



Skin Lesions Classification Using Deep Learning Techniques: Review

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Authors' contributions

This work was carried out in collaboration among all authors. Authors OSK and AMA prepared the detailed review of previous works related to Skin Lesions Classification Using Deep Learning Techniques. Author DQZ wrote the introduction and skin lesions image analysis techniques draft of the manuscript. In addition, all authors administered the analyzes and discussion portions of the study. All authors read and approved the final manuscript.

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ABSTRACT

Skin cancer is a significant health problem. More than 123,000 new cases per year are recorded. Melanoma is the most popular type of skin cancer, leading to more than 9000 deaths annually in the USA. Skin disease diagnosis is getting difficult due to visual similarities. While Melanoma is the most common form of skin cancer, other pathology types are also fatal. Automatic melanoma screening systems will be useful in identifying those skin cancers more appropriately. Advances in technology and growth in computational capabilities have allowed machine learning and deep learning algorithms to analyze skin lesion images. Deep Convolutional Neural Networks (DCNNs) have achieved more encouraging results, yet faster systems for diagnosing fatal diseases are the need of the hour. This paper presents a survey of techniques for skin cancer detection from images. The paper aims to present a review of existing state-of-the-art and effective models for automatically detecting Melanoma from skin images. The result of classifications and segmentation from the skin lesion images will be processed better using the ensemble deep learning algorithm.

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1. INTRODUCTION

The skin protects many important organs like the heart, kidney, liver, and other sensitive bodies from the outside environment. This part of the body is a shield that must be kept so that the lifestyle is safe. Skin generate different vitamins the most popular is vitamin D. Worldwide has different forms of weather, humidity, and food habit that can directly or indirectly influence our skin [1]. The revealed skin area is referred to as the epidermis, and the hidden skin region is the dermis. The skin consists of three cells: basal cell, squamous cells, and melanocytes cell. Skin cancers evolve because of Ultra-Violet (UV) exposure, causing changes in genetic material such as the composition of DNA [2-3]. Skin cancer is considered one of the most common cancers and one of the most malignant and has developed enormously in the past three decades. The World Health Organization (WHO) statistics show that almost 132000 new cases of Melanoma are recorded worldwide each year [4-5].

Whereas Melanoma is considered to be the deadliest skin cancer, it is a threat to human life. Early diagnosis and treatment greatly improve the probability of survival. However, clinical diagnosis is highly subjective and complex; thus, it relies heavily on dermatologists' expertise and is estimated to be between 75 – 85% [6-7]. Dermoscopy is one of the most common imaging techniques for dermatologists. It magnifies the surface of the skin lesion, and the structure becomes more apparent for an exam. However, only qualified doctors can use this procedure effectively since it focuses solely on the practitioners' visual sharpness and expertise. Dermoscopic photographs showing malignant or non-malignant lesions can be seen in Fig. 1 [8].

The automated framework still exists with the ability to distinguish Melanoma from benign in its very initial stages. Computer-aided diagnosis (CAD) may be beneficial for doctors to use technological advances in dermoscopy and may also provide a second view [9-13]. The CAD techniques support various methods of machine learning, for instance, to extract different features (color, form, and texture) from each dermoscopic image and to use an advanced classifier [14]. A convolutional neural network (CNN) is an example of a deep learning technique that

imitates brain activity information processing [15-18]. Many recent literature publications have explored the use of deep learning architectures such as CNNs for dermoscopic images. CNN's are based on layers that alternate with pooling layers of trainable weights of receptive fields, which progressively reduce input image size. The weights of the receptive fields during the training process will differ arbitrarily; a huge training set is required. During CNN preparation, proper weight values are sought without using the acquired knowledge of signal processing and analysis [19-20].

They can generate discriminatory attributes from raw data, gradually forming abstract descriptors that replace the conventional way of carefully handling features and algorithms [21-23]. Deep CNN methods are still limited despite their high performance. They usually require data sets of tens of thousands of pictures. However, in the case of dermoscopic images, CNN models are not as accurate as they should be in this application due to the limited number of datasets available. So this another problem that can appear during a deep-CNN training is overfitting, which occurs when a network adapts to describe the relationship between training labels and input data. Therefore, it fits into this training set too well. In this situation, the model would emphasize memorizing the successful training but contributes to the bad performance of new ones that it has not observed yet [24-25]. Deep CNN based data augmentation methods for the increase in skin patterns need to be modified and a wide range of parameters adapted to obtain satisfactory results. The data increase approach's main drawback is that it requires incredibly long training periods and high computational costs. When transfer learning addresses these limitations, the network weights are initialized by training in non-clinical imaging and adapted to the dermoscopy dataset. CNN deep Web on small datasets is a standard solution that helps network optimization, leading to quicker convergence for training [4,26-27]. In this study, a systematic review has been conducted of different methods used to examine skin lesions for melanoma detection. A review of new methods for finding skin lesions is presented in a paper. This study highlights different ways to diagnose melanoma skin cancer based on photographs. In popular use, methods, these techniques include the preprocessing

techniques, segmentation techniques, and classifier techniques. Also, focus on important segmentation technique like, Encoder-decoder Fully Convolutional Network (FCN) method. The paper is organized as: Section 2 presents various methods and techniques of skin lesions image analysis used in literature review. Section 3 and Section 4 focuses on literature review and discussions. Finally, Section 5 depicts the conclusions.

2. SKIN LESIONS IMAGE ANALYSIS TECHNIQUES

Skin lesions cannot easily be detected as a result of variation in image kinds and sources. There is such an enormous variation in the appearance of human skin that it is difficult and complicated to discover the skin. There are many drawbacks related to the skin lesion image: multiple sizes and shapes, noise and artifacts presence, irregular fuzzy boundaries, low contrast, and color illumination [28].

2.1 Preprocessing Skin Lesions Image Techniques

Pre-processing is mainly used in the preparation of images for enhanced identification and processing of features [29]. Preprocessing includes image acquisition as an input, grayscale acquisition, noise filtering, and binary image generation [30-32]. These techniques include an image histogram extension to better visibility and intensity adjustment that improves the picture's intensity values for an output picture to produce a high-quality picture and a histogram equalization that evenly distributes pixel intensities across the entire intensity range to increase the overall contrast [33]. Also, there is a binarisation process that reduces the information within an image from gray to a binary black and white image and

converts it into Black and White colors; it is a morphological function, and erosion and dilation of images are carried out to extract certain characteristics and location of all objects into an image [34].

2.2 Segmentation Techniques of Skin Lesion Image

Segmentation of images is an important method for automating the diagnosis of skin lesions. In the study of skin lesion images, this step is essential [35-37]. This method is accomplished by distinguishing diseased areas from stable areas in the areas of concern. However, this segmentation is difficult due to the wide variations in the structure, scale, color, texture, and position of skin lesions in dermoscopic images. Furthermore, their low contrast with adjacent tissues presents further problems. Additional considerations like hair, blood vessels, air bubbles, ruler marks, ebony frames, and color lighting also contribute to the division mission [17]. Examples of those obstacles can be found in Fig. 2.

2.2.1 Traditional methods based on intelligence

These systems are based on artificial intelligence and can perform image analyses based on understanding, thought, and interpretation from current large image datasets [38-39]. For the extraction of the features, the majority of image segments use conventional machine learning methods [40-41]. Semi-supervised skin lesion divisions focused on system training and learning from existing datasets such as Grab-cut techniques, fuzzy C-means (FCM), genetic algorithms, and K-means are used together for segmentation [42-43].

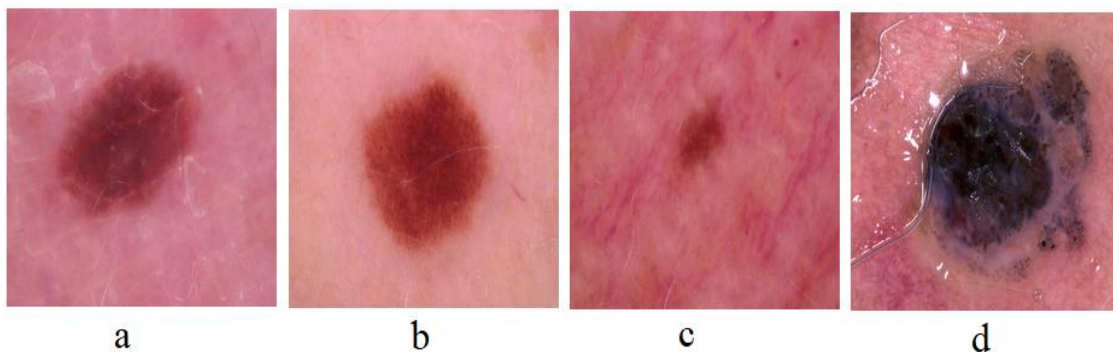


Fig. 1. Dermoscopy images with non-malignant lesions (a–c) and melanoma lesion (d)

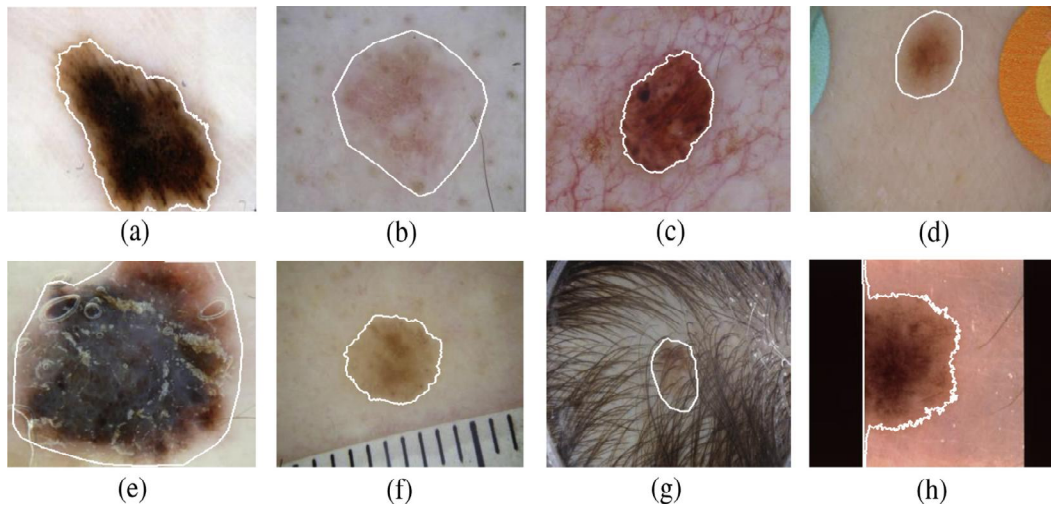


Fig. 2. Examples of some complicated cases of skin lesions including (a) irregular boundary, (b) low contrast, (c) blood vessels, (d) illumination color, (e) bubble, (f) artifact ruler, (g) artifact hair and (h) artifact frame

2.2.2 Deep learning techniques

Deep learning approaches have very effective in the segmentation of skin lesion images, which is a challenging challenge in computer vision. Several deep learning models are available to provide outstanding efficiency in segmenting skin lesions. Some types of these architectures like DCNN, U-Net, the Completely Convolutional Network (FCN), and Deep Fully Convolutional Residual Networks (FCRN) (CDCNN) [17,44]. The models for segmentation of medical images, including the models ResU-Net, U-Net, LadderNet, R2U-Net, and Fussnet, consist of two units: encoder and decoder. Several layers of convolution and sub-sampling operations are performed in the encoding unit, which produces different features represented in the various stages of the unit. The coded features begin to decode from bottleneck layers called latent space. Several transpose convergence transactions are carried out in the decoding unit, and a concatenation transaction takes place between encoding and decoding features [45-46]; as below:

2.2.2.1 U-Net architecture

Two symmetrical paths are used for the model architecture: Encoder (on the left) and Decoder (at the right). Each pixel in the input image is tested and determined by which class it belongs to the encoder. Furthermore, the Decoder Path restores the original high-dimensional input in the classmark by assigning the position of each pixel. There are four distinct blocks in the

encoder line (also called the down-sampling path). Each block involves two layers of convolution, followed by the activation feature for ReLu and the layer for Max pooling [47]. As shown in Fig 3.

2.2.2.2 FCN

Deep learning techniques focused on fully convolutional networks (FCN) have been outperformed in solving the challenges of natural image segmentation. The FCN's ability to use massive data sets to multilevel learn the features that best correlate to the image's presentation and semantics is mostly responsible for its popularity. Furthermore, FCN can be trained from end to end to effectively deduce pictures, i.e., as inputs, and the results are produced directly from segmentation [48-49]. As shown in Fig. 4.

2.2.2.3 Deep residual network

It is a particular kind of ANN that is structured by skip connections over convolutional layers on a pyramidal structure. It consists mainly of several convolutional layers of the two-stages FCRN approach that use deep residual networks to segment and classify skin lesions. For more prosperous and more discriminative functionality, a deep residual network with over 50 layers was used. An additional framework used for segmenting skin lesions using an FCRN Lesion Index Measurement Unit (LICU) to give pathologists useful pieces of information, a new

part has been proposed called the Lesion Index Calculation Unit, to refine FCRN coarse skin lesion maps, as the correct possible map of different lesion categories for the skin lesion

picture. The deep architecture of the network needs a lot of computing resources. In real-life situations, this can hinder the use of architecture [50]. As shown in Fig. 5.

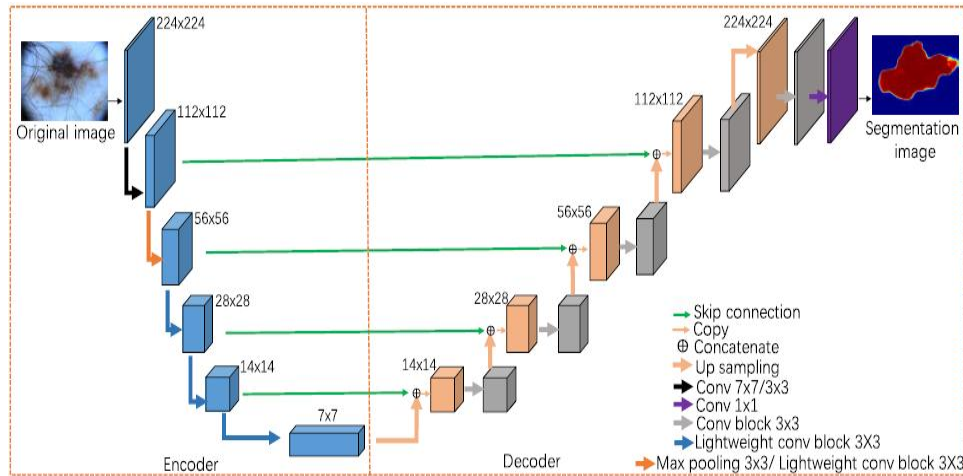


Fig. 3. The Proposed U-net architecture

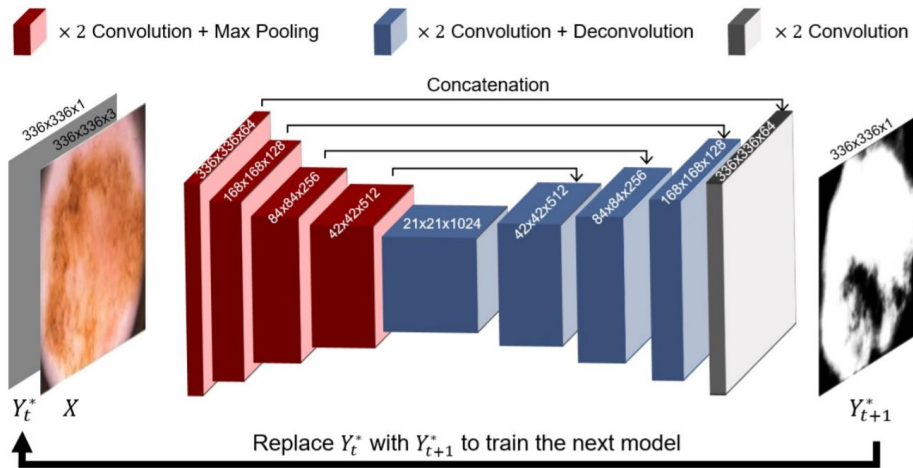


Fig. 4. A fully convolutional model for skin-lesion segmentation

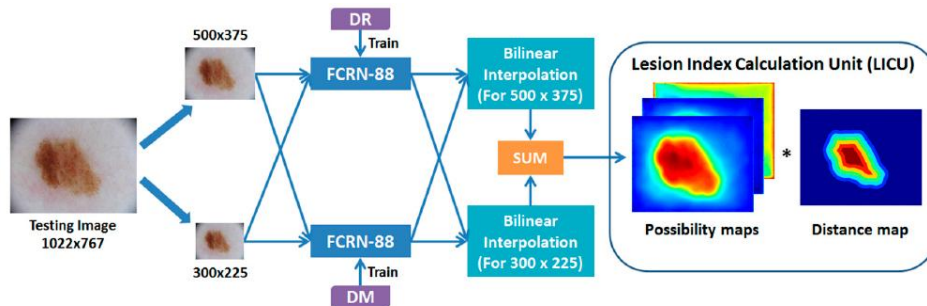


Fig. 5. Flowchart of LICU

2.2.3 Buzzard Optimization (BUZO) algorithm for detection of skin Cancer

For skin lesions, a new classification algorithm for dermis images was developed and it has proved highly effective. After the analysis and preprocessing are completed, the lesion is performed on healthy areas using the Otsu process. By comparison, this feature selection approach selects numerous features but their impact on the process is important. Global optimization and rapid convergence are excellent features of the BUZ algorithm [51].

2.3 Classification Technique of Skin Lesions

Images of the skin lesion can be categorized to allow melanoma detection. In images of skin lesions, different types of cancer may be observed. These may primarily be marked as malignant and benign. They can also be classified in the following categories: Squamous cell carcinoma, Basal cell carcinoma, Actinic keratosis, Keratosis seborrheic, Nevi, Melanoma, Solar Lentigo, and Vascular Lesions. Melanoma is the deadliest of these groups and a malignant lesion. So the traditional classification and the newly developed techniques were examined [52-53].

2.3.1 Conventional classification techniques

These classifiers are previously used and are primarily based on standard methods of either pixel-based or regional extraction approaches, which are sent to the classifier to verify the skin cancer form [54-55]. Some of the common approaches have been intelligent in recent times. These algorithms include classifiers such as Naive Bayesian, K-Nearest Neighbor, ANN, and SVM [56-57]. The first parameter k, needs to be specified for the k-NN classifier. While the classification precision is maximized, the influence of the different K parameters is explored using this metric [58,54].

2.3.2 Deep neural networks

Another promising means of increasing the supply of dermatology knowledge would be the use of artificial intelligence software. A recent development in deep learning has made it easier for artificial intelligence tools to help diagnose skin disorders, particularly in developing

profound learning models such as CNN and the rapid development of computer vision. These successful formulations in deep learning models and excellent and state-of-the-art efficiency in processing and classification of images have been achieved [59-60]. These techniques have proved to be better than conventional methods. However, in deep learning image processing, several difficult problems exist [61].

2.3.2.1 AlexNet

It is an architecture that is basic but efficient and consists of the convolutional and pooling layers. There is more than a hidden layer in deep architectures. These hidden layers help to refine and better extract features. Thus, the success of image rating on deep networks has shown that they attain a high rate of rating relative to other systems, which allows others to use deep networks. The benefit is that it uses GPU for preparation and executing activities. In deep neural networks, AlexNet also acts as a starting point in computer vision and voice recognition [62-63]. As shown in Fig. 6.

2.3.2.2 VGGNet

The Visual Graphics Group researchers at the University of Oxford created this network. Its pyramidal structure characterizes it. It consists of a number of convolutional layers followed by pool layers with bundling layers that contribute to a narrower layer form. The benefits include providing very good infrastructure to benchmark every specific mission [64-66]. The pre-trained VGG networks are widely used in many applications as well. However, a lot of computational is needed and is incredibly slow to practice [67], as described in Fig. 7.

2.3.2.3 ResNet

Architecture consists of many residual modules that form the architecture's basic building block. The residual modules are stacked to form one end-to-end network over the other. The architecture consists of many residual layers that can be used for network preparation. It's a deep CNN 152-layer residual blocks architecture. It is twenty and eight times wider than both AlexNet and VGG. It is less complicated than previously proposed networks computationally. E.g., ResNet of 50, ResNet of 101, and ResNet of 152 layers are examples [68-69], as shown in Fig. 8.

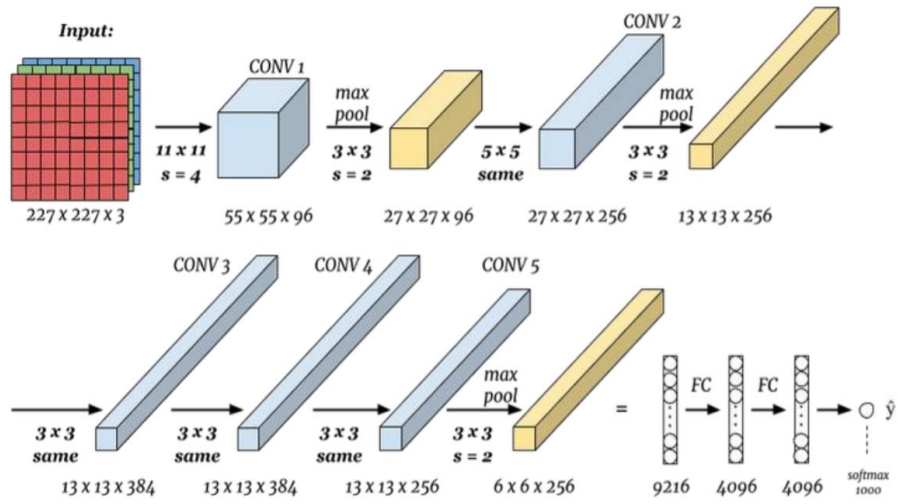


Fig. 6. AlexNet architecture

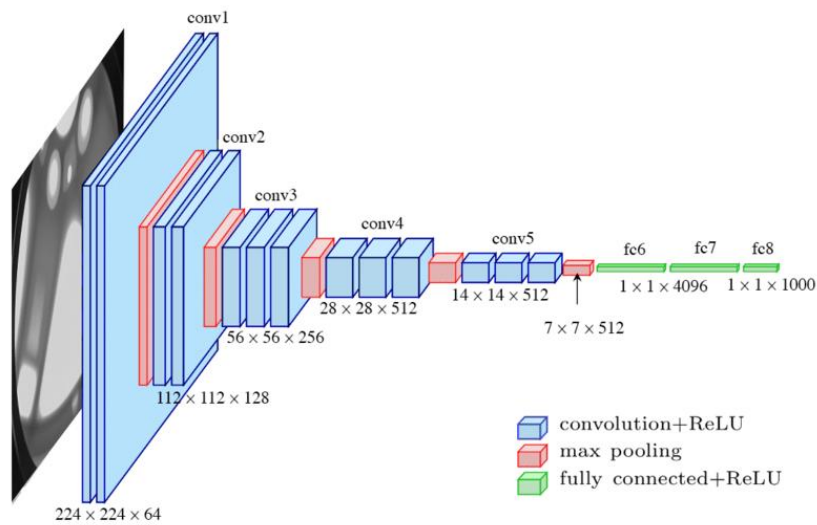


Fig. 7. VGG 16 architecture

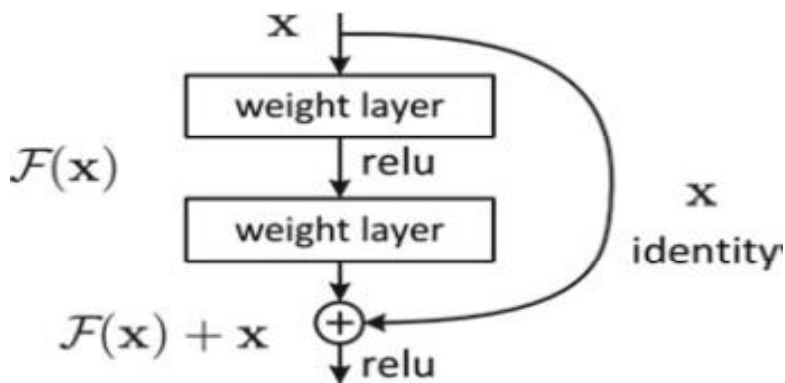


Fig. 8. ResNet architecture

2.3.2.4 DenseNet

It is close to ResNet, and the vanishing gradient problem has been resolved. DenseNet uses layer-overlay communication, connecting each layer to the next next, feed-forward-based layer to resolve ResNet's problem, which specifically preserves information by adding identity changes that add complexity. It uses dense blocks to input features of all previous layers in all subsequent layers [70-71], as described in Fig. 9.

3. LITERATURE REVIEW

Zhang et al. [72] suggested deep learning algorithms assist in diagnosing four common dermoscopic skin diseases. The model blends the efforts of both human ability and machine algorithms in dermatological diagnoses based on the GoogleNet and Inception-v3. The algorithm achieved an accuracy of 87.25% tested on a dataset of Peking Union Medical College Hospital.

The efficacy and ability of neural convolutional networks in the classification of 8 skin diseases were proposed in [73]. A total of 10135 dermoscopic skin images (PH2: 120, HAM10000: 10015) were used and applied to different advanced architecture (ResNet 152, DenseNet 201, InceptionResNet v2, Inception v3). The used dataset contains eight diagnostic categories: basal cell carcinoma, Melanoma,

melanocytic nevi, Actinic Keratosis, benign Keratosis, vascular lesions, intraepithelial carcinoma, a dermatofibroma. The purpose is to equate deep learning capability with the performance of professional dermatologists. The mean results indicate that all deep learning models performed better than dermatologists (at least 11%). DenseNet 201 typically obtained better results with the highest macro and micro averaged AUC values for overall classification compared to other models in the dermoscopic skin cancer classification 98.16%, 98.79%, respectively.

Ashour et al. [74] implemented a new genetic algorithm (GA) skin lesion detection system for optimizing neutrosophic set (NS) operations to minimize dermoscopic image indeterminacy. K-means clustering is then implemented in the skin lesion segment. The proposed approach is, therefore, called optimized neutrosophic k-means (ONKM). The proposed ONKM method finds optimum α to be $\alpha_{optimal} = 0.0014$, hitting the highest JAC (fitness function) levels in GA optimization, where 50 pictures are randomly selected from a public data set (ISIC 2016) to train the proposed process. 850 pictures are used for the evaluation of the proposed ONKM method during the testing process. The findings revealed the ONKM system's superiority with an average accuracy of 99.29% to k-means and γ -k-means and Dice =91.26% through five cross-validations.

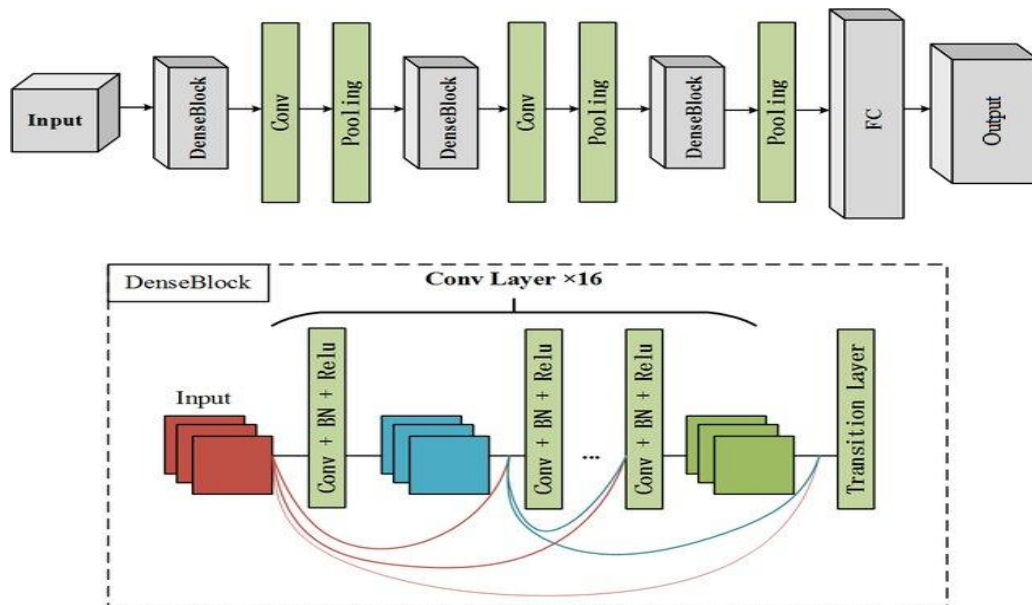


Fig. 9. DenseNet architecture

The main drawback is that the machine-based approaches need many labeled pictures per class for training. Harangi [75] explored how convolutional neural networks could further develop their precision to classify dermoscopic images into three groups of nevus, Melanoma, and seborrhoeal Keratosis, not have an opportunity to train them on a suitable number of annotated images. Researcher fuse the results of the classification layers of four separate deep neural network architectures to achieve high classification accuracy. Aggregating robust neural networks (CNNs) in a single framework, where the final classification is performed based on the CNNs weighted output. Results also show that establishing a group of different neuronal networks is a logical strategy because each fusion strategy is more successful than the individual classification accuracy networks. The average area under the recipient operating curve was AUC 89.1% for the three classification tasks.

A comparative study is discussed in this proposed work [76] to identify the melanoma category with supervised machine learning algorithms. The classification of dermoscopic image melanoma is suggested to assist the clinical use of dermatoscopy imaging methods for the classification of skin sores. The images have been improved through anisotropic diffusion filters and unsharp masking. The Melanoma was isolated by different segmentation algorithms from the background: Otsu thresholds, fuzzy c-means, k-means, and adaptive k-means. The results show that adaptable K-means had a substantially higher Dice coefficient value and were more suitable for the segmentation of pictures. Function extraction methods are used after segmentation to extract features that will be helpful in the classification of images. The method was evaluated with five separate classifiers: k-NN, SVM, Decision Tree, MLP, and Random Forest. Classification findings are obtained with 10-fold cross-validation for each classification. According to the result obtained from the classification techniques, the Random Forest has been higher because its accuracy is higher than that of the other classifications; accuracy is 93.47%.

The author of [77] proposed an image processing-based skin disease detection tool. This approach uses the digital picture of the skin region of the disease effect and then image analysis to detect disease. The solution proposed is easy, quick, and requires no more expensive equipment than a camera and a

computer. The method works on the color picture inputs. Then resize the image to extract features using a pre-trained convolutional neural network AlexNet is a deep CNN model. The Multiclass SVM would be used after features extraction to disease classification, and the results will be displayed to the user, including disease form, spread, and severity. The machine detects three distinct skin diseases with 100% accuracy.

Kumar et al. [78] suggested a procedure to assess whether a sample is affected by Melanoma is affected or not. The phases involved in this study include the collection of labeled data from pictures preprocessed and pre-improved, i.e., techniques such as hair removal, image centering, softening. Then, the images were flattened. The image intensities were put in an array; all these arrays were added to a database. SVM was used for training labeled data using a suitable kernel, and the trained data were used to identify samples successfully. The idea is very restricted to one method for the classification of two or more diseases. The results showed that the classification accuracy achieved was about 90%.

An automatic classification system for skin lesions is proposed in [79]. A deep learning network and transfer learning are used in this process. In addition, transfer learning is extended to AlexNet by replacing the last layer with a softmax for three separate lesions (Melanoma, common nevus, and atypical nevus). The model proposed is trained and validated using the ph2 dataset. The results obtained indicate that the approach proposed surpassed the current methods. The achieved rates are 98.61%, 98.33%, 98.93%, and 97.73%, respectively, for accuracy, sensitivity, specificity, and precision.

Abbas and Celebi [8] suggested that a new classification method should be established with a fusion of multiple visual features and a deeper-neural-network approach for pigmented skin lesions (PSLs). For better classification outcomes, the combination of visual features and a multilayer deep learning algorithm architecture are combined. The DermoDeep framework is incorporated with the fusion of multiple features and the best deep neural network (DNN) techniques model. The DermoDeep comprises five key steps: 1) creating the visual features layer (VF-L) by transforming color space. 2) While features are extracted from stack-based autoencoders (SAE) to minimize the loss of information, a deep layer of features (DF-L). 3)

The design of the fusion features layer (FF-L) is a method that combines the features from the layer of visual features (VF-L) with the layer of more in-depth features (DF-L) through a transformation technique known as the principal component analysis (PCA). 4) The feature optimization layer of the model Recurrent Neural Networks (RNNs) will optimize features of the fusion (FF-L) layer. 5) The construction of the classification layer features of the Softmax linear classification shall be used to differentiate in a supervised way between Melanoma and nevi. The findings show that the DermatDeep can be used in the screening process to support dermatologists with Skin-EDRA, with AUC = 96%.

Hosny et al. [80] presented a higher classification system for automatic skin lesions, which uses transfer learning theory and the pre-trained deep neural network. The transfer applied to the Alexnet in a variety of ways, such as fine-tuning the weight of architecture, changing the classification layer to a softmax layer that deals for two to three types of skin lesions, and increasing the dataset by fixed and random angles of rotation to overcome the overfitting problem. The three well-known MED-NODE, Derm (IS & Quest), and ISIC datasets are used to validate and verify the method proposed. The segmented color picture lesions can be categorized into nevus, seborrheic Keratosis, and Melanoma in the current softmax layer. The proposed method is achieved higher accuracy for three datasets IS & Quest, MED-NODE, and ISIC, as 97.70%, 96.86%, and 95.91%, respectively.

Bakkouri and Afdel [81] presented a powerful CAD system that used transfer learning and a multilayer blend network to diagnose problematic skin conditions. It is a convenient method for preventing convergence speed, overfitting, and processing of high morphological features. The suggested solution has been tested using the HAM10000 dataset, which comprises seven types of skin lesions. Firstly, by incorporating CNN models of continuous sophistication: ResNet-18, VGG-16, and DenseNet-121, powerful low-level features have been selected for the right blocks, minimizing computational costs by considering high-efficiency performance. Secondly, a new high-level CNN model is implemented, known as the Convolutional Fusion Unit (CFU), focused on the fusion of convolutional layers to draw important discriminatory features. Finally, the problem of high visual similarity among classes was avoided

by the fusion of three high-level semantical maps (ResNet4-CFU, VGG4-CFU, and DenseNet3-CFU). The experimental results demonstrate that the proposed system carries out the most representative state-of-the-art strategies in dermoscopic recognition. With an average accuracy of 98.09%, the proposed produced encouraging performance.

The authors of [82] introduced a method in which a non-programmer may build complex, profound learning models. It opened the possibilities for versatility in the development of profound learning classification by pointing to general procedures and looping patterns in deep learning models. The model used Deep Learning Studio as a model of deep learning guided architecture. In the identification of cancer cells, the DLS models achieved an AUC of 99.77%.

Mabrouk et al. [83] introduced a model composed of four essential features used to detect Melanoma, which is feasible for visual examination depends on the ABCD model. The PSL, preprocessing, and segmentation using appropriate algorithms, feature detecting will happen regarding the ABCD rule. According to the ABCD system, the study aims to extract asymmetric, boundary, and color features, in addition to various parameters "D" is introduced. In addition, this study also takes final decisions under the Total Dermoscopic Score (TDS) index, and three other common machines learn classifications, as the international definition of ABCD rule of cancer diagnoses has been discussed. These are likely to be significant contributions of the ANN, SVM, and K-Nearest Neighbors in segmented lesions in addition to the traditional TDS. The model offers excellent results to automatically measure the ABCD score that represents its viability. The diverse feature experiments and different classification methods were developed to achieve 98.1%, 95%, and 98.75% accuracy, TDS, Automatic ANN, and linear SVM were categorized, respectively.

This research [84] explored the capacity of profound convolutional neural networks to distinguish benign and malignant skin cancer. The model takes advantage of previous experience and prevents from scratch. Transfer learning is commonly expressed in image classification by using pre-trained models. A pre-trained model is a model that has been trained on a large dataset to overcome a like problem. Three pre-trained models – Inception-v3, InceptionResNet-v2, and ResNet-152 have been

used as pre-trained weights for work and ISIC databases used to training and evaluate our model. The model achieves a 93.5 percent accuracy that is higher than previous approaches.

WEI et al. [85] proposed a lightweight skin cancer detection model in image classification using fine-grained classification theory based on MobileNet and DenseNet. In this model, a lesion classification network and a feature discrimination network are made up of feature extraction. Firstly, the training sets have two different, separate classifications for positive and negative classifications. After that, two sets of feature vectors output from the feature extraction module are used to train two separate classifier networks together. The model fusion strategies will boost the recognition efficiency of a model by improved lesion function discriminative extraction method in a limited number of model parameters. Even to achieve much more precise segmentation of skin lesions on the skin surface, the method built a lightweight U-Net model, the best accuracy result obtained is 96.2%.

A new deep convolutional method of classification based on neural networks is proposed in [86]. The approach proposed involves three key measures. Firstly, the input color images of the skin where the region of interest (ROI) is segmented are preprocessed. Second, the segmented ROI images are increased by rotation and translation. Third, various architectures of the deep convolutional neural network (DCNN), such as Alex-net, ResNet101, and GoogleNet, are used. In Alex-net, the last three layers have been replaced by multiclass SVM, ResNet101, and GoogleNet with fully connected, SoftMax, and output classification layers. Three separate datasets were used for evaluating the proposed models MED-NODE, ISIC 2017, and DermIS & DermQuest. The best results for the updated GoogleNet model were 99.29%, 98.14%, and 99.15% for MED-NODE, ISIC2017 and DermIS, and DermQuest, respectively.

Harangi et al. [87] introduced a deep convolutional neural network architecture that enables multiclass classification by including the more reliable result of binary classification in the final probability class. The CNN architecture (GoogLeNet Inception-v3) has been trained to incorporate this concept model, both for the binary and multiclass tasks at the same time as integrating their softmax output into a support

layer with multiplying the multiclass confidences with those of the binary. In order to achieve the stated objectives, the pre-trained GoogLeNet model has been fine-tuned on the image, and its layers have been updated to be able to recognize seven classes of objects. Then, these two fine-tuned models were composed into one network architecture. The result was obtained from the model for binary class with an accuracy of about 95%.

The authors [88] suggested a model based on transfer learning and the pre-trained model on GoogleNet. The model parameters are initial values, and after training, the model parameters will be updated. The model will differentiate eight different types of lesions, even with the imbalanced amounts from two classes. The proposed methods achieved the performance indicators of accuracy, sensitivity, specificity, and precision, and the values were 94.92%, 79.8%, 97%, and 80.36%, respectively.

This work [89] presented a hybrid diagnostic system for classifying multiclass skin (MCS) cancer with extremely high accuracy. The method outperformed both deep learning algorithms and dermatologists on the classification of MCS cancer. Researchers fine-tuned seven classes of HAM10000 with five kinds of CNN pre-trained models and conducted a comparative analysis of the performance of the CNNs and four ensemble models. Several independent experiments were conducted to find the best model-trainings hyper-parameters for five models, like NASNetLarge, ResNetXt101, InceptionV3, InceptionResNetV2, and Xception and their ensembles InceptionV3 + Xception, InceptionResNetV2 + Xception, InceptionResNetV2 + ResNetXt101 + Xception, and InceptionResNetV2 + ResNetXt101. The models in these frameworks are fine-tuned further in order to extract a priori features pertaining to different types of cancers in the HAM10000 dataset using Transfer Learning. The best-obtained accuracy is 93.20% for individual model ResNetXt101, whereas the highest accuracy obtained in ensemble model ResNetXt101 and InceptionResNetV2 is 92.83%.

Anerjee et al. [90] presented a deep learning-based 'YOLO' algorithm, which uses a DCNN to detect Melanoma from dermoscopic images. Segmentation and feature extraction is recommended by efficient mathematical modeling. The studies were conducted on three main datasets, entitled PH2, ISBI 2017, and ISIC

2019. The two-step algorithm combined with fuzzy number-based approximation increased segmentation results, which positively affected the recognition process classification accuracy and improved the mathematical extraction of the actual affected region during the feature extraction process. The proposed method obtained the best accuracy of the other ML algorithm like VSM, decision tree, and KNN up to 99%.

Filali et al. [91] suggested a potent lesional skin classification technique based on a mixture of the most potent DL architectures (VggNet, ResNet, GoogLeNet, and AlexNet) and features of handcrafted (color, texture, skeleton, and shape) in order to diagnostic melanoma cancer. The model extracts from each pre-trained CNN 1000 features, and all the pre-trained models extracted 4000 features. This combination will enable ML and DL approaches to be remedied when dealing with large and small datasets. To increase the efficiency of feature extraction and improve the accurate classification, features engineering, which consists of features selection and features normalization, will be used. Using these features to identify skin cancer is the last step after selection. In this work, both datasets can be calculated using the Support Vector Machine (SVM). Finally, the specified features are classified by supporting vector machine and obtain an accuracy rate equal to 98% for PH2 data, and ISIC data obtain an accuracy of 87.7%.

ADEGUN et al. [92] suggested a modern system for recognizing and segmentation of skin lesions that could be used in the automatic diagnosis of skin cancer. The presented method is formed from two phases. The first stage consolidates from an Encoder-Decoder Fully Convolutional Network (FCN) to learn complicated skin lesions characteristics during the encoding stage knows the coarse appearance. The decoder learns information like lesion boundaries. The Conditional Random Field strategy used in CNN's design often uses a linear blend of Gaussian kernels for detecting edges and localized lesions. A novel FCN-based DenseNet architecture consists of dense blocks that are linked and merged by concatenation. The proposed model for prediction was validated on the HAM10000 dataset obtained the following results 98 % accuracy, 98.5 % recall, and 99% AUC score.

The authors [93] have suggested that skin diseases be classified using deep neural

networks that are already qualified for use by the user without any parameter settings. The model tests the efficiency through the implementation of transfer learning of state-of-the-art deep networks for melanoma detection. This study's key challenge is to create a model by using a few images and dealing with unbalanced classes. In addition to the standard plain classifier in which one neural network classifies, a hierarchical classifier is proposed two levels. One neural network distinguishes the nevi class from the other six classes, and the second level classifier the rest six classes. In addition, it also requires excellent data augmentation techniques to achieve the best results. Experiments show that the DenseNet201 network is around 10% stronger than any other network. Table 1 shows an overview of recent methods based on different parameters used for skin lesions classification.

Arshaghi et al. [94] modified a median filter algorithm for the image de-noising in the medical skin image. The pros of CNN approaches are that they usually have higher PSNR values and can outperform other filters (Adaptive Wiener filter, Median filter, Adaptive Median filter, and Wiener filter). Arshaghi et al. [51] a new classification algorithm for dermabbed images designed for classification skin lesions malignant from benign conditions. The image quality is improved by a pre-processing stage. After the analysis is over, the lesioning is performed on the healthy regions using the Otsu process. The SVM, KNN, and Decision Tree classifiers were used to classify. According the result obtained from a buzzard optimization function extraction algorithm and SVM classifier provides accuracy 94.3% and the buzzard optimization for function extraction is awesome.

4. DISCUSSION

In the proposed skin lesion classification methods, different algorithms and techniques are utilized to enhancement the detection and classification accuracy of the models. Through Table 1 there are some authors use preprocessing methods to enhance the image before classification stages [72,78,81], like removal hair and the line also standardization brightness unbalanced and in [76], using anisotropic diffusion filter and unsharp masking is intended to remove the visual noise such as lines and edges and improve the image information for feature extraction methods usually based on convolution neural network to extract the most

Table 1. Comparative study of related work

#	Ref.	Dataset	Preprocessing	Feature Extraction	Segmentation/ Classification Techniques	Contribution of Publication	Results
1	[72]	Peking Union Medical College Hospital	Hair/Line, Air Bubbles/ Dermoscopic Gel, and Brightness Unbalanced	Hidden layers	CNN GoogleNet and Inception-v3	Blends the efforts of both human ability and machine algorithm	ACC = 87.25%
2	[73]	HAM10000 and PH ²	NA	NA	CNN DenseNet 201	Classification 8 class and easily implemented on smartphones in order to assist dermatologists.	AUC(macro)=98.16 % AUC(micro)=98.79%
3	[74]	ISIC 2016	NA	NA	Optimized neutrosophic k-means (ONKM)	Genetic algorithm for optimizing the value of α in α -mean operation in the neutrosophic set	ACC = 99.29%
4	[75]	(ISBI) 2017	NA	NA	Ensemble CNNs	ensemble of robust convolutional neural networks for skin lesion classification	AUC = 89.1%
5	[76]	ISDIS	Anisotropic diffusion filtering, unsharp masking	Fast Fourier transform, Gray level co-occurrence matrix (GLCM), and local binary pattern (LBP)	adaptive k-means and Random Fores	segmentation of Melanoma using various unsupervised clustering methods, and 30 features were extracted and trained using random forest.	ACC= 93.47%
6	[77]	collecting images from different websites	Image Resizing	pre-trained convolutional neural network	Multiclass SVM	skin disease detection and require a camera and computer	ACC = 100%
7	[78]	NA	hair removal, centering of the image, softening	NA	SVM	Using one particular method to classify two or more different diseases	ACC = 90%

#	Ref.	Dataset	Preprocessing	Feature Extraction	Segmentation/ Classification Techniques	Contribution of Publication	Results
8	[79]	PH ²	NA	NA	DCNN pre-trained AlexNet	Classification skin using pre-trained AlexNet and replacing the last layer to softmax with three classes only	ACC = 98.61%
9	[8]	Skin-EDRA	color space transform	Stack-based-AutoEncoders (SAE)	CNN	A novel DermoDeep method, a multilayer with the VF-L, DF-L, FF-L, OF-L, and prediction layer, is constructed (FF-PL)	AUC = 96%
10	[80]	MED-NODE, Derm (IS & Quest) and ISIC	NA	NA	DCNN Alex-Net	Used Alex-Net work for binary and multiclass classification	ACC = 96.86%
11	[81]	HAM10000	Class balancing, Image size normalization, contrast enhancement, and Hair artifact removal	Low-level feature, high-level feature using convolutional Fusion Unit	CNN	CNN based transfer learning technique in multiclass classification using Convolutional Fusion Unit (CFU)	ACC = 98.09%
12	[82]	HAM10000	cleaning and formatting convert to comma separated variables (.csv) files	NA	Deep Learning Studio (DLS)	Detecting Skin Cancer by Classifying Dermal Cell Images Using a Model-Driven Architecture in the Cloud	AUC = 99.77%
13	[83]	http://dermoscopic.blogspot.com	contrast filtered and threshold filter for lesion segmentation	ABCD scoring system	SVM, ANN, KNN, and TDV	Classified by ABCD score automatically TDS, Automatic ANN, and linear SVM	ACC=98.75% (SVM) ACC=98.1% (TDV)
14	[84]	ISIC	NA	NA	CNN transfer learning	Skin cancer classification using three pretrain model	ACC =93.5%

#	Ref.	Dataset	Preprocessing	Feature Extraction	Segmentation/ Classification Techniques	Contribution of Publication	Results
15	[85]	ISBI 2016	Building positive and negative sample pair training sets	DC-MobileNetV1 and DC-DenseNet121	U-Net/ fusion MobileNet and DenseNet	Inception v3, InceptionResNet-v2, and ResNet 152 The recognition method includes three steps: image preprocessing, model construction and model training, and model fusion for classification and segmentation.	ACC = 96.2%
16	[86]	MED-NODE, DermIS & DermQuest and ISIC 2017	Segmenting the ROI	NA	DCNN	Three pre-training Alex-net, ResNet101, and GoogleNet architectures replace the last three layers of multiclass SVM	GoogleNet ACC= 99.29% for MED-NODE dataset
17	[87]	ISIC 2018	NA	NA	CNN pre-training GoogLeNet and Inception-v3	GoogLeNetInception-v3 pre-trained model and its layers have been fine-tuned two times; once for the binary and once for the 7-class	ACC =95%
18	[88]	ISIC 2019	NA	Fully connected layer in GoogleNet	Transfer learning with GoogleNet	Redesigned the architecture of the GoogleNet by building more sophisticated filters for each layer to improve on features.	ACC = 94.92%
19	[89]	HAM10000	reconcile an image	different layers of Xception model	CNN transfer learning	Five pre-trained CNNs and four ensemble models	ACC=92.83% for ensemble model ResNetXt101 and InceptionResNetV2
20	[90]	PH ² , (ISBI) 2017 and (ISIC) 2019	DullRazor algorithm and	ABCD rule	DCNN	Deep Learning and L-type fuzzy number	ACC= 99%

#	Ref.	Dataset	Preprocessing	Feature Extraction	Segmentation/ Classification Techniques	Contribution of Publication	Results
			histogram equalization				
21	[91]	PH2 and ISIC	NA	handcrafted features and extract features from the pre-trained CNNs	SVM	skin-lesion classification approach based on a fusion of handcrafted features and features extracted from DL	ACC = 98% for PH ²
22	[92]	HAM10000	NA	Encoder-decoder Fully Convolutional Network (FCN)	FCN-based DenseNet	Multi-scale encoder- decoder segmentation network and an FCN-based DenseNet classification network merged and connected via the concatenation strategy and transition layer.	ACC = 98%
23	[93]	HAM10000	NA	NA	CNN Transfer learning	create a plain and a hierarchical (with 2 levels) classifiers to recognize between seven classes	ACC= 95.09% DenseNet201
24	[94]	NA	de-noising to wavelet transforms and Non-local means (NLM)	DnCNN	NA	Modified median filter	PSNR values of CNN methods is higher and better than to filters (Adaptive Wiener filter and Median filter).
25	[51]	NA	Gaussian noise, sharp edges, and homomorphic filter	buzzard optimization algorithm	Otsu threshold method/SVM classifier	A novel method is proposed for feature selection of BUZO optimization.	ACC = 94.3%

important between them, while in [76] used different methods like Fast Fourier transform, Gray level co-occurrence matrix (GLCM), and local binary pattern (LBP). GLCM was constructed to extract elements such as contrast, correlation, energy, homogeneity, and entropy. For segmentation unsupervised clustering methods, and 30 features were extracted based method used. To reduce burden computation. Convolutional Fusion Unit (CFU) was used [81] to generate high-level features based on combining stacked convolutional neural networks in order to extract important discrimination features. ABCD rule is preferred for checking skin diseases worldwide as a common reference, [83] proposed ABCD for extracting the features like Asymmetry, Border, and Color features, as well as the diameter. Another method to extract features based on deep learning [92], which use Encoder-decoder Fully Convolutional Network (FCN) method, is suitable for small volumes of input data and requires only a few parameters, making the method easy to interpret. Also, up to 73% of the reviewed skin lesion classification methods were based on the deep learning algorithm (KNN), where these models based on transfer learning like GoogleNet and Inception-v3 in [72], DenseNet 201 in [73], AlexNet in [79,80] Inception v3, InceptionResNet-v2, and ResNet 152 in [84], fusion MobileNet and DenseNet in [85], DenseNet in [8]. The best accuracy was obtained among them in [86] GoogleNet 99.29%, in [79] AlexNet 98.61%, and the DenseNet area under curve AUC is 98.16%. While other reviewed skin lesion classification methods were based on Optimized neutrosophic k-means (ONKM) in [74] Genetic algorithm for optimizing the value of α in α -mean operation in the neutrosophic set. Also, adaptive k-means and Random Forest in [76], Multiclass SVM in [77,78, 91], SVM, ANN, KNN, and TDV in [83]. A buzzard optimization function extraction algorithm and SVM classifier provides accuracy 94.3% and the buzzard optimization for feature extraction is awesome. Best results were obtained in [74] accuracy is 99.29%, in [77] combine pre-training CNN and multiclass SVM accuracy is 100% based on camera and computer, also in [83] using SVM best accuracy obtained 98.75%.

5. CONCLUSION

Methods of CNN encourage skin cancer diagnosis, but the limitation of annotated datasets is still an obstacle to establishing procedures appropriate for clinical application.

Classification methods are difficult to compare because some methods use nonpublic data for training and testing. A paper provides a summary of the new techniques to examine skin lesion images. This paper provides an analysis of the methods that are used to diagnosis Melanoma skin cancer from skin images. These methods include preprocessing techniques, feature extraction methods, segmentation techniques, and classification algorithms. The capabilities of constructing ensembles of deep neural networks to increase the accuracy of classification with combining their architectures to benefit from their strengths while overcoming their weaknesses when the amount of annotated images available for training is inadequate, such as DenseNet121, Resnet-50, InceptionResNetV2, InceptionV3, VGG-16, Xception, AlexNet and provides satisfactory performance, which is excellent. Furthermore, these models need a heavy time and resource and a significant training requirements. Many deep learning models perform better on well-segmented images. There are some metrics like Accuracy, AUC, Sensitivity, and Dice-coefficient to evaluate the deep learning models.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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