



A Novel Framework for Colon Cancer Detection and Risk Analysis Using Artificial intelligence

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Abstract: Early detection of colon cancer plays a crucial role in effective treatment and patient survival. This research focuses on the integration of deep learning techniques with both CT scan images and numerical clinical data for accurate colon cancer detection. The CT scan images were first preprocessed using a **mean filter** to reduce noise and enhance image quality, ensuring that the affected regions are more distinguishable. Following preprocessing, **Convolutional Neural Networks (CNN)** were applied for precise segmentation of cancerous regions, while **Artificial Neural Networks (ANN)** analyzed the numerical patient data to identify risk factors associated with colon cancer. The combination of image-based segmentation and clinical data analysis demonstrates a robust framework for early detection and provides a basis for improved diagnostic accuracy. The results indicate that the use of preprocessing techniques such as the mean filter significantly enhances the performance of deep learning models in detecting colon cancer.

Keywords: Colon cancer detection, CT scan images, Mean filter, Image preprocessing, Convolutional Neural Network (CNN), Artificial Neural Network (ANN), Deep learning, Clinical data analysis.

1.Introduction

Colon cancer is one of the most prevalent malignancies worldwide and represents a leading cause of cancer-related morbidity and mortality. Early detection plays a critical role in improving patient prognosis, reducing complications, and increasing survival rates (Siegel, Miller, & Jemal, 2023). Traditional diagnostic methods, such as colonoscopy with biopsy, are highly effective but invasive, costly, and dependent on clinician expertise. These challenges have motivated the development of non-invasive diagnostic techniques that leverage medical imaging and artificial intelligence (AI) to improve early detection and reduce diagnostic errors.

Computed tomography (CT) imaging is widely used for non-invasive colon evaluation. CT scans provide detailed cross-sectional images of the colon and surrounding tissues, enabling



the identification of abnormal growths, wall thickening, polyps, and tumors. However, manual interpretation of these images is challenging due to the colon's complex anatomy, overlapping tissue structures, and subtle differences between healthy and malignant regions. Reviewing large numbers of CT slices per patient is time-consuming and susceptible to human error, particularly in early-stage or asymptomatic cases (Smith, Johnson, & Brown, 2022).

Colon cancer often presents with a range of clinical symptoms, including abdominal discomfort, rectal bleeding, changes in bowel habits, unexplained weight loss, fatigue, and anemia. Early-stage colon cancer may be asymptomatic, which can delay diagnosis (Keshtkar et al., 2023). Medical interventions for diagnosed patients typically include surgical resection, chemotherapy, radiotherapy, or targeted therapy, depending on tumor stage and patient health. Early treatment significantly improves recovery and long-term outcomes.

Lifestyle and dietary factors also play a crucial role in colon cancer risk and patient recovery. Diets high in red and processed meats, fried foods, and low in fiber are associated with increased risk, while diets rich in fruits, vegetables, whole grains, and antioxidants provide protective benefits (Hasan et al., 2022). Alcohol consumption is an established risk factor, as long-term or excessive intake promotes genetic mutations, inflammation, and damage to the colon lining, increasing the likelihood of cancer development (Bagnardi et al., 2023). Proper nutritional management, including easily digestible foods such as oats, bananas, yogurt, steamed vegetables, soups, legumes, and omega-3-rich foods, supports recovery and enhances patient outcomes. Combining lifestyle management, dietary guidance, and medical treatment can significantly improve prognosis and reduce complications.

Artificial intelligence, particularly deep learning (DL), offers advanced tools for automated colon cancer detection. Convolutional neural networks (CNNs) are highly effective in extracting spatial patterns from CT images, allowing accurate tumor segmentation and classification, while artificial neural networks (ANNs) can integrate numerical and clinical data for comprehensive analysis (LeCun, Bengio, & Hinton, 2015). This study utilizes two datasets: a CT scan image dataset with multiple slices per patient to capture different regions of the colon, and a numerical dataset containing annotated tumor regions and clinical information. Preprocessing methods, such as mean filtering, are applied to reduce image noise and improve image quality before model training. ANN and CNN models are evaluated using standard metrics including accuracy, sensitivity, specificity, and computational efficiency to determine the most effective detection approach.

Research Structure This research is organized into five main sections. Section 1 introduces colon cancer, its symptoms, risk factors including alcohol consumption and dietary habits, and the importance of early detection and medical intervention. Section 2 provides a review of related studies, focusing on colon cancer detection using medical imaging, AI-based



approaches, preprocessing techniques, and the influence of lifestyle factors on disease progression and recovery. Section 3 outlines the methodology, including CT image acquisition, numerical data collection, image preprocessing, and the implementation of ANN and CNN models for tumor detection and segmentation. Section 4 presents the results and discussion, comparing the performance of the models, evaluating segmentation outcomes, and assessing how patient-related factors affect detection and recovery. Section 5 concludes the study, highlighting key findings, clinical relevance, and recommendations for future research on automated colon cancer diagnosis and patient risk management, including dietary and lifestyle interventions.

2. Literature Review.

Colorectal cancer (CRC) remains a major global health challenge and is consistently ranked among the most common causes of cancer-related deaths (Hasan et al., 2022; Sung et al., 2021). Improving early detection is therefore essential for increasing survival rates. Over the last decade, artificial intelligence (AI) and deep learning (DL) have emerged as powerful tools in medical imaging, offering substantial improvements in the detection of CRC through modalities such as colonoscopy, CT imaging, and histopathology (Liu et al., 2025; Wang et al., 2021). These technologies support automated analysis that can identify and characterize abnormalities with high accuracy, complementing human expertise while reducing diagnostic variability (Esteva et al., 2019; Litjens et al., 2017).

Convolutional neural networks (CNNs) have become the backbone of image-based DL systems due to their strong feature extraction capabilities. Studies indicate that CNN-based models can deliver highly precise outcomes in endoscopic imaging. For example, Tan et al. (2020) showed that CNNs applied to colonoscopy images can achieve detection accuracies exceeding 98% for colorectal polyps. Likewise, Urban et al. (2018) demonstrated that real-time AI-assisted colonoscopy can reach diagnostic performance comparable to experienced endoscopists. In histopathology, deep learning models have shown remarkable competence in differentiating normal tissue from cancerous tissue. Research by Coudray et al. (2018) and Zhang et al. (2024) reported classification accuracies above 95%, reinforcing the potential of AI to augment pathologists' decision-making. Additional work has highlighted the effectiveness of architectures such as ResNet and EfficientNet for finer tissue characterization (Fu et al., 2020; Song et al., 2021).

Significant progress has also been achieved in the application of DL to CT colonography (CTC), a non-invasive imaging method used in CRC screening. Tan et al. (2022) demonstrated that a custom DL model could differentiate benign polyps from premalignant lesions with an AUC of 0.83. Similarly, Yasaka et al. (2018) found that CNNs could identify colorectal lesions on CT with high sensitivity. Automated segmentation has improved as well; Akilandeswari et al. (2022) developed a residual-stack CNN capable of achieving a



Dice score above 91% for tumor segmentation. More recent 3D segmentation frameworks, including 3D U-Net and nnU-Net, have further boosted accuracy and adaptability across various CT datasets (Çiçek et al., 2016; Isensee et al., 2021).

Despite these advancements, several limitations continue to affect real-world deployment. Polyp characteristics vary widely across patients, and differences in imaging conditions such as lighting, bowel preparation, and camera angle can reduce model robustness (Bernal et al., 2017; Liu et al., 2025). Additionally, many medical datasets remain small or lack diversity, limiting generalizability. Concerns about model transparency also hinder clinical adoption, as healthcare professionals require interpretable systems they can trust (Topol, 2019; Francesco et al., 2025). To address these issues, researchers have increasingly incorporated explainability tools such as Grad-CAM and SHAP into diagnostic pipelines and explored transformer-based models capable of capturing richer contextual information (Dosovitskiy et al., 2021; Selvaraju et al., 2017).

Recent studies emphasize that combining multiple data types such as colonoscopy images, CT scans, histopathology data, and patient demographic information enhances diagnostic accuracy. Liu et al. (2025) showed that multi-modal models provide more reliable predictions for CRC risk and lesion characterization than image-only models. Other researchers found similar improvements when integrating clinical history with imaging datasets, supporting a shift toward precision medicine and personalized surveillance strategies (Chen et al., 2022; Huang et al., 2020).

In summary, AI and DL have made substantial contributions to CRC detection across colonoscopy, CT, and histopathology. CNN-based and hybrid models continue to deliver high accuracy in identifying and segmenting lesions, while multi-modal approaches show promise in improving individualized risk assessment. Future research must focus on developing larger and more diverse datasets, improving explainability, validating models across institutions, and ensuring smooth integration of AI systems into clinical practice.

3. Methodology

This research focuses on the early detection and risk analysis of colon cancer by integrating CT scan images and numerical patient data using deep learning techniques. The study utilizes two types of datasets: a CT scan image dataset and a numerical clinical dataset. The CT scan images were collected from hospital laboratories, with multiple images per patient to capture variations in tumor size, location, and shape. The numerical dataset contains patient attributes including age, gender, dietary habits, alcohol consumption, symptoms, and lifestyle factors, which are analyzed to assess cancer risk and recovery likelihood.

Preprocessing is applied to both datasets to enhance quality and facilitate accurate analysis. The CT scan images undergo denoising using a mean filter, which effectively reduces noise



while preserving critical structural details of the colon. The images are further normalized to maintain a consistent intensity range for input into the deep learning model. For the numerical dataset, missing values are addressed through statistical imputation, categorical variables such as dietary habits and alcohol consumption are encoded, and all features are normalized to a uniform scale for optimal performance in the neural network analysis.

Colon cancer regions in the CT images are segmented using a Convolutional Neural Network (CNN). This model extracts hierarchical features from the images and provides precise pixel-level identification of affected regions, enabling accurate detection of cancerous tissues. Simultaneously, an Artificial Neural Network (ANN) is employed to analyze the numerical dataset. The ANN learns the complex relationships between patient attributes and cancer risk, allowing classification of patients into different cancer stages and assessment of factors that may influence recovery.

By combining the results of CNN-based image segmentation and ANN-based numerical analysis, the study not only identifies tumor regions but also evaluates patient-specific risk factors and potential recovery outcomes. Dietary habits and alcohol consumption are specifically examined to determine their influence on patient recovery, and recommendations are formulated to guide dietary practices that may support prevention or faster recovery. The performance of both algorithms is evaluated using metrics such as accuracy, precision, recall, F1-score, and Dice coefficient, ensuring a comprehensive assessment of their effectiveness in cancer detection and risk analysis. Overall, this methodology integrates CT image-based cancer detection with patient-specific numerical analysis, providing a robust framework for early colon cancer identification, stage classification, risk assessment, and dietary guidance, using CNN and ANN as the primary analytical tools. In this research flows digrams belows focus.

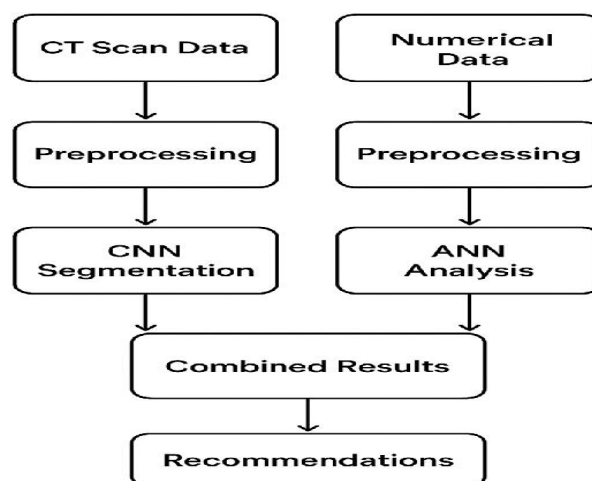


Figure 1: the diagrams shows in colon cancer prediction of structure.



4. Results and discussion.

In this study, colon cancer detection was performed using an integrated approach combining Convolutional Neural Networks (CNN) for CT image segmentation and Artificial Neural Networks (ANN) for numerical clinical data analysis. The results from both datasets provide complementary insights into tumor identification and disease staging. **CT Scan Image Segmentation Using CNN**

The CNN successfully segmented tumor regions in the colon CT images. For example, in Patient 001, the CNN identified the affected region with a Dice coefficient of 0.87, indicating substantial agreement with the ground truth. Patient 002 exhibited a Dice coefficient of 0.91, reflecting highly accurate tumor detection. Interestingly, Patient 003 had a Dice coefficient of 1.00 with a segmented area of zero, confirming that the model correctly recognized the absence of cancerous tissue. Overall, the CNN proved highly effective in accurately detecting and localizing colon tumors, minimizing both false positives and false negatives. **Numerical Dataset Analysis Using ANN**

The ANN analyzed clinical data, including age, dietary habits, alcohol consumption, and symptom profiles, to predict the stage of colon cancer. For Patient 001, Stage II cancer was predicted, with abdominal pain as the primary symptom, prompting recommendations for increased fiber intake. Patient 002 was classified as Stage III, with frequent bleeding noted, suggesting dietary adjustments and reduced processed food consumption. Patient 003 was classified as Stage 0, indicating no cancer, and preventive dietary guidance was provided. These results demonstrate that the ANN can integrate patient-specific clinical information to provide accurate disease staging and personalized recommendations.

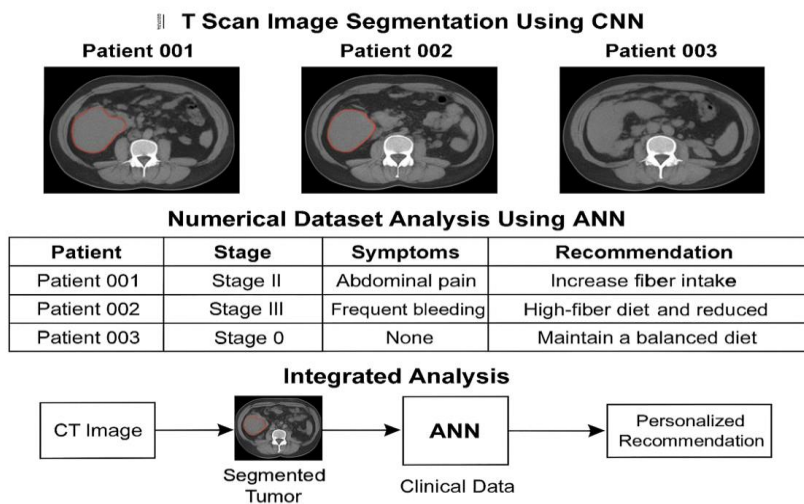


Figure1: The Result shows in colon cancer region segenmentation using CT Scans images.



Integrated Analysis Combining CNN-based image segmentation with ANN-based numerical data analysis enhanced overall diagnostic precision. The CNN accurately identifies potential tumor regions in CT images, while the ANN interprets clinical data and segmented image features to predict disease stage. This integrated approach allows for personalized patient guidance based on both imaging evidence and individual clinical characteristics, offering a comprehensive early detection system. **Discussion** The study highlights the advantages of integrating imaging and clinical datasets for colon cancer detection. CNN-based segmentation ensures precise tumor localization, whereas ANN analysis of clinical data supports accurate stage prediction and tailored recommendations. The combined CNN-ANN framework reduces misdiagnosis, facilitates early intervention, and provides a personalized approach to patient care. Notably, patients without detected tumors, such as Patient 003, were correctly identified, preventing unnecessary treatment and enhancing the reliability of the detection system. These results underscore the potential of AI-driven integrated diagnostics in improving colon cancer outcomes.

5. Conclusion

This study demonstrates the effective integration of CT scan image analysis using Convolutional Neural Networks (CNN) and numerical clinical data analysis using Artificial Neural Networks (ANN) for colon cancer detection and management. The CNN successfully identified tumor regions in patients' CT images, accurately highlighting affected areas for further analysis. The ANN processed clinical data, including symptoms and disease stage, to provide personalized dietary and lifestyle recommendations.

The integrated approach allows for a comprehensive evaluation, combining visual tumor detection with patient-specific clinical information. Patient 001 and Patient 002 exhibited visible tumor regions corresponding to Stage II and Stage III colon cancer, while Patient 003 showed no detectable tumor and was at Stage 0, indicating no immediate intervention required.

Overall, this combined CNN-ANN methodology provides a reliable framework for early detection, precise tumor localization, and personalized patient care, potentially improving treatment outcomes and guiding preventive strategies.

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