

Picture classification project-Team 02

Members:

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Choice of classification technique: Convolutional Neural Networks

Computer Vision and Deep Learning project -Presentation01



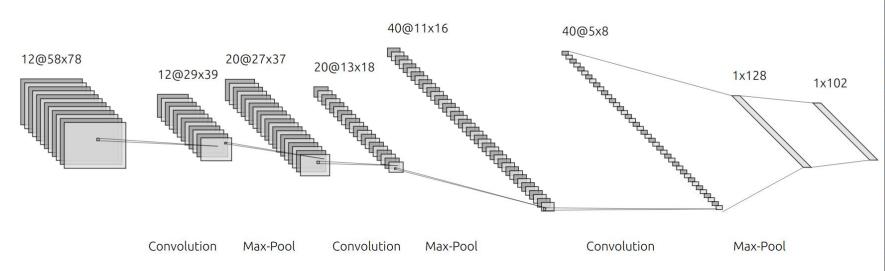
2. Neural Network

The simple network increments convolutions with each layer followed by a

max-pooling layer to control the number of trainable parameters.

30% Drop out after each convolution layer to control overfitting.

Number of trainable parameters = 227,842



Model: "sequential"			
Layer (type)	Output	Shape	Param #
conv2d (Conv2D)	(None,	58, 78, 12)	336
max_pooling2d (MaxPooling2D)	(None,	29, 39, 12)	Θ
dropout (Dropout)	(None,	29, 39, 12)	0
conv2d_1 (Conv2D)	(None,	27, 37, 20)	2180
max_pooling2d_1 (MaxPooling2	(None,	13, 18, 20)	0
dropout_1 (Dropout)	(None,	13, 18, 20)	0
conv2d_2 (Conv2D)	(None,	11, 16, 40)	7240
max_pooling2d_2 (MaxPooling2	(None,	5, 8, 40)	0
dropout_2 (Dropout)	(None,	5, 8, 40)	0
flatten (Flatten)	(None,	1600)	0
dense (Dense)	(None,	128)	204928
dense_1 (Dense)	(None,	102)	13158
Total params: 227,842 Trainable params: 227,842 Non-trainable params: 0			

3.Parameters

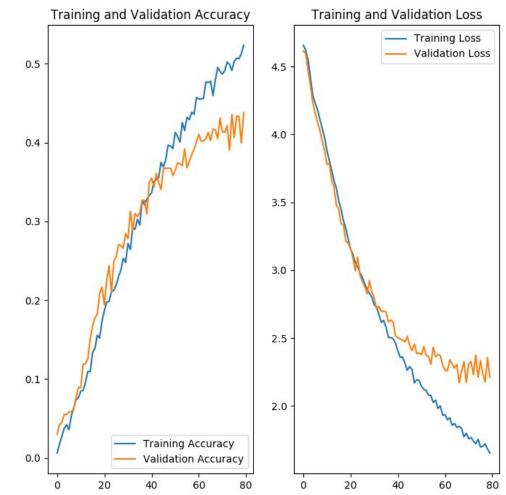
3.1- Layers -

- Network with too many convolution layers will require more processing time, for it has to train large number of parameters. Too few layers do not generate effective features.
- parameters like stride, kernel size, max pool kernel size etc will impact processing time and performance.
- 3.2 Drop out Being solution to over fitting, Drop out parameter is to be set precise enough to ensure that major learning of neurons is not lost. At the same time initial layers should have less drop out.
- 3.3 Epoch If the increment of epoch does not contribute to improvement of accuracy the epoch count should be reduced. This will save computation cost. We chose to run for 80 epochs based on accuracy and loss data of training and validation data sets.



Accuracy and Loss plots for Training and Validation datasets

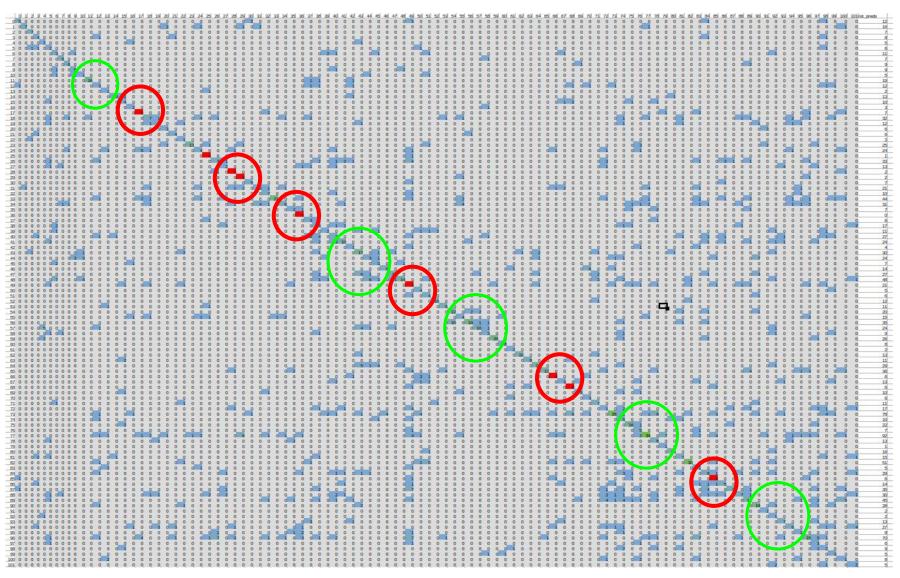
- Training:
 - Accuracy 50.56%
 - o Loss- 1.732
- Validation:
 - Accuracy 41.3%
 - o Loss- 2.18
- Testing:
 - o Accuracy 40%
 - o Loss- 2.43



4. Results

4.1 Confusion Matrix:

- Areas highlighted in red circles show classes with zero 'True Positive' instances.
- Green highlighted classes had more than 10 'True Positives' instances (correct - predictions)





Bildverarbeitung Bildverstehen

4.2 Performance stats:

- Classification report from sklearn library shows the following
 - accuracy = 40.42%
 - Precision = 42.7%
 - Recall = 40.42%
 - o F1 score = 37.7%

	orecision	recall f	1-score		precision r	ecall	1-score		precision	recall	f1-score
0	00.417	00.625	00.500	36		00.000	00.000	72		00.050	00.054
1	00.438	00.778	00.560	37	00.500	00.214	00.300	73	00.359	00.718	00.479
2	01.000	00.700	00.824	38	00.235	00.154	00.186	74	00.500	00.143	00.222
3	00.500	00.333	00.400	39	00.182	00.167	00.174	75	00.727	00.667	00.696
4	00.400	00.200	00.267	40	00.259	00.269	00.264	76	The second secon	00.227	00.345
5	00.333	00.111	00.167	41	00.417	00.526	00.465	77	00.424	00.765	00.545
6	00.273	00.167	00.207	42	00.250	00.125	00.167	78		00.286	00.390
7	00.857	00.600	00.706	43	00.567	00.425	00.486			00.111	00.200
8	00.667	00.600	00.632	44	00.125	00.214	00.158	100000000000000000000000000000000000000		00.824	00.848
9	00.556	00.500	00.526	45	00.429	00.200	00.273		The second secon	00.333	00.389
10	00.200	00.111	00.143	46	00.429	00.600	00.500			00.882	00.706
11	00.842	00.941	00.889	47	00.370	00.769	00.500		The state of the s	00.043	00.071
12	00.250	00.176	00.207	48	00.292	00.737	00.418			00.296	00.286
13	00.500	00.100	00.167	49	00.000	00.000	00.000	85		00.000	00.000
14	00.769	00.833	00.800	50	00.800	00.235	00.364			00.385	00.370
15	00.400	00.333	00.364	51	00.667	00.211	00.320	1000			00.383
16	00.667	00.250	00.364	52	00.833	00.769	00.800			00.538	00.326
17	00.000	00.000	00.000	53	00.818	00.600	00.692			00.419	00.342
18	00.219	00.368	00.275	54	00.600	00.545	00.571	90		00.514	00.585
19	00.250	00.333	00.286	55	00.267	00.286	00.276			00.200	00.333
20	00.500	00.333	00.400	56	00.543	00.826	00.655		The second section of the second seco	00.059	00.105
21	00.667	00.444	00.533	57 58	00.417	00.714	00.526			00.438	00.483
22	00.500 00.520	00.125	00.200 00.667	59	00.333	00.333	00.333		1 10 10 10 10 10 10 10 10 10 10 10 10 10	00.429	00.293 00.222
23 24	00.520	00.250	00.867	60	00.769	00.909	00.833			00.200 00.455	00.222
25	00.000	00.230	00.200	61	01.000	00.800	00.308			00.455	00.291
26	00.212	00.412	00.280	62	00.769	00.102	00.833			00.115	00.143
27	00.212	00.412	00.260	63	00.703	00.727	00.727	99		00.103	00.316
28	00.000	00.000	00.000	64	00.517	00.714	00.600			00.059	00.080
29	00.000	00.000	00.000	65	00.333	00.923	00.490				00.222
30	00.714	00.625	00.667	66	00.000	00.000	00.000		00.100	00.10	00.222
31	00.143	00.333	00.200	67	00.231	00.273		accuracy	0.4042806	0.404281	0.40428
32	00.700	00.467	00.560	68	00.000	00.000		macro avg	0.4340789		
33	00.477	00.955	00.636	69	00.500	00.625		weighted avg			0.37717
34	00.194	00.500	00.279	70	00.500	00.231	00.316	the state of the s			
35	00.286	00.222	00.250	71	00.636	00.438	00.519				



Inferences from results:

- Many of the classes with least performance are the classes with least number of samples. The classes with zero performance stats were 18, 26, 28, 29, 36, 49, 66, 68, 85.
- Most of the wrong predictions are inexplicable. Number of samples, flower's appearance, inter-class similarity etc, are the factors from dataset.
- The CNN architecture, convolutions, generated feature vectors etc can be equally responsible, which can all be improved.

class 18: dissimilar flowers



class 67: dissimilar flowers & smaller dataset



class 29 & 27: mispredictions due to similar features



5. Problem Faced

- **Processing time**: There are around 15 hyper parameters which should be tweaked when a desired result is not evident. While the network took around 1-2 hours ,at least, per configuration of these hyper parameters, this makes it important to trial with extreme caution.
- **overfitting**: There is a lot of room left for data augmentation to increase the samples, so that much deeper networks can learn without overfitting.



6.Self Assessment

6.1 QUALITY OF RESULTS:

1. More performance metrics could be extracted to better assess the problems and misclassifications.

6.2 METHODS APPLIED

- CNN has better performance in image classification.
- In CNN, networks with numerous layers like VGG16 or Mobilenet have greater performance only when the sample size is high because these networks have high computation power and parameters.
- Hence a small neural network is good enough to classify the given set.



Questions?