IMAGE ANALYTICS: PREDICTING SEED QUALITY FROM SEED X-RAY IMAGES

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Automatic Feature Extraction by using CNN-Deep Learning

https://devblogs.nvidia.com/parallelforall/deep-learning-nutshell-core-concepts/
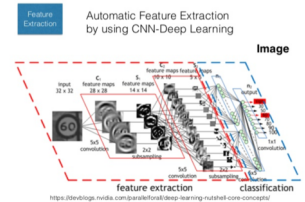
Introduction

- Seed quality is often a key consideration for seed growers, when choosing from the different seed brands available on the market.

- To the farmer, high quality seeds implies a high crop yield and revenue. For seed companies, this translates to fewer returned seeds, increased customer trust and satisfaction, customer retention, increased market share and revenue.

- Seed quality assurance and control is therefore, an important step in ensuring that the seeds which eventually reach the customer, are of acceptable quality.

- The current seed quality assessment method involve sampling some seeds (< 1%) from each batch and performing germination tests. The germination performance (in %) is then assumed to be representative of the entire seed batch.

- The combination of X-ray imaging and machine learning presents a huge opportunity for automating, scaling and speeding up the entire seed quality assessment process.

- This will provide a faster quality metric as well as the ability to screen entire seed batches. The ability to screen every single seed for quality before sending it off to the farmer is one huge opportunity that a fast, automated seed testing method may guarantee.

- This POC project seeks to determine the possibility of predicting seed germination test outcomes from seed x-ray images using machine learning.

Seed Germination Testing (Marcos-Filho, 2015)

Flowchart for predicting seed quality from X-ray Images
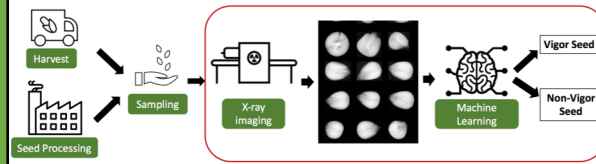
Methods

- Above is the proposed flowchart for seed quality predictions.

- The data set of 48000 x-ray images was randomly partitioned into training, validation and test sets using a 70:15:15 ratio respectively.

- Downsampling, upsampling and data augmentation techniques were used to mitigate the high class imbalance (92% vigor, 8% non-vigor)

- Two CNN architectures, VGG16 and ResNet50, were tried. In each case, the 1000-output fully connected layer was replaced with batch normalization, dropout and densely-connected layers with a binary output in the final layer.

- Different models were developed from the 2 architectures by varying the learning rate, L1/L2 regularization parameters, dropout rate and training time among others.

- Different models were also developed by sub-grouping the seeds according to shape and size.

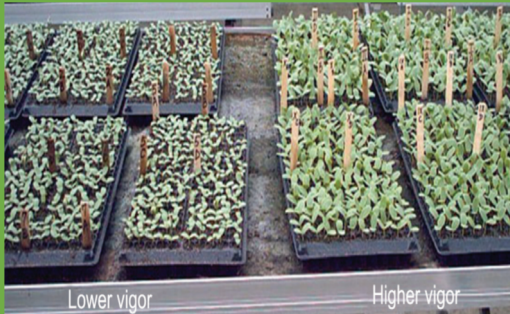- Single models and different ensemble model combinations were then compared.

Seed quality model base architectures

```
Layer (type)                 Output Shape              Param #
=================================================================
vgg16 (Model)                (None, 8, 8, 512)         14714688
batch_normalization_1 (Batch (None, 8, 8, 512)         2048
gaussian_dropout_1 (Gaussian (None, 8, 8, 512)         0
flatten_1 (Flatten)          (None, 32768)             0
dense_1 (Dense)              (None, 8)                 262152
batch_normalization_2 (Batch (None, 8)                 32
dropout_1 (Dropout)          (None, 8)                 0
dense_2 (Dense)              (None, 8)
=================================================================
Total params: 14,978,929
```
VGG16

```
Layer (type)                 Output Shape              Param #
=================================================================
resnet50 (Model)             (None, 1, 1, 2048)        23587712
batch_normalization_1 (Batch (None, 1, 1, 2048)        8192
gaussian_dropout_1 (Gaussian (None, 1, 1, 2048)        0
flatten_1 (Flatten)          (None, 2048)              0
dense_1 (Dense)              (None, 8)                 16392
batch_normalization_2 (Batch (None, 8)                 32
dropout_1 (Dropout)          (None, 8)                 0
dense_2 (Dense)              (None, 8)
=================================================================
Total params: 23,612,337
```
ResNet50
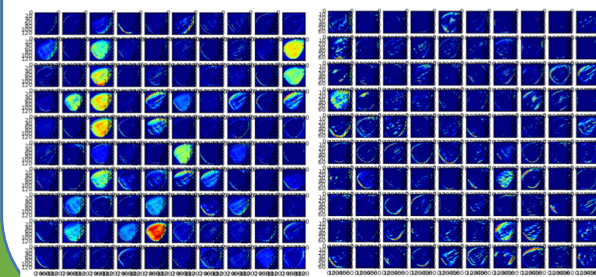
Some feature maps from the convolution filters

Results

1. The best class predictions were 99.6% and 77.0% for vigor and non-vigor classes respectively.

2. Generally, flat seed models (Flats, LF, MF) performed better than round seed models (Rounds, LR, MR) but size/shape sub-grouping did not significantly improve model performance.

3. For the same model, hyper-parameter tuning results lay on the same vigor-nonvigor inverse correlation curve.

4. Increasing from 760 to 1321 (a factor of 1.7) nonvigor training images improves non-vigor prediction by 1.3 times (0.22 to 0.28). Similarly, increasing from 760 to 2077 (a factor of 2.7) nonvigor images improves non-vigor prediction by 1.8 times (0.22 to 0.39).

5. Hence, the biggest gain in model performance was achieved by increasing the number of non-vigor images, rather than through CNN architecture selection or hyper-parameter tuning.

6. The best single model achieves 99.6% & 20.0% across vigor and nonvigor classes. However, an ensemble of the 9 best models achieves 99.6% & 59.3% across vigor and nonvigor classes.

BEST MODEL RESULTS BY SEED SHAPE AND SIZE

Legend: Flats, Rounds, LF, LR, MR, MF

Data points: 0.930, 0.420 · 0.996, 0.290 · 0.960, 0.220 · 0.970, 0.210 · 0.990, 0.260 · 0.920, 0.170

MODEL RESULTS SUMMARY - TEST DATA

Legend: VGG_1300, VGG_2100, ResNet_2100, Poly. (VGG_1300), Poly. (VGG_2100), Poly. (ResNet_2100)

Learning Curve - NonVigor Prediction at 96% Vigor Prediction

Data points: 760, 0.22 · 1321, 0.28 · 2077, 0.39
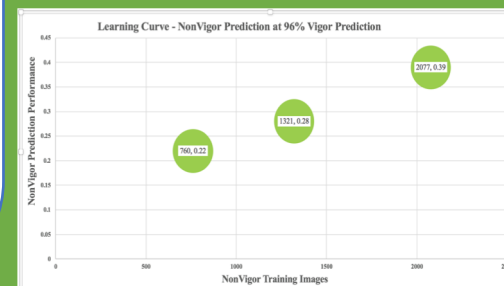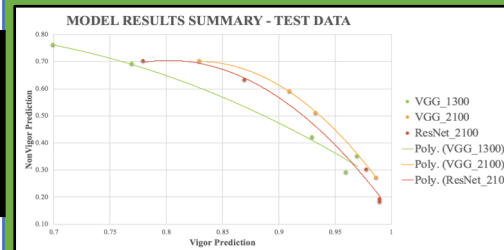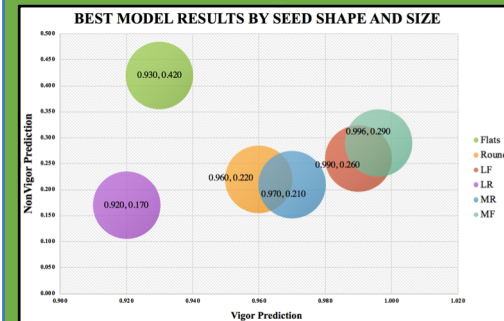
Conclusions

1. The best model (99.6% vigor | 59.3% nonvigor) is an ensemble of the top 9 single models.

2. The class imbalance affected model training, even after data augmentation.

3. Results suggest that increasing the number of nonvigor images could improve model training.

Novelty / Impact

- This study provides promising evidence that machine learning could be used for seed vigor predictions.

- There is the potential to significantly reduce the occurrence of seed returns.

- Pilot phase testing is currently underway.

- Plans are in place to obtain more non-vigor data for model improvements.

References

Marcos Filho, J. (2015). Seed vigor testing: an overview of the past, present and future perspective. *Scientia Agricola*, *72*(4), 363-374.