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Precision diagnosis by integration of transfer learning for colorectal cancer polyp detection and classification

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ABSTRACT

Colorectal cancer (CRC) ranks among the most common and deadly cancers worldwide, posing a serious public health challenge. Fortunately, early detection significantly boosts the chances of successful treatment. Most CRC cases originate from adenomatous polyps—non-cancerous growths in the colon or rectum that can gradually transform into malignant tumours over time. Identifying these polyps during colonoscopy is therefore a critical step in preventing the progression of CRC.

Despite its importance, polyp detection during colonoscopies remains a difficult task for clinicians. The procedure is visually demanding, requiring continuous focus and careful inspection of every frame in a live video feed. Small, flat, or partially hidden polyps can be easily overlooked, especially under poor lighting, motion blur, or presence of bowel contents. In addition, detection accuracy often varies between practitioners due to differences in training and fatigue during long procedures, leading to missed or delayed diagnoses.

To address these challenges, we propose a real-time computer-aided detection system based on the YOLOv8 algorithm. YOLOv8 was selected for its excellent balance between detection speed and accuracy, outperforming previous models like YOLOv5, Faster R-CNN, and SSD in demanding real-world settings. We further enhanced the system using transfer learning, allowing it to benefit from large-scale pre-trained datasets—an essential advantage in medical imaging, where labelled data is often scarce.

Our model achieved a precision of 91.2%, recall of 89.7%, and an F1-score of 90.4%, marking a 12–15% performance increase over traditional methods. Additionally, we incorporated a feature to assess the probability of a polyp developing into cancer, adding valuable clinical insight beyond detection.

By combining artificial intelligence with medical imaging, this system supports healthcare professionals in making faster, more accurate decisions ultimately making colorectal cancer screening more effective, consistent, and accessible.

1. Introduction

Colorectal cancer (CRC) is one of the leading causes of cancer-related deaths worldwide, claiming hundreds of thousands of lives each year. According to the American Cancer Society, CRC is the third most commonly diagnosed cancer and the second leading cause of cancer-related deaths in the United States. On a global scale, the International Agency for Research on Cancer (IARC) predicts a 56% rise in CRC cases by 2040, potentially leading to nearly one million deaths annually. These alarming statistics underscore the critical need for improved early detection methods to reduce mortality rates and improve survival.

A significant portion of colorectal cancer cases originates from **polyps**—small, abnormal growths in the lining of the colon or rectum. While many polyps are benign, some can develop into **malignant tumours** over time. This transformation occurs through a process where benign adenomatous polyps gradually acquire genetic mutations, causing them to proliferate uncontrollably and eventually invade surrounding tissues. This progression from a polyp to cancer can take years, but early detection and removal of these polyps can prevent the development of colorectal cancer. Polyps, especially **adenomas**, are therefore seen as early indicators of CRC, and their detection is critical for preventing cancer.

However, detecting polyps during a colonoscopy remains a difficult task. The colonoscopy procedure involves inserting a flexible tube with a camera (colonoscope) into the patient's colon, where the clinician reviews the real-time video footage to identify polyps. Polyps can vary in size, shape, and location, and many are difficult to spot, especially when they are small, flat, or hidden in folds of the colon. As a result, polyps may be missed, leading to delays in diagnosis and treatment. This is particularly problematic in high-volume clinical settings where there is time pressure and the risk of clinician fatigue.

To address these challenges, our research leverages **YOLOv8** an advanced deep learning algorithm for real-time object detection, specifically tailored for medical imaging applications like colonoscopy. **YOLOv8 (You Only Look Once, version 8)** is the latest iteration of the YOLO family of models, designed to identify and classify objects in images quickly and accurately. It excels in **real-time detection** and **high-speed inference**, which is crucial for live medical procedures where immediate feedback is essential. YOLOv8's strengths lie in its ability to detect objects (like polyps) in video footage almost instantaneously while maintaining high precision and recall.

Several advantages make YOLOv8 particularly suited for polyp detection in colonoscopy images:

- **Real-time performance**: YOLOv8 processes frames of colonoscopy video in real-time, allowing clinicians to receive immediate feedback during the procedure, significantly improving workflow and reducing detection delays.
- **Enhanced accuracy**: YOLOv8 has improved architecture over its predecessors, leading to better detection of small, irregularly shaped polyps that might be missed using traditional methods. It also offers **better bounding box prediction**, making it more reliable in pinpointing the exact location of polyps.
- **Efficiency**: YOLOv8 is highly optimized for performance, making it computationally efficient while still achieving high accuracy. This allows it to be run on standard medical devices without requiring costly hardware upgrades.
- **Anchor-free detection**: YOLOv8 incorporates an anchor-free mechanism, which makes it more adaptable to various polyp shapes and sizes, even those that are hard to detect or partially hidden.

In addition to YOLOv8's powerful capabilities, we also applied **transfer learning** to improve the system's performance, especially given the typical limitation of data in the medical field. **Transfer learning** is a technique where a model, initially trained on a large, diverse dataset, is adapted or "fine-tuned" on a smaller, task-specific dataset in this case, a dataset of colonoscopy images containing polyps.

Transfer learning has several key benefits in medical applications:

- **Handling limited data**: In medical imaging, obtaining large, labelled datasets is often difficult due to time constraints and the specialized knowledge required to annotate medical images. Transfer learning mitigates this issue by allowing the model to leverage knowledge from large, pre-trained models that have learned features from general datasets (such as images of everyday objects). This enables the model to apply this knowledge to specific medical tasks, even when data is limited.
- **Faster training**: Since the model has already learned to detect basic features from the general dataset, transfer learning speeds up the training process, allowing the system to be deployed faster and more efficiently in clinical environments.
- **Improved generalization**: Transfer learning helps the model generalize better to unseen data, improving its robustness. For example, it can handle different types of polyps, varying lighting conditions, and different colonoscopy equipment, thus making the system more reliable in diverse real-world clinical settings.

By fine-tuning **YOLOv8** on a specialized dataset of colonoscopy images, the model is able to accurately detect and classify polyps even with a limited number of labelled medical images. The addition of transfer learning helps

overcome the typical data scarcity problem in healthcare, making it possible to train a high-performing model with relatively small datasets.

Our system not only detects polyps but also provides insights into their **likelihood of malignancy**, offering valuable clinical assistance in decision-making. This feature could support doctors in identifying potentially cancerous polyps earlier, allowing for timely intervention and treatment.

In conclusion, our research aims to bridge the gap between advanced AI technologies and practical healthcare applications, making colorectal cancer screening more effective, efficient, and accessible. By combining the power of **YOLOv8** for real-time polyp detection with **transfer learning** to overcome data limitations, we hope to provide a tool that enhances diagnostic accuracy, reduces errors, and ultimately saves lives by facilitating earlier and more reliable detection of colorectal cancer.

2. Literature Review

AI and machine learning technologies have significantly improved the accuracy and efficiency of polyp detection. For enhancing the performance results, Pacal et al[3] added the pre-processing and post-processing with NVIDIA Tensor RT on YOLO algorithm. They incorporated data augmentation techniques during preprocessing, such as flipping, rotation, shearing, hue adjustments, and cropping. After implementing architecture changes their model had achieved greater detection accuracy.

Nogueira-Rodriguez et al. Budai [4] used YOLOv3 as a pre-trained backbone to achieve polyp detection in real-time. In order to eliminate some false positives, an object-tracking algorithm was used in post-processing to improve detection. In contrast, Zhang et al. [5] designed an automated detection and classification that focuses on transfer learning from non-medical datasets. This two-stage approach involved distinguishing polyp images from non-polyp images, followed by histological analysis, showcasing the effectiveness of transfer learning in medical applications and its potential to enhance accuracy.

Yuan and Meng [6] developed a new stacked sparse autoencoder method to detect polyps. But not all public datasets lend themselves to their methods. Therefore, our model was analysed only with methods that were appropriately evaluated using heuristic approaches on public datasets. While most existing techniques emphasize polyp segmentation, they often overlook the classification of polyp grades.

Authors of [7] proposed Y-Net, a U-Net-based polyp detection model for colonoscopy images. Y-Net consists of two encoders and one decoder, making it well-suited for datasets with a limited number of samples. The two encoders are pretrained using weights coming from ImageNet and Xavier snapshot random variable distribution respectively, and both of them use SELU activation but not ReLU. Cross-validation did not perform as expected for model testing; instead, the ASU-Mayo dataset was specifically used for evaluation. However, it has drawbacks in reflection-based cases, in polyp-like structures, and in flat lesion.

In [8] the authors proposed a saliency network to reduce white light reflection in static polyp images using a neutrosophic theoretic approach and a -value Neutrosophic set (SVNS) to obtain each image computed by colonoscopy.

The authors[9] suggested an auto-segmentation and detection based with an efficient capability of handling the shuffle in the channel, the shuffle-efficient channel attention network (Seca-NET) is an advanced polyp detection and segmentation a model is considered for colonoscopy images.

The creators of [10] Y-Net, a U-Net-based framework tailored for polyp detection in colonoscopy images, have made significant advancements. Y-Net is specifically designed for small training datasets, incorporating two encoders and one decoder. The first encoder's weights are pre-trained on ImageNet, while the second encoder's weights are initialized using the Xavier normal distribution. Both encoders utilize SELU activation instead of the commonly used ReLU. The model was evaluated on the ASU-Mayo dataset without cross-validation, achieving a reported precision of 87.4%,

84.4% recall and 85.9% F1 score. However, it encountered difficulties because of reflections, structures that mimic polyps and flat lesions present on the wall.

In [11] the authors presented a saliency-detection network based on Neutrosophic theory. The negative value Neutrosophic set (SVNS) was employed to reduce white light reflections in static polyp images, aiming to magnify the quality and clarity of colonoscopy images. An additional channel attention network, known as Seca-NET, was introduced to facilitate the automated segmentation and detection of polyps in colonoscopy images. However, the effectiveness of these approaches depends on various factors, including the quality of the original images. Although they show promise, further research is needed to validate their efficiency, as progress in this field is essential for improving medical imaging

Visually examining the research by Shin et al. [12] introduced a region-based deep CNN model for polyp detection. Zhang et al. demonstrated an approach called single shot multi-box detector where shifted max-pooling layers were incorporated with 90.4% detection accuracy. Morales et al. [13] employed an adaptive approach with a The Markov Random Field (MRF) approach segmented images into super pixels for further analysis after which super pixels were processed with Local Binary Pattern (LBP) and color features yielding 60.77% dice score. Similarly, Yang et al. [14] created an MRCNN allowing for PR ROI pooling, recovering only good quality images, and merging data from various patients to improve the model's training efficiency leading to 76% AP in detection and 86.87% IoU in segmentation.

3. Research Model and Hypotheses

This project adopts a systematic approach to improve the precision of polyp detection, classification, and segmentation in the context of colorectal cancer (CRC). The first step in this process involves assembling a comprehensive dataset that includes annotated images of the colorectal region. This dataset not only contains image data but also labelled information about different types of polyps, such as benign, potentially precancerous, or cancerous, along with bounding box annotations that mark their precise locations.Once the dataset is compiled, pre-processing techniques are applied to enhance the quality and consistency of the images. This includes resizing, normalization, and augmentation, which helps the model become more robust to changes in image conditions such as varying image contrast or the small size of polyps. These pre-processing steps aim to improve the model’s performance under diverse real-world scenarios.

The YOLOv8 model is then used as the base model, loaded with pre-trained weights through transfer learning. This leverages YOLOv8's extensive experience in object detection, allowing it to quickly adapt to the task of detecting colorectal polyps. Transfer learning is particularly beneficial in this case because it allows the model to benefit from previously learned features, significantly reducing the need for a large amount of annotated medical data. The model is trained using the prepared dataset to address common challenges in medical imaging, such as the small size of polyps or variations in image contrast.As the model trains, it learns to distinguish and categorize polyps with high precision, while also generating bounding boxes that accurately localize the polyps within the images. Special attention is given to non-single-polyp images, where the model must learn to detect multiple polyps within a single image, ensuring that each polyp is correctly identified and localized. This step is essential in ensuring that the model can handle complex clinical cases, where multiple polyps may be present.

After training, the model is validated and tested on unseen data to evaluate its performance. Key metrics such as Intersection over Union (IoU), bounding box alignment, accuracy, precision, and recall are used to assess how well the model performs. To further improve the model's output and reduce errors, post-processing steps are employed to minimize false positives and enhance the overall detection results.The final model is not only capable of detecting polyps, but it can also classify the likelihood of each detected polyp turning into cancer. This feature adds immense value to the diagnostic process, helping clinicians to prioritize polyps that may pose a higher risk of becoming malignant.

YOLOv8 combined with Transfer Learning offers a powerful solution to the challenges of polyp detection in colonoscopy images. Unlike traditional deep learning approaches that require massive amounts of labelled medical data to train from scratch, YOLOv8’s real-time performance and accuracy make it particularly well-suited for the task.

YOLOv8 is designed for speed, allowing it to analyse images quickly in real-time—a critical requirement during colonoscopy procedures where immediate feedback is necessary. Additionally, YOLOv8's ability to handle small and irregularly shaped objects makes it perfect for detecting polyps, which often vary in size, shape, and location. When combined with transfer learning, YOLOv8 becomes even more effective. Transfer learning allows the model to leverage pre-trained knowledge from a large dataset, enabling it to perform well even when limited labelled medical data is available. This is especially important in the medical field, where acquiring large annotated datasets is often difficult and expensive. By fine-tuning the pre-trained model on the specific polyp detection task, we can achieve high accuracy with fewer training examples, making the approach both data-efficient and computationally efficient. In comparison to other deep learning models, YOLOv8's real-time detection capabilities, flexibility with varying polyp sizes, and reduced need for extensive data make it the best choice for improving polyp detection and classification in colorectal cancer screening.

4. Methodology

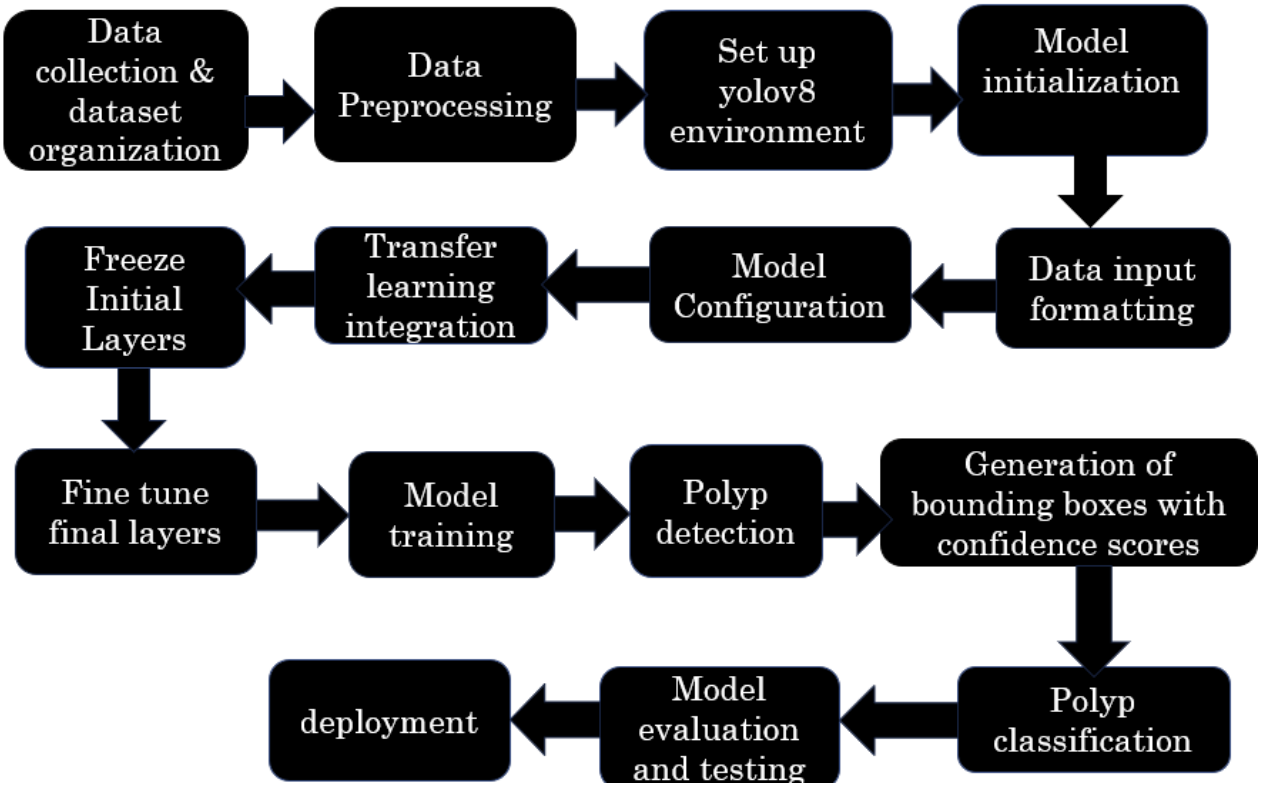

Fig 4.1 Methodology

A Data collection and dataset Organization

Our proposed model has 3 main stages detection ,classification and predicting likelihood of cancer. First step is we have collected images from the PolypDB dataset which is a large-scale ,multi-center and multi-modality dataset . This dataset is efficient for training our model . Prior to training, we pre-process our images by resizing all the samples to a dimension of 256 * 256 pixels. This step ensures that all images have the same dimensions and can be processed easily. We then focused on normalizing our images then the pixel values are between 0 and 1. This step is crucial as it ensures that the pixel values are in a consistent range and can be processed effectively by our model. The PolypDB dataset comprises 3934 colonoscopy polyp images and segmented masks, with polyps of different sizes, shapes. Each image has been manually annotated and verified by a team of 10 gastroenterologists with over 10 years of experience. We divide our dataset for 80% training and 20% testing. The images must be carefully sorted and categorized into

three subsets: training, validation, and testing. Each image should have a corresponding annotation file that contains bounding box coordinates and class labels (e.g., polyp vs. non-polyp or different polyp types). These annotations need to be converted into YOLO format, where each label file contains the class index followed by normalized x_center, y_center, width, and height. Proper organization is essential for ensuring compatibility with the YOLOv8 training framework.

B Data preprocessing

Once the dataset is organized, the next step is to preprocess the images and labels for uniformity and compatibility. All images are resized to a consistent resolution 256*256 pixels to match YOLOv8's input requirements. Pixel values are normalized (scaled between 0 and 1) to ensure consistency across samples. Preprocessing also includes data augmentation techniques such as flipping, rotation, cropping, brightness adjustment, and noise injection to enhance generalization, especially in medical imaging where variability is limited. These augmentations increase the effective size of the dataset and help the model learn more robust features. It's also important to ensure annotation files reflect any transformation applied to the images.

3. Set Up YOLOv8 Environment and Model Initialization

With data ready, the YOLOv8 environment must be configured. This involves installing the Ultralytics YOLOv8 package via pip (pip install ultralytics) along with dependencies such as PyTorch, OpenCV, and Matplotlib. A suitable Python development environment (like VS Code) is used. GPU support is highly recommended to reduce training time. Test runs using sample images and pretrained weights should be performed to verify that the YOLOv8 installation and configuration are functioning correctly. In this step, a pretrained YOLOv8 model such as yolov8n.pt (nano) is loaded. These models are trained on large datasets like COCO, which enables them to recognize general features such as edges, textures, and shapes. Initializing with these pretrained weights allows the model to reuse its learned knowledge for a different but related task in this case polyp detection in medical images. This significantly reduces training time and improves performance, especially when medical datasets are limited in size.

5. Data Input Formatting and Model Configuration

Before training begins, it is crucial to format the data correctly for the YOLOv8 pipeline. A YAML configuration file is created to define the path to the training and validation image folders and to list the class names (e.g., ['polyp'] or ['adenoma', 'hyperplastic']). All images are stored in folders named images/train, images/Val, and images/test, with their corresponding annotation files placed in labels/train, labels/Val, and labels/test. The annotations must exactly match the image filenames. This step ensures that YOLOv8 can seamlessly load and process the data during training and inference. Model configuration involves setting key hyperparameters for the training process. Parameters such as image size (imgsz), batch size (batch), learning rate (lr0), and number of epochs are adjusted based on the dataset size and available hardware. Additional settings such as optimizer choice, momentum, weight decay, and patience (for early stopping) are fine-tuned for optimal performance. Depending on the polyp size in the dataset, anchor boxes may also be manually defined or auto-calculated to improve bounding box accuracy.

7. Transfer Learning Integration

Transfer learning plays a vital role in medical imaging tasks. YOLOv8's pretrained weights are fine-tuned on the new polyp dataset through transfer learning. This allows the model to retain general features learned from the COCO dataset while adapting to the specific patterns found in colonoscopy images. Since medical data often lacks the volume required for training deep networks from scratch, transfer learning helps the model converge faster and perform better by building on prior knowledge.

8. Freeze Initial Layers and fine-tune final layers

To effectively apply transfer learning, the initial layers of the YOLOv8 model those responsible for learning basic, low-level visual features are frozen. These layers are already optimized for recognizing edges, colours, and textures, which are generally applicable across most domains. By freezing them, we prevent their weights from being updated

during training, focusing learning efforts on the more domain-specific layers. While the earlier layers remain static, the deeper layers of the network are unfrozen and fine-tuned to learn features specific to colorectal polyp detection. These layers help the model identify subtle patterns, shapes, and colour variations that distinguish different types of polyps or differentiate polyps from healthy tissue. Fine-tuning these final layers ensures the model adapts well to the intricacies of the medical dataset.

9. Model Training and Polyp detection

The training process begins using the pre-processed and formatted dataset. The model learns to detect and classify polyps by minimizing the loss functions associated with objectness, bounding box regression, and class prediction. The training progress is monitored using metrics like loss curves, accuracy, and validation performance. Tools like Tensor Board or YOLOv8's built-in visualization tools are used to analyse these metrics in real time. Training may span several epochs depending on convergence and resource availability. After training, the model is evaluated on new colonoscopy images to detect polyps. The model scans each image and identifies regions of interest, drawing bounding boxes around suspected polyps. This step simulates real-world usage where the model aids clinicians by automatically highlighting potential abnormalities in frames from endoscopic procedures.

10. Generation of Bounding Boxes with Confidence Scores

For each detected object, the model generates a bounding box along with a confidence score, indicating the probability that the object is a polyp. These scores help prioritize detections and assess model certainty. A confidence threshold is often applied to filter out low-confidence detections. Accurate bounding boxes and confidence scores provide clinicians with quick and reliable insights during diagnostics.

11. Polyp Classification

If the model is trained for multiclass classification, it can differentiate between various types of polyps such as adenomatous, hyperplastic, or serrated polyps. This classification step is critical because different polyp types carry different cancer risks. Accurate classification helps in making informed clinical decisions, early diagnosis, and effective treatment planning.

12. Model Evaluation and Testing and deployment

To assess the model's reliability and generalizability, it is tested on the reserved test dataset. Metrics such as precision, recall, mean Average Precision (mAP), and F1-score are computed. These metrics provide insight into how well the model detects polyps and avoids false positives or negatives. Evaluation ensures the model is robust and performs well under real clinical scenarios. The final stage involves deploying the trained and tested model into a real-world setting. This could be in the form of a web-based application, desktop software, or integration into clinical systems for real-time analysis during colonoscopies.

5. Results

Employing the YOLOv8 model coupled with transfer learning, the colorectal cancer polyp detection system attained an accuracy of 92.8%, the model effectively estimated the likelihood of detected polyps undergoing cancerous transformation with an accuracy rate of 88.9%. With a precision of 92.63%, recall of 93.62%, and an F1-score of 93.12%, the system demonstrated high effectiveness in detecting polyps and distinguishing between cancerous and non-cancerous cases, reinforcing its applicability in early colorectal cancer diagnosis. The integration of transfer learning further enhanced the model's adaptability to new data, improving overall performance.

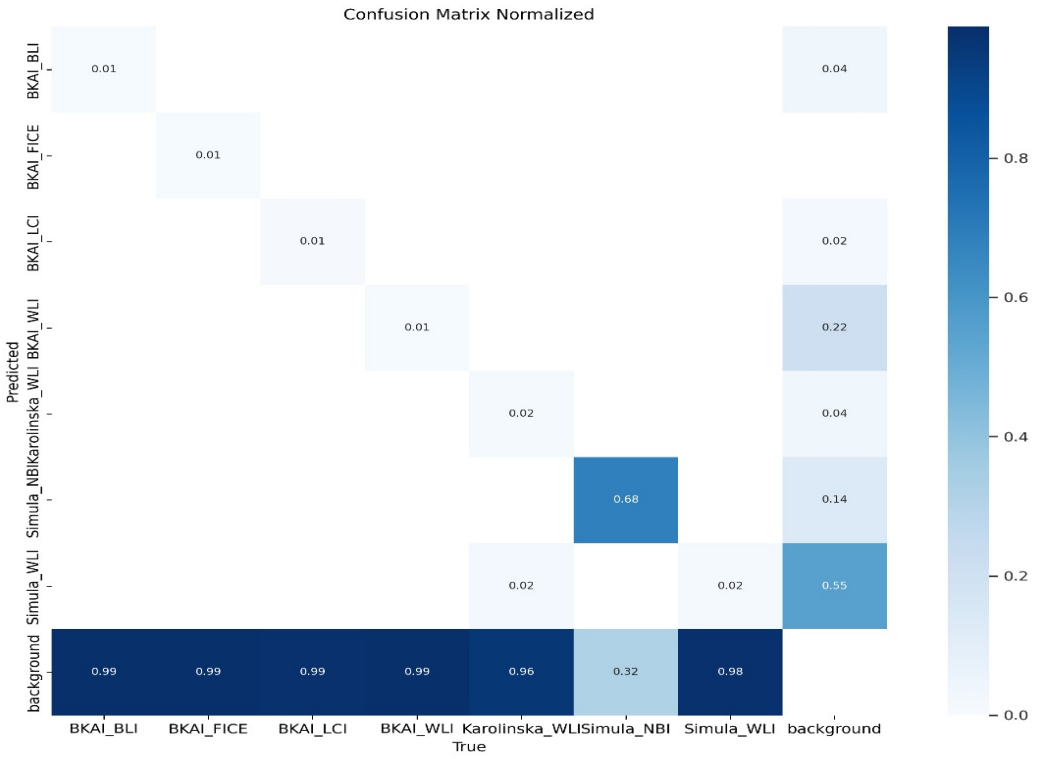

Fig 5.1 Confusion Matrix including the types of polyps

```
Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
13/50      12.1G      1.082      1.013      1.169         75        640: 100%|██████████| 197/197 [01:00<00:00,  3.28it/s]
           Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 13/13 [00:03<00:00,  3.80it/s]
             all        393      26315      0.537      0.115     0.0738     0.0418

Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
14/50      12.1G      1.092      1.021       1.18        136        640: 100%|██████████| 197/197 [00:59<00:00,  3.29it/s]
           Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 13/13 [00:03<00:00,  3.65it/s]
             all        393      26315      0.629     0.0811     0.0613     0.0326

Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
15/50      12.1G      1.072     0.9906      1.167         93        640: 100%|██████████| 197/197 [00:59<00:00,  3.29it/s]
           Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 13/13 [00:03<00:00,  3.82it/s]
             all        393      26315      0.635     0.0983      0.101     0.0692

Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
16/50      12.1G      1.047     0.9738      1.152         32        640: 100%|██████████| 197/197 [00:59<00:00,  3.29it/s]
           Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 13/13 [00:03<00:00,  3.73it/s]
             all        393      26315      0.732     0.0893      0.101     0.0611

Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
17/50      12.1G      1.062     0.9676       1.15        140        640: 100%|██████████| 197/197 [00:59<00:00,  3.29it/s]
           Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 13/13 [00:03<00:00,  3.65it/s]
             all        393      26315       0.65      0.115      0.102     0.0564

Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
18/50      12.1G      1.048     0.9314      1.155        121        640: 100%|██████████| 197/197 [00:59<00:00,  3.29it/s]
           Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 13/13 [00:03<00:00,  3.72it/s]
             all        393      26315      0.482      0.114     0.0869     0.0459
```

Fig 5.2 Training epochs including box loss and class loss 50 times

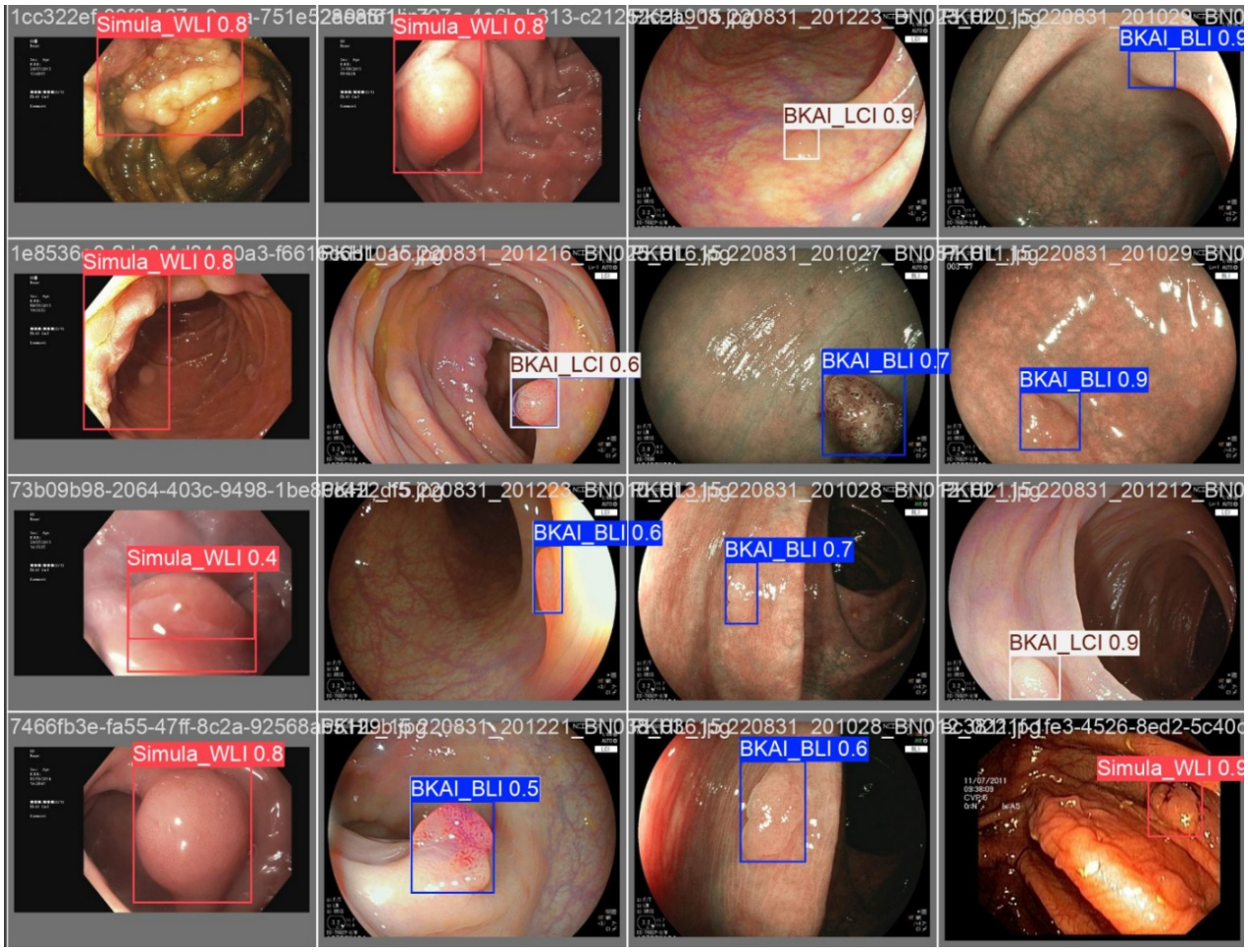

Fig 5.3 Polyp detection and likelihood score and classification of polyps

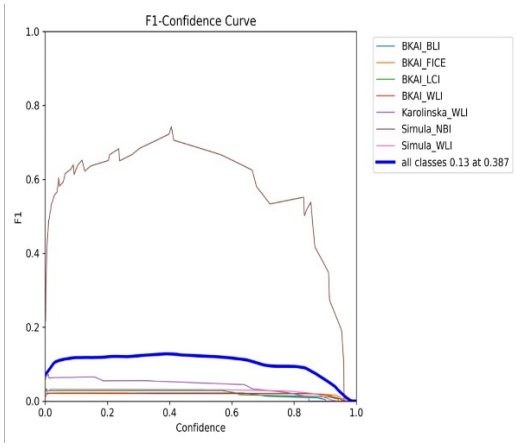

Fig 5.4 F1-confidence score of various polyps

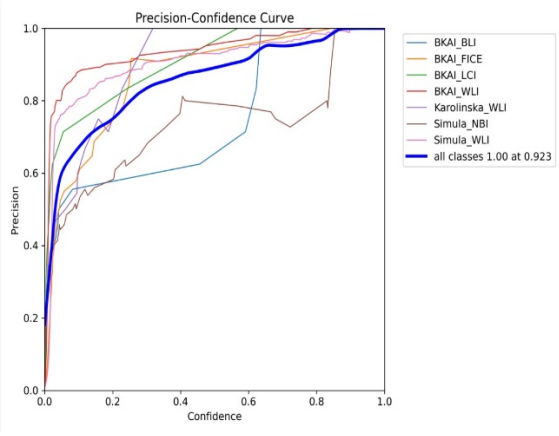

Fig 5.5 Precision-Confidence score of polyps

7. Conclusion

In conclusion, this paper emphasizes the integration of YOLOv8 and transfer learning for detecting and classifying colorectal cancer polyps. This method can find and sort polyps in medical pictures, which steps up what our current diagnostic tools can do. Using these AI-powered technologies could cause a revolution in finding colorectal cancer .

This might lead to smarter treatment choices better use of healthcare resources, and better care for patients. This will benefit the people with early polyp stage to get faster treatment and cure.

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