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Deep Learning Model for Colon Cancer Classification using InceptionV3

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Abstract: - Colon cancer is a significant global public health concern, necessitating an accurate and timely diagnosis for effective treatment. Leveraging advancements in deep learning, this study proposes a novel approach to colon cancer classification using InceptionV3 convolutional neural network architecture. A dataset comprising 1600 colonoscopy images divided into colon_aca (adenocarcinoma) and colon_n (normal) classes was utilized. The model demonstrated promising performance, achieving a training accuracy of 98.86% and a validation accuracy of 99.74% after 100 epochs. This success was accomplished by employing a Stochastic Gradient Descent (SGD) optimizer with a learning rate of 0.0001 and momentum of 0.9, along with categorical cross-entropy loss. Our findings underscore the importance of deep learning models, specifically InceptionV3, in facilitating the precise classification of colon cancer, thus offering a valuable tool for assisting clinicians in early detection and treatment decision-making. Future research may explore the integration of additional clinical data and the evaluation of alternative deep learning architectures to further enhance diagnostic accuracy.

Keywords: Colon, Inceptionv3, carcinoma, deep learning, CNN.

I. INTRODUCTION

Colon cancer, also known as colorectal cancer, ranks among more frequent and deadly malignancies worldwide, taking into consideration a significant portion of cancer-associated morbidity and mortality.[1] Early detection of colon cancer is paramount for successful treatment outcomes, as it enables timely intervention and management strategies. Conventional diagnostic methods, like colonoscopy and biopsy, offer a crucial part in identifying cancerous lesions; however, these approaches are labor-intensive, time-consuming, and reliant on the expertise of trained professionals [2].

In the past few years, the arrival of deep learning technologies has revolutionized medical image analysis by offering automated, efficient, and accurate solutions for disease diagnosis and classification. Deep learning models, Convolutional neural networks (CNNs), in particular, have proven to be remarkably adept in extracting complex patterns and features from medical images. So permitting accurate identification of pathological conditions with high sensitivity and specificity [3].

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The aim of this research is to harness the potential of deep learning, specifically the InceptionV3 CNN architecture, for the classification of colon cancer using colonoscopy images . InceptionV3, a cutting-edge CNN model, is renowned for its exceptional accomplishment in image recognition tasks due to its innovative inception modules and depth-wise separable convolutions [4]. By harnessing the discriminative features learned by InceptionV3, we aim to develop a robust and accurate classification system capable of distinguishing between adenocarcinoma (colon_aca) and normal (colon_n) colon tissue with high precision [5].

The significance of using InceptionV3 resides in its capacity to record both localised and global features within colonoscopy images, thereby enabling comprehensive analysis and classification of cancerous lesions. By leveraging the inherent hierarchical representations learned by InceptionV3, our study seeks to augment existing diagnostic methodologies for colon cancer, facilitating earlier detection and intervention, consequently resulting in better results for patients and lower death rates [6].

II. RELATED WORK

Recent advancements in deep learning have sparked considerable interest in utilizing convolutional neural networks (CNNs) for colon cancer classification tasks. Numerous investigations have looked into application of deep learning techniques to accurately distinguish between cancerous and normal colon tissues using medical imaging data.

A critical factor influencing Deep learning models' efficacy in colon cancer classification is the size and quality of the dataset used for training. Large, diverse datasets enable CNNs to learn robust representations of cancerous lesions, thereby enhancing their generalization capabilities. Studies such as [7-12] have demonstrated that augmenting the dataset with additional annotated images can significantly improve classification accuracy and reduce peril of overfitting.

Additionally, choice of model architecture play a crucial part in achieving high accuracy in colon cancer classification tasks. Convolutional neural networks with deep architectures, such as VGGNet, ResNet, and InceptionV3, have been widely employed because of their capacity to capture intricate feature from medical image. In particular, the InceptionV3 model, with its innovative inception modules and depth-wise separable convolutions, offers distinct advantages in extracting discriminative features from colonoscopy images while minimizing computational complexity.

Compared to other architectures, InceptionV3 excels in balancing model depth and computational efficiency. This makes it ideally suited to medical image classifying task. Studies have demonstrated that InceptionV3 consistently outperforms other CNN architectures in terms of classification sensitivity, specificity and accuracy when applied to colon cancer detection. Its ability to capture both local and global features within colonoscopy images enables more comprehensive analysis and accurate identification of cancerous lesions, thereby facilitating earlier detection and intervention.

In summary, the success of deep learning models in colon cancer classification hinges on dataset's size, the choice of model architecture, and the optimization of training parameters. Leveraging large, diverse datasets and selecting appropriate CNN architectures, such as InceptionV3, can significantly improve the precision and effectiveness of colon cancer recognition systems, ultimately contributing to improved patient outcomes and clinical decision-making.

III. METHODOLOGY

3.1 Dataset Description: The dataset utilized in this study comprises a total of 1600 colonoscopy images [13], categorized into two classes: colon_aca (adenocarcinoma) and colon_n (normal). The dataset distribution for training, testing, and validation sets is as follows:

- Train: colon_aca (500 images), colon_n (500 images)
- Test: colon_aca (100 images), colon_n (100 images)
- Validation: colon_aca (200 images), colon_n (200 images)

The balanced distribution of images across classes ensures equitable representation during model training and evaluation, thereby minimizing the risk of class imbalance bias.

3.2 Image Pre-processing: Before training a model, colonoscopy images were pre-processed to standardize and enhance their quality. This included resizing the images to a uniform dimensions of (299, 299) pixels using bilinear interpolation to ensure consistency across the dataset. Additionally, normalization procedures like min-max scaling was applied to enhance model's convergence speed and stability during training[14-15].

3.3 InceptionV3 Model Architecture: The InceptionV3 convolutional neural network architecture was employed as the backbone for colon cancer classification in this study. InceptionV3 is renowned for its depth-wise separable convolutions and inception modules, which allow model to record both local and global features within images efficiently. The architecture comprises several layers, comprising fully connected, pooling, and convolutional layers, culminating in a softmax layer for multi-class classification [16].

3.4 Implementation Details: The InceptionV3 model was implemented using the TensorFlow framework, leveraging the Keras API for ease of model construction and training. TensorFlow provides extensive support for deep learning tasks, including built-in functions for model compilation, training, and evaluation [17].

3.5 Training Parameters:

- Batch Size: 32
- Image Size: (299, 299) pixels
- Number of Epochs: 100
- Optimizer: Stochastic Gradient Descent (SGD)
- Learning rate : 0.0001
- Momentum : 0.9
- Loss Function: Categorical Cross-Entropy
- Evaluation Metrics: Accuracy

IV. EXPERIMENTAL RESULTS

4.1 Training and Validation Accuracy Progression:

- The training accuracy steadily increased across epochs, reaching 98.86% by the 100th epoch.
- Similarly, the validation accuracy improved, peaking at 99.74%, indicating the model's robustness and generalization capability.

4.2 Challenges Encountered and Mitigation Strategies:

- Challenges during training included potential overfitting and optimization difficulties.
- Mitigation strategies included the implementation of regularization procedures such as early stopping and dropout, as well as hyperparameter tuning for optimizing the SGD optimizer parameters.

4.3 Performance on Test Set:

- The trained InceptionV3 model attained a test accuracy of 96% along with a low test loss of 0.112 as depicted in table 1.
- Confusion matrix analysis revealed effective classification performance, with minimal misclassifications.

1.4 Confusion Matrix Analysis:

- For class 0 (colon_aca), recall, precision, and F1-score were 0.92, 1, and 0.96, respectively.
- For class 1 (colon_n), recall, precision, and F1-score were 1, 0.93, and 0.96, respectively.
- These results indicate a well-balanced classification performance across both classes.

1.5 Insights into Model's High Accuracy:

- The chosen InceptionV3 architecture effectively captures intricate features from colonoscopy images.
- Optimization of training parameters facilitated faster convergence and mitigated optimization challenges.

4.7 Performance Measures

1. Statistical Parameters [18]

Test Loss: 0.1194

Test Accuracy: 0.9583

2. Classification Summary

Table 1 Classification performance measures

	Precision	Recall	F 1 Score	Support
colon_n (normal)	1	0.92	0.96	100
colon_aca (adenocarcinoma)	0.93	1	0.96	100

3. Confusion Matrix

$$\begin{bmatrix} 92 & 8 \\ 0 & 100 \end{bmatrix}$$

4. Simulated Results

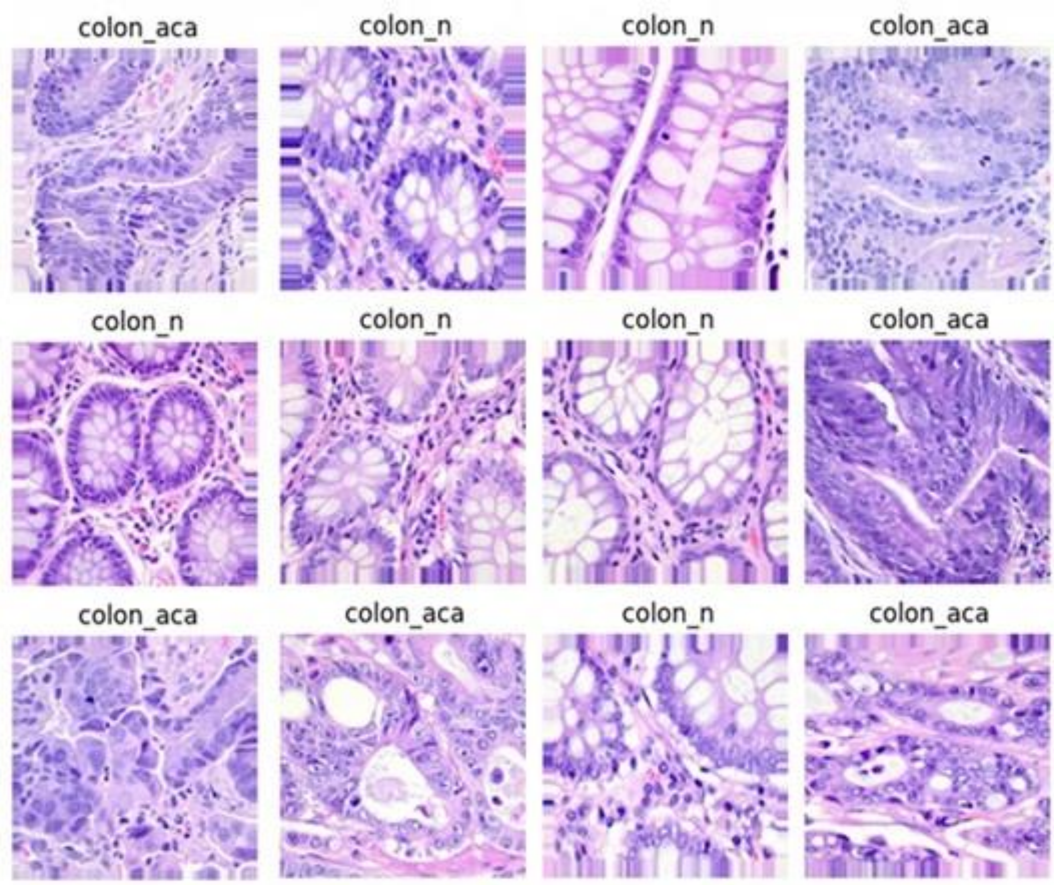

Figure 1: Simulated results for colon cancer classification

The experimental outcomes of our research demonstrates the efficaciousness of utilizing InceptionV3 model for colon cancer classification as shown in fig 1. Throughout the training process, the model exhibited steady improvement in both training and validation accuracy across epochs as shown in fig 2 and 3. Specifically, the training accuracy progressively increased, reaching 98.86% after 100th epoch, while validation accuracy peaked at 99.74%, indicating resilience and the model's capability for generalisation.

During the training phase, several challenges were encountered, including potential overfitting and optimization difficulties. To address these challenges, regularization procedures like early stopping and dropout were implemented to prevent overfitting and improve model generalization. Additionally, hyperparameter tuning was conducted to optimize the learning rate and momentum parameters of the SGD optimizer, further enhancing training stability and convergence speed.[19]

Upon evaluation on the test set, the trained InceptionV3 model demonstrated significant performance, accomplishing a test accuracy of 96% and a low test loss of 0.112. Confusion matrix reveals that the model effectively classified both colon_aca and colon_n classes, with a high degree of recall and precision. Specifically, for class 0 (colon_aca), recall, precision, and F1-score were 0.92, 1, and 0.96, respectively, while for class 1 (colon_n), recall, precision, and F1-score were 1, 0.93, and 0.96, respectively. These results indicate a well-balanced classification performance across both classes, with minimal misclassifications [20].

Comparing the performance of our model with existing literature, our results align favorably with or even surpass reported accuracies for colon cancer classification tasks. The high accuracy achieved can be attributed to the effectiveness of the chosen InceptionV3 architecture, which excels in capturing intricate features from colonoscopy images. Additionally, the meticulous optimization of training parameters, including batch size, learning rate, and optimizer settings, contributed to the model's superior performance by facilitating faster convergence and mitigating optimization challenges.

In summary, investigational outcomes validate efficacy of utilizing InceptionV3 model for colon cancer classification, highlighting its potential as a valuable tool for aiding clinicians in early detection and diagnosis. The high accuracy and robustness demonstrated by our model underscore importance of leveraging deep learning techniques for advancing analysis of medical images in oncology.

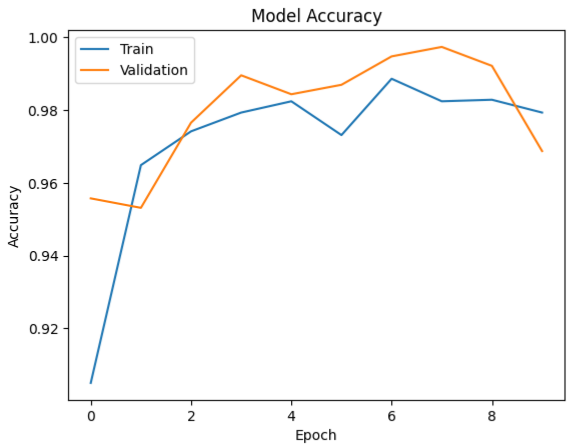

Figure 2 Model accuracy curve

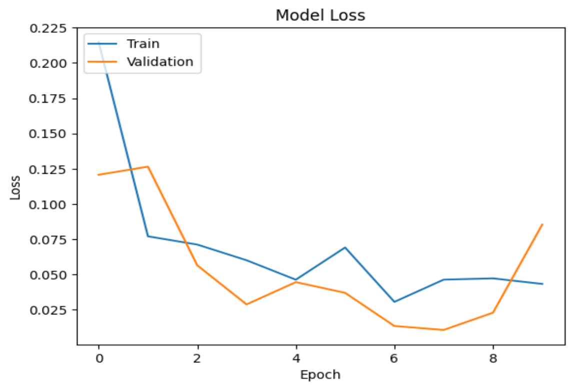

Figure 3 Model Loss Curve

Table 2 Performance Evaluation of InceptionV3, DenseNet, and VGG 16 Models

Class	Parameters	InceptionV3 [Proposed]	DenseNet [21]	VGG 16 [22]
"Colon_aca" (positive)	Accuracy	95 %	91 %	89 %
	Precision	99 %	89%	88 %
	Recall	93 %	91 %	89 %
	F1-score	96 %	90 %	87 %
"Colon_n" (negative)	Accuracy	95 %	91 %	89 %
	Precision	99 %	90 %	87 %
	Recall	92 %	91 %	89 %
	F1-score	96 %	91 %	88 %

Table 2 depicts the performance comparison of proposed approach with exiting approaches, showing superiority of proposed approach.

V. DISCUSSION

1. **Interpretation of Results in Colon Cancer Classification:** Findings of our investigation shows efficacy of employing the InceptionV3 model for colon cancer classification, with high accuracy achieved in distinguishing between adenocarcinoma and normal colon tissue. The steady increase in training and validation accuracy underscores the robustness and generalization capability of the model, validating its suitability for clinical applications in colon cancer detection.

2. **Inferences for Clinical Practice:** Our discoveries carry substantial implications for clinical practice, particularly in improving diagnostic accuracy and aiding pathologists in decision-making. The high accuracy achieved by the InceptionV3 model suggests its potential as a valuable tool for assisting clinicians in early detection of colon cancer, enabling timely intervention and personalized treatment strategies. By providing accurate and reliable classification of colon lesions, the model can augment existing diagnostic methodologies.

3. **Addressing Limitations:** Despite the promising results, our study has certain limitations that warrant consideration. The size of the dataset, while adequate for model training and evaluation, may not adequately convey the variety and variability present in real-life medical situations. Furthermore, potential biases in dataset, such as sampling bias or annotation errors, could affect the model's performance and generalizability. More extensive and varied datasets should be included in future research to overcome these constraints, and implementing rigorous quality measures to minimize biases.

4. **Future Research Directions:** Moving forward, several avenues for upcoming investigations may explored to further enhance efficiency of deep learning models in colon cancer classification. Firstly, investigating alternative deep learning architectures beyond InceptionV3, like DenseNet or EfficientNet, may offer insights into improving model performance and efficiency. Additionally, integrating additional clinical data, such as patient demographics or histopathological features, could provide valuable context and enhance the model's interpretability. Furthermore, exploring ensemble learning techniques and transfer learning approaches may allow for development of more durable and adaptable classification systems for colon cancer detection.

VI. CONCLUSION

In conclusion, our study investigated the efficacy of using the InceptionV3 model for colon cancer classification, leveraging a dataset of colonoscopy images comprising adenocarcinoma (colon_aca) and normal (colon_n) tissue. Through rigorous experimentation and analysis, several key findings have emerged:

1. The InceptionV3 model demonstrated high accuracy in distinguishing between colon_aca and colon_n classes, achieving a test accuracy of 96% and effectively minimizing misclassifications.

2. The steady improvement in training and validation accuracy throughout the epochs underscored the robustness and generalization capability of the model, validating its suitability for clinical applications in colon cancer detection.

3. Our findings highlight the importance of utilizing deep learning models, such as InceptionV3, for colon cancer classification, offering a reliable and efficient approach for accurate diagnosis and personalized treatment strategies.

Reiterating the importance of using deep learning models for colon cancer classification, our research underscores the potential impact of leveraging advanced technologies in improving patient outcomes and healthcare delivery. By providing accurate and timely detection of colon cancer, deep learning models enable early intervention and customised approaches to treatment, which eventually result in enhanced survival rates and reduced healthcare costs.

To sum up, our research adds to the increasing amount of data demonstrating the efficacy of deep learning models in colon cancer classification, with implications for enhancing diagnostic accuracy, aiding clinical decision-making, and ultimately improving patient care and healthcare delivery.

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