FLOWER RECOGNITION

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Data Collection:

- Bougainvillea
- Daffodil
- Dahlia
- Foxglove
- Hibiscus
- Hydrangea
- Orchid
- Rose
- Sunflower
- Tulip



Google Images: Web scraping (Selenium and Chrome driver).

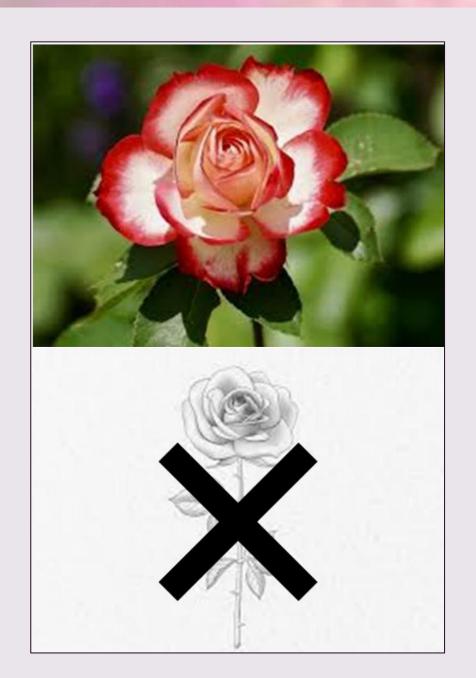


Flickr: API (good API call limit 3600 queries per hour), used flickrapi python package.



Pixabay: API (100 requests per minute limit)

Data Cleaning





Data preprocessing

- Labeling
- Saving as .npy
- Resizing
- Rescaling

```
img folder
                                        img label
0 ../Combined flowers/bougainvillea bougainvillea
        ../Combined flowers/daffodil
                                           daffodil
          ../Combined flowers/dahlia
                                            dahlia
2
       ../Combined flowers/foxglove
                                          foxglove
        ../Combined flowers/hibiscus
                                           hibiscus
      ../Combined flowers/hydrangea
                                        hydrangea
         ../Combined flowers/orchid
                                            orchid
           ../Combined flowers/rose
                                              rose
      ../Combined flowers/sunflower
                                         sunflower
           ../Combined flowers/tulip
                                             tulip
```

```
def make_train_data(flower_type,DIR):
    for img in tqdm(os.listdir(DIR)):
        label = assign_label(img,flower_type)
        path = os.path.join(DIR,img)
        img = cv2.imread(path, cv2.IMREAD_COLOR)
        img = cv2.resize(img, (256, 256))

        X.append(np.array(img))
        Z.append(str(label))
```

```
X = np.load("dataset/data-256.npy")
labels = np.load("dataset/label-256.npy")

from sklearn.preprocessing import LabelEncoder
from keras.utils import to_categorical

labelEncoder = LabelEncoder()
y = labelEncoder.fit_transform(labels)
y = to_categorical(y, 10)
```

Model Architecture: Convolutional Neural Network

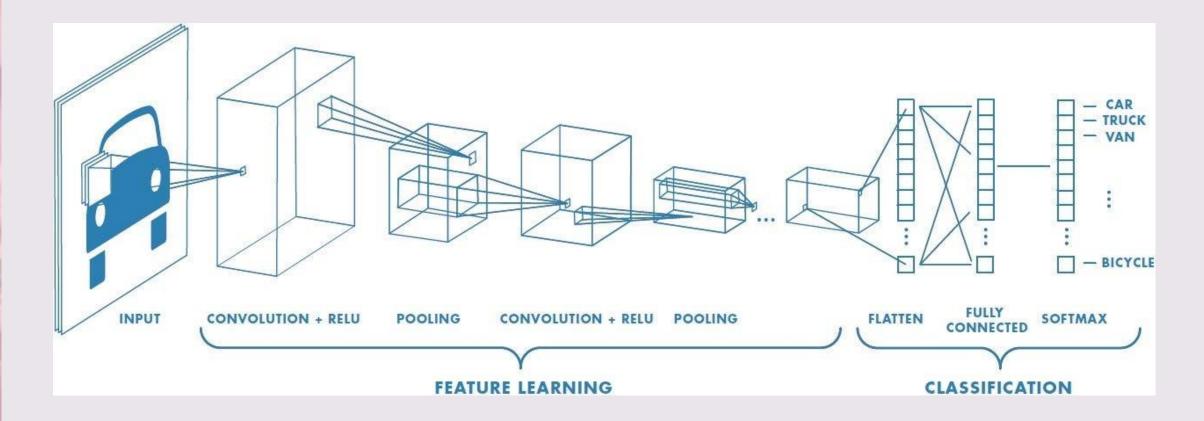


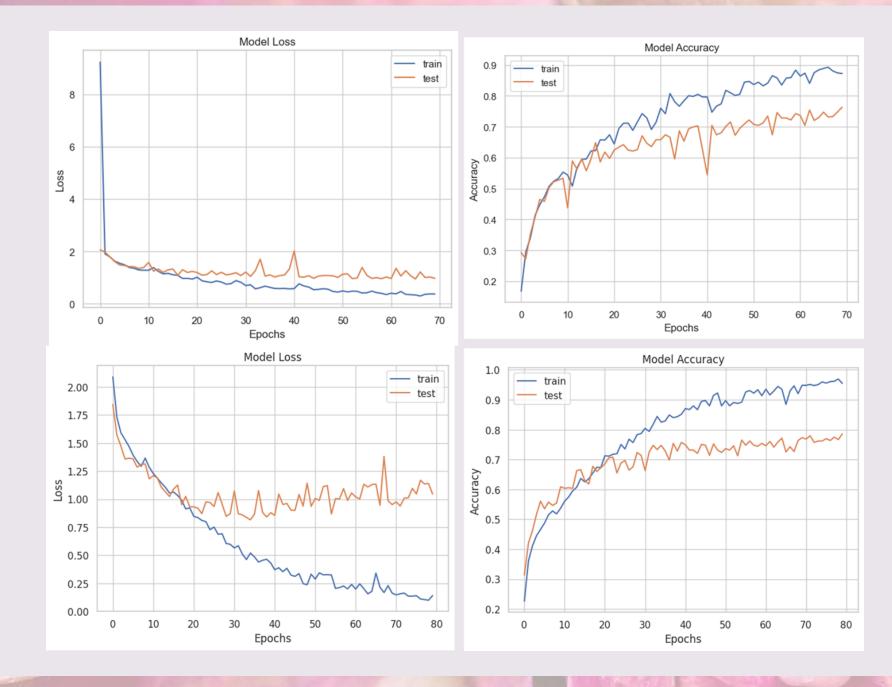
Image source: https://www.interviewbit.com/blog/cnn-architecture/

Model Comparison

Batch Size	Epoch	Parameters	Accuracy
32	50	9,599,882	60
64	70	4,146,314	74
64	70	3,393,770	76
64	80	4,146,314	79

Accuracy: 76

Accuracy: 79



Accuracy: 76

Accuracy: 79

					(Confusio	n Matrix	(
В	ougainvillea	56	0	2	9	2	4	1	6	1	4		precision	recall	f1-score	support
	Daffodil	1	46	1	0	2	0	4	2	5	4					
	Darroun	1	40	1	U	2	U	4	2	,	4	0	0.66	0.67	0.67	83
	Dahlia	4	0	41	1	3	3	3	2	0	0	1	0.71	0.92	0.80	50
	Foxglove	2	1	0	69	0	2	2	0	0	0	2	0.72	0.84	0.77	49
	Hibiscus	4	2	2	0	52	0	2	2	0	1	3	0.91	0.79	0.85	87
Actual			_						_			4	0.80	0.78	0.79	67
⋖	Hydrangea	3	0	1	3	0	34	3	0	0	2	5	0.74	0.72	0.73	47
	Orchid	6	0	0	2	4	2	42	0	1	2	6	0.71	0.67	0.69	63
	Rose	5	0	1	2	3	1	3	42	0	5	7	0.68	0.72	0.70	58
												8	1.00	0.88	0.93	64
	Sunflower	0	0	0	0	0	0	0	0	56	0	9	0.73	0.69	0.71	58
	Tulip	2	1	1	1	1	1	3	4	1	40				0.76	626
		lea	Ξ	lia	e v	sn	ea	pid	Rose	/er	Tulip	accuracy	0.76	0.77	0.76	626
		livuie	Daffodil	Dahlia	Foxglove	Hibiscus	Hydrangea	Orchid	S.	Sunflower	F	macro avg	0.76	0.77	0.76	626
		Bougainvillea			L.	_	НУ			Su		weighted avg	0.77	0.76	0.76	626
						Predi	ictod									
					,	CUIIIUSIU										
E	Bougainvillea	68	0	1	1			0	1	0	1		precision	recall	f1-score	support
E	Bougainvillea Daffodil	68	0	1		CUIIIUSIU	ווושויו ווע		1	0	1		precision	recall	f1-score	support
E	Daffodil	0	39	1	0	1	1 0	0	0	20	3	0	precision 0.92	recall 0.75	f1-score 0.82	support 91
E	-				1	1	лі таці. 1	0				Ø 1	•			
E	Daffodil	0	39	1	0	1	1 0	0	0	20	3	1 2	0.92 0.59 0.93	0.75 0.89 0.66	0.82 0.71 0.77	91 44 85
	Daffodil Dahlia	0	39	1 56	1 0 0	1 3 0	1 0	0 0 1	0	20	3	1	0.92 0.59 0.93 0.88	0.75 0.89 0.66 0.98	0.82 0.71 0.77 0.93	91 44 85 58
	Daffodil Dahlia Foxglove Hibiscus	0 0 1 3	0 0	1 56 0 2	1 0 0 57	1 3 0 0	1 0 1 3	0 0 1 1 2	2 2	20 0 0	3 0 1 0	1 2 3 4	0.92 0.59 0.93 0.88 0.85	0.75 0.89 0.66 0.98 0.84	0.82 0.71 0.77 0.93 0.85	91 44 85 58 62
Actual	Daffodil Dahlia Foxglove	0 0 1	39 0 0	1 56 0	0 0 57	1 3 0	1 0 1	0 0 1 1	2	0	3 0 1	1 2 3 4 5	0.92 0.59 0.93 0.88 0.85 0.66	0.75 0.89 0.66 0.98 0.84 0.80	0.82 0.71 0.77 0.93 0.85 0.73	91 44 85 58 62 41
	Daffodil Dahlia Foxglove Hibiscus	0 0 1 3	0 0	1 56 0 2	1 0 0 57	1 3 0 0	1 0 1 3	0 0 1 1 2	2 2	20 0 0	3 0 1 0	1 2 3 4 5	0.92 0.59 0.93 0.88 0.85 0.66	0.75 0.89 0.66 0.98 0.84 0.80	0.82 0.71 0.77 0.93 0.85 0.73	91 44 85 58 62 41 56
	Daffodil Dahlia Foxglove Hibiscus Hydrangea	0 0 1 3 2	39 0 0 0	1 56 0 2 6	1 0 0 57 0	1 3 0 0 52 0	1 0 1 3 0 33	0 0 1 1 2	0 2 2 2	20 0 0 0	3 0 1 0	1 2 3 4 5 6 7	0.92 0.59 0.93 0.88 0.85 0.66 0.70 0.47	0.75 0.89 0.66 0.98 0.84 0.80 0.80	0.82 0.71 0.77 0.93 0.85 0.73 0.75	91 44 85 58 62 41 56
	Daffodil Dahlia Foxglove Hibiscus Hydrangea Orchid Rose	0 0 1 3 2 4	39 0 0 0	1 56 0 2 6 9	1 0 0 57 0 0	1 3 0 0 52 0 1 3	1 0 1 3 0 33 3 0	0 0 1 1 2 5	0 2 2 2 0 1	20 0 0 0 1 0	3 0 1 0 2 0	1 2 3 4 5 6 7 8	0.92 0.59 0.93 0.88 0.85 0.66 0.70 0.47 0.97	0.75 0.89 0.66 0.98 0.84 0.80 0.70 0.75	0.82 0.71 0.77 0.93 0.85 0.73 0.75 0.57	91 44 85 58 62 41 56 37
	Daffodil Dahlia Foxglove Hibiscus Hydrangea Orchid Rose Sunflower	0 0 1 3 2 4 10	39 0 0 0	1 56 0 2 6 9 9 1	1 0 0 57 0 0	1 3 0 0 52 0 1 1 3 0 0	1 0 1 3 3 3 3 0 0 0	0 0 1 1 2 5 45 2	0 2 2 2 0 1 26	20 0 0 0 0 1 0 1	3 0 1 0 2 0 3	1 2 3 4 5 6 7	0.92 0.59 0.93 0.88 0.85 0.66 0.70 0.47	0.75 0.89 0.66 0.98 0.84 0.80 0.80	0.82 0.71 0.77 0.93 0.85 0.73 0.75	91 44 85 58 62 41 56 37
	Daffodil Dahlia Foxglove Hibiscus Hydrangea Orchid Rose	0 0 1 3 2 4	39 0 0 0	1 56 0 2 6 9	1 0 0 57 0 0	1 3 0 0 52 0 1 3	1 0 1 3 0 33 3 0	0 0 1 1 2 5	0 2 2 2 0 1	20 0 0 0 1 0	3 0 1 0 2 0	1 2 3 4 5 6 7 8 9	0.92 0.59 0.93 0.88 0.85 0.66 0.70 0.47 0.97	0.75 0.89 0.66 0.98 0.84 0.80 0.70 0.75	0.82 0.71 0.77 0.93 0.85 0.73 0.75 0.57 0.84	91 44 85 58 62 41 56 37 87
	Daffodil Dahlia Foxglove Hibiscus Hydrangea Orchid Rose Sunflower	0 0 1 3 2 4 10 0	39 0 0 0 1 1 1 1	1 56 0 2 6 9 9	1 0 0 57 0 0 0 0 0 0 0 0	1 3 0 0 52 0 1 3 0 0 2	1 0 1 3 3 3 3 0 0 0 0	0 0 1 1 2 5 45 2 0	0 2 2 2 0 1 26 0 3	20 0 0 0 1 0 1 65	3 0 1 0 2 0 3 0	1 2 3 4 5 6 7 8 9	0.92 0.59 0.93 0.88 0.85 0.66 0.70 0.47 0.97	0.75 0.89 0.66 0.98 0.84 0.80 0.70 0.75	0.82 0.71 0.77 0.93 0.85 0.73 0.75 0.57 0.84 0.85	91 44 85 58 62 41 56 37 87 65
	Daffodil Dahlia Foxglove Hibiscus Hydrangea Orchid Rose Sunflower	0 0 1 3 2 4 10 0	39 0 0 0 1 1	1 56 0 2 6 9 9 1	1 0 57 0 0	1 3 0 0 52 0 1 1 3 0 0	1 0 1 3 3 3 3 0 0 0 0	0 0 1 1 2 5 45 2	0 2 2 2 0 1 26	20 0 0 0 1 0 1 65	3 0 1 0 2 0 3	1 2 3 4 5 6 7 8 9 accuracy macro avg	0.92 0.59 0.93 0.88 0.85 0.66 0.70 0.47 0.97 0.86	0.75 0.89 0.66 0.98 0.84 0.80 0.70 0.75 0.85	0.82 0.71 0.77 0.93 0.85 0.73 0.75 0.57 0.84 0.85	91 44 85 58 62 41 56 37 87 65
	Daffodil Dahlia Foxglove Hibiscus Hydrangea Orchid Rose Sunflower	0 0 1 3 2 4 10	39 0 0 0 1 1 1 1	1 56 0 2 6 9 9	1 0 0 57 0 0 0 0 0 0 0 0	1 3 0 0 52 0 1 3 0 0 2 SNDSiQIH	1 0 1 3 3 3 3 0 0 0	0 0 1 1 2 5 45 2 0	0 2 2 2 0 1 26 0 3	20 0 0 0 0 1 0 1	3 0 1 0 2 0 3 0	1 2 3 4 5 6 7 8 9	0.92 0.59 0.93 0.88 0.85 0.66 0.70 0.47 0.97	0.75 0.89 0.66 0.98 0.84 0.80 0.70 0.75	0.82 0.71 0.77 0.93 0.85 0.73 0.75 0.57 0.84 0.85	91 44 85 58 62 41 56 37 87 65

Actual: Rose Predicted: Orchid



Actual : Dahlia Predicted : Tulip



Actual : Rose Predicted : Rose



Actual: Hydrangea Predicted: Hydrangea



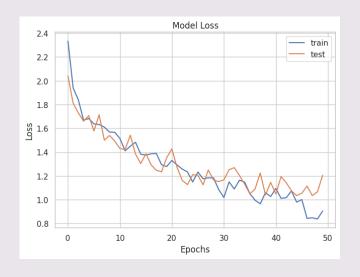
Accuracy: 76

Layer (type)	Output Shape	Param #
	(None, 256, 256, 32)	2432
max_pooling2d (MaxPooling2D)	(None, 128, 128, 32)	0
conv2d_1 (Conv2D)	(None, 128, 128, 64)	18496
<pre>max_pooling2d_1 (MaxPooling 2D)</pre>	(None, 64, 64, 64)	0
conv2d_2 (Conv2D)	(None, 64, 64, 96)	55392
max_pooling2d_2 (MaxPooling 2D)	(None, 32, 32, 96)	0
conv2d_3 (Conv2D)	(None, 32, 32, 96)	83040
max_pooling2d_3 (MaxPooling 2D)	(None, 16, 16, 96)	0
conv2d_4 (Conv2D)	(None, 16, 16, 96)	83040
max_pooling2d_4 (MaxPooling 2D)	(None, 8, 8, 96)	0
flatten (Flatten)	(None, 6144)	0
dense (Dense)	(None, 512)	3146240
dense_1 (Dense)	(None, 10)	5130
otal params: 3,393,770 Trainable params: 3,393,770 Trainable params: 0		======

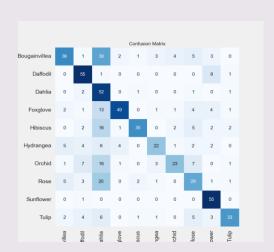
Accuracy: 79

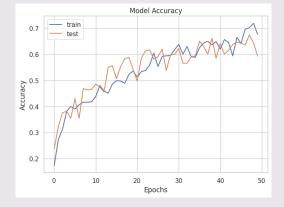
Layer (type)	Output Shape	Param #
conv2d_10 (Conv2D)		
<pre>max_pooling2d_10 (MaxPoolin g2D)</pre>	(None, 75, 75, 32)	0
conv2d_11 (Conv2D)	(None, 75, 75, 64)	18496
max_pooling2d_11 (MaxPoolin g2D)	(None, 37, 37, 64)	0
conv2d_12 (Conv2D)	(None, 37, 37, 96)	55392
max_pooling2d_12 (MaxPoolin g2D)	(None, 18, 18, 96)	0
conv2d_13 (Conv2D)	(None, 18, 18, 96)	83040
max_pooling2d_13 (MaxPoolin g2D)	(None, 9, 9, 96)	0
flatten_2 (Flatten)	(None, 7776)	0
dense_4 (Dense)	(None, 512)	3981824
activation (Activation)	(None, 512)	0
dense_5 (Dense)	(None, 10)	5130

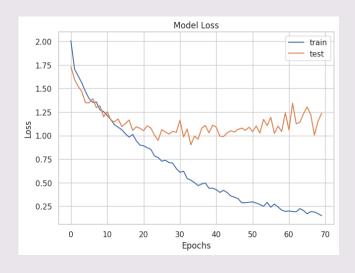
Total params: 4,146,314
Trainable params: 4,146,314
Non-trainable params: 0



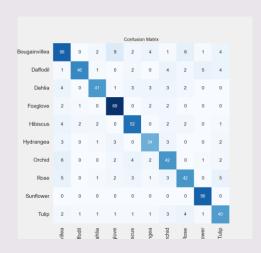
	precision	recall	f1-score	support
0	0.42	0.71	0.53	51
1	0.85	0.69	0.76	80
2	0.91	0.33	0.48	160
3	0.64	0.86	0.74	57
4	0.54	0.88	0.67	40
5	0.48	0.71	0.57	31
6	0.39	0.74	0.51	31
7	0.47	0.50	0.48	58
8	0.98	0.71	0.82	78
9	0.60	0.82	0.69	40
accuracy			0.62	626
macro avg	0.63	0.69	0.63	626
weighted avg	0.72	0.62	0.62	626

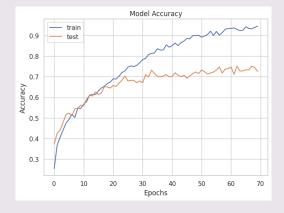


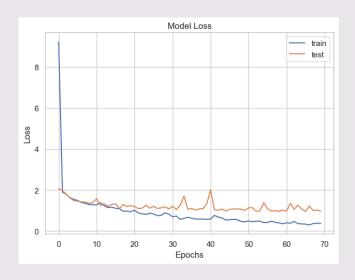




	precision	recall	f1-score	support
0	0.68	0.76	0.72	76
1	0.63	0.89	0.74	46
2	0.96	0.34	0.51	160
3	0.78	0.91	0.84	65
4	0.69	0.83	0.76	54
5	0.50	0.85	0.63	27
6	0.41	0.80	0.54	30
7	0.60	0.71	0.65	52
8	0.95	0.79	0.86	67
9	0.82	0.92	0.87	49
accuracy			0.70	626
macro avg	0.70	0.78	0.71	626
veighted avg	0.77	0.70	0.69	626

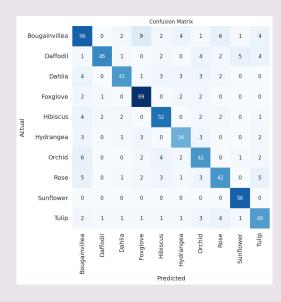


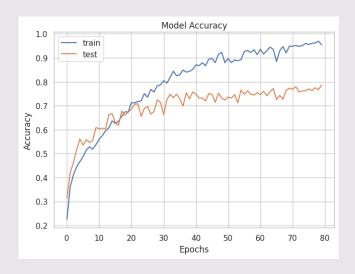




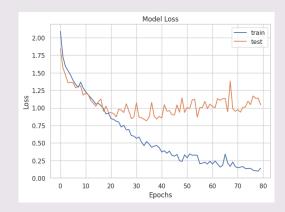
	precision	recall	f1-score	support
0	0.66	0.67	0.67	83
1	0.71	0.92	0.80	50
2	0.72	0.84	0.77	49
3	0.91	0.79	0.85	87
4	0.80	0.78	0.79	67
5	0.74	0.72	0.73	47
6	0.71	0.67	0.69	63
7	0.68	0.72	0.70	58
8	1.00	0.88	0.93	64
9	0.73	0.69	0.71	58
accuracy			0.76	626
macro avg	0.76	0.77	0.76	626
weighted avg	0.77	0.76	0.76	626

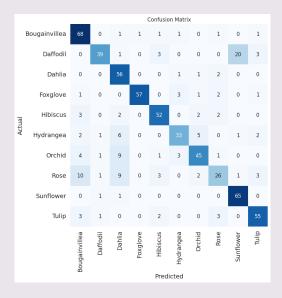


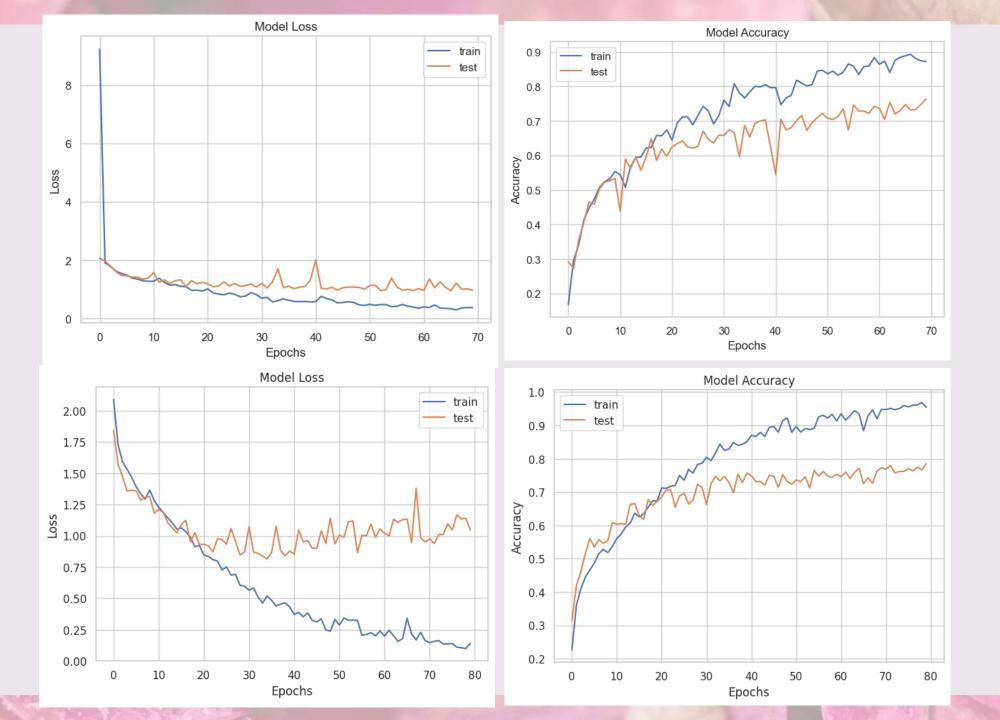




	precision	recall	f1-score	support	
0	0.92	0.75	0.82	91	
1	0.59	0.89	0.71	44	
2	0.93	0.66	0.77	85	
3	0.88	0.98	0.93	58	
4	0.85	0.84	0.85	62	
5	0.66	0.80	0.73	41	
6	0.70	0.80	0.75	56	
7	0.47	0.70	0.57	37	
8	0.97	0.75	0.84	87	
9	0.86	0.85	0.85	65	
accuracy			0.79	626	
macro avg	0.78	0.80	0.78	626	
weighted avg	0.83	0.79	0.80	626	







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				(Confusio	on Matri	Х					precision	rocall	f1-score	support
Bougainvill	ea 56	0	2	9	2	4	1	6	1	4		precision	recarr	11-30016	зиррог с
Daffo	dil 1	46	1	0	2	0	4	2	5	4	0	0.66	0.67	0.67	83
Dah	ia 4	0	41	1	3	3	3	2	0	0	1	0.71	0.92	0.80	50
											2	0.72	0.84	0.77	49
Foxglo	/e 2	1	0	69	0	2	2	0	0	0	3	0.91	0.79	0.85	87
Hibisc	us 4	2	2	0	52	0	2	2	0	1	4	0.80	0.78	0.79	67
Hydrang	ea 3	0	1	3	0	34	3	0	0	2	5	0.74	0.72	0.73	47
Orch	id 6	0	0	2	4	2	42	0	1	2	6	0.71	0.67	0.69	63
											7	0.68	0.72	0.70	58
Ro	se 5	0	1	2	3	1	3	42	0	5	8	1.00	0.88	0.93	64
Sunflow	er 0	0	0	0	0	0	0	0	56	0	9	0.73	0.69	0.71	58
Tu	ip 2	1	1	1	1	1	3	4	1	40					
	g	≡	<u>a</u>	ø	S	Œ	Ф	ų.	Į.	ġ.	accuracy			0.76	626
	nville	Daffodil	Dahlia	Foxglove	Hibiscus	Hydrangea	Orchid	Rose	Sunflower	Tulip	macro avg	0.76	0.77	0.76	626
	Bougainvillea			Š	Ī	Hydr			Sun		weighted avg	0.77	0.76	0.76	626
	ñ					icted	10								
Bougainvil	ea 68	0	1	1	1	1	0	1	0	1		precision	recall	f1-score	support
Daffo	odil 0	39	1	0	3	0	0	0	20	3					
											0	0.92	0.75	0.82	91
Dah	ılia 0	0	56	0	0	1	1	2	0	0	1	0.59	0.89	0.71	44
Foxglo	ve 1	0	0	57	0	3	1	2	0	1	2	0.93	0.66	0.77	85
_ Hibise	cus 3	0	2	0	52	0	2	2	0	0	3	0.88	0.98	0.93	58
Hydrang	ea 2	1	6	0	0	33	5	0	1	2	4	0.85	0.84	0.85	62
- nyurang	ea z	1	0	U	U	33	5	U	1	2	5	0.66	0.80	0.73	41
Orc	nid 4	1	9	0	1	3	45	1	0	0	6	0.70	0.80	0.75	56
Ro	se 10	1	9	0	3	0	2	26	1	3	7	0.47 0.97	0.70 0.75	0.57 0.84	37 87
Sunflov	ver 0	1	1	0	0	0	0	0	65	0	9	0.86	0.75	0.85	65
											,	0.80	0.05	0.05	0.5
IL	llip 3	1	0	0	2	0	0	3	0	55	accuracy			0.79	626