Programming Challenge II

Classification of Anomalies in Gastrointestinal Tract through Endoscopic Imagery with Deep Learning

Final Report

Team DeepCoders

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INTRODUCTION

The gastro-intestinal (GI) tract refers to the pathway taken by food in the human body. It is a vital part of the body and is prone to various diseases. These diseases are characterized by the appearance of varying types of anomalies in the GI tract, which can be viewed through an endoscope. Early location and diagnosis of such anomalies contributes to slowing or stopping the spread of the disease and may save lives.

The current widely used diagnostic procedure for such diseases involves passing an endoscope through the GI tract, while a human professional watch the image feed from the attached camera. Any anomalies will be detected and classified in real time.

In this method, disease diagnosis depends on the skill level of the medical professional. The time limits while performing the endoscopy may also influence the correctness of the diagnosis. Therefore, in recent years, computer-aided diagnostic methods have been rising in popularity.

The original computer-aided diagnostic tools utilized algorithms to manually extract features from an image, such as vertical and horizontal edges, colored regions, and texture. These features were then fed to a Support Vector Machine (SVM) which would output the image classification. However, drawbacks of this method lay in the manual identification of features. Human influence remains in the manually extracted features, which cannot automatically be optimized.

Deep convolutional neural networks (DCNNs) offer a solution to this problem. Convolutional layers are used to automatically extract features from an image. This feature extraction is automatically fine-tuned by the network during its process of learning weights, so that it learns which features best correspond to the required classifications.

In this report, we propose a system based on a deep convolutional neural network utilizing transfer learning, to classify gastro-intestinal endoscopy images quickly and accurately. The system is trained on the KVASIR dataset, and will classify images based on the anatomical landmarks, pathological findings, and polyp removal anomalies present.

LITERATURE REVIEW

Overview

Deep learning is considered as a subfield of Machine learning, where both falls under Artificial Intelligence. Moreover, Deep learning is considered as Artificial Neural Networks with multiple layers [5]. An ANN mainly made of a large group of computational nodes interconnected together [4]. With the time, the focus towards implementation of deeper hidden layers has gradually increased in many fields relative to classical methods, due to the higher performance [5]

Convolutional Neural Network (CNN)

CNN is considered as one of the most popular types of ANN which is self-optimized through learning and is mostly focused on pattern-recognition tasks in images mainly through classification with supervised learning [4].

When considering differences between CNN and ANN, CNN is mainly focused to be used in pattern recognition within images [4]. Working principal of CNN comprises of main two steps. Firstly, over a provided labelled data set, the network is trained and multi scale features are extracted. Secondly, a classification will be performed based on the features that were extracted first [1].

When considering components of CNN, it comprises of convolutional layers, non-linearity layer, pooling layers and fully connected layers [1] [5]. The convolutional and fully connected layers do have parameters however in pooling and non-linearity layers' parameters do not exist [5] Convolutional layers are considered as the crucial part of CNN as every single neuron corresponds to a small part in images [1]. On the other hand, selection of activation function for CNN is important as well. Currently, ReLU is preferred to be used as the activation function [1]. ReLU mainly aims on applying an elementwise activation function to the output of the activation which was produced by the previous layer [4]. Moreover, the pooling layer acts mainly to reduce the computational costs and Max pooling layer is considered as the type which is most popularly used and it computes the maximum value of the adjacent rectangular area [1] and the last layers of CNN are considered as the fully connected layers where each neuron in the layer is connected to each neuron in the next layer acting as a standard layer in ANNs to produce class scores from activations [1], [5].Number of layers in the model varies according to the complexity of the model where simple CNN might contain several layers while some deep networks would contain a vast number of layers. For instance, ResNet (One of the CNN architectures) consists 152 layers [1].When considering the terminology of CNN, input is referred as the first parameter of convolution, second parameter is called the kernel and output is referred as feature map [1]

TABLE I SUMARRY OF DEEP ARCHITECTURES USED IN GASTROINTESTINAL IMAGE ANALYSIS

		Deep Architectures	N.
Supervised	NN	ANN, DNN	2
	CNN	LeNet, AelxNet, GoogLeNet, VGGNet, ResNet, InceptionResNet, SSD, FCN, Fast R-CNN, Faster R-CNN, DeepLab, SegNet	44
Unsupervised		GAN	1

N.=the number of papers

figure1 [3]

Many researches have been conducted in medical image classification in CNN for instances, GI tract endoscopy images classification [1], system to determine the invasion depth of gastric cancer with high accuracy and specificity [6], system to classify breast cancers [7] and system to identify diabetic retinopathy on color fundus images [8]. This study shows CNN could be used to research more systems on image classification.

Supervised Deep Learning Architectures

In this section we give an overview of the commonly used DL architectures based on the supervised manner in GI image analysis.

1) Classification Architectures

VGGNet

- The visual geometry group network which also called OxfordNet (VGGNet) [11] is used widely for image classification and has proven to be very effective method.
- VGGNet which is also relatively shallow and consists 16-19 layers.
- Most existing approaches use features of just one type, and traditional fusion methods generally use multiple manually created features.
- We then choose two convolutional (mid-level) and two fully connected layers produced by VGGNet in which each layer is treated as a separated feature descriptor.
- Next, canonical correlation analysis (CCA) is used as a feature fusion strategy to refine the extracted features, and to fuse them with more discriminative power.
- Finally, the support vector machine (SVM) classifier is used to construct the 4-layer representation of the scene's images.

Nowadays, there is a preference for deeper models and smaller kernels instead of a single layer and kernels with large receptive field, because a smaller function means fewer parameters, such as GoogleNet and ResNet. Szegedy et al. [12] proposed [13].

GoogleNet

- **GoogLeNet** is a type of convolutional neural network based on the Inception architecture.
- GoogLeNet introduced an inception block that has been shown to be able to achieve very good performance at low computational cost
- It utilizes Inception modules, which allow the network to choose between multiple convolutional filter sizes in each block.
- An Inception network stacks these modules on top of each other, with occasional max-pooling layers with stride 2 to halve the resolution of the grid.

Transfer Learning

Deep neural networks require training to be able to classify data accurately. The more complex the architecture of the network, the greater number of examples it must train on. However, in a niche area such as gastro-intestinal imagery, the collection and labeling of large amounts of data present issues, and the training of the network from scratch, are time consuming [1]

Transfer learning is a method of building a Deep neural network which avoids the above problem. It does so by taking a model which was previously trained for a different task and modifying its structure, perhaps by adding further layers or tweaking parameters, and then re-training it specifically for the intended task. [22]

These models trained on ImageNet and other non-medical domains have been shown to perform quite well in medical applications, despite the difference in the nature of the data. In [25], a study on polyp detection and classification, it was shown that this manner of transfer learning worked quite well when the non-medical source domain contained many classes with subtle differences between them.

There are a few distinct methods which fall under the umbrella of transfer learning. Feature extraction is perhaps the most well-known one. It involves replacing the lower, fully connected layers of the pre-trained model with custom-made classifier layers which are then trained separately on example datasets of the target domain [1]. This combination has been shown to perform better on medical images, than both the original model and one trained specifically for the task [26]. Feature extraction is best suited for target domains with small datasets, such as that of gastrointestinal endoscopy.

Applications

Polyps

Polyps are considered as one of the most common symptoms of Gastrointestinal tract. It can be divided into two types called hyperplastic polyps (non-adenomatous polyps) and adenomatous polyps according to the possibility of it turning into a cancer. In this review, main focus will be given to research that has been conducted to support this problem detection with the help of deep learning.

Research works.

Using deep learning a number of researches have been done in order to detect polyps. In [1], it mentions the research conducted by [28] is considered as the first to use a Faster R-CNN combined with a deep CNN model in detecting colonic polyps in images and videos. In [28], it has used R-CNN model as a transfer learning scheme in detecting. It mentions, "The detector system consists of three main part, region proposal network, detector and post-learning. For training the detector system, domain-specific image augmentation and transfer learning using pre-trained deep CNN are adopted."

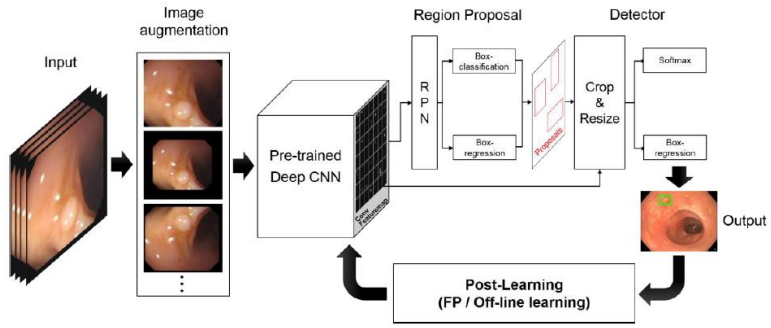


Figure 1:Proposed polyp detection method of [9]

The originality of this [28] research is the reduction of the number of FP in the sample by the proposed post learning. However, it mentions that the MPT is about 0.39 sec per frame as the deep CNN used and it mentions the important of improving it as it matters in real time detection. Although, it has achieved a detection precision of 91.4% at the end from one of the augmentation methods (included it in below figure).

In this another specialty which is highlighted is in this research they have focused on detecting polyps in videos as well rather than only focusing on images.

COMPARISON OF POLYP FRAME DETECTION RESULTS USING FOUR DIFFERENT AUGMENTATION STRATEGIES

Training dataset	TP	FP	FN	Pre (%)	Rec (%)	F1 (%)	F2 (%)
w/o augmentation	82	89	126	48	39.4	43.3	40.9
Rot-augmentation	147	99	61	59.8	70.7	64.8	68.2
Augmentation-I	167	26	41	86.5	**80.3**	**83.3**	**81.5**
Augmentation-II	148	14	60	**91.4**	71.2	80	74.5

Figure 2comparison of polyp frame detection results of different augmentation strategies has used in [9]

Gastrointestinal Cancers

GI cancers are considered as the cancers that affect the digestive system. Unfortunately, [27] states that GI cancers are considered as one of the most popular cancers in Asia. The damage occur by cancer can be reduced if it is able to identify early and give correct treatments before getting worse. Therefore, to help doctors to improve the accuracy of diagnosis and reduce misdiagnosis rate, a study of CAD system to classify images according to the probability of leading to a cancer is indeed.

Research work
In [24], the study of application is mainly EGC classification based. It has used transfer learning by fine tuning deep CNN and applied to automatically classify M-NBI images into two groups named normal gastric images and EGC images. Moreover, that study shows how transfer learning affects the classification performance from four aspects (training dataset, basic architectures of the deep CNN, the number of fine-tuned network layers and size of the network input image) On the other hand, in this research, evaluation is established by applying three efficient DCNN models, VGG16, InceptionV3 and InceptionResNetV2. And according to results it shows the results showed for InceptionV3 was better. It gives and top accuracy, sensitivity and specificity are 0.985, 0.981 and 0.989 respectively.

Haemorrhages

Haemorrhages (bleeding) in the GI tract can be a symptom of several diseases. The task of deep learning algorithms which are focused on the detection of haemorrhages is usually to either classify specific images as bleeding or non-bleeding, or to detect bleeding segments in an image or video taken by an endoscope.

The greatest challenge presented to deep learning algorithms in this area is the comparative sizes of each class of images [23] “Normal” images, which have no bleeding present, make up a higher proportion of available data, which can lead to overfitting and a higher rate of error when classifying images where bleeding is present. The authors of [23], Abouelenien et al., presented a cluster-based sampling method which learns from such an imbalanced dataset with high accuracy.

In 2016, Jia et.al. [2] conducted the first study which utilized a DCNN for automatic feature extraction in classifying bleeding vs. non-bleeding images. They proposed an eight-layered CNN, built on the Caffe framework [20]. The CNN consisted of three convolutional layers, three pooling layers, and two fully

connected layers. A precision of 0.9255 was obtained. However, the drawbacks of the proposed method were that it involved a high degree of computational complexity and required a large volume of labeled instances to train on.

METHODOLOGY

CNNs were built based on different existing architectures for image recognition, namely Inception v3[], ResNet50[], and VGG16[]. The models and their weights after training are available in the public domain. They were trained on version 2 of the publicly available KVASIR dataset, which contains 8,000 images of the gastro-intestinal tract, divided evenly into 8 classes.

We first preprocess the dataset as described in the section 'Preprocessing' below. Then we feed the dataset, batch by batch, to the customized input layer of the imported CNN model. We choose a layer near the base of the model below which we add a few customized layers. We then train the newly added layers.

The model is evaluated primarily by its accuracy on the validation set, and also by the class-wise precision, recall and f1-score as described in the 'Results Analysis' section.

Preprocessing

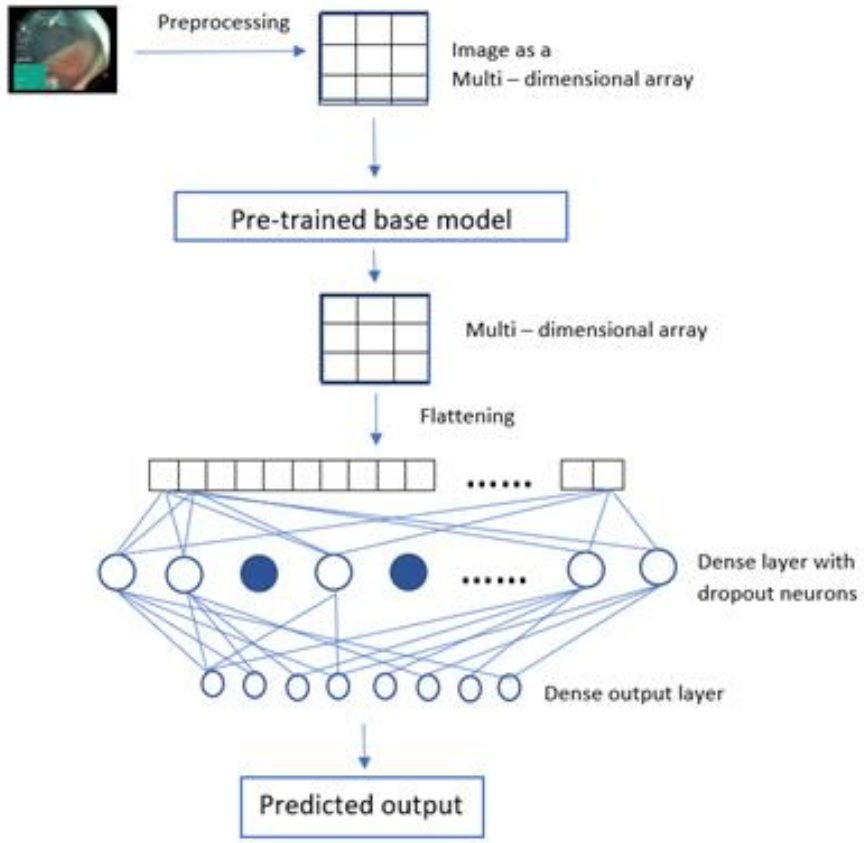
The images in the dataset were of varying resolutions, therefore they were down sampled to a uniform resolution of 288x360. The pixel values which originally ranged from 0 to 255, were divided by 255 to present a small range of 0 to 1 to the network.

Data augmentation was used to prevent overfitting. Every image in the training dataset was duplicated multiple times by the following augmentations: rotation by up to 90 degrees, width shift of 20 percent, height shift of 20 percent, zoom in up to 20 percent, and a horizontal flip.

Structure of the Network

We choose one of the lower layers of the base model upon which to add customized layers. There are four additional layers in total.

The first is a layer which flattens the output of the base model. It is followed by a dense hidden layer which contains a certain number of neurons and uses a ReLU activation. The third layer is a dropout layer, which invalidates the output of a certain fraction of neurons in the previous layer. The dropout layer is active only during training. The final layer contains eight output neurons and uses the softmax activation function. Each of the eight neurons outputs the probability of the input being in the corresponding class.



Hyperparameters

Hyperparameters such as the batch size, number of neurons in the second layer, and dropout fraction, were fine-tuned manually, based on the accuracy yielded on the validation set.

CLASSIFICATION EXPERIMENTS AND DISCUSSION OF RESULTS

As in explained in methodology, we have conducted our analysis using a publicly available dataset (Kvasir dataset) which consists of endoscopy images taken inside the gastrointestinal (GI) tract from 8 different parts (normal-cecum, normal-z-line, esophagitis, polyps, ulcerative-colitis, dyed-lifted-polyps, dyed-resection-margins, normal-pylorus). We have divided the data set (8000 images) into two parts: 6400 images (80%) to training and 1600 images (20%) from 8 classes to test the model. To train the classifier features was extracted from training data and performance of our model was tested using different metrics (accuracy, precision, F1 score, recall and loss) with different methods as mentioned in above section.
Following are some definitions of metrics we used.

True positive (TP)	The number of correctly identified samples. The number of frames with an endoscopic finding which correctly is identified as a frame with an endoscopic finding.
True negative (TN)	The number of correctly identified negative samples, i.e., frames without an endoscopic finding which correctly is identified as a frame without an endoscopic finding.
False positive (FP)	The number of wrongly identified samples, i.e., a commonly called a "false alarm". Frames without an endoscopic finding which is erroneously identified as a frame with an endoscopic finding.
False negative (FN)	The number of wrongly identified negative samples. Frames without an endoscopic finding which erroneously is identified as a frame with an endoscopic finding.
Recall (REC)	This metric is also frequently called sensitivity, probability of detection and true positive rate, and it is the ratio of samples that are correctly identified as positive among all existing positive samples.
Precision (PREC)	This metric is also frequently called the positive predictive value and shows the ratio of samples that are correctly identified as positive among the returned samples (the fraction of retrieved samples that are relevant).
Accuracy (ACC)	The percentage of correctly identified true and false samples.
F1 score (F1)	A measure of a test's accuracy by calculating the harmonic mean of the precision and recall.

First experiment was done using a simple sequential model only. It showed the below results with an accuracy of 0.6587 and loss of 0.7177.

Classification Report

	precision	recall	f1-score	support
dyed-resection-margins	0.56	0.71	0.63	200
dyed-lifted-polyps	0.66	0.51	0.57	200
ulcerative-colitis	0.57	0.88	0.69	200
normal-cecum	0.66	0.92	0.77	200
normal-z-line	0.85	0.95	0.90	200
esophagitis	0.69	0.23	0.35	200
polyps	0.64	0.48	0.55	200
normal-pylorus	0.72	0.59	0.65	200
accuracy			0.66	1600
macro avg	0.67	0.66	0.64	1600
weighted avg	0.67	0.66	0.64	1600

Figure 3:basic model classification results

Moreover, the model showed an overfitting nature while training the dataset by this method (following figure shows it clearly)

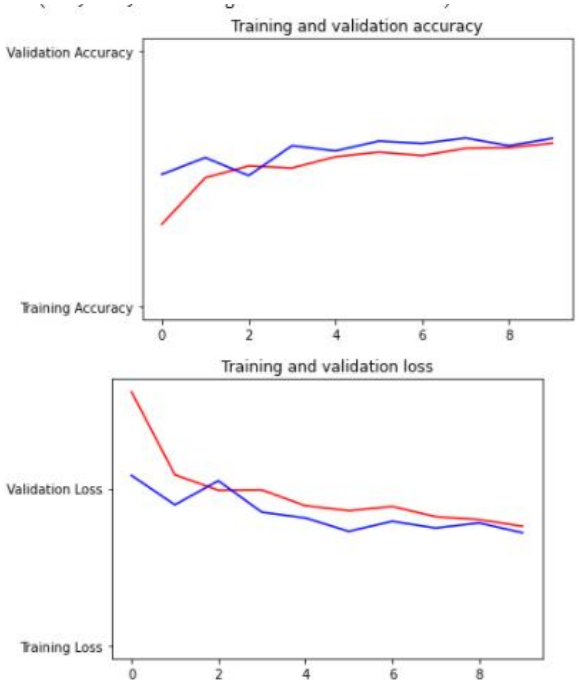


Figure 4:Accuracy and loss of basic model

Therefore, next experimenting methods was based on using various architectural models of CNN such as ResNet50, VGG16 and InceptionV3 (transfer learning with the help of pre trained models) to improve the classification performance and accuracy. Following table gives a summary of the results obtained by all experiments carried out.

Model	Accuracy	Loss
Basic model	0.6587	0.7177
ResNet50 with SGD optimizer	0.4125	3.7696
VGG16 with Adam optimizer	0.7650	0.5794
VGG16 with RMSprop optimizer with a learning rate of 0.0001	0.7850	0.5103
InceptionV3 using Adam optimizer	0.8687	0.3144

The above results show best outcome was obtained by using InceptionV3 architectural model of CNN. Moreover, to analyze more details of this model, the following metrics and a confusion matrix were obtained.

Classification Report

	precision	recall	f1-score	support
dyed-resection-margins	0.89	0.72	0.80	200
dyed-lifted-polyps	0.77	0.93	0.84	200
ulcerative-colitis	0.86	0.69	0.76	200
normal-cecum	0.89	0.96	0.92	200
normal-z-line	0.97	0.97	0.97	200
esophagitis	0.74	0.89	0.81	200
polyps	0.97	0.84	0.90	200
normal-pylorus	0.92	0.94	0.93	200
accuracy			0.87	1600
macro avg	0.88	0.87	0.87	1600
weighted avg	0.88	0.87	0.87	1600

Figure 5: Classification report of InceptionV3 infused model

CONCLUSION

Machine-based gastro-intestinal endoscopy image classification helps medical professionals to diagnose gastrointestinal diseases at the early stages. With that intention, we developed and tested many different systems to classify gastric endoscopy images into main 8 categories based on anatomical landmarks using KVASIR public dataset. Finally, we investigated a system with an accuracy of 86.87%. This system was developed using the help of deep neural networks utilized with transfer learning with the architectural model InceptionV3. Further research deserves studying methods to classify GI images into more detailed subcategories with improved accuracy.

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Terminology

ANN-artificial neural network
CNN-convolutional neural network
ReLU- Rectified Linear Unit
CAD-computer aided design
FP-False Positives
MPT- mean detection processing time
GI-Gastrointestinal