COSC 2673/2793 | Machine Learning

Assingment 2

Wing Hang Chan S3939713

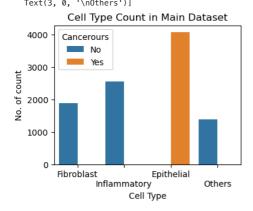
```
In [1]: import keras
import matplotlib.pyplot as plt
            import numpy as np
import pandas as pd
            import seaborn as sns
import tensorflow as tf
            from keras.regularizers import L2, L1
from PIL import Image
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay, f1_score, roc_curve
             from sklearn.model_selection import train_test_split
            from tensorflow.keras.layers import Conv2D, Dense, Dropout, Flatten, MaxPooling2D
from tensorflow.keras.models import Sequential
             from tensorflow.keras.preprocessing.image import ImageDataGenerator
In [2]: df_main = pd.read_csv('./Image_classification_data/data_labels_mainData.csv')
df_extra = pd.read_csv('./Image_classification_data/data_labels_extraData.csv')
```

Classification

	Ехр	lorato	ry Da	ta Analy	sis			
In [3]:	df_main.head()							
Out[3]:	Ins	tanceID	patientI) ImageNam	e cellTypeNar	ne cellType	isCancerous	IS
	0	22405		1 22405.pr	g fibrobla	ast 0	0	0
	1	22406		1 22406.pr	g fibrobla	ast 0	0	0
	2	22407		1 22407.pr	g fibrobla	ast 0	0	0
	3	22408		1 22408.pr	g fibrobla	ast 0	0	0
	4	22409		1 22409.pr	g fibrobla	ast 0	0	0
In [4]:	df_ma	in.descr	ibe()					
Out[4]:		Inst	anceID	patientID	cellType	isCancerous	_	
	count	9896.0	000000	9896.000000	9896.000000	9896.000000		
	mean	10193.8	380154	29.762025	1.501516	0.412187		
	std	6652.9	912660	17.486553	0.954867	0.492253		
	min	1.0	00000	1.000000	0.000000	0.000000		
	25%	4135.7	750000	14.000000	1.000000	0.000000		
	50%	9279.5	500000	26.000000	2.000000	0.000000		
	75%	16821.2	250000	47.000000	2.000000	1.000000		
	max	22444.0	000000	60.000000	3.000000	1.000000		
In [5]:	df_ex	tra.head	I()					
Out[5]:	Ins	tanceID	patientII) ImageNam	e isCancerous	S		
	0	12681	6	1 12681.pr	g ()		
	1	12682	6	1 12682.pr	g ()		
	2	12683	6	1 12683.pr	g ()		
	3	12684	6	1 12684.pr	g ()		
	4	12685	6	1 12685.pr	g ()		
T- [C]	J.E.,	h						
In [6]:	ат_ех	tra.desc	ribe()					

```
Out[6]:
                   InstanceID
                                  patientID
                                              isCancerous
         count 10384.000000 10384.00000 10384.000000
         mean 12087.866333
                                  80.38203
                                                 0.287943
                                   9.40388
                                                 0.452826
                 6173.866838
           std
                 1631.000000
                                  61.00000
                                                 0.000000
           min
          25%
                 6655.750000
                                  71.00000
                                                 0.000000
                                                 0.000000
          50% 12377.500000
                                  81.00000
          75% 16374.250000
                                  88.00000
                                                 1.000000
           max 22235.000000
                                  99.00000
                                                 1.000000
In [7]: fig = plt.figure(figsize=(4,3))
         sns.countplot(x='cellType', data=df_main, hue='isCancerous')
         plt.title("Cell Type Count in Main Dataset")
         plt.xlabel('Cell Type')
plt.ylabel('No. of count')
         plt.legend(title='Cancerours', labels=['No', 'Yes'])
plt.xticks([0, 1, 2, 3])
```

```
plt.gca().set_xticklabels(['Fibroblast', '\nInflammatory', 'Epithelial', '\nOthers'])
```



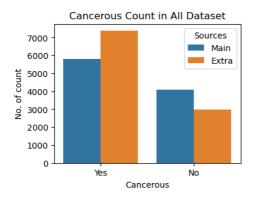
```
In [8]: df_main_2 = df_main.copy(True)
    df_extra_2 = df_extra.copy(True)
            df_main_2['Source'] = 'Main'
df_extra_2['Source'] = 'Extra'
            df_all = pd.concat([df_main_2, df_extra_2])
```

[8]:		InstanceID	patientID	ImageName	cellTypeName	cellType	isCancerous	Source
	0	22405	1	22405.png	fibroblast	0.0	0	Main
	1	22406	1	22406.png	fibroblast	0.0	0	Main
	2	22407	1	22407.png	fibroblast	0.0	0	Main
	3	22408	1	22408.png	fibroblast	0.0	0	Main
	4	22409	1	22409.png	fibroblast	0.0	0	Main
	10379	20028	99	20028.png	NaN	NaN	0	Extra
	10380	20029	99	20029.png	NaN	NaN	0	Extra
	10381	20030	99	20030.png	NaN	NaN	0	Extra
	10382	20031	99	20031.png	NaN	NaN	0	Extra
	10383	20032	99	20032.png	NaN	NaN	0	Extra

20280 rows × 7 columns

```
In [9]: fig = plt.figure(figsize=(4,3))
         sns.countplot(x='isCancerous', data=df_all, hue='Source')
         plt.title("Cancerous Count in All Dataset")
         plt.xlabel('Cancerous')
         plt.ylabel('No. of count')
plt.legend(title='Sources')
         plt.gca().set_xticklabels(['Yes','No'])
```

Out[9]: [Text(0, 0, 'Yes'), Text(1, 0, 'No')]



```
In [10]: cell_types = {0, 1, 2, 3}
NO_OF_IMAGE_SHOW = 4
    r_inx = np.random.choice(1000, NO_OF_IMAGE_SHOW)

fig, axs = plt.subplots(len(cell_types), NO_OF_IMAGE_SHOW + 1, figsize=(NO_OF_IMAGE_SHOW + 2, 3))
    for i, cell_type in enumerate(cell_types):
        rand_image_name = df_main[df_main['cellType'] == cell_type].reset_index().loc[r_inx, 'ImageName']
        axs[i,0].taxt(0, 0.5, df_main[df_main['cellType'] == cell_type]['cellTypeName'].iloc[0])
        axs[i,0].axis('off')
    for j, image_path in enumerate(rand_image_name):
        im = np.asarray(Image.open('./Image_classification_data/patch_images/'+image_path))
        axs[i,j+1].imshow(im,cmap='gray')
        axs[i,j+1].axis('off')

plt.show()

fibroblast

inflammatory

epithelial
```

```
In [11]: df_main.dtypes

Out[11]: InstanceID int64
    patientID int64
    ImageName object
    cellTypeName object
    celType int64
    isCancerous dtype: object
```

others

Data Preprocessing

Cell Type Classification - Multi-class

Baseline Model - Multi-class

```
In [14]: # [1] Ref:
def plot_learning_curve(train_loss, val_loss, train_metric, val_metric, metric_name='Accuracy'):
    plt.figure(figsize=(10,5))
    plt.subplot(1,2,1)
```

```
plt.plot(train_loss, 'r--')
               plt.plot(val_loss, 'k
plt.xlabel("epochs")
plt.ylabel("Loss")
               plt.legend(['train', 'val'], loc='upper left')
               plt.subplot(1.2.2)
               plt.plot(train_metric, 'r--')
plt.plot(val_metric, 'b--')
               plt.plot(val_metric,
plt.xlabel("epochs")
               plt.vlabel(metric name)
               plt.legend(['train', 'val'], loc='upper left')
               plt.show()
In [15]: train_datagen = ImageDataGenerator(rescale=1./255, data_format='channels_last')
           val_datagen = ImageDataGenerator(rescale=1./255, data_format='channels_last')
           directory='./Image_classification_data/patch_images/',
                    x_col="ImageName",
y_col="cellTypeName",
target_size=(27, 27),
                    batch_size=BATCH_SIZE
                    class_mode='categorical',
                    seed=7,
                    shuffle=True
           validation_generator = val_datagen.flow_from_dataframe(
                    dataframe=val_data,
                    directory='./Image_classification_data/patch_images/',
x_col="ImageName",
y_col="cellTypeName",
                     target_size=(27, 27)
                    batch_size=BATCH_SIZE,
                    class_mode='categorical',
                    shuffle=False
         Found 6939 validated image filenames belonging to 4 classes.
         Found 1472 validated image filenames belonging to 4 classes.
In [16]: cell_type_count = np.bincount(train_generator.classes)
           total = np.sum(cell_type_count)
          class_weight = {}
print(type(cell_type_count))
print(train_generator.class_indices)
           for i, each_type_count in enumerate(cell_type_count):
               class_weight[i] = 1/each_type_count * total/len(cell_type_count)
          print(f'Class Weight: {class_weight}')
         <class 'numpy.ndarray'>
         ('epithelial': 0, 'fibroblast': 1, 'inflammatory': 2, 'others': 3}
Class Weight: {0: 0.611904761904762, 1: 1.2708791208791208, 2: 0.9751264755480608, 3: 1.8070312499999999}
In [17]: early_stopping = tf.keras.callbacks.EarlyStopping(
    monitor='val_categorical_accuracy',
               verbose=1.
               patience=10,
               mode='max
               restore_best_weights=True)
In [18]: LOG_DIR = 'logs'
```

Model Architecture

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 27, 27, 32)	896
<pre>max_pooling2d (MaxPooling2 D)</pre>	(None, 9, 9, 32)	0
conv2d_1 (Conv2D)	(None, 9, 9, 64)	18496
conv2d_2 (Conv2D)	(None, 9, 9, 64)	36928
<pre>max_pooling2d_1 (MaxPoolin g2D)</pre>	(None, 3, 3, 64)	0
conv2d_3 (Conv2D)	(None, 3, 3, 128)	73856
conv2d_4 (Conv2D)	(None, 3, 3, 128)	147584
<pre>max_pooling2d_2 (MaxPoolin g2D)</pre>	(None, 1, 1, 128)	0
flatten (Flatten)	(None, 128)	0
dense (Dense)	(None, 512)	66048
dense_1 (Dense)	(None, 512)	262656
dense_2 (Dense)	(None, 4)	2052
conv2d_3 (Conv2D) conv2d_4 (Conv2D) max_pooling2d_2 (MaxPoolin g2D) flatten (Flatten) dense (Dense) dense_1 (Dense) dense_2 (Dense)	(None, 3, 3, 128) (None, 1, 1, 128) (None, 128) (None, 512) (None, 512)	147584 0 0 66048 262656 2052

Total params: 608516 (2.32 MB) Trainable params: 608516 (2.32 MB)

```
Non-trainable params: 0 (0.00 Byte)
```

```
In [20]: model_1.compile("adam", loss=tf.losses.CategoricalCrossentropy(), metrics=['categorical_accuracy'])
         tensorboard_callback = tf.keras.callbacks.TensorBoard(log_dir=LOG_DIR)
         hist_1 = model_1.fit(
             train_generator, epochs=100,
             validation_data=validation_generator,
             callbacks=[tensorboard_callback, early_stopping],
             class_weight=class_weight
```

Epoch 1/100

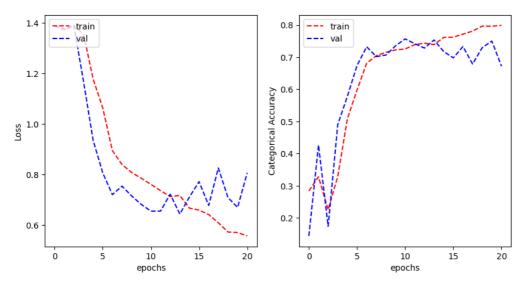
2023-05-17 11:24:34.130818: I tensorflow/core/common_runtime/executor.cc:1210] [/device:CPU:0] (DEBUG INFO) Executor start aborting (this does not indicate an error and you can ignore this message): INVALID_ARGUMENT: You must feed a value for placeholder tensor 'Pl aceholder/_0' with dtype int32
 [[{{node Placeholder/_0}}]]

2023-05-17 11:24:36.244386: I tensorflow/core/common_runtime/executor.cc:1210] [/device:CPU:0] (DEBUG INFO) Executor start aborting (this does not indicate an error and you can ignore this message): INVALID_ARGUMENT: You must feed a value for placeholder tensor 'Pl aceholder/_0' with dtype int32

```
217/217 [=====
                                rical_accuracy: 0.1440
Fnoch 2/100
217/217 [===
                           ================ ] - 2s 10ms/step - loss: 1.3710 - categorical accuracy: 0.3281 - val loss: 1.3761 - val catego
rical_accuracy: 0.4266
Epoch 3/100
217/217 [============] - 2s 10ms/step - loss; 1.3857 - categorical accuracy; 0.2255 - val loss; 1.3894 - val categorical accuracy; 0.2255 - val loss; 1.3894 - val categorical accuracy; 0.2255 - val loss; 1.3894 - val categorical accuracy; 0.2255 - val loss; 1.3894 - val categorical accuracy; 0.2255 - val loss; 1.3894 - val categorical accuracy; 0.2255 - val loss; 1.3894 - val categorical accuracy; 0.2255 - val loss; 1.3894 - val categorical accuracy; 0.2255 - val loss; 1.3894 - val categorical accuracy; 0.2255 - val loss; 1.3894 - val categorical accuracy; 0.2255 - val loss; 1.3894 - val categorical accuracy; 0.2255 - val loss; 1.3894 - val categorical accuracy; 0.2255 - val loss; 1.3894 - val categorical accuracy; 0.2255 - val loss; 1.3894 - val categorical accuracy; 0.2255 - val loss; 1.3894 - val categorical accuracy; 0.2255 - val loss; 1.3894 - val categorical accuracy; 0.2255 - val loss; 1.3894 - val categorical accuracy; 0.2255 - val loss; 1.3894 - val categorical accuracy; 0.2255 - val loss; 1.3894 - val categorical accuracy; 0.2255 - val loss; 1.3894 - val categorical accuracy; 0.2255 - val loss; 1.3894 - val categorical accuracy; 0.2255 - val loss; 1.3894 - val categorical accuracy; 0.2255 - val loss; 1.3894 - val categorical accuracy; 0.2255 - val loss; 1.3894 - val categorical accuracy; 0.2255 - val categorical ac
rical_accuracy: 0.1739
Epoch 4/100
217/217 [===
                     rical_accuracy: 0.4905
Epoch 5/100
217/217 [===
                                 :========] - 3s 12ms/step - loss: 1.1770 - categorical_accuracy: 0.5086 - val_loss: 0.9354 - val_catego
rical_accuracy: 0.5781
Epoch 6/100
217/217 [===
                                       ========] - 3s 13ms/step - loss: 1.0630 - categorical_accuracy: 0.5976 - val_loss: 0.8062 - val_catego
rical_accuracy: 0.6739
Epoch 7/100
217/217 [===
                                       ========] - 3s 13ms/step - loss: 0.8947 - categorical accuracy: 0.6811 - val loss: 0.7207 - val catego
rical_accuracy: 0.7323
Epoch 8/100
217/217 [===
                                         =======| - 3s 12ms/step - loss: 0.8395 - categorical accuracy: 0.7044 - val loss: 0.7542 - val catego
rical_accuracy: 0.7018
Epoch 9/100
217/217 [===
                            rical_accuracy: 0.7065
Epoch 10/100
217/217 [====
                                       =======] - 2s 11ms/step - loss: 0.7854 - categorical_accuracy: 0.7226 - val_loss: 0.6818 - val_catego
rical_accuracy: 0.7351
Epoch 11/100
217/217 [====
                               rical_accuracy: 0.7568
Epoch 12/100
217/217 [===
                                ========== ] - 3s 13ms/step - loss: 0.7364 - categorical_accuracy: 0.7390 - val_loss: 0.6557 - val_catego
rical_accuracy: 0.7418
Epoch 13/100
217/217 [====
                              rical_accuracy: 0.7283
Epoch 14/100
217/217 [===:
                                        =======] - 3s 13ms/step - loss: 0.7172 - categorical_accuracy: 0.7390 - val_loss: 0.6440 - val_catego
rical_accuracy: 0.7534
Epoch 15/100
217/217 [===
                                  ========] - 3s 14ms/step - loss: 0.6672 - categorical_accuracy: 0.7613 - val_loss: 0.7114 - val_catego
rical accuracy: 0.7174
Epoch 16/100
217/217 [===
                                            ======] - 3s 14ms/step - loss: 0.6594 - categorical_accuracy: 0.7622 - val_loss: 0.7720 - val_catego
rical_accuracy: 0.6977
Epoch 17/100
217/217 [====
                                       =======] - 3s 14ms/step - loss: 0.6419 - categorical_accuracy: 0.7716 - val_loss: 0.6780 - val_catego
rical_accuracy: 0.7330
Epoch 18/100
217/217 [====
                                 :========] - 3s 15ms/step - loss: 0.6095 - categorical accuracy: 0.7809 - val loss: 0.8260 - val catego
rical_accuracy: 0.6787
Epoch 19/100
rical_accuracy: 0.7296
Epoch 20/100
217/217 [====
                           rical_accuracy: 0.7500
Epoch 21/100
214/217 [===
                               ========>.] - ETA: 0s - loss: 0.5574 - categorical_accuracy: 0.7988Restoring model weights from the end
of the best epoch: 11.
217/217 [==
                                      ========] - 3s 15ms/step - loss: 0.5575 - categorical accuracy: 0.7988 - val loss: 0.8067 - val catego
rical_accuracy: 0.6719
Epoch 21: early stopping
```

Training and Valuation result

```
In [21]: plot_learning_curve(
    hist_1.history['loss'],
    hist_1.history['val_loss'],
    hist_1.history['categorical_accuracy'],
    hist_1.history['val_categorical_accuracy'],
    metric_name='Categorical Accuracy'
)
```



```
In [22]: # model_1.save('baseline')
         # model_1 = keras.models.load_model("baseline")
```

Test & Evaluate

```
In [23]: test_datagen = ImageDataGenerator(rescale=1./255, data_format='channels_last')
           TEST_BATCH_SIZE = 1
           test_generator = test_datagen.flow_from_dataframe(
                    dataframe=test_data,
directory='./Image_classification_data/patch_images/',
                    x_col="ImageName",
y_col="cellTypeName",
target_size=(27, 27),
                    batch_size=TEST_BATCH_SIZE,
                     class_mode='categorical',
                    shuffle=False
```

Found 1485 validated image filenames belonging to 4 classes.

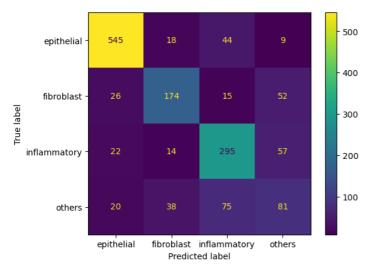
```
In [24]: def plot_cm(test_gen, predictions, is_binary=False):
                   cm = confusion_matrix(test_gen.classes, predictions)
                  \label{disp} {\tt disp} = {\tt ConfusionMatrixDisplay(confusion\_matrix=cm, display\_labels=test\_gen.class\_indices.keys())}
                  disp.plot()
                  plt.grid(False)
                  plt.show()
                  if is_binary == True:
    print(f'{"Non Cancerous Cell Detected (True Negatives):":<60}{cm[0][0]}')
    print(f'{"Non Cancerous Cell Incorrectly Detected (False Positives):":<60}{cm[0][1]}')
    print(f'{"Cancerous Cell Missed (False Negatives):":<60}{cm[1][0]}')</pre>
                        print(f'{"Cancerous Cell Detected (True Positives):":<60}{cm[1][1]}')</pre>
                        print(f'{"True Positives Count:":<60}{np.sum([cm[0][0], cm[1][1], cm[2][2], cm[3][3]])}')</pre>
                  print(f'{"Total Cell Counts:":<60}{np.sum(cm)}')</pre>
```

```
In [25]: def test_and_evaluate(model, test_gen, is_binary=False):
    results = model.evaluate(test_gen)
                test_pred_prob = model.predict(test_gen)
if is_binary == True:
                     test_pred = np.where(test_pred_prob > 0.5, 1, 0)
                else:
                     test_pred = np.argmax(test_pred_prob, axis=1)
                for name, value in zip(model.metrics_names, results):
    print(f'{name} : {value}\n')
                plot_cm(test_gen, test_pred, is_binary)
                print(f'{"F1 Score (Weighted):":<60}{f1_score(test_gen.classes, test_pred, average="weighted")}')</pre>
                return (results, test_pred_prob)
```

In [26]: test_and_evaluate(model_1, test_generator)

```
145/1485 [=>.....] - ETA: 1s - loss: 0.6580 - categorical_accuracy: 0.7517
2023-05-17 \ 11:25:32.099933: \ I \ tensorflow/core/common\_runtime/executor.cc:1210] \ [/device:CPU:0] \ (DEBUG \ INFO) \ Executor \ start \ aborting \ (DEBUG \ INFO) \ Executor \ start \ aborting \ (DEBUG \ INFO) \ Executor \ start \ aborting \ (DEBUG \ INFO) \ Executor \ start \ aborting \ (DEBUG \ INFO) \ Executor \ start \ aborting \ (DEBUG \ INFO) \ Executor \ start \ aborting \ (DEBUG \ INFO) \ Executor \ start \ aborting \ (DEBUG \ INFO) \ Executor \ start \ aborting \ (DEBUG \ INFO) \ Executor \ start \ aborting \ (DEBUG \ INFO) \ Executor \ start \ aborting \ (DEBUG \ INFO) \ Executor \ start \ aborting \ (DEBUG \ INFO) \ Executor \ start \ aborting \ (DEBUG \ INFO) \ Executor \ start \ aborting \ (DEBUG \ INFO) \ Executor \ start \ aborting \ (DEBUG \ INFO) \ Executor \ start \ aborting \ (DEBUG \ INFO) \ Executor \ start \ aborting \ (DEBUG \ INFO) \ Executor \ start \ aborting \ (DEBUG \ INFO) \ Executor \ start \ aborting \ (DEBUG \ INFO) \ Executor \ start \ aborting \ (DEBUG \ INFO) \ Executor \ start \ aborting \ (DEBUG \ INFO) \ Executor \ start \ aborting \ (DEBUG \ INFO) \ Executor \ start \ aborting \ (DEBUG \ INFO) \ Executor \ start \ aborting \ (DEBUG \ INFO) \ Executor \ start \ aborting \ (DEBUG \ INFO) \ Executor \ start \ aborting \ (DEBUG \ INFO) \ Executor \ start \ aborting \ (DEBUG \ INFO) \ Executor \ start \ aborting \ (DEBUG \ INFO) \ Executor \ start \ aborting \ (DEBUG \ INFO) \ Executor \ start \ aborting \ (DEBUG \ INFO) \ Executor \ start \ aborting \ (DEBUG \ INFO) \ Executor \ aborting \ (DEBUG \ INFO) \ Abort
(this does not indicate an error and you can ignore this message): INVALID_ARGUMENT: You must feed a value for placeholder tensor aceholder/_0' with dtype int32
[[{{node Placeholder/_0}}]]
97/1485 [>..... - ETA: 1s
2023-05-17 11:25:33.484999: I tensorflow/core/common_runtime/executor.cc:1210] [/device:CPU:0] (DEBUG INFO) Executor start aborting
(this does not indicate an error and you can ignore this message): INVALID_ARGUMENT: You must feed a value for placeholder tensor 'Pl aceholder/_0' with dtype int32
                           [[{{node Placeholder/_0}}]]
1485/1485 [
                                                                                                                     ====] - 1s 895us/step
loss: 0.6433002948760986
```

categorical_accuracy : 0.7373737096786499



Additional Model

Oversampling

ref: https://www.tensorflow.org/tutorials/structured_data/imbalanced_data#oversampling

```
In [27]: largest_no = 50000
             e_features = train_data[train_data['cellTypeName'] == 'epithelial']['ImageName'].to_numpy()
e_labels = train_data[train_data['cellTypeName'] == 'epithelial']['cellTypeName'].to_numpy()
             e_ids = np.arange(len(e_features))
             e_choices = np.random.choice(e_ids, largest_no)
             e_pick_feature = e_features[e_choices]
e_choices_labels = np.random.choice(e_labels, largest_no)
             f_features = train_data[train_data['cellTypeName'] == 'fibroblast']['ImageName'].to_numpy()
f_labels = train_data[train_data['cellTypeName'] == 'fibroblast']['cellTypeName'].to_numpy()
             f_ids = np.arange(len(f_features))
             f_choices = np.random.choice(f_ids, largest_no)
f_pick_feature = f_features[f_choices]
             f_choices_labels = np.random.choice(f_labels, largest_no)
             i_features = train_data[train_data['cellTypeName'] == 'inflammatory']['ImageName'].to_numpy()
i_labels = train_data[train_data['cellTypeName'] == 'inflammatory']['cellTypeName'].to_numpy()
             i_ids = np.arange(len(i_features))
             i_choices = np.random.choice(i_ids, largest_no)
             i_pick_feature = i_features[i_choices]
             i_choices_labels = np.random.choice(i_labels, largest_no)
             o_features = train_data[train_data['cellTypeName'] == 'others']['ImageName'].to_numpy()
o_labels = train_data[train_data['cellTypeName'] == 'others']['cellTypeName'].to_numpy()
             o_ids = np.arange(len(o_features))
             o_choices = np.random.choice(o_ids, largest_no)
o_pick_feature = o_features[o_choices]
             o_choices_labels = np.random.choice(o_labels, largest_no)
             resampled_features = np.concatenate([e_pick_feature, f_pick_feature, i_pick_feature, o_pick_feature], axis=0) resampled_labels = np.concatenate([e_choices_labels, f_choices_labels, i_choices_labels, o_choices_labels], axis=0)
             order = np.arange(len(resampled_labels))
             np.random.shuffle(order)
             resampled_features = resampled_features[order]
             resampled_labels = resampled_labels[order]
             resampled_features_tr = resampled_features.transpose()
resampled_labels_tr = resampled_labels.transpose()
             resampled_train_data = pd.DataFrame({'ImageName': resampled_features_tr, 'cellTypeName': resampled_labels_tr})
             resampled_train_data.head()
```

Out[27]: ImageName cellTypeName 9110.png inflammatory **1** 1333.png epithelial 2 13239.png fibroblast 8251.png epithelial 9213.png epithelial

Data Augmentation

```
In [28]: train_datagen_aug = ImageDataGenerator(
                 rescale=1./255,
data_format='channels_last',
                  zoom_range=0.3,
                  channel_shift_range=50,
                  rotation_range=359,
                  brightness_range=[1.0,1.2],
            train_generator_aug = train_datagen_aug.flow_from_dataframe(
    dataframe=resampled_train_data,
                  directory='./Image_classification_data/patch_images/',
                  x_col="ImageName",
y_col="cellTypeName",
target_size=(27, 27),
                  batch_size=BATCH_SIZE,
                  class_mode='categorical'
            IMAGE_N0 = 5
fig, axs = plt.subplots(1, IMAGE_N0, figsize=(IMAGE_N0, 3))
for i in range(IMAGE_N0):
                 axs[i].axis('off')
img, label = train_generator_aug.next()
axs[i].imshow(img[0])
            plt.show()
```

Found 200000 validated image filenames belonging to 4 classes.











Model Architecture

```
In [63]: REG RATE = 0.0001
          model_23 = Sequential([
              Conv2D(32, (3, 3), padding="same", activation="relu", input_shape=(27, 27, 3)), MaxPooling2D(pool_size=(3,3)),
               \label{lower_conv2D} \begin{tabular}{ll} Conv2D(128, (3, 3), padding="same", activation="relu", kernel_regularizer=L2(REG_RATE)), \\ Conv2D(128, (3, 3), padding="same", activation="relu", kernel_regularizer=L2(REG_RATE)), \\ \end{tabular} 
              MaxPooling2D(pool_size=(3,3)),
              Flatten(),
              Dense(512, activation="relu", kernel_regularizer=L2(REG_RATE)),
              Dropout(0.1),
              Dense(512, activation="relu", kernel_regularizer=L2(REG_RATE)),
              Dropout(0.1),
              Dense(4, activation='softmax'),
          ])
          model_23.compile("sgd", loss=tf.keras.losses.CategoricalCrossentropy(), metrics=['categorical_accuracy'])
          tensorboard_callback_23 = tf.keras.callbacks.TensorBoard(log_dir=LOG_DIR)
          model_23.summary()
```

Model: "sequential_5"

Layer (type)	Output Shape	Param #
conv2d_25 (Conv2D)	(None, 27, 27, 32)	896
<pre>max_pooling2d_15 (MaxPooli ng2D)</pre>	(None, 9, 9, 32)	0
conv2d_26 (Conv2D)	(None, 9, 9, 64)	18496
conv2d_27 (Conv2D)	(None, 9, 9, 64)	36928
<pre>max_pooling2d_16 (MaxPooli ng2D)</pre>	(None, 3, 3, 64)	0
conv2d_28 (Conv2D)	(None, 3, 3, 128)	73856
conv2d_29 (Conv2D)	(None, 3, 3, 128)	147584
<pre>max_pooling2d_17 (MaxPooli ng2D)</pre>	(None, 1, 1, 128)	0
flatten_5 (Flatten)	(None, 128)	0
dense_15 (Dense)	(None, 512)	66048
dropout_6 (Dropout)	(None, 512)	0
dense_16 (Dense)	(None, 512)	262656
dropout_7 (Dropout)	(None, 512)	0
dense_17 (Dense)	(None, 4)	2052

Total params: 608516 (2.32 MB)

Trainable params: 608516 (2.32 MB) Non-trainable params: 0 (0.00 Byte)

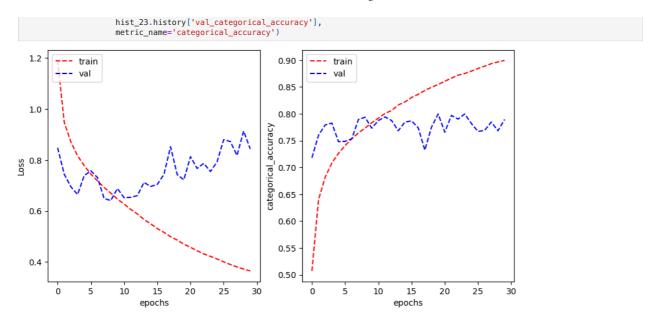
```
In [64]: hist_23 = model_23.fit(
              train_generator_aug, epochs=100,
              validation_data=validation_generator,
              callbacks=[tensorboard_callback_23, early_stopping]
```

2023-05-17 15:04:45.044551: I tensorflow/core/common_runtime/executor.cc:1210] [/device:CPU:0] (DEBUG INFO) Executor start aborting (this does not indicate an error and you can ignore this message): INVALID_ARGUMENT: You must feed a value for placeholder tensor 'Pl aceholder/_0' with dtype int32

[[{{node Placeholder/_0}}]]

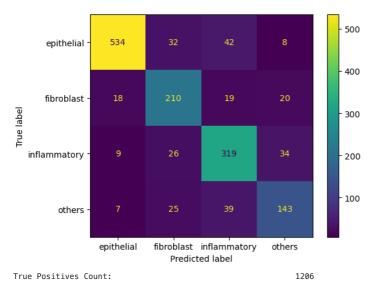
```
6250/6250 [======
                egorical_accuracy: 0.7181
Fnoch 2/100
egorical_accuracy: 0.7602
Epoch 3/100
egorical accuracy: 0.7792
Epoch 4/100
egorical_accuracy: 0.7826
Epoch 5/100
6250/6250 [===
                   =========] - 95s 15ms/step - loss: 0.7782 - categorical accuracy: 0.7263 - val loss: 0.7387 - val cat
egorical accuracy: 0.7480
Epoch 6/100
6250/6250 [=
                    ========] - 89s 14ms/step - loss: 0.7450 - categorical_accuracy: 0.7408 - val_loss: 0.7580 - val_cat
egorical_accuracy: 0.7486
Epoch 7/100
6250/6250 [=
                    :=======] - 92s 15ms/step - loss: 0.7183 - categorical accuracy: 0.7534 - val loss: 0.7313 - val cat
egorical_accuracy: 0.7534
Epoch 8/100
                    ========] - 93s 15ms/step - loss: 0.6923 - categorical_accuracy: 0.7644 - val_loss: 0.6494 - val_cat
6250/6250 [=========
egorical_accuracy: 0.7894
Epoch 9/100
6250/6250 [====
                   ========] - 91s 15ms/step – loss: 0.6705 – categorical_accuracy: 0.7732 – val_loss: 0.6411 – val_cat
egorical accuracy: 0.7935
Epoch 10/100
6250/6250 [==
                     :======] - 93s 15ms/step - loss: 0.6468 - categorical_accuracy: 0.7832 - val_loss: 0.6885 - val_cat
egorical_accuracy: 0.7731
Epoch 11/100
6250/6250 [==
                egorical_accuracy: 0.7874
Epoch 12/100
6250/6250 [==
                :========] - 90s 14ms/step - loss: 0.6065 - categorical_accuracy: 0.8006 - val_loss: 0.6537 - val_cat
egorical_accuracy: 0.7942
Fnoch 13/100
                :========] - 92s 15ms/step - loss: 0.5888 - categorical_accuracy: 0.8061 - val_loss: 0.6606 - val_cat
6250/6250 [===
egorical_accuracy: 0.7874
Epoch 14/100
6250/6250 [===
                    :========] - 94s 15ms/step - loss: 0.5669 - categorical_accuracy: 0.8165 - val_loss: 0.7124 - val_cat
egorical_accuracy: 0.7683
Epoch 15/100
6250/6250 [==
                  :=======] - 92s 15ms/step - loss: 0.5502 - categorical_accuracy: 0.8219 - val_loss: 0.6964 - val_cat
egorical accuracy: 0.7846
Epoch 16/100
6250/6250 [==
                         :===] - 94s 15ms/step - loss: 0.5311 - categorical_accuracy: 0.8304 - val_loss: 0.7045 - val_cat
egorical_accuracy: 0.7867
Epoch 17/100
6250/6250 [==
                   ========] - 94s 15ms/step - loss: 0.5164 - categorical_accuracy: 0.8363 - val_loss: 0.7435 - val_cat
egorical_accuracy: 0.7738
Epoch 18/100
6250/6250 [==:
                  ========] - 90s 14ms/step - loss: 0.4993 - categorical accuracy: 0.8433 - val loss: 0.8523 - val cat
egorical_accuracy: 0.7323
Epoch 19/100
egorical_accuracy: 0.7751
Epoch 20/100
6250/6250 [==:
           egorical accuracy: 0.7996
Epoch 21/100
6250/6250 [==:
          egorical_accuracy: 0.7656
Epoch 22/100
6250/6250 [==
                   =========] - 94s 15ms/step - loss: 0.4443 - categorical_accuracy: 0.8664 - val_loss: 0.7670 - val_cat
egorical_accuracy: 0.7969
Epoch 23/100
6250/6250 [==
                egorical_accuracy: 0.7901
Fnoch 24/100
                        :=====| - 91s 15ms/step - loss: 0.4222 - categorical accuracy: 0.8750 - val loss: 0.7552 - val cat
6250/6250 [==
egorical_accuracy: 0.7996
Epoch 25/100
6250/6250 [====
               egorical_accuracy: 0.7819
Epoch 26/100
6250/6250 [==
                egorical accuracy: 0.7670
Epoch 27/100
6250/6250 [==
                    :=======] - 89s 14ms/step - loss: 0.3901 - categorical_accuracy: 0.8886 - val_loss: 0.8726 - val_cat
egorical_accuracy: 0.7690
Epoch 28/100
6250/6250 [==
                egorical_accuracy: 0.7846
Epoch 29/100
6250/6250 [===
               egorical_accuracy: 0.7683
Epoch 30/100
           6250/6250 [===
d of the best epoch: 20.
6250/6250 [==
                       ======] - 94s 15ms/step - loss: 0.3651 - categorical_accuracy: 0.8995 - val_loss: 0.8434 - val_cat
egorical_accuracy: 0.7894
Epoch 30: early stopping
```

Training and Valuation result



Test & Evaluate

categorical_accuracy : 0.8121212124824524



Cancerous Classification - Binary

Baseline Model Binary

```
In [33]: df_all.head()
```

```
Out[33]:
             InstanceID patientID ImageName cellTypeName cellType isCancerous Source
                  22405
                                     22405.png
                                                                                     0
                                  1
                                                      fibroblast
                                                                                           Main
          1
                  22406
                                      22406.png
                                                      fibroblast
                                                                     0.0
                                                                                     0
                                                                                           Main
          2
                  22407
                                      22407.png
                                                      fibroblast
                                                                      0.0
                                                                                     0
                                                                                          Main
           3
                  22408
                                     22408.png
                                                      fibroblast
                                                                     0.0
                                                                                     0
                                                                                           Main
           4
                  22409
                                     22409.png
                                                      fibroblast
                                                                     0.0
                                                                                     0
                                                                                           Main
In [34]: df_all['isCancerous_str'] = df_all['isCancerous'].apply(lambda x: 'No' if x == 0 else 'Yes' )
          df_all['ImageName'] = df_all['ImageName'].astype('str')
df_all['isCancerous_str'] = df_all['isCancerous_str'].astype('str')
In [35]: train_data_binary, test_data_binary = train_test_split(df_all, test_size=0.15, random_state=7)
train_data_binary, val_data_binary = train_test_split(train_data_binary, test_size=0.175, random_state=7)
In [36]: train_data_binary.head()
Out[36]:
                 InstanceID patientID ImageName cellTypeName cellType isCancerous Source isCancerous_str
           1215
                                           4956.png
          3434
                       2369
                                    77
                                           2369.png
                                                              NaN
                                                                         NaN
                                                                                         0
                                                                                              Extra
                                                                                                                 No
           7615
                        808
                                    48
                                            808.png
                                                           epithelial
                                                                         2.0
                                                                                         1
                                                                                              Main
                                                                                                                 Yes
           8041
                       3379
                                    51
                                           3379.png
                                                            others
                                                                          3.0
                                                                                         0
                                                                                                                 No
           6080
                      20548
                                    37
                                         20548.png
                                                          fibroblast
                                                                         0.0
                                                                                         0
                                                                                              Main
                                                                                                                 No
In [37]: val_data_binary.head()
                 InstanceID patientID ImageName cellTypeName cellType isCancerous Source isCancerous_str
           1076
                                    67
                      12843
                                          12843.png
                                                                                         0
                                                              NaN
                                                                         NaN
                                                                                              Extra
                                                                                                                 No
           4993
                       2878
                                    80
                                           2878.png
                                                              NaN
                                                                                                                 Yes
           9614
                      21538
                                    92
                                          21538.png
                                                              NaN
                                                                         NaN
                                                                                         0
                                                                                              Extra
                                                                                                                 Nο
           5041
                      16881
                                    29
                                          16881.png
                                                                          1.0
                                                                                         0
                                                                                              Main
                                                                                                                 No
                                                       inflammatory
           2409
                       3126
                                    14
                                           3126.png
                                                           epithelial
                                                                         2.0
                                                                                         1
                                                                                              Main
In [38]: train_datagen_binary = ImageDataGenerator(rescale=1./255, data_format='channels_last')
          val_datagen_binary = ImageDataGenerator(rescale=1./255, data_format='channels_last')
          BATCH_SIZE = 32
          train_gen_binary = train_datagen_binary.flow_from_dataframe(
                   dataframe=train_data_binary,
                   directory='./Image_classification_data/patch_images/',
                    x_col="ImageName"
                    y_col="isCancerous_str",
                    target_size=(27, 27)
                   batch_size=BATCH_SIZE,
                   class_mode='binary'
          val_gen_binary = val_datagen_binary.flow_from_dataframe(
                   dataframe=val_data_binary,
directory='./Image_classification_data/patch_images/',
                   x_col="ImageName",
                   y_col="isCancerous_str",
                    target_size=(27, 27)
                   batch_size=BATCH_SIZE,
class_mode='binary',
                    shuffle=False
         Found 14221 validated image filenames belonging to 2 classes.
         Found 3017 validated image filenames belonging to 2 classes.
In [39]: cancerous_count = np.bincount(train_gen_binary.classes)
           total = np.sum(cancerous_count)
          binary_class_weight = {}
          print(type(cancerous_count))
          print(train_gen_binary.class_indices)
for i, each_type_count in enumerate(cancerous_count):
               binary\_class\_weight[i] = 1/each\_type\_count * total/len(cancerous\_count)
          print(f'Binary Class Weight: {binary_class_weight}')
         <class 'numpy.ndarray'>
         Binary Class Weight: {0: 0.7609696061643835, 1: 1.4579659626819768}
          Model Architecture
In [40]: early_stop_binary = tf.keras.callbacks.EarlyStopping(
               monitor='val_binary_accuracy',
               verbose=1,
               patience=10.
               mode='max
               restore_best_weights=True)
In [41]: REG_RATE_BINARY = 0.0001
```

```
model_binary_1 = Sequential([
    Conv2D(32, (3, 3), padding="same", activation="relu", input_shape=(27, 27, 3)),
    MaxPooling2D(pool_size=(3,3)),

    Conv2D(64, (3, 3), padding="same", activation="relu"),
    Conv2D(64, (3, 3), padding="same", activation="relu"),
    MaxPooling2D(pool_size=(3,3)),

    Conv2D(128, (3, 3), padding="same", activation="relu"),
    Conv2D(128, (3, 3), padding="same", activation="relu"),
    MaxPooling2D(pool_size=(3,3)),

Flatten(),
    Dense(512, activation="relu"),
    Dense(512, activation="relu"),
    Dense(512, activation="relu"),
    Dense(1, activation="relu"),
    Dense(1,
```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
conv2d_10 (Conv2D)	(None, 27, 27, 32)	896
<pre>max_pooling2d_6 (MaxPoolin g2D)</pre>	(None, 9, 9, 32)	0
conv2d_11 (Conv2D)	(None, 9, 9, 64)	18496
conv2d_12 (Conv2D)	(None, 9, 9, 64)	36928
<pre>max_pooling2d_7 (MaxPoolin g2D)</pre>	(None, 3, 3, 64)	0
conv2d_13 (Conv2D)	(None, 3, 3, 128)	73856
conv2d_14 (Conv2D)	(None, 3, 3, 128)	147584
<pre>max_pooling2d_8 (MaxPoolin g2D)</pre>	(None, 1, 1, 128)	0
flatten_2 (Flatten)	(None, 128)	0
dense_6 (Dense)	(None, 512)	66048
dense_7 (Dense)	(None, 512)	262656
dense_8 (Dense)	(None, 1)	513

Total params: 606977 (2.32 MB) Trainable params: 606977 (2.32 MB) Non-trainable params: 0 (0.00 Byte)

Epoch 1/100

2023-05-17 11:49:51.592704: I tensorflow/core/common_runtime/executor.cc:1210] [/device:CPU:0] (DEBUG INFO) Executor start aborting (this does not indicate an error and you can ignore this message): INVALID_ARGUMENT: You must feed a value for placeholder tensor 'P aceholder/_0' with dtype int32 [[{{node Placeholder/_0}}]]

2023-05-17 11:49:57.779927: I tensorflow/core/common_runtime/executor.cc:1210] [/device:CPU:0] (DEBUG INFO) Executor start aborting (this does not indicate an error and you can ignore this message): INVALID_ARGUMENT: You must feed a value for placeholder tensor 'Pl aceholder/_0' with dtype int32 [[{{node Placeholder/_0}}]]

```
445/445 [===
                                      ==] - 7s 15ms/step - loss: 0.4389 - binary_accuracy: 0.7887 - val_loss: 0.3156 - val_binary_accu
racy: 0.8681
Epoch 2/100
445/445 [===
                                         - 7s 15ms/step - loss: 0.3466 - binary accuracy: 0.8528 - val loss: 0.3577 - val binary accu
racy: 0.8462
Epoch 3/100
445/445 [===
                                         - 7s 15ms/step - loss: 0.3023 - binary_accuracy: 0.8765 - val_loss: 0.2847 - val_binary_accu
racy: 0.8770
Epoch 4/100
445/445 [==
                                         - 7s 15ms/step - loss: 0.3063 - binary_accuracy: 0.8782 - val_loss: 0.3477 - val_binary_accu
racv: 0.8412
Epoch 5/100
445/445 [==
                                           7s 16ms/step - loss: 0.2863 - binary_accuracy: 0.8831 - val_loss: 0.2907 - val_binary_accu
racy: 0.8750
Epoch 6/100
445/445 [==
                                           7s 15ms/step - loss: 0.2700 - binary_accuracy: 0.8903 - val_loss: 0.3732 - val_binary_accu
racy: 0.8459
Epoch 7/100
445/445 [==
                                           7s 15ms/step - loss: 0.2577 - binary accuracy: 0.8950 - val loss: 0.2771 - val binary accu
racy: 0.8813
Epoch 8/100
445/445 [==
                                           6s 14ms/step - loss: 0.2537 - binary_accuracy: 0.8987 - val_loss: 0.2997 - val_binary_accu
racy: 0.8707
Epoch 9/100
445/445 [==
                                         - 7s 15ms/step - loss: 0.2471 - binary_accuracy: 0.9017 - val_loss: 0.3009 - val_binary_accu
racv: 0.8687
Epoch 10/100
445/445 [==
                                           7s 15ms/step - loss: 0.2373 - binary_accuracy: 0.9052 - val_loss: 0.3133 - val_binary_accu
racy: 0.8631
Epoch 11/100
445/445 [===
                                         - 7s 15ms/step - loss: 0.2281 - binary_accuracy: 0.9062 - val_loss: 0.3784 - val_binary_accu
racy: 0.8316
Epoch 12/100
445/445 [===
                                         - 7s 15ms/step - loss: 0.2223 - binary_accuracy: 0.9126 - val_loss: 0.3148 - val_binary_accu
racy: 0.8697
Epoch 13/100
445/445 [===
                                         - 7s 15ms/step - loss: 0.2028 - binary accuracy: 0.9173 - val loss: 0.3292 - val binary accu
racy: 0.8774
Epoch 14/100
445/445 [===
                                         - 7s 15ms/step - loss: 0.1952 - binary_accuracy: 0.9198 - val_loss: 0.3593 - val_binary_accu
racy: 0.8777
Epoch 15/100
445/445 [==
                                           7s 15ms/step - loss: 0.1814 - binary_accuracy: 0.9272 - val_loss: 0.3666 - val_binary_accu
racy: 0.8575
Epoch 16/100
445/445 [===
                                           7s 15ms/step - loss: 0.1723 - binary_accuracy: 0.9339 - val_loss: 0.3359 - val_binary_accu
racy: 0.8727
Epoch 17/100
444/445 [===
                                         - ETA: 0s - loss: 0.1564 - binary_accuracy: 0.9379Restoring model weights from the end of th
e best epoch: 7.
445/445 [====
                         ==========] - 6s 14ms/step - loss: 0.1561 - binary_accuracy: 0.9380 - val_loss: 0.3857 - val_binary_accu
racy: 0.8704
Epoch 17: early stopping
```

Training and Valuation result

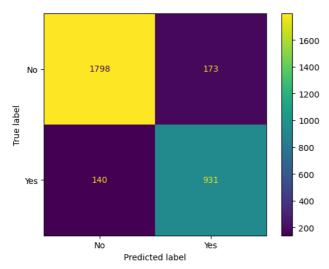
```
In [43]: plot_learning_curve(
                    hist_binary_1.history['loss'],
                   hist_binary_1.history['val_loss'],
hist_binary_1.history['binary_accuracy'],
hist_binary_1.history['val_binary_accuracy'],
metric_name='binary_accuracy'
                0.45
                                                                                                  0.94
                           --- train
                                                                                                            --- train
                                                                                                  0.92
                0.40
                                                                                                  0.90
                0.35
                                                                                                  0.88
            0.30
                                                                                                  0.86
                                                                                              binary
                                                                                                  0.84
                0.25
                                                                                                  0.82
                0.20
                                                                                                  0.80
                0.15
                         0.0
                                   2.5
                                            5.0
                                                      7.5
                                                               10.0
                                                                         12.5
                                                                                  15.0
                                                                                                           0.0
                                                                                                                     2.5
                                                                                                                              5.0
                                                                                                                                        7.5
                                                                                                                                                 10.0
                                                                                                                                                           12.5
                                                                                                                                                                    15.0
                                                     epochs
                                                                                                                                       epochs
```

Test & Evaluate

```
x_col="ImageName",
y_col="isCancerous_str",
target_size=(27, 27),
batch_size=TEST_BATCH_SIZE,
class_mode='binary',
shuffle=False
)
```

Found 3042 validated image filenames belonging to 2 classes.

binary_accuracy : 0.8971071839332581



Non Cancerous Cell Detected (True Negatives): 1798

Non Cancerous Cell Incorrectly Detected (False Positives): 173

Cancerous Cell Missed (False Negatives): 140

Cancerous Cell Detected (True Positives): 931

Total Cell Counts: 3042

F1 Score (Weighted): 0.897453419089635

Oversampling Model - Binary

```
In [46]: train_data_binary[train_data_binary['isCancerous']==0]['isCancerous_str'].value_counts()
Out[46]: No 9344
            Name: isCancerous_str, dtype: int64
In [47]: largest no = 50000
             t_features = train_data_binary[train_data_binary['isCancerous']==1]['ImageName'].to_numpy()
             t_labels = train_data_binary[train_data_binary['isCancerous']==1]['isCancerous_str'].to_numpy()
            t_ids = np.arange(len(t_features))
t_choices = np.random.choice(t_ids, largest_no)
t_pick_feature = t_features[t_choices]
             t_choices_labels = np.random.choice(t_labels, largest_no)
             f_features = train_data_binary[train_data_binary['isCancerous']==0]['ImageName'].to_numpy()
f_labels = train_data_binary[train_data_binary['isCancerous']==0]['isCancerous_str'].to_numpy()
             f_ids = np.arange(len(f_features))
f_choices = np.random.choice(f_ids, largest_no)
f_pick_feature = f_features[f_choices]
             f_choices_labels = np.random.choice(f_labels, largest_no)
             resampled\_features = np.concatenate([t\_pick\_feature, f\_pick\_feature], axis=0) \\ resampled\_labels = np.concatenate([t\_choices\_labels, f\_choices\_labels], axis=0) \\
             order = np.arange(len(resampled_labels))
             np.random.shuffle(order)
             resampled_features = resampled_features[order]
resampled_labels = resampled_labels[order]
             resampled_features_tr = resampled_features.transpose()
resampled_labels_tr = resampled_labels.transpose()
             resampled_train_data_binary = pd.DataFrame({'ImageName': resampled_features_tr, 'isCancerous': resampled_labels_tr})
             resampled_train_data_binary.head()
```

```
        ImageName
        isCancerous

        0
        19604.png
        No

        1
        8328.png
        Yes

        2
        1356.png
        Yes

        3
        8968.png
        Yes

        4
        11047.png
        No
```

Model Architecture

```
In [48]:
    train_datagen_aug_binary = ImageDataGenerator(
        rescale=1./255,
        data_format='channels_last',
        zoom_range=0.3,
        channel_shift_range=50,
        rotation_range=359,
        brightness_range=[1.0,1.2],
)

    train_generator_aug_binary = train_datagen_aug_binary.flow_from_dataframe(
        dataframe=resampled_train_data_binary,
        directory='./Image_classification_data/patch_images/',
        x_col="ImageName",
        y_col="isCancerous",
        target_size=(27, 27),
        batch_size=BATCH_SIZE,
        class_mode='binary'
)

IMAGE_NO = 5
    fig, axs = plt.subplots(1, IMAGE_NO, figsize=(IMAGE_NO, 3))
    for i in range(IMAGE_NO):
        axs[i].axis('off')
        img, label = train_generator_aug.next()
        axs[i].imshow(img[0])
    plt.show()
```

Found 100000 validated image filenames belonging to 2 classes.











Model: "sequential_3"

(None, 27, 27, 32)	896
(None, 9, 9, 32)	0
(None, 9, 9, 64)	18496
(None, 9, 9, 64)	36928
(None, 3, 3, 64)	0
(None, 3, 3, 128)	73856
(None, 3, 3, 128)	147584
(None, 1, 1, 128)	0
(None, 128)	0
(None, 512)	66048
(None, 512)	0
(None, 512)	262656
(None, 512)	0
(None, 1)	513
	(None, 9, 9, 32) (None, 9, 9, 64) (None, 9, 9, 64) (None, 3, 3, 64) (None, 3, 3, 128) (None, 1, 1, 128) (None, 128) (None, 512) (None, 512) (None, 512) (None, 512)

Total params: 606977 (2.32 MB)

Trainable params: 606977 (2.32 MB) Non-trainable params: 0 (0.00 Byte)

```
In [50]: hist_binary_2 = model_binary_2.fit(
                 train_generator_aug_binary, epochs=100,
                 validation_data=val_gen_binary,
callbacks=[tb_callback_binary_2, early_stop_binary]
```

.
2023-05-17 11:51:51.574647: I tensorflow/core/common_runtime/executor.cc:1210] [/device:CPU:0] (DEBUG INFO) Executor start aborting (this does not indicate an error and you can ignore this message): INVALID_ARGUMENT: You must feed a value for placeholder tensor 'Pl aceholder/_0' with dtype int32

[[{{node Placeholder/_0}}]] ====>.] - ETA: 0s - loss: 1.5938 - binary_accuracy: 0.6524 3124/3125 [==:

2023-05-17 11:52:34.290817: I tensorflow/core/common_runtime/executor.cc:1210] [/device:CPU:0] (DEBUG INFO) Executor start aborting (this does not indicate an error and you can ignore this message): INVALID_ARGUMENT: You must feed a value for placeholder tensor 'Pl aceholder/_0' with dtype int32

[[{{node Placeholder/_0}}]]

```
3125/3125 [====
                                        ===] - 43s 14ms/step - loss: 1.5937 - binary_accuracy: 0.6525 - val_loss: 1.3005 - val_binary_a
ccuracy: 0.8422
Fnoch 2/100
3125/3125 [=
                                            - 45s 15ms/step - loss: 1.2937 - binary accuracy: 0.8083 - val loss: 1.1504 - val binary a
ccuracy: 0.8578
Epoch 3/100
3125/3125 [==
                                            - 46s 15ms/step - loss: 1.1509 - binary_accuracy: 0.8320 - val_loss: 1.0362 - val_binary_a
ccuracy: 0.8668
Epoch 4/100
3125/3125 [=
                                            - 47s 15ms/step - loss: 1.0390 - binary_accuracy: 0.8454 - val_loss: 0.9395 - val_binary_a
ccuracy: 0.8740
Epoch 5/100
3125/3125 [=
                                              48s 15ms/step - loss: 0.9520 - binary_accuracy: 0.8506 - val_loss: 0.8737 - val_binary_a
ccuracy: 0.8747
Epoch 6/100
3125/3125 [=
                                            - 47s 15ms/step - loss: 0.8766 - binary_accuracy: 0.8526 - val_loss: 0.7949 - val_binary_a
ccuracy: 0.8734
Epoch 7/100
3125/3125 [=
                                            - 45s 14ms/step - loss: 0.8095 - binary accuracy: 0.8573 - val loss: 0.7343 - val binary a
ccuracy: 0.8813
Epoch 8/100
3125/3125 [=
                                            - 44s 14ms/step - loss: 0.7513 - binary_accuracy: 0.8602 - val_loss: 0.6807 - val_binary_a
ccuracy: 0.8840
Epoch 9/100
3125/3125 [=
                                            - 45s 14ms/step - loss: 0.7005 - binary_accuracy: 0.8614 - val_loss: 0.6328 - val_binary_a
ccuracy: 0.8847
Epoch 10/100
3125/3125 [==
                                            - 45s 15ms/step - loss: 0.6551 - binary_accuracy: 0.8638 - val_loss: 0.6157 - val_binary_a
ccuracy: 0.8674
Epoch 11/100
3125/3125 [==
                                            - 48s 15ms/step - loss: 0.6138 - binary_accuracy: 0.8655 - val_loss: 0.5625 - val_binary_a
ccuracy: 0.8803
Epoch 12/100
3125/3125 [==
                                            - 47s 15ms/step - loss: 0.5788 - binary_accuracy: 0.8683 - val_loss: 0.5300 - val_binary_a
ccuracy: 0.8856
Fnoch 13/100
3125/3125 [==
                                            - 45s 14ms/step - loss: 0.5474 - binary accuracy: 0.8692 - val loss: 0.4972 - val binary a
ccuracy: 0.8837
Epoch 14/100
3125/3125 [==
                                            - 44s 14ms/step - loss: 0.5184 - binary_accuracy: 0.8713 - val_loss: 0.4693 - val_binary_a
ccuracy: 0.8860
Epoch 15/100
3125/3125 [=
                                            - 45s 15ms/step - loss: 0.4944 - binary_accuracy: 0.8730 - val_loss: 0.4441 - val_binary_a
ccuracy: 0.8953
Epoch 16/100
3125/3125 [=
                                            - 46s 15ms/step - loss: 0.4725 - binary_accuracy: 0.8725 - val_loss: 0.5287 - val_binary_a
ccuracy: 0.8359
Epoch 17/100
3125/3125 [=
                                        ===] - 48s 15ms/step - loss: 0.4522 - binary_accuracy: 0.8741 - val_loss: 0.4090 - val_binary_a
ccuracy: 0.8926
Epoch 18/100
3125/3125 [=:
                                    ======] - 45s 14ms/step - loss: 0.4350 - binary accuracy: 0.8759 - val loss: 0.3935 - val binary a
ccuracy: 0.8886
Epoch 19/100
3125/3125 [==
                             ccuracy: 0.8956
Epoch 20/100
3125/3125 [==
                              :=======] - 49s 16ms/step - loss: 0.4040 - binary_accuracy: 0.8785 - val_loss: 0.3643 - val_binary_a
ccuracy: 0.8972
Epoch 21/100
3125/3125 [==
                             :=======] - 45s 14ms/step - loss: 0.3937 - binary_accuracy: 0.8790 - val_loss: 0.3764 - val_binary_a
ccuracy: 0.8910
Epoch 22/100
3125/3125 [=
                                            - 47s 15ms/step - loss: 0.3812 - binary_accuracy: 0.8812 - val_loss: 0.3450 - val_binary_a
ccuracy: 0.8943
Epoch 23/100
3125/3125 [=
                                    ======] - 46s 15ms/step - loss: 0.3719 - binary_accuracy: 0.8814 - val_loss: 0.3334 - val_binary_a
ccuracy: 0.8972
Epoch 24/100
3125/3125 [=
                                         ≔l – 44s 14ms/step – loss: 0.3608 – binarv accuracv: 0.8832 – val loss: 0.3484 – val binarv a
ccuracy: 0.8840
Epoch 25/100
3125/3125 [=:
                                    :=====] - 47s 15ms/step - loss: 0.3543 - binary accuracy: 0.8826 - val loss: 0.3710 - val binary a
ccuracy: 0.8737
Epoch 26/100
3125/3125 [==
                                            - 46s 15ms/step - loss: 0.3481 - binary_accuracy: 0.8842 - val_loss: 0.3351 - val_binary_a
ccuracy: 0.8896
Epoch 27/100
3125/3125 [=
                                            - 50s 16ms/step - loss: 0.3400 - binary_accuracy: 0.8877 - val_loss: 0.3096 - val_binary_a
ccuracy: 0.9012
Epoch 28/100
3125/3125 [=
                                            - 52s 17ms/step - loss: 0.3357 - binary_accuracy: 0.8858 - val_loss: 0.3048 - val_binary_a
ccuracy: 0.9039
Epoch 29/100
3125/3125 [==
                                 =======] - 187s 60ms/step - loss: 0.3310 - binary_accuracy: 0.8868 - val_loss: 0.3434 - val_binary_
accuracy: 0.8754
Epoch 30/100
3125/3125 [==
                              ========] – 1621s 519ms/step – loss: 0.3255 – binary_accuracy: 0.8886 – val_loss: 0.2931 – val_binar
y_accuracy: 0.8989
Epoch 31/100
3125/3125 [=====
accuracy: 0.9052
                                            - 174s 56ms/step - loss: 0.3203 - binary_accuracy: 0.8888 - val_loss: 0.2921 - val_binary_
Epoch 32/100
3125/3125 [==
                                            - 51s 16ms/step - loss: 0.3169 - binary_accuracy: 0.8898 - val_loss: 0.2968 - val_binary_a
ccuracy: 0.8982
Epoch 33/100
3125/3125 [=
                                            - 49s 16ms/step - loss: 0.3135 - binary accuracy: 0.8902 - val loss: 0.2997 - val binary a
ccuracy: 0.8910
Epoch 34/100
3125/3125 [=
                                  =======] - 52s 17ms/step - loss: 0.3101 - binary_accuracy: 0.8901 - val_loss: 0.3523 - val_binary_a
```

ccuracy: 0.8677

```
Epoch 35/100
3125/3125 [==
                                             - 50s 16ms/step - loss: 0.3064 - binary_accuracy: 0.8926 - val_loss: 0.2786 - val_binary_a
ccuracy: 0.9079
Epoch 36/100
3125/3125 [=
                                             - 50s 16ms/step - loss: 0.3051 - binary_accuracy: 0.8920 - val_loss: 0.3247 - val_binary_a
ccuracy: 0.8794
Epoch 37/100
3125/3125 [=
                                              - 50s 16ms/step - loss: 0.3036 - binary_accuracy: 0.8912 - val_loss: 0.2750 - val_binary_a
ccuracy: 0.9065
Epoch 38/100
3125/3125 [==
                                             - 48s 15ms/step - loss: 0.3010 - binary_accuracy: 0.8932 - val_loss: 0.2983 - val_binary_a
ccuracy: 0.8943
Epoch 39/100
3125/3125 [==
                                             - 49s 16ms/step - loss: 0.2995 - binary accuracy: 0.8934 - val loss: 0.2681 - val binary a
ccuracy: 0.9132
Epoch 40/100
3125/3125 [==
                                  =======] - 50s 16ms/step - loss: 0.2968 - binary_accuracy: 0.8945 - val_loss: 0.3056 - val_binary_a
ccuracy: 0.8900
Epoch 41/100
3125/3125 [===
                                             - 50s 16ms/step - loss: 0.2944 - binary_accuracy: 0.8958 - val_loss: 0.3038 - val_binary_a
ccuracy: 0.8890
Epoch 42/100
3125/3125 [=
                                             - 52s 17ms/step - loss: 0.2935 - binary_accuracy: 0.8954 - val_loss: 0.3105 - val_binary_a
ccuracy: 0.8893
Epoch 43/100
3125/3125 [=
                                               52s 17ms/step - loss: 0.2930 - binary_accuracy: 0.8948 - val_loss: 0.3189 - val_binary_a
ccuracy: 0.8803
Epoch 44/100
3125/3125 [=
                                             - 52s 17ms/step - loss: 0.2899 - binary accuracy: 0.8962 - val loss: 0.3283 - val binary a
ccuracy: 0.8784
Epoch 45/100
3125/3125 [=:
                                             - 50s 16ms/step - loss: 0.2883 - binary_accuracy: 0.8967 - val_loss: 0.2844 - val_binary_a
ccuracy: 0.9002
Epoch 46/100
3125/3125 [=
                                             - 52s 17ms/step - loss: 0.2879 - binary_accuracy: 0.8967 - val_loss: 0.2718 - val_binary_a
ccuracy: 0.9085
Epoch 47/100
3125/3125 [=
                                             - 52s 17ms/step - loss: 0.2853 - binary_accuracy: 0.8990 - val_loss: 0.2684 - val_binary_a
ccuracy: 0.9098
Epoch 48/100
3125/3125 [=
                                             - 53s 17ms/step - loss: 0.2853 - binary_accuracy: 0.8987 - val_loss: 0.2847 - val_binary_a
ccuracy: 0.8982
Epoch 49/100
3124/3125 [==
                                             - ETA: 0s - loss: 0.2855 - binary_accuracy: 0.8976Restoring model weights from the end of
the best epoch: 39.
3125/3125 [==
                                             - 51s 16ms/step - loss: 0.2855 - binary_accuracy: 0.8976 - val_loss: 0.2861 - val_binary_a
ccuracy: 0.8989
Epoch 49: early stopping
```

Training and Valuation result

```
In [51]: plot learning curve(
                hist_binary_2.history['loss'],
                hist_binary_2.history['val_loss'],
hist_binary_2.history['binary_accuracy'],
                hist_binary_2.history['val_binary_accuracy'],
                metric_name='binary_accuracy
                          train
                                                                                              train
                                                                               0.90
                      -- val
                                                                                              val
             1.4
                                                                                0.85
             1.2
                                                                            accuracy
                                                                               0.80
             1.0
                                                                            binary
             0.8
                                                                               0.75
             0.6
                                                                               0.70
             0.4
                                                                                0.65
                    Ó
                              10
                                         20
                                                   30
                                                              40
                                                                         50
                                                                                                  10
                                                                                                             20
                                                                                                                       30
                                                                                                                                  40
                                                                                                                                             50
```

Test & Evaluate

epochs

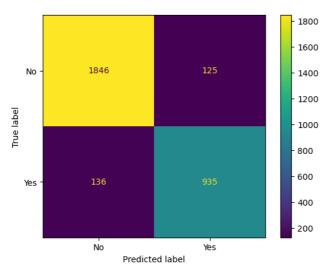
epochs

2023-05-17 13:01:45.289148: I tensorflow/core/common_runtime/executor.cc:1210] [/device:CPU:0] (DEBUG INFO) Executor start aborting (this does not indicate an error and you can ignore this message): INVALID_ARGUMENT: You must feed a value for placeholder tensor 'Pl aceholder/_0' with dtype int32 [[{{node Placeholder/_0}}]]

3042/3042 [== =====] - 3s 863us/step

loss : 0.27222928404808044

binary_accuracy : 0.9142012000083923



Non Cancerous Cell Detected (True Negatives): Non Cancerous Cell Incorrectly Detected (False Positives): 1846 125 Cancerous Cell Missed (False Negatives): 136 Cancerous Cell Detected (True Positives): Total Cell Counts: F1 Score (Weighted): 935 3042 0.9140991171967641