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A Machine Learning Framework for Robust Detection Of Healthy And Ulcer Tissue In Endoscopic Images

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Abstract
In clinical endoscopy, rapid and reliable tissue classification between healthy and ulcerated regions is crucial for effective diagnosis and treatment planning purposes. This study proposes a novel computational pipeline that integrates deep feature extraction with classical machine learning to discriminate healthy and ulcer tissues from endoscopic images. A pre-trained EfficientNetB0 model was used to extract high-level image features, which were then reduced using supervised Partial Least Squares (PLS) and classified with a Radial Basis Function Support Vector Machine (RBF-SVM). With the incorporation of class imbalance mitigation strategies, such as controlled oversampling and probability reweighting, the framework demonstrates strong performance and interpretability. The effectiveness of the proposed method is demonstrated through an evaluation of a curated endoscopy image dataset, achieving high accuracy and robustness in distinguishing tissue types. The results indicate its potential for clinical decision support in gastroenterology.

Keywords- *EfficientNet, Endoscopy, Medical Image Classification, Partial Least Squares, Support Vector Machine, Ulcer Detection*

1. Introduction
Endoscopic imaging plays an essential role in the diagnosis of gastrointestinal diseases, including peptic ulcers and related mucosal abnormalities. Traditional visual inspection techniques rely on clinician experience and are susceptible to variability and subjectivity issues. Advances in computational image analysis and machine learning have enabled automated and quantitative methods for analysing medical images, improving diagnostic precision and reducing human error. In this study, we present a hybrid framework that combines deep learning and classical machine learning techniques to detect healthy and ulcerous tissues in endoscopic images. By using pre-trained deep networks for feature extraction and efficient classifiers for discrimination, this approach balances the representation power with interpretability and computational efficiency. Compared to prior work on ulcer detection, which often focuses on segmentation or deep neural networks alone, our method leverages supervised dimensionality reduction to extract meaningful features that are highly predictive and less redundant. This results in improved generalization and easier integration into the clinical workflow.

2. Literature review
Qian Zhao et al. [1] addressed the challenge of large image volumes in wireless capsule endoscopy (WCE) by proposing a computer-aided diagnosis system for automatic polyp detection. Their method combined opponent color features with LLE-based LBP texture features and used an SVM classifier, achieving an accuracy of 97%. Alexandros Karargyris et al. [2] highlighted the effectiveness of WCE for minimally invasive diagnosis of gastrointestinal diseases and proposed a synergistic approach for automatic detection of polyps and perforated ulcers in WCE video frames, demonstrating improved performance over existing methods. Baopu Li et al. [3] focused on tumor detection in WCE images using illumination-invariant color–texture features based on LBP and wavelet transforms, refined through SVM-based feature selection, and reported a tumor recognition accuracy of 92.4%. Dongmei Chen *et al.* [4] proposed a real-time abnormality detection method for WCE

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using a Frame Abnormality Index based on data density ratios. Yanan Fu *et al.* [5] developed a rapid bleeding detection approach using RGB color features to improve diagnostic accuracy. Baopu Li *et al.* [6] introduced a polyp detection scheme combining illumination-invariant color features with Zernike shape descriptors. Yong-Gyu Lee *et al.* [7] proposed a fast spectral analysis method for bleeding detection in WCE images using contrast- and brightness-based weighting factors, achieving 87% sensitivity and 90% specificity. Sae Hwang *et al.* [8] introduced an unsupervised polyp detection approach based on Gabor texture features, k-means clustering, and watershed segmentation, reporting 100% sensitivity. Yanan Fu *et al.* [9] developed a rapid bleeding detection method using RGB color features, outperforming existing WCE software. Xiaoying Liu *et al.* [10] proposed a computer-aided diagnosis approach using color wavelet covariance features optimized via feature selection to discriminate normal and abnormal tissues. Guolan Lv *et al.* [11] proposed an automatic bleeding detection method for WCE images using combined color–spatial descriptors and kernel-based classifiers, demonstrating effective detection performance. Yina Liu *et al.* [12] introduced a 2D-to-3D mapping and image alignment technique for WCE to reduce diagnostic time. Charisis *et al.* [13] emphasized clinically motivated color–texture features for WCE image diagnosis. Li *et al.* [14] presented a time-varying filter-based empirical mode decomposition to address mode mixing in non-stationary signals. Yussif Moro *et al.* [15] showed that combining adaptive EMD filtering with nonlinear RBF neural networks significantly improves modeling accuracy and noise reduction in biomedical signal analysis. Krizhevsky *et al.* [16] demonstrated the effectiveness of deep convolutional neural networks (CNNs) for large-scale image classification using the ImageNet dataset, establishing CNNs as a powerful tool for visual recognition. Support Vector Machines (SVMs), introduced by Cortes and Vapnik [17], remain a robust supervised learning method for classification tasks, particularly with limited training data. The ImageNet database, presented by Deng *et al.*[18], enabled large-scale benchmarking and accelerated advances in computer vision. Feature selection techniques, as reviewed by Guyon and Elisseeff [19], are essential for improving the model performance and reducing the dimensionality. Foundational works in machine vision and statistical learning by Jain *et al.* [20] and Hastie *et al.* [21] provide a theoretical and practical framework for modern image analysis and machine learning systems.

3. Dataset description

The dataset used in this study consisted of endoscopic images collected from clinical imaging sources and curated to represent multiple tissue conditions. The images were categorized into distinct classes, primarily healthy and ulcer-affected tissues. In some cases, additional categories, such as polyps or abnormal mucosal structures, may be included to improve the generalization capability of the classification model shown in Figure 1 .

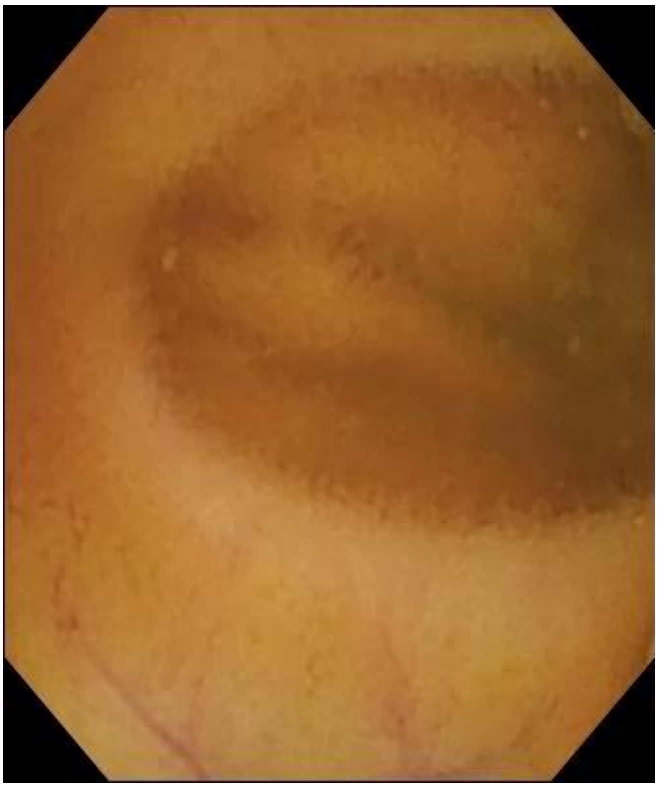

Figure.1: Healthy tissue

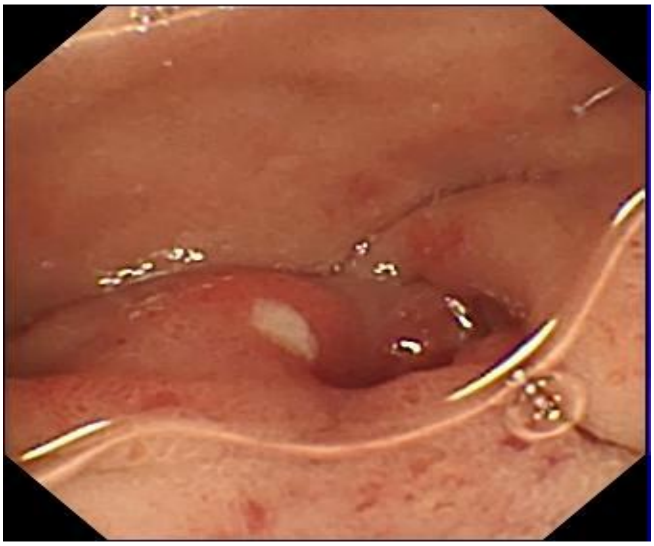

Figure.2 Ulcer Tissue

Each image in the dataset was stored in the standard RGB format with varying spatial resolutions, reflecting real-world clinical acquisition conditions. Prior to training, all images were resized to a uniform input resolution compatible with the selected deep feature extraction backbone. The dataset was partitioned into three non-overlapping subsets: training, validation, and testing. The traiSning set was used to learn the model parameters, the validation set was utilized for hyper parameter tuning and early stopping, and the test set was reserved strictly for unbiased performance evaluation. To address the inherent class imbalance in medical imaging datasets, the distribution of samples across classes was analysed in detail. In cases where ulcer images were underrepresented compared to healthy images, controlled oversampling techniques were applied during training to ensure that minority class patterns were adequately learned. Additionally, data augmentation strategies, such as rotation, horizontal flipping, brightness adjustment, and slight zooming, were applied to increase dataset diversity and reduce the risk of over fitting. Metadata associated with each image, such as acquisition conditions or imaging device variations, were not directly used as input to the model but were considered during the result interpretation to analyse the performance stability across different imaging conditions. The dataset organization followed a structured directory hierarchy, enabling reproducible experimentation and ease of integration with standard deep learning pipelines.

4. Image Enhancement Strategy

Endoscopic images often suffer from nonuniform illumination, low contrast, specular reflections, and sensor noise, which can adversely affect feature extraction and classification performance. To mitigate these issues, an image enhancement strategy was employed as a preprocessing step prior to feature extraction. The primary goal of this enhancement stage was to improve visual clarity and emphasize diagnostically relevant structures without introducing artificial patterns that could mislead the learning model shown in Figure 3 .

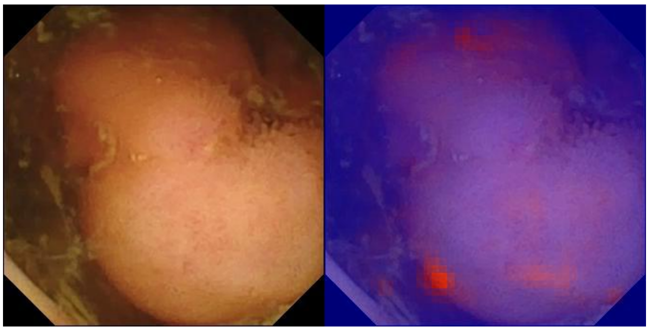

Figure.3 Visual comparison of endoscopic image (a) before enhancement and (b) after enhancement.

Initially, colour normalization was applied to reduce variations caused by different lighting conditions and camera settings. This step ensured that the colour distribution across the images remained consistent, enabling the model to focus on the tissue characteristics rather than illumination artifacts. Contrast enhancement techniques, such as adaptive histogram equalization, are then used to improve the visibility of subtle texture variations in ulcerated regions. Noise suppression is achieved using edge-preserving filtering methods that reduce high-frequency noise while maintaining important structural details. This is particularly important in medical imaging, where subtle texture differences can provide significant diagnostic information.

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Additionally, intensity normalization was applied to map the pixel values into a standardized range, facilitating the stable and efficient training of the deep feature extractor shown in Figure 4.
S

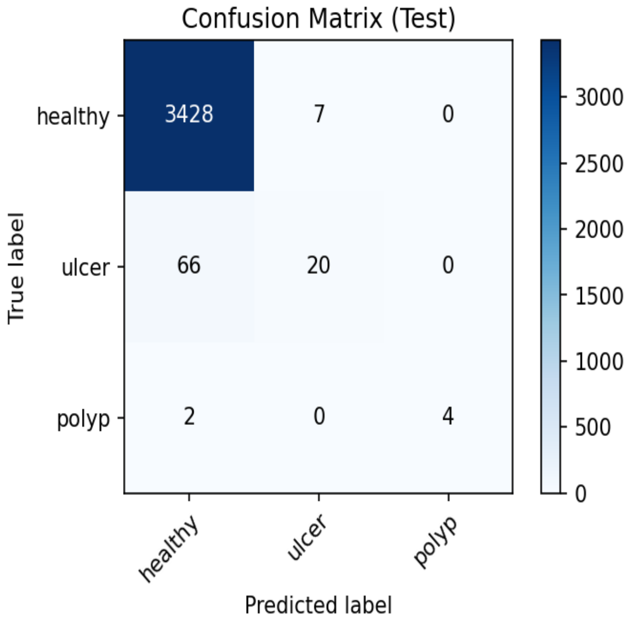

Figure 4 Confusion Matrix For Healthy And Ulcer Tissue Classification In The Test Dataset.

The effectiveness of the enhancement strategy was qualitatively verified by visual inspection and quantitatively assessed by comparing the classification performance with and without pre-processing. The results indicate that the enhancement stage contributes to improved convergence during training and leads to more consistent feature representations, particularly in low-contrast or poorly illuminated images.

5. Mathematical modeling and formulation

The proposed framework can be mathematically modeled as a sequence of transformations applied to an input image, followed by classification. Let an input endoscopic image be represented as

$$I\in RH\times W\times C,$$

where H, W, and C denote the height, width, and number of channels, respectively. The pre-processing and enhancement stage can be represented as a function $\phi(\cdot)$, producing an enhanced image

$$I'=\phi(I)$$

The deep feature extraction stage is modeled using a pre-trained convolutional neural network $(\cdot)$, Parameterized by weights θ. The network maps the enhanced image I' to a high-dimensional feature vector $z\in Rd$, such that:

$$z=f\theta(I')$$

To reduce redundancy and focus on discriminative components, supervised dimensionality reduction is applied using Partial Least Squares (PLS).

Let $\in RN\times d$

denote the feature matrix for N samples and

$$Y\in RN\times K$$

represent the corresponding one-hot encoded class labels. PLS projects Z onto a lower-dimensional latent space

$$U\in RN\times m,$$

where m≪d, by maximizing the covariance between projected features and class labels. The classification stage employs a Support Vector Machine with a radial basis function kernel. Given a reduced feature vector ui, the decision function is expressed as:

$$g(u_i)={}_{j=1}\sum^{N}\alpha_j y_j \exp(-\gamma\|u_i-u_j\|^2) + b$$

where αj are Lagrange multipliers, yj are class labels, γ is the kernel width parameter, and b is the bias term. The predicted class $y\hat{}i$ is obtained by evaluating the sign or maximum probability of the decision function output. To handle class imbalance, weighted loss terms are introduced, assigning higher penalties to misclassification of ulcer samples. The overall optimization objective seeks to minimize classification error while maximizing the margin between healthy and ulcer classes in the projected feature space.

6. Methodology

The proposed methodology follows a structured pipeline that integrates image pre-processing, deep feature extraction, supervised dimensionality reduction, and classical machine learning–based classification. The overall objective was to build a robust and generalizable framework for distinguishing between healthy and ulcerated tissues in endoscopic images.

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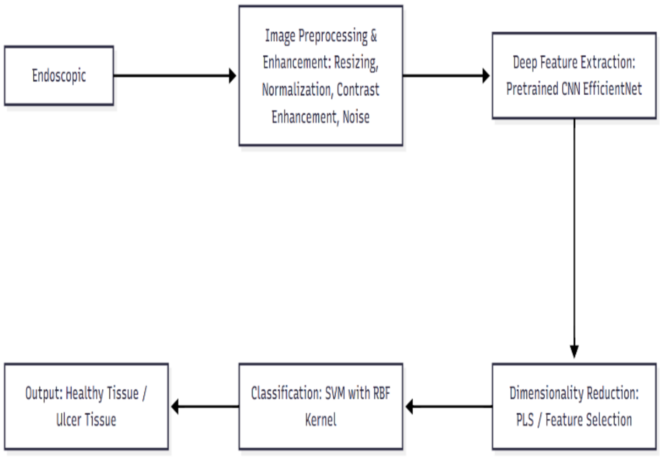

Flowchart 1 Methodology Textual Block Diagram

The process begins with dataset preparation and pre-processing. All input images were first resized to a fixed spatial resolution compatible with the selected convolutional neural network backbone. Basic normalization was applied to scale the pixel intensities into a standardized range. In addition, the image enhancement strategy described earlier was employed to mitigate the effects of illumination variations, low contrast, and sensor noise. This pre-processing step ensured that diagnostically relevant texture patterns and colour variations were preserved while suppressing irrelevant visual artifacts.

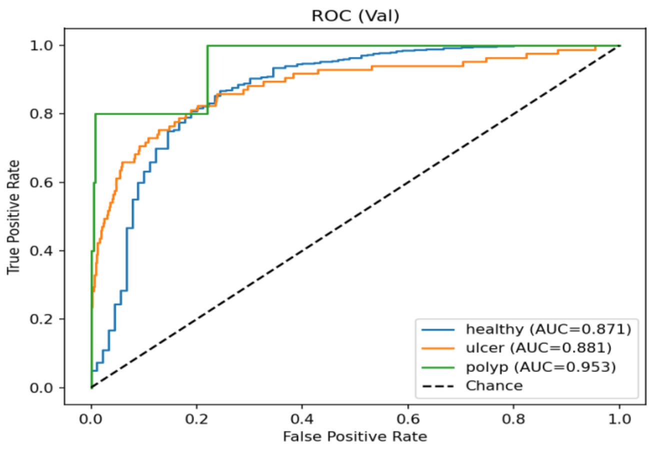

Figure 5 Classification performance curve across training epochs.

In the second stage, deep feature extraction was performed using a pre-trained convolutional neural network. Instead of training a deep network from scratch, transfer learning is adopted to leverage the generic visual representations learned from large-scale image datasets. Intermediate feature maps from the network were aggregated into compact feature vectors that encoded high-level semantic information regarding tissue appearance. This approach significantly reduces the computational cost and data requirements while retaining a strong discriminative capability.The extracted deep features were then passed through a supervised dimensionality reduction module. Partial Least Squares (PLS) is employed to project the high-dimensional feature vectors into a lower-dimensional latent space that maximizes the correlation with the class labels. This step reduces feature redundancy, improves class separability, and helps prevent overfitting, particularly in scenarios where the number of training samples is limited compared to feature dimensionality. Finally, classification is performed using a Support Vector Machine (SVM) with a radial basis function kernel. SVM was selected because of its strong generalization performance in high-dimensional spaces and its ability to model nonlinear decision boundaries. Hyper parameters, such as kernel width and regularization strength, were optimized using the validation dataset. To address class imbalance, class weights were incorporated into the training process, ensuring that the misclassification of ulcer samples was penalized more heavily than the majority class errors. The complete pipeline was evaluated using a strictly separated test set. Performance metrics, including accuracy, precision, recall, F1-score, and confusion matrices, were computed to provide a comprehensive assessment of the classification effectiveness. This modular methodology enables easy replacement or enhancement of individual components, making the framework extensible for future improvements.

7.Results And Discussion

The proposed framework demonstrated a strong performance in classifying healthy and ulcerative tissues from endoscopic images. Quantitative evaluation of the test dataset indicated high overall

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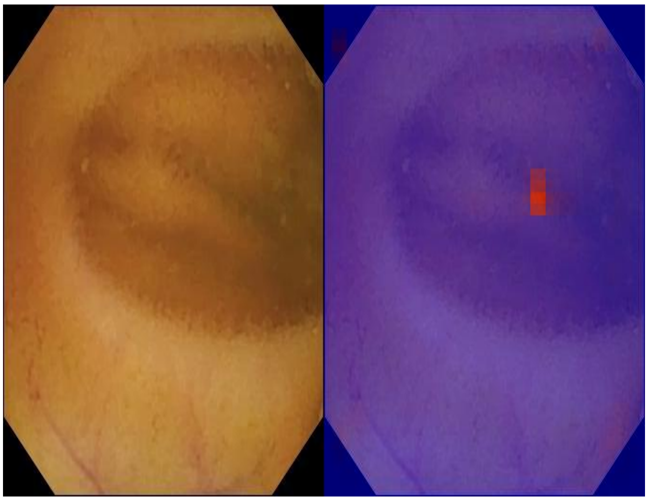
accuracy and balanced performance across classes, confirming the effectiveness of combining deep feature extraction with supervised dimensionality reduction and SVM classification. The inclusion of image enhancement techniques contributes to more stable feature representations, particularly in cases where raw images exhibit poor lighting or low contrast. Comparative experiments conducted with and without the enhancement stage showed a consistent improvement in the classification metrics when pre-processing was applied, highlighting the importance of visual normalization in medical imaging tasks.The supervised dimensionality reduction stage plays a crucial role in improving the generalization of the model. By projecting deep features into a compact latent space aligned with the class labels, the classifier becomes less sensitive to noise and redundant information. This results in improved convergence during training and reduced variance in performance across different dataset splits. From a clinical perspective, the high recall observed for ulcer samples is particularly significant because it reflects the system's ability to minimize false negatives. Missing an ulcer case can have serious medical implications; therefore, prioritizing sensitivity to pathological classes is essential. The proposed class-weighted learning strategy effectively addresses this requirement by emphasizing ulcer detection during optimization.



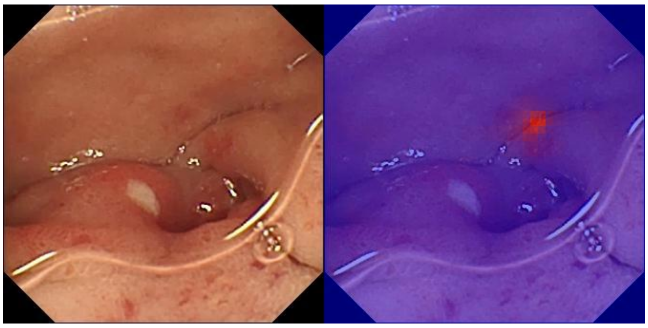


Figure 6 Two-dimensional visualization of extracted features showing class separability between healthy and ulcer samples.

Qualitative analysis using visualization techniques, such as feature space projections and activation heat maps, suggests that the model focuses on medically relevant tissue regions when making decisions. This interpretability aspect is important for building trust in AI-assisted diagnostic tools. Overall, the results indicate that the proposed framework can serve as a reliable decision support system for endoscopic tissue assessment with the potential for real-world clinical integration.

Conclusion

This study presents a comprehensive machine learning framework for the automated classification of healthy and ulcerated tissues in endoscopic images. By integrating image enhancement, deep feature extraction, supervised dimensionality reduction, and nonlinear classification, the proposed approach achieves a robust and accurate performance under various imaging conditions. The hybrid design effectively balances the representation power and generalization capability, making it suitable for medical datasets where labeled samples are limited and class distributions are imbalanced. The results demonstrate that the framework not only achieves high classification accuracy but also maintains a clinically meaningful sensitivity toward ulcer detection. Future work may focus on extending the framework to multi-class tissue classification, incorporating temporal information from endoscopic video streams and exploring lightweight model variants for real-time deployment in clinical settings. Additionally, integrating explainable AI techniques and clinician-in-the-loop validation can further improve trust and adoption in healthcare environments.

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