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Research Article

Polyp Detection in Endoscopy Images Using Deep Learning

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Abstract

Colonic Polyps are predecessors to colorectal cancer, hence timely detection is crucial to reduce the mortality rate. However, polyp detection of various morphological structures and texture has been proven to be very challenging. This work pro-poses a deep learning method for the detection of various types of colonic polyps of various morpho-logical structures and texture.

Deep learning has recently demonstrated high level prediction accuracy in the classification of medical images. In this paper, five state-of-art Keras Deep Learning image classifiers using convolutional neural network architecture namely VGG16, VGG19, ResNet, Inception V3 and Xception has been employed to train deep network to predict polyps in Endoscopy images. The training sets are collected from various colon polyp image datasets and testing has been performed on wireless capsule endoscopy images. The experimental results show that for WCE datasets (training:testing ratio of 2:3) achieves an accuracy of 94.45% and precision of 94%.

The results suggest that deep learning techniques can extract more information on polyps structure and texture thereby helps to train better and achieves higher detection accuracy and precision.

Keywords: *Support Vector Machine; Neural Net-Work; Classification; Learning (Artificial Intelligence); Computer Vision*

Introduction

Colorectal cancer is a major cause of mortality throughout the world [1]. Early diagnosis is particularly required for colorectal cancer. Early detection and removal of precancerous polyps in the colon helps to prevent cancer. Colorectal cancer is the third most cause of deaths due to cancer, for both women and men. Early detection may increase the chances of survival of a patient from as low as 10 - 30% to 90% [2].

Based on the morphology, polyps are classified into various types such as Pedunculate polyps which are mushroom shaped structures with a thin stalk, whereas sessile polyps are mushroom shaped with no stalk shown in figure 1. There are some polyps which have non-prominent structure and are slightly depressed and difficult to identify.

Due to the highly varying morphological and textural variations of polyps, it is highly difficult to develop hand-crafted algorithms for detection of polyps using geometrical feature identification and segmentation. There are certain polyps which are highly unusual in shape. In this work, a deep learning technique has been proposed for the detection of polyps in GI tract. The main contributions of the work are:

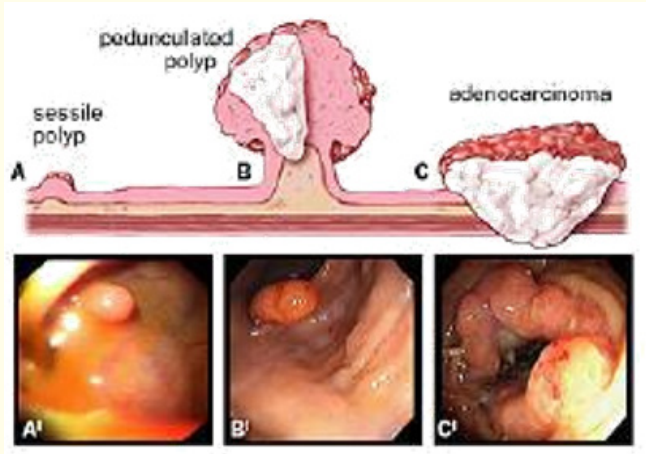

Figure 1: *Types of Polyps A: Sessile, B: Pedunculated, C: Adenocarcinoma [18,19].*

- Automation of polyp detection in endoscopy datasets using deep learning.
- Comparison of performance of proposed techniques with other machine learning classifiers such as Naive Bayes, Nearest Neighbours, Lin-ear SVM (Support Vector Machine), Random forest, MLP (Multi-Layer Perceptron) classifier, RBF (Radial Basis Function) SVM, SGD (Stochastic Gradient Descent) classifiers, Gaussian process, adaboost and decision tree.
- Evaluating the performance of the proposed technique on cross datasets available online [14]. Owing to the limited availability of datasets for polyps in wireless capsule endoscopy, the datasets for various types of polyps have been collected and trained from classical endoscopy and colonoscopy techniques. The testing has been performed on WCE datasets for polyps and non-polyps, comprising of various types of polyps.

Previous work

Various hand crafted techniques for localization of polyps using colonoscopy images exist in the literature. Bernal et.al. proposed modeling of polyps to help filter out the valley-rich structures like blood vessels [3]. Silva et.al. employed Hough transformation and texture feature extraction along with ad-hoc boosting-based classifier for polyp classification [4]. However, hand crafted feature extraction techniques are specific to the structure of polyps and results in high false positive rates. Machine learning and Deep Convolution Neural Networks (CNN) on the other hand, offers generic techniques for polyp detection with lower false positive rates. A summary of polyp detection techniques using various machine learning and deep CNN is demonstrated in the table 1.

Authors	Methodology	Endoscopy technique	Classifier used	Datasets	Precision%	Recall%	F1-score %	Accuracy %
Pogorelov., *et al*. [5]	Machine learning, image recognition and extraction of global and local image features	Colonoscopy	Global Feature and the Deep classifiers	300	93.88	98.50	96.13	
Lequan Yu., et al. [6]	Fusion model	Colonoscopy	2D-CNNs	3000 - 4000	88.1	71	78.6	

Lequan Yu., *et al.* [6]	Offline 3D-net	Colonoscopy 2	D-CNNs	3000 - 4000	78.5	70.8	74.5	
Nima Tajbakhsh., *et al.* [7]	Shape and texture feature extraction with CNN colonoscopy	CNN	7000 polyp and 28000 non polyps	50% sensitivity				
Shijun Wang [8]	Shape descriptors based on statistical curvature details	Colonoscopy SVM		5763 polyp image	77 - 83% sensitivity			
Mohammed [9]	Y-Net CNN	Deep colonoscopy	Deep CNN	4278 frames polyps for training 4300 frames for testing	87.4	84.4	85.9	
Byrne [10]	Deep CNN	Colonoscopy	Deep CNN	106 polyps	-	-	-	94
Caelen [11]	Shape feature extraction and stateofart machine learning classifiers	Computed Tomography Colonography	Lazy Learning, SVM and Nave Bayes classifiers	569 non-polyp, 81 polyp	99% sensitivity		-	-

Table 1: *Summary of various polyp detection techniques available in literature; with methodology along with its experimental performance.*

Materials and Methods

Datasets and data augmentation

The experimental datasets have been collected from various sources for polyps of various types and nor-mal mucosal structures of GI tract. Due to the limited availability of datasets of polyps in Wireless Capsule Endoscopy, datasets for polyps have been used from colonoscopy datasets for the purpose of training; and testing is performed on polyps and non-polyp images obtained from endoscopy and WCE. The training datasets are collected from CVC colon datasets [14] and colon endoscopy images [12]. The testing datasets are collected from Shaily endoscopy and BGS Global Hospital for real time WCE video frames [13] and endoatlas capsule endoscopy [14]. Non overlapping datasets have been used for training the feature models and classifier model. The input datasets were split into training and testing images. The test size was chosen as 0.10; which indicates the percentage of the data that should be held over for testing. It is usually around 90/10 for training/testing.

However, the splitting of data into training and testing may use a data of certain category of polyps al-ways, resulting in overfitting. Hence K-folds cross validation technique have been used to reduce the overfitting, where k = 1 represents the subsets used for training.

Data augmentation is a commonly used method to improve the generality of deep learning models. The images are subjected to rotation, zooming, flipping, rescaling and shifting. The polyp and non-polyp images were retrieved randomly and balanced datasets were

used to avoid imbalance with data problems. Specifically, we obtained samples with width and height shift range from the range [-0.2, +0.2] and [-0.2, +0.2] of the image respectively, with rotation from [+/ - 90 degrees], and with zoom range of [(1+0.2), (1-0.2)]. All images were organized according to the image size of the pre-trained model (224 x 224 pixels) during the oversampling.

Architecture of the network

In this work, Keras State-of-art deep learning image classifiers namely VGG16, VGG19, ResNet50, Inception V3 and Xception has been employed for pre-training. The figure 2 shows architecture of VGG16 with many convolution layers followed by maxpooling, to reduce the dimensionality. In this study, we compared and analysed four distinct deep learning models. Keras State-of-art deep learning image classifiers namely VGG16, VGG19, ResNet50, Inception V3, Xception have been pre-trained on endoscopy image dataset. The VGG network architecture proposed by Zisserman., *et al.* [15] has been used for training. ResNet is used to ease the training of networks as compared to the traditional sequential network AlexNet and VGG [12]. The input to the Convolutional Networks is a fixed size 224*224*3 RGB image. There is no pre-processing conducted on the available image. The input image is sent through a stack of convolutional layers and pooling layers as shown in figure 2, which are then followed by two fully-connected layers and softmax classifier.

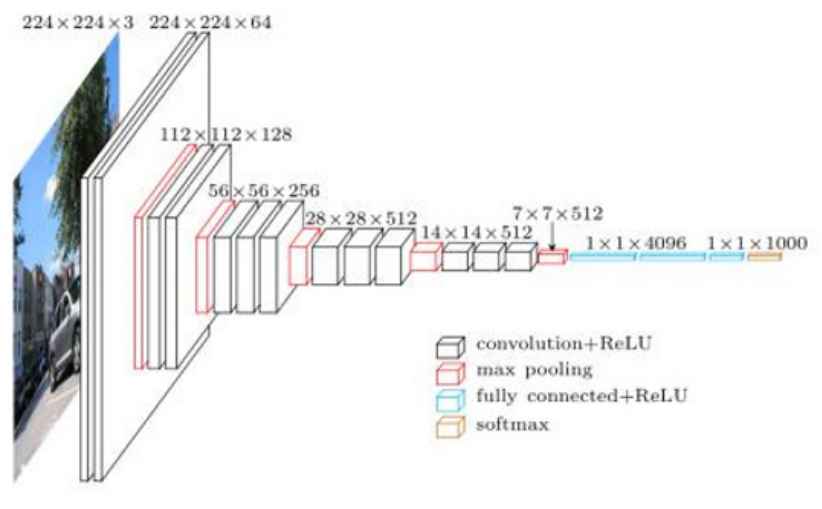

Figure 2: *Architecture of VGG [16].*

VGG16 and VGG19 are considered very deep with number of weight layers in the network being 16 and 19 respectively. Although VGG networks are considerably very slow during training and very huge network architecture weights, VGG16 alone weighs 533 MB and VGG19 consumes 574 MB. Thus, deployment of VGG is very difficult. However, ResNet shown in figure 3 offers a much deeper network than VGG up to 50 to 200; yet the overall size of the model is much smaller owing to the global aver-age pooling rather than fully connected layers. The ResNet occupies just 102MB, much lesser as compared to VGG architecture.

The Inception module by GoogLeNet shown in figure 4 proposed by Franois Chollet [17], computes 1 x 1, 3 x 3 and 5 x 5 convolutions with the same module in the network. The output is then fed to the next layer in the network. The size of Inception is much smaller than VGG and ResNet, weighing just around 96MB.

The Xception architecture is a deep CNN inspired by Inception, proposed and created by Chollet. It weighs as small as 91 MB [17]. Figure 5 shows the complete specification of Xception architecture with 36 convolutional layers, form feature extraction. These 36 layers have been formed into 14 components with linear residual connections between them.

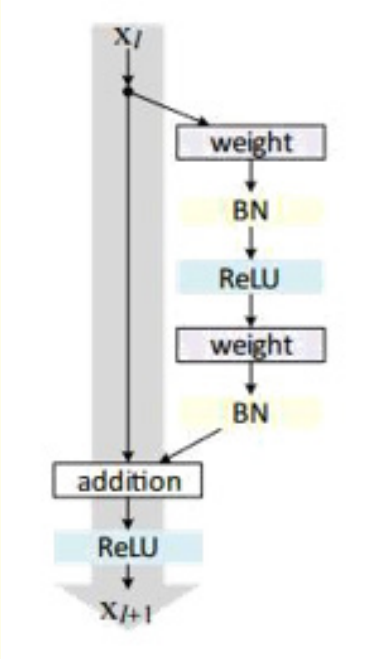

Figure 3: *Residual model by ResNet.*

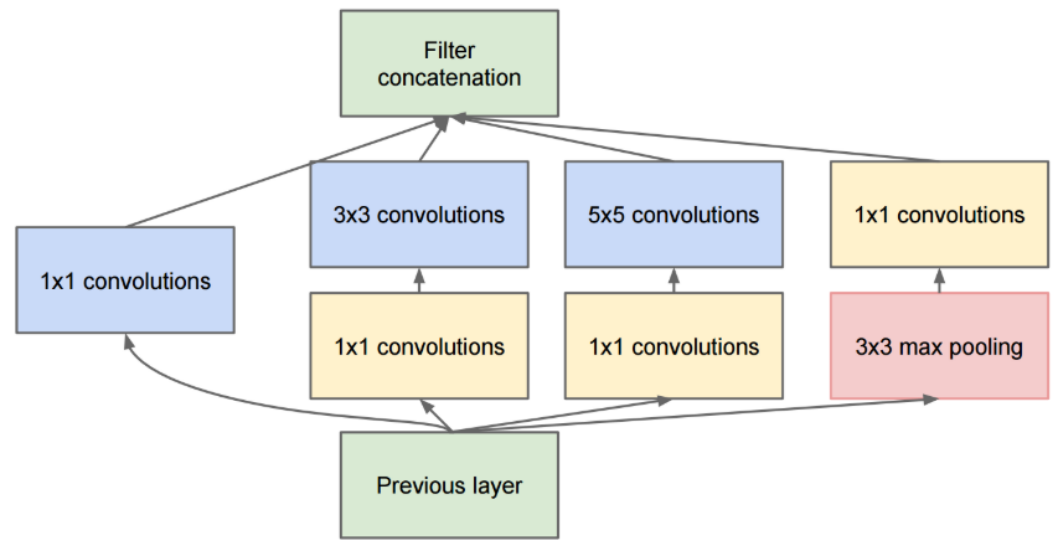

Figure 4: *Inception model.*

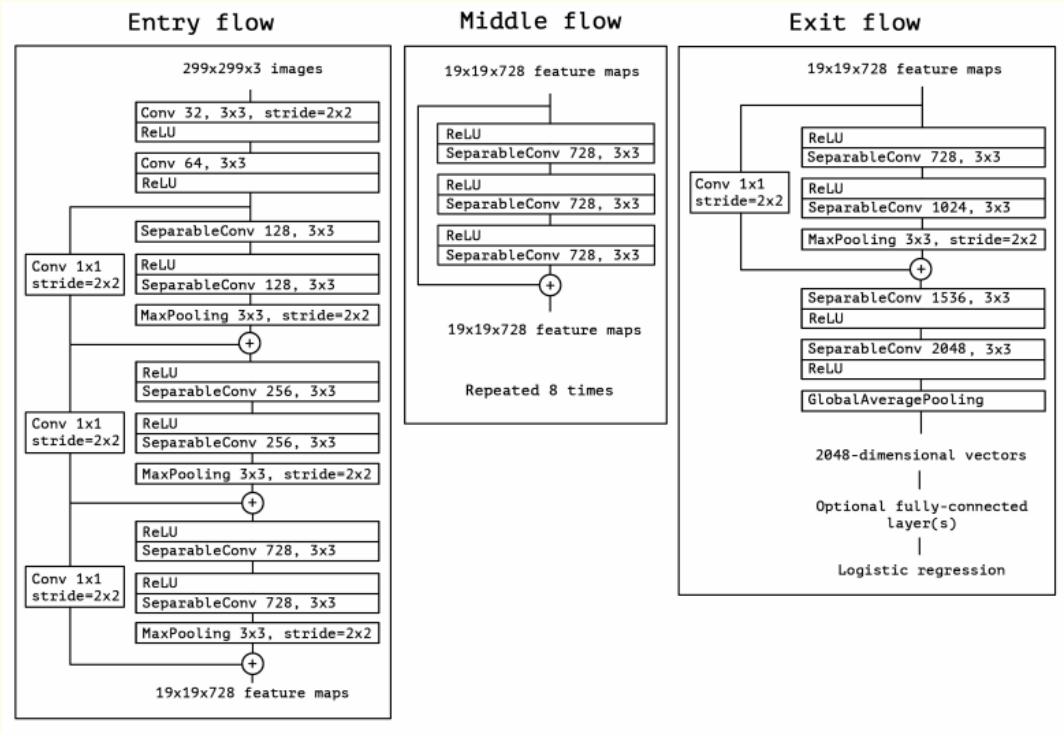

Figure 5: *The Xception architecture [8].*

Experimental setup

The networks were implemented using the Keras framework. The comparison of polyp classification using Keras framework is shown in table 2 and table 3. Overall, the best accuracy is obtained at rank 5. The accuracy was calculated by taking the Top 1 or the Top 5 predictions and calculating the percentage of accuracy having at least one correct prediction ranked Top 1, or within the Top 5, to obtain Top 1 and Top 5 respectively.

DL Techniques	Top1 accuracy (%)	Top5 accuracy (%)
VGG16	94.03	92.51
VGG19	94.45	100
ResNet	93.34	100
InceptionV3	92.46	100

Table 2: *Comparison of accuracy obtained for different DL techniques.*

DL Techniques	Precision (%)	Recall (%)	F1-score (%)
VGG16	94	94	92
VGG19	94	94	93
ResNet	92	93	91
InceptionV3	85	92	89

Table 3: *Comparison of precision, recall and F1-score for different DL techniques.*

Results and Discussion

This work is an investigation of state of the art deep learning image classifiers in Keras. The findings of this work reveals that the pre trained net-works VGG16, VGG19, ResNet50, Inception V3, and Xception with core Keras library were very effective in classifying the various types of polyps in Wireless capsule endoscopy images.

There were several challenges during the implementation of deep learning to clinical practice. The major drawback was deep learning requires huge database for training and testing. WCE has be-come more popular among the patients only in re-cent years. It is difficult to collect various real time WCE frames related to polyps. However, this challenge was overcome by training the Deep learning architecture with polyps image datasets from classical endoscopy, colonoscopy and WCE. Another major obstacle is actual classification of polyps into multi classification problem. Due to numerous types of polyps but limited datasets, the present work was concluded as binary classification prediction of polyps and non-polyps. The limitation of the pro-posed work is non availability of larger polyp image datasets. Deep Learning requires a variety and huge datasets for training without overfitting. However, we have overcome the problem by employing data augmentation techniques. Nevertheless, this work would be extended in future to achieve the effectiveness through increased dataset. The reference for diagnosis of image datasets were obtained by experienced Gastroenterologists from BGS global hospitals, Bengaluru. Further this work would be extended to include multi classification problem, based on the availability of real time WCE frames corresponding to different types of polyps.

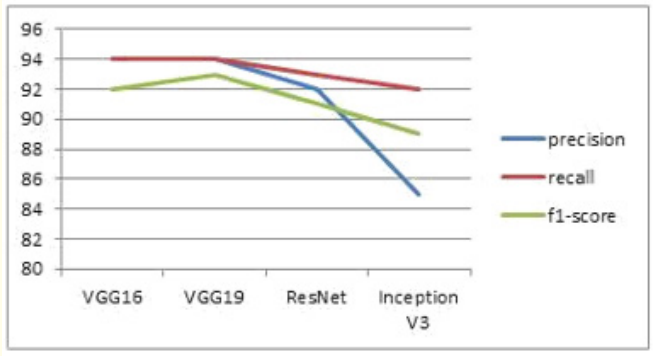

Figure 6: *Comparison of precision, recall and F1-score for state-of-art deep learning techniques.*

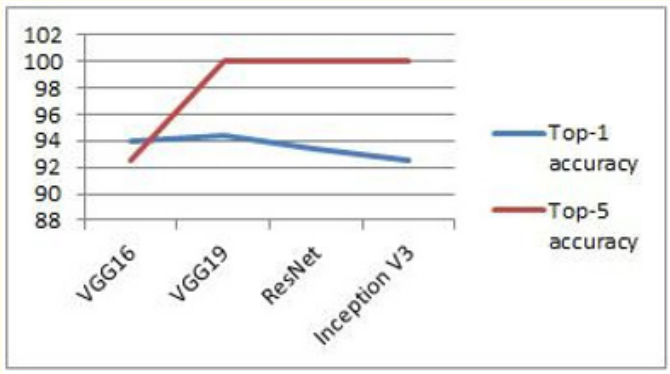

Figure 7: Comparison of Rank-1 and Rank-5 accuracy for state-of-art deep learning techniques.

Evaluation metrics

The effectiveness of the proposed model is evaluated through comparative results of accuracy, recall, precision and F1-score. The performance metrics are calculated using False Negative (FN), True Positive (TP), True Negative (TN) and False Positive (FP). TP is a correctly predicted polyp. TN is correct pre-diction as normal. FP is an incorrect prediction as polyp. FN is an incorrect prediction as normal. Re-call, F1-Score, Accuracy and Precision are computed as presented in Equations 1, 2, 3 4 respectively.

$$Recall = TP/TP + FN \quad (1)$$

$$F1 - score = 2TP/(2TP + FP + FN) \quad (2)$$

$$Accuracy = TP + TN/TP + TN + FP + FN \quad (3)$$

$$Precision = TP/TP + FP \quad (4)$$

If recall or true positive rate is low, then the model will miss finding the polyps which can lead to late stage diagnosis of colorectal cancer. If the precision is low, then it will add further examination and work for the gastroenterologist. Moreover, negative classes outnumber the positives with large margin, i.e. there are more frames without polyp than with polyp. Hence, we employed F1-score so as to provide a balance between missed polyps and false alarms.

The results obtained shows that the deep learning technique of identification of different types of polyps is a proficient method for computer aided diagnosis of polyps in endoscopy images. The proposed technique obtains accuracy of 94.45% at Rank1 and 100% at Rank5. All the experiments have been conducted using Intel core i3 processor, running at 1.9 GHz.

The study has been compared with other ma-chine learning classifiers such as Nearest neighbors, SVM, RBF SVM, SGD classifiers, Gaussian process, decision tree, random forest, MLP classifiers and Adaboost [20]. The accuracy of proposed work achieves an accuracy of 94.45% for rank-1 and 100% for rank-5. The comparison has been illustrated in the table 4 and figure 8.

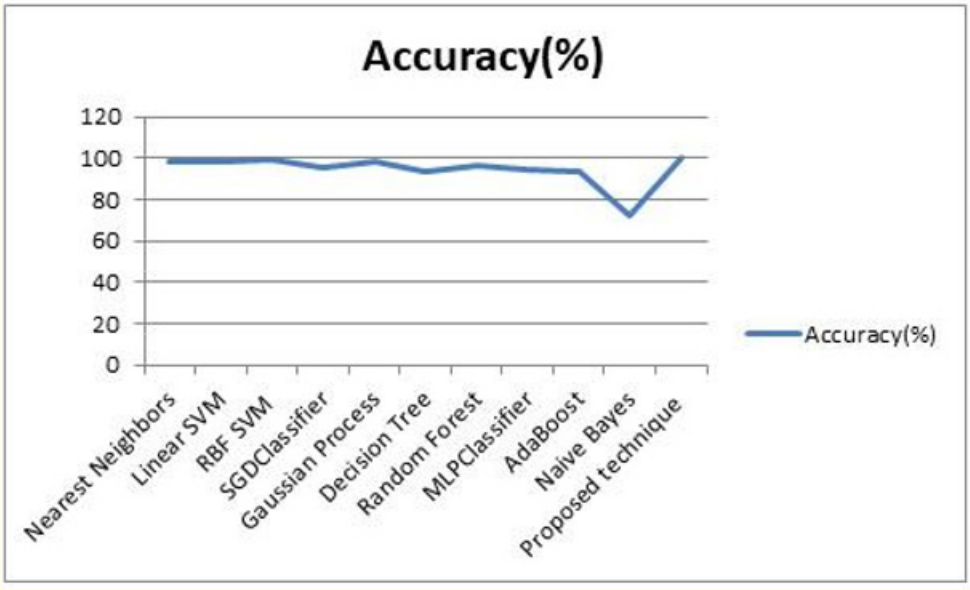

Figure 7: *Comparison of Rank-1 and Rank-5 accuracy for state-of-art deep learning techniques.*

Classifiers	Accuracy (%)
Nearest Neighbors	98.04
Linear SVM	98.62
RBF SVM	98.89
SGD Classifier	95.07
Gaussian Process	98.02
Decision Tree	93.85
Random Forest	96.06
MLP Classifier	94.4
AdaBoost	93.23
Naive Bayes	72.62
Proposed technique	94

Table 4: *Comparison of proposed work with ma-chine learning classifiers.*

Conclusion

In this work an investigation of binary classification of deep learning models for automated diagnosis of polyps was conducted. An attempt to employ deep learning state-of-the-art models for polyp identification was done. The diagnosis with deep learning models using Googlenet and Keras core library achieved high classification performance. Further studies would be focused on construction of a huge diversified datasets of real time polyps using Wireless Capsule endoscopy frames. This study hopes to help Gastroenterologists in their clinical use to improve the speed of diagnosis in the huge database of WCE images with better prediction accuracy.

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