

Efficacy and reproducibility of the AI-assisted Gubra Histopathological Objective Scoring Technique (GHOST) in preclinical rodent models of fibrosing NASH

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Background & Aim

Drug efficacy testing in animal models of NASH should include clinical primary endpoint assessment for histopathological NAFLD Activity Score and Fibrosis Stage/Ishak Fibrosis Score. Manual histopathological scoring are prone to inter- and intra-observer variability which can significantly influence reproducibility of results.

To enable objective and unbiased histopathological assessment in liver biopsies from mouse models of NASH, we developed and validated **Gubra Histopathological Objective Scoring Technique (GHOST)**, an automated deep learning-based digital imaging analysis pipeline for the NAFLD Activity Score and fibrosis staging/scoring system.

Methods

Liver biopsies were obtained from two industry-standard rodent models of NASH:

- GAN diet-induced obese (GAN DIO-NASH) mouse
- Choline-deficient L-amino acid defined high-fat diet (CDAA-HFD) rat

Automated GHOST analysis was performed on HE and PSR stained sections and validated against manual scoring:

- NAFLD Activity Score (NAS):
 - Steatosis (score 0-3)
 - Lobular inflammation (score 0-3)
 - Ballooning degeneration (score 0-2)
- Fibrosis stage (score 1-4)
- Ishak score (score 0-6)

Corresponding quantitative histomorphometrics:

- Density of hepatocytes with lipid droplets
- Number of inflammatory foci
- Ballooning cell index
- Fractional area of periportal/perisinusoidal fibrosis

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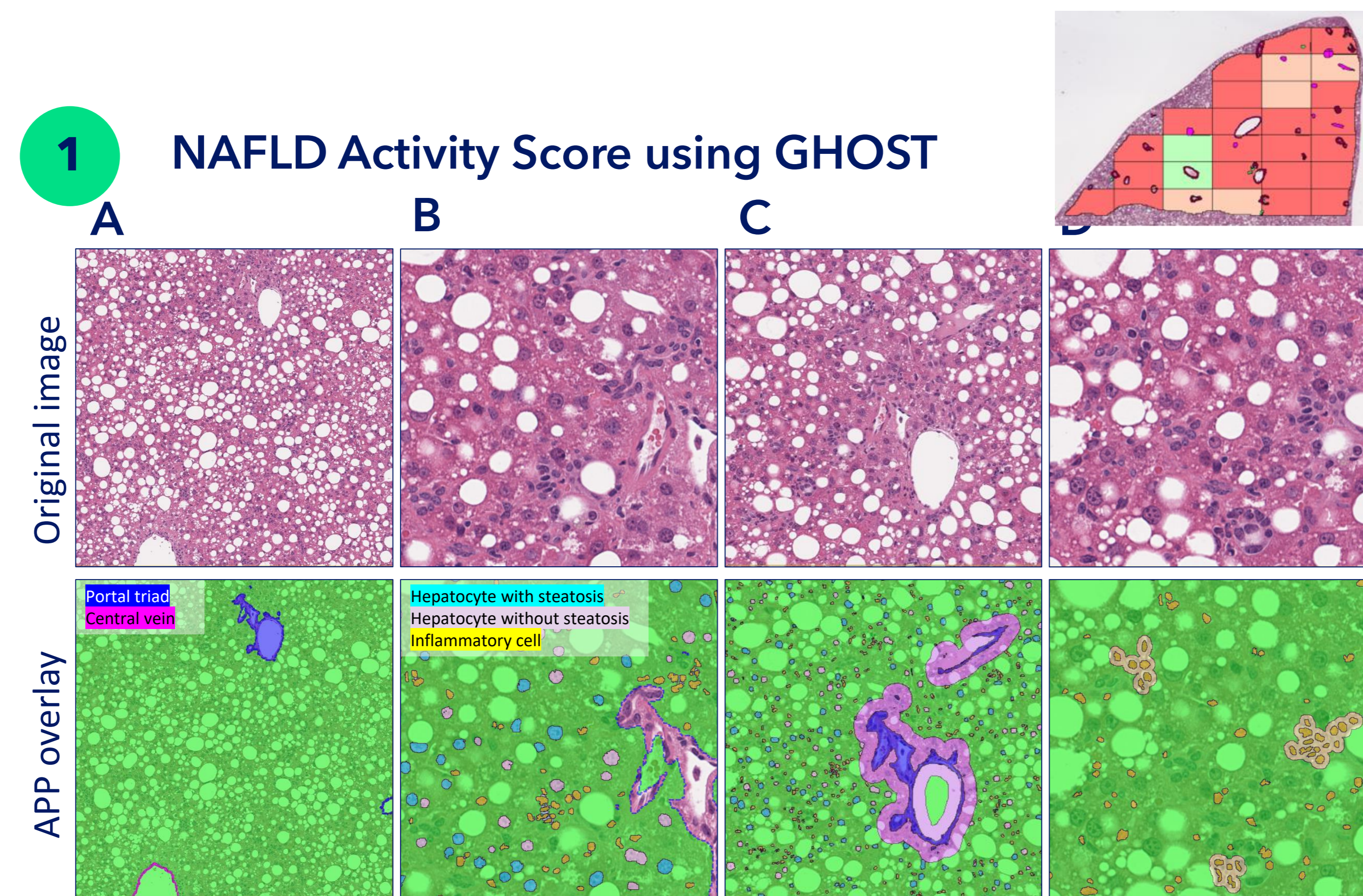


Figure 1. GHOST-based NAFLD Activity Score (NAS). (A) Portal triads and central veins were detected using deep learning (10X). (B) Deep learning detected nuclei of hepatocytes with steatosis, hepatocytes without steatosis, and inflammatory cells (20X). (C) Post-processing excludes periportal inflammation. (D) Post-processing converted clusters of ≥ 4 inflammatory cells into foci. Scores were calculated based on simple threshold.

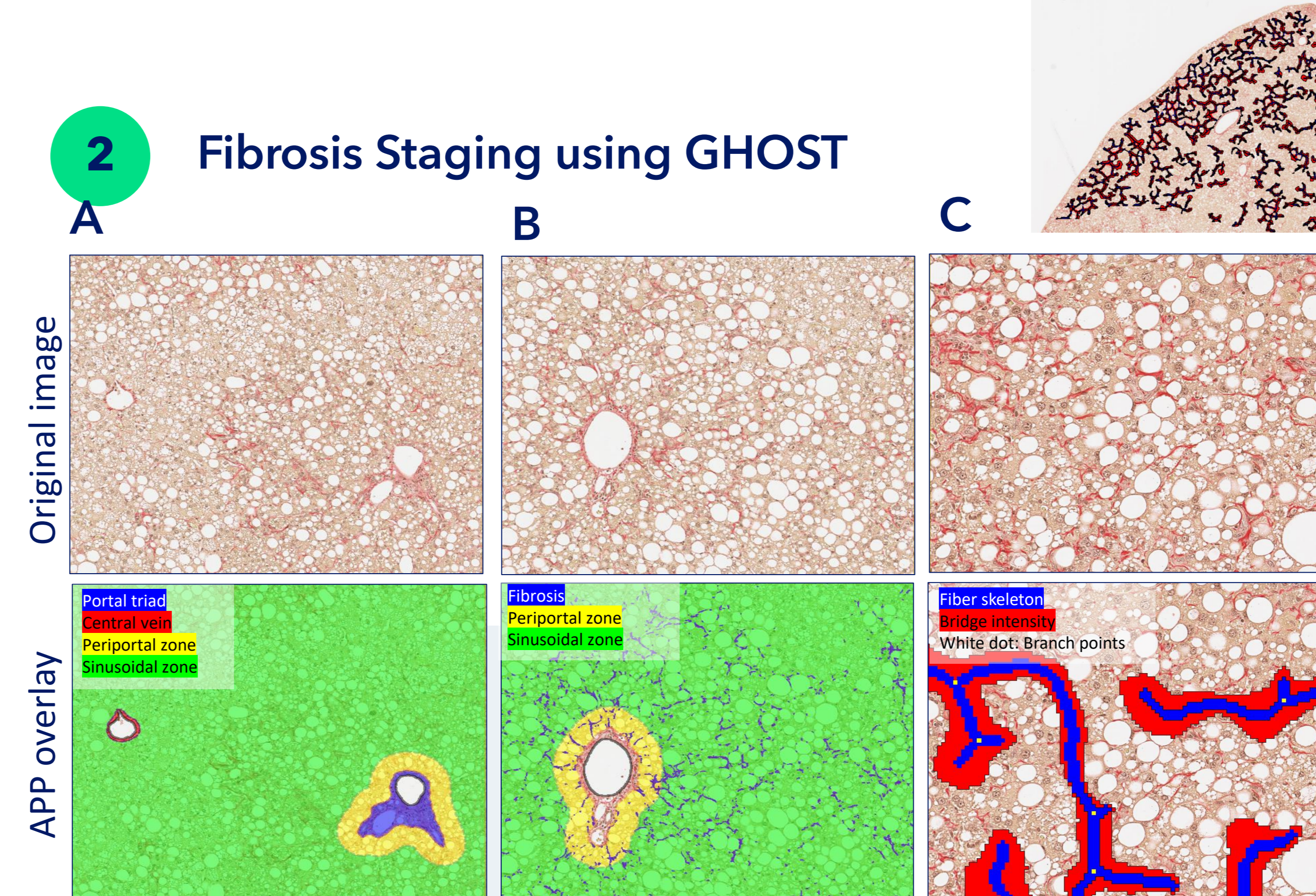


Figure 2. GHOST-based fibrosis score. (A) Portal triads and central veins were detected using deep learning (post-processing creates a periportal zone of 100 μ m). (B) Fibrosis was detected using the linear Bayesian image analysis method in the periportal and sinusoidal zones, and different measures of collagen fiber fragment size and shape was used to predict bridging. (C) Bridging was also detected using the Threshold image analysis method based on a polynomial local linear filter feature.

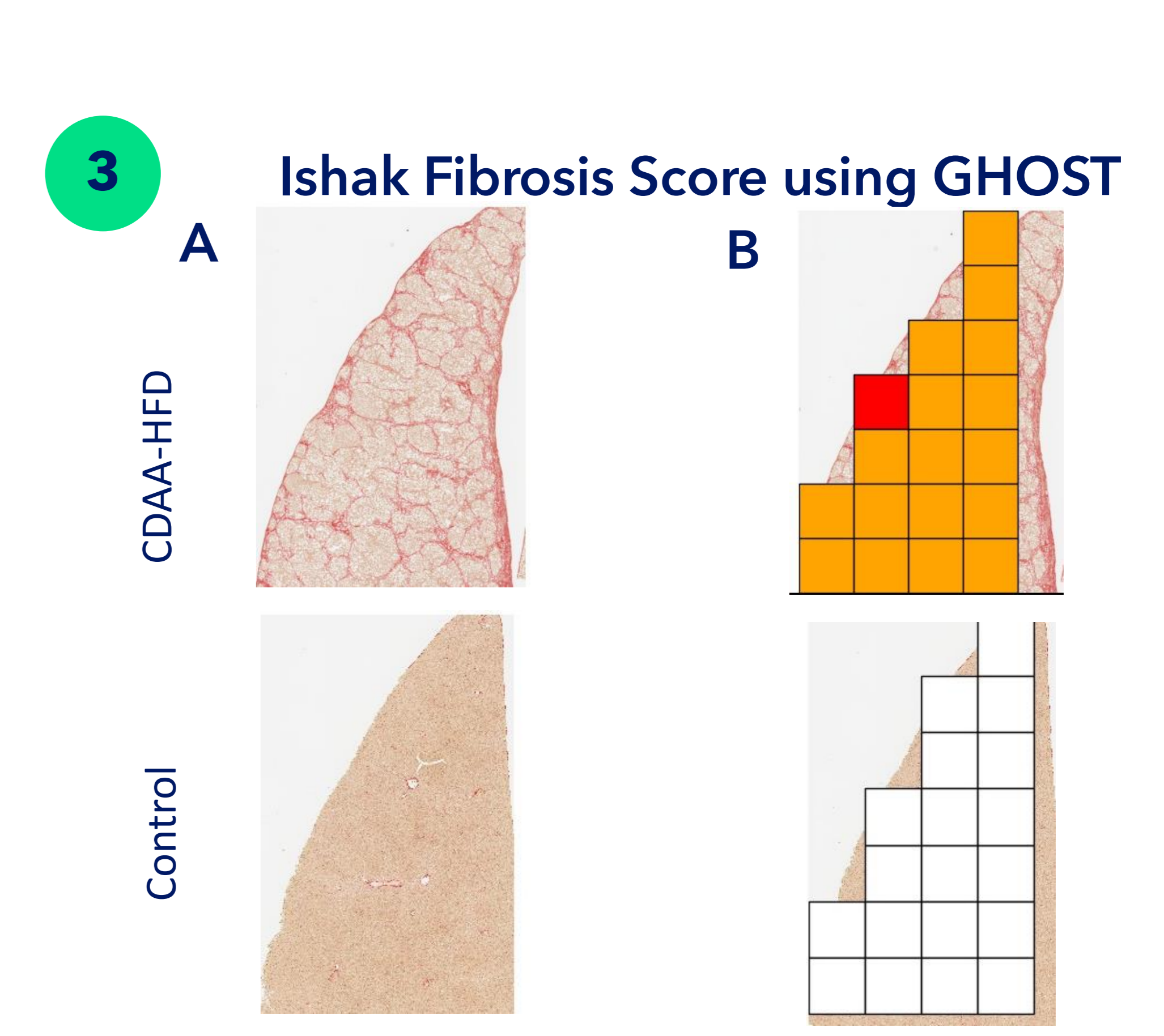
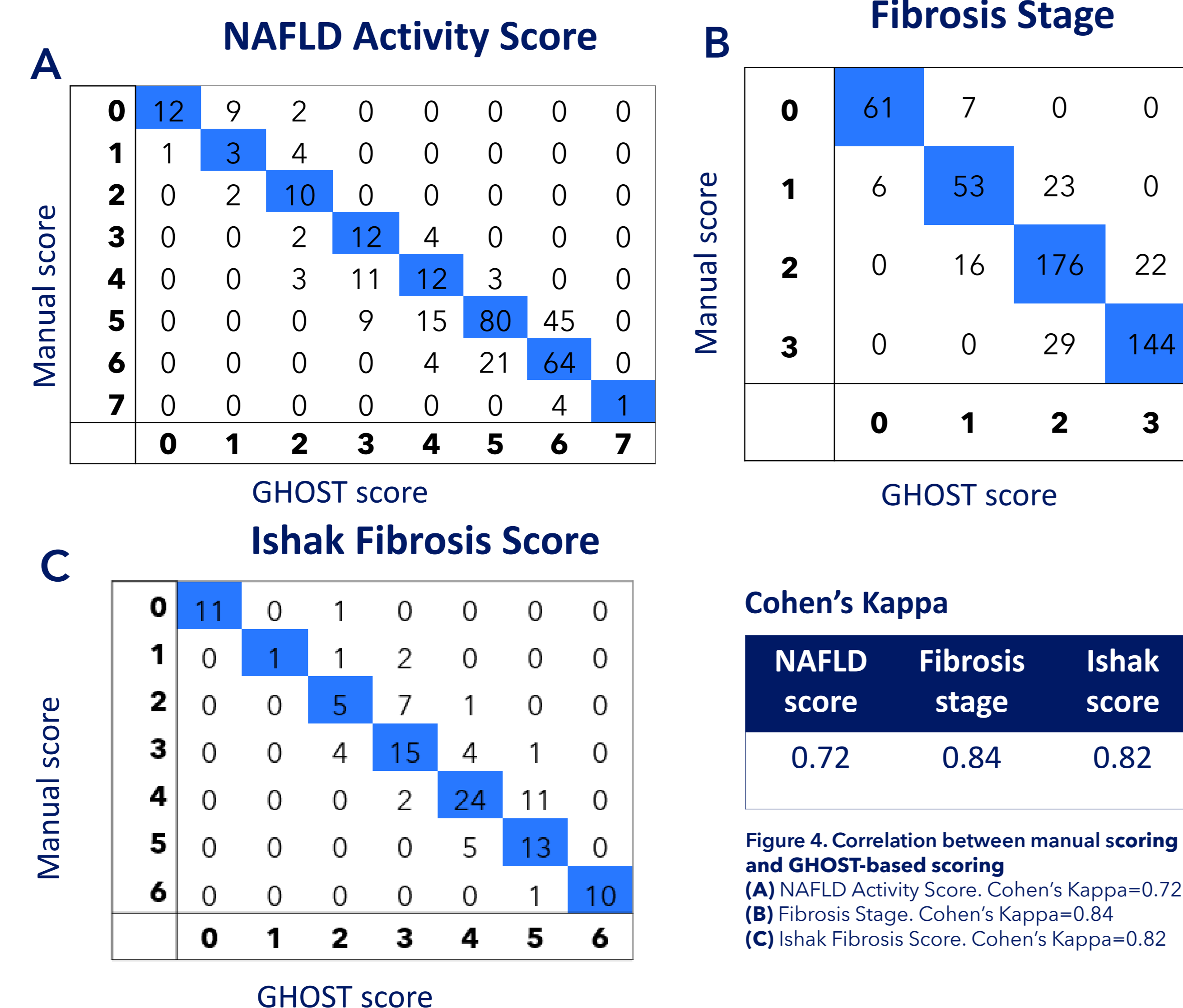
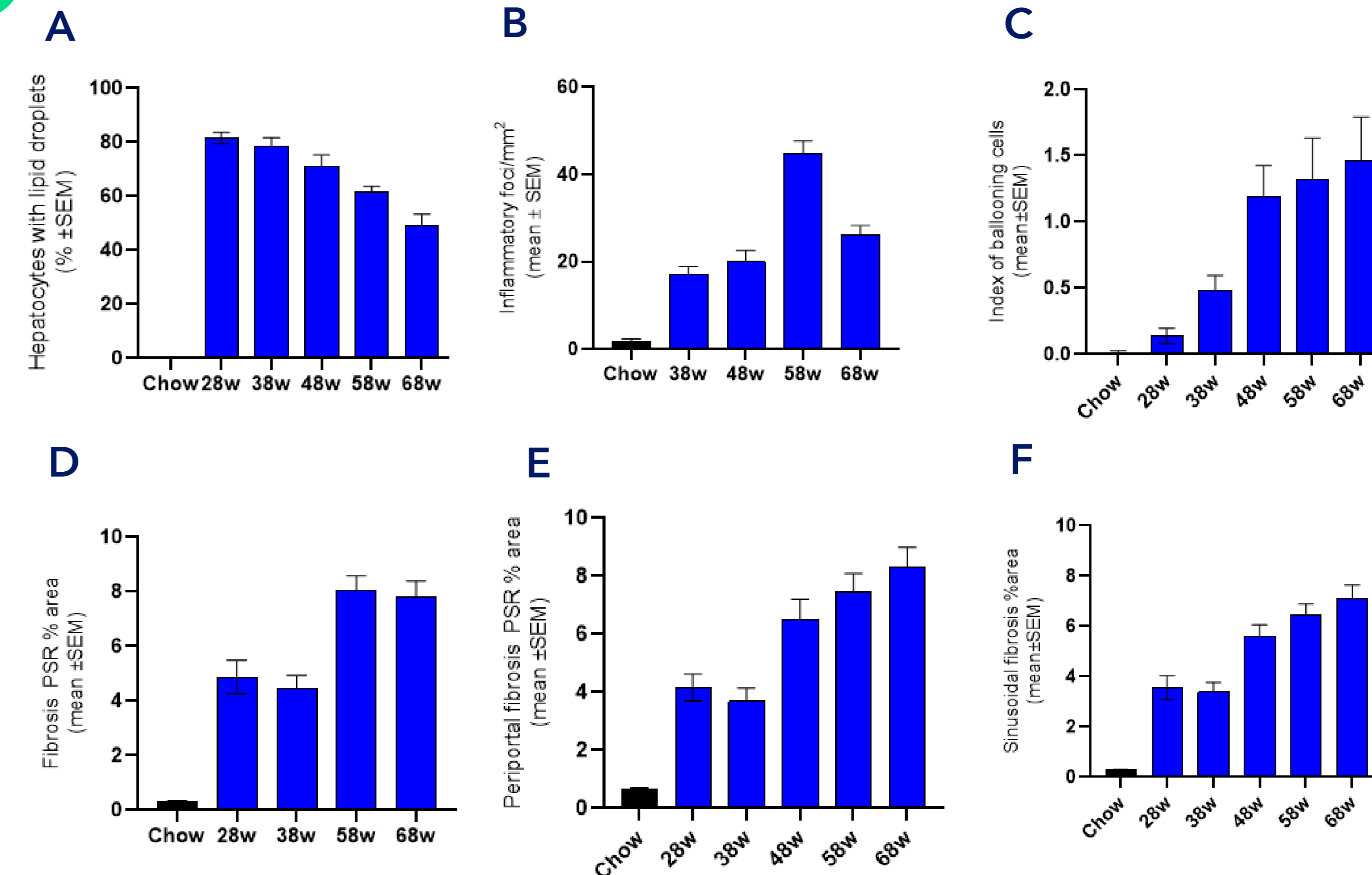


Figure 3. GHOST-based Ishak fibrosis score. (A) PSR-stained liver section from CDAA-HFD rat (top right panel) and age-matched control (lower left panel). (B) Images divided into squares and classified using convolutional neural network (CNN) analysis. Output of the CNN model was used in a machine learning algorithm (random forest) to predict fibrosis. Boxes of different colors indicated different scores.

4 Agreement between GHOST and manual scoring



5 Corresponding histomorphometric variables by GHOST analysis



Conclusion

- + GHOST shows high agreement with manual scoring by expert histopathologist in industry-standard rodent models of NASH
- + GHOST provides fast, accurate and reproducible histopathological scoring
- + GHOST enables quantitative analysis of scoring-derived variables
- + GHOST is highly applicable for assessment of test drug effects on histopathological hallmarks in preclinical models of NASH



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