Out-of-Distribution Learning:

Preventing Fatal Neural Network Mistakes

In Distribution v. Out-of-Distribution

- Traditional Neural Networks (NNs) accurately classify objects seen during training
  - These are **In-Distribution (ID)** objects[1]

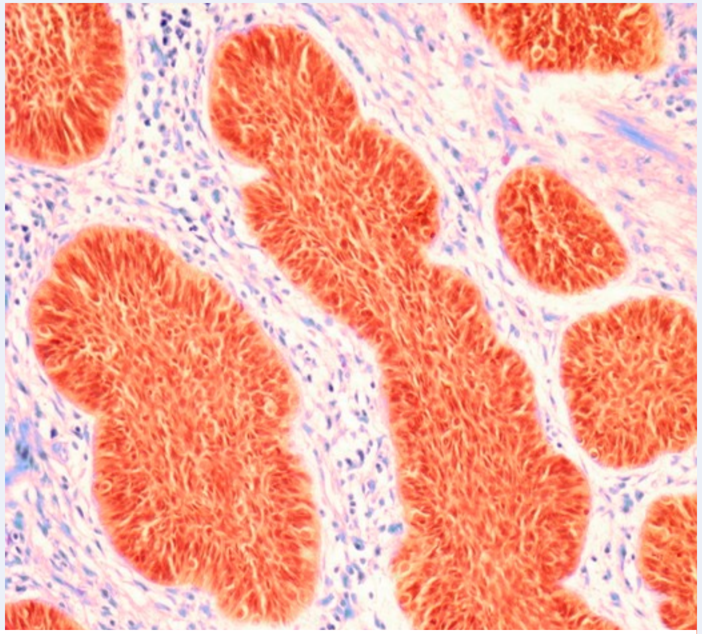
eg. cancer-detecting NN accurately classifies ID tumor

- Traditional NNs confidently misclassify objects NOT seen during training
  - These are **Out-of-Distribution (OOD)** objects[1]

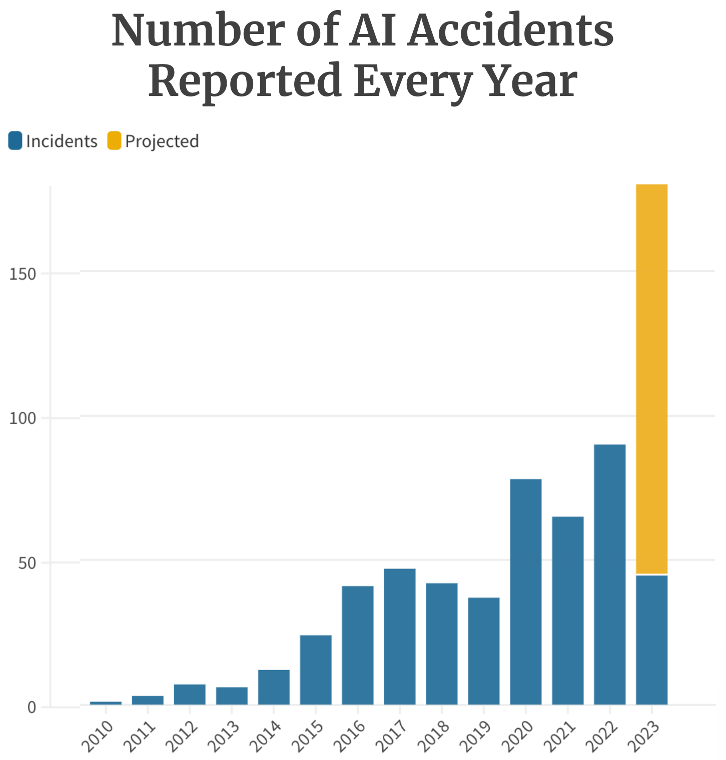
eg. cancer-detecting NN ***misclassifies*** OOD debris as cancer, causing ***misdiagnosis***

Fatal Out-of-Distribution Misclassifications

Experts predict NN accidents will double every year



The Atlantic: “Cancer Detector Misdiagnoses Black Users” due to lack of training & testing with Black samples[2]



Source: AI Incident Database, founded by Sean McGregor Ph.D. in machine learning[3]

NBC: Self-driving car killed a woman because it was trained to “only classify an object as a pedestrian [if it’s] near a crosswalk”[4]

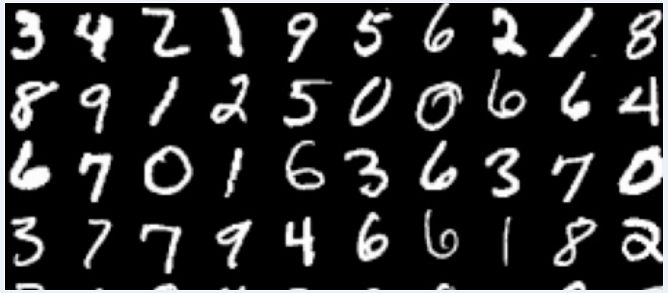
When NNs are implemented in the world, they encounter OOD objects and make fatal misclassifications

OOD Classification Issue

- Unfeasible to predict which OOD objects a NN will encounter
- Unfeasible to train NNs on all OOD objects

New algorithm that can classify OOD objects w/ minimal training must be implemented

Datasets

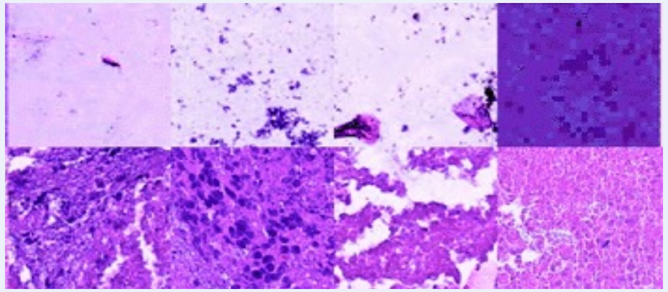


MNIST[5]

- handwritten digits
- 60000 train, 10000 test images

OrganAMNIST[6]

- low-res organ scans
- 34581 train, 6491 test images



PathMNIST[6]

- colorectal tissue
- 89996 train, 10004 test images

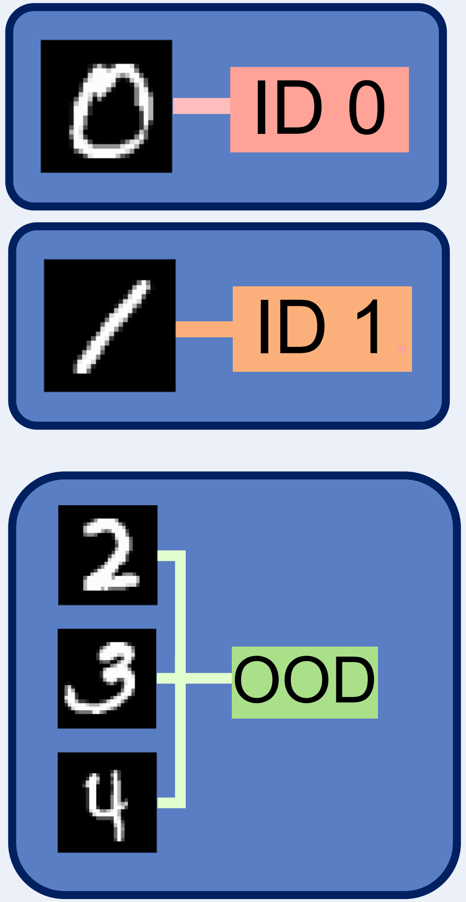
Step 1: Train NN w/ OOD class to Differentiate ID & OOD

Train **10 NNs** to account for chance differences during training

Start w/ traditional NN (**2 ID classes**, 5-layer LeNet CNN, exponential learning rate, 15 epochs)

Add *general* **OOD class** (mix of 3 non-ID objects)

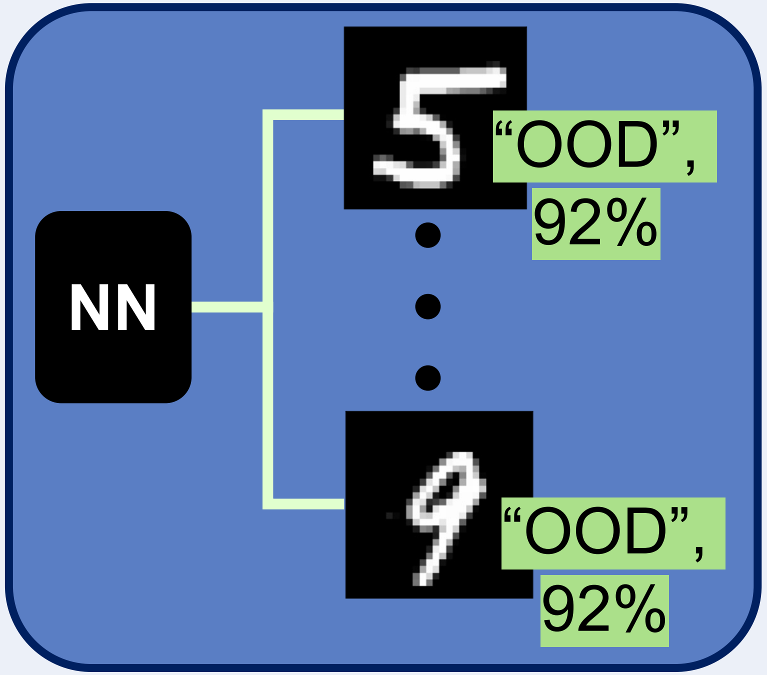
Train NN



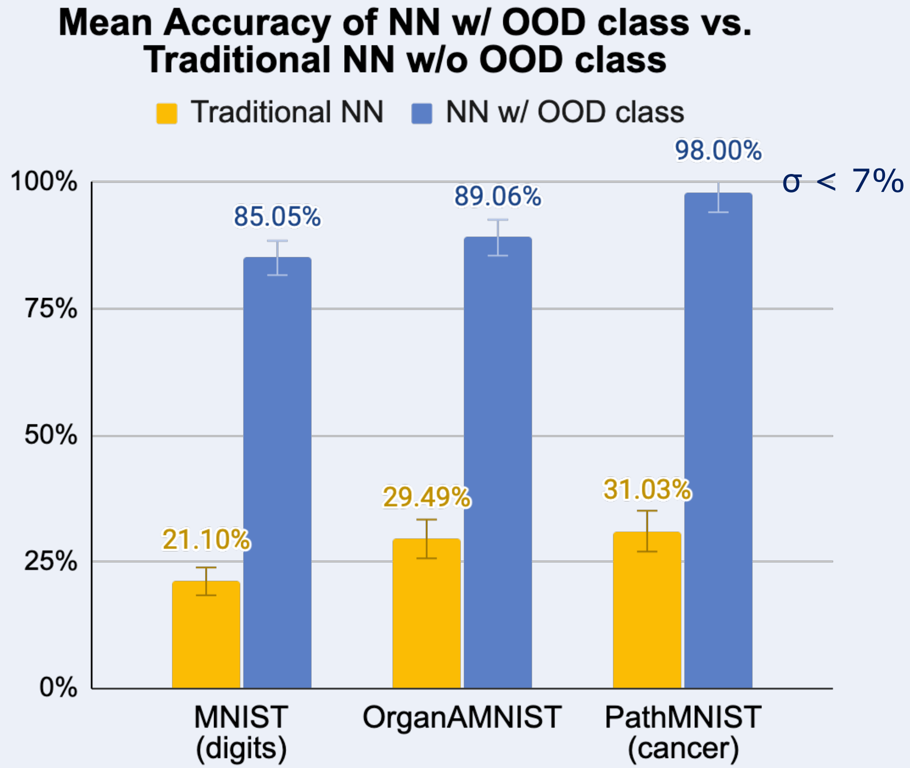
NN trained to classify all non-ID objects as OOD

Test NN's Ability to Differentiate ID & OOD

Test new NN w/ OOD class on OOD objects not seen during training



NN w/ OOD class classifies digits 5-9 as "OOD" even though it wasn't trained using these digits



NN w/ OOD class ~60% more accurate than Traditional NN w/o OOD class

NN generalizes trained concept of OOD to objects not seen during training

Discovering OOD Objects Not Seen During Training

There are 2 types of OOD objects: **OOD seen** (seen during training) & **OOD unseen** (not seen during training) both stored in NN’s “OOD” class

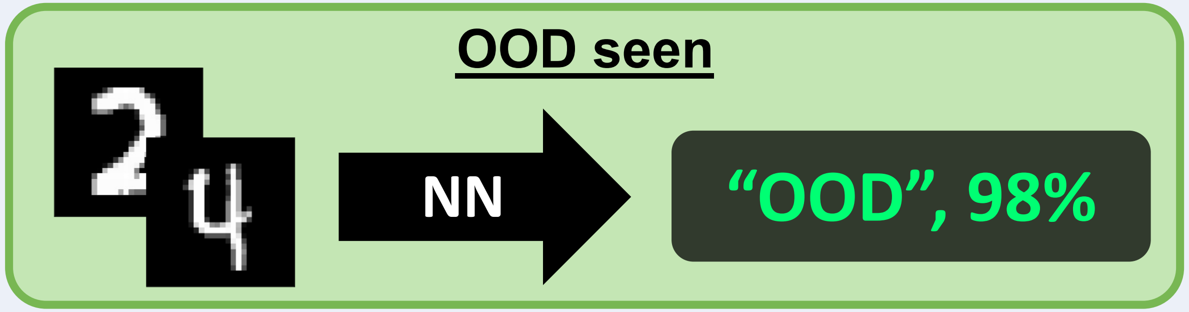
Fig. PathMNIST NN’s ID, OOD seen, OOD unseen classes

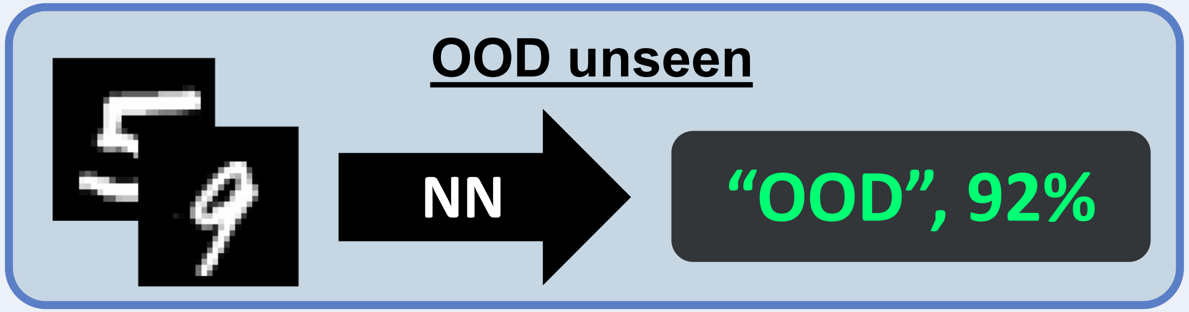
Algorithm should create new class for undiscovered **OOD unseen** objects like carcinoma to alert users to existence of important undiscovered objects

Step 2: Unsupervised Algorithm to Discover OOD Unseen Objects

NN classifies **OOD seen** objects with ***higher confidence***

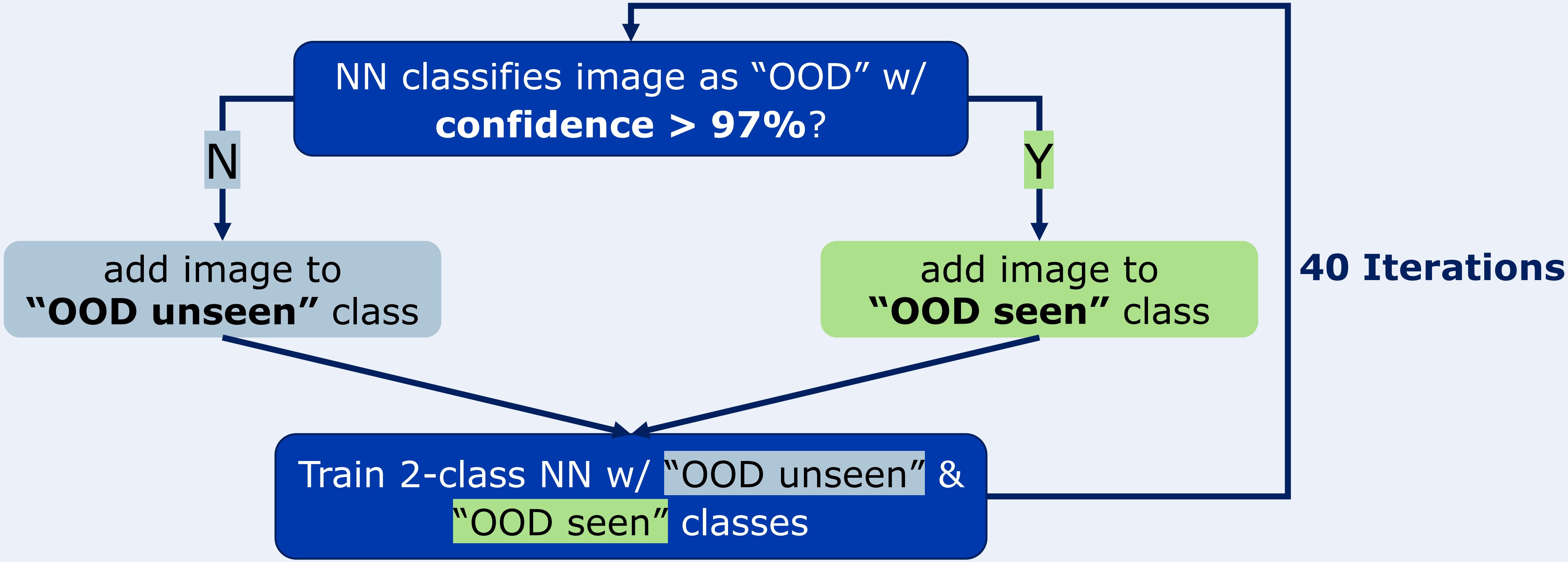
than **OOD unseen** objects





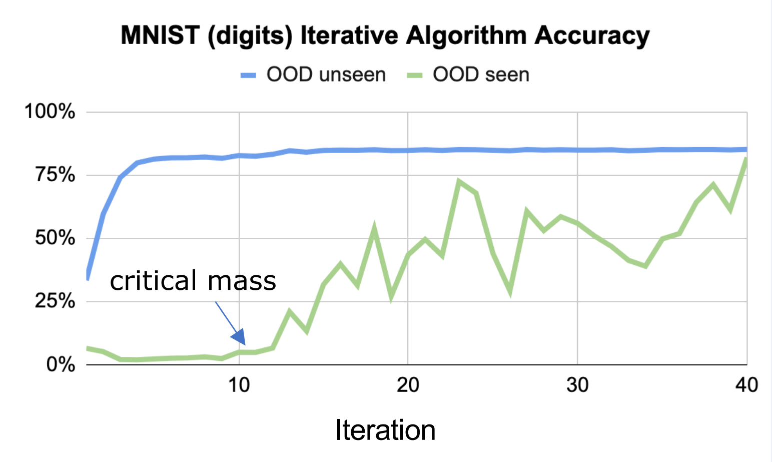
Step 2: Unsupervised Algorithm to Discover OOD Unseen Objects

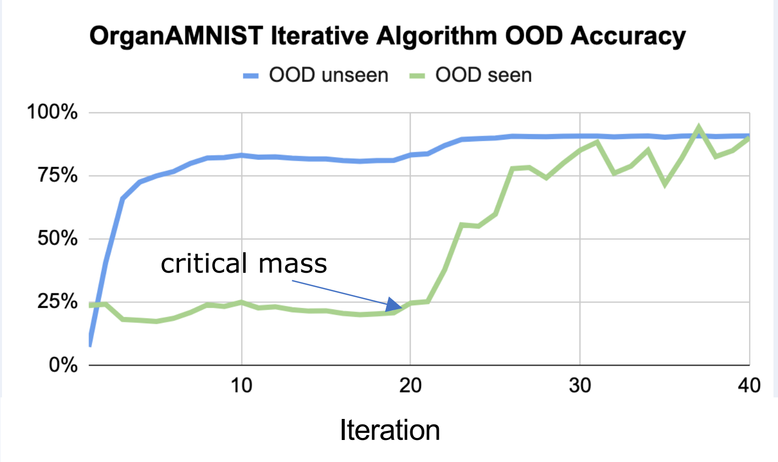
Novel unsupervised algorithm uses confidence scores & NN training to differentiate **OOD seen** & **unseen** objects w/o user labeling:

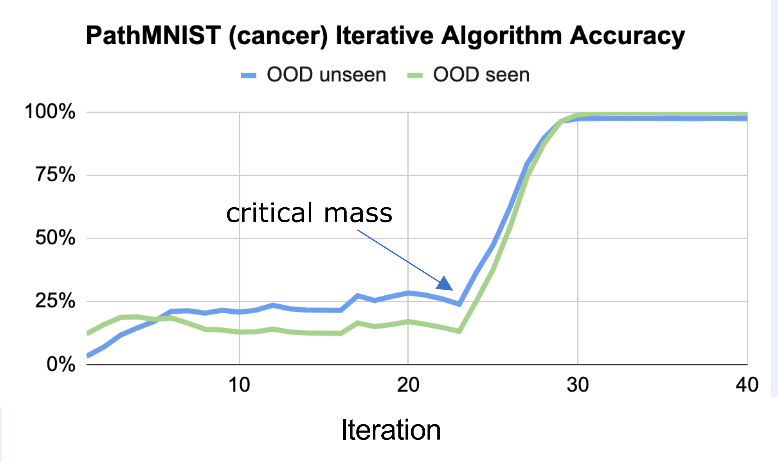


Algorithm **iterates 40 times**, correcting misclassifications & improving understanding of differences between **OOD unseen** & **seen** classes

Test Unsupervised Algorithm's Ability to Differentiate OOD Seen & OOD Unseen







Accuracies increase quickly after critical mass is reached (~25%)

Unsupervised Algorithm's Accuracies After 40 Iterations

	OOD seen	OOD unseen
MNIST (digits)	82.05%	85.14%
OrganAMNIST	90.02%	90.70%
PathMNIST (cancer)	99.25%	97.37%

Unsupervised Algorithm attains above 80% accuracies, some reaching 99%

Conclusion

- Addition of OOD class improved accuracy by ~60%
- Algorithm can now classify objects not seen in training
- Algorithm discovers new objects before humans
- Saves on user image labeling
  - Trained w/ ~3000 images
  - Self-labels ~9000 images

Cancer, Organ, Digit classification success → algorithm has wide range of applicability

Limitations

- Neural Networks only successful if Out-of-Distribution objects look notably different from In-Distribution

Future Work

- Implement image augmentation & JSD loss for low-res datasets & datasets with very similar classes

Bibliography

My GitHub Repo: https://github.com/olimu/OOD

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Comparing NN w/ OOD class to Traditional NN

T-Test Comparing Accuracies of NN w/ OOD class to Accuracies of Traditional NN

Dataset	p-value ($\alpha = 0.05$)
MNIST (digits)	5.68×10^{-12}
OrganAMNIST	3.01×10^{-9}
PathMNIST (cancer)	3.41×10^{-11}

P-values $< \alpha$
so NN w/ OOD class
is more accurate
than Traditional NN
w/o OOD class