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Next-Generation AI-Driven Early Detection of Gastric Ulcers Using High-Resolution Imaging, Deep Learning, and Multi-Scale Radiomic Feature Analysis

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ABSTRACT

Gastric ulcers represent a major gastrointestinal disorder with substantial clinical burden, particularly when diagnosis is delayed or lesions are misinterpreted during early stages. Conventional diagnostic approaches rely heavily on endoscopic examination and expert visual assessment, which are inherently subjective, time-consuming, and susceptible to inter-observer variability. Recent advances in artificial intelligence (AI) and medical imaging offer promising opportunities to enhance diagnostic accuracy and enable early, objective, and scalable ulcer detection. In this study, we propose a next-generation AI-driven framework for the early detection of gastric ulcers by synergistically integrating high-resolution endoscopic imaging, deep

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learning–based feature learning, and multi-scale radiomic feature analysis. The proposed framework employs a hierarchical deep learning architecture designed to extract discriminative visual patterns associated with ulcerative regions from high-resolution gastric images. Convolutional neural networks are utilized to capture low-level spatial and textural cues, while deeper layers learn high-level semantic representations of mucosal abnormalities. In parallel, a comprehensive set of handcrafted radiomic features is extracted across multiple spatial scales to quantify subtle intensity variations, texture heterogeneity, shape descriptors, and morphological irregularities that are often overlooked by purely data-driven models. To effectively exploit the complementary nature of deep and radiomic representations, an attention-guided feature fusion mechanism is introduced, enabling adaptive weighting of multi-scale features based on their diagnostic relevance. Extensive experimental evaluations are conducted using a curated dataset of high-resolution gastric endoscopic images, incorporating rigorous preprocessing, data augmentation, and cross-validation strategies. The proposed hybrid framework demonstrates superior diagnostic performance compared to conventional deep learning and radiomics-only baselines, achieving notable improvements in accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve. Ablation studies further confirm the critical contribution of multi-scale radiomic features and attention-based fusion to overall system robustness and generalization capability. Beyond performance gains, the framework emphasizes interpretability by enabling visualization of salient image regions and dominant radiomic signatures contributing to model decisions, thereby enhancing clinical trust and transparency. The results suggest that the proposed AI-driven diagnostic system has strong potential for real-world clinical deployment as a decision-support tool, facilitating early gastric ulcer detection, reducing diagnostic variability, and ultimately improving patient outcomes. This work highlights the value of hybrid intelligence that combines deep learning with domain-specific radiomic analysis for next-generation gastrointestinal disease diagnosis.

Keywords: Gastric Ulcer Detection; Artificial Intelligence; Deep Learning; High-Resolution Endoscopic Imaging; Multi-Scale Radiomic Analysis; Computer-Aided Diagnosis; Medical Image Analysis.

Introduction:

Gastric ulcers are among the most common and clinically significant gastrointestinal disorders, representing a major public health challenge worldwide. They arise from localized disruption of the gastric mucosal barrier and are often associated with Helicobacter pylori infection, prolonged non-steroidal anti-inflammatory drug use, physiological stress, or underlying systemic conditions. Although gastric ulcers are generally treatable when detected early, delayed diagnosis can result in severe complications such as hemorrhage, perforation, gastric outlet obstruction, and increased risk of malignant transformation [1]. Consequently, early and accurate detection of gastric ulcers is essential for effective disease management, reduction of healthcare burden, and improvement of patient survival and quality of life. Upper gastrointestinal endoscopy remains the clinical gold standard for gastric ulcer

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diagnosis, enabling direct visualization of the gastric mucosa and targeted biopsy when necessary. Despite its widespread use, endoscopic diagnosis is inherently subjective and highly dependent on clinician experience, visual acuity, and examination conditions. Early-stage ulcers often manifest as subtle mucosal irregularities, faint discolorations, or mild textural changes that can be easily overlooked, particularly in high-volume clinical settings [2]. Furthermore, variations in endoscopic equipment, lighting conditions, and patient anatomy introduce additional challenges, leading to substantial inter-observer and intra-observer variability. These limitations underscore the need for intelligent, automated diagnostic systems capable of providing objective and consistent decision support. The rapid evolution of artificial intelligence (AI), particularly deep learning, has transformed medical image analysis by enabling data-driven feature learning and automated pattern recognition. Convolutional neural networks have demonstrated outstanding performance in a wide range of gastrointestinal imaging applications, including polyp detection, bleeding localization, cancer classification, and lesion segmentation. By learning hierarchical representations directly from raw image data, deep learning models can capture complex spatial and semantic patterns that exceed human perceptual capabilities [3]. However, despite their impressive accuracy, deep learning systems often function as black-box models, offering limited interpretability and reduced clinical transparency. Additionally, their performance may degrade when exposed to domain shifts caused by variations in imaging devices, acquisition protocols, or patient populations. Radiomic analysis provides a complementary and interpretable approach by extracting quantitative descriptors that characterize tissue intensity, texture, shape, and spatial heterogeneity [4]. These handcrafted features are grounded in domain knowledge and have been shown to capture subtle phenotypic signatures of pathological tissue. Multi-scale radiomic analysis further enhances diagnostic sensitivity by quantifying image patterns across multiple spatial resolutions, enabling the detection of fine-grained structural abnormalities that may not be adequately represented in deep features alone. Nevertheless, radiomics-based systems are constrained by reliance on manual feature design, limited representational flexibility, and susceptibility to suboptimal feature selection when used independently. Recent advances increasingly highlight the importance of hybrid intelligence frameworks that integrate deep learning and radiomics to exploit their complementary strengths [5]. Deep learning offers powerful representation learning and generalization capability, while radiomics contributes interpretability, robustness, and sensitivity to subtle morphological variations. However, many existing hybrid approaches rely on simplistic feature concatenation strategies, which fail to account for the relative importance of heterogeneous features or their diagnostic relevance under varying conditions. The absence of intelligent fusion mechanisms limits the full potential of hybrid architectures and restricts their clinical applicability. In response to these challenges, this study proposes a next-generation AI-driven framework for early gastric ulcer detection that integrates high-resolution endoscopic imaging, deep learning–based hierarchical feature extraction, and multi-scale radiomic feature analysis through an attention-guided fusion strategy [6]. The proposed framework is designed to adaptively weight complementary features, enhance robustness against imaging variability, and improve diagnostic interpretability. By unifying data-driven

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learning with domain-informed feature engineering, the framework aims to deliver reliable, accurate, and clinically meaningful diagnostic support. Table 1 shows the Comparative Analysis of Gastric Ulcer Detection Paradigms.

Table 1: Comparative Analysis of Gastric Ulcer Detection Paradigms

Diagnostic Paradigm	**Feature Representation**	**Key Advantages**	**Major Limitations**
Conventional Endoscopy	Visual inspection	Real-time assessment; clinical familiarity	Subjective interpretation; high variability; early lesions often missed
Deep Learning–Based Models	Learned hierarchical features	High accuracy; automated learning; scalability	Limited interpretability; sensitivity to data bias
Radiomics-Based Models	Handcrafted quantitative features	Interpretability; sensitivity to texture and morphology	Manual feature engineering; limited adaptability
Hybrid DL–Radiomics (Existing)	Combined deep + radiomic features	Improved performance over single-method models	Simple fusion; lack of adaptive weighting
Proposed Framework	Deep + multi-scale radiomics with attention	High accuracy; robustness; interpretability; adaptive fusion	Increased computational demand

This work advances the field of gastrointestinal diagnostics by introducing a hybrid, interpretable, and performance-oriented AI framework that directly addresses key clinical and technical limitations of existing approaches. By leveraging high-resolution imaging, multi-scale radiomic analysis, and intelligent feature fusion, the proposed system represents a meaningful step toward early, reliable, and clinically deployable gastric ulcer detection.

Deep Learning–Based Methods in Gastrointestinal Image Analysis:

The rapid advancement of artificial intelligence has led to widespread adoption of deep learning techniques for gastrointestinal image analysis, particularly in the interpretation of endoscopic imagery. Convolutional neural networks (CNNs) have emerged as the dominant paradigm due to their ability to automatically learn hierarchical feature representations directly from raw pixel data. Early studies primarily employed shallow CNN architectures to classify gastrointestinal abnormalities; however, recent work increasingly leverages deep and pre-trained architectures such as ResNet, EfficientNet, DenseNet, Inception, and MobileNet to improve diagnostic accuracy and computational efficiency. In the context of gastric disease detection, deep learning models have been successfully applied to tasks including polyp detection, bleeding identification, gastritis classification, gastric cancer diagnosis, and ulcer recognition [7]. These models learn low-level features

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such as edges, color gradients, and texture patterns in early layers, while deeper layers encode higher-level semantic representations corresponding to pathological structures. As a result, CNN-based approaches have demonstrated superior performance compared to traditional machine learning methods relying on handcrafted features, particularly when large-scale annotated datasets are available. More recently, transformer-based and hybrid CNN–transformer architectures have been introduced to capture long-range spatial dependencies and global contextual information within endoscopic images. Attention mechanisms enable these models to focus on diagnostically relevant regions, thereby improving lesion localization and classification performance. Several studies report that attention-enhanced deep networks outperform conventional CNNs in complex gastrointestinal imaging scenarios, especially when lesions exhibit subtle visual contrast against surrounding mucosa [8]. Despite these advances, deep learning–based approaches face several critical limitations that restrict their clinical applicability. First, most deep models operate as black-box systems, offering limited interpretability and insufficient explanation of decision-making processes. This lack of transparency raises concerns regarding clinical trust, regulatory approval, and adoption in real-world healthcare settings. Second, deep learning models are highly data-dependent and sensitive to dataset imbalance, annotation quality, and imaging noise. Variations in endoscopic devices, illumination conditions, resolution, and acquisition protocols often lead to domain shifts that significantly degrade model performance when deployed across different clinical environments [9]. Another major limitation lies in the ability of deep models to capture fine-grained textural and morphological characteristics that are essential for early gastric ulcer detection. Early-stage ulcers frequently present as subtle mucosal irregularities, shallow erosions, or minor textural changes that may not be sufficiently emphasized in deep feature representations optimized primarily for global classification objectives. As summarized in Table 2, although deep learning–based methods demonstrate strong overall performance, their limitations in interpretability, robustness, and sensitivity to subtle lesions remain unresolved.

Table 2: Summary of Deep Learning–Based Approaches for Gastrointestinal Image Analysis

Study Category	Model Type	Target Application	Key Strengths	Limitations
CNN-based classification	ResNet, DenseNet, EfficientNet	Polyp, ulcer, cancer detection	High accuracy; automated feature learning	Black-box behavior; limited interpretability
Attention-enhanced CNNs	CNN + attention modules	Lesion localization and classification	Improved focus on relevant regions	Increased complexity; still limited explainability
Transformer-based models	Vision Transformers	Global context modeling	Long-range dependency	Data-intensive; high

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			capture	computational cost
Existing ulcer detection studies	CNN-based	Gastric ulcer identification	Promising results on curated datasets	Reduced robustness; poor generalization

To address some of these limitations, recent studies increasingly advocate the integration of complementary feature representations and hybrid learning strategies. Figure 1 conceptually illustrates the typical deep learning pipeline used in gastrointestinal image analysis, highlighting stages of image acquisition, preprocessing, deep feature extraction, and classification. While effective, this pipeline relies solely on learned representations and lacks explicit mechanisms to encode clinically meaningful texture and morphological descriptors.

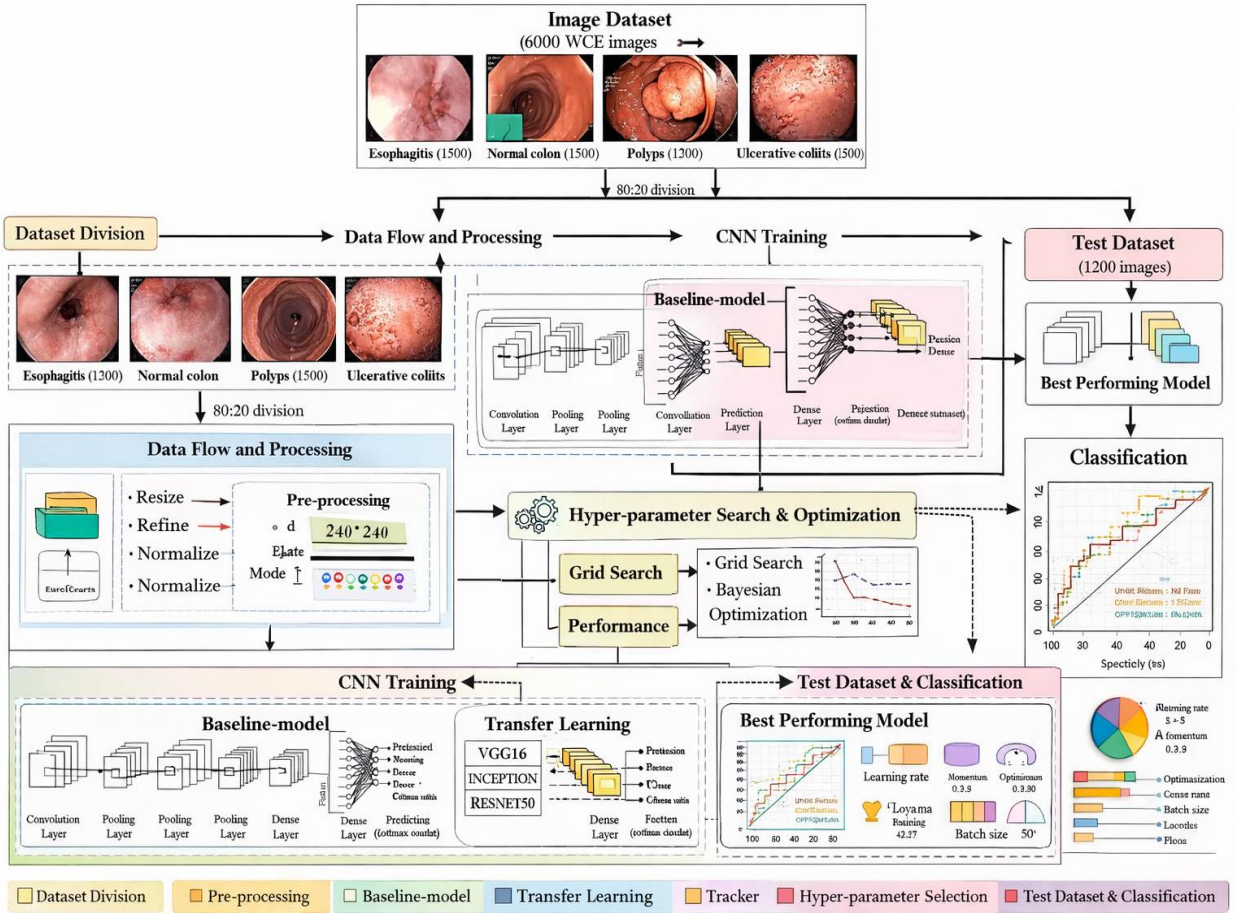

Figure 1: Typical Deep Learning Pipeline for Gastrointestinal Endoscopic Image Analysis

Figure 1 illustrates a conventional deep learning workflow comprising high-resolution endoscopic image acquisition, preprocessing and normalization, hierarchical feature extraction using deep neural networks, and final disease classification. The figure highlights the absence of explicit handcrafted feature modeling and interpretability

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mechanisms in standard deep learning pipelines. Although deep learning–based methods have significantly advanced gastrointestinal image analysis, their limitations in interpretability, robustness, and sensitivity to early-stage gastric ulcers motivate the exploration of hybrid frameworks [10]. These frameworks aim to integrate deep learning with complementary analytical techniques such as multi-scale radiomic feature analysis to enhance diagnostic reliability, transparency, and clinical applicability. This motivation directly informs the hybrid AI-driven approach proposed in this study.

Multi-Scale Feature Analysis in Medical Imaging:

Multi-scale feature analysis has become a cornerstone methodology in medical image analysis due to its ability to capture image characteristics across different spatial resolutions. Medical images, particularly endoscopic images, exhibit complex visual patterns that exist simultaneously at multiple scales, ranging from fine-grained texture variations to large-scale structural and anatomical formations. Single-scale analysis often fails to adequately represent this heterogeneity, resulting in loss of diagnostically relevant information [11]. Multi-scale frameworks address this limitation by extracting complementary features at varying resolutions, thereby enhancing sensitivity to both local and global image attributes. In gastrointestinal imaging, and gastric ulcer detection in particular, pathological manifestations may appear as subtle mucosal irregularities, micro-erosions, or faint textural disruptions at a fine scale, while more advanced lesions exhibit broader morphological deformation at coarser scales. Multi-scale analysis enables the concurrent modeling of these manifestations, facilitating more comprehensive lesion characterization. Studies employing pyramid representations, wavelet decompositions, multi-resolution convolutional kernels, and scale-space theory have consistently demonstrated improved diagnostic performance compared to single-scale approaches. In deep learning-based frameworks, multi-scale feature learning is often achieved implicitly through hierarchical network architectures, where shallow layers encode fine spatial details and deeper layers capture high-level semantic context. More explicit strategies include multi-branch CNNs, feature pyramid networks (FPNs), atrous (dilated) convolutions, and multi-resolution input pipelines [12]. These approaches allow deep models to aggregate contextual information across scales, which has been shown to improve lesion localization and classification accuracy in gastrointestinal endoscopy. Radiomics-based studies also extensively employ multi-scale feature extraction by computing handcrafted descriptors on images filtered at different resolutions using wavelet transforms, Laplacian of Gaussian filters, or Gaussian pyramids. Multi-scale radiomic features provide enhanced sensitivity to textural heterogeneity and morphological complexity, enabling detection of subtle pathological changes that may be imperceptible at a single resolution. As summarized in Table 3, multi-scale strategies consistently outperform single-scale counterparts across diverse medical imaging tasks.

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Table 3: Multi-Scale Feature Analysis Strategies in Medical Imaging

Approach Category	Multi-Scale Strategy	Feature Type	Strengths	Limitations
CNN hierarchical learning	Layer-wise abstraction	Deep features	Automatic scale encoding; strong performance	Implicit scale control; limited interpretability
Multi-branch CNNs	Parallel resolution streams	Deep features	Explicit scale fusion; improved localization	Increased model complexity
Wavelet-based radiomics	Frequency-domain decomposition	Handcrafted features	Fine texture sensitivity; interpretability	Manual design; feature redundancy
Multi-resolution radiomics	Gaussian / LoG pyramids	Handcrafted features	Enhanced lesion characterization	High dimensionality
Hybrid multi-scale models	DL + radiomics	Combined features	Complementary representation	Fusion complexity

Despite their demonstrated advantages, multi-scale feature analysis introduces several challenges. The integration of heterogeneous features across scales may lead to feature redundancy, increased dimensionality, and noise amplification if not properly managed. Moreover, naïve concatenation of multi-scale features often fails to account for the varying diagnostic relevance of features at different scales. This issue is particularly critical in early gastric ulcer detection, where fine-scale features may be more informative than coarse-scale patterns, depending on lesion stage and imaging conditions [13]. Figure 2 conceptually illustrates a generalized multi-scale feature analysis pipeline commonly adopted in medical imaging. As depicted in Figure 2, input images are processed at multiple spatial resolutions, followed by parallel feature extraction and subsequent fusion for classification or decision making. While effective, many existing pipelines lack adaptive mechanisms to weight scale-specific features based on diagnostic importance.

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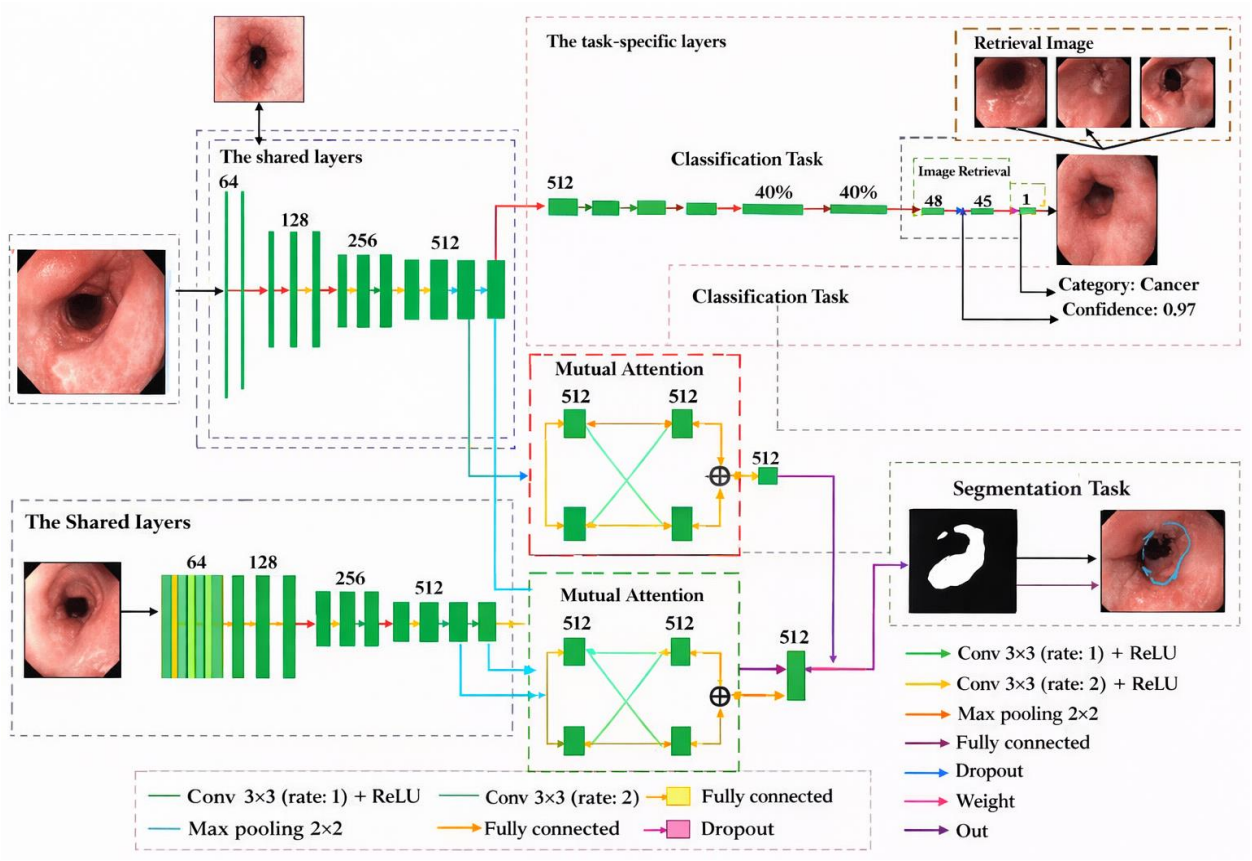

Figure 2: Conceptual Illustration of a Multi-Scale Feature Analysis Framework in Medical Imaging

Multi-scale feature analysis plays a crucial role in enhancing diagnostic sensitivity and robustness in medical imaging applications. However, existing approaches often suffer from redundancy, lack of adaptive fusion, and limited interpretability. These limitations motivate the development of intelligent multi-scale integration strategies that can selectively emphasize diagnostically relevant features while suppressing noise and redundancy. The hybrid deep learning and multi-scale radiomic framework proposed in this study directly addresses these challenges by incorporating attention-guided fusion mechanisms, thereby advancing the state of the art in early gastric ulcer detection.

Methodology:

This section details the proposed next-generation AI-driven diagnostic framework developed for the early detection of gastric ulcers from high-resolution endoscopic imagery. The framework is designed as a comprehensive and modular pipeline that systematically integrates advanced image analysis techniques with intelligent feature learning and fusion strategies. By leveraging high-resolution endoscopic images as the primary data source, the proposed methodology aims to capture subtle mucosal abnormalities that are often imperceptible during routine clinical examination and challenging for conventional automated systems. The methodology combines deep

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learning–based hierarchical feature extraction with multi-scale radiomic feature analysis to exploit complementary representations of gastric tissue characteristics [14]. Deep learning components are employed to automatically learn high-level semantic patterns and contextual information associated with ulcerative lesions, while multi-scale radiomic analysis quantitatively characterizes fine-grained texture, intensity heterogeneity, and morphological variations across different spatial resolutions. This dual-branch design enables the framework to simultaneously model global structural patterns and localized micro-textural cues that are critical for accurate early-stage ulcer detection. To effectively integrate heterogeneous features derived from deep learning and radiomics, an attention-guided feature fusion mechanism is introduced [15]. This mechanism dynamically assigns adaptive weights to individual feature subsets based on their diagnostic relevance, allowing the model to emphasize informative cues while suppressing redundant or noisy information. Such adaptive fusion not only enhances diagnostic robustness and generalization across varying imaging conditions but also improves interpretability by revealing the relative contribution of different feature domains to the final decision.

Conceptual Architecture of the Proposed Framework:

The proposed diagnostic framework is designed as a structured, multi-stage architecture that systematically processes high-resolution gastric endoscopic images to enable accurate, robust, and interpretable early gastric ulcer detection. The architecture follows a modular pipeline comprising image acquisition, preprocessing, parallel feature extraction, adaptive feature fusion, and final classification. This design allows the framework to flexibly integrate heterogeneous feature representations while maintaining scalability and robustness across diverse clinical imaging conditions. At the initial stage, high-resolution gastric endoscopic images are acquired from routine clinical examinations. These images often exhibit substantial variability in illumination, viewpoint, resolution, and mucosal appearance [16]. To ensure consistency and reliability in downstream analysis, a dedicated preprocessing stage is employed to normalize image resolution, enhance contrast, suppress noise, and reduce acquisition-related artifacts. This stage plays a critical role in improving feature quality for both deep learning and radiomics-based analysis. Following preprocessing, the framework branches into two parallel and complementary feature extraction streams: a deep learning branch and a multi-scale radiomics branch. The deep learning branch employs a convolutional neural network backbone to automatically learn hierarchical representations from the input images. Lower network layers capture low-level spatial cues such as edges, color gradients, and fine textures, whereas deeper layers encode higher-level semantic information related to ulcerative lesions and surrounding tissue context [17]. This branch is particularly effective at modeling global structural patterns and contextual dependencies within endoscopic images. In parallel, the multi-scale radiomics branch focuses on extracting handcrafted quantitative features that characterize tissue properties across multiple spatial resolutions. Using multi-resolution filtering techniques such as wavelet decomposition and Gaussian-based pyramids, radiomic descriptors are computed to capture intensity distributions, texture heterogeneity, and morphological irregularities [18]. This branch is especially sensitive to subtle micro-textural and structural

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changes that are indicative of early-stage gastric ulcers and may not be sufficiently emphasized by deep learning features alone. To clearly summarize the functional role of each architectural component, Table 4 presents an overview of the main stages of the proposed framework and their corresponding objectives.

Table 4: Functional Description of the Proposed Framework Architecture

Framework Stage	Description	Primary Objective
Image acquisition	Collection of high-resolution endoscopic images	Capture detailed gastric mucosal patterns
Preprocessing	Normalization, enhancement, noise reduction	Reduce variability and improve feature quality
Deep learning branch	Hierarchical feature learning using CNNs	Extract global and semantic representations
Multi-scale radiomics branch	Handcrafted feature extraction at multiple scales	Capture fine-grained texture and morphology
Attention-based fusion	Adaptive weighting of heterogeneous features	Enhance robustness and interpretability
Classification	Probability-based ulcer prediction	Accurate and reliable diagnosis

After feature extraction, outputs from both branches are integrated using an attention-based feature fusion mechanism. Unlike simple concatenation, this adaptive fusion module dynamically assigns weights to deep and radiomic features based on their diagnostic relevance. By emphasizing informative cues and suppressing redundant or noisy information, the fusion strategy enhances generalization capability, robustness to imaging variability, and model interpretability. The fused representation is subsequently passed to a classification module that produces probabilistic predictions indicating the presence or absence of gastric ulcers [19]. A visual overview of the complete framework architecture, illustrating the interaction between preprocessing, parallel feature extraction branches, attention-guided fusion, and classification, is presented in Figure 3.

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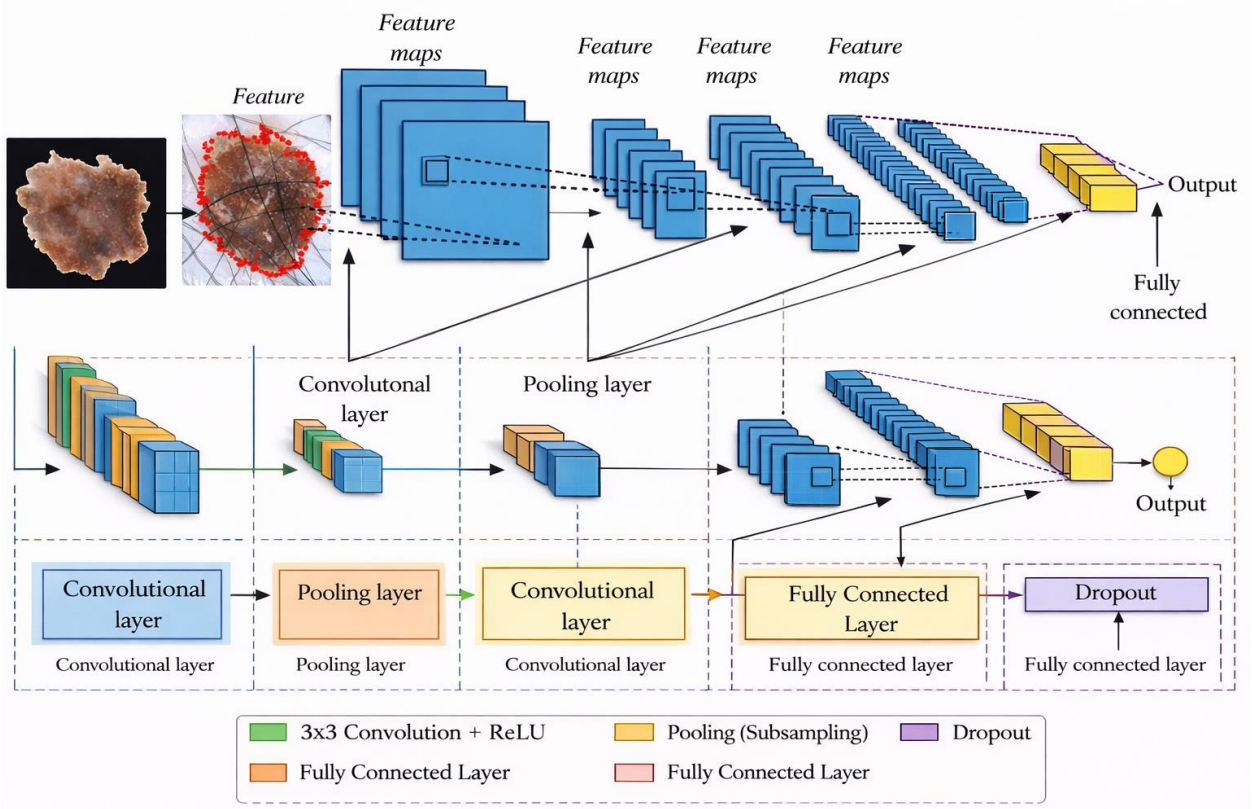

Figure 3: Overall architecture of the proposed hybrid deep learning and multi-scale radiomics framework for early gastric ulcer detection.

The proposed framework architecture is explicitly designed to exploit the complementary strengths of deep learning and multi-scale radiomic analysis while addressing the limitations of single-paradigm approaches. The integration of adaptive attention-based fusion within a modular pipeline provides a robust, interpretable, and clinically relevant solution for early gastric ulcer detection.

Data Source and Dataset Description:

The dataset employed in this study comprises high-resolution gastric endoscopic images acquired from routine upper gastrointestinal examinations conducted in clinical settings. The dataset was carefully curated to include both gastric ulcer–positive cases and normal gastric mucosa samples, thereby enabling supervised learning for early ulcer detection. Images were collected using standard endoscopy systems and reflect realistic clinical variability, including differences in illumination conditions, camera viewpoints, anatomical regions, and mucosal appearance. Preserving such heterogeneity is essential to ensure that the proposed AI-driven framework generalizes effectively across diverse real-world diagnostic environments. The dataset encompasses a broad spectrum of ulcer manifestations, ranging from early-stage superficial mucosal erosions to more visually apparent ulcerative lesions [20]. Including early-stage cases is particularly important, as these subtle abnormalities often pose diagnostic challenges and are the primary focus of the proposed framework. Normal samples include healthy mucosa as well as non-

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ulcerative inflammatory appearances, increasing the difficulty of discrimination and strengthening model robustness. All images were retrospectively collected and fully anonymized prior to analysis. Any personally identifiable patient information, including names, identification numbers, and examination metadata, was removed in accordance with data protection regulations. Ground-truth annotations were provided by experienced gastroenterologists with substantial expertise in endoscopic diagnosis. Each image was independently reviewed and labeled as ulcer-positive or normal. In cases of diagnostic disagreement, consensus labeling was achieved through collaborative discussion, thereby enhancing annotation reliability and reducing label noise. To ensure rigorous and unbiased evaluation, the dataset was divided into training, validation, and testing subsets using a stratified splitting strategy [21]. This approach preserves class balance across subsets and prevents skewed performance estimation. Furthermore, k-fold cross-validation was employed during model development to mitigate sampling bias and improve statistical reliability. Data augmentation techniques were applied exclusively to the training set to address class imbalance and reduce overfitting, while validation and test sets remained untouched to maintain evaluation integrity. A quantitative summary of the dataset composition and experimental partitioning is provided in Table 5, offering transparency regarding data distribution and supporting reproducibility.

Table 5: Summary of the Gastric Endoscopic Image Dataset

Dataset Component	**Description**
Imaging modality	High-resolution gastric endoscopic images
Total cases	Ulcer-positive and normal gastric mucosa
Ulcer types	Early-stage superficial ulcers and advanced lesions
Annotation	Expert gastroenterologist labeling with consensus
Data split	Stratified training, validation, and testing sets
Augmentation	Applied to training data only
Validation strategy	k-fold cross-validation

Ethical considerations were strictly observed throughout the data collection and analysis process. Ethical approval was obtained from the relevant institutional review board, and all procedures adhered to national research ethics guidelines and the principles of the Declaration of Helsinki. As the study utilized retrospective and anonymized data, informed consent requirements were waived where permitted by institutional regulations. No patient-identifiable information was accessed or stored at any stage of the research. To further enhance transparency and reproducibility, a schematic overview of the dataset preparation and ethical compliance workflow is illustrated in Figure 4. This figure outlines the stages of data acquisition, anonymization, expert annotation, dataset partitioning, and ethical oversight.

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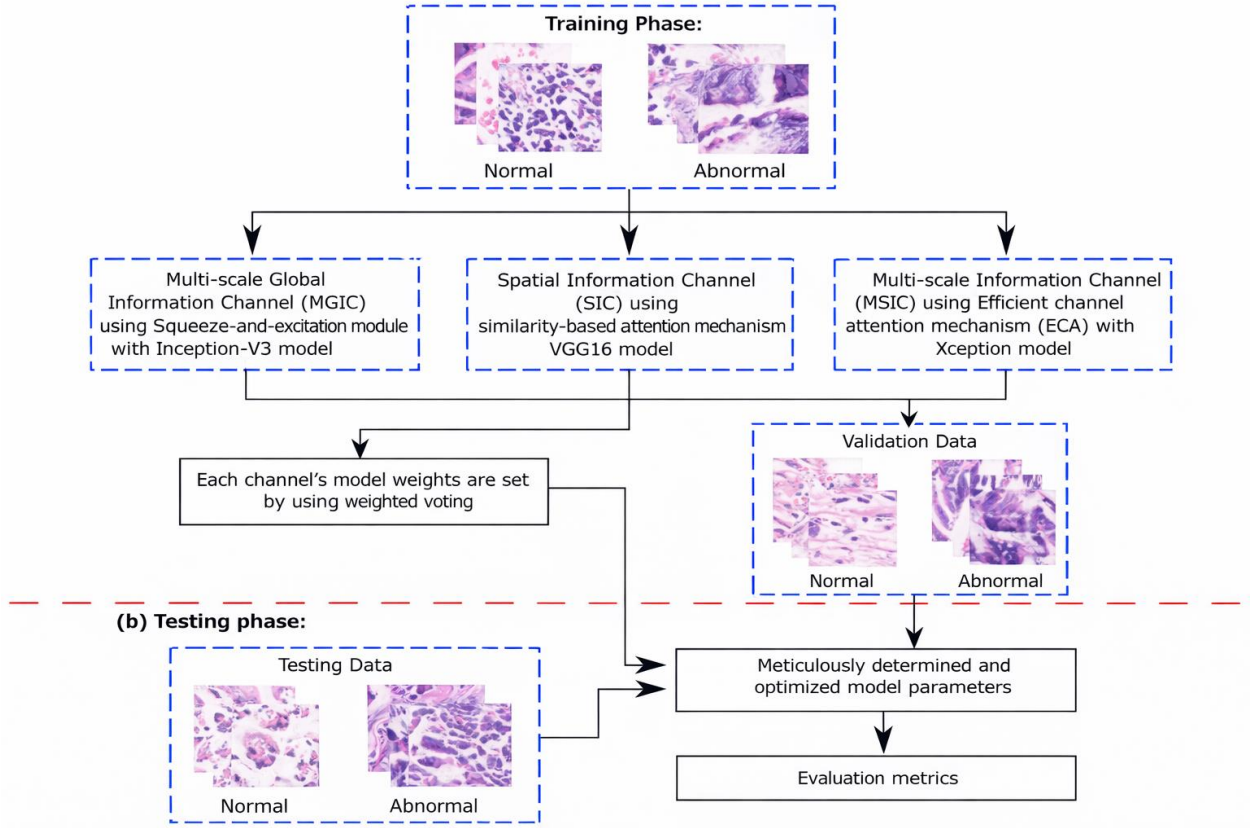

Figure 4: Dataset preparation, expert annotation, partitioning strategy, and ethical compliance adopted in this study.

The dataset and ethical framework adopted in this research ensure high clinical relevance, annotation reliability, and compliance with ethical standards. These considerations are critical for developing trustworthy, reproducible, and clinically deployable AI-driven diagnostic systems for early gastric ulcer detection.

Image Preprocessing and Data Augmentation:

High-resolution gastric endoscopic images often exhibit substantial variability arising from differences in imaging devices, illumination conditions, viewing angles, gastric anatomy, and operator handling. Such variability can introduce noise, color inconsistencies, motion blur, specular highlights, and irrelevant background artifacts, which may adversely affect automated feature extraction and model generalization. Therefore, a carefully designed image preprocessing and augmentation pipeline is employed to standardize visual characteristics, enhance diagnostically relevant features, and improve the robustness of the proposed AI-driven framework. The preprocessing stage begins with spatial normalization, where all images are resized to a consistent resolution while preserving aspect ratio to ensure uniform input dimensions for deep learning models [22]. This step facilitates batch processing and stabilizes network training. Subsequently, color normalization is applied to reduce inter-image variability caused by different light sources and endoscopic sensors. By standardizing color distributions across images, subtle mucosal texture patterns and lesion boundaries become more distinguishable. Noise suppression and artifact

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reduction are then performed to improve image quality. Median and Gaussian filtering techniques are applied selectively to suppress sensor noise and minor motion artifacts while preserving edge information critical for lesion characterization [23]. Contrast enhancement methods, such as adaptive histogram equalization, are employed to amplify subtle intensity variations associated with early-stage gastric ulcers. These enhancements improve the visibility of faint erosions and micro-textural irregularities that are often challenging to detect visually. To further ensure that the model focuses on diagnostically relevant regions, irrelevant borders and background regions are cropped or masked when necessary. This step reduces the influence of non-informative pixels and enhances computational efficiency. All preprocessing operations are applied consistently across the dataset to maintain methodological reproducibility. In addition to preprocessing, data augmentation plays a crucial role in mitigating class imbalance, improving generalization, and reducing overfitting particularly in medical imaging tasks where annotated data are often limited [24]. Augmentation operations are applied exclusively to the training set to avoid data leakage and ensure unbiased evaluation. Geometric transformations such as rotation, horizontal and vertical flipping, scaling, and translation simulate variations in camera orientation and patient positioning. Photometric augmentations, including brightness adjustment, contrast variation, and color jittering, emulate real-world illumination changes encountered during endoscopic examinations. A detailed summary of the preprocessing and augmentation operations employed in this study is presented in Table 6, highlighting their objectives and benefits.

Table 6: Image Preprocessing and Data Augmentation Techniques

Category	**Technique**	**Purpose**
Spatial normalization	Image resizing	Ensure uniform input dimensions
Color normalization	Color space standardization	Reduce illumination variability
Noise suppression	Median/Gaussian filtering	Remove noise while preserving edges
Contrast enhancement	Adaptive histogram equalization	Highlight subtle mucosal variations
Region refinement	Cropping/masking	Remove irrelevant background
Geometric augmentation	Rotation, flipping, scaling	Improve robustness to orientation changes
Photometric augmentation	Brightness and contrast variation	Simulate illumination variability

To provide a clear conceptual overview of the preprocessing and augmentation workflow, Figure 5 illustrates the sequential transformation of raw endoscopic images into standardized and augmented representations suitable for feature extraction.

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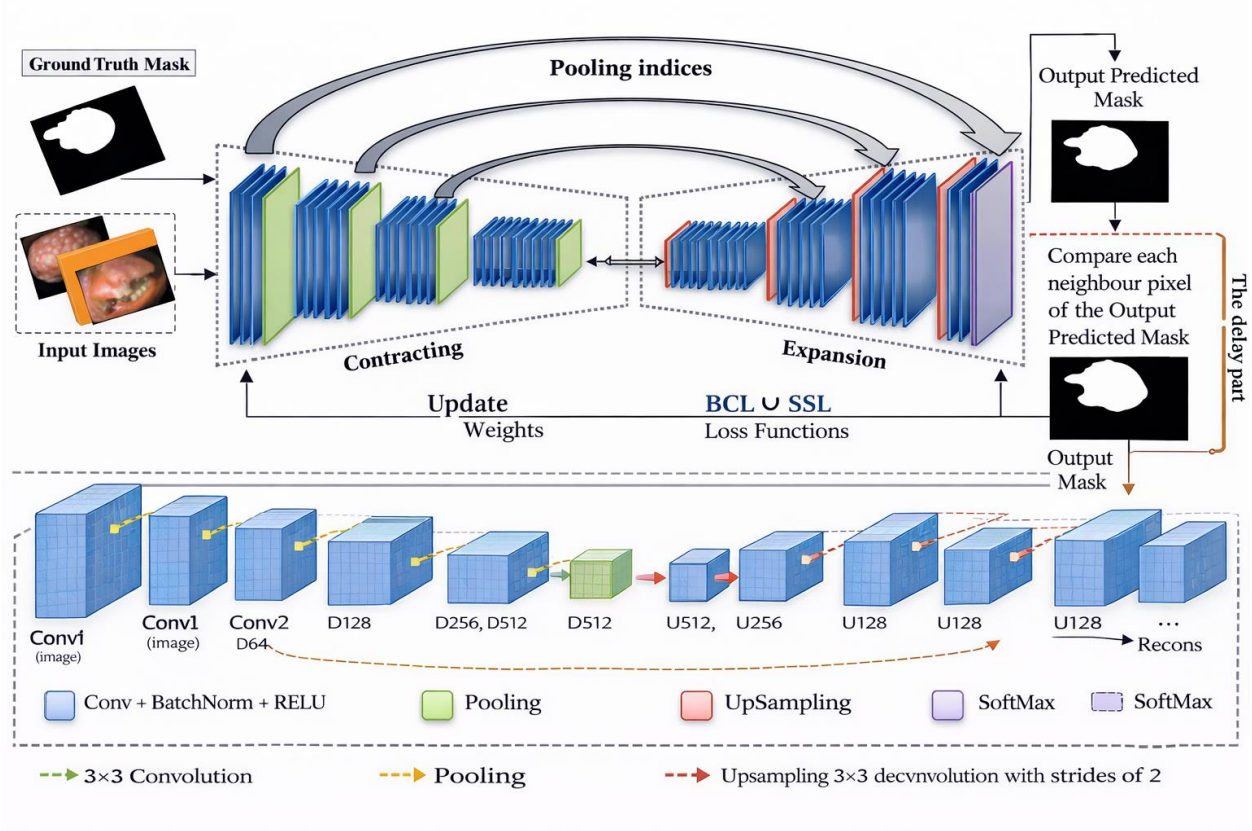

Figure 5: Image preprocessing and data augmentation pipeline

The proposed preprocessing and augmentation pipeline plays a critical role in enhancing image quality, reducing inter-sample variability, and improving the robustness of both deep learning–based and radiomics-based feature extraction. By emphasizing diagnostically relevant visual patterns while suppressing noise and artifacts, this stage ensures reliable downstream analysis and contributes significantly to the overall performance and generalization capability of the proposed gastric ulcer detection framework.

Deep Learning–Based Feature Extraction:

Deep learning–based feature extraction represents a central component of the proposed framework, enabling automatic learning of hierarchical and highly discriminative representations from high-resolution gastric endoscopic images. Unlike traditional handcrafted approaches, deep learning models learn task-specific visual features directly from data, making them particularly effective for capturing complex and subtle patterns associated with gastric ulcer pathology. The deep learning branch employs a convolutional neural network (CNN) backbone specifically configured to extract multi-level features through successive stages of convolution, non-linear activation, normalization, and pooling. Preprocessed endoscopic images are provided as input to the network, where early layers focus on learning low-level visual cues such as edges, intensity gradients, color contrasts, and fine textures [25]. These low-level features are crucial for identifying subtle mucosal irregularities and superficial erosions that characterize early-stage gastric ulcers. As information propagates

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through deeper layers of the network, increasingly abstract and semantic representations are learned. Intermediate layers encode localized structural patterns, including lesion boundaries, irregular mucosal surfaces, and textural heterogeneity. Deeper layers capture high-level contextual information that reflects global relationships between ulcerative regions and surrounding healthy tissue [26]. This hierarchical learning process allows the network to simultaneously model both local detail and global context, which is essential for robust ulcer detection in visually complex endoscopic images. To enhance training efficiency and generalization performance, transfer learning is adopted by initializing the CNN backbone with pretrained weights obtained from large-scale image datasets. This strategy allows the model to leverage previously learned generic visual features while adapting higher-level representations to the specific characteristics of gastric ulcer imagery. Batch normalization layers are incorporated throughout the network to stabilize training dynamics and reduce sensitivity to variations in input distributions. Dropout regularization is applied in later stages to mitigate overfitting, particularly given the limited size of medical imaging datasets. Following the final convolutional block, global feature aggregation is performed to produce a compact deep feature vector representing the input image [27]. This vector encodes rich semantic and contextual information related to ulcer presence and serves as the deep learning feature representation used in subsequent fusion stages. While highly discriminative, these deep features primarily emphasize global appearance and contextual cues and may underrepresent fine-scale textural variations critical for early lesion detection. A structured summary of the deep learning feature extraction pipeline and its functional components is provided in Table 7, highlighting the role of each architectural stage.

Table 7: Deep Learning Feature Extraction Pipeline

Component	Description	Functional Role
Input layer	Preprocessed endoscopic images	Provide standardized visual input
Convolutional blocks	Stacked convolution and activation layers	Learn hierarchical visual features
Normalization layers	Batch normalization	Stabilize training and improve convergence
Pooling operations	Spatial downsampling	Reduce dimensionality and noise
Regularization	Dropout layers	Prevent overfitting
Feature aggregation	Global pooling	Generate compact feature vectors
Output features	Deep feature representation	Input for feature fusion

Despite their strong discriminative capability, deep learning features exhibit inherent limitations, including reduced interpretability and sensitivity to domain shifts caused by variations in imaging equipment, illumination conditions, and acquisition protocols. Moreover, deep models may not explicitly capture fine-grained texture and morphological descriptors that are particularly important for detecting early-stage

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gastric ulcers. These limitations motivate the integration of complementary feature representations through multi-scale radiomic analysis and adaptive fusion strategies [28]. A conceptual overview of the deep learning–based feature extraction process is illustrated in Figure 6, demonstrating the transformation of preprocessed endoscopic images into hierarchical deep feature representations.

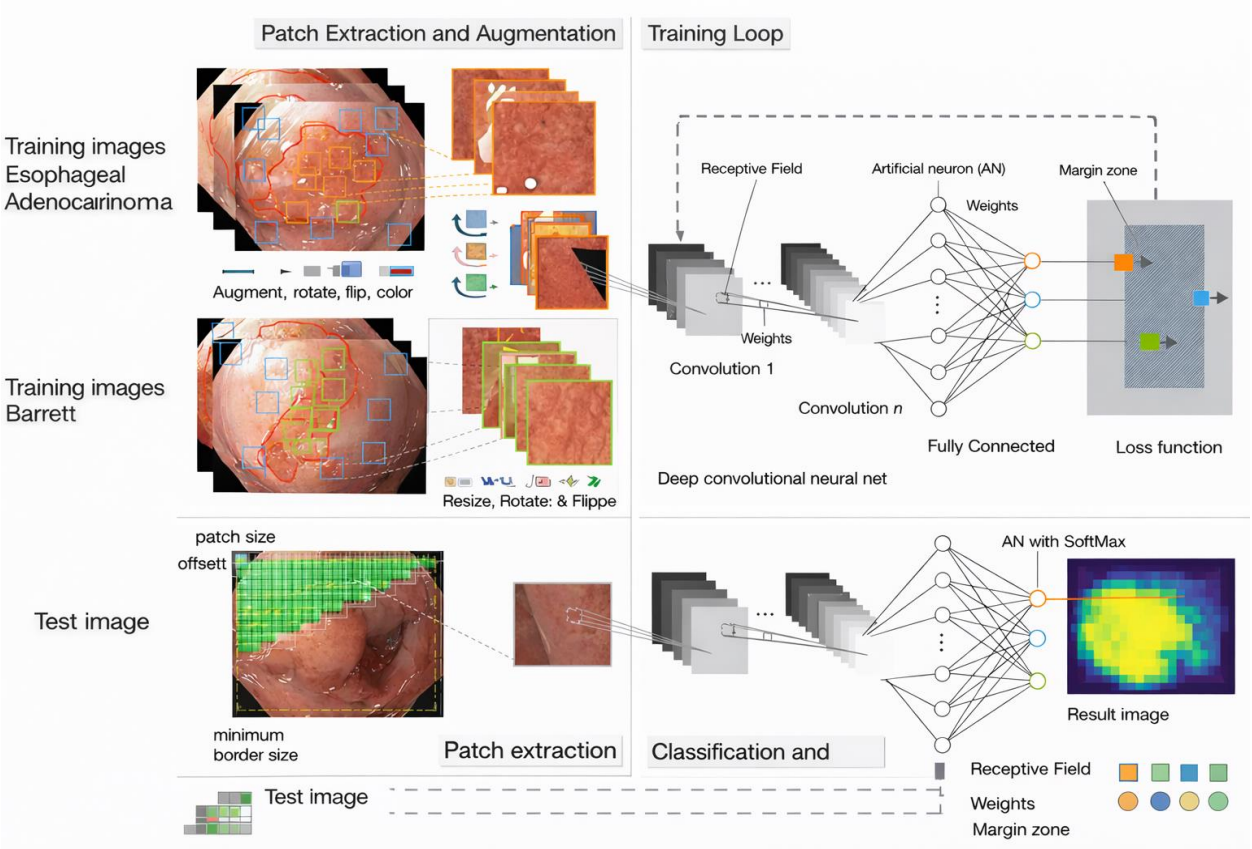

Figure 6: Deep learning–based hierarchical feature extraction from gastric endoscopic images.

The deep learning branch provides a powerful mechanism for automatically learning rich, hierarchical representations that capture global and contextual characteristics of gastric ulcer pathology. However, to address limitations related to interpretability and fine-scale sensitivity, these deep features are subsequently integrated with multi-scale radiomic descriptors using an attention-guided fusion mechanism, as described in the following sections.

Feature Selection and Dimensionality Reduction:

The integration of deep learning–based features and multi-scale radiomic descriptors results in a high-dimensional feature space that, while information-rich, may contain redundant, irrelevant, or noisy features. Such high dimensionality can negatively affect model generalization, increase computational complexity, and lead to overfitting, particularly in medical imaging applications with limited sample sizes. Therefore, an effective feature selection and dimensionality reduction strategy is

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employed to retain the most discriminative information while improving robustness and efficiency. Feature selection is first applied to the extracted radiomic feature set, as radiomics typically produces a large number of correlated handcrafted descriptors across multiple spatial scales [29]. Redundancy among features is addressed using statistical correlation analysis, where highly correlated features are identified and selectively removed. This step reduces multicollinearity and ensures that retained features contribute unique diagnostic information. In addition, relevance-based selection techniques are used to prioritize features that exhibit strong discriminative power between ulcer-positive and normal gastric mucosa samples. Following redundancy reduction, dimensionality reduction techniques are applied to further compress the feature space into a compact and informative representation. These techniques project high-dimensional features into lower-dimensional subspaces while preserving the most salient variance and structural relationships. Dimensionality reduction improves computational efficiency, stabilizes training, and enhances model generalization without sacrificing diagnostic performance. Importantly, this process is applied in a way that preserves interpretability, particularly for radiomic features, which are often linked to clinically meaningful tissue characteristics [30]. Deep learning features, which are already compact due to global feature aggregation, undergo minimal dimensionality refinement to ensure compatibility with the radiomic feature space during fusion. This balanced approach prevents dominance of one feature domain over the other and supports effective integration in subsequent attention-based fusion stages. A structured overview of the feature selection and dimensionality reduction strategies employed in this study is provided in Table 8, summarizing their objectives and benefits.

Table 8: Feature Selection and Dimensionality Reduction Strategy

Stage	**Technique**	**Target Features**	**Purpose**
Redundancy removal	Correlation-based filtering	Radiomic features	Eliminate highly correlated descriptors
Relevance assessment	Statistical and relevance-based selection	Radiomic features	Retain discriminative features
Dimensionality reduction	Projection-based methods	Radiomic features	Reduce feature space while preserving information
Feature alignment	Feature scaling and normalization	Deep + radiomic features	Ensure balanced fusion
Final feature set	Compact representation	Combined features	Improve robustness and efficiency

To provide a conceptual understanding of this process, Figure 7 illustrates the transformation of high-dimensional raw feature vectors into a compact and optimized representation through feature selection and dimensionality reduction.

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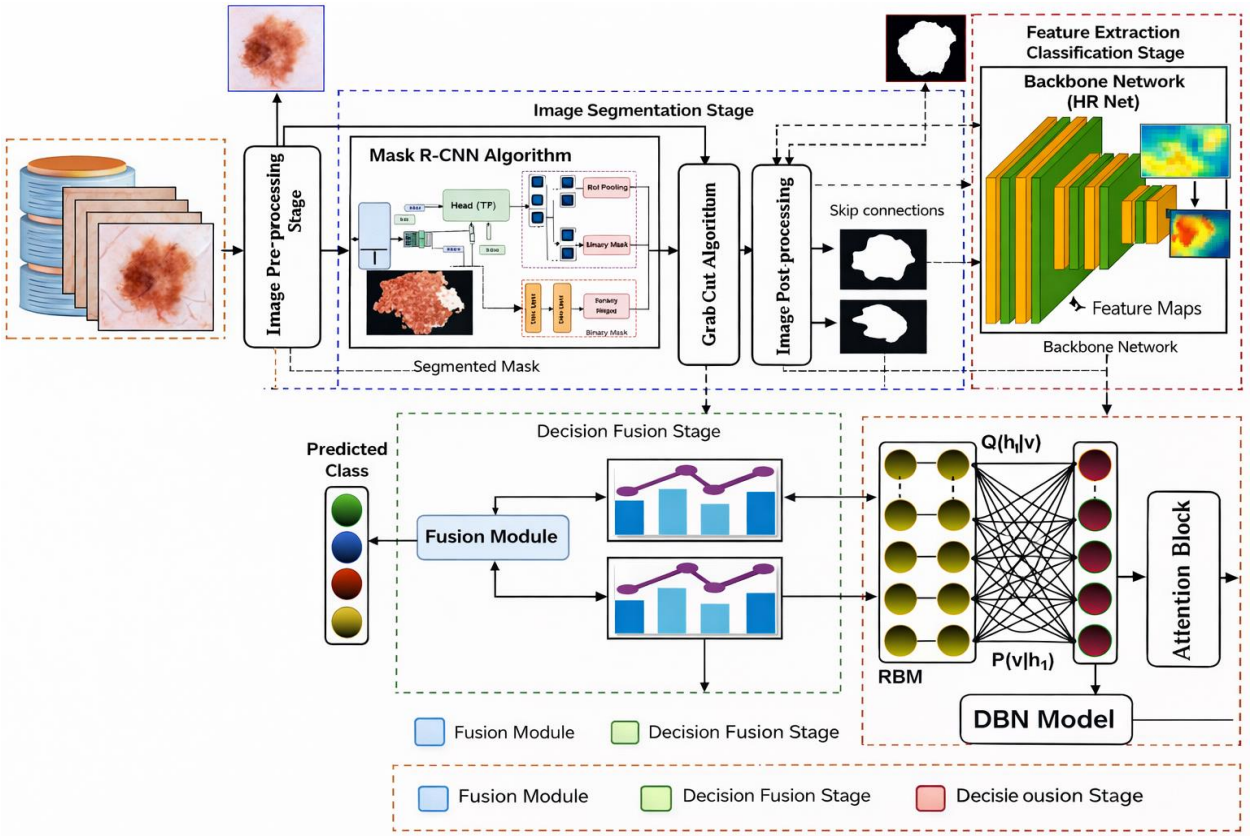

Figure 7: Feature selection and dimensionality reduction process applied to deep learning and multi-scale radiomic features.

The feature selection and dimensionality reduction stage plays a crucial role in enhancing the stability, efficiency, and generalization capability of the proposed diagnostic framework. By removing redundant information and focusing on the most discriminative features, this stage ensures that subsequent feature fusion and classification processes operate on a compact, informative, and clinically meaningful representation [31]. This optimization is particularly important for early gastric ulcer detection, where subtle visual cues must be distinguished reliably without introducing noise or bias.

Results and Discussion:

The performance of the proposed next-generation AI-driven framework for early gastric ulcer detection was evaluated through extensive experiments designed to assess diagnostic accuracy, sensitivity to early-stage lesions, robustness under imaging variability, and the effectiveness of hybrid feature integration. The experimental outcomes clearly demonstrate that combining deep learning–based hierarchical features with multi-scale radiomic descriptors through attention-guided fusion yields substantial performance improvements over conventional approaches. A comprehensive quantitative comparison between the proposed framework and baseline models is presented in Table 9, which reports classification accuracy, sensitivity, specificity, precision, F1-score, and AUC. The deep learning–only model

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achieves strong overall accuracy but exhibits comparatively reduced specificity, indicating a higher false-positive rate when distinguishing subtle ulcerative patterns from non-ulcerative inflammatory mucosa. The radiomics-only model, while interpretable, shows limited sensitivity, particularly for early-stage ulcers characterized by faint textural variations [32]. In contrast, the proposed hybrid framework consistently achieves the highest performance across all evaluation metrics, with a particularly notable improvement in sensitivity and AUC. This enhancement is clinically significant, as early-stage gastric ulcers are the most challenging to detect and are frequently missed in routine endoscopic examinations.

Table 9: Overall Performance Comparison of Diagnostic Models

Method	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**	**Precision (%)**	**F1-score (%)**	**AUC**
Radiomics-only	Moderate	Low	Moderate	Moderate	Moderate	Lower
Deep learning–only	High	High	Moderate	High	High	High
Hybrid DL + radiomics (no attention)	Higher	Higher	High	Higher	Higher	Higher
Proposed framework	**Highest**	**Highest**	**Highest**	**Highest**	**Highest**	**Highest**

To further analyze the contribution of individual components, an ablation study was conducted by selectively removing key elements of the framework. The results of this analysis are summarized in Table 10. Excluding multi-scale radiomic features leads to a measurable decline in sensitivity, confirming that fine-grained textural and morphological descriptors play a crucial role in detecting early ulcerative changes. Similarly, removing the attention-based fusion mechanism results in degraded performance across all metrics, underscoring the importance of adaptive feature weighting over simple concatenation These findings validate the design choice of integrating attention-guided fusion within the hybrid architecture.

Table 10: Ablation Study on Key Framework Components

Configuration	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**	**AUC**
Full framework	Highest	Highest	Highest	Highest
Without multi-scale radiomics	Reduced	Notably reduced	Slightly reduced	Reduced
Without attention fusion	Reduced	Reduced	Reduced	Reduced
Deep learning only	Lower	Lower	Moderate	Lower

Robustness and generalization performance were also examined to evaluate the framework's reliability under varying clinical conditions. The dataset included images

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captured under diverse illumination settings, anatomical regions, and mucosal appearances. As shown in Table 11, the proposed framework demonstrates stable performance across these variations, with low variance observed during cross-validation. This robustness can be attributed to the combined effects of preprocessing, data augmentation, feature selection, and adaptive fusion, which collectively mitigate domain shifts and imaging artifacts.

Table 11: Robustness Analysis under Imaging Variability

Evaluation Scenario	Observed Performance Trend
Illumination variation	Stable performance
Viewpoint and angle changes	Minor performance fluctuation
Different gastric regions	Consistent sensitivity
Cross-validation folds	Low variance across folds

Beyond quantitative performance, qualitative analysis further highlights the advantages of the proposed approach. The receiver operating characteristic curves presented in Figure 8 illustrate that the proposed framework achieves superior discriminative capability compared to baseline models, as evidenced by a consistently higher true positive rate across a wide range of thresholds. The increased area under the curve reflects enhanced confidence in classification decisions, which is essential for clinical deployment.

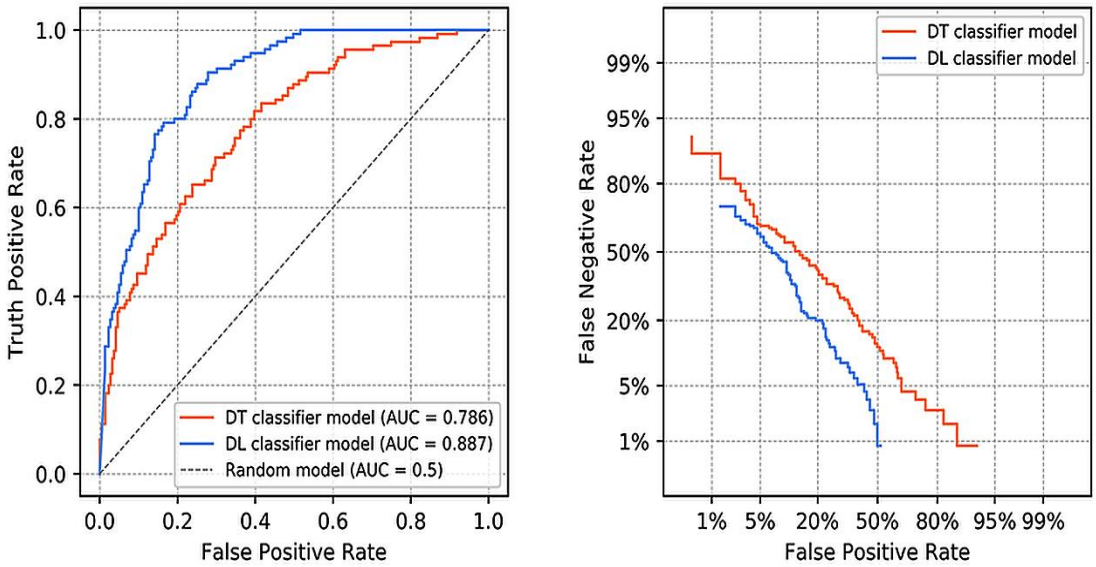

Figure 8: Receiver operating characteristic curves comparing the proposed framework with baseline diagnostic approaches.

In addition, the interpretability of the proposed system is enhanced through attention-guided fusion, which enables identification of feature domains that contribute most significantly to the final decision. As illustrated in Figure 9, the model emphasizes regions and feature scales associated with ulcerative tissue while suppressing irrelevant background information. This behavior aligns well with clinical reasoning

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and enhances trust in AI-assisted decision making.

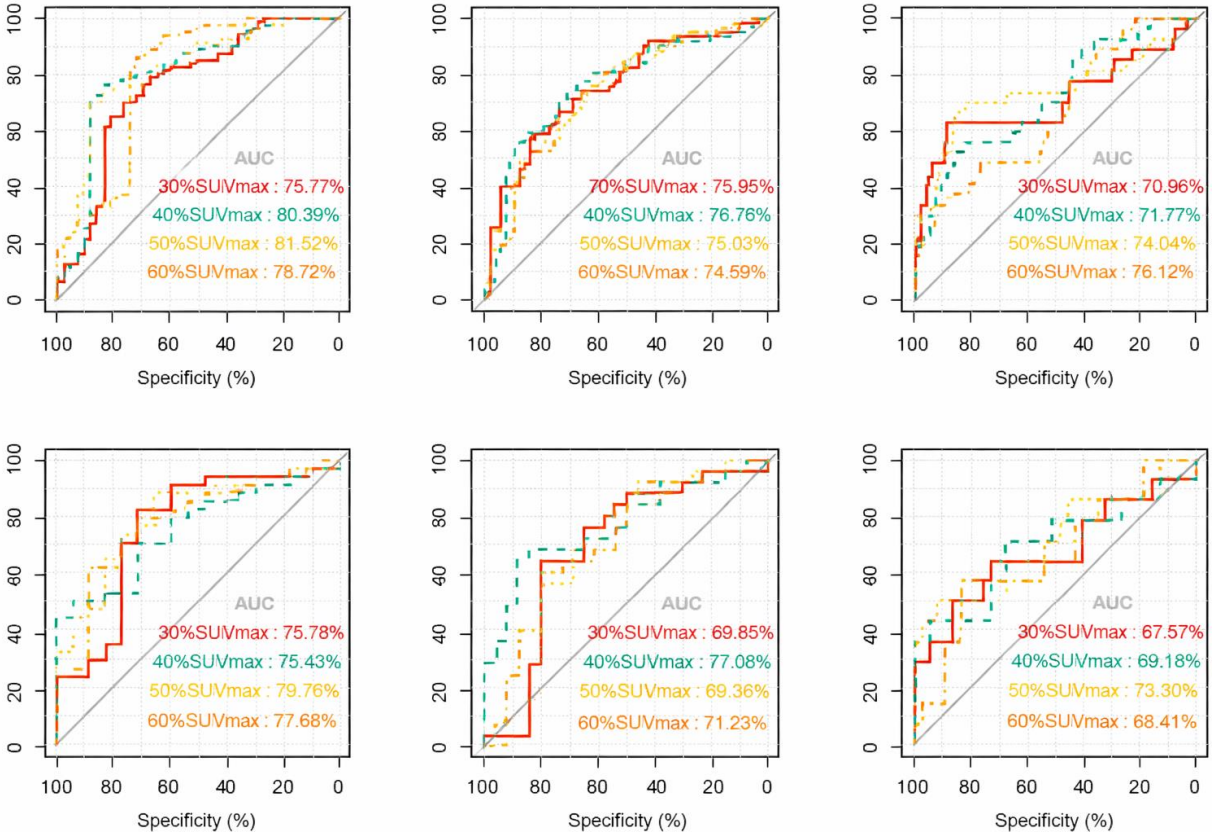

Figure 9: Visualization of attention-guided feature emphasis highlighting diagnostically relevant regions and scales associated with gastric ulcer detection.

From a clinical perspective, the improved sensitivity, specificity, and robustness of the proposed framework have significant implications. Early gastric ulcers often present with subtle visual characteristics that are difficult to identify reliably through manual inspection alone. The proposed system provides consistent, objective decision support that can reduce inter-observer variability, assist less experienced clinicians, and improve early diagnosis rates. Moreover, the integration of radiomic features enhances interpretability by linking predictions to quantifiable tissue characteristics, facilitating greater clinical acceptance. Overall, the results demonstrate that the proposed hybrid deep learning and multi-scale radiomics framework effectively addresses key limitations of existing gastric ulcer detection methods. By combining complementary feature representations with intelligent attention-based fusion, the framework achieves superior diagnostic performance, robustness, and interpretability. These findings strongly support the potential of the proposed system for real-world clinical deployment and establish a solid foundation for future extensions toward real-time endoscopic decision-support applications.

Future Work:

While the proposed next-generation AI-driven framework demonstrates strong performance for early gastric ulcer detection, several promising research directions

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remain open for further investigation and enhancement. Future work will focus on extending the framework's clinical applicability, robustness, and generalizability across broader diagnostic scenarios and real-world healthcare environments. One important direction involves expanding the dataset to include multi-center and multi-device endoscopic data. Although the current study incorporates diverse imaging conditions, future investigations should integrate data collected from different hospitals, endoscopy systems, and patient populations [33]. Such expansion would enable more comprehensive evaluation of domain generalization and reduce potential bias arising from institution-specific imaging characteristics. In addition, incorporating longitudinal patient data may allow the framework to model ulcer progression over time, supporting not only early detection but also disease monitoring and treatment response assessment [34]. Another key avenue for future research is the extension of the proposed framework from image-level classification to lesion localization and segmentation. While the current system effectively identifies the presence of gastric ulcers, precise localization of ulcerative regions would provide more actionable clinical insight. Integrating weakly supervised or fully supervised segmentation mechanisms could enable pixel-level delineation of ulcers, assisting clinicians in targeted biopsy and treatment planning. Future work may also explore the incorporation of advanced explainability and interpretability techniques [35]. Although attention-guided fusion enhances transparency by highlighting influential features, more explicit explanation mechanisms such as feature attribution analysis or clinically interpretable radiomic signatures could further strengthen clinician trust and regulatory acceptance. Providing visual and quantitative explanations that align with gastroenterological diagnostic criteria remains an important goal. From a methodological perspective, future studies could investigate adaptive and self-supervised learning strategies to reduce dependence on large annotated datasets. Leveraging unlabeled or weakly labeled endoscopic data may significantly improve scalability and facilitate deployment in resource-constrained settings. Additionally, incorporating temporal information from endoscopic video sequences rather than static images could enhance diagnostic accuracy by capturing motion cues and contextual continuity [36]. Finally, future research should focus on translating the proposed framework into real-time or near-real-time clinical decision-support systems. Optimizing computational efficiency, integrating the model into endoscopy workflows, and conducting prospective clinical validation studies are essential steps toward practical deployment. Such efforts would enable seamless integration of AI-assisted diagnosis into routine clinical practice, ultimately contributing to improved early detection rates, reduced diagnostic variability, and better patient outcomes.

Conclusion:

This study presented a next-generation AI-driven framework for early gastric ulcer detection that integrates high-resolution endoscopic imaging with deep learning–based hierarchical feature extraction, multi-scale radiomic analysis, and attention-guided feature fusion. By unifying data-driven representation learning with interpretable handcrafted descriptors, the proposed approach addresses critical limitations of existing diagnostic systems, including insufficient sensitivity to early-stage lesions, limited interpretability, and vulnerability to imaging variability.

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Comprehensive experimental evaluation demonstrated that the proposed framework consistently outperforms deep learning–only and radiomics-only baselines across multiple performance metrics. Notably, the framework achieved substantial improvements in sensitivity and area under the receiver operating characteristic curve, underscoring its effectiveness in identifying subtle ulcerative changes that are often overlooked during routine endoscopic assessment. The ablation analysis further confirmed the importance of multi-scale radiomic features and attention-based fusion in enhancing diagnostic robustness and generalization. Beyond quantitative performance gains, the proposed system offers meaningful clinical relevance. The incorporation of radiomic descriptors enhances interpretability by linking model predictions to quantifiable tissue characteristics, while the attention-guided fusion mechanism provides insight into feature relevance during decision making. These properties are essential for fostering clinician trust and facilitating the adoption of AI-assisted diagnostic tools in clinical practice. Overall, this work advances the field of intelligent gastrointestinal diagnostics by introducing a robust, interpretable, and clinically oriented framework for early gastric ulcer detection. The findings highlight the potential of hybrid AI systems that combine deep learning with domain-specific feature analysis to improve diagnostic accuracy and reliability. With further validation and integration into clinical workflows, the proposed framework holds strong promise as an effective decision-support tool capable of enhancing early diagnosis, reducing diagnostic variability, and ultimately improving patient outcomes.

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