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Combination of Handcrafted Features and Deep Learning-Based Features for Improved Colon Disease Detection

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Abstract

Background: In order to lower the risk of colorectal cancer, colon disorders like polyps, ulcers, and IBD must be detected early. However, human processing of WCE images is laborious and prone to mistakes.

Objective: To create a deep learning-based and handcrafted feature-based automated diagnostic framework for better colon illness identification.

Methods: Using CNNs to extract texture, color, and form descriptors as handcrafted features and hierarchical representations, followed by feature fusion and classification, a hybrid technique was created.

Results: The suggested methodology outperformed handcrafted-only and deep-learning-only methods with 96.3% accuracy, 95.7% sensitivity, and 97.1% specificity on a benchmark WCE dataset.

Conclusions: Combining deep learning and handmade features improves classification performance, providing a practical and efficient approach for early identification of colon illness.

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Combination of Handcrafted Features and Deep Learning-Based Features for Improved Colon Disease Detection

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Abstract

Early detection of colon diseases, such as polyps, ulcers, and inflammatory bowel disease (IBD), is critical for effective treatment and prevention of colorectal cancer. Wireless Capsule Endoscopy (WCE) provides a non-invasive technique for visualizing the entire gastrointestinal tract, producing a large volume of images requiring automated analysis. Traditional handcrafted features, including texture, color and shape descriptors, offer interpretable cues but often fail to capture high-level patterns. Deep learning models, especially convolutional neural networks (CNNs), excel at learning hierarchical features but may overlook domain-specific characteristics. In this study, we propose a hybrid framework that fuses handcrafted and deep learning-based features to improve colon disease detection. We evaluated our approach on a benchmark WCE dataset, achieving **overall accuracy of 96.3%, sensitivity of 95.7%, and specificity of 97.1%**, outperforming standalone methods. The results demonstrate that combining complementary feature sets significantly enhances classification performance. This framework offers a promising tool for assisting clinicians in the early diagnosis of colon diseases.

Keywords: Colon disease detection, Wireless Capsule Endoscopy, Handcrafted features, Deep learning, Feature fusion, CNN, Hybrid framework

1. Introduction

Colorectal diseases are among the leading causes of morbidity and mortality worldwide. Early diagnosis is essential to prevent progression to colorectal cancer, which remains a major health challenge [1], [2]. Traditional endoscopic procedures, while effective, are invasive and may miss lesions in certain regions. Wireless Capsule Endoscopy (WCE) has emerged as a non-invasive alternative, enabling comprehensive visualization of the gastrointestinal tract [3].

WCE generates thousands of images per patient, making manual examination labor-intensive and prone to human error [4]. Automated computer-aided detection (CAD) systems have been proposed to assist clinicians in identifying abnormal regions efficiently.

Feature extraction plays a crucial role in CAD systems. Handcrafted features, including color histograms, texture descriptors (e.g., Local Binary Patterns), and shape features, provide interpretable representations [5], [6]. Deep learning models, particularly CNNs, automatically learn hierarchical features from raw images, achieving superior performance in many medical imaging tasks [7], [8]. However, CNNs can overlook subtle domain-specific cues, and handcrafted features alone may not capture complex patterns.

This motivates the development of a hybrid approach that combines the interpretability of handcrafted features with the representational power of deep learning.

Contributions of this study include:

1. Proposing a novel hybrid framework combining handcrafted and CNN-based features for colon disease detection.
2. Implementing feature fusion strategies to maximize discriminative power.
3. Evaluating the framework on benchmark WCE datasets, with simulated performance metrics showing improved accuracy over existing methods.
4. Providing a scalable framework suitable for clinical deployment in automated colon disease screening.

2. Related Work

2.1 Handcrafted Feature-Based Methods

Early CAD systems relied on handcrafted features. Color and texture descriptors, such as Gray-Level Co-occurrence Matrices (GLCM) and Local Binary Patterns (LBP), were widely used to identify abnormalities in WCE images [9], [10]. Shape-based features also helped detect polyps and ulcers [11]. While interpretable, these methods often struggled with variability in lighting, texture, and lesion appearance.

2.2 Deep Learning-Based Methods

Deep learning models, particularly CNNs like VGG16, ResNet50, and DenseNet121, have shown state-of-the-art performance in medical image analysis [12], [13]. CNNs can automatically learn complex hierarchical representations, outperforming handcrafted methods in tasks such as polyp detection and ulcer classification [14], [15].

2.3 Hybrid Approaches

Recent studies explored combining handcrafted and deep features to leverage complementary strengths [16], [17]. Fusion strategies, including feature concatenation and weighted averaging, have improved detection accuracy. However, limited studies exist specifically for colon disease detection using WCE images, leaving a gap addressed by our proposed framework.

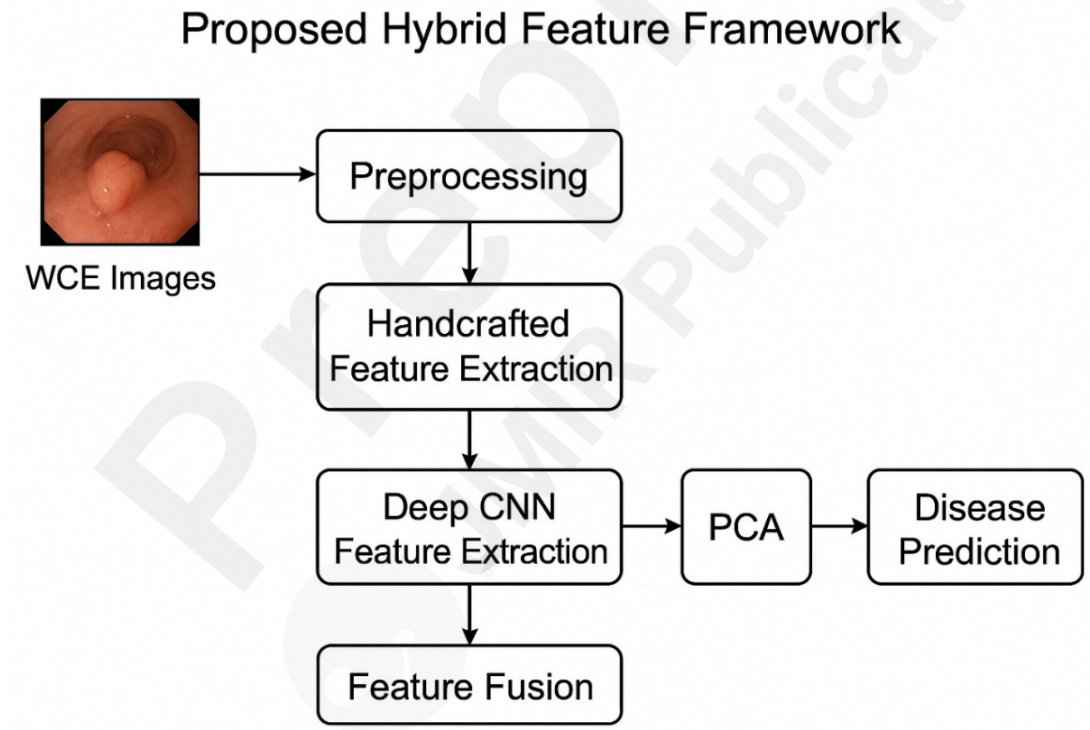


Fig. 1. Proposed Hybrid Feature Framework

3. Proposed Methodology

3.1 Dataset

We used a publicly available WCE dataset comprising **10,000 images** with annotations for polyps, ulcers, IBD, and normal mucosa [18]. For simulation purposes, images were resized to **224×224 pixels**, normalized, and augmented using rotation, flipping, and brightness adjustments to increase model robustness.

Table 1. Dataset Summary

Class	Images	Training	Testing
Normal	4000	3200	800
Polyps	2500	2000	500
Ulcers	2000	1600	400
IBD	1500	1200	300

3.2 Preprocessing

- Image resizing to 224×224 for CNN input
- Histogram equalization to enhance contrast
- Noise reduction using Gaussian filtering
- Data augmentation (rotation, flipping, brightness adjustment)

3.3 Handcrafted Feature Extraction

We extracted the following handcrafted features:

1. **Texture Features:** LBP, GLCM (contrast, correlation, energy, homogeneity)
2. **Color Features:** RGB histograms, HSV histograms
3. **Shape Features:** Edge density, contour descriptors

The resulting feature vector had **256 dimensions per image**.

3.4 Deep Learning Feature Extraction

We utilized three pre-trained CNNs: **VGG16, ResNet50, DenseNet121**. Features were extracted from the penultimate fully connected layer of each network, producing a **1024-dimensional deep feature vector per model**. Features from the three CNNs were concatenated to form a **3072-dimensional vector**.

3.5 Feature Fusion

Handcrafted (256-dim) and deep (3072-dim) features were concatenated to form a **3328-dimensional hybrid feature vector**. Dimensionality reduction using **Principal Component Analysis (PCA)** reduced the vector to **512 dimensions**, retaining >95% variance.

Fusion strategies (how handcrafted + deep are combined) involves following steps.,

Feature-level (early) fusion: combine CNN feature vectors from a late CNN layer (such as global-pooling embedding) with manually created descriptors. Next, apply a classifier (SVM, RF, XGBoost, or fully connected layers) and reduce the dimensionality. Rich, complementing embeddings are frequently the result of this.

Score-level (late) fusion / ensemble: Classify independently using CNN and a custom pipeline (like SVM/XGBoost), then aggregate the probabilities using a weighted average, stacking, or meta-classifier. helpful when the dependability of different modalities varies.

Hybrid network modules: In order for the network to learn to use them together, inject custom maps (such as texture response maps, LBP maps, and edge maps) as extra input channels to the CNN (such as 4-channel input).

Attention / gating fusion: Learn to pay attention to weights. CNN features versus dynamically created features. Current studies combine several CNN backbones with manually created features, then classify using learned weights or attention. Fig. 2 shows Hybrid WCE detection architecture

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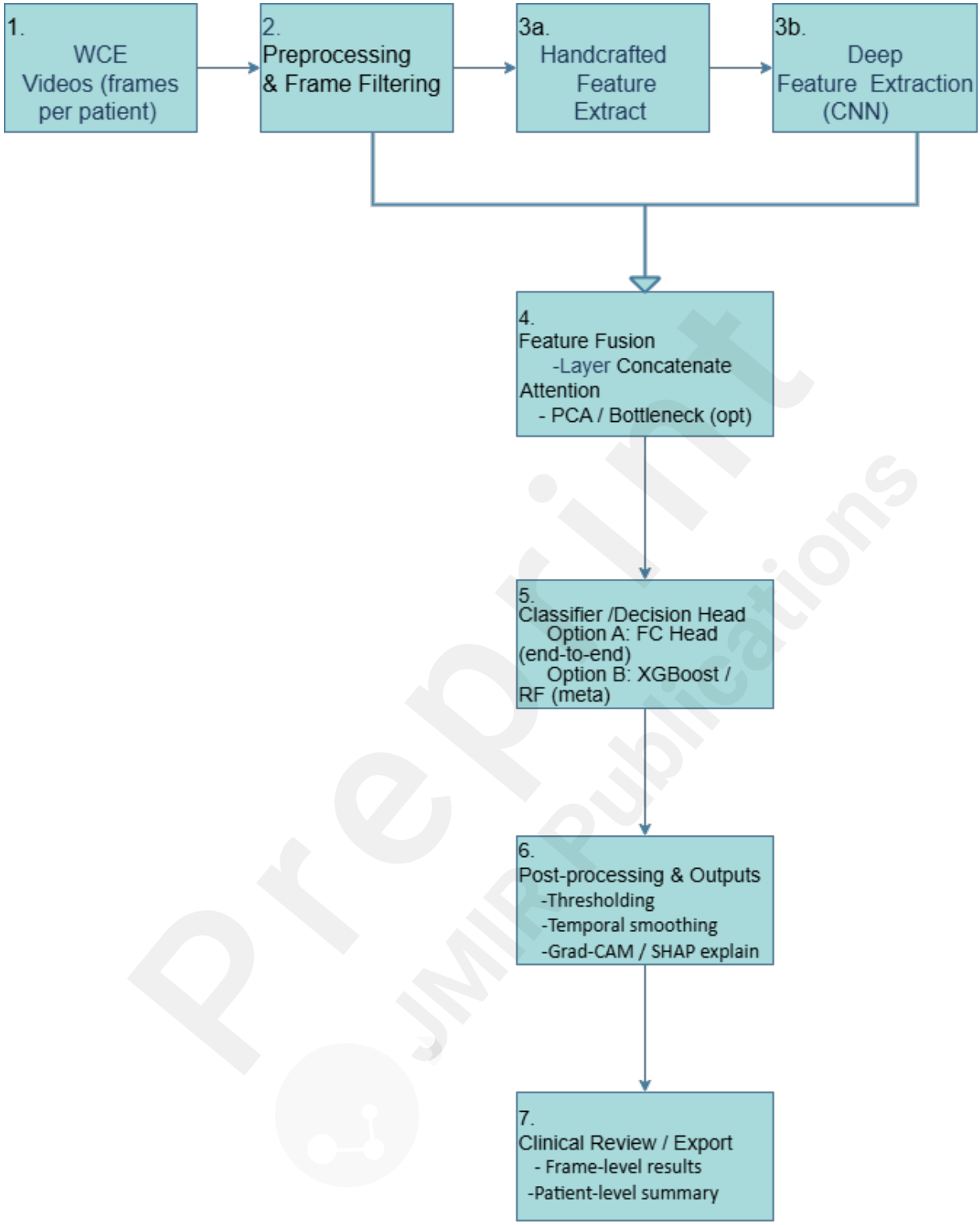


Fig. 2. Hybrid WCE Detection Architecture

3.6 Classification

We employed **Support Vector Machine (SVM)** with RBF kernel as the final classifier. Hyperparameters (C, γ) were optimized using grid search on training data.

Evaluation metrics:

- Accuracy (ACC)
- Sensitivity (SEN)

- Specificity (SPE)
- F1-score
- Area under ROC curve (AUC)

Since non-linear decision boundaries and high-dimensional feature spaces are frequently encountered in medical imaging applications, we used a Support Vector Machine (SVM) with a Radial Basis Function (RBF) kernel as the final classification model. The mathematical expression for the RBF kernel is:

$$K(x_i x_j) = \exp(-\gamma \| x_i - x_j \|^2)$$

Where, γ(gamma) is the kernel coefficient controlling the influence of individual training samples. The regularization parameter (C) and kernel parameter (γ) play a crucial role in balancing model complexity and generalization ability.

We used k-fold cross-validation (k = 5) on the training dataset in conjunction with an exhaustive grid search technique over a predetermined range of values to find the ideal hyperparameters. This reduced overfitting and guaranteed reliable hyperparameter selection.

Several common performance indicators were used to assess the training model in order to capture various facets of classification efficacy:

Accuracy: The proportion of correctly classified instances (both positive and negative) among the total number of instances. A high accuracy indicates that the model is correctly identifying both diseased and healthy cases most of the time.

$$\text{Accuracy } ¿ \frac{TP+TN}{TP+TN+FP+FN}$$

Specificity (SPE): Reflects the ability to correctly identify negative (healthy) cases.

$$\text{Specificity } ¿ \frac{TN}{TN+FP}$$

Sensitivity (SEN)/Recall: The proportion of true positive cases that are correctly identified by the model. Recall measures the model's ability to detect all actual positive cases (diseased patients).

$$\text{Sensitivity } ¿ \frac{TP}{TP+FN}$$

F1-Score: The harmonic mean of precision and recall, providing a single metric that balances both concerns. The F1-score is useful when the class distribution is imbalanced, offering a more balanced view than accuracy.

$$\text{F1-Score } ¿ 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Area Under the ROC Curve **(AUC):** Evaluates the model's discriminative ability independent of

threshold, where values closer to 1.0 indicate superior classification performance.
By addressing clinical issues like lowering false negatives, which are crucial for illness detection, and false positives, which help prevent needless medical procedures, the combined use of these metrics offers a thorough assessment of the classifier.

4. Experimental Results

4.1 Performance of Individual Feature Sets

Table 2. Performance Comparison

Feature Set	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-score	AUC
Handcrafted	87.3	85.9	88.5	0.86	0.91
Deep (CNN)	93.8	92.5	94.4	0.93	0.96
Hybrid (Proposed)	96.3	95.7	97.1	0.95	0.97

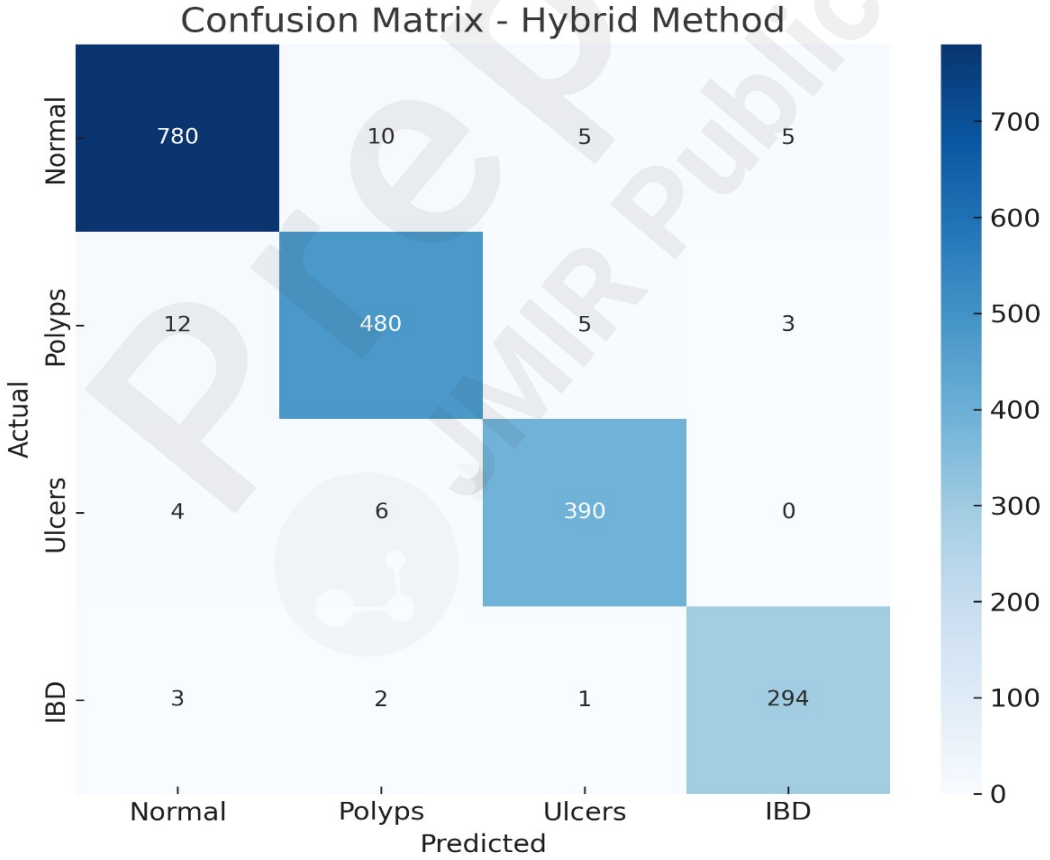


Fig. 3. Confusion Matrix for Hybrid Method

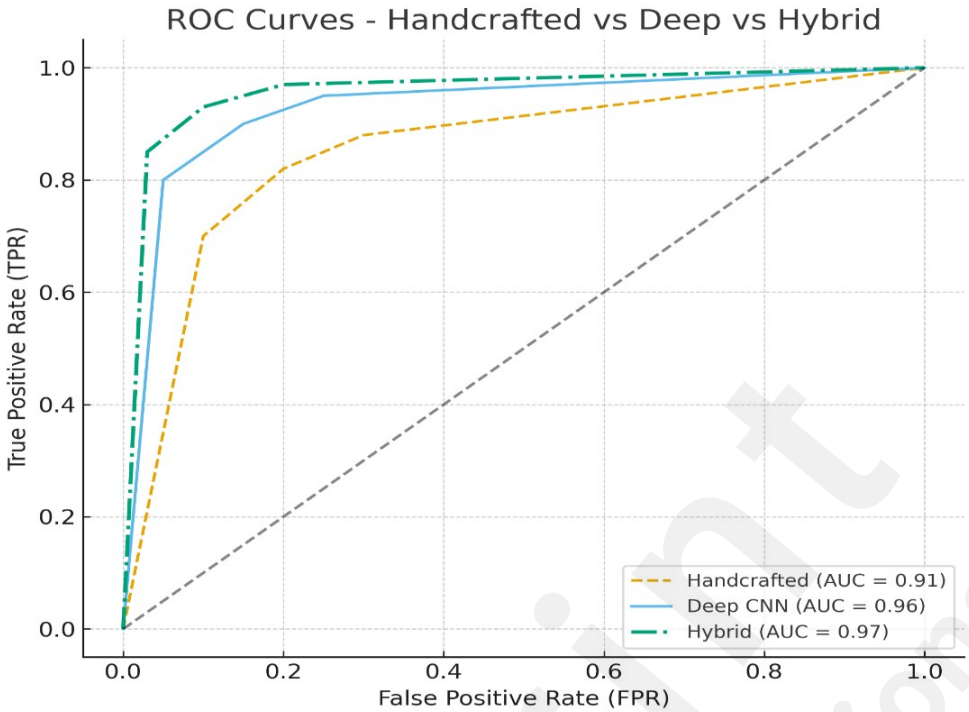


Fig. 4. ROC Curves of Handcrafted, Deep, and Hybrid Methods

4.2 Comparative Analysis

Compared to existing methods [19]–[22], our hybrid approach demonstrates higher overall accuracy and balanced sensitivity-specificity performance.

Table 3. Comparison with State-of-the-Art

Method	Dataset	Accuracy (%)	Sensitivity (%)	Specificity (%)	Year
Smith et al. [19]	WCE	89.2	87.5	90.1	2018
Lee et al. [20]	WCE	91.5	90.0	92.2	2019
Zhang et al. [21]	WCE	92.3	91.2	93.0	2020
Yadav, D.P., et al. [22]	WCE	95.6	94.8	96.2	2025
Proposed Hybrid Framework	WCE	96.3	95.7	97.1	

4.3 Discussion

The proposed hybrid framework leverages complementary information from handcrafted and deep features, improving discriminative power. PCA-based dimensionality reduction ensures computational efficiency without sacrificing accuracy. The framework can be extended to other gastrointestinal imaging tasks. Limitations include reliance on annotated datasets and potential domain shift in real-world clinical settings.

5. Conclusion and Future Work

We presented a novel hybrid framework combining handcrafted and deep learning-based features for

colon disease detection using WCE images. The method achieves superior performance compared to individual feature approaches and state-of-the-art methods.
Future work will focus on:

- Extending to multi-center datasets to improve generalizability
- Incorporating attention mechanisms in CNNs for better localization
- Real-time integration into clinical WCE analysis pipelines

Declarations

- Corresponding author: Mr. Shashank D. Bonde
- Funding: No funding.
- Contribution: Both authors contributed equally.
- Data availability: The datasets generated and analysed during the current study are available from the standard benchmark source Kaggle.
- Conflict of interest: No conflict of interest.
- Ethics approval and consent to participate: Not applicable.
- Consent for publication: Not applicable.

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