



# Deep Learning for Histopathology Image Analysis

**EE 350  
PRESENTATION**

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# Introduction



HISTOPATHOLOGY IMAGES ARE IMAGES OF HUMAN TISSUE CAPTURED THROUGH A MICROSCOPE, WHICH CAN BE USED TO DETECT DISEASES, DAMAGE, OR OTHER ABNORMALITIES IN THE BODY.



THE USE OF ARTIFICIAL INTELLIGENCE (AI) TO EXAMINE THESE IMAGES SAVES CLINICIANS FROM HAVING TO GO THROUGH THEM MANUALLY AND LOOK FOR ABNORMALITIES.



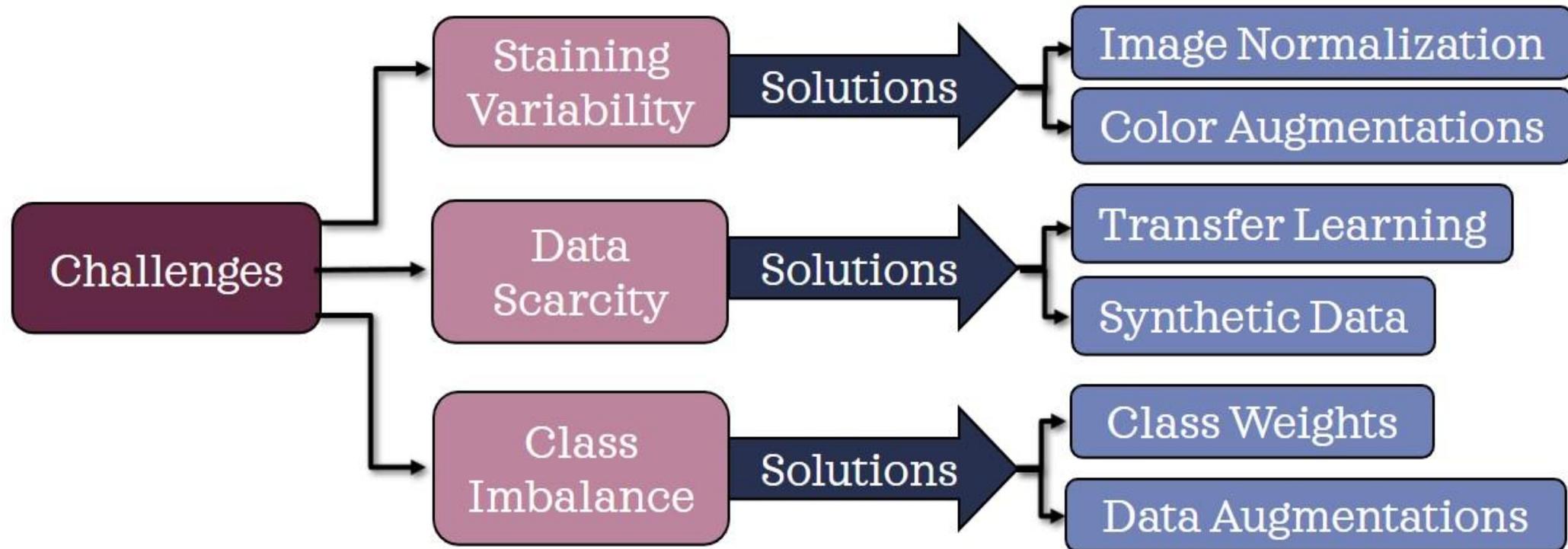
EARLY DIAGNOSIS AND DETECTION OF DISEASE USING AI SAVES PATIENTS FROM INTENSIVE TREATMENT PROCEDURES AND GIVES THEM A BETTER PROGNOSIS.

# Aims and Objectives

1) To understand the different challenges faced in the application of deep learning networks on histopathology images and to discuss their solutions.

2) To explore multiple deep learning methods used on histopathology images for the diagnosis of prevalent diseases

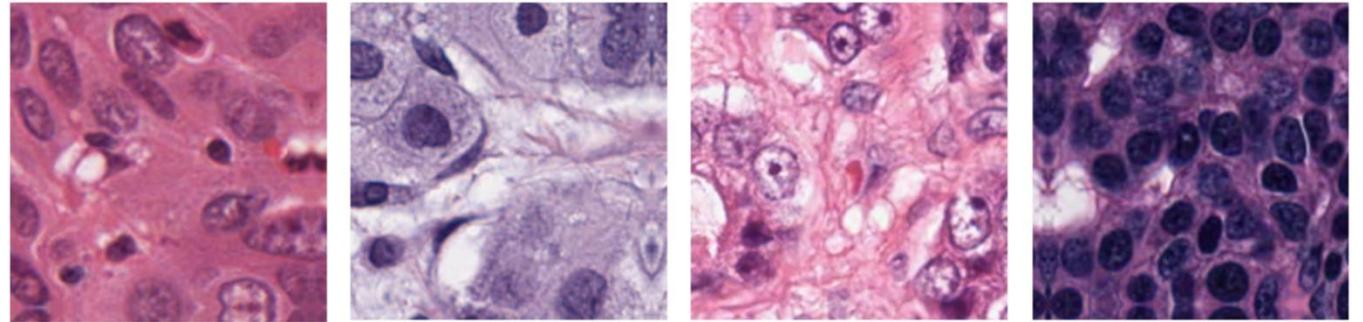
# Challenges and Solutions



# Challenge: Stain Variability

The color distribution in H&E-stained images varies based on:

- Dye concentration
- The scanning device used
- Staining time
- Environmental light
- Noise during image transmission.

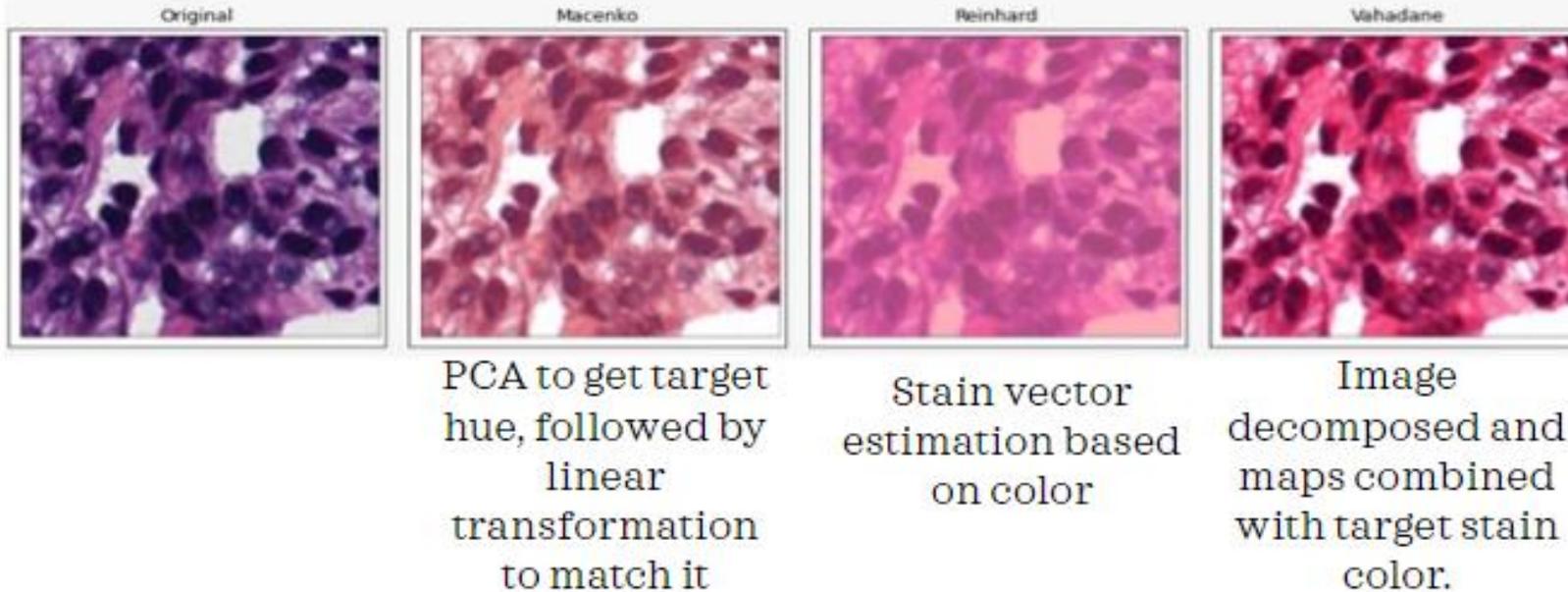


These color variations\* adversely affect the model performance.

\*Source: N. Kumar, R. Verma, S. Sharma, S. Bhargava, A. Vahadane and A. Sethi, "A Dataset and a Technique for Generalized Nuclear Segmentation for Computational Pathology," in IEEE Transactions on Medical Imaging, vol. 36, no. 7, pp.1550-1560, July 2017

# Solution: Color Normalization

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# Solution: Brightness and Hue Augmentations

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Different types of pixel-wise color augmentations were used in [3], like random brightness and hue variations, which helped train models that generalized well to new data.

# Challenge: Data Scarcity



Deep Learning networks require a large amount of annotated data.



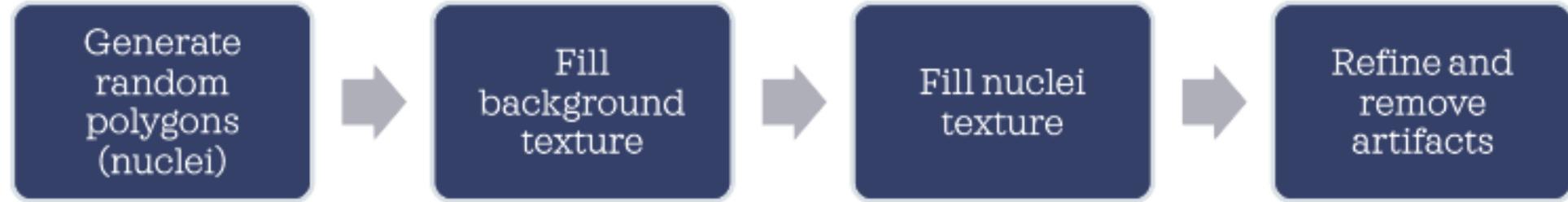
The annotation of histopathology images is time-taking and expensive.



Most Datasets have few images

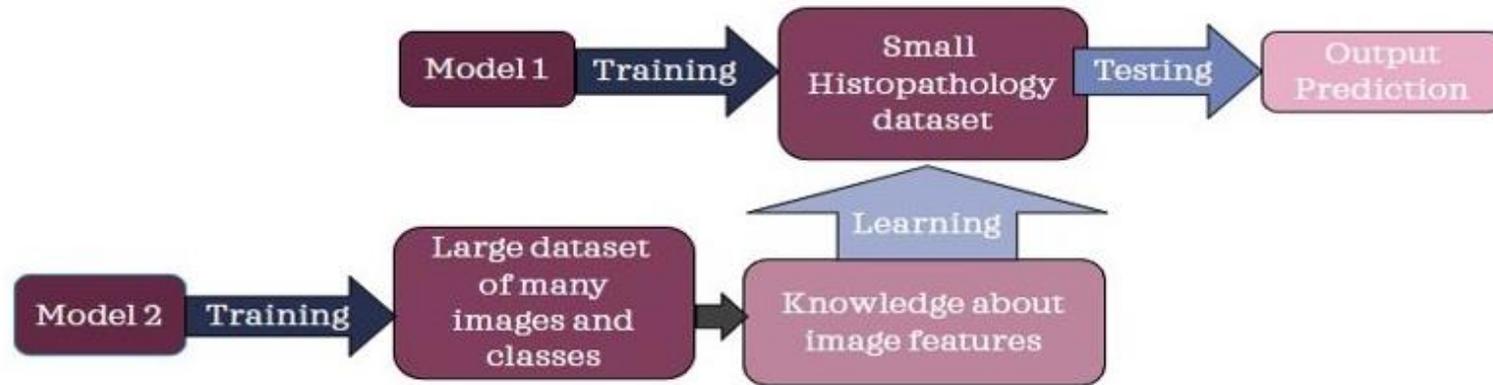
# Solution: Generation of Synthetic Images

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# Solution: Transfer Learning

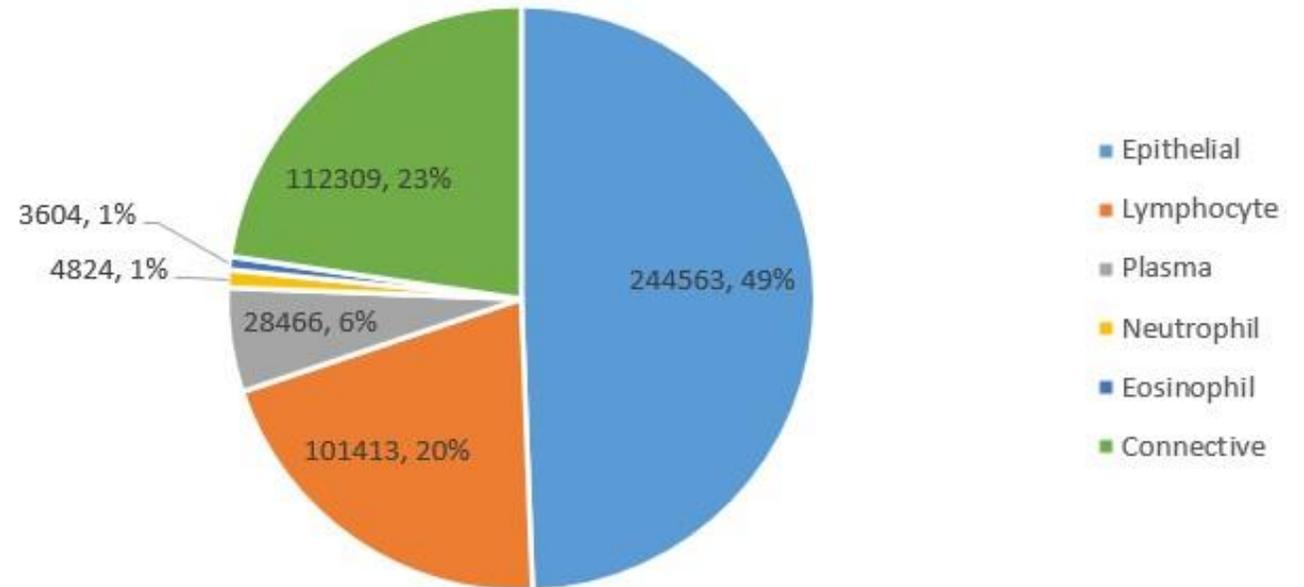
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# Challenge: Class Imbalance

Biological datasets usually have class imbalance, wherein some classes have abundant instances while other classes are scarce.

For example, distribution of nuclei in the Lizard dataset\* of colon biopsy images:



\*Source: Simon Graham, Mostafa Jahanifar, Ayesha Azam, Mohammed Nimir, Yee-Wah Tsang, KatherineDodd, Emily Hero, et al., "Lizard: A large-scale dataset for colonic nuclear instance segmentation and classification," in ICCV Workshops, October 2021.

## Solution: Adjusting Class Weights

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Adjusting the class weights for the loss, in inverse proportion to the class frequency is one remedy for class imbalance

## Solution: Class-based Data Augmentation

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Geometric augmentations such as flips, rotations, elastic deformations and simple resampling of the training data roughly proportional to the inverse of the class frequency is another remedy for class imbalance

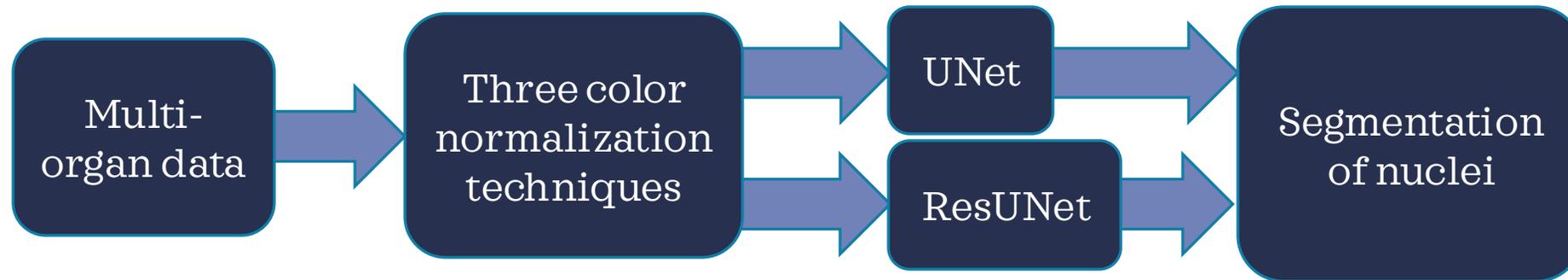
# Experiments and Results

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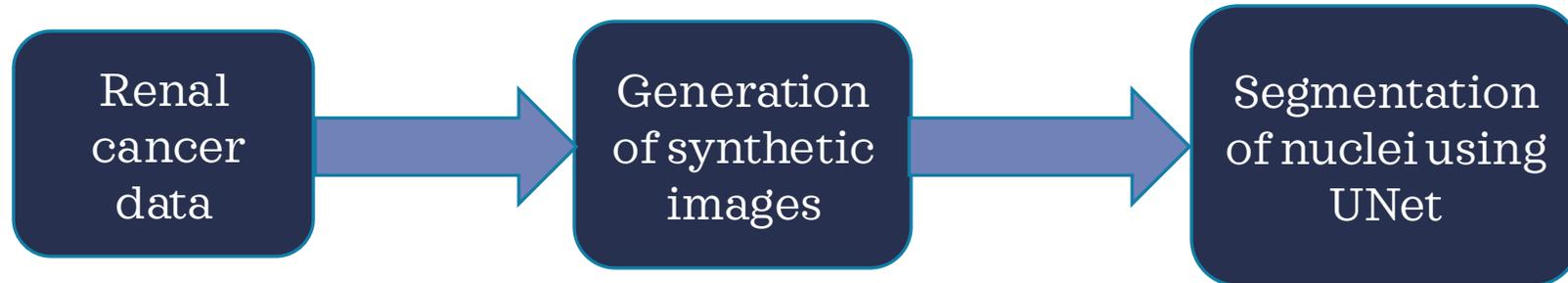
# Experiment [1]

Aim: To study the effect of different image normalization techniques on segmentation of nuclei using UNet and ResUNet



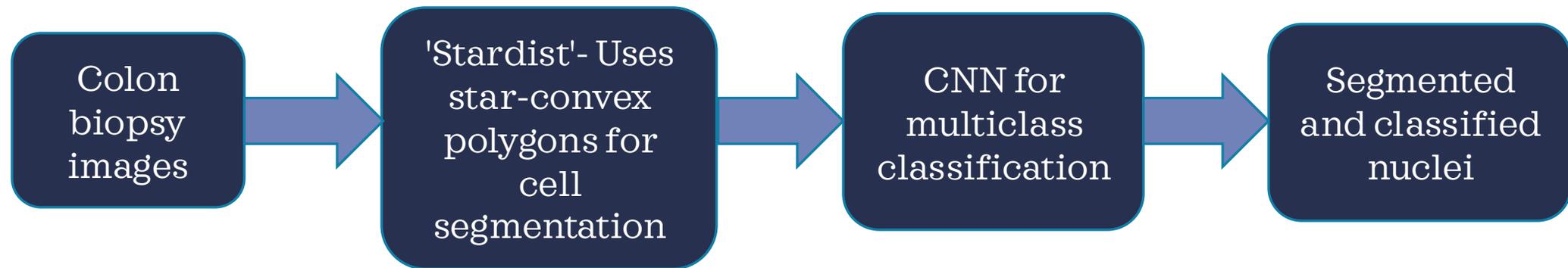
# Experiment [2]

Aim: To analyse how well a UNet model can segment histopathology images when trained on synthetic data



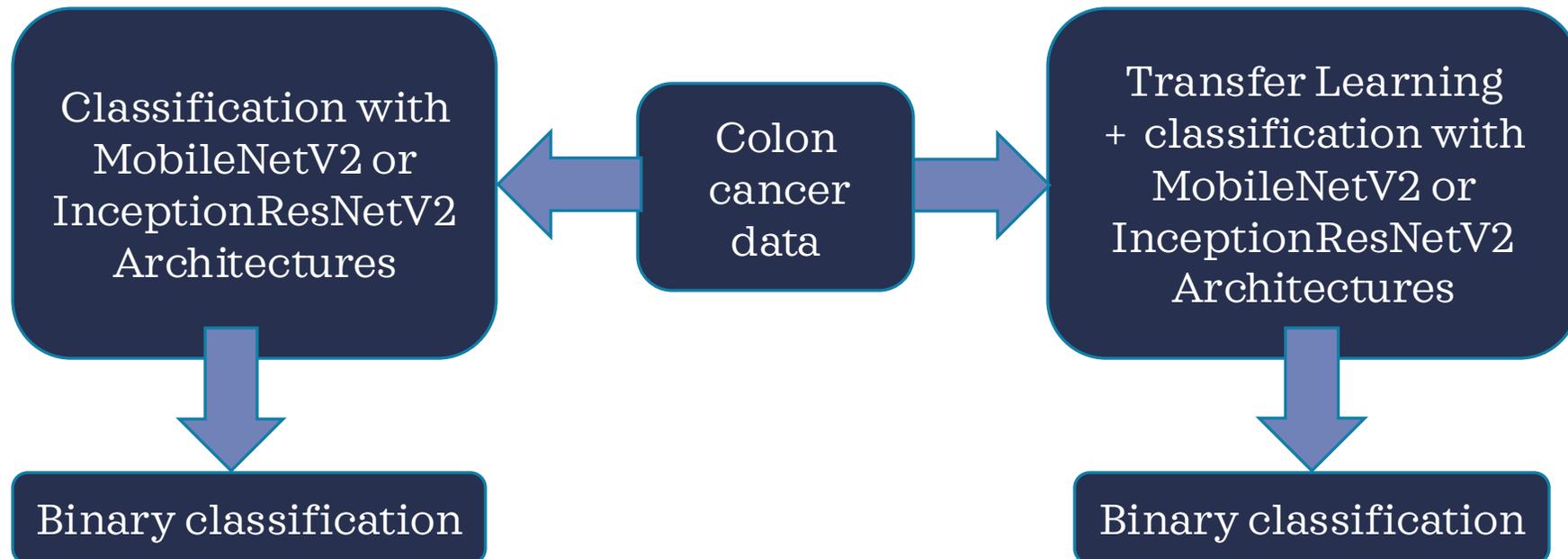
# Experiment [3]

Aim: To study nuclei instance segmentation and classification for colon biopsy images



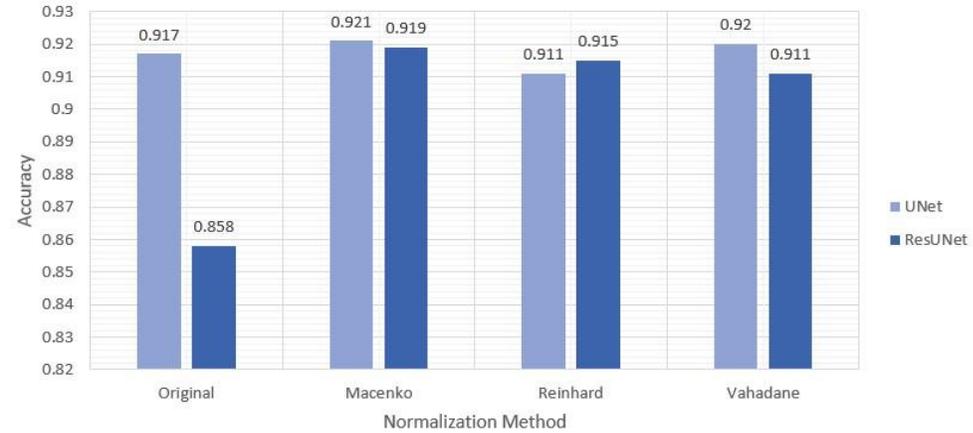
# Experiment [4]

Aim: To study the benefits of using transfer learning on histopathology data for classification



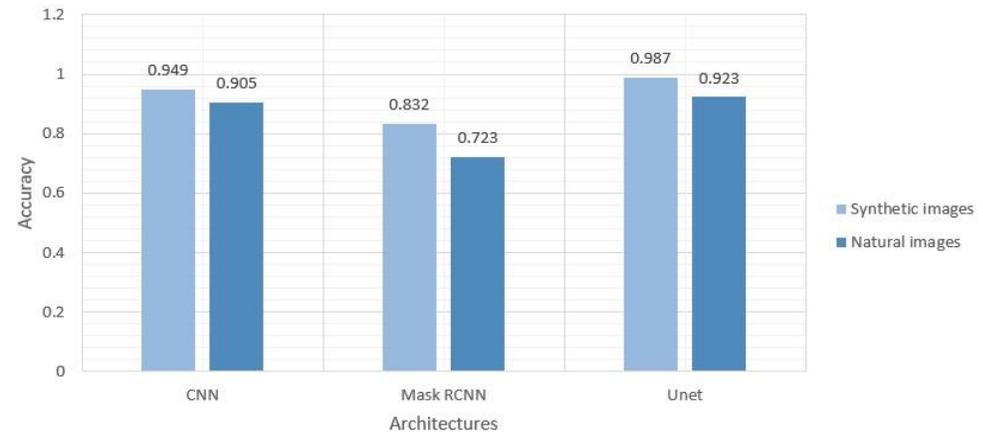
# Segmentation Results

1)A comparative analysis of the accuracy of the Unet and ResUnet models before and after trying three different image normalization techniques[1]



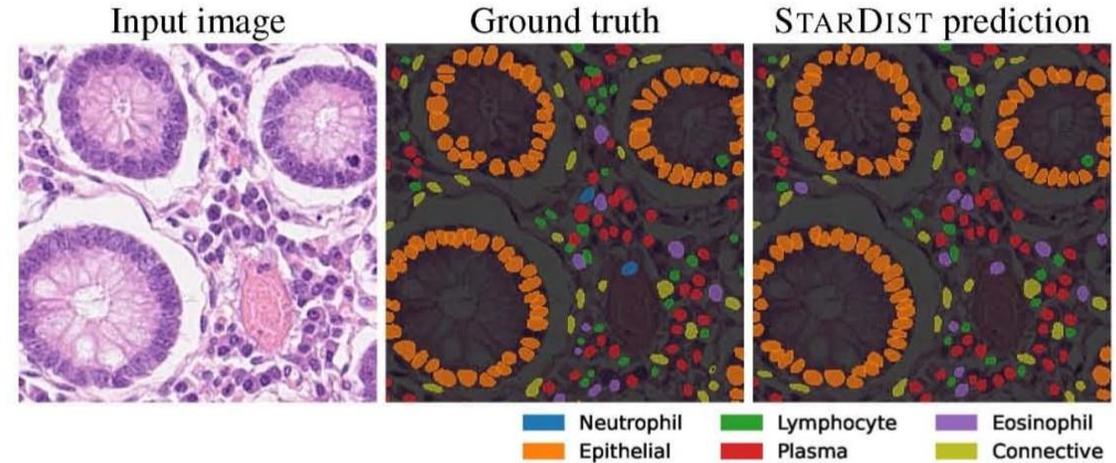
The Macenko technique is observed to be the best normalization technique

2)A comparative analysis of the accuracy of three types of segmentation models on synthetic and actual data.[2]



# Classification Results

1) The segmentation and classification of cells by Stardist.[3]



The final multi class panoptic quality was 0.4971.

2) Comparison of the classification results in Expt. 4 with and without using transfer learning[4]

Metric	Without Transfer Learning	With Transfer Learning
Accuracy	99.95	99.98
Time (min)	6	5

We can see that the accuracy has increased and training time has reduced.

# Conclusions

1) Thus we can see that techniques like image normalization, transfer learning and synthetic image generation lead to a considerable improvement in the DL model performance on histopathology images

2) We have successfully explored different deep learning architectures for the segmentation and classification of histopathology images.

# References

- [1] Z. Yildirim, E. Hancer, R. Samet, M. T. Mali and N. Nemati, "Effect of Color Normalization on Nuclei Segmentation Problem in H&E Stained Histopathology Images," 2022 30th Signal Processing and Communications Applications Conference (SIU), Safranbolu, Turkey, 2022, pp. 1-4, doi: 10.1109/SIU55565.2022.9864814.
- [2] M. S. Hossain and N. Sakib, "Renal Cell Cancer Nuclei Segmentation from Histopathology Image Using Synthetic Data," 2020 16th IEEE International Colloquium on Signal Processing and its Applications (CSPA), Langkawi, Malaysia, 2020, pp. 236-241, doi: 10.1109/CSPA48992.2020.9068701.
- [3] [3] M. Weigert and U. Schmidt, "Nuclei Instance Segmentation and Classification in Histopathology Images with Stardist," 2022 IEEE International Symposium on Biomedical Imaging Challenges (ISBIC), Kolkata, India, 2022, pp. 1-4, doi: 10.1109/ISBIC56247.2022.9854534.
- [4] M. S. Naga Raju and D. B. Srinivasa Rao, "Classification of Colon Cancer through analysis of histopathology images using Transfer Learning," 2022 IEEE 2nd International Symposium on Sustainable Energy, Signal Processing and Cyber Security (iSSSC), Gunupur, Odisha, India, 2022, pp. 1-6, doi: 10.1109/iSSSC56467.2022.10051631.

Thank you

