Importing packages

In [1]:
```
import numpy as np
import pandas as pd
import os
from os import listdir
import cv2

import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
sns.set()
from PIL import Image
from glob import glob
from skimage.io import imread

import sklearn
from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_auc_score

import torch
import torch.nn as nn
import torch.nn.functional as F
import torchvision
import torchvision.transforms as transforms
from torch.utils.data import TensorDataset, DataLoader, Dataset
import torch.optim as optim

import time
import copy
from tqdm import tqdm_notebook as tqdm

import warnings
warnings.filterwarnings("ignore", category=DeprecationWarning)
warnings.filterwarnings("ignore", category=UserWarning)
warnings.filterwarnings("ignore", category=FutureWarning)
```

Configurations

In [2]:
```
# Model Parameters
num_epochs = 10
batch_size = 128
num_classes = 2
learning_rate = 0.002

# Device configuration
device = torch.device('cuda:0' if torch.cuda.is_available() else 'cpu')
device
```

Out[2]:
```
device(type='cuda', index=0)
```

Loading and understanding the data structure

In [3]:
```
base_dir = '../input/histopathologic-cancer-detection/'
print(os.listdir(base_dir))
```

```
['sample_submission.csv', 'train_labels.csv', 'test', 'train']
```

In [4]:
```
labels = pd.read_csv(base_dir + "train_labels.csv")
labels.head()
```

Out[4]:

	id	label
0	f38a6374c348f90b587e046aac6079959adf3835	0
1	c18f2d887b7ae4f6742ee445113fa1aef383ed77	1
2	755db6279dae599ebb4d39a9123cce439965282d	0
3	bc3f0c64fb968ff4a8bd33af6971ecae77c75e08	0
4	068aba587a4950175d04c680d38943fd488d6a9d	0

In [5]:
```
labels.shape
```

Out[5]:
```
(220025, 2)
```

In [6]:
```
labels.info()
```

```
<class 'pandas.core.frame.DataFrame'>

RangeIndex: 220025 entries, 0 to 220024

Data columns (total 2 columns):

 #   Column  Non-Null Count   Dtype

---  ------  --------------   -----

 0   id      220025 non-null  object

 1   label   220025 non-null  int64

dtypes: int64(1), object(1)

memory usage: 3.4+ MB
```

This file contains the ids of images for training and their labels for cancer.

In [7]:
```
train_path = base_dir + "train/"
test_path = base_dir + "test/"
train_files = listdir(train_path)
test_files = listdir(test_path)
```

In [8]:
```
train_files[:5]
```

Out[8]:
```
['d43c081bafa286f9c1f7e921883f26ceafebc912.tif',
 '092d0eedebce504847715ee046b6ad74b57599b4.tif',
 'b0d2582c6218a8764323fc940b41312282b99bf4.tif',
 '187c99df762f13f99818e5593d4bab4c6577e7e3.tif',
 '7c5270c83837de5a5cbb2dca511559dc39d19d53.tif']
```

In [9]:
```
test_files[:5]
```

Out[9]:
```
['a7ea26360815d8492433b14cd8318607bcf99d9e.tif',
 '59d21133c845dff1ebc7a0c7cf40c145ea9e9664.tif',
 '5fde41ce8c6048a5c2f38eca12d6528fa312cdbb.tif',
 'bd953a3b1db1f7041ee95ff482594c4f46c73ed0.tif',
 '523fc2efd7aba53e597ab0f69cc2cbded7a6ce62.tif']
```

In [10]:
```
# Number of images in train and test
print("Train size: ", len(train_files))
print("Test size: ", len(test_files))
```

```
Train size:  220025

Test size:  57458
```

In [11]:
```
print((len(train_files)/(len(train_files)+len(test_files)))*100, (len(test_f
```

```
79.29314588641466 20.706854113585337
```

The directories train and test contain the actual images with 79.3% and 20.7% of the total images respectively.

In [12]:
```
sub = pd.read_csv(base_dir + "sample_submission.csv")
sub.head()
```

Out[12]:

	id	label
0	0b2ea2a822ad23fdb1b5dd26653da899fbd2c0d5	0
1	95596b92e5066c5c52466c90b69ff089b39f2737	0
2	248e6738860e2ebcf6258cdc1f32f299e0c76914	0
3	2c35657e312966e9294eac6841726ff3a748febf	0
4	145782eb7caa1c516acbe2eda34d9a3f31c41fd6	0

In [13]:
```
sub.shape
```

Out[13]:
```
(57458, 2)
```

In [14]:
```
sub.info()
```

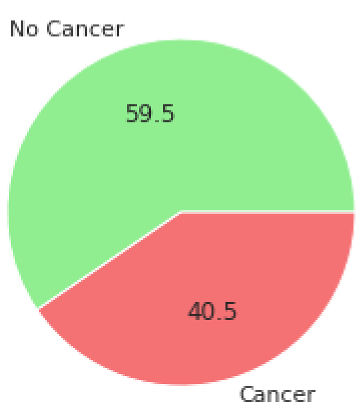
```
<class 'pandas.core.frame.DataFrame'>

RangeIndex: 57458 entries, 0 to 57457

Data columns (total 2 columns):

 #   Column  Non-Null Count  Dtype

---  ------  --------------  -----

 0   id      57458 non-null  object

 1   label   57458 non-null  int64

dtypes: int64(1), object(1)

memory usage: 897.9+ KB
```

This file contains the ids of test images and all the labels are set to 0. We need to modify the labels in this file according to our predictions.

Exploratory Data Analysis

Visualizing the number of patches with cancer vs without cancer.

In [15]:
```
plt.pie(labels.label.value_counts(), labels=['No Cancer', 'Cancer'], colors=
plt.show()
```



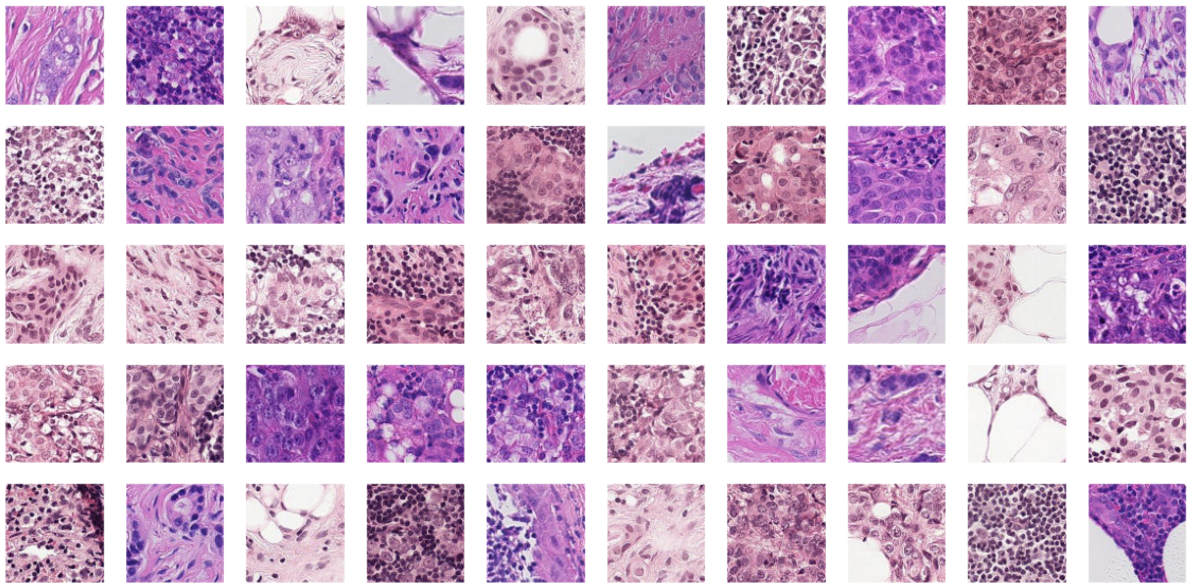
Visualizing healthy and cancer patches

In [16]:
```
positive_images = np.random.choice(labels[labels.label==1].id, size=50, repl
negative_images = np.random.choice(labels[labels.label==0].id, size=50, repl
```

Cancer patches

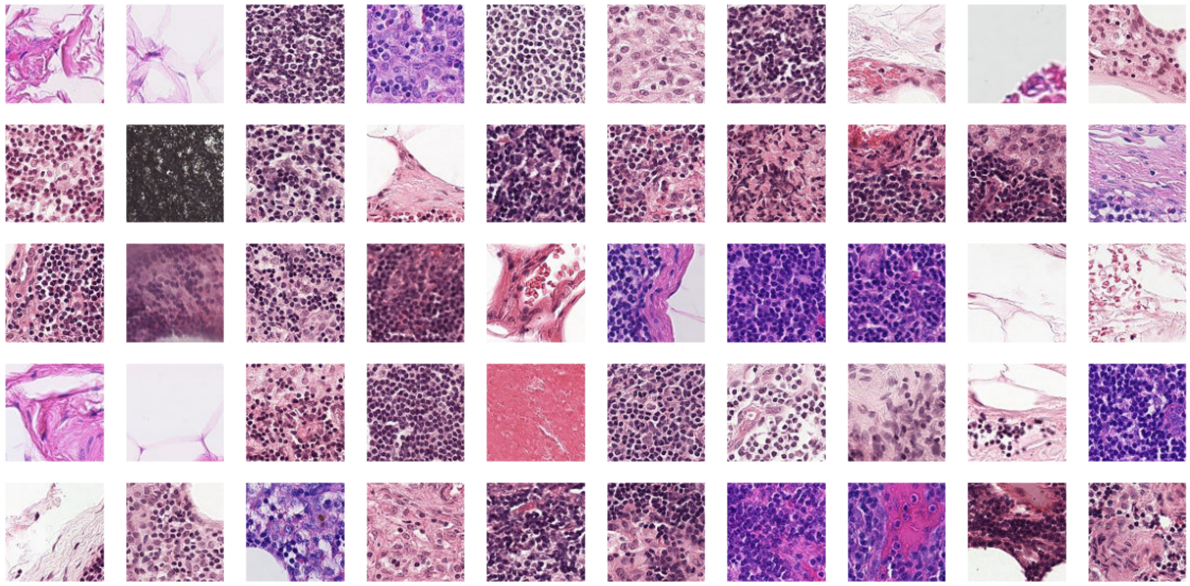
In [17]:
```
fig, ax = plt.subplots(5, 10, figsize=(20,10))
```

```
for n in range(5):
    for m in range(10):
        img_id = positive_images[m + n*10]
        image = Image.open(train_path + img_id + ".tif")
        ax[n,m].imshow(image)
        ax[n,m].grid(False)
        ax[n,m].tick_params(labelbottom=False, labelleft=False)
```



Healthy patches

In [18]:
```
fig, ax = plt.subplots(5, 10, figsize=(20,10))

for n in range(5):
    for m in range(10):
        img_id = negative_images[m + n*10]
        image = Image.open(train_path + img_id + ".tif")
        ax[n,m].imshow(image)
        ax[n,m].grid(False)
        ax[n,m].tick_params(labelbottom=False, labelleft=False)
```



Analysis

Visualising cancerous and healthy patches, it is hard to identify metastatic cancer for an untrained eye. One observation could be that the healthy patches have higher contrast than the cancerous patches. However, this observation doesn't seem to be applicable on all the images. It would be interesting to see what criterion pathologists use for identification of metastatic cancer!

Data Preprocessing

Splitting the data into train and validation sets

In [19]:
```
train, val = train_test_split(labels, stratify=labels.label, test_size=0.1)
print(len(train), len(val))
```

```
198022 22003
```

Custom Dataset

I have created a dataset that loads an image patch, converts it to RGB, performs the augmentation if it's desired, and returns the image and its label.

In [21]:
```
class CancerDataset(Dataset):
    def __init__(self, df_data, data_dir = './', transform=None):
        super().__init__()
        self.df = df_data.values
        self.data_dir = data_dir
        self.transform = transform

    def __len__(self):
        return len(self.df)
```

```
    def __getitem__(self, index):
        img_name,label = self.df[index]
        img_path = os.path.join(self.data_dir, img_name + '.tif')
        image = cv2.imread(img_path)
        if self.transform is not None:
            image = self.transform(image)
        return image, label
```

Data Augmentation

Now to increase the data size, I have applied transformation like flipping and rotation to the train dataset, and then converted the datasets into tensors.

In [22]:
```
transform_train = transforms.Compose([transforms.ToPILImage(),
                                  transforms.RandomHorizontalFlip(),
                                  transforms.RandomVerticalFlip(),
                                  transforms.RandomRotation(20),
                                  transforms.ToTensor(),
                                  transforms.Normalize(mean=[0.5, 0.5, 0.5],

transform_val = transforms.Compose([transforms.ToPILImage(),
                                  transforms.ToTensor(),
                                  transforms.Normalize(mean=[0.5, 0.5, 0.5],

transform_test = transforms.Compose([transforms.ToPILImage(),
                                  transforms.ToTensor(),
                                  transforms.Normalize(mean=[0.5, 0.5, 0.5],
```

In [23]:
```
train_dataset = CancerDataset(df_data=train, data_dir=train_path, transform=
val_dataset = CancerDataset(df_data=val, data_dir=train_path, transform=trar
test_dataset = CancerDataset(df_data=sub, data_dir=test_path, transform=trar
```

Creating pytorch dataloader

- The training data is shuffled after epochs so that the batches in the epochs are different every time and the model doesn't learn in a specific sequence.
- The last batch is dropped as it might contain less images than the batch size.

In [24]:
```
train_dataloader = DataLoader(train_dataset, batch_size=batch_size, shuffle=
val_dataloader = DataLoader(val_dataset, batch_size=batch_size, shuffle=Fals
test_dataloader = DataLoader(test_dataset, batch_size=batch_size, shuffle=Fa
```

In [25]:
```
print(len(train_dataloader), len(val_dataloader), len(test_dataloader))
```

```
1547 171 449
```

Defining the Model

I am using a CNN as the model with 5 layers.

In [26]:
```
class CNN(nn.Module):
    def __init__(self):
        super(CNN,self).__init__()

        self.conv1 = nn.Sequential(
                        nn.Conv2d(3, 32, 3, stride=1, padding=1),
                        nn.BatchNorm2d(32),
                        nn.ReLU(inplace=True),
                        nn.MaxPool2d(2,2))

        self.conv2 = nn.Sequential(
                        nn.Conv2d(32, 64, 3, stride=1, padding=1),
                        nn.BatchNorm2d(64),
                        nn.ReLU(inplace=True),
                        nn.MaxPool2d(2,2))

        self.conv3 = nn.Sequential(
                        nn.Conv2d(64, 128, 3, stride=1, padding=1),
                        nn.BatchNorm2d(128),
                        nn.ReLU(inplace=True),
                        nn.MaxPool2d(2,2))

        self.conv4 = nn.Sequential(
                        nn.Conv2d(128, 256, 3, stride=1, padding=1),
                        nn.BatchNorm2d(256),
                        nn.ReLU(inplace=True),
                        nn.MaxPool2d(2,2))

        self.conv5 = nn.Sequential(
                        nn.Conv2d(256, 512, 3, stride=1, padding=1),
                        nn.BatchNorm2d(512),
                        nn.ReLU(inplace=True),
                        nn.MaxPool2d(2,2))

        self.fc=nn.Sequential(
                nn.Linear(512*3*3, 256),
                nn.ReLU(inplace=True),
                nn.BatchNorm1d(256),
                nn.Dropout(0.4),
                nn.Linear(256, num_classes))

    def forward(self,x):
        x=self.conv1(x)
        x=self.conv2(x)
        x=self.conv3(x)
        x=self.conv4(x)
        x=self.conv5(x)
#        print(x.shape)
        x=x.view(x.shape[0],-1)
        x=self.fc(x)
        return x
```

Printing the training model.

In [27]:
```
model = CNN().to(device)
```

```
print(model)
```

```
CNN(

  (conv1): Sequential(

    (0): Conv2d(3, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))

    (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_runnin
g_stats=True)

    (2): ReLU(inplace=True)

    (3): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mod
e=False)

  )

  (conv2): Sequential(

    (0): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))

    (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_runnin
g_stats=True)

    (2): ReLU(inplace=True)

    (3): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mod
e=False)

  )

  (conv3): Sequential(

    (0): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))

    (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_runni
ng_stats=True)

    (2): ReLU(inplace=True)

    (3): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mod
e=False)

  )

  (conv4): Sequential(

    (0): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))

    (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_runni
ng_stats=True)

    (2): ReLU(inplace=True)

    (3): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mod
e=False)
```

```
  )

  (conv5): Sequential(

    (0): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))

    (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)

    (2): ReLU(inplace=True)

    (3): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)

  )

  (fc): Sequential(

    (0): Linear(in_features=4608, out_features=256, bias=True)

    (1): ReLU(inplace=True)

    (2): BatchNorm1d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)

    (3): Dropout(p=0.4, inplace=False)

    (4): Linear(in_features=256, out_features=2, bias=True)

  )

)
```

Loss and Optimizer

This task is a binary classification problem that has two classes, 1 for cancer positive images and 0 for cancer negative images. For loss function, I have used cross entropy loss. I have used adam for optimizer.

In [28]:
```
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adamax(model.parameters(), lr=learning_rate)
```

Training the Model

Building the training loop for the model. It prints the loss and accuracy for training and validation after each epoch. For accuracy, I have calculated the area under the ROC curve between the predicted probability and the observed target. The losses and accuracies are also saved in an array for further evaluation of the model.

In [29]:
```python
train_losses = []
val_losses = []
train_auc = []
val_auc = []
train_auc_epoch = []
val_auc_epoch = []
best_acc = 0.0
min_loss = np.Inf

since = time.time()

for e in range(num_epochs):

    train_loss = 0.0
    val_loss = 0.0

    # Train the model
    model.train()
    for i, (images, labels) in enumerate(tqdm(train_dataloader, total=int(le
        images = images.to(device)
        labels = labels.to(device)

        # Forward pass
        outputs = model(images)
        loss = criterion(outputs, labels)

        # Backward and optimize
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        # Loss and accuracy
        train_loss += loss.item()
        y_actual = labels.data.cpu().numpy()
        y_pred = outputs[:,-1].detach().cpu().numpy()
        train_auc.append(roc_auc_score(y_actual, y_pred))

    # Evaluate the model
    model.eval()
    for i, (images, labels) in enumerate(tqdm(val_dataloader, total=int(len(
        images = images.to(device)
        labels = labels.to(device)

        # Forward pass
        outputs = model(images)
        loss = criterion(outputs, labels)

        # Loss and accuracy
        val_loss += loss.item()
        y_actual = labels.data.cpu().numpy()
        y_pred = outputs[:,-1].detach().cpu().numpy()
        val_auc.append(roc_auc_score(y_actual, y_pred))

    # Average losses and accuracies
    train_loss = train_loss/len(train_dataloader)
    val_loss = val_loss/len(val_dataloader)
```

```python
    train_losses.append(train_loss)
    val_losses.append(val_loss)
    training_auc = np.mean(train_auc)
    validation_auc = np.mean(val_auc)
    train_auc_epoch.append(training_auc)
    val_auc_epoch.append(validation_auc)

    # Updating best validation accuracy
    if best_acc < validation_auc:
        best_acc = validation_auc

    # Saving best model
    if min_loss >= val_loss:
        torch.save(model.state_dict(), 'best_model.pt')
        min_loss = val_loss

    print('EPOCH {}/{}'.format(e+1, num_epochs))
    print('-' * 10)
    print("Train loss: {:.6f}, Train AUC: {:.4f}".format(train_loss, trainin
    print("Validation loss: {:.6f}, Validation AUC: {:.4f}\n".format(val_los

time_elapsed = time.time() - since
print('Training completed in {:.0f}m {:.0f}s'.format(time_elapsed // 60, tim
print('Best validation accuracy: {:4f}'.format(best_acc))
```

100% 1547/1547 [31:42<00:00, 1.20s/it]

100% 171/171 [03:12<00:00, 1.11s/it]

EPOCH 1/10

Train loss: 0.333041, Train AUC: 0.9179

Validation loss: 0.264933, Validation AUC: 0.9596

100% 1547/1547 [07:49<00:00, 3.19it/s]

100% 171/171 [00:41<00:00, 3.59it/s]

EPOCH 2/10

Train loss: 0.249792, Train AUC: 0.9383

Validation loss: 0.333774, Validation AUC: 0.9611

100% 1547/1547 [07:42<00:00, 3.04it/s]

100% 171/171 [00:42<00:00, 4.15it/s]

EPOCH 3/10

Train loss: 0.212781, Train AUC: 0.9490

Validation loss: 0.163256, Validation AUC: 0.9682

100% 1547/1547 [07:55<00:00, 3.18it/s]

100% 171/171 [00:41<00:00, 4.27it/s]

EPOCH 4/10

Train loss: 0.191328, Train AUC: 0.9558

Validation loss: 0.211653, Validation AUC: 0.9694

100% 1547/1547 [07:38<00:00, 3.32it/s]

100% 171/171 [00:41<00:00, 4.34it/s]

EPOCH 5/10

Train loss: 0.175456, Train AUC: 0.9606

Validation loss: 0.165111, Validation AUC: 0.9727

100% 1547/1547 [07:42<00:00, 3.57it/s]

100% 171/171 [00:38<00:00, 4.65it/s]

EPOCH 6/10

Train loss: 0.160295, Train AUC: 0.9644

Validation loss: 0.174787, Validation AUC: 0.9744

100% 1547/1547 [07:52<00:00, 3.21it/s]

100% 171/171 [00:40<00:00, 4.41it/s]

```
EPOCH 7/10

----------

Train loss: 0.157974, Train AUC: 0.9671

Validation loss: 0.168022, Validation AUC: 0.9760
```

100% 1547/1547 [07:45<00:00, 3.41it/s]

100% 171/171 [00:41<00:00, 4.24it/s]

```
EPOCH 8/10

----------

Train loss: 0.150209, Train AUC: 0.9694

Validation loss: 0.194931, Validation AUC: 0.9760
```

100% 1547/1547 [07:49<00:00, 3.50it/s]

100% 171/171 [00:40<00:00, 4.14it/s]

```
EPOCH 9/10

----------

Train loss: 0.141605, Train AUC: 0.9714

Validation loss: 0.118717, Validation AUC: 0.9776
```

100% 1547/1547 [07:37<00:00, 3.46it/s]

100% 171/171 [00:41<00:00, 4.32it/s]

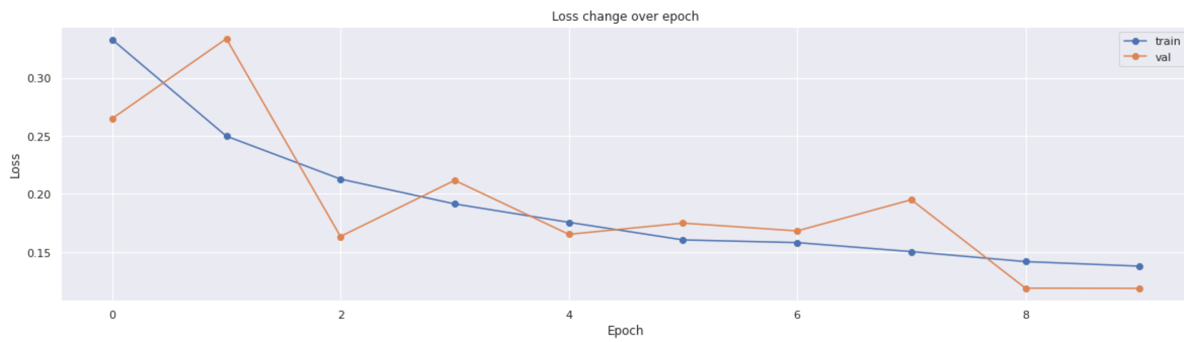
```
EPOCH 10/10

----------

Train loss: 0.137685, Train AUC: 0.9730

Validation loss: 0.118524, Validation AUC: 0.9788


Training completed in 110m 58s

Best validation accuracy: 0.978804
```

Plotting training history

Loss Convergence

In [30]:
```
plt.figure(figsize=(20,5))
plt.plot(train_losses, '-o', label="train")
plt.plot(val_losses, '-o', label="val")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.title("Loss change over epoch")
plt.legend()
```

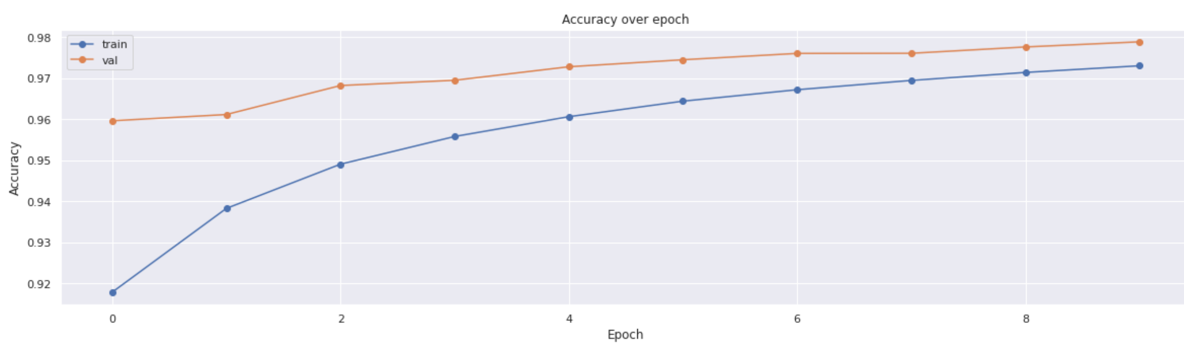
Out[30]: <matplotlib.legend.Legend at 0x7fb772631c50>



Accuracy trend

In [31]:
```
plt.figure(figsize=(20,5))
plt.plot(train_auc_epoch, '-o', label="train")
plt.plot(val_auc_epoch, '-o', label="val")
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.title("Accuracy over epoch")
plt.legend()
```

Out[31]: <matplotlib.legend.Legend at 0x7fb77009d250>



Loading the best model

In [32]:
```
model.load_state_dict(torch.load('best_model.pt'))
```

Out[32]: <All keys matched successfully>

Making & Visualising Predictions

Predictions on test dataset

I have used my best model to make predictions on the test dataset.

In [33]:
```
model.eval()

predictions = []

for i, (images, labels) in enumerate(tqdm(test_dataloader, total=int(len(tes
    images = images.to(device)
    labels = labels.to(device)

    outputs = model(images)
    pred = outputs[:,1].detach().cpu().numpy()

    for j in pred:
        predictions.append(j)
```

100% 449/449 [08:39<00:00, 1.08s/it]

Modifying the submission file

Now I am using the predictions made by the model to create a submission file.

In [34]:
```
sub['label'] = predictions
sub.to_csv('submission.csv', index=False)
sub.info()
```

```
<class 'pandas.core.frame.DataFrame'>

RangeIndex: 57458 entries, 0 to 57457

Data columns (total 2 columns):

 #   Column  Non-Null Count  Dtype

---  ------  --------------  -----

 0   id      57458 non-null  object

 1   label   57458 non-null  float32

dtypes: float32(1), object(1)

memory usage: 673.5+ KB
```

Visualizing predictions

First I have written a function to convert the image from tensor and then displayed some of the test images along with their predicted result. For a probability less than 0.5, images are labelled 'Healthy', otherwise they are labelled 'Cancer'.

In [35]:
```
test_images = np.random.choice(sub.id, size=50, replace=False)

fig, ax = plt.subplots(5, 10, figsize=(20,10))

for n in range(5):
    for m in range(10):
        img_id = test_images[m + n*10]
        image = Image.open(test_path + img_id + ".tif")
        pred = sub.loc[sub['id'] == img_id, 'label'].values[0]
        label = "Cancer" if(pred >= 0.5) else "Healthy"
        ax[n,m].imshow(image)
        ax[n,m].grid(False)
        ax[n,m].tick_params(labelbottom=False, labelleft=False)
        ax[n,m].set_title("Label: " + label)
```