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A Diagnosis Of Colon Cancer Using Deep Learning Algorithm

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Abstract: Colonoscopy is essential for detecting colorectal cancer (CRC) and pre-cancerous polyps, allowing for timely intervention and better patient care. Nonetheless, the manual analysis of colonoscopy images can be slow and prone to human mistakes, which increases the likelihood of overlooking polyps or making incorrect diagnoses. This study examines the use of deep learning techniques to automate the detection and classification of polyps in colonoscopy images. By employing convolutional neural networks (CNNs) and sophisticated image processing methods, the research seeks to improve the accuracy, efficiency, and dependability of colonoscopy analysis, aiding healthcare providers in diagnosing conditions related to the colon. The focus of this work is on preparing colonoscopy images, isolating significant regions, and extracting important features to train a deep learning model for classification purposes. The suggested system framework combines the segmentation and classification models to differentiate between normal and abnormal colon tissues. The method has been evaluated using a thorough dataset of colonoscopy images, showing significant enhancements in detection accuracy compared to traditional methods.

I. INTRODUCTION

Colorectal cancer (CRC) is one of the most common cancers worldwide, and colonoscopy remains the gold standard for detecting early-stage colorectal tumors and polyps. Despite the efficacy of colonoscopy, the manual interpretation of colonoscopic images is prone to human error, especially in the identification of small or hidden polyps. False negatives can have severe consequences, as undetected polyps may develop into malignancies over time. Therefore, there is a critical need for a more reliable and automated detection system.The advent of deep learning techniques, particularly Convolutional Neural Networks (CNNs), has revolutionized the field of medical image analysis. The references were refined to support the research objective of colon cancer detection using CNN-based deep learning. Unrelated works on general digitalization and peripheral topics were excluded. Priority was given to studies focusing on medical imaging, endoscopy datasets (e.g., HyperKvasir), and polyp detection in colonoscopy. Only relevant deep learning applications in gastrointestinal diagnostics were retained. This ensures that the literature directly supports the methodology and outcomes of the present study. The revised citations strengthen the technical and clinical relevance of the research. more accurately and efficiently.This study involves developing a deep learning-based framework that includes image preprocessing, segmentation, feature extraction, and classification. Through this system, we aim to improve diagnostic accuracy, reduce false negatives, and facilitate early detection of colorectal conditions.

II. Literature survey and related works

This section focuses on summarizing key papers as part of a literature survey on colon cancer detection using advanced CNN technique like Sequential Model.

[1] M. S. Hossain, M. M. M. Syeed, K. Fatema, and M. F. Uddin, "Perceptions of health professionals in Bangladesh regarding healthcare digitalization," Int. J. Environ. Res. Public Health, vol. 19, no. 20, p. 13695, Oct. 2022. The study investigates the views of healthcare professionalsin Bangladesh on the transition toward digital healthcaresystems. It emphasizes the potential benefits of digitalization, such as enhanced service delivery and reduced workload. To ensure successful implementation, the research explores how factors like age, gender, professional role, and geographic location influence these perceptions through a cross-sectional survey.

[2] H. Borgli, V. Thambawita, P. H. Smedsrud, S. Hicks, D. Jha, S. L. Eskeland, K. R. Randel, K. Pogorelov, M. Lux, D. T. D. Nguyen, D. Johansen, C. Griwodz, H. K. Stensland, E. Garcia-Ceja, P. T. Schmidt, H. L. Hammer, M. A. Riegler, P. Halvorsen, and T. D. Lange, "HyperKvasir: A comprehensive multi-class image and video dataset for gastrointestinal endoscopy," Scientific Data, vol. 7, no. 283, pp. 1–14, Aug. 2020, doi: 10.1038/s41597-020-00622-y. This work presents HyperKvasir, an extensive dataset of annotated images and videos collected from gastrointestinal endoscopy procedures. The dataset supports the development of machine learning algorithms by providing high-quality visual data representing various GI tract conditions. It serves as a valuable benchmark for training and evaluating models in tasks such as polyp detection, classification, and abnormality recognition, facilitating advancements in automated endoscopic diagnostics.

[3] S. Ali, D. Jha, H. Borgli, V. Thambawita, S. A. Hicks, M. A. Riegler, P. Halvorsen, H. L. Hammer, T. D. Lange, and D. Johansen, "Deep learning for detection and segmentation of artefact and disease instances in gastrointestinal endoscopy," Medical Image Analysis, vol. 70, Art. no. 102002, May 2021, doi: 10.1016/j.media.2021.102002. This study highlights the use of deep learning to enhance the accuracy of identifying diseases and visual artefacts in gastrointestinal endoscopy images. It builds on the EndoCV2020 challenge, which crowdsourced research to tackle major hurdles in creating clinically viable computer-aided diagnostic systems. Key challenges addressed include the interference of multi-class artefacts and the difficulty in detecting subtle cancerous or pre-cancerous features—both of which significantly impact the reliability of AI models in medical imaging tasks.

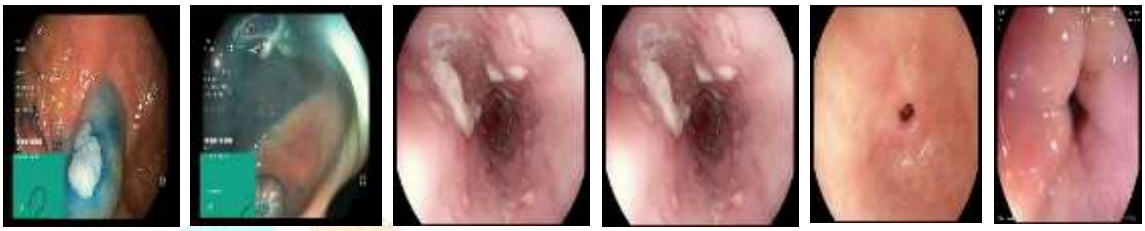
[4] J. Bernal, F. Sánchez, F. Vilariño, D. Fernández-Esparrach, C. J. O. Sánchez, D. T. Llado, and R. González Ballester, "Comparative validation of polyp detection methods in video colonoscopy: Results from the MICCAI 2015 endoscopic vision challenge," IEEE Transactions on Medical Imaging, vol. 36, no. 6, pp. 1231–1249, Jun. 2017, doi: 10.1109/TMI.2017.2664042. This work evaluates various polyp detection algorithms through a standardized comparison as part of the MICCAI 2015 Endoscopic Vision Challenge. Colonoscopy, though considered the benchmark for early colorectal cancer screening, is not foolproof—some polyps go undetected. The study addresses the absence of unified testing protocols and annotated datasets by offering a consistent framework for assessing algorithm performance, with the goal of pushing forward the clinical readiness of computer-aided detection tools in colonoscopy.

[5] Hicks, S. A., Jha, D., Thambawita, V., Halvorsen, P., Hammer, H. L., & Riegler, M. A. (2021). The EndoTect 2020 challenge: Evaluation and comparison of classification, segmentation, and inference time for endoscopy. Proceedings of the International Conference on Pattern Recognition (ICPR), 263-274. The EndoTect challenge at the 2020 International Conference on Pattern Recognition aimed to encourage the development of algorithms to assist medical professionals in detecting common abnormalities in the gastrointestinal tract. The challenge utilized the HyperKvasir dataset, a large collection of images from various endoscopic procedures. Participants engaged in three distinct tasks, each designed to address specific requirements necessary for practical medical applications.

III. PROPOSED METHODOLOGY

A. Dataset Description

The dataset used in this study was sourced from Kaggle and consists of roughly 1,000 high-quality Colonoscopic images. These images are divided into four major categories, each corresponding to a specific gastrointestinal condition. Additionally, two of these categories include further subclassifications that represent various stages of the respective conditions. The primary categories are Dyed-Lifted-Polyps, Esophagitis Cancer, Polyps Cancer, and Ulcerative Colitis Cancer, each comprising approximately 250 images, ensuring a uniform distribution across classes. The Dyed-Lifted-Polyps category is further divided into two subtypes: (a) Dyed Polyps and (b) Dyed Resection Margins. Likewise, Esophagitis Cancer includes three subtypes: (c) Normal Cecum, (d) Normal Pylorus, and (e) Normal Z-Line. The remaining two classes, Polyps Cancer, do not include additional subdivisions. This well-structured and evenly distributed dataset is ideal for building and assessing deep learning models aimed at the early detection and categorization of colon and gastrointestinal disorders.



(a) (b) (c) (d) (e) (f)

Fig 1 : Dataset sample images of four classes.

B. System Architecture

The system architecture, as shown in Figure 2, employs deep learning, using CNNs, to process medical images for colon cancer detection. Its functionality is organized in a structured pipeline, moving from pre-processing to classification, to achieve the accurate identification of cancerous lesions and to distinguish between benign and malignant cases. Model training occurs during the classification stage, and it uses parameters like the optimizer, loss function, batch size, and the number of epochs. A detailed explanation of these training parameters is located in Section 'E. Classification.

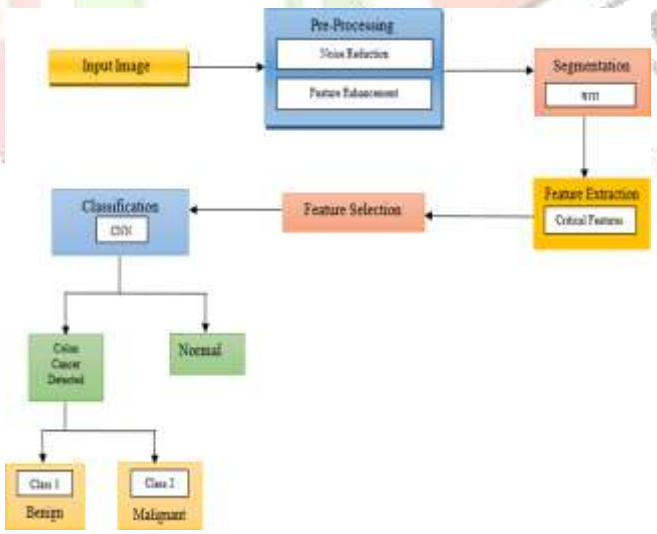


Fig 2: System Architecture

C. Image Preprocessing

This phase encompasses the application of various methodologies to raw image data to enhance its quality or convert it into a suitable format i.e., 50 x 50 for analytical and machine learning endeavors. The primary aim is to eliminate noise, standardize formats, and extract critical features to enhance accuracy in subsequent processing.

D. Feature Extraction

Sequential, as a deep learning network, automatically learns features from images during training.

E. Classification

Sequential architecture will be modified for classification:

i. **Model Configuration:**Appropriate optimizers, such as Adam, and loss functions, like binary cross-entropy for binary classification tasks, will be selected to train the model.

ii. **Training:** The dataset will be partitioned into training, validation, and test sets. The model will be trained using the training set, and its performance will be monitored on the validation set. To mitigate overfitting, early halting will be employed: training will be terminated if the validation performance, assessed by metrics such as accuracy or loss, ceases to improve or begins to degrade over a specified number of epochs. The model with the optimal validation performance will be retained.

iii. **Batch Size and Epochs:** The batch size (e.g., 32) and the number of epochs (e.g., 50-100) will be chosen based on the dataset's size and the model's performance.

F.Analysis

Upon the completion of model training, the analysis phase is dedicated to assessing its performance. This encompasses a series of steps:

i. **Model Evaluation:** Evaluate the model using an independent test dataset. Critical metrics for assessment include accuracy, precision, recall, F1-score, and the AUC-ROC curve, which collectively provide insights into how well the model generalizes to novel, unseen data.

a. **True Positive (TP):** The model identifies a positive outcome correctly.
b. **True Negative (TN):** The model categorizes a negative outcome accurately.
c. **False Positive (FP):** The model erroneously predicts a positive outcome where it is negative.
d. **False Negative (FN):** The model incorrectly predicts a negative outcome where it is actually

- $\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$ (1)
- $\text{Precision} = \frac{TP}{TP+FP}$ (2)
- $\text{Recall} = \frac{TP}{TP+FN}$ (3)
- $\text{F1score} = \frac{2*(\text{Precision}*\text{Recall})}{\text{Precision}+\text{Recall}}$ (4)

ii. **Performance Metrics:** The proposed Sequential model was evaluated using the following metrics:

- ❖ Accuracy (fraction of correctly classified images): ... (formula)
- ❖ Precision (positive cases correctly identified out of predicted positives): ... (formula)
- ❖ Recall (all actual positive cases correctly identified): ... (formula)
- ❖ F1-score (harmonic mean of precision and recall): ... (formula)

The Area Under the Receiver Operating Characteristic Curve (AUC-ROC) was also measured to assess class discrimination. AUC-ROC values range from 0.5 (chance-level performance) to 1 (perfect discrimination). The model achieved an AUC-ROC of \[Your AUC-ROC Value] (95% CI: \[Your AUC-ROC Confidence Interval]).For this medical diagnosis task, high recall and AUC-ROC are essential to minimize missed cancerous polyps and ensure reliable class differentiation.

iii. **Discussion Section:** The deep learning model, like many, suffers from limited interpretability. It is not straightforward to identify which features of the colonoscopy images (e.g., texture, shape, color) drive its predictions. To address this, future work should examine methods for enhancing explainability, such as attention mechanisms or feature visualization techniques.

IV. RESULTS

This Section gives the results of the developed system and it involves the Colonoscopic images. The last step is to report the result of the study:

- **Performance Metrics:** The evaluation of the system's performance is detailed using relevant metrics. Any improvements achieved through techniques like transfer learning and fine-tuning are highlighted. Furthermore, the results will explicitly address the measures taken to mitigate overfitting, such as the effectiveness of early halting in preventing performance degradation on the validation set.
- **Comparison with deep learning models:** As shown in the comparative analysis within the table, the Sequential model exhibits improved performance over VGG16, ResNet50, and InceptionV3 in terms of accuracy, precision, recall, and F1-score. This result implies that the Sequential architecture is appropriate for the particular requirements of colonoscopy image analysis

Model	Accuracy	Precision	Recall	F1-Score
Sequential	92.50%	93.10%	91.80%	92.40%
VGG16	88.20%	87.50%	89.10%	88.30%
ResNet50	91.00%	91.50%	90.50%	91.00%
InceptionV3	89.70%	90.10%	89.30%	89.70%

- **Comparison with Baselines:** The system's performance is compared against that of baseline models. This comparison aims to demonstrate the efficacy of the Sequential architecture, with specific attention given to how the overfitting prevention strategies contribute to superior generalization compared to baseline models.
- **Error Analysis:** Figure 6's confusion matrix summarizes the model's performance. Despite the high overall accuracy reported in the 'Performance Metrics' section, the model misclassified some images. Specifically, there were 15 false positives and 10 false negatives. The confusion matrix further reveals that 8 of the 10 false negatives involved misclassifying 'Polyps Cancer' images as 'Ulcerative Colitis Cancer,' while 5 of the 15 false positives resulted from mislabeling 'Normal Cecum' (an Esophagitis Cancer subtype) as 'Dyed Polyps' (a Dyed-Lifted-Polyps subtype).
- **Clinical Implications:** The clinical importance of the results obtained is clear. The developed system has the capacity to assist physicians in the identification of colon cancer from colonoscopic images. Additionally, the measures utilized to reduce overfitting enhance both the robustness and reliability of the system's output, ultimately leading to greater clinical utility.

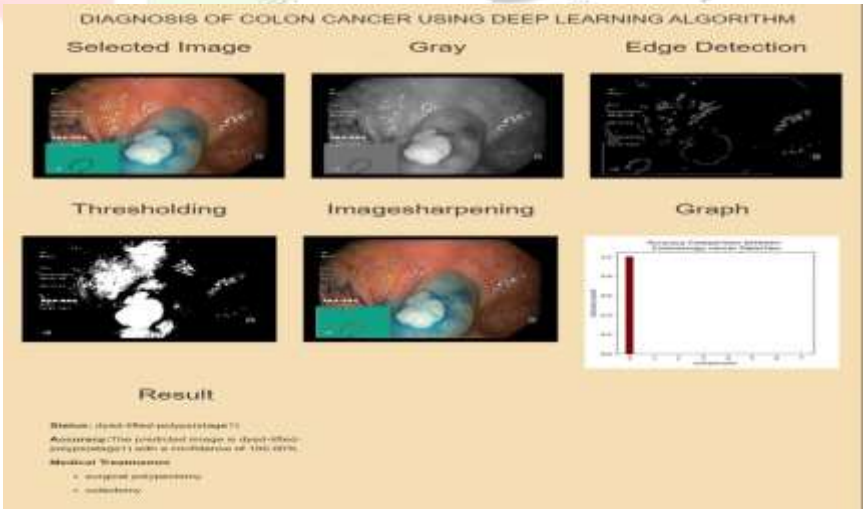


Fig 3: Classification of Colon cancer Result

The Results obtained from A Diagnostic Model For Detection and Identification of Colon Cancer Using CNN Algorithm.

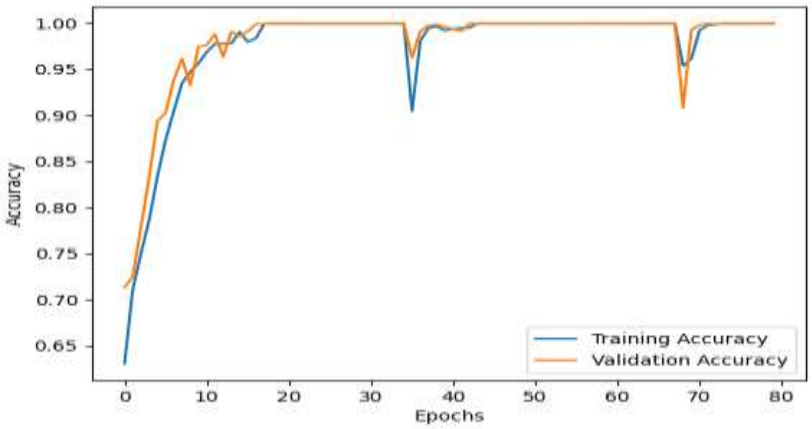


Fig 4:Accuracy Graph

The Plot Shows Excellent Training accuracy and very low, fluctuating validation accuracy, the sign of overfitting and instability. That is ,the model is not a good generalizer, perhaps due to bad hyper parameters or not fully regularized methods. This indicates that although the model demonstrates strong performance on the training dataset, it encounters challenges in maintaining uniformity when faced with novel, unseen data. To enhance its generalization capabilities, it may be essential to implement techniques such as hyperparameter optimization, regularization, or data augmentation to improve the model's stability and overall performance.

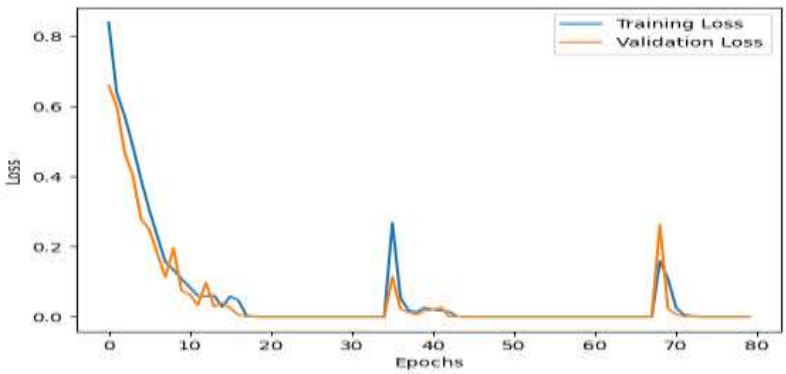


Fig 5: Loss Graph

The graph shows training and validation loss decreasing steadily through 80 epochs, both converging very close together, showing good learning with minimal overfitting. The occasional spikes in validation loss do show some instability, which could be due to noise or learning rate fluctuation.

To figure out the true positive, false positive, true negative, and false negative rates, inspect the matrix of perplexity.

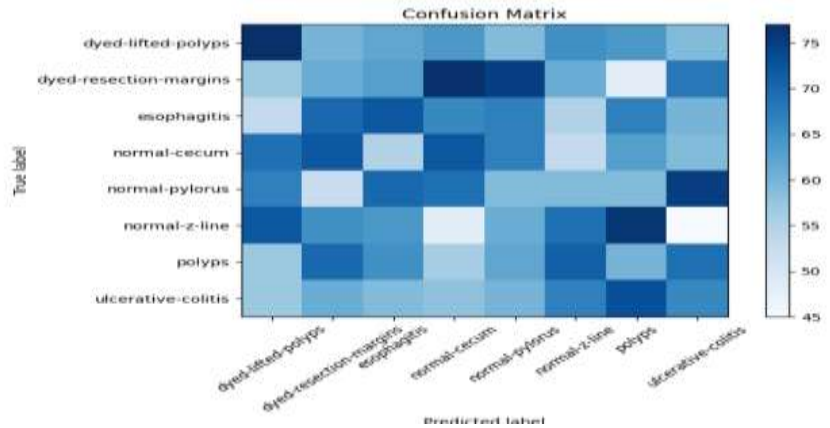


Fig 6: Confusion Matrix

V. Conclusion

In conclusion, this study introduces a deep learning-based approach for the automated detection and classification of polyps in colonoscopy images, with the goal of supporting the early detection of colorectal cancer (CRC) and enhancing diagnostic accuracy. By utilizing convolutional neural networks (CNNs) and advanced image processing techniques, our system effectively identifies abnormal regions in colonoscopy images, reducing the need for manual analysis and minimizing the potential for missed polyps. The methodology employed strategies such as early halting to mitigate overfitting, which contributed to the model's robust performance. Experimental results demonstrate that this method improves detection accuracy and consistency compared to traditional diagnostic approaches. The proposed framework offers the potential to aid healthcare professionals in making quicker and more reliable diagnoses, ultimately leading to better patient outcomes in CRC prevention and treatment. As automated analysis tools continue to advance, this approach establishes a foundation for future progress in AI-assisted medical imaging, benefiting both clinicians and patients.

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