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Original Article

Advancing Skin Cancer Lesion Detection and Classification: A State-of-the-Art Approach Integrating Convolutional Neural Networks and Graph Neural Networks

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Abstract *- Identifying skin cancer on time is very important for effective treatment and enhanced results in patients. In this study, an innovative approach is proposed that harnesses the power of deep learning through a hybrid model. The hybrid model of Convolutional Neural Network (CNN) architectures like Graph-Convolutional-Neural-Network (GCNN) or even ResNet for improvement in cancer detection accuracy. To address challenges related to image quality and noise, we employ preprocessing on images, such as image resizing and purifying on skin cancer images. For completing the tasks of augmented training data set and enhancing the quality of the hybrid CNN-GNN model, different augmentation methods are used. Through rigorous evaluation it is demonstrated that the hybrid CNN-GCNN approach surpasses emerging methods, emerging as the most effective solution for skin cancer detection. The proposed hybrid model achieves dramatic performance on the skin cancer dataset, and the accuracy obtained is around 99.8% with a loss of 0.1212. The accuracy of validation is 96.8%, with a loss of 0.1401. The obtained results underscore the efficacy of the hybrid CNN-GNN model in accurately identifying skin cancer lesions. By leveraging the complementary dominance of architectures of CNN and GNN, the hybrid approach showcases promising outcomes for the timely finding of skin cancer. The research plays a very important role in the advancements of clinical settings and offers a valuable tool in the diagnosis of skin cancer by clinicians. The diagnosis is prompt and effective, which improves patient care and outcomes.*

Keywords *- Computer-Aided Cancer Detection, Data Augmentation, Graphical Convolutional Neural Network (GCNN) and Convolutional Neural Network (CNN).*

1. Introduction

Cancer of the skin ranks among the widespread forms of cancer worldwide, and its incidence rates are on an upward trajectory. As stated by the "World Health Organization" (WHO), there are around 2.9 million non-melanocytic skin carcinoma cases and more than one lakh thirty-two thousand melanocytic skin cancer cases diagnosed worldwide each year. Quick identification and accurate diagnosis are imperative for enhancing patient results, as advanced-stage skin carcinoma can pose significant treatment challenges and frequently results in substantial morbidity and mortality [1]. Cancer of the skin can be defined as the proliferation of malignant cells, which are generally present within skin tissue. Generally, there are many reasons for its commencement like ultraviolet ray's direct exposure, which originates from sunlight. The damage causes mutations in the DNA of the Skin cells to undergo damage, resulting in uncontrolled growth and the formation of tumours [2].

Various categories of skin cancer exist; the type of basal cell carcinoma is dominating among all and is approximately 80% of all the occurrences, followed by melanoma and squamous cell carcinoma. Squamous Cell Carcinoma (SCC) follows, constituting approximately 16% of cases, commonly characterized by a red, scaly patch or a persistent sore. Melanoma, although less frequent, poses the highest risk due to its potential to metastasize to other organs. [1]. A history of sunburn or having fair skin, are familial predisposition to the disease, a weakened immune system, and UV light exposure, which emerges from sunlight, are included among the risk factors for skin cancer. The prevention of all this is possible by using protective cloth over the skin, sunscreens can also be used with high SPF, and the last is avoiding outdoor activities during the peak of the day. Dermatologists typically diagnose skin cancer through visual inspection, which is subjective and can lead to variations in diagnosis between clinicians. In recent years, growing interest has been shown in the usage of different algorithms from machine learning as a domain for diagnosing cancer associated with the skin. Numerous studies have demonstrated that deep learning algorithms can attain high accuracy in classifying skin lesions, often matching or surpassing the diagnostic performance of dermatologists [2]. Deep learning techniques for the categorization of cutaneous malignancies typically rely on Convolutional Neural Networks (CNNs), which are designed to process images and learn complex features automatically.

However, skin lesion images have an inherent graph structure, with pixels representing nodes and edges connecting neighbouring pixels. Graph Neural Networks (GNNs) have shown promise in modelling the relationships between features in graph-structured data and have been used in various applications, including drug discovery, traffic prediction, and social network analysis. Current skin cancer diagnostic techniques mainly depend on image processing methods, such as Convolutional Neural Networks (CNNs), but frequently disregard the graph-structured characteristics of skin lesion images. This oversight presents a significant research gap, as it limits the potential for accurate primary findings of skin melanoma.

Therefore, there is a serious need for innovative approaches that effectively leverage both image processing and graph structures to enhance the precision associated with the diagnosis of carcinoma. The combination of GNNs and CNNs is studied, which can be considered as a new hybrid method for the classification of skin cancer. By representing skin lesion images as graphs, the method capitalizes on their inherent structure. Initially, CNNs extract features from the graph representations, followed by GNNs to capture intricate relationships. Integrating both CNN and GNN components aims to improve the accuracy of skin carcinoma diagnosis by using graph structures, addressing existing limitations in current diagnostic methods [3].

2. About Skin Cancer

Unregulated cell growth in the skin leads to the development of anomalous masses or lesions, marking skin cancer as a malignancy arising from skin cells. The World Health Organization (WHO) reports a staggering global prevalence of skin cancer. Annually, over 1.9 million new cases are diagnosed, with notably high incidence rates observed in regions such as New Zealand, Australia, and South Africa. These areas are known for housing populations with lighter skin tones in sun-exposed environments, which contribute to prolonged UV exposure. [4]. Cells forming tumors can be broadly categorized into benign and malignant types. Benign cells typically demonstrate organized structures and restrained growth, posing a minimal risk of spreading to adjacent tissues. In contrast, malignant cells possess the capacity for uncontrolled proliferation and invasion into surrounding tissues, making them potentially life-threatening. As a result, treatment modalities like chemotherapy, radiotherapy, or surgical excision are frequently required to manage malignant skin cancer. [5]. The distribution of skin carcinoma tumors may vary across different demographic groups, including disparities based on gender and age. Additionally, the presentation of symptoms can differ based on the specific type of carcinoma and the affected area of the skin. Early diagnosis is paramount in curing cancer, especially related to skin, as the detection can help in improved outcomes of treatment. Presently, extraordinary advancements have occurred in the medical imaging domain as new techniques of deep learning architecture are used. The emergence of deep learning models is considered as powerful tool for disease detection and diagnosis from image data, offering unprecedented accuracy and efficiency. These advanced computer systems possess the capability to analyse intricate medical images, including those of skin lesions, with exceptional precision. This aids healthcare professionals in faster detection at an early stage and amazing management for the cases of carcinoma cases [6]. Emphasizing that skin carcinoma is an avoidable condition is crucial, with the adoption of preventive measures significantly diminishing the likelihood of its occurrence.

Preventive measures for skin cancer include:

1) It is advisable to use the sunscreen cream with an SPF value of more than 30 for broad-spectrum protection, which should be applied to all exposed areas of the skin, including the neck, ears, face, and hands.
2) Steering clear of direct sunlight during the peak hours of morning 10 to afternoon 4.
3) Wearing protective clothing like full-sleeved shirts, pants, and a broad-brimmed hat when in the sun.
4) Avoiding the use of tanning beds entirely, as they elevate the likelihood of experiencing skin cancer. [2]

Regular skin checks are essential for detecting and seeking immediate action for suspicious skin problems. The few most occurring cancers comprise basal and squamous cell carcinoma as well as melanoma carcinoma. BCC is the most common, representing 80% of cases, typically manifesting as a red or shiny bump, a slow-growing, scaly patch. SCC, the second most common (16% of cases), SCC typically presents a solid, crimson nodule or a scaly lesion that proliferates swiftly and has the capacity to disseminate.

Melanoma, although less prevalent (accounting for 4% of cases), poses the greatest threat, often manifesting as a rapidly enlarging, dark, and irregularly shaped mole. [7] [8]. Timely examination of moles or wounds on the skin is crucial, especially if they exhibit characteristics associated with high-risk skin cancer, as outlined in Table 1.The characteristics listed in Table 1 play a crucial role in evaluating the risk associated with moles or skin lesions. Utilizing the mnemonic ABCDEFG, each factor provides valuable insights into the potential malignancy of these dermatological features. Here is an explanation for each characteristic [9].

Table 1. Cancer of skin traits

Traits	Description
A - Asymmetry:	Asymmetry indicates an irregularity in the shape of the mole or lesion, where one half differs noticeably from the other. This can be indicative of abnormal cell growth or the presence of malignant cells.
B - Boundary Irregularity:	The anomaly in the boundaries of a mole or abnormality, denoted by the letter B, emphasizes the importance of well-defined borders. Lack of uniformity in border characteristics may suggest potential malignancy, requiring closer scrutiny.
C – Color Variation:	Color variation, encompassing various shades of brown, black, or other hues, broadens the diagnostic range. Moreover, the existence of gray, pink, white, or red regions within the mole or abnormality may indicate heightened risk, prompting further examination.
D - Diameter:	The diameter criterion underscores the importance of size assessment, with a mole or lesion surpassing the dimensions of a pencil eraser warranting increased attention. Larger sizes may correlate with an increased likelihood of malignancy.
E - Evolving:	Evolving characteristics in terms of size, shape, or color of abnormality raise concerns. Continuous monitoring is essential, as dynamic changes may indicate an evolving malignancy, necessitating timely intervention.
F - Firmness:	The tactile aspect, denoted by firmness, provides an additional layer of diagnostic information. A mole or lesion exhibiting firmness or raised features may suggest an underlying pathology, requiring thorough examination.
G - Growing:	The growth pattern of a mole or lesion, especially rapid growth or a significant increase in size, serves as a potent signal of potential malignancy. Monitoring growth trends is pivotal in assessing the trajectory of skin abnormalities.

Table 2. Illustrates aided diagnosis for skin cancer detection

Publication	Number of Images	Model Used	Accuracy
Sara Medhat et al. [10]	2298	AlexNet with transfer learning	99%
Yunendah et al. [11]	4000	CNN with SGD optimizer	99%
A. Mankawade et al. [12]	1000	CNN	86%
Setiawan, A.W. [13]	19932	CNN	92%
Atta, Ayesha; Khan et al. [14]	3600	CNN with transfer learning	86.23%

Understanding these characteristics empowers individuals to conduct informed self-assessments and aids healthcare professionals in efficiently identifying high-risk skin conditions.

3. Recent Advances in Deep Learning for Computer-Aided Cancer Diagnosis and Literature Review

Aided Diagnosis (CAD) for cancer detection. Recent research publications highlight the success of these approaches across various cancer types. The integration of deep learning in CAD has yielded promising results, marking a notable advancement in the field of cancer diagnosis.

4. Literature Review

Timely detection of skin cancers is paramount for powerful treatment, and Computer-aided Diagnosis (CAD) structures play a pivotal role in this undertaking. As clinical generation continues to boost, an array of imaging modalities has been developed to facilitate the early detection of most cancers. Among all the different modalities available, a promising implement for the recognition as well as classification of cancer skin is possible using CNNs. The literature review focuses on the detection of different skin cancers using CNNs and their efficacy in a particular domain. A few researchers named Ravi Manne, Snigdha Kantheti, and Sneha Kantheti shared a review on the classification of skin cancer using CNNs. They highlighted the successful evolution of CNNs in classifying various skin cancer types and the overall improvements in machine learning and deep learning methodologies. Their review emphasized CNNs' superiority in classification compared to other architectures. The analysis incorporated datasets like HAM10000, Asan, University of Tsukuba Hospital, and ISBI 2016, each contributing to the evaluation of classification accuracy. [15]

Jinen Daghrir et al. presented research on melanoma skin cancer detection”. Their study emphasized the importance of early diagnosis for improving melanoma survival rates, highlighted the efficacy of combining various detection methods, and explored the potential of integrating multiple model predictions to enhance detection system performance. Utilizing a dataset from the ISIC archive, comprising over 23,000 melanoma images, the analysis is based on 640 images of problems associated with skin, which covers both categories benign and malignant, that were utilized in the study. Among the total number of images, there are around 512 images which can be used for training the model, and the others can be used for testing the model. [16]

The factors affecting the sun protective behavior, particularly in skin cancers in adults, were examined by Amy F. Bruce et al. in 2017. Their findings highlighted the interdependence of modifiable and non-modifiable factors, emphasizing the impact of cultural, familial, and community values and norms. The study was carried out using 18 quantitative studies which focused on the Caucasian and Hispanic population who have an age greater than 18 years and have a history of skin cancer [17]. In their 2023 Healthcare publication, Tehseen Mazhar et al. delved into the realm of machine learning's potential to enhance dermatologists' endeavors, focusing particularly on skin cancer diagnosis and tailored patient care [18]. “In their 2020 study published in Materials Today: Proceedings, M. Krishna Monika et al. investigated skin cancer detection and classification using machine learning techniques”. The usage of the 2019 ISIC challenge dataset, which consists of dermoscopic images with ultra-high resolution, can be classified into different categories [19].

In their 2019 study published in EBioMedicine, A. Dascalu and E. O. David examined the effectiveness of sound analysis algorithms and rudimentary skin magnification in diagnosing skin cancer. Surprisingly, they discovered that the quality of the dermoscopy had minimal impact on the accuracy of deep learning diagnosis. Their findings suggested that the technology used in the study could significantly improve diagnostic accuracy, potentially assisting physicians in diagnosing skin cancer. The research utilized the International Skin Imaging Collaboration (ISIC) dataset, which was created in 2017 and consists of non-dermoscopic images which count more than 800 in number. [20] Lisheng Wei, Kun Ding, and Huosheng Hu, in their 2020 IEEE Access paper, introduced an automated method for identifying melanoma in dermoscopy images. They emphasized achieving higher segmentation accuracy with minimal model parameters and underscored the significance of primary treatment and primarily the detection of cancer associated with the skin. Utilizing the ISBI 2016 dataset, which contains 900 training and 379 test images alongside professional annotations, the study focused on distinguishing between the two categories of lesions, out of which around 80% of the total dataset represents benign cases [21].

“Another major breakthrough was presented by Geetika Sharma and Raman Chadha at the IEEE International Conference on Distributed Computing and Electrical Circuits and Electronics in the year 2022, which presented the best methods for oral and skin carcinoma with deep learning”. Their article encompassed the review of a work, proposing a methodology depicted in a flowchart, with achieved accuracies reaching up to 92% based on various research papers. The dataset employed comprised diverse cancer disease images from a hospital, focusing on patients aged 18 and above in the early stages of cancer after excluding individuals with other diseases or surgical records. Image preprocessing, feature extraction, and rigorous training/testing data division were integral steps in dataset preparation [22].

In their 2022 review titled "State-of-the-art machine learning techniques for melanoma skin cancer detection and classification," authored by Harsh Bhatt and team, published in Intelligent Medicine, the authors focused on global health concern of primary finding of skin carcinoma. The results focus on the deep learning technique as well as the machine learning technique's efficiency in finding skin cancer at an early stage. The review primarily utilizes the "HAM10000" set of data with ten thousand and fifteen images, alongside ISIC datasets of varying sizes for training and testing, to assess the effectiveness of these techniques comprehensively [23]. The study published in the year 2020 which was in “Informatics in Medicine Unlocked”, “Mohammad Ali Kadampur and Sulaiman Al Riyaee unveiled The outstanding accuracy and effectiveness of deep learning models in distinguishing skin cancer from dermal cell images”. Their research showcased an impressive area below the arc of 99.77% and an average accuracy of approximately 98.89% (with a confidence level of 90). Employing the HAM10000 dataset, a widely acknowledged benchmark in machine learning, they meticulously divided it into 80:10:10 ratios for training, validation, and testing, ensuring a robust assessment of their model's capabilities [24].

Bein Doina, Verma Abhisheck and Philip presented a short “deep learning model for skin cancer recognition at the 2018 Ubiquitous Computing, Electronics and Mobile Communication Conference”. Outperforming the baseline model, their CNN achieved enhanced accuracy and efficiency, with 60% fewer parameters, particularly optimized for mobile platforms and advanced frameworks like Keras and TensorFlow. Their study utilized the "PHDB" composite dataset, derived from publicly available sources, including the NZ Dermnet, PH2, MED-NODE and ISIC Archive, meticulously partitioned into benign and malignant classes [25].

Karri, Annavarapu, and Acharya (2023) explored the use of transfer learning with an attention mechanism for skin cancer classification, achieving a high accuracy of 97.3%. Their approach demonstrated significant potential, although the diversity of the data used somewhat limited it. This highlights the importance of diverse datasets in developing robust diagnostic models and suggests that further research is needed to address these limitations [26]. Similarly, Sinha and Gupta, 2022 utilized a DenseNet architecture on the ISIC dataset, achieving an accuracy of 91.6%. Their study focused on comparing various deep learning architectures, underlining the effectiveness of DenseNet for skin carcinoma classification. However, a comparison also emphasizes the need for continued exploration of different neural network architectures to enhance diagnostic accuracy and reliability [27].

In another study, Singh et al. (Khamparia et al., 2021) implemented an Inception-v3 model on the ISIC dataset, achieving an accuracy of 91.26%. This research highlighted the model's computational efficiency, which is crucial for practical applications in clinical settings. Their findings indicate the potential benefits of efficient models but also suggest the necessity for balancing accuracy and computational demands. [28] Dutta, Kamrul Hasan, and Ahmad, 2021, introduced a multimodal CNN approach, combining dermoscopy and clinical images, and achieved an accuracy of 89.5%. This study underscores the advantages of using multiple image modalities to improve diagnostic performance, demonstrating that integrating diverse data sources can enhance model robustness and accuracy. [29] The amalgamation of diverse research endeavors underscores the multifaceted method closer to skin cancer detection and type. From systematic opinions exploring the evolution of CNNs for classification to studies emphasizing the importance of early analysis and the efficacy of machine-mastering strategies, each contribution sheds light on the continued efforts to fight this commonplace malignancy. Through meticulous evaluation of various datasets, inclusive of HAM10000 and ISIC, researchers have proven the remarkable capacity of deep studying architectures in accurately figuring out and classifying pores and skin most cancer lesions. Moreover, the integration of more than one detection strategy, attention to social determinants, and optimization of model parameters for better performance similarly exemplify the interdisciplinary nature of this research area. Ultimately, these findings collectively underscore the essential importance of early detection and the promising role of superior technologies in enhancing skin cancer analysis and patient care.

5. Data Repository Used

The major role for validating, testing and training any machine learning algorithm is played by a proper dataset, which makes it a fundamental component for getting precise output. The quality and quantity of the dataset terribly influence the results of any model. An optimal dataset is characterized by its comprehensiveness, diversity, uniform distribution, and absence of errors and biases. Furthermore, it should include annotations or labels that accurately reflect the ground truth pertinent to the specific problem domain. The availability of good datasets is a must for the advancement of machine learning techniques, which enable researchers to evaluate the newly constructed models over a wide range of domains.

5.1. Dataset Insights Based on Skin Deformity Class

The dataset comprises more than 25,100 images depicting various types of skin problems, the ones which are under research. This collection, provided by the ISIC is considered outstanding from all the available datasets. The images are captured using high-grade cameras and dermoscopy devices from various origins, ensuring diversity and high quality (Fig 1). The dataset is enriched with supplementary metadata, including patient demographics and diagnoses, providing valuable context for analysis and research in dermatology and skin cancer detection. [30] [31] [32]. The HAM10000 dataset is another significant dataset, which showcases more than 10,000 images portraying various types of skin lesions, encompassing seven distinct categories such as nevus, melanoma and basal cell carcinoma. All images are acquired from different origins, including consumer-grade cameras and clinical environments, with annotations meticulously curated by dermatologists. It is worth noting that HAM10000 is recognized as a subset within the broader ISIC dataset [32].

The usage of the PAD-UFES-20 dataset with joint efforts of the Dermatological and Surgical Assistance Program in Brazil. There were six categories of skin abnormality, namely Bowen’s disease, Actinic and Seborrheic keratosis, squamous carcinoma and melanoma. Squamous cell carcinoma, Actinic Keratosis, Seborrheic Keratosis, Basal Cell Carcinoma, Bowen’s disease, Melanoma and Nevus. The total number of samples was around 2298 [33]. Utilized for the experiment are elaborated in detail within Figure 1.

5.2. Data Cleansing Strategies

This article applies a hybrid model of machine learning to a dataset of skin abnormalities. Prior to utilization, the data necessitates preprocessing procedures hybrid model for that purpose.

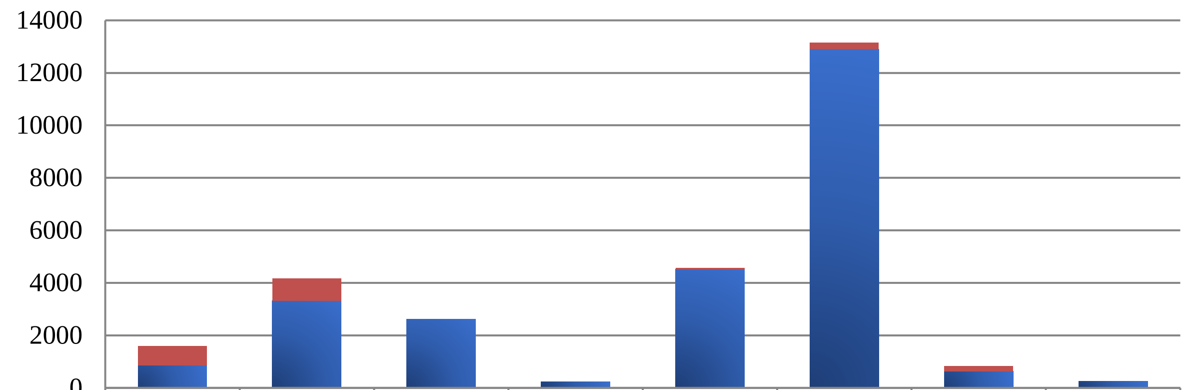
5.2.1. Image Enhancement:

Image Scaling: Resizes images to a fixed width while maintaining variable heights to address varying image sizes. [34]

Image Restoration:

- Restoration from Noise: Denoising methods like spatial filtering and transform domain filtering are utilized to suppress noise while preserving edges. [34]
- Restoration from Blur: Addresses image blurring caused by focusing or motion, employing techniques like Wiener filtering for effective deblurring while minimizing noise. [34]
- Removing Thick Hairs: Various methods are employed to eliminate thick hairs in skin cancer images, including mathematical morphology, curvilinear structure detection, and automated software, to ensure accurate segmentation and analysis of lesions [34].

Image augmentation: This method entails producing additional images from the original ones through transformations like rotation, scaling, and flipping. Such modifications serve to expand the dataset's volume and enhance its suitability for training machine learning models. In this experiment incorporating image augmentation is a common practice to augment the dataset utilized for training machine learning models, thereby enhancing its diversity and robustness.



	Actinic keratos is	Basal Cell Carcino ma	Benign keratos is	Dermat ofibro ma	Melan oma	Melan ocytic Nevus	Squam ous cell carcino ma	Vascul ar lesion
PDA No of Data	730	845	0	0	52	244	192	0
ISIC No of Data	867	3323	2624	239	4522	12900	628	253

Fig. 1 Insights of skin dataset

Image augmentation encompasses the process of creating additional images from existing ones by implementing a range of transformations, including rotation, scaling, flipping, and cropping. These transformations help increase the diversity of the dataset and make it more robust for training, as they introduce variations that mimic real-world scenarios. Additionally, hair removal techniques are implemented to pre-process the images and improve their suitability for analysis. Thick hairs present in skin cancer images can often obstruct the accurate segmentation and analysis of lesions. Therefore, various methods are applied to remove these hairs, including mathematical morphology, curvilinear structure detection, and automated software tools. By eliminating thick hairs from the images, the pre-processing step ensures that the resulting dataset is free from potential impediments and ready for further analysis and model training.

6. Methodology

This section focuses on the proposed methodology for skin cancer classification leveraging both CNNs as well as GNNs. The approach aims to capture both local and global information from skin lesion images to improve classification accuracy.

6.1. CNN for High-Level Features

Using ResNet-50, a pre-trained CNN, involves extracting high-level features from an image. The input given to ResNet-50 is preprocessed image I', yielding a feature vector $f$high-level(I′) ∈Rd, where d is the dimensionality of the feature space. This vector captures semantic information about the image content.

6.2. Extracting Local Features using CNN

Using the aforementioned pre-trained model, ResNet-50, local features from skin lesion images can be effectively extracted. The pre-processed image I' is passed through the network, resulting in a feature map fCNN(I') capturing local patterns such as textures, edges, and shapes within the lesions. These local features are denoted as

$$\text{flocal}=\text{fCNN}(I')\in \text{RH}'\times \text{W}'\times \text{C}, \tag{1}$$

Where the spatial dimensions of the feature map are H, W and the number of channels is C.

6.3. Extracting Global Features using GNN

To capture global context, each image is shown in a graphical format G=(V, E), in which V shows the collection of nodes. (pixels or patches within the image), and E can be considered as the number of edges in spatial relationships. The high-level feature vector f high-level(I') obtained from. The CNN is assigned to each node. The feature of node i in image j is denoted as

$$Xij=f\text{high-level}(I')\in \text{R}^{d}. \tag{2}$$

Graph Neural Network (GNN) layers are then applied to propagate information between nodes iteratively, leading to the extraction of global features. Specifically, Graph convolutional layers are utilized to update node features:

$$H^{(l+1)}=\sigma(D^{-1/2}AD^{-1/2}H^{(l)}W^{(l)}) \tag{3}$$

Where $H^{(l)}$ is the node features, $W^{(l)}$ is the weight matrix of the l-th GNN layer, A is the adjacency matrix of the graph, D is the degree matrix of the graph, and σ serves as the activation function. Node features across the entire image are aggregated using global mean pooling:

$$f_{global} = \frac{1}{|V|}\sum_{i\in v} H_{ij}^{L} \tag{4}$$

Where L is the total number of GNN layers. number of GNN layers.

6.4. Combining Local and Global Features

Local features f_{local} extracted by the CNN are concatenated with the global features obtained from the GNN. The resulting combined feature vector, f_{combined}, encompasses both local and global information:

6.4.1. Combined Feature Vector

The Combined Feature Vector f_{Combined} results from the fusion of features extracted at both the local and global levels from images. Let's denote the dimensionality of this feature vector as D.

$$f_{combined} = [f_{local}, \; f_{global}] \tag{5}$$

Here, f_{local} represents the local features captured by the CNN, which encode detailed information about the characteristics of the lesions, such as textures, edges, and shapes. On the other hand, f_{global} represents the global features obtained from the GNN, which capture contextual information about the entire image.

6.5. Classifier (Fully Connected Neural Network)

Once the combined feature vector fCombined , pass it through a classifier, which is FCNN in this case. FCNN consists of multiple layers of neurons, each layer fully connected to the next layer. The final layer typically outputs the predicted probability distribution over the classes.

Mathematically, the operation of the FCNN can be described as follows: Let x=f_{combined} denote the input feature vector, and $\hat{y}$ denote the output of the FCNN, representing the predicted probability distribution over the classes.

$$\hat{y} = FCNN\,(x) \tag{6}$$

$$z^1 = W^{(1)}.x + b^{(1)} \tag{7}$$

$$a^1 = ReLU\big(z^{(1)}\big) \tag{8}$$

$$z^2 = W^{(2)}.a^{(1)} + b^{(2)} \tag{9}$$

$$a^2 = ReLU(z^{(2)}) \tag{10}$$

$$z^L = W^{(L)}.a^{(L-1)} + b^{(L)} \tag{11}$$

$$\hat{y} = Softmax(Z^{(L)}) \tag{12}$$

Here, $z^i =$ represents the pre-activation of the i[th] layer., $W^i =$ shows the matrix of weight at layer i.,
$b^i =$ shows the vector at layer i,
$a^i =$ means the activation function, which is at layer i obtained by applying the ReLU activation function to z^i.
L is the total number of layers in FCNN.

Softmax is the activation function which can be applied to obtain class probabilities.

6.6. Model Training and Analysis

The FCNN is trained using the labeled data from the dataset, where each image is associated with a label indicating its malignancy status (e.g., malignant or benign). During training, the parameters (weights and biases) of the FCNN are optimized to minimize the most effective loss function like cross-entropy. Some efficient techniques for optimization are stochastic gradient descent, and another available technique is Adam optimization.

Once trained, the FCNN is evaluated on a separate validation that involves analyzing the overall performance of the model. The assessment can be done by using general metrics like recall, accuracy, precision and the most generic F2-score.

Overall, the combined feature vector fCombined serves as input to an FCNN, which learns to predict the malignancy status of skin lesions based on the extracted features. Through training and dataset evaluation, the FCNN aims to classify skin lesion images in the dataset accurately.

7. Experiment and Findings

The accuracy and quality of cancer detection are mostly dependent and affected by the data quality used in the model. The primary task is to make sure that the used dataset is diverse and also comprises a large number of high-quality images is paramount for constructing an accurate and dependable model. The steps followed for training remarkable precision and effectiveness of deep learning models in identifying skin cancer from dermal cell images.

7.1. Compilation of Data for Model

Begin by collecting a comprehensive dataset of skin cancer images from reputable sources, ensuring representation across various skin types and cancer subtypes. Curate the dataset to include high-quality images with diverse characteristics. The process involves standardizing image sizes and eliminating noise from images before any model, which is associated with identifying the cancer of the skin.

7.2. Prepossessing of Data

Standardize image sizes, remove the noise from images, and normalize pixel values for consistency.

7.3. Partitioning of Data

The data should be partitioned into major categories, classified into 3 categories: the data used for training 70%, data for validation 20%, and data for testing in a 10% ratio.

7.4. Construction of Model

The model construction involves designing the combined CNN-GNN architecture using frameworks such as Keras, PyTorch, or TensorFlow. PyTorch Geometric, Deep GraphLibrary, Spektral, and Graph Nets progressively enhance their complexity based on requirements.

7.5. Hyperparameters and Hardware

For network training, the following hyperparameters were employed: a batch size of 32, trained over 20 epochs with a learning rate set at 0.0001. The Rectified Linear Unit (ReLU) function served as a function of activation, while the Adam optimizer was utilized in tandem. As for the hardware and tools employed in the training process, Google Colab Pro was utilized as the Integrated Development Environment (IDE), leveraging a Tensor Processing Unit (TPU) for processing tasks. The implementation was done using Python 3 on the Google Computer Engine platform, with 36 GB of RAM available for computations. Key libraries and APIs used include Python 3, TensorFlow, Keras, and Matplotlib for data visualization. PyTorch Geometric, is a Python library designed for conducting deep learning tasks on irregular input data types such as graphs, point clouds, and manifolds.

7.6. Output

The performance metrics illustrated in Figures 3 and 4 demonstrate strong results for the hybrid model. The training accuracy achieved is around 99.8%, and the accuracy of validation is around 96.8%. Also, the loss in training is 12.12, and the loss in validation is 14.01, indicating effective optimization during the training process.

Table 3. Hardware, tools and hyperparameters used for network training

GPU	Google colab
Rate of Learning	0.0001
Size of Batch	32
Optimizer	Adam
Epoch	20
Loss Function	Binary Cross Entropy

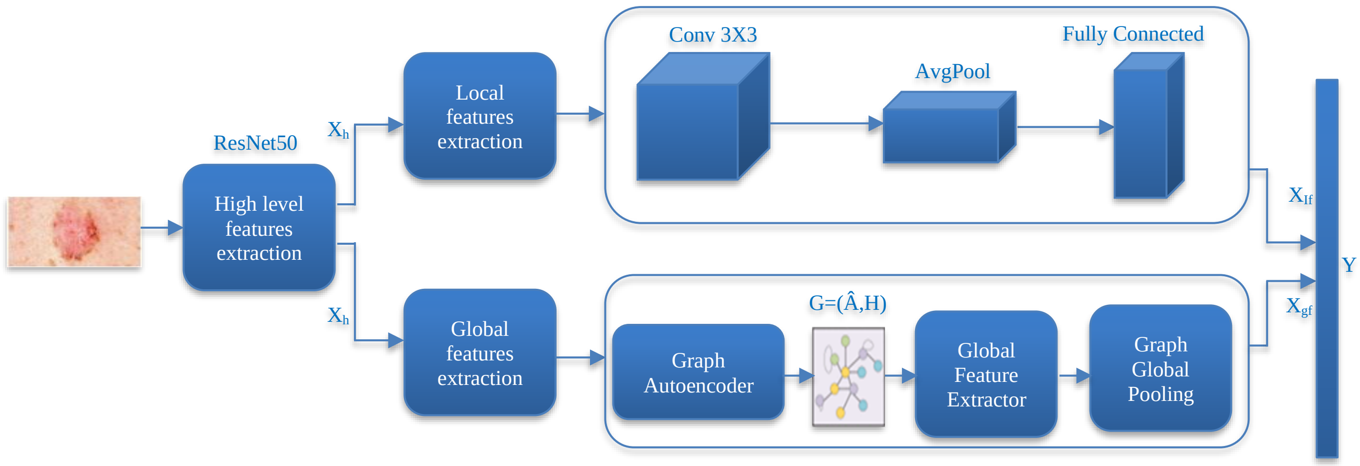


Fig. 2 Hybrid approach using CNN and GNN [3]

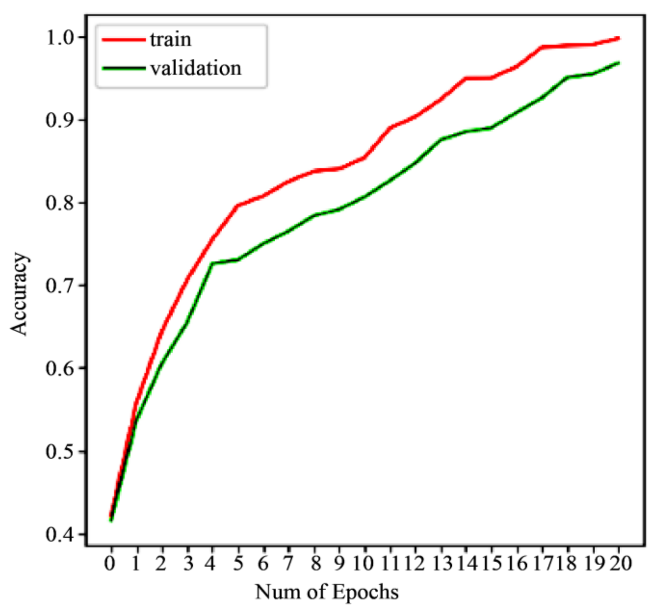


Fig. 3 Training accuracy vs. validation accuracy

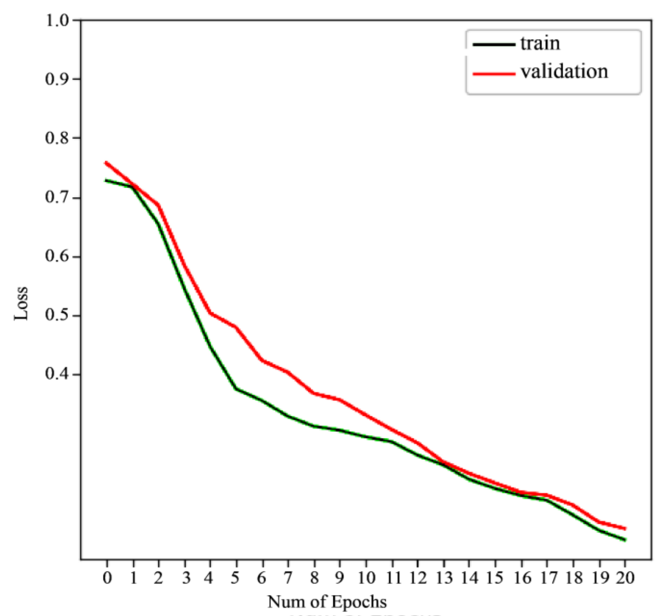


Fig. 4 Training loss vs. validation loss

8. Conclusion

The focus of the study revolves around early detection in cancer of skin using a combination of two techniques which cover the weakness of both. The novel approach is a merger of CNN and GNN, which provides considerable results in specific domains. The methodology uses a pre-trained CNN, specifically ResNet-50, which helps in extracting high-level features from images of skin lesions, along with local features through CNN and global features through GNN. The combined features were then given to FCNN for classification. Data preprocessing, such as resizing, denoising, deblurring, and hair removal, were applied to enhance image quality and remove potential impediments.

Additionally, data augmentation methods for augmentation of the data are used for training for the purpose of increasing robustness and diversity. The performance of the model under research is evaluated on the basis of critical metrics accuracy in training, validation and training loss. Through rigorous evaluation, the hybrid approach demonstrated amazing performance, achieving a remarkable accuracy in training, i.e. 99.8% with a corresponding loss of 0.1212, and accuracy in terms of validation is of validation is 96.8% with a minimal scope of loss that is 0.1401. The results obtained using the hybrid CNN-GNN model show efficacy in finding the problems related to cancer of the skin.

The work also showcased the complementary strengths of CNNs and GNNs in capturing both local and global information from skin lesion images, leading to improved classification accuracy. The innovative hybrid approach presented promising outcomes for the primary revealing of skin carcinoma, contributing significantly to advancements in clinical settings and offering one of the best tools for clinicians, specifically for diagnosing skin cancer promptly and effectively.

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