Neural Cellular Automata for Pathology Classification

Waleed Ahmed Shahid, Maximilian Roth

Summary

Colorectal cancer is the **third most common cancer** worldwide and accounts for the **second highest number of cancer-related deaths**. In this work, we employ **neural cellular automata** (NCA) to classify histopathological images of colorectal cancer patients. We have also tested a conventional convolutional neural network (CNN) model on the same dataset as a baseline. Our NCA classifier not only exceeds all benchmarks reported in the original MedMNIST paper [2] but also outperforms the CNN model and **matches the performance of the best model from the MedMNIST v2 paper** [4].

Motivation

Colorectal cancer is the **third most common** cancer type and has the **second highest mortality** [1]. It is **crucial to identify it as early as possible** to ensure the best treatment outcome. Our work proposes a **N**eural **C**ellular **A**utomaton for histopathological image classification of the colorectum.

Neural Cellular Automata

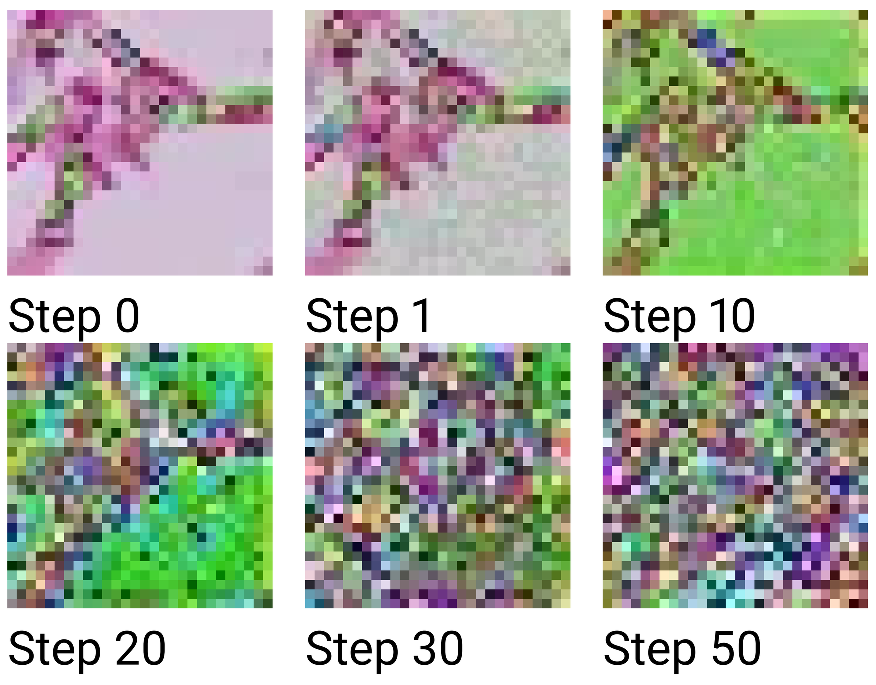

Figure 1: NCA steps 0, 1, 10, 20, 30, 50

- **Neural Cellular Automata** are cellular automata that learn their own update rules
- Access only neighbour cells of grid
- Grid form resembled images
- NCA learns to manipulate pixels such that they are easier to classify

Dataset

- **PathMNIST** [2]: 107k samples
- Test partition from other clinic resulting in **distribution shift**
- Multiple **image augmentations**
- Color jitter for better **stain generalization**

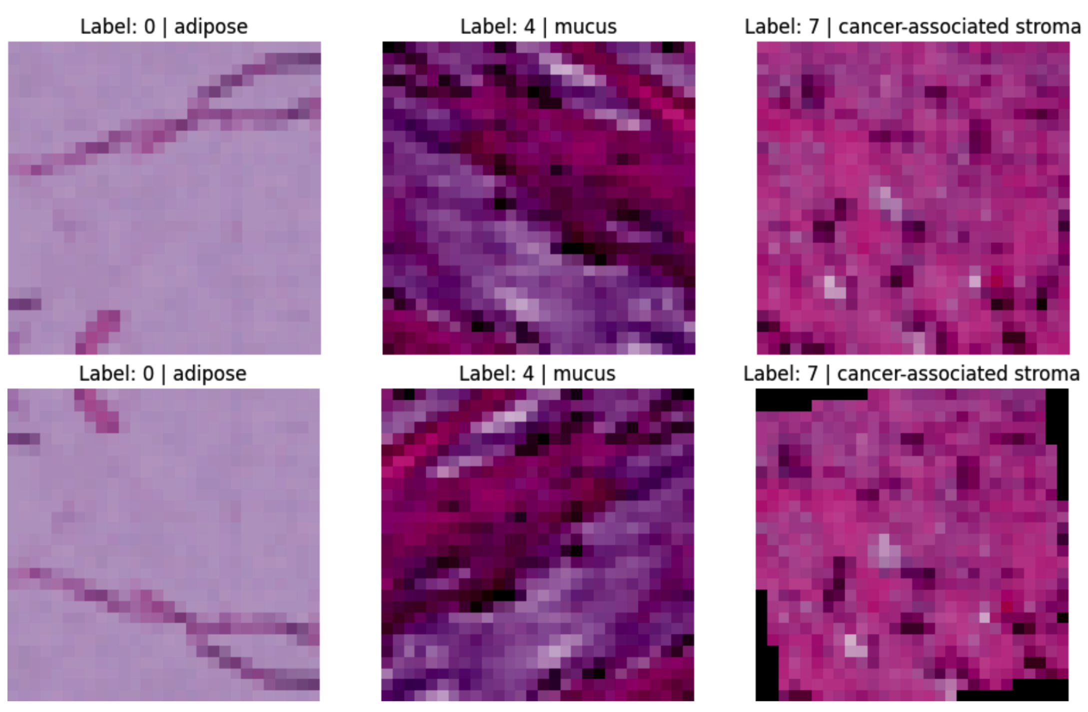

Figure 2: (Top) Non-augmented samples, (Bottom) Augmented samples

Methodology

- **NCA classifier** that supports arbitrary image sizes (e.g., 28×28, 64×64)
- Each pixel has a hidden state, **updated over 50 steps** using local neighbor info
- Updates include randomness through firign rate of 0.5 to promote robustness
- **Linear classifier** follows the pooling step
- **CNN baseline** with 5 conv and a fully connected layer
- Both models trained using Adam optimizer, Cross Entropy Loss and automated mixed precision (AMP)
- CNN trained for 50 epochs; NCA for 35 epochs

Results

- NCA Model is **on par with best MedMNIST v2 model** [4]
- Also exceeds all models in the original MedMNIST paper [2]
- Noticeable **accuracy drop from distribution shift** in test split
- NCA performance is significantly worse if image not resized
- 28x28 and 224x224 (resized) perform similarly, 64x64 and 128x128 worse, likely due to different downsampling artifacts
- Significant difference in classification ability, **cancer-associated stroma very hard**
- Inference time per 1024 samples: NCA 0.2235s, CNN 0.0098s

Our Methods	AUC	ACC
CNN-5 (28)	0.962	0.842
CNN-5 (64)	0.961	0.831
CNN-5 (128)	0.961	0.840
CNN-5 (224)	0.962	0.842
NCA-50 (28)	0.965	**0.910**
NCA-50 (64)	**0.967**	0.908
NCA-50 (64 no resize)	0.931	0.775
NCA-50 (128)	0.966	**0.910**
NCA-50 (128 no resize)	0.832	0.401
NCA-50 (224)	0.965	0.909
NCA-50 (224 no resize)	0.702	0.262

Table 1: Our Results

MedMNIST v2 [4]	AUC	ACC
ResNet-18 (28)	0.983	0.907
ResNet-18 (224)	0.989	0.909
ResNet-50 (28)	**0.990**	**0.911**
ResNet-50 (224)	0.989	0.892
auto-sklearn	0.934	0.716
AutoKeras	0.959	0.834
Google AutoML Vision	0.944	0.728

Table 2: MedMNIST v2 Results [4]

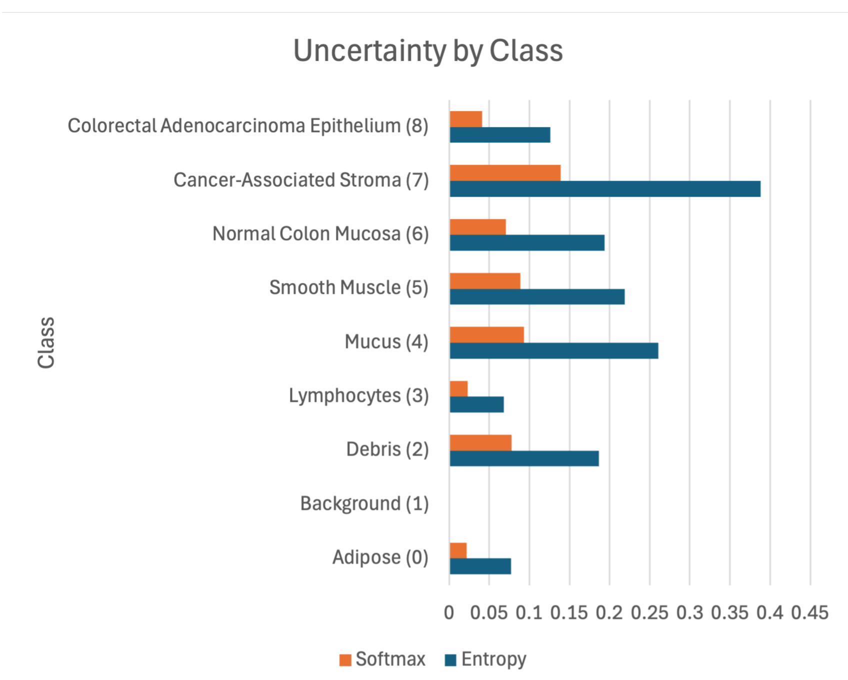

Figure 3: NCA Uncertainty Graph

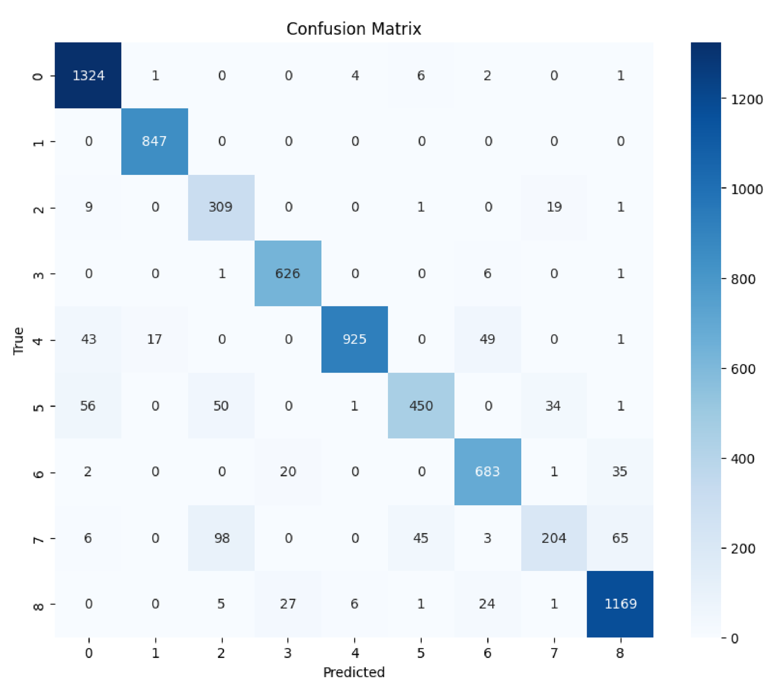

Figure 4: NCA Confusion Matrix

Sources

[1] SUNG, Hyuna, et al. Global cancer statistics 2020: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. CA: a cancer journal for clinicians, 2021, 71. Jg., Nr. 3, S. 209-249.

[2] Yang, J., Shi, R., Ni, B. (2021, April). Medmnist classification decathlon: A lightweight automl benchmark for medical image analysis. In 2021 IEEE 18th International Symposium on Biomedical Imaging (ISBI) (pp. 191-195). IEEE.

[3] KATHER, Jakob Nikolas, et al. Predicting survival from colorectal cancer histology slides using deep learning: A retrospective multicenter study. PLoS medicine, 2019, 16. Jg., Nr. 1, S. e1002730.

[4] YANG, Jiancheng, et al. Medmnist v2-a large-scale lightweight benchmark for 2d and 3d biomedical image classification. Scientific Data, 2023, 10. Jg., Nr. 1, S. 41.