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Skin cancer disease analysis using classification mechanism based on 3D feature extraction

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ABSTRACT

Dermoscopic image analysis is essential for effective skin cancer diagnosis and classification. Extensive research work has been carried out on dermoscopic image classification for the early detection of skin cancer. However, most of the research works are concentrated on 2D features. Therefore, a 3D lesion establishment mechanism is presented in this work to generate 3D features from the obtained 3D lesions. The objective of this work is to reconstruct 3D lesion image from 2D lesion images and a multi-spectral reference IR light image. The 3D lesion establishment is achieved by designing an efficient convolutional neural network (CNN) architecture. Details of CNN design architecture are discussed. After reconstruction of 3D lesions, 2D and 3D features are extracted and classification is performed on the obtained 2D and 3D features. Classification performance is evaluated using the images from PH2 database. The mean classification accuracy using K-nearest neighbors (KNN) classifier based on the 3D lesion establishment using the CNN architecture is 98.70%. The performance results are compared against varied classification methods in terms of accuracy, sensitivity, specificity and are proved to be better.

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1. INTRODUCTION

Cancer disease has become the most frequently occurring disease all across the world in recent times. The occurrence of cancer disease can be of many types such as skin cancer, breast cancer, stomach cancer, and lung cancer. However, among these cancer types, skin cancer is the most dangerous and most commonly occurring cancer disease [1]. Millions of people are diagnosed with skin cancer disease each year. Therefore, the mortality rate of skin cancer disease is the highest among all cancer diseases. Skin cancer disease can be of different types namely Melanoma, Basal cell, and Squamous cell carcinoma. Among these skin cancer diseases, Melanoma is one of the deadliest and least occuring skin cancer diseases. Melanoma is of two different types namely Benign Melanoma and Malignant Melanoma. However, in the last few years, the incidence rate of Melanoma has drastically surged. According to a statistical report, the number of people who die due to Melanoma disease each year in the United Kingdom (UK) is 1800 [2]. The occurrence of malignant tumors depends on the abnormal rise of melanocytes. Melanoma can occur anywhere on the body and Melanoma is the most lethal form of skin cancer. Based on the statistical report, it is estimated that millions of new cases will be diagnosed with skin cancer and thousands of patients will die due to the occurrence of Melanoma [3]-[5]. However, melanoma is treatable effectively if melanoma is detected in earlier stages and melanoma spread can be protected [6]. However, the detection of skin cancer types through

dermoscopic images in earlier stages is a very complicated and challenging process due to the similarities in disease characteristics. Skin cancer experts or dermatologist specialists can only treat skin cancer efficiently and can classify the type of skin cancer disease.

Nevertheless, the number of skin cancer experts is very less and the classification of Melanoma requires tiresome training and clinical analysis. Therefore, automatic skin cancer detection and classification techniques are required to identify skin cancer types efficiently. Thus, computer vision technologies can be used for different biomedical applications to analyze specific patterns of dermoscopic skin images [7] and [8]. Numerous computer-aided diagnosis methods, artificial neural networks (ANN), deep learning (DL), varied classification methods, and convolutional neural network (CNN) models have also shown decent performance for skin lesion classification. The common features extracted to analyze skin tumors are color, shape, texture, and histogram gradients. The performance and efficiency of varied skin lesion classification methods get suffered from insufficient medical data, inadequate prediction models, and impractical feature extraction methods. Therefore, efficient classification of melanoma tumors is still a vast research area. Another interesting research area can be the classification of skin tumors based on 3D feature reconstruction. There is a lot of research work has been carried out in the skin lesion analysis field to detect skin cancer types. Some of the classification methods regarding skin cancer detection analysis are demonstrated in the following paragraph.

Kassem *et al.* [9], a systematic review based on machine learning (ML) and DL model is presented for the classification of skin lesion analysis. This article discusses varied skin lesion datasets namely PH2, ISIC challenge 2016, 2017, and 2018. The presented model compares the classification performance of different skin lesion detection models. This study summarizes around 53 ML methods and 49 different DL models. Thurnhofer-Hemsi *et al.* [10], a deep CNN model is employed for skin lesion classification analysis based on the regular space-shifting method. This is used to design varied versions of the testing set to shift displacement vectors. Output is obtained based on the extracted features and test images are tested on the HAM10000 dataset in terms of classification accuracy. Ramadan and Aly [11], an improvised color U-Net model is employed for skin lesion detection analysis. Three different U-Net models have been discussed namely single input U-Net, dual input U-Net model, and triple input U-Net model. Each network handle training of different color space images. These models are tested on varied datasets namely International Skin Imaging Collaboration (ISIC 2017, ISIC 2018) and PH2 datasets. Rasel *et al.* [12], a CNN model is introduced for the analysis of skin lesion classification based on the variable non-linear activation functions. The presented CNN model helps to enhance classification performance from dermoscopic images. The role of the activation functional layer in the CNN model is to design the output layer and to identify which information needs to be passed to a particular layer. The obtained classification accuracy using this model is 97.5%.

Cancer identification is a critical step in the disease detection process. The existing procedures that are manual or semi manual need a [13] significant amount of computerized resources, take a long time, and are inaccurate. To overcome these limitations, the histogram of oriented gradients, a feature descriptor, is combined with neural network for extracting features as a classification method proposed for identifying the various class labels of cancerous skin in medical images. To complete the assessment, the found class labels are compared to the original labels. The ISIC 2019 dataset is being utilised to construct and test this research project. Accuracy of 95.7% is attained. ML methods have been put into use to detect skin cancer in several melanoma detection systems; nevertheless, the performance to identify [14] the malignancy was restricted. As a result, the approach taken into consideration here built a model using a CNN, the most sophisticated DL technique. This study combines residual network (ResNet) and visual geometry group (VGG) based models for melanoma skin detection by using transfer learning techniques. 94.5% accuracy was achieved using this strategy. However, classification of skin lesions with high accuracy considering 3D lesion reconstruction is not discussed in this literature and it is a recent research area for future medical applications.

Early detection of Melanoma is a high priority to control the rise in incidence and mortality rate of skin cancer cases. Therefore, the establishment of 3D structures is discussed using prior knowledge of 2D dermoscopic lesion image and infrared light dermoscopic images present in the Multispectral dataset with the help of a CNN architecture. Here, IR light images are used as a reference to create 3D lesion structures by exploiting color and depth characteristics. After the generation of 3D lesion structures, high-quality multiple features are obtained namely color, texture, histogram gradients, spatial distribution, and shape. Some of the obtained features are in 2D and some features remain in 3D obtained based on the analysis of the generated 3D lesion structures. At last, efficient classification is performed on the basis of obtained features. High-performance results are obtained and compared against varied lesion classification methods. The focus area of this work is the establishment of 3D lesion structures using CNN architecture. After the 3D lesion structure establishment, high-quality multiple features are obtained and the classification process is performed from the obtained feature maps. This paper is structured in the following sections which are as follows. Section 2, describes the proposed methodology for the classification of skin lesion analysis. In section 3, simulation results are demonstrated and section 4 concludes the paper.

2. METHOD

Skin cancer disorders can be diagnosed by leveraging key performance metrics such as sensitivity, specificity, precision, and accuracy. Figure 1 outlines the overall flow of the proposed feature extraction and classification model. This model integrates both 3D and 2D features, along with 3D lesion structures, using infrared (IR) images. The process starts with inputting a 2D segmented image into a CNN block, which generates a 3D structure from the input. Features are then extracted from this 3D representation. Ultimately, the images are classified as either benign or malignant using a K-nearest neighbors (KNN) algorithm based on the extracted features.

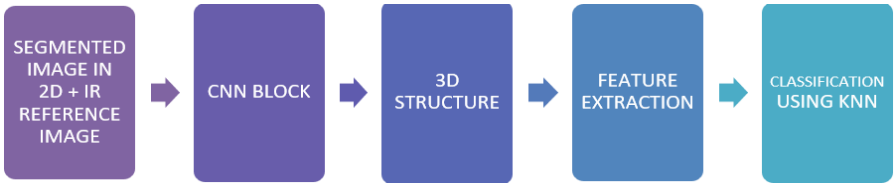


Figure 1. General flow diagram for the proposed FEC model

The Algorithm 1 through which the 3D reconstructed structure is built is given in table below. The objectives to be fulfilled by this algorithm is to identify the 2D features and 3D features.

Algorithm 1. The 2D and 3D reconstructed structure

- **Input:** Dermoscopic segmented 2D image and infrared (IR) image
- **Output:** 3D structure

1. The segmented image is provided as input.
2. **Convolution Layers 1 and 2** are applied to extract feature maps using filters at each layer.
3. **Pooling Layers 1 and 2** employ max pooling to reduce the dimensionality of the image.
4. **Convolution Layers 3 to 5** are used to extract more complex and abstract features.
5. **Pooling Layer 5** further reduces the dimensionality of the image obtained from convolution layers 3 to 5.
6. The **fully connected layer** integrates the features learned from the previous layers, with additional loss functions applied at the end to fine-tune the model.

This section provides the architecture design of CNN to establish the 3D lesion structures of a given dataset. Efficient reconstruction of 3D lesions can provide multiple 2D and 3D features. Thus, classification performance can be significantly improved in comparison with state-of-art methods. Figure 2 demonstrates the design architecture of CNN to achieve the objective of 3D lesion establishment. This section focuses on utilizing joint optimization of 2D lesion information obtained from the dermoscopic images and IR light reference images from the multispectral dataset to generate proper 3D lesions using CNN architecture. Initially, the combination of 2D dermoscopic lesion images and reference images is given to the CNN as input, and the presence of multiple layers and filters of varied sizes and strides perform processing on those given images. After effective training, 3D lesions are established as the output of CNN architecture. To get the proper 3D lesion structures, a deep knowledge of the design architecture of CNN, and understating of the CNN working process is a foremost priority and requisite of this work. Therefore, in this work, the design architecture of CNN for 3D lesion structure establishment is studied.

CNN architecture is a combination of multiple layers, several filters, different processing blocks, and varied hyper-parameters. Mainly CNN architecture contains multiple convolutional layers, pooling layers, activation functions, and dense blocks. However, a combination of fewer blocks and layers is adopted to reduce computational complexity. Significant and essential feature weights are generated using varied CNN filters. Combined optimization of IR reference images and 2D lesion images helps to enhance the quality of obtained feature maps. In CNN design architecture to analyze training loss or information loss, loss functions are added. It is demonstrated in Figure 1 that multiple convolutional layers and pooling layers are present in the CNN architecture and share information with each other. Then, fully linked layers are used to receive the output of convolution and pooling layers. A total number of two fully linked layers are utilized in CNN architecture and both the fully linked layers are connected to the loss functional blocks to evaluate training loss. In the end, based on the feature map outputs obtained from fully linked layers, the 3D lesion structures are established. In this way, CNN architecture is designed to reconstruct 3D lesions.

CNN is the main category of neural networks to analyze problems of image classification, image-based identification, and image reconstruction. The CNN architecture follows a DL mechanism in which an image is fed as input, processed using different layers, and the desired output is obtained for specific tasks. CNN provides high-performance results by extracting important features from the given input images. However, CNN architecture designing is a complicated process and the model needs to learn significant end-to-end information from the large datasets. In CNN architecture, convolutional layers are massively important for the proper analysis of given input data. A detailed overview is presented and important functional parts are discussed below.

Convolutional layers: convolutional layers are one of the most important layers of CNN architecture. The output of convolutional layers generates feature maps using multiple feature detectors present in the design of convolutional layers from the given input. Convolutional layers consist of a variety of filters namely edge detection, edge enhancement, emboss, sharpen, and blur. The objective of this layer in this work is to generate high-quality feature maps based on the given 2D dermoscopic lesion image and IR reference image. Computational complexity in 3D lesion establishment is reduced by lowering the size of convolutional filters and by using fewer filters.

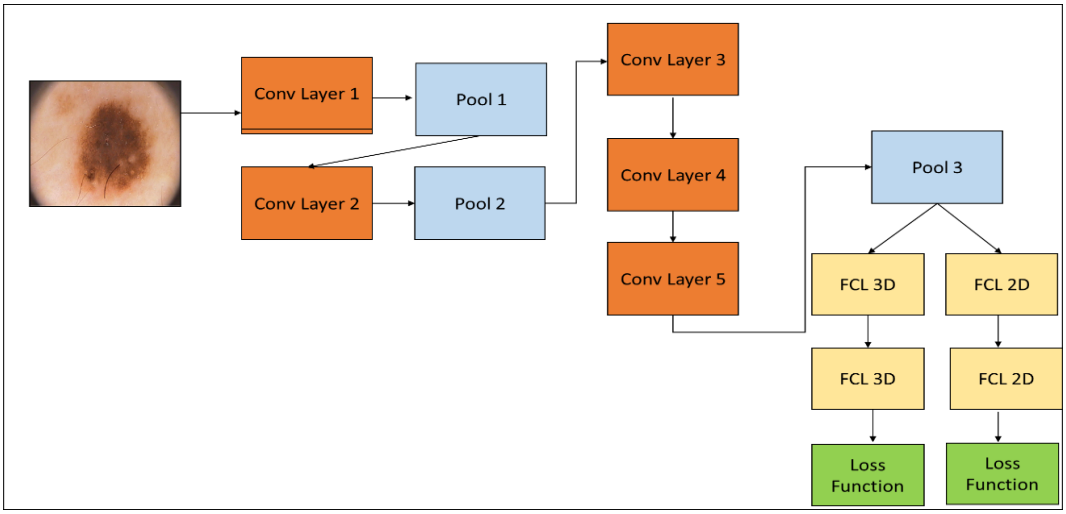


Figure 2. Block diagram of CNN architecture

ReLU activation functions: CNN architecture is made up of multiple layers. These layers constantly get updated due to continuous backend processing. Hence the input to these multiple layers can be different. Therefore, to normalize the processing of these layers in mini-batches a batch normalization process is used. The normalization of given data is obtained using the batch normalization layer in terms of standard deviation. Furthermore, the ReLU activation function is used to improve performance efficiency by minimizing training errors. This layer is used to improve the non-linearity of training data and to avoid over-fitting. ReLU activation functions are mainly used for improving training speed in object detection, object classification, and image reconstruction applications. The main work of the ReLU activation function in this work is to keep all positive pixel values and modify negative pixel values to zero. The weights are obtained in form of tensor values. Then, tensor values and weighted kernels are processed together based on element-wise multiplication. Then, obtained output values are added together to get the final output in form of tensor values.

Pooling layers: another key building block after convolutional layers is pooling layers in the design of [15], [16] CNN architecture. The pooling layer is mainly employed to minimize the size of convoluted feature maps and compress the dimensions of obtained data. These layers encode only the height and width data of feature maps and channel configuration remains the same. To minimize computational complexity and generate effective feature maps, this layer is massively important. Pooling layers can be of different types. However, two main categories of pooling layers are the average pooling layer and the max pooling layer. Both layers have their own functionalities. The average layer provides average values of all the pixels of an image whereas the max-pooling layer gives maximum values of all the pixels of an image. This layer also minimizes spatial resolution and enables translational invariance to get proper features. From

the convoluted feature maps, different average and maximum values are computed using pooling layers. The output of the pooling layer is fed to the fully linked layers.

Fully connected layers: another important layer in CNN architecture design is the fully linked layer. A hidden flattened layer is also present to get the pooled feature maps and convert those feature maps into feature vectors. Those feature vectors are used in fully connected layers for further processing into final feature maps. The main task of the fully linked layer is to convert those feature maps into the final desired output. For instance, in this case, fully connected layers provide 3D lesion structures from the feature maps. Based on the characteristics and attributes of the given input, feature maps get generated to build 3D lesions. In this way, CNN architecture is designed to get the 3D lesion structures from given data. This work can be summarized as the desired features are extracted from the input data using convolutional layers and down-sampled using pooling layers. Then, the flattened layer converts feature maps into feature vectors and fully linked layers provide the final output.

3. RESULT AND DISCUSSION

This section evaluates the performance of the proposed feature extraction and classification mechanism for diagnosing melanoma skin cancer using dermoscopic images. The model uses both 2D lesion images and IR reference images to generate 3D lesion structures through multiple CNN layers and filters. The core objective is to design an efficient CNN architecture that establishes 3D lesion structures, enabling the extraction of high-quality features. These features are then used for accurate classification of melanoma skin cancer images.

The performance of the model is tested on the PH2 dermoscopic image dataset, which contains 200 images with varying lesion sizes and colors. The dataset is divided into three categories: common nevi (80 images), atypical nevi (80 images), and melanoma (40 images). In some studies, melanoma is further divided into normal melanoma and in-situ melanoma, emphasizing the need for a multi-class classification approach. To handle this complexity, the KNN classifier is used for effective classification of the melanoma images.

The performance of the proposed classification mechanism is tested using the KNN classifier due to their past records [17] and even, in this case, the KNN classifier accurately predicts all three classes and a sub-class with a high accuracy percentage. The performance of the proposed feature extraction and classification mechanism is presented based on 3D lesion structures. Therefore, for dermoscopic images, different 3D spatial and shape features are obtained. Thus, Table 1 demonstrates the variety of 3D spatial features obtained from a dermoscopic image. It is visible from Table 1 results that the intensity and contrast of obtained spatial features are clear and uniformly centered. Similarly, Table 2 demonstrates the different 3D shape features obtained from a dermoscopic image. It is evident from Table 2 results that the borders and boundaries of obtained lesions features are clear and sharp.

Table 1. 3D lesion reconstruction representation in terms of spatial features

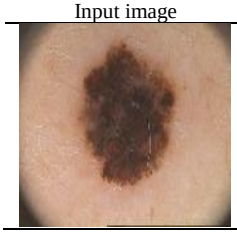
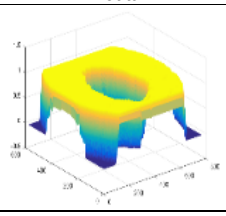
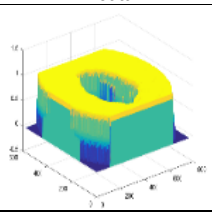
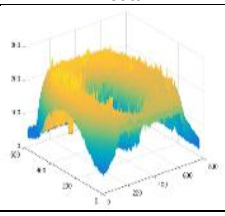
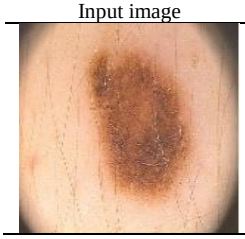
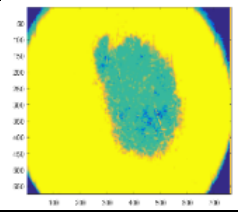
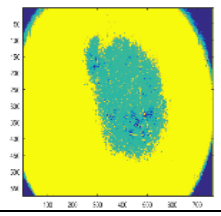
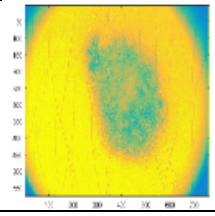
Input image	X-data	Y-data	Z-data
			

Table 2. 3D lesion reconstruction representation in terms of 3D shape features

Input image	X-data	Y-data	Z-data
			

Additionally, class-wise classification performance using the KNN classifier against varied classification methods namely RESNET 50 and RESNET 101 [18], SQUEEZE NET [19], VGG19 [20], and Leaky RELU [12] is presented in Table 3 in terms of accuracy, sensitivity, and specificity. In this Table 3, N stands for Nevi skin cancer class, TN stands for atypical nevi skin cancer class, and M stands for Melanoma skin cancer class in PH2 dermoscopic images. The classification accuracy was obtained using the proposed classification mechanism based on the extracted features from 3D lesion structure establishments for common nevi class is 98.01%, atypical nevi class is 99.21%, melanoma is 98.89%. These results show that 3D lesion establishment using the CNN architecture generates high-quality efficient features.

Finally, a graphical representation of the proposed classification mechanism against different classification models is also presented in terms of mean classification accuracy in Figure 3. Those classification models are Leaky ReLU [12], Clipped ReLU [12], ALEXNET [21], GOOGLE NET [22], RESNET [18], KM-HOSNY [23], KONDAVEETI [24], YOUNIS [25], and VGG16 [20]. These all models utilize a CNN architecture to get efficient classification performance. The mean classification accuracy using KNN classifier based on the 3D lesion establishment using the CNN architecture is 98.70%. This result shows the superiority of the overall proposed classification mechanism.

Table 3. Classification performance against varied classification methods

Methods	Accuracy			Sensitivity			Specificity		
	N	TN	M	N	TN	M	N	TN	M
[18]	70	63	93	31	88	75	96	46	97
[18]	70	70	95	94	31	88	54	96	97
[19]	78	73	85	88	38	88	71	96	84
[20]	78	73	90	50	88	75	96	63	94
[12]	75	73	98	63	75	88	83	71	100
Proposed	98	99	98	99	100	99	98	99	100

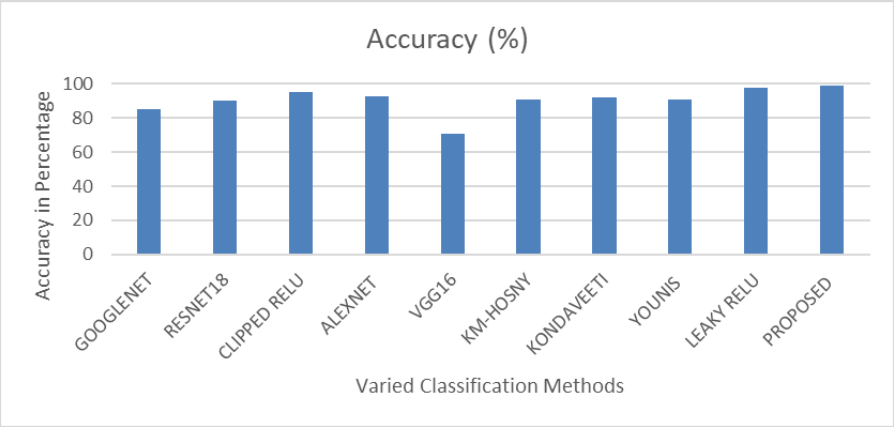


Figure 3. Classification performance comparison considering varied classification methods

4. CONCLUSION

Melanoma skin cancer classification plays a critical role in medical applications due to the high prevalence of skin cancer. This paper presents a methodology for establishing 3D lesion structures from 2D dermoscopic images and IR reference images using a CNN architecture. While reconstructing 3D lesions is a complex process, it allows for the extraction of high-quality, information-rich features. These features form the basis for the classification process. The paper provides a comprehensive discussion on the methodology for creating 3D lesion structures and the design of the CNN architecture. The existing methods dealt with 2D images, whereas the proposed method arrived at better accuracy values with 3D image. The proposed classification model is evaluated using the PH2 dermoscopic image database, with results presented in terms of 3D spatial and shape feature representations. The classification accuracy achieved using this method is 98.01% for the common nevi class, 99.21% for the atypical nevi class, and 98.89% for melanoma. The overall mean classification accuracy is 98.70%, outperforming other classification methods.

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AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Ramya Srikanteswara	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	
Ramachandra A. C.	✓	✓				✓		✓	✓	✓	✓	✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available online from the Kaggle database.

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