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THE IMPACT OF COLOR AND CONTRAST ENHANCEMENT FOR DIAGNOSING GASTROINTESTINAL DISEASES BASED DEEP LEARNING

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Abstract— *Endoscopy is a crucial tool for diagnosing digestive tract diseases—colon cancer and polyps using a camera with LED lighting, but often results in low-quality images with poor contrast and luminance. This study evaluates the performance of two contrast-based image quality enhancement—Contrast Limited Adaptive Histogram Equalization (CLAHE) and Improved Adaptive Gamma Correction with Weighting Distribution (IAGCWD)—along with various color space transformations (RGB, HSV, YCbCr, CIELAB, Grayscale) in deep learning-based digestive tract diseases detection system. The detection system using EfficientNetV2S model and Quadratic Weighted Kappa (QWK) loss function to obtain the balance of prediction results for each class. The experiment shows that CLAHE is able to achieve 79% accuracy which is superior in clarifying important information in endoscopy images. CLAHE performs well due to its ability to reduce noise and enhance contrast. The classification model with HSV and CLAHE on KVASIR is able to recognize all classes well. RGB, HSV, and YCbCr color spaces have stable performance in most tests. This study contributes insights for enhancing endoscopic image quality to support both computer-aided and clinical diagnosis.*

Keywords*: Biomedical, Cohen kappa loss, Color space, Endoscopy, Image enhancement.*

Intisari— *Endoskopi merupakan alat penting untuk mendiagnosis penyakit saluran pencernaan kanker usus besar dan polip—dengan menggunakan kamera yang dilengkapi pencahayaan LED, namun sering menghasilkan citra berkualitas rendah dengan kontras dan luminansi yang kurang baik. Penelitian ini mengevaluasi kinerja dua metode peningkatan kualitas citra berbasis kontras—Contrast Limited Adaptive Histogram Equalization (CLAHE) dan Improved Adaptive Gamma Correction with Weighting Distribution (IAGCWD)—bersama dengan berbagai transformasi ruang warna (RGB, HSV, YCbCr, CIELAB, Grayscale) dalam sistem deteksi penyakit saluran pencernaan berbasis deep learning. Sistem deteksi ini menggunakan model EfficientNetV2S dan fungsi loss Quadratic Weighted Kappa (QWK) untuk mendapatkan keseimbangan hasil prediksi pada setiap kelas. Hasil eksperimen menunjukkan bahwa CLAHE mampu mencapai akurasi sebesar 79% yang unggul dalam memperjelas informasi penting pada citra endoskopi. CLAHE bekerja dengan baik karena kemampuannya mengurangi noise dan meningkatkan kontras. Model klasifikasi dengan HSV dan CLAHE pada KVASIR mampu mengenali seluruh kelas dengan baik. Ruang warna RGB, HSV, dan YCbCr menunjukkan kinerja yang stabil di sebagian besar pengujian. Penelitian ini memberikan wawasan untuk meningkatkan kualitas citra endoskopi guna mendukung diagnosis berbantuan komputer maupun klinis.*

Kata Kunci*: Biomedis, Cohen kappa quadratic loss, Endoskopi, Peningkatan gambar, Ruang warna.*

INTRODUCTION

The digestive system, also known as the gastrointestinal (GI) tract—consisting of the mouth to the anus—which is responsible for processing food. Diseases of the digestive tract—polyps, gastric ulcers, and colon cancer—affect the health of the body. Polyps are abnormal tissue growths that often appear in the stomach and large intestine. Most polyps are benign tumors that do not pose a risk of cancer, but if left untreated in the long term (5 to 10 years) will become cancer.

Colon cancer is suffered by 8.6% of the population in Indonesia (34,189 people), and the incidence of colon cancer globally is 19.5% [1], [2]. Diagnosing polyps and colon cancer in the digestive tract using an endoscopy. Endoscopy is used to observe the digestive tract to find anatomical abnormalities and diseases. Traditional endoscopy uses a wired tube, while modern endoscopy uses a wireless capsule.

The main problem with endoscopic images acquisition with the White Light Imaging (WLI) technique is that the image quality is depends by the acquisition environment and LED lighting. The resulting image can be low/high contrast and uneven illumination [3]. This has an impact on the level of accuracy and interpretation by doctors and computer-aided diagnosis. Computer-aided diagnosis uses machine vision (camera), mostly represented by the RGB color space, as input to diagnose disease.

Color is represented based on color theory, which maps real-world colors into pixels using either a linear model (YCbCr and YUV) or a nonlinear model (HSV and CIELAB) [4]. Most color spaces can be described by a three-dimensional channel, except for grayscale, which only has a single channel. The color model is not only the representation of color information but also the representation of texture information.

Color representation and image quality issues can be addressed using image enhancement techniques. Image enhancement is installed on a computer endoscope receiver such as Narrow Band Imaging (NBI) [5], Linked Color Imaging (LCI), and Blue Laser Imaging [6]. Apart from that, image enhancement is carried out after the shooting process.

Research [7] uses color conversion from RGB to CIELAB color space to separate images with bleeding and without bleeding based on K-Means Clustering. CIELAB makes it easy to see the difference between objects and backgrounds. Research [8] evaluates the enhanced results of CLAHE, HE, and Gamma Correction on endoscopy data. CHALE provides better results than HE, and Gamma Correction, however, research [8] did not provide the results of a medical examination by a doctor or a machine. By enhancing the texture of the detail layer and tone mapping using gamma correction [9], it has become easier for doctors to detect adenomas [10].

Detecting digestive tract diseases can also be performed using deep learning models by utilizing the transfer learning process. Transfer learning is a method that accelerates the training process by refining the pre-trained model with large data. This technique is frequently used to address issues in the medical field due to the scarcity of available data.

In the diagnosis of malaria parasites in red-blood smears, a study [11] using transfer learning techniques on ResNet50, EfficientNetB0, and InceptionV3 models achieved an accuracy above 77%. In the study of diagnosis of digestive tract diseases, a previous study [12] used pre-trained models, namely DenseNet121, Dense169, Dense201, and ResNet50V2, to classify endoscopy with 78,5%, 78,5%, 81.25% and 78.44% accuracy.

In a similar study [13] using the Kvasir Capsule Dataset, the EfficientNet model with an F1-score of 95.58% outperformed four other pretrained models, namely, GoogleNet, LeNet, MobileNet-V2, and ResNet50. Among the previous studies [11] – [13], classification tasks exclusively used the RGB color space, and none applied image enhancement techniques. Additionally, an in-depth analysis of the impact of color and enhancement remains to be required.

This research paper presents a comparative analysis of color transformation and contrast enhancement techniques for endoscopy images, exploring their impact on classification models using EfficientNetV2S. Color transformation converts RGB images into another color model, such as Grayscale, HSV, CIELAB, and YCbCr.

The selection of this color model is due to its ability to approximate human vision. HSV color model offers an intuitive way to express the shade of color, hue, and vividness. Each color transformation result was contrast-enhanced using CLAHE and IAGCWD. The Quadratic Weighted Kappa loss function is used to help the model achieve the same performance in each class. This study aims to provide comprehensive insights into the differences in combination image enhancement and color models for improving accuracy. The experiment shows that CLAHE improves class

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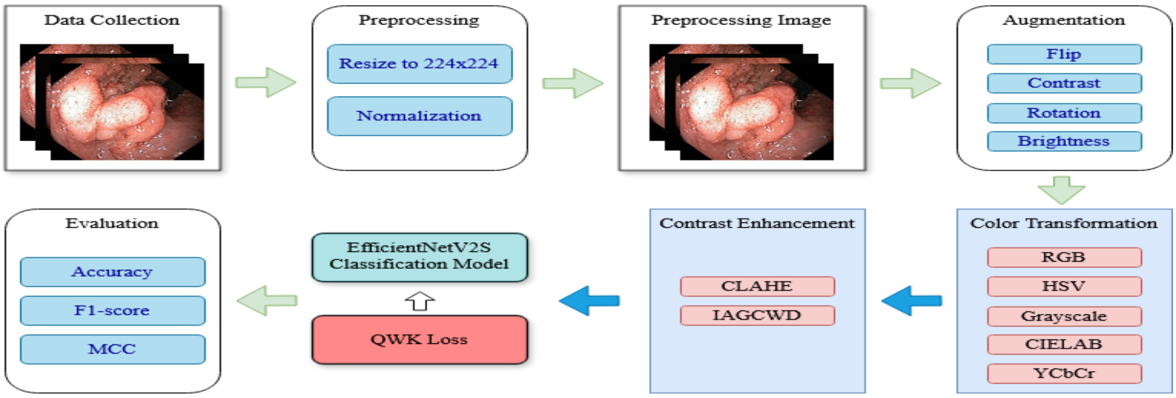


Source: (Research Results, 2024)

Figure 1. Workflow of proposed methodology

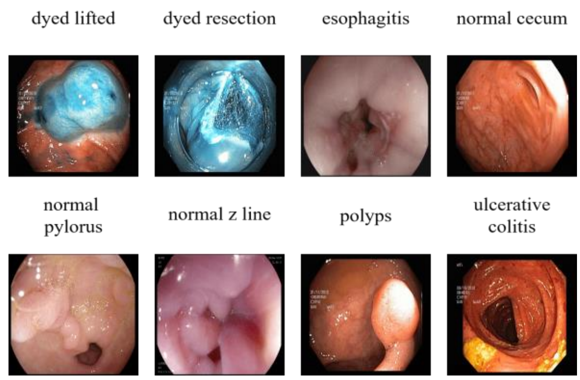
distinction and overall performance. Additionally, this research introduced a new collection of endoscopy multi-house dataset for classification of cancer, polyps, and normal, this dataset represents of high overlap between each class, an imbalanced dataset, and low resource.

The rest of this paper is carried out as follows: Materials and Methods explain the proposed methodology, Results and Discussion address the experimental findings of the proposed method, and Conclusions is the conclusion of the proposed work.

MATERIALS AND METHODS

This study focuses on analyzing the impact of different color models and contrast enhancement techniques, tested on the deep learning-based prediction model EfficientNetV2S. The study comprises several stages as shown in Figure 1, starting from data collection and preprocessing, data augmentation, color transformation, contrast enhancement, model architecture, loss function, to model evaluation.

A. Data Collection and Preprocessing



Source : (KVASIR Dataset, 2024)

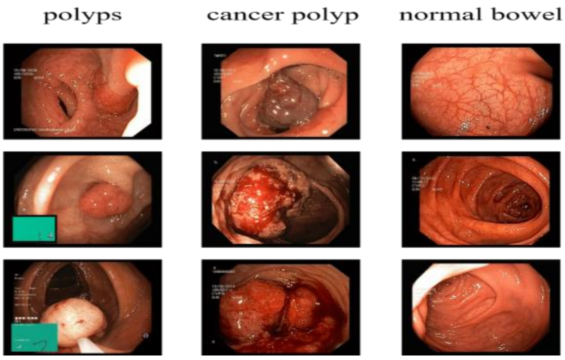
Figure 2. Image sample of KVASIR dataset

In this stage, the dataset is taken from a collection of endoscopy images of KVASIR and DCMH that have overlapping class characteristics with the balance and imbalance dataset. KVASIR (https://datasets.simula.no/kvasir/) is a collection of 4,000 images divided into 8 class, for gastrointestinal (GI) track disease detection. For each class contains 500 images, each image annotated by medical experts from Vestre Viken Health Trust center and Norwegian Cancer Registry and each image with different size resolution between 720 × 576 and 1920 × 1072 pixels. This dataset is used to represent balanced data case in the upper and lower gastrointestinal tract.

DCMH collection used Gastrovision [14] data on colon polyps, colorectal cancer, and colon mucosa and vascular patterns with total 2,426 images data. Additional data from unlabeled data in HyperKvasir (https://datasets.simula.no/hyper-kvasir/) that had been labeled by gastroenterologists from Petrokimia Gresik Hospital, was included due to the insufficient number of images (fewer than 200) in the colorectal cancer class. To prevent redundant data, duplicate images between Gastrovision and HyperKvasir were removed.

This process resulted in 921 colon polyps, 517 colorectal cancers, and 1,407 normal colon images. DCMH dataset is represented imbalanced data, low resource, and overlapping between class. By using two different datasets, this research can provide a more comprehensive understanding of the effects of enhancement and color representation.

In Figure 2. shows random images for each class in KVASIR Dataset, with their respective names. In Figure 3. shows randomly two selected images from DCMH for each class. The DCMH dataset represent high similarity, most of image have overlapping, between each class.



Source : (Research Results, 2024)
Figure 3. Image sample of DCMH dataset

The distributions of the number of images in the train, validation, and test is divided by a ratio of 80:10:10 and divided into mini-batches with a batch size of 16. Since the dataset images have been collected from various sources with varying dimensions, each image undergoes a resizing process to 224x224 pixels. The next step is to normalize the pixels within the value range of 0-225 to 0-1.

B. Data Augmentation

To enhance the diversity of the dataset, an augmentation process is employed. Geometric augmentation was selected due to minimal noise introduction. Geometric transformations techniques, provided by the Keras library, including operations such as flipping the image (right or left), rotation, contrast adjustment was performed randomly (range 0.2 – 1.8), and brightness variation (delta = 0.1).

C. Color Transformation

Colorful images based on human vision are represented by computers into RGB color spaces in composed with three basic colors, Red (R), Green (G), and Blue (B). Grayscale is color model that refers to a range of shades of gray as a brightness, from black to white. Using (1) to transform the RGB color into Grayscale (GY) color. HSV stand for Hue, Saturation, and Value is an intuitive color model for the human eye. To transform RGB Color to HSV Color using equation (2) – (5).

$$GY = 0.299R + 0.587G + 0.114B \tag{1}$$

$$max = \max(R, G, B) \tag{2}$$

$$min = \min(R, G, B) \tag{3}$$

$$S = \frac{max - min}{max} \tag{4}$$

In CIELAB, L* as lightness represent intensity, a* color represent Red channel minus Green channel, and b* color represent for Green channel minus Blue channel [15]. YCbCr color model separates Luminance represented by Y from chrominance represented by Cb as blue component and Cr as red component. The Y channel carries the grayscale information. Y, Cb, and Cr obtained from the calculation of (1), (6) and (7).

$$H = \begin{cases} 0, & \text{if } max = min \\ 60 \times \frac{G-B}{max-min}, & \text{if } max = R \\ 60 \times \frac{B-R}{max-min} + 120, & \text{if } max = G \\ 60 \times \frac{R-G}{max-min} + 240, & \text{if } max = B \end{cases} \tag{5}$$

$$Cb = 128 - 0.16874R - 0.33126G + 0.5B \tag{6}$$

$$Cr = 128 + 0.5R - 0.41869G - 0.08131B \tag{7}$$

D. Contrast Enhancement

One of the popular methods for contrast enhancement is Contrast Limited Adaptive Histogram Equalization (CLAHE) which is capable to improving the visibility of images in low-light conditions. CLAHE adaptively performs a histogram equalization on each images block with certain contrast limits [16]. There is two parameters in CLAHE, size of grid for histogram equalization and clip limit, the more higher size of grid the results will be better [17]. By utilizing the clip limit as the maximum height limit of a histogram, CLAHE can prevent excessive contrast enhancement.

In the majority of cameras, there is a nonlinear relationship between the signal voltage and light intensity [18]. The level of illumination incident on a scene represents a significant factor that directly impacts the reliability of performance in many computer vision systems. Improved Adaptive Gamma Correction with Weighting Distribution (IAGCWD) [19], [20] to enhance the contrast of low-light images and reduce over-brightness by choosing gamma value as a function of cumulative density function. IAGCWD performs enhancement for data that is too bright or too dark, which is better than enhancing the entire data.

E. Model Architecture

This study used EfficientNetV2S pre-trained models. The EfficientNet was developed in 2020, is architecture that focuses on achieving higher

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accuracy with less parameter by scaling depth, width and resolution. The new version of EfficientNet [21] is faster and more parameter-efficient by combining training-aware neural architecture search and scaling. EfficientNetV2S has 20.33M parameters and six convolutional blocks. A transfer learning approach using models trained on large common data sets, exp. ImageNet, provides a better chance of classification success by using less training data and shorten the time for the training phase.

After passing the pre-trained EfficientNetV2S model to ImageNet, a high-level feature representation of the input data is obtained. This representation is passed to the top layer as a fully connected layer. The top layer has two dense layers with 128 and 64 neurons, activation ReLU, regularizer L2 0.0001, and a batch normalization. The selection of parameter settings was chosen to equalize the model environment in the testing and analyzing proses.

The last layer or output layer for classification will have the same neuron as the total number of classes with SoftMax activation. Training phase uses AdamW optimization with learning rate 0.001 and weight decay 0.004. AdamW is able to adapt the learning rate to handle overfitting. Instead of categorical cross-entropy, we employ QWK loss, this loss will help to maintain the model performs in each class. To reduce time proses, we using 25 epoch for model training phase. .

F. Quadratic Weighted Kappa Loss

Quadratic Weighted Kappa (QWK) [22] measures the level of agreement between two raters on ordinal categorical data. In the context of deep learning, it compares the classification model results with the standardized expert agreement. It handles data imbalance better than categorical cross entropy [23], [24]. QWK results are in the range of -1 and 1; negative stands for worse than random, zero for random, and one is perfect. The weight W is calculated using (8) based on the power-of-two value of the difference between actual i and predicted j values divided by the number of classes C minus one. Matrix O which contains observation values of size $C \times C$ and Matrix of expected outcomes E which measures the outer product between predicted and actual values. (9) calculates the normalized W, O, and E matrix values. The loss function uses a minimization problem [25], so the loss is calculated using (10), the result values between the range of $-\infty$ and $log\ 2$.

$$w_{i,j} = \frac{(i-j)^2}{(C-1)^2} \quad (8)$$

$$QWK = 1 - \frac{\sum_{i,j} W_{i,j} O_{i,j}}{\sum_{i,j} W_{i,j} E_{i,j}} \quad (9)$$

$$loss = log(1 - QWK) \quad (10)$$

G. Model Evaluation

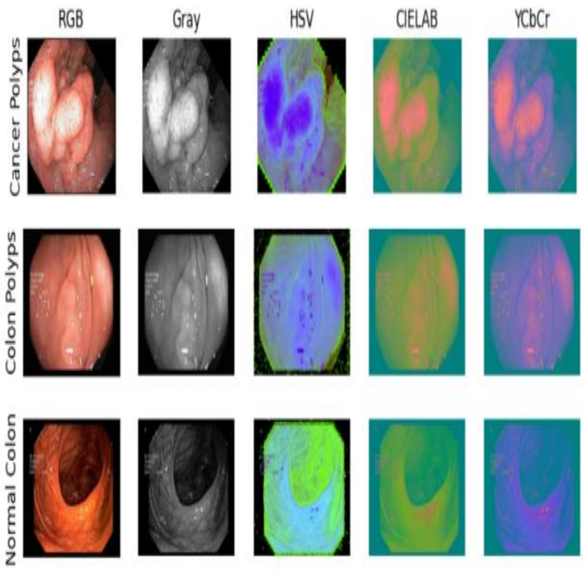
To quantitatively evaluate the experiment, this study used a confusion matrix as the evaluation metric. Confusion matrix contains true positive (TP) value, true negatives (TN) value, false positive (FP) value, and false negatives (FN) value. From the values in the confusion matrix, we calculated several metrics, such as $accuracy$, $precision$, $recall$, $f1-score$, and $matthews\ correlation$ (MCC). $Accuracy$ is the percentage of the total data that the model correctly predicts. In the context of unbalanced data, MCC gives a better picture of performance than f1-score. The accuracy and f1-score result in imbalance dataset were unreliable.

RESULTS AND DISCUSSION

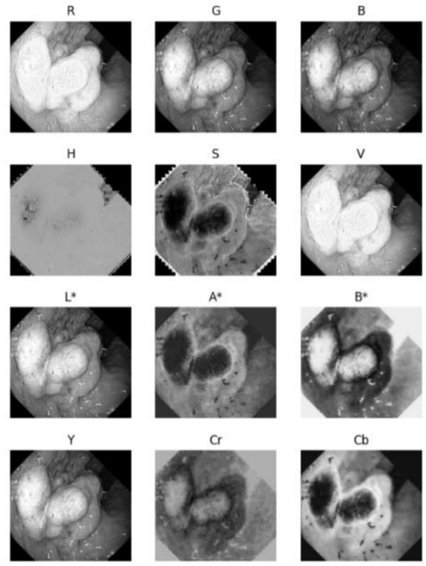
The results of the color transformation and contrast enhancement stages and their impact on the classification model are explained below.

A. Visual Results

The results of color transformation are reported in Figure 4, the sample image used are from DCMH dataset. In Figure 5, shows each channel from different color space in Grayscale images.



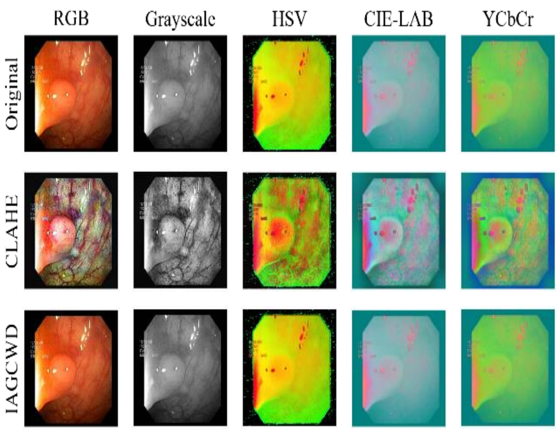
Source : (Research results, 2024)
Figure 4. Sample color transformation results.



Source : (Research results, 2024)

Figure 5. Sample channel color in grayscale.

In Figure 4. each color model shows differences in highlighting important information. In gray, it provides a contrast between the cancer and the mucosa. After the image is color transformed, then contrast enhancement is performed using CLAHE to each channel and IAGCWD to Y channel for YCbCr, R channel for RGB, H channel for HSV, and L* for LAB. The sample result of this proses using colon polyp image presented in Figure 6.



Source : (Research results, 2024)

Figure 6. Sample contrast enhancement.

B. Classification Model without Enhancement Results.

In this experiment, we tested the model performance using difference channel in color space, namely Red, Green, Blue, Hue, Saturation, Value, L*, a*, b*, Y, Cb, and Cr channel. The results experimented on the DCMH Dataset are shown in Table 1.

Table 1. Results of different channel on DCMH

Color	*Accuracy*	*F1-score*	*MCC*
Red	0.7052	0.7079	0.5157
Green	0.7719	0.7734	0.6335
Blue	0.7824	0.7822	0.6469
Hue	0.6736	0.6886	0.5020
Saturation	0.7508	0.7534	0.6058
Value	0.7824	0.7693	0.6205
L*	0.7473	0.7335	0.6017
a*	0.6947	0.6803	0.5111
b*	0.6912	0.7034	0.5077
Y	**0.8140**	**0.8149**	**0.6972**
Cb	0.6421	0.6286	0.4120
Cr	0.6280	0.6119	0.4115

Source : (Research Results, 2024)

As show on Table 1, the Red channel produced the best model performance compared to the Blue and Green channels, with high accuracy and MCC score. Accuracy shows how many correct predictions from all test data while MCC shows the model performance in correct and incorrect predictions on all classes independent of the class distribution. In the HSV color model, the Value channel performed best, achieving the same accuracy as the Blue channel, but worse in recognizing the same three classes according MCC score. The L* channel in the CIELAB color space achieved the highest performance compared to the a* and b* channels but was lower than each channel in RGB and HSV color models.

The Y channel showed the highest performance of all channels tested, with high accuracy and an F1 score above 80%, this is because Y information highlights important information and makes it easier for machines to learn. However, according to the MCC metrics, the overall model failed to adequately detect all three classes, often struggling to identify the Cancer class. This problem may be due to the cancer polyp class, which has the smallest number of cases in comparison to the normal colon and colon polyp classes. After compare model results in different channel then, we compare the performance of EfficientNetV2S model on images with RGB, Grayscale, HSV, CIELAB, and YCbCr color spaces. The experiments were conducted on DCMH and KVASIR datasets, which are shown in Table 2.

Table 2. Model results with different color space

Dataset	Color	*Accuracy*	*F1-score*	*MCC*
DCMH	**RGB**	**0.7770**	**0.7778**	**0.6292**
	Grayscale	0.6858	0.6477	0.5148
	HSV	0.6689	0.6523	0.4826
	CIELAB	0.6689	0.6720	0.4831
	YCbCr	0.7466	0.7507	0.6088
KVASIR	**RGB**	**0.7775**	**0.7326**	**0.7565**
	Grayscale	0.5150	0.4485	0.4603
	HSV	0.5575	0.4416	0.5263
	CIELAB	0.7075	0.6735	0.6746
	YCbCr	0.6675	0.6326	0.6329

Source : (Research Results, 2024)

Accredited Rank 2 (Sinta 2) based on the Decree of the Dirjen Penguatan RisBang Kemenristekdikti No.225/E/KPT/2022, December 07, 2022. Published by LPPM Universitas Nusa Mandiri

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In Table 2, the test using the DCMH dataset shows that the RGB color space has the best results, and the closest value is the YCbCr color space. YCbCr performs poorly on the DCMH dataset but performs well on the KVASIR dataset. Same in DCMH, RGB color space give the best result compared to Grayscale, HSV, CIELAB, and YCbCr. It is interesting that HSV shows low performance compared to the other five models. This is probably because more information is highlighted and the model experiences overlearning.

The decrease in MCC results in DCMH is possible because the model fails to recognize one of the three classes. In addition, the unbalanced amount of data makes a difference in MCC weighting which results in MCC values smaller than accuracy. This decrease occurs in the HSV and CIELAB color spaces on the DCMH dataset with MCC values below 0.5.

C. Classification Model with Contrast Enhancement

After experimenting with the color space, we continue to experiment the impact of using contrast enhancement techniques. Table 3 shows the performance results of the EfficientNetV2S model with images enhanced using CLAHE, and Table 4 presents the results using IAGCWD.

Table 3. Model results with CLAHE Enhancement

Dataset	Color	*Accuracy*	*F1-score*	*MCC*
DCMH	**RGB**	**0.7929**	**0.7977**	**0.6768**
	Grayscale	0.7438	0.7233	0.5654
	HSV	0.6701	0.6727	0.4721
	CIELAB	0.7754	0.7704	0.6253
	YCbCr	0.7649	0.7614	0.6282
KVASIR	**RGB**	**0.7575**	**0.7326**	**0.7565**
	Grayscale	0.4825	0.4263	0.4266
	HSV	0.5875	0.5071	0.5497
	CIELAB	0.6275	0.6105	0.5985
	YCbCr	0.6900	0.6672	0.6566

Source : (Research Results, 2024)

The test results using contrast enhancement techniques, specifically CLAHE in Table 3 and IAGCWD in Table 4, indicate that the model's ability to recognize the disease class *declines* compared to without contrast enhancement. This is evidenced by the lower MCC values, all below 60%. However, the RGB color space with CLAHE enhancement yields better results, achieving 79% accuracy and 67% MCC on the DCMH dataset, and 75% accuracy and 75% MCC on the KVASIR dataset. Contrast enhancement using IAGCWD in Table 4 shows that Grayscale and HSV are the best performers with Accuracy 75%, F1-score 74%, MCC 60% for DCMH and Accuracy 73%, F1-score 69%, MCC 70% for IAGCWD.

Table 4. Model results with IAGCWD Enhancement

Dataset	Color	*Accuracy*	*F1-score*	*MCC*
DCMH	RGB	0.7473	0.7403	0.5740
	Grayscale	**0.7543**	**0.7495**	**0.6047**
	HSV	0.6771	0.6808	0.4993
	CIELAB	0.7087	0.7039	0.5260
	YCbCr	0.6807	0.6616	0.4799
KVASIR	RGB	0.6675	0.5898	0.6506
	Grayscale	0.5175	0.4473	0.4693
	HSV	**0.7375**	**0.6922**	**0.7068**
	CIELAB	0.4600	0.3733	0.3962
	YCbCr	0.6375	0.6375	0.5988

Source : (Research Results, 2024)

RGB performs well, with the highest accuracy is 79%. CLAHE improves the model on DCMH, increasing the MCC metric from 48% to 63% for CIELAB and from 51% to 57% for grayscale. IAGWD also increases the MCC metric in grayscale color space from 51% to 60%.

In the DCMH dataset, the cancer class is difficult to detect by the model, this is possible due to the similarity between the colon polyps class and the cancer polyps class, both in terms of color and texture. In addition to the small amount of data, the cancer class has a low-quality image such as blurred, even though it has apply image enhancement it still does not highlight important information on the cancer polyps class.

The IAGCWD algorithm enhances images that are too dark or too bright. With the existing threshold, only 30% of the image in DCMH dataset is enhanced. The problem with this threshold is that it doesn't consider the presence of a black background. This makes it inaccurate in recognizing illumination. In Kvasir, the most difficult is to detect between the dyed lifted polyps class with dyed resection margins class and the normal pylorus class with esophagitis class. This is due to the similar characteristics of the two classes.

CONCLUSION

This study demonstrates that combining color transformation and contrast enhancement can improves accuracy and generalization in GI disease detection using deep learning. Among the different color channels, the Y channel achieved the highest performance, with an accuracy of 81%, F1-score of 81%, and MCC of 70%. CLAHE enhancement outperformed IAGCWD by making the model more effective at detection; however, the IAGCWD method was limited by a threshold value that reduced the number of usable images. For colorful images, combining HSV with IAGCWD improved classification results, whereas for grayscale images, CLAHE proved to be the more effective enhancement method.

In future work, we plan to further investigate the influence of individual color channels and employ vision transformers for classifying endoscopic diseases. Additionally, future researchers could replicate this experiment using expert diagnoses from medical professionals rather than relying solely on machine models. There is also potential to develop reinforcement learning approaches to predict the presence of diseases more accurately.

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