

Deep Learning for Medical Image Analysis: Diagnosis and Segmentation of Lung Cancer

Team:

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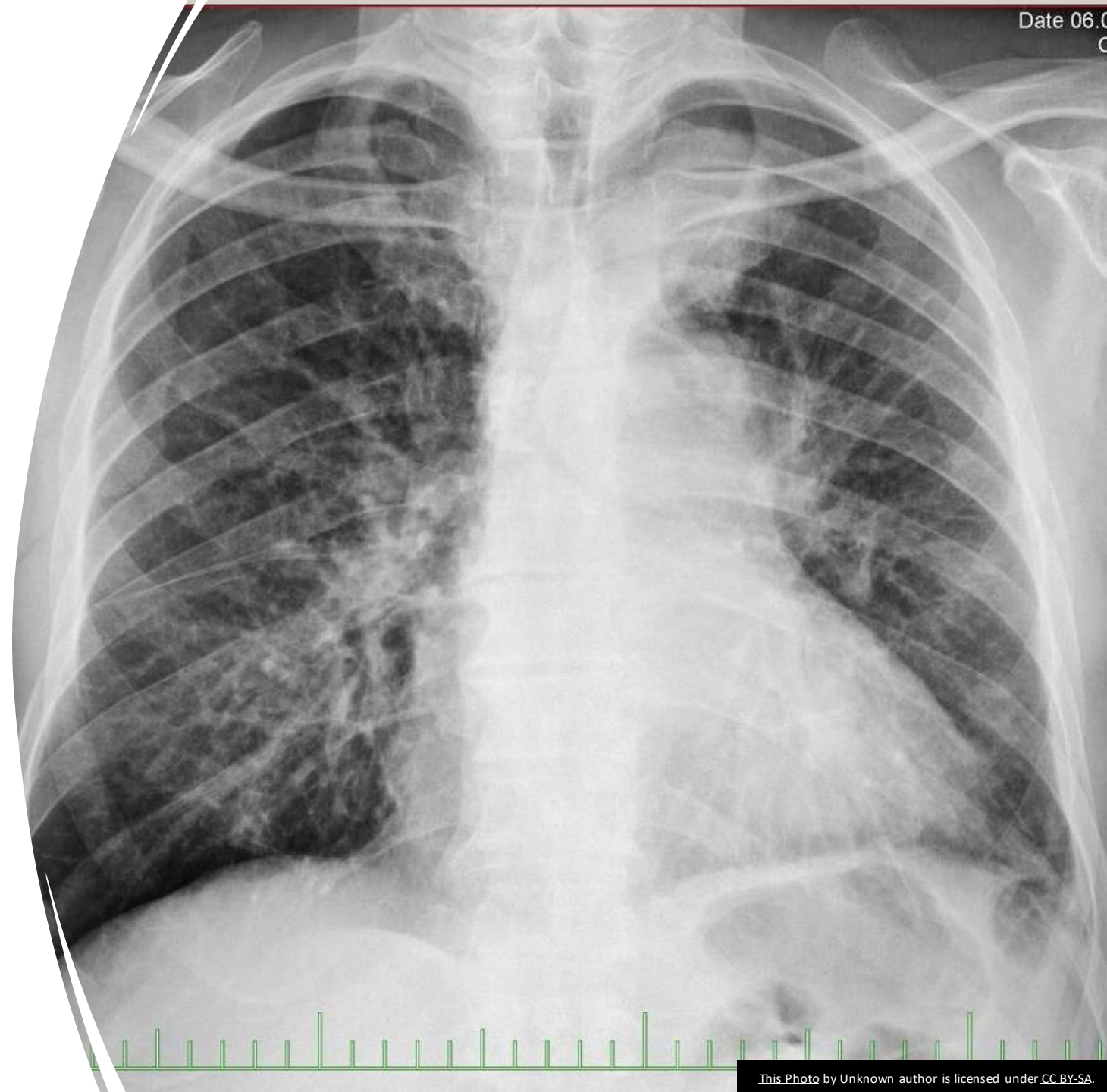
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PROBLEM

- WHO has reported that Lung cancer causes of 2.09 million deaths annually.
- It is a well-established fact that early diagnosis leads to better prognosis. One of the most difficult tasks in this field is detecting and segmenting lung cancer in CT scan
- Hence my group's project focuses on using Convolutional Neural networks (CNN) to analyze lung scans to detect if the lesions are cancerous. Using AI in healthcare could be a turning point in early detection and as a result early intervention which could save many lives.



PROJECT WORKFLOW



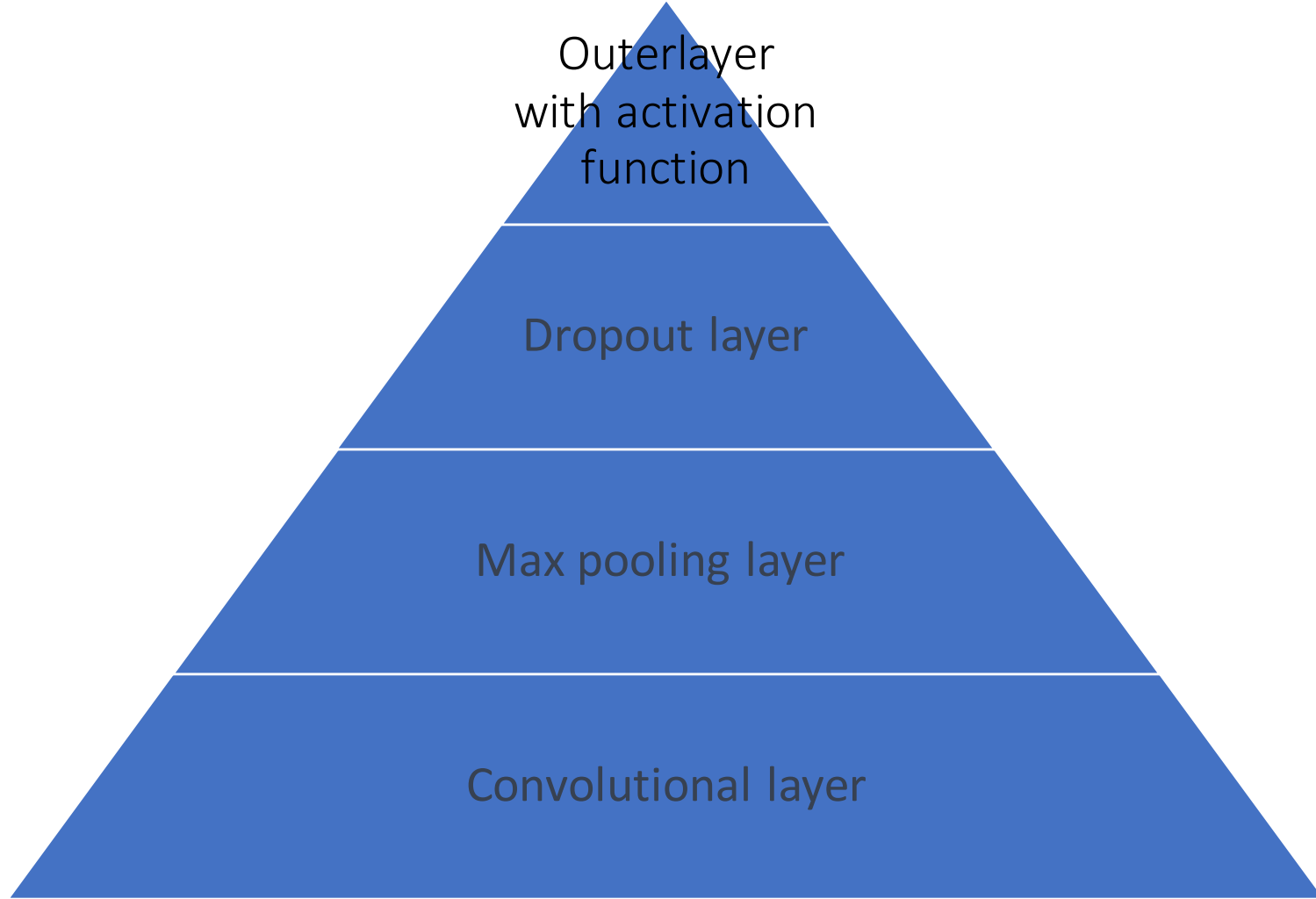
Downloaded dataset from kaggle

the necessary libraries and dependencies are imported

CNN model is created

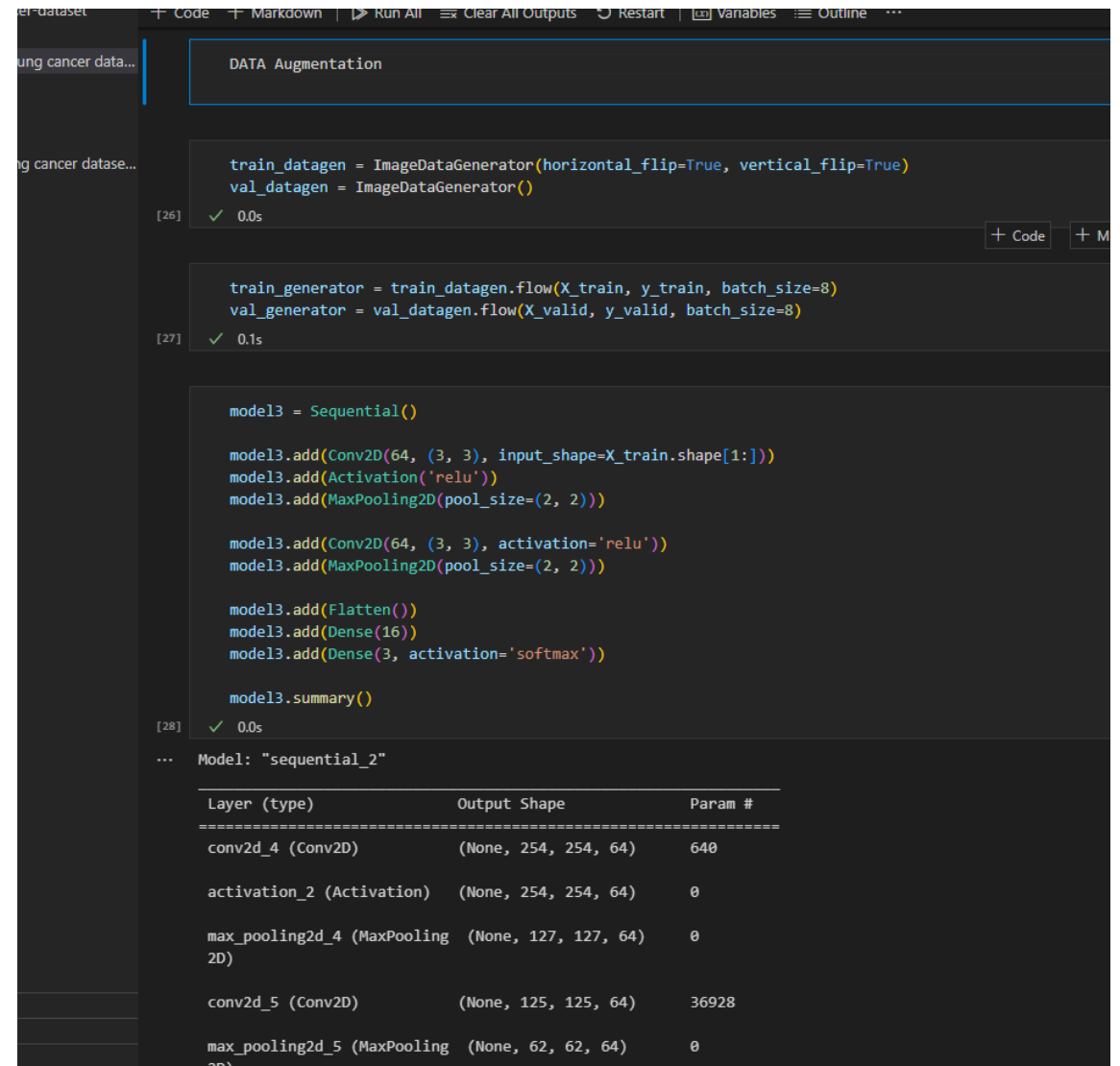
model is compiled and trained on the training data

model's performance is evaluated on the validation data



DATA AUGMENTATION

- Data augmentation is done using SMOTE TECHNIQUE and 'Imagedatagenerator'
- This function allows for techniques such as random rotations, flips, zooms, and brightness adjustments to be applied on input images during training.
- This helps to increase the variability of input data, thus improving the generalization of data.



The screenshot shows a Jupyter Notebook interface with a dark theme. The left sidebar contains file explorer and search tabs. The main area displays code cells for data augmentation and model building. The first cell defines `train_datagen` and `val_datagen` using `ImageDataGenerator` with `horizontal_flip=True` and `vertical_flip=True`. The second cell creates `train_generator` and `val_generator` using the `flow` method. The third cell builds a `Sequential` model with three convolutional layers, two max pooling layers, a flatten layer, a dense layer of 16 units, and a final dense layer of 3 units with softmax activation. The fourth cell calls `model3.summary()`. Below the code, the model summary is displayed as a table.

```
train_datagen = ImageDataGenerator(horizontal_flip=True, vertical_flip=True)
val_datagen = ImageDataGenerator()

train_generator = train_datagen.flow(X_train, y_train, batch_size=8)
val_generator = val_datagen.flow(X_valid, y_valid, batch_size=8)

model3 = Sequential()
model3.add(Conv2D(64, (3, 3), input_shape=X_train.shape[1:]))
model3.add(Activation('relu'))
model3.add(MaxPooling2D(pool_size=(2, 2)))

model3.add(Conv2D(64, (3, 3), activation='relu'))
model3.add(MaxPooling2D(pool_size=(2, 2)))

model3.add(Flatten())
model3.add(Dense(16))
model3.add(Dense(3, activation='softmax'))

model3.summary()
```

Layer (type)	Output Shape	Param #
conv2d_4 (Conv2D)	(None, 254, 254, 64)	640
activation_2 (Activation)	(None, 254, 254, 64)	0
max_pooling2d_4 (MaxPooling 2D)	(None, 127, 127, 64)	0
conv2d_5 (Conv2D)	(None, 125, 125, 64)	36928
max_pooling2d_5 (MaxPooling 2D)	(None, 62, 62, 64)	0

IMPLEMENTATION


```
val_generator = val_datagen.flow(X_val, y_val, batch_size=8)
[27] ✓ 0.1s
```

```
model3 = Sequential()

model3.add(Conv2D(64, (3, 3), input_shape=X_train.shape[1:]))
model3.add(Activation('relu'))
model3.add(MaxPooling2D(pool_size=(2, 2)))

model3.add(Conv2D(64, (3, 3), activation='relu'))
model3.add(MaxPooling2D(pool_size=(2, 2)))

model3.add(Flatten())
model3.add(Dense(16))
model3.add(Dense(3, activation='softmax'))

model3.summary()
```

```
[28] ✓ 0.0s
```

... Model: "sequential_2"

Layer (type)	Output Shape	Param #
=====		
conv2d_4 (Conv2D)	(None, 254, 254, 64)	640
activation_2 (Activation)	(None, 254, 254, 64)	0
max_pooling2d_4 (MaxPooling 2D)	(None, 127, 127, 64)	0
conv2d_5 (Conv2D)	(None, 125, 125, 64)	36928
max_pooling2d_5 (MaxPooling 2D)	(None, 62, 62, 64)	0
flatten_2 (Flatten)	(None, 246016)	0
dense_4 (Dense)	(None, 16)	3936272
dense_5 (Dense)	(None, 3)	51

```
=====
Total params: 3,973,891
Trainable params: 3,973,891
Non-trainable params: 0
```

```
model2 = Sequential()

model2.add(Conv2D(64, (3, 3), input_shape=X_train.shape[1:]))
model2.add(Activation('relu'))
model2.add(MaxPooling2D(pool_size=(2, 2)))

model2.add(Conv2D(64, (3, 3), activation='relu'))
model2.add(MaxPooling2D(pool_size=(2, 2)))

model2.add(Flatten())
model2.add(Dense(16))
model2.add(Dense(3, activation='softmax'))

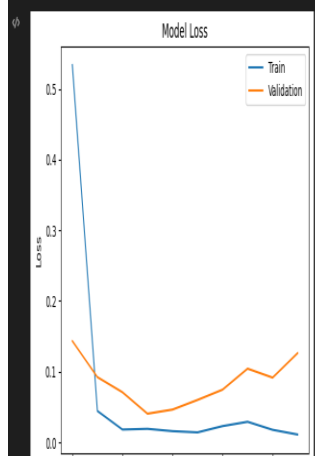
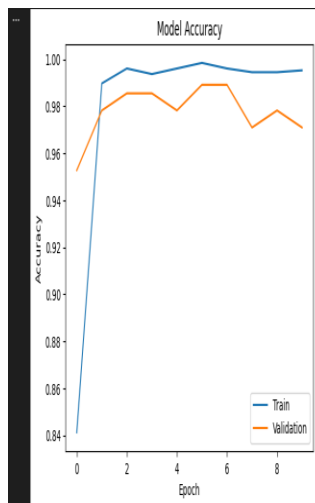
model2.summary()
```

```
✓ 0.0s
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
=====		
conv2d_2 (Conv2D)	(None, 254, 254, 64)	640
activation_1 (Activation)	(None, 254, 254, 64)	0
max_pooling2d_2 (MaxPooling 2D)	(None, 127, 127, 64)	0
conv2d_3 (Conv2D)	(None, 125, 125, 64)	36928
max_pooling2d_3 (MaxPooling 2D)	(None, 62, 62, 64)	0
flatten_1 (Flatten)	(None, 246016)	0
dense_2 (Dense)	(None, 16)	3936272
dense_3 (Dense)	(None, 3)	51

```
=====
Total params: 3,973,891
Trainable params: 3,973,891
Non-trainable params: 0
=====
```



```

model3.compile(loss='sparse_categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

[29] ✓ 0.0s

history = model3.fit_generator(train_generator, epochs=5, validation_data=val_generator, class_weight=

[30] ✓ 1m 56.5s

... Epoch 1/5
C:\Users\sjkom\AppData\Local\Temp\ipykernel_43684\2485142853.py:1: UserWarning: `Model.fit_generator` is
history = model3.fit_generator(train_generator, epochs=5, validation_data=val_generator, class_weight=n
103/103 [=====] - 24s 225ms/step - loss: 1.5052 - accuracy: 0.4732 - val_loss: 0
Epoch 2/5
103/103 [=====] - 23s 228ms/step - loss: 0.6682 - accuracy: 0.7372 - val_loss: 0
Epoch 3/5
103/103 [=====] - 23s 225ms/step - loss: 0.3581 - accuracy: 0.8698 - val_loss: 0
Epoch 4/5
103/103 [=====] - 23s 225ms/step - loss: 0.2861 - accuracy: 0.9185 - val_loss: 0
Epoch 5/5
103/103 [=====] - 23s 223ms/step - loss: 0.1762 - accuracy: 0.9392 - val_loss: 0

+ Code + Markd

y_pred = model3.predict(X_valid, verbose=1)
y_pred_bool = np.argmax(y_pred, axis=1)

print(classification_report(y_valid, y_pred_bool))

print(confusion_matrix(y_true=y_valid, y_pred=y_pred_bool))

[31] ✓ 1.8s

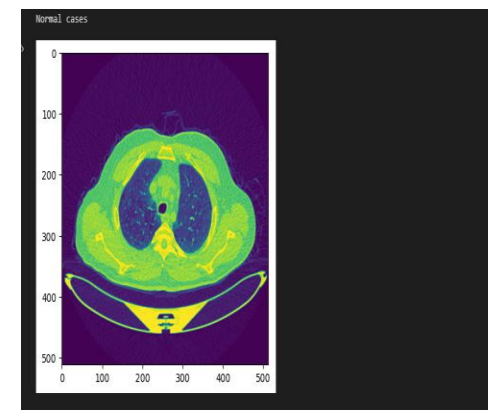
... 9/9 [=====] - 2s 188ms/step
precision recall f1-score support

0 1.00 0.80 0.89 30
1 0.99 0.91 0.95 141
2 0.85 0.99 0.92 104

accuracy 0.93 275
macro avg 0.95 0.90 0.92 275
weighted avg 0.94 0.93 0.93 275

[[ 24  0  6]
 [  0 129 12]
 [  0  1 103]]

```





CHALLENGING PART

- Most challenging part was working with Keras. It took some time for us to understand which pre-trained model to use.

REFERENCES

- Kermany, Daniel; Zhang, Kang; Goldbaum, Michael (2018), “Labeled Optical Coherence Tomography (OCT) and Chest X-Ray Images for Classification”, Mendeley Data, V2, doi: 10.17632/rscbjbr9sj.2
<https://data.mendeley.com/datasets/rscbjbr9sj/2>
- Shimazaki, A., Ueda, D., Choppin, A. *et al.* Deep learning-based algorithm for lung cancer detection on chest radiographs using the segmentation method. *Sci Rep* **12**, 727 (2022).
<https://doi.org/10.1038/s41598-021-04667-w>
- R. Pandian, V. Vedanarayanan, D.N.S. Ravi Kumar, R. Rajakumar, Detection and classification of lung cancer using CNN and Google net, Measurement: Sensors, Volume 24, 2022, 100588, ISSN 2665-9174, <https://doi.org/10.1016/j.measen.2022.100588>.