

ProjectCore

March 13, 2023

1 Import necessary packages

```
In [1]: #import modules and pytorch libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import random

import torch
import torchvision
from torch.utils.data import Dataset, DataLoader
from torch.utils.data import random_split
from torchvision import datasets
from torchvision.transforms import ToTensor
from torchvision.datasets import ImageFolder
import torchvision.transforms as transforms

import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten, Conv2D, MaxPooling2D, BatchNormali
from tensorflow.keras.layers import Dropout
print(tf.__version__)
tf.config.set_visible_devices([], 'GPU')

# reproducibility
random.seed(147)
np.random.seed(147)
torch.manual_seed(147)
tf.random.set_seed(147)
```

2.11.0

```
In [2]: # run this cell if your jupyter notebook kernel has died
import os
#os.environ['KMP_DUPLICATE_LIB_OK'] = 'True'
```

2 Import all images and split for training, validation, and testing

```
In [3]: #importing training and test dataset
        transform = transforms.Compose([
            transforms.Grayscale(num_output_channels=1), # Convert to grayscale (if needed)
            transforms.Resize((256, 256)), # Resize the image to (256, 256) pixels
            transforms.ToTensor() # Convert to a tensor
        ])

        # Load the images from the two folders
        # firstly create new folder named 'data' containing yes_output and no_output files
        image_set = ImageFolder(root='Br35H/data', transform=transform)

        # Define the ratio for each set
        train_ratio = 0.8 # 80% for training
        val_ratio = 0.1 # 10% for validation
        test_ratio = 0.1 # 10% for testing

        # Calculate the lengths of each set
        train_len = int(len(image_set) * train_ratio)
        val_len = int(len(image_set) * val_ratio)
        test_len = len(image_set) - train_len - val_len

        # Split the dataset using random_split
        train_set, val_set, test_set = random_split(image_set, [train_len, val_len, test_len])

        batch_size = 32
        train_loader = torch.utils.data.DataLoader(train_set, batch_size=batch_size, shuffle=True)
        val_loader = torch.utils.data.DataLoader(val_set, batch_size=batch_size)
        test_loader = torch.utils.data.DataLoader(test_set, batch_size=batch_size)
```

3 Here I chose to work with tensorflow model for its convenience

3.1 Define a converter here so pytorch dataloader can work with tensorflow

```
In [4]: # pytorch to tensorflow converter, so that data can be read by tf model
        def convert_to_numpy(loader):
            data = []
            labels = []
            for batch in loader:
                images, batch_labels = batch
                data.append(images.numpy())
                labels.append(batch_labels.numpy())
            data = np.concatenate(data, axis=0)
            labels = np.concatenate(labels, axis=0)
            # Reshape the data to (batch_size, height, width, channels)
            data = data.reshape(-1, 256, 256, 1)
            return data, labels
```

```
x_train, y_train = convert_to_numpy(train_loader)
x_val, y_val = convert_to_numpy(val_loader)
x_test, y_test = convert_to_numpy(test_loader)
```

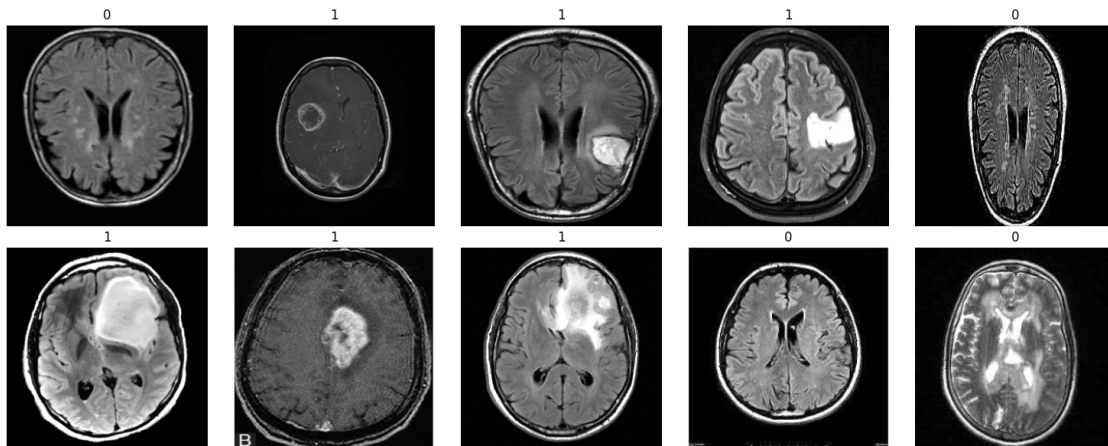
4 Display few images in the folder with corresponding labels

4.1 0: absence of brain tumour, 1: brain tumour positive

```
In [12]: # Display 10 random original images
n_samples = 10
indices = np.random.randint(x_train.shape[2], size=n_samples)

fig, axes = plt.subplots(2, 5, figsize=(15, 6))
for i, idx in enumerate(indices):
    row = i // 5
    col = i % 5
    axes[row, col].imshow(x_train[idx], cmap='gray')
    axes[row, col].set_title(y_train[idx])
    axes[row, col].axis('off')

plt.tight_layout()
plt.show()
```



5 Define CNN model architecture and compile it

```
In [7]: #define neural network class (CNN model architecture)
model = Sequential([

    # Convolutional layer 1
    Conv2D(32, (3, 3), padding='same', activation = 'relu', input_shape=(256, 256, 1))
```

```

        BatchNormalization(),
        MaxPooling2D((2, 2)),
        Dropout(0.25),

        # Convolutional layer 2
        Conv2D(32, (3, 3), padding='same', activation = 'relu',
              kernel_initializer = 'he_uniform'),
        BatchNormalization(),
        MaxPooling2D((2, 2)),

        Flatten(),

        # Dense layer 1
        Dense(512, activation='relu'),
        Dropout(0.5),

        # Dense layer 3 (output)
        Dense(1, activation='sigmoid')
    ])

    # Compile the model
    model.compile(optimizer = 'sgd', loss='binary_crossentropy', metrics=['accuracy'])
    model.summary()

```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 256, 256, 32)	320
batch_normalization (Batch Normalization)	(None, 256, 256, 32)	128
max_pooling2d (MaxPooling2D)	(None, 128, 128, 32)	0
dropout (Dropout)	(None, 128, 128, 32)	0
conv2d_1 (Conv2D)	(None, 128, 128, 32)	9248
batch_normalization_1 (Batch Normalization)	(None, 128, 128, 32)	128
max_pooling2d_1 (MaxPooling2D)	(None, 64, 64, 32)	0
flatten (Flatten)	(None, 131072)	0

dense (Dense)	(None, 512)	67109376
dropout_1 (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 1)	513

```
=====
Total params: 67,119,713
Trainable params: 67,119,585
Non-trainable params: 128
-----
```

6 Training the CNN for 14 epochs with validation

```
In [8]: # training
```

```
history = model.fit(x_train, y_train, epochs = 14, batch_size= 32, validation_data=(x_val, y_val))
```

```
Epoch 1/14
```

```
2023-03-08 21:47:58.903530: W tensorflow/tsl/platform/profile_utils/cpu_utils.cc:128] Failed to get CPU frequency: 0 Hz
2023-03-08 21:47:59.732177: I tensorflow/compiler/xla/service/service.cc:173] XLA service 0x2a1b1b1b1b1b1b1b: CreateThreadpool failed
2023-03-08 21:47:59.732804: I tensorflow/compiler/xla/service/service.cc:181] StreamExecutorCreateThreadpool failed
2023-03-08 21:48:00.143052: I tensorflow/compiler/jit/xla_compilation_cache.cc:477] Compiled cluster compatible with device(s): [NVIDIA GeForce RTX 3090]
```

```
75/75 [=====] - 56s 742ms/step - loss: 1.7454 - accuracy: 0.7429 - val_loss: 1.7454 - val_accuracy: 0.7429
Epoch 2/14
75/75 [=====] - 59s 780ms/step - loss: 0.3325 - accuracy: 0.8537 - val_loss: 0.3325 - val_accuracy: 0.8537
Epoch 3/14
75/75 [=====] - 56s 741ms/step - loss: 0.2286 - accuracy: 0.9096 - val_loss: 0.2286 - val_accuracy: 0.9096
Epoch 4/14
75/75 [=====] - 56s 742ms/step - loss: 0.1589 - accuracy: 0.9388 - val_loss: 0.1589 - val_accuracy: 0.9388
Epoch 5/14
75/75 [=====] - 56s 743ms/step - loss: 0.1090 - accuracy: 0.9617 - val_loss: 0.1090 - val_accuracy: 0.9617
Epoch 6/14
75/75 [=====] - 51s 681ms/step - loss: 0.0670 - accuracy: 0.9779 - val_loss: 0.0670 - val_accuracy: 0.9779
Epoch 7/14
75/75 [=====] - 49s 651ms/step - loss: 0.0559 - accuracy: 0.9808 - val_loss: 0.0559 - val_accuracy: 0.9808
Epoch 8/14
75/75 [=====] - 48s 634ms/step - loss: 0.0457 - accuracy: 0.9829 - val_loss: 0.0457 - val_accuracy: 0.9829
Epoch 9/14
75/75 [=====] - 49s 647ms/step - loss: 0.0275 - accuracy: 0.9917 - val_loss: 0.0275 - val_accuracy: 0.9917
Epoch 10/14
75/75 [=====] - 48s 642ms/step - loss: 0.0207 - accuracy: 0.9937 - val_loss: 0.0207 - val_accuracy: 0.9937
Epoch 11/14
75/75 [=====] - 52s 697ms/step - loss: 0.0195 - accuracy: 0.9950 - val_loss: 0.0195 - val_accuracy: 0.9950
```

```
Epoch 12/14
75/75 [=====] - 52s 691ms/step - loss: 0.0113 - accuracy: 0.9979 - val_
Epoch 13/14
75/75 [=====] - 77s 1s/step - loss: 0.0098 - accuracy: 0.9983 - val_l
Epoch 14/14
75/75 [=====] - 75s 996ms/step - loss: 0.0117 - accuracy: 0.9975 - va
```

7 Evaluate CNN on testing image data

7.1 model displays 98.33% accuracy on unseen data

```
In [9]: # evaluation on testing data
        test_loss, test_acc = model.evaluate(x_test, y_test)

10/10 [=====] - 1s 138ms/step - loss: 0.0470 - accuracy: 0.9900
```

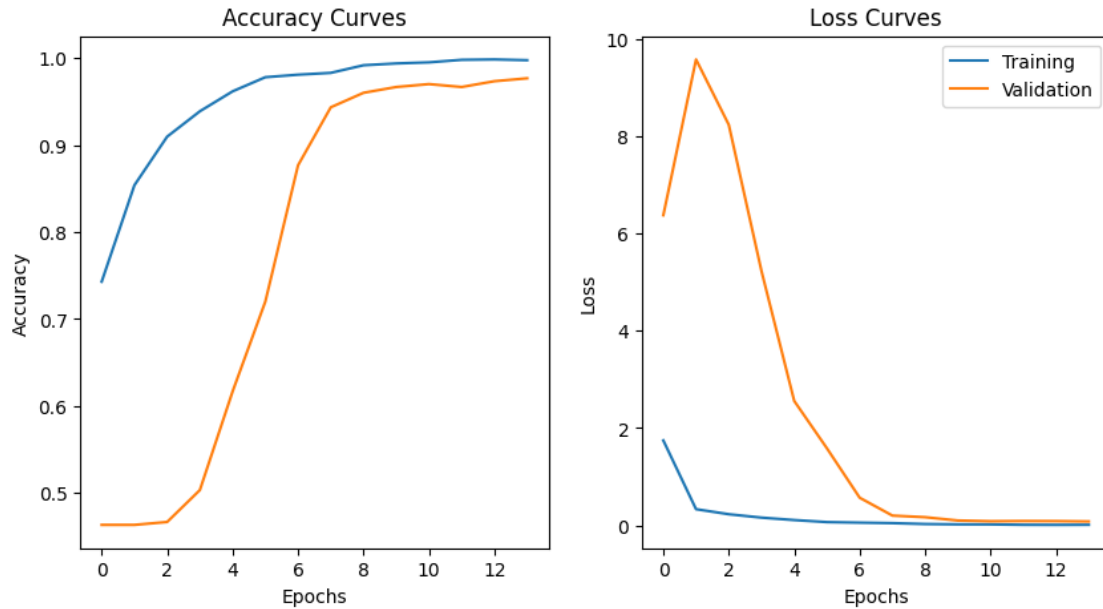
8 Visualise accuracy and loss values over training epochs

```
In [10]: # plot accuracy and loss over training epochs
         accuracy = history.history['accuracy']
         val_accuracy = history.history['val_accuracy']
         loss = history.history['loss']
         val_loss = history.history['val_loss']

         # Plot the accuracy and loss curves side by side
         plt.figure(figsize=(10,5))
         plt.subplot(1, 2, 1) # Create the left subplot
         plt.plot(accuracy, label='Training Accuracy')
         plt.plot(val_accuracy, label='Validation Accuracy')
         plt.title('Accuracy Curves')
         plt.xlabel('Epochs')
         plt.ylabel('Accuracy')

         plt.subplot(1, 2, 2) # Create the right subplot
         plt.plot(loss, label='Training')
         plt.plot(val_loss, label='Validation')
         plt.legend()
         plt.title('Loss Curves')
         plt.xlabel('Epochs')
         plt.ylabel('Loss')

         plt.show() # Show the plots
```



9 Save model into HDF5 file or read the file when reopening python

```
In [11]: # Save the entire model to a HDF5 file
         model.save('tumour_detector.h5')
```

```
In [12]: # OR YOU CAN LOAD THE TRAINED MODEL FOR ANALYSIS when reopen python
         model = tf.keras.models.load_model('tumour_detector.h5')
```

10 Visualise CNN decision making in some of testing images

10.1 Y-axis values represent model confidence on each choices

```
In [13]: # visualise our model's relative confidence (decision making) on testing images
         num_test_images = x_test.shape[0]

         random_inx = np.random.choice(num_test_images, 4)
         random_test_images = x_test[random_inx, ...]
         random_test_labels = y_test[random_inx, ...]

         predictions = model.predict(random_test_images)
         complement = np.ones_like(predictions) - predictions
         predictions = np.concatenate((complement, predictions), axis=1)

         fig, axes = plt.subplots(4, 2, figsize=(16, 12))
         fig.subplots_adjust(hspace=0.4, wspace=-0.2)
```

```

for i, (prediction, image, label) in enumerate(zip(predictions, random_test_images, r
    axes[i, 0].imshow(np.squeeze(image), cmap = 'gray')
    axes[i, 0].get_xaxis().set_visible(False)
    axes[i, 0].get_yaxis().set_visible(False)
    axes[i, 0].text(10., -1.5, f'Class {label}')
```

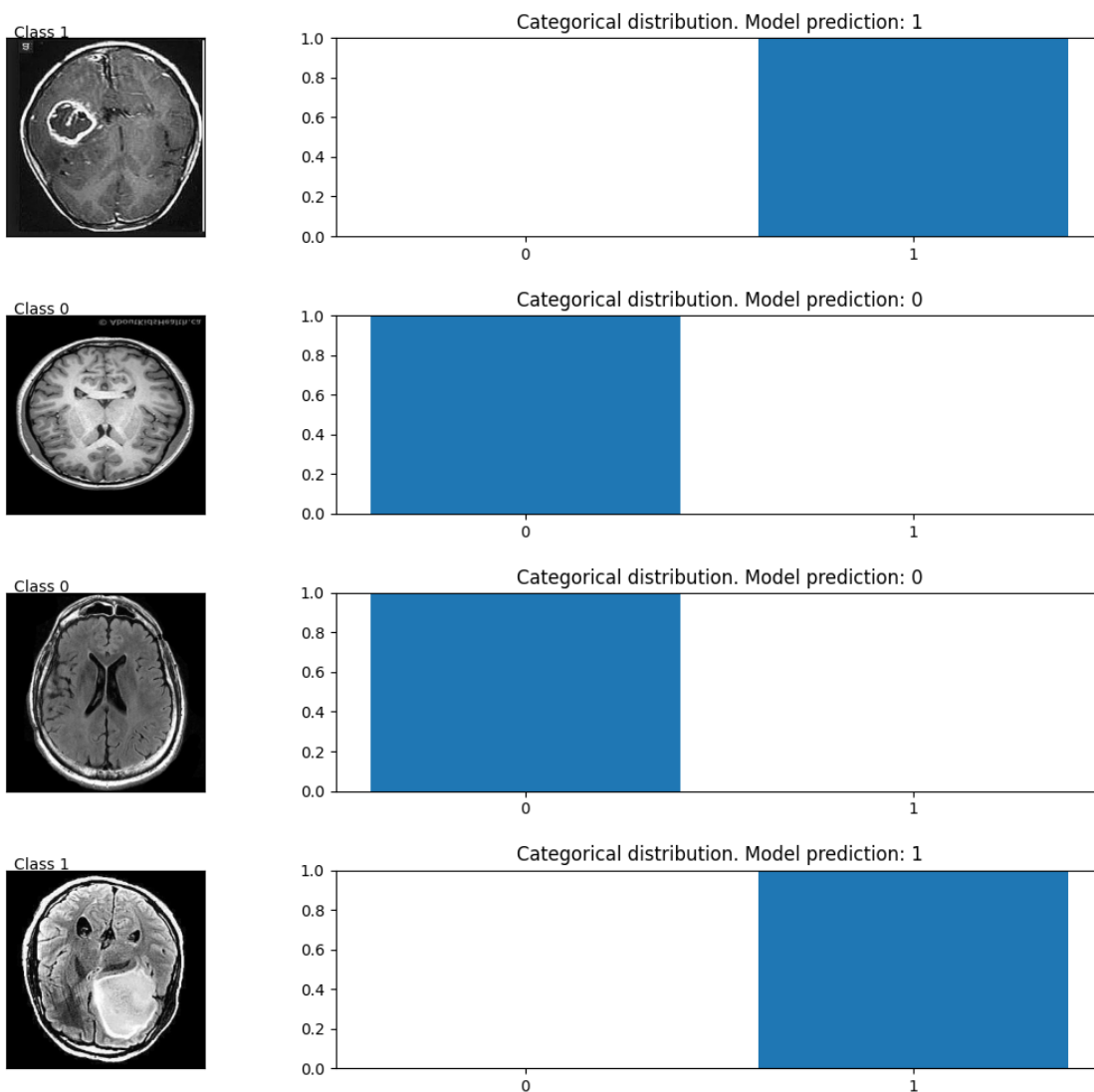
```

    axes[i, 1].bar(np.arange(len(prediction)), prediction)
    axes[i, 1].set_xticks(np.arange(len(prediction)))
    axes[i, 1].set_title(f"Categorical distribution. Model prediction: {np.argmax(pre

for ax in axes[:,1]:
    ax.set_ylim([0,1])

plt.show()
```

1/1 [=====] - 0s 88ms/step



11 Confusion matrix on testing data: 99% accuracy

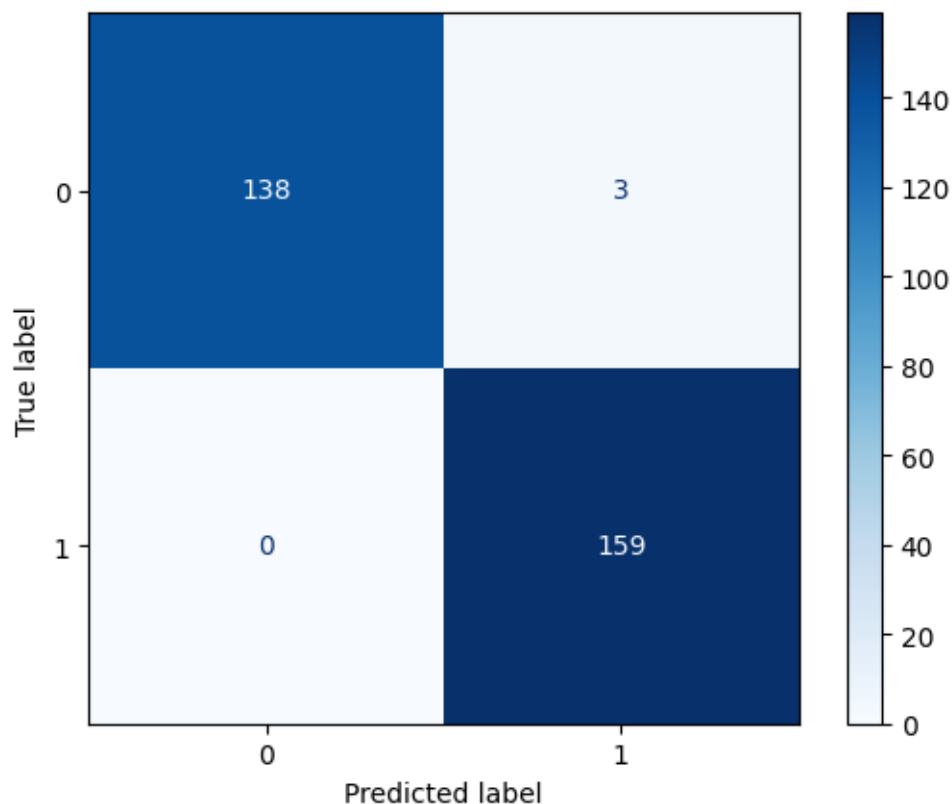
```
In [14]: # Confusion matrix on testing set to get an overall picture
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

predictions = model.predict(x_test)
predictions = [1 if x>0.5 else 0 for x in predictions]

accuracy = accuracy_score(y_test, predictions)
print('Testing Accuracy = %.3f' % accuracy)

confusion_mtx = confusion_matrix(y_test, predictions)
disp = ConfusionMatrixDisplay(confusion_matrix=confusion_mtx)
disp = disp.plot(cmap=plt.cm.Blues)

10/10 [=====] - 2s 173ms/step
Testing Accuracy = 0.990
```



12 Confusion matrix for validation data: 97.7% accuracy

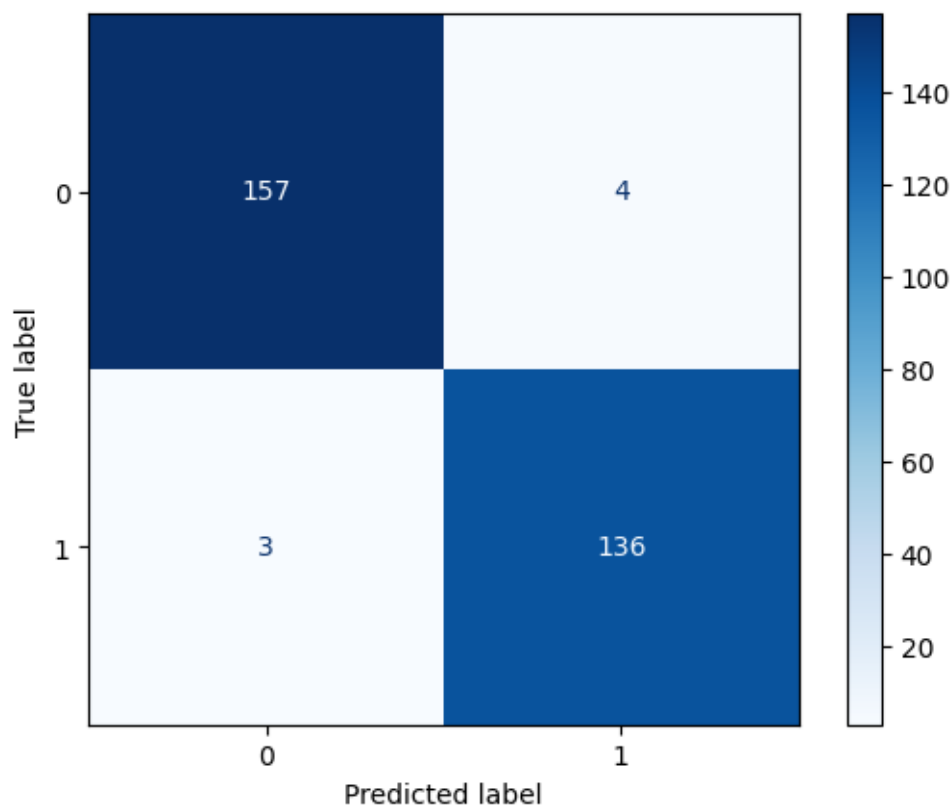
```
In [15]: predictions = model.predict(x_val)
         predictions = [1 if x>0.5 else 0 for x in predictions]

         accuracy = accuracy_score(y_val, predictions)
         print('Val Accuracy = %.3f' % accuracy)

         confusion_mtx = confusion_matrix(y_val, predictions)
         disp = ConfusionMatrixDisplay(confusion_matrix=confusion_mtx)
         disp = disp.plot(cmap=plt.cm.Blues)
```

10/10 [=====] - 2s 173ms/step

Val Accuracy = 0.977



12.1 Define functions that read an image folder and process images inside just like before. Processed images are ready to plug into model for prediction

```
In [20]: # Define a convert_to_numpy function which reads in image folders and process them
         from PIL import Image
         import os
```

```

def read_images(pred_path, transform):
    img_filenames = os.listdir(pred_path)
    img_width, img_height = 256, 256

    # Create a numpy array to store the images:
    imgs = np.zeros((len(img_filenames), img_width, img_height), dtype=np.float32)

    # Loop through the image filenames, load each image, and preprocess it:
    for i, filename in enumerate(img_filenames):
        img = Image.open(os.path.join(pred_path, filename))
        img = transform(img)
        imgs[i] = img

    # Reshape the data to (batch_size, height, width, channels)
    imgs = imgs.reshape(-1, img_width, img_height, 1)
    return imgs

# Get prediction images from pred_output image folder
pred_path = 'Br35H/pred_output'
img_filenames = os.listdir(pred_path)
img_width, img_height = 256, 256
pred_imgs = read_images(pred_path, transform)

```

13 Visualise model predictions of some images from folder 'pred_output'

In [21]: # visualise CNN decision making by displaying confidences

```

num_test_images = pred_imgs.shape[0]
random_inx = np.random.choice(num_test_images, 4)
random_test_images = pred_imgs[random_inx, ...]

predictions = model.predict(random_test_images)
complement = np.ones_like(predictions) - predictions
predictions = np.concatenate((complement, predictions), axis=1)

fig, axes = plt.subplots(4, 2, figsize=(16, 12))
fig.subplots_adjust(hspace=0.4, wspace=-0.2)

for i, (prediction, image) in enumerate(zip(predictions, random_test_images)):
    axes[i, 0].imshow(np.squeeze(image), cmap = 'gray')
    axes[i, 0].get_xaxis().set_visible(False)
    axes[i, 0].get_yaxis().set_visible(False)
    axes[i, 1].bar(np.arange(len(prediction)), prediction)
    axes[i, 1].set_xticks(np.arange(len(prediction)))
    axes[i, 1].set_title(f"Categorical distribution. Model prediction: {np.argmax(pre

```

```

for ax in axes[:,1]:
    ax.set_ylim([0,1])

```

```

plt.show()

```

1/1 [=====] - 0s 117ms/step

