Detection of Multi-class Skin Cancer using Stochastic Gradient Descent Augmentation Model and Activation Mapping

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Abstract

Early detection of skin abnormalities is essential in lowering fatality rates and ensuring timely treatment. However, currently available techniques encounter limitations such as small datasets, variability within the same lesion classes, imbalanced complex data and minor visual differences. These challenges make it difficult for conventional machine learning to accurately classify multi-class skin cancer abnormalities. To overcome these issues, this paper presents a computational model for the efficient identification of skin abnormalities using an applied deep learning framework. In this study, a Dense Convolutional Networks (DenseNets) model with Spatial Pyramid Pooling (SPP) and active learning is applied for data enrichment and the identification of eight classes of dermoscopic skin cancer images, which are extracted from the International Skin Imaging Collaboration (ISIC) Challenge Datasets 2016 and 2018, respectively. In the proposed system, a data augmentation technique is realized by subjecting the features to the Stochastic Gradient Descent with Warm Restarts (SGDR) model, which reduces the overfitting problem and selects effective model parameters. The performance achieves a recall, precision, and F1-score of 96.2%, 97.8%, and 97.0%, respectively. In addition, the application of the Gradient-weighted Class Activation Mapping (GRAD-CAM) image visualization method guarantees model transparency. This technique supports medical experts in the efficient and early-stage detection of cancerous images.

Keywords: Melanoma Classification, Dense Convolutional Networks (DenseNets), Spatial Pyramid Pooling (SPP), Active Learning, Feature Optimization.

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1. Introduction

Skin cancer represents one of the most common illnesses worldwide, with millions of victims. The symptoms develop as a result of uncontrolled growth of cells within the skin, causing tumors or lesions. According to the International Agency for Research on Cancer, more than 1.5 million new skin cancer cases were estimated worldwide in 2022 [26]. There are various types of skin cancer, some of which are not life-threatening. Melanoma is the most life-threatening form, with a high chance of spreading to other regions of the body. It can also be life-terminating. According to recent statistics, more than 330,000 people suffer from the most aggressive form of melanoma every year. Additionally, more than 1.5 million skin abnormalities were predicted worldwide, with 60,000 deaths caused by it [26]. According to the American Cancer Society, there were 101,388 new cases of melanoma predicted, with approximately 8,214 deaths [27]. Nonetheless, survival rates are high if it can be detected early, depending on the cancer stages. Melanoma begins in cells called melanocytes, which are responsible for generating the skin pigment melanin. Cancer may arise from any area of the skin, including areas with minimal sun exposure, such as the soles and nails [1]. Symptoms of melanoma may not be recognized through visible observation; they require subjective assessment.

Dermatologists rely on a technique known as the ‘ABCDE rule’ (Asymmetry, Border, Color, Diameter, Evolving). Asymmetry (uneven spots), Border (irregular spots with jagged edges), Changes in Color (spots with various shades and colors), Diameter (beyond that of a pencil eraser), and Evolution (morphing spots) [2]. It becomes imperative to seek medical attention as soon as these criteria are recognized. It should be noted that early diagnosis and treatment of melanoma significantly reduce complications.

During the initial phases of melanoma, the most effective method of treatment is the surgical removal of the area at high temperature [3]. However, if the disease is discovered at an advanced stage, treatment will be greatly hampered. Treatment for advanced melanoma can involve intricate methods like chemotherapy, radiation therapy, and biologically targeted therapies, which may be less fruitful. The use of dermoscopy, on the other hand, allows for the observation of skin with magnified lenses and provides insights beyond the capabilities of the naked eye. Additionally, there are confocal microscopy and optical coherence imaging, which can project images of skin below its surface without the use of a knife. Furthermore, there have been developments in the use of AI tools and learning methods for the diagnosis and detection of melanoma. These methods allow computers to analyze thousands of skin images and scan for common and specific features beyond the capabilities of the naked or even experienced eye [4]. By utilizing these tools and technologies, accuracy similar to that of professional dermatologists can be attained at a very early stage for cancerous growths.

There are various levels of incidence, ranging from practical steps for self-diagnosis, which include basic home checks, to the utilization of advanced technologies that can aid in the early detection of melanoma. This will improve survival rates for skin cancer patients, reduce the need for aggressive therapies, and ultimately save lives. As technologies continue to improve and our knowledge about skin and cancer expands, we aim to make early detection easier, quicker, and more accessible for all individuals. Thus, there will be better therapies, improved survival rates, and a brighter future for those at risk of melanoma and skin cancers. The main contribution of this research work includes:

- This technique integrates Dense Convolutional Networks and Spatial Pyramid Pooling. The result is an accurate method for skin lesion detection.
- Active Learning traditionally concentrates on the most significant samples, thus eliminating the need for a large number of labeled images.
- The Stochastic Gradient Descent with Warm Restarts (SGDR) technique is employed for optimizing the process with fast and efficient convergence.
- Heatmaps are created using Gradient-weighted Class Activation Mapping (Grad-CAM) techniques, which allow visualization and understanding of the interpretations and decisions made by the model.
- This will offer a universal solution for the early and precise diagnosis of skin cancer, specifically melanoma. It will set a foundation for developing useful AI-based medical tools.

This research will be further divided into the following sections: Section 2 will explain the literature review, Section 3 will discuss the datasets selected for research, Section 4 will discuss the method adopted for multi-class cancer image classification, and Sections 5 and 6 will discuss the results and conclusion.

2. Related Work

Skin cancer is a significant public health concern, and its early detection is crucial for successful treatment. Recent technological advancements, particularly in the fields of computer vision and deep learning, have led to the development of various automated systems for skin cancer detection. This analysis compares several research papers that propose different approaches to skin cancer detection using deep learning techniques. Salomi et al. [5] presented a mobile application-based approach to the classification of skin lesions based on the ABCD rule and K-means clustering, in which the results are reliant on the centroids to initialize the algorithm. Pattanaik et al. [6] suggested a better performance of image segmentation and classification techniques in a cascaded approach. In this approach, the segmentation stage tends to be very intensive, which affects the performance of the system. Rajasekar et al. [7] proposed an intelligent system that employs a mix of deep learning techniques such as CNNs and recurrent neural networks (RNNs). Ezzat et al. [8] investigated the performance of virtual skin cancer detection by applying two pre-trained CNN architectures, MobileNet and VGG-16. These pre-trained models can ease the process of training the model for skin cancer detection.

Pilania et al. [9] introduced a skin cancer detection system based on a binary classifier, a residual network, and CNN. Mittal et al. [10] analyzed whether a DenseNet201 model could be employed to detect skin cancer. It is well known that DenseNet models can reuse features and lower the number of parameters. In this regard, DenseNet models tend to be more efficient and effective than traditional CNN designs, thus aiding in the prevention of overfitting. However, the use of DenseNet architectures has certain disadvantages, as their complexity makes them more difficult to train and implement. Naqvi et al. [11] introduced a portable microwave system to detect skin cancers in real-time. This method also reduces the need for invasive procedures by utilizing the technique of skin cancer diagnosis at a distance, without actual contact with the skin.

Tiwari et al. [12] conducted a survey on different classification approaches to classify skin abnormalities and optimized the models. Jackulin et al. [13] recommended skin cancer detection using EfficientNet models. EfficientNet models are CNNs optimized to require fewer resources than other traditional CNN models. However, EfficientNet models may be more complicated to comprehend and customize. Prakash et al. [14] described the integration of deep learning, transfer learning, and a hybrid model for skin cancer detection. The device synthesizes dissimilar methods to enhance the precision of the outcomes and reduce operational expenses.

This literature review highlights the fundamental advances that have been made over time in dermatology regarding the identification of skin neoplasms, especially using deep learning [15]. Nevertheless, more studies are required to overcome these challenges and guarantee the safe and efficient use of advanced AI technologies in real-world clinical settings [16].

3. Description of the Dataset

This study considers a total of 3,154 skin lesions of substantial resolution derived from open-access repositories of images, ISIC 2016 [17] and 2018 Challenge [18] [19] Datasets (https://challenge.isic-archive.com/data/), respectively. The applied datasets holds high-quality expert annotated images, which provide a standard multi-class evaluation framework for researchers concerning state-of-the-art methods. The dataset resources include skin conditions ranging from melanoma to non-melanoma, benign lesions of the skin, and many others. All the images are categorized to fall under one category, such as "melanoma" or "a benign lesion" which enables the model to learn and differentiate among the conditions.

The eight classes of the dataset considered in this study are as follows:

1. Melanoma: A type of skin cancer. Because it is very easy to metastasize, the disease can be fatal unless diagnosed early due to its many different shapes and color patterns.

2. Benign Nevus (Moles): Normal skin pigmentation that, despite having similar features to melanoma, makes it easier to design a model to distinguish these benign moles from malignant ones.

3. Basal Cell Carcinoma (BCC): Recurrent malignant less aggressive tumors that assume the appearance of shiny nodules or scar-like regions

4. Squamous Cell Carcinoma (SCC): A form of malignant skin tumor that assumes the appearance of red plaques and ulcerations. Therefore, early intervention is needed to prevent its spread.

5. Actinic Keratosis (AK): Scaly pre-cancerous lesions that are symptom-free and carry the risk of turning into malignant skin lesions. Hence, fast identification is needed.

6. BKL: A non-serious growth that might emerge on the skin yet has characteristics that make it seem abnormal.

7. Dermatofibroma: These skin tumors rarely become malignant. They are small and hard, appearing simply as harmless lesions.

8. VASC: This lesion is related to blood vessels. It appears in red and purple and is benign.

In this study, the dataset of uniform distribution of eight classes of skin cancer images is considered. The total dataset of 3,154 images is divided into three subsets, namely, training (70%, 2,208 images), validation (15%, 473 images), and testing (15%, 473 images), for learning, fine-tuning, and checking the reliability of the model, respectively. This dataset contains multiple classes that represent particular types of skin lesions. The classes encompass both malignant and benign diseases, allowing the model to learn how to distinguish between different types of skin diseases.

4. Methodology

In this paper, the advanced approach of deep learning applied to dermoscopic image analysis enhances early and accurate skin cancer detection, particularly for multi-class melanoma detection. The methodology utilizes neural networks, optimizations, and visualizations to improve diagnostic accuracy. The steps and key components of the proposed approach are illustrated in Figure 1. Furthermore, this section explains the workflow of the DenseNets model and its integration with Spatial Pyramid Pooling (SPP), as well as the application of an optimization model with warm reset for efficient and precise detection of multi-class skin cancer images.

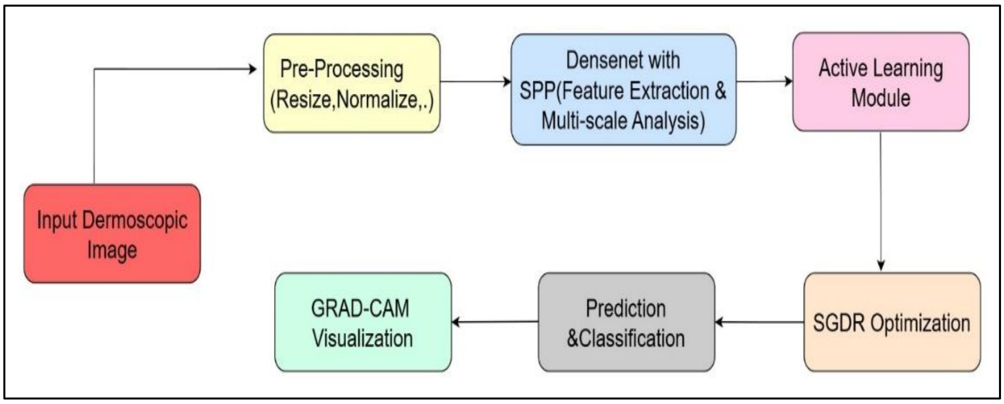


Figure 1. Flow Diagram to Detect the Multi-Classes of Skin Cancer Images

4.1 Deep Learning Architecture: Dense Convolutional Networks (DenseNets)

The proposed model is based on Dense Convolutional Networks (DenseNets); it is connected by feed-forward learning in an efficient manner that allows feature maps to be passed from all layers before being fed directly into every subsequent layer thereby offering better feature reuse and propagation. Consequently, DenseNets can learn both local fine-grained patterns and larger global structures within skin lesion images thus; they are particularly useful for this application.

DenseNets constitute a densely connected architecture. In this architecture, each layer takes feature maps from all preceding layers as inputs, and its output is propagated to all succeeding layers. This architecture addresses some of the typical challenges of deep learning, such as vanishing gradients and poor reuse of features, making it more capable of extracting detailed features from complex dermoscopic images.

Consider a DenseNets with l layers, the l^{th} layer output as follows:

$$x_l = H_l([x_0, x_1, \dots, x_{l-1}]) \tag{1}$$

where,

x_l: Output of the `$l^{th}$` layer.

H_l: A composite function of operations such as batch normalization, ReLU activation, and convolution.

$[x_0, x_1, \dots, x_{l-1}]$: Concatenation of feature maps from all the preceding layers.

This dense connectivity, as shown in Figure 2, helps efficiently extract detailed features from images, making it possible to learn both local and global patterns present in different types of skin lesions.

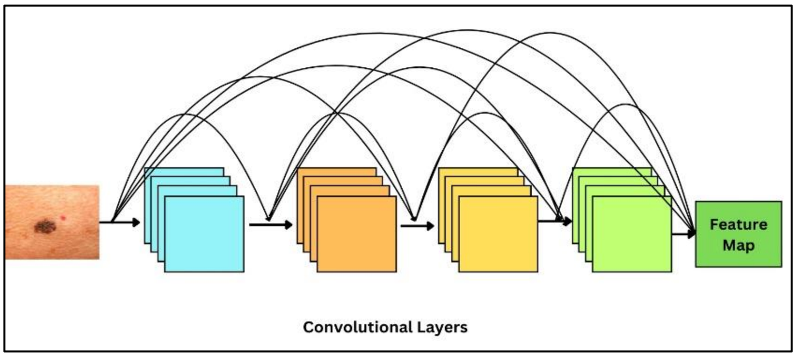


Figure 2. Layered Architectural Representation of DenseNets Model

4.2 Spatial Pyramid Pooling (SPP)

Spatial Pyramid Pooling (SPP) was included to make the model more robust in handling images of varying sizes and resolutions. This ensures that the input images are processed without resizing to a specific dimension, which is a common shortcoming of most conventional CNNs. The application of multi-scale pooling operations enables the model to extract multi-scale features from images, allowing critical information from lesions of different sizes and shapes to be captured.

Let the feature map input F, SPP allows for windows of various sizes, and the pooled feature vectors are as follows:

$$SPP(F) = \left[P_{n_1}(F), P_{n_2}(F), \dots, P_{n_k}(F)\right] \tag{2}$$

where,

$P_{n_i}(F)$: Feature map pooled at window size n_i.

k: Number of pyramid levels.

This helps the model analyze the images at various spatial dimensions, enhancing its ability to generalize and detect lesions of different sizes and shapes.

4.3 Integration of DenseNets with SPP

Figure 3 represents the structure of DenseNets, indicating a dense connection in which each layer receives feature maps from every preceding layer. However, this architecture supports effective feature reuse, allowing the model to capture not only fine-grained local details but also broad global patterns of the input image. Additionally, the dense connections efficiently pass through complicated dermoscopic images of skin lesions, making this network highly suitable for extracting detailed and multi-scale features from the input. Following the DenseNets feature map formation, the next step consists of integrating the SPP model. In this model, the SPP uses an output feature map and applies numerous pooling operations at multiple scales, generating fixed-size feature representations irrespective of the size of the input images. This ensures that images of any dimension are considered, capturing features at various spatial resolutions. This capability ensures the model can detect skin lesions of various sizes and shapes, improving the generalization ability of the model. The DenseNets features are rich and detailed, and the integration of SPP makes them adaptable to any input size, amplifying the overall performance and accuracy of the model.

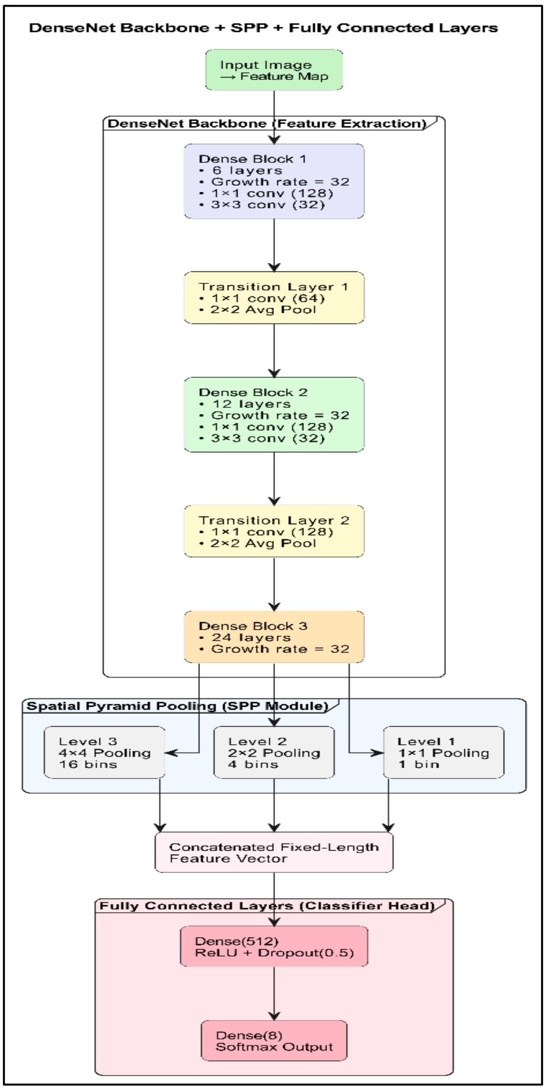


Figure 3. Architecture of DenseNets Feature Map to Enable Spatial Pyramid Pooling (SPP)

DenseNet ensures feature consistency through feature reuse and progressive aggregation, where each layer receives all previous feature maps. When these multi-scale, high-resolution DenseNet features enter the SPP module, the pooling operations (1×1, 2×2, 4×4) generate fixed-length outputs regardless of the input image size. Feature consistency is maintained through:

- Uniform pooling kernels: SPP pools each feature map into equally partitioned spatial bins, ensuring comparable representations across scales.
- Concatenation into a fixed vector: Despite variations in spatial dimensions, SPP produces a fixed-length vector, allowing seamless integration with the fully connected classifier.
- Dense connectivity: Because each DenseNet layer uses all previous layers' outputs, the feature distribution remains stable, preventing mismatches when passed to SPP.

Consequently, the combination of dense feature propagation and scale-normalized pooling guarantees stable and consistent features across the entire pipeline.

4.4 Active Learning for Efficient Training

Active Learning significantly increases efficiency by presenting crucial examples for training. In this model, the most challenging or ambiguous cases of images are selected which represent, the least confidence for training. Moreover, such impactful samples learning with complex and relevant cases improves generalization and accuracy [20]. This selective process reduces the amount of labeled data required for training and addresses the issues of time and cost constraints in active learning.

The active learning flow consists of four stages:

- **Initial Training:** Train the DenseNet+SPP model on an initial labeled dataset.
- **Uncertainty Sampling:** For each unlabeled image, compute prediction confidence. Images with confidence below a threshold (< 0.6) are marked as high-uncertainty.
- **Expert Annotation:** Only these high-uncertainty and ambiguous lesion images are sent to dermatologists for labeling. This reduces labeling costs and focuses on clinically difficult cases.
- **Retraining / Iterative Loop:** The newly labeled samples are added back into the training pool. SGDR retrains the model to adapt to the newly added high-value samples.
- This loop continues until performance stabilizes.

4.5 Optimization using Stochastic Gradient Descent with Warm Restarts (SGDR)

In this study, after the successive execution of the active learning stage, the SGDR optimization technique is applied for the augmentation process. Active learning selects the most difficult and informative samples for training. These samples often introduce higher variance in gradients. SGDR helps stabilize training by:

- Starting with a higher learning rate, which quickly adapts to new challenging samples.
- Gradually annealing the learning rate to refine the model on these critical samples.
- Preventing premature convergence that may occur due to data imbalance or difficult samples.

Thus, SGDR complements active learning by ensuring fast adaptation and stable optimization. SGDR help the model to escape local minima and encourage exploration of new solution regions. By periodically resetting the learning rate to a higher value, the optimizer avoids stagnation and accelerates overall convergence. This leads to better generalization and reduces the risk of overfitting, especially in complex multi-class datasets.

In this case, the learning rate is adjusted according to a cosine annealing schedule. The cosine annealing schedule adjusts the learning rate by gradually decreasing it following a cosine function. Initially, the learning rate is high, and it smoothly decays toward a minimum value. This controlled decay stabilizes training and improves fine-tuning. After completing one cycle, the learning rate is reset (warm restart), and the cycle repeats. This mechanism results in efficient exploration during early iterations and precise convergence toward the end. This annealing method helps the model converge better.

Consider the stochastic gradient descent function with warm restarts, where the learning rate at each iteration (t) $\eta(t)$ given by

$$\eta(t) = \eta_{min} + \frac{1}{2}(\eta_{max} - \eta_{min})\left(1 + \cos\left(\frac{t}{T_i}\pi\right)\right): \quad (3)$$

where,

η_{min} and η_{max}: Minimum and maximum learning rate, respectively.

T_i: Number of iterations within the i^{th}cycle.

However, the traditional augmentations do not improve optimization stability, whereas the proposed SGDR-based augmentation (with learning rate warm restarts) which modifies the training dynamics, and like a “training-time augmentation” of optimization trajectories. It also, improves the convergence speed and stability after each active learning cycle.

The hyperparameters used for SGDR are:

- Maximum learning rate: $\eta_{max} = 0.01$
- Minimum learning rate: $\eta_{min}0.0001$
- Warm restart cycle length: T_0=10 epochs
- Cycle multiplier: $T_{mult} = 2$
- Batch size: 32
- Optimizer: SGD with momentum = 0.9
- Weight decay: 1×10^{-4}

These settings provide a balance between rapid exploration early in training and strong convergence later process.

4.6 Model Transparency with Gradient-weighted Class Activation Mapping (GRAD-CAM)

In this study, for more interpretable image classification, a Gradient-weighted Class Activation Mapping (GRAD-CAM) network is utilized for explainability and image visualization. GRAD-CAM produces visual explanations by focusing on parts of the image that are significant to the model's classification decision.

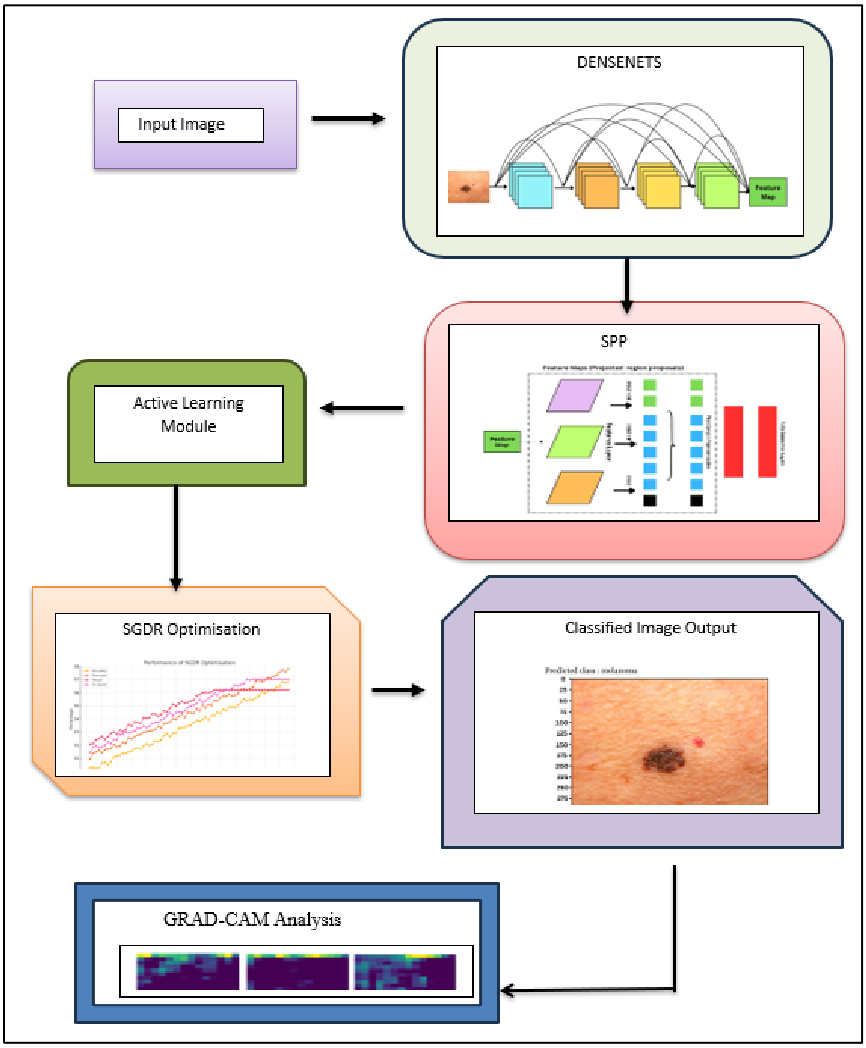


Figure 4. Comprehensive Methodology Using Applied Deep Learning for Eight Classes of Skin Cancer Detection

Given a class c, the Grad-CAM heatmap is defined as:

$$L^{c}_{\text{Grad-CAM}} = \text{ReLU}\left(\sum_k \alpha^{c}_{k} A^{k}\right) \tag{4}$$

where,

(α^{c}_{k}): Weights calculated based on the gradient of the class score for the feature mapsA^{k}.

A^k: Feature map of convolutional layer k.

In this way, this approach clarifies the decision-making procedure and visualizes the parts of the image classification. This supports in an easier understanding and increases trust in the model's results by doctors for objective evaluation of abnormalities. Transparency is very important in medical image prediction because doctors must trust and understand how an AI model arrives at its decision. When the model points out the exact skin-lesion regions, used for prediction, dermatologists can check whether it is focusing on the correct medical patterns. This also helps identify mistakes and understand why a wrong prediction occurred. Clear explanations make the system safer to use in hospitals and support accountability. In addition, medical AI tools must follow strict regulations, which require models to show how decisions are made. Grad-CAM helps achieve this by creating heatmaps that visually highlight the important areas influencing the prediction, making the AI system more reliable and suitable for real-world clinical practice.

The proposed methodology shown in Figure 4, combines DenseNets for extracting image features, SPP for multi-scale feature pooling, Active Learning for fast training on the most informative images, SGDR for optimal learning rate adjustment, and finally Grad-CAM for visual interpretation. The steps are explained in Algorithm 1, which offers a comprehensive and strong approach to detecting skin cancer. The proposed model, in addition to improving detection accuracy, also reveals transparent insights in analyzing dermoscopic images. This diagnosis support system using an applied deep learning framework assists medical experts in early diagnosis and treatment.

Algorithm 1: Proposed Multi-Class Skin Cancer Detection Framework

i. Input: Dermoscopic image
ii. Preprocessing: a) Resize b) Normalize and c) Color channel standardization
iii. Feature Extraction:
   a. Pass image through DenseNet backbone
   b. Extract multi-scale features using SPP
iv. Active Learning Cycle:
   a. Identify low-confidence predictions
   b. Query these samples for expert labelling
   c. Add them to the training pool
v. Optimization using SGDR:
   a. Initialize learning rate η_{max}
   b. Apply Cosine annealing
   c. Perform warm restart at end of each cycle
vi. Prediction: a) Fully connected classifier and b) softmax output
vii. Explainability: Apply Grad-CAM to generate heatmaps over suspicious regions
viii. Output: Predicted class + visual explanation

5. Results

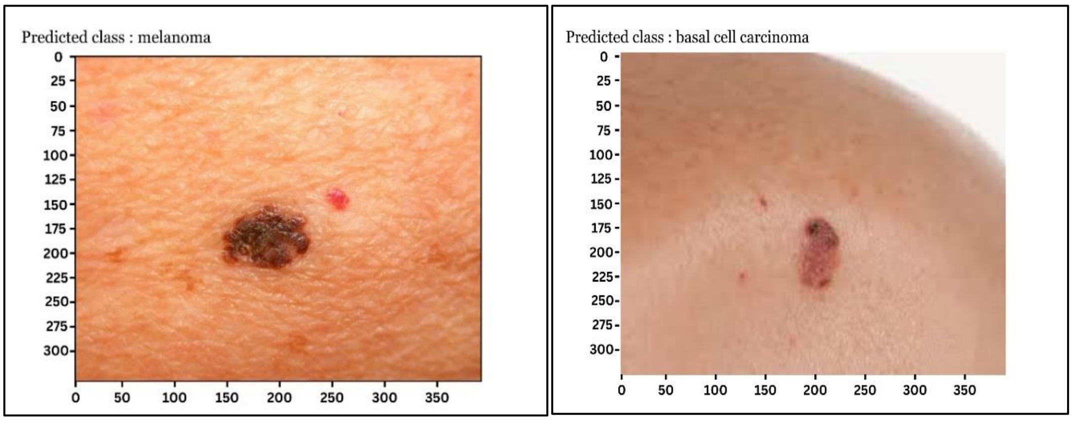
The proposed model is executed by integrating DenseNets with SPP and active learning techniques. In this study, the performance of the model is verified against the ISIC 2016 and 2018 Challenge Datasets, which include an extensive range of skin lesions, to perform robustness testing under different conditions. The data is pre-processed, and features are enhanced to increase classification performance, distinguishing intra-class and inter-class variability. The importance of the steps applied in this study for handling noisy skin cancer images is represented in Table 1. The overall dataset images considered in this study are divided into three parts of 70%, 15%, and 15% for training, validation, and testing, respectively. Further, the splitting of data is justified as follows:

- Train: 70% of the data is subjected to training, which ensures a sufficiently large sample for DenseNet's high-capacity features.
- Validation: 15% of the validation samples support stable hyperparameter tuning without data leakage.
- Test: 15% of the testing patterns considered provide a statistically meaningful evaluation for eight classes.

Table 1. Procedure for Handling Noisy Data of Skin Cancer Images

Process	Significance
Image normalization	Reduces illumination differences.
Data augmentation	Steps such as rotation, zoom, and flip, which simulates real clinical variance.
Active learning	Naturally ignores noisy/low-confidence samples until corrected by expert labeling.
Spatial Pyramid Pooling (SPP)	Improves robustness to non-uniform lesion sizes and noise at edges.

Observed that the results demonstrate significantly improved accuracy in terms of skin cancer detection compared to traditional diagnostic techniques. Classification images of skin abnormalities using the proposed methodology are shown in Figure 5, which represents the typical plots of melanoma and basal cell classes, respectively.



a) b)

Figure 5. Predicted Typical Output for the Classes Namely: a) Melanoma, and b) Basal Cell Carcinoma

Figure 6 describes the performance of the model for eight classes using the confusion matrix considering a total of 473 samples from the testing data. In this, an overall testing accuracy of 90.27% was obtained, with 427 samples detected as true positive images.

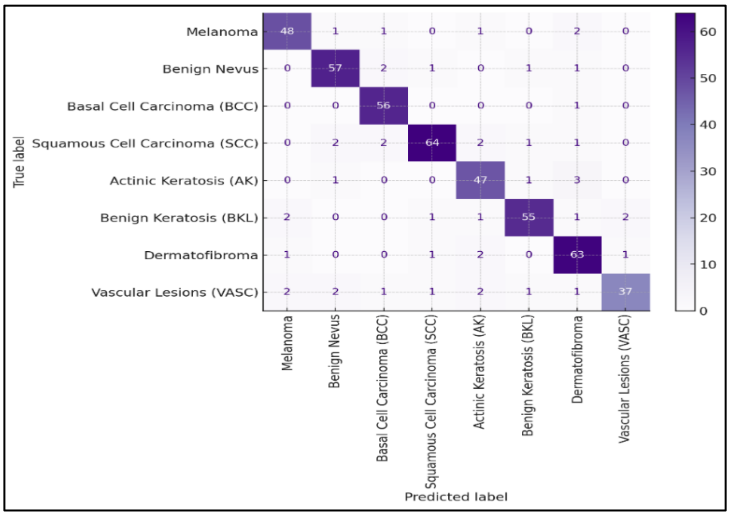


Figure 6. Confusion Matrix for Eight Classes of Skin Cancer Images

The Detection rate refers to the proportion of true positive cases correctly identified by the model. In multi-class classification, it is equivalent to recall, calculated as:

$$\text{Detection Rate} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

Using the testing dataset of 473 images, our model correctly detected 427 samples, giving an overall detection rate of:

$$\text{Detection Rate} = \frac{427}{473} = 90.27\%$$

Precision and recall of more than 0.9 were reported for all eight classes of skin lesions considered in this study. Specifically, the precision achieved for the classes melanoma and BCC is 97% and 96%, respectively. This represents a maximum point in terms of the efficiency of the model developed for differentiating the types of skin abnormalities shown in Table 2.

Table 2. Performance of the Skin Cancer Classes Classification Model

Classes of Skin Cancer Considered	Precision	Recall
Melanoma	0.97	0.96
Benign Nevus	0.95	0.94
Basal Cell Carcinoma (BCC)	0.96	0.95
Squamous Cell Carcinoma (SCC)	0.94	0.93
Actinic Keratosis (AK)	0.93	0.92
Benign Keratosis (BKL)	0.92	0.91

Dermatofibroma	0.91	0.9
Vascular Lesions (VASC)	0.9	0.89

The classes of skin cancer detection rates (recall values) ranged from 89% to 96%, indicating strong consistency in identifying both malignant and benign lesions.

The AUC-ROC curve represents the Area Under the Receiver Operating Characteristics Curve, a plot of the True Positive Rate against the False Positive Rate at different threshold levels. In addition, AUC measures the degree of separation between the classes. A model with an AUC closer to one has better performance. However, for a higher AUC, the model is superior, distinguishing between the positive and negative classes. The curve helps visualize the trade-off between sensitivity (recall) and specificity. The AUC-ROC curve for the proposed model is shown in Figure 7. The performance metrics considered in this study are given in Table 2.

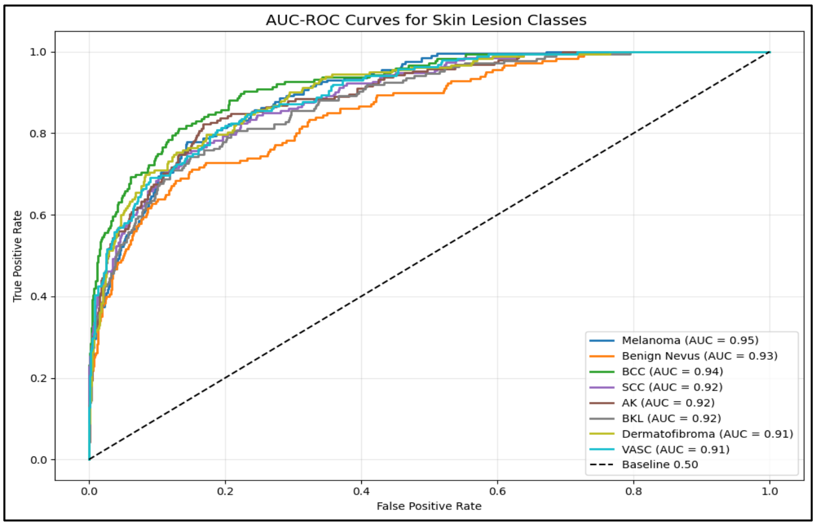
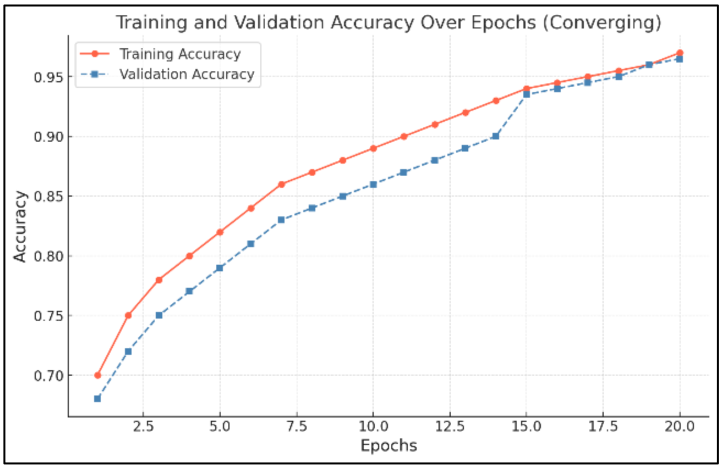


Figure 7. AUC-ROC Curve for Eight Classes of Skin Diseases Using DenseNets Model Classification

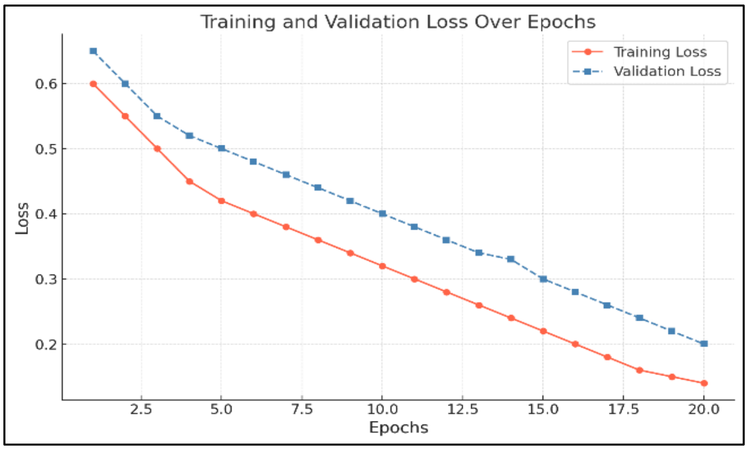
Table 3. Comparative Analysis of Proposed Method and Traditional Models for Skin Abnormality Classification

Deep Learning Models	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC (%)
Proposed Model (DenseNets+ SPP + Active Learning)	97.3	97.8	96.2	97	98
ResNet-50	91.5	92	89.5	90.7	92.3
VGG-16	88.7	89	86.5	87.7	90
InceptionV3	90.8	91.5	89	90.2	93.1
MobileNet	87.9	88.2	86	87.1	88.5
EfficientNet	94.1	95	93.5	94.2	95

One of the useful tools to consider for the effective assessment of a classification model is the accuracy and loss graph of training and validation series, as shown in Figure 8. The accuracy graph (Figure 8 a) provides a time-series indication of whether the model can predict the right output; the higher the values, the better the performance. The loss graph as shown in Figure 8 b), follows the development of how poorly the model's error is, or how far the predictions are from the actual targets, with lower values indicating better accuracy. Moreover, the dataset was executed using different deep learning models along with the proposed model as shown in Table 3. In this context, the DenseNets integrated models show sustainable performance.



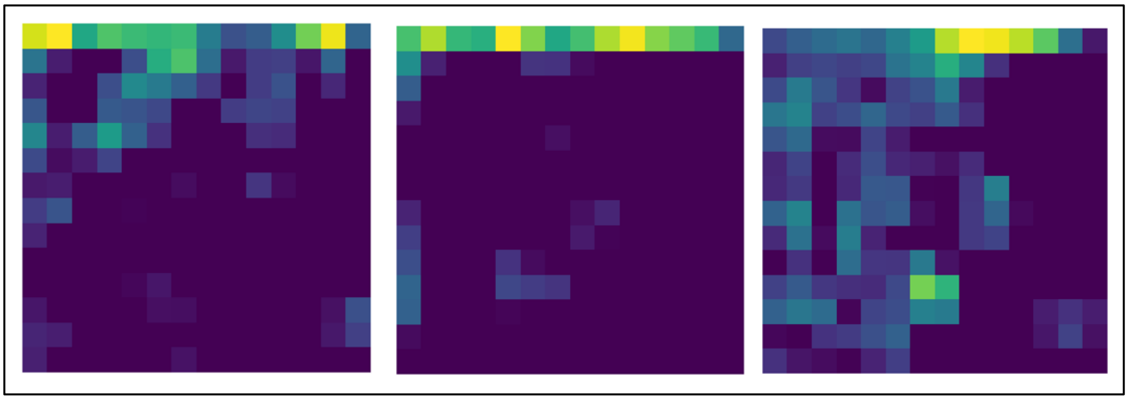
(a)



(b)

Figure 8. Simulation Epochs: a) Shows the Training and Validation Accuracy Graphs, and b) Loss Comparison

Grad-CAM is used in CNNs to identify parts of the input image and make decisions. This allows the use of gradients of any target class to create a class activation map that points to which parts of the image are most relevant to the class prediction, thereby showing how the model interprets the data. Grad-CAM visualization plots for typical classes of skin cancer are represented in Figure 9 a)-c) for Melanoma, Benign Nevus and Basal Cell Carcinoma (BCC), respectively.



(a) (b) (c)

Figure 9. Heatmaps Generated for Typical Classes of Skin Using GRAD-CAM: a) Melanoma b) Benign Nevus c) Basal Cell Carcinoma (BCC)

6. Discussion

Utilizing feature augmentation and optimization techniques, such as stochastic gradient descent, allows the model to improve quickly in terms of sustainable accuracy. Grad-CAM heatmaps explain the reasoning behind the decisions made by the model, allowing for better comprehension of how it identifies different lesions. Compared to various studies on skin cancer detection [21]-[23] and traditional models in Table 3, the proposed model performs efficiently in terms of factors such as accuracy and reliability. Furthermore, in this study addresses the overfitting of data samples by sensibly choosing the SDG-based argumentation parameters to increase diversity while preserving feature distortion.

The present study adopts the challenging and clinically realistic multi-class ISIC 2016 and 2018 datasets and follows strict, bias-free data splitting and evaluation procedures. Rather than optimizing solely for accuracy, the proposed approach emphasizes clinically meaningful metrics such as recall, precision, and F1-score (96.2%, 97.8%, and 97.0%, respectively), which more accurately represent diagnostic reliability, especially for malignant lesions. In addition, benchmark datasets have shown significant results in the studies conducted [26]-[27] for developing and analysing automated skin cancer computational models.

Furthermore, the reasons behind the slight incorrect distinction between benign nevi and melanoma are due to the sharing of similar color patterns and border shapes, making misclassification common even for dermatologists. Moreover, the model tends to confuse the two which depends on the following reasons:

- Overlapping pigmentation patterns: Irregular light–dark brown regions.
- Shared asymmetry: Early-stage melanoma may appear symmetric, similar to many nevi.
- Border ambiguity: Benign nevus with fuzzy or blurred edges resemble early melanoma margins.
- Low lesion contrast: In some images, melanoma indicators (dots, streaks) are faint or partially occluded.

- Presence of artifacts: Hair shadows, or color variation from dermoscope lighting can mask melanoma-specific structures.

Therefore, subtle morphological features rather than gross shape cause misclassification. This is confirmed by Grad-CAM visualizations, where the model sometimes focuses on non-discriminative areas of the lesion.

Significant methods were further applied to manage the overlapping classes for Dermatofibroma and Vascular Lesions (VASC) lesions. In addition, both classes have uncommon morphological traits, causing feature overlap. The proposed model manages such overlaps using the following mechanisms:

- DenseNet's deep feature hierarchy: Captures subtle vascular patterns in VASC versus fibrous textures in dermatofibroma.
- SPP multi-scale pooling: Allows the model to differentiate structural features at multiple spatial levels—VASC patterns are often central and circular, while dermatofibroma tends to show a uniform texture.
- Active learning selection: Uncertain predictions between these rare classes are flagged and reintroduced into training with expert labels, improving discrimination.
- SGDR optimization: Helps the model adjust weights around difficult overlapping boundaries instead of collapsing into majority-class behavior.
- Grad-CAM validation: Ensures the model focuses on diagnostically relevant vascular regions in VASC and not on irrelevant background areas.

Thus, the system manages class overlap via multi-scale representation, uncertainty-driven sampling, and interpretable feedback loops.

In this study, the shortcomings of using a dataset limited to 3,154 ISIC dermoscopic images and the respective overcoming strategies are elaborated. Rare lesion categories such as VASC or dermatofibroma are underrepresented, increasing the risk of overfitting and poor class separation. The dataset also lacks full real-world variability, including differences in lighting conditions, skin tones, and imaging devices, which limits model robustness. High inter-class similarity within such a small dataset further exacerbates confusion between challenging classes like melanoma and benign nevus, while the overall restricted diversity leads to weaker generalization on external clinical data.

Active learning provides an effective strategy to counter limited dataset size by improving dataset quality rather than quantity. Instead of sampling images randomly, the model selectively chooses the most informative samples—typically those with low confidence or ambiguous features. This approach prioritizes images that will yield the greatest performance improvement and avoids redundant "easy" samples that contribute little new information. Through repeated cycles, active learning gradually constructs a curated set of diverse and difficult cases, strengthening the model's ability to recognize subtle lesion patterns. When combined with SGDR, the model adapts smoothly to newly introduced challenging samples. Although active learning does not expand the dataset numerically, it significantly increases its effectiveness, which is crucial in medical imaging where labeled data is scarce and costly.

Following are the observations to enhance the sustainable performance of the proposed model of skin cancer analysis:

- This model works best on images with high clarity. It also, operates with images of different quality in a real-world clinic, where images may not be of good quality due to variations in different camera equipment.
- Needs expert Labeling: Active learning shrinks the demand for a large number of labeled images, however this requires dermatologists to label some images, which can be time-consuming and expensive.
- High Computation Requirement: The complexity of the structure of this model requires more computing power.
- This study extends to images tested under actual clinical conditions to confirm the reliability of usage for real-world applications.

7. Conclusion

The structure of deep learning will be based on DenseNets architecture, Spatial Pyramid Pooling, and active learning for an early and reliable detection technique for skin lesions like melanoma. In the current research, a sustainable accuracy value of 97.3% was achieved for classifying images of skin cancer among eight classes. Moreover, DenseNet represents a rich feature in-depth learning for capturing skin lesions, and SPP will allow the system to be independent and maintain resolution size in images. Active learning will facilitate learning without wasting much time and with high precision, recall, and F1 value. Also, the subsequent use of transfer learning will enable better performance and shorter training times on smaller datasets. The addition of unsupervised and semi-supervised learning will assist in learning from fewer labeled images. Adding functionality for more skin disorders will be an added advantage. The use of additional explainable AI methods will allow for a better understanding of decisions made by an AI system by medical professionals. The model can be optimized for use on mobile platforms or low-power architectures. Regular testing with live clinical data will be essential for validating the efficacy of the model.

Conflict of Interest

The authors declare that they do not have a conflict of interest in regard to this research article.

Declarations

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