

Becky Arbiv^{1,2}, Yuval Shachaf¹, Tal Dankovich¹, Ron Elran¹, Shai Bookstein¹, Avi Laniado¹, Tomer Dicker¹, Sun Dagan¹, Amit Bart¹, Oscar Puig¹, Kenneth Bloom¹, Ettai Markovits^{1,2}

¹Nucleai, Tel Aviv, Israel, ²Corresponding authors: becky@nucleai.ai, ettai.markovits@nucleai.ai



Introduction

nucleai

- Deep learning-based algorithms are powerful tools for modeling tissue architecture and understanding spatial biology but require a large number of accurate cell annotations for model training.
- Hematoxylin and eosin (H&E) stained slides offer valuable morphological information to pathologists but lack detailed cell type information.
- As a result, pathologist annotations for training these models are limited in both quality and quantity.
- Multiplex immunofluorescence imaging (mIF) provides a more comprehensive and accurate method for classifying cells.
- This study leverages mIF-based cell type predictions to create a large-scale dataset of H&E cell type annotations.

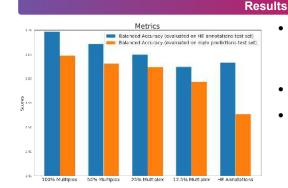
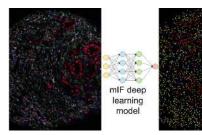
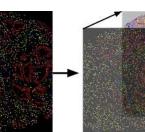


Figure 3: Balanced accuracy on H&E and mIF-based test annotations by amount of training annotations. Increasing the quantity of mIF based annotations improves model performance on both the H&E and mIF-based validation set.

Methods

- Employed a deep learning-based mIF analysis pipeline¹ to predict 12 cell types in a CODEX dataset which consisted of 140 tissue cores from 35 colorectal cancer patients, stained with 56 protein markers, and matched with H&E slides².
- Generated over 60,000 mIF-based annotations on corresponding H&E-stained slides using the mIF model predictions.
- Trained multiple H&E deep learning classifiers with an increasing amount of mIF-based annotations and compared performance to a classifier trained solely on pathologist-based H&E annotations.
- Evaluation was conducted on 11 test tissue cores using manual H&E-based annotations and mIF cell type predictions.





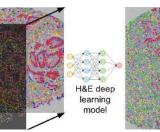
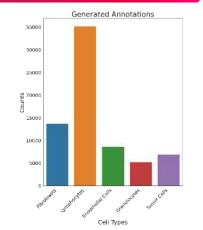


Figure 1: Workflow diagram: mIF slide is analyzed using Nucleai's deep learning analysis pipeline to generate cell type predictions. These predictions are then transferred to H&E slides and used as annotations to train deep learning models for H&E slides.



With equivalent annotation guantities,

annotations on H&E test annotations

model on the mIF-based test set.

With an expanded training dataset,

comparative analyses showed similar accuracy

between the model trained on mIF-based

annotations and one trained on H&E-based

The mIF-based model outperformed H&E-based

incorporating more mIF-based annotations.

model performance significantly improved,

annotations and 0.90 on mIF predictions.

reaching an average AUC of 0.91 on H&E test

Figure 2: Number of generated annotations by cell class. Over 60,000 annotations were generated across all classes.

Conclusion

- This study underscores the value of mIF model predictions in advancing deep learning-based cell typing models in histopathology.
- A substantial dataset of accurate mIF-based annotations was successfully generated, significantly enhancing the accuracy and robustness of H&E cell typing models.
- These results highlight the emergence of mIF-based annotations as the next generation of H&E analysis, enabling pathologists to extract deeper insights from H&E-stained slides.
- Future work can leverage this method to identify challenging and rare cell types, capitalizing on the enhanced accuracy of mIF-based annotations.

References

- 1. Markovits, E. et al. A novel deep learning pipeline for cell typing and phenotypic marker quantification in multiplex imaging. bioRxiv 2022.11.09.515776 (2022) doi:10.1101/2022.11.09.515776.
- 2. C. M. Schürch et al., "Coordinated Cellular Neighborhoods Orchestrate Antitumoral Immunity at the Colorectal Cancer Invasive Front." Cell. vol. 182, no. 5, pp. 1341-1359.e19, Sep. 2020, doi: 10.1016/j.cell.2020.07.005.