Automating Myelin Defect Detection

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Background

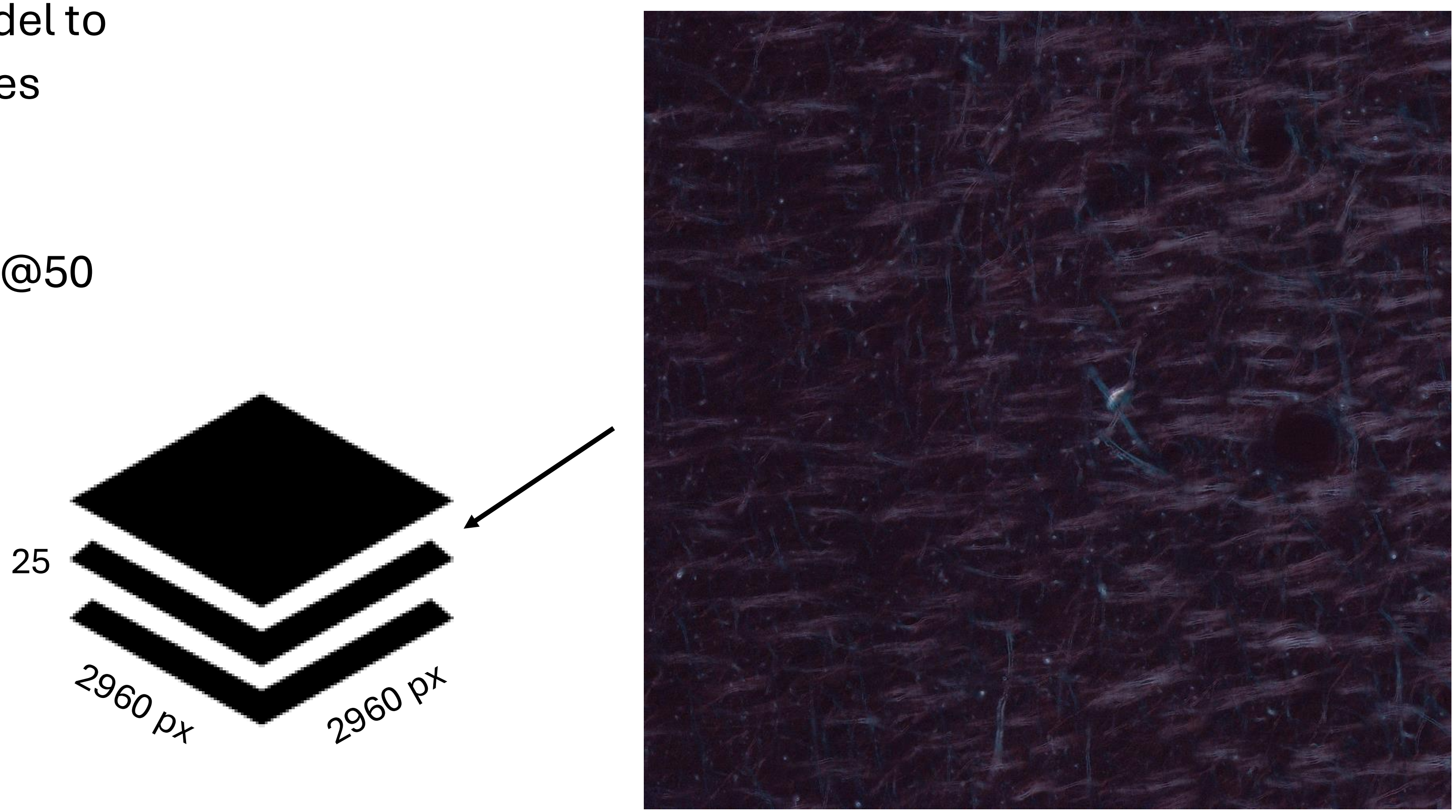
Goal: Train an object detection model to detect myelin defects in BRM images

Progress:

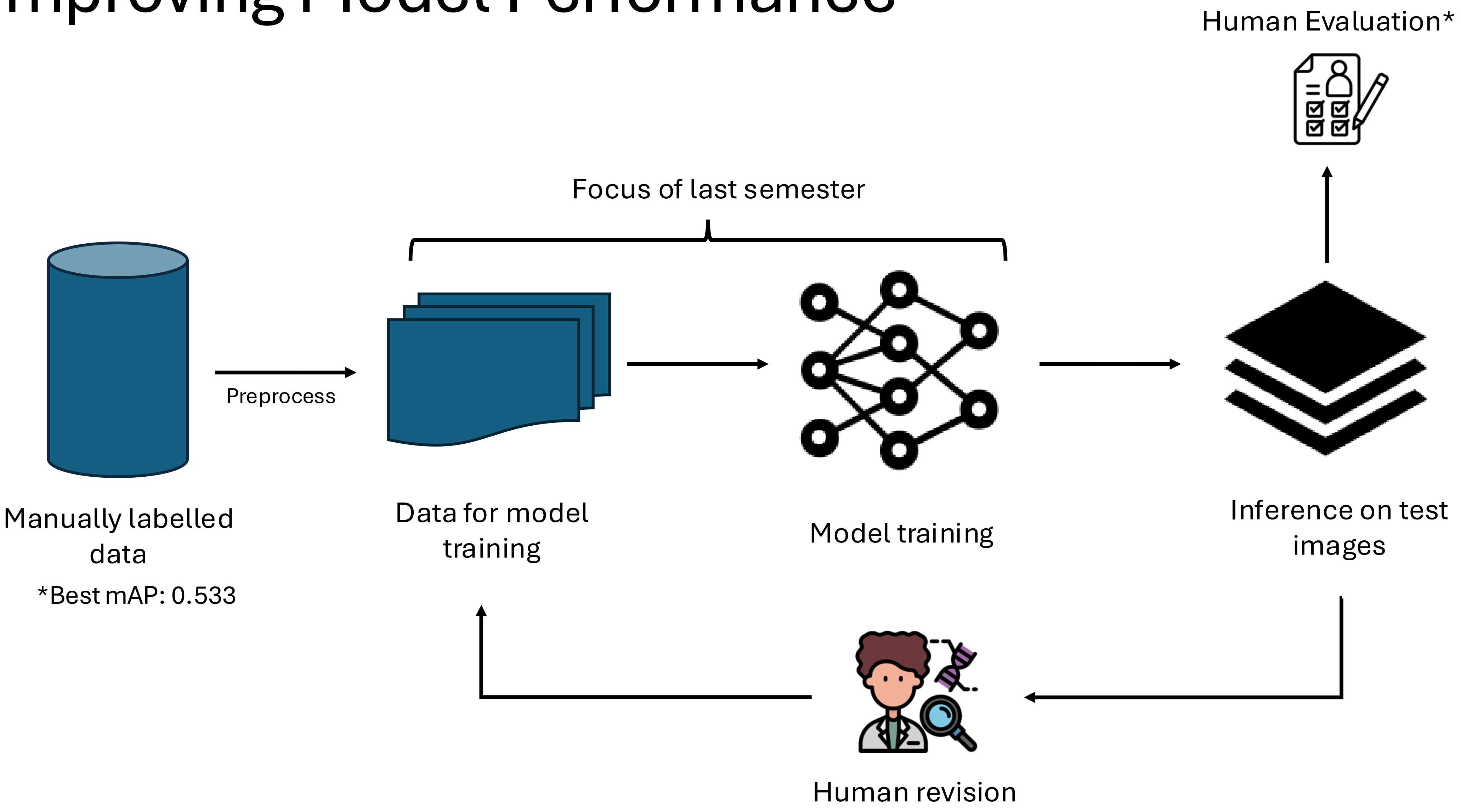
- Model performance: 0.533 mAP@50

To Do:

- Improve model performance
- Classification

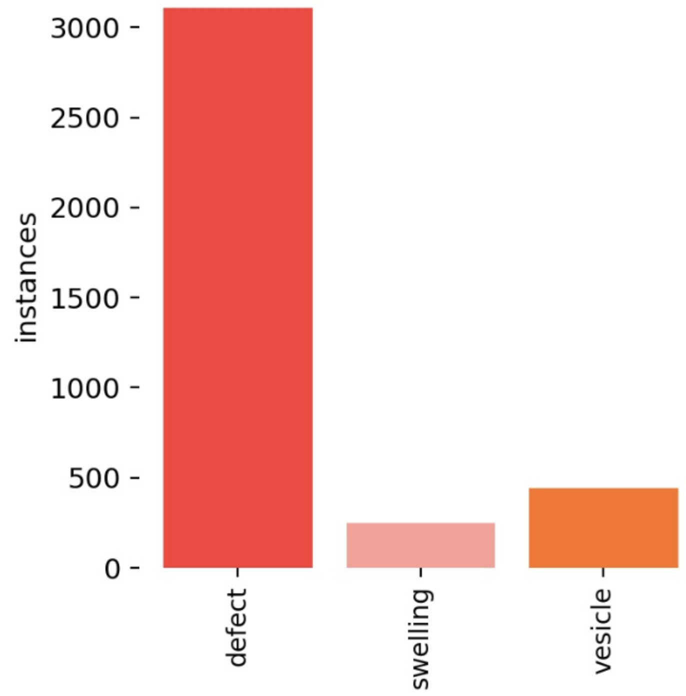


Improving Model Performance

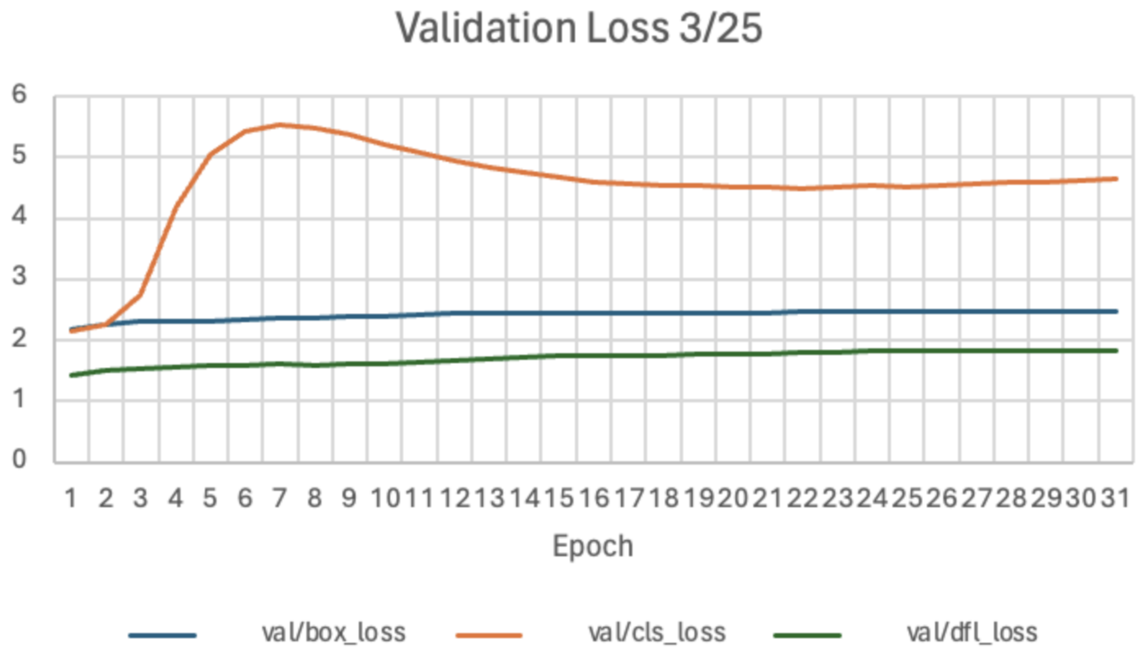


Classification

Motivation for new classification:

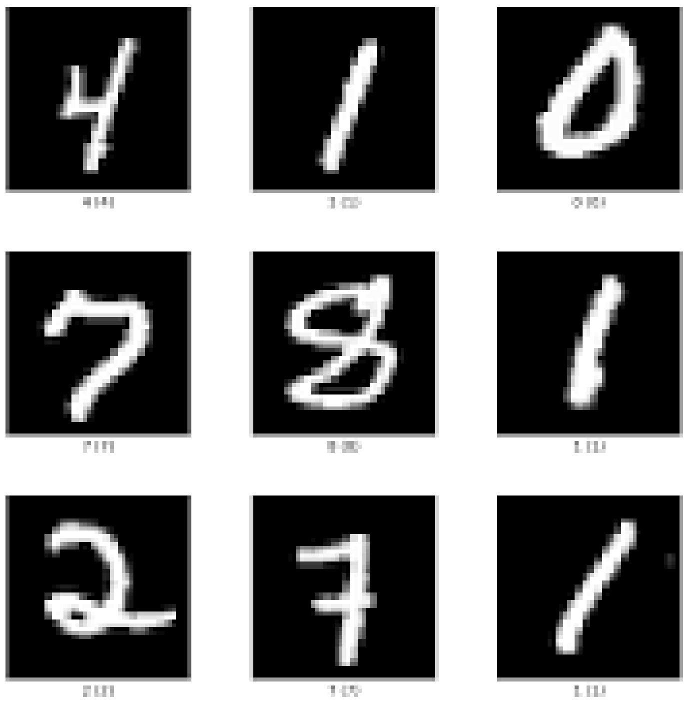


Class Imbalance

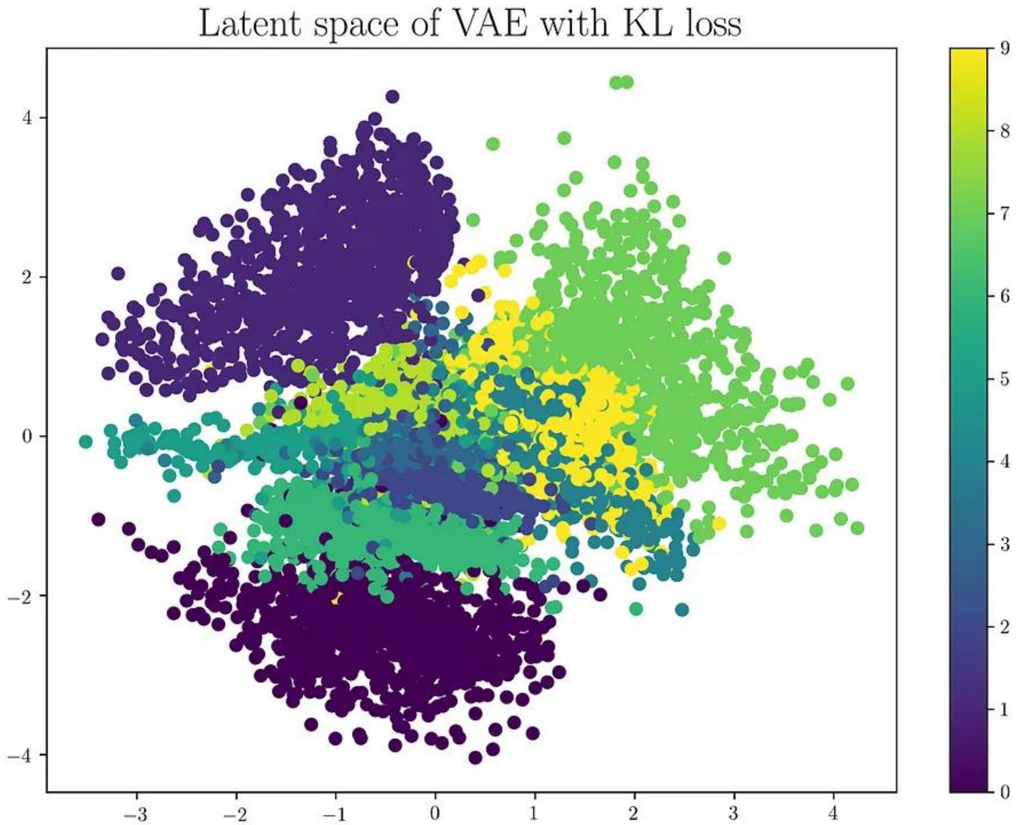


Classification Loss

Classification – MNIST example

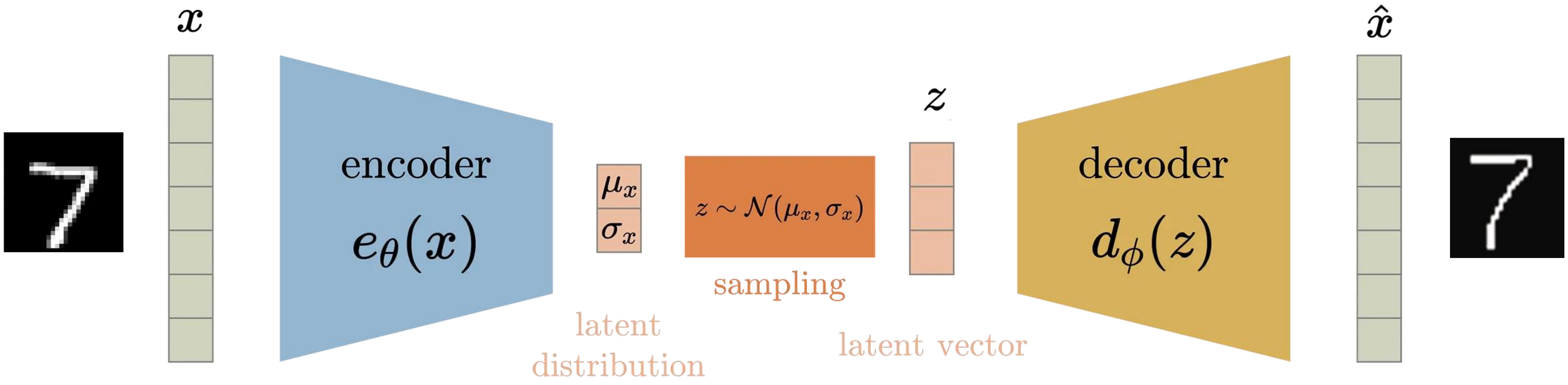


MNIST Dataset: 28 x 28 px



MNIST Dataset Representations

Classification - VAE



$$\text{reconstruction loss} = \|x - \hat{x}\|_2 = \|x - d_\phi(z)\|_2 = \|x - d_\phi(\mu_x + \sigma_x \epsilon)\|_2$$

$$\mu_x, \sigma_x = e_\theta(x), \quad \epsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$$

$$similarity\ loss = KL\ Divergence = D_{KL}(\mathcal{N}(\mu_x, \sigma_x) \parallel \mathcal{N}(\mathbf{0}, \mathbf{I}))$$

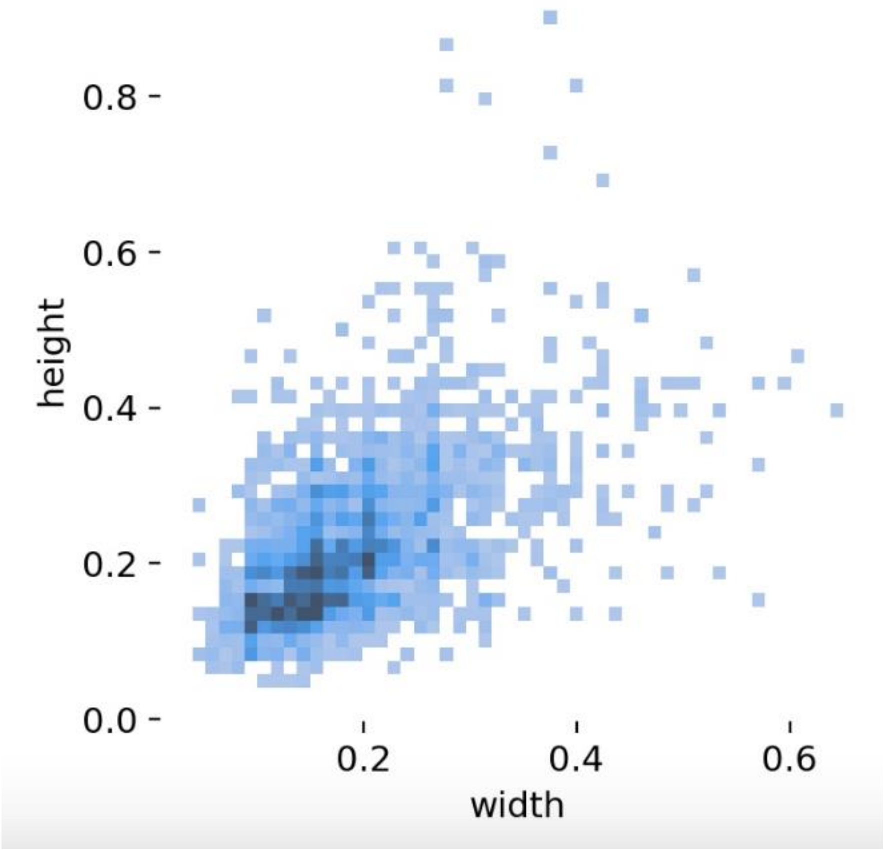
$$loss = reconstruction\ loss + similarity\ loss$$

Classification

- Our defect sizes are on a similar scale as the MNIST dataset → easier to learn representative features

- VAE reconstruction loss directly emphasizes learning representations based on visual features similar to our previous classes (swelling & vesicles)

- We can improve object detection performance by introducing classification
  - Observe model performance by class
  - Remove outliers from dataset
  - Identify underrepresented class



Distribution of Defect Sizes (normalized 100px)