Convolution Neural Network Models to Detect Melanoma: A Review

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Abstract. Skin cancer is one of the most serious health issues that humans face. Dermatologists face difficulty in making a skin cancer diagnosis because many skin cancer pigments seem alike. Early detection of skin cancers like Melanoma means a better chance of survival for the patient otherwise it can be life-threatening. For computer vision problems like image classification, deep learning has proven to be the state-of-the-art. There has been a great deal of research into the use of deep learning to automate skin cancer screening. The objective of this paper is to review the state-of-the-art CNN techniques used for Melanoma detection. This paper presents an overview of CNN, followed by analysing the existing work carried out in the area of Melanoma skin cancer detection using Convolution Neural Network (CNN).

Keywords: Melanoma · Convolution neural networks · Machine learning · Skin cancer detection

1 Introduction

According to a World Health Organization (WHO) report, cancer is one of the leading causes of death worldwide [1]. It greatly affects the quality of life. Skin cancer is one type of cancer and the most prevalent cause is overexposure of skin to UV light from the sun. The most dangerous form of skin cancer is Melanoma and it develops in melanin-producing cells, the pigment in the skin that gives it its colour. Melanoma skin cancer has become much more common in recent decades. In the United States, 197,700 new cases of Melanoma are expected to be diagnosed in 2022, with 7650 people dying from the disease [2]. Early detection and prevention are the most effective ways to control skin cancer.

In general, a dermatologist, who specialises in skin cancer diagnosis follows a set of steps, starting by visually examining the suspected lesion, after that, there will be a dermoscopy and a biopsy. Dermoscopy, the most common imaging technique used by dermatologists, magnifies the surface and structure of the skin lesion, increasing its visibility for examination by a dermatologist. However, only trained physicians can use this

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technique effectively, because. It is entirely dependent on the practitioner's visual acuity and previous experience. Furthermore, using Dermoscopy, an expert dermatologist can only achieve a classification accuracy of 65 to 75% [1]. These difficulties prompted the researchers to investigate the possibilities of automatically detecting Melanoma using Machine Learning. The steps involved in the ML pipeline are Pre-processing, segmentation, feature extraction, and classification. This approach will train the data first, then test it by using their parameters. The ML community focused its efforts on statistical methods for Melanoma classification, which requires extensive domain knowledge, human intervention, and it can also be inconclusive in borderline cases. Hence, to reduce the human intervention and to improve the accuracy the researches start to focus on deep learning (DL). It is the ML that deals with artificial neural network algorithms, which are based on the structure and function of the human brain. The convolutional neural network (CNN), a type of DL that simulates biological neuron processing, is the current state-of-the-art network for pattern recognition in medical image analysis.

A convolution is essentially sliding a filter over the input. A convolution can be thought of as looking at the environment of a function in order to make more accurate predictions about its outcome. Over the last few years, a lot of research has been done on CNN-based automatic Melanoma detection. The objective of this paper is to collect, classify and summarize the state-of-the-art CNN techniques used for Melanoma detection. We will provide the overview of the CNN and the techniques used to detect Melanoma skin cancer.

2 Need and Overview of CNN

The melanoma diagnosis commonly uses five characteristics to differentiate between benign and malignant melanoma skin lesion. The characteristics are asymmetry (A), border irregularity (B), color variability (C), diameter greater than 6 mm (D), and evolution (E) or any kind of changes and these signs are shortly referred as ABCDE signs, which serves as a reliable indicator for melanoma diagnosis. The processes involved in Melanoma detection are image acquisition and a traditional ML pipeline, which includes, pre-processing, lesion segmentation, characterisation and classification.

The image acquisition process involves the collection of digital images of the tissue; majority of current systems rely on dermoscopic images, which have been shown to be very effective in melanoma detection. Next, the ML pipeline was used. The dermoscopy image classification process is still perplexing for a number of reasons. First, the dermoscopy image contains noises, artifacts. Next, the structure of the skin lesion is changeable as well as it is complex. Also, the requirements for the border detection, feature extraction, and classification processes to distinguish between a lesion and normal skin becomes unable to meet because of the prevalence of air bubbles, lack of contrast, illumination variation while capturing the image, dense hairs, etc., which might result in a wrong classification. Furthermore, selecting an acceptable feature is time consuming because feature extraction requires clear and specific knowledge and understanding of an abnormal state of use is required as the lesions spectral distributions overlaps.

To detect Melanoma accurately in its early stages and distinguish it from healthy tissue DL methods based on data are used. CNN, a DL method, employs multiple nonlinear data processing layers. These layers identify the most important features in the images so that they can be classified accurately. CNN learns functions from images in order to distinguish one pattern from another. CNN's pre-processing steps are more manageable, with fewer steps than that of other classification algorithms.

The CNN is designed to deal with image data in two-dimensions and it can also be utilized with one-dimensional and three-dimensional data. Convolution, in the context of CNN, is a linear method that, like a standard neural network, involves the multiplication of inputs with a set of weights. Since the approach was developed for two-dimensional input, the multiplication takes place between an array of input data and a filter or kernel, which is a two-dimensional array of weights.

The input data is larger than the filter, and uses dot product as the multiplication method between the input and filter's filter-sized patch. A dot product always returns a single value. The use of a filter is smaller because at various point on the input, the same filter will be multiplied with the input array several times. Each overlapping component of the input data is subjected to the filter in order, from left to right, top to bottom. If the filter is meant to detect a specific type of feature in the input, applying it methodically across the entire image allows it to detect that feature anywhere in the image is known as the translation invariance, which refers to the general interest in whether a feature is present rather than where it was present.

Each of Convolution layers, when fed with an image to it will produce a number of activation maps, which emphasize important image's features. A patch of pixels is given as input to each neuron, colour values are multiplied by their weights, the results are totaled, and then runs them through the activation function. Basic features such as diagonal, horizontal and vertical edges are identified by the initial layer of CNN. The output of the initial layer is given to the next layer as input, where complex features are extracted, such as edge and corner combinations. As you progress through the layers of the convolutional neural network, it begins to recognize higher-level features such as objects, faces, and so on.

A CNN typically consists of multiple convolution layers, and a classification layer as the final layer as shown in Fig. 1. When the number of convolution layers are higher, then it will be able to detect more complex features. Based on the activation map of the final convolution layer, the classification layer generates a series of confidence ratings ranging from 0 to 1, indicating how likely the image is to belong to a "class".

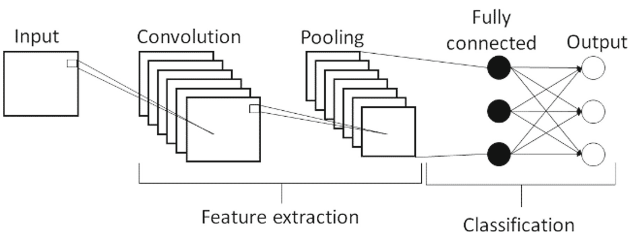

Fig. 1. Convolution neural network [3]

Table 1. Search keywords

Search Term	Keywords
Skin*	Skin cancers, Skin cancer detection, Skin lesion images, Skin lesion segmentation
Cancer*	Cancer, Cancer detection, Cancer diagnosis, Cancer classification
Lesion*	Lesion classification
Melanoma*	Melanoma, Melanoma detection, Melanoma skin cancer
Deep*	Deep Learning
Conv*	Convolution Neural Network

All words beginning with the string written before the asterisk *.

3 Materials and Methods

There are many research papers, which discussed about the DL methods to identify the skin cancer and in this paper, we will review those papers mainly focused on the CNN to detect the Melanoma skin cancer by using lesion images. Scientific database Scopus were queried with the relevant search keywords to collect the research papers as shown in Table 1. Next, non-English articles were excluded. Our review will focus on the research papers published from the year 2017 through 2022. Also, we considered only journal and conference papers that are published. From our initial search query, we are able to come up with 657 papers based on the key words search.

However, we further narrow down the search key words such as cancer diagnosis, cancer classification, lesion classification, skin lesion segmentation to obtain the 96 papers. From the reduced set of 96 papers, we considered the papers with CNN techniques and then the abstract section was read to take a final decision on the inclusion. After undergoing the refinement, 22 items were added final list of papers which we used for the review in this paper.

4 Literature Review

In recent years, many models and methods have emerged to detect Melanoma skin cancer detection by CNN. In this section, those models and methods were discussed in categories namely the traditional CNN, filtering and feature extraction techniques used in CNN, and pre-trained transfer learning.

4.1 Traditional CNN

We can observe from the review that many of the authors proposed CNN's for detecting the Melanoma skin cancer. Tanna and Sharma [4] proposed a 3 layer CNN, which was able to achieve the accuracy of 84.39%. Abdullah et al., [5] proposed a new algorithm based on CNN, which used the straight active-contour and morphological processes to divide the cutaneous lesion into cutaneous images and was tested in the Al-Kindi Hospital and Baghdad Medical City's real database. In another study by Filali et al. [6], proposed a CNN model that used lesion skeleton as input for the classification instead of the original image. The proposed helped in improving the classification rate with an accuracy of 95% and reduced the number of layers in creating the deep network. In another study by Castro et al. [7] used a CNN model with evolution algorithm to deal the imbalance dataset issue and able to achieve 92% accuracy. Additionally, Dai et al. [8] and Ly et al. [9], proposed CNN model to be trained in detecting the skin cancer images and deployed on the mobile devices successfully.

In the paper [10], the authors attempted to assess the ability of CNN, for skin cancer detection by classifying malignant and benign moles. The ISIC dataset, which contains 2460 coloured images, was used for this study. After a few tweaks to the parameters and classification functions, the proposed VGG-16 model shows 87.6% accuracy.

4.2 CNN with Filtering and Feature Extraction Techniques

A classification method proposed by Setiawan [11] used CNN model with simple image processing techniques of contrast limited adaptive histogram equalization (CLAHE) and multiscale Retinex with color restoration (MSRCR) for contrast enhancements. According to the findings of this study, for early detection of skin cancer using CNN, CLAHAE is better suited for colour image enhancements.

In [12], proposed Deep Convolution Neural Network to classify skin lesions. The image was pre-processed with various filters before being segmented with the Fuzzy C-means and K-means clustering algorithms. Gaussian and Bottom hat were the filters used in this approach. High frequency noise in an image was reduced using Gaussian filtering. Bottom hat filtering determines the image's morphological closure and uses that information to reconstruct the original image. The proposed methodology achieved 98.43% of accuracy.

Chabi Adjobo et al. [8] proposed a CNN model combines with Gabor filtering (GCN). Gabor filter banks generation, CNN construction and filter injection are the three functions of the model. To have a vision system similar to the visual perception in humans a gabor filter bank is designed to respond to the textures and edges of varying orientations and frequencies. A gabor filter bank is a set of linear filters that work together. This model was tested with the Dermoscopic images and obtained the best accuracy rate of 96.39% while the traditional CNN model achieved 94.02%.

A classification method proposed by Jeny et al. [13] uses novel CNN based approach to classify the different types of skin cancers. This CNN developed by using SKNet which consists of 19 Convolution layers. SKNet is a CNN with selective kernel units and selective kernel convolutions. On a dataset of 4800 images, the proposed model outperformed the previous performance, achieving an accuracy of 95.26%.

In [14], Lin and Lee proposed an ensemble model and compared the performance with the CNN model. The proposed methodology was supported combining image pre-processing, deep learning, and risk management on skin cancer dermoscopy images Meta-data. This demonstrates the ensemble flow with general stacking through stages such as data preprocessing, CNN grouping, Meta-data concatenation, and the first CNNs and second meta-classifiers ensemble. The result demonstrated excellent performance, particularly the contribution from the first ensemble. When compared to the best single CNN, accuracy in the ensemble model reached a maximum of 91% with the 5% holdout validation dataset.

This study [15] proposed a less complex and lightweight deep CNN for automated melanoma classifier. The DCNN's structure is meticulously planned, with many layers responsible for low to high-level features extraction from skin images in a unique way. The design also considered determining network depth, optimising hyperparameters, selecting multiple filters and their sizes, and employing appropriate DL layers. The proposed algorithm showed a accuracy of 90.48% on ISIC 2020 dataset.

Bozorgtabar et al. [16] proposed a superpixel-based fine-tuning strategy for accurately extracting the lesion border by utilising the skin image pixels' characteristics. The proposed method learns both lesion boundary, local contextual information, and skin lesions global map. As a result, even with complex textures and fuzzy boundaries, it can segment lesions accurately within a skin image. The proposed method outperforms the fully CNN by 92.3%.

The paper [17] proposed a convolutional neural network-based enhanced deep learning-based solution to automate the classification of benign and malignant skin lesions in dermoscopic images. To prevent the CNN model from over-fitting the model employed data augmentation, dropout and regularisation. When tested on the ISBI 2017 dataset, the model outperforms other state-of-the-art models with an accuracy of 98.44%.

In [18], a hybrid deep learning (HDL) approach was proposed, which used simple median filtering to remove hair, noise, etc. unwanted information and 3D wavelet transform was employed to extract textural information from the dermoscopic image. The HDL approach can effectively distinguish benign, malignant, and normal skin images and showed an accuracy of 99.33% when tested with PH2.

4.3 Pre-trained Transfer Learning Models

In transfer learning, a machine uses previous task knowledge to improve generalisation on a new task. For example, the knowledge gained to recognize drinks while training could be used in training to predict an image contains food. Increased efficiency, when training new models, and resource savings are the significant advantages of transfer learning. The papers under this category are discussed below.

For the classification of skin cancer, a Deep Learning-based transfer learning approach was proposed by Jain [19]. Using the HAM10000 dataset, six different transfer learning nets were compared for their performance in multi-class skin cancer classification. It compensates for the dataset's imbalance by replicating images of low-frequency classes. InceptionV3, VGG19, Xception, InceptionResNetV2, MobileNet and ResNet50 were the transfer learning nets used. XceptionNet's accuracy was 90.48%, which concludes that XceptionNet performs better the other transfer learning nets used in the study.

Mishra et al. [20] proposed a pre-trained Deep-CNN models via transfer learning technique for classifying the non-Melanoma and Melanoma skin cancer types. The pre-trained models used were Inception V3, VGC16, ResNet 50, VCG19, and ResNet 101. With an accuracy of 97.9%, it can be inferred that Inception V3 outperformed other pre-trained models.

Rezaoana et al. [21] proposed an automated classification method for skin cancer, which could classify nine types of skin cancers. Melanoma, basal cell carcinoma, dermatofibroma, -actinic keratosis, benign keratosis, etc. were the types of skin cancer that could be classified. The goal is to use the Convolution Neural Network to create a model that detects and categorizes skin cancer into different classes. The deep learning and image processing concepts are used in the diagnostic methodology. The number of images has also been increased by employing various image augmentation techniques. Finally, the transfer learning method is used to enhance classification task accuracy by up to 79.45%.

Hasan and Ibrahim [22] presented a comparative analysis of different pre-trained models to find out the best architecture to detect skin cancer. The architectures VGG19, VGG16, InceptionV3, ResNet50, MobileNet, Xception and MobileNetV2 are used on that dataset, which contained more than 3000 images of patients having benign and malignant skin cancers. The Xception architecture's accuracy was 85.303% while the lowest accuracy was shown by MobilenetV2.

A MobileNet architecture has been proposed by Gasa et al. [23] to detect skin disease. For the classification of skin lesions, the proposed skin disease detector uses a Raspberry Pi-based MobileNet convolutional neural network with the Keras architecture for training. The user uses a Telegram chat bot to snap a picture and receive a prediction as outcome. The input image can be captured with the device's camera or uploaded. When compared to standard convolution, MobileNet CNN uses the Depthwise Separable Convolution process, which uses 8–9 times fewer computing resources. For skin cancer lesions classification, including Melanoma, the proposed model achieves an accuracy of 91%.

An integrated diagnostic framework was proposed by Al-masni et al. [24], which combines multiple skin lesions classification stage and skin lesion boundary segmentation stage. The proposed study first uses a deep learning full resolution convolutional network for segmenting the skin lesion boundaries from the dermoscopy images. The segmentation stage extracts the distinguishing features of various skin lesions, making it a crucial necessary step for diagnosing skin lesion. The segmented skin lesions are then classified using a CNN pre-trained CNN classifier. DenseNet-201, Inception-v3, Inception-ResNet-v2, and ResNet-50 are the pre-trained models used in this paper. With proper balancing, segmentation, and augmentation, the proposed method has been tested in three independent datasets containing maximum of seven types of skin lesions, respectively. ResNet-50 achieved the superior performance.

Using a transfer learning approach, an intelligent Region of Interest (ROI) based system was proposed [25] to detect and differentiate nevus cancer and Melanoma. In order to extract ROIs from the images, an improvised k-mean algorithm is used. Because the system is only trained on images containing Melanoma cells, this ROI-based approach aids in the identification of discriminative features. It also used a CNN-based transfer learning model for ROI images from the two datasets and datasets, as well as data augmentation. For the two datasets, the proposed system has accuracy of 97.9% and 97.4%, respectively.

We have reviewed 20 papers from Scopus database under the categories traditional CNN, CNN with filtering and feature extraction techniques, pre-trained transfer learning for detecting skin cancers. As shown in Table 2, the traditional CNN has better accuracy when compared to pre-trained transfer learning models but on some studies it has obtained around 80%. In the case of papers reviewed under the category of CNN with filtering and feature extraction techniques has the accuracy greater than 90%. It is observed that CNN performs even better when there are some handcrafted feature extraction or filtering methods on the image processing techniques are incorporated in the process of Melanoma skin cancer detection.

5 Conclusion

In this paper, the current state of Melanoma detection using CNN is discussed. Furthermore, this paper looked into Convolution Neural Networks, Deep Convolution Neural Networks, Ensemble methods, Transfer learning with pre-trained models used for Melanoma cancer detection. Moreover, it has been discovered that highest accuracy is achieved on those models which has done some handcrafted feature extraction and image segmentation techniques. It is clear that we need more robust methods in order to extract the best features from the images to obtain the highest level of accuracy. It also understood that we need more data to make sure our model is trained enough to understand the features so that it can able to predict well in the new data. In future, the best filtering and feature extraction research options from the images need to be explored to make sure the prediction accuracy is increased.

Table 2. Summary of literature review

Categories	References	Accuracy
CNN	[4]	84.39%
	[5]	98.00%
	[6]	95.00%
	[7]	92.00%
	[8]	94.02%
	[9]	90.00%
	[10]	87.60%
CNN with filtering and feature extraction	[8]	96.39%
	[11]	98.43%
	[12]	92.00%
	[13]	95.26%
	[14]	91.00%
	[15]	90.48%
	[16]	92.30%
	[17]	98.44%
	[18]	99.33%
Pre-trained transfer learning models	[19]	90.00%
	[20]	97.90%
	[21]	79.45%
	[22]	85.30%
	[23]	91.00%
	[24]	89.00%
	[25]	97.00%

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