How to Use AI for Classifying Cell Types & Phenotypes in the Cloud: The Live/Dead Assay

Featuring Dr. Ilya Goldberg

Presented by

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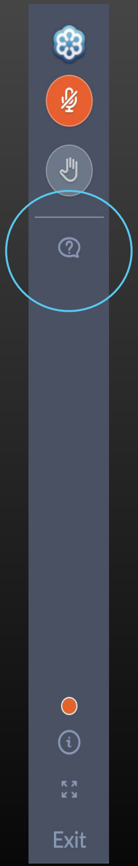
3. We will provide a recording of the webinar afterward



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- ➔ Visualize, analyze, annotate, and store over 250 types of image and data formats in one central repository (including individual files over a terabyte in size)

- ➔ Automate and scale unique research workflows through machine learning and AI (we can help build them or integrate our partners' existing analyses)

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- ➔ Visualize, analyze, annotate, and store over 250 types of image and data formats in one central repository (including individual files over a terabyte in size)

- ➔ Automate and scale unique research workflows through machine learning and AI (we can help build them or integrate our partners' existing analyses)

- ➔ Problem-solve complex image and data challenges (we have a team of experts who have been developing this infrastructure for over 15 years starting at UCSB in addition to 20+ years in bio-imaging informatics and AI that Dr. Goldberg brings to the table)

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The Speaker | Dr. Ilya Goldberg

Dr. Goldberg has a long career that lies at the intersection of biology, imaging, and AI.

- Co-founded a company that developed the first medical device to receive regulatory clearance for using an AI to predict malignancy in lung nodules in CT exams.
- The research group he led at the NIH National Institute on Aging developed machine learning software for image processing in biology and medicine.
- At MIT he co-founded the OME project, which is still used for imaging infrastructure in large image repositories.
- He has over 60 peer-reviewed scientific articles from time at Johns Hopkins, Harvard, MIT, and NIH in molecular and cell biology, pattern recognition, image informatics and the basic biology of aging.

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Agenda |

What You'll Learn

- Different kinds of AIs
- How to train an AI to perform a simple classification task
- How to evaluate AI performance
- What to look out for

Let’s start with an **audience poll**

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A series of webinars for experimental biologists

How to use AIs for imaging problems in an experimental setting

Not focusing on the details of how AIs work

- **Introduction to AI & classification**
  - Simple classification problems e.g. Live/dead assay
  - Multiclass problems
- **Quantitative problems**
  - Ordered class problems, regression, dose-response
- **Phenotypic similarity**
  - Clustering, dendrograms
- **Localization**
  - AI-based segmentation, heat-maps, etc.

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Two types of machine learning

Supervised: Training on known answers, controls

- Typical experimental setups are a natural fit
- Positive and negative controls
- Standard curves

Unsupervised: No known classes/groups

- Open-ended, Exploratory, Clustering, PCA
- Completely different AI technologies

Semi-supervised: Really just supervised, but bootstrapping from known classes to new classes/clusters

Two AI systems: Deep-learning and Feature-based

Deep Learning

Neural networks, "Perceptrons", the first AIs

1961 Bernard Widrow. Earliest learning rule for networks with multiple elements.

1971 Paul Werbos. Backpropagation, multilayer networks. Published in his doctoral dissertation, remained almost unknown until 1986!

2010 Dan Ciresan. Backpropagation on GPUs.

2011 "Superhuman" handwritten digit recognition

2012 Alex Krizhevsky ImageNet Large Scale Visual Recognition Challenge

Feature-based AIs

"Handcrafted features"

Feature extraction: Numerical representations of image content

Dimensionality reduction

Classification

2001 Boland and Murphy. Bank of feature algorithms + neural network. Superhuman subcellular localization.

2002 Murphy lab: PSLID

2008 Goldberg lab: WND-CHARM

2008 Carpenter lab: CellProfiler-Analyst

Two AI systems: Technology overview

Deep Learning

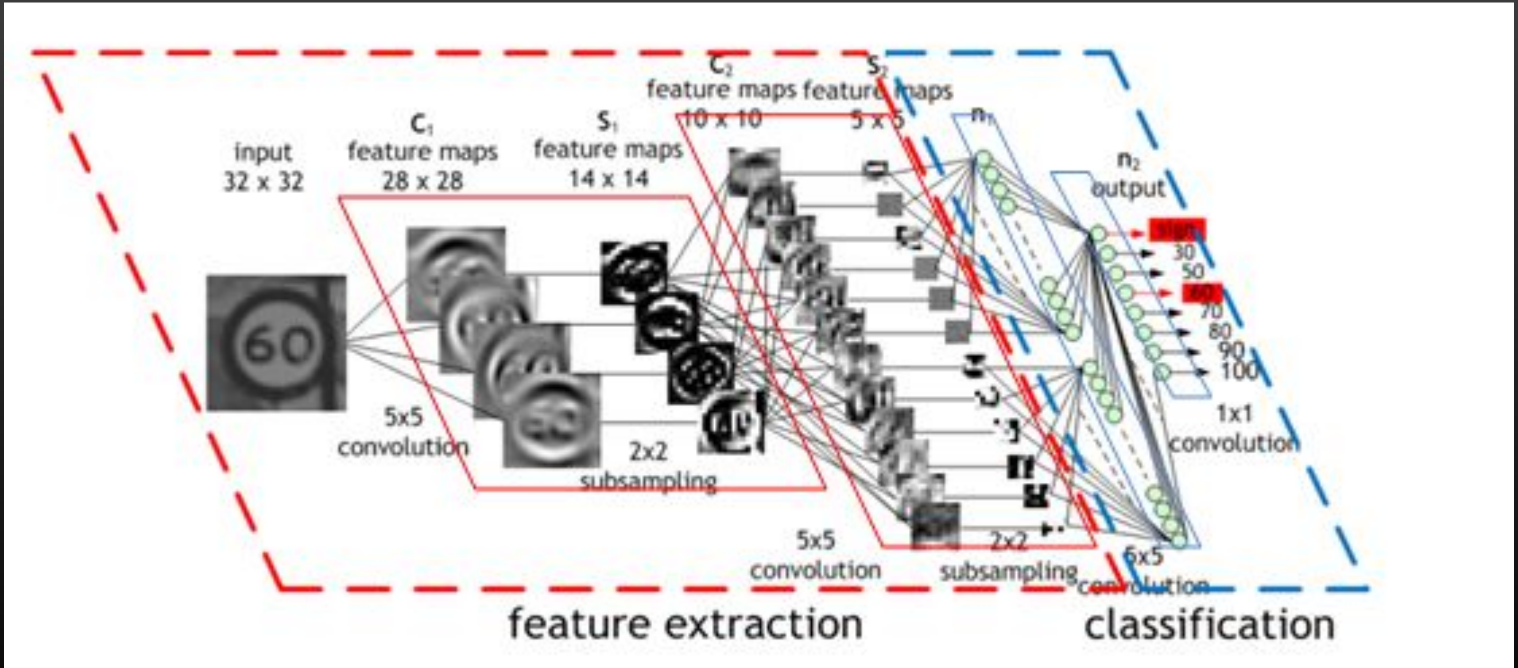

Image credit: Maurice Peemen
parse.ele.tue.nl/mpeemen

Two AI systems: Technology overview

Feature-based AIs

- **Feature Extraction & Normalization**
  - Statistics, texture descriptors, shape descriptors, etc.
- **Scoring, Weighting, & Reducing**
  - Pearson correlation, Fisher discriminant, mRMR, etc.
- **Classifying**
  - Random Forest, Support Vector Machines, Distance methods, etc.

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Two AI systems: Pros and Cons

Deep Learning

Pro: No feature algorithms, no feature reduction algorithms, no classifier algorithms.

Pro: Feature reduction occurs in-network.

Con: Classification prone to over-training (too many degrees of freedom). This requires a lot of data to overcome.

Con: Hard to train. Need GPU clusters.

Con (for now): Still requires manual model assembly and training. No "push-button" AI. Yet.

Pro: Large community of developers.

Feature-based AIs

Pro: Lots of 2D features. Decades of digital signal processing for 1D and 2D data.

Con: 3D+ requires "tricks" to extract features.

Con: Fast feature reduction uses filters - each feature evaluated one-at-a-time. Features are not evaluated in-classifier.

Pro: Modern classifiers are robust to overtraining (too many features). Can use less data.

Pro: Conventional CPUs, fewer resources.

Pro: Several models can be tried and parameters optimized automatically.

Con: May be considered "retro".

Hybrid and Ensemble AIs

Why not take the best parts of each?

- 2D Features + Deep Learning dimensionality reduction + Classifiers
- Multi-D CNNs + dimensionality reduction + Classifiers
- Multiple AIs "voting"

Next: Training AIs.

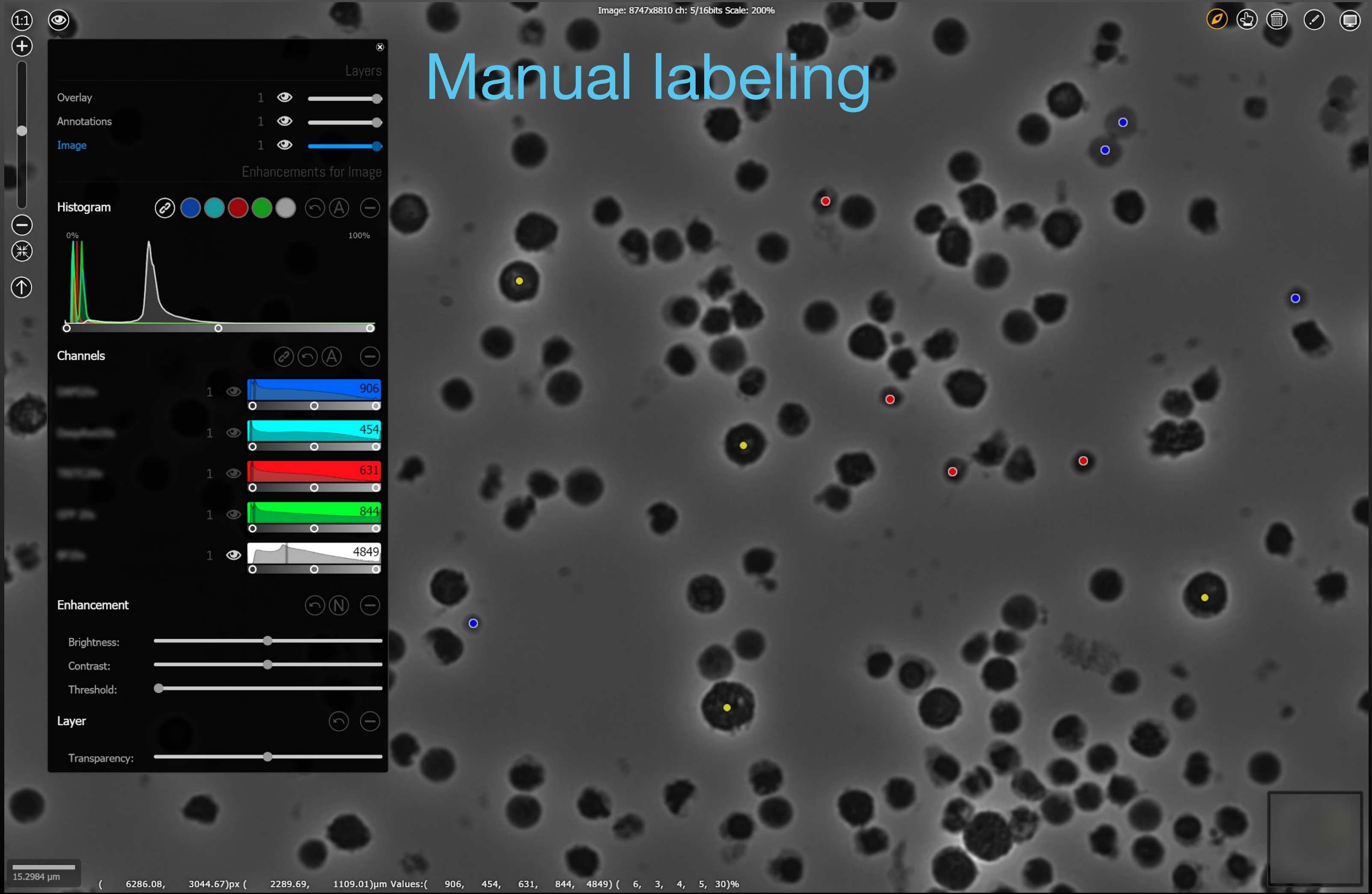
How to train an AI - binary classifiers

- **Live/Dead**
- **Positive/negative controls**
- **Treated/untreated**
- **Case/control: benign/malignant**

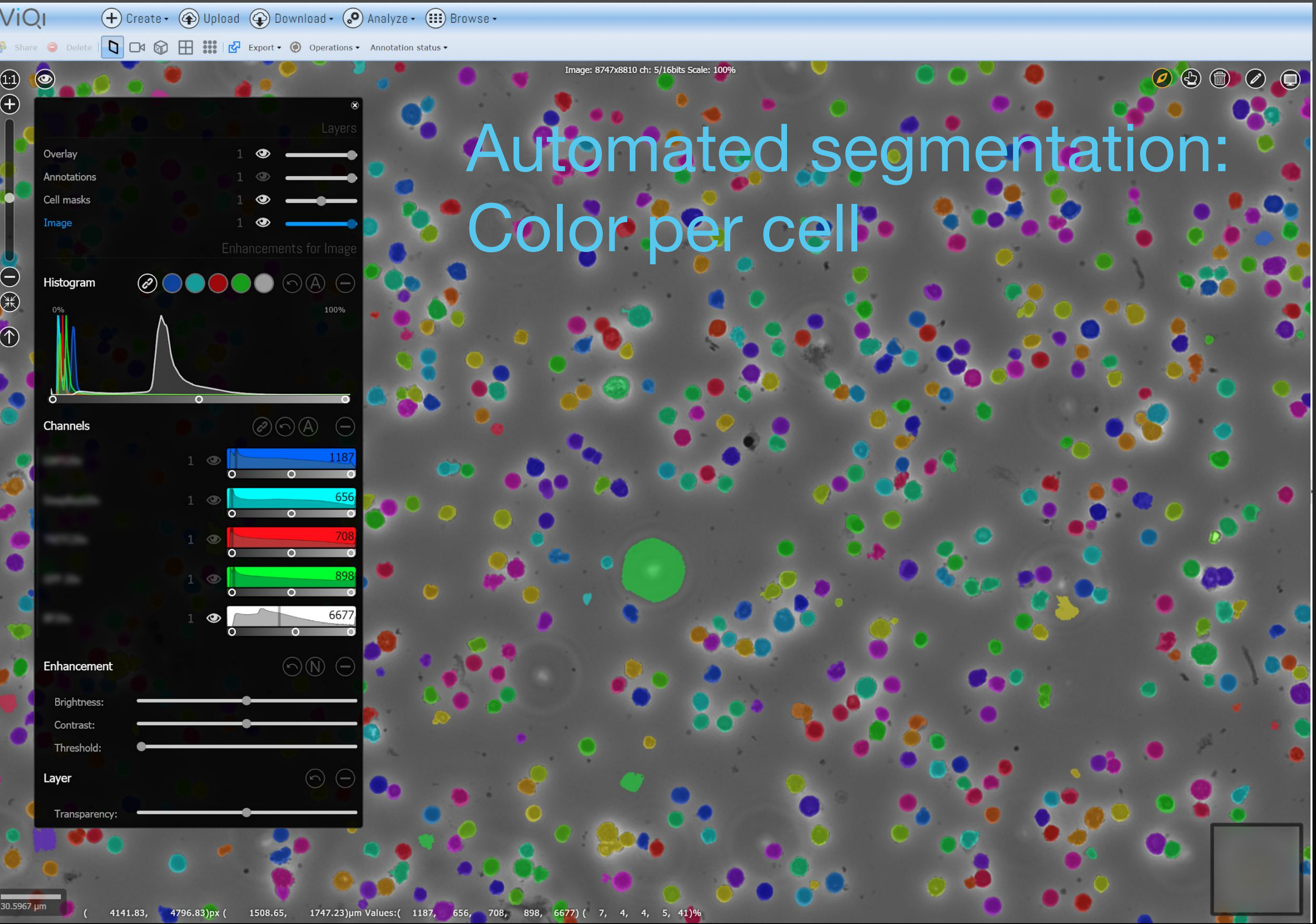
Tag areas of an image (e.g. cells) with labels

Tag whole images with class (e.g. treatment)

Manual labeling



Automated segmentation: Color per cell



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Feature table

ViQi | Create | Upload | Download | Analyze | Browse | Dmitry Fedorov | ?

Share | Delete | table: 14.nd2_00-DJgUx62xajMj5fZboVMVgK.45646437_classified.h5

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Metadata

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0		854...	26.63	97	35.31	2.7...	11.11	0.9...	0.2...	0.6...	1.5...	1	0.8...	13.85	8.9...	-1.55	367...	0.6...	408...	-1.74	1.0...	4.0...	0.4...	0.1...	0.7...
1		209...	41.42	145	43.80	3.3...	13.59	0.9...	0.7...	0.9...	1.2...	1	0.7...	13.90	13.36	-0.70	367...	0.8...	312...	-1.09	-0.81	3.7...	0.5...	0.2...	0.6...
2		246...	87.76	5607	569...	9.8...	84.49	0.4...	0.6...	0.7...	1.2...	-9	0.6...	97.77	91.56	1.3...	367...	0.6...	286...	-0.69	-1.52	3.8...	0.6...	0.3...	0.9...
3		786...	60.88	128	41.21	3.1...	12.77	0.9...	0.3...	0.7...	1.4...	1	0.7...	14.50	11.42	-0.03	367...	0.7...	340...	-1.23	-0.49	4.0...	0.4...	0.2...	0.7...
4		4545	68.49	415	73.70	5.6...	22.99	0.9...	0.5...	0.8...	1.1...	1	0.8...	24.56	21.53	-0.04	4524	0.7...	441...	0.4...	-1.32	5.6...	0.1...	0.1...	0.9...
5		654...	71.43	106	43.01	2.4...	11.62	0.8...	0.3...	0.7...	1.2...	1	0.6...	13.85	10.43	-0.96	367...	0.6...	276...	-0.54	-1.71	3.4...	0.5...	0.2...	0.7...
6		456...	74.77	220	55.36	3.9...	16.74	0.9...	0.3...	0.7...	1.1...	1	0.6...	19.88	14.39	-1.05	367...	0.6...	503...	-0.06	-1.49	4.7...	0.3...	0.2...	0.9...
7		287...	84.94	123	40.04	3.0...	12.51	0.9...	0.4...	0.8...	1.1...	1	0.6...	13.80	11.46	-1.06	367...	0.7...	314...	-0.75	-1.44	3.7...	0.5...	0.2...	0.6...
8		450...	94.63	298	70.18	4.2...	19.48	0.8...	0.4...	0.7...	1.1...	1	0.5...	21.93	18.21	1.4...	367...	0.7...	396...	0.2...	-1.52	4.5...	0.3...	0.3...	0.9...
9		468...	94.16	257	56.53	4.5...	18.09	0.9...	0.6...	0.9...	1.1...	1	0.7...	18.66	17.63	1.2...	4524	0.8...	571...	-0.16	-1.23	5.1...	0.2...	0.1...	0.9...
10		4371	92.73	184	47.80	3.8...	15.31	0.9...	0.3...	0.7...	1.1...	1	0.8...	17.50	13.40	1.5...	4524	0.7...	697...	-0.79	-0.46	5.0...	0.1...	0.13	0.8...
11		666...	143...	5448	679...	8.0...	83.29	0.3...	0.6...	0.7...	1.2...	-11	0.5...	97.04	92.55	-0.09	367...	0.6...	263...	-0.40	-1.84	3.5...	0.6...	0.3...	0.9...
12		804...	95.13	139	42.38	3.2...	13.30	0.9...	0.2...	0.7...	1.4...	1	0.7...	15.80	11.27	-1.25	367...	0.6...	349...	-1.30	-0.32	4.0...	0.4...	0.2...	0.7...
13		405...	102...	503	85.84	5.8...	25.31	0.9...	0.2...	0.6...	1.1...	1	0.7...	30.45	21.68	1.4...	4524	0.6...	327...	0.6...	-1.01	5.2...	0.3...	0.2...	0.9...
14		446...	106...	685	96.91	7.0...	29.53	0.9...	0.5...	0.8...	1.0...	1	0.7...	31.35	27.97	-1.54	622...	0.7...	110...	-1.23	-0.46	5.1...	0.4...	0.2...	0.8...
15		478...	100...	105	36.14	2.9...	11.56	0.9...	0.4...	0.8...	1.1...	1	0.7...	12.80	10.54	0.5...	367...	0.7...	103...	-1.46	0.1...	4.4...	0.3...	0.1...	0.6...
16		401...	113...	298	61.70	4.8...	19.48	0.9...	0.5...	0.8...	1.1...	1	0.7...	20.77	18.27	0.0...	4524	0.7...	548...	-0.67	-1.04	5.3...	0.2...	0.1...	0.9...
17		448...	114...	292	71.36	4.0...	19.28	0.8...	0.4...	0.7...	1.0...	1	0.6...	21.56	18.21	0.5...	4524	0.7...	461...	-0.16	-1.38	5.0...	0.2...	0.2...	0.9...
18		419...	121...	455	82.98	5.4...	24.07	0.9...	0.6...	0.9...	1.0...	1	0.7...	25.26	23.27	-0.29	622...	0.8...	233...	0.1...	-1.34	5.3...	0.3...	0.2...	0.9...
19		440...	121...	277	60.04	4.6...	18.78	0.9...	0.6...	0.9...	1.0...	1	0.8...	19.49	18.38	-1.36	622...	0.8...	352...	-0.36	-1.18	5.3...	0.2...	0.1...	0.8...
20		463...	127...	389	71.94	5.4...	22.26	0.9...	0.6...	0.9...	1.0...	1	0.7...	23.04	21.65	0.9...	622...	0.8...	302...	0.0...	-1.23	5.5...	0.2...	0.1...	0.9...
21		398...	126...	279	59.70	4.6...	18.85	0.9...	0.6...	0.9...	1.0...	1	0.7...	19.53	18.21	-0.62	4524	0.8...	524...	-0.20	-1.52	5.2...	0.2...	0.1...	0.9...
22		409...	131...	387	73.25	5.2...	22.20	0.9...	0.5...	0.8...	1.0...	1	0.6...	23.97	20.77	-0.44	4524	0.7...	395...	0.3...	-1.37	5.1...	0.3...	0.2...	0.9...
23		403...	128...	339	73.36	4.6...	20.78	0.8...	0.3...	0.6...	1.0...	1	0.7...	25.25	18.06	1.3...	4524	0.6...	478...	0.4...	-1.30	4.9...	0.3...	0.2...	0.9...
24		444...	130...	263	66.77	3.9...	18.30	0.8...	0.2...	0.6...	1.0...	1	0.6...	22.15	15.81	-0.42	622...	0.6...	334...	-0.15	-1.74	4.6...	0.3...	0.3...	0.8...
25		437...	130...	263	60.53	4.3...	18.30	0.9...	0.5...	0.8...	1.0...	1	0.6...	19.49	17.53	-0.41	4524	0.7...	397...	-0.37	-1.47	4.8...	0.3...	0.2...	0.8...
26		455...	132...	224	58.28	3.8...	16.89	0.9...	0.3...	0.7...	1.0...	1	0.7...	19.48	15.14	-0.26	627...	0.6...	312...	-0.45	-1.32	5.1...	0.2...	0.1...	0.8...
27		406...	137...	488	82.43	5.9...	24.93	0.9...	0.6...	0.9...	1.0...	1	0.7...	25.85	24.31	-0.98	622...	0.8...	343...	-0.23	-1.29	5.7...	0.2...	0.1...	0.9...
28		421...	139...	592	89.25	6.6...	27.45	0.9...	0.4...	0.8...	1.0...	1	0.7...	29.71	25.46	-0.27	1161	0.7...	323...	-0.36	-1.42	5.7...	0.2...	0.1...	0.9...
29		285...	172...	5787	487...	11.86	85.84	0.5...	0.8...	0.7...	1.1...	-4	0.6...	96.19	94.73	1.4...	367...	0.7...	340...	-0.78	-1.38	4.6...	0.5...	0.2...	0.9...
30		457...	134...	250	58.63	4.2...	17.84	0.9...	0.4...	0.7...	1.0...	1	0.7...	19.97	16.23	0.2...	1161	0.7...	387...	-0.50	-1.22	5.2...	0.2...	0.1...	0.8...
31		294...	134...	209	53.11	3.9...	16.31	0.9...	0.4...	0.8...	1.1...	1	0.69	17.89	15.17	1.3...	367...	0.7...	341...	-0.81	-1.35	3.7...	0.5...	0.2...	0.7...
32		446...	138...	284	62.53	4.5...	19.02	0.9...	0.4...	0.8...	1.0...	1	0.7...	20.71	17.69	0.3...	627...	0.7...	498...	-0.16	-1.47	5.1...	0.2...	0.2...	0.9...
33		435...	140...	401	76.77	5.2...	22.60	0.9...	0.5...	0.8...	1.0...	1	0.7...	24.27	21.22	0.2...	1161	0.7...	419...	-0.21	-1.44	5.3...	0.2...	0.2...	0.9...
34		411...	138...	302	65.11	4.6...	19.61	0.9...	0.5...	0.8...	1.0...	1	0.7...	20.92	18.65	-1.03	4524	0.7...	373...	0.7...	-0.87	5.1...	0.2...	0.1...	0.9...
35		617...	141...	280	66.15	4.2...	18.88	0.8...	0.4...	0.8...	1.1...	1	0.6...	21.08	17.64	-0.03	367...	0.7...	292...	-0.43	-1.81	3.8...	0.5...	0.3...	0.8...
36		470...	143...	417	75.36	5.5...	23.04	0.9...	0.5...	0.8...	1.0...	1	0.7...	24.84	21.55	-0.13	1161	0.7...	363...	-0.05	-1.40	5.5...	0.2...	0.1...	0.9...
37		402...	145...	380	70.77	5.3...	22.00	0.9...	0.6...	0.9...	1.0...	1	0.7...	22.99	21.12	-0.02	4524	0.8...	395...	-0.49	-1.40	5.3...	0.2...	0.2...	0.9...
38		423...	144...	306	63.46	4.8...	19.74	0.9...	0.4...	0.8...	1.0...	1	0.8...	21.80	17.94	-0.06	4524	0.7...	464...	-0.75	-0.84	5.4...	0.2...	0.1...	0.8...
39		440...	142...	153	45.21	3.3...	13.96	0.9...	0.2...	0.6...	1.0...	1	0.7...	16.72	11.76	0.3...	367...	0.6...	701...	-0.21	-1.29	4.8...	0.2...	0.2...	0.8...
40		104...	155...	1004	175...	5.7...	35.75	0.6...	0.5...	0.8...	1.4...	0	0.6...	39.12	35.21	-0.22	367...	0.6...	271...	-0.69	-1.52	3.4...	0.6...	0.3...	0.8...
41		426...	143...	203	55.87	3.6...	16.08	0.9...	0.3...	0.7...	1.0...	1	0.7...	18.57	14.34	1.4...	4524	0.6...	653...	-0.17	-1.27	5.0...	0.2...	0.1...	0.8...
42		467...	147...	426	74.77	5.6...	23.29	0.9...	0.6...	0.9...	1.0...	1	0.7...	24.25	22.43	-0.42	1161	0.8...	225...	-0.40	-1.16	5.5...	0.2...	0.1...	0.9...
43		481...	148...	509	82.18	6.1...	25.46	0.9...	0.6...	0.9...	1.0...	1	0.7...	26.31	24.68	-0.84	1161	0.8...	382...	0.1...	-1.26	5.7...	0.2...	0.1...	0.9...
44		465...	145...	221	52.87	4.1...	16.77	0.9...	0.6...	0.9...	1.0...	1	0.7...	17.46	16.14	-1.43	4524	0.8...	551...	-0.93	-0.77	5.1...	0.2...	0.1...	0.8...
45		474...	150...	446	76.77	5.8...	23.83	0.9...	0.6...	0.9...	1.0...	1	0.7...	24.45	23.25	0.2...	1161	0.8...	306...	-0.27	-1.10	5.6...	0.2...	0.1...	0.9...
46		449...	150...	347	69.36	5.0...	21.02	0.9...	0.4...	0.8...	1.0...	1	0.7...	23.13	19.38	1.2...	622...	0.7...	491...	-0.56	-1.07	5.5...	0.2...	0.1...	0.9...
47		389...	151...	321	67.36	4.7...	20.22	0.9...	0.5...	0.8...	1.0...	1	0.6...	21.50	19.33	1.5...	4524	0.7...	555...	0.0...	-1.34	5.0...	0.2...	0.2...	0.9...
48		393...	153...	406	78.56	5.1...	22.74	0.9...	0.7...	0.9...	1.0...	1	0.7...	23.32	22.38	0.6...	4524	0.8...	383...	-0.25	-1.41	5.5...	0.2...	0.2...	0.9...
49		415...	154...	422	75.01	5.6...	23.18	0.9...	0.4...	0.8...	1.0...	1	0.7...	25.19	21.34	0.8...	4524	0.7...	356...	-0.12	-1.45	5.5...	0.2...	0.1...	0.9...
50		410...	159...	365	72.53	5.0...	21.56	0.9...	0.7...	0.9...	1.0...	1	0.7...	22.23	21.39	1.2...	622...	0.8...	208...	-0.43	-1.19	5.3...	0.2...	0.1...	0.9...

object	ch1.in	ch2.m	ch2.sk	ch2.ku	ch2.er	ch2.hc	ch2.er	ch2.cc	ch2.in	ch3.m	ch3.sk	ch3.ku	ch3.er	ch3.hc	ch3.er	ch3.cc	ch3.in	ch4.m	ch4.sk	ch4.ku	ch4.er	ch4.hc	ch4.er
0	883...	326...	-1.75	1.0...	2.8...	0.6...	0.2...	0.7...	914...	372...	-1.75	1.0...	4.0...	0.4...	0.1...	0.7...	895...	445...	-1.75	1.0...	4.1...	0.4...	0.1...
1	111...	292...	-1.09	-0.81	3.1...	0.5...	0.2...	0.6...	113...	299...	-1.09	-0.81	3.3...	0.5...	0.2...	0.6...	110...	348...	-1.09	-0.81	3.9...	0.4...	0.2...
2	336...	261...	-0.69	-1.52	2.9...	0.6...	0.3...	0.9...	345...	272...	-0.69	-1.52	3.5...	0.6...	0.3...	0.9...	340...	309...	-0.69	-1.52	3.8...	0.5...	0.3...
3	862...	300...	-1.23	-0.49	3.1...	0.5...	0.2...	0.7...	893...	319...	-1.23	-0.49	3.7...	0.5...	0.2...	0.7...	871...	383...	-1.22	-0.49	4.4...	0.3...	0.1...
4	117...	386...	-1.69	0.8...	4.6...	0.4...	0.1...	0.7...	466...	766...	-0.85	-0.30	5.7...	0.2...	0.1...	0.8...	169...	748...	0.0...	-0.82	5.6...	0.2...	0.1...
5	127...	257...	-0.54	-1.71	3.2...	0.5...	0.3...	0.7...	127...	258...	-0.54	-1.71	3.1...	0.6...	0.3...	0.7...	127...	311...	-0.54	-1.71	3.6...	0.5...	0.2...
6	220...	307...	-0.61	-1.62	4.0...	0.5...	0.2...	0.7...	794...	508...	-0.60	-1.62	4.4...	0.4...	0.2...	0.8...	729...	188...	0.0...	-1.29	4.7...	0.3...	0.2...
7	111...	268...	-0.75	-1.44	3.2...	0.6...	0.2...	0.6...	113...	288...	-0.75	-1.44	3.4...	0.5...	0.2...	0.6...	112...	326...	-0.75	-1.44	3.7...	0.5...	0.2...
8	160...	304...	-0.39	-1.84	4.0...	0.5...	0.3...	0.8...	579...	532...	-0.37	-1.84	4.4...	0.5...	0.3...	0.8...	533...	272...	-0.14	-1.66	4.5...	0.4...	0.3...
9	141...	399...	-1.15	-0.66	4.7...	0.4...	0.2...	0.7...	479...	968...	-0.79	-0.94	5.0...	0.2...	0.1...	0.8...	248...	211...	-0.26	-1.02	5.0...	0.2...	0.1...
10	237...	420...	-1.71	1.0...	4.2...	0.4...	0.1...	0.7...	374...	869...	-1.62	0.8...	5.0...	0.2...	0.1...	0.7...	430...	178...	-1.22	0.3...	4.9...	0.2...	0.1...
11	375...	245...	-0.40	-1.84	3.4...	0.6...	0.3...	0.9...	379...	245...	-0.40	-1.84	3.2...	0.6...	0.3...	0.9...	378...	295...	-0.40	-1.84	3.6...	0.6...	0.3...
12	851...	304...	-1.30	-0.32	3.4...	0.5...	0.2...	0.7...	850...	326...	-1.30	-0.32	3.9...	0.4...	0.2...	0.7...	853...	387...	-1.30	-0.32	3.9...	0.4...	0.2...
13	977...	325...	-0.90	-1.19	4.5...	0.5...	0.2...	0.8...	504...	845...	-0.06	-1.14	5.3...	0.3...	0.2...	0.9...	104...	816...	-0.13	-1.48	5.1...	0.3...	0.2...
14	320...	778...	-0.59	-0.97	5.8...	0.2...	0.1...	0.9...	134...	192...	-0.72	-0.89	5.7...	0.3...	0.1...	0.9...	131...	123...	-1.17	-0.49	5.2...	0.4...	0.2...
15	104...	406...	-1.46	0.1...	3.9...	0.4...	0.1...	0.6...	105...	714...	-1.38	0.0...	4.5...	0.2...	0.1...	0.6...	778...	277...	-1.01	-0.39	4.5...	0.1...	0.1...
16	214...	365...	-1.35	-0.05	4.4...	0.4...	0.1...	0.7...	309...	114...	-0.89	-0.70	5.3...	0.2...	0.1...	0.8...	241...	247...	-0.84	-0.64	5.3...	0.2...	0.1...
17	215...	417...	-0.71	-1.25	4.6...	0.5...	0.2...	0.7...	345...	605...	-0.82	-1.29	4.8...	0.4...	0.2...	0.8...	589...	262...	-0.46	-1.37	5.0...	0.3...	0.2...
18	117...	650...	-0.47	-1.38	5.4...	0.3...	0.2...	0.9...	133...	248...	0.1...	-1.48	5.4...	0.3...	0.2...	0.9...	100...	101...	-1.03	-0.91	5.0...	0.4...	0.2...
19	233...	445...	-1.03	-0.30	5.3...	0.2...	0.1...	0.8...	271...	308...	-0.23	-1.51	5.3...	0.2...	0.1...	0.8...	252...	140...	-1.33	0.2...	5.0...	0.4...	0.1...
20	139...	686...	-0.84	-0.77	5.5...	0.2...	0.1...	0.8...	242...	362...	0.0...	-1.41	5.5...	0.2...	0.1...	0.9...	124...	140...	-0.74	-0.02	4.6...	0.5...	0.1...
21	199...	350...	-1.30	-0.31	4.1...	0.4...	0.1...	0.7...	631...	619	-1.26	-0.35	5.1...	0.3...	0.1...	0.7...	513...	469...	-0.91	-0.65	5.2...	0.2...	0.1...
22	126...	355...	-0.69	-1.46	4.7...	0.5...	0.2...	0.8...	428...	708...	-0.54	-1.46	5.0...	0.3...	0.2...	0.8...	324...	779...	-0.11	-1.51	5.0...	0.3...	0.2...
23	135...	359...	-0.86	-1.11	4.6...	0.5...	0.2...	0.8...	349...	635...	-0.89	-1.13	5.0...	0.4...	0.2...	0.8...	498...	319...	0.2...	-1.25	5.1...	0.3...	0.2...
24	346...	340...	0.1...	-1.12	4.6...	0.4...	0.3...	0.8...	263...	365...	0.0...	-1.70	4.6...	0.3...	0.3...	0.8...	284...	105...	-0.49	-1.72	4.4...	0.5...	0.3...
25	251...	436...	-0.78	-1.31	4.7...	0.4...	0.2...	0.8...	497...	620...	-0.82	-1.31	4.4...	0.5...	0.2...	0.8...	562...	336...	-0.65	-1.38	4.8...	0.3...	0.2...
26	401...	398...	-1.07	-0.85	4.6...	0.4...	0.2...	0.7...	888...	235...	0.6...	0.1...	5.1...	0.2...	0.1...	0.8...	239...	540...	-0.59	-1.15	5.1...	0.2...	0.1...
27	109...	478...	-0.68	-0.89	5.7...	0.2...	0.1...	0.9...	177...	371...	-0.02	-1.48	5.7...	0.2...	0.1...	0.9...	121...	113...	-1.34	-0.18	5.2...	0.4...	0.1...
28	115...	783...	-0.93	-0.87	5.6...	0.3...	0.1...	0.9...	210...	137...	-0.78	-1.02	5.7...	0.2...	0.1...	0.9...	202...	115...	-1.08	-0.62	5.4...	0.4...	0.2...
29	270...	272...	-0.79	-1.38	3.0...	0.6...	0.3...	0.9...	295...	302...	-0.79	-1.38	4.1...	0.6...	0.3...	0.9...	283...	340...	-0.79	-1.38	4.3...	0.5...	0.2...
30	288...	561...	-0.99	-0.59	5.1...	0.2...	0.1...	0.8...	300...	325...	-0.38	-1.41	5.1...	0.2...	0.1...	0.8...	246...	141...	-1.27	-0.25	4.9...	0.4...	0.1...
31	692...	273...	-0.81	-1.35	2.8...	0.6...	0.3...	0.7...	707...	303...	-0.81	-1.35	3.4...	0.5...	0.2...	0.7...	701...	345...	-0.81	-1.35	3.7...	0.5...	0.2...
32	251...	337...	-0.72	-1.17	5.1...	0.3...	0.2...	0.8...	3495	259...	-0.24	-1.50	5.1...	0.3...	0.2...	0.9...	352...	193...	-0.08	-1.15	5.0...	0.4...	0.2...
33	156...	597...	-0.72	-1.08	5.3...	0.3...	0.2...	0.8...	231...	302...	-0.06	-1.56	5.3...	0.2...	0.2...	0.9...	215...	133...	-0.81	-0.95	4.9...	0.4...	0.2...
34	122...	397...	-1.16	-0.59	4.8...	0.4...	0.1...	0.7...	526...	140...	0.4...	-0.73	5.2...	0.3...	0.1...	0.8...	182...	404...	-0.33	-1.00	5.3...	0.2...	0.1...
35	697...	258...	-0.43	-1.81	3.5...	0.5...	0.3...	0.8...	707...	264...	-0.43	-1.81	3.6...	0.5...	0.3...	0.8...	706...	312...	-0.43	-1.81	3.8...	0.5...	0.3...
36	125...	819...	-0.62	-0.96	5.5...	0.2...	0.1...	0.9...	183...	259...	0.0...	-1.18	5.5...	0.2...	0.1...	0.9...	953...	103...	-0.86	-0.44	5.0...	0.4...	0.1...
37	208...	357...	-1.17	-0.61	4.6...	0.5...	0.2...	0.8...	487...	635...	-1.15	-0.63	5.0...	0.4...	0.2...	0.8...	358...	388...	-0.73	-1.02	5.4...	0.2...	0.2...
38	264...	489...	-1.46	0.3...	5.1...	0.4...	0.1...	0.7...	348...	706...	-1.54	0.4...	5.0...	0.3...	0.1...	0.8...	462...	640...	-0.74	-0.70	5.4...	0.2...	0.1...
39	327...	652...	0.8...	2.0...	4.2...	0.5...	0.2...	0.6...	198...	758...	-1.01	-0.89	4.7...	0.3...	0.2...	0.7...	684...	287...	-0.67	-1.07	4.8...	0.3...	0.2...
40	634...	259...	-0.69	-1.52	3.1...	0.6...	0.3...	0.8...	636...	277...	-0.69	-1.52	3.5...	0.6...	0.3...	0.8...	636...	334...	-0.69	-1.52	3.9...	0.5...	0.2...
41	257...	483...	-1.04	-0.71	4.9...	0.3...	0.1...	0.6...	538...	840...	-1.11	-0.69	4.9...	0.3...	0.1...	0.7...	665...	440...	-0.11	-1.31	5.0...	0.2...	0.1...
42	134...	812...	-1.01	-0.67	5.5...	0.2...	0.1...	0.9...	234...	179...	-0.42	-1.19	5.5...	0.2...	0.1...	0.9...	135...	108...	-1.19	-0.39	5.1...	0.4...	0.1...
43	695...	631...	-0.86	-0.84	5.7...	0.2...	0.1...	0.9...	187...	267...	-0.00	-1.37	5.7...	0.2...	0.1...	0.9...	987...	996...	-1.34	-0.15	5.2...	0.3...	0.1...
44	356...	534...	-1.19	-0.45	4.8...	0.3...	0.1...	0.7...	529...	652...	-1.25	-0.41	4.6...	0.4...	0.1...	0.7...	565...	401...	-0.74	-0.90	5.1...	0.2...	0.1...
45	120...	765...	-0.88	-0.73	5.6...	0.2...	0.1...	0.9...	187...	357...	0.0...	-1.05	5.6...	0.2...	0.1...	0.9...	945...	108...	-1.28	-0.29	5.3...	0.4...	0.1...
46	184...	503...	-1.04	-0.35	5.4...	0.2...	0.1...	0.8...	306...	436...	-0.50	-1.23	5.5...	0.2...	0.1...	0.9...	178...	204...	-0.61	-0.63	5.2...	0.4...	0.1...
47	124...	339...	-0.83	-1.26	4.6...	0.4...	0.2...	0.8...	471...	623...	-0.81	-1.27	4.9...	0.3...	0.2...	0.8...	451...	339...	-0.06	-1.03	5.1...	0.2...	0.2...
48	159...	343...	-1.06	-0.86	4.6...	0.4...	0.2...	0.7...	693...	609...	-1.05	-0.87	5.1...	0.4...	0.2...	0.7...	634...	684...	-0.24	-1.29	5.5...	0.2...	0.2...
49	150...	515...	1.6...	10.45	4.2...	0.5...	0.2...	0.7...	129...	653...	-1.15	-0.50	5.0...	0.4...	0.1...	0.7...	350...	873...	-0.64	-0.92	5.5...	0.2...	0.1...
50	182...	462...	-0.81	-0.93	5.4...	0.2...	0.1...	0.8...	247...	285...	0.0...	-1.41	5.4...	0.2...	0.1...	0.9...	137...	108...	-1.16	-0.62	5.0...	0.4...	0.1...

ViQi   Create ▾   Upload   Download ▾   Analyze ▾   Browse ▾

Training the AI

AI Trainer

Version: 2 Authors: ViQi

Train ML classification models on various data types.

1. Select data for processing:

Input data:

Select an Image   or   Select a set of images   or even   Upload local images

2. Parameters:

Annotation level: Objects (cells)

Objects origin: cell_segmentation

Specific annotations:

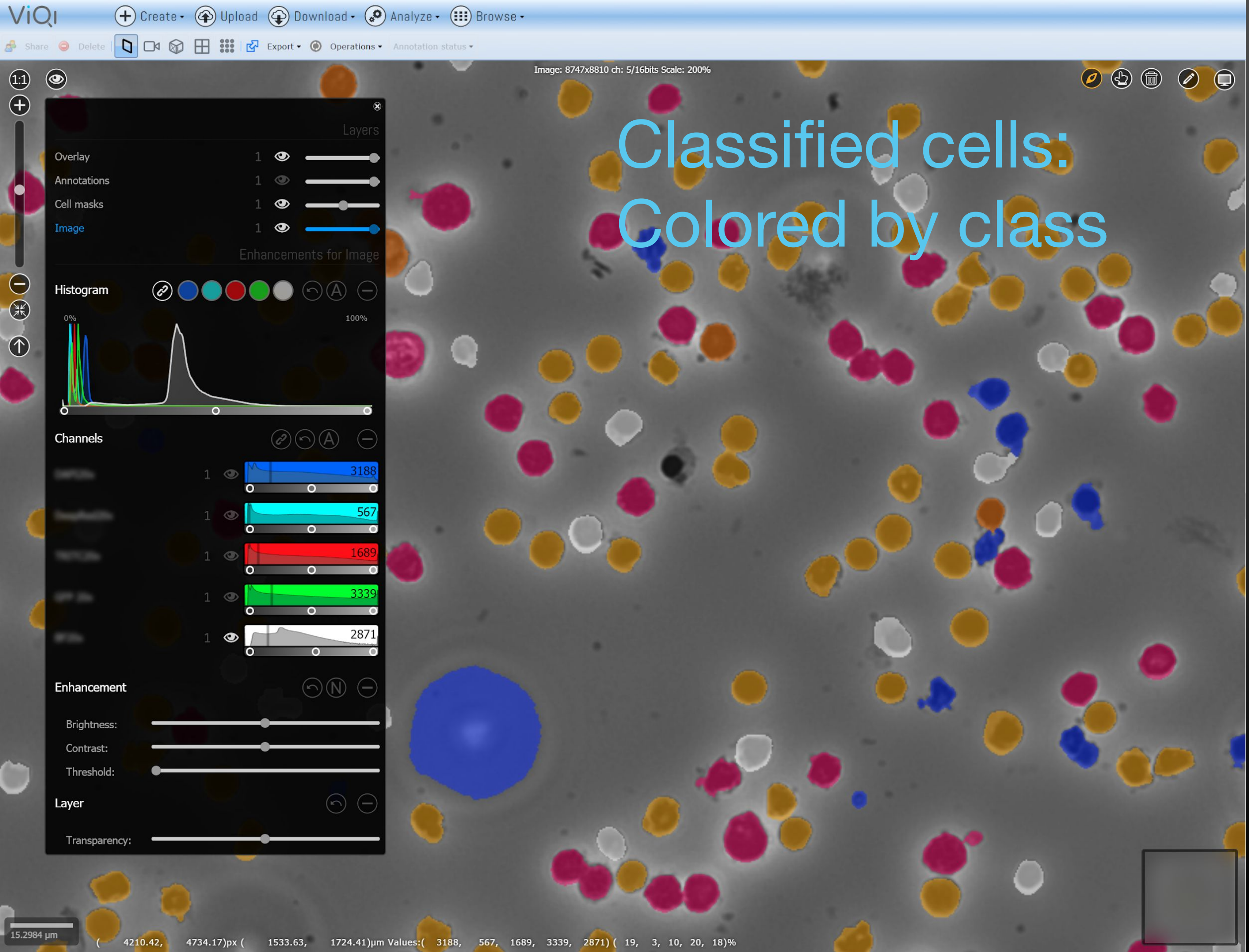
Ground truth

Update training with latest annotations: ☑

3. Run algorithm:

STOP   Progress: 80.0% of Testing on [illegible], (80/100)

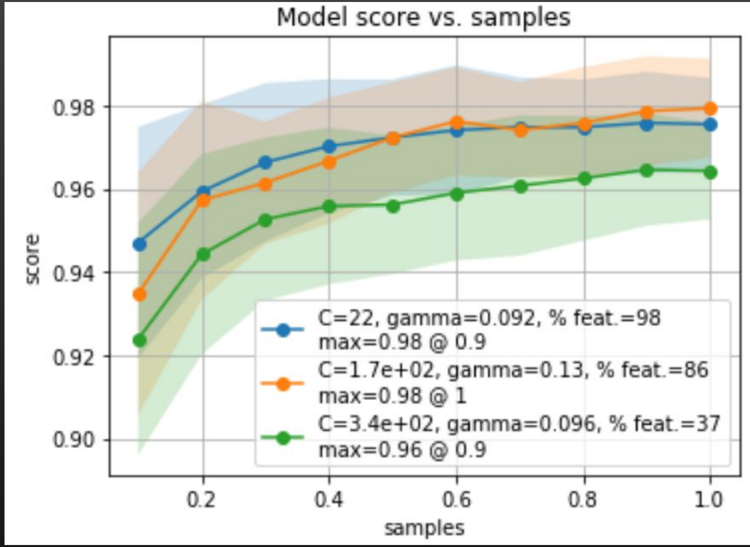
ViQi

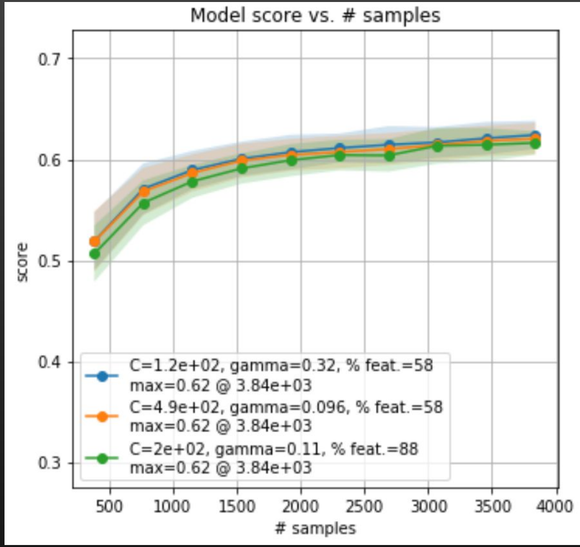

Classified cells:
Colored by class
ViQi
Create
Upload
Download
Analyze
Browse
Share
Delete
Export
Operations
Annotation status
Image: 8747x8810 ch: 5/16bits Scale: 200%
Layers
Overlay
Annotations
Cell masks
Image
Enhancements for Image
Histogram
0%
100%
Channels
3188
567
1689
3339
2871
Enhancement
Brightness:
Contrast:
Threshold:
Layer
Transparency:
15.2984 µm
(4210.42, 4734.17)px (1533.63, 1724.41)µm Values:(3188, 567, 1689, 3339, 2871) (19, 3, 10, 20, 18)%

ViQi

AI Performance: Things to look for.

Training curve



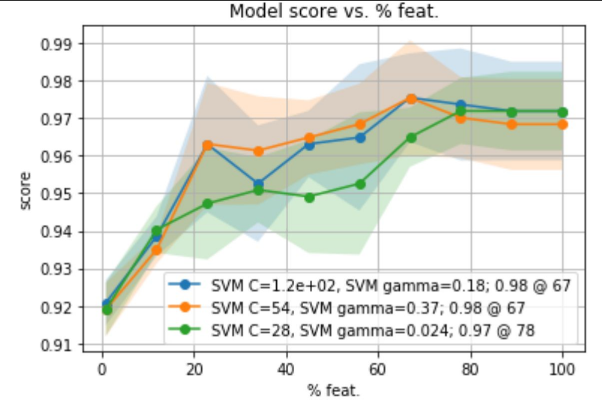


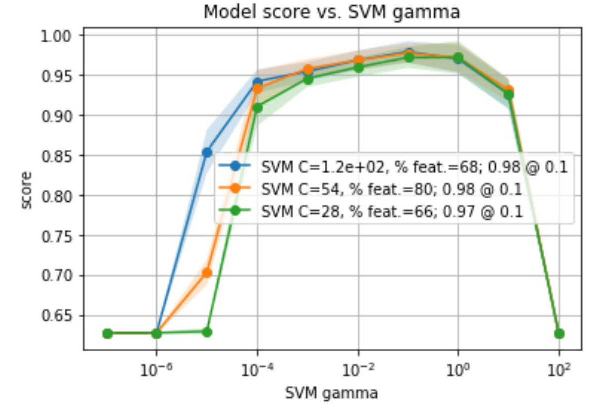
Was there enough data? Is it saturated?

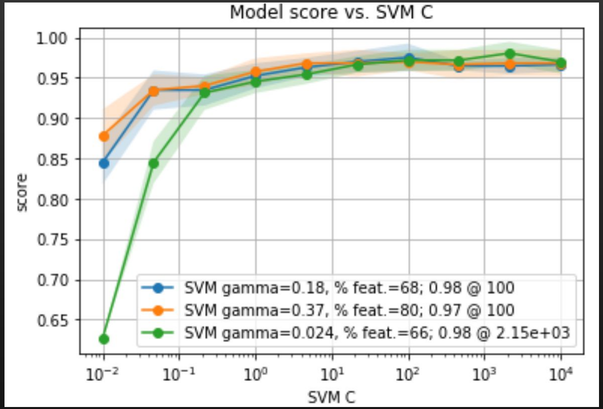
Error bars: Is each subsample substantially different from the others?
If so, not enough data, or too much variation.

AI Performance: Things to look for.

Parameter Sensitivity (feature-based classifiers)







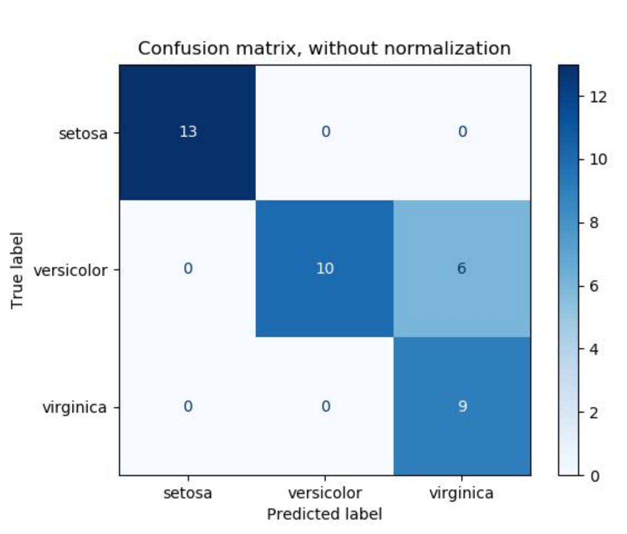
Are any parameters in sharp peaks?

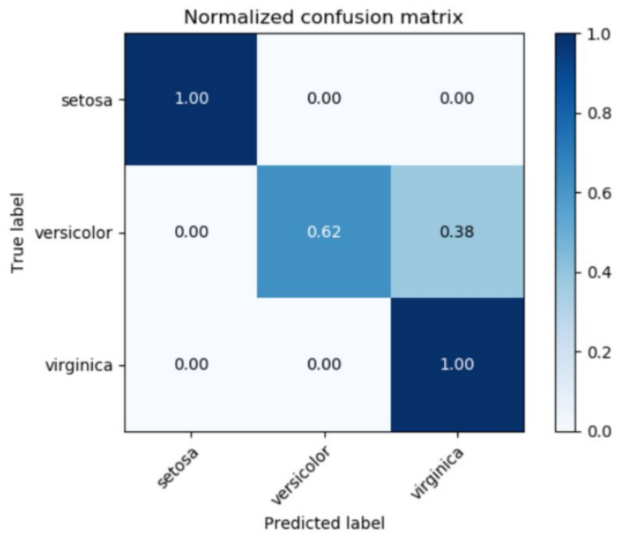
May not generalize to a different sample.

Parameters in plateaus result in more robust models.

AI Performance: Things to look for.

Confusion matrix





Source: Scikit-learn

Should confused classes be combined into a single class?
Should a confused class be separated into subclasses?
Should a classifier be trained just on the confused classes?

AI Performance: Things to look for.

Overtraining

How well does the predictor perform on new data?

- Cross-validation.
- Reserve some data and never let the AI see it during training: 10% at a bare minimum.
- Especially important for Deep Learning, because it is more prone to overtraining.
- Modern feature-based classifiers are very resistant to overtraining, or excess features.

Testing vs. validation in different fields.

- ML/AI/DL/DS:
  - Validation set: Internal subset used by the AI training algorithm.
  - Test set: an externally withheld set used to test the final trained AI.
- Regulatory, common use:
  - Validation is a higher standard than testing.
  - Validation set: Used to validate the final product.
  - Test sets: Used for "bench tests" - internal tests of the AI as it's being developed.

AI Performance: Things to look for.

Bias: Disproportionate class sizes

> If a dataset is 90% Class A, and 10% Class B,
> a predictor can be 90% accurate by always guessing Class A.

Some AIs claim to compensate for this, but it requires making assumptions that may not hold in your case.

Best defense is to force the classes to be equal sizes.

AI Performance: Things to look for.

Biases in data - hidden, known & unknown.

- Can result in biased models
- Random sampling may not be enough to correct for bias.

Measure the bias:

- Ask the AI if it can distinguish classes based on your bias variable
- If it can't then you have nothing to worry about.

Correct for known sources of bias:

- Confuse the AI with regards to bias.
  - Distribute the bias evenly in each class
- "Train out" known bias variables

Parting thought:

An AI will only perform as well as
the accuracy of the class labels and
the degree to which the training set represents reality.

Let’s have another **audience poll**

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Q&A |

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