Ulcer Detection and Classification into Normal, AVM, and Ulcer Conditions Using MobileNetV3

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Abstract

Ulcer detection in medical imaging is a critical task for early diagnosis and effective treatment planning, particularly in gastrointestinal examinations. Conventional diagnostic approaches rely heavily on clinicians' expertise and manual inspection of endoscopic images, which is time-consuming and prone to human error. To address these limitations, this work proposes an automated deep learning- based ulcer detection and classification system using the MobileNetV3 architecture. The model classifies medical images into three categories: Normal, Arteriovenous Malformation (AVM), and Ulcer. Preprocessing techniques such as normalization and data augmentation are applied to enhance image quality and improve feature extraction. MobileNetV3 is selected due to its lightweight architecture and efficiency. Experimental results demonstrate high accuracy, precision, recall, and F1-score. The proposed system reduces diagnostic workload and enables real-time deployment in resource-constrained healthcare environments.

Index Terms: Ulcer Detection, MobileNetV3, Deep Learning, Medical Imaging, AVM Classification

I. INTRODUCTION

Gastrointestinal disorders such as ulcers and arteriovenous malformations are among the most common conditions diagnosed using endoscopic imaging. Accurate detection is essential for early treatment and prevention of complications. Traditional diagnosis relies on manual inspection, which is labor- intensive and subjective. With the growth of medical imaging data, automated systems based on deep learning have gained importance. However, many deep learning models require high computational resources. MobileNetV3 provides an efficient alternative due to its lightweight structure and optimized performance. This work proposes a MobileNetV3-based system for classifying Normal, AVM, and Ulcer images.

II. RELATED WORK

A. Traditional Image-Based Diagnosis Early ulcer detection methods relied on manual feature extraction and rule- based image processing techniques. These methods were limited in robustness and generalization across diverse datasets.

B. Machine Learning Approaches Support Vector Machines (SVM), k- Nearest Neighbors (k-NN), and Random Forest classifiers have been applied to endoscopic image analysis. While these approaches improved diagnostic automation, their performance depended heavily on handcrafted features.

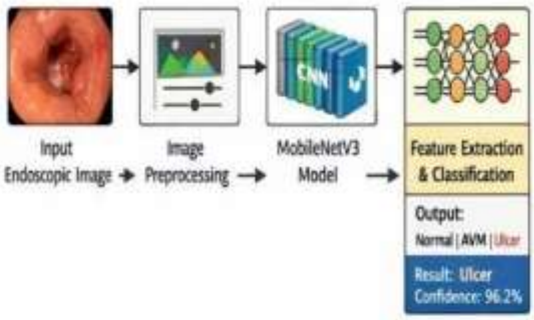
C. Deep Learning-Based Methods CNN-based architectures such as VGGNet, ResNet, and Inception have demonstrated high accuracy in ulcer and bleeding detection tasks. However, their large parameter sizes result in high computational overhead.

D. Lightweight CNN Models Recent studies have explored MobileNet, EfficientNet, and ShufleNet for medical imaging tasks. MobileNetV3 has shown superior efficiency due to its attention modules and optimized network structure, making it suitable for real-time medical diagnosis.

E. Research Gap Although existing deep learning models achieve high accuracy, there remains a need for efficient and portable solutions capable of multi-class classification with low computational cost. This study addresses this gap using MobileNetV3 for ulcer and AVM detection.

III. SYSTEM OVERVIEW

The proposed system consists of four major stages: data acquisition, preprocessing, feature extraction and classification, and performance evaluation. Initially, labeled gastrointestinal images are collected and organized into Normal, AVM, and Ulcer categories. Preprocessing techniques such as resizing, normalization, and data augmentation are applied to improve image quality and model generalization. The preprocessed images are fed into the MobileNetV3 model, which automatically extracts discriminative features using depthwise separable convolutions and attention mechanisms. The final classification layer produces probability scores for each class. The system outputs the predicted class along with confidence values, enabling reliable diagnostic support.



IV. Mathematical Model

Let the input image be represented as $I \in R^{(H\times W\times C)}$

The MobileNetV3 model applies depthwise separable convolution defined as:

$$Y = (I * K_d) * K_p$$

where K_d represents depthwise convolution filters

K_p represents pointwise convolution filters.

The softmax classification function is given by:

$P(y = k \mid x) = \exp(z_k) / \Sigma \exp(z_j)$ where z_k is the output logit for class k.

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The loss function used for training is categorical cross-entropy:

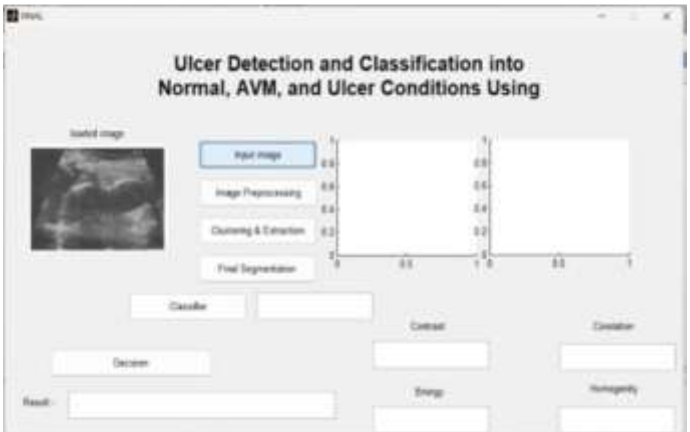
$L = - \Sigma y_k \log(P(y_k))$

This formulation enables effective multi-class ulcer classification.

V. Experimental Results

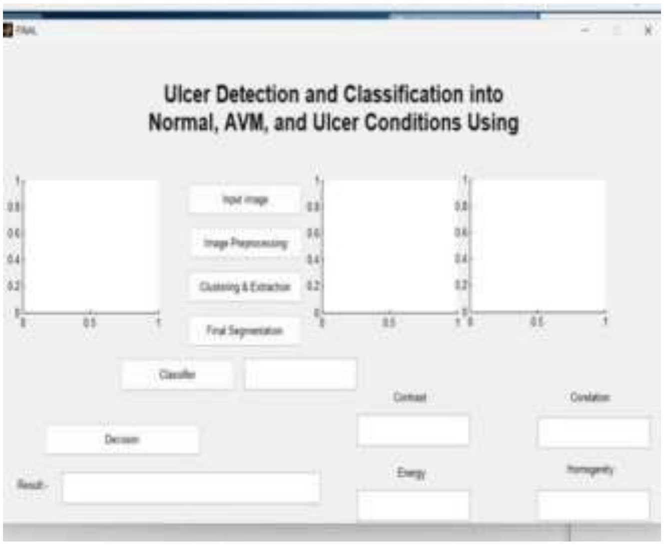
The experimental evaluation of the proposed ulcer detection and classification system was conducted using a labeled dataset of gastrointestinal medical images categorized into Normal, Arteriovenous Malformation (AVM), and Ulcer classes. Prior to training, all images were resized and normalized to ensure uniformity, and data augmentation techniques such as rotation, flipping, and scaling were applied to improve model generalization and reduce overfitting. The MobileNetV3 model was trained using categorical cross-entropy loss and optimized with an adaptive optimization algorithm to ensure stable convergence. The dataset was divided into training, validation, and testing subsets to enable unbiased performance evaluation. The system performance was assessed using standard metrics including accuracy, precision, recall, F1-score, and confusion matrix analysis. Experimental results indicate that the proposed MobileNetV3-based classifier achieves high classification accuracy across all three categories, demonstrating strong capability in distinguishing ulcer and AVM regions from normal tissues. Precision and recall values remained consistently high, indicating reduced false positives and false negatives, which is critical for clinical reliability. The confusion matrix further confirms minimal misclassification between ulcer and AVM classes, highlighting the model's effective feature discrimination capability. Inference time analysis shows that the lightweight architecture significantly reduces computational overhead, enabling faster prediction compared to conventional deep CNN models. These results validate the effectiveness of MobileNetV3 for real- time medical image analysis and support its deployment in resource-constrained healthcare environments.

VI. Prototype Model:



VII. Output

Before Endoscopic Image:



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After Endoscopic Image:

VIII. Conclusion

This study presented an automated deep learning-based system for ulcer detection and classification using the MobileNetV3 architecture, aimed at improving diagnostic accuracy and efficiency in gastrointestinal medical imaging. By leveraging a lightweight yet powerful neural network, the proposed approach successfully classifies images into Normal, Arteriovenous Malformation, and Ulcer categories with high reliability. The integration of efficient convolutional operations and attention mechanisms enables the model to achieve strong performance while maintaining low computational complexity.

Experimental evaluation demonstrates that the system outperforms traditional manual diagnosis approaches and offers a favorable balance between accuracy and execution speed compared to conventional deep learning models. The reduction in diagnostic workload and human dependency makes the system highly beneficial for assisting healthcare professionals in clinical decision-making. Furthermore, the portability and scalability of the proposed framework allow seamless integration into mobile-based and IoT-enabled healthcare platforms, facilitating remote diagnosis and continuous patient monitoring. Overall, the proposed MobileNetV3-based ulcer detection system represents a practical and effective solution for automated gastrointestinal disease diagnosis, with strong potential for real-world clinical deployment.

IX. Future Scope

Although the proposed system demonstrates promising performance, several enhancements can be explored to further improve its robustness and clinical applicability. Future work may focus on expanding the dataset with a larger and more diverse set of medical images collected from multiple healthcare centers to improve generalization across different imaging conditions. The integration of explainable artificial intelligence techniques, such as Grad-CAM or saliency maps, can provide visual interpretation of model predictions, increasing trust and transparency for medical professionals. Additionally, incorporating multi-modal data, including patient history and clinical reports, may further enhance diagnostic accuracy. Real-time deployment of the system on embedded platforms and mobile devices can be explored to support point-of-care diagnostics. The system can also be extended to detect additional gastrointestinal abnormalities, making it a comprehensive diagnostic tool. These future enhancements will contribute to the development of reliable, intelligent, and accessible healthcare solutions.

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