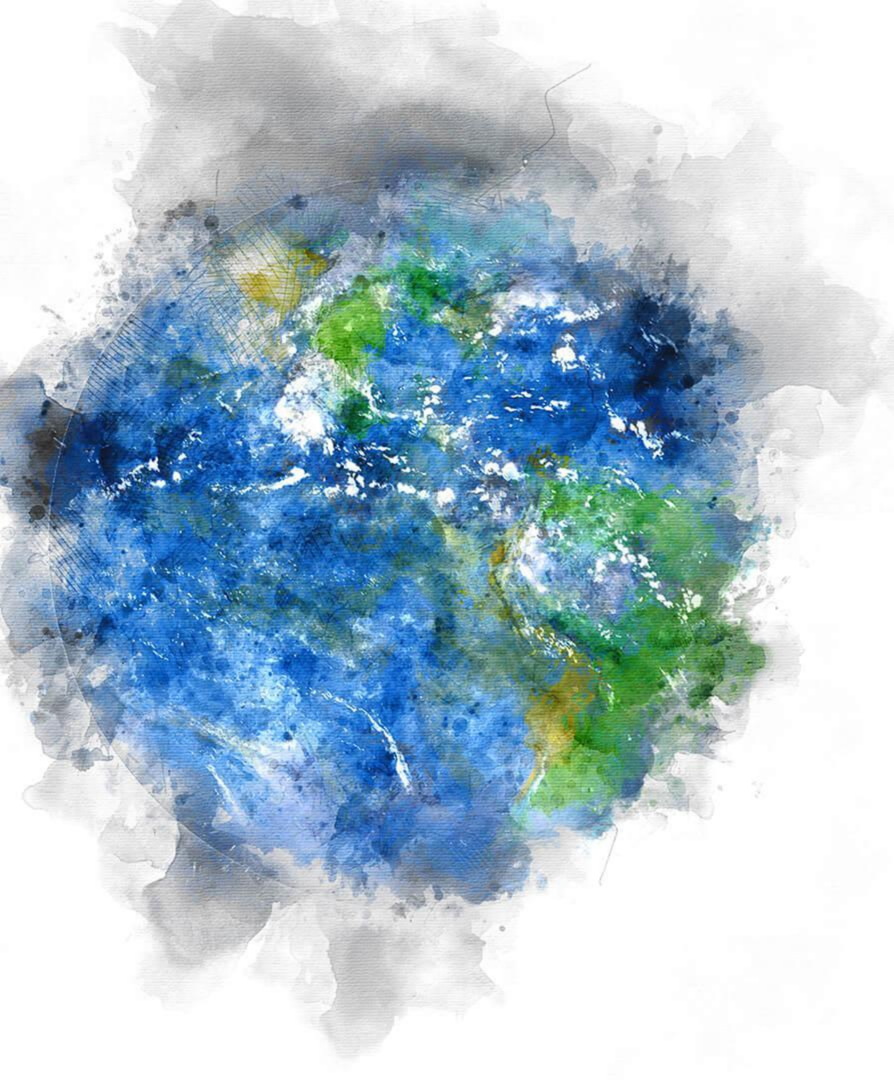

Understanding the AMAZON from Space

Using satellite data to track human footprint in the Amazon rainforest

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Sahana Subramanian
Onyekachi Ugo
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Introduction

84%

Increase in Amazon Forest Fires since 2018

39%

Increase in Deforestation since 2018

- The Amazon is home to one million indigenous people and three million species of plants and animals.
- It is essential to understand the location of deforestation and human encroachment to enable speedy response times and curb further damage to the ecosystem.
- Advancement in satellite imagery coupled with machine learning has paved way for detecting small-scale deforestation and differentiating between human and natural causes of deforestation

AGENDA

- Problem Statement
- Dataset and Exploration
- Challenges
- Pre-Processing
- Evaluation
- Models
- Optimizing Model Performance
- Conclusion
- Future Scope

PROBLEM STATEMENT

- Multi-label image classification with one or more of 17 labels.
- Amazonian land surfaces - Single image covers 1 sq km.
- Color is an important factor in classifying rainforest images, so we had to work with all three channels (RGB).

DATASET AND EXPLORATION

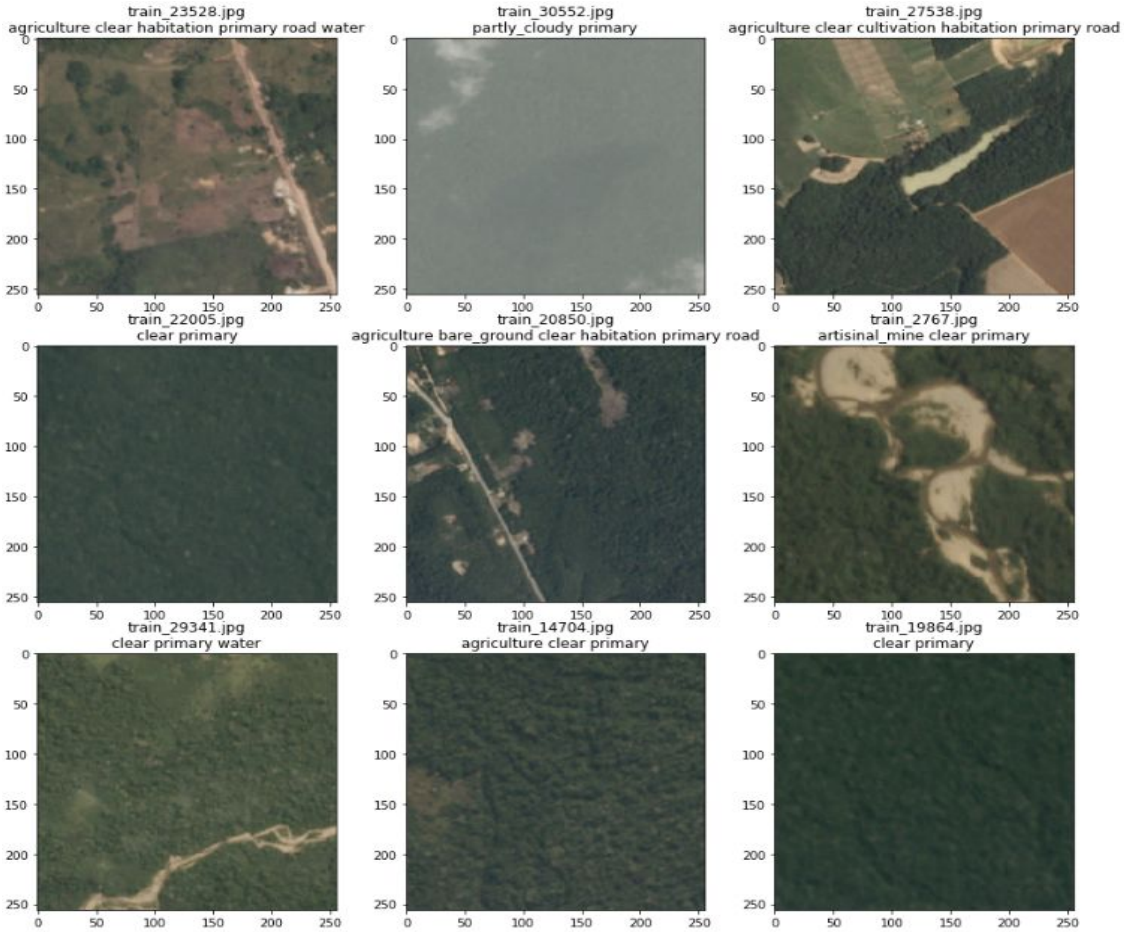
DATA

Source: Kaggle Competition

Content:

- Data consists of 40,479 training samples and 61,192 test samples from satellite imagery.
- Each image is of size (256, 256, 3), with the channels representing R,G,B.
- Each image has one or more atmospheric labels and zero or more common and rare labels.
- The data was also provided in 4-channel TIF format, with the fourth channel being infrared.

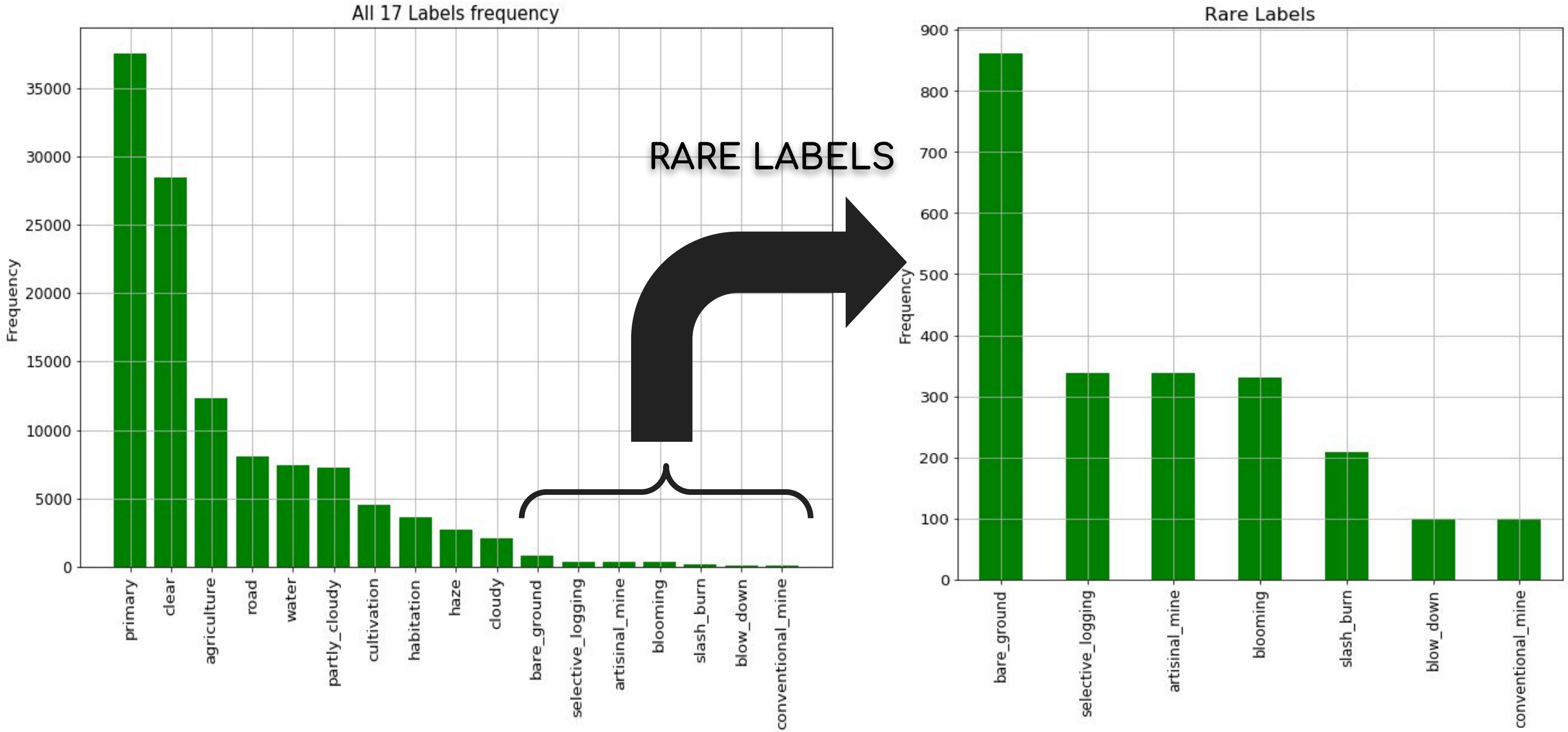
SAMPLE IMAGES



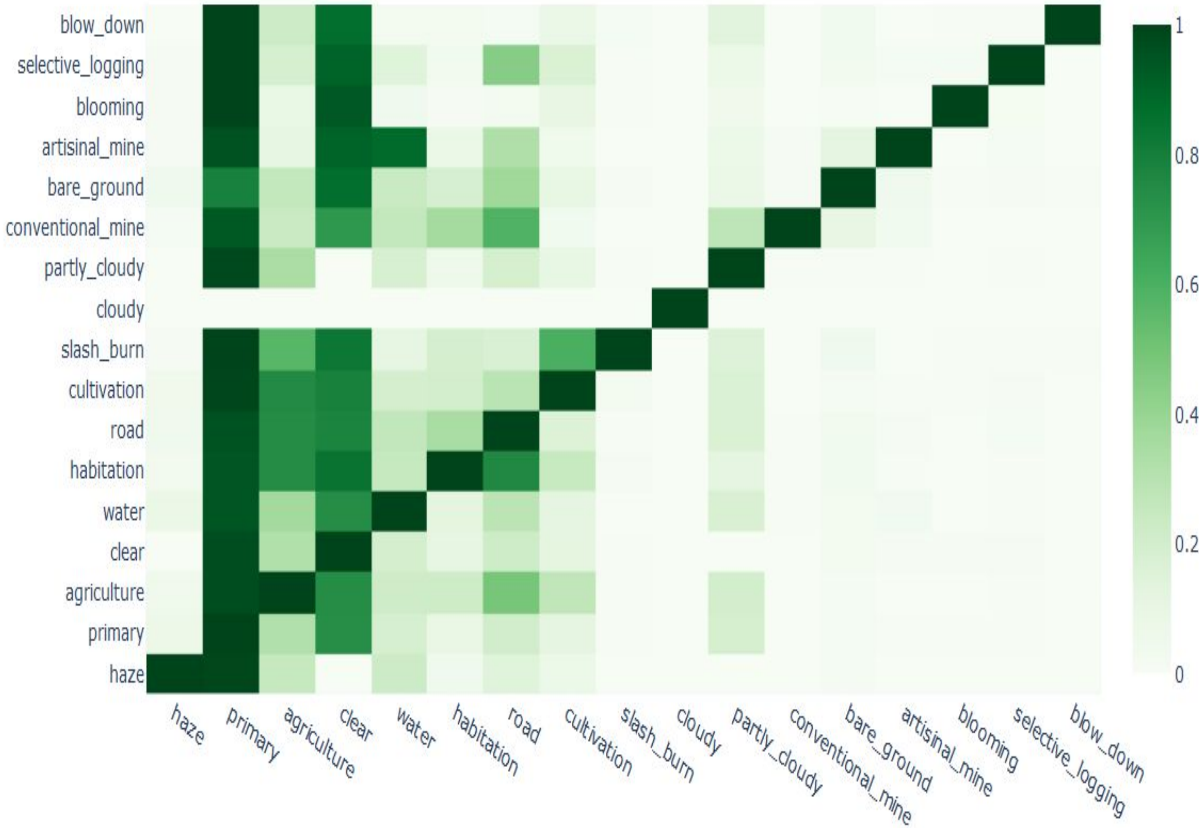
LABEL DISTRIBUTION

17 Labels

7 Rare labels - 0.2%



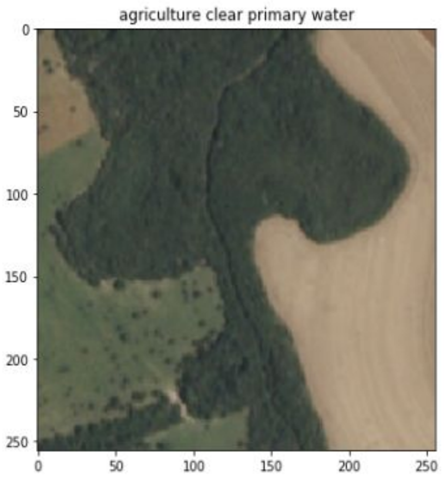
CO-OCCURRENCE MATRIX



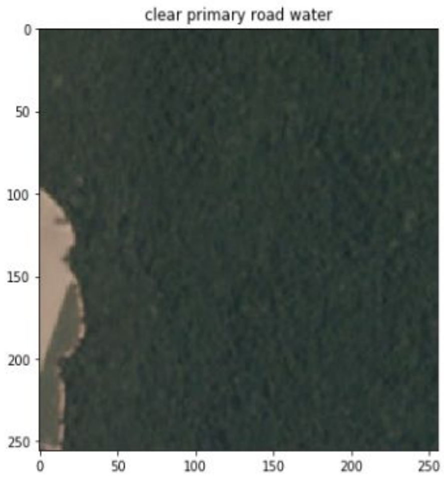
CHALLENGES

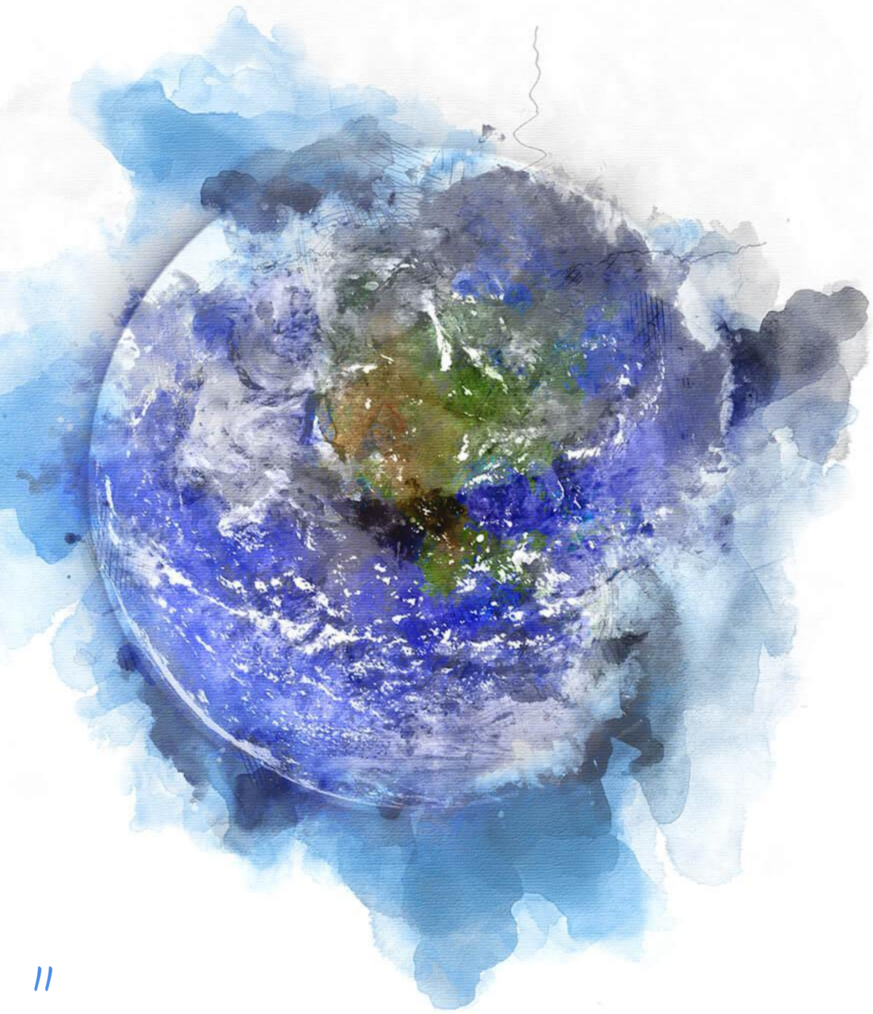
- Data Quality Issues: Inconsistencies with label assignment
- TIF files have some misalignments with the JPG files. We might not be able to use the entire TIF data
- Rare Labels are very infrequent and together only account for less than 0.5% of all the labels found in the dataset.

Can see road, but not labelled!



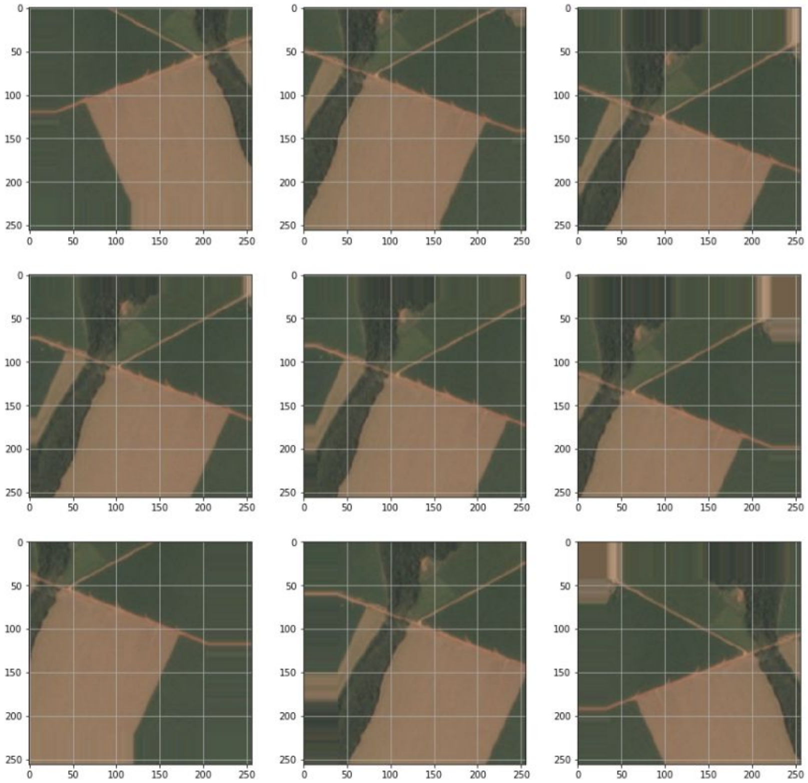
Can you spot the road?

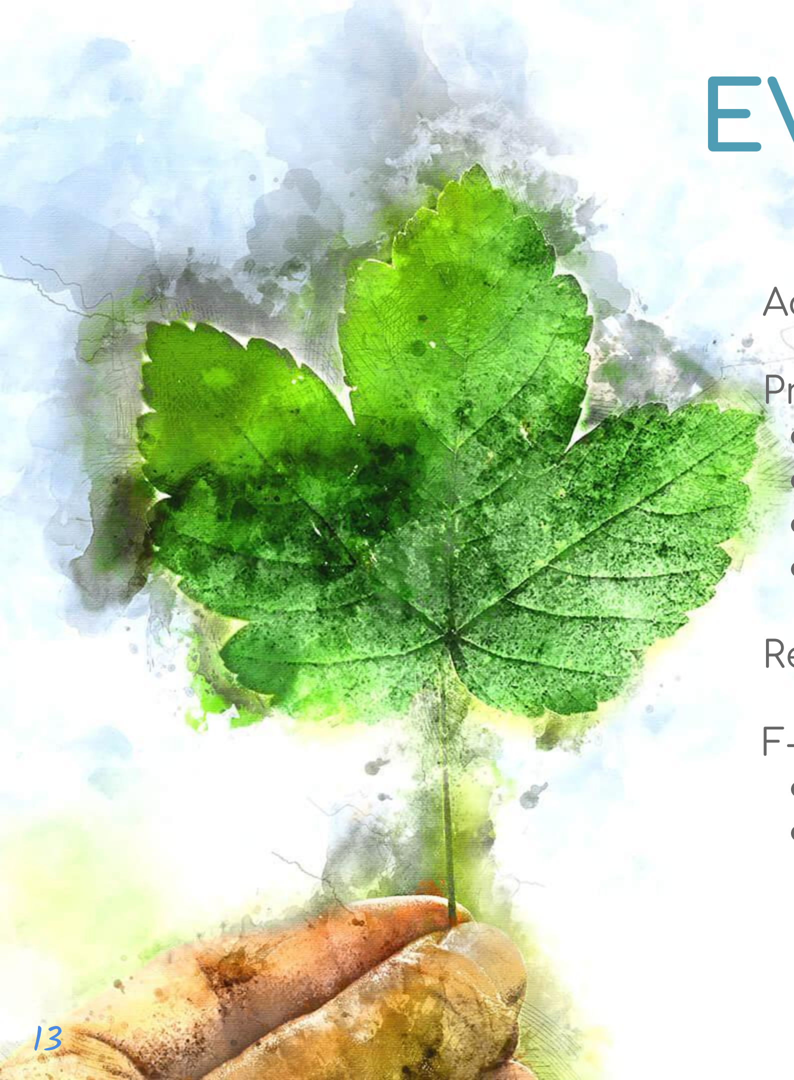




PRE-PROCESSING

IMAGE AUGMENTATION





EVALUATION METRICS

Accuracy doesn't work!

Precision - for every image:

- TP - no. of labels correctly classified(is river, classified as river)
- FP - no. of labels falsely classified (is river, did not classify as river)
- TN - no. of labels correctly left out (is not river, not classified as river)
- FN - no. of labels incorrectly left out (is not river, classified as river)

Recall - for evaluating no of rare labels classified

F-beta-score

- Generalised formula: $(1+\beta^2)\dfrac{pr}{\beta^2 p + r}$
- For our purpose, $\beta = 2$

MODEL IMPLEMENTATION

HYPERPARAMETER TUNING

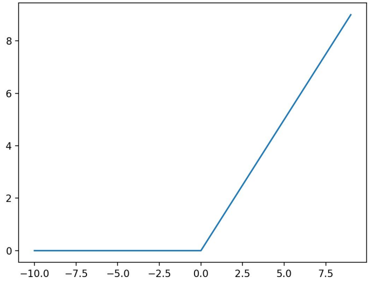
Tuned a sample of the data on different combinations of hyperparameters

- Loss function - binary cross entropy,
- Activation function : sigmoid and relu
- #epochs, #layers
- Learning rate, dropout rate
- Batch size
- No. of folds in cross-validation

LET'S START - BASIC CNN

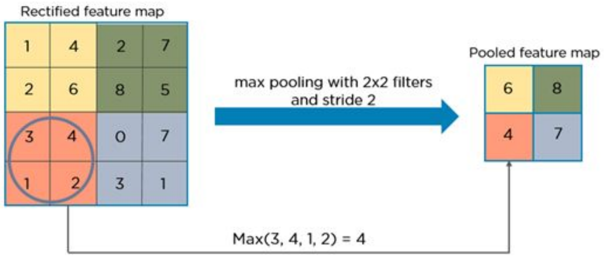
No. of filters: first two of 32 filters, then two of 64, then 3 of both 128 and 256

Conv2D(32, kernel_size=(3, 3), activation='relu',
padding='same',
input_shape=(128, 128, 3))



Then we perform max pooling to get the original size of the image back

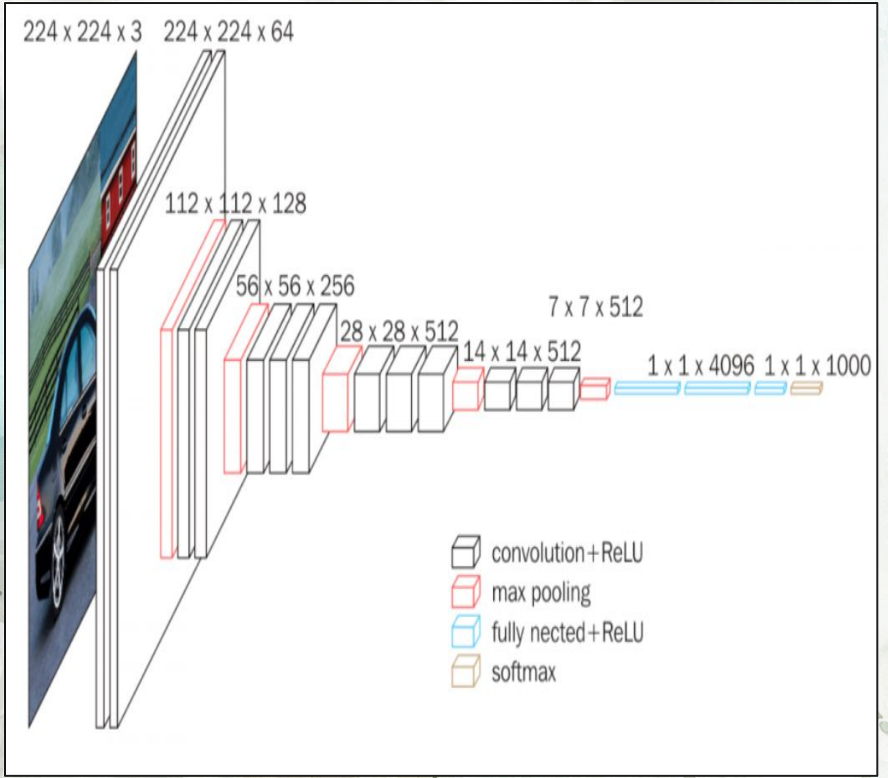
MaxPool2D(pool_size=(2, 2))



We dropout 10% of our nodes, flatten the matrix and fully connect the network

F-Score - 0.89041

VGG16



Transfer Learning with VGG16

Very Deep CNN, trained on ImageNet data

Output : 1 x 17 Dense with Sigmoid Activation

Equipped with ReLu non-linearity

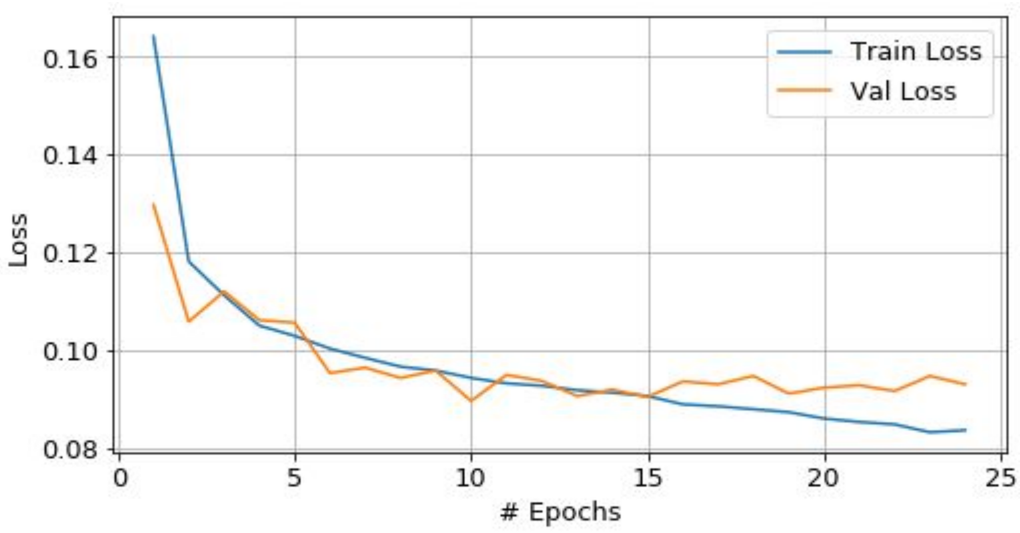
Tried 2 Dense layers with 4096 channels and ReLU activation before the output , but didn't result in much improvement.

VGG16

Learning Rate: 0.0001
Optimization: Adam
Adam Yielded an average val-f2 score of 0.9 per epoch; SGD gave around 0.85
Regularization: 0.01
Dropout: 0.5
Mini batch gradient descent with **batch size: 128**
5 fold cross validation with **25 epochs** each

VGG16 – RESULTS

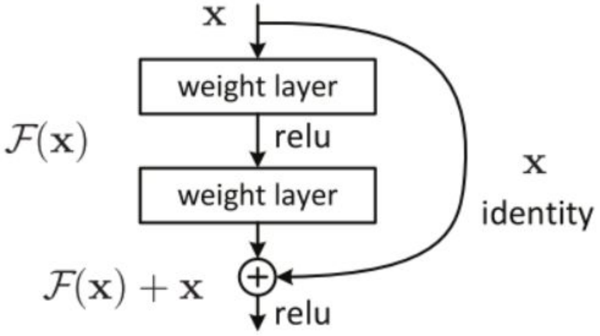
Average Val-f2 Score of 0.9
Kaggle Score – 0.92595
Not much gain after 15 epochs



RESNET

Why RESNET?

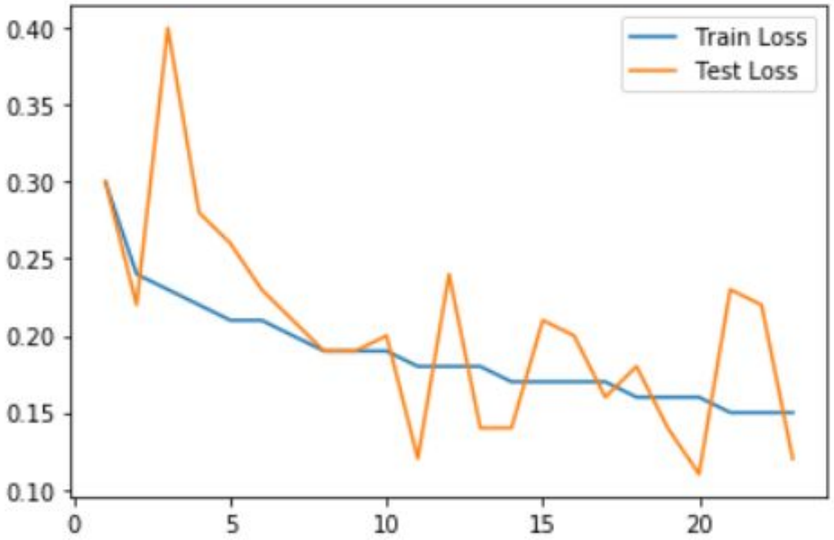
- As the network goes deeper, gradient starts diminishing
- Hence, identity shortcut connection:
    - Skips one or more connections



a residual block

RESNET-50 MODEL PARAMETERS

- Learning Rate= 0.0001
- Activation Function= ReLu
- Batch Size= 256
- Dropout= 0.2
- Epochs = 23

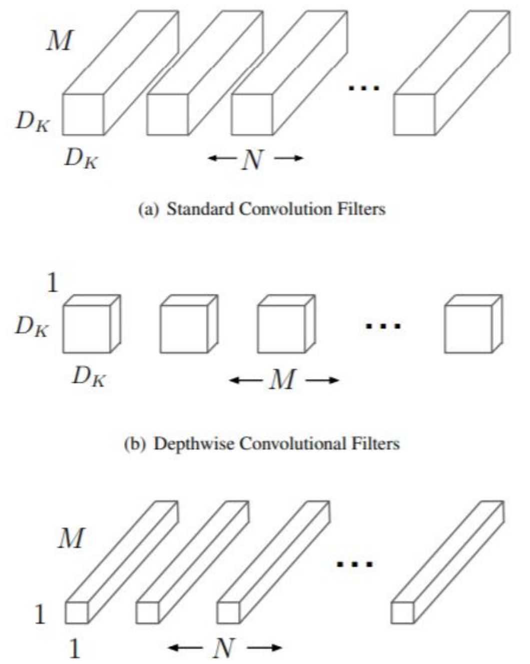


RESNET RESULTS

f2 Score = 0.8625

Labels	Precision	Recall	f1-score	Support
agriculture	30%	42%	35%	12,315
artisinal_mine	1%	2%	1%	339
bare_ground	2%	1%	1%	862
blooming	2%	2%	2%	332
blow_down	0%	0%	0%	98
clear	70%	79%	74%	28,431
cloudy	5%	7%	6%	2,089
conventional_mine	0%	1%	0%	100
cultivation	11%	23%	15%	4,477
habitation	9%	12%	10%	3,660
haze	7%	9%	8%	2,697
partly_cloudy	18%	22%	20%	7,261
primary	93%	98%	95%	37,513
road	19%	29%	23%	8,071
selective_logging	1%	1%	1%	340
slash_burn	1%	1%	1%	209
water	18%	31%	23%	7,411

MOBILENET



(a) Standard Convolution Filters

(b) Depthwise Convolutional Filters

(c) 1×1 Convolutional Filters called Pointwise Convolution in the context of Depthwise Separable Convolution

Why MobileNet?

- This architecture uses depthwise separable convolutions which significantly reduces the number of parameters
- Depthwise convolution is the channel-wise $D_K \times D_K$ spatial convolution. This is followed by pointwise convolution which is the 1×1 convolution to change the dimension.
- Drastically reduces computation and model size

MOBILENET PARAMETERS AND RESULTS

- Image Size= 128 x 128 x 3
- Learning Rate= 0.001
- Activation Function= Relu
- Batch Size= 256
- Epochs = 25

F2-beta Score = 0.9244

IMPROVING MODEL PERFORMANCE

HAZE REMOVAL

- Satellite Images taken from outside of the atmosphere will be distorted
- Haze occurs because light is forced to pass through particles in the air that scatter light like dust, smoke, water vapor etc.
- Used a Single-Image Haze Removal Algorithm using a Dark-Channel Prior

HAZE REMOVAL

- In clear images, at least one color channel has some pixels whose intensities are very close to 0
- In hazy images, the additive airlight increases the intensity in regions with denser haze

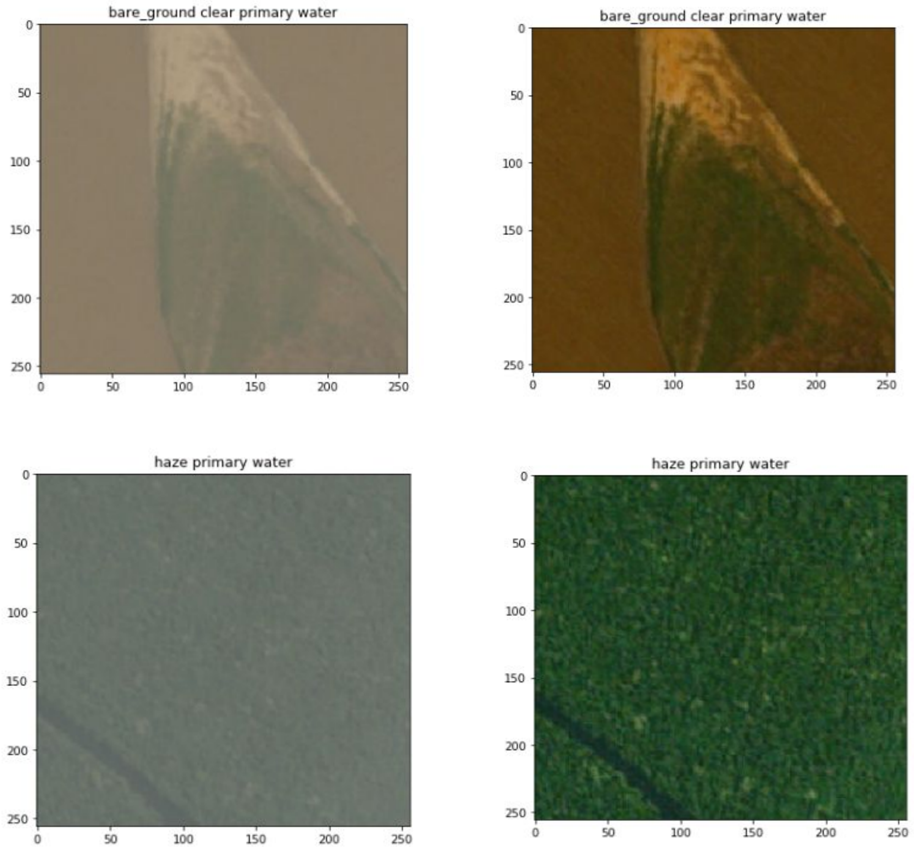
Dark Channel Prior

$$J^{\mathrm{dark}}(\mathbf{x}) = \min_{\mathbf{y}\in\Omega(\mathbf{x})}\left(\min_{c\in\{r,g,b\}} J^{c}(\mathbf{y})\right),$$

Clear Image

Hazy Image

HAZE REMOVAL



HAZE REMOVAL - RESULTS

Before

Labels	Precision	Recall	f1-score	Support
agriculture	30%	42%	35%	12,315
artisinal_mine	1%	2%	1%	339
bare_ground	2%	1%	1%	862
blooming	2%	2%	2%	332
blow_down	0%	0%	0%	98
clear	70%	79%	74%	28,431
cloudy	5%	7%	6%	2,089
conventional_mine	0%	1%	0%	100
cultivation	11%	23%	15%	4,477
habitation	9%	12%	10%	3,660
haze	7%	9%	8%	2,697
partly_cloudy	18%	22%	20%	7,261
primary	93%	98%	95%	37,513
road	19%	29%	23%	8,071
selective_logging	1%	1%	1%	340
slash_burn	1%	1%	1%	209
water	18%	31%	23%	7,411

After

Labels	Precision	Recall	f1-score	Support
agriculture	76%	96%	85%	12315
artisinal_mine	79%	92%	85%	339
bare_ground	46%	68%	55%	862
blooming	28%	52%	37%	332
blow_down	60%	26%	36%	98
clear	93%	99%	96%	28431
cloudy	76%	97%	85%	2089
conventional_mine	76%	73%	74%	100
cultivation	48%	88%	62%	4477
habitation	61%	86%	72%	3660
haze	73%	82%	78%	2697
partly_cloudy	92%	96%	94%	7261
primary	98%	100%	99%	37513
road	74%	95%	83%	8071
selective_logging	41%	64%	50%	340
slash_burn	36%	48%	41%	209
water	75%	89%	81%	7411

THE IMBALANCE CLASS PROBLEM

	Frequency
blow_down	100
blooming	331
slash_burn	208
artisinal_mine	338
selective_logging	339
conventional_mine	99
bare_ground	861

- Heavy class imbalance
- Total training images : 40,479
- 7 labels under 1000. Least being Conventional Mines - just 99 images (0.2%)
- Many rare labels tend to coexist, so in total we have only 2180 images with the rare labels.

XGBOOST

F2-beta Score = 88.2%

Labels	Precision	Recall	f1-score	Support
habitation	62%	96%	75%	12,315
blooming	73%	86%	79%	339
conventional_mine	64%	42%	51%	862
clear	74%	27%	40%	332
agriculture	97%	35%	51%	98
blow_down	89%	99%	94%	28,431
road	72%	96%	82%	2,089
primary	94%	77%	85%	100
slash_burn	41%	70%	52%	4,477
partly_cloudy	55%	83%	66%	3,660
bare_ground	59%	87%	71%	2,697
selective_logging	76%	95%	84%	7,261
water	96%	100%	98%	37,513
cultivation	54%	91%	68%	8,071
artisinal_mine	73%	26%	39%	340
cloudy	100%	19%	31%	209
haze	42%	83%	56%	7,411

A 'RARE' CNN

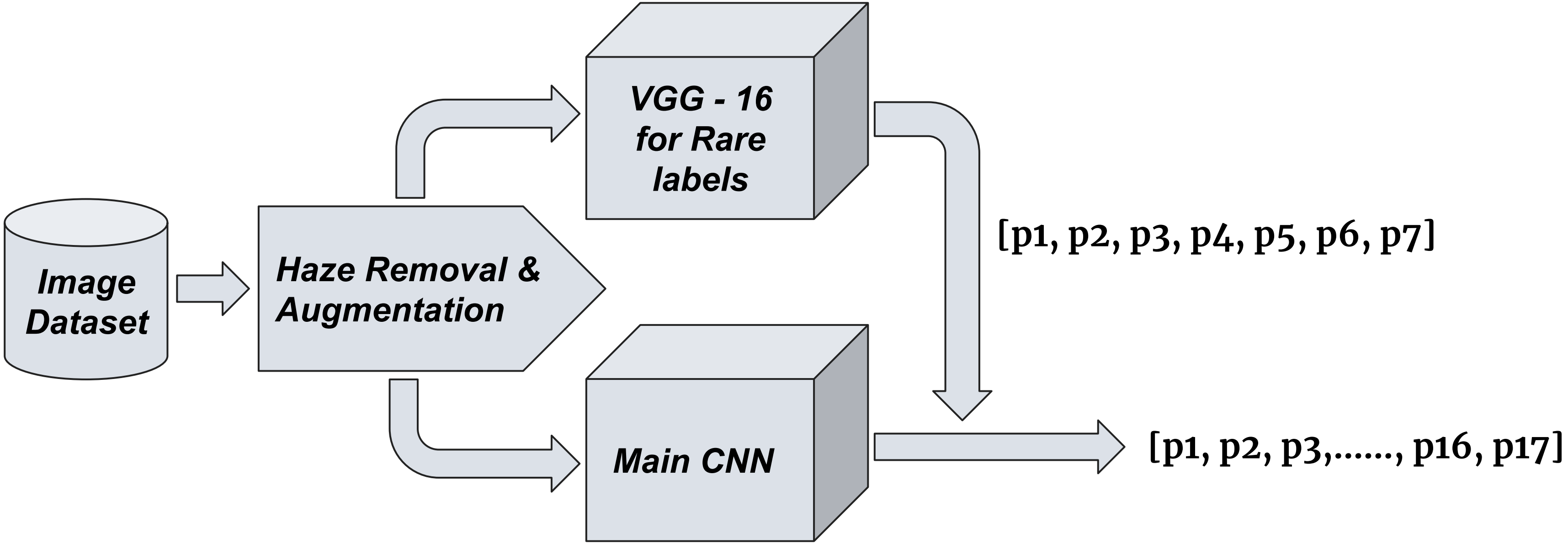
What about building an additional model just to detect the rare labels?

- We stacked another VGG16 on top.
- Created new training data with the rare images and equal # of 'non-rare' images
- Output:

    7 classes instead of 17

    All Zeros for not-rare images
- During testing phase, the data is first sent to this model to detect rare images
- Scale up the corresponding probabilities for rare labels in the output from the 2nd model

MODEL ARCHITECTURE



IMPROVEMENT IN F1 SCORE

Before

	precision	recall	f1-score	support
agriculture	0.89	0.63	0.74	17287
artisinal_mine	0.00	0.14	0.01	7
bare_ground	0.04	0.16	0.07	232
blooming	0.20	0.10	0.14	649
blow_down	0.00	0.00	0.00	29
clear	0.71	0.95	0.81	21278
cloudy	0.87	0.75	0.80	2436
conventional_mine	0.00	0.00	0.00	0
cultivation	0.06	0.62	0.11	445
habitation	0.74	0.48	0.58	5580
haze	0.65	0.63	0.64	2782
partly_cloudy	0.99	0.34	0.51	21332
primary	1.00	0.96	0.98	38899
road	0.85	0.66	0.75	10324
selective_logging	0.00	0.00	0.00	7
slash_burn	0.00	0.00	0.00	0
water	0.90	0.43	0.59	15310
avg / total	0.89	0.70	0.75	136597

After

	precision	recall	f1-score	support
agriculture	0.89	0.63	0.74	17287
artisinal_mine	1.00	0.65	0.78	525
bare_ground	1.00	0.15	0.25	5915
blooming	0.94	0.15	0.26	2046
blow_down	0.99	0.10	0.18	951
clear	0.71	0.95	0.81	21278
cloudy	0.87	0.75	0.80	2436
conventional_mine	1.00	0.57	0.73	175
cultivation	0.06	0.62	0.11	445
habitation	0.74	0.48	0.58	5580
haze	0.65	0.63	0.64	2782
partly_cloudy	0.99	0.34	0.51	21332
primary	1.00	0.96	0.98	38899
road	0.85	0.66	0.75	10324
selective_logging	0.94	0.23	0.37	1401
slash_burn	1.00	0.12	0.21	1765
water	0.90	0.43	0.59	15310
avg / total	0.90	0.66	0.72	148451


WHAT NEXT ?

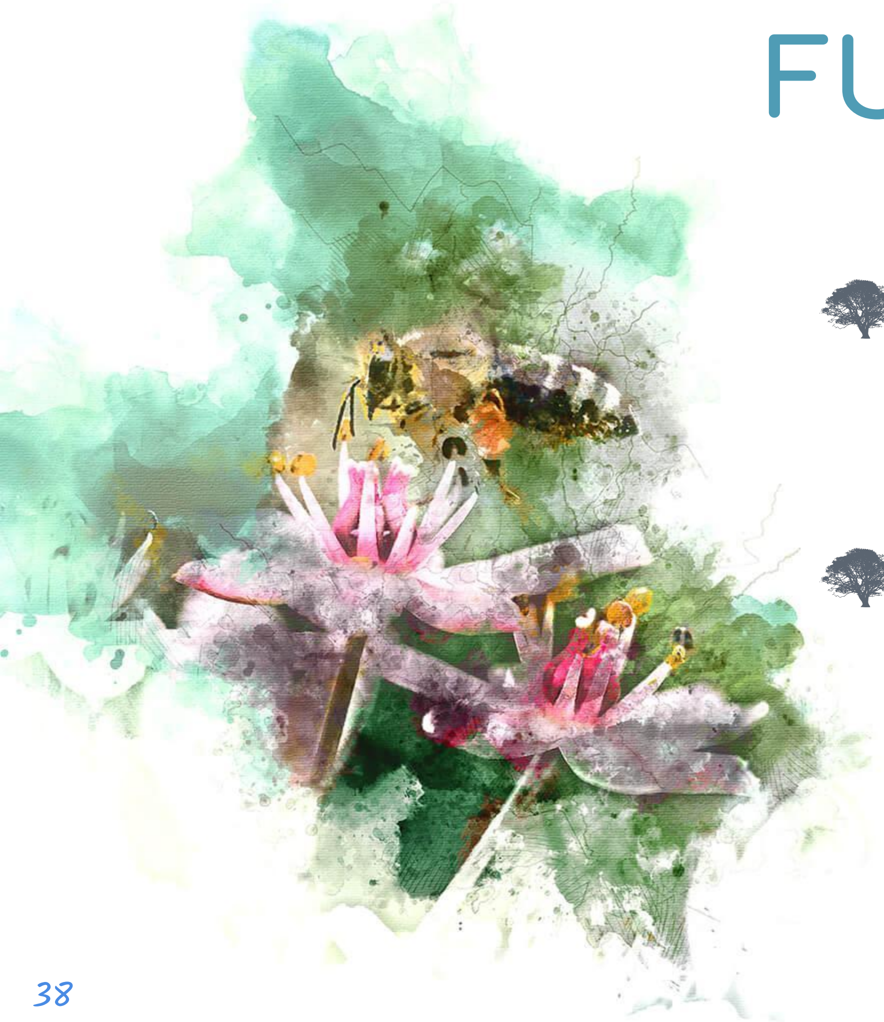
ENSEMBLE

Models				Kaggle (F- Score Beta)
VGG16	MobileNet	Custom	XGBoost	0.91911
	VGG16	MobileNet	Custom	0.92067
		VGG16	MobileNet	0.92758
Preprocess with Rare Label Training & Haze Removal		VGG16	MobileNet	0.92751

CONCLUSION

- TUNING >>> TRAINING
- Noisy data posed challenges, but the real issue was the class imbalance
- Spotting illegal mines and logging is of utmost importance, which we did not want to miss out
- In Kaggle Leaderboard - top 15%, Rank 1 score - 0.93371.
- Our Kaggle Score - 0.92751 with improved F-Score for the rare labels
- We wish to use our model to locate encroachment and potentially curb the damage to the lungs of planet Earth, the Amazon rainforest

FUTURE SCOPE



- Image data across time and with geospatial coordinates, to address the problem of human encroachment
- Labeling the exact location of the objects like mines, river etc.

QUESTIONS?