COVID-19 Detection

By
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The Problem:

COVID-19 tests can be costly and slow.

The Solution:

Use convolutional neural networks and computer vision to detect COVID-19 based on chest X-ray.

The Data

```
Data columns (total 30 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   patientid               950 non-null    object
 1   offset                  697 non-null    float64
 2   sex                     870 non-null    object
 3   age                     713 non-null    float64
 4   finding                 950 non-null    object
 5   RT_PCR_positive         593 non-null    object
 6   survival                361 non-null    object
 7   intubated               248 non-null    object
 8   intubation_present      250 non-null    object
 9   went_icu                397 non-null    object
 10  in_icu                  335 non-null    object
 11  needed_supplemental_O2  90 non-null     object
 12  extubated               37 non-null     object
 13  temperature             78 non-null     float64
 14  pO2_saturation          119 non-null    float64
 15  leukocyte_count         16 non-null     float64
 16  neutrophil_count        28 non-null     float64
 17  lymphocyte_count        40 non-null     float64
 18  view                    950 non-null    object
 19  modality                950 non-null    object
 20  date                    661 non-null    object
 21  location                894 non-null    object
 22  folder                  950 non-null    object
 23  filename                950 non-null    object
 24  doi                     382 non-null    object
 25  url                     950 non-null    object
 26  license                 705 non-null    object
 27  clinical_notes          768 non-null    object
 28  other_notes             436 non-null    object
 29  Unnamed: 29             5 non-null      object
```

Data Source: https://github.com/ieee8023/covid-chestxray-dataset.

Data Wrangling

- Dropped columns not needed.
- Replaced nulls with ‘Unknown’/Avg.
- Removed 21 records with no image.
- Images are considered “Positive” if “finding” column in meta data has “COVID-19”. Otherwise, “Negative”.
- 75/15/15 split for training/validation/test

Exploratory Data Analysis

- Data is relatively balanced (563 positive cases and 366 negative)
- Images have different sizes. So we changed all to 256x256.
- As training set is small (650 images total), it is augmented by generating 11 new images per image.

Model Selection

- MobileNet is used as base model after discarding the last layer of 1000 neurons.
- MobileNet has lightweight architecture. It uses depthwise separable convolutions.
- Weights in the base model are pre-trained on ImageNet.

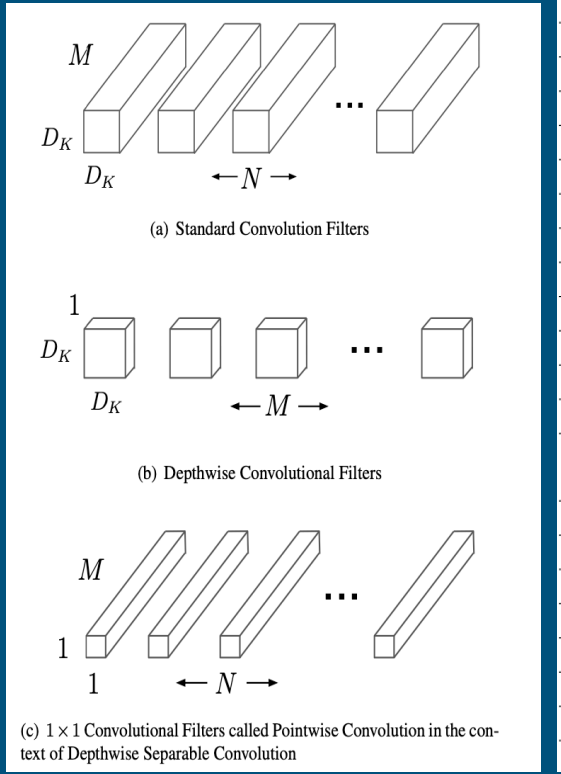


Table 1. MobileNet Body Architecture

Type / Stride	Filter Shape	Input Size
Conv / s2	$3 \times 3 \times 3 \times 32$	$224 \times 224 \times 3$
Conv dw / s1	$3 \times 3 \times 32$ dw	$112 \times 112 \times 32$
Conv / s1	$1 \times 1 \times 32 \times 64$	$112 \times 112 \times 32$
Conv dw / s2	$3 \times 3 \times 64$ dw	$112 \times 112 \times 64$
Conv / s1	$1 \times 1 \times 64 \times 128$	$56 \times 56 \times 64$
Conv dw / s1	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 128$	$56 \times 56 \times 128$
Conv dw / s2	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 256$	$28 \times 28 \times 128$
Conv dw / s1	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 256$	$28 \times 28 \times 256$
Conv dw / s2	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$
$5\times$ Conv dw / s1	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
$5\times$ Conv / s1	$1 \times 1 \times 512 \times 512$	$14 \times 14 \times 512$
Conv dw / s2	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
Conv / s1	$1 \times 1 \times 512 \times 1024$	$7 \times 7 \times 512$
Conv dw / s2	$3 \times 3 \times 1024$ dw	$7 \times 7 \times 1024$
Conv / s1	$1 \times 1 \times 1024 \times 1024$	$7 \times 7 \times 1024$
Avg Pool / s1	Pool 7×7	$7 \times 7 \times 1024$
FC / s1	1024×1000	$1 \times 1 \times 1024$
Softmax / s1	Classifier	$1 \times 1 \times 1000$

Model Selection

- Base model is frozen.
- 2 models are considered with 1 layer added to the base model and different dropout values.
- Notice that dropout values are relatively large as lower values lead to overfitting.

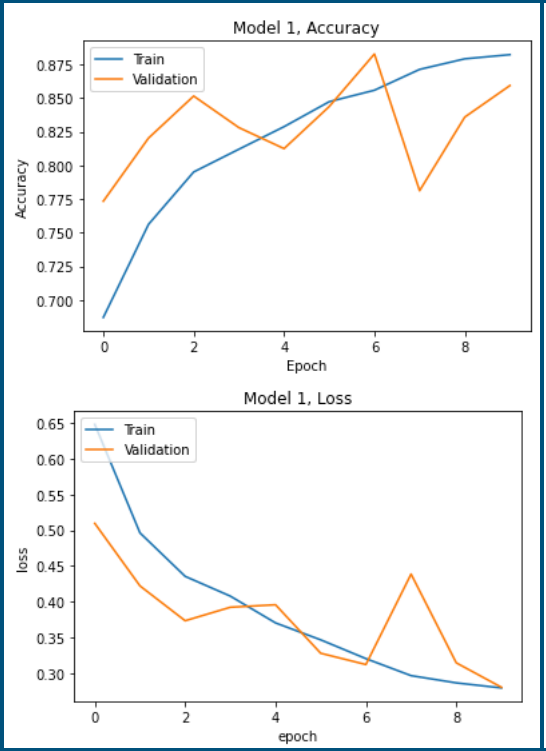
```
base_model = MobileNet(weights='imagenet',include_top=False)

# Freeze the base_model
base_model.trainable = False
```

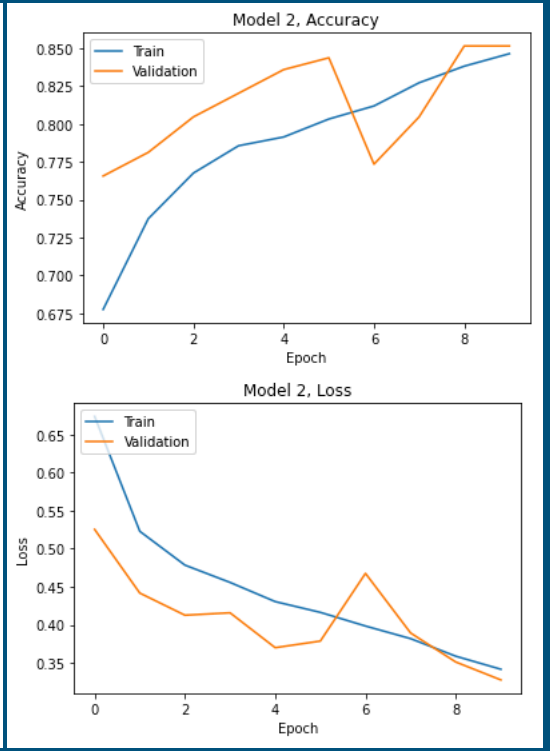
```
x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dense(1024,activation='relu')(x)
x = keras.layers.Dropout(0.6)(x)
preds = Dense(2,activation='softmax')(x)
model1 = Model(inputs=base_model.input,outputs=preds)

x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dense(1024,activation='relu')(x)
x = keras.layers.Dropout(0.7)(x)
preds = Dense(2,activation='softmax')(x)
model2 = Model(inputs=base_model.input,outputs=preds)
```

```
datagen = ImageDataGenerator(preprocessing_function=preprocess_input)
train_generator = datagen.flow_from_directory(
    directory=root_dir+"/train/",
    target_size=(256,256),
    color_mode="rgb",
    batch_size=32,
    class_mode="categorical",
    shuffle=True,
    seed=42
)
valid_generator = datagen.flow_from_directory(
    directory=root_dir+"/val/",
    target_size=(256,256),
    color_mode="rgb",
    batch_size=32,
    class_mode="categorical",
    shuffle=True,
    seed=42
)
test_generator = datagen.flow_from_directory(
    directory=root_dir+"/test/",
    target_size=(256,256),
    color_mode="rgb",
    batch_size=1,
    class_mode='categorical',
    shuffle=False,
    seed=42
)
```

Loss and Accuracy

- In both models, accuracy and loss for training set are improved as value of epoch is increased.
- On validation set, we see some fluctuations but both accuracy and loss seem relatively stable.
- If we increase number of epochs to 20 or 30, we see gaps between the two curves for each model which means the model will overfit.
- We choose Model 1 as it has slightly higher accuracy and lower loss.





Performance on Test Set

- Accuracy: 78 %

- Confusion matrix = $\begin{bmatrix} 39 & 16 \\ 15 & 70 \end{bmatrix}$

Takeaways

- As training set is small, augmenting images seem to be important.
- To avoid overfitting, we had to use relatively large drop out values.
- It seems that accuracy levels over 80% are not easy to achieve with this set of data.
- Given that the ultimate goal of our model is to detect a disease, it may be better to consider precision-recall rather than accuracy.

Future Research

- Study further optimizing the models.
- Consider other metrics such as Precision, Recall and F1-score.
- Investigate using additional patients' information to further enhance models.

Thank You!

- Kaggle and Dr. Joseph Paul Cohen (University of Montreal) for providing data
- Lucas Allen for guidance during project

Questions?