Machine Learning Algorithms for Automated NIF Capsule Mandrel Selection

By

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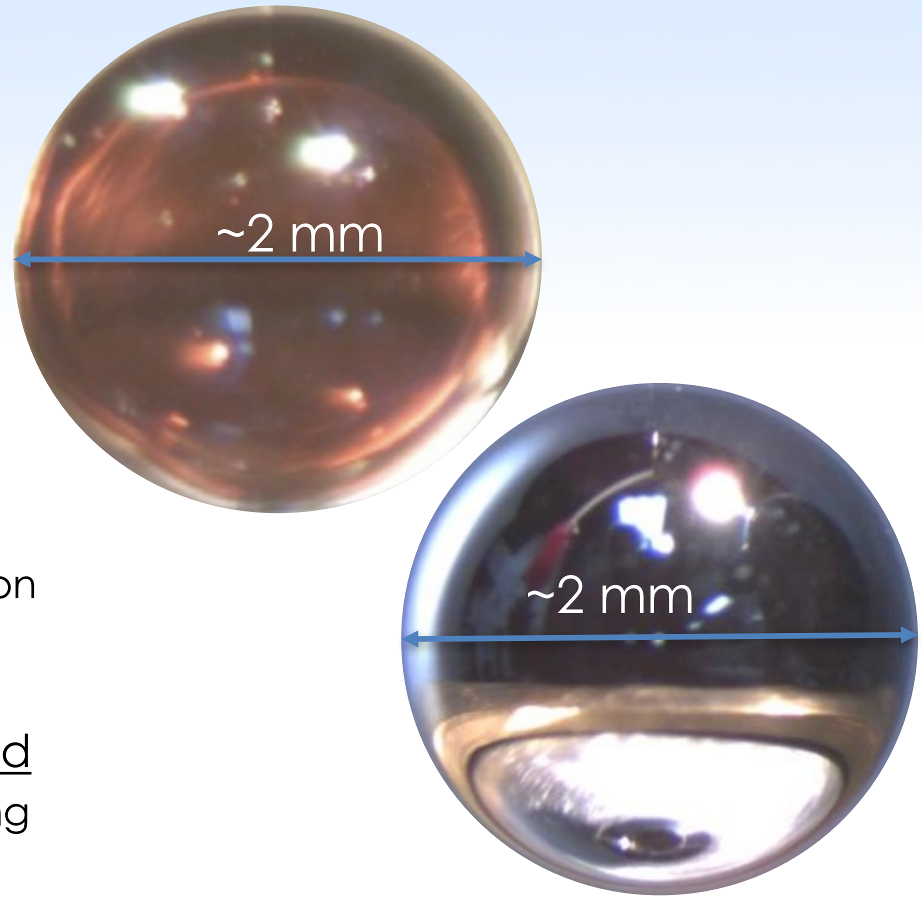
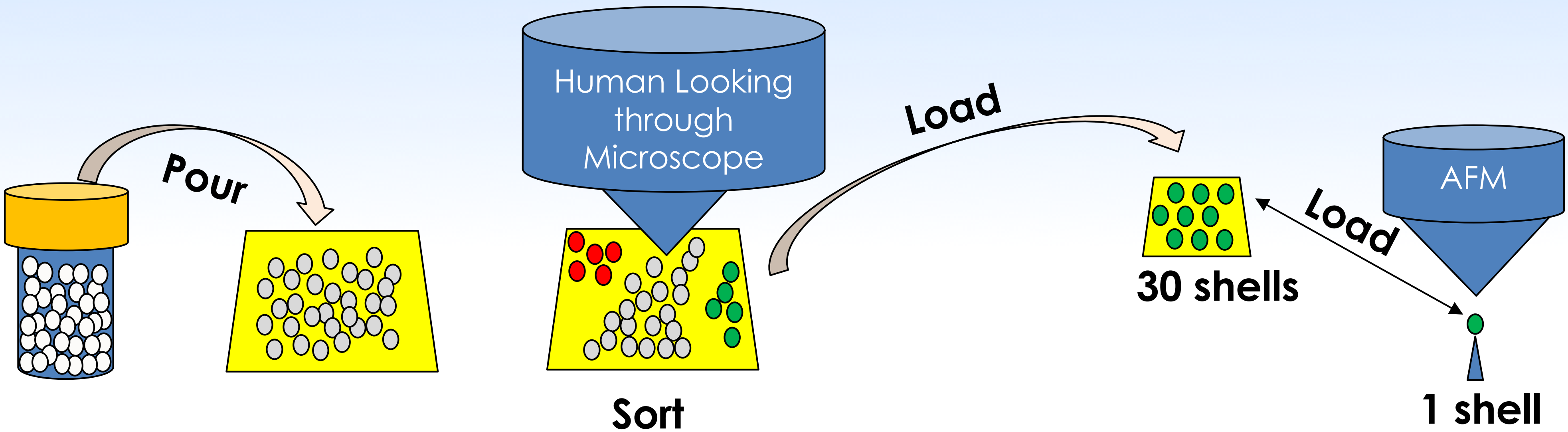
Motivation: Use Machine Vision and Machine Learning Techniques for PAMS Mandrels Selection

- **PAMS capsule mandrels are used for production of GDP and beryllium shells**
- **Each mandrel is inspected for roundness and surface defects**

- **Automation leads to:**
  - <u>Better shells</u>
    - Higher throughput
    - Consistent results
  - <u>Less human interaction</u>
    - Less labor hours
    - Operator independent results
  - <u>Provide statistics</u>
    - Quantitative feedback mechanism on batch quality
    - How many defects and what type?
  - <u>Increase downstream production yield</u>
    - More costly to discover defects during downstream operations

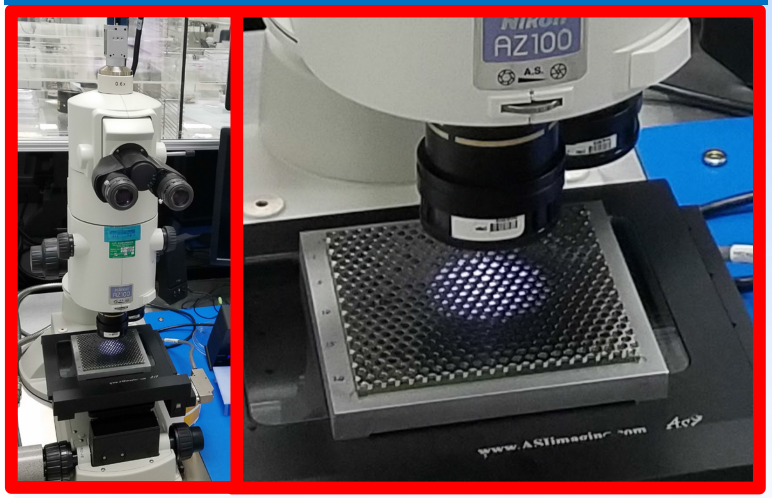


Shell selection process with no automation

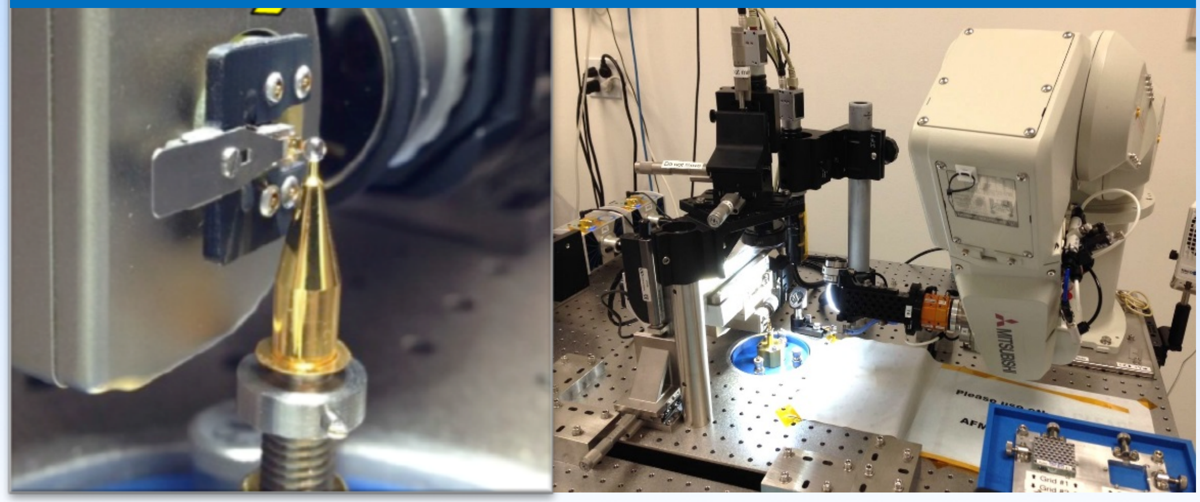


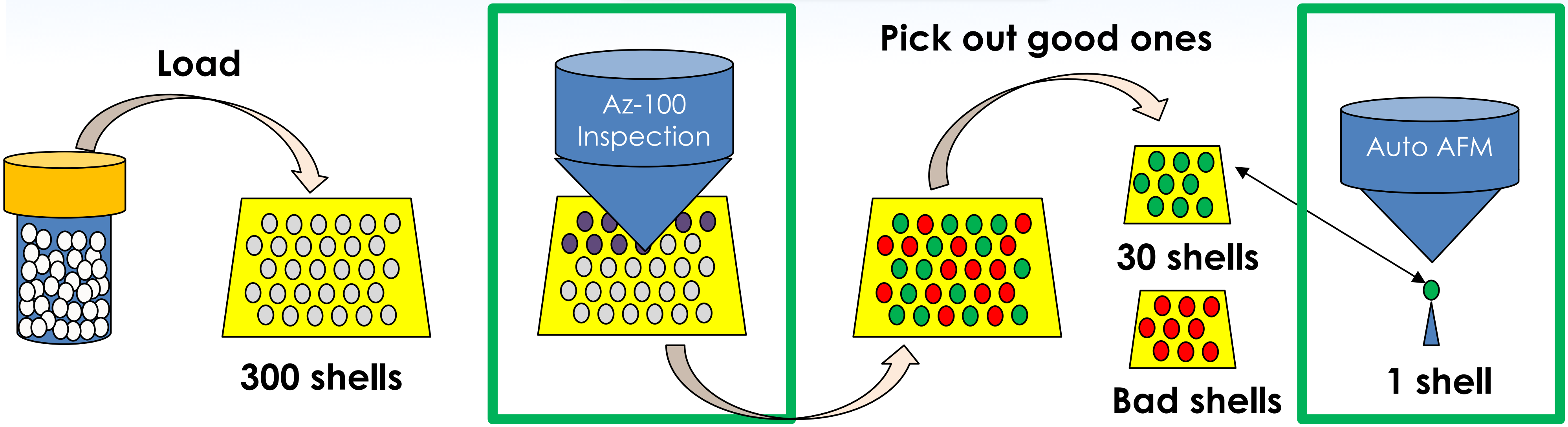
Some Automaton was added to the process in 2015

Automated AZ-100 Microscope



Robot-loaded atomic force microscope (AFM)





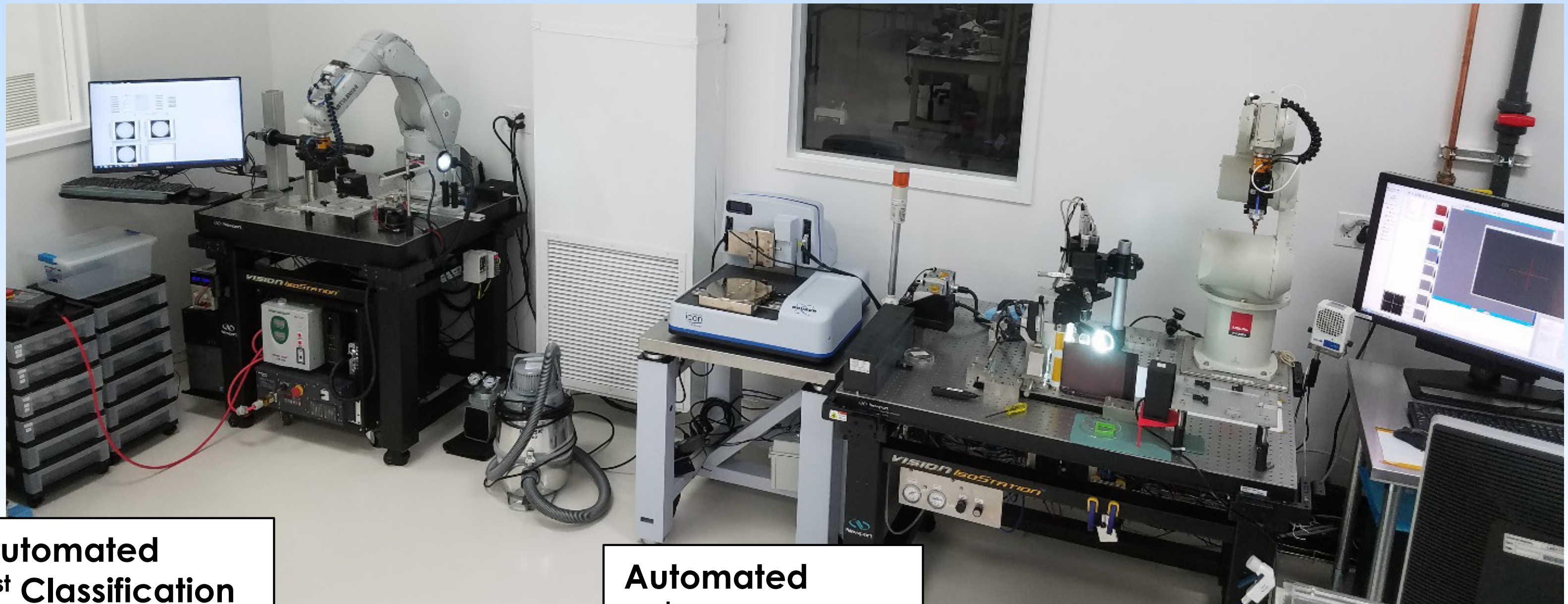
*Carlson, L. et. al., "Automation of NIF target fabrication", *Fusion Sci. and Tech.*, **70,** 247-287, (2016).

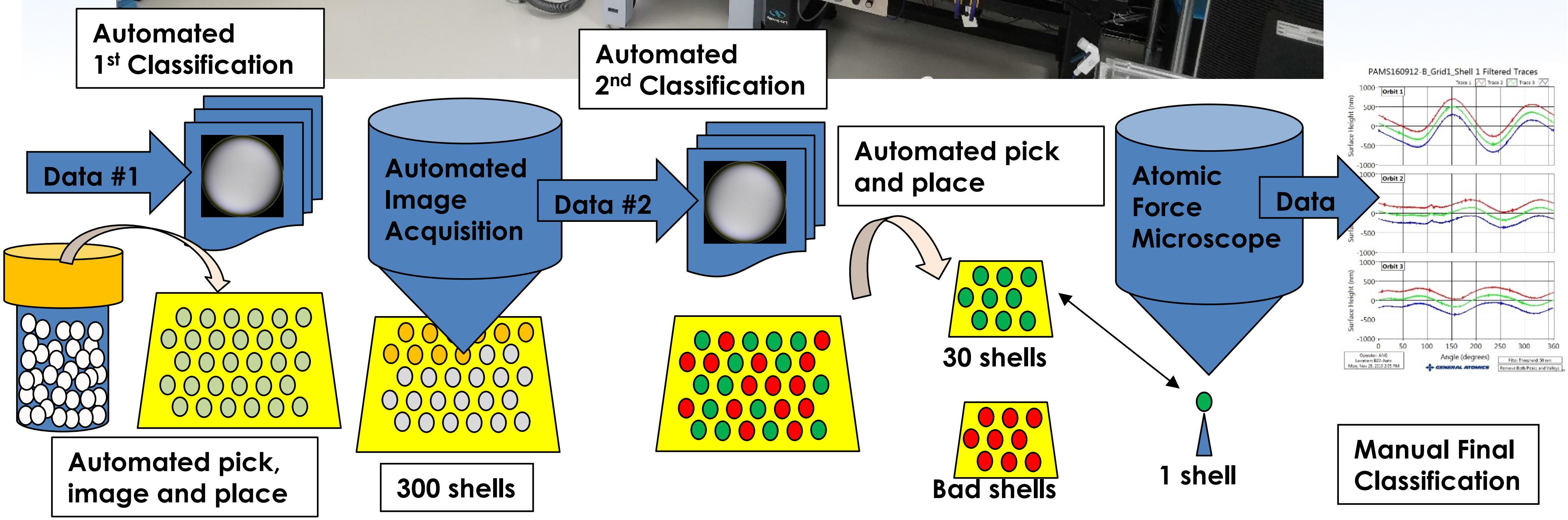
Current Demand requires 0.25 FTE to sift and sort through shells

- **Inspect ~650 shell mandrels image sets/week**
  - 4-6 man hours of loading and placing shells into grids
  - 4-6 man hours /week of looking at images and recording results
    - Optical Yield: 30 %
    - AFM Yield: 30 %
    - TOTAL Yield <10%
- **Identify 24 shell mandrels to go into GDP coater**
  - 2-3 batches of 24 shells/ month
  - Metrologize, select best ones
- **Capsules are built into CFTA's and shipped to LLNL**
  - 2 CFTA's/week (2017 and 2018)

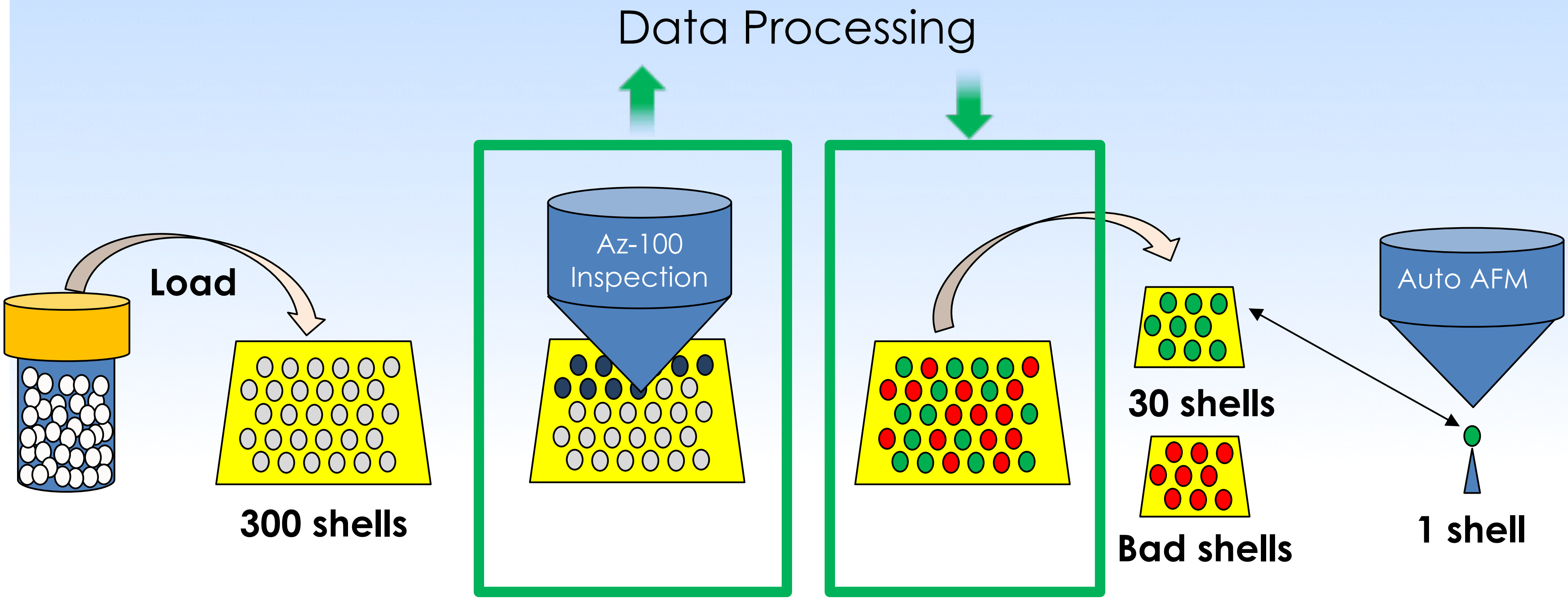
Increase in Shells' Value

Complete Mandrel Selection Process Has Been Automated





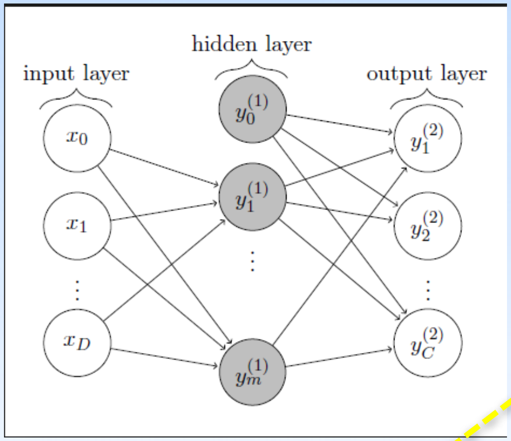
Automated Shell Classification Pass/Fail based on AZ-100 images using Deep Learning Algorithm



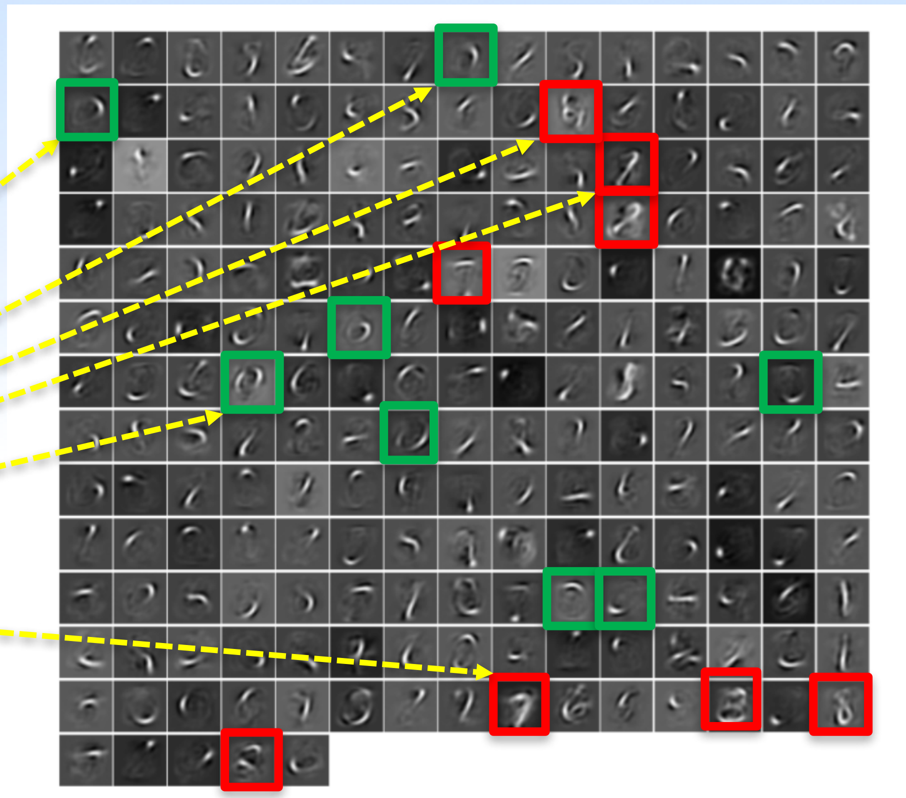
Deep Learning requires large data set

- 1000's of classified images are available from past production runs
- Algorithm looks at top and bottom image of shell and classifies as pass or fail by comparing it to historical data

Example: Recognizing MNIST Handwritten Digits using a Two-Layer Network



Input Layer

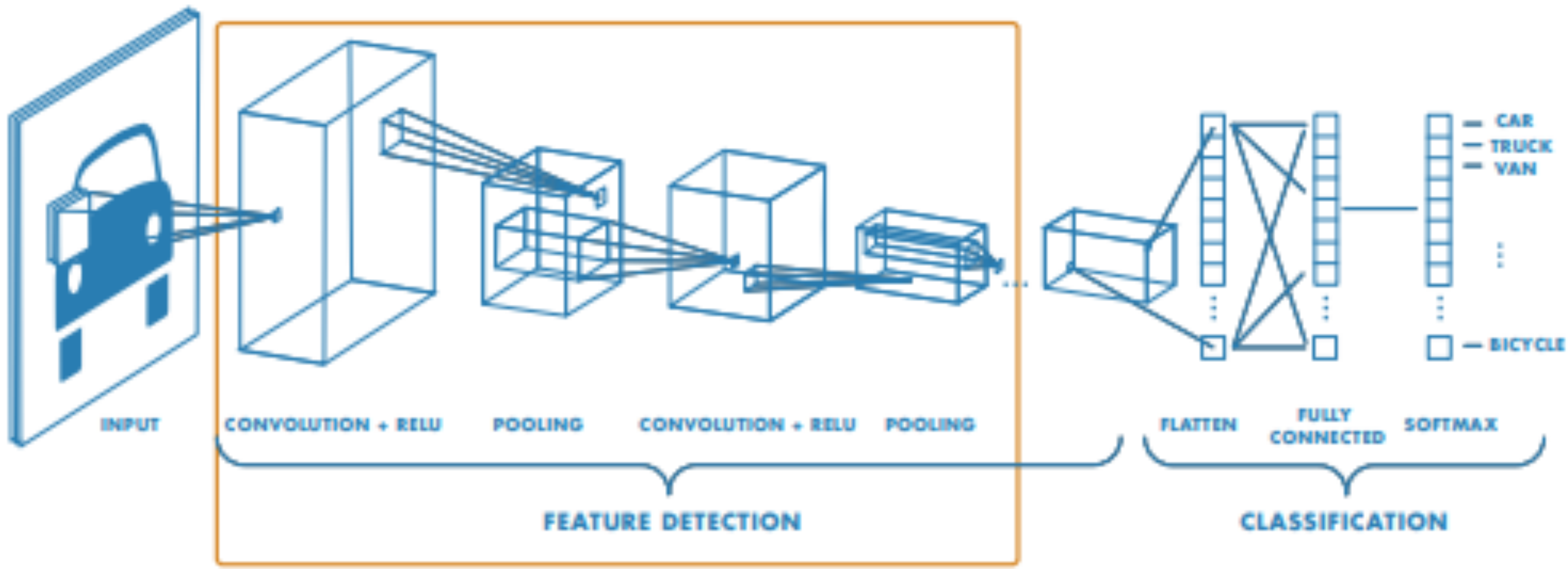


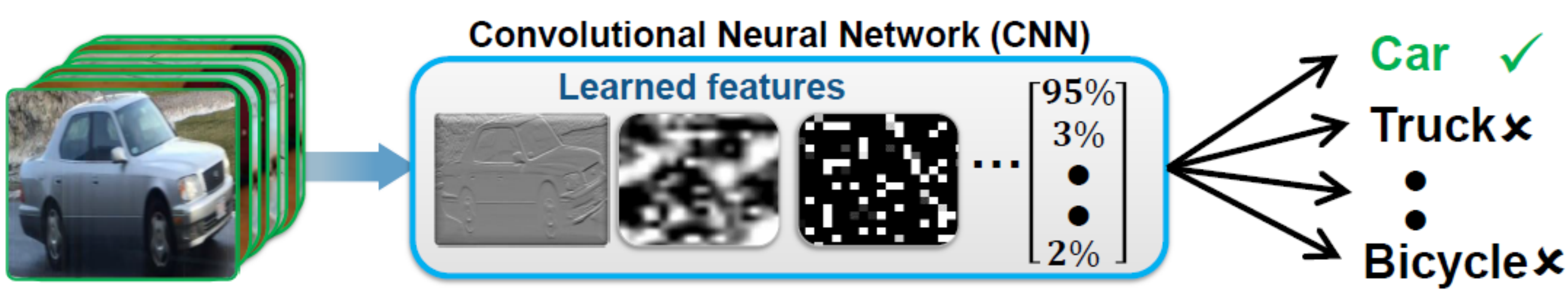
Hidden Layer

#	%
0	53%
1	2%
2	1%
3	4%
4	1%
5	7%
6	4%
7	1%
8	15%
9	12%

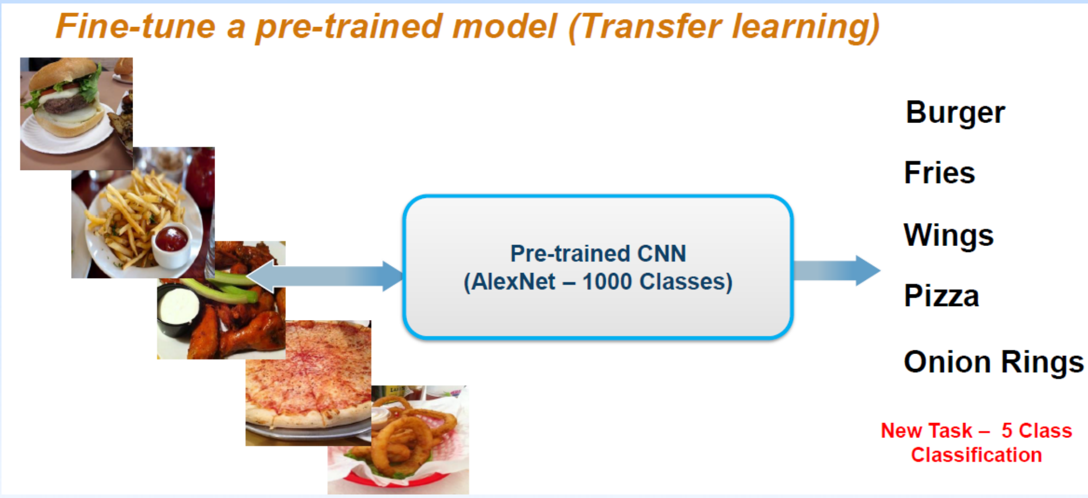
Output Layer

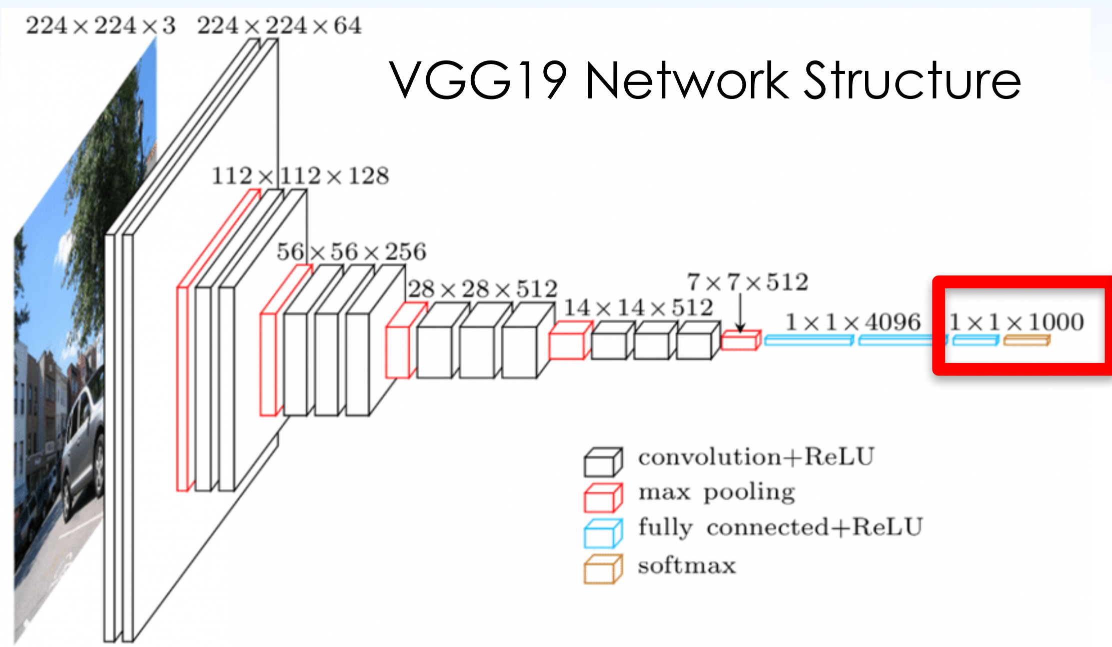
Convolutional Neural Networks add more and more Network Layers and use a "Sliding Filter"





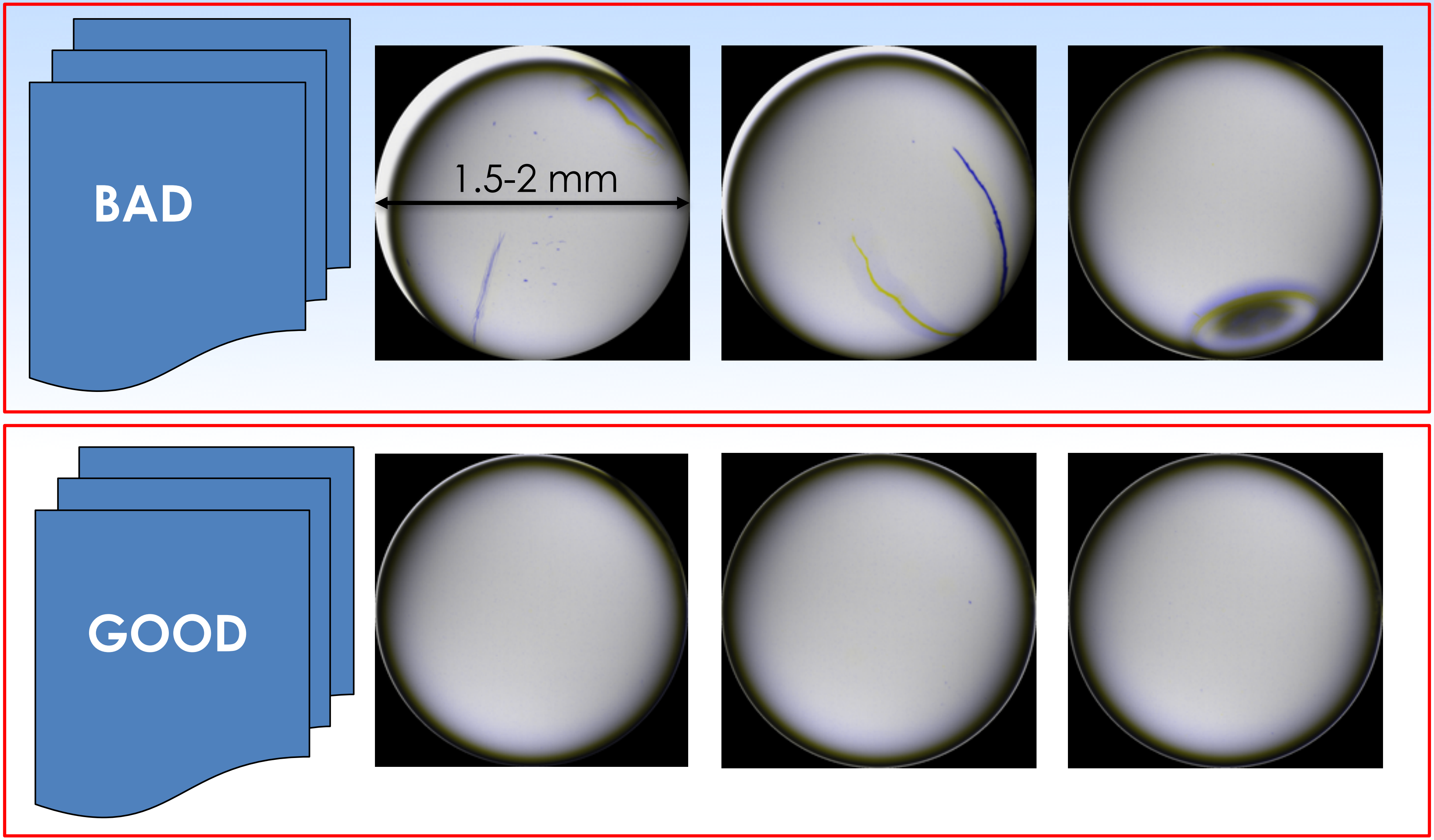
Transfer Learning Allows Application of Existing Architectures and their Trained Weights to new Problems



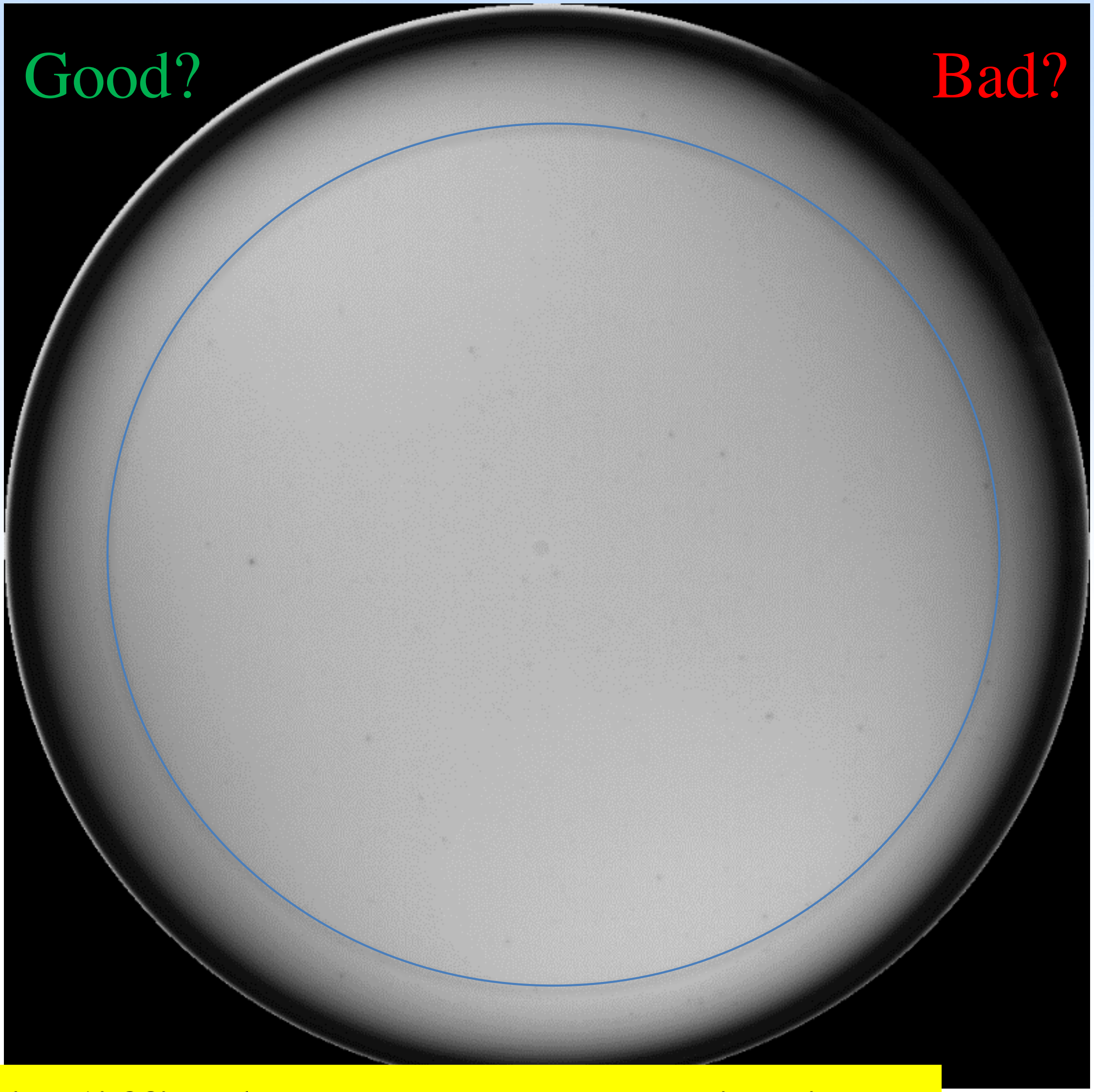


Modify these two layers and re-train on new problem data set

Machine Learning for Image Classification can Automate Microscope Image Inspection



Classification Suffers from Ambiguity of Data Set



Operator dependency makes it difficult to set success criterion

Reasonable results could be achieved using pre-trained networks on commercially available software packages

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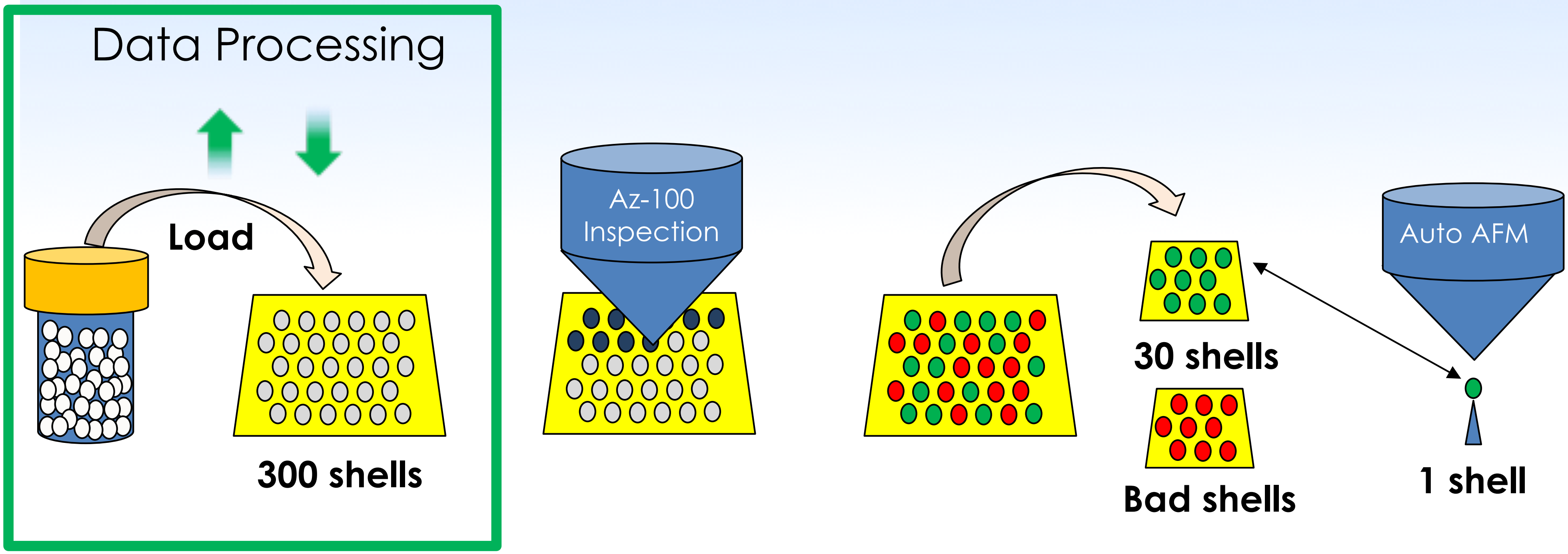
VGG19

- Only small modification needed in the last couple of layers to apply these networks to our problem
- Ran four network architectures to compare
- Used increasing size of input data (500, 1000, 2000 images) of past production data
- Test Data set of 206 images, 103 good ones 103 bad ones

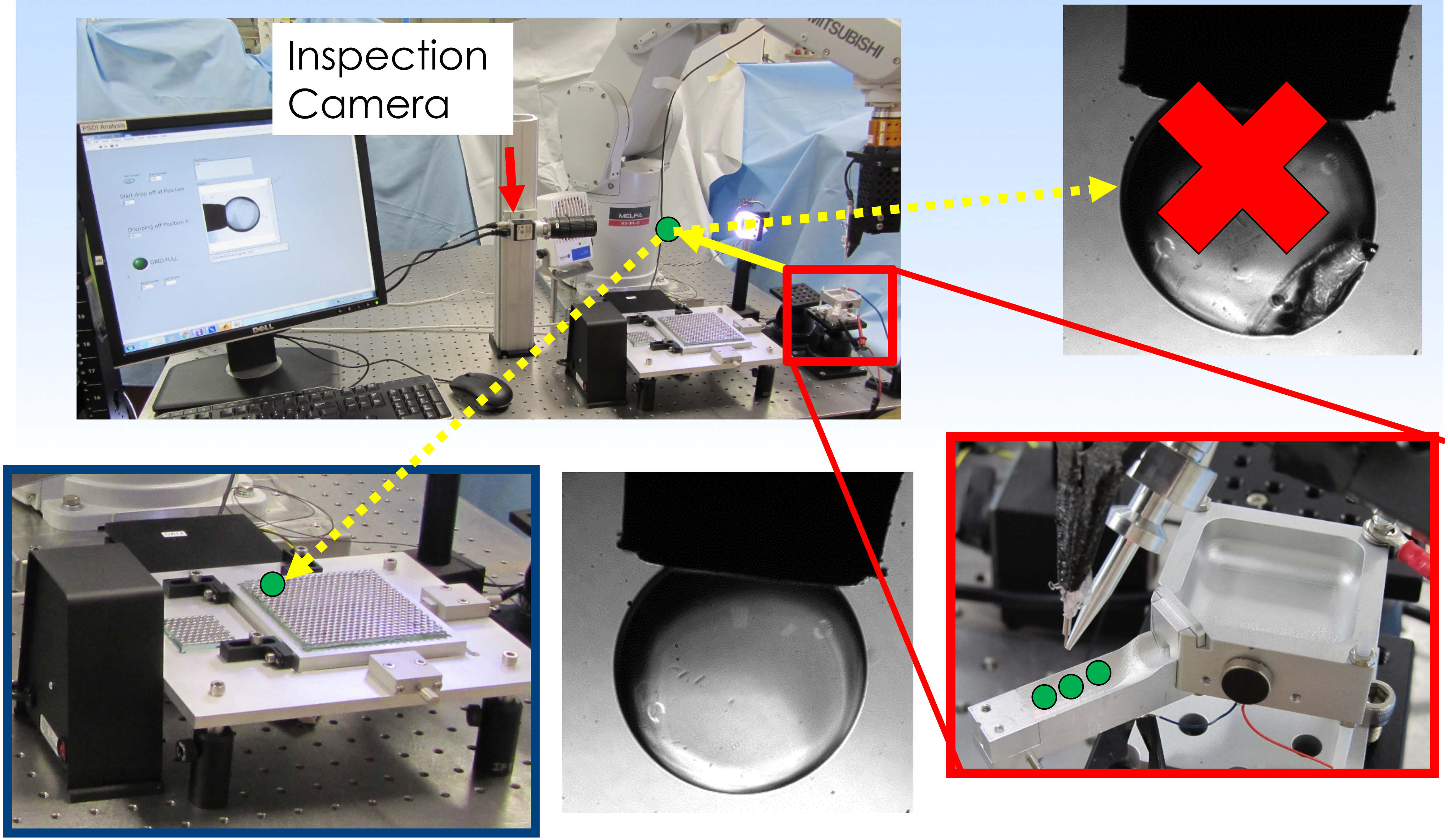
	TOTAL	% age accuracy	BAD	% age	GOOD	% - age
AlexNet	176	0.85	84	0.82	92	0.89
VGG16	179	0.87	86	0.83	93	0.90
GoogleNet	177	0.86	87	0.84	90	0.87
VGG19	177	0.86	76	0.74	99	0.96
Operator Reclassify	155	0.75	70	0.68	85	0.83

VGG19 recognizes good shells, but can’t find all the bad ones

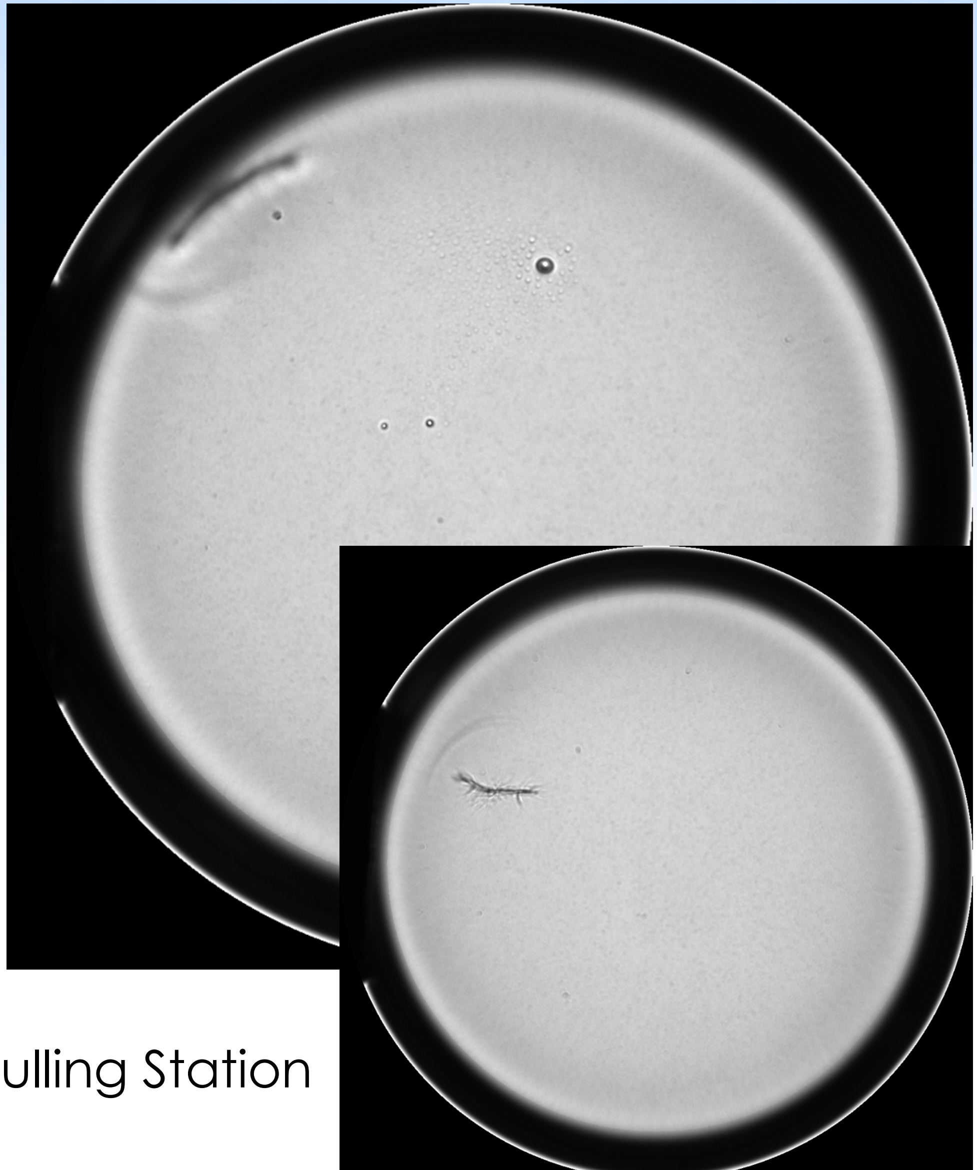
Complimentary inspection was implemented while loading shells into inspection tray



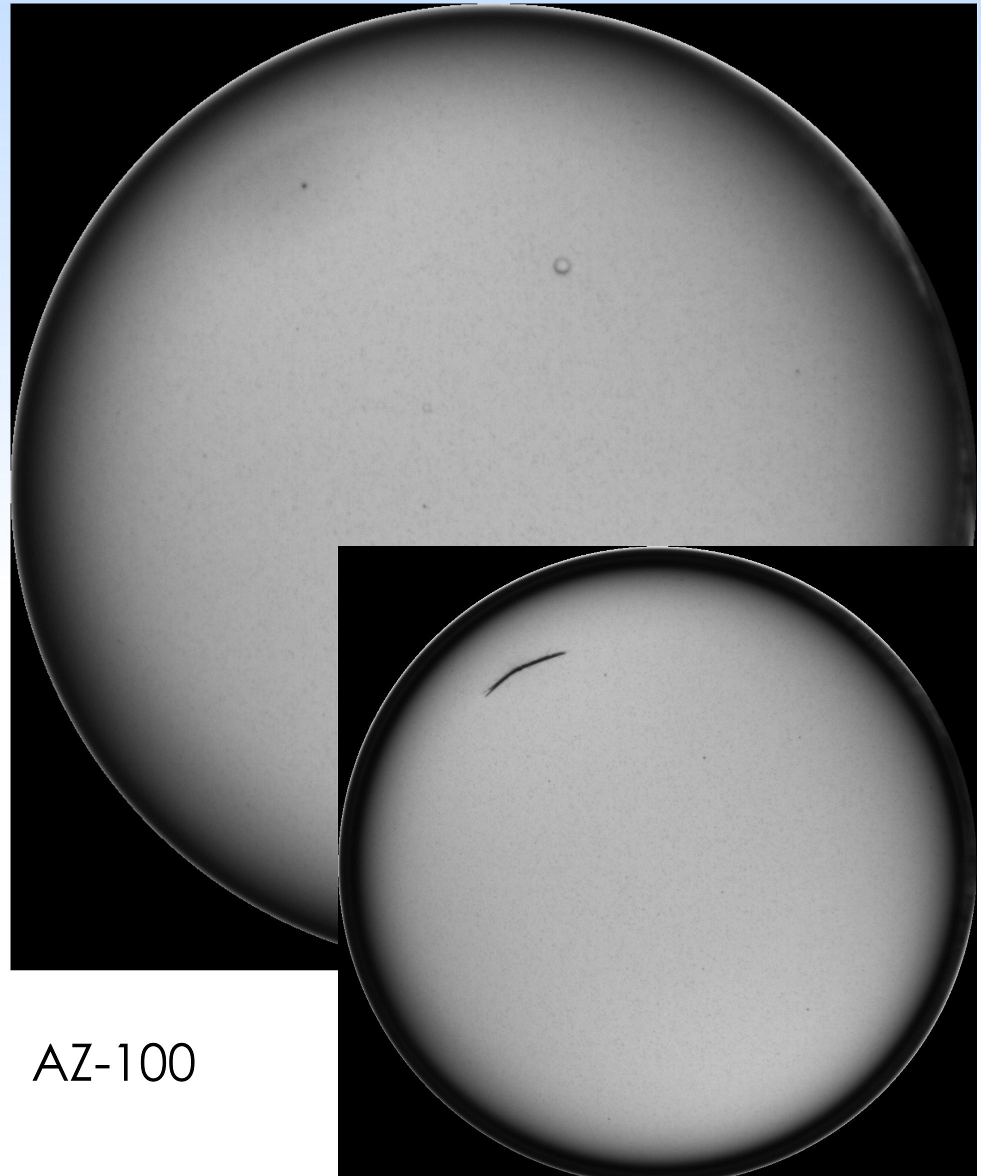
Concept: Using Machine Learning Algorithms to sort shells in pre-inspection step



Optical system on culling robot yields higher contrast images showing defects with higher clarity

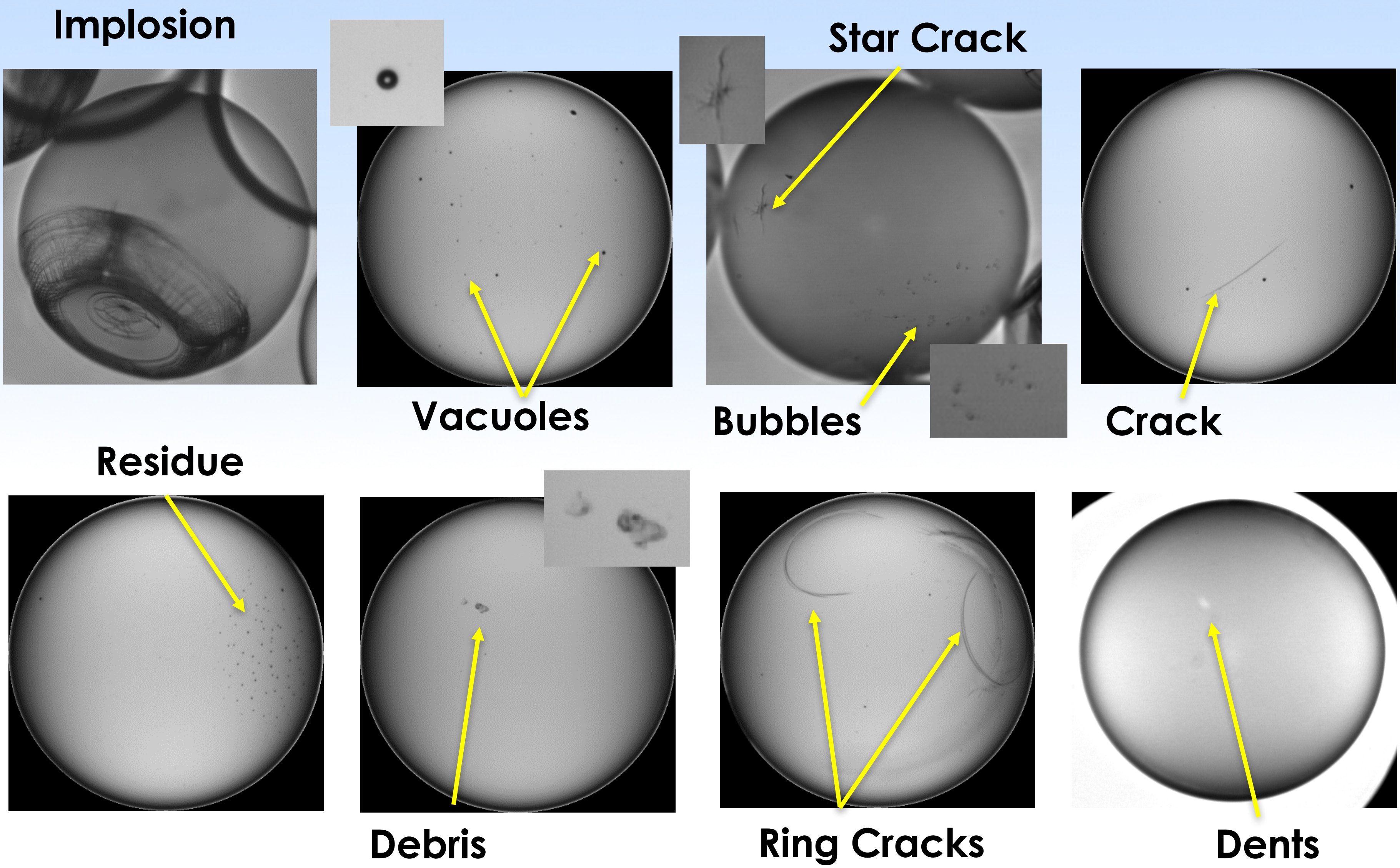


Culling Station



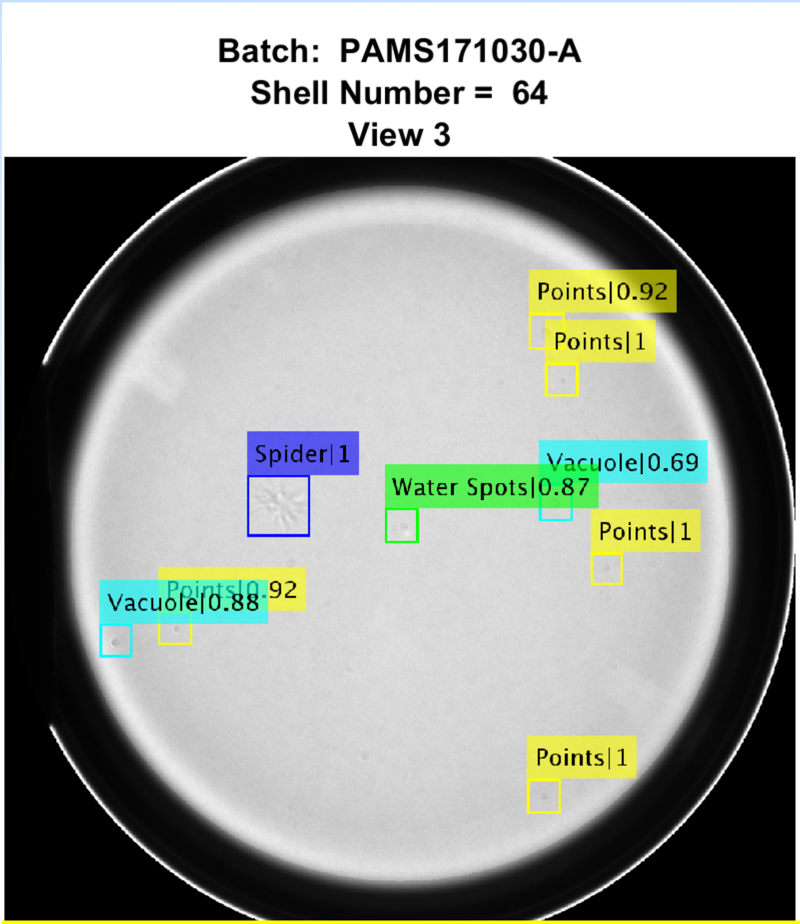
AZ-100

We looked at what kind of defect is on the shell to determine pass / fail



Courtesy of Wendy Sweet

For Culling Images: Find things that are interesting in an image and then find out what they are

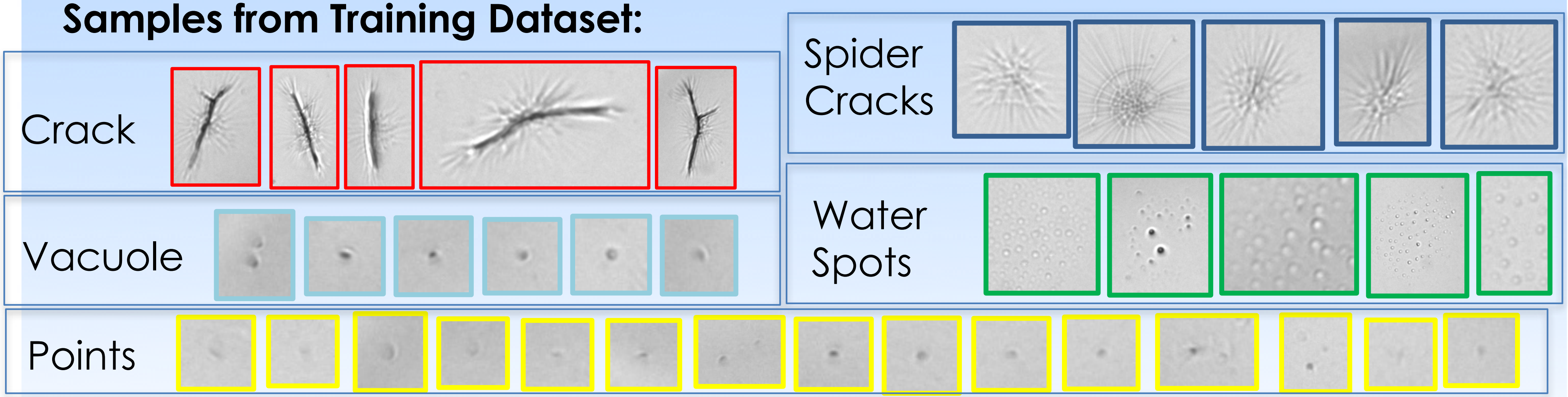


More common commercial application of this problem:
- Identify multiple objects in an image

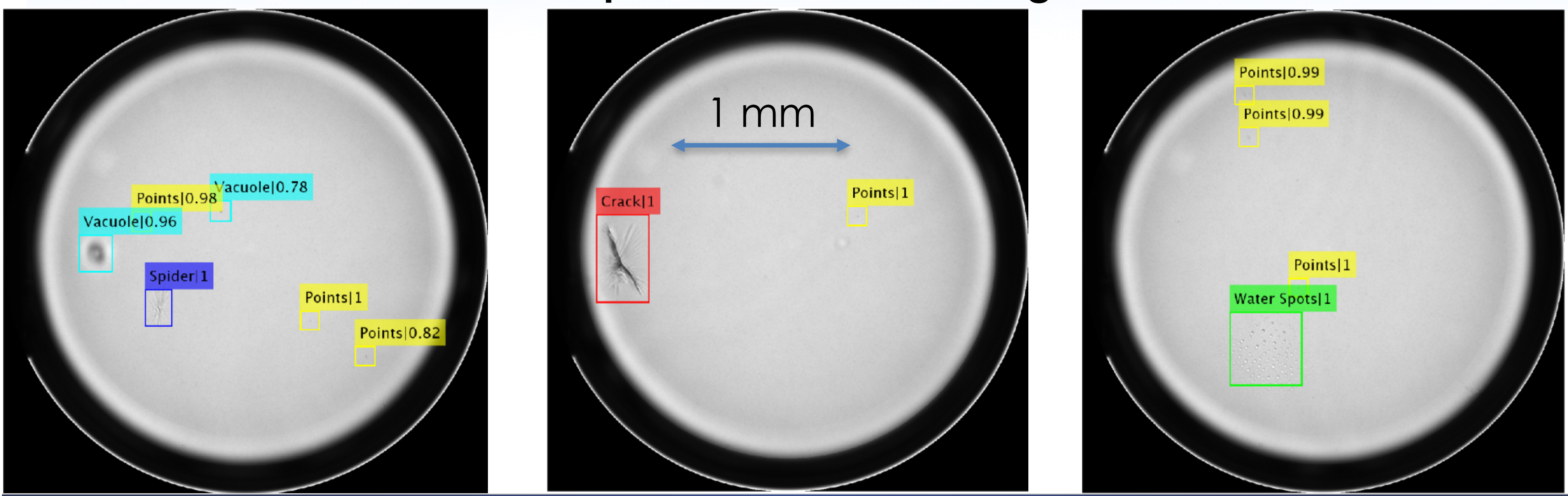
Process:
- Draw a box around an object of interest
- Query a different CNN to figure out what the object is

Defect recognition reaches >95% accuracy

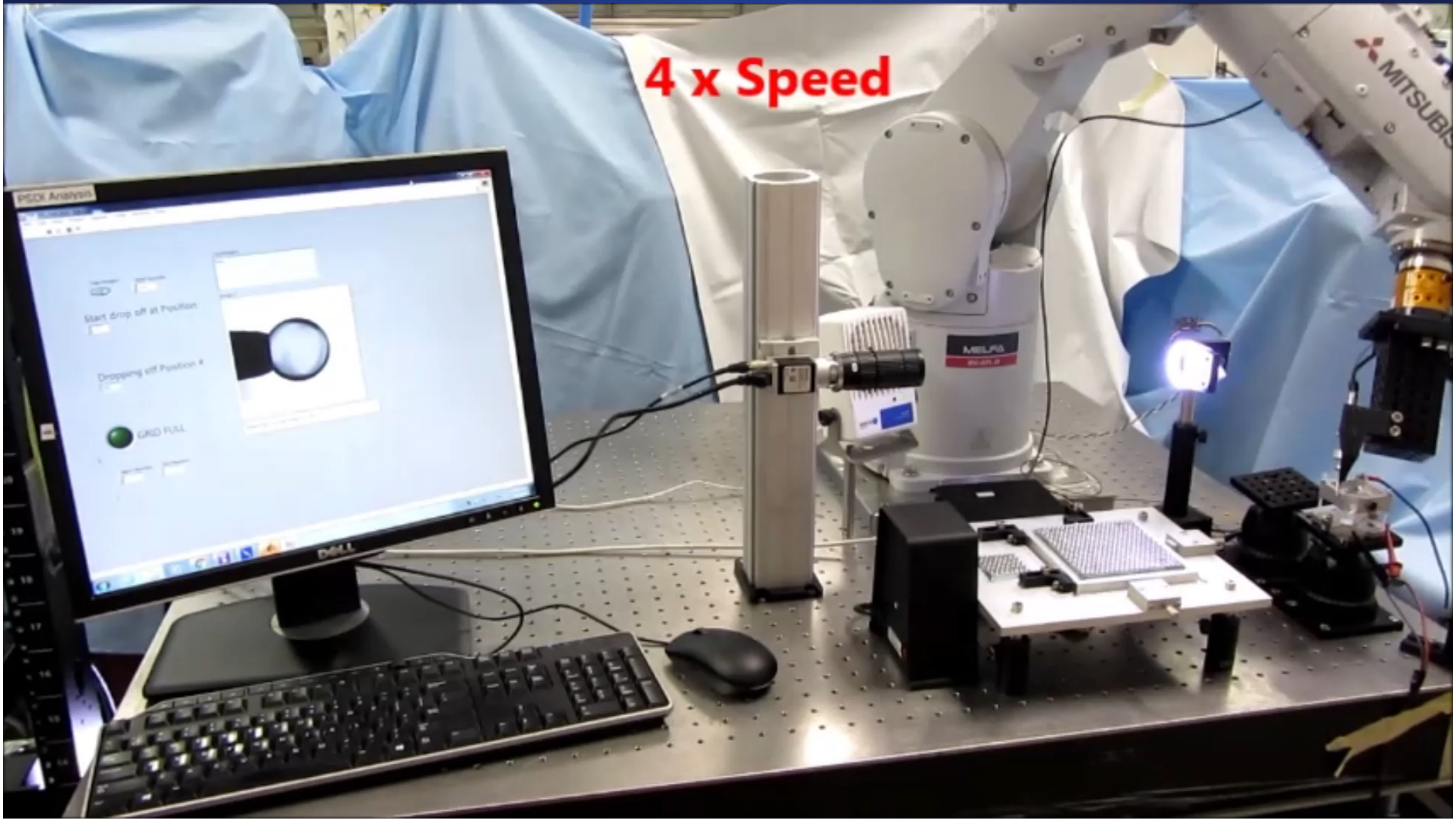
Samples from Training Dataset:



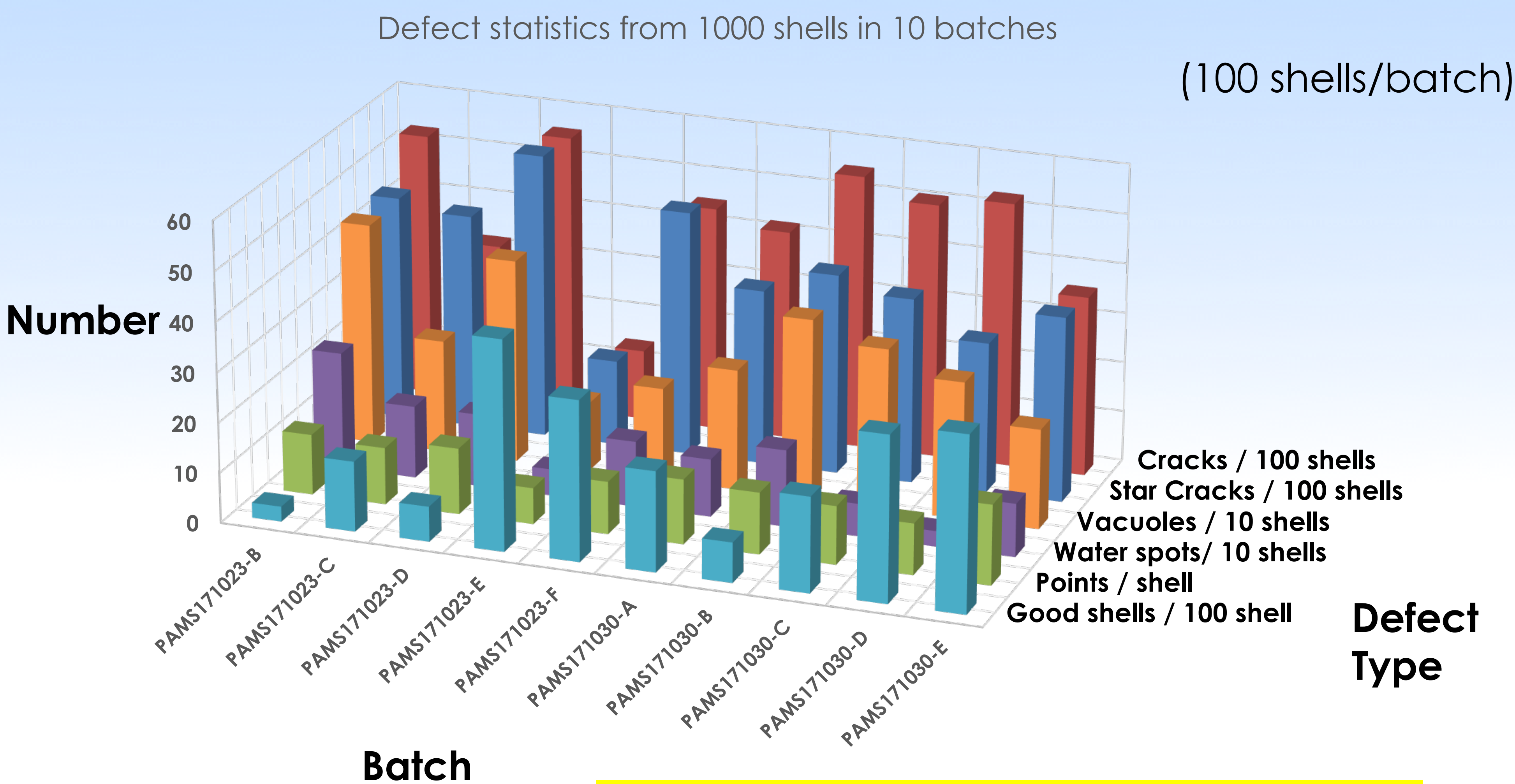
Example results from running the code



Defect Analysis in Action



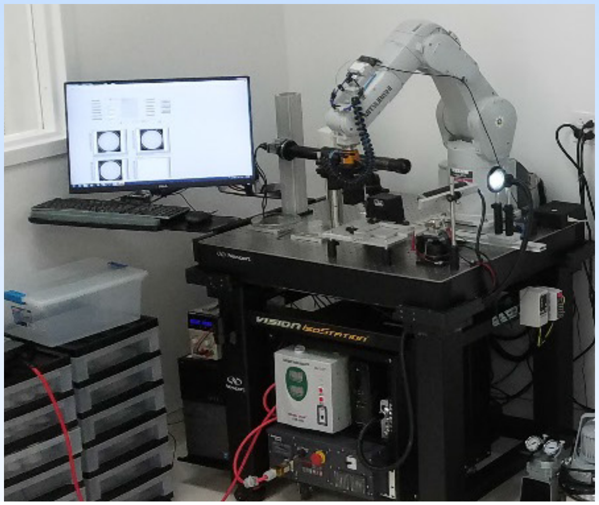
Defect type statistics will be used to improve shell production processes

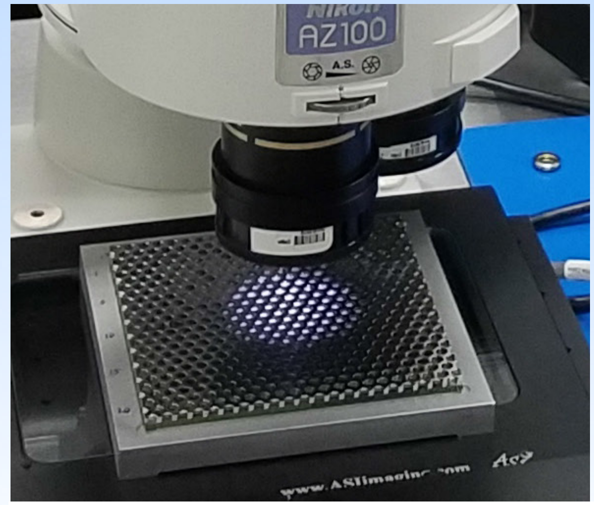


Getting this level of detailed statistics from a manual process is prohibitively expensive

Combining both Machine Learning-algorithms shows 91 % accuracy for good shells with a 10-20 % drop in yield*

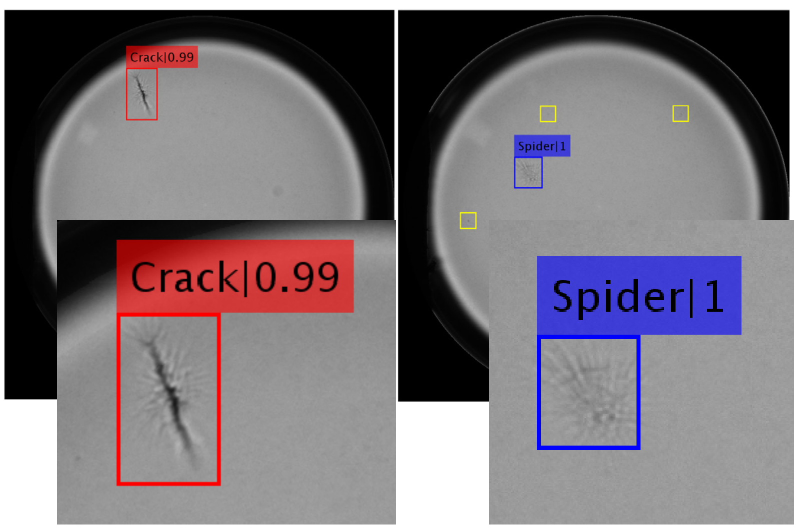
*Compared to manual process

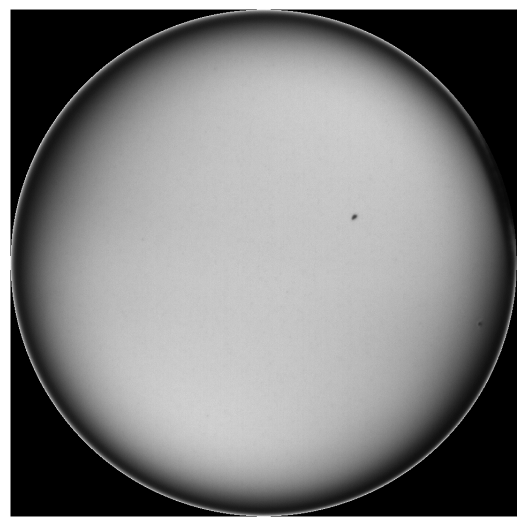


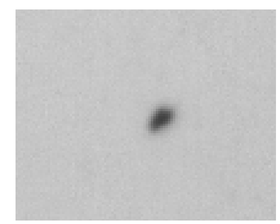


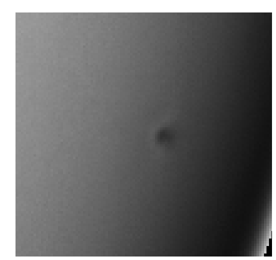
Load Trays + Pre-Inspect
Looking for individual defects

Secondary Inspection
Looking at entire surface area



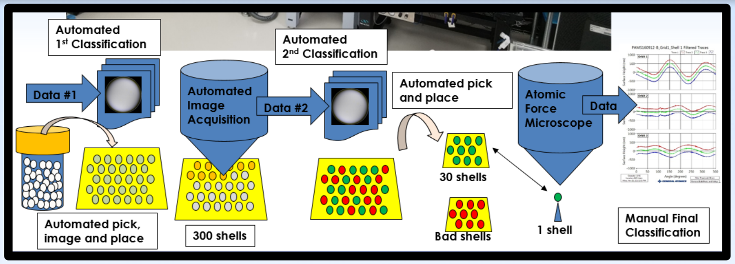




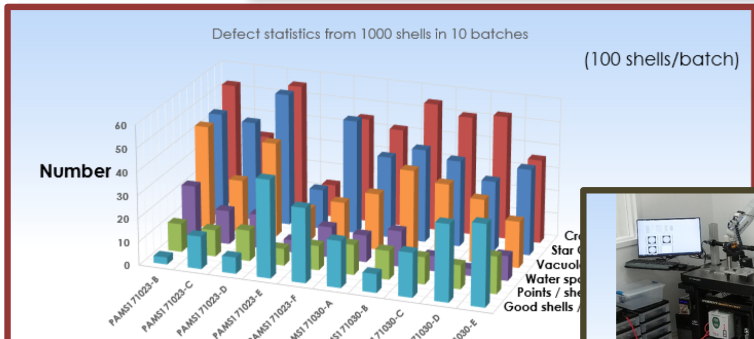


Summary: Applying Computer Vision, Machine Learning and Automation Fulfills its Promise for Capsule Selection

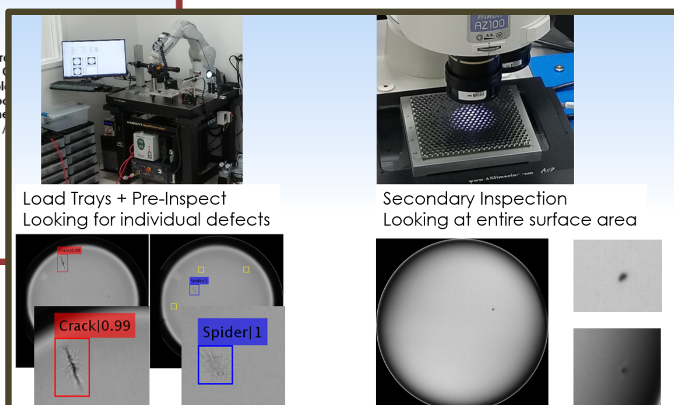
VGG19	177	0.86	76	0.74	99	0.96
Operator Reclassify	155	0.75	70	0.68	85	0.83



Reduce operator involvement from 8-12 hours / week to handling trays



For free!!!



Better shells

- Higher throughput
- Consistent results

Less human interaction

- Operator independent results
- Less labor hours

Provide statistics

- Quantitative feedback mechanism on batch quality

Increase downstream production yield

- Additional and complimentary inspection of shells