Unsupervised Hyperspectral Segmentation on Placenta Database

Industrial Project

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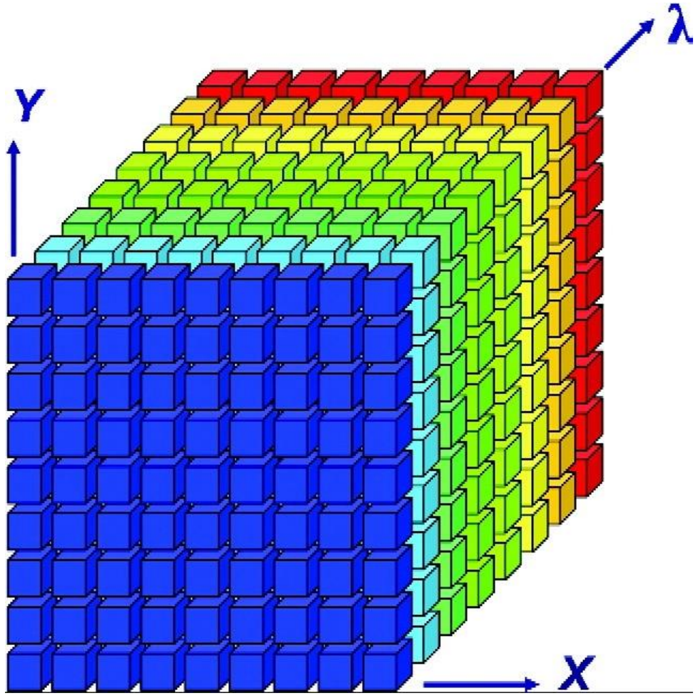
Contents

Introduction

Introduction

- Hyper Spectral Images (HSI)
- Normal Image (RGB) vs HSI.
- Number of bands defines whether RGB, multi-spectral or hyper-spectral.



[1]

Dataset

- Placenta dataset
- There are 107 Hyperspectral images.
- Each image has 37 bands.

(a) Set 1, upper 6, icg (b) Set 1, lower 3 (c) Set 1, lower 6, icg

Hyper Spectral Images

(a) Set 1, upper 6, icg (b) Set 1, lower 3 (c) Set 1, lower 6, icg

Masks of Hyper Spectral Images

Dimensionality Reduction Methods

Dimensionality Reduction Methods

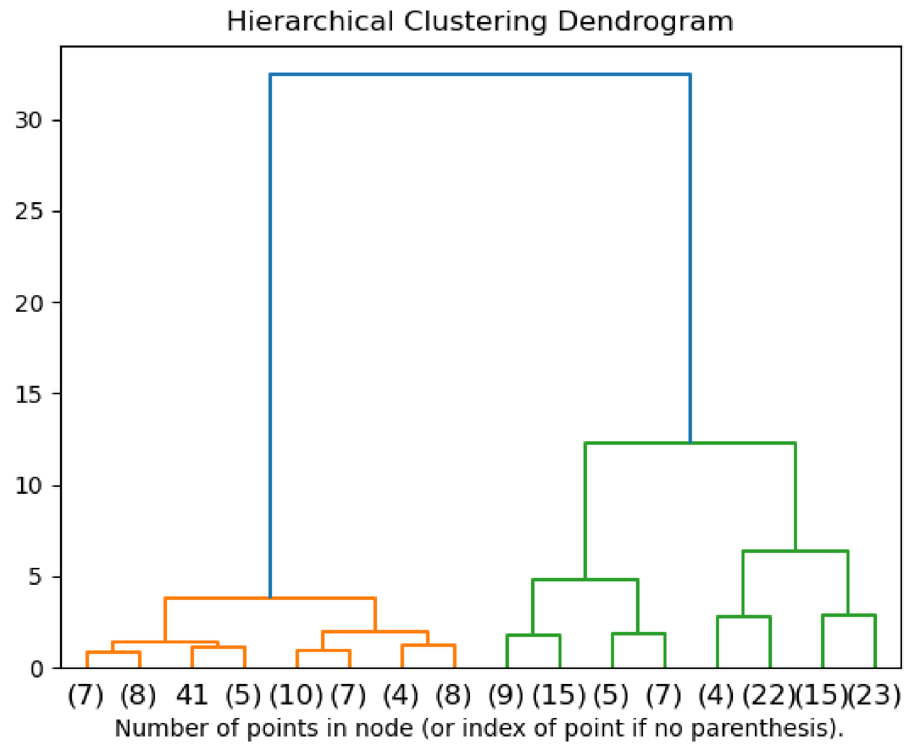
- Three reduction methods used in this project.
  - Eigen images
  - Feature Agglomeration
  - Optimal band selection

Eigen images

- PCA can be extended to images.
- Get PCs treating each pixel spectrum as a sample.
- Dot product with hyperspectral cube to get eigen images

Feature Agglomeration

- Based on the Hierarchical Clustering.
- Recursively merges pair of clusters.
- Cluster as a tree-based dendrogram.
- Cut to get reduced features.

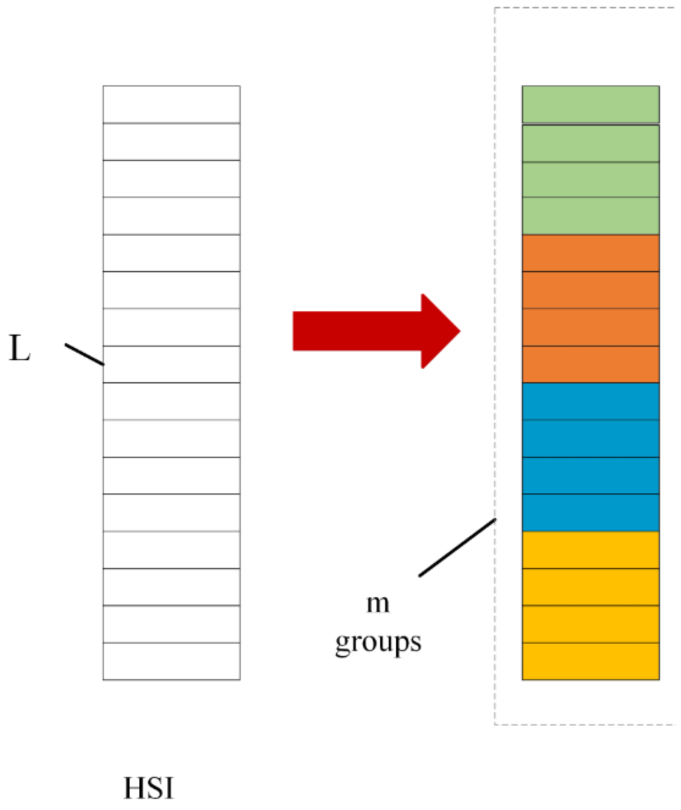


An Example of Dendrogram **[3]**

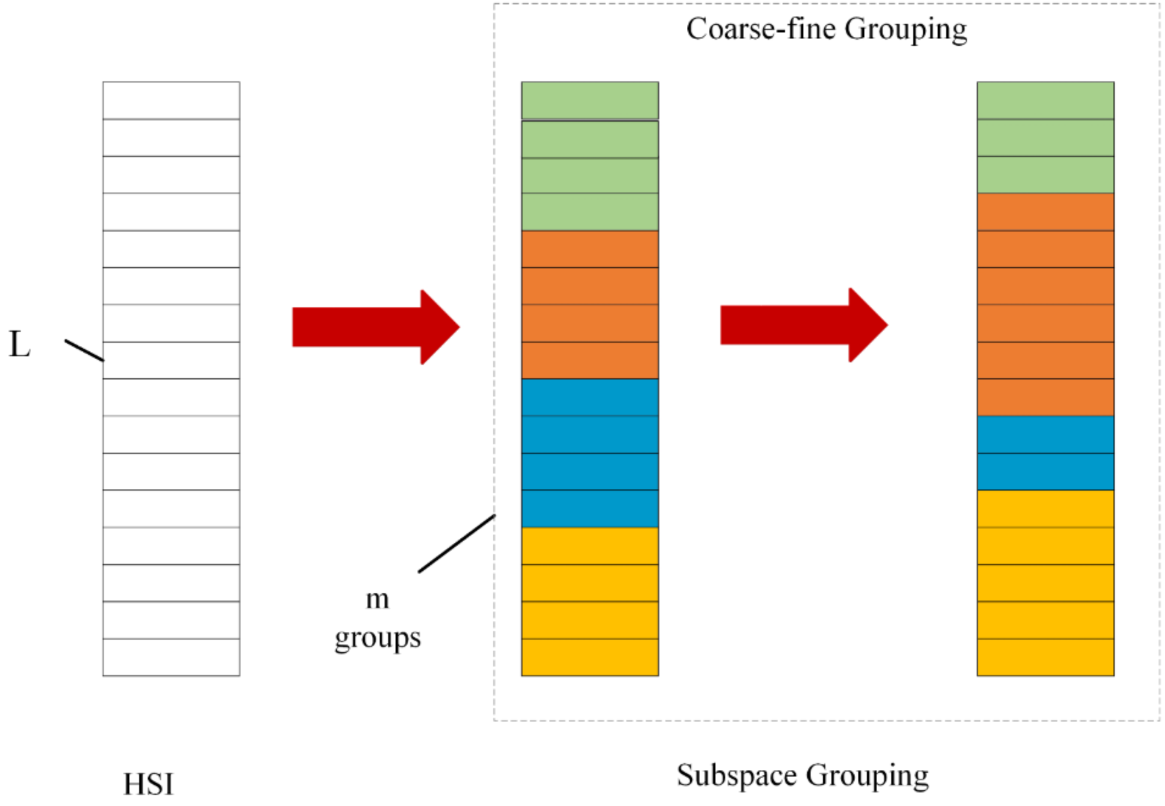
Optimal band selection

- Best bands selection for the hyperspectral image
- Reduces computational cost
- Unchanged feature space
- Grouping based on energy and desired number of sub-bands
- Final selection based on similarity matrix and local density.

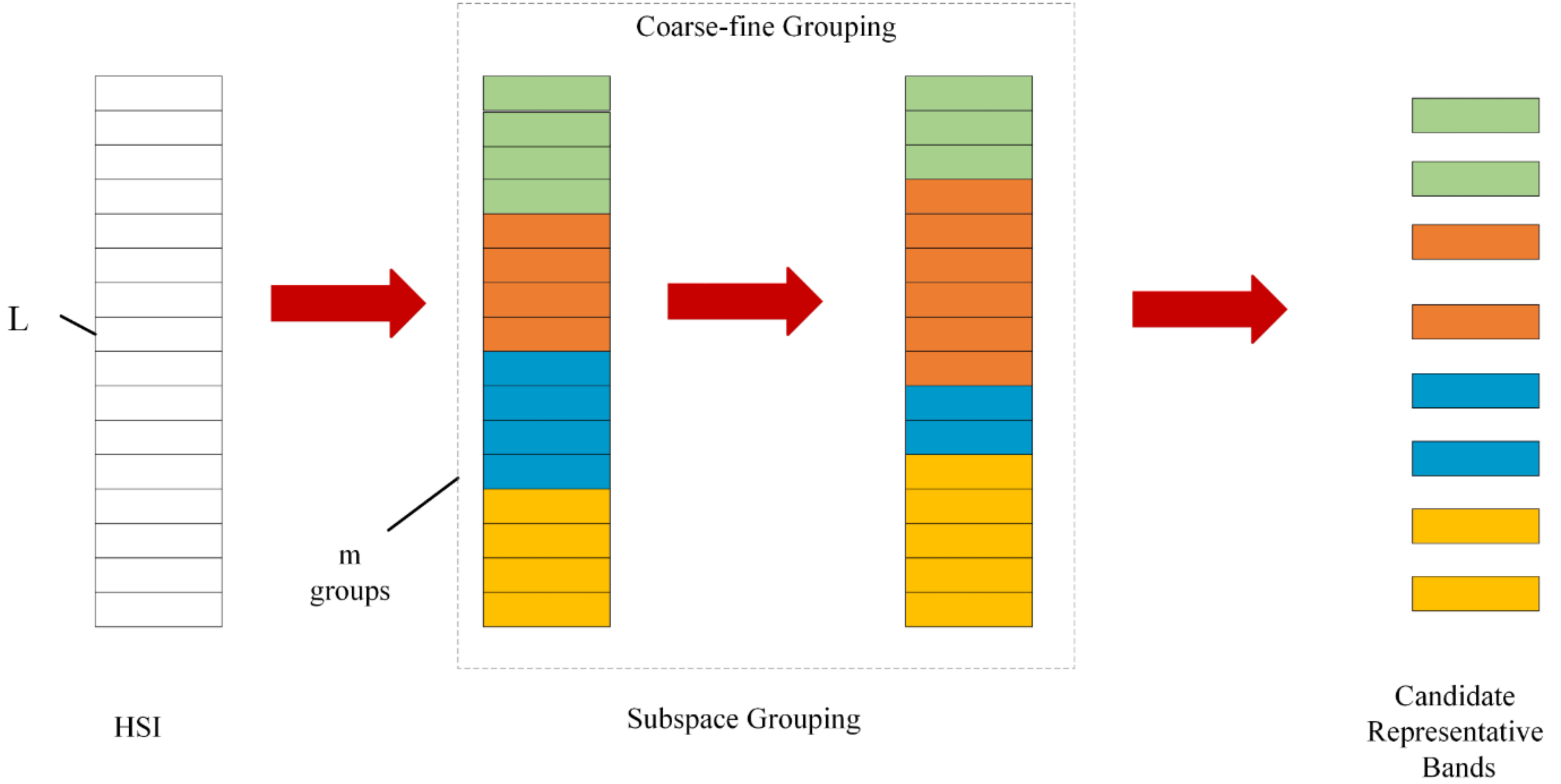
[2]



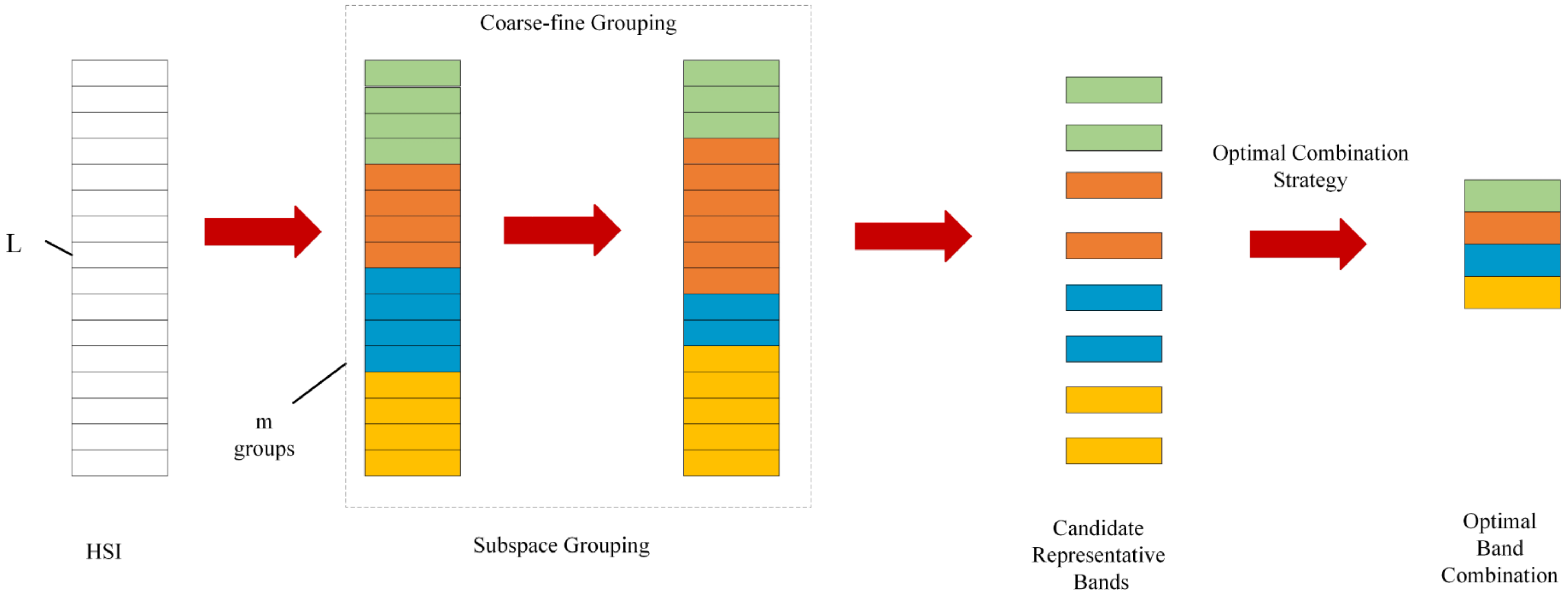
[2]



[2]


Coarse-fine Grouping
L
m
groups
HSI
Subspace Grouping
Candidate
Representative
Bands

[2]


Coarse-fine Grouping
L
m
groups
HSI
Subspace Grouping
Optimal Combination
Strategy
Candidate
Representative
Bands
Optimal
Band
Combination

Segmentation Methods

Segmentation Methods

- Following Segmentation Methods were explored
  - K-Means
    - Vanilla
    - With Feature Agglomeration
    - Spectral
  - Deep Learning based Cluster Segmentation (Variant I and II)
  - ResUnet based deep model (DLR-V1, -V2, -V3)

K-Means

Vanilla

- Euclidean distance between points in cluster.
- Based on the optimal band selection.
- It uses 11 bands out of 37 bands of HSI for computation.

With Features Agglomeration

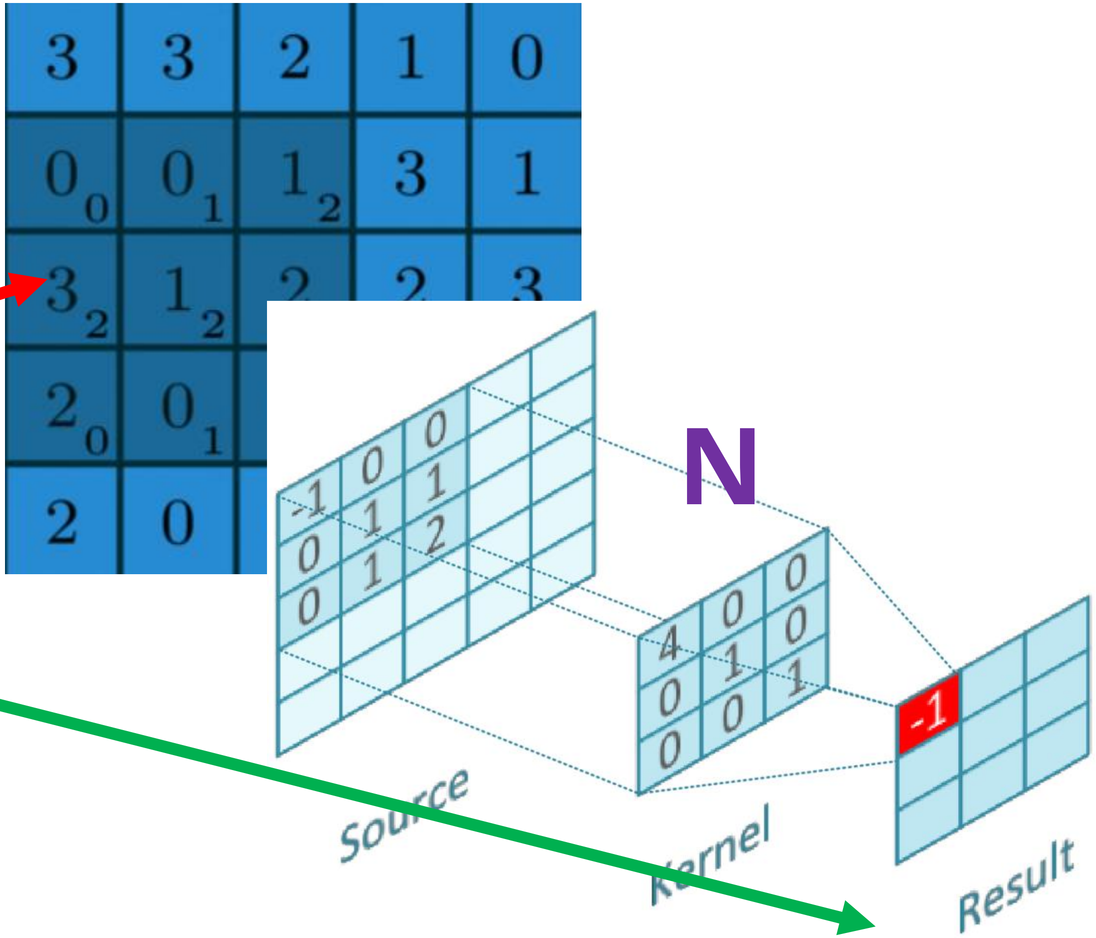
- Works same like Vanilla K-Means
- This is based on the feature agglomeration reduction method.
- It uses 3 bands out of 37 bands of HSI for computation.

Spectral K-Means

- Based on projection of a normalized Laplacian.
- PCA for dimension Reduction
- It uses 11 bands out of 37 bands for computation and spatial coordinates of pixels as feature.

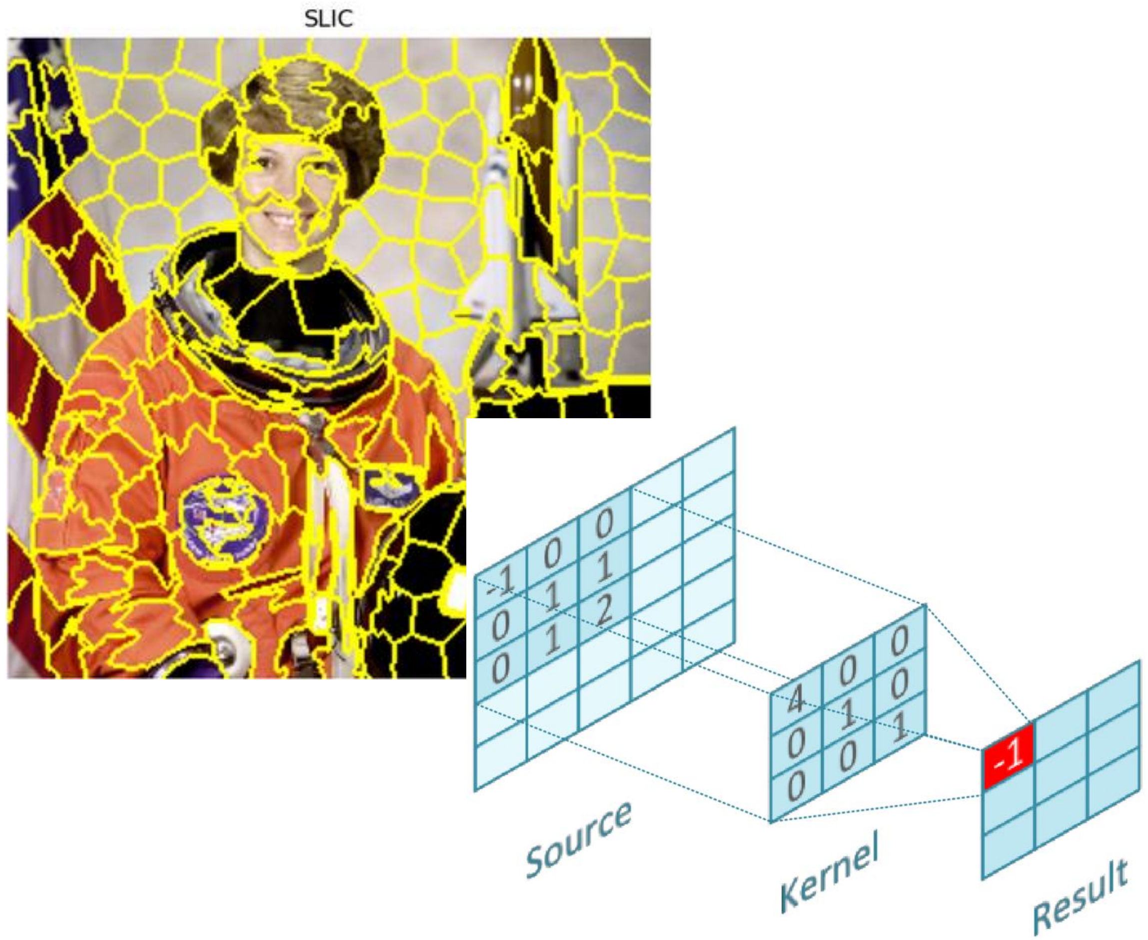
DL Segmentation (Via Differentiable Features) [4]

- Two loss functions:
  - Similarity of Spectra
  - Spatial windows sliding
- Starting point: maximum classes
- Optimization criteria: min classes



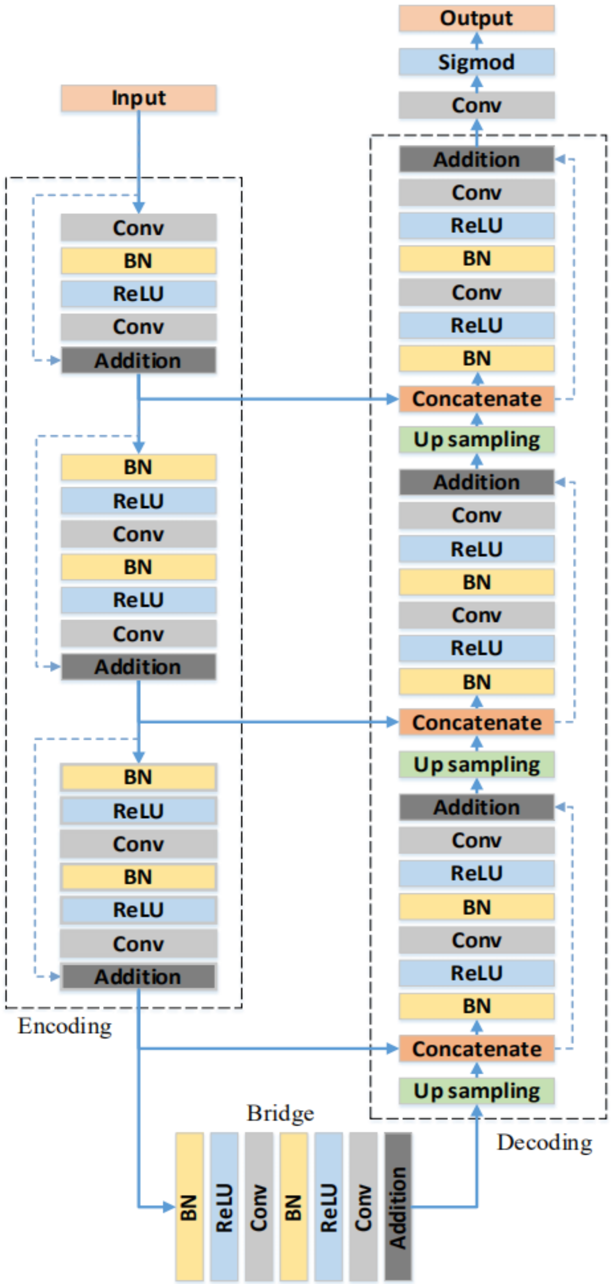
DL Segmentation (Via Back Propagation) [5]

- Same as Variant 1 but the input is preprocessed by simple linear iterative clustering (SLIC).



ResUnet based deep model (DLR) [6]

- Deep residual U-Net (ResUnet)
- Advantages of both deep residual learning and U-Net



ResUnet based deep model (DLR)

- 1) DLR-V1: Use all 37 bands.
- 2) DLR-V2: 3 PCs extracted from individual images.
- 3) DLR-V3: 3PCs extracted from the whole database.

Evaluation metrics

Evaluation metrics [7]

- Considering **C** is the set of clusters and **GT** is the set of ground-truth classes:
- **TP**: The number of data pairs found in the same cluster, in both **C** and **GT**.
- **FP**: The number of data pairs found in the same cluster in **C** but in different clusters in **GT**.
- **FN**: The number of data pairs found in different clusters in **C** but same cluster in **GT**.
- **TN**: The number of data pairs found in different clusters both in **C** and **GT**.

Evaluation metrics

- **m1**: Total number of pairs found in the same **C**: **TP + FP**
- **m2**: Total number of pairs found in the same **GT**: **TP +FN**

Evaluation metrics

- **Precision**: Counts true positives that how many examples are properly included in the same **GT**.

$$\frac{TP}{m1}$$

- **Recall**: Percentage of elements that are properly included in the same cluster

$$\frac{TP}{m2}$$

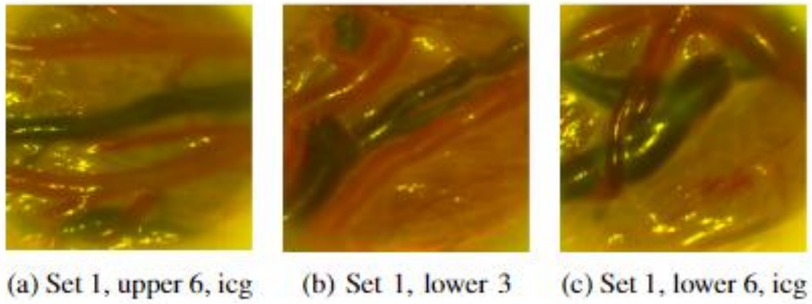
Evaluation metrics

- **F-measure**: combines Precision and Recall

$$\frac{1+\alpha}{\frac{1}{Precision}+\frac{\alpha}{Recall}}$$

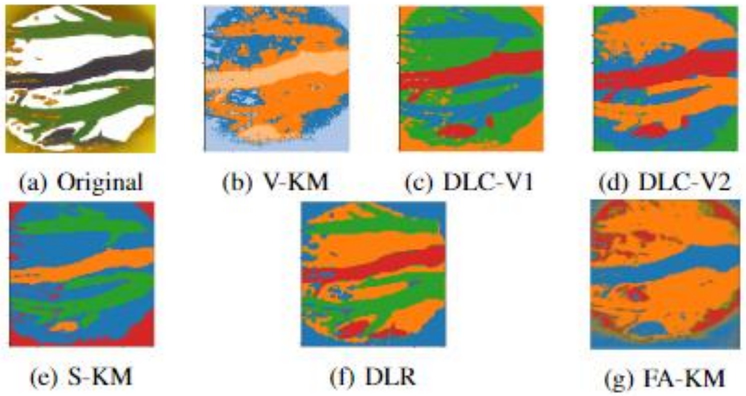
Results

Visual Results

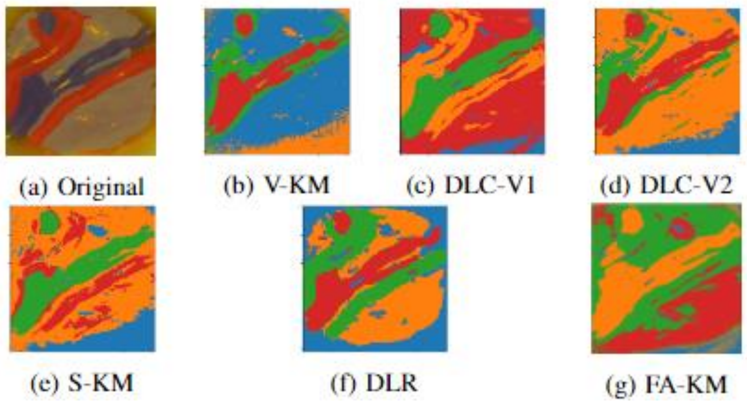


Hyper Spectral Images

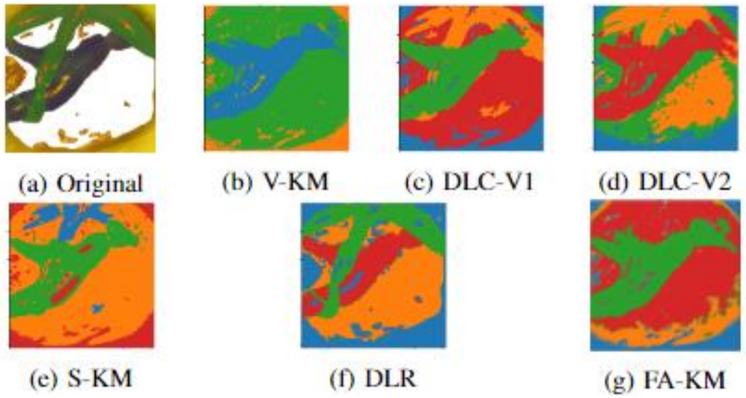
V-KM = Vanilla K-Means
DLC–V1 = Deep Learning based cluster segmentation Variant 1
DLC –V2 = Deep Learning based cluster segmentation Variant 1
S-KM = spectral clustering
DLR = ResUnet
FA-KM = K-Means with Feature Agglomeration



Results of Set 1 upper 6, icg



Results of Set 1 lower 3

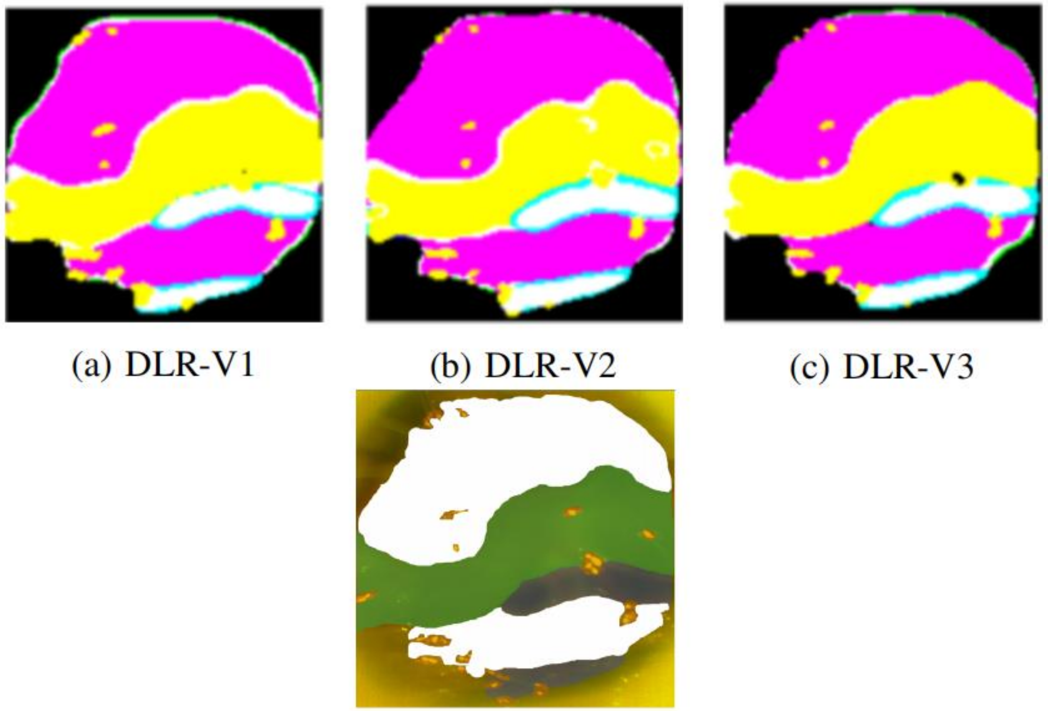


Results of Set 1 lower 6, icg

Visual Results

- Predicted masks and ground truth from the three ResUnet derivative models

- Set 1, upper 2, icg.tif



(a) DLR-V1 (b) DLR-V2 (c) DLR-V3

(d) Ground Truth

Quantitative Results

	Vein			Artery, ICG			Stroma, ICG			Specular reflection		
	Precision	Recall	F-Meas	Precision	Recall	F-Meas	Precision	Recall	F-Meas	Precision	Recall	F-Meas
V-KM	0.953	0.931	0.942	0.753	0.646	0.695	0.580	0.681	0.626	0.827	0.871	0.848
DLC-V1	0.941	0.900	0.920	0.903	0.927	0.915	0.711	0.680	0.695	0.800	0.942	0.865
DLC-V2	0.937	0.877	0.906	0.831	0.712	0.767	0.604	0.631	0.617	0.739	0.956	0.834
FA-KM	0.934	0.974	0.954	0.889	0.926	0.907	0.703	0.667	0.684	0.775	0.952	0.855
DLR-V3	0.973	0.976	0.974	0.946	0.919	0.933	0.891	0.921	0.906	0.956	0.955	0.956
FA-KM	0.925	0.947	0.936	0.703	0.588	0.640	0.516	0.542	0.529	0.781	0.909	0.841

Segmentation results for Set 1, upper 2, icg

	Vein			Artery			Stroma			Specular reflection		
	Precision	Recall	F-Meas	Precision	Recall	F-Meas	Precision	Recall	F-Meas	Precision	Recall	F-Meas
V-KM	0.921	0.967	0.943	0.654	0.746	0.697	0.587	0.567	0.577	0.811	0.891	0.850
DLC-V1	0.963	0.926	0.944	0.859	0.885	0.872	0.679	0.652	0.665	0.753	0.931	0.832
DLC-V2	0.961	0.938	0.950	0.749	0.883	0.811	0.624	0.605	0.615	0.778	0.911	0.839
S-KM	0.963	0.935	0.949	0.750	0.840	0.792	0.588	0.565	0.576	0.778	0.858	0.816
DLR-V3	0.981	0.969	0.975	0.955	0.958	0.956	0.822	0.888	0.854	0.946	0.862	0.902
FA-KM	0.852	0.950	0.899	0.575	0.717	0.639	0.701	0.597	0.645	0.903	0.971	0.936

Segmentation results for Set 1, lower 3

	Vein			Artery, ICG			Stroma, ICG			Specular reflection		
	Precision	Recall	F-Meas	Precision	Recall	F-Meas	Precision	Recall	F-Meas	Precision	Recall	F-Meas
V-KM	0.937	0.808	0.868	0	0	0	0.607	0.637	0.622	0.750	0.958	0.842
DLC-V1	0.946	0.814	0.875	0.819	0.915	0.864	0.773	0.745	0.759	0.789	0.951	0.863
DLC-V2	0.909	0.744	0.818	0.707	0.618	0.659	0.578	0.672	0.622	0.801	0.933	0.862
S-KM	0.910	0.817	0.861	0.736	0.959	0.833	0.703	0.686	0.694	0.772	0.917	0.838
DLR-V3	0.975	0.972	0.973	0.964	0.947	0.955	0.884	0.924	0.904	0.947	0.904	0.925
FA-KM	0.763	0.926	0.837	0.702	0.634	0.666	0.549	0.569	0.559	0.966	0.857	0.908

Segmentation results for Set 1, lower 6, icg

Deep Learning Methods Give Best Results with a good accuracy/cost trade-off

Quantitative Results

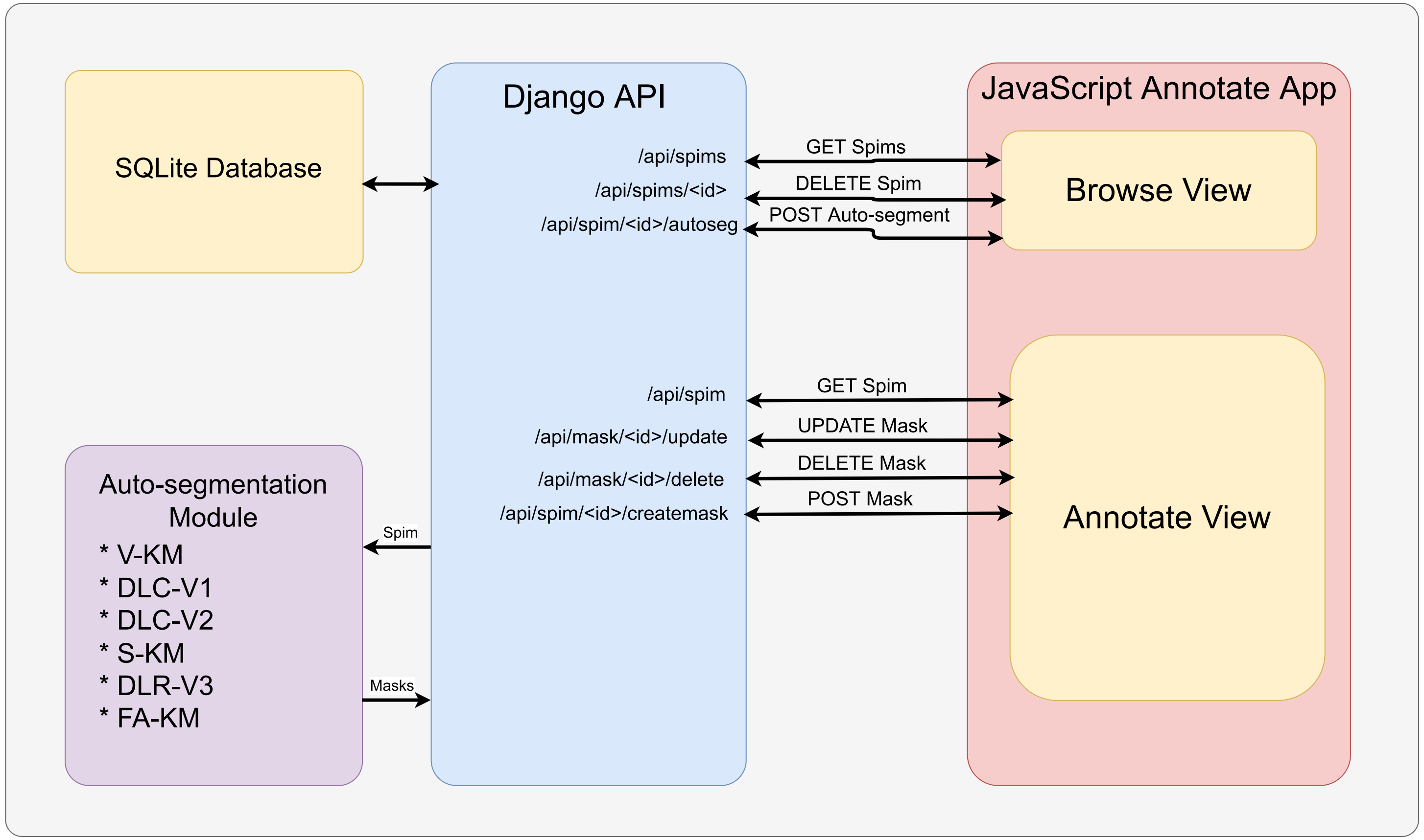
Vein and Specularities with best Accuracy

		Vein	Artery Artery, ICG	Stroma Stroma ICG	Specular Reflection
Set 1, upper 2, icg	AVG	0.939	0.809	0.676	0.8665
	MAX	0.974	0.933	0.906	0.956
	MIN	0.906	0.64	0.529	0.834
Set 1, lower 3	AVG	0.943	0.794	0.655	0.862
	MAX	0.975	0.956	0.854	0.936
	MIN	0.899	0.639	0.576	0.816
Set 1, lower 6, icg	AVG	0.872	0.662	0.69	0.873
	MAX	0.973	0.955	0.904	0.925
	MIN	0.818	0	0.559	0.838

TABLE V: F-Measure Summary results for tested images

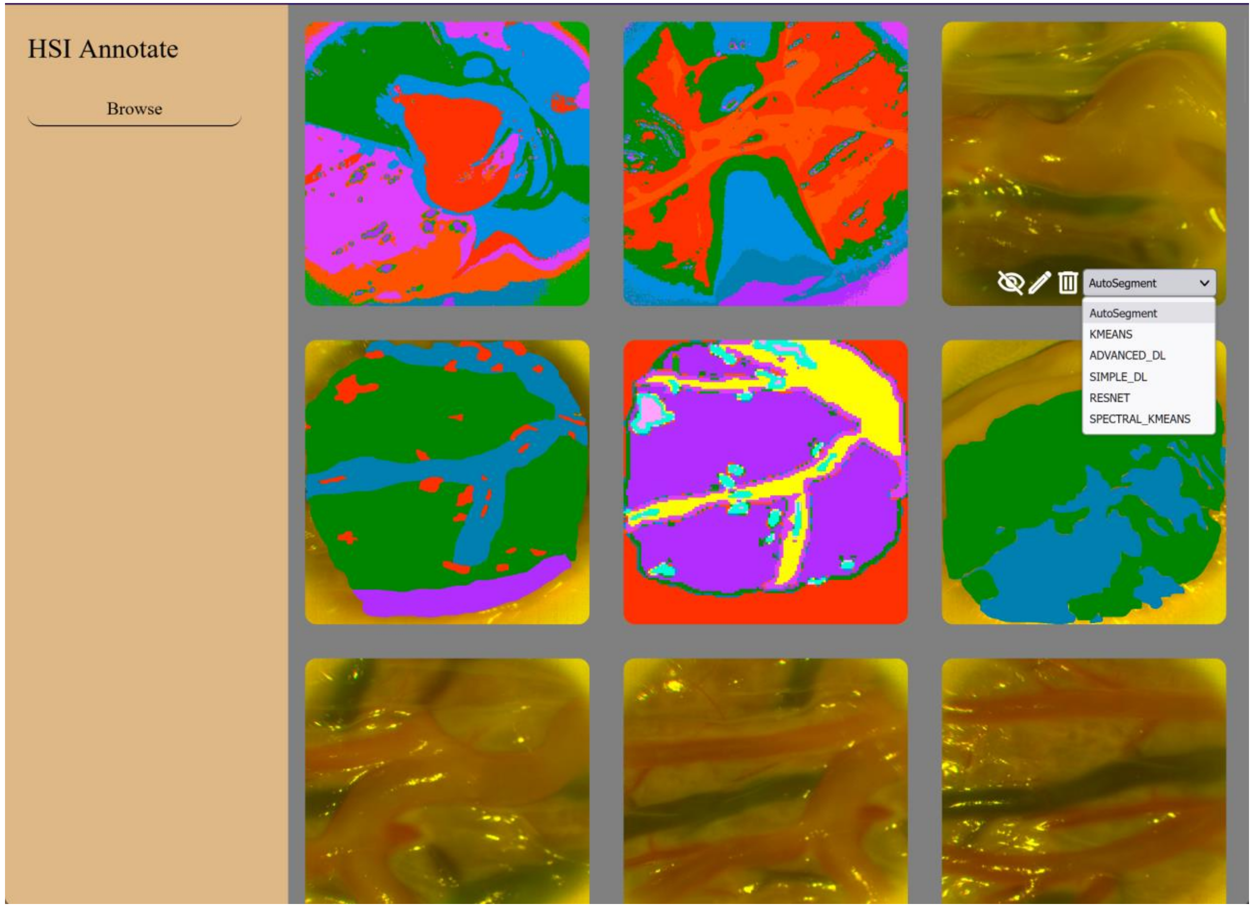
Annotation Application

Annotation Application



- Uses database services and shared API among group teams
- Integrates auto-segmentation methods with services and GUI
- Provides basic CRUD editing for masks and an editing canvas for mask corrections and merging

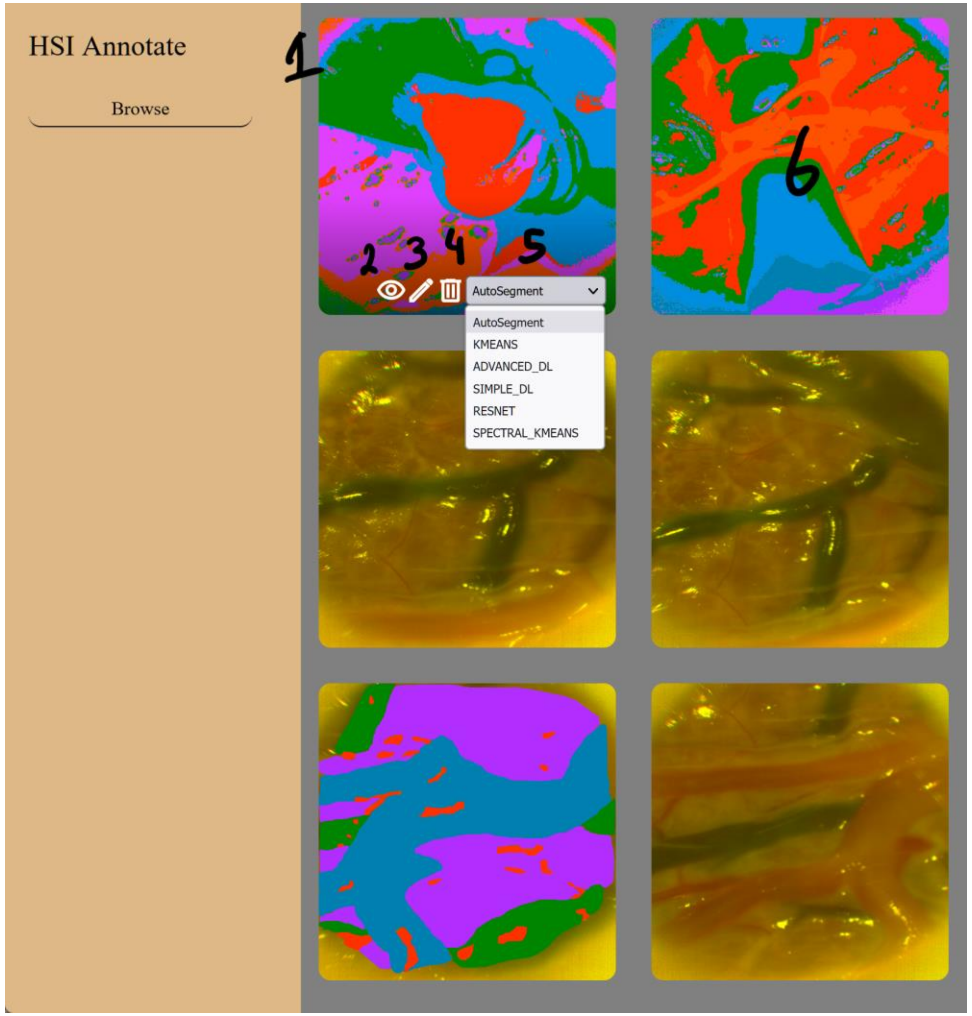
Browse View



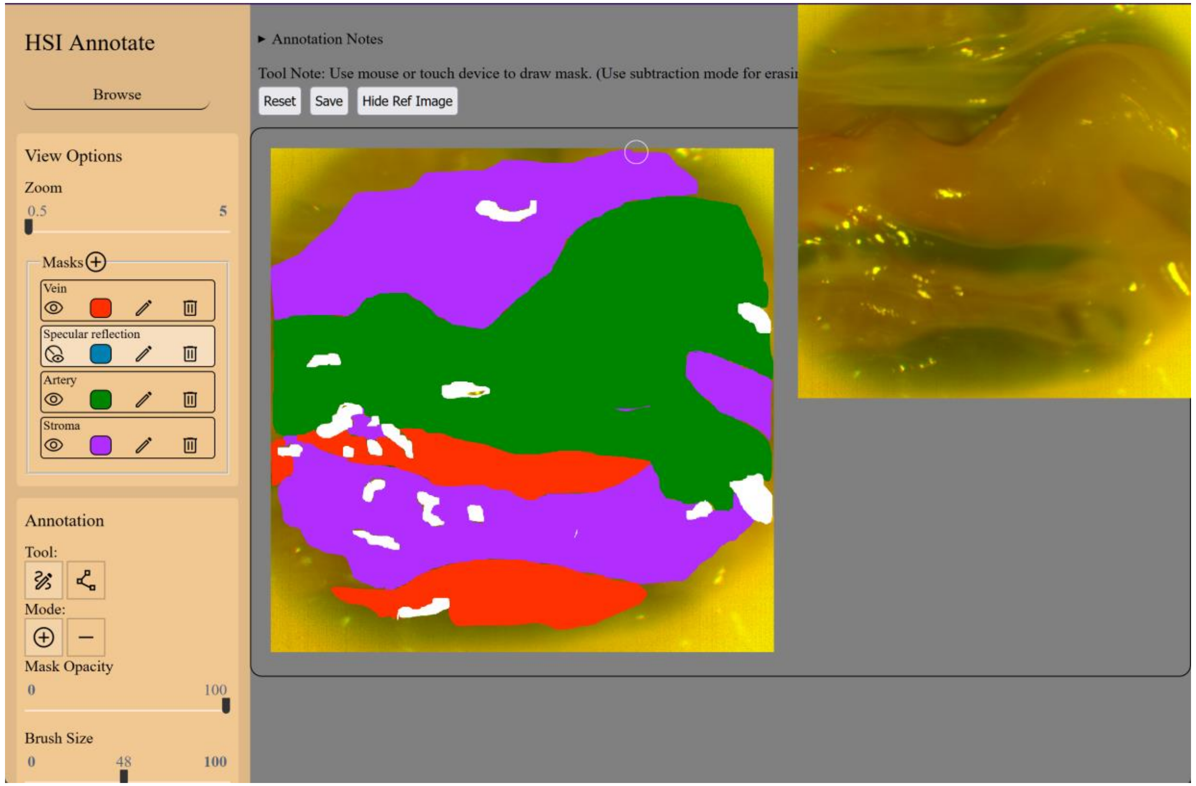
- View images
- Delete images
- Trigger segmentation
- Enter annotation view

Browse View

1. RGB preview
2. Mask visibility indicator
3. Edit action button
4. Delete image action button
5. Auto-segmentation trigger select
6. Mask Overlays



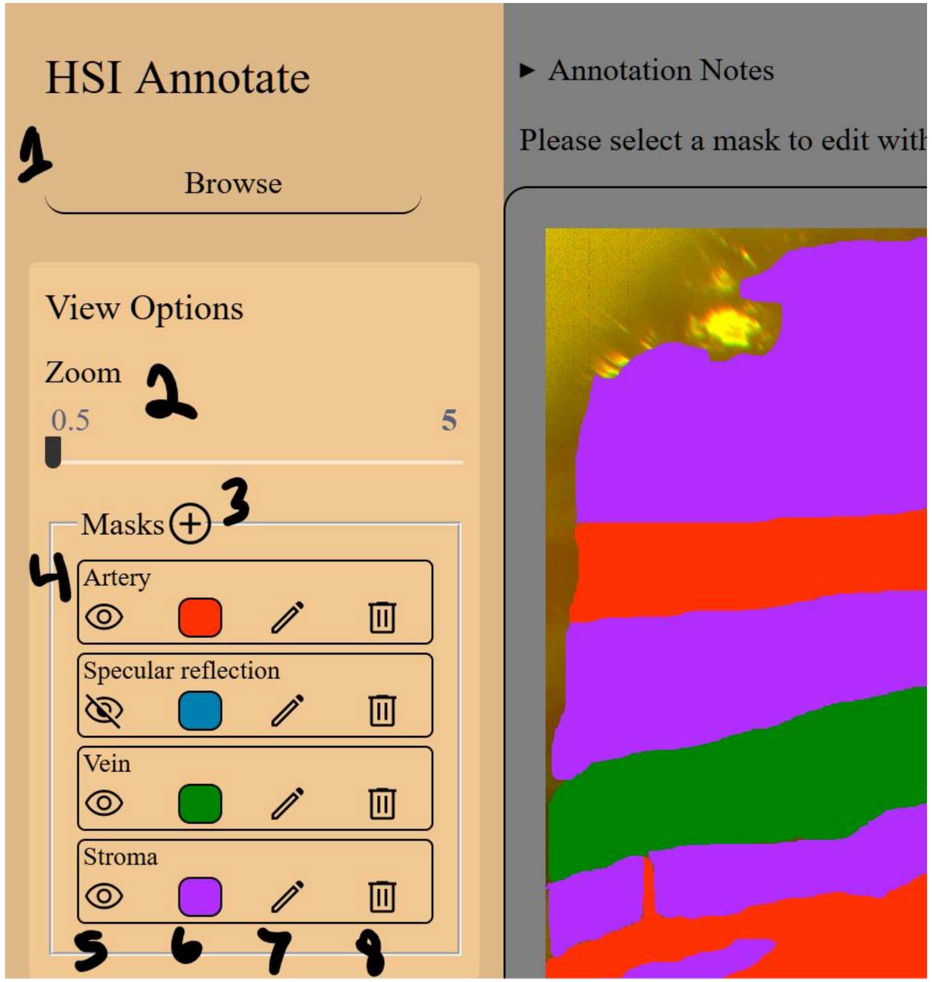
Annotation View



- CRUD for masks
- Canvas for making raster changes to mask
- Reference image

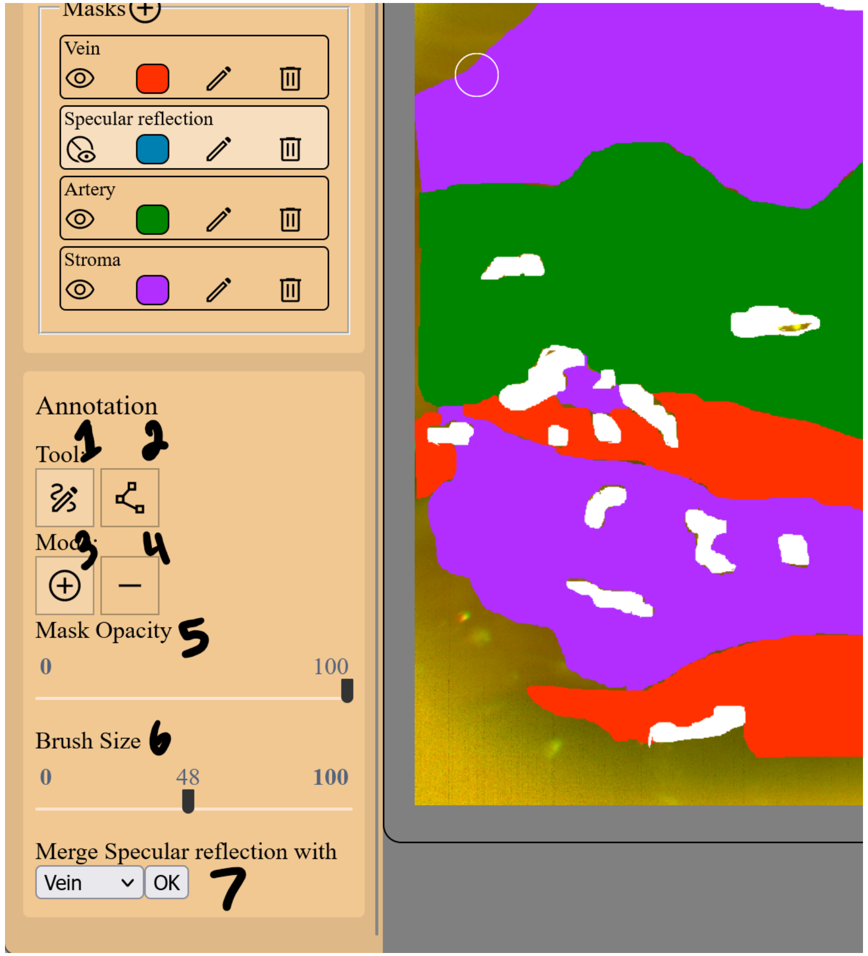
Annotation View

1. Navigate back to browse
2. Change image zoom
3. Add a mask
4. Change mask name
5. Toggle mask visibility
6. Select mask render color
7. Edit mask
8. Delete mask

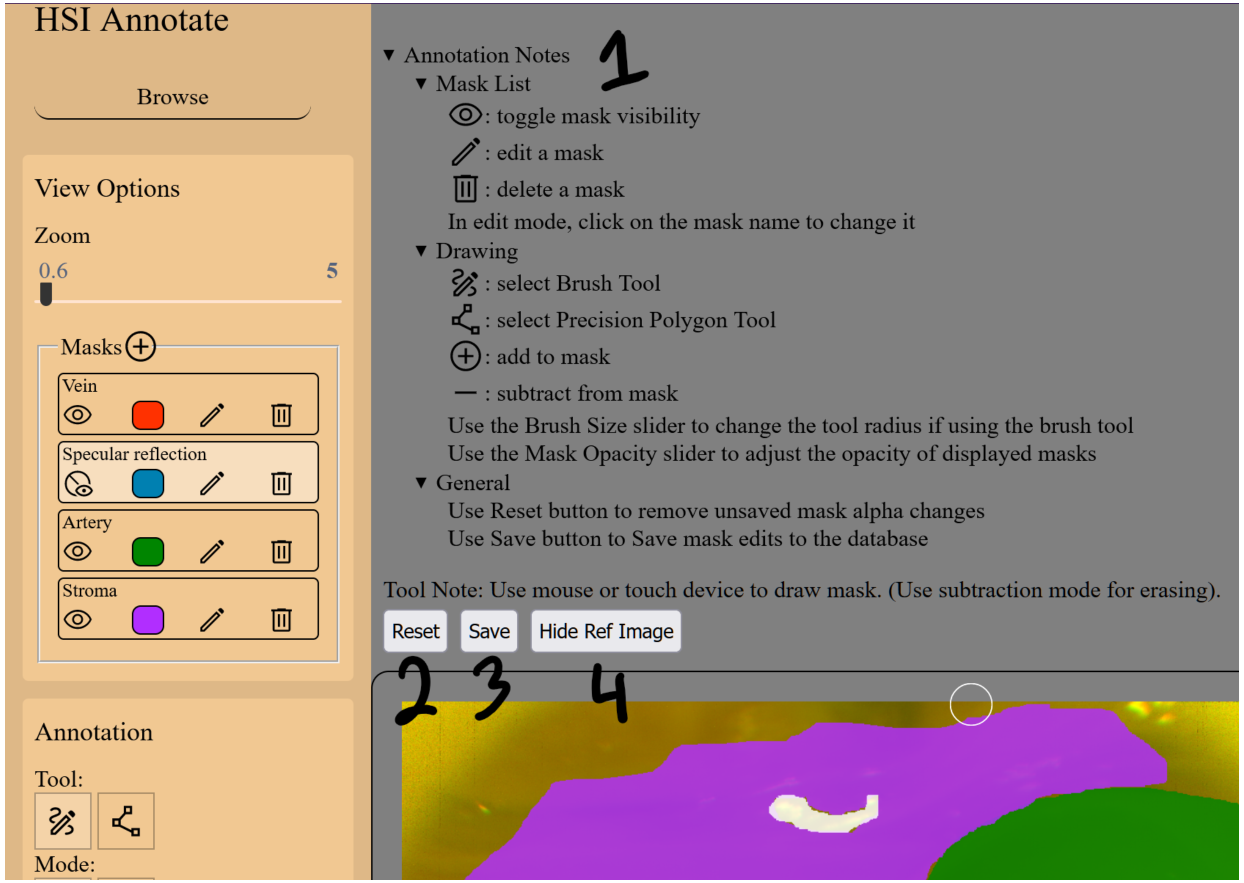


Annotation View

1. Draw Tool
2. Polygon-fill Tool
3. “Add” mode
4. “Subtract” mode
5. Adjust mask opacity
6. Adjust Draw Tool size
7. Merge another mask into currently edited one

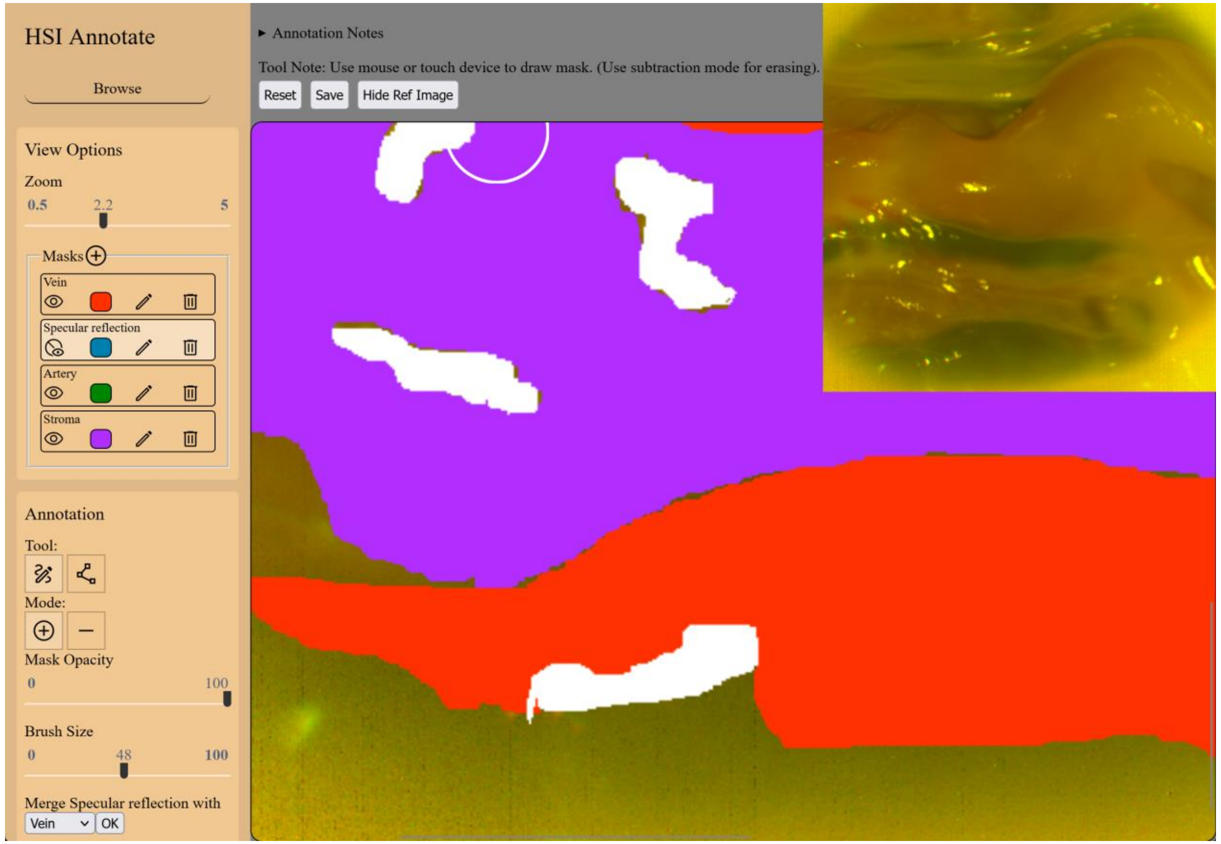


Annotation View



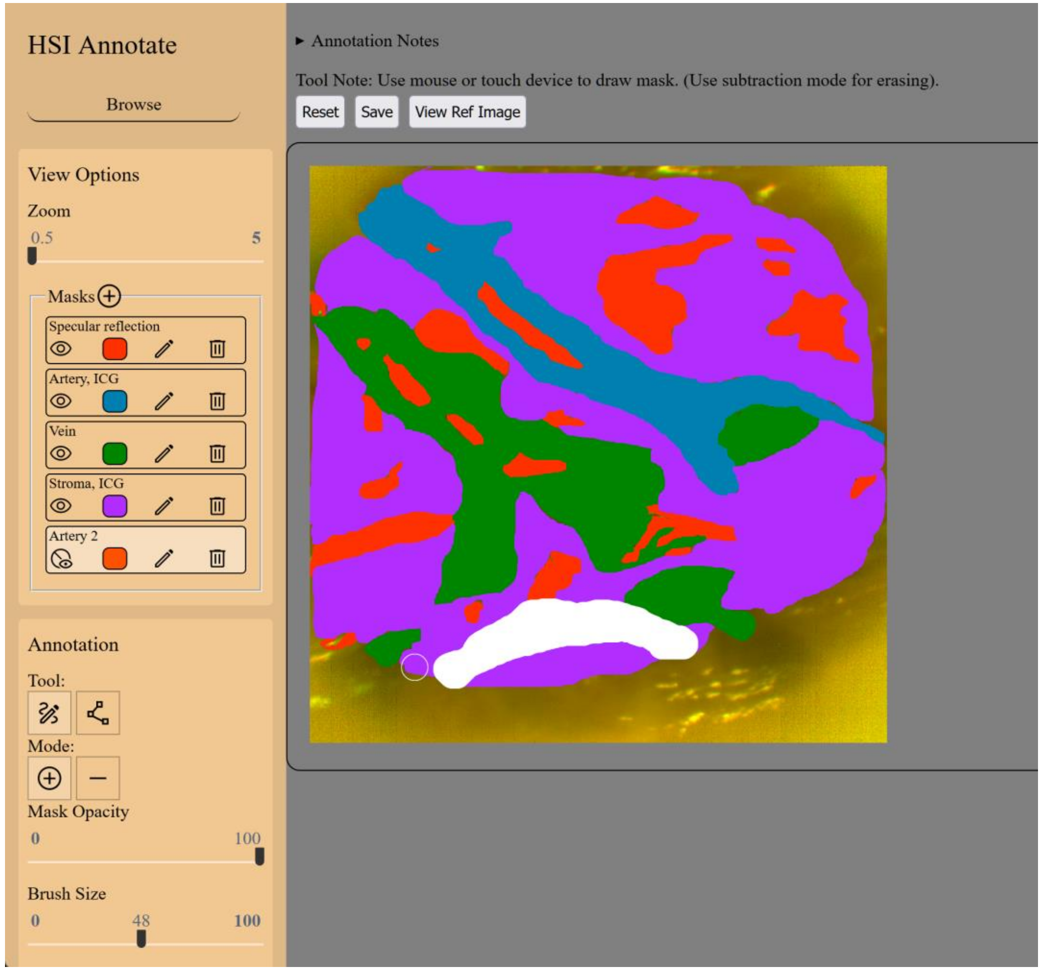
1. Annotation usage notes
2. Discard current edits
3. Save current edits
4. Toggle reference image visibility

Annotation View



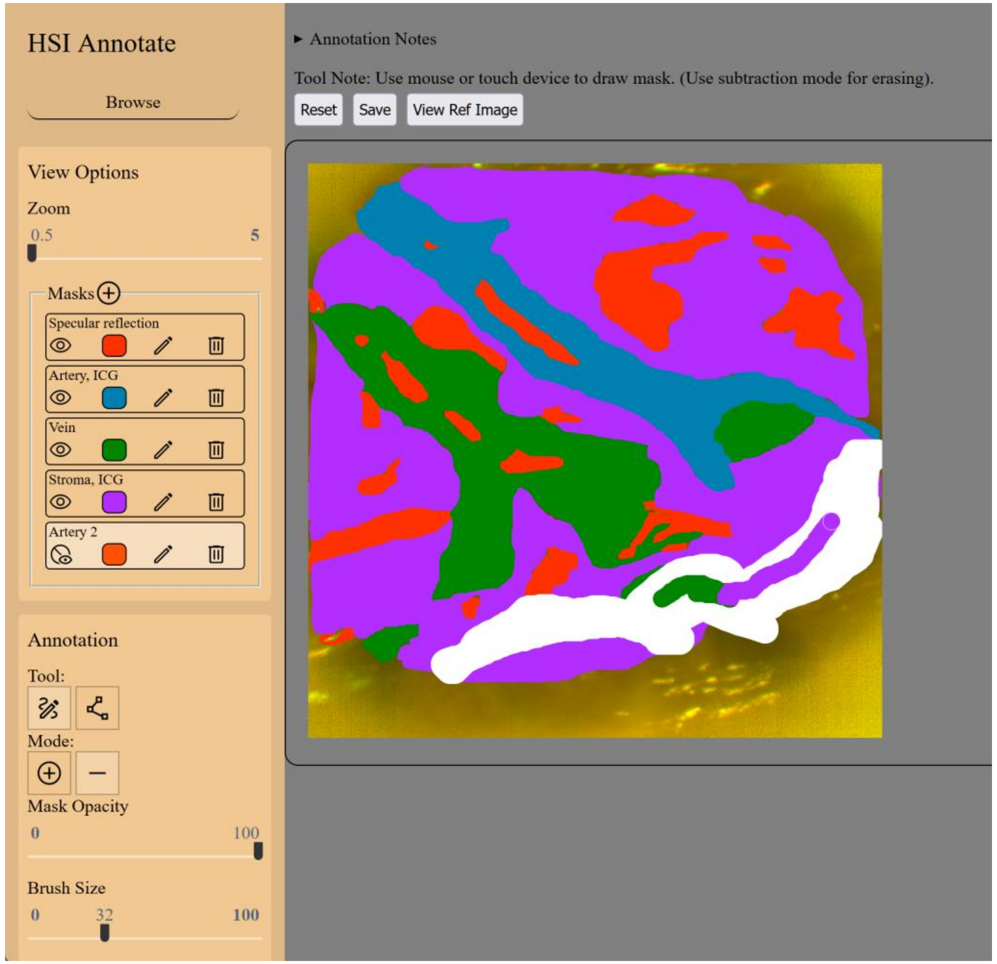
Reference image is useful when zoomed in.

Editing Raster Mask



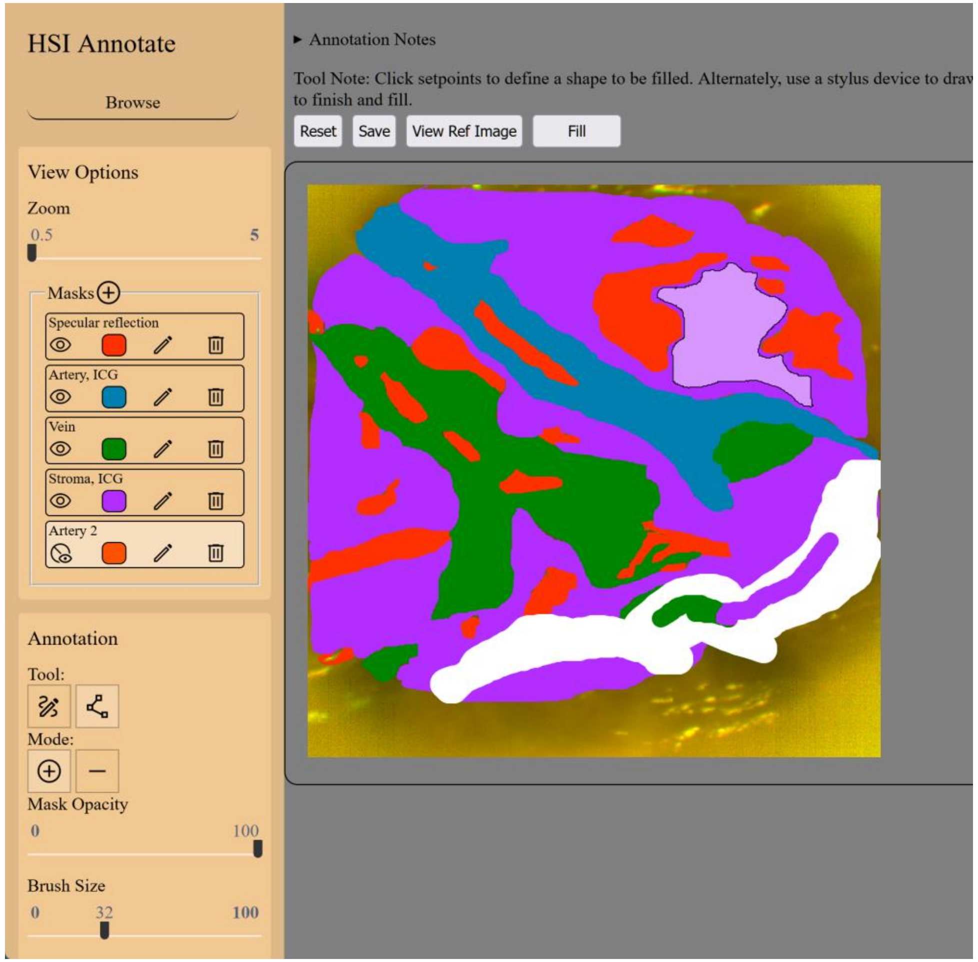
Draw Tool is sufficient for making geometrically simple/smooth annotations

Editing Raster Mask



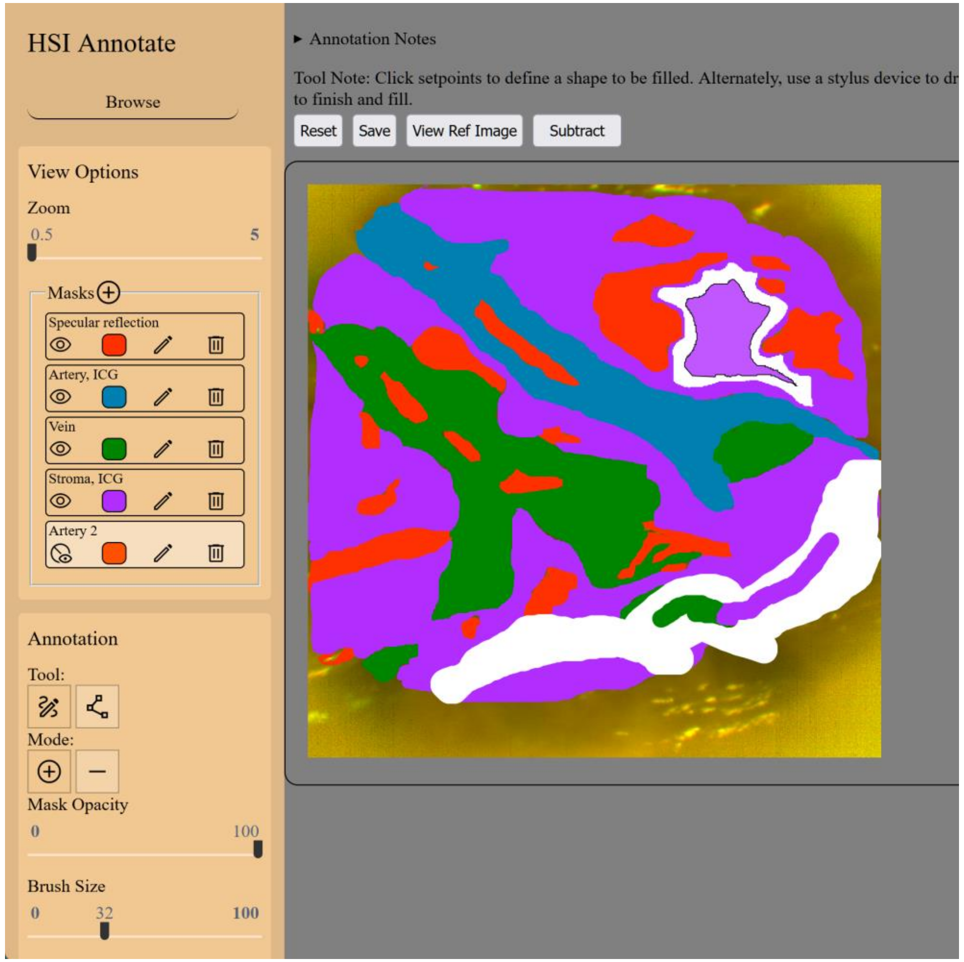
Use Subtract mode to erase out areas.

Editing Raster Mask



Polygon-fill tool best for precision shapes. Place or draw with stylus the shape edge points, and click Fill or double-click to complete.

Editing Raster Mask



And use Subtract mode to open areas or erase.

Work Distribution

Work Distribution

Alvaro Flores-Romero

- Optimal Combination Strategy Implementation for Band Selection
- Differentiable Feature Clustering Unsupervised Segmentation for HSI
- Unsupervised Segmentation via Backpropagation for HSI
- Report and slides

Ali Raza Syed

- Preprocessing and classical methods
- Evaluation metrics
- Report and slides

Austin Ryan English

- Annotation application GUI
- Integration with services, database, and our segmentation methods
- Client server configuration

Akash Harijan

- K-Means with Feature Agglomeration
- Report and Slides

Kang Yuan

- 3 deep models based on ResUnet architecture
- 2 methods to reduce dimensionality of bands with PCA
- Report and slides

Conclusion

Conclusion

- Consistent good results for Vein and specularities.
- Artery and Stroma difficult to distinguish due to high variations on spectra in measurement
- Specular Reflections and noise can be removed as a preprocessing step for example as an outlier.
- Effectively reducing the dimensions is a key step
- Annotation app can have parameters to tune for specific algorithms
- Morphological filter can be added for smoother masks in annotation app.

References

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[2] Shuying Li et al. “Hyperspectral Band Selection via Optimal Combination Strategy”. In: Remote Sensing 14.12 (), p. 2858. ISSN: 2072-4292. DOI: 10 . 3390 / rs14122858. URL: [https://www.mdpi.com/2072- 4292/ 14/12/2858](https://www.mdpi.com/2072-4292/14/12/2858).

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[4] Wonjik Kim, Asako Kanezaki, and Masayuki Tanaka. “Unsupervised Learning of Image Segmentation Based on Differentiable Feature Clustering”. In: IEEE Trans- actions on Image Processing 29 (2020), pp. 8055–8068. ISSN: 1057-7149, 1941-0042. DOI: 10.1109/TIP.2020. 3011269. arXiv: 2007.09990[cs]. URL: http://arxiv.org/ abs/2007.09990

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