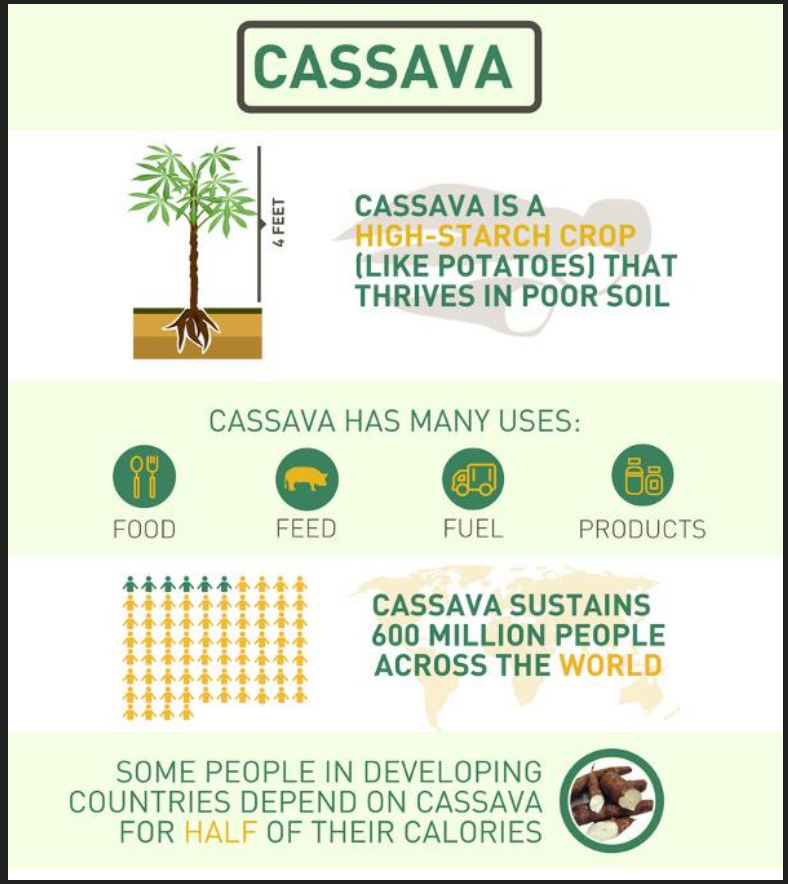
Cassava Image Classification

Melanie Butler - Final Springboard Capstone

Google Slide Deck

Agbeli (There is life)

- Ewe word for cassava
- Food security crop in vulnerable areas
- Robust to difficult climates
- Primary food staple for over 800 million people
- Potential biofuel source - extra income for farmers



https://www.newphytologist.org/news/view/135

The Problem

- Disease and pestilence:
  - Cassava Mosaic Disease (CMD)
  - Cassava Brown Streak Disease (CBSD)
  - Cassava Bacterial Blight (CBB)
  - Cassava Green Mottle (CGM)
- Yield reduction of 10% to 70%, up to 100% with CBSD

https://www.eurekalert.org/multimedia/pub/215556.php

Mitigation Strategies

- Cassava is propagated with plant cuttings - spreads disease
- Quarantine / burn diseased plants
- Critical to identify disease plants for separation

https://www.africa-uganda-business-travel-guide.com/howtogrowcassavainuganda.html

Project Goals and Metrics

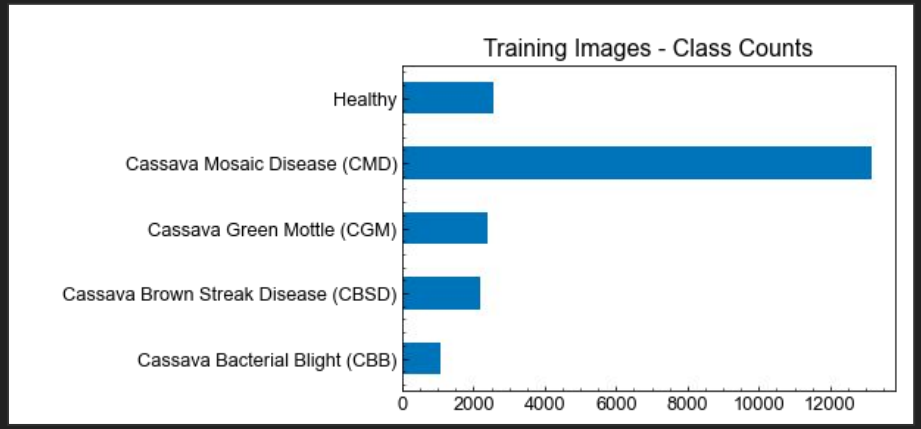
1. Develop a model capable of classifying an image of a cassava plant into one of four disease categories or as healthy.
    a. False disease classification → unwarranted destruction of valuable crops
    b. False healthy classification → propagation of disease
    c. Both are unacceptable - overall accuracy as metric
2. Deploy the model in an API that farmers could use to aid in their crop management decisions.

Data Source

- National Crops Resources Research Institute / AI lab at Makarere University, Kampala
- Crowd-sourced images from farmers in Uganda
- 21,367 Images
- Four disease categories, one healthy category

Preprocessing

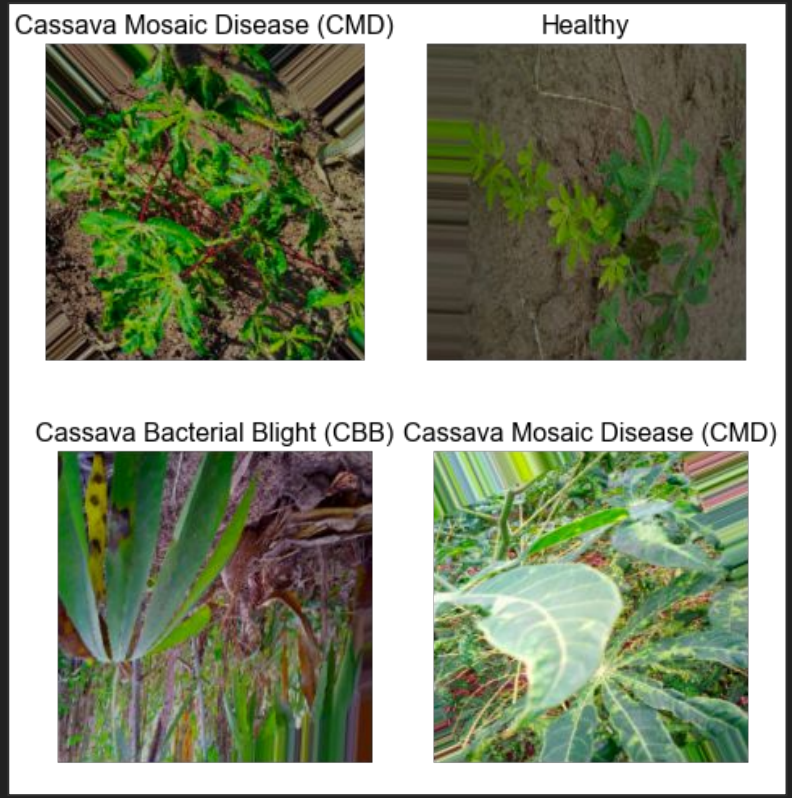
- Highly class- imbalanced



- Initial training - resampled 2000 images per class

Preprocessing

- Train / Val split (85:15)
- Hidden test set - Kaggle (~10,000 images)
- Random image augmentation:
  - Basic - variability expected from images in the field
  - Rotation, Brightness, Zoom
  - H / W / Channel Shift
  - Shearing
- Generated each batch - regularizing effect



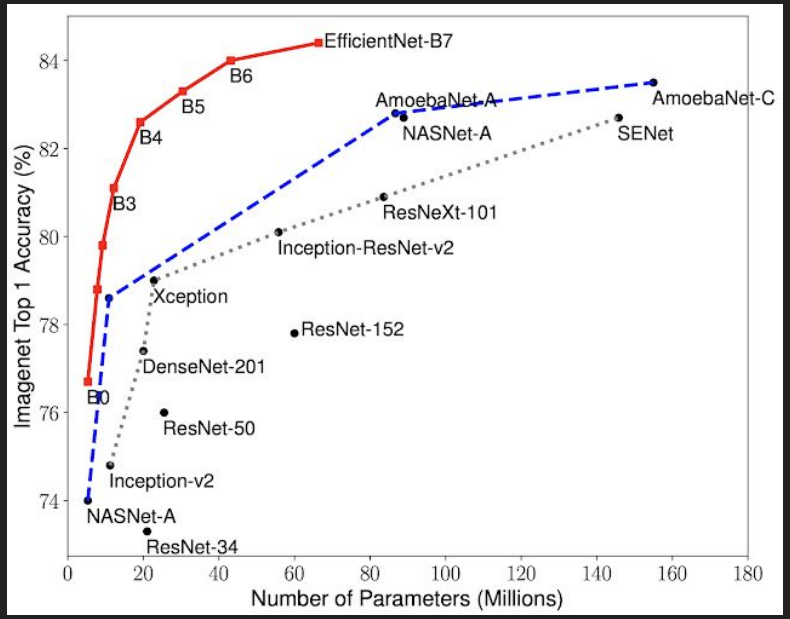
Preprocessing

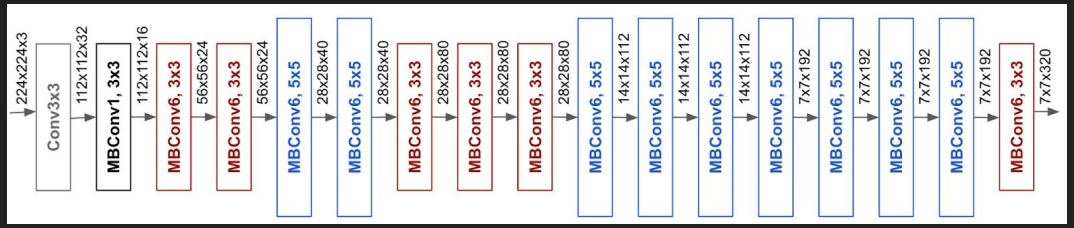
- Cutmix Image Augmentation:
  - Randomly crop two images together
  - Label weighted according to area of each image
  - Better model generalization, object localization
  - Similar to dropout effect, more efficient pixel use

Yun, S. et al, arXiv:1905.04899 [cs.CV]

Model Architecture

- Keras Applications
- Preliminary training - balanced, basic augmentation:
  - ResNet50
  - ResNet152v2
  - Xception
  - **EfficientNet-B4**

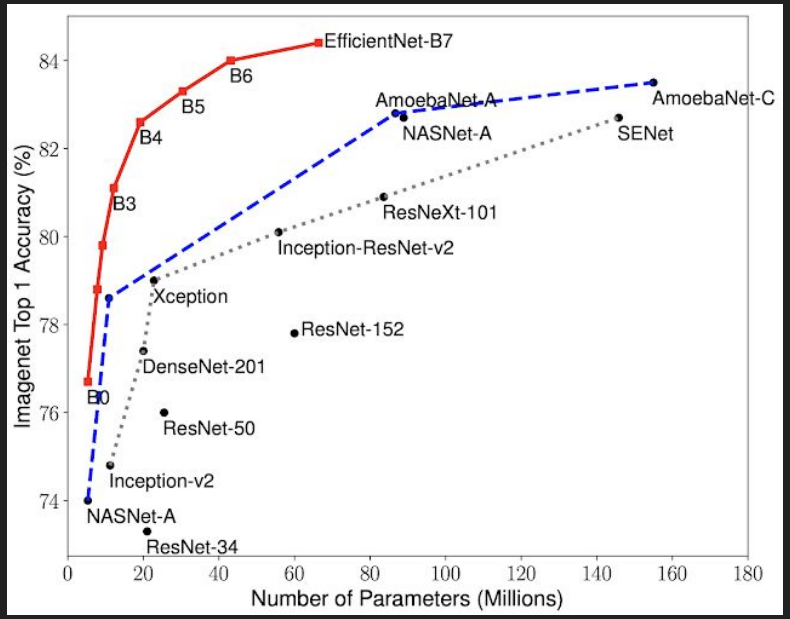


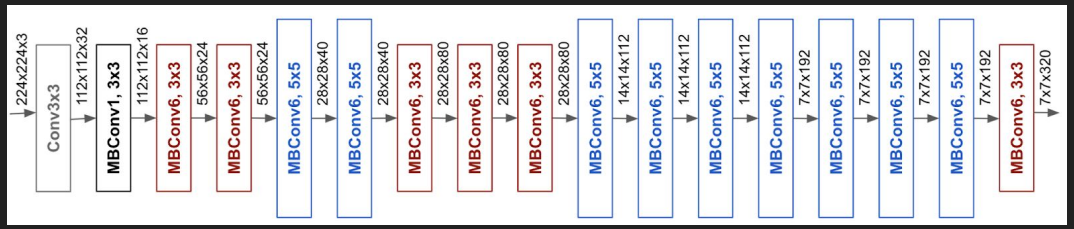


arXiv:1905.11946 [cs.LG]

Model Architecture

- EfficientNet-B4 base
- Scaling factor
  - Optimize depth / width / resolution given resource constraints
- 2D Global Average Pooling
- Dropout (rate 0.2 → 0.1)
- Dense output (softmax)

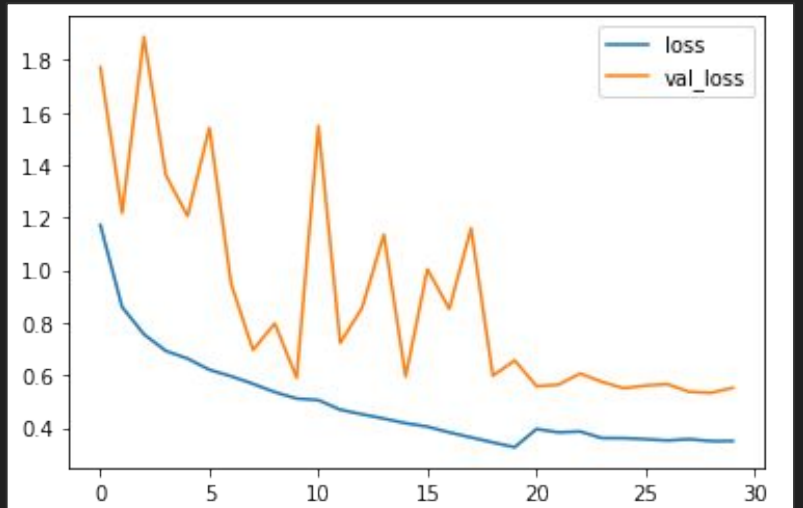


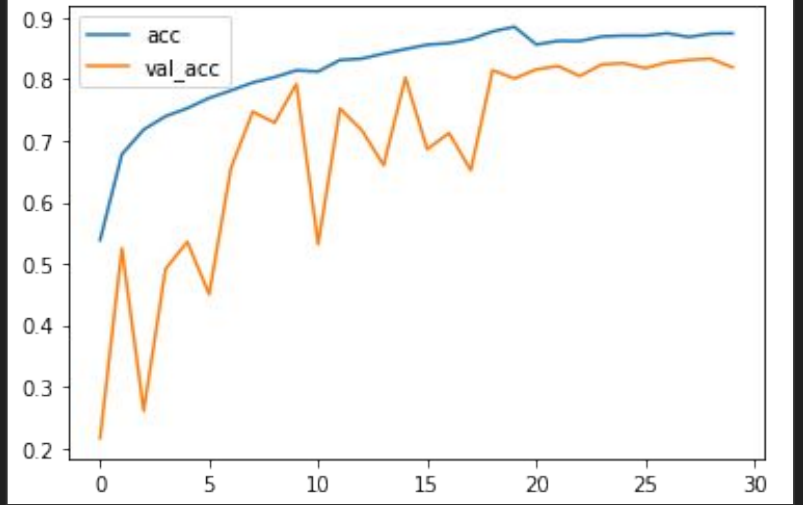


arXiv:1905.11946 [cs.LG]

Model Training

- Adamax optimizer
- Initial LR of 0.001, reduce on plateau callback
- First 30 epochs -
  - balanced training
  - basic augmentation
  - first two blocks frozen
- Unfroze layers
- Cutmix augmentation
- Decreased dropout to 0.1





arXiv:1905.11946 [cs.LG]

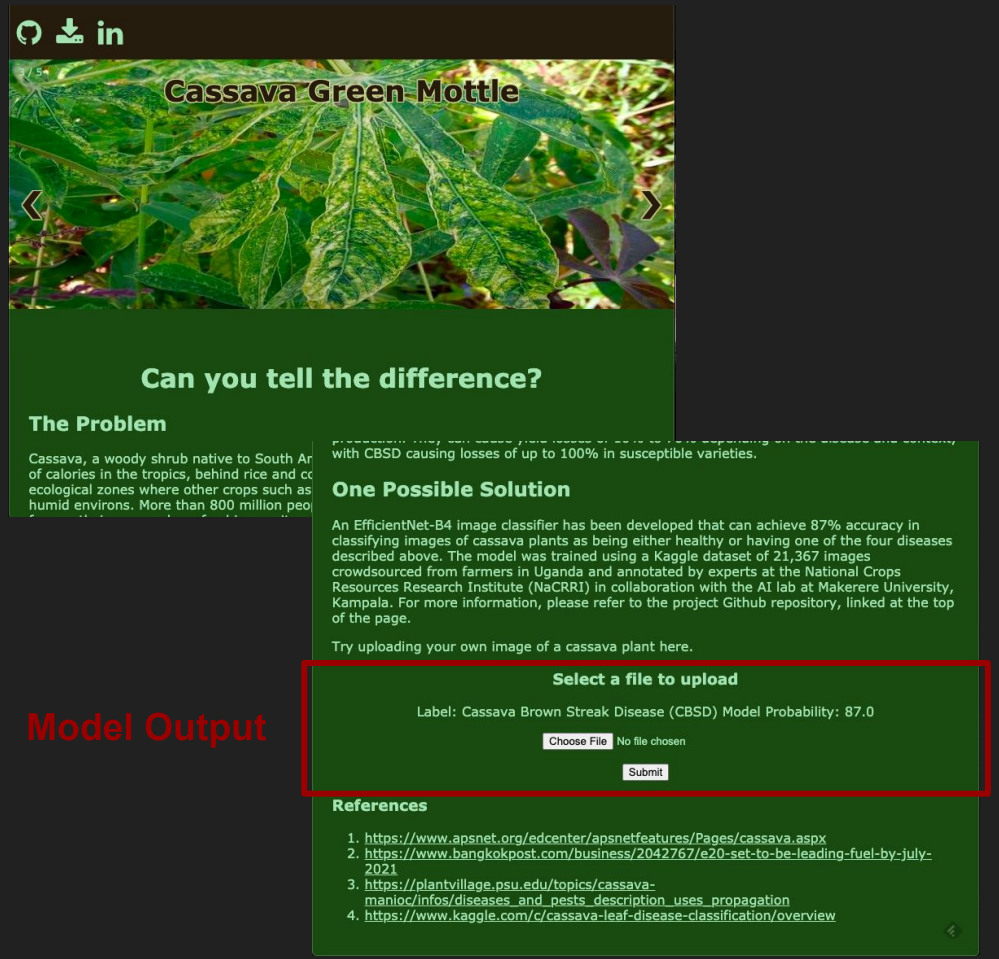
Model Evaluation

Model Evaluation

Weakness

	Precision	Recall	F1-Score	Support
Cassava Bacterial Blight	0.74	0.87	0.8	148
Cassava Brown Streak Disease	0.86	0.87	0.86	326
Cassava Green Mottle	0.78	0.86	0.82	365
Cassava Mosaic Disease	0.99	0.9	0.94	1984
Healthy	0.68	0.88	0.77	386
Accuracy			0.89	3209
Macro Average	0.81	0.88	0.84	3209
Weighted Average	0.9	0.89	0.89	3209

Test Accuracy on Kaggle - 87.8%



Model Output

Model Deployment

- Website Developed on Flask
- Upload Image
- Receive Classification / Model Probabiity

Future Work

- Improve model performance w.r.t Healthy class
- Binary classification appropriate for application - disease response is generally the same regardless of disease:
  a. Healthy - no action needed
  b. Diseased (CBB, CBSD, CMD, CGM) - quarantine / burning
- Train binary classifier, able to tune for desired precision / recall

Thank You

Thank you for your attention, feedback, questions!

Mentor -
Giovanni Bruner