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# Medical image processing using graph convolutional networks: A review

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## Highlights

- The development history of convolutional neural networks and the transition to graph convolutional networks are introduced, as well as the evolution of network layers.
- Graph convolutional networks have been widely demonstrated to be applicable in various perioperative medical image processing scenarios.
- This is the first comprehensive review of the applications of graph convolutional networks in image segmentation, image reconstruction, disease prediction, lesion detection and localization, disease classification and diagnosis, and surgical interventions.

## Abstract

Deep learning, especially graph convolutional networks (GCNs), has been widely applied in various scenarios. Particularly in the field of medical image processing, the research on GCNs have continued to make breakthroughs and has been successfully applied to various tasks, such as medical image segmentation, as well as disease detection, localization, classification and diagnosis. GCNs have demonstrated the capacity to autonomously learn latent disease features from vast medical image datasets. Their potential value and enhanced capabilities in prediction, analysis, and decision-making in perioperative medical imaging have become evident. In recent years, GCNs have rapidly emerged as a research focus in the realm of medical image analysis. First, this review provides a concise overview of the development from convolutional neural networks to GCNs, delineating their algorithmic foundations and network structures. Subsequently, the diverse applications of GCNs in perioperative medical image processing are extensively reviewed, including medical image segmentation, image reconstruction, disease prediction, lesion detection and localization, disease classification and diagnosis, and surgical intervention. Finally, this review discusses the prevailing challenges and offers insights into future research directions for the utilization of GCN methods in the medical field.

**Keywords**: Deep learning, graph convolutional networks, medical image processing, perioperative medical applications

## Introduction

In recent years, the rapid development of the big data has led to the swift emergence of artificial intelligence technologies. Specifically, machine learning and deep learning have made significant strides in various fields, such as speech, image, computer vision, and natural language processing. In the field of medical image mining, the traditional approach reliant on manual feature extraction by experienced experts has been gradually replaced by end-to-

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end deep learning technologies, represented by convolutional neural networks (CNNs). A series of groundbreaking research achievements have been made in areas like image classification, object detection,and image segmentation, showcasing the powerful feature learning and classification capabilities of CNNs [1-3]. These achievements have garnered widespread attention and pose significant values for research analysis.

The origins of graph convolutional networks (GCNs) can be traced back to 1943 when the renowned psychologist McCulloch and the mathematician Warren proposed the concept of neurons [4]. They realized that a simplified neuron model could be represented using simple addition and threshold processing. Inspired by this, in 1958, psychologist Rosenblatt constructed the first device, called the "perceptron" which truly applied these principles [5]. At that time, the perceptron was simulated on computers and demonstrated the ability to classify simple graphic data, marking the first successful experiment after the proposal of neurons. In 1985, Rumelhart proposed the error backpropagation algorithm, which facilitated the exchange of weights among multiple hidden layers and addressed the issue of network parameterization between these layers [6]. However, this algorithm suffered from slow computation speed. In 1989, LeCun introduced the term "convolution" in the early version of LeNet, and subsequently, LeCun et al. introduced the classic LeNet-5 model in 1998, which was the first successful application of a CNN to handwritten digit recognition [7].

As research progressed, although CNNs have advantages such as parameter sharing and automatic feature extraction, they have clear limitations when dealing with graph-rich data. This often leads to the loss of critical structural information, and their results are heavily depending on the preprocessing of the graph data. To address these challenges, the introduction of graph neural networks (GNNs) allows the data processing process to be directly built on graph data. This not only extends existing neural network models but also improves the accuracy of graph data processing. In 2009, Scarselli established the theoretical foundation for GNNs [8]. Scarselli and Micheli further inherited and developed GNNs algorithms, making certain improvements. In the early stages, GNNs primarily relied on recurrent neural networks as the main framework, generating vector representations for each node through simple feature mapping and node aggregation, but they could not effectively handle real-world complex and diverse graph data. To address this, Bruna et al. proposed applying CNNs to graphs and, through clever transformations of the convolution operator, introduced frequency-based and spatial-based GCNs [9]. In 2015, Defferrard et al. proposed using Chebyshev polynomials to approximate graph convolutions, enabling efficient computation of convolutions in the frequency domain [10]. They also introduced regularization techniques to improve the model performance, which is a critical milestone in the development of GCNs. In 2016, Kipf et al. proposed the first-generation GCN, which utilized the graph Laplacian matrix and learned node representations through convolutional operations [11]. This model has good performance and interpretability in handing single-layer graph data. With the introduction of GCNs, researchers continuously attempted to improve the performance of the networks and proposed various variants, including GraphSAGE, graph attention network, and others. These variants can handle multi-layer and multi-type graph data, offering better performance and flexibility [12, 13].

With the continuous advancement of GCNs, they have been synergistically integrated into the perioperative medical domain. Promising outcomes have been achieved in perioperative medical image processing realms, encompassing medical image segmentation, lesion detection and localization, medical image classification and diagnosis, as well as disease prognosis. Since 2000, research related to GCNs has been experiencing a significant surge in the Web of Science database. A total of 5,183 papers on this topic have been published during this period. The number of papers published in 2016 was 78, which increased to 1,825 in 2022. Among these papers, 1,121 papers report the application of GCNs in the field of medicine, demonstrating that research on medical applications based on GCNs has become another research hotspot following the usage of CNNs. This review will commence its narrative with the structural process outlined in **Figure 1**.

## Fundamentals of GCN algorithm

### *Concepts and definitions*

#### *Graph symbols and definitions*

A graph is made up of nodes and the edges connecting them, usually denoted as $G= (V, E)$, where $V = \{v_1, v_{1,} \dots v_n\}$ represents the set of

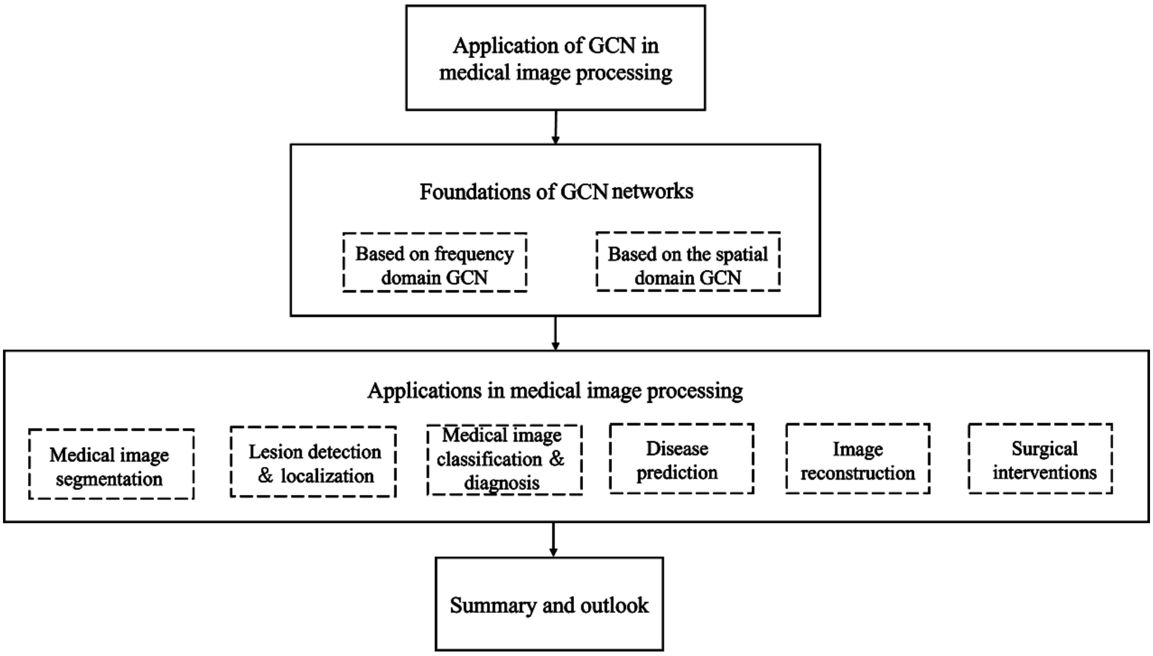


**Figure 1. Structure of review.** GCN, graph convolutional network.

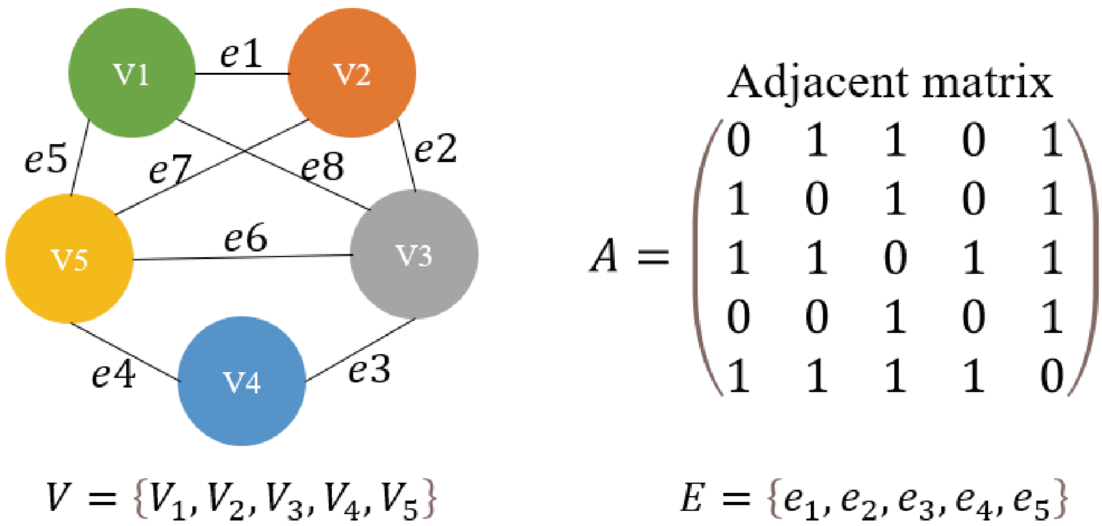


**Figure 2. Undirected graphs and adjacency matrices.**

nodes. The generic representation of a graph is a five-tuple *G (V, E, A, X, D)*, where *A* is the adjacency matrix, represented as a square matrix of $A^{N \times N}$. $X^{N \times F}$ denotes the feature matrix of the nodes, and $D^{N \times N}$ represents the degree matrix. *N* and *F* represent the number of nodes and the feature dimension of the nodes, respectively. An undirected graph structure containing 5 nodes and 8 edges as well as its adjacency matrix are shown in **Figure 2**.

A combined Laplace matrix, which includes both a diagonal matrix and an adjacency matrix, is represented as shown in equation (1):

$$L = D - A$$

where D is the diagonal matrix, and A is the adjacency matrix, which contains non-zero elements only at the central node and the nodes connected at first order, while the rest are 0.

*Types of graphs*

The types of graphs have different classifications and interpretations in various fields. Graphs can be classified into directed graphs and undirected graphs based on the directionality of their edges. A weighted graph or an unweighted graph is determined by whether the edges of a graph have weights. A connected graph or a disconnected graph is determined by the existence of a path between any two nodes in a graph. They can also be classified as a labeled graph or an unlabeled graph according

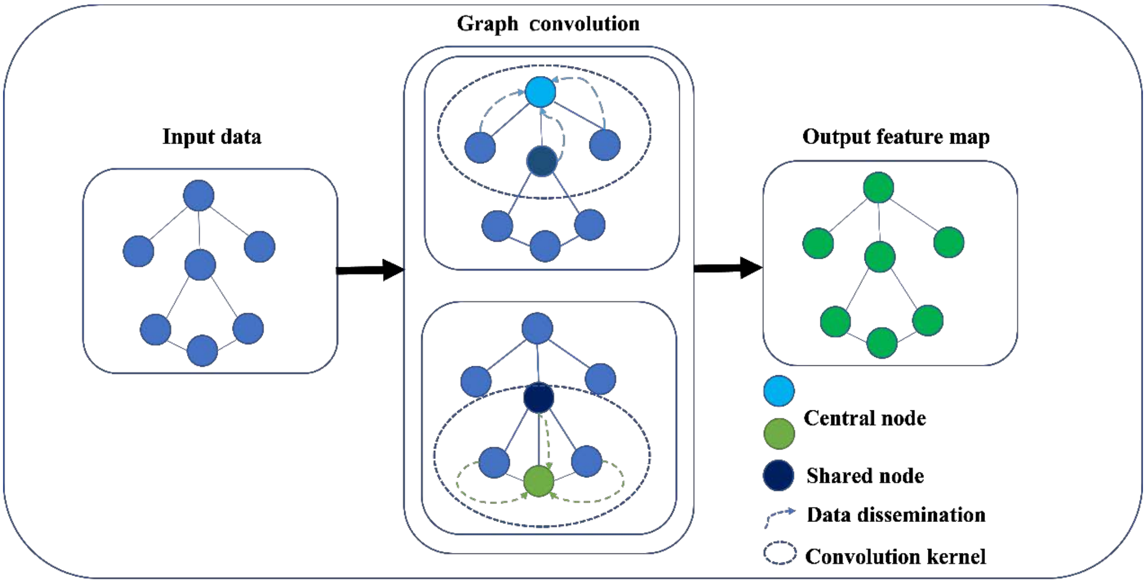


**Figure 3. Graph convolutional network structure diagram.**

to whether the nodes or edges of a graph have attributes.

*GCNs*

*Framework for information diffusion*

Information diffusion involves iteratively updating and training the parameters of graph convolutional layers. This mainly includes initializing node features, aggregating neighbors, transforming features, updating node features, and outputting prediction results. The GCN architecture for information diffusion is illustrated in **Figure 3**, while the information diffusion framework is represented by Equation (2):

$$H^{l+1} = f(H^{l}, A)$$

where *A* is the adjacency matrix, and $H^l$ is the feature information output of the *(l+1)*th layer of the GCN. By normalizing and applying an activation function to A, the forward propagation of graph feature information can be achieved. The basic process of message propagation is shown in Equation (3):

$$f(H^{l}, A) = \sigma(\widetilde{D}^{-\frac{1}{2}} \widetilde{A} \widetilde{D}^{-\frac{1}{2}} H^{l} W^{l})$$

where $\widetilde{A} = A + I$ (*I* is the unit matrix), $\widetilde{A}$ in $\widetilde{D} = \sum_{j} \widetilde{A}_{i,j}$ is the normalized degree matrix, $W^l$ is the matrix of parameters to be trained in the model, *σ* is the activation function.

Based on the aforementioned diffusion framework, following the operational paradigm of GCNs, there are two types of graph convolutions: spectral-based and spatial-based.

*Graph convolution*

The purpose of the graph convolutional layer is to extract features from the input information. The convolutional layer consists of multiple convolutional units, and the parameters of each unit are optimized through the backpropagation algorithm. Based on the message propagation framework described in Section Framework for information diffusion, there are two types of data processing methods for graph convolution: spectral-based graph convolution and spatial-based graph convolution.

Spectral-based graph convolution is a commonly used method, which utilizes the eigenvalues and eigenvectors of the graph Laplacian matrix for signal propagation and transformation in the graph. It addresses the issue of lacking translational invariance in node domain data, preventing conventional convolutions. Common graph filters include low-pass filters and high-pass filters. Low-pass filters preserve low-frequency signals while suppressing high-frequency noise and details, making them suitable for smoothing and capturing global structural information. High-pass filters enhance high-frequency signals, highlighting details and edge information, making them suitable for edge detection and local structures. As spectral-based graph convolution methods have gained wide applications in graph signal processing and GNNs, there has been an increasing number of improvements and variants in the spectral domain. **Table 1** summarizes the spectral-based

**Table 1. Spectral-based convolution methods and their variants**

| Presenters | Year | Model | Salient points or key elements |
|---|---|---|---|
| Bruna et al. [9] | 2013 | Spectral CNN | The first spectral-based graph convolution method |
| Defferrard et al. [10] | 2016 | ChebNet | Convolution kernel with locality |
| Kipf et al. [11] | 2016 | First-order ChebNet | Small parameter count |
| Li et al. [14] | 2017 | AGCN | Parameterizing the Laplacian matrix, introducing an adaptive spectral graph convolution algorithm |
| Xu et al. [15] | 2019 | GWNN | Model interpretability |
| Chiang et al. [16] | 2019 | Cluster-GWCN | Handling large-scale data |
| Jiang et al. [17] | 2019 | GLCN | Adaptive Learning |
| Derr et al. [18] | 2020 | DS-SGS-GCN | Semi-supervised graph convolution integrated with symbolic theory |
| Wang et al. [19] | 2020 | AM-GCN | Enhanced feature extraction capability |
| Fu et al. [20] | 2021 | GpLCN | Applying the Laplacian matrix to spectral graph filters |
| Zhu et al. [21] | 2021 | S2GCN | Effectively addressing the over-smoothing issue |
| Bo et al. [22] | 2021 | FAGCN | Effectively addressing the over-smoothing issue |
| Wang et al. [23] | 2021 | Bi-GCN | Reducing the number of parameters |
| Bo et al. [24] | 2023 | Specformer | Trainable convolutional kernel |

Note: CNN, convolutional neural network; GCN, graph convolutional network; AGCN, adaptive graph convolutional neural network; GWNN, graph wavelet neural network; GWCN, gate way core network; GLCN, graph learning-convolutional network; FAGCN, frequency adaptation graph convolutional network; AM-GCN: adaptive multi-channel graph convolutional; GpLCN: graph p-Laplacian convolutional network.

**Table 2. Spatial-based convolution methods and their variants**

| Presenters | Year | Model | Salient points or key elements |
|---|---|---|---|
| Hamilton et al. [12] | 2018 | GraphSAGE | Three types of message aggregation functions, and selecting a subset of neighboring nodes for information aggregation |
| Veličković et al. [13] | 2018 | GAT | Constructing an attention mechanism for aggregating information from neighboring nodes |
| Zhang et al. [25] | 2009 | NN4G | Fast computation speed |
| Niepert et al. [26] | 2016 | PATCHY-SAN | The node sequence transitions from ordered to unordered |
| Atwood et al. [27] | 2016 | DCNN | Simple computation |
| Chen et al. [28] | 2018 | FastGCN | Smaller sampled adjacency matrix |
| Cui et al. [29] | 2019 | KGCN | Implementing aggregation of three types of messages |
| Xu et al. [30] | 2019 | GIN | Introducing graph isomorphism into graph convolutional networks |
| Cai et al. [31] | 2020 | Graph Transformer | Not limited by the distance between nodes |
| Yang et al. [32] | 2021 | Graph -CTA | Capable of comprehensive modeling of relationships between nodes |

Note: GAT, graph attention network; CTA, computed tomography angiography; GraphSAGE, graph sample and aggregate; DCNN, dynamic convolution neural network; KGCN, knowledge graph convolutional network; GIN, graph isomorphism network.

convolution methods and their variants.

Spatial-based graph convolution, in the context of GNNs, propagates information by clustering node features within the neighborhood of a graph. This approach primarily relies on the adjacency matrix and node connectivity, enabling aggregation and propagation within the neighborhood to facilitate the interaction and fusion of local and global information. Compared to spectral-based graph convolution, spatial-based methods are more intuitive and easier to understand as they do not require explicit computation of graph spectral decomposition. They are particularly suitable for handling sparse or large-scale graph data. **Table 2** provides an overview of spatial-based convolution methods and their variants.

*Graph pooling*

Similar to CNNs, the graph pooling layer in GCNs is primarily used to reduce the spatial dimension of feature maps, decrease the number of model parameters, and extract key features. Common pooling operations include max pooling and average pooling. Max pooling selects the maximum value within a local region as

Table 3. Development or improvement of graph convolutional networks pooling

| Presenters | Year | Model | Application scenarios |
|---|---|---|---|
| Ying et al. [33] | 2018 | Diff Pooling | Graph classification |
| Zhang et al. [34] | 2018 | Sort Pooling | |
| Bianchi et al. [35] | 2019 | Mincut Pooling | Graph classification& Node clustering |
| Ma et al. [36] | 2019 | Eigen Pooling | Graph classification |
| Lee et al. [37] | 2019 | SAG Pooling | |
| Gao et al. [38] | 2021 | IPooling | |

Note: SAG, self-attention graph.

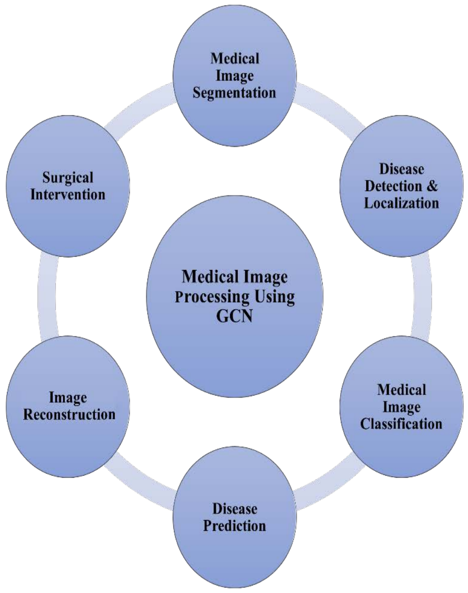


**Figure 4. Applications of GCNs in medical image processing**. GCN, graph convolutional network.

the pooled result, aiming to capture the salient features. On the other hand, average pooling computes the average value of the local region, aiming to preserve more detailed information.
Current research on GCNs mainly focuses on adapting convolutional operators to graph-structured data and designing effective aggregation functions to achieve efficient representation of central node features. Therefore, the role of pooling operations in graph convolution is significant. **Table 3** summarizes the development or improvements of pooling layers in relevant GCNs.

### Applications of GCNs in medical image processing

As depicted in **Figure 4**, this section provides an overview of the relevant applications of GCNs in medical image processing.

#### *Medical image segmentation*

Medical image segmentation is to segment medical images based on medical features, such as grayscale, texture, frequency domain features. Compared to general segmentation tasks, medical image segmentation exhibits a certain level of complexity and diversity. In the realm of perioperative medical image segmentation, the segmentation process exhibits enhanced celerity and precision, accompanied by heightened maneuverability. Its salient attributes endow it with substantial academic significance and research value in medical investigation, clinical diagnosis, pathological analysis, as well as related research and practical undertakings. This section provides a comprehensive overview of pertinent applications utilizing GCNs for perioperative medical image segmentation.

Vessel segmentation is an important task in medical image processing, aiming to extract vascular structures from medical images to assist in disease diagnosis and treatment. Zhou et al. proposed a hybrid method that utilizes GCN to enhance the propagation of feature information [39]. They constructed graph data by depicting the structural configuration of vessels, where in vascular segments in the arterial tree were designated as nodes, with physiological features of vessels as node features. This approach achieved segmentation of arterial vessels in CT images. However, a limitation of this method is the inability to perform end-to-end training. Wolterink et al. proposed a GCN-based method for coronary artery segmentation in cardiac CT images [40]. They constructed graph data by considering the vertices on the arterial lumen surface mesh as nodes, using the K-nearest neighbor approach. The optimization of information propagation among nodes was achieved through the combination of GCN. This method enables vessel segmentation in CT images without relying on mesh interactions. Shin et al. were the first to combine CNN with GCN, jointly learning the overall structure and local appearance of vessels [41]. They employed CNN for feature extraction and used GCN to establish graph connectivity among vessels. By learning this connectivity, they effectively captured the relationships

**Table 4. Application of graph convolutional networks in medical image segmentation**

| Presenters | Segmentation targets | Data modalities | Model | Results | Limitations |
|---|---|---|---|---|---|
| Zhou et al. [39] | Coronary artery | CT | GCN | A segmentation accuracy of 82.5% and an F1 score of 95.4% | End-to-end training is not feasible in this case |
| Wolterink et al. [40] | Coronary artery | CT | KNN+ GCN | Dice similarity coefficient range from 0.73 to 0.75 | The segmentation performance is dependent on the location of the vascular centerline |
| Shin et al. [41] | Retina | CT | CNN+ GCN | mAP and ROC better than or comparable to current state-of-the-art methods | Further validation is necessary to ascertain its generalizability |
| Zhai et al. [42] | Pulmonary arteries and veins | CT | CNN+ GCN | Effective single separation of arteries and veins can be achieved | Over-fitting may occur during training |
| Yang et al. [43] | Coronary artery | CT | CNN+ GCN | The average recall, average precision, and average F1 score all exceeded 95%. | May lead to the loss of some subtle features, resulting in model instability |
| Zhang et al. [44] | Brain tissue | MRI | KNN+ GCN | The average DSC on the two datasets was 91.6% and 79.3%, respectively | High model complexity |
| Wu et al. [45] | Cerebral cortex | MRI | CNN+ GCN | The average overlap between the segmentation results and the labels reached 94%±3 | High model complexity |
| Tian et al. [46] | Prostate | MRI | CNN+ GCN | The segmentation results achieved 93.8 ± 1.2% and 94.4 ± 1.0%, respectively | Limited by the amount of MRI data |
| Zhao et al. [47] | Pancreatic diseases | CT | GCN | Promising in terms of segmentation quality and detection accuracy | High model complexity |

Note: GCN, graph convolutional network; KNN, K-nearest neighbor; CNN, convolutional neural network; ROC, receiver operating characteristic; DSC, dice similarity coefficient.

between vascular structures. Inspired by this, Zhai et al. performed vessel segmentation on chest CT images by preprocessing them using vessel segmentation and skeletonization [42]. They constructed feature maps using CNN and directly inputted the extracted feature maps into GCN to predict each vessel segment, thereby achieving the segmentation of arteries and veins. Yang et al. proposed a conditional partial residual GCN for automatic labeling of coronary arteries [43]. This network utilized GCN to process the structural information of coronary arteries and employed conditional partial residual to capture the local appearance information. By inputting coronary artery CT angiography images and initial labels, more accurate coronary artery labels were generated as output.

Tissue segmentation involves dividing pixels in an image into tissue regions to facilitate the identification of pathological structures and the analysis of disease progression. GCNs can improve the performance of tissue segmentation by learning the surrounding pixel features of each pixel, thereby enhancing the accuracy of pathological analysis. Zhang et al. proposed a method that departs from voxel-based segmentation and employs GCN to extract feature maps from superpixels [44]. The feature maps are then fused and classified using ChebNet, and the labels are projected back onto voxels to achieve segmentation of brain tissues in MRI images. Wu et al. utilized the powerful learning capability of GCNs to directly segment regions of interest (ROIs) within the cerebral cortex without the need for spherical mapping and registration [45]. GCNs not only demonstrate excellent results in brain tissue segmentation

**Table 5. Application of graph convolutional networks in lesion detection and localization**

| Presenters | Analytical objectives | Model | Results |
|---|---|---|---|
| Wu et al. [48] | Basal cell carcinoma | GCN | The method does not rely on pixel segmentation labels and achieves results with mAP and AUC of 0.9556 and 0.9502, respectively, in basal cell carcinoma recognition |
| Du et al. [49] | Breast cancer | CNN+GCN+GAT | Efficiently accomplished breast cancer detection |
| Liang et al. [50] | Musculoskeletal abnormalities | MSCNN+GCN | High accuracy and robustness in the identification of skeletal muscle abnormalities |
| Luo et al. [51] | Diabetic retinopathy | CNN+GCN | Automatic identification of the location and severity of diabetic retinopathy lesions |

Note: GCN, graph convolutional network; CNN, convolutional neural network; GAT, graph attention network; MSCNN, multiscale convolutional neural network.

but also exhibit promising performance in feature extraction and fusion of other organ tissues. In the context of pancreatic tissue segmentation, Tian et al. introduced a multi-layer GCN model that leverages residual modules to obtain spatial features of multi-scale ROIs, achieving segmentation of the prostate edge contour in MRI images [46]. Zhao et al. employed GCN for multi-dimensional and multi-angle feature extraction [47]. This approach effectively utilizes the geometric and positional information of ROIs, enabling the segmentation of different pancreatic diseases. **Table 4** provides a comprehensive summary of the applications of GCNs in medical image segmentation, including segmentation targets, data modalities, models, results, and limitations.

***Lesion detection and localization***

The detection and localization of lesions hold paramount significance in the context of perioperative clinical diagnosis and treatment. Utilizing automated detection and localization techniques can realize rapid and precise identification of lesions, helping clinicians to obtain faster and more accurate diagnoses and formulate treatment plans. Moreover, this approach can effectively improve the efficiency of medical image processing, reduce the workload of physicians, and minimize manual diagnostic errors. Currently, GCNs have made notable advancements in various perioperative medical imaging domains, including pathological images, radiographic images, and retinal images. **Table 5** presents a summarized overview of the applications of GCNs in lesion detection and localization.

In cancer diagnosis, representing pathological structures allow GCNs to capture the spatial relationships and size of tumors through convolutional operations, assisting clinicians in further disease analysis and treatment. Wu et al. proposed a method called weakly-and semi-supervised graph CNN for identifying basal cell carcinoma in pathological images, demonstrating its potential in enabling faster and more accurate cancer diagnosis, which indirectly improves patient outcomes [48]. GCNs are also effective in anomaly detection in radiographic images. Du et al. combined the concepts of CNN and GCN for breast cancer detection in mammograms [49]. By employing graph attention network to discriminate the indicative features of lesions, they efficiently emulated radiologists' focal scrutiny of the lesion areas, culminating with the successful detection of breast cancer in X-ray images via graph attention network. Liang et al. constructed a novel multi-network architecture consisting of a multiscale CNN and a fully connected GCN for abnormality detection in musculoskeletal X-ray images [50]. Experimental results demonstrated the model's high accuracy and robustness in musculoskeletal X-ray images. In the field of retinal imaging, retinal lesions are a common ocular disease that, if severe, can lead to blindness. Therefore, the detection of lesions in retinal images is of great importance. Luo et al. fused the correlation information of lesions learned by GCNs with the retinal image features obtained by a CNN model to achieve automated detection and severity grading of diabetic retinopathy lesions [51].

***Medical image classification and diagnosis***

During the perioperative period, GCNs adeptly capture the spatial characteristics delineating inter-tissue relationships within histopathological imagery. Consequently, within the domain of computer-aided diagnosis rooted in histopathological images, GCNs inherently exhibit commendable adaptive capabilities, thereby affording a high degree of feasibility. Gao et al. proposed a novel computer-aided diagnosis classification framework for breast tissue histopathological images, aiming to learn and extract spatially related features from the images [52]. The framework utilizes CNNs to extract high-level features from the histopathological images and inputs the generated graphs into

Table 6. Application of graph convolutional networks in medical image classification and diagnosis

| Presenters | Analytical objectives | Model | Results |
|---|---|---|---|
| Gao et al. [52] | Breast cancer | GCN+GCN | Experimental results on two public breast histopathology datasets outperform other algorithms |
| Shi et al. [53] | Cervical cell classification | GCN+GCN | The model substantially improved the classification of cervical cells |
| Marzullo et al. [54] | Classification of multiple sclerosis | GCN | Through clinical validation on MS patients, the results indicate that the proposed method can effectively perform clinical classification of MS-related categories |
| Zhou et al. [55] | Colorectal Cancer Grading | GCN | The results demonstrate that the proposed colorectal cancer -Net can achieve an optimal classification performance on colorectal cancer |

Note: GCN, graph convolutional network.

GCN to learn the spatial features of the histopathological images, thereby accomplishing the classification task. Shi et al., in their study on cervical cell classification, introduced a method that effectively enhanced the representation capability of CNN features by propagating node relationships through GCN, resulting in improved classification performance [53]. This approach has significant implications for cervical cell classification and can be well applied in automated cervical cytology screening systems.

In addition to capturing spatial feature expressions between pathological tissues, GCNs can also be applied to other medical image analyses, such as disease grading. Marzullo et al., in their study on automatic classification of clinical features in multiple sclerosis, proposed the use of GCN models to describe the topological structures of brain network [54]. By leveraging the information between graph structures, multiple sclerosis patients were classified into four clinical features: Clinically Isolated Syndrome, Relapsing Remitting, Secondary Progressive, Primary Progressive. Compared to classical convolutional network models, the proposed GCN architecture achieved good results with relatively fewer parameters. Zhou et al., in their research on colorectal cancer grading, introduced a novel cell-graph convolutional network [55]. This method employs cell graph convolutional layers and pooling layers to process cell graphs, capturing the relationships and interactions between different cells. It was tested on multiple datasets, demonstrating more accurate grading of colorectal histopathological images compared to other existing methods. This approach holds the potential to facilitate early diagnosis and treatment of colorectal cancer. **Table 6** summarizes the applications of GCNs in medical image classification and diagnosis based on analysis objectives, utilized models, and analysis results.

### *Disease prediction*

GCNs find extensive application in disease prediction, encompassing the entirety of the perioperative continuum. Leveraging the inherent graph structure of data, GCNs facilitate enhanced capture of intricate disease relationships and interaction patterns. This capability enables medical practitioners to more accurately prognosticate patients' disease conditions and recovery trajectories preoperatively, intraoperatively, and postoperatively. By furnishing heightened precision in prognostic and diagnostic outcomes, GCNs have gained widespread adoption in diverse domains, including gene expression prediction, disease diagnosis and treatment, and drug response forecasting. **Table 7** provides a comprehensive summary of the applications of GCNs in disease prediction.

Gene prediction is a critical task in bioinformatics, aiming to predict the interactions and regulatory relationships among genes to better understand the functionality and regulatory mechanisms of the genome. By utilizing GCNs to learn the interactions between genes, more accurate gene classification and prediction can be achieved. Mudiyanselage et al. proposed two circRNA-disease association prediction models, namely GCNs for Node Classification and GCNs for Link Prediction, to address the limited quantity of circRNA-disease associations and the constraints of scalability, time, and labor costs [56]. The effectiveness of the proposed models was further demonstrated through a case study on colorectal cancer. Li et al. proposed a novel approach called neural inductive matrix completion GCN for predicting microRNA-disease associations [57]. Through the verification on breast cancer cases, the proposed method achieved a prediction accuracy of 100%. Xuan et al. proposed a GCN and CNN-based method for inferring disease-related lncRNA candidate genes in a study of lncRNA -disease associa-

**Table 7. Application of graph convolutional networks in disease prediction**

| Presenters | Predict Targets | Model | Results |
|---|---|---|---|
| Mudiyanselage et al. [56] | Colorectal cancer | GCN | The two models achieved AUC values of 97% and 98%, respectively, in predicting colorectal cancer |
| Li et al. [57] | Breast cancer | GCN | The accuracy rate of breast cancer prediction reached 100% |
| Xuan et al. [58] | Tumors and cancers | CNN+GCN | The proposed model effectively discovered potential lncRNA-disease associations, as confirmed by case studies in gastric cancer, osteosarcoma, and lung cancer |
| Wang et al. [59] | Cancer | SNF+GCN | Combining SNF and GCN algorithms and fusing multi-gene data for cancer survival prediction |
| Wang et al. [60] | Breast cancer | GCN | It contributes to the accurate prediction of breast tumor malignancy or benignity, thereby improving the accuracy of cancer diagnosis in breast X-ray examinations |
| Song et al. [61] | Memory and cognitive impairment | GCN | The model showed an average increase of 8.64% in accuracy, 9.93% in sensitivity, and 7.91% in specificity across six multimodal tasks, demonstrating its applicability for predicting disease progression |
| Yao et al. [62] | Brain diseases | GCN | MMTGCN demonstrates high performance in identifying brain disorders |

Note: GCN, graph convolutional network; AUC, area under the curve; CNN, convolutional neural network; lncRNA, long noncoding RNA; SNF, similarity network fusion; MMTGCN, mutual multi-scale triplet GCN.

tions [58]. Through case studies on gastric cancer, osteosarcoma, and lung cancer, GCNLDA effectively discovered potential lncRNA -disease associations and demonstrated superior performance compared to other methods. Wang et al. proposed a GCN-based fusion of multiple genomic data for cancer survival prediction [59]. Building upon the similarity network fusion algorithm, they integrated multiple genomic data and clinical data, selected features from cancer samples, and utilized GCN for semi-supervised training on these two matrices, resulting in a GCN-based fusion approach for cancer survival prediction.

In addition to gene expression prediction, GCNs can also utilize clinical data and imaging data to construct disease networks and predict/diagnose diseases by learning the features of nodes and edges in the network. Wang et al. proposed a decoupling autoencoder with GCN that learns disease-related image features and explicitly separates them from other features [60]. This method shows excellent performance in predicting benign or malignant outcome in breast X-ray examinations, contributing to improved accuracy in cancer diagnosis. In cognitive impairment scenarios, GCNs play a vital role by automatically localizing, segmenting, and classifying brain structures for early diagnosis and treatment of neurological diseases, preventing further deterioration. Song et al. proposed a similarity-aware adaptive calibrated GCN (SAC-GCN), which combines functional and structural information for predicting disease-induced deteriorations [61]. Similar to the former, Yao et al. introduced a multi-scale triplet GCN for analyzing functional and structural connections in brain disease diagnosis [62]. Multiple GCN modules were used to extract features from brain multi-scale templates, and these features were input into a fusion module for multi-scale information integration. Experimental results demonstrated that multi-scale triplet GCN achieved high performance in identifying and predicting brain diseases.

### *Image reconstruction*

The application of GCNs in the field of image reconstruction involves the task of image restoration or reconstruction using local structural information of the image. Traditional image reconstruction methods typically rely on pixel-level processing, while GCNs, by leveraging both global and local structural information of the image, can provide better image reconstruction results. In recent years, an increasing number of researchers have begun exploring the application of GCNs in the field of medical image reconstruction and have achieved a series of advancements. Lang et al. proposed an automatic key point localization method based on the local attention GCN, which can be applied in craniofacial and oral maxillofacial surgery, with the potential to improve the success rate and efficiency of the surgery [63]. Tang et al. introduced a neighborhood feature reconstruction algorithm to extract the underlying relationships between obtained features and reconstructed them as graph-structured data [64]. Based on this, they proposed a deep GCN model called node self-convolution GCN, which can effectively diagnose COVID-19 using graph-structured data. Wang et al. presented an instantiation network that utilizes Dynamic Convolution Neural Network to extract features from 2D images and employs GCNs to reconstruct 3D meshes [65]. This method enables the reconstruction of the target's 3D mesh from a single 2D image, bridging the gap between the 2D image acquisition in current minimally invasive surgery and the 3D navigation requirements.

### *Surgical interventions*

Surgical intervention refers to a medical procedure performed inside the body using interventional devices such as catheters and stents. In recent years, GCNs have been increasingly utilized in research related to surgical interventions. For instance, in the perioperative context, GCNs find applications in surgical planning, navigation, postoperative assessment, and monitoring. Wang et al. proposed a GCN-based method for detecting the presence and location of surgical instruments [66]. Compared to traditional CNN and recurrent neural network methods, this approach achieves more accurate detection of surgical instruments, demonstrating the potential of GCNs in tool detection tasks in surgical videos. Xi et al. introduced a Feedback Graph Convolutional Network-based method that can be used for multiple tasks in endoscopic videos, such as surgical action recognition, surgical step detection, and surgical process monitoring [67]. This method effectively improves surgical efficiency and quality, thereby enhancing patient treatment outcomes.

## Discussion

GCNs are deep learning models based on graph-structured data, which have been widely applied in the medical field in recent years. By reviewing the research progress of GCNs in the medical domain, it is evident that with continuous algorithmic updates and iterations, GCNs will achieve greater success in the medical field. This section summarizes the future research directions of GCNs in medical applications.

### *Deep network structures*

Traditional deep learning models have yielded substantial outcomes in numerous challenges by utilizing extensive network structures. However, some GCNs can achieve feature extraction and desired outcomes with fewer network structures. Increasing the stack of convolutional layers may lead to over-smoothing of features between nodes, resulting in deteriorated performance. In clinical applications, precise identification and localization are pursued. Therefore, designing deeper network structures that can avoid feature loss is an urgent problem to be addressed.

### *Large-scale data*

Obtaining and annotating medical data often requires specialized medical knowledge and experience, which is not only limited in quantity but also consumes substantial human and material resources. However, deep learning typically requires a large amount of data to train models. Therefore, future research can focus on developing efficient GCN algorithms and optimization techniques to enhance the processing capability and scalability of large-scale graph data.

### *Dynamic graph data*

Currently, most GCN models are designed for static graph data. However, in clinical applications, most medical features are dynamic. Consequently, a prospective research direction for GCNs involves expanding their applicability to model dynamic graphs and temporal graphs, thereby enabling the capturing of changes in graph data over time.

### *Interpretability*

In the future, it is crucial to improve the generalization capability of models in clinical applications and reduce the difficulty of understanding results for medical professionals. Aligning the research focus with clinical requirements is a key aspect to address when further investigating the application of GCNs in the medical field.

## Conclusion

This review initially elucidates the developmental trajectory of CNNs and GCNs, introducing the algorithmic foundations of the latter, including the concept of graphs, types of graphs, and the propagation framework of GCNs. Extensive discourse is dedicated to the pertinent applications of GCNs in the domain of perioperative medicine, encompassing medical image segmentation, lesion detection and localization, and medical image classification. While GCNs have made groundbreaking strides in several facets of perioperative medical scenarios, certain knowledge gaps persist, warranting further in-depth investigation. One such avenue pertains to the application of GCNs in the fusion of multimodal data. Perioperative medical images typically involve diverse modalities, such as MRI and CT images. Future exploration could entail devising GCN-based strategies for processing multimodal medical image data to enhance the efficacy of medical image analysis and diagnosis. Additionally, there is potential in the realms of intraoperative monitoring and feedback. During surgical procedures, GCNs can real-time analyze intraoperative image data, assisting physicians in monitoring surgical progress and furnishing instantaneous feedback, thereby facilitating timely decision-making and adjustment of surgical strategies. Finally, intraoperative planning and navigation represent another prospect. GCNs can preoperatively analyze patients' medical image data to aid surgeons in devising more precise surgical plans, thereby ensuring the accuracy and safety of surgical procedures.

In conclusion, although there are still many directions that require further research and exploration in the field of GCNs and their application in medicine, this does not impede their future development and application in domains such as artificial intelligence. GCNs will continue to be a prominent area of research for a significant period of time, serving as a focal point for scholars and researchers.

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