Setting up TPU for faster processing.

```
%tensorflow_version 2.x
import tensorflow as tf
print("Tensorflow version " + tf.__version__)

try:
  tpu = tf.distribute.cluster_resolver.TPUClusterResolver()  # TPU detection
  print('Running on TPU ', tpu.cluster_spec().as_dict()['worker'])
except ValueError:
  raise BaseException('ERROR: Not connected to a TPU runtime; please see the previous cell in t

tf.config.experimental_connect_to_cluster(tpu)
tf.tpu.experimental.initialize_tpu_system(tpu)
tpu_strategy = tf.distribute.TPUStrategy(tpu)

print('Number of replicas:', tpu_strategy.num_replicas_in_sync)
```

```
Tensorflow version 2.8.0
Running on TPU  ['10.15.131.250:8470']
INFO:tensorflow:Deallocate tpu buffers before initializing tpu system.
INFO:tensorflow:Deallocate tpu buffers before initializing tpu system.
INFO:tensorflow:Initializing the TPU system: grpc://10.15.131.250:8470
INFO:tensorflow:Initializing the TPU system: grpc://10.15.131.250:8470
INFO:tensorflow:Finished initializing TPU system.
INFO:tensorflow:Finished initializing TPU system.
INFO:tensorflow:Found TPU system:
INFO:tensorflow:Found TPU system:
INFO:tensorflow:*** Num TPU Cores: 8
INFO:tensorflow:*** Num TPU Cores: 8
INFO:tensorflow:*** Num TPU Workers: 1
INFO:tensorflow:*** Num TPU Workers: 1
INFO:tensorflow:*** Num TPU Cores Per Worker: 8
INFO:tensorflow:*** Num TPU Cores Per Worker: 8
INFO:tensorflow:*** Available Device: _DeviceAttributes(/job:localhost/replica:0/task:0/de
INFO:tensorflow:*** Available Device: _DeviceAttributes(/job:localhost/replica:0/task:0/de
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INFO:tensorflow:*** Available Device: _DeviceAttributes(/job:worker/replica:0/task:0/devic
INFO:tensorflow:*** Available Device: _DeviceAttributes(/job:worker/replica:0/task:0/devic
```

```
INFO:tensorflow:*** Available Device: _DeviceAttributes(/job:worker/replica:0/task:0/devic
Number of replicas: 8
```

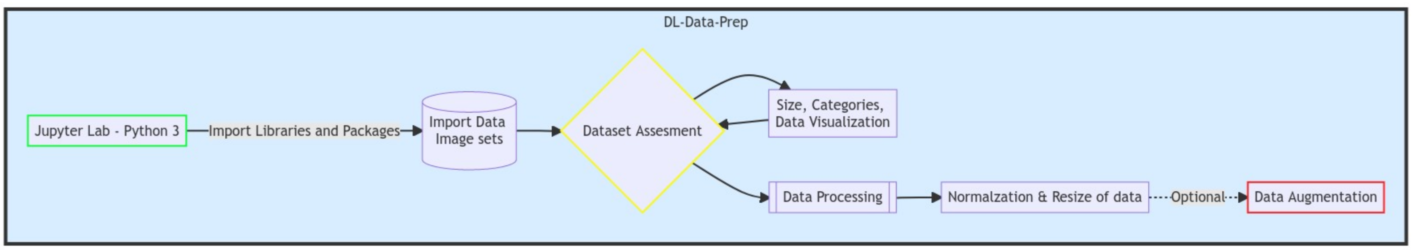
Introduction 💡:

The aim of this project is to create a deep learning algorithm that is able to accurately characterize pneumonia via chest x-rays for pediatric patients. The data set that is being used is coming from Kaggle.com and is being utilized for this project.

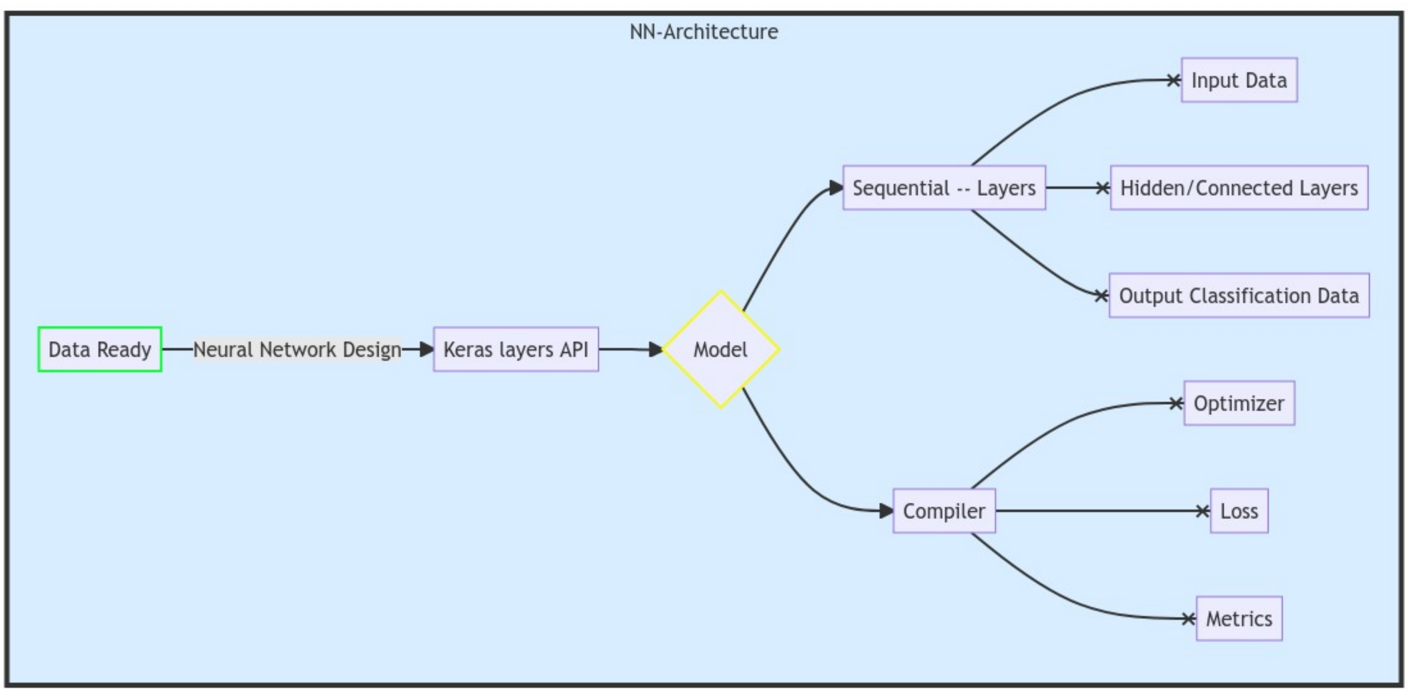
Process 🗒️:

Workflows illustrating the process typically taken for creating a DL project.

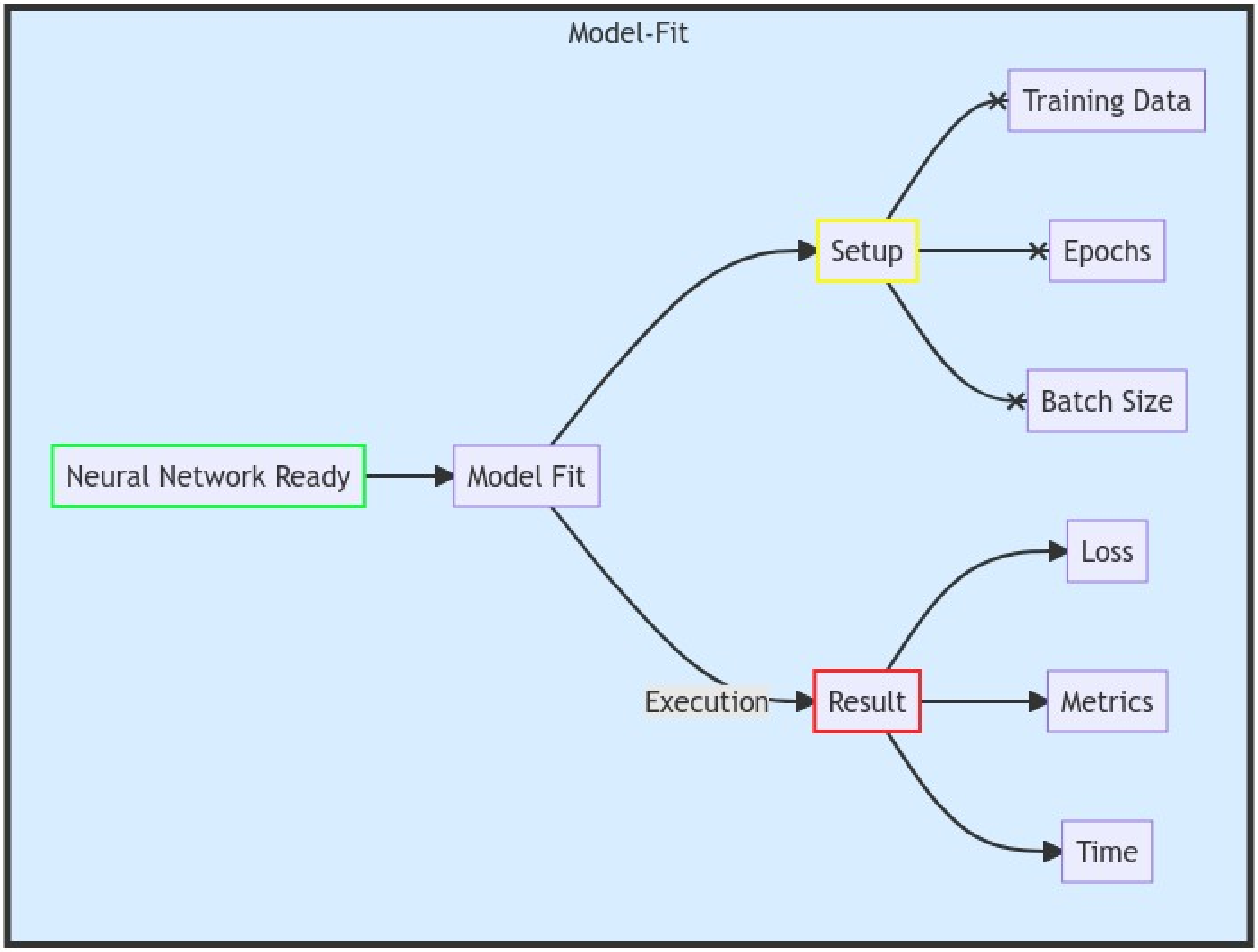
Data Preparation



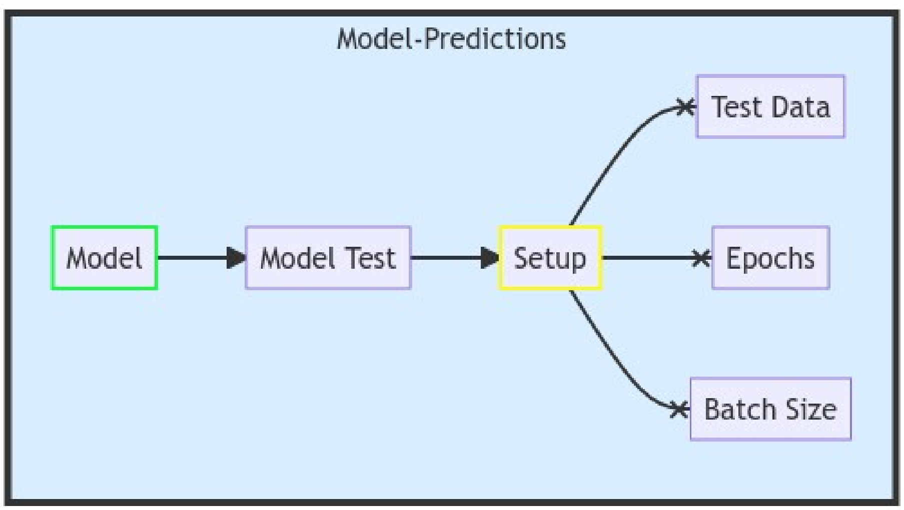
Neural Network Architecture

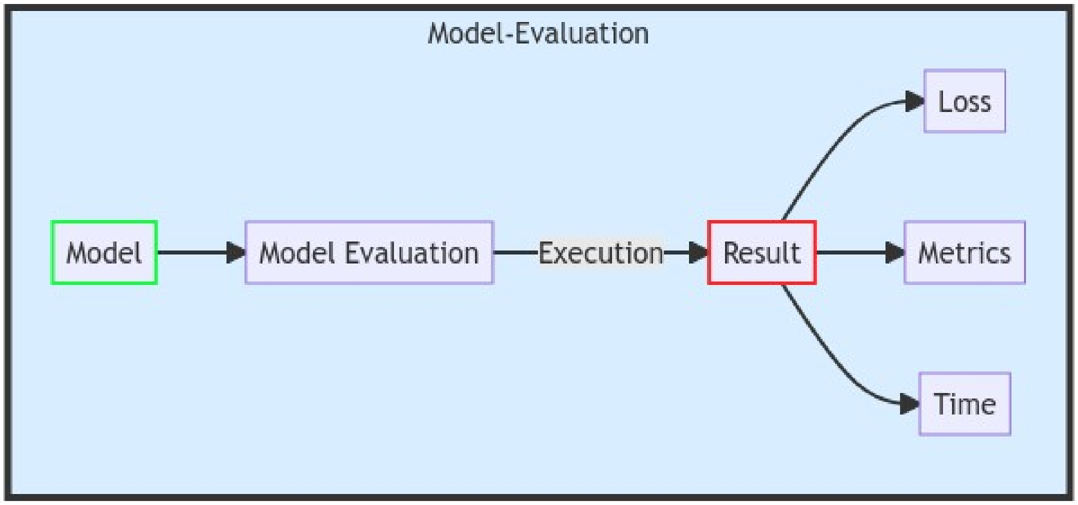


Fitting the Model



Model Predictions and Evaluation





```
!pip install colorama
!pip install opendatasets
```

```
    Collecting colorama
      Downloading colorama-0.4.4-py2.py3-none-any.whl (16 kB)
    Installing collected packages: colorama
    Successfully installed colorama-0.4.4
    Collecting opendatasets
      Downloading opendatasets-0.1.22-py3-none-any.whl (15 kB)
    Requirement already satisfied: click in /usr/local/lib/python3.7/dist-packages (from openc
    Requirement already satisfied: kaggle in /usr/local/lib/python3.7/dist-packages (from oper
    Requirement already satisfied: tqdm in /usr/local/lib/python3.7/dist-packages (from opend
    Requirement already satisfied: certifi in /usr/local/lib/python3.7/dist-packages (from kag
    Requirement already satisfied: urllib3 in /usr/local/lib/python3.7/dist-packages (from kag
    Requirement already satisfied: six>=1.10 in /usr/local/lib/python3.7/dist-packages (from k
    Requirement already satisfied: requests in /usr/local/lib/python3.7/dist-packages (from ka
    Requirement already satisfied: python-slugify in /usr/local/lib/python3.7/dist-packages (f
    Requirement already satisfied: python-dateutil in /usr/local/lib/python3.7/dist-packages (
    Requirement already satisfied: text-unidecode>=1.3 in /usr/local/lib/python3.7/dist-packag
    Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.7/dist-packages (fro
    Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python3.7/dist-packages
    Installing collected packages: opendatasets
    Successfully installed opendatasets-0.1.22
```

```
import numpy as np
import pandas as pd
import re
import os
import opendatasets as od
import matplotlib.pyplot as plt
from tensorflow import keras
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Activation, Flatten
from tensorflow.keras.layers import Conv2D, MaxPooling2D
from sklearn.model_selection import train_test_split
import colorama
```

Execution 👨‍💻

```
#Importing data set kaggle API for inital data reivew
dataset = 'https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia'
od.download(dataset)
```

```
Please provide your Kaggle credentials to download this dataset. Learn more: http://bit.ly
Your Kaggle username: mdespinoza
Your Kaggle Key: ··········
Downloading chest-xray-pneumonia.zip to ./chest-xray-pneumonia
100%|██████████| 2.29G/2.29G [00:12<00:00, 200MB/s]
```

Data Review

In this section we will perform an assesment of the dataset without manipulating any of the data.

After importing the data we will need to go through and identify the following:

> - How many data sets are we given?
> - How many classes are there in the dataset?

```
data_dir = './chest-xray-pneumonia'
os.listdir(data_dir)
```

```
['chest_xray']
```

```
# Identifying the number folders
os.listdir('./chest-xray-pneumonia/chest_xray')
```

```
['val', 'train', 'test', '__MACOSX', 'chest_xray']
```

```
# Identifying the categories
os.listdir('./chest-xray-pneumonia/chest_xray/test')
```

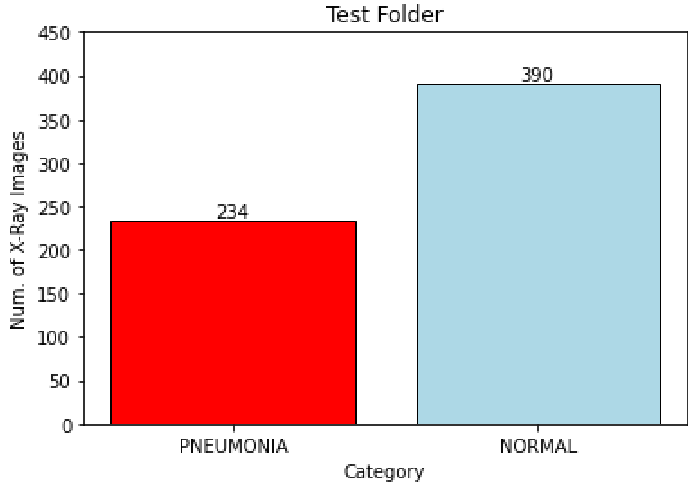
```
['NORMAL', 'PNEUMONIA']
```

```
CATEGORIES = ["PNEUMONIA", "NORMAL"]

# Identify the number of images per folder
test_set = ('./chest-xray-pneumonia/chest_xray/test')
train_set = ('./chest-xray-pneumonia/chest_xray/train')
val_set = ('./chest-xray-pneumonia/chest_xray/val')
```

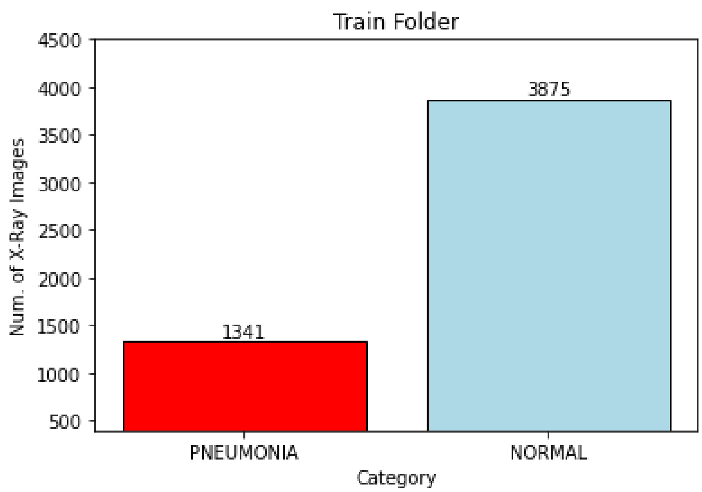
```
# function to calculate the number of images in a dataset folder
```

```
def count_xray_images(title, dataset, color):
    print(color + title)
    pneumonia = len(os.listdir(os.path.join(dataset, 'PNEUMONIA')))
    normal = len(os.listdir(os.path.join(dataset, 'NORMAL')))
    print(f"Pnuemonia = {pneumonia}")
    print(f"Percent Pnuemonia = {pneumonia/(pneumonia + normal)*100:.1f}%")
    print(f"Normal = {normal}")
    print(f"Percent Normal = {normal/(pneumonia + normal)*100:.1f}%")
    print(f"TOTAL = {pneumonia + normal}")


# function to create a bargraph for the number of images per category in any dataset folder
def data_visual(title, dataset, y_limit):
    pneumonia = len(os.listdir(os.path.join(dataset, 'PNEUMONIA')))
    normal = len(os.listdir(os.path.join(dataset, 'NORMAL')))
    x_pos = CATEGORIES
    y = (normal, pneumonia)
    plt.title(title)
    # define color for bars
    c = ("#FF0000", "#ADD8E6")
    # Adding labels, and the title
    plt.xlabel("Category")
    plt.ylabel("Num. of X-Ray Images")
    plt.bar(x_pos, y, color = c, ec = "black")
    plt.ylim(y_limit)

    for i in range(len(x_pos)):
        plt.text(i, y[i], y[i], ha="center", va="bottom")

    plt.show()

# Calling the function to provide the calculations for each folder and visualization
count_xray_images("Test Folder", test_set, colorama.Fore.BLUE)
data_visual("Test Folder", test_set,[0, 450])
count_xray_images("Train Folder", train_set, colorama.Fore.GREEN)
data_visual("Train Folder", train_set,[400, 4500])
count_xray_images("Val Folder", val_set, colorama.Fore.RED)
data_visual("Val Folder", val_set,[0, 10])
```

```
Test Folder
Pnuemonia = 390
Percent Pnuemonia = 62.5%
Normal = 234
Percent Normal = 37.5%
TOTAL = 624
```



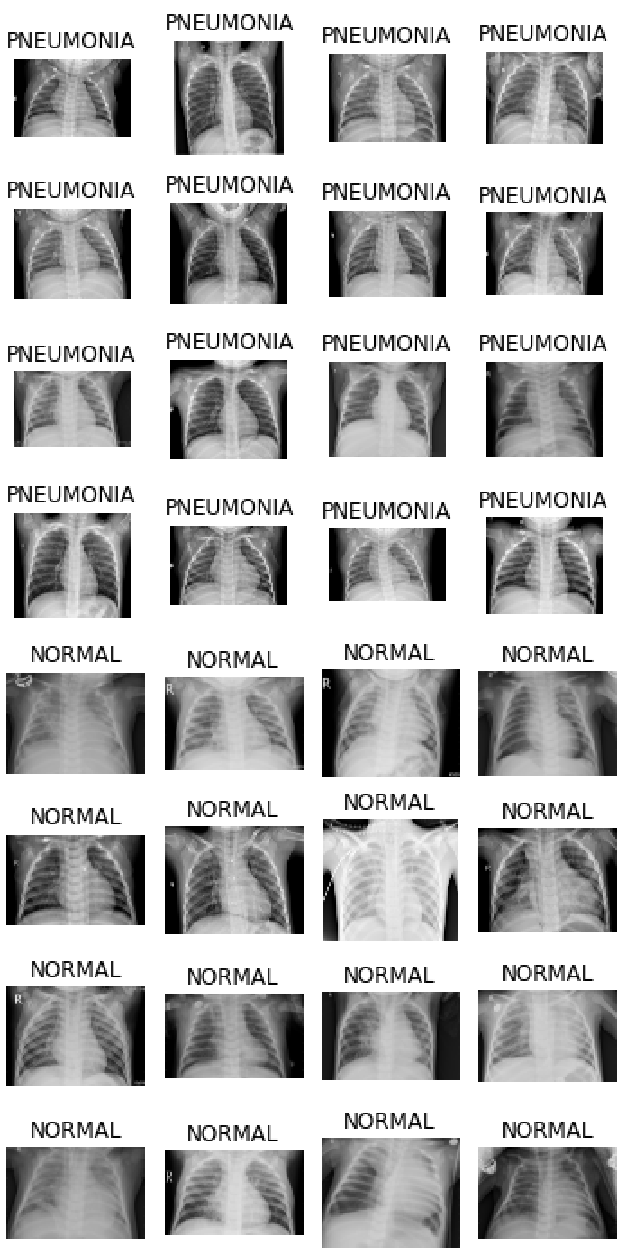

```
Train Folder
Pnuemonia = 3875
Percent Pnuemonia = 74.3%
Normal = 1341
Percent Normal = 25.7%
TOTAL = 5216
```




```
Val Folder
Pnuemonia = 8
Percent Pnuemonia = 50.0%
```

```
# function to display images
def image_xray_batch(path1, path2, title):
    image_list = os.listdir(path1)
    image = path2

    plt.figure(figsize=(5,5))

    for i in range(16):
        plt.subplot(4, 4, i + 1)
        img = plt.imread(os.path.join(image, image_list[i]))
        plt.imshow(img, cmap='gray')
        plt.axis('off')
```

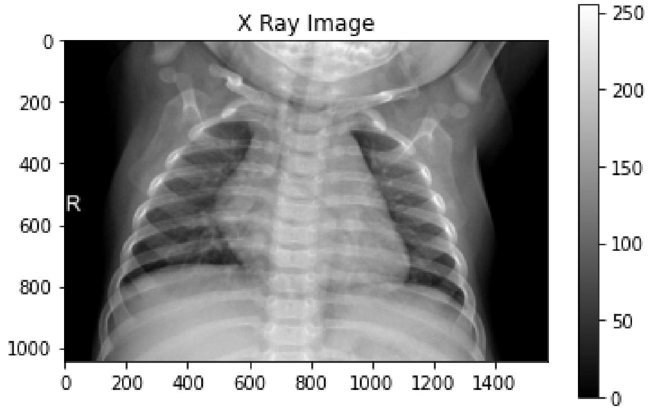
```
        plt.title(title)
    plt.tight_layout()

image_xray_batch(
'./chest-xray-pneumonia/chest_xray/train/NORMAL',
'./chest-xray-pneumonia/chest_xray/train/NORMAL',
    "PNEUMONIA")

image_xray_batch(
    './chest-xray-pneumonia/chest_xray/train/PNEUMONIA',
    './chest-xray-pneumonia/chest_xray/train/PNEUMONIA',
    "NORMAL")
```




```
norm_img = os.listdir("./chest-xray-pneumonia/chest_xray/train/NORMAL")[0]
norm_dir = "./chest-xray-pneumonia/chest_xray/train/NORMAL"
sample_img = plt.imread(os.path.join(norm_dir, norm_img))
plt.imshow(sample_img, cmap='gray')
plt.colorbar()
```

```
plt.title('X Ray Image')

print(f"The max px value = {sample_img.max():.1f} and the min = {sample_img.min():.1f}")
```

```
The max px value = 255.0 and the min = 0.0
```



Data Review Summary:

The scope of this project is based on a classification problem that is to asses and predict if a Pediatric patient has pnuemonia or not (2 Categories = Pneumoina, Normal). However in reviewing the training data it is evident that the observations for "Normal" (majority class), is significantly higher than the "Pneumonia" (minority class) observations. Which implies that the dataset is imbalanced and will need to be corrected in the data preparation to avoid any bias towards the "Normal" class.

The process to balanace the data between both classes would be to adjust the weights of each class.

Also, the validation data is very small n=16 and not sufficent for creating a model that we could trust. Thus in the next section we will also split the training and validation data using a standard split of 80:20 to create a larger validation dataset

---

Data Preparation 🔢

```
#accessing the data via googlecloudstorage - which allows for the utliizaiton of Google's TPU

GCS_PATH = 'gs://kds-7d8d6352305c640b40842856161690798 53d84b5df55d6be0bc51958'
```

```
# paths defined to variables
test_image_folder = (GCS_PATH + '/chest_xray/test/*/*')
train_set_folder = (GCS_PATH + '/chest_xray/train/*/*')
val_set_folder = (GCS_PATH + '/chest_xray/val/*/*')
```

```
# Split our trianing dataset into a training and validaiton set via "train_test_split" by a spl
train_files = tf.io.gfile.glob(str(train_set_folder))
train_files.extend(tf.io.gfile.glob(str(val_set_folder)))
```

```
training, validation = train_test_split(train_files, test_size=0.2)
```

```
# Verification of (n) of train dataset in each category folder created after the split.
normal_n = len([train_files for train_files in training if "NORMAL" in train_files])
print("Normal images: " + str(normal_n))

pneu_n = len([train_files for train_files in training if "PNEUMONIA" in train_files])
print("PNEUMONIA images: " + str(pneu_n))
```

```
Normal images: 1063
PNEUMONIA images: 3122
```

```
# creating slices from our defined dataset arrays

# training
data_struc_train = tf.data.Dataset.from_tensor_slices(training)
# validation
data_struc_val = tf.data.Dataset.from_tensor_slices(validation)
# test
test_data_struc  = tf.data.Dataset.list_files(str(test_image_folder))
```

```
# train data
train_count = tf.data.experimental.cardinality(data_struc_train).numpy()
print("Training (80%) = " + str(train_count))
# val data
val_count = tf.data.experimental.cardinality(data_struc_val).numpy()
print("Validating (20%) = " + str(val_count))
# test data
test_count = tf.data.experimental.cardinality(test_data_struc).numpy()
print("Test = " + str(test_count ))
```

```
Training (80%) = 4185
Validating (20%) = 1047
Test = 624
```

```
# defining data labels as an array
categories_labels = np.array([str(tf.strings.split(item, os.path.sep)[-1].numpy())[2:-1]
                              for item in tf.io.gfile.glob(str(GCS_PATH + '/chest_xray/train/*'
```

```
categories_labels
```

```
array(['NORMAL', 'PNEUMONIA'], dtype='<U9')
```

```
# Setting dataset to be labeled with categories(0)|(1)
def define_label(file_path):
    parts = tf.strings.split(file_path, os.path.sep)
    return parts[-2] == "PNEUMONIA"
```

```
# defining image size constant
IMAGE_SIZE = [180, 180]

# Establish unfiormity with the images (3D Tensor) and scaling them down
# to smaller sizes.
```

```
def img_conversion(img):
  img = tf.image.decode_jpeg(img, channels=3)
  img = tf.image.convert_image_dtype(img, tf.float32)
  return tf.image.resize(img, IMAGE_SIZE)



def path(file_path):
    label = define_label(file_path)
    img = tf.io.read_file(file_path)
    img = img_conversion(img)
    return img, label


autotune = tf.data.experimental.AUTOTUNE

BATCH_SIZE = 16 * tpu_strategy.num_replicas_in_sync

train_data_st = data_struc_train.map(path, num_parallel_calls=autotune)

val_data_st = data_struc_train.map(path, num_parallel_calls=autotune)

test_data_st = test_data_struc.map(path, num_parallel_calls=autotune)

test_data_st = test_data_st.batch(BATCH_SIZE)



# verify data normalization = image shape and label
for image, label in train_data_st.take(1):
  print("Image shape: ", image.numpy().shape)
  print("Label: ", label.numpy())

     Image shape:  (180, 180, 3)
     Label:  True


def prep_data_pre_training(ds, cache=True, shuffle_buffer_size=1000):
    # This is a small dataset, only load it once, and keep it in memory.
    # use `.cache(filename)` to cache preprocessing work for datasets that don't
    # fit in memory.
    if cache:
        if isinstance(cache, str):
            ds = ds.cache(cache)
        else:
            ds = ds.cache()

    ds = ds.shuffle(buffer_size=shuffle_buffer_size)

    # Repeat forever
    ds = ds.repeat()

    ds = ds.batch(BATCH_SIZE)

    # `prefetch` lets the dataset fetch batches in the
    # background while the model is training.
    ds = ds.prefetch(buffer_size=autotune)
```

```
train_data_st = prep_data_pre_training(train_data_st)
val_data_st = prep_data_pre_training(val_data_st)

image_batch, label_batch = next(iter(train_data_st))


# Adjusting the weights for both classes to compensate for the
# data not being equal
weight_for_0 = (1 / normal_n)*(train_count)/2.0
weight_for_1 = (1 / pneu_n)*(train_count)/2.0

class_weight = {0: weight_for_0, 1: weight_for_1}

print('Normal Weight: {:.2f}'.format(weight_for_0))
print('Pneumonia Weight: {:.2f}'.format(weight_for_1))
```

```
Normal Weight: 1.97
Pneumonia Weight: 0.67
```

Neural Network Architecture ⛓

```
def build_model():
    # The model is going to consist of a sequence of layers as
    # noted by tf.keras.Squential
    model = tf.keras.Sequential([
        tf.keras.Input(shape=(IMAGE_SIZE[0], IMAGE_SIZE[1], 3)), # expected input shape

        # Conv2D = convolution layer
        # setting filters (16) and kernel size (3)
        # padding defined as 'same' which implies the preservation
        # of spatial dminensions
        # with activation Rectified Linear Unit = 0 or greater is the ouput
        tf.keras.layers.Conv2D(16, 3, activation='relu', padding='same'),
        tf.keras.layers.Conv2D(16, 3, activation='relu', padding='same'),
        # Maxpool2D - pooling of max values
        tf.keras.layers.MaxPool2D(),

        tf.keras.Sequential([
        tf.keras.layers.SeparableConv2D(32, 3, activation='relu', padding='same'),
        tf.keras.layers.SeparableConv2D(32, 3, activation='relu', padding='same'),
        tf.keras.layers.BatchNormalization(),
        tf.keras.layers.MaxPool2D()]),

        tf.keras.Sequential([
        tf.keras.layers.SeparableConv2D(64, 3, activation='relu', padding='same'),
        tf.keras.layers.SeparableConv2D(64, 3, activation='relu', padding='same'),
        tf.keras.layers.BatchNormalization(),
        tf.keras.layers.MaxPool2D()]),

        tf.keras.Sequential([
        tf.keras.layers.SeparableConv2D(128, 3, activation='relu', padding='same'),
        tf.keras.layers.SeparableConv2D(128, 3, activation='relu', padding='same'),
```

```
        tf.keras.layers.BatchNormalization(),
        tf.keras.layers.MaxPool2D()]),

        tf.keras.layers.Dropout(0.2),

        tf.keras.Sequential([
        tf.keras.layers.SeparableConv2D(256, 3, activation='relu', padding='same'),
        tf.keras.layers.SeparableConv2D(256, 3, activation='relu', padding='same'),
        tf.keras.layers.BatchNormalization(),
        tf.keras.layers.MaxPool2D()]),

        # prevents over fitting the model
        tf.keras.layers.Dropout(0.2),

        # reshape the input
        tf.keras.layers.Flatten(),

        tf.keras.Sequential([
        # Dense implies adding a layer of neurons
        tf.keras.layers.Dense(512, activation='relu'),
        # normalizing the data
        tf.keras.layers.BatchNormalization(),
        tf.keras.layers.Dropout(0.7)]),

        tf.keras.Sequential([
        tf.keras.layers.Dense(128, activation='relu'),
        tf.keras.layers.BatchNormalization(),
        tf.keras.layers.Dropout(0.5)]),

        tf.keras.Sequential([
        tf.keras.layers.Dense(64, activation='relu'),
        tf.keras.layers.BatchNormalization(),
        tf.keras.layers.Dropout(0.3)]),

        tf.keras.layers.Dense(1, activation='sigmoid')
    ])

    return model


# Distribute training across the TPU
with tpu_strategy.scope():
    model = build_model()
    # defining metrics to be as outputs in the neural network
    METRICS = ['accuracy', # fration of predictions the model gets correct
        # measure what proportion of "+" id's were correct
        tf.keras.metrics.Precision(name='precision'),
        # measure what prportion of actual positives weere id correctly
        tf.keras.metrics.Recall(name='recall')]

    #setting up compiler
    model.compile(
         # Applying gradient descent algorithm
        optimizer='adam',
        # cross entropy loss for binary (0 or 1 )
        # classifications = NORMAL or PNEUMONA
```

```
        loss='binary_crossentropy',
```

Fitting the Model 🛠️

```
EPOCHS = 15

#initial - 1st model fit training
history = model.fit(
    train_data_st,
    steps_per_epoch= train_count // BATCH_SIZE, # num of sample / batch size
    epochs=EPOCHS,
    validation_data=val_data_st,
    validation_steps= val_count // BATCH_SIZE, # num of sample / batch size
    class_weight=class_weight, # data imbalance correction by weights
)
```

```
Epoch 1/15
32/32 [==============================] - 145s 3s/step - loss: 0.5094 - accuracy: 0.7363 -
Epoch 2/15
32/32 [==============================] - 45s 1s/step - loss: 0.3118 - accuracy: 0.8652 - p
Epoch 3/15
32/32 [==============================] - 46s 1s/step - loss: 0.2411 - accuracy: 0.9043 - p
Epoch 4/15
32/32 [==============================] - 46s 1s/step - loss: 0.2158 - accuracy: 0.9163 - p
Epoch 5/15
32/32 [==============================] - 46s 1s/step - loss: 0.1961 - accuracy: 0.9294 - p
Epoch 6/15
32/32 [==============================] - 47s 2s/step - loss: 0.1702 - accuracy: 0.9399 - p
Epoch 7/15
32/32 [==============================] - 49s 2s/step - loss: 0.1733 - accuracy: 0.9333 - p
Epoch 8/15
32/32 [==============================] - 47s 2s/step - loss: 0.1908 - accuracy: 0.9355 - p
Epoch 9/15
32/32 [==============================] - 47s 2s/step - loss: 0.1680 - accuracy: 0.9414 - p
Epoch 10/15
32/32 [==============================] - 52s 2s/step - loss: 0.1384 - accuracy: 0.9451 - p
Epoch 11/15
32/32 [==============================] - 46s 1s/step - loss: 0.1397 - accuracy: 0.9500 - p
Epoch 12/15
32/32 [==============================] - 48s 2s/step - loss: 0.1272 - accuracy: 0.9556 - p
Epoch 13/15
32/32 [==============================] - 48s 2s/step - loss: 0.1313 - accuracy: 0.9536 - p
Epoch 14/15
32/32 [==============================] - 47s 2s/step - loss: 0.1264 - accuracy: 0.9556 - p
Epoch 15/15
32/32 [==============================] - 49s 2s/step - loss: 0.1105 - accuracy: 0.9607 - p
```

```
model.summary()
```

```
Model: "sequential_7"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 180, 180, 16)      448

 conv2d_1 (Conv2D)           (None, 180, 180, 16)      2320
```

```
 max_pooling2d (MaxPooling2D  (None, 90, 90, 16)       0
 )

 sequential (Sequential)     (None, 45, 45, 32)        2160

 sequential_1 (Sequential)   (None, 22, 22, 64)        7392

 sequential_2 (Sequential)   (None, 11, 11, 128)       27072

 dropout (Dropout)           (None, 11, 11, 128)       0

 sequential_3 (Sequential)   (None, 5, 5, 256)         103296

 dropout_1 (Dropout)         (None, 5, 5, 256)         0

 flatten (Flatten)           (None, 6400)              0

 sequential_4 (Sequential)   (None, 512)               3279360

 sequential_5 (Sequential)   (None, 128)               66176

 sequential_6 (Sequential)   (None, 64)                8512

 dense_3 (Dense)             (None, 1)                 65

=================================================================
Total params: 3,496,801
Trainable params: 3,494,433
Non-trainable params: 2,368
_________________________________________________________________
```

```
# Save keras model so that model may be used later to continue training the data
# from the saved state.
checkp_cb = tf.keras.callbacks.ModelCheckpoint("pneumonia_model.h5",
                                               save_best_only=True)

# training will terminate if loss does not improve after "5" epochs
early_stop_cb = tf.keras.callbacks.EarlyStopping(patience=5,
                                                 restore_best_weights=True)


# defining learning rate decay to be applied accross the 2nd model fit training
# until local  minima is obtained
def exponential_decay(lr0, s):
    def exponential_decay_fn(epoch):
        return lr0 * 0.1 **(epoch / s)
    return exponential_decay_fn

exponential_decay_fn = exponential_decay(0.01, 20)

lr_scheduler = tf.keras.callbacks.LearningRateScheduler(exponential_decay_fn)


#second - 2nd model fit training
history = model.fit(
    train_data_st,
    steps_per_epoch= train_count // BATCH_SIZE,
    # increased batch size as callbacks has been added to stop training after
    # defined criteria has been achieved.
    epochs= 100,
```

```
    validation_data=val_data_st,
    validation_steps= val_count // BATCH_SIZE,
    class_weight=class_weight,
    callbacks=[checkp_cb, early_stop_cb, lr_scheduler]
)
```

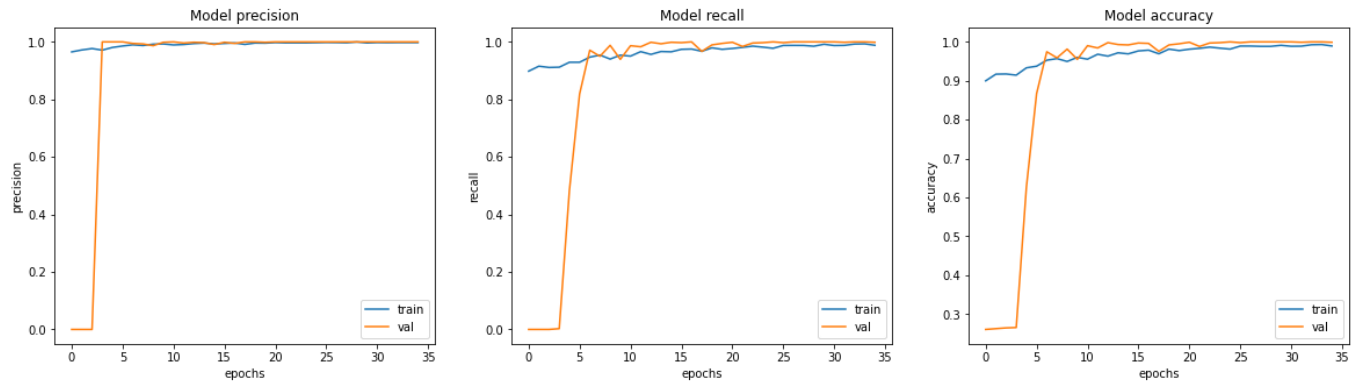
```
Epoch 1/100
32/32 [==============================] - 51s 2s/step - loss: 0.2618 - accuracy: 0.8999 - p
Epoch 2/100
32/32 [==============================] - 49s 2s/step - loss: 0.2102 - accuracy: 0.9170 - p
Epoch 3/100
32/32 [==============================] - 49s 2s/step - loss: 0.1995 - accuracy: 0.9175 - p
Epoch 4/100
32/32 [==============================] - 51s 2s/step - loss: 0.2140 - accuracy: 0.9146 - p
Epoch 5/100
32/32 [==============================] - 49s 2s/step - loss: 0.1648 - accuracy: 0.9333 - p
Epoch 6/100
32/32 [==============================] - 48s 2s/step - loss: 0.1520 - accuracy: 0.9375 - p
Epoch 7/100
32/32 [==============================] - 50s 2s/step - loss: 0.1162 - accuracy: 0.9529 - p
Epoch 8/100
32/32 [==============================] - 49s 2s/step - loss: 0.1115 - accuracy: 0.9570 - p
Epoch 9/100
32/32 [==============================] - 50s 2s/step - loss: 0.1197 - accuracy: 0.9497 - p
Epoch 10/100
32/32 [==============================] - 47s 2s/step - loss: 0.1044 - accuracy: 0.9602 - p
Epoch 11/100
32/32 [==============================] - 50s 2s/step - loss: 0.1055 - accuracy: 0.9556 - p
Epoch 12/100
32/32 [==============================] - 49s 2s/step - loss: 0.0914 - accuracy: 0.9683 - p
Epoch 13/100
32/32 [==============================] - 51s 2s/step - loss: 0.0852 - accuracy: 0.9634 - p
Epoch 14/100
32/32 [==============================] - 50s 2s/step - loss: 0.0898 - accuracy: 0.9719 - p
Epoch 15/100
32/32 [==============================] - 50s 2s/step - loss: 0.0907 - accuracy: 0.9692 - p
Epoch 16/100
32/32 [==============================] - 52s 2s/step - loss: 0.0650 - accuracy: 0.9768 - p
Epoch 17/100
32/32 [==============================] - 50s 2s/step - loss: 0.0558 - accuracy: 0.9788 - p
Epoch 18/100
32/32 [==============================] - 49s 2s/step - loss: 0.0826 - accuracy: 0.9695 - p
Epoch 19/100
32/32 [==============================] - 51s 2s/step - loss: 0.0546 - accuracy: 0.9814 - p
Epoch 20/100
32/32 [==============================] - 51s 2s/step - loss: 0.0687 - accuracy: 0.9775 - p
Epoch 21/100
32/32 [==============================] - 50s 2s/step - loss: 0.0505 - accuracy: 0.9812 - p
Epoch 22/100
32/32 [==============================] - 51s 2s/step - loss: 0.0446 - accuracy: 0.9834 - p
Epoch 23/100
32/32 [==============================] - 49s 2s/step - loss: 0.0397 - accuracy: 0.9866 - p
Epoch 24/100
32/32 [==============================] - 49s 2s/step - loss: 0.0521 - accuracy: 0.9839 - p
Epoch 25/100
32/32 [==============================] - 51s 2s/step - loss: 0.0432 - accuracy: 0.9814 - p
Epoch 26/100
32/32 [==============================] - 50s 2s/step - loss: 0.0367 - accuracy: 0.9893 - p
Epoch 27/100
32/32 [==============================] - 51s 2s/step - loss: 0.0364 - accuracy: 0.9893 - p
Epoch 28/100
32/32 [==============================] - 48s 2s/step - loss: 0.0293 - accuracy: 0.9885 - p
```

```
Epoch 29/100
32/32 [==============================] - 50s 2s/step - loss: 0.0278 - accuracy: 0.9885 - p
```

```
model.summary()
```

```
Model: "sequential_7"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d (Conv2D)             (None, 180, 180, 16)      448       
                                                                 
 conv2d_1 (Conv2D)           (None, 180, 180, 16)      2320      
                                                                 
 max_pooling2d (MaxPooling2D  (None, 90, 90, 16)       0         
 )                                                               
                                                                 
 sequential (Sequential)     (None, 45, 45, 32)        2160      
                                                                 
 sequential_1 (Sequential)   (None, 22, 22, 64)        7392      
                                                                 
 sequential_2 (Sequential)   (None, 11, 11, 128)       27072     
                                                                 
 dropout (Dropout)           (None, 11, 11, 128)       0         
                                                                 
 sequential_3 (Sequential)   (None, 5, 5, 256)         103296    
                                                                 
 dropout_1 (Dropout)         (None, 5, 5, 256)         0         
                                                                 
 flatten (Flatten)           (None, 6400)              0         
                                                                 
 sequential_4 (Sequential)   (None, 512)               3279360   
                                                                 
 sequential_5 (Sequential)   (None, 128)               66176     
                                                                 
 sequential_6 (Sequential)   (None, 64)                8512      
                                                                 
 dense_3 (Dense)             (None, 1)                 65        
                                                                 
=================================================================
Total params: 3,496,801
Trainable params: 3,494,433
Non-trainable params: 2,368
_________________________________________________________________
```

```
# plotting training results
fig, ax = plt.subplots(1, 3, figsize=(20, 5))
ax = ax.ravel()

for i, met in enumerate(['precision', 'recall', 'accuracy',]):
    ax[i].plot(history.history[met])
    ax[i].plot(history.history['val_' + met])
    ax[i].set_title('Model {}'.format(met))
    ax[i].set_xlabel('epochs')
    ax[i].set_ylabel(met)
    ax[i].legend(['train', 'val'])
```



Model Predictions ⏰

```
loss, acc, prec, rec = model.evaluate(test_data_st)
```

```
5/5 [==============================] - 20s 4s/step - loss: 1.0036 - accuracy: 0.8029 - pre
```

Summary 📈

1. The model overall has an 98.95% accuracy and a loss of 3.55%.
    - model may be improved by adjusting the CNN (Fine-tunning)
2. The model predicition accuracy is 80.29% which is less than both the training and validation accuracy. (Can be improved!)
3. The model prediction Recall is larger than the precision. Precision may be imrpoved by adding more data that is of high quality.
    - 76.33 % of total class outcomes was predicted correctly
4. To improve the results there are two options:
    - Fine-tunning of the CNN and re-training it.
    - Capture more data

Sources 📝

Acknowledgements Data: https://data.mendeley.com/datasets/rscbjbr9sj/2

License: CC BY 4.0

Citation: http://www.cell.com/cell/fulltext/S0092-8674(18)30154-5

Kaggle Project: https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia

Other Kaggle opensource review on dataset:

1. https://www.kaggle.com/code/aakashnain/beating-everything-with-depthwise-convolution
2. https://www.kaggle.com/code/amyjang/tensorflow-pneumonia-classification-on-x-rays
3. https://towardsdatascience.com/deep-learning-for-detecting-pneumonia-from-x-ray-images-fc9a3d9fdba8
4. https://towardsdatascience.com/detecting-covid-19-induced-pneumonia-from-chest-x-rays-with-transfer-learning-an-implementation-311484e6afc1

Colab TPU Use With Flowes modeling:
https://colab.research.google.com/notebooks/tpu.ipynb#scrollTo=LtAVr-4CP1rp

Webiste:
https://colab.research.google.com/notebooks/snippets/accessing_files.ipynb#scrollTo=z1_FuDjAozF1