

Application of Deep Learning Methodology for Early Detection of Melanoma

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Abstract—Early diagnosis of melanoma warning signs can help prevent cancer from spreading to other parts of the body. Dermatologists use their skills and knowledge to assess skin lesion imaging data to identify malignant melanoma. The error can be overcome by using computer vision and deep learning algorithms for automatic segmentation and detection for accurately identifying the disease. Deep learning in melanoma detection can speed up diagnosis, buy time for medical treatment, lowering treatment costs, allow for home-based diagnostics and monitoring, and provide the best value to the patient. Medical image segmentation or detection based on deep learning methods is an efficient method that outperforms human-level accuracy. Deep learning algorithms are used in dermoscopy for the improvement of analysis, segmentation, and melanoma classification. These algorithms are trained using deep neural networks on many annotated malignant and benign melanoma images. This study presents a comprehensive and systematic literature review of the conventional approach used in melanoma detection using CNN. A large number of datasets are available to detect melanoma and some of them are ISIC archive, HAM10000, PH2, MED-NODE, and other image libraries are widely used datasets. Dice-coefficient, sensitivity, specificity, accuracy, and area under the receiver operating characteristic curve (AUC-ROC) are the commonly adopted metrics by different researchers across the globe.

Index Terms— classification, convolutional neural network, deep learning, melanoma, skin cancer, skin lesion.

I. INTRODUCTION

Skin cancer is the most common disease in humans specifically in the last decade. The disease can be benign or malignant. The benign lesion is usually stable means that it doesn't change its color, or shape size while the malignant one can change accordingly. The main cause of such disease is DNA damage caused by UV radiation exposed by uncontrolled cell multiplication. For decades, dermatologists have relied on image analysis for the identification and classification of diseases. One of the most popular skin lesion study subjects is the detection of melanoma skin cancer, a possibly fatal dermatological illness. The deadliest kind of skin cancer, melanoma, is lethal if not treated and identified at an early stage. Melanoma is caused by melanocytes, which create melanin, and can occur in any region of the body, most evident on the skin. Melanoma can be treated at an early stage by removing the melanoma-affected lesion[1]. This type of cancer is said to be at stage 4 when it is spread to internal organs such as the lungs, liver, brain, or gastrointestinal system. For diagnosis, dermatologists analyse the visual analysis and identify medicinal features of the stated disease such as color change, asymmetric nature, diameter larger than 6mm, uneven borders and changing nature of the mole. Techniques including clinical

screening, visual inspection, biopsy investigation and dermoscopic analysis of skin lesions still experience difficulty in accurately and quickly identifying the melanoma from the images of skin lesions because of the complicated properties of the skin lesion such as fuzzy borders, multi-shapes, and the presence of noise (hair, air and oil). The help of deep learning in analysis of images of skin can help global population for early detection of disease that will result in the instant and automated categorization of the malignant tumour using non-invasive methods.

As a result, an effective CAD(Computer Aided Diagnosis) system is used for detecting and diagnosing the skin cancer, melanoma Figure 1 by decreasing the mortality rate. The most common kind of melanoma is cutaneous, which forms on the skin, particularly in locations where the skin is exposed. Melanomas are most typically discovered on the neck or face, as well as in sun-exposed locations such as the groin or beneath the fingernails. The many forms of melanoma are superficial spreading melanomas, nodular melanoma, acral lentiginous and lentigo maligna[3].

A. Challenges Of Skin Lesion Images

Detection of malignant melanoma from the skin lesion images becomes difficult as a result of color variations and the source of the skin[4][5][6].

1. Multi-shape and size:- As skin lesion images have a wide range, so they become very tough and tricky for detection. The region, size and kinds of lesions vary differently. For, this image pre-processing is required for exact and accurate analysis of the skin lesions.
2. Artifacts and noise presence:- During the image acquisition, some noise objects of the image are added. This may lead to the presence of noise and artefacts for the improper detection of the skin lesion. As these are not present originally so they can affect the signals and the interpretation with computer-aided diagnosis.
3. Irregular fuzzy boundaries:- As the images of the skin lesion have hazy and uneven borders, making many approaches for contour refinement and lesion boundary identification are challenging. It might be challenging to obtain an exact boundary of skin lesion images during the preprocessing step.
4. Low contrast:- By low contrast images there is difficulty in examining the skin lesions. So for that segmentation is needed.
5. Color illumination:-Color illumination is another major factor of challenges for examining the skin lesions as the shadow, and the lighting of the images may provide the multi-resolution.

II. RELATED WORK

A. A. Adegun and S. Viriet al [7] ensured the segmentation and the identification of lesions, and a new architecture based on CNN were employed. CNN had a series of the interconnection of networks with skip pathways. To reduce the computational costs an encoder-decoder network was used[8]. To overcome the limitations of coarsely segmented techniques in deep convolutional networks it processes the skin lesions into multistage techniques. With this approach, the architecture of the CNN reduces its complexity of identifying malignant melanoma and creating an efficient system that will help in the diagnosis of malignancy and the approach takes 5s for the dermoscopic images for practice.

S. Albahli, et al.[9] introduced a new approach that was proposed on Yolov4 and activated contouring segmenting for segmentation and melanoma identification. The whole architecture was divided into three stages:- skin augmentation, melanoma localization, and melanoma segmentation. The suggested approach identifies and segments the melanoma lesion efficiently and exactly. YOLOv4 enables the technique to accurately and efficiently distinguish numerous types of skin disorders and can be used for other medical picture segmentation challenges.

B. A. Albert[10] introduced a unique method that trains to learn using minimal data for a deep ensemble network with 153 non-dermoscopic images for the lesion known as Predict-Evaluate-Correct K-fold. To develop an introspective learning method, the PECK algorithm uses a combination of deep CNN with random forest classifiers and SVM. In building a hierarchical ensemble, the deeper layers will catch the predictions from the prior levels and receive more training layers. To identify lesion contours in non-dermoscopic images, a unique segmentation technique with an aspect of hair, and high levelled noises was proposed. This technique is known as the Synthesis and convergence of Intermediate Decaying Omnigradients (SCIDOG). SCIDOG is non-learning in nature so it is not constrained by the quantity of data. SCIDOG's automated and accurate segmentation enables extracting 1,812 lesion characteristics which enumerate color, texture, and shape. These characteristics are used to train PECK ensembles with the help of a convolutional neural network. With the use of automatized analysis of digital images on the dataset(MED-NODE), a combination of PECK, SCIDOG algos is utilized to predict

melanomas and benign. The proposed methods provide dramatically improved diagnostic capability when tested using 10-fold cross-validation.

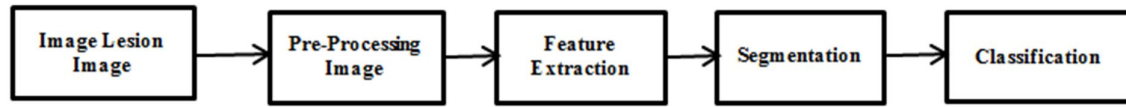


Figure 1. Detection system for melanoma disease

M. A. Rasel, et al., [11] used a computerized approach to assess dermoscopic lesions by minimizing the complexity of diagnosis during the massive screening. With the result, numerous ways have been given for the detection of abnormalities in the skin by applying dermoscopic images. The main aim of the study was that the proposed model can detect lesions in less time in the training phase of CNN, allowing for high-precision diagnosis. In terms of performance, this model beats other current models in the literature (sensitivity). The F1 score and average sensitivity for melanoma in the three datasets are 96.67% and 98.33% respectively. P. M. M. Pereira, et al., [12] This methodology has demonstrated the capability to give rich values for the classification of images by making use of both color and deep information in the classification. A multi-dimensional imaging dataset that provides rich information for image classification is used.

Z. Yu, et al., [2] demonstrated a methodology for earlier disease diagnosis by analyzing the growth of lesions with the use of a series of dermoscopic images and displaying the advantages of integrating sequential indications in diagnosis, as well as the superior quality of the proposed method for capturing adjustments through the sequential images for sooner detection of melanoma in comparison to other sequential models. The methodology indicates that the method is effective for acknowledging the disease at a clinical standard irrespective of the danger of over-report benign lesions and that the suggested model may detect the given disease sooner than physicians, proving the algos utility as a prognosis and diagnostic tool.

L.D.Biasi, et al., [13] In this literature the results indicate that the AlexNet is the most resilient network in terms of transfer learning. CNNs, without segmentation or data augmentation, achieved higher average ACC. A thorough analysis containing earlier research work and strategies used is presented in Table 1.

III. PROPOSED SYSTEM

Deep learning, the subset of Artificial Intelligence discovers patterns and makes predictions from enormous datasets using a machine learning method known as artificial neural networks. Deep learning in melanoma detection can speed up diagnosis, buy time for medical treatment, lowering treatment costs, all allow for home-based diagnostics and monitoring, and provide the best value to the patient. The common steps in skin cancer detection (melanoma detection) is, preprocessing, segmentation, extraction, and classification illustrated in Figure 2.

TABLE I. LITERATURE REVIEW

Authors	Contribution Of Publication	Architecture	Training Technique	Dataset	Cited By
P. Sabouri, et al., [14]	Skin cancer classification using a pre-trained model on a large dataset	Deep neural network	Transfer learning	Non-published medical dataset	5953
Peyman Sabouri, et al.,[15]	Melanoma detection using CNN	Deep neural network	Deep neural network	Dermis, DermQuest	10
K. Hosny, et al.,[16]	Skin cancer classification using a pre-trained model(AlexNet)	Convolutional neural network	Convolutional neural network	PH2	90
Amira Soudani, et al.,[17]	Melanoma detection using VGG-16 and RestNet 50	Convolutional neural network	Transfer learning + crowdsourcing	ISIC 2017	47
D. Bisla et al.,[18]	Automated melanoma detection using transfer learning	Convolutional neural network	Transfer learning	PH2, ISIC 2017, ISIC 2018	77
Tammineni Sreelatha, et al.,[19]	Skin cancer detection by performing image segmentation and noise reduction	Convolutional neural network	Gradient and Feature Adaptive Contour(GFAC)	PH2	31
Milton, et al.,[20]	Skin cancer classification using ensemble deep learning model	Convolutional neural network	Ensemble deep neural network	ISIC 2018	69

A. Procedure

1. **Image Preprocessing:** It is used for increasing the quality and analyzing the images[22] by removing the unwanted distortions and improving specific properties. These properties may vary depending upon the application. An image must be preprocessed to function effectively and produce the desired results. The fully connected layers of a convolutional neural network is required so that all images are of equal size. It reduces the training time of the model and accelerates its inference. If the incoming images are large, decreasing their size will dramatically reduce the duration of time required for training the model without significantly compromising the model's performance.

2. **Image Segmentation:** It is a method of breaking a digitized picture into several sub-groupings known as an image segment, which will reduce the complex nature of the picture and transform it for further processing or analysis easily[5]. In simplified terms, segmentation is the procedure by which the application of a series of labels to pixels is carried out. The simple label is applied to every image part or pixel that is of the same category.

3. **Feature Extraction:** It is a dimensional reduction approach that lows down a greater value of raw data into small units for purpose of processing.

Classification: It is a method in which a subset of target classes (objects to classify in images) is created and a model is trained to discriminate them using annotated example images. Early computer vision algorithms were fed raw pixel data. The task of providing a label or class to a complete image is known as image classification. Images are supposed to contain no more than one class. Image classification algorithms accept an image as input and estimate the class the image. Image classification can be done by ANN, CNN, KNN and GAN.

B. Dataset

Collection of dermoscopic images have been used for the diagnostic performance and the results for the computer-aided diagnosis. Unlike melanoma, there is a lack of datasets for other skin cancers. Due to the small dataset size and the challenges of the melanoma, it gets difficult to train the dataset over the artificial neural network for skin lesion classification. So, CNN is probably used as it is more powerful and solves the classification problem easily. However patients usually suffer from non-melanocytic lesions, the past research mainly focused on melanocytic lesions and it results in a slight variation in diagnosis. So the availability of a reliable dataset is critical. Table 2 summarizes the important details of some of the available datasets.

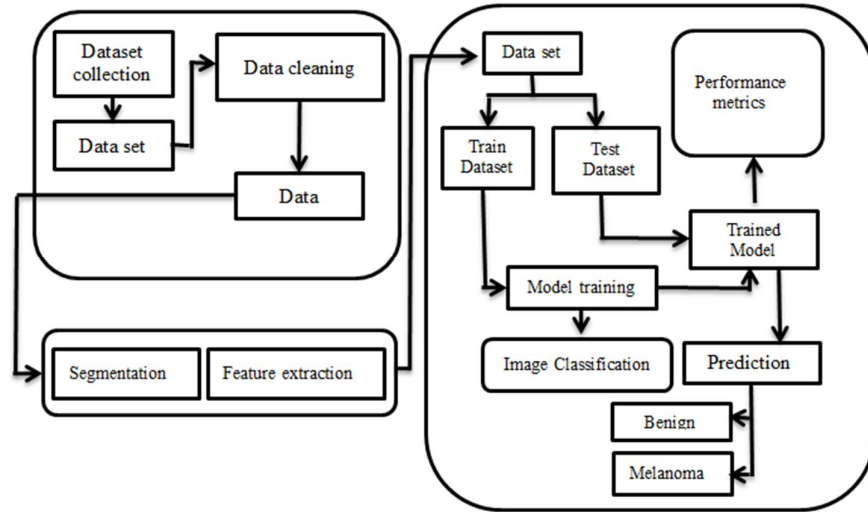


Figure 2. Architecture of melanoma detection[21]

TABLE II. SKIN CANCER DATASETS

Sr. No	Dataset	Total Images	Reference
1	PH2	200	[7]
2	HAM10000	10014	[23]
3	SKINNL2	814	[12]
4	MED-NODE	170	[13]

IV. DISCUSSION

Convolutional neural networks (CNN/ConvNet) are deep neural network models that learn from data directly and are used to analyse visual images in deep learning. These networks are composed of several layers of neurons and employ a method known as convolution. CNNs are effective in detecting the patterns in an image and help in classification. CNN model normalises information acquired by the convolving layer and helps the network to identify the attributes independently.

CNN is divided into two stages: extraction of features and classification of images. Extracting features comprised of convolutional layers, pooling layers and the classifying stage contains the flattening of images and the fully connected layer. In the convolutional layer, the feature map provides information on boundaries and corners which is then fed to the succeeding layer, which will learn different features from the given image. The convolutional layer transmits the output to the next layer after utilizing the convolution operation to the input[24]. This layer proceeds with the convolutional layer. Its basic aim is to decrease the dimension of the convolving feature map to save computational costs by minimizing links within the layers. The fully connected layer which includes weights, and biases and the neurons make connections to a nearby neuron from multiple numbers layers and are placed before the output and form the final level of the CNN architecture. The pooling layer's input image is flattened and given to the fully connected layer. The process of classifying begins at this point. The purpose of connecting two layers is that two completely linked layers outperform a single connected one. These CNN layers help to decrease the need for human supervision[25].

A. Convolutional Neural Network(CNN) Based Melanoma Detection Techniques

Remarkable performance in medical imaging detection, segmentation, and classification activities has been attained by CNN-based automated deep learning systems [25]. A deep CNN was introduced for the identification of melanoma [26]. For segmentation, FCRN- a fully convolutional residual network with 16 residual blocks was used. For the classification process, it served as an average of the Support Vector Machine (SVM) and softmax classifiers. With segmentation, this method had an accuracy of 85.5%, whereas, without segmentation, it had an accuracy of 82.8%.

DeVries and Ramachandram[27] proposed deep learning on the ImageNet dataset that was based on multiscale CNN using an inception v3 network. Inception v3 was fine-tuned as coarse scale and finer scale for skin cancer classification. The coarse scale was used to assess and identify the characteristics of the lesion's appearance as well as its general context while the finer scale, collected textual information about lesions to distinguish between different kinds of skin lesions.

Dorj et al. [28] suggested a technique for categorising the images into four types as BCC, SCC, melanoma and AK. AlexNet(A pre-trained model deep CNN model) was used and in which SVM was used as classifier. The model obtained 94.17% accuracy, 95.1% sensitivity, and 98.9% specificity.

Kalouche [29] proposed the CNN architecture with five convolutional layers and, three fine-tuned layers at the end. The proposed VGG-16 model demonstrated 78% accuracy in identifying melanoma skin cancer in lesion images. As the proposed model attains low accuracy, a deep learning architecture i.e deep CNN was used to identify borders and edges of the skin lesion images to achieve higher accuracy. An overview of different CNN-based skin cancer detection methods is illustrated in Table III.

TABLE III. DIFFERENT CNN-BASED SKIN CANCER DETECTION METHODS

Ref	Architecture	Dataset	Skin Cancer Classes	Accuracy(%)	Sensitivity(%)	Specificity(%)
[24]	LightNet	ISIC 2016	2	81.6	14.9%	98
[28]	SVM with deep Convolution neural network	3753 dermoscopic images	4	SCC: 95.1, AK: 98.9, BCC:94.17	-	-
[25]	Convolutional neural network	MED-NODE	2	81	81%	80
[30]	Deep Convolution neural network	ISIC Archive	3	72.1	-	-
[31]	Predict-Evaluate -Correct k- fold	MED-NODE	2	91	89	93
[32]	Transfer learning followed by pre trained deep neural network	ISIC Archive	8	92.3	88.4	93
[33]	High-Resolution feature blocks (HRFB)	PH2	-	94.9	96.3	94.2
[34]	FCNs based on VGG-16 and GoogleNet	ISBI 2016	-	88.92	69.33	93.75

V. PERFORMANCE METRICS

Performance metrics, also known as evaluation metrics, are measures for the evaluation of performance of a model, system, algorithm or process. These metrics are used for checking workflow in architectures with deep learning techniques for segmentation and classification of images.

A. Dice-Coefficient(D)

In this metric assessment of similarity/overlapping within the observed, expected outputs value.

$$D = \frac{2TP}{2TP + FP + FN}$$

B. Sensitivity(SE)

Ratio of predicted positive outputs among the positive values.

$$SE = \frac{TP}{TP + FN}$$

C. Specificity(SP)

The percentage of predicted negative results and actually tested negative.

$$SP = \frac{TN}{TN + FP}$$

D. Accuracy(A)

It calculates the fraction of true outcomes (including true positives and true negatives) to all instances analysed.

$$A = \frac{TP + TN}{TP + TN + FP + FN}$$

Area under the receiver operating characteristic curve (AUC-ROC): measures efficiently across all categorization levels and varies between 0 - 1. The curve compares the true positivity rate (TPR) to the false positivity rate (FPR), or sensitivity value against 1-specified with AUC being area beneath the whole curved surface. FP stands for false positive value, FN stands for false negative value, TP stands for true positivity, and TN stands for true negative.

The choice of performance metric depends on the specific problem being solved and the goals of the system or model being evaluated.

VI. CONCLUSION

Melanoma detection using Convolutional Neural Networks has depicted favourable results in recent years. CNNs are deep learning models that extract features from images automatically and classify them into different categories. Several studies have reported high accuracy rates of CNN-based melanoma detection systems, ranging from 90% to 98% [28][31][32]. These systems have the potential to help dermatologists for detection and diagnosis of melanoma in early stages, which can improve the prognosis and save lives. However, there are still some limitations and challenges to overcome in the development and deployment of CNN-based melanoma detection systems. One of the main challenges is the lack of diverse and representative datasets that can capture the full spectrum of melanoma variability. Another challenge is the interpretability of CNN-based models, which can make it difficult to understand how they make decisions and to identify potential biases.

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