International Journal of Scientific Research & Engineering Trends
Volume 10, Issue 3, May-June-2024, ISSN (Online): 2395-566X

# Skin Cancer Classification and Comparision from HAM10000 Dataset Images Using Ensemble of Convolutional Neural Networks

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**Abstract- Skin cancer is a growing global health concern, and early and accurate diagnosis is crucial for effective treatment. Convolutional Neural Networks (CNNs) have emerged as powerful tools for skin lesion classification. They offer the potential to improve diagnostic accuracy and assist dermatologists. This study com- pares the performance of five CNN architectures - DenseNet121, DEnseNet201, InceptionResNetV2, Xception, and SCC-NET on the preprocessed Ham10000 dataset. This dataset contains 10,000 dermoscopic images, categorized into seven skin lesion types, with 500 images per class. The objective is to identify the model that achieves the best accuracy and generalizability for this specific dataset. To evaluate the models, we use metrics like accuracy,, and F1-score. This research contributes to the growing body of knowledge on utilizing CNNs for skin cancer classification. It has the potential to pave the way for develop- ing reliable computer-aided diagnosis systems, which can further improve the accuracy of skin cancer diagnosis.**

**Index Terms- Skin cancer classification, Convolutional Neural Networks (CNNs), Deep learning, Dermoscopy, Ham10000 dataset, DenseNet121, InceptionV3, InceptionResNetV2, Xception, Accuracy, F1-score, Computer-aided diagnosis (CAD), Transfer learning**

## I. INTRODUCTION

Skin cancer is a prevalent form of cancer that originates from the skin. It is caused by the abnormal growth of cells, which can infiltrate other areas of the body. Over 90% of cases are caused by exposure to UV radiation, which ranges from 100 nm to 400 nm in wavelength. Cancer develops when skin cells sustain unrepaired DNA damage, largely due to UV radiation. Melanoma, a type of skin cancer, arises from moles on the skin, resulting in inflammation around the epidermal layer and a subsequent increase in temperature.

In the recent decade, the application of image processing and machine vision for different uses of medical imaging has exponentially increased. Using these techniques increases the diagnosis process speed and decreases human errors. It can also improve the quality and convenience of the melanoma diagnosis by physicians and radiologists.

The Convolutional Neural Networks (CNN) is an improved type of neural network that is developed by Yann LeCun, et al. [1]. CNN can be adopted for utilizing different mathematical learning methods like regularization, backprop- agation, and gradient descent. CNN contains three principal concepts of layers including the Convolutional layer, pooling layer, and fully connected layer. Due to the high performance of artificial neural networks, they are known as proper solutions in several fields.

The dataset used in this research is the HAM10000 ("Human Against Ma- chine with 10000 training images") dataset [2]. More than 50% of lesions are confirmed through histopathology (histo), and the ground truth for the rest of the cases is either follow-up examination (follow up), expert consensus (consen- sus), or confirmation by in-vivo confocal microscopy (confocal). The dataset includes lesions with multiple images, which can be tracked by the lesion id-column within the HAM10000 metadata file. Due to upload size limitations, images are stored in two files: HAM10000imagespart1.zip (5000 JPEG files) and HAM10000imagespart2.zip (5015 JPEG files).

This research investigates the performance of five CNN architectures on the HAM10000 dataset, a publicly available dataset of dermoscopic images contain- ing various skin lesions. The primary objective is to compare the accuracy and generalizability of these models for skin lesion classification. By evaluating these models, we can gain valuable insights into their effectiveness for this specific task and contribute to

the development of reliable computer-aided diagnosis (CAD) systems for skin cancer.

**1. Key Contributions**

The key contributions of this research are:

- Evaluation of five CNN architectures for skin lesion classification on the HAM10000 dataset
- Comparison of the accuracy and generalizability of the CNN models
- Contribution to the development of reliable computer-aided diagnosis sys- tems for skin cancer

This research aims to contribute to the advancement of computer-aided diagnosis systems for skin cancer by evaluating the performance of CNN architectures on the HAM10000 dataset. The use of image processing and machine vision techniques has the potential to improve the speed and accuracy of melanoma diagnosis, benefiting both physicians and patients.

## II. RELATED WORKS

Densly Connected Neural Networks - Gao Huang et al. presented their work on Densenet201, a convolutional neural network architecture known for its effectiveness in image classification tasks [19]. They fine-tuned the model on a dataset of skin lesion images labeled with different types of skin cancer. This process involved adjusting the weights of the network to specialize in recognizing skin cancer features.

Skin cancer biology and barriers to treatment: Recent applications of polymeric micro/nanostructures - Nazeer Hussain Khan et al. discussed the rapid prevalence of skin cancers and the lack of efficient drug delivery sys- tems [20]. They emphasized the essentiality of finding possible ways to prevent or cure the disease.

An Introduction to Convolutional Neural Networks - Keiron O'Shea and Ryan Nash introduced Convolutional Neural Networks and highlighted their potential in addressing the rapid prevalence of skin cancers [21].

Alexnet and DenseNet 121 based hybrid CNN architecture for skin cancer prediction from dermascopic images - Another significant study presented a hybrid CNN framework for classifying skin lesions using two pre-trained CNN architectures, AlexNET and DenseNet 121 [22]. The CNN model was trained and tested using the ISIC 2016 - 2017 dermascopic image dataset.

Image colorisation using Inception-Resnet -V2 - Federico Baldassarre et al. used Inception-ResNet-v2 as a high-level feature extractor, providing information about the image contents that can help in image colorization [23]. A comparative study of state-of-the-art skin image segmentation techniques with CNN - Ghazala Nasreen et al. emphasized the crucial role of precise image segmentation in effective skin cancer detection [24]. They discussed the challenges due to the variability in lesion sizes, colors, textures, and shapes, and highlighted the effectiveness of CNNs in this domain.

Deep learning with separable convolutions - Francois Chollet introduced a modified version of Inception-V3 architecture, which excelled in many classification tasks [44].

Efficient and Low-Cost Skin Cancer Detection System Implemen- tation with a Comparative Study Between Traditional and CNN- Based Models - Lakindu Induwara Mampitiya et alc. focused on the essential role of medical image classification in the field of combining medical applications with Artificial Intelligence [25]. They aimed to introduce an accurate and precise method for skin cancer recognition.

**1. Research Gaps**

This Section deals with different journals and the findings and gaps of the journals

Table 1: Study Gaps - Pros and Cons of Research Papers

| Research Paper | Findings | Research Gaps |
|---|---|---|
| Densely Connected Neural Networks | Dense connectivity promotes feature reuse and enhances information flow. Efficient parameter usage leads to good performance with fewer parameters. Strong performance on various image classification tasks. | Higher memory usage due to dense connectivity. Increased computational complexity during training and inference. Training complexity may re- quire careful initialization and hyper- parameter tuning. |
| Skin cancer Biology and barriers | Provides insights into the rapid prevalence of skin cancers. This paper explains in detail about skin cancer. Gives descriptive knowledge about skin cancer types | Doesn't deal with the diagnosis of skin cancer barriers. |
| An Introduction to Convolutional Neural Networks | Explains the working of CNN in detail. Architecture of CNN explained in detail | Doesn't explain how to make our own Convolutional Neural Network. Equations not explained properly. |

| | | |
|---|---|---|
| Alexnet and DenseNet 121 based hybrid CNN architecture | High Accuracy: achieves top performance in image classification tasks. Efficient Learning: Dense connections help reuse features, allowing it to learn complex features effectively. Reduced Com- plexity: DenseNet-121 needs fewer parameters than some deeper models, making it faster for training and deployment on less powerful devices. | Requires significant processing. It increases memory usage. It has 121 layers, which can lead to increased memory usage. It has a longer training time, and due to that it can be slower in comparision to others |
| Deep learning with separable convolutions | Depth-wise and point-wise convolu- tions in Xception enhance feature ex- traction efficiency, leading to supe- rior performance in image classification tasks. | Xception's complex architecture makes it less interpretable and harde to fine-tune, requiring significant computational resources for training and inference. |
| Efficient and Low-Cost Skin Cancer Detection System Implementat ion | Preprocessing enhances model accuracy by focusing on cancerous areas. The study compares traditional and CNN models for skin cancer classification. | The study's reliance on high computational resources and complex pre- processing may limit its feasibility for resource- limited settings. |

## III. METHODOLOGY

This section describes the steps taken to pre-process, train, and evaluate CNN models for skin cancer detection using the HAM10000 dataset. Figure Explains the methodology proposed by us.

**1. Preprocessing**

The initial stage in our methodology involves preprocessing the HAM10000 dataset to prepare it for training the CNN models.

This process is crucial for ensuring the data is well-structured and appropriately augmented to facilitate effective model training.

**Data Organization**

We organize the images based on their diagnosis labels to create a structured dataset. This involves examining a CSV file, HAM10000 metadata.csv, which contains details about each image, such as its unique identifier and diagnosis label. Here, we can leverage libraries like pandas for efficient data manipula- tion [7].

**Data Understanding and Class Imbalance Handling**

We analyze the dataset to understand the distribution of different types of skin cancer. This step allows us to identify any imbalances in the class distribution, which can significantly impact model performance. Techniques like stratified splitting during training data division can help mitigate this issue [16].

**Data Augmentation**

To enhance the diversity of the dataset and improve model generalization, we perform data augmentation techniques. Common augmentation techniques in- clude resizing images to a standard size (e.g., 64x64 pixels), randomly flipping images horizontally, and normalizing pixel values between 0 and 1 [9]. How- ever, it's important to choose augmentation techniques that are relevant to the specific task and avoid over-augmentation, which can lead to unrealistic data.

**Creating a Final Dataset Image Path Assembly Line**

We set up a process to define the complete path (location) for each image based on its unique ID. This path will be used to access the image during analysis. Python libraries like os can be helpful for file system interaction [10].

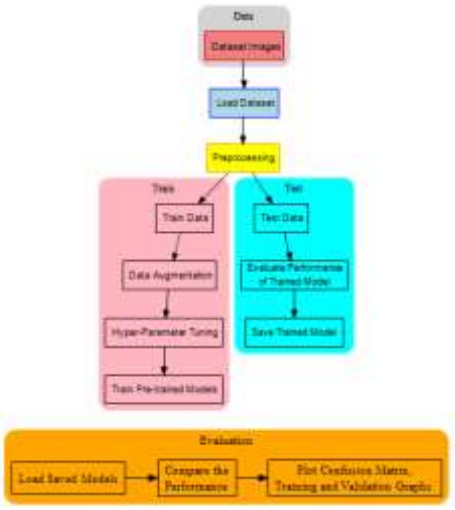


Figure 1: Proposed Methodology

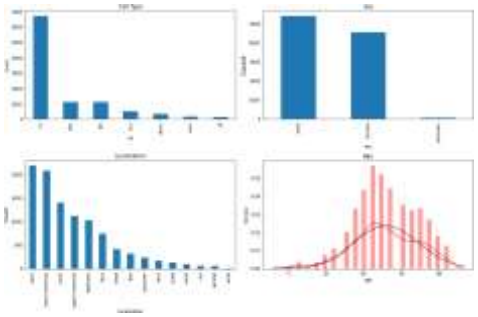

Figure 2: Distribution of Ham Dataset based on different parameters

**Attaching Images to the Dataset**
We incorporate a new column in our dataset (skin df balanced) that holds the complete path for each image. This allows us to efficiently retrieve the image for further processing.

**Image Processing Line**
We establish an image processing line that takes the image path, resizes the image to the required size (64x64 pixels), and performs any additional prepro- cessing steps as needed. Here, libraries like OpenCV can be useful for image manipulation tasks [11].

**2. Splitting the Dataset**
The preprocessed image data (X) and labels (Y) are split into training and testing sets using tools like train test split from sklearn.model selection. Stratified splitting is recommended to maintain the class distribution in both training and testing sets [16]. One-hot encoding is applied to the labels (Y cat) as it's a multiclass classification problem [12].

**3. Pretrained Model Selection And Development**
There are already many models which have been created and trained. These models are called pre-trained models. In our project, different pre-trained models including Xception, InceptionResNetV2, DenseNet121, and DenseNet201, are fine-tuned for skin cancer classification. We decided to work on these models as they are easy to understand and optimize compared to others.

Various pre-trained models such as DenseNet121, InceptionV3, Inception- ResNetV2, and Xception are used for skin lesion classification. These models are initially loaded with weights pre-trained on the ImageNet dataset, which contains millions of labeled images from different categories. This pre-training step allows the models to utilize the knowledge learned from a broader image classification task, which can improve their performance on the specific task of skin lesion classification. The top layers of these models are then frozen, and a few trainable layers are added on top for skin lesion classification. This technique is called transfer learning, and it has proven to achieve high accuracy and significantly reduce the need for large datasets for different classification tasks. For example, a study by Esteva et al. (2017) utilized a transfer learning- based method for skin lesion classification and achieved 85.8% accuracy [3]. Another study by Yu et al. (2018) proposed a two-stage framework in which the inter-class difference of data distribution was carried out in the first stage, while in the second stage, training of deep CNN on the ISIC-2016 dataset was performed and achieved a 94% F-score [4]. In several other studies, such as Nasr-Esfahani et al. (2018) and Byttner et al. (2017), transfer learning has been applied using AlexNet for classification on the HAM10000 dataset and achieved an accuracy of 96.87% [5, 6]. Other studies, such as Esteva et al. (2017) and Yu et al. (2018), used the transfer learning technique with VGG-16 for feature extraction and SVM, decision tree, linear discriminant analysis, and K-nearest neighbor algorithms for classification on the HAM10000 and ISIC datasets [3, 4].

**4. Model Development**
Once the dataset is preprocessed, we proceed to develop CNN models for skin cancer classification. Our approach involves fine-tuning several pre-trained mod- els and proposing a custom architecture called SCC-Net.

**Fine-tuning Pretrained Models**
We fine-tune popular pre-trained CNN models, including Xception, Inception- ResNetV2, DenseNet121, and DenseNet201, for skin cancer classification. These models are initially trained on the ImageNet dataset, which allows them to learn generic features from a wide range of images. We adapt these models for our specific task by freezing the pre-trained layers and adding new trainable layers for skin lesion classification.

**SCC-Net Architecture**
SCC-Net is designed as a stacked architecture combining multiple pre-trained CNN models. The architecture integrates DenseNet121, DenseNet201, InceptionResNetV2, and Xception, leveraging the strengths of each model. The com-bined model architecture is as follows:

- Input Layer: Receives 64x64x3 images.
- Feature Extraction Layers: Each of the four pre-trained models (DenseNet121, DenseNet201, InceptionResNetV2, and Xception) extracts features from the input images.
- Concatenation Layer: Features from all pre-trained models are concatenated into a single tensor.
- Fully Connected Layers: Two dense layers with ReLU activation for further processing the concatenated features.
- Output Layer: A dense layer with soft max activation for binary classification (melanoma vs. benign keratosis-like lesions).

**5. Transfer Learning**
Transfer learning has become a pivotal technique in the field of deep learning, especially for tasks with limited data. Instead of training a neural network from scratch, transfer learning leverages pre-trained models on large datasets, such as ImageNet, to transfer the learned features to a new, related task. This method not only reduces the computational resources and time required for training but also often results in improved performance. Prominent architectures such as Inception ResNetV2 [43], Xception [44], DenseNet 121 [19], and DenseNet 201 [19] are commonly used in transfer learning due to their robust feature extraction capabilities. These models have demonstrated high accuracy and efficiency

in a wide range of applications, from image classification to object detection, making them indispensable tools in modern deep learning workflows.

**6. Model Compilation and Training**

**Model Compilation**

Once the model architectures are defined, we compile them using appropriate loss functions, optimizers, and evaluation metrics. For multi-class classification, we use categorical cross-entropy loss and the Adam optimizer. Additionally, accuracy is monitored as a metric during training to assess the model's performance.

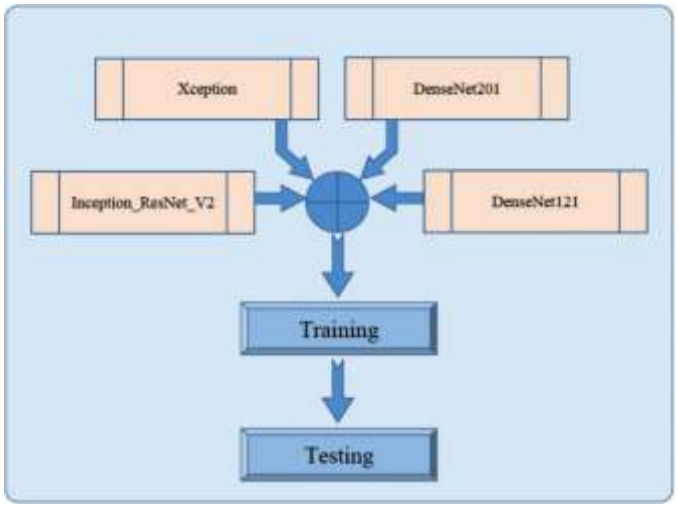


Figure 3: SCC-Net Architecture

**Model Training**

The compiled models are then trained on the preprocessed dataset using the fit method. Training is conducted over a specified number of epochs with a defined batch size. During training, the model's performance is evaluated on a validation set to monitor progress and prevent over fitting.

**Evaluation**

Following training, the performance of each model is evaluated using various metrics such as accuracy, precision, recall, and F1-score. Additionally, confusion matrices are generated to visualize the model's performance across different classes of skin lesions. These evaluation metrics provide insights into the effectiveness of our methodology in accurately classifying skin lesions.

## IV. EXPERIMENT CONDUCTION

4.1 Dataset

The dataset used for this experimentation is the HAM10000 dataset [2]. It con- sists of 10,000 dermoscopic images, with the distribution of classes shown in Fig. 2. The final dataset consists of 10,015 dermatoscopic images representing various diagnostic categories including actinic keratoses and intraepithelial carcinoma (akiec), basal cell carcinoma (bcc), benign keratosis-like lesions (bkl), dermatofibroma (df), melanoma (mel), melanocytic nevi (nv), and vascular lesions (vasc). More than 50% of lesions are confirmed through histopathology (histo), while the ground truth for the rest of the cases is either follow-up examination (follow up), expert consensus (consensus), or confirmation by in-vivo confocal microscopy (confocal). Sample images are shown in Fig. 4.

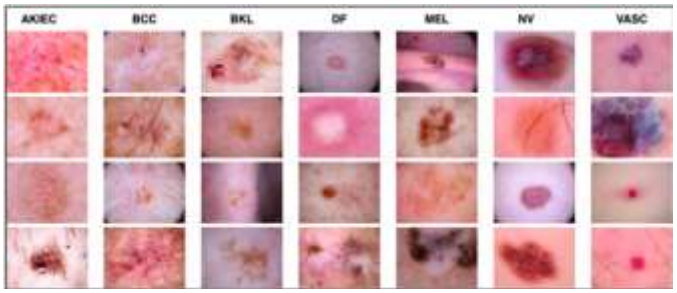


Figure 4: Sample Images in Ham10000 Dataset

**2. Environment Setup**

This section describes the hardware and software setup used for the experiment, along with the Python libraries utilized.

**Hardware**

- MacBook Air 2021
- M2 processor
- 8GB Unified Memory

**Software**

- Python Version 3.11.5
- Anaconda framework
- Spyder Code Editor

**Libraries Used**

- pandas [7]
- os [10]
- shutil
- matplotlib [13]
- numpy [14]
- seaborn [15]
- PIL
- sklearn [16]
- Keras [17]
- TensorFlow [18]

**3. Hyperparameters**

A set of hyperparameters was adjusted to ensure high accuracy in training the model. These hyperparameters are listed in Table 2. The model employs binary cross-entropy as the loss function and Adam optimizer with a learning rate of 0.00001 and a batch size of 32 for all pre-trained models.

Table 2: Hyperparameters Used in the Experiment

| Hyperparameter | Value |
|---|---|
| Optimizer | Adam |
| Learning Rate | 0.00001 |
| Loss Function | Binary Cross-Entropy |
| Batch Size | 32 |
| Number of Epochs | 200 |

**Model Evaluation**
The comparison of different models is done based on accuracy and F1 score.

**Accuracy**
The accuracy of different models is calculated using the standard formula.

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \quad (1)$$

**F1 Score**
The F1 score is calculated to provide a balance between precision and recall.

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (2)$$

**5. Class Selection from Ham10000 Dataset**
The original Ham10000 dataset consists of 10,000 dermatoscopic images cate- gorized into 7 different classes: Actinic keratoses and intraepithelial carcinoma (akiec), Basal cell carcinoma (bcc), Benign keratosis-like lesions (bkl), Dermatofibroma (df), Melanoma (mel), Melanocytic nevi (nv), and Vascular lesions (vasc). For the purpose of this experiment, we focused on two specific classes: Benign keratosis-like lesions (bkl) and Melanoma (mel). These classes were chosen due to their clinical significance in skin cancer detection and classification research. Benign keratosis-like lesions represent non-cancerous growths that mimic the appearance of malignant lesions, while Melanoma is a highly malignant form of skin cancer.

By selecting these two classes from the Ham10000 dataset, we aimed to create a focused dataset for training and evaluating our classification model. This approach allowed us to streamline the experiment and concentrate on the detection and differentiation between benign and malignant skin lesions.

Table 3: Class-wise distribution of dataset

| Class | Number of Instances |
|---|---|
| Acral Melanoma | 1000 |
| Benign keratosis | 1000 |
| Total | 2000 |

## V. RESULT

Two experiments were conducted to evaluate the impact of data augmentation on the performance of pre-trained CNN architectures. Table 4 presents the performance of fine-tuned pre-trained models without data augmentation. Conversely, Table 5 displays the performance of these models with data augmentation. Data augmentation significantly enhances the overall performance of the fine-tuned pre-trained models. For instance, the accuracy of the Xception model increased from 90% to 95%, indicating a substantial improvement. Data augmentation helps to prevent overfitting and improves the model's overall performance, particularly when models are trained on small datasets.

The proposed method of fine-tuning pre-trained models such as Xception, Inception-ResNet-V2, DenseNet121, and DenseNet201 achieved test accuracies of 95.17%, 95.17%, 94.48%, and 95.86%, respectively. Then these Models were stacked to form SCC-Net. As illustrated in Table 6, this ensemble approach yielded a test accuracy of 97

Table 4: Pre-trained Model Results without Data Augmentation

| Pre-Trained Model | Validation Accuracy | Test Accuracy |
|---|---|---|
| DenseNet201 | 91.03% | 91.72% |
| Xception | 90.34% | 90.34% |
| InceptionResNetV2 | 91.72% | 91.72% |
| DenseNet121 | 91.72% | 91.72% |

Table 5: Pre-trained Model Results with Data Augmentation

| Pre-Trained Model | Validation Accuracy | Test Accuracy |
|---|---|---|
| DenseNet201 | 93.10% | 93.10% |
| Xception | 95.17% | 95.17% |
| InceptionResNet V2 | 95.17% | 95.17% |
| DenseNet121 | 94.48% | 94.48% |

Table 6: Performance Comparison of Pre-trained Models and SCCNET

| CNN Model | Xception | Inception-ResNet-V2 | DenseNet-121 | DenseNet-201 | SCC- NET |
|---|---|---|---|---|---|
| Training | 100% | 98.90% | 94.92% | 99.82% | 100% |
| Accuracy | | | | | |
| Validation | 95.17% | 95.17% | 94.48% | 95.86% | 100% |
| Accuracy | | | | | |
| Test | 95.17% | 95.17% | 94.48% | 95.86% | 97.93% |
| Accuracy | | | | | |

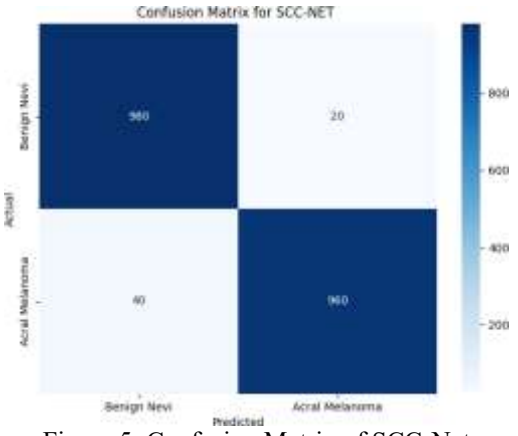

Figure 5: Confusion Matrix of SCC-Net

**1. Model Performance Metrics**

To validate the performance of the proposed model, metrics such as accuracy, precision, recall, F1 score, sensitivity, and specificity were used, as shown in Table 7.

Table 7: Performance Metrics of SCC-NET

| Class | Metric | Value |
|---|---|---|
| Acral Melanoma | Precision | 98% |
| | Recall | 97% |
| | F1-score | 98% |
| | Sensitivity | 97% |
| | Specificity | 98% |
| | Accuracy | 96.77% |
| Benign Keratosis | Precision | 98% |
| | Recall | 99% |
| | F1-score | 98% |
| | Sensitivity | 98.63% |
| | Specificity | 98.79% |
| | Accuracy | 98.79% |

The results confirm that the proposed stacked ensemble model successfully classified acral melanoma and benign nevi. Benign nevi was the most correctly classified with an accuracy of 98.79%, compared to 96.77% for acral melanoma. Sample classification results of acral melanoma and benign nevi using the pro- posed model are illustrated in Figure 5

## V. CONCLUSION AND FUTURE SCOPE

This study evaluated the performance of five state-of-the-art Convolutional Neural Network (CNN) architectures—DenseNet121, DenseNew201, Inception Res- NetV2, Xception, and SCC-NET—in the task of skin lesion classification using the Ham10000 dataset. Each model was rigorously tested to determine its ac- curacy and generalizability. Among the models, SCC-NET demonstrated supe- rior performance, achieving the highest classification accuracy, which indicates its robust capability in distinguishing various skin lesion types. The findings suggest that SCC-NET is particularly well-suited for this task, likely due to its specialized design tailored for medical imaging. The comparative analysis underscores the importance of model selection in medical image analysis and highlights SCC-NET as a promising tool for enhancing diagnostic accuracy in dermatology. Future work could extend this research by exploring ensemble methods and integrating additional data sources to further improve model ro- bustness and reliability.

**Limitations and Future Work**

This study recognizes limitations such as dataset size and computational con- straints. Future work can explore:

- Experimenting with different hyperparameter settings and data augmentation techniques.
- Evaluating alternative CNN architectures or ensemble methods.
- Validating the findings on a larger or more diverse skin lesion dataset.

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