Implementing a Fine Tuning Feature in Bell Jar: A Tool for Neurohistological Image Analysis

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Introduction

- **Importance of Accurate Quantification**: Essential for understanding neuronal structures and advancing neuroscience research.
- **Challenges of Manual Annotation**: Subject to human error, biases, and inconsistencies, making it unreliable for large datasets.
- **Automation in Neurohistology**: Automation enhances both the speed and accuracy of histological analysis, reducing the dependency on time-consuming manual annotations and increasing the reliability of results.

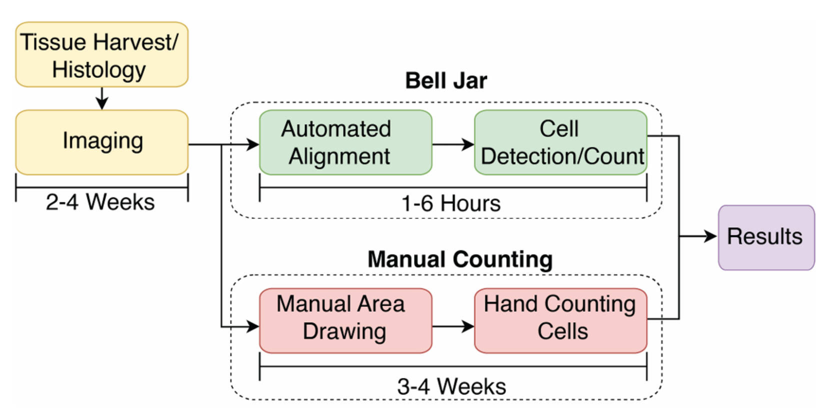

Figure 1. Bell Jar: A Semiautomated Registration and Cell Counting Tool for Mouse Neurohistology Analysis Alec L. R. Soronow, Matthew W. Jacobs, Richard G. Dickson, Euiseok J. Kim eNeuro 5 February 2025, 12 (2) ENEURO.0036-23.2025; **DOI:** 10.1523/ENEURO.0036-23.2025 Accessed on [PDF page 12].

- **Bell Jar Application**: Bell Jar, developed in our lab, uses advanced algorithms for automated signal detection and alignment in neurohistological images, improving efficiency and accuracy over traditional methods.

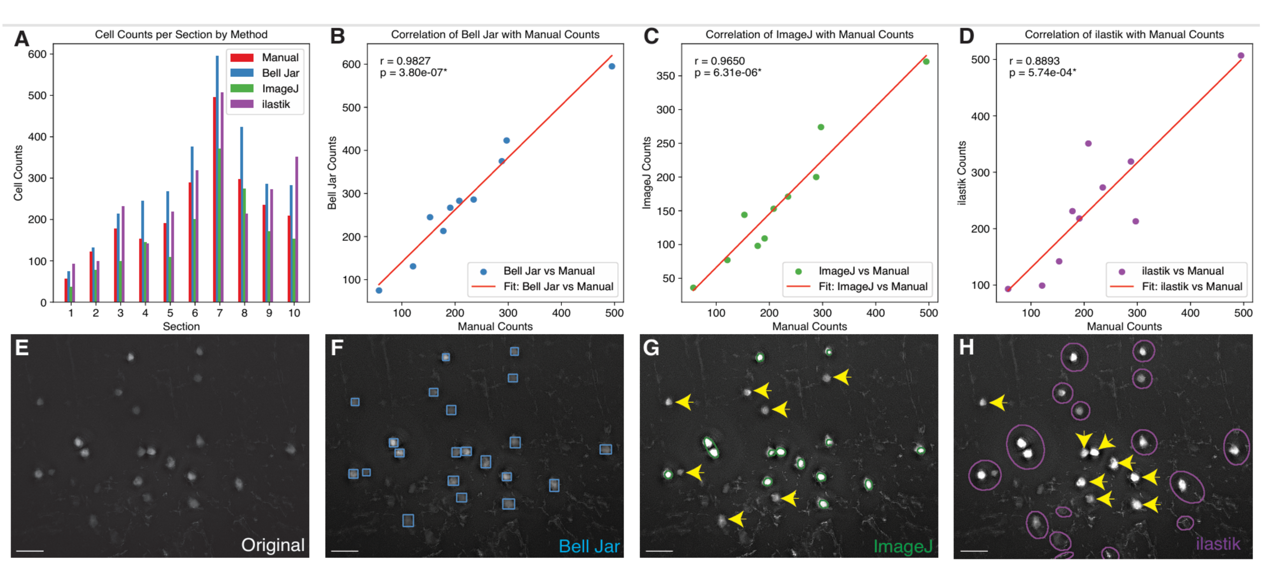

Figure 2. (A) Cell counts by section from Bell Jar, Manual, ImageJ, and ilastik show variability in detection accuracy; (B) Correlation plot demonstrates a high correlation (r = 0.9827) between Bell Jar and manual counts, indicating close alignment; (C-D) Additional correlation plots for ImageJ and ilastik revela varying levels of correlation, highlighting performance differences; (E) The original neurohistological image serves as the input for these detection methods; (F-H) Detection results exhibit precise detection by Bell Jar (F) with fewer misses and false positives, while ImageJ (G) and ilastik (H) showed varied accuracies and precision.

- **"Fine Tune" Feature Introduction**: Enhances the Bell Jar application by allowing users to refine machine learning predictions through manual corrections, directly integrating these improvements into the model's training process.

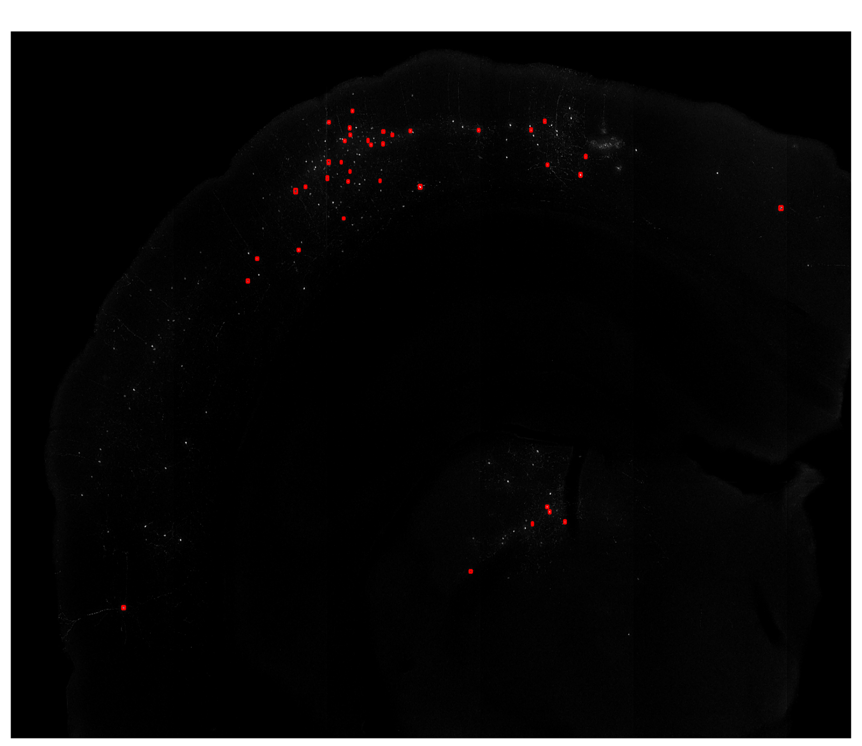

Figure 3: Initial Predictions by the Bell Jar Application. Shows detected neurons (red), highlighting missed neurons (visible as faint white dots). This underscores the "Fine Tune" feature's role in allowing manual adjustments to improve detection accuracy.

- **User Feedback Loop**: Integrates user corrections into the model's training process, leading to continuous improvement in prediction accuracy and reliability, ensuring that Bell Jar stays at the forefront of neurohistological analysis technology.

References

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Hypothesis

The integration of a "Fine Tune" feature in the Bell Jar application, which allows users to provide real-time feedback by manually correcting machine learning annotations, will significantly improve the model's accuracy for neurohistological image analysis. This feedback loop, which involves retraining the model with corrected annotations, will lead to more precise and reliable quantification of neuronal structures.

Methodology

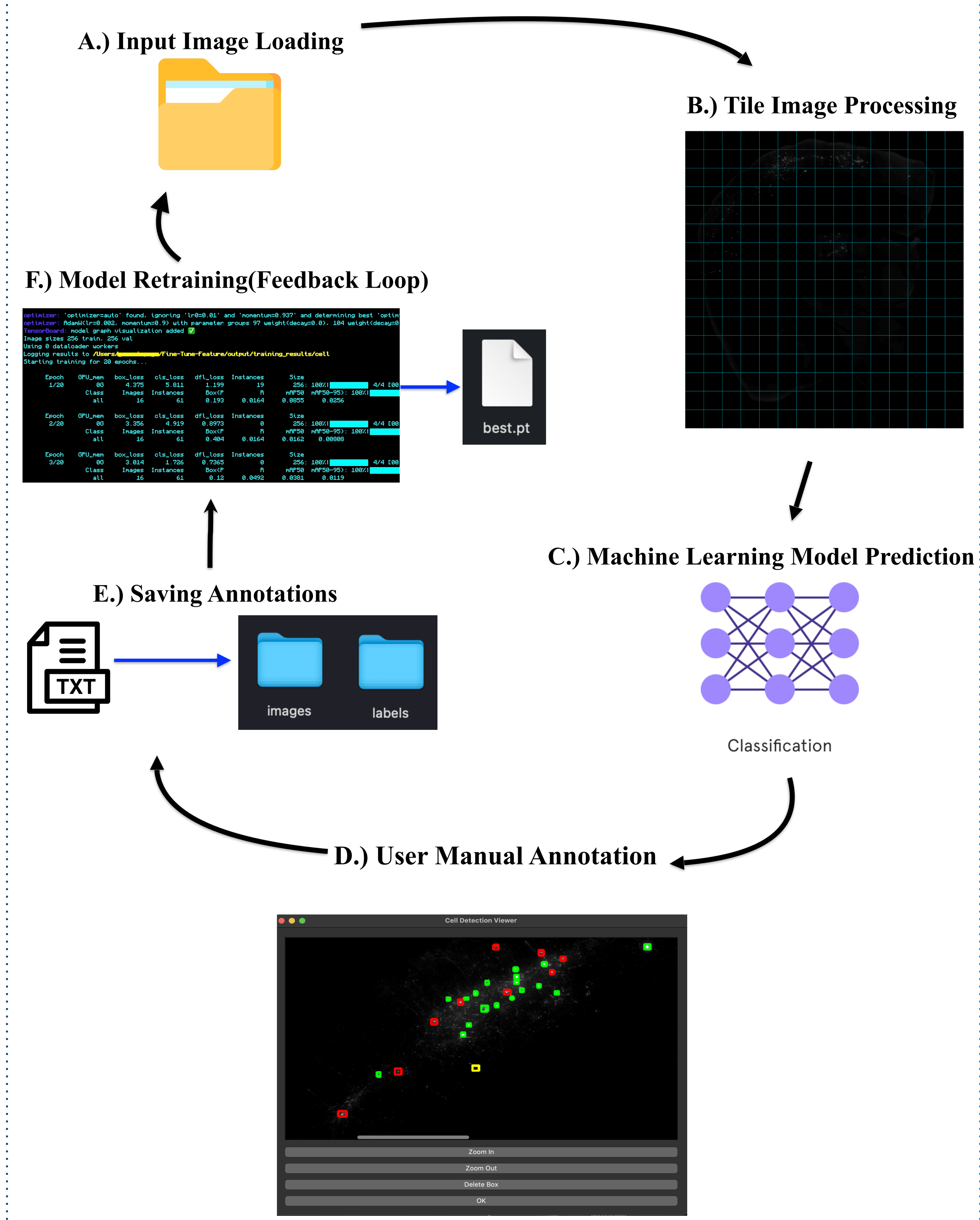

Figure 4. (A) High-resolution images are loaded from a specified directory to initiate the analysis process; (B) Images are segmented into smaller, manageable tiles to facilitate detailed examination of each section; (C) A pre-trained YOLOv8 model automatically identifies and predicts neurons locations within each tile, ensuring accurate detection; (D) An interactive platform allows users to correct or add annotations manually. Red bounded boxes represent user annotations. Green bounded boxes are from the Cell Detection. Yellow represents the user-selected bounded box; (E) The system saves each tile that contains neurons or annotations in a dedicated 'images' folder while the corresponding bounding box data is saved in a 'labels' folder in YOLO format, maintaining alignment and order. This structured data is then used to retrain the model, refining its ability to accurately predict neuron locations based on enhanced datasets from user corrections and initial detections. (F) The newly retrained model is applied, integrating feedback to improve detection accuracy and model robustness significantly, showcasing improvements with each cycle.

Results

1.) Initial Model Predictions

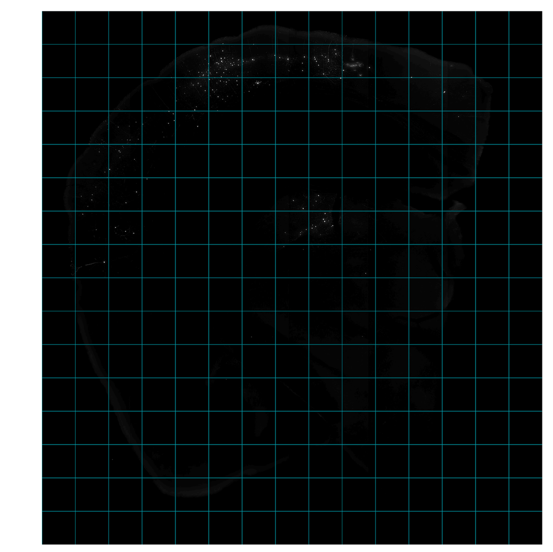

Figure 5. YOLOv8 model identifies potential neuron locations in tiled images, marking initial areas for detailed analysis.

2.) User Annotations

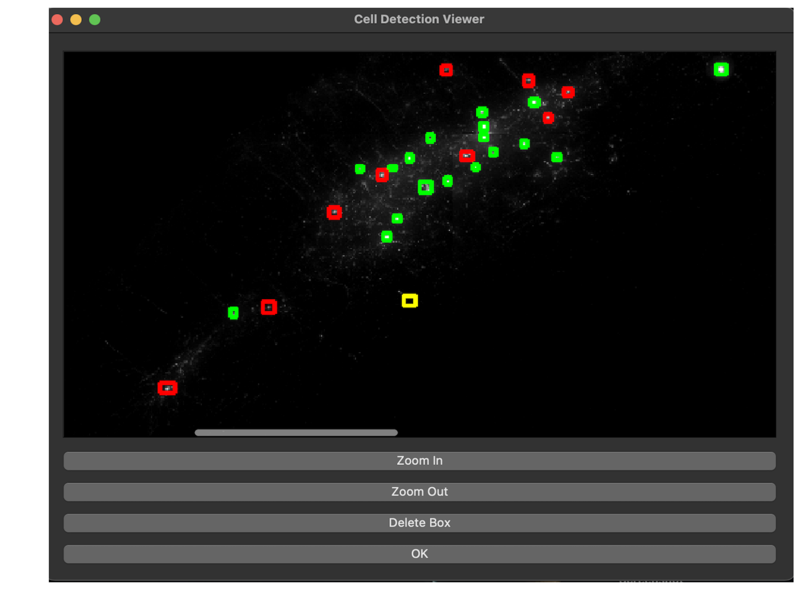

Figure 6. Users modify cell detection outputs by adding, adjusting, or removing annotations: Red boxes indicate manual corrections; green boxes show initial detections; yellow marks selections.

3.) Comparison of Predictions and Annotations

A.)Before User Annotations: B.)After User Annotations:

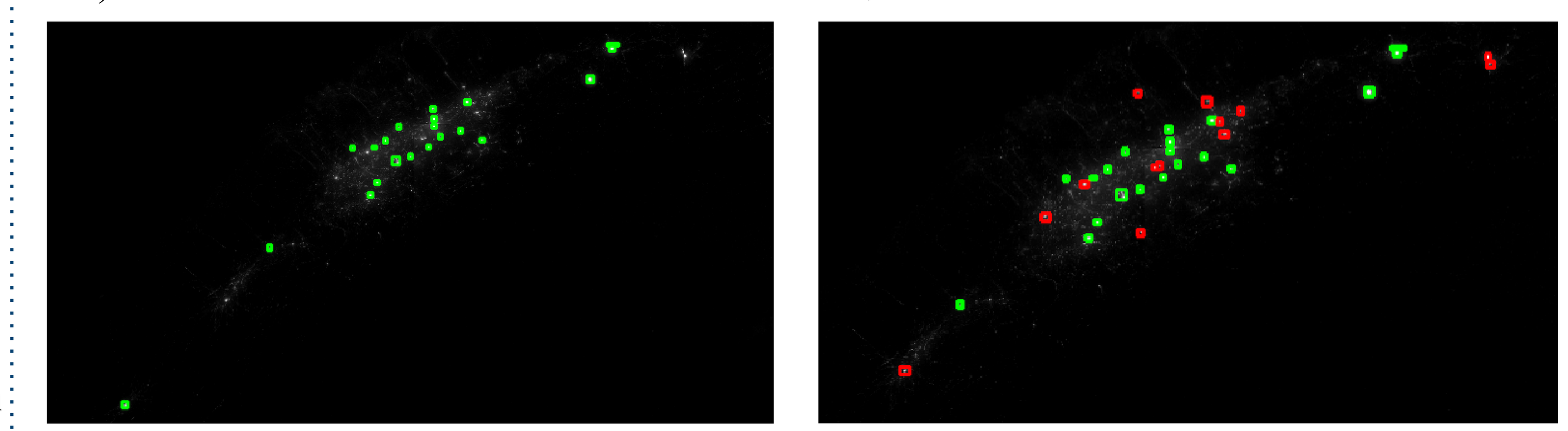

Figure 7. (A) Initial cell detections by the model (green); **(B)** Enhanced accuracy after user annotations (red) highlight areas needing refinement. This visual comparison underscores the importance of user input in improving model performance.

4.) Saved Annotations and Tile Images

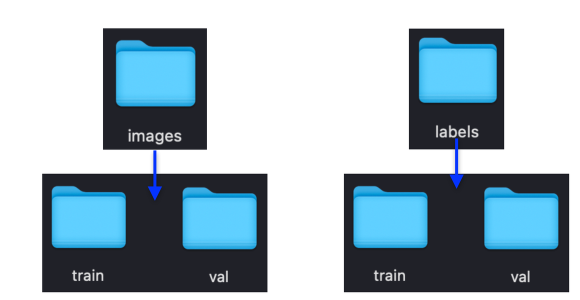

Figure 8. Annotations and tile images are stored in 'train' (80%) and 'val' (20%) folders to facilitate model training and validation, ensuring improved accuracy without overfitting.

5.) Data Utilization for Model Retraining

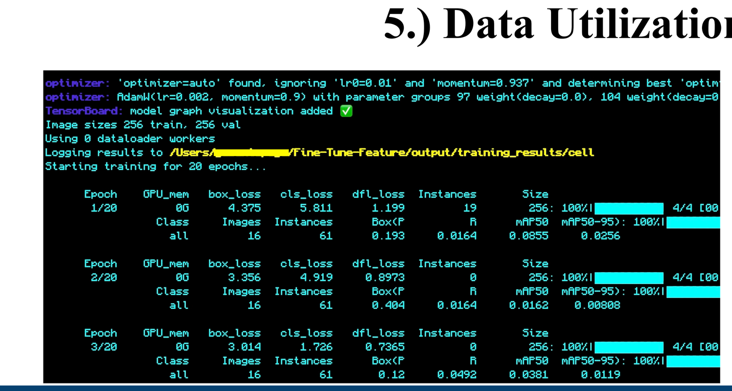

Figure 9. This screenshot captures the model retraining process in the terminal, utilizing annotated data to optimize detection accuracy. The output displays epoch-by-epoch updates, leading to the generation of an improved 'best.pt' model.

Future Directions

- **Retrained Model Detection Gaps:** The new model sometimes misses neurons the old model found unless confidence is lowered from 0.5 to 0.1. This workaround can increase false positives, so further training is needed to match or exceed the old model's coverage reliably.
- **Window Closure and Tile-Slicing Options:** Test on more operating systems to fully fix fullscreen closure. Add an optional setting to keep a small fraction of empty tiles if needed.
- **Bell Jar Integration:** Integrate the Fine Tune feature into the Bell Jar application.

Acknowledgments

- This research was funded by University of California Leadership Excellence Through Advanced Degrees(UC LEADS) - UCOP
- Euiseok J. Kim for allowing me to work in the Kim Lab
- Alec L.R. Soronow, for guiding me through this project