Global Journal of Engineering and Technology Advances
eISSN: 2582-5003
Cross Ref DOI: 10.30574/gjeta
Journal homepage: https://gjeta.com/

(RESEARCH ARTICLE)

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Skin melanoma detection and classification with deep learning

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Global Journal of Engineering and Technology Advances, 2024, 20(01), 242–252

Publication history: Received on 15 June 2024; revised on 28 July 2024; accepted on 31 July 2024

Article DOI: https://doi.org/10.30574/gjeta.2024.20.1.0136

Abstract

Because of its rapid growth and high mortality rate, melanoma skin cancer is among the most dangerous types of skin cancer. Consequently, melanoma treatment relies heavily on early detection. Based on the U-Net architecture with VGG-16 encoder and semantic segmentation, we present a skin lesion segmentation approach for dermoscopic pictures in this study. Diagnostic imaging systems can assess the characteristics of the segmented skin lesion and assign them a classification based on those aspects. Even on computers without powerful GPUs, the training accuracy is still high enough (over 95%) using the suggested strategy, which uses fewer resources. We use the ISIC dataset, which contains dermoscopy images, to train the model in our trials. We compare the suggested skin lesion segmentation method to others that use deep learning and analyze the Sorensen-Dice and Jaccard scores to determine how well it performs. In terms of skin lesion segmentation, the experimental findings demonstrated that the proposed method outperformed the alternatives.

Keywords: CNN (Convolutional Neural network); Skin Melanoma; Deep Learning; VGG-16; FCNs (Fully convolutional networks)

1. Introduction

The term "skin cancer" refers to malignancies that start on the skin. They arise when aberrant cells proliferate and gain the capacity to infiltrate or metastasize. Melanoma, Basal and Squamous Cell Cancer, Merkel Cell Cancer, Skin Lymphoma, and Kaposi Sarcoma are the five subtypes of skin cancer. Skin cancer, specifically melanoma, is the focus of this investigation. One of the worst kinds of skin cancer is melanoma. It is the leading cause of skin cancer mortality due to its rapid growth. Doctors may help avert metastasis — one of the most common causes of cancer mortality — by early identification, which is a highly essential role for cancer in general and skin cancer in particular. Melanoma can be diagnosed using the ABCD rule, which is an essential approach. Segmenting skin lesions from dermoscopy pictures is essential for improving diagnostic quality using the ABCD rule. Features of skin lesions can be derived from the segmented region in order to assess the lesion. A significant role is played by the skin lesion segmentation problem in medical image processing. Many ways were investigated, some of which relied on learning and others that did not, including thresholding and level set methods. The learning-based approaches that have recently emerged as a prominent area of study are the primary emphasis of this work. Image segmentation is only one of several image processing problems that deep learning has effectively solved in recent years. Because of this, CNNs and ANNs quickly rose to the position of most powerful tool in computer vision, image processing, pattern recognition, and other STEM disciplines. Many medical picture segmentation challenges, including tumor, organ, and brain segmentation, are addressed using CNNs. Some CNN-based approaches for skin lesion segmentation include: a method utilizing deep fully convolutional networks with Jaccard distance; an approach utilizing multistage fully convolutional networks; and a method utilizing fully convolutional-deconvolutional networks.

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Fuly convolutional-networks (FCNs) are the basis of all these approaches. Several studies have shown that FCN training is difficult, and that FCNs lack the sensitivity necessary to divide low-intensity regions and minute details, such as skin lesions. In addition, a substantial quantity of training data is usually necessary for FCNs.

Figure 1 Skin Sample Images (Normal and Melanoma)

In addition to the high-resolution CNN and the combined deep convolution networks and unsupervised learning models, there are a few more CNN-based models that have been suggested for skin lesion segmentation. On the other hand, skin lesion segmentation algorithms aren't very accurate, particularly when it comes to low-density lesion zones. Dense deconvolution network–based skin lesion segmentation algorithms were suggested. These techniques work fine for skin lesion segmentation; however, they aren't very excellent in accurately segmenting areas with low intensity. There have been a number of further CNN-based skin lesion segmentation algorithms proposed. Nevertheless, the techniques are unable to directly process images with color. Consequently, we have to adjust colors, process on different channels, or turn dermoscopy images into grayscale. Skin lesion photos must first undergo preprocessing before certain procedures, such as hair removal, ROI extraction, and shadow removal, may be applied.

2. Literature review

An automated method has been developed to detect skin lesions [1] and classify nine distinct types of skin cancer by integrating deep learning with image processing. A deep convolutional neural network (CNN) achieves an accuracy of 79.45% with a f1-score of 0.76, recall of 0.78, and weighted average precision of 0.76. Utilizing image enhancement and transfer learning enhances performance. Lower accuracy for uncommon skin cancers could be a result of the system's performance fluctuating on unknown datasets. The model's scalability and reliability in real-world clinical settings require further testing. The system relies heavily on input data quality and diversity, which may limit its generalizability.

Skin cancer [2] is a deadly disease that can be fatal if not diagnosed early. Visual inspection is the primary method, but it can be inaccurate. Deep-learning-based methods aim to assist dermatologists in early and accurate diagnosis. Recent research has focused on using deep learning for skin cancer classification, employing various models and datasets. However, deep-learning methods may not be widely accessible in all medical settings, and their performance can be affected by biased or limited datasets. Implementing deep-learning methods may require significant computational resources and expertise, posing challenges in resource-constrained environments. Ensuring patient privacy and ethical use of deep-learning methods in healthcare is essential, but challenging.

A new skin lesion segmentation network, DSNet,[3] has been proposed for melanoma detection using depth-wise separable convolutions. It outperformed U-Net and FCN8s on the ISIC-2017 dataset, with significant Intersection over Union scores of 77.5% and 87.0% on ISIC-2017 and PH2 datasets. DSNet's lightweight design reduces parameters while maintaining segmentation accuracy. However, its performance may vary on different datasets, skin types, and lesion variations, and its efficacy on diverse skin types and lesion variations is not fully explored. Complex network structures may also hinder interpretability for clinicians.

The paper [4] discusses the use of machine learning and deep learning in analyzing skin lesion images for melanoma detection. It covers techniques like pre-processing, segmentation, comparative analysis, classification, and performance evaluation. The study highlights the effectiveness of ensemble deep learning models on pre-processed and segmented images. However, the survey may not cover the latest techniques or explore other potential approaches, potentially limiting its scope. Additionally, it may not consider nuances related to different ethnicities and skin types, potentially impacting the generalizability of the techniques.

Skin cancer [5] is a major public health issue, with over 5 million cases identified annually in the US. It consists of two main types: melanoma and non-melanoma. Early detection is crucial, with a survival rate exceeding 95%. A skin cancer detection CNN model is being developed using deep learning techniques to aid in early detection. However, the model's effectiveness depends on the quality and size of the dataset, and its interpretability may be challenging. External factors like lighting conditions and image quality can also influence the model's performance. The model's generalizability to unseen cases or different populations needs to be assessed for real-world applicability.

The paper [6] investigates the use of machine learning techniques to improve skin cancer prediction using pre-trained models like VGG19. The models categorize skin lesions into malignant and benign types. By combining the E-VGG19 model with traditional classifiers, the overall accuracy of skin cancer detection is significantly improved. The research compares performance metrics of different models and classifiers, providing insights for automated technologies in early skin cancer detection. However, the study lacks specific datasets, generalizability to different demographics or skin types, computational resources, time required for training and testing, potential bias in dataset selection, and information on interpretability. Future studies could focus on integrating real-time imaging technologies or patient-specific data for more personalized skin cancer detection solutions.

To enhance the precision of skin lesion classification, especially for melanoma diagnosis, a model by the Visual Geometry Group using a Deep Convolutional Neural Network [7] has been suggested. The International Skin Imaging Collaboration provided the data used to train the model, and transfer learning was employed to shorten the training period. Evaluation metrics such as Accuracy, Positive Predictive Value, Negative Predictive Value, Specificity, and Sensitivity assess the classifier's performance. The model achieved an improved classification accuracy of 85% compared to 81% with a standard Convolutional Neural Network. However, the model's generalization to new data may be affected by biases from the source data. The study does not address challenges in deploying the improved classifier in real clinical settings or its integration with existing diagnostic workflows.

A new deep learning IoHT framework [8] uses transfer learning for skin lesion classification in images, extracting features from pretrained architectures like VGG19, Inception V3, ResNet50, and SqueezeNet. These features are fed into a convolutional neural network for benign and malignant cell classification. The system is integrated with IoHT for remote use by medical specialists, outperforming other architectures in accuracy, precision, and recall metrics for skin cancer detection. However, dependability on pretrained models, performance based on training dataset quality and size, and effectiveness impacted by image quality or resolution in real-world applications are potential challenges.

The SCDC-Net [9] is a transfer learning-based system for skin cancer detection and classification, using UG-Net and HU-Net to eliminate hair artifacts and segment lesion regions. It extracts features using GLCM and DWT and uses a DQNN model to classify skin cancer categories. The system outperformed existing methods on the ISIC-2019 dataset, demonstrating potential for early skin cancer detection. However, challenges like skin type variations and lesion sizes may affect performance. Further validation is needed for practical applications.

Skin cancer [9] is rapidly advancing, and early detection is crucial. Deep learning models like CNN have been used for accurate diagnosis. The MNIST: HAM10000 dataset, with 10015 samples of seven skin lesion types, was pre-processed using sampling and segmentation techniques. Transfer learning with DenseNet169 and ResNet50 was used for training. However, limited resources and the dataset's size may not fully represent the diversity of skin lesions in the population, affecting the model's performance.

A proposed algorithm [11] aims to detect skin lesions for early malignant melanoma detection. Pre-processing improves lesion quality, and Geodesic Active Contour (GAC) is used for segmentation. ABCD rule, GLCM, and HOG feature extraction are applied for symmetry, color, and textural features. Machine learning techniques achieve 97.8% accuracy and 86.2% sensitivity.

Skin cancer [12], a major public health concern, has two main types: melanoma and non-melanoma. Early detection is crucial, with a survival rate exceeding 95% if detected early. A skin cancer detection CNN model is being developed using Convolutional Neural Networks to classify skin cancer types and aid in early detection. The model will use different network architectures and Transfer Learning techniques for improved accuracy. However, the model's accuracy depends on the quality and diversity of the dataset obtained from the ISIC challenge archives. CNN models can sometimes lack interpretability, making it challenging to understand classifications. The model's performance may vary when applied to real-world scenarios outside the training dataset. To ensure fairness and prevent biases, the model must undergo rigorous testing and regulatory approval before deployment in clinical settings.

An automated approach to skin lesion categorization utilizing a pre-trained deep learning network and transfer learning on the Ph2 dataset is suggested in the paper [13]. With a classification rate that exceeds current methods and an accuracy of 98.61%, the model successfully distinguishes between melanoma, common nevus, and atypical nevus. However, the method's performance is evaluated only on the Ph2 dataset, limiting its generalizability to other datasets. Studying the computational resources utilized for training and inference, along with the false positive and false negative rates, would have allowed for a more comprehensive evaluation of the model's performance.

The alarming rise in the incidence of skin cancer [14] has prompted researchers to create automated diagnostic computer systems to detect the disease at an earlier stage. A study on ResNet, VGG16, GoogleNet, and AlexNet for melanoma classification showed high accuracy and low false-positives. However, the study focused only on four specific deep learning architectures, overlooking other models. It also did not consider potential variations in datasets used for training and testing, computational resources required for real-world applications, ethical implications, interpretability, transparency, limitations of data collection methods, and demographic differences on the performance of DL models.

Automated systems [15] that use deep learning to identify and treat skin cancer early are crucial because the disease is a growing worry for many individuals. If detected in their early stages, basal cell carcinoma, squamous cell carcinoma, and melanoma—the three most common forms of skin cancer—are all curable. Using Convolutional Neural Networks (CNN) and picture pre-processing, the accuracy of skin cancer detection and classification is improved. The use of varied datasets introduces the possibility of bias and necessitates constant adaption to novel skin cancer variations.

3. Proposed methodology

The modules showed in figure 2 in the proposed work are

- Segmentation
- Classification
- Feature Extraction
- Segmentation

By dividing a digital image into smaller, more manageable pieces, or "image segments," segmentation makes it easier to handle and analyze the image later on. Simply said, segmentation is the process of giving names to individual pixels.

- Classification

Classification is the method for categorizing and labeling groups of pixels or vectors within an picture based on specific rules. The categorization law can be devised using one or more spectral or textural characteristics. Two general methods of classification are 'supervised' and 'unsupervised'.

- Feature Extraction

One step in dimensionality reduction is feature extraction, which involves splitting and merging large sets of raw data into smaller, more manageable ones. This will make processing it easy when the time comes. Having a huge number of variables is the most essential attribute of these enormous data sets. Processing these variables demands a significant amount of computational resources. By choosing and merging variables into features, feature extraction significantly reduces the amount of data while getting the best feature from those enormous data sets. These characteristics are simple to handle while also providing a unique and accurate description of the real data set.

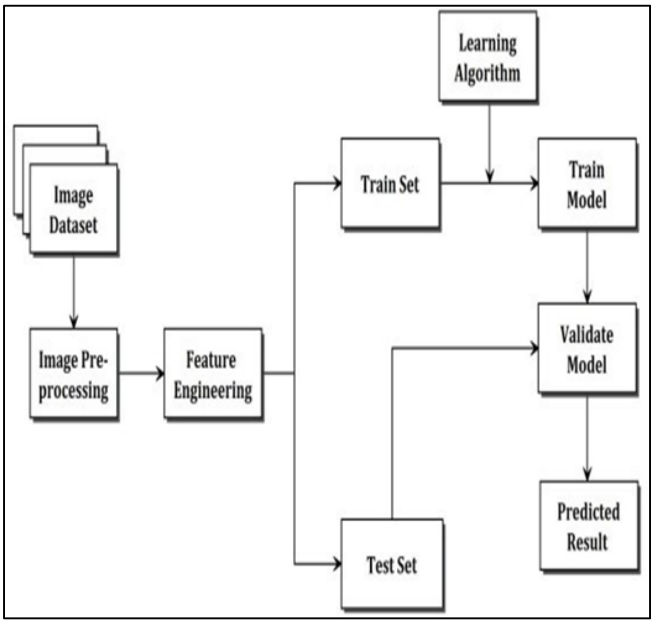

Figure 2 System Architecture

3.1. Image Dataset

Here are publicly available datasets that we can consider using for this proposed work:

- ISIC-(International-Skin-Imaging-Collaboration) Datasets:
- ISIC-archive and ISIC-Challenge.

This set consists of 2357 images of malign and normal oncological diseases, which were formed.

3.2. Feature Engineering and Image-Preprocessing

- Resize and Normalize: Preprocess uploaded images to a standardized size and normalize pixel values.
- Data Augmentation: Apply techniques like rotation, flipping, and zooming to augment dataset and improve model generalization.

3.3. Split data into train-test

Given datasets were splitted into train and test in ration of 85:15. With the dataset 2003 images were taken as train data and 354 images were taken as test data.

3.4. Learning Algorithm

DL and TL(Transfer-Learning) model were used which as CNN and VGG to train the dataset to build the model. The CNN comprises various layers, each serving a specific purpose:

- Convolutional Layers: These layers apply filters (kernels) to data as input, convolving over it to detect local patterns and features. This helps capture spatial information and identify low-level features like edges, textures, and shapes.
- Pooling Layers: After convolution, pooling layers down-sample the spatial dimensions, reducing the data's size. Commonly, max pooling is used, where the highest value is chosen for each pooling region. Pooling reduces the computational complexity while extracting pertinent information.
- Fully Connected Layers: These layers establish connections between every neuron in the layers before and after. They are located at the network's end and use the features retrieved from them to make high-level predictions.

3.5. The VGG

A set of convolutional neural network (CNN) architectures developed to perform exceptionally well in picture recognition and classification tasks is known as the Visual Geometry Group (VGG) algorithm. The VGG framework, developed by the Visual Geometry Group at Oxford University, gained popular acclaim for its remarkable combination of ease of use and effectiveness. The VGG architecture has several versions; the most popular one is VGG16, which has 16 layers total (13 convolutional and 3 fully linked). Another variation, VGG19, has 19 layers and is deeper. The fundamental novelty of VGG was its constant and straightforward structure across all layers, which greatly facilitates understanding and replication.

3.5.1. Input Layer

Accepts input images of a fixed size (e.g., 224x224 pixels).

3.5.2. Convolutional Layers

Consist of multiple convolutional blocks, each containing two or more convolutional layers followed by a max-pooling layer. Convolutions use small 3x3 filters with a stride of 1, preserving spatial dimensions. Padding is used to maintain the spatial size after convolutions.

3.5.3. Max-Pooling Layers

Reduce spatial dimensions by down sampling, capturing important features while reducing computational complexity. Typically use 2x2 max-pooling with a stride of 2.

3.5.4. Fully Connected Layers

Flattens the output from the convolutional layers and connects it to one or more fully connected (dense) layers. concludes with an output layer that has the same number of neurons as the classes involved in the classification operation.

Image classification tasks, such as those on the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) dataset, were particularly well-suited to the VGG16 architecture's deep stack of layers and compact convolutional filters. Training and deploying VGG models can be computationally expensive due to their depth and large number of parameters, in contrast to more modern designs such as ResNet and Inception. The VGG architecture, however simpler than some newer models, was crucial in establishing the efficacy of deep convolutional neural networks (CNNs) for computer vision applications. Experts in the field have improved upon VGG's ideas to develop even more sophisticated and effective models. Following the architecture's guidelines, you can construct the VGG algorithm by defining the convolutional blocks, max-pooling layers, fully connected layers, and output layer. When training the model on your unique dataset, you need also employ suitable activation functions (like ReLU), loss functions (such categorical cross-entropy), and optimization methods (like SGD, Adam). We also use the built model to verify the test data and calculate performance metrics like loss and accuracy. Use the trained model to make predictions about the unknown input.

4. Results

The following figures define the results or outputs that we will get after step-by-step execution of all the modules of the system.

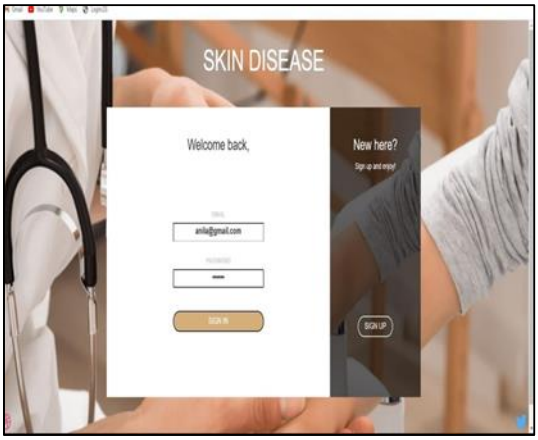

Figure 3 Login Page

The above Figure 3 shows the snapshot of login page where the web page application prompts users to enter their credentials: Sign In for existing users and Sign up for new users.

Figure 4 Home Page

The above figure 4 shows the home page, this page provides overview of the website's content and redirection to different sections.

Figure 5 Uploading image

The above figure 5 shows the snapshot of uploading the image where the user will upload the image for melanoma detection. This includes the choose file button and once the image is chosen from the dataset need to click on submit for further processing.

Figure 6 Masking image

The above figure 6 shows the image masking, where masking an image typically involves segmenting the image to isolate the region of interest. This is done using image processing techniques.

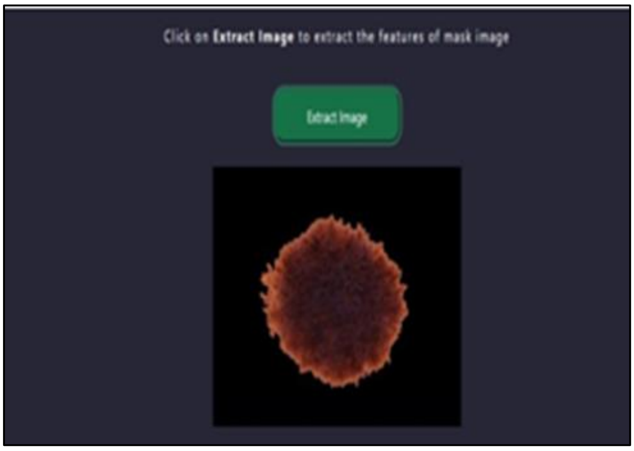

Figure 7 Extracting image

The above figure 7 shows image extraction, where the relevant features from the segmented region is extracted. Features like asymmetric, border, color, dimension of the skin lesion is extracted.

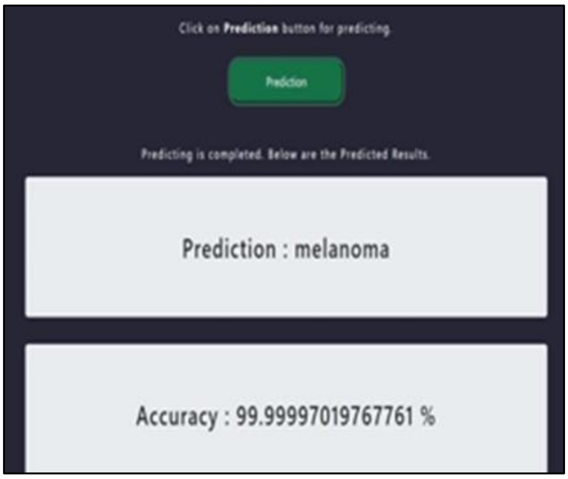

Figure 8 Prediction of Melanoma cell

The above figure 8 shows the prediction of melanoma cell with accuracy rate.

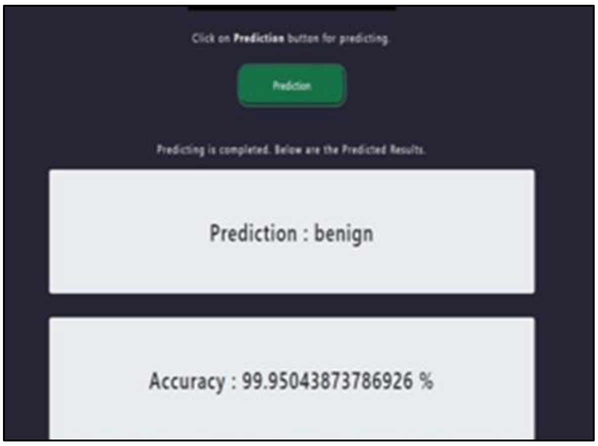

Figure 9 Prediction of Benign cell

The above figure 9 shows the prediction of benign cell with accuracy rate.

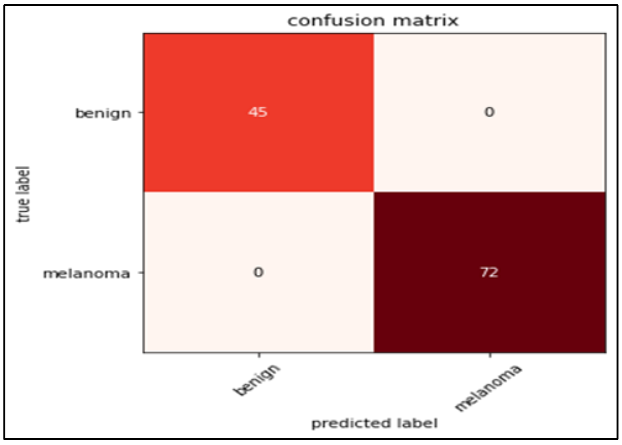

Figure 10 Confusion Matrix

Above figure explain the confusion matrix with the CNN Model clearly showing the True Positive, True Negative, False Positive and False Negative counts with the dataset considered as two types benign and melanoma. In the Confusion Matrix itself we come to see the more accurate output as Count are proper.

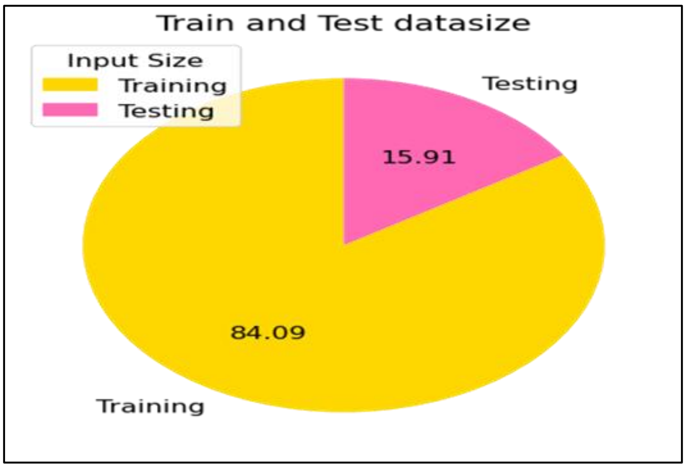

Figure 11 Visualization Graph

Above figure explain the Visualization Graph with the ratio of split-up during training 70:15:15. 70 % for Train 15% for Test 15% for Valid.

5. Conclusion

The study discovered that a novel convolutional neural network (CNN) technique has the potential to aid in the detection of skin cancer from photographs. The method effectively captures the distinguishing characteristics of skin cancer through the utilization of parallel convolution blocks. In comparison to widely used VGG-CNN architectures, the model exhibits exceptional performance in terms of classification. The skin cancer classification system employed in this study, which consists of nine categories, is currently the most widely utilized. To effectively train and implement a CNN-based architecture, data augmentation techniques were employed to fulfill the substantial data requirements. By following this procedure, our objective was successfully achieved, as evidenced by significant improvements in recall, F1 score, and precision.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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