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ANALYSIS, PREDICTION AND CLASSIFICATION OF SKIN CANCER USING ARTIFICIAL INTELLIGENCE – A BRIEF STUDY AND REVIEW

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Abstract. World Health Organization (WHO) records that skin cancer has vigorously affected people in recent decades. Worldwide, many people are affected by skin cancer, and its affected count will increase yearly. Hence, skin cancer has become a threatening disease. Skin cancer prediction at an earlier time is becoming the higher priority and most challenging task worldwide. A computer-based diagnosis is needed to perform the automatic prognosis of skin cancer. It assists dermatologists in many ways, including the prediction of skin cancer at the earlier stages, easy to diagnose and effective. Nowadays, artificial intelligence-based machine learning approaches have been implemented for an early prediction of cancer in the skin through medical images. This paper is focused on a detailed, comprehensive review of skin cancer analysis, forecast, and algorithmic-based procedures for classifying skin diseases. Moreover, this review paper focused on various stages of algorithm approaches for skin tumor detection like pre-processing data, segmenting data, feature selection, and disease classifier. This detailed review of neoplasm diseases like cancer on the skin is done based on machine and deep learning algorithms to help further research.

Key words: Skin cancer, Deep learning, Algorithmic based detection, Artificial intelligence, Machine learning, dermatologist.

1. Introduction. Analysis of health images using image processing, segmentation, and disease classification plays an essential part in skin cancer diagnosis. It assists the dermatologist in making proper decisions and earlier diagnosis of disease [48]. The Society of American Cancer reports showed that high mortality rates of cancer in the derma increase the mortality rate of patients by 75%. The highest mortality rate of melanoma increased by 14%. Similarly, based on the cancer report of the American Association in the year 2022, in the US, the mortality rate of tumor patients has steadily declined [65, 57]. Compared to the United States in China, new cancer patient cases have increased daily. Therefore, the mortality rate also increased five times [66].

Due to tremendous changes in the world's environmental situation, we noticed that many people are affected by cancer. Skin cancer causes mainly due to ultraviolet radiation (UV). In recent decades people have been vigorously affected by skin neoplasm. Skin cancer is differentiated into melanoma and nonmelanoma skin tumors. A statistical report by the American Cancer Reports that melanoma-type cancer has a high mortality rate in humans [8, 63, 15, 13]. Skin cancer is diagnosed visually using clinical screening. Then it can be analyzed by applying a biopsy procedure, histopathological images, and the Dermoscopic method [5]. This examination procedure is time-consuming, slow, and painful. Therefore, algorithmic-based diagnosis of skin cancer produces accurate, less expensive, and speedy processes [21].

Heckler et al [29] described implementing artificial intelligence concepts used in the predictive skin cancer analysis and classifying the severity of diseases. Also, this method applies the convolutional neural (CNN) network concept for differentiating skin viruses. Brinker et al. [12] described a CNN for skin cancer classification of patients along with dermatologists for speedy diagnosis. Guha et al. [59] proposed the SVM algorithm with VGGNet for predicting and classifying skin tumor cells. Attia et al. [9], presented an analysis of skin lesion images based on generative adversarial networks with realistic hair simulators.

The process of skin cancer detection using deep learning typically involves several stages. Firstly, a large dataset of annotated skin images is collected, consisting of both cancerous and non-cancerous lesions. These images serve as the training data for the deep learning model. The CNN architecture is then designed and trained on this dataset to learn the intricate patterns and features that distinguish different types of skin cancer.

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During training, the deep learning model learns to automatically extract relevant features from the skin images, allowing it to identify specific patterns associated with malignant tumors. The model is optimized by iteratively adjusting the network's weights and biases to minimize the error between the predicted and actual labels of the training data.

Once the model is trained, it can be deployed for real-time skin cancer detection. New, unseen skin images can be fed into the trained model, and it will output a prediction or probability score indicating the likelihood of malignancy. Dermatologists can then utilize these predictions as an aid in their diagnosis, combining the model's output with their clinical expertise for a more accurate assessment. The use of deep learning for skin cancer detection offers several advantages. These models have demonstrated high accuracy rates, often comparable to or even surpassing human dermatologists. They can analyze images rapidly, potentially reducing the time required for diagnosis. Deep learning algorithms can also handle large amounts of data and generalize well to new, unseen cases, making them valuable tools in screening and triage scenarios.

However, there are still challenges to overcome in this field. Deep learning models heavily rely on the availability of large, diverse, and accurately annotated datasets for training. Obtaining such datasets can be time-consuming and resource-intensive. Furthermore, the interpretability of deep learning models remains a concern, as understanding the internal workings and decision-making processes of these complex networks can be challenging.

The main motivation behind this research study is to reduce the death in skin cancer, which is curable when predicted in early stage. Many research works have been implemented in the prediction of cancer in the skin. This article is focused on a detailed, comprehensive review of skin cancer detection and algorithmic-based procedures for classifying skin diseases. As well as reviewed various processing algorithms on image data for the prediction of skin tumor cells. It also implements the various image-processing-based classification algorithms associated with detecting skin lesions and their severity.

The paper is presented as shown: Related work section on skin cancer was discussed in Section 2, and Section 3 is about an overview of skin layers and their diseases. Section 4 describes the types of skin cancer. Section 5 describes various types of algorithmic procedure for skin cancer identification, Section 6 discusses the detection of skin tumor using computer vision processing techniques, Section 7 about description of the dataset, Section 8 discuss challenges in skin cancer prediction, Section 9 discusses the performance of metric measures in the prediction of skin cancer, Section 10 finally summarizes the paper.

2. Related Work. Due to the increasing complexities, environmental changes will automatically affect human beings, and dermatological disorders arise become a significant challenging medical issue. Especially recently, skin cancer has become a significant issue and may increase the death rate. For earlier skin cancer prediction, dermatologists expect an automated model of algorithmic-based approaches. Therefore, based on the image processing techniques. A skin cancer diagnosis is a better technique to implement it.

One of the predominant tumor types is skin-related cancers, categorized into melanoma and non-melanoma. High ultraviolet (UV) exposure to sun rays is one of the reasons for skin cancer. The categories of Melanoma cancer develops the pigment cells in the skin (melanocytes). This pigment cell creates changes in your skin color. But it is most commonly found on the chest, back, or men's and women's legs. It can also affect the mouth, anus, or genital area. The reasons behind melanoma are genetic factors, fair skin, unusual moles, less body immunity, tanning beds, and excessive exposure to UV rays [33].

Long Zhang et. al [73] presents that metaheuristic optimization algorithm for skin cancer image classification using a CNN model. This classification algorithm uses a whale optimization model to improve the weight and bias value in the CNN. It is analyzed using the DermIS Digital Database and Dermquest Database datasets. This approach produces better precision values compared with other classification techniques. Amirreza Mahbod et.al [40] propose automation for lesions classification in the skin with the CNN technique for extracting the features of the tumor image and pre-trained the model using various deep models of ResNet-18, AlexNet, and VGG16 for the classification of lesions in skin; it uses an SVM classifier. Hardik Nahata et. al establish the CNN model in diagnosing and detecting tumors in the skin using images. Enhancing robustness in the image classification in skin lesions requires pre-processing data augmentation techniques. For the early diagnosis purpose, this paper implements the Transfer Learning techniques. Francesco Rundo et. al [53] proposed that an early diagnosis of skin neoplasms, or abnormal growths of cells, is essential for effective treatment and

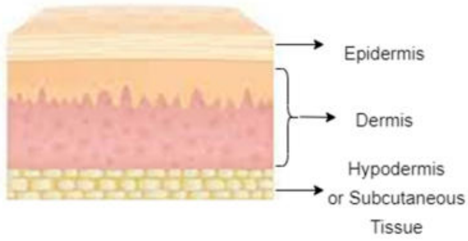

Fig. 3.1: Layers of Skin

management. Non-invasive techniques, such as deep learning CNN, can be helpful. It analysis the skin Lesion using a morphological operator. Table 2.1 shows the survey on the study of skin cancer.

In this literature review, we analyse many researches works on detecting skin cancer.The study analyse major limitation of the conventional methods. Some dataset remains small and achieving results on small datasets are not permanent. The more studies use deep learning models which proves that deep learning achieves promising results on the classifying the cancerous part in the skin. Fuzzy clustering algorithms like KFCM can be complex and challenging to interpret, making it difficult for clinicians to understand the rationale behind the classification decisions. This lack of interpretability could hinder the adoption of the approach in clinical practice. Although modified KNN is traditional classifier, sensitive applications like skin cancer prediction needs strong segmenting and classifying technique.

3. Overview of Skin Layers and Their Diseases. This section presents these in structure and discusses the outline of skin diseases. Skin is the human body's largest organ. It is formed up of multiple layers of cells and tissues that protect our parts from the environment and it guards our body against harmful things like extremely high temperatures, sunlight, etc. It consists of the dermis, hypodermis, and epidermis. This structure of the skin provides thermoregulation sensation, and protection [47, 42]. The layers of skin are shown in Figure 3.1.

The observation of Figure 3.1 shows that the outermost layer is the epidermis, which protects our body from the aggressiveness of the environment through the aegis. The dermis layer appears below the epidermis layer, composed of tough tissue, sweat glands, hair follicles, sensors, collagen fibers, and blood vessel receptors. This composition of the dermis layer provides variations in the appearance of the skin. The hypodermis/subcutaneous tissue is the skin's inner layer. This layer interconnects the layer called the dermis with muscles and bones. It protects our body from sweat, cold, and heat and regulates the body temperature [47, 41].

The main causes of skin diseases are environmental factors of temperature, harmful ultraviolet (UV) sunrays, and friction. And also depends on biological factors like allergies, viral infections, and insect bites. Due to genetic factors also, it creates skin diseases. The appearance of skin diseases is air bubbles, different forms of skin tone, hair fall in the skin, non-uniformity of skin, and so on [71]. Skin diseases are mostly because by bacterial, fungi, and viral infections. These infections include erysipelas, trauma-related infections, skin ulcers etc. These skin infections are spread further, and their severity may create health issues like fever and pain or without pain [69]. In some cases, symptoms of skin diseases are rashes; these rashes are used to diagnose certain diseases like rubella, measles, chickenpox, and erythema infectiosum [58].

4. Skin Cancers Types. Here we present the various types of skin cancer. Healthy growth cells of melanocytes will grow beyond the control, creating skin tumors. Melanoma is a tumor infection of the derma that begins in the derma cells that produce pigments called melanin. These cells are called melanocytes. It gives colors to eyes, hair, and skin. Melanoma occurs in all body parts, but it commonly occurs in skin that exposes in the sun. Sometimes skin areas not exposed to sunlight can also be affected. For example, hand palm and feet sole. Melanoma skin cancer can be cured early at the detection and diagnosis. Otherwise, it can be spread all over the body [34]. Types of melanomas are 1.Nodular, 2. Spreading superficially 3. Maligna Lentigo 4. Lentiginous in Acral, and 5. Mucosal. The non-melanoma cancer can classify as three types: 1. sebaceous gland carcinoma (SGC), 2. Basel Cell (BCC) and 3. squamous cells scarcinoma (SCC). This non-melanoma

Table 2.1: Skin cancer survey

Author	**Algorithm used**	**Diagnosis of Skin Cancer**	**Dataset**
Fu, Zexian et.al (2022)	The kernel fuzzy C-means (KFCM) is a variant of the fuzzy C algorithm, with an optimized Red Fox Optimization algorithm	melanoma using dermoscopy lesions	ISIC 2020 database
Arun Raj et.al [36] (2022)	CNN, AdaBoosting, Gradient Boosting, and Decision Tree	Melanoma	100 dermoscopicimages
Jojoa Acosta et.al [32] (2021)	Region-based CNN withResNet152	Benign/malignant	ISICdataset
Kim et.al [35] (2021)	Generative Adversarial Networks used as Unsupervised Feature Elimination	Melanoma Classification	ISICdataset
Wang et.al [64] (2021)	Random Forest, k-means,SVM and ResNet	Benign/malignant	122 malignant (i.e., cancerous) and 196 benign skin lesions(non-cancerous).
Sikkandar et.al [67] (2021)	Adaptive NeuroFuzzy (ANFC) classifier and grab cut model.	skin lesion segmentation	ISICdataset
Bumrungkun et.al [14] (2021)	Geometrical templates of gradient vector flow (GVF) and active contours are techniques used for boundary segmentation of skin cancer.	Segmentation of skin lesions(non-cancerous)	227 skin lesion images of skin cancer
Sagar et.al [54] (2020)	ResNet-50 is a CNN architecture with deep transfer.learning	Melanoma Classification of Images	ISIC dataset
Abder-Rahman Ali et.al [7] (2020)	NaiveBayes algorithm, CNN is used to detect cancer.	skin lesion segmentation	307 images from the “ISIC 2018
K Srinidhi et.al [56] (2020)	CNN model using ReLUactivation function	Detection o fmelanoma skin cancer	ISIC 2019
Nida N et.al [46] (2019)	For clustering the similarity of pixel values by fuzzy C-means clustering with Deep region-based CNN	Lipoma/ fibroma/ sclerosis/ melanoma	ISIC dataset
Albahar [5] (2019)	CNN with 2-layer architecture.	Benign/malignant	The used dataset is ISIC
Bisla, D et.al [11] (2019)	Deep convolutionalGAN	Melanoma	ISIC 2017, ISIC2018, PH2
Vijayalakshmi [62] (2019)	CNN and SVM	Malignant	ISIC dataset
Ali et.al [1] (2019)	Self-attention-basedPGAN	BCC, benign keratosis	ISIC 2018
Mendes, D.B et.al [43] (2018)	CNN with Res-Net 152architecture	Malignant melanoma and BC carcinoma	Two datasets are used. The first data set contains 170 skin images and another dataset contains 1300 skin images
Dorj et.al [22] (2018)	SVM with deep CNN	CC/ SCC/ melanoma	3753 dermoscopicimages
Rezvantalab et.al [51] (2018)	Deep CNN architecture in the version of Inception ResNet v2, Inception v3,DenseNet 201	malignant (i.e., cancerous) benign skin lesion (non-cancerous).	HAM10000 and PH2dataset
Sajid et.al [55] (2018)	Modified KNN	Automated Otsu method of thresholding for segmentation	500 lesion images

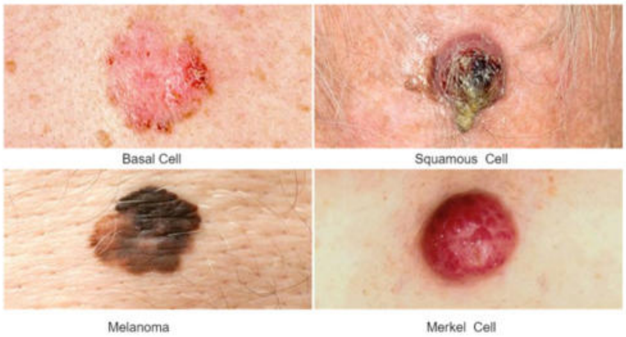

Fig. 4.1: Types of Skin Cancer

type tumor grows slowly that begin in the basal cell, that located in the lower region of the epidermis (skin-outer layer). When compared with melanoma cancer, this nonmelanoma is a curable one. Therefore, it is necessary for early skin cancer diagnosis and treatment [60]. Figure 4.1 shows the various skin tumor types.

Figure 4.1 shows four types of derma tumors Merkel cell, basal cell, Melanoma, and Squamous cell cancer.

Basal cell type carcinoma. This type of basal cell will appear in the lower epidermis as a round. It is probably in the neck and head and can be identified anywhere on the skin. The main reason this type of cancer is prevalent in areas that have sun exposure, such as the neck, face, and arms. It develops in the body and slowly spreads to the remaining parts of the body. Similarly, 80% of skin cancers belong to this type of skin cancer.

Squamous cell carcinoma. The structure of Squamous cell type carcinoma is the form of flat cells called squamous cells. This type of cancer is caused by exposure to the skin in sunlight. It can be shown in the skin as burned or injured by chemicals. Nearly 20 % of skin cancers belong to this tumor type. Similarly, this variant of Squamous cell carcinoma cancer is developed in the lips, outside the mouth, vagina, and anus. This cancer can be affected the remaining parts of the body in the ratio of 20 % to 50 %.

Merkel cell cancer. This is a rarely occurring cancer, but it is fast, aggressive growth in the skin. It is produced in the skin because of hormonal changes in the cells under the skin and also in the hair follicles. Usually, this type of skin cancer appears in the head and neck region. It is also called neuroendocrine tumors.

Melanoma Skin cancer. The cells affected by melanoma are called melanocytes, in which the epidermis meets the dermis. This cell creates the pigment, and it changes the color of the skin. It is aggressively found in skin cancer.

5. Analysis of Skin Cancer Based on Various Algorithmic Procedures. This section explains the analysis of skin cancer using different algorithms. Skin ailments are diagnosed using visual analysis of the appearance of the skin or analysis of clinical screening. For the accurate diagnosis of skin disease,algorithmic-based techniques are implemented. Figure 5.1 shows the algorithmic procedure for skin cancer analysis. Deep learning (DL) and machine learning (ML) algorithmic procedures used to analyze skin cancer diseases developed various approaches like supervised learning and unsupervised learning.

The automatic intelligent model of prediction, detection, and skin cancer diseases classifier is implemented in healthcare development, including dermatology. And it can be used to develop a model for evaluating the skin images from the dataset to analyze skin cancer. For efficient, accurate, and early skin cancer diagnosis, the DL and ML approaches were used. It saves the life of human beings and reduces the health of the patients [20]. The artificial intelligence concept can accomplish skin cancer detection, which is better than human qualities. The deep learning algorithm is used in the dataset of International Skin Image Collaboration (ISIC)-2016 for the analysis of skin diseases like benign or malignant, and it compares 100 skin lesions along with dermatologists [18]. Train the

Dermoscopic dataset with large benign lesions and melanoma images using deep learning algorithm and it uses the InceptionV4. This performance is compared and analyzed by 58 dermatologists [27].

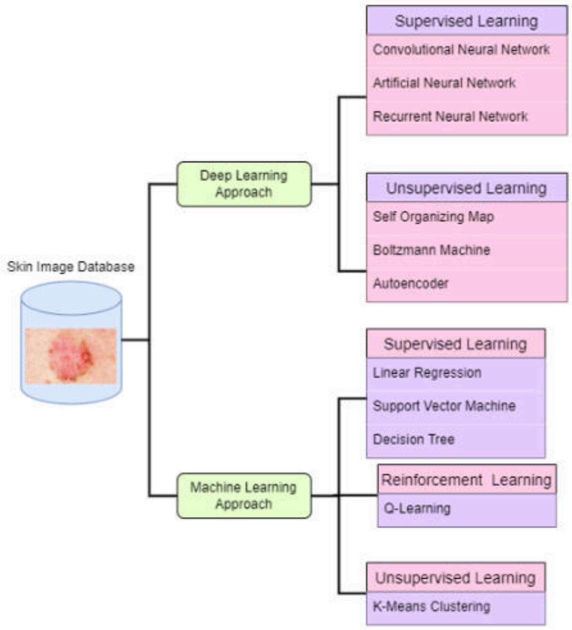

Fig. 5.1: Algorithmic Approaches for the Analysis of Skin Cancer

Figure 5.1 shows that based on the algorithmic procedure of Deep (DL) and machine learning (ML) used to analyze skin cancer diseases developed, various approaches like supervised learning and unsupervised learning. For the DL approach, CNN, ANN, and RNN come under the categories of supervised learning approach. Similarly, SOM, BM, and autoencoder are implemented in the unsupervised learning algorithm. In the machine learning algorithm, LR, SVM, and DT are implemented in supervised learning algorithms. The reinforcement learning algorithm of Q-Learning, KCM for unsupervised learning algorithm is implemented.

Unsupervised Learning Algorithm. To make effective decision-making in the skin images analysis using a training dataset this unsupervised learning algorithm is used. It trains the dataset of skin images, using DL and ML for the analysis and classification of skin tumors [50]. Unsupervised DL approaches use the techniques of an iterative procedure, thresholding, and statistical region merging [10]. High-level extraction of features from the image and classifies the input image based on its probability distribution of features. Even though it does not require an extensive training input dataset and for the medical image analysis of skin lesions implement the diffusion of brightness of the medical image which contains multiple peaks. It also has limited capacity for accurately segmenting medical images like skin lesions since their appearance is in various variations like rough skin tone, artifacts, etc. Nowadays, for the study of medical illustrations the DL and ML techniques of Restricted Boltzmann machines (RBM), Deep Boltzmann machines (DBM), Generative adversarial network (GAN) auto-encoders, Deep belief networks (DBN) are used.

Unsupervised learning algorithms play a crucial role in skin cancer detection, particularly in tasks such as clustering, anomaly detection, and feature extraction. Although supervised learning methods dominate the field of skin cancer classification, unsupervised learning techniques offer unique advantages and can complement traditional approaches. Here are a few examples of unsupervised learning algorithms used in skin cancer detection:

1. Clustering Algorithms: Clustering algorithms group similar instances together based on the inherent patterns and structures in the data. In the context of skin cancer detection, clustering algorithms can be used to identify different subtypes or clusters of lesions. This can help dermatologists gain insights into the heterogeneity of skin cancer and potentially uncover new patterns or correlations. Popular clustering algorithms include k-means clustering, hierarchical clustering, and density-based clustering.

2. Dimensionality Reduction Techniques: Unsupervised dimensionality reduction techniques are employed to reduce the complexity and dimensionality of the input data while preserving the most relevant information. Principal Component Analysis (PCA) and t-Distributed Stochastic Neighbor Embedding (t-SNE) are commonly used techniques in skin cancer detection. By transforming the high-dimensional image data into a lower-dimensional space, these algorithms facilitate visualization and analysis of the data, aiding in the identification of meaningful patterns and features.
3. Anomaly Detection: Anomaly detection algorithms identify instances that significantly deviate from the expected patterns or behavior in a dataset. In the context of skin cancer detection, these algorithms can be used to identify rare or unusual lesions that may require further investigation. Anomaly detection algorithms, such as One-Class Support Vector Machines (SVM) and Isolation Forest, can help in detecting outliers or abnormal skin lesions that may potentially be malignant or indicative of a rare condition.
4. Generative Models: Generative models are unsupervised learning algorithms that aim to capture the underlying data distribution and generate new samples. These models, such as Variational Autoencoders (VAEs) and Generative Adversarial Networks (GANs), have shown potential in generating synthetic skin lesion images. They can be utilized to augment the limited training data, improve generalization, and enhance the performance of skin cancer classification models.

It's important to note that while unsupervised learning algorithms have valuable applications in skin cancer detection, they are often used in combination with supervised learning methods. Unsupervised techniques can aid in exploratory analysis, data preprocessing, and feature extraction, which can subsequently be utilized in supervised models for classification and prediction tasks.

Supervised Learning. Analysis and detection of lesions using supervised learning techniques based on ML approaches are CNN, ANN, Linear Regression (LR), RNN, Support vector regression (SVR), and Decision Tree (DT). It implements the binary classifications of images that change the appearance of the skin as benign seborrheic keratosis versus keratinocyte-carcinomas and malignant melanomas. It utilizes the ensemble based multiresolution of CNN composed of SENet, EfficientsNets, and ResNeXt for tutor detection [25]. Similarly, the transfer learning technique of AlexNet could be used to analyze images of skin lesions and melanoma, nevus, or seborrheic keratosis are classified. In classifying skin lesion images, three popular datasets of ISIC, MED-NODE, and Derm-Quest [30]. In the segmentation of affected skin regions by applying the segmentation algorithm of FRCN, CDNN was used. It uses the publicly available datasets of ISBI 2017 and PH2 [4]. Deep learning-based dilated convolutional-based transfer learning techniques of VGG16, VGG19, MobileNet, Inception-V3, and K-Means Clustering were applied for the skin cancer classification. For that, the dataset of HAM10000 with 10015 dermoscopic images [49].

Supervised learning algorithms are widely employed in skin cancer detection for their ability to learn from labeled data and make predictions based on learned patterns. These algorithms require a labeled dataset consisting of skin images with corresponding class labels (e.g., malignant or benign) to train a model. Here are some commonly used supervised learning algorithms in skin cancer detection:

1. Support Vector Machines (SVM): SVM is a popular algorithm that separates data points by constructing a hyperplane in a high-dimensional feature space. In skin cancer detection, SVM can be used to classify skin lesions based on extracted features. It aims to find the optimal decision boundary that maximally separates malignant and benign lesions. SVM can handle both linear and non-linear classification tasks through the use of appropriate kernel functions.
2. Decision Trees: Decision tree algorithms partition the data based on different features and create a hierarchical structure of decision rules. Each internal node represents a decision based on a specific feature, while leaf nodes correspond to class labels. Decision trees can be employed in skin cancer detection by considering various visual features of skin lesions, such as color, texture, and shape. They provide interpretable models that can aid dermatologists in understanding the decision-making process.
3. Random Forests: Random forests combine multiple decision trees to form an ensemble model. Each tree is trained on a subset of the data, and the final prediction is determined by aggregating the predictions of individual trees. Random forests are known for their ability to handle high-dimensional data and mitigate overfitting. In skin cancer detection, random forests can leverage a diverse set of features to

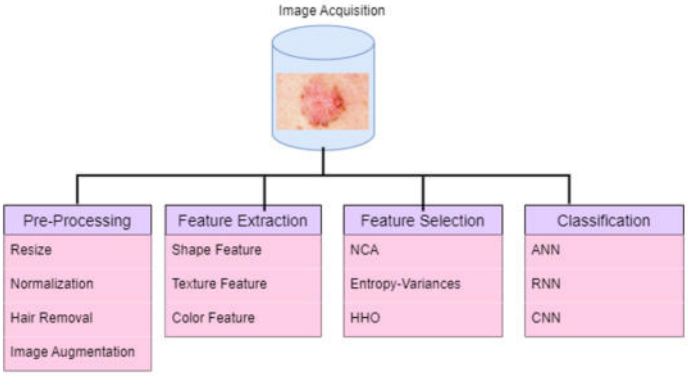

Fig. 6.1: Analysis of Image Processing Tools in Skin Cancer

make accurate predictions.

4. Neural Networks: Neural networks, particularly convolutional neural networks (CNNs), have gained significant attention in skin cancer detection due to their ability to automatically learn hierarchical representations from images. CNNs consist of multiple layers of interconnected neurons that can extract features at different levels of abstraction. They are trained on large labeled datasets and can capture intricate patterns in skin lesions. CNNs have achieved state-of-the-art performance in skin cancer classification tasks.
5. Ensemble Methods: Ensemble methods combine multiple models to make collective predictions. Bagging and boosting are common techniques used in ensemble learning. Bagging methods, such as the Bootstrap Aggregating (or Bagging) algorithm, create multiple models trained on different subsets of the data. Boosting methods, like AdaBoost, iteratively train models, giving more weight to previously misclassified instances. Ensemble methods can enhance the accuracy and robustness of skin cancer detection models.

6. Image Processing Techniques Skin tumor detection. This section presents the image processing techniques required for skin lesion image analysis. The unusual growth of cells or tissue in any place of the human being is considered malignant cells or tumor cells. Digital image processing techniques are instrumental in analyzing biomedical images because they can help filter important features from the images and are used to make accurate diagnoses and treatment decisions. In the analysis of cancer images of skin with various parameters of Asymmetry, Border, Colour, and Diameter (ABCD) using, image processing tools like extraction of texture feature, color feature, and shape feature is used to detect the cancerous or non-cancerous image. Figure 6.1 analysis the image processing tools in the skin tumors classification.

The observation of Figure 6.1 shows that image processing tools like a collection of data, pre-processing, extracting features of the skin image, feature selection, and classification of images as cancerous or non-cancerous.

Image Acquisition. Image acquisition is collected from various sources and DL; ML algorithms are used to feature extraction of the image. Skin image datasets are collected from the internet, clinical-based images, and open dermatology databases. Expert dermatologists analyze these datasets for the removal of blurry images. Fine-tuning of skin images is collected in the dataset for further processing by applying processing tools like pre-processing, extracting features, selecting image pixels, and classification of cancer [28, 72, 23].

Pre-Processing. To enhance image quality, pre-processing needs to be done. It minimizes the irrelevant data from the pictures, improvising relevant data intensities and reliability. It consists of four stages: resizing, normalization, hair removal, and data augmentation.

Resize of Image. To accurately detect skin cancer and minimize the execution time, resizing the image is required. Skin images are resized by applying scaling and clipping procedures [39]. It resizes the images into 224×224 or 128×128 pixels.

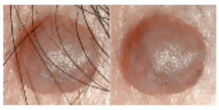

Fig. 6.2: Removal of Hair using DullRazor technique [2]

Normalization of Image . The skin image data are normalized into the exact dimension of the interval between $[0, 1]$ or $[-1, 1]$ .Normalizing data is one type of linear transformation that improves skin data performance.

Augmentation of Image. The technique used in the augmentation process implements the methods of multiplication and transformation. In this augmentation process of the image, conversion is carried out by implementing a Gaussian filter. It produces the smoothing of the image and applies its displacement operators: rotation, flipping operation horizontally, zooming effect in the range of 0.2, and shearing operation in the range of 0.2 [3].

Removal of Hair. In diagnosing cancer in skin image, accurately and effectively remove the hair available in the skin lesion. Processing the image with hair will create confusion in extracting the feature or segmenting the affected area. Therefore, applying the DullRazor technique to remove the hair [2]. The concept behind this technique is applying a morphological operator of close to determine the hair's position in the image. Applying the substitution and bilinear interpolation operation to identify the structure of hair like long or short hair as in pixel values. Finally, applying the median filter it smoothing the image. Figure 6.2 shows the removal of hair in the skin image by applying the DullRazor technique.

Feature Extraction. Early diagnosis of cancer from the skin lesions are done by extracting image features. It reduces the image dimensionality which converts the pixel values into a vector format. To investigate skin cancer images with various parameters of Asymmetry, Border, Colour, and Diameter, (ABCD) using image processing tools like extraction of texture feature, color feature, and shape features are used to detect the cancerous or non-cancerous images [45]. Extracting the features of texture, color, and shape from the skin lesions using a pixel-based method. To filter out the shape features of the lesions is done by implementing the Geometric Feature. The operations in the geometric feature are area, perimeter, diameter, Irregularity Index, and Circularity Index. Texture features are extracted in skin images using a gray levels co-occurrence matrix (GLCM), LBP, and Gabor Filter. Shape feature extractions extracted from skin lesions are Wavelet transform, Fourier descriptors, Shape signature harmonic embedding, and so on. Color feature extractions are implemented by using Discrete Cosine Transform (DCT) [6].

Feature Selection. Feature selection is made by relevant features subset extraction of a skin image. It reduces the irrelevant features of the picture. The feature selection techniques are filter-based technique, wrapper-based, and hybrid-based process. The feature selection process is carried out by Harris Hawks optimization (HHO), Entropy-Variances, and Neighborhood Component Analysis (NCA) [31].

Skin Cancer Classifier. In the classification of skin cancer from large datasets by evaluating the classification algorithms of ANN, RNN, CNN with AlexNet, VGGNet, and ResNet-50. These traditional techniques are used to diagnose skin diseases accurately [38]. Computer vision technologies require an intelligent analysis model for classifying the image feature in an accurate way.

Feature selection plays a crucial role in skin cancer detection by identifying the most relevant and informative features from the input data. It aims to reduce the dimensionality of the feature space, eliminate irrelevant or redundant features, and improve the performance of the classification model. Here are some commonly used feature selection techniques in skin cancer detection:

1. Filter Methods: Filter methods evaluate the relevance of features based on statistical measures or heuristics. These methods assess each feature independently of the classification model. Common filter methods used in skin cancer detection include:
   (a) Pearson correlation coefficient: Measures the linear correlation between features and the target class.
   (b) Mutual information: Quantifies the mutual dependence between features and the target class.

Table 7.1: Summary of datasets

Dataset	**Number of Images**
Dermnet	23,000
DermQuest	22,082
AtlasDerm [68]	1024
PH2 [37]	200
HAM10000	10,015
ISIC archive	25,331

   (c) Chi-square test: Assesses the independence between features and the target class for categorical data.
2. Wrapper Methods: Wrapper methods evaluate subsets of features by training and testing a classification model with different combinations of features. These methods consider the interaction between features and their impact on the model's performance. Popular wrapper methods include:
   (a) Recursive Feature Elimination (RFE): Starts with all features and recursively eliminates the least important ones based on model performance.
   (b) Genetic Algorithms (GA): Uses an evolutionary approach to search for an optimal feature subset by evaluating different combinations of features.
3. Embedded Methods: Embedded methods incorporate feature selection within the training process of the classification model. These methods select the most relevant features while simultaneously training the model. Some common embedded methods used in skin cancer detection include:
   (a) L1-based regularization (e.g., Lasso or L1-regularized logistic regression): Encourages sparsity in the feature weights, effectively selecting the most informative features.
   (b) Decision tree-based feature importance: Decision tree algorithms provide a measure of feature importance based on how much they contribute to the decision-making process.
4. Principal Component Analysis (PCA): PCA is a dimensionality reduction technique that transforms the original features into a new set of orthogonal variables, called principal components. These components capture the maximum variance in the data. In skin cancer detection, PCA can be used to reduce the dimensionality while preserving the most relevant information

7. Data sets. In the diagnosis of skin cancer, various algorithmic-based techniques are implemented. Evaluating and validating the detection of skin cancer results which requires the datasets collected from multiple open datasets and clinically based skin images. Training the algorithmic-based model for the classification of skin cancer by using datasets. Table 7.1 summarizes the datasets implemented in the type of skin cancer.

Dermnet. The Dermnet website provides information on dermatology and skin health. Dr. Thomas Habif New implemented this data source. Hampshire in the year 1998. It contains 24,000 000 or more dermoscopic pictures. And also has 643 various categories of skin diseases. These diseases are classified as two layers in the dataset. The upper layer contains 23 various types of skin diseases like melanoma, benign tumors, moles, tissue disease, and so on. The lower layer has more than 600 skin diseases.

DermQuest. This dataset contains 22,082 dermoscopic images. In this dataset, lesion tags are assigned to every skin lesion. Therefore, 136 lesion tags are required in the dataset.

AtlasDerm. This dataset is an atlas of Dermoscopic images, and it is called AtlasDerm. The images in the dataset assist dermatologists in analyzing skin cancer and detecting melanoma. It comprises 5 images of AK, BCC images 42, benign keratosis 70 images, dermatofibroma images 20, 583 melanoma, 276 melanocytic nevus, and 32 vascular skin lesions.

PH2 Dataset. PH2 dataset contains dermoscopic images gathered from the Center of Dermatology in Hospital Pedro Hispano, Portugal. These dataset images are 8-bit RGB color images with 768 56*and* pixel resolution. And also contains 200 dermoscopic images, with 40 melanoma skin cancers images, atypical nevi images 80, and 80 common nevi images. PH2 dataset contains lesion images with annotations like a clinical

Table 7.2: ISIC Archive [16]

Dataset	**Training Dataset**	**Testing Dataset**	**Total Images**
ISIC_ 2016	Timg_900	Testimg_379	Totimg_1279
ISIC_ 2017	Timing2000	Testimg_600	Totimg_2600
ISIC_ 2018	Timing10,015	Testimg_1512	Totimg_11,527
ISIC_ 2019	Timing25,331	Testimg_8238	Totimg_33,569
ISIC _2020	Timing33,126	Testimg_10,982	Totimg_44,108

diagnosis of skin diseases and segmentation of medical images of pigmented skin lesions.

HAM10000. The publicly available dataset of skin lesions contains 11,000 training images. It includes 10,022 dermoscopic piuctures gathered from the Austria-based university in Vienna called Medical University and Cliff Rosendahl's skin tumor practice at Australia Queensland. Here data is compiled by using photographic prints of lesions and digital cameras and stored in the Dermatology Department of the Medical University of Vienna, Austria. Digitized lesions photographic prints uses a Nikon-Coolscan-5000-ED scanner and convert the image into JPEG format of 8-bit images with 300 DPI quality. Cropping the image and saving it in the resolution ofpixels at 72 DPI [61].

ISIC Archive. Data is collected from various skin lesions and stored at the ISIC archive. In 2016, the International Collaboration of Skin Imaging released ISIC dataset at the International Biomedical Imaging (ISBI) Symposium on Challenge 2016, termed ISIC 2016. The dataset of ISIC 2016 is categorized into two sections training and testing datasets. The dataset of ISIC contains 900.00 training dataset images and 379 dermoscopic image testing datasets. This data set includes two variations of skin lesion images, namely malignant melanomas and benign nevi. In the archive of ISIC, every year, many skin lesion images are included; also, 30.3% are melanoma lesions, and 69.7% are benign nevi images. These images are established for the analysis of images on skin lesions.

The archive of ISIC 2017 contains three types of images, namely benign nevi, melanomas, and seborrheic keratoses (SK). This archive includes training images of 2000, 600 testings, and validation images of 150. In this training dataset, melanoma images are 374, SK images are 254, and benign nevi images are 1372. Similarly, the dataset for validating the skin cancer images like melanoma 30 images, SK 42 images, and benign nevus 78 images. The testing dataset contains 117 melanoma pictures, SK 90 images, and benign nevus images 393.

ISIC2018 archive dataset contains a training dataset of 12,594 skin lesions, a testing dataset of 1000 images, and validation images of 100. ISIC2019 archive dataset contains 25,331 images with eight types of skin lesion images like AK, BCC, melanoma, benign keratosis, melanocytic-nevus, SCC, vascular lesion, and dermatofibroma. For the dataset for testing the 8239 images. The summary of the ISIC archive dataset is given in Table 7.2. The table shows the summary of the ISIC archive from the years 2016 to 2020. Every year, more images are included in the archive. In the ISIC 2016 archive, training images are 900, testing images are 379, and its total images are 1279. It is also classified into two varieties of malignant or benign skin lesions [26]. In the ISIC 2017 archive, training images are 2000, testing images are 600, and its total images are 2600. Skin cancers are differentiated into different categories based on the appearance of the lesion or growth. Nevus, also known as a mole, is a common type of benign skin growth (non-cancerous). Seborrheic keratosis is a soft growth that appears as a waxy or scaly patch on the skin. Melanoma is a skin cancer type characterized by the uncontrolled growth of pigment-producing cells (melanocytes) in the skin [17]. In the ISIC 2018 archive, training images are 10,015, testing images are 1512, and its total images are 11,527. It also contains melanocytic nevus, melanoma, vascular lesion, dermato fibroma, , and benign and actinic keratosis. In the ISIC 2019 archive, training images are 25,331, testing images are 8238, and its total images are 33,569. It also contains melanocytic nevus, melanoma, basal cell cancer, dermato fibroma, vascular lesions, benign keratosis, and actinic keratosis of the training dataset. The testing dataset contains 9 group classes dataset. it also includes the metadata of patient age, gender, and lesion ID [19]. In the ISIC 2020 archive, training images are 33,126; testing images are 10,982 and total images are 44,108. It is mainly focused on melanoma skin lesions. The metadata of ISIC

2020 contains the ID of the patient, ID of the lesion, gender, age, anatomical site, and diagnosis [52].

8. Challenges in the Skin cancer examine. This section presents those open research challenges in the diagnosis of skin lesions. It includes the factors of training the algorithmic model, variations in the size of skin lesions, light-skinned images in the dataset, subgroup class of skin lesions, an unbalanced dataset of skin cancer images, lack of hardware, lack of age-wise categorization of skin images.

Training the Algorithmic Model. The significant challenges in training the algorithmic model for skin cancer identification images from the standard dataset. A minimum computation time is required to identify cancer images from dermoscopic pictures [21] effectively.

Variations in Size of Skin Lesions. Another research challenge in identifying and analyzing skin cancer is the dataset's image size variations. Since data is collected from various sources and varies in size. Therefore, handling the multiple dimensions of images takes a lot of work. If the image is small, it's too difficult to diagnose the earlier stage of skin cancer.

Light Color Skinned Images in the Dataset. The benchmark dataset contains light color -skinned patients from the United States, Australia, and Europe. The accurate and efficient detection of cancer disease of light color skinned patients required a standard algorithmic-based model [12].

Sub-Group Class of Skin Lesions. In the categorization of subgroups, class skin lesions are in various forms. It defines the variation between cancerous and non-cancerous skin cancer images. These minor variations in the subgroup class are difficult to predict for melanoma cancer and the birthmark of the patient [70].

Unbalanced Dataset of Skin Cancer Image. The collected images could be more balanced from the several sources of skin lesions. Since it contains various types of skin cancer images. It is also a great challenge to handle this unbalanced data. Unbalanced data in the dataset is difficult to generalize from the subset relevant intensity values of dermoscopic images [44].

Detection of Skin Cancer and Hardware Issues. Training a dataset of dermoscopic images using algorithmic-based techniques requires powerful hardware and software resources. To detect skin cancer effectively, extract unique, relevant subset pixel values from the image of the skin lesion. To do this requires powerful resources of hardware and software. This lack of hardware availability is a great challenge.

Lack of Age-Wise Categorization of Skin Images. The collected data of skin cancer types like BCC, SCC, and Merkel cell cancer are most probably available below age 65. The existing standard dataset contains only young-age patient skin cancer images. To accurately evaluate the process of skin cancer analysis for elderly people, images are lacking in the dataset [24].

9. Performance of Metric Measures in Skin Cancer Images. For the practical analysis of algorithmic-based detection of cancer in the skin by evaluating the performance of error metric measures are reviewed by Root Mean Squared Error (RMSE), Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), Structural Similarities Index (SSIM), accuracy, sensitivity, specificity.

MSE. The mean squared error (MSE) calculates the average of the squares of the differences between predicted and actual values.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_{pi} - y_{ai})^2 \tag{9.1}$$

RMSE. It is similar to MSE but computes this by the root of MSE.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_{pi} - \hat{y}_{ai})^2} \tag{9.2}$$

Peak Signal-to-Noise Ratio (PSNR).

$$PSNR = 20\log_{10}\left(\frac{MAX_f}{\sqrt{MSE}}\right) \tag{9.3}$$

Structural Similarity Index (SSIM). SSIM Index quality assessment index is a combination of three factors like luminance (l), contrast (c) and structure (s) of the image.

$$SSIM\,(x,y) = [l\,(x,y)]^{\propto} \times [c\,(x,y)]^{\beta} \times [s\,(x,y)]^{\gamma} \tag{9.4}$$

Sensitivity.

$$Sensitivity = \frac{TP}{TP+FN}X100 \tag{9.5}$$

Specificity. It is used to evaluate the rate between True Negative (TN) and True Positive (TP)

$$Specificity = \frac{TN}{TN+FP}X100 \tag{9.6}$$

Accuracy.

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN}X100 \tag{9.7}$$

10. Limitations.

Limited and Imbalanced Datasets. Skin cancer detection often relies on labeled datasets for training machine learning models. However, obtaining large and diverse datasets with balanced representation of different skin cancer types can be challenging. Limited data can lead to overfitting, reduced generalization, and biased results. Imbalanced datasets, where one class dominates over others, can lead to poor performance in detecting minority classes.

Variability in Image Quality. Skin lesion images used in detection can vary in terms of image quality, lighting conditions, resolution, and image artifacts. These variations can affect the performance of the detection algorithms, making it difficult to generalize the model across different imaging devices or settings.

Interclass Variability and Similarity. Skin cancer encompasses various subtypes, each with unique visual characteristics. However, there can be considerable overlap and similarity between different classes, making accurate classification challenging. Distinguishing between benign and malignant lesions or differentiating between subtypes can be particularly difficult, even for expert dermatologists.

Subjectivity and Variability in Dermatologist Diagnosis. Dermatologists' diagnosis of skin cancer can have a level of subjectivity and inter-observer variability. This subjectivity can impact the accuracy of labeled data used for training machine learning models. Disagreements among dermatologists can lead to inconsistent labeling and ambiguous ground truth, affecting the performance of the detection algorithms.

Limited Interpretability of Deep Learning Models. Deep learning models, such as convolutional neural networks (CNNs), have shown impressive performance in skin cancer detection. However, their complex architectures often lack interpretability, making it challenging to understand the decision-making process or extract meaningful insights from the model's predictions. This limited interpretability can hinder the adoption and trust in deep learning-based detection systems.

Generalization to Diverse Populations. Skin cancer detection algorithms are typically developed and evaluated on specific populations or datasets. The performance of these algorithms on diverse populations, including different ethnicities, skin types, and age groups, may vary. Models trained on one population may not generalize well to others, leading to potential biases and reduced accuracy in real-world scenarios.

Ethical and Privacy Concerns. Skin cancer detection systems often require the collection and storage of sensitive medical data, including images and patient information. Ensuring the privacy and security of this data, as well as obtaining proper informed consent, is crucial. Additionally, biases in the data or algorithmic predictions could result in unfair treatment or disparities in healthcare access and outcomes.

11. Conclusion. This paper mainly focused on a detailed, comprehensive review of the algorithmic-based analysis of skin cancer. Initially, we surveyed related works of skin cancer detection, then discussed overview layers of skin and its diseases. This paper analyzed skin cancer identification methods and analysis of various deep learning and machine learning techniques for the study of skin cancer, in addition to this present image processing techniques for the analysis of skin cancer diseases. Another paper is focused on various datasets in cancer analysis. This survey was effectively used in skin cancer identification based on performance of metric measures of Roots Mean Squared Error (RMSE), Peak Signal-to-Noise Ratios (PSNR), Mean Squared Error (MSE), Structural Similarity (SSIM) Index, sensitivity, accuracy and specificity. These metrics are used for significantly improving the presentation of the analysis of skin cancer systems.

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