Enhanced Colon Cancer Screening with Endoscopic Images Using Deep Learning Techniques

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***Abstract*—— Colon cancer is a leading cause of cancer-related deaths worldwide, where early detection is vital for improving outcomes. This study focuses on a deep-learning approach for detecting colon cancer using endoscopy images. By employing four pre-trained models—EfficientNetB2, InceptionV3, MobileNetV3, and ResNet50—images are classified into normal, ulcerative colitis, polyps, and esophagitis categories. Public datasets like KVASIR and ETIS-Larib-Polyp DB are utilized, with the original 800 images expanded to 3,200 through data augmentation to enhance model generalization. Performance is measured using metrics such as accuracy, precision, recall, and F1-score. The results indicate that the accuracies of InceptionV3, EfficientNetB2, ResNet50, and MobileNetV3 are 94%, 93%, 89.12%, and 87%, respectively. Given its strong accuracy and resource efficiency, InceptionV3 emerges as the best-performing model, making it suitable for deployment in low-resource settings. This study highlights the potential of deep learning to provide reliable, automated tools for early colon cancer detection.**

Keywords— Cancer, Colon Cancer, Endoscopy images, Ulcerative colitis, Polyps, esophagitis, normal.

I. INTRODUCTION

Cancer occurs when certain cells in the body grow uncontrollably and spread to other areas. Normally, cells divide to replace old or damaged ones, which then die off naturally. Cancer cells, however, avoid this programmed death (apoptosis), allowing abnormal cells to persist and grow [1]. As a major global health issue, cancer significantly impacts both developing and developed countries. In developing nations, such as China, limited healthcare resources contribute to lower survival rates, but as China's economy grows, cancer patterns increasingly resemble those seen in Western countries [2]. In the U.S., cancer is the second leading cause of death, with nearly 38% of people affected during their lifetime. Colon cancer alone accounts for nearly 500,000 deaths annually. Histopathological analysis remains a key detection method, but accuracy can vary based on the pathologist's experience and workload [3]. Colorectal cancer, which starts as abnormal polyps in the large intestine and rectum, leads to over 142,000 new cases and 50,000 deaths each year [4].While white-light endoscopy remains the standard for screening colonoscopy, it has a 24.1% miss rate for adenomas and even higher for smaller or flat polyps; advanced molecular imaging techniques like fluorescence endoscopy, which targets tumor-specific molecules, have been developed to improve diagnostic sensitivity for CRC lesions. Automated systems for detecting colon cancer aim to enhance accuracy and reduce variability in histopathological analysis across different magnifications [5]. Endoscopic imaging, using a camera-equipped flexible tube, is essential for identifying colon abnormalities, such as polyps and tumors, improving early diagnosis and treatment planning through advanced computer-assisted analysis [6]. Regular screening is vital for effective colon cancer management.

Medical imaging for colon cancer detection can be challenging due to the large volume of images, which can delay diagnosis and treatment. To address this, deep learning has been effectively used in computer-assisted diagnosis systems to automate and enhance cancer detection, with AI approaches focusing on both machine learning and deep learning for analyzing histopathological and endoscopy images. In machine learning for colon cancer detection, the process involves several stages: preprocessing to clean the data, feature extraction to identify unique characteristics, feature selection to choose the most relevant features, and classification to make the final diagnosis. Despite recent advancements achieving good results, these systems are complex and time-consuming, especially with large datasets, and often suffer from overfitting and accuracy issues. Additionally, their performance is heavily reliant on the quality of feature extraction methods. Deep learning methods address many of the limitations of earlier machine learning approaches by integrating feature extraction and classification into a single stage using advanced models. Typically, these systems utilize pretrained models and transfer learning, with convolutional neural networks (CNNs) being the most common and effective model for accurately detecting colon cancer.

Several studies have advanced colon cancer research. Godkhindi et al. demonstrated that Convolutional Neural Networks (CNNs) significantly outperformed classical methods like Random Forest (RF) and k-nearest neighbor (KNN) for colon cancer detection, achieving 87% accuracy in

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segmentation and 88% in polyp detection [1]. Lim et al. highlighted the role of computational methods in gene identification, using the Digital Gene Expression Displayer to discover novel overexpressed genes in colon cancer tissues [2]. Ozsahin et al. compared various colon cancer treatments using Fuzzy PROMETHEE and concluded that surgery remains the most effective [3]. Vuong et al. applied a multi-task learning approach to digital pathology, achieving 85.91% accuracy in classifying colon tissues [4]. Bouazza et al. found that combining SNR with SVM classifiers yielded the highest cancer classification accuracy [5]. Kho et al. proposed color-based segmentation methods that improved accuracy in GI endoscopy for detecting lesions and bleeding [6]. Eskandari et al. used Active Contour Method and geometric features for automatic polyp detection, achieving high sensitivity and specificity [7].

Mamonov et al. developed an algorithm for detecting colorectal polyps with capsule endoscopy, achieving 81% sensitivity per polyp [8]. Harish et al. employed MobileNet for histopathological image analysis, achieving 98% accuracy [9]. Chiou et al. proposed an optimized virtual colonoscopy method using skeleton simplification to improve navigation efficiency [10]. Zhang et al. explored the use of Generative Adversarial Networks (GANs) for augmenting endoscopic image datasets, which significantly improved the performance of diagnostic models by enhancing the variety of training data [11]. Patel et al. investigated the application of Transformer models in the classification of colon cancer images, demonstrating improved contextual understanding and accuracy compared to conventional convolutional approaches [12]. Singh et al. developed an ensemble learning method that combined multiple deep learning models to achieve superior performance in polyp detection, surpassing single-model approaches [13].

The study addresses the need for automated colon cancer detection to support early diagnosis. Using data augmentation, the endoscopic images from KVASIR and ETIS-Larib-Polyp DB datasets are expanded from 800 to 3,200. Four pre-trained models—InceptionV3, EfficientNetB2, ResNet50, and MobileNetV3—are evaluated to classify images into normal, ulcerative colitis, polyps, and esophagitis categories. InceptionV3 demonstrates the highest accuracy, precision, recall, and F1 score among the models tested. Its accuracy and efficiency make it the recommended model for reliable colon cancer detection in low-resource settings.

In this study, we introduced a novel, lightweight deep learning approach using CNN for colon cancer detection, which simplifies the process by integrating feature extraction and classification into a single end-to-end model. Our method, evaluated against an endoscopy image database, demonstrated superior accuracy compared to existing approaches, even with a smaller dataset, and represents a significant advancement for automated colon cancer detection systems.

II. COLLECTION OF DATASET AND PREPROCESSING

The preprocessing methodology for colon cancer detection using endoscopic images is a crucial step in optimizing model performance. The initial dataset consists of 800 endoscopic images, divided equally across four classes: normal, polyp, esophagitis, and ulcer, sourced from the KVASIR and ETIS-Larib-Polyp DB datasets. Each image has a resolution of 768 x 768 pixels, capturing detailed views necessary for accurate classification. To enhance the dataset and prevent overfitting, data augmentation techniques such as rotations, zooms, flips, and shifts are applied, expanding the dataset to 3,200 images, with each class containing 800 images.

Following this, the images are resized to 224 x 224 pixels to ensure uniformity and reduce computational complexity while preserving critical features. The augmented dataset is then split into training and testing sets, ensuring that the deep learning models are evaluated on unseen data. Pre-trained models, including EfficientNetB2, InceptionV3, MobileNetV3, and ResNet50, are utilized for transfer learning, allowing the models to leverage prior knowledge for detecting colon abnormalities. Performance is thoroughly evaluated using metrics such as precision, recall, F1-score, accuracy, and error rate, ensuring a comprehensive assessment of each model's effectiveness in classifying endoscopic images accurately. This systematic preprocessing approach is key to achieving reliable results in colon cancer detection.

The proposed methodology for colon cancer detection using endoscopy images involves five key stages. First, it uses the KVASIR and ETIS-Larib-Polyp DB datasets, containing diverse gastrointestinal images, to train and test deep learning models. The approach employs a multi-layered CNN model with techniques from F. J. P. Montalbo to improve diagnostic accuracy. To avoid overfitting and enhance generalization, the dataset is augmented using rotations, zooms, flips, and shifts, expanding from 800 to 3,200 images. The data is then split into training, testing, and validation sets. Four pre-trained models—EfficientNetB2, InceptionV3, MobileNetV3, and ResNet50—are used for transfer learning and fine-tuned for detecting abnormalities. Performance is assessed with precision, recall, F1-score, accuracy, and error rate to gauge the models' effectiveness.

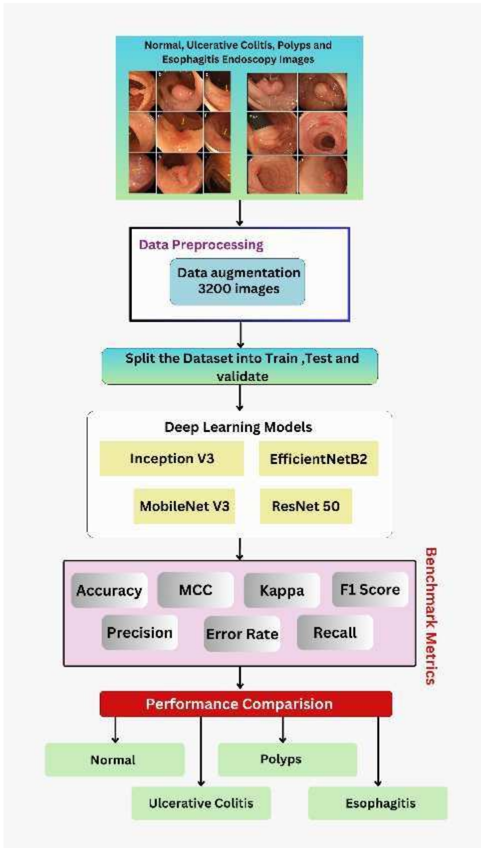

Fig. 1. Methodology proposed for colon cancer classification

III. DEEP LEARNING MODELS FOR FEATURE EXTRACTION

For our study, we utilized pre-trained deep-learning models such as EfficientNetB2, InceptionV3, MobileNetV3, and ResNet50 for the classification of colon cancer using endoscopy images.

A. EfficientNetB2

EfficientNetB2, part of the EfficientNet family by Google, is designed for high accuracy with minimal computational resources. It employs compound scaling to uniformly balance depth, width, and resolution, optimizing efficiency.

Key features include inverted bottlenecks and squeeze-and-excitation (SE) modules to reduce computational load while retaining accuracy. Its smooth activation functions further enhance performance. EfficientNetB2's lightweight design enables versatile deployment in medical imaging, such as colon cancer detection.

The EfficientNetB2 architecture shown in Figure 2 starts with a 3x3 convolution layer to extract basic features. It uses MBConv blocks with depthwise separable convolutions to manage complexity. MBConv1 with a 3x3 filter is used in Block 1, while Blocks 2-4 employ MBConv6 layers with 3x3 and 5x5 filters. Blocks 5-6 feature deeper MBConv6 layers with 5x5 filters, refining feature extraction. The final MBConv layer consolidates features into a map for classification tasks.

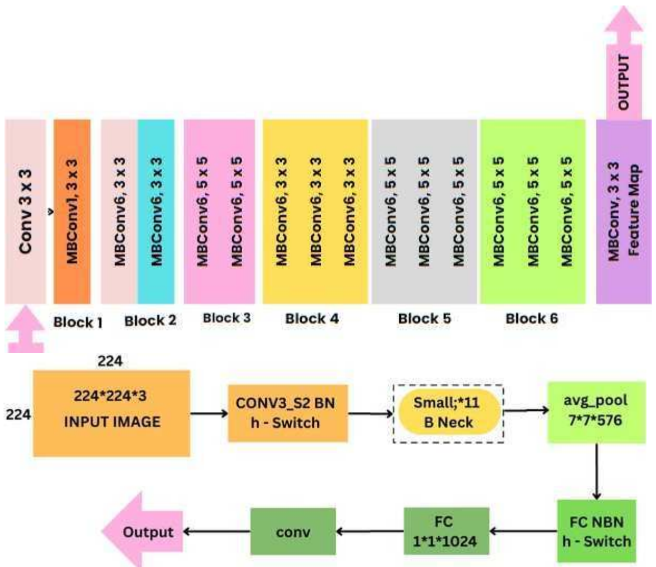

Fig. 2. EfficientnetB2 model Architecture

B. InceptionV3

The Inception V3 is a sophisticated convolutional neural network (CNN) developed by Google, notable for its efficiency and accuracy in medical imaging and cancer detection. It enhances earlier Inception models with innovations like inception modules, which perform convolutions with multiple filter sizes simultaneously to capture complex image patterns. The network uses factorized convolutions to cut down computational costs and auxiliary classifiers to mitigate the vanishing gradient problem, improving generalization. Batch normalization stabilizes training, and global average pooling replaces fully connected layers to reduce parameters and overfitting. Inception V3 strikes a balance between performance and efficiency, making it well-suited for large-scale image classification tasks, including cancer detection.

The Inception V3 architecture, illustrated in the figure 3, begins with an initial convolution layer that extracts basic features from the input image. The network then progresses through three key Inception blocks (A, B, and C), each applying parallel convolutions with different filter sizes to capture features at multiple scales.

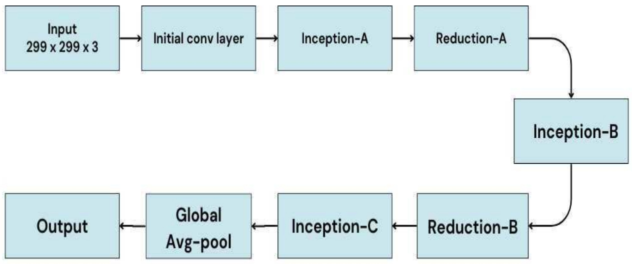

Fig. 3. Inceptionv3 model Architecture

Reduction-A and Reduction-B blocks follow each Inception block, reducing spatial dimensions to optimize computation. The network ends with global average pooling, which condenses feature maps into a compact representation for the output layer. This architecture efficiently balances feature extraction and computational complexity, making it ideal for tasks like colon cancer detection.

C. MobilenetV3

MobileNetV3Large is an advanced CNN optimized for efficiency and performance on mobile and edge devices, building on MobileNetV2 with Neural Architecture Search (NAS) for improved design. It achieves high accuracy with lower computational demands, making it suitable for real-time tasks like colon cancer detection on portable devices. Key features include depthwise separable convolutions, which streamline the convolution process, and linear bottleneck layers that reduce complexity while retaining important features. Squeeze-and-excitation (SE) modules enhance feature relevance, and the "hard-swish" activation function boosts network nonlinearity. Designed for quantization, MobileNetV3Large performs well even with 8-bit integer formats on constrained hardware.

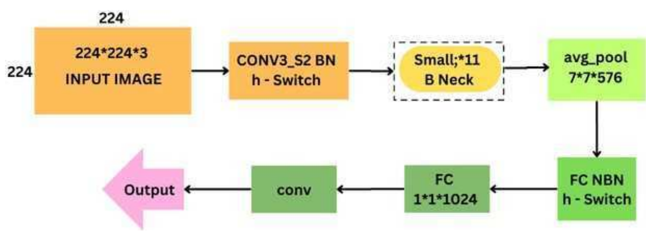

Fig. 4. MobileNetV3 model Architecture

D. ResNet50

A ResNet50, developed by Microsoft, is a deep learning model using residual learning to address vanishing gradients in deep networks. Its 50-layer architecture includes convolutional layers, batch normalization, ReLU activation, and residual blocks with shortcut connections, enabling high accuracy in complex tasks such as medical imaging and colon cancer detection. The model starts with zero padding, a

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convolution, ReLU activation, and max pooling. It then features convolutional and identity blocks with skip connections, and concludes with average pooling and a fully connected layer for classification. For reference, see Figure 5 for an illustration of the ResNet50 architecture.

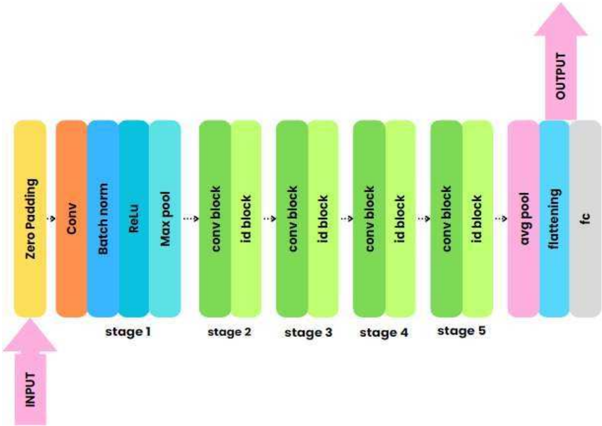

Fig. 5. ResNet50 model Architecture

IV. RESULTS AND DISCUSSION

In this section, we focus on performance of each deep learning model with its benchmark metrics with the help of confusion matrix which contains TP, TN, FP, FN from that we can evaluate the Precision, F1-Score, Recall, Accuracy, MCC and Kappa.

Precision measures how accurately a model's positive predictions are. It is calculated by dividing the number of true positives by the total number of predicted positives,

$$\Pr ecision = \frac{TP}{TP + FP} \tag{1}$$

The F1-score measures a classification model's overall performance by calculating the harmonic mean of precision and recall.

$$F1-Score = \frac{2 * \Pr ecision * \operatorname{Re} call}{\Pr ecision + \operatorname{Re} call} \tag{2}$$

Recall measures a model's ability to identify all relevant instances in a dataset. It is computed as the ratio of true positive (TP) instances to the sum of true positive and false negative (FN) instances.

$$\operatorname{Re} call = \frac{TP}{TP + FN} \tag{3}$$

Accuracy measures how well the model performs by calculating the ratio of correctly predicted instances to the total number of instances.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

Matthews correlation coefficient (MCC) evaluates binary classifiers by factoring in true positives, false positives, true negatives, and false negatives. Ranging from −1 to +1, it indicates +1 for perfect predictions, 0 for random chance, and −1 for total disagreement.

$$MCC = \frac{TP + TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{5}$$

Cohen's kappa measures agreement between two raters on categorical data, indicating how much their agreement exceeds what would be expected by chance

$$k = \frac{p_O - p_e}{1 - p_e} \tag{6}$$

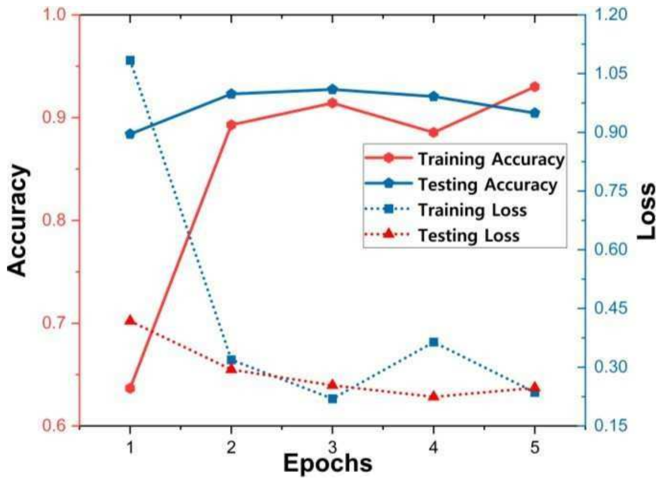

Fig. 6. Training and Testing graph for Accuracy and Loss for Efficient B2 model

Figure 6 shows the EfficientNetB2 model's performance over five epochs. Training accuracy improves to about 92.5% by the second epoch but then fluctuates, while test accuracy remains higher and drops slightly by the final epoch, suggesting mild overfitting. Training loss decreases sharply in the first two epochs but fluctuates afterward, indicating instability. Test loss declines more consistently and stabilizes, reflecting good generalization despite training loss fluctuations.

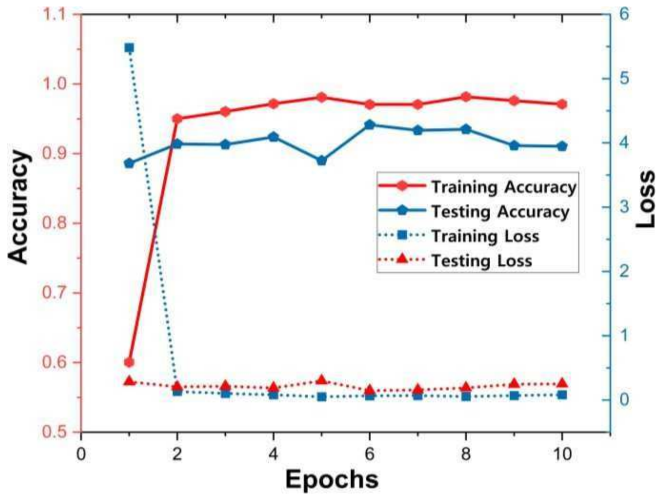

Fig. 7. Training and Testing graph for Accuracy and Loss for Inception V3 model

Figure 7 shows the InceptionV3 model's performance. Training accuracy quickly rises above 95% after a few epochs, while test accuracy fluctuates between 88% and 92%, suggesting some overfitting. Training loss drops rapidly and nears zero within two epochs, indicating efficient fit to training data. In contrast, test loss remains stable with minor fluctuations, indicating good performance but room for improvement in generalization.

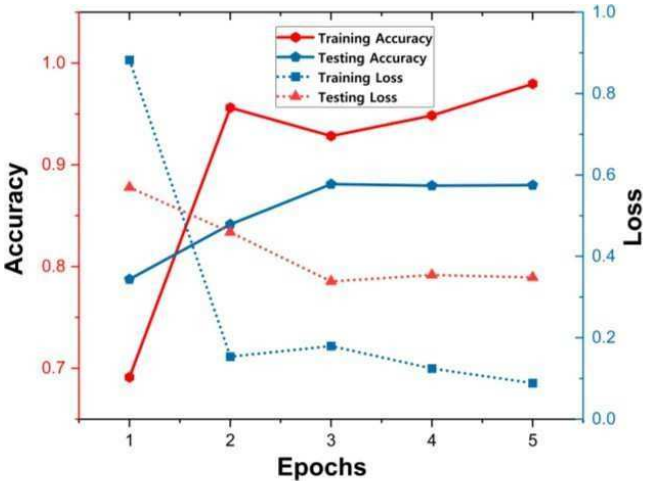

Fig. 8. Training and Testing graph for Accuracy and Loss for MobilenetV3 model

The figure 8 depicts the training and testing performance of a MobileNetV3 model over five epochs. Training accuracy steadily improves, reaching approximately 97.5% by the fifth epoch, while test accuracy also improves but levels off around 87.5%, indicating the model performs better on training data than on unseen data. Training loss decreases sharply, showing that the model is effectively reducing errors during training, whereas test loss decreases initially but then flattens out, suggesting the potential onset of overfitting as the model's performance on new data starts to lag behind.

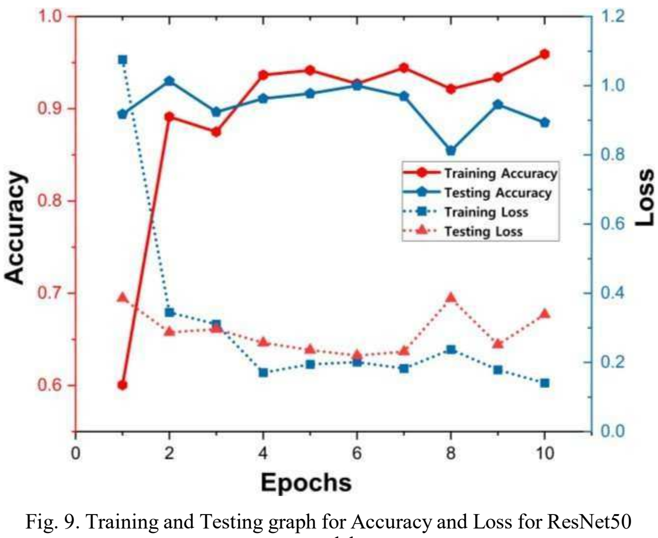

Fig. 9. Training and Testing graph for Accuracy and Loss for ResNet50 model

Figure 9 shows the ResNet50 model's performance over ten epochs. The training accuracy steadily increases to over 95%, while test accuracy peaks around 92% but fluctuates, showing variability. Training loss consistently decreases, indicating effective learning, whereas test loss decreases initially but fluctuates, suggesting inconsistent performance on new data and possible overfitting. Its 50-layer architecture includes convolutional layers, batch normalization, ReLU activation, and residual blocks with shortcut connections, enabling high accuracy in complex tasks such as medical imaging and colon cancer detection. The model starts with zero padding, a convolution, ReLU activation, and max pooling. It then features convolutional and identity blocks with skip connections, and concludes with average pooling and a fully connected layer for classification. For reference, see Figure 5 for an illustration of the ResNet50 architecture.

TABLE I. PERFORMANCE ANALYSIS OF DEEP LEARNING MODELS

Model	Accuracy	Precision	Recall	F1-Score	MCC	Kappa
EfficientNetB2	93	93	93	92	0.902	0.91
InceptionV3	94	94	94	94	0.917	0.92
MobileNetV3	87	89	87	86	0.835	0.82
ResNet50	89	91	89	89	0.861	0.85

Table 1 compares the performance of four deep learning models—EfficientNetB2, InceptionV3, MobileNetV3, and ResNet50—using various metrics for a classification task. InceptionV3 stands out with the highest accuracy (94%), precision, and recall (both at 94%), and it achieves the top F1-Score at 94%, indicating balanced performance. EfficientNetB2 closely follows with 93% accuracy, precision, and recall, and a 92% F1-Score. ResNet50, with an accuracy of 89.12%, scores 91% in precision and 89% in recall, resulting in an 89% F1-Score. MobileNetV3 lags behind with 87% accuracy, 89% precision, 87% recall, and an 86% F1-Score. InceptionV3 also leads in MCC (0.917) and Kappa (0.92), showing strong reliability, while EfficientNetB2 also performs well with an MCC of 0.9022 and a Kappa of 0.9. ResNet50 and MobileNetV3 have lower scores in these metrics. InceptionV3 has the lowest error rate at 6, making it the most reliable, followed by EfficientNetB2 with an error rate of 7, ResNet50 at 10.88, and MobileNetV3 with the highest error rate at 13.

V. CONCLUSION AND FUTURE WORK

In conclusion, The comparison of EfficientNetB2, InceptionV3, MobileNetV3, and ResNet50 provides valuable insights into their performance on a classification of image as Ulcerative colitis, Polyps, esophagitis, normal. InceptionV3 is the best overall model, followed closely by EfficientNetB2, while ResNet50 and MobileNetV3 are less robust options. InceptionV3 stands out as the top performer with the highest accuracy, precision, recall, and F1-Score, all at 94%. This indicates that InceptionV3 is not only accurate but also balanced in identifying both positive and negative cases. Its high MCC (0.917) and Kappa (0.92), along with a low error rate of 6, make it the most reliable model. EfficientNetB2 is a close second, with slightly lower accuracy (93%) and similar precision and recall, along with a solid F1-Score of 92%. Its MCC (0.9022) and Kappa (0.9) are also strong, with an error rate of 7, making it almost as dependable as InceptionV3. ResNet50 has respectable performance with 89.12% accuracy, 91% precision, and 89% recall, leading to an F1-Score of 89%. While it is reliable, it falls short of the top two models and has a higher error rate of 10.88. MobileNetV3 lags behind with 87% accuracy, lower precision (89%), recall (87%), and F1- Score (86%), and the highest error rate of 13, making it the least reliable model.

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