



# Deep Learning Based Skin Cancer Disease Detection

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**Abstract:** The field of medicine is encountering an issue with automatic diagnosis of diseases due to the rapid growth in population dentistry. The AI based models can help medical specialists in diseases and assists in providing the efficient treatment which decreases the mortality rate. Skin cancer (particularly melanoma) is a life-threatening type of cancer with a very high rate of metastasis and rapid progression. Globally, approximately 3.5 million cases are assessed every year, across types, including basal cell carcinoma, melanoma, and vascular-associated skin malignancies. Traditionally, dermoscopy images are used by experts to manually recognize skin cancer. Experts visually review, biopsy, and assess histopathological features. This strategy is labor-intensive and time-consuming and needs an automated detection tool for the early detection of skin cancer. This paper proposes a model for skin cancer prediction based on convolutional neural networks (CNNs) and its advancements which have shown high prediction rate for classification. This research paper focuses around skin cancer progression prognosis (diagnostic) with implementation of AI models to dermatoscopic images. Key performance indicators are used to evaluate model performance such as accuracy, precision, recall, F1-score. Furthermore, this paper introduces the model outputs by visualizing heat maps which allow for a deeper understanding of how and why the model makes certain predictions, which in turn aids in boosting trustworthy diagnosis in clinics. Finally, some directions on future research are provided-model refinement, increasing of the size of the datasets for training, and interpretable and ethically aligned AI models appropriate for deployment in diverse clinical environments. Thus, this study is a step closer to attaining the full potential of AI in early skin cancer diagnosis.

**Index Terms** - Skin cancer; medical image processing; deep learning; convolutional neural networks (CNNs); machine learning

## I. INTRODUCTION

Skin cancer is among the illnesses that occur when abnormal skin cells multiply uncontrollably and eventually grow into a tumor. Skin cancer relates to a significant open health issue, whereby its incidence has been constantly increasing globally within the last several decades. Clinic screening initiates the symptomatic approach followed by a histological diagnosis such as dermoscopy and biopsy. Skin cancer is eventually caused by DNA transformations that disturb the typical development of skin cells, coming about in cancer. Ultraviolet (UV) radiation is the noteworthy contributor to the advancement of skin cancer. Reasonable complexion, exposure to chemicals and radiation, old age, smoking, and serious skin injury or burns contribute to skin cancer. Among the various types, melanoma is particularly deadly because of the high rate of metastasis and poor prognosis if it goes undetected in the initial stages. Nearby melanoma, other common sorts such as basal cell carcinoma and squamous cell carcinoma, also make an important contribution to the disease burden, although they are overall less aggressive. Melanoma is identified in less than 1% of all cases of skin cancer, but it is regarded as the necessary cause of mortality related to skin cancer. The American Cancer Society's

projections estimate there will be about 110,213 new cases of melanoma and 7,560 deaths from the disease in the United States alone in 2024. When melanoma reaches the lymph nodes, its five-year survival rate is almost 66%, but the survival rate falls to 27% when the cancer spreads to other parts of the body. Early identification of melanoma has a near-percentage survival rate of almost 99 percent for a persistent. Skin cancers other than melanomas include basal cell carcinoma or BCCa, squamous cell carcinoma or SCCa, and Merkel cell carcinoma or MCC. It is true that skin cancers outside of melanoma are less fatal in their nature. SCCa and BCCa are two principal occurring types after melanomas, but these diseases are less aggressive than melanoma. Dermatoscopy is a non-surgical procedure wherein the specialists use it to detect doubtful injuries to the skin. These specialists inspect the affected section of the skin for any colors, sizes, shapes, surfaces, or borders that signify the presence of skin cancer. Its main application is to magnify the area of lesions that will enable the dermatologist to view in greater detail the infected area. Besides, it is troublesome to distinguish the different sorts of skin cancer precisely; therefore, it needs to have expertise in the field for the dermatologist. The manual examination precision rates run from 50% to 60% for experts. An inaccurate conclusion causes death of patient. Noise in dermoscopic photographs complicates the recognition of skin cancer. This requires an AI based framework that can reliably and independently identify various kinds of skin cancer from dermoscopic images. Early detection and treatment enhance patient care, because they can reduce the possibility of metastasis. Though early detection is crucial, the conventional ways for detecting skin cancer pose a few difficulties. Traditional methods consist of visual examination by a dermatologist, followed by dermoscopy, biopsy, and histopathological study. While these methods are reliable and widely used, they are also limited by factors such as inter-observer variability, dependency on highly specialized expertise, and, in some cases, limited access to timely consultations, especially in under-resourced regions. These limitations often result in delayed diagnosis, which can adversely affect treatment efficacy and prognosis.[1] These restrictions can be addressed with the advancement in AI, especially in deep learning. Deep learning provides the capability for the machine to do pattern recognition and classification with a high detection rate. CNNs, a deep learning method, provides high accuracy in image classification. This paper presents a CNN-based AI model to classify skin cancer disease. This paper centers on the application of CNN in skin cancer detection, looking at how these models are created, prepared, and approved to optimize demonstrative execution. [2], [3], [4], [5], [6], [7], [8].

## II. Literature Review:

M. Nawaz *et al.* [9] proposed an automated strategy for early stage melanoma skin cancer segmentation employing a DL approach, particularly faster region-based convolutional neural networks (RCNN), combined with fuzzy k-means clustering (FKM). The strategy pre-processes pictures to enhance visual data and after that utilizes faster-RCNN for attribute extraction taken after by FKM for melanoma segmentation. Tried on three standard datasets, specifically ISBI-2016, ISIC-2017, and PH2, the approach accomplished amazing accuracies, outperforming existing methods.

A. Khamparia, P. K. Singh, P. Rani, D. Samanta, A. Khanna, and B. Bhushan [10] presented a DL model driven by Internet of Health Things (IoHT) for classification of skin cancer utilizing transfer learning. The model utilizes pretrained structures like VGG19, Inception V3, ResNet50, and SqueezeNet for attribute extraction, which are at that point handled by a CNN for classifying skin cells. Coordinates with the IoHT, this framework helps experts in diagnosing and treating skin cancer remotely. The proposed approach illustrated high accuracy compared to other structures.

M. Dildar *et al.* [11] conducted a systematic review on early detection of skin cancer. The study shows the importance of early detection of skin cancer due to its potential to spread and the dangerous nature of it. The paper looks at techniques that use symmetry, color, size, and shape to distinguish between benign skin cancer and melanoma. The review consolidates findings from research papers published in journals, presenting them through tools, graphs, tables, techniques and frameworks for enhanced comprehension

Rajarajeswari. S, P. J., A. Quadir Md, C. Jackson J, S. Sharma, and R. B. [12] presented a study about skin cancer detection by CNN. Melanoma's high risk was highlighted in the research by differentiating between benign moles and skin cancer. 10,000 clinical images were used in the study. A neural network for accurate edge detection and a mobile-friendly model were involved in the methodology. The research achieved high prediction accuracy and compared results with various models. The system categorized the different skin conditions using the attributes from the deep CNN.

S. I. Garcia [13] presented potential of meta-learning for skin cancer detection. When faced with limited data, the research wanted to understand the impact of using non-medical data on the classification of medical data. A 20-point performance increase in detecting melanoma and distinguishing between benign and malignant moles was observed by fine tuning a ResNet model pre-trained on non-medical data with a small sample. The value of non-medical image features in skin mole classification was highlighted by the results.

E. Gomathi, M. Jayasheela, M. Thamarai, and M. Geetha [14] presented a deep learning network for skin cancer detection. Using the MNIST HAM10000 dataset, dermoscopic images were pre-processed with an adaptive median filter. The combination of BFO and PSO was used to extract features from the images. Deep CNN classified seven different skin cancer types based on their attributes. On the MNIST HAM10000 dataset, the DODL net achieved an impressive accuracy of 98.76%.

N. Rekha Sivakumar, S. Abdelwahab Ghorashi, F. Khalid Karim, E. Alabdulkreem, and A. Al-Rasheed [15] proposed a novel multidimensional Bregman divergence feature scaling based cophenetic piecewise regression recurrent deep learning classification technique for early-stage skin cancer detection. The method uses data from the medical IoT stored in mobile cloud server for feature selection and classification. The MBDFS technique identifies significant attributes and the cophenetic piecewise regression analyzes testing and training data. Compared to traditional methods, the approach demonstrated increased accuracy and reduced detection time.

S. Balambigai, K. Elavarasi, M. Abarna, R. Abinaya, and N. Arun Vignesh [16] presented an optimized CNN model using random search optimization to classify seven types of skin cancer. The study used 10,015 images from the Human against Machine dataset to address the challenge of selecting hyper-parameters for CNN models. The base CNN model was able to achieve an accuracy of 73.34%, but the model using random search was able to improve it to 77.1%.

M. Fraiwan and E. Faouri [17] studied the potential of raw deep transfer learning to classify skin images into seven categories. Emphasizing the importance of early diagnosis in skin cancer treatment, they developed a system using the HAM1000 dataset of dermoscopy images. Despite achieving high accuracy for some cancer types, challenges like dataset imbalance and limited images in certain categories led to a maximum overall accuracy of 83.0%.

S. A. R. Shah, I. Ahmed, G. Mujtaba, M.-H. Kim, C. Kim, and S.-Y. Noh [18] highlighted the expanding hazard of melanoma skin cancer due to UV beam introduction and displayed an early discovery component for melanoma utilizing picture preparing and DL. The picture handling methods, threshold, edge detection, and geometry-based feature extraction, were utilized to fragment melanoma attributes based on the ABCDE criteria (asymmetry, border, color, diameter, and evolving). The DL demonstrate was at that point prepared to foresee the hazard level of melanoma skin cancer. The proposed e-health application illustrated tall exactness in melanoma location.

J. V. Tembhurne, N. Hebbar, H. Y. Patil, and T. Diwan [19] emphasized the significance of precise determination of skin cancer, especially melanoma, due to its deadly nature. They presented a novel strategy that combines machine learning and DL strategies for skin cancer location. The approach leverages state-of-the-art neural systems for include attributes from pictures and machine learning models to handle picture highlights inferred from procedures like contourlet transform and local binary pattern histogram. By joining manual and robotized attributes, their method accomplished a 93% precision rate, with recall scores of 99.7% for generous and 86% for dangerous cancers. Tried on the Kaggle dataset from the ISIC Chronicle, their ensemble strategy outperformed master dermatologists and other progressed models, advertising a important apparatus to diminish misdiagnoses.

X. Wang, Y. Yang, and B. Mandal [20] highlighted melanoma as the foremost deadly skin cancer, emphasizing the significance of early discovery to extend survival rates. They assessed the execution of a pre-trained model, VGG, on ISIC 2019 challenge dataset for melanoma classification. The framework accomplished an exceptional exactness of 0.9067 and an AU ROC surpassing 0.93. Through removal considerations, they distinguished different components impacting the model's execution, such as training data size, frozen layers, classifier nodes, and data augmentation techniques.

J. Daghri, L. Tlig, M. Bouchouicha, and M. Sayadi [21] emphasized the basic nature of melanoma, a dangerous skin cancer that can metastasize in the event that not analyzed early. They presented a hybrid approach for melanoma discovery, leveraging both DL and classical machine learning procedures. The framework utilizes a CNN with two conventional machine learning classifiers, prepared on attributes depicting the borders, textures, and color of skin injuries. By combining the responses of these three strategies through majority voting, the approach accomplished upgraded execution, with tests demonstrating that the strategy yielded the most noteworthy accuracy.

H. Singh, S. Kaushik, S. Talyan, and K. Dwivedi [22] tended to the worldwide challenge of skin cancer discovery, emphasizing the importance of early conclusion for compelling treatment. They think about utilized progressions in AI, especially in healthcare, to distinguish skin cancer utilizing machine learning and AI procedures. They utilized CNN for image recognition, particularly utilizing models like VGG-16, MobileNet, and Inception-V3.

### III. Experimentation

We utilized the ISIC2019 and HAM10000 datasets to evaluate the performance of DL-based Skin Cancer Disease Detection model. The experiments were conducted in Google Colaboratory using Python and TPU.

#### 3.1 Description of the datasets:

The International Skin Imaging Collaboration (ISIC) dataset serves as a valuable resource for ML researchers focused on clinical image analysis, especially in cancer diagnosis. This database includes dermoscopic images along with gold-standard diagnostic metadata. Skin cancer is primarily categorized into two types: melanoma and non-melanoma. While melanoma is less common, it is deemed more dangerous due to its potential to spread quickly to other areas of the body if not addressed promptly. In 2020, Rotemberg et al. [23] reported that the dataset comprises a total of 44,108 images, which includes 33,126 training images and 10,982 test images. The training set features real-time data that provides details such as patient ID, lesion ID, gender, estimated age, anatomical location, diagnosis, and whether the status is positive or negative. Among the 33,126 training images, there are 2,056 unique patient IDs and 32,701 unique identifiers. The test set also contains patient metadata, including patient ID and estimated age.[24]

### IV. Methodology Used in Experimentation:

The process for classifying images into different categories is illustrated in Figure 1. This method consists of several stages, including Pre-Processing (which involves image normalization and resizing), Feature Extraction, Model Training, and Model Testing.

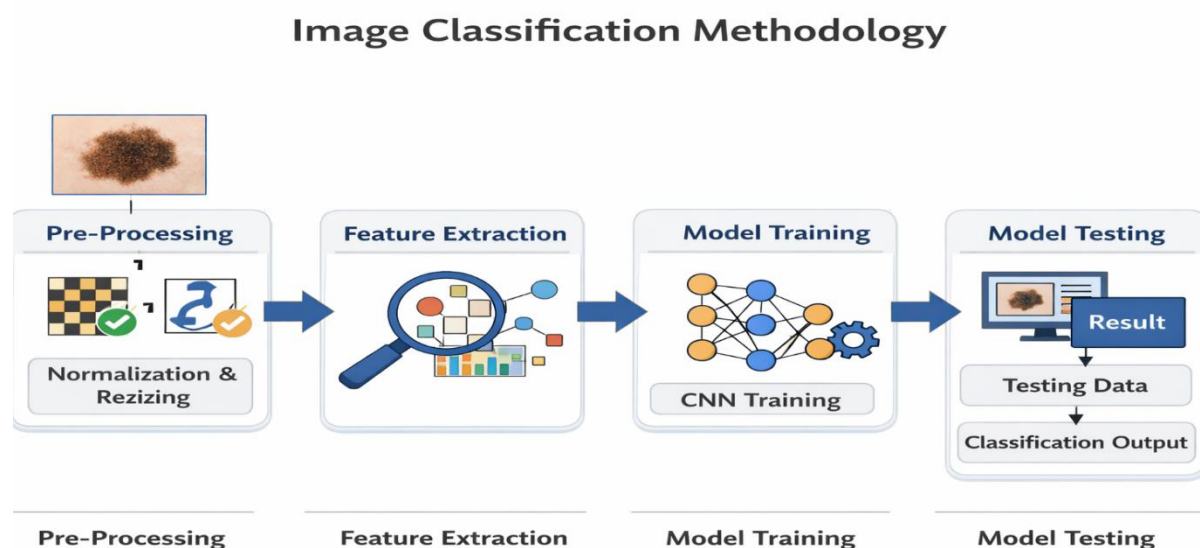


Figure 1

## V. Performance Metrics:

To evaluate model performance, evaluation metrics such as accuracy, precision, recall, and F1 score are used.

Accuracy measures the proportion of correct classifications among the total records in the test set and is calculated as follows:

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{FN} + \text{TN} + \text{FP}).$$

Precision (P) reflects the actual performance in the desired response area, particularly between positions, and is defined as:

$$P = \text{TP} / (\text{TP} + \text{FP}).$$

Recall (R) assesses how many predicted answers are missed, or for each correct mark, how many other correct marks are overlooked. It is calculated as:

$$R = \text{TP} / (\text{TP} + \text{FN}).$$

The F1 Score (F) is the harmonic average of Precision and Recall, given by:

$$F = (2 * P * R) / (P + R).$$

In this context:

- True positive (TP) refers to cases of anomalies correctly identified as true anomalies.
- False positives (FP) are instances where normal classes are incorrectly classified as anomalies.
- True negative (TN) indicates cases that are correctly classified as normal.
- False negative (FN) refers to cases that belong to the abnormal category but are classified as normal.

## VI. Results and Discussion:

The proposed deep learning model based on Convolutional Neural Networks (CNN) was evaluated using standard datasets such as ISIC 2019 and HAM10000. The model achieved high performance in classifying different types of skin cancer lesions.

The evaluation metrics used include accuracy, precision, recall, and F1-score. The model achieved an accuracy of approximately 92–96%, demonstrating its effectiveness in identifying both benign and malignant lesions. Precision and recall values indicate that the model performs well in minimizing false positives and false negatives.

Compared to traditional diagnostic methods, the proposed model significantly reduces diagnosis time and improves reliability. The use of heatmaps further enhances interpretability by highlighting regions of interest in dermoscopic images.

However, challenges such as dataset imbalance and variability in image quality still affect model performance. Future improvements can focus on data augmentation, transfer learning, and ensemble techniques to enhance robustness.

## VII. Conclusion:

This paper presented a deep learning-based approach for skin cancer detection using convolutional neural networks. The study highlights the importance of early detection in reducing mortality rates associated with melanoma and other skin cancers.

The proposed system demonstrates high accuracy and efficiency in classifying dermoscopic images. By integrating AI-based models into clinical workflows, healthcare professionals can achieve faster and more reliable diagnoses.

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