Poster
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Automated NASH CRN Scoring Pipeline Through Lesion Segmentation for Alcohol-Associated Liver Disease

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Introduction

The prevalence of alcohol-associated liver disease is increasing, and diagnosis usually relies on invasive and non-invasive methods, including liver biopsies.

The quantification of disease activity of ALD relies on scores derived from the NAFLD activity score NAS based on NASH-CRN scoring system.

There are significant inconsistencies in SLB scoring among human experts, which are considered a major issue.

Most machine learning (ML) NAS scores relies on NAFLD cases and are not sufficiently reproducible in ASH.

Objective

1. Develop an automated pipeline using artificial intelligence that provides a consistent NAS score for patient with ALD.

Method

1. Obtained liver biopsy 132 ASH slides.
2. Slides were digitalized with partial annotations.
3. Cropped 1024x1024 patches from region of interesting.

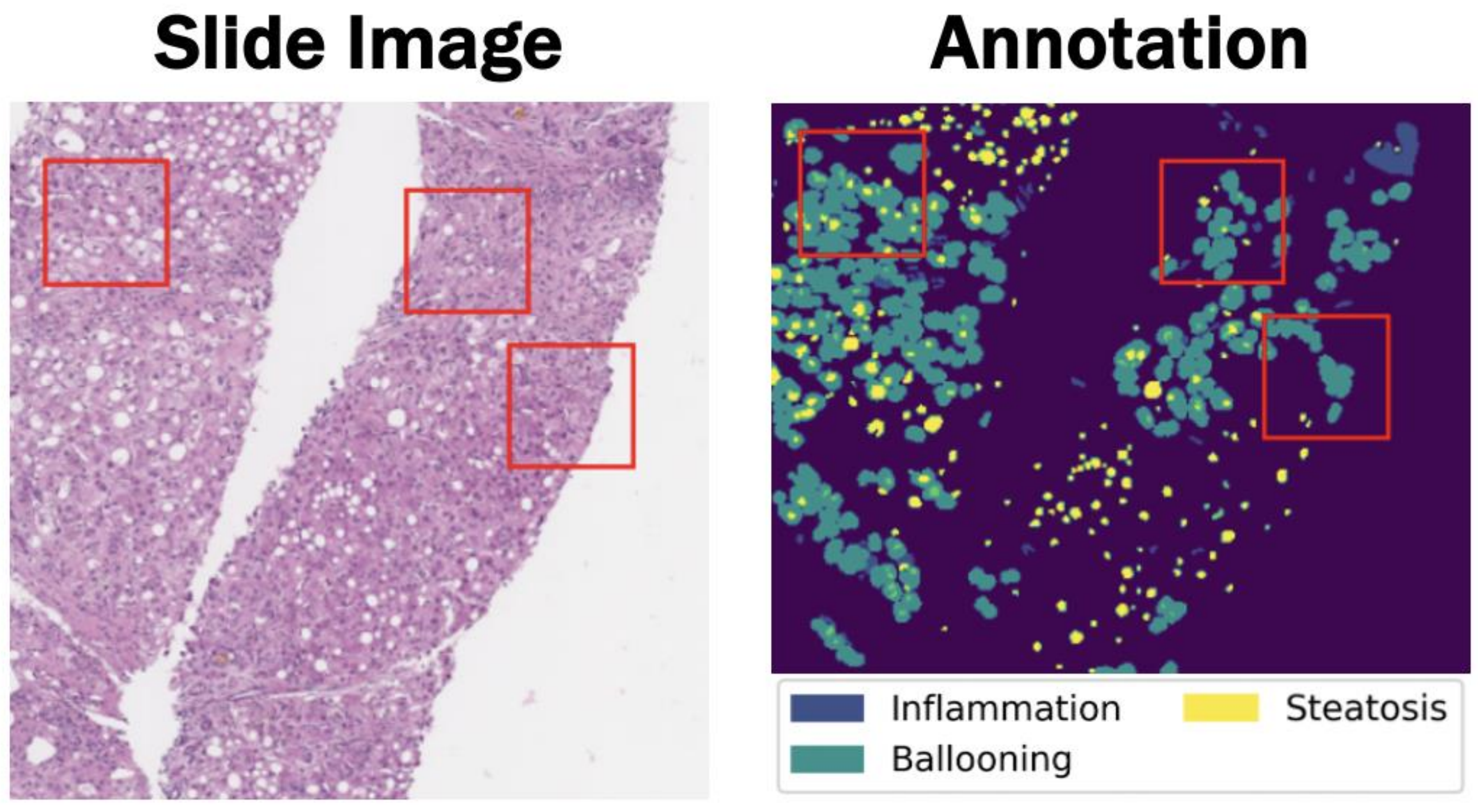

Figure 1. Example of patch sampling.

4. Train fully convolutional network (FCN) model with patches using focal loss.

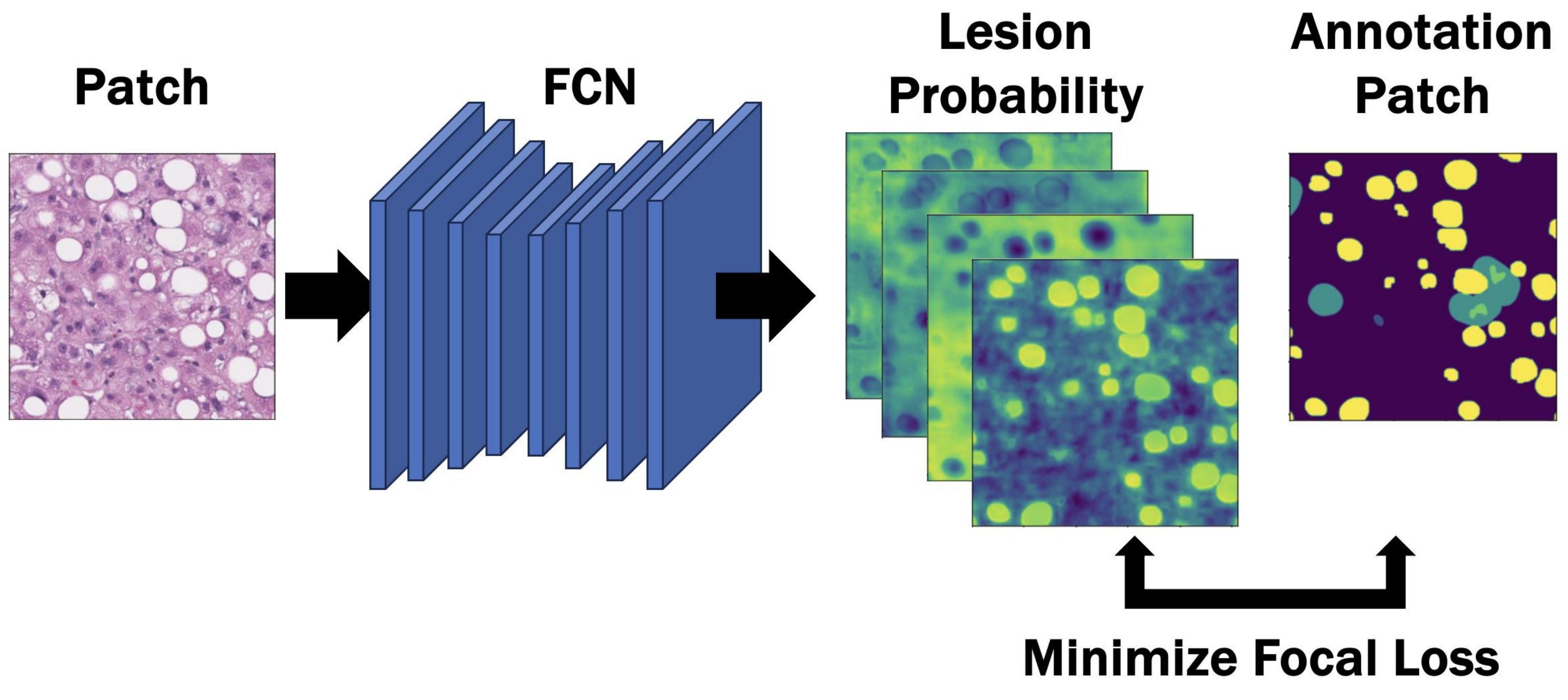

Figure 2. Processing of patch to probability prediction.

$$\text{Cross Entropy} = -\log(P_t)$$
$$\text{Focal Loss} = -(1-P_t)^{\gamma}\log(P_t)$$

Using focal loss resolves class imbalance problem.

5. Count contour or area of lesions for scoring.

Results

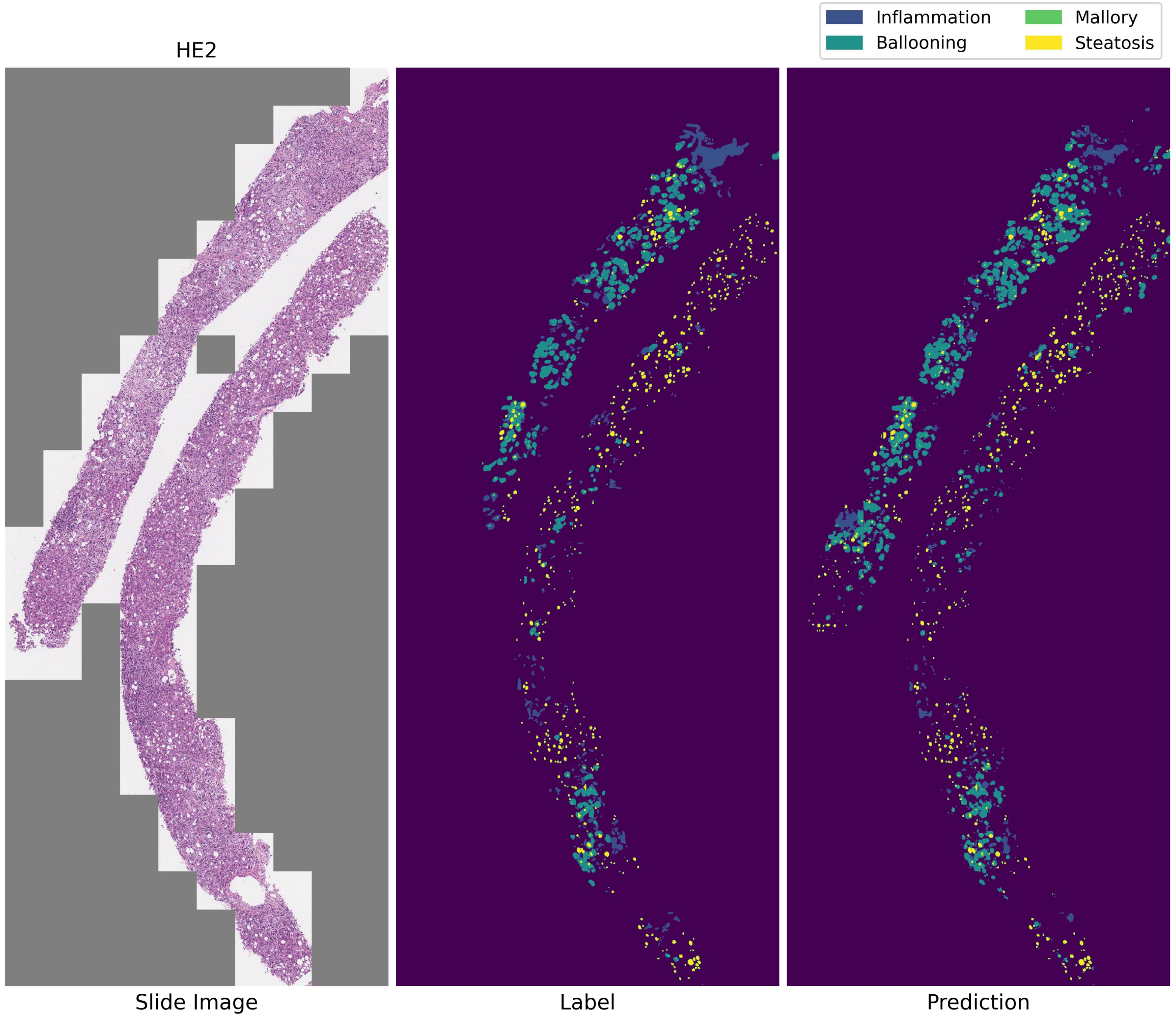

Figure 3. The FCN model's prediction and Label.

Predicted Steatosis Score

Given Steatosis Score

	0	1	1.5	2	2.5	3
0	5	3	-	-	-	-
1	8	26	-	5	-	1
1.5	-	3	-	4	-	-
2	-	15	-	20	-	1
2.5	-	1	-	7	-	1
3	-	2	-	16	-	14

Accuracy = 65/132 = 49.2%
Correlation = 0.715

Predicted Lobular Inflammation Score

Given Lobular Inflammation Score

	0	1	2	3
0	-	6	-	-
1	4	62	3	5
2	-	19	5	5
3	1	6	3	13

Accuracy = 80/132 = 60.6%
Correlation = 0.491

Predicted Ballooning Score

Given Ballooning Score

	0	1	2
0	6	4	2
1	10	37	17
2	2	9	45

Accuracy = 88/132 = 66.7%
Correlation = 0.533

Table 1 –3. Performance of the model's prediction.

Conclusion

The demonstrated fully automated scoring system consistently provided accurate **automated NAS scoring pipeline** using artificial intelligence.

Using partially annotated lesions, FCN successfully segmented most of the lesion regions, yielding robust and trustworthy results NAS scoring.

The model can even identify slides that are obviously mislabeled by human experts.