

Hybrid Learning with Convolutional Feature Fusion for Automated Colon Disease Diagnosis from Capsule Endoscopy

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ABSTRACT

Colon diseases significantly contribute to gastrointestinal disorders and, if undetected, can lead to serious complications. The diagnosis of colon diseases is critical for early treatment and improved patient outcomes. Wireless Capsule Endoscopy (WCE) has emerged as a non-invasive and effective diagnostic tool. However, the manual interpretation of WCE images is time-intensive and prone to errors. Deep learning techniques offer promising solutions for automated analysis, but individual models often lack generalizability. This paper proposes a hybrid learning framework for classifying colon diseases by fusing features from multiple pre-trained deep convolutional neural network models, aiming for robust and accurate classification of colon diseases. WCE images were processed using fused pre-trained VGG16 and Inception V3 models to extract high-level deep convolutional features. Four machine learning classifiers were trained and evaluated on the fused features. Standard performance metrics were used for performance evaluation based on the proposed classification. Among the four classifiers, XG-Boost on the fused feature set achieved an accuracy of 0.96 for classification. Experimental results demonstrate the effectiveness of feature fusion and highlight the superior performance of the hybrid approach in accurately identifying colon diseases. This study contributes to advancing automated diagnostic systems, paving the way for more reliable and efficient clinical decision-making.

Keywords: Convolutional Neural Network, Deep Learning, WCE Image, Machine Learning.

I. INTRODUCTION

The healthcare domain is witnessing an increasing burden of gastrointestinal (GI) disorders, particularly colon-related diseases such as polyps, ulcers, and bleeding, which, if left undiagnosed or untreated, can lead to severe complications, including colorectal cancer. Colorectal cancer remains one of the leading causes of cancer-related deaths globally, emphasizing the critical need for early diagnosis and intervention. Traditional diagnostic methods, such as colonoscopy, while effective, are invasive and often uncomfortable for patients, deterring many from undergoing timely examinations. In this context, Wireless Capsule Endoscopy (WCE) has emerged as a non-invasive alternative, offering a comprehensive visual examination of the GI tract through a swallowable capsule equipped with a miniature camera. This innovation has revolutionized diagnostic procedures by reducing patient discomfort and enabling broader diagnostic reach [1]. Despite its advantages, WCE introduces a significant challenge: the enormous volume of data generated during each procedure. A single WCE examination produces thousands of images, demanding extensive

manual review by clinicians. This process is time-consuming, labor-intensive, and susceptible to human error, resulting in variability in diagnostic accuracy. These limitations underscore the need for automated, intelligent systems that can efficiently and accurately analyze WCE images to assist clinicians in the diagnostic process [2].

In recent years, Artificial Intelligence (AI) and Deep Learning (DL) have demonstrated remarkable capabilities in medical image analysis. Specifically, Deep Convolutional Neural Networks (DCNNs), such as VGG16 and Inception V3, have achieved state-of-the-art performance in feature extraction and image classification tasks across various domains [3]. These pre-trained models, developed using large-scale datasets like ImageNet, are particularly effective in transfer learning scenarios, where knowledge from general datasets is adapted to specific domains, including medical imaging. By leveraging their deep hierarchical architectures, these models capture intricate patterns and features from input images, making them well-suited for WCE image analysis [4]. However, while DCNNs have shown promise, their standalone application in domain-specific tasks such as WCE image classification faces several challenges, Data Scarcity and Overfitting, Computational Complexity and Lack of Interpretability. To address these challenges, hybrid learning frameworks have gained traction. A hybrid learning approach combines the powerful feature extraction capabilities of deep learning models with the interpretability and efficiency of traditional machine learning classifiers. This approach provides a balanced trade-off between accuracy, computational feasibility, and model transparency. The primary contributions of this paper are:

- Design a hybrid learning framework for colon disease classification using fused deep convolutional features from VGG16 and Inception V3.
- Evaluate the effectiveness of fused deep convolutional features from VGG16 and Inception V3 in representing WCE images for colon disease classification.
- Compare the classification performance of RF, XGBoost, DT, and SVM on the fused feature set.

The remainder of this paper is organized as follows: Section 2 offers the existing literature with its methodology. Section 3 details the methodology, including feature extraction techniques and the machine learning models employed. Section 4 presents the experimental results and the findings in the context of clinical applicability. Finally, Section 5 concludes the paper with future research directions and potential improvements to the proposed approach.

II. LITERATURE REVIEW

WCE-based automated systems for colon disease classification are an active area of research. Current research methods often suffer from limited generalization due to dataset-specific training and the lack of robust feature representation. This section discusses the colon disease classification using machine learning and deep learning approaches.

Two novel architectures are developed for polyp and surgical instrument segmentation to aid colorectal cancer diagnosis, assessment, and treatment [5]. A novel computer-aided approach is presented with ROI-based color histogram and SVM2 to find the cancer tumor in WCE

images [6]. A new computer-based diagnosis method is proposed for the detection and classification of gastrointestinal diseases from WCE images [7]. A new computer-aided diagnosis method for abnormalities detection in WCE images is proposed based on extreme learning machine [8]. A novel technique is proposed to improve the quality of images captured by the WCE [9]. The aim of the study was to develop an algorithm and identify features that discriminate between pediatric UC and colonic Crohn disease (CD) [10]. The study aims to design and develop a generalized multiclass CNN classification algorithm to be used in CAD system for diagnosis of various GI tract diseases by analyzing WCE GI tract images with varying tract lining lesions [11]. The optimized methodology introduced for the detection of both colorectal and gastric cancers. Our performance metrics analysis reveals remarkable results [12].

A convolutional neural network presented capable of classifying the CE images to identify those affected by lesions indicative of the disease [13]. The aim of the study is to develop a machine-learning (ML) model based on chemical descriptors that will recognize CRC-associated metabolites [14]. A cost-effective computer-aided detection system is proposed based on machine learning for the classification of colorectal cancer tissues [15]. The gene expression profiling data used from The Cancer Genome Atlas (TCGA) for the diagnosis of colon cancer and its staging [16]. The classification of colon cancer tissues by means of machine learning approaches is evaluated [17]. An efficient, robust, and light-weight multi-class classification framework is proposed for screening different gastrointestinal diseases [18]. A robust colon cancer diagnosis method is presented based on the feature selection method [19]. Hybrid methodologies (CNN–FFNN and CNN–XGBoost) were developed based on the GVF algorithm and achieved promising results for diagnosing disease based on endoscopy images of gastroenterology [20]. The latest progress in AI in diagnosing and treating CRC is reviewed based on a systematic collection of previous literature [21]. The study aimed to predict metastasis in CRC patients using machine learning (ML) approaches in terms of demographic and clinical factors [22].

The objective of the paper was to develop computer-aided diagnostic (CAD) tools for automated analysis of capsule endoscopic (CE) images, more precisely, to detect small intestinal abnormalities like bleeding [23]. A deep learning model was developed based on convolutional neural network architecture to accurately classify and detect colon cancer [24]. To explore whether machine learning models using serological markers can predict the relapse of Ulcerative colitis (UC) [25]. A hybrid ensemble feature extraction model is introduced to efficiently identify lung and colon cancer, integrating deep feature extraction and ensemble learning with high-performance filtering for cancer image datasets [26]. The novel sparse coded features are proposed to detect bleeding in WCE images using Scale-Invariant Feature Transform (SIFT) based key points as regions of interest. The SIFT and uniform Local Binary Pattern (LBP) features are computed around the key points using support vector machine (SVM) classification [27]. An automated system is proposed based on Gaussian mixture model super-pixels for bleeding detection and segmentation of candidate regions [28]. A deep neural network approach proposed a model named BIR (bleedy image recognizer) that combines MobileNet with a custom-built convolutional neural network (CNN) model to classify WCE bleedy images [29].

METHODOLOGY

The proposed framework for classification of Gastrointestinal Tract or Colon Diseases Images based on WCE images is defined as shown in Figure 1.

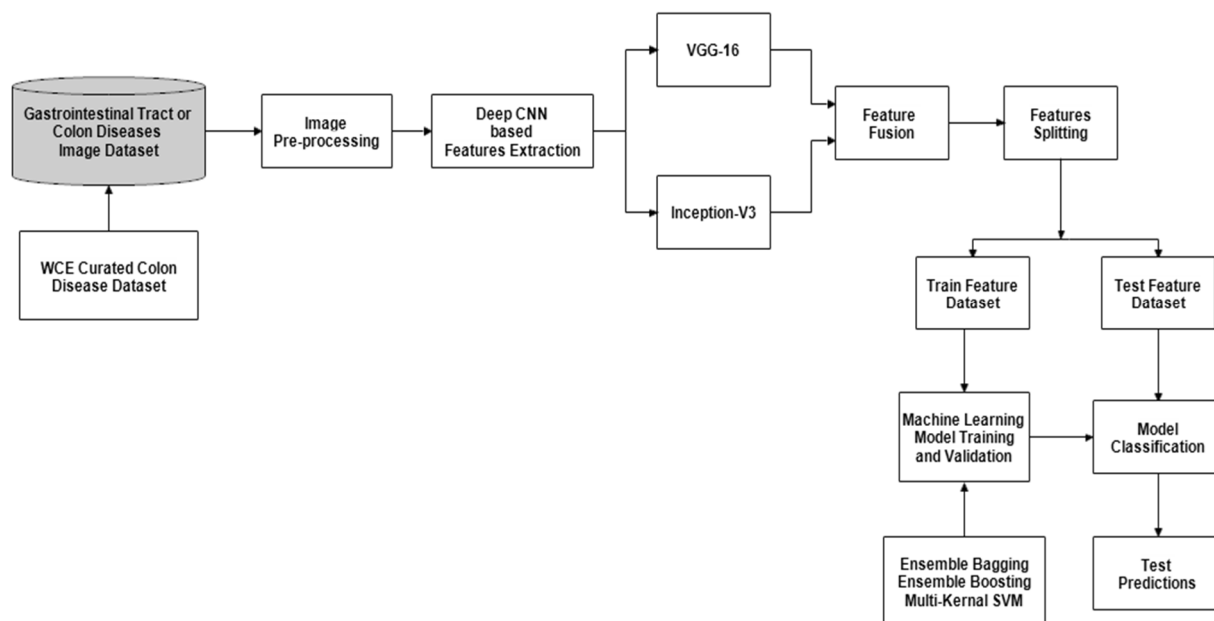


Figure 1: Hybrid Learning Approach for Classification of Colon Disease

A. Dataset

The dataset was sourced from Kaggle, titled WCE Curated Colon Disease Dataset Deep Learning. The dataset is comprised of WCE images from data source [30]. The dataset is comprised of 4 different classes which are Normal, Ulcerative Colitis, Polyps and Esophagitis. The dataset is comprised of training, validation, and testing sets. The training dataset consists of 800 images for each class, totaling 3200 images overall. The validation set is made up of 500 images for each class, totaling up to 2000 images. The test set is made up of 200 images for each class, totaling up to 800 images. The quantity of images for all classes in all 3 sets are balanced. The images vary in terms of width and height.

B. Image Preprocessing

Feature engineering for a dataset of Wireless Capsule Endoscopy (WCE) images labeled with colon disease classes involves extracting meaningful features from the images that can be used to train machine learning or deep learning models. In this context, image preprocessing and feature extraction are the key component operations. The image dimensions are normalized to ensure consistency across the dataset. The pixel values are scaled in a range between 0 and 1, to improve the model's ability to learn.

C. Feature Extraction - Deep Convolutional Neural Network (CNN)

The pre-trained Deep CNN models are used to extract the features from an image. It was loaded with weights from ImageNet and configured to exclude their fully connected layers, retaining only the convolutional layers. The WCE images are passed through each model to extract deep convolutional features from the feature layer of the individual model, which represent high-level patterns in the images. A convolutional neural network with 16 layers that specializes in extracting fine-grained spatial features. It is characterized by its depth, consisting of 16 layers, including 13 convolutional layers and 3 fully connected layers. The model’s architecture features a stack of convolutional layers followed by max-pooling layers, with progressively increasing depth. This design enables the model to learn intricate hierarchical representations of visual features, leading to robust and accurate predictions. Figure 2 shows the VGG-16 architecture composing a set of convolution and max pooling feature layers and a fully connected layer as a classification layer.

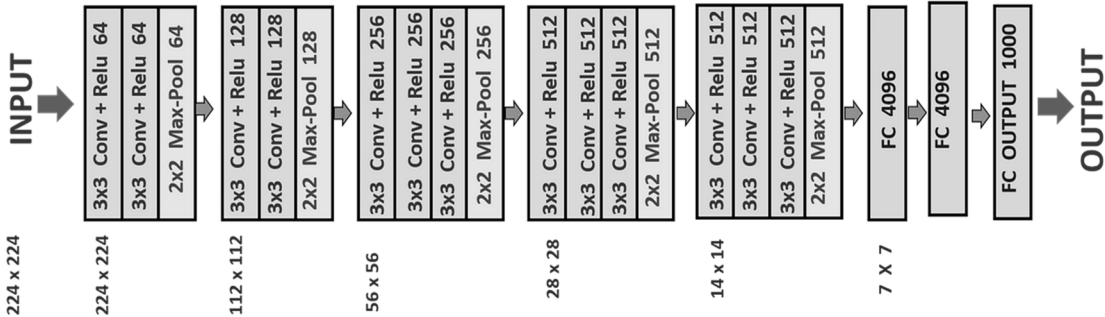


Figure 2: VGG 16 architecture

A deeper and more complex network designed to capture multi-scale features through its inception modules. Inception-v3 is a pre-trained convolutional neural network that is 48 layers deep. This pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. As a result, the network has learned rich feature representations for a wide range of images. The network has an image input size of 299-by-299. The model extracts general features from input images in the first part and classifies them based on those features. Figure 3 shows the architecture layers of the Inception-v3 deep learning model consists of feature and classification layers.

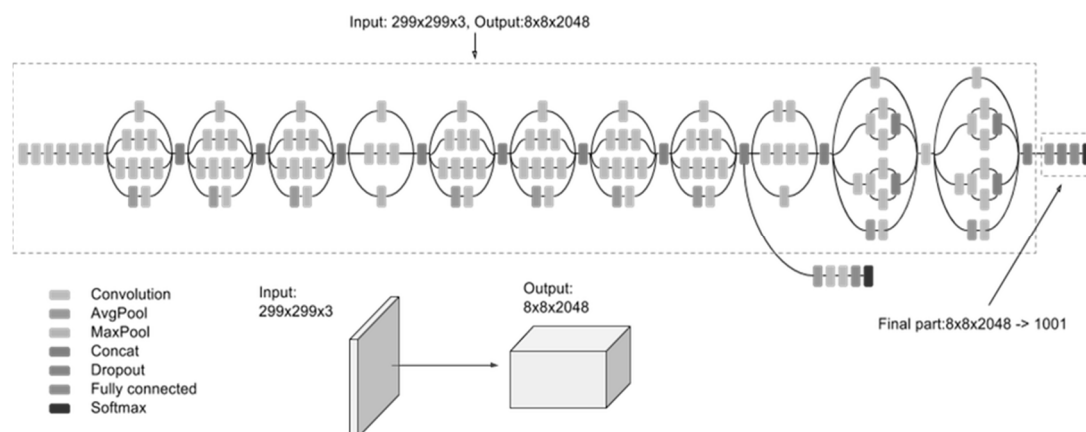


Figure 3: Inception V3 architecture

D. Feature Fusion

The feature vectors from VGG16 and Inception V3 are concatenated to create a unified representation. This fused feature vector combines the strengths of both models, capturing complementary information. The fused feature vectors are scaled to have zero mean and unit variance, ensuring compatibility with machine learning classifiers.

E. Feature Splitting

Feature splitting is a technique used in machine learning and data preprocessing to divide features into subsets, which can then be processed separately or used in different stages of a machine learning pipeline. This technique is especially useful when dealing with high-dimensional data, heterogeneous data types, or when certain features are more relevant to specific tasks within a model. The dataset is splitted into training and test sets (e.g., 70% training, 30% testing).

F. Machine Learning Modelling

Random Forest Classifier: Random Forest is an ensemble bagging method that combines multiple decision trees trained on bootstrapped subsets of the data. Predictions are aggregated via majority voting, reducing variance and overfitting. This makes the model more robust and accurate for classification tasks.

XG Boost Classifier: XGBoost is a boosting-based ensemble that trains weak learners sequentially, with each focusing on correcting errors from previous models. The final prediction is a weighted combination of all learners, improving accuracy and handling difficult cases effectively.

Decision Tree Classifier: Decision Tree is a supervised algorithm that splits data based on feature tests, forming a tree structure of decisions. Each leaf node represents a class label or probability, making it easy to interpret and useful for classification and regression.

Multi-kernel Support Vector Machine Classifier: MK-SVM extends SVM by combining multiple kernel functions to capture different patterns in the data. The model learns optimal

kernel weights, enhancing flexibility and improving classification performance across diverse datasets.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The objective is to develop a prediction model to classify healthy and colon tissue images using various machine learning techniques. Experiments were conducted on a system with at least Intel Core i5 CPU, 16 GB RAM, PyCharm, Anaconda, OpenCV, and Scikit-learn. Classifier performance was evaluated using 70:30 train-test split with cross-validation. The WCE Curated Colon Disease Dataset [39] served as the benchmark for assessment. To evaluate colon disease classification using WCE images, common performance metrics include: Accuracy, the proportion of correctly classified instances; Precision, the ratio of true positives to all positive predictions; Recall, the proportion of actual positives correctly identified; and F1-Score, the harmonic mean of precision and recall, balancing both metrics for imbalanced datasets. Formulas:

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

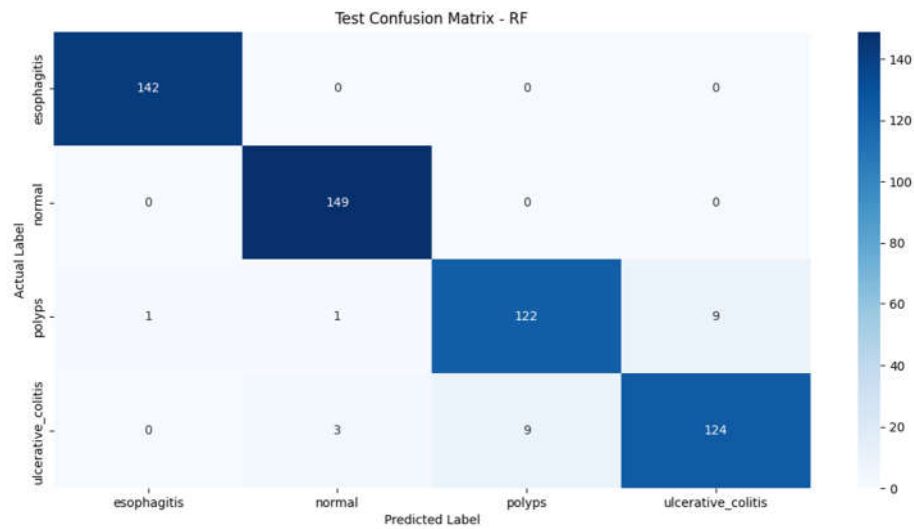
$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

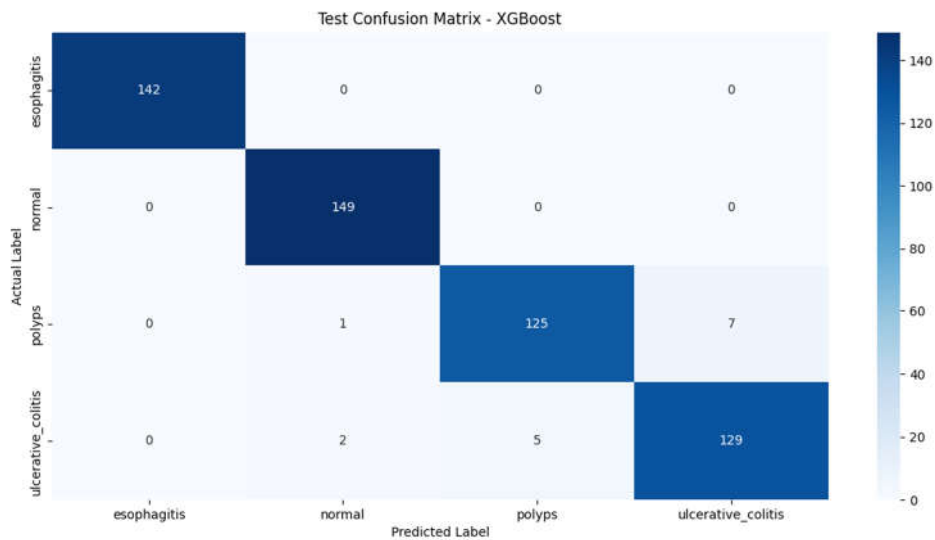
$$F1score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

The evaluation results of binary classification models trained on fused deep convolutional features extracted from VGG16 and InceptionV3 architectures. These deep features, when combined, provide enriched and abstract representations of WCE images, significantly improving the discrimination between healthy and unhealthy colon tissues. The performance is assessed using confusion matrices on both training and test data and further validated through ROC curve analysis, highlighting the robustness of the proposed feature fusion strategy across various classifiers.

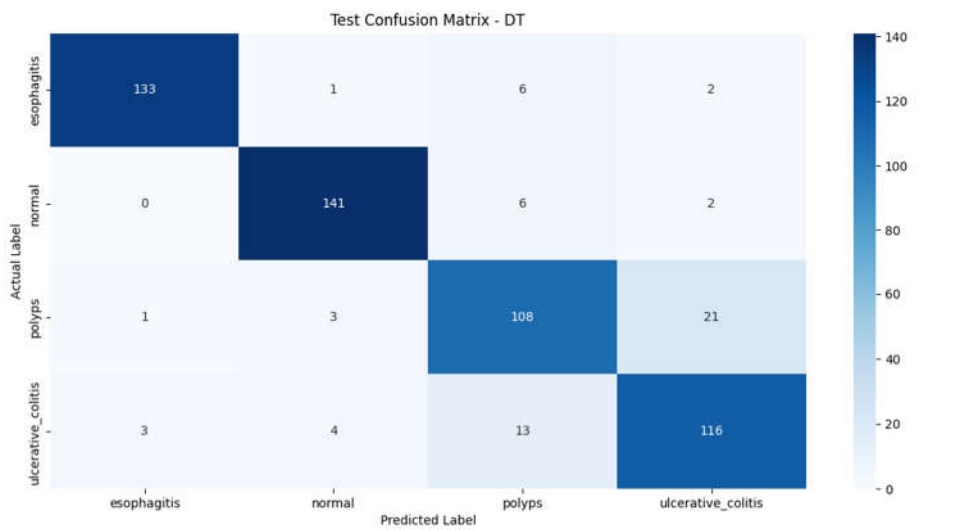
Figure 4 represents the multiclass classification confusion matrix for all four classifiers listed below. It shows the relationship between actual output with predicted output which is categorized into four output classes, ‘esophagitis’, ‘normal’, ‘polyps’, and ‘ulcerative colitis’.



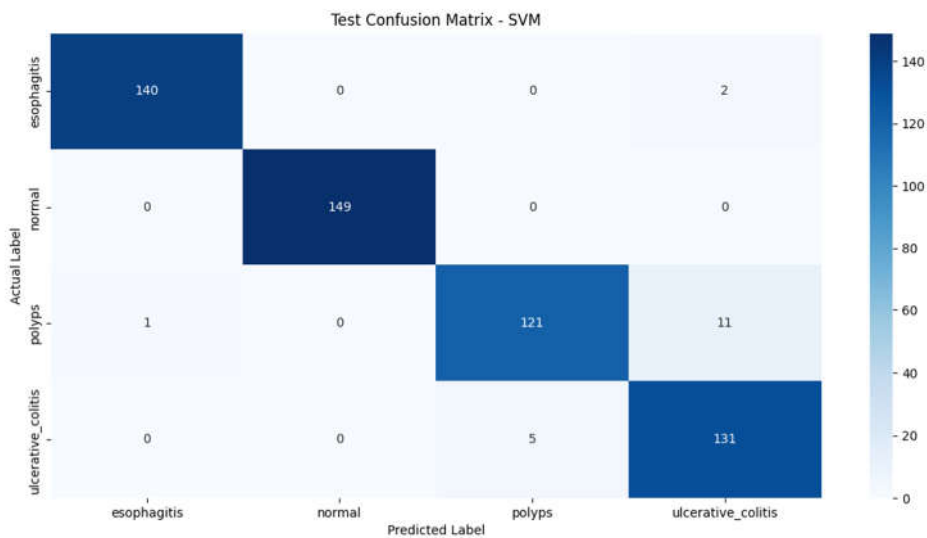
(a)Random Forest Classifier



(b) XG-Boost Classifier



(c)Decision Tree Classifier



(d) Multi-kernel SVM Classifier

Figure 4: Multi-class classification-based confusion matrix using (a) Random Forest Classifier (b) XG-Boost Classifier (c) Decision Tree Classifier (d) Multi-kernel SVM

Tables 1 to 4 show the multiclass classification performance using all four classifiers with precision, recall, and f-score performance measures for the four output classes shown in the confusion matrix. MK-SVM and RF show better classification performance compared to the other two machine learning classifiers.

Table 1: Classification report based on multi-classification using Random Forest

Output Class	Precision	Recall	F-score
Esophagitis	0.95	0.97	0.96
Normal	0.98	1.00	0.99

Polyps	0.86	0.86	0.86
Ulcerative Colitis	0.93	0.89	0.91

Table 2: Classification report based on multi-classification using XG-Boost

Output Class	Precision	Recall	F-score
Esophagitis	0.97	0.97	0.97
Normal	0.96	1.00	0.98
Polyps	0.92	0.94	0.93
Ulcerative Colitis	0.98	0.91	0.94

Table 3: Classification report based on multi-classification using Decision Tree

Output Class	Precision	Recall	F-score
Esophagitis	0.91	0.84	0.87
Normal	0.88	0.86	0.87
Polyps	0.60	0.69	0.64
Ulcerative Colitis	0.73	0.71	0.72

Table 4: Classification report based on multi-classification using Multi-kernel SVM

Output Class	Precision	Recall	F-score
Esophagitis	0.97	0.95	0.96
Normal	1.00	1.00	1.00
Polyps	0.91	0.89	0.90
Ulcerative Colitis	0.87	0.91	0.89

Table 5 shows the multiclass classification performance in terms of overall accuracy among all classifiers, showing the best value of 0.9562 for the XG Boost classifier compared to other classifiers as shown in Figure 5.

Table 5: Overall Accuracy Evaluation of Multi-class Classification

ML Classifier Models	Accuracy	Precision	Recall	F-score
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Random Forest	0.9312	0.9308	0.9312	0.9308
XG Boost	0.9562	0.9568	0.9562	0.9560
Decision Tree	0.775	0.7833	0.775	0.7781
Multi-kernel SVM	0.9375	0.9383	0.9375	0.9377

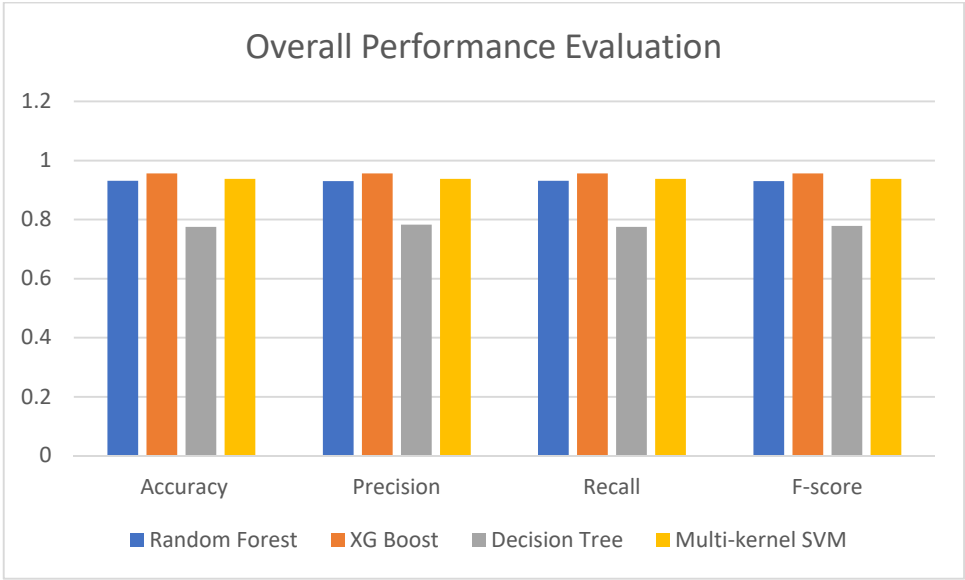


Figure 7: Overall accuracy performance in multi-class classification

V. CONCLUSION

This paper presents a novel hybrid learning framework for colon disease classification from WCE images. By fusing deep convolutional features from VGG16 and Inception V3 and leveraging machine learning classifiers, the proposed method achieves high accuracy in distinguishing between healthy and diseased tissue, and the model achieves superior performance compared to traditional methods. The results demonstrated that only XG-Boost performed better in multi-class classification with a 0.96 accuracy rate. The results underline the potential of combining deep learning and traditional approaches for medical image analysis. The proposed approach balances computational efficiency, accuracy, and interpretability, making it a promising tool for clinical diagnostics. This highlights the significant potential of deep learning models in medical image analysis, particularly in the context of gastrointestinal diagnostics.

Future work will focus on expanding the dataset, incorporating temporal information from WCE videos, and exploring lightweight models for real-time applications. Also, real-time deployment and integration with electronic health records are explored for a comprehensive diagnostic system.

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