Skin Cancer Detection Using GNN

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*Abstract*— In order to diagnose skin cancer, this study applies Graph Convolutional Networks (GCN) to the HAM10000 dataset, which consists of 10,015 dermatoscopic pictures classified into several diagnostic categories. A RandomUnderSampler was used to solve the problem of data imbalance, producing a balanced dataset with 115 samples per category. After then, the dataset was divided into training and testing sets, with 70% going toward training and 30% going toward testing. Additionally, a 50% split of the training data was added to the validation set. The GCN model underwent approximately 50 epochs of training with unique architectural configurations.The results showed that it was difficult to achieve high accuracy, with validation and training accuracies of about 23.97% and 26.47%, respectively. The performance that has been seen highlights the necessity for more optimization, which may involve modifying the model design and investigating other preprocessing methods. It also highlights how important dataset diversity and quality are to prediction abilities.To sum up, this work expands the use of GCN in skin cancer diagnosis and lays the groundwork for other research projects. There is room for improvement in the areas of using cutting-edge methods, investigating a variety of datasets, and fine-tuning model architecture. Evaluation of the suggested approach's generalizability will require validation on external datasets.

Keywords—Skin Cancer, SLIC Superpixels, Deep Learning, Graph Neural Network, Delaunay Trianggulation.

# Introduction

Computer Vision is a type of deep learning that have been widely used to detect or to classify object by image or video. The most used deep learning technique to be used for computer vision is Convolutional Neural Network (CNN). This technique has produced large numbers of models that can be used by Artificial Intelligence Engineer. For example, VGG, MobileNetV2, YOLO are used for detecting object and face recognition. However, CNN is not completely perfect. There is still some flaw in the output of the detection. There’s still some missing information to make the model be more detailed. Therefore, in this paper, Graph Neural Network will be used to be more precise in detecting an object. The object that will be used in this project is Skin Cancer image.

The HAM10000 dataset, which consists of 10,015 dermatoscopic images classified into different diagnostic classes, presents challenges related to data imbalance, which is addressed by using a RandomUnderSampler to create a balanced dataset with 115 samples per category. Skin cancer is a common and potentially fatal condition, so it is necessary to have effective diagnostic tools to enable timely intervention and treatment. In response to this imperative, this research aims to improve skin cancer diagnosis through the application of GCN on the HAM10000 dataset.

In this work, the dataset is carefully partitioned, with 70% designated for training and 30% for testing. Additionally, a validation set is created with a 50% split from the training data. The GCN model, which has distinct architectural configurations, is trained over roughly 50 training epochs. In spite of these efforts, the accuracy that is obtained is still difficult to interpret, with validation and training accuracies of 23.97% and 26.47%, respectively.

The results highlight the difficulty of the task at hand and the necessity of additional optimization, which could entail a review of the model design and an investigation of alternative preprocessing techniques. The results also highlight the critical role that diversity and quality of the datasets play in influencing prediction capabilities.

To put it briefly, this study expands the use of GCN for skin cancer diagnosis and sets the stage for further research. Some of the areas that need to be improved upon are the investigation of novel approaches, a variety of datasets, and the optimization of model architecture. Most importantly, the feasibility of the suggested method requires external dataset validation, which is an essential step in determining its robustness and real-world applicability. By investigating these avenues, we hope to improve both the field of skin cancer diagnostics and the field of medical image analysis.

# Related Work

A rich tapestry of inventive approaches and procedures is shown by the broad landscape of research in the subject of graph-based methods for image analysis and classification. Every study adds distinct insights and methodology, laying the groundwork for further advancements in the field.

Building on the work presented in [1], [2] investigates ensemble frameworks, GATRes and GATGIN, incorporating Graph Neural Network (GNN) models and a pretrained ResNet18 for medical applications. The study highlights improved sensitivity and accuracy in classification tasks, particularly in cervical cancer screening. The work presented in [1] introduces the Vision GNN (ViG) architecture, using a graph structure representation for image-level feature extraction.

[3] presents an automated technique for myocardium segmentation using maskSLIC clustering and Otsu thresholding, demonstrating the versatility of graph based methods beyond dermatology.[4] introduces DTO-SMOTE, a preprocessing technique based on Delaunay tessellation, which shows superior performance across different classification methods and datasets, highlighting the significance of creative preprocessing approaches.

[5] presents WaveMesh, a new wavelet-based superpixeling method that advances the investigation of various superpixel approaches. [6] provides a scalable convolutional neural network on graph-structured data that surpasses related approaches in semi-supervised learning tasks. [7] presents an effective superpixel creation method that prioritizes speed, simplicity, and segmentation quality. [8] compares the suggested method with SLIC superpixels to confirm its efficacy.

The combination of fuzzy C-means and SLIC superpixels for image segmentation in [9] emphasizes the ability of various techniques to work together to achieve better classification outcomes. [10] examines the various applications of Delaunay Triangulation in computer vision, with a focus on feature extraction from images. [11] describes the parallel Delaunay triangulation technique, which shows notable speed improvements when processing large point cloud data.

Building upon Delaunay triangulation, [12] suggests a novel approach for creating neighbor connections between instances in space, contributing to effective pattern mining. Lastly, [13] presents a Graph Convolutional Network (GCN) technique using Delaunay triangulation for feature extraction in skin cancer classification, concentrating on boundary extraction for accurate cancer prediction.

The variety of approaches, from novel architectures to preprocessing techniques, highlights the ongoing evolution of methodologies aimed at enhancing accuracy, efficiency, and applicability across various domains. This synthesis of related works highlights the breadth of applications and advancements within the domain of graph-based methods in image analysis. The combined findings offer insightful information and suggest future directions for research in the intersection of graph-based methods and image analysis.

# Research methodology

## Dataset Gathering

MNIST : HAM10000 were used as the dataset in this research. The dataset were consist of 10015 dermatoscopic images that provide a comprehensive assortment of all significant diagnostic classifications related to pigmented lesions: Actinic keratoses and intraepithelial carcinoma / Bowen's disease (akiec), basal cell carcinoma (bcc), benign keratosis-like lesions (solar lentigines / seborrheic keratoses and lichen-planus like keratoses, bkl), dermatofibroma (df), melanoma (mel), melanocytic nevi (nv) and vascular lesions (angiomas, angiokeratomas, pyogenic granulomas and hemorrhage, vasc). There are csv and images folder in the dataset. But there are shortcomings in this data, namely the uneven distribution of data. To overcome this, RandomUnderSampler were used to balance the data distribution which produce a new data frame with balance distribution of the data. Next, the dataset were divided into two new folder : train folder and test folder.

## Proposed Methodology

Fig. 1. Methodology workflow.

1. *Visualization*

By using an image from the dataset as an example to carry out the pre-processing process to see the pre-processing results of the superpixels and delaunay method. First, the image were converted to a grayscale, after the images convert into grayscale, the image dimensions was collected to add nodes and edges into the graph that was created.

A black spot on a white surface

Description automatically generated

Fig. 2. The visualization of the data.

1. *Data Pre-Processing*

SLIC Superpixels and Delaunay Triangulation are used as pre-processing methods in this research. After seeing the visualize example of the pre-processing. A looping process were conducted to apply the pre-processing to all the dataset and stored on google drivc.

1. *Modeling and Model Evaluation*

Graph Convolutional Network model were used as the model to train the deep learning architecture. The model were created from scratch. To evaluate the model, cross entropy loss were used.

## SLIC Superpixels

One of the most important phases in the processing and interpretation of medical images is medical image segmentation. The goal of medical image segmentation is to separate a picture into many non-overlapping areas according to certain standards, including similarity in texture, color, etc. Many academics offered a wide range of automated segmentation techniques, such as thresholding, edge detection, and active contours, based on different classical methodologies [2]. Superpixel techniques are designed to maximize computing efficiency by clustering a set of pixels together. Superpixel algorithms can take the role of the rigid pixel grid structure by grouping pixels into larger sections. Superpixels improve computing efficiency by collecting the picture similarities in each location. These days, they are employed in a wide range of applications, such as segmentation and depth estimation [2].

Superpixels may be produced in two ways using separate technique approaches based on graphs and gradient ascents.

* Graph based.

Each pixel is handled as a node in a network in graph-based algorithms, and the edge weights connecting nodes are determined in proportion to how similar the pixels are. Superpixel segments are obtained by the efficient minimization of a cost function that is specified on the graph [7].

* Gradient Ascents based.

Gradient ascent methods are used to improve the clusters from the previous iteration to gain better segmentation until convergence, starting from an initial rough grouping [7].

A red and yellow mosaic

Description automatically generatedIn SLIC superpixels, the number of segments that are used are 200 with the compactness of 20.

Fig. 3. SLIC Superpixels applied.

## Delaunay Triangulation

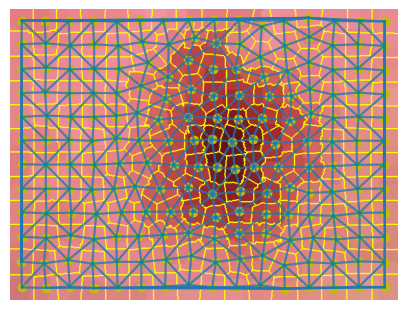
This method is used in feature extraction in this paper. The Delaunay triangulation is a network of triangles that ensures one particular property: each triangle's circumcircle only includes its vertices; no other triangle's points are present inside the circumcircle. This distinguishes the Delaunay triangulation from other triangulations. Making use of the distinctiveness [10]. In 2D, there might be a tight relationship between the convex hull and the Delaunay triangulation given a collection of points. The convex hull of the points is formed by the edges of the Delaunay triangulation.

Fig. 4. Delaunay Triangulation.

## Graph Convolutional Network

On graph-structured data, a Graph Convolutional Network, or GCN, is a semi-supervised learning method. It's based on a convolutional neural network variation that performs well and works directly on graphs. A localized first-order approximation of spectral graph convolutions serves as the motivation for the convolutional design selection. The model learns hidden layer representations that encode both local graph structure and node attributes, and it grows linearly in the number of graph edges [6].

In computer vision, GCN primarily involves action recognition, scene graph creation, and point cloud categorization. A collection of three-dimensional points in space, called a point cloud, is often gathered by LiDAR scans. Point cloud segmentation and classification have been investigated using GCN. Scene graph generation, which is often accomplished by combining object detector and GCN, attempts to parse the input picture intro a graph with the objects and their connection. GCN was used to the challenge of human action recognition by processing the naturally produced graph of connected human joints. Only some visual tasks with organically built graphs may be handled by GCN. It is necessary to have a GCN-based backbone network that processes picture data directly for generic computer vision applications [1].

The requirements for GCN model that are used in this paper are :

1. Optimizer : Adam Optimizer with learning rate of 0.01
2. Input Dimension : 3 , Hidden Dimension : 64, Output Dimension : 7
3. Convolutional layer 1 (Input Dimension) : ReLU Activator
4. Convolutional layer 2 (Hidden Dimension): ReLU Activator, Dropout Regularization : 0.3
5. Convolutional layer 3 (Hidden Dimension): ReLU Activator
6. Convolutional layer 4 (Hidden Dimension): Softmaz Activator
7. Dropout Regularization : 0.5
8. Linear Layer ( Output Dimension )

# Result and Discussion

Before the data were evenly distributed, the data have significant differences in distribution. Because of this, to normalize the data, RandomUnderSampler were used to evenly the distribution of the data with the result of all of the category get the total of 115 data.

A graph with numbers and a bar

Description automatically generated

Fig. 5. Data Distribution Graph.

The dataset were splitted into train and test dataframe named df\_train and df\_test. About 30% of the data were alocated for testing and the 70% of the data for training. To train the data, the training data were splitted again for validation data with 50% split. The training and validation results over 50 epochs are presented below:

1. Training and validation Result

| No. | Result | | | | |
| --- | --- | --- | --- | --- | --- |
| Epoch | Train Acc | Train loss | Val Acc | Val loss |
| 1 | 001 | 0.1421 | 0.0623 | 0.1570 | 0.0643 |
| 2 | 005 | 0.2060 | 0.0618 | 0.1901 | 0.0652 |
| 3 | 010 | 0.1616 | 0.0619 | 0.0826 | 0.0653 |
| 4 | 015 | 0.2043 | 0.0605 | 0.1653 | 0.0660 |
| 5 | 020 | 0.2202 | 0.0601 | 0.1901 | 0.0661 |
| 6 | 025 | 0.2149 | 0.0595 | 0.1736 | 0.0659 |
| 7 | 030 | 0.2575 | 0.0503 | 0.2149 | 0.0668 |
| 8 | 035 | 0.2789 | 0.0500 | 0.1901 | 0.0665 |
| 9 | 040 | 0.2966 | 0.0582 | 0.1736 | 0.0665 |
| 10 | 045 | 0.2735 | 0.0573 | 0.2397 | 0.0667 |
| 11 | 050 | 0.2647 | 0.0571 | 0.2397 | 0.0680 |

With 50 epochs of the training, the result of the accuracy still remains low as well as the validation accuracy result. It shows that there is something that needs to be improved to raise the accuracy.

A graph of blue and orange lines

Description automatically generated

Fig. 6. Training and Validation Accuracy Plot.

In figure 6, there was a drastic decline at 10 epochs and 18 epochs in validation accuracy. With the drastic decline of the accuracy, it shows that the performance of the model was not good enough therefore there needs to be some improvement and alteration in the model building.

A graph of a graph

Description automatically generated with medium confidence

Fig. 7. Training and Validation Loss Plot.

The loss of validation data and training data have contradicted each other. The training loss have decresead as the epoch progresses, but the opposite of the training loss, the validation loss have increased as the epoch progresses.

1. Model comparatioon

|  |  |  |
| --- | --- | --- |
| Model | Training Accuracy | Validation Accuracy |
| Proposed Model | 26.47% | 23.97% |
| [13]’s Model | 66% | 32% |

Compared to [13], which uses the same method and GCN model, the proposed model is still lacking in comparison with the [13]’s model accuracy with the difference around 40%. However, if it’s about validation accuracy, both models are still lacking with the accuracy below 50%. The results of this comparison show that the method used is not suitable for this kind of case. It can still be improved by improving the model building.

# Conclusion

After 50 epochs, the model's findings show that it obtained a training accuracy of around 26.47% and a validation accuracy of roughly 23.97%. The losses for validation and training were 0.0680 and 0.0571, respectively. The model's performance indicates that in order to increase classification accuracy, more optimization or investigation of various architectures or methodologies would be required. Better outcomes could also come from experimenting with various preprocessing techniques and hyperparameter adjustment. It is important to understand that the dataset's quality and variety have a significant impact on the model's ability to predict outcomes. The HAM10000 dataset, which offers a wide variety of diagnostic categories, was used in the study. But it's crucial to recognize that real-world data could provide other difficulties, such noise, class imbalances, and differences in picture quality.

In conclusion, the use of a Graph Convolutional Network in skin cancer detection studies has advanced. The acquired results serve as a basis for further research, which can entail improving the model architecture, looking into different datasets, and implementing cutting-edge methods to improve performance. Furthermore, determining the generalizability of the suggested strategy would require further assessment and validation on outside datasets.

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