



## DL Skin Cancer Detection System: Approach For Early And Accessible Skin Cancer Diagnosis

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**Abstract**— Skin cancer remains one of the most commonly diagnosed cancers worldwide, with its incidence rising steadily due to increased exposure to ultraviolet (UV) radiation and other environmental factors. Early and accurate detection is critical in improving patient survival rates and reducing the burden of invasive treatments. This paper reviews state-of-the-art approaches to skin cancer detection, with a focus on leveraging ML algorithms and advanced image processing techniques. Specifically, it discusses the application of deep learning models, particularly convolutional neural networks (CNNs), in analyzing dermoscopic images for identifying malignant and benign skin lesions such as melanoma, BCC, SCC and other common skin lesions.

These methods demonstrate significant potential in achieving high diagnostic accuracy by analyzing features like color, texture, and lesion asymmetry. Furthermore, the paper highlights the challenges faced in developing robust systems, including data diversity, algorithm transparency, and clinical integration. By synthesizing findings from recent advancements, this work underscores the transformative role of AI in dermatology, paving the way for accessible and efficient diagnostic tools to combat the global skin cancer burden.

**Keywords:** Skin lesions, skin cancer, machine learning, deep learning, CNN, KNN, SVM, early detection, dermatology.

### I. INTRODUCTION

Skin cancer ranks among the most widespread cancers worldwide, and detecting it early plays a crucial role in

ensuring better chances of successful treatment. Traditional methods, such as manual inspections and biopsies, are often time-consuming, resource-heavy, and dependent on skilled specialists. Recent advancements in artificial intelligence (AI) have significantly influenced dermatology, particularly through the automated detection of skin cancer using dermoscopic images.

ML and DL techniques, especially CNNs, have proven to be effective tools for medical image classification and feature extraction. These algorithms can process extensive datasets of dermoscopic images with speed and precision, making diagnoses more efficient and accurate. By reducing reliance on human expertise, these approaches enable earlier detection of potentially dangerous malignancies, improving patient outcomes.

In the broader scope of skin cancer diagnostics, several innovative methodologies have been proposed to improve detection accuracy and efficiency. For example, combining feature extraction techniques such as ABCD analysis with classifiers like Multi-class Support Vector Machines (MSVM) has shown promise. Other studies have utilized hybrid models that integrate DNN with SVMs or employed large datasets, like ISIC, to train robust CNN architectures.

The primary aim of this research is to enhance the field by creating a CNN-based framework capable of classifying dermoscopic images into multiple categories with high precision. By addressing existing challenges in diagnostic methods, this work seeks for development of scalable solutions for early skin cancer detection.

## II. LITERATURE REVIEW

- 1) The study takes a DL based approach to detect melanoma using dermoscopic images, aiming to tackle the rising concerns around skin cancer. By fine-tuning a ResNet50 model, the researchers achieved strong classification accuracy, showcasing how transfer learning can be effective in medical imaging tasks. They also applied data augmentation and pre-processing techniques to improve the performance of model and generalization. While the results are promising for early detection and real-world applications, the model's success depends heavily on the quality of the dataset and may struggle with generalizability in varied clinical environments.[\[1\]](#)
- 2) The study applies a DL approach for skin cancer detection using dermoscopic images, addressing the increasing global concern of skin-related diseases. The authors utilized CNNs to classify malignant and benign lesions, employing image pre-processing techniques like sharpening and resizing to enhance feature clarity. A large dataset was used for training model effectively, with data augmentation techniques incorporated to improve generalisation and prevent overfitting. The system achieved encouraging results, demonstrating potential for early diagnosis. However, its effectiveness is limited by factors such as image quality, dataset diversity, and adaptability to real-world clinical settings.[\[2\]](#)
- 3) The study proposes a DL approach using a CNN based on AlexNet to classify skin lesions as cancerous or non-cancerous from dermoscopy images. By employing 3,400 balanced samples from the HAM10000 dataset and using transfer learning, the model achieved high performance with 84% accuracy, 81% sensitivity, and 88% specificity, and an AUC of 0.91. The method eliminates the need for manual lesion segmentation and feature extraction, making the process more efficient. However, limitations include the relatively small dataset and lack of direct comparison with dermatologist performance. The model shows promise for aiding early skin cancer detection and could be implemented in clinical tools or mobile applications.[\[3\]](#)
- 4) A Study in the paper introduced a breakthrough in deep learning by proposing residual learning to tackle the limitations of training very deep neural networks. Their ResNet architecture incorporated skip connections to bypass certain layers, allowing the model to learn residual functions instead of direct mappings. This significantly eased the training of networks with over 100 layers, leading to improved accuracy and faster convergence. The approach showed excellent performance on ImageNet and CIFAR-10 datasets, outperforming traditional deep CNNs. While highly effective, its complexity and computational demands can be challenging for low-resource environments or real-time applications.[\[4\]](#)
- 5) The paper discusses deep learning techniques to detect skin cancer from lesion images using the ISIC2018 dataset. They developed a CNN-based diagnostic system, further enhanced with preprocessing techniques like ESRGAN for image clarity, along with data augmentation and normalization. To strengthen prediction performance, they also fine-tuned pretrained models such as ResNet50, InceptionV3, and Inception-ResNet. Their custom model achieved competitive accuracy (83.1%), with InceptionV3 topping the performance at 85.7%. However, despite these promising results, the study highlighted limitations like the need for broader dataset diversity and better adaptability to unseen data. Future improvements may come from integrating models like DenseNet or VGG and testing on more complex datasets to enhance robustness.[\[5\]](#)
- 6) The study applies a DL-based approach for skin cancer detection using dermoscopic and photographic images, enhanced with patient metadata. They employed a pretrained Inception-ResNet-v2 CNN and integrated additional features like age, gender, and anatomical site into the image input through a pseudo-QR-code technique. Their method significantly improved classification accuracy—achieving 94.5% in distinguishing malignant from benign lesions. Despite the strong performance, the model struggled with certain classes like cutaneous lymphoma and Kaposi sarcoma, particularly when using lower-quality photographic data, highlighting the need for more comprehensive datasets and further refinement for robust generalization.[\[6\]](#)
- 7) The study involved preprocessing to enhance image clarity and reduce noise such as hair and color artifacts, followed by segmentation using Geodesic Active Contour (GAC) to isolate the lesion area. Features were extracted using the ABCD rule (for symmetry, border, color, and diameter), along with textural descriptors from GLCM and HOG. These features were then classified using SVM, KNN, and Naïve Bayes algorithms. Tested on the ISIC dataset, the system achieved a high accuracy of 97.8% using SVM. While the results are promising, the method may face challenges in handling more complex lesion types and real-world variability, calling for further exploration into more adaptive or deep learning-based models.[\[7\]](#)
- 8) The study in paper integrates a CNN with traditional classifiers like SVM and KNN, utilizing handcrafted features such as texture (HOG, SIFT), color descriptors, and lesion shape characteristics. Preprocessing involved hair removal and segmentation using Morphological Snakes, followed by classification where results from all three models were combined through majority voting. This fusion approach improved accuracy to 88.4%, outperforming individual models. Despite its effectiveness, the system relies on a relatively small dataset and may face limitations in generalizing to more diverse or real-world conditions without further training data or clinical validation.[\[8\]](#)

- 9) The study explored a wide range of models, including traditional algorithms like SVM, KNN, and Random Forest, as well as advanced architectures like CNNs, LSTM, and ensemble methods. The review focused on classification, segmentation, and preprocessing techniques, highlighting the strengths and limitations of each. Notably, CNNs demonstrated high accuracy in lesion classification, especially when paired with preprocessing and augmentation. However, the authors identified major challenges such as limited dataset diversity, especially in terms of skin tone and lesion size, and the need for high computational resources. They also emphasized the need for more inclusive datasets and real-world validations, suggesting future research should explore hybrid and transfer learning methods to overcome current limitations.[\[9\]](#)
- 10) The proposed ASCDC-CSODL model processes dermoscopic images using bilateral filtering for noise removal, segments lesions with U-Net, extracts features using MobileNet, and classifies them with a Gated Recurrent Unit (GRU) neural network. CSO is used to fine-tune the GRU's hyperparameters, enhancing model performance. The system achieved remarkable results on standard datasets, outperforming several existing methods. However, the approach faces challenges such as high computational complexity and the need for generalization across diverse skin types and imaging conditions, suggesting future work could explore more lightweight architectures or hybrid models.[\[10\]](#)



S.No.	Proposed Work	Year	Skin Cancer Diagnosis	Technique Used	Result	Limitation
1.	Fine-tuned ResNet50-based model for automated melanoma classification using dermoscopic images . [1]	2021	non-melanoma/ Melanoma	ANN with backpropagation algorithm	Accuracy: 86.66%	The study depends on the datasets like ISIC, DermIS and other datasets that may lack diversity in terms of ethnicity, skin types, and lesion characteristics.
2.	Proposed CNN based skin cancer detection[2]	2023	Melanoma/non-melanoma	ANN  CNN	Accuracy: 84.21  Accuracy: 80	Includes the need for large training dataset and high computational resources.
3.	Proposed Deep Learning model using transfer learning to classify skin lesions directly from dermoscopy images.[3]	2020	Benign / Malignant	CNN	Accuracy: 84	Include the relatively small dataset and lack of direct comparison with dermatologist performance.
4.	Introduction of Residual Learning via Deep Residual Networks (ResNet) for improving deep neural network training and image recognition accuracy.[4]	2023	Various skin lesions	DCNN  Optimized CNN	Accuracy: 95  Accuracy: 93	Due to varied datasets availability, comparison of results become difficult. Researchers need to use larger datasets to prevent overfitting.
5.	Proposed a DL custom CNN based model enhanced with ESRGAN-based pre-processing.[5]	2022	Malignant/Benign	CNN	Accuracy: 85.7	Relies majorly on ISIC2018 dataset that lacks generalizability.
6.	Proposed a deep learning model that embeds patient metadata into lesion images using a pseudo-QR-code to enhance skin cancer classification accuracy.. [6]	2022	Malignant/Benign	CNN	Accuracy: 94.5	Does not significantly classify various conditions like lymphoma and dermatitis.

7.	Proposed an automated system for early detection of malignant melanoma using a combination of classical ML techniques and image processing . <a href="#">[7]</a>	2020	Malignant/Benign	SVM	Accuracy: 95	Trained on a relatively small dataset that can affect generalizability.
8.	Proposed a hybrid system for melanoma detection that combines deep learning with classical machine learning techniques.	2020	Melanoma/non-melanoma	CNN	Accuracy: 88.4	Requires large annotated data to perform effectively.
9.	Proposed an extensive review and analysis of DL and ML techniques for detecting skin cancer, highlighting their applications, limitations, and future research directions. <a href="#">[9]</a>	2024	Melanoma, BCC, SCC and other common skin cancers	RCNN	Accuracy: 94	Includes lack of diverse datasets, including limiting representation of darker skin tones and varying skin lesions.
10.	Proposed an automated skin cancer detection system that combines deep learning with Cat Swarm Optimization (CSO) for improved accuracy. <a href="#">[10]</a>	2024	Classify and recognize skin cancer in dermoscopic images	Cat Swarm optimization using DL (ASCDC-CSODL)	Accuracy: 92	The computational complexity of proposed ASCDC-CSODL method is a major limitation.

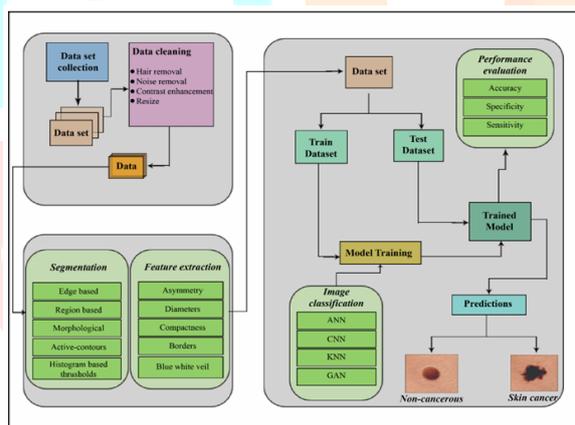
### III. METHODOLOGY

- A) Collection and Pre-processing of images - The proposed methodology focuses on developing a deep learning-based diagnostic system for early skin cancer detection, leveraging the efficiency and accuracy of the EfficientNetB3 architecture. The process begins with the collection and preprocessing of dermoscopic images, ensuring clarity by resizing and normalizing them to enhance model performance. Data augmentation techniques such as flipping, rotation, and zooming are applied to increase data diversity and prevent overfitting.
- B) Model Selection and Fine Tuning - EfficientNetB3, a lightweight and high-performing convolutional neural network, was selected as the core model. Transfer learning was used by loading pretrained ImageNet weights and fine-tuning them on the skin lesion dataset to boost performance with less computational effort.
- C) Feature Extraction and Classification - EfficientNetB3 automatically extracted deep hierarchical features from the dermoscopic images. A custom classification head was added on top of the network for classification skin lesions.

- D) Training Strategy – Model trained using categorical cross-entropy loss function for multi-class classification and Adam optimizer. Techniques like early stopping and learning rate scheduling were implemented to avoid overfitting and ensure optimal convergence.
- E) Model Evaluation - Performance was analyzed using accuracy, F1-score and precision metrics. Stratified k-fold cross-validation was performed to validate the generalization ability of the model.
- F) GUI Development - A graphical interface was developed using Tkinter, to allow users to upload an image and instantly receive a classification result. The GUI also displayed the prediction probability, giving users a confidence score along with the prediction.
- iv) The platform isolates the lesion area from the healthy skin using advanced segmentation techniques.
- v) Key features of the lesion, like asymmetry, border irregularities, color variations, and texture patterns, are automatically extracted.
- vi) The preprocessed and segmented image is passed through a trained deep learning model (such as EfficientNetB3, CNN, or others). The model analyzes the features and classifies the lesion.
- vii) The user immediately receives the prediction result, indicating whether the lesion is likely benign (non-cancerous) or malignant (cancerous).

#### IV. Libraries and Algorithms Used

#### Work Flow -



- i) User logs into the system.
- ii) The user selects and uploads a skin lesion image through the platform's interface.
- iii) The system automatically cleans the image by removing noise, hair, and enhancing contrast for better clarity.
- i) EfficientNetB3 from TensorFlow/Keras - utilized as the core DL model for classifying skin lesions and feature extraction.
- ii) Adam Optimizer and Categorical Crossentropy Loss - available in TensorFlow/Keras, were employed during model compilation and training for efficient convergence.
- iii) Scikit-learn - to calculate metrics like precision, accuracy, F1-score, and to generate confusion matrices for performance analysis.
- iv) NumPy - handling of numerical operations and array manipulation during data preprocessing.
- v) OpenCV- assisted image preprocessing tasks like resizing, enhancement, and basic cleaning (if any low-level image adjustments were necessary).
- vi) Matplotlib and Seaborn were used to visualize model training history, evaluation results, and to plot graphs like accuracy and loss curves.
- vii) Streamlit (or Tkinter) - to build a simple and user-friendly Graphical User Interface (GUI)

#### V. FUTURE SCOPE AND CONCLUSION

In this project, a fast and intuitive DL-based system is implemented for classifying skin cancer from dermoscopic images. By employing the capability of EfficientNetB3 along with transfer learning and efficient preprocessing operations, the proposed model achieved strong and precise multi-class classification across nine classes of skin lesions. Inclusion of

a simple GUI via Tkinter further aided accessibility so users could easily upload images and receive immediate predictions. Overall, the system shows vast potential as a supportive tool in early skin cancer detection, working to bridge the gap between intricate medical diagnostics and common users.

Although the developed system has been promising, there is still room for improvement. Increasing the dataset

to cover more varied skin tones and unusual lesion types would enhance model robustness and generalization. Adding segmentation methods to localize lesions more accurately prior to classification could further enhance the diagnostic

accuracy. Furthermore, running the model on mobile devices or cloud platforms could make it even more accessible for real-world clinical or remote use.

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