An Extensive Survey on Segmentation and Classification of Skin Lesions using AI Techniques

Prasanna Ujjani Mutt C.K. Roopa B.S. Harish M.S. Maheshan

JSS Science and Technology University, JSS TI Campus, Mysuru 570 006
Karnataka State, India

ABSTRACT

This review of the literature covers more than 100 research articles from reputed journals, conferences, and workshops proceedings and offers a thorough examination of skin lesion segmentation and classification techniques from the year 2008 to the present. Two main parts of the survey are the segmentation of skin lesions and the subsequent classification of those lesions. It also covers different evaluation measures for algorithm and model assessment and provides a comprehensive collection of publicly available datasets. The three main techniques of diagnosis are clinical, dermatoscopic, and histopathologic. From clinical examination to the development of dermatoscopy and histology, it describes the progression of diagnostic procedures, stressing the significant contributions and difficulties encountered with each approach. Details of all the Artificial Intelligence techniques for segmentation and classification of skin lesions are summarized.

Keywords

Skin disease, Segmentation, Classification, Clinical, Dermatoscopic, Histopathologic

1. INTRODUCTION

1.1 Global stats

Cancer is a disease, which is one of the major cause for mortality. Between 1990 to 2019 the recorded deaths due to cancer is 1,359,777,807, and out them skin cancer alone, both Melanoma and Non melanoma cancers inclusive, accounted for 16,022,388. [9]. The estimated number of new cancer cases in USA from all cancer sites for 2023 is 1,958,310. Out of which 97,610 cases are probable cases of Skin cancer (Melanoma). The estimated deaths due to cancer in USA in 2023 is estimated to be around 609,820 for all cancer sites and for Melanoma, it is estimated to be around 7,990 [10]. Australia and Newzeland leads the world in skin cancer cases. The major cause for skin cancers, both melanoma and non-melanoma is Ultra violet radiation [11]. Statistics above motivates to conduct extensive research to understand better the various cancers and methods to cure them. Particularly in this work, the focus being skin cancer, covering both Melanoma and non-melanoma types. On one hand, research on adoption of various computational methods to assist early detection segmentation and classification assist the physicians to plan the treatment earlier, thereby improving the survival rate. Latest trend being usage of Artificial Intelligence (Machine learning and Deep Learning) for early detection, segmentation and classification of the cancer [12]. On the other hand, research in improved imaging techniques, which can help in capturing more better images which can be used for detection, segmentation and classification of cancers [13]. Research on Identifying the stage of the cancer and estimating the survival rate, such as five-year survival rate, and understanding the prognosis and predictive treatment are other key area which help in curbing the disease and improving the survival rate of the patients [14,15].

1.2 Types of Skin Cancers

Cancer are basically tumours, which are formed due to the growth of cells in an uncontrolled manner. All tumours are not cancerous, but tumours can become malignant, which are cancerous.

Skin cancer are of type Melanoma or Non melanoma category. Non melanoma cancer is formed in either of Basal cells, or Squamous cells or Merkel cells. Melanoma occurs in melanocytes. Life expectancy of non-melanoma cancers are higher than that of melanoma cancers.Ultra violet radiation is one of the main mutagens, which causes DNA damage\Mutation in the skin, which trigger the onset of tumour formation, as the tumour suppression genes are made inactive [16].

1.3 Methodology used for survey

The survey is conducted from publication related to cancer and especially for skin cancer and skin diseases. The survey focusses on three aspects, preprocessing, segmentation and classification of skin lesions using machine learning, deep learning and other AI methods.

1.4 Skin cancer detection workflow

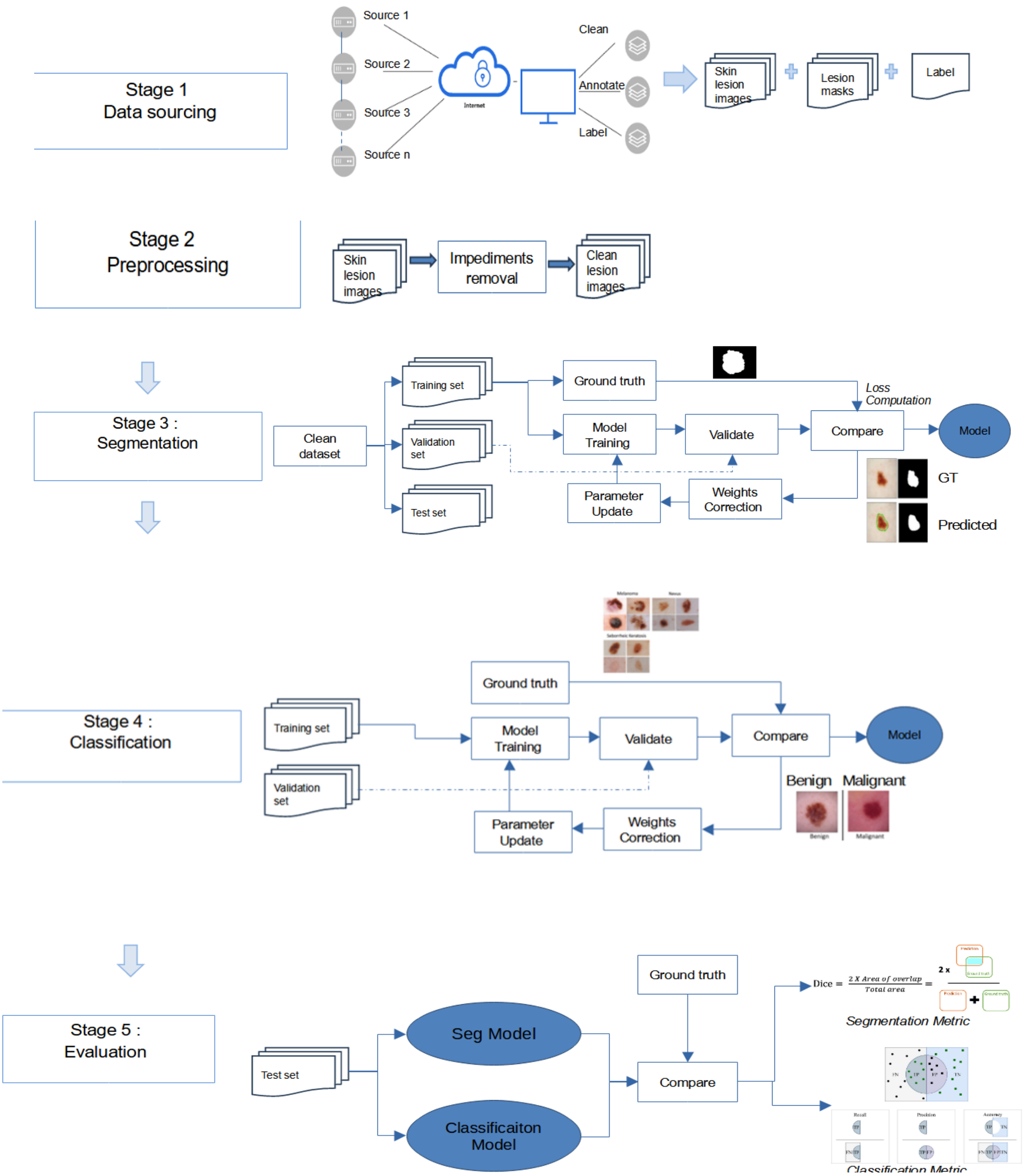

Fig 1: Process for detecting skin cancer

1.5 Datasets

One of the key missing aspects in skin cancer research using computational techniques, is adoption of the models/algorithms to live clinical practices.

Majority of the published papers, researchers have used the online available datasets. Few of the researchers have also directly collected the data from clinics / hospitals. Added to the above, the online datasets have images of white skin. Datasets of brown / black skin tone, for computational approaches like ML and DL are scarcely available online [18].

2. LITERATURE SURVEY

A detailed survey has been conducted by referring to publications in the period 2008 to till date. About 100+ publication from key journals, conferences and workshops proceedings have been considered for survey. The survey focuses on two aspects, one segmentation of skin lesion and the second one on skin lesion classification. A detailed listing of the available public dataset is also provided. Various metrics for evaluation of the algorithms and models has been discussed.

2.1 Clinical, Dermatoscopic and Histopathologic diagnosis

2.1.1 Clinical Diagnosis

Identifying a given patch on the skin and deciding if the patch is a benign or malignant is a crucial and tricky task. Expertise is required in taking this decision. Before the arrival of dermatoscope, clinical examination with naked eye was the only way to detect malignancy. A thumb rule guideline was set up by a group of dermatologist in 1985 [3] called ABCDE and another one called 7 Point checklist in 1989 [4][5]. A comparison of both the rule has been done in [6].

2.1.2 Dermatoscopic Diagnosis

With the advent of dermatoscope [7] the ABCDE rules and the 7-point checkpoints were reconsidered and modified. Key contribution for the dermatoscope development was done in [8].

Dermatoscopic images in later years become the key input for machine learning and deep learning models for skin lesion detection, segmentation and classification.

2.1.3 Histopathologic Diagnosis

In Histopathology, part of the skin lesion is dissected using biopsy and the extracted tissue are processed and observed under high magnification microscope.

The histopathology images are too large in size of the order of 100K X 100K or sometimes even larger. As there is availability of images, researchers have adopted machine learning and deep learning approaches to detect the tumour. Since the image are of very large size, smaller patches of key interest are cropped and passed to Convolution Neural Network models for detection of tumour [162, 165].

2.2 Pre-processing and Augmentation

Irrespective of the data is from online or taken from clinics/hospitals, the raw data shall have some impediments which hinders the detection, segmentation and classification of skin lesions.

One of the key essential steps in skin lesion detection is to remove impediments (unwanted artifacts) in the input images. Removal of these impediments helps in achieving better accuracy of detection and segmentation and in turn classification.

Some of the key issues in the images of skin lesions available online are shown subsequently. The images have different types of artifacts which can hinder the detection of the skin lesion.

The list of impediments is as listed:

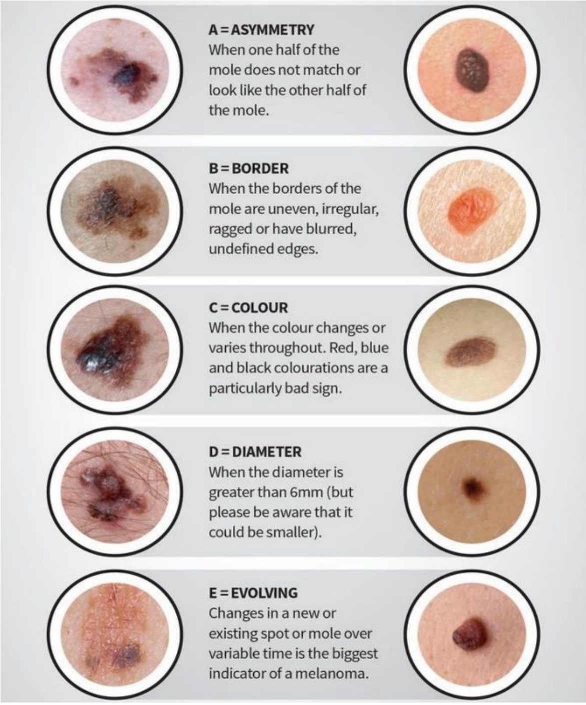

Fig 2: ABCDE method for melanoma detection

1.Hair
2.Bubbles
3.Ruler Markings
4.Pen Markings
5.Dark Boundaries

These artifacts need to be removed before feeding the image to the detection algorithm/model [18].

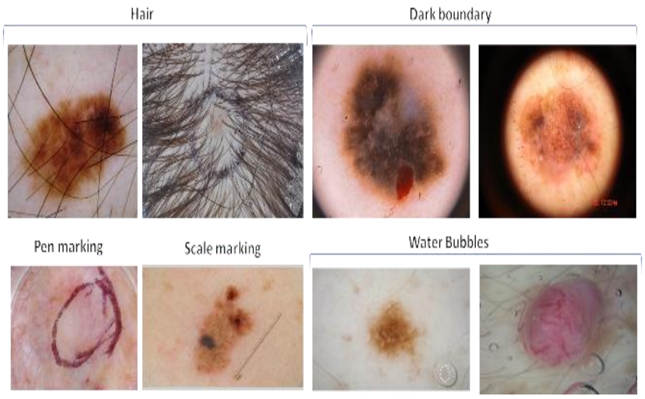

Fig 3: Samples from ISIC 2018 data set

Fig 4: Varying Colour Sample ISIC 2018 data set

Apart from the above artifacts, the data set has other challenges too. Within respective skin lesion classes, it is observed variations and also between skin lesion classes, and similarities. Blood vessels are another challenge need to be addressed during skin lesion segmentation [166, 167].

One of the impediments is hair and removal of it from the input image is essential for better accuracy. A notable review is done, on methods used for hair removal using image processing and machine learning approaches by [2]. Hairs could actually occlude the lesion and it could hamper the accurate detection, segmentation of the skin lesion. From the existing literature, there are three categories of approaches used by researchers. (1) Linear interpolation (2) Non-linear Partial differential equation based diffusion algorithms and (3) Exemplar based methods.

Dullrazor software [20] is one of the early works done in the area of hair removal using bilinear interpolation approach. The steps used are identifying the dark hair locations by morphological closing operation, replacing the hair pixels by bilinear interpolation and smoothing the final result by adaptive median filter. An improved version was developed by using median filter to reduce the effect of the hair on segmentation [21]. Researchers have also adopted detection and remove hair using morphological operations and thresholding in CIE L*u*v* colour space. In these techniques, a hair mask was generated by a fixed thresholding procedure on these thin structures based on their luminosity [22, 23].

The key downside of removal of hair using interpolation method, is that the original lesion maybe changed, and post removal there could be blurring, the boundaries may get altered, the texture could also get changed.

Another approach for hair removal is non-linear-PDE diffusion based inpainting method. The advantage of using non-linear diffusion over linear interpolation is that it utilizes neighbouring information in a natural manner through non-linear diffusion, filling large gaps while maintaining a sharp boundary [24, 25, 26]. Here as well, the texture information is not considered for processing, hence dermoscopic images does not perform well in this approach. In this method, both the PDE approach and texture information are used for hair removal. In inpainting method, for filling missing information, texture synthesis methods are used. Though texture-based synthesis is used, the results are not very satisfactory [27,28,29].

Contrast enhancement adjusts the relative brightness and darkness of lesions to improve their visibility. The contrast or tone of the skin image can be modified by mapping the grey levels in the image to new values through a grey-level transform. [30,31,32]. Normalization, median filtering, sharpening and histogram equalization are other preprocessing approaches applied [33].

Augmentation methods are adopted to overcome the bias in the dataset [35]. Basic augmentation techniques include vertical and horizontal flipping, scaling, adaptive histogram equalization, shearing, gaussian noise, additive noise. Further with the propose of deep learning, generative adversarial networks (GAN) have been very affective in generating accurate data [36].

2.3 Segmentation

Before the advent of Deep learning, researchers used Image processing and Machine learning approaches for skin lesion segmentation and classification respectively. A detailed survey of the computing approaches, machine learning and deep learning approaches are presented in [1, 168, 169].

Exact lesion border detection is not a trivial step. Researches have used various features for accurately finding the border of the lesion. Segmentation can be achieved either by detecting the edges, or grouping the pixels to different regions, or applying thresholds. In recent trends, artificial intelligence approaches are being adopted as well.

Finding the edges could be achieved either manually by using semi-automatic tools, which have tracking facility or edges could be detected automatically using algorithms. Researchers have used watershed [37] in which post the noise elimination, the edges are detected using Sobel operator and then the watershed transformation is applied for segmentation. The border of melanoma tumour, have a differential structure as compared to a normal birth mark on skin, which has a smooth border. Researchers have considered these features for detecting the border using contour detection algorithms [38, 39, 40,41, 42]. Canny edge based algorithms [43,44] uses the canny algorithm to detect the boundary of the lesion.

Images can be grouped into regions based on certain attributes for segmentation, The pixels in these individual regions have matching values for the attribute. Clustering is performed by comparing neighbouring pixels, and grouped based on certain defined condition. Centroid based clustering algorithms like iterative region-based methods in [45,46,47]. Clustering approaches like MDCUT [46], a density based clustering algorithm, the colour variation in the image is studied and the threshold for each colour level is identified. These become the thresholds for the regions and these pixels become the seed point for the region growing algorithm. The regions so formed will separate the image into skin and lesion regions.

In iterative stochastic region-merging [48], a region adjacency graph is formed, by starting with a pixel as a region and stochastic region merging is done iteratively. Based on Markov Random Field, a region merging likelihood function is used for merging the regions using the regional statistics. A modified active contour method, using gradient vector is used for segmentation in [49].

K-means and Fuzzy C-means clustering are one of the popular traditional methods for segmentation. In one of the method, K means is employed to cluster the pixels to obtain the foreground and background region in RGB colour space. This output is provided to a Fire fly algorithm to better optimize the thresholds used in K means and improves the segmentation [50], In another approach, a GrabCut algorithm is used to segment the foreground, and the lesion segment is fine-tuned using K means clustering algorithm[53]. Few researchers have used Fuzzy algorithms [51], in which Fuzzy C-Means algorithm is used for segmentation of the lesion. In few others, a Gaussian distribution and Markov Random Field are combined, and the Bayesian probability technique is used to determine whether a pixel is part of a specific region. In another approach researchers have used K-means clustering for getting an initial set of clusters and then suitable set of 10 features are calculated for each region and score for region is calculated using an ensemble of random forest and support vector regression [54].

Threshold based approaches either use a global threshold, or adaptive threshold. Due to the complexity in dermoscopic images, defining a suitable threshold is a very difficult activity. An adaptive thresholding approach using Gabor filter and PCA is used for segmentation in [55]. Another approach uses merging of texture and geometric features for segmentation [56]. Detection of anomalous growth of skin lesion using threshold-based segmentation algorithm and Fuzzy K-Nearest Neighbour classifier are used in [57]. Cross entropy based thresholding approach, and the best suitable threshold is estimated using a gaussian and gamma distribution for segmentation [58]. Histogram based thresholding methods are used by few researchers [59, 60].

In artificial intelligence based approach many researchers have used CNN based networks for skin lesion segmentation and classification. A deep CNN-based framework, with two encoders for parallel detection and recognition of the skin lesions, named Dermo-DOCTOR, is used in [61]. A modified version by same author has developed DermoExper [62], in which preprocessing steps, segmentation, rebalancing and augmentation are applied. A semantic segmentation of skin lesion using encoder and decoder architecture is proposed in DSNet publication [63]. Other deep learning based approaches are also tried by researchers. They can be grouped based on below criteria.

U-Net architecture is widely used in medical domain. Researchers have used it in its original form or modified form. Few approaches where the original Unet is used for segmentation [66,67,68]. Some with modified Unet architecture [69,70] and few customised approaches [71,72]. Residual networks use residual blocks, which are basically skip connections. The output one layer is added to the input of a future layer, which have been more accurate and faster convergence. Some researchers have implemented only on encoder [73,74,75]. Similar residual networks implemented in both encoder and decoder on in [76,77,78,79,80].

Skip connections are very effective when used in encoder-decoder architectures for segmentation tasks. These connections help in retaining the information, like boundaries, which would have been lost in a deep network kind of architecture due to up sampling and down sampling. [81,82,83]. Dense connection approaches are used in couple of research where in all the layers output are connected to all other layers output for concatenating features [84,85,86].

Dilated Convolution or atrous convolution, is a technique that expands the kernel (input) by inserting holes between its consecutive elements. In simpler terms, it is the same as convolution but it involves pixel skipping, so as to cover a larger area of the input [87,88]. A spatial separable convolution simply divides a kernel into two, smaller kernels. The most common case would be to divide a 3×3 kernel into a 3×1 and 1x3 kernel [89,90]. A Global Convolutional Network, or GCN, is a semantic segmentation building block that uses a large kernel to help perform classification and localization tasks simultaneously [91]. Factorization can be used to break a higher dimensional convolution into a sequence of effectively lower dimensional convolutions which has a lower computational complexity and approximately the same result [92].

In order to handle multi scale capabilities, image pyramids, with multiple resolution images are passed on to the network [93,94]. Researchers have used single resolution image, with multiple varying dilated convolutions or multiple filters with varying kernel sizes [95,96]. Alternatively, researchers have adopted pyramid pooling for handling multi scale images [97]. Attention mechanism is adopted to differentiate between lesions and normal skin [92,95,98]. Recurrent convolutional neural network and Convolutional LSTM approaches are used in [99]. Ensemble techniques, wherein researchers have used multiple deep learning models to segment the lesions are used in [100 87, 101]. Multi task networks, where multiple models are used to do segmentation and classification in sequence [102, 97, 103,104,105]. GAN Model only be used for generating image, but also directly applied to enhance segmentation models [81, 88, 106,107]. Here a generator takes a dermoscopic image as input, and outputs the segmentation, and the discriminator is a CNN which tries to compare the generated segmentation output with ground truth data.

Approaches, by combining preprocessing and post processing with CNN, by using feature information to the model, like shape, colour, texture, additional segmentation mask, applying filters have been explored by few researchers [108,109,110,111,112,113]. Transformers Models have shown promising performance in image segmentation as well [114,115,116,117].

2.4 Classification

Skin lesion classification approaches can be grouped into two categories, machine learning based and deep learning based approaches.

In machine learning based approaches, suitable features are very essential for accurate classifica-tion. Lesion features can generally be organized into different categories: shape, colour variation, texture analysis, and other. Below are listed few features which are used for classification of the skin lesion while using traditional machine learning techniques.

Border irregularity features are used in [118,119,120]. Skin lesions which are cancerous are asymmetric as compared to a benign birth mark. Asymmetry features were extracted and used for classification in [121, 122]. Statistical approaches like maximum, minimum, mean, and variance of the intensities of the pixels inside the lesion segment, skewness, and entropy features used in [123, 124]. Histogram based features are used in [125,126]. Generalized co-occurrence matrices features are used in [127,128]. Texture-based features are explored in [129,130,131,132,133]. Post feature extraction, selection of suitable feature and dimensionality reduction is also a crucial step before classification [134,135,136]. Post a suitable feature is selected, classification is done based on the information extracted from the features. SVM based classification is one of the widely used approach [137,138,139,140,141]. KNN based approaches [142,143,144], AdaBoost [145, 146], Decision tree method [147,148], Random forest [147], LDA [138] ,Naive Bayes [148] , K Means clustering [147] are reported in the literature.

Machine learning based approach requires lot of feature engineering. Extracting suitable features from dermoscopic images is a complex activity. However, deep learning approaches do not need the feature engineering step and have also shown higher performance as compared to machine learning approaches. Deep Learning based methods are mostly based upon CNN architecture. Most of the approaches use a pre-trained model and fine tune them with skin lesion datasets.

Few pre trained models used are MobileNet, DenseNet, VGGNet [151] and it variants VGG16 [152,153], VGG19 [154,155], GoogleNet [156,157], AlexNet[158], ResNet [159], Custom architecture are also created [160, 161].

2.5 Datatsets

The dataset from the following sources were used by researchers:

1. International Skin Imaging Collaboration (ISIC) Dataset: University of Queensland, Hospital Clinic de Barcelona, Medical University of Vienna, Memorial Sloan Kettering Cancer Center, Melanoma Institute Australia, and the University of Athens Medical School.
2. Non-ISIC Dataset: The Seoul National University Hospital, Inje University Hospital, and Hallym University Hospital clinical photos were used to produce the SNU dataset. The PAD-UFES-20 dataset comprises 2298 pictures, 1641 skin lesions, and 1373 individuals for six distinct diagnoses, including three skin disorders and three skin malignancies. 58.4% of all skin lesions, including all skin malignancies, have been confirmed by biopsy. The University Medical Center Groningen (UMCG) Department of Dermatology's digital picture library contains 70 melanoma and 100 naevus photos. These photographs are part of the MED-NODE Dataset, which was utilized in the creation and testing of the MED-NODE system for skin cancer identification from macroscopic images. There are 376 light fields in the SKINL2 dataset that were collected in comparable circumstances. Melanoma / C43 Melanocytic Nevus / D22 are the two categories that were used to categorize the photos based on the type of skin lesion and ICD code. The goal of the PH² dataset is to enable comparative studies on dermoscopic image segmentation and classification algorithms through research and benchmarking. Hospital Pedro Hispano in Matosinhos, Portugal's Dermatology Service is the source of the dermoscopic picture database known as PH². Creating a framework for evaluating and analyzing melanoma risk from dermatological photos captured with an ordinary consumer-grade camera is the aim of the skin cancer detection project. Vision and Image Processing Lab at Waterloo University is responsible for maintaining the dataset.
3. Seven regulated access datasets that need to be paid for, have official institutional ar-rangements in place, or have ethical clearance, has been listed in Table 1.

3. CHALLENGES IN EXISTING AND FUTURE WORK

- Processing challenges: Publicly available datasets are not uniform and are not captured from same device. This leads to images have different varying features. A single preprocessing algorithm may not suffice for all types of images. Various types of impediments would need different types of preprocessing algorithms for removal. Impediment removal methods when applied, may at time distort the actual lesion region, making key features being tampered. Choosing a suitable set or preprocessing algorithm for all types of impediments, and also making sure that actual lesion region is not tampered too much is essential.
- Type of melanoma: Most of the research mostly focusses on pigmented melanoma. Research opportunities in the area of Non pigmented melanoma lesion detection, segmentation and classification has to be explored further.
- Dataset Limitation: Currently the available datasets are of white skin. Though skin cancer is not very common in brown skin races, research on detection of skin cancer in brown skin cases are explorable.
- Brown skin dataset scarcity: Synthetic brown skin lesions generation from existing white skin lesion are possible opportunities. The synthetically generated brown skin images can be further used as input for developing algorithms/models for skin lesion detection, segmentation and classification.
- Other Skin diseases: Detection of non-cancerous skin diseases are less explored as compared to research on cancerous skin lesions.
- Unsupervised Learning: Unsupervised learning approaches are explored less as compared to supervised learning approaches. Unsupervised learning approaches avoids the tedious job of annotation and labelling.
- Multi disease model: Single model to handle multiple types of skin cancers and non-cancerous skin diseases are seldom researched.
- Dataset creation and Expert annotation: Creation of individual dataset by visiting clinics and capturing skin lesion images of patients and taking expert dermatologist annotation can be explored.
- Small sized skin lesions: Annotating small lesions and detecting, segmentation and classification are not accurate in current research.
- Low contrast images: Handling low contrast images are challenging and currently the accuracy of algorithms and models for low contrast images are not up to mark, and hence newer better approaches can be explored.
- Model Explainabilty: Understanding and interpreting the decision made by algorithms and models are very important. Clinical adoption is possible only when the trust of the model decision is increased. Exploring explainable models are essential.
- Multi-data set hybrid model: Current research focusses on usage of individual datasets for training and evaluation. Exploring models which can handle a combination of datasets from various sources, thereby handling more variability could be explored.
- Multimodal and non dermatoscopic dataset: Limited research is being done in images which are non dermatoscopic images, like images captured from mobiles, histopathologic images, other imaging sources. Also combining multiple types of datasets can be explored.
- Prognostic Analysis: Adoption of approaches, wherein genomic information, radiomic information, histopathologic images, dermatoscopic images, can be combined for better analysis of the stage of the

cancer and also improve the accuracy of life space expectance prediction.

- Hybrid Model: Ensemble of multiple approaches can improvise the results of skin disease detection, segmentation and classification.
- Transfer learning: Foundation models have been the trend in recent deep learning approaches. Exploring transfer learning using foundation models for segmentation can be explored. For instance, transfer learning using SAM (Segment Anything Model)
- Image based Transformer: Transformers have been very promising in NLP applications. Recent approaches have adopted transformers in image based models as well, but limited work done in this aspect.

Table 1: Seven regulated access datasets

Archive	Name	Year of dataset publication	Imaging modality	Image format	Number of skin lesion categories included	Number of participants	Number of images
ISIC archive	ISIC 2020 Hospital Clinic Barcelona42	2020	Dermoscopic	DICOM or .jpg	2	356	7311
	ISIC 2020 University of Queensland42	2020	Dermoscopic	DICOM or .jpg	Not reported	304	8449
	ISIC 2020 Medical University Vienna42	2020	Dermoscopic	DICOM or .jpg	2	432	4374
	ISIC 2020 Memorial Sloan Kettering Cancer Centre42	2020	Dermoscopic	DICOM or .jpg	5	523	11 108
	ISIC 2020 Sydney Melanoma Diagnosis Centre and Melanoma Institute Australia42	2020	Dermoscopic	DICOM or .jpg	8	441	1884
	BCN20,000	2019	Dermoscopic	.jpg	9	Not reported	12 413
	HAM10,000	2018	Dermoscopic	.jpg	8	Not reported	10 015
	2018 JID editorial images	2018	Macroscopic	.jpg	3	Not reported	100

ISIC challenge only	ISIC 2020 challenge test set42	2020	Dermoscopic	DICOM or .jpg	Not reported	690	10 982
	ISIC 2019 challenge test set	2018 and 2019	Dermoscopic	.jpg	Not reported	Not reported	8238
	ISIC 2018 test set (tasks 1 and 2)26	2018	Dermoscopic	.jpg	Not reported	Not reported	1000
Non-ISIC datasets	PAD-UFES	2020	Macroscopic	.png	6	1373	2298
	PH2	2013	Dermoscopic	.bmp	3	Not reported	200
	Derm7pt 7-point criteria evaluation database46	2018	Dermoscopic and macroscopic (paired)	.jpg	15	1011	2013
	MED-NODE	2015	Macroscopic	.jpg	2	Not reported	170
	SKINL2	2019	Light field photographs, dermoscopic photographs (paired)	.png	8	Not reported	814
	SNU dataset	2018	Macroscopic	.png	81	Not reported§	240
	University of Waterloo dataset	Not reported	Macroscopic	.jpg and .png for contours	2	Not reported	206
Regulated access datasets	Asan dataset50**	2017	Macroscopic	Not reported	12	4867	17 125
	Hallym dataset50	2017	Not reported	Not reported	1	106	152
	DERMOFIT Image Library: Edinburgh dataset	Not reported	Not reported	Not reported	10	Not reported	1300
	IMA205	2018	Not reported	Not reported	Not reported	Not reported	Not reported
	MoleMapper app patient photos	2017	Macroscopic	Not reported	2	2069	2422

	SNU dataset entire test set10 (2201 images)	2018	Macroscopic	Not reported	134	1608	2201
	Severance dataset (test subset)54	2020	Macroscopic	Not reported	43	10 426	40 331

4. DISCUSSION

Overall, the way skin diseases are detected and treated might be completely changed by incorpo-rating research findings into web portals, mobile health applications, and clinical support tools. These applications have the potential to improve patient outcomes and save healthcare costs re-lated to skin diseases by using technology to improve diagnostic capabilities and enable early de-tection. To optimize their influence on patient care, it is imperative to guarantee the precision, dependability, and accessibility of these instruments. To fully realize the potential of these appli-cations in clinical practice, additional research and development is required to address issues in-cluding algorithm robustness, validation, and regulatory considerations.

5. CONCLUSION

In conclusion, there are many different and intricate difficulties in the field of skin lesion detec-tion, segmentation, and classification. These difficulties include methodological, technological, and dataset-related aspects. It will take interdisciplinary cooperation and the investigation of novel strategies to overcome these challenges. In order to address current issues, this paper offers a thorough analysis of skin lesion analysis techniques and suggests possible directions for further research. The goal is to use deep learning and machine learning approaches to improve the effi-ciency and accuracy of skin lesion recognition and classification, which will ultimately help with early skin condition diagnosis and treatment.

6. REFERENCES:

[1] Korotkov, K., & Garcia, R. (2012). Computerized analysis of pigmented skin lesions: a review. Artificial intelligence in medicine, 56(2), 69-90. https://doi.org/10.1016/j.artmed.2012.08.002.

[2] Abbas, Q., Celebi, M. E., & García, I. F. (2011). Hair removal methods: A comparative study for dermoscopic images. Biomedical Signal Processing and Control, 6(4), 395-404. https://doi.org/10.1016/j.bspc.2011.01.003

[3] Friedman, R. J., Rigel, D. S., & Kopf, A. W. (1985). Early detection of malignant melanoma: the role of physician examination and self-examination of the skin. CA: a cancer journal for clinicians, 35(3), 130-151. https://doi.org/10.3322/canjclin.35.3.130

[4] MacKie, R. M. (1989). Malignant Melanoma: A Guide to Early Diagnosis: Including Advice on Differential Diagnosis, Management and Prevention. Cancer Research Campaign.

[5] MacKie, R. M. (1990). Clinical recognition of early invasive malignant melanoma. BMJ: British Medical Journal, 301(6759), 1005. https://doi.org/10.1136/bmj.301.6759.1005

[6] Argenziano, G., Fabbrocini, G., Carli, P., De Giorgi, V., Sammarco, E., & Delfino, M. (1998). Epiluminescence microscopy for the diagnosis of doubtful melanocytic skin lesions: comparison of the ABCD rule of dermatoscope and a new 7-point checklist based on pattern analysis. Archives of dermatology, 134(12), 1563-1570. https://doi.org/10.1001/archderm.134.12.1563

[7] Hubert Pehamberger, Andreas Steiner, Klaus Wolff, In vivo epiluminescence microscopy of pigmented skin lesions. I. Pattern analysis of pigmented skin lesions, Journal of the American Academy of Dermatology, Volume 17, Issue 4, 1987, Pages 571-583, ISSN 0190-9622, https://doi.org/10.1016/S0190-9622(87)70239-4.

[8] Argenziano, G., Soyer, H. P., Chimenti, S., Talamini, R., Corona, R., Sera, F., ... & Kopf, A. W. (2003). Dermoscopy of pigmented skin lesions: results of a consensus meeting via the Internet. Journal of the American Academy of Dermatology, 48(5), 679-693. https://doi.org/10.1067/mjd.2003.281

[9] Ritchie, H., & Roser, M. (2018). Causes of Death. https://ourworldindata.org/causes-of-death

[10] Siegel, R. L., Miller, K. D., Wagle, N. S., & Jemal, A. (2023). Cancer statistics, 2023. Ca Cancer J Clin, 73(1), 17-48. https://doi.org/10.3322/caac.21763

[11] Giesey, R. L., Mehrmal, S., Uppal, P., & Delost, G. (2021). The global burden of skin and subcutaneous disease: a longitudinal analysis from the Global Burden of Disease Study from 1990-2017. SKIN The Journal of Cutaneous Medicine, 5(2), 125-136. https://jofskin.org/index.php/skin/article/view/1125

[12] Naqvi, M., Gilani, S. Q., Syed, T., Marques, O., & Kim, H. C. (2023). Skin Cancer Detection Using Deep Learning—A Review. Diagnostics, 13(11), 1911. https://www.mdpi.com/2075-4418/13/11/1911

[13] Dobre, E. G., Surcel, M., Constantin, C., Ilie, M. A., Caruntu, A., Caruntu, C., & Neagu, M. (2023). Skin cancer pathobiology at a glance: a focus on imaging techniques and their potential for improved diagnosis and surveillance in clinical cohorts. International Journal of Molecular Sciences, 24(2), 1079. https://www.mdpi.com/1422-0067/24/2/1079

[14] Kaiserman, I., Rosner, M., & Pe'er, J. (2005). Forecasting the prognosis of choroidal melanoma with an artificial neural network. Ophthalmology, 112(9), 1608-e1.

https://www.sciencedirect.com/science/article/abs/pii/S0161642005006056

[15] Huang, S., Yang, J., Fong, S., & Zhao, Q. (2020). Artificial intelligence in cancer diagnosis and prognosis: Opportunities and challenges. Cancer letters, 471, 61-71. https://www.sciencedirect.com/science/article/abs/pii/S0304383519306135

[16] Cadet, J., & Douki, T. (2018). Formation of UV-induced DNA damage contributing to skin cancer development. Photochemical & Photobiological Sciences, 17(12), 1816-1841. https://link.springer.com/article/10.1039/c7pp00395a

[17] PRISMA: Transparent reporting of systematic reviews and meta-analyses http://www.prisma-statement.org/

[18] Wen, D., Khan, S. M., Xu, A. J., Ibrahim, H., Smith, L., Caballero, J., ... & Matin, R. N. (2022). Characteristics of publicly available skin cancer image datasets: a systematic review. The Lancet Digital Health, 4(1), e64-e74. https://www.thelancet.com/journals/landig/article/PIIS2589-7500(21)00252-1/fulltext

[19] Hoshyar, A. N., Al-Jumaily, A., & Hoshyar, A. N. (2014). The beneficial techniques in preprocessing step of skin cancer detection system comparing. Procedia Computer Science, 42, 25-31. https://www.sciencedirect.com/science/article/pii/S1877050914014677

[20] Lee, T., Ng, V., Gallagher, R., Coldman, A., & McLean, D. (1997). Dullrazor®: A software approach to hair removal from images. Computers in biology and medicine, 27(6), 533-543. https://doi.org/10.1016/S0010-4825(97)00020-6

[21] Schmid, P. (1999). Segmentation of digitized dermatoscopic images by two-dimensional color clustering. IEEE Transactions on Medical Imaging, 18(2), 164-171. https://doi.org/10.1109/42.759124

[22] Fleming, M. G., Steger, C., Zhang, J., Gao, J., Cognetta, A. B., & Dyer, C. R. (1998). Techniques for a structural analysis of dermatoscopic imagery. Computerized medical imaging and graphics, 22(5), 375-389. https://doi.org/10.1016/S0895-6111(98)00048-2

[23] Schmid-Saugeona, P., Guillodb, J., & Thirana, J. P. (2003). Towards a computer-aided diagnosis system for pigmented skin lesions. Computerized Medical Imaging and Graphics, 27(1), 65-78. https://doi.org/10.1016/S0895-6111(02)00048-4

[24] Chung, D. H., & Sapiro, G. (2000). Segmenting skin lesions with partial-differential-equations-based image processing algorithms. IEEE transactions on Medical Imaging, 19(7), 763-767. https://doi.org/10.1109/ICIP.2000.899419

[25] Xie, F. Y., Qin, S. Y., Jiang, Z. G., & Meng, R. S. (2009). PDE-based unsupervised repair of hair-occluded information in dermoscopy images of melanoma. Computerized Medical Imaging and Graphics, 33(4), 275-282. https://doi.org/10.1016/j.compmedimag.2009.01.003

[26] Barcelos, C. A. Z., & Pires, V. B. (2009). An automatic based nonlinear diffusion equations scheme for skin lesion segmentation. Applied Mathematics and Computation, 215(1), 251-261. https://doi.org/10.1016/j.amc.2009.04.081
https://doi.org/10.1016/j.amc.2009.04.081

[27] Criminisi, A., Pérez, P., & Toyama, K. (2004). Region filling and object removal by exemplar-based image inpainting. IEEE Transactions on image processing, 13(9), 1200-1212. https://doi.org/10.1109/TIP.2004.833105

[28] Wighton, P., Lee, T. K., & Atkins, M. S. (2008, March). Dermascopic hair disocclusion using inpainting. In Medical Imaging 2008: Image Processing (Vol. 6914, pp. 735-742). SPIE. https://doi.org/10.1117/12.770776

[29] Zhou, H., Chen, M., Gass, R., Rehg, J. M., Ferris, L., Ho, J., & Drogowski, L. (2008, March). Feature-preserving artifact removal from dermoscopy images. In Medical Imaging 2008: Image Processing (Vol. 6914, pp. 439-447). SPIE. http://dx.doi.org/10.1117/12.770824

[30] Malik, S., Akram, T., Ashraf, I., Rafiullah, M., Ullah, M., & Tanveer, J. (2022). A hybrid preprocessor DE-ABC for efficient skin-lesion segmentation with improved contrast. Diagnostics, 12(11), 2625. https://doi.org/10.3390/diagnostics12112625

[31] Malik, S., Akram, T., Ashraf, I., Rafiullah, M., Ullah, M., & Tanveer, J. (2022). A hybrid preprocessor DE-ABC for efficient skin-lesion segmentation with improved contrast. Diagnostics, 12(11), 2625. https://doi.org/10.3390/diagnostics12112625

[32] Filali, Y., Ennouni, A., Sabri, M. A., & Aarab, A. (2018, April). A study of lesion skin segmentation, features selection and classification approaches. In 2018 International Conference on Intelligent Systems and Computer Vision (ISCV) (pp. 1-7). IEEE. https://doi.org/10.1109/ISACV.2018.8354069

[33] Al-abayechia, A. A. A., Guoa, X., Tana, W. H., & Jalabc, H. A. (2014). Automatic skin lesion segmentation with optimal colour channel from dermoscopic images. Science Asia, 40(1), 1-7. http://dx.doi.org/10.2306/scienceasia1513-1874.2014.40S.001

[34] Umbaugh S, Moss R, Stoecker W. Automatic color segmentation of images with application to detection of variegated coloring in skin tumors. IEEE Engineering in Medicine and Biology 1989;8(4):43–50.

[35] Mikołajczyk, A., & Grochowski, M. (2018, May). Data augmentation for improving deep learning in image classification problem. In 2018 international interdisciplinary PhD workshop (IIPhDW) (pp. 117-122). IEEE.

[36] Zunair, H., & Hamza, A. B. (2020). Melanoma detection using adversarial training and deep transfer learning. Physics in Medicine & Biology, 65(13), 135005.

[37] Chakkaravarthy, A. P., & Chandrasekar, A. (2018, March). An automatic segmentation of skin lesion from dermoscopy images using watershed segmentation. In 2018 International Conference on Recent Trends in Electrical, Control and Communication (RTECC) (pp. 15-18). IEEE.

[38] Riaz, F., Naeem, S., Nawaz, R., & Coimbra, M. (2018). Active contours based segmentation and lesion periphery analysis for characterization of skin lesions in dermoscopy images. IEEE journal of biomedical and health informatics, 23(2), 489-500.

[39] Nasir, M., Attique Khan, M., Sharif, M., Lali, I. U., Saba, T., & Iqbal, T. (2018). An improved strategy for skin lesion detection and classification using uniform segmentation and feature selection based approach. Microscopy research and technique, 81(6), 528-543.

[40] Jyothilakshmi, K. K., & Jeeva, J. B. (2014, April). Detection of malignant skin diseases based on the lesion segmentation. In 2014 International Conference on Communication and Signal Processing (pp. 382-386). IEEE.

[41] Ivanovici, M., & Stoica, D. (2012, August). Color diffusion model for active contours-an application to skin lesion segmentation. In 2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (pp. 5347-5350). IEEE.

[42] Cavalcanti, P. G., & Scharcanski, J. (2013). Macroscopic pigmented skin lesion segmentation and its influence on lesion classification and diagnosis. In Color medical image analysis (pp. 15-39). Dordrecht: Springer Netherlands.

[43] Rashid Sheykhahmad, F., Razmjooy, N., & Ramezani, M. (2015). A novel method for skin lesion segmentation. International Journal of Information, Security and Systems Management, 4(2), 458-466.

[44] JaseemaYasmin, J. H., & Mohamed Sadiq, M. (2012). An improved iterative segmentation algorithm using canny edge detector with iterative median filter for skin lesion border detection. International Journal of Computer Applications, 50(6), 37-42.

[45] Singh, L., Janghel, R. R., & Sahu, S. P. (2021). SLICACO: An automated novel hybrid approach for dermatoscopic melanocytic skin lesion segmentation. International Journal of Imaging Systems and Technology, 31(4), 1817-1833.

[46] Louhichi, S., Gzara, M., & Abdallah, H. B. (2018, June). Skin lesion segmentation using multiple density clustering algorithm mdcut and region growing. In 2018 IEEE/ACIS 17th International Conference on Computer and Information Science (ICIS) (pp. 74-79). IEEE.

[47] Schaefer, G., Rajab, M. I., Celebi, M. E., & Iyatomi, H. (2011). Colour and contrast enhancement for improved skin lesion segmentation. Computerized Medical Imaging and Graphics, 35(2), 99-104.

[48] Wong, A., Scharcanski, J., & Fieguth, P. (2011). Automatic skin lesion segmentation via iterative stochastic region merging. IEEE Transactions on Information Technology in Biomedicine, 15(6), 929-936.

[49] Zhou, H., Schaefer, G., Celebi, M. E., Lin, F., & Liu, T. (2011). Gradient vector flow with mean shift for skin lesion segmentation. Computerized Medical Imaging and Graphics, 35(2), 121-127.

[50] Garg, S., & Jindal, B. (2021). Skin lesion segmentation using k-mean and optimized fire fly algorithm. Multimedia Tools and Applications, 80, 7397-7410.

[51] Reddy, D. A., Roy, S., Tripathi, R., Kumar, S., De, A., & Dutta, S. (2021, December). Handling uncertainty with fuzzy lesion segmentation improves the classification accuracy of skin diseases using deep convolutional networks. In 2021 International Conference on Computational Performance Evaluation (ComPE) (pp. 451-456). IEEE.

[52] Das, S., & Das, D. (2021, October). Skin lesion segmentation and classification: A deep learning and Markovian approach. In 2021 IEEE Mysore Sub Section International Conference (MysuruCon) (pp. 546-551). IEEE.

[53] Jaisakthi, S. M., Mirunalini, P., & Aravindan, C. (2018). Automated skin lesion segmentation of dermoscopic images using GrabCut and k-means algorithms. IET Computer Vision, 12(8), 1088-1095.

[54] Alvarez, D., & Iglesias, M. (2017). k-Means clustering and ensemble of regressions: an algorithm for the ISIC 2017 skin lesion segmentation challenge. arXiv preprint arXiv:1702.07333.

[55] Thanh, D. N., Hien, N. N., Surya Prasath, V. B., Erkan, U., & Khamparia, A. (2020). Adaptive thresholding skin lesion segmentation with gabor filters and principal component analysis. In Intelligent Computing in Engineering: Select Proceedings of RICE 2019 (pp. 811-820). Springer Singapore.

[56] Bansal, N., Sridhar, S., & Priya, P. D. (2020). Improved skin lesion detection and segmentation by fusing texture and geometric features. International Journal of Applied Engineering Research, 15(12), 1116-1121.

[57] Sivaraj, S., Malmathanraj, R., & Palanisamy, P. (2020). Detecting anomalous growth of skin lesion using threshold-based segmentation algorithm and Fuzzy K-Nearest Neighbor classifier. Journal of cancer research and therapeutics, 16(1), 40-52.

[58] Rawas, S., & El-Zaart, A. (2019, October). HCET-G 2: dermoscopic skin lesion segmentation via hybrid cross entropy thresholding using Gaussian and gam ma distributions. In 2019 Third International Conference on Intelligent Computing in Data Sciences (ICDS) (pp. 1-7). IEEE.

[59] Gupta, A., Issac, A., Dutta, M. K., & Hsu, H. H. (2017, March). Adaptive thresholding for skin lesion segmentation using statistical parameters. In 2017 31st International Conference on Advanced Information Networking and Applications Workshops (WAINA) (pp. 616-620). IEEE.

[60] Pereira, J., Mendes, A., Nogueira, C., Baptista, D., & Fonseca-Pinto, R. (2015). An adaptive approach for skin lesion segmentation in dermoscopy images using a multiscale Local Normalization. In Dynamics, Games and Science: International Conference and Advanced School Planet Earth, DGS II, Portugal, August 28–September 6, 2013 (pp. 537-545). Springer International Publishing.

[61] Hasan, M. K., Roy, S., Mondal, C., Alam, M. A., Elahi, M. T. E., Dutta, A., ... & Ahmad, M. (2021). Dermo-DOCTOR: A framework for concurrent skin lesion detection and recognition using a deep convolutional neural network with end-to-end dual encoders. Biomedical Signal Processing and Control, 68, 102661.

[62] Hasan, M. K., Elahi, M. T. E., Alam, M. A., Jawad, M. T., & Martí, R. (2022). DermoExpert: Skin lesion classification using a hybrid convolutional neural network through segmentation, transfer learning, and augmentation. Informatics in Medicine Unlocked, 28, 100819.

[63] Hasan, M. K., Dahal, L., Samarakoon, P. N., Tushar, F. I., & Martí, R. (2020). DSNet: Automatic dermoscopic skin lesion segmentation. Computers in biology and medicine, 120, 103738.

[64] Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. nature, 542(7639), 115-118.

[65] Codella, N. C., Nguyen, Q., Pankanti, S., Gutman, D., Helba, B., Halpern, A., & Smith, J. R. (2016). Deep learning ensembles for melanoma recognition in dermoscopy images. CoRR abs/1610.04662 (2016).

[66] Codella, N. C., Nguyen, Q., Pankanti, S., Gutman, D., Helba, B., Halpern, A., & Smith, J. R. (2016). Deep learning ensembles for melanoma recognition in dermoscopy images. CoRR abs/1610.04662 (2016).

[67] Pollastri, F., Bolelli, F., Paredes, R., & Grana, C. (2020). Augmenting data with GANs to segment melanoma skin lesions. Multimedia Tools and Applications, 79, 15575-15592.

[68] Roja Ramani, D., & Siva Ranjani, S. (2019). U-Net based segmentation and multiple feature extraction of dermascopic images for efficient diagnosis of melanoma. In Computer Aided Intervention and Diagnostics in Clinical and Medical Images (pp. 81-101). Springer International Publishing.

[69] Tang, P., Liang, Q., Yan, X., Xiang, S., Sun, W., Zhang, D., & Coppola, G. (2019). Efficient skin lesion segmentation using separable-Unet with stochastic weight averaging. Computer methods and programs in biomedicine, 178, 289-301.

[70] Alom, M. Z., Yakopcic, C., Hasan, M., Taha, T. M., & Asari, V. K. (2019). Recurrent residual U-Net for medical image segmentation. Journal of Medical Imaging, 6(1), 014006-014006.

[71] Yuan, Y., Chao, M., & Lo, Y. C. (2017). Automatic skin lesion segmentation using deep fully convolutional networks with jaccard distance. IEEE transactions on medical imaging, 36(9), 1876-1886.

[72] Al-Masni, M. A., Al-Antari, M. A., Choi, M. T., Han, S. M., & Kim, T. S. (2018). Skin lesion segmentation in dermoscopy images via deep full resolution convolutional networks. Computer methods and programs in biomedicine, 162, 221-231.

[73] Sarker, M. M. K., Rashwan, H. A., Akram, F., Banu, S. F., Saleh, A., Singh, V. K., ... & Puig, D. (2018). SLSDeep: Skin lesion segmentation based on dilated residual and pyramid pooling networks. In Medical Image Computing and Computer Assisted Intervention–MICCAI 2018: 21st International Conference, Granada, Spain, September 16-20, 2018, Proceedings, Part II 11 (pp. 21-29). Springer International Publishing.

[74] Baghersalimi, S., Bozorgtabar, B., Schmid-Saugeon, P., Ekenel, H. K., & Thiran, J. P. (2019). DermoNet: densely linked convolutional neural network for efficient skin lesion segmentation. EURASIP Journal on Image and Video Processing, 2019(1), 1-10.

[75] Yu, L., Chen, H., Dou, Q., Qin, J., & Heng, P. A. (2016). Automated melanoma recognition in dermoscopy images via very deep residual networks. IEEE transactions on medical imaging, 36(4), 994-1004.

[76] He, X., Yu, Z., Wang, T., & Lei, B. (2017). Skin lesion segmentation via deep RefineNet. In Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support: Third International Workshop, DLMIA 2017, and 7th International Workshop, ML-CDS 2017, Held in Conjunction with MICCAI 2017, Québec City, QC, Canada, September 14, Proceedings 3 (pp. 303-311). Springer International Publishing.

[77] Venkatesh, G. M., Naresh, Y. G., Little, S., & O'Connor, N. E. (2018). A deep residual architecture for skin lesion segmentation. In OR 2.0 Context-Aware Operating Theaters, Computer Assisted Robotic Endoscopy, Clinical Image-Based Procedures, and Skin Image Analysis: First International Workshop, OR 2.0 2018, 5th International Workshop, CARE 2018, 7th International Workshop, CLIP 2018, Third International Workshop, ISIC 2018, Held in Conjunction with MICCAI 2018, Granada, Spain, September 16 and 20, 2018, Proceedings 5 (pp. 277-284). Springer International Publishing.

[78] Tu, W., Liu, X., Hu, W., & Pan, Z. (2019). Dense-residual network with adversarial learning for skin lesion segmentation. IEEE Access, 7, 77037-77051.

[79] Song, L., Lin, J., Wang, Z. J., & Wang, H. (2019). Dense-residual attention network for skin lesion segmentation. In Machine Learning in Medical Imaging: 10th International Workshop, MLMI 2019, Held in Conjunction with MICCAI 2019, Shenzhen, China, October 13, 2019, Proceedings 10 (pp. 319-327). Springer International Publishing.

[80] He, X., Yu, Z., Wang, T., Lei, B., & Shi, Y. (2018). Dense deconvolution net: Multi path fusion and dense deconvolution for high resolution skin lesion segmentation. Technology and Health Care, 26(S1), 307-316.

[81] Tu, W., Liu, X., Hu, W., & Pan, Z. (2019). Dense-residual network with adversarial learning for skin lesion segmentation. IEEE Access, 7, 77037-77051.

[82] Singh, V. K., Abdel-Nasser, M., Rashwan, H. A., Akram, F., Pandey, N., Lalande, A., ... & Puig, D. (2019). FCA-Net: Adversarial learning for skin lesion segmentation based on multi-scale features and factorized channel attention. IEEE Access, 7, 130552-130565.

[83] Zhang, G., Shen, X., Chen, S., Liang, L., Luo, Y., Yu, J., & Lu, J. (2019). DSM: A deep supervised multi-scale network learning for skin cancer segmentation. IEEE Access, 7, 140936-140945.

[84] Hasan, M. K., Dahal, L., Samarakoon, P. N., Tushar, F. I., & Martí, R. (2020). DSNet: Automatic dermoscopic skin lesion segmentation. Computers in biology and medicine, 120, 103738.

[85] Li, X., Yu, L., Chen, H., Fu, C. W., Xing, L., & Heng, P. A. (2020). Transformation-consistent self-ensembling model for semisupervised medical image segmentation. IEEE Transactions on Neural Networks and Learning Systems, 32(2), 523-534.

[86] Wei, Z., Song, H., Chen, L., Li, Q., & Han, G. (2019). Attention-based DenseUnet network with adversarial training for skin lesion segmentation. IEEE Access, 7, 136616-136629.

[87] Goyal, M., Oakley, A., Bansal, P., Dancey, D., & Yap, M. H. (2019). Skin lesion segmentation in dermoscopic images with ensemble deep learning methods. IEEE Access, 8, 4171-4181.

[88] Jiang, F., Zhou, F., Qin, J., Wang, T., & Lei, B. (2019, April). Decision-augmented generative adversarial network for skin lesion segmentation. In 2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019) (pp. 447-450). IEEE.

[89] Cui, Z., Wu, L., Wang, R., & Zheng, W. S. (2019). Ensemble transductive learning for skin lesion segmentation. In Pattern Recognition and Computer Vision: Second Chinese Conference, PRCV 2019, Xi'an, China, November 8–11, 2019, Proceedings, Part II 2 (pp. 572-581). Springer International Publishing.

[90] Canalini, L., Pollastri, F., Bolelli, F., Cancilla, M., Allegretti, S., & Grana, C. (2019). Skin lesion segmentation ensemble with diverse training strategies. In Computer Analysis of Images and Patterns: 18th International Conference, CAIP 2019, Salerno, Italy, September 3–5, 2019, Proceedings, Part I 18 (pp. 89-101). Springer International Publishing.

[91] Peng, C., Zhang, X., Yu, G., Luo, G., & Sun, J. (2017). Large kernel matters--improve semantic segmentation by global convolutional network. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 4353-4361).

[92] Sarker, M. M. K., Rashwan, H. A., Abdel-Nasser, M., Singh, V. K., Banu, S. F., Akram, F., ... & Puig, D. (2019). MobileGAN: Skin lesion segmentation using a lightweight generative adversarial network. arXiv.

[93] He, X., Yu, Z., Wang, T., Lei, B., & Shi, Y. (2018). Dense deconvolution net: Multi path fusion and dense deconvolution for high resolution skin lesion segmentation. Technology and Health Care, 26(S1), 307-316.

[94] Zeng, G., & Zheng, G. (2018). Multi-scale fully convolutional DenseNets for automated skin lesion segmentation in dermoscopy images. In Image Analysis and Recognition: 15th International Conference, ICIAR 2018, Póvoa de Varzim, Portugal, June 27–29, 2018, Proceedings 15 (pp. 513-521). Springer International Publishing.

[95] Wang, H., Wang, G., Sheng, Z., & Zhang, S. (2019). Automated segmentation of skin lesion based on pyramid attention network. In Machine Learning in Medical Imaging: 10th International Workshop, MLMI 2019, Held in Conjunction with MICCAI 2019, Shenzhen, China, October 13, 2019, Proceedings 10 (pp. 435-443). Springer International Publishing.

[96] Chen, S., Wang, Z., Shi, J., Liu, B., & Yu, N. (2018, April). A multi-task framework with feature passing module for skin lesion classification and segmentation. In 2018 IEEE 15th international symposium on biomedical imaging (ISBI 2018) (pp. 1126-1129). IEEE.

[97] Jahanifar, M., Tajeddin, N. Z., Koohbanani, N. A., Gooya, A., & Rajpoot, N. (2018). Segmentation of skin lesions and their attributes using multi-scale convolutional neural networks and domain specific augmentations. arXiv preprint arXiv:1809.10243.

[98] Fu, J., Liu, J., Tian, H., Li, Y., Bao, Y., Fang, Z., & Lu, H. (2019). Dual attention network for scene segmentation. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition (pp. 3146-3154).

[99] Azad, R., Asadi-Aghbolaghi, M., Fathy, M., & Escalera, S. (2019). Bi-directional ConvLSTM U-Net with densley connected convolutions. In Proceedings of the IEEE/CVF international conference on computer vision workshops (pp. 0-0).

[100] Bi, L., Kim, J., Ahn, E., Kumar, A., Feng, D., & Fulham, M. (2019). Step-wise integration of deep class-specific learning for dermoscopic image segmentation. Pattern recognition, 85, 78-89.

[101] Bi, L., Kim, J., Ahn, E., Kumar, A., Fulham, M., & Feng, D. (2017). Dermoscopic image segmentation via multistage fully convolutional networks. IEEE Transactions on Biomedical Engineering, 64(9), 2065-2074.

[102] Zhang, Y., & Yang, Q. (2021). A survey on multi-task learning. IEEE Transactions on Knowledge and Data Engineering, 34(12), 5586-5609.

[103] Xie, Y., Zhang, J., Xia, Y., & Shen, C. (2020). A mutual bootstrapping model for automated skin lesion segmentation and classification. IEEE transactions on medical imaging, 39(7), 2482-2493.

[104] Jin, Q., Cui, H., Sun, C., Meng, Z., & Su, R. (2021). Cascade knowledge diffusion network for skin lesion diagnosis and segmentation. Applied soft computing, 99, 106881.

[105] Al-Masni, M. A., Kim, D. H., & Kim, T. S. (2020). Multiple skin lesions diagnostics via integrated deep convolutional networks for segmentation and classification. Computer methods and programs in biomedicine, 190, 105351.

[106] Lei, B., Xia, Z., Jiang, F., Jiang, X., Ge, Z., Xu, Y., ... & Wang, S. (2020). Skin lesion segmentation via generative adversarial networks with dual discriminators. Medical Image Analysis, 64, 101716.

[107] Peng, Y., Wang, N., Wang, Y., & Wang, M. (2019). Segmentation of dermoscopy image using adversarial networks. Multimedia Tools and Applications, 78, 10965-10981.

[108] Mirikharaji, Z., & Hamarneh, G. (2018). Star shape prior in fully convolutional networks for skin lesion segmentation. In Medical Image Computing and Computer Assisted Intervention–MICCAI 2018: 21st International Conference, Granada, Spain, September 16-20, 2018, Proceedings, Part IV 11 (pp. 737-745). Springer International Publishing.

[109] Tschandl, P., Sinz, C., & Kittler, H. (2019). Domain-specific classification-pretrained fully convolutional network encoders for skin lesion segmentation. Computers in biology and medicine, 104, 111-116.

[110] Adegun, A. A., & Viriri, S. (2020). FCN-based DenseNet framework for automated detection and classification of skin lesions in dermoscopy images. IEEE Access, 8, 150377-150396.

[111] Qiu, Y., Cai, J., Qin, X., & Zhang, J. (2020). Inferring skin lesion segmentation with fully connected CRFs based

on multiple deep convolutional neural networks. IEEE Access, 8, 144246-144258.

[112] Jayapriya, K., & Jacob, I. J. (2020). Hybrid fully convolutional networks-based skin lesion segmentation and melanoma detection using deep feature. International Journal of Imaging Systems and Technology, 30(2), 348-357.

[113] Zhang, L., Yang, G., & Ye, X. (2019). Automatic skin lesion segmentation by coupling deep fully convolutional networks and shallow network with textons. Journal of Medical Imaging, 6(2), 024001-024001.

[114] Gulzar, Y., & Khan, S. A. (2022). Skin lesion segmentation based on vision transformers and convolutional neural networks—A comparative study. Applied Sciences, 12(12), 5990.

[115] Chen, J., Lu, Y., Yu, Q., Luo, X., Adeli, E., Wang, Y., ... & Zhou, Y. (2021). Transunet: Transformers make strong encoders for medical image segmentation. arXiv preprint arXiv:2102.04306.

[116] Shamshad, F., Khan, S., Zamir, S. W., Khan, M. H., Hayat, M., Khan, F. S., & Fu, H. (2023). Transformers in medical imaging: A survey. Medical Image Analysis, 102802.

[117] He, K., Gan, C., Li, Z., Rekik, I., Yin, Z., Ji, W., ... & Shen, D. (2023). Transformers in medical image analysis. Intelligent Medicine, 3(1), 59-78.

[118] Almaraz-Damian, J. A., Ponomaryov, V., Sadovnychiy, S., & Castillejos-Fernandez, H. (2020). Melanoma and nevus skin lesion classification using handcraft and deep learning feature fusion via mutual information measures. Entropy, 22(4), 484.

[119] Cavalcanti, P. G., & Scharcanski, J. (2013). Macroscopic pigmented skin lesion segmentation and its influence on lesion classification and diagnosis. In Color medical image analysis (pp. 15-39). Dordrecht: Springer Netherlands.

[120] Ramlakhan, K., & Shang, Y. (2011, November). A mobile automated skin lesion classification system. In 2011 IEEE 23rd International Conference on Tools with Artificial Intelligence (pp. 138-141). IEEE.

[121] Imtiaz, I., Ahmed, I., Jeon, G., & Muramatsu, S. (2021, December). An efficient image processing and machine learning based technique for skin lesion segmentation and classification. In 2021 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC) (pp. 1499-1505). IEEE.

[122] Mete, M., Ou, Y. L., & Sirakov, N. M. (2012). Skin lesion feature vector space with a metric to model geometric structures of malignancy for classification. In Combinatorial Image Analaysis: 15th International Workshop, IWCIA 2012, Austin, TX, USA, November 28-30, 2012. Proceedings 15 (pp. 285-297). Springer Berlin Heidelberg.

[123] Khan, M. A., Akram, T., Sharif, M., Shahzad, A., Aurangzeb, K., Alhussein, M., ... & Altamrah, A. (2018). An implementation of normal distribution based segmentation and entropy controlled features selection for skin lesion detection and classification. BMC cancer, 18, 1-20.

[124] Yildirim-Yayilgan, S., Arifaj, B., Rahimpour, M., Hardeberg, J. Y., & Ahmedi, L. (2021). Pre-trained CNN based deep features with hand-crafted features and patient data for skin lesion classification. In Intelligent Technologies and Applications: Third International Conference, INTAP 2020, Grimstad, Norway, September 28–30, 2020, Revised Selected Papers 3 (pp. 151-162). Springer International Publishing.

[125] Rastgoo, M., Garcia, R., Morel, O., & Marzani, F. (2015). Automatic differentiation of melanoma from dysplastic nevi. Computerized Medical Imaging and Graphics, 43, 44-52.

[126] Moldovanu, S., Damian Michis, F. A., Biswas, K. C., Culea-Florescu, A., & Moraru, L. (2021). Skin lesion classification based on surface fractal dimensions and statistical color cluster features using an ensemble of machine learning techniques. Cancers, 13(21), 5256.

[127] Nersisson, R., Iyer, T. J., Joseph Raj, A. N., & Rajangam, V. (2021). A dermoscopic skin lesion classification technique using YOLO-CNN and traditional feature model. Arabian Journal for Science and Engineering, 46, 9797-9808.

[128] Ballerini, L., Fisher, R. B., Aldridge, B., & Rees, J. (2012, May). Non-melanoma skin lesion classification using colour image data in a hierarchical K-NN classifier. In 2012 9th IEEE International Symposium on Biomedical Imaging (ISBI) (pp. 358-361). IEEE.

[129] Peter Soosai Anandaraj, A., Gomathy, V., Amali Angel Punitha, A., Abitha Kumari, D., Sheeba Rani, S., & Sureshkumar, S. (2021). Internet of medical things (iomt) enabled skin lesion detection and classification using optimal segmentation and restricted Boltzmann machines. Cognitive Internet of Medical Things for Smart Healthcare: Services and Applications, 195-209.

[130] Chatterjee, S., Dey, D., & Munshi, S. (2019). Integration of morphological preprocessing and fractal based feature extraction with recursive feature elimination for skin lesion types classification. Computer methods and programs in biomedicine, 178, 201-218.

[131] Rajesh, A. (2017, April). Classification of malignant melanoma and Benign Skin Lesion by using back propagation neural network and ABCD rule. In 2017 IEEE International Conference on Electrical, Instrumentation and Communication Engineering (ICEICE) (pp. 1-8). IEEE.

[132] Abbas, Z., Rehman, M. U., Najam, S., & Rizvi, S. D. (2019, February). An efficient gray-level co-occurrence matrix (GLCM) based approach towards classification of skin lesion. In 2019 amity international conference on artificial intelligence (AICAI) (pp. 317-320). IEEE.

[133] Ghalejoogh, G. S., Kordy, H. M., & Ebrahimi, F. (2020). A hierarchical structure based on stacking approach for skin lesion classification. Expert Systems with Applications, 145, 113127.

[134] Mohanty, N., Pradhan, M., Reddy, A. V., Kumar, S., & Alkhayyat, A. (2022). Integrated design of optimized weighted deep feature fusion strategies for skin lesion image classification. Cancers, 14(22), 5716.

[135] Melbin, K., & Raj, Y. J. V. (2021). Integration of modified ABCD features and support vector machine for

skin lesion types classification. Multimedia Tools and Applications, 80(6), 8909-8929.

[136] Iyatomi, H., Norton, K. A., Celebi, M. E., Schaefer, G., Tanaka, M., & Ogawa, K. (2010, August). Classification of melanocytic skin lesions from non-melanocytic lesions. In 2010 Annual International Conference of the IEEE Engineering in Medicine and Biology (pp. 5407-5410). IEEE.

[137] Javed, R., Saba, T., Shafry, M., & Rahim, M. (2019, October). An intelligent saliency segmentation technique and classification of low contrast skin lesion dermoscopic images based on histogram decision. In 2019 12th International Conference on Developments in eSystems Engineering (DeSE) (pp. 164-169). IEEE.

[138] Khan, M. A., Akram, T., Sharif, M., Saba, T., Javed, K., Lali, I. U., ... & Rehman, A. (2019). Construction of saliency map and hybrid set of features for efficient segmentation and classification of skin lesion. Microscopy research and technique, 82(6), 741-763.

[139] Batista, L. G., Bugatti, P. H., & Saito, P. T. (2022). Classification of skin lesion through active learning strategies. Computer Methods and Programs in Biomedicine, 226, 107122.

[140] Guha, S. R., & Rafizul Haque, S. M. (2020). Performance comparison of machine learning-based classification of skin diseases from skin lesion images. In International Conference on Communication, Computing and Electronics Systems: Proceedings of ICCCES 2019 (pp. 15-25). Springer Singapore.

[141] Wahba, M. A., Ashour, A. S., Napoleon, S. A., Abd Elnaby, M. M., & Guo, Y. (2017). Combined empirical mode decomposition and texture features for skin lesion classification using quadratic support vector machine. Health information science and systems, 5, 1-13.

[142] Afza, F., Sharif, M., Khan, M. A., Tariq, U., Yong, H. S., & Cha, J. (2022). Multiclass skin lesion classification using hybrid deep features selection and extreme learning machine. Sensors, 22(3), 799.

[143] Fisher, R. B., Rees, J., & Bertrand, A. (2020). Classification of ten skin lesion classes: Hierarchical knn versus deep net. In Medical Image Understanding and Analysis: 23rd Conference, MIUA 2019, Liverpool, UK, July 24–26, 2019, Proceedings 23 (pp. 86-98). Springer International Publishing.

[144] Shetty, B., Fernandes, R., Rodrigues, A. P., Chengoden, R., Bhattacharya, S., & Lakshmanna, K. (2022). Skin lesion classification of dermoscopic images using machine learning and convolutional neural network. Scientific Reports, 12(1), 18134.

[145] Mporas, I., Perikos, I., & Paraskevas, M. (2020). Color models for skin lesion classification from dermatoscopic images. In Advances in Integrations of Intelligent Methods: Post-workshop volume of the 8th International Workshop CIMA 2018, Volos, Greece, November 2018 (in conjunction with IEEE ICTAI 2018) (pp. 85-98). Springer Singapore.

[146] Satheesha, T. Y., Satyanarayana, D., Prasad, M. G., & Dhruve, K. D. (2017). Melanoma is skin deep: a 3D reconstruction technique for computerized dermoscopic skin lesion classification. IEEE journal of translational engineering in health and medicine, 5, 1-17.

[147] Dhivyaa, C. R., Sangeetha, K., Balamurugan, M., Amaran, S., Vetriselvi, T., & Johnpaul, P. (2020). Skin lesion classification using decision trees and random forest algorithms. Journal of Ambient Intelligence and Humanized Computing, 1-13.

[148] Ozkan, I. A., & Koklu, M. (2017). Skin lesion classification using machine learning algorithms. International Journal of Intelligent Systems and Applications in Engineering, 5(4), 285-289.

[149] Afza, F., Sharif, M., Mittal, M., Khan, M. A., & Hemanth, D. J. (2022). A hierarchical three-step superpixels and deep learning framework for skin lesion classification. Methods, 202, 88-102.

[150] Celebi, M. E., & Zornberg, A. (2014). Automated quantification of clinically significant colors in dermoscopy images and its application to skin lesion classification. IEEE systems journal, 8(3), 980-984.

[151] Lopez, A. R., Giro-i-Nieto, X., Burdick, J., & Marques, O. (2017, February). Skin lesion classification from dermoscopic images using deep learning techniques. In 2017 13th IASTED international conference on biomedical engineering (BioMed) (pp. 49-54). IEEE.

[152] Anand, V., Gupta, S., Altameem, A., Nayak, S. R., Poonia, R. C., & Saudagar, A. K. J. (2022). An enhanced transfer learning based classification for diagnosis of skin cancer. Diagnostics, 12(7), 1628.

[153] Swathi, B., Kannan, K. S., Chakravarthi, S. S., Ruthvik, G., Avanija, J., & Reddy, C. C. M. (2023, July). Skin Cancer Detection using VGG16, InceptionV3 and ResUNet. In 2023 4th International Conference on Electronics and Sustainable Communication Systems (ICESC) (pp. 812-818). IEEE.

[154] Abuared, N., Panthakkan, A., Al-Saad, M., Amin, S. A., & Mansoor, W. (2020, November). Skin cancer classification model based on VGG 19 and transfer learning. In 2020 3rd International Conference on Signal Processing and Information Security (ICSPIS) (pp. 1-4). IEEE.

[155] Volkan, K. A. Y. A., & AKGÜL, İ. (2023). Classification of skin cancer using VGGNet model structures. Gümüşhane Üniversitesi Fen Bilimleri Dergisi, 13(1), 190-198.

[156] Barman, S., Biswas, M. R., Marjan, S., Nahar, N., Hossain, M. S., & Andersson, K. (2022, September). Transfer Learning Based Skin Cancer Classification Using GoogLeNet. In International Conference on Machine Intelligence and Emerging Technologies (pp. 238-252). Cham: Springer Nature Switzerland.

[157] Yilmaz, E., & Trocan, M. (2021). A modified version of GoogLeNet for melanoma diagnosis. Journal of Information and Telecommunication, 5(3), 395-405.

[158] Nurlitasari, D. A., Fuadah, R. Y. N., & Magdalena, R. (2022, June). Skin Cancer Classification Systems Using Convolutional Neural Network with Alexnet Architecture. In Proceedings of the 2nd International Conference on Electronics, Biomedical Engineering, and Health Informatics: ICEBEHI 2021, 3–4 November, Surabaya, Indonesia (pp. 227-236). Singapore: Springer Nature Singapore.

[159] Rasel, M. A., Obaidellah, U. H., & Kareem, S. A. (2022). convolutional neural network-based skin lesion classification with Variable Nonlinear Activation Functions. IEEE Access, 10, 83398-83414.

[160] Khan, M. A., Zhang, Y. D., Sharif, M., & Akram, T. (2021). Pixels to classes: intelligent learning framework for multiclass skin lesion localization and classification. Computers & Electrical Engineering, 90, 106956.

[161] Camacho-Gutiérrez, J. A., Solorza-Calderón, S., & Álvarez-Borrego, J. (2022). Multi-class skin lesion classification using prism-and segmentation-based fractal signatures. Expert Systems with Applications, 197, 116671.

[162] De Logu, F., Ugolini, F., Maio, V., Simi, S., Cossu, A., Massi, D., ... & Laurino, M. (2020). Recognition of cutaneous melanoma on digitized histopathological slides via artificial intelligence algorithm. Frontiers in oncology, 10, 565026.

[163] https://masced.uk/abcde-of-melanoma.htm

[164] www.dermatologyinpractice.co.uk_data_diged_87_ DIP19-1.pdf

[165] Ghazvinian Zanjani, F., Zinger, S., Piepers, B., Mahmoudpour, S., Schelkens, P., & de With, P. H. (2019). Impact of JPEG 2000 compression on deep convolutional neural networks for metastatic cancer detection in histopathological images. Journal of Medical Imaging, 6(2), 027501-027501.

[166] Malik, S., Akram, T., Awais, M., Khan, M. A., Hadjouni, M., Elmannai, H., ... & Tariq, U. (2023). An Improved Skin Lesion Boundary Estimation for Enhanced-Intensity Images Using Hybrid Metaheuristics. Diagnostics, 13(7), 1285.

[167] Liu, L., Mou, L., Zhu, X. X., & Mandal, M. (2020). Automatic skin lesion classification based on mid-level feature learning. Computerized Medical Imaging and Graphics, 84, 101765.

[168] Hasan, M. K., Ahamad, M. A., Yap, C. H., & Yang, G. (2023). A survey, review, and future trends of skin lesion segmentation and classification. Computers in Biology and Medicine, 106624.

[169] Mirikharaji, Z., Abhishek, K., Bissoto, A., Barata, C., Avila, S., Valle, E., ... & Hamarneh, G. (2023). A survey on deep learning for skin lesion segmentation. Medical Image Analysis, 102863.