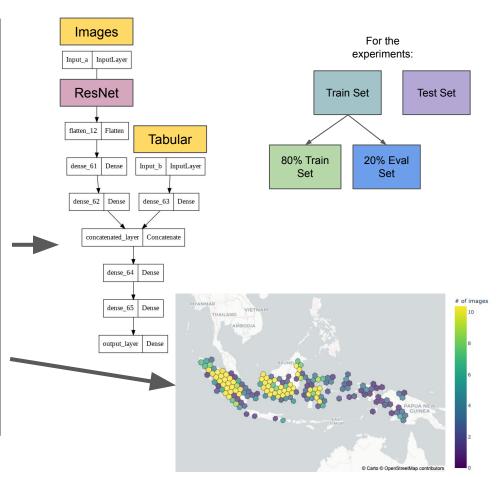
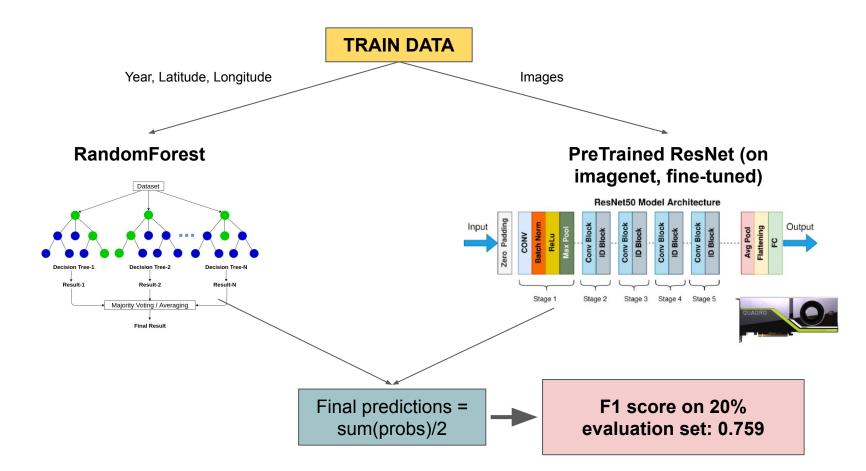
IIII N □ W ≡ Group: Random For(r)est Gump (DT5). Summary

Idea	Result	Conclusion
Simple data exploration	V	Data looks good, images from Malaysia, detection of class imbalances
Check F1 score of simple model with tabular data (year, coordinates)	V	F1 score of around 0.65 with default lightgbm - there is predictive power in the tabular data.
Build CNN network for images and train from scratch (Keras)		Training from scratch (random weights) did not seem to work well, not achieving more than F1 score 0.4.
Build custom Keras model fine-tuning ResNet50 + tabular data concat		Quite difficult and slow to train - had to be done with a very low learning rate to not have unstable training. F1 score 0.742.
Build FastAl CNN with pretrained resnet50	V	FastAl gave very nice results, F1 score 0.745.
Test the <u>h3 hexagons</u> of the coords as features		Did not provide any extra predictive power.
Average ensemble of tabular ML models + Pretrained ResNet50	24.7	We got our best results by ensembling the probability predictions of a random forest and the CNN. F1 Score 0.76.

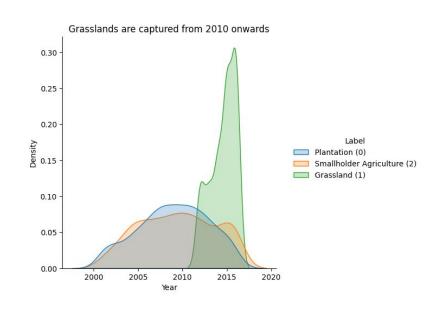


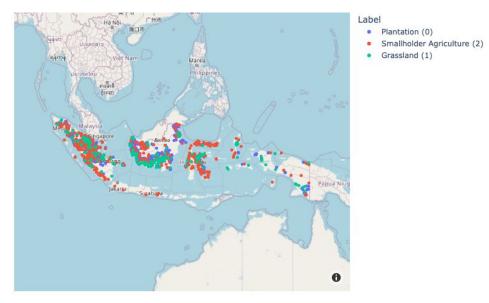
III N ⊔ W ≡ Final model: Ensemble approach



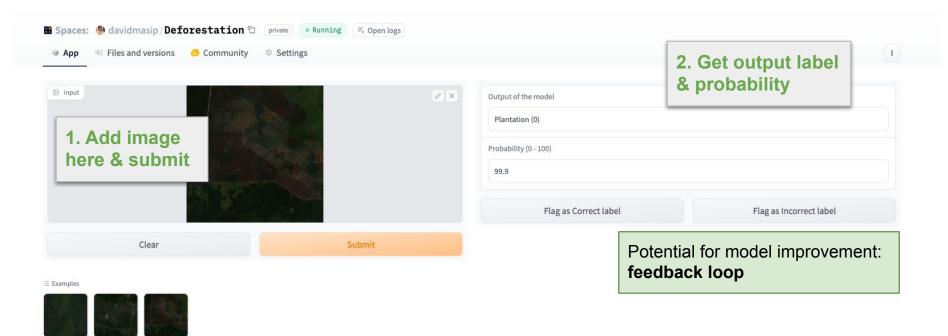
I▶N⊔W≡ Final key insights

- Since there are very few training samples (1714), **overfitting** is an issue. Data augmentation (image transformations, like flipping, random cropping, etc) and ensembling are critical.
- For the tabular data, **bagging** works better than boosting due to the small size of the dataset.
- Leveraging pre-trained CNNs is great to boost performance, be able to iterate fast and get decent results quickly.
- Tabular features matter: year to identify grasslands, each island has their own biodiversity and geography.









Thank you for organising this challenge, we had fun!

Anne, Miquel & David aka the Random For(r)est Gumpers:)