

Review of Graph Neural Networks for Medical Image Denoising

Jing Wang^{1,*}

¹1st School of Computer Science and Technology, Henan Polytechnic University, Jiaozuo, Henan 454000, P R China

Abstract

As deep learning continues to evolve, more and more applications are generating data from non-Euclidean domains and representing them as graphs with complex relationships and interdependencies between objects. This poses a significant challenge to deep learning algorithms. Because, due to the uniqueness of graphs, applying deep learning to ubiquitous graph data is not an easy task. To solve the problem in non-Euclidean domains, graph Neural Networks (GNNs) have emerged. A graph neural network (GNN) is a neural model that captures dependencies between graphs by passing messages between graph nodes. With the continuous development of medical image technology, medical image diagnosis plays a crucial role in clinical practice. However, in practice, medical images are often affected by noise, artifacts, and other interfering factors, which may lead to inaccurate and unstable diagnostic results. Therefore, image-denoising techniques become especially critical in medical image processing. Therefore, researchers have proposed innovative methods based on graph neural networks for effective noise removal, preserving the key features of the image and improving the quality and usability of medical images. This paper reviews the research progress of graph neural networks in the field of medical image denoising. It also summarises the problems and challenges of current research and looks at the future direction of medical image-denoising research.

Keywords: graph neural networks, deep learning, graph data, medical images, denoising

Received on 10 November 2023, accepted on 28 November 2023, published on 06 December 2023

Copyright © 2023 J. Wang *et al.*, licensed to EAI. This is an open access article distributed under the terms of the [CC BY-NC-SA 4.0](https://creativecommons.org/licenses/by-nc-sa/4.0/), which permits copying, redistributing, remixing, transformation, and building upon the material in any medium so long as the original work is properly cited.

doi: 10.4108/eetel.4358

1. Introduction

With the rapid development of neural networks in recent years, deep learning has become a "jewel" in the field of artificial intelligence and machine learning [1]. Many machine learning tasks [2, 3] that used to rely on manual methods to extract feature information (e.g., image recognition, machine translation) have been replaced by a variety of more advanced deep learning methods. Of course, the success of deep learning in image classification [4], video processing [5], speech recognition [6], natural language understanding [7] is no accident. This is due not only to big data [8] and high-performance computing power [9] but also to the effectiveness of deep learning

itself in extracting potential representations from Euclidean data [10].

For graphs can be regular or irregular. A graph may simultaneously have unordered nodes of different sizes, nodes from the same graph may have different numbers of neighbors as well as each node neighborhood in the graph may be different. This leads to the fact that some operations of deep learning algorithms (e.g., convolution operations [11]) can achieve good results in the Euclidean domain, but are difficult to apply to the graph domain.

Graphs are ubiquitous and widely used in the real world to represent objects and their relationships in various domains. Examples include large-scale social networks[12], traffic networks [13], chemical molecule analysis[14], recommender systems [15], ecosystems, and so on. More and more applications rely on representing data generated in non-Euclidean [16] domains as graphs

*Corresponding author. Email: wangjing@home.hpu.edu.cn

