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A COMPARATIVE APPROACH TO PREDICTING COLORECTAL CANCER USING DEEP LEARNING-BASED FRAMEWORKS

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Abstract

Colorectal cancer (CRC) is the most serious condition that affects both men and women globally. Recently, growing interest in technological resources has been noticed in diagnosis of cancer of various types. The colorectal cancer is also major cause of death worldwide. High resolution medical images are great source of cancer prediction by using the power of deep learning (DL) algorithms in effective way. Present work focuses on comparative analysis of three deep learning models to predict colorectal cancer using publicly available 7180 images dataset for CRC classification. These frameworks are MobileNetV2, ResNet50 and VGG-16. This can be helpful for practitioners and investigators to understand the challenges in predicting cancer by utilizing new technologies based on deep learning methodologies. Generally, different deep learning methods for colorectal cancer detection are inspected for better understanding of more useful method. The efficiency of deep learning models is evaluated with standard error metrics. The performance metrics of models show that ResNet50 model is more reliable for cancer prediction as compared to MobileNetV2 and VGG-16 applied on selected dataset utilized in this study. The findings highlight the potential of deep learning-based approaches as supportive tools for automated colorectal cancer diagnosis, while also emphasizing the importance of model selection, accuracy, and reliability for future clinical applications.

1 Introduction

Cancer is the major reason of death worldwide and affecting human rapidly. Detection of cancer at an early stage is crucial in order to reduce the death rate. Among males and females, colorectal cancer (CRC) ranks as the third major frequently detected type of cancer. Colorectal cancer (CRC) remains a substantial global health challenge and is accountable for a remarkable amount of cancer associated deaths around the global [1]. Among CRC patients with clinical manifestations, around 60–70% receive a diagnosis after the disease has progressed to an advanced stage [2]. Late-stage recognition drastically reduces survival and detection at early stage may contribute to improved clinical outcomes by minimizing treatment delays and lowering morbidity and mortality associated with the disease.

Conventional diagnostic methods like colonoscopy and biopsy-based histopathology are effective but controlled by operator expertise, cost, and accessibility. The recent surge in

artificial intelligence (AI) framework and methodologieshave created opportunities to augment existing workflows, enabling earlier detection, better prediction, and reduction in diagnostic errors. Artificial intelligence techniques are involved in the healthcare domain and exceptionally growing rapidly. The application of machine learning significantly exceed in improving diagnostic accuracy, treatment selection, and prognostic assessment [3]. Use of AI driven strategies is cost effective and healthcare providers get clear understanding of the factors influencing cancer assessments to make treatment decisions and effectively care for patients. The AI-based predictions possess significant information to clinical implementation. AI can effectively recognize complex patterns in clinical healthcare data and obtains insights in order to develop predictions, diagnoses, prognoses, more accurately.

Convolutional neural networks are widely engaged in various clinical purposes and colorectal lesions can be identified from colonoscopy images for the recognition and categorization of polyps. Medical devices are the physical aspects of AI and deep learning falls in subcategory of machine learning (ML) which belongs to the virtual element of AI [4]. CNNs are deep learning networks learn important pattern form images and provide predictive information from new image data. Studies report strong performance in automated lesion detection. Results obtained from the experiments confirm the efficiency of CNNs in classifying CRC tissue types and strong performance observed in case of presegmented regions [5]. Among deep learning approaches, convolutional neural networks (CNNs) are referred to specialized form of multilayer artificial neural networks known for their superior performance and computational efficiency [6]. The rapid advancements of neural network models have significantly improved medical image analysis and diagnostic systems. Recently, researchers designed models based on AI to progress CRC screening outputs through the reduction of missed adenomas and the associated danger of developing cancerous cells [7].

A framework for the analysis of multispectral colorectal cancer based on convolution neural network was suggested in [8], to facilitate early diagnosis from trained model on the data from the electronic medical record (EMR). The study [9] designed a deep learning algorithm which use H&E whole slide imaging help in determining the survival period for patients suffering from stage II-IV CRC cancer. The deep learning models for colorectal cancer prognosis have been developed in research work [10] based on multicentre retrospective data of 4,428 patients from Australia, Germany, and USA. In [11], researchers introduced AI4CRC that is a deep learning framework designed to enhance early detection and prevention of colorectal cancer. The researchers used different models in the diagnosis of polyps. In [12], an approach for identification of colorectal cancer using pathology slides was introduced. A framework was proposed for colorectal cancer identification utilizing whole-slide images using weak supervision and a reduced-sample training strategy.

In research attempt [13], machine and deep learning methods utilized for colorectal cancer identification were examined for the future opportunities and challenges for cancer cure. The work [14] presented methods to develop a multistain model that targets prognosis and therapy response of CRC cancer. A multistain deep learning framework was constructed to calculate an AI-derived immunoscore in more than 1,000 colorectal cancer patients. In [15], researchers have proposed an ensemble-based deep learning framework for multi-tissue grouping of CRC cancer. This study proposes a hybrid framework combining a conjunction of dilated ResNet with an attention mechanism, dimensionality reduction and DeepSVM classifier. The research attempt [16] carried out a study deep learning techniques utilized in histopathology imaging for the purpose of CRC diagnosis. The work [17] introduced a residual deep learning model along with nursing care data

for colorectal cancer prediction, which helped in identifying the disease at an early stage and risk assessment in the clinical setting. Residual convolution neural network was used for training purposes. In [18], authors have designed a clinical decision support tool that involves the pathologic markers for optimal choices in terms of adjuvant chemotherapy in colorectal cancer. DoMore-v1-CRC is an advanced deep learning marker based on H&E staining was utilized in this study.

The CNN model for predicting colon cancer patients using deep learning was presented in [19] which analyze MobileNetV2 with regard to their accuracy in classifying and predicting colon cancer. The research conducted in [20] entailed prediction of the outcomes of colorectal cancer with the utilization of DoMore-v1-CRC classifier applied on digitally scanned H&E-stained tissue slides. The investigator [21] used Inception V3 in histopathological analysis for perceiving and segmenting colorectal cancer in digitized histology images. The model showed very high accuracy, particularly in identifying normal tissue, and strong performance in cancer detection. In [22], the researchers identified pathogenic genes and applied deep learning models to forecast colorectal cancer diagnosis to enhance genome and clinical precision.

2 Methodology

(a) The Proposed Models

Three convolutional neural network (CNN) structures were chosen and used to perform the multiclass classification of colorectal cancer histopathological images. EfficientNet-V2, ResNet50, and MobileNetV2 are the selected three models under consideration. EfficientNet-V2 was selected due to its more efficient training and a scaling procedure that balances the model's accuracy in classifying the images, while simultaneously reducing its computational requirements. Architecture designed for improving feature extraction process reduces the complexity of training suitable for large scale image classification problem. ResNet50 is a powerful mechanism of deep residual learning. ResNet50 overcomes the vanishing gradient problem by using the residual connections, and is able to learn the complexity of the image features. MobileNetV2 is a lightweight architecture and is efficient in computational demand as it requires lesser computation. The model also uses depth wise separable convolutions and inverted residual blocks that considerably reduce the number of involvingfactors without compromising the classification accuracy. The short comparison of selected CNN models is presented in Table 1.

Table 1: Comparative analysis of selected deep learning models.

Model Type	Advantages	Limitations
MobileNetV2	Lightweight and fast	Lower feature depth
VGG-16	Simple architecture	Large model size
ResNet50	Deep feature learning	Higher computation

(b) Dataset

The dataset include microscopic images of colorectal cancer and related tissues, which are used for image classification and medical image analysis tasks. In this study 7,180 histopathological images were used. The number of normal colorectal tissue images and abnormal colorectal tissue images are shown in Table 2 according to selected dataset. The images were stored in .tif image format to maintain the image quality and detailed information about the tissues that is necessary for feature extraction from the images by the convolutional neural network (CNN) model. This dataset contains nine classes of different tissue types related to the diagnosis and classification of CRC.

Table 2: Distribution of normal and abnormal colorectal tissue images in the dataset.

Type	Number of Images	Description
Normal	741	Normal colorectal tissue images
Abnormal/Cancer	6439	Abnormal and cancer-related colorectal tissue images
Total	7180	Total dataset images

(c) Data Preprocessing

The quality and consistency of medical images used for deep learning-based medical image investigation are crucial to success of CNN models and data preprocessing a critical step. The reason of this work was to construct several preprocessing methods to improve the training and classification of the histopathological images. First of all the images were resized to the same size of 224 × 224 pixels to ensure uniformity of input size throughout the data set. The standardization of the image size is crucial since in the training process the CNN requires fixed-size images as input. Resizing also reduces the computational cost and the efficiency of the training. The image was resized and then pixel values of the image were normalized prior to feeding it to the deep learning models. Normalization ensures that pixel intensity values fall within a more compressible extent, thereby causing the learning process to be more stable, converging when optimizing the parameters, and less likely to result in an unstable gradient.

(d) Data Augmentation

Data augmentation is a very popular one in the area of deep learning that involves the creation of multiple or similar versions of the data available to train. In medical image analysis, data augmentation can play an essential role by developing the generalizability of the CNN architect and avoiding overfitting, especially in the case of smaller amounts of data. The model is designed to resist changes in the orientation and structure of tissues through image rotation up to 20°. By doing this, the models learned important features that were taken from images from different angles. The training images were also horizontally and vertically flipped. The CNN models demonstrated their ability to identify tissue patterns as the transformations included in the dataset did not cause them to lose their ability to classify and learn features. Moreover, zoom augmentation with the zoom range of 0.2 was applied. The models were taught both local and global tissue features by randomly zooming in on image sections during training using this technique. Width and height shifting operations were also used to slightly shift an image in the horizontal and vertical directions by 0.1 in the range of 0-1. Moreover, shift ranges of 0.1 were used for width and height shifting operations for slight shift along the horizontal and vertical directions, respectively. These changes enhanced the sensitivity of the models to identify meaningful patterns even if the tissue structures were seen in different locations in the images.

(e) Model Training

The deep learning models used in present study were trained with the same set of training parameters to make the comparisons between the selected CNN architectures. The training configuration was carefully chosen to get efficient learning while keeping the computation efficiency. During training a batch size of 32 was employed and 32 images were processed at a time. The use of mini-batch training improves memory efficiency and helps stabilize the optimization process. During each epoch, the entire training dataset was passed through the network once, allowing the models to progressively learn discriminative features from the histopathological images. The training process was performed on a multiclass classification problem consisting of nine classes. To estimate model generalization efficiency, the dataset was divided into two parts training and validation utilizing an 80% and 20% ratio, respectively. The validation dataset was used to

examine model learning behaviour and assess classification performance on unseen images during training. The models included in this study are coded in python language and supporting libraries were used for training process.

3 Results

The evaluation of the adopted models implemented is given in Table 3. Validation data were used to evaluate the process after the training was finished. Accuracy, precision, recall, and F1-score defined below are taken to evaluate models under consideration. The relevant formulas are given as

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN},$$
$$\text{Precision} = \frac{TP}{TP+FP}, \text{Recall} = \frac{TP}{TP+FN}, \quad (1)$$
$$\text{F1 – Score} = \frac{2(\text{Precision})(\text{Recall})}{\text{Precision}+\text{Recall}}.$$

Here, TP and TN show number of true positive and negative predictions respectively. In addition, FP and FN signify number of false positive and negative predictions accordingly. From results obtained, it was observed that each the CNN models have a good classification accuracy on the colorectal cancer histopathological image dataset. The performance results indicate that the deep learning methods can well learn discriminative tissue features and make multiple colorectal tissue categories correctly classified.

Table 3: Classification results and comparison of CNN architectures performance.

Model Name	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
MobileNetV2	96.79%	96.81%	96.79%	96.78%
ResNet50	97.14%	97.23%	97.14%	97.10%
VGG-16	96.86%	96.99%	96.86%	96.86%

4 Discussion

The model with the best overall performance was ResNet50, which attained an accuracy of 97.14%, precision of 97.23%, recall of 97.14% and F1-score of 97.10% among the evaluated models. The performance advantage of ResNet50 over other models is due to the residual learning mechanism which allows deeper network for extracting features and also mitigates the difficulty of controlling gradients during training. The residual connections help network to learn more complex tissue properties than traditional CNN architectures. MobileNetV2 also showed good classification performance, achieving an accuracy of 96.79%. Although the model was lightweight, it performed competitively on all evaluation metrics, while having fewer parameters. The design of a MobileNetV2 is efficient and computational efficient with a good classification accuracy. This feature enables the model to be used in resource-limited contexts such as medicine and real-time diagnostic systems. VGG-16 also yielded good classification performance with a classification accuracy of 96.86%. It demonstrated good stability and feature learning ability for histopathological image classification in the model. The performance of VGG-16 was slightly lower than ResNet50, however, this could be attributed as there are no residual learning mechanisms in deeper layers for VGG-16. In general, the results obtained from the experiments show that CNNs are suitable to classify colorectal cancer histopathological images with high accuracy and reliability. All models performed well, but ResNet50 performed better than the other architectures in classification accuracy. The comparative analysis of the three CNN models shows that the architecture of the CNN is an important factor in medical image classification performance. ResNet50 had the best overall performance, as its residual connections enabled the network to learn deeper and more meaningful image representations without the vanishing gradient problem. Although slightly less accurate than ResNet50, the lightweight architecture of MobileNetV2 has benefits in terms of computational efficiency and the

simplicity of the model. This renders MobileNetV2 as a viable choice for the hardware constrained and inference-speed-critical applications. Good feature extraction ability was also demonstrated by VGG-16 when applied to colorectal cancer tissue classification, with competitive performance. However, the model has more parameters and demands more computational resources than MobileNetV2 and ResNet50. The overall findings validate that the deep learning-based CNN models are extremely effective in colorectal cancer detection utilizing the histopathological images. The achieved best accuracy and well-balanced precision, recall, and F1-score values in this work show that the selected models were able to learn important tissue characteristics and perform the multiclass classification well.

5 Conclusion

The results of present work demonstrate that deep learning models are very efficient for the task of medical image classification in the context of the classification of images related to colorectal cancer. The outcomes demonstrate that the three models, MobileNetV2, ResNet50 and VGG-16 models can be used to obtain good classification performance, among which the ResNet50 model has the best overall stability of accuracy, precision, recall and F1- score. The ResNet50 have better feature extraction ability in comparison with other models use in this study for CRC classification. In conclusion, the results demonstrate that deep learning can contribute a lot in the field of medical diagnosis, especially in the early and accurate diagnosis of diseases. There could be some other factors that affect the performance, such as the size, quality, and the imbalance of classes in the data sets. Expansion of the dataset, the implementation of more sophisticated architectures, hybrid model utilization and to optimize the model to improve the predictive power and clinical value can be taken up for future work.

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