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RESEARCH PAPER

# Automated Skin Lesion and Cancer Classification Using AI-Driven-Deep Convolutional Networks

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***Abstract*—Skin cancer is one of the most common cancers worldwide, and the longer it remains untreated, the greater the likelihood of serious consequences or even death. Traditional diagnostic techniques depend on the expert's visual evaluation and are thus subjective, laborious, and very variable. As a result, getting a proper diagnostic done quickly is crucial. To enhance the accuracy and efficacy of skin lesion diagnosis, this effort seeks to develop an automated classification system using dermoscopy images. The authors of this study propose building and testing a skin lesion classification AI system that makes use of various ML and DL techniques, including Xception, ResNet, CNN, ANN, and LSTM models. The proposed convolutional neural network (CNN) model achieved the highest reliability and accuracy in skin cancer diagnosis (98.49 F1-score, 98.58% ACC, 98.57% PRE, and 98.59% REC) compared to all other models. This method can help dermatologists identify skin disorders earlier and more accurately, which in turn improves clinical decision-making and decreases the incidence of misdiagnosis.**

***Keywords—Skin Cancer Detection, Deep Learning, Image Classification, Dermoscopic Images, Medical Image Analysis, Automated Diagnosis, Early Detection.***

## I. INTRODUCTION

Skin cancer is a very common and possibly deadly skin disease. Skin cancer occurs when the skin's cell multiplication becomes unchecked and abnormal, typically as a result of long-term exposure to UV radiation from the sun or tanning beds. Any one of the skin's three layers—the epidermis, dermis, or hypodermis—can become cancerous [1][2]. The most deadly and dangerous form of skin cancer is melanoma, while basal cell carcinoma (BCC), squamous cell carcinoma (SCC), and Merkel cell carcinoma (MCC) are the most prevalent types. The importance of skin cancer screenings and preventative measures is underscored by the fact that millions of new instances of cancer are reported annually [3][4].

In order to improve treatment results and increase patient survival rates, early identification of skin cancer is crucial. Dermatologists have long relied on dermoscopy, ocular examinations, and biopsies to confirm the presence of skin cancer [5][6]. Dermatoscopes give magnified and illuminated images of skin lesions, so that detailed inspection of suspicious regions is possible [7]. Traditional diagnosis methods, however, are time-consuming, subjective, expensive, and very dependent on clinical skills. Furthermore, diagnosis using biopsy may be invasive and uncomfortable for the patient. Therefore, early detection skin cancer testing tools that are both automated and non-invasive are in high demand [8][9][10].

Emerging technologies in medical imaging and computer-aided diagnosis have seen tremendous progress over the last few years, greatly enhancing the ability to identify skin abnormalities. Acquisition of images, preprocessing of images, segmentation of lesions, extraction of features, and classification are the typical components of automated skin cancer diagnostic systems. These systems can help healthcare professionals get quicker and more consistent diagnostic results [11][12][13]. The more and more widespread use of dermoscopic image databases and computing power has further stimulated the research in automated analysis of skin lesions [14]. Skin cancer screening services may be expanded with the use of these technologies, which can also reduce the number of incorrect diagnoses and improve clinical decision-making [15][16].

AI, ML, and DL have recently taken the lead in both the interpretation of medical imagery and the diagnosis of diseases [17][18]. CNNs' capacity to learn discriminative features from raw pictures on their own has led to impressive performance in picture classification challenges. CNN models eliminate the need for human feature engineering and have a high ACC for skin lesion identification and classification [19]. Computers may discover useful patterns from medical data and provide useful predictions using ML approaches, all without being expressly trained to do so. DL, a branch of machine learning, can automatically extract useful information from dermoscopy images; this enhances the reliability, precision, and effectiveness of skin cancer diagnosis and classification [20][21][22].

### *A. Motivation and Contribution*

This research primarily aims to address the high prevalence of skin cancer and emphasizes the need for early detection in ensuring an accurate diagnosis. The traditional diagnostic procedures are subjective, time-consuming, and require expertise. Therefore, the project's goal is to create a CNN model for automatically classifying skin cancer images obtained by dermoscopy. This allows for earlier medical action, lowers the chance of human error, and improves the diagnostic ACC and PRE. These findings are the primary contributions of the study:

- This study is concerned with automatic detection and classification of thermoscopic images for skin cancer.
- The model was trained and evaluated using the HAM10000 dataset, which contains 10,015 photos of seven different kinds of skin lesions.
- Used the ADASYN method to address class imbalance, so minority classes are better represented and the models work better.

- Developed and assessed a number of ML and DL models, including ResNet, ANN, Xception, LSTM, and CNN.
- Presented evidence that the suggested CNN model works better than all models evaluated, with the best ACC.
- The main goals are to support medical personnel in efficiently and accurately identifying skin cancer and to enhance ACC for early diagnosis.

### B. *Justification and Novelty*

Skin cancer is becoming more common, and human diagnosis has its limits; thus, a reliable and automated detection method is needed. The study's justification rests on the recognition that dermoscopy picture categorization needs improvement in order to decrease the rate of misdiagnosis and improve patient outcomes. The novelty of this work consists of comparative evaluation of multiple DL and ML models such as ResNet, ANN, Xception, LSTM and CNN on the HAM10000 dataset and proposing and optimizing CNN based approach to achieve better model performance. The proposed framework includes advanced preprocessing method and class balancing using ADASYN for improving the learning of the model, which is able to achieve better classification ACC and robustness than other existing methods

### C. *Organization of the Paper*

This paper is organized in the following way: A literature review on skin cancer diagnosis is provided in Section II. The dataset, preparation procedures, and suggested model implementation are detailed in Section III. In Section IV, evaluate and contrast the experimental outcomes across different models. Finally, as a conclusion to the study, Section V summarises the key findings and suggests options for further research.

## II. Literature Review

A review and analysis of important research studies on Skin Cancer Diagnosis was completed to guide and improve the development of this study.

S. Adablanu et al. (2026) introduce VINCE-NET, a DL model that combines elements from stroke detection with those from dermoscopy to classify melanoma. For the purpose of capturing global, local, and spatial characteristics, the model integrates the strengths of Vision Transformer, CNN, and LSTM. On the HAM10000 dataset, VINCE-NET was more accurate (with 94.1%), more precise (with 95.5%), more sensitive (with 90.4%), more specific (with 92.9%) and more effective (with an AUC of 0.98) than CNN, LSTM, ResNet-50, VGG-16/19 and DenseNet-121/201, while being less computation-intensive [23].

P. R and S. G (2025) introduce a method that uses artificial intelligence to identify skin cancer early on by integrating lesion segmentation and risk assessment for improved diagnosis. The method is built on the HAM10000 dataset, where the lesion segmentation is performed with a U-Net model and the benign/malignant classification is performed with a custom CNN. The pipeline consists of image preprocessing, segmentation, classification and risk assessment with a hybrid loss function. The proposed model attained 92% classification ACC, 0.88 IoU for segmentation and 89% risk prediction ACC compared to the baseline CNN, with 8% improvement in segmentation ACC and also tackled the problem of an imbalanced dataset [24].

S. R. Gaddam et al. (2025) provide a way to identify skin cancer early by analyzing dermoscopy photos with artificial intelligence. The suggested method relies on DL models such as Convolutional Neural Networks (CNNs), ResNet50, EfficientNetB0, and Vision Transformers - ViT to detect malignant or benign lesions. Enhancements to preprocessing, transfer learning, and visual explanations (such as Grad-CAM) are incorporated into the system to enhance ACC and interpretability. Clinical applications and real-time telemedicine should benefit from the ViT-based model's exceptional accuracy (ACC of 95.3% and F1 score of 95.0%) when evaluated using publicly accessible datasets (HAM10000 and ISIC) [25].

N. R. Rajalakshmi, P. M. Sankar, and K. Raju (2024) present a new approach to skin cancer detection utilizing AI, namely CNNs and DL. Over 90% accuracy in cancer detection and healthy skin detection was reached by the suggested model, which also successfully diagnosed different forms of skin cancer using dermoscopy pictures. There is great promise for early detection and a decrease in the strain on healthcare systems brought about by the AI-powered deep CNN system, which allows for quick and precise diagnosis [26].

A. Barbadekar, V. Ashtekar, and A. Chaudhari, (2023) used dermoscopy pictures as input to carry out lesion segmentation and cancer classification. Apply the BCDU-Net model in skin lesion segmentation system. Segmentation system IOU is 84.09% and dice coefficient is 90.66% and compare the DenseNet model's performance with that of VGG-19 in skin cancer classification. VGG-19 outperforms several earlier models with an ACC of 97.29% [27].

P. Zhu (2022) introduces the fact that current ML models can only handle a small subset of skin cancer types. This study examines three separate convolutional neural network (CNN) models; VGG-19, a self-designed network, and VGG-16 are compared and contrasted for skin cancer classification, utilizing nine classifications. A web application is then built using the top-performing model. According to the findings of the experiments, VGG-19 was the most effective model for skin cancer diagnosis, with an ACC of 0.9290 and a loss of 1.2842 [28].

Table I provides an overview of recent research on Skin Cancer Diagnosis, detailing the proposed models, utilized datasets, major findings, and encountered challenges.

TABLE I. Comparative ANALYSIS on Skin Cancer Diagnosis using Machine Learning techniques

| Author | Proposed Work | Dataset | Findings | Limitations & Future Work |
|---|---|---|---|---|
| S. Adablanu et al., (2026) | Proposed VINCE-NET combining ViT, CNN, and LSTM for melanoma classification. | HAM10000 | Achieved 94.1% accuracy and outperformed conventional CNN and transfer learning models. | Focused mainly on melanoma classification; future work can explore multi-class skin cancer diagnosis and external clinical validation. |
| P. R and S. G (2025) | Integrated lesion segmentation, classification, and risk | HAM10000 | Obtained 92% classification accuracy and | Limited to benign/malignant classification; future work may include multi-class classification and larger datasets. |

| | | | | |
|---|---|---|---|---|
| | estimation using U-Net and CNN. | | improved segmentation performance. | |
| S. R. Gaddam et al., (2025) | Developed an AI system using CNN, ResNet50, EfficientNetB0, and ViT with Grad-CAM. | HAM10000, ISIC | ViT achieved 95.3% accuracy and enhanced interpretability. | Requires extensive computational resources; future work should focus on lightweight models for real-time applications. |
| N. R. Rajalakshmi, P. M. Sankar, and K. Raju, (2024) | Proposed a deep CNN framework for skin cancer detection and classification. | Dermoscopic Images | Achieved over 90% accuracy in distinguishing cancerous and healthy skin. | Limited details on multi-class performance and dataset diversity; future work should improve generalization across populations. |
| A. Barbadekar, V. Ashtekar, and A. Chaudhari, (2023) | Combined BCDU-Net for segmentation and VGG-19/DenseNet for classification. | Dermoscopic Images | VGG-19 achieved 97.29% accuracy with effective lesion segmentation. | Evaluated on limited datasets; future work can investigate advanced architectures and larger datasets. |
| P. Zhu, (2022) | Compared VGG-16, VGG-19, and a custom CNN for nine-class skin cancer classification. | Skin Cancer Image Dataset | VGG-19 achieved the best performance with 92.9% accuracy. | Limited to CNN-based architectures; future work may explore transformer-based and hybrid deep learning models. |

**Research gaps:** CNN, Vision Transformer and hybrid DL methods have made significant advances in the diagnosis of skin cancer, however, there are several gaps in the research. Most studies are focused on melanoma or binary classification, which is not applicable to multi-class skin cancer diagnosis. Furthermore, most methods make use of small data sets and are not clinically validated externally, thereby impacting the ability of the model to generalize. The problems of class imbalance, high computational complexity, and comparison of various architectures still remain. Thus, a general and efficient framework for DL that can effectively classify multi-class skin cancers in a wide variety of clinical datasets is necessary.

## III. RESEARCH METHODOLOGY

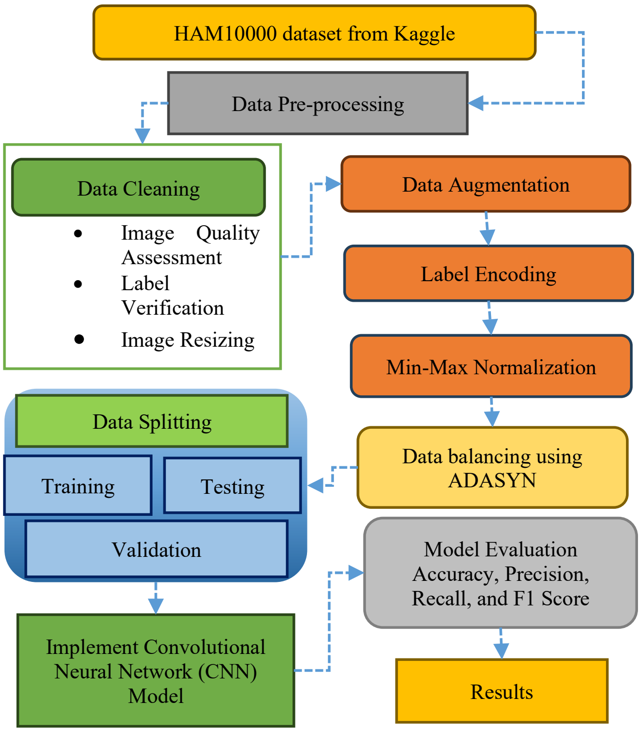


Fig. 1. Proposed flowchart for Skin Cancer Diagnosis

### A. Description of each class for Skin Cancer Diagnosis

This study made use of the HAM10010 dataset, which contains 10,015 dermoscopy photos from seven distinct skin cancer types. Pre-process the data by resizing, normalizing, augmenting, and label encoding it so it's more consistent and of higher quality. The ADASYN approach is used to preprocess the data before it is divided into training, validation, and testing sets. Train a CNN to classify and test it using ACC, PRE, REC, and F1. Figure 1 shows the suggested flow diagram for skin cancer diagnostics using ML. This section offers a thorough explanation of every step in the suggested process.

### B. Data Gathering and Analysis

The HAM10000 dataset, which stands for "Human Against Machine with 10,000," was used for training and evaluation purposes by the suggested system for skin cancer classification. Ten thousand fifteen dermoscopy images of seven distinct pigmented skin lesion types were used to compile this data. To analyze the characteristics of the data, detect class imbalance, and help with good data preprocessing, data visualization was performed:

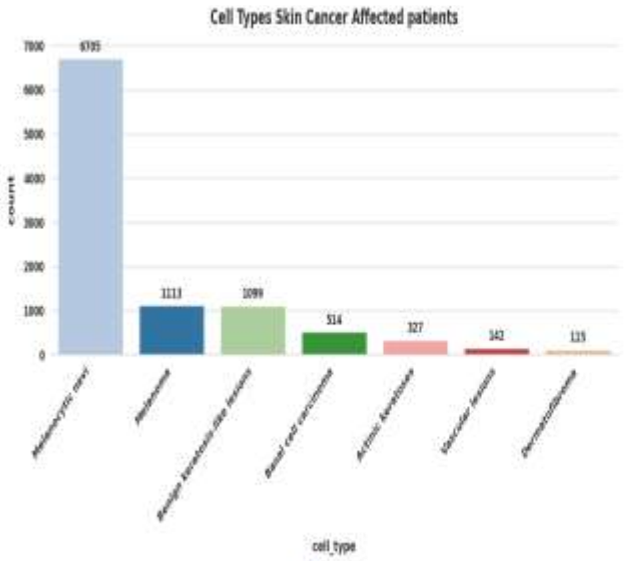


Fig. 2. Description of each class for Skin Cancer Diagnosis

The distribution of various skin lesion types classified into diagnosis skin cancer is shown in Figure 2. The highest number of samples is labeled Melanocytic nevi and the lowest number of samples is labeled Vascular lesions and Dermatofibroma. The imbalance in classes is evident, as seen from the difference in class frequencies, which can affect the performance of classification models.

Thermoscopic images of representative cases in each of the categories of skin lesions used in this study are shown in Figure 3. The images show a variety of colors, textures, shapes, and boundary features, revealing the complexity of skin cancer diagnosis and the need for automated classification methods to achieve the accurate detection of skin cancer.

 

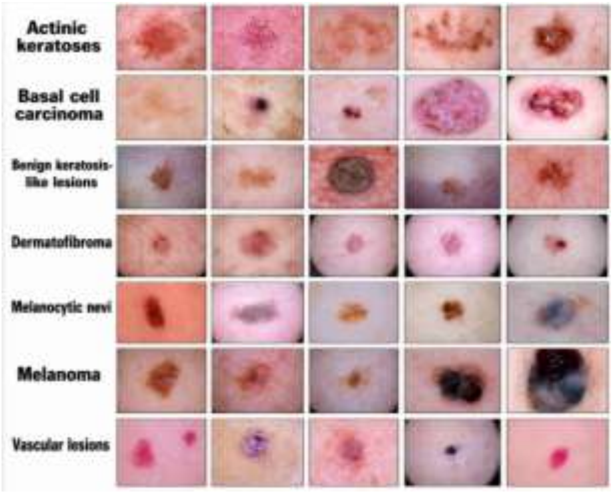


Fig. 3. Five samples of each class for Skin Cancer Diagnosis

### *C. Data Pre-processing*

The data were processed and analyzed using the HAM10000 data set. The preprocessing stage included several critical steps to enhance data quality and model performance, such as data cleaning, data augmentation, image labeling, and data normalization. These procedures helped remove inconsistencies, enhance dataset diversity, and ensure that the images were properly prepared for training and evaluation. The following major preprocessing steps are followed in the suggested approach:

### *D. Data Cleaning*

The data were carefully analyzed in the image quality assessment, label verification and image resizing process to obtain consistency and reliability of the data. Corrupted images and mislabeled or low-quality images were detected and discarded to maintain data quality and to boost the skin cancer classification model's performance. The data cleaning techniques employed in this study are briefly summarized.

- Image Quality Assessment: All dermoscopic images were visually evaluated to ensure image integrity and visibility of the lesions. Poor-quality images containing excessive artifacts or incomplete lesion information were excluded from further analysis.
- Label Verification: Consistency and correctness of class labels were verified for all classes of skin lesions. This step ensured that there is a correct mapping of images to their respective diagnostic classes.
- Image Resizing: A consistent size of 64 × 64 pixels was used to resize the initial photos. Standardizing image size reduces the computational complexity and it is easy to extract features from the proposed model.
- Data Augmentation: These techniques included rotating, flipping, zooming and shifting to create more training samples. Data Augmentation is an approach that enlarges the dataset diversity and reduces overfitting.

### *E. Label Encoding*

The dataset was prepared for use with ML algorithms by converting categorical variables into numerical values using label encoding. These variables may have included assault kinds or class labels.

### *F. Min-Max Normalization*

The dataset records were normalized using the Min–Max normalization technique, which scales feature values to the range of 0 to 1. This preprocessing step helps to make the classification model more efficient and accurate by assigning each feature the same contribution and by minimizing the impact of extreme values. The normalization process is given in Equation (1).

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

the feature's smallest value $X_{min}$ and its highest value $X_{max}$, with X representing the original value and $X'$ denoting its normalized value.

### *G. Data balancing using ADASYN*

The number of classes was analyzed to overcome the data imbalance among lesion categories. Representation of minority classes by augmentation and sampling strategies. In this work, data balancing was performed using an ADASYN method to obtain a more balanced dataset and improve the performance of the classifiers. This is a technique for generating synthetic samples for minority classes.

### *H. Data Splitting*

Training (representing 70% of the dataset), validation (20%), and testing (10%) were the three subsets produced. The class distribution was maintained across all three sets (training, validation, and testing) using a stratified splitting strategy to prevent misleading assessment metrics caused by imbalanced splits.

### *I. Proposed Convolutional Neural Networks (CNN)Model*

Automation of skin cancer detection and categorization using a CNN is presented in this study. CNN learns features by applying a cascade of multi-layer non-linear transformations. The input data is stored as a tensor with several dimensions, and when the pictures are processed by hidden layers, more and more abstract characteristics are extracted. A 2D kernel h calculates the 2D convolution for a 2D input x according to Eq. (2).

$$(x * h)i,j = x[i,j] * h[i,j] = \sum n \sum m x[n,m] \cdot h[i-n][j-m] \quad (2)$$

Their weights multiplied by the dot product of a tiny input region to which they are attached.

The output of a convolutional layer, $h^l$, is where a feature map is created by adding a bias term and applying a point-wise nonlinearity g. The input $x$, bias $bl$, and coefficients or weights $W^l$Define the filters of this layer. Equation (3) shows how to create the l-th feature map at this particular convolutional layer.

$$h^l_{i,j} = g(W^l * x)_{ij} + b_l \quad (3)$$

The activation function is denoted by $g\ (\cdot)$, and Equation (4) defines the 2D convolution as $*$. The rectifier activation function is commonly used by DNN and is specified as

$$g(x) = x^+ = max(0, x) \quad (4)$$

A batch size of 32, fixed hyperparameters, and 25 epochs were used to train the proposed CNN model, which had an input picture size of 64 × 64 × 3. A learning rate of 0.001 was utilized in conjunction with the Adam optimizer and a categorical cross-entropy loss function. Used Softmax in hidden layers and triggered with ReLU for multi-class categorization. A 3 x 3 kernel with 1 stride and the same padding was utilized in the convolutional layers, and a dropout rate of 0.5 was applied to decrease overfitting.

### *J. Evaluation metrics*

A confusion matrix, which shows the prediction results in terms of TP, TN, FP, and FN, was used to assess the effectiveness of the suggested skin cancer classification model. To determine the model's efficacy and dependability, these parts were used to compute a number of evaluation measures, including ACC, PRE, REC, and F1. The following equations are given for each of the Equation (5) to (8)

$$Accuracy = \frac{TP+TN}{TP+Fp+TN+FN} \quad (5)$$

$$Precision = \frac{TP}{TP+FP} \quad (6)$$

$$Recall = \frac{TP}{TP+FN} \quad (7)$$

$$F1-score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \quad (8)$$

As a measure of the classification model's efficacy, the ACC of classification rate is relevant. It is the percentage of all photographs examined that have been correctly classified. A PRE is the number of correct predictions as a percentage of all predictions. The PRE is used to see how well the model reduces the number of FP predictions. Relative Enumeration Coverage (REC) is the proportion of positive cases a model can identify compared to a set of target cases. The F1 is a composite of PRE and REC that is a balanced indicator of classification performance, especially when datasets are unbalanced. It is calculated by taking the harmonic mean, or the average of the two scores.

## IV. RESULTS AND DISCUSSION

The tests were run on a machine that has an Intel Core i9-11900KF (3.5 GHz) CPU, 64 GB of DDR4 RAM, and an NVIDIA GeForce RTX 3090 graphics card with 24 GB of GDDR6X memory. The operating system used was Ubuntu 20.04 LTS, and the data storage was a solid-state drive of 4.57 TB.

### *A. Performance Metrics Analysis*

The experimental setup and certain metrics for judging the proposed system are detailed in this section. The results show the ability and efficient processing of the proposed model in the diagnosis of skin cancer. CNNs excellent model of ACC in skin lesion image categorization was shown in the model that was suggested and achieved an ACC of 98.58%. A remarkably low rate of misclassification between positive and negative instances was shown by the model's PRE of 98.57%, REC of 98.59%, and F1 of 98.49%. Using the suggested CNN model, we get findings that are robust, dependable, and show great diagnostic promise for accurate skin cancer detection and categorization.

TABLE II. CLASSIFICATION RESULTS OF PROPOSED MODEL FOR SKIN CANCER DIAGNOSIS

| Matrix | Convolutional Neural Network (CNN) |
|---|---|
| Accuracy | 98.58 |
| Precision | 98.57 |
| Recall | 98.59 |
| F1-score | 98.49 |


Fig. 4. Accuracy curve for proposed CNN Model

Figure 4 shows the ACC of the proposed CNN model for multiple epochs of training and validation. The ACC curve for both models shows a steady rise throughout the training process, which suggests successful learning and gradual improvement in the classification ACC. The ACC of the training and validation sets remains very close, indicating strong generalization power and a lack of overfitting.


Fig. 5. Loss curve for proposed CNN Model

Figure 5 displays the proposed CNN model's learning and validation loss over all epochs. Both exhibit a consistent decay, indicating that the model does a reasonable job of learning the underlying trends in the images of skin lesions. Validation loss is highly correlated with training loss, indicating strong generalisability and consistent learning. The low final loss values indicate that the model is not overfitting, but rather making accurate classifications with minimal loss.

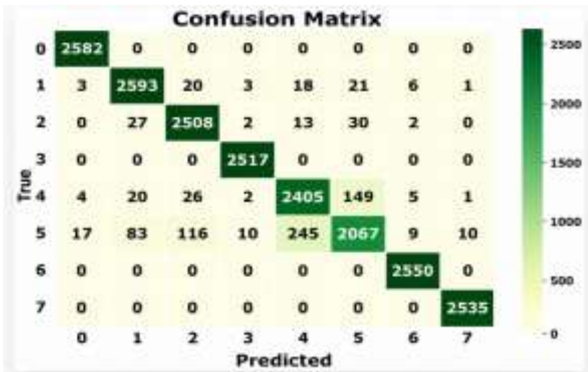


Fig. 6. Confusion matrix of the proposed CNN Model

Figure 6 shows the confusion matrix for the eight classes' classification performance using the suggested model. The diagonal cells have high values, indicating the samples are correctly classified, with the majority of the samples falling within this region. There are very few misclassifications in Classes 0, 3, 6 and 7; a few in Classes 4 and 5 and a few in

Classes 1, 2 and 5. The darker diagonal cells and lighter cells off the diagonal show how accurately the model can differentiate between various classes. Overall, the confusion matrix indicated the reliability, robustness and strong classification capability of the proposed model.P

### B. Comparative analysis

The suggested model is compared to other models that already exist, as shown in Table III. To evaluate and contrast the suggested CNN's performance, used a number of ML and DL techniques, including ResNet, ANN, Xception, and LSTM. The proposed CNN model gave an ACC of 98.58%, PRE of 98.57%, REC of 98.59% and F1 of 98.49% among all the models evaluated. ResNet got 77%, ANN achieved 79.80%, Xception reached 80.3%, and LSTM obtained 91.98% ACC. The CNN model outperforms the other tested models in all aspects. This demonstrates its excellent ability to identify features, categorize them and make correct diagnoses of skin cancer.

TABLE III. COMPARISON OF DIFFERENT MACHINE LEARNING AND DEEP LEARNING MODELS FOR SKIN CANCER DIAGNOSIS

| Model | Accuracy | Precision | Recall | F1-score |
|---|---|---|---|---|
| ResNet[29] | 77 | 78 | 77 | 76 |
| ANN[30] | 79.80 | 79.80 | 86.30 | - |
| Xception[31] | 80.3 | 80.5 | 49.8 | 86.8 |
| LSTM[23] | 91.98 | 93.16 | 90.78 | 91.96 |
| CNN | 98.58 | 98.57 | 98.59 | 98.49 |

### C. Discussion

The suggested CNN achieved a higher accuracy of 98.58% on the ACC, indicating its ability to accurately categorize skin cancer photos with few mistakes. It shows high PRE, REC and F1, suggesting balanced and reliable performance in both detecting positive and negative cases. The model automatically learns discriminative features from dermoscopic images thus eliminating manual feature engineering. Furthermore, it performs very well in terms of learning ability which can enhance the diagnostic ACC and is suitable for early and efficient skin cancer detection.

## V. CONCLUSION AND FUTURE STUDY

Skin cancer is quite common and can strike people of any age. The effectiveness of treatments and the likelihood of survival from skin cancer can be greatly improved with early identification. In this study, it is proposed to create an AI diagnosis tool for dermoscopy diagnosis based on the classification of skin cancers. The feasibility of the suggested system to perform accurate classification of data relies on a range of DL and ML models, including CNN, Xception, LSTM and ResNet. The suggested CNN model outperforms all others in terms of ACC, which is 98.58%, according to the experimental findings. LSTM is in second place with 91.98%, followed by Xception with 80.3%, ANN with 79.80%, and ResNet with 77%. These results show that CNN outperforms the feature extraction and generalization ability in skin lesion classification. Thus, the proposed method is found to be very effective and reliable for an automatic skin cancer diagnosis. The suggested CNN model for classifying skin cancer has some problems, like needing the HAM10000 dataset, possibly still having class imbalances even with ADASYN, and high processing needs that make it hard to use on low-power devices. The lack of generalization because it is not validated on data from other hospitals is another problem. Larger datasets, more sophisticated architectures, and AI that can be explained will be utilized in future studies to address real-time clinical applications.

## REFERENCES


[1] N. S. ALKolifi ALEnezi, "A Method Of Skin Disease Detection Using Image Processing And Machine Learning," Procedia Comput. Sci., vol. 163, pp. 85–92, 2019, doi: 10.1016/j.procs.2019.12.090.

[2] L. S. Fonacier, S. C. Dreskin, and D. Y. M. Leung, "Allergic skin diseases," J. Allergy Clin. Immunol., vol. 125, no. 2, pp. S138–S149, Feb. 2010, doi: 10.1016/j.jaci.2009.05.039.

[3] S. Saravanan, B. Heshma, A. V. Ashma Shanofer, and R. Vanithamani, "Skin cancer detection using dermoscope images," Mater. Today Proc., vol. 33, pp. 4823–4827, 2020, doi: 10.1016/j.matpr.2020.08.388.

[4] N. H. Khan et al., "Skin cancer biology and barriers to treatment: Recent applications of polymeric micro/nanostructures," J. Adv. Res., vol. 36, pp. 223–247, Feb. 2022, doi: 10.1016/j.jare.2021.06.014.

[5] R. V. S. S. B. R, R. R. Al-Fatlawy, S. M. Sundaram, E. A. Rathnakumari, and M. Sudha, "Quantum variational-based support vector machine for early detection of sepsis," in 2024 4th International Conference on Mobile Networks and Wireless Communications (ICMNWC), Tumkuru, India: IEEE, 2024, pp. 1–5, December. doi: 10.1109/ICMNWC63764.2024.10872228.

[6] J. S M, M. P, C. Aravindan, and R. Appavu, "Classification of skin cancer from dermoscopic images using deep neural network architectures," Multimed. Tools Appl., vol. 82, no. 10, pp. 15763–15778, Apr. 2023, doi: 10.1007/s11042-022-13847-3.

[7] J. Vineeth, S. Hemanth, C. V Rao, N. Pavankumar, H. Jayanna, and C. Janardhan, "Skin cancer detection using deep learning," in 2022 Fourth International Conference on Cognitive Computing and Information Processing (CCIP), IEEE, Dec. 2022, pp. 1–6. doi: 10.1109/CCIP57447.2022.10058685.

[8] Z. Li et al., "A classification method for multi-class skin damage images combining quantum computing and Inception-ResNet-V1," Front. Phys., vol. 10, Nov. 2022, doi: 10.3389/fphy.2022.1046314.

[9] M. Abd Elaziz, A. Dahou, A. Mabrouk, S. El-Sappagh, and A. O. Aseeri, "An Efficient Artificial Rabbits Optimization Based on Mutation Strategy For Skin Cancer Prediction," Comput. Biol. Med., vol. 163, p. 107154, Sep. 2023, doi: 10.1016/j.compbiomed.2023.107154.

[10] V. Chaturvedi, "Disease Diagnostic Systems based on AI-Applications in Healthcare: Models, Challenges, and Future Directions," Int. J. Emerg. Res. Eng. Technol., vol. 6, no. 4, pp. 207–217, Dec, 2025, doi: https://doi.org/10.63282/3050-922X.IJERET-V6I4P125.

[11] Mui-zzud-din, K. T. Ahmed, F. Rustam, A. Mehmood, I. Ashraf, and G. S. Choi, "Predicting skin cancer melanoma using stacked convolutional neural network model," Multimed. Tools Appl., vol. 83, no. 4, pp. 9503–9522, Jan. 2024, doi: 10.1007/s11042-023-15488-6.

[12] D. Khamsa, L. Pascal, B. Zakaria, M. Lokman, and M. Y. Zakaria, "Skin Cancer Diagnosis and Detection Using Deep Learning," in 2023 International Conference on Electrical Engineering and Advanced Technology (ICEEAT), IEEE, Nov. 2023, pp. 1–6. doi: 10.1109/ICEEAT60471.2023.10426611.

[13] R. K. Gadiraju, "Edge AI Framework for Real-Time Device Diagnostics and Autonomous Maintenance in Manufacturing and Healthcare," J. Comput. Anal. Appl., vol. 31, no. 3, 2023, doi: 10.48047/jocaaa. 2023.31.03.46.

[14] V. C. Mihir Patel, "A Survey on Artificial Intelligence Techniques for Disease Prediction in Healthcare," ESP J. Eng. Technol. Adv., vol. 5, no. 4, pp. 201–210, December, 2025, doi: 10.5281/zenodo. 19509023.

[15] L. Yu, H. Chen, Q. Dou, J. Qin, and P.-A. Heng, "Automated Melanoma Recognition in Dermoscopy Images via Very Deep Residual Networks," IEEE Trans. Med. Imaging, vol. 36, no. 4, pp. 994–1004, Apr. 2017, doi: 10.1109/TMI.2016.2642839.

[16] M. Q. Hatem, "Skin lesion classification system using a K-nearest neighbor algorithm," Vis. Comput. Ind. Biomed. Art, vol. 5, no. 1, p. 7, Dec. 2022, doi: 10.1186/s42492-022-00103-6.

[17] S. Mahmud, D. P. Mishra, G. . G. Ramani, M. I. Patel, M. S. Soumik, and R. Manivannan, "Design of intelligent healthcare IT infrastructure using graph theory, network analysis, and artificial intelligence," Int. J. Appl. Math., vol. 38, no. 12s, pp. 2267–2280, December, 2025.

[18] A. V. S. R. Dantuluri, "A Scalable Deep Learning Analytics Pipeline for Converting Longitudinal Real-World Data Into Predictive Disease Trajectories," in IEEE Access, IEEE, 2026, pp. 24871–24878, February. doi: 10.1109/ACCESS.2026.3663571.


 

[19] A. C, D. V, P. S, K. S, and A. V, "Development of an AI-Based Diagnostic Tool for Skin Cancer Classification using Dermoscopic Images," in 2024 International Conference on Emerging Research in Computational Science (ICERCS), IEEE, Dec. 2024, pp. 1–6. doi: 10.1109/ICERCS63125.2024.10895383.

[20] N. N. Prakash, V. Rajesh, D. L. Namakhwa, S. Dwarkanath Pande, and S. H. Ahammad, "A DenseNet CNN-based liver lesion prediction and classification for future medical diagnosis," Sci. African, vol. 20, p. e01629, Jul. 2023, doi: 10.1016/j.sciaf. 2023. e01629.

[21] R. Sadik, A. Majumder, A. A. Biswas, B. Ahammad, and M. M. Rahman, "An in-depth analysis of Convolutional Neural Network architectures with transfer learning for skin disease diagnosis," Healthc. Anal., 2023, doi: 10.1016/j.health.2023.100143.

[22] B. S. Sambit Ranjan Pattanayak, Janmejaya Mishra, VNLN Murthy, Abhilash Pati, Amrutanshu Panigrahi, "Harnessing Grey Wolf Optimization for Early Thyroid Cancer Prediction," in 2025 International Conference on Responsible, Generative and Explainable AI (ResGenXAI), Bhubaneswar, India: IEEE, 2025, pp. 10–12, September. doi: 10.1109/ResgenXAI64788.2025.11344005.

[23] S. Adablanu, U. Barman, D. Das, and T. J. Dweh, "Transforming Skin Cancer Detection With AI-Based Convolutional and Transformer Models," iRADIOLOGY, vol. 4, no. 1, pp. 51–62, 2026, doi: 10.1002/ird3.70058.

[24] P. R and S. G, "AI-based Skin Cancer Detection with Lesion Segmentation and Risk Prediction," in 2025 4th International Conference on Applied Artificial Intelligence and Computing (ICAAIC), IEEE, Dec. 2025, pp. 372–376. doi: 10.1109/ICAAIC64647.2025.11331065.

[25] S. R. Gaddam et al., "AI-Based System for Early Detection of Skin Cancer Using Image Analysis," in 2025 IEEE 4th International Conference for Advancement in Technology (ICONAT), IEEE, Sep. 2025, pp. 1–5. doi: 10.1109/ICONAT66879.2025.11362657.

[26] N. R. Rajalakshmi, P. M. Sankar, and K. Raju, "AI-Based Skin Cancer Diagnosis," in 2024 International Conference on Emerging Research in Computational Science (ICERCS), IEEE, Dec. 2024, pp. 1–6. doi: 10.1109/ICERCS63125.2024.10895732.

[27] A. Barbadekar, V. Ashtekar, and A. Chaudhari, "Skin Cancer Classification and Detection Using VGG-19 and DesNet," in 2023 International Conference on Computational Intelligence, Networks and Security (ICCINS), IEEE, Dec. 2023, pp. 1–6. doi: 10.1109/ICCINS58907.2023.10449996.

[28] P. Zhu, "Convolutional Neural Networks Based Study and Application for Multicategory Skin Cancer Detection," in 2022 3rd International Conference on Electronic Communication and Artificial Intelligence (IWECAI), IEEE, Jan. 2022, pp. 558–561. doi: 10.1109/IWECAI55315.2022.00114.

[29] M. Shaheer, T. Arooj, H. Adeel, T. Saleem, and I. R. Rao, "AI-based skin cancer detection algorithms: opportunities, challenges and a way forward," Asian J. Sci. Eng. Technol., vol. 4, no. 1, pp. 87–109, 2025, doi: 10.47264/idea.ajset/4.1.6.

[30] S. P. A. Claret, J. P. Dharmian, and A. M. Manokar, "Artificial intelligence-driven enhanced skin cancer diagnosis: leveraging convolutional neural networks with discrete wavelet transformation," Egypt. J. Med. Hum. Genet., vol. 25, no. 1, 2024, doi: 10.1186/s43042-024-00522-5.

[31] S. A. H. Shah et al., "Explainable AI-Based Skin Cancer Detection Using CNN, Particle Swarm Optimization and Machine Learning," J. Imaging, vol. 10, no. 12, 2024, doi: 10.3390/jimaging10120332.

 