

# Final\_Project\_ADL

December 23, 2022

Mounting the drive and importing/downloading the necessary libraries

```
[1]: from google.colab import drive
drive.mount('/content/drive',force_remount=True)

import os
import tensorflow as tf

import cv2    ##used to save the patches in .jpeg format
from sklearn.model_selection import train_test_split

import IPython.display as display
import matplotlib.pyplot as plt
import random

from tensorflow.keras import datasets, layers, models
```

Mounted at /content/drive

```
[2]: # Install the OpenSlide C library and Python bindings
!apt-get install openslide-tools
!pip install openslide-python
```

```
Reading package lists... Done
Building dependency tree
Reading state information... Done
The following package was automatically installed and is no longer required:
  libnvidia-common-460
Use 'apt autoremove' to remove it.
The following additional packages will be installed:
  libopenslide0
Suggested packages:
  libtiff-tools
The following NEW packages will be installed:
  libopenslide0 openslide-tools
0 upgraded, 2 newly installed, 0 to remove and 20 not upgraded.
Need to get 92.5 kB of archives.
After this operation, 268 kB of additional disk space will be used.
```

```

Get:1 http://archive.ubuntu.com/ubuntu bionic/universe amd64 libopenslide0 amd64
3.4.1+dfsg-2 [79.8 kB]
Get:2 http://archive.ubuntu.com/ubuntu bionic/universe amd64 openslide-tools
amd64 3.4.1+dfsg-2 [12.7 kB]
Fetched 92.5 kB in 0s (191 kB/s)
Selecting previously unselected package libopenslide0.
(Reading database ... 124016 files and directories currently installed.)
Preparing to unpack .../libopenslide0_3.4.1+dfsg-2_amd64.deb ...
Unpacking libopenslide0 (3.4.1+dfsg-2) ...
Selecting previously unselected package openslide-tools.
Preparing to unpack .../openslide-tools_3.4.1+dfsg-2_amd64.deb ...
Unpacking openslide-tools (3.4.1+dfsg-2) ...
Setting up libopenslide0 (3.4.1+dfsg-2) ...
Setting up openslide-tools (3.4.1+dfsg-2) ...
Processing triggers for libc-bin (2.27-3ubuntu1.6) ...
Processing triggers for man-db (2.8.3-2ubuntu0.1) ...
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Collecting openslide-python
  Downloading openslide-python-1.2.0.tar.gz (338 kB)
    | 338 kB 15.3 MB/s
Requirement already satisfied: Pillow in /usr/local/lib/python3.8/dist-
packages (from openslide-python) (7.1.2)
Building wheels for collected packages: openslide-python
  Building wheel for openslide-python (setup.py) ... done
  Created wheel for openslide-python:
filename=openslide_python-1.2.0-cp38-cp38-linux_x86_64.whl size=27716
sha256=c17f09f5d43990110a3aeefc5c98797839728d283cddffed78c0fb698148c53a
  Stored in directory: /root/.cache/pip/wheels/ae/74/4e/f8654d229eb249d1345e3df0
191030ad77e7a6a2114df7cd28
Successfully built openslide-python
Installing collected packages: openslide-python
Successfully installed openslide-python-1.2.0

```

```

[3]: %matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
from openslide import open_slide, __library_version__ as openslide_version
import os
from PIL import Image
from skimage.color import rgb2gray

```

Using the address of the shortcut (created in my drive) for the folder containing the slides and the masks and selecting a few of them

```

[4]: data_dir = "/content/drive/MyDrive/slides/"
files = os.listdir(data_dir)

```

```
[5]: ## adding all the tumor slide names to a list
all_image_names = []
for x in files:
    if (".xml" not in x) and ("mask" not in x):
        all_image_names.append(x)
```

```
[6]: ## adding the corresponding tumor mask file names to a list
all_image_masks = []
for x in files:
    if "mask" in x:
        all_image_masks.append(x)
```

```
[7]: ## we remove tumor_038.tif if present as it does not have it's corresponding
    ↪ mask
remove = "tumor_038.tif"
for n,x in enumerate(all_image_names):
    if x == remove:
        all_image_names.pop(n)

## creating two new lists containing the image paths to the above tumors and
    ↪ their corresponding masks
image_paths = []
image_paths_mask = []
for x in range(len(all_image_names)):
    image_paths.append(data_dir + all_image_names[x])
    image_paths_mask.append(data_dir + all_image_masks[x])
```

Uploading all the slides and their corresponding masks from the folder to a GCP bucket for easier access and use

```
[ ]: ## configuring the project and user authentication to use GCP
from google.colab import auth
auth.authenticate_user()
project_id = 'computer-systems-341920'
!gcloud config set project {project_id}
!gsutil ls
```

```
[ ]: ## uploading the slides and their corresponding masks to a specified bucket
bucket_name = 'hw3_adl'
for x in zip(image_paths, image_paths_mask):
    n1 = x[0]
    n2 = x[1]
    !gsutil -m cp $n1 gs://{bucket_name}/
    !gsutil -m cp $n2 gs://{bucket_name}/
```

Download few slides and tumor masks from the bucket (this is optional, we have directly accessed the slides folder in google drive)

```
[8]: colab_root = "/content/"
def download_if_missing(url, target, extract=True):
    if os.path.exists(target):
        return target
    return tf.keras.utils.get_file(target, origin=url, extract=extract)
```

```
[ ]: ## downloading a few slides and their masks from the bucket
BUCKET_URL = "https://storage.googleapis.com/hw3_adl/"
files = 15
count = 0
for x in zip(all_image_names, all_image_masks):
    count = count + 1
    n1 = x[0]
    n2 = x[1]
    file_path = colab_root + n1
    file_path_mask = colab_root + n2
    download_if_missing(BUCKET_URL + n1, file_path)
    download_if_missing(BUCKET_URL + n2, file_path_mask)
    if count >= files:
        break
```

```
Downloading data from https://storage.googleapis.com/hw3_adl/tumor_002_mask.tif
97697336/97697336 [=====] - 1s 0us/step
Downloading data from https://storage.googleapis.com/hw3_adl/tumor_110.tif
1485042280/1485042280 [=====] - 21s 0us/step
Downloading data from https://storage.googleapis.com/hw3_adl/tumor_012_mask.tif
95879690/95879690 [=====] - 4s 0us/step
Downloading data from https://storage.googleapis.com/hw3_adl/tumor_005.tif
1467903916/1467903916 [=====] - 14s 0us/step
Downloading data from https://storage.googleapis.com/hw3_adl/tumor_002.tif
1680307170/1680307170 [=====] - 25s 0us/step
Downloading data from https://storage.googleapis.com/hw3_adl/tumor_016_mask.tif
98694816/98694816 [=====] - 1s 0us/step
Downloading data from https://storage.googleapis.com/hw3_adl/tumor_019.tif
1536279242/1536279242 [=====] - 21s 0us/step
Downloading data from https://storage.googleapis.com/hw3_adl/tumor_084_mask.tif
25949822/25949822 [=====] - 1s 0us/step
Downloading data from https://storage.googleapis.com/hw3_adl/tumor_012.tif
1626791654/1626791654 [=====] - 18s 0us/step
Downloading data from https://storage.googleapis.com/hw3_adl/tumor_096_mask.tif
43253974/43253974 [=====] - 0s 0us/step
Downloading data from https://storage.googleapis.com/hw3_adl/tumor_016.tif
1524584022/1524584022 [=====] - 14s 0us/step
Downloading data from https://storage.googleapis.com/hw3_adl/tumor_110_mask.tif
32922630/32922630 [=====] - 0s 0us/step
Downloading data from https://storage.googleapis.com/hw3_adl/tumor_023.tif
1687969860/1687969860 [=====] - 14s 0us/step
```

```

Downloading data from https://storage.googleapis.com/hw3_adl/tumor_031_mask.tif
99493514/99493514 [=====] - 1s 0us/step
Downloading data from https://storage.googleapis.com/hw3_adl/tumor_031.tif
1487082070/1487082070 [=====] - 19s 0us/step
Downloading data from https://storage.googleapis.com/hw3_adl/tumor_081_mask.tif
41073180/41073180 [=====] - 1s 0us/step
Downloading data from https://storage.googleapis.com/hw3_adl/tumor_035.tif
1605582132/1605582132 [=====] - 17s 0us/step
Downloading data from https://storage.googleapis.com/hw3_adl/tumor_059_mask.tif
97703912/97703912 [=====] - 1s 0us/step
Downloading data from https://storage.googleapis.com/hw3_adl/tumor_057.tif
1459755832/1459755832 [=====] - 18s 0us/step
Downloading data from https://storage.googleapis.com/hw3_adl/tumor_078_mask.tif
52204056/52204056 [=====] - 1s 0us/step
Downloading data from https://storage.googleapis.com/hw3_adl/tumor_059.tif
1480993338/1480993338 [=====] - 13s 0us/step
Downloading data from https://storage.googleapis.com/hw3_adl/tumor_101_mask.tif
46053642/46053642 [=====] - 0s 0us/step
Downloading data from https://storage.googleapis.com/hw3_adl/tumor_064.tif
1645432562/1645432562 [=====] - 17s 0us/step
Downloading data from https://storage.googleapis.com/hw3_adl/tumor_094_mask.tif
54282736/54282736 [=====] - 1s 0us/step

```

## Read the slides using Openslide

```

[9]: ## printing the various zoom levels and their respective downsampling factors
## along with the dimensions of the image at every zoom level
## also applying certain sanity checks
file_path = data_dir+"tumor_101.tif"
file_path_mask = data_dir + "tumor_101_mask.tif"

slide = open_slide(file_path)
print ("Read WSI from %s with width: %d, height: %d" % (file_path,
                                                         slide.
                                                         ↳level_dimensions[0][0],
                                                         slide.
                                                         ↳level_dimensions[0][1]))

tumor_mask = open_slide(file_path_mask)
print ("Read tumor mask from %s" % (file_path_mask))

print("Slide includes %d levels", len(slide.level_dimensions))
for i in range(len(tumor_mask.level_dimensions)):
    print("Level %d, dimensions: %s downsample factor %d" % (i,
                                                              slide.
                                                              ↳level_dimensions[i],
                                                              slide.
                                                              ↳level_downsamples[i]))

```

```

    assert tumor_mask.level_dimensions[i][0] == slide.level_dimensions[i][0]
    assert tumor_mask.level_dimensions[i][1] == slide.level_dimensions[i][1]

# Verify downsampling works as expected
width, height = slide.level_dimensions[7]
assert width * slide.level_downsamples[7] == slide.level_dimensions[0][0]
assert height * slide.level_downsamples[7] == slide.level_dimensions[0][1]

```

Read WSI from /content/drive/MyDrive/slides/tumor\_101.tif with width: 139264, height: 71680

Read tumor mask from /content/drive/MyDrive/slides/tumor\_101\_mask.tif

Slide includes %d levels 10

Level 0, dimensions: (139264, 71680) downsample factor 1

Level 1, dimensions: (69632, 35840) downsample factor 2

Level 2, dimensions: (34816, 17920) downsample factor 4

Level 3, dimensions: (17408, 8960) downsample factor 8

Level 4, dimensions: (8704, 4480) downsample factor 16

Level 5, dimensions: (4352, 2240) downsample factor 32

Level 6, dimensions: (2176, 1120) downsample factor 64

Level 7, dimensions: (1088, 560) downsample factor 128

Level 8, dimensions: (544, 280) downsample factor 256

```

[ ]: ## applying certain checks on all the files in the slides folder
## making sure that the mask and the slide have same dimensions at same levels
## also making sure that the downsampling factor is correct
for x in all_image_names:
    file_path = data_dir + x
    file_path_mask = data_dir + x.split(".")[0] + "_mask." + x.split(".")[1]
    slide = open_slide(file_path)
    tumor_mask = open_slide(file_path_mask)
    for i in range(len(tumor_mask.level_dimensions)):
        try:
            tumor_mask.level_dimensions[i][0] == slide.level_dimensions[i][0]
            tumor_mask.level_dimensions[i][1] == slide.level_dimensions[i][1]
        except:
            print("File" , x , "is corrupted")
    # Verify downsampling works as expected
width, height = slide.level_dimensions[7]
assert width * slide.level_downsamples[7] == slide.level_dimensions[0][0]
assert height * slide.level_downsamples[7] == slide.level_dimensions[0][1]

```

```

[11]: # Note: x,y coords are with respect to level 0.
# Read a region from the slide
# Return a numpy RGB array
def read_slide(slide, x, y, level, width, height, as_float=False):
    ## top left on the image is the origin.
    ## (x,y) -- coordinates of the top left point on the patch

```

```

## height and width of the patch are also passed onto the fn.
im = slide.read_region((x,y), level, (width, height))
im = im.convert('RGB') # drop the alpha channel
if as_float:
    im = np.asarray(im, dtype=np.float32)
else:
    im = np.asarray(im)
## making sure the read_region function and conversion to RGB has taken
→ place
assert im.shape == (height, width, 3)
return im

```

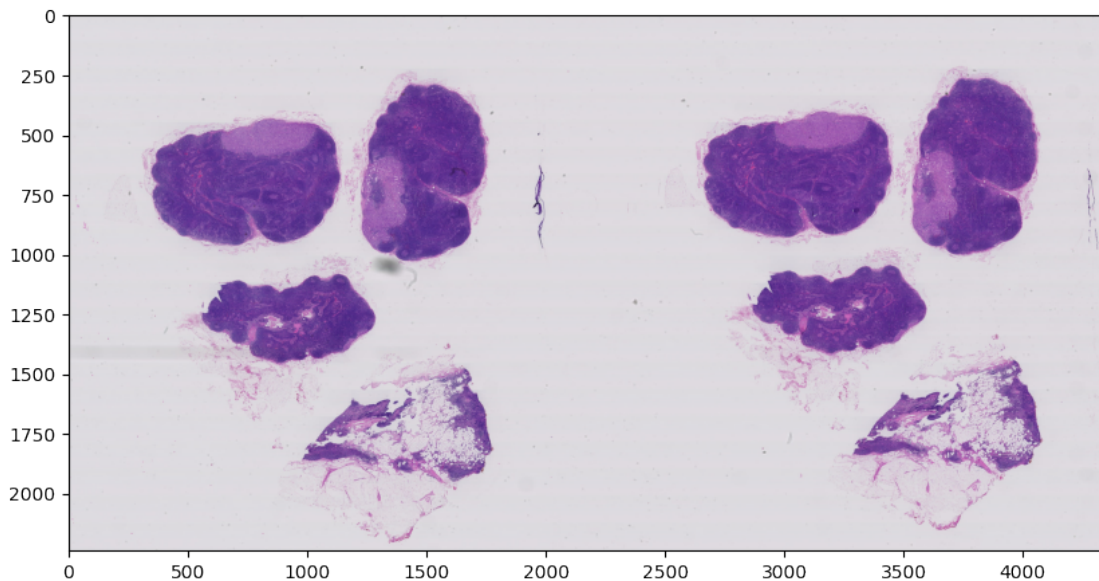
```

[11]: # reading the entire slide at level 5
slide_image = read_slide(slide,
                        x=0,
                        y=0,
                        level=5,
                        width=slide.level_dimensions[5][0],
                        height=slide.level_dimensions[5][1])

plt.figure(figsize=(10,10), dpi=100)
plt.imshow(slide_image)

```

[11]: <matplotlib.image.AxesImage at 0x7f6186d23580>



```

[12]: #read the entire mask at the same zoom level (NOTE: the mask is binary, pixel
→ values are either 0 or 1)

```

```

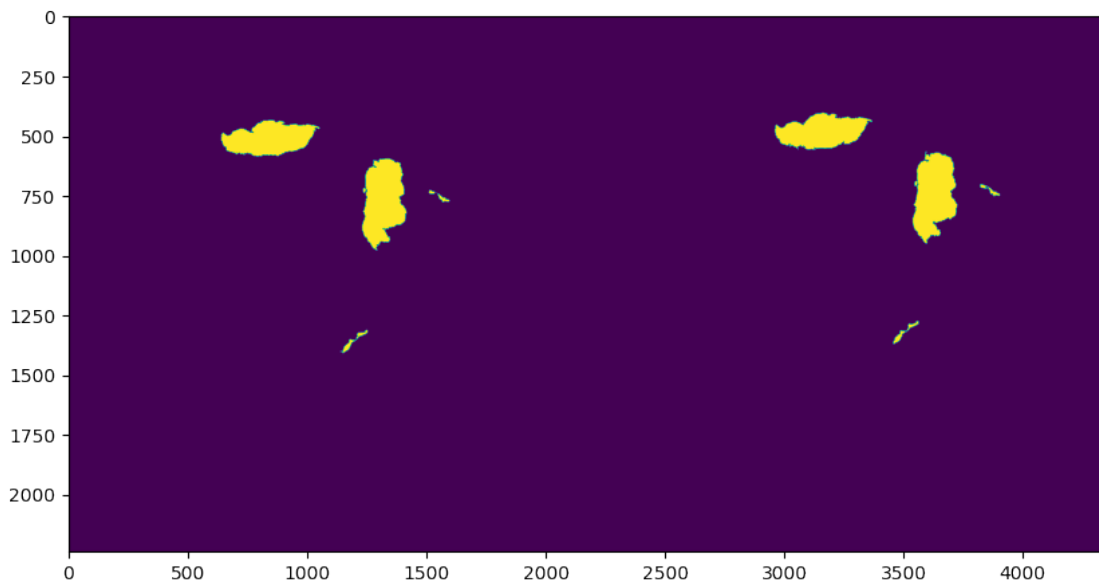
mask_image = read_slide(tumor_mask,
                        x=0,
                        y=0,
                        level=5,
                        width=slide.level_dimensions[5][0],
                        height=slide.level_dimensions[5][1])

# the above generates a mask with R,G,B channels.
# The mask info we need is in the first channel only.
mask_image = mask_image[:, :, 0]

plt.figure(figsize=(10,10), dpi=100)
plt.imshow(mask_image)

```

[12]: <matplotlib.image.AxesImage at 0x7f6186816490>



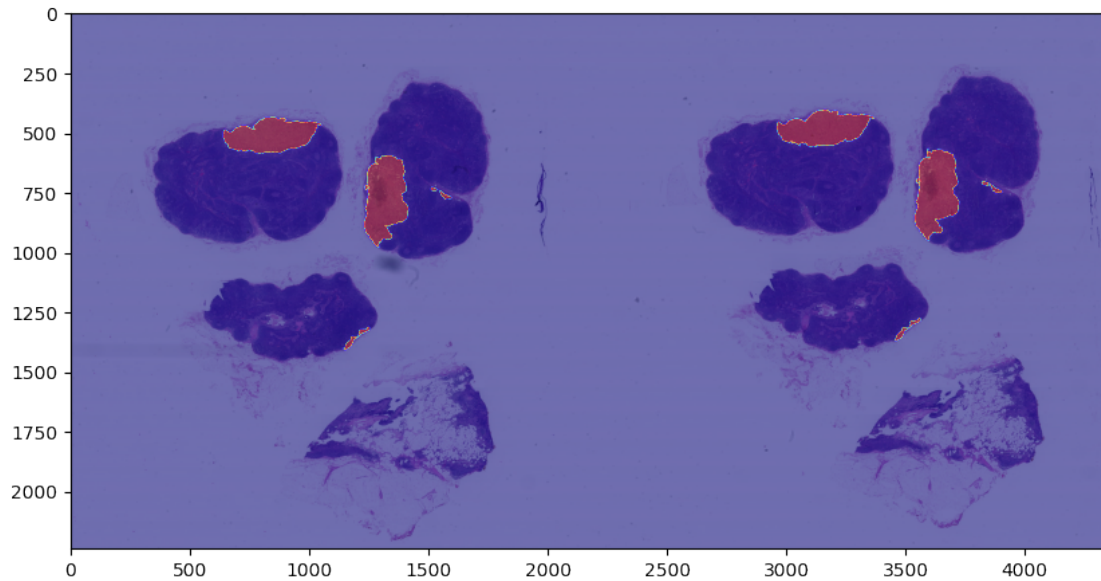
```

[13]: # Overlay them. The idea is that the mask shows the region of the slide that
# contain cancerous cells.
plt.figure(figsize=(10,10), dpi=100)
plt.imshow(slide_image)
plt.imshow(mask_image, cmap='jet', alpha=0.5) # Red regions contains cancer.

```

[13]: <matplotlib.image.AxesImage at 0x7f61857db3d0>





Performing the sliding window operation at Level 5 zoom and visualizing the cancerous patches (based on a 20% threshold) along with their masks and overlaps for one example to check if the sliding window operation is working properly

```
[14]: ## Rolling a non overlapping sliding window of size 299X299 (size taken from
      ↪ the paper)
      ## Setting the threshold at 20%, the patch will be labelled as cancerous if
      ↪ more than 20% of the pixels are cancerous
      ## Visualizing the cancerous patches, their corresponding masks and the overlap
      ↪ of the two images to verify if the results look correct

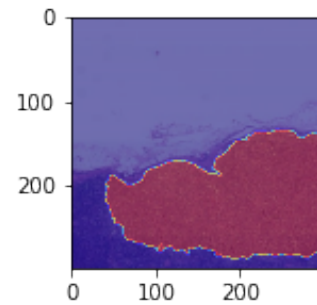
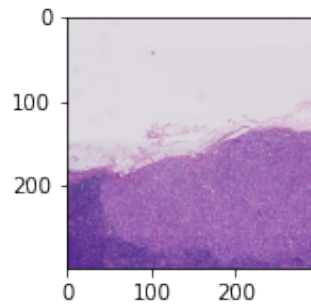
      slide_dim = 299
      level = 5
      dwn_smpls = int(slide.level_downsamples[level])
      x_range = slide.level_dimensions[level][0]
      y_range = slide.level_dimensions[level][1]
      x_lt = int(x_range/slide_dim)
      y_lt = int(y_range/slide_dim)
      fig = plt.figure(figsize=(10, 10))
      count = 0
      for x in range(x_lt):
          for y in range(y_lt):
              # region = read_slide(slide, x=slide_dim*x, y=slide_dim*y, level=level,
              ↪ width=slide_dim, height=slide_dim)
              region_mask = read_slide(tumor_mask, x=x*slide_dim*dwn_smpls,
              ↪ y=y*slide_dim*dwn_smpls, level=level, width=slide_dim, height=slide_dim)[:,:]
              ↪ ,0]
```

```

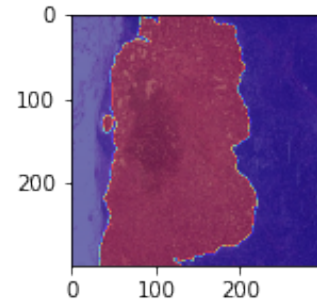
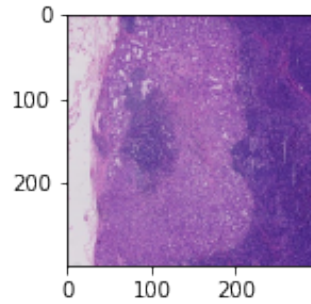
cancer_tissue = round((sum(map(sum, region_mask))/slide_dim**2)*100,2)
## if there is more than 20% cancerous pixels in the patch, consider it
→ cancerous
if cancer_tissue > 20:
    count = count + 1
    fig.add_subplot(4, 3, count)
    plt.imshow(region_mask)
    plt.axis('off')
    plt.title("Cancer %age: " + str(round((sum(map(sum, region_mask))/
→ slide_dim**2)*100,2)))
    region = read_slide(slide, x=x*slide_dim*dwn_smpls,
→ y=y*slide_dim*dwn_smpls, level=level, width=slide_dim, height=slide_dim)
    count = count + 1
    fig.add_subplot(4, 3, count)
    plt.imshow(region)
    count = count + 1
    fig.add_subplot(4, 3, count)
    plt.imshow(region)
    plt.imshow(region_mask, cmap='jet', alpha=0.5)

```

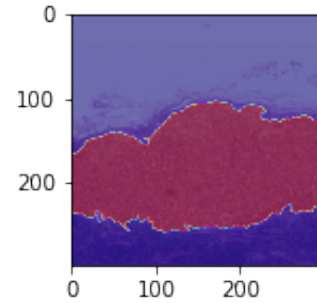
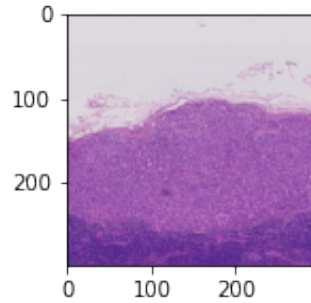
Cancer %age: 32.22



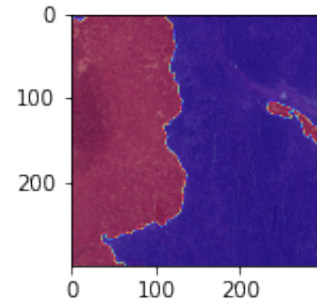
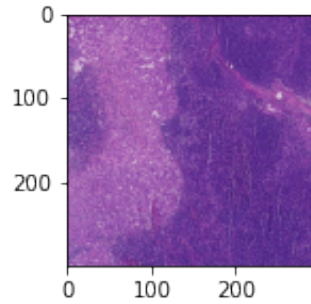
Cancer %age: 49.58



Cancer %age: 39.4



Cancer %age: 38.56



## Function definitions

```
[10]: ## the below function returns the pixels that belong to a tissue using an  
      ↪ intensity threshold on the grayscale img  
def find_tissue_pixels(image, intensity=0.8):  
    im_gray = rgb2gray(image)  
    assert im_gray.shape == (image.shape[0], image.shape[1])  
    indices = np.where(im_gray <= intensity)  
    return list(zip(indices[0], indices[1]))
```

```

## defining a function to perform the sliding window operation on a slide and
↳ save the patches along with the labels
## the function takes in the following inputs
## -- filename (e.g. tumor_075.tif)
## -- zoom level
## -- height and width of the sliding window
## -- thresholds for %age tissue and %age cancer
## -- paths to the slide directory and where to save the patches

def
↳ patch_save(filename,level,height,width,tissue_thresh,cancer_thresh,path_to_dir,path_to_save
↳

    slide = open_slide(path_to_dir + filename)
    tumor_mask = open_slide(path_to_dir + filename.split(".")[0] + "_mask." +
↳ filename.split(".")[1])
    dwn_smpls = int(slide.level_downsamples[level])
    x_range = slide.level_dimensions[level][0]
    y_range = slide.level_dimensions[level][1]
    x_lt = int(x_range/width)
    y_lt = int(y_range/height)
    count = 0
    for x in range(x_lt):
        for y in range(y_lt):
            region = read_slide(slide, x= x*width*dwn_smpls, y= y*height*dwn_smpls,
↳ level=level, width=width, height=height)
            region_mask = read_slide(tumor_mask, x=x*width*dwn_smpls,
↳ y=y*height*dwn_smpls, level=level, width=width, height=height)[:,:,:0]

            cancer_tissue = round((sum(map(sum, region_mask))/height*width)*100,2)
            percent_tissue = len(find_tissue_pixels(region)) / float(height * width)
↳ * 100
            count = count + 1
            if (percent_tissue > tissue_thresh):
                if cancer_tissue > cancer_thresh:
                    save_file = filename.split(".")[0] + "_patch_" + str(count) + "_lvl_"
↳ str(level) + "_" + "01.jpeg"
                    cv2.imwrite(path_to_save + save_file,region)
                else:
                    save_file = filename.split(".")[0] + "_patch_" + str(count) + "_lvl_"
↳ str(level) + "_" + "00.jpeg"
                    cv2.imwrite(path_to_save + save_file,region)
            else:
                continue

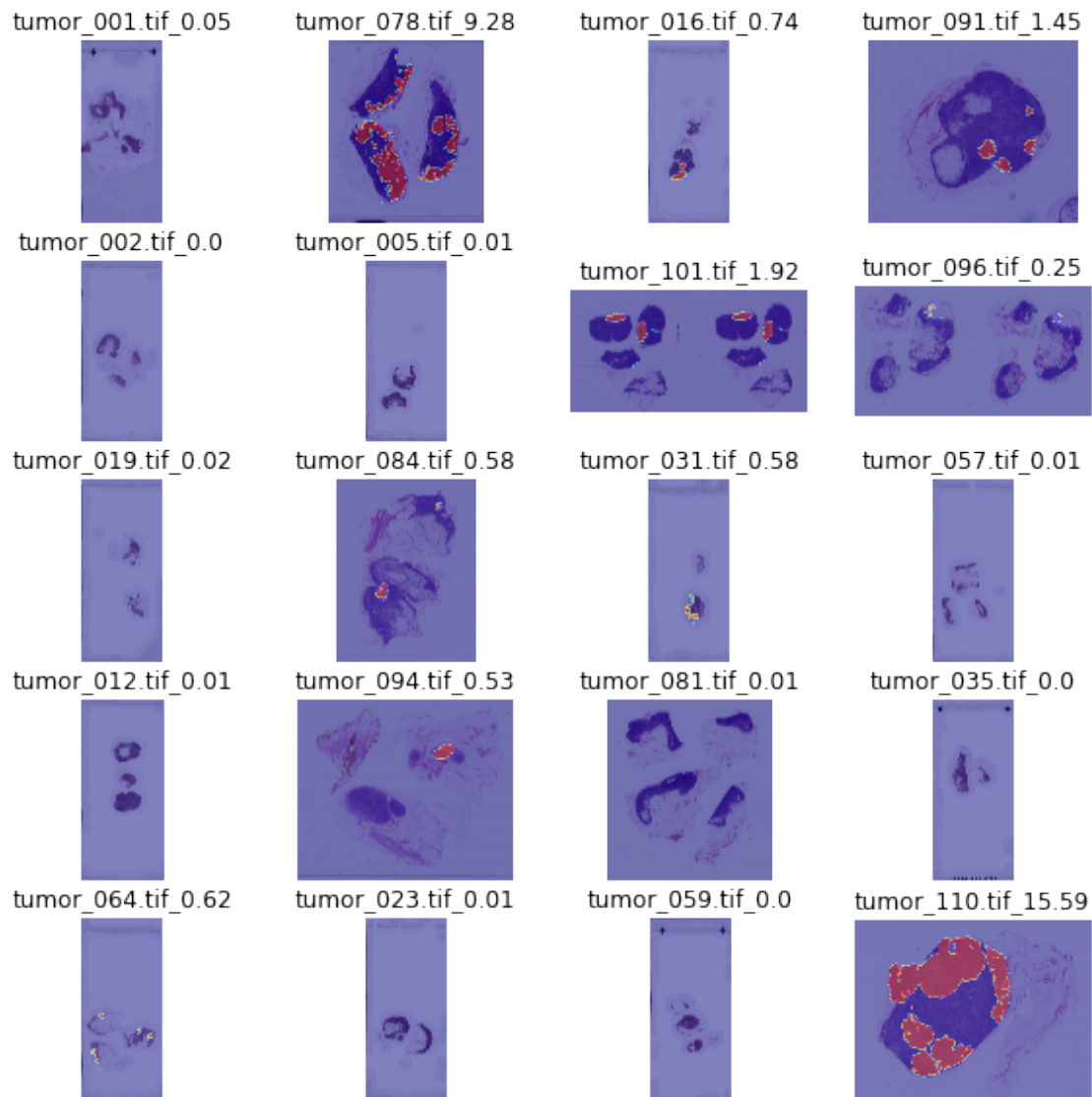
```

Due to limitation of computational power we look at all the slides and their cancer percentage and select the 9 most decent looking samples just by visual inception (as

we only have 22 slides this works here, in case of large datasets a threshold on tissue and cancer percentage can be created)

```
[ ]: fig, axs = plt.subplots(5,4, figsize=(10, 10))
for i,x in enumerate(all_image_names):
    slide = open_slide(data_dir + x)
    tumor_mask = open_slide(data_dir + x.split(".")[0] + "_mask." + x.split(".")
    ↪)[1])
    region_mask = read_slide(tumor_mask, x=0, y=0, level=5, width=slide.
    ↪level_dimensions[5][0], height=slide.level_dimensions[5][1])[:, :, 0]
    slide_image = read_slide(slide,
                             x=0,
                             y=0,
                             level=5,
                             width=slide.level_dimensions[5][0],
                             height=slide.level_dimensions[5][1])
    # percent_tissue = round(len(find_tissue_pixels(slide_image)) /
    ↪float(slide_image.shape[0] * slide_image.shape[1]), 2) * 100
    cancer_tissue = round((sum(map(sum, region_mask)) / float(slide_image.shape[0]
    ↪* slide_image.shape[1])) * 100, 2)

    axs[i%5, i%4].axis('off')
    axs[i%5, i%4].set_title(str(x) + "_" + str(cancer_tissue))
    axs[i%5, i%4].imshow(slide_image)
    axs[i%5, i%4].imshow(region_mask, cmap='jet', alpha=0.5)
```



Creating a split of 4, 3, 2 for train, validation and test from the 9 slides above

```
[12]: train_slide_names = ["tumor_016.tif", "tumor_110.tif", "tumor_075.tif", "tumor_096.
      ↪tif"]
      val_slide_names = ["tumor_078.tif", "tumor_101.tif", "tumor_081.tif"]
      test_slide_names = ["tumor_091.tif", "tumor_084.tif"]
```

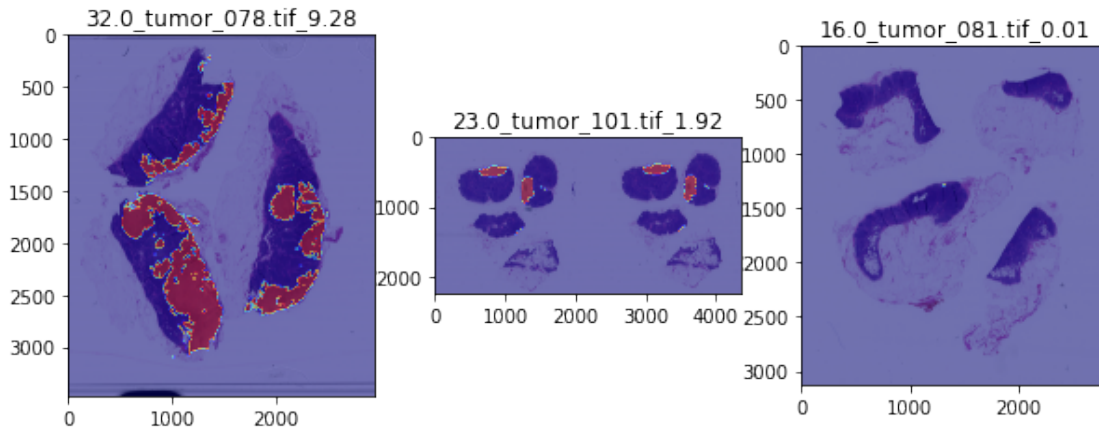
```
[ ]: ## printing the overlap of mask and slides in the validation set
      fig, axs = plt.subplots(1, 3, figsize=(10, 10))
      for i, x in enumerate(val_slide_names):
          slide = open_slide(data_dir + x)
          tumor_mask = open_slide(data_dir + x.split(".")[0] + "_mask." + x.split(".
          ↪").[1])
```

```

region_mask = read_slide(tumor_mask, x=0, y=0, level=5, width=slide.
↪level_dimensions[5][0], height=slide.level_dimensions[5][1])[:, :, 0]
slide_image = read_slide(slide,
                        x=0,
                        y=0,
                        level=5,
                        width=slide.level_dimensions[5][0],
                        height=slide.level_dimensions[5][1])
percent_tissue = round(len(find_tissue_pixels(slide_image)) /
↪float(slide_image.shape[0] * slide_image.shape[1]), 2) * 100
cancer_tissue = round((sum(map(sum, region_mask)) / float(slide_image.shape[0]
↪* slide_image.shape[1])) * 100, 2)

axs[i].set_title(str(percent_tissue)+"_"+str(x)+"_"+str(cancer_tissue))
axs[i].imshow(slide_image)
axs[i].imshow(region_mask, cmap='jet', alpha=0.5)

```



```

[13]: ## location of saving the patches
labelled_data_dir = "/content/drive/MyDrive/Final_Project_Data/"

```

```

[14]: ## sanity check
for x in train_slide_names:
    if (x in test_slide_names) or (x in val_slide_names):
        print("Overlapping slides in data split")
for x in val_slide_names:
    if x in test_slide_names:
        print("Overlapping slides in data split")

```

Creating the training, validation and test dataset by calling the patch save function at two different zoom levels and saving the patches in respective folders in Google Drive

```
[ ]: ## running the patch_save function on all the training slides at Zoom level 4
    ↳and 5 and saving the patches in GDrive
## we run this with a 25% tissue threshold and a 0% cancer threshold
for x in train_slide_names:
    patch_save(x,4,299,299,25,0,data_dir,labelled_data_dir + "Level4_Train/")
    patch_save(x,3,299,299,25,0,data_dir,labelled_data_dir + "Level3_Train/")

[15]: print("We have",len(os.listdir(labelled_data_dir + "Level4_Train")), "Patches in
    ↳the Training set at zoom level 4")
print("We have",len(os.listdir(labelled_data_dir + "Level3_Train")), "Patches in
    ↳the Training set at zoom level 3")

# saving all the patch paths and their labels in a list
train_image_paths_zoom1 = []
train_labels_zoom1 = []
train_image_paths_zoom2 = []
train_labels_zoom2 = []
for x in os.listdir(labelled_data_dir + "Level4_Train"):
    ## files names have label after the last "_" in the file name (00 or 01)
    label = int((x.split(".")[0]).split("_")[-1])
    train_labels_zoom1.append(label)

    image_path = labelled_data_dir + "Level4_Train/" + x
    train_image_paths_zoom1.append(image_path)

for x in os.listdir(labelled_data_dir + "Level3_Train"):
    ## files names have label after the last "_" in the file name (00 or 01)
    label = int((x.split(".")[0]).split("_")[-1])
    train_labels_zoom2.append(label)

    image_path = labelled_data_dir + "Level3_Train/" + x
    train_image_paths_zoom2.append(image_path)
print("% age of patches having cancer in the training set at Level 4 is: ",
    ↳sum(train_labels_zoom1)*100/len(train_labels_zoom1))
print("% age of patches having cancer in the training set at Level 3 is: ",
    ↳sum(train_labels_zoom2)*100/len(train_labels_zoom2))
```

```
We have 317 Patches in the Training set at zoom level 4
We have 1194 Patches in the Training set at zoom level 3
% age of patches having cancer in the training set at Level 4 is:
36.90851735015773
% age of patches having cancer in the training set at Level 3 is:
30.569514237855948
```

```
[ ]: ## similarly running the save_patch function to create validation patches at
    ↳the same zoom levels
for x in val_slide_names:
```



```

patch_save(x,4,299,299,25,0,data_dir,labelled_data_dir + "Level4_Val/")
patch_save(x,3,299,299,25,0,data_dir,labelled_data_dir + "Level3_Val/")

```

```

[16]: print("We have",len(os.listdir(labelled_data_dir + "Level4_Val")), "Patches in_
↳the Validation set at zoom level 4")
print("We have",len(os.listdir(labelled_data_dir + "Level3_Val")), "Patches in_
↳the Validation set at zoom level 3")

# saving all the patch paths and their labels in a list
val_image_paths_zoom1 = []
val_labels_zoom1 = []
val_image_paths_zoom2 = []
val_labels_zoom2 = []
for x in os.listdir(labelled_data_dir + "Level4_Val"):
    ## files names have label after the last "_" in the file name (00 or 01)
    label = int((x.split(".")[0]).split("_")[-1])
    val_labels_zoom1.append(label)

    image_path = labelled_data_dir + "Level4_Val/" + x
    val_image_paths_zoom1.append(image_path)

for x in os.listdir(labelled_data_dir + "Level3_Val"):
    ## files names have label after the last "_" in the file name (00 or 01)
    label = int((x.split(".")[0]).split("_")[-1])
    val_labels_zoom2.append(label)

    image_path = labelled_data_dir + "Level3_Val/" + x
    val_image_paths_zoom2.append(image_path)
print("% age of patches having cancer in the Validation set at Level 4 is: ",_
↳sum(val_labels_zoom1)*100/len(val_labels_zoom1))
print("% age of patches having cancer in the Validation set at Level 3 is: ",_
↳sum(val_labels_zoom2)*100/len(val_labels_zoom2))

```

```

We have 383 Patches in the Validation set at zoom level 4
We have 1385 Patches in the Validation set at zoom level 3
% age of patches having cancer in the Validation set at Level 4 is:
35.50913838120105
% age of patches having cancer in the Validation set at Level 3 is:
28.231046931407942

```

```

[ ]: ## similarly running the save_patch function to create validation patches at_
↳the same zoom levels
for x in test_slide_names:
    patch_save(x,4,299,299,25,0,data_dir,labelled_data_dir + "Level4_Test/")
    patch_save(x,3,299,299,25,0,data_dir,labelled_data_dir + "Level3_Test/")

```

```
[17]: print("We have",len(os.listdir(labelled_data_dir + "Level4_Test")), "Patches in_
↳the Test set at zoom level 4")
print("We have",len(os.listdir(labelled_data_dir + "Level3_Test")), "Patches in_
↳the Test set at zoom level 3")

# saving all the patch paths and their labels in a list
test_image_paths_zoom1 = []
test_labels_zoom1 = []
test_image_paths_zoom2 = []
test_labels_zoom2 = []
for x in os.listdir(labelled_data_dir + "Level4_Test"):
    ## files names have label after the last "_" in the file name (00 or 01)
    label = int((x.split(".")[0]).split("_")[-1])
    test_labels_zoom1.append(label)

    image_path = labelled_data_dir + "Level4_Test/" + x
    test_image_paths_zoom1.append(image_path)

for x in os.listdir(labelled_data_dir + "Level3_Test"):
    ## files names have label after the last "_" in the file name (00 or 01)
    label = int((x.split(".")[0]).split("_")[-1])
    test_labels_zoom2.append(label)

    image_path = labelled_data_dir + "Level3_Test/" + x
    test_image_paths_zoom2.append(image_path)
print("% age of patches having cancer in the Validation set at Level 4 is: ",_
↳sum(test_labels_zoom1)*100/len(test_labels_zoom1))
print("% age of patches having cancer in the Validation set at Level 3 is: ",_
↳sum(test_labels_zoom2)*100/len(test_labels_zoom2))
```

```
We have 126 Patches in the Test set at zoom level 4
We have 466 Patches in the Test set at zoom level 3
% age of patches having cancer in the Validation set at Level 4 is:
19.047619047619047
% age of patches having cancer in the Validation set at Level 3 is:
11.587982832618026
```

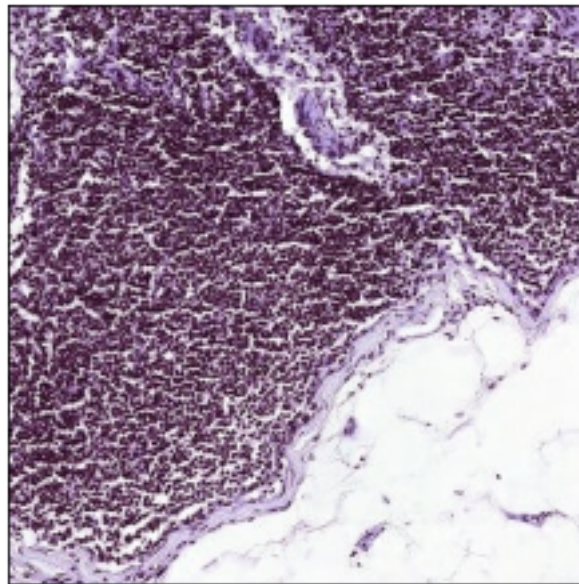
Packaging the data into tensorflow format for the model to digest

```
[18]: ## function to read the image from the image paths we pass
## also normalizes the image
def load_and_preprocess_image(img):
    img = tf.io.read_file(img)
    img = tf.image.decode_jpeg(img, channels=3)
    #convert image pixel data type to float and normalize pixels to 0,1
    img_final = tf.cast(img, tf.float32) / 255.0
    return img_final
```

```
[19]: def show(img, label):  
      plt.imshow(img)  
      plt.title(label)  
      plt.xticks([])  
      plt.yticks([])  
      print()
```

```
[20]: ## visualizing a patch after preprocessing  
img = load_and_preprocess_image(train_image_paths_zoom2[0])  
label = train_labels_zoom2[0]  
show(img, label)
```

0



```
[21]: ## having different batch and shuffle sizes  
## this is because as we go to higher zoom levels we get more patches  
SHUFFLE_SIZE_1 = 25  
SHUFFLE_SIZE_2 = 100  
BATCH_SIZE_1 = 16  
BATCH_SIZE_2 = 32  
IMG_SIZE = 299
```

```
[22]: # a dataset that returns image paths  
path_ds = tf.data.Dataset.from_tensor_slices(train_image_paths_zoom1)  
# a dataset that returns images (loaded off disk, decoded, and preprocessed)
```

```

AUTOTUNE = tf.data.experimental.AUTOTUNE
image_ds = path_ds.map(load_and_preprocess_image, num_parallel_calls=AUTOTUNE)
# a dataset that returns labels
label_ds = tf.data.Dataset.from_tensor_slices(tf.cast(train_labels_zoom1, tf.
    ↪int64))
# a dataset that returns images and labels
image_label_ds = tf.data.Dataset.zip((image_ds, label_ds))
# checking the concatenated dataset by prining image shape and label
for img, label in image_label_ds.take(2):
    print(img.shape, label.numpy())

```

```

(299, 299, 3) 0
(299, 299, 3) 0

```

```

[23]: ## using in memory caching as we do not have a large dataset right now
train_ds_zoom1 = image_label_ds.cache()
train_ds_zoom1 = train_ds_zoom1.shuffle(SHUFFLE_SIZE_1)
train_ds_zoom1 = train_ds_zoom1.batch(BATCH_SIZE_1).
    ↪prefetch(buffer_size=AUTOTUNE)

```

```

[24]: ## following the similar steps as above for zoom level 2 for training
path_ds = tf.data.Dataset.from_tensor_slices(train_image_paths_zoom2)
image_ds = path_ds.map(load_and_preprocess_image, num_parallel_calls=AUTOTUNE)
label_ds = tf.data.Dataset.from_tensor_slices(tf.cast(train_labels_zoom2, tf.
    ↪int64))
image_label_ds = tf.data.Dataset.zip((image_ds, label_ds))
train_ds_zoom2 = image_label_ds.cache()
train_ds_zoom2 = train_ds_zoom2.shuffle(SHUFFLE_SIZE_2)
train_ds_zoom2 = train_ds_zoom2.batch(BATCH_SIZE_2).
    ↪prefetch(buffer_size=AUTOTUNE)

```

```

[25]: ## following the similar steps as above for zoom level 1 for validation
path_ds = tf.data.Dataset.from_tensor_slices(val_image_paths_zoom1)
image_ds = path_ds.map(load_and_preprocess_image, num_parallel_calls=AUTOTUNE)
label_ds = tf.data.Dataset.from_tensor_slices(tf.cast(val_labels_zoom1, tf.
    ↪int64))
image_label_ds = tf.data.Dataset.zip((image_ds, label_ds))
val_ds_zoom1 = image_label_ds.cache().batch(BATCH_SIZE_1)

## following the similar steps as above for zoom level 2 for validation
path_ds = tf.data.Dataset.from_tensor_slices(val_image_paths_zoom2)
image_ds = path_ds.map(load_and_preprocess_image, num_parallel_calls=AUTOTUNE)
label_ds = tf.data.Dataset.from_tensor_slices(tf.cast(val_labels_zoom2, tf.
    ↪int64))
image_label_ds = tf.data.Dataset.zip((image_ds, label_ds))
val_ds_zoom2 = image_label_ds.cache().batch(BATCH_SIZE_2)

```

```
[26]: ## following the similar steps as above for zoom level 1 for test
path_ds = tf.data.Dataset.from_tensor_slices(test_image_paths_zoom1)
image_ds = path_ds.map(load_and_preprocess_image, num_parallel_calls=AUTOTUNE)
label_ds = tf.data.Dataset.from_tensor_slices(tf.cast(test_labels_zoom1, tf.
    ↪int64))
image_label_ds = tf.data.Dataset.zip((image_ds, label_ds))
test_ds_zoom1 = image_label_ds.cache().batch(BATCH_SIZE_1)

## following the similar steps as above for zoom level 2 for test
path_ds = tf.data.Dataset.from_tensor_slices(test_image_paths_zoom2)
image_ds = path_ds.map(load_and_preprocess_image, num_parallel_calls=AUTOTUNE)
label_ds = tf.data.Dataset.from_tensor_slices(tf.cast(test_labels_zoom2, tf.
    ↪int64))
image_label_ds = tf.data.Dataset.zip((image_ds, label_ds))
test_ds_zoom2 = image_label_ds.cache().batch(BATCH_SIZE_2)
```

Below we create two identical Models (one for each zoom level) by using Transfer Learning and doing fine tuning of the InceptionV3 model

```
[27]: from tensorflow.keras.applications.inception_v3 import InceptionV3
from tensorflow.keras.layers import GlobalAveragePooling2D, concatenate, Input,
    ↪Dense, Dropout, BatchNormalization, Flatten
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.optimizers import Adam, SGD
from tensorflow.keras.utils import plot_model

inception_base_zoom1 = InceptionV3(weights='imagenet',
                                   include_top=False,
                                   input_shape=(IMG_SIZE, IMG_SIZE, 3))

inception_base_zoom2 = InceptionV3(weights='imagenet',
                                   include_top=False,
                                   input_shape=(IMG_SIZE, IMG_SIZE, 3))

# freeze the inception model to increase training speed
inception_base_zoom1.trainable = True
inception_base_zoom2.trainable = True

# Let's take a look to see how many layers are in the base model
print("Number of layers in the base model: ", len(inception_base_zoom1.layers))

# Fine-tune from this layer onwards
fine_tune_at = 100

# Freeze all the layers before the `fine_tune_at` layer for zoom1 model
for layer in inception_base_zoom1.layers[:fine_tune_at]:
    layer.trainable = False
```

```
# Freeze all the layers before the `fine_tune_at` layer for zoom2 model
for layer in inception_base_zoom2.layers[:fine_tune_at]:
    layer.trainable = False
```

Downloading data from [https://storage.googleapis.com/tensorflow/keras-applications/inception\\_v3/inception\\_v3\\_weights\\_tf\\_dim\\_ordering\\_tf\\_kernels\\_notop.h5](https://storage.googleapis.com/tensorflow/keras-applications/inception_v3/inception_v3_weights_tf_dim_ordering_tf_kernels_notop.h5)  
87910968/87910968 [=====] - 3s 0us/step  
Number of layers in the base model: 311

```
[28]: input_z1 = Input(shape=(IMG_SIZE, IMG_SIZE, 3))
      input_z2 = Input(shape=(IMG_SIZE, IMG_SIZE, 3))

      ## we do global average pooling after adding the inception model to reduce the
      ## number of trainable params
      model_z1 = Sequential()
      model_z1.add(inception_base_zoom1)
      model_z1.add(GlobalAveragePooling2D())

      model_z2 = Sequential()
      model_z2.add(inception_base_zoom2)
      model_z2.add(GlobalAveragePooling2D())

      encoded_input_z1 = model_z1(input_z1)
      encoded_input_z2 = model_z2(input_z2)
```

```
[29]: ## create a model for the 1st zoom level
      dense1 = Dense(256, activation='relu')(encoded_input_z1)
      drop_layer = Dropout(0.5)(dense1)
      dense2 = Dense(126, activation='relu')(drop_layer)

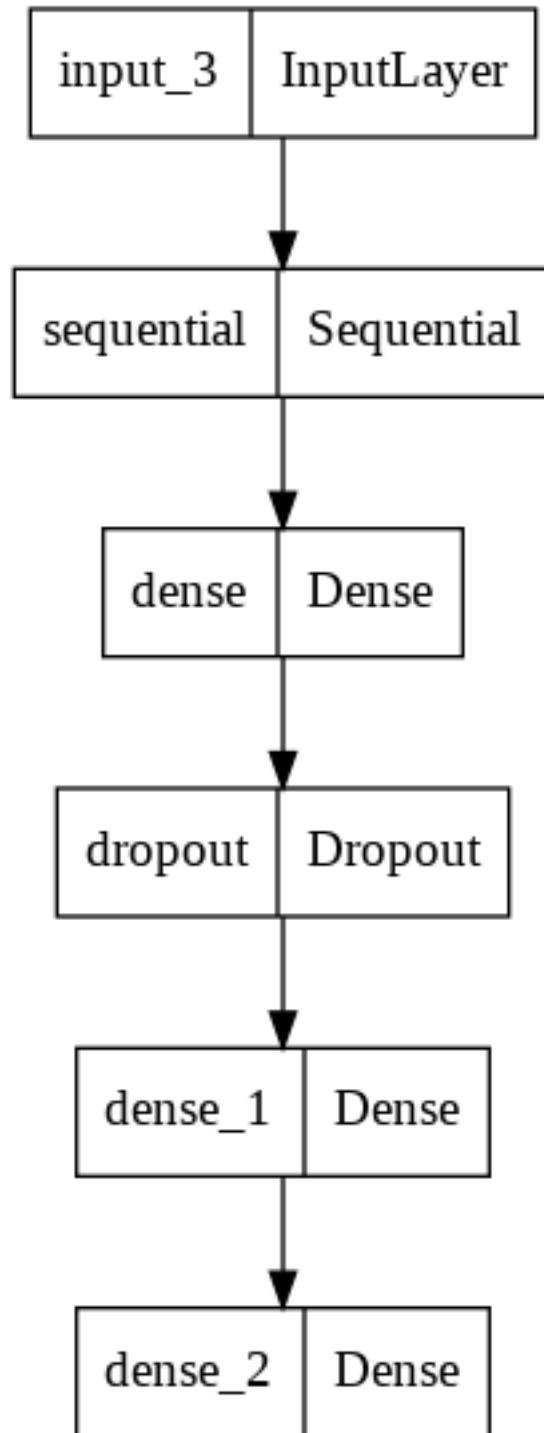
      output = Dense(1, activation='sigmoid')(dense2)
      model1 = Model(inputs=input_z1, outputs=output)
```

```
[30]: ## create a model for the 2nd zoom level
      dense1 = Dense(256, activation='relu')(encoded_input_z2)
      drop_layer = Dropout(0.5)(dense1)
      dense2 = Dense(126, activation='relu')(drop_layer)

      output = Dense(1, activation='sigmoid')(dense2)
      model2 = Model(inputs=input_z2, outputs=output)
```

```
[31]: ## we have two models like the one shown below in the plot
      plot_model(model1, to_file='model.png')
```

```
[31]:
```



```
[32]: model1.summary()
```

```
Model: "model"
```

---

Layer (type)	Output Shape	Param #
input_3 (InputLayer)	[(None, 299, 299, 3)]	0
sequential (Sequential)	(None, 2048)	21802784
dense (Dense)	(None, 256)	524544
dropout (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 126)	32382
dense_2 (Dense)	(None, 1)	127

```

=====
Total params: 22,359,837
Trainable params: 20,183,421
Non-trainable params: 2,176,416
-----

```

```

[33]: model1.compile(optimizer='adam',
                    loss='binary_crossentropy',
                    metrics=['accuracy'])
model2.compile(optimizer='adam',
               loss='binary_crossentropy',
               metrics=['accuracy'])

```

Below we train both the models and create checkpoints to save the weights after every epoch

```

[39]: ## creating checkpoint directory
checkpoint_path1 = labelled_data_dir + "training2_dec22_batch_8_lvl_4/cp.ckpt"
checkpoint_dir1 = os.path.dirname(checkpoint_path1)

## loading the weights from the last checkpoint before we further continue_
↳ training
latest1 = tf.train.latest_checkpoint(checkpoint_dir1)
if latest1 != None:
    print("Loading weights from", latest1)
    model1.load_weights(latest1)
else:
    print("Checkpoint not found. Starting from scratch")

```

Loading weights from  
/content/drive/MyDrive/Final\_Project\_Data/training2\_dec22\_batch\_8\_lvl\_4/cp.ckpt



```
[ ]: # Create a callback that saves the model's weights
cp_callback = tf.keras.callbacks.ModelCheckpoint(filepath=checkpoint_path1,
                                                save_weights_only=True,
                                                verbose=1)

# Train the model with the new callback
hist1 = model1.
    ↪fit(train_ds_zoom1,validation_data=val_ds_zoom1,epochs=20,callbacks=[cp_callback])
```

```
Epoch 1/20
40/40 [=====] - ETA: 0s - loss: 0.7118 - accuracy:
0.6688
Epoch 1: saving model to
/content/drive/MyDrive/Final_Project_Data/training2_dec22_batch_8_lvl_4/cp.ckpt
40/40 [=====] - 7s 177ms/step - loss: 0.7118 -
accuracy: 0.6688 - val_loss: 6.4968 - val_accuracy: 0.6710
Epoch 2/20
40/40 [=====] - ETA: 0s - loss: 0.6050 - accuracy:
0.7476
Epoch 2: saving model to
/content/drive/MyDrive/Final_Project_Data/training2_dec22_batch_8_lvl_4/cp.ckpt
40/40 [=====] - 7s 170ms/step - loss: 0.6050 -
accuracy: 0.7476 - val_loss: 2.6530 - val_accuracy: 0.6762
Epoch 3/20
40/40 [=====] - ETA: 0s - loss: 0.6341 - accuracy:
0.7192
Epoch 3: saving model to
/content/drive/MyDrive/Final_Project_Data/training2_dec22_batch_8_lvl_4/cp.ckpt
40/40 [=====] - 7s 167ms/step - loss: 0.6341 -
accuracy: 0.7192 - val_loss: 2.0366 - val_accuracy: 0.6475
Epoch 4/20
40/40 [=====] - ETA: 0s - loss: 0.5804 - accuracy:
0.7855
Epoch 4: saving model to
/content/drive/MyDrive/Final_Project_Data/training2_dec22_batch_8_lvl_4/cp.ckpt
40/40 [=====] - 7s 179ms/step - loss: 0.5804 -
accuracy: 0.7855 - val_loss: 3.3922 - val_accuracy: 0.6841
Epoch 5/20
40/40 [=====] - ETA: 0s - loss: 0.6062 - accuracy:
0.6562
Epoch 5: saving model to
/content/drive/MyDrive/Final_Project_Data/training2_dec22_batch_8_lvl_4/cp.ckpt
40/40 [=====] - 7s 172ms/step - loss: 0.6062 -
accuracy: 0.6562 - val_loss: 2.4476 - val_accuracy: 0.6762
Epoch 6/20
40/40 [=====] - ETA: 0s - loss: 0.5770 - accuracy:
0.7539
```

Epoch 6: saving model to  
/content/drive/MyDrive/Final\_Project\_Data/training2\_dec22\_batch\_8\_lvl\_4/cp.ckpt  
40/40 [=====] - 7s 169ms/step - loss: 0.5770 -  
accuracy: 0.7539 - val\_loss: 1.2721 - val\_accuracy: 0.6867  
Epoch 7/20  
40/40 [=====] - ETA: 0s - loss: 0.5552 - accuracy:  
0.7603  
Epoch 7: saving model to  
/content/drive/MyDrive/Final\_Project\_Data/training2\_dec22\_batch\_8\_lvl\_4/cp.ckpt  
40/40 [=====] - 8s 193ms/step - loss: 0.5552 -  
accuracy: 0.7603 - val\_loss: 0.5684 - val\_accuracy: 0.7180  
Epoch 8/20  
40/40 [=====] - ETA: 0s - loss: 0.3707 - accuracy:  
0.8549  
Epoch 8: saving model to  
/content/drive/MyDrive/Final\_Project\_Data/training2\_dec22\_batch\_8\_lvl\_4/cp.ckpt  
40/40 [=====] - 7s 174ms/step - loss: 0.3707 -  
accuracy: 0.8549 - val\_loss: 2.6376 - val\_accuracy: 0.6919  
Epoch 9/20  
40/40 [=====] - ETA: 0s - loss: 0.5659 - accuracy:  
0.7792  
Epoch 9: saving model to  
/content/drive/MyDrive/Final\_Project\_Data/training2\_dec22\_batch\_8\_lvl\_4/cp.ckpt  
40/40 [=====] - 7s 168ms/step - loss: 0.5659 -  
accuracy: 0.7792 - val\_loss: 0.8598 - val\_accuracy: 0.6110  
Epoch 10/20  
40/40 [=====] - ETA: 0s - loss: 0.4609 - accuracy:  
0.8170  
Epoch 10: saving model to  
/content/drive/MyDrive/Final\_Project\_Data/training2\_dec22\_batch\_8\_lvl\_4/cp.ckpt  
40/40 [=====] - 7s 177ms/step - loss: 0.4609 -  
accuracy: 0.8170 - val\_loss: 3.7010 - val\_accuracy: 0.6449  
Epoch 11/20  
40/40 [=====] - ETA: 0s - loss: 0.6006 - accuracy:  
0.7886  
Epoch 11: saving model to  
/content/drive/MyDrive/Final\_Project\_Data/training2\_dec22\_batch\_8\_lvl\_4/cp.ckpt  
40/40 [=====] - 7s 180ms/step - loss: 0.6006 -  
accuracy: 0.7886 - val\_loss: 0.9316 - val\_accuracy: 0.5979  
Epoch 12/20  
40/40 [=====] - ETA: 0s - loss: 0.6139 - accuracy:  
0.6909  
Epoch 12: saving model to  
/content/drive/MyDrive/Final\_Project\_Data/training2\_dec22\_batch\_8\_lvl\_4/cp.ckpt  
40/40 [=====] - 7s 171ms/step - loss: 0.6139 -  
accuracy: 0.6909 - val\_loss: 0.9265 - val\_accuracy: 0.7441  
Epoch 13/20  
40/40 [=====] - ETA: 0s - loss: 0.5046 - accuracy:

0.8139  
Epoch 13: saving model to  
/content/drive/MyDrive/Final\_Project\_Data/training2\_dec22\_batch\_8\_lvl\_4/cp.ckpt  
40/40 [=====] - 7s 180ms/step - loss: 0.5046 -  
accuracy: 0.8139 - val\_loss: 13.8190 - val\_accuracy: 0.3969  
Epoch 14/20  
40/40 [=====] - ETA: 0s - loss: 0.5641 - accuracy:  
0.7413  
Epoch 14: saving model to  
/content/drive/MyDrive/Final\_Project\_Data/training2\_dec22\_batch\_8\_lvl\_4/cp.ckpt  
40/40 [=====] - 7s 172ms/step - loss: 0.5641 -  
accuracy: 0.7413 - val\_loss: 1.7725 - val\_accuracy: 0.6527  
Epoch 15/20  
40/40 [=====] - ETA: 0s - loss: 0.4687 - accuracy:  
0.7918  
Epoch 15: saving model to  
/content/drive/MyDrive/Final\_Project\_Data/training2\_dec22\_batch\_8\_lvl\_4/cp.ckpt  
40/40 [=====] - 7s 170ms/step - loss: 0.4687 -  
accuracy: 0.7918 - val\_loss: 1.3162 - val\_accuracy: 0.6815  
Epoch 16/20  
40/40 [=====] - ETA: 0s - loss: 0.3652 - accuracy:  
0.8517  
Epoch 16: saving model to  
/content/drive/MyDrive/Final\_Project\_Data/training2\_dec22\_batch\_8\_lvl\_4/cp.ckpt  
40/40 [=====] - 7s 169ms/step - loss: 0.3652 -  
accuracy: 0.8517 - val\_loss: 0.9764 - val\_accuracy: 0.6423  
Epoch 17/20  
40/40 [=====] - ETA: 0s - loss: 0.4148 - accuracy:  
0.8486  
Epoch 17: saving model to  
/content/drive/MyDrive/Final\_Project\_Data/training2\_dec22\_batch\_8\_lvl\_4/cp.ckpt  
40/40 [=====] - 7s 168ms/step - loss: 0.4148 -  
accuracy: 0.8486 - val\_loss: 0.9407 - val\_accuracy: 0.7389  
Epoch 18/20  
40/40 [=====] - ETA: 0s - loss: 0.2821 - accuracy:  
0.8927  
Epoch 18: saving model to  
/content/drive/MyDrive/Final\_Project\_Data/training2\_dec22\_batch\_8\_lvl\_4/cp.ckpt  
40/40 [=====] - 7s 172ms/step - loss: 0.2821 -  
accuracy: 0.8927 - val\_loss: 0.7549 - val\_accuracy: 0.6449  
Epoch 19/20  
40/40 [=====] - ETA: 0s - loss: 0.3888 - accuracy:  
0.8959  
Epoch 19: saving model to  
/content/drive/MyDrive/Final\_Project\_Data/training2\_dec22\_batch\_8\_lvl\_4/cp.ckpt  
40/40 [=====] - 7s 183ms/step - loss: 0.3888 -  
accuracy: 0.8959 - val\_loss: 1.3595 - val\_accuracy: 0.6867  
Epoch 20/20

```
40/40 [=====] - ETA: 0s - loss: 0.2920 - accuracy:
0.9401
Epoch 20: saving model to
/content/drive/MyDrive/Final_Project_Data/training2_dec22_batch_8_lvl_4/cp.ckpt
40/40 [=====] - 7s 167ms/step - loss: 0.2920 -
accuracy: 0.9401 - val_loss: 0.7707 - val_accuracy: 0.7050
```

```
[34]: checkpoint_path2 = labelled_data_dir + "training2_dec22_batch_16_lvl_3/cp.ckpt"
checkpoint_dir2 = os.path.dirname(checkpoint_path2)

latest2 = tf.train.latest_checkpoint(checkpoint_dir2)
if latest2 != None:
    print("Loading weights from", latest2)
    model2.load_weights(latest2)
else:
    print("Checkpoint not found. Starting from scratch")
```

Checkpoint not found. Starting from scratch

```
[35]: # Create a callback that saves the model's weights
cp_callback = tf.keras.callbacks.ModelCheckpoint(filepath=checkpoint_path2,
                                                save_weights_only=True,
                                                verbose=1)

# Train the model with the new callback
hist2 = model2.
    ↪ fit(train_ds_zoom2, validation_data=val_ds_zoom2, epochs=20, callbacks=[cp_callback])
```

```
Epoch 1/20
38/38 [=====] - ETA: 0s - loss: 0.4481 - accuracy:
0.8208
Epoch 1: saving model to
/content/drive/MyDrive/Final_Project_Data/training2_dec22_batch_16_lvl_3/cp.ckpt
38/38 [=====] - 657s 16s/step - loss: 0.4481 -
accuracy: 0.8208 - val_loss: 16.7383 - val_accuracy: 0.7177
Epoch 2/20
38/38 [=====] - ETA: 0s - loss: 0.5809 - accuracy:
0.8015
Epoch 2: saving model to
/content/drive/MyDrive/Final_Project_Data/training2_dec22_batch_16_lvl_3/cp.ckpt
38/38 [=====] - 17s 454ms/step - loss: 0.5809 -
accuracy: 0.8015 - val_loss: 1095.0538 - val_accuracy: 0.7177
Epoch 3/20
38/38 [=====] - ETA: 0s - loss: 0.5520 - accuracy:
0.7680
Epoch 3: saving model to
/content/drive/MyDrive/Final_Project_Data/training2_dec22_batch_16_lvl_3/cp.ckpt
38/38 [=====] - 17s 451ms/step - loss: 0.5520 -
```

accuracy: 0.7680 - val\_loss: 39.6817 - val\_accuracy: 0.3495  
Epoch 4/20  
38/38 [=====] - ETA: 0s - loss: 0.4302 - accuracy: 0.8509  
Epoch 4: saving model to  
/content/drive/MyDrive/Final\_Project\_Data/training2\_dec22\_batch\_16\_lvl\_3/cp.ckpt  
38/38 [=====] - 17s 454ms/step - loss: 0.4302 - accuracy: 0.8509 - val\_loss: 70.6496 - val\_accuracy: 0.7126  
Epoch 5/20  
38/38 [=====] - ETA: 0s - loss: 0.5743 - accuracy: 0.7831  
Epoch 5: saving model to  
/content/drive/MyDrive/Final\_Project\_Data/training2\_dec22\_batch\_16\_lvl\_3/cp.ckpt  
38/38 [=====] - 17s 459ms/step - loss: 0.5743 - accuracy: 0.7831 - val\_loss: 5.9755 - val\_accuracy: 0.7076  
Epoch 6/20  
38/38 [=====] - ETA: 0s - loss: 0.4044 - accuracy: 0.8585  
Epoch 6: saving model to  
/content/drive/MyDrive/Final\_Project\_Data/training2\_dec22\_batch\_16\_lvl\_3/cp.ckpt  
38/38 [=====] - 17s 448ms/step - loss: 0.4044 - accuracy: 0.8585 - val\_loss: 15.4169 - val\_accuracy: 0.7112  
Epoch 7/20  
38/38 [=====] - ETA: 0s - loss: 0.4533 - accuracy: 0.8425  
Epoch 7: saving model to  
/content/drive/MyDrive/Final\_Project\_Data/training2\_dec22\_batch\_16\_lvl\_3/cp.ckpt  
38/38 [=====] - 17s 461ms/step - loss: 0.4533 - accuracy: 0.8425 - val\_loss: 3.4799 - val\_accuracy: 0.7509  
Epoch 8/20  
38/38 [=====] - ETA: 0s - loss: 0.3730 - accuracy: 0.8760  
Epoch 8: saving model to  
/content/drive/MyDrive/Final\_Project\_Data/training2\_dec22\_batch\_16\_lvl\_3/cp.ckpt  
38/38 [=====] - 17s 446ms/step - loss: 0.3730 - accuracy: 0.8760 - val\_loss: 2.2902 - val\_accuracy: 0.7025  
Epoch 9/20  
38/38 [=====] - ETA: 0s - loss: 0.3127 - accuracy: 0.8911  
Epoch 9: saving model to  
/content/drive/MyDrive/Final\_Project\_Data/training2\_dec22\_batch\_16\_lvl\_3/cp.ckpt  
38/38 [=====] - 17s 447ms/step - loss: 0.3127 - accuracy: 0.8911 - val\_loss: 0.3807 - val\_accuracy: 0.8708  
Epoch 10/20  
38/38 [=====] - ETA: 0s - loss: 0.2460 - accuracy: 0.9305  
Epoch 10: saving model to  
/content/drive/MyDrive/Final\_Project\_Data/training2\_dec22\_batch\_16\_lvl\_3/cp.ckpt

```

38/38 [=====] - 17s 457ms/step - loss: 0.2460 -
accuracy: 0.9305 - val_loss: 0.8465 - val_accuracy: 0.7422
Epoch 11/20
38/38 [=====] - ETA: 0s - loss: 0.2441 - accuracy:
0.9196
Epoch 11: saving model to
/content/drive/MyDrive/Final_Project_Data/training2_dec22_batch_16_lvl_3/cp.ckpt
38/38 [=====] - 17s 454ms/step - loss: 0.2441 -
accuracy: 0.9196 - val_loss: 1.8561 - val_accuracy: 0.8079
Epoch 12/20
38/38 [=====] - ETA: 0s - loss: 0.2465 - accuracy:
0.9213
Epoch 12: saving model to
/content/drive/MyDrive/Final_Project_Data/training2_dec22_batch_16_lvl_3/cp.ckpt
38/38 [=====] - 17s 446ms/step - loss: 0.2465 -
accuracy: 0.9213 - val_loss: 0.3539 - val_accuracy: 0.9249
Epoch 13/20
38/38 [=====] - ETA: 0s - loss: 0.2013 - accuracy:
0.9447
Epoch 13: saving model to
/content/drive/MyDrive/Final_Project_Data/training2_dec22_batch_16_lvl_3/cp.ckpt
38/38 [=====] - 17s 460ms/step - loss: 0.2013 -
accuracy: 0.9447 - val_loss: 3.4616 - val_accuracy: 0.5292
Epoch 14/20
38/38 [=====] - ETA: 0s - loss: 0.1771 - accuracy:
0.9414
Epoch 14: saving model to
/content/drive/MyDrive/Final_Project_Data/training2_dec22_batch_16_lvl_3/cp.ckpt
38/38 [=====] - 17s 449ms/step - loss: 0.1771 -
accuracy: 0.9414 - val_loss: 1.2235 - val_accuracy: 0.8137
Epoch 15/20
38/38 [=====] - ETA: 0s - loss: 0.1767 - accuracy:
0.9481
Epoch 15: saving model to
/content/drive/MyDrive/Final_Project_Data/training2_dec22_batch_16_lvl_3/cp.ckpt
38/38 [=====] - 17s 460ms/step - loss: 0.1767 -
accuracy: 0.9481 - val_loss: 0.8978 - val_accuracy: 0.8570
Epoch 16/20
38/38 [=====] - ETA: 0s - loss: 0.2025 - accuracy:
0.9389
Epoch 16: saving model to
/content/drive/MyDrive/Final_Project_Data/training2_dec22_batch_16_lvl_3/cp.ckpt
38/38 [=====] - 17s 449ms/step - loss: 0.2025 -
accuracy: 0.9389 - val_loss: 0.5122 - val_accuracy: 0.8245
Epoch 17/20
38/38 [=====] - ETA: 0s - loss: 0.1857 - accuracy:
0.9464
Epoch 17: saving model to

```

```

/content/drive/MyDrive/Final_Project_Data/training2_dec22_batch_16_lvl_3/cp.ckpt
38/38 [=====] - 17s 447ms/step - loss: 0.1857 -
accuracy: 0.9464 - val_loss: 0.2280 - val_accuracy: 0.9350
Epoch 18/20
38/38 [=====] - ETA: 0s - loss: 0.0982 - accuracy:
0.9665
Epoch 18: saving model to
/content/drive/MyDrive/Final_Project_Data/training2_dec22_batch_16_lvl_3/cp.ckpt
38/38 [=====] - 17s 457ms/step - loss: 0.0982 -
accuracy: 0.9665 - val_loss: 1.1710 - val_accuracy: 0.6628
Epoch 19/20
38/38 [=====] - ETA: 0s - loss: 0.1137 - accuracy:
0.9673
Epoch 19: saving model to
/content/drive/MyDrive/Final_Project_Data/training2_dec22_batch_16_lvl_3/cp.ckpt
38/38 [=====] - 17s 449ms/step - loss: 0.1137 -
accuracy: 0.9673 - val_loss: 0.3826 - val_accuracy: 0.8845
Epoch 20/20
38/38 [=====] - ETA: 0s - loss: 0.1162 - accuracy:
0.9665
Epoch 20: saving model to
/content/drive/MyDrive/Final_Project_Data/training2_dec22_batch_16_lvl_3/cp.ckpt
38/38 [=====] - 17s 447ms/step - loss: 0.1162 -
accuracy: 0.9665 - val_loss: 0.4748 - val_accuracy: 0.8621

```

### Plotting the validation and training accuracy/loss

```

[37]: def plot(history):
    # The history object contains results on the training and test
    # sets for each epoch
    acc = history.history['accuracy']
    val_acc = history.history['val_accuracy']
    loss = history.history['loss']
    val_loss = history.history['val_loss']

    # Get the number of epochs
    epochs = range(len(acc))

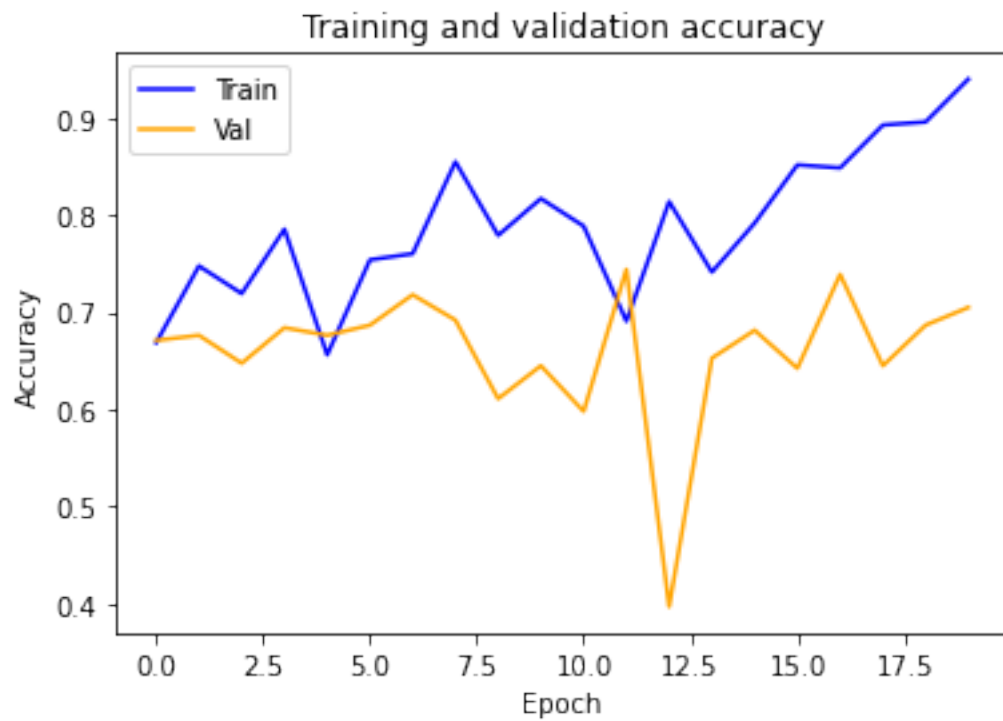
    plt.title('Training and validation accuracy')
    plt.plot(epochs, acc, color='blue', label='Train')
    plt.plot(epochs, val_acc, color='orange', label='Val')
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.legend()

    _ = plt.figure()
    plt.title('Training and validation loss')
    plt.plot(epochs, loss, color='blue', label='Train')

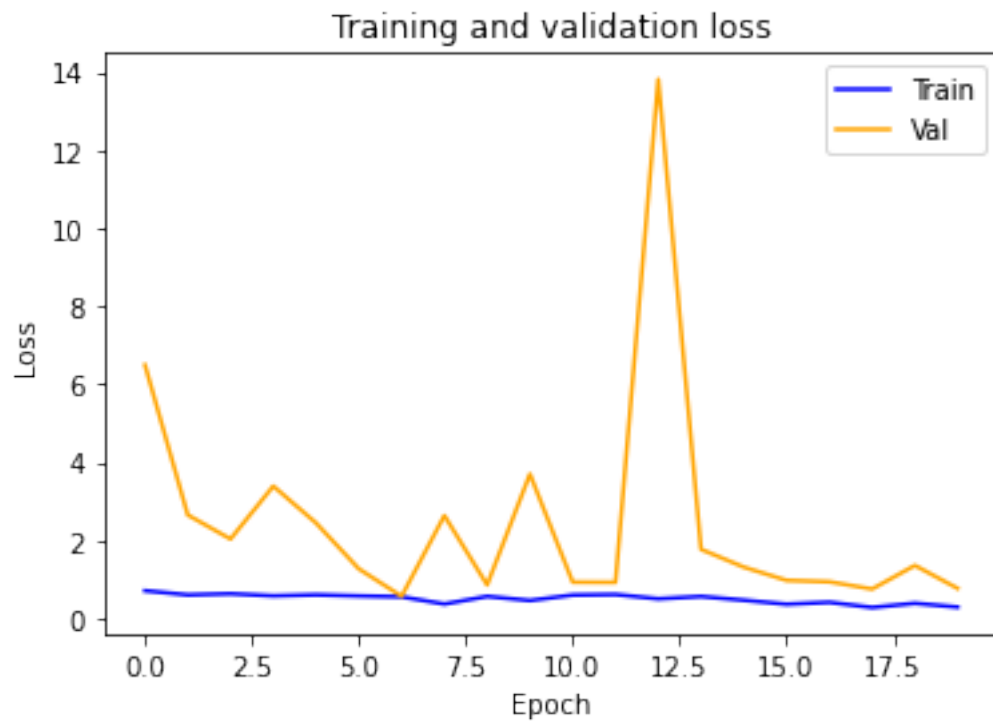
```

```
plt.plot(epochs, val_loss, color='orange', label='Val')  
plt.xlabel('Epoch')  
plt.ylabel('Loss')  
plt.legend()
```

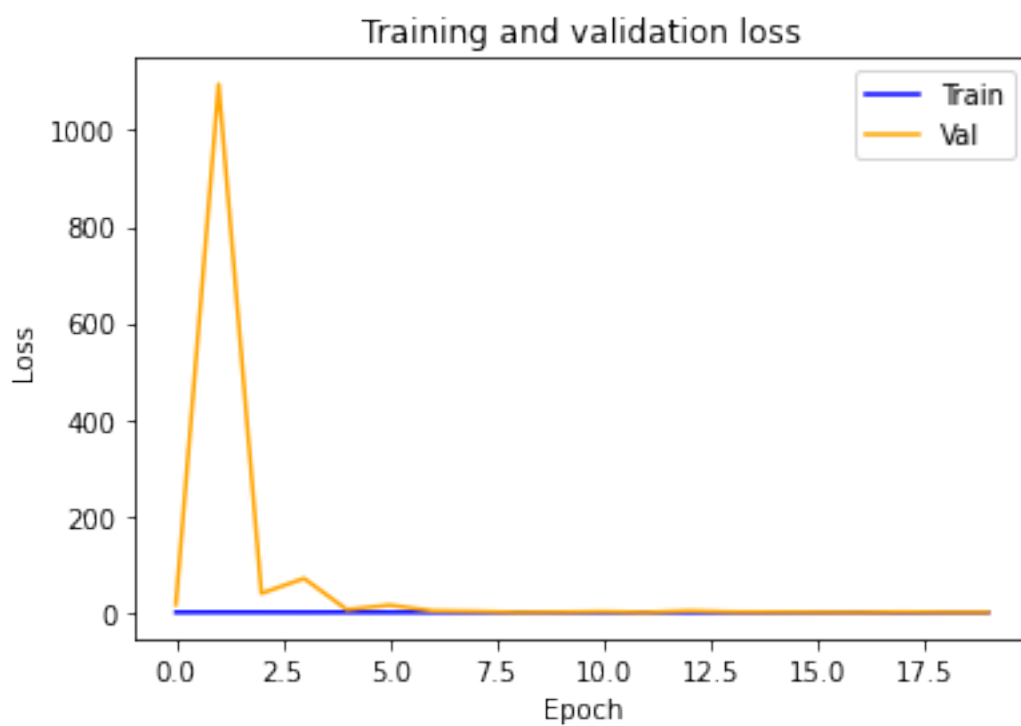
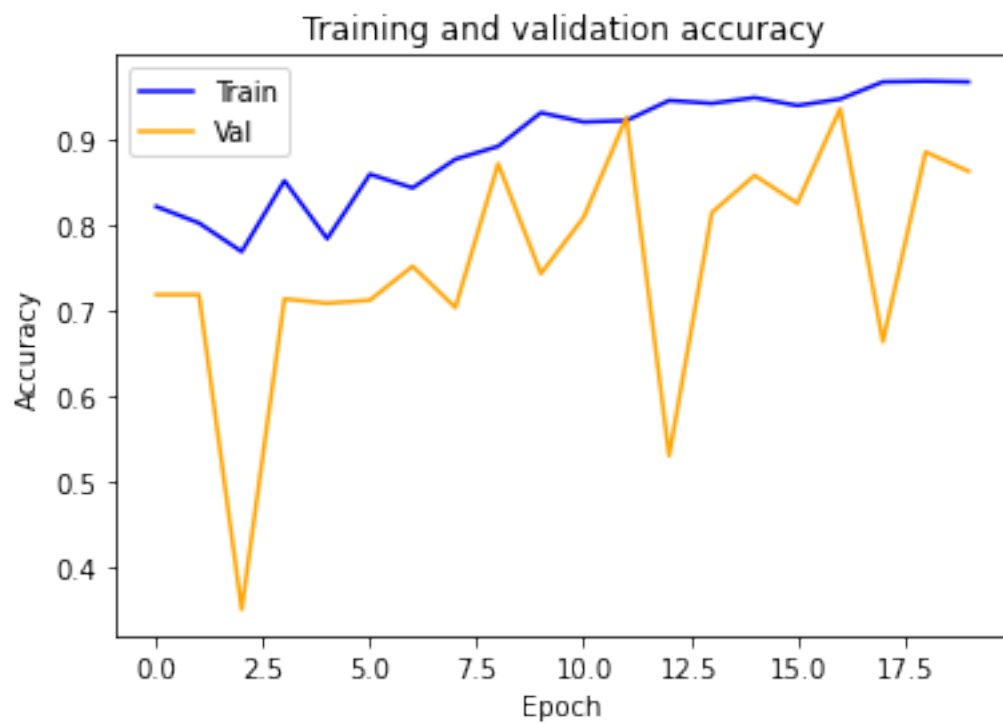
```
[ ]: plot(hist1)
```







```
[38]: ## plotting the training and validation loss and accuracy over the epochs for ↪ model2  
plot(hist2)
```



Testing both the models on the test dataset we created

```
[40]: ## define a function to evaluate the model using the test set
def test_evaluate(test_ds,model,max_steps=None):
    steps = 0
    for path_batch,label_batch in test_ds:
        if max_steps != None and steps == max_steps:
            break
        predictions = model.predict(path_batch)
        steps += 1
        # Record metrics after each batch
        test_loss(label_batch, predictions)
        test_accuracy(label_batch, predictions)
```

```
[48]: test_loss = tf.keras.metrics.BinaryCrossentropy(name='test_loss')
test_accuracy = tf.keras.metrics.BinaryAccuracy(name='test_accuracy')
test_evaluate(test_ds_zoom1,model1)
```

```
1/1 [=====] - 5s 5s/step
1/1 [=====] - 3s 3s/step
1/1 [=====] - 3s 3s/step
1/1 [=====] - 3s 3s/step
1/1 [=====] - 3s 3s/step
1/1 [=====] - 5s 5s/step
1/1 [=====] - 4s 4s/step
1/1 [=====] - 3s 3s/step
```

```
[51]: print("The test loss for model1 (Zoom level 4) is: ",test_loss.result().
        ↪numpy(), "\nThe test accuracy is: ",test_accuracy.result().numpy()*100,"%")
```

```
The test loss for model1 (Zoom level 4) is:  0.77775586
The test accuracy is:  78.57142686843872 %
```

```
[41]: test_loss = tf.keras.metrics.BinaryCrossentropy(name='test_loss')
test_accuracy = tf.keras.metrics.BinaryAccuracy(name='test_accuracy')
test_evaluate(test_ds_zoom2,model2)
```

```
1/1 [=====] - 1s 1s/step
1/1 [=====] - 0s 45ms/step
1/1 [=====] - 0s 54ms/step
1/1 [=====] - 0s 53ms/step
1/1 [=====] - 0s 55ms/step
1/1 [=====] - 0s 54ms/step
1/1 [=====] - 0s 55ms/step
1/1 [=====] - 0s 54ms/step
1/1 [=====] - 0s 55ms/step
1/1 [=====] - 0s 49ms/step
1/1 [=====] - 0s 44ms/step
```

```

1/1 [=====] - 0s 45ms/step
1/1 [=====] - 0s 46ms/step
1/1 [=====] - 0s 54ms/step
1/1 [=====] - 3s 3s/step

```

```

[42]: print("The test loss for model2 (Zoom level 3) is: ",test_loss.result().
      ↪numpy(), "\nThe test accuracy is: ",test_accuracy.result().numpy()*100,"%")

```

The test loss for model2 (Zoom level 3) is: 0.32616392

The test accuracy is: 91.84549450874329 %

Below we define a function to generate a mask heatmap which would tell us as to where the cancer is present using the above models that we trained

```

[43]: def create_mask(filename,model,level,height,width,path_to_dir):

    slide = open_slide(path_to_dir + filename)
    tumor_mask = open_slide(path_to_dir + filename.split(".")[0] + "_mask." +
    ↪filename.split(".")[1])
    dwn_smpls = int(slide.level_downsamples[level])
    x_range = slide.level_dimensions[level][0]
    y_range = slide.level_dimensions[level][1]
    x_lt = int(x_range/width)
    y_lt = int(y_range/height)
    prediction = []
    tissue_perc = []
    count = 0
    for x in range(x_lt):
        for y in range(y_lt):

            region = read_slide(slide, x=x*width*dwn_smpls, y=y*height*dwn_smpls,
    ↪level=level, width=width, height=height)
            region_mask = read_slide(tumor_mask, x=x*width*dwn_smpls,
    ↪y=y*height*dwn_smpls, level=level, width=width, height=height)[:,:,:0]

            percent_tissue = len(find_tissue_pixels(region)) *100 / float(height *
    ↪width)
            count = count + 1
            tissue_perc.append(percent_tissue)
            temp = model.predict(np.expand_dims(region, axis=0))[0][0]
            ## converting any non zero prediction value to 1
            if temp > 0:
                temp = 1
            prediction.append(temp)
    return np.array(prediction).reshape((x_lt,y_lt))

```

```

[56]: test_file = "tumor_078.tif"
      test_pred = create_mask(test_file,model1,4,299,299,data_dir)

```

1/1 [=====] - 2s 2s/step  
1/1 [=====] - 0s 275ms/step  
1/1 [=====] - 0s 267ms/step  
1/1 [=====] - 0s 272ms/step  
1/1 [=====] - 0s 285ms/step  
1/1 [=====] - 0s 266ms/step  
1/1 [=====] - 0s 268ms/step  
1/1 [=====] - 0s 343ms/step  
1/1 [=====] - 0s 275ms/step  
1/1 [=====] - 0s 264ms/step  
1/1 [=====] - 0s 279ms/step  
1/1 [=====] - 0s 276ms/step  
1/1 [=====] - 0s 278ms/step  
1/1 [=====] - 0s 410ms/step  
1/1 [=====] - 0s 469ms/step  
1/1 [=====] - 0s 404ms/step  
1/1 [=====] - 0s 400ms/step  
1/1 [=====] - 0s 270ms/step  
1/1 [=====] - 0s 266ms/step  
1/1 [=====] - 0s 330ms/step  
1/1 [=====] - 0s 265ms/step  
1/1 [=====] - 0s 254ms/step  
1/1 [=====] - 0s 286ms/step  
1/1 [=====] - 0s 266ms/step  
1/1 [=====] - 0s 275ms/step  
1/1 [=====] - 0s 285ms/step  
1/1 [=====] - 0s 267ms/step  
1/1 [=====] - 0s 276ms/step  
1/1 [=====] - 0s 286ms/step  
1/1 [=====] - 0s 273ms/step  
1/1 [=====] - 0s 292ms/step  
1/1 [=====] - 0s 284ms/step  
1/1 [=====] - 0s 267ms/step  
1/1 [=====] - 0s 276ms/step  
1/1 [=====] - 0s 302ms/step  
1/1 [=====] - 0s 259ms/step  
1/1 [=====] - 0s 285ms/step  
1/1 [=====] - 0s 298ms/step  
1/1 [=====] - 0s 270ms/step  
1/1 [=====] - 0s 273ms/step  
1/1 [=====] - 0s 283ms/step  
1/1 [=====] - 0s 262ms/step  
1/1 [=====] - 0s 274ms/step  
1/1 [=====] - 0s 282ms/step  
1/1 [=====] - 0s 262ms/step  
1/1 [=====] - 0s 265ms/step  
1/1 [=====] - 0s 276ms/step  
1/1 [=====] - 0s 267ms/step

```

1/1 [=====] - 0s 259ms/step
1/1 [=====] - 0s 296ms/step
1/1 [=====] - 0s 445ms/step
1/1 [=====] - 0s 483ms/step
1/1 [=====] - 0s 452ms/step
1/1 [=====] - 0s 353ms/step
1/1 [=====] - 0s 323ms/step
1/1 [=====] - 0s 409ms/step
1/1 [=====] - 0s 425ms/step
1/1 [=====] - 0s 387ms/step
1/1 [=====] - 0s 429ms/step
1/1 [=====] - 0s 296ms/step
1/1 [=====] - 0s 273ms/step
1/1 [=====] - 0s 280ms/step
1/1 [=====] - 0s 283ms/step
1/1 [=====] - 0s 276ms/step
1/1 [=====] - 0s 272ms/step
1/1 [=====] - 0s 273ms/step
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1/1 [=====] - 0s 268ms/step
1/1 [=====] - 0s 285ms/step
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1/1 [=====] - 0s 277ms/step
1/1 [=====] - 0s 287ms/step
1/1 [=====] - 0s 263ms/step
1/1 [=====] - 0s 270ms/step
1/1 [=====] - 0s 273ms/step
1/1 [=====] - 0s 284ms/step

```

1/1 [=====] - 0s 271ms/step  
1/1 [=====] - 0s 277ms/step  
1/1 [=====] - 0s 289ms/step  
1/1 [=====] - 0s 339ms/step  
1/1 [=====] - 0s 477ms/step  
1/1 [=====] - 0s 447ms/step  
1/1 [=====] - 0s 361ms/step  
1/1 [=====] - 0s 285ms/step  
1/1 [=====] - 0s 288ms/step  
1/1 [=====] - 0s 281ms/step  
1/1 [=====] - 0s 279ms/step  
1/1 [=====] - 0s 296ms/step  
1/1 [=====] - 0s 287ms/step  
1/1 [=====] - 0s 282ms/step  
1/1 [=====] - 0s 286ms/step  
1/1 [=====] - 0s 305ms/step  
1/1 [=====] - 0s 271ms/step  
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1/1 [=====] - 1s 651ms/step  
1/1 [=====] - 0s 293ms/step  
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```

Plotting the overlap of the mask and slide by using both the original mask and the predicted heatmap mask

```

[62]: slide_test = open_slide(data_dir + test_file)
mask_test = open_slide(data_dir + test_file.split(".")[0] + "_mask." + test_file.
    ↪split(".")[1])

slide_image = read_slide(slide_test,
                        x=0,
                        y=0,
                        level=5,
                        width=slide_test.level_dimensions[5][0],
                        height=slide_test.level_dimensions[5][1])
mask_image = read_slide(mask_test,
                        x=0,
                        y=0,
                        level=5,
                        width=mask_test.level_dimensions[5][0],
                        height=mask_test.level_dimensions[5][1][:,:,0])
predict_mask = cv2.resize(test_pred.T, (slide_test.
    ↪level_dimensions[5][0], slide_test.level_dimensions[5][1]))

plt.figure(figsize=(10,10), dpi=100)
plt.imshow(slide_image)
plt.imshow(mask_image, cmap='jet', alpha=0.5)

plt.figure(figsize=(10,10), dpi=100)
plt.imshow(slide_image)
plt.imshow(predict_mask, cmap='jet', alpha=0.5)

```

```

[62]: <matplotlib.image.AxesImage at 0x7f617c4d5df0>

```

