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Survey on Skin cancer Detection

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Abstract: Skin cancer is a serious and dangerous form of cancer. It happens when DNA in skin cells gets damaged, leading to genetic changes or mutations. If not treated early, skin cancer can spread to other parts of the body. Early detection makes it easier to cure, which is why recognizing symptoms at the initial stages is important .The rise in skin cancer cases, high death rates, and costly treatments make early diagnosis crucial. Researchers have developed various methods to detect skin cancer early. Features like symmetry, color, size, and shape of skin lesions help differentiate harmless growths from melanoma, the most severe type of skin cancer .This paper reviews deep learning techniques for early skin cancer detection. It analyzes research from top journals and presents findings through tools, graphs, tables, and frameworks to make the information clear and easy to understand.

Keywords: deep learning; deep neural network (DNN); machine learning; melanoma; support vector machine (SVM)

I. INTRODUCTION

skin lesion Skin cancer has become one of the most prevalent and active types of cancer in recent years. As the largest organ of the human body, the skin is particularly susceptible to cancer, making skin cancer the most common form of cancer globally. Skin cancer is classified into two major categories: **melanoma** and **non melanoma**.

Melanoma, while rare, is highly dangerous and often fatal. Despite accounting for only 1% of skin cancer cases, it contributes to a disproportionately high death rate, as reported by the American Cancer Society. Melanoma originates in melanocytes, the cells responsible for producing pigment in the skin.

These cells can grow uncontrollably, forming tumors that may occur anywhere on the body but are more common in sun-exposed areas like the face, neck, hands, and lips. Early detection is crucial for curing melanoma; if left untreated, it can spread to other organs and lead to severe outcomes.

There are several subtypes of melanoma, including nodular melanoma, superficial spreading melanoma, acral lentiginous melanoma, and lentigo maligna melanoma. On the other hand, **non melanoma skin cancers**, such as basal cell carcinoma (BCC), squamous cell carcinoma (SCC), and sebaceous gland carcinoma (SGC), are far more common and less aggressive. These cancers primarily develop in the middle and upper layers of the epidermis . They rarely spread toot her parts of the body and are more easily treated than rate, as reported by the American Cancer Society. Melanoma originates in melanocytes, the cells responsible for producing pigment in the skin.

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Diagnosis Methods and Challenges: The primary method for diagnosing skin cancer is a biopsy, where a sample of the suspected lesion is removed and examined under a microscope. While effective, this process is invasive, time-consuming, and uncomfortable for patients. To address these challenges, researchers have explored computer-based diagnostic technologies that are faster, less invasive, and more cost-effective.

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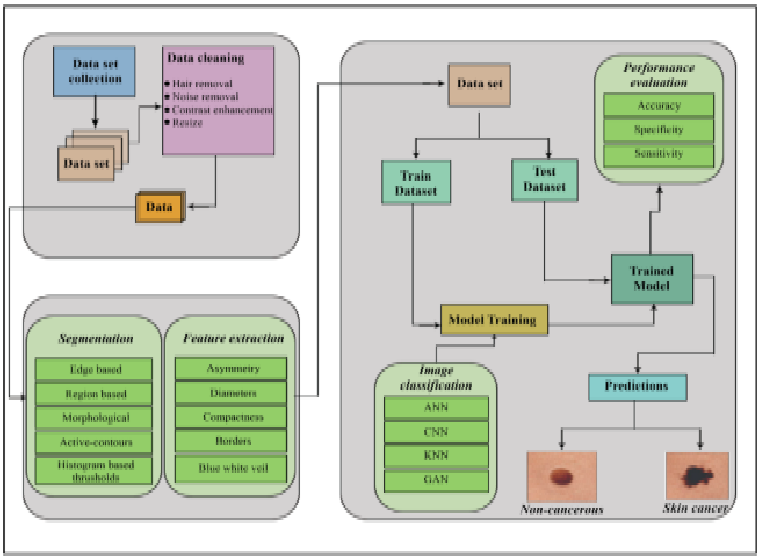

Figure1.The process of skin cancer detection.

Role of Deep learning in Skin Cancer Detection

Deep learning has emerged as a transformative technology within machine learning, inspired by the human brain's structure and functionality. It is highly effective in fields like speech recognition, pattern analysis, and bioinformatics. Recent advancements have applied deep learning to skin cancer detection, yielding promising results compared to traditional machine learning techniques.This paper provides a systematic review of deep learning approaches, focusing on key models such as Artificial Neural Networks (ANNs), Convolutional Neural Networks (CNNs), Kohonen Self-Organizing Networks (KNNs), and Generative Adversarial Networks (GANs). These methods have shown significant potential for accurate and efficient skin cancer diagnosis.

II. RESEARCH METHODOLOGY

This systematic literature review aimed to identify, organize, and evaluate the most effective methods for detecting skin cancer using neural networks (NNs). By following predefined evaluation criteria, systematic reviews gather and analyze existing research to understand the current knowledge in a particular field. The review process involves collecting data from primary sources, organizing it systematically, and conducting a thorough analysis. The result is a well-structured and logical response to the core research question, providing valuable insights into the topic.

III. DEEP LEARNING TECHNIQUES FOR SKIN CANCER DETECTION

Deep neural networks (DNNs) have proven to be highly effective in detecting skin cancer. Their structure mimics the human brain, consisting of interconnected nodes (neurons) that work together to solve problems. These networks are trained on specific tasks, enabling them to perform as experts in those areas. In skin cancer detection, DNNs are trained to classify images and differentiate between types of skin cancer. Using the International Skin Imaging Collaboration (ISIC) dataset, researchers explored different DNN techniques, including Artificial Neural Networks (ANNs), Convolutional Neural Networks (CNNs), Kohonen Networks (KNNs), and Generative Adversarial Networks (GANs).

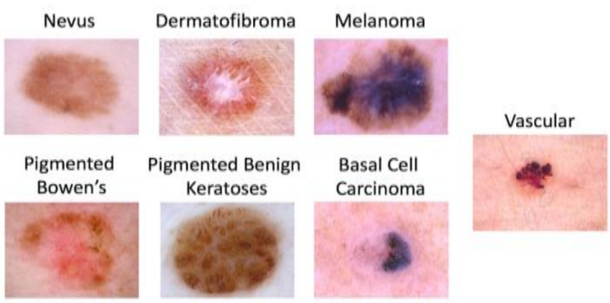

Figure2. Skin disease categories from International Skin Imaging Collaboration (ISIC) dataset.

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3.1. Artificial Neural Networks (ANNs) for Skin Cancer Detection

Artificial Neural Networks (ANNs) are computational models inspired by the biological structure and functioning of the human brain. They consist of three main layers: the input layer, which receives data such as images or features; hidden layers, which process the data through interconnected neurons and extract meaningful patterns; and the output layer, which generates the final results, such as classifying a skin lesion as melanoma or non-melanoma. ANNs learn the relationships between inputs and outputs through methods like back propagation, which adjusts weights based on error minimization, and feed forward mechanisms, where data flows in a unidirectional manner from input to output. Several key studies highlight advancements in skin cancer detection using Artificial Neural Networks (ANNs). Xie et al. developed a three-phase system to classify skin lesions into benign and malignant categories by extracting 57 features, including unique details like lesion borders. Principal Component Analysis (PCA) was employed to reduce unnecessary data, and the system achieved an accuracy of 91.11%, outperforming models like Support Vector Machines (SVM) and K-Nearest Neighbors (KNN). Masood et al. proposed an ANN-based system that evaluated different learning algorithms, with the Levenberg–Marquardt (LM) algorithm achieving the highest specificity of 95.1% for benign lesions, while the Scaled Conjugate Gradient (SCG) algorithm performed better with extended training, reaching 92.6% sensitivity. Another significant approach focused on early melanoma detection using the ABCD rule, where asymmetry (A) was detected using specialized algorithms, borders (B) were assessed through border analysis techniques, color (C) abnormalities were flagged, and diameter (D) criteria highlighted moles larger than 6 mm. This system achieved a remarkable accuracy of 97.51%. Choudhari and Biday utilized an ANN that segmented images using thresholding and extracted features via a gray-level co-occurrence matrix (GLCM), classifying skin lesions with an accuracy of 86.66%. Aswin et al. combined Genetic Algorithms (GAs) with ANNs to create a hybrid model, where preprocessing steps included hair removal and region of interest (ROI) extraction. Features were analyzed using GLCM, and the hybrid classifier achieved an accuracy of 88%. These studies underscore the potential of ANN-based systems in improving the accuracy and efficiency of skin cancer detection.

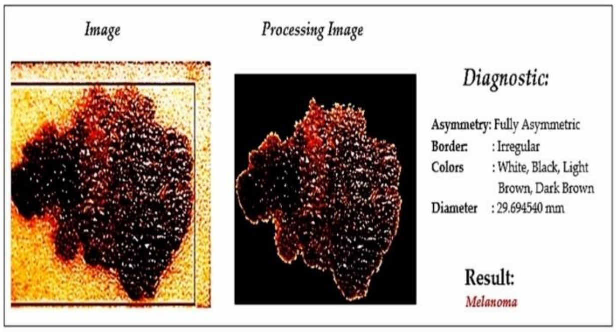

Figure3. Skin cancer detection using ANN

Image processing in skin cancer detection using Artificial Neural Networks (ANNs) involves several critical steps to ensure high-quality and feature-rich inputs for the model. First, dermatoscopic images are acquired from sources like the ISIC Archive and undergo quality checks to ensure clarity and focus. These images are resized to standardized dimensions, such as 128x128 or 224x224 pixels, to match the ANN input size. Normalization scales pixel intensities to a uniform range, typically between 0 and 1, to stabilize training.

Preprocessing also includes data augmentation, where techniques like rotation, flipping, and brightness adjustment increase dataset diversity, reducing over fitting risks. Noise reduction methods, such as Gaussian blur or median filtering, are applied to remove artifacts, while contrast enhancement techniques like histogram equalization improve lesion visibility. Hair removal is another important step, achieved through morphological operations and in painting, to eliminate distracting hair artifacts. Focusing on the lesion area, Region of Interest (ROI) detection is performed using methods like thresholding, edge detection, or advanced deep learning models like U-Net to segment the lesion. Lastly, feature extraction highlights critical aspects of the lesion, such as texture, color, and shape. Techniques like the Grey Level Co-occurrence Matrix (GLCM) analyze patterns, while geometric measures evaluate asymmetry or border irregularity. These processed and enriched images serve as optimal inputs for the ANN, enhancing its ability to classify and detect skin cancer with high accuracy. An automated skin cancer diagnostic system based on back propagation ANN was proposed, represented in Figure .This system employed a 2D-wavelet transform technique for feature extraction .The proposed ANN model classified the input images into two classes, such as cancerous or non cancerous. Another ANN-based skin cancer diagnostic system was proposed by Choudhari and Biday. Images were segmented with a maximum entropy threshold measure.

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A gray-level co-occurrence matrix (GLCM) was used to extract unique features of skin lesions. Finally,a feed-forward ANN classified the input images into either a malignant or benign stage of skin cancer, achieving an accuracy level of 86.66%.

Artificial Neural Networks (ANNs) play a vital role in the early detection and diagnosis of skin cancer, offering a transformative approach in dermatology. They excel in processing complex medical imaging data, such as dermoscopic images, by identifying subtle patterns and features that may not be easily visible to the human eye. ANNs are trained on large datasets of labeled skin lesion images, enabling them to distinguish between malignant and benign lesions with high accuracy.

This enhances diagnostic precision, reduces the risk of misdiagnosis, and ensures timely intervention. Moreover, ANNs can analyze images rapidly, making them invaluable for real-time screening in clinical settings or telemedicine applications. Their ability to generalize across diverse skin types and conditions further supports equitable and accessible healthcare. Overall, ANNs significantly improve the efficiency, reliability, and scalability of skin cancer detection methods.

Table1. A comparative analysis of skin cancer detection using ANN-based approaches.

Ref	Skin Cancer Diagnoses	Classifier and Training Algorithm	Dataset	Description	Result(%
[23]	Melanoma	ANN with back propagation algorithm	31 dermoscopic image	ABCD parameters for feature extraction	Accuracy (96.9)
[20]	Melanoma/Non melanoma	ANN with back propagation algorithm	90 dermoscopic images	maximum entropy for thresholding, and gray level co-occurrence matrix for features extraction	Accuracy (86.66)
[19]	Cancerous/noncancerous	ANN with back propagation algorithm	31 dermoscopic images	2D-wavelet transform for feature extraction and thresholding for segmentation	Nil
[24]	Malignant/bening	Feed-forward ANN with the back propagation training algorithm	326 lesion images	Color and shape characteristics of the tumor were used as discriminant features for classification	Accuracy(80)
[25]	Malignant/non-malignant	Back propagation neural network as NN classifier	448 mixed-type images	ROI and SRM for segmentation	Accuracy(70.4)
[21]	Cancerous/noncancerous	ANN with back propagation algorithm	30cancerous/noncancerous images	RGB color features and GLCM techniques for feature extraction	Accuracy (86.66)
[18]	Common mole/non-common mole/melanoma	Feed-forward BPNN	200 dermoscopic images	Features extracted according to ABCD rule	Accuracy (97.51)

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3.2. Convolutional Neural Network (CNN)-Based Skin Cancer Detection Techniques

Convolutional Neural Networks (CNNs) are a class of deep learning models that excel in image analysis tasks, including skin cancer detection. CNNs are particularly effective because they automatically extract relevant features from input images, eliminating the need for manual feature engineering. This makes them well-suited for analyzing skin lesions to classify them as benign or malignant.

Structure of CNN:

Convolutional Layers: Extract features like edges, textures, and patterns from images.

Pooling Layers : Reduce the dimensionality of the feature maps while retaining important information, enhancing computational efficiency.

Fully Connected Layers: Perform classification based on the features extracted by convolutional and pooling layers.

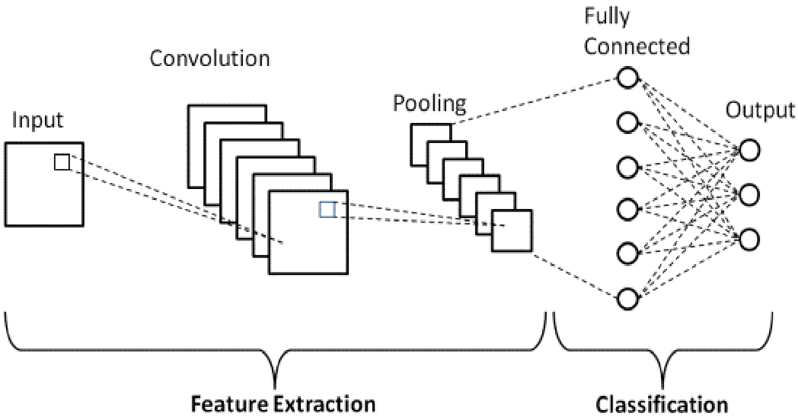

Figure4. Basic CNN Architecture .

Applications in Skin Cancer Detection:

CNN-based techniques have been widely used in skin cancer detection to identify melanoma and non melanoma skin lesions. These systems utilize large datasets, such as the **International Skin Imaging Collaboration (ISIC)** dataset, to train and validate their models.

Key Studies:

Esteva et al. (2017)

- Developed a CNN model trained on over 129,000 skin images to identify skin cancer types.
- The model performed comparably to dermatologists, achieving a high accuracy rate for melanoma detection.

Han et al. (2018)

- Proposed a deep CNN system for multiclass classification of skin lesions.
- The model was trained on the ISIC dataset to classify lesions into melanoma, basal cell carcinoma (BCC), and other categories.
- Achieved a sensitivity of 90% for melanoma detection

Techniques to improve CNN performance in skin cancer detection focus on enhancing model accuracy and generalization. Data augmentation is commonly employed to artificially increase the dataset size by generating variations of existing images through rotations, flips, and other transformations , which helps the model learn diverse patterns.

Transfer learning leverages pre-trained CNN models like ResNet, Inception, or VGG Net, which are fine-tuned for skin cancer detection, significantly reducing training time while maintaining high accuracy. Ensemble models combine predictions from multiple CNN architectures to improve robustness and predictive performance, while attention mechanisms guide the model to focus on critical lesion regions, ignoring irrelevant areas.

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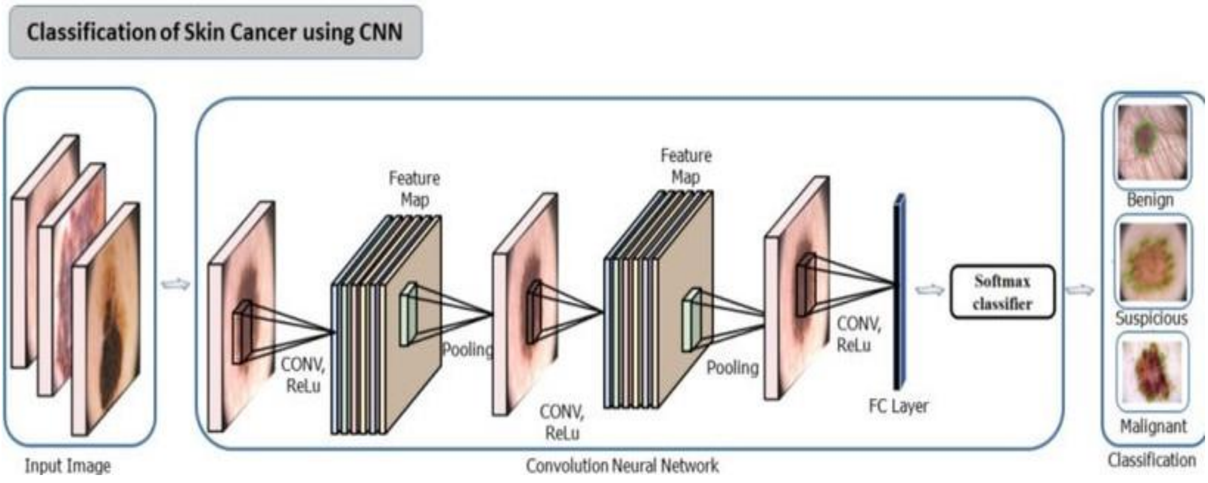

Figure5. Skin cancer diagnosis using CNN.

CNNs offer several advantages for skin cancer detection, including their ability to achieve high accuracy by identifying subtle patterns in skin lesions, process large datasets effectively, and generalize across various skin types and conditions. Their capability to automate feature extraction minimizes reliance on domain expertise, making them highly efficient for medical applications. By providing rapid, accurate, and scalable solutions, CNN-based systems have revolutionized skin cancer detection, offering significant potential for early diagnosis and reducing mortality rates through timely and effective treatment.

Table 2. A comparative analysis of skin cancer detection using CNN-based approaches

Ref	Skin Cancer Diagnoses	Classifier and Training Algorithm	Dataset	Description	Results (%)
[38]	Benign/malignant	Light Net (deep learning framework), used for classification	ISIC 2016 dataset	Fewer parameters and well suited for mobile applications	Accuracy (81.6), sensitivity (14.9), specificity (98)
[31]	Melanoma/benign	CNN classifier	170 skin lesion images	Two convolving layers in CNN	Accuracy (81), sensitivity (81), specificity (80)
[36]	BCC/SCC/melanoma/AK	SVM with deep CNN	3753 dermoscopic images	Pertained to deep CNN and AlexNet for features extraction	Accuracy (SCC: 95.1, AK: 98.9, BCC: 94.17
[39]	Melanoma /benign Keratinocyte carcinomas/benign SK	Deep CNN	ISIC-Dermoscopic Archive	Expert-level performance against 21 certified dermatologists	Accuracy (72.1)
[35]	Malignant melanoma and BC carcinoma	CNN with Res-Net 152 architecture	The first dataset has 170 images the second dataset contains 1300 images	Augmentor Python library for augmentation.	AUC (melanoma: 96, BCC: 91)
[40]	Melanoma/nonmelanoma	SVM-trained, with CNN, extracted features	DermIS dataset and DermQuest data	A median filter for noise removal and CNN for feature extraction	Average AUC:9 84.8), average accuracy (83.8)

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[41]	Malignant melanoma/nevus/SK	CNN as single neural-net architecture	ISIC 2017 dataset	CNN ensemble of AlexNet, VGGNet, and GoogleNetfor classification	Accuracy (95.93), sensitivity (95.2), specificity (96.54)
[41]	Cancerous/noncancerous	CNN	1730 skin lesion and background images	Focused on edge detection	Accuracy (86.67)
[37]	Benign/melanoma	VGG-16 and CNN	ISIC dataset	Dataset was trained on three separate learning models	Accuracy (78)
[44]	**Benign**/malignant	CNN	ISIC database	ABCD symptomatic checklist for feature extraction	Accuracy (89.5)
[45]	Melanoma/benign keratosis/ melanocytic nevi/BCC/AK/IC/atypical nevi/dermatofibroma/ vascular lesions	Deep CNN architecture (DenseNet 201, Inception v3, ResNet 152 and Inception ResNet v2)	HAM10000 and PH2 dataset	Deep learning models outperformed highly trained dermatologists in overall mean results by at least 11%	ROC AUC (DenseNet 201: 98.79–98.16, Inception v3: 98.60–97.80, ResNet 152: 98.61–98.04

3.3. Generative Adversarial Network

Generative Adversarial Networks (GANs) are a specialized type of deep neural network (DNN) inspired by zero-sum game theory. These networks consist of two key components: a generator and a discriminator, which work in opposition to each other to analyze and capture variations within a dataset. The generator's role is to create synthetic data samples that mimic the distribution of the real data, aiming to "trick" the discriminator. Meanwhile, the discriminator’s task is to differentiate between real and synthetic samples. During the training process, these two networks iteratively compete, refining their performance with each interaction.

The generator's ability to produce realistic synthetic data, such as photorealistic images, is a defining strength of GANs. This capability addresses a significant challenge in deep learning: generating high-quality data samples that can augment existing datasets. By learning the underlying data distribution, GANs excel in creating fake samples that closely resemble real ones, making them particularly valuable for applications like skin cancer detection, where high-quality image data is critical.

Through this adversarial training process, both the generator and discriminator continuously improve, enhancing the overall performance of the GAN-based system. One of the standout features of GANs is their ability to generate high-quality synthetic data, such as lifelike images, even when training data is limited.

This makes them particularly useful in domains like skin cancer detection, where large, diverse datasets are crucial but not always readily available. GANs can generate additional images of skin lesions, including variations in size, shape, color, and texture, to augment training datasets, reducing the risk of over fitting and improving the robustness of machine learning models.

Moreover, GANs have proven effective in addressing challenges such as data imbalance, where certain types of skin lesions may be underrepresented in the dataset. By generating synthetic samples of these underrepresented classes, GANs ensure that the model learns to detect all types of skin lesions more effectively. GANs are also used for enhancing image quality through noise reduction and resolution improvement, making diagnostic images clearer and more useful for clinical analysis.

In the context of skin cancer detection, GANs can also simulate realistic variations of lesions for training models to recognize diverse conditions. This ensures that diagnostic systems are not only accurate but also

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adaptable to variations in skin tones and lesion characteristics across populations. The iterative competition between the generator and discriminator during training ensures that both components reach a high level of sophistication, enabling the GAN to create synthetic data that is almost indistinguishable from real-world data. This unique capability makes GANs a transformative tool in medical imaging and early cancer detection.

Generative Adversarial Networks (GANs) offer several advantages in skin cancer detection, making them a powerful tool in the medical imaging and diagnostic domain:

1. Data Augmentation: GANs can generate synthetic images of skin lesions that closely resemble real-world examples. This is especially valuable when dealing with limited datasets, enabling models to learn from a larger, more diverse set of samples. Such augmentation improves model training and reduces the risk of over fitting.

2.Addressing Data Imbalance :In skin cancer datasets, some lesion types (e.g., rare cancers) are often underrepresented. GANs can generate synthetic images of these minority classes, balancing the dataset and ensuring the model is trained to recognize all lesion types effectively.

IV. CONCLUSION AND FUTURE WORK

Systematic review has explored various neural network approaches for the detection and classification of skin cancer, emphasizing their noninvasive nature. Skin cancer detection involves multiple stages, including preprocessing, image segmentation, feature extraction, and classification. The review examined the application of algorithms such as Artificial Neural Networks (ANNs), Convolutional Neural Networks (CNNs), k-Nearest Neighbors (KNNs), and Radial Basis Function Networks (RBFNs). Each method has unique strengths and limitations, but CNNs typically outperform other techniques in image-based classification tasks due to their strong alignment with computer vision applications. While most existing research focuses on determining whether a specific lesion image is cancerous, it fails to address broader questions, such as identifying potential skin cancer symptoms across the entire body. Current studies largely center on the classification of isolated lesion images.

Future work could expand to incorporate full-body imaging systems, enabling automated detection of symptoms across multiple regions. Autonomous full-body imaging would streamline and enhance the image acquisition process, providing a more comprehensive diagnostic tool.

Emerging advancements in deep learning, such as auto-organization, present exciting possibilities. Auto-organization refers to unsupervised learning techniques designed to uncover features, patterns, or relationships within image datasets. Within the scope of convolutional neural networks, auto-organization can enhance the representation of features extracted by expert systems. Though still under active research and development, this approach has the potential to significantly improve the accuracy of image processing systems. This is particularly relevant in medical imaging, where capturing the minutest details is critical for accurate disease diagnosis. Future studies should focus on leveraging auto-organization to advance skin cancer detection and classification.

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