To Learn or Not to Learn Features for Deformable Registration?

Raghav Mehta

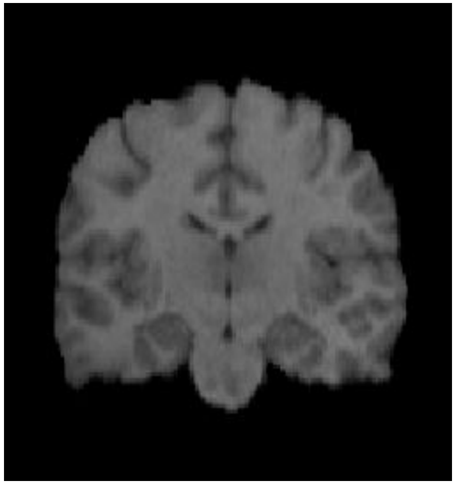
Centre for Intelligent Machines (CIM),
McGill University, Canada

To Learn or Not to Learn Features for Deformable Registration?

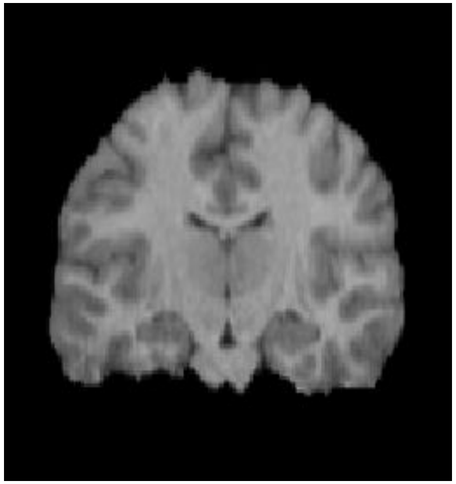
Aabhas Majumdar, Raghav Mehta, and Jayanthi Sivaswamy

Centre for Visual Information Technology (CVIT)
IIIT Hyderabad, India

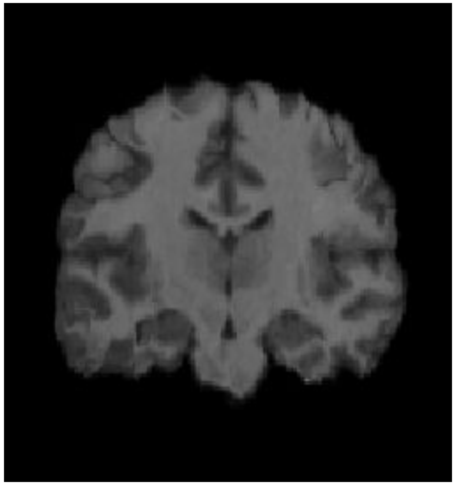
Registration problem



Fixed Image



Moving Image



Registered Image

[1]

Introduction

- Feature-based registration has been a very popular technique to solve the registration problem.

- Following features have been explored
  - Intensity values, edges
  - Geometric moment [1]
  - 3D Gabor attributes [2]
  - Modality Independent Neighborhood Descriptor (MIND) [3]
  - Self-Similarity Context (SSC) [4]

(1) Shen et al., IEEE TMI 2002 (HAMMER)
(2) Ou et al., MedIA 2011 (DRAMMS)
(3) Heinrich et al., MedIA 2012 (MIIND)
(4) Heinrich et al., MICCAI 2013 (SSC)

Introduction

- A very natural question to feature-based registration in the current time would be
  "Can *learning* of features lead to better registration?"

- Some initial works:
  - Deep features learnt using an unsupervised method [5]
  - A Co-Registration and Co-Segmentation framework [6]

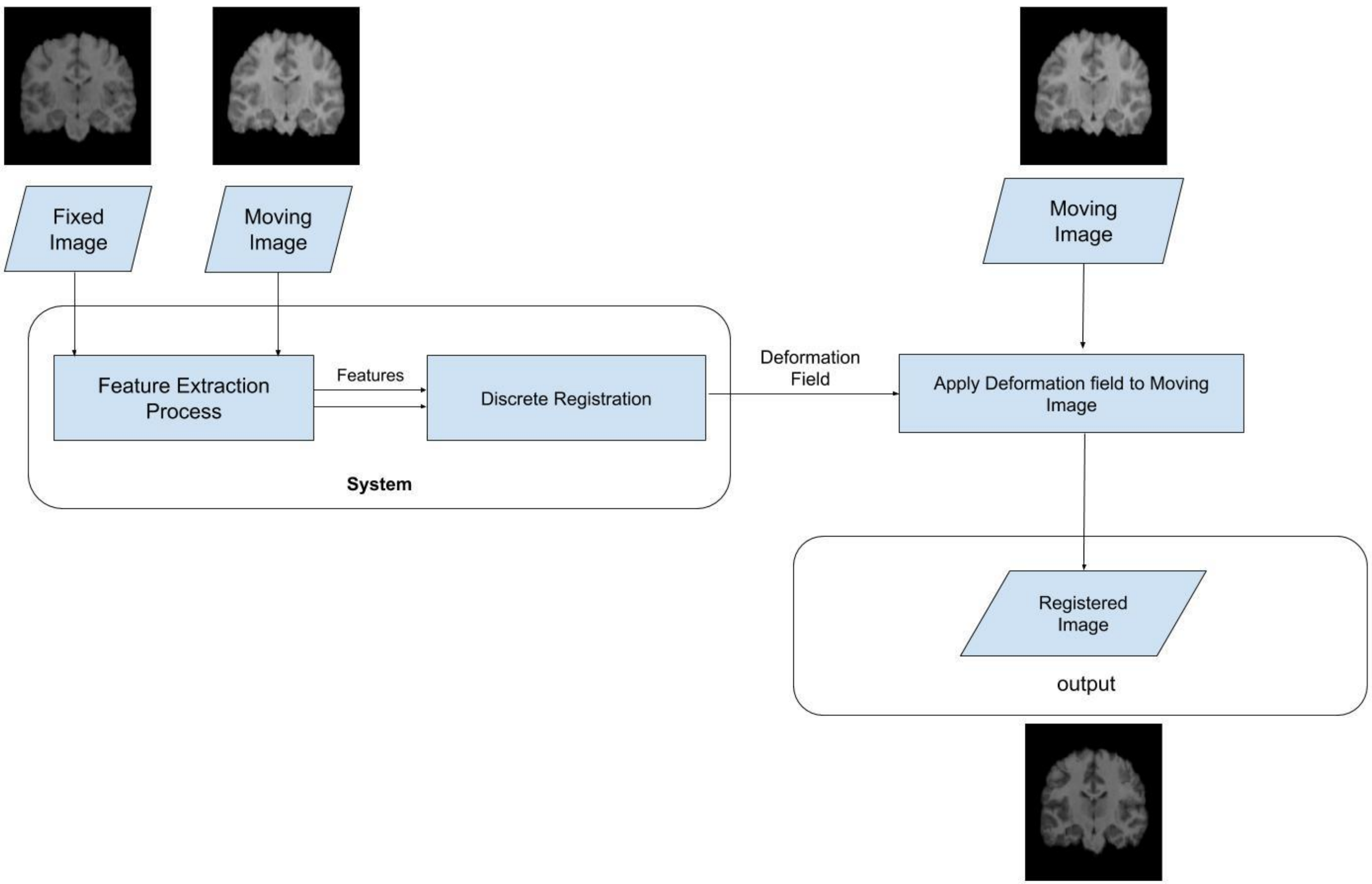
(5) Wu et al., IEEE TBME 2016
(6) Shakeri et al, MICCAI 2016

In this paper..

- We explores the pros and cons of using different DNNs to learn features in the context of registration.

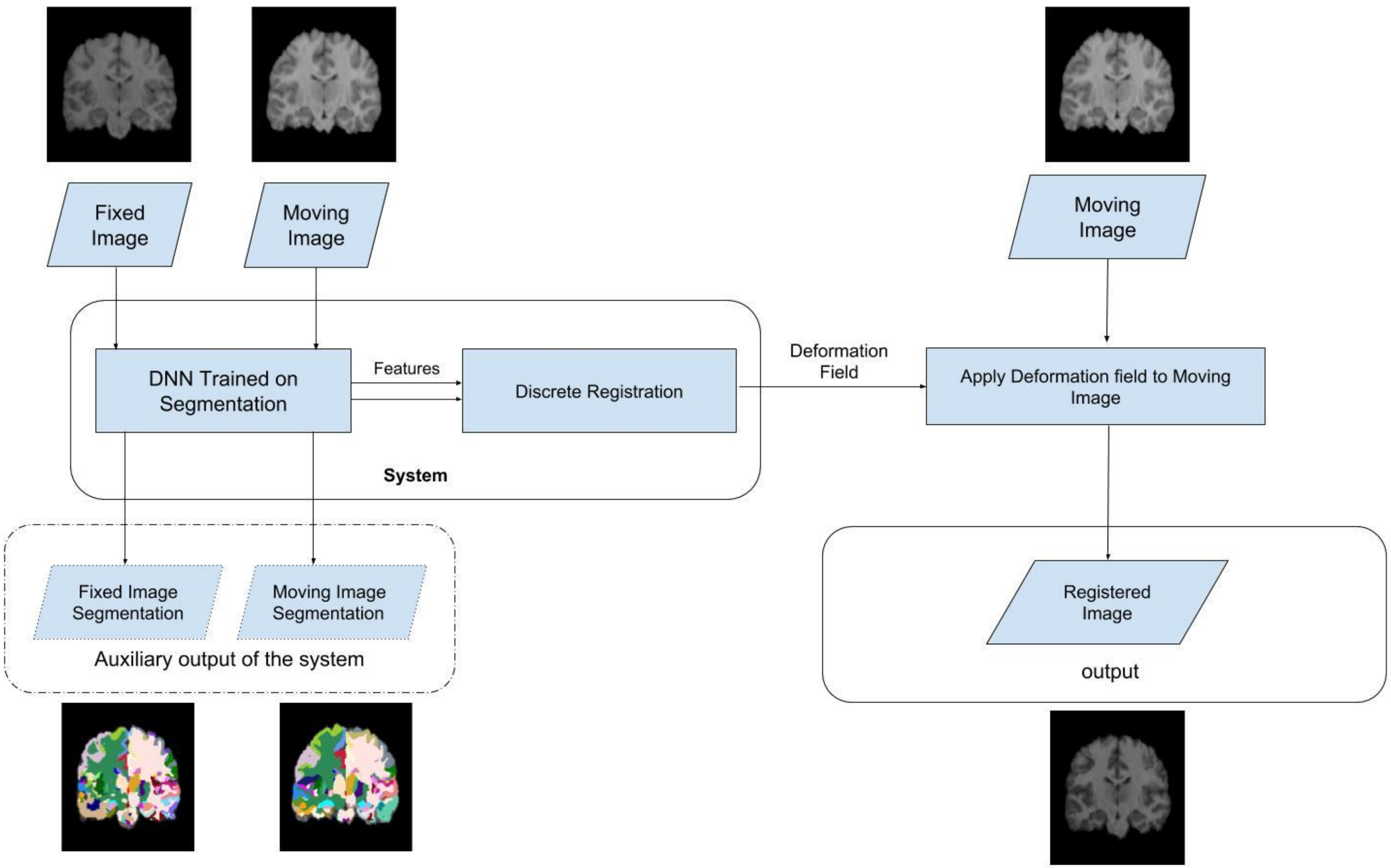
- Features are learnt by training DNNs for structure segmentation task on Brain MRIs

Feature-Based Registration



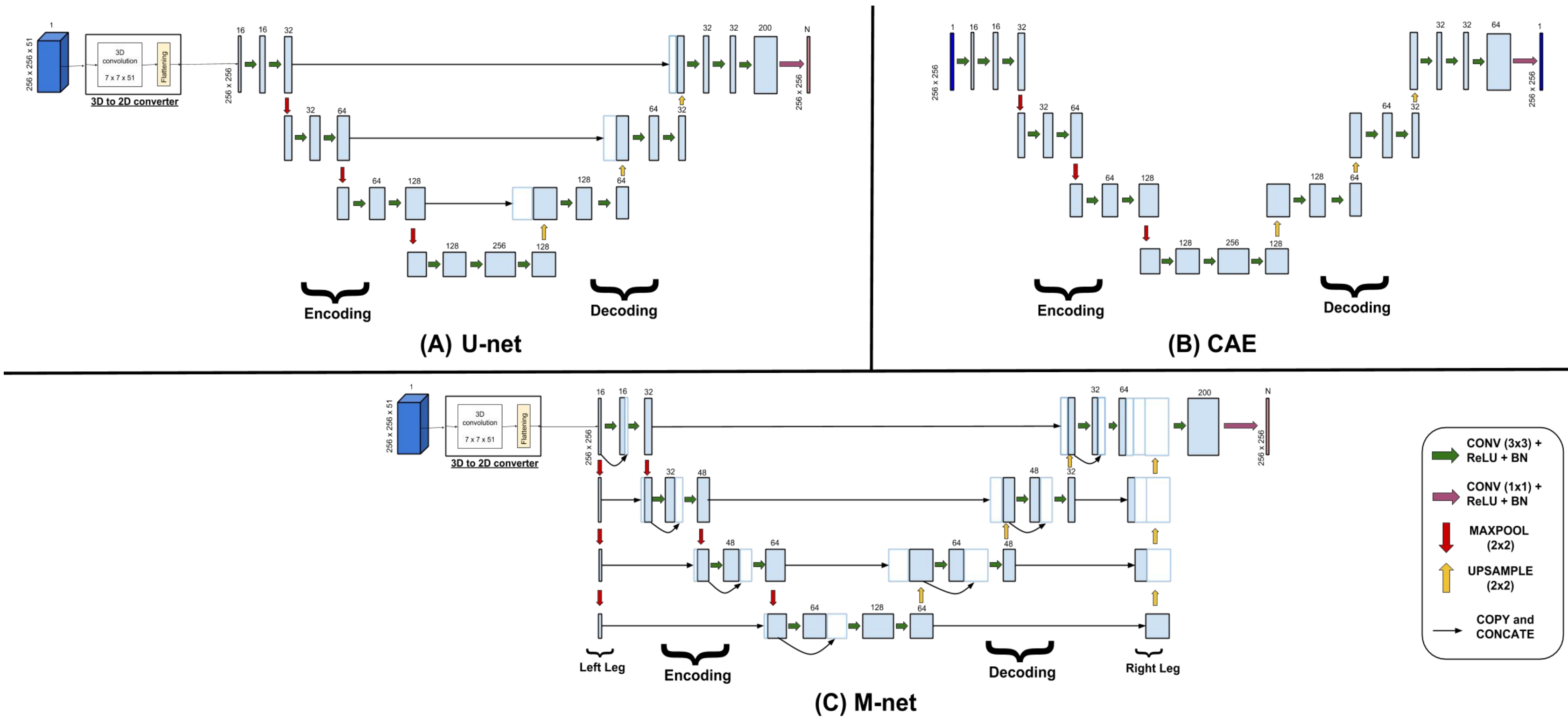
(7) Heinrich et al., WBIR 2014

Our Method



(7) Heinrich et al., WBIR 2014

Architecture of DNNs used

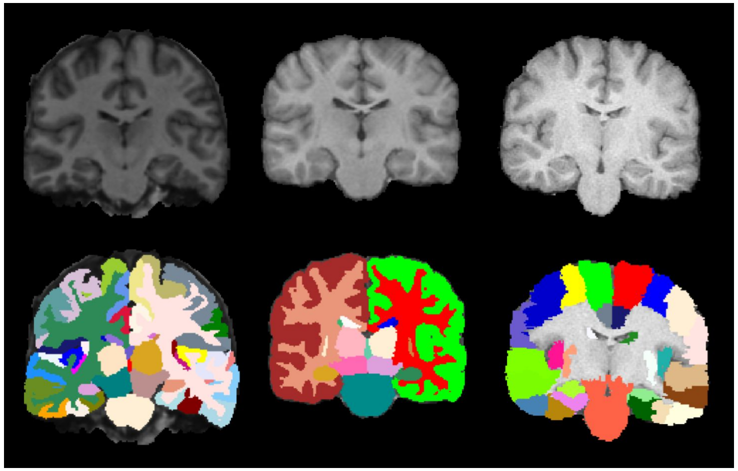


(8) Ronneberge et al., MICCAI 2015
(9) Mehta et al, ISBI 2017
(10) Masci et al., ICANN 2011

Datasets Used

DNN Training Dataset

1. **MICCAI-2012** : 135 labels, Whole brain parcellated
2. **IBSR18** : 32 labels, Whole brain parcellated
3. **LPBA40** : 57 labels, Partial brain parcellated



MICCAI-2012 [11] **IBSR18** [12] **LPBA40** [13]

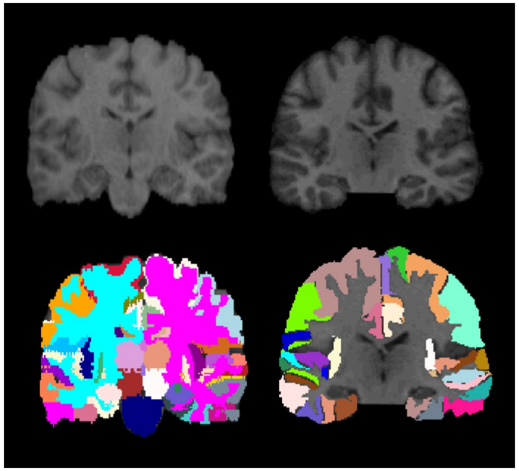
(11) Landman and Warfield, MICCAI 2012 workshop on multi-atlas labeling.
(12) Rohlfing, TMI 2012
(13) Shattuck et al., NeuroImage 2008

Datasets Used

Registration Testing Dataset

Chosen based on their popularity for evaluating registration [14].

1. **CUMC12** : 12 volumes, 130 labels
2. **MGH10** : 10 volumes, 106 labels



CUMC12 **MGH10**

(14) Klein et al., NeuroImage 2009

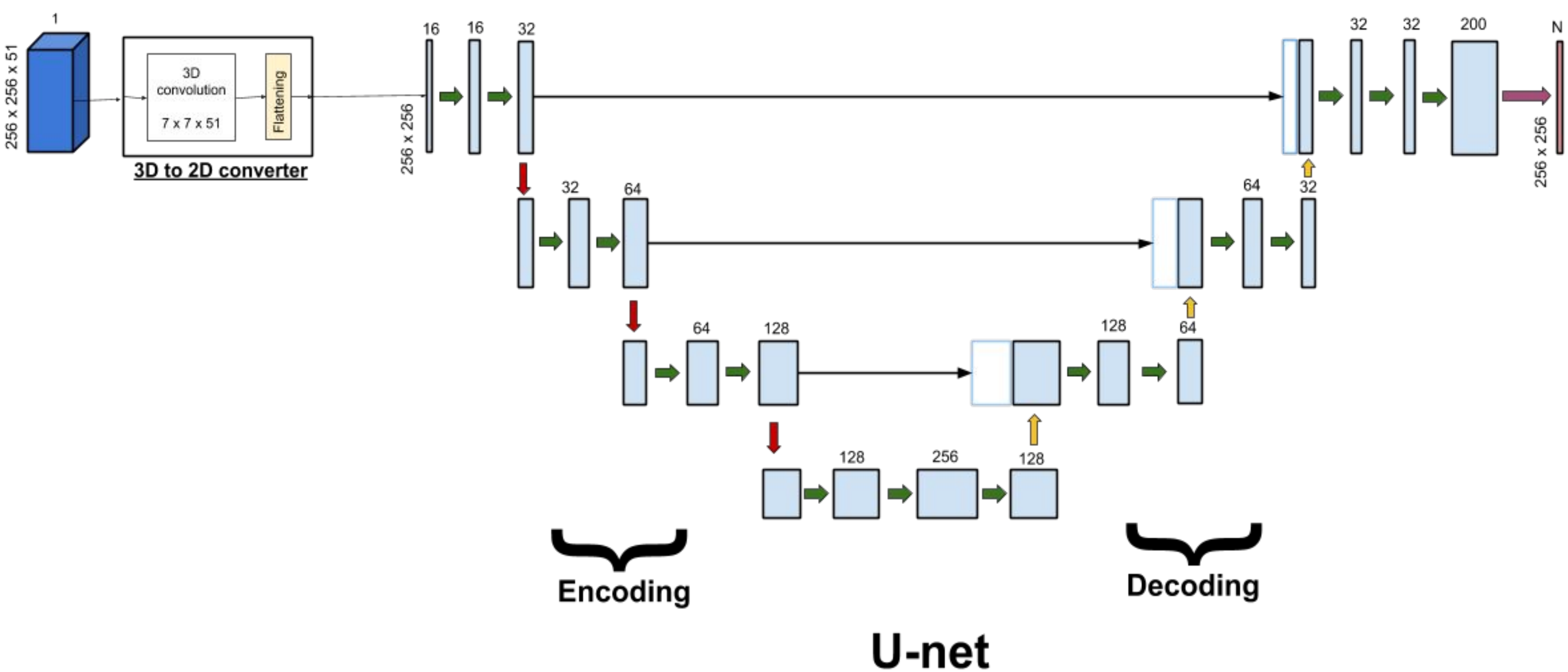
Implementation

- DNNs trained on a NVIDIA K40 GPU with 12 GB RAM
- Training time ~ 3 days
- Code for Deep Learning in Python with Keras Library
- Code for Discrete Registration in C++
- Optimiser: Adam
- Hyper parameters: LR = 0.001, β_1 = 0.9, β_2= 0.99 and ϵ = 10 * e^{-8}
- Evaluation: mean Jaccard Coefficient over all pair-wise registration

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|}.$$

Insights

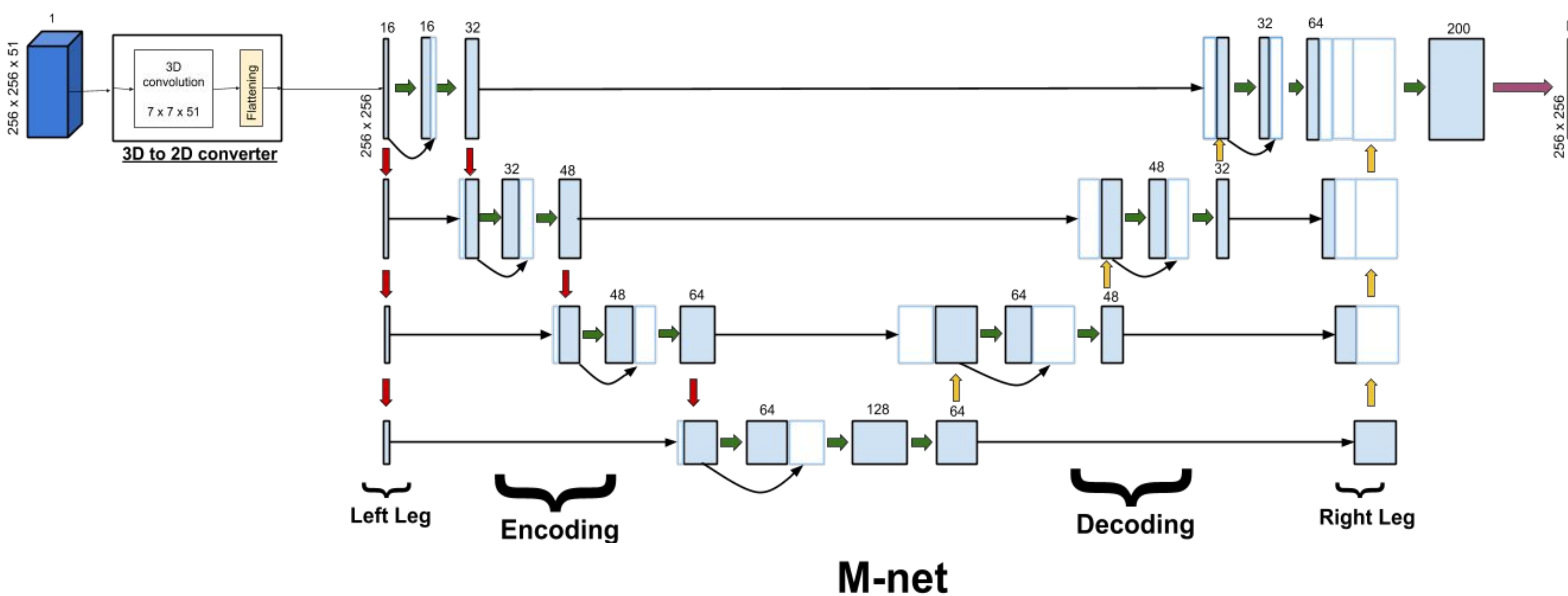
1. Role of complexity of learning architecture:



(8) Ronneberge et al., MICCAI 2015

Insights

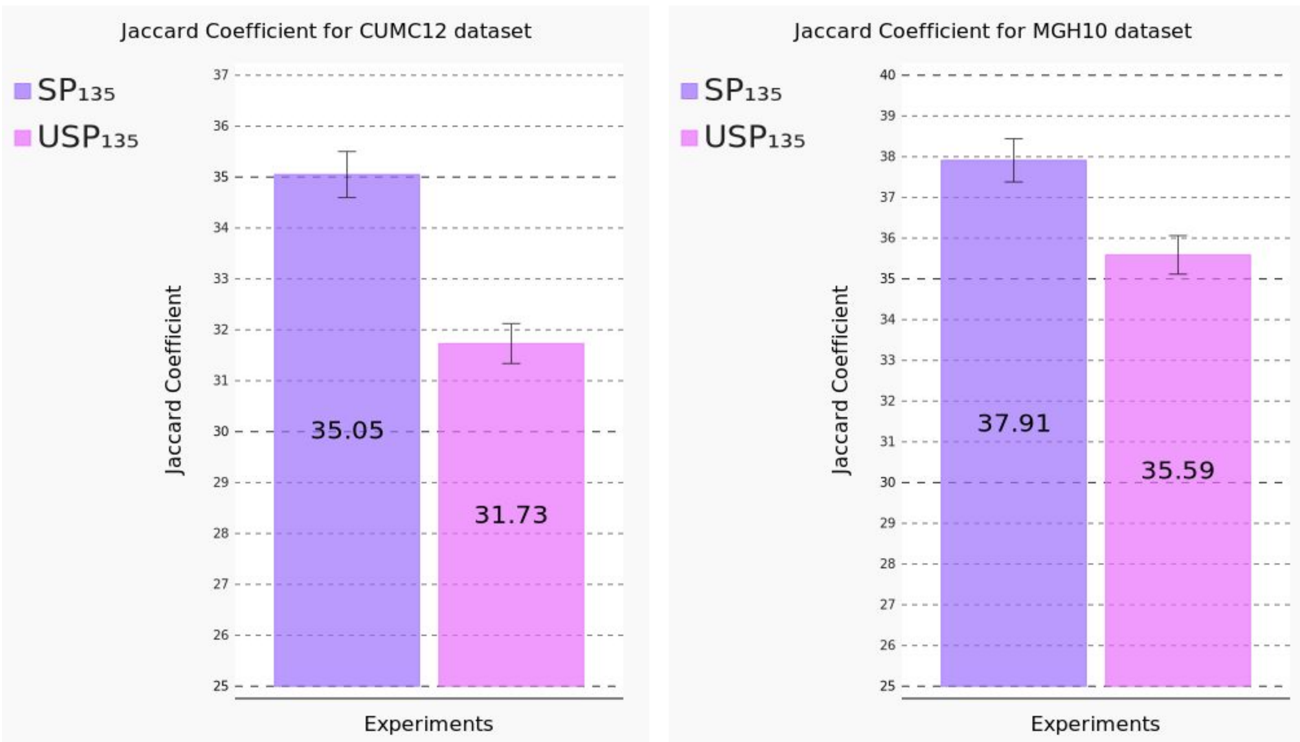
1. **Role of complexity of learning architecture:**



(9) Mehta et al., ISBI 2017

Insights

1. **Role of complexity of learning architecture:** M-net with added residual and supervision connections gives better performance than U-net

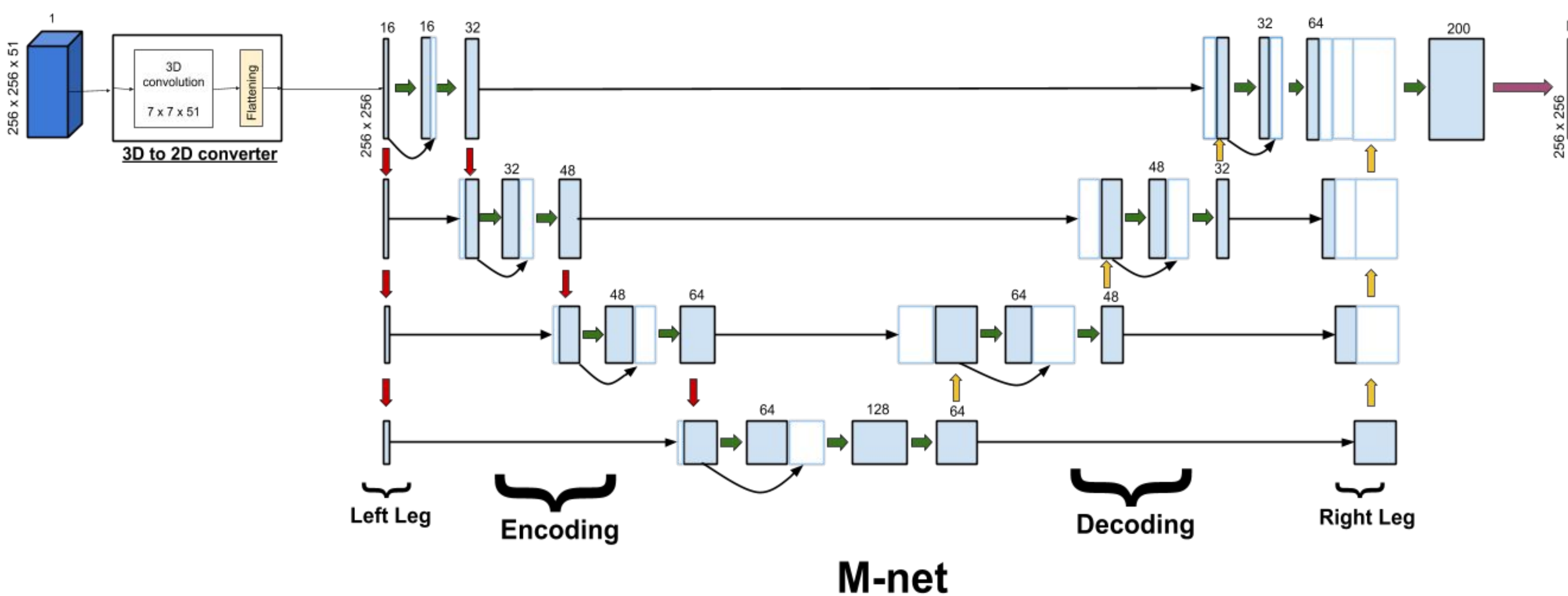


SP$_{135}$: Segmentation Priors from M-net trained on MICCAI-2012

USP$_{135}$: Segmentation Priors from U-net trained on MICCAI-2012

Insights

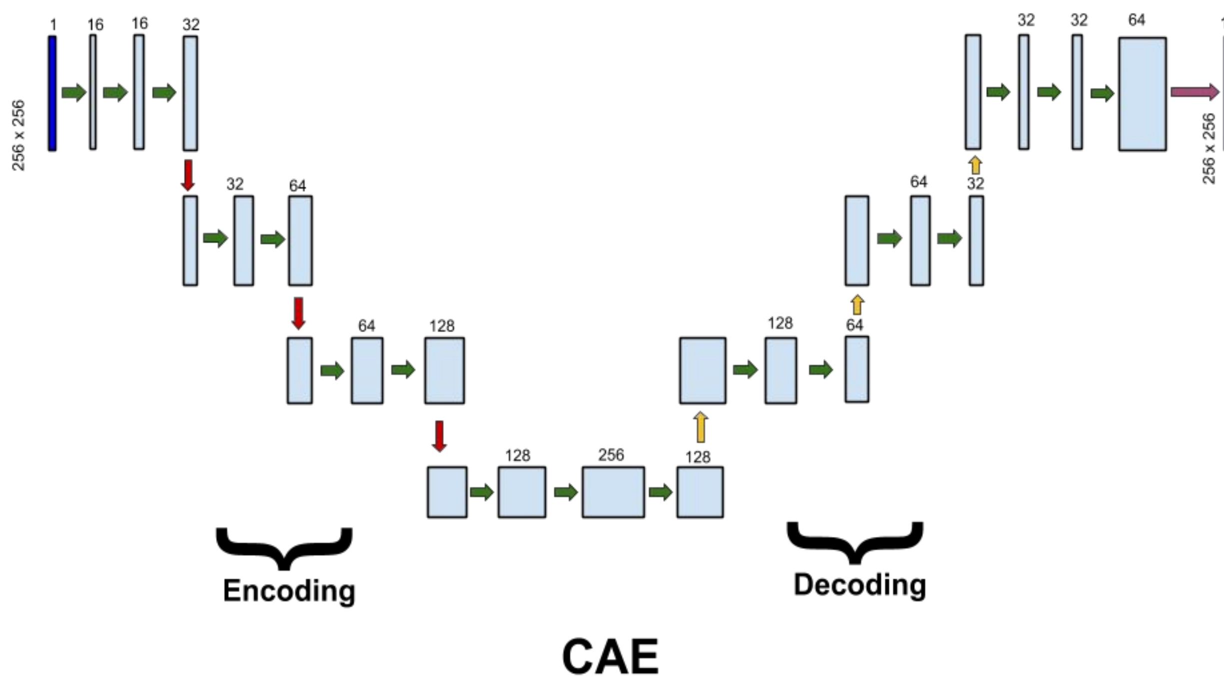
2. **Supervised vs Unsupervised Learning:**



(9) Mehta et al., ISBI 2017

Insights

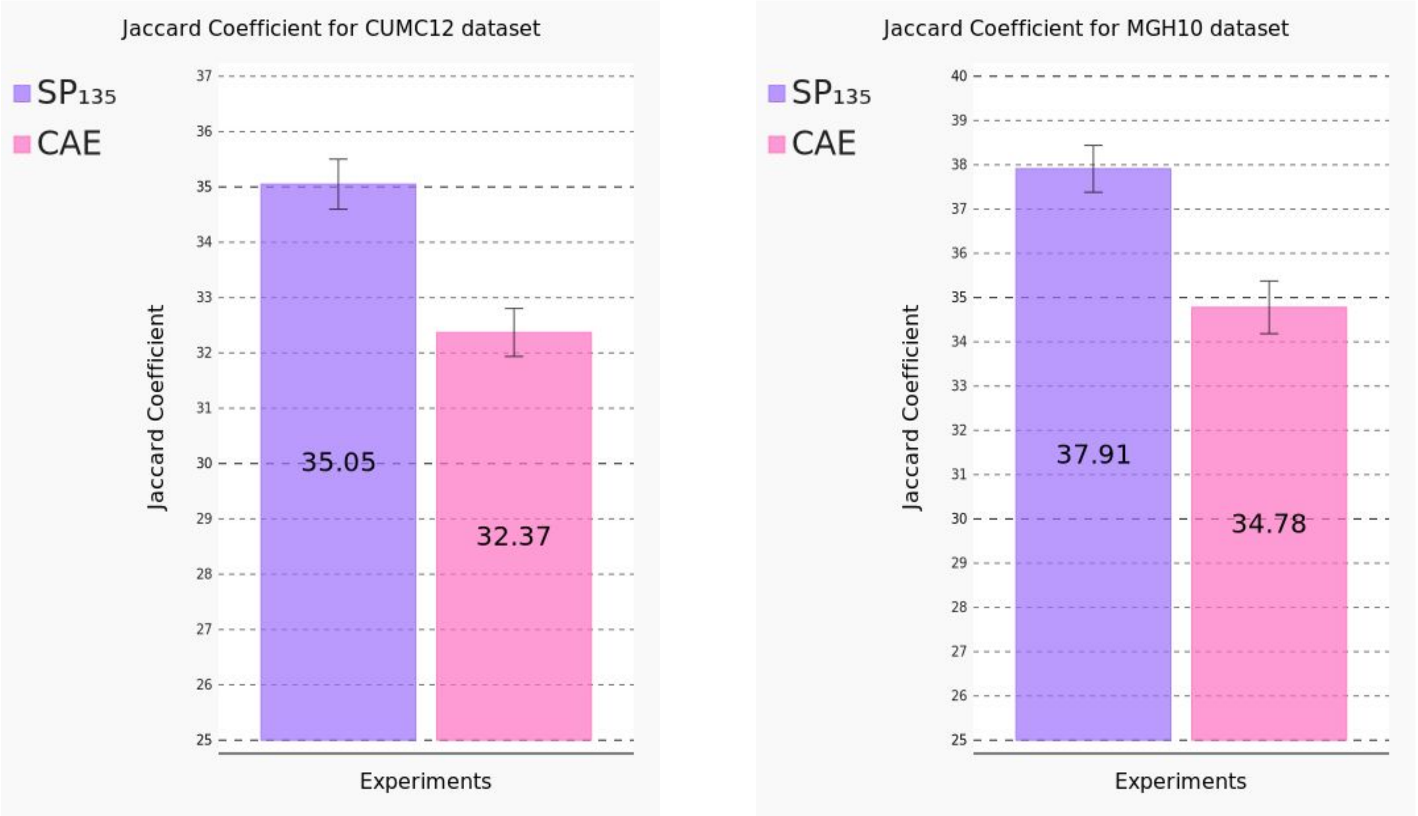
2. **Supervised vs Unsupervised Learning:**



(9) Masci et al., ICANN 2011

Insights

2. **Supervised vs Unsupervised Learning:** Supervised Learning gave better performance than Unsupervised Learning.

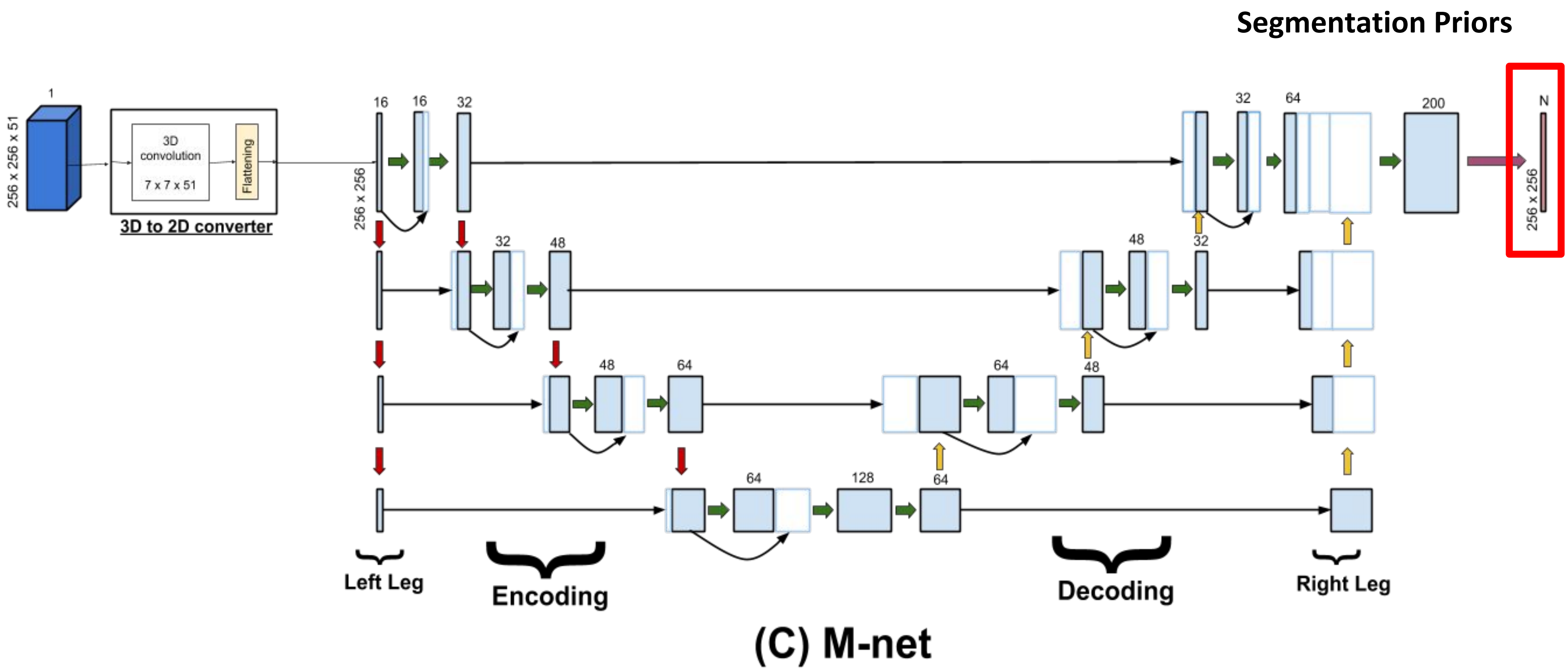


SP_{135} : Segmentation Priors from M-net trained on MICCAI-2012

CAE: Features from Convolutional Auto-Encoder (CAE) trained on MICCAI-2012

Insights

3. Choice of learnt features:

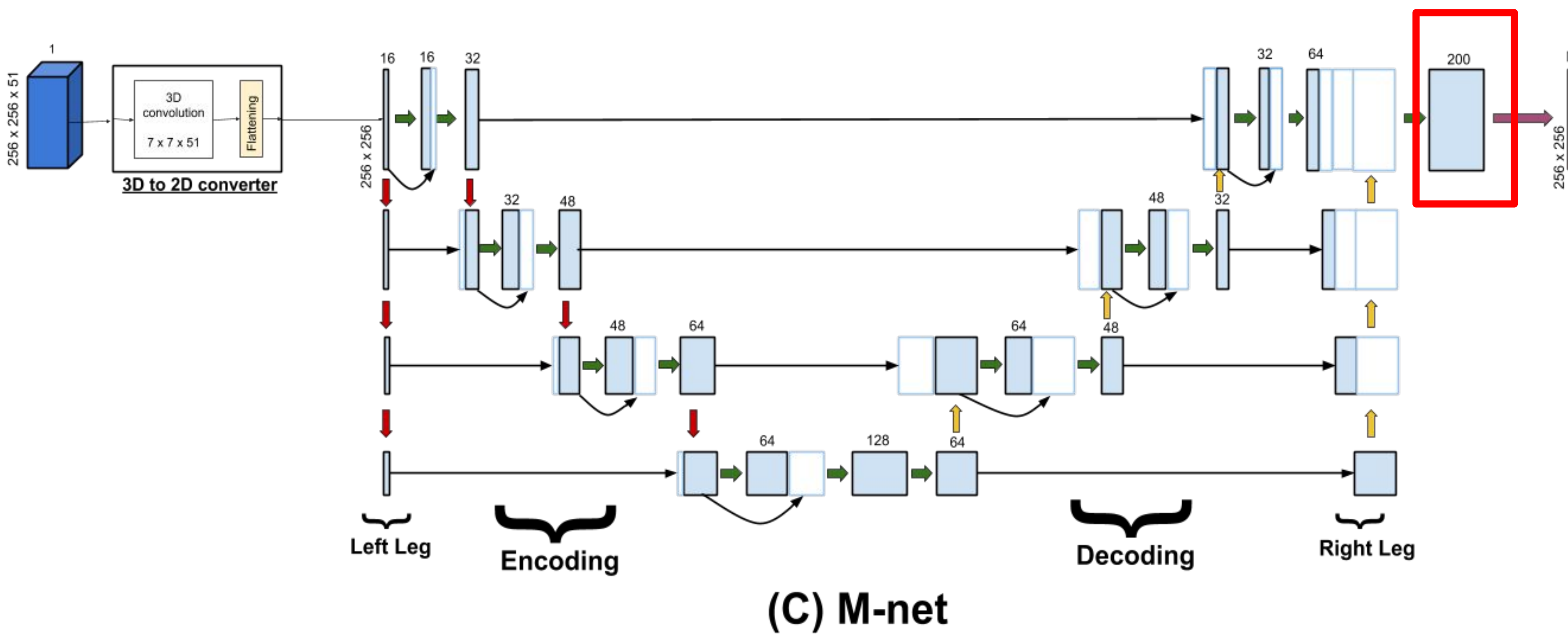


(9) Mehta et al., ISBI 2017

Insights

3. Choice of learnt features:

Penultimate Layer Features

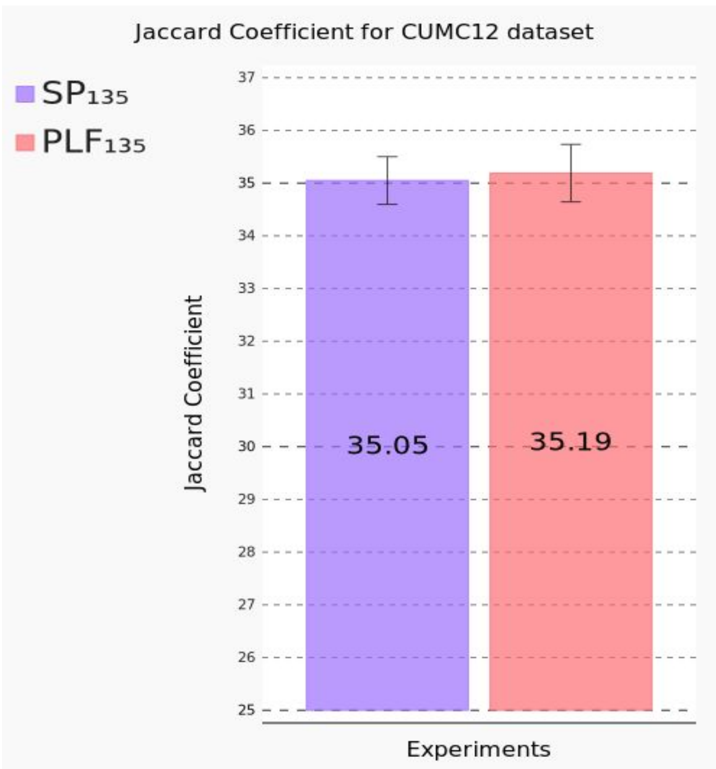


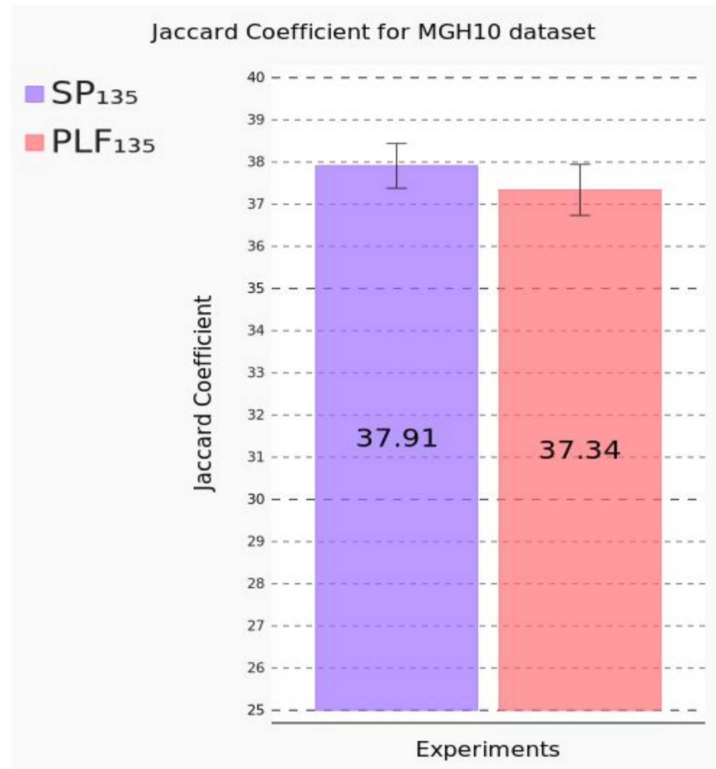
(C) M-net

(9) Mehta et al., ISBI 2017

Insights

3. **Choice of learnt features:** Both PLF and SP provided features which were comparable in performance.



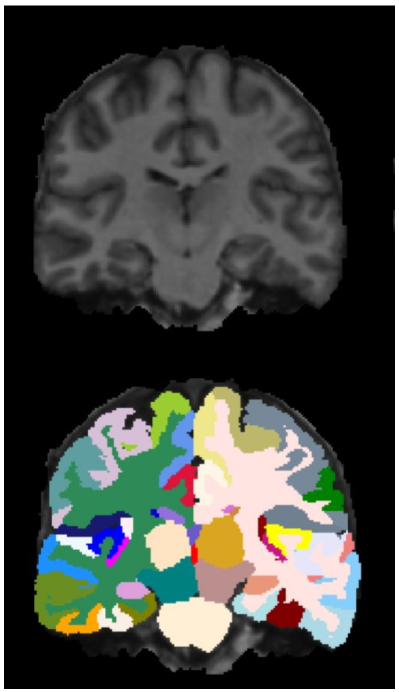


SP$_{135}$: Segmentation Priors from M-net trained on MICCAI-2012

PLF$_{135}$: Penultimate Layer Features from M-net trained on MICCAI-2012

Insights

4. **Role of the number of labeled structures in training data:**

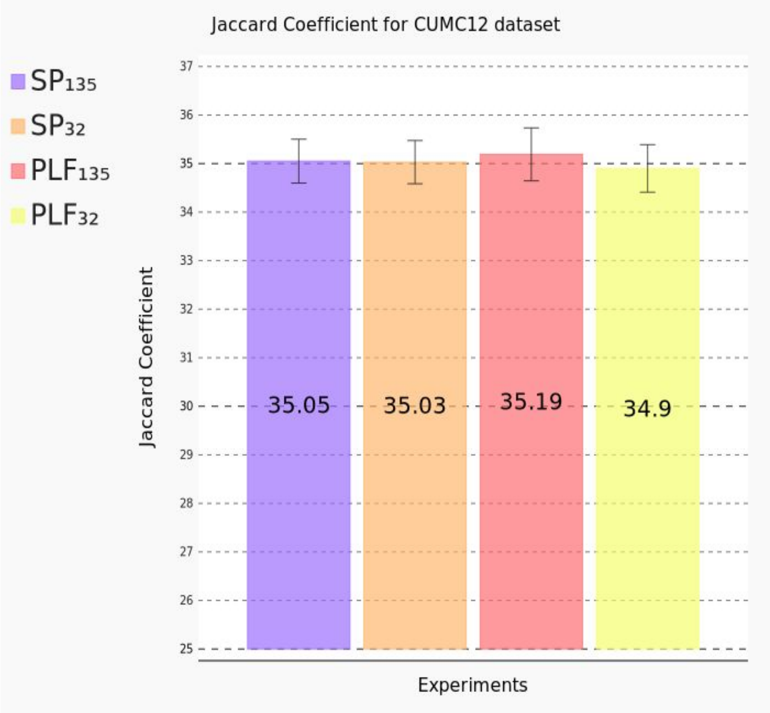


MICCAI-2012

IBSR18

Insights

4. **Role of the number of labeled structures in training data:** Features learned from different number of structures in training dataset appeared to be equally effective.

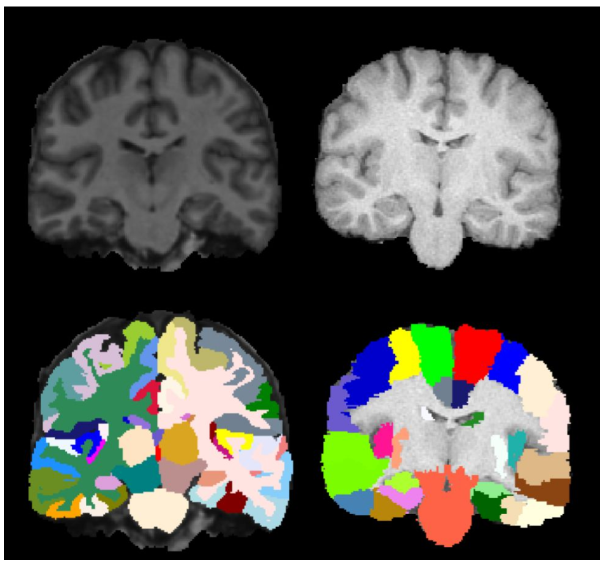


SP_{135} and **SP_{32}** : Segmentation Priors from M-net trained on MICCAI-2012 and IBSR18 respectively

PLF_{135} and **PLF_{32}** : Penultimate Layer Features from M-net trained on MICCAI-2012 and IBSR18 respectively

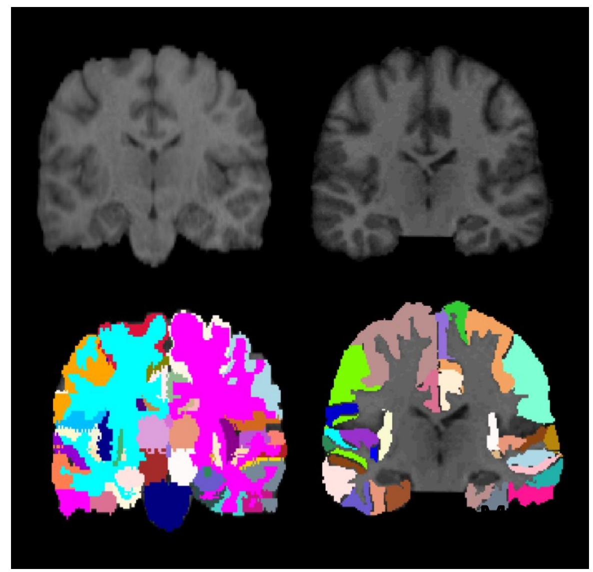
Insights

5. **Parcellation of training dataset:**



MICCAI-2012 **LPBA40**

DNN Training Datasets

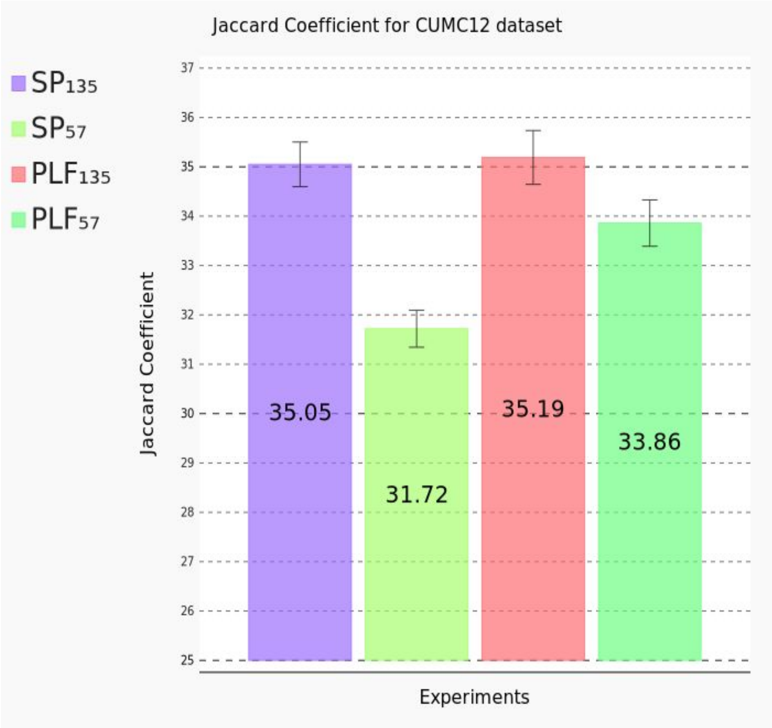


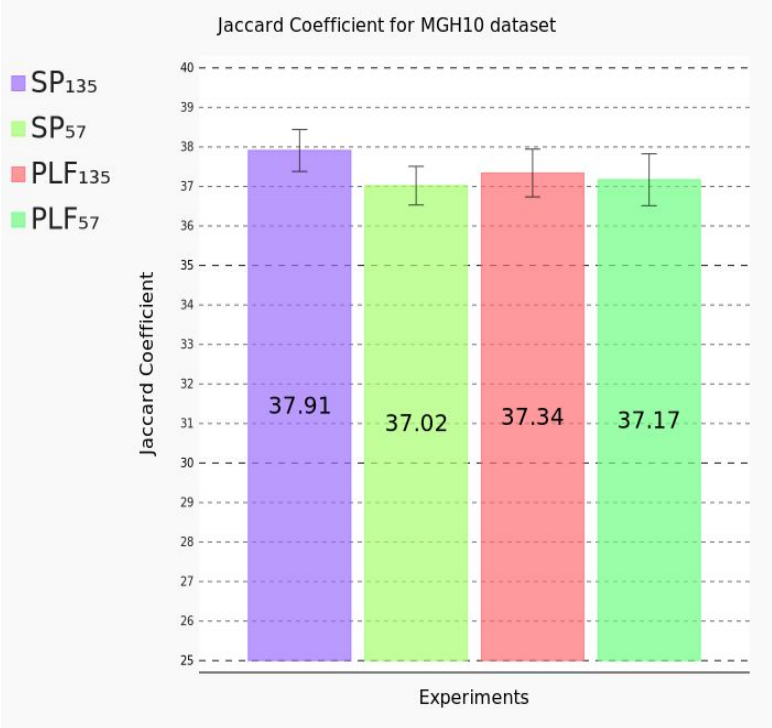
CUMC12 **MGH10**

Registration Testing Datasets

Insights

5. **Parcellation of training dataset:** CNN trained on whole brain parcellated dataset gave better results than partial brain parcellated dataset.





SP_{135} and **SP_{57}** : Segmentation Priors from M-net trained on MICCAI-2012 and LPBA40 respectively

PLF_{135} and **PLF_{57}** : Penultimate Layer Features from M-net trained on MICCAI-2012 and LPBA40 respectively

Insights

6. **Learnt Features vs Hand-crafted Features:**

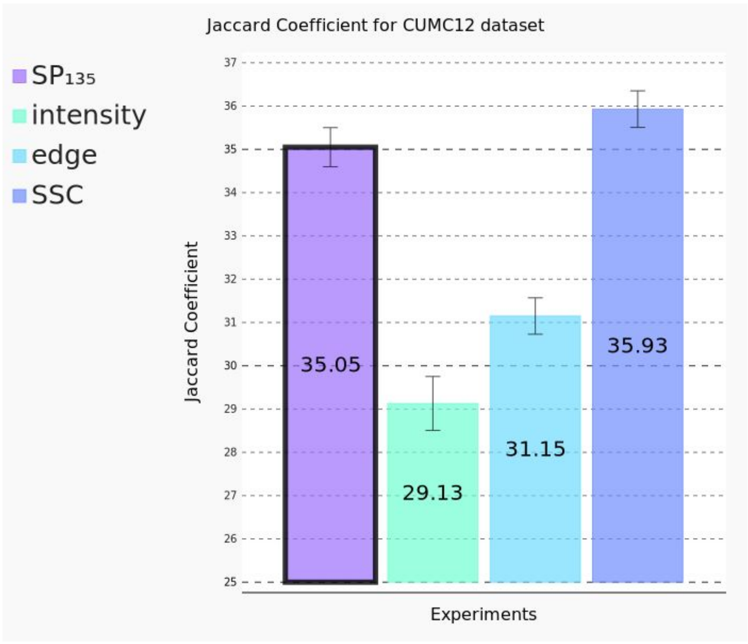
- Hand-crafted Feature:
  - Intensity
  - Edge
  - SSC [4]

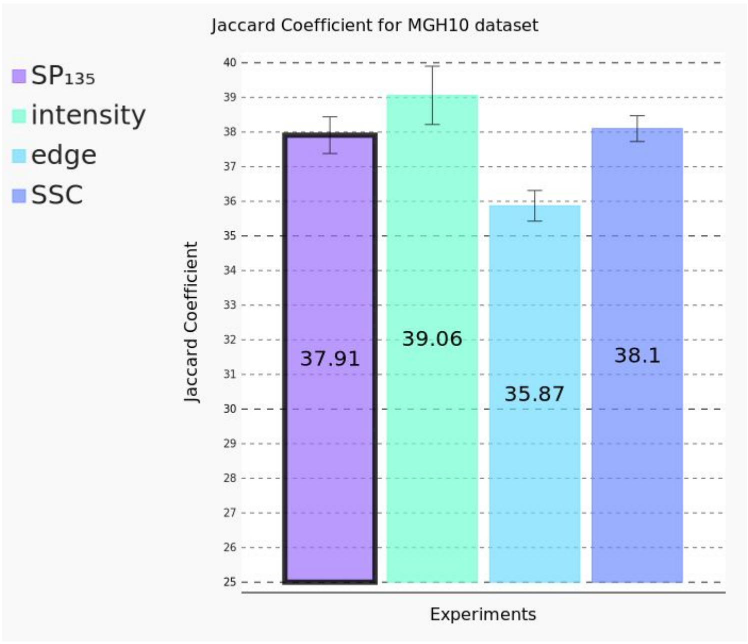
- Segmentation Priors from M-net trained on MICCAI-2012

(4) Heinrich et al., MICCAI 2013 (SSC)

Insights

6. **Learnt Features vs Hand-crafted Features:** Features learned using ***<u>Deep Learning Failed</u>*** to give better performance then SSC.





Conclusions

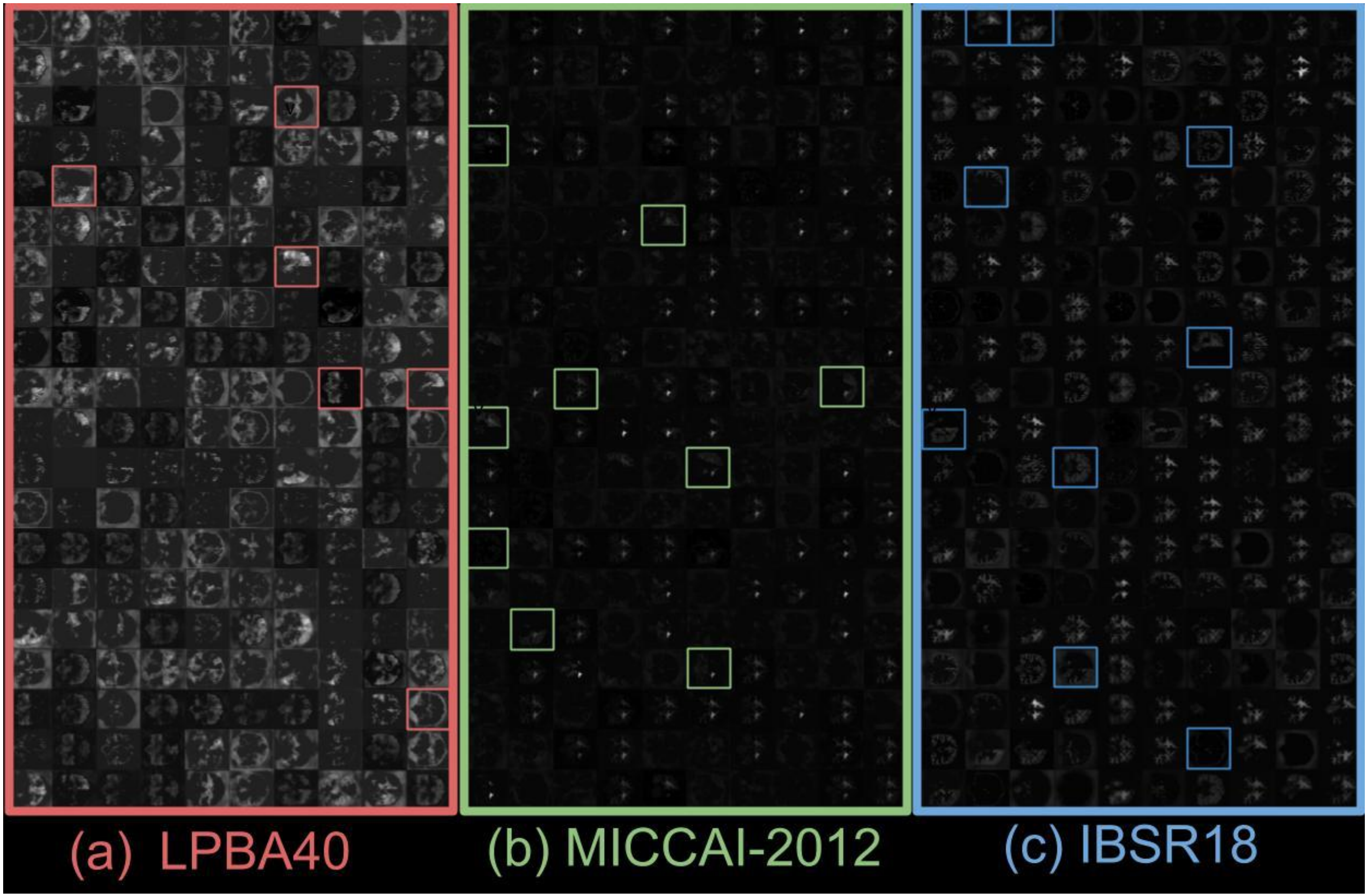
Learning features was explored with different DNN architectures and training regimes.

- Learning features requires high computational resources
  - A feature which need not be learnt (SSC) is the best option in **low-resource settings** and **limited annotated data** scenario, especially if only registration is of interest.

- In a scenario where **both registration and segmentation are of interest**, learning is the better option.

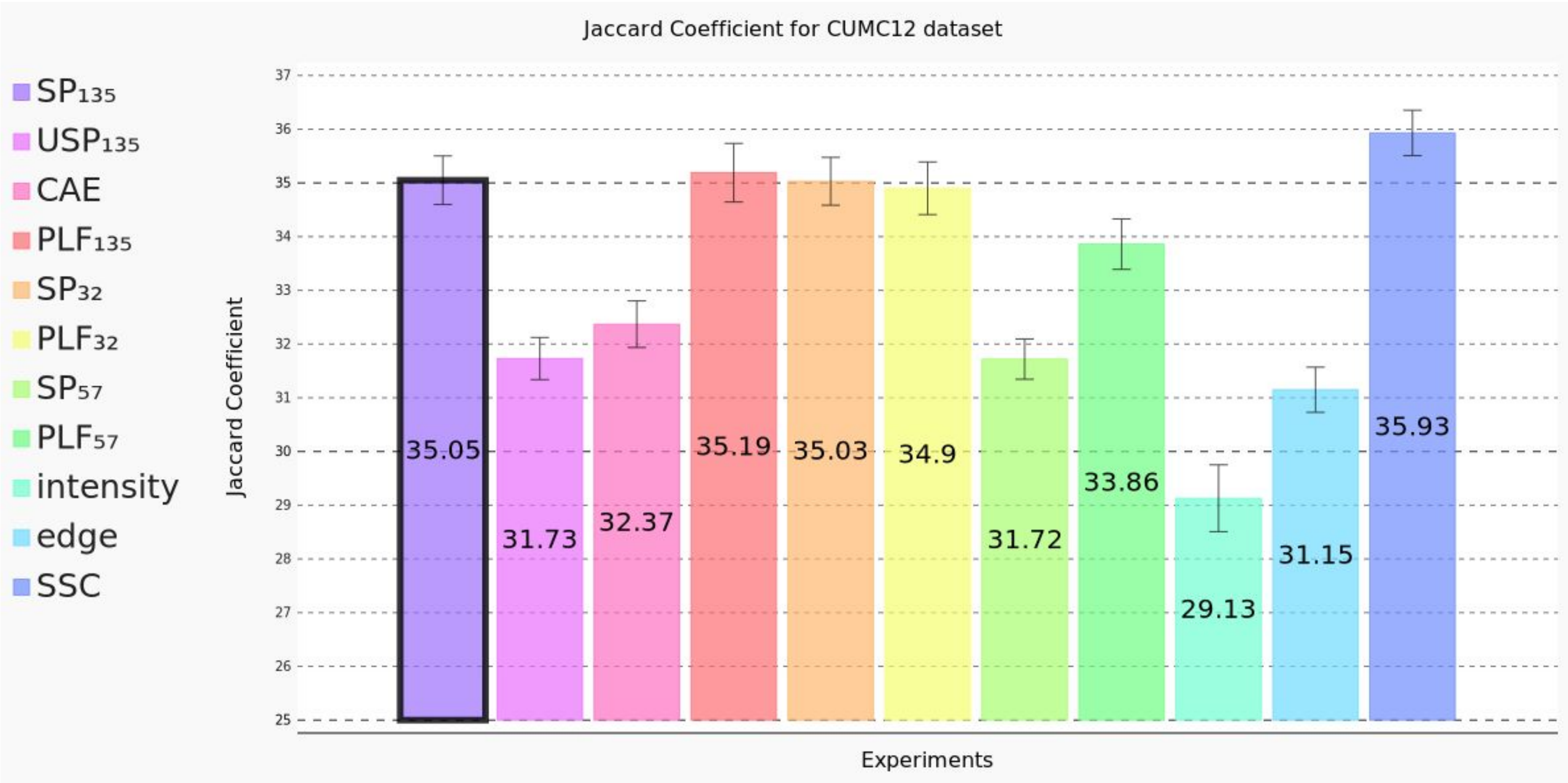
Thank You!

Visualisation of Features



[E1]

Results

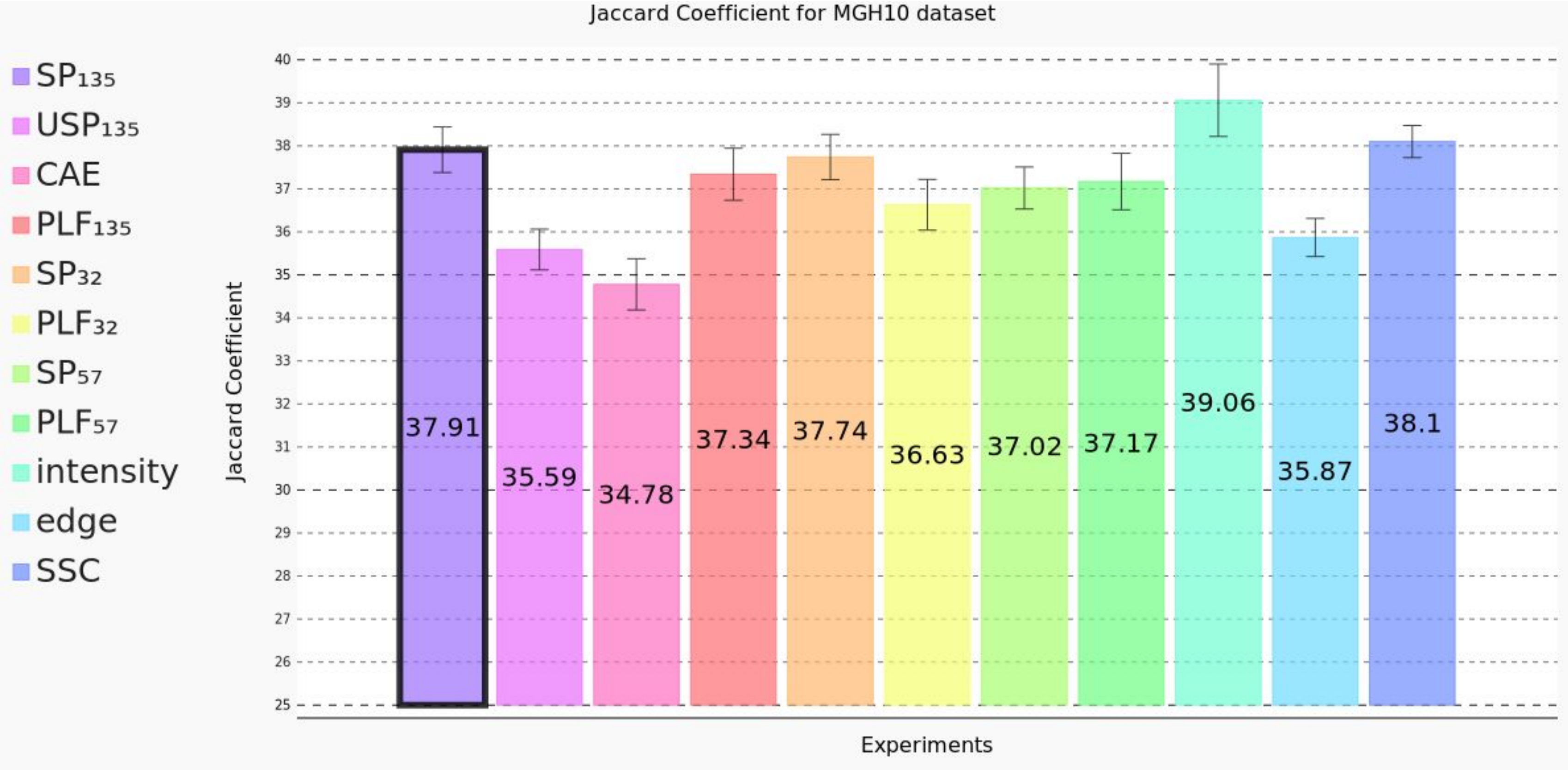


SP$_{135}$: Segmentation Priors from M-net trained on MICCAI-2012 **CAE**: Convolutional AutoEncoder

USP$_{135}$: Segmentation Priors from U-net trained on MICCAI-2012 **PLF**: Penultimate Layer Features

$_{135}$: trained on MICCAI-2012 $_{32}$: trained on IBSR18 $_{57}$: trained on LPBA40

Results



SP$_{135}$: Segmentation Priors from M-net trained on MICCAI-2012 **CAE**: Convolutional AutoEncoder

USP$_{135}$: Segmentation Priors from U-net trained on MICCAI-2012 **PLF**: Penultimate Layer Features

$_{135}$: trained on MICCAI-2012 $_{32}$: trained on IBSR18 $_{57}$: trained on LPBA40

[E3]

Computational Time

- 1 Pairwise Registration takes 2 mins of CPU and 8 min of GPU time for Registration using Learnt Features

- SSC only takes 2-3 mins of CPU time for 1 Pairwise Registration.

[E4]

Discrete Registration [7]

- The Cost function to be minimised consists of a similarity and regularisation term.

$$E(u) = \sum_{\Omega} S(I_f, I_m, u) + \alpha |\nabla u|^2$$

- The deformation field is only allowed values from a quantised set of 3-D displacement.
- A 6 dimensional displacement space volume is created for storing the cost of translating a voxel x with a displacement d.

$$DSV(x, d) = S(I_f(x), I_m(x + d))$$

(7) Heinrich et al., WBIR 2014

Discrete Registration [7]

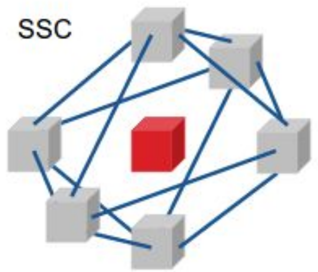
- The displacement field is obtained by winner-takes-all method by selecting the field with the lowest cost for each voxel.

(7) Heinrich et al., WBIR 2014

Why SSC better than learnt features?

- SSC is a feature explicitly derived for registration whereas learnt features such as SP are optimised for good segmentation as they are trained on a segmentation dataset.
- It gives a good context of within the neighbourhood of the voxel.
    - Uses pairs of patches in six neighbourhood (with a spatial distance √2)
    - Avoids central patch for robustness against noise

$$\mathcal{S}(I, \mathbf{x}, \mathbf{y}) = \exp\left(-\frac{SSD(\mathbf{x}, \mathbf{y})}{\sigma^2}\right) \quad \mathbf{x}, \mathbf{y} \in \mathcal{N}$$



[E7]