Gastrointestinal Disease Classification

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Gastrointestinal (GI) tract diseases are on the rise in the world. These diseases can have fatal consequences if not diagnosed in the initial stages. WCE (wireless capsule endoscopy) is the advanced technology used to inspect gastrointestinal diseases such as ulcerative-colitis, polyps, esophagitis, and ulcers. WCE produces thousands of frames for a single patient's procedure for which manual examination is tiresome, time-consuming, and prone to error; therefore, an automated procedure is needed.

gastrointestinal disease deep learning WCE images

1. Introduction

The digestive system is affected by gastrointestinal (GI) tract diseases. Medical imaging is a key component of these diseases' diagnoses. Huge image data is difficult for radiologists and medical professionals to process, which makes it susceptible to inaccurate medical assessment [1]. The most prevalent digestive system disorders include ulcerative colitis, esophagitis, ulcers, and polyps that can develop into colorectal cancer. One of the leading causes of death worldwide is colorectal cancer [2].

According to a survey of the disease, 11% of women and 26% of men worldwide have been diagnosed with colorectal cancer [3]. In the US, 338,090 new cases of colorectal cancer were detected in 2021, with a 44% increase in fatalities [4]. Each year, 0.7 million new cases of illnesses are recorded globally [5]. Due to the high death rate, early diagnosis is exceedingly challenging. The development of ulcers in the GI tract is a serious sickness that goes hand in hand with GI malignant growth. As [6] reported, the most notable yearly predominance of ulcers retained in Spain was 141.9 per 100,000 individuals and the least was 57.75 in Sweden.

Many lesions are overlooked during a typical endoscopic examination because of the presence of feces and the organs' complex architecture. The rate of missing polyps is very high, ranging from 21.4% to 26.8% [7], even when the bowel is cleansed to facilitate the diagnosis of cancer or its precursor lesions. Furthermore, it can be difficult to identify lesions because of their similarities between classes. A new treatment called wireless capsule endoscopy (WCE) [8] allows medical professionals to view the stomach, which was previously exceedingly difficult to access via standard endoscopy. In WCE, patients ingest a camera-encased capsule that records several images as it travels through the GI system. The experts (experienced gastroenterologists) stitch these images together to create a film, which is then analyzed to look for deformations. However, this approach has some drawbacks, including time requirements and a dearth of expertise. The primary issue with this procedure is the time commitment required for a manual diagnostic. Additionally, the poor contrast in the WCE images makes it difficult to see an ulcer properly [9]. As a result, there is a possibility that a doctor will overlook the ulcer throughout the detection phase. Another issue that arises during a diagnosis with the naked eye has to do with the similarity of color, texture, and shape variations [10][11].

Different techniques for the diagnosis of colorectal cancer and its precursor lesions utilizing the WCE images have been developed by numerous researchers [4][11]. These techniques have some basic steps such as contrast enhancement and noise removal from the image, followed by segmentation of diseased area within an image, important features extraction, and finally, classification of a specified class. An integral part of a computerized process is contrast enhancement. The primary goal of this phase is to increase an infected region's intensity range to improve accuracy and retrieve pertinent features [12]. The resultant images are then passed into the segmentation phase for the detection of disease and subsequently for features extraction, but this step faces several difficulties (such as the alteration in the topology of the infected lesion and the similarity in color between the healthy and infected parts) that lower the segmentation accuracy. Later, a disease can be incorrectly classified into an inappropriate class as a result of the decrease in segmentation accuracy.

Recently, the performance of a deep convolutional neural network (CNN) for the identification and classification of medical infections has increased [13][14] as they outperformed traditional machine learning models. These techniques extracted features using pre-trained CNN models, which were then optimized for features. Due to memory and time constraints, the pre-trained CNN models are trained via transfer learning (TL). Most of the researchers are focusing more on using the complex CNN models as well as fusing multiple models and optimizing the features for achieving better accuracy. As WCE images are subject to several challenges and limitations, work on image improvement is an area upon which focus is needed. The quality of WCE images is not good because of volume and power limitations. As a result, WCE images exhibit weak contrast [15]. Furthermore, the great similarity between normal and abnormal frames further complicates the process of disease classification [16].

2. Gastrointestinal Disease Classification

The use of medical imaging to identify diseases has gained popularity in recent years, particularly in the field of the gastrointestinal system. Another active field of research is the classification of digestive illnesses. Although machine learning algorithms have demonstrated amazing performance in the literature [15][16], CNN algorithms outperform ML techniques and produce superior results [17].

Several research [18][19][20][21][22][23][24] works have examined the detection of abnormal frames in capsule endoscopy images, including the detection of tumors, Crohn's disease, polyp, hemorrhages, ulcers, lymphangiectasia, and other intestinal lesions. Existing techniques often start with feature extraction and then apply a detection technique. The detection techniques either use multi-label approaches to find and classify various types of abnormality [19] or distinguish between frames with a lesion and normal ones [18]. These methods frequently extract features from the images' texture and morphological analysis, statistical feature analysis, and color descriptors. These techniques either use region-based [20][21] or pixel-based [18][19] methodologies. Artificial neural networks (ANNs) and support vector machines (SVMs) are the two commonly utilized classification techniques in the literature [22][23][24]. Many other studies related to gastrointestinal diseases such as polyp, colon, and capsule endoscopy have been conducted in the literature [25][26][27][28][29][30].

DL models such as ResNet-50, VGG16, and Inception-V3 were used by Lee et al. [31] to categorize normal and ulcer GI pictures. Resnet-50 outperformed the other deep networks using this technique. A saliency-based strategy was presented by Khan et al. [32] to segment GI diseases, whereas DL architecture is employed for classification. They combined a YIQ color space with an HSI color space, which was then fed into a segmentation method based on contours. An automated technique for identifying an ulcer from the WCE frames was introduced by Yuan et al. [33]. To begin with, a saliency technique based on superpixels is used to define the boundaries of the ulcer zone. The level-by-level texture and color properties are then computed and combined to produce the final saliency map. Then, to achieve a recognition rate of 92.65%, the saliency max-pooling (SMP) and locality-constrained linear coding (LLC) techniques are combined. With a dataset of 854 photos, the authors of [34] proposed the VGGNet model, which was built on a CNN (convolutional neural network), to accurately identify gastrointestinal ulcers, even though these tests used images from a standard endoscopy. The dataset used in [35] comprised 5360 WCE images with ulcers and erosions and only 440 normal images; the authors created a model based on a CNN. This method’s detection accuracy was 90.8%. An attention-based DL architecture for classifying and localizing stomach diseases from WCE images was presented by Jain et al. [36]. They started by effectively classifying stomach illnesses using CNN. Later, for the localization of contaminated areas, they combined Grad-CAM++ and a unique SegNet. On a KID dataset, the proposed technique was tested, and it showed enhanced accuracy. For WCE video summarization, Lan et al. [37] developed a combination of unsupervised DL techniques. They employed several networks, including LSTM and autoencoder, among others. This research’s major goal was to assist medical professionals in their examination of the complete WCE videos. In [38], a gastrointestinal disease classification framework is proposed in which deep features are selected and fused from two deep models, i.e., ResNet-50 and ResNet-152. Subsequently, the features were optimized and it achieved 96.43% classification performance. In another work, [25], alimentary diseases such as Barret, Polyp, and Esophagitis were classified by applying discrete wavelet transform and CNN. This framework achieved a 96.65% accuracy on the Hyper Kvasir dataset.

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