AI in Agriculture Leveraging technology for smallholder farmers

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I mean smallholder Agriculture

83% of the 570m farms are <2ha

What is my motivation?

Not much has changed in 170 years

Ireland in 1847

Africa in 2017

Irish Famine was the beginning of Extension

"to supply them [farmers] with sound practical instruction….to raise upon their lands the greatest possible quantity of food, and thus obtain for themselves pecuniary profit, and secure the state from a recurrence of the great calamities through which we just passed"

Lord Clarendon, Dublin, Sept. 23rd 1847
£300 pound = $300,274

Motivation

Leverage technology to help small holder farmers

The goal: grow more

The solution: diagnosis and advice

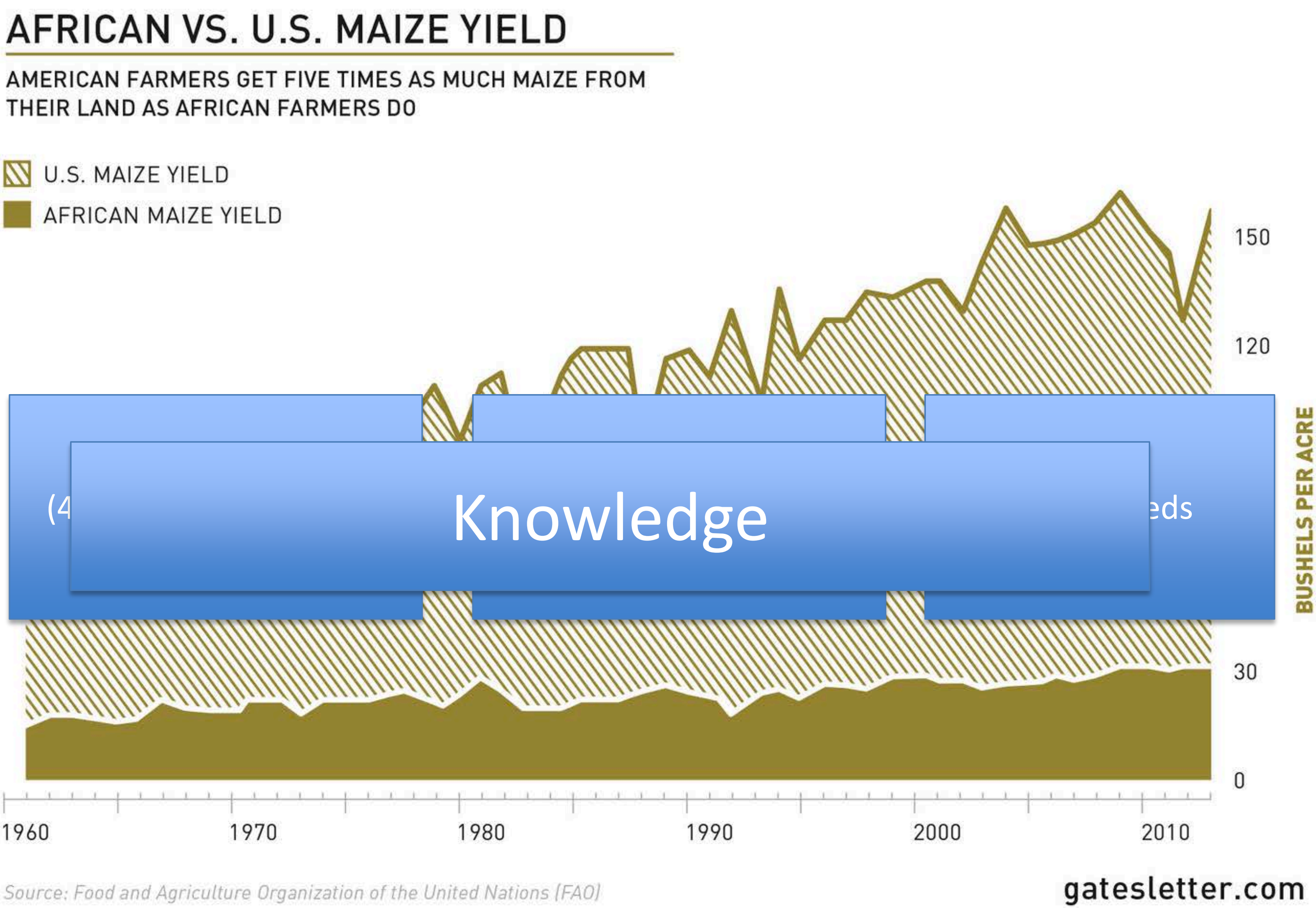
The problems

1. Knowledge: Not accessible!
2. Experts: We are not training enough

Talk Outline

1. Knowledge: Make available existing knowledge
2. Experts: Use machines and Artificial Intelligence

1. Make available existing knowledge


AFRICAN VS. U.S. MAIZE YIELD
AMERICAN FARMERS GET FIVE TIMES AS MUCH MAIZE FROM THEIR LAND AS AFRICAN FARMERS DO
U.S. MAIZE YIELD
AFRICAN MAIZE YIELD
150
120
30
0
BUSHELS PER ACRE
1960
1970
1980
1990
2000
2010
Knowledge
Source: Food and Agriculture Organization of the United Nations (FAO)
gatesletter.com

Knowledge is increasingly behind paywalls
“Tragedy of the knowledge commons’ (Ostrom & Hess)

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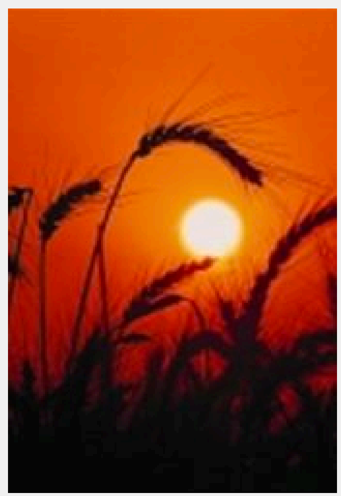


Crop Protection Compendium

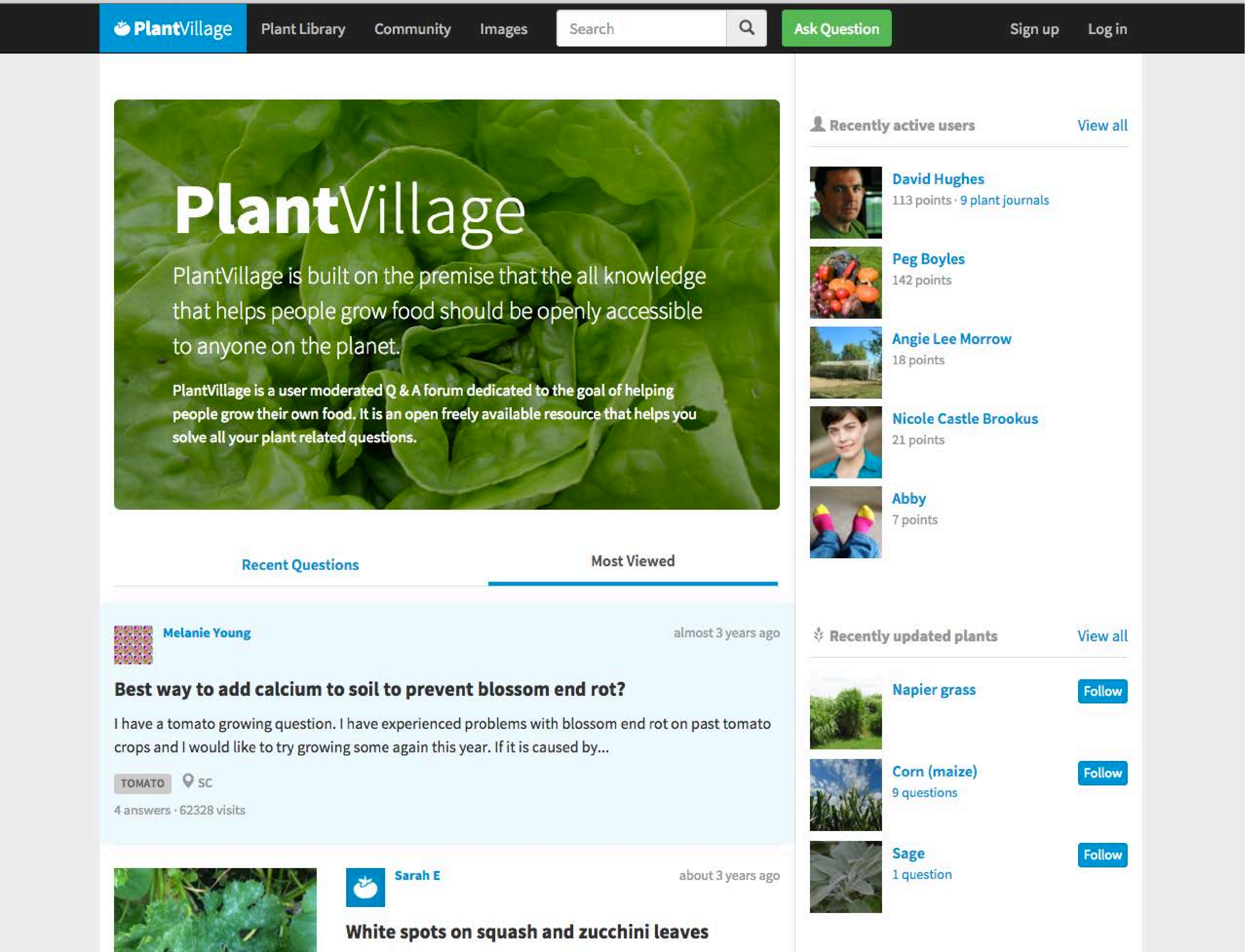
Free Trial

Recommend

"Extensive global coverage of pests, diseases, weeds and their natural enemies, the crops that are their hosts, and the countries in which they occur."

New Crop Protection Compendium site now live!
The CPC has undergone some enhancements and moved to a new platform - to see what's new, go to www.cabi.org/cpc

Code AGRS-045D. The complete publication in PDF format
containing an interactive table of contents, hyperlinks, and bookmarks. Orders will be distributed via email.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PlantVillage
PlantVillage is built on the premise that the all knowledge that helps people grow food should be openly accessible to anyone on the planet.
PlantVillage is a user moderated Q & A forum dedicated to the goal of helping people grow their own food. It is an open freely available resource that helps you solve all your plant related questions.
Recent Questions
Most Viewed
Melanie Young
almost 3 years ago
Best way to add calcium to soil to prevent blossom end rot?
I have a tomato growing question. I have experienced problems with blossom end rot on past tomato crops and I would like to try growing some again this year. If it is caused by...
TOMATO
SC
4 answers · 62328 visits
Sarah E
about 3 years ago
White spots on squash and zucchini leaves
Recently active users
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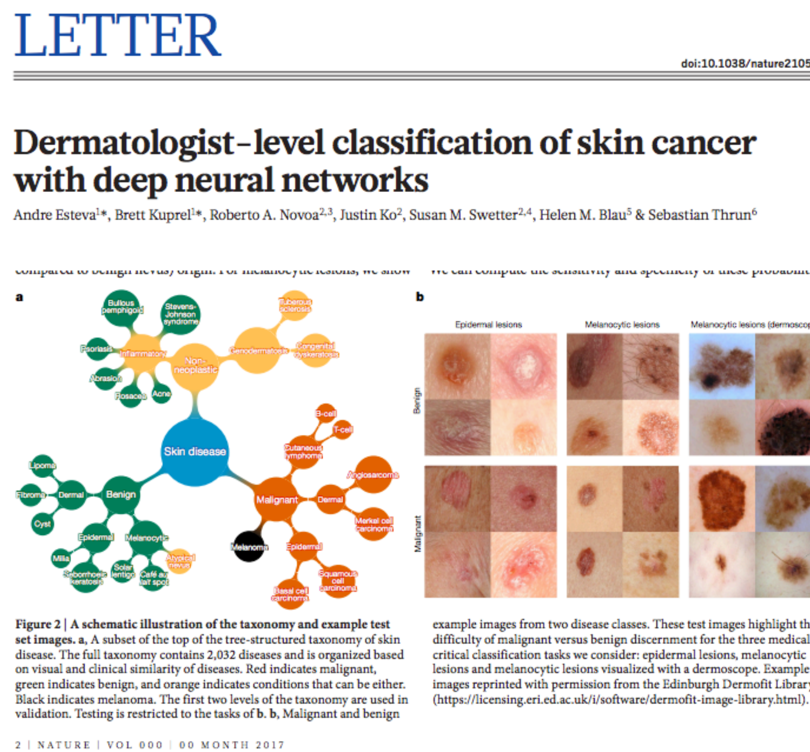
David Hughes
113 points · 9 plant journals
Peg Boyles
142 points
Angie Lee Morrow
18 points
Nicole Castle Brookus
21 points
Abby
7 points
Recently updated plants
View all
Napier grass
Follow
Corn (maize)
9 questions
Follow
Sage
1 question
Follow

How much did this cost? And is it sustainable?

- $350,000 internal funds (PSU)
- About $240,000 for next 3 years
- Needs a path to sustainability
- Connections with GGIAR Big Data Platform and FAOSTAT

Part 2: Use machines and Artificial Intelligence

- Artificial Intelligence is now very powerful


LETTER

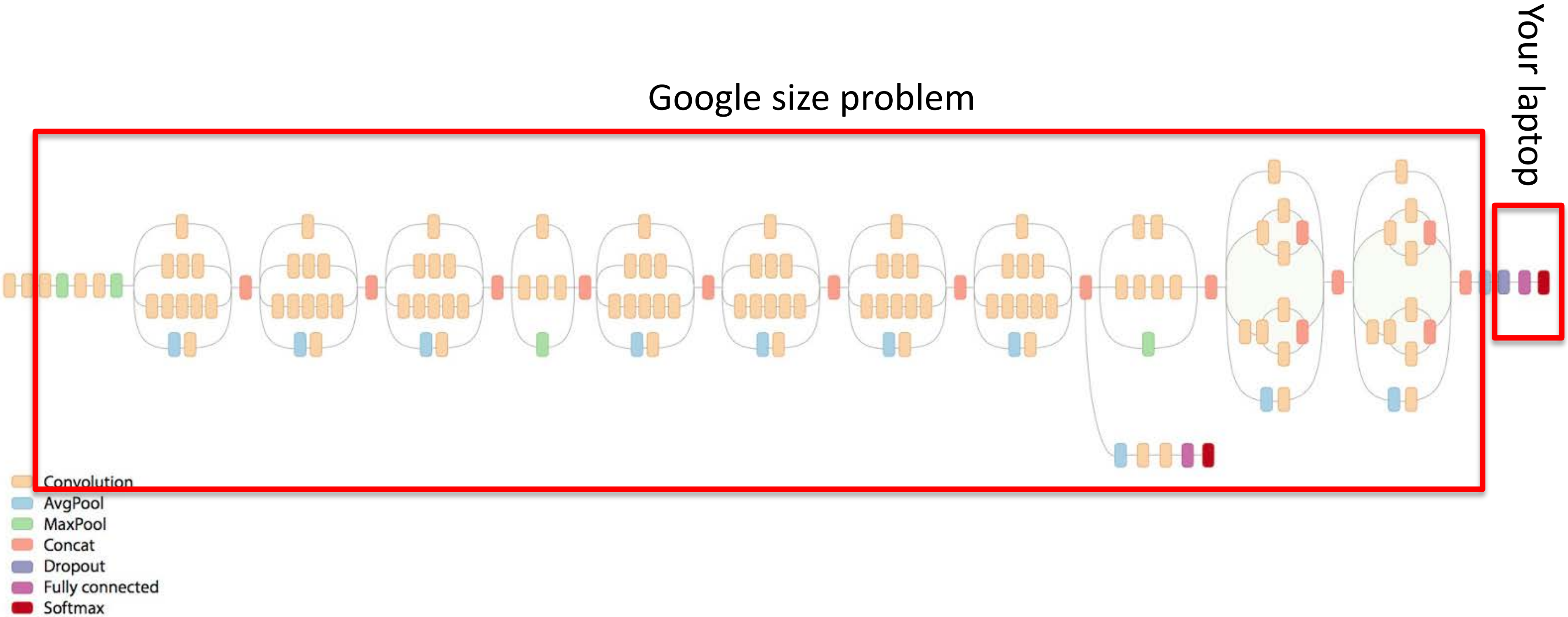
doi:10.1038/nature21056

Dermatologist-level classification of skin cancer with deep neural networks

Andre Esteva[1]*, Brett Kuprel[1]*, Roberto A. Novoa[2,3], Justin Ko[2], Susan M. Swetter[2,4], Helen M. Blau[5] & Sebastian Thrun[6]

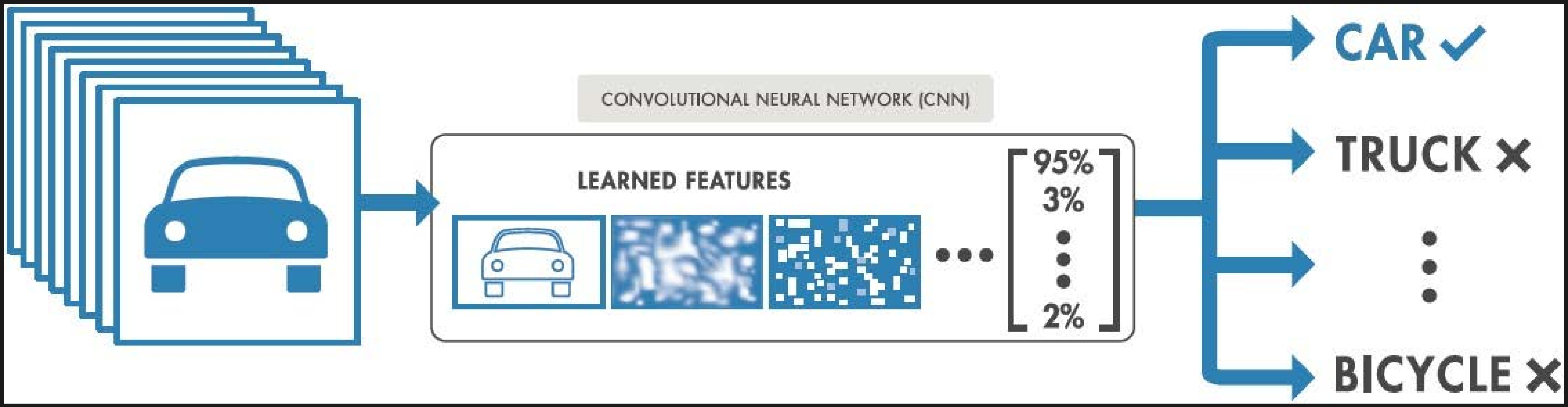
Figure 2 | A schematic illustration of the taxonomy and example test set images. a, A subset of the top of the tree-structured taxonomy of skin disease. The full taxonomy contains 2,032 diseases and is organized based on visual and clinical similarity of diseases. Red indicates malignant, green indicates benign, and orange indicates conditions that can be either. Black indicates melanoma. The first two levels of the taxonomy are used in validation. Testing is restricted to the tasks of **b. b,** Malignant and benign example images from two disease classes. These test images highlight the difficulty of malignant versus benign discernment for the three medically critical classification tasks we consider: epidermal lesions, melanocytic lesions and melanocytic lesions visualized with a dermoscope. Example images reprinted with permission from the Edinburgh Dermofit Library (https://licensing.eri.ed.ac.uk/i/software/dermofit-image-library.html).

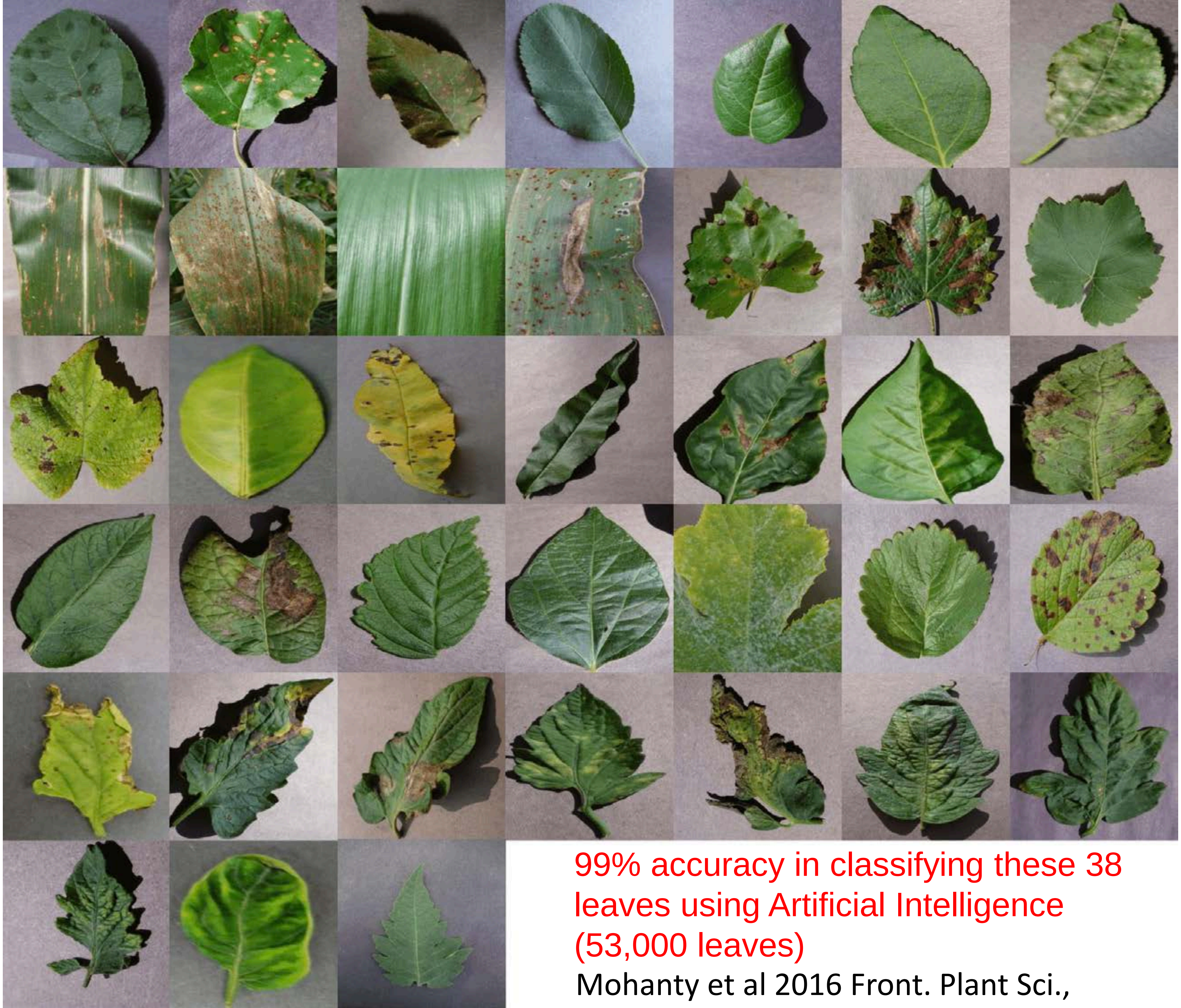
Why is AI so good now?



V3 inception model of TensorFlow

Machine Learning Model Example:





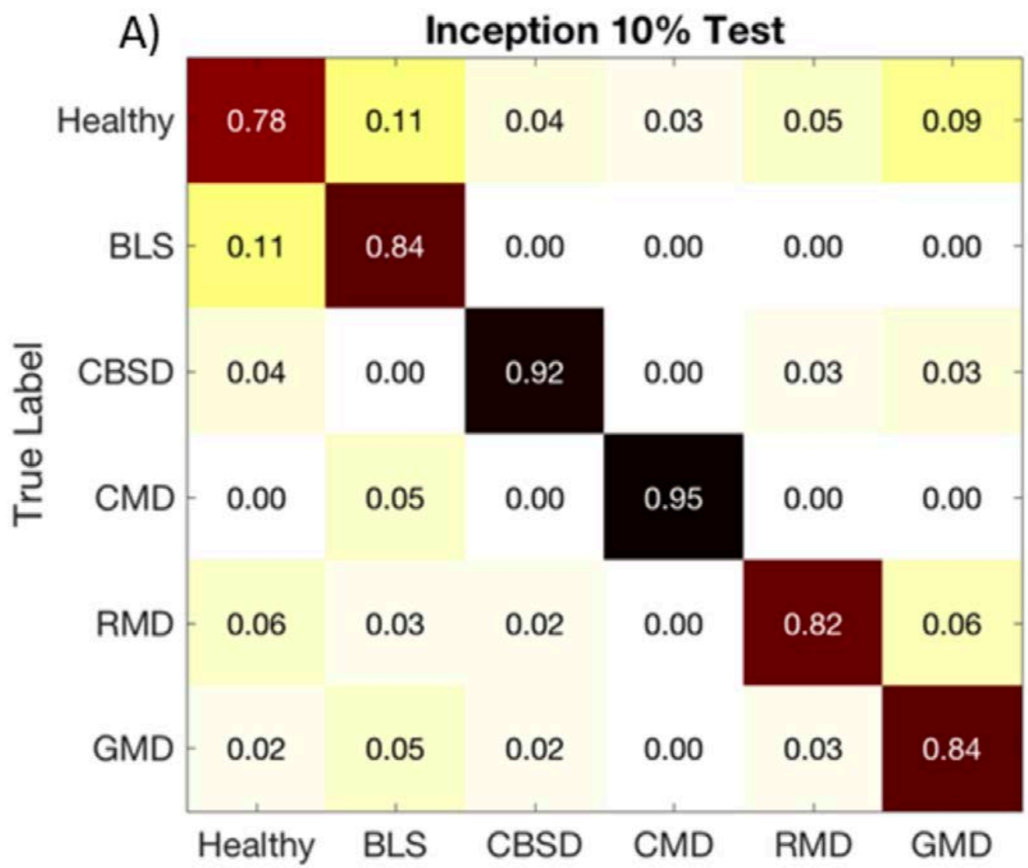
99% accuracy in classifying these 38 leaves using Artificial Intelligence (53,000 leaves)

Mohanty et al 2016 Front. Plant Sci.,

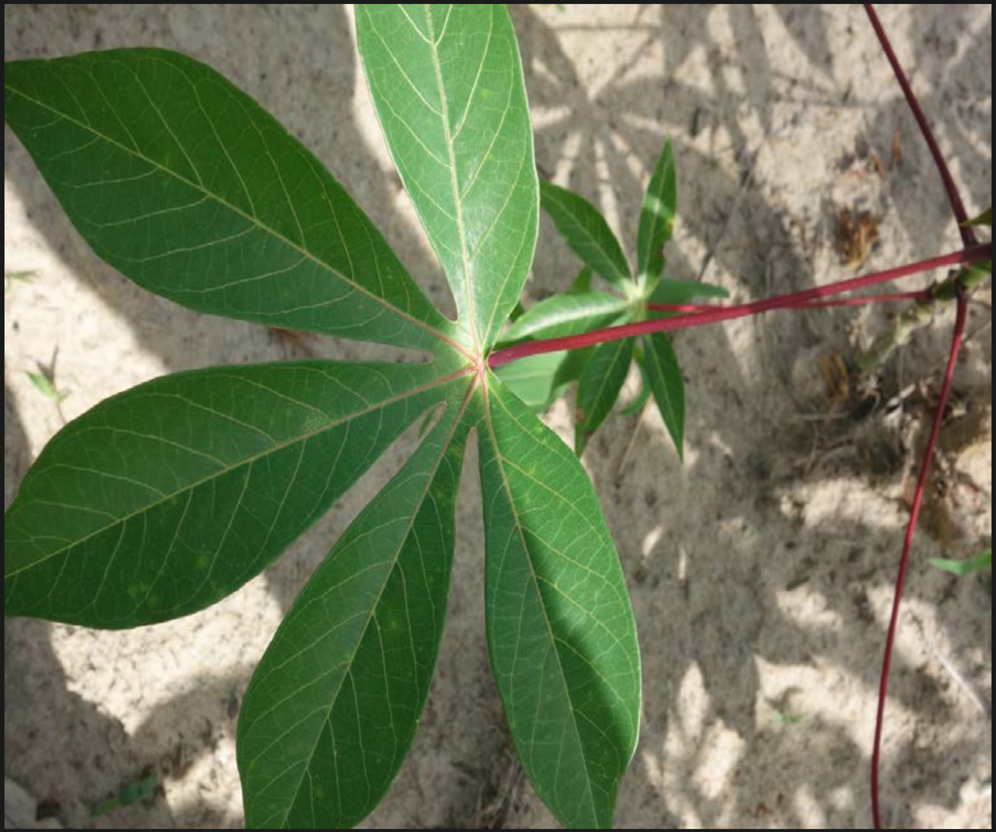
>200,000 images collected

Cassava (ca. 12,000)

AI will help in-field decision making



Video of beta app with James Legg of IITA (Tanzania)



Healthy (score = 0.57)
Brown streak disease (score = 0.23)
Brown leaf spot (score = 0.16)
Mosaic disease (score = 0.02)
Green mite damage (score = 0.02)

Mosaic disease (score = 0.98)
Green mite damage (score = 0.01)
Brown streak disease (score = 0.01)
Brown leaf spot (score = 0.0)
Red mite damage (score = 0.0)

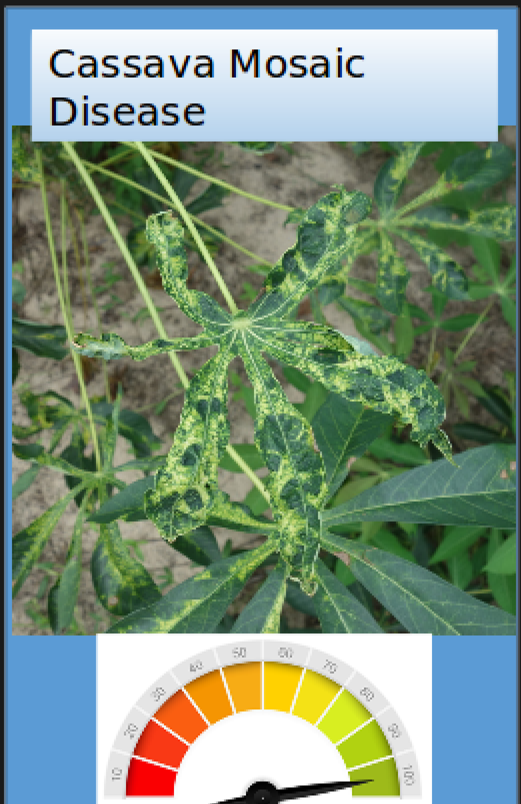
Brown streak disease (score = 0.42)
Green mite damage (score = 0.35)
Brown leaf spot (score = 0.13)
Mosaic disease (score = 0.09)
Healthy (score = 0.01)

Red mite damage (score = 0.65)
Green mite damage (score = 0.22)
Brown streak disease (score = 0.08)
Mosaic disease (score = 0.03)
Brown leaf spot (score = 0.03)

Brown leaf spot (score = 0.55)
Green mite damage (score = 0.26)
Red mite damage (score = 0.14)
Brown streak disease (score = 0.04)
Healthy (score = 0.01)

Screen 2: The person chooses cassava and video opens

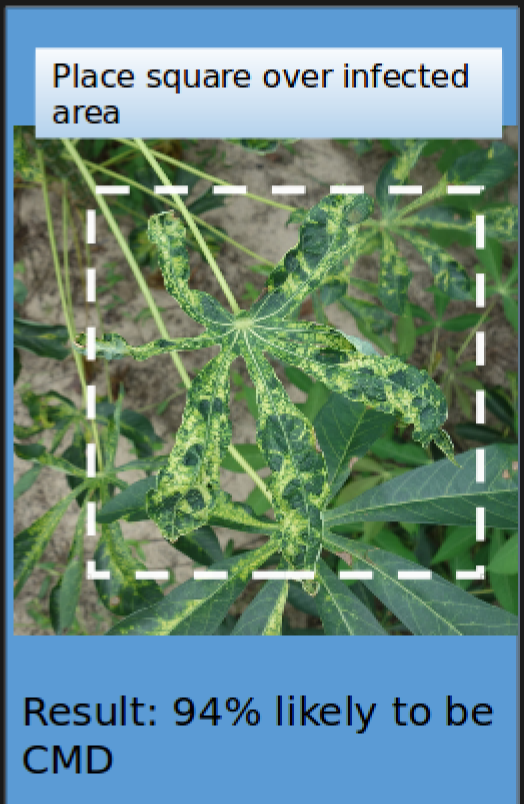
2a



Live video

Meter linked to tensor flow probability

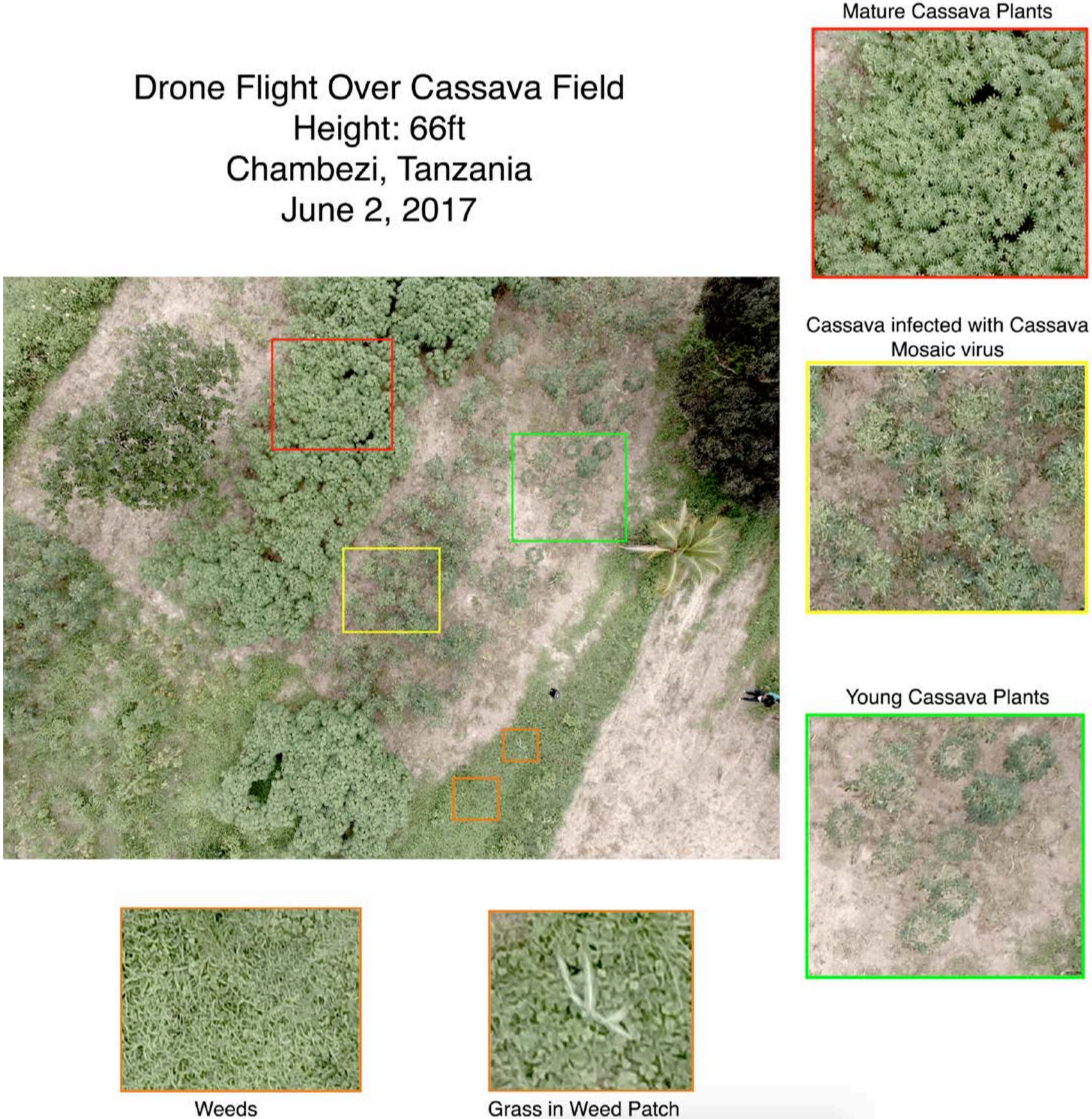
2b



User takes image and in-phone diagnosis based on image

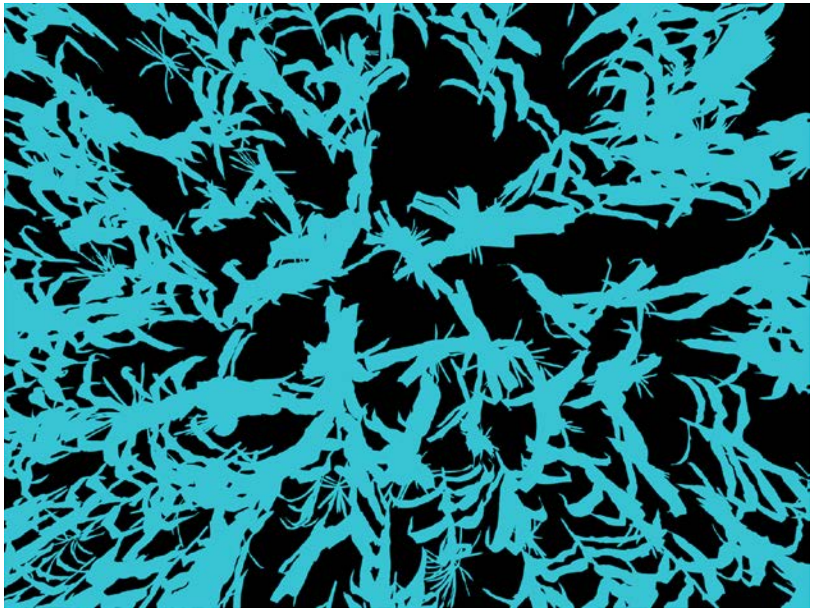
Use machines to compensate for lack of experts: **drones**

Drone Flight Over Cassava Field
Height: 66ft
Chambezi, Tanzania
June 2, 2017



AI can do biomass estimation

Drone picture of maize

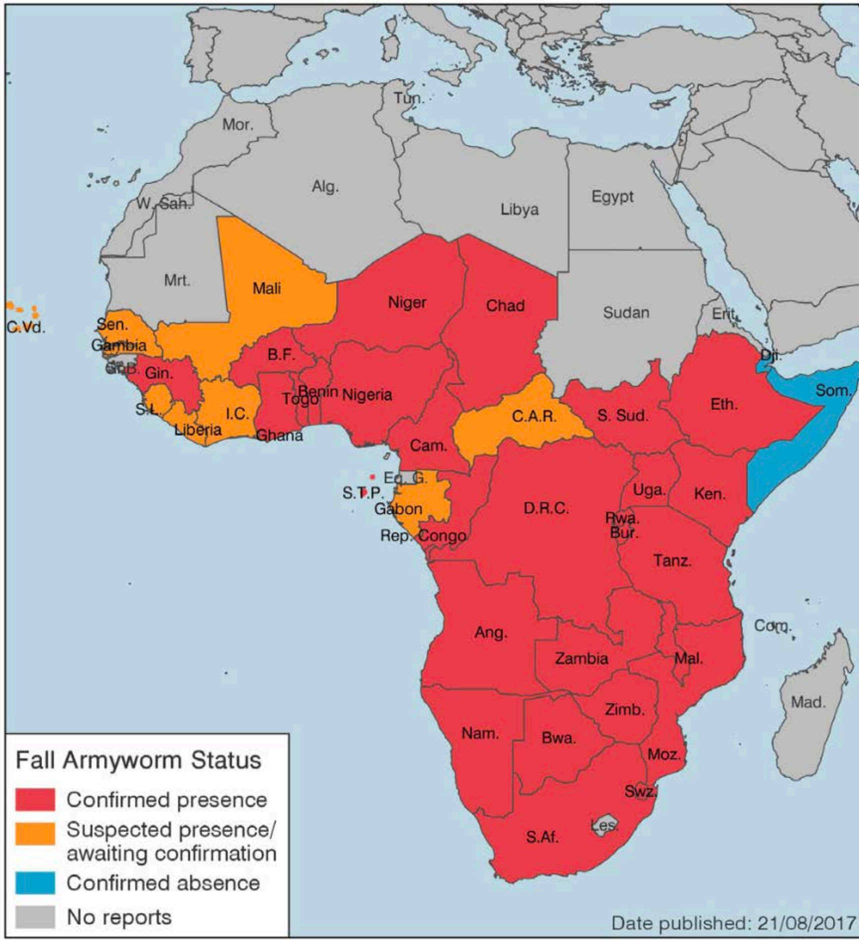


Machine accurately detects maize

Notice weeds ignored

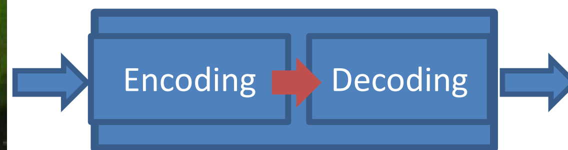
Fall Armyworm: invasive in 28 countries Losses between US$2.4m-US$6.1 m/year (CABI)

Map 1: Current FAW distribution in Africa (August 2017)

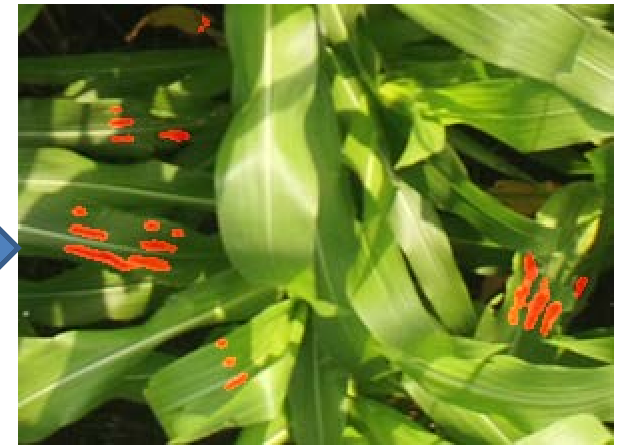


Our proposed FCN model for diseased maize image segmentation

Raw input image



A fully convolutional network (FCN) model



Segmented hole areas (overlapped with the raw image for better visualization)

- Fully convolutional networks (FCN): A widely used deep learning model for semantic image segmentation
- It takes a raw maize image as input, and produces label maps for the segmentation objects
- It consists of encoding part (multiple convolution and max-pooling layers) and decoding part (up-convolution layers)
- A key challenge: Obtain an effective model using a small amount of labeled ground truth data

Quantify FAW damage
(an advantage of a University)

5,525 m^2 fall armyworm damage maize took 120 human hours to annotate and 6 machine hours

Talk Outline

1. Knowledge: Make available existing knowledge
2. Experts: Use machines and Artificial Intelligence

Conclusion

We cannot be here in 10 years!

Acknowledgements

- Kelsee Baranowski, image curator
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Thank You

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