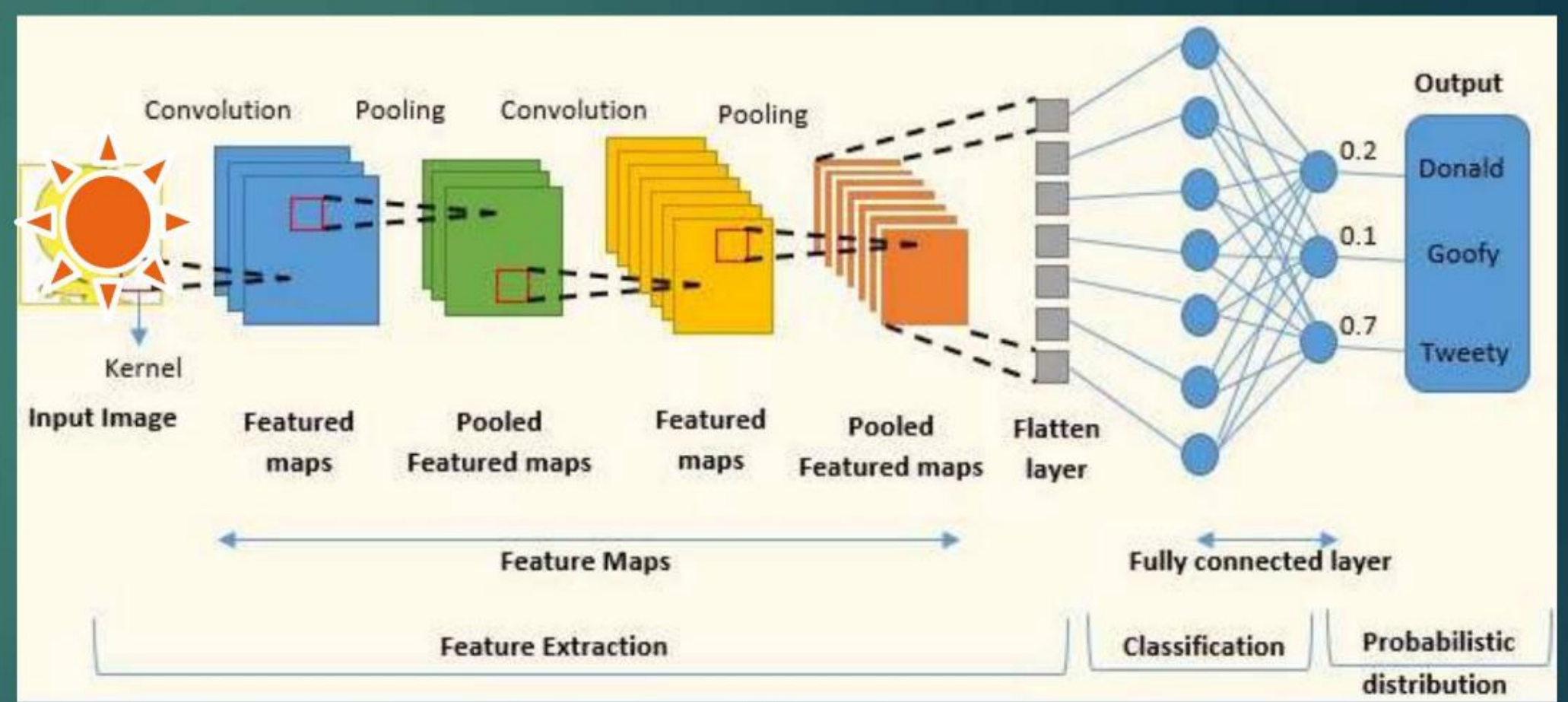
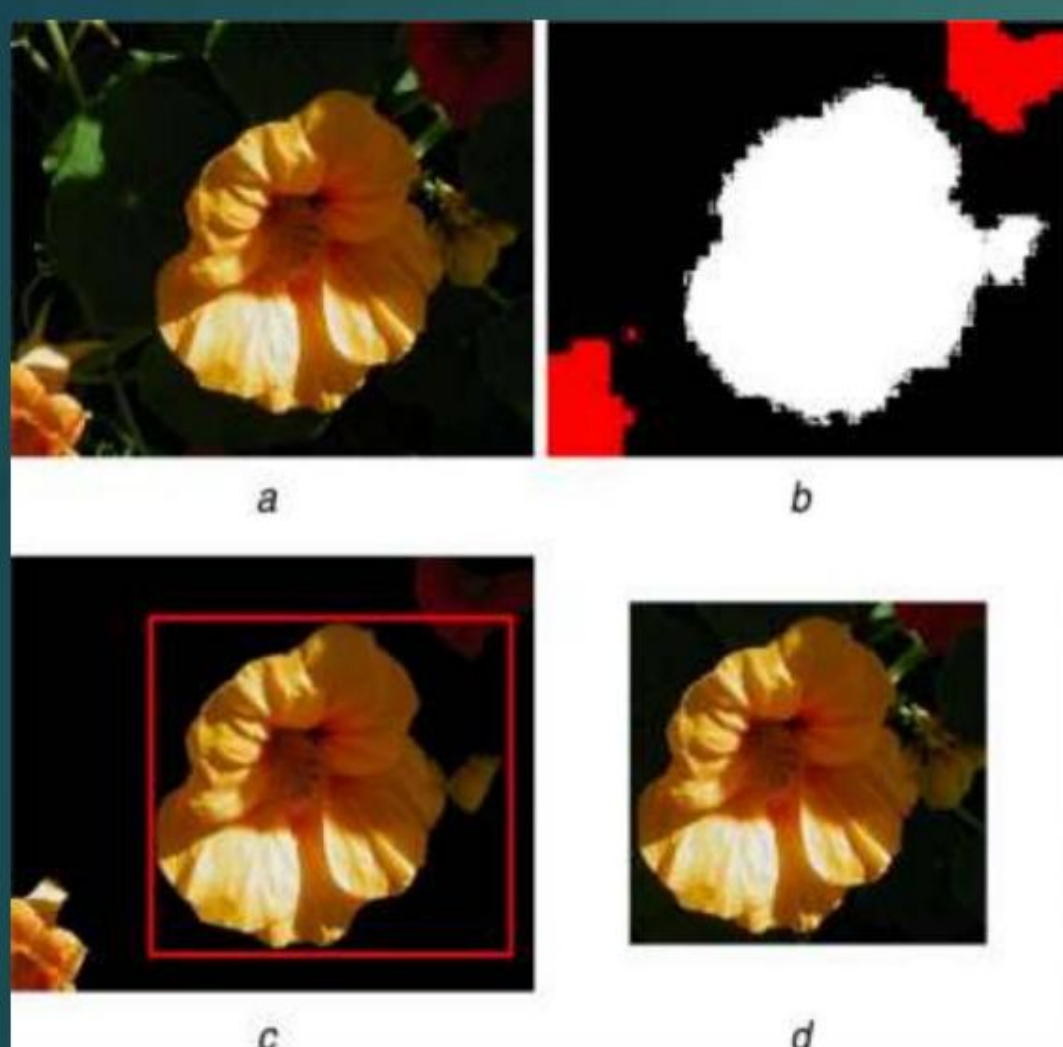


# CNN MODEL FOR CLASSIFICATION OF FLOWERS

## ASSIGNMENT - 3



# Contents

- Introduce
- Preparing the data
- Model Deign
- Model Training



## INTRODUCE

### Approach

- This project is about recognising the type of flowers.
- This project trained Convolution Neural Network written in Keras to predict the type of flower on the validation set.
- Also used ImageDataGeneration to augment the training set and avoid overfitting problem and a LR annealer to schedule the learning rate.



## PREPARING THE DATA

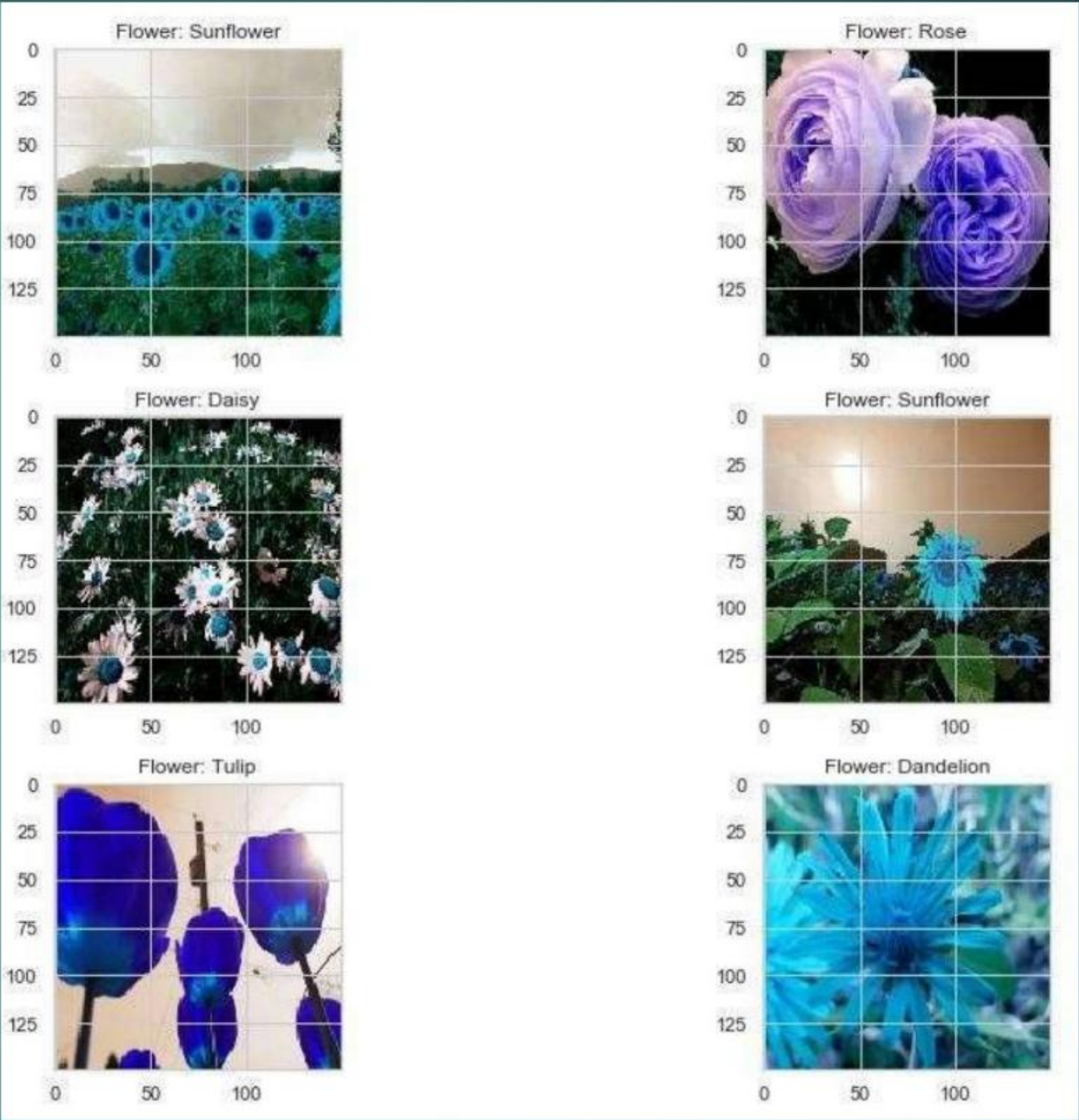
### Dataset

- This dataset contains 4242 image of flowers. The data collection is based on scraped data from flicker, google image, and Yandex image.
- The picture are divided into five classes: chamomile, tulip, rose, sunflower, dandelion.
- For each class there are about 800 photos. Photos are not high resolution, about 30\*240 pixels. Photos are not reduce to a single size, they have different proportions.



Preparing the Data

# Dataset



## Preparing the Data

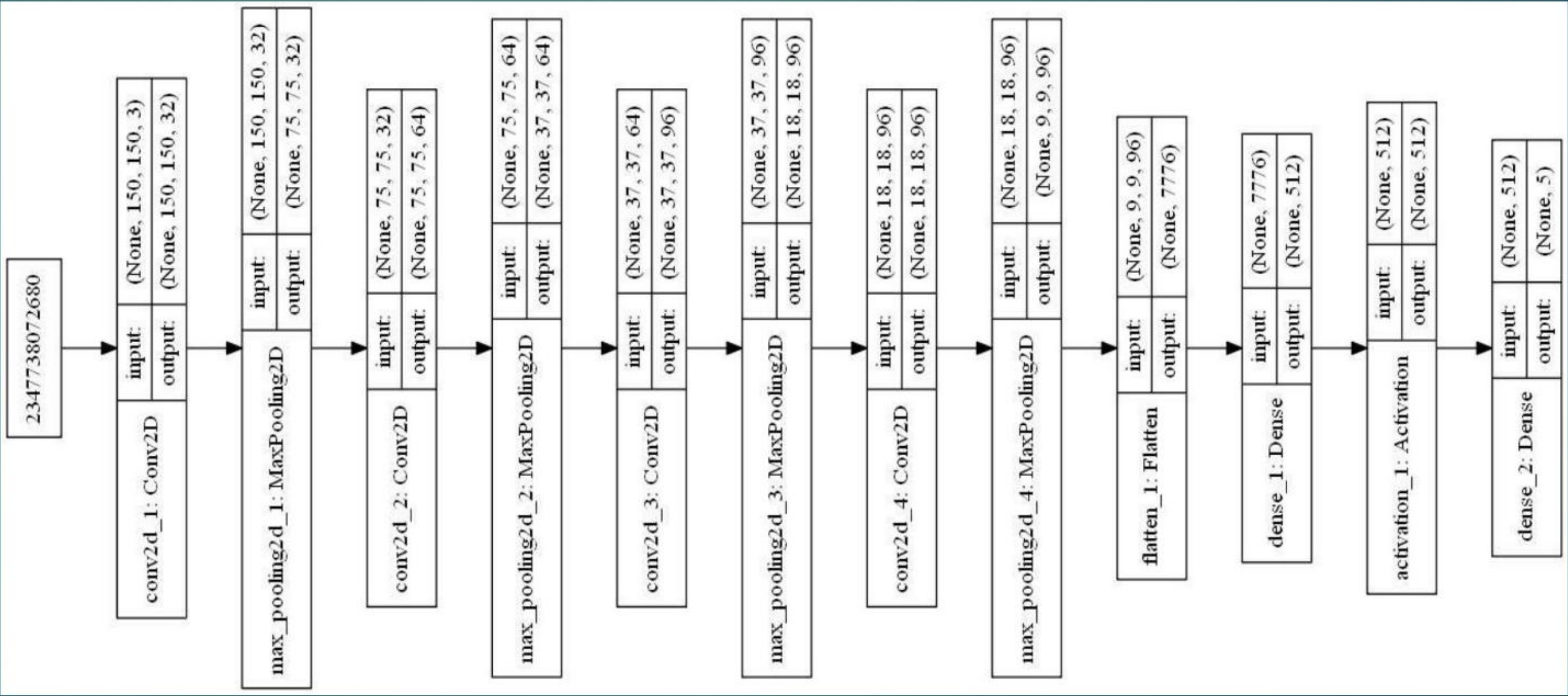
### Resize

- **Smaller and constant size of all image are required for CNN** to do image classification, because the model requires a constant input dimensionality and low resolution will speed up the model training.
- In the project, reasonable resolution of 150\*150 pixels is applied to each image.



Model design

Build CNN architecture



Using plot\_model to visualize the model

Model design

## Build CNN architecture

➤ 4x(conv2d+max-pooling)+flatten+dense+activation+dense



Model Design

## Conv2D layer

- This layer creates a convolution kernel that is convolved with the layer input to produce a tensor of outputs.

## Model Design

### Conv2D layer

```
model.add(Conv2D(filters = 32, kernel_size = (5, 5), padding = 'Same', activation = 'relu', input_shape = (1
```

- When using this layer in a model, provide the keyword argument `input_shape` (tuple of integers, does not include the batch axis), e.g. `input_shape=(128,128,3)` for 128x128 RGB picture in `data_format="channels_last"`.
- The ordering of the dimensions in the inputs. “channels\_last” corresponds to inputs with shape (batch,height,width,channels).



## Pooling layer

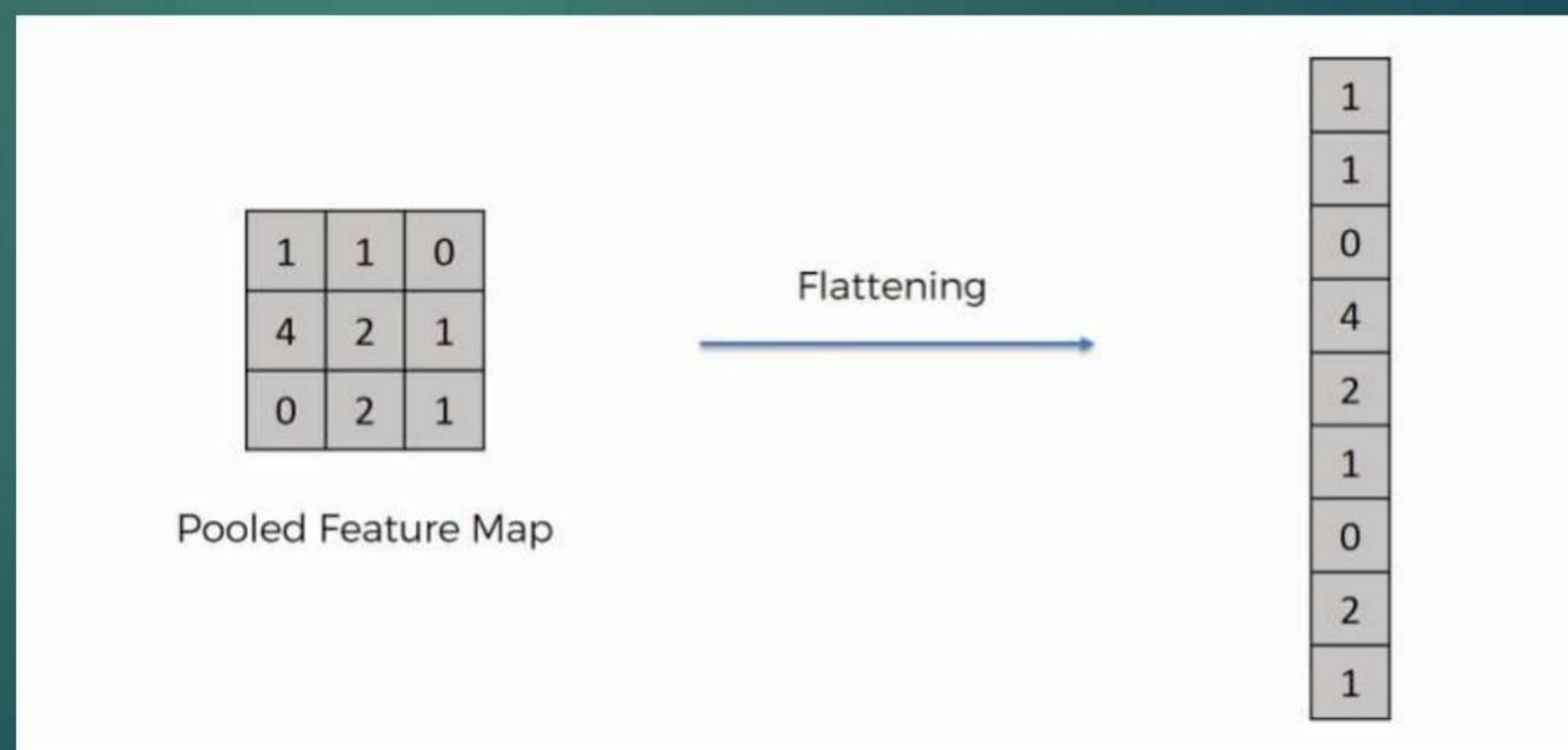
- In pooling layers, features are extracted and compressed into a small map, which simplifies the neural network computation complexity, leading to the decrease of the volume of parameters and computation.
- In this project, we use max pooling.



## Model Design

# Flatten layer

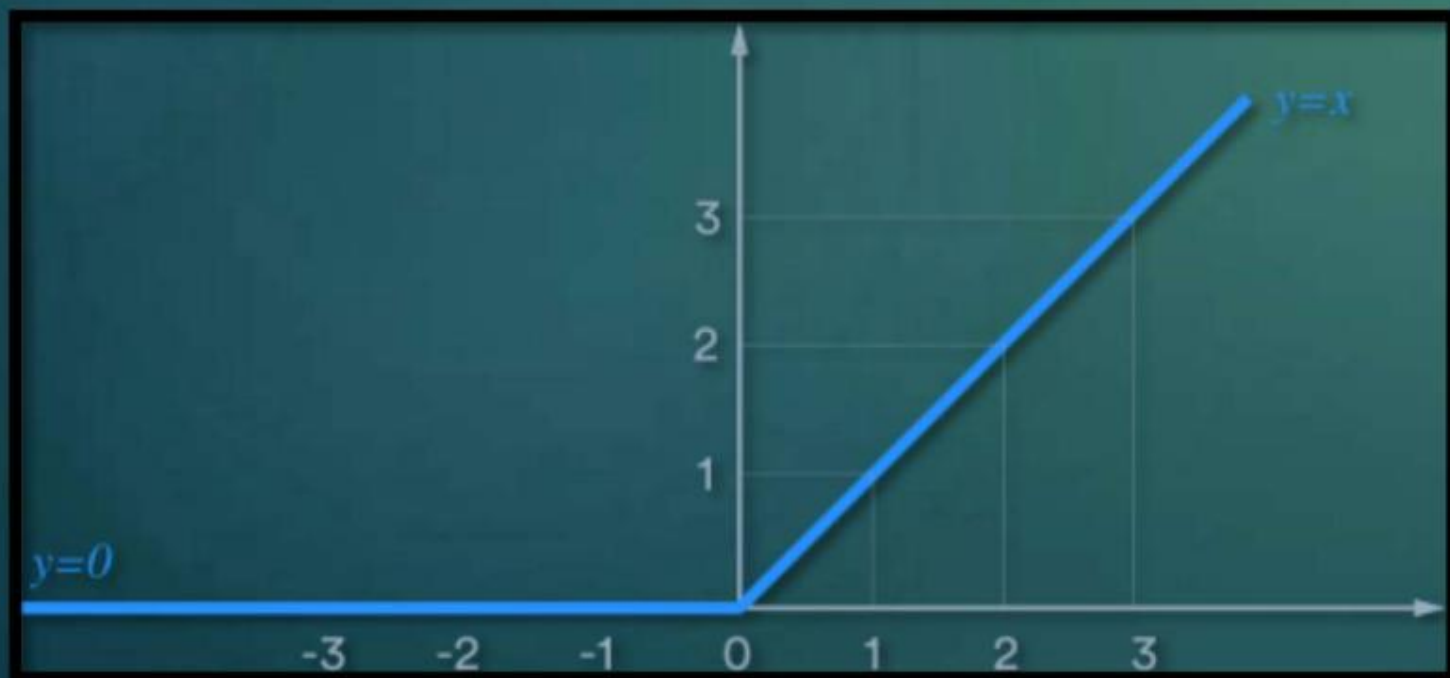
- A flatten layer collapses the spatial dimensions of the input into the channel dimension.





## Activation layer(ReLU)

- Rectified Linear Unit (ReLU) is a piecewise linear function implemented in this model. The ReLU activation function is given by : different proportions.

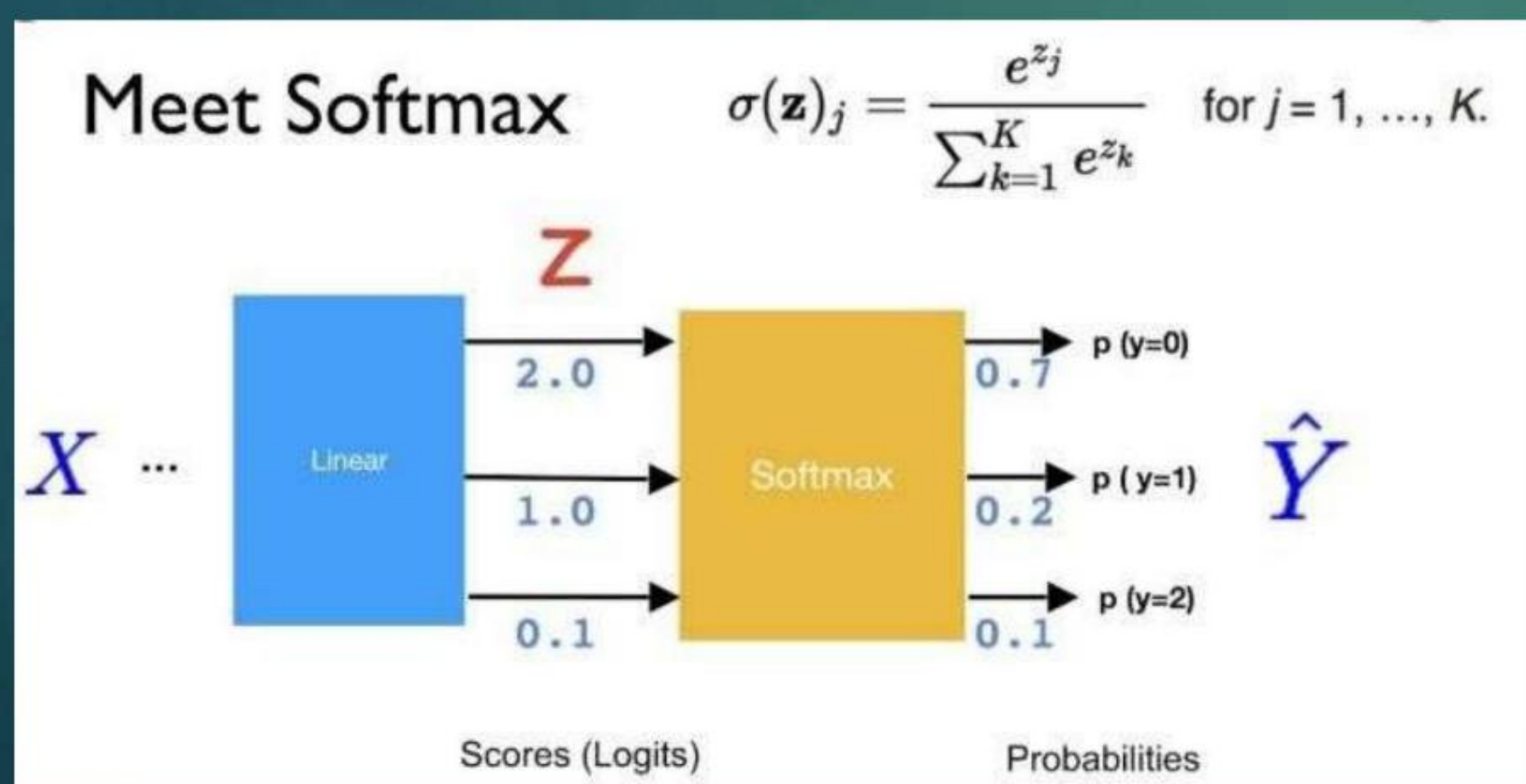


$$ReLU = \begin{cases} x, & \text{if } x > 0 \\ 0, & \text{if } x \leq 0 \end{cases}$$

## Model Design

# Softmax Function

- ✓ The softmax function is used in neural network when we want to build a multi-class classifier which solves the problem of assigning an instance to one class when the number of possible classes is larger than two.





Model Design

## Softmax Function

- The softmax function is used in neural networks when we want to build a multi-class classifier which solves the problem of assigning an instance to one class when the number of possible classes is larger than two.

Model Design

## Learning rate annealing(`ReduceLROnPlateau`)

- Reduce learning rate when a metric has stopped improving.
- Models often benefit from reducing the learning rate by a factor of 2-10 once learning stagnates. This callback monitors a quantity and if no improvement is seen for a 'patience' number of epochs, the learning rate is reduced.



Model Design

## Data Augmentation(ImageDataGenerator class)

The Keras ImageDataGenerator class actually works by:

- Accepting a batch of image used for training.
- Taking this batch and applying a series of random transformations to each image in the batch (including random rotation, resizing, shearing, ect.)
- Replacing the original batch with the new, randomly transformed batch.
- Training the CNN on this randomly transformed batch(i.e., the original data itself is not used for training)



## Model Design

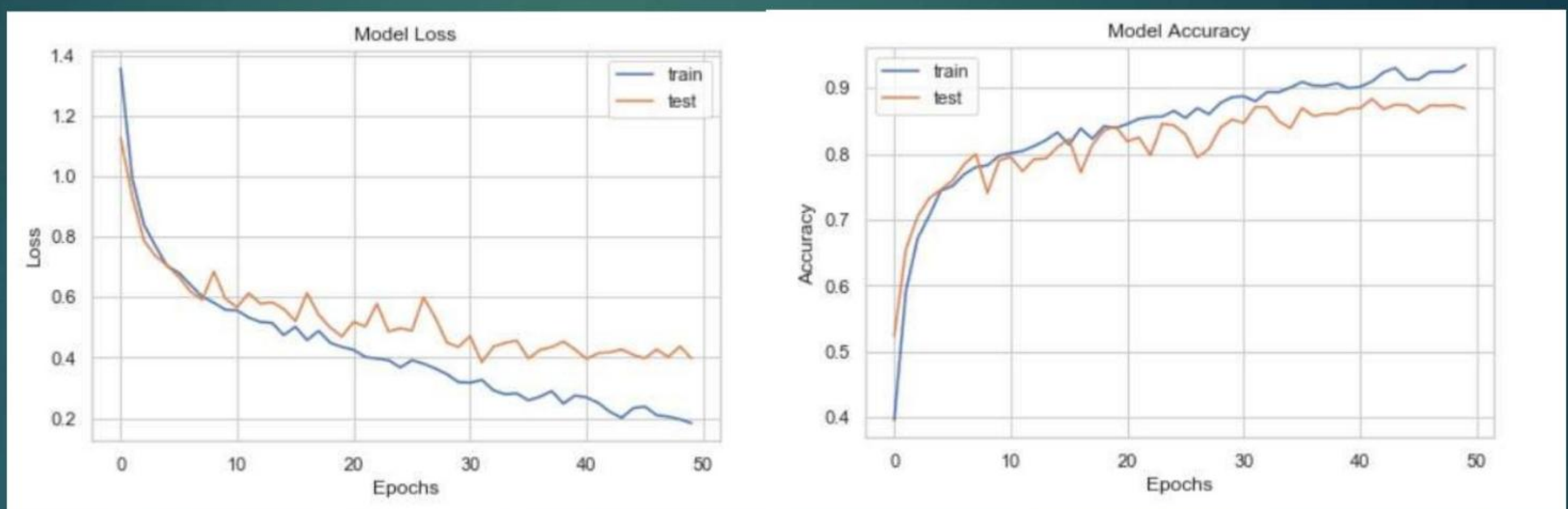
# Model architecture-4

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 150, 150, 32)	2432
max_pooling2d_1 (MaxPooling2D)	(None, 75, 75, 32)	0
conv2d_2 (Conv2D)	(None, 75, 75, 64)	18496
max_pooling2d_2 (MaxPooling2D)	(None, 37, 37, 64)	0
conv2d_3 (Conv2D)	(None, 37, 37, 96)	55392
max_pooling2d_3 (MaxPooling2D)	(None, 18, 18, 96)	0
conv2d_4 (Conv2D)	(None, 18, 18, 96)	83040
max_pooling2d_4 (MaxPooling2D)	(None, 9, 9, 96)	0
flatten_1 (Flatten)	(None, 7776)	0
dense_1 (Dense)	(None, 512)	3981824
activation_1 (Activation)	(None, 512)	0
dense_2 (Dense)	(None, 5)	2565
Total params: 4,143,749		
Trainable params: 4,143,749		
Non-trainable params: 0		



## Model Design

## Result



Finally the accuracy on the validation set using the self-laid ConvNet is over 85%.

Model Design

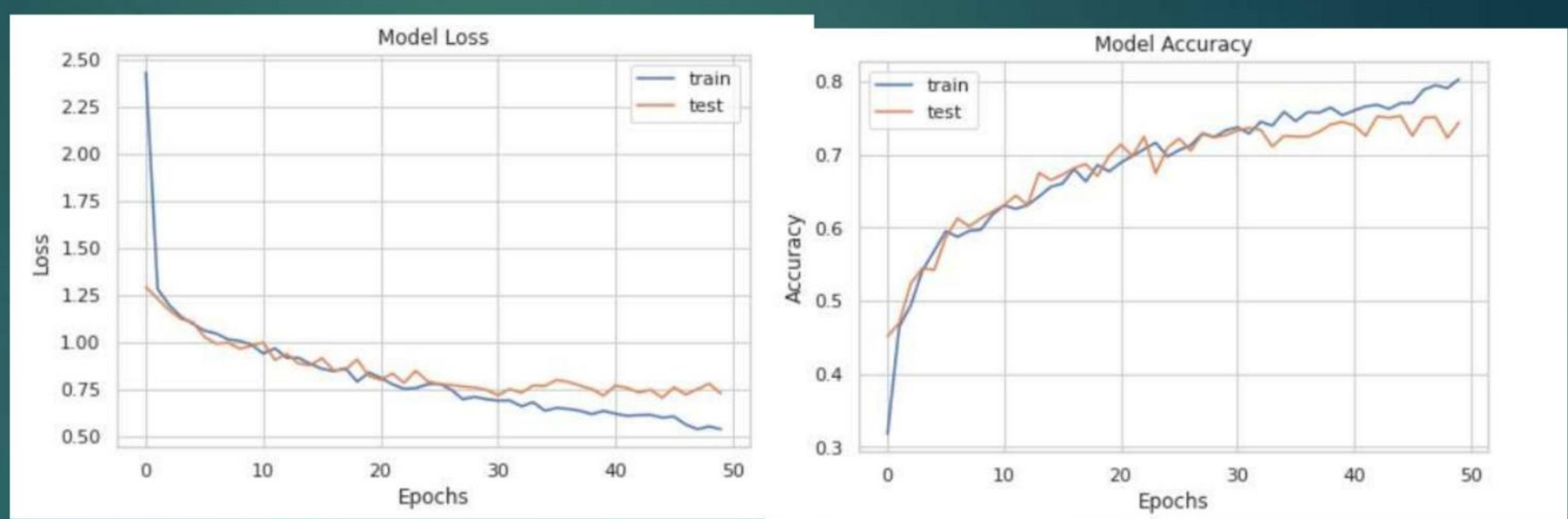
Model  
architecture-2

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 150, 150, 32)	2432
max_pooling2d_1 (MaxPooling2D)	(None, 75, 75, 32)	0
conv2d_2 (Conv2D)	(None, 75, 75, 64)	18496
max_pooling2d_2 (MaxPooling2D)	(None, 37, 37, 64)	0
flatten_1 (Flatten)	(None, 87616)	0
dense_1 (Dense)	(None, 512)	44859904
activation_1 (Activation)	(None, 512)	0
dense_2 (Dense)	(None, 5)	2565
Total params: 44,883,397		
Trainable params: 44,883,397		
Non-trainable params: 0		



## Model Design

### Result-2



Finally the accuracy on the validation set using the self-laid ConvNet is close to 75%.

Model Design

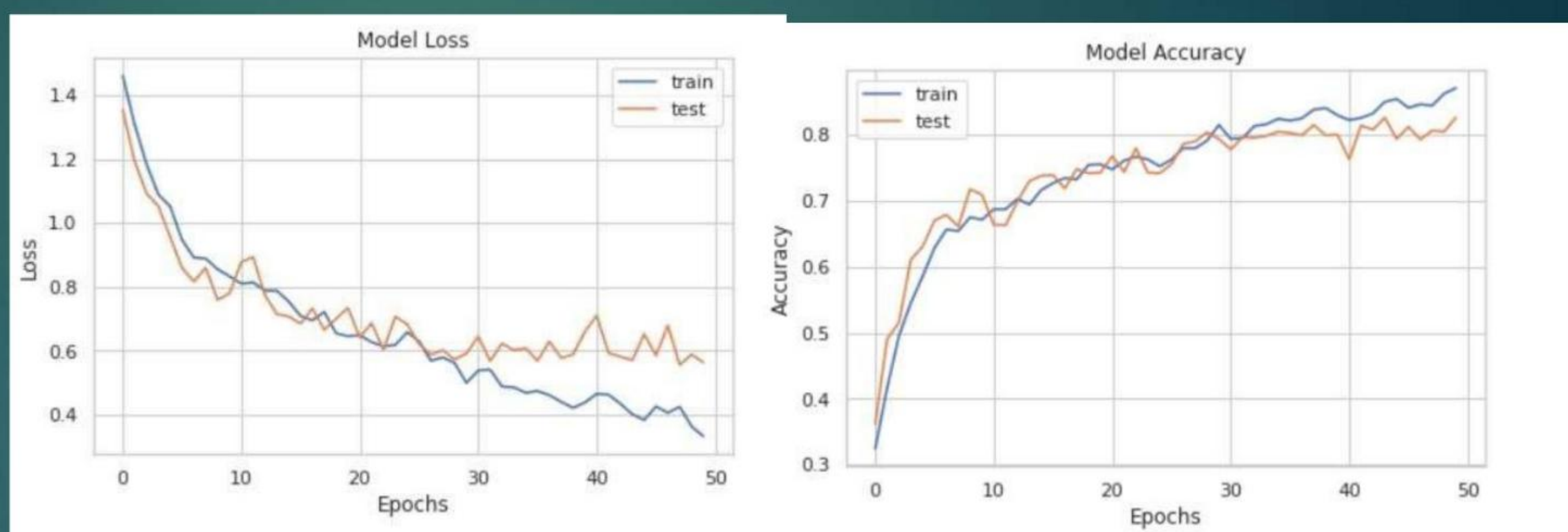
Model  
architecture-6

Layer (type)	Output Shape	Param #
conv2d_5 (Conv2D)	(None, 150, 150, 32)	2432
max_pooling2d_5 (MaxPooling2	(None, 75, 75, 32)	0
conv2d_6 (Conv2D)	(None, 75, 75, 64)	18496
max_pooling2d_6 (MaxPooling2	(None, 37, 37, 64)	0
conv2d_7 (Conv2D)	(None, 37, 37, 96)	55392
max_pooling2d_7 (MaxPooling2	(None, 18, 18, 96)	0
conv2d_8 (Conv2D)	(None, 18, 18, 96)	83040
max_pooling2d_8 (MaxPooling2	(None, 9, 9, 96)	0
conv2d_9 (Conv2D)	(None, 9, 9, 96)	83040
max_pooling2d_9 (MaxPooling2	(None, 4, 4, 96)	0
conv2d_10 (Conv2D)	(None, 4, 4, 96)	83040
max_pooling2d_10 (MaxPooling	(None, 2, 2, 96)	0
flatten_2 (Flatten)	(None, 384)	0
dense_3 (Dense)	(None, 512)	197120
activation_2 (Activation)	(None, 512)	0
dense_4 (Dense)	(None, 5)	2565
Total params: 525,125		
Trainable params: 525,125		
Non-trainable params: 0		



Model Design

## Result-6



Finally the accuracy on the validation set using the self-laid ConvNet is around 80%.

## Model Design

### Why

When there are too many hidden layers, the accuracy may decline.

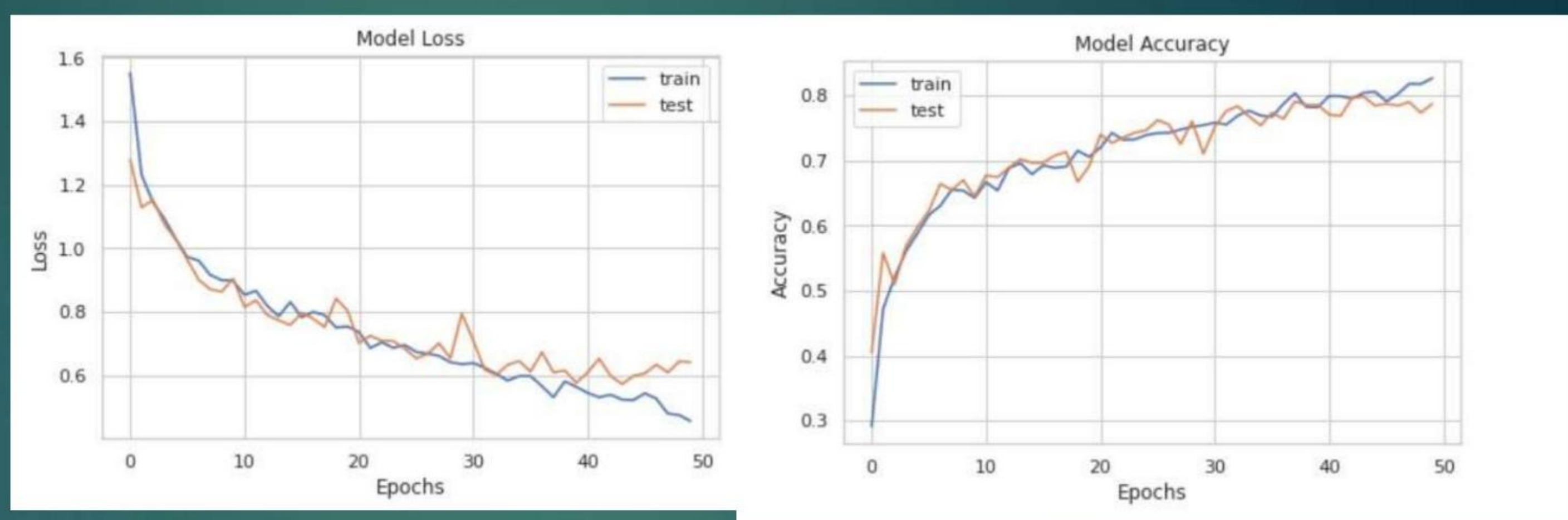
This is because the more hidden layers the Gradient in the Back Propagation algorithm goes through, the smaller it will be and gradually approaches zero.

This phenomenon is called Vanishing Gradient Problem.



## Model Design

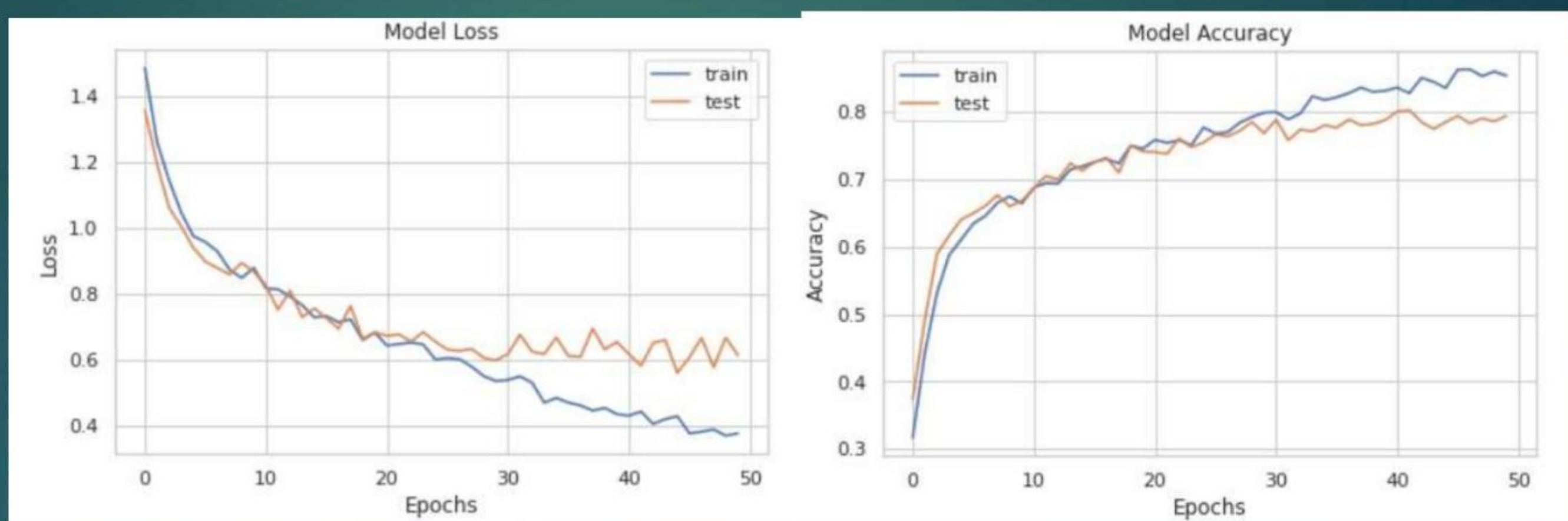
### Result-4x32



Finally the accuracy on the validation set using the self-laid ConvNet is around 80%.

## Model Design

### Result-4x64

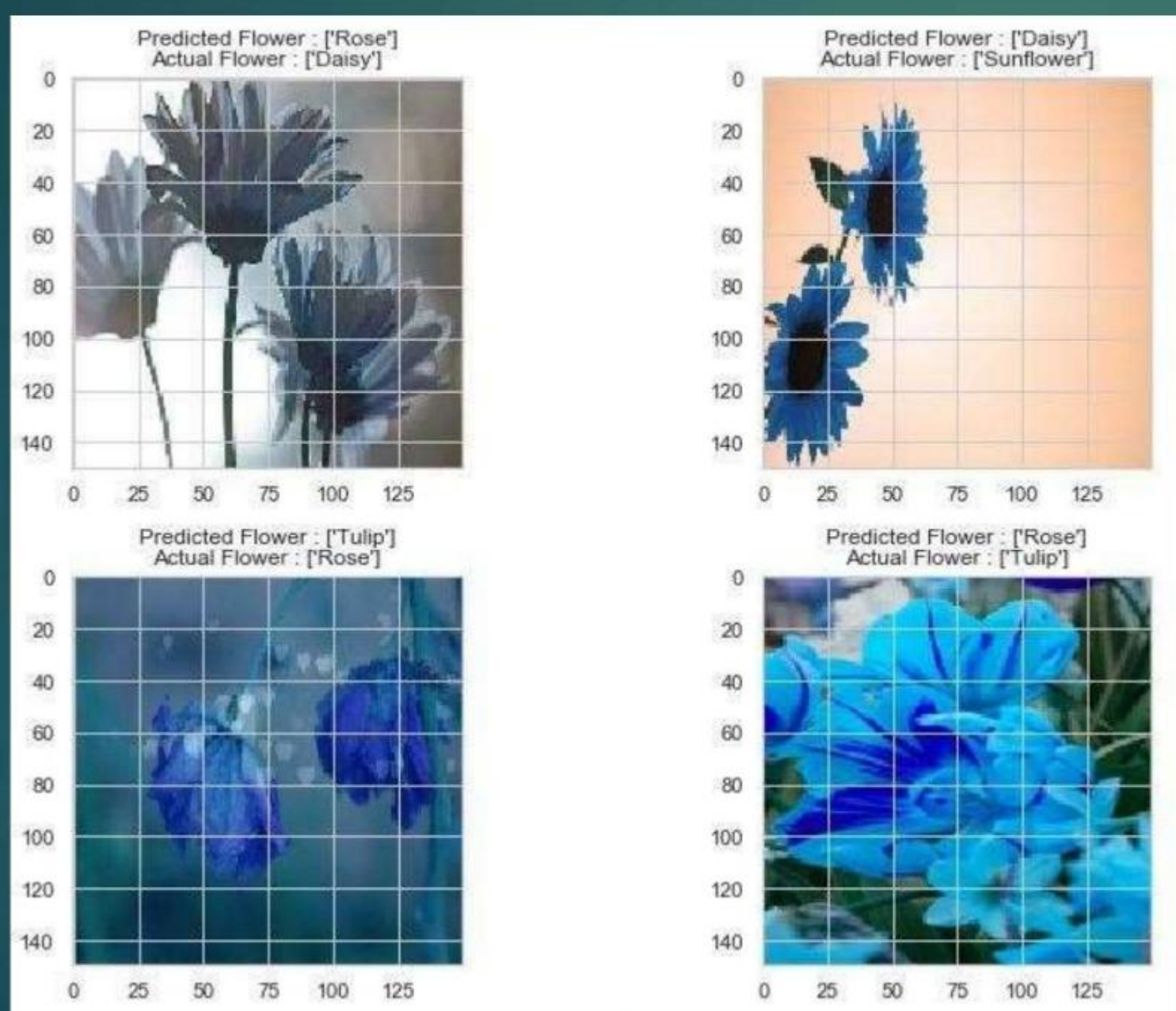


Finally the accuracy on the validation set using the self-laid ConvNet is around 80%.



## Model Design

# Misclassified images of flowers



- The reason why the model misclassified could be because the flowers are not front facing, too big, too small and so on.