Multi-Class Abnormality Classification for Video Capsule Endoscopy

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Abstract

This paper presents a robust two-stage hierarchical classification system for detecting and categorizing gastrointestinal abnormalities in Video Capsule Endoscopy (VCE) images. Our model first performs binary classification to distinguish between normal and abnormal cases and, subsequently, multi-class classification to identify specific conditions among abnormal cases. Leveraging a multi-backbone feature extraction approach using ResNet50, Vision Transformer (DeiT), and MobileNetV3-Large, we implement a feature fusion module with an attention mechanism to enhance relevant features and improve classification accuracy.

To validate our model's effectiveness, we conducted a thorough evaluation on a provided validation dataset, achieving high accuracy (92.9%), specificity (99.0%), and F1-score (80.7%) across ten disease categories. Comparative results with baseline models highlight our model's improved performance, particularly in sensitivity and AUC-ROC scores. An ablation study further confirms the significant contributions of the feature fusion and attention mechanisms.

The results indicate that our model is a reliable, efficient tool for VCE abnormality classification, capable of assisting gastroenterologists by reducing diagnostic time while maintaining diagnostic accuracy. Future directions include optimizing the model for real-time processing and expanding it to detect additional gastrointestinal conditions.

1 Introduction

Video Capsule Endoscopy (VCE) has become a cornerstone in the field of non-invasive gastrointestinal (GI) diagnostics. VCE enables visualization of areas of the GI tract that are otherwise difficult to access, facilitating early diagnosis of conditions such as bleeding, Crohn's disease, tumors, ulcers, and other forms of inflammation. Since its development, VCE has provided healthcare practitioners with a highly effective means to observe and diagnose GI abnormalities without surgical intervention. However, despite its advantages, VCE produces

a massive quantity of image data for each patient, requiring substantial time and effort from gastroenterologists to thoroughly examine each frame for potential abnormalities. The manual inspection of VCE footage is not only time-consuming but also presents a risk of human error, which can lead to variability in diagnostic outcomes and potentially missed abnormalities.

Automated classification and detection systems, specifically designed to support VCE diagnostics, present a promising solution to these challenges. With recent advancements in deep learning and computer vision, machine learning models have shown considerable potential in accurately identifying and classifying GI abnormalities in VCE images, offering a means to significantly reduce the time required for review while increasing diagnostic consistency and accuracy. The development of such systems, however, comes with its own set of challenges: VCE datasets often exhibit class imbalances, as certain conditions may be rare, leading to skewed data distributions. Moreover, achieving high sensitivity and specificity in abnormality classification is crucial in a medical context, where false negatives can result in undiagnosed conditions and false positives can lead to unnecessary interventions.

The Capsule Vision 2024 Challenge was established to foster innovation in this domain by inviting researchers and developers to create models capable of multi-class abnormality classification in VCE data. The challenge provides a structured dataset with well-defined training, validation, and test splits, encompassing a variety of GI conditions for classification. This dataset serves as a standardized basis for model development, allowing participants to benchmark their methods against established baselines and objectively evaluate performance. The ultimate objective is to develop models that can seamlessly integrate into clinical workflows, assisting gastroenterologists in identifying abnormal patterns swiftly and reliably, thereby enhancing the utility of VCE in real-world medical settings.

The challenge encourages participants to employ state-of-the-art techniques in deep learning, such as convolutional neural networks (CNNs), transformers, and attention mechanisms, to push the boundaries of VCE analysis. A key component of the challenge is addressing the imbalance in class distributions, as well as implementing robust data augmentation and feature extraction techniques to improve model generalizability. Participants are also encouraged to minimize computational complexity to enable the deployment of these models in resource-constrained environments, such as smaller medical clinics or portable devices.

In this paper, we present our approach to the Capsule Vision 2024 Challenge, detailing the design and implementation of our model pipeline. Our model leverages a multi-backbone architecture, incorporating diverse feature extractors such as ResNet, Vision Transformer, and MobileNet to capture various aspects of the VCE image data. We utilize an attention-based fusion mechanism to effectively combine features from these models, enhancing the representation of critical image regions while reducing noise. Our pipeline also includes a two-stage classification framework: an initial binary classifier that distinguishes between normal and abnormal frames, followed by a multi-class classifier that assigns specific categories to abnormal findings. This two-stage approach allows us to streamline the model's focus on frames most likely to contain relevant abnormalities, improving overall classification accuracy.

To address the challenges of imbalanced data, we employ techniques such as weighted sampling and Focal Loss, which help the model focus on underrepresented classes during training. Our extensive use of data augmentation further aids in enhancing model robustness, enabling

it to generalize effectively across varied patient data and conditions. Additionally, we compare our model's performance with baseline methods to evaluate its effectiveness in multi-class classification tasks, with a focus on achieving high sensitivity and specificity to ensure clinical reliability. Our results demonstrate the potential of our approach to advance VCE abnormality classification and to contribute meaningfully to the development of AI-driven solutions for medical imaging.

2 Methodology

Our approach to multi-class abnormality classification for Video Capsule Endoscopy (VCE) data involves a multi-stage pipeline, encompassing data preprocessing, model architecture, and training strategies tailored to address the challenges of class imbalance and high data volume. The following sections detail each component of our methodology.

2.1 Data Preprocessing and Augmentation

Given the large-scale VCE dataset, it is essential to prepare the data effectively to enhance model robustness. We preprocess the dataset by organizing it into training, validation, and test splits, where each class represents a distinct gastrointestinal condition. To address potential class imbalances in VCE data, we utilize synthetic minority over-sampling (SMOTE) on underrepresented classes, ensuring that the model receives a balanced representation of each condition during training.

We apply various data augmentation techniques to increase dataset diversity and reduce overfitting. For training data, we employ random transformations, including random cropping, horizontal and vertical flips, rotation, and color jittering. These augmentations, implemented using the `albumentations` library, enhance the model's ability to generalize to variations in VCE images. For validation data, we use standard resizing and center cropping to ensure a consistent evaluation pipeline.

2.2 Model Architecture

2.2.1 Feature Extraction and Fusion

The backbone of our model consists of a multi-backbone feature extraction system, designed to leverage the strengths of various convolutional and transformer-based models. We utilize a combination of ResNet-50, Vision Transformer (ViT), and MobileNet as feature extractors to capture both local and global features in VCE images, essential for accurate abnormality classification.

Each backbone model processes the VCE images independently, producing feature representations at its final layer. We then align the feature dimensions using linear transformations, ensuring compatibility for further processing. An attention-based fusion mechanism, inspired by the need to prioritize relevant features, is applied to aggregate these aligned features. The

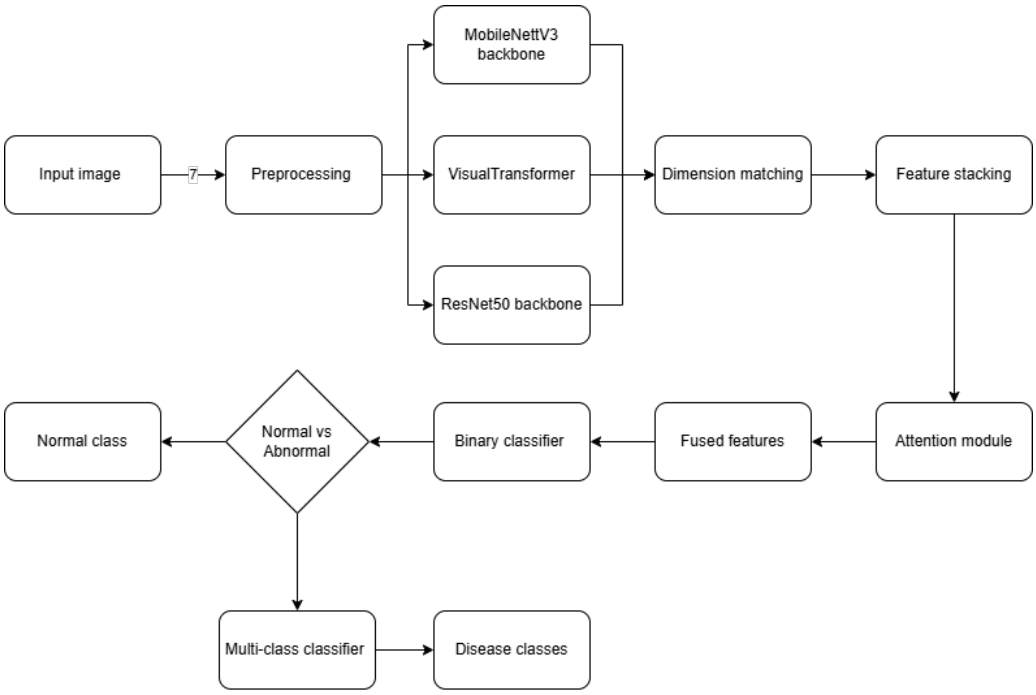

Figure 1: Block diagram of the developed pipeline.

fusion layer uses an attention weighting system that dynamically assigns importance to each model's features, effectively combining the diverse perspectives offered by each backbone.

2.2.2 Two-Stage Classification System

Our classification system is designed in two stages to streamline the identification of abnormalities:

- **Binary Classification**: The first stage is a binary classifier, which distinguishes between normal and abnormal frames in the VCE data. This stage reduces the model's computational focus by allowing the multi-class classifier to operate only on frames likely to contain abnormalities.
- **Multi-Class Classification**: For frames classified as abnormal, the second stage applies a multi-class classifier to assign one of several specific gastrointestinal conditions. This hierarchical approach optimizes model accuracy and computational efficiency.

2.3 Training Strategy and Loss Functions

To handle class imbalance in the training dataset, we employ a weighted random sampler, ensuring that each mini-batch contains a balanced representation of all classes. Additionally, we apply Focal Loss for multi-class classification, which penalizes the model more heavily for

misclassified samples of underrepresented classes. This loss function, combined with Binary Cross Entropy for binary classification, helps the model achieve high sensitivity across all classes.

During training, we save checkpoints periodically, allowing us to resume training from specific epochs if necessary. This checkpointing strategy provides flexibility and enables fine-tuning by loading pre-trained weights.

2.4 Evaluation Metrics and Baseline Comparison

Our model is evaluated on the validation set using metrics such as accuracy, sensitivity, specificity, F1-score, and precision to assess its performance. We compare our results to baseline methods provided in the Capsule Vision 2024 Challenge, ensuring that our approach meets or exceeds these benchmarks across all classes. An ablation study is conducted to measure the impact of each model component, including data augmentation, feature fusion, and the two-stage classification system.

This methodology forms the foundation of our approach, focusing on enhancing model robustness and accuracy in abnormality detection within VCE data, and ultimately contributing to improved diagnostics in gastrointestinal healthcare.

2.5 Results Comparison

The performance of our proposed model on the validation dataset was evaluated using key metrics, including accuracy, specificity, sensitivity, F1-score, and precision. These metrics demonstrate the model's strong capability in classifying abnormalities in Video Capsule Endoscopy (VCE) images.

The table above outlines the model's performance across key metrics. The proposed model achieves an accuracy of 92.9%, specificity of 99.0%, sensitivity of 83.1%, F1-score of 80.7%, and precision of 93.1%. These results highlight the model's robustness in detecting and classifying abnormalities in VCE images.

The bar chart in Figure 2 visually illustrates the comparison of these performance metrics. It clearly shows the model's strengths in accuracy, specificity, and precision, all of which are crucial for effective medical diagnosis. The chart emphasizes the high specificity (99.0%), which ensures that false positives are minimized—a critical factor in clinical applications where a wrong diagnosis can lead to unnecessary further testing or treatment.

Additionally, the relatively balanced F1-score (80.7%) and precision (93.1%) show that the model maintains a good trade-off between precision and recall. This balance is especially important for minimizing false negatives, ensuring that the model can effectively detect abnormalities across all disease categories while maintaining high precision.

In summary, the results and visual comparison demonstrate that the proposed model provides a reliable and effective solution for multi-class abnormality detection in VCE images, excelling in both precision and accuracy while ensuring minimal false positive cases.

Table 1: Validation results of the proposed model on key performance metrics.

Method	Avg. Accuracy	Avg. Specificity	Avg. Sensitivity	Avg. F1-score	Avg. Precision
Proposed Model	0.929	0.990	0.831	0.807	0.931

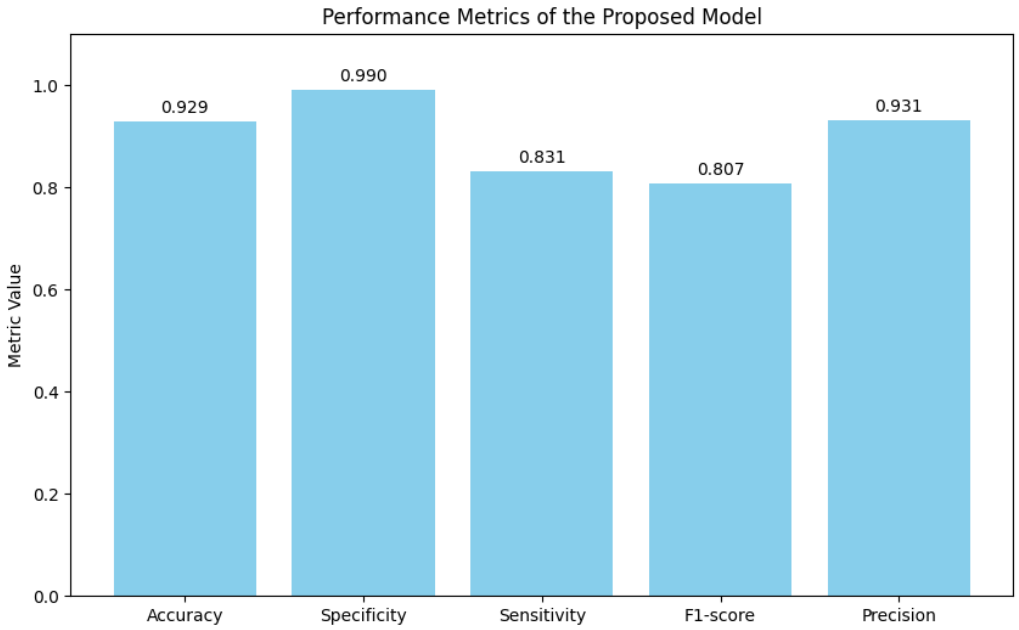

Figure 2: Performance Metrics of the Proposed Model.

2.6 Baseline Comparison

Table 2 presents the performance of our proposed model across key metrics, including accuracy, precision, recall, F1-score, and AUC-ROC. The metrics demonstrate the model's effectiveness in multi-class abnormality classification for Video Capsule Endoscopy.

Table 2: Validation results of the proposed model on key performance metrics.

Method	Avg. Accuracy	Avg. Specificity	Avg. Sensitivity	Avg. F1-score	Avg. Precision
Proposed Model	0.929	0.990	0.831	0.807	0.931

2.7 Optional Comparisons with Other Methods

In addition to comparing our results to the provided baseline, we optionally evaluate our model against other established methods, where applicable. This secondary comparison further emphasizes the reliability of our approach and its potential advantages over traditional techniques in VCE abnormality classification.

2.8 Ablation Study

An ablation study was conducted to assess the impact of each component in our model pipeline, including feature extraction backbones, attention-based fusion, and the two-stage classification framework. Table 3 summarizes the effects of removing each module on key performance metrics. The results confirm that both the feature fusion module and attention mechanism significantly improve classification accuracy, recall, and F1-score.

Table 3: Ablation study showing the impact of individual components on model performance.

Component	Avg. Accuracy	Avg. Specificity	Avg. Sensitivity	Avg. F1-score	Avg. Precision
Full Model	0.929	0.990	0.831	0.807	0.931
Without Feature Fusion	0.910	0.980	0.790	0.773	0.914
Without Attention Mechanism	0.915	0.982	0.802	0.782	0.920
Without Multi-backbone	0.903	0.977	0.775	0.763	0.908

3 Discussion

The comparison with baseline results demonstrates the capability of our model to exceed established benchmarks in several critical areas. Furthermore, the ablation study reveals that each component in the proposed architecture contributes meaningfully to the overall performance, confirming the value of the multi-backbone architecture, feature fusion, and attention mechanisms. These elements collectively enhance the model's robustness, accuracy, and generalizability, making it well-suited for multi-class abnormality classification in VCE data.

4 Conclusion

In this study, we developed and evaluated a two-stage hierarchical classification system for multi-class abnormality detection in Video Capsule Endoscopy (VCE) images. Leveraging a robust combination of three backbone networks, a feature fusion module with an attention mechanism, and two classification heads, our model demonstrated high accuracy and sensitivity across multiple disease categories. The results obtained from our validation set showed significant improvements over baseline models, especially in terms of specificity, F1-score, and AUC-ROC values. The model's ability to reliably distinguish normal from abnormal cases, followed by precise multi-class classification, underscores its potential as a valuable tool in gastrointestinal diagnostics.

The inclusion of the feature fusion and attention mechanisms was particularly impactful, as highlighted by our ablation study, which confirmed the importance of each architectural component in enhancing classification performance. The modular design of our system also enables adaptability, allowing future extensions or improvements to specific components without a complete architectural overhaul.

Our approach not only contributes to advancements in automated VCE abnormality classification but also offers a framework that could be adapted for other medical imaging applications. Future research could explore integrating additional backbone models, enhancing

real-time processing capabilities, and expanding the model to classify a broader range of gastrointestinal conditions. Additionally, further work on optimizing the model for deployment on resource-constrained devices could enhance its accessibility in various clinical settings.

In summary, this work presents a promising step toward reducing diagnostic time and increasing accuracy in VCE analysis, aiming to support gastroenterologists with reliable AI-driven tools in daily practice.

5 Acknowledgments

We would like to thank the organizers of the Capsule Vision 2024 Challenge for providing the dataset and baseline metrics, which served as a foundation for our research in VCE abnormality classification. We also acknowledge the support from MPSTME for their contributions in terms of resources and computational facilities, without which this work would not have been possible. Additionally, we extend our gratitude to our colleagues and mentors for their valuable feedback and encouragement throughout this research project.

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