End-to-end convolutional selective autoencoder for Soybean Cyst Nematode eggs detection

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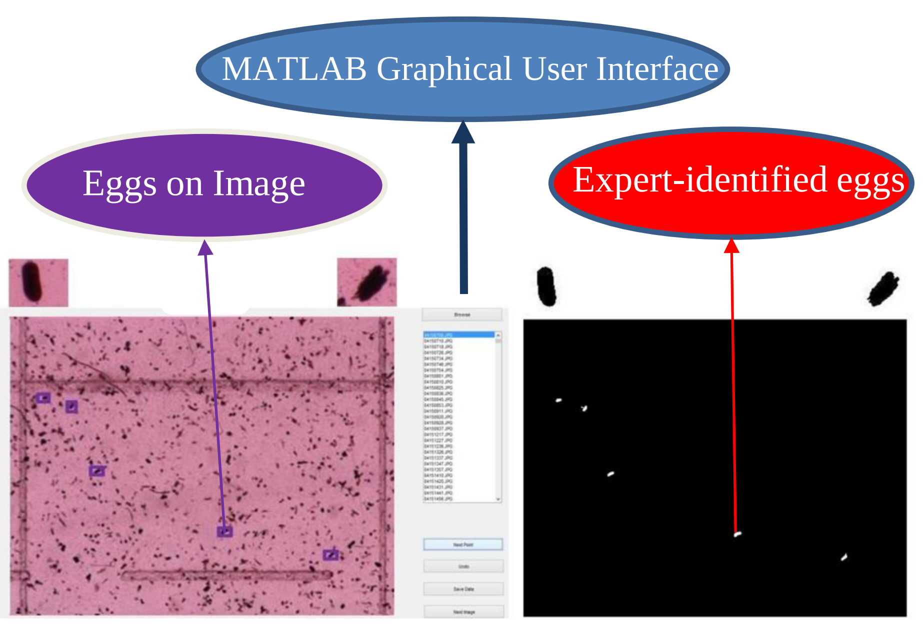
Objectives

Soybean Cyst Nematode (SCN) eggs detection using a **novel selective autoencode**r:

- Deep Convolutional neural network framework
- Significantly expedite the process of identifying Soybean Cyst Nematode eggs
- Train a deep convolutional autoencoder to suppress undesired parts of an image
- Demonstrate the proposed method on image cluttered with disturbances that are very similar to objects of interests

Introduction

- **Billions of $$$** lost in revenue due to SCN infestation on soybean in USA alone
- Time consuming and tedious to identify and count eggs
- Fully connected layers usually complements the learned
- Improving the efficiency and accuracy of detection and counting using machine learning tools
- Improving SCN phenotyping by mapping populations to find new sources of SCN resistant soybean genes

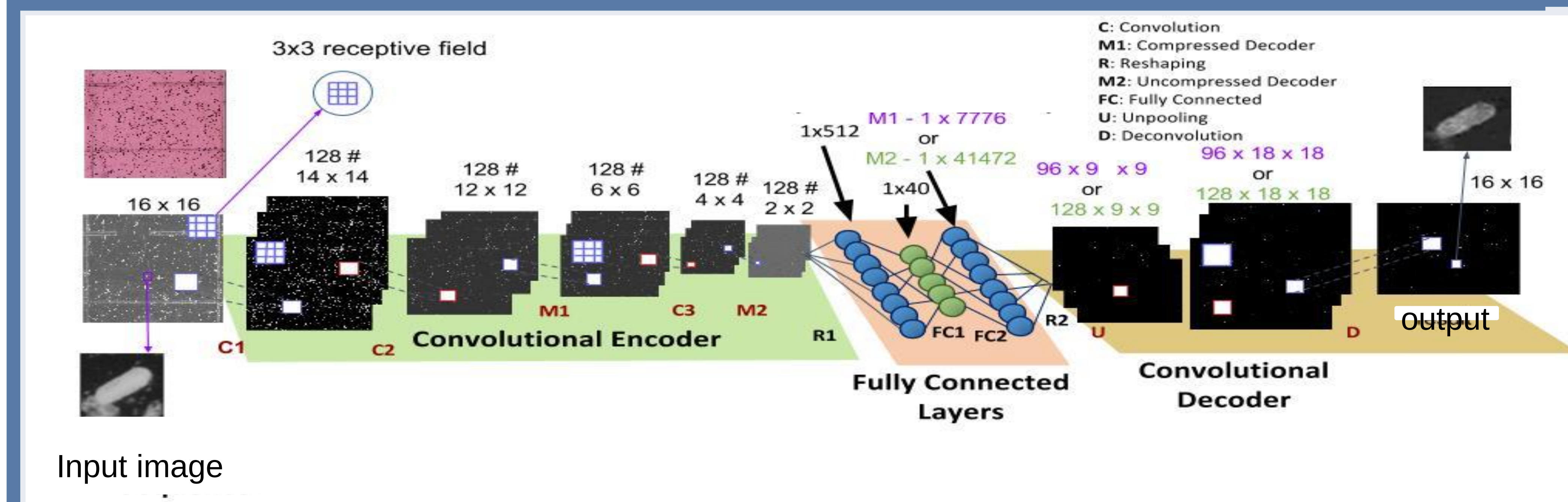


Motivation

Convolutional Selective Autoencoders

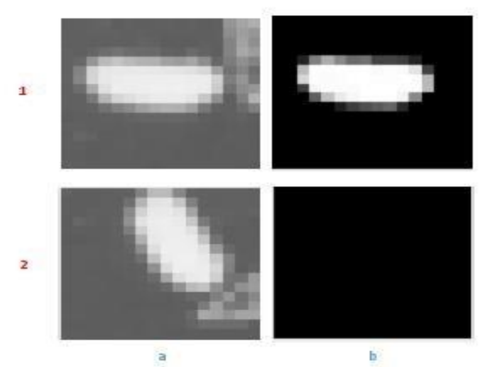
- Discriminative models that rely on local neighborhood matching to reduce dimension
- Two main components are feature extraction and classifier learning
- Fully connected layers usually complements the learned features by propagating highly active weights and classifiers
- Utilizes distributed map-reduced frameworks as well as GPU computing
- Extract hierarchical features to capture concise information of an image
- Ability to suppress undesired parts allow efficient object detection

Convolutional Autoencoder Architecture



Model1 - M1(compressed decoder) and Model2 - M2(uncompressed decoder)

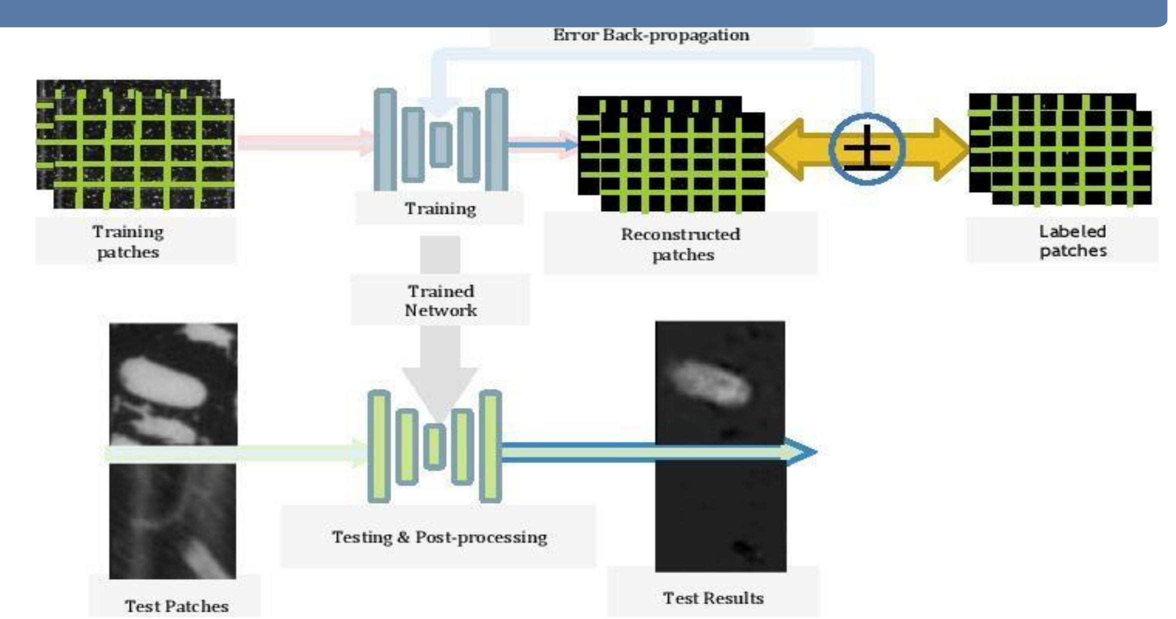
Selective Training and Implementation



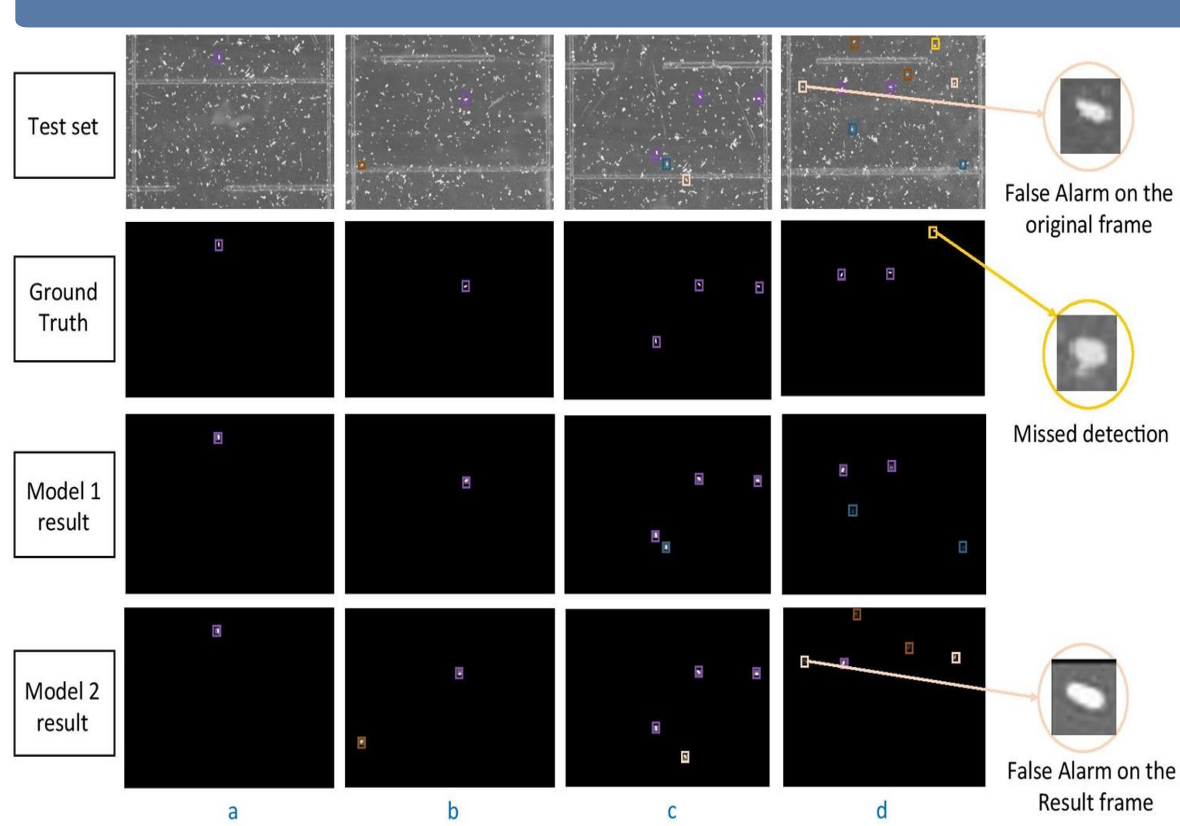
1a). Fully centered egg; 1b). Training label for 1a; 2a). Partly-centered egg; 2b). Training label for 2a

Images collection process:

- Soil is collected, washed, dyed and put under a microscope
- Images taken using camera through microscope and SCN eggs labeled by expert plant pathologist
- Extract image patches and run through the selective autoencoder algorithm



Qualitative detection results



2). Boundary situated object (egg) scenario: (a) test frame, (b) ground truth with egg shown in a purple box, (c) missed detection (shown in yellow box) due to lack of boundary padding and (d) successful detection (shown in purple box) as a result of end correction

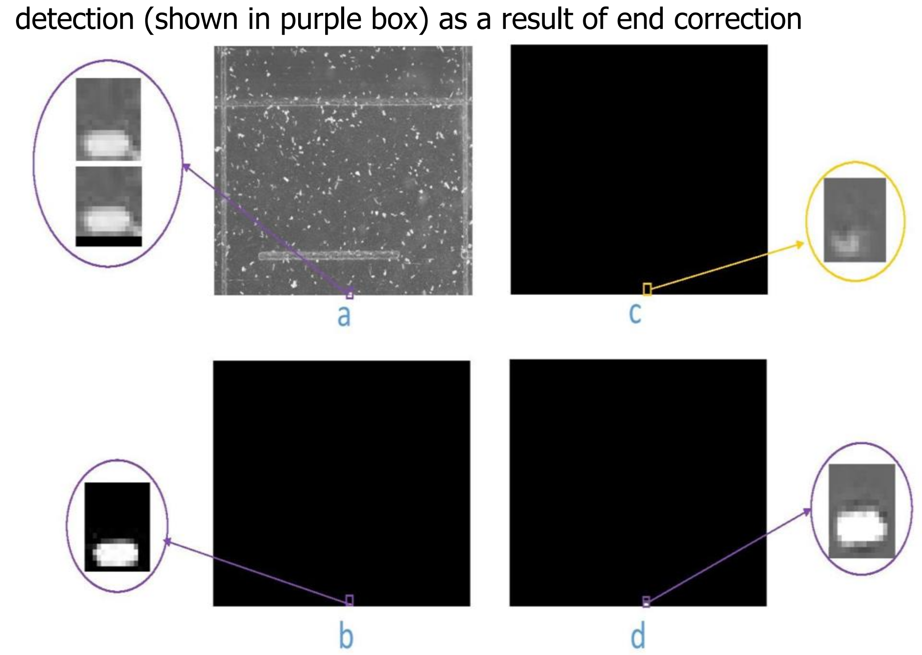


Fig 1. Purple boxes indicating correctly labeled eggs, deep blue and light blue boxes for Model 1's clear and contentious (possibly human labeling error) false alarms respectively, deep orange and light orange boxes for Model 2's clear and contentious false alarms respectively and yellow boxes for missed detection. The gray scale threshold values of Models 1a).192, 1b).179, 1c).180, 1d).180, 2a).193, 2b).180, 2c).187 and 2d).173

Detection efficiency

stride	P - #of patches/frame	detection time(sec)
1 × 1	358821	435
2 × 2	77361	77.5
4 × 4	19481	18.05
8 × 8	4941	5.6
16 x 16	1271	1.8

Average detection accuracy, $ADA = \frac{\#\ of\ eggs\ detected}{Actual\ \#\ of\ eggs}$

Average miss-to-egg ratio,

$$AMER = \frac{\#\ of\ false\ alarms\ per\ frame}{Actual\ \#\ of\ eggs\ per\ frame}$$

Average non-eggs discarded,

$$AND = \frac{\#\ of\ non-eggs\ discarded\ per\ frame}{\#\ of\ non-eggs\ originally\ per\ frame}$$

Model #	ADA (%)	AMER (%)	AND (%)
1	94.33	18.18	99.77
2	83.17	36.36	99.30

Conclusion

- An end-to-end convolutional selective autoencoder is developed for a complex rare object detection problem.
- Exploration of hyper parameters and model structures for the convolutional network

Future work

- Explore other machine learning classifiers
- Exploring various unpooling strategies and interfacing classifiers at the fully connected layers
- Learning to automatically count the rare objects within the automated pipeline

Acknowledgements

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References

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[2]. Kin Gwn Lore, Adedotun Akintayo, and Soumik Sarkar. "LLNet: A deep autoencoder approach to natural low-light image enhancement" *arXiv: 1511.03995v1 [cs.CV]*, pages 1–11, November 2015.