Crop Detection from Satellite Imagery using Deep Learning

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Crop Detection from Satellite Imagery

- One of the important monitoring tasks for EO systems.
- Classifying planted crop types across any country can help governments in:
  - Monitoring the national agricultural plans
  - Early yield estimation
  - Harvest planning

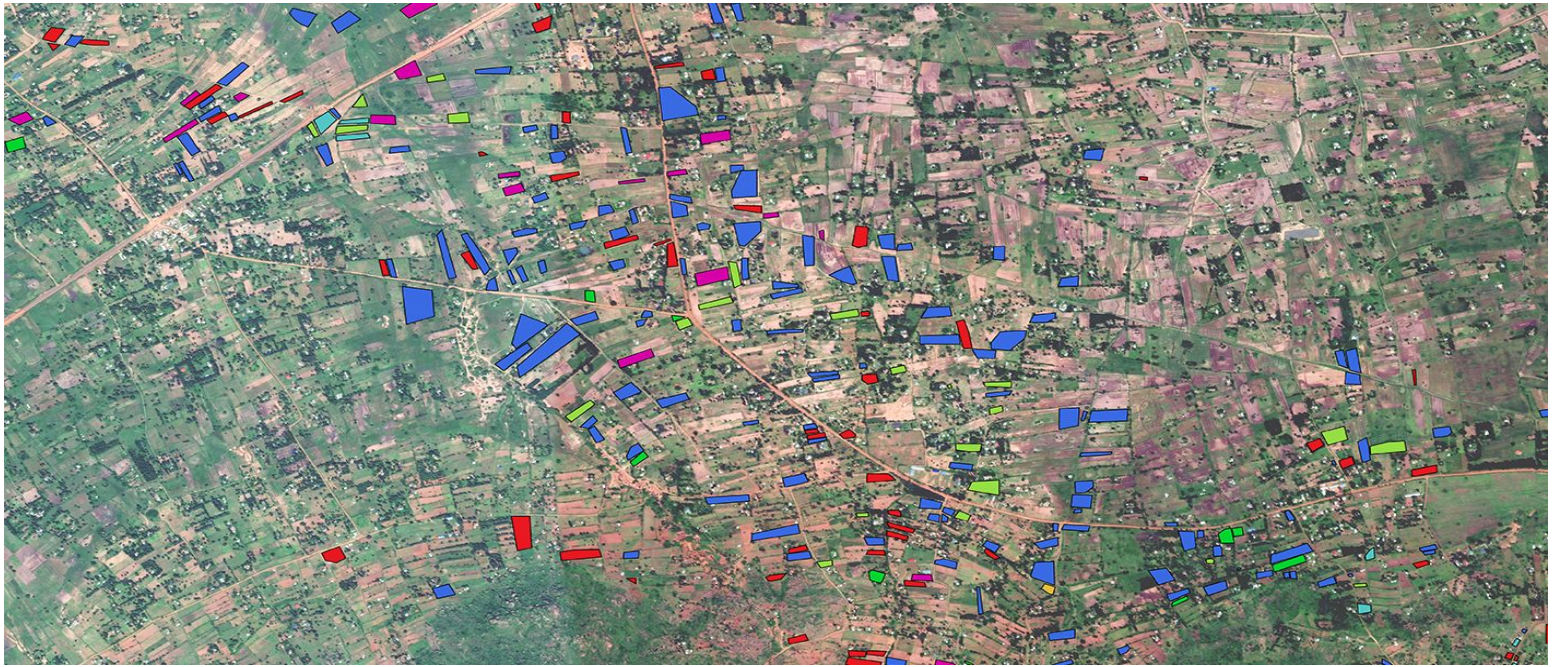
Crop Detection from Satellite Imagery

- Given a small crop field (farm), classify the planted crop into one of the following:
  - Maize
  - Cassava
  - Common Bean
  - Maize & Common Bean (intercropping)
  - Maize & Cassava (intercropping)
  - Maize & Soybean (intercropping)
  - Cassava & Common Bean (intercropping)

Crop Detection from Satellite Imagery

- Time series of high resolution satellite images of an agricultural area in west Kenya acquired in 13 different days within 5 months.
- Each image has
  - Size of 4032 X 6070 pixels.
  - 13 spectral bands.
- Number of annotated crop fields in the area is 4688.
  - 3286 for training.
  - 1402 for testing.

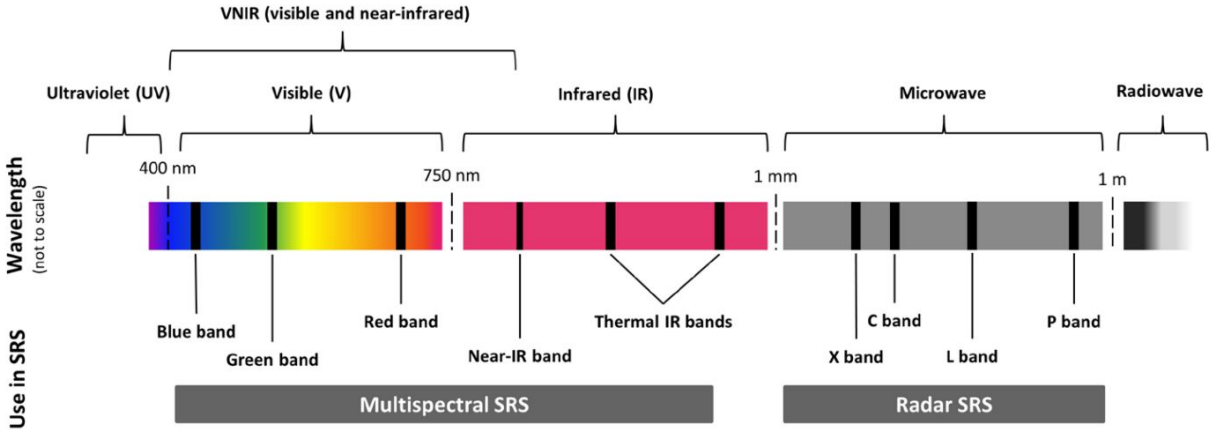
Crop Detection from Satellite Imagery



Sample fields (color coded with their crop class) overlayed on Google basemap from Western Kenya. (Image Source)

Crop Detection from Satellite Imagery

- Provided spectral bands:
  - RGB
  - Visual and Near Infrared
  - Ultra-Blue
  - Short Wave Infrared
  - Cloud probability layer

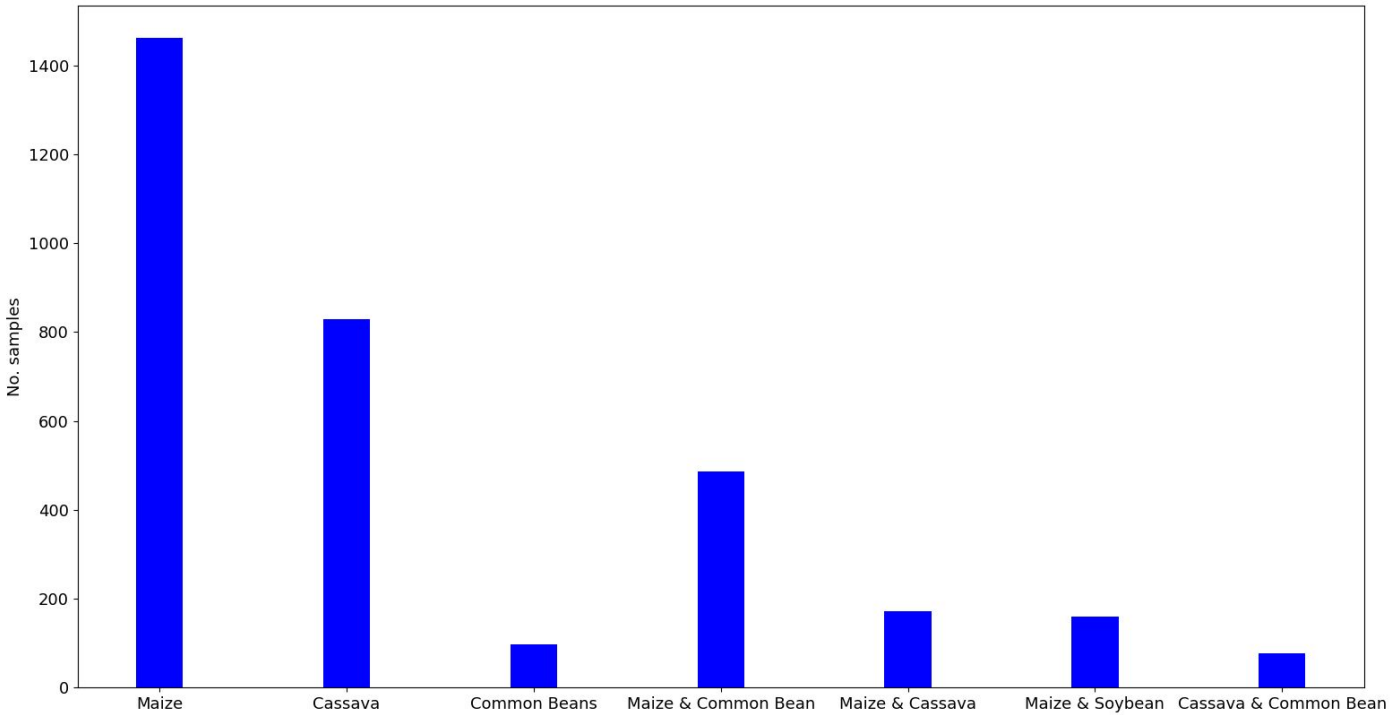


Some Starter Questions for ML Projects

- What does my data look like?
- What is the best validation strategy?
- Is there any previous work on the same problem?
- What do you think is the best solution before starting to code?
- What is the plan to reach such solution?

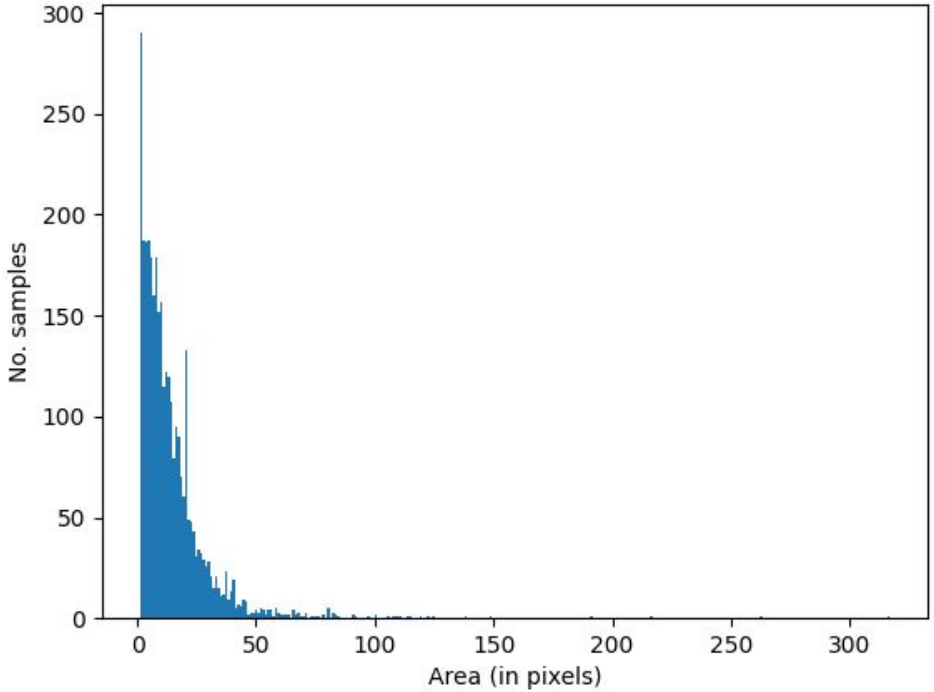
Data Exploration

- Class frequency



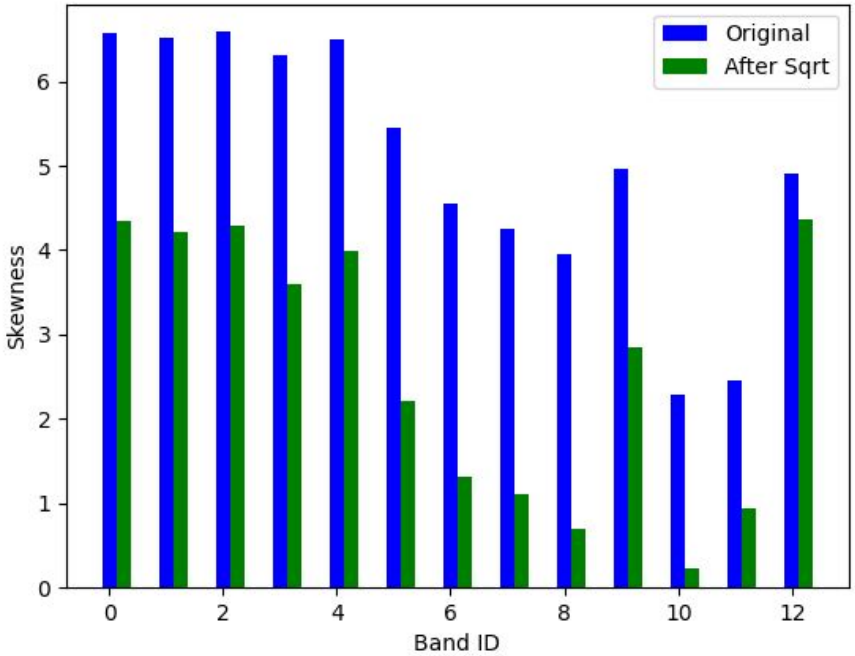
Data Exploration

- Field area distribution



Data Exploration

- Band skewness



Challenges

- Small dataset.
- High dimensionality (spatio-temporal data).
- Unbalanced classes.
- A lot of crop fields is only couple of pixels.

Related Work

- 3D Convolutional Neural Networks
  - Ji, S., Zhang, Z., Zhang, C., Wei, S., Lu, M., & Duan, Y. (2020). Learning discriminative spatiotemporal features for precise crop classification from multi-temporal satellite images. International Journal of Remote Sensing, 41(8), 3162-3174.
- Random Forest
  - Viskovic, L., Kosovic, I. N., & Mastelic, T. (2019, September). Crop classification using multi-spectral and multitemporal satellite imagery with machine learning. In 2019 International Conference on Software, Telecommunications and Computer Networks (SoftCOM) (pp. 1-5). IEEE.
  - Ok, A. O., Akar, O., & Gungor, O. (2012). Evaluation of random forest method for agricultural crop classification. European Journal of Remote Sensing, 45(1), 421-432.

Summary of Approach

- A patch is cropped around each field and pass it to a deep neural network model for classification.
- The model was trained with extensive augmentation to avoid overfitting.

Local Validation Strategy

- Initial experiment: 1 split with 75% training, 25% validation.
- Submission experiment: 10 splits with 85% training, 15% validation.
- Splits are stratified.
  - Stratification produces similar distribution between training and validation.
- Why stratification rather than random splitting?
  - Competition metric is cross entropy which is highly sensitive to class distribution.

Data Generation

1. Calculate the center of each crop field.
2. Input patch: crop a 32X32 patch around the center so each patch has size (T, C, H, W) where:
    - T: number of time steps = 13
    - C: number of spectral bands = 13
    - H: height = 32
    - W: width = 32
3. Input field mask: crop a 32X32 binary mask around the same center where field pixels are ones and others are zeros. The size of each field mask is (1, 1, H, W).

Data Preprocessing

- Feature Engineering
  - Remove one short-wave infrared band (B11, 1610 nm).
  - Add 3 vegetation indices. [1], [2]
  - Total number of spectral bands become ***15***.
- Normalization
  - Square root (to decrease skewness).
  - Standard scaling (transform to zero mean and unit std).

[1] A. Karnieli, N. Agam, R. T. Pinker et al., “Use of NDVI and land surface temperature for drought assessment: merits and limitations,” Journal of Climate, vol. 23, no. 3, pp. 618–633, 2010.
[2] S. K. McFeeters, “The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features,” International Journal of Remote Sensing, vol. 17, no. 7, pp. 1425–1432, 1996.

Data Augmentation

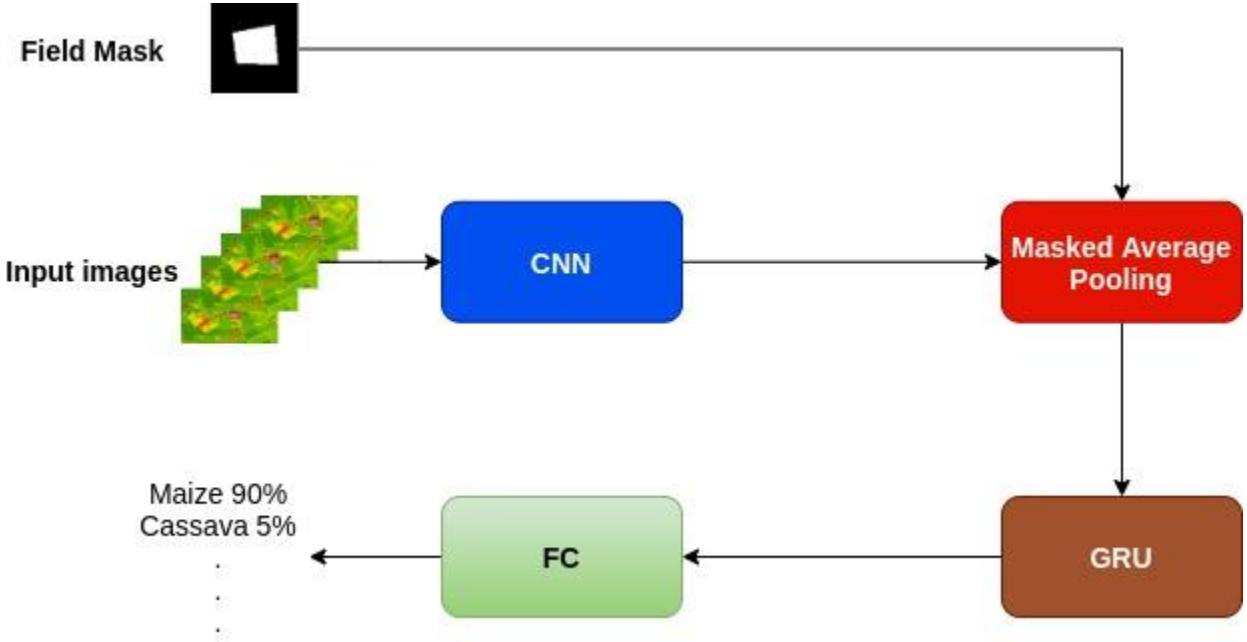
- Spatial augmentations: rotation, flipping and random cropping.
- Mixup [3]: weighted summation of input patch and a random patch cropped from any satellite image.
- Time augmentation: randomly drop one time step.

[3] Zhang, Hongyi, et al. "mixup: Beyond empirical risk minimization." arXiv preprint arXiv:1710.09412 (2017).

Design Loop

1. Start with simple model or standard model.
2. Increase model complexity.
    - Try adding more layers.
    - Try different layers.
    - Try increasing layers width.
3. Decrease overfitting.
    - Do more augmentation.
    - Try improving input features (preprocessing or engineering).
    - Try adding pooling layers.
    - Try smoothing predictions by: bagging ensemble, Snapshot ensemble, SWA, … etc.
4. Repeat 2 & 3.

Model Architecture



Masked Average Pooling

$$output = \frac{\sum_{H}\sum_{W} input * mask}{\sum_{H}\sum_{W} mask}$$

Ensemble

- Bagging ensemble of 10 models of the same architecture each trained on a different subset (85%) of the training data.
- Each model is trained using Snapshot ensemble [4]
  - Train the model with cyclical scheduler for 6 cycles.
  - Create ensemble of model snapshots taken at the end of each cycle.

[4] Huang, Gao, et al. "Snapshot ensembles: Train 1, get m for free." arXiv preprint arXiv:1704.00109 (2017).

Results

SCORE	RANK		SUBMISSIONS	SUBMITTED
		This is the final leaderboard. The competitions is officially closed and will not accept any more submissions. Congratulations to all that participated.		
1.102264609	1	KarimAmer oh, hi!	31	~1 month ago
1.168877091	2	youngtard	154	~1 month ago
1.174099923	3	team Be_CarEFuL	91	~2 months ago
1.176934328	4	team Threshold	116	~2 months ago
1.177508763	5	overfitting_PLB Axa Mansard(Nigeria)	114	~1 month ago