The second part of this manuscript describes

the different deep learning techniques, such as convolutional neural networks (CNNs), generative

adversarial models (GANs), deep autoencoders (DANs), restricted Boltzmann’s machine (RBM),

stacked autoencoders (SAE), convolutional autoencoders (CAE), recurrent neural networks (RNNs),

long short-term memory (LTSM), multi-scale convolutional neural network (M-CNN), multi-instance

learning convolutional neural network (MIL-CNN).

model-driven architecture

pre-processing, image segmentation and post-processing

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pattern analysis according to the 7-point checklist

Table 1: A summary of the recent deep learning models proposed to skin cancer detection

Ref. Objective Model Main findings

1) Diagnose melanoma and non-melanoma using dermoscopic image

A two-stage framework composed of a fully convolutional residual network (FCRN) and a Deep Residual Network (DRN)

It was one of the first deep learning models applied to skin cancer detection and experimental results demonstrate the significant performance gains of the proposed framework compared to handcrafted feature models

2) Diagnose melanomas and nevus using dermoscopic images

Inception v4 CNN model

The authors compared the model performance to a group of 58 dermatologists using 100 images in the test set. The model AUC was greater than the average AUC of the dermatologists

3)Diagnose melanomas and nevus using dermoscopic images

ResNet50 CNN model

The authors compared the model to a group of 157 dermatologists using 100 images. The model outperformed 136 of them in terms of average specificity and sensitivity

4) Diagnose benign and malignant cutaneous tumors among 12 types of skin diseases using clinicalimages

ResNet-152 CNN model

The results achieved by the model were comparable to the performance of 16 dermatologists.

The authors also affirm that it is necessary to collect images with a broader range of ages and ethnicities in

order to improve the model

5) Diagnose 757 types of skin diseases using clinical images

GoogleNet Inception v3 CNN model

The model achieved performance on par with 21 dermatologists considering the binary classification of the most common and the deadliest cases of skin cancer

6)Diagnose melanoma and non-melanoma using dermoscopic images

An ensemble composed of DRNs, CNNs and Fully CNNs

The ensemble of models was compared to the average of 8 dermatologists on a subset

of 100 testing images and provided higher accuracy and specificity, and an equivalent

sensitivity

7)Diagnose 7 different types of skin diseases using dermoscopic images

An ensemble composed of ResNets, Densenets and Senets

The authors presented a new strategy based on a vast amount of unscaled image crops to generate final predictions. This approach outperforms most of the current models proposed for the ISIC archive

T-SNE Visualization

***various techniques for detecting the skin cancer base on the characteristics of the images shape, colour, textures.***

They applied four machine learning methods to classify the lesion into melanoma, abnormal, and normal where the highest accuracy percentage, 92.50%, was achieved by the artificial neural networks (ANN). Bi et al. [14] proposed a melanoma detection system using the multi-scale lesion-biased representation (MLR) and joint reverse classification (JRC).

deep convolutional neural network (DCNN).

A DCNN has been used in a number of application to improve performance such visual tasks, natural language processing, action recognition [24, 25]. VGGNet, ZFNet, ResNet, GoogLeNet, AlexNet, and LeNet [26] are different DCNN architectures that can be used in different applications. The AlexNet is the utilized DCNN architecture in the proposed skin cancer classification model.

**CNN MODEL WITH NOVEL REGULARIZER**

**Image acquisition**

**Image Pre-processing**

Segmentation

Feature extraction

Img classification :melanoma , non -melanoma

**In this paper, an automated skin lesion classification method is proposed. In this method, a pre-trained deep learning network and transfer learning are utilized. In addition to fine-tuning and data augmentation, the transfer learning is applied to AlexNet by replacing the last layer by a softmax to classify three different lesions (melanoma, common nevus and atypical nevus)**

The earlier methods [8, 9], required extensive pre-processing, segmentation and feature extraction processes in order to classify the skin images.

Recently, researchers around the world successfully utilized deep learning in visual task [10,11] and object recognition [12]. Codella et al. [3] proposed a hybrid system for melanoma classification. In this system, support vector machine (SVM), sparse coding, and a deep learning method were combined where the classification accuracy was 93.1%

They applied four machine learning methods to classify the lesion into melanoma, abnormal, and normal where the highest accuracy percentage, 92.50%, was achieved by the artificial neural networks (ANN). Bi et al. [14] proposed a melanoma detection system using the multi-scale lesion-biased representation (MLR) and joint reverse classification (JRC)