

Colon Cancer Detection Using YOLOv5 Architecture

Reshmaja K Ramesh
Electronics and Communication
Engineering
Sri Sairam Engineering College
Chennai, India
reshmjakramesh@ieee.org

C.N. Savithri
Electronics and Communication
Engineering
Sri Sairam Engineering College
Chennai, India
savithri.ece@sairam.edu.in

Abstract— Cancer is a disease where the cell divides exponentially and damages the body tissues. Early diagnosis of cancer can help the person from witnessing complicated treatments and indeed death. According to a study, early detection of curable cancer can save a person's life up to 99%. The exponential cell division in other words is known as tumor development in the body. The condition where the tumor has not started to spread to other body parts is known as benign. Utmost of the cysts in the colon are benign. The condition when the tumor became cancerous it is known as adenocarcinomas. Colorectal cancer is the 2nd leading cause of cancer death. It is found that human evolved cell slides aren't accurate enough to detect cancer. It takes about 1 or 2 weeks to get the result from a laboratory. However accurate and quick discovery of benign/adenocarcinomas is essential to detect colon cancer. A convolutional neural network increases the standard of the diagnosis by giving an accurate and quick result. The deep convolutional neural network can best serve the purpose to detect colon cancer. In the proposed system, yolov5 architecture is used to descry cancerous cells. A custom dataset of about 2000 images is used to train the model. The proposed model helps to separate the tumor cell into benign or adenocarcinomas. The training of the model in yolov5 is processed using PyTorch. The time taken to train the Colon Cancer Detection model is 78 minutes. The model is tested with 140 images and the accuracy is 99.28%. The latency for each image is 0.031 seconds. This proves that the proposed method has better efficiency when compared to the traditional laboratory system of detection of colon cancer. The proposed work may assist the clinicians in reducing the missed diagnosis during endoscopy.

Keywords— *YOLOv5, Colon Cancer, PyTorch, benign, adenocarcinomas*

I. INTRODUCTION

World Health Organization (WHO) proclaims that cancer is one of the largest causes of mortality. Around 18.5 million people are affected by cancer and out of that 10 million people die every. Among the most common cancers caused, colon cancer is second with 1.93 million cases around the world [1]. The world's economy of \$895 billion is utilized for cancer treatment. So, the only way to reduce the mortality rate and the amount spent on complicated treatments is through early diagnosis and screening. The tumor formed is classified into two types, namely; benign and adenocarcinomas. If the tumor has not started to spread, the tumor is of the former type. If the tumor has already started to spread, it is a cancerous tumor, hence it is of lateral type. Figure 1 depicts the pie chart of the estimated number of new collateral cancer cases in 2020 that is published by WHO [2].

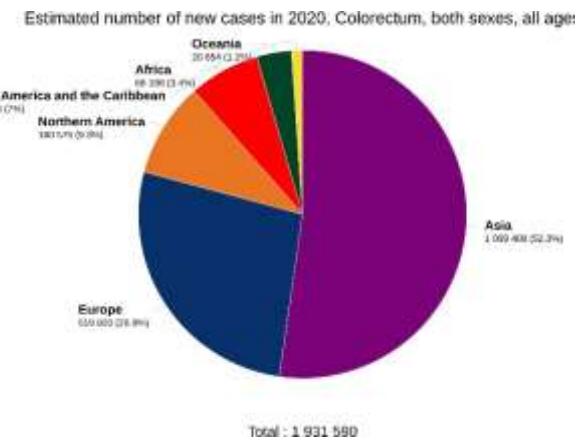


Fig.1. Pie chart represents the estimated number of new collateral cancer cases in 2020. Published by WHO

This paper focuses on Colon Cancer Detection. Med-tech has developed widely in recent years, but still automatic cyst detection through endoscopy is an unsolved problem. It is due to large variations in size, texture, shape of the cyst. A Neural Network-based system is commonly performed for such detections, in which there are several subsystems and methods. Most of the models found in the literature are executed through Convolutional Neural Network (CNN). Even though CNN provides lesser accuracy to the model, the efficiency and accuracy can be increased through post-learning methods like automatic false-positive learning and offline learning. But this post-learning method leads to a delay in processing time, which can take up to an average of 0.39 seconds for each frame [3]. To increase the processing time multi-thread processing system can be used. Such a system is capable of processing at least 25 frames per second [4]. Operational models of CNN such as max pooling, average pooling, MobileNetV2, ANN, VGG19, SEGNET, employed CNN can also increase the efficiency. Out of these MobileNetV2 is considered as the best-performed model [5].

However, the recent trends in technology have outranged all the conventional methods. Because conventional methods have more drawbacks when compared to the AI detection models. AI detection models produce better accuracy and efficiency when compared to human error-prone manual diagnosis also consumes a lot of time. Histopathological classification of colon tumors is one of the major reasons for the huge workload of clinical pathologists. Adapting computational pathological techniques through a recurrent neural network (RNN) would help the pathologist to reduce their workload [6]. Hence, clinical pathologists have started

using AI models through pre-developed tools that are readily available [7].

The success of this computational and digital histopathology detection completely depends on the successful quantification of the features in the histopathological domain. Such efficient feature extraction has three modules. Firstly, the model has to identify the domain-specific subregion and pre-process it to fit in the system without any noise. Secondly, the desired deep learning algorithm is implied to process the image to classify and detect based on the pixel ratings. And, thirdly the restricted Boltzmann Machine (RBM) is executed to cluster the features [8].

Wireless Capsule Endoscopy (WCE) is one of the recent advancements made in MedTech to detect polyps [9]. You Only Look Once (YOLO) architecture is one of the leading computer vision models that is widely used in medical institutions and clinical research departments [11]. It is clear from the literature survey that deep learning proffers structured methods for polyp detection [10]. But still, just detecting the tumor is not important. Classification of tumors into benign or adenocarcinomas plays a vital role. Thus, the proposed work focuses on classifying the colon tumor.

II. METHODOLOGY

The literature survey made it clear that an efficient tumor detection model is needed of the hour. The proposed model classifies the colon tumor into two classes namely: colon benign and colon adenocarcinomas using the You Only Look Once Version 5 (YOLOv5) architecture. Figure 2 depicts the workflow of the proposed work. The entire work is divided into four steps.

- Data Collection
- Data Pre-processing
- Data Classification
- Performance Evaluation

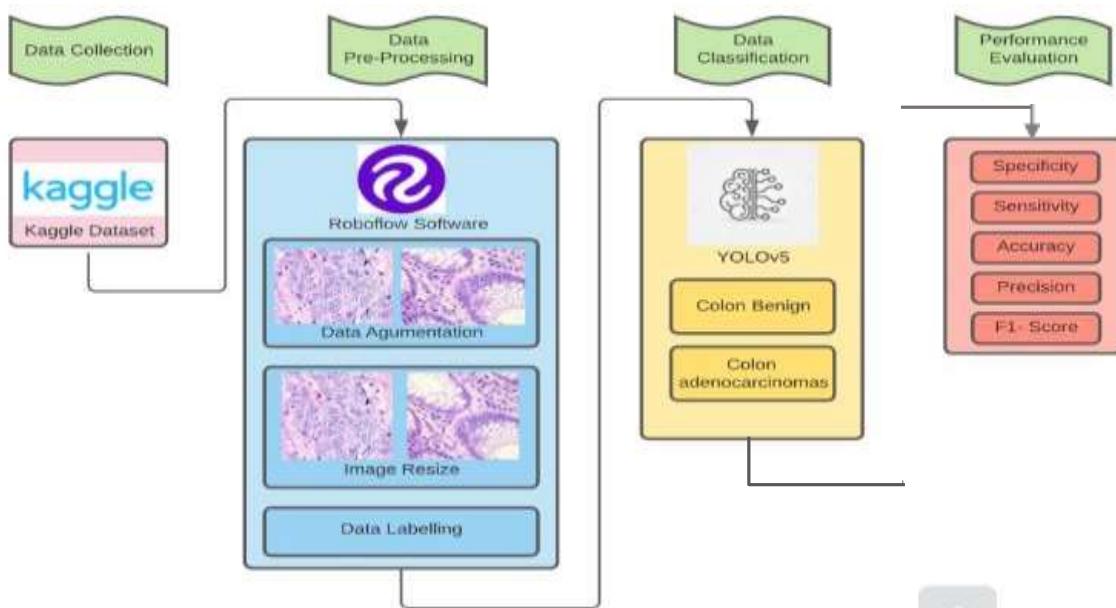


Fig.2. Work flow of the proposed work

A. Data Collection

The dataset for the Colon Cancer Detection model was collected from the Kaggle dataset. Around 2000 images of two classes were collected.

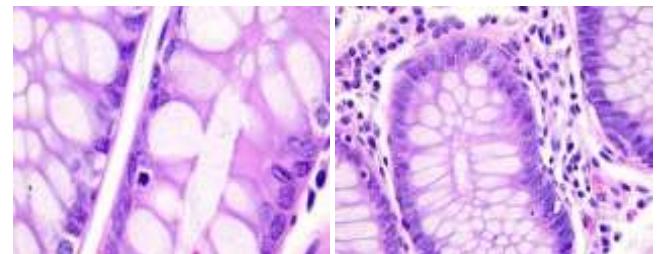


Fig. 3(a). Colon benign cells

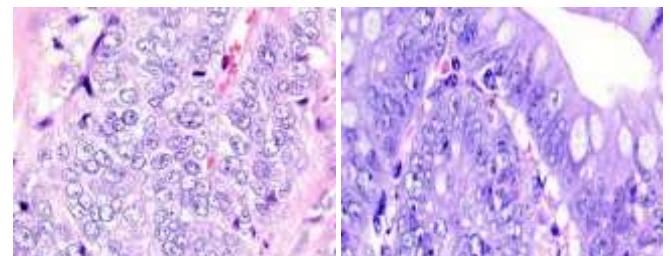


Fig. 3(b). Colon adenocarcinomas cells

The images were in 768 x 768-pixel resolution. Sample images are shown in figure 3. Figure 3(a) is colon benign cells and Figure 3(b) colon adenocarcinomas cells before image resizing.

- colon benign (1000)
- colon adenocarcinomas (1000)

B. Data Pre-Processing

Data pre-processing was done using Roboflow software which is a CV developer framework. As the first process images were augmented. Table 1 shows the attributes of augmented images.

TABLE I. ATTRIBUTES OF AGUMENTED IMAGES

Attributes	Value
Rotation Range	20
Zoom Range	0.15
Width Range	0.2
Height Range	0.2
Shear Range	0.15
Horizontal Flip	True
Vertical Flip	True
Mode	Nearest

Images were resized to 224 X 224-pixel resolution. At last, the resized images were tagged into their respective classes.

- Colon_n (colon benign)
- Colon_aca (colon adenocarcinomas)

C. Data Classification

Colon Cancer Detection model is performed with YOLOv5 architecture in PyTorch environment. The data is split into three batches; Training, Validation, and Testing with the ratio of 75: 18: 7. High importance is given to training because it decides the accuracy of the model. Then the model is trained with 100 epochs. The time taken to train the Colon Cancer Detection model is 78 minutes. It is assessed with the loss and accuracy of training data vs loss and accuracy of validation data. Validation data is used for predicting the model.

The Colon Cancer Detection model is tested using test data. Figure 4 depicts the detected image where figure 4(a) is colon benign cells and figure 4(b) colon adenocarcinomas.

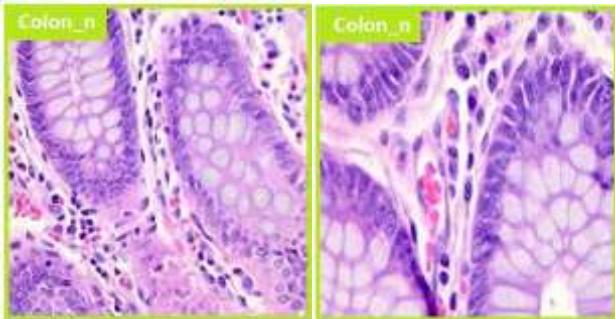


Fig. 4(a). Colon benign

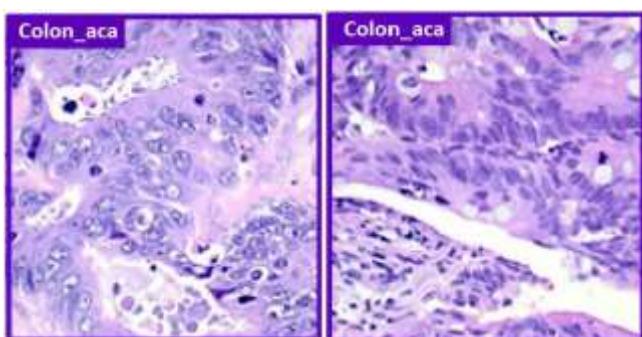


Fig. 4(b). Colon adenocarcinomas

D. Performance Evaluation

The performance of the model is evaluated using certain terminologies:

- Specificity = $\frac{TN}{TN + FP}$
- Sensitivity = $\frac{TP}{TP + FN}$
- Precision = $\frac{TP}{TP + FP}$
- Accuracy = $\frac{TN + TP}{TN + FP + TP + FN}$
- F1 – Score = $2 \times \frac{Precision \times Sensitivity}{Precision + Sensitivity}$

Where, TN is True Negative

TP is True Positive

FN is False Negative

FP is False Positive

These values are obtained from the confusion matrix which is depicted in figure 5.

		Predicted 0	Predicted 1
Actual 0	TN	FP	
	FN	TP	
Actual 1			

Fig. 5. Confusion matrix

III. RESULTS AND DISCUSSION

This section briefs about the result obtained from the Colon Cancer Detection model. The model is very efficient and evaluated through the following terminologies from the confusion matrix with test data depicted in figure 6.

Total images in test dataset = 140

- Colon_n (colon benign) = 67
- Colon_aca (colon adenocarcinomas) = 73

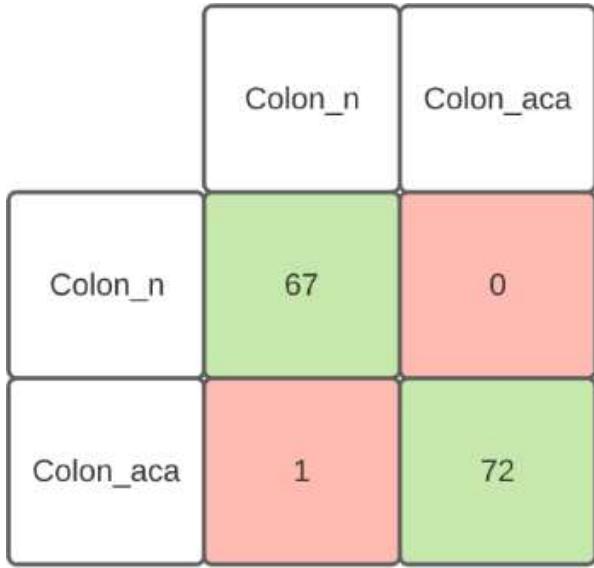


Fig. 5. Confusion matrix with Test Dataset

The performance evaluation of the model with test data is depicted in Table 2. The accuracy and loss graphs are depicted in figure 6(a) and 6(b) respectively which is plotted using table 3.

TABLE II. PERFORMANCE EVALUATION OF THE MODEL

Performance Evaluation	Percentage (%)
Specificity	100
Sensitivity	98.63
Precision	100
Accuracy	99.28
F1 - Score	99.03

The training set contains 75%, the validation set contains 18% and the test set contains the remaining 7%. The training data reaches the peak training accuracy in the 94th epoch and the validation data obtains the maximum accuracy in the 88th epoch. Whereas the data loss in training data decreases rapidly from the 60th epoch and data loss in validation data decreases rapidly from the 46th epoch.

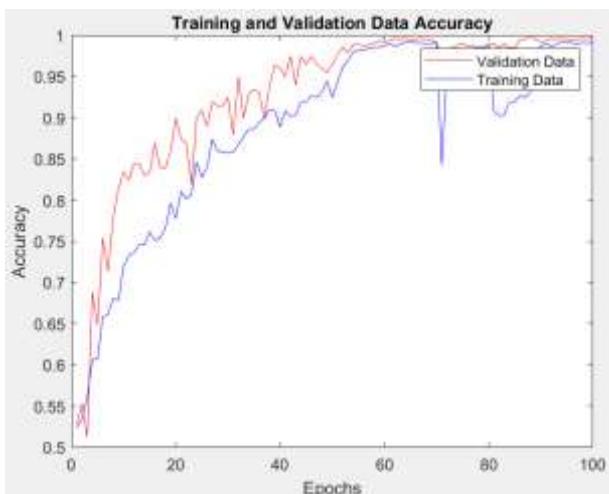


Fig. 4(a). Training and Validation Data Accuracy graph

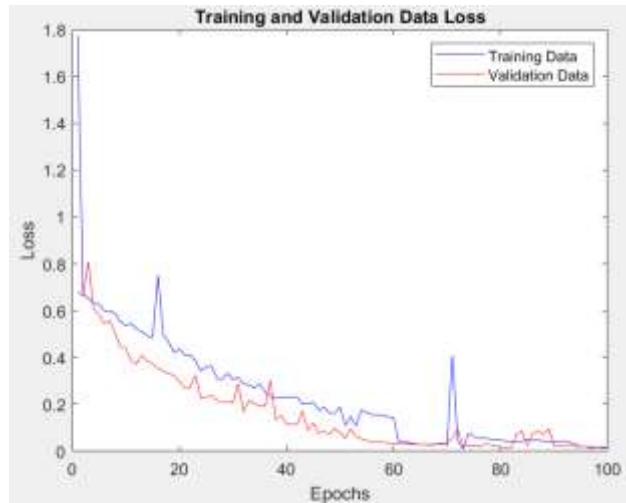


Fig. 4(b). Training and Validation Data Loss graph

The latency to process each frame was 0.031 seconds which is considered the quickest in the literature. The model is capable of providing an appreciable accuracy with less latency. Thus, the Colon Cancer Detection model is efficient.

TABLE III. LOSS AND ACCURACY OF THE MODEL

Epoch	Training Data Loss	Training Data Accuracy	Validation Data Loss	Validation Data Accuracy
1	1.7743	0.5232	0.6825	0.5276
2	0.6733	0.5338	0.6610	0.5528
3	0.6535	0.5603	0.8085	0.5126
4	0.6317	0.6066	0.6061	0.6884
5	0.6292	0.6066	0.5827	0.6482
6	0.5984	0.6583	0.5451	0.7538
7	0.6000	0.6609	0.5580	0.7136
8	0.5875	0.6808	0.5037	0.7789
9	0.5531	0.6781	0.4449	0.8141
10	0.5364	0.7205	0.4406	0.8342
11	0.5450	0.7325	0.3826	0.8241
12	0.5221	0.7364	0.3723	0.8442
13	0.5113	0.7457	0.4109	0.8442
14	0.4927	0.7457	0.3840	0.8291
15	0.4860	0.7616	0.3745	0.8342
16	0.7510	0.7510	0.3551	0.8693
17	0.4967	0.7536	0.3428	0.8392
18	0.4662	0.7656	0.3323	0.8392
19	0.4205	0.7960	0.3235	0.8593
20	0.4362	0.7775	0.2994	0.8995
21	0.4114	0.8106	0.2682	0.8744
22	0.4127	0.8013	0.2726	0.8693
23	0.3863	0.8066	0.3230	0.8191
24	0.3425	0.8464	0.2279	0.8995
25	0.3594	0.8278	0.2297	0.9095
26	0.3644	0.8397	0.2388	0.8894
27	0.3101	0.8742	0.2190	0.9196
28	0.3074	0.8596	0.2089	0.9146
29	0.3329	0.8583	0.2119	0.9146
30	0.3069	0.8570	0.2064	0.9246
31	0.3153	0.8583	0.2890	0.8794
32	0.2862	0.8675	0.1678	0.9497

33	0.2834	0.8768	0.2158	0.8995
34	0.2698	0.8861	0.2034	0.9296
35	0.2902	0.8861	0.1936	0.9347
36	0.2554	0.8940	0.1924	0.9296
37	0.2363	0.8993	0.3039	0.8995
38	0.2246	0.9099	0.1353	0.9397
39	0.2312	0.9086	0.1523	0.9648
40	0.2290	0.8887	0.1172	0.9598
41	0.2334	0.9086	0.1160	0.9497
42	0.2321	0.9020	0.1153	0.9749
43	0.2002	0.9033	0.1717	0.9397
44	0.2028	0.9192	0.0879	0.9749
45	0.2091	0.9192	0.1232	0.9648
46	0.1759	0.9272	0.0756	0.9749
47	0.1881	0.9245	0.0874	0.9648
48	0.1636	0.9311	0.0718	0.9598
49	0.1634	0.9444	0.0968	0.9548
50	0.1898	0.9245	0.0802	0.9648
51	0.1092	0.9426	0.0551	0.9765
52	0.1478	0.9611	0.0962	0.9856
53	0.1086	0.9693	0.0632	0.9791
54	0.1784	0.9795	0.0532	0.9883
55	0.1636	0.9818	0.0460	0.9896
56	0.1550	0.9828	0.0405	0.9869
57	0.1564	0.9838	0.0392	0.9883
58	0.1520	0.9858	0.0387	0.9909
59	0.1471	0.9855	0.0349	0.9935
60	0.1440	0.9875	0.0328	0.9922
61	0.0411	0.9898	0.0322	0.9935
62	0.0444	0.9871	0.0312	0.9961
63	0.0361	0.9888	0.0295	0.9948
64	0.0310	0.9924	0.0287	0.9961
65	0.0281	0.9924	0.0287	0.9948
66	0.0289	0.9908	0.0289	0.9948
67	0.0275	0.9911	0.0253	0.9961
68	0.0305	0.9898	0.0295	0.9948
69	0.0333	0.9901	0.0288	0.9948
70	0.0257	0.9921	0.0360	0.9896
71	0.4092	0.8426	0.0551	0.9765
72	0.0478	0.9611	0.0962	0.9791
73	0.0086	0.9693	0.0232	0.9856
74	0.0784	0.9795	0.0232	0.9883
75	0.0636	0.9818	0.0260	0.9896
76	0.0550	0.9828	0.0205	0.9869
77	0.0564	0.9838	0.0292	0.9883
78	0.0520	0.9858	0.0287	0.9809
79	0.0471	0.9855	0.0249	0.9835
80	0.0490	0.9887	0.0172	0.9898
81	0.0434	0.9086	0.0160	0.9897
82	0.0421	0.9020	0.0153	0.9849
83	0.0402	0.9033	0.0717	0.9897
84	0.0428	0.9192	0.0879	0.9849
85	0.0491	0.9192	0.0232	0.9848
86	0.0459	0.9272	0.0756	0.9949
87	0.0481	0.9245	0.0874	0.9948
88	0.0436	0.9311	0.0718	0.9998
89	0.0434	0.9444	0.0968	0.9948
90	0.0440	0.9875	0.0228	0.9922
91	0.0411	0.9898	0.0222	0.9935
92	0.0444	0.9871	0.0212	0.9961
93	0.0361	0.9888	0.0295	0.9948

94	0.0310	0.9924	0.0187	0.9961
95	0.0181	0.9924	0.0187	0.9948
96	0.0189	0.9908	0.0189	0.9948
97	0.0105	0.9898	0.0195	0.9948
98	0.0175	0.9911	0.0153	0.9961
99	0.0133	0.9901	0.0188	0.9948
100	0.0157	0.9921	0.0160	0.9986

IV. CONCLUSION

AI deployed model for histopathological detection plays a vital role in the development of MedTech advancement. The proposed work classifies the tumor cells into benign and adenocarcinomas which helps the clinical pathologist to determine whether the condition of the patient has turned cancerous or not. The model is capable of providing an appreciable accuracy of 99.28% with less latency (0.031 sec). Thus, the Colon Cancer Detection model is efficient. The ultimate aim of the study is to make the model effective and applicable for real-time use that can ease the workload in the field of histopathological detection. As a part of future work, the model will be trained with much more datasets. The proposed work can be collaborated with medical institutions and clinical research departments to get a better picture of real-time problems as well as to increase the dataset.

REFERENCES

- [1] Cancer. Available online: <https://www.who.int/news-room/factsheets/detail/cancer>
- [2] Collateral cancer. Available online: <https://gco.iarc.fr/>
- [3] Shin, Younghak, Hemin Ali Qadir, Lars Aabakken, Jacob Bergsland, and Ilangko Balasingham. "Automatic colon polyp detection using region based deep cnn and post learning approaches." *IEEE Access* 6 (2018): 40950-40962.
- [4] Wang, P., Xiao, X., Glissen Brown, J.R. *et al.* Development and validation of a deep-learning algorithm for the detection of polyps during colonoscopy. *Nat Biomed Eng* 2, 741–748 (2018).
- [5] Tasnim, Zarrin, S. Chakraborty, F. M. J. M. Shamrat, A. N. Chowdhury, H. Alam Nuha, A. Karim, Sabrina Binte Zahir, and M. Billah. "Deep learning predictive model for colon cancer patient using CNN-based classification." *Int. J. Adv. Comput. Sci. Appl* 12 (2021).
- [6] Iizuka, Osamu, Fahdi Kanavati, Kei Kato, Michael Rambeau, Koji Arihiro, and Masayuki Tsuneki. "Deep learning models for histopathological classification of gastric and colonic epithelial tumours." *Scientific Reports* 10, no. 1 (2020): 1-11.
- [7] M. M. K. Sarker, Y. Makhlouf, S. G. Craig, M. P. Humphries, M. Loughrey, J. A. James, M. Salto-Tellez, P. O'Reilly, and P. Maxwell, "A Means of Assessing Deep Learning-Based Detection of ICOS Protein Expression in Colon Cancer," *Cancers*, vol. 13, no. 15, p. 3825, Jul. 2021.
- [8] C. T. Sari and C. Gunduz-Demir, "Unsupervised Feature Extraction via Deep Learning for Histopathological Classification of Colon Tissue Images," in *IEEE Transactions on Medical Imaging*, vol. 38, no. 5, pp. 1139-1149, May 2019.
- [9] X. Jia, X. Xing, Y. Yuan, L. Xing and M. Q. . -H. Meng, "Wireless Capsule Endoscopy: A New Tool for Cancer Screening in the Colon With Deep-Learning-Based Polyp Recognition," in *Proceedings of the IEEE*, vol. 108, no. 1, pp. 178-197, Jan. 2020.
- [10] R. Buettner, M. Bilo, N. Bay and T. Zubac, "A Systematic Literature Review of Medical Image Analysis Using Deep Learning," *2020 IEEE Symposium on Industrial Electronics & Applications (ISIEA)*, 2020, pp. 1-4.
- [11] Wan, Jingjing, Bolun Chen, and Yongtao Yu. "Polyp Detection from Colorectum Images by Using Attentive YOLOv5." *Diagnostics* 11, no. 12 (2021): 2264.