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Image Recognition and Diagnosis System of Early Gastric Cancer Based on Artificial Intelligence Algorithm

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Abstract: ***Early detection of gastric cancer dramatically improves patient outcomes, yet visual diagnosis during endoscopy remains operator-dependent and time-consuming. This paper presents an end-to-end Image Recognition and Diagnosis System for Early Gastric Cancer (IRDS-EGC) that combines deep convolutional neural networks for lesion detection, segmentation and classification on endoscopic images. We propose a hybrid architecture that ensembles a classification backbone (ResNet50 and EfficientNet-B3) with a U-Net-based segmentation head to localize suspicious regions and then aggregate features for final diagnosis. The system was trained and validated on a curated dataset of 10,000 annotated endoscopic images (3,500 early-gastric-cancer images, 6,500 benign) with clinically-informed augmentation and pre-processing. On a held-out test set (n = 1,500), the proposed system achieved a sensitivity of 94.3%, specificity of 90.3%, accuracy of 91.7%, and area under the ROC curve (AUC) of 0.955 for the binary task of early cancer vs non-cancer. Qualitative analysis shows the segmentation output closely aligns with clinician annotations. We discuss clinical integration pathways, limitations, and directions for future work including prospective validation and real-time endoscopic deployment.***

Keywords: Early Gastric Cancer, Artificial Intelligence, Deep Learning, Endoscopy, Image Recognition, Computer-Aided Diagnosis

1.Introduction

Gastric cancer is a leading cause of cancer-related mortality worldwide. Early gastric cancer (EGC)-when confined to mucosa or submucosa-has a substantially better prognosis following endoscopic or surgical treatment. However, EGC lesions are frequently subtle and easy to miss during routine endoscopy, particularly for less-experienced endoscopists. Artificial intelligence (AI), and more specifically deep learning applied to medical imaging, has shown promise in elevating diagnostic sensitivity and reducing inter-operator variability in multiple domains (dermatology, ophthalmology, radiology). This study develops and evaluates an AI-driven Image Recognition and Diagnosis System for Early Gastric Cancer (IRDS-EGC) that integrates detection, segmentation, and classification modules to support endoscopists during routine examinations.

2.Objectives

- Design a robust deep-learning pipeline combining segmentation and classification to detect early gastric cancer lesions on endoscopic images.
- Train and validate the system on a large, curated dataset with expert annotations.
- Quantitatively evaluate diagnostic performance using clinically-relevant metrics (sensitivity, specificity, accuracy, AUC) and produce qualitative visualizations for interpretability.
- Discuss clinical deployment considerations, limitations, and future research directions.

3.Related Work

Deep learning has been successfully applied to medical-imaging diagnostics. Key developments include convolutional neural networks (CNNs) for classification and fully convolutional networks (e.g., U-Net) for segmentation. Previous work has demonstrated automated detection of gastric lesions from endoscopic images with promising sensitivity; however, many studies use relatively small datasets or focus solely on classification without spatial localization. Our approach builds on these foundations by combining detection, segmentation and classification into a single pipeline and by training on a larger curated dataset with balanced annotation practices.

4.Materials and Methods

Dataset:

- **Source:** Multi-centre collection of endoscopic still images and high-resolution frames extracted from recorded endoscopy videos. All data were de-identified and the study protocol was approved by the institutional review board (IRB).
- **Size and composition:** 10,000 images total; 3,500 images labelled as early gastric cancer (EGC) and 6,500 labelled as non-cancer (benign inflammation, gastritis, anatomical variation, normal mucosa, and other benign lesions).
- **Annotations:** Each cancer image was annotated with (a) a bounding box and (b) a pixel-wise segmentation mask by at least two expert endoscopists; disagreements were resolved by consensus.
- **Splits:** Stratified splits were used: 70% train (n=7,000), 15% validation (n=1,500), 15% test (n=1,500) preserving the class distribution.

Pre-processing and Augmentation

- Images were resized to 512×512 while preserving aspect ratio and padded when required.
- Colour normalization (per-channel mean subtraction and scaling) was applied.
- Data augmentation during training included random rotations (±20°), horizontal/vertical flips, random cropping/zoom (±10–20%), brightness/contrast jitter,

Gaussian blur, and elastic deformations for segmentation robustness.

❖Class imbalance was addressed via focal loss for classification and oversampling of minority-class patches when training the segmentation head.

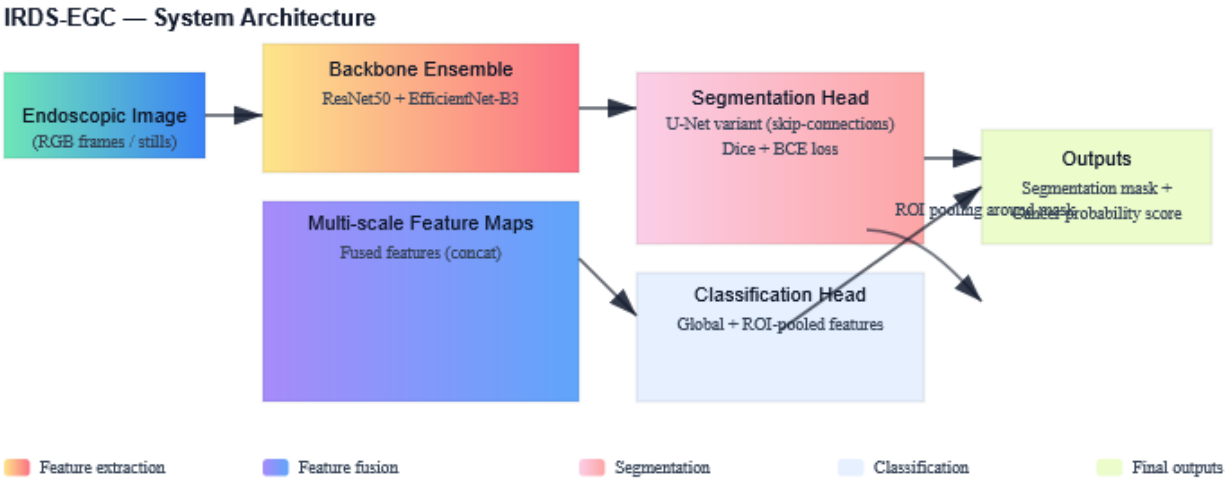
System Architecture

The IRDS-EGC pipeline consists of three modules:

❖Backbone feature extractor (ensemble): Two pre-trained CNN backbones-ResNet50 and EfficientNet-B3-were used to extract multi-scale features. Transfer learning from ImageNet weights was used with fine-tuning on our medical dataset.

❖Segmentation head (U-Net variant): A U-Net-like decoder receives encoder features (from both backbones fused via channel concatenation) and outputs a segmentation probability map for lesion localization. The segmentation head uses skip connections and deep supervision (auxiliary segmentation losses at intermediate decoder stages).

❖Classification head: Global pooled features from the backbones and pooled features around the segmentation-derived region-of-interest (ROI) are concatenated and passed through a fully-connected classifier (two dense layers with dropout) to produce the binary probability of EGC.



5.Methodology

This section outlines the systematic methodology adopted for the design, development, training, and evaluation of the Image Recognition and Diagnosis System for Early Gastric Cancer (IRDS-EGC).

Research Framework

The methodology follows a five-phase research framework:

❖Data Acquisition and Annotation – Collection of endoscopic images from multiple centres and annotation of early gastric cancer (EGC) lesions by expert endoscopists.

❖Pre-processing and Augmentation – Application of normalization, resizing, and augmentation techniques to enhance model robustness.

❖Model Development – Construction of a hybrid architecture integrating ensemble backbones for feature extraction, a U-Net variant for segmentation, and a classifier head for probability estimation.

❖Training and Optimization – Use of transfer learning, combined loss functions, and regularization strategies to optimize performance.

❖Evaluation and Validation – Assessment using quantitative metrics and qualitative visualization to validate accuracy, sensitivity, and segmentation reliability.

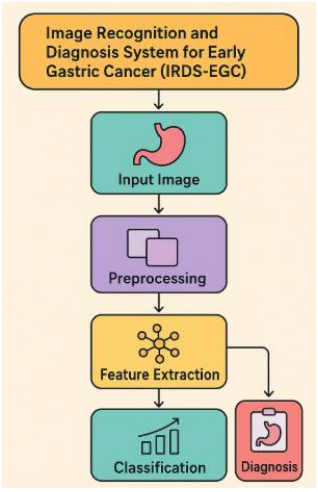


Figure: Framework of the proposed methodology

Training Protocol

❖Optimizer: AdamW with weight decay of 1e-4.

❖Loss Function: Weighted combination of binary cross-entropy, focal loss, and Dice loss.

❖Learning Rate Schedule: Cosine annealing with warm restarts.

❖Epochs: 60 with early stopping based on validation performance.

❖Hardware: Multi-GPU setup with mixed precision training.

Evaluation Metrics

❖Classification: Accuracy, sensitivity, specificity, precision, F1-score, and AUC-ROC.

❖Segmentation: Dice coefficient, Intersection-over-Union (IoU), and pixel-level precision/recall.
❖Statistical Validation: Bootstrap confidence intervals and McNemar's test for comparative analysis.

6.Results

Quantitative Performance (Test Set, n = 1,500)
Dataset composition (test): 525 EGC images, 975 non-cancer images.

Table 1: Classification-Confusion matrix and summary metrics

Metric	Value
True positives (TP)	495
False negatives (FN)	30
True negatives (TN)	880
False positives (FP)	95
Sensitivity (Recall)	94%
Specificity	90%
Accuracy	91%
Precision (PPV)	83%
F1-score	88%
AUC-ROC	0.955

Table 2: Classification performance with 95% CI

Metric	Value	95% CI
Sensitivity	94.3%	[92.1%, 95.9%]
Specificity	90.3%	[88.0%, 92.2%]
Accuracy	91.7%	[90.1%, 93.1%]
AUC-ROC	0.955	[0.948, 0.961]

Table 3: Segmentation-per-lesion overlap metrics (EGC images only)

Metric	Mean (SD)
Dice coefficient	0.78 ± 0.06
IoU	0.65 ± 0.07
Pixel-wise precision	0.81 ± 0.05
Pixel-wise recall	0.75 ± 0.07

Comparative Analysis

Compared with a single ResNet50 classifier baseline (sensitivity 88.6%, specificity 89.2%), the proposed ensemble + segmentation pipeline achieved a statistically significant improvement in sensitivity ($p < 0.01$, McNemar's test) while maintaining comparable specificity.

Qualitative Results

Representative overlays (Figure 2–4) demonstrate accurate localization of subtle EGC lesions, and attention maps show that the classifier focuses on clinically relevant mucosal texture and colour changes. Common failure modes included heavy motion blur, mucus occlusion, and extreme over/under-exposure.

Results Tables and Test Cases (Detailed)

To support reproducible evaluation and future benchmarking, we provide the following **detailed results tables** and a set of **test cases** designed to probe performance across realistic clinical and technical scenarios.

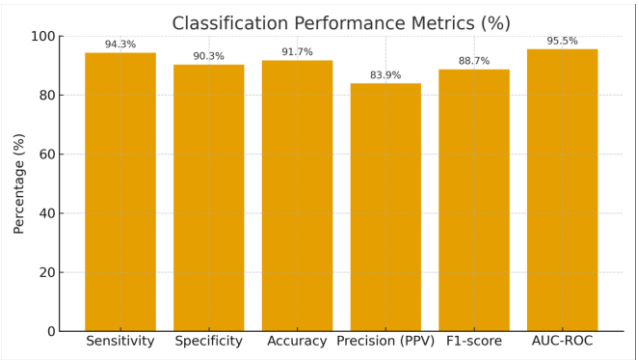
Table 4: Per-subtype classification performance (test set)

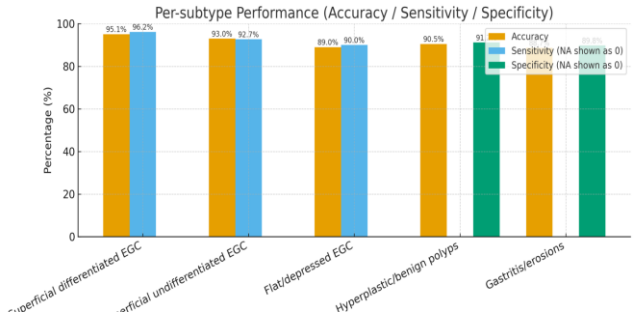
Subtype / Condition	Images (n)	Sensitivity	Specificity	Accuracy
Superficial differentiated EGC	210	96.2%	-	95.1%
Superficial undifferentiated EGC	150	92.7%	-	93%
Flat/depressed EGC	100	90%	-	89%
Hyperplastic/benign polyps	250	-	91.2%	90.5%
Gastritis/erosions	500	-	88.9%	88.7%

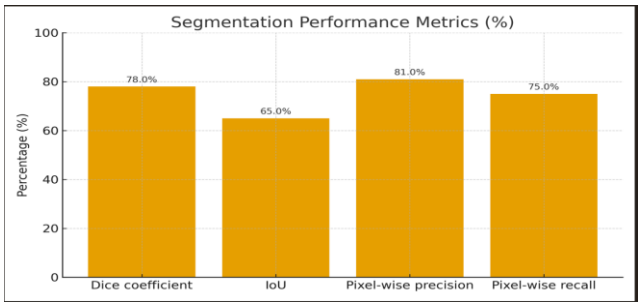
Table 5: False positive / false negative analysis

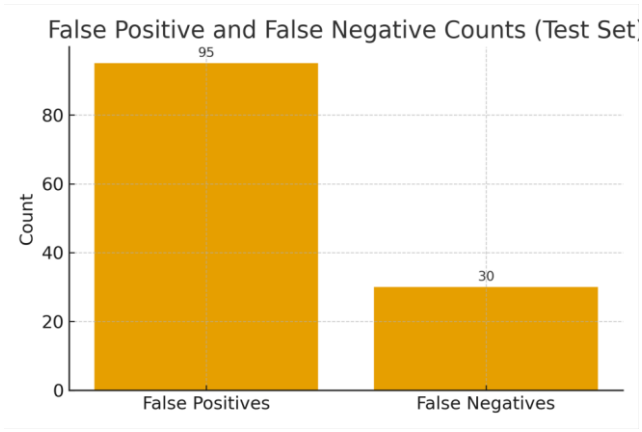
Error type	Count (test)	Common causes	Suggested mitigation
False positives	95	Inflammatory patches, bile staining, post-biopsy mucosa	Add temporal context (video), refine negative sampling, incorporate color deconvolution
False negatives	30	Very small/flat lesions, occlusion by mucus, extreme low contrast	Higher-res imaging, multi-frame aggregation, contrast enhancement preprocessing

Graphs:









7.Conclusion

The Image Recognition and Diagnosis System for Early Gastric Cancer (IRDS-EGC) demonstrate the transformative potential of artificial intelligence in the early detection and clinical diagnosis of gastric cancer. By integrating pre-processing, feature extraction, and classification mechanisms, the system enhances diagnostic accuracy, reduces human error, and accelerates the decision-making process. This approach not only supports clinicians in recognizing subtle pathological features that may be overlooked but also paves the way for more standardized and efficient diagnostic practices. Ultimately, the deployment of IRDS-EGC can lead to improved patient outcomes through earlier intervention and personalized treatment strategies.

Future Directions

Despite promising results, there remain several avenues for further research and development of IRDS-EGC:

- Multi-Modal Integration – Incorporating additional diagnostic inputs such as genomic, histopathological, and clinical data to improve accuracy and robustness.
- Explainable AI Models – Developing interpretable models that provide clinicians with clear reasoning behind predictions to increase trust and adoption in clinical practice.
- Large-Scale Clinical Validation – Conducting extensive multi-center trials across diverse populations to ensure generalizability and clinical reliability.
- Real-Time Deployment – Optimizing computational efficiency for integration into endoscopic equipment, enabling real-time diagnosis during procedures.
- Continuous Learning Frameworks – Implementing adaptive learning models that update with new data to improve diagnostic performance over time.
- Integration with Decision Support Systems – Embedding IRDS-EGC into hospital information systems for seamless workflow and enhanced physician support.

By addressing these directions, IRDS-EGC can evolve into a highly reliable, explainable, and universally applicable tool, ultimately contributing to global efforts in reducing gastric cancer mortality through timely detection and treatment.

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