DTLNet: Deep Transfer Learning-based Hybrid Model for Skin Lesion Detection and Classification

Doma Murali Krishna
Research Scholar,
School of Electronics and Electrical Engineering Lovely Professional University Phagwara, Punjab, India
mkrishna557@gmail.com

Sanjay Kumar Sahu
Associate Professor,
School of Electronics and Electrical Engineering Lovely Professional University Phagwara, Punjab, India
sanjay.23393@lpu.co.in

G R L V N Srinivasa Raju
Professor, Department of ECE
Shri Vishnu Engineering College for Women
Bhimavaram, Andhra Pradesh, India
grlvnsr@svecw.edu.in

Abstract- The skin of the human body is the most exposed part of the body, and it requires regular protection and care from the various elements including heat, light, dust, and direct exposure to other hazardous radiation, such as ultraviolet rays. Skin cancer is one of the most serious illnesses that people may get. In humans, MELs are a kind of skin cancer that develops in the pigment-producing cells (melanocytes) that are responsible for producing pigment in the skin. Skin cancer, such as melanoma (MEL) must be detected and diagnosed as early as possible in order to limit the number of people who die from the disease. Deep transfer learning (DTL)-based skin lesion detection and classification (SLDC) system, referred to as DTLNet, is the subject of this article, which focuses on its implementation in a computer network. Initially, the skin lesions are preprocessed by using the hybrid gaussian-wiener filter (HGWF), which removes the noises from skin images. Secondly, skin lesion segmentation operation is performed by using transfer learning based AlexNet model. Then, the hybrid features were extracted by using deep learning convolutional neural network (DLCNN) model. Finally, multi class classification operation is performed by using SoftMax Classifier of DLCNN, which classifies the eight different types of skin cancers. Further simulations performed on ISIC-2019 dataset showed that the proposed framework resulted in superior performance as compared to the state of art approaches.

Keywords: Skin cancer detection and classification, deep learning, transfer learning, convolutional neural network, ISIC-2019 dataset.

I. INTRODUCTION

In the human body, the skin is the most mysterious and outermost layer, shielding the body from dangerous radiations such as ultraviolet light, heat, light, dust, and other harmful rays. The dermis and epidermis are the two layers that make up the surface of the human skin. The epidermis is the outermost layer of the skin, and it is comprised of three types of scaly and flat cells on the surface of the skin, which are referred to as squamous cells. Basal cells and melanocytes are the cells that protect the skin from injury and are responsible for the generation of skin colour. Many disorders may cause harm to the skin, and cancer is one of the most aggressive and serious diseases that may affect the human body's surface.

MEL and non-MEL skin cancers are frequently the two most well-known forms of skin cancer [1]. But the patients are suffering with the many forms of skin cancers, they include MEL, melanocytic nevus (NV), basal cell carcinoma (BCC), actinic keratosis (AKIES), benign keratosis (BKL), dermatofibroma (DF), vascular lesion (VASC), and squamous cell carcinoma (SCC) (SCC). Figure 1 illustrates the all these eight forms of skin cancers and they are considered from ISIC-2019 dataset. MEL is the deadliest and most serious skin cancer that is the source of practically all forms of skin cancers whose development begins with the cells of melanocytes situated on the outermost layer of the skin. MEL is also termed malignant MEL, which may expand and damage neighboring healthy cells. This process is usually termed as metastasis [2]. As contrast to males, this form of MEL often occurs more in women [3].

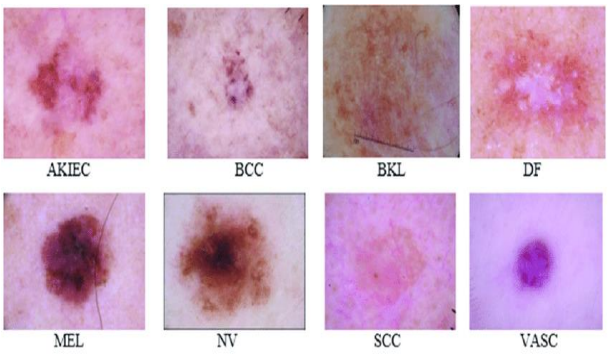

Figure 1. Sample images of ISIC-2019 dataset.

MEL instances are increasing as a result of increased UV radiation from the sun, as well as skin burns as a result of exposure to sunlight. Acral lentiginous MEL manifests itself as a small flat area of discolored skin that is frequently black or dark brown in appearance. Men are more likely than women to get it on the back of their hands, while women are more likely to develop it on their fingers and legs [4]. Acral MEL and acral nevus are difficult to distinguish from one another, which makes diagnosis difficult in this case. Typically, it is discovered at a later stage in the development of MEL and is associated with a reduction in patient survival rates [5]. MEL is a treatable condition if detected and treated at an early stage [6]. Biopsy, pathology report, and medical imaging analysis are all methods of detecting MEL in its early stages. Dermoscopy is a non-invasive imaging tool that is often used to identify MEL early in order to increase the likelihood of a positive outcome. A high-resolution magnified skin lesion of the malignant area is acquired during the dermoscopy procedure to find the cancerous spot on the skin, which is subsequently evaluated

by dermatologists for the presence of MEL [7]. When dermatologists examine dermoscopy photos, it is costly and needs a high degree of competence in order to accurately diagnose the condition. In light of this difficulty, it has been determined that effective computer-aided diagnostic procedures are required to help in the early detection of MEL from skin lesions [8]. However, due of the variety of challenges, it was an interesting profession. The presence of MEL may be associated with a higher visual similarity between cancerous and non-cancerous cells, making it difficult to distinguish between MEL and non-MEL skin cancer [9]. Second, due of the poor contrast, it was difficult to distinguish between the skin lesion and normal skin areas in the image. The third point is that MEL and non-MEL are both visually identical, and the skin diseases that exist in various persons have MEL that is visually distinct. Third, because of the substantial intra-class diversity in MEL size, position, form, and colour in skin lesions, it is difficult to distinguish MEL from other skin lesions. Aside from that, additional artefacts, such as colour calibration charts and hair as well as ruler lines and veins, may also produce blurriness and occlusions, further complicating the situation and making it more difficult to resolve [10].

Numerous computer-added SLDC methods were proposed for skin cancer identification, which can assist dermatologists in MEL diagnosis in recent years. Further, these skin cancer detection methods were developed by using basic image processing approaches [11], machine learning algorithms [12], deep learning models [13], transfer learning [14] and ensemble learning [15-16] prototypes. Among those various models, deep learning resulted in high performance but suffering with computation complexity problems and transfer learning models are resulted in better performance with low complexity. Hence, this article is focused on utilization of both deep learning transfer learning models and developed a hybrid network called as DTLNet for SLDC. The major contributions of this work are as follows:

- Implemented a HGWF for removal of noises and also enhances the skin lesions by using hybrid gaussian-wiener kernel function. Then, transfer learning based AlexaNet is used for skin lesion segmentation.
- In addition, DLCNN model is developed for the extracting the deep features and SoftMax classifier is used to classify the multiple classes of skin lesion.
- The proposed DTLNet model is capable of classifying the multiple classes of skin lesion including SCC, VASC, DF, BKL, AKIES, BCC, NV and MEL. Simulation results shows that the performance of proposed DTLNet resulted in superior as compared to the conventional approaches.

The organization of article is, section 2 deals with literature survey with their drawbacks. Section 3 deals with the detailed analysis of proposed DTLNet. Section 4 deals with summary of the article with possible future scope.

II. LITERATURE SURVEY

This section gives the detailed analysis of diverse related works on SLDC system using segmentation model, ensemble models, and transfer learning models.

A. Survey on segmentation methods

Deep learning approaches [17] are resulting in superior performance in various applications including SLDC models. In [18], the authors performed a study of 19 research on skin lesions categorization that used a CNN-based classifier and then compared their performance with that of clinical practitioners. In this study, suspected lesions were used to perform the trials. In [19], the author reviewed automated skin cancer diagnosis as well as the use of image processing and machine learning in skin cancer detection and prevention. In [20], the authors conducted a poll to learn more about integrating patient data into SLDC using CNN. Another article [21] provided an overview of the most recent research efforts in skin lesion detection and classification using CNN, transfer learning, and ensemble techniques, as well as their results. In addition, the researchers in [22] built their own dataset and employed data augmentation to improve the quality of the dataset, resulting in an accuracy of 80.23 percent for the dataset. Another study [23] employed numerous CNN models, such as VGG-19 and ResNet, for MEL classification, and got an accuracy of 76 percent, but this was still not good enough for the researchers.

Deep learning architecture was employed by the authors in [24] to deal with this problem. In their study, they concentrated mostly on lesion attribute recognition, lesion border segmentation, and lesion diagnosis, and they achieved the highest accuracy of 92.74 percent on the ResNet neural network. The ISIC-2017 database was utilised in another work [25], which used deep learning models for three key tasks: segmentation, feature extraction, and classification. These tasks were accomplished using deep learning models on the ISIC-2017 database. Further, the authors of [26] employed deep convolutional-deconvolutional neural networks (CDNN) to separate skin lesions for the purpose of segmentation. When the ISIC-2017 challenge was over, they took first place. The most significant disadvantage of this strategy is that training loss is not taken into account. As a result, since the network was not properly trained, several critical characteristics of the skin lesions were deleted. As a result, the segmentation performance did not reach its optimum potential. Further, the fully convolutional residual networks (FCRN) were utilized by the authors in [27] for better segmentation performance, and they obtained second place in task-2 of the ISIC-2017 competition. The most significant problem of FCRN is the difficulty in retrieving low-level characteristics for segmentation operations. To overcome those problem, ResNet [28] was used for more accurate skin lesion segmentation, and they achieved third rank in task-2 of the

ISIC-2017 competition. But the training loss optimization [29] is not performed in this method.

A deep learning architecture for segmentation was created in [30] by the authors, who named it the pyramid scene parsing network (PSPNet). But the system segmentation accuracy is measured for lesser epochs. Further, an extension to this work is carried out by using advanced transfer learning (ATL) [31] is developed for segmentation by using ResNet50, MobileNet, and DenseNet-121. Among the key disadvantages of this technique were that the models were not fully synced and that optimization was not carried out. In addition, U-Net [32] is implemented for skin lesion segmentation with tversky index for loss optimization. Further, the complexity of this work is increased as number of layers are increased. Finally, multi-layer residual convolutional neural network (MLRNet) [33] is developed for skin lesion segmentation, which is also utilized modified gaussian and guided image filters for noise removal. Compared to all other approaches, MLRNet resulted in superior performance.

B. Survey on deep learning transfer learning-based classification

With transfer learning-based approaches, great accuracy was attained while reducing the demand for huge datasets for a variety of classification tasks. The detection of MEL skin cancer using machine learning and image biomarker cues using datasets supplied by IBC's was successful in another research [34] and reached a 77 percent accuracy rate. Also, in [35], authors employed pixel-based fusion and multilayer feature reduction to run two tests on the ISBI-2016 and ISIC-2017 datasets for segmentation and classification, and they were able to reach an accuracy of 95 percent for MEL classification. Deep learning-based models must be trained from the ground up, which takes longer and requires additional computer resources. In [36] describes the extraction of additional characteristics from skin lesions for the categorization of MEL type and the reduction of the false-positive rate. SVM, neural network, and random forest classifiers were all used another dataset, with the random forest classifier achieving the greatest accuracy and the highest precision. For example, in [37], the authors used AlexNet-based transfer learning models for SLDC and attained an accuracy of 85.8 percent with their results. The training of deep CNN on the ISIC-2016 dataset was carried out in the second stage, and it obtained an F-score of 94 percent, according to another research [38], which offered data distribution based inter-class difference for SLDC. Many additional research, such as [39], have used transfer learning to classify data from the HAM1000 database, with AlexNet serving as the training data. Some other studies [40], extracted the features using VGG-16 model and performed the classification using various machine learning models like support vector machine. The simulations were carried on both ISIC and HAM10000 dataset.

C. Survey on ensemble learning-based techniques

Recent research has concentrated on creating an ensemble of multiple models in order to obtain high accuracy while utilizing dermoscopic lesions. When it comes to boosting the overall accuracy of diverse applications, the Ensemble approach has shown to be effective time and time again. For SLDC, an ensemble of Deep Neural Networks models, such as AlexNet, VGGNet, and GoogleNet, were used. In order to classify skin lesions, deep learning-based techniques such as artificial neural networks (ANN), backpropagated-ANN [41], DenseNet 201[42], CNN with data augmentation (CNN-DG) [43], DLCNN [44], and Hybrid CNN (HCNN) [45] have been used. The authors of [46] obtained the first place in the ISIC-2018 sub challenge with their algorithm, they utilized Ensembling CNN (ECNN) for SLDC. Further, DenseNet, ResNet, and SENet based transfer learning (DRS-TL) [47] with loss optimization mechanism. This complexity of this work is increased due to synchronization failure between various models. However, the fundamental disadvantage of this strategy is that it can only identify a small number of illnesses, and that increasing the number of layers increases computing complexity, resulting in higher loss and requiring more time for training of network. Prior studies [48] concentrated mostly on the categorization of skin lesions photos into specific cancer kinds, but did not give any more information regarding the subtypes of cancer that were discovered. Using the GoogleNet model, for example, the researchers [49] divided skin lesions into MEL and non-MEL categories by optimizing the loss values of the skin lesions. Another research [50] was implement SLDCNet model, where the authors implemented a hybrid model for real time prediction of SLDC.

III. PROPOSED METHOD

The evaluated proposed DTLNet were applied on ISIC-2019 dataset for multi class classification. This dataset was collected under different conditions and had different characteristics.

Table 1. Proposed DTLNet algorithm.

Input: ISIC-2019 training dataset, test skin lesion
Output: Predicated Classes, Quantitative evaluation.
Training process
Step 1: Perform the HGWF pre-processing operation on ISIC-2019 dataset, which eliminates the different types of artifacts from the dataset.
Step 2: Apply the AlexNet based transfer learning model for skin lesion segmentation on pre-processed outcomes.
Step 3: Apply the DLCNN architecture for extracting the multiple disease dependent features with high correlation and create the feature database.
Testing process
Step 4: Consider the test skin lesion and perform the steps 1 to 3, which extracts the test skin lesion features.
Step 5: Perform the SLDC by comparing the test features with trained features using SoftMax classifier, which classifies the multiple classes of skin

lesion.

Step 6: Perform the quantitative evaluation and calculate the various performance metrics.

The dataset has several inherent challenges. The most important of which are (i) isolating the lesion from healthy skin (segmentation), (ii) localizing the features and patterns, (iii) and extracting and classifying the features of each lesion. Therefore, skin lesions may be detected by the systems, and skin cancer may be distinguished from other kinds of lesions.

In Figure 2, the mechanism the proposed DTLNet for diagnosing skin diseases is presented and Table 1 presents the proposed DTLNet algorithm. Images were enhanced, and the noise was removed using HGWF. The lesion segmentation was performed using the AlexNet algorithm. Feature extraction was conducted using DLCNN, where the deep feature maps were contained inter disease dependent and disease specific features. These features were classified using SoftMax classifier for multi class classification including SCC, VASC, DF, BKL, AKIES, BCC, NV and MEL.

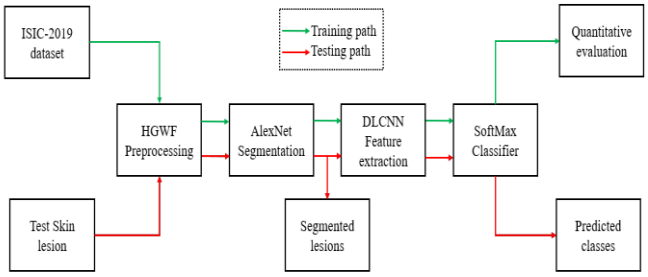

Figure 2. Proposed DTLNet framework.

A. HGWF-Preprocessing.

Skin lesions are suffering with the different types of noises such as salt-pepper, gaussian, random, jitter, poison, etc. Further, the skin lesions are also suffering with the hair artifacts, which also degrades the performance of segmentation and classification. Thus, this article newly introduces the HGWF based preprocessing for skin lesion enhancement. Figure 3 presents the block diagram of skin lesion preprocessing using HGWF and Table 2 presents the algorithm of HWGF.

Table 2. Proposed HGWF algorithm.

Input: Skin lesion image
Output: Pre-processed skin lesion.

Step 1: Apply the skin lesion image to the gaussian filter, which is used to remove the different types of noise artefacts from skin lesion.

Step 2: In addition, apply the wiener filter, which enhances the colour levels of the skin lesion and also highlights the cancer region.

Step 3: Update the kernel function for wiener filter based on gaussian properties, repeat the operation until the noise levels are eliminated.

Step 4: Generate the final enhanced and denoised skin lesion through updated filter responses.

Consider the $f(x,y)$ is the input skin lesion image and it is applied to HGWF, which contains noise degradation function (joint gaussian-wiener kernel function) $u(x,y)$. Consider the artifacts (noises and hair region) presented in the skin lesion as $n(x,y)$. Thus, the preprocessing is the major step for overcome all those artifacts in skin lesion analysis. But the conventional preprocessing methods are suffering with feature loss, feature elimination problems, which removes the statistical characteristics of skin lesions during the noise removal process. Here, $g(x,y)$ is the degraded skin lesion, it is applied to HGWF function (F_{HGWF}) for preprocessing and generates preprocessed skin lesion as $h(x,y)$.

$$g(x,y) = f(x,y) * u(x,y) + n(x,y) \quad (1)$$

$$h(x,y) = F_{HGWF}[g(x,y)] \quad (2)$$

The HGWF contains both gaussian and wiener kernel functions with average distributions for noise removal. Here, gaussian distribution function is used to remove the texture noise with linear properties, whereas wiener distribution is used to remove the spatial noise with non-linear properties. Initially, the skin lesion image is applied to gaussian filter.

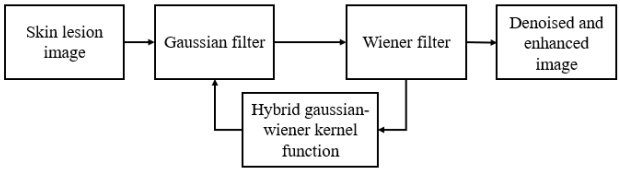

Figure 3. HGWF based skin lesion preprocessing.

Gaussian Filter: The background quality of skin lesion is improved by using gaussian filter with edge persevering properties. This filter removes the basic noises such as salt-pepper and gaussian noise using gaussian distribution function. Further, gaussian filter is unable to remove the hair artifacts from skin lesion, as hair region contains darker shadows. This filter utilizes both mean (μ_g) and variance (σ_g^2) computations for kernel generation.

$$\mu_g = \frac{1}{NM} \sum_{n,m \in \eta} a(n,m) \quad (3)$$

$$\sigma_g^2 = \frac{1}{NM} \sum_{n,m \in \eta} a^2(n,m) - \mu_g^2 \quad (4)$$

Here, the variance contains properties of gaussian noise, which is updated in probabilistic manner with hybrid and joint gaussian-wiener kernel function. Let the size of the kernel is $n \times m$, N represents number of rows of skin lesion, M represents number of columns of skin lesion, η represents the area of kernel and $a(n,m)$ represents pixel of skin lesions covered in the area η.

Further, the convolution operation is performed between the kernel generated by mean, variance to the skin lesion and

removes the basic noises. Usually, the default distribution function of gaussian filter is in static nature, which does not enhance the sharpness, colour, brightness, contrast of the skin lesion. In addition, output of gaussian filter is applied as input to the wiener filter.

Wiener Filter: The foreground quality of skin lesion is improved by using wiener filter with edge persevering properties. It is used to remove the hair artifacts from skin lesion and also highlights the cancer region by enhancing the colour, brightness, saturation and contrast properties through edge preserving mechanisms. This filter also contains the mean (μ_w) and variance (σ_w^2), which are also updated by using with hybrid gaussian-wiener kernel function.

$$b_w(n,m) = \mu_w + \frac{\sigma_w^2 - v^2}{\sigma_w^2}.\left(a_g(n,m) - \mu_w\right) \quad (5)$$

Here, $a_g(n,m)$ represents the output of gaussian filter, v^2 represents the variance of complicated noises and hair artifacts in skin lesion and $b_w(n,m)$ represents the denoised outcome of wiener filter.

Hybrid gaussian-wiener kernel function: The Hybrid gaussian-wiener kernel function is used to synchronize the individual operations of gaussian filter, wiener filter by controlling their kernel functions. This function is developed with size $n \times m$, which contains the properties of hair artifacts and noise elimination characteristics. This function is used to generate the denoising function of HGWF as follows:

$$F_{HGWF} = \left(\mu_g + \frac{\sigma_g^2 - \eta^2}{\sigma_g^2}\right).\left(\mu_w + \frac{\sigma_w^2 - v^2}{\sigma_w^2}\right).\left(b_w(n,m)\right) \quad (6)$$

Finally, the convolution operation (also denoted by * in equation 1) is performed between the $f(x,y)$ and F_{HGWF}in pixel wise manner. This operation generates the new pixel values for each iteration and generates the final denoised outcome.

B. Segmentation using AlexNet

Segmentation plays the key role in the process of SLDC. Traditional image processing approaches are concentrated only on colour of cancer region for segmentation. Few approaches are focused on pixel wise analysis for segmentation. But these approaches are failed to provide the maximum segmentation performance for all skin lesions. This work considered the ISIC-2019 dataset, which contains the eight different classes of skin lesions. The conventional methods are failed to segment all these images and resulted in poor performance.

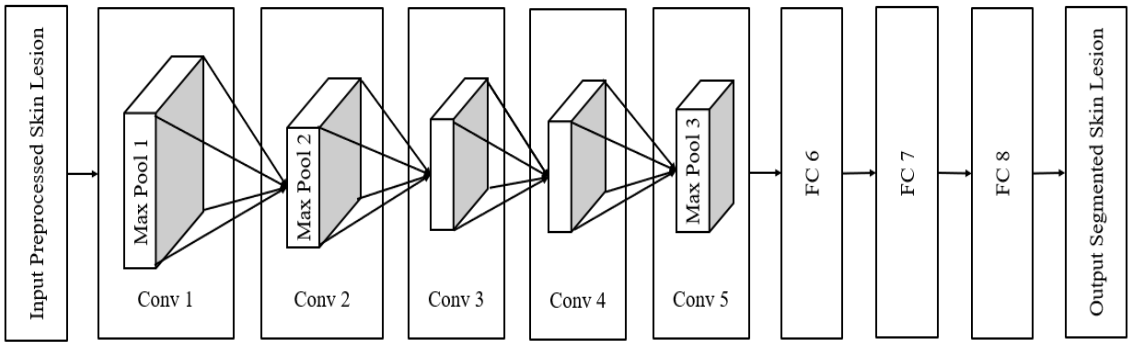

Figure 4. AlexNet architecture for skin lesion segmentation.

Table 3. Layer details of AlexNet model

Layer	Number of Filters	Filter size	Stride	Padding	Feature map size	Activation function
Conv 1	96	11 x 11	4	-	55 x 55x 96	ReLU
Max Pool 1	-	3x3	2	-	27x27x96	-
Conv 2	256	5x5	1	2	27x27x256	ReLU
Max Pool 2	-	3x3	2	-	13 x 13x 256	-
Conv 3	384	3x3	1	1	13 x 13x 384	ReLU
Conv 4	384	3x3	1	1	13 x 13x 384	ReLU
Conv 5	256	3x3	1	1	13 x 13x 256	ReLU
Max Pool 3	-	3x3	2	-	6 x 6 x 256	-
FC 6	-	-	-	--	1 x 4096	ReLU
FC 7	-	-	-	--	1 x 4096	ReLU
FC 8 (output)	-	-	-	--	1 x 1000	SoftMax

Later on, deep learning models are used to segment the skin lesions. But the standard deep learning models are suffering with the vanishing gradient problems for the huge datasets like ISIC-2019. Even though, the deep learning models are

resulted in better performance by analyzing each pixel, but they are suffering with the high computational complexity. Thus, this work is focused on adaption of transfer learning model for skin lesion segmentation.

Transfer learning models are resulting the superior performance in image analysis applications including image recognition, image segmentation, background extraction and edge analysis. AlexNet is one such transfer learning model, which contains the low computational complexity than other transfer learning models like ResNet, GoogleNet, and MobileNet. Figure 4 shows the segmentation process of skin lesion using AlexNet architectures, which is used to highlight the cancer region by classifying the pixels. Table 3 shows the detailed information of each layer presented in AlexNet model. Further, the AlexNet performs the skin lesion segmentation operation by analyzing the Asymmetry, Border, Colour, Diameter, Edge (ABCDE) properties.

In transfer learning models, the performance is solely determined by the number of layers and activation units present. A total of five convolutional layers and three fully connected layers are used in the AlexNet model to achieve this result. The preprocessed skin lesion input image is applied as an input to the convolution layer 1 of the image processing algorithm (Conv1). The kernel or filter-based feature detectors are located in the convolution layer, and they are responsible for extracting the features by executing the convolution operation between the input and the kernel matrix. Edges, horizontal lines, borders, bends, and vertical lines, among other things, are extracted using feature detectors in this case for efficient segmentation purpose. The feature detector segments the skin lesion by analyzing all these environments. Further, rectified linear unit (ReLU) is also used to select segmented region. In addition, convolution layers are responsible for data pooling, which is required for the conversion of invariance to translation in the convolution layer.

One of the most distinguishing characteristics of the convolution layer is that, even when the size of the input changes from layer to layer, the pooled layer output does not vary. The earliest convolution layers include a lower number of filters and they are responsible for extracting the more detailed characteristics from the data. As the number of layers is increased in comparison to the previous layer, the number of filters that are capable of extracting the higher ordered characteristics grows in proportion.

$$f_s(i,j) = \sum_m^M \sum_n^N h(i-m, j-n) * W(m,n) \qquad (7)$$

Here, $h\,(m,n)$ represents the preprocessed skin lesion, which is an input image with "m" number of rows and "n" number of columns. $W(m,n)$ represents the weight matrix with kernel properties and $f_s(i,j)$ represents the segmented output.

In the same way that these five convolution layers are coupled in a serial fashion, the output characteristics of Conv1 are applied to Conv2. Then, the output characteristics of Conv 5 are linked to the completely connected layer 6 of the system (FC6). The FC layer is a flattening layer that links all of the neurons in the network with an equal likelihood of connection. In order to get the output feature, the input features are coupled in a linear transformation fashion. In all, three FC layers are employed to construct the robust characteristics of skin lesions that are based on different classes of skin lesion images. Further, these FC layers are acts as a classifier, which classifies disease effected region of skin lesion by analyzing each pixel. Finally, it generates a binary map as segmented output, where white colour is generated by assigning the binary-1 to the cancer effected region and black colour is generated by assigning the binary-0 to the non-cancer region.

C. Feature extraction and classification

After the segmentation, feature extraction plays the major role in SLDC operation. Features are the statistical parameters, which holds the different attributes of skin lesions based on their individual classes. The conventional image processing-based feature extractors are failed to extract the detailed ABCDE from the huge datasets and they are supported to low level feature extraction on small datasets.

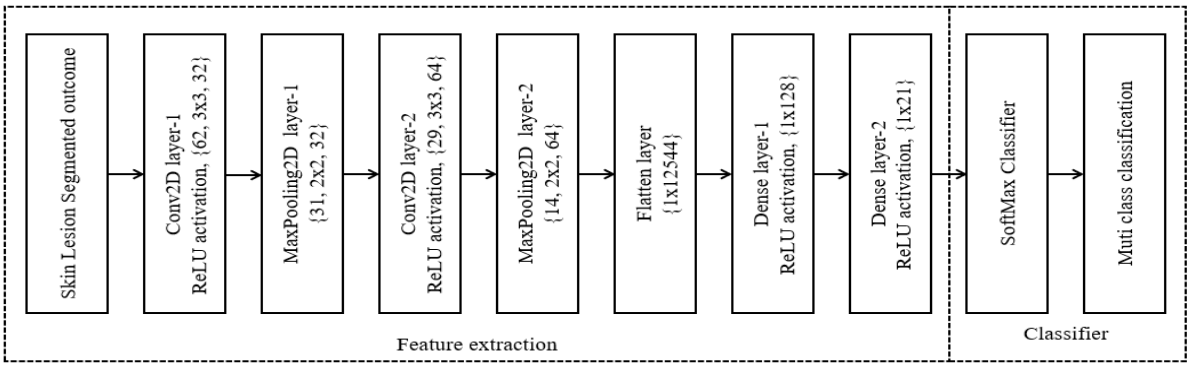

Figure 5. DLCNN feature extraction and classifier.

Recently, deep learning models are played the vital role in feature extraction and classification process. The DLCNN models are capable of extracting the detailed spatial, spectral, texture, and color features from the segmented images with high correlation. The DLCNN models also capable of identifying the relationship between various pixels of segmented images and extracts the inter dependent relationships as the features. Finally, the DLCNN models trained with these features and performs the SLDC operation. DLCNN is one of the greatest options for the classification process since it takes the local features from higher levels of input and combines them into more intricate features at lower levels, making it one of the most effective solutions. It is also possible to increase the speed of the DLCNN by adjusting the weights and kernel sizes in conjunction with the local connections. The DLCNN model for feature extraction and classification is seen in Illustration 5. Table 3 gives a full analysis of each layer, including the layer's dimension, filter size or kernel size, number of filters, and parameters, as well as the number of filters and parameters. All of the layers are merged together and formed as DLCNN model, the joint feature extraction and classification process of skin cancer is carried out by the different layers as follows:

Convolutional Layer: It is the most important operational block in DLCNN since it is responsible for performing the convolution operation between the skin lesion and the weight matrix and for generating local features. The characteristics of the weight matrix in this case are determined by the size of the kernel and the activation function. This layer is responsible for extracting the fundamental connection between all pixels in a skin lesion. The mathematical operation of convolution layer is given as follows:

$$F_c(i,j) = \sum_m^M \sum_n^N f_s\,(i+m, j+n) K(m,n) \qquad (8)$$

Table 3: Layer wise analysis of DTLNet.

Layer name	Layer dimension	Filter size	filters	Parameters
Conv2D-1	62x62	3x3	32	896
MaxPooling2D-1	31x31	2x2	32	0
Conv2D-2	29x29	3x3	64	18496
MaxPooling2D-2	14x14	2x2	64	0
Flatten	1x12544	-	-	0
Dense-1	1x128	-	-	1605760
Dense-2	1x21	-	-	2709
SoftMax	1x8	-	-	0

In this case, the input image or matrix is designated by f_s, the 2D filter is denoted by k with mxn as the filter size, and the 2D feature map output is marked by F c. In this case, the 2D feature map output is denoted by F_c. In this case, the convolution process between F_c and K is conducted, and the resulting F_c is generated. After the convolution layer is completed, the resulting output is applied to the ReLU-based activation function, which adds the non-linearity connection between distinct features. This is done by assuming that the threshold value is zero, then comparing that threshold value to the input. If the input feature is less than zero, the output is equal to zero; otherwise, the output is the input feature. The following diagram illustrates the mathematical analysis of the ReLU activation function (f_{relu}).

$$f_{relu}(x) = \max(0, x) \qquad (9)$$

MaxPooling Layer: In the DLCNN environment, the MaxPooling layer is used for down sampling purposes. It is used to reduce the input spatial size and also reduces the network parameters by a factor of two, which results in a reduction of the input spatial size and a reduction of the network parameters. In contrast to the AvgPool and L2-Norm pooling layers, the MaxPooling layer extracts the data by looking for the largest number of features in the input feature range and selecting the features with the best attributes.

Flatten Layer: This layer is used to transform the input pooled three-dimensional feature map into a column wise feature map, which is then utilised to create a column wise feature map. This architecture has a large number of pooling layers and a large number of pooled feature maps, all of which are organised in a series fashion. As a result, this layer arranged them in a single long column, one by one, one after the other. This layer is mostly used to consolidate all of the skin lesion characteristics into a single vector.

Dense Layer: Dense layer is an output layer that is used to construct all potential linkages between neurons in the previous layer and neurons in the next layer. Dense layer neurons are connected to neurons in the previous layer and to neurons in the following layer. As a result, the categorization process involves the participation of all neurons. The matrix vector multiplication action is carried out between the row vector neurons of the previous layer and the column vector neurons of the next layer.

SoftMax Classifier: All of the layers given in the proposed DTLNet architecture are layered together to form a DLCNN model that can recognize multiple classes. Among the features of the proposed DLCNN model are a SoftMax classifier, which helps to minimize the complexity by reducing the training time, and which also distinguishes between skin cancer and skin lesion multiclass categorization. During the training phase, the filter sizes are progressively increased by this research. The classifier, which is composed of a bias vector, a weight matrix, and an activation function, is used to execute the classification process. The following is the definition of the mathematical connection between these properties:

$$Output = ReLU(dot(input, kernel) + bias) \qquad (10)$$

Here, the Output holds the different classified classes of skin cancer.

IV. Simulation Results

This section gives detailed simulation analysis of proposed DTLNet with respect to subjective and objective analysis. Further, the performance of the proposed method is compared with state of art approaches using same ISIC-2019 dataset.

A. Dataset

For the purpose of DTLNet training and testing, the publicly accessible and real-time ISIC-2019 challenge dataset is taken into consideration. This dataset comprises the BCN 20000 and HAM10000 images, which are both available on the internet. In this case, the HAM10000 contains 10000 images, each of which has a resolution of 600x450 pixels.

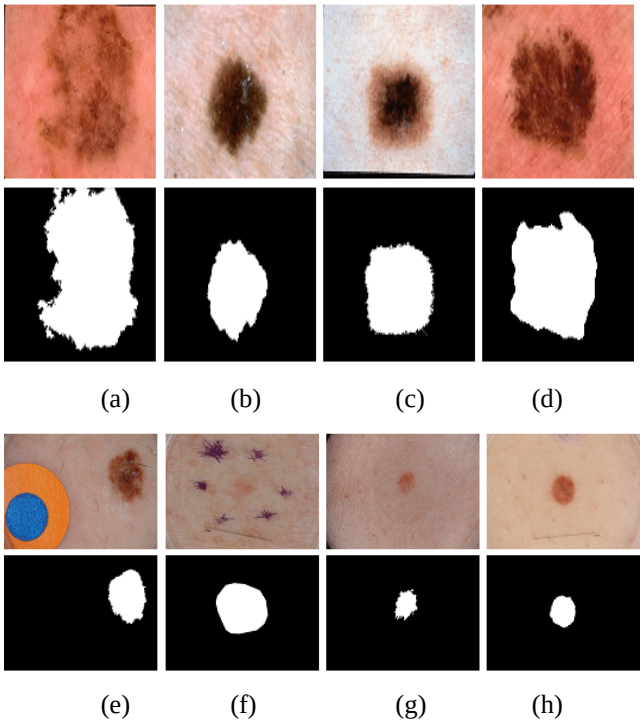

Figure 6. Segmented outcomes using AlexNet. (a) SCC, (b) VASC, (c) DF, (d) BKL, (e) AKIES, (f) BCC, (g) NV and (h) MEL

The BCN 20000 is a collection of 19424 images, each having a resolution of 1024 by 1024 pixels. The ISIC dataset comprises a total of 25,331 images, which are distributed in the following ways: SCC has 628 images, VASC has 253, DF has 239, BKL has 2,624 images, AKIEC has 867 images, BCC has 3,323 images, NV has 12,875 images, and MEL images have 4,522 images. Essentially, the whole dataset is divided into three categories. They are as follows: 10% of the dataset is considered for testing, 10% for validation, and 80% of the dataset is considered for training. In order to segment and extract features from the skin lesions, deep learning models were used. The transfer learning model is used to carry out the eight-class classification procedure. Figure 6 depicts the segmented outputs obtained via the use of the proposed AlexNet model.

B. Objective evaluation

The performance of any system cannot be estimated just on the basis of visual or subjective evaluations. In this way, objective assessment is quite beneficial for estimating the performance of different algorithms. As a result, it is straightforward to compare the performance of the proposed DTLNet with that of existing segmentation and classification systems.

Segmentation performance analysis: An examination of the six objective factors for determining the segmentation effectiveness of AlexNet is presented in this article. They are segmentation accuracy (SACC), sensitivity (SSEN), specificity (SSPE), precision (SPR), recall (SRE), F1-Score (SF1).

Table 4 compares the segmentation performance of proposed AlexNet model with the existing methods such as U-Net [32], ATL [31], PSPNet [30], ResNet [28], FCRN [27], CDNN [26] and MLR-Net [33]. Further, the proposed method resulted in superior performance for all the segmentation performance metrics. Here, the methods such as ResNet [28], FCRN [27], and CDNN [26] are participated in skin lesion segmentation challenge. Thus, it is proved that the proposed method resulted in outstanding performance as compared to challenge participated teams, where the proposed AlexNet model minimizes the vanishing gradient problems presented in the existing approaches.

Table 4. Performance comparison various segmentation approaches

Method	SACC (%)	SPR (%)	SRE (%)	SF1 (%)	SSEN (%)	SSPE (%)
CDNN [26]	82.50	86.50	84.90	76.50	93.40	95.39
FCRN [27]	82.00	87.80	84.70	76.20	93.20	95.20
ResNet [28]	80.20	89.50	84.40	76.00	93.40	96.93
PSPNet [30]	85.34	90.88	86.73	78.83	95.23	96.29
ATL [31]	90.38	91.23	90.46	82.48	96.37	97.38
U-Net [32]	93.86	92.40	93.23	86.35	96.45	97.45
MLR-Net [33]	92.07	90.18	98.19	93.19	98.18	81.81
Proposed AlexNet	96.42	98.23	97.82	97.93	100	100

Classification Performance Analysis: This article considers classification accuracy, sensitivity, specificity, precision, recall, F1-Score for analyzing the classification performance of eight diseases. Table 5 compares the

classification performance of proposed DTLNet with the various existing methods such as DLCNN [44], DenseNet-201[42], CNN-DG [43] and HCNN [45]. These existing approaches were implemented with the segmentation and classification models only, whereas the proposed DTLNet model contains preprocessing, segmentation, feature extraction, and classification steps. Finally, proposed DTLNet is outperformed due to its novel design

Table 5. Classification performance comparison of various SLDC methods

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Sensitivity (%)	Specificity (%)
DLCNN [44]	81	74	84.4	77.45	83.4	84.84
DenseNet-201[42]	85.8	82.4	89.35	84.67	89.3	84.63
CNN-DG [43]	86.2	87.2	85.32	78.14	91.5	90.39
HCNN [45]	95.39	93.24	94.58	92.28	90.2	93.48
Proposed DTLNet	**96.42**	**98.23**	**97.82**	**97.93**	**100**	**100**

C. Performance comparison with ISIC-2019 Challenge

Table 6. Classification performance comparison of ISIC-2019 Challenge

Method	Rank	Accuracy (%)	Sensitivity (%)	Specificity (%)
DRS-TL [47]	1	63.6	50.7	97.7
Cancerless	2	63.8	53.1	97.4
ForCure	3	64.8	53.4	97.4
Proposed DTLNet	-	**98.92**	**98.8**	**97.56**

On ISIC-2019 challenge dataset, Table 6 compares the classification performance of the DTLNet with that of the DRS-TL [47], Cancerless and ForCure algorithms. Here, the Cancerless and ForCure are unpublished works, but participated in ISIC-2019 classification challenge and these approaches are developed with transfer learning based ResNet and GoogleNet models. These participated teams are mainly suffering with the training loss due to dataset size, so they resulted in reduced performance. The proposed method divides the dataset into batch wise and trains the dataset with low complexity, which reduces the losses in DTLNet. It causes to improve the classification performance of proposed method as compared to the participated teams for all performance metrics.

V. Conclusion

This research proposed a DTLNet model, which is deep transfer learning-based method and it is used to perform the preprocessing, segmentation and classification operations. Initially, HGWF based preprocessing method is developed for removal of noises and also enhances the skin lesions. Then, transfer learning based AlexaNet is used for skin lesion segmentation, which is accurately localize the area of disease effected regions. In addition, DLCNN model is developed for the extracting the deep features and SoftMax classifier is utilized to classify the eight different classes of skin lesion. The proposed DTLNet model is capable of classifying the multiple classes of skin lesion including SCC, VASC, DF, BKL, AKIES, BCC, NV and MEL. Simulation results shows that the performance of proposed DTLNet resulted in superior as compared to the conventional methods. This work can be extended to implement with bio-optimization approaches for enhancing the classification accuracy.

References

[1]. Codella, N.C.; Nguyen, Q.B.; Pankanti, S.; Gutman, D.A.; Helba, B.; Halpern, A.C.; Smith, J.R. Deep learning ensembles for melanoma recognition in dermoscopy images. *IBM J. Res. Dev.* 2017, *61*, 5:1–5:15.

[2]. Alasadi, A.H.H.; Alsafy, B.M. Diagnosis of Malignant Melanoma of Skin Cancer Types. *Int. J. Interact. Multimed. Artif. Intell.* 2017, *4*, 44–49.

[3]. Darmawan, C.C.; Jo, G.; Montenegro, S.E.; Kwak, Y.; Cheol, L.; Cho, K.H.; Mun, J.H. Early detection of acral melanoma: A review of clinical, dermoscopic, histopathologic, and molecular characteristics. *J. Am. Acad. Dermatol.* 2019, *81*, 805–812.

[4]. Vocaturo, E.; Perna, D.; Zumpano, E. Machine learning techniques for automated melanoma detection. In Proceedings of the 2019 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), San Diego, CA, USA, 18–21 November 2019; pp. 2310–2317.

[5]. Yu, C.; Yang, S.; Kim, W.; Jung, J.; Chung, K.Y.; Lee, S.W.; Oh, B. Acral melanoma detection using a convolutional neural network for dermoscopy images. *PLoS ONE* 2018, *13*, e0193321.

[6]. Nezhadian, F.K.; Rashidi, S. Melanoma skin cancer detection using color and new texture features. In Proceedings of the 2017 Artificial Intelligence and Signal Processing Conference (AISP), Shiraz, Iran, 25–27 October 2017; pp. 1–5.

[7]. Shorten, C.; Khoshgoftaar, T.M. A survey on image data augmentation for deep learning. *J. Big Data* 2019, *6*, 1–48.

[8]. Ganster, H.; Pinz, P.; Rohrer, R.; Wildling, E.; Binder, M.; Kittler, H. Automated melanoma recognition. *IEEE Trans. Med. Imaging* 2001, *20*, 233–239.

[9]. Rezaoana, N.; Hossain, M.S.; Andersson, K. Detection and Classification of Skin Cancer by Using a Parallel CNN Model. In Proceedings of the 2020 IEEE International Women in Engineering (WIE) Conference on Electrical and Computer Engineering (WIECON-ECE), Bhubaneswar, India, 26–27 December 2020; pp. 380–386.

[10]. Hosny, K.M.; Kassem, M.A.; Foaud, M.M. Classification of skin lesions using transfer learning and

augmentation with Alex-net. *PLoS ONE* 2019, *14*, e0217293.

[11]. Lee, S.; Chu, Y.; Yoo, S.; Choi, S.; Choe, S.; Koh, S.; Chung, K.; Xing, L.; Oh, B.; Yang, S. Augmented decision-making for acral lentiginous melanoma detection using deep convolutional neural networks. *J. Eur. Acad. Dermatol. Venereol.* 2020, *34*, 1842–1850.

[12]. Russakovsky, O.; Deng, J.; Su, H.; Krause, J.; Satheesh, S.; Ma, S.; Huang, Z.; Karpathy, A.; Khosla, A.; Bernstein, M.; et al. Imagenet large scale visual recognition challenge. *Int. J. Comput. Vis.* 2015, *115*, 211–252.

[13]. Simonyan, K.; Zisserman, A. Very deep convolutional networks for large-scale image recognition. *arXiv* 2014, arXiv:1409.1556.

[14]. Chollet, F. Deep learning with separable convolutions. *arXiv* 2016, arXiv:1610.02357.

[15]. Szegedy, C.; Ioffe, S.; Vanhoucke, V.; Alemi, A.A. Inception-v4, inception-resnet and the impact of residual connections on learning. In Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence, San Francisco, CA, USA, 4–9 February 2017.

[16]. Huang, G.; Liu, Z.; Van Der Maaten, L.; Weinberger, K.Q. Densely connected convolutional networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Honolulu, HI, USA, 21–26 July 2017; pp. 4700–4708.

[17]. He, K.; Zhang, X.; Ren, S.; Sun, J. Deep residual learning for image recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Las Vegas, NV, USA, 27–30 June 2016; pp. 770–778.

[18]. Haggenmüller, S.; Maron, R.C.; Hekler, A.; Utikal, J.S.; Barata, C.; Barnhill, R.L.; Beltraminelli, H.; Berking, C.; Betz-Stablein, B.; Blum, A.; et al. Skin cancer classification via convolutional neural networks: Systematic review of studies involving human experts. *Eur. J. Cancer* 2021, *156*, 202–216.

[19]. Razmjooy, N.; Ashourian, M.; Karimifard, M.; Estrela, V.V.; Loschi, H.J.; Do Nascimento, D.; França, R.P.; Vishnevski, M. Computer-aided diagnosis of skin cancer: A review. *Curr. Med. Imaging* 2020, *16*, 781–793.

[20]. Höhn, J.; Hekler, A.; Krieghoff-Henning, E.; Kather, J.N.; Utikal, J.S.; Meier, F.; Gellrich, F.F.; Hauschild, A.; French, L.; Schlager, J.G.; et al. Integrating patient data into skin cancer classification using convolutional neural networks: Systematic review. *J. Med. Internet Res.* 2021, *23*, e20708.

[21]. Saeed, J.; Zeebaree, S. Skin lesion classification based on deep convolutional neural networks architectures. *J. Appl. Sci. Technol. Trends* 2021, *2*, 41–51.

[22]. Kassani, S.H.; Kassani, P.H. A comparative study of deep learning architectures on melanoma detection. *Tissue Cell* 2019, *58*, 76–83.

[23]. Krizhevsky, A.; Sutskever, I.; Hinton, G.E. Imagenet classification with deep convolutional neural networks. *Adv. Neural Inf. Process. Syst.* 2012, *25*, 1097–1105.

[24]. Li, Y.; Shen, L. Skin lesion analysis towards melanoma detection using deep learning network. *Sensors* 2018, *18*, 556.

[25]. Barata, C.; Marques, J.S. Deep learning for skin cancer diagnosis with hierarchical architectures. In Proceedings of the 2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019), Venice, Italy, 8–11 April 2019; pp. 841–845.

[26]. Y. Yuan, M. Chao and Y.-C. Lo, "Automatic skin lesion segmentation with fully convolutional-deconvolutional networks," arXiv: 1703.05165, 2017

[27]. Li, Yuexiang, and Linlin Shen. "Skin Lesion Analysis Towards Melanoma Detection Using Deep Learning Network." *arXiv preprint arXiv:1703.00577* (2017).

[28]. L. Bi, K. Jinman, E. Ahn and D. Feng, "Automatic skin lesion analysis using large-scale dermoscopy images and deep residual networks," in arXiv: 1703.04197, 2017.

[29]. Deep-Learning Ensembles for Skin-Lesion Segmentation, Analysis, Classification: RECOD Titans at ISIC Challenge 2018

[30]. Zou, J., Ma, X., Zhong, C., Zhang, Y.: Dermoscopic image analysis for ISIC challenge (2018). arXivPrepr arXiv:180708948

[31]. Hardie, Russell C., et al. "Skin lesion segmentation and classification for ISIC 2018 using traditional classifiers with hand-crafted features." *arXiv preprint arXiv:1807.07001* (2018).

[32]. Abraham, Nabila, and NaimulMefraz Khan. "A novel focal tversky loss function with improved attention u-net for lesion segmentation." *2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019)*. IEEE, 2019.

[33]. D. M. Krishna, S. K. Sahu and G. R. L. V. N. Srinivasa Raju, "MLRNet: Skin Lesion Segmentation using Hybrid Gaussian Guided Filter with CNN," 2021 5th InternationalConference on Electronics, Communication and Aerospace Technology (ICECA), 2021,pp.1337-1343,doi:10.1109/ICECA52323.2021.9676020.

[34]. Gareau, D.S.; Browning, J.; Da Rosa, J.C.; Suarez-Farinas, M.; Lish, S.; Zong, A.M.; Firester, B.; Vrattos, C.; Renert-Yuval, Y.; Gamboa, M.; et al. Deep learning-level melanoma detection by interpretable machine learning and imaging biomarker cues. *J. Biomed. Opt.* 2020, *25*, 112906.

[35]. Rehman, A.; Khan, M.A.; Mehmood, Z.; Saba, T.; Sardaraz, M.; Rashid, M. Microscopic melanoma detection and classification: A framework of pixel-based fusion and multilevel features reduction. *Microsc. Res. Tech.* 2020, *83*, 410–423.

[36]. Parmar, B.; Talati, B. Automated Melanoma Types and Stages Classification for dermoscopy images. In Proceedings of the 2019 Innovations in Power and Advanced Computing Technologies (i-PACT), Vellore, India, 22–23 March 2019; Volume 1, pp. 1–7.

[37]. Rahman, Z.; Ami, A.M. A Transfer Learning Based Approach for Skin Lesion Classification from Imbalanced Data. In Proceedings of the 2020 11th International Conference on Electrical and Computer Engineering (ICECE), Dhaka, Bangladesh, 17–19 December 2020; pp. 65–68.

[38]. Zunair, H.; Hamza, A.B. Melanoma detection using adversarial training and deep transfer learning. *Phys. Med. Biol.* 2020, *65*, 135005.

[39]. Al Nazi, Z.; Abir, T.A. Automatic skin lesion segmentation and melanoma detection: Transfer learning approach with u-net and dcnn-svm. In *Proceedings of the International Joint Conference on Computational Intelligence*; Springer: Singapore, 2020; pp. 371–381.

[40]. Younis, H.; Bhatti, M.H.; Azeem, M. Classification of skin cancer dermoscopy images using transfer learning. In Proceedings of the 2019 15th International Conference on Emerging Technologies (ICET), Peshawar, Pakistan, 2–3 December 2019; pp. 1–4.

[41]. Hekler, Achim, et al. "Superior skin cancer classification by the combination of human and artificial intelligence." *European Journal of Cancer* 120 (2019): 114-121.

[42]. Guissous, AllaEddine. "Skin lesion classification using deep neural network." *arXiv preprint arXiv:1911.07817* (2019).

[43]. Sun, Qilin, et al. "Skin Lesion Classification Using Additional Patient Information." *BioMed Research International* 2021 (2021).

[44]. [Kassem, Mohamed A., Khalid M. Hosny, and Mohamed M. Fouad. "Skin lesions classification into eight classes for ISIC 2019 using deep convolutional neural network and transfer learning." *IEEE Access* 8 (2020): 114822-114832.

[45]. A. Mahbod, G. Schaefer, C. Wang, G. Dorffner, R. Ecker, and I. Ellinger, "Transfer learning using a multi-scale and multinetwork ensemble for skin lesion classification," Computer Methods and Programs in Biomedicine, vol. 193, 2020.

[46]. Nozdryn-Plotnicki, A., Yap, J., &Yolland, W. (2018). Ensembling convolutional neural networks for skin cancer classification. International Skin Imaging Collaboration (ISIC) Challenge on Skin Image Analysis for Melanoma Detection. MICCAI.

[47]. N. Gessert, T. Sentker, F. Madesta et al., "Skin lesion diagnosis using ensembles, unscaled multi-crop evaluation and loss weighting," 2018, http://arxiv.org/abs/1808.01694.

[48]. Pacheco, Andre GC, Abder-Rahman Ali, and Thomas Trappenberg. "Skin cancer detection based on deep learning and entropy to detect outlier samples." *arXiv preprint arXiv:1909.04525* (2019).

[49]. Marc Combalia, Noel C. F. Codella, Veronica Rotemberg, Brian Helba, Veronica Vilaplana, Ofer Reiter, Allan C. Halpern, Susana Puig, JosepMalvehy: "BCN20000: Dermoscopic Lesions in the Wild", 2019; arXiv:1908.02288.

[50]. Varma, P. Bharat Siva, et al. "SLDCNet: Skin lesion detection and classification using full resolution convolutional network-based deep learning CNN with transfer learning." *Expert Systems*: e12944.