# Detection of angiodysplasia from wireless capsule endoscopy images

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**Abstract**— Angiodysplasia, also known as telangiectasia, is a lesion in the small and large intestine and the second most bleeding causing lesion in the lower gastrointestinal tract. Due to its severe bleeding nature, it can cause anemia, chronic intestinal hemorrhage, chronic kidney disease, aortic stenosis, von Willebrand disease when undetected, and these lesions are prone to higher detection miss rate during the examination. Angiodysplasia lesions are highly correlated in all channels and features that describe these lesions are not robust, which makes it hard to detect using traditional image processing methods. In this an automatic pixel-wise angiodysplasia detection system has been introduced based on deep learning semantic segmentation technique, to detect the lesion in an early stage before bleeding. This approach is a binary classification where each pixel is labeled. The designed model for detecting consists of a handcrafted convolutional neural network based on the SegNet architecture. This model is designed and implemented in MATLAB 2019. When testing the performance, the model achieved an accuracy of 99%, the sensitivity of 91%, the specificity of 99%, intersection over union (IOU) of 84.97%, Matthews correlation coefficient (MCC) of 91.6%. The obtained performance metric is compared with other state of the art approach.

**Index Terms**— Angiodysplasia, convolutional neural network, pixel-wise classification, SegNet, semantic segmentation, wireless capsule endoscopy, medical image processing.

## 1 Introduction

Bleading in gastrointestinal (GI) track is more common and caused by different kind of diseases and lesions. Angiodysplasia is a gastrointestinal (GI) bleeding commonly associated with the aging process, it is due to small ectasias in the GI tract. These vascular lesions commonly occur between the age group of 60-70 years patients and responsible for the second most bleeding causes in lower GI-track [1]. It is found that 5-6% of the bleeding is due to the angiodysplasia lesions [1]. These lesions can occur in multiple (two-three lesion together) and 80% of these lesions occur in the ascending colon. Angiodysplasia leads to chronic intestinal hemorrhage, chronic kidney disease, aortic stenosis, von Willebrand disease [2]. These lesions can occur anywhere in a small bowel, which can be hard for physicians to find. Severe bleeding in angiodysplasia leads to death. These lesions are hard to find using any traditional image processing techniques, as they are highly correlated in all colour channels. Due to this correlation, non-pathological region and pathological region have similar colour and features, which makes them hard to predict and locate them.

Most small bowel examination involves the use of conventional procedure colonoscopy and double balloon entroscopy, compared to these painful procedures, capsule endoscopy became a patient-friendly diagnostic method, involves a small 12mm – 24mm swallowable pill-shaped device with a tiny camera and LED light source Fig. 1. shows the given imaging pill-cam device. The capsule endoscopy device can work for 8hr 30 min in a single transit to the small bowel and can take 60000 images at the frame sample rate of 0.5Hz [2] is more time consuming and prone to more miss rate when manual processing.

The present state of the art device WCE pillcam from Given imaging can detect the angiodysplasia with the sensitivity of 41% and the specificity of 67%. From the 60000 images, the endoscopist can only detect 69% of the angiodysplasia remain are undetected, leading to life-threatening obscure gastrointestinal bleeding (OGIB) [3]. In a study conducted in 2012, by analysis conventional procedure (colonoscopy) with 642 people, it was found that about 12.1% and 11.9% with and without irritable small bowel syndrome (IBS) was found to have angiodysplasia [4]. In a [5], conducted a review on capsule endoscopy sign and symptoms between 2000 to 2008 published papers and found that 227 studies involving 22804 small bowel examinations. The obscure gastrointestinal bleeding (OGIB) was the main small bowel indication consuming 66% and in that 50% of the cases were caused by angiodysplasia. In another study [6], showed that 35% of OGIB is caused by the angiodysplasia which life-threatening. Almost 90% of angiodysplasia's immediately cease bleeding. The intense amount of bleeding, hemodynamic instability, age, comorbid medical conditions is major factors causing death for patients with angiodysplasia [9].

The main drawback of the wireless capsule endoscopy is that it produces a large set of images 60000 images for a single patient which can be hard for clinicians to process for a specific pathology. And the angiodysplasia is highly correlated with the surrounding region in all colour channels which makes it prone to the higher miss detection rate.

In this, an automatic deep-learning based angiodysplasia segmentation method has been presented, based on the convolutional neural network for classifying each pixel. This method has achieved a better result than existing approaches by utilizing the SegNet model [10] with 2 encoder and decoder blocks.

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## 2 Related work

So far, only four related work has been carried out in computer-based automatic angiodysplasia detection, in four only 3 were based on the deep-learning based detection system. Most of the existing methods use histogram equalization and contrast limited adaptive histogram equalization (CLAHE) for image preprocessing to enhance the image and for performance accuracy and to overcome low illumination in the small bowel [14], [17].

In [2] author used colour thresholding, geometric thresholding, variance thresholding method to threshold each channel of RGB, and HSV to split partial ROI from the surrounding background regions and used conventional machine learning techniques to classify the region to detect the angiodysplasia, with 96% of accuracy, 89.51 of sensitivity and 97% of specificity.

In [1]author used deep-learning method to detect the angiodysplasia lesion, publicly available dataset is utilized. The author used UNet architecture [15] for the pixel-wise classification task. With a 300 image for training and 60 images for testing, the author achieved a better result and correctly proposed to intersection over union (IOU) for performance evaluation with IOU of 75.35%.

In [3] author used generative adversal network (GAN) network for the pixel classification and used the same publicly available dataset with 300 training images, achieved a performance of sensitivity of 88%, specificity of 99% and Mathews correlation coefficient (MCC) of 86.69%. MCC is used for the perfect balance of the dataset.

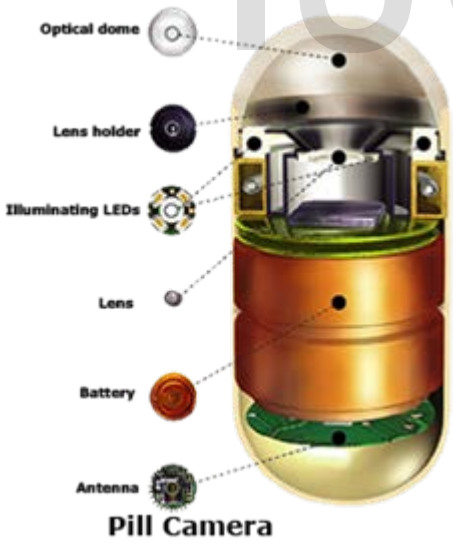


Fig. 1. Pill-cam wireless capsule endoscopy (WCE) [16].

## 3 Method

Angiodysplasia is a bright strawberry colored and 2-9mm [7] in diameter. The size and shape of the angiodysplasia lesion vary according to the bleeding probability. The pixel of the angiodysplasia lesion appear random anywhere in the image due to the colour and feature similarity between surrounding pixels, the image obtained is prone to low illumination.

### 3.1 Image database

The images and data used in this paper are attained from the Given imaging wireless capsule pillcam SB 3 from Gastrointestinal Image ANAlysis (GIANA), MICCAI 2017 endoscopic vision challenge database [8]. The images are in 576 X 576-pixel resolution and 24-bit depth per channel. The database contains a total of 1200 images for training which has a subsection of 600 annotated images by the experts and 600 unannotated images. The 600 images were further divided into 300 images containing vascular angiodysplasia lesion and 300 normal images without any angiodysplasia lesion. The dataset contains the reference images which is ground truth used for know value for computing the loss or performance evaluation during the testing phase.

The main reason to choose this dataset is a large number of dataset compared to other data and it is a publicly available dataset which can be used for comparison with other methods. The perfect balance of the dataset makes it more suitable for the analysis.

A total of 300 images were used for the training of the convolutional neural network and with two-fold cross-validation of 60, 60. The raw image from the dataset contains canvas and annotated text so, the image is cropped and resized evenly to 512 x 512 to remove such factors.

The images are scaled to [0 to 255] and histogram equalized and contrast limited adaptive histogram equalization(CLAHE) with Rayleigh 0.2 [11]. colour channels are converted to LAB colour space.

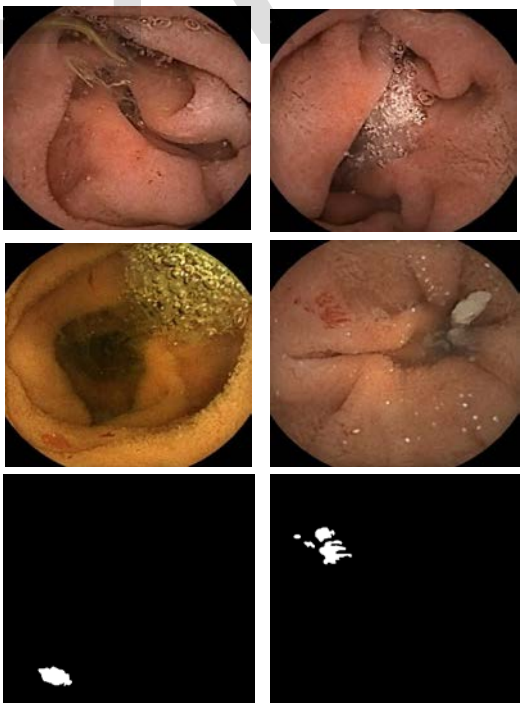

Fig. 2. Training images sample 1st row shows the image without any angiodysplasia lesion and middle row represents the images with apparent angiodysplasia lesion and the last row represents the ground truth images

### 3.3 Proposed method

As said before the angiodysplasia lesions are highly correlated in all colour channels and the area defining the lesion and the surrounding area have similar features, which make it hard for detection and images have low illumination. Fig. 2. shows the image of the lesion, where we can see a similar colour description between the lesion and the surrounding area having red and shades of red in both the region.

To overcome these problems a semantic segmentation network SegNet has been used to detect and localize the angiodysplasia lesion. This network is based on the principle of the fully convolutional network (FCN) [9] using encoder and decoder block. The proposed method is shown in Fig. 3.

For the network training, both input image and the reference image (ground truth) are used. The loss of the designed architecture is estimated through ground truth image.

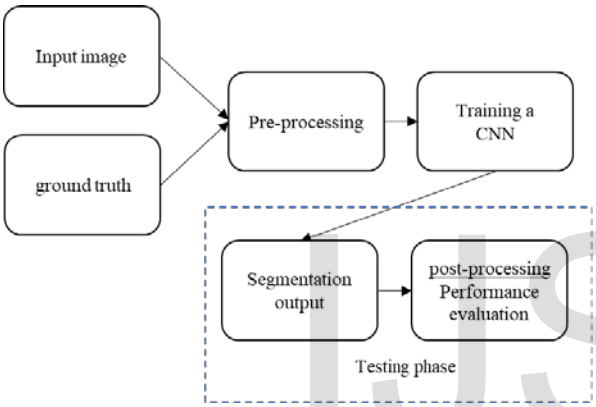


Fig. 3. Proposed model

#### 3.3.1 SegNet – proposed network architecture

The proposed model is a pixel classification model, were each pixel are labeled (0 – background, 255 – angiodysplasia) and feed as an input to the network.

The network is designed with 2 encoder and decoder blocks with 8 convolutional layers each followed by the batch normalization and ReLu containing 31 layers. Images are in size 512 x 512 x 3.

The SegNet has a contracting path and expanding path, each contracting path is connected to the expanding path of similar size to upsample. The feature maps predicted in each encoder block (contracting block) are transferred to the corresponding block in the decoder block to upsample [15].

In each block of the encoder, the image input size is reduced spatially by subsampling and max-pooling, by creating translational invariance. So, due to this only boundary information will be stored by max pooling, representing the max values of the feature maps, which is then moved to a corresponding decoder block to upsample. Fig. 4. shows the max values of the feature maps a,b,c,d and indices of the max values transferred to the corresponding decoder block (expanding path) to upsample. Decoder block uses the deconvolutional layer to upsample [11].

The advantage of the SegNet is that it does not depend on


Fig. 4. Max value of feature maps and their indices from max-pooling [14]

the channels Lab or RGB, it builds channels upon itself depending on the number of kernels or filters in addition to Lab, RGB [12]. It also avoids the need for learning to upsample due to the use of the pooling indices. This network is less memory and time-consuming. Unlike other CNN this does not require a fully connected layer as each pixel belongs to a class, so each pixel gets a probabilistic score of classes by the softmax layer.

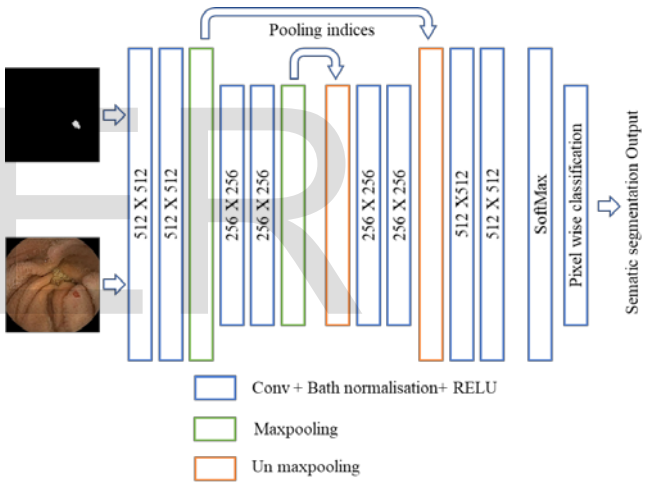


Fig. 4. Max value of feature maps and their indices from max-pooling

#### 3.3.2 Training and testing

For better accurate detection of the angiodysplasia lesion, the network uses an input size of 512 with 3 channels. Increasing the input image size increases performance accuracy during training. The network is trained for 100 epochs, with a $10^{-3}$ learning rate to find local minima, with 0.9 momentum plus Adam optimizer and a minibatch of 2.

The network is fully trained with cross-entropy loss for 28hours with 21933 iterations. Rectified linear unit (ReLU) is used as the activation function (1) shows the ReLU function. Equation (2) shows the cross-entropy loss function. The model is regularized with L2norm regularization. The network is trained with single GPU NVIDIA GT-940. Table 1 shows the list of hyperparameter used.

$$a_j^i = \sigma(z_j^i) = \max(0, z_j^i) \quad (1)$$

$$\cos t(X,Y) = -1/N \sum_{i=1}^{n} y^{(i)} \ln a(x^{(i)}) + (1-y^{(i)}) \ln(1-a(x^{(i)})) \quad (2)$$

(where '*l*' refer to a layer of the network, '*j*' refers to neuron in the layer, $\sigma$ refers to the activation function and $a_j^l$ refers to activation function of a neuron in the current layer, $z_j^i$ refers to the output of a j[th] neuron in the i[th] layer).

TABLE 1
HYPERPARAMETERS FOR TRAINING

| Hyperparameter | |
|---|---|
| learning rate | 0.001 with adam |
| momentum | 0.9 |
| regularization | l2norm |
| loss/cost | cross-entropy |
| minibatch | 2 |
| dropout | 50% |
| epochs | 100 |
| decay rate | 0.9 |

### 3.3.3 Performance metrics

The pixel-wise classification model is evaluated using the properties of the confusion matrix by calculating no of the pixel belonging to each that are correctly classified. For this task 2 main metrics are used Intersection over union (IOU) and Mathews correlation coefficient (MCC) [3]. Other than this sensitivity, specificity, and accuracy has been used for performance evaluation. Fig. 5. shows the IOU in the example.

$$\begin{aligned} sensitivity &= \frac{TP}{TP+FN} \\ specificity &= \frac{TN}{TN+FP} \\ accuracy &= \frac{TP+TN}{TP+TN+FP+FN} \\ MCC &= \frac{TP*TN-FP*FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \\ \text{IOU} &= \frac{TP}{TP+FN+TN}(or)\frac{|A\cap B|}{|A|+|B|-|A\cap B|} \end{aligned} \quad (3)$$

(where '*TP*' refer to a true positive, '*TN*' refers to true negative, '*FP*' refers to false negative and '*FN*' refers to false negative).

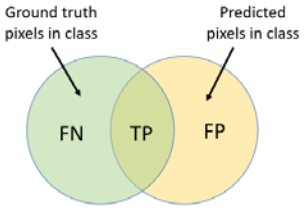


Fig. 5. Intersection over union (IOU) [11].

## 4 RESULT

The obtained performance metric and the result in the detection of angiodysplasia lesion are shown in Fig. 6. Moreover, the designed model was successfully able to detect the lesion in all testing images, the model can predict the image with multiple lesion. During the training phase model was trained for 100 epoch the designed model based on Seget converged after 5[th] epoch and increased in accuracy.

The performance measure of the proposed model is compared with other state of the art of approach shown in Table. 3 with an accuracy of 99%, sensitivity of 91%, the specificity of 99%, Mathews correlation coefficient (MCC) of 91.6% and intersection over union (IOU) of 84.91%.

Table 2. shows the confusion matrix in no of pixels to each class, where 8.96% of angiodysplasia lesion is classified as the background, the 8.96 is acceptable in medical term and 0.165% of the background is classified as the angiodysplasia lesion.

TABLE 2
CONFUSION MATRIX OF ANGIODYSPLASIA DETECTION (NO OF PIXEL)

| | Predicted class | |
|---|---|---|
| | **Angiodysplasia** | **background** |
| **Angiodysplasia** | 285358<br>91.1% | 28117<br>8.9% |
| **background** | 22346<br>0.165% | 13449631<br>99% |
| **Actual class** | | |

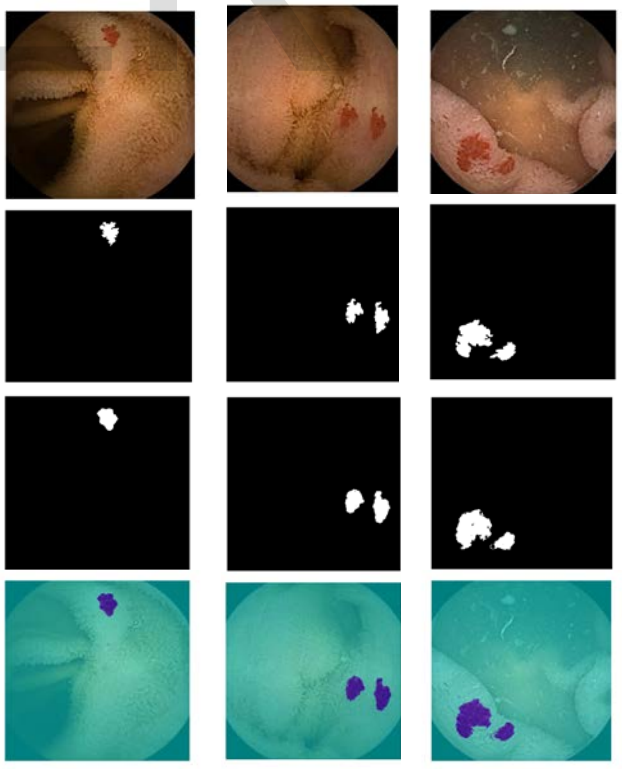

Fig. 6. Angiodysplasia detection output 1[st] row represents the input image, a 2[nd] row represents ground truth image, 3[rd,] and 4[th] row show the detected lesion output.

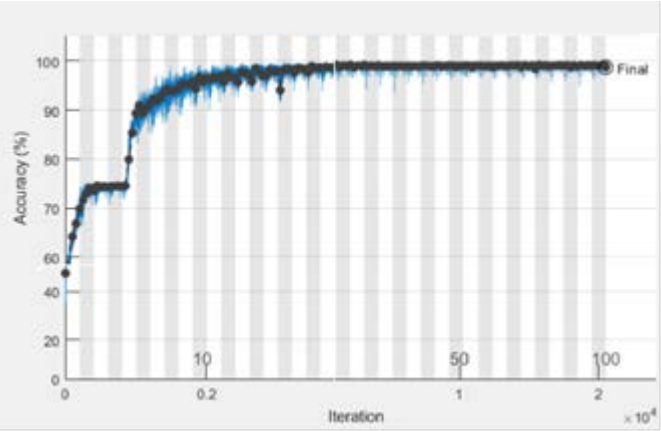


Fig. 7. Training accuracy during training.

TABLE 3
PERFORMANCE COMPARISON

| Method | Accuracy | Sensitivity | Specificity | MCC | IOU |
|---|---|---|---|---|---|
| F.Noya et al [ 2] | 96.6% | 89% | 97% | - | - |
| Konstantin Pogorelov et al [ 3] | 99% | 88% | 99% | 86.9% | - |
| Alexey A. Shvets [ 1] | - | - | - | - | 73.18% |
| TernausNet-11 [ 1] | - | - | - | - | 764,94% |
| TernausNet -16 [ 1] | - | - | - | - | 73.83% |
| Albunet-34 [1] | - | - | - | - | 75.35% |
| Proposed model | 99% | 91% | 99% | 91.6% | 84.97% |

Fig. 7. And Table 3. shows the training accuracy and performance comparison respectively of the proposed model. The performance is compared with the approaches that use the same database and same amount of dataset. The performance comparison shows that the designed model achieves a state of the art performance in angiodysplasia detection. Moreover, Fig. 7. shows the training accuracy during the training, the designed architecture started to converge from the 5th epoch.

## 4. CONCLUSION

In this, a novel deep learning architecture is presented to detect and localize angiodysplasia lesion. The proposed model was able to detect the angiodysplasia lesion and achieved better performance results than the existing approaches. Moreover, the angiodysplasia found to have a less correlation in Lab colour space channel 'a' were the lesion does not show any feature similarities with the surrounding pixels. Combining Lab channel with proposed SegNet architecture can accurately localize the lesion with higher detection rate, with an accuracy of 99%, the sensitivity of 91.1%, the specificity of 99%, Mathews correlation coefficient (MCC) of 91.6% and intersection over union (IOU) of 84.91%.

This model can assist clinicians by reducing the time in manual processing of large image set and helps accurately detect and localize the angiodysplasia lesion.

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