

Visual Concept Detection Machine learning challenge

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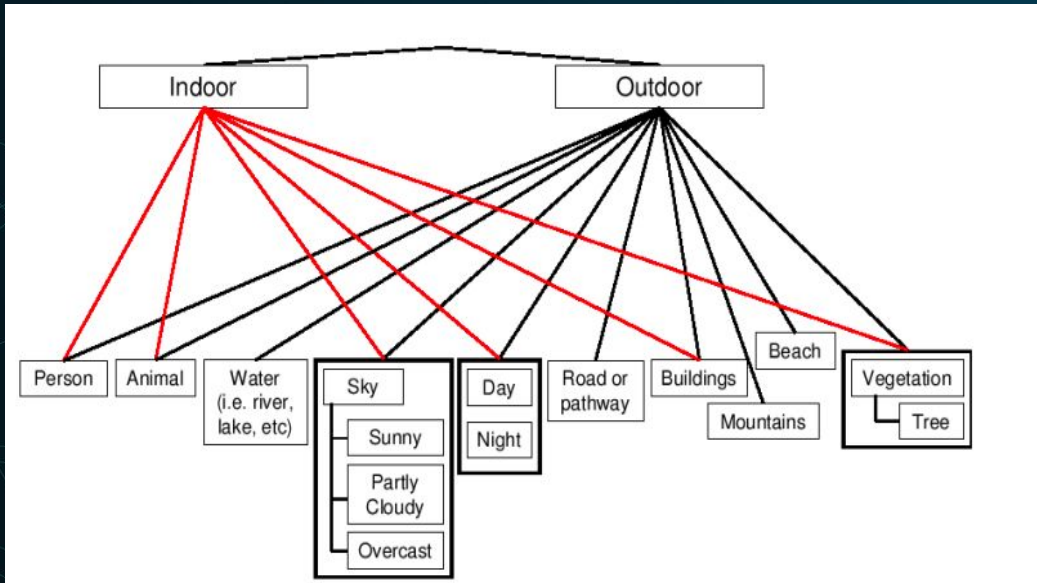
Professor : Dr. Vladimir Despotovic

Out lines

- The problem
- The data set
- Libraries
- Data preparation
- Model
- Results

Visual Concept Detection

Identify the presence/absence of 17 visual concepts in Images



Format of the annotation

```
27-27700.jpg 0 1 0 0 1 0 0 1 1 1 0 0 1 0 0 0 0
27-27704.jpg 0 1 0 1 0 0 0 0 0 1 0 0 1 0 1 0 0
27-27705.jpg 0 1 0 0 1 0 0 1 0 1 0 0 1 0 0 1 0
27-27706.jpg 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
27-27709.jpg 0 1 0 1 0 0 1 0 0 0 0 0 1 0 0 1 0
27-27712.jpg 0 1 0 0 0 0 0 1 0 1 0 0 1 0 1 0 0
```

IAPR TC-12 Data set

Tensorflow+Keras

Tensorflow :

**Google Open-source library for
developing and training
machine learning models**

Keras :

**Acts as an interface for the
TensorFlow library**

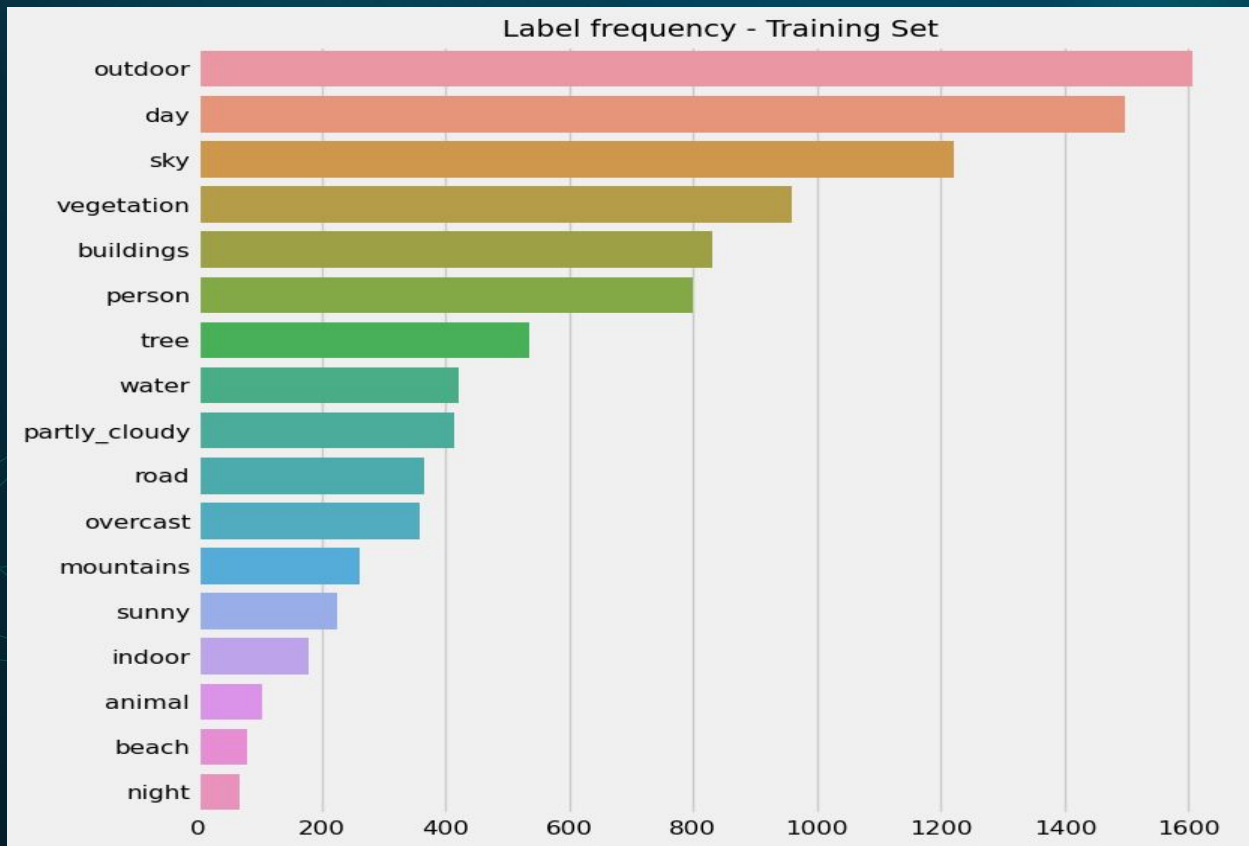


Data preparation Challenges

1. GIF types

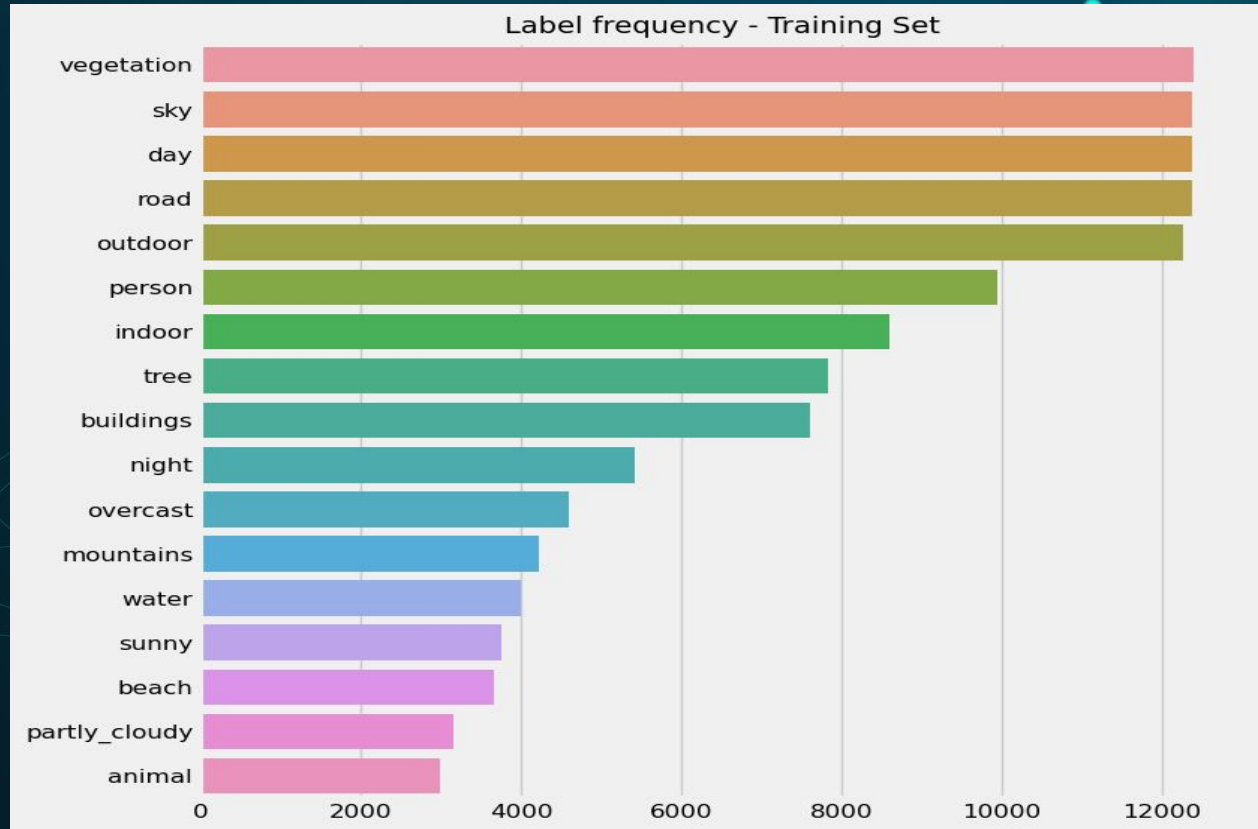
Removed from the train dataset because they were less than 1%. (3 images)

2. Unbalanced data set



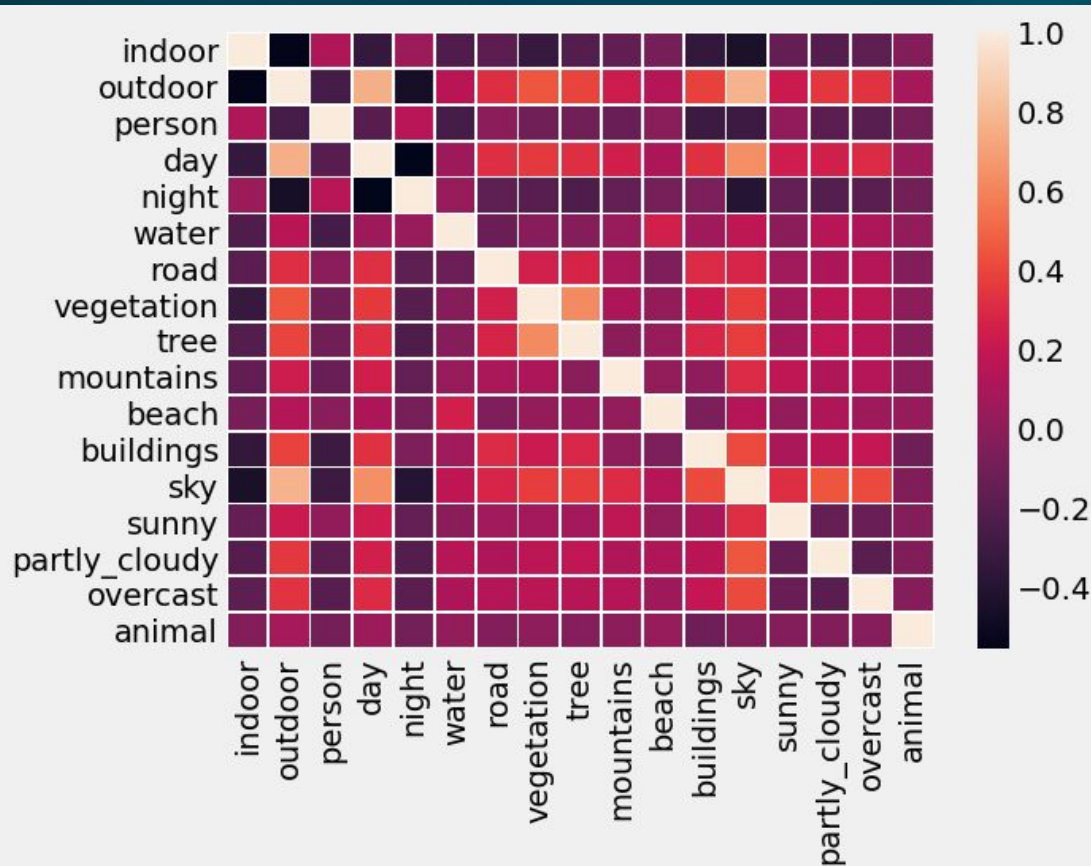
Data preparation Challenges

- SMOTETomek



Data preparation Challenges

Features are correlated so
oversampling and
undersampling weren't
effective in the results.



Data preparation Challenges

Classes Weights

'indoor': 2.12	'buildings': 1.0
'Outdoor': 1.0	'sky': 1.0
'person': 1.0	'sunny': 1.89
'day': 1.0	'partly_cloudy': 1.28
'night': 3.0	'overcast': 1.42
'water': 1.26,	'animal': 2.67
'road': 1.40	
'vegetation': 1.0	
'tree': 1.02	
'mountains': 1.74	
'beach': 2.92	

Data Argumentation

Vertical flip

Shear

Rotation

Zoom

Horizontal flip

Model choice

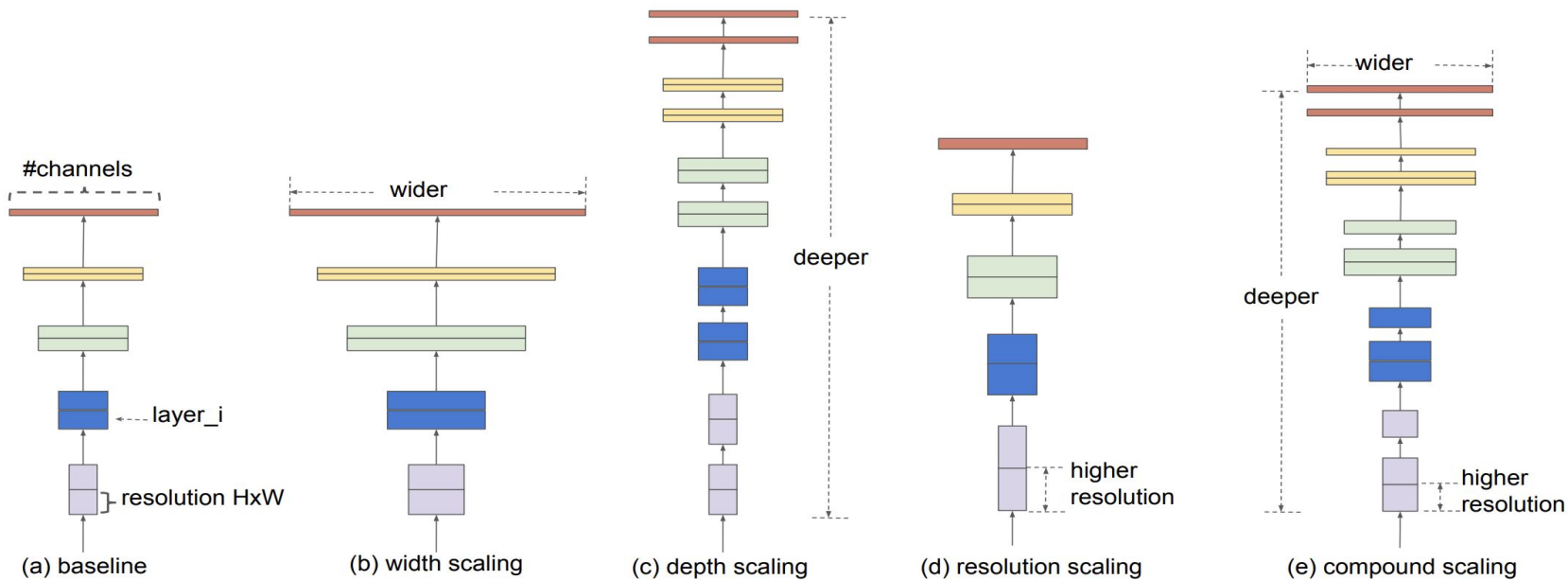
Tested models

- ResNet 50
- EfficientNet B1
- EfficientNet B2

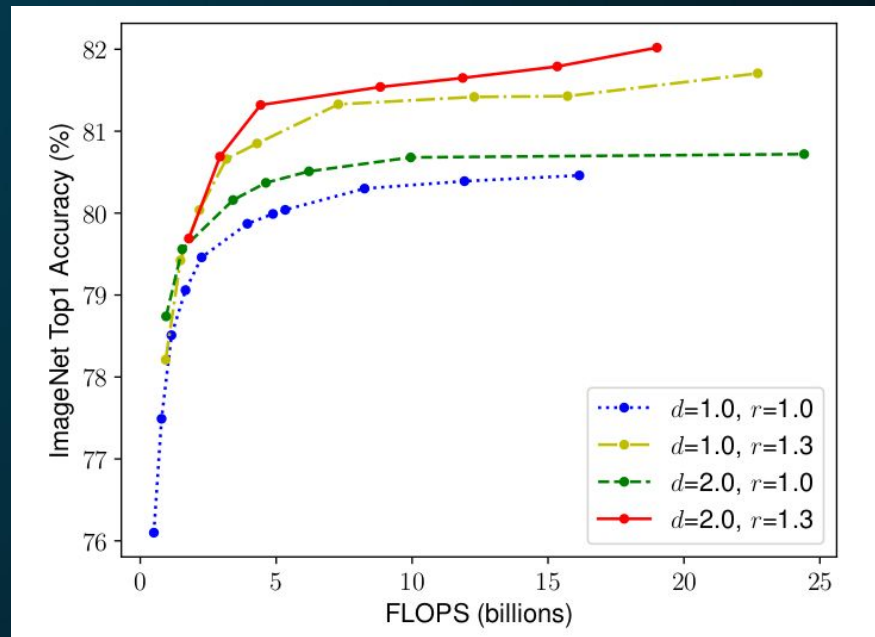
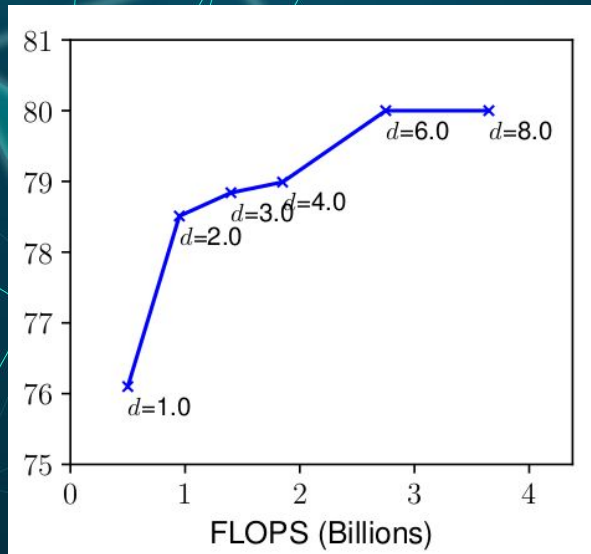
Selected

- EfficientNet B2

ResNet vs EfficientNet - I



ResNet vs EfficientNet - II



ResNet vs EfficientNet - III

Model	Top-1 Acc.	Top-5 Acc.	#Params	Ratio-to-EfficientNet	#FLOPs	Ratio-to-EfficientNet
EfficientNet-B0	77.1%	93.3%	5.3M	1x	0.39B	1x
ResNet-50 (He et al., 2016)	76.0%	93.0%	26M	4.9x	4.1B	11x
DenseNet-169 (Huang et al., 2017)	76.2%	93.2%	14M	2.6x	3.5B	8.9x
EfficientNet-B1	79.1%	94.4%	7.8M	1x	0.70B	1x
ResNet-152 (He et al., 2016)	77.8%	93.8%	60M	7.6x	11B	16x
DenseNet-264 (Huang et al., 2017)	77.9%	93.9%	34M	4.3x	6.0B	8.6x
Inception-v3 (Szegedy et al., 2016)	78.8%	94.4%	24M	3.0x	5.7B	8.1x
Xception (Chollet, 2017)	79.0%	94.5%	23M	3.0x	8.4B	12x
EfficientNet-B2	80.1%	94.9%	9.2M	1x	1.0B	1x
Inception-v4 (Szegedy et al., 2017)	80.0%	95.0%	48M	5.2x	13B	13x
Inception-resnet-v2 (Szegedy et al., 2017)	80.1%	95.1%	56M	6.1x	13B	13x
EfficientNet-B3	81.6%	95.7%	12M	1x	1.8B	1x
ResNeXt-101 (Xie et al., 2017)	80.9%	95.6%	84M	7.0x	32B	18x
PolyNet (Zhang et al., 2017)	81.3%	95.8%	92M	7.7x	35B	19x
EfficientNet-B4	82.9%	96.4%	19M	1x	4.2B	1x
SENet (Hu et al., 2018)	82.7%	96.2%	146M	7.7x	42B	10x
NASNet-A (Zoph et al., 2018)	82.7%	96.2%	89M	4.7x	24B	5.7x
AmoebaNet-A (Real et al., 2019)	82.8%	96.1%	87M	4.6x	23B	5.5x
PNASNet (Liu et al., 2018)	82.9%	96.2%	86M	4.5x	23B	6.0x
EfficientNet-B5	83.6%	96.7%	30M	1x	9.9B	1x
AmoebaNet-C (Cubuk et al., 2019)	83.5%	96.5%	155M	5.2x	41B	4.1x

EfficientNet B0 architecture

Stage i	Operator F_i	Resolution $H_i \times W_i$	#Channels C_i	#Layers L_i
1	Conv3x3	224×224	32	1
2	MBConv1, k3x3	112×112	16	1
3	MBConv6, k3x3	112×112	24	2
4	MBConv6, k5x5	56×56	40	2
5	MBConv6, k3x3	28×28	80	3
6	MBConv6, k5x5	14×14	112	3
7	MBConv6, k5x5	14×14	192	4
8	MBConv6, k3x3	7×7	320	1
9	Conv1x1 & Pooling & FC	7×7	1280	1

Class	precision	recall	f1 score
indoor	0.66	0.68	0.67
outdoor	0.95	0.95	0.95
person	0.63	0.65	0.64
day	0.88	0.95	0.92
night	0.00	0.00	0.00
water	0.47	0.16	0.24
road	0.00	0.00	0.00
vegetation	0.74	0.77	0.76
tree	0.66	0.55	0.60
mountains	0.50	0.01	0.01
beach	0.00	0.00	0.00
buildings	0.67	0.67	0.67
sky	0.94	0.84	0.88
sunny	0.61	0.39	0.47
partly_cloudy	0.52	0.24	0.33
overcast	0.76	0.45	0.57
animal	0.00	0.00	0.00
Average precision: 0.80			
Average recall: 0.67			
Average f1 score: 0.73			

ResNet50

Class	precision	recall	f1 score
indoor	0.68	0.69	0.68
outdoor	0.96	0.96	0.96
person	0.64	0.54	0.59
day	0.90	0.96	0.93
night	0.00	0.00	0.00
water	0.50	0.29	0.36
road	0.70	0.04	0.07
vegetation	0.73	0.83	0.78
tree	0.56	0.55	0.56
mountains	0.48	0.07	0.13
beach	0.00	0.00	0.00
buildings	0.67	0.69	0.68
sky	0.93	0.93	0.93
sunny	0.58	0.60	0.59
partly_cloudy	0.56	0.39	0.46
overcast	0.76	0.34	0.47
animal	1.00	0.02	0.03
Average precision: 0.79			
Average recall: 0.70			
Average f1 score: 0.74			

EfficientNet B1

Model Parameters

Efficient Net B2:

- Weights: None
- Pooling: Average
- DropOut Rate: 0.2
- Input Shape: 260 x 260 x 3

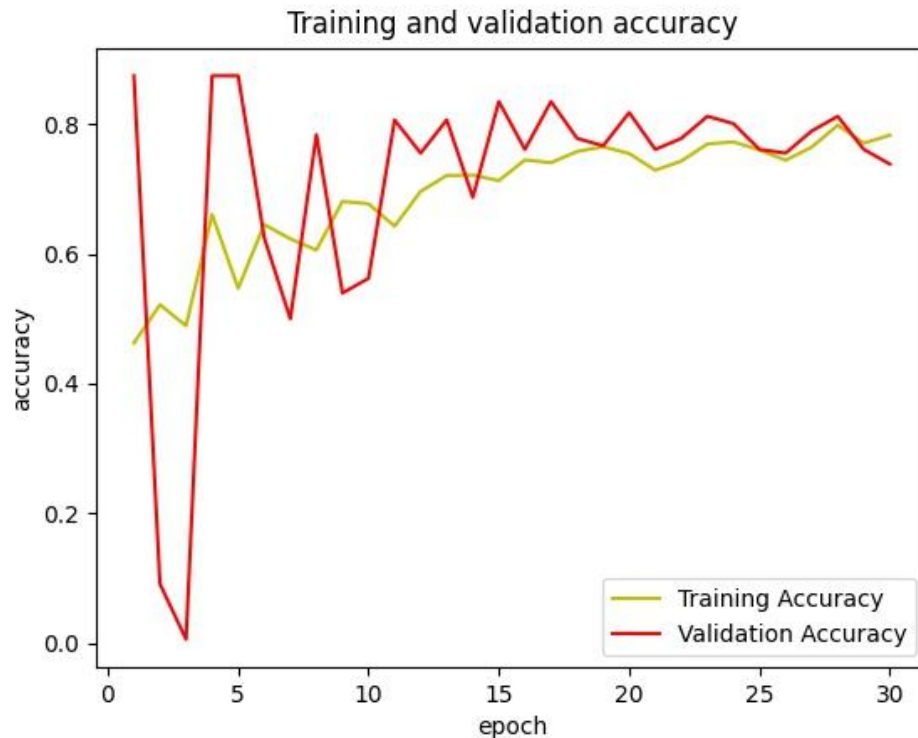
Model:

Layer (type)	Output Shape	Param #
efficientnetb2 (Functional)	(None, 1408)	7768569
dense_1 (Dense)	(None, 512)	721408
dropout (Dropout)	(None, 512)	0
dense_2 (Dense)	(None, 17)	8721
Total params: 8,498,698		
Trainable params: 8,431,123		
Non-trainable params: 67,575		

- Batch Size: 32

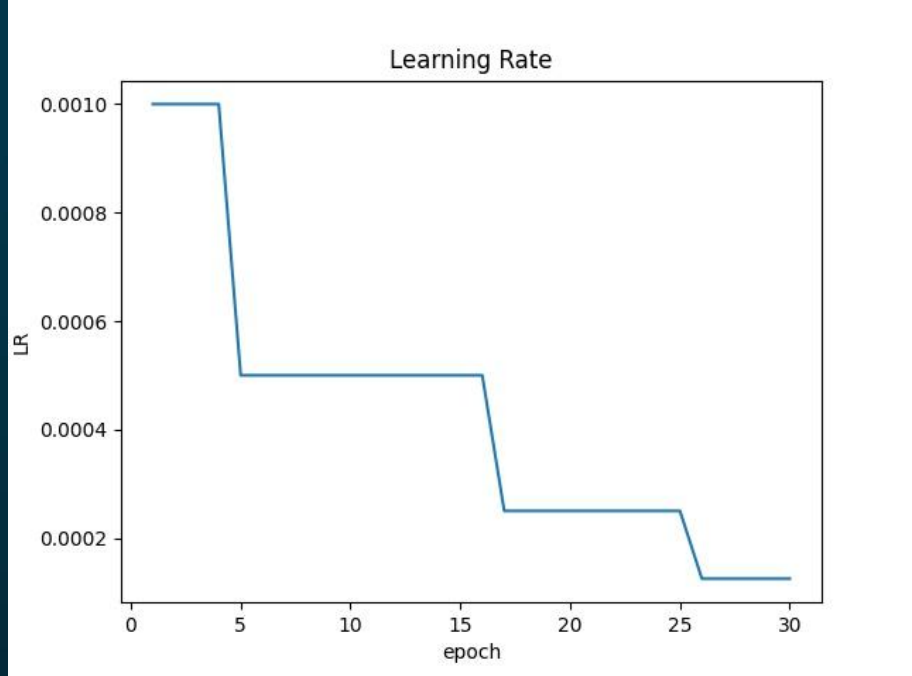
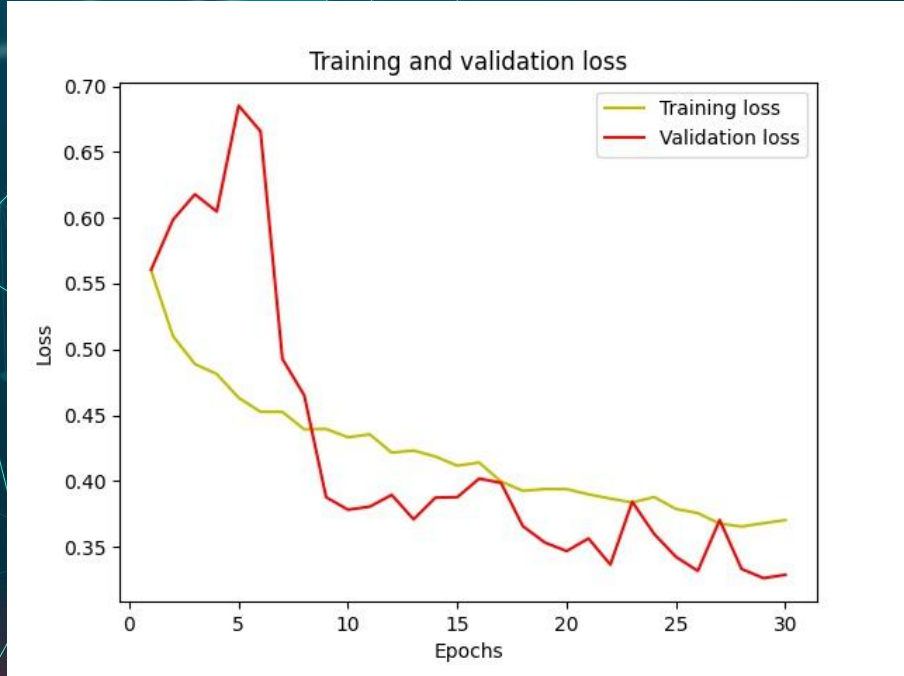
- Output Activation: Sigmoid
- Optimizer: Adam
- Loss: Binary Cross Entropy
- Callbacks: ReduceLROnPlateau

Results



Class	precision	recall	f1 score
indoor	0.88	0.35	0.50
outdoor	0.92	0.99	0.95
person	0.72	0.45	0.56
day	0.88	0.97	0.92
night	0.47	0.39	0.43
water	0.50	0.35	0.41
road	0.54	0.10	0.17
vegetation	0.72	0.86	0.78
tree	0.61	0.69	0.65
mountains	0.63	0.27	0.38
beach	0.00	0.00	0.00
buildings	0.70	0.76	0.73
sky	0.93	0.91	0.92
sunny	0.73	0.27	0.39
partly_cloudy	0.57	0.53	0.55
overcast	0.67	0.69	0.68
animal	0.60	0.05	0.10

Average precision: 0.79
Average recall: 0.73
Average f1 score: 0.76





Questions?