

Early detection of esophageal cancer: Evaluating AI algorithms with multi- institutional narrowband and white-light imaging data

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INTRODUCTION

According to data, esophageal cancer is one of the most common cancers in the world [1], and what makes it worse is the fact that patients tend to be diagnosed way too late in the disease [2], resulting in quite a poor survival rate. With all that said, if the cancer were to be found early in its stages, it's quite curable [3]. Unfortunately, doctors have been mainly using white-light imaging (WLI) during the endoscopy procedure to diagnose a patient, and that doesn't yield the best results as it's quite cumbersome and ineffective to do [4]. Another useful technique is to identify the structure from the surface of the esophagus using narrowband imaging (NBI) [5]. NBI works much better for helping diagnose and detect early signs of esophageal cancer [6].

Due to the cancer's complexity and the challenge it is to accurately detect [7], the procedure barely takes place in a person's life and is often overlooked, resulting in a shortage of high-definition (HD) scans [8]. With the advancements of technology and the effect of artificial intelligence (AI) on medical practices [9], there is hope that using this tool might ease and optimize the early detection of such cancers and be of aid to lesser experienced doctors [10].

Using deep learning (DL), specifically its Convolutional Neural Networks' (CNNs) variants, has been utilized for detecting signs from images [11]. Even though there are many CNN-based studies, data for esophageal cancer is still limited compared to others, which has led to poor performance on new inputs [12]. Here, Baik et al.

are building a new AI model that helps with recognizing early signs of esophageal cancer by checking information on already collected datasets that contain both WLI and NBI formats.

Materials and methods

Dataset came from a collection of 2,674 images from 619 patients who had done WLI procedure between 2016 and 2020, plus 480 images from 121 patients with NBI. Every image from one patient was put into either the training, validation, or test set, making sure there is zero overlap and data leakage. Since WLI and NBI samples had multiple dimensions, everything was resized to 640x640.

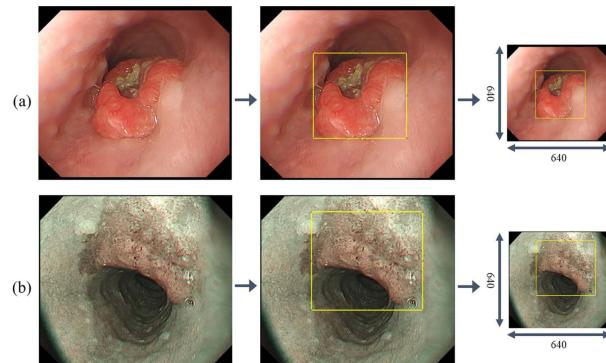


Fig 1. Labeling data for regions of interest, (a) WLI, (b) NBI

A gastroenterologist with 10+ years of experience was present during the model training to label the tumors. To detect tumors in the endoscopy images, authors used the YOLOv5 model, which is known as a single stage object detection model (ODM). After training, model's performance and precision, and false positives per image (FPPI) were checked.

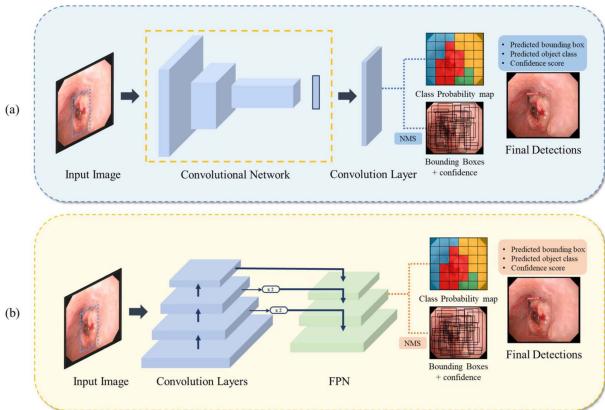


Fig 2. Tumor detection in esophageal Endoscopy, (a) YOLOv5, (b) RetinaNet.

Results and discussion

Finally, models were tested on two types of data: normal images and images with esophageal lesions. Basically, lesion were marked as true and vice versa. For the WLI dataset, the YOLOv5 model hit a precision of 93.7%, and for NBI it scored 86.5% in precision. So, based on the results, this model could definitely help spot tumors by analyzing the images. While prior studies mainly focused on polyp detection, this one goes a step further by focusing on early-stage esophageal cancer [11-19]. That said, a few limitations are still present, such as the poor results against unseen and rare shapes the cancer might take upon.

Going forward, collecting more data, re-training, and tweaking the hyperparameters are some of the recommendations from the authors [20]. Also, optimizing the speed and size of the model could help it run in real-time, which would be useful in medical clinics, resulting in helping new and unexperienced doctors make quick and accurate decisions on the fly.

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