# A DECADE SURVEY ON SKIN CANCER TYPES CLASSIFICATION USING DEEP LEARNING

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**Abstract**

Detecting skin cancer at an early stage is crucial for effective treatment and improved patient outcomes. This survey paper comprehensively reviews the advancements in skin cancer detection leveraging neural networks, with a primary focus on convolutional neural networks (CNNs) and their variants. We begin by elucidating the background of skin cancer, emphasizing the limitations of traditional detection methods. Neural networks, being versatile in image analysis, have demonstrated promising results in automating skin cancer diagnosis through the analysis of dermatoscopic images. The survey navigates through various datasets commonly employed in skin cancer research, discussing preprocessing techniques crucial for optimizing model performance. In-depth exploration of neural network architectures used in skin cancer detection, including notable models and their evolution, is presented. Transfer learning, a powerful technique, is investigated for its role in leveraging pre-trained models for improved generalization to skin cancer detection tasks. The paper delves into performance metrics, shedding light on the evaluation criteria shaping the effectiveness of these neural network-based systems. Challenges and limitations inherent in current methodologies are analyzed, paving the way for future research directions. This survey aims to provide a comprehensive understanding of the current state of skin cancer detection using neural networks, offering insights into potential advancements that could revolutionize early diagnosis and patient care.

**Keywords**

Neural networks, Convolutional neural networks (CNNs), Dermatoscopic images, Early diagnosis, Preprocessing techniques, Transfer learning, Model architectures, Performance metrics, Evaluation criteria.

## 1. INTRODUCTION

Skin cancer is the most common cancer worldwide, with melanoma being the deadliest form. Dermoscopy is a skin imaging modality that has shown an improvement in the diagnosis of skin cancer compared to visual examination without support [1]. Skin cancer poses a significant global health concern, with increasing incidence rates underscoring the need for accurate and timely detection. Traditional methods, such as dermatoscopy and biopsy, while effective, are inherently dependent on human expertise, leading to potential diagnostic variability. In response to this challenge, the integration of neural networks in skin cancer detection has emerged as a transformative approach. This survey paper seeks to elucidate the landscape of skin cancer detection, specifically exploring the role of neural networks, with a primary emphasis on convolutional neural networks (CNNs). The introduction outlines the prevalence and impact of skin cancer, emphasizing the critical importance of early detection in improving patient outcomes. Highlighting the limitations of conventional diagnostic methods sets the stage for the exploration of neural networks as a promising alternative. The section provides a brief overview of neural networks and their applications in computer vision, establishing a foundation for their role in analyzing dermatoscopic images for skin cancer detection. By framing the context within the broader scope of public health and technological advancements, this introduction aims to captivate the reader's interest and underscore the significance of the subsequent survey on neural network applications in skin cancer detection.

## 2. Literature survey

Skin cancer is the most common cancer worldwide, with melanoma being the deadliest form. Dermoscopy is a skin imaging modality that has shown an improvement in the diagnosis of skin cancer compared to visual examination without support. We evaluate the current state of the art in the classification of dermoscopic images based on the ISIC2019 Challenge for the classification of skin lesions and current literature. Various deep neural network architectures pre-trained on the ImageNet data set are adapted to a combined training data set comprised of publicly available dermoscopic and clinical images of skin lesions using transfer learning and model finetuning. The performance and applicability of these models for the detection of eight classes of skin lesions are examined. Realtime data augmentation, which uses random rotation, translation, shear, and zoom within specified bounds is used to increase the number of available training samples [1].

The proposed work has chosen a subset of the dataset and performed augmentation. A model with data augmentation tends to learn more distinguishing characteristics and features rather than a model without data augmentation. Involving data augmentation can improve the accuracy of the model. But that model cannot give significant results with the testing data until it is robust. The k-fold cross-validation technique makes the model robust which has been implemented in the proposed work. We have analyzed the classification accuracy of the Machine Learning algorithms and Convolutional Neural Network models. We have concluded that Convolutional Neural Network provides better accuracy compared to other machine learning algorithms implemented in the proposed work. In the proposed system, as the highest, we obtained an accuracy of 95.18% with the CNN model. The proposed work helps early identification of seven classes of skin disease and can be validated and treated appropriately by medical practitioners [2].

One of the most serious illnesses is skin cancer, and one of the primary methods for diagnosing cancer is medical imaging. Tumour lesions' location, size, and evolutionary stage may all be determined from the photos. To evaluate the classification performance of convolutional neural networks (CNNs) in differentiating between distinct skin lesions, this research focuses on the classification of skin lesion pictures using a framework of four experiments. Utilizing ImageNet weights, the CNNs are based on transfer learning. As a result, several process phases, such as data augmentation and fine-tuning optimization, are assessed in each trial. Using the HAM10000 dataset, three CNN models based on DenseNet-201, Inception-ResNet-V2, and Inception-V3 are suggested and compared. The three models yielded findings with corresponding accuracies of 98%, 97%, and 96% [3].

Skin cancer is the most common cancer and is often ignored by people at an early stage. There are 5.4 million new cases of skin cancer worldwide every year. Deaths due to skin cancer could be prevented by early detection of the mole. They propose a skin lesion classification system that has the ability to detect such moles at an early stage and is able to easily differentiate between a cancerous and noncancerous mole. Using this system, we would be able to save time and resources for both patients and practitioners. They created a deep convolutional neural network using an Inceptionv3 and DenseNet-201 pretrained model. They found that using the concepts of fine-tuning and the ensemble learning model yielded superior results. Fine-tuning the whole model helped models converge faster compared to fine-tuning only the top layers, giving better accuracy overall. Based on our research, we conclude that deep learning algorithms are highly suitable for classifying skin cancer images [4].

Using the ISIC2018 dataset, the deep learning technique convolution neural network (CNN) was utilized to identify the two main categories of tumors: benign and malignant. There are 3533 skin lesions in this dataset, including melanocytic, nonmelanocytic, and malignant tumors. The images were initially enhanced and edited using ESRGAN. Preprocessing involved resizing, normalizing, and augmenting the images. A CNN technique might classify skin lesion photographs based on an overall result acquired after several iterations. Afterward, a variety of transfer learning models were employed for fine-tuning, including Resnet50, InceptionV3, and Inception Resnet. This study's originality and contribution include using ESRGAN as a preprocessing step and testing with different models (the designed CNN, Resnet50, InceptionV3, and Inception Resnet) [5].

Proposed system rely on the prediction of three different methods: A convolutional neural network and two classical machine learning classifiers trained with a set of features describing the borders, texture, and the color of a skin lesion. These methods are then combined to improve their performances using majority voting. The experiments have shown that using the three methods together, gives the highest accuracy level. Index Terms—Melanoma detection, deep learning, classical machine learning, data fusion, majority voting [6].

Identified and categorized different forms of skin cancer using machine learning and image processing techniques. We produced a pre-processing image for this endeavor. We lowered the dataset's size, To fit the needs of each model, the photos were resized and had their hairs removed. The Efficient Net B0 skin ISIC dataset was trained using pre-trained ImageNet weights and modified convolution neural networks [7].

The Xception model with an accuracy of 97% and the Flask web app demonstrate promising results for detecting melanoma skin cancer. The high accuracy achieved by the model and web app shows that machine learning can play a significant role in assisting dermatologists in early detection of skin cancer, which can improve patient outcomes and potentially save lives. However, it is important to note that the model and web app are not intended to replace a dermatologist's diagnosis, but rather to complement their expertise and aid in screening for skin cancer [8].

Because many skin cancer colors appear similar, diagnosing skin cancer is a difficult task for dermatologists. Consequently, prompt diagnosis of lesions is crucial and beneficial in ensuring that patients fully recover from skin cancer. The goal of studying deep convolutional neural network (DCNN) models is to identify skin problems. These simulations have even produced diagnostic outcomes that are on par with or better than dermatologists' in several instances. Important components of DCNN design include network depth, filter selection, size selection, hyperparameter tuning, and the deployment of suitable computational layers. The application of DCNN in the diagnosis of skin illnesses is, however, hindered by the small amount and uneven data of publicly available skin lesion datasets [9].

The main subtypes of skin cancer are scaled and rudimentary cell lymphomas, and carcinoma, which is clinically aggressive and responsible for utmost deaths. Thus, skin cancer webbing is necessary. One of the stylish styles to identify skin cancer directly and fleetly is using deep literacy (DL). To ensure better prognostic and death rates, early skin cancer identification is pivotal, yet solid excrescence discovery generally relies substantially on screening mammography with shy perceptivity, which is also validated by clinical samples. Cancer webbing and treatment response evaluations are generally not applicable uses for this approach. An adding number of healthcare providers are using artificial intelligence (AI) for medical diagnostics to ameliorate and accelerate the opinion decision- making procedure [10].

Early diagnosis is crucial in increasing the likelihood of successful treatment and recovery for fatal diseases like melanoma, which is a dangerous type of skin cancer that is increasing in prevalence. To aid in early detection, we have developed an automated system for dermatological disease recognition using lesion images. Our system integrates multiple AI algorithms, including Convolutional Neural Network and Support Vector Machine, with image processing tools to achieve a high accuracy rate of 85%. The system is composed of three phases: collecting the data and augmentation, modelling the design, and prediction. While this system can be a valuable tool for dermatologists and physicians, it should not be relied upon as a complete substitute for medical personnel-based detection [11].

Melanoma, Basal and Squamous cell Carcinoma are the most common types of skin cancer, with Melanoma being the most unpredictable. Early detection and identification of the type of cancer can aid in its cure. Many technologies have demonstrated that AI and computer science can play a key role in picture scanning. We describe a mobile technique for detecting Melanoma Skin Cancer utilizing Image Processing and basic portable equipment in this technical study. The cancer image is fed into the system, which analyses it using unique image processing algorithms to determine the existence of skin cancer. The cancer picture analysis software looks for asymmetry, border, color, diameter, and other Melanoma properties, as well as size, frequency, and form, to identify the image and feature phases. The scanned feature parameters are used to distinguish between normal skin and melanoma cancer lesions in the image [12].

Depicted in Each image was partitioned into two regions: healthy skin - shadowed skin - background and burns. Furthermore, burns were classified as first-degree burns, second-degree burns or third-degree burns. Image segmentation was performed by using a batchwise classification process. Each image patch was classified by extracting a feature vector from a larger patch red square classifying the feature vector based on its best sparse reconstruction over various dictionaries. CNN model for skin burn images works as automatic skin burn wound recognition and computer aided in the burning victim's diagnosis [13].

The skin cancer dataset consists of types of malignant skin cancer datasets. According to researchers in earlier stages, it is hard to detect due to minute differences compared to normal skin lesions. Therefore, the identification of cancerous skin lesions in the early stages is a difficult matter. In this process, we are going to discuss various technologies that can be used for skin cancer detection and classification and their results. The common approach for early detection of skin lesions is divided into four steps they are as follows: Data Collection, pre-processing, feature selection, and classification. The deep learning algorithm is used to identify skin cancer disease. It will help to easily identify earlier stages of skin cancer [14].

Early identification of melanoma is essential and attainable through visual examination of pigmented lesions on the skin, treated by extirpating the cancerous cells. Standard vision detection of melanoma in skin lesion images might be imprecise. The visual similarity between the benign and malignant types poses hardship in identifying melanoma. To solve the problems in identifying melanoma, automated models are needed to assist dermatologists in the identification task. This paper presents a comprehensive review and analysis of the various deep learning techniques used to diagnose and classify skin lesions [15].

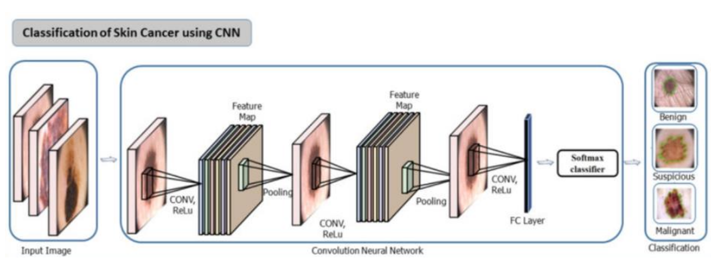
Presented a study and exploration of various segmentation techniques used to detect the type of skin lesions, including Region-based segmentation, Otsu's Thresholding, Boundary, and spot detection, and Entropy based segmentation. Furthermore, support vector machines, Decision Trees, Random Forests have been used to classify skin diseases. Melanotic nevi, Melanoma Benign, Keratosis, Basal cell Carcinoma, Actinic Keratosis, Vascular Lesions, and Dermatofibroma are the seven types of skin cancer. The primary goal of this project is to improve diagnostic system accuracy by utilizing image segmentation and classification techniques [16].

Proposed a Deep learning diagnosing diseases through modern technology becomes easy to access and convenient. Due to the emergence of smartphone analysis and providing results in less time. This system will utilize computational techniques to analyze, process, and relegate the image data predicated on various features of the images. Skin images are filtered to remove unwanted noise and process it for enhancement of the image. Using a machine-learning algorithm (Convolutional Neural network) can predict the type of disease and show in the output to the IOT page of the predicted disease [17].

Melanoma is the most lethal type of skin cancer in the world. Several attempts have been made to detect melanoma early using deep learning techniques based on dermoscopic images. For an accurate diagnosis of melanoma, it is important to distinguish complex lesion patterns. The typical lesion patterns, on the other hand, are not consistently present, resulting in sparse labelling issues in the results [18].

In this development, different segments of image processing be located applied on skin Nodules. From this different image handing out performances, the incoherent filter will provide the competent denoising. Segmentation completed by marker-based watershed algorithm, gives various state of image. GLCM is used to extract the different features of image too which takes less time for generating the result. These results are passed over and done with CNN Classifier, which pigeon-holes the nodules as benign or malignant. CNN classifier arranges for 92.5% accuracy [19].

**CNN architecture in detecting**



## Reviewed outcomes

| Citations | Datasets | Results in accuracy | Remarks |
|---|---|---|---|
| Josef Steppan et al | ISIC-2019 | 0.634 | Ensemble (excluding NasNet) |
| Bhuvaneshwari Shetty et al | HAM10000 | CNN 94%<br>RF 87%<br>DT 68%<br>LR 58%<br>LDA 57%<br>SVM 53%<br>KNN 48%<br>NB 36% | Neural network has better accuracy compare to others. |
| Juan Pablo Villa-Pulgarin et al | HAM10000 | 98% | DenseNet-201 |
| Arnab Rayn et al | HAM10000 | 95% | It only works on GPU machines. |
| Walaa Gouda et al | HAM10000 | 85.85% | In the proposed approach, the Inception model had an overall accuracy rate of 85.7%, which is comparable to that of experienced dermatologists. In addition to experimenting with several models (designed CNN, Resnet50, InceptionV3, and Inception Resnet) |
| Mehwish Dildar et al | AtlasDerm | 86.1% | This review focused on ANNs, CNNs, KNNs, and RBFNs for classification of lesion images. Each algorithm has its advantages and disadvantages. Proper selection of the classification technique is the core point for best results. |
| Jinen Daghrir et al | ISIC (International Skin Imaging Collaboration) | 88.4% | Used different models like KNN, SVM, CNN. |

## 3. Motivation:

The motivation behind undertaking this survey paper on skin cancer detection using neural networks stems from the critical need to enhance early diagnosis and treatment of a disease that poses a substantial threat to public health. Skin cancer's increasing incidence necessitates innovative approaches, and the integration of neural networks holds tremendous promise in transforming traditional diagnostic paradigms.

By delving into the evolving landscape of neural network applications, particularly convolutional neural networks (CNNs), We aim to provide a comprehensive understanding of the state-of-the-art methodologies. The potential impact on patient outcomes and healthcare efficiency drives our exploration of datasets, model architectures, and performance metrics. By shedding light on the challenges and limitations in existing approaches, we aspire to catalyze future research, fostering advancements that contribute to more accurate, accessible, and timely skin cancer detection. Ultimately, this project seeks to bridge the gap between technology and healthcare, empowering practitioners, and researchers to combat skin cancer with cutting-edge solutions.

## 4. Challenges:

Navigating the landscape of skin cancer detection using neural networks presents several challenges. Data quality and diversity, inherent biases within datasets, and the need for large annotated datasets pose obstacles to model training and generalization. Interpretability of neural network decisions in a clinical context remains a concern, hindering widespread adoption. Addressing the computational demands of training complex models and ensuring real-time performance also emerges as a challenge. Moreover, the evolving nature of skin cancer and the rapid development of new technologies demand continuous adaptation, underscoring the dynamic challenges in deploying neural networks for effective and reliable skin cancer detection.

## 5. Dataset

The dataset used in skin cancer detection research plays a pivotal role in training and evaluating neural network models. Commonly employed datasets, such as the International Skin Imaging Collaboration (ISIC) dataset and the Human Against Machine with 10,000 training images (HAM10000), provide diverse collections of dermatoscopic images for model development. These datasets encompass various skin cancer types, facilitating a comprehensive evaluation of algorithmic performance. Challenges within the datasets, such as imbalances in class distribution, varied image qualities, and potential biases, need careful consideration. Rigorous preprocessing techniques, including normalization and augmentation, are often applied to enhance model robustness. The selection and characterization of datasets significantly influence the generalizability and reliability of skin cancer detection models, making them integral components in advancing the state of the art in this critical area of medical research.

## 6. Discussion and Future Enhancement

The discussion section delves into the nuanced aspects of skin cancer detection using neural networks, critically analyzing the findings and implications outlined in the survey. It addresses the strengths and limitations of current methodologies, emphasizing the importance of benchmarking, standardization, and transparency in research practices. Comparisons between different neural network architectures and the impact of transfer learning on model performance are explored. Additionally, the discussion delves into the practical applicability of these models in real-world clinical settings, considering factors such as interpretability, ethical considerations, and user acceptance.

In outlining future directions, the survey paper identifies key avenues for advancing the field of skin cancer detection. This includes the exploration of multi-modal approaches, combining imaging with other diagnostic modalities for enhanced accuracy. Incorporating explainable AI techniques to improve model interpretability is suggested. Moreover, the need for collaborative efforts in building larger and more diverse datasets, addressing specific skin cancer subtypes, and accommodating diverse populations is highlighted. Continuous refinement of neural network architectures, adapting to evolving technological landscapes, and the integration of emerging technologies like 3D imaging or molecular analysis are proposed as promising areas for future research. The discussion and future directions aim to guide researchers towards impactful contributions in the ongoing quest for more effective and accessible skin cancer detection solutions.

## 7. Conclusion

In conclusion, this survey paper has navigated through the expansive terrain of skin cancer detection, emphasizing the pivotal role played by neural networks, particularly convolutional neural networks (CNNs). The advancements in automated diagnosis presented in this review underscore the transformative potential of neural networks in revolutionizing the field of dermatology. The integration of technology not only complements traditional diagnostic methods but also addresses their inherent limitations, offering a more robust and scalable solution for early skin cancer detection. As highlighted in the exploration of datasets, preprocessing techniques, and various neural network architectures, the evolution of this technology is evident. Transfer learning has emerged as a powerful tool, showcasing the adaptability of pre-trained models to the intricacies of skin cancer detection tasks. The discussion on performance metrics and evaluation criteria provides insights into the quantitative aspects of model efficacy. Acknowledging the challenges and limitations within the current landscape, the survey paves the way for future research endeavors. The outlined future directions suggest opportunities for refining existing methodologies and exploring novel avenues, promising further advancements in accuracy and efficiency. As the realm of neural network applications in dermatology continues to evolve, this survey encapsulates the present state of knowledge, offering a comprehensive perspective on the intersection of technology and healthcare in the context of skin cancer detection.

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