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A Review on Skin Disease Classification and Detection Using Deep Learning Techniques

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Abstract— Skin cancer ranks among the most dangerous cancers. Skin cancers are commonly referred to as Melanoma. Melanoma is brought on by genetic faults or mutations on the skin, which are caused by Unrepaired Deoxyribonucleic Acid (DNA) in skin cells. It is essential to detect skin cancer in its infancy phase since it is more curable in its initial phases. Skin cancer typically progresses to other regions of the body. Owing to the disease's increased frequency, high mortality rate, and prohibitively high cost of medical treatments, early diagnosis of skin cancer signs is crucial. Due to the fact that how hazardous these disorders are, scholars have developed a number of early-detection techniques for melanoma. Lesion characteristics such as symmetry, colour, size, shape, and others are often utilised to detect skin cancer and distinguish benign skin cancer from melanoma. An in-depth investigation of deep learning techniques for melanoma's early detection is provided in this study. This study discusses the traditional feature extraction-based machine learning approaches for the segmentation and classification of skin lesions. Comparison-oriented research has been conducted to demonstrate the significance of various deep learning-based segmentation and classification approaches.

Keywords- Melanoma, computer vision, segmentation, classification, literature review.

I. INTRODUCTION

Melanoma is among the most common and harmful cancers. The American Cancer Society predicts that there were around 100,350 newly diagnosed cases of melanoma and 6850 deaths from the condition in 2020. Several cancers besides melanoma additionally cause a large number of fatalities [1]. The World Health Organization (WHO) estimates that 2-3 million non- melanoma benign tumors and 132,000 melanoma skin cancers are reported annually globally [2]. As per the predictions made by the American Cancer Society regarding the prevalence of skin cancer in the nation in 2023, [3]:

- There will be approx. 99,780 newly discovered skin cancers (57,180 in males and 42,600 in females).
- Almost approx. 7,650 people are expected to die from melanoma. (2,570 females and 5,080 males).

White complexion people have a higher chances of melanoma frequency that is over 20x than that of African Americans (Dark complexion). White populace had a 2.6% (1 in 38) lifelong risk of having skin cancer, compared to 0.1% (1in 1,000) for dark skin people and 0.6% (1 in 167) for Hispanics[3]. In accordance with the Indian Council of Medical Research's (ICMR) 2021 report, India has a lower probability of melanoma in contrast to other countries worldwide. The study investigated information from India's Population-Based Cancer Registry and was published in the Journal of Cancer Research and Therapeutics. They found that the highest incidence—5.14 for men and 3.98 for women —was in the northern region of India. Men in the Eastern region had a greater frequency of 6.2 [4].

Melanoma can, however, be easily removed to guarantee complete healing with early discovery and diagnosis. In cases ofearly diagnosis, survival rates approach 95%, but in cases of late detection, survival rates are fewer than 20% [6]. Therefore, for the early detection and treatment of skin diseases, precise image analysis is crucial.

A. Skin Cancer and its Types

The most aggressive form of skin cancer is melanoma, and cases are rising at a rate of 4-6% per year worldwide [7]. Skin pigmentation or color scheme is produced by the melanocyte, the particles that are found above the dermis layer of the skin. Melanoma begins to set in and become a malignant tumor in specific circumstances in which cells are located, altered and enlarged out of proportion [8]. Melanoma can develop from a common skin mole. These moles exhibit visible changes in theirborder, size, shape, or color. Early-stage melanoma detection greatly increases patient survival rates and is frequently managed surgically. Anywhere on the body, including the head and the bottoms of the feet, melanoma can form. It may be somewhat red or have no color, in which case it is referred to as amelanotic melanoma. While metastatic melanoma, which invades

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blood vessels and spreads to distant parts of the body, develops deep within the skin. This might transmit malignancy to several organs, including the blood, liver, lungs, and brain [9]. feature selection, as well as categorization, shared by all artificial vision system proposals [16]. The morphological distinctions among benign skin lesions and melanoma, however, is often quite subtle, as shown in figure 2, making it challenging to tell the two cases apart, even for experienced medical professionals.

A tumor is created as the injured cells grow in number. Skin cancer is easily identifiable because it develops in many layers of the skin, typically the epidermis. Different types of skin have varying propensities to develop skin cancer. Depending on the kind and color of the skin, its occurrence varies, but it typically affects the skin that is exposed to sunlight. Additionally, skin cancer is also influenced by hereditary factors [15]. According to [10,11], Skin cancer exists in three distinct forms: basal cell carcinoma, squamous cell carcinoma, and melanoma.

a. Basal Cell Carcinoma:

The cancer basal cell carcinoma is one form of skin cancer.Basal cells, a type of skin cell that produces new cells when old ones deteriorate, are where basal cell cancer begins. Basal cell carcinoma often presents as a tiny, slightly translucent lump onthe body, even though the fact that it can appear in a variety of ways [12]. Basal cell carcinoma most usually manifests itself on the skin of your head and neck, which is exposed to the sun. The bulk of basal cell carcinomas is believed to be caused by prolonged exposure to the sun.

b. Squamous cell carcinoma:

A typical form of skin cancer called squamous cell carcinoma develops in squamous cells, which make up the middle and outer layers of the skin [13]. Skin carcinoma with squamous cells is frequently not an existing concern, despite the fact that it can be malignant. If skin squamous cell carcinoma is not treated, it might grow or extend to other regions of the system, which can have fatal effects.

c. Melanoma:

The most hazardous variety of skin cancer arises in the melanocytes, which are responsible for producing the coloring agent in the human epidermis melanin. Moreover, melanoma might manifest itself in the eyes and, very infrequently, in internal organs such as the oesophagus or nose[14].

Contrarily, melanoma is the most common kind of curable cancer and has a likelihood of success if discovered in its initial beginnings [15]. Therefore, creating computerized diagnostic tools to aid in melanoma early detection becomes essential. A few fundamentally similar image acquisition, pre-processing, segmentation, and extraction of features are examples of stages,

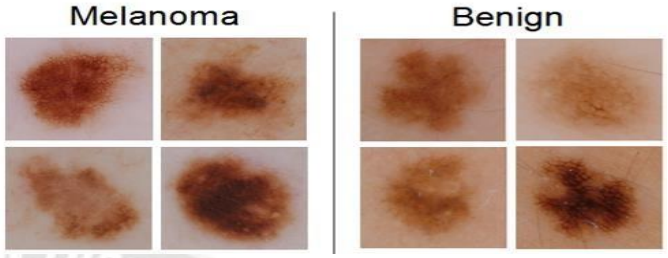

Figure 1. Perceived resemblance between melanoma and benign lesions (ISIC Dataset)

Thus, the creation of an effective Computer Aided Diagnosis (CAD) system is necessary for the identification as well as analysis of melanoma cancer. As a result, melanoma diagnoses will increase, and early identification will increase the likelihood of effective treatment and lower the disease's fatality rate.

B. Stages of Melanoma

When melanoma spreads through tissue, it develops into a malignant tumor that is challenging to treat. A complete cure is quite likely if discovered at an early stage since the malignant development happens on the skin's surface, which enables detection by a quick visual check. A mole or suspected lesion must be removed or biopsied before the melanoma stage can beconfirmed, which is unfortunate [17]. The tumor thickness, ulceration, its dissemination to nearby lymph nodes, or such to any part of the body are taken into account to establish the stage[18, 19]. The definitions of the five main melanoma stages— Stage 0, I (A/B), II (A/B/C), III, and IV—are compiled in Table1.

Table 1. Melanoma stages

Stage	**Definition**
Stage 0	Abnormal melanocytes might be identified inthe skin's outer layer (epidermis). They could develop into cancerous cells. Thisphase is known as "melanoma in situ."
Stage I	Melanoma has developed. Evaluates the ulceration and thickness. Stage IA and Stage IB are the different phases of thisstage. Stage IA: The tumor has no ulceration and is less than 1 mm thick. The creation of a skin break.

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	Stage IB: Either the tumor has ulceration but is less than 1 mm thick, or it has ulceration but isbetween 1 mm and 2 mm thick.
Stage II	Take the thickness and ulceration into account.Stage IIA, Stage IIB, and Stage IIC make up this stage. Stage IIA: Either the tumor is larger than 1 mm in thickness but not larger than 2 mm, or it is between 2 mm and 4 mm in thickness but is not ulcerated. Stage IIB: Either the tumor is more than 2 mm thick but not more than 4 mm thick and the tumor has ulceration, or it is more than 4 mm thick but does not have ulceration. Stage IIC: The tumor has ulceration and is thicker than 4 mm.
Stage III	Examine metastasis. With or without ulceration, the tumor might be of any thickness. The primary tumor could have metastasized to any number of the lymphatic system, melanoma cells could be 2 cm or more distance out of major cancer and possibly connect the minor tumors on the surface or underneath the epidermis within a 2 cm radius of the original tumor are also possible.
Stage IV	The liver, lungs, brain, and other organs, some of which may be far from the initial tumor, could all have experienced cancerous metastasis.

Table 2. Details about various imaging techniques for skin analysis

The prognosis and development of the best treatment bothrely heavily on staging. A number of procedures can be used during "staging," including a more thorough physical examination, a CT scan, an outline of lymph nodes (during which a chemical infused close to the skin cancer may be followed along with lymph vessels), a lymph node biopsy, and more. PET scan (patient is given radioactive glucose, which tumor cells absorb more of than healthy cells, making them appear brighter on the scan); Finally, blood chemistry tests (which can examine Lactate Dehydrogenase (LDH) levels in the blood collection, since elevated concentrations of LDH, may indicate the presence of skin cancer, andGadolinium-Enhanced MRI (i.e., melanoma cells appear higher by gadolinium in MRIs) (PDQ Adult Treatment Editorial Board, 2018a). Finally, the biopsy of the suspected lesion is coupled with the results of all these procedures to get the stage information. The excision is inadequate for a diagnosis of the lesion based on the surgery of melanoma cases in Stage III or Stage IV. It is much more difficult to treat it at this point, as previously indicated, and may call for therapies like chemotherapy [20], radiation therapy [21], immunotherapy [22], and targeted therapy [23]. For early-stage detection, a patient must therefore have a suspected lesion or mole checked.

C. Dermoscopy and Automation of Melanoma Detection

Melanoma can be treated successfully with a high cure rate,as was previously said, but it must be caught early. The state- of-the-art reports on a variety of non-invasive skin imaging techniques, including Confocal Laser Scanning Microscopy (CLSM), Optical Coherence Tomography (OCT), MultispectralImaging, Magnetic Resonance Imaging (MRI), ultrasound, and dermatoscopy. Table 2 compares several imaging methods from a birds-eye perspective. According to an examination of skin imaging techniques, dermatoscopy is far more effective at detecting skin cancer since it produces a picture of the skin that is typically 10 times more magnified than what can be seen with the naked eye.

Table 2. Details about various imaging techniques for skin analysis

	Advantages	**Limitations**	**Penetration Depth**
Multispectral Imaging	Limited frequency Stability	Inadequate depth information and imaging inthe Z-axis	0.1–1 mm
CLSM	gh definition Create 3D structures	Tiny structures	0.3 mm
Ultrasound	High-pitched ultrasound (100 MHz) Continuous observation	Calculate theskin's thickness and penetration depth	1 mm
MRI	Calculate the thickness or volume. Tissueinformatio nand depth.	MRIs cannotbe performedon patients who have metal insidetheir bodies.	Total body penetration
OCT	More precise resolution (5–15 m) Lack of coherenceTissue Organization	Restrictions tothin tumors (strongly scattered epidermic tissue) Low resolution	0.5–1.5 mm

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	Display a 3D image		
Dermoscopy	Superior-quality Effective lighting setup Deeper Visibility Levels Eliminate surface reflection	Skin's outermostlayer	2mm

Dermoscopy and computer-aided diagnosis technologies are currently extensively used in these applications. Skin cancer spreads rapidly, therefore deepens to other areas from head to toe, a delayed diagnosis could be fatal for the patient [31]. When melanoma is advanced, it is challenging to treat. Figure 3 depicts a slice of glowing skin and a section of the epidermis where cancer is present occurred to make it easier to understand. Melanoma starts at the outermost layer of the skin, which is made up of squamous cells at the surface, then basal cells at level 2, and finally deepest melanocyte cells [32].

Using a dermoscopy is not an intrusive procedure that examines the skin's sub-surface structures by using incident light beams and, potentially, a specific oil bath. Dermoscopy does a better job of melanoma detection than a naked eye
examination, but a dermatologist's training is still the deciding factor in a proper diagnosis [32]. Although skilled Dermoscopy is used by dermatologists during operations, differentiating skin cancer originating from a melanocytic lesion is difficult, particularly in the early stages. According to estimates, 75-84% of these cases correctly identify the presence of melanoma [33]. Metrics like delicacy, Dice frequency, Jaccard coefficient, uniqueness, receptivity, reliability, etc are frequently used to assess the system's performance [34] [35]. The speed and accuracy of diagnosis can both be improved using computer- aided diagnostics. In terms of color variation, asymmetry, and textural qualities, the computer can extract some information that may not be readily perceptible to the human eye. In this area of melanoma detection, several methods based on computer vision have been identified.

According to computer-based innovation, it is possible to rapidly, conveniently, and much more economically detect melanoma indications. Numerous non-invasive approaches are suggested for examining melanoma symptoms to evaluate whether skin cancer is the reason or not. The overall technique used to identify skin cancer is shown in Figure 4 and involves obtaining acquiring the pre-processed image, segregating it, removing the desired feature, and categorizing it [36].

Using a deep learning technique, a computer vision approach is the foundation of the majority of recent research. As a result, our primary focus is on deep learning-based melanoma detection methods. Recently, the field of machine learning has undergone a complete revolution thanks to deep learning. The domain of machine learning that deals with artificial neural network methods are regarded as the most complex [37]. Several techniques were influenced by the design and function of the human brain. Numerous industries, such as bioinformatics [41], reinforcement learning [39], cloud technology [40], and voice recognition [38], employ deep learning techniques. In these applications, deep neural networks have outperformed other conventional machine learning techniques in terms of the results they have generated. Many deep-learning approaches have been used recently to improve computer-based melanoma diagnosis. In this study, we comprehensively review and discuss deep learning-based approaches for melanoma detection.

II. LITERATURE SURVEY

The recognition, segmentation, and characterization of modern melanoma approaches are briefly discussed in this section. As was previously mentioned, the main focus of contemporary techniques is automated dermoscopic image analysis of skin lesions. Various strategies have been created and extensively researched for automated melanoma detection. Decision trees, artificial neural networks, and basic thresholding techniques for segmentation are some examples of the more well-known ones [42, 43]. There was, however, scant information at the time. The scant images available were either taken using standard cameras or as digital slides, which is why there are so few of them. This presented a challenge for two reasons. A system couldn't be trained to recognize an illness with multiple variations since there wasn't enough data. Second, due to the technology's limitations and the available data, the majority of a lesion's features (textures, boundaries, etc.) could not be identified or detected. Even though the suggested approach did not require a phase of development, the latter in particular was a severe issue.

Dermoscopy's development was a pivotal moment. Dermatologists and visual investigators can take and gather images of a lesion that is brightly lighted and significantly enlarged using dermoscopy. By introducing multiple details and key features to the photos that were being acquired, this advancement significantly improved the visual quality of the data that was being collected and so resolved the issue of data scarcity. The early 2000s saw the emergence of publicly accessible melanoma databases with the growth of

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dermoscopy. The International Skin Imaging Collaboration (ISIC) Archive and PH2 are the only publicly accessible datasets, though (ISIC, 2017b). Recent advances in automated melanoma detection research have been made thanks to these databases.

A melanoma case can be automatically identified from a dermoscopic image in three main stages. When a skilled dermatologist examines a lesion visually, these stages closely match the diagnostic outcomes and characteristics of the lesion. A broad schematic illustration for a sketch of both problems is shown in Figure 5, with the three main processes being (i) Lesion Segmentation, (ii) Clinical Feature Segmentation, and
(iii) Feature Synthesis, Selection, and Classification [44]. Please be aware that the bias is transforming quickly and is fact progressing, therefore state-of-the-art approaches might not strictly adopt including using these steps, for example, a few phases may be skipped or consolidated.

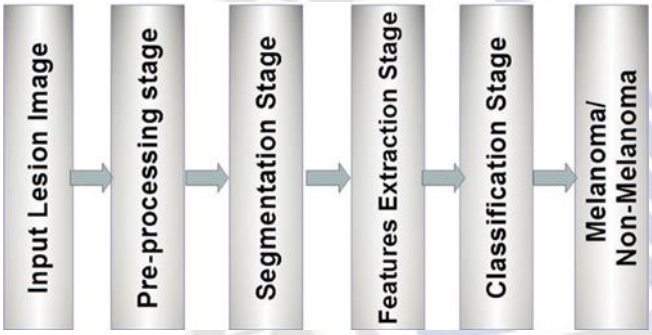

Figure 2. Phases for the categorization of Melanomas

The current methodology used to complete these phases for the categorization of melanomas is discussed in this article,though.

A. Image Pre-Processing Stage

Pre-processing is frequently recommended as a method for improving segmentation results, however, it slows down the processing. In addition, the majority of segmentation techniques now in use rely heavily on pre-processing techniques, and determining the parameters necessary to fit the varied characteristics of input images can be challenging. The diverse characteristics of dermoscopic pictures frequently impede the correct melanoma categorization. The varied characteristics incorporate the presence of undesirable artifacts including hairs, capillary arteries, color charts, ruler lines, marker inks, vignettes, noise, uneven lighting, and dazzling reflections caused by the dermoscopy image collection techniques. A large portion of fragmentation techniques now in use rely heavily on various pre-processing stages to avoid the final results of undesirable artifacts that can jeopardize the precise segmentation of skin lesions. The correct fragmentation of melanoma in dermoscopic images can suffer greatly from the occlusion caused by unwelcome artifacts [45]. The destruction of many artifact techniques about occlusion in manually segmented images has been developed as a result of this problem. The thresholding [46, 47], morphology [48, 49],
filtering [50], and Dull Razor [16, 51, 52]-based artifact removal techniques are discussed below.

Dermoscopic images have low intensity and non-uniform lighting, which is also commonly corrected using image enhancement pre-processing techniques. These enhancement techniques are built on the principles of contrast adjustment [50, 53], filtering [53, 54, 55], Adaptive Histogram Equalization [49, 56], and Contrast-Limited Adaptive Histogram Equalization (CLAHE) [57, 58, 59]. The CLAHE islargely acknowledged as the top technique among the currently used enhancement techniques for preparing medical images. Additionally, research has demonstrated the existence of pre- processing phases rely on histogram [33], mean subtraction [31], deep learning [34], multi-scale decomposition [21], adaptive gamma correction [23], Z-score transformation [52], and Frangi Vesselness filter [41]. Before segmentation and post-processing techniques are used to reduce residual noise, usually, methods for feature extraction and image improvementare used.

B. Lesion Segmentation

In the workflow of robotic melanoma analysis, sectioning is a difficult and critical element. To identify the purpose of skin cancer, shape information including size, symmetry, boundary delineation, and irregularity is crucial. An image is segmented when it is divided up into relevant regions. In particular, semantic segmentation gives each region the proper class labels. The task is typically binary when dealing with skin lesions, i.e., separating the lesion from the surrounding skin. Lighting and contrast problems, inherent exist in different, artifacts, and the diversity of imaging, as well as inter-class parallelism and intra- class variations methods employed make automated skin lesionsegmentation difficult.

Consistency and other conventional image processing and machine learning techniques served as the foundation for categorization, active contours, region growth, and unsupervised clustering before the Deep Learning (DL) revolution. These methods rely on manually created attributes that seem to be hard to build and frequently constrict discriminatory and inconsistent capability from the start. Consequently, similar traditional

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sectioning techniques can struggle to handle larger and more complicated information. However, DL not only manages but demands larger datasets since it seamlessly blends feature extraction and task-specific decision-making.

Many semantic segmentation tasks now use deep learning approaches as conventional baselines, particularly CNN. The majority of CNN's innovations came from its capacity to learn significantly greater characteristics which are harder beyond typical raw picture features as well as hierarchies. The most recent CNN segmentation architectures, Fully Convolutional Neural Network (FCN), U-Net, SegNet, and DeepLab [22] are a few examples, among others. Due to their superior capacity to learn from a variety of datasets, researchers have recently begun using Cognitive categorization of melanomas using a Deep convolutional neural network. The ensuing paragraphs provide a review of a few cutting-edge techniques based on CNN.

The symmetric encoders and decoders of the U-Net neural network have demonstrated outstanding results in the medical imaging industry. The U-Net is made up of symmetric extendedpathways for localization and contracted paths for capturing feature information. High-resolution data is transmitted via the U-Net using skip links between encoders and decoders of similar quality. The U-Net architecture's ability to skip connections is arguably its most inventive feature. The network skipping connection layer [77] can regain these spatial characteristics that pooling procedures have lost [78]. Wei et al.

[78] presented an Att-DenseUnet network based on U-Net that combined dense net and U-attention Net's mechanics, producing positive outcomes in the excision of melanoma. Ibtehaz et al [79] in-depth analysis of the U-Net model resultedin the proposal of a unique U-Net architecture called the biomedical segmentation process has effectively employed MultiResUNet.

Mechanisms of attention are essential for human perception. Humans are equipped with focusing techniques that process them to choose wisely and concentrate on important knowledge skills disregarding inconsequential data. Deep CNN can learn more quickly, extract more important and distinct characteristics for the target job, strengthen the routing protocol robustness, and is still greater suited to tiny processing collection of information the concentration component was helpful. When the squad behind Google Deep Mind was working on a categorization of images job, they made the initial proposal for the attention mechanism, which spurred a wave of attention mechanism research. Focus-Net is an FCN that conducts segmenting a diagnostic image using extracted features produced by a different convolutional autoencoder. Kaul et al. [80] suggested a way for incorporating attention into an FCN. By explicitly modeling the dependencies between channels, Hu et al. [18] claimed that SENet calibrates filtered component reactions adaptively. The SE-Net squeeze-and- excitation module was subsequently further expanded by Woo et al. [81]. A compact, all-purpose module called theConvolutional Block Attention Module (CBAM) is what the creators suggest. Based on a provided intermediate feature map,it can perform adaptive feature refining with almost minimal computing overhead. The organization of a few common attention modules in network topology is shown in Figure 6. Allof the aforementioned strategies, however, begin with the same focal point.

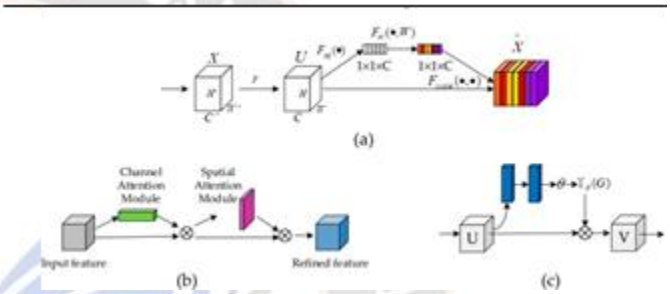

Figure 3. Several common attentional network structures (the left to the right Specifically, SENet [82], CBAM [81], and SpatialNet [83])

Convolutional Block Attention Module (CBAM), in which (a) the primary concentration is on channel connections among image input features, (b) the major emphasis is on combining spatial and multichannel consideration, and (c) the main focus is on spatial correlations among feature representation.

By combining categorization and fragmentation, Xie et al [67] MB-DCNN suggested improving melanoma clustering quality. In a bootstrapping manner, each activity assists the others. A coarse Segmentation Network (coarse-SN) and a Segmentation Connectivity directed by a mask both receive and exchange coarse masks and location data using this technique (mask-CN). A Deep Extreme Cut (DEXTR) model was suggested by Manini et al. [68] that uses inordinate points (vertices of the curves) in addition to the initial RGB images to feed the network's information. They have demonstrated that merging these two can enhance the effectiveness of categorization by illustration even if this method necessitates entering critical examples, whose quality affects the fractionation's effectiveness. By exploiting the illumination invariant of various tissues, Abhishek et al. [69] created a unique technique that enhances skin lesion semantic segmentation. They merged data from shading-attenuated images, particular color regions, and imagesin grayscale with constant illumination.

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Wu et al [70] Feature Adaptive Transformer Network (FAT-Net), which is based on the conventional encoder-decoder design, successfully captures global context data and distant dependencies by incorporating an additional transformer branch. The characteristic fusing between the characteristics at different levels is improved using their method, which employs a feature adaption a memory-efficient parser, and a component. In this manner, they switch on the productive channels and reactivate the unimportant background noise. When used for image super-resolution, the Laplacian Pyramid Super- Resolution Network (LapSRN) developed by Lai et al. [71] is competent to gradually rebuild the high-resolution image sub- band residuals. The elevated values are estimated using coarse-resolution image features as the intake.

A two-stage attention method for segmenting skin lesions was suggested by Azad et al. [72]. In order to capture the relationship between the channels, they assigned a weight for each channel based on a collection of feature maps. This context-gating mechanism network might emphasize channels that are more educational and significant, similar to bi-directional techniques [73]. Furthermore, they integrate the several Atrous convolutional layers using a second-level attention approach, which enables using the connection to concentrate on a perspective more concerned with goals. For the skin lesion segmentation challenge, Liu et al. [74] made use of supplementary information depending on the edge prediction method. Using a component for the cross-connection layer, the network was made to concentrate on the segmentation task's boundary region. Each task's intermediate feature maps were passed into the other task's sub-blocks using this component. Researchers also utilized a multi-scale characteristic aggregating component to enhance the performance of the network by utilizing different scale features. Multi-scale Residual Encoding and Decoding fusion (MS RED), which allows for the adaptive fusion of multi-scale information, was used by Dai et al. [75] to segment a variety of skin lesions. Additionally, to increase the ability to learn the visual features, they recommended a multi-resolution and multi-channel feature fusion component. They deployed a brand-new pooling module (Soft-pool) throughout the down-sampling phases that preserve more beneficial data and improved segmentation efficiency. The inability of these multi-level fusion tactics to combine different-level features due to their weak aggregation strategies is a major drawback. For each known class, Bi et al. [76] trained a separate CNN model, allowing them to take advantage of the category data. The result of segmentation was refined using a Step-wise Integration (PSI) model built on creating a hierarchy approach.

C. Skin Cancer Classification

The goal of the machine-learning community has long been to categorize skin lesions. The clinical examination makes utilization of computerized categorization of lesions to aid doctors and enable quick, low-cost access to life-saving diagnoses. For the detection and diagnosis of lesions, high-performance CAD systems are required. For the creation of a CAD system, feature selection is an essential process. Traditional machine learning techniques required some effort to select the proper features for automatically identifying photos of pigmented skin lesions. Similarly, the classification rate is significantly impacted by mistakes and deleted information.

a. Traditional Machine Learning

The authors in [84] employed the rule Asymmetry, Border, Color, and Diameter (ABCD) to assess the location, size, and hue of melanomas. A Multilayer Perceptron Network (MLP) based on instruction by the training algorithm was used to classify the features. Geodesic active contours with a Gabor filter were employed in [85] for the image, and hair removal. Following that, features were extracted using the ABCD scoring technique. Finally, to classify lesions, several currently utilized techniques were combined. According to three different values for lesion thickness, the authors of [86] categorized melanoma. Lesions were categorized using two different classification schemata: the first divided lesions into thinner or thicker categories, and the next into thinner, moderate, and extensive categories. Artificial Neural Networks and logistic regression were coupled for classification. A band in the RGB color space was individually improved for lesions in [87]. Following segmentation based on a deformable model, these lesions were finally divided. [88] suggested a Chan-Vese model-based segmentation technique. The partitioned areas' characteristics were extracted using ABCD after the images had first been improved with an isotropic diffusion filter. Using a support vector machine, these features were categorized (SVM). Using Para-consistent Logic (PL) annotated with two parameters, because, the authors of [89] suggested a classification scheme for BCC and MEL. The levels of evidence, the pattern of formation, and the diagnosis comparison were retrieved to differentiate among "regular,""BCC," and "MEL", and the spectra values of 30, 96, and 19, respectively, were employed. To remove the ternary ROI mask, a Delaunay triangulation was employed [90]. The histological images were segmented by the authors of [91] by removing the granular layer boundary, and only two lesions were classified using the intensity profiles.

A self-generated utilized a neural network [92] to remove

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the lesion. Then, the illustrative border, texture, and color elements were eliminated. To categorize depending mostly on the lesion collected a system of classifiers using characteristics that combines Utilizing fuzzy neural network models a Back Propagation (BP) utilized a computational model. To improve and segregate skin lesions, [93] employed a network of finite capacity wavelets. The quest of symmetric pairing towards d- optimality was then used to categorize these attributes. Khodadadi et al [94] examination of the uneven Lyapunov exponent and Kolmogorov-Sinai entropy are used to determine the perimeter of an infectious melanoma. was based on a chaotic time series analysis of the boundary. Three distinct aspects of skin lesions, including simple geometric shapes, proportional hues, and surface aspects, were used in [95] in order to divide melanomas into ant colonies. Finally, two classifiers— Artificial Neural Network (ANN) and K-nearest neighbor— classified these features (KNN). The authors of [96] merged several traits after segmenting them using ABCD based on form and color. These features were then categorized and put to the test both separately and together. The creation of a variety of characteristics for every person individually was done in [97] using the Histogram of Gradients (HOG) and the Histogram of Lines (HL). characteristics of color and pattern for spotting skin lesions were extracted from the bag of features. Utilizing third Zernike moments, color characteristics were retrieved. depending on characteristic modification using the optimization technique, Roberta et al. [98] suggested a method for diagnosing skin lesions. Multispectral lesion analysis using fractal techniques was suggested by Przystalski et al. [99]. The Grab-Cut algorithm and k-means were combined in Jaisakthi et al [100] segmentation approach for skin lesions. A technique for melanoma detection using a smartphone was introduced by Do et al. [101]. Images were captured with a smartphone camera. The optimum processing technique that was compatible with cell phones was then sought after. This strategy was used to categorize a skin lesion using a equations numerically and a classification based technique characteristics. Wavelet transform, curvelet transforms, and Local Binary Patterns (LBP) are used in the feature extraction approach presented by Adjed et al. [102]. An SVM was used to categorize the retrieved characteristics at the end. Lesion images were segmented by fabric properties according to Hosseinzade [103]. The Gabor filter was used to define fabric qualities, and k-means were used to categorize these characteristics.

Particle Swarm Optimization (PSO) was improved by Tan et al.

[104] for optimizing the purpose of optimizing skin lesion features. The scientists updated two PSO methods used to choose discriminant features; the first model carried out a thorough later find by segregating lesions into a search term using lesion characteristics and distinct sections. For random acceleration coefficients, the second modified PSO was used. Different categorization techniques were then used to categorize these traits. Based on highly discriminative traits, Tajeddin et al. [105] divided cutaneous melanoma into different categories. Researchers began with contour transmission for lesion classification. Applying Daugman's rearrangement in log-polar form, lesions were MapReduce - based upon it periphery from which features were extracted. Finally, various classifiers were contrasted. The prevalence of the structure Frequency vector generated from dermoscopy images was used by the authors in [106] to categorize skin lesions. Fourier transform infrared analysis of skin cells was used by Pearanda et al. [107] to categorize skin lesions. Finally, a study was carried out to identify the appropriate impacts by using the perturbations that affected the outcomes. A technique for categorizing predicated on the Grey Level co- occurrence Abnormal situation for melanomas was suggested by Wahba et al. [108]. Through feature extraction utilizing ABCD and cumulative level-difference mean, they attempted to distinguish between four lesions. The SVM was then used to categorize these features. To distinguish between melanoma and dysplastic tumors, Zakeri et al. [109] suggested a CAD system. To detect edges, the grey-level co-occurrence matrices were modified. Eventually, an SVM was used to categorize these attributes.

b. Deep Learning-Based Classification

The thickness of lesions was used by Monedero et al. [110] to use the Breslow index to identify melanoma. To categorize lesions into five kinds, GoogleNet was used to classify the lesion' derived structure, size, pigmentation structure, and color characteristics. To extract several skin lesion traits, Hagerty et al. [111] combined robust learning with traditional image processing. The retrieved characteristics from deep learning and conventional image processing were integrated and blended. The classification of lesions was completed using the newly created features. A residue is a complex detachable deep convolutional network that was proposed by Sarkar et al. [112] to categorize melanoma. Based on the Discrete Wavelet Transform (DWT) technique, the Contrast Limited Adaptive Histogram Equalization (CLAHE) replaced the non-local implies filter. Melanomas are divided into three categories. was proposed by Zhang et al. [113] utilizing an attentiveness differential retraining CNN model. The deep model has 50

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layers altogether, which is comprised offour residual blocks. A technique for detecting skin lesions that can be categorized as benign or malignant was introduced by Albahar [114]. A CNN model with seven layers was his suggestion. He also suggested using the weight matrix's standard deviation as a regularisation strategy to limit the complexity of the classifier.

González-Dáz [115] unveiled DermaKNet, a skin lesion CAD system that makes use of CNN. The writer proceeded by placing a phase modification over through the outputs of the convolutional ResNet50 layer before proposing the CNN. It was simultaneously worked on two pooling layers (AVG and Polar AVG). CNN's final layer used three fully connected layers. The asymmetrical block is placed first before the third completely linked component, though, since melanoma grows differently. To find the various melanoma growth strategies, the asymmetry block was employed. Kawahara et al. [116] suggested a CNN- based system for classifying skin lesions that could handle several jobs at once. The suggested CNN can categorize the seven factors on the melanoma checklist. Images of skin lesionsand patient meta-data were categorized using the suggested CNN skin lesion diagnosis. A melanoma categorization system utilizes Yu et al. [117] suggested CNN and the localized description embedding approach. ResNet50 and ResNet101were applied to the images to determine the lesion characteristics. The ResNet features were then retrieved and utilized to create a Fisher Vector (FV) that represented the entire image. Eventually, classification was accomplished using an SVM and a Chi-squared kernel. CNN was suggested as a categorization system for skin cancer by Dorj et al. [118]. The Error-Correcting Output Codes (ECOC) SVM was used to categorize the wavelet transforms after the features had been extracted using the pre-trained Alex-Net.

A classification approach for cutaneous neoplasms (cancer) utilizing CNN was proposed by Gavrilov et al. [119]. Transfer learning was used with conception V3 (Googlenet). Consequently, the emergence of website and smartphone applications has enabled patients to appraise their lesions and provide a tentative diagnostic using images they have taken independently. An approach for categorizing illnesses of the facial skin was suggested by Chen et al. [120]. To categorize five skin conditions affecting the face, they employed three CNN models with transfer learning. A cloud- based platform was used to develop the suggested model.

Tan et al. [121] adopted PSO to segment skin lesions. Spiraling investigation effort, probabilistic dispersion, recombination, and modification; the Firefly Algorithm (FA); were some of the techniques they used to try to optimize PSO. K-Means was employed to improve lesion segmentation. CNN's development made use of the Hybrid Learning PSO (HLPSO). Lesions could be divided into melanoma and nevus according to the classification scheme. For image segmentation, Khan et al [122] deep pre-trained CNN model has ten layers, whereas, for feature extraction, a bespoke CNN had ten layers. The next phase involves defining features using the Improved Moth Flame Optimization (IMFO) algorithm. Leveraging the Investigation of multiple-set evidence-based practice, the chosen features were fused, and the Kernel Extreme Learning Machine (ELM) classifier was utilized to categorize them. Melanoma categorization and identification were suggested by Tschandl et al. [123] by integrating and expanding various CNNs. Three well-known benchmark datasets were utilized. The researchers also observed that using a sample with noise during post-processing minimized Jaccard damage. An active contour segmentation system for melanoma using morphological data was proposed by Vasconcelos et al. [124]. Various CNN models, including Deep Class-Specific Learning with Probability-based Step-wise Integration and Full-Resolution Convolutional Networks (FrCNs), were employed (DCL-PSI). Skin lesions might be categorized as melanoma andnevus using the suggested methodology.

A classification of skin lesions utilizing a CNN for the solution space that includes hill mountaineering was proposed by Kwasigroch et al. [125]. Due to the network's size being expanded, the computational cost was decreased. A network of encoders and decoders with sub-networks linked together by skip connections was suggested by Adegun et al. [126]. Segmenting skin lesions and classifying them pixel-by-pixel were done using the proposed CNN. According to Song et al. [127], CNNs are able to segment, identify, and categorize skin lesions. They used a prediction depending on the Jaccard distance and the focused loss to manage the unbalanced datasets a technique for identifying melanomas depending on fragile categorization to separate features was proposed by Wei et al. [128]. The segmentation and classification processes used a distinct lightweight CNN.

Skin lesion classification guidelines were proposed by Amin et al. [128]. Images were first improved, and then lesions were segmented using the Otsu technique and biorthogonal 2-D wavelet transformations. Ultimately, a serial fusion of two pre-trained models was performed to extract features for PCA- based categorization. Mahbod et al. [129] suggested utilizing transfer learning with trained models to examine how changing image sizes of skin lesions affect the results. A multiclass multilevel algorithm-based method for

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classifying skin lesions was proposed by Hameed et al. [130]. The suggested model was created using both conventional and deep machine-learning techniques. To reduce the categorization of melanoma result network inaccuracy, Zhang et al. [131] suggested an optimization technique for the best weight selection. As for the intention of segmenting skin lesions, Hasan et al. [132] presented a network named DSNet for semantic segmentation. Researchers employed depth-wise occurring to create an ultralight system, reducing the number of parameters, and reducing computation. A diagnostic framework for skin lesion classification systems was put up by Al-masni et al. [133] and incorporated melanoma boundary categorization with several identification stages. A Full-Resolution Convolutional Network (FrCN) of four CNN was utilized in categorization by the suggested method to segment the lesions.

III. DATASET FO SKIN LESION ANALYSIS

Many computerized approaches to a melanoma cancer diagnosis have been suggested. A strong and reliable assemblage of dermoscopic images is essential for analyzing their predictive execution and validation of anticipated outcomes. Even though the fact skin lesions or nevi lesions are in images, particular skin cancer databases have been limited and lacking in diversity. The absence of diverse data and the

Table 3. Dataset details used for the study

Dataset	Year	Modality	Class Distribution	Additional Information
DermQ uest	2012	Clinical	61 non-melanoma,76 melanoma	RGB pictures captured with multiple lenses and environment al condition
DermoFit	2013	Clinical	1224 non-melanoma,76 melanoma	RGB imagesof sizes ranging from 177x189 to 2176x2549 pixels
Pedro Hispan o Hospita l (PH2)	2013	Dermoscopy	160 benignnevi 40 melanomas	RGB imagesof sizes 553x763 to 577x769 pixels acquired at 20x magnification
ISIC2016	2016	Dermoscopy	Training:173 melanoma and 727 non-melanoma Test: 75 melanomas and 34 non-melanomas	RGB imagesof sizes ranging from 566x679 to 2848x4288 pixels
ISIC2017	2017	Dermoscopy	Training: 1626 non-melanomas,374 melanomaTest: 483 non-melanomas,	RGB imagesof sizes ranging from 540x722 to 4499x6748 pixels

The following sections provide a brief explanation of these datasets:

A. HAM10000 Dataset

The HAM10000 human-versus-machine dataset [84] consists of 10,000 training images. It addresses the scarcity of diversity problem and serves the far more recently accessible dataset on melanoma. The Dermatology Department of the Australian state of Queensland's Skin Cancer Exercise and the Medical University of Vienna in Austria contributed to the 10,015 dermoscopic images that make up the ultimate dataset of HAM10000. The compilation of this collection took twenty years. Before the widespread deployment of photography and multimedia copies of lesions were produced and maintained onfile at the Medical University of Vienna's Department of Dermatology in Austria. Several digital traces were found digitally transformed converting to 8-bit color JPEG images utilizing a Nikon Coolscan 5000-ED scanning having 300 DPI performance developed in Japan by Nikon Corporation. Subsequently, the images are digitally cropped and published at a 72 DPI pixelation of 800 by 600 pixels. An automated semi- spy approach was created utilizing using a computational model of various communities after the images experienced a variety of capture functions and cleaning methodologies.

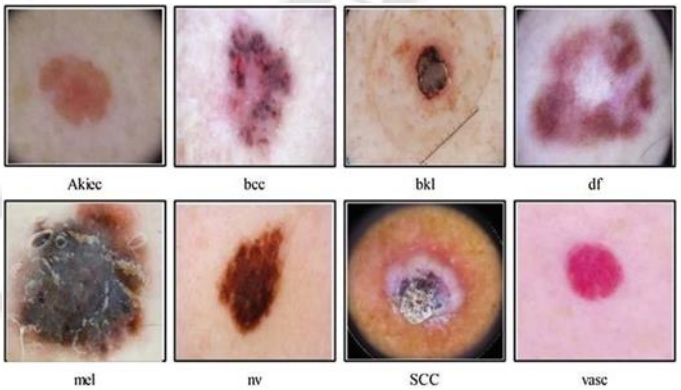

Figure 4. Sample Images of HAM10000 dataset

a. Dataset

The Dermatology Center of Pedro Hispano Hospital in Portugal is where the dermoscopic images for said PH2 dataset were retrieved [85]. The identical settings and a 20x magnification rate were used to obtain these images using Tuebinger Mole-Analyzer equipment. The PH2 data comprises images with an 8-bit RGB color depth and a 768

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× 560 pixels dimension. 200 dermoscopic images overall in the collection, 40 of which are melanoma tumors, 80 are conventional nevi, and 80 of which are normal nevi. Medically annotating the images of the lesions are included in this dataset, encompassing diagnostic categorization of pigmented skin lesions, an examination from several dermoscopy images criterion, and pathological and medical diagnostic. Dermoscopic criteria including globules of the blue-and-white veil, colors, regions of recurrence, and streaks, colors, and regression areas were utilized to accomplishthe assessment.

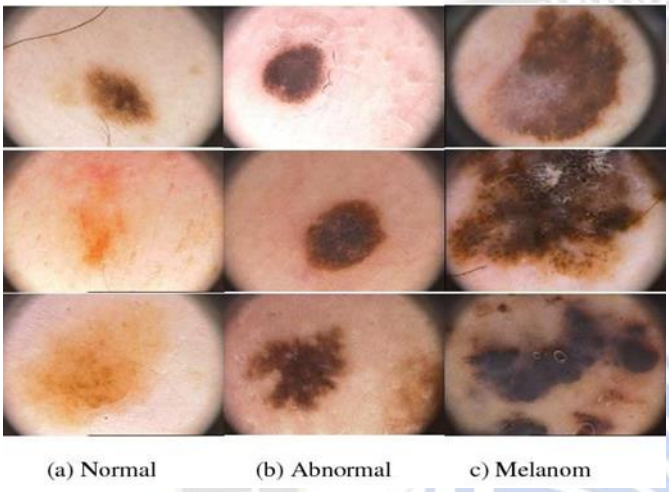

Figure 5. Sample lesions in the PH^2 dataset

b. ISIC Archive (ISIC2016, ISIC2017, ISIC2018, ISIC2019)

Dermatological lesion datasets are included in the ISIC archive [86]. The International Skin Imaging Collaboration initially unveiled the ISIC dataset at the 2016 International Symposium on Biomedical Imaging (ISBI) challenge, which was designated as ISIC 2016. Training and testing are segregated into separate compartments of the ISIC2016 repository. ISIC comprises 379 dermoscopic images in the testing subset and 900 images in the training subset. Malignant melanomas and benign nevi are depicted by images from two distinct categories. The collection includes melanoma lesions in images in around 30.3% of images, whereas the majority are benign nevi.

ISIC has initiated a technological issue for the creation of an algorithm for automated melanoma detection, and it grows the number of images in its repository annually. Three types were present of image classifications in the ISIC2017 dataset: benign nevi, Seborrheikeratoses (SK), and melanomas. 150 training images out of 2000 for validation further 600 test images have comprised the dataset. 1372 benign nevi, 254 SK images, and 374 melanomas images are included in the training dataset. The validation database contains 78 benign nevus images, 42 SK images, and 30 melanoma images. The test includes a set of 393benign nevus images, 90 SK images, and 117 melanoma images. 12,594 training images, 100 validation images, and 1000 test images overcompensate ISIC2018. The 25331 images in the ISIC2019 database reflect eight distinct kinds of Various skin lesions, including SCC, BCC, AK, melanoma, melanocytic nevus, dermatofibroma, and benign keratosis properly identify. It contains an unexpected outlier classification it did not appear in the instruction examples and 8239 the testing dataset's images. Such images need to be easily recognizable by the proposed learning melanoma detection techniques. Images from the ISIC2019 dataset also have correlated information, including the identity, birth date, and locality of the individual.

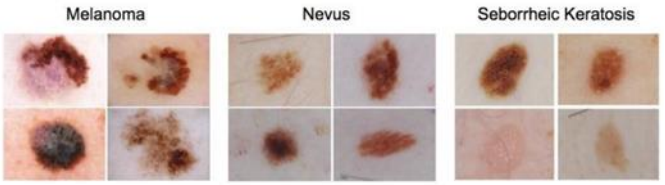

Figure 6. Images from the ISIC2019 dataset

c. DermQuest

22,082 dermoscopic images were part of the DermQuest dataset, which was made accessible to the general public [87]. The only dataset with lesion tags for skin lesions throughout all dermoscopic datasets was DermQuest. For just about every image in the collection, there have been 134 attributes for lesions. Derm101 received the database from DermQuest in 2018. On the contrary, this database was deactivated on December 31, 2019.

d. DermIS

Dermoscopic data set: The abbreviation DermIS is used to refer to the dermatology information system [88]. Departments of Clinical Social Medicine of the Universities of Heidelberg and Erlangen, respectively, and the Department of Dermatology collaborated to develop this dataset. There seem to be 6588 images in it. A pediatric Dermatology Online Image Atlas (DOIA) and a Pediatric Dermatology Online Image Atlas (PeDOIA) have recently been segregated in this dataset. Around 600 dermatological diagnoses are depicted by the 3000 lesion images in the DOIA. It provides details on almost all kinds of skin conditions, encompassing case studies, comparative and tentative diagnoses on dermoscopic images, and other aspects.

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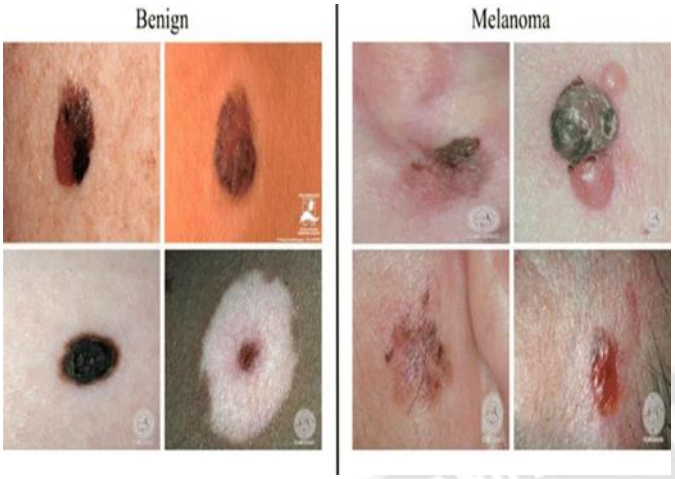

Figure 7. Benign ad melanoma lesions

e. AtlasDerm

AtlasDerm is renowned for the dataset from the Atlas of Dermoscopy [89]. It is an inventive and well-structured fusion of a CD-ROM featuring images from a book practice examples for learning. It was reportedly developed as a resource to facilitate medical practitioners in generating diagnoses of melanoma and detecting melanoma-related dermoscopic parameters. The AtlasDerm dataset requires taking into consideration a broad range of skin lesion cases, each one with corresponding dermoscopic images. It includes 30 images of vascular skin lesions, 582 images of skin lesions and 275 images of melanocytic nevi, 70 images of benign keratoses, 70 images of benign cellular carcinoma, and 5 images each of benign keratoses, dermatofibromas, and benign keratoses.

f. Dermnet

The terminology "Dermnet" pertains to the Dermnet Skin Disease Atlas dataset [90]. Dr. Thomas Habif It was created in 1998 in Portsmouth, New Hampshire. Featured are more than 23,000 dermoscopic images. Images of 643 distinct forms of skin conditions may be discovered in this database. A two-level taxonomy has been developed to classify these disorders physiologically. A total of 600 skin disorders are represented in fine granularity on the lowest level. There are 23 separate kinds of skin conditions included in the top-level taxonomy, including eczema, benign tumors, melanomas, moles, nevi, and connective tissue disorders, rather than more.

IV. PREFORMANCE MESUREMENT

The symbol Acc stands for accuracy, which is a measurement of the rate of accurate classification. It results from splitting the total amount of forecasts by the proportion of the right forecasts. It can be explained as follows:

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

The sensitivity analysis of the model is another parameter. Calculating the genuine ratio is possible by finding the appropriately categorized. This is comprehensible as:

$$Sensitivity = \frac{TP}{TP + FN} \quad (2)$$

The following parameter, which computes as a true negative rate and may be written as follows, shows the measurement of effectively classified data:

Next, we calculate the Precision of the suggested technique. By dividing the number of True Positives by the total number of

Positives (True and False), it is estimated.

$$P = \frac{TP}{TP + FP} \quad (5)$$

Eventually, the mean of the precision and sensitivity performance, or F-measure, is computed. It is phrased as:

$$F = \frac{2 * P * Sensitivity}{P + Sensitivity} \quad (6)$$

V. CHALLENGES IN SKIN LESION ANALYSIS

For the categorization of melanoma, several datasets were accessible. Some datasets were made available to the public, while others weren't. The number of images in various databases was determined to vary. Furthermore, several articles of confederation established their online image collection by collecting images independently.

A. Extensive Training

The lengthy development period needed for the detection of skin cancer using neural network models approaches is one of the major objections. To put it differently, the system needs to go through a thorough training process which necessitates a significant amount of time and requires incredibly powerful hardware to correctly evaluate and evaluate the dermoscopic images' characteristics.

B. Variation in Lesion Sizes

Size variations among lesions present another complication. The 1990s saw a large collection of benign and malignant melanoma lesion images gathered by an Italian and Austrian research team [73]. As high as 95% to 96% of the lesions might be accurately diagnosed [75]. But the diagnostic approach was far more challenging and error-prone when

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lesions were smaller, at 1mm or 2mm in size, specifically at earlier stages.

C. Light-Skinned Individuals Images in Common Feature sets

Images of mostly European, Australian, and American individuals with lighter-skinned, can be found in the existing standard dermoscopic datasets. A neural network is necessary to be programmed to take skin tone into account for the timely and accurate diagnosis of individuals with dark skin [76]. The neural network can only achieve this if it observes enough images of people with dark skin while being trained. Consequently, databases containing sufficient lesion images of skin lesions are needed to increase the precision of melanoma detection techniques individuals with dim and brightskin are obliged.

D. Small Interclass Variation in Skin Cancer Images

Medical images, in contrast to other types of images, exhibit extremely little interclass variance; for example, there is significantly less different depictions of cats and dogs than between images of skin cancer lesions with and without melanoma. Additionally, it might be quite challenging to differentiate a birthmark from a skin lesion. Certain illnesses have so similar lesions that it is very challenging to differentiate them. The process of image analysis and categorization is extremely difficult as a result of this constrained variation [32].

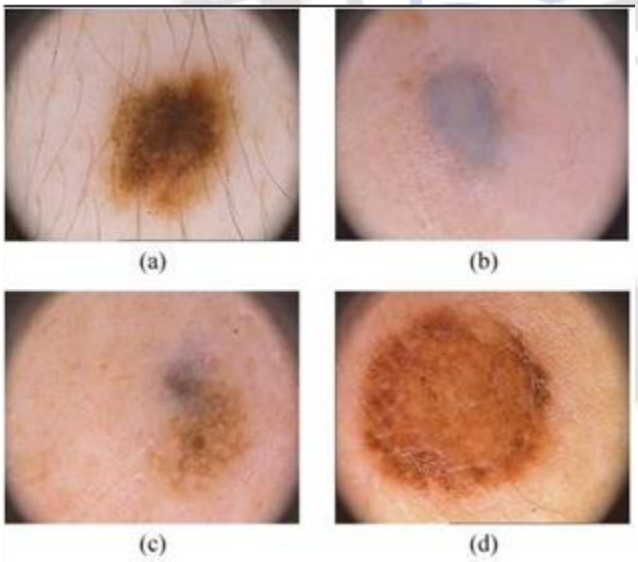

Figure 8. Difficulties of dermoscopic images; (a) presence of hair; (b) smooth transition between lesion and skin; (c) multiple colored lesions; and (d) specular reflections

E. Unbalanced Skin Cancer Datasets

The datasets from the real world that are utilized to diagnose skin cancer are quite imbalanced. For each type of skin cancer, unbalanced datasets have a considerably diverse quantity of photos. It is challenging to generalize from the dermoscopic images' visual characteristics, for instance, since they onlyinclude a small number of photos of unusual skin cancer kinds compared to hundreds of images of common skin cancer types [12].

F. Lack of Availability of Powerful Hardware

Strong technological devices with substantial Graphical Processing Unit (GPU) capabilities are required for the NN algorithm to be capable of extracting the precise parts of a lesion's picture, which is vital for gaining an enhanced skin cancer diagnosis. The absence of powerful computation is a fundamental barrier to deep learning-based skin cancer screening training.

G. Lack of Availability of Age-Wise Division of Images

Within Standard Datasets Several other skin malignancies, including Merkel cell carcinoma, BCC, and SCC, often manifest after the age of 65 [77]. Currently, available standard dermoscopic databases include pictures of children. However, neural networks must seem necessary for neural networks to seeenough images of persons over the age of 50 to accurately diagnose skin cancer in older patients.

H. Use of Various Optimization Techniques

The automated detection of skin cancer requires several key steps, including pre-processing and lesion edge detection. The efficiency of technological systems for diagnosing melanoma can be improved by investigating several optimization methods including the artificial bee colony algorithm [78], ant colony optimization [79], social spider optimization [80], and particle swarm optimization [81].

I. Analysis of Genetic and Environmental Factors

Fair skin, bright eyes, red hair, many moles on the body, and a history of melanoma in the family are just a few of the hereditary risk factors for melanoma that researchers have uncovered. The likelihood of developing skin cancer increases dramatically when certain environmental risk factors, such as prolonged exposure to UV light, are included [82]. Performance can be improved by combining these elements with current deep-learning techniques.

J. Noise and Artifacts Presence

During image acquisition, noise is the inclusion of new objects. The presence of noise and artifacts can have an impact on the ability to identify skin lesion images. These are referred to as compromising signals that were not originally visible but that may nonetheless have an impact on

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manual image interpretation approaches and even on some computer-assisted skin lesion segmentation methods. Examples include blood veins, bubbles, bubbles, and hair artifacts.

K. Irregular Boundaries

Uneven fuzzy boundaries many strategies for contour refinement and lesion boundary localization are challenged by some skin lesion images, which have hazy and uneven borders.Achieving a precise border for the skin lesion images during the pre-processing stage might occasionally be difficult to boundary predict asymmetry easily.

L. Low Contrast

Low contrast from nearby tissues does exist in some circumstances, which can cause further challenges. Accurate lesion segmentation is difficult since there is little difference between the lesion and the epidermal layer.

M. Color Illumination

Dermoscopic images can have multiple resolutions depending on how the color, texture, and light rays of the skin lesion image are illuminated.

VI. CONCLUSION

A comprehensive assessment of the evidence on the categorization and identification of melanomas is conducted inthe research in images. The processing, segmentation, and classification of skin lesion images are all covered in-depth in this examination of techniques and algorithms. We investigated deep convolutional neural network models as well as conventional machine learning techniques. It proceeded with a discussion of the known and accessible datasets and a comparison of them. Data gathering (collection), pre-processing, segmentation, feature extraction, deep learning, and final model construction are the five main components of the effective melanoma detection process. Classification and segmentation are extremely vital in this situation. As a result, we provide a thorough analysis of various strategies. Both conventional machine learning and cutting-edge deep learning techniques are explored. The intricacy and problems that other methods continue to struggle with can be handled by deep learning techniques.

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