FLOWER RECOGNITION

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Data Collection:

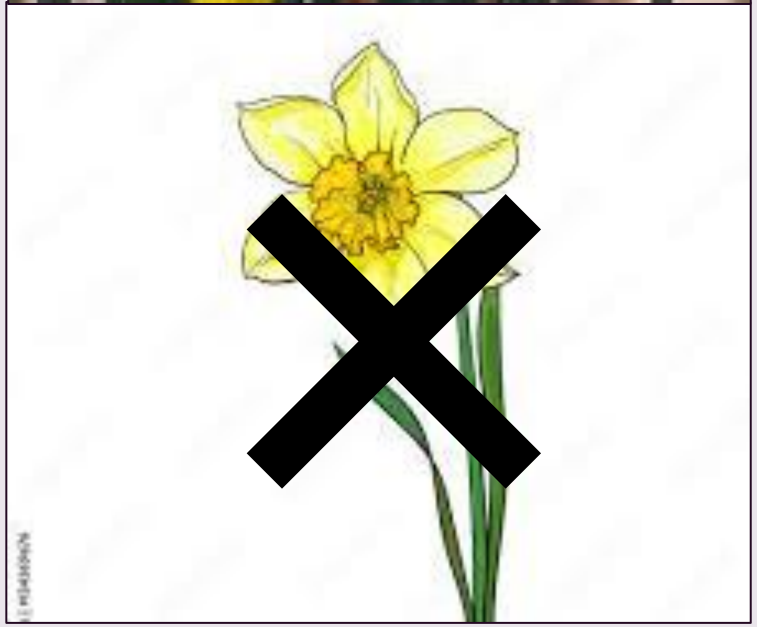
- Bougainvillea
- Daffodil
- Dahlia
- Foxglove
- Hibiscus
- Hydrangea
- Orchid
- Rose
- Sunflower
- Tulip

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
1	../Combined flowers/daffodil	daffodil
2	../Combined flowers/dahlia	dahlia
3	../Combined flowers/foxglove	foxglove
4	../Combined flowers/hibiscus	hibiscus
5	../Combined flowers/hydrangea	hydrangea
6	../Combined flowers/orchid	orchid
7	../Combined flowers/rose	rose
8	../Combined flowers/sunflower	sunflower
9	../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

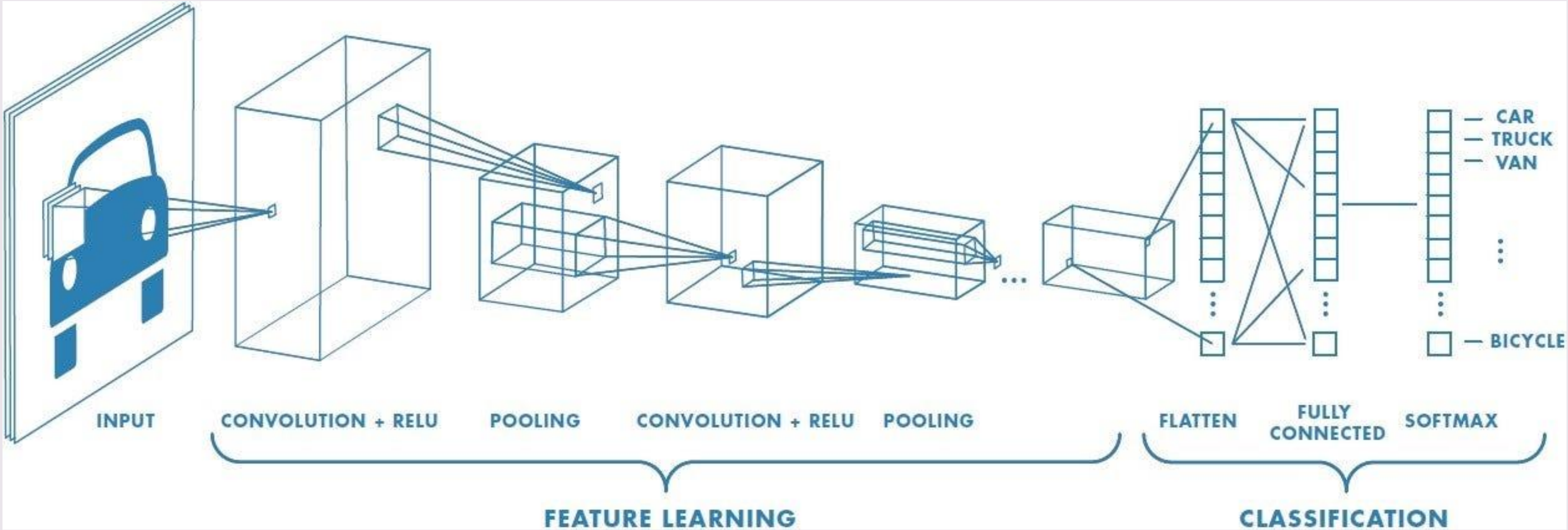
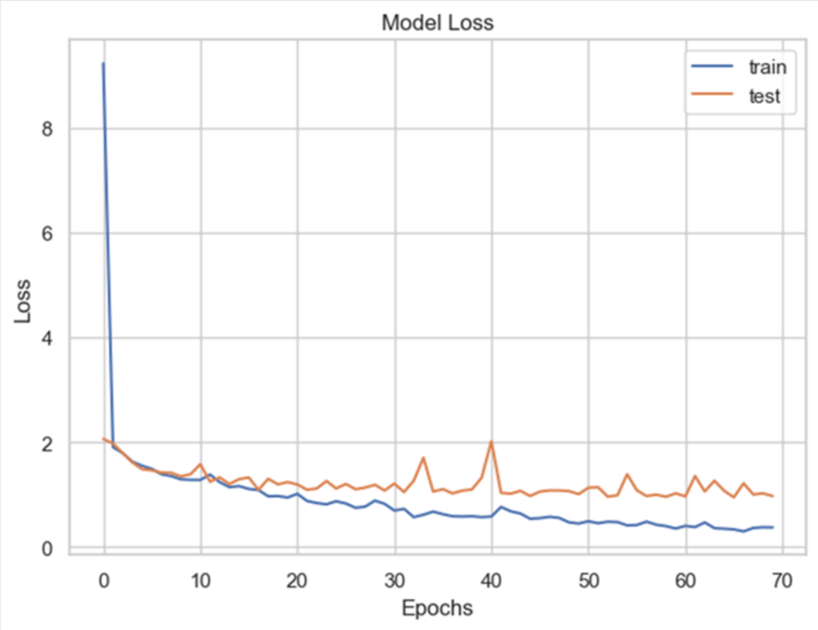


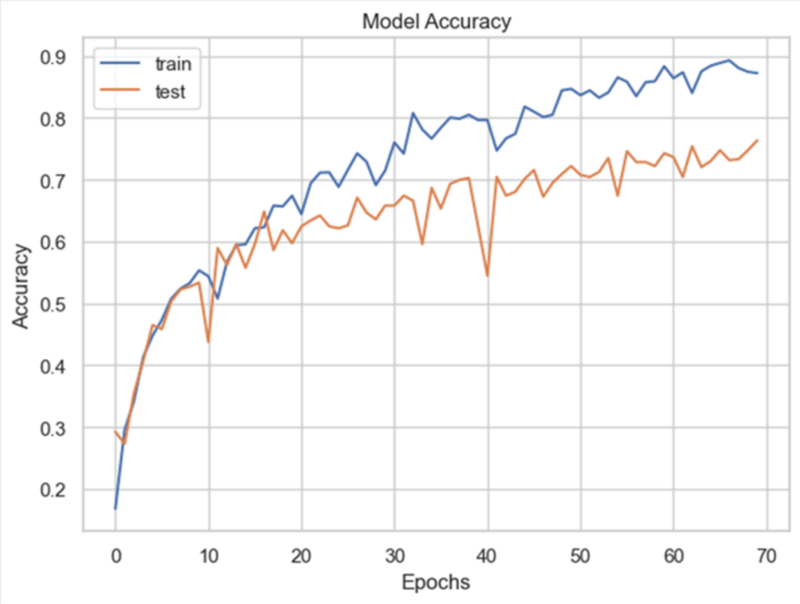
Image source : https://www.interviewbit.com/blog/cnn-architecture/

Model Comparison

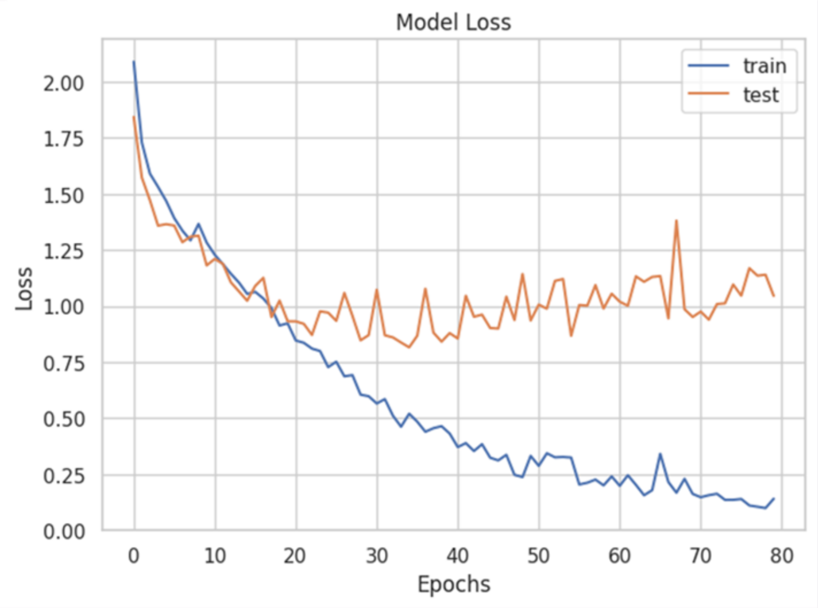
Batch Size	Epoch	Parameters	Accuracy
32	50	9,599,882	60
64	70	4,146,314	74
64	70	3,393,770	76
64	80	4,146,314	79

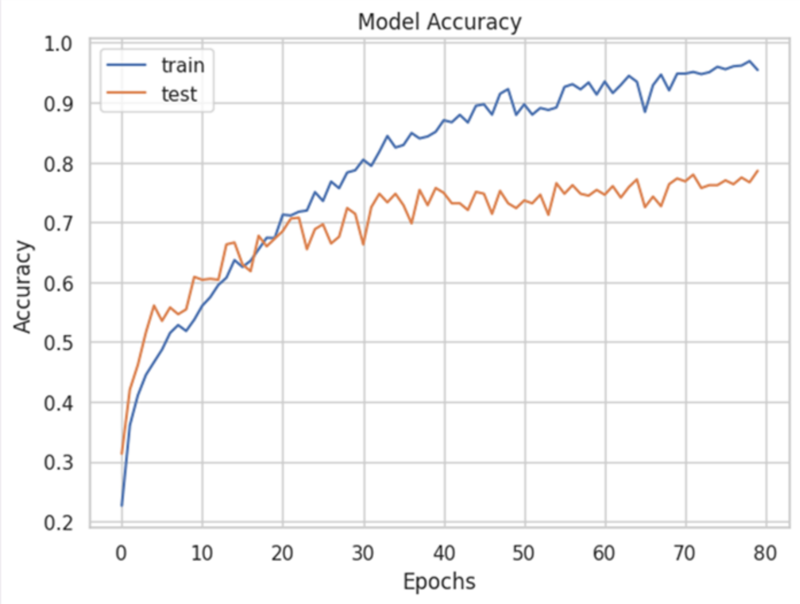
Accuracy : 76





Accuracy : 79





Accuracy : 76

Confusion Matrix

Actual \ Predicted	Bougainvillea	Daffodil	Dahlia	Foxglove	Hibiscus	Hydrangea	Orchid	Rose	Sunflower	Tulip
Bougainvillea	56	0	2	9	2	4	1	6	1	4
Daffodil	1	46	1	0	2	0	4	2	5	4
Dahlia	4	0	41	1	3	3	3	2	0	0
Foxglove	2	1	0	69	0	2	2	0	0	0
Hibiscus	4	2	2	0	52	0	2	2	0	1
Hydrangea	3	0	1	3	0	34	3	0	0	2
Orchid	6	0	0	2	4	2	42	0	1	2
Rose	5	0	1	2	3	1	3	42	0	5
Sunflower	0	0	0	0	0	0	0	0	56	0
Tulip	2	1	1	1	1	1	3	4	1	40

	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

Accuracy : 79

Confusion Matrix

Actual \ Predicted	Bougainvillea	Daffodil	Dahlia	Foxglove	Hibiscus	Hydrangea	Orchid	Rose	Sunflower	Tulip
Bougainvillea	68	0	1	1	1	1	0	1	0	1
Daffodil	0	39	1	0	3	0	0	0	20	3
Dahlia	0	0	56	0	0	1	1	2	0	0
Foxglove	1	0	0	57	0	3	1	2	0	1
Hibiscus	3	0	2	0	52	0	2	2	0	0
Hydrangea	2	1	6	0	0	33	5	0	1	2
Orchid	4	1	9	0	1	3	45	1	0	0
Rose	10	1	9	0	3	0	2	26	1	3
Sunflower	0	1	1	0	0	0	0	0	65	0
Tulip	3	1	0	0	2	0	0	3	0	55

	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

Actual : Rose
Predicted: Orchid

Actual : Rose
Predicted : Rose

Actual : Dahlia
Predicted : Tulip

Actual : Hydrangea
Predicted : Hydrangea

Accuracy : 76

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 256, 256, 32)	2432
max_pooling2d (MaxPooling2D)	(None, 128, 128, 32)	0
conv2d_1 (Conv2D)	(None, 128, 128, 64)	18496
max_pooling2d_1 (MaxPooling 2D)	(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

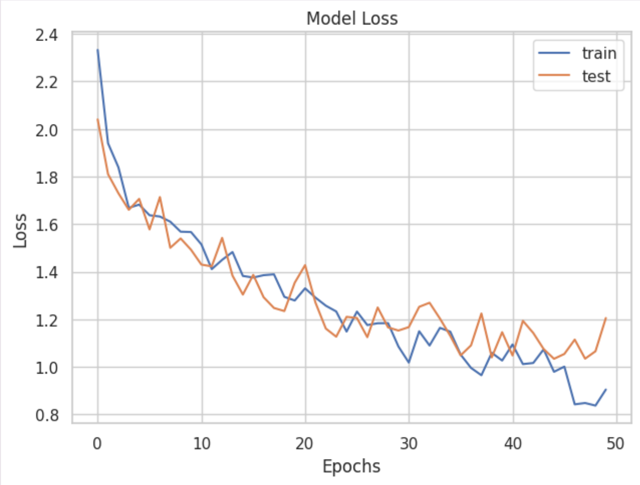
Total params: 3,393,770
Trainable params: 3,393,770
Non-trainable params: 0

Accuracy : 79

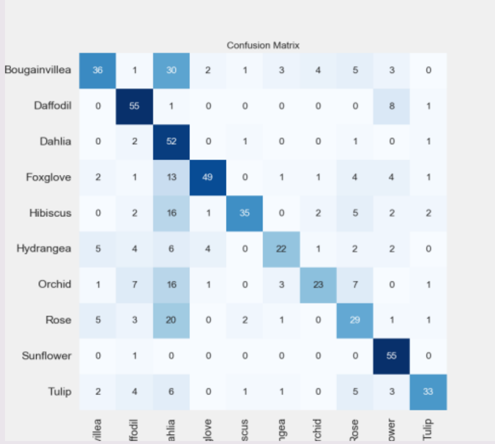
Layer (type)	Output Shape	Param #
conv2d_10 (Conv2D)	(None, 150, 150, 32)	2432
max_pooling2d_10 (MaxPoolin g2D)	(None, 75, 75, 32)	0
conv2d_11 (Conv2D)	(None, 75, 75, 64)	18496
max_pooling2d_11 (MaxPoolin g2D)	(None, 37, 37, 64)	0
conv2d_12 (Conv2D)	(None, 37, 37, 96)	55392
max_pooling2d_12 (MaxPoolin 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

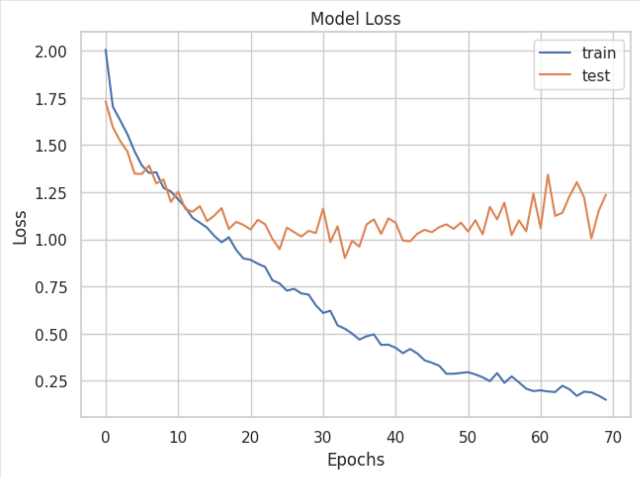
For Accuracy 62



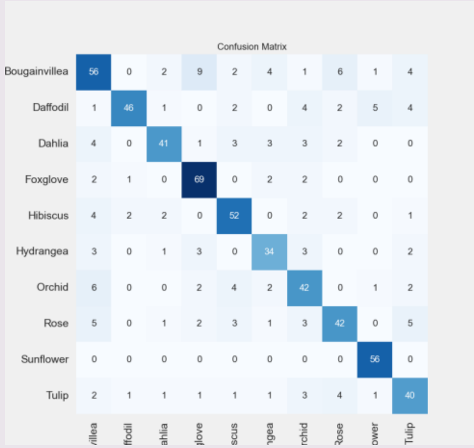
	precision	recall	f1-score	support
0	0.42	0.71	0.53	51
1	0.85	0.69	0.76	80
2	0.91	0.33	0.48	160
3	0.64	0.86	0.74	57
4	0.54	0.88	0.67	40
5	0.48	0.71	0.57	31
6	0.39	0.74	0.51	31
7	0.47	0.50	0.48	58
8	0.98	0.71	0.82	78
9	0.60	0.82	0.69	40
accuracy			0.62	626
macro avg	0.63	0.69	0.63	626
weighted avg	0.72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

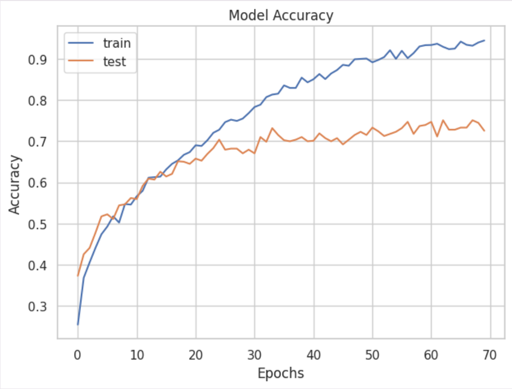


For Accuracy 70

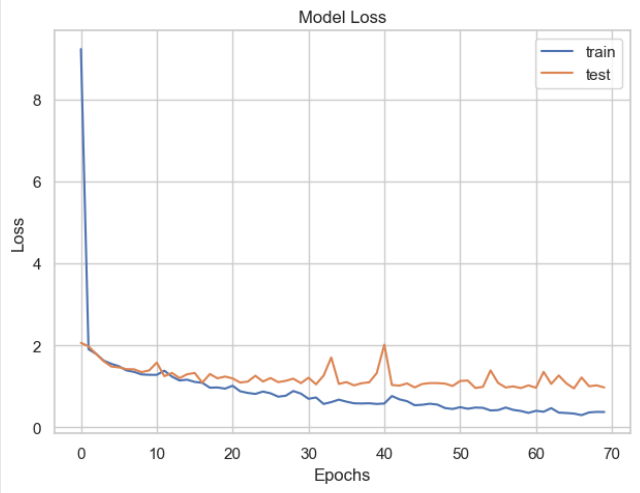


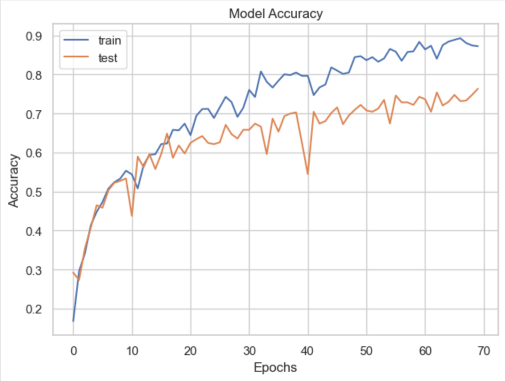
	precision	recall	f1-score	support
0	0.68	0.76	0.72	76
1	0.63	0.89	0.74	46
2	0.96	0.34	0.51	160
3	0.78	0.91	0.84	65
4	0.69	0.83	0.76	54
5	0.50	0.85	0.63	27
6	0.41	0.80	0.54	30
7	0.60	0.71	0.65	52
8	0.95	0.79	0.86	67
9	0.82	0.92	0.87	49
accuracy			0.70	626
macro avg	0.70	0.78	0.71	626
weighted avg	0.77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





For Accuracy 76





	precision	recall	f1-score	support
0	0.66	0.67	0.67	83
1	0.71	0.92	0.80	50
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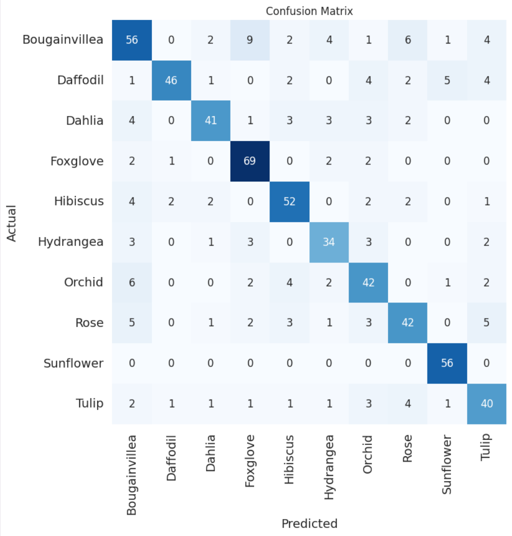

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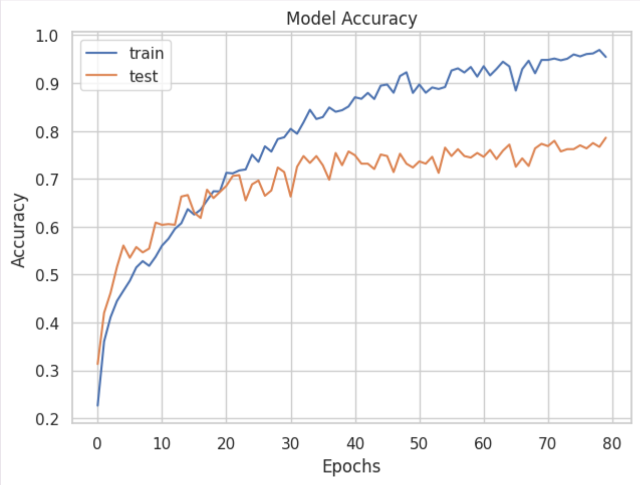

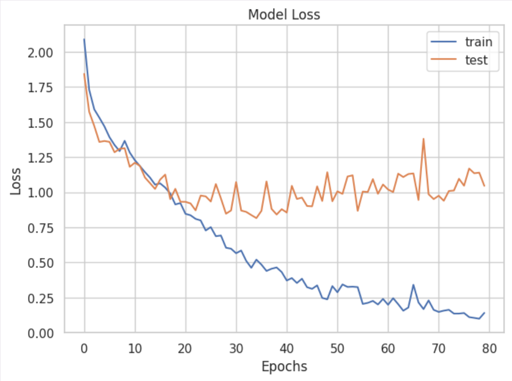

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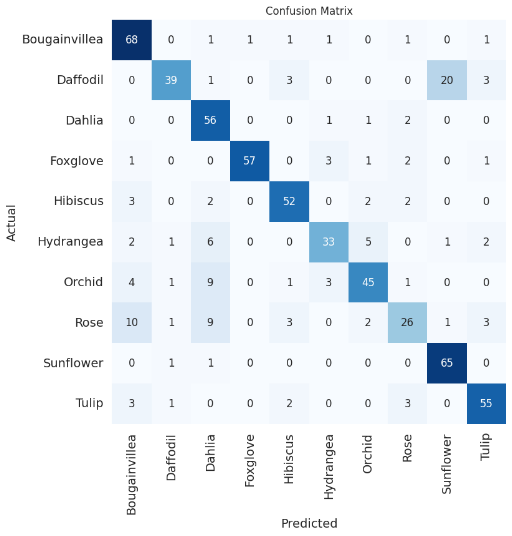
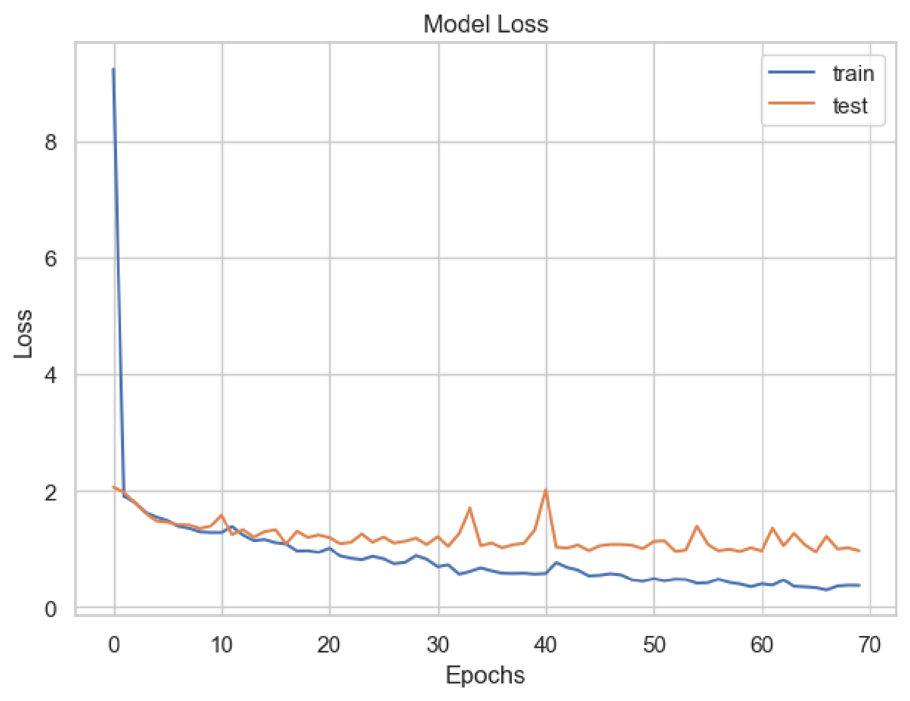
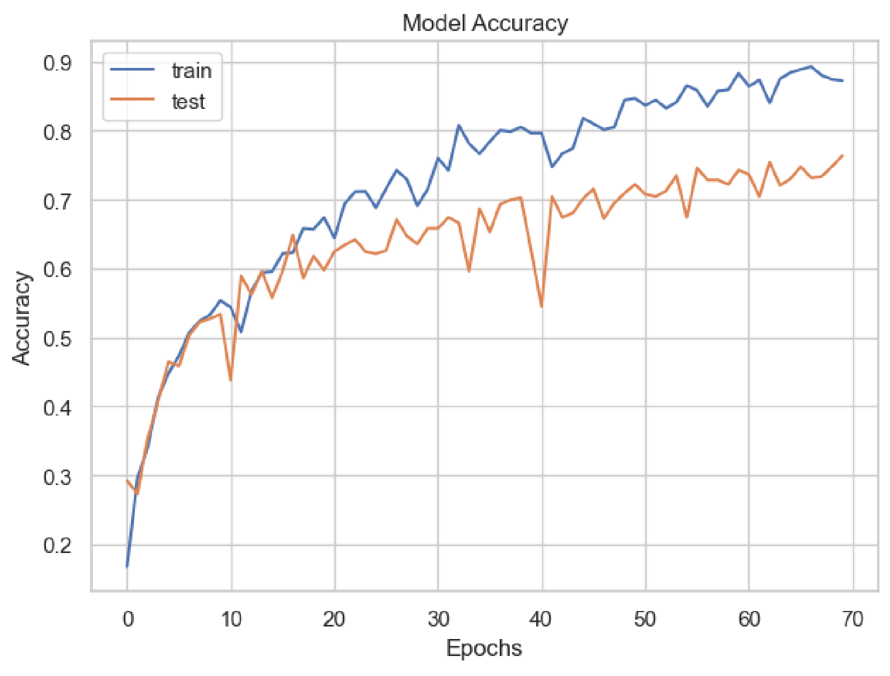
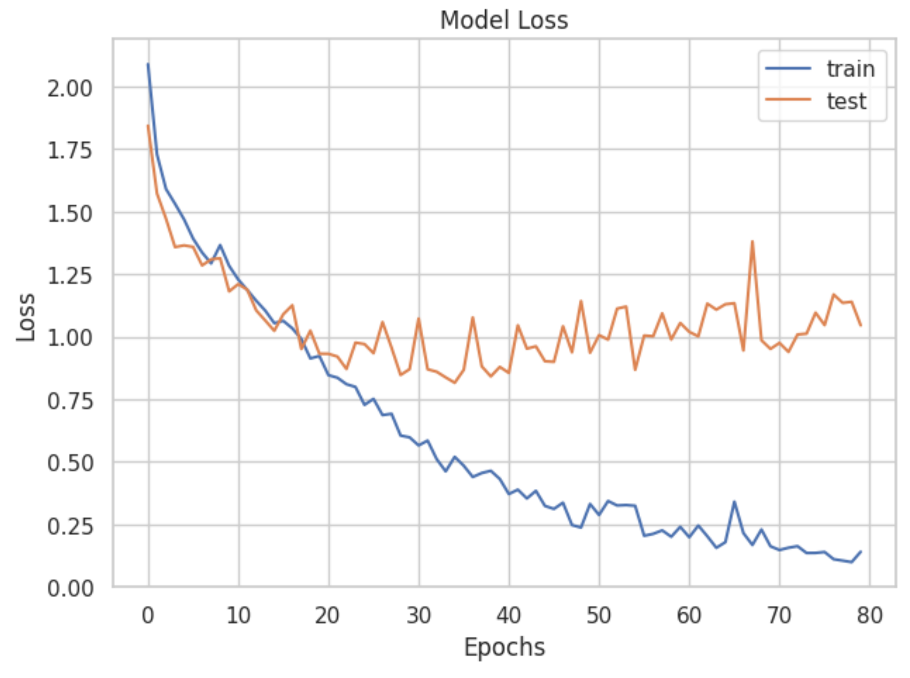
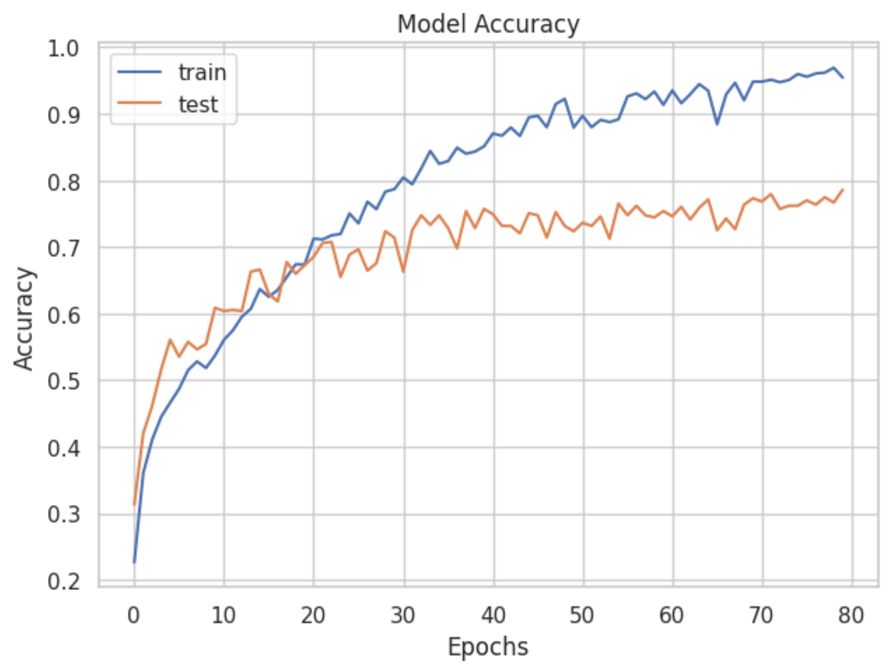
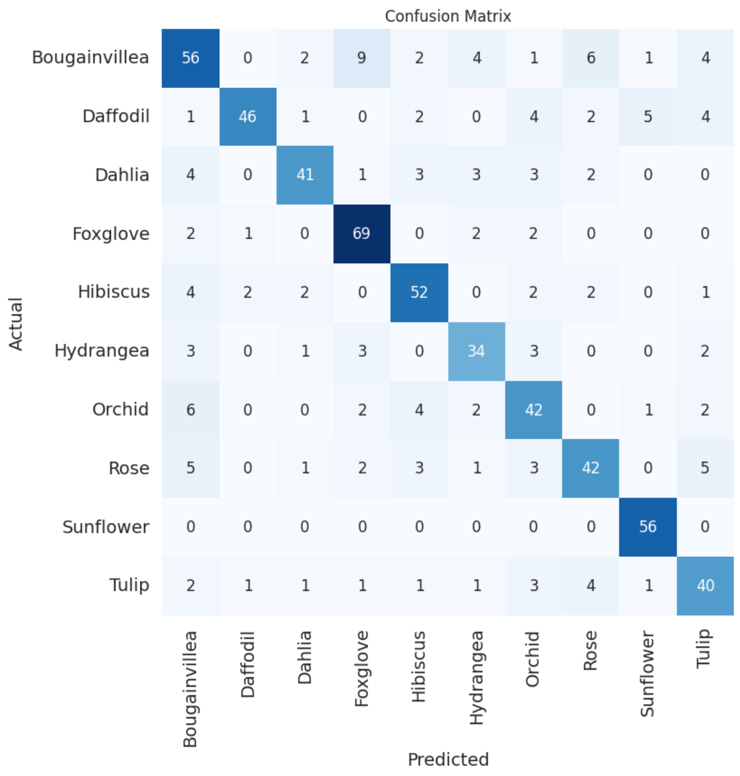



Model Loss
train
test
Loss
Epochs


Model Accuracy
train
test
Accuracy
Epochs


Model Loss
train
test
Loss
Epochs


Model Accuracy
train
test
Accuracy
Epochs



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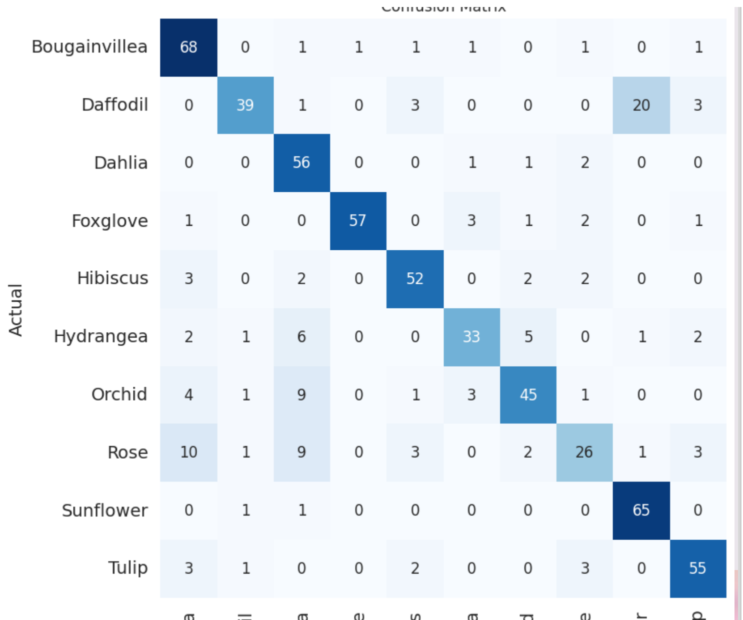

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