International Journal of Innovative Research in Computer Science and Technology (IJIRCST)
ISSN(Online): 2347-5552, Volume-12, Issue-2, March 2024
https://doi.org/10.55524/ijircst.2024.12.2.14
Article ID IJIRD-1279, Pages 81-86
www.ijircst.org

Innovative Deep Learning Methods for Precancerous Lesion Detection

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Received 5 March 2024; Revised 18 March 2024; Accepted 28 March 2024

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ABSTRACT- With the continuous advancement of socio-economic levels and relentless innovation in modern medical technologies, there's been a significant increase in the importance people place on their physiological health, particularly in the context of colorectal cancer—a prevalent malignant tumor that has captivated widespread attention within the medical community for its prevention and treatment. Notably, colorectal polyps, identified as precursors to colorectal c ancer, are crucial for early diagnosis and precise detection, serving as fundamental elements in averting the disease and diminishing both its incidence and mortality rates. The swift progression of deep neural network technology in recent years has revolutionized computer-assisted medical diagnosis, especially for the detection of colorectal polyps. Deep learning technology, with its robust capability for feature learning and representation, has emerged as an invaluable aid for physicians, markedly enhancing diagnostic accuracy and efficiency. This study centers on colorectal polyps, striving to develop a detection model with superior accuracy by meticulously analyzing contemporary leading target detection algorithms. By fully exploiting the potent capabilities of deep neural networks, the model aims to boost the precision of colorectal polyp detection significantly, aiding physicians in elevating detection efficiency and simplifying diagnostic processes. By undertaking this research, we aim to make a significant contribution toward more accurate and efficient technological support for the early diagnosis and prevention of colorectal polyps, thereby aiding in the reduction of both the incidence and mortality rates associated with colorectal cancer.

KEYWORDS- Precancerous Lesion, Colorectal Polyp, Deep Learning, Target Detection, Neural Network.

I. INTRODUCTION

Colorectal polyps are identifiable as minute, elevated formations that protrude into the colon's lumen from the colorectal mucosal layer, signifying early polypoid growths that have not progressed to colorectal cancer [1]. The disease burden of colorectal cancer is significant, with the Global Cancer Statistics report from the International Agency for Research on Cancer (IARC) citing around 935,200 fatalities and 1,931,600 new cases globally, placing it third and second for malignant tumor prevalence, respectively [2]. Intercepting colorectal polyps in their initial stages is a vital measure to thwart the development of colorectal cancer, thus decreasing both death and occurrence rates. Research indicates that the prompt detection and excision of these polyps can avert the advent and subsequent advance of colorectal cancer [3]. It is widely accepted that the progression of colorectal cancer begins with adenomatous polyps, with the transition from an adenomatous stage to early invasive cancer spanning approximately 10 to 15 years. The field of artificial intelligence has seen exponential growth, with deep learning achieving notable feats in visual recognition, occasionally outdoing human performance. By incorporating deep learning techniques into computer vision and objective diagnosis, it becomes possible to carry out precise, automated polyp detection in colonoscopy imagery with diminished subjective human error [4] [5].

The algorithm in focus leverages deep learning to assess and distinguish the FCOS algorithm, YOLO algorithm [6], and Faster RCNN algorithm [7] in terms of their performance and utilizes an extensive compendium of authentic CT scans from patients with colorectal polyps to design and appraise various RCNN-based polyp detection algorithms. The paramount objective is to pinpoint the most effective model parameters tailored for a specific CT image corpus, thereby facilitating methodological advances in machine-assisted polyp identification.

II. RELATED WORK

A. *Overview of Neural Networks*

In the realm of artificial neurons, the input X_i emulates the role of dendrites in biological neurons, acting as the receivers of external information[8]. The weight *Wi* is analogous to the synaptic input strength, reflecting the intensity of the signal transmitted from the dendrites to the nucleus in natural neurons[9]. The summation function mirrors the integrative function of the nucleus, amalgamating all incoming signals. This is further refined by the neuron's bias, which influences the threshold of activation. Subsequently, the activation function corresponds to the axonal process in biological neurons, where it modulates the generation of an output signal y, analogous to a neural impulse, which then proceeds to the next neuron. When multiple such artificial neurons are connected, they constitute an artificial neural network [10], as exemplified by the diagram in Figure 1.

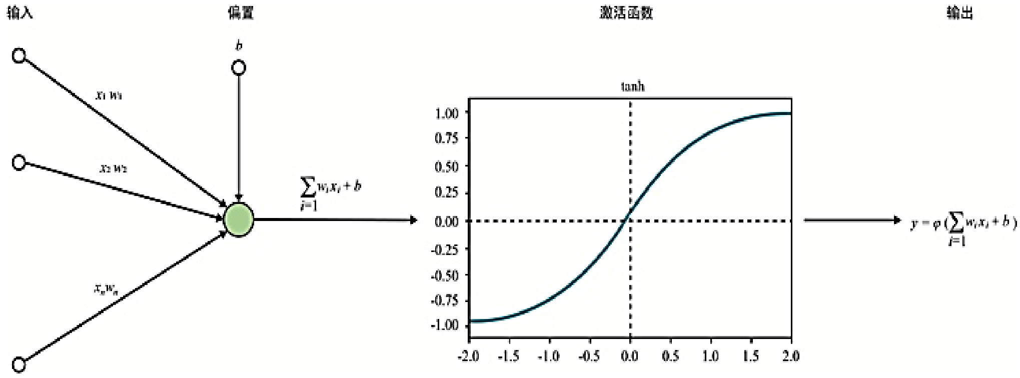


Figure 1: Schematic representation of a simulated artificial neural network

B. *Theoretical Foundation of Convolutional Neural Networks*

Convolutional Neural Networks (CNNs) represent a specialized category within the broader family of deep neural networks, having evolved from their fully connected predecessors[11]. They are distinguished by their incorporation of convolutional processes[12]. Structurally, a CNN is composed of multiple distinct layers, which include convolutional layers, activation functions, pooling layers, and layers that are fully connected. These networks are typified by their intricate feedforward architecture[13], often referred to as the backpropagation (BP) structure. In the domain of deep learning, CNNs have emerged as a widely utilized methodology[14][15], primarily recognized for their adeptness in the extraction of both image and abstract features. Their importance is particularly pronounced in computer vision[16], where their ability to adeptly manage a variety of visual recognition tasks is unmatched.

C. *Theoretical Framework of Object Detection Algorithms*

Object detection, alternatively known as object extraction, entails the recognition, correct categorization, and exact placement of objects within a given image. Yan et al. [17] unveil an unsupervised deep learning approach that adeptly separates content from noise in MRI images without the need for paired training data, a notable advancement given the complexities of diagnosing conditions like novel coronavirus pneumonia. This methodology employs a combination of content and random noise encoders, Kullback-Leibler divergence loss, and adversarial loss to not only extract but also refine the quality of the imagery, ensuring a more realistic depiction of denoised images. Additionally, by integrating cycle consistency and perceptual losses, these methods guarantee the preservation of content integrity between noisy and denoised outputs, marking a significant leap in visual quality enhancement.

The application of unsupervised learning techniques serves as a pivotal reference point for our research in object detection. Specifically, the innovative use of noise and content separation parallels our efforts to accurately identify and delineate objects in complex visual environments. By drawing on this methodology, we aim to enhance our bounding box regression and non-maximum suppression techniques, ensuring that our object detection algorithms are not only more accurate but also capable of operating efficiently in noisy or visually cluttered images. The ability to maintain high levels of precision in object categorization and localization, despite the presence of background noise or artifacts, could significantly broaden the applicability of our object detection frameworks, particularly in fields requiring nuanced visual analysis such as medical imaging and surveillance[18].

D. *Research on YOLOv3 and FCOS Object Detection Algorithms*

YOLOv3 [19], recognized as a single-stage detection framework, harnesses the power of Darknet-53, which is comprised entirely of convolutional layers, to extract fundamental features effectively. Within the domain of algorithms that detect on multiple scales, YOLO employs a residual network approach that ensures direct connections, merging upsampled high-level feature maps with the existing ones. This fusion enables the network to assimilate both intricate and elementary information simultaneously[20][21]. Subsequently, the network carries out feature categorization and bounding box adjustments, concluding with the application of Non-Maximum Suppression (NMS) to refine the outputs based on predefined thresholds.

Conversely, FCOS stands as a fully convolutional one-stage object detection network that operates on individual pixels through the feature pyramid network (FPN) mechanism. FCOS advances its detection prowess by extracting features and blending them via both up and down sampling, applying pixel-level analysis across different scales to adeptly detect objects of various sizes. FCOS sets itself apart from other networks with its unique 'center-ness' feature, which leads to a comprehensive, anchor-free and proposal-free detection solution [22][23].

E. *Research on Faster-RCNN Object Detection Algorithm*

Faster RCNN is a prominent exemplar of a two-stage detection network algorithm. The process initiates with the extraction of features to form a feature map, utilizing renowned architectures like VGG and ResNet for this extraction[24][25]. Within the region proposal network, this model employs an anchor box generator to produce a diversity of nine anchor boxes of different sizes and ratios at every point on the feature map[26][27]. Following a preliminary classification and bounding box refinement in the region proposal network, the model preserves 2,000 proposal boxes with the highest scores, ensuring an equilibrium between positive and negative examples. During the ROI Pooling stage, these proposal boxes are standardized in size[28][29], and the relevant image sections are excerpted from the feature map. The journey concludes with a fully connected network that undertakes the classification of the features within these proposal boxes and refines the prediction of the anchor boxes to yield highly accurate predictive information[30][31].

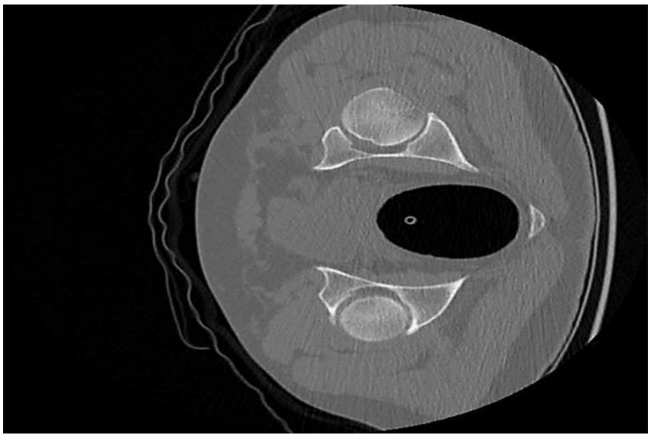
III. EXPERIMENTAL DESIGN

A. Colorectal Polyp Network Transfer Learning

Based on how the dataset is divided, algorithms for neural networks are classified into three categories: supervised, unsupervised, and semi-supervised learning[32]. Algorithms for object detection, which fall under the umbrella of supervised learning, are significantly reliant on the procurement of a high-caliber dataset to ensure the precision of the model[33]. In an effort to hasten the model's adaptation, this research utilizes transfer learning by further training the colorectal model on pre-existing public training sets. This method also serves to incrementally improve the precision of the algorithmic model[34].

B. Acquisition and Construction of Colorectal Image Dataset

The dataset for this investigation was compiled from a multitude of CT scans of patients and corresponding files detailing the locations of colorectal polyps, all gathered from publicly accessible online resources. These images are standardized at a resolution of 512 by 512 pixels, with the labeling data and coordinates for the anchor boxes meticulously documented in text files, which are named to correspond with their associated images. CT scans represent a non-intrusive imaging technique that provides visual representations of internal human tissues. As illustrated in Figure 2(a) (b), the image on the left displays a CT scan of a patient's colorectum, where one can observe small protruding polyps of diverse sizes and shapes on the colorectal wall, a factor that amplifies the complexity of their detection; on the right, the image portrays a CT scan of a healthy adult's colorectum, characterized by a smooth and unblemished colon wall.



(a)

(b)

Figure 2(a) (b): Patients' Colorectal CT Images

In the process of training neural networks, the performance of each developed detection model is assessed to verify its capacity for convergence. The acquired datasets are typically partitioned into distinct sets for training, validation, and testing, ensuring there is no overlap between them. The training set functions as the primary resource for educating the model's algorithm. To bolster the model's generalizability, data augmentation techniques such as rotation, scaling, and cropping are often implemented on the training images. The validation set plays a crucial role in fine-tuning the model's parameters, informed by interim performance outcomes to heighten the model's efficacy and resilience[35][36]. Conversely, the test set is instrumental in appraising the definitive performance of the model, thereby validating the model's ultimate proficiency. For streamlined integration of data into the model, the datasets are eventually converted and preserved in the COCO format [37].

C. Design of Model Evaluation Metrics

In the field of object detection, the accuracy of bounding boxes is quantified using the Intersection over Union (IoU) metric. This calculates the overlap between the predicted and actual bounding boxes as a proportion of their combined area. Typically, an IoU score above 0.5 is indicative of a correct detection, with values approaching 1 denoting an increasingly precise match between the predicted and true boxes.

To compute precision and recall, it's necessary to understand the components of a confusion matrix: TP (True Positive) reflects the count of actual positives accurately identified; FP (False Positive) signifies the number of actual negatives mislabeled as positives; FN (False Negative) represents the count of actual positives mistakenly marked as negatives. Precision and recall are then calculated as per Equations (1) and (2). There exists an inverse relationship between precision and recall, meaning adjustments in the IoU threshold can lead to reciprocal changes in these metrics.

$$Precision = \frac{TP}{TP+FP}$$

$$Recall = \frac{TP}{TP+FN}$$

The Average Precision (AP) metric represents the area under the Precision-Recall (P-R) curve. For any given threshold, a larger AP value signifies a better classification capability of the model. Following this, the Mean Average Precision (mAP) is an aggregate metric that gauges the average precision across all categories for object detection tasks. It is determined by computing the mean of the AP values for each category, as formulated in Equation (3).

$$mAP = \frac{\sum_{q=1}^{Q} AveP(q)}{Q} \tag{3}$$

The primary evaluation metric for this study employs the same assessment method used in the COCO dataset, adopting the most commonly used evaluation metric in the field of object detection, mAP.

D. Experimental Design

In terms of feature extraction, given the critical role of feature extraction algorithms in subsequent object detection algorithms, this study parallelly constructed Faster RCNN networks based on ResNet50, ResNet101, and ResNeSt50 as the basic feature extraction networks, comparing the model accuracy of different feature extraction networks.

The efficacy of an object detection algorithm is intrinsically linked to the prowess of its feature extraction network, which is pivotal to the final detection accuracy of the model. ResNet (Residual Neural Network) is a widely recognized and utilized feature extraction network, commonly integrated into various renowned object detection algorithms [38]. ResNet's innovative concept lies in the integration of residual blocks with direct connection channels within its architecture, which facilitates the blending of raw input data with data that has undergone nonlinear transformations.

This research not only benchmarks fundamental feature extraction networks but also examines the ResNet network model in depth, introducing the ResNeSt network as a comparative subject. The underlying principle of ResNeSt, a network equipped with an attention mechanism[39], is its Split-Attention group-wise channel attention mechanism, which substantially improves the feature extraction of colorectal polyps.

To expedite the model's convergence and enhance accuracy, transfer learning was employed at the outset for model training[40][41]. The colorectal polyp model was then fine-tuned using pre-trained models, with a suitably adjusted learning rate. The chosen optimizer was Stochastic Gradient Descent (SGD) with momentum[42], set at 0.9 to mitigate the risks of saddle points or local minima during gradient descent. Training duration was flexible, concluding when the validation set's mAP stabilized.

A series of ablation experiments were conducted to derive the optimal model. The research juxtaposed single-stage and two-stage object detection networks by comparing FCOS and Faster RCNN, both using ResNet50 for feature extraction, against the YOLOv3 model that employs Darknet53 as its feature extractor.

Concerning feature extraction, the study created parallel Faster RCNN networks based on ResNet50, ResNet101, and ResNeSt50 to serve as the primary feature extraction networks, enabling a comparative analysis of model accuracy across different feature extraction architectures.

E. Results and Analysis

The research commenced with the training and assessment of both single-stage and two-stage object detection networks, inputting the same segmented training and validation sets. Referring to Table 1, the evaluation encompassed three models—YOLOv3, FCOS, and Faster RCNN—and was based on three performance metrics: mean average precision (mAP), mAP for small objects, and mAP for medium-sized objects, along with the time taken for model convergence. The collected experimental results indicated that two-stage object detection models have a substantial edge over single-stage models in terms of accuracy. In light of the precise accuracy demands for the colorectal polyp detection algorithm, the research undertook further refinement and enhancement of the two-stage object detection model.

Table 1: Analytical juxtaposition of three fundamental frameworks

model	mAP	mAP_s	mAP_m	time
YOLOv3	0.474	0.523	0.71	7 h 32 m
Faster RCNN	0.531	0.501	0.813	7 h 58 m
FCOS	0.505	0.511	0.77	8 h 32 m

Acknowledging the enhanced precision of two-stage object detection algorithms compared to their single-stage counterparts, the research also scrutinized the effect of varying feature extraction networks on the model's performance. The networks under examination were ResNet50, ResNet101, ResNeSt50, and ResNeSt101, referred to succinctly as r50, r101, s50, and s101, respectively. The experiments suggested a correlation between the depth of the feature extraction network and the model's mAP; more profound networks tend to abstract richer information, capturing a more diverse array of intricate features. Moreover, advanced feature extraction networks generally contribute to an uptick in model accuracy, as observed with the implementation of ResNeSt networks. In this specific set of experiments, the ResNeSt101 architecture stood out, demonstrating exceptional performance capabilities and only a slight reduction in training velocity when compared to its counterparts. As depicted in Figure 3, networks with greater depth exhibited enhanced feature extraction capabilities, accelerated convergence, and improved accuracy.

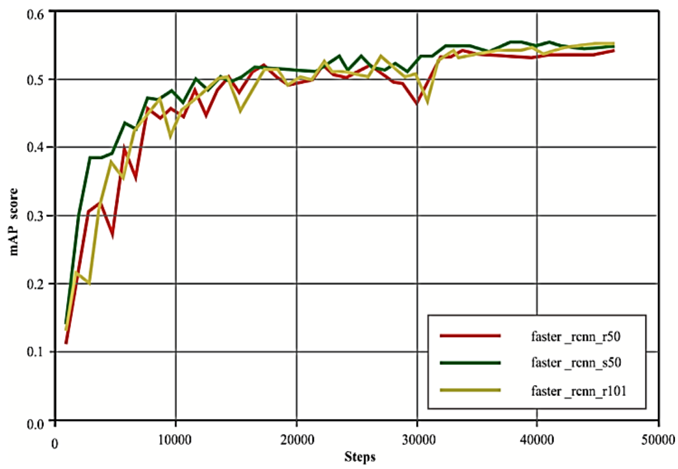


Figure 3: Comparative analysis of networks.

IV. CONCLUSION

The ability to accurately identify colorectal polyps during clinical assessments is significantly influenced by the clinician's expertise. Leveraging computer-aided diagnostic tools offers a substantial opportunity to decrease the likelihood of missed diagnoses, a critical advancement for patient outcomes in the medical industry. The breakthroughs in deep learning technologies, especially in deep convolutional neural networks (CNNs) for image analysis, have prompted this research to explore a range of leading deep CNN-based object detection strategies. This investigation is particularly relevant for enhancing diagnostic precision in the detection of colorectal anomalies, addressing a vital need in medical diagnostics. By conducting a comprehensive evaluation of one-stage and two-stage detection architectures, this study seeks to identify the most efficient model for clinical application. The research further distinguishes itself by refining the feature extraction process of the two-stage model, which is crucial for accurate anomaly detection. Through extensive experimentation with various architectures and depths of feature extraction networks, ResNeSt50 emerged as the optimal choice for the two-stage detection framework, Faster RCNN, thereby significantly improving the model’s detection accuracy. This enhancement not only represents a technical advancement but also a significant step forward for the medical industry, potentially revolutionizing the early detection and treatment of colorectal diseases.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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