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Original Article

Attention Based Fused CNN for the Early Prediction of Gastrointestinal Disease

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Abstract - *This study proposes a standardized framework for early prediction of gastrointestinal disease diseases leveraging advanced image pre-processing, data augmentation, and an attention-based fused Convolutional Neural Network (CNN). The framework initiates meticulous image pre-processing, encompassing cropping, standardization and resizing methodologies to standardize image inputs and accentuate pertinent features. Following pre-processing, data augmentation strategies are implemented to diversify the training dataset, enhancing model robustness and generalization. By artificially generating diverse variations of the original images, data augmentation helps expand the training dataset. Techniques such as rotation, translation, scaling, and flipping are applied to augment the dataset, enabling the CNN algorithm to generalize better and capture a broader range of disease patterns. The key component of the framework is an attention-based fused CNN architecture designed to capture spatial and channel-wise dependencies within gastrointestinal images effectively. The attention mechanism allows the network to concentrate on informative regions while suppressing irrelevant noise, enhancing feature representation and classification performance. The experimental outcomes proved that the developed framework attains superior performance in the early prediction of gastrointestinal diseases with a high accuracy of 98.9%. The combination of image pre-processing, data augmentation and attention-based fused CNN contributes to improved accuracy and robustness.*

Keywords - *Attention mechanism, Convolutional neural networks, Data augmentation, Early prediction, Gastrointestinal disease, Image pre-processing.*

1. Introduction

Gastrointestinal diseases incorporate a wide range of disorders affecting the digestive system, including the stomach, esophagus, intestines, and associated organs. Accurate detection and early prediction of gastrointestinal illnesses play a crucial role in efficient treatment planning and improving patient outcomes [1]. With the advancements in medical imaging technology and the growing availability of large-scale medical datasets, deep learning approaches have developed as promising tools for early prediction and diagnosis [2, 3]. Early prediction of gastrointestinal diseases is particularly challenging due to the diverse and complex nature of these conditions. The traditional clinical approach relies heavily on invasive procedures such as endoscopy and biopsy, which are not only time-consuming but also carry potential risks and discomfort for patients [4]. Therefore, there is a pressing need to develop non-invasive and efficient methods that can accurately predict gastrointestinal diseases at an early stage. Deep learning methods have exposed tremendous potential in medical image analysis, including the realm of gastrointestinal disease prediction [5].

Various researches has been proposed for identifying gastrointestinal diseases, which are reviewed in the below section. For instance, in [6], the computer-aided gastrointestinal disease prediction using a Cubic Support Vector Machine (C-SVM) based classifier was proposed. Using direct feature extraction yields more discriminatory results. However, this approach increases system computational time, which is a significant shortcoming of this study. This paper presents [7] three networks, ResNet-50, GoogleNet, and AlexNet, for diagnosing gastrointestinal diseases. These methods provide promising results in identifying gastrointestinal diseases, but the efficiency of the proposed system needs to be implemented with the aid of advanced algorithms. Subsequently, Multi-class Support Vector Machine (MSVM) [8], Deep CNN [9, 10], Extreme Learning Machine (ELM) [11]. These mentioned methodologies efficiently classify the different types of gastrointestinal disease with improved accuracy. But, extracting deep learning features using these methods has certain difficulties, such as impertinent information and redundancy. A residual network-based machine learning algorithm for gastrointestinal disease detection is proposed in [12]. It has significant implications for using networks to diagnose diseases. However, this method is limited in high computational cost. Using residual LSTM layered CNN to classify gastrointestinal tract disorders is proposed in [13]. This method attains high performance, is more time-consuming and increases computing complexity. The Multi-scale Context-guided Deep Network (MCNet) for gastrointestinal tract disease detection is presented in [14]. The suggested model outperforms other models by a significant margin, as demonstrated by the experimental findings. The MCNet may not accurately distinguish between lesions and normal tissues due to imprecise borders. This research [15] proposes using a Weakly Supervised Convolutional Neural Network (WCNN) for autonomous gastrointestinal identification and localization. This approach achieves the highest AUC for identifying anomalies in standard gastroscopy images. However, it faces some challenges in identifying and localizing anomalies in completely new datasets. A summary of conventional methods is presented in Table 1.

Henceforth, to address the issues mentioned above, this work proposes an efficient computer-assisted diagnosis system for gastrointestinal detection using an attention-fused CNN classifier. Numerous evaluations have been performed to identify retrained models for diagnosing different types of intestinal diseases.

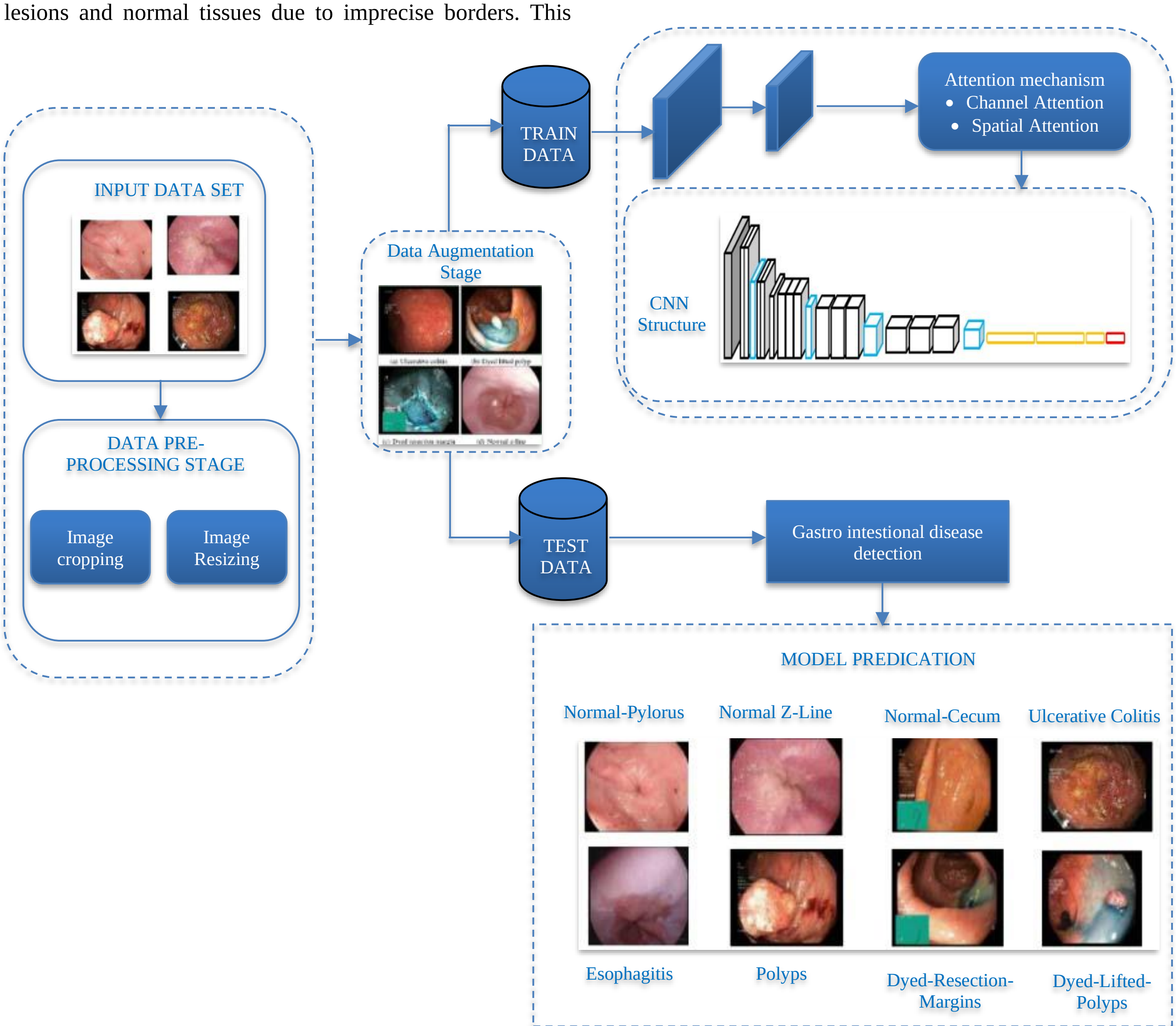

Fig. 1 An efficient attention-fused CNN method for gastrointestinal disease prediction

Table 1. Summary of conventional methods

References	Goal	Method	Accuracy (%)	Limitations
In ref [16]	Classify several GI diseases	AlexNet	96.5 %	High computational cost.
In ref [17]	Classification of multiple GI diseases	LSTM and ResNet-18	89.95 %	Low accuracy
In ref [9]	Ulcer and bleeding detection	VGG-19	95.4%	Limited classes and small datasets.
In ref [19]	Esophagitis, polyp, and colitis classification	DCT, VGG-16	96.5 %	High computational cost.
In ref [20]	Classification of multiple GI diseases	DenseNet	95.75%	Low accuracy

2. Proposed System Description

Gastrointestinal diseases pose significant challenges to public health, emphasizing the importance of early detection and accurate prediction for effective treatment. Thereby, this study proposes an inclusive framework for the early prediction of gastrointestinal diseases using image pre-processing, data augmentation, and an attention-based fused CNN, as seen in Figure 1.

The initial step in the proposed framework involves image pre-processing techniques, including cropping and resizing. Cropping is employed to remove irrelevant background information and focus solely on the region of interest, namely the gastrointestinal area. Resizing ensures consistent input dimensions for subsequent processing steps, facilitating seamless integration of the images into the deep learning pipeline. To address the limited availability of annotated medical images, a data augmentation technique is employed to artificially boost the training dataset's size and diversity.

Augmentation methods like rotation, translation, flipping, and scaling are applied to generate variations of the input images. This helps the CNN model generalize better and improves its ability to detect gastrointestinal disease patterns. The core component of the framework is an attention-based fused CNN. The fused CNN combines multiple CNN architectures to leverage their complementary strengths and enhance disease prediction performance. Attention mechanisms are incorporated to selectively concentrate on informative regions within the input image, allowing the model to allocate more attention to disease-related features.

3. System Modelling

3.1. Image Pre-Processing

The image pre-processing phase is important in gastrointestinal disease detection to remove irrelevant information, standardize input dimensions, reduce computational complexity, improve feature extraction, and ensure consistency and comparability. These are achieved by cropping, standardization and resizing techniques. By incorporating these techniques into the analysis pipeline, the accuracy, efficiency, and reliability of the disease prediction model are enhanced, leading to improved outcomes in gastrointestinal disease detection.

3.1.1. Removal of Irrelevant Information

Input gastrointestinal images often contain a considerable amount of irrelevant background information that is not relevant to the specific region of interest, i.e., the gastrointestinal area. Cropping the image allows us to extract and focus solely on the relevant region, eliminating unnecessary distractions. By removing irrelevant information, the subsequent analysis can be performed with a higher level of accuracy and efficiency.

3.1.2. Standardization of Input Dimensions

Deep learning models, i.e. CNN, typically require input images with consistent dimensions to ensure compatibility and optimal performance. Resizing the images to a standard size ensures uniformity in input dimensions, enabling seamless integration into the CNN architecture. This standardization simplifies the learning process and allows the algorithm to learn and extract features consistently across different images.

3.1.3. Reduction of Computational Complexity

In gastrointestinal medical imaging, high-resolution images are often captured to capture fine details. However, these high-resolution images also come with increased computational complexity, which can be a significant burden in terms of memory and processing power. Lowering the resolution of the images reduces the computational requirements without compromising the essential features necessary for disease detection. This leads to faster processing times and improved overall efficiency.

3.2. Data Augmentation

In image processing-based gastrointestinal disease detection, data augmentation is a crucial stage that enhances the performance and generalization ability of the deep learning models used for detection. Increasing the training dataset's size and diversity is the main goal of data augmentation. By introducing variations in the form of transformations, such as rotation, scaling, translation, flipping, or adding noise, the model becomes better equipped and more robust to handle different variations and real world circumstances. It improves the model's learning and generalization by exposing it to a larger range of variances in the original images. Augmenting the dataset tends to prevent overfitting, whereby a model acquires too specialized training data and fails to generalize successfully to new and unknown data.

3.2.1. Rotation

Rotating the image by a certain angle (e.g., a random angle or 90°, 180°) to introduce rotational invariance.

3.2.2. Translation

Shifting the image horizontally or vertically by a certain number of pixels to simulate variations in object position.

3.2.3. Scaling

Resizing the image by either enlarging or reducing its dimensions, which helps the model learn to recognize objects at different scales.

3.2.4. Flip

Flipping the image horizontally or vertically to create mirror images, which aids in capturing symmetrical patterns and orientations.

3.2.5. Noise Injection

Adding random noise to the image to simulate imperfections or variations in the imaging process.

By introducing variations through transformations, data augmentation supports the model to generalize better and improves its ability to detect gastrointestinal diseases accurately across different patients and imaging conditions.

3.3. Image Classification Using Attention Fused CNN

Attention Fused CNN is an advanced deep learning architecture that integrates the power of CNNs and attention based methods to enhance the accuracy of image classification tasks, with a specific emphasis on gastrointestinal disease classification. This innovative approach combines the strengths of both CNNs and attention (which include both channel and spatial) mechanisms to improve disease detection and classification in gastrointestinal imaging.

The architectural structure of the proposed CNN is illustrated in Figure 2, which consists of 3 full connection layers and 13 convolution layers with 16 layer depth. The 2×2 convolution layers and 3×3 max pooling layers compose a complete CNN network organization. The neural network's input size is $224\ x\ 224\ x\ 3$, which is subsequently transmitted via five convolution layer groups. The max-pooling layer divides every layer of the convolution group, resulting in outputs that are half the size of the preceding group.

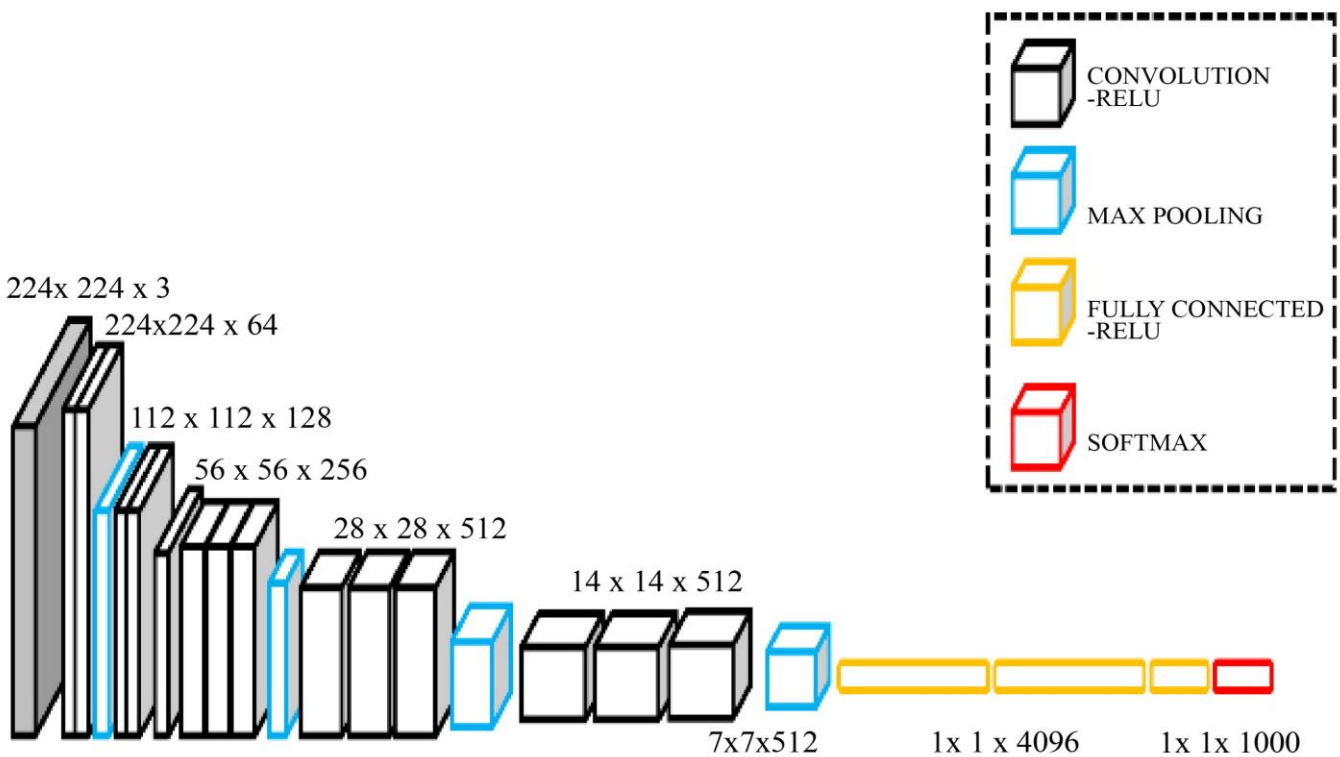

Fig. 2 Architectural diagram of proposed CNN model

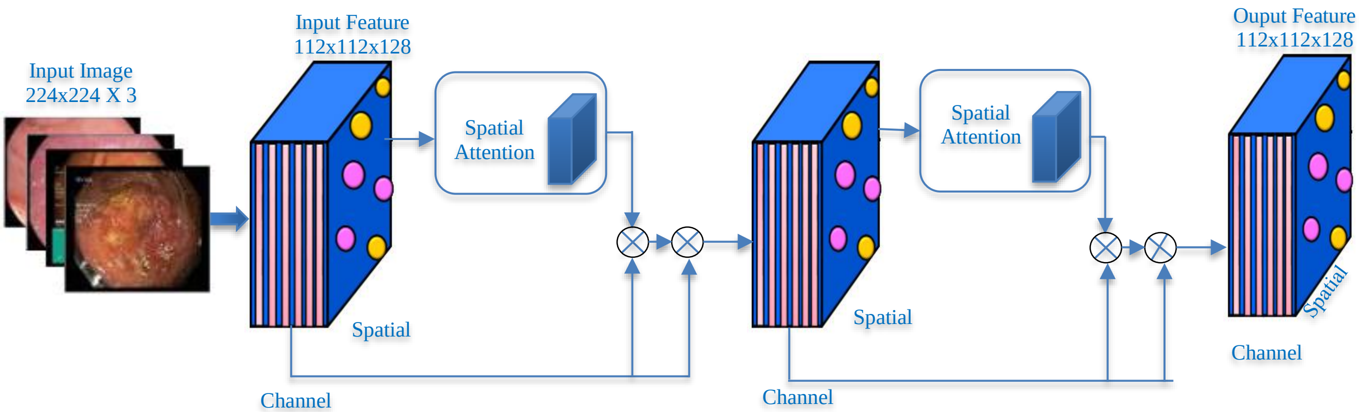

Fig. 3 Attention fused CNN model

Furthermore, a 7 x 7 convolutional feature is generated. The entire connection layer has three layers and produces 1000 classification categories. Lastly, the softmax layer predicts categorization outcomes. In the realm of gastrointestinal disease image classification, the Attention Fused CNN operates by following a multi-step process.

First, it employs convolutional layers to extract essential and discriminative features from the input images. These layers are designed to capture intricate visual patterns and structures present in gastrointestinal disease images, enabling the network to learn and discern disease-specific features. One of the key differentiators of the Attention Fused CNN is the integration of attention mechanisms.

3.3.1. Attention Mechanism (Channel and Spatial)

Attention mechanisms enable the neural network to vigorously focus on the furthermost relevant regions of the input image while suppressing less informative or irrelevant regions. By doing so, the network allocates its computational resources to the regions that are most likely to contain disease-related information, enhancing the classification accuracy. The attention mechanism accomplishes this by assigning attention weights to different image regions based on their importance. These weights are learned during the training process, enabling the network to allocate higher weights to disease-specific regions and lower weights to less informative areas.

As a result, the Attention Fused CNN can effectively highlight and emphasize the crucial regions of interest within the gastrointestinal images, facilitating accurate disease classification. Figure 3 displays an attention approach which integrates both channel and spatial attention. Spatial attention focuses on the location of the target when predicting gastrointestinal disease, and it prioritizes the image's targeted area. In Figure 3, the disease is highlighted in orange following spatial attention, indicating increased disease weights. The absence of disease causes the colour at that position to lighten, resulting in decreased background weight. Channel attention prioritizes and emphasizes disease-related channels.

In Figure 3, channel attention causes disease streams to turn orange and background channels to turn lighter. This attention mechanism is capable of improving gastrointestinal disease detection accuracy by focusing on disease position during feature extraction, reducing background interference. The process of the attention module uses a subsequent collection of features of the convolution layer from the fundamental CNN as the source feature X_i.

A convolution layer with variables W_{sp} and b_{sp} is composed of a spatial attention layer, which represents the bias and weight of the convolution layer correspondingly. A convolution layer with variables including bias b_{ch} and weight W_{ch} is composed of a channel attention layer, the resultant feature is indicated by X_o.

Initially, the input feature X_i is processed by the spatial attention layer via a block that includes a ReLU layer and a $3 \, x \, 3$ convolutional layer. The implemented sigmoid activation with a gating mechanism for generating weights W_{sp} for each position.

After applying spatial attention, the characteristic of the output X_{sp} can be stated as,

$$X_{sp} = X_i + (X_i + W_{sp} + b_{sp}) \tag{1}$$

An additional global average pooling layer is inserted in the channel attention layer before a block consisting of a 1 x 1 convolutional and ReLU layer. The sigmoid activation is used to generate weights W_{ch} for each channel. After passing through the channel attention, the feature X_{sp} becomes the output feature X_o.

$$X_o = X_{sp} + (X_{sp} * W_{ch} + \ b_{ch}) \tag{2}$$

Where * denotes the dot multiplication of matrix members. The integration of attention mechanisms allows the network to concentrate on disease-specific regions, enhancing the classification and prediction of gastrointestinal diseases. Additionally, the Attention Fused CNN can handle complex and diverse gastrointestinal images with varying sizes and resolutions. This attention-based approach supports reducing false positives and false negatives, leading to improved diagnostic accuracy.

4. Results and Discussion

The proposed computer-assisted diagnosis method uses deep learning to determine gastrointestinal disorders based on anatomical landmarks, pathological observations, and polyp removal. The kvasir-v2 dataset has eight sets of 1000 images, all of which include anatomical markers, pathological findings, and polyp removal.

The dataset includes images with resolutions ranging from 720×576 to 1920×1072 pixels. Endoscopes can detect anatomical landmarks in the gastrointestinal tract. It acts as a reference point for navigating and describing discovery locations. The markers could represent specific pathological locations, such as ulcers or inflammation. Figure 4 displays a representative image from the collection, while Figure 5 illustrates its distribution.

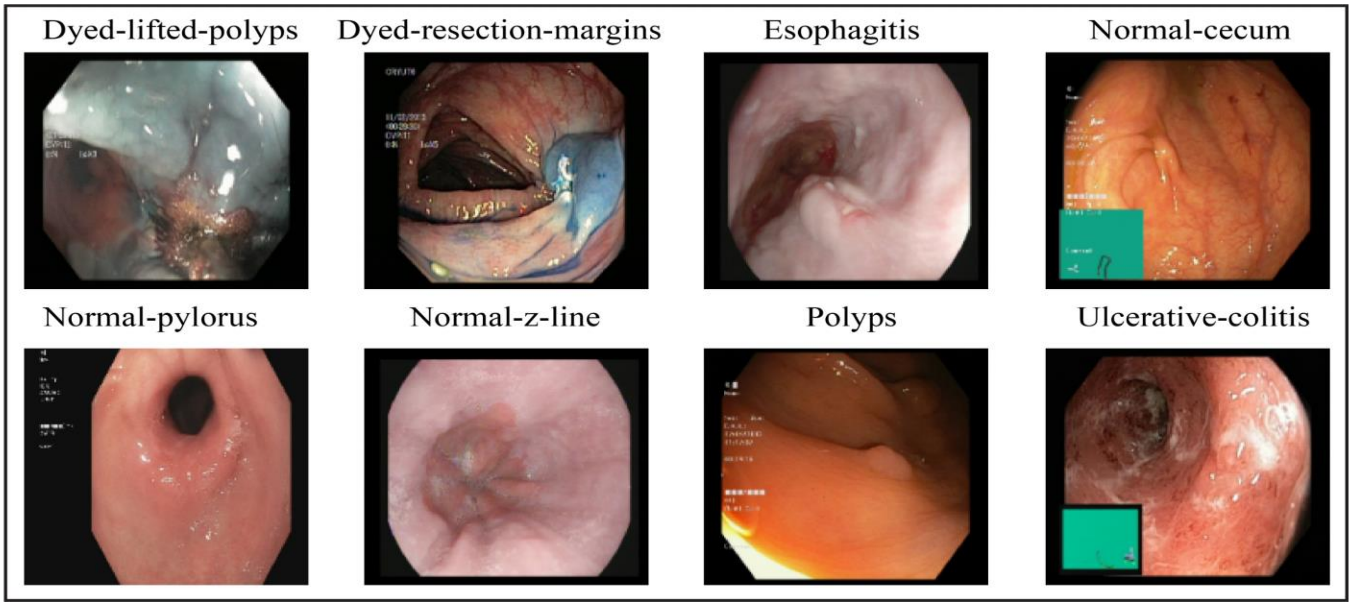

Fig. 4 Sample gastrointestinal images from the Kvasir v2 dataset

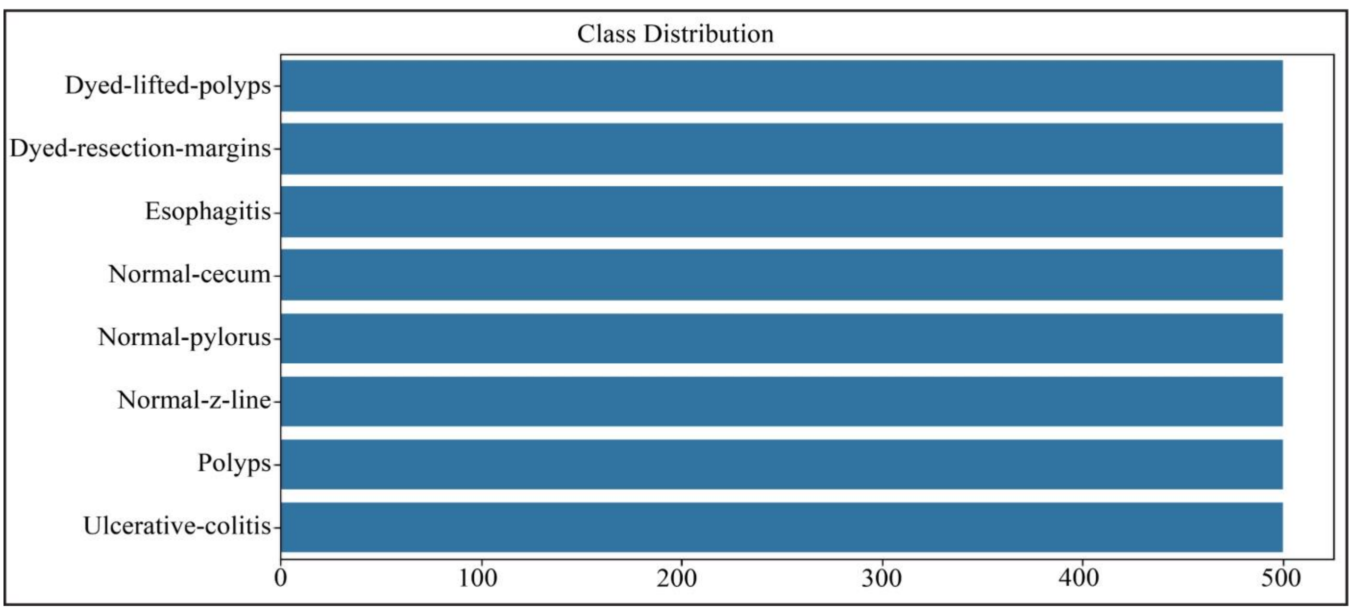

Fig. 5 Different Class Distribution

The original and augmented gastrointestinal images are illustrated in Figure 6 to enhance the predictive performance of models. This includes rotation, flipping and scaling to artificially increase the diversity of a dataset. Transformations of the original images generate new images with variations in orientation, perspective, and size. This assists in training attention infused CNN to be more robust and generalize better to unseen data.

The accuracy and loss metrics serve as crucial benchmarks in evaluating the performance of an attention-fused CNN classifier model designed for gastrointestinal disease prediction, as seen in Figure 7. From the output graph it shows that the proposed classifier achieves maximum accuracy (98.9 %) with minimized loss, thereby enhancing its predictive accuracy.

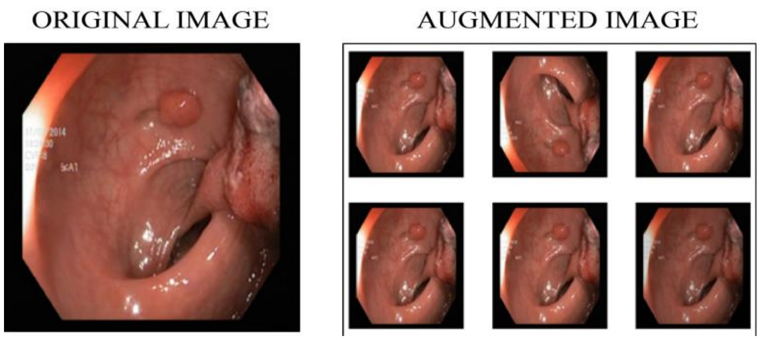

Fig. 6 Original and augmented image of gastrointestinal disease

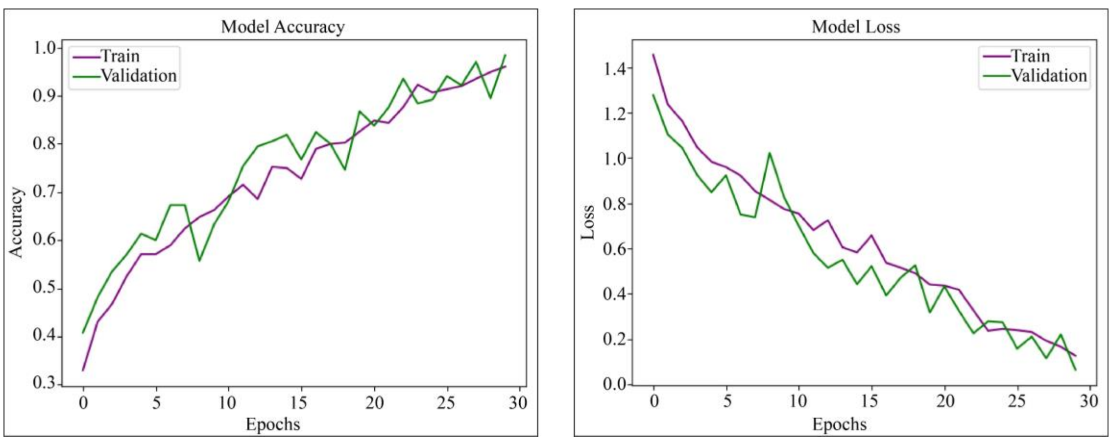

Fig. 7 Model Accuracy and Loss

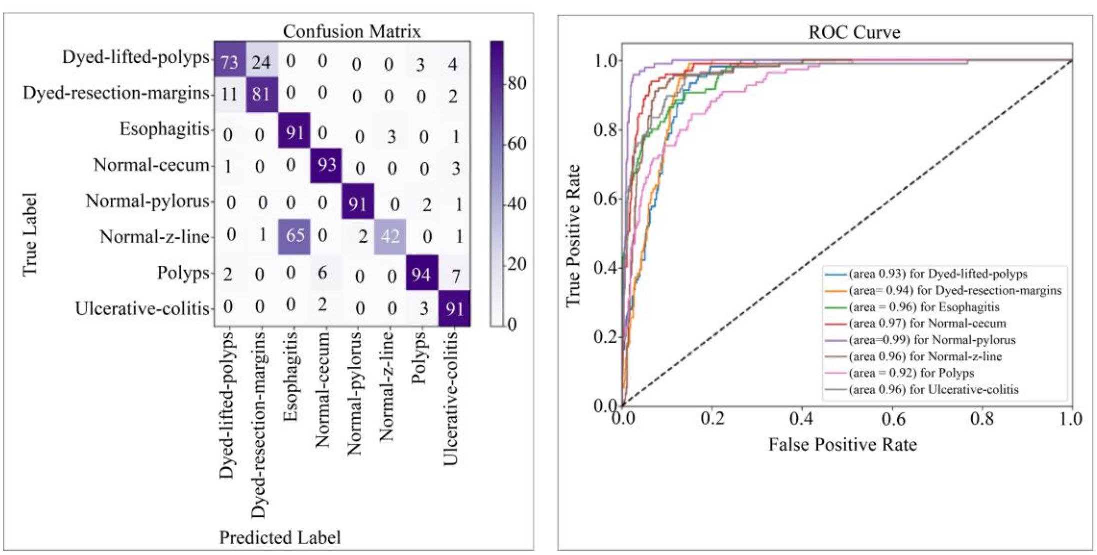

Fig. 8 ROC Curve Illustration for DenseNet-201

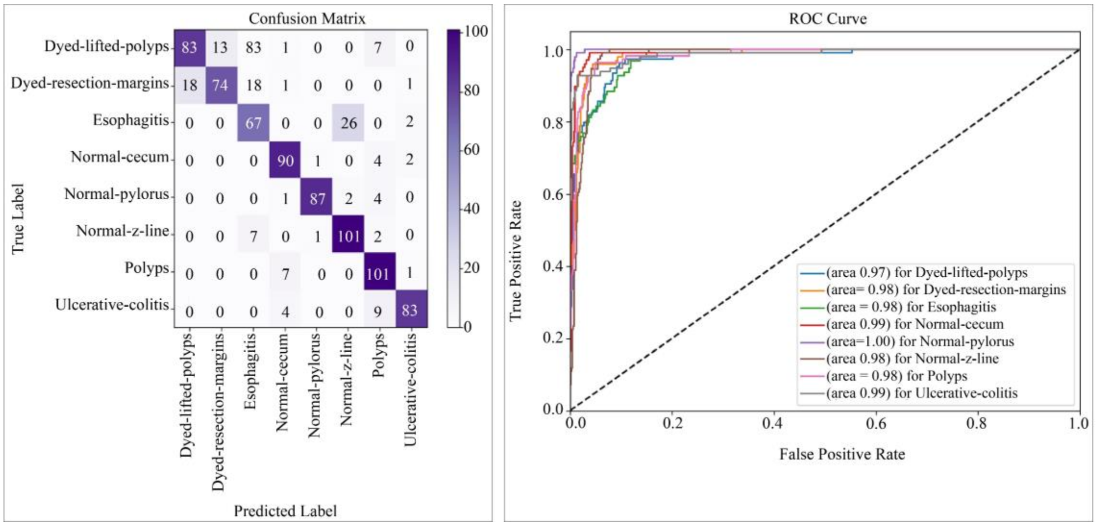

Fig. 9 ROC curve illustration for ResNet-18

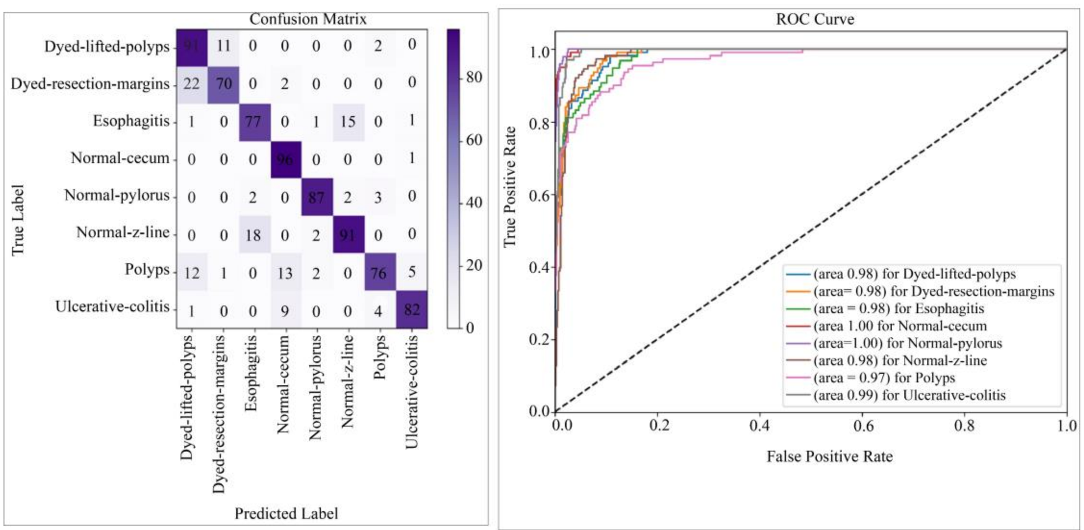

Fig. 10 ROC curve illustration for GoogleNet

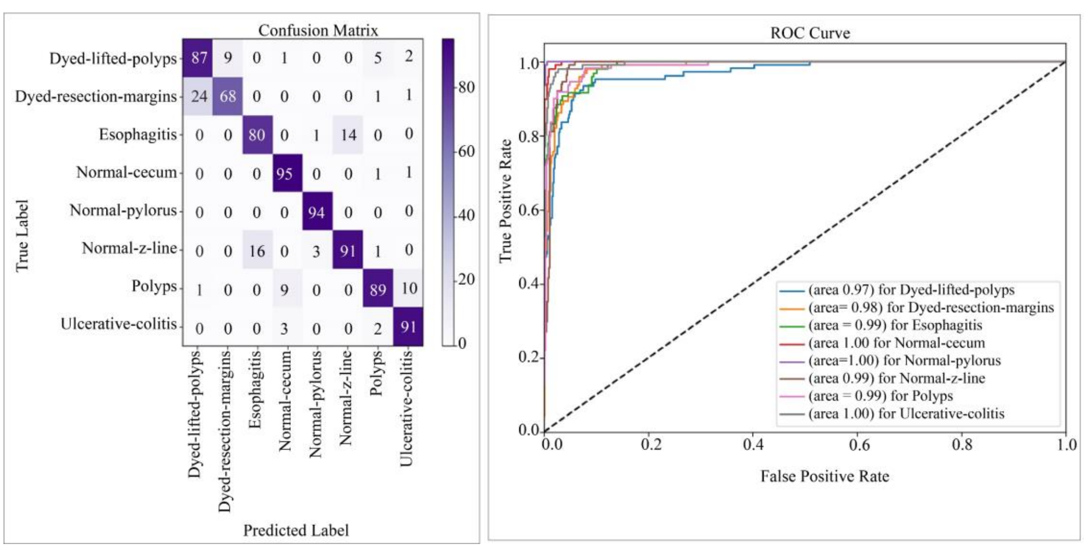

Fig. 11 ROC curve illustration for attention fused CNN

The implemented classifiers, comprising GoogleNet, ResNet-18, and DenseNet-201, along with the proposed attention-fused CNN, are assessed for their efficacy in gastrointestinal disease detection, as evidenced by the Receiver Operating Characteristic (ROC) curve evaluation depicted in Figures 8, 9, 10 and 11. The ROC curve visually represents the trade-off between the true positive rate and the false positive rate across various threshold values. When compared to other classifier models, the proposed attention-fused CNN achieves improved results, and this analysis reinforces the notion that the attention-fused CNN model offers enhanced predictive capabilities for gastrointestinal disease detection. Table 2 displays training selections and execution times for the four networks in the Python environment.

Table 2. Defining the parameters for deep learning networks' training

Options	DenseNet-201	GoogleNet	ResNet-18	Proposed Model
Minibatch size	25	25	25	100
Initial learn rate	0.0010	0.0009	0.0009	0.0003
Max epochs	30	30	30	30
Training time	500 mins	550 mins	600 mins	100 mins
Frequency of Validation	3	5	10	30
Execution Environment	GPU	GPU	GPU	GPU

Table 3. Outcomes obtained from using deep learning algorithms to diagnose gastrointestinal diseases

Measurement	DenseNet-201	ResNet-18	GoogleNet	Proposed Model
Accuracy (%)	97.5	97.2	97.8	98.9
Specificity (%)	96.02	96.3	97.2	98.6
Sensitivity (%)	97.3	97.7	96.8	98.7
ROC (%)	98.9	99.2	99.8	100

Table 4. Performance assessment results for the gastrointestinal disease datasets

Types of Diseases	DenseNet-201	ResNet-18	GoogleNet	Proposed Model
Dyed-lifted polyps	93	97	98	97
Dyed-resection-margins	94	98	98	98
Esophagitis	96	98	98	99
Normal-cecum	97	99	100	100
Normal-pylorus	99	100	100	100
Normal-z-line	96	98	98	99
Polyps	92	98	97	99
Ulcerative-colitis	96	99	99	100

Table 5. Comparison of accuracy

Methods	Accuracy
Applied logistic and ridge regression [21]	83.3%
Modified VGGNet model [22]	86.64%
Second glance based on CNN [23]	85.69%
DenseNet201 [24]	78.55%
ResNet-50 [18]	90.42%
Proposed Model	98.9%

Table 3 displays the assessment of the dataset for four CNN models with regard to sensitivity, accuracy, specificity, and AUC are determined. Similarly, Table 4 displays the classification performance of GoogleNet, ResNet-18, DenseNet-201, and attention-fused CNN for each disease. The proposed model performs better than the previous three techniques, according to the table analysis. Table 5 shows a comparison to existing GI tract disease classification approaches. The proposed strategy surpasses existing methodologies and significantly improves accuracy.

5. Conclusion

This research presents a standardized framework for the early detection of gastrointestinal disorders using advanced image pre-processing, data augmentation, and an attention-based fused CNN. The architecture begins with thorough image pre-processing, which includes cropping, standardization, and resizing techniques to standardize image inputs and highlight relevant elements. Following pre-processing, data augmentation procedures are used to diversify the training dataset, hence increasing model robustness and generalization. Data augmentation contributes to the expansion of the training dataset by synthesizing numerous versions of the original images. Rotation, translation, scaling, and flipping techniques are utilized to expand the dataset, allowing the CNN approach to generalize more effectively and capture a wider spectrum of diseases. The main component of the proposed work is an attention-based fused CNN architecture, which is intended to capture spatial and channel-wise dependencies within gastrointestinal images effectively. The attention method allows the network to focus on useful regions while reducing irrelevant noise, hence improving feature representation and classification performance. The experimental outcomes indicate that the proposed structure outperforms other methods for early prediction of gastrointestinal diseases in terms of accuracy (98.9%), sensitivity (98.7%) and specificity (98.6%).

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