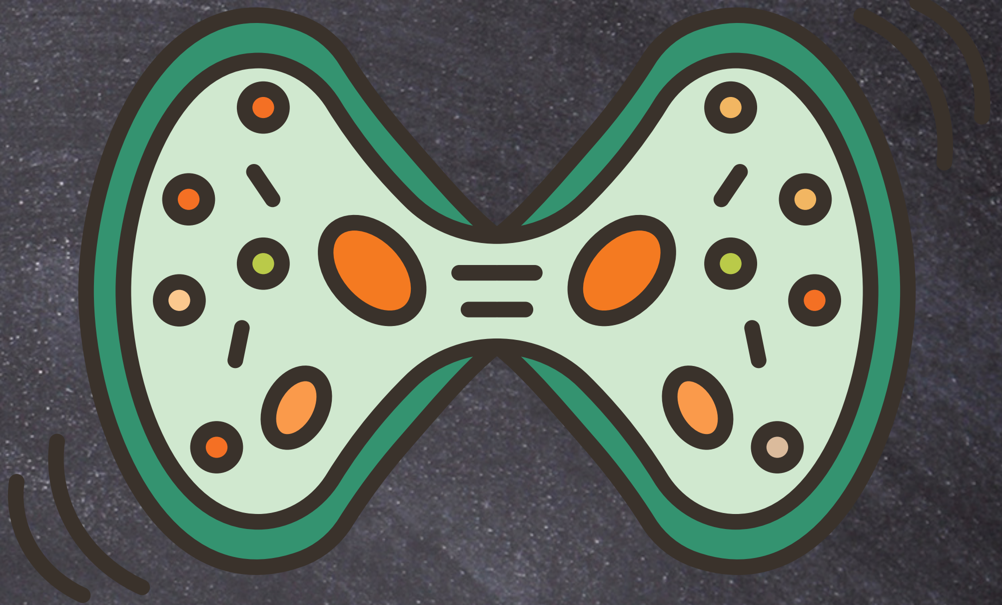
Cell Nuclei Segmentation

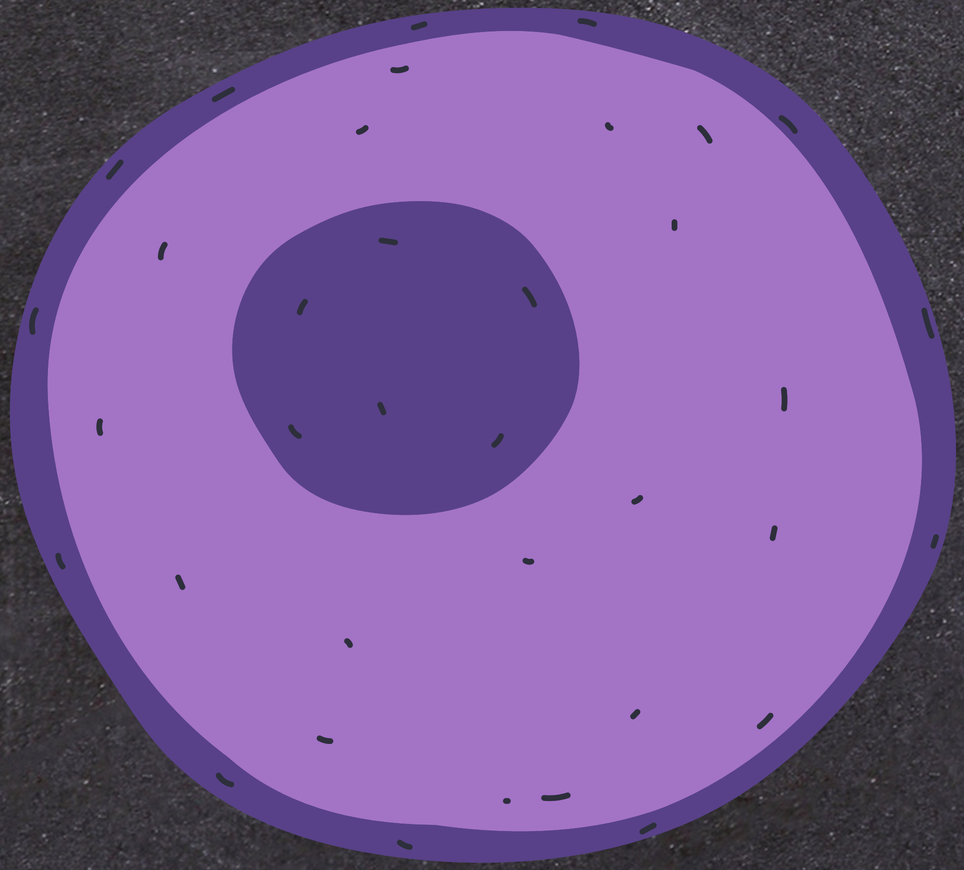
Introduction:

We've all seen people suffer from diseases like cancer, heart disease, chronic obstructive pulmonary disease, Alzheimer's, and diabetes. Many have seen their loved ones pass away. We can save many lives if cures came faster. By automating nucleus detection, you could help unlock cures faster.



Objective

The primary objective of this project is to leverage the potent UNet architecture for the development of an efficient algorithm capable of precise cell nucleus segmentation.



Benefit Of Project

Identifying the cells' nuclei is the starting point for most analyses. Identifying nuclei allows researchers to identify each individual cell in a sample, and by measuring how cells react to various treatments, the researcher can understand the underlying biological processes at work.

Literature Review

1. **Image Segmentation Based on Watershed and Edge Detection Techniques**
   Author: Salman, N. (2006)

- used a multi-step approach combining K-means, watershed segmentation, and Difference In Strength (DIS) map techniques.
- Overcome the problem of over-segmentation when applying the watershed algorithm directly to raw image data.
- Watershed Technique, Over Segmentation, Clustering Solution
- One limitation of this approach is it depends on the clustering step, incorrect clustering can lead to inaccurate results in downstream techniques.

2. **Microscopy cell nuclei segmentation with enhanced U-Net**
   Author: Long, F. (2020)

- Enhance cell nuclei segmentation with DL U-Net while reducing image preprocessing and post-processing, making it suitable for low-computing systems.
- U-Net+ - a modified U-Net for microscopy cell image segmentation.
- U-Net+ has encoded branch with densely connected convolutional blocks, boosting segmentation accuracy.
- U-Net+ significantly improves segmentation, with 15%-25% fewer model weights and shorter inference times, leading to a 1.0%-3.0% performance gain.

3. **A Novel Approach Towards Clustering Based Image Segmentation**
   Authors: Bora, D. J., & Gupta, A. K. (2015)

- Used K-means clustering with a "cosine" distance measure.
- Emphasized the importance of the l*a*b* color space for analysis.
- Applied the Sobel filter to generate the absolute gradient magnitude in the image.
- Utilized the watershed algorithm to analyze the filtered image.

4. Unet++: A nested u-net architecture for medical image segmentation

Author: Zhou, Z., Rahman Siddiquee, M. M., Tajbakhsh, N., & Liang, J. (2018)

- U-Net++ is an improved version of the classic U-Net architecture.
- It uses a deeply supervised encoder-decoder network with nested, dense skip pathways.
- The re-designed skip pathways help to reduce the semantic gap between the feature maps of the encoder and decoder sub-networks.
- The model was compared with U-Net and wide U-Net, achieving the highest IOU scores for the datasets Data Science Bowl 2018, ASU-Mayo, MICAAI 2018 LiTS Challenge, and LIDC-IDRI.

5. U-net: Convolutional networks for biomedical image segmentation

Author: Ronneberger, O., Fischer, P., & Brox, T. (2015)

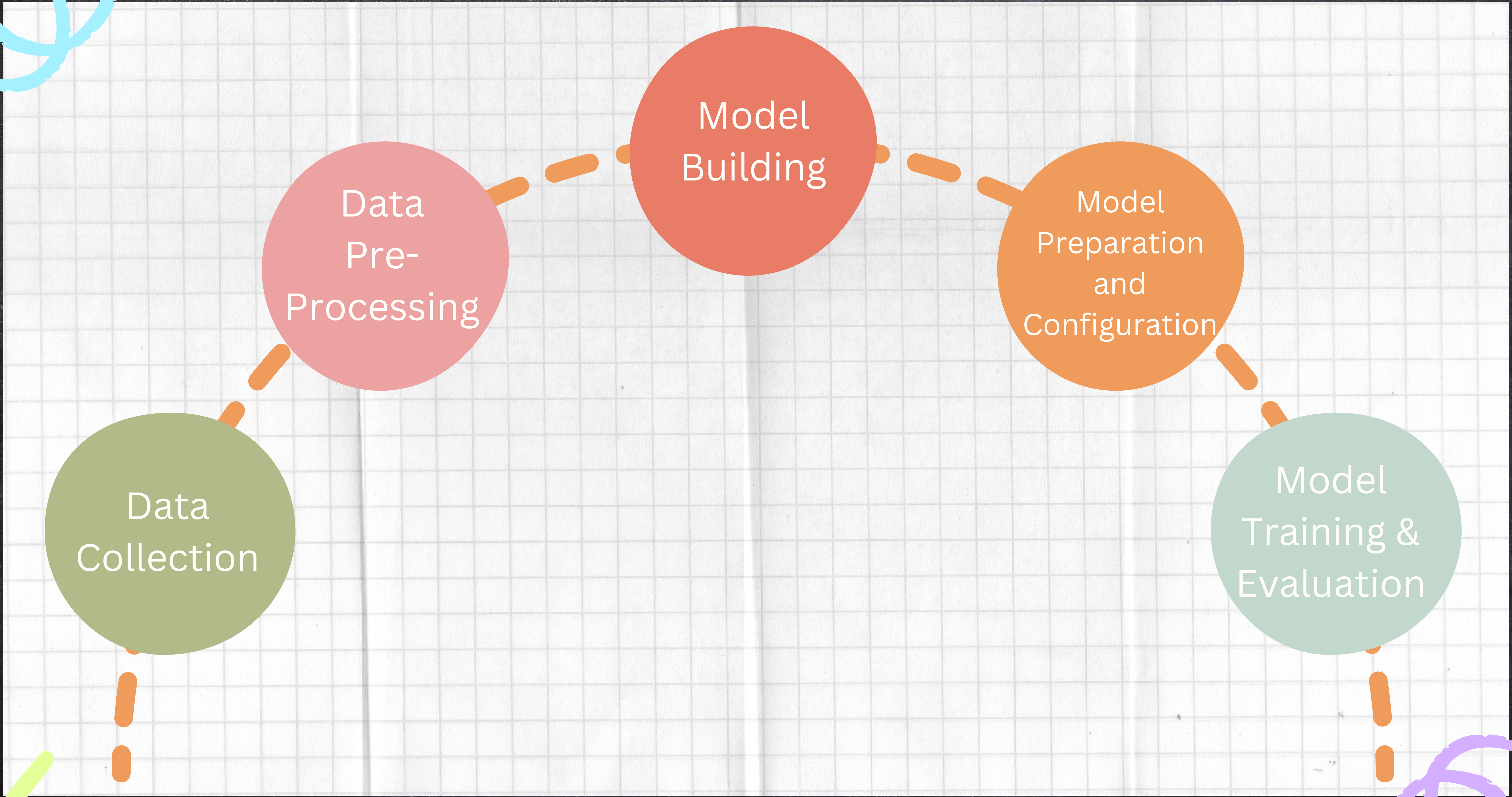
- The UNet architecture is a convolutional neural network (CNN) architecture used for biomedical image segmentation.
- The architecture consists of a contracting path and an expansive path.
- The contracting path consists of repeated applications of two 3x3 convolutions, each followed by a rectified linear unit (ReLU) and a 2x2 max pooling operation with stride 2 for downsampling.
- The expansive path consists of upsampling, 2x2 convolution, concatenation with the corresponding cropped feature map from the contracting path, and two 3x3 convolutions, each followed by a ReLU.
- The U-Net architecture was applied to neuronal structure segmentation in EM stacks and achieved the lowest Warping Error (0.000353), Rand Error (0.0382), and Pixel Error (0.0611).
- The IOU was 0.9203 on the PhC-U373 dataset and 0.7756 on the DIC-HeLa dataset.

6. Sharp dense U-Net: an enhanced dense U-Net architecture for nucleus segmentation

Authors: Senapati, P., Basu, A., Deb, M., & Dhal, K. G. (2023)

- Sharp Dense UNet is a variation of the UNet architecture for nucleus segmentation.
- It uses dense and transition operations in the downsampling path instead of max pooling and convolution.
- It uses a new up-sampling layer, merging, and dense blocks in the up-sampling path.
- It uses sharpening spatial filters instead of skip connections.
- The proposed model achieved accuracy of 0.6856, 0.5248, 84.49, respectively.

Methodology


Data Collection
Data Pre-Processing
Model Building
Model Preparation and Configuration
Model Training & Evaluation

1. Data Collection

Dataset

Number of images
Images: 670
Masks: 670

Dimension of Images: 256 X 256

Channel: 3

Link to the Dataset

* masks contain the segmented masks of each nucleus.

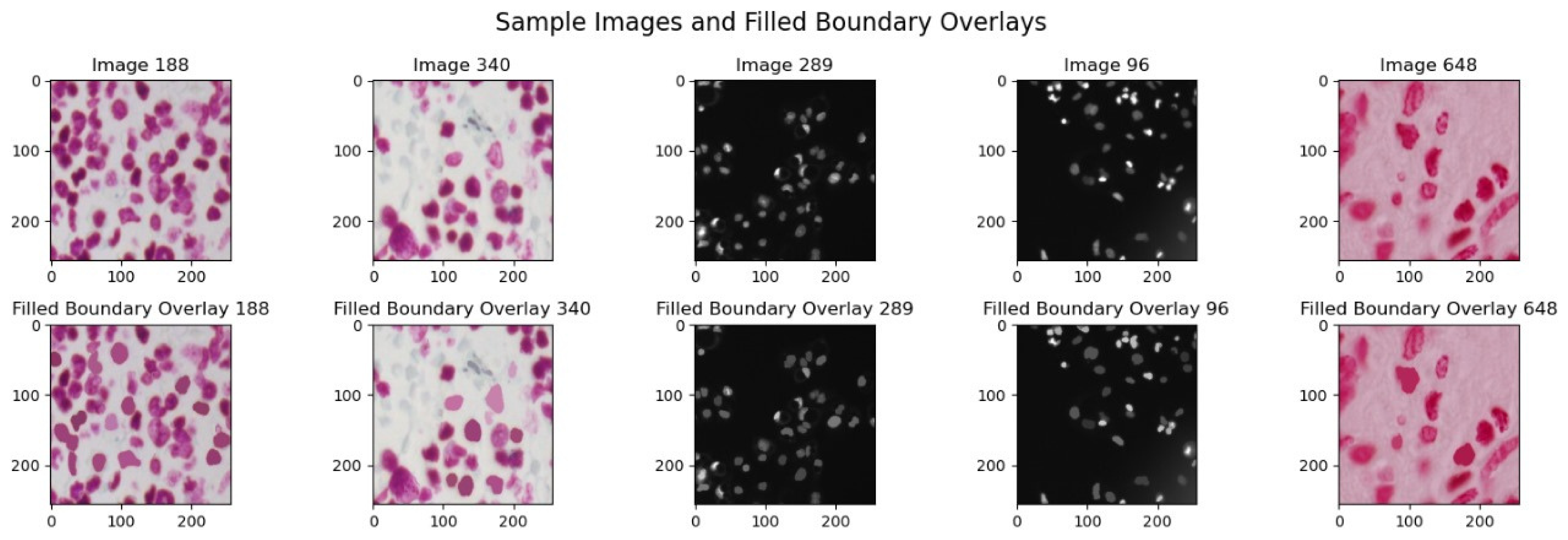
2. Data Pre-Processing

1. Image Resizing.

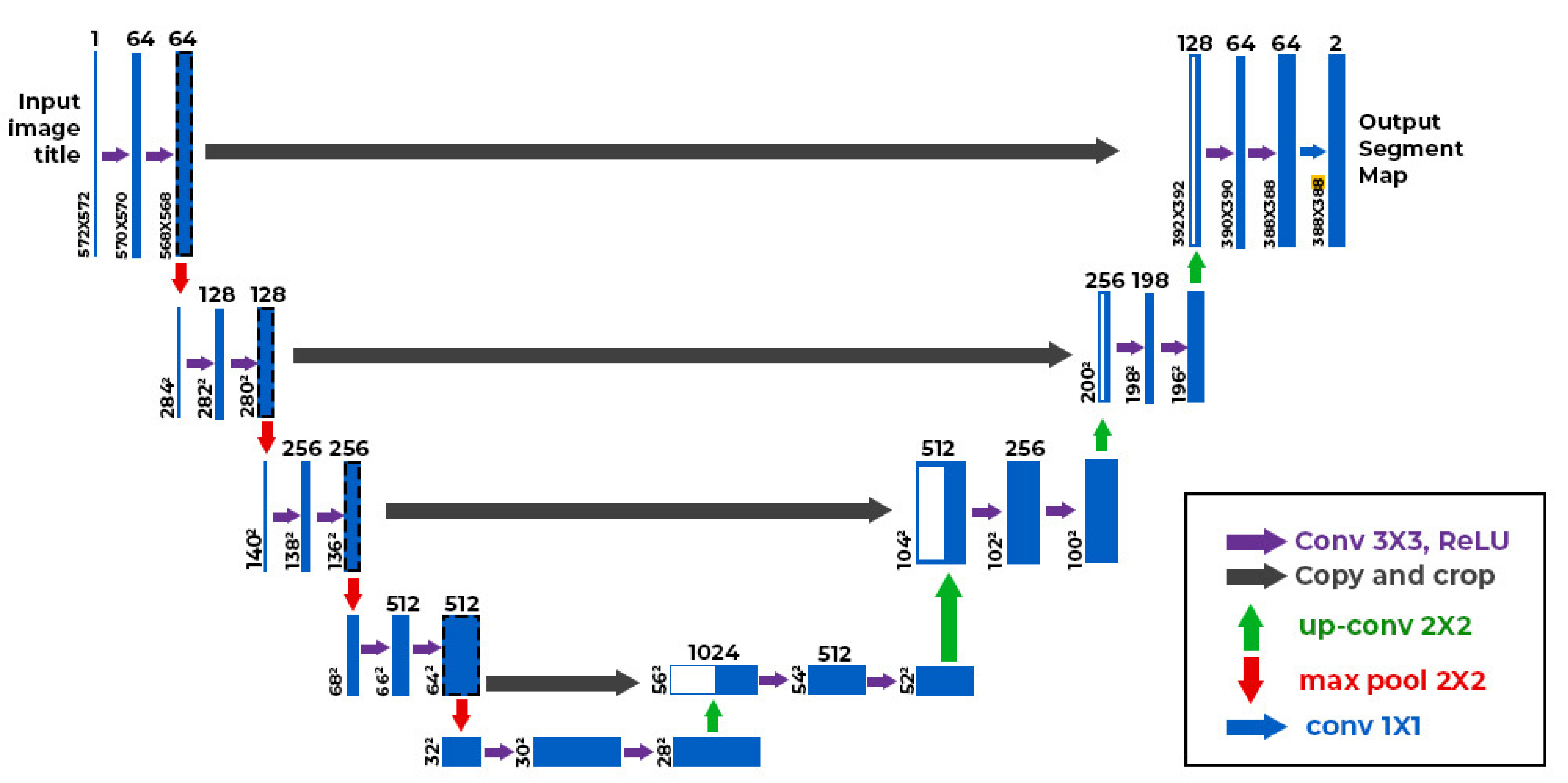
2. Normalization of Pixel values in range of 0 & 1

3. Boundary Extraction

4. Region Filling


Sample Images and Filled Boundary Overlays
Image 188
Image 340
Image 289
Image 96
Image 648
Filled Boundary Overlay 188
Filled Boundary Overlay 340
Filled Boundary Overlay 289
Filled Boundary Overlay 96
Filled Boundary Overlay 648
0
100
200

3. Model Building



The model comprises four blocks

1. Encoder - 16
2. Bottleneck - 2
3. Decoder - 16
4. Output Layer - 1

Total 35 Conv2D Layers.

4. Model Preparation and Configuration

1. Data Shuffling

2. Data Splitting
Train - 402
Validation - 134
Test - 134

3. Training Configuration
- Batch Size
- Learning Rate
- Epochs

4. Model Compilation
- loss function, optimizer, and evaluation metrics

5. Callback

Results

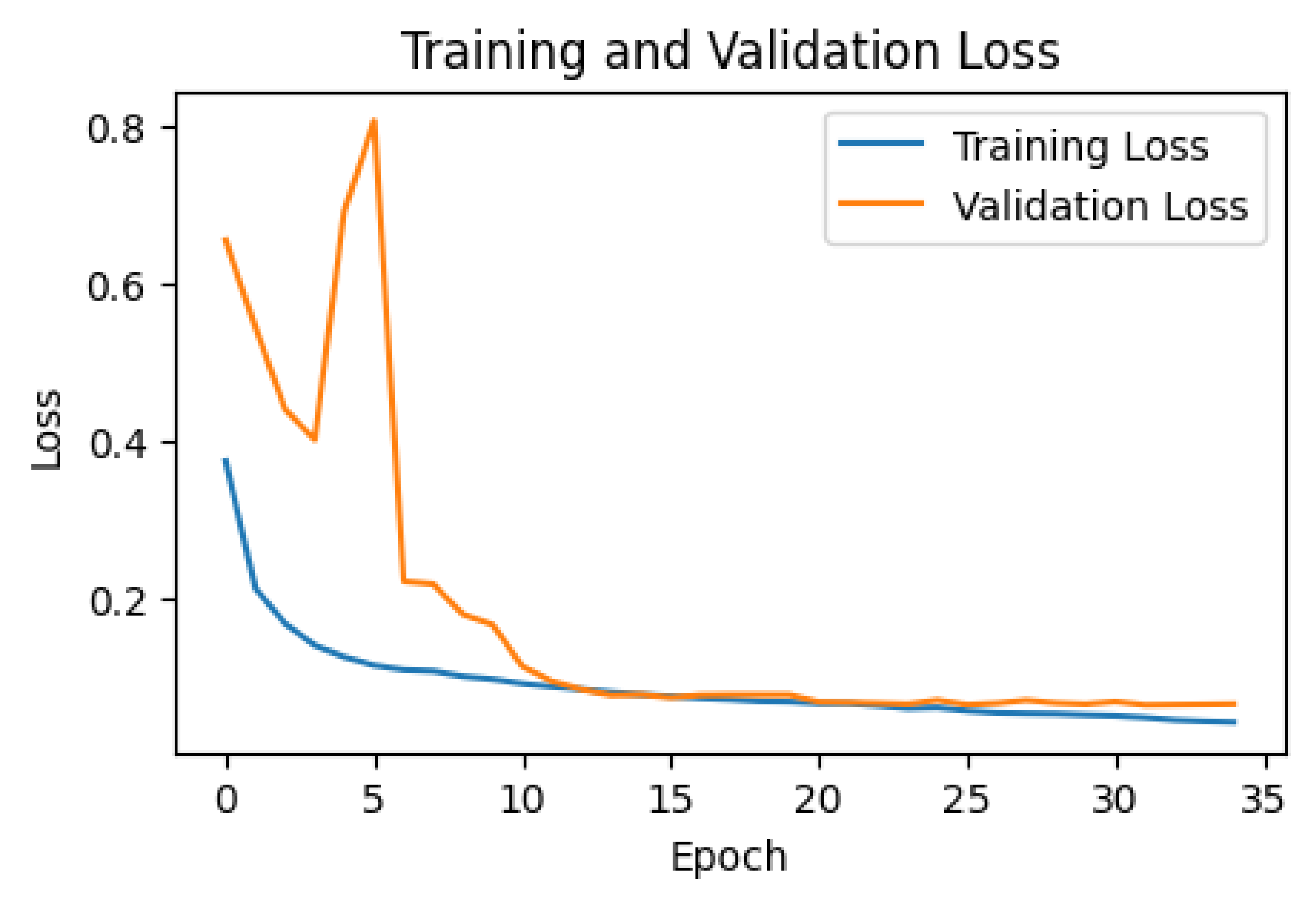
Table 1 - Result of the model after training 35 epochs

Metric	Value
Accuracy	97.15%
F1 Score	89.73%
Jaccard Score	0.8269
Precision	90.7%
Recall	90.4%

To assess the efficiency of our U-Net-based cell nucleus segmentation model, we used these-

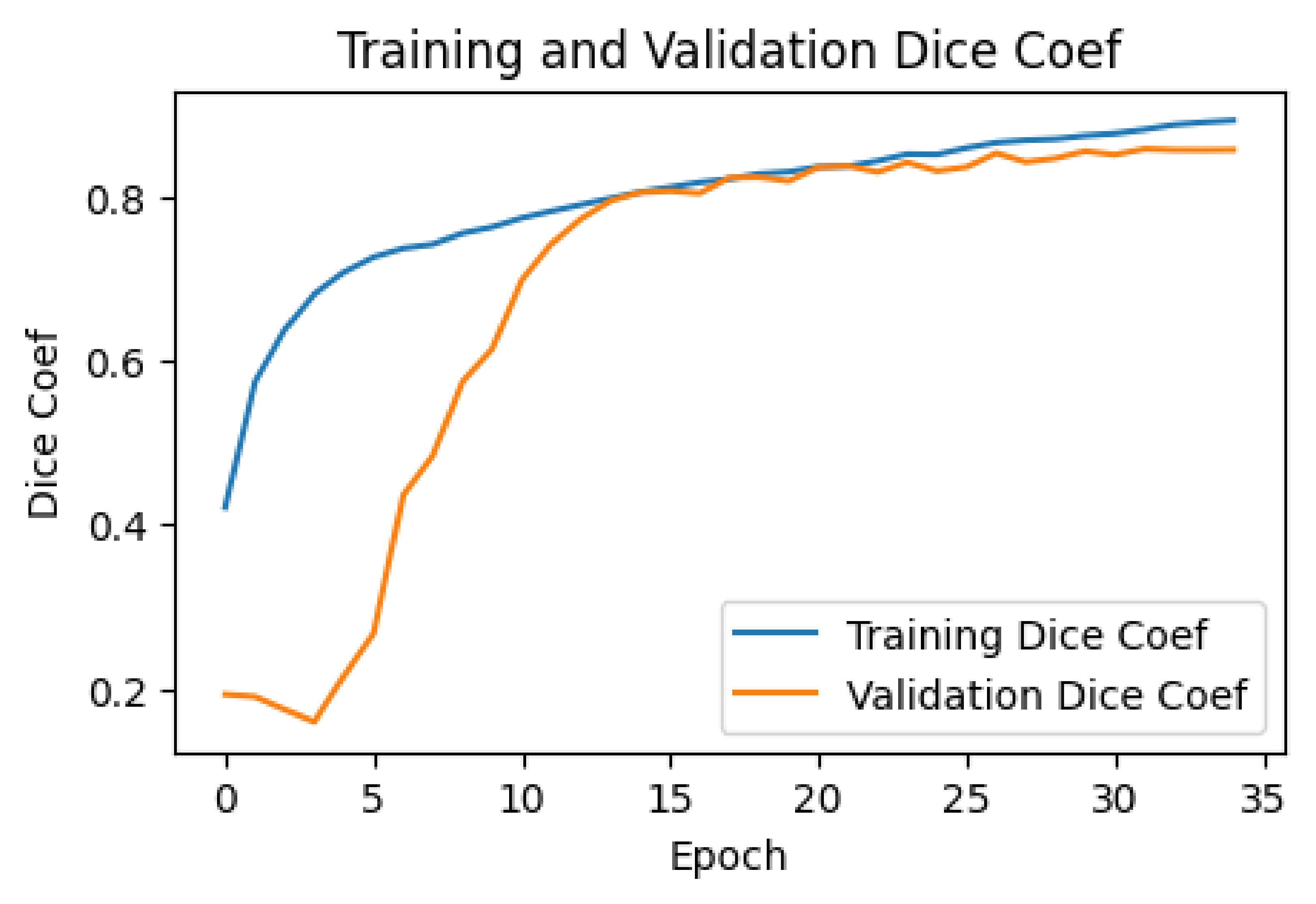
- Accuracy
- F1 Score
- Jaccard Score
- Precision
- Recall

Analysis of Training and Validation Metrics Over Epochs - 35



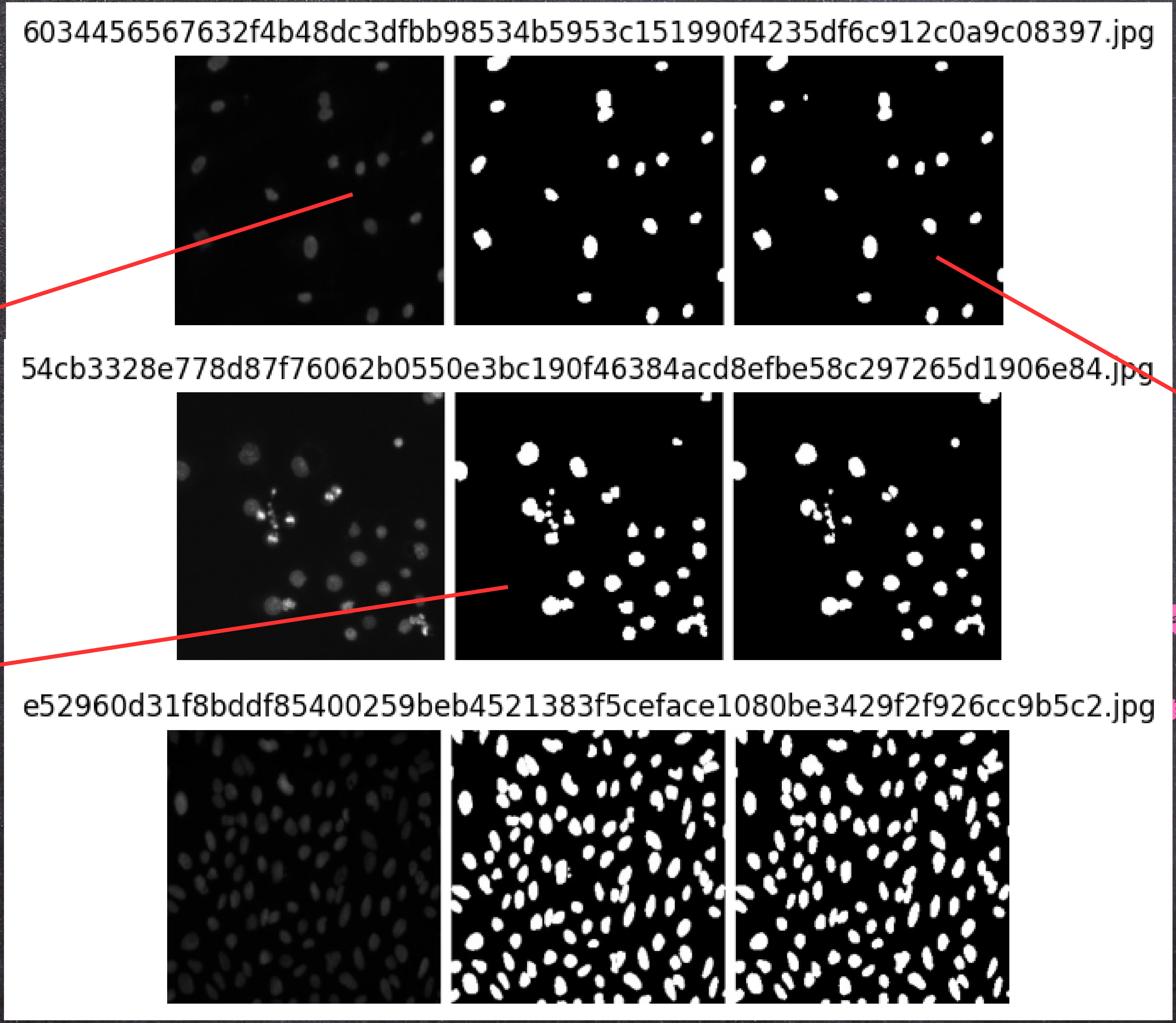
Training Loss
vs
Validation Loss

Training Dice Coef
vs
Validation Dice Coef



Original Image

Ground Truth



Predicted Masks

Below are the segmentation metrics for a few sample images:

Table 2 - Evaluation metrics on specific images

Image	Accuracy	F1	Jaccard	Recall	Precision
6034456567632f4b48dc3dfbb98534b5953c151990f4235df6c912c0a9c08397.jpg	99.65%	95.7%	0.9179	94.25%	97.22%
54cb3328e778d87f76062b0550e3bc190f46384acd8efbe58c297265d1906e84.jpg	98.8%	90.33%	0.823	86.3%	94.76%
e52960d31f8bddf85400259beb4521383f5ceface1080be3429f2f926cc9b5c2.jpg	98.03%	95.67%	0.9171	94.12%	97.2%


THANK YOU