# Supervised Segmentation Model for Improved Detection of OSSN using Slit Lamp Images

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## Overview

- Ocular surface squamous neoplasia (OSSN) is a very rare vision threatening eye disease
- Reported incidence ranges from 0.2–35 cases per million per year, with higher rates near the equator.
- Most patients are aged 60–70 in Europe, while youngs are more affected in Africa & Asia [3].
- We present a self-explainable deep neural network-based segmentation architecture to predict the pixel-level probability of OSSN in slit lamp images.

## Motivation

- Early detection of OSSN is crucial for timely intervention and improved patient outcomes.
- However, clinical diagnosis can be challenging due to overlapping features with benign ocular lesions and limited access to expert evaluation.
- This motivates the development of an automated, deep learning-based system to assist clinicians in accurate and efficient OSSN detection from ocular surface images.

## Dataset Used

- To evaluate our framework, we used a labelled dataset of *632 slit-lamp (SL) photographs* collected and used in Obaidur *et al.*, [1].


Figure 1: Sample slit-lamp images from dataset

- These images were categorized by the eye specialist into two primary classes: OSSN (163 images) and non-OSSN (469 images).
- The non-OSSN group was further divided into Normal (269 images) and Other Ocular Surface Disorders (OOSD) (200 images).

We further curated the dataset as follows:

- The original dataset lacked pixel-level annotations.
- Pixel-level masks for OSSN images were generated using Roboflow, with empty masks assigned to non-OSSN images.
- All annotations were verified by an ophthalmologist specializing in OSSN and conjunctival diseases.

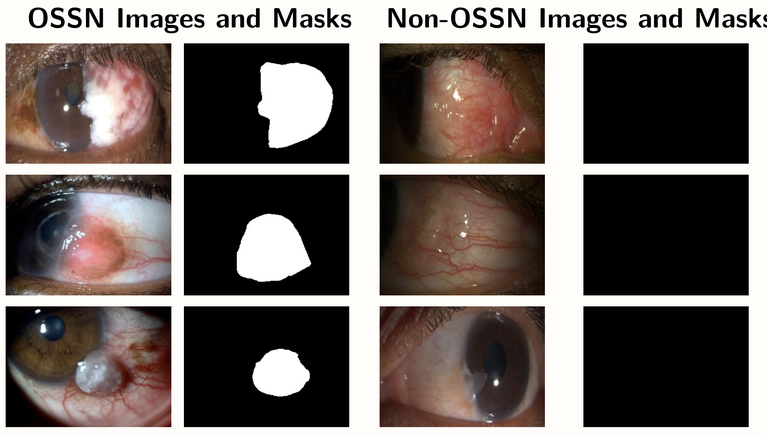


Figure 2: Sample OSSN and Non-OSSN images with their corresponding masks.

## Proposed Framework

- We propose a self-explainable deep neural network framework comprising an encoder, decoder, and classifier to accurately predict image- and pixel-level probabilities of Ocular Surface Squamous Neoplasia (OSSN) in slit-lamp images.
- The framework includes pixel-level annotation of the dataset from [1] and extensive evaluation against several state-of-the-art segmentation methods.
- We used three loss functions to evaluate the goodness of the model parameters.

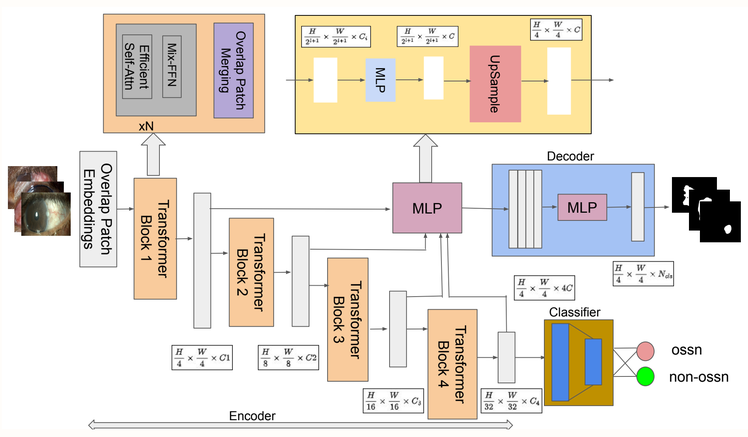


Figure 3: Proposed framework for OSSN detection using SegFormer as the backbone segmentation networks.

### *Training with Limited Samples*

■ For the classifier, we used binary cross entropy loss defined as:

$$\mathcal{L}_c = -\frac{1}{n}\sum_{i=1}^{n} y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i), \quad (1)$$

where $y_i \in \{0,1\}$ and $\hat{y}_i \in [0,1]$ are the true class and predicted class score of the $i^{th}$ image from the dataset, and $n$ is the total number of images in the dataset.

■ Since a network with large-number of trainable parameters may easily be overfitted especially when training from the limited number of samples.

■ We regularized the classification loss $\mathcal{L}_c$ with the segmentation loss $\mathcal{L}_s = \ell_{BCE} + \ell_{Dice}$ composed of two loss functions $\ell_{BCE}$ and $\ell_{Dice}$ defined over the predicted mask $\widehat{S}_i$, threshold predicted mask $S_i = \widehat{S}_i > \tau$, and ground truth mask $M_i$ as follows:

$$\ell_{BCE} = -\frac{1}{n}\sum_{i=1}^{n}\frac{1}{|M_i|}\sum_{(s,m)\in(\widehat{S}_i,M_i)} m\log(s) + (1-m)\log(1-s), \quad (2)$$

$$\ell_{Dice} = -\frac{1}{n}\sum_{i=1}^{n} 1 - \frac{2\cdot\sum_{(s,m)\in(S_i,M_i)} s\cdot m + \epsilon}{\sum_{s\in S_i} s + \sum_{m\in M_i} m + \epsilon}, \quad (3)$$

where $\epsilon$ is a smoothing constant (set to 1.0).

■ The final loss function $\mathcal{L}$ is defined as

$$\mathcal{L} = \lambda\cdot\mathcal{L}_c + (1-\lambda)\mathcal{L}_s, \quad (4)$$

where $\lambda$ controls the trade-off between the classification and segmentation losses. We empirically choose $\lambda = 0.3$.

## Implementation Details

- We implemented the proposed framework in Python using the PyTorch deep learning library.
- We trained our models on a high-performance computing system featuring 2 Intel Xeon Silver 4310 processors (48 cores) and 8 NVIDIA RTX A6000 GPUs with 48GB VRAM each.

## Empirical Evaluation

Table 1: OSSN classification and segmentation

| Models | Precision | Recall | F1-Score | Accuracy | Dice Score |
|---|---|---|---|---|---|
| DeepLabV3 | 0.75 | 0.73 | 0.74 | 0.90 | 0.727 |
| DeepLabV3+ | 0.90 | 0.89 | 0.89 | 0.97 | 0.776 |
| U-Net++ [5] | 1.00 | 1.00 | 1.00 | 1.00 | 0.773 |
| U-Net w/o attn. | 1.00 | 1.00 | 1.00 | 1.00 | 0.771 |
| U-Net w/ attn. | 0.90 | 0.89 | 0.89 | 0.97 | 0.782 |
| FPN [4] | 0.95 | 0.94 | 0.94 | 0.99 | 0.798 |
| SegFormer [2] | 0.95 | 0.94 | 0.94 | 0.99 | **0.802** |

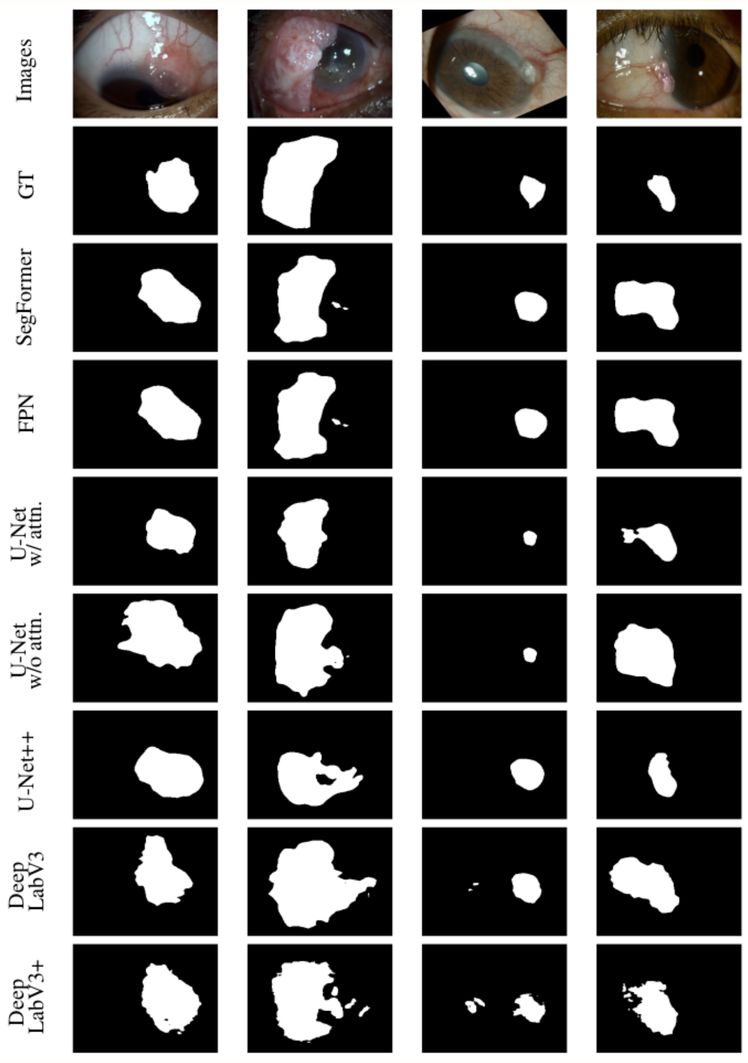


Figure 4: Qualitative results from various models

## Summary and conclusions

- The proposed self-explainable DNN accurately localizes and classifies OSSN in slit-lamp images.
- Using SegFormer as the backbone helps learn better representations from relevant pixels.
- It achieves high classification accuracy with explainable segmentation masks.

### *References*

[1] Obaidur *et al.* (2025). *DL-Based Detection of OSSN from Ocular Surface Images. Ocular oncology and pathology*

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[3] Basti *et al.* (2003). *Ocular Surface Squamous Neoplasia: A Review. Cornea, 22(7), 687–704.*

[4] Tsung-Yi *et al.* (2017). *FPN for Object Detection. CVPR*

[5] Zongwei *et al.* (2018). *Unet++: A nested u-net architecture for medical image segmentation. Springer*

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