

# A Comprehensively Detailed Survey on Deep Learning Methods Applied to the Classification of Skin Cancer

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**Abstract:** Skin cancer is one of the common dermatological diseases where the recognition of the skin lesions is highly important for making an exact diagnosis and treating the disease. Due to the similarity between benign and malignant lesions, diversity of dermoscopic images, and the necessity of expert clinical knowledge for interpreting the information, the automated skin cancer classification is an advanced task. In the last years, machine learning and deep learning algorithms show the great potential in the field of the computer-aided skin lesion analysis. The review covers the current methods of the automated skin cancer classification with the special focus on CNNs, transfer learning, segmentation techniques, and ViT-based architectures. The reviewed works use common benchmarks of dermoscopic images datasets, for example, HAM10000 and ISIC with preprocessing, data augmentation, balanced sampling, and lesion segmentation for improving classification performance. CNN-based architecture like ResNet, VGG, DenseNet, and others with transfer learning approach show the best results, at the same time, the transformer-based architecture offers self-attention and multi-scale feature representation for detecting key features of the lesion. Moreover, the recent works also consider the hybrid approach that combines deep learning feature extraction with classifier, for instance, SVM, or segmentation method, for example, XGBoost. Despite the positive results, some challenges exist such as the class imbalance problem, lack of clinical validation, presence of artifacts, high similarity between lesion classes, overfitting, computation complexity, and others.

**Keywords** -Skin Cancer Classification, Deep Learning, Convolutional Neural Networks (CNNs), Transfer Learning, Vision Transformers, Dermoscopic Images, HAM10000 Dataset, ISIC, Image Segmentation, Data Augmentation, Class Imbalance, Automated Skin Cancer Diagnosis.

## I. INTRODUCTION

Cancer of the skin is an urgent problem that should be diagnosed in time for treatment and therapy. The most dangerous forms of skin cancers include BCC (basal cell carcinoma), SCC (squamous cell carcinoma), and malignant melanoma. Melanoma occurs rarer but it has higher malignancy and becomes hard to treat at an advanced stage [1]. Hence, automatic classification of skin lesions has turned out to be an urgent issue for researchers engaged in medical image analysis.

The development of deep learning and, in particular, Convolutional Neural Network (CNN) has led to a breakthrough in automated skin cancer classification. CNNs allow the system to automatically extract hierarchical and discriminative features from images. Gururaj et al. proposed an automated skin cancer classification framework based on the use of deep learning architecture (DenseNet169 and ResNet50). This method included preprocessing and segmentation stages before classification and has shown the efficiency of deep learning architectures for multiclass skin lesion recognition [2]. Other studies have examined architectures such as ResNet, VGG, Inception, MobileNet, and DenseNet for skin lesion classification [4].

Transfer learning has become a new technique for skin cancer classification. It is known that training deep neural networks requires the large amount of labeled data. Pre-

trained models give a possibility to receive good feature representations and then tune them to solve classification task. Recent studies compared conventional CNNs with transfer-learning architectures such as ResNet50 and VGG-based models. The 2026 study demonstrated an improvement in the performance on the validation set when using a fine-tuned ResNet50 model pre-trained on ImageNet [5]. Similarly, previous studies showed the usefulness of transfer learning and data augmentation in classification tasks on skin lesion datasets [2], [4].

Along with CNNs, Vision Transformer (ViT) architectures are also widely used now for skin cancer classification. Unlike conventional CNNs, transformers use self-attention mechanisms to represent relations between different parts of the image. Xin et al. proposed an improved transformer-based architecture called SkinTrans which used multi-scale patch embedding, overlapping sliding windows, and contrastive learning for better representation of skin lesions. The proposed architecture was tested on HAM10000 and clinical dermoscopic datasets. SkinTrans achieved accuracy of 94.3% and 94.1% respectively [1]. The results showed the potential of transformer-based architectures as an alternative approach to CNN for skin lesions classification.

Another research direction is a combination of classification and lesion segmentation. Segmentation task helps to identify the region of the lesion in the image and this information can be helpful in solving the classification task. The 2025 study examined the SLC-CNN-based approach for feature

extraction and combined it with SVM for classification and XGBoost for lesion segmentation. The authors compared the proposed approach with other architectures including VGG16, VGG19, DenseNet121, ResNet50, and ResNet152. The results showed the growing interest in combined classification and segmentation frameworks [3]. Such systems can provide additional information about the lesion region boundaries while performing automated diagnosis. Despite the achieved success of ML and deep learning approaches, there are still some challenges that influence the implementation of automated skin cancer classification systems. They include class imbalance, limited clinical datasets, similarity between different lesion classes, image artifacts, overfitting, computational costs, and differences in image acquisition conditions. Differences in shooting distance and view angle can introduce additional variability to dermoscopic images. Limited clinical datasets can influence the train and validation of models [1], [5].

In addition, excellent classification performance on standard benchmarks does not always translate into similar results among other patients and under different imaging settings. In this regard, an organized comprehension of the existing techniques is needed to understand the pros, cons, and research areas of automated skin cancer classification. This review presents a brief overview of the recent advances in skin cancer classification based on the five chosen papers, discussing traditional machine learning, CNN models, transfer learning, segmentation-based solutions, and Vision Transformer techniques. Additionally, common data sources, data preparation and augmentation methods, classification methods and evaluation metrics, current problems and perspectives are discussed. The main goal of this literature review is to present a comprehensive review of deep learning methods used in skin cancer classification and to determine potential research directions.

## II. LITERATURE SURVEY

Recent researches on skin cancer classification algorithms focus on deep learning techniques used in dermoscopic images. Previous methods were mostly based on handcrafted image features and classical machine-learning classifiers, whereas now studies use convolutional neural networks (CNNs), transfer learning, Vision Transformers and hybrid architectures. The discussed literature also indicates preprocessing, segmentation, augmentation and class balancing as essential aspects affecting classification performance.

Xin et al. [1] proposed SkinTrans, an advanced Vision Transformer architecture designed for skin cancer classification. It introduces the usage of multi-scale and overlapping image patches as well as contrastive learning for better features representation. Experimentations performed on the HAM10000 and clinical dermoscopic datasets resulted in 94.3% and 94.1% accuracy, correspondingly.

Nevertheless, computational limitations related to high-resolution images and the lack of large clinical validation set were detected.

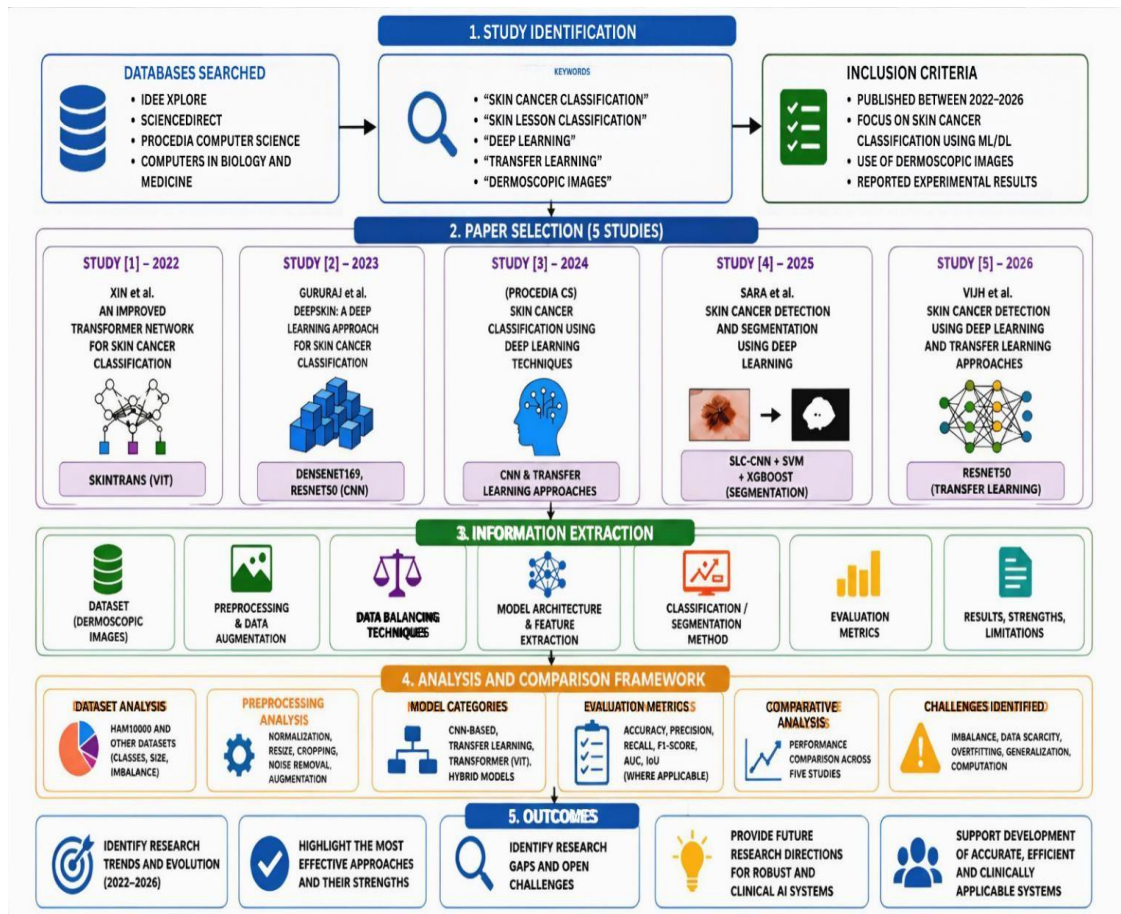
SM, J., P, M., ARAVINDAN, C [2] proposed DeepSkin, which uses CNN architecture including DenseNet169 and ResNet50 with the HAM10000 dataset. Preprocessing, segmentation and sampling methods were analyzed to address the issue of class imbalance. DenseNet169 model with undersampling achieved 91.2% accuracy and 91.7% F1-score, and ResNet50 obtained 83% accuracy and 84% F1-score according to the reported configuration.

Kavitha et al. [3] investigated the problem of skin cancer detection using CNN and transfer learning methods. They included image preprocessing, segmentation, feature extraction and augmentation into their approach. An accuracy of 84.32% achieved by R-CNN was reported showing the importance of deep learning for the task of automated lesion detection and classification.

SHAHZAD, K., [4] proposed a hybrid SLC-CNN + SVM + XGBoost architecture for classification and segmentation tasks. SLC-CNN was used for feature extraction, SVM was responsible for benign/malignant classification, and XGBoost classified lesions for segmentation. This approach managed to achieve 99.60% classification accuracy and 95.25% segmentation accuracy, with 99.75% precision, 99.45% recall and 99.55% F1-score. Vijn et al. [5] evaluated the performance of CNN and transfer learning models using the HAM10000 dataset. Results of their work show that ResNet50 reached approximately 94% accuracy, outperforming the CNN model trained from scratch. Moreover, improvement in melanoma recall was achieved with its value of approximately 87%. However, minority classes such as dermatofibroma and vascular lesions proved to be difficult because of class imbalance.

## III. RESEARCH METHODOLOGY

This review employs a comparative literature review methodology with a defined structure to evaluate current methods for automated classification of skin cancer. A total of five research papers published between 2022 and 2026 have been analyzed to determine the development of the techniques of machine learning and deep learning, common datasets, image preprocessing methods, classification approaches, segmentation procedures, metrics of assessment, and limitations. These papers have been selected since they explicitly deal with automated skin lesion/skin cancer classification by employing image-based artificial intelligence methods. This review methodology encompasses four major steps, namely: (1) selection of papers; (2) extraction of information; (3) classification of reviewed methods; and (4) comparative analysis. and the review was done through selection of five articles published between 2022 and 2026. Selected articles involve several stages of advancement in automation of skin cancer classification through Vision Transformers, conventional



**Figure 1. The Proposed Review Framework for Classifying Skin Cancer by Utilizing Deep Learning**

CNNs, transfer learning, assisted segmentation and hybrid deep learning techniques. These studies have been analyzed in accordance with their research objective, dataset, preprocessing technique, architecture of the model, classification approach, evaluation criteria, results obtained and limitations involve.

These five selected articles have been categorized on the basis of the major methodology used. The 2022 article focused on an advanced vision transformer architecture through multi-scale patch embeddings and contrastive learning [1]. The DeepSkin 2023 study focused on the application of CNN-based classification with DenseNet169 and ResNet50 through the use of different preprocessing, segmentation and sampling strategies [2]. The 2024 article reviewed and implemented deep CNNs and transfer learning methods such as ResNet and Inception networks with augmentation and class weighted learning [3]. The 2025 paper focused on the implementation of an integrated SLC-CNN framework with SVM for classification and XGBoost for lesion segmentation [4]. The 2026 paper focused on comparison of a baseline CNN with

transfer learning methods like ResNet50 on the HAM10000 dataset [5].

#### **A. Dataset and Preprocessing Analysis**

The reviewed studies make extensive use of images of skin lesion from dermoscopy. HAM10000 is the most frequently cited benchmark dataset in the selected studies. This dataset consists of 10,015 dermoscopic images classified into seven categories of lesions. The class distribution of images, however, is highly skewed. For this reason, most of the studies preprocess their data in order to balance the data classes before model training. The 2022 study employed normalization, random cropping, rotation, color jitter, and balanced sampling in an attempt to minimize the effect of class imbalance [1]. The 2023 DeepSkin study also experimented with undersampling and oversampling approaches, as well as segmenting and preprocessing images before classification [2]. The 2024 study discussed approaches such as augmentation, class-weighted learning, and data synthesis using GANs in case of limited or imbalanced training dataset [3].

**B. Classification Architecture Analysis**

The proposed approaches were classified according to four main groups of methods

**1) Classification Based on CNN:**

Many of the considered approaches are based on CNNs, since they allow learning hierarchical visual features from the dermoscopic images. In 2023, the DeepSkin approach used DenseNet169 and ResNet50 due to the transfer learning method, while in 2026, the authors tested the baseline CNN and ResNet50 for multi-class classification [2], [5].

**2) Transfer Learning:**

Transfer learning was applied to benefit from learned representations trained on big data sets such as ImageNet. ResNet50, DenseNet169, VGG and other pre-trained architectures were analyzed in the reviewed literature. In the 2026 paper, first the authors froze the pre-trained layers of ResNet50 and then fine-tuned the last layers applying the lower learning rate. The result was the increase of validation accuracy from about 90% in the initial training stage to about 94% at fine-tuning stage [5].

**3) Vision Transformer-Based Classification:**

In the 2022 paper, the authors presented SkinTrans – an enhanced transformer-based approach, which applies multi-scale and overlapping patches along with contrastive learning. The goal of this method is to extract relationships between the regions of an image by means of self-attention for visually similar skin lesions [1].

**4) Hybrid Classification and Segmentation:**

In 2025, the paper represents a hybrid approach, where SLC-CNN is used for feature extraction, SVM is applied for classification, and XGBoost is used for the lesions segmentation [4]. Thus, the analysis of skin cancer is not only a classification but also localization problem.

**C. Comparative Evaluation Methods**

Since the five studies employ varied experimental conditions, this review considers the accuracy values provided by the five studies as not being comparable. In this regard, performance is evaluated based on the evaluation methods described by each study, which include accuracy, precision, recall, F1-score, AUC and Intersection over Union (IoU) where available.

Accuracy refers to the overall percentage of correct predictions. Precision indicates the percentage of the predicted positives that are true, whereas recall indicates the model's capability to predict positive instances. F1-score ensures that there is a balance between precision and recall, and it is useful for unbalanced datasets such as HAM10000.

For instance, the 2025 study also employed IoU to measure how well the predicted lesion areas overlap with the manually annotated ground-truth areas [4]. The 2026 study, on the other hand, focused on precision, recall, F1-score, accuracy and confusion matrix when evaluating classification models [5].

**D. Comparative Analysis of the Five Selected Studies**

Table I presents the findings from the studies and these are not to be considered as controlled benchmark since these have different datasets, classification problems, data pre-processing methods, and setups. The study conducted in 2023 found an accuracy and F1-score of 91.2% and 91.7%, respectively, for the same undersampling setup, while the study conducted in 2025 found an accuracy of 99.60% for their SLC-CNN with XGBoost approach [2], [4].

**E. Review Analysis Framework**

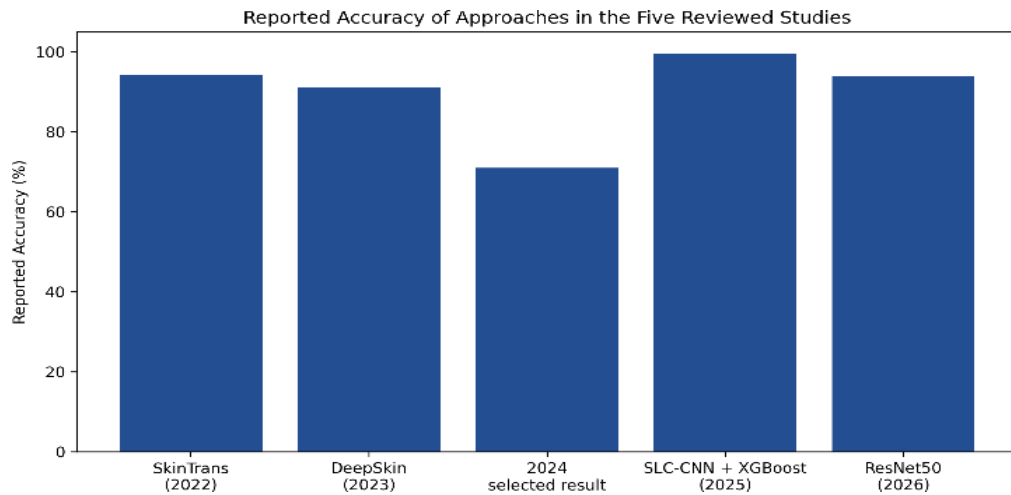
The analysis at hand compares the selected papers based on four different dimensions – data, model, evaluation, and limitations. The data dimension looks at dataset size, lesion types, class imbalance, and preprocessing. The model dimension analyses CNNs, transfer learning, Vision Transformers, and hybrid segmentation and classification models. The evaluation dimension takes into account accuracy, precision, recall, F1 score, AUC, and IoU. Lastly, the limitations dimension analyzes class imbalance, data insufficiency, overfitting, computing demands, image variability, and clinical relevance.

This analysis framework allows the review to trace the development from traditional machine learning and CNNs to the emergence of transfer-learning, transformers, and hybrid models. It also identifies research gaps that need to be addressed in the future skin cancer classification systems.

TABLE I

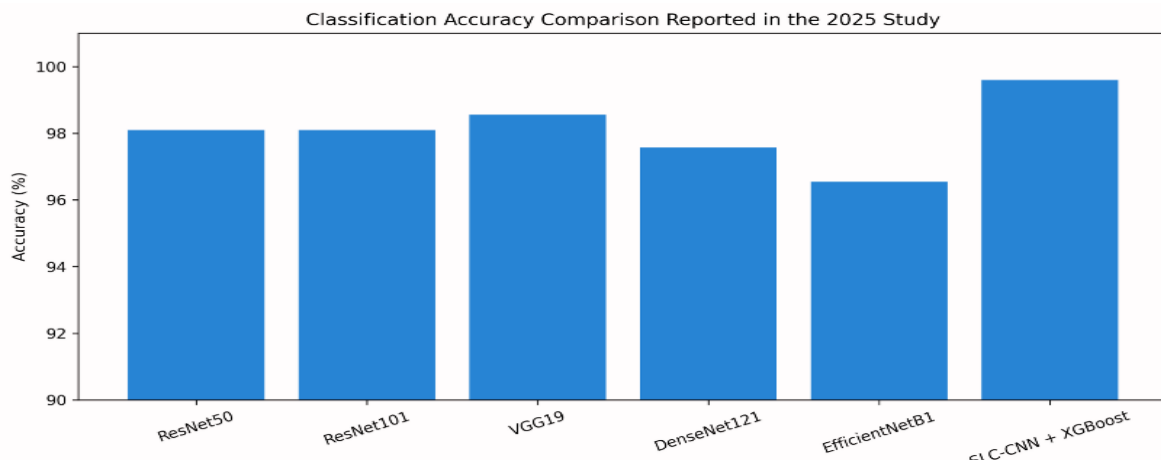
| Year | Main Approach                    | Dataset                              | Major Technique                                                          | Reported Performance                                                                        |
|------|----------------------------------|--------------------------------------|--------------------------------------------------------------------------|---------------------------------------------------------------------------------------------|
| 2022 | SkinTrans / ViT                  | HAM10000 + clinical dataset          | Multi-scale patch embedding + contrastive learning                       | 94.3% HAM10000 accuracy                                                                     |
| 2023 | DeepSkin                         | HAM10000                             | DenseNet169, ResNet50, segmentation, sampling                            | 91.2% accuracy, 91.7% F1 for reported undersampling result                                  |
| 2024 | CNN / Transfer Learning          | HAM10000 and other reviewed datasets | ResNet, Inception, augmentation, class weighting, GAN-based augmentation | Performance varied by approach; synthetic data improved one reported result from 53% to 71% |
| 2025 | SLC-CNN + SVM + XGBoost          | Multiple datasets                    | CNN feature extraction + classification + segmentation                   | 99.60% accuracy; 99.55%F1                                                                   |
| 2026 | CNN + ResNet50 Transfer Learning | HAM10000                             | Image augmentation + class weighting + ResNet50 finetuning               | ~94% accuracy for ResNet50                                                                  |

#### A. Accuracy of Five Selected Methods as Reported



- a) SkinTrans (2022) : 94.3%
- b) Deepskin (2023) : 91.2%
- c) 2024 selected reported result : 99.6%
- d) SLC-CNN + XGBoost (2025) : 99.6%
- e) ResNet50 (2026) : ~94%

### B Comparison of Model Accuracies – Study 2025



- a) ResNet50
- b) ResNet101
- c) VGG19
- d) DenseNet121
- e) EfficientNetB1
- f) SLC-CNN + XGBoost

## IV. RESULTS AND DISCUSSION

The comparative analysis revealed a trend of moving away from classic machine-learning approaches using hand-crafted features like ABCD, GLCM, and HOG towards CNNs, transfer learning, Vision Transformers, and hybrid models. In previous SVM-based researches, the accuracies up to 97.8% and AUC equal to 0.94 were reported, while in case of CNNs, automatic feature extraction and classification were possible [8]-[10].

Another aspect that affects the effectiveness is the dataset quality, preprocessing, and segmentation. For example, HAM10000 dataset includes 10,015 images categorized into seven lesion types and is widely used for evaluation of approaches [14]. DeepSkin achieves 91.2% accuracy and 91.7% F1-score with DenseNet169 by applying undersampling technique. Some other works use additional techniques such as segmentation, artifact removal,

augmentation, and class balancing to enhance robustness of the model [12], [13].

Transfer learning is another tendency. The approaches like ResNet, InceptionV3, VGG16, and MobileNet are used for dealing with limited number of medical training samples [15], [16]. For example, the SkinTrans approach achieves 94.3% accuracy on HAM10000 dataset by utilizing multi-scale patches and contrastive learning [1]. In addition, GAN-based artificial generation of data improves the previously published result from approximately 53% to 71% [3].

As for the hybrid approaches, 2025 SLC-CNN framework combines the feature extraction via CNNs, SVM classifier, and XGBoost for segmentation and achieves 99.60% accuracy, 99.75% precision, 99.45% recall, and 99.55% F1-score. Nevertheless, it is impossible to rank those results as they are obtained under different conditions.

In summary, CNNs and transfer learning are still good approaches, and Vision Transformers and hybrid

segmentation-classification approaches are promising ones. Nevertheless, the problems like class imbalance, limited clinical datasets, computational complexity, and population generalization are significant issues to be solved in future.

## V. CONCLUSIONS

In this review, the five most recent studies that used deep learning approaches and other techniques to classify skin cancers were discussed. It is evident that there has been an evolution from using traditional machine learning techniques to CNNs, transfer learning, Vision Transformer and hybrid approaches that combine classification and segmentation. Data augmentation, class balancing, segmentation, and synthetic data generation are some of the other techniques that have contributed to improving the performance of skin cancer classification. Among all the reviewed studies, the highest performance was seen in the study that used a hybrid approach (SLC-CNN). SkinTrans and ResNet50 are some of the other techniques that showed high performance in skin cancer classification. But there are certain limitations in this field including class imbalance, small clinical datasets, computational complexity, and generalization.

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## Appendix

| Ref<br>. | Year | Main Model                 | Dataset                  | Key Finding                                |
|----------|------|----------------------------|--------------------------|--------------------------------------------|
| [1]      | 2022 | SkinTrans( ViT)            | HAM10000                 | 94.3%<br>accuracy                          |
| [2]      | 2023 | DenseNet169/<br>ResNet50   | HAM10000                 | 91.2%<br>accuracy , 91.7% F1               |
| [3]      | 2024 | CNN /<br>transfer learning | Skin Lesions<br>Datasets | Synthetic data improved<br>reported result |