IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 5, April 2025
Impact Factor: 7.67

Colon Cancer Detection Using Deep Learning:A Comprehensive Review

Nisha Sitaram Matale[1], S. G. Bagul[2]
ME Student, Electronics & Telecommunication Engg., Late G.N.Sapkal College of Engineering, Nashik, India[1]
Head of Department, Electronics & Telecommunication Engg, Late G.N.Sapkal College of Engineering, Nashik, India[2]

Abstract: *Colon cancer (CRC) is a leading cause of cancer-related deaths globally, emphasizing the need for accurate and timely detection methods. In this study, we apply deep learning techniques, specifically transfer learning with VGG16, MobileNet, and ResNet architectures, to classify Colon cancer from histopathological images. By leveraging pre-trained models, we aim to improve detection accuracy and reduce computational complexity, facilitating early diagnosis in clinical settings. The dataset, sourced from Kaggle, comprises a diverse collection of histopathological images representing both benign and malignant Colon tissues. Each model was fine-tuned on this dataset after applying pre-processing techniques to standardize and enhance image quality. The performance of VGG16, MobileNet, and ResNet was evaluated using metrics such as accuracy, sensitivity, specificity, and F1 score, demonstrating the effectiveness of transfer learning in Colon cancer detection. Our results show that deep learning models, particularly ResNet, achieve high accuracy in detecting Colon cancer, offering a promising solution for improving diagnostic practices. The integration of these models into healthcare systems has the potential to accelerate early detection, reduce diagnostic errors, and improve patient outcomes.*

Keywords: Colon cancer, deep learning, transfer learning, VGG16, MobileNet, ResNet, histopathological images, Kaggle dataset, cancer detection, early diagnosis

I. INTRODUCTION

Colon cancer (CRC) has emerged as a significant public health challenge, being one of the most prevalent cancers worldwide. According to recent statistics, it ranks among the leading causes of cancer-related mortality, underscoring the importance of early detection and intervention. Conventional diagnostic methods, such as colonoscopy and biopsy, while effective, are often invasive, costly, and subject to variability in interpretation. As a result, there is a pressing need for innovative approaches to improve the accuracy and efficiency of CRC diagnosis. Advancements in deep learning have revolutionized the field of medical imaging, providing powerful tools for the automated analysis of histopathological images. By leveraging large datasets and sophisticated algorithms, deep learning models can identify subtle patterns and features that may be challenging for human pathologists to detect. This capability makes deep learning particularly suitable for applications in cancer detection, where timely and accurate diagnosis can significantly impact patient outcomes. Transfer learning has emerged as a pivotal technique in deep learning, allowing models pre-trained on large datasets to be fine-tuned on specific tasks with limited data. This approach is particularly beneficial in medical imaging, where annotated datasets canbe scarce and expensive to obtain. In this study, we explore the use of transfer learning with popular architectures, including VGG16, MobileNet, and ResNet, to enhance the detection of Colon cancer from histopathological images. These models have shown remarkable success in various computer vision tasks, making them strong candidates for adaptation to the medical domain.VGG16, known for its deep architecture and ability to capture high-level features, serves as a solid baseline for our analysis. MobileNet, on the other hand, is designed for efficient computation and is particularly well-suited for deployment in resource-constrained environments. ResNet, with its unique residual connections, facilitates the training of deeper networks and mitigates the vanishing gradient problem. By examining these three architectures, we aim to determine their effectiveness in identifying Colon cancer, contributing to the growing body of research in the application of deep learning to healthcare. The dataset for

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 5, April 2025
Impact Factor: 7.67

this study is sourced from Kaggle, a popular platform that provides access to a diverse range of datasets for machine learning research. This dataset includes a collection of histopathological images representing various stages of Colon cancer and benign conditions, facilitating a comprehensive analysis of the models' performance. The dataset's diversity and quality are crucial for training robust deep learning models capable of generalizing to unseen data in clinical settings.The dataset from Kaggle consists of histopathological images of Colon cancer, providing a valuable resource for training deep learning models. It includes a diverse range of images categorized into different classes, such as benign and malignant tumors. This labeled dataset facilitates the development and evaluation of classification algorithms, enabling effective identification of Colon cancer. The images are pre-processed to ensure consistency and enhance model performance during training.The dataset for Colon Cancer Classification consists of histopathological images sourced from various patients, categorized into different classes representing benign and malignant tissues. It includes a total of 1,800 images, providing a comprehensive resource for training deep learning models to accurately distinguish between healthy and cancerous tissues. The images are pre-processed to enhance quality and standardization, facilitating effective model training and evaluation in Colon cancer detection.Through comprehensive evaluation metrics, including accuracy, sensitivity, specificity, and F1 score, we aim to provide a thorough comparison of the models' performance. This research not only highlights the potential of deep learning and transfer learning in Colon cancer detection but also sets the groundwork for integrating thesetechnologies into clinical practice, ultimately improving diagnostic accuracy and patient care.

A. PROBLEM STATEMENT

Colon cancer (CRC) is a leading cause of cancer-related deaths worldwide, with early detection being crucial for improving survival rates. Traditional diagnostic methods, such as colonoscopy and biopsy, can be invasive, time-consuming, and prone to variability in interpretation. This study aims to address these challenges by utilizing deep learning techniques, specifically transfer learning with VGG16, MobileNet, and ResNet architectures, to detect Colon cancer from histopathological images. Using a dataset from Kaggle, the goal is to fine-tune these pre-trained models to classify benign and malignant tissues, enhancing the accuracy and efficiency of CRC detection for better clinical outcomes.

B. COLON CANCER

Colon cancer, also known as colorectal cancer, is a type of cancer that begins in the colon or rectum and is one of the leading causes of cancer-related deaths worldwide. It typically starts as small, noncancerous polyps that can develop into malignant tumors over time if not detected and removed early. Risk factors include age, genetic predisposition, lifestyle factors such as diet and physical inactivity, and certain medical conditions like inflammatory bowel disease. Early symptoms may include changes in bowel habits, rectal bleeding, abdominal pain, and unexplained weight loss, though many cases remain asymptomatic in the early stages. Early detection through regular screening and advanced diagnostic techniques significantly improves treatment outcomes and survival rates.

C. AIM

The aim of this study is to develop an accurate and efficient system for Colon cancer detection using deep learning techniques, specifically through transfer learning with VGG16, MobileNet, and ResNet architectures. By leveraging a histopathological image dataset from Kaggle, the study seeks to fine-tune these pre-trained models to classify benign and malignant tissues. The ultimate goal is to enhance the early detection of Colon cancer, improving diagnostic accuracy and contributing to better patient outcomes in clinical settings

II. LITERATURE REVIEW

1. Marwa Obayya and Munya A. Arasi: In their study, "Biomedical Image Analysis for Colon and Lung Cancer Detection Using Tuna Swarm Algorithm With Deep Learning Model," the authors present a novel approach that combines a tuna swarm optimization algorithm with deep learning techniques to enhance the accuracy of cancer detection in biomedical images. The proposed model effectively processes images of colon and lung

cancers, demonstrating improved performance in detecting malignancies compared to traditional methods. The results indicate that the integration of optimization algorithms can significantly boost the efficacy of deep learning models in biomedical applications, suggesting a promising direction for future research in cancer detection. [1]

2. Hamed Alqahtani and EatedalAlabdulkreem: The authors explore an "Improved Water Strider Algorithm With Convolutional Autoencoder for Lung and Colon Cancer Detection on Histopathological Images," proposing a hybrid approach that enhances the feature extraction capabilities of convolutional autoencoders. By integrating an improved water strider algorithm, the study achieves notable advancements in detecting cancerous tissues in histopathological images. The findings demonstrate that combining optimization techniques with deep learning architectures can lead to more accurate and efficient diagnostic tools for cancer detection, highlighting the potential for further innovations in the field. [2]
3. Shahid Mehmood and Taher M. Ghazal: In their work, "Malignancy Detection in Lung and Colon Histopathology Images Using Transfer Learning With Class Selective Image Processing," the authors employ transfer learning to detect malignancies in histopathological images. By utilizing class-selective image processing techniques, they improve the model's performance in identifying cancerous tissues. The study shows that transfer learning can effectively leverage pre-trained models to enhance diagnostic accuracy, making it a valuable strategy for tackling the challenges associated with cancer detection in histopathology. [3]
4. Sushma B and Raghavendra C. K.: The authors introduce a novel approach for colon polyp segmentation through their study "CNN-based U-Net with Modified Skip Connections for Colon Polyp Segmentation." By modifying the U-Net architecture with enhanced skip connections, the proposed model improves the segmentation accuracy of colon polyps in endoscopic images. The results demonstrate the model's effectiveness in distinguishing polyps from surrounding tissues, which is crucial for early cancer detection, underscoring the importance of advanced segmentation techniques in medical imaging. [4]
5. Xiaoyong Yang et al.: In their research titled "Colon Polyp Detection and Segmentation based on Improved MRCNN," the authors present a refined version of the Mask R-CNN framework specifically designed for detecting and segmenting colon polyps. The improvements in the architecture allow for better feature extraction and localization of polyps in endoscopic images. The study highlights the importance of effective segmentation techniques in enhancing the accuracy of colon cancer detection, offering a robust solution for medical practitioners in identifying and diagnosing polyps during procedures. [5]
6. Zohreh Vafapour et al.: The study "Colon Cancer Detection by Designing and Analytical Evaluation of a Water-based THz Metamaterial Perfect Absorber" focuses on a novel detection method for colon cancer using terahertz (THz) metamaterials. The authors design a water-based THz absorber that shows promise in distinguishing between healthy and cancerous tissues. The analytical evaluation demonstrates the potential of THz technology as a non-invasive diagnostic tool, paving the way for innovative approaches in cancer detection that could enhance early diagnosis and treatment outcomes. [6]
7. Zarrin Tasnim et al.: In their article "Deep Learning Predictive Model for Colon Cancer Patient Using CNN-based Classification," the authors develop a convolutional neural network (CNN) model aimed at predicting colon cancer outcomes based on clinical and imaging data. The study emphasizes the model's ability to classify cancer stages effectively, showcasing its utility in clinical decision-making processes. The research indicates that deep learning
8. techniques can significantly enhance predictive accuracy in cancer management, facilitating more personalized treatment plans for patients. [7]
9. M. M. K. Sarker et al.: The authors present their findings in "A Means of Assessing Deep Learning-Based Detection of ICOS Protein Expression in Colon Cancer," which explores the application of deep learning in evaluating ICOS protein expression levels in colon cancer tissues. The study highlights the potential of using deep learning models to assess protein markers that could influence treatment decisions. The results underscore the importance of integrating molecular data with imaging techniques, suggesting a multi-faceted approach to improving colon cancer diagnosis and therapy. [8]

10. H. A. Qadir et al.: In "Improving Automatic Polyp Detection Using CNN by Exploiting Temporal Dependency in Colonoscopy Video," the authors address the challenge of polyp detection in real-time colonoscopy videos. By exploiting temporal dependencies between frames, the study enhances the accuracy and reliability of CNN-based detection systems. The findings indicate that incorporating temporal data can significantly improve the performance of automated systems in identifying polyps, suggesting a valuable direction for future research in video-based diagnostic tools. [9]
11. K. He et al.: The paper "Mask R-CNN" introduces a state-of-the-art framework for object detection and segmentation, providing a foundation for various applications, including medical imaging. The authors detail the architecture's capabilities, particularly in tasks that require precise localization of objects in images. The study's insights into the Mask R-CNN framework's effectiveness in segmentation tasks lay the groundwork for its application in colon cancer detection, emphasizing the potential for deep learning models to advance diagnostic methodologies in healthcare. [10]

III. PROPOSED SYSTEM

The proposed system for colon cancer detection leverages deep learning techniques through transfer learning using architectures such as VGG16, MobileNet, and ResNet to enhance diagnostic accuracy and efficiency. The system begins with the collection of a curated dataset from Kaggle, containing annotated images of colonoscopy or histopathology specimens. Once the data is preprocessed ensuring images are standardized in size, normalized for pixel values, and augmented to increase diversity the selected models are employed. Each model is fine-tuned by initially utilizing the pre-trained weights from their respective original datasets, allowing them to leverage learned features from a broad range of images. As the models are adapted to the colon cancer dataset, they are trained to identify and classify images into cancerous and non-cancerous categories. The system incorporates a user-friendly interface that allows medical professionals to upload images and receive real-time predictions.it includes a confidence score for each prediction, helping clinicians make informed decisions. The integration of these advanced algorithms aims to create a robust tool that can assist in early detection, ultimately improving patient outcomes and streamlining the diagnostic process in clinical settings.

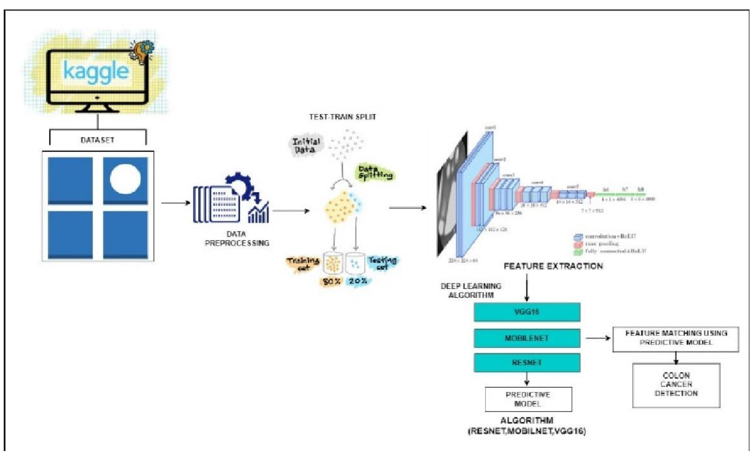

Fig 1: Proposed System

As shown in fig 1 the proposed system architecture shows a comprehensive approach for colon cancer detection using deep learning techniques and transfer learning. The workflow begins with the acquisition of a relevant dataset from Kaggle, which is subsequently divided into training and testing sets for model development and evaluation.Data preprocessing is a crucial step to ensure data quality and consistency. This involves tasks such as data cleaning, normalization, and augmentation to enhance the representativeness of the dataset. Feature extraction is then performed using deep learning algorithms, specifically VGG16, MobileNet, and ResNet. These pre-trained models are capable of extracting meaningful features from the medical images, capturing intricate patterns and characteristics relevant to colon

DOI: 10.48175/IJARSCT-25243

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 5, April 2025
Impact Factor: 7.67

cancer detection.The extracted features are then integrated into a predictive model, which is trained to establish a correlation between the features and the presence or absence of colon cancer. The predictive model serves as the decision-making engine, classifying new, unseen images as either benign or malignant based on the learned patterns. This approach leverages the power of deep learning and transfer learning to provide accurate and efficient colon cancer detection, aiding in early diagnosis and potentially improving patient outcomes.

A. DATASET

Colon cancer (CRC) is a major contributor to global cancer-related deaths, necessitating precise and early detection methods. This study employs deep learning approaches, specifically transfer learning using VGG16, MobileNet, and ResNet architectures, to classify colon cancer from histopathological images. The dataset, obtained from Kaggle.com, consists of a diverse set of benign and malignant colon tissue images. Pre-processing steps were applied to enhance and standardize image quality before fine-tuning the pre-trained models. Model performance was evaluated using metrics such as accuracy, sensitivity, specificity, and F1 score, with ResNet achieving the highest classification performance. These findings demonstrate the effectiveness of transfer learning in colon cancer detection and suggest its potential integration into clinical settings to support early diagnosis, reduce errors, and improve patient outcomes.

B. METHODOLOGY

The methodology for colon cancer detection using deep learning with transfer learning techniques, such as VGG16, MobileNet, and ResNet, involves several key steps. First, a suitable dataset of colonoscopy or histopathology images is obtained from Kaggle, where the images are labeled as cancerous or non-cancerous. Preprocessing techniques, such as resizing, normalization, and augmentation, are applied to ensure the images are compatible with the input requirements of the chosen models and to enhance the robustness of the network. The next step is transfer learning, where pre-trained models like VGG16, MobileNet, and ResNet, initially trained on large datasets like ImageNet, are fine-tuned on the colon cancer dataset. This involves freezing the initial layers of the model to retain the general features and retraining the final layers to adapt the model to the specific task of cancer detection. During the training phase, the models learn to distinguish cancerous tissue patterns from normal tissue. Performance is then evaluated using metrics like accuracy, precision, recall, and F1-score.Hyperparameter tuning and validation techniques are employed to optimize the model for improved accuracy in real-world scenarios. The goal is to create a reliable, automated system capable of assisting in early diagnosis with high precision

C. ALGORITHM

1) VGG16:

The VGG16 algorithm is a deep convolutional neural network architecture widely recognized for its effectiveness in image classification tasks, making it a suitable choice for colon cancer detection through deep learning and transfer learning. Initially developed by the Visual Geometry Group at the University of Oxford, VGG16 consists of 16 layers with trainable weights, characterized by its uniform architecture of stacked convolutional layers followed by max-pooling layers. For colon cancer detection, the pre-trained VGG16 model is leveraged to capitalize on its ability to extract hierarchical features from images, such as edges, textures, and shapes, which are crucial for distinguishing between cancerous and non-cancerous tissues. By fine-tuning the model with a dataset of colonoscopy or histopathology images, the last few layers are retrained to adapt to the specific nuances of the colon cancer classification task. This approach not only accelerates the training process but also enhances the model's accuracy and robustness in identifying cancerous lesions, thus aiding medical professionals in making timely and informed diagnoses. The use of VGG16 in this context underscores the potential of transfer learning to improve diagnostic tools in healthcare.

2) MobileNet:

MobileNet is an advanced deep learning architecture specifically designed for efficient performance on mobile and embedded vision applications, making it an excellent choice for colon cancer detection using deep learning and transfer learning. Its unique architecture employs depthwise separable convolutions, whichsignificantly reduce the number of parameters and computational load without compromising accuracy. This lightweight design allows MobileNet to process images quickly, making it suitable for real-time applications in clinical settings where timely diagnosis is critical. When applied to colon cancer detection, the pre-trained MobileNet model is fine-tuned on a dataset of colonoscopy or histopathology images, enabling it to adapt to the specific task of identifying cancerous tissues. The transfer learning process involves leveraging the model's previously learned features from extensive datasets, thereby enhancing its capability to recognize complex patterns in the medical images. By utilizing MobileNet, healthcare professionals can benefit from a powerful yet efficient tool that not only maintains high diagnostic accuracy but also facilitates faster analysis, ultimately contributing to improved patient outcomes in the early detection of colon cancer.

3) ResNet:

ResNet, or Residual Network, is a groundbreaking deep learning architecture that introduces the concept of residual learning through skip connections, allowing the network to effectively train very deep models without facing the vanishing gradient problem. This characteristic makes ResNet particularly advantageous for complex tasks like colon cancer detection, where identifying subtle differences between cancerous and non-cancerous tissues is critical. When applied to colon cancer detection using transfer learning, a pre-trained ResNet model is adapted to the specific task by fine-tuning its layers on a dataset of colonoscopy or histopathology images. The model leverages its extensive knowledge gained from large-scale datasets to extract intricate features and representations, enhancing its ability to discern pathological patterns. The use of ResNet in this context enables the creation of a robust diagnostic tool that not only achieves high accuracy but also enhances model interpretability, making it easier for medical professionals to understand the decision-making process. By incorporating ResNet into the diagnostic workflow, the system can significantly improve early detection rates of colon cancer, leading to better patient management and outcomes.

IV. CONCLUSION

In conclusion, the application of deep learning and transfer learning techniques, particularly using models like VGG16, MobileNet, and ResNet, represents a significant advancement in the field of colon cancer detection. By leveraging pre-trained models on diverse datasets, these approaches enhance diagnostic accuracy, reduce training time, and improve the efficiency of image analysis in clinical settings. The ability to detect cancerous tissues with high precision can lead to earlier diagnoses, better treatment outcomes, and ultimately, a reduction in mortality rates associated with colon cancer. However, it is crucial to address challenges related to data quality, model interpretability, and potential biases to fully realize the benefits of these technologies. As research and development in this area continue to evolve, the integration of AI-driven diagnostic tools in healthcare has the potential to transform patient management, improve clinical workflows, and contribute significantly to personalized medicine. The future of colon cancer detection using deep learning is not only promising but also essential for advancing healthcare practices and enhancing the quality of care provided to patients.

REFERENCES

[1]. Marwa Obayya and Munya A. Arasi conducted biomedical image analysis for colon and lung cancer detection by applying the Tuna Swarm Algorithm with a deep learning model in their paper published in IEEE Access on August 29, 2023. [DOI: 10.1109/ACCESS.2023.3309711].

[2]. Hamed Alqahtani and EatedalAlabdulkreem improved the Water Strider Algorithm using a convolutional autoencoder to detect lung and colon cancer in histopathological images, as they reported in IEEE Access on December 25, 2023. [DOI: 10.1109/ACCESS.2023.3346894].

[3]. Shahid Mehmood and Taher M. Ghazal detected malignancy in lung and colon histopathology images through transfer learning and class selective image processing, as documented in IEEE Access on February 10, 2022. [DOI: 10.1109/ACCESS.2022.3150924].

[4]. Sushma B and Raghavendra C. K. developed a CNN-based U-Net model with modified skip connections for colon polyp segmentation and presented it at the 5th International Conference on Computing Methodologies and Communication (ICCMC) in 2021. [DOI: 10.1109/ICCMC51019.2021.941803].

[5]. Xiaoyong Yang, Qianxing Wei, Changhe Zhang, Kaibo Zhou, Li Kong, and Weiwei Jiang proposed an improved MRCNN-based model to detect and segment colon polyps, as they reported in IEEE Transactions on Instrumentation and Measurement. [DOI: 10.1109/TIM.2020.3038011].

[6]. Zohreh Vafapour, William Troy, and Ali Rashidi designed and analytically evaluated a water-based THz metamaterial perfect absorber for colon cancer detection, as published in the IEEE Sensors Journal. [DOI: 10.1109/JSEN.2021.3087953].

[7]. Zarrin Tasnim, S. Chakraborty, F. M. J. M. Shamrat, A. N. Chowdhury, H. Alam Nuha, A. Karim, and collaborators developed a deep learning predictive model using CNN for classifying colon cancer patients, as they described in IJACSA, Vol. 12, 2021.

[8]. M. M. K. Sarker, Y. Makhlouf, S. G. Craig, M. P. Humphries, M. Loughrey, J. A. James, and others assessed deep learning-based detection of ICOS protein expression in colon cancer in their study published in Cancers, Vol. 13, No. 15, p. 3825, July 2021.

[9]. H. A. Qadir, I. Balasingham, J. Solhusvik, J. Bergsland, L. Aabakken, and Y. Shin improved automatic polyp detection in colonoscopy videos by exploiting temporal dependency with CNNs, as published in IEEE Journal of Biomedical and Health Informatics, Vol. 24, No. 1, pp. 180–193, January 2020.

[10]. K. He, G. Gkioxari, P. Dollár, and R. Girshick introduced Mask R-CNN for object detection and segmentation in their influential work published in IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 42, No. 2, pp. 386–397, February 2020.