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Capstone Project 2 - Milestone Report 2

Springboard Data Science Career Track

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November 13, 2019

Cancer Detection in Histological Slides

OVERVIEW

Cancer is deadly and early diagnosis will play an important role in treatment and improvement of the patient's survival rate. Cancer can be benign or metastatic. One of the most important early diagnosis is detection in lymph nodes to find out whether the cancer has metastasized. The method to do this is H & E staining of histological slides of lymph nodes taken from biopsies.

GOALS

Currently pathologists manually examine the slides and decide if the patient has metastatic cancer or not. Because human judgement is not consistent and the diagnosis can vary between person to person and even between different days by the same person. Thus by developing deep learning algorithm we can automate the process and give unbiased results.

DATA SOURCE

The data for my project are downloaded from Kaggle website (<https://www.kaggle.com/c/histopathologic-cancer-detection/data>). Following data are provided:-

1. Sample_submission.csv - a sample submission file in the correct format
2. Train_labels.csv - a file with labels of 0 or 1 (0 for cancer not detected and 1 for cancer detected) for corresponding images in training dataset.

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3. Train - a folder with 220,025 images from histopathological slides. These are the images I have to train my model on.
 4. Test - a folder with 57,458 images. These are the images I will use to predict cancer detection.

EXPLORATORY DATA ANALYSIS

The training set has 220,025 images. The dataset is imbalanced (number of images in each class is not equal) as seen in figure 1 below:-

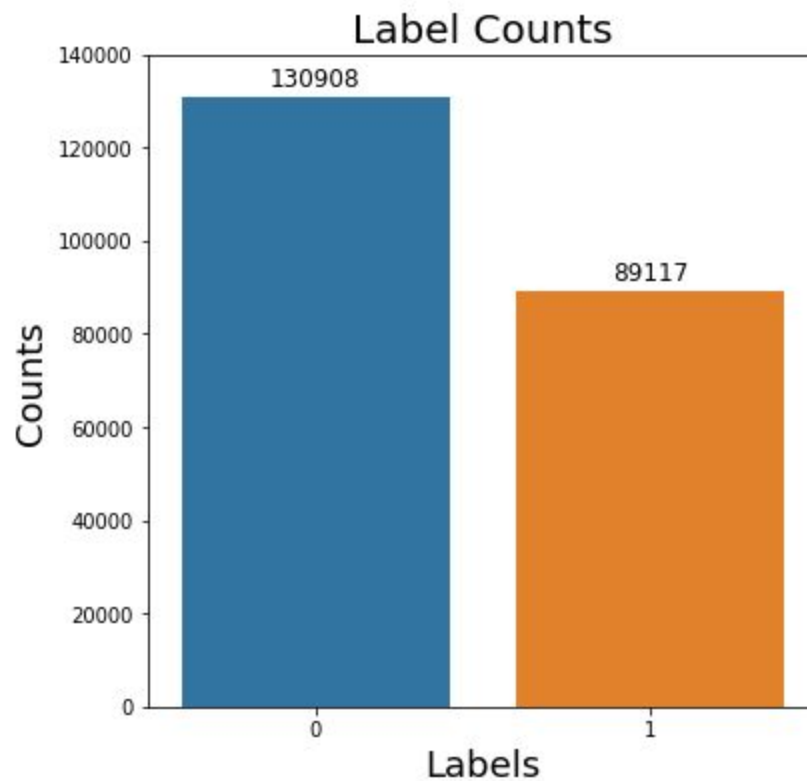


Figure 1: Distribution of images in the datasets

Images of normal tissue comprised of 59.5% and cancerous tissue only 40.5%.

Shown below, in figure 2, are representative images of normal (0) and cancerous (1) tissues.

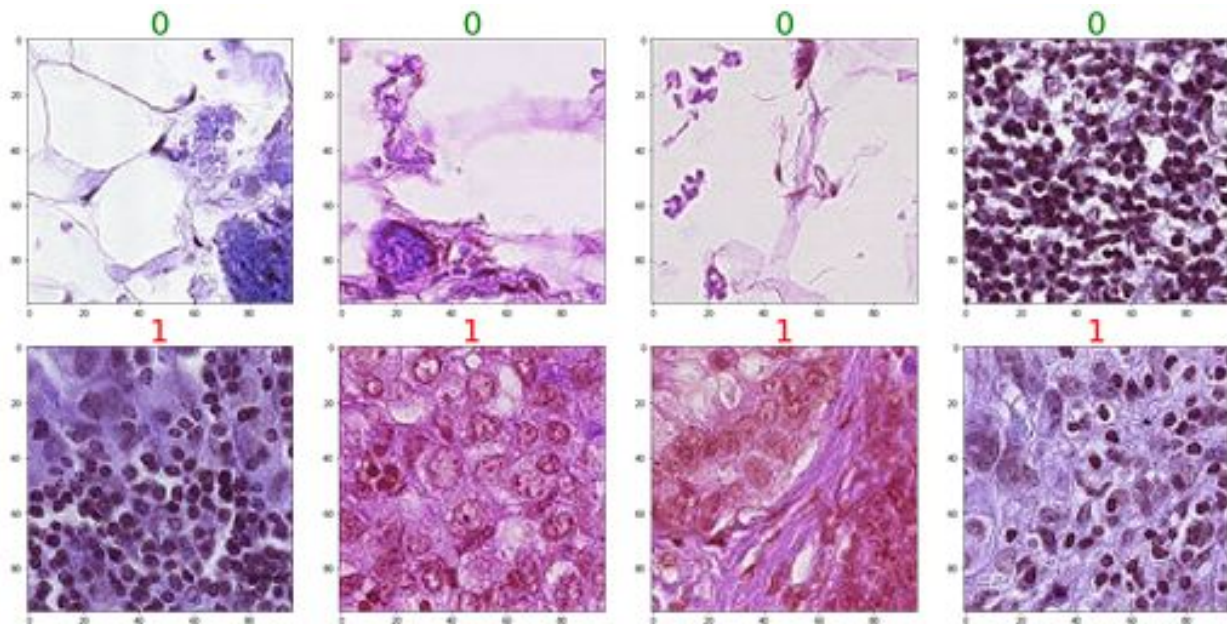


Figure 2: Representative images

DATA WRANGLING / SAMPLING OF IMAGES FOR TRAINING

Since the dataset is imbalanced and very large and neural networks take very long to train on all the datasets, I decided to sample 20,000 images in each class (a total of 40,000 images) to make the dataset balanced and smaller yet containing enough images to train my models. After sampling, I put them into separate folders to be consistent in training different models multiple times. Then I split the data 80/20 into training and validation sets. This will be my training and validation datasets for all the models.

CONVOLUTIONAL NEURAL NETWORK MODELS

I built five CNN models and two pretrained models that were fed features extracted from the image sequences. Machine learning was performed using Python, primarily with Keras with TensorFlow in the backend on MacBookPro with 2.3 GHz Quad-core Intel Core i5 and 16 GB memory.

Model Descriptions:

Model-1: "sequential_1"

Layer (type)	Output Shape	Param #
=====		
conv2d_1 (Conv2D)	(None, 95, 95, 32)	416

conv2d_2 (Conv2D)	(None, 94, 94, 32)	4128
conv2d_3 (Conv2D)	(None, 93, 93, 32)	4128
max_pooling2d_1 (MaxPooling2D)	(None, 46, 46, 32)	0
conv2d_4 (Conv2D)	(None, 45, 45, 32)	4128
conv2d_5 (Conv2D)	(None, 44, 44, 32)	4128
conv2d_6 (Conv2D)	(None, 43, 43, 32)	4128
max_pooling2d_2 (MaxPooling2D)	(None, 21, 21, 32)	0
conv2d_7 (Conv2D)	(None, 20, 20, 64)	8256
conv2d_8 (Conv2D)	(None, 19, 19, 64)	16448
conv2d_9 (Conv2D)	(None, 18, 18, 64)	16448
max_pooling2d_3 (MaxPooling2D)	(None, 9, 9, 64)	0
flatten_1 (Flatten)	(None, 5184)	0
dense_1 (Dense)	(None, 64)	331840
dropout_1 (Dropout)	(None, 64)	0
dense_2 (Dense)	(None, 2)	130
=====		
Total params: 394,178		
Trainable params: 394,178		
Non-trainable params: 0		

Model-2: "sequential_2"

Layer (type)	Output Shape	Param #
=====		
conv2d_10 (Conv2D)	(None, 95, 95, 32)	416
conv2d_11 (Conv2D)	(None, 94, 94, 32)	4128

conv2d_12 (Conv2D)	(None, 93, 93, 32)	4128
max_pooling2d_4 (MaxPooling2D)	(None, 46, 46, 32)	0
conv2d_13 (Conv2D)	(None, 45, 45, 32)	4128
conv2d_14 (Conv2D)	(None, 44, 44, 32)	4128
conv2d_15 (Conv2D)	(None, 43, 43, 32)	4128
max_pooling2d_5 (MaxPooling2D)	(None, 21, 21, 32)	0
conv2d_16 (Conv2D)	(None, 20, 20, 64)	8256
conv2d_17 (Conv2D)	(None, 19, 19, 64)	16448
conv2d_18 (Conv2D)	(None, 18, 18, 64)	16448
max_pooling2d_6 (MaxPooling2D)	(None, 9, 9, 64)	0
conv2d_19 (Conv2D)	(None, 8, 8, 128)	32896
conv2d_20 (Conv2D)	(None, 7, 7, 128)	65664
conv2d_21 (Conv2D)	(None, 6, 6, 128)	65664
max_pooling2d_7 (MaxPooling2D)	(None, 3, 3, 128)	0

flatten_2 (Flatten)	(None, 1152)	0
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dense_3 (Dense)	(None, 64)	73792
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dropout_2 (Dropout)	(None, 64)	0
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dense_4 (Dense)	(None, 2)	130
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=====		
Total params: 300,354		
Trainable params: 300,354		
Non-trainable params: 0		
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Model-3: "sequential_3"

Layer (type)	Output Shape	Param #
<hr/>		
conv2d_22 (Conv2D)	(None, 95, 95, 32)	416
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conv2d_23 (Conv2D)	(None, 94, 94, 32)	4128
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conv2d_24 (Conv2D)	(None, 93, 93, 32)	4128
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max_pooling2d_8 (MaxPooling2D)	(None, 46, 46, 32)	0
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conv2d_25 (Conv2D)	(None, 45, 45, 32)	4128
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conv2d_26 (Conv2D)	(None, 44, 44, 32)	4128
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conv2d_27 (Conv2D)	(None, 43, 43, 32)	4128
max_pooling2d_9 (MaxPooling2D)	(None, 21, 21, 32)	0
conv2d_28 (Conv2D)	(None, 20, 20, 64)	8256
conv2d_29 (Conv2D)	(None, 19, 19, 64)	16448
conv2d_30 (Conv2D)	(None, 18, 18, 64)	16448
max_pooling2d_10 (MaxPooling2D)	(None, 9, 9, 64)	0
conv2d_31 (Conv2D)	(None, 8, 8, 128)	32896
conv2d_32 (Conv2D)	(None, 7, 7, 128)	65664
conv2d_33 (Conv2D)	(None, 6, 6, 128)	65664
max_pooling2d_11 (MaxPooling2D)	(None, 3, 3, 128)	0
flatten_3 (Flatten)	(None, 1152)	0
dense_5 (Dense)	(None, 64)	73792
dropout_3 (Dropout)	(None, 64)	0
dense_6 (Dense)	(None, 2)	130
=====		
Total params: 300,354		

Trainable params: 300,354

Non-trainable params: 0

Model-4: "sequential_4"

Layer (type)	Output Shape	Param #
=====		
conv2d_34 (Conv2D)	(None, 94, 94, 32)	896
conv2d_35 (Conv2D)	(None, 92, 92, 32)	9248
conv2d_36 (Conv2D)	(None, 90, 90, 32)	9248
max_pooling2d_12 (MaxPooling)	(None, 45, 45, 32)	0
dropout_4 (Dropout)	(None, 45, 45, 32)	0
conv2d_37 (Conv2D)	(None, 43, 43, 64)	18496
conv2d_38 (Conv2D)	(None, 41, 41, 64)	36928
conv2d_39 (Conv2D)	(None, 39, 39, 64)	36928
max_pooling2d_13 (MaxPooling)	(None, 19, 19, 64)	0
dropout_5 (Dropout)	(None, 19, 19, 64)	0
conv2d_40 (Conv2D)	(None, 17, 17, 128)	73856

conv2d_41 (Conv2D)	(None, 15, 15, 128)	147584
conv2d_42 (Conv2D)	(None, 13, 13, 128)	147584
max_pooling2d_14 (MaxPooling)	(None, 6, 6, 128)	0
dropout_6 (Dropout)	(None, 6, 6, 128)	0
flatten_4 (Flatten)	(None, 4608)	0
dense_7 (Dense)	(None, 256)	1179904
dropout_7 (Dropout)	(None, 256)	0
dense_8 (Dense)	(None, 2)	514

=====
Total params: 1,661,186

Trainable params: 1,661,186

Non-trainable params: 0

Model-5: "sequential_5"

Layer (type)	Output Shape	Param #
=====		
conv2d_43 (Conv2D)	(None, 95, 95, 32)	416

conv2d_44 (Conv2D)	(None, 94, 94, 32)	4128
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conv2d_45 (Conv2D)	(None, 93, 93, 32)	4128
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max_pooling2d_15 (MaxPooling)	(None, 46, 46, 32)	0
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dropout_8 (Dropout)	(None, 46, 46, 32)	0
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conv2d_46 (Conv2D)	(None, 45, 45, 64)	8256
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conv2d_47 (Conv2D)	(None, 44, 44, 64)	16448
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conv2d_48 (Conv2D)	(None, 43, 43, 64)	16448
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max_pooling2d_16 (MaxPooling)	(None, 21, 21, 64)	0
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dropout_9 (Dropout)	(None, 21, 21, 64)	0
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conv2d_49 (Conv2D)	(None, 20, 20, 128)	32896
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conv2d_50 (Conv2D)	(None, 19, 19, 128)	65664
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conv2d_51 (Conv2D)	(None, 18, 18, 128)	65664
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max_pooling2d_17 (MaxPooling)	(None, 9, 9, 128)	0
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dropout_10 (Dropout)	(None, 9, 9, 128)	0
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conv2d_52 (Conv2D)	(None, 8, 8, 128)	65664
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conv2d_53 (Conv2D)	(None, 7, 7, 128)	65664
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conv2d_54 (Conv2D)	(None, 6, 6, 128)	65664
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max_pooling2d_18 (MaxPooling)	(None, 3, 3, 128)	0
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dropout_11 (Dropout)	(None, 3, 3, 128)	0
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flatten_5 (Flatten)	(None, 1152)	0
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dense_9 (Dense)	(None, 256)	295168
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dropout_12 (Dropout)	(None, 256)	0
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dense_10 (Dense)	(None, 2)	514
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Total params: 706,722

Trainable params: 706,722

Non-trainable params: 0

Model-6 ResNet50: "model_1"

Layer (type)	Output Shape	Param #
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input_2 (InputLayer)	(None, 96, 96, 3)	0

resnet50 (Model)	(None, 3, 3, 2048)	23587712

global_average_pooling2d_1 ((None, 2048)	0

dropout_1 (Dropout)	(None, 2048)	0

dense_1 (Dense)	(None, 2)	4098
=====		
Total params: 23,591,810		
Trainable params: 23,538,690		
Non-trainable params: 53,120		

Model-7 NASNet: "model_1"

Layer (type)	Output Shape	Param #	Connected to
=====			
input_2 (InputLayer)	(None, 96, 96, 3)	0	

NASNet (Model)	(None, 3, 3, 1056)	4269716	input_2[0][0]

global_max_pooling2d_1 (GlobalM	(None, 1056)	0	NASNet[1][0]

global_average_pooling2d_1 (Glo	(None, 1056)	0	NASNet[1][0]

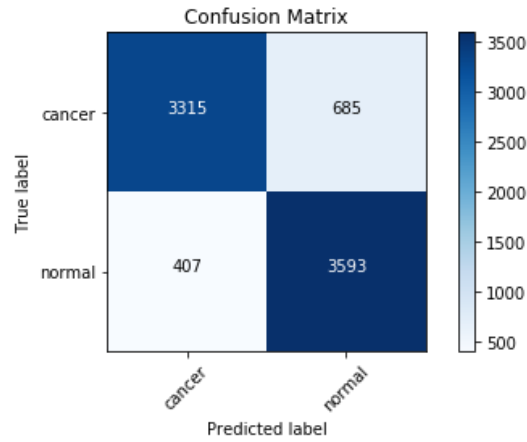
flatten_1 (Flatten)	(None, 9504)	0	NASNet[1][0]
<hr/>			
concatenate_5 (Concatenate)	(None, 11616)	0	global_max_pooling2d_1[0][0] global_average_pooling2d_1[0][0] flatten_1[0][0]
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dropout_1 (Dropout)	(None, 11616)	0	concatenate_5[0][0]
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3_ (Dense)	(None, 2)	23234	dropout_1[0][0]
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Total params: 4,292,950			
Trainable params: 4,256,212			
Non-trainable params: 36,738			

Model performances:

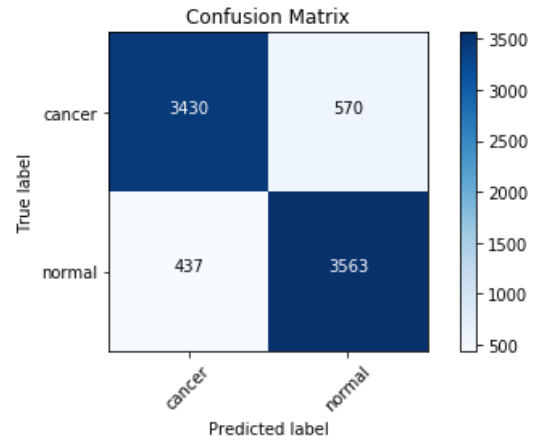
	Val_loss	val_acc	roc_auc_scores
Model1	0.023002	0.865250	0.940067
Model2	0.018761	0.869687	0.945249
Model3	0.014563	0.871375	0.945899
Model4	0.025661	0.838375	0.921132
Model5	0.056837	0.853500	0.925100
Model6	0.008133	0.935375	0.980530
Model7	0.031510	0.840813	0.925162

Based on the above data, it looks like Model6 performed the best.

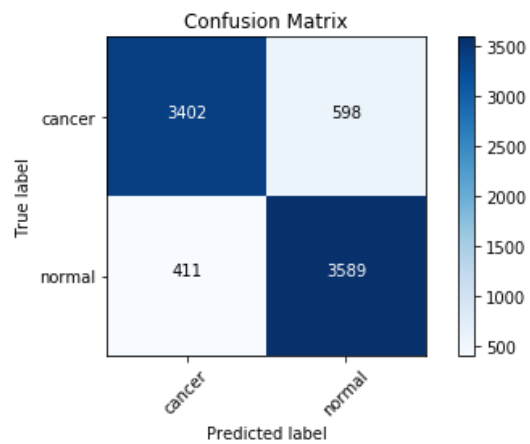
Model 1



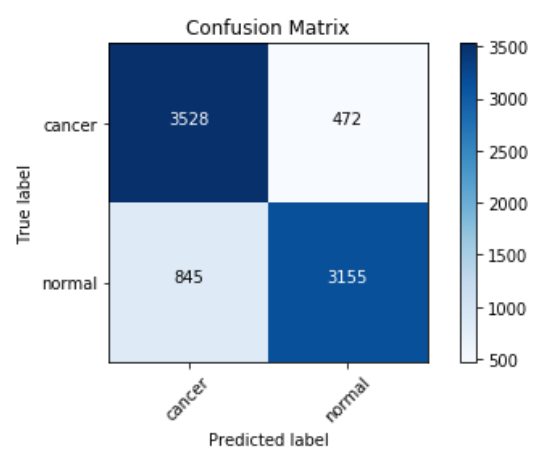
Model 2



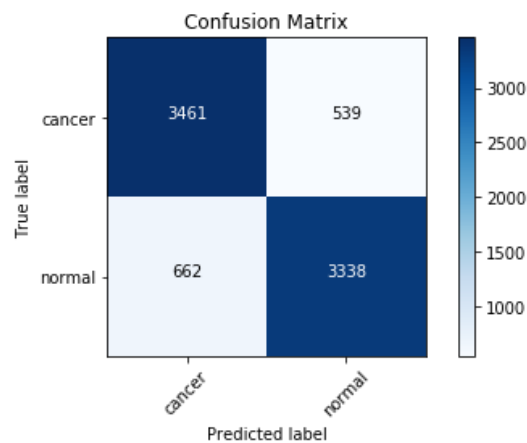
Model 3



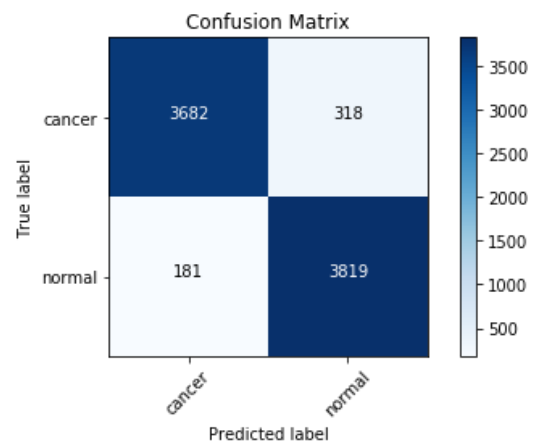
Model 4



Model 5



Model 6



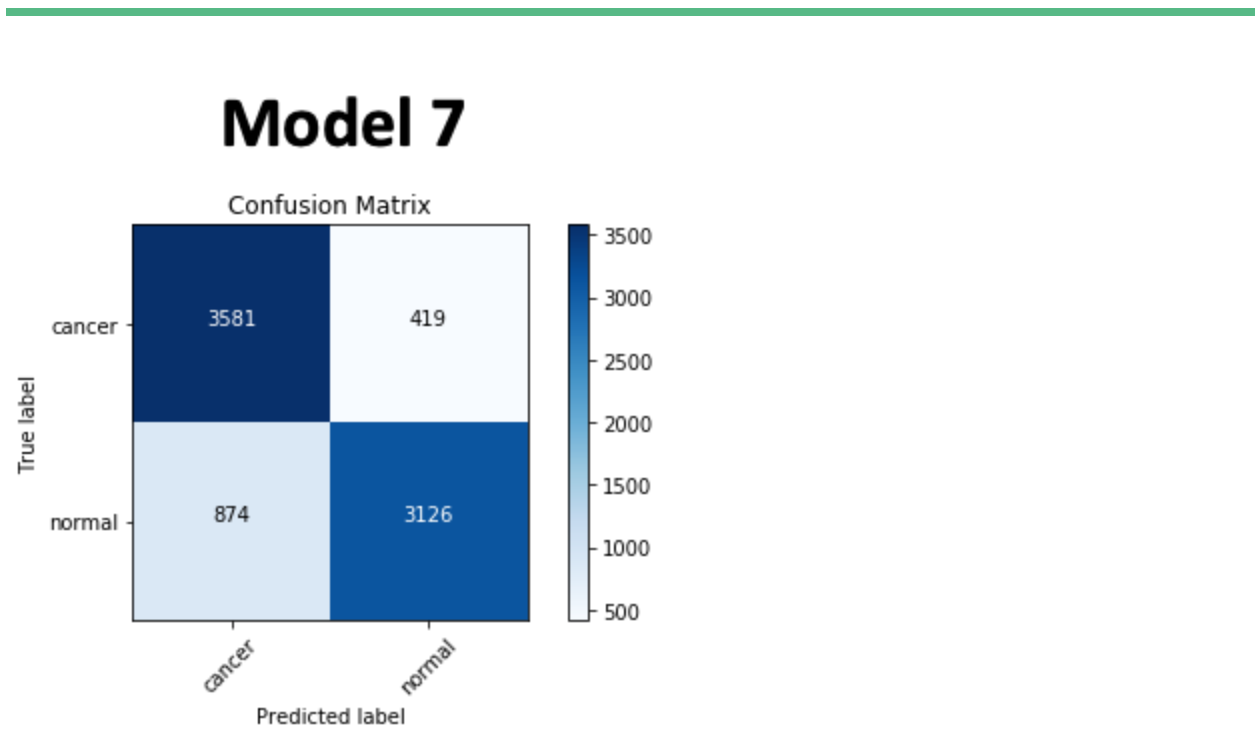


Figure 3: Confusion matrices of the model performances.

Table1: Precision and recall of the models tested.

	precision		recall		f1-score	
	cancer	normal	cancer	normal	cancer	normal
model1	0.89	0.84	0.83	0.9	0.86	0.87
model2	0.89	0.86	0.86	0.89	0.87	0.88
model3	0.89	0.86	0.85	0.9	0.87	0.88
model4	0.81	0.87	0.88	0.79	0.84	0.83
model5	0.84	0.86	0.87	0.83	0.85	0.85
model6	0.95	0.92	0.92	0.95	0.94	0.94
model7	0.8	0.88	0.9	0.78	0.85	0.83

FUTURE DIRECTIONS:

In this project I trained the model using 20,000 images in each class. Based on the computing power the entire dataset with 220,025 could be utilized to train the models.

PROJECT LINK

https://github.com/leukemia/Capstone_Projects/tree/master/Capstone_Project02/Milestone_Report-02