

Schneider Electric

TEAM: ZeroOne



NUWE ZERO DEFORESTATION MISSION

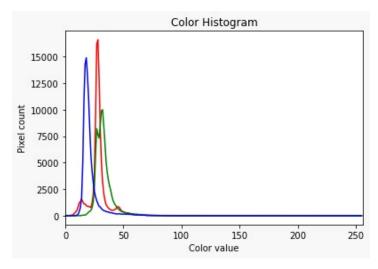
Sai Thejeshwar, Abhay Joshi

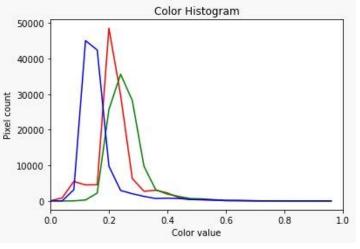
EXECUTIVE PROJECT SUMMARY

The hackathon presented an opportunity to work with a real-time captured satellite imagery data to detect signs of early deforestation in protected areas.

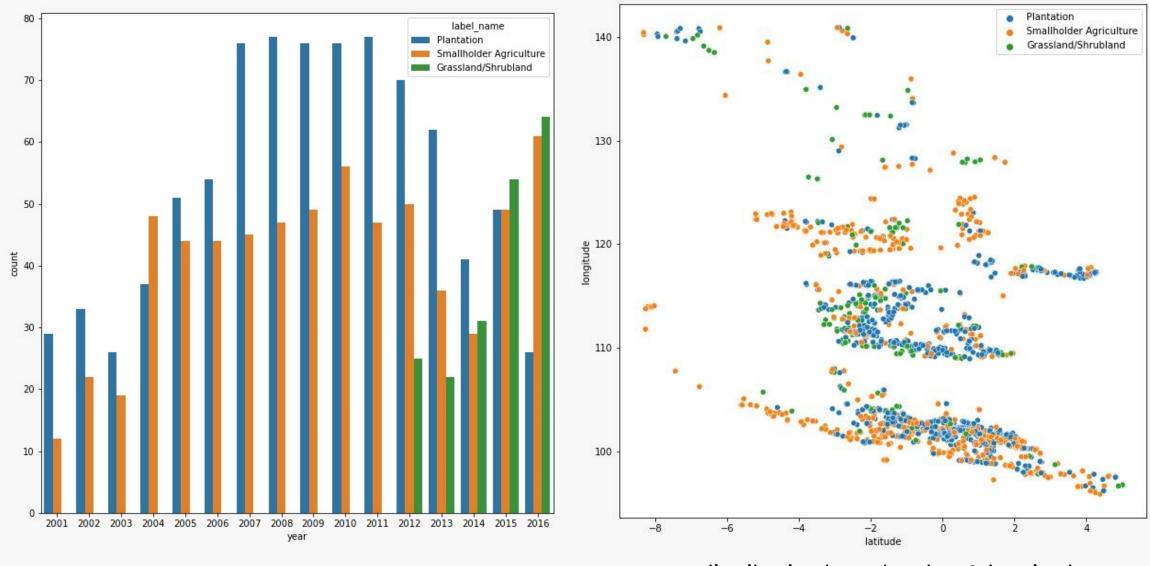
The initial architecture was based on utilizing a homebrewn CNN. However, as the obtained F1-score was quite low (0.32), we decided to use explore the possibility of using pre-trained models such as ResNet and DenseNet.

The pre-trained models (SVM, resnet34, resnet50, densenet121, vgg16), augmented by ensemble learning led to a satisfactory **F1-score of 0.95.**





1. DATASET VISUALIZATION



distribution over a period of time

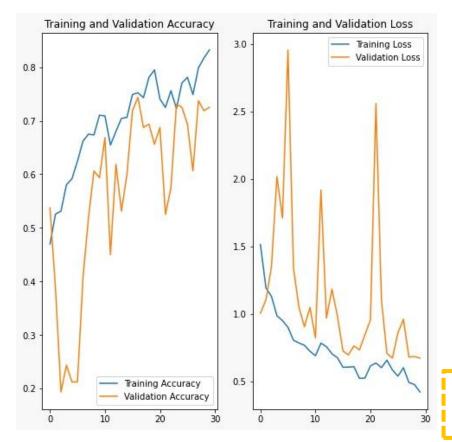
distribution based on lat. & longitude

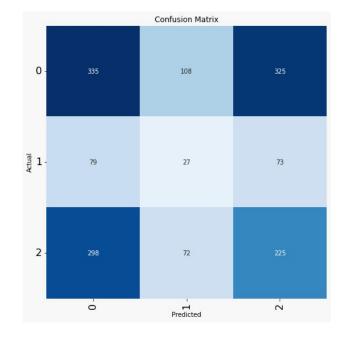
2. CONSTRUCTING A CNN WITH 17 LAYERS

Model: "sequential_12"

Layer (type)	Output Shape	Param #			
conv2d_32 (Conv2D)	(None, 298, 298, 32)	896			
batch_normalization_40 (BatchNormalization)	(None, 298, 298, 32)	128			
<pre>max_pooling2d_30 (MaxPoolin g2D)</pre>	(None, 149, 149, 32)	0			
dropout_40 (Dropout)	(None, 149, 149, 32)	0			
conv2d_33 (Conv2D)	(None, 147, 147, 64)	18496			
<pre>batch_normalization_41 (Bat chNormalization)</pre>	(None, 147, 147, 64)	256			
<pre>max_pooling2d_31 (MaxPoolin g2D)</pre>	(None, 73, 73, 64)	0			
dropout_41 (Dropout)	(None, 73, 73, 64)	0			
conv2d_34 (Conv2D)	(None, 71, 71, 128)	73856			
<pre>batch_normalization_42 (Bat chNormalization)</pre>	(None, 71, 71, 128)	512			
<pre>max_pooling2d_32 (MaxPoolin g2D)</pre>	(None, 35, 35, 128)	0			
dropout_42 (Dropout)	(None, 35, 35, 128)	0			
flatten_10 (Flatten)	(None, 156800)	0			
dense_20 (Dense)	(None, 512)	80282112			
<pre>batch_normalization_43 (Bat chNormalization)</pre>	(None, 512)	2048			
dropout_43 (Dropout)	(None, 512)	0			
dense_21 (Dense)	(None, 3)	1539			

Total params: 80,379,843 Trainable params: 80,378,371 Non-trainable params: 1,472 The obtained training accuracy was 83.22%, while the validation accuracy was 72.50% - albeit with a low F1-score





Classification Report:

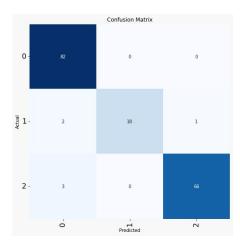
	precision	recall	f1-score	support
0	0.47	0.44	0.45	768
1	0.13	0.15	0.14	179
2	0.36	0.38	0.37	595
accuracy			0.38	1542
macro avg	0.32	0.32	0.32	1542
weighted avg	0.39	0.38	0.38	1542

3. CONSTRUCTING AN ENSEMBLE MODEL

The obtained training accuracy and validation accuracy was around 97% - with a satisfactory F1-score of 0.95

ensemble model layers

```
prediccionesSVC=clasificadores.predict(Xval)
#VGG16
learnerV16=load_learner("model/vgg16_bn.pkl", cpu=False)
prediccionesV16=[]
#Resnet34
learnerR34=load_learner("model/resnet34.pkl", cpu=False)
prediccionesR34=[]
#Resnet50
learnerR50=load_learner("model/resnet50.pkl", cpu=False)
prediccionesR50=[]
#Densenet121
learnerD121=load_learner("model/densenet121.pkl", cpu=False)
prediccionesD121=[]
```



Classification Report:

	precision	recall	f1-score	support
0 1 2	0.94 1.00 0.99	1.00 0.86 0.96	0.97 0.92 0.97	82 21 69
accuracy macro avg weighted avg	0.98 0.97	0.94 0.97	0.97 0.95 0.96	172 172 172

