



**KLE** Technological  
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Creating Value  
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# Outdoor Scene Classification based on CNN

Project guide  
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# Problem Statement

Scene Image Classification: Identify which kind of natural scenes can the image be categorised into.

# Motivation

- Classification is very important as we use it in daily life. It makes things easier to find and recognise. Differentiation of objects is what allows us to classify them into groups.
- Image Classification is one of the core problems in Computer Vision that, despite its simplicity, has a large variety of practical applications.
- Moreover, as we can see, many other seemingly distinct Computer Vision tasks (such as object detection, segmentation) can be reduced to image classification.



The background of the slide is a tropical beach scene. At the top, there are green palm fronds. Below them is a light beige sandy beach. At the bottom, there are blue ocean waves with white foam. The entire scene is framed by a white border.

# Objectives

- Identify the image.
- Classify into respective category.

# Image dataset

mountain



mountain



mountain



mountain



sea



sea



sea



sea



forest



forest



forest



forest





buildings



buildings



buildings



buildings



glaciers



glaciers



glaciers



glaciers



street



street



street



street



## **Dataset:**

This Data contains around 25k images of size 150x150 distributed under 6 categories. {'buildings' -> 0, 'forest' -> 1, 'glacier' -> 2, 'mountain' -> 3, 'sea' -> 4, 'street' -> 5 }

The Train, Test and Prediction data is separated in each zip files. There are around 14k images in Train, 3k in Test and 7k in Prediction.

## **Preprocessing:**

Resize all the input images to 150x150

# Requirements

## A. Functional Requirements

### ❖ User level

- User shall be able to view images.
- User shall be able to see the category under which it belongs to.

### ❖ System level

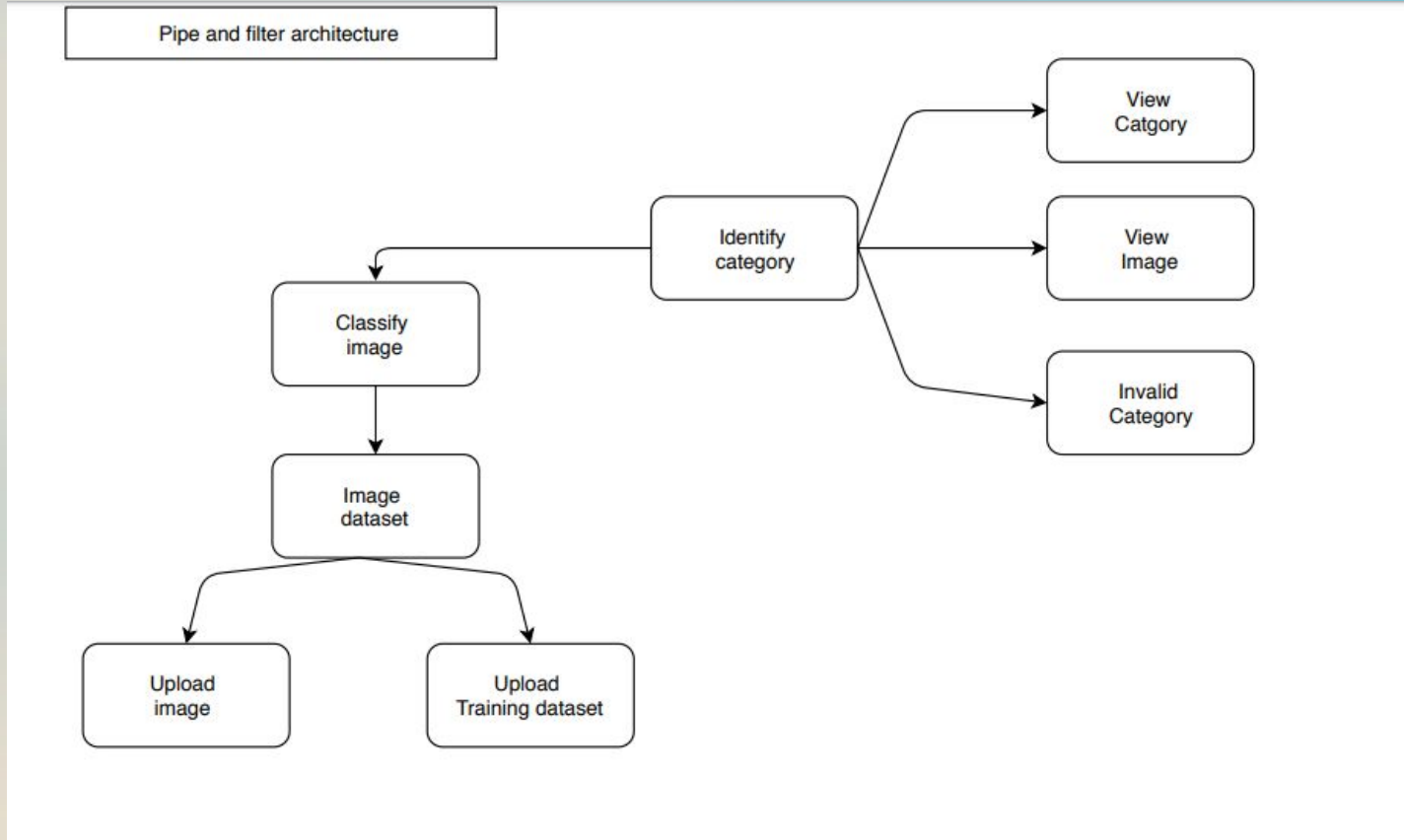
- System shall be able to store data.
- System shall be able to extract features.
- System shall be able to resize the images.
- System shall be able to categorise the images.



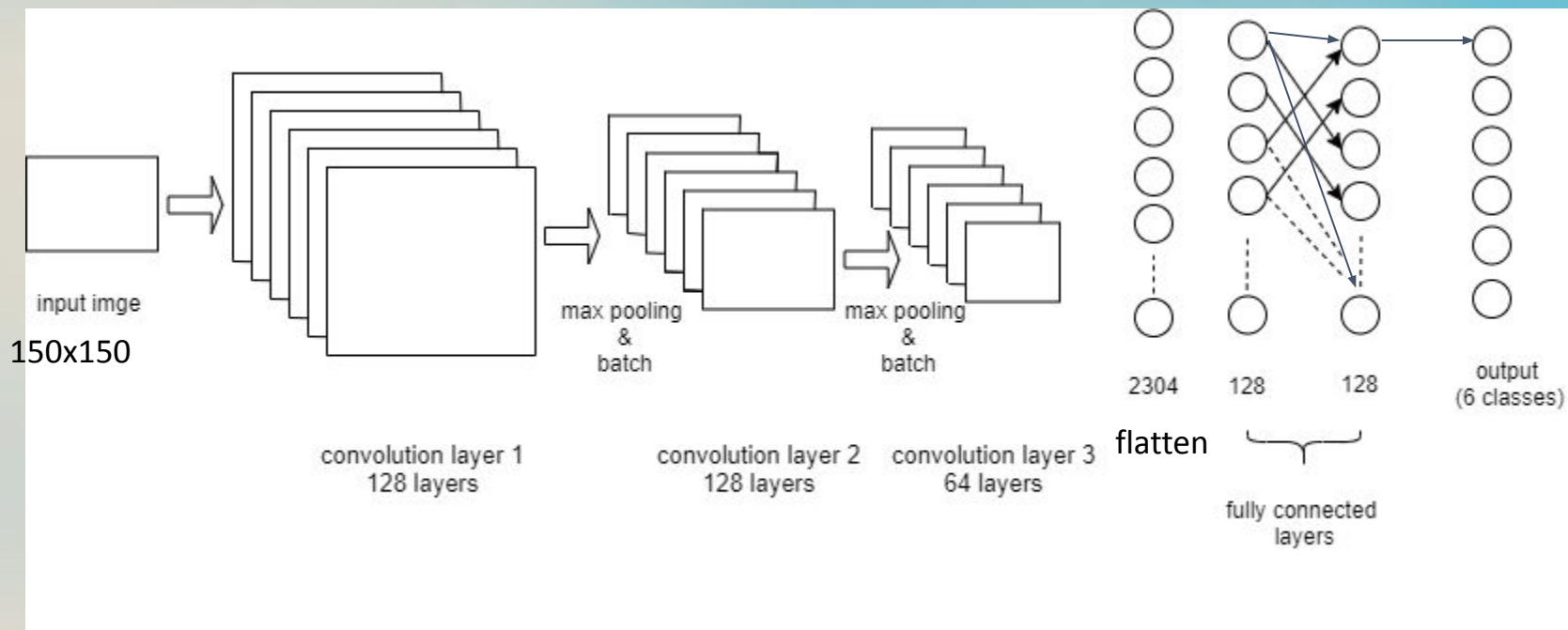
# Non-Functional Requirements

- Ease of use
- The system should be able to expand for further storing.
- The system should be compatible with any browser on any environment.
- The system should be able to perform a failure-free operation for a specified period of time in a specified environment.

# Architecture



# Convolutional Neural Network

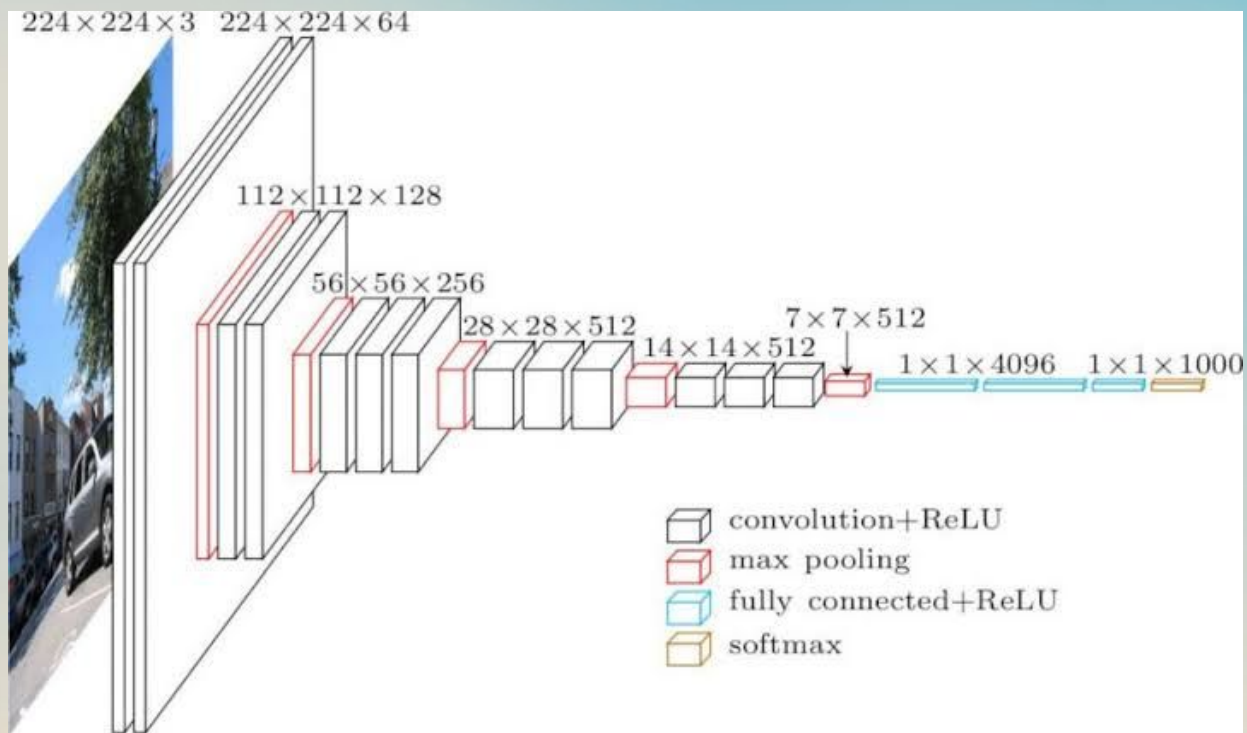




# Output visualisations

conv2d_1 (Conv2D)	(None, 148, 148, 128)	3584
max_pooling2d_1 (MaxPooling2D)	(None, 74, 74, 128)	0
batch_normalization_1 (Batch Normalization)	(None, 74, 74, 128)	512
conv2d_2 (Conv2D)	(None, 72, 72, 128)	147584
max_pooling2d_2 (MaxPooling2D)	(None, 36, 36, 128)	0
batch_normalization_2 (Batch Normalization)	(None, 36, 36, 128)	512
conv2d_3 (Conv2D)	(None, 34, 34, 64)	73792
max_pooling2d_3 (MaxPooling2D)	(None, 6, 6, 64)	0
flatten_1 (Flatten)	(None, 2304)	0
dense_1 (Dense)	(None, 128)	295040

# VGG16



Model: "sequential\_1"

Layer (type)	Output Shape	Param #
=====	=====	=====
vgg16 (Model)	(None, 4, 4, 512)	14714688
flatten_1 (Flatten)	(None, 8192)	0
dense_1 (Dense)	(None, 180)	1474740
dense_2 (Dense)	(None, 100)	18100
dense_3 (Dense)	(None, 50)	5050
dropout_1 (Dropout)	(None, 50)	0
dense_4 (Dense)	(None, 6)	306
=====	=====	=====

Total params: 16,212,884

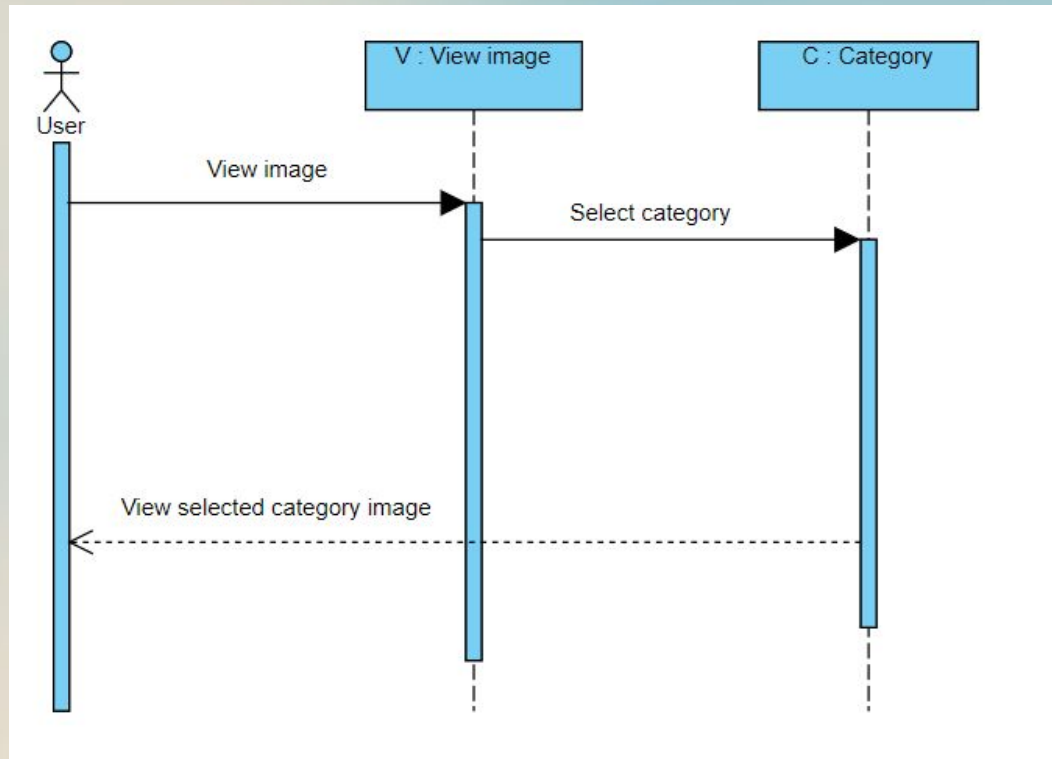
Trainable params: 16,212,884

Non-trainable params: 0

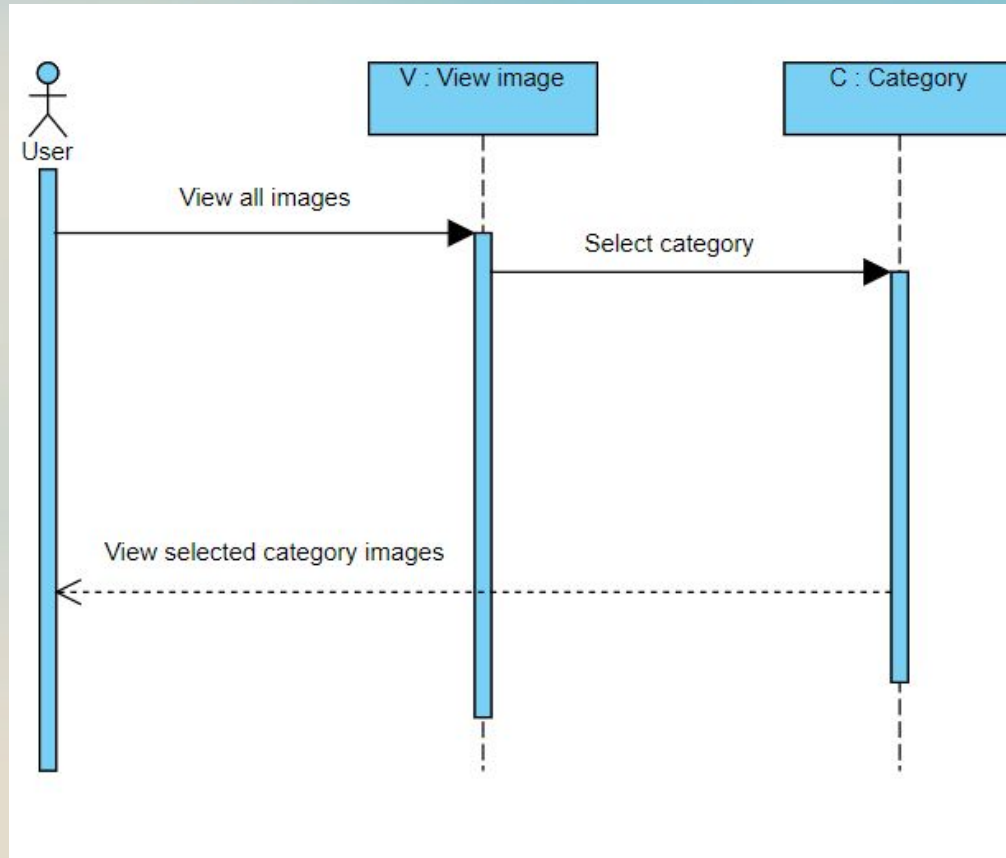


# Sequence Diagram

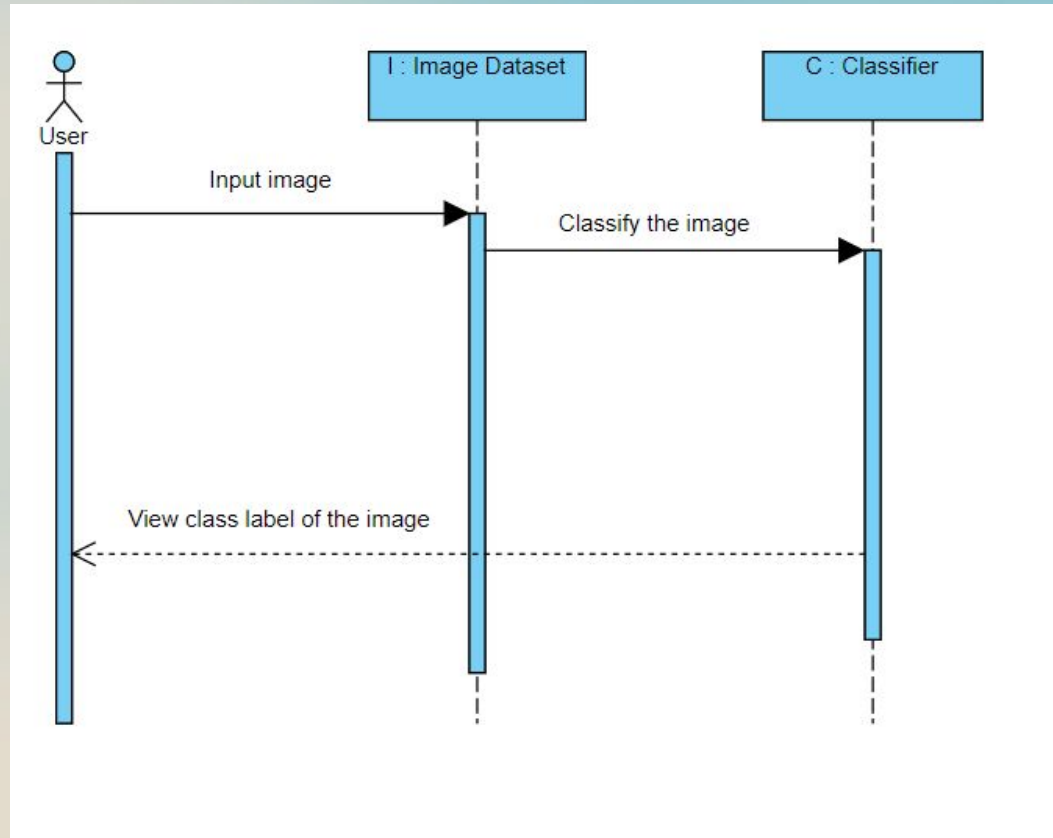
- Sequence diagram for view image



- Sequence diagram to view all images.

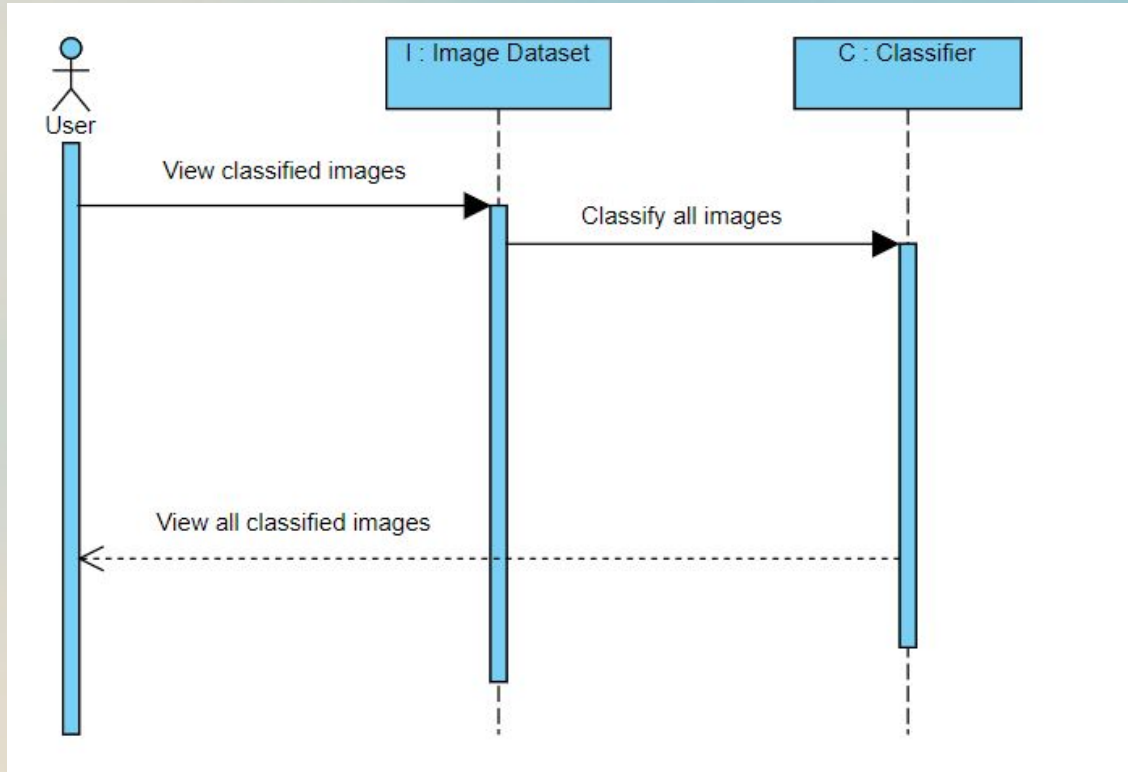


- Sequence diagram to categorize the image.





- Sequence diagram for classify all images.



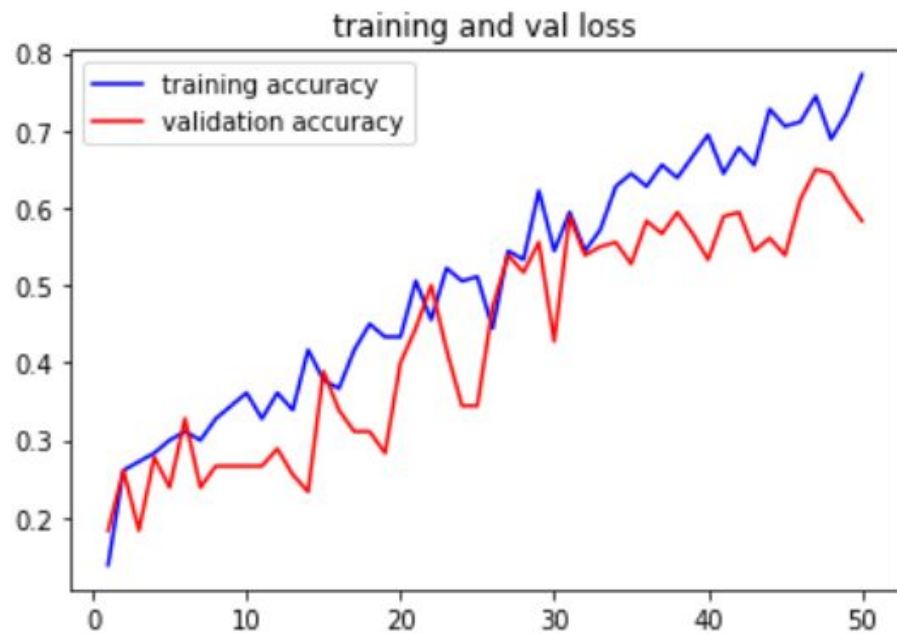
# Status of implementation

- CNN using 180 sample dataset

```
Epoch 11/20
18/18 [=====] - 5s 259ms/step - loss: 1.1254 - accuracy: 0.5722 - val_loss: 1.5289 - val_accuracy: 0.5
444
Epoch 12/20
18/18 [=====] - 5s 265ms/step - loss: 1.0056 - accuracy: 0.6167 - val_loss: 0.6549 - val_accuracy: 0.6
111
Epoch 13/20
18/18 [=====] - 5s 257ms/step - loss: 1.0669 - accuracy: 0.5944 - val_loss: 1.0264 - val_accuracy: 0.5
833
Epoch 14/20
18/18 [=====] - 4s 246ms/step - loss: 0.9645 - accuracy: 0.6278 - val_loss: 1.6021 - val_accuracy: 0.5
611
Epoch 15/20
18/18 [=====] - 4s 245ms/step - loss: 0.9067 - accuracy: 0.6889 - val_loss: 1.1841 - val_accuracy: 0.6
278
Epoch 16/20
18/18 [=====] - 4s 243ms/step - loss: 1.0602 - accuracy: 0.6278 - val_loss: 1.5115 - val_accuracy: 0.5
833
Epoch 17/20
18/18 [=====] - 4s 239ms/step - loss: 0.8839 - accuracy: 0.6778 - val_loss: 1.5035 - val_accuracy: 0.5
889
Epoch 18/20
18/18 [=====] - 4s 246ms/step - loss: 0.8747 - accuracy: 0.6333 - val_loss: 3.5019 - val_accuracy: 0.5
833
Epoch 19/20
18/18 [=====] - 4s 245ms/step - loss: 0.9635 - accuracy: 0.6556 - val_loss: 1.1756 - val_accuracy: 0.5
056
Epoch 20/20
18/18 [=====] - 4s 240ms/step - loss: 0.8739 - accuracy: 0.6500 - val_loss: 0.8842 - val_accuracy: 0.5
111
```

Layer (type)	Output Shape	Param #
=====		
conv2d_4 (Conv2D)	(None, 148, 148, 32)	896
activation_6 (Activation)	(None, 148, 148, 32)	0
max_pooling2d_4 (MaxPooling2D)	(None, 74, 74, 32)	0
conv2d_5 (Conv2D)	(None, 72, 72, 32)	9248
activation_7 (Activation)	(None, 72, 72, 32)	0
max_pooling2d_5 (MaxPooling2D)	(None, 36, 36, 32)	0
conv2d_6 (Conv2D)	(None, 34, 34, 64)	18496
activation_8 (Activation)	(None, 34, 34, 64)	0
max_pooling2d_6 (MaxPooling2D)	(None, 17, 17, 64)	0
flatten_2 (Flatten)	(None, 18496)	0
dense_3 (Dense)	(None, 64)	1183808
activation_9 (Activation)	(None, 64)	0
dropout_2 (Dropout)	(None, 64)	0
dense_4 (Dense)	(None, 6)	390
activation_10 (Activation)	(None, 6)	0
=====		
Total params: 1,212,838		
Trainable params: 1,212,838		
Non-trainable params: 0		

```
0.5611
Epoch 45/50
18/18 [=====] - 5s 269ms/step - loss: 0.7973 - accuracy: 0.7056 - val_loss: 0.9434 - val_accuracy:
0.5389
Epoch 46/50
18/18 [=====] - 5s 271ms/step - loss: 0.7712 - accuracy: 0.7111 - val_loss: 1.5107 - val_accuracy:
0.6111
Epoch 47/50
18/18 [=====] - 5s 287ms/step - loss: 0.7185 - accuracy: 0.7444 - val_loss: 2.0767 - val_accuracy:
0.6500
Epoch 48/50
18/18 [=====] - 5s 286ms/step - loss: 0.9956 - accuracy: 0.6889 - val_loss: 1.2893 - val_accuracy:
0.6444
Epoch 49/50
18/18 [=====] - 5s 299ms/step - loss: 0.8007 - accuracy: 0.7222 - val_loss: 1.3065 - val_accuracy:
0.6111
Epoch 50/50
18/18 [=====] - 5s 300ms/step - loss: 0.6717 - accuracy: 0.7722 - val_loss: 2.8436 - val_accuracy:
0.5833
```



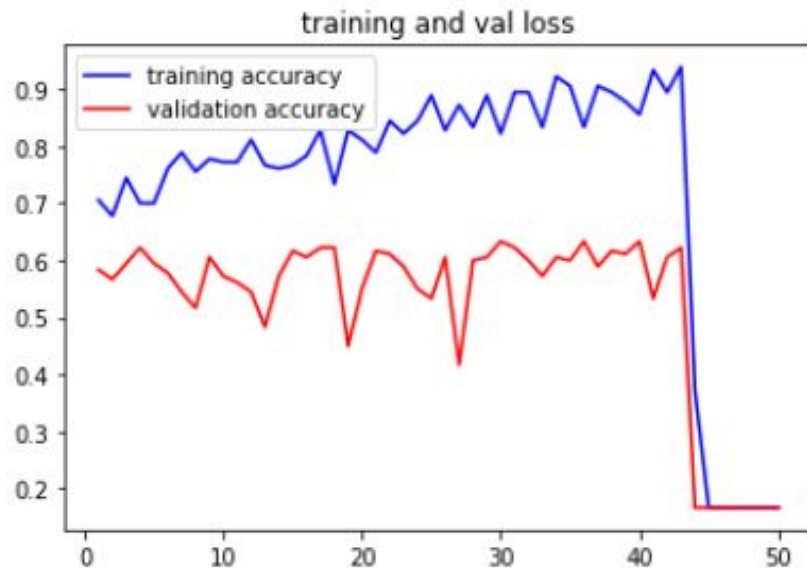


model: sequential\_b

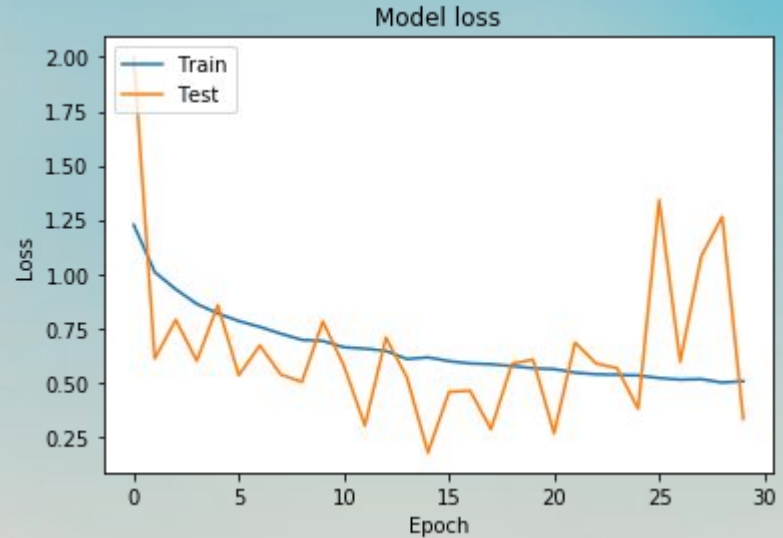
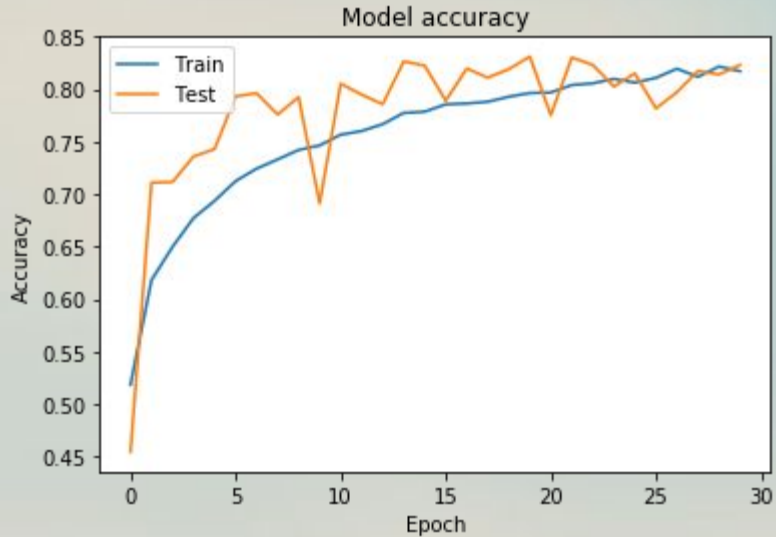
Layer (type)	Output Shape	Param #
conv2d_18 (Conv2D)	(None, 148, 148, 32)	896
activation_28 (Activation)	(None, 148, 148, 32)	0
max_pooling2d_18 (MaxPooling)	(None, 74, 74, 32)	0
conv2d_19 (Conv2D)	(None, 72, 72, 32)	9248
activation_29 (Activation)	(None, 72, 72, 32)	0
max_pooling2d_19 (MaxPooling)	(None, 36, 36, 32)	0
conv2d_20 (Conv2D)	(None, 34, 34, 64)	18496
activation_30 (Activation)	(None, 34, 34, 64)	0
max_pooling2d_20 (MaxPooling)	(None, 17, 17, 64)	0
conv2d_21 (Conv2D)	(None, 15, 15, 128)	73856
activation_31 (Activation)	(None, 15, 15, 128)	0
max_pooling2d_21 (MaxPooling)	(None, 7, 7, 128)	0
conv2d_22 (Conv2D)	(None, 5, 5, 256)	295168
activation_32 (Activation)	(None, 5, 5, 256)	0
max_pooling2d_22 (MaxPooling)	(None, 2, 2, 256)	0
flatten_6 (Flatten)	(None, 1024)	0
dense_11 (Dense)	(None, 64)	65600
activation_33 (Activation)	(None, 64)	0
dropout_6 (Dropout)	(None, 64)	0
dense_12 (Dense)	(None, 6)	390
activation_34 (Activation)	(None, 6)	0
Total params: 463,654		
Trainable params: 463,654		
Non-trainable params: 0		

## Overfitting

Out[18]: <function matplotlib.pyplot.show(\*args, \*\*kw)>



# Results CNN

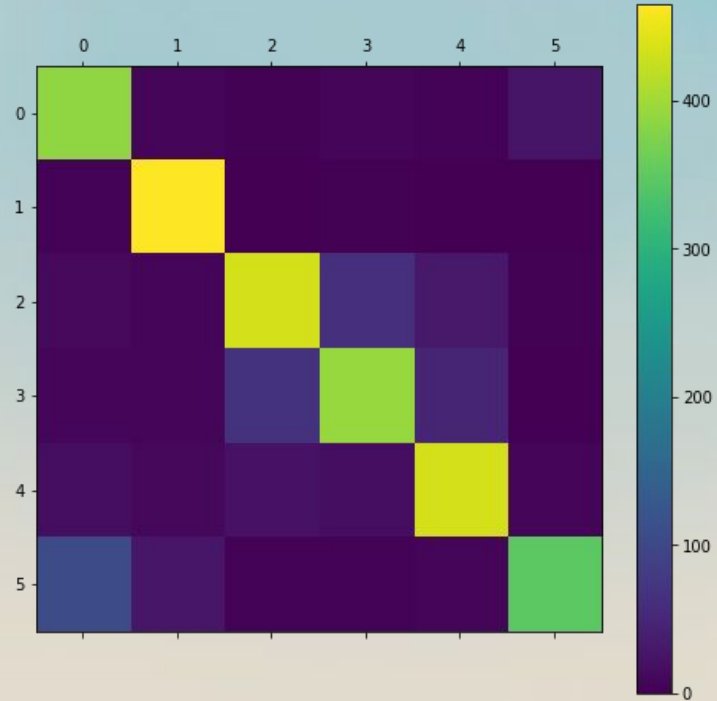


**The model does not seem to overfit, it has a better accuracy on the validation set**

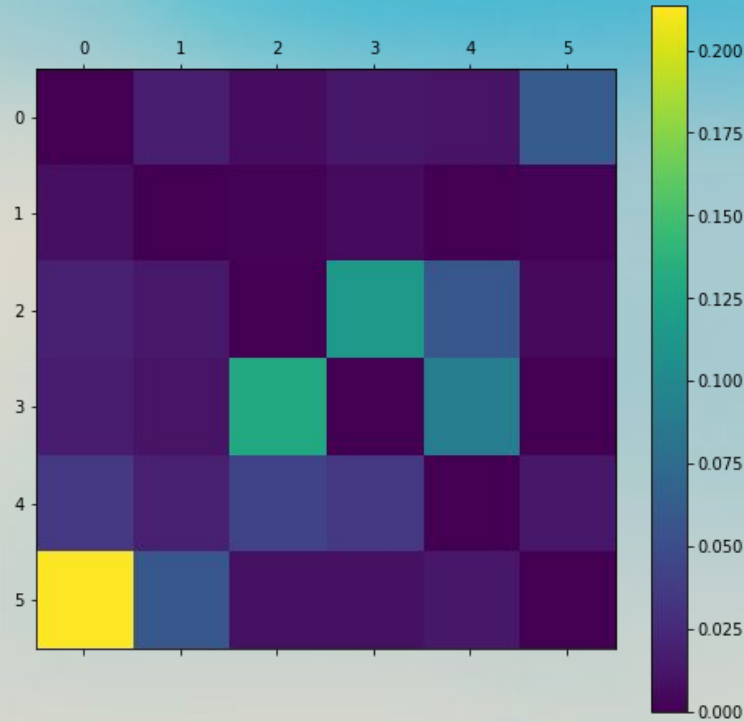
```
437/437 [=====] - 789s 2s/step - loss: 0.5440 - accuracy: 0.8040 - val_loss: 0.6835 - val_accuracy: 0.8302
Epoch 23/30
437/437 [=====] - 790s 2s/step - loss: 0.5364 - accuracy: 0.8056 - val_loss: 0.5863 - val_accuracy: 0.8231
Epoch 24/30
437/437 [=====] - 786s 2s/step - loss: 0.5344 - accuracy: 0.8098 - val_loss: 0.5648 - val_accuracy: 0.8026
Epoch 25/30
437/437 [=====] - 794s 2s/step - loss: 0.5318 - accuracy: 0.8063 - val_loss: 0.3771 - val_accuracy: 0.8150
Epoch 26/30
437/437 [=====] - 789s 2s/step - loss: 0.5188 - accuracy: 0.8108 - val_loss: 1.3408 - val_accuracy: 0.7817
Epoch 27/30
437/437 [=====] - 785s 2s/step - loss: 0.5123 - accuracy: 0.8195 - val_loss: 0.5945 - val_accuracy: 0.7972
Epoch 28/30
437/437 [=====] - 789s 2s/step - loss: 0.5140 - accuracy: 0.8118 - val_loss: 1.0801 - val_accuracy: 0.8174
Epoch 29/30
437/437 [=====] - 782s 2s/step - loss: 0.4984 - accuracy: 0.8216 - val_loss: 1.2630 - val_accuracy: 0.8140
Epoch 30/30
437/437 [=====] - 784s 2s/step - loss: 0.5051 - accuracy: 0.8172 - val_loss: 0.3312 - val_accuracy: 0.8231
```

**The confusion matrix will show us the most frequent mistakes made by this classifier**

	B	F	G	M	S	St
B	[[388	8	3	6	5	27 ]
F	[ 4	465	1	3	0	1 ]
G	[11	8	435	64	32	3 ]
M	[ 9	6	68	394	48	0 ]
S	[18	10	22	18	435	7 ]
St	[107	29	5	5	7	348 ]]

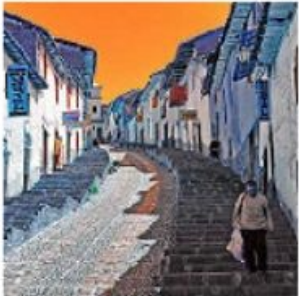






This matrix shows us that the most common confusions are between **streets and buildings**, there are also confusions between **glaciers and mountains**.

predicted : buildings



predicted : buildings



predicted : buildings



predicted : buildings



predicted : buildings



Images of streets classified as buildings

## Let's look at some badly classified images

```
#Images of buildings classified as streets  
errors(y_pred,0,5,10)
```

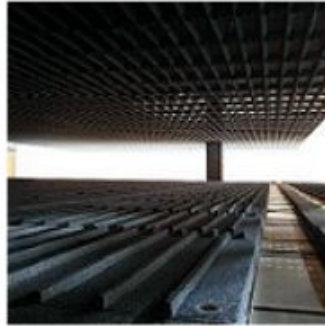
predicted : street



predicted : street



predicted : street



predicted : street



predicted : street



Images of buildings classified as streets

```
#Images of mountains classified as glaciers  
errors(y_pred,3,2,10)
```

predicted : glacier



predicted : glacier



predicted : glacier



predicted : glacier



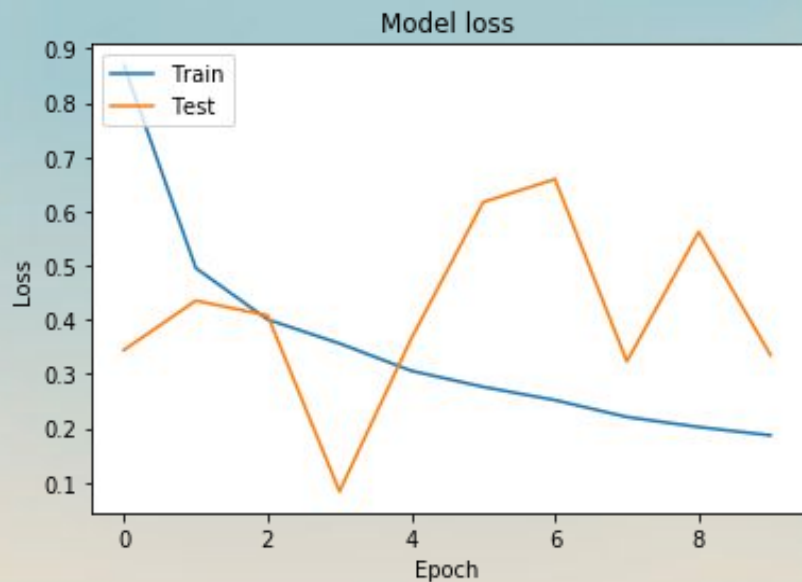
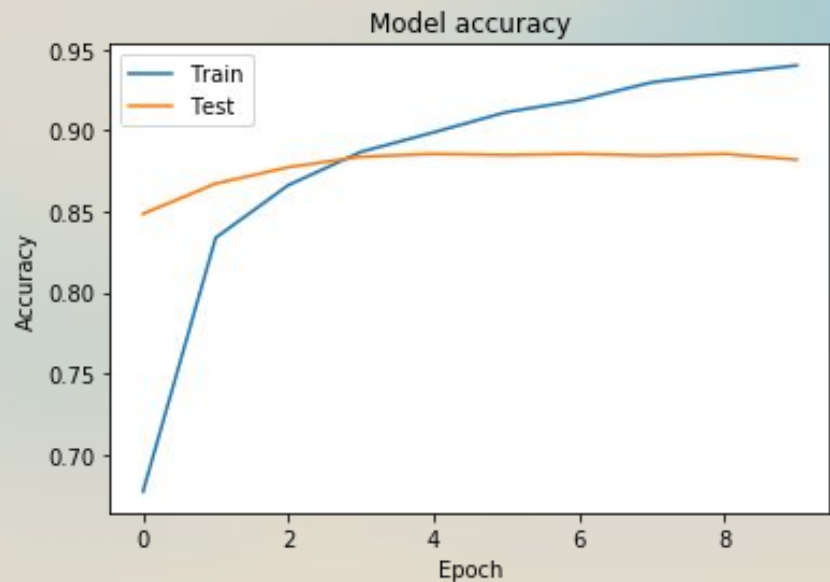
predicted : glacier



Images of mountains classified as glaciers

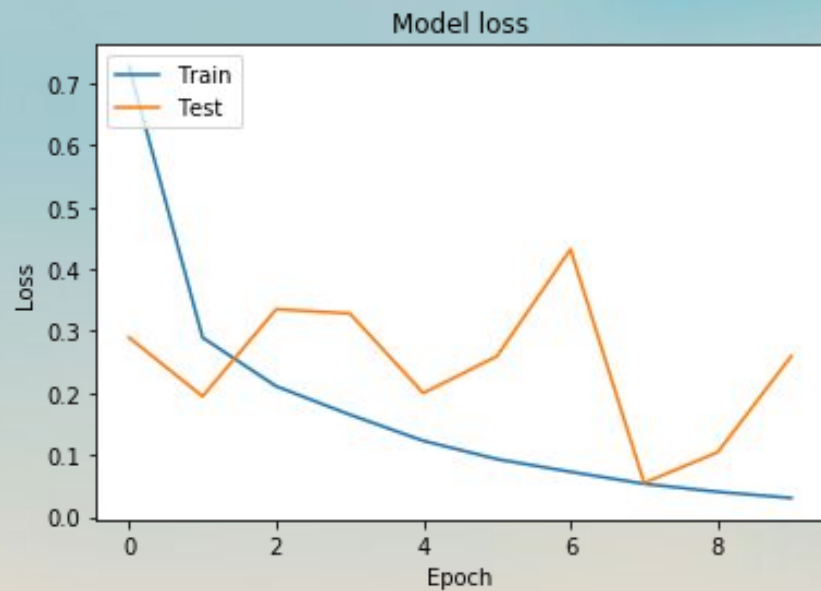
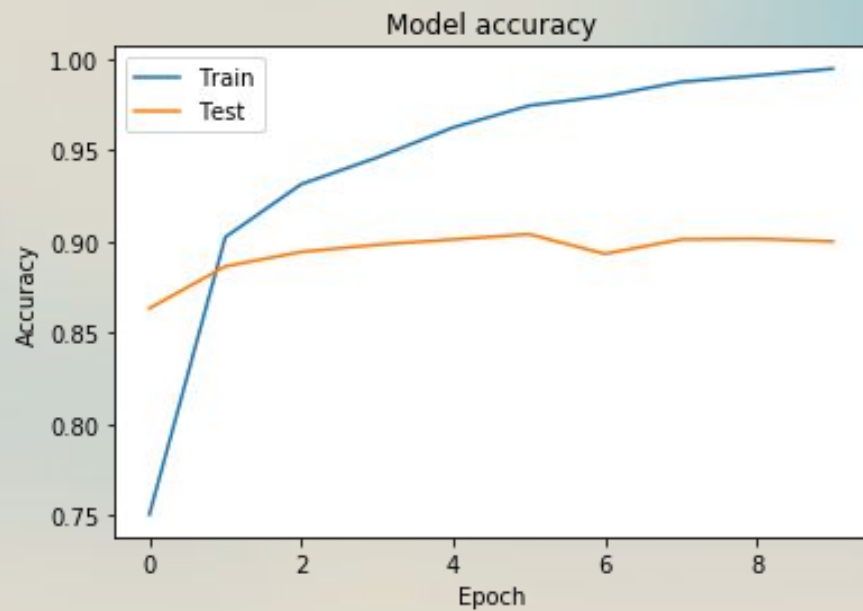
# Transfer learning( VGG16)

## Training:





# Testing



Accuracy:91%

269 wrongly predicted output.

mountain-buildings



street-buildings



street-buildings



buildings-sea



street-buildings



mountain-glacier



street-buildings



glacier-mountain



street-buildings



buildings-sea



mountain-forest



sea-mountain



glacier-mountain



buildings-street



glacier-mountain



glacier-mountain



glacier-mountain



mountain-glacier



mountain-sea



buildings-street



mountain-sea



glacier-sea



mountain-glacier



buildings-sea



glacier-sea

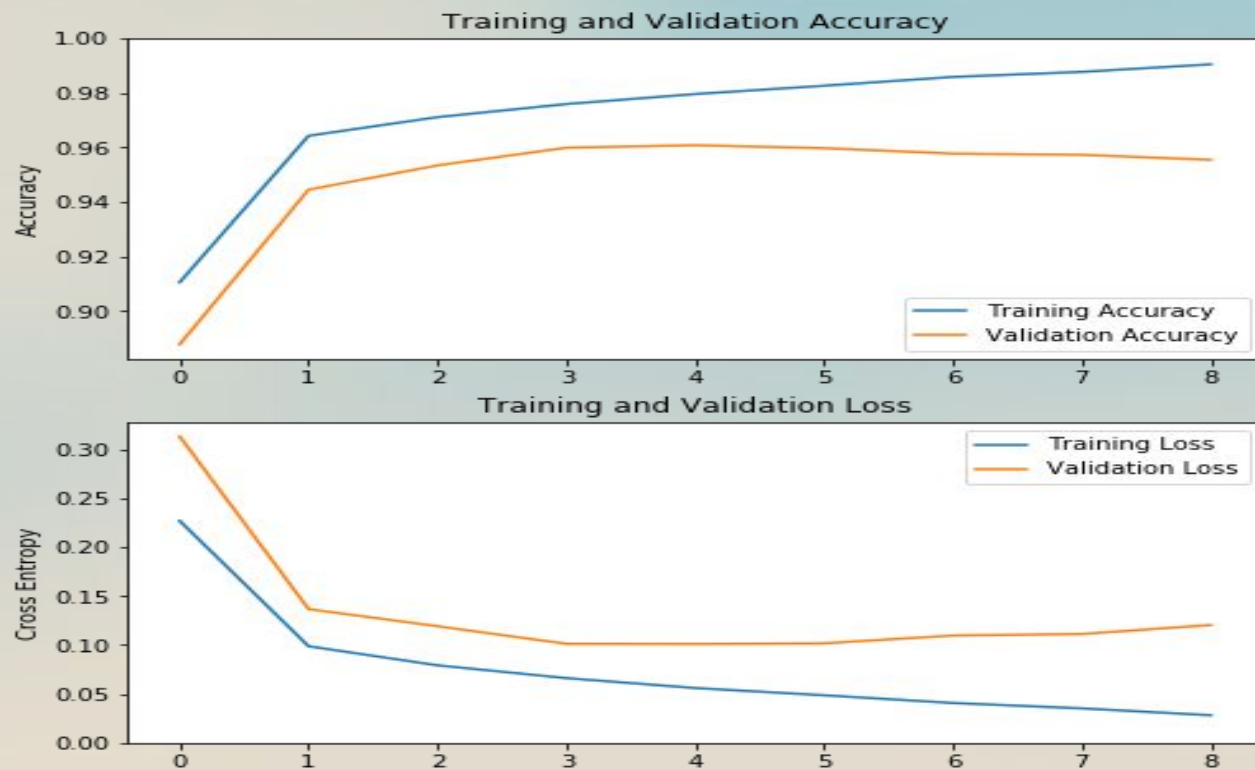


buildings-street



glacier-mountain

## MobileNet



# Conclusion

In this project, we have used different classification models for classifying images into their respective categories. But, in the final classification, a few of the images were misclassified. Therefore, in order to improve the accuracy of classification, it is necessary to include additional knowledge about discarding the image.

In future work, it would be interesting to include additional feature information.

# References



THANK You

