Abstract—Precise and programmed analysis of retinal images has been considered as an effective way for the determination of retinal diseases. The look at the recent application of deep learning (DL) methods in automated fine-grained segmentation of spectral domain optical coherence tomography (OCT) images of the retina. Let’s describe a new method combining fully convolutional networks (FCN) with Gaussian Processes for post processing. The report performance comparisons between the proposed approach, human clinicians, and other machine learning (ML) such as graph based approaches.

The approach is demonstrated on an OCT dataset consisting of mild non-proliferative diabetic retinopathy from the University of Miami. The method is shown to have performance on par with humans, also compares favorably with the other ML methods, and appears to have as small or smaller mean unsigned error (equal to 1.06), versus errors ranging from 1.17 to 1.81 for other methods, and compared with human error of 1.10.

Keywords: optical coherence tomography (OCT), fully convolutional networks (FCN), Comparisons, INTRODUCTION-

Classification of optical coherence tomography images can be achieved with high accuracy using classical convolution neural networks (CNN), a commonly used deep learning network for computer-aided diagnosis. Classical CNN has often been criticized for suppressing positional relations in a pooling layer. Therefore, because capsule networks can learn positional information from images, we attempted application of a capsule network to OCT images to overcome that shortcoming. This study is our attempt to improve classification accuracy by replacing CNN with a capsule network.

Early detection and prompt treatment can prevent AMD leading to vision loss. To detect these diseases, optical OCT is the most commonly used imaging modality in ophthalmology. These initial diseases can be detected by screening with OCT, but increased screening with OCT images multiplies the burdens on ophthalmologists, who must interpret these images. Therefore, an automatic diagnostic screening system has been developed actively to reduce ophthalmologists’ burdens.

In the field of medical image classification with deep learning, OCT image classification has been undertaken in earnest. However, traditional CNNs have sometimes been criticized because their pooling operations nearly eliminate positional information. Losing positional information might be a bottleneck hindering efforts to improve OCT image classification accuracy.

1. The four major causes of blindness are age-related diseases, out of which three affects the retina.
2. A critical element of the clinical diagnosis is the analysis of individual retinal layer properties, as the manifestation of the dominant eye diseases has been shown to correlate with structural changes to the retinal layers.
3. Regrettably, manual segmentation is dependent on the ophthalmologist’s level of expertise, and currently becoming impractical due to advancement in imaging modalities.
4. Inherently, much research on computer-aided diagnostic methods is conducted to aid in extracting useful layer information from these images, which were inaccessible without these techniques. However, speckle noise and intensity inhomogeneity remain a challenge with a detrimental effect on the performance of automated methods. In this paper, we propose a method comprising of fuzzy image processing techniques and graph-cut methods to robustly segment optical coherence tomography (OCT) into five (5) distinct layers. Notably, the method establishes a specific region of interest to suppress the interference of speckle noise, while Fuzzy C-means is utilized to build data terms for better integration into the continuous max-flow to handle inhomogeneity.

METHODS-

1) Preprocessing and data augmentation:- The proposed network model requires a 512 × 2 image.

However, the dataset images were 384–1536 pixels wide and 496–512 pixels high. Therefore, the images were resized in terms of width and height to 512 pixels using linear interpolation. In addition, the OCT images were shifted by up to 16 pixels in each direction with zero padding to increase the number of learning data.

As a result, the number of images used for learning was increased to 65,536 times (16 × 16 × 16) × 16. Validation...
dataset comprises 4000 images from 1000 images extracted randomly from each class. The sub-training dataset consists of the remaining training dataset. The test dataset had 250 images for each class. The training data-set, the sub-training dataset, the validation dataset, and the test data-set were designated respectively as Xtrain, Xsub-train, Xvalid, and Ytest.

The model was trained with Xsub-train and Xvalid using Adam optimizer [19]. The batch size was set to 128. The model was trained for 50 epochs. Early stopping occurred when the Xvalid accuracy became the best in learning. This learning curve is depicted in Fig. 5. Then, the proposed model was evaluated using the test dataset.

Additionally, we trained Inception-v3 under the same learning conditions to compare the proposed model and those of earlier research. Then, Inception-V3, which was trained, was evaluated using the test dataset.

2) Visualizing feature maps: We visualized feature maps using a method inspired by class activation mapping (CAM) [20] to elucidate which parts in the OCT image were strongly influential. An image was input to the trained model. Then 256 feature maps (6 x 6) were generated from Convolution layer 6.

After the averaged feature map (6 x 6) was resized to input size (512 x 512), it was superimposed on the input image as a heat map image.

A series of steps were performed to carry out BM segmentation. If we analyze the OCT image, we can observe that BM segmentation is relatively easier than choroid layer segmentation. The reason is that the choroid layer has inhomogeneous intensity and inconsistent texture, so it requires more image statistics to accurately segment. We first segmented the BM followed by segmentation of choroid layer. In this case, we can consider the segmented BM as a constraint while carrying out choroid layer segmentation. The segmentation of BM was performed using a sequence of morphological operations.

Using ILM and BM boundaries segmented by a graph-cut technique, a relative distance map was generated and concatenated with each B-scan as an input to train a fully convolutional deep neural network. Pixels classified as potential fluid by the network were then grouped into different regions based on their 8-connectivity. For each type of fluid, a random forest classifier was trained on those candidate regions to rule out false positive samples and determine the fluid presence in each volume. The proposed method showed good performance in the leave-one-out classification experiments with 3 different training sets, and had the best performance on the testing set especially for the detection of fluid presence in each volume. The excellent performance on the unseen, independent.

Kermany dataset with 530 volumes suggests the potential for generalizability of the proposed framework for unseen data in clinical applications. Due to the limited number of training samples in the given datasets, the segmentation results are comparatively not as high as the detection result.

RESULT:

Nature of images=

```python
import matplotlib.pyplot as plt
fig=pl.figure(figsize=(10,10))
for i in range(20):
    ax=fig.add_subplot(10,10,i+1,xticks=[],yticks=[])
    ax.imshow(abnormal_images_array[i],cmap=plt.cm.bone)
```

![Fig. 1. Classification of images](image)

```python
import matplotlib.pyplot as plt
fig=pl.figure(figsize=(10,10))
for i in range(20):
    ax=fig.add_subplot(10,10,i+1,xticks=[],yticks=[])
    ax.imshow(normal_images_array[i],cmap=plt.cm.bone)
```

```python
normal_labels=np.ones((204))
abnormal_labels=np.zeros((102))
```

![Fig. 2. Extracting prominent features for segmentation](image)

```python
from sklearn.decomposition import PCA

pca_train=PCA()
for i in range(len(train_set_array)):
    pca_train.fit(train_set_array[i])

x_transformed=[]
for i in range(len(train_set_array)):
    pca_temp=PCA(n_components=25,whiten=True)
    x_temp=pca_temp.fit_transform(train_set_array[i])
    x_transformed.append(x_temp)

XT_array=np.array(x_transformed)
XT_array.shape
(260, 64, 25)
```

![Fig. 3. Selection of principal components=25 for an image](image)
CONCLUSIONS

This network model with four convolution layers of an added capsule network achieved high accuracy for the released OCT dataset. Results obtained for the four classifications compare favorably with those reported from earlier research. This system can reduce ophthalmologists’ burdens and can be expected to improve patient access to rapid treatment.

REFERENCES-
https://doi.org/10.1364/BOE.8.001638.