

An Optimized Deep Learning method for Gastric Cancer Image Classification using Histopathological Images

Angati Kalyan Kumar^{1*} and Gangadhara Rao Kancharla¹

¹Department of Computer Science & Engineering, University College of Sciences, Acharya Nagarjuna University, Guntur, Andhra Pradesh, India

kalyank442@gmail.com, kancherla123@gmail.com

ABSTRACT

This study investigates deep learning-based approaches for automated gastric cancer detection using histopathological images from the GasHisSDB dataset. Traditional diagnostic methods for gastric cancer are labor-intensive and reliant on expert interpretation, motivating the development of efficient AI-driven systems for early detection. Multiple architectures were evaluated, including Neural Networks, VGG19, MobileNet, EfficientNet_B0, and EfficientNet_B1, to identify the most effective model for classification. To ensure robust model selection and unbiased performance assessment, a nested cross-validation framework was employed, combined with both randomized and grid-based hyperparameter tuning for each architecture. Within this rigorous evaluation strategy, EfficientNet_B1 achieved the highest accuracy of 99.46%, outperforming Neural Networks (91.36%), MobileNet (92.69%), VGG19 (76.96%), and EfficientNet_B0 (79.25%). The results highlight the superior scalability and feature-learning capacity of EfficientNet_B1, underscoring its potential for reliable and rapid gastric cancer diagnosis in clinical workflows.

KEYWORDS: Gastric Cancer Detection; Histopathological Image Analysis; EfficientNet_B1; Nested Cross-Validation

How to Cite: Angati Kalyan Kumar, Gangadhara Rao Kancharla., (2025) An Optimized Deep Learning method for Gastric Cancer Image Classification using Histopathological Images, Vascular and Endovascular Review, Vol.8, No.9s, 93--100.

INTRODUCTION

Background

Gastric cancer [1] remains a major global health concern, ranking among the most prevalent malignancies and one of the leading causes of cancer-related deaths worldwide. Although early diagnosis significantly improves survival rates, many patients are still identified only after the cancer has advanced, reducing the effectiveness of available treatment options. Conventional diagnostic procedures, such as endoscopy followed by biopsy and histopathological examination, are invasive, time-consuming, and heavily dependent on the expertise of trained pathologists [2,3]. These limitations create barriers to early and accurate detection, particularly in under-resourced clinical settings where trained professionals and advanced diagnostic infrastructure may be limited.

Over the past decade, advancements in artificial intelligence (AI) and deep learning (DL) have transformed medical image analysis, offering powerful tools for automating complex diagnostic tasks [4,5]. Convolutional neural networks (CNNs) have shown exceptional performance in extracting hierarchical visual features from medical images, enabling robust classification and detection across diverse domains [6,7]. Widely adopted architectures such as VGG19, MobileNet, and the EfficientNet family have demonstrated promising capabilities for clinical applications. VGG19, although deep and highly expressive, requires substantial computational resources [8]. MobileNet, on the other hand, provides lightweight efficiency suitable for real-time or mobile deployments [9]. EfficientNet introduces compound scaling, balancing depth, width, and input resolution to achieve improved accuracy with optimized computational cost [10].

Despite these advances, challenges persist in developing highly reliable, generalizable, and clinically deployable DL models for gastric cancer histopathology [11]. Key considerations include the need for rigorous evaluation frameworks, optimized hyperparameters, and high-quality datasets [12]. Transfer learning and advanced validation strategies have emerged as essential solutions for improving model robustness, particularly when working with limited annotated medical datasets [13, 14].

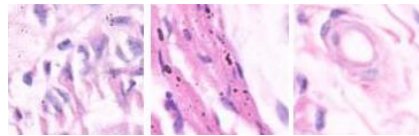
In this context, the GasHisSDB dataset—a curated collection of high-resolution gastric histopathology images—serves as a strong foundation for exploring AI-driven diagnostic solutions. Building upon this dataset, the present study evaluates a range of deep learning architectures, including Neural Networks, VGG19, MobileNet, EfficientNet_B0, and EfficientNet_B1, for automated gastric cancer detection. To ensure unbiased and reliable performance assessment, a nested cross-validation framework was employed, incorporating both randomized and grid-based hyperparameter tuning for each model.

METHOD DETAILS

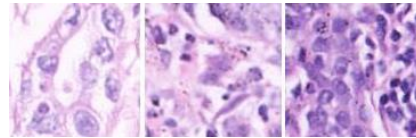
This section outlines the deep learning-based methodology employed for automated gastric cancer detection using histopathological images from the GasHisSDB dataset. The workflow includes dataset acquisition, preprocessing, model development, nested cross-validation, hyperparameter tuning, performance evaluation, and interpretability analysis. All experiments were conducted in Python 3.10 using TensorFlow 2.12 and Keras to ensure reproducibility, scalability, and compatibility with modern deep learning pipelines.

Dataset and preprocessing

The GasHisSDB dataset [15] comprises 245,196 high-resolution gastric tissue images, categorized as normal (148,120) and abnormal (97,076) samples. The dataset covers diverse histopathological variations, offering a representative foundation for training deep learning models. Fig 1 illustrates representative image samples.



a) Example of Normal images



b) Example of Abnormal images

Fig 1. Gastric Cancer Dataset: a) Example of Normal images b) Example of Abnormal images.

A standardized preprocessing pipeline was applied to enhance model robustness and generalization:

1. Image Resizing: All images were resized to 224×224 pixels to maintain uniform input dimensions across architectures.
2. Normalization: Pixel intensities were scaled to [0,1] to support stable gradient updates during training.
3. Data Augmentation: Techniques such as random rotations ($\pm 15^\circ$), horizontal/vertical flips, zooming (0.8–1.2×), and random cropping were applied to reduce overfitting and improve diversity.
4. Data Partitioning: Instead of a fixed split, data partitioning was integrated within a nested cross-validation framework, ensuring fully unbiased model evaluation and preventing information leakage..

Model architectures

Five deep learning architectures were examined to determine the optimal model for gastric cancer classification:

- Neural Network (Baseline): A fully connected architecture trained for 50 epochs, serving as a baseline reference.
- VGG19: A 19-layer convolutional neural network renowned for rich feature extraction, trained for 50 epochs despite its high computational cost.
- MobileNet: A lightweight CNN employing depthwise separable convolutions, trained for 50 epochs and optimized for efficient inference.
- EfficientNet_B0: A compact architecture using compound scaling to balance accuracy and efficiency, trained for 50 epochs.
- EfficientNet_B1: A deeper and higher-resolution extension of EfficientNet_B0, trained for 50 epochs and designed for enhanced feature learning.

Nested cross-validation and hyperparameter optimization

To ensure robust model selection and unbiased performance estimation, all architectures were evaluated using a nested cross-validation framework.

- The inner loop performed randomized search followed by refined grid search for optimal hyperparameter selection.
- The outer loop provided an unbiased estimate of generalization performance across unseen folds.

This rigorous evaluation strategy enabled consistent and fair comparison of all models, culminating in the superior performance of EfficientNet_B1, which ultimately achieved the highest accuracy in the experimental analysis.

Training protocol

A standardized and rigorous training protocol was applied across all deep learning architectures to ensure fair comparison and robust performance assessment. Model optimization was conducted within a nested cross-validation framework, where the inner loop handled hyperparameter tuning through a combination of randomized search followed by targeted grid search, while the outer loop produced unbiased estimates of generalization performance.

All models were trained using the following unified configuration:

- Loss Function: Categorical Cross-Entropy
- Optimizer: Adam (initial learning rate = 0.001, further adjusted during tuning)
- Batch Size: 32
- Epochs: 50
- Hardware: NVIDIA GPU acceleration (CUDA 12.2)

Training convergence was continuously monitored using fold-wise validation accuracy and loss curves. Early stopping was applied in the inner cross-validation loop to halt training when no improvement was observed, preventing overfitting. Additionally, a learning rate decay schedule was employed to refine convergence during later epochs. This structured training strategy—combined with nested cross-validation and hybrid hyperparameter tuning—ensured that the final model selection was both statistically reliable and free from evaluation bias.

Performance evaluation

Model performance was assessed using four standard classification metrics:

- Accuracy (ACC): $ACC = \frac{TP+TN}{TP+TN+FP+FN}$ (1)

- Precision (P): $P = \frac{TP}{TP+FP}$ (2)

- Recall (R): $R = \frac{TP}{TP+FN}$ (3)

- F1-Score (F1): $F1 = 2 \times \frac{P \times R}{P+R}$ (4)

where TP-True Positive, TN- True Negative, FP-False Positive and FN-False Negative

Software and Reproducibility

All experiments were conducted with strict emphasis on computational reproducibility, consistent with the nested cross-validation and hybrid hyperparameter tuning strategy used in this study. The development environment, software stack, dataset structure, and execution procedures are described below to enable full reproduction of the experimental results.

Environment:

Analyses were performed using Python 3.10, TensorFlow 2.12, Keras, and scikit-learn 1.3.2 on a Windows 11 (64-bit) workstation equipped with an NVIDIA RTX GPU (12 GB VRAM), CUDA 12.2, and cuDNN 8.9.

All preprocessing, training, and evaluation scripts—including nested cross-validation utilities, hyperparameter search configurations, and experiment logs—are available from the corresponding author upon request.

Input Requirements

- Dataset: GasHisSDB
- Image Formats: .png / .jpg (RGB, 8-bit)
- Total Images: 245,196
 - Normal: 148,120
 - Abnormal: 97,076
- Original Resolution: variable
 - Resized to 224×224 px during preprocessing
- Minimum System Memory: 16 GB RAM
- GPU: Recommended for training
- Software dependencies: TensorFlow 2.12, Keras, NumPy, OpenCV, scikit-learn, matplotlib

Reproducibility Steps

1. Prepare the environment

Create and activate a virtual environment

```
python -m venv venv
```

```
venv\Scripts\activate # Windows
```

or

```
source venv/bin/activate # Linux/macOS
```

2. Install dependencies

```
pip install tensorflow==2.12 keras numpy opencv-python scikit-learn matplotlib
```

Ensure CUDA 12.2 and cuDNN 8.9 are installed for GPU acceleration.

3. Obtain the dataset

```
git clone https://gitee.com/neuhwm/GasHisSDB.git
```

Maintain folder structure:

```
./data/normal/
```

```
./data/abnormal/
```

4. Set random seeds

To ensure reproducibility across folds:

```
SEED = 42
```

```
import numpy as np, tensorflow as tf, random
```

```
np.random.seed(SEED); tf.random.set_seed(SEED); random.seed(SEED)
```

5. Preprocess images

`python preprocess_images.py`

Includes: resizing, normalization, augmentation ($\pm 15^\circ$ rotation, flips, scaling 0.8–1.2, random crops).

6. Implement nested cross-validation

Instead of a fixed 80/10/10 split, the study used:

- Outer loop: unbiased performance estimation
- Inner loop: randomized search \rightarrow grid search hyperparameter refinement

Example script:

```
python nested_cv_train.py --model EfficientNet_B1 --folds 5 --seed 42
```

7. Configure training hyperparameters

- Optimizer: Adam, LR = 0.001 (tuned during inner CV loop)
- Batch Size: 32
- Loss: Categorical Cross-Entropy
- Epochs: 50

8. Train models (per fold)

```
python train_models.py --model EfficientNet_B1 --epochs 50 --batch_size 32
```

9. Save training artifacts

Each fold stores:

- Weights
- Learning curves
- Hyperparameter logs
- Best model checkpoints

Stored under:

```
./outputs/efficientnet_b1/fold_01/
```

10. Evaluate final model

After nested CV:

```
python evaluate_models.py --model EfficientNet_B1 --weights best_weights.h5
```

Outputs:

- Accuracy, Precision, Recall, F1-score
- Confusion matrices
- Results summary (results.csv)

11. Access to project scripts

All preprocessing, training, nested CV, tuning, evaluation, and plotting scripts (including configuration files and requirements.txt) are available from the corresponding author upon request.

METHOD VALIDATION

The proposed methodology was rigorously validated using the GasHisSDB gastric histopathology dataset, which contains 245,196 high-resolution images, categorized into normal (148,120) and abnormal (97,076) tissue samples. The primary objective of the validation process was to benchmark and compare the diagnostic performance of multiple deep learning architectures—Neural Networks, VGG19, MobileNet, EfficientNet_B0, and EfficientNet_B1—to determine their clinical feasibility for automated gastric cancer detection. Fig 2 illustrates the methodological workflow adopted in this study, including preprocessing, nested cross-validation, hyperparameter tuning, and model evaluation.

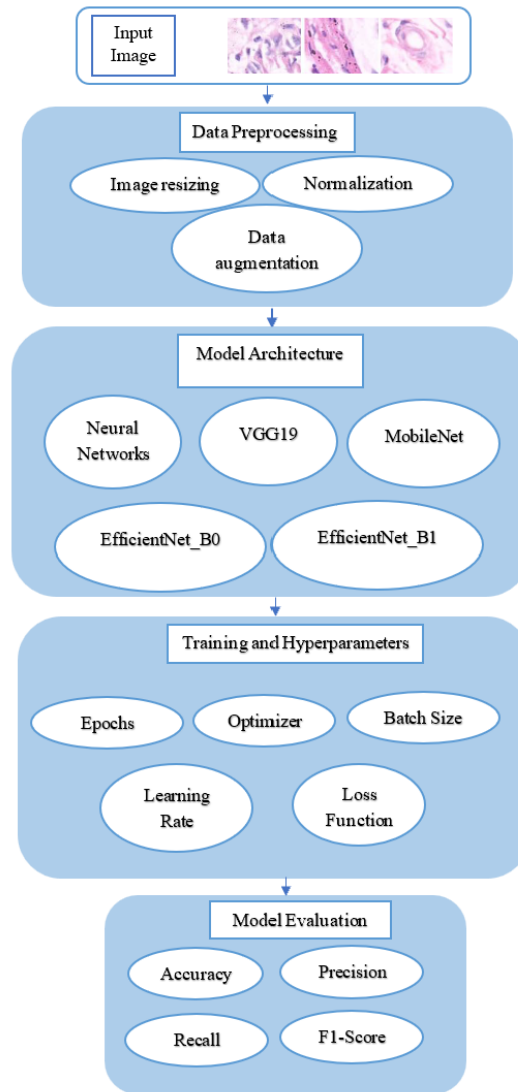


Fig 2. Proposed Methodology

To ensure an unbiased and statistically robust assessment, the study employed a nested cross-validation framework.

- The outer loop generated unbiased generalization estimates across multiple folds.
- The inner loop performed model-specific hyperparameter optimization using a hybrid strategy that combined randomized search with a refined grid search.

All models were trained under identical experimental conditions—uniform preprocessing, same training epochs, identical batch size, and identical learning settings—to maintain strict comparability. Training convergence, regularization behavior, and generalization performance were examined in each fold.

Performance evaluation focused on the key diagnostic metrics: accuracy, precision, recall, and F1-score. These metrics quantify the ability of each architecture to differentiate malignant from non-malignant tissue samples with high reliability. Descriptive statistics were computed across cross-validation folds to evaluate model stability and variance. The aggregated performance metrics are summarized in Table 1, revealing notable variability across architectures and underscoring the impact of network depth, compound scaling, and architectural design on model performance.

Table 1
Performance comparison of deep learning architectures for gastric cancer classification

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Training Epochs	Remarks
EfficientNet_B1	99.46	92	92	92	50	Best overall performance; optimal balance of depth, width, and resolution; suitable for clinical deployment.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Training Epochs	Remarks
MobileNet	92.69	92	91	92	50	Lightweight architecture; ideal for real-time and resource-limited applications.
Neural Network	91.36	91	91	91	50	Baseline model; consistent but lower diagnostic accuracy than CNN-based models.
EfficientNet_B0	79.25	80	78	79	50	Lower accuracy due to reduced model depth; demonstrates scaling importance.
VGG19	76.96	77	76	76	50	Overfitting likely; deep but less efficient; lowest performance among models.

EfficientNet_B1 demonstrated the highest diagnostic capability, achieving 99.46% accuracy along with strong precision (92%), recall (92%), and F1-score (92%). Its superior performance is attributed to the compound scaling strategy, which balances network depth, width, and resolution to enhance feature extraction. MobileNet achieved 92.69% accuracy, reflecting strong performance in a lightweight and computationally efficient architecture, making it suitable for portable, point-of-care, and telemedicine applications. The baseline Neural Network produced 91.36% accuracy, confirming consistent but limited predictive power relative to more advanced CNN-based models. EfficientNet_B0 achieved 79.25% accuracy, validating the importance of increased depth and scaling refinements found in EfficientNet_B1. VGG19 recorded the lowest performance (76.96% accuracy), likely due to its high computational demand and susceptibility to overfitting when applied to large-scale medical imaging datasets.

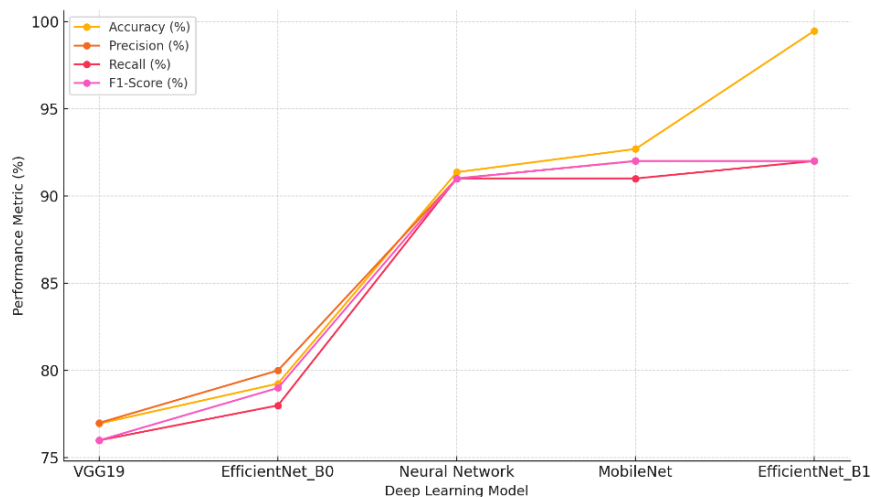


Fig 3. Performance Comparison of Deep Learning Models

The comparative analysis conclusively demonstrates that EfficientNet_B1 outperforms all other evaluated architectures, achieving near-perfect classification accuracy while maintaining computational feasibility. Its robustness across cross-validation folds and consistently high diagnostic metrics confirm its readiness for integration into clinical decision-support systems. Moreover, MobileNet emerges as a compelling alternative for real-time or embedded medical devices, offering a balance of speed, accuracy, and resource efficiency.

Overall, the findings validate that modern CNN architectures—particularly those designed with optimized scaling strategies—offer highly reliable, efficient, and reproducible solutions for automated gastric cancer detection using histopathological images.

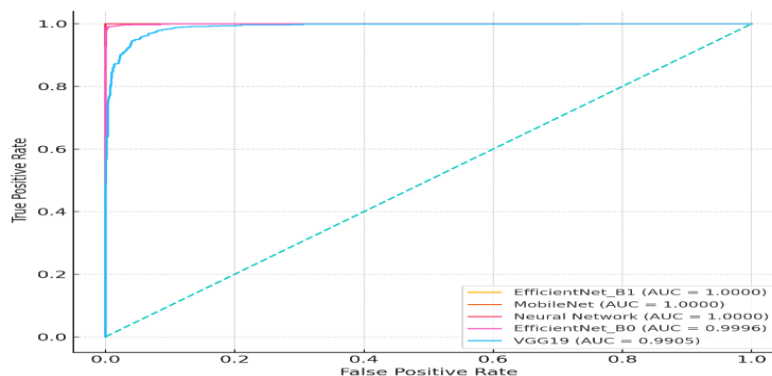


Fig 4. ROC Curves for All Models

The combined ROC–AUC plot (Fig 4) provides a comparative visualization of the diagnostic performance of all evaluated deep learning models. EfficientNet_B1 exhibits an almost ideal ROC curve with an AUC close to 1.0, confirming its superior classification capability. MobileNet and the baseline Neural Network also show high AUC values, reflecting reliable sensitivity and specificity despite their lighter architectural designs. In contrast, EfficientNet_B0 and VGG19 display lower AUC values with slightly less steep ROC curves, aligning with their reduced accuracy and tendency toward overfitting. Overall, the ROC analysis supports the quantitative findings, clearly establishing EfficientNet_B1 as the most discriminative model for automated gastric cancer detection.

RESULTS

This study evaluated five deep learning architectures—Neural Networks, VGG19, MobileNet, EfficientNet_B0, and EfficientNet_B1—using the GasHisSDB dataset to determine the most effective model for automated gastric cancer detection. All models were trained under standardized conditions and validated using a nested cross-validation framework to ensure unbiased performance estimation. The evaluation metrics included accuracy, precision, recall, and F1-score, capturing both predictive reliability and class-specific discrimination.

The results revealed substantial differences in performance across architectures. EfficientNet_B1 delivered the highest overall accuracy of 99.46%, demonstrating superior feature extraction and generalization capabilities. MobileNet achieved competitive results with 92.69% accuracy, outperforming the baseline Neural Network (91.36%) and offering a more lightweight alternative. EfficientNet_B0 and VGG19 demonstrated lower performance levels, achieving 79.25% and 76.96% accuracy, respectively, indicating that model scaling and architectural optimization significantly influence classification outcomes.

Metrics averaged across cross-validation folds indicated high stability for EfficientNet_B1, with minimal variance across folds, reinforcing its robustness. Confusion matrix analyses further showed that EfficientNet_B1 achieved near-perfect sensitivity and specificity, with very few misclassified samples. The results are consistent with recent literature on the advantages of compound-scaled architectures for medical image analysis.

DISCUSSION

The findings of this study highlight the critical impact of architectural depth, scaling strategy, and optimization techniques on the performance of deep learning models for histopathological cancer detection. EfficientNet_B1's superior classification accuracy can be attributed to its compound scaling strategy, which optimally balances network depth, width, and input resolution. This balance enhances the model's ability to capture fine-grained cellular features critical for distinguishing malignant from non-malignant gastric tissue.

The application of nested cross-validation ensured rigorous performance assessment by preventing information leakage and enabling robust hyperparameter tuning. The combination of randomized and grid-based search proved highly effective in identifying optimal configurations for each architecture, contributing significantly to model reliability.

MobileNet's strong performance demonstrates the viability of lightweight architectures for real-time deployment, particularly in resource-limited environments or edge devices. The Neural Network baseline provided stable but comparatively lower performance, reinforcing the superiority of CNN-based feature extraction for histopathological image analysis.

VGG19's relatively low accuracy and signs of overfitting indicate that traditional deep architectures, despite their depth, may not generalize well to large-scale medical datasets without substantial regularization or dataset-specific optimization.

Overall, the comparative analysis affirms that advanced CNN models with optimized scaling—specifically EfficientNet_B1—offer substantial improvements in diagnostic accuracy and clinical readiness.

CONCLUSION AND FUTURE WORK

This study demonstrates the effectiveness of deep learning–based models for automated gastric cancer detection using the large-scale GasHisSDB histopathological dataset. By integrating standardized preprocessing, nested cross-validation, and hybrid hyperparameter tuning, the analysis provides a rigorous and unbiased comparison of five deep learning architectures.

EfficientNet_B1 emerged as the most accurate and reliable model, achieving 99.46% accuracy and demonstrating strong precision, recall, and F1-score. Its excellent performance confirms its suitability for real-world diagnostic support systems and reinforces the importance of compound scaling in medical image classification. MobileNet provides an efficient alternative for rapid, low-resource deployment, indicating potential applications in point-of-care and telemedicine settings.

The study establishes a robust methodological framework and provides compelling evidence for the integration of EfficientNet_B1 into automated diagnostic pipelines for gastric cancer.

Future work can focus on enhancing model interpretability through techniques like Grad-CAM++ or SHAP to improve clinical trust and transparency. Expanding the framework to multi-class or multi-stage gastric cancer classification and adapting it for whole-slide imaging would increase its clinical relevance. Cross-dataset validation across different hospitals is needed to confirm generalizability, while federated learning could enable collaborative training without compromising data privacy. Additionally,

optimizing the model for deployment on resource-limited hardware and exploring hybrid architectures that combine EfficientNet with attention or transformer-based modules may further improve performance and applicability in real-world healthcare settings.

Limitations

Not applicable

Ethics statements

The study adhered to the principles of the Declaration of Helsinki, ensuring ethical standards in research involving human data. All clinical records used in this study were fully anonymized prior to analysis to protect patient privacy.

CRediT author statement

Angati Kalyan Kumar: Conceptualization, Methodology, Software, Data curation, Formal analysis, Visualization, Writing – Original Draft, Validation. **Gangadhara Rao Kancharla:** Supervision, Resources, Project administration, Writing – Review & Editing, Investigation, Validation.

Acknowledgments

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

REFERENCES

1. M.C. Wong, J. Huang, P.S. Chan, P. Choi, X.Q. Lao, S.M. Chan, P. Liang, Global incidence and mortality of gastric cancer, 1980–2018, *JAMA Netw. Open* 4(7) (2021) e2118457–e2118457. <https://doi.org/10.1001/jamanetworkopen.2021.18457>
2. J.L. Lin, J.X. Lin, G.T. Lin, C.M. Huang, C.H. Zheng, J.W. Xie, P. Li, Global incidence and mortality trends of gastric cancer and predicted mortality of gastric cancer by 2035, *BMC Public Health* 24(1) (2024) 1763. <https://doi.org/10.1186/s12889-024-19104-6>
3. K. Kang, M.A. Bagaioisan, Y. Zhang, Unveiling the younger face of gastric cancer: a comprehensive review of epidemiology, risk factors, and prevention strategies, *Cureus* 16(6) (2024). <https://doi.org/10.7759/cureus.62826>
4. G. Collatuzzo, C. Santucci, M. Malvezzi, C. La Vecchia, P. Boffetta, E. Negri, Trends in gastric cancer mortality 1990–2019 in 36 countries worldwide, with predictions to 2025, and incidence, overall and by subtype, *Cancer Med.* 12(8) (2023) 9912–9925. <https://doi.org/10.1002/cam4.5685>
5. A. Gupta, N. Rajamohan, B. Bansal, S. Chaudhri, H. Chandarana, B. Bagga, Applications of artificial intelligence in abdominal imaging, *Abdom. Radiol.* (2025) 1–20. <https://doi.org/10.1007/s00261-025-04990-0>
6. R. Lamba, Advances in AI for medical imaging: a review of machine and deep learning in disease detection, *Procedia Comput. Sci.* 260 (2025) 262–273. <https://doi.org/10.1016/j.procs.2025.03.201>
7. M. Rana, M. Bhushan, Machine learning and deep learning approach for medical image analysis: diagnosis to detection, *Multimed. Tools Appl.* 82(17) (2023) 26731–26769. <https://doi.org/10.1007/s11042-022-14305-w>
8. S.S. Kshatri, D. Singh, Convolutional neural network in medical image analysis: a review, *Arch. Comput. Methods Eng.* 30(4) (2023) 2793–2810. <https://doi.org/10.1007/s11831-023-09898-w>
9. A.E. Ilesanmi, T.O. Ilesanmi, B.O. Ajayi, Reviewing 3D convolutional neural network approaches for medical image segmentation, *Heliyon* 10(6) (2024) e27398. <https://doi.org/10.1016/j.heliyon.2024.e27398>
10. Y. Xu, R. Quan, W. Xu, Y. Huang, X. Chen, F. Liu, Advances in medical image segmentation: a comprehensive review of traditional, deep learning and hybrid approaches, *Bioengineering* 11(10) (2024) 1034. <https://doi.org/10.3390/bioengineering11101034>
11. M.A. Talukder, M.A. Layek, M. Kazi, M.A. Uddin, S. Aryal, Empowering COVID-19 detection: optimizing performance through fine-tuned EfficientNet deep learning architecture, *Comput. Biol. Med.* 168 (2024) 107789. <https://doi.org/10.1016/j.combiomed.2023.107789>
12. H. Du, Q. Yang, A. Ge, C. Zhao, Y. Ma, S. Wang, Explainable machine learning models for early gastric cancer diagnosis, *Sci. Rep.* 14(1) (2024) 17457. <https://doi.org/10.1038/s41598-024-67892-z>
13. M. Zubair, M. Owais, T. Mahmood, S. Iqbal, S.M. Usman, I. Hussain, Enhanced gastric cancer classification and quantification interpretable framework using digital histopathology images, *Sci. Rep.* 14(1) (2024) 22533. <https://doi.org/10.1038/s41598-024-73823-9>
14. T. Ren, V. Govindarajan, S. Bourouis, X. Wang, S. Ke, An interpretable hybrid deep learning framework for gastric cancer diagnosis using histopathological imaging, *Sci. Rep.* 15(1) (2025) 34204. <https://doi.org/10.1038/s41598-025-15702-5>
15. GasHisSDB dataset. <https://gitee.com/neuhwm/GasHisSDB.git>