Graph Convolutional Neural Network as a Chest X-Ray images classifier

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Motivation

- In present days of medical diagnosis, **factor identification** for a specific sickness is crucial to give out appropriate and in-time cure.

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- Manual diagnosis with CXR images is a **specialized-specific labour** requiring high specialty doctors from medical image analysis.
- Recent advances in classifying and segmenting medical images have achieved **remarkable performance** on various tasks [1].

[1] Vo and Pham (2021). Detecting COVID-19 and Pneumonia with Chest X-Ray images using Deep Convolutional Neural Networks. In *Introduction to Computer Vision*. https://github.com/DTA-UIT /Detect-COVID19

Motivation

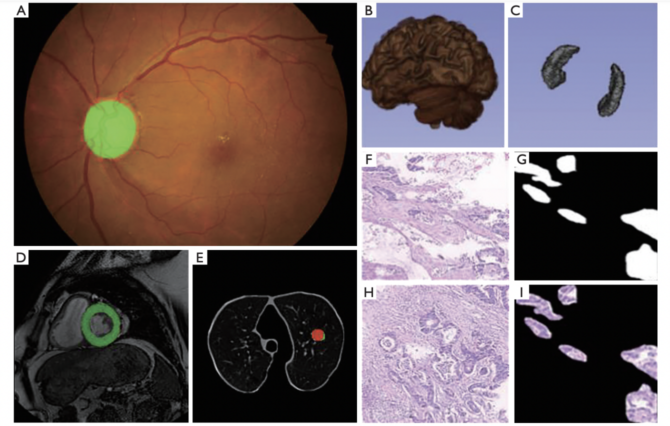

Figure: Deep learning application in medical image analysis[2].

[2] Cai, L., Gao, J., & Zhao, D. (2020). A review of the application of deep learning in medical image classification and segmentation. *Annals Of Translational Medicine*, *8*(11), 713. doi:10.21037/atm.2020.02.44

Motivation

- A crucial need on **visually explained** breakthroughs to practically deploy for computer-aided design (CAD) used in hospitals and medical centers[2].

[2] Lee, L., Kanthasamy, S., Ayyalaraju, R. S., & Ganatra, R. (2019). The Current State of Artificial Intelligence in Medical Imaging and Nuclear Medicine. *BJR open*, 1(1), 20190037. https://doi.org/10.1259/bjro.20190037

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- Medical images are **explicit**, especially annotated ones, due to patients' privacy and lack of expertised resources.

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Motivation

- A crucial need on **visually explained** breakthroughs to practically deploy for computer-aided design (CAD) used in hospitals and medical centers[2].
- Medical images are **explicit**, especially annotated ones, due to patients' privacy and lack of expertised resources.
- CNN- and Attention-based methods require tons of computational resources (GPUs) and data, i.e., DETR [3], ResNet[4].

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[2] Lee, L., Kanthasamy, S., Ayyalaraju, R. S., & Ganatra, R. (2019). The Current State of Artificial Intelligence in Medical Imaging and Nuclear Medicine. *BJR open*, 1(1), 20190037. https://doi.org/10.1259/bjro.20190037

[3] Carion, N., Massa, F., Synnaeve, G., Usunier, N., Kirillov, A., & Zagoruyko, S. (2020, August). End-to-end object detection with transformers. In *European conference on computer vision* (pp. 213-229). Springer, Cham.

[4] K. He, X. Zhang, S. Ren and J. Sun, "Deep Residual Learning for Image Recognition," *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 770-778, doi: 10.1109/CVPR.2016.90.

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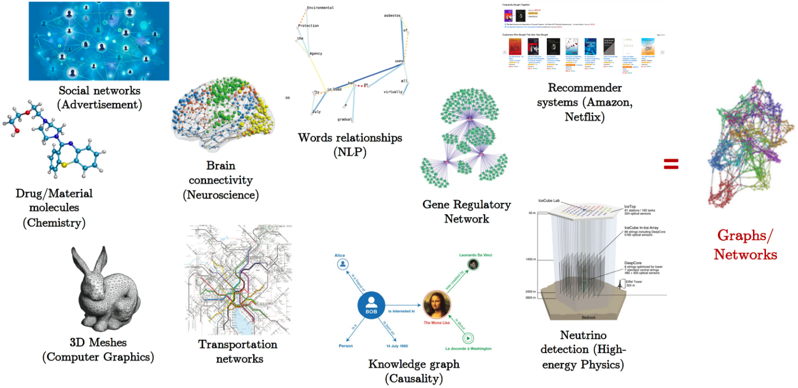
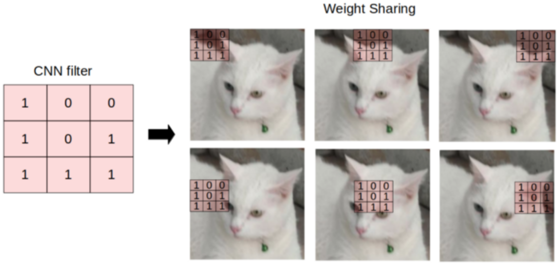
Graph Neural Network

- Previously, graph-based DL methods are used to solve problems that requires to understand **connections** and **contributions from entities** within the problem formation.



Graph Neural Network

- In Convolutional Neural Networks (CNNs), **kernels (filters)** are applied to synthesize neighboring pixels from original image to generalize image features.



Graph Neural Network

- In Convolutional Neural Networks (CNNs), **kernels (filters)** are applied to synthesize neighboring pixels from original image to generalize image features.
- In Graph Neural Networks (GNNs), neighboring pixels are also synthesized to generalize images by using **nodes and edges** instead of kernels.

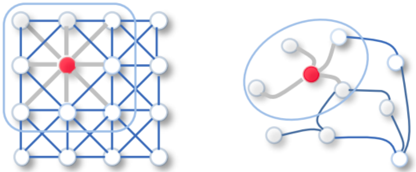


Figure: CNNs (left) versus GNNs (right) on neighboring pixels synthesis.

Assumption: nearer nodes often share more common features

Graph Neural Network

Strengths

- GNN is introduced to **overcome problems of overfitting and class imbalance**.
- GNN is usually **independent of GPUs** and performs faster but better compared to other DL-bases methods (based on evidence from experimental results, i.e., Xu et al. (2019)[5], Ma et al. (2021)[6]).

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[5] Xu, P., Joshi, C. K., & Bresson, X. Multi-graph transformer for free-hand sketch recognition (2019). *arXiv preprint arXiv:1912.11258*

[6] Ma, C., Yang, F., Li, Y., Jia, H., Xie, X., & Gao, W. (2021). Deep human-interaction and association by graph-based learning for multiple object tracking in the wild. *International Journal of Computer Vision*, 129(6), 1993-2010.

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Weaknesses

- Graph construction is a **problem-variant** work and depends a lot on **expertised knowledge**.

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Graph Convolutional Network

- To apply GNN for CV problems, Graph Convolutional Network[7] (GCN) is proposed as a means to extract features from images.

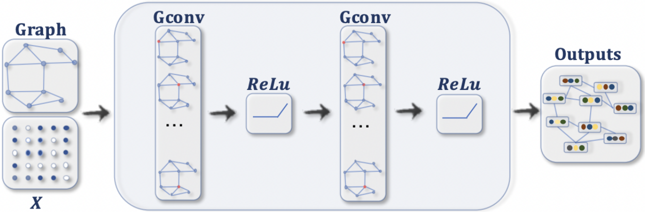

Figure: A typical Graph Convolutional Network architecture

[7] Kipf, T. N., & Welling, M. (2016). Semi-supervised classification with graph convolutional networks. *arXiv preprint arXiv:1609.02907*.

- To apply GNN for CV problems, Graph Convolutional Network[7] (GCN) is proposed as a means to extract features from images.
- In this work, GCN convolutional layers are designed to exchange information toward each other the same as the mechanism in *message-passing neural network* (MPNN)[8].

[7]Kipf, T. N., & Welling, M. (2016). Semi-supervised classification with graph convolutional networks. *arXiv preprint arXiv:1609.02907.*

[8]Gilmer, J., Schoenholz, S. S., Riley, P. F., Vinyals, O., & Dahl, G. E. (2017, July). Neural message passing for quantum chemistry. In *International conference on machine learning* (pp. 1263-1272). PMLR.

Graph Convolutional Network

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2. The final graph is pooled via a Log-Softmax activation.

Architecture construction

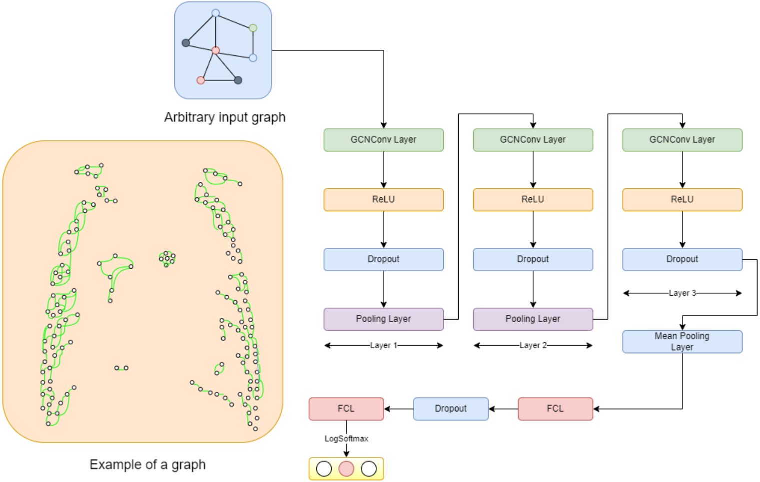

Figure: Our architecture used in this work

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Dataset

- To validate the applied method, we use "Labeled Optical Coherence Tomography (OCT) and Chest X-Ray Images for Classification dataset"[9] (6114 CXR images).

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Figure: Examples on dataset: Bacteria (left), Normal (middle), Virus (right).

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	Train	Val	Test	Total
Bacteria	2045	503	242	2790
Normal	1058	291	234	1583
Virus	1090	503	148	1741
Total	3193	1297	624	6114

Table: Distribution of labels on dataset

[9] Kermany, D., Zhang, K., & Goldbaum, M. (2018). Labeled optical coherence tomography (oct) and chest x-ray images for classification. *Mendeley data*, 2(2).

Methodological pipeline

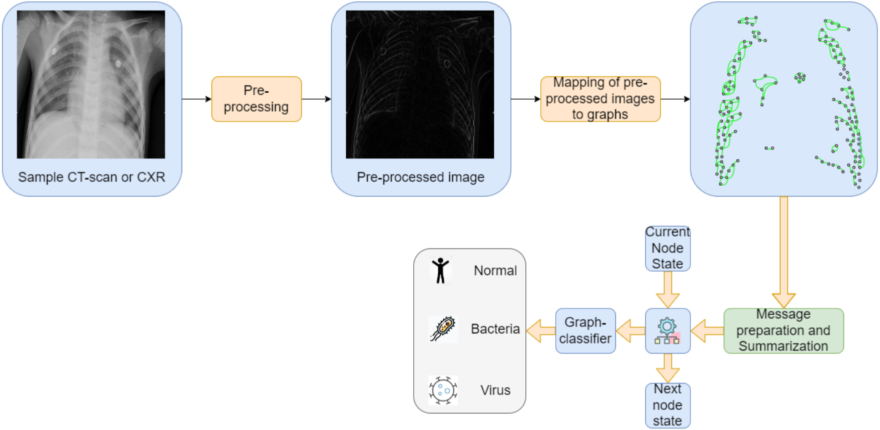

Figure: Experimental pipeline

Preprocessing

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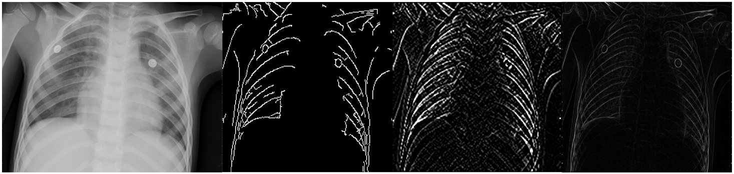

Figure: Comparison among edge detection methods. From left to right: Original image, Sobel image, Canny image, and Prewitt image.

Graph construction

Graphs from edge detected CXR images are constructed from 3 steps:

1. Pixels having grayscale intensity value of 128 is qualified as a node and feature of a node consists of the grayscale intensity of the corresponding pixels.

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1. Pixels having grayscale intensity value of 128 is qualified as a node and feature of a node consists of the grayscale intensity of the corresponding pixels.
2. Edge exists between 2 nodes representing neighboring pixels from original images.
3. Node attributes, which are grayscale values, are normalized graph-wise.

Metrics

	Predicted 0	Predicted 1
Actual 0	TN	FP
Actual 1	FN	TP

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$PPV(Precision) = \frac{TP}{TP + FP}$$

$$Sensitivity(Recall) = \frac{TP}{TP + FN}$$

$$F1\ score = \frac{2 \times PPV \times Sensitivity}{PPV + Sensitivity}$$

Experimental configuration

- Graph Convolutional Network
  - Adam(learning rate = 1e-4)
  - batch size = 64
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- Graph Convolutional Network
  - Adam(learning rate = 1e-4)
  - batch size = 64
  - 50 epochs
- ResNet50, VGG16
  - pretrained on ImageNet
  - Adam (learning rate = 1e-3)
  - Reduce learning rate (factor = 0.1, patience = 3, min lr = 1e-6)
  - 50 epochs

Results comparison

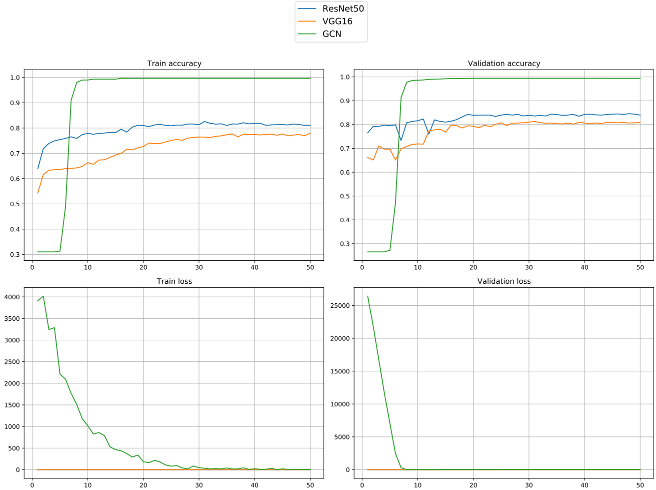

Figure: Training curve among Graph Convolutional Network(GCN), ResNet50, and VGG16.

Results comparison

	GCN	ResNet50	VGG16
Test accuracy	**96.75%**	83.81%	80.29%
Number of parameters	**37,955**	16,088,067	126,014,955
Training time (s)	9642 + 317	4715	5442

Table: Comparison among Graph Convolutional Network (GCN), ResNet50[10], and VGG16[11]

[10]He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 770-778).

[11]Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*

Results comparison

		GCN	ResNet50	VGG16
PPV	Bacteria	**1.000**	0.875	0.765
	Normal	0.979	**0.982**	0.952
	Virus	**0.903**	0.656	0.712
Sensitivity	Bacteria	0.949	0.954	**0.958**
	Normal	**0.967**	0.717	0.683
	Virus	**1.000**	0.837	0.736
F1 score	Bacteria	**0.974**	0.913	0.851
	Normal	**0.973**	0.829	0.796
	Virus	**0.949**	0.735	0.724

Table: Comparison among Graph Convolutional Network(GCN), ResNet50, and VGG16.

Confusion matrix

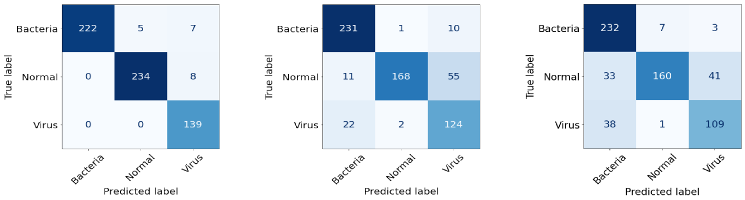

Figure: Confusion matrix among: GCN (left), ResNet50 (middle), VGG16 (right).

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- GCN overcame the problem of overfitting and class imbalance.
- GCN is not an end-to-end method and requires specialised knowledge on constructing graphs for specific problems.

The end.