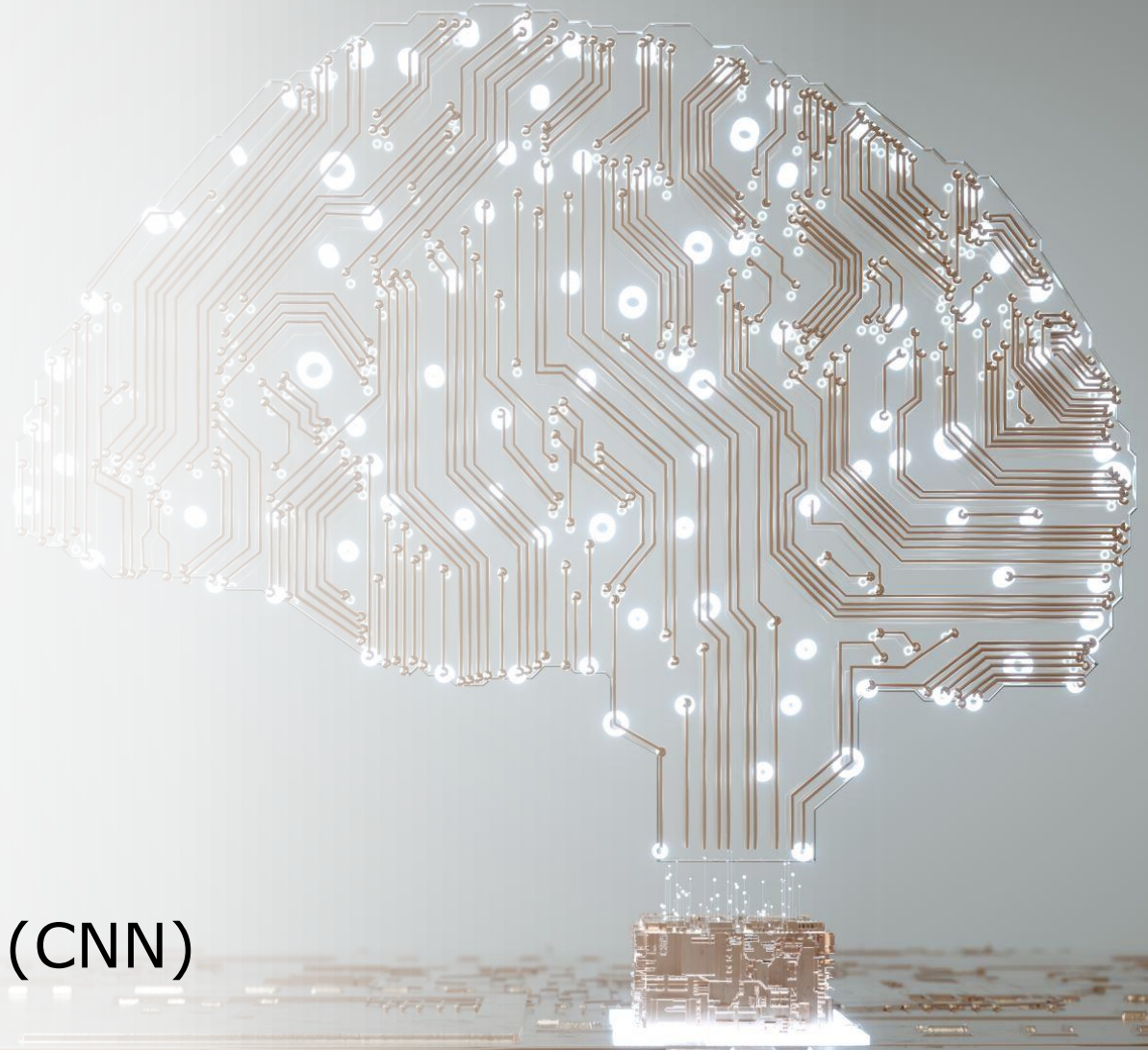




# Artificial intelligence

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Image recognition using  
Convolutional Neural Networks (CNN)



- Initially check the impact of several parameters
- Refine parameters where accuracy increased

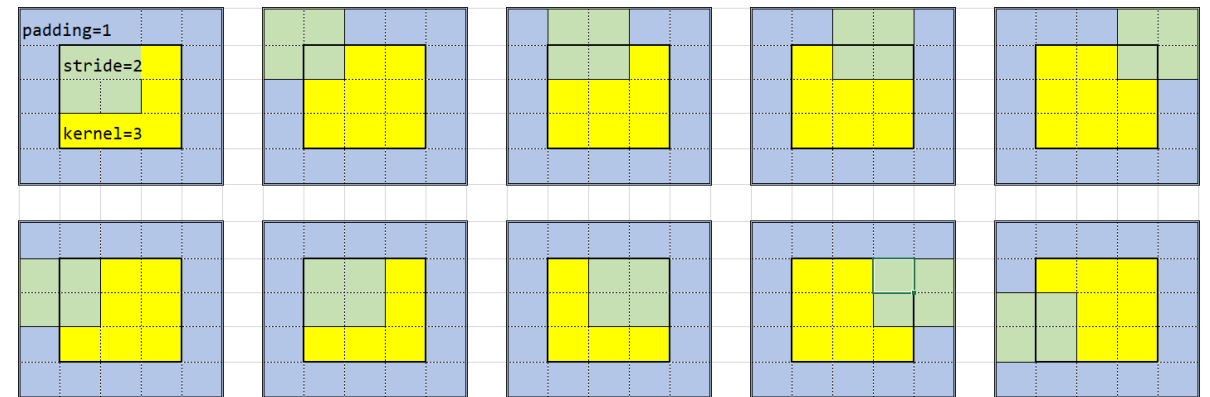
The graph illustrates the model's performance during training and testing. The training accuracy (blue line) shows a consistent upward trend, reaching nearly 0.8 by epoch 350. The testing accuracy (orange line) follows the training accuracy initially but plateaus around 0.5 after epoch 100, with some fluctuations indicating overfitting.

Epoch	Train Accuracy	Test Accuracy
0	0.15	0.12
50	0.45	0.42
100	0.58	0.48
150	0.65	0.48
200	0.70	0.48
250	0.75	0.48
300	0.78	0.48
350	0.78	0.48

conv_count	dense_algo	target_size	filters	padding	batch_size	dense	epochs	learning_rate	aug	bias	batch_norm	flatten	avg_pool	Run	compare_to	parameters	acc	loss	val_acc	val_loss	t_epoch
2	softmax	128	16	none	n/100	32	10	0,01	0	0	0	1	0	1		496614	0,0743	4,2048	0,0289	5,2127	41
2	softmax	128	16	none	n/100	32	10	0,01	0	0	1	0	1	2	1	5222	0,3806	2,2551	0,3800	2,3841	43
2	softmax	128	16	none	n/100	32	10	0,01	1	0	1	0	1	3	2	5222	0,3154	2,5809	0,2941	2,7442	67
2	softmax	128	16	none	n/100	32	10	0,01	0	1	1	0	1	4	2	5286	0,3898	2,2411	0,2978	2,6682	42
2	softmax	128	16	none	n/100	32	10	0,01	1	1	1	0	1	5	2	5286	0,3614	2,4047	0,2837	2,9009	63
2	softmax	128	16	none	n/100	32	10	0,01	1	1	0	1	0	6	2	496678	0,0282	4,5004	0,0281	4,5302	60
2	softmax	128	16	none	n/100	32	10	0,01	0	0	1	1	1	7	2	5286	0,3689	2,3395	0,3496	2,6694	66
2	softmax	128	16	none	n/100	32	10	0,001	0	0	1	0	1	8	2	5222	0,2677	2,8866	0,3007	2,8789	45
2	softmax	128	16	none	n/100	32	50	0,001	0	0	1	0	1	9	8	5222	0,4204	2,1502	0,4000	2,4079	43
2	softmax	128	16	none	n/100	32	100	0,001	0	0	1	0	1	10	9	5222	0,5138	1,7637	0,4037	2,3401	45
2	softmax	256	16	none	n/100	32	50	0,001	0	0	1	0	1	11	9	5222	0,3964	2,2416	0,3585	2,5857	107
2	softmax	64	16	none	n/100	32	50	0,001	0	0	1	0	1	12	9	5222	0,4435	2,0499	0,4030	2,3588	28
2	softmax	32	16	none	n/100	32	50	0,001	0	0	1	0	1	13	9	5222	0,4382	2,0284	0,4148	2,3039	25
2	softmax	64	32	none	n/100	32	50	0,001	0	0	1	0	1	14	12	9126	0,5488	1,6164	0,4644	2,0828	32
2	softmax	64	32/16	none	n/100	32	50	0,001	0	0	1	0	1	15	14	6502	0,4752	1,9108	0,4148	2,3326	31
2	softmax	64	32/16	none	n/100	32/64	50	0,001	0	0	1	0	1	16	12	11878	0,4886	1,7951	0,4267		xx
2	softmax	64	32/16	none	n/100	16/32	36	0,001	0	0	0/1	0	1	17	12	6646	0,3764	2,3469	0,3348	2,5420	32
3	softmax	64	32/16/8	none	n/100	128/64/32	50	0,001	0	0	1	0	1	18	12	17996	0,4494	1,9199	0,4022	2,2293	34
2 * 2	softmax	64	32/16	none	n/100	16/32	50	0,001	0	0	1	0	1	17	16	13142	0,5152	1,6146	0,3630	2,5115	33
3 * 2	softmax	64	32/16/8	none	n/100	32/64/128	50	0,001	0	0	1	0	1	18	17	32198/224	0,5479	1,4959	0,4052	2,5187	60
3 * 2	sigmoid	64	32/16/8	none	n/100	32/64/128	50	0,001	0	0	1	0	1	19	17	32198/224	0,5134	1,6010	0,3919	2,4017	67

# Parametrization

- Use overlapping areas (padding) around the input data (kernel)  
→ Allows use of more filter w/o running into sizing error disaster

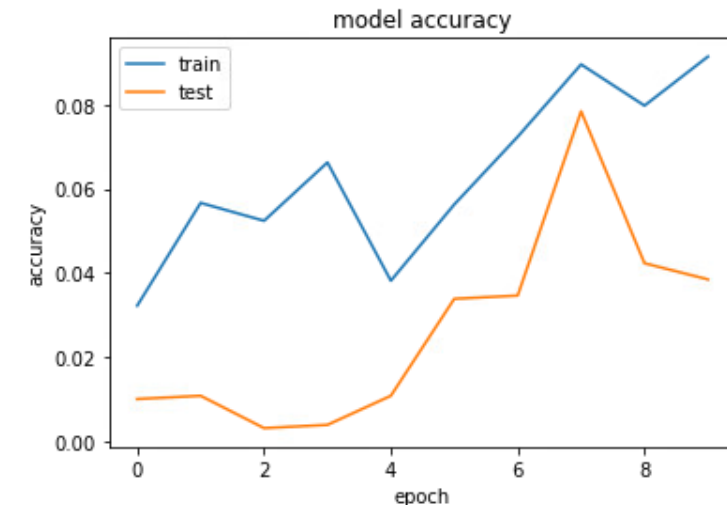
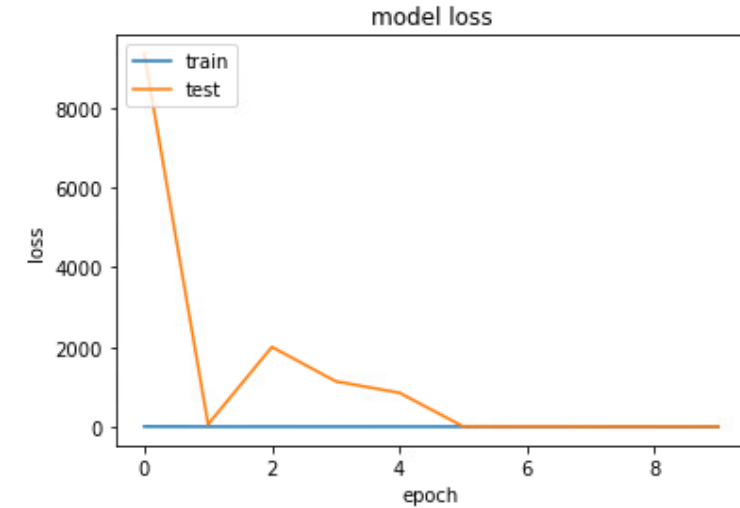


# Trials & Findings

- Lower learning rate = lower distance btw. train/test
- Changing target size only has no effect (waste of time)
- AveragePooling2D() >> Flatten()

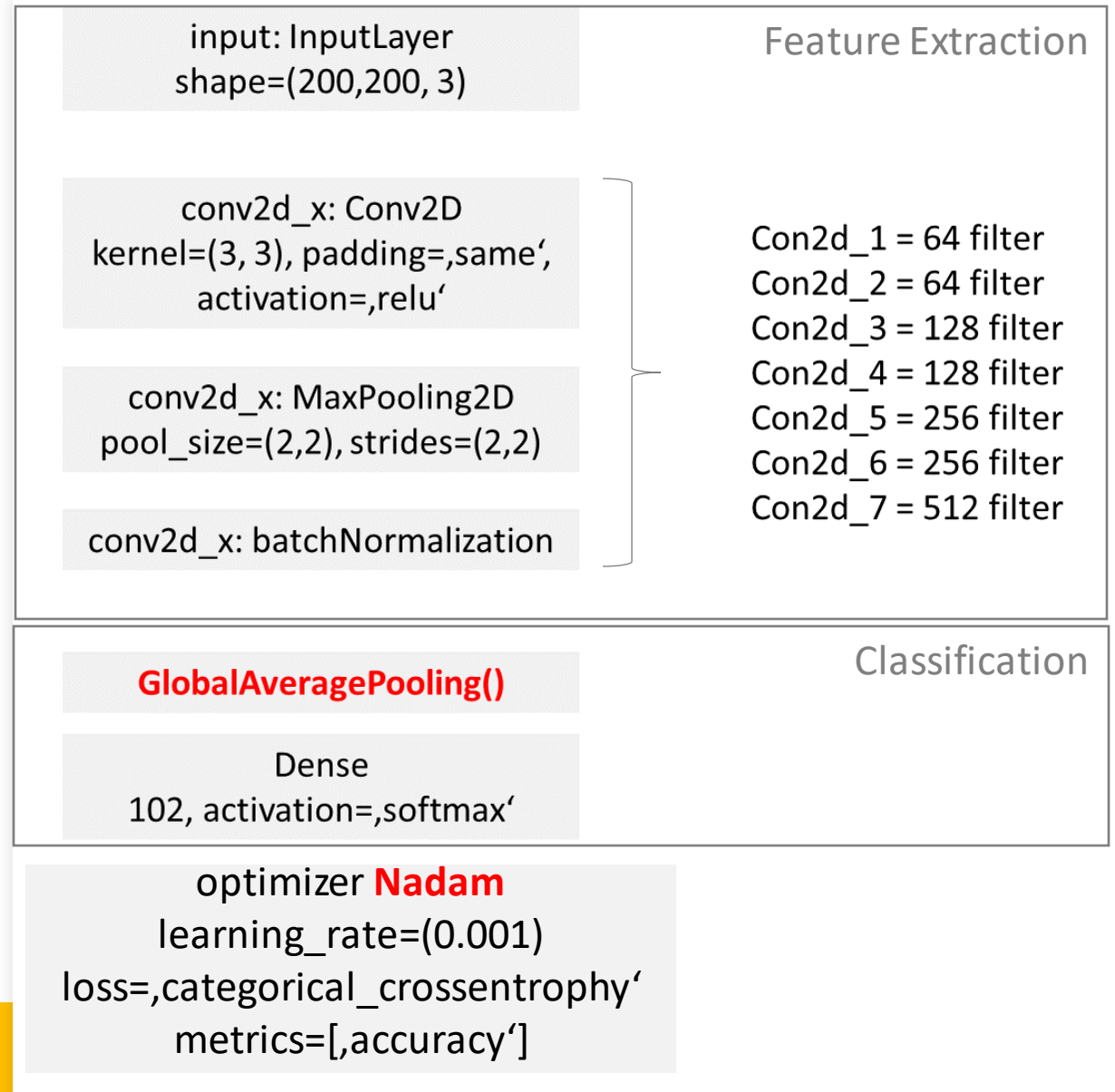
```
Epoch 1/10  
54/54 [=====] - 636s 12s/step - loss: 8.3678 - accuracy: 0.0322 - val_loss: 9351.1035 - val_accuracy: 0.0100  
Epoch 2/10  
54/54 [=====] - 605s 11s/step - loss: 4.8615 - accuracy: 0.0567 - val_loss: 61.7247 - val_accuracy: 0.0108  
Epoch 3/10  
54/54 [=====] - 591s 11s/step - loss: 4.8345 - accuracy: 0.0524 - val_loss: 2002.5267 - val_accuracy: 0.0031  
Epoch 4/10  
54/54 [=====] - 575s 11s/step - loss: 4.3010 - accuracy: 0.0663 - val_loss: 1140.8383 - val_accuracy: 0.0038  
Epoch 5/10  
54/54 [=====] - 590s 11s/step - loss: 4.7794 - accuracy: 0.0381 - val_loss: 852.8815 - val_accuracy: 0.0108  
Epoch 6/10  
54/54 [=====] - 575s 11s/step - loss: 4.3914 - accuracy: 0.0563 - val_loss: 8.5325 - val_accuracy: 0.0338  
Epoch 7/10  
54/54 [=====] - 591s 11s/step - loss: 4.2114 - accuracy: 0.0724 - val_loss: 5.2387 - val_accuracy: 0.0346  
Epoch 8/10  
54/54 [=====] - 592s 11s/step - loss: 4.0803 - accuracy: 0.0896 - val_loss: 4.8771 - val_accuracy: 0.0785  
Epoch 9/10  
54/54 [=====] - 579s 11s/step - loss: 4.1038 - accuracy: 0.0798 - val_loss: 4.6874 - val_accuracy: 0.0423  
Epoch 10/10  
54/54 [=====] - 577s 11s/step - loss: 4.0881 - accuracy: 0.0915 - val_loss: 4.4181 - val_accuracy: 0.0385
```

```
# Defining the Optimizer  
from tensorflow.keras import layers  
from tensorflow.keras.optimizers import Adam  
opt = Adam(learning_rate=0.1, beta_1=0.9, beta_2=0.999, epsilon=1e-07, amsgrad=False)  
model.compile(optimizer=opt, loss='categorical_crossentropy', metrics=['accuracy'])  
model.summary()
```



# Optimized Model

- ▽ 7 Conv2D Layer
- ▽ ReLU
- ▽ Filters (64/128/256/512)
- ▽ GlobalAveragePooling2D()
- ▽ Optimizers: Nadam





# Results & Conclusions

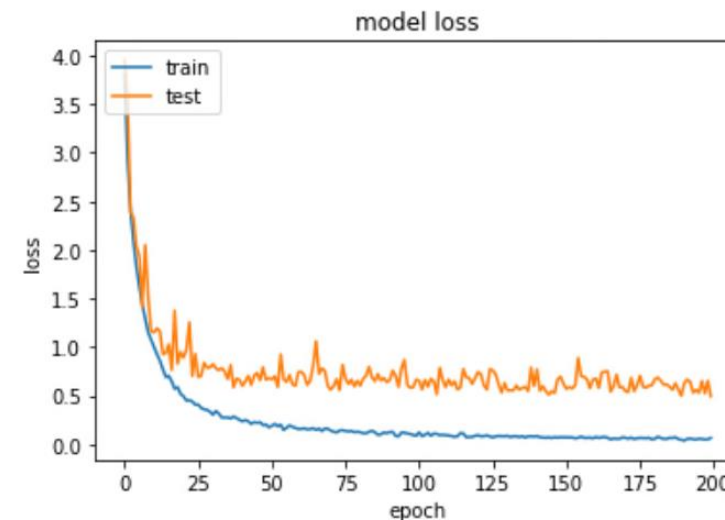
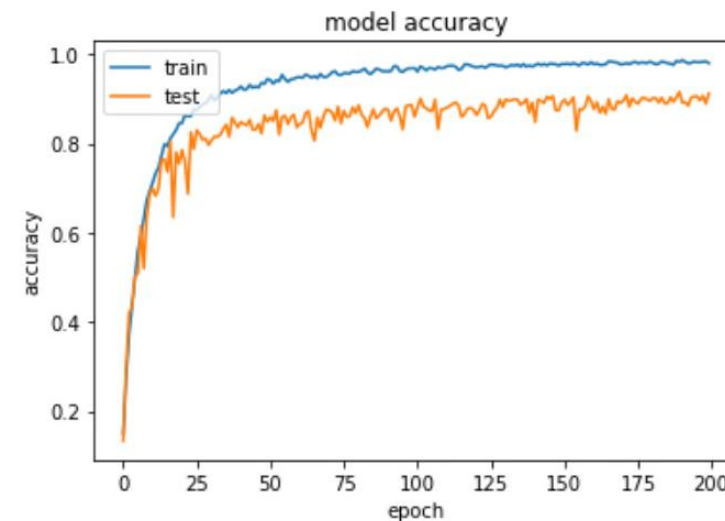


**accuracy**  
**98,03%**



**val\_accuracy**  
**91,19%**

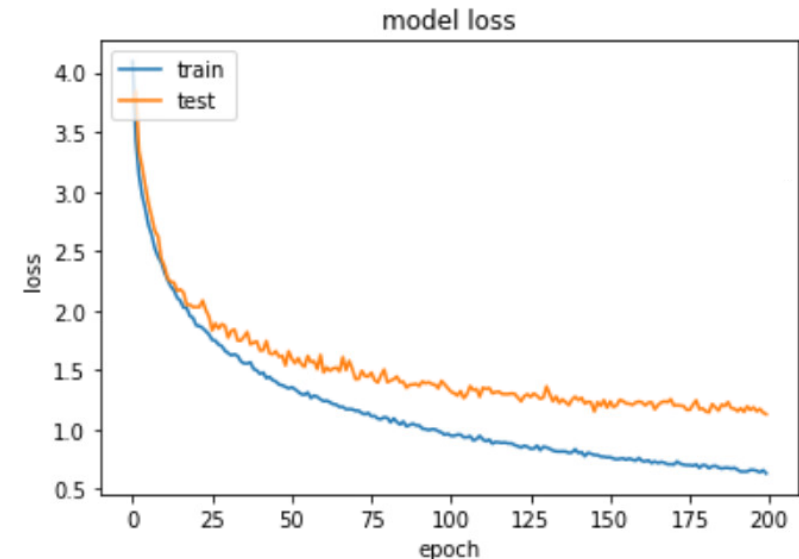
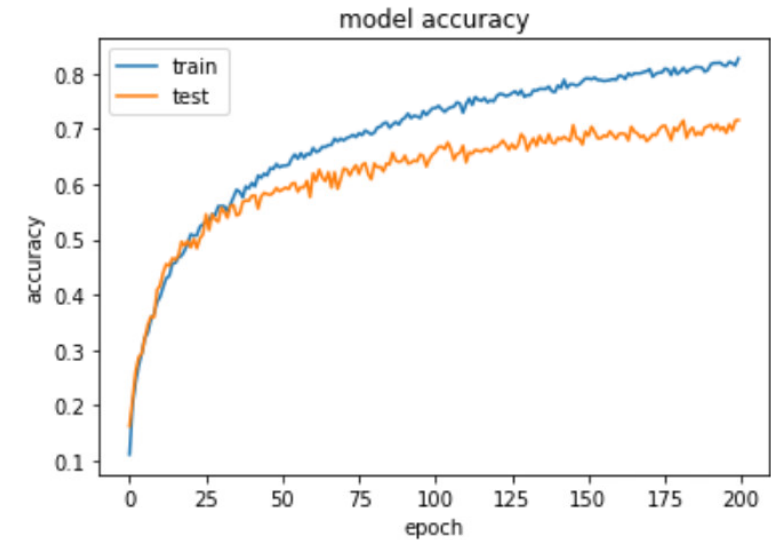
```
Epoch 195/200
422/422 [=====] - 494s 1s/step - loss: 0.0496 - accuracy: 0.9836 - val_loss: 0.5592 - val_accuracy: 0.9052
Epoch 196/200
422/422 [=====] - 490s 1s/step - loss: 0.0578 - accuracy: 0.9823 - val_loss: 0.5300 - val_accuracy: 0.9059
Epoch 197/200
422/422 [=====] - 484s 1s/step - loss: 0.0554 - accuracy: 0.9823 - val_loss: 0.6505 - val_accuracy: 0.8969
Epoch 198/200
422/422 [=====] - 487s 1s/step - loss: 0.0501 - accuracy: 0.9834 - val_loss: 0.5260 - val_accuracy: 0.9066
Epoch 199/200
422/422 [=====] - 488s 1s/step - loss: 0.0509 - accuracy: 0.9841 - val_loss: 0.6538 - val_accuracy: 0.8895
Epoch 200/200
422/422 [=====] - 488s 1s/step - loss: 0.0655 - accuracy: 0.9803 - val_loss: 0.4954 - val_accuracy: 0.9119
```



# Additional Discoveries

Adagrad is an optimizer with parameter-specific learning rates, which are adapted relative to how frequently a parameter gets updated during training. The more updates a parameter receives, the smaller the updates.

(<https://www.tensorflow.org/api>)



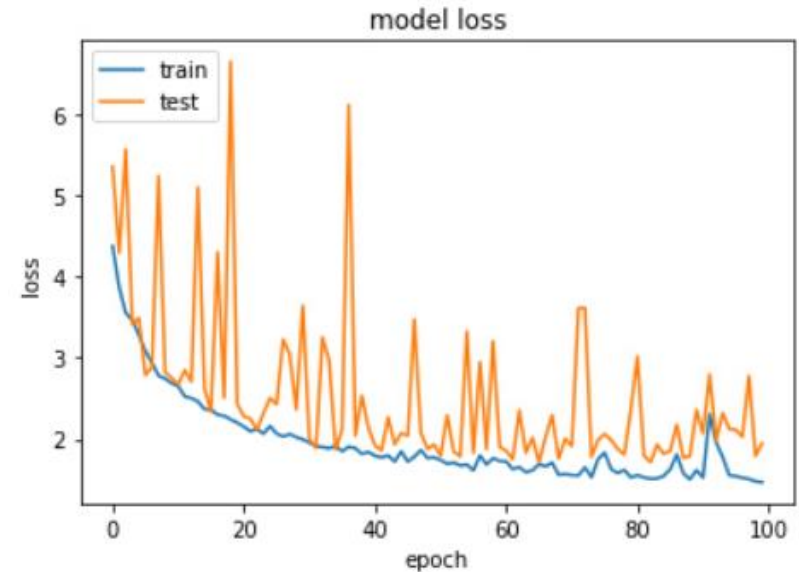
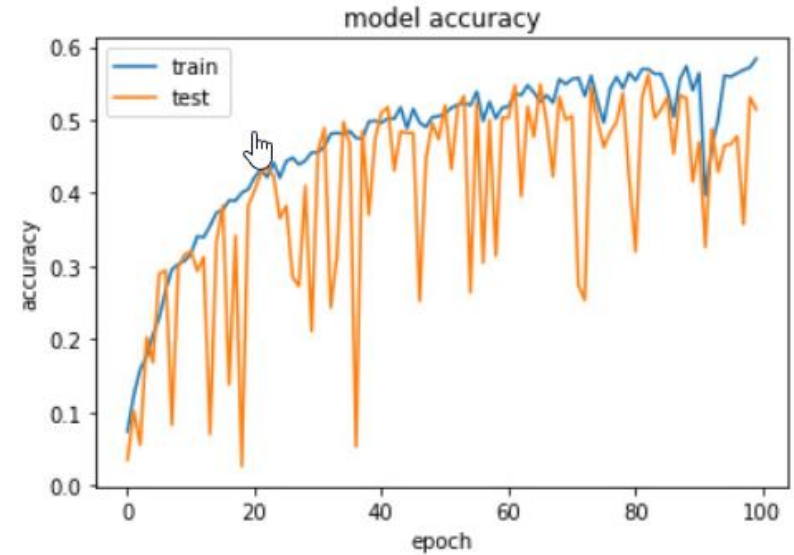


# Additional Discoveries

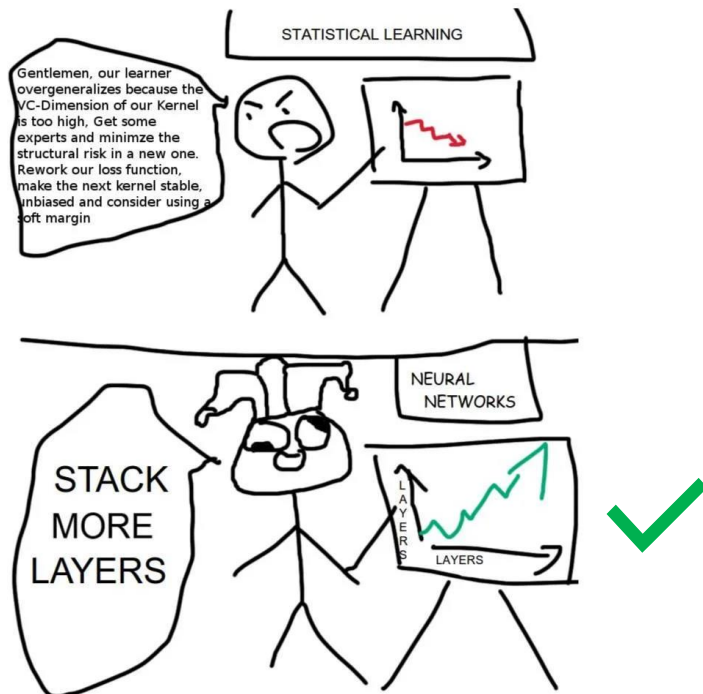
Activation function 'tanh'

## Disadvantage

Also facing the same issue of Vanishing Gradient Problem like a sigmoid function.



# Key Findings



Conv2D  
Layers



Filters



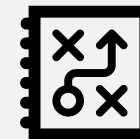
CPU  
Speed



Batch Size

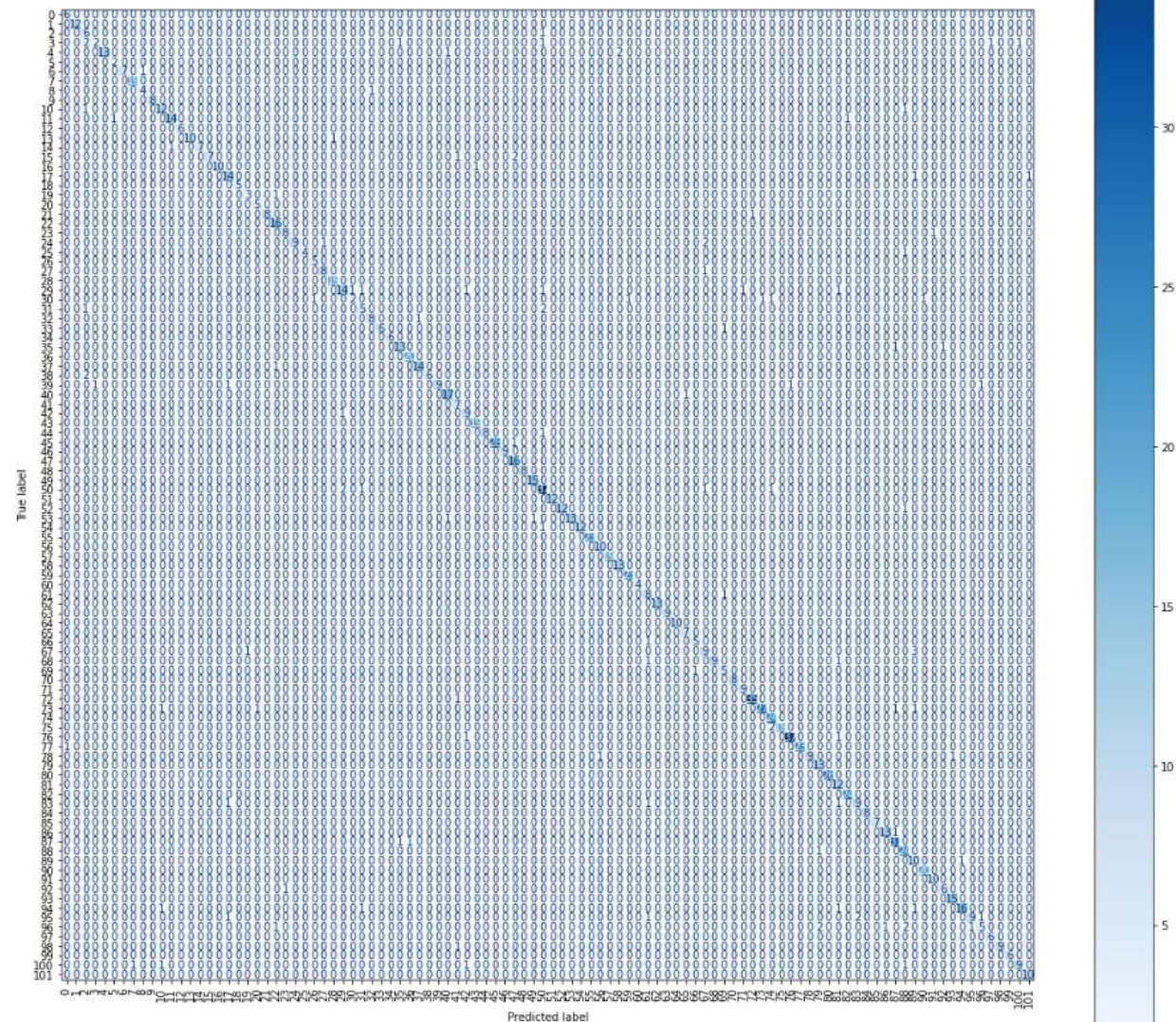
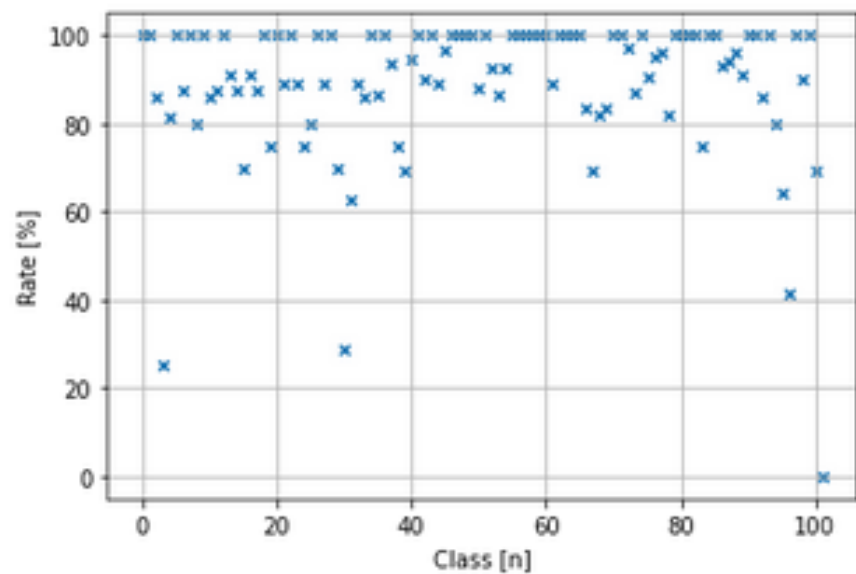


Dense Layer



Normali-  
zation

# Confusion Matrix



# Wrong predictions

## **'sweet pea'**

Class 3: Total=8, matched=2, mismatched=6, rate=25.0%

## **'carnation'**

Class 30: Total=7, matched=2, mismatched=5,  
rate=28.57142857142857%

## **'garden phlox'**

Class 31: Total=8, matched=5, mismatched=3, rate=62.5%

## **'lenten rose'**

Class 39: Total=13, matched=9, mismatched=4,  
rate=69.23076923076923%

## **'camellia'**

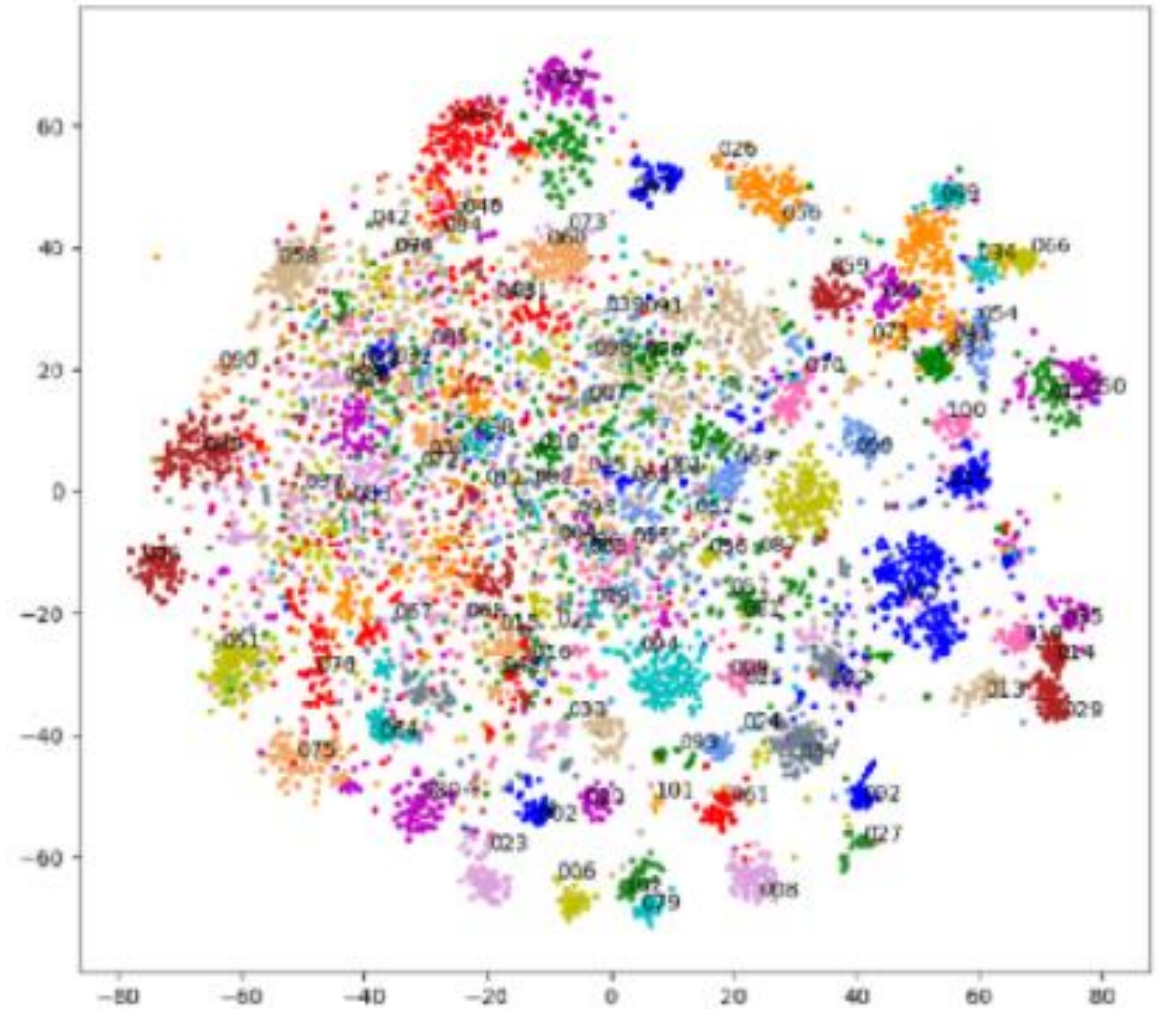
Class 95: Total=14, matched=9, mismatched=5,  
rate=64.28571428571429%

## **'mallow'**

Class 96: Total=12, matched=5, mismatched=7,  
rate=41.66666666666667%



# Overview of classification



b) Oxford 102 Flowers Dataset

# Literature

- [https://www.tensorflow.org/api\\_docs/python/tf/keras/optimizers/Adagrad#:~:text=Adagrad%20is%20an%20optimizer%20with,receives%2C%20the%20smaller%20the%20updates.](https://www.tensorflow.org/api_docs/python/tf/keras/optimizers/Adagrad#:~:text=Adagrad%20is%20an%20optimizer%20with,receives%2C%20the%20smaller%20the%20updates.)
- [https://colab.research.google.com/github/kirankamat/mgm/FlowerImageClassifier/blob/master/FlowerspeciesClassifier.ipynb#scrollTo=suYIKhT3v\\_ZH](https://colab.research.google.com/github/kirankamat/mgm/FlowerImageClassifier/blob/master/FlowerspeciesClassifier.ipynb#scrollTo=suYIKhT3v_ZH)
- <https://www.aitude.com/comparison-of-sigmoid-tanh-and-relu-activation-functions/#:~:text=ReLU%20is%20the%20best%20and,compare%20to%20other%20activation%20function.>
- <https://ietresearch.onlinelibrary.wiley.com/doi/full/10.1049/iet-cvi.2017.0155>
- <https://www.technologiesinindustry4.com/2021/08/plantnet-plant-identification.html>