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Deep learning techniques for skin lesion analysis and melanoma cancer detection: a survey of state-of-the-art

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Abstract

Analysis of skin lesion images via visual inspection and manual examination to diagnose skin cancer has always been cumbersome. This manual examination of skin lesions in order to detect melanoma can be time-consuming and tedious. With the advancement in technology and rapid increase in computational resources, various machine learning techniques and deep learning models have emerged for the analysis of medical images most especially the skin lesion images. The results of these models have been impressive, however analysis of skin lesion images with these techniques still experiences some challenges due to the unique and complex features of the skin lesion images. This work presents a comprehensive survey of techniques that have been used for detecting skin cancer from skin lesion images. The paper is aimed to provide an up-to-date survey that will assist investigators in developing efficient models that automatically and accurately detects melanoma from skin lesion images. The paper is presented in five folds: First, we identify the challenges in detecting melanoma from skin lesions. Second, we discuss the pre-processing and segmentation techniques of skin lesion images. Third, we make comparative analysis of the state-of-the-arts. Fourth we discuss classification techniques for classifying skin lesions into different classes of skin cancer. We finally explore and analyse the performance of the state-of-the-arts methods employed in popular skin lesion image analysis competitions and challenges of ISIC 2018 and 2019. Application of ensemble deep learning models on well pre-processed and segmented images results in better classification performance of the skin lesion images.

Keywords Skin cancer · Skin lesion images · Machine learning · Deep learning · Survey · Pre-processing · Segmentation · Classification

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1 Introduction

Recent development in the application of machine learning techniques in computer vision has led to great improvement in computer aided diagnosis and detection system for early detection of deadly cancerous skin diseases (Masood and Al-Jumaily 2013; Adeyinka and Viriri 2018). Diagnosis and detection of skin cancer diseases have been traditionally carried out via manual screening and visual inspection. These approaches of visual inspection and screening of lesion images by dermatologists are time consuming,complex, subjective, and error prone (Yu et al. 2016; Vestergaard et al. 2008). This is majorly due to the complex nature of the skin lesion images (Esteva et al. 2017; Adegun and Viriri 2019; Olugbara et al. 2018; Al-Masni et al. 2018). In order to perform analysis, interpretation and understanding of skin lesion images, the lesion pixels need to be identified unambiguously. This may be difficult due to the reasons outlined below (Vestergaard et al. 2008; Esteva et al. 2017; Adegun and Viriri 2019): First, skin lesion images may contain hair, blood vessels, oils, bubbles and other noise presence that interfere with segmentation process. Also low contrast in-between the surrounding skin and the lesion area poses challenges in segmenting the lesion accurately. Finally, skin lesions usually possess different sizes, shapes, and colors which can limit the efficiency of the methods in achieving higher level of accuracy. This has made manual screening difficult for dermatologist and made automatic computerized diagnostic systems a high necessity for skin lesions analysis and to help and support dermatologists in quick decision-making (Masood and Al-Jumaily 2013; Al-Masni et al. 2018). This has aided the clinicians in making faster and accurate decisions in skin cancer detection (Masood and Al-Jumaily 2013; Mobiny et al. 2019). Skin cancer disease such as Melanoma cancer has a very high mortality rate but can however be cured easily when detected early (Al-Masni et al. 2018; Balch et al. 2009). Over the years various computerized methods have been adopted in the detection and diagnosis of skin cancer. The conventional approach of medical image analysis is usually carried out through a series of low-level pixel processing methods. Generally,the whole pipeline process of melanoma cancer detection and diagnosis have been summarized into major processing techniques such as image pre-processing, image segmentation, feature extraction and classification of lesions images (Koundal and Sharma 2019; Ünver and Ayan 2019) as illustrated in Fig. 1.

The pre-processing techniques also include methods such as contrast and intensity adjustment, binarization, morphological operation, color gray-scaling and data augmentation. In the stage, noises and some other artifacts are removed from images (Oliveira et al. 2016). Image standardization is also ensured through image resizing to generally reduce the computation complexity. Image segmentation process which is executed immediately after the image preprocessing obtains region of interests by segmenting diseased area from the healthy flesh (Koundal and Sharma 2019). It is the process of separating normal

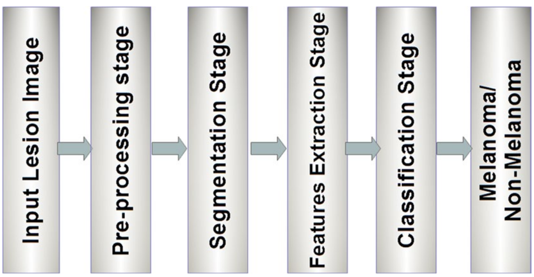

Fig. 1 Pipeline process of melanoma cancer diagnosis from skin lesion image analysis

tissues before extracting the features from the lesions for accurate diagnosis (Al-Masni et al. 2018; Ganster et al. 2001; Schaefer et al. 2014). Conventional segmentation methods such as thresholding methods, clustering methods, edge and region-based techniques and the popular ABCDE approach have been used for skin lesions analysis in detecting melanoma (Olugbara et al. 2018; Emre Celebi et al. 2013; Zhou et al. 2009; Abbas et al. 2011). These techniques still experience challenges in dealing with the complex visual appearance (Pennisi et al. 2016; Gómez et al. 2007) of skin lesions and are are unable to segment the Melanoma region accurately (Okuboyejo et al. 2014; Premaladha and Ravichandran 2016). Recently, intelligent based segmentation methods such as fuzzy logics, genetic algorithms , Artificial Neural Networks (ANN), and very recently deep learning techniques have been utilized for accurate and reliable segmentation of skin lesions (Nasir et al. 2018). Feature extraction techniques are applied to get the lesion features for recognizing the skin cancer type from the images (Barata et al. 2018). Widely used feature extraction methods include template matching, image transformation, graph analysis, Projection Histograms, Contour methods, Fourier descriptors technique, Gradient feature and Gabor features approaches (Barata et al. 2018). The extracted features are finally sent to classification methods for identifying the specific type of skin tumor present on the skin lesion. The conventional classification techniques for skin lesion images include; Decision Tree, Fuzzy Classification methods, Support Vector Machine (SVM) and ANN (Mohan and Dharan 2019). Recently, deep learning methods have achieved state-of-the-art performance in skin lesion analysis (Shen et al. 2017; Goceri 2019) to the extent of using photographs to diagnose skin diseases (Goceri 2019). Their performance is leveraged in their capacity to learn and extract deep and hierarchical features from complex image dataset (Shen et al. 2017). For example, Deep Convolutional Neural Networks (DCNNs) which is a popular deep learning method, possess capacity to process general and highly variable tasks in fine-grained objects (Esteva et al. 2017) which is an important characterisitics of skin lesion images. This powerful technique has the capability to extract eminent features from the entire skin lesion image better than hand crafted features (LeCun et al. 2015; Krizhevsky et al. 2012; Al-masni et al. 2012). Convolutional Neural Networks (CNNs) are composed of many layers that transform input image data to outputs such as disease pattern while learning increasingly higher level features. In this study, a comprehensive analysis of various approaches that have been used for skin lesion lesion analysis towards melanoma detection have been performed. Comparative analysis of both the conventional and deep learning based techniques have also been performed. First, we describe the essential image preprocessing techniques used in medical image analysis algorithms. We also discussed segmentation techniques and categorized them into different groups according to their mode of operation in algorithmic application. We also discussed and categorized feature extraction and classification methods.

2 Challenges of skin lesion detection

The difficulties in detecting skin lesions can be attributed to variation in image types and sources (Al-Masni et al. 2018; Aljanabi et al. 2018). There is a tremendous variation in the appearance of human skin color which makes skin detection a diificult and complex task (Naji et al. 2019). These are illustrated in Fig. 2. Various challenges from the complex visual characteristics of skin lesions image are highlighted below (Al-Masni et al. 2018; Naji et al. 2019):

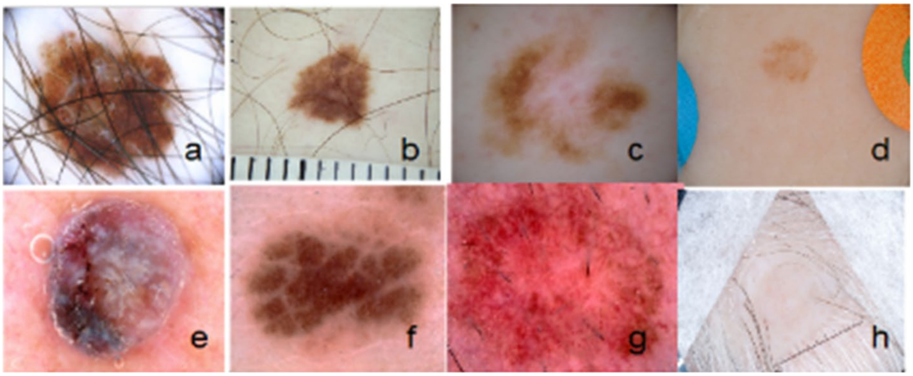

Fig. 2 Challenges of skin lesion detection : **a** hair artefact, **b** ruler mark artefact, **c** low contrast, **d** color illumination, **e** bubbles, **f** irregular boundaries, **g** blood vessels, **h** frame artefact

1. *Multi-size and shape* The large variations among skin lesions increase the complexity of these images and makes accurate identification of skin lesions extremely difficult. There is huge variability in lesion location, size and shape. Most image analysis techniques for skin lesion images thus require to first perform image pre-processing for accurate analysis.
2. *Noise and artifacts presence* Noise are objects introduced to images during acquisition. The identification of a skin lesion images may be affected by the presence of noise and artifacts. These are described as compromising signals that are not originally part of the image but can affect the image interpretation through manual methods and can even affect some computer aided skin lesion segmentation techniques. Examples include hair artifacts, hair artifacts, bubbles, and blood vessels.
3. *Irregular fuzzy boundaries* Some skin lesion images are characterized with fuzzy and irregular borders making it difficult for many techniques for contour refinement and lesion boundaries localization. In the preprocessing stage, sometimes it is challenging to acquire accurate border of skin lesion images for easy prediction of asymmetry.
4. *Low contrast* In some cases, there exist low contrast from neighboring tissues which poses additional difficulties. The low contrast exists in-between the lesion area and the surrounding skin causes difficulty in segmenting the lesion accurately.
5. *Color illumination* The skin lesion image color texture, light rays and reflections can affect the illumination of the dermoscopic images thereby giving the images multi-resolution.

3 Skin lesion image analysis techniques

3.1 Preprocessing techniques for skin lesion images

Preprocessing is majorly used for preparing images for better processing and accurate feature detection. Preprocessing includes acquisition of image as input, obtaining the gray-scale image, noise filtering and binary image generation (Zaqout 2019). These methods include contrast adjustment which performs the extension of histogram of an image for better visibility (Beuren et al. 2012); intensity adjustment which enhances image's intensity values in order to produce an output image with high quality display; and histogram equalization which distributes the pixel intensities evenly forthe entire range of intensities with the aim of increasing the global contrast of images (Zaqout 2019). We also have binarization which is the process of taking a grayscale image and converting it to black and white colors only by reducing the information contained within the image from 256 shades of gray to a binary image of black and white (Zaqout 2019); morphological operation which performs erosion and dilation on images to extract some features and location of every objects in an image (Zaqout 2019).

3.2 Segmentation techniques for skin lesions

Image segmentation is a major process in automating skin lesion diagnosis. It is an important step in skin lesion images analysis. This process obtains region of interests by separating diseased area from the healthy region (Al-Masni et al. 2018). This section discusses various techniques for segmentation of skin lesions. These techniques include handcrafts-features based methods such as threshold based (Emre Celebi et al. 2013; Møllersen et al. 2010; Peruch et al. 2013; Yüksel and Murat 2009), edge and region based methods (Abbas et al. 2011; Emre et al. 2008; Zhou et al. 2011) and intelligence based supervised segmentation (Al-Masni et al. 2018). Intelligent based approaches include artificial neural networks and deep learning methods. Table 1 shows the comparison between these segmentation techniques, stating their strengths and weaknesses.

3.2.1 Conventional intelligence-based methods

These are system based on artificial intelligence with the ability to perform image analysis based on through learning, reasoning, and perception from existing large image datasets. They are both supervised an unsupervised based approach to skin lesion segmentation based on training a system and learning from existing dataset. Popular intelligence-based segmentation methods models include ANN (Mathew and Sathyakala 2015), Genetic Algorithms (Amelio and Pizzuti 2013; Xie and Bovik 2013) and Fuzzy C-Means (FCM) (Mohamed et al. 2017; Zhou et al. 2008) . Deep learning approaches have been recently added as part of intelligence based methods.

3.2.2 Deep learning-based techniques

Deep learning techniques have achieved great success in skin lesion image segmentation which is a difficult tasks in computer vision (Al-Masni et al. 2018). Various deep learning based models have been proposed by researchers. These techniques produce excellent performance for skin lesion segmentation (Al-Masni et al. 2018). Some of the architectures which have been critically reviewed in this paper include DCNNs, U-Net, Fully Convolutional Network (FCN), Deep Fully Convolutional Residual Network (FCRN) and Convolutional DE- Convolutional Neural Networks (CDCNN). These are discussed below:

1. *U-Net architecture* This architecture was developed from FCN. It is an encoder-decoder network in which both the encoder and the decoder sections are composed of convolutional layers. The encoder section in addition with the convolutional layers possess pooling layers while the decoder possesses upsampling layers. It contains shortcut skip connection in-between the encoder and decoder sections. This architecture has been

Table 1 Table showing comparison between traditional techniques commonly used for segmentation of skin lesions and the state-of-the-arts

Techniques	Description	Advantages (merits)	Disadvantages (demerits)
Threshold and clustering (Emre Celebi et al. 2013; Møllersen et al. 2010; Peruch et al. 2013; Yüksel and Murat 2009)	This is a partitioning approach to images in which foreground are segregated from background. In this approach, an initial threshold value is first selected and the original image is then divided into portions.	It is simple and fast to implement. It does not require the knowledge of spatial characteristic of an image.	It is sensitive to noise and experiences intensity inhomogeneity (Dar and Padha 2019).
Edge and region based (Abbas et al. 2011; Emre et al. 2008; Zhou et al. 2011)	These methods perform edge detection and region identification using the search-based methods to identify region of interest on dermoscopy images.	The methods satisfy some homogeneity criteria and take the advantage of split and merge hybrid approach for better segmentation process.	The primary disadvantage is its requirement of manual interaction for seed point initialization for some regions processing and are also sensitive to noise (Dar and Padha 2019).
Conventional intelligence-based method (Mathew and Sathyakala 2015) Amelio and Pizzuti (2013) Xie and Bovik (2013) Mohamed et al. (2017) Zhou et al. (2008)	These are system based on artificial intelligence with the ability to perform image analysis based on through learning, reasoning, and perception from existing large image datasets. They are both supervised an unsupervised based approach to skin lesion segmentation. Popular intelligence-based segmentation methods models include Artificial Neural Network, genetic algorithms and Fuzzy C-Means (FCM)	The detection accuracy of is always higher with lower false positives when compared with threshold and region-based segmentation methods.	It does not consider spatial modeling. It is also sensitive to noise and experiences uncertainty in precise data processing.
Deep learning (Yuan and Tavildar 2018)	Deep learning allows computational models of multiple processing layers to learn and represent data with multiple levels of abstraction. Deep learning is a rich family of methods comprising of neural networks, hierarchical probabilistic models, and a variety of unsupervised and supervised feature learning algorithms.	It performs hierarchical feature representation from pixel to high-level semantic features. It has ability to implicitly capture intricate structures of large–scale data better than conventional intelligence-based methods.	Training is more expensive than other techniques. It takes a long time to process a relatively small training set and requires large storage memory.

employed for skin lesions segmentation by some researchers. Berseth (2017) utilized the architecture to provide a probability estimate for each pixel while segmenting skin lesion images. Vesal et al. (2018) modified the U-Net architecture in a system called skinNet by applying dilated convolutions in the lowest layer of the encoder branch of the U-Net system. Its weakness includes image details getting lost through the U-Net shortcut skip connection and weaker decoder section in recovering feature maps (Vesal et al. 2018). An enhanced UNet architecture is illustrated in Fig. 3.

2. *FCN* FCN is a set of convolutional and pooling layers. Bi et al. (2017) developed a multi-stage FCN with the parallel integration (PI) method for skin lesions segmentation. This PI technique was used to further enhance the boundaries of the segmented skin

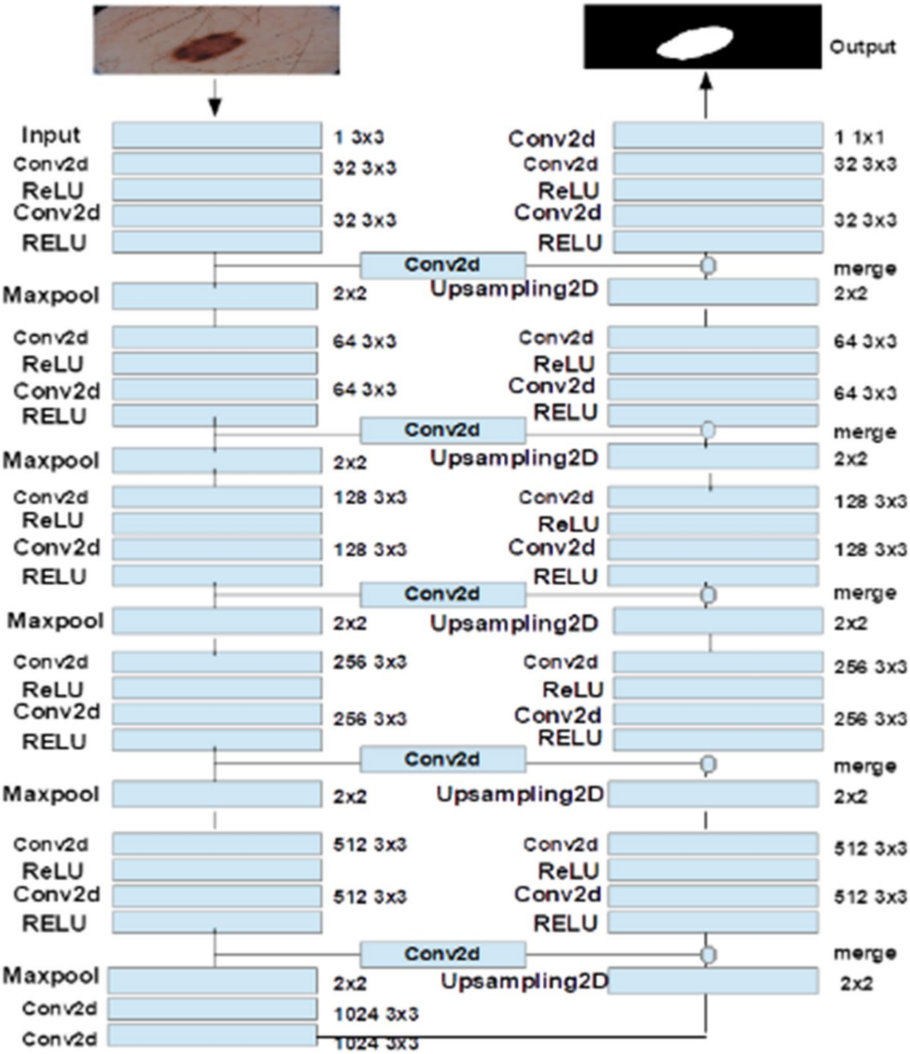

Fig. 3 An enhanced U-Net architecture diagram

lesions. The system achieved state-of-the-arts performance of 95.51% segmentation accuracy and 91.18% dice coefficient score when evaluated on International Symposium on Biomedical Imaging (ISBI) 2016 dataset (Bi et al. 2017). Al-Masni et al. (2018) developed a modified FCN which is a Deep Full Resolution Convolutional Networks for the segmentation of dermoscopy images. It also gives a state-of-the-arts performance. Ramachandram and DeVries (2017) utilized atrous convolutions with an FCN network to perform training and segmentation of skin lesions. This increases the view of the network's receptive field. FCN models however have a likelihood of over segmentation that can lead to coarse segmentation output with limited training dataset (Ramachandram and DeVries 2017).

3. *Deep residual network* Deep residual network is a special type of ANN that builds on a pyramidal structure by utilizing skip connections that jump over some convolutional layers. It is majorly composed of multiples convolutional layers. A two-stage FCRN approach that utilized deep residual networks for the segmentation and classification of melanoma skin lesions was proposed by Yu et al. (2016). A deep residual network with more than fifty layers was employed for extracting richer and more discriminative features. The system performs accurate skin lesion segmentation on ISBI 2016 skin lesion images. Another framework that utilizes a Lesion Index Calculation Unit (LICU) with FCRN was proposed by Li and Shen (2018) for skin lesion segmentation. Deep residual network based architecture requires a lot of computational resources. This can limit the use of the architecture in real-life practical scenarios.
4. *CDCNN* This architecture is made up of two major parts: Convolutional and Deconvolutional networks. Deconvolutional networks are CNNs that operate in a reversed process. Both networks are used for extracting discriminative features. The deconvolution layers are applied for smoothening the segmentation maps in orderto obtain final high-resolution output. This architecture was deployed by Yuan and Lo (2017) on different color spaces of skin lesion images. He et al. (2018) applied a multi-path deep network known to extend deep dense convolutional layer. This is known as RefineNet for segmentation of dermoscopic images. System with CDCNN requires high computational cost. The segmentation results of CDCNN-based methods are still coarse and limited most especially with insufficient training data set. These methods have achieved enhanced performances in skin lesion segmentation and analysis however some of these methods still apply heavy tuning of large number of parameters and pre-processing techniques, which increases computational resources consumption (Bi et al. 2018).

3.3 Classification techniques for skin lesions

Skin lesion images can be classified to facilitate the process of detecting melanoma cancer. Several forms of skin cancer can be detected from the skin lesions images. These can be categorized majorly into malignant and benign. They can further be categorized into: Basal Cell Carcinoma, Actinic Keratosis, Squamous Cell Carcinoma, Seborrheic Keratosis, Solar Lentigo, Dermatofibroma, Nevi, Melanoma, and Vascular Lesions. Melanoma is a malignant lesion and the most deadly of these classes.

In this section we have examined both the traditional based classification techniques and the recently developed state-of-the-arts.

3.3.1 Traditional classification algorithms and techniques

These are earlier classifiers and are mostly based on traditional approach using either pixel-based or region-based approach to extract features which are sent to the classifier for the detection of the type of skin cancer. In the recent past, some of the conventional methods are intelligent-based. These algorithms include techniques (Jamil and Khalid 2014; Khan et al. 2019) such as Instance based classifiers (like K-Nearest Neighbor), Naive Bayesian Algorithm, SVM and ANN Classifiers. Table 2 shows the comparison between these classification techniques, stating their strengths and weaknesses.

3.3.2 Deep neural networks: state-of-the-arts

Exponential increase in computing resources (such as Graphical Processing Units) as predicted by Moore's law in 1971 (Moore 1965) has continued to lead to rapid development in computer vision technology most especially in the development of deep learning models such as CNN (Li and Shen 2018). This development with efficient formulations in the deep learning models has led to excellent and state-of-the-arts performance in processing and classifying images (Li and Shen 2018; Goceri 2018). These methods have been proven to produce better performance than the traditional methods. However, there are still some challenging issues in deep learning based image analysis (Goceri 2019).

1. *CNN components* CNN is a class of artificial neural networks that is primarily used for analyzing images (O'Shea and Nash 2015; Sakib et al. 2019), and is made up of neurons that are capable of self-optimization through learning. It is also composed of set of layers that are characterised with various functionalities which accept and process images that are of high dimensional vectors as input. General layout diagram of CNN architecture is described in Fig. 4 with major components including: layers, activation function and hyper parameters. Layers in CNN are mainly categorized into convolutional , pooling and fully connected layers (Yamashita et al. 2018). Activation function is a transformation function that maps the input signals into output signals that are required for the neural network to function (Sakib et al. 2019). Popular types of activation functions include linear activation, Sigmoid functions (logistic and hyperbolic tangent functions), Rectified linear units (ReLU) also known as piecewise linear functions, Exponential Linear Unit and Softmax which is represented with the equation below (Nwankpa et al. 2018; Karlik and Vehbi Olgac 2011; Yamashita et al. 2018)

$$P(y = i|y) = \frac{e^{y^T w_i}}{\sum\limits_{n=1} e^{y^T w_n}} \tag{1}$$

where $y^T w$ represents the product of y and w, y is the input feature map and w is the kernel operator.

Hyper parameters include (Yamashita et al. 2018; Aszemi 2019) filter kernel, batch size, padding, learning rate and optimizers etc. Optimizers are used to produce maximum performance from a network model. Examples include Adam, rmsprop, Nesterov and Sobolev gradient based optimizers (Goceri 2019).

2. *CNN architectures* There are various architectures of CNNs available. These architectures are key factors in building deep learning algorithms. They are discussed below:

Table 2 Table showing comparison between traditional techniques commonly used for classification of skin lesions and the state-of-the-arts

Techniques	Description	Merits	Demerits
Instance based classifiers Jamil and Khalid (2014)	They compare new pattern instances with instances recognised in training and do not perform generalization like some other classifiers. Examples include K-Nearest Neighbor algorithms (1-NN, K-NN), kernel machines and RBF networks.	They are simple to implement, and do not require training phase	These classifiers can become complex and computationally insensitive with slow processing time (Jamil and Khalid 2014).
Decision trees (Khan et al. 2019)	They are tree-like models that represent attributes in form of a tree with each attribute acting as a node and the best attribute serving as the root node to create decision rules for classifying image samples. Examples include random forest.	They do not require parameters setting.	They are insensitive to training data outliers and may not be able to predict beyond the training data range. Results are influenced by noise.
SVM (Jamil and Khalid 2014)	It is supervised learning model that performs image classification and analysis . It identifies patterns by applying rules-based model for performing binary classification using a right hyper-plane as a decision boundary for maximum separation.	It optimizes every cost function.	It possesses tendency to produce a biased result when the class membership probability is unavailable and cannot process vague and uncertain information.
Traditional intelligence-based methods	They are based on intelligence computing of inference making. Examples include artificial neural network, fuzzy based inference system and genetic algorithms, swarm intelligence.	They are capable of processing vague and uncertain information such as uncertain medical data. They are also capable of making inference from rules via reasoning.	They are not efficient with spatial modeling and can be sensitive to noise and intensity inhomogeneities.
Deep Neural Networks	They employ computational models of multiple processing layers with deeper architecture for learning and representing data with multiple levels of abstraction.	They perform hierarchical feature representation and very efficient with spatial modeling.	Training cost is high and they require large memory space

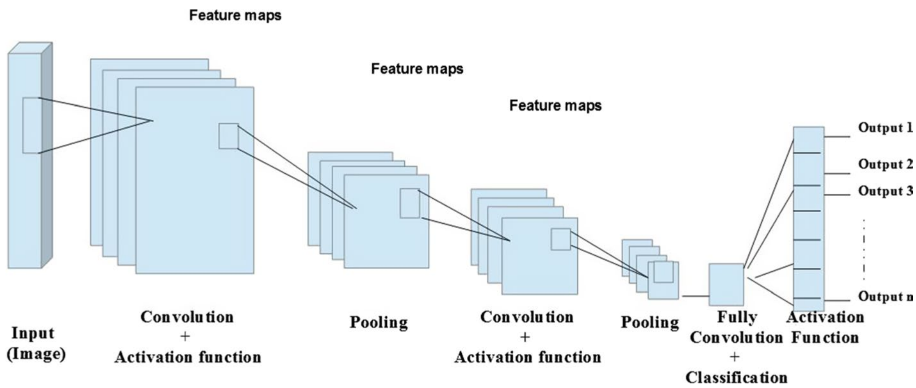

Fig. 4 General CNN layout architecture diagram

1. *AlexNet* AlexNet is a simple but powerful CNN architecture consisting both the convolutional and pooling layers. These are then followed by fully connected layers at the top. The advantage include the scale with which it utilizes GPU for training and perform task. AlexNet is still used as a starting point in the application of deep neural networks most especially in computer vision and speech recognition (Krizhevsky et al. 2012). This is illustrated in Fig. 5.
2. *VGG Net* This network was developed by Visual Graphics Group researchers at Oxford University. It is characterized by its pyramidal shape. It is composed of series of convolutional layers followed by pooling layers with the pooling layers contributing to the narrower shape of the layers (Simonyan and Zisserman 2014). This is desribed in Fig. 6. The advantages include possessing a very good architecture suitable for benchmarking on any particular task. The pre-trained networks for VGG are also commonly used out for many applications. It how-

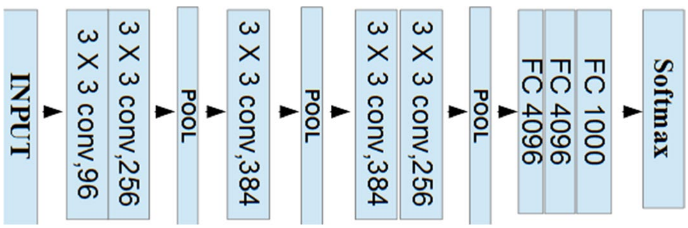

Fig. 5 Layout diagram of Alexnet Architecture

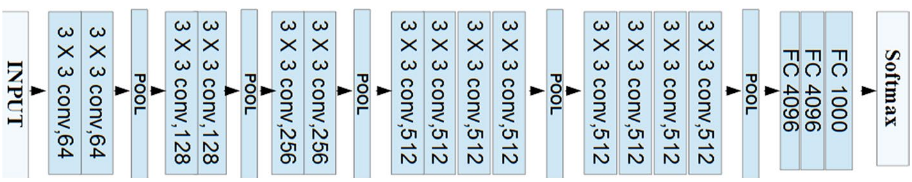

Fig. 6 Layout diagram of VGG 19 Architecture

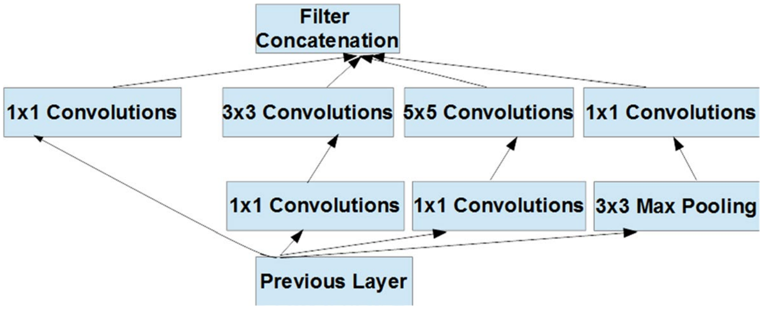

Fig. 7 An Inception module diagram

ever, requires a lot of computational resources and is very slow to train; most especially when training from scratch.

3. *GoogleNet* This is also known as Inception Network and it was designed by researchers at Google. It is made up of twenty-two (22) layers. It has the ability to either convolve an input or pool the input. The architecture contains multiples of inception modules stacked over one another as shown in Fig. 7. This stacking allows joint training as well as parallel training; thus assisting the model in faster convergence. The advantages include faster training with reduced size. It however, possess an Xception Network which can increase the limit of divergence of inception module (Szegedy et al. 2015; Chollet 2017).
4. *ResNet* A ResNet architecture also known as residual network is composed of multiple subsequent residual modules which are the basic building block of the architecture (Wu et al. 2018). These residual modules are stacked one above the other to form a complete end-to-end network. The advantage is that there is improved performance since the architecture is created from thousands of residual layers that can be used for network training. It is a 152-layers deep CNN architecture of the residual blocks. It is 20 and 8 times deeper than AlexNet and VGG, respectively (He et al. 2015a). It is less computationally complex than previously proposed networks. Examples include ResNet with 50, ResNet with 101, and ResNet with 152 layers.
5. *ResNeXt* ResNeXt is the current state-of-the-art technique for object recognition that builds on the hybridization of both inception and ResNet architectures (Xie et al. 2017; Szegedy et al. 2017). ResNeXt is also known as Aggregated Residual Transform Network. It is an improvement over the Inception Network which exploits the concept of the split, transform, and merge in a powerful but simple way by introducing cardinality (Szegedy et al. 2016). Cardinality simply refers to the size of the set of transformations. It utilized the combination of VGG topology and GoogleNet architecture by fixing spatial resolution to 3x3 filters within the split, transform and merge block (Xie et al. 2017). It also used residual learning to improve the convergence of deep and wide network. It used multiple transformations within a split, transform and merge block and defined these transformations in terms of cardinality. The increase in cardinality significantly improves the performance and produces a new and enhanced architecture.
6. *Deep reinforcement learning* This is a system that is trained completely from scratch, starting from random behavior to really knowledge base from the expe-

rience. It is the combination of reinforcement learning and deep learning using lesser amounts of computation resources and data (Francois-Lavet et al. 2018). The agent is able to learn from its environment and applies the knowledge for any sequential decision making problems including image analysis. Examples include AlphaGo and AlphaGo Zero. AlphaGo Zero requires less computation than previous versions and yet still able to perform at a much higher level due to the adaptation of much more principled algorithms.

7. *Advanced inception network* These include Inception-V3, Inception-V4 and Inception-ResNet. They are improved versions of Inception-V1, Inception-V2 and googlenet. Inception-V3 reduces the computational cost of deep networks without affecting the generalization. Szegedy et al. (2017) replaced large size filters (5x5 and 7x7) with small and asymmetric filters (1x7 and 1x5) and used 1x1 convolution as a bottleneck before the large filters. In Inception-ResNet, the strength of residual learning and inception block were combined.
8. *DenseNet* It is similar to ResNet and was proposed to solve the vanishing gradient problem. DenseNet utilizes cross-layer connectivity and connects each preceding layer to the next coming layer in a feed-forward fashion to solve the problem with ResNet that explicitly preserves information through additive identity transformations which increases the complexity. It utilizes dense blocks and the feature-maps of all previous layers are thus used as inputs into all subsequent layers (Huang et al. 2017). This is illustrated with the diagram in Fig. 8
9. *Xception* It is known as extreme Inception architecture that exploits depth-wise separable convolution. The original inception block is modified by making it wider and replacing different spatial dimensions ($1x1$, $5x5$, and $3x3$) with a single dimension ($3x3$) followed by a $1x1$ convolution to regulate computational complexity (Chollet 2017). This makes the network computationally efficient by decoupling spatial and feature-map channels.
10. *Squeeze and Excitation(SE) network*Hu et al. (2018) proposed a new block for the selection of feature-maps for object discrimination. The new block named as SE-block suppresses the less important feature-maps and excites the class specifying feature-maps. It is designed to be added in any CNN architecture before the convolution layer. It consists of two major operations; squeeze and excitation (also known as fire module). The convolution kernel captures local information but ignores the contextual relation of features while the Squeeze operation captures global information of the feature maps. The network generates feature map statistics such that is a more powerful architecture and is extremely useful in low bandwidth scenarios like mobile platforms.

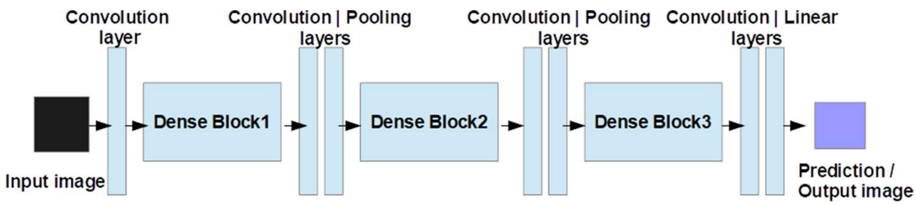

Fig. 8 Layout diagram of Densenet Architecture

11. *Residual Attention Neural (RAN) network*Wang et al. (2017) designed RAN that improves the feature representation of CNN by incorporating attention modules in CNN. This is to make a network capable of learning object aware features. It employs a feed-forward CNN built by stacking residual blocks with attention module. It is a combination of two different learning strategies into the attention module that enables fast feed-forward processing and top-down attention feedback in a single feed-forward process to produce dense features that makes inference of each pixel. The bottom-up feed-forward structure produces low-resolution feature maps with strong semantic information. The top-down learning strategy globally optimizes the network in such a way that it gradually outputs the maps to input during the learning process.
12. *Convolutional Block Attention Module (CBAM)*Woo et al. (2018) developed an attention-based CNN,CBAM, which infers attention maps sequentially by applying both feature-map attention and the spatial attention; to find the refined feature-maps unlike the SE-Network that only considers the feature-maps in image classification without considering the spatial locality of the object in images (Khan et al. 2019).

    The performances of these CNN architectures, including their strengths and weaknesses are summarised in Table 3.

4 Recent applications of CNN architectures

In the past one year, trailblazing CNN architectures have been applied in various areas most especially in the analysis of skin lesion images. Ratul and Mozaffari (2019) developed an automated computer-aided detection system for early diagnosis of malignant skin lesions. They utilized dilated convolution with four different architectures such as VGG16, VGG19, MobileNet, and InceptionV3. They employed HAM10000 dataset for training, validating, and testing of the system and achieved classification accuracy of 87.42%, 85.02%, 88.22%, and 89.81%, respectively for the architectures. Gessert et al. (2020) also performed skin lesion classification with an ensemble of deep learning models including EfficientNets, SENet, and ResNeXt WSL by utilizing a search strategy. Brinker et al. (2019) employed an enhanced deep learning architecture of a CNN trained on 12,378 dermoscopic images for classification of skin lesion images. They utilized the system to classify 100 images and compared the performance of the architecture to that of the 157 dermatologists from 12 university hospitals in Germany. The system was shown to outperform the dermatologist.

GoogleNet and AlexNet architectures were employed with transfer learning and gradient descent adaptive momentum learning rate (ADAM) for classification of skin lesion images by Alqudah et al. (2019). The system was evaluated on ISIC database to classify skin lesion images into three classes of benign, melanoma, and seborrheic keratosis. This was carried out on both segmented and non-segmented lesion images with the overall accuracy of the non-segmented classification database as 92.2% and 89.8% for the non-segmented dataset. A deep learning framework that integrates deep features information to generate most discriminant feature vector was developed by Akram et al. (2020). They employed Entropy-Controlled Neighborhood Component Analysis (ECNCA) for discriminant feature selection and dimensionality reduction. Selected layers of deep architectures, including DenseNet 201, Inception-ResNet-v2, and Inception-V3, were employed as

Table 3 Performance comparison of state-of-the-arts (CNN architectures)

Techniques	Description	Merits	Demerits
AlexNet	It utilizes large and small size filters on initial (5*x*5 and 11*x*11) and last layers (3*x*3) for features extraction	It introduces regularization in CNN ,and employs parallel use of GPUs as an accelerator to deal with complex architectures	It has a tendency of generating artifacts from the learned feature-maps due to large filter size.
VGG	It is characterized by a pyramidal shape and is composed of series of convolutional layers followed by pooling layers with the pooling layers contributing to the narrower shape of the architecture	It utilizes an effective receptive field with a simple and homogenous topology	VGG utilizes computationally expensive fully connected layers (Khan et al. 2019)
GoogleNet	It utilizes mutiscale filters within the layers and employs a system of split, transform,and merge processes	The number of parameters are reduced through the use of bottleneck layer, global average-pooling at last layer. It also utilizes auxiliary classifiers to improve the convergence rate	It utilizes heterogeneous topology that makes parameter customization difficult. Useful information can also be lost due to the representational bottleneck (Khan et al. 2019).
Inception-V3 and Inception-V4 (Khan et al. 2019)	They employ deep feature hierarchies and multilevel feature representation	Asymmetric filters and bottleneck layer are employed to reduce the computational cost of deep architectures	They employ complex architecture design. The architectures also lack homogeneity
Inception-ResNet (Khan et al. 2019)	It utilizes the architecture of both the ResNet and Inception blocks	It combines the power of residual learning and inception block	It is very slow in learning
ResNet	It employs identity based skip connections and residual learning architecture	It utilizes residual learning and alleviates the effect of vanishing gradient problem	The architecture is complex and degrades information of feature-map during the process of feed forwarding.
DenseNet (Khan et al. 2019)	It employs depth-wise and cross-layer dimension which ensures maximum data flow between the layers in the network	It eliminates redundant feature-maps.	There is large increase in parameters due to increase in number of feature-maps at each layer
Xception (Khan et al. 2019)	It employs depth-wise separable convolution	It utilizes cardinality to learn features abstractions	The computational cost is high
ResNeXt (Khan et al. 2019)	It uses Aggregated Residual Transform Network and cardinality process for diverse transformations at each layer	It uses parameter customization and grouped convolution	The computational cost is high

Table 3 (continued)

Techniques	Description	Merits	Demerits
Squeeze and Excitation Network	It is a block-based concept that introduces generic block that can be added easily.	Very simple to implement and squeezes less important features away	It only considers residual information for determining the weight of each channel which can be less efficient

classifiers in the system. The proposed system was evaluated to categorize the skin lesion with 98.8%, 99.2% and 97.1% and 95.9% accuracy on the four datasets of PH2, ISIC MSK, ISIC UDA, and ISBI-2017 respectively.

Three machine learning architectures comprising of SVM, VGGNet and Inception-ResNet-v2 were utilized to classify seven types of skin diseases from skin lesion images. The Inception-ResNet-v2 architecture was found to be superior in performance Guha et al. (2020). El-Khatib et al. (2020) also developed an system that is able to diagnose skin lesions using deep learning–based methods. They proposed a system that utilizes both deep neural networks and feature–based methods. They employed architectures such as GoogleNet, ResNet-101, and NasNet-Large already pretrained on large ImageNet and Places365 databases. They also utilized SVM for object detection with the system giving higher accuracy results. The system was able to differentiate melanoma from benign nevus. Almaraz-Damian et al. (2020) utilized a fusion of ABCD rule into deep learning architecture for efficient preprocessing, feature extraction, feature fusion, and classification for detection of melanoma skin cancer. The ABCD rule was employed for handcrafts feature extraction and deep learning features were extracted by the CNN architecture. The proposed framework was evaluated on ISIC 2018 and the performance was compared with other techniques such as Linear Regression (LR), SVMs, and Relevant Vector Machines (RVMs). The proposed framework appears to demonstrate an improved performance in terms of the accuracy, specificity, and sensibility. Zhang et al. (2019) also performed automatic segmentation of the skin lesion on dermoscopy images via a Deep Supervised Multi-scale network (DSM network). The system utilized side-output layers of the network to aggregate information from shallow and deep layers with a multi-scale connection block to perform skin lesion segmentation. They also employed a Conditional Random Field (CRF) model to further improve the segmentation results.

CNN architectures have also been applied for image analysis in some other areas for example, a deep learning-based framework named DNCIC that can accurately predict normal mitochondria and drug-affected cells was developed by Iqbal et al. (2019). They utilized CNN trained on mitochondrial images dataset. The proposed model achieved an accuracy of 98% in images and videos classification. Iqbal et al. (2019) also developed a three-step feature description strategy that utilized GoogLeNet to extract local descriptions and used ResNet-50 for the production of mid-level features. They also extracted global descriptor features using Inception-V3 model for final classification of the position of mitochondrial organelle movement. The method utilized a deep classification network, MOMC, for gathering the organelle position. This approach was evaluated against machine learning methods such as logistic regression (LR), and SVM for the classification of the shape of mitochondrial organelles on 24 different position of images. The system produced the highest accuracy of 96.32%Ȧ CNN architecture was also proposed for classification of the images of various cannabis leaves into their respective classes of strains and types by Rajora et al. (2018). The system performs segmentation and foreground extraction in the images and utilizes the segmentation output for the result classification task. The proposed system utilizes ConvNets for the classification task using two training approaches of transfer learning and training from scratch. A two-layer deep CNN was employed by Cheng et al. (2019) for feature extraction and sparse representation classification and for identification. This was utilized for developing a facial recognition model. The model was made up a two-layer deep CNN for feature extraction and SRC for classification. The system utilizes SRC to construct a training dictionary and to sparsely represent the test image. Adegun et al. (2018) did the survey of various deep learning architectures that have been applied in the analysis of satellite images. In summary, application of CNN architectures have been generally shown to outperform the traditional machine learning techniques in various areas.

5 Standard skin lesion images databases for model evaluation

5.1 DERMOFIT project datasets

This is ownned by the University of Edinburgh. The skin lesion images are normal RGB that were captured with a quality camera in a controlled environment. It contains 1300 images of 45 Actinic Keratosis, 239 Basal Cell Carcinoma , 331 Melanocytic Nevus, 88 Squamous Cell Carcinoma, 257 Seborrhoeic Keratosis, 78 Intraepithelial carcinoma, 24 Pyogenic Granuloma , 96 Haemangioma , 65 Dermatofibroma , and 76 Melanoma images (https://licensing.eri.ed.ac.ukli/software/dermofit-image-library.html).

5.2 PH2

PH2 contains dermoscopic images with a resolution of 768x560 pixels. It contains 200 dermoscopic images of melanocytic lesions which includes: 80 common nevi, 80 atypical nevi and 40 melanomas. There is also medical annotation for all the images . The images were obtained from Hospital Pedro Hispano (https://www.fc.up.pt/addi/ph2database.html).

5.3 ISIC 2018

This contains 2594 images of training data and 2594 corresponding ground truth. It also contains 1000 images of test data Codella et al. (2018) that is sourced from HAM10000 .

5.4 ISIC 2019

This contains 25,331 JPEG images of training data and corresponding metadata with entries such as age, sex, and general anatomic site. It also has corresponding GroundTruth label of standard lesion diagnoses. It also contains 8238 JPEG images of test data skin lesion images. Its sources are BCN20000, HAM10000 and MSK Datasets Codella et al. (2018)

5.5 HAM10000

HAM10000 known as Human Against Machine with 10000 training images dataset were collected from dermatoscopic images from different populations. They were acquired and stored via different modalities. The dataset contains 10015 dermatoscopic images and mostly used for academic machine learning purposes (Tschandl et al. 2018). They are publicly available in the ISIC archive.

5.6 Performance evaluation metrics

The major metrics for performance evaluation of the segmentation and classification deep learning models include: Accuracy(Acc), Dice Coefficient (Dice), Sensitivity , and AUC . These metrics have been used for evaluation of various models reviewed in this paper. They are described below :

Dice Coefficient This measures the similarity and overlap between the ground truth and the predicted output. It is defined as

$$\mathrm{DSC} = \frac{2TP}{FP + 2TP + FN} \tag{2}$$

Sensitivity(SEN) This is the proportion of positive outcomes(prediction) among those who are actually positive.

$$\text{Sensitivity} = \frac{TP}{TP + FN} \tag{3}$$

Specificity(SPE) This is the proportion of negative outcomes(prediction) among those who actually tested negative.

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{4}$$

Accuracy(ACC) : It measures the proportion of true results (both true positives and true negatives) among the total number of cases examined.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

Area under the receiver operating characteristic (ROC) Curve (AUC): It provides a measure of performance across all possible classification thresholds. AUC ranges in value from 0 to 1. ROC is a curve of true positive rate (TPR) against false positive rate (FPR), that is, sensitivity against 1-specificity with the AUC as the area under the entire curve.

Where *FP* is false positive , *FN* is false negative, *TP* is true positive and *TN* is true negative (Adegun and Serestina 2019).

6 Performance analysis of state-of-the-arts

6.1 Skin lesion segmentation algorithms and techniques in ISIC 2018

In this section, some of the best performing state-of-the-arts techniques employed in ISIC 2018 have been explored and their performance tabularised in the Table 4. Chengyao et al. (2018) designed an encode-decode architecture of network based on DeepLab and PSP-Net for segmentation skin lesions. In the architecture, features were extracted by ResNet 101. These feature maps were feed into a multi-scale block. Different size of pooling and dilation convolution were used to extract different scale features. A deep learning model named SegAN was proposed by Yuan et al. (2018), consisting two parts which are segmentor and the critic network . The segmentor generates probability label maps from input

Table 4 Performance evaluation results of state-of-the-arts algorithms in skin lesion segmentation of ISIC 2018

Techniques	ACC %	SPE %	SEN %	Dice %	Jaccard Index %
Encoder–Decoder with DeepLab and PSPNet Chengyao et al. (2018)	94.2	96.3	90.6	89.8	83.8
Ensemble VGG16, U-net, DenseNet and Inception v3 with CRF post processing Hao et al. (2018)	94.5	95.2	93.4	90.4	83.7
Encoder–Decoder with ResNet34 and Deconvolution Networks Yuanfeng et al. (2018)	94.3	96.4	91.8	90.0	83.4
Fully convolutional encoder–decoder network with CRF Navid et al. (2018)	94.5	94.2	94.0	90.3	83.7
UNet with DeepLabV3 Molina-Moreno et al. (2018)	94.7	94.5	94.5	90.3	83.6
FCN with region-proposal network (RPN) and CRF Xue et al. (2018)	93.7	91.8	92.1	89.8	83.6
Mask-RCNN Sorokin (2018)	93.9	96.8	90.4	89.0	82.3
Mask R-CNN model with ResNet50 Yang and Chen (2018)	93.7	94.3	93.6	89.0	82.2
U-Net variants Dandi et al. (2018)	93.8	93.9	94.5	89.0	81.6
U-Net Yuan and Tavildar (2018)	93.7	97.9	87.9	89.0	82.6

images was utilized. The critic network separates the two inputs types and the system produces promising results.

A deep learning model was built by Hao et al. (2018) with the network architecture from the deep-lab model adopting a pre-trained weight from PASCAL VOC-2012. The final model was ensemble using bagging method on models VGG16, U-net, DenseNet and Inception v3. A CRF that post-processed segmentation mask and obtained the final prediction for the segmentation region was also utilized. The model was trained with 20,000 iterations. The convolution and the decoder layers were also fine-tuned with another 20,000 iterations. A state-of-the-arts performance was obtained.

A feature aggregation network architecture that employed ResNet34 as the backbone network was developed by Yuanfeng et al. (2018). This was used to build the encoder module while the decoder part consists of several deconvolution operators to recover the spatial resolution of the feature maps. A dense connection modules that helps the flow between the high-level feature and the low-level feature was built to enrich features between the encoder and decoder part. This was utilized for the effective aggregation and to recover the spatial information with enriched context information. Auxiliary loss was also employed at the encoder part of the network to minimize difficulty in the model training.

A segmentation framework was proposed by Navid et al. (2018) that utilized pretrained networks which include ResNet152 (152-layered ResNet), DensNet169 (169-layered DensNet), Xception, and Inception-ResNet v2 (ResNetV2) .These models are referred to as the base model in our proposed. Bottleneck convolutions were employed to equalize the number of feature maps in the corresponding levels which were then gathered in a pyramid feature pooling manner. A hybrid network which combines a FCN and an Elliptical-shaped Region Proposal Network was designed by Molina-Moreno et al. (2018) for automatic segmentation of skin lesion. The proposed system was trained end-to-end using augmented dataset of clinical cases of skin lesion images. The FCN model provides a pixel-wise segmentation for the images while the Region-Proposal Network (RPN) extracts a low-resolution segmentation map from the elliptical regions.

6.2 Skin lesion classification algorithms and techniques in ISIC 2019

Some state-of-the-arts algorithms recently used in ISIC 2019 challenge for classification of skin lesion image have been summarized in this section. These algorithms have been executed on ISBI 2019 skin lesion image dataset. This dataset is a collection of more than 25,000 skin lesion images from various sources such as HAM10000. This section captures the performance on these classification algorithms.

Nils et al. (2019) employed a deep learning model named EfficientNets (EN) already pre-trained on the ImageNet dataset. The model applies some scaling rules that makes it scalable for any image size and it produces state-of-the-art classification performance. An ensemble of some state-of-the-art deep learning models such as densenet121, se-resnext50, se-resnext101, efficientnet-b2, efficientnet-b3 and efficientnet-b4 were used as the base model for transfer learning by Zhou et al. (2019). Adam optimizer was then used for training the system for 90 epochs. Pollastri et al. (2019) approach was also based on ensembling of different state-of-the-art CNN such as ResNet-152, DenseNet-201 and SeResNext-101. They employed data augmentation techniques, stochastic gradient descent, momentum and plateau learning rate scheduler in training the model.

Pachecoa et al. (2019) adopted an ensemble of several CNN models such as SENet, PNASNet, InceptionV4, ResNet-50, ResNet-101, ResNet-152, DenseNet-121,

Table 5 Performance evaluation results of state-of-the-arts algorithms in skin lesion classification of ISIC 2019

Techniques	AUCs %	ACC %	SEN %	SPE %	DICE %
Ensemble of multi-res efficientNets with SEN154 2 Nils et al. (2019)	92.3	92.6	50.7	97.7	51.5
Ensemble of EfficienetB3-B4-Seresnext101 Zhou et al. (2019)	78.0	91.7	60.7	95.2	53.2
Ensemble classifiers Pachecoa et al. (2019)	89.2	91.9	50.7	96.5	50.2
Densenet-161 Chouhan (2019)	87.0	91.0	47.3	96.7	43.2
CNNs based on inception-resnet, exception net, and EfficientNet Dat et al. (2019)	87.2	91.4	55.5	95.0	49.8
Malanet based on DenseNet Zhang (2019)	89.7	89.7	66.6	91.6	52.1
Class-centroid-based openset ensemble CNNs Xing et al. (2019)	75.4	91.9	55.7	95.1	54.2
Long-tail distribution based classifiers Subhranil et al. (2019)	85.5	91.3	49.7	95.8	47.5
Softmax ensemble and sigmoid ensemble classifier model Yousef zadeh and Motahari (2019)	88.5	92.0	51.9	95.6	52.4
Test time augmentation on ensemble models Cohen and Shimoni (2019)	88.4	92.4	46.9	96.3	51.4
Xception, Inception-ResNet-V2, and NasNetLarge Sara et al. (2019)	89.2	92.1	46.0	96.2	48.5

DenseNet-169, DenseNet-201, MobileNetV2, Google Net, VGG-16 and VGG-19. They adapted only the classifiers to fit the task requirements. The model was fine-tuned and pretrained on ImageNet. Chouhan (2019) employed Densenet-161 for skin lesion classification. The model was trained and fine-tuned on pre-trained image-net dataset with good performance. Dat et al. (2019) employed state-of-the-art CNNs, EfficientNet and Inception Resnet to solve data imbalance issues and over-fitting using standard up-sampling techniques and a novel loss functions. They achieve high accuracy training. Zhang (2019) formulated a deep learning model named MelaNet is formulated using a 169-layer dense attention networks as backbones. This was formulated from Fully Connected (FC) layer with eight output units for building multi-class and multi-label classifier. They also employed softmax nonlinearity and a sigmoid nonlinearity modules respectively. Xing et al. (2019) propose an ensembling model and trained a set of networks of the same structure with the same hyper-parameters. They also used the mean softmax vector for probability distribution. Subhranil et al. (2019)utilized the combination of EfficientNets, DenseNet161 and Se-ResNext101-32x4d which were trained independently. This was applied at the Level-0 models of multi-stage classification. Another neural network with two FC layers in-between before the final output for the Level-1 was also employed. Heavy data augmentation, test-time augmentation and color constancy approach were utilized for data non-uniformity.

Yousef zadeh and Motahari (2019) employed seven models with high Top-1 accuracy on ImageNet dataset which include DenseNet121, InceptionV3,InceptionResNetV2, Xception, EfficientNetB1, EfficientNetB2 and EfficientNetB3 in developing a classification model for skin lesion analysis. They also used both Softmax and Sigmoid activation layer as their prediction layer. Cohen and Shimoni (2019) utilized ensemble methods and generated diverse models from different point of views. They developed an inducer with an induction algorithm that obtains a training set and forms a model that represents the generalized relationship between the input attributes and the target attribute. They also used Diversity Generator for generating diverse models and combiner for combining the results of the various models. CNN architecture was adopted for training the data using different loss functions and test time augmentation. Sara et al. (2019) proposed an approach based on fine-tuning and ensembling of three popular deep learning models, namely Xception, Inception-ResNet-V2, and NasNetLarge. The proposed model was pre-trained on ILSVRC 2012 dataset with over 1.2 million labeled images of 1000 object classes. In general, ensemble model with state-of-the-art models such as such as Resnext, NASNet, SENet, DenseNet121, InceptionV3, InceptionResNetV2, Xception, EfficientNetB1, EfficientNetB2 and EfficientNetB3 seems to perform extremely well. However, these models require heavy resources and are time consuming to train which may not give allowance for much fine tuning of the models.

The details are summarised in Table 5.

7 Result analysis and discussion

Figure 9 and Table 6 show the classification results of the best classification models in ISCI 2019 challenge (ISIC 2019). Tables 4 and 6 shows the segmentation and classification results of skin lesion images in ISIC 2018 (ISIC 2018). In ISIC 2018, the lesion images were first segmented; these segmented images were then classified via improved deep learning models. The comparison of the classification results of the ISIC 2018 and ISIC 2019 clearly shows

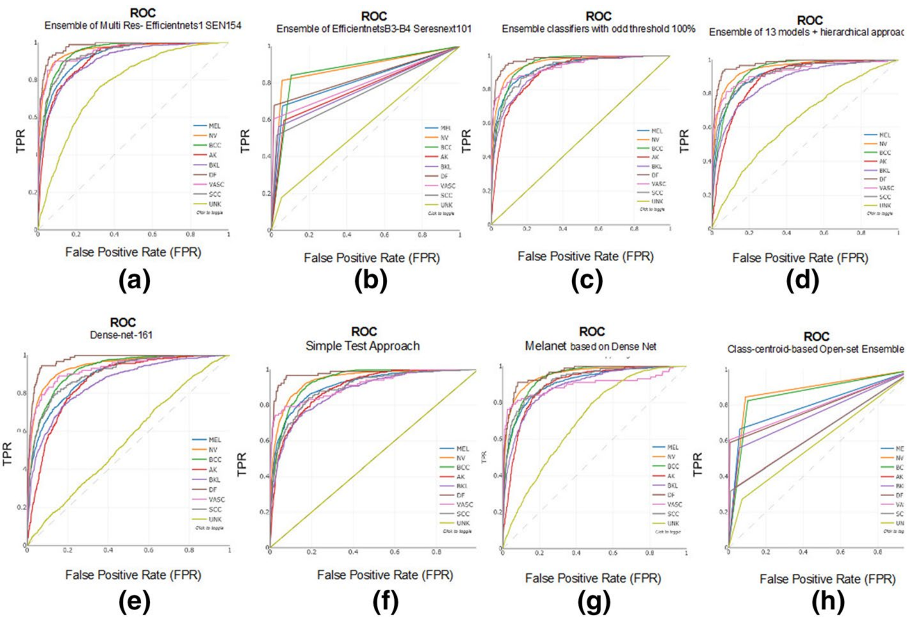

Fig. 9 ROC curves of the best 8 models in skin lesion classification of ISIC 2019 (Plot of TPR against FPR for nine different diagnostic categories: Melanoma, Melanocytic nevus, Basal cell carcinoma, Actinic keratosis, Benign keratosis, Dermatofibroma, Vascular lesion, Squamous cell carcinoma and None of the others for the best 8 models)

better performance from the models in ISIC 2018 than the models in ISIC 2019. Looking at the results from Tables 5 and 6 closely, it can be inferred that the models in Table 6 for the ISIC 2018, records better performance than the models in the Table 5 for ISIC 2019 most especially in terms of Accuracy, AUC, Sensitivity and Dice-coefficient for the top performing models. It can also be observed from the classification results of ISIC 2019 that the highest dice-coefficient recorded is 54.2% from Class-centroid-Based Openset Ensemble method Xing et al. (2019) and highest sensitivity result of 66.6% from the Malanet model Zhang (2019). It is also observed that the Multi-Res-EfficientNets method Nils et al. (2019) produces the highest classification accuracy of 92.6% and AUC score of 92%Ṫhese are better than the results from Table 5 which are for ISIC 2018. In Table 6, it can be observed that an higher dice coefficient score of 84.1% from Large Ensemble model Gessert et al. (2018) and sensitivity score of 83.3% from Top-Models-Averaged method Nozdryn-Plotnicki et al. (2018) . Table 6 also records an accuracy score of 98.7% and AUC score of 97.2% from Large Ensemble method Gessert et al. (2018). These results are far better than the results from Table 5 of ISIC 2019. It can thus be concluded that the models in ISIC 2018 actually perform better than the models in ISIC 2019 in classification metrics such as Accuracy , Dice coefficiet, Sensitivity and AUC . This can be attributed to the the positive effects of segmentation of lesions images used in ISIC 2018 classification. These images have been pre-processed and segmented before been sent into the models for classification. This shows that classifying segmented lesion images give better performance than classifying un-segmented lesion images. It can also be inferred

Table 6 Performance evaluation results of state-of-the-arts algorithms in skin lesion classification of ISIC 2018

Techniques	AUC %	ACC %	SEN %	SPE %	DICE %
Top 10 models averaged Nozdryn-Plotnicki et al. (2018)	98.3	95.8	83.3	98.6	82.3
Large ensemble with heavy multi-cropping and loss weighting Gessert et al. (2018)	98.7	97.2	80.9	98.4	84.1
Emsemble Of SENET and PNANET with Data Augmentation Li and Shen (2018)	97.8	96.8	80.4	98.0	83.0
densenet Li and Li (2018)	98.0	96.9	78.9	97.6	82.6
Models average Amro et al. (2018)	96.9	95.0	73.8	97.9	76.4
Average of 15 deep learning models Bissoto et al. (2018)	97.4	95.5	70.5	98.1	76.8
FV+Res101 Pan and Xia (2018)	87.6	95.9	78.6	96.7	78.9
WonDerM: skin lesion classification with fine-tuned neural networks Lee et al. (2018)	97.4	95.9	75.7	97.2	77.2
Resnext101 and DPN92, Snapshot ensamble, D4 TTA Dobrenkii et al. (2018)	87.6	96.2	78.4	96.8	80.6
Emsemble Of ResNet-152 Zhuangy et al. (2018)	97.4	95.1	74.7	97.4	77.6

that a less complex model gives better classification results on segmented lesion images since the models in ISIC 2018 are less complex than their counterparts in ISIC 2019 (ISIC 2019, 2018).

8 Conclusion

The paper is a critical and analytical survey of the state-of the-art methods for performing analysis of skin lesion images. It is a comprehensive review of the techniques and algorithms used in the processing of skin lesion images in detecting melanoma skin cancer diseases. These techniques cover pre-processing techniques, feature extraction methods and segmentation algorithms and finally classification techniques. Both conventional and the recent approaches have been explored. The state-of-the-arts algorithms in ISIC 2018 and 2019 challenges were also analysed for their performance on skin lesion images. The best performing algorithms were critically analyzed. Generally, ensemble model with state-of-the-art models such as such as Resnext, NASNet, SENet, DenseNet121, InceptionV3, InceptionResNetV2, Xception, EfficientNetB1, EfficientNetB2 and EfficientNetB3 seems to perform extremely well. However, this models requires heavy resources and are time consuming to train. It was discovered that the application of deep learning models on well pre-processed and segmented images results in better classification performance of the images in evaluation metrics such as AUC, Sensitivity, Dice-coefficient and Accuracy. Pre-processsing techniques such as grab-cut and deep learning segmentation techniques have been shown to perform excellently well and are therefore recommended for improved classificaton performance. This will overcome the challenges in analyzing skin lesions images due to the fine-grained appearance of the skin lesion images.

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