 3/10
136/136 [==============================] - 16s 118ms/step - loss: 0.2034 - acc
Epoch 4/10
136/136 [==============================] - 16s 117ms/step - loss: 0.1588 - acc
Epoch 5/10
136/136 [==============================] - 16s 118ms/step - loss: 0.0990 - acc
Epoch 6/10
136/136 [==============================] - 16s 118ms/step - loss: 0.0734 - acc
Epoch 7/10
136/136 [==============================] - 16s 117ms/step - loss: 0.0509 - acc
Epoch 8/10
136/136 [==============================] - 16s 118ms/step - loss: 0.0434 - acc
Epoch 9/10
136/136 [==============================] - 16s 118ms/step - loss: 0.0320 - acc
Epoch 10/10
136/136 [==============================] - 16s 120ms/step - loss: 0.0259 - acc
```

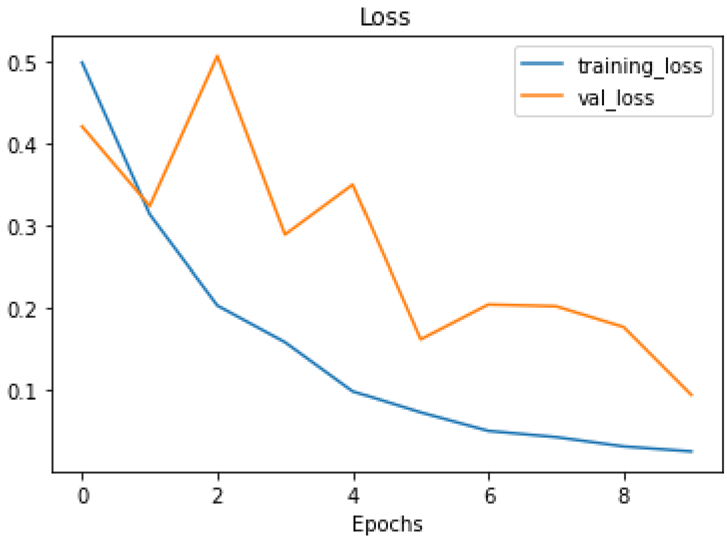
```
# Check out the layers in our model
model_1.summary()
```

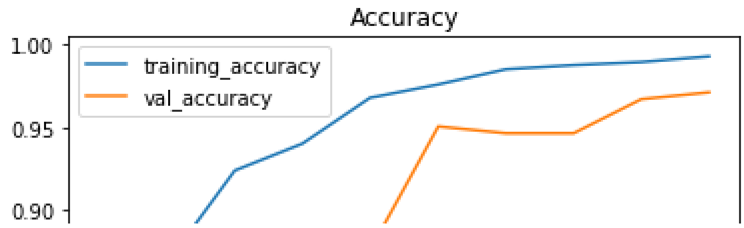
```
Model: "sequential_9"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_39 (Conv2D)          (None, 148, 148, 10)      280

 conv2d_40 (Conv2D)          (None, 146, 146, 10)      910

 max_pooling2d_18 (MaxPoolin  (None, 73, 73, 10)       0
 g2D)

 conv2d_41 (Conv2D)          (None, 71, 71, 10)        910
```

```
 conv2d_42 (Conv2D)          (None, 69, 69, 10)        910

 max_pooling2d_19 (MaxPoolin  (None, 34, 34, 10)       0
 g2D)

 flatten_9 (Flatten)         (None, 11560)             0

 dense_9 (Dense)             (None, 1)                 11561

=================================================================
Total params: 14,571
Trainable params: 14,571
Non-trainable params: 0
_________________________________________________________________
```

```
# Plot the validation and training data separately
def plot_loss_curves(history):
  """
  Returns separate loss curves for training and validation metrics.
  """
  loss = history.history['loss']
  val_loss = history.history['val_loss']

  accuracy = history.history['accuracy']
  val_accuracy = history.history['val_accuracy']

  epochs = range(len(history.history['loss']))

  # Plot loss
  plt.plot(epochs, loss, label='training_loss')
  plt.plot(epochs, val_loss, label='val_loss')
  plt.title('Loss')
  plt.xlabel('Epochs')
  plt.legend()

  # Plot accuracy
  plt.figure()
  plt.plot(epochs, accuracy, label='training_accuracy')
  plt.plot(epochs, val_accuracy, label='val_accuracy')
  plt.title('Accuracy')
  plt.xlabel('Epochs')
  plt.legend();
```

```
# Check out the loss curves of model_1
plot_loss_curves(history_1)
```






```
# Evaluate on the test data
model_1.evaluate(valid_data )
```

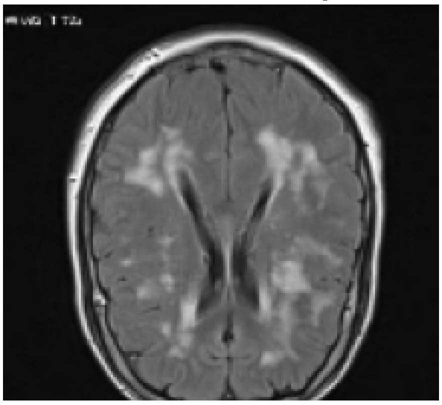
```
8/8 [==============================] - 1s 76ms/step - loss: 0.0948 - accuracy:
[0.0948067158460617, 0.9710744023323059]
```

```
def view_random_image(target_dir, target_class):
  # Setup target directory (we'll view images from here)
  target_folder = target_dir+target_class

  # Get a random image path
  random_image = random.sample(os.listdir(target_folder), 1)

  # Read in the image and plot it using matplotlib
  img = mpimg.imread(target_folder + "/" + random_image[0])
  plt.imshow(img)
  plt.title(target_class)
  plt.axis("off");

  print(f"Image shape: {img.shape}") # show the shape of the image

  return img


# Create a function to import an image and resize it to be able to be used with our
def load_and_prep_image(filename, img_shape=150):
  """
  Reads an image from filename, turns it into a tensor
  and reshapes it to (img_shape, img_shape, colour_channel).
  """
  # Read in target file (an image)
```

```
  img = tf.io.read_file(filename)

  # Decode the read file into a tensor & ensure 3 colour channels
  # (our model is trained on images with 3 colour channels and sometimes images hav
  img = tf.image.decode_image(img, channels=3)

  # Resize the image (to the same size our model was trained on)
  img = tf.image.resize(img, size = [img_shape, img_shape])

  # Rescale the image (get all values between 0 and 1)
  img = img/255.
  return img


def pred_and_plot(model, filename, class_names):
  """
  Imports an image located at filename, makes a prediction on it with
  a trained model and plots the image with the predicted class as the title.
  """
  # Import the target image and preprocess it
  img = load_and_prep_image(filename)

  # Make a prediction
  pred = model.predict(tf.expand_dims(img, axis=0))

  # Get the predicted class
  pred_class = class_names[int(tf.round(pred)[0][0])]

  # Plot the image and predicted class
  plt.imshow(img)
  plt.title(f"Prediction: {pred_class}")
  plt.axis(False);


# Test our model on a custom image
pred_and_plot(model_1, "/content/brain-tumor /pred/Cancer (2415).jpg", class_names)
```


```
pred_and_plot(model_1, "/content/brain-tumor /pred/Not Cancer  (2075).jpg", class_n
```

Prediction: Healthy



IT SEEMS THAT CNN HAS OUT PERFORMED FNN

ACCURACY

FNN - ~88% (model_d)

CNN- ~97% (model_1)