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

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***Abstract* - Medical image classification and diagnosis with deep learning, specially, gastrointestinal(GI) tract disease diagnosis through endoscopic image classification is recently become a very popular research area. Even if there are variety of new proposals to identify and characterize abnormalities or lesions, still it is a challenge to achieve an effective and comprehensive accuracy and performance. In this research work, we propose to use pre trained model like VGG-19 and InceptionV3 to extract features and then extracted vectors were flattened and final classification was obtained by sending the resultant vector of the pre trained model, through few dense layers with Re-LU activation and SoftMax activation.**

***Keywords*- Gastrointestinal (GI), Classification**

I. INTRODUCTION

Intervention of deep learning with medical domain play a vital role in saving lives. Even if there are tremendous advancement in image acquisition devices the leading of deaths due to Gastrointestinal tract infections such as ulcers, bleeding, polyps, Crohn's disease and cancers causes to gain the attention and tends to seek more effective solutions. As a result, early recognitions and automatic detection of polyps, especially cancer cells and gastroenterology diseases are recognized as solutions to reduce the risk of mortality.

The combination of deep learning with the medical sector outputs an effective performance in decease detection and classification. It has great potential to affect image-based specialties such as radiology, pathology, and gastroenterology (GE). And used frameworks and models illustrate supercilious performance over different methodologies and manifest potentials of the proposed models for clinical applications by detecting various type of gastrointestinal (GI) diseases or abnormalities. Even more exciting is the finding that in some cases, computers seem to be able to see patterns that are beyond human perception. Furthermore, it is a solution for human's limited capability and prevent human errors as well as give machines some reliable autonomy and increase work productivity and efficiency.

II. LITERATURE REVIEW

Gastrointestinal diseases (GI diseases) refer to diseases involving the gastrointestinal tract, namely the esophagus, stomach, small intestine, large intestine and rectum, and the accessory organs of digestion, the liver, gallbladder, and pancreas [1]. As common symptoms of this disorder include, change in normal bowel habits, blood on or in the stool, unusual abdominal or gas pains etc. According to the reports of World Health Organization (WHO), they inform that there are 1.8 million deaths per year occur due to diseases of GI diseases [2]. However unable to diagnosis the symptoms in early stages have cause this much death rate per year. In other hand effective diagnosis for GI diseases is a tiresome and time-consuming task. Therefore, necessity of a computerized approach was exalted to overcome the situation. The main reason of computerizing the diagnosis was to identify the symptoms of disease at the early stage and hence avoid the fatal situation of patients. So, the main focus is to train a classification model to categorize anomalies in Gastrointestinal Tract using endoscopic imagery.

Basic concept of endoscopy refers to look inside the body to observe the interior of a hollow organ or cavity of the body. A flexible endoscope is used for this procedure. Although there are many other medical imaging techniques are used to diagnosis the diseases, specialty of this method is endoscope can insert into the cavity or organ directly. Since this is a nonsurgical procedure, observation can be done by either doctor or a surgeon.

Endoscope is most probably a fiber-optic flexible tube consist with a light and a camera. Flexibility and the size of endoscope gave the opportunity of inserting it into through the openings of the body such as the mouth or anus. But as alternatives, depending on the situation small incisions in the knee or abdomen are used to insert the endoscopes as well.

To examine the interior of a body, a small camera is used which is placed on the tube, and path of endoscope is controlled by the doctors looking at the screen which connected to the endoscope. Screen's view helps to reach the infected area and can used to observe the disease stand by before getting the captured images. So, the intention is to computerize the image scanning and process part via artificial intelligent (AI) based computer-aided diagnosis (CAD) application [3]. However, CAD on endoscopy stream used deep learning algorithms (a set of advanced machine learning algorithms) to analyze the endoscopy scans. Moreover, as the deep learning algorithm, CNN is used for CAD application approach.

CNN or convolutional neural network (also known as ConvNet) is a deep learning algorithm that used to analyze visual imageries. The core of CNN is a machine learning algorithm, Perceptron[4] which basically used to analyze data. As an extend version of perceptron, CNNs able to process and analyze images based on set of data. Structure of CNN follows almost same fundamental of other artificial neural networks. Such as input layer, output layer and various abstract layers which some of are passed on results to successive layers using a mathematical model. Specialty of CNN is it uses convolution in general matrix multiplication at least one of its layers.

The main objective of CNN is to analyses and identify the images. So, the basic structure of that process is taking inputs, process the inputs based on its details and output the results. But it is impossible to directly pass an image to the input layer. Before that it needs to convert images into pixel values and that values are taken as the input for the whole process.[5]

As a deep learning algorithm CNN is far more accurate in image recognitions. It can capture and able to learn relevant features from an image. CNN has more efficient complexity and memory management because its weight sharing feature. Basically, weight sharing refers to lower the degrees of freedom in concerned problem which leads to reduce the parameters that has to optimized, faster convergence to some minimum etc.

Furthermore, CNN can consider as a good feature extractor. That means anyone can extract useful attributes from already trained CNN, depending on the newly modeled task, and feed their own data to accomplish the specific task. This procedure known as pre-training and compared to the other deep learning algorithms CNN is far more efficient in pre-training process. Since this process provides the common functionality of the trained data for the new specific task modeler does not have to train their own data up to specific level. Therefore, memory usage and time consumption also can be reduced.

The main reasons for high death rate due to GI diseases were unable to identify the symptoms in early stages and time-consuming task in diagnosis process. So, the computer aided diagnosis (CAD) process must overcome this drawback. Since the focus is to implement the process based on deep learning algorithms, the algorithm must be effective and accurate as much as possible. These qualities are satisfied by the convolutional neural network (CNN) compared to the other kind of algorithms such as Recurrent Neural Network (RNN), Generative Adversarial Networks (GAN) etc. [6]

Considering the mostly used deep learning algorithms, CNN is more preferable for CAD process based on its own unique specifications. The main application area of the CNN is Natural language processing and image recognition sections. That is the basic reason for using CNN as the algorithm. Besides, the main objective of CNN is to identify the images of anything or anyone as similar to a human's identification process. And that identification happens with the help of features in the object. So, this approach can used to identify the GI disease at its early stages by distinguish the differences between affected and non-affected areas through the endoscope scans.

In addition to that, Pre-training techniques also consider as specific feature of CNN algorithm. Since it allows to model new tasks using existing data, modifications and updating of the system can be done easily. And also, it is easy to update the system with newly discovered data about the disease and improve the process without any frustration.

Muhammad Owais, Muhammad Arsalan, Jiho Choi, Tahir Mahamood and Kang Ryoung Park [7] from Division of Electronics and Electrical Engineering, Dongguk propose a complete framework based on Artificial Intelligence for the classification of multiple gastrointestinal(GI) diseases using endoscopic videos which is able to extract both spatial and temporal features at the same time for effective performance in classification. According to the authors of this research which was published on 7 July 2020 most of previous studies had been done only using the spatial features for classification of gastrointestinal(GI) diseases which was not successful nor had low performance when it comes to classification of multiple gastrointestinal(GI) diseases. Combined data set which consists of vast endoscopic videos with 53,471 frames was used in this experiment.

Contribution of this research approach classification of multiple gastrointestinal(GI) diseases can be recapped as following steps. Instead of limiting the classes by the specific type of gastrointestinal(GI) diseases they develop a framework based on deep learning using the spatiotemporal features for effective classification for gastrointestinal(GI) diseases. Figure 1 illustrate a brief flow chart of the methods used in the research. The conventional framework consists of two main stages which are feature extracting stage and the classification stage. But preprocessing should be done before classification to ensure the data is compatible using the methods like image resizing and batch normalization (BN).

This framework is based on Novel cascaded ResNet and LSTM rather than conventional handcrafted features and simple 2D-CNNs, to extract spatial and temporal features and effectively govern low interclass variations and large interclass variations among different classes. CNN model is used to extract certain sequence of spatial feature vectors and then these spatial feature vectors eventually used in LSTM to extract the temporal features. Eventually single feature vector containing both spatial and temporal information for given sequence of frames is outputted from LSTM. Then the extracted spatiotemporal feature vector is classified by grouping the video sequence into one of 37 various group which present the normal and diseased cases related to the human gastrointestinal(GI) diseases.

Performance of multilevel spatial features was examined thoroughly using principal component analysis (PCA) and choosing multilevel spatial features for LSTM (Long-short term memory) from the different layers of the ResNet network analysis were done by the research. Further, comparing to the various state-of the-art CNN models and various handcrafted feature-based approaches, this research was more comprehensive.

Proposed classification framework showed effective result for classification of multiple gastrointestinal(GI) diseases and illustrate supercilious performance over the state-of-art-methods and this manifest potentials of this proposed model in for clinical application by detecting various type of gastrointestinal(GI) diseases or abnormalities, such as polyps, ulcers, or cancers. Further this AI-based CAD system can be hopeful for diagnosing of complex gastrointestinal(GI) diseases and treat them. Additionally, they suggest that the classification of endoscopic video can be used to retrieve the previously stored videos related to the patient's current situation and guide the diagnostic decisions for accurate results. Furthermore, researchers suggest that predicted class table can be used to further utilize the proposed framework.

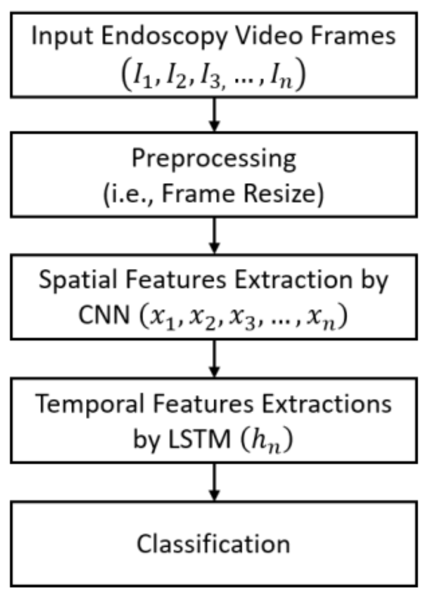


Figure 1

Chathurika Gamage, Isuru Wijesinghe, Charith Chitranjan and Indika Perera from University of Moratuwa [8] propose combining of three pre-trained CNNs (DeenseNet-201, ResNet-18 and VGG-16) with GAP layer for extracting features and KVASIR dataset is used to train the model. Methodology used in this research is, feature vectors which were extracted from pre-trained CNN feature extractor, are fed into an independent classifier to obtain the predicted class table.

First all the imagery in dataset is downscaled into 224 x 224 pixels. Then, the set of prominent CNNs with global average pooling layer is used to gain feature vectors. Afterward, the feature vectors that are needed for the classification is gained by appending the vectors which were outputted by the CNNs and pooling layer. There is a single hidden layer Artificial Neural Network (ANN) which contain 128 hidden units with ReLU activation functions. They feed the gained feature vectors into this ANN layer. Eventually, SoftMax activation function is used in classification layer which proffered the accuracy of 97.38% in classification. Stratified five-fold cross validation is used for training the proposed model. Furthermore, redundant, and noisy features are removed by normalizing the features and passing into truncated Singular Value Decomposition (SVD). They have used 95% variance as the threshold to select the optimal number of features.

They have experimented six different CNN architectures, that is DenseNet-201, ResNet-18, InceptionV3, InceptionRes-NetV2, VGG-16 and Xception with three classifiers (ANN, SVM, and Random forest). Furthermore, by fine tuning the hyper parameters, they have tried to improve validation accuracy. This proposed system indicates 97% accuracy which is very promising accuracy compared to the state-of-the-art approaches.

Dimitris K. Iakovidis et. al [9] propose a system which can analyze numerous video endoscopy sources with cost effective manner while suggesting possible location of gastrointestinal (GI) anomalies in the video frame. MICCAI Gastroscopy Challenge dataset and KID dataset are used in this research as they contain different kinds of anomalies and normal images. Propose methodology targets not only the detection of gastrointestinal(GI) anomalies but also localizing them. It is done in three phases. First, a deep WCNN which is trained independently, using weakly annotated image classifies the GIE images as having gastrointestinal(GI) anomalies or not. Then using the feature map of deeper WCNN convolutional layer, silent points in the images are detected applying the DSD. Later, Iterative Cluster Unification (ICU) identify the subset of salient points that probably belong to the GI anomalies. Indication of possible location of gastrointestinal(GI) anomalies is done by matching the spatial resolution of the input endoscopic image with the help of the transformed coordinates of salient points which are outputted by ICU. Only weakly annotated training images are needed to the ICU to extract the PCFM Features, forming clusters and labeling the images as anomalous or not.

This approach dominates in both detection and localizing the anomalies over the conventional, patch-based anomaly detection and localization approaches in GIE since they need costly detailed annotation of training images. Further, location, the area covered by an anomaly can be detected and the size measurement is possible as well since this approach uses the unsupervised image segmentation method. According to author even though this approach is architecturally simpler than the state-of-the-art CNN-based approaches, it outperforms or have equal performance compared to patch-based CNN-based approaches and state-of-the-art weakly supervised approaches. They suggest further improvements in proposed method by coping with intestinal content which has been identified as a source of FPs, investigating of WCNN training algorithm with less computational requirements, trying out alternative weakly-supervised approaches and experimenting on large data set.

The leading cause of deaths related to colorectal cancers are noticed. Experimental results evidenced that most colorectal cancers originate from adenomas. Moreover, early detection and removal of adenomas cause effectively to prevent the development of colon cancers. However, it should be noted, that small colorectal polyps include both adenomatous polyps and non-adenomatous polyps. It is a difficult task to discriminate between hyperplastic polyps and adenomas by conventional white light observation, image-enhanced endoscopy, and chromoendoscopy even for well experienced endoscopists. The need of an accurate and objective diagnostic tools for differentiate colon polyps is very useful for the medical operations.

Convolution Neutral Network (CNN) system based on CAD which is utilizing Artificial intelligence (AI) has been developed rapidly as it avoids the complications associated with endoscopic resections and, it achieves a higher diagnostic accuracy than conventional CAD without CNN system. The CNN system is useful for the rapid diagnosis of colorectal polyp classification.

Department of Gastroenterology and Hepatology, Faculty of Medicine, and the Faculty of Science Engineering at Kindai University did a research [10] by using 1200 images of colonoscopy performed between January 2010 and December 2016 at Kindai University hospital to classify diagnosis as either an adenomatous or non-adenomatous polyp.

In this system CNN perceives an image as an input and results the classification. This denotes the filtering method in different layers and that procedure is done simultaneously. The entire process works as a filter that extracts features from images or data in the previous layer.

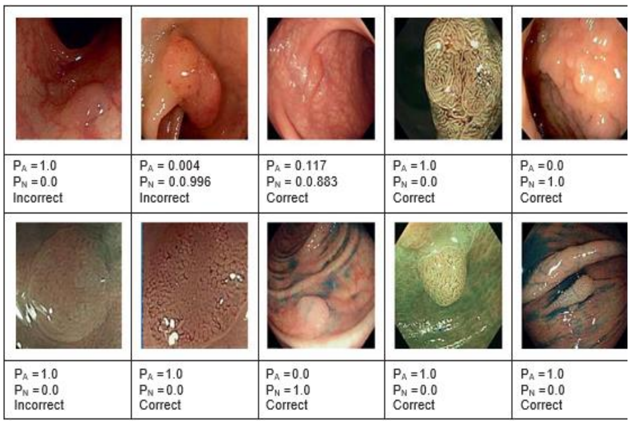


Figure 2

Above (Figure 2) are the experimental results for unread data. PA denotes probabilities of adenomatous and PN denotes probabilities of non-adenomatous. The output with the higher probability was regarded as a decision by the CNN. The research results that the accuracy of the 10-hold cross-validation is 0.751, where the accuracy is the ratio of the number of correct answers over the number of all the answers produced by the CNN. As a result, this system has the potential to avoid the complications related to unnecessary endoscopic procedure. The final evaluation of the CNN was to compare the results of pathological examinations. The decisions by the CNN were correct in 7 of 10 cases.

Department of Electronics and Electrical Engineering, Indian Institute of Technology Guwahati, Department of Computer Science, Chubu University, Kasugai, 487-8501 Japan, and Department of Gastroenterology, Aichi Medical University, Nagasakute, 480-1195 Japan [11] together did a research for detecting abnormality in the gastrointestinal tract using an automated framework for efficient classification of such polyps as malignant or benign in endoscopic images. The research introduced a fully trained CNN for classification of endoscopic polyps.

In this research, the state-of-the art approaches for image classification are broadly divided into three groups as hand crafted features based, deep neural network based and integration of both the methods. The problem with hand crafted features-based method is that these feature extractors need huge domain knowledge and skills. The experimental results evidenced that the number of images were not sufficient to train the CNN. To overcome this limitation, data augmentation was performed. As medical images are completely different from data coming from other domain, the result ends up by achieving low accuracy. By tunning, the hyper parameters and doing some modifications in network topology, finally the proposed system ends up with 99.85% overall accuracy.

The following is a review on the research regarding Computer-Aided Diagnosis Based on Convolutional Neural Network System for Colorectal Polyp Classification: The article "Exploring Deep Learning and Transfer Learning for Colonic Polyp Classification" by Eduardo Ribeiro, 2 Andreas Uhl, and Michael Häfner[12]. The aim of this article was to develop a model for robust feature extraction and efficient colonic polyp classification. This research checks several methodologies to achieve a high accuracy.

CNNs Trained from Scratch is the first method mentioned in the research. In order to differentiate medical images properly, this method initializes the CNN weights randomly and according to the medical image database, it is trained. But this is ended up with only a 79% accuracy because of some limitations. The major problem with this method can be explained by the fact that in training Neutral Networks involving a large number of inputs and it requires a great amount of computation in training, requiring more data to avoid overfitting. The main advantage of this approach is that the same method can be used for the extraction of strong features that are invariant to distortion and position at the same time of the image classification. But this methodology is not widely use because of lack of large, annotated, and publicly available medical image databases. However, some techniques like data augmentation can assist the CNN training from scratch with small datasets.

The second method is proposed to extract sub images of size 128x128 from the original images. Then use the same approach which is used in the first method. In this case, researchers explore the fact that colonic polyp classification with the CNN can be done only with a part of the image. Instead of using the entire image, this methodology trained the network with smaller sub images. This cause to reduce the complexity and can diminish the degree of intra image variances in the dataset. In addition to that this can allow different polyp classifications in the same image using different sub images in different parts of the image. In this experiment, 89% accuracy was gained by using total 16384 sub images for each image. The research describes how it finally achieved an effective accuracy of 93.55% by improving the base system step by step.

As a conclusion of the research, they ended up with the fact that deep learning using Convolutional Neutral Networks is an effective option for colonic poly classification. To achieve the best results, it highlights the use of pretraining CNNs. Furthermore, In the domain of medical, CNNs are used for histopathological image classification, digestive organs classification in wireless capsule endoscopy images, and automatic colonic polyp classification. Besides that, CNNs have also been explored to improve the accuracy of CADe systems knee cartilage segmentation using tri planar CNNs.

These research are evidenced the effective and useful contribution of deep learning in medical imaging as the accurate diagnosis of a disease depends on both image acquisition and image interpretation. It is an obvious fact that, an early detection of diseases helps to reduce the risk of patients, therefore detecting any abnormalities before it becomes malignant is a great deal for the medical domain. These research shows that training model is required enormous computational resources and gaining higher accuracy is challenging with the resources that we possess. Therefore, transfer learning would be a better option for our project since we can use pre-trained model as a starting point and improve that model to our task.

III. METHODOLOGY

Since our task was to classify anomalies in Gastrointestinal Tract through Endoscopic Imagery with Deep Learning, we used transfer learning to customize few pre trained model to our task. Keras and TensorFlow were used for generating data set and train model. There are many deep learning models that are available alongside pre-trained weights like VGG16 , VGG19, InceptionV3, MobileNetV2, MobileNetV2, ResNet50. We used VGG19 and InceptionV3.

With InceptionV3 model, all the layers were taken, and we made first 40 layers untrainable. The KVASIR data set was split into 20% of validation data and 80% of testing data and then images were resized to 224 X 224. Before feeding to the model, obtained vectors were flattened. Three dense layers were added to the InceptionV3 model to increase accuracy. First, flattened data in inserted to (1024) dense layer with RE-LU activation. After that resultant vector is a def into another (512) dense layer with same RE-Lu activation. Further to reduce overfitting and improve generalization 0.1 dropout was done. Ultimately, 8 dense layer with Soft Max activation gives the output. Further, RMSProp optimizer was run with 50 epochs.

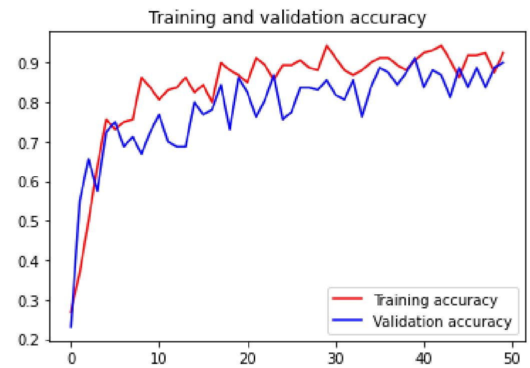
With VGG19 model, all the layers were taken and all the layers except first 30 layers were set to untrainable. Same as in InceptionV3 model the KVASIR data set was split into 20% of validation data and 80% of testing data and then images were resized to 224 X 224 as it was the recommended size by the VGG19 model. First the output of the last trainable layer was flattened and then it is fed in to (1024) dense layer with Re-LU activation. Then that layer was subsampled with 0.5 drop out and again output data was fed into 1024 dense layer with Re-LU activation. Finally, data goes through (8) dense layer with SoftMax activation and training was run 20 epochs with Keras SGD optimizer class.

IV. CLASSIFICATION EXPERIMENTS AND DISCUSSION OF RESULTS

We used InceptionV3 and VGG19 models for transfer learning process. Among the two models we checked best result was received by the model that used InceptionV3 model as base model and we got 92.73% training accuracy and 90.00% validation accuracy. Even though we got 93.12% validation accuracy from the model which used VGG19 as the base model, validation accuracy was 87.25%.

Training and Validation accuracy graphs of each models are displayed below.

InceptionV3



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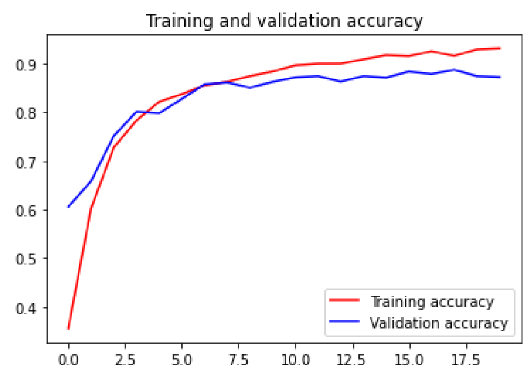
VGG19



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V. CONCLUSION

In this project we focused on classifying anomalies in Gastrointestinal Tract through Endoscopic Imagery with Deep Learning. We developed two models for this project and out of that modules, when used InceptionV3 model as base model, we got 92.73% training accuracy and 90.00% validation accuracy. Even though we got 93.12% training accuracy from the model which used VGG19 as the base model, validation accuracy was 87.25%. Therefore, as the appropriate model we selected InceptionV3 model and then as the first step we extracted and flattened the feature vector. Final classification was obtained by sending the resultant vector of the first step, through two dense layers with Re-LU activation and one dense layer with SoftMax activation.

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