

# A Novel Data Augmentation-Based Brain Tumor Detection Using Convolutional Neural Network

- It is crucial to detect brain tumors early enough for successful treatment.
- Brain tumors are the 10<sup>th</sup> leading cause of death worldwide. In 2020, almost 308,102 people were diagnosed with brain tumors.
- In recent years, deep learning has contributed a lot to the health industry medical diagnoses. CNNs have shown great performance in detecting many diseases including brain tumors.

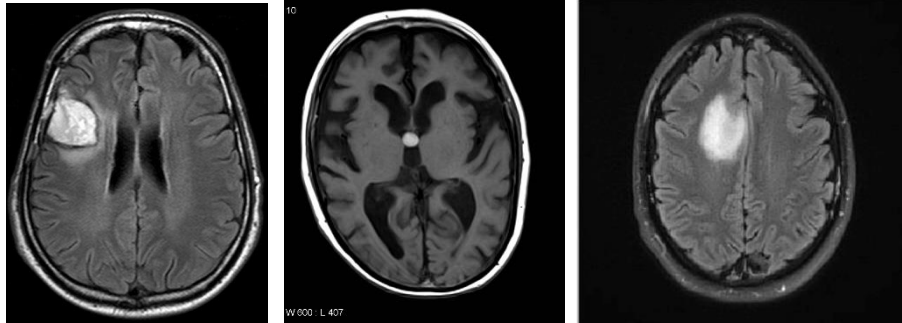
# Dataset

- We work on a dataset from kaggle.com:

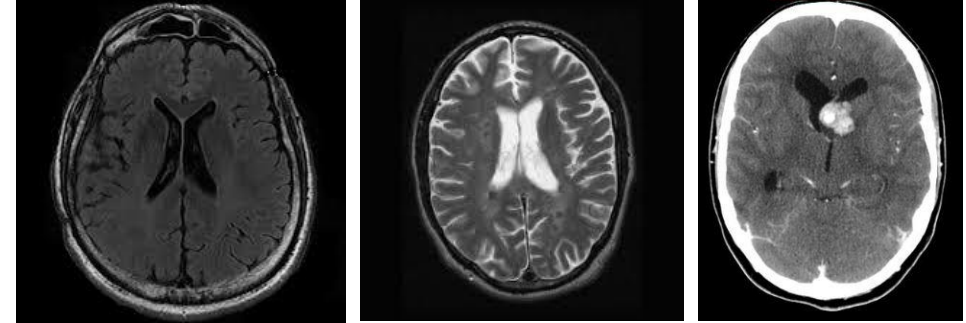
## **Brain MRI Images for Brain Tumor Detection**

- The dataset includes 253 images of brain with 155 positive cases and 98 negative cases.
- Our task is to use a CNN model to predict whether or not one has a brain tumor given an image.jpg  $224 \times 224$ .

# Dataset



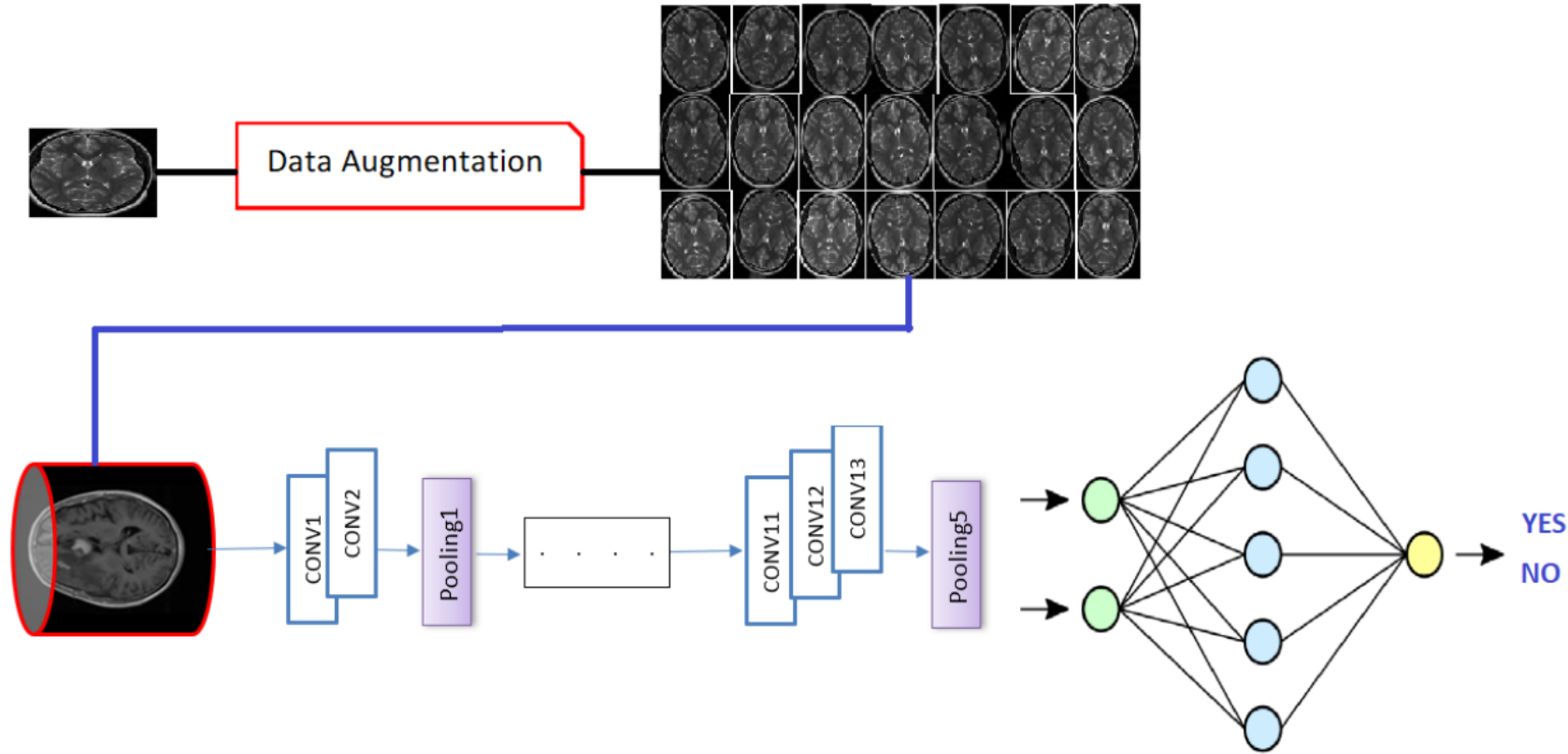
yes



no

- In this paper, we use the popular CNN called VGG-16 to predict the result. We will use Data Augmentation because 253 images are not enough.

# Methodology

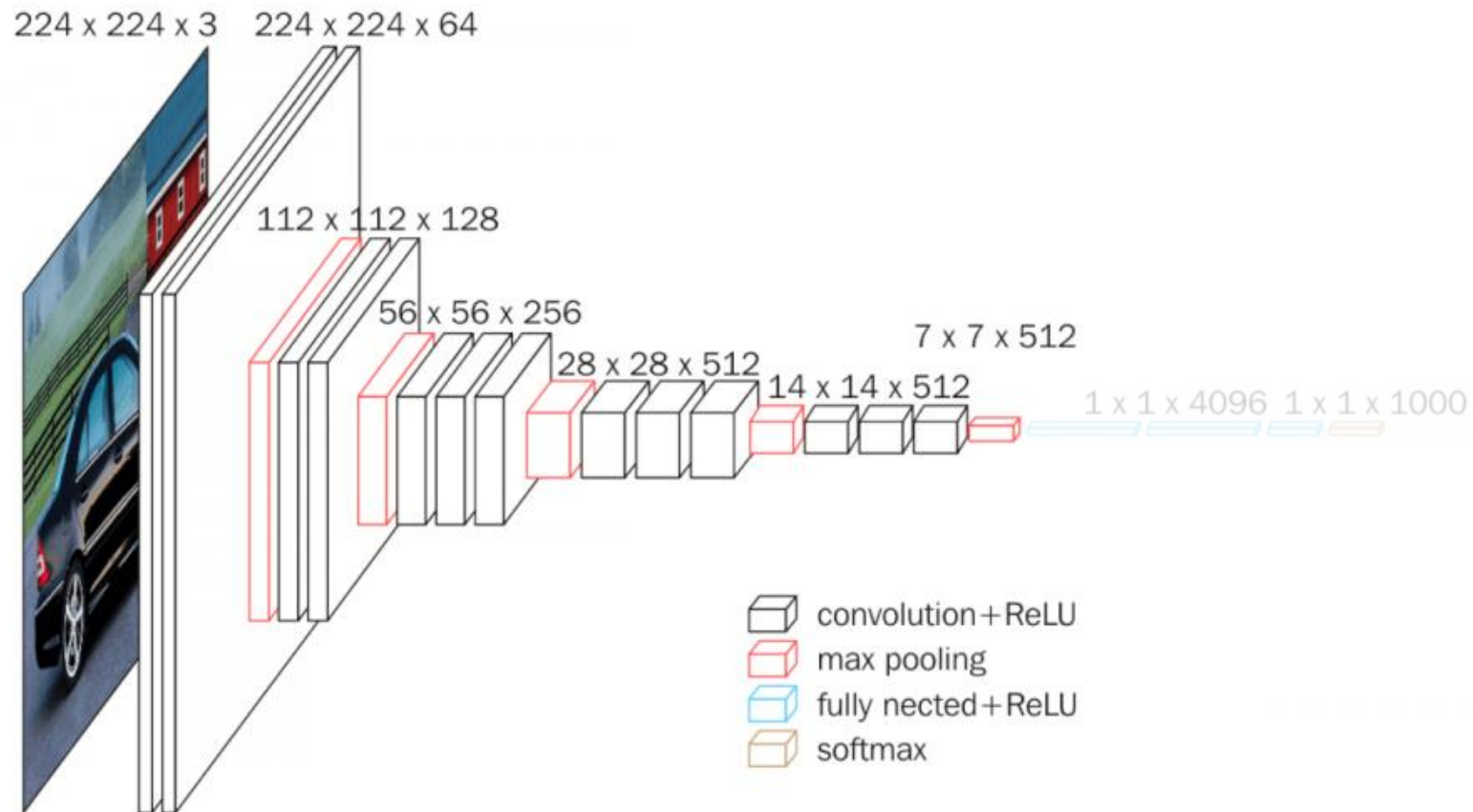


- We make use of a VGG16 CNN up to the ending pooling layer.
- Then we add a [2, 5, 1] fully connected neural network.

# Implementation

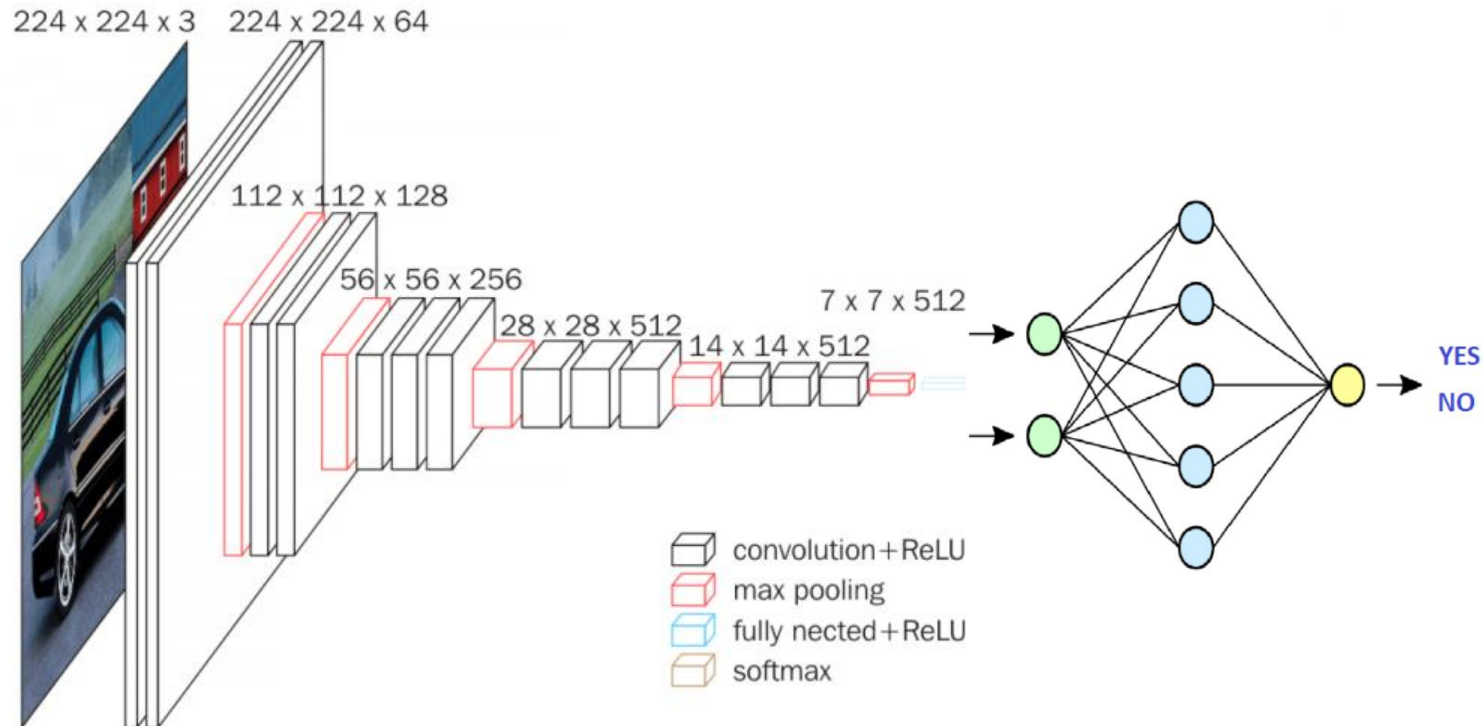
```
from tensorflow.keras.applications.vgg16 import VGG16
```

```
vgg16 = VGG16( weights='imagenet', include_top=False, input_shape=(224,224,3))
```



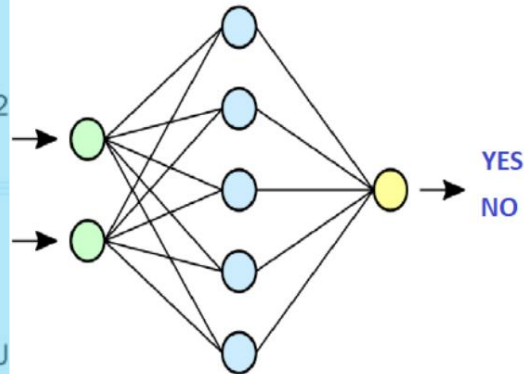
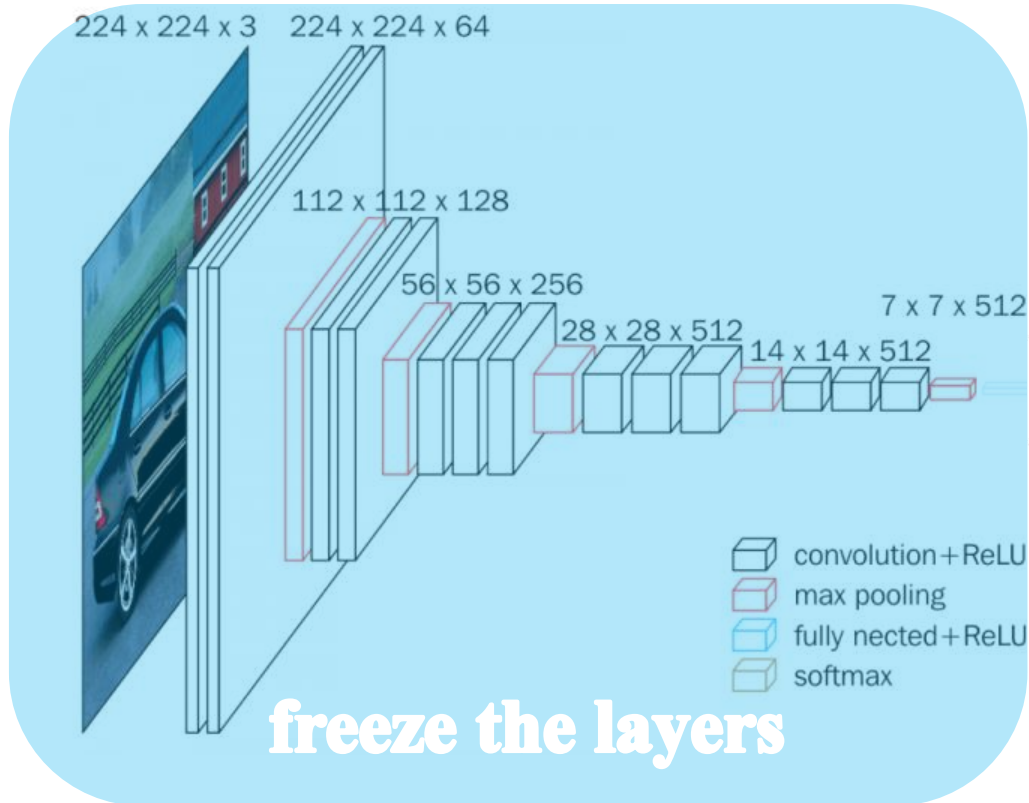
# Implementation

```
1 vgg16.trainable=False
2
3 myModel = tf.keras.Sequential()
4 myModel.add(vgg16)
5 myModel.add(tf.keras.layers.Flatten())
6 myModel.add(keras.layers.Dense(2,activation='relu'))
7 myModel.add(keras.layers.Dense(5, activation='relu'))
8 myModel.add(keras.layers.Dense(1,activation='sigmoid'))
```



# Implementation

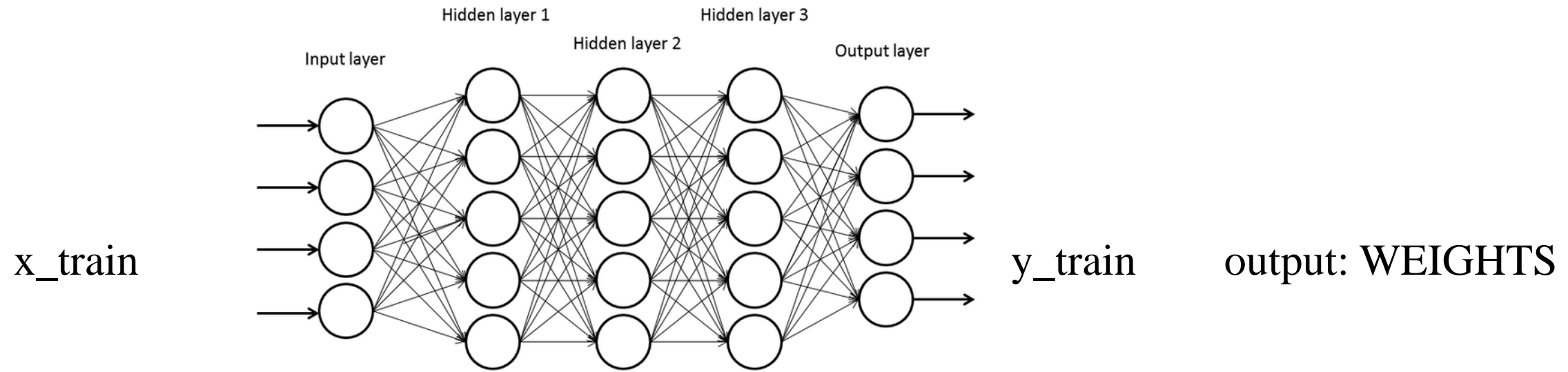
```
1 vgg16.trainable=False
2
3 myModel = tf.keras.Sequential()
4 myModel.add(vgg16)
5 myModel.add(tf.keras.layers.Flatten())
6 myModel.add(keras.layers.Dense(2,activation='relu'))
7 myModel.add(keras.layers.Dense(5, activation='relu'))
8 myModel.add(keras.layers.Dense(1,activation='sigmoid'))
```



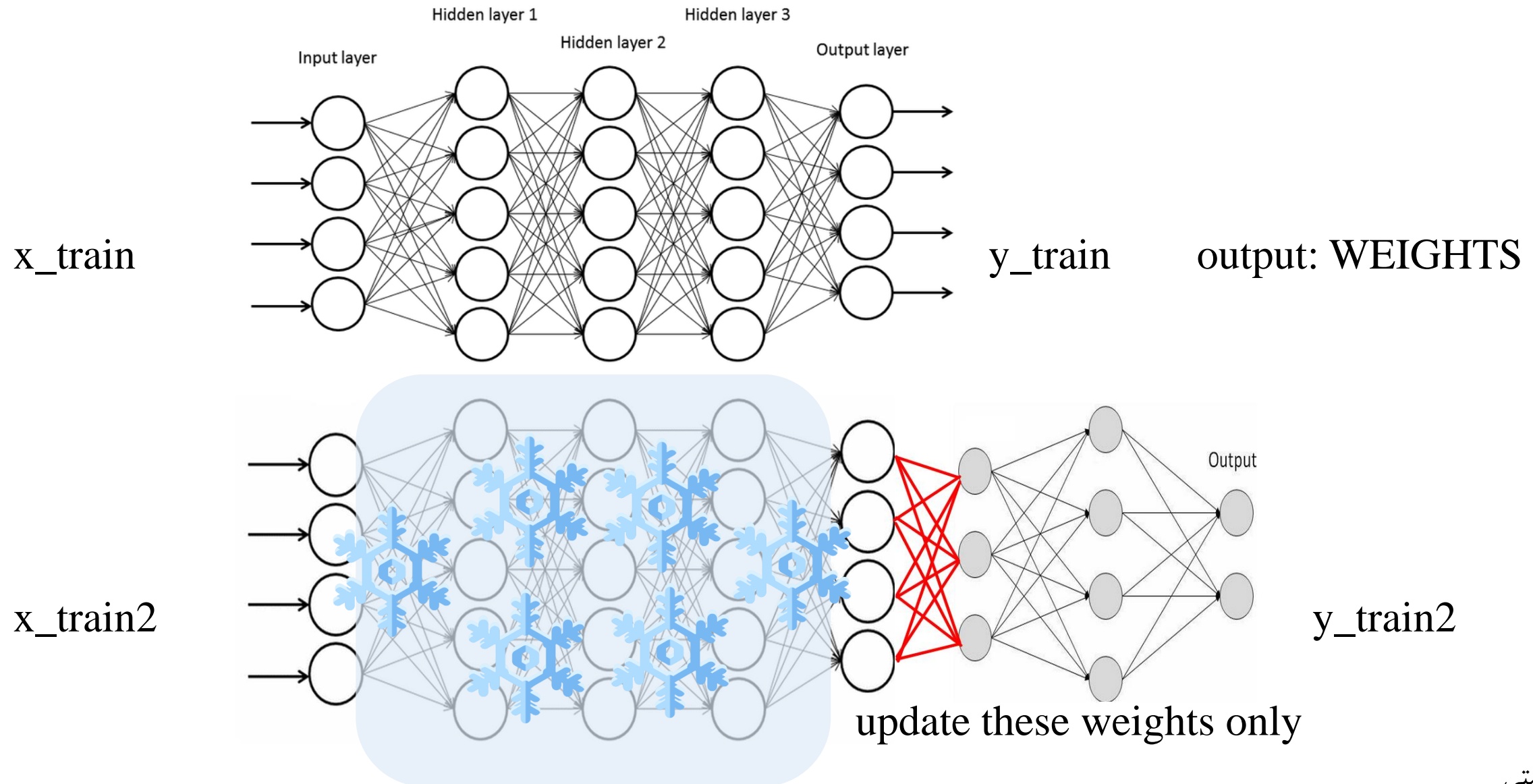
**14M weights → 50K weights**



# Transfer Learning

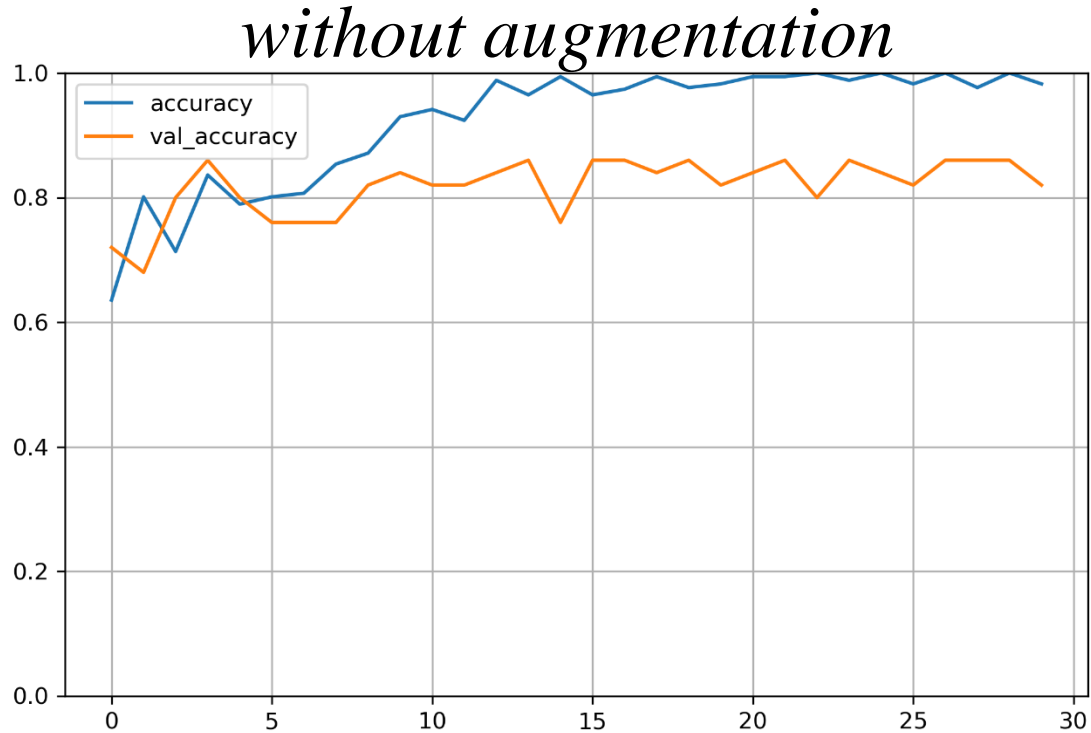


# Transfer Learning



# Implementation and results

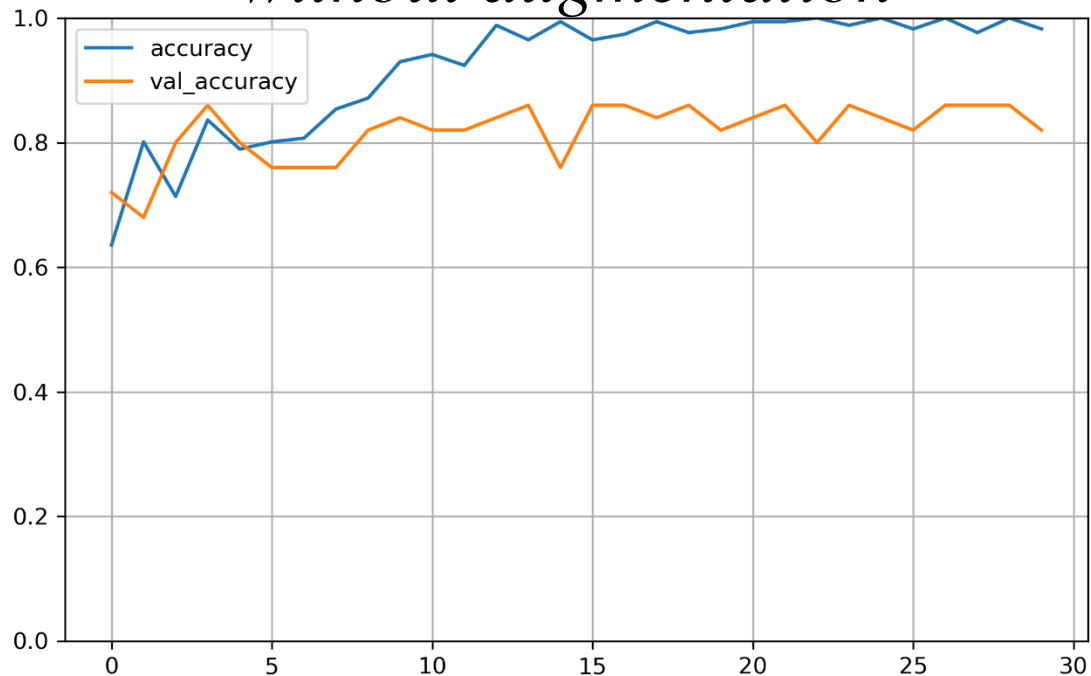
- For comparison, we first train this model on the data we have. (No Augmentation) The result will be:



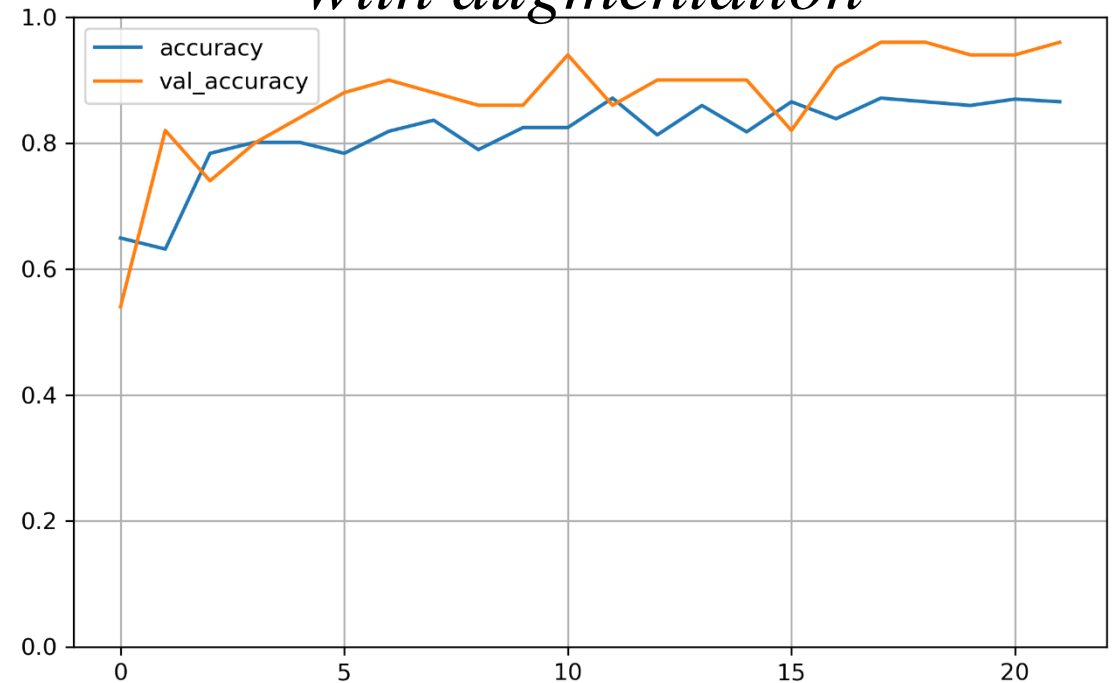
# Implementation and results

- For comparison, we first train this model on the data we have. (No Augmentation) The result will be:

*without augmentation*



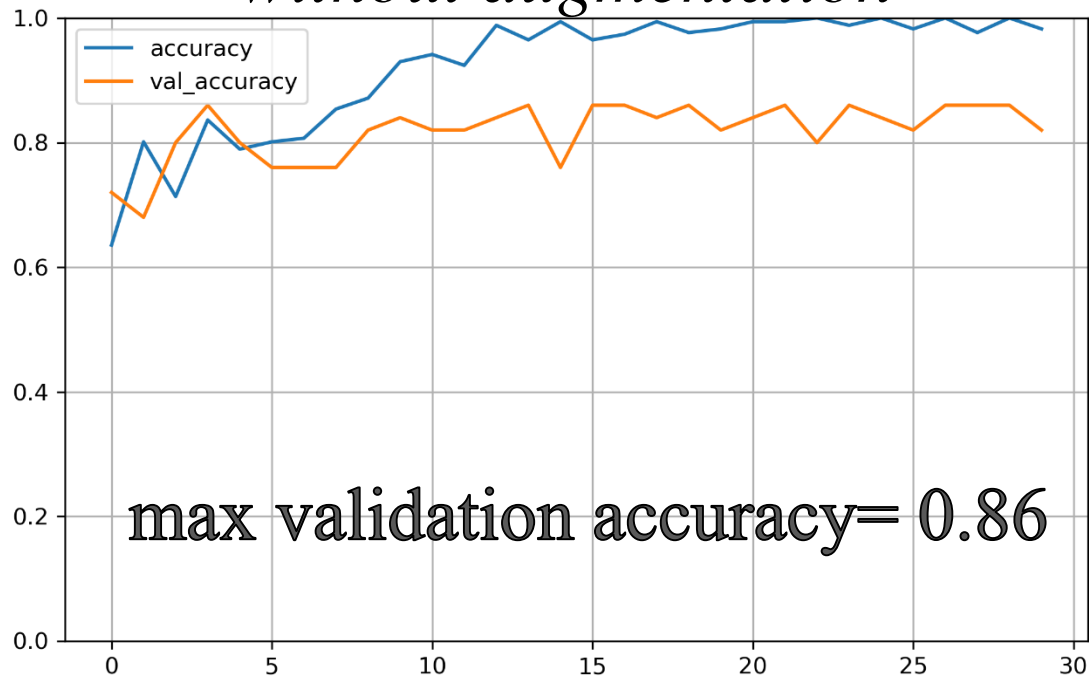
*with augmentation*



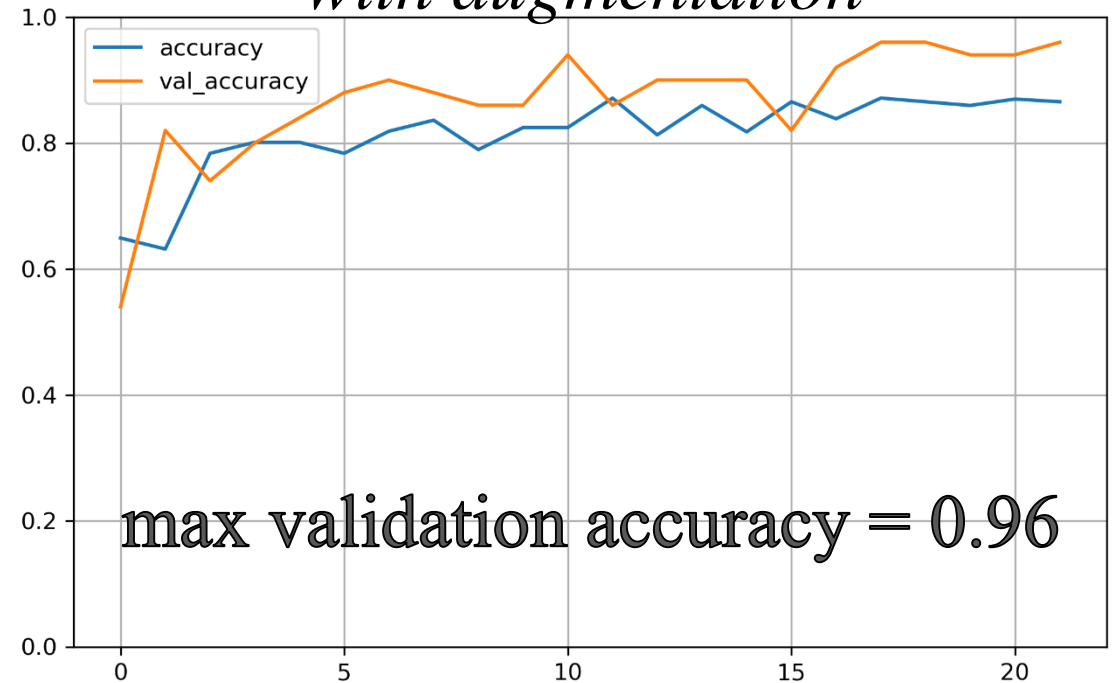
# Implementation and results

- For comparison, we first train this model on the data we have. (No Augmentation) The result will be:

*without augmentation*



*with augmentation*



# Implementation tips

- During training we will use: *ModelCheckpoint* and *Earlystopping* call backs

```
temp = tf.keras.callbacks.ModelCheckpoint(  
    filepath="presentOne",  
    save_weights_only=False,  
    monitor='val_accuracy',  
    mode='max',  
    save_best_only=True)
```

```
temp2 = tf.keras.callbacks.EarlyStopping(  
    monitor="accuracy",  
    patience=10)
```

meaning: save the model with  
maximum val\_acc  
that has been gained so far

meaning: stop if train\_acc is not  
improving for 10 consecutive  
epochs

# Implementation tips

- During training we will use a library called *ImageDataGenerator* for data augmentation

```
from tensorflow.keras.preprocessing.image import ImageDataGenerator
```

```
train_datagen2 = ImageDataGenerator(rescale=1./255,  
                                    rotation_range=15,  
                                    width_shift_range=0.1,  
                                    height_shift_range=0.1,  
                                    shear_range=0.1,  
                                    brightness_range=[0.5, 1.5],  
                                    horizontal_flip=True,  
                                    vertical_flip=True,  
                                    preprocessing_function=preprocess_input)
```

```
test_datagen2 = ImageDataGenerator(preprocessing_function=preprocess_input)
```



# Implementation tips

- How ImageDataGenerator works:

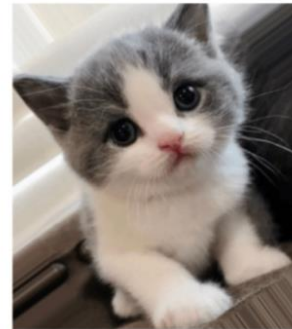
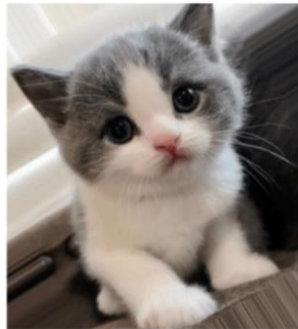
**width\_shift**



**height\_shift**



**rotation**





# Implementation tips

- How ImageDataGenerator works:

**brightness**



**shear**



# Implementation tips

- How ImageDataGenerator works:

**horizontal flip**



**vertical flip**



# Implementation tips

- Why ImageDataGenerator?
- Because it provides *real-time* data augmentation.
- We don't have to save thousands of images anywhere. They will be produced automatically when needed and then removed.

# Finally

- Now let's go to python implementation and compare results with the article.

**Table 4.** Comparison table between different models.

| Model                | Accuracy | Precision | Recall | F1-Score |
|----------------------|----------|-----------|--------|----------|
| VGG16                | 0.96     | 0.93      | 1.0    | 0.97     |
| ResNet-50            | 0.89     | 0.87      | 0.93   | 0.90     |
| VGG-19               | 0.93     | 0.94      | 0.93   | 0.93     |
| Inception-V3         | 0.75     | 0.77      | 0.71   | 0.74     |
| ResNet-101           | 0.74     | 0.74      | 0.74   | 0.73     |
| DenseNet121          | 0.49     | 0.50      | 0.48   | 0.49     |
| <a href="#">[69]</a> | 0.97     | 0.98      | 0.95   | 0.96     |
| <a href="#">[70]</a> | 0.96     | 0.96      | 0.98   | 0.95     |
| <a href="#">[71]</a> | 0.97     | 0.97      | 0.97   | 0.97     |
| <a href="#">[72]</a> | 0.79     | 0.76      | 0.86   | 0.81     |
| <a href="#">[73]</a> | 0.96     | 0.97      | 0.80   | 0.88     |