A Novel Integrated Machine Learning Approach Utilizing Radar and Satellite Imagery for Selective Logging Remote Sensing Detection

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Background

USAID estimates illegal logging to be a $150 billion industry, destroying the world's forests. More than half of all tropical deforestation is illegal, and contributes to the 1.5 gigatons of carbon released from deforestation annualy (WWF). However, developing countries struggle without the funding or human resources to monitor their vast expanse of forests through forest patrol. The advent of machine learning allows for a remote sensing solution able to monitor the large region of forestry at low costs. However, current monitoring solutions focus on clear cut deforestation and not selective logging, and thus, illegal logging at these smaller disturbances goes undetected. At the mass quantities of selective logging occuring, forests are left with significant reductions in tropical biomass, growth of weeds/ poor quality - low diversity trees, loss in biodiversity, and are more susceptible to forest fires and soil erosion.

Selective Logging

Clear Cut Logging

In the world's humid tropics, home to vast majority of forestry, persistent cloud cover often hinders the acquisition of clear optical satellite imagery. However, radar imagery overcomes this limitation by penetrating cloud cover, presenting an untapped opportunity for monitoring these regions. Moreover, integrating radar with optical imagery can improve the timeliness of detection, as the differing orbits of Sentinel 1 / Sentinel 2 satellites can halve the interval for data acquisition from 12 to 6 days.

Data Acquistion

Sentinel 1 and 2 imagery was obtained through Google Earth Engine. The dataset selected location as Jamari National Park.

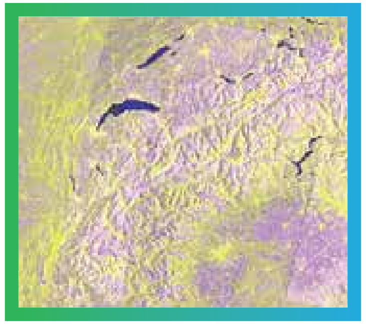


Image credited to Google Earth Engine

Sentinel 1 Radar Imagery

Image credited to Google Earth Engine

Sentinel 2 Optical Imagery

Data Location

Image credited to Google Earth Engine

Selected Sentinel 1 Bands

Sentinel 1 Features

	Resolution
VH	10m
VV	10m

Selected Sentinel 2 Bands

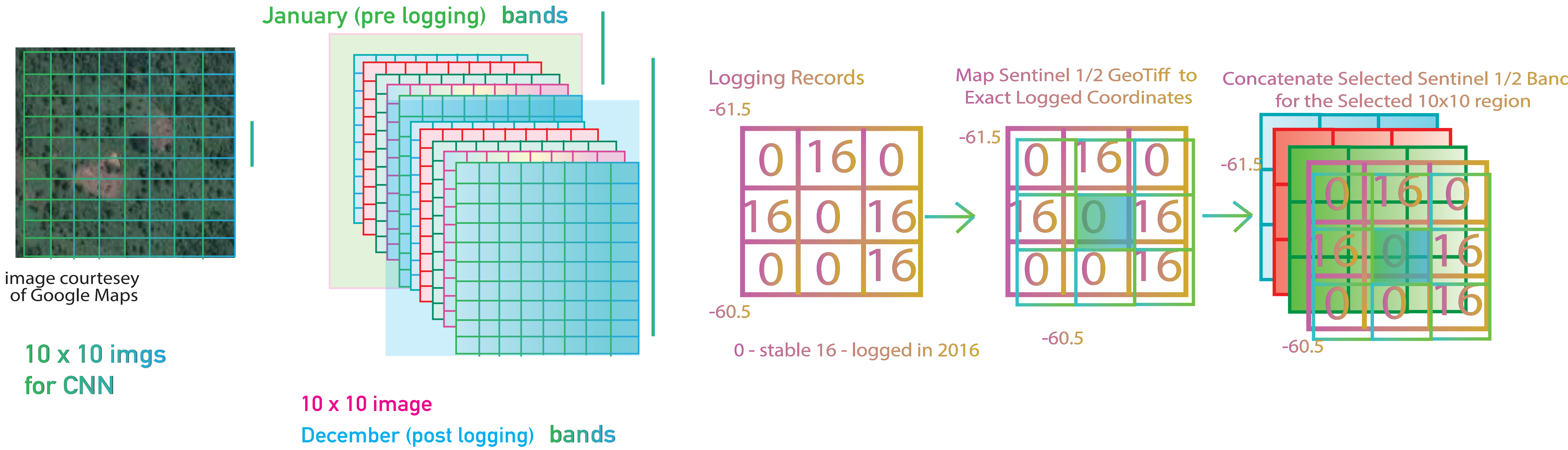
Sentinel 2 Features

	Resolution	Wavelength	Description
B2	10m	443.9nm (S2A) / 442.3nm (S2B)	Blue
B3	10m	496.6nm (S2A) / 492.1nm (S2B)	Green
B4	10m	560nm (S2A) / 559nm (S2B)	Red
B5	20m	664.5nm (S2A) / 665nm (S2B)	Red Edge 1
B6	20m	703.9nm (S2A) / 703.8nm (S2B)	Red Edge 2
B7	20m	740.2nm (S2A) / 739.1nm (S2B)	Red Edge 3
B8	10m	782.5nm (S2A) / 779.7nm (S2B)	NIR(Near Infrared)
B8A	20m	835.1nm (S2A) / 833nm (S2B)	Red Edge 4
B11	20m	864.8nm (S2A) / 864nm (S2B)	SWIR 1
B12	20m	945nm (S2A) / 943.2nm (S2B)	SWIR 2

The data sets compromised the following 12 band values from Sentinel 1 and Sentinel 2. The Sentinel 1 VH and VV bands were selected for both January and December. The Sentinel 2 B2, B3, B4, B5, B6, B7, B8, B8A, B11, and B12 bands were selected for both January and December. In all, 24 band values were used for the combined Sentinel 1 and Sentinel 2 data set.

Data Processing

Logged pixels and a subset of the stable forest pixels were identified to create a balanced dataset for unbiased model. Raw 10x10 images were used. The December and January bands were then merged for model to learn the difference in band values before/after logging. For the combined Sentinel 1/2 data-set, the Sentinel 1 + 2 imagery was merged through concatenation.



Data Sets

$$RVI = \frac{4\sigma VH}{\sigma VV + \sigma VH}$$

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

$$= \frac{B8 - B4}{B8 + B4}$$

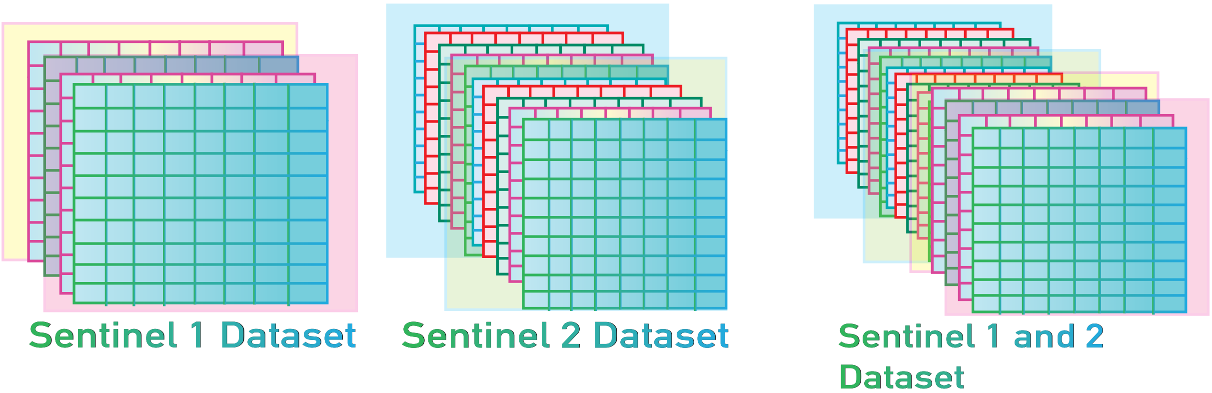
NDVI is a measure of vegetation using the difference between near infrared which vegetation reflects back and red light which the vegetation absorbs. Meanwhile RVI is similar, but uses radar data and instead measures the scattering randomness of vegetation. RVI was calculated for Sentinel 1 data. NDVI was calculated for Sentinel 2 data.

This is the first study to create concatenated Sentinel 1/2 logging datasets. The integration of Sentinel 1/2 Data for iogging detection has not been achieved prior to this study.

a.

134,606 samples

One of the largest selective logging data sets created

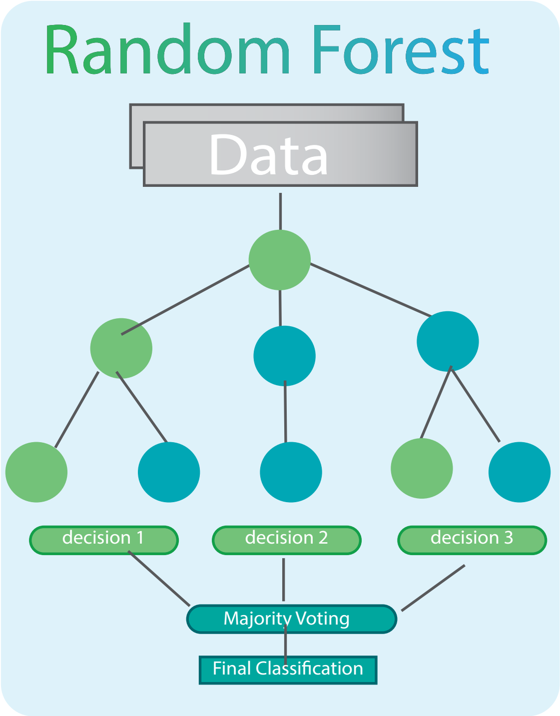


3 different data sets were created: Sentinel 1, Sentnel 2, and Sentinel 1 and 2 Combined data set in Numpy Array format for CNN.

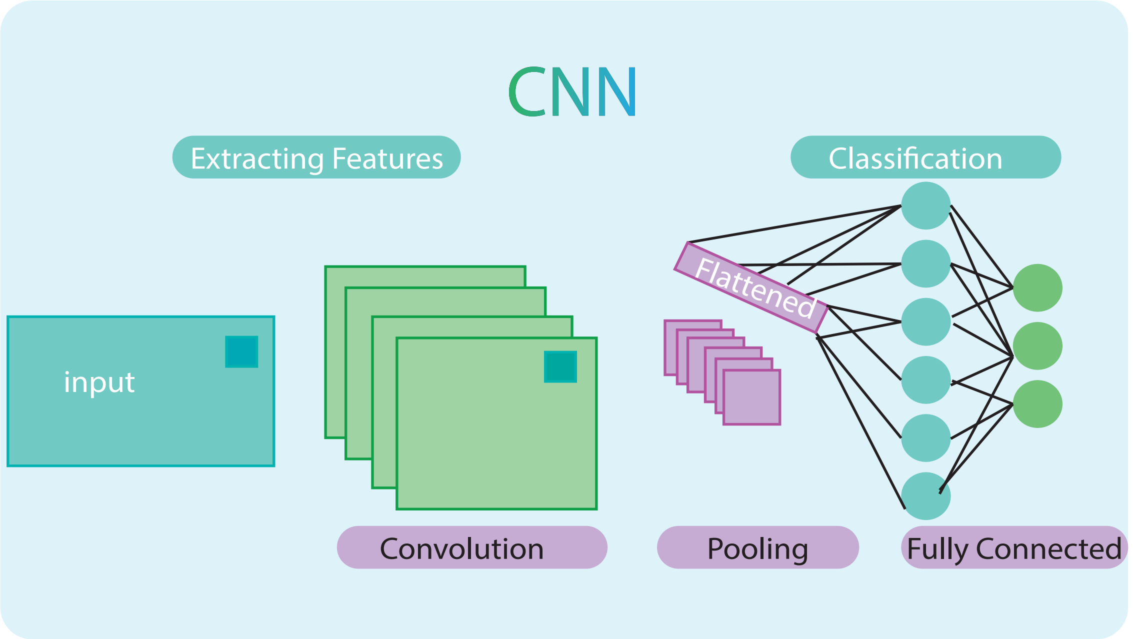
Models

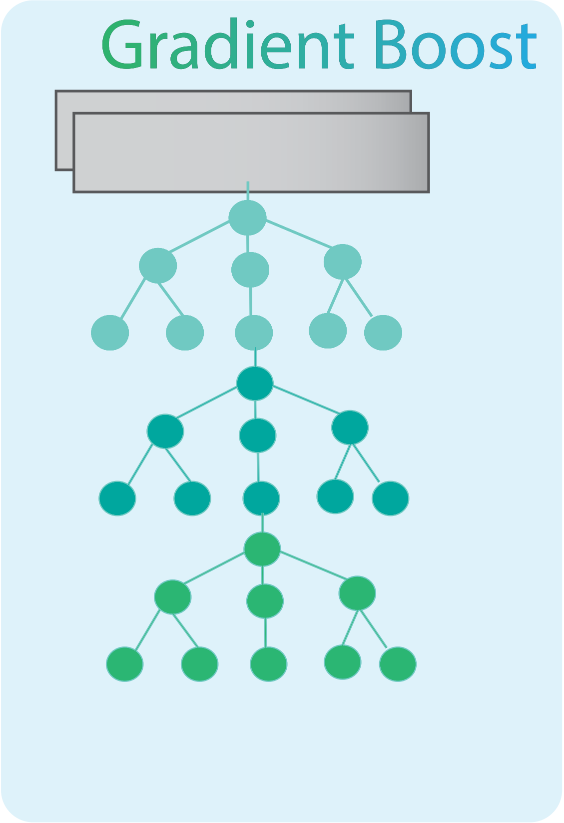
The various models explored are CNN (U- Net), Random Forest, Gradient Boosted Trees. The models are built using python libraries and trained and tested on the Sentinel 1, Sentinel 2, and Sentinel 1 and 2 datasets.

Machine Learning

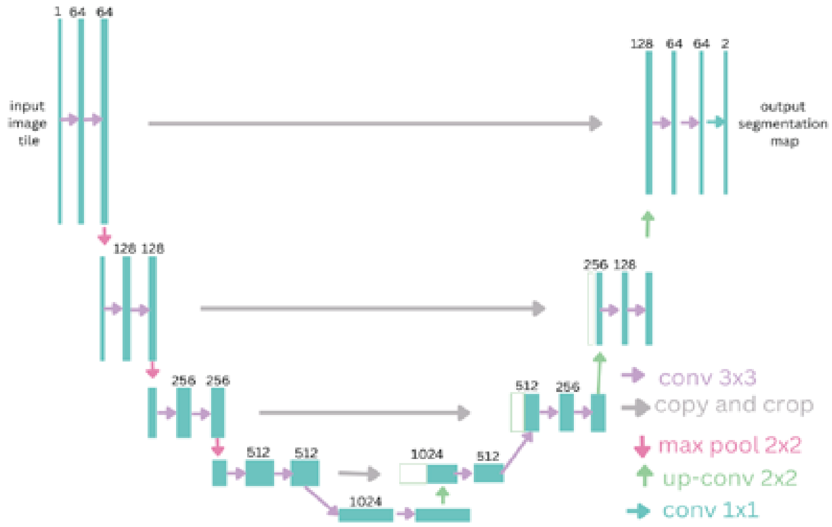


Deep Learning





U-Net Implementation of CNN



Adapted from Ronneberger et al.

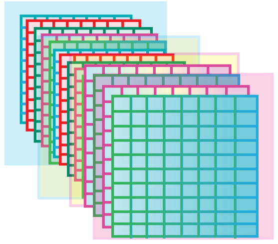
Diagram of U-Net Architecture

. The U-Net is a fully convolutional neural network which can take in input images of any sizes. The U net architecture is able to do semantic segmentation using repeated application of 3 x 3 unpadded convolutions, batch normalization, and a 2 x 2 max pooling operation followed by doubling feature channels To compensate for the small 10x10 image sizes, the U – Net was modified by removing one of the down sampling layers and one of the up-sampling layers..

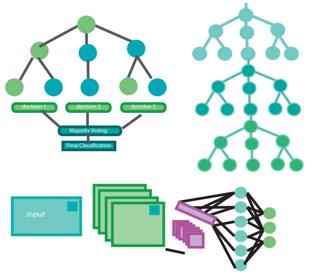
Random forest models construct multiple decision trees (similar to a forest) and each tree casts a vote on which class the input data should be labeled as.

Gradient boosted trees are similar to random forest in that they're both ensemble methods, combining decision trees. The difference lies in random forests building independent decision trees and combining them at the end whereas gradient boosted trees use a method called boosting to learn from the errors of the past trees.

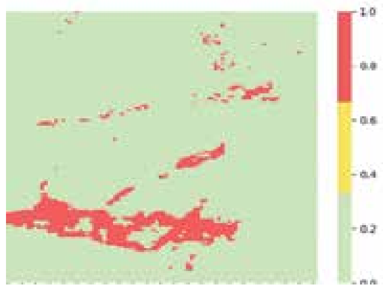
Data Inputted



3 models run



Map Output



To gather data on the accuracy/F1 score for each model, the main hyperparameters (learning rate and batch size) were tuned using both brute force optimization and grid search. The CNN model performed the best loss and accuracy wise when using a batch size of 64 and a learning rate of1.1e-4.

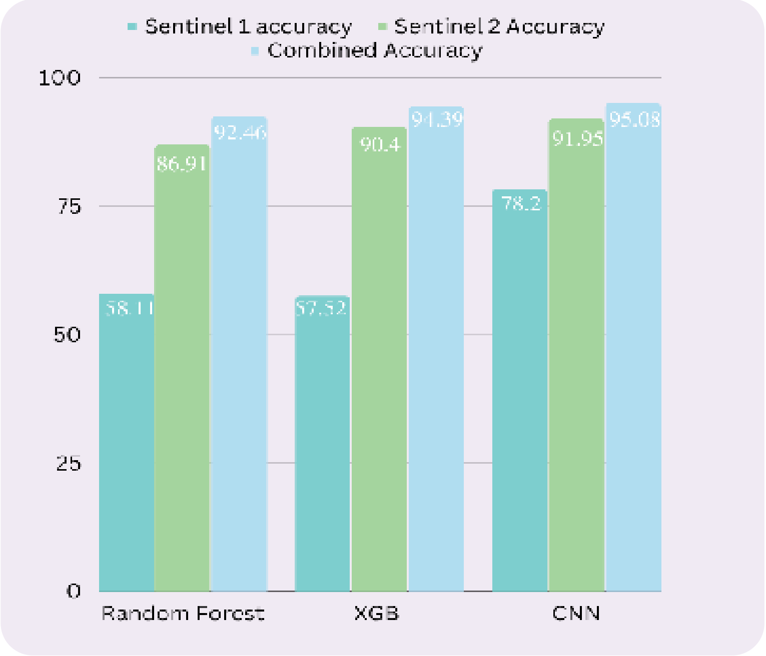
Split 10% Evaluating (5% Testing 5% validation) / 90% Training

Results

The models all improved from the integration of radar and satellite imagery, with the CNN performing best at 95.08 % accuracy and 94.73 F1.

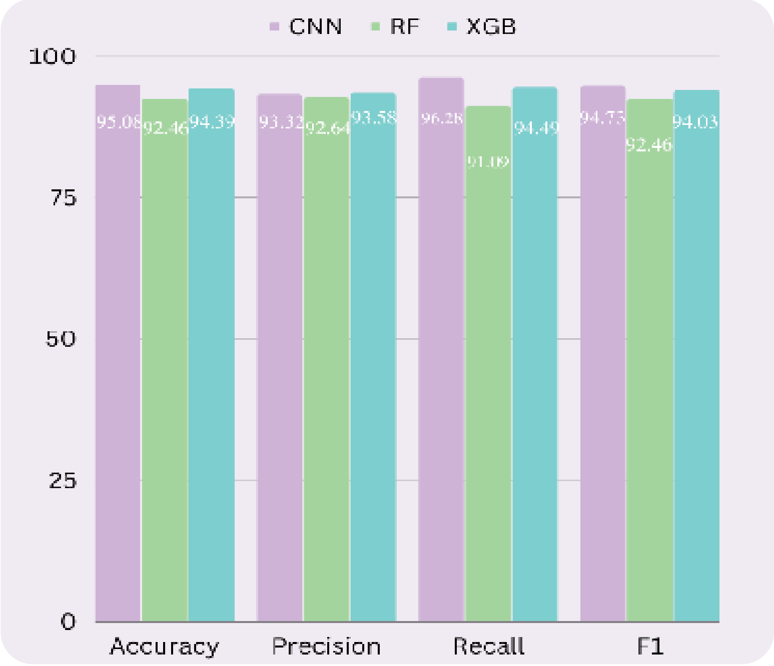
Pre existing solutions record 88% accuracy rate using only Sentinel 1, so this is a 7.08% increase.

Accuracy With/ Without Sentinel 1/2 Integration



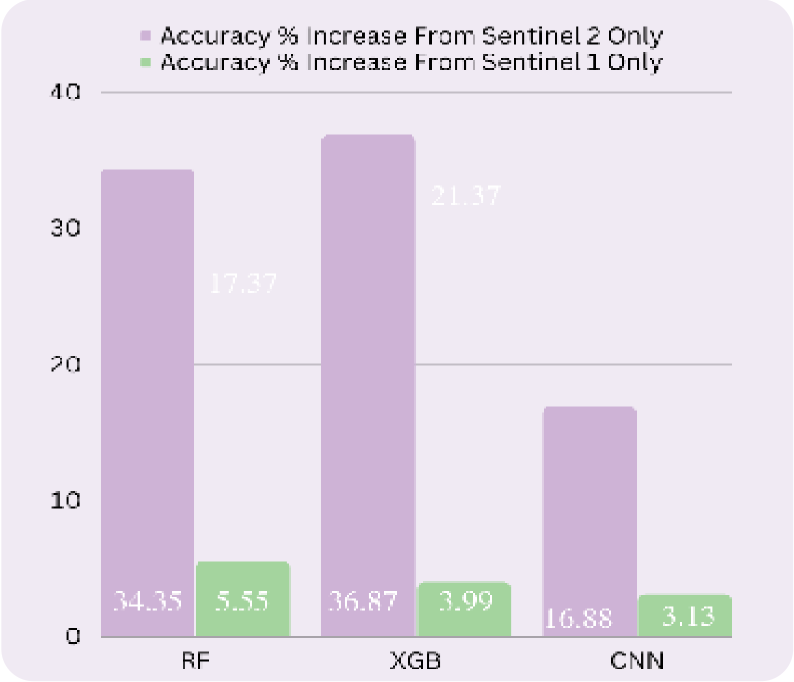
Graph depicts accuracy integrated/individual for all models evaluated

All Models on Integrated Data Set



Graph depicts several metrics (Accuracy, Precision, Recall, F1) for all models evaluated

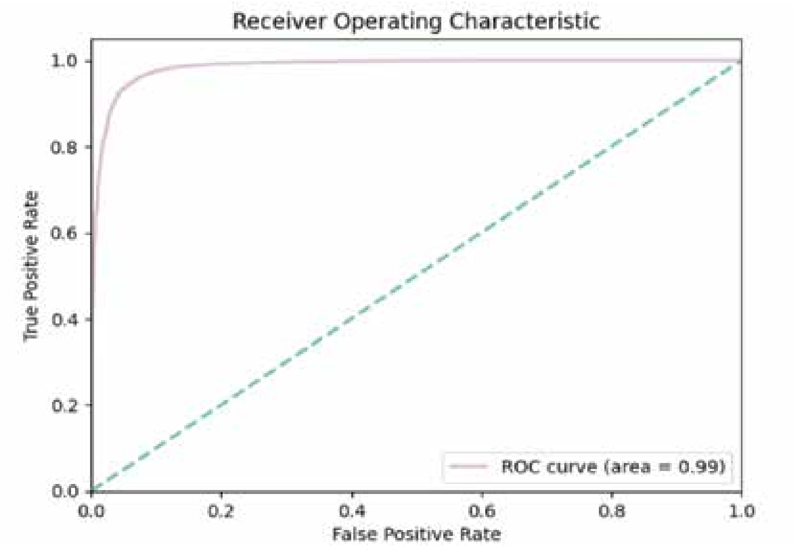
Accuracy Increase From Integration



Graph depicts accuracy increase from integration for all models evaluated

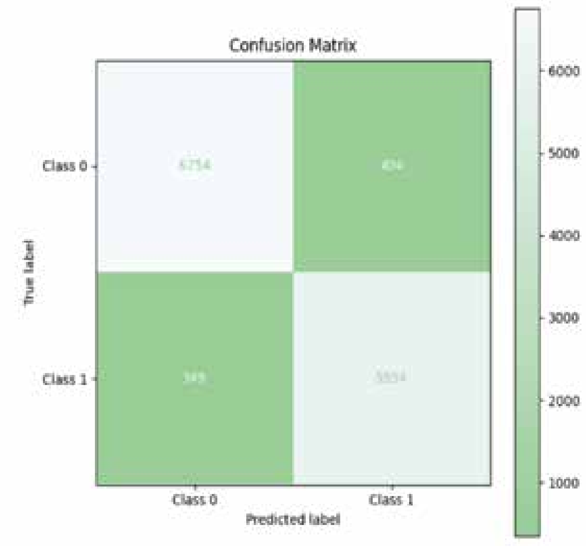
Results

AUROC



The XGB model achieved an AUROC score of 0.98537 which shows high potential in detecting logged/stable forest as an ideal classifier achieves a score of 1.

Confusion Matrix



In Order from Left to Right, Top to Bottom, TP, FP, FN, TN

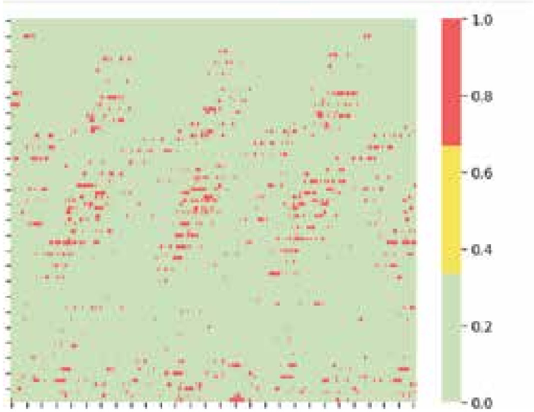
All images/graphs were created by the student researcher unless otherwise noted.

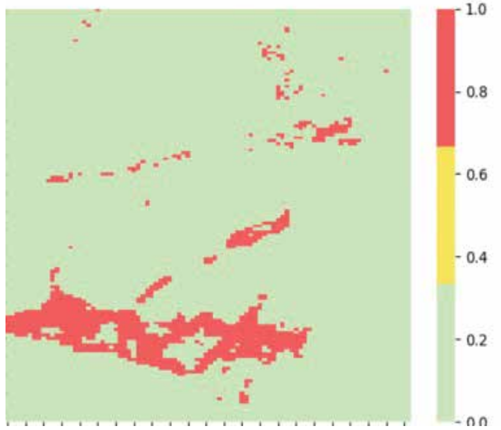
Metrics

TP = True positives, i.e. the number of deforested areas classified as deforested.
TN = True negatives, i.e. the number of forested areas classified as forested.
FP = False positives, i.e. the number of forested areas classified as deforested.
FN = False negatives, i.e. the number of deforested areas classified as forested

Accuracy = (TP + TN) / (TP + TN + FP + FN)
Precision = TP / (TP + FP)
Recall = TP / (TP + FN)
F1 = 2 x (Precision x Recall) / (Precision + Recall)

Logging Maps





Small regions were selected for use as testing locations for logged /stable forest prediction maps. Using MATLAB and sea-born libraries, the models will be used to output prediction for each pixel and gen-

Significance

Integrating both optical and radar imagery for deforestation classification results in massive performance improvements (CNN - 3.13%) and 7.08% increase from existing models

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