Intelligent Histopathological Image Classification for the Accurate Diagnosis of Colorectal Cancer Using Transfer Learning-based Efficient Attention Network

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Abstract: Colorectal Cancer (CRC) is a deadly disease that emerges in the part of the large intestine colon. Early diagnosis is significant for the successful treatment. The traditional method of diagnosing using the biopsy requires medical expertise and is more time-consuming. Therefore, it is replaced by various automatic image analysis models to categorize colorectal cancer. However, the existing investigations still suffer from unreliable accuracy classification because of the complex structure and variability. To solve these challenges, this work introduces a new strategy.In this work, the novel classification methodology is designed based on the Transfer Learning (TL) technique. Here the effective deep learning model is used to distinguish the benign and malignant class. Initially, the required histopathological images are collected from the available dataset. Further, the collected images are subjected directly to the classification phase, where the Efficient Attention Network (EANet) is adopted to classify colorectal cancer from histopathological images. Further, TL is utilized to boost performance and to get accurate classification results.From the experimentation, it is noted that the designed approach offers greater accuracy in categorizing the histopathological images to diagnose CRC than the existing techniques. Hence this methodology is expected to have higher potential to assist the healthcare professionals that can achieve clinical diagnosis of colorectal cancer.

Keywords: Colorectal Cancer Diagnosis; Histopathological Image; Transfer Learning; Efficient Attention Network

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Nomenclature

Abbreviation	Expansion
CRC	Colorectal Cancer
TL	Transfer Learning
EANet	Efficient Attention Network
CAD	Computer Aided Diagnostic
AI	Artificial Intelligence
DL	Deep Learning

1. Introduction

CRC is one of the predominant causes of mortality globally. CRC is considered to be the second most extensive cancer worldwide, which poses to major threat to human health [1]. CRC is the kind of cancer that emerges in the large intestine colon. Early screening and treatment can prevent the death rate effectively and improve the patient's survival rate [2]. In the traditional method of diagnosis, the CRC includes the previous experience of the physician in the clinical setting. The typ`ical diagnostic approach is seen to be less efficient and there is a need for CAD technologies [3]. Compared with the traditional methods, CAD is more effective and it utilizes an extensive dataset and AI for the training [4]. These dependencies generate the explanatory need to minimize the reliance on extensive labeling and improve the early diagnosis of CRC using CAD technologies.

For timely detection, medical imaging is the major tool that helps in diagnosing CRC. For the CRC diagnosis, histopathologists are more frequently adopted to detect the abnormal tissue and cells in the colon tissue sample [5]. However, histopathological images are considered to be a complex task because it requires more expertise [6]. To address this limitation, DL techniques have emerged as an effective solution for histopathological image classification.

In medical image research, DL captured recent attention, which exhibits the potential to achieve the automatic image analysis task. This characteristic strengthens the exceptional performance of DL in classifying the histopathology image [7]. Even though DL performs better, its effectiveness mainly depends on the well-annotated dataset to attain generalizability

and high performance [8]. Tragically, the histopathology domain faces complexity with the annotated data because of its high cost.

To solve this complexity, TL has been designed as the general strategy in the histopathology sector [9]. The impressive detection is reported in multiple types of research using TL. This is the pre-trained method, instead of training the dataset from scratch [10]. The TL effectively fine-tunes the model for large datasets to achieve the target solution. Although TL is more advanced it minimizes the efficiency of the DL approaches that include the pre-trained model like the less useful information from the smaller patches [11]. In addition, the complexity of traditional TL hampered the efficiency of the pre-trained network and the feature extraction process [12]. To overcome this limitation in the traditional TL-based model, this work initiated the advanced DL model to enhance the histopathology patch analysis in diagnosing CRC.

The following components are considered in this work. The process of diagnosing the CRC includes the data collection and classification phase. The available histopathology image dataset is taken from the open dataset to evaluate the designed approach. Further, the EANet is selected, which is the most significant model that operates with the image dataset. The main aim of the implementation is to develop an approach, which can help the specialist by the process automation in CRC classification. Hence TL is utilized to classify the CRC by training the EANet on histopathology images. TL is implemented mainly to enhance the classification accuracy based on the pre-trained model to fine-tune it for the corresponding new task. This helps in minimizing the computation power and the time consumption without compromising accuracy.

The key contributions of this study are summarized below:

- To introduce the novel DL technique tailored for the histopathology image classification task in diagnosing CRC. In addition, the classification task is enhanced by utilizing the TL mechanism, which allows the model to readily adapt to different datasets.
- To employ an EANet for histopathology image classification to detect the CRC. This approach enhances the performance based on its linear memory and allows the implementation of more attention mechanisms to determine the higher resolution part, which helps to boost the classification task.
- To design the TL scheme along with the EANet, which can transfer knowledge among the histopathological dataset of different types of images. This mechanism effectively solves the scarcity of annotated data based on the knowledge gained from the earlier task.

The organization of the work is listed below. Section II explores the different methodological frameworks for classifying the CRC based on the histopathology images, which includes the TL network along with the classifiers. Section III presents a detailed discussion of the network model used in this article and highlights the classification performance of the designed approach. Section IV provides the experimental outcome including the comparative analysis. Section V outlines the discussion of the presented work with its identified limitations and future work suggestions.

2. Related Works

2.1. Transfer Learning Networks

The multiple traditional DL network based on TL was implemented for image analysis in the earlier experimentations, some of the corresponding methodologies were explained here. In 2024, Chughtai *et al*. [13] implemented DL with the divide-and-conquer strategy for the CRC classification task. This methodology initiated the pre-trained network to analyze the corresponding feature by incorporating the TL principle. Clinical standard datasets were utilized to determine the efficacy of the approach resulting in the remarkable accuracy of the proposed model. In 2024, Ping *et al*. [14] designed an intra-domain TL-based ensemble network for determining the histopathology images. The achieved result defined the capability of the proposed ensemble network in extracting the rich features and function better on the low-resolution histopathology images. The outcome shows the network's potential to enhance the patient's survival rate.

In 2022, Souaidi *et al*. [15] introduced deep TL to enable feature extraction to take out the highly representative feature from the given histopathology image dataset. The feature map was forwarded to the multi-box identifier to determine the result. In 2022, Mehmood *et al*.

[16] developed an accurate and efficient approach for detecting colon cancer from histopathology images. The TL-based AlexNet was designed to classify the given image to diagnose the CRC with greater accuracy. From the outcome, the developed approach enhanced the overall accuracy and also boosted the computational efficiency. However, other than the advancement in the TL application in medical image analysis, there were still some limitations like poor interpretability and insufficient data. Hence there was the need for solving the presented challenges to further enhance the image analysis through TL.

2.2. Applications of Transfer Learning in Image Classification

Various existing research utilized the TL approach for histopathology image classification tasks in the CRC diagnosis. Some of the outstanding efforts are explained here. In 2021, Wang *et al*. [17] have suggested the deep Convolutional Neural Network (CNN) in AI for CRC diagnosis. In the clinical setting, the patch aggregation strategy was involved to train and validate the available dataset. The pre-trained model effectively detected the CRC for the open dataset and attained an accurate result. In 2023, Khan *et al*. [18] recommended an ensemble model and TL to create the detection mechanism for analyzing the histopathology images. The excellent performance was generated from the proposed ensemble model with maximum specificity and sensitivity. In 2024, Prezja *et al*. [19] presented the hybrid ensemble machine learning and deep TL to enhance the classification result of histopathology images in the medical field. This work integrated the random forest mechanism with the EfficientNetV2 to achieve an accurate image classification model. In 2023, Haider *et al*. [20] initiated the multi-scale feature retention and aggregation network (MFRA-Net) to enhance the segmentation result. TL was included to pre-train the approach, which helps in boosting the performance of segmentation. The result effectively supported the medical professional in the surgical process based on the CRC diagnosis result.

3. Methods

3.1. Transfer Learning Model

Image processing tasks in the medical field needed professionals to annotate the medical images. Data labeling is one of the most expensive and tedious tasks because the clinical data is more related to the confidentiality of the patient. Therefore it is more complex to construct the clinical dataset. One of the most significant strategies in the present DL network is TL, which helps to alleviate the issues. TL [21] is a kind of DL approach that is influenced by the human thinking system. It utilizes prior knowledge or previous problem-solving techniques to improve the performance ability of the corresponding task. TL expands the current knowledge based on the existing information and heavily minimizes the model training time. In TL, the large dataset is used to train the network and analyze the information based on the knowledge gained from the small dataset. There are different investigations have been done on the TL in the image classification task. While compared with the general baseline neural network, TL only needed a small dataset to train the network which resulted in the maximum accuracy with less training time. The diagrammatic flow of the TL mechanism is defined in Fig. 1

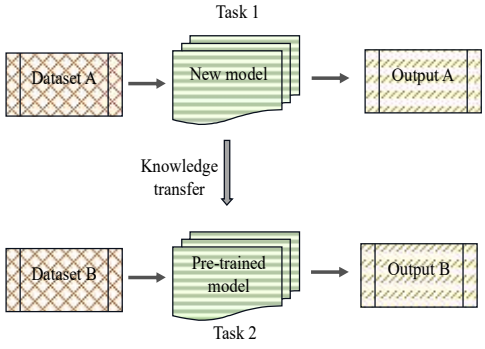

Fig 1. Diagrammatic representation of transfer learning

3.2. Efficient Attention Network

EANet [22] is generally constructed based on the dot-product attention mechanism. EANet achieves higher and quicker memory efficiency. In the network, the single feature vector

$W \in Q^{m \times c}$ moved towards the different linear layers to generate the queries, keys, and values in terms of $P \in Q^{m \times c_j}$, $J \in Q^{m \times c_j}$ and $U \in Q^{m \times c_j}$.Moreover, other than combining the keys in the feature vector, the system managed them into the single channel feature map along with the c_k. Each feature map is utilized by the EANet as a weighting factor to attain the overall formation and the aggregation of the value feature summed with its weight to generate the global context vector. For the corresponding position, the vector is not specified, but it determines the input feature global description. EANet mechanism is formulated using Eq. (1)

$$D(P,J,U) = \rho_p(P)(\rho_j(J)^T U) \tag{1}$$

Here the key and query normalization function is indicated as ρ_j and ρ_q. The formulation of the two normalization mechanisms is evaluated using Eq. (2) and (3)

$$\rho_p(X) = \rho_j(X) = \frac{X}{\sqrt{m}} \tag{2}$$

$$\begin{aligned} \rho_p(X) &= \sigma_{rw}(X), \\ \rho_k(X) &= \sigma_{cl}(X), \end{aligned} \tag{3}$$

Here the softmax function application based on the column and row is specified as σ_{cl} and σ_{rw} for the matrix X. The matrix gets flattened by the module in the input feature map and initiates the efficient attention strategy to reshape the output. In the end, the residual structure is constructed with the added mechanism to the input feature.

3.3. TL-based EANet for Classification of Colorectal Cancer

For classifying CRC from the histopathology images, the EANet is developed, in which the network performance is enhanced by implementing the TL strategy.

While training the EANet model with a smaller number of images, there is the presence of an overfitting issue. Hence TL is initiated to bring a solution to this issue. In TL the method utilizes the knowledge gained from the training of the relatively large dataset. Initially, the collected histopathology images CR_n^{Hi} are directly given to the designed TL-based EANet model. The EANet model has been pretrained using the given histopathology image dataset. TL strategy helps in utilizing less training data, by selecting the best possible medical images for the training and generating successful results. TL has the generalization ability that uses a limited number of histopathology images to train the EANet. Utilization of TL-based EANet in classification tasks attains several benefits. The network training does not require a larger number of images, whereas it can be effectively performed with a smaller number of images. Based on the knowledge gained from a similar type of task, TL improves the new task learning. TL-based models minimize the computational cost, training time, and generalization error. Fig. 2 shows the visualization of the TL-EANet structure for classifying CRC.

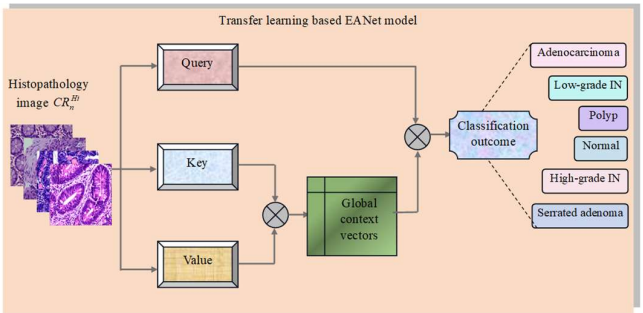

Fig 2. Architectural illustration for TL-EANet model

4. Results

4.1. Dataset Details

This investigation utilized the standard dataset to validate the effectiveness of the designed approach and it was taken from the link https://www.kaggle.com/datasets/lavensrivastava/ebhi-seg/data Access date 2024-11-08. The EBHI Seg dataset contains the different classes of histopathological images that help to detect CRC in patients. The different classes of images the high-grade, low-grade, adenocarcinoma, normal, serrated adenoma, and polyp.

Based on the given dataset the collected images are specified as CR_n^{Hi}. Here $n = 1,2,3,\ldots,N$, the term C is the total number of images. The sample histopathology images with different classes are defined in Fig. 1

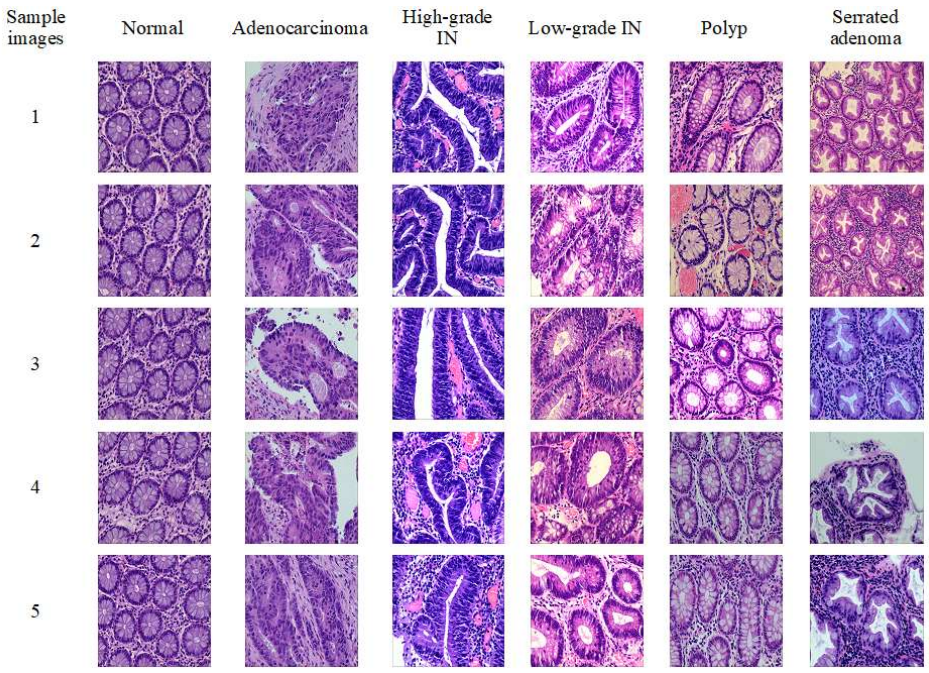

Fig 3. Sample histopathological images from the given dataset

4.2. Experimental Setup

The experimentation of the designed TL-based EANet for the CRC classification task was performed using the Python platform, which assisted with all computational modeling. Different methods were used to compare the proposed TL-based EAN model such as CNN [14], AlexNet [16], Xception [18], and MFRA-Net [20] were adopted.

4.3. Performance Evaluation of the Classification Task

Fig. 4 shows the performance analysis of the proposed TL-EANet model, by comparing it with the classical techniques. Here different classes of images collected from the given dataset are utilized to determine the functionality of the proposed classification task. By taking the adenocarcinoma class image, the balanced accuracy of the proposed TL-EAN was enhanced by 6.2% of CNN, 4.1% of AlexNet, 2.6% of Xception, and 1% of MFRA-Net. From the result, it is observed that the balanced accuracy of the model on each class histopathology image gradually enhanced as the number of training increased.

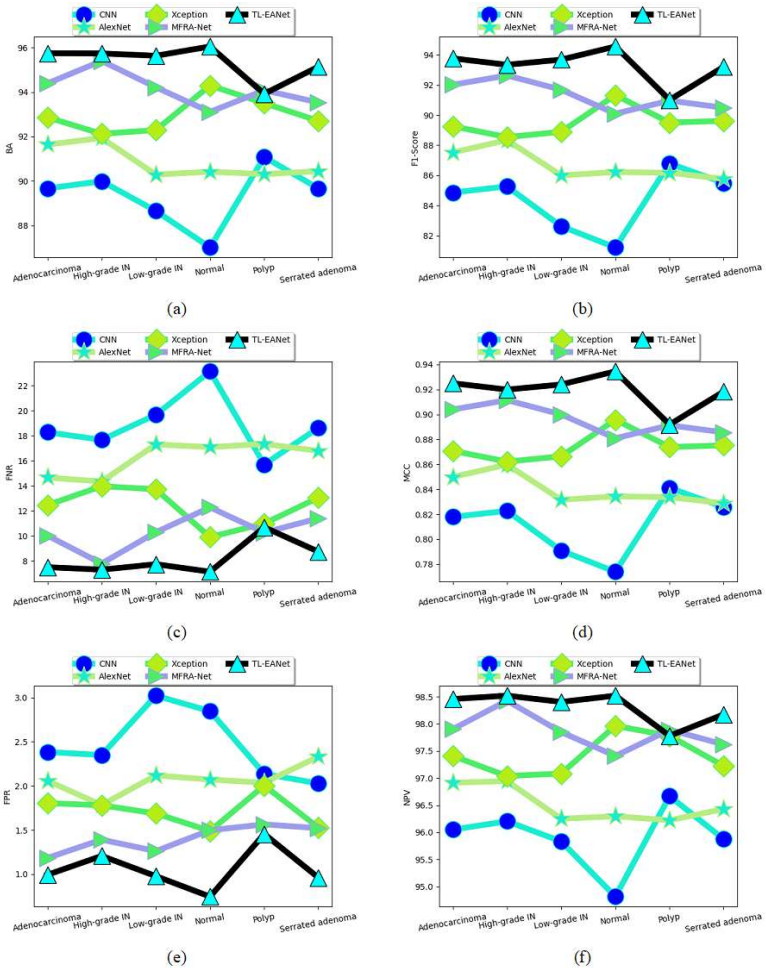

Fig 4. Comparison of designed TL-EANet-based CRC classification with other literature models for different classes of histopathological images regarding "(a) Balanced accuracy, (b) F1 score, (c) False negative rate, (d) Matthew's correlation coefficient, (e) False positive rate, and (f) Negative predictive value"

4.4. Comparing the Proposed Technique with Baseline Approaches

Comparative experiments are conducted to demonstrate the superiority of the approach. Here some common literature models are taken under the experimental parameter to train and test the accuracy. The accuracy of the model for the CRC classification is documented in Table I by varying the epoch value. From the graphical representation, the accuracy of the TL-EAnet was enhanced by 7.6% of CNN, 5.7% of AlexNet, 3.7% of Xception, and 1.1% of MFRA-Net respectively by taking the epoch value as 50. By analysing the experimental outcome the traditional approaches do not perform well in the classification accuracy. From the investigation, it is noted that the proposed TL-EANet achieves more excellent classification results than other approaches.

Table 1.Comparative Result For Evaluating Classification Accuracy Based On Varying Epoch Value

Epoch value	CNN [14]	AlexNet [16]	Xception [18]	MFRA-Net [20]	TL-EANet
50	87.53086	89.32099	91.23457	93.64198	94.75309
100	87.53561	89.17379	91.59544	92.66382	94.94302
150	88.13131	89.14141	91.91919	92.76094	93.77104
200	88.7037	87.96296	90.92593	91.85185	96.2963
250	86.77249	88.49206	91.53439	94.17989	94.84127

5. Discussion

5.1. Summary

In this work, the TL-based EAN model was proposed to classify the CRC from histopathology images. Initially, the required histopathological images for classifying the CRC were collected

from the EBHI Seg dataset. Different classes of histopathological images were taken and tested using the proposed TL-based EANet approach. TL effectively enhanced the performance of the classification task based on the prior knowledge. In the end, comparative experimentation was conducted with the other state-of-the-art model to demonstrate the performance of the proposed classification task. From the achieved result, the better classification attained by the proposed TL-EANet than other traditional approaches.

5.2. Limitation and Future Work

This work provides some challenges that are significant to acknowledge and solve in future research.

- The present experiment directly analyses the histopathology images from the dataset for CRC classification and has not been enlarged to other processes like image preprocessing and segmentation. Therefore future work should focus on implementing the effective image segmentation task to improve the accuracy of the detection.
- Our proposed methodology is based on the pre-trained detection network by following the TL principle. This reliance achieved maximum accurate detection, but there is a complexity in the generalizability of the model. Hence in future work, the feature extraction approach will be explored to enhance the generalization of the model.
- The fine-tuning process and the pre-trained approach tend to be highly computationally expensive and need specialized hardware. To address this issue, the new heuristic algorithm-based optimization DL approach will be suggested in the future.

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