

Detecting Mitoses with a Convolutional Neural Network for MIDOG 2022 Challenge

Hongyan Gu¹, Mohammad Haeri², Shuo Ni¹, Christopher Kazu Williams³, Neda Zarrin-Khameh⁴, Shino Magaki³, Xiang 'Anthony' Chen¹

1. University of California Los Angeles, USA
2. University of Kansas Medical Center, USA
3. UCLA David Geffen School of Medicine, USA
4. Baylor College of Medicine, USA



Samueli
School of Engineering



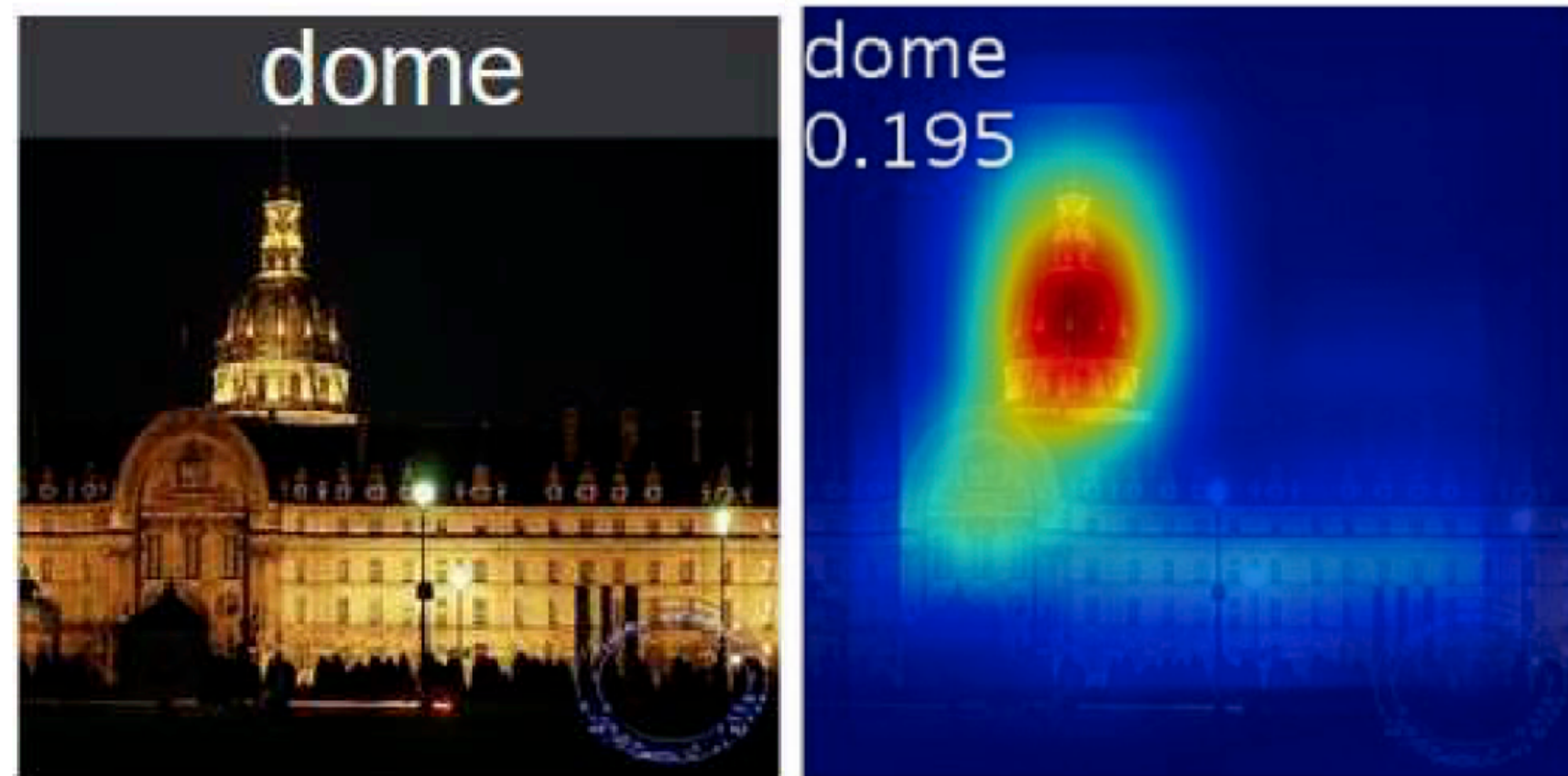
David Geffen
School of Medicine



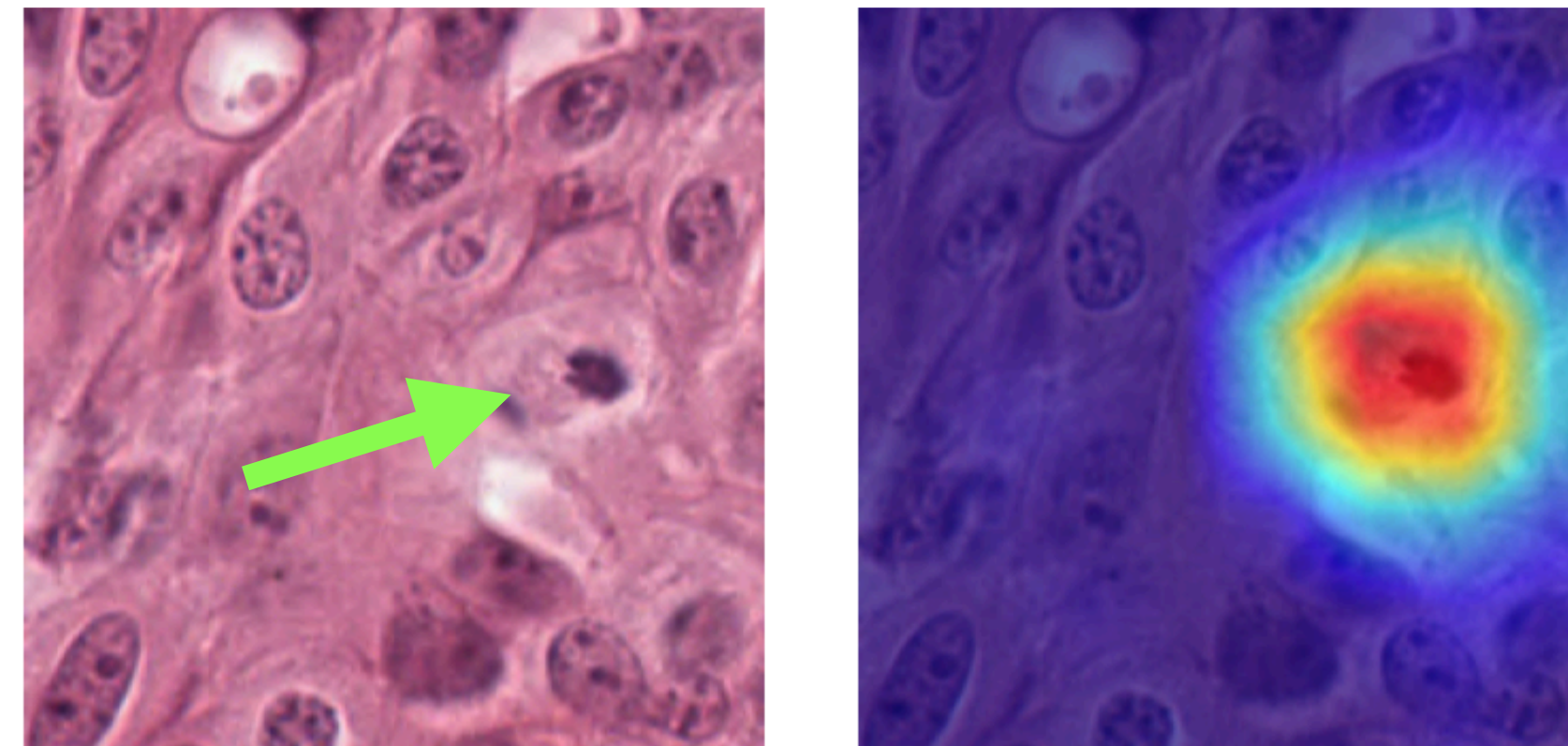
Extracting Locations with Class Activation Map

Class Activation Map (CAM) [Zhou, 2016]:

- Indicates discriminative image regions used by the CNN to identify a category;

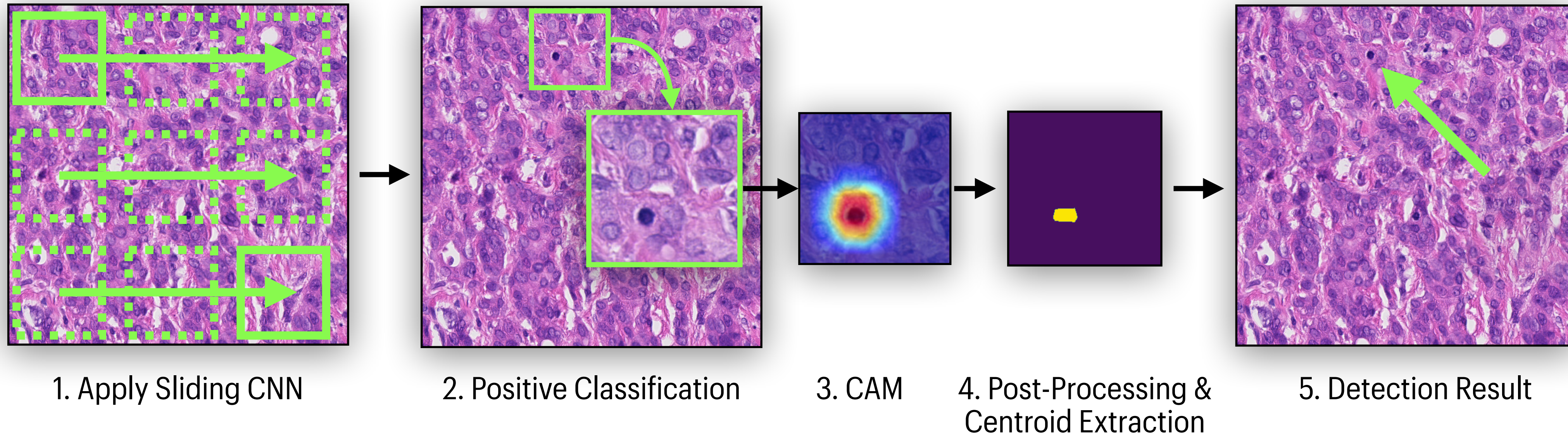


Left: an image sample (class label: dome);
Right: a CAM for the 'dome' class. [Zhou, 2016]



Left: H&E patch (size=240x240) with mitosis (pointed by arrow);
Right: a CAM for the 'mitosis' class

Data Processing Pipeline



1. EfficientNet-b3, window size=240x240, step size=30, no normalization method was used;
2. Probability threshold: 0.84, non-max suppression threshold: 0.22;
3. Grad-CAM++ [Chattopadhyay, 2017];
4. Binarizations with Otsu's thresholding;

Coping with Domain Generalization Challenge

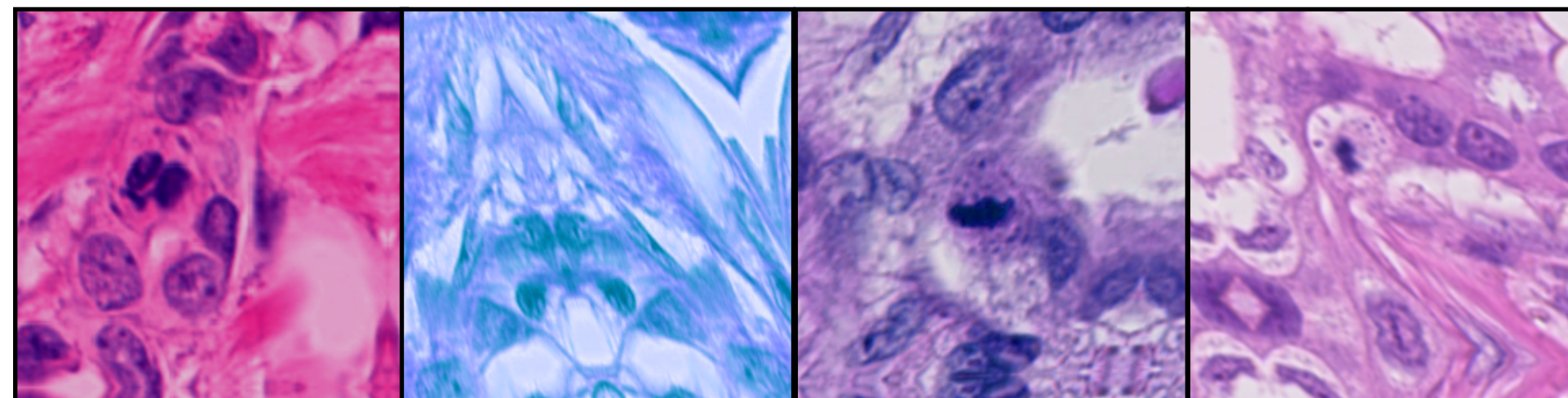
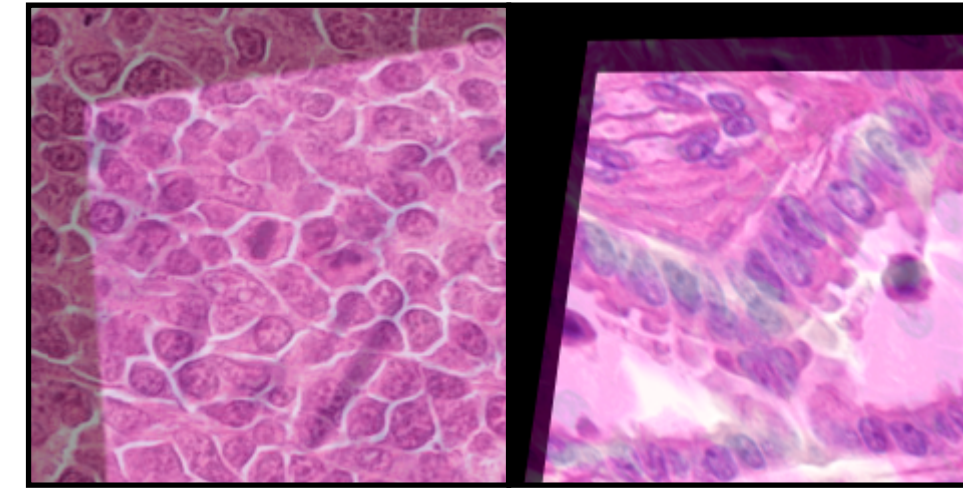
Three techniques were used to cope with the domain generalization challenge:

1. Data augmentation with balance-mixup and stain augmentation;
2. Leveraging the unlabeled images for model training;
3. Train CNNs with an active learning strategy.

Data Augmentation

Two special online augmentation techniques:

1. Balance-mixup [Galdran, 2021] to deal with class imbalance.
2. Stain augmentation [Tellez, 2017] to deal with domain shift.



Other online augmentation methods used: random rotation, flip, elastic transform, grid distortion, affine, color jitter, Gaussian blur, and Gaussian noise

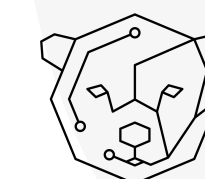
Galdran, Adrian, Gustavo Carneiro, and Miguel A. González Ballester. "Balanced-mixup for highly imbalanced medical image classification." *International Conference on Medical Image Computing and Computer-Assisted Intervention*. Springer, Cham, 2021.

Tellez, David, et al. "Whole-slide mitosis detection in H&E breast histology using PHH3 as a reference to train distilled stain-invariant convolutional networks." *IEEE transactions on medical imaging* 37.9 (2018): 2126-2136.

UCLA

Samueli

School of Engineering



UCLA HCI
RESEARCH

Training with Noisy Labels

Leveraging the unlabeled images for training:

- ~90% of MIDOG2022 images for model training, including unlabeled images;
- Treat unlabeled images as all negative (no mitoses);
- Use Online Uncertainty Sample Mining [Xue, 2019] to enable CNNs to deal with noisy labels.

Train CNNs with an Active Learning Strategy

While CNN's F1 score on validation images does not increase

DO: {

1. **Train** the CNN (with 240x240 patches) and select the best model;
 2. **Inference** the CNN on validation images;
 3. **Add** false-positive, false-negative, hard-negative patches (size: 240x240).
- }

After six rounds of active learning, there are

- 103,816 patches in the training set;
- 23,638 patches in the validation set;

Result and Take-Aways

Result: with an EfficientNet-b3 CNN (12M parameters)

- Preliminary test phase: overall F1 0.7323 (precision: 0.7313, recall: 0.7333).

Take-Aways:

- Class activation map can bridge the gap between CNNs and mitosis detection task;
- An active-learning sampling approach can improve the performance.

Manuscript:

- Gu, Hongyan, et al. "Detecting Mitoses with a Convolutional Neural Network for MIDOG 2022 Challenge." *arXiv preprint arXiv:2208.12437* (2022).

