Using UAV-Collected Ground-Truth Data and Computer Vision for Identification of Crop Type for Sustainable Agriculture and Food Security in Rwanda

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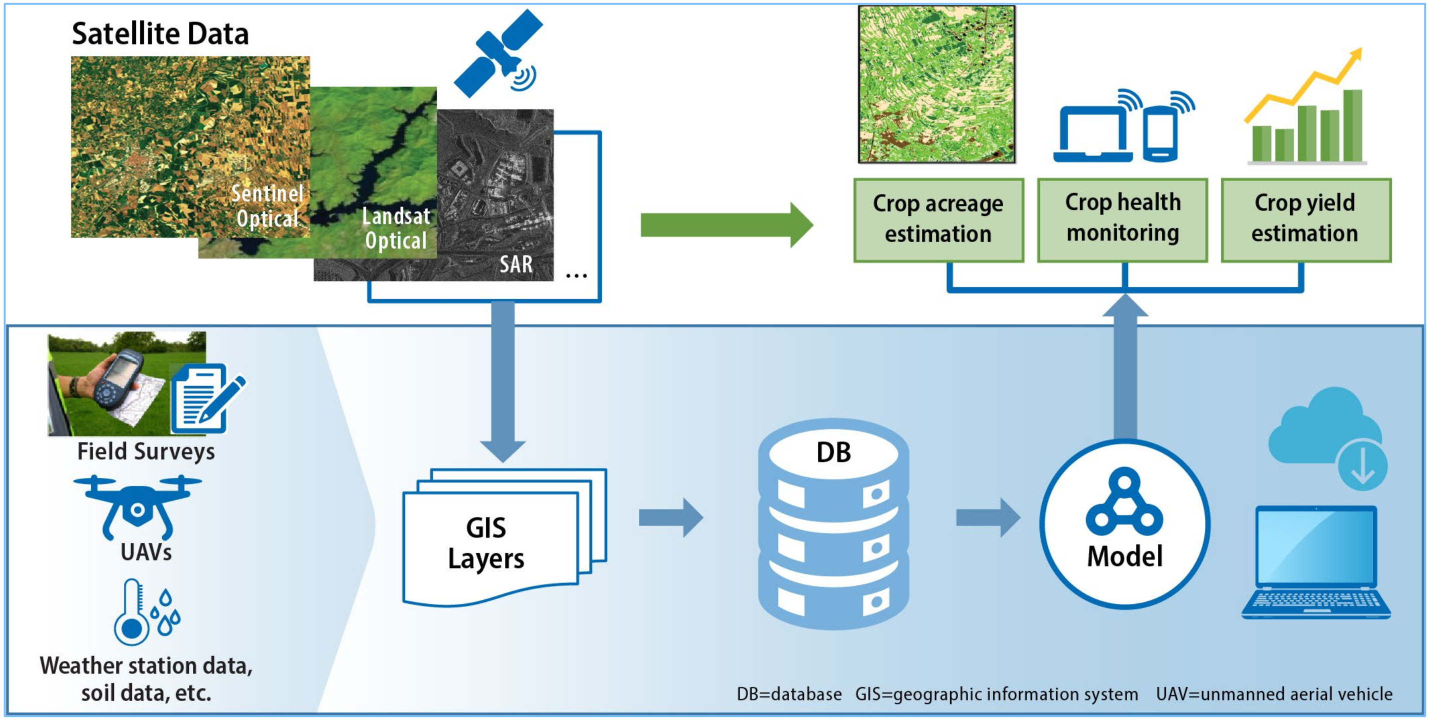
This Paper: Focus on Ground-Truth Datasets

This paper builds on earlier RTI presentation in this session and explores an aspect of development of computer models for crop classification from remote sensing images, pertaining to the creation of **ground-truth datasets**.

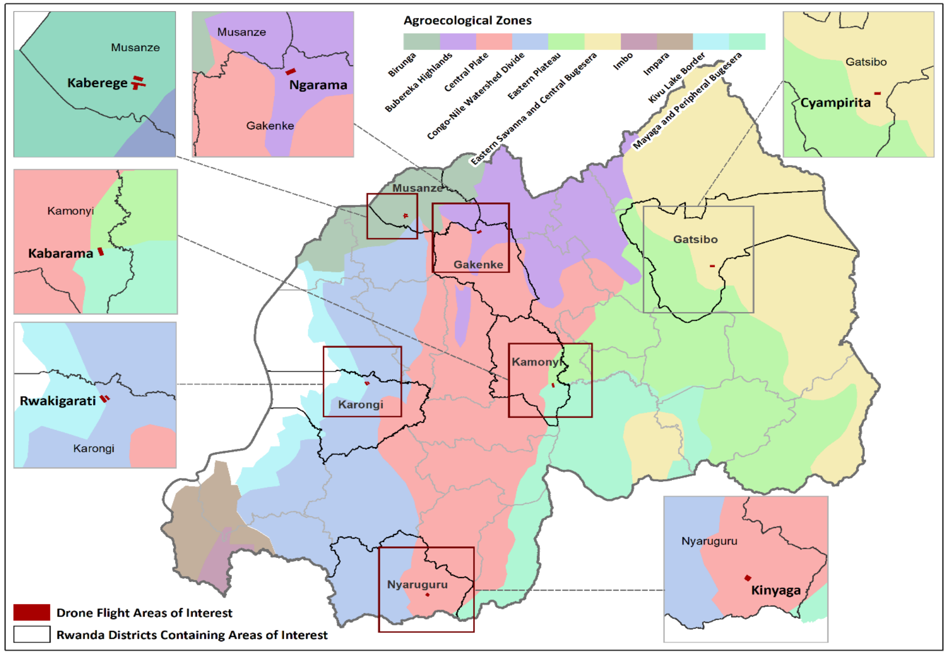


To develop **machine-learning (ML)** models for e.g. crop classification, we need to train the computer to recognize crop types by providing verified georeferenced examples of crop type – **ground truth (GT).**

Ground-Truth Datasets for Crop Classification

- Most common and most-true to the concept is the creation of ground-truth datasets by humans inspecting fields on the ground.
  - Surveyor uses GPS device and records crop type.
  - Process is time-consuming and costly, some fields may be difficult to access
- Last 5 years brought significant improvements in technologies for small unmanned aerial vehicles – “eye in the sky”
  - Is there potential to use UAVs for “ground-truth” data collection?
- RTI worked with Rwandan company Charis Unmanned Aerial Services to execute a series of flights in Rwanda to explore this question.

UAV Flight Sites



Location	Agro-Ecological Zone	Early Season Flight	Mid-Season Flight	End-of-Season Fight
Kaberege	Birunga	Dec 27, 2018	Jan 29, 2019	February 2019
Ngarama	Bubereka Highlands	Dec 22, 2018	Jan 30, 2019	February 2019
Cyampirita	Eastern Savanna & Central Bugesera	Dec 17, 2018	Jan 25, 2019	February 2019
Rwakigarati	Congo-Nile Watershed Divide / Kivu Lake Border	Dec 27, 2018	Jan 31, 2019	February 2019
Kabarama	Mayaga and Peripheral Bugesera	Dec 10, 2018	Jan 21, 2019	February 2019
Kinyaga	Central Plateau	Dec 12, 2018	Jan 24, 2019	February 2019

- 6 individual sites were selected across Rwanda for UAV flights
  - Chosen in collaboration with AgriTAF to reflect different agricultural zones and contain both consolidated land use areas and small farms
- For each location, flights were performed three times during 2019 Season A

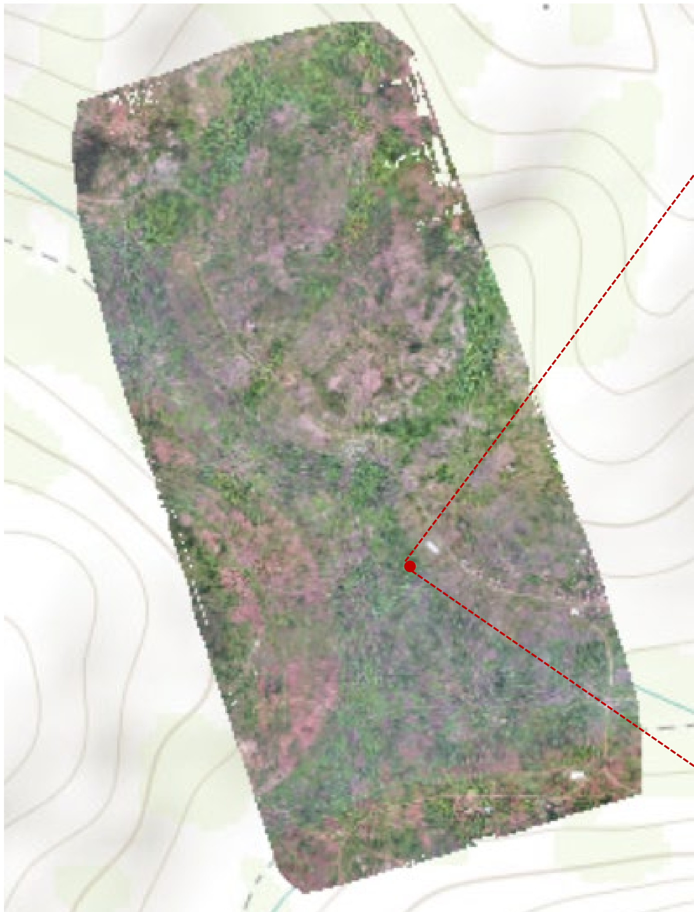
UAV Hardware and Software

- SenseFly eBee Plus is a large-coverage photogrammetric mapping UAV.
- Includes built-in GPS correction technology for survey-grade accuracy of 10 cm, without the need for ground control points.
- SenseFly S.O.D.A camera is optimized for UAV applications.
  - 1-inch 20-megapixel RGB sensor
  - Ultra-compact, ultra-light & fully configurable
  - Ground resolution (flying at 122 m/400 ft AGL): 2.9 cm/pixel
  - Built-in dust & shock protection — keep mapping across the most challenging terrain
- Flight planning & control software
- Commercial software used for processing of UAV-acquired images to create orthomosaics

eBee SenseFly Plus RTK

SenseFly S.O.D.A camera

Orthomosaic of UAV-acquired RGB Images

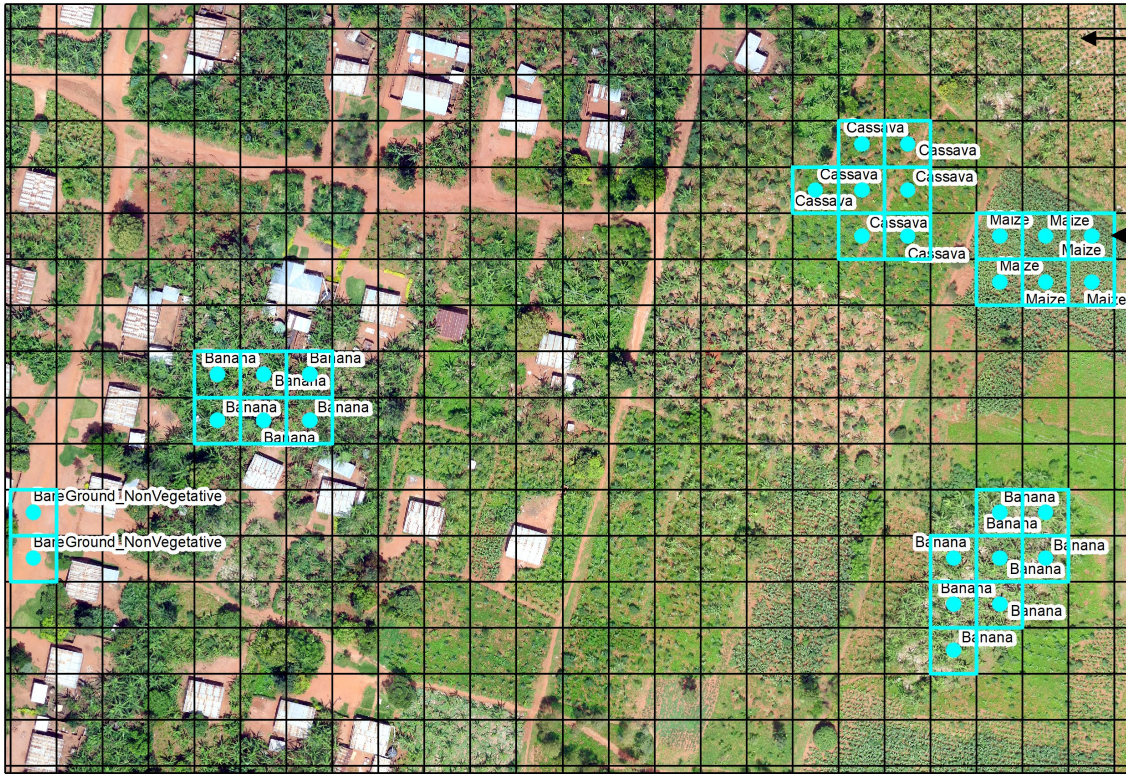


Example of orthomosaic of UAV-acquired images from Kabarama site; area of 80 ha

Close-up at higher resolution.

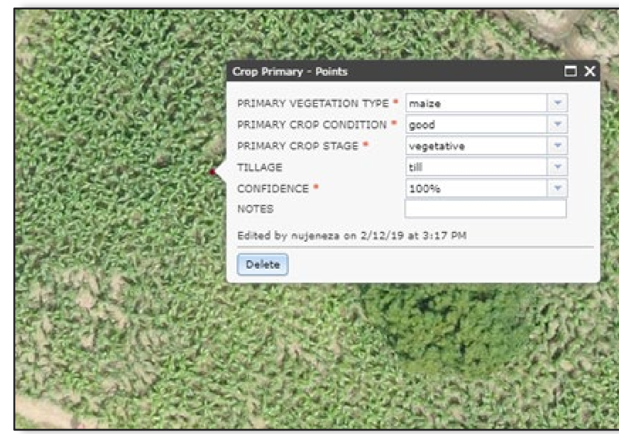
Labeling of UAV images for GT Dataset

We developed custom viewer using ESRI ArcGIS platform.



Sentinel-2 cells

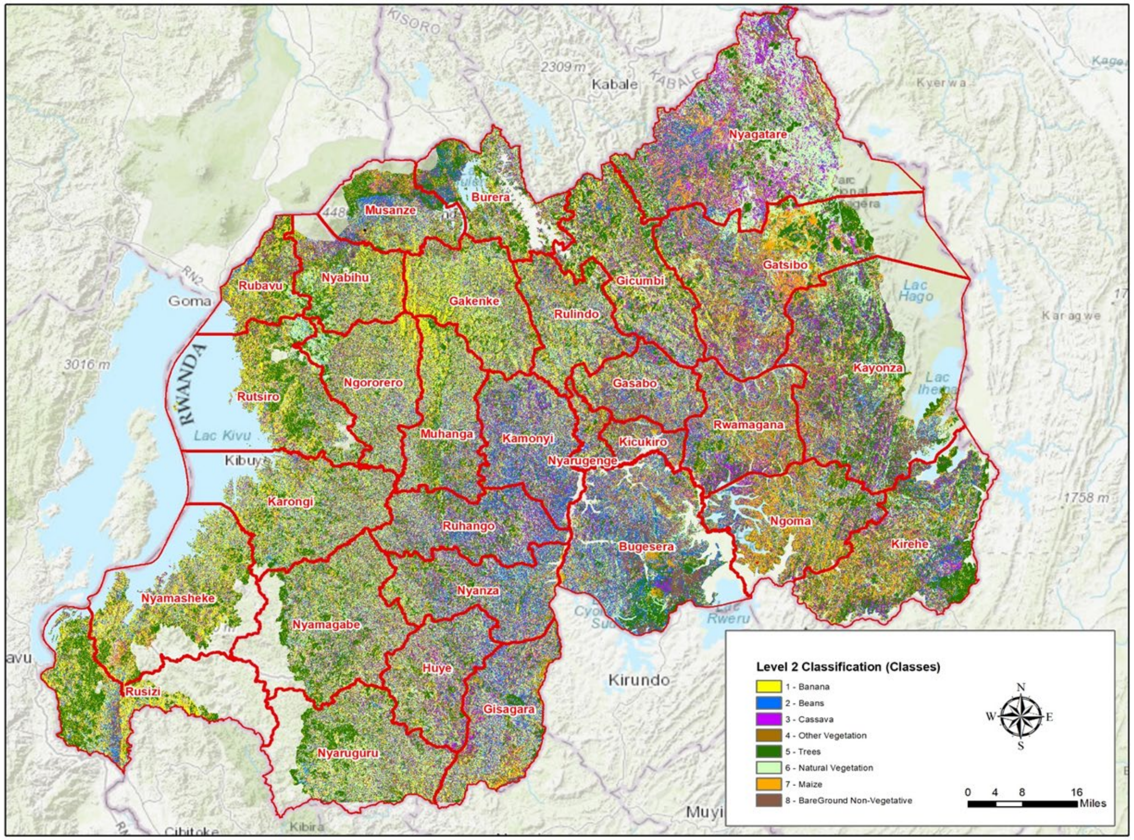
Ground-truth datapoint label



- In-country expert is heading the data labeling.
- GT set contains values of signals in selected optical and radar bands of Sentinel satellite sensors, along with the label specifying crop type.

Classification Model is Applied to Satellite Image

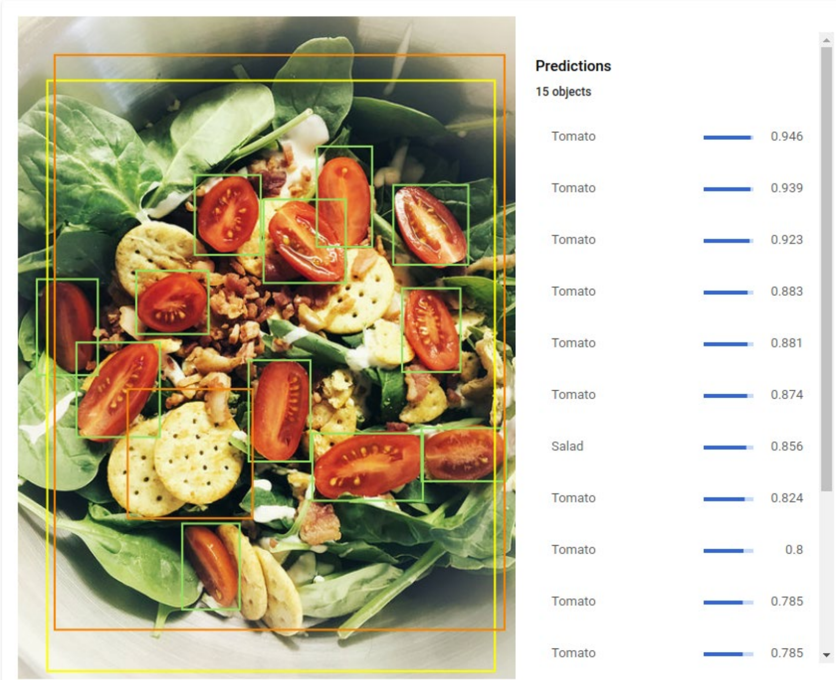
Using UAV GT datasets and Google Earth Engine (GEE) data processing platform, RTI has developed models for crop classification of Sentinel satellite images.



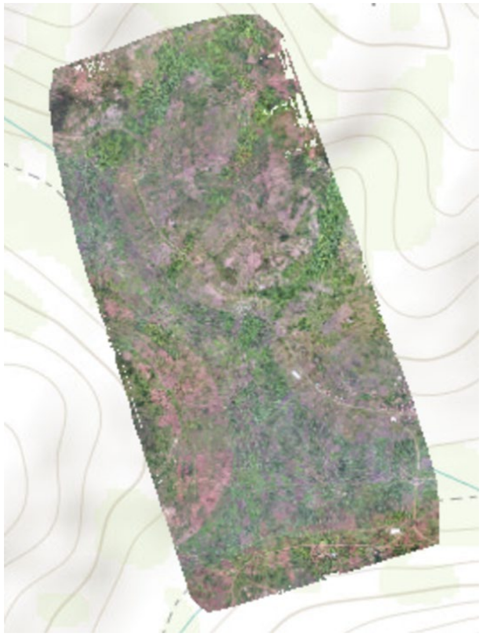
- Map shows output of random forest model developed by RTI on GEE platform using human-labelled UAV GT dataset for training and testing.
- Model applied to Sentinel images from January 2019

Back to Labeling: Can Computers Help?

- Can we use a computer-vision algorithm to label crops in UAV images?
- If the answer is yes, this algorithm could potentially be used to generate additional ground truth data and/or in QA/QC process of human-in-the-loop labeling process.
- Computer-vision algorithms are key part of recent AI revolution.



Source: https://cloud.google.com/vision/automl/object-detection/docs/



Can we use similar capability to recognize crop types in UAV image?

First Step: Training Data for Computer Vision Model

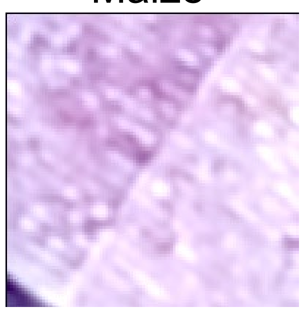
- All human-labeled features in UAV images (polygon and points) were used to create image sections (chits) corresponding to area of 5m by 5m on the ground.
- The chits were grouped into six mutually exclusive classes:
  - Banana, Maize, Legumes, Forest, Structure and Other


Banana


Maize


Legumes


Forest

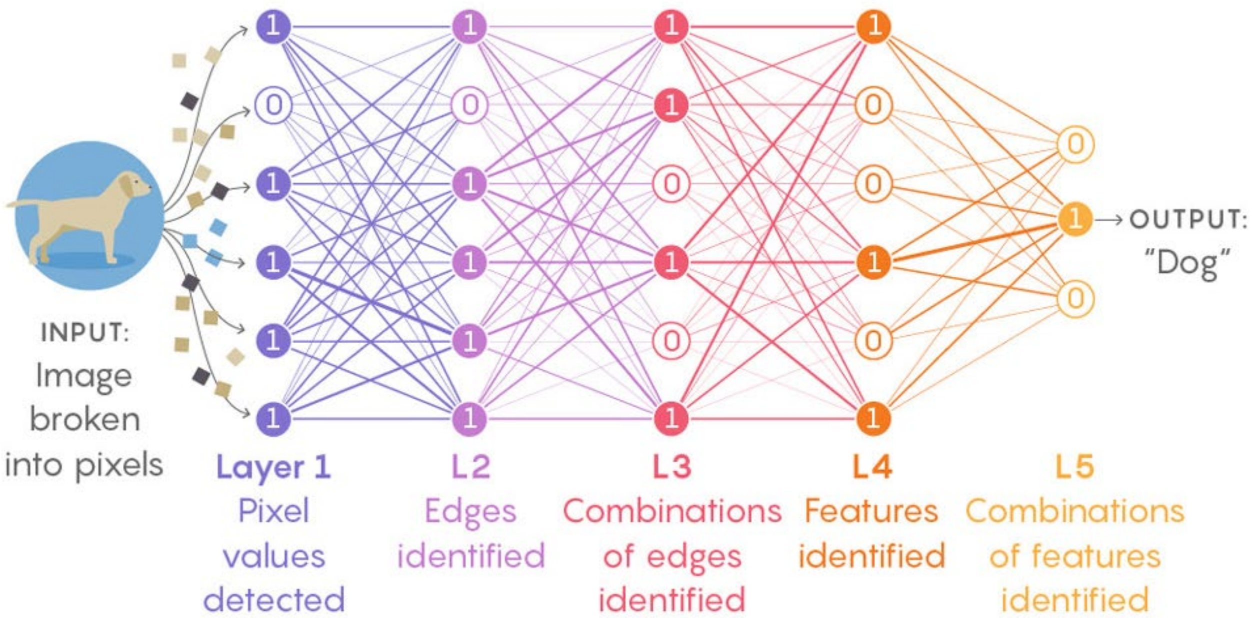

Structure


Other

Class	# Training	# Test
Maize	1,660	415
Banana	1,329	332
Forest	1,016	254
Other	600	150
Legume	290	73
Structure	265	66
Total	**5,160**	**1,290**

Next Step: Model Framework

Our approach is based on neutral networks.

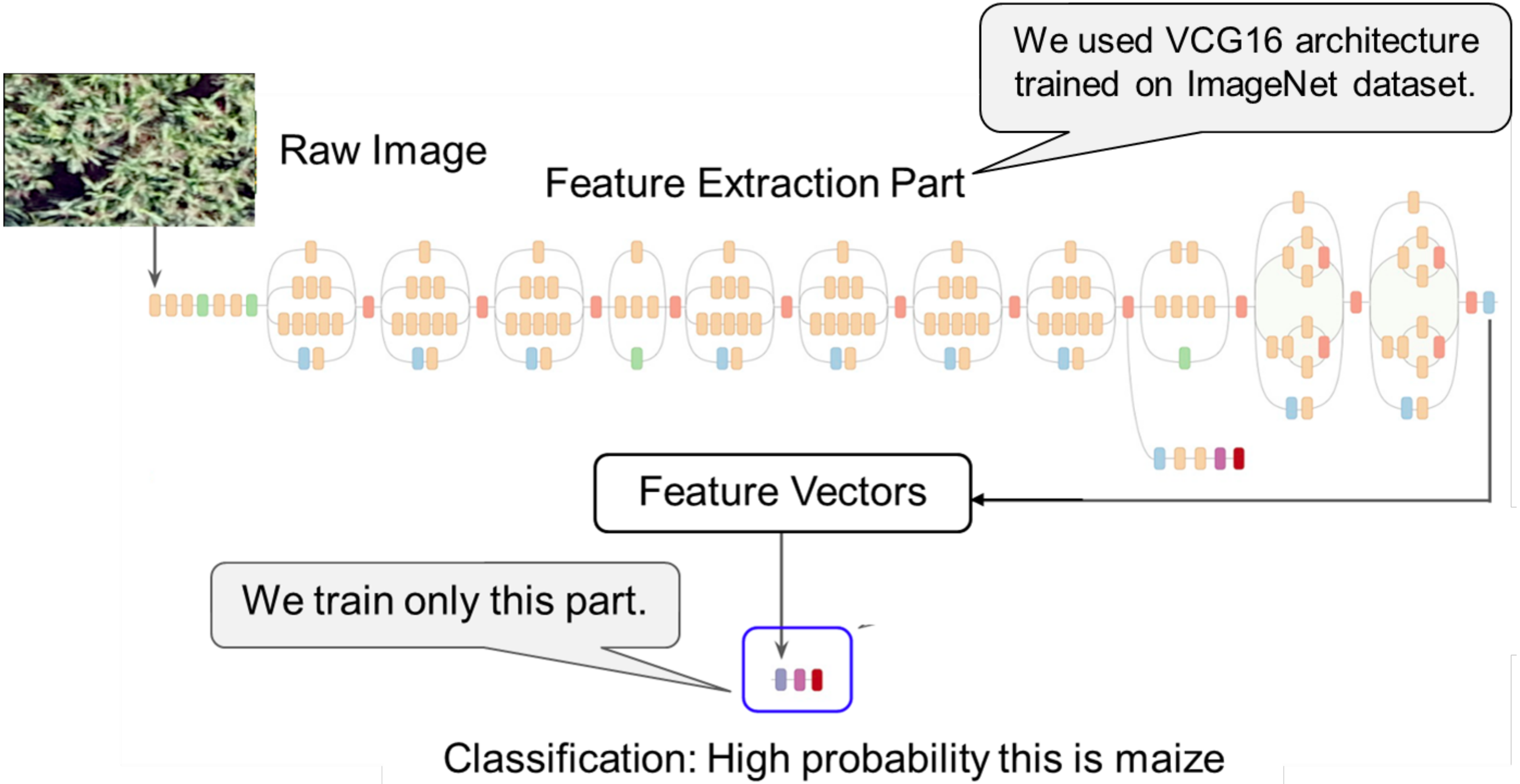


When data is fed into a network, each artificial neuron that fires (labeled "1") transmits signals to certain neurons in the next layer, which are likely to fire if multiple signals are received. The process filters out noise and retains only the most relevant features.

Source: https://www.quantamagazine.org/new-theory-cracks-open-the-black-box-of-deep-learning-20170921/

Specifics of Our Computer Vision Model

- We utilized a specific-type of deep neural networks, called convolutional neural networks (CNNs).
- We used transfer learning to initialize the CNN model in order to limit the amount of required training data.



Model Performance

		PREDICTED						
		Banana	**Forest**	**Legumes**	**Maize**	**Other**	**Structure**	
ACTUAL	**Banana**	**315**	3	0	9	5	0	332
	Forest	0	**229**	4	6	12	3	254
	Legumes	1	5	**31**	20	15	1	73
	Maize	3	6	9	**388**	9	0	415
	Other	5	17	10	23	**87**	8	150
	Structure	0	1	0	0	2	**63**	66
		324	261	54	446	130	75	

	F1 score	Precision	Recall
Banana	0.96	0.97	0.95
Forest	0.89	0.88	0.90
Legumes	0.49	0.57	0.42
Maize	0.90	0.87	0.93
Other	0.62	0.67	0.58
Structure	0.89	0.84	0.95
Average	*0.86*	*0.86*	*0.86*

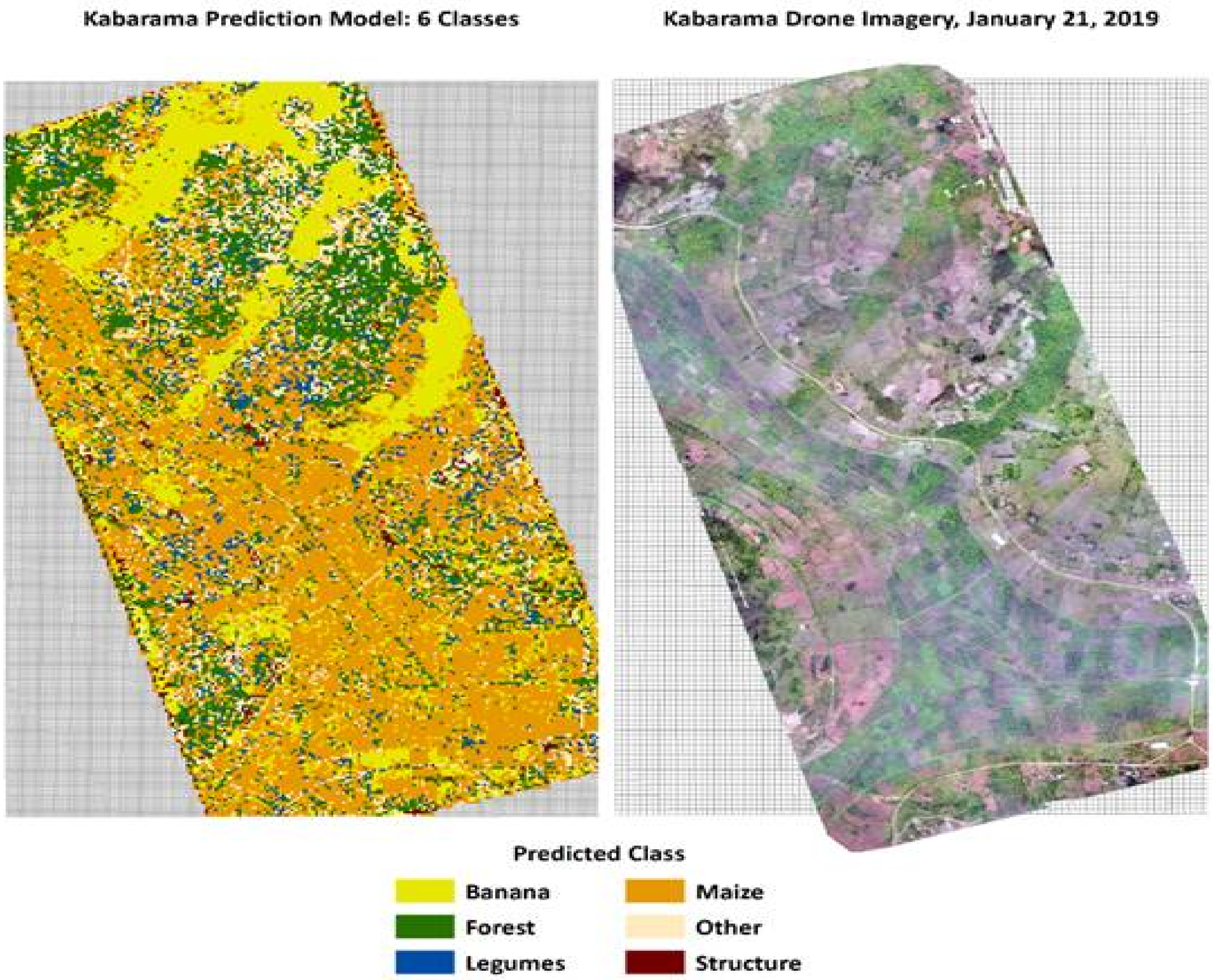
- Best performance for bananas and maize
- Worst performance for legumes, possibly because of smaller training datasets

Precision=TP/(TP+TN)

Recall=TP/(TP+FN)

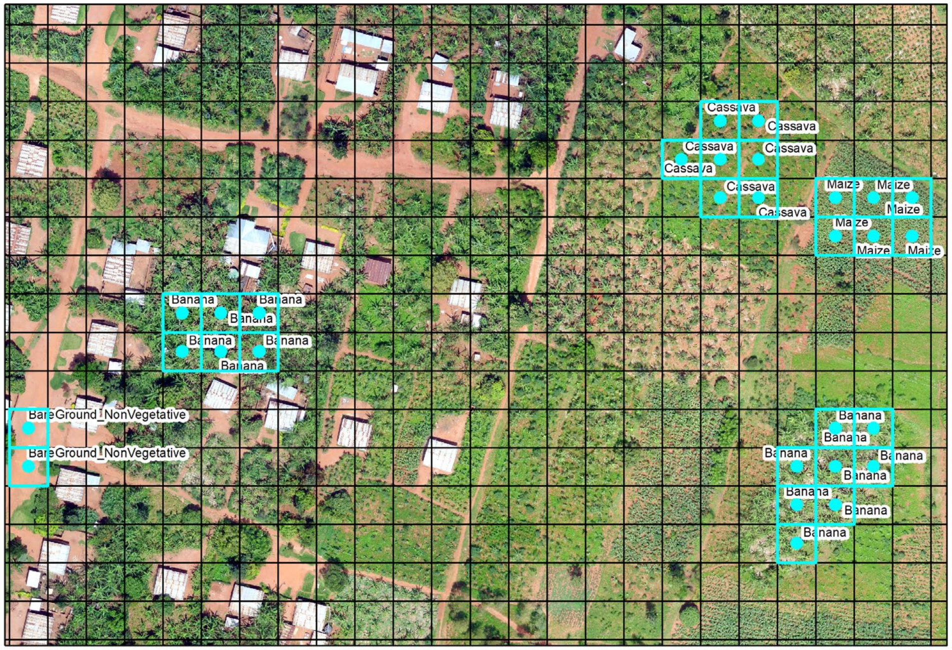
F_1*-score = 2 × Precision × Recall/(Precision + Recall)*

Application to Labeling of UAV Site



Summary

- We explored using computer vision for labeling selected crop types, trees and structures in UAV images with promising results.
  - The model assigned correct labels to test chits with the overall precision of 86%. Model precision for maize was 87% and for bananas 97%.
  - Model classified imagery of UAV site of 80 ha in seconds.
- The ultimate goal is to use the model for labeling UAV images to create training dataset for classifying images obtained by satellites.



Future Work

- Aggregate computer-vision classification to satellite-image cell to create GT label for each satellite cell
- Train RTI-developed random forest model with computer-generated labels and apply it to Sentinel images
- Compare performance of models in three cases
  - Human-labeled data using geospatial viewer alone
  - Computer-generated label data from the CNN model alone
  - Human-labeled data + computer-generated label data
- Perform cost-benefit analysis of computer and human-in-the-loop labeling processes to identify best methodologies for satellite-based crop analytics at scale

> *"Solutions leveraging ML to automate labeling will be best-positioned to win because they won't need to build a large workforce, train labelers, and deal with quality control to the same degree. Their solution will also offer a better margin structure for the customer and accelerated time to value."*
> *A.Myer at https://medium.com/memory-leak/, April 15, 2019.*

Acknowledgments

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