Image Segmentation by Deep Learning of Disjunctive Normal Shape Model Shape Representation

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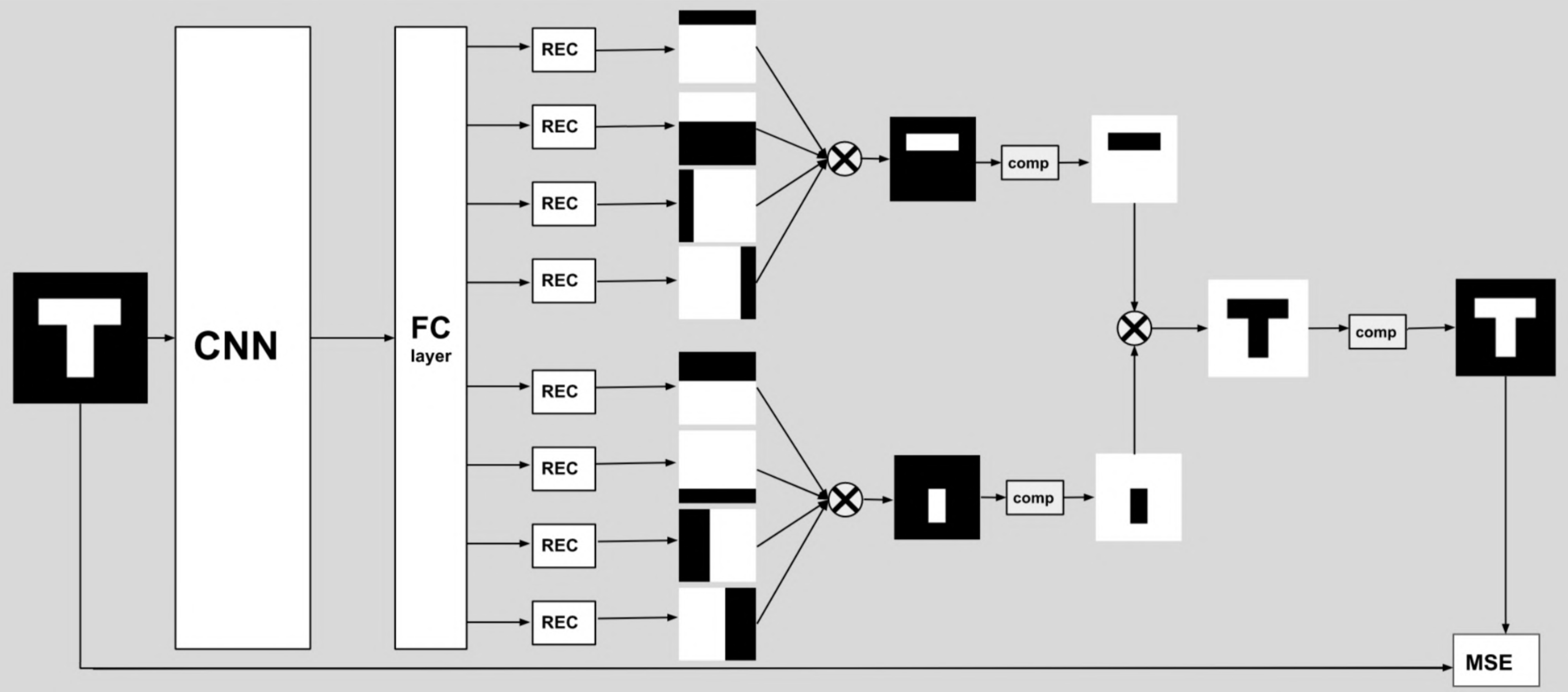
Introduction

- We propose a deep learning framework that allows learning parametric implicit shape models, using shape priors together with appearance
- Objective of segmenting low-quality images or datasets:
  - o Low signal-to-noise ratio
  - o Limited amount of training data
  - o Missing parts
  - o Occlusion of parts

Approach

- Model receives an image and outputs a segmentation or image reconstruction
- We use a parametric Disjunctive Normal Shape Model (DSNM) [1] together with deep learning:
  - A CNN produces image features
  - Last FC layer outputs parameters of the implicit shape model (each 2D half–space needs 3 coefficients to be reconstructed: $Ax+By+C>0$)
  - Subsets (groups) of half-spaces create polytopes from their intersection
  - Union of polytopes creates final shape
- Half-spaces are relaxed to logistic functions to make the model differentiable
- Training uses MSE as loss, comparing the output of the network to an image ground truth (we do not use shape parameters as ground truth)



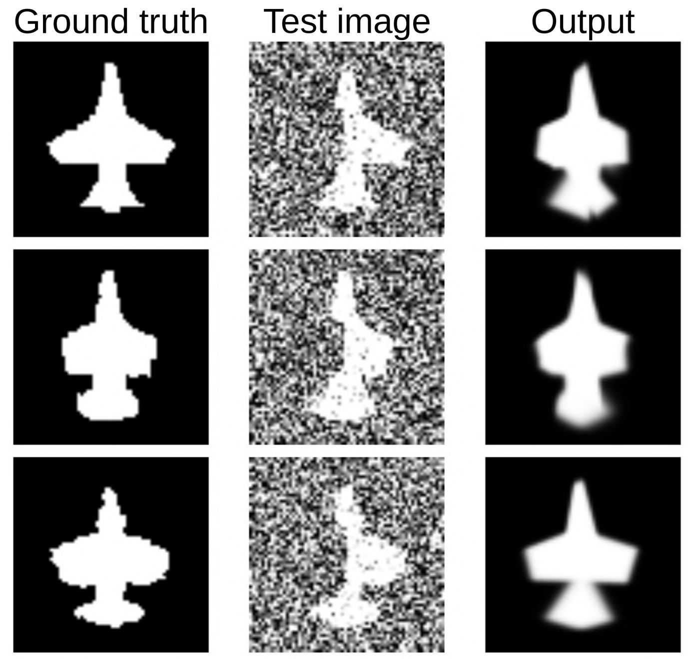
Experiments

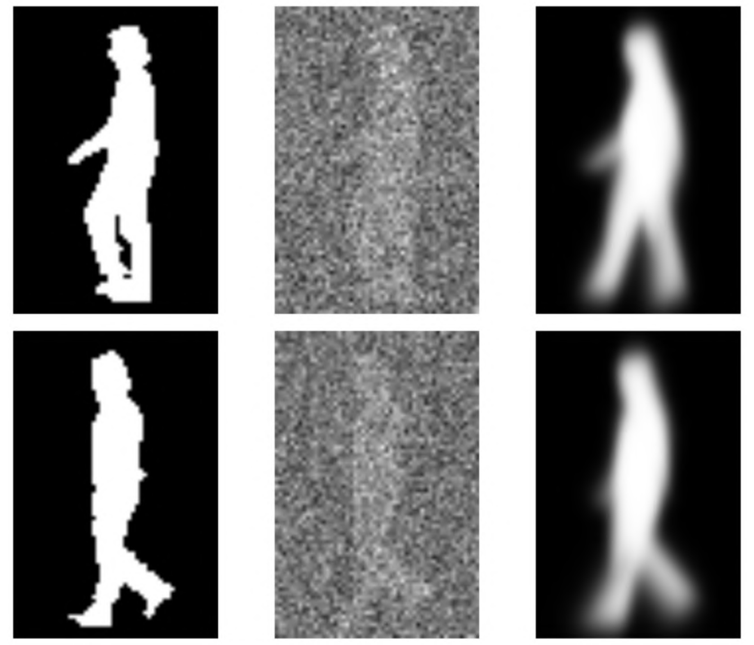
- We used models with 2 convolutional layers, 2 fully connected layers, 24 polytopes and 8 half-spaces per polytope.
- We use Dice coefficients to report results.

Aircraft Dataset [2]

- 11 binary images of aircrafts
- Test images have noise in two different levels and occlusion of left wing
- We trained the model in a leave-one-out setting

	Kim et al. [2]	Erdil et al. [3]	Proposed approach
Image 1, low noise	91.12	**94.49**	94.23
Image 2, low noise	92.69	94.75	**98.51**
Image 3, low noise	89.97	94.66	**96.96**
Image 1, high noise	87.15	89.86	**94.80**
Image 2, high noise	90.31	93.25	**98.14**
Image 3, high noise	88.03	90.05	**97.83**





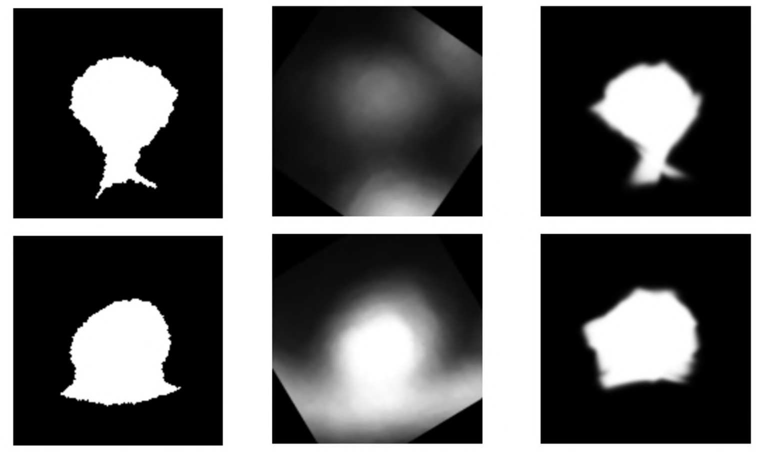
Walking Silhouettes dataset [4]

- 30 images selected – 16 for training
- Images have high level of additive white noise

	Kim et al. [2]	Erdil et al. [3]	Proposed approach
Image 1	87.13	88.10	**91.38**
Image 2	89.87	89.87	**93.30**
Image 3	85.43	86.58	**92.06**

Dendritic Spine Dataset [5]

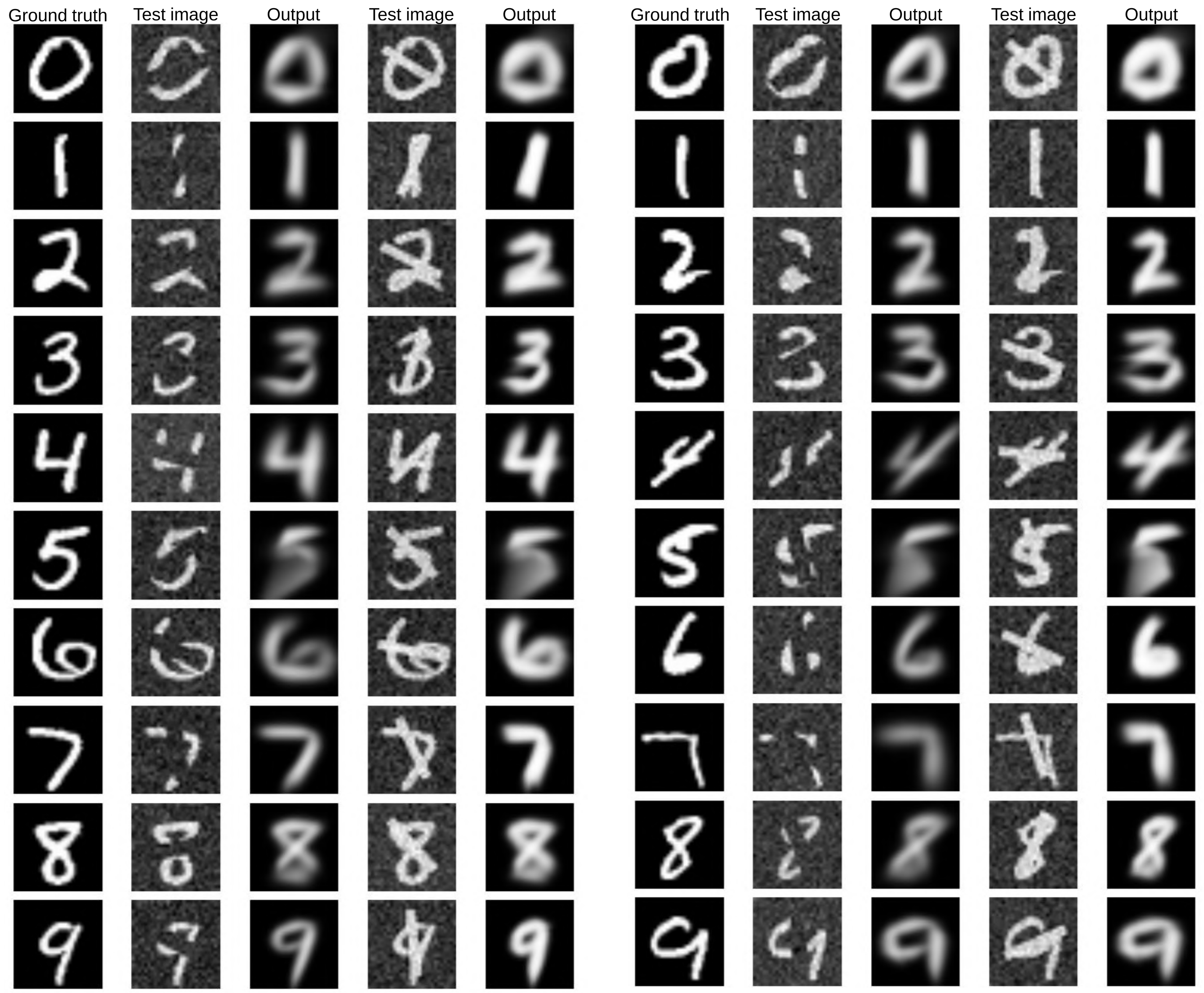
- We trained two shape models, one for mushroom spines and one for stubby spines
- 88 mushroom spines and 27 stubby spines
- We trained models using 8 examples of each



Foulonneau et al. [6]	Kim et al. [2]	Chen et al. [7]	Erdil et al. [8] with geometric priors	Erdil et al. [8] with appearance priors	Proposed approach
73.48	64.24	72.38	74.74	74.92	**75.25**

MNIST dataset [9]

- Model predicts 10 different shapes and 10 class probabilities
- Model outputs the shape corresponding to the class with highest probability
- We added Gaussian noise and occlusions/exclusion of parts to test set



Conclusion

- Our framework of CNN+DSNM was able to segment data with noise, with occlusion/removal of parts and with limited amount of training data
- We achieved superior scores against previous methods in 3 datasets
- The model is computationally efficient and fully automated, with no need for deliberate initialization

References

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