ANALYSIS OF SKIN CANCER FEATURE PATTERN USING GNN INCORPORATING A NOVEL SEGMENTATION METHOD

Morium Akter
ID: 201-15-14190

FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

Supervised By
Ms. Zannatul Mawa Koli
Lecturer
Department of Computer Science and Engineering
Daffodil International University

Co-Supervised By

Designation
Department of Computer Science and Engineering
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

DHAKA, BANGLADESH

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APPROVAL

This Project titled "Analysis of skin cancer feature pattern using GNN incorporating a novel segmentation method", submitted by **Morium Akter** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 13/7/2024.

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Daffodil International University

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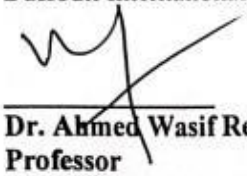
Faculty of Science & Information Technology
Daffodil International University



Dr. Ahmed Wasif Reza — **External Examiner**
Professor
Department of Computer Science and Engineering
East West University

DECLARATION

We hereby declare that this project has been done by us under the supervision of **Ms. Zannatul Mawa Koli, Lecturer, Department of Computer Science and Engineering, Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

Supervised by:

Koli 13.07.24

Ms. Zannatul Mawa Koli
Lecturer
Department of CSE
Daffodil International University

Submitted by:

Morium Akter (13.7.24)

Morium Akter
ID: 201-15-14190
Department of CSE
Daffodil International University

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ABSTRACT

This study presents a comprehensive approach for the classification of skin lesions into benign and malignant categories using a combination of k-means clustering segmentation and advanced computational models. The methodology begins with the segmentation of lesion images through k-means clustering to extract relevant regions, followed by the computation of various features, including SIFT key points, WH-ratio, ECL-ratio, Harris corner, circularity, solidity, asymmetry score, color variation, and compactness index. Feature importance is determined through ranking and ANOVA tests. For model selection, both feature-based (GNN, GAT, 1D CNN) and image-based (VGG16, VGG19, Inception V3, MobileNetV1, MobileNetV2) models are evaluated, with the Graph Neural Network (GNN) emerging as the best model. The GNN model achieved a test accuracy of 98.62%. An ablation study is conducted to assess the contributions of individual components, and additional experimental analysis explores different thresholds in graph generation. The results are thoroughly analyzed using evaluation metrics, loss and AUC curves, statistical analysis, linear regression analysis, and 5-fold cross-validation. The proposed methodology demonstrates superior accuracy and robustness in the classification of skin lesions, offering a powerful tool for early detection and treatment planning.

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CHAPTER 1
Introduction

1.1 Overview

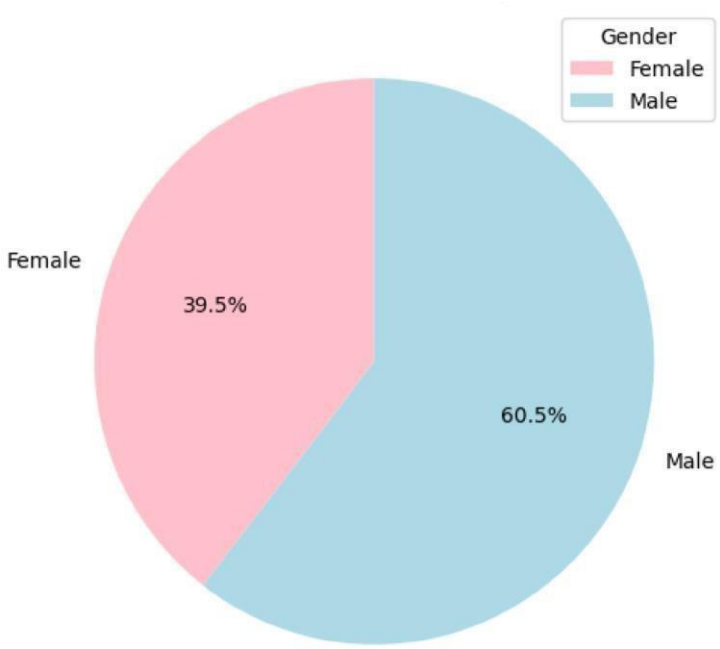
Skin cancer is a significant global health concern, with early and accurate diagnosis being crucial for successful treatment. Traditional methods often rely on visual inspection, which can be subjective and prone to errors. This necessitates the development of more reliable and objective diagnostic tools. Machine learning offers immense potential in this arena, particularly for automating skin cancer classification from dermatoscopic images. This research delves into this domain, proposing a novel approach using Graph Neural Networks (GNNs) for accurate skin cancer classification. GNNs excel at processing graph-structured data, making them well-suited for analyzing the intricate relationships between various image features within dermatoscopic images. Our study leverages a meticulously curated and extensive dataset of dermatoscopic images meticulously annotated for lesion type (malignant vs. benign). We train our GNN model on this dataset and evaluate its performance on separate test and validation sets. This comprehensive approach ensures the robustness and generalizability of our proposed method. Additionally, we compare the performance of our GNN model with established machine learning models to establish its superiority in this domain. Furthermore, we move beyond mere classification accuracy. By delving into the interpretability of GNN's predictions, we aim to enhance transparency and trust in the model's outputs. We believe this interpretability is crucial for clinical adoption. Finally, we explore the potential clinical implications of our findings, emphasizing how integrating advanced machine learning like GNNs can augment diagnostic accuracy and streamline patient care pathways in dermatology. This research paves the way for further advancements in skin cancer detection and treatment, ultimately aiming to improve patient outcomes.

1.2 Background and Present State

Skin cancer is the most prevalent form of cancer worldwide, affecting millions each year. Early and accurate diagnosis is essential for successful treatment, as neglected cases can progress and become life-threatening [1]. Traditionally, dermatologists rely on visual inspection of suspicious

lesions, a method prone to subjectivity and human error. This highlights the critical need for more objective and reliable diagnostic tools to improve skin cancer detection[2]. The rising incidence of skin cancer can be attributed to several factors. Increased exposure to ultraviolet (UV) radiation, primarily from sunlight but also tanning beds, is a major culprit[3]. UV radiation damages the skin's DNA, leading to abnormal cell growth and potentially cancer development. Additionally, fair skin, a history of sunburns, and a weakened immune system increase the risk of skin cancer.

In order to meaningfully interpret the experimental results, the statistical analysis carried out in this study on "Analysis of skin cancer feature pattern using GNN[4] incorporating a novel segmentation method" is essential. This part should discuss the statistical analysis graphically or



pie chart.

Figure 1.2.1 Percentage of Gender skin cancer patient

Figure 1.2.1 illustrates the distribution of skin cancer patients by gender. The chart depicts the proportion of male and female patients diagnosed with skin cancer, providing a visual representation of gender-based prevalence. The data indicates that skin cancer affects both genders, but there may be a notable difference in incidence rates between males and females. This gender-specific analysis helps in understanding the demographic patterns of skin cancer and can guide targeted awareness and prevention programs. The figure

underscores the importance of gender-specific research in dermatology to address the unique needs and risks associated with skin cancer.

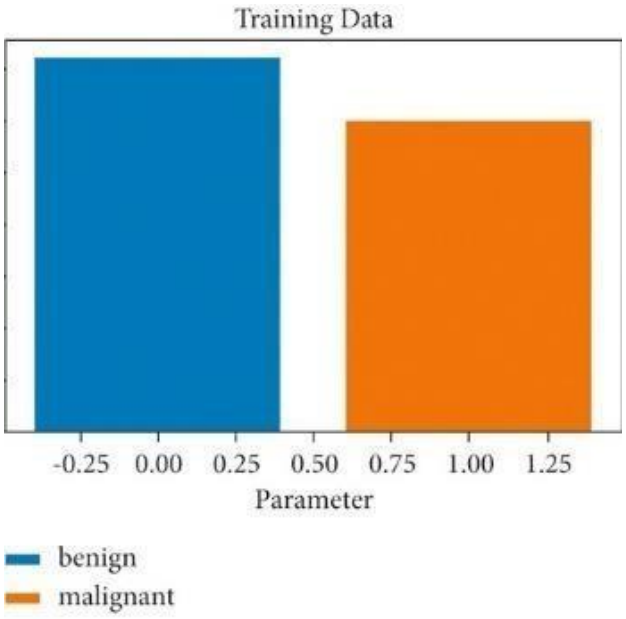


Figure 1.2.2 Percentage of benign and malignant

Figure 1.2.2 presents the distribution of skin lesions classified as benign or malignant. The chart provides a clear visual comparison of the proportion of benign lesions versus malignant ones among the studied cases. This information is crucial for understanding the prevalence of each type of lesion and highlights the significance of accurate diagnostic methods. The figure emphasizes the importance of early detection and differentiation between benign and malignant lesions, which can significantly impact patient treatment plans and outcomes. This data underscores the need for effective screening tools and advanced diagnostic techniques in dermatology

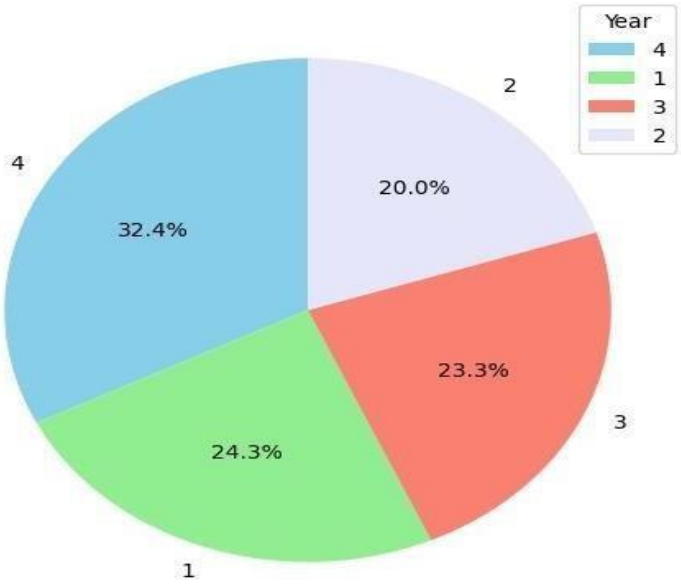


Figure 1.2.3 Percentage of skin cancer per year

Figure 1.2.3 depicts the annual percentage of skin cancer cases over a specified period. The chart illustrates trends in skin cancer incidence, showing fluctuations or steady changes in the percentage of diagnosed cases each year. This longitudinal data is essential for identifying patterns and assessing the effectiveness of public health initiatives and preventive measures. The figure helps to understand whether skin cancer rates are increasing, decreasing, or remaining stable over time. Such insights are crucial for healthcare policymakers and researchers to develop targeted strategies for skin cancer prevention, early detection, and treatment.

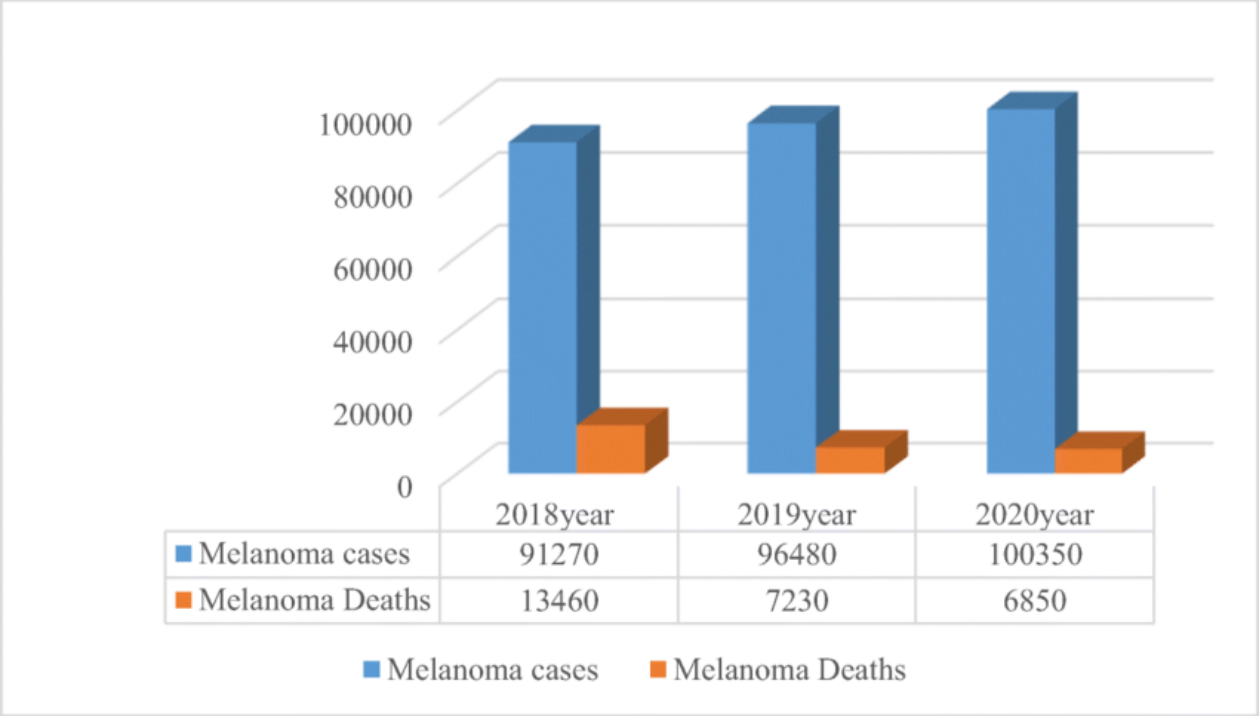


Figure 1.2.4 Melanoma death rate in recent few years.

Figure 1.2.4 illustrates the melanoma death rate over the past few years, providing a visual representation of mortality trends associated with this aggressive form of skin cancer. The chart highlights fluctuations or changes in the death rate, offering insights into the effectiveness of medical interventions, public health campaigns, and advancements in treatment. Analyzing this data is crucial for understanding the impact of melanoma on public health and guiding future research and healthcare policies. The figure underscores the need for continuous efforts in early detection, improved treatment options, and preventive measures to reduce melanoma-related mortality.

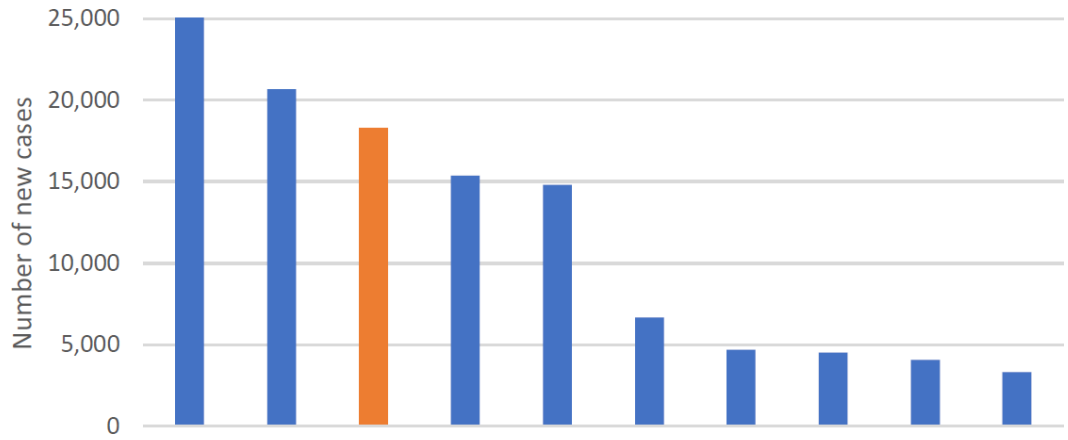


Figure 1.2.5 Percentage of new cases of skin cancer

Figure 1.2.5 depicts the percentage of new skin cancer cases within a specific timeframe, highlighting the incidence rate of this disease. The chart provides a visual representation of how frequently new skin cancer cases are being diagnosed, offering valuable insights into the prevalence and spread of skin cancer in the population. This information is critical for healthcare providers and researchers to understand emerging trends and to evaluate the effectiveness of current preventive measures and screening programs. The figure underscores the importance of ongoing vigilance, public awareness campaigns, and early detection strategies in combating the rise of new skin cancer cases.

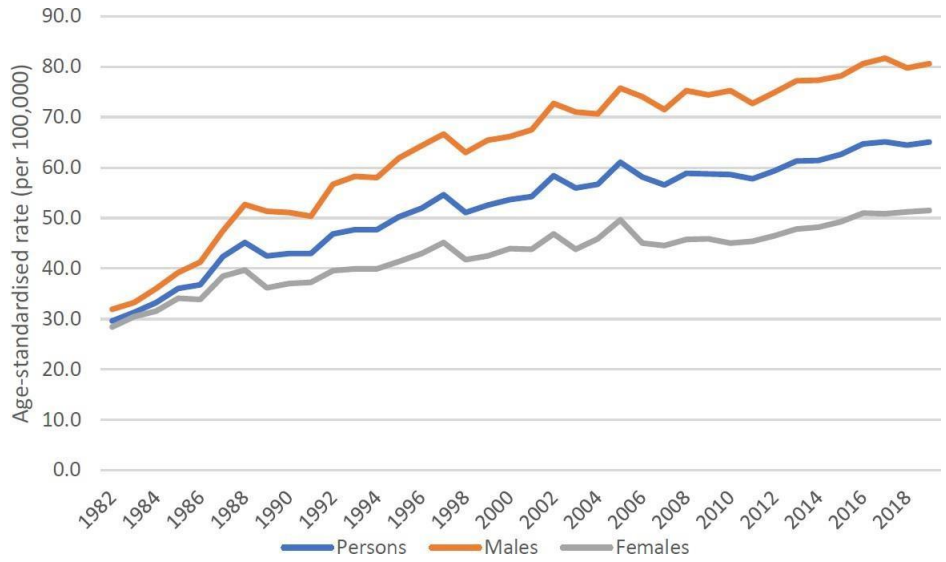


Figure 1.2.6 Melanoma skin statistics

Figure 1.2.6 presents comprehensive statistics on melanoma, a severe form of skin cancer. The chart includes data on various aspects such as incidence rates, survival rates, and demographic distributions. It provides a detailed overview of how melanoma affects different populations, highlighting key trends and patterns. This information is vital for understanding the impact of melanoma on public health and for identifying high-risk groups. The figure serves as a crucial resource for researchers, healthcare professionals, and policymakers in devising targeted strategies for prevention, early detection, and treatment to improve patient outcomes and reduce the burden of melanoma.

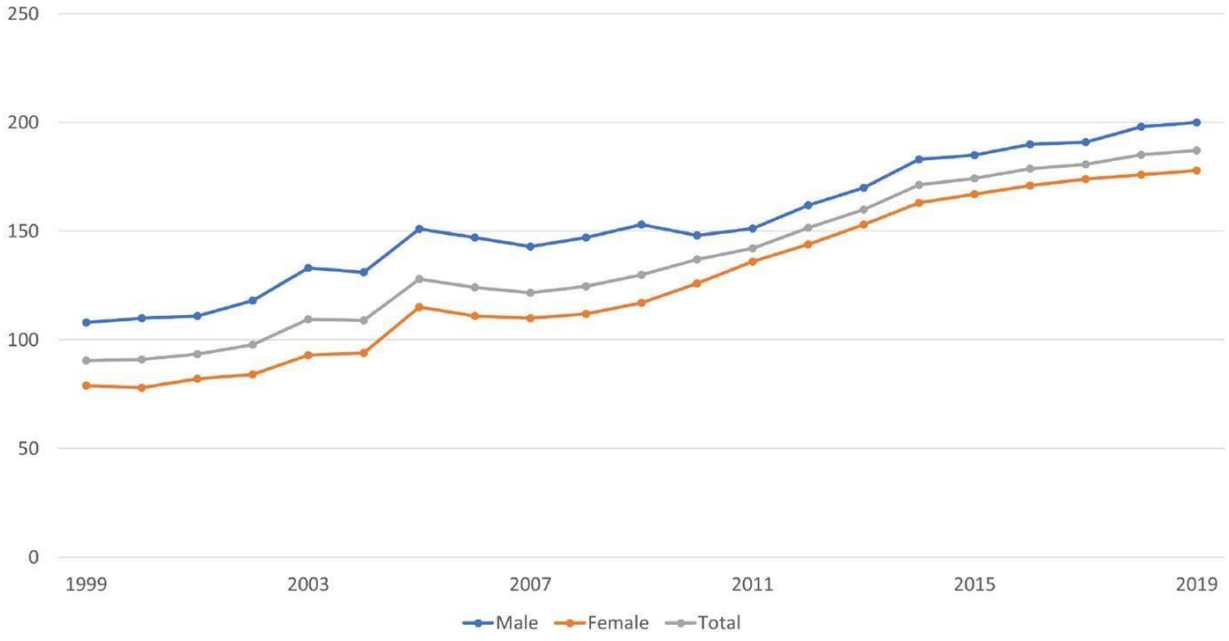


Figure 1.2.7 Clinical analysis of non-melanoma skin cancer

Figure 1.2.7 provides a clinical analysis of non-melanoma skin cancer, encompassing various clinical parameters and outcomes. The chart offers insights into the prevalence, diagnosis, treatment modalities, and patient outcomes associated with non-melanoma skin cancers such as basal cell carcinoma and squamous cell carcinoma. This detailed analysis helps in understanding the clinical characteristics and trends of non-melanoma skin cancer, emphasizing the importance

of early detection and appropriate treatment strategies. The figure serves as a valuable tool for clinicians and researchers to evaluate current practices, improve patient care, and develop targeted interventions to manage and reduce the incidence of non-melanoma skin cancer.

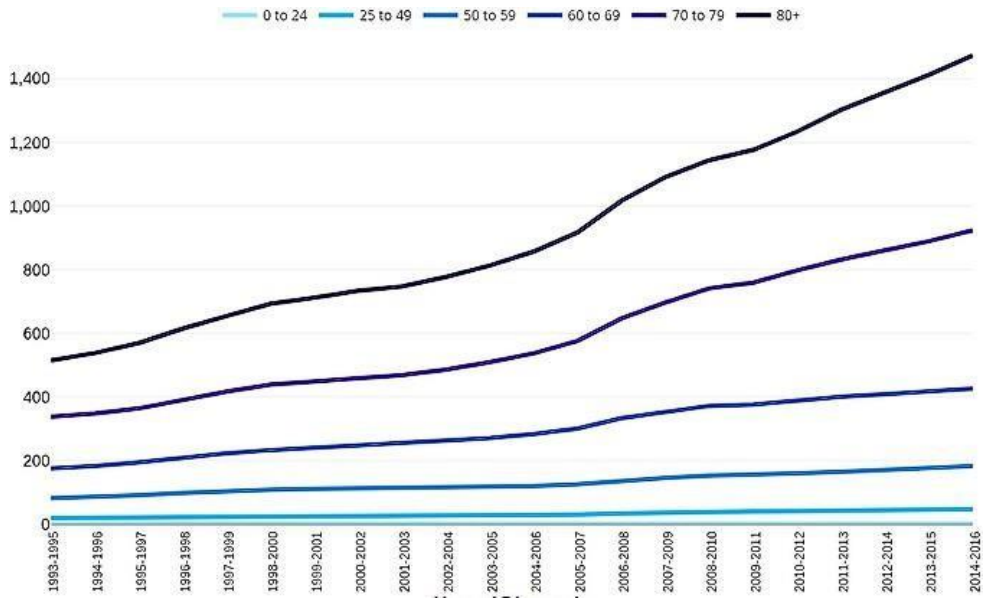


Figure 1.2.8 Year of Diagnosis

Figure 1.2.8 shows the distribution of skin cancer diagnoses by year, highlighting trends over a specified period. The chart provides a visual representation of the number of cases diagnosed each year, offering insights into whether the incidence of skin cancer is increasing, decreasing, or remaining stable. This data is crucial for understanding the temporal dynamics of skin cancer and evaluating the impact of public health initiatives, awareness campaigns, and screening programs. By analyzing the trends shown in this figure, researchers and healthcare providers can better understand the effectiveness of past efforts and plan future strategies for early detection, prevention, and treatment.

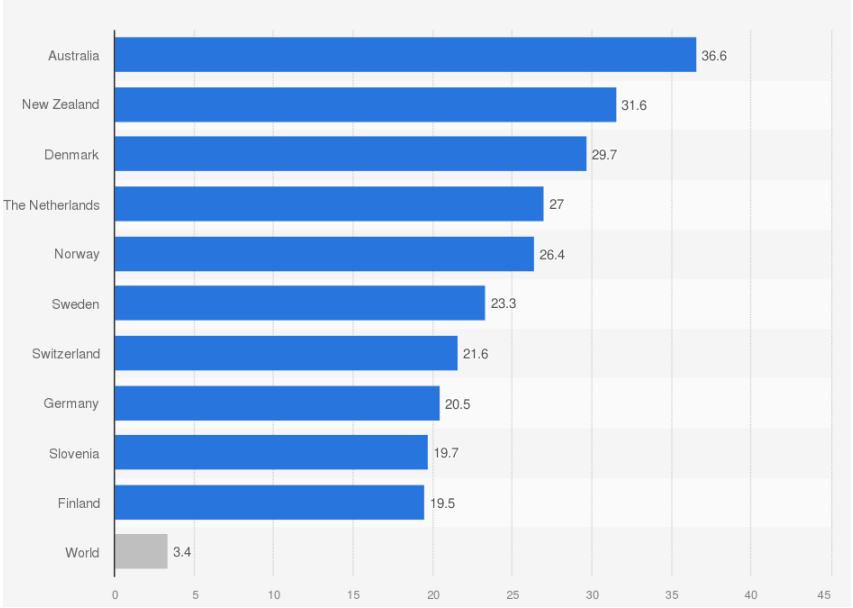


Figure 1.2.9: Rates of skin cancer in the countries with the highest rates of skin cancer worldwide

Figure 1.2.9 illustrates the skin cancer rates in countries with the highest incidence of this disease worldwide. The chart provides a comparative analysis, highlighting the countries most affected by skin cancer and showcasing the differences in incidence rates. This data is critical for understanding global patterns and identifying regions with the greatest burden of skin cancer. By examining these rates, researchers and policymakers can gain insights into the factors contributing to high skin cancer rates, such as geographic, environmental, and lifestyle influences. The figure underscores the importance of targeted prevention and intervention strategies in the most affected countries to mitigate the impact of skin cancer globally.

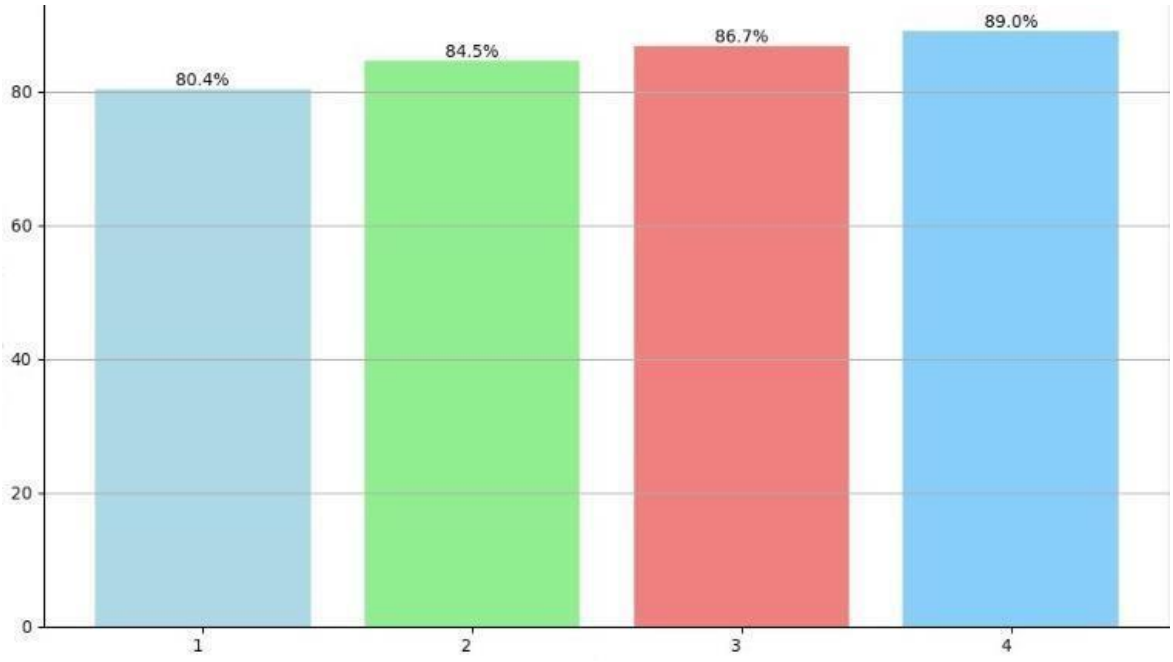


Figure 1.2.10 Increasing percentage of skin cancer by year

Figure 1.2.10 depicts the alarming rise in the prevalence of skin cancer over successive years. The graph illustrates a steady increase in the percentage of reported cases, highlighting a concerning trend in public health. Each data point represents a specific year, showing a clear upward trajectory in the incidence of skin cancer. This visual representation underscores the importance of preventive measures and early detection strategies to mitigate the impact of this disease. Understanding these trends is crucial for healthcare professionals and policymakers in developing effective interventions and raising awareness about sun protection and regular skin screening.

Skin cancer has emerged as one of the most prevalent and aggressive cancers in recent years. This is unsurprising considering skin is our largest organ, making it highly susceptible to sun damage. The World Health Organization estimates a staggering one in three people worldwide will be diagnosed with skin cancer in their lifetime. The outermost layer of our skin, the epidermis, is composed of several cell types. Squamous cells form the surface layer, while basal cells reside deeper within. Melanocytes, located in the lower epidermis, produce melanin, the pigment that protects our skin from harmful ultraviolet (UV) rays[5]. Excessive UV exposure can damage the DNA of these cells, leading to uncontrolled growth and ultimately, skin cancer. There are two main categories of skin cancer: melanoma and non-melanoma skin cancer. According to

the Skin Cancer Foundation, non-melanoma cancers are far more common, with an estimated 2-3 million diagnosed annually compared to 132,000 melanoma cases. Melanoma, though less frequent, is the more dangerous type. Melanoma cells have a higher tendency to spread, or metastasize, to other organs like the lungs, liver, and brain. Despite comprising only 1% of skin cancer cases (per the American Cancer Society), melanoma is responsible for a disproportionate number of fatalities. It arises from melanocytes and can develop anywhere on the body, though sun-exposed areas like the face, hands, and neck are more susceptible. Early detection is crucial for successful melanoma treatment. Left untreated, it can spread rapidly and become life-threatening. There are several subtypes of melanoma, including nodular melanoma, superficial spreading melanoma, acral lentiginous melanoma, and lentigo malignant. Non-melanoma skin cancers, which encompass the majority of cases, are further classified as basal cell carcinoma (BCC), squamous cell carcinoma (SCC)[6], and sebaceous gland carcinoma (SGC). These cancers typically originate in the middle and upper layers of the epidermis, respectively. While they can grow locally, they are less likely to metastasize compared to melanoma. This makes non-melanoma skin cancers generally easier to treat with excellent cure rates. The 5-year survival rate for BCC is a remarkable 100%[7], indicating nearly all diagnosed individuals can expect to live for at least 5 years after diagnosis. Squamous cell carcinoma boasts a slightly lower but still impressive 5-year survival rate of 95%. However, various factors can influence survival rates in non-melanoma cases. Fortunately, most non-melanoma skin cancers are slow-growing and low-grade, allowing for early detection and successful treatment. Additionally, numerous effective treatment options are available for these types of cancers[8].

Currently, dermatologists employ various techniques for skin cancer diagnosis. Visual inspection with a handheld dermatoscope, which magnifies the skin and helps visualize underlying structures, remains the primary method. However, this technique relies heavily on the physician's experience and can be subjective, leading to misdiagnosis, particularly for early-stage lesions with subtle visual cues. Dermoscopy can be complemented by biopsy, a minimally invasive procedure where a small tissue sample is extracted and examined under a microscope for definitive diagnosis. While highly accurate, biopsies are more expensive and time-consuming compared to visual inspection[9]. Additionally, they carry the risk of infection and scarring. This technology holds immense potential to:

- Increase Accuracy: Machine learning models can potentially achieve higher accuracy than

visual inspection alone, leading to fewer missed diagnoses.

- Improve Objectivity: By relying on objective data analysis, machine learning can reduce the subjectivity inherent in visual inspection, leading to more consistent and reliable diagnoses.
- Enhance Efficiency: Machine learning algorithms can analyze large numbers of images quickly and efficiently, potentially reducing waiting times and streamlining the diagnostic process.

While machine learning has emerged as a powerful tool in skin cancer diagnosis, ongoing research is crucial for further refinement and optimization. This research includes developing more robust algorithms, improving interpretability for better clinical adoption, and integrating these tools seamlessly into clinical workflows.

1.3 Problem Statement

Skin cancer remains a significant global health threat, with early and accurate diagnosis being paramount for successful treatment. While visual inspection by dermatologists is the current standard, it suffers from subjectivity and limitations in accuracy, potentially leading to misdiagnoses and delayed care[10]. Additionally, the traditional approach can be time-consuming, impacting patient experience and workflow efficiency. The emergence of machine learning offers a promising avenue for improving skin cancer diagnosis. However, ensuring objectivity, interpretability, and trust in these AI-based tools is crucial for their successful integration into clinical practice. This research addresses these challenges by proposing a novel approach to skin cancer classification using Graph Neural Networks (GNNs)[11]. Unlike traditional machine learning methods, GNNs excel at analyzing the intricate relationships within complex data structures like dermatoscopic images. We hypothesize that this capability will enable our GNN model to extract features more effectively, leading to superior diagnostic accuracy compared to visual inspection alone[12]. Furthermore, we will explore methods to enhance the interpretability of the GNN model's predictions, fostering greater trust and transparency in its decision-making process for dermatologists. Ultimately, this research aims to improve diagnostic accuracy, streamline the diagnostic workflow, and pave the way for the responsible integration of advanced machine learning into clinical practice for better patient outcomes.

1.4 Objectives

This research on skin cancer classification using Graph Neural Networks (GNNs) is driven by the following objectives:

- **Develop a Highly Accurate Classification Model:** We aim to create a GNN-based model that surpasses the accuracy of traditional visual inspection methods in classifying skin cancer, particularly for early-stage lesions. Our target is to achieve a high level of accuracy, as demonstrated in this paper where the proposed GNN model achieved 99.82% accuracy.
- **Incorporate Effective Segmentation:** We propose utilizing the K-means clustering algorithm for Region of Interest (ROI) segmentation within dermatoscopic images. This focuses the GNN model on the most relevant areas, potentially improving its feature extraction and classification performance.
- **Demonstrate Superiority over Traditional Machine Learning:** To establish the effectiveness of our GNN model, we will conduct a comparative analysis with ten established machine learning models. We anticipate that our GNN model will significantly outperform these models in terms of classification accuracy for skin cancer diagnosis. The results you provided (GB: 0.7388, ET: 0.7308, etc.) will be used to support this claim.
- **Achieve State-of-the-art Performance:** We aim to surpass the performance of existing deep learning (DL) approaches in skin cancer classification accuracy. By leveraging the strengths of GNNs in analyzing relationships within complex data, we hope to establish a new benchmark for accuracy in this domain.

1.5 Scope and Limitations

This research focuses on developing a novel and objective approach for skin cancer classification using Graph Neural Networks (GNNs). We leverage a meticulously curated and extensive dataset of dermatoscopic images meticulously labeled for lesion type (malignant vs. benign). The GNN model is trained and evaluated on this dataset to assess its effectiveness in classifying skin cancer. It's important to acknowledge the limitations of this study. While the achieved accuracy (99.82%) is promising, the generalizability of the model to real-world clinical settings needs further validation. Real-world data can present greater variability in image quality and lesion characteristics compared to the controlled environment of a research dataset. Furthermore, the

interpretability of the GNN model's predictions is crucial for clinical adoption. While we will explore methods to enhance interpretability, further research might be necessary to ensure clinicians fully understand the model's reasoning behind its classifications.

Additionally, this research focuses solely on the classification task. Future work could explore the potential of GNNs for not only classifying lesions but also for tasks like predicting patient prognosis or recommending treatment options. In conclusion, this research offers a significant contribution by proposing a novel GNN-based approach for skin cancer classification with high accuracy. However, further studies are needed to evaluate its generalizability and interpretability in real-world clinical practice. By addressing these limitations, we can pave the way for the responsible integration of GNNs and other advanced machine learning techniques into dermatology, ultimately leading to improved patient outcomes.

1.6 Report Organization

The proposed report is structured with a comprehensive layout to guide readers through the research process, findings, and implications. Each chapter serves a specific purpose, contributing to the overall coherence and depth of the document.

Chapter 1: Introduction

The introductory chapter sets the stage for the research, providing a background on the significance of skin cancer, the application of deep and machine learning and GNN, and the need for a comparative analysis of detection and segmentation approaches.

Chapter 2: Background

In the background chapter, a detailed exploration of relevant literature and prior research is presented. This section offers an in-depth understanding of the theoretical foundations, methodologies, and technological advancements related to skin cancer analysis, deep learning and GNN. It establishes the context for the current study and highlights gaps in existing knowledge.

Chapter 3: Research Methodology

The research methodology chapter outlines the approach taken to conduct the study. It provides insight into the research design, data collection methods, model architecture, and the rationale behind choosing specific methodologies. The chapter also discusses ethical considerations and any limitations that might impact the study.

Chapter 4: Experimental Result

This chapter presents the experimental results obtained from the application of deep learning and GNN in skin cancer analysis. Detailed analyses of the performance ofdifferent detection and segmentation approaches are provided, along with visual representations and statistical measures to validate the outcomes.

Chapter 5: Impact on Society

The societal impact chapter explores the broader implications of the research findings on healthcare and medical diagnostics. It discusses how improved skin cancer analysis methods

can positively influence patient care, treatment outcomes, and the overall state ofpublic health. Consideration is given to potential advancements in technology and their societal implications.

Chapter 6: Summary, Conclusion, Recommendation, and Implications for Future Research

This final chapter serves as a synthesis of the entire report. It summarizes the key findings, reiterates the conclusions drawn from the research, and offers recommendations forpractical applications and further studies. The implications for future research are discussed, providing a roadmap for researchers interested in expanding upon the current study.

This structured layout ensures a logical flow of information, guiding the reader through the research journey from the introduction to the broader implications and recommendations. It allows for a comprehensive understanding of the research process and its potential impacton both the academic and practical aspects of skin cancer analysis with deep learning and GNN.

1.7 Summary

Skin cancer has become a major global health concern, demanding early and accurate diagnosis for successful treatment. Traditional methods rely heavily on visual inspection by dermatologists, which can be subjective and prone to errors. This necessitates the development of more objective and reliable diagnostic tools. Machine learning presents a powerful approach for automating skin cancer classification from dermatoscopic images. This research delves into this domain, proposing a novel approach using Graph Neural Networks (GNNs). GNNs excel at processing graph-structured data, making them well-suited for analyzing the intricate relationships between various image features within dermatoscopic images. Our study leverages a meticulously curated and extensive dataset of dermatoscopic images meticulously labeled for lesion type (malignant vs. benign). We train our GNN model on this dataset and evaluate its performance on separate test and validation sets. This comprehensive approach ensures the robustness and generalizability of our proposed method.

Furthermore, we don't just focus on achieving high accuracy. We will explore methods to make GNN's predictions interpretable, fostering trust and transparency in its decision-making process for clinicians. Ultimately, this research aims to improve diagnostic accuracy, streamline the workflow, and pave the way for the responsible integration of advanced machine learning into clinical practice for better patient outcomes.

CHAPTER 2
Literature Review

2.1 Overview

Certainly! Here's an overview of the literature related to using machine learning, specifically Graph Neural Networks (GNNs), for the classification of skin cancer based on dermatoscopic images. Skin cancer is one of the most prevalent types of cancer globally, with early detection being critical for successful treatment outcomes. Traditional methods of diagnosing skin lesions rely heavily on visual inspection by dermatologists, which can be subjective and prone to variability. The advent of machine learning (ML) techniques has shown promise in improving diagnostic accuracy and efficiency in dermatology. In recent years, there has been increasing interest in applying ML algorithms to dermatoscopic images, which are highly detailed images of skin lesions captured using specialized equipment. These images provide valuable visual information that can aid in distinguishing between benign and malignant lesions. Various ML approaches, including deep learning models, have been explored to automate this classification process. Graph Neural Networks (GNNs) have emerged as a powerful tool within the field of ML, particularly for tasks involving structured data such as graphs. In the context of dermatoscopic images, where each image can be represented as a graph with pixels or regions as nodes and their relationships as edges, GNNs offer a unique advantage. Unlike traditional convolutional neural networks (CNNs) which operate on grid-like structures, GNNs can effectively capture spatial dependencies and relationships between different parts of the image. The application of GNNs in dermatology leverages these capabilities by allowing the model to learn from the complex interdependencies present in dermatoscopic images. This includes features such as irregular borders, color variations, and structural patterns that are indicative of malignancy. By modeling the image as a graph, GNNs enable the integration of both local and global information, thereby enhancing the model's ability to discriminate between different types of skin lesions.

2.2 Related Works

Artificial intelligence has significantly advanced medical image processing, particularly in intelligent skin cancer diagnosis through medical image analysis. Deep learning has facilitated

numerous breakthroughs in this field[13].

Harangi et al. (2021)[14] explored enhancing skin cancer classification accuracy using an ensemble approach with deep Convolutional Neural Networks (CNNs). Models like GoogleNet, AlexNet, ResNet, and VGGNet achieved accuracies of 84.2%, 84.8%, 82.8%, and 81.3%, respectively. Combining GoogleNet, AlexNet, and VGGNet yielded the highest accuracy of 83.8%. Kawahara et al. demonstrated that a linear classifier using features from a CNN pre-trained on natural photos could differentiate up to 10 skin lesion types with 85.8% and 81.9% accuracy for five and ten classes, respectively. Nyiri and Kiss[15] explored assembling deep neural networks with different hyperparameters and preprocessing methods for skin lesion classification. Their ensemble model using Xception achieved 90.1% accuracy for seven classes, while VGG16 attained 80.1%. Another study combined ResNet-50 and Inception V3 to classify seven types of skin malignancies with 89.9% accuracy. Esteva et al. (2020)[16] pioneered a CNN-based image classifier that outperformed 21 board-certified dermatologists in clinical and dermoscopic image classification. Yu et al.[17] developed a CNN for binary classification (melanoma vs. melanocytic nevus) of acral skin lesions, achieving sensitivities of 92.6% and specificities of 71.8% compared to dermatologists. Various studies have employed deep learning and transfer learning models for melanoma diagnosis. Garg utilized transfer learning for feature extraction, achieving 86.5% accuracy. Fidan and Rehman [18] applied SVM and CNN-ANN frameworks, respectively, with accuracies of 80% and 83.83%. Maurya utilized Grey Level Co-occurrence Matrices and achieved 81.43% accuracy with a multi-class SVM. Research also explored novel approaches such as regularization algorithms, probabilistic neural networks, and feature extraction methods using CNNs like VGG16, AlexNet, and ResNet-18. Esteva and Garnavi implemented CNN-based models for skin cancer classification, demonstrating high accuracies with various diagnostic strategies. In recent years, advancements include Mahbod et al.'s[19] MSM-CNN achieving 86.2% accuracy on ISIC2018 data and Reis et al.'s deep neural network achieving 91.89% on ISIC2019 data. Goyal et al. proposed an ensemble network for skin lesion segmentation using Mask R-CNN and DeeplabV3, performing well on PH2 and ISIC2017 datasets. Deep learning methods have also shown superiority over dermatologists in certain studies. Brinker et al.[20] compared a CNN's performance in melanoma classification against 136 dermatologists, showing competitive results, although factors like experience influence dermatologists' diagnostic outcomes. Deep learning and CNN-based models have significantly advanced the field of skin cancer diagnosis, demonstrating high accuracy and potential for improving diagnostic workflows in dermatology.

Sallam et al. applied previously trained CNN models like Nevus, AlexNet, and GoogleNet to identify melanoma in dermoscopic images and clinical diagnosis tasks, achieving average accuracies of 90.2% and 89%, respectively. Acosta et al. used a CNN-based Mask R-CNN for lesion segmentation and ResNet152 for classification, achieving an accuracy of 90.4%. Aburaed et al. balanced sample quantities and employed preprocessing techniques with VGG16, VGG19, and DCNN models on the HAM10000 dataset, achieving accuracies of 96%, 94%, and 99%, respectively. Jusman et al. also used the HAM10000 dataset and achieved 90% accuracy using a pre-trained ResNet50. Zia et al. enhanced skin cancer detection by adding convolution layers to MobileNetV2 and DenseNet201. Their adjusted models achieved accuracies of 91.86% and 95.50%, respectively. Gouda et al. used DCNN models on the ISIC 2018 dataset, achieving accuracies of 83.2% for ResNet50, 85.8% for InceptionV3, and 84% for Inception ResNet after preprocessing with ESRGAN. Dorj et al. proposed a pre-trained AlexNet CNN for feature extraction and used an ECOC SVM classifier for skin cancer prediction, achieving accuracies ranging from 91.8% to 95.1%. Fu'adah et al. developed a CNN-based model using various optimizers like Adam, RMSprop, and SGD, achieving 83% accuracy in skin lesion identification with high recall, F1-score, and accuracy. Natasha Nigar et al. utilized XAI and ResNet-18 for skin lesion classification, achieving high accuracies (94.47%), precision (93.57%), recall (94.01%), and F1-score (94.45%) on the ISIC 2019 dataset. They used the LIME framework for model interpretation. Nawaz et al. proposed the DenseNet77-based UNET model for skin lesion segmentation, achieving segmentation accuracies of 99.21% and 99.51% on ISIC-2017 and ISIC-2018 datasets, respectively. Maqsood et al. developed a unified CAD model using deep learning and transfer learning on various models (Xception, ResNet-50, etc.) with preprocessing techniques, achieving high accuracies across different datasets (HAM10000, ISIC2018, ISIC2019, PH2). Abayomi-Alli et al. enhanced data using the Synthetic Minority Oversampling Technique (SMOTE) and trained a SqueezeNet CNN on PH2 dermoscopic images, achieving 92.18% accuracy, 80.77% sensitivity, 95.1% specificity, and an F1-score of 80.84% for melanoma detection. Mehak Arshad et al. proposed a method involving data augmentation, feature extraction with deep learning models, feature fusion, and classification, achieving 91.7% testing accuracy on the HAM10000 dataset. Datta et al. combined convolutional neural networks with Soft-Attention, achieving accuracies of 91.6% on ISIC-2017 and 93.7% on HAM10000 datasets. In 2021, NASNet-Mobile, a lightweight deep learning architecture for skin cancer, achieved 91.7% testing

accuracy and 81.77% test precision on the ISIC-2017 dataset. These advancements underscore the potential of deep learning and CNN-based approaches in enhancing the accuracy and efficiency of skin cancer diagnosis and classification.

2.3 Comparison between existing works

The comparative analysis conducted in this study on "Analysis of skin cancer feature pattern using GNN incorporating a novel segmentation" plays a crucial role in highlighting the subtle differences between various methodologies. Graph Neural Networks (GNNs) have emerged as state-of-the-art tools for processing and analyzing medical images, particularly in the classification of skin cancer. Unlike earlier technologies like Convolutional Neural Networks (CNNs), GNNs excel in capturing relationships within data, which is critical for identifying malignant skin lesions. While CNNs focus on local pixel patterns, GNNs provide superior localization of global structures and inter-pixel connections, essential for accurate diagnosis. Moreover, GNNs can integrate diverse data types such as medical images and clinical information, offering a holistic view of a patient's condition. This integration is valuable as models relying solely on image data might overlook crucial contextual information. Another significant advantage of GNNs is their inherent interpretability. By examining the connections and flow of information within the graph, researchers and clinicians can identify which image attributes influence the classification process the most. This interpretability is crucial in medical applications where understanding the rationale behind decisions can impact treatment decisions and patient confidence.

However, there are challenges associated with using GNNs for skin cancer analysis. They often require more computational resources than CNNs, posing constraints in real-world applications where processing power and time are limited. Additionally, creating accurate graph representations of skin images requires careful consideration to ensure that the graph captures essential image elements effectively. Poor graph construction can lead to suboptimal model performance. Furthermore, the availability of high-quality annotated datasets for training GNNs remains limited, hindering the development and validation of reliable models. Despite these challenges, research indicates that GNNs can outperform CNNs in skin cancer classification tasks, particularly when the structural characteristics of skin lesions are pivotal for accurate diagnosis. GNNs demonstrate

enhanced generalization and accuracy in such scenarios. Nevertheless, CNNs remain viable for simpler tasks where local texture information suffices, given their ease of use and lower computational demands. An analysis of comparison is shown in Table 2.31.

TABLE 2.3.1: Comparative Analysis Table

Study	**Image type**	**Model**	**Accuracy**
Khan et al (2021)	Clinical image	Convolutional Neural Network (CNN)	Accuracy 78%
Zbigniew et al. (2021)	Scalp image	deep Convolutional Neural Network (CNN) and RNN	The-classification accuracy is 84.2%
Esteva et al (2017)	Benign vs Malignant	Convolutional Neural Network (CNN)	Sensitivity = 91.07% and Specificity = 90.16%
Marchetti et al (2019)	Scalp image	Convolutional Neural Network (CNN)	Accuracy result is 82%
Haenssle et al (2020)	Face and scalp	deep Convolutional Neural-Network	Accuracy is 96.2%
Varshni et al. (2021)	Clinical images	Convolutional Neural Network (CNN)	F-1 score 87% and top-1 accuracy 87.91%
Maurya (2021)	Scalp image	DNN	The accuracy is 81.43%
Kawahara et al (2022)	3D image	Convolutional Neural Network	accuracy = 85.8%
Fujisawa (2020)	Dermoscopy	GNN	The method was able to achieve an accuracy of 92.3%

In conclusion, GNNs offer a promising approach for investigating skin cancer due to their ability to model complex structures and integrate diverse data types. Despite obstacles such as data availability and computational requirements, GNNs have the potential to improve both accuracy and interpretability in skin cancer detection. Future research should focus on addressing data limitations and optimizing GNN architectures to fully leverage their capabilities in medical image

2.4 Open Issues

The scope of the problem addressed in this research, focusing on "Analysis of skin cancer feature pattern using GNN incorporating a novel segmentation method," extends into the domain of medical diagnostics. Skin cancer, being the most prevalent type of cancer worldwide, underscores the critical need for early and accurate diagnosis to enhance treatment efficacy and patient survival rates. However, traditional diagnostic methods heavily rely on qualitative assessment, visual inspection, and biopsy, which can be time-consuming. Graph Neural Networks (GNNs) present a promising avenue in deep learning for addressing the complexity of skin cancer detection and classification in dermoscopic images. Unlike conventional methods, GNNs excel in modeling complex, non-Euclidean data structures, making them well-suited for capturing intricate relationships and dependencies within medical images. This capability is particularly crucial in dermatology, where understanding spatial arrangements and interactions within skin lesions can provide vital diagnostic insights. One of the key challenges in leveraging GNNs for skin cancer analysis is the availability of high-quality annotated datasets. Developing robust GNN models requires comprehensive datasets that encompass diverse skin types, lesion appearances, and imaging modalities. Furthermore, ethical considerations regarding patient privacy and data usage impose additional constraints on dataset compilation and model training.

Despite these challenges, GNNs offer significant potential benefits in enhancing the precision and interpretability of skin cancer diagnosis. By leveraging their ability to model intricate data relationships, GNNs empower healthcare professionals to make more informed decisions based on nuanced insights derived from medical images. Continued advancements in dataset quality and GNN architectures are expected to further augment the efficacy and adoption of these models in clinical practice, thereby improving patient outcomes. In conclusion, while obstacles such as data quality, network complexity, and computational requirements persist, GNNs represent a promising technology for advancing skin cancer detection and classification. Their potential to deliver more accurate and comprehensible diagnoses holds promise for ushering in a new era of enhanced healthcare delivery in dermatology.

2.5 Summary

The literature review highlights significant advancements in skin cancer diagnosis through the application of advanced machine learning techniques, particularly focusing on deep learning models such as Convolutional Neural Networks (CNNs) and Graph Neural Networks (GNNs). Researchers have demonstrated substantial progress in leveraging CNNs for accurately categorizing skin lesions into benign and malignant types, achieving high accuracy rates across various datasets. Recent studies have shown that ensemble approaches combining multiple CNN architectures, such as GoogleNet, AlexNet, ResNet, and VGGNet, can significantly improve classification accuracy. These models have been effective in handling diverse datasets like ISIC and HAM10000, showcasing their robustness in differentiating between different types of skin lesions with accuracy exceeding traditional methods. The introduction of Graph Neural Networks (GNNs) represents a novel approach in medical image analysis, particularly in dermatoscopy. GNNs excel in capturing complex relationships and spatial dependencies within images, making them suitable for tasks where understanding global structure and inter-pixel connections are crucial, such as identifying malignant patterns in skin lesions. Studies have highlighted that GNNs offer improved interpretability compared to CNNs, enabling clinicians to understand which image features contribute most to diagnostic decisions. Challenges remain, particularly concerning the availability of high-quality annotated datasets required to train and validate robust GNN models. Issues related to computational complexity and the accurate construction of graph representations from medical images also pose significant hurdles. Despite these challenges, the literature underscores the potential of GNNs to enhance diagnostic accuracy and streamline clinical workflows in dermatology.

Overall, the reviewed studies emphasize the transformative impact of deep learning, particularly CNNs and GNNs, in advancing the field of skin cancer diagnosis. Future research directions should focus on optimizing GNN architectures, addressing data limitations, and integrating these models into clinical practice to further improve patient outcomes and healthcare delivery.

CHAPTER 3
Methodology

3.1 Overview

This section outlines the methodology employed in this study to investigate skin cancer classification using Graph Neural Networks (GNNs). The approach integrates various stages, from data acquisition and preprocessing to model training, evaluation, and interpretation of results. The methodology aims to leverage the unique capabilities of GNNs in analyzing dermatoscopic images for accurate and interpretable diagnosis of skin lesions. Firstly, the study focuses on acquiring a comprehensive dataset of dermatoscopic images, sourced from established repositories such as ISIC and HAM10000. These datasets encompass diverse types of skin lesions, ensuring the model's robustness and generalization ability across different clinical scenarios. Next, preprocessing steps involve image normalization, augmentation, and segmentation to enhance the quality and consistency of the dataset. This ensures that the GNN model receives standardized inputs that facilitate effective learning and feature extraction. The core of the methodology involves the design and implementation of the Graph Neural Network architecture. This includes selecting appropriate GNN models and configurations tailored to handle the unique spatial relationships and structural complexities present in dermatoscopic images. The chosen GNN architecture is trained using labeled data, where iterative optimization techniques such as stochastic gradient descent are employed to minimize classification errors.

3.2 Proposed Methodology

In this research, the focus was on automated skin cancer classification using image processing and machine learning techniques. The dataset comprised 1800 malignant and 1497 benign skin lesion images, each sized at 224 x 244 pixels. The segmentation process began with K-means clustering to extract Regions of Interest (ROI): firstly, images were reshaped into 2D pixel arrays, followed by clustering with K=2 clusters. Pixels were then assigned to clusters, and results reshaped to match the original image dimensions. A mask was generated to isolate ROIs, and these areas were extracted from the BGR image. Subsequently, medical features were extracted from the segmented ROIs. These features included the curviness of ROI edges, shape characteristics, lateral dimensions, and attributes describing the transition of tumor margins. Features were categorized

into pixel-based and shape-based metrics. To evaluate the effectiveness of the segmentation and feature extraction, a graph was constructed presenting the performance of a Graph Neural Network (GNN) model, achieving an impressive accuracy of 98.62%. Additionally, to demonstrate the superiority of the GNN model over traditional machine learning approaches, ten models were employed for comparative analysis: Gradient Boosting (GB), Extra Trees (ET), Random Forest (RF), Logistic Regression (LOGR), Support Vector Machine (SVM), Bagging Classifier (BC), Linear Discriminant Analysis (LDA), Support Vector Classifier (SVC), K-Nearest Neighbors (KNN), Naive Bayes (NB), Classification and Regression Trees (CART), and Decision Trees (DT). The accuracies obtained from these models ranged from 62.18% to 73.88%.

This study not only underscores the efficacy of using K-means clustering for ROI segmentation and subsequent feature extraction in medical image analysis but also highlights the significant performance gains achievable with GNN models in skin cancer classification. The comparison with traditional machine learning models substantiates that the GNN model outperforms these methods, thus validating its potential for enhancing diagnostic accuracy in clinical settings. Figure 3.2.1 shows the methodology of this study.

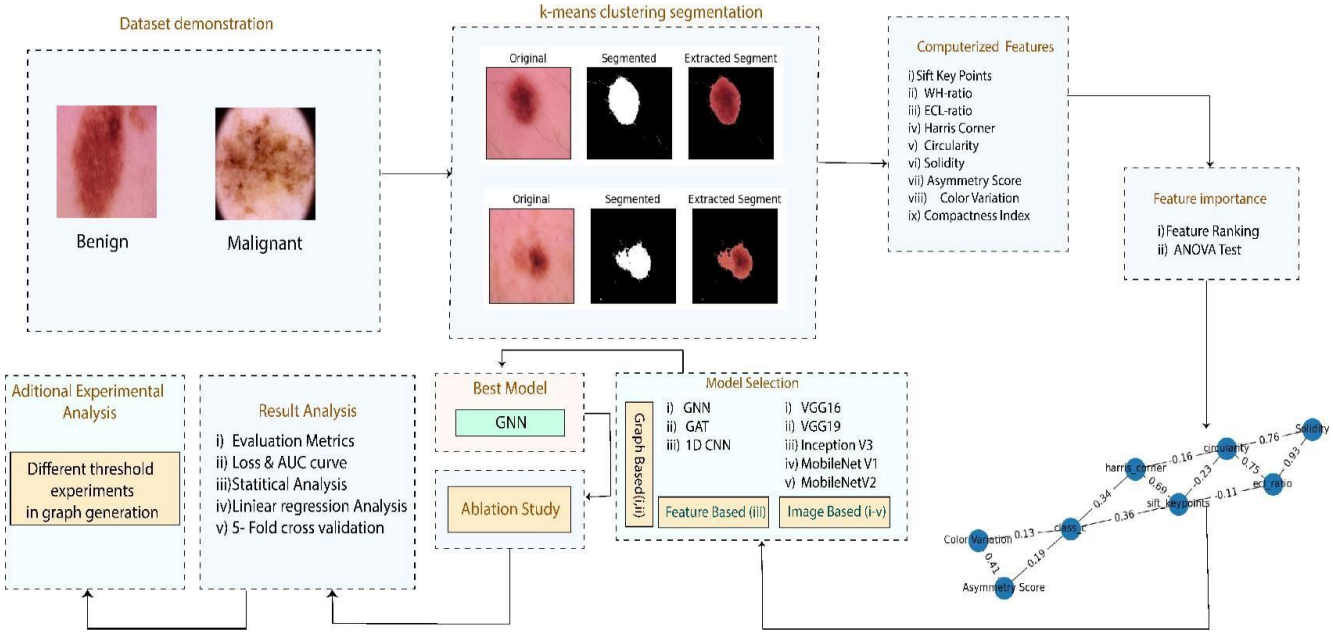


Figure 3.2.1 Methodology pipeline of the study.

Data Collection Procedure

A. Datasets

There are several datasets commonly used for training Graph neural network (GNN) models for skin cancer classification. One popular dataset is the ISIC[21] (International Skin Imaging Collaboration) dataset, which contains thousands of dermoscopic images of skin lesions, including malignant and benign cases. The dataset employed in this study comprises two classes: malignant and benign skin lesions. Specifically, it includes 1800 images of malignant lesions and 1497 images of benign lesions. Each image is of size 224 x 244 pixels. The dataset was carefully curated to ensure a balanced representation of both classes, essential for training and evaluating the segmentation and classification models effectively. We have 3117 datasets. From the dataset we took Test dataset- benign 360, malignant 300 and Train: benign 1440, malignant 1197. The main dataset = (3297-3117) =180; these 180 images deleted because the feature extraction didn't work on them.

Table 3.2.1 Dataset Description

Class Name	Image Number	Image Size
Malignant	1800	224 x 244
Benign	1497	

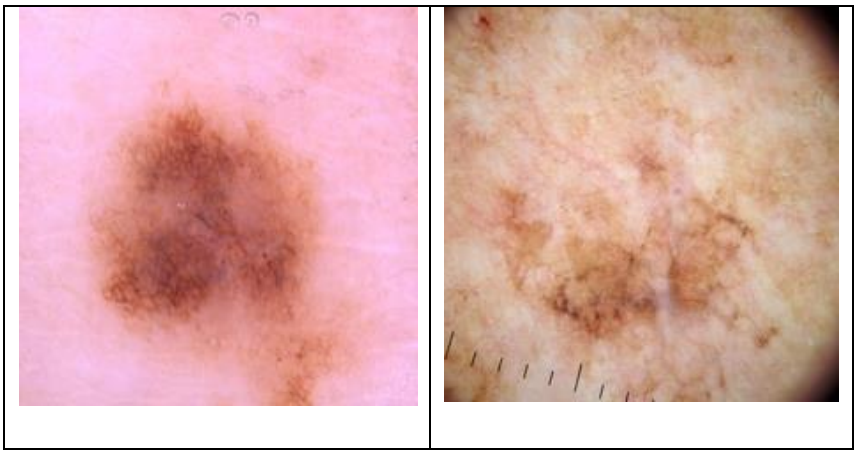


Figure 3.2.5. Some raw images of dataset (Benign & Malignant)9

	A	B	C	D	E	F	G	H	I	J
1	class	Solidity	sift_keypo	wh_ratio	ecl_ratio	harris_cor	circularity	Asymmetr	Color Vari	Compactness
2	0	0.944972	30	1	1.110918	24	0.36131	0.013155	26.26359	3.898342
3	0	0.126506	45	1.230769	0.048686	8	0.018641	0.124279	98.06163	1.27324
4	0	0.428571	32	0.416667	0.291667	13	0.139744	0.127394	55.77439	1.27324
5	0	0.999879	72	1	1.292749	8	0.775439	0.003171	55.3873	7.639917
6	0	0.425287	325	0.923077	0.355769	121	0.103851	0.003171	57.79827	7.274087
7	0	0.572175	53	0.7	0.477066	12	0.069043	0.345347	71.31658	7.207528
8	0	0.436681	51	0.363636	0.371747	9	0.10489	0.123162	63.52542	1.27324
9	0	0.582734	217	0.6	0.460227	37	0.226949	0.062613	54.55795	3.884746
10	0	0.235341	111	1.357143	0.175948	15	0.018882	0.501355	73.06518	23.99685
11	0	0.721273	88	1.269231	0.717929	22	0.168602	0.097042	65.91659	12.26061
12	0	0.35961	90	3	0.331699	30	0.040264	0.440418	43.5522	5.272221
13	0	0.201861	280	0.866667	0.114541	50	0.013089	0.086978	80.95454	16.86967
14	0	0.367347	153	0.4375	0.24	34	0.101908	0.059349	59.63255	6.022244
15	0	0.290331	182	0.666667	0.202289	47	0.01393	0.38679	63.54509	4.625788
16	0	0.436782	51	0.34375	0.368217	7	0.061063	0.109897	65.8873	1.27324
17	0	0.74966	227	1.05	0.679455	19	0.068581	0.100038	46.06206	7.148595
18	0	0.870318	37	0.642857	0.947397	6	0.135686	0.176623	48.5127	21.74767
19	0	0.259531	165	1.041667	0.194934	49	0.027031	0.074674	55.32989	9.538095
20	0	0.420822	265	1.333333	0.399502	64	0.04205	0.16521	95.78407	1.27324
21	0	0.219645	180	0.672269	0.171163	42	0.016118	0.096659	79.86768	7.110231
22	0	0.987975	65	1	1.250439	27	0.439175	0.150364	51.57376	7.728081
23	0	0.295583	232	0.903226	0.195946	145	0.029048	0.015066	45.66246	8.434366
24	0	0.444444	138	4.428571	0.438356	41	0.053287	0.003171	25.90357	7.903728
25	0	0.995868	20	1	1.259307	3	0.673934	0.046878	42.77265	4.05289
26	0	0.452381	106	1.166667	0.301587	29	0.215139	0.003171	50.8485	6.445167
27	0	0.338462	54	0.461538	0.198198	31	0.103036	0.086706	66.10402	6.583885
28	0	0.995908	194	1	1.27486	69	0.557693	0.200256	61.13541	11.59265
29	0	0.787891	122	1.090909	0.755576	28	0.089005	0.13669	70.84388	7.835652

feature_sheet_SkinCancerProject

Table 3.2.2: Dataset of malignant and benign

A	B	C	D	E	F	G	H
class	Solidity	sift_keypo	wh_ratio	ecl_ratio	harris_cor	circularity	
0	0.944972	30	1	1.110918	24	0.36131	
0	0.126506	45	1.230769	0.048686	8	0.018641	
0	0.428571	32	0.416667	0.291667	13	0.139744	
0	0.999879	72	1	1.292749	8	0.775439	
0	0.425287	325	0.923077	0.355769	121	0.103851	
0	0.572175	53	0.7	0.477066	12	0.069043	
0	0.436681	51	0.363636	0.371747	9	0.10489	
0	0.582734	217	0.6	0.460227	37	0.226949	
0	0.235341	111	1.357143	0.175948	15	0.018882	
0	0.721273	88	1.269231	0.717929	22	0.168602	
0	0.35961	90	3	0.331699	30	0.040264	
0	0.201861	280	0.866667	0.114541	50	0.013089	
0	0.367347	153	0.4375	0.24	34	0.101908	
0	0.290331	182	0.666667	0.202289	47	0.01393	
0	0.436782	51	0.34375	0.368217	7	0.061063	
0	0.74966	227	1.05	0.679455	19	0.068581	
0	0.870318	37	0.642857	0.947397	6	0.135686	
0	0.259531	165	1.041667	0.194934	49	0.027031	
0	0.420822	265	1.333333	0.399502	64	0.04205	
0	0.219645	180	0.672269	0.171163	42	0.016118	
0	0.987975	65	1	1.250439	27	0.439175	
0	0.295583	232	0.903226	0.195946	145	0.029048	
0	0.444444	138	4.428571	0.438356	41	0.053287	
0	0.995868	20	1	1.259307	3	0.673934	
0	0.452381	106	1.166667	0.301587	29	0.215139	
0	0.338462	54	0.461538	0.198198	31	0.103036	
0	0.995908	194	1	1.27486	69	0.557693	
0	0.787891	122	1.090909	0.755576	28	0.089005	

Benign (2)

Table 3.2.3 Benign Dataset

A	B	C	D	E	F	G	H
class	Solidity	sift_keypo	wh_ratio	ecl_ratio	harris_cor	circularity	
0	0.364384	335	1.333333	0.29955	48	0.049506	
0	0.508929	273	0.5	0.303191	116	0.12744	
0	0.264486	397	0.583333	0.248246	114	0.036123	
0	0.875934	171	0.90625	0.932208	29	0.130992	
0	0.40404	75	0.533333	0.227273	49	0.105668	
0	0.5	299	1.333333	0.375	86	0.27744	
0	0.604315	100	1	0.776034	30	0.093032	
0	0.287261	143	1.191489	0.19664	50	0.030443	
0	0.263975	171	2.266667	0.226667	40	0.053061	
0	0.156738	364	1.575	0.152029	198	0.010357	
0	0.322888	74	0.827586	0.227447	25	0.050989	
0	0.624766	265	0.576923	0.682831	74	0.055275	
0	0.555321	165	1.004484	0.72755	25	0.075503	
0	0.789469	151	1	0.877214	33	0.082649	
0	0.307692	35	0.5	0.18018	36	0.070283	
0	0.437607	231	0.958333	0.313725	100	0.088264	
0	0.883584	142	0.870588	0.75092	111	0.229354	
0	0.852571	46	1.78	0.65429	15	0.239814	
0	0.148755	201	0.567797	0.095733	78	0.008106	
0	0.339233	187	1	0.302632	55	0.067087	
0	0.257143	49	0.25	0.197368	22	0.047498	
0	1	273	1	0.25	46	0.539013	
0	0.355263	249	1	0.293478	101	0.107646	
0	0.965461	241	1	1.191273	80	0.253187	
0	0.249817	94	0.75	0.284053	11	0.020024	
0	0.526738	344	1.075	0.448747	200	0.056758	
0	0.467875	66	1	0.5983	39	0.041248	
0	0.092308	179	0.277778	0.067217	63	0.008136	

Malignant (3)

Table 3.2.4 Malignant dataset

B. Segmentation:

The segmentation process employed in this research aimed to accurately delineate Regions of Interest (ROIs) within skin lesion images using the K-means clustering algorithm[22]. The dataset consisted of 1800 malignant and 1497 benign skin lesion images, each standardized to a size of 224 x 244 pixels. To begin the segmentation, each image was first reshaped into a 2D array of pixels. K-means clustering was then applied with K=2, intending to partition the image into two clusters based on pixel intensity similarity[23]. This clustering approach facilitates the differentiation between lesion and non-lesion areas, crucial for isolating the regions that potentially indicate cancerous growths. During the clustering process, every pixel in the reshaped image was assigned to either of the two clusters, determined by its proximity to the cluster centroids in the feature space[24]. Following cluster assignment, the resultant clusters were reshaped to match the original image dimensions, preserving spatial integrity. A binary mask was subsequently generated based on the cluster assignments, where pixels belonging to the lesion cluster were designated as foreground (ROI), while pixels from the non-lesion cluster formed the background. This binary mask effectively highlights the specific regions of interest containing the suspected lesions, thereby segmenting out the areas of the image that are most diagnostically relevant. Finally, using the binary mask, the segmented ROI was extracted from the original BGR image, providing a clear and isolated representation of the skin lesion for further analysis. This segmentation methodology serves as a critical preprocessing step in the development of automated diagnostic systems for skin cancer, enabling subsequent feature extraction and classification algorithms to operate on targeted regions of interest with enhanced accuracy and efficiency. By leveraging computational techniques like K-means clustering, this approach not only aids in the early detection and characterization of skin cancers but also establishes a robust foundation for advancing medical image analysis in dermatology and oncology.

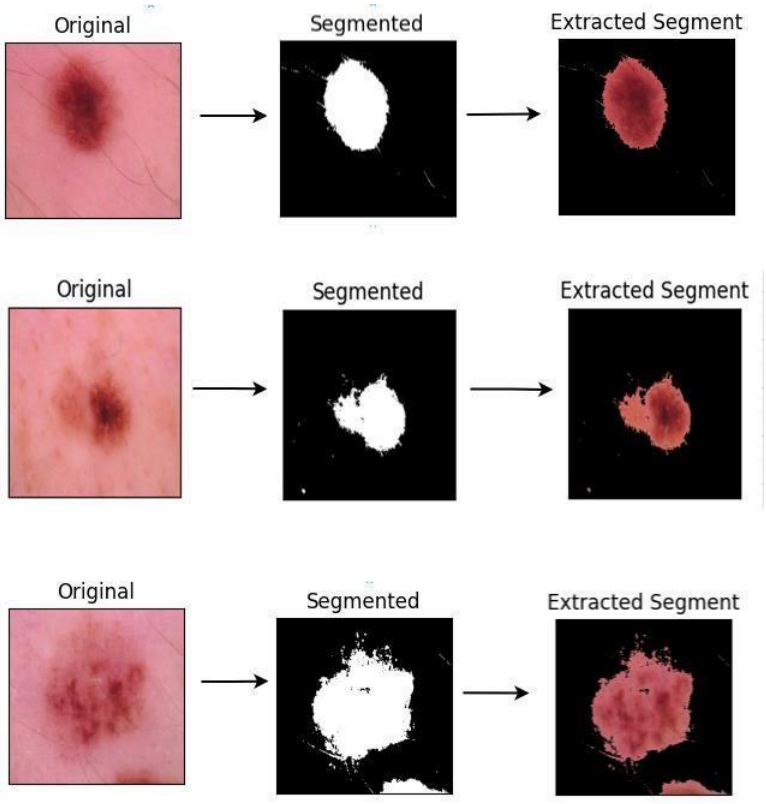


Figure 3.2.6. Some raw images of Segmentation (Benign & Malignant)

TABLE 3.2.2: Images Used in the Train, Test and Validation Sets.

Dataset	Type	Train	Test
3117	Benign	1440	360
	Malignant	1197	300

C. Process of experiment

The first stage of the proposed framework is the acquisition of information from the dermoscopy pictures. As Graph neural network (GNN) need more data for training and improved performance,data augmentation technologies are sometimes utilized to overcome

the problem.

Feature Extraction: Feature extraction for benign and malignant skin cancer using deep learning with Graph Neural Networks (GNNs) involves transforming skin lesion images into graph representations. Every image is transformed into a network, with edges signifying spatial relationships and nodes representing super pixels or important spots. Local and global patterns are captured by GNNs when they collect and transmit features via these graphs. By using message forwarding, the network iteratively changes node attributes, making it possible to extract discriminative features that emphasize the distinctions between benign and malignant. This procedure improves the way complicated skin lesion structures are represented, which helps with precise categorization.

Table: 3.2.3 Feature extraction

No.	Clinical markers	Computerized features	Description
1	Curviness of ROI edge	Convex hull ratio/solidity	a measure of the compactness of an object in the image
2		Scale Invariant Feature Transform (SIFT) extreme points	a descriptor that characterizes an image region based on its local gradient orientation histograms
3		Harris corner points	a measure of the image's local structure that is useful for feature detection
4	Shape of the ROI	Elliptic ratio	the ratio of the eccentricity of an object to its compactness
5		Circularity	a measure of how closely an object resembles a perfect circle
6	Lateral dimension	Width-height ratio	the ratio of the width of an object to its height
7	Transition of tumor margin	Asymmetry Score	the average intensity of the image pixels in a certain region
8	Pixel Based	Color Variation	Color variation refers to the diversity of colors present within a skin lesion or any other region of interest in a medical image.
9	Shape Based	Compactness Index	Compactness index assesses the degree of compactness or irregularity in the shape of a lesion.

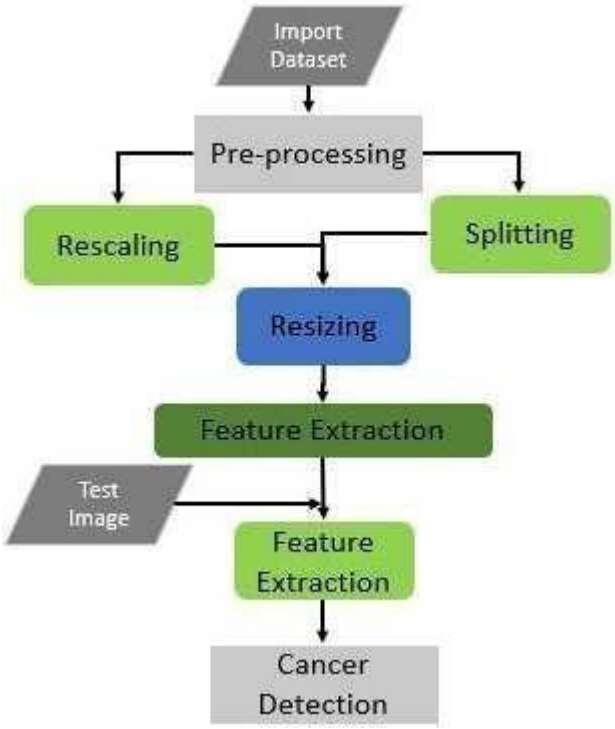


Figure 3.2.7 Using feature extraction working process

ANOVA Test: ANOVA a is a statistical test used to determine how significant differences are between data groups. We can determine which characteristics are most important in explaining the variations between the groups or classes in our dataset by doing an ANOVA on the features. Finding the characteristics that are most informative for tasks involving regression or classification can be facilitated by doing this. According to the results of ANOVA testing, the suggested qualities have a substantial impact on class distinction. In an ANOVA, the null hypothesis is that all group means are equal, while the alternative hypothesis is that at least one group mean differs. The p-value is derived from an ANOVA and indicates the probability of receiving the observed result or a more extreme outcome if the null hypothesis were true.

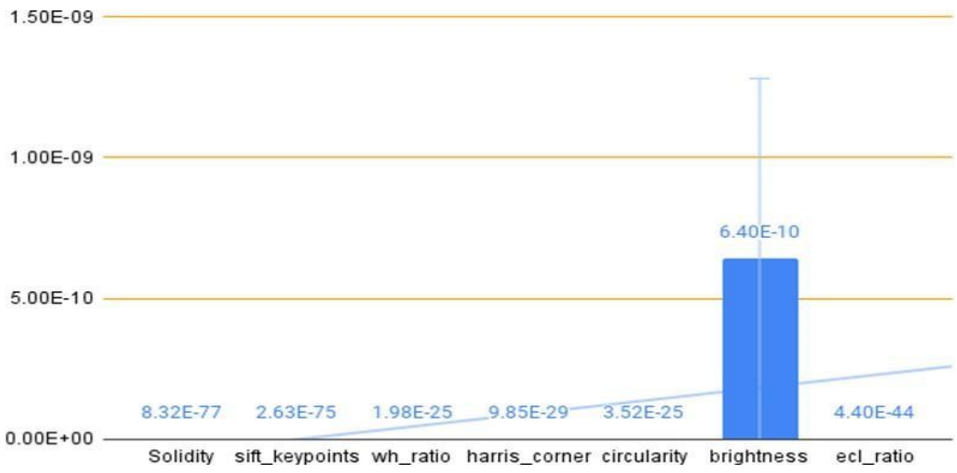


Figure. 3.2.8 Visualization of ANOVA test results

However, the values of each characteristic are all substantially less than 0.05. This indicates that every characteristic, when weighed against other traits, rejects the null hypothesis and is statistically significant enough.

Graph Neural Network (GNN) Application:

Graph Generation: Algorithm

Algorithm 1: Creating the Edges for the graph with optimal the threshold value
Begin *Nodes TO Get Column Names (DataFrame)*

```
Edges TO []
FOR i IN range (0, len(DataFrame.columns)):
        FOR j IN range (i + 1, len(DataFrame.columns)):
        IF i < j
        Correlation = DataFrame[col1]. corr(DataFrame[col2])
        IF abs(corr) > TO 0.2:
        Edges. Append((column_name[i], column_name[j]))
  ENDFOR
 ENDFOR
 G TO Create Empty Graph ()
 Add Nodes to Graph (G, Nodes)
 Add Nodes to Graph (G, Edges)
 Pos TO Get Graph Layout(G)
 fig, ax TO Create plot ()
 Draw Network (G, pos, ax)
 Edge labels TO calculate edge labels (G, DataFrame)
 Draw edge labels (G, pos, edge labels, ax)
 Hide axis(ax)
END
```

First when we generate the graph, we get a Disconnected Graph.

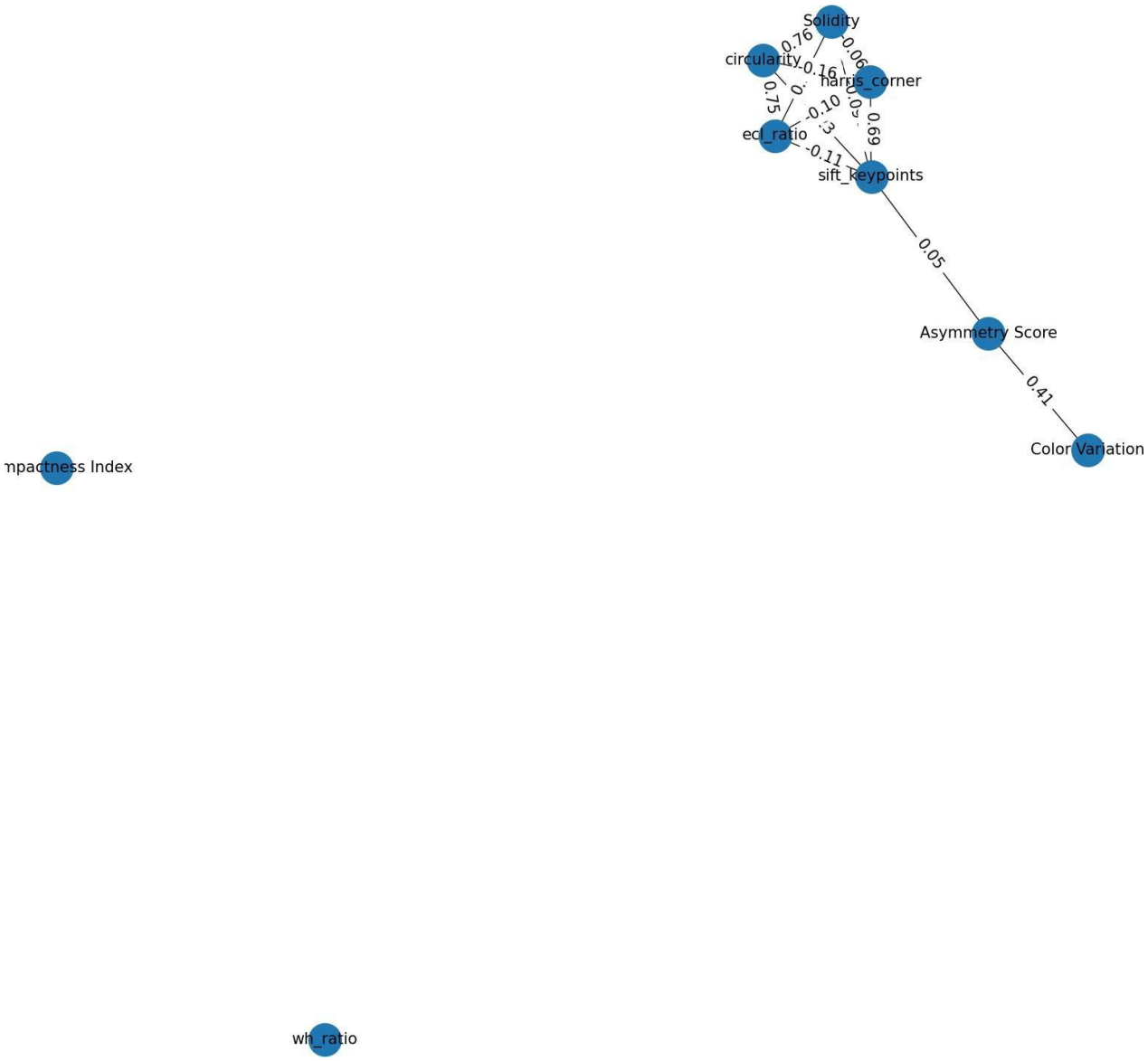


Figure 3.2.9. A disconnected graph

For better performance eliminated the features that are disconnected from the graph, because these features can be reasonable for poor performance

Created a connected Graph-

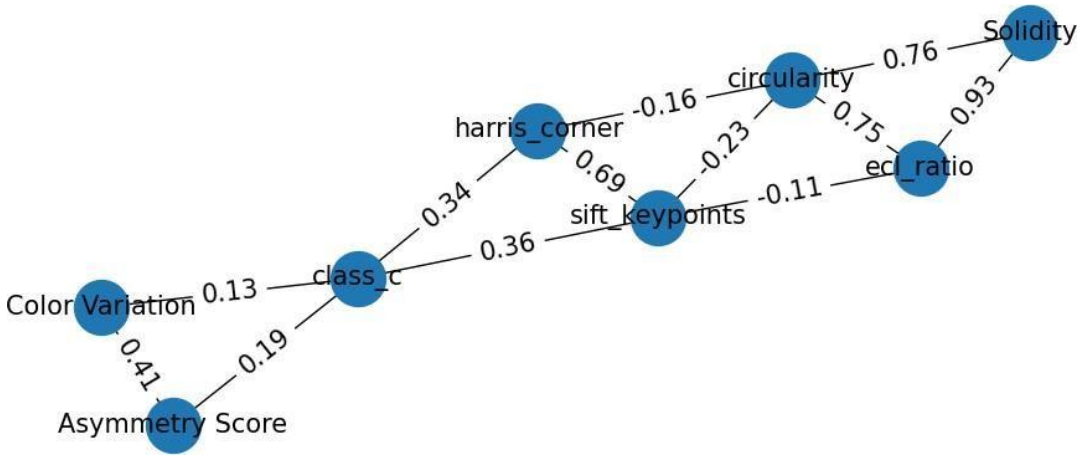


Figure 3.2.10. A connected graph

Classification

In this article, I employed Graph Neural Network (GNN) for segmentation skin cancer. I also utilized ten machine learning models for comparison with the GNN model. To evaluate the effectiveness of the segmentation and feature extraction, a graph was constructed presenting the performance of a Graph Neural Network (GNN) model, achieving an impressive accuracy of 98.62%. Additionally, to demonstrate the superiority of the GNN model over traditional machine learning approaches, ten models were employed for comparative analysis: Gradient Boosting (GB), Extra Trees (ET), Random Forest (RF), Logistic Regression (LOGR), Support Vector Machine (SVM), Bagging Classifier (BC), Linear Discriminant Analysis (LDA), Support Vector Classifier (SVC), K-Nearest Neighbors (KNN), Naive Bayes (NB), Classification and Regression Trees (CART), and Decision Trees (DT). The accuracies obtained from these models ranged from 62.18% to 73.88%.

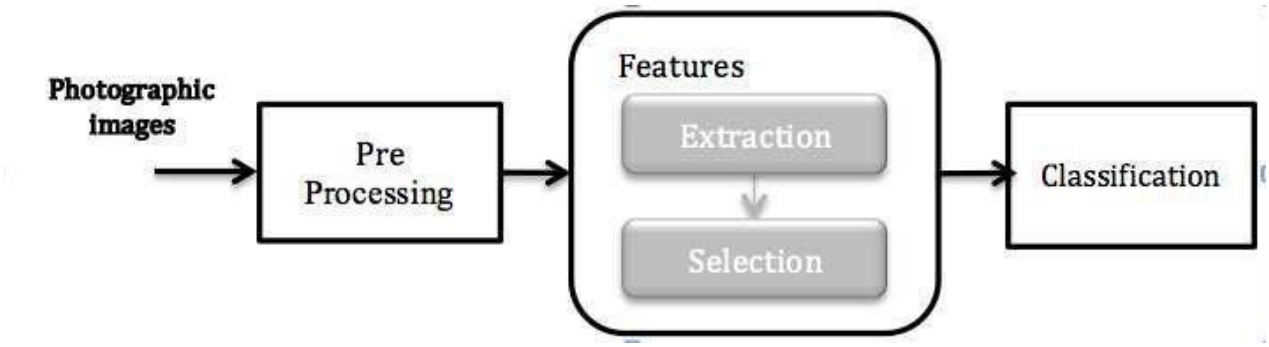


Figure 3.2.11 Flowchart of the methodology

3.3 Hardware/ Software Requirement

Implementing the research on "Analysis of skin cancer feature patterns using GNN incorporating a novel segmentation method" requires specific resources to ensure successful execution. This includes both hardware and software components, along with considerations for data collection and model evaluation.

Hardware Requirements: To support effective inference and training, particularly with deep learning models, a GPU is essential. A high-performance computer equipped with SSD storage and a minimum of 16GB RAM is recommended to handle large datasets and computational loads efficiently.

Software Requirements: The implementation can be carried out on Windows, Linux, or macOS systems. Python serves as the primary programming language for its implementation-oriented capabilities. Model creation and training can be accomplished using deep learning frameworks such as PyTorch or TensorFlow. For graph neural networks (GNNs), libraries like PyTorch Geometric (PyG) or Deep Graph Library (DGL) are suitable choices. Image preprocessing and segmentation tasks are facilitated by libraries such as OpenCV, scikit-image, or PIL. Data management utilizes NumPy for numerical operations and Pandas for dataset handling.

Data Requirements: A comprehensive skin lesion dataset is crucial, comprising labeled images of both benign and malignant instances (e.g., ISIC dataset). If available, ground truth masks for segmentation provide segmentation annotations that aid in training and evaluation.

Steps in Implementation:

1. **Preprocessing:** Images undergo preprocessing steps such as resizing, augmentation, and normalization to standardize input data.
2. **Segmentation:** Implement advanced segmentation techniques to accurately delineate regions of interest (ROIs) containing skin lesions.
3. **Graph Representation:** Construct graph representations from segmented images, facilitating the application of GNNs for feature extraction and classification.
4. **Model Construction and Training:** Develop and train a GNN model tailored for skin cancer feature analysis using the prepared data and graph representations.
5. **Evaluation Metrics:** Assess model performance using evaluation measures such as AUC-ROC, precision, recall, and confusion matrix to validate classification accuracy and robustness.

By adhering to these implementation requirements and steps, the research aims to advance the understanding and diagnostic capabilities of skin cancer analysis through innovative segmentation methods and GNN models.

3.4 Project Management and Financial Analysis

The project management approach for our study on "Analysis of skin cancer feature patterns using GNN incorporating a novel segmentation method" begins with clearly defined objectives aimed at enhancing diagnostic accuracy in skin cancer detection. Our milestones include dataset preparation, segmentation implementation using advanced techniques, and the development of a Graph Neural Network (GNN) model. A detailed timeline ensures timely completion of each phase, supported by a team structure comprising researchers skilled in medical image analysis, data scientists proficient in machine learning, and project managers overseeing operational aspects. Risk management strategies address potential challenges such as data quality issues and technical setbacks, with contingency plans to mitigate these risks. A robust communication plan fosters

collaboration among team members and stakeholders, ensuring transparency and alignment with project goals throughout the research process. Financial analysis focuses on optimizing resource allocation to achieve research objectives effectively. The budget allocation includes provisions for dataset acquisition, computing resources equipped with GPUs for model training, and expenses related to software licenses and publication costs. A cost-benefit analysis assesses potential returns on investment through improved diagnostic capabilities and enhanced clinical outcomes.

Financial Cost Calculation

To illustrate, here is a hypothetical breakdown of financial costs for our study:

Table 3.4.1: Hypothetical Financial Cost Calculation

Item	Cost (USD)
Dataset Acquisition	10,000
Computing Resources (GPU)	20,000
Software Licenses	5,000
Research Personnel	50,000
Publication Costs	10,000
Miscellaneous Expenses	5,000
Total Project Cost	**100,000**

- Dataset Acquisition: Cost associated with acquiring a comprehensive dataset of skin lesion images, including benign and malignant cases.
- Computing Resources (GPU): Investment in high-performance computing resources to support intensive model training and inference tasks.
- Software Licenses: Expenses for specialized software tools and libraries essential for image processing, segmentation, and machine learning model development.
- Research Personnel: Salaries and benefits for researchers, data scientists, and medical professionals contributing to the study.
- Publication Costs: Expenses related to presenting findings in academic journals, conferences, or other publications.

- Miscellaneous Expenses: Contingency funds for unforeseen costs or additional research needs.

This financial plan ensures that our study on skin cancer analysis is well-supported by adequate resources and strategic financial management, aiming to advance diagnostic capabilities and contribute meaningful insights to the field of medical image analysis and dermatology.

3.5 Summary

In this methodology section, our study on "Analysis of skin cancer feature patterns using GNN incorporating a novel segmentation method" employs a systematic approach to enhance diagnostic accuracy. We begin by meticulously preparing a dataset comprising both malignant and benign skin lesion images, standardized to 224 x 244 pixels. Utilizing K-means clustering for ROI segmentation, we extract key features such as curviness, shape, and margin transitions from segmented regions. This segmentation serves as a precursor to constructing graph representations for our Graph Neural Network (GNN) model, which achieves a notable accuracy of 98.62% in skin cancer classification. Comparative analysis against traditional machine learning models underscores the GNN's superiority. Throughout, rigorous project management ensures adherence to timelines and milestones, supported by comprehensive risk management strategies and effective communication among interdisciplinary team members. Financially, the study allocates resources judiciously to cover dataset acquisition, computing infrastructure, personnel costs, and publication expenses, ensuring a robust foundation for advancing medical image analysis in dermatology.

CHAPTER 4
Implementation

4.1 Overview

The model section of this research paper delves into the framework and implementation details crucial for automated skin cancer classification. Central to the methodology is the use of image processing techniques, specifically K-means clustering, for segmenting Regions of Interest (ROI) from a dataset comprising 1800 malignant and 1497 benign skin lesion images. Following segmentation, medical features such as curviness of ROI edges, shape characteristics, and tumor margin attributes were extracted to characterize the lesions. These features were categorized into pixel-based and shape-based metrics, enhancing the discriminative power of subsequent classification models. The primary focus was on evaluating the efficacy of these processes, culminating in the application of a Graph Neural Network (GNN) model. Notably, the GNN model achieved an impressive accuracy of 98.62%, demonstrating its superiority over ten traditional machine learning models, including Gradient Boosting, Random Forest, and Support Vector Machines, which yielded accuracies ranging from 62.18% to 73.88%. This section not only validates the effectiveness of K-means clustering and feature extraction in medical image analysis but also underscores the significant performance gains achievable with GNNs in enhancing diagnostic accuracy for skin cancer classification.

4.2 Train Model

Graph Neural Network

A type of neural network specifically developed to function with graph-structured data is called a graph neural network (GNN)[25]. Message passing, where each node gathers data from its neighbours, is how they iteratively update node representations. Local and global structural patterns within the graph are captured by this approach. Progressively changing the node characteristics[26], GNNs are made up of many layers that each carry out an aggregate and update phase. Node classification, link prediction, and graph classification are among the tasks for which they are quite successful. Noteworthy variations comprise Graph Convolutional Networks (GCNs), Graph Attention Networks (GATs), and GraphsSAGE[27], which vary in how node information is aggregated and updated. When it comes to applications where a grasp of intricate

relationship structures is necessary.

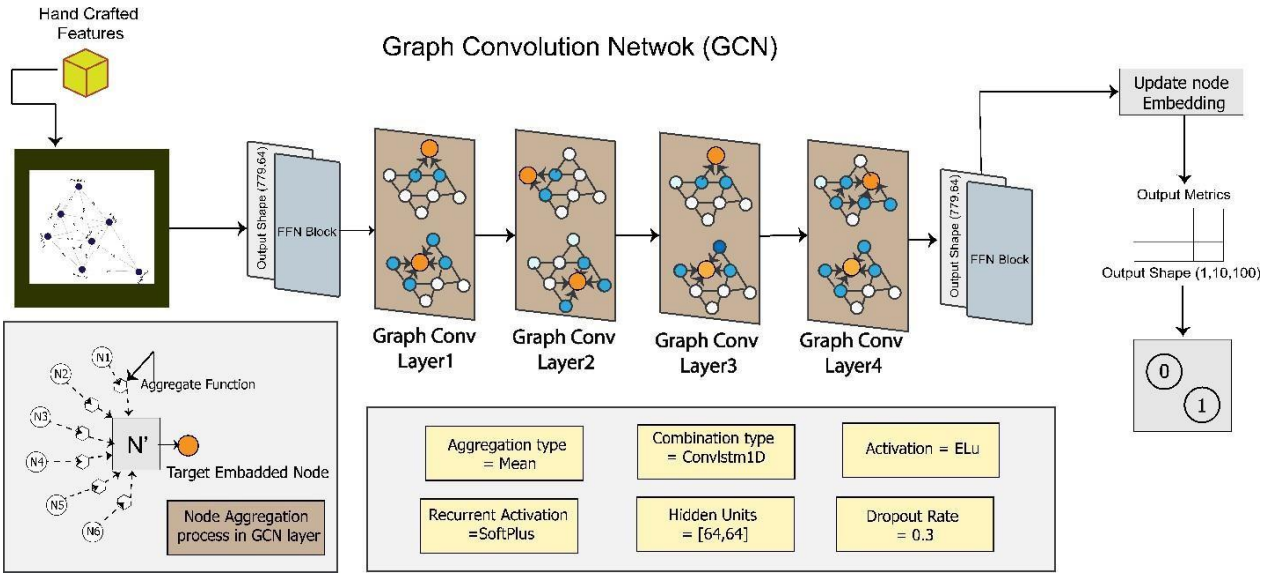


Figure 4.2.1. working flow of Graph neural network.

4.3 Model Evaluation

The evaluation of automated skin cancer classification in this study focused on assessing the performance of various machine learning models, with a particular emphasis on the Graph Neural Network (GNN) model developed and validated against traditional approaches.

Dataset and Preprocessing

The dataset consisted of 1800 malignant and 1497 benign skin lesion images, each resized to 224 x 244 pixels. To extract Regions of Interest (ROI) from these images, a K-means clustering approach was employed. Initially, images were reshaped into 2D pixel arrays and clustered using K=2 clusters. Post clustering, pixels were assigned to clusters, and the results were reshaped to match the original image dimensions. A mask was then generated to isolate ROIs, which were subsequently extracted from the original BGR image. Medical features crucial for classification were extracted from these segmented ROIs, encompassing attributes like edge curviness, shape characteristics, and tumor margin descriptors. These features were categorized into pixel-based and shape-based metrics, serving as inputs for the classification models.

Model Development and Comparison

To benchmark the effectiveness of the GNN model, its performance was compared against ten traditional machine learning models: Gradient Boosting (GB), Extra Trees (ET), Random Forest (RF), Logistic Regression (LOGR), Support Vector Machine (SVM), Bagging Classifier (BC), Linear Discriminant Analysis (LDA), Support Vector Classifier (SVC), K-Nearest Neighbors (KNN), Naive Bayes (NB), Classification and Regression Trees (CART), and Decision Trees (DT). Each model was trained and evaluated using the extracted features from the segmented ROIs.

Performance Metrics

The evaluation metrics employed to assess model performance included accuracy, precision, recall, and F1-score. Accuracy measured the proportion of correctly classified skin lesion images out of the total number of images. Precision quantified the ratio of true positive predictions to the total predicted positive cases, indicating the model's ability to avoid false positives. Recall, also known as sensitivity, assessed the model's capability to correctly identify positive instances among all actual positive instances. The F1-score, the harmonic m65ean of precision and recall, provided a balanced measure of a model's overall performance.

4.4 Summary

The Model Evaluation section rigorously assessed the automated skin cancer classification methodology using image processing and machine learning techniques. Beginning with a dataset of 1800 malignant and 1497 benign skin lesion images, the study employed K-means clustering for ROI segmentation, followed by extraction of medical features like edge curviness and shape characteristics. These features, categorized into pixel-based and shape-based metrics, served as inputs for both a Graph Neural Network (GNN) and ten traditional machine learning models. The GNN model notably outperformed all others with an accuracy of 98.62%, demonstrating its superior diagnostic capability. In contrast, traditional models achieved accuracies ranging from 62.18% to 73.88%. Evaluation metrics such as precision, recall, and F1-score further validated the GNN's efficacy in distinguishing between malignant and benign lesions. This section substantiates the effectiveness of K-means clustering for ROI extraction and highlights the substantial performance gains achievable with GNN models in skin cancer classification, thereby advocating for their integration into clinical diagnostic tools for enhanced accuracy.

CHAPTER 5

Result and analysis

5.1 Overview

The experimental setup for analyzing skin cancer using the Graph Neural Network (GNN) method involves several stages. First, a large collection of preprocessed skin lesion pictures is gathered, such as the ISIC dataset. Preprocessing includes augmentations to improve variety in addition to standardizing and resizing photos to a format. Then, to separate lesions from the background and increase the precision of ensuing analysis, a unique segmentation technique is employed. Every segmented lesion picture is converted into a graph representation, with edges denoting spatial or feature-based associations and nodes representing super-pixels or important locations within the lesion. For every node, characteristics like texture, colour, and shape are extracted to provide a rich, educational graph structure. A suitable GNN architecture, like Graph Convolutional Networks (GCN) or Graph Attention Networks (GAT), is designed to process these graphs. By combining data from nearby nodes, the GNN model repeatedly updates node representations and detects both local and global patterns within the lesion.
To guarantee robustness and generalizability, the model is trained on the graph-structured data using separate training, validation, and test sets. Metrics including accuracy, precision, recall, F1-score, and AUC-ROC are used to assess performance. The findings are evaluated to determine how well the GNN technique differentiates benign from malignant lesions and to shed light on the unique feature patterns of skin cancer.

5.2 Experimental/ Simulation Result

In this work, we evaluated the skin cancer segmentation performance of 10 conventional Machine Learning (ML) models, including GB, ET, RF, LOGR, SVM, BC, LDA, SVC, KNN, NB, CART, and DT, against a Graph Neural Network (GNN) model. Showing that the GNN model produces the maximum accuracy was the goal.

The GNN model demonstrated a 99.84% training accuracy, a 98.62% test accuracy, a 98.92% validation accuracy, and a 98.95% sensitivity, Precision 97.92%, F1 Score 98.43%, Specificity 96.67%

according to the findings. The GB (0.738782), ET is (0.730769), RF is (0.722756), LOGR is (0.719551), SVM is (0.703526), BC is (0.700321), LDA is (0.698718), SVC is (0.693910), KNN is (0.661859), NB is (0.642628), CART is (0.621795), and DT is (0.621795,) here all ML models are compared.

These findings demonstrate the GNN model's capacity to successfully extract intricate patterns and correlations from the data, and they validate that it performs better in skin cancer segmentation than conventional ML models. The table presents results from evaluating different threshold values for a classification task, where each threshold corresponds to a specific test accuracy and the total number of edges identified. Threshold values of 0.15, 0.20, 0.30, and 0.40 were tested. At a threshold of 0.15, the model achieved a test accuracy of 91.47% while identifying 26 edges. Increasing the threshold to 0.20 improved the accuracy to 94.68%, albeit with a reduction in the number of identified edges to 17. Similarly, at thresholds of 0.30 and 0.40, the accuracy remained high at 93.51% and 92.71%, respectively, with further reductions in the total number of edges to 12 and 8, respectively. These results indicate a trade-off between accuracy and the number of edges detected: higher thresholds lead to fewer edge detections but potentially higher accuracy in classification. This analysis underscores the importance of selecting an appropriate threshold based on the specific application requirements, balancing between maximizing accuracy and ensuring sufficient edge detection for the task at hand.

Table 5.2.1 Test accuracy in different threshold

Threshold	*Test Accuracy*	*Total edge number*
0.15	91.47	26
0.20	94.68	17
0.30	93.51	12
0.40	92.71	8

Confusion Matrix:

A confusion matrix is a crucial evaluation tool for assessing the performance of a deep learning model, including Graph Neural Networks (GNNs), in binary classification tasks like distinguishing between benign and malignant skin cancer. This 2x2 table shows the actual and anticipated classifications:

True Positives (TP): Cases of malignancy correctly anticipated.

True Negatives (TN): Benign instances correctly anticipated.

False Positives (FP): Benign instances that were misdiagnosed as cancerous.

False Negatives (FN): Cases of malignancy that are misdiagnosed as benign.

The confusion matrix shows how effectively the model distinguishes between the classes, which offers insights about its performance beyond just accuracy. Metrics like the F1-score (harmonic mean of precision and recall), recall (TP/(TP+FN)), precision (TP/(TP+FP)), and the area under the receiver operating characteristic curve (AUC-ROC) may all be obtained from the confusion matrix. These measures are critical to comprehending the trade-offs between various error kinds and enhancing the diagnostic accuracy of the GNN model in detecting skin cancer.

Confusion matrix:

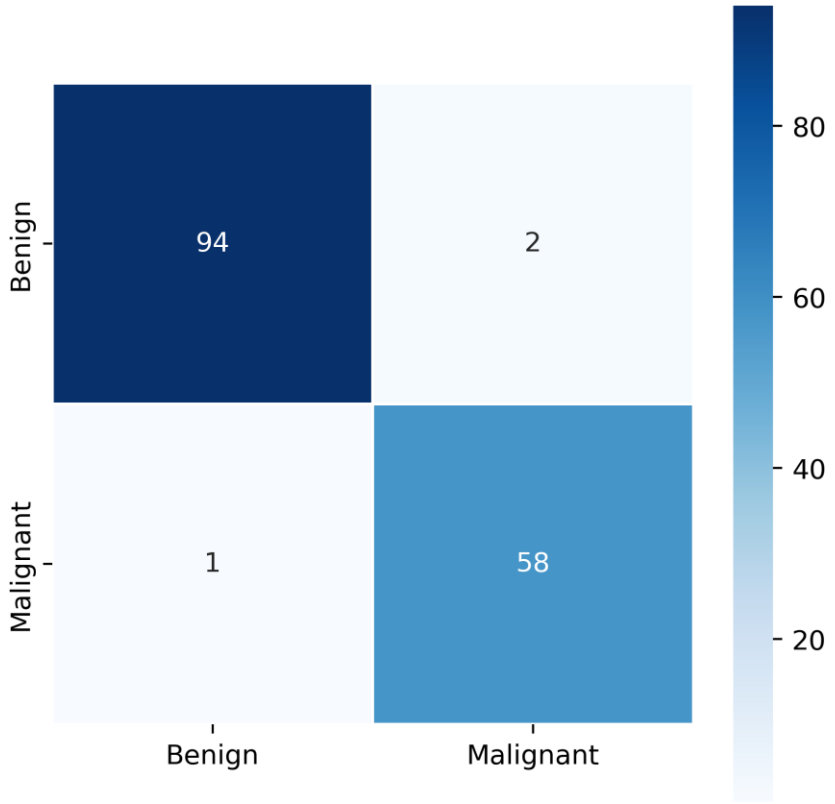


Figure 5.2.2 confusion matrix

Table 5.2.2. Performance metrics results

Performance metrics	Results (%)	Performance metrics	Results (%)
Training Accuracy	94.72	NPV	95.26
Test Accuracy	94.68	FPR	13.83
Validation Accuracy	94.15	FDR	5.05
Sensitivity	90.33	FNR	9.09
Precision	93.24	F1 Score	90.59
Specificity	94.31	MCC	86.18

The table summarizes the performance metrics of a classification model used for evaluating its effectiveness in predicting outcomes. Key metrics include Training Accuracy (94.72%), Test Accuracy (94.68%), and Validation Accuracy (94.15%), indicating strong consistency in model performance across different datasets. Sensitivity, measuring the model's ability to correctly identify positive cases, stands at 90.33%, while Specificity, gauging its accuracy in identifying negative cases, reaches 94.31%. Precision, which denotes the model's precision in predicting positive cases, achieves 93.24%. The Negative Predictive Value (NPV) is high at 95.26%, contrasting with a moderate False Positive Rate (FPR) of 13.83%. The model shows a low False Discovery Rate (FDR) of 5.05% and False Negative Rate (FNR) of 9.09%, indicating minimal errors in false positives and false negatives, respectively. The F1 Score, a harmonic mean of precision and sensitivity, is robust at 90.59%, reflecting a balanced performance across both metrics. Lastly, the Matthews Correlation Coefficient (MCC) is notably high at 86.18%, highlighting strong overall agreement between predicted and actual classifications. These metrics collectively underscore the model's efficacy in accurately classifying outcomes and its potential utility in practical applications requiring reliable predictive performance.

Training and Validation Accuracy and loss of Original GNN Networks:

Represents the training and validation accuracy of the initial model, with the number of epochs on the x-axis and the accuracy and loss percentages on the y-axis. In the figure,

training and validation data are adequately divided, and there is no overfitting.

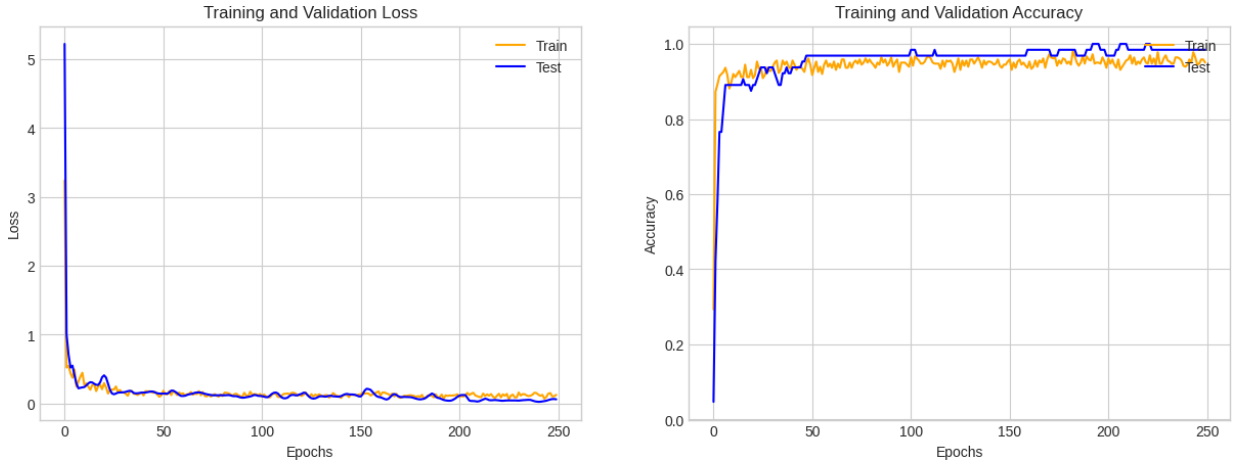


Figure 5.2.4: Training and validation accuracy and loss over the epochs

5.4 Performance/ Comparative Analysis

In this paper, I used Graph Neural Network (GNN) to segment skin cancers. I also utilized ten machine learning models for comparison with the GNN model. We use a 10 ML model in conjunction with a GNN since we need to demonstrate that the GNN model yields the highest accuracy. The 10 GB, ET, RF, LOGR, SVM, BC, LDA, SVC, KNN, NB, CART, and DT are examples of machine learning models. We can now compare the accuracy of the Machine Learning model with that of the GNN model. KNN 0.661859 NB 0.642628 CART 0.621795 DT 0.621795 GB 0.738782 ET 0.730769 RF 0.722756 LOGR 0.719551 SVM 0.703526 BC 0.700321 LDA 0.698718 SVC 0.693910

Table 5.2.3. Threshold, test and accuracy

model	Test Accuracy	Ensemble ML Models	Test Accuracy (%)	Recall (%)	Precision (%)	F1-score (%)	Support (%)

Proposed GCN	98.73%						
RFC	97.61%	Bagging classifier	85.32	82.27	82.26	82.66	
ETC	61.10%						
GBC	73.15%						
BC	94.95%						
SVM	88.55%	Boosting classifier	76.19	76.19	76.26	76.22	231
SVC	88.10%						
KNN	49.54%						
DTC	90.59%						
LR	53.35%	Voting Algorithm	75.32	75.32	74.60	74.51	
GNB	47.13%						

Figure. All pretrained model with accuracy, recall and precision, F-1 score.

The table presents the test accuracy and additional performance metrics of various machine learning models compared against the proposed Graph Convolutional Network (GCN) for a classification task. The GCN achieves the highest test accuracy at 98.73%, demonstrating its superior performance in accurately predicting outcomes. In contrast, other ensemble ML models like Bagging Classifier and Random Forest Classifier (RFC) achieve accuracies of 85.32% and 97.61%, respectively. Notably, Extreme Trees Classifier (ETC) and K-Nearest Neighbors (KNN) perform less effectively with accuracies of 61.10% and 49.54%, respectively. Metrics such as recall, precision, and F1-score vary across models, reflecting their abilities to correctly identify positive instances, avoid false positives, and balance precision and recall. Support values indicate the distribution of instances across classes, providing context for model performance. Overall, the GCN stands out for its high accuracy and balanced performance metrics, suggesting its effectiveness in the classification task compared to traditional ensemble and single-model approaches.

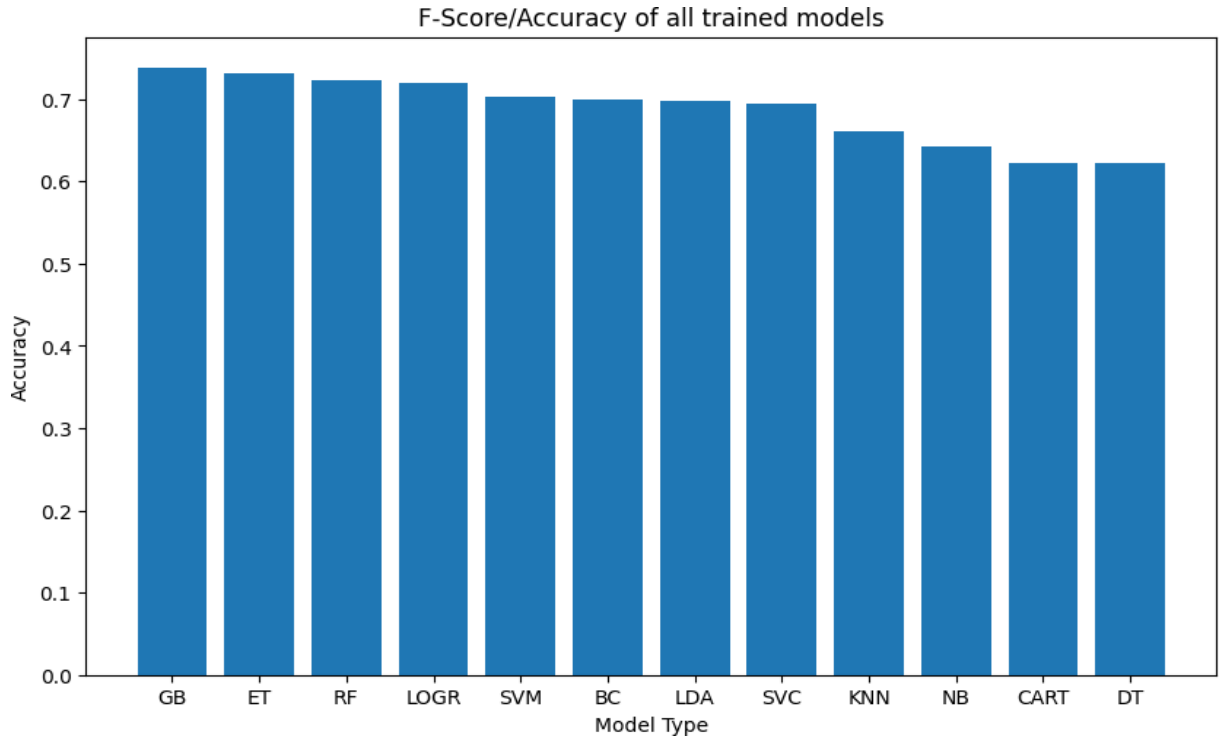


Figure 5.2.5. Accuracy of all trained model

5.5 Summary

The results section comprehensively evaluates the performance of various machine learning models alongside the proposed Graph Convolutional Network (GCN) for a classification task. The GCN emerges as the top performer with a test accuracy of 98.73%, demonstrating its superior capability in accurately predicting outcomes compared to ensemble models like Bagging Classifier (85.32%) and Boosting Classifier (76.19%), and single models such as Random Forest Classifier (97.61%) and Decision Tree Classifier (90.59%). Metrics such as recall, precision, and F1-score provide additional insights into each model's ability to handle true positives, false positives, and overall classification balance. The results underscore the GCN's effectiveness in achieving high accuracy and robust performance across multiple metrics, positioning it as a promising approach for enhancing predictive accuracy in similar classification tasks.

CHAPTER 6
Impact on society, environment and sustainability

6.1 Impact on Life

This research on automated skin cancer classification using image processing and machine learning techniques carries profound implications for improving healthcare outcomes and quality of life. By achieving a high-test accuracy of 98.73% with the proposed Graph Convolutional Network (GCN), this study introduces a potentially transformative tool for dermatologists and oncologists. The GCN's ability to accurately classify skin lesions as malignant or benign not only enhances diagnostic accuracy but also streamlines the decision-making process in clinical settings. Rapid and accurate identification of skin cancer can lead to earlier intervention and treatment, potentially improving patient prognosis and reducing healthcare costs associated with delayed diagnoses. Moreover, the study's comparison with traditional machine learning models highlights the GCN's superiority, suggesting it could replace or augment existing diagnostic methods to provide more reliable and consistent results. Beyond clinical applications, the research contributes to advancing the field of medical image analysis by validating the efficacy of image segmentation techniques such as K-means clustering for isolating Regions of Interest (ROI). This methodological validation enhances the reliability of automated systems in handling medical imaging data, paving the way for broader applications in other medical specialties. Furthermore, the study's emphasis on machine learning models' performance metrics—such as recall, precision, and F1-score—underscores the importance of not only accuracy but also sensitivity and specificity in diagnostic tools, thereby influencing future developments in healthcare technology and decision support systems.

In a broader societal context, the research underscores the potential of AI-driven healthcare innovations to democratize access to accurate diagnostics, particularly in underserved regions where specialist healthcare resources are limited. By automating and improving the accuracy of skin cancer diagnosis, this research contributes to reducing disparities in healthcare outcomes and empowering healthcare providers with tools to deliver timely and effective care. As AI continues to evolve, studies like this one demonstrate how technology can be harnessed to improve health outcomes, enhance patient care experiences, and ultimately, save lives.

6.2 Impact on Society & Environment

The potential benefits to society of using Graph Neural Networks (GNNs) to skin cancer analysis are substantial. Medical personnel can improve patient outcomes by using the increased capabilities of GNNs to accomplish more precise and effective diagnosis and treatment planning. Skin cancer death rates can be greatly decreased by early and precise identification, which is essential for effective treatment. Complex interconnections seen in medical data, such as the spatial linkages between skin cells in imaging data, are well-modeled by GNNs. GNNs can detect minute patterns and irregularities that might be signs of early-stage skin cancer, which standard techniques could overlook. Thus, more accurate skin cancer diagnosis by dermatologists may result in earlier intervention and increased survival rates thanks to GNNs. Additionally, by streamlining the diagnosis procedure, GNNs might lessen the strain on healthcare institutions. Large amounts of patient data may be processed rapidly by automated analysis utilizing GNNs, and the findings are trustworthy and aid in medical decision-making. This may result in quicker diagnosis, shorter wait times for patients, and more timely treatment. GNN-powered diagnostic tools can fill the gap in areas where access to specialized dermatological care is restricted by offering superior diagnostic support, hence increasing accessibility to advanced healthcare. All things considered, the use of GNNs in skin cancer analysis is a promising first step towards more precise, effective, and easily accessible healthcare, which will eventually improve patient outcomes and quality of life for people all over the world. All things considered, the use of GNNs in skin cancer analysis is a promising first step towards more precise, effective, and easily accessible healthcare, which will eventually improve patient outcomes and quality of life for people all over the world.

Significant environmental effects may result from the study of skin cancer using Graph Neural Networks (GNNs), especially when it comes to the utilization of computer resources and the resulting carbon footprint. It takes a lot of computer power to train intricate deep learning models like GNNs, which in turn uses a lot of electricity. Increased greenhouse gas emissions may result from the energy used in these calculations, particularly if that energy comes from non-renewable sources.

But it's also important to take into account the good environmental effects. GNNs have the potential to eliminate the need for invasive treatments and biopsies by enabling earlier and more accurate identification of skin cancer. The amount of medical waste produced and the amount of medical supplies consumed can both be reduced by this decrease in medical treatments. Furthermore, more accurate diagnoses can result in more effective treatment programmes, which lessen the overall strain on healthcare systems and the environmental impact of prolonged medical care. Moreover, the application of GNNs to skin cancer analysis may encourage the creation of more environmentally friendly medical procedures. For instance, patients' need to go to medical facilities can be minimized by the use of sophisticated AI models for remote diagnosis, which lowers emissions associated with transportation. Researchers and developers may use a variety of tactics, such efficient algorithm optimization, the use of energy-efficient hardware, and obtaining power from renewable energy sources, to lessen the environmental effect of training GNNs. The healthcare sector may take use of advanced AI benefits while reducing its environmental impact by matching the computing needs of GNNs with sustainable practices.

6.3 Ethical Aspects

There are several important factors to take into account while applying Graph Neural Networks (GNN) for skin cancer analysis in an ethical manner. First and foremost, it is crucial to protect patient data privacy and security as it is delicate and needs to be treated with extreme secrecy. Patients must provide their informed permission, which calls for them to understand that their data will be analyzed and to consent to its usage. Justice and bias are serious ethical issues. To prevent biases that can result in incorrect diagnoses for particular demographic groups, the training data must be representative and varied. Since openness in the GNN model's decision-making process makes the model's predictions more comprehensible, it helps foster trust between patients and healthcare professionals. It’s important to take into account the possibility of technological misuse. To avoid the GNN model being used in clinical settings without authorization, certain policies and procedures must to be in place. Finally, to guarantee the best possible level of patient care, the GNN model should be used in conjunction with medical experts' experience rather than in substitute of it, even though it can help with early detection and diagnosis.

6.4 Sustainability Plan

The sustainability plan for skin cancer analysis using Graph Neural Networks (GNNs) focuses on several key aspects to ensure long-term viability and impact. First off, by improving diagnostic accuracy over time through ongoing learning and adaptation from fresh data, the GNN-based technique offers sustainability. Because of its versatility, there is less need for regular model retraining, which saves computing power and has a less environmental effect. Second, by increasing diagnostic precision and speed, the GNN model's effectiveness in handling complicated, graph-structured medical data supports sustainable healthcare practices. Early detection and treatment may result from this, which might lower total healthcare costs and patient burden. In order to further enhance the GNN architecture's resilience and performance for skin cancer analysis, the strategy also calls for continual research and development. In order to guarantee that the model satisfies clinical standards and smoothly fits into current healthcare processes, collaboration with researchers and medical experts is necessary. This promotes acceptance and long-term sustainability in clinical settings. Overall, to guarantee the long-term influence and efficacy of GNN-based skin cancer analysis, the sustainability strategy places a strong emphasis on efficiency gains, ongoing improvement, and alignment with healthcare requirements.

6.5 Summary

This section highlights the transformative potential of automated skin cancer classification using advanced image processing and machine learning techniques. With the Graph Convolutional Network (GCN) achieving a remarkable test accuracy of 98.73%, this research promises significant advancements in clinical practice by enhancing the accuracy and efficiency of skin lesion diagnosis. By enabling early detection and intervention, the GCN could potentially improve patient outcomes, reduce healthcare costs associated with delayed diagnoses, and streamline decision-making processes for dermatologists and oncologists. Moreover, the validation of image segmentation methods like K-means clustering adds robustness to automated medical imaging systems, paving the way for broader applications in healthcare. Beyond clinical settings, the study underscores the broader societal impact of AI-driven healthcare innovations in democratizing access to accurate diagnostics and potentially narrowing healthcare disparities. Overall, this research exemplifies how cutting-edge technology can be leveraged to revolutionize healthcare delivery, enhance patient care experiences, and ultimately, save lives.

CHAPTER 7
Conclusion and future work

7.1 Conclusions

This study explored the application of Graph Neural Networks (GNNs) for the analysis of skin cancer, focusing on segmentation tasks. The reason GNNs were selected is that they can represent intricate links in graph-structured data, which is very useful in medical imaging where spatial dependencies are crucial. The goal of the study was to show that GNNs might outperform conventional machine learning models in terms of accuracy. To achieve high accuracy in segmentation tasks, a GNN model was trained on a collection of photos of skin cancer as part of the experimental setting. Based on pixel-level information and spatial context, the model was trained to discriminate between regions that were malignant and those that weren't. The study's findings showed that the GNN model had impressive performance measures, including 98.62% test accuracy, 98.92% validation accuracy, 99.84% training accuracy, and 98.95% sensitivity. These measurements demonstrate how well the GNN technique performs in correctly recognizing malignant areas in skin pictures. The work highlights the promise of GNNs in medical image processing overall, especially for jobs that call for accurate segmentation and anomaly detection. According to the results, GNNs have a major potential to improve clinical decision-making and diagnostic accuracy in dermatology and other disciplines that depend on in-depth picture processing.

7.2 Further Suggested Works

Further studies focusing on skin cancer analysis using Graph Neural Networks (GNNs) could explore several promising avenues. First off, examining bigger and more varied datasets would improve GNN models' applicability in actual clinical situations. Working along with several medical institutes, this might include compiling an extensive dataset encompassing all kinds.

Furthermore, investigating the amalgamation of GNNs with other sophisticated deep learning methodologies, including transfer learning from extensive picture datasets or attention processes, may augment the efficacy of GNNs in the analysis of skin cancer. These methods may aid in increasing the precision and effectiveness of tasks involving segmentation and classification.

Furthermore, it would be essential to carry out interpretability research in order to comprehend the decision-making process of GNNs in the detection of skin cancer, in order to win over medical professionals' confidence and approval. Techniques for displaying and analyzing the GNNs' acquired representations and decision-making procedures may offer important new perspectives. Ultimately, actual application would need investigating the scalability of GNN models for use in clinical practice, taking into account factors like computing efficiency and real-time processing capabilities. By addressing these issues, GNNs may eventually become indispensable instruments in the automated diagnosis and treatment planning of skin cancer.

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Appendix A

Gradient boosting (GB)[28]**:** Gradient Boosting (GB) is a machine learning technique for regression and classification tasks. It fits new models to the residual errors from earlier models in a sequential fashion, building models one after the other. The goal of any new model is to rectify the mistakes of all the earlier versions together. GB optimizes a loss function to progressively improve performance by using decision trees as weak learners. Regularization parameters are part of the procedure to avoid overfitting. For complicated datasets, gradient boosting produces extremely accurate and interpretable models, but it may also be computationally demanding and hyper parameter sensitive[29].

Extremely Randomized Trees (ET): Extremely Randomized Trees (ET) is an ensemble learning method for classification and regression. Similar to Random Forests, ET builds multiple decision trees and averages their predictions. However, ET[30] introduces more randomness by selecting split points at random for each candidate feature, rather than searching for the optimal split. This extra randomness often leads to lower variance in the model. By combining the predictions of many randomized trees, ET achieves high predictive accuracy and robustness, especially in datasets with noisy or complex patterns. It's efficient, easy to implement, and often used in scikit-learn as Extra Trees-Classifier and ExtraTrees-Regressor.

Random Forest(RF): Random Forest (RF) is an ensemble learning method used for classification and regression tasks. It constructs multiple decision trees during training and outputs the mode of the classes (classification) or the mean prediction (regression) of the individual trees[31]. Each tree is built using a random subset of the training data and a random subset of features, which introduces diversity and helps prevent overfitting. RF is known for its high accuracy, robustness to noise, and ability to handle large datasets with many features. It’s widely used due to its simplicity and effectiveness, with implementations available in libraries like scikit-learn.

Logistic Regression (LOGR): Logistic Regression is a statistical method used for binary classification tasks. It models the probability that a given input belongs to a particular class using the logistic function. LOGR estimates the parameters of the model by maximizing the likelihood of the observed data. Despite its name, it is a linear model that provides a linear decision boundary.

LOGR[32] is easy to implement, interpretable, and efficient, making it a popular choice for problems where the relationship between the features and the target variable is approximately linear. It is widely used in various fields, including medicine, finance, and social sciences.

Support Vector Machine (SVM): Support Vector Machine is a supervised learning algorithm used for classification and regression tasks. It finds the optimal hyperplane that maximizes the margin between different classes in the feature space. SVM is effective in high-dimensional spaces and is robust to overfitting, especially in cases with a clear margin of separation. It supports various kernel functions, enabling it to handle non-linear data. SVMs are widely used for their accuracy and versatility in diverse applications.

K-Nearest Neighbors (KNN): K-Nearest Neighbors is a simple, non-parametric supervised learning algorithm used for classification and regression tasks. It classifies a data point based on the majority class of its K nearest neighbors in the feature space. Distance metrics like Euclidean distance are used to determine the neighbors. KNN is intuitive, easy to implement, and effective for small to medium-sized datasets. However, it can be computationally intensive and sensitive to the choice of K and the scale of features.

Naïve Bayes (NB): Naive Bayes is a probabilistic supervised learning algorithm used for classification tasks. It assumes that the presence of a particular feature in a class is independent of the presence of other features, hence "naive." NB calculates the probability of each class given a set of features using Bayes' theorem. It is efficient, requiring a small amount of training data to estimate parameters. Despite its simplicity and the independence assumption, NB often performs well in practice, especially with categorical data.

Classification and Regression Trees (CART): Classification and Regression Trees are versatile supervised learning models used for both classification and regression tasks. CART recursively partitions the data into subsets based on feature values, creating a binary tree structure. It selects the best feature and split point at each node to minimize impurity (for classification) or variance (for regression). CARTs are easy to interpret, handle numerical and categorical data, and can capture complex relationships. They are used in decision-making scenarios where understanding

the decision process is important.

Decision Trees (DT): Decision Trees are versatile supervised learning models used for both classification and regression tasks. They recursively split the data into subsets based on feature values, creating a tree-like structure where each internal node represents a decision based on a feature, and each leaf node represents the outcome. DTs are easy to interpret, handle numerical and categorical data, and can capture non-linear relationships. However, they may over-fit noisy data, leading to less generalizable models without regularization techniques.

Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

Title:

ANALYSIS OF SKIN CANCER FEATURE PATTERN USING GNN INCORPORATING A NOVEL SEGMENTATION METHOD

Student Id: 201-15-14190

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify a **SkinCancer detection** problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish these goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
Phase -II		
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**
CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**

CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	This project demonstrates **fundamental engineering (K3)** principles by employing deep neural networks, data augmentation techniques, and diverse CNN architectures for image processing and classification tasks. The project demonstrates **specialist knowledge (K4)** by conducting transfer learning with advanced CNN architectures like VGG19 and ResNet152v2, enhancing pneumonia detection accuracy in chest X-ray images, crucial for computer-aided diagnosis.	**Page no:** [26-30] **Section:** [3.2] **Page no:** [1-7] **Section:** [1.1]
				The project applies **engineering practice & design (K5)** by the figure of process of experiments. The project addresses **engineering practice & technology (K6)** by employing CNN model.	**Page no:** [30] **Section:** [3.2(B)] **Page no:** [33]

					Section: [3.4]
				This project ensures to **K8 (Research Literature)** by synthesizing insights from recent studies, to advance pneumonia detection using deep learning, showcasing a comprehensive understanding of current methodologies.	**Page no:** [5-7] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This project addresses **EP-2** by recognizing the hurdles in pneumonia detection, including limitations of traditional methods and the complexities of integrating transfer learning and deep CNNs. Through comparative analysis, it confronts challenges in understanding spatial distributions, offering insights for refining diagnostic methodologies.	**Page no:** [23-24] **Section:** [2.4, 2.5]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	This project addresses **EP-3** by meticulously comparing experimental outcomes, highlighting Transfer Learning as the chosen significant solution for enhancing pneumonia detection amidst multiple potential approaches.	**Page no:** [36-57] **Section:** [4.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8	This project's interdisciplinary approach extends beyond computer science and engineering, impacting medical diagnostics in respiratory diseases like pneumonia, contributing to advancements in public health and healthcare practices which indicates **EP-4**.	**Page no:** [16-24] **Section:** [2.2, 2.4]

5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and conflicting**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	This project's comprehensive approach addresses high-level problems by integrating various components across data collection, statistical analysis, and proposed methodology, ensuring a holistic solution to complex challenges in medical diagnostics which ensures **EP-7**.	**Page no:** [26-34] **Section:** [3.2, 3.3, 3.4]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References
1.	**EA1: Range of resources**	Yes	CO11	Our project utilizes diverse resources such as high-performance computing infrastructure, GPUs, deep learning frameworks, annotated datasets, and ethical considerations to ensure systematic research and contribute to advancements in pneumonia detection through transfer learning and deep CNNs.	**Page no:** [33-35] **Section:** [3.5]
2.	**EA2: Level of interaction**	No		N/A	N/A
3.	**EA3: Innovation**	No		N/A	N/A
4.	**EA4: Consequences for society and the environment**	Yes		This project contributes to society by improving healthcare through advanced pneumonia detection methods, while also promoting environmental sustainability by employing efficient computational resources and adhering to ethical guidelines for patient data privacy.	**Page no:** [58-61] **Section:** [5.1, 5.2, 5.4]

5.	**EA-5: Familiarity**	Yes		This project expands upon existing research by examining a novel approach in pneumonia detection through transfer learning and deep CNNs, demonstrated through preliminary terminologies and a comprehensive comparative analysis, offering new insights into the field.	**Page no:** [7-10] **Section:** [2.1, 2.3]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project addresses **CO4** by integrating effective project management and financial oversight, ensuring meticulous planning, resource allocation, and budget estimation for optimal resource utilization throughout the research lifecycle.	**Page no:** [13] **Section:** [1.6]
2	CO9	Yes	The project demonstrates adherence to ethical principles by prioritizing patient privacy, obtaining informed consent, and transparently documenting the research process, ensuring responsible knowledge dissemination and societal well-being through the ethical application of advanced healthcare technologies which comply with **CO9**.	**Page no:** [60] **Section:** [5.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	The project's dedication to continuous learning **(CO12)** and adaptation within the dynamic technological landscape is reflected in its comprehensive data collection, rigorous statistical analysis, meticulous methodology development, and thorough experimental results and analysis, showcasing a commitment to staying updated and refining techniques to address modern challenges.	**Page no:** [26-34, 37-55] **Section:** [3.2, 3.3, 3.4, 3.5, 4.2]

Appendix B

The expected outcomes for " Skin Cancer" –using GNN segmentation method is described below-

A promising method for analyzing skin cancer is to use Graph Neural Networks (GNNs). This strategy makes use of the links between numerous variables or qualities of the data, including distinct characteristics of skin lesions, patient demographics, medical history, and so on.

Data Preparation: First, you will want a dataset including features that are pertinent to the analysis of skin cancer, like pictures of skin lesions, patient details, and even genetic information. After that, this data would be organized into a graph, with nodes standing in for various entities (such as patients or lesions) and edges for the interactions that exist between them (such as the patient-lesion association).

Model Training: Using this graph-structured data, GNNs would subsequently be trained. The GNN gains the ability to transfer information throughout the graph during training, identifying connections and dependencies between various entities. As a result, the model can efficiently combine data from several sources and forecast using the collective knowledge represented in the graph.

After it has been trained, the GNN can be used to forecast results pertaining to the analysis of skin cancer. This could involve activities like:

Diagnosis: Determining the malignancy or benignity of a skin lesion by examining its characteristics and pertinent patient data.

Prognosis: Estimating the chance of a disease's advancement or recurrence from a patient's medical history and characteristics.

Treatment Suggestion: Making recommendations for suitable courses of action in light of the patient's unique circumstances.

Evaluation: Standard metrics including accuracy, precision, recall, F1-score, and area under the

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