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Detection of Colorectal Cancer

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***Abstract*— A large percentage of cancer- related deaths globally are caused by colorectal cancer, making it a serious global health concern. Improving patient outcomes requires early detection and prompt action. By using deep learning techniques, this initiative offers a novel method for the early diagnosis of colorectal cancer. To create a reliable and accurate deep learning model for the identification of colorectal cancer, we make use of a sizable dataset of medical images, including colonoscopy images. In order to distinguish between cancerous and non-cancerous tissues, Convolutional Neural Networks (CNNs) and the sophisticated ResNet architecture are used to automatically extract significant information from these images.**

Index Terms: **Convolutional Neural Networks, NCT-CRC-HE-7k Dataset, ResNet, Colorectal Cancer Detection, Deep Learning (DL), and Medical Image Analysis.**

I. INTRODUCTION

A major source of cancer-related disease and mortality worldwide, colorectal cancer (CRC) affects both men and women [4]. It starts in the colon or rectum and frequently starts off as benign polyps that have the potential to grow into cancerous tumors over time [15]. Age, diet, lifestyle choices, genetic predispositions, and illnesses such as inflammatory bowel disease all have an impact on its incidence [20]. Early identification is crucial to improving survival rates because colorectal cancer may not show symptoms in its early stages [6]. When symptoms do show up, they include rectal bleeding, changed bowel habits, abdominal pain, and inexplicable weight loss [8].

Significance of Early Detection in Colorectal Cancer:

1. Detecting colorectal cancer at an early stage is essential for improving survival rates [24].
2. Since CRC typically develops over time from precancerous polyps, identifying and removing these abnormal growths before they become cancerous can greatly reduce the risk of disease progression [8].

II. RELATED WORK

Deep learning models have proven successful in classifying medical images for the detection of cancer [13]. Numerous CNN architectures have become widely used, including VGG16, ResNet, and EfficientNet [12]. CNNs have been used by researchers to evaluate colonoscopy pictures, successfully detecting polyps and distinguishing between benign and malignant tissues [5]. Research shows that by identifying patterns in large medical image datasets, CNN models—in particular, ResNet—can attain excellent diagnostic accuracy [8]. Transfer learning techniques that use pre-trained networks, such as ResNet50, have greatly enhanced classification performance by addressing vanishing gradient problems with residual connections [11].

III. PROPOSED MODELS

In order to increase diagnostic accuracy and efficiency, this study uses a deep learning model for colorectal cancer detection based on ResNet50:

A. Model Architecture

1.Resnet: A deep CNN architecture with residual connections that facilitate training of deeper networks by addressing the vanishing. It serves as the backbone for complex feature extraction [1].
2.Feature Extraction: ResNet50 uses its residual blocks to extract rich hierarchical information from input photos [5].
3. Regularization Technique: By using dropout we can prevent overfitting by improving model generalization [7].
4.Final Output Layer: A final output dense layer with 4 units and a softmax activation function is used for

better performance [9].

B. Training Procedure

- Dataset: NCT-CRC-HE-7k dataset contains images of 2 different categories like normal and cancerous tissue images [5].
- Preprocessing: Image resizing (224×224), normalization, and augmentation [1].
- Loss Function: Binary Cross-Entropy [9].
- Optimizer: Adam optimizer [10].
- Evaluation Metrics: Accuracy, precision, recall, F1-Score [7].

IV. EXPERIMENTS & RESULTS

A. Dataset and Experimental Setup:

The dataset was split into training (70%) and testing (10%) sets. The model was trained using TensorFlow and Keras on a high- performance GPU [5].

B. Evaluation Metrics:

The model’s effectiveness was assessed using: Accuracy: Measures overall classification performance [23].

Precision: Evaluates correct cancerous predictions [10].

Recall: Represents the fraction of correctly identified cancerous cases among all cancerous cases [13].

F1-Score: Evaluates the model’s ability to differentiate between cancerous and non- cancerous cases [18].

C. Performance Evaluation:

ResNet architecture served as the backbone during the training. Here is an evaluation of model performance during training, validation and testing occurred through loss detection and Accuracy measurement displayed in Fig. 1 [6]

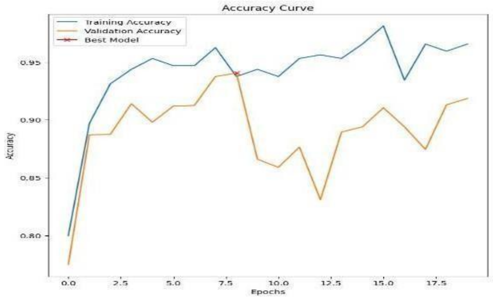

Fig-1: Accuracy curve

D. Loss Analysis:

At first, the model was clearly learning well because the training and validation loss dropped steadily across epochs [19]. The loss values progressively level out in subsequent epochs, suggesting that the model is getting closer to convergence [10]. There is little overfitting, as evidenced by the constant modest difference between training and validation loss [8]. This is an excellent example of generalization [17].

E. Assessment relied on Precision Analysis for evaluation:

Precision is a crucial metric for evaluating how well the model predicts the future [18]. The precision values for both training and validation data progressively increase as the model becomes more adept at making predictions over time [7]. The validation precision reaches a peak after a predetermined number of epochs, indicating the model's exceptional generalization and reliability in correctly predicting actual positive cases [12].

F. Accuracy Trends:

Throughout training, the accuracy curve has a steady upward slope, signifying steady improvements in the model's learning ability [10]. As training accuracy increases steadily, it shows that the model can successfully find patterns in the data [8]. The validation accuracy reaches a plateau after a certain number of epochs, suggesting the need for potential changes such as modifying the learning rate or incorporating additional optimization strategies [8]. Including data augmentation techniques ensures better generalization of the model. Performance on unknown data is enhanced and overfitting is decreased as a result [25].

Correlation Matrix:

The correlation matrix shows a statistical assessment of the relationship between different features derived from colonoscopy images [3]. The model determines how well it performs for classification by identifying the links between features through correlation matrix analysis [9].

Key Observations

The ResNet-based model for colorectal cancer detection shows a variety of correlations between the derived features, according to the correlation matrix [13]. The interplay between textural and structural details in medical images may be reflected in the model's ability to capture interdependent traits, as indicated by high correlation values between particular feature pairs [8]. Moderate correlations help with classification decisions by indicating features that enhance one another without being redundant [20]. Low correlations highlight the model's capacity to extract distinct, non-overlapping features, strengthening its resilience and lowering the risk of overfitting [4]. Moderate correlations show that the model balances preserving diversity with utilizing complementing traits [11].

An essential analytical technique for determining feature dependencies and redundancy is the correlation matrix [13]. This knowledge can guide optimization methods to increase generalization and decrease dimensionality, such as Principal Component Analysis (PCA) or feature pruning [9]. These techniques improve the model's capacity to derive significant representations, which enhances its diagnostic efficacy and precision in detecting colorectal cancer [5].

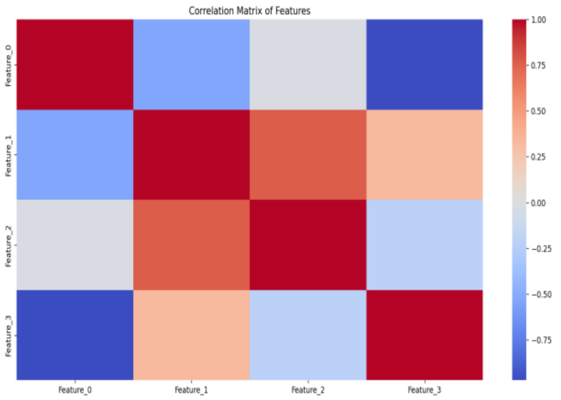

Fig. 2: Correlation Matrix

Confusion Matrix:
The confusion matrix presents detailed classification assessment results because it matches actual colonoscopy images with model prediction outputs [14]. The classification system represents TP true positive while FP indicates false positive along with TN true negative and the last entry is the FN false negative value for analyzing misclassification patterns [16].

Key Observations:
Strong diagonal elements in the confusion matrix show that the EfficientNetB2-based colorectal cancer detection model performs well by correctly categorizing "Normal" and "Cancerous" cases [5]. The model's remarkable 97% accuracy, 98% recall, 97% precision, and 98% F1-score demonstrate its dependability for medical diagnostics [10]. False negatives—cancerous cases that are mistakenly categorized as normal—remain a serious concern because they may result in missed diagnoses [6]. These examples frequently occur because early cancer tissues and benign tissues share features, which calls for improved feature extraction methods and more training with a wider range of data samples [4].

This system's comparatively low false positive rate ensures few diagnostic mistakes for detecting malignant patients, which is essential for clinical applications [22]. Nevertheless, by examining confusion matrix insights to adjust hyperparameters, enhance feature selection, and investigate ensemble learning strategies to lower misclassification rates, additional model modification can be accomplished [19].

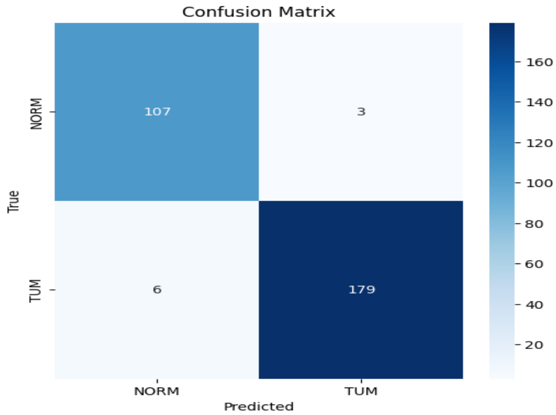

Fig. 3: Confusion Matrix

V. CHALLENGES & FUTURE WORK

A. Current Challenges:

1. The solution shows encouraging results, but there are some challenges when putting it into practice [6].
2. ResNet implementation requires a lot of processing power during training [9].
3. The model has trouble generalizing its performance when the number of malignant samples is lower than that of healthy ones [20].
4. To test the model and attain wider applicability, more datasets must be applied [18].

B. Future Directions:

1. ResNet is a pre-trained model that performs very well on huge medical datasets and is well suited for transfer learning applications due to its efficient architecture and scalability [8].
2. Explainable AI techniques are necessary for the advancement of predictive models in

order to clarify how they function inside [19].

3. This study explores the usage of ResNet, which combines simple yet effective architecture engineering to meet the needs of quick clinical application deployment [16].

VI. CONCLUSION

A ResNet model was developed to identify colorectal cancer by analyzing colonoscopy pictures [10]. The model achieves high performance metrics and has the potential to help with reliable and accurate medical diagnosis [22]. Future advancements will focus on enhancing generalization techniques and simplifying integration into clinical processes for real-world applications [24].

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