International Journal on Science and Technology (IJSAT)
E-ISSN: 2229-7677 ● Website: www.ijsat.org ● Email: editor@ijsat.org

# Comparative Analysis of Automated Melanoma Recognition Algorithms in Dermoscopy

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**Abstract**
This paper presents a comparative analysis of automated melanoma recognition algorithms in dermoscopy, highlighting the strengths and limitations of various state-of-the-art techniques. The study evaluates different image processing and machine learning approaches used for early melanoma detection, focusing on accuracy, sensitivity, specificity, and computational efficiency. Publicly available dermoscopic image datasets were utilized to ensure consistency in performance assessment. The results emphasize the critical role of data quality, algorithmic architecture, and preprocessing techniques in determining diagnostic performance. This analysis aims to guide future research toward more robust, interpretable, and clinically viable melanoma detection systems.

**Keywords:** melanoma detection, dermoscopy, image analysis, machine learning, algorithm comparison, computer-aided diagnosis

## 1. Introduction

Melanoma originates predominantly in the melanocytes of the skin and represents the deadliest form of skin cancer, accounting for nearly three-quarters of all fatalities linked to skin cancer. As per 2020 statistics by the American Cancer Society, around 76,380 new melanoma cases were projected, with an estimated 10,130 deaths in the United States. Timely detection of skin abnormalities, followed by suitable medical intervention, is crucial for improving survival prospects. To assist in precise diagnosis, dermoscopy has been developed as a non-invasive visualization method, delivering magnified and illuminated images of the skin.

This clarity allows for more accurate evaluation of pigmented lesions and other dermatological conditions. By eliminating surface reflections, it allows for the visualization of subsurface skin structures, offering a more detailed examination of skin abnormalities. This technique is extensively applied in melanoma diagnosis, achieving significantly higher diagnostic accuracy compared to unaided visual inspection. Manual assessment of dermoscopic imagery is a prevalent diagnostic practice; however, it is restricted by time demands and proneness to human error. Variability in diagnostic outcomes among skilled dermatologists reflects the subjective nature of interpretation.

Emerging automated melanoma detection strategies aim to enhance accuracy and reduce variability, with AI-driven computer-aided diagnostic solutions receiving substantial research attention as a means of addressing these obstacles. Convolutional neural networks (CNNs), which form a branch of deep learning, have demonstrated exceptional performance in applications such as image segmentation and image classification.

## 2. LITERATURE REVIEW

Automated melanoma recognition has become an essential area of research in dermatology due to the increasing prevalence of skin cancer. Dermoscopy, a non-invasive imaging technique, plays a crucial role in detecting melanoma, as it captures detailed features of skin lesions. The application of machine learning (ML) and deep learning (DL) algorithms to analyze dermoscopy images has proven to be an effective solution for early melanoma detection. In this literature survey, we present a comparative analysis of various automated melanoma recognition algorithms in dermoscopy, highlighting the advancements, challenges, and effectiveness of different techniques. Traditional Machine Learning Algorithms such as Support Vector Machines (SVM), Random Forests (RF), and K-Nearest Neighbors (KNN), have been widely applied to dermoscopy image classification.

In these methods, feature extraction is critical. Early studies used handcrafted features such as color, texture, and shape from dermoscopic images to train classifiers. For instance, Celebi et al. (2007) applied SVM on color and texture features for melanoma detection, achieving moderate success. While these methods showed promising results, they are often limited by the need for human intervention in feature selection and the inability to automatically learn complex patterns from raw image data.

## 3. Need for the Study

The early detection of melanoma significantly increases the chances of successful treatment and long-term survival. However, manual diagnosis through dermoscopic image interpretation is prone to human error, subjectivity, and requires expert dermatologists—resources that are often limited, especially in remote or under-resourced regions. As the incidence of skin cancer continues to rise globally, there is a critical need for automated, accurate, and efficient diagnostic tools to assist clinicians and improve early detection rates.

Deep learning has revolutionized image-based diagnostics, with convolutional neural networks (CNNs) achieving state-of-the-art results in various medical imaging tasks. Among these, Deep Residual Networks (ResNets) have shown exceptional performance due to their ability to train very deep architectures while avoiding problems like vanishing gradients. These models can extract high-level, discriminative features from dermoscopic images, making them highly sui+table for melanoma recognition.

## 4. OBJECTIVES OF THE STUDY

The primary aim of this study is to evaluate and compare the effectiveness of various Deep Residual Network (ResNet) architectures in the automated recognition of melanoma using dermoscopic images. To achieve this, the study is guided by the following specific objectives:

1. Detailed study on Melanoma Recognition using Residual Networks.
2. Skin lesion classification is performed using a deep residual network applied to segmented.
3. The integration of Convolutional Neural Networks represents a pivotal approach for resolving advanced issues in medical imaging analysis.
4. A fully convolutional residual network (FCRN) is utilized for the segmentation of skin lesions. Performance evaluation and comparative analysis of automated melanoma recognition algorithm.

## 5. HYPOTHESES

$H_1$: Deeper ResNet architectures (e.g., ResNet-50, ResNet-101) will achieve higher classification accuracy and AUC scores compared to shallower ones (e.g., ResNet-18, ResNet-34).

$H_2$: There exists a trade-off between model accuracy and computational cost, with deeper models requiring significantly more time and resources for training and inference.

$H_3$: An optimal ResNet architecture can be identified that provides a good balance between diagnostic performance and computational efficiency for melanoma recognition.

$H_4$: ResNet-based models will outperform traditional CNN models in terms of classification metrics on dermoscopic melanoma datasets.

## 6. METHOD ADOPTED IN THE PRESENT STUDY

To implement an automated melanoma recognition algorithm in dermoscopy images using deep residual networks (ResNets), a PC or laptop with MATLAB software installed is an essential setup for developing and testing the model.

### 6.1 TOOLS USED

The following tools are used to collect data relevant to the

1. PC/Laptop with MATLAB Software installed.
2. USB Camera.
3. Infected Skin for examination.

### 6.2 SAMPLE

A comparative experimental method was used, implementing and evaluating multiple ResNet architectures on a benchmark dermoscopic image dataset for melanoma classification.

### 6.3 Deep Learning Techniques used

Suitable deep learning techniques using various ResNet architectures for feature extraction and classification of dermoscopic images.

1. Image preprocessing technique,
2. Dermoscopy enables skin visualization without surgical intervention.
3. Transfer learning,

4. Deep residual network-based classification for automated melanoma recognition in dermoscopic images.

## 7. Skin Lesion Analysis Towards Melanoma Detection Challenge dataset

Experimental results demonstrate the significant performance gains of the proposed framework,
The main contributions of our work can be summarized as follows:
1)We propose a novel and comprehensive two-stage approach based on very deep CNNs with a set of effective training schemes to ensure the performance gains of increasing network depth with limited training data for automated melanoma recognition. we are not aware of any previous work that employs such substantially deeper networks (more than 50 layers) in medical image analysis field as shown in fig. 1.1. Experiments demonstrate that, compared with much shallower counterparts,

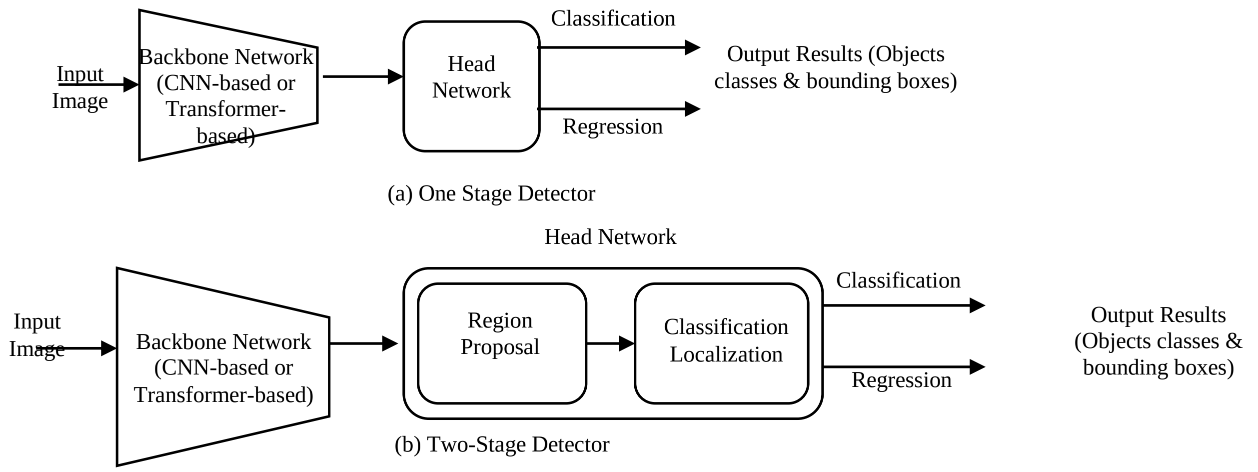



Fig.1.1 System One stage and two stage detector methodology

2) We propose a very deep fully convolutional residual network (FCRN) for accurate skin lesion segmentation, low contrasts and obscure boundaries between skin lesions (especially at their early stages) and normal skin regions make the automated recognition task even harder. Finally, the presence of artifacts, either natural (hairs, veins) or artificial (air bubbles, ruler marks as shown in fig 1.2, color calibration charts, etc.) may blur or occlude the skin lesions. survival rate is very high. In order to improve the diagnostic performance of melanoma, dermoscopy technique was developed.

Dermoscopy is a noninvasive skin imaging technique of acquiring a magnified and illuminated image of a region of skin for increased clarity of the spots on the skin. By removing surface reflection of skin, it can enhance the visual effect of deeper levels of skin and hence provide more details of skin lesions. Dermoscopy assessment is widely used in the diagnosis of melanoma and obtains much higher accuracy rates than evaluation by naked eyes. Nevertheless, the manual inspection from dermoscopy images made by dermatologists is usually time- consuming, error-prone and subjective (even well trained dermatologists may produce widely varying diagnostic results).

In fine-tuning, the earlier layers of the model (those that capture low-level features) may be kept frozen (not updated) while the later layers (which capture higher-level, more task-specific features) are updated to better fit the new task.One of the most significant benefits of transfer learning is that it allows you to train high-performing models on relatively small datasets. This is because the pre-trained model has already learned general features that are broadly applicable.

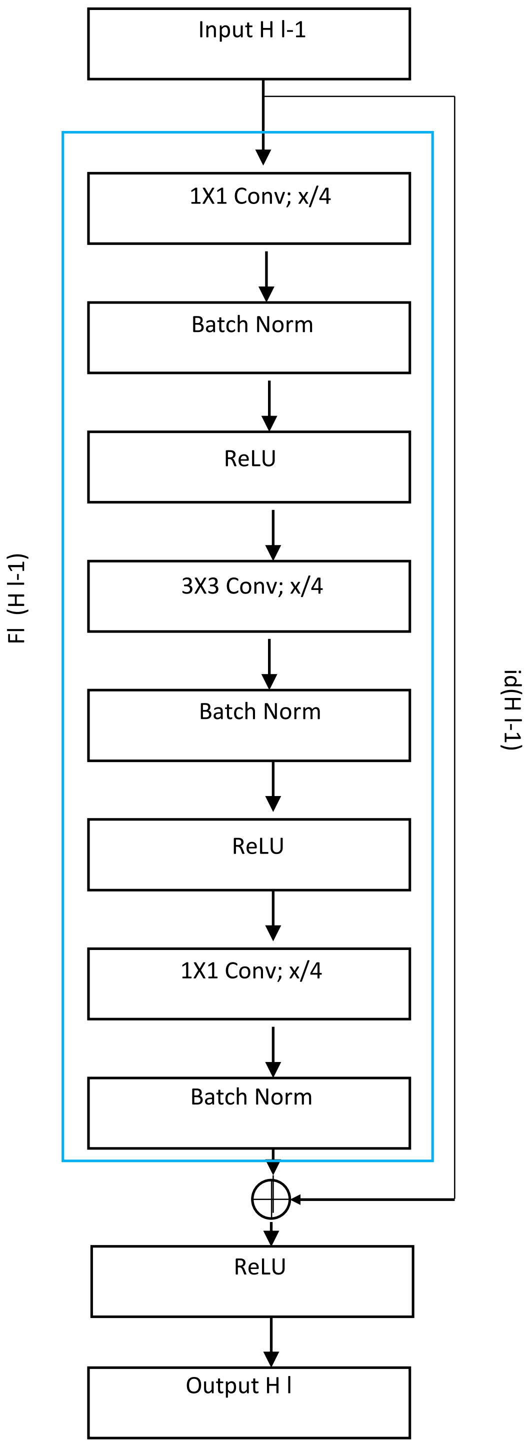



Fig. 1.2 for accurate skin lesion segmentation

## 8. FCRN for Skin Lesion Segmentation

Fully convolutional residual network: The networks proposed in are designed for classification. In order to achieve accurate and efficient skin lesion segmentation.

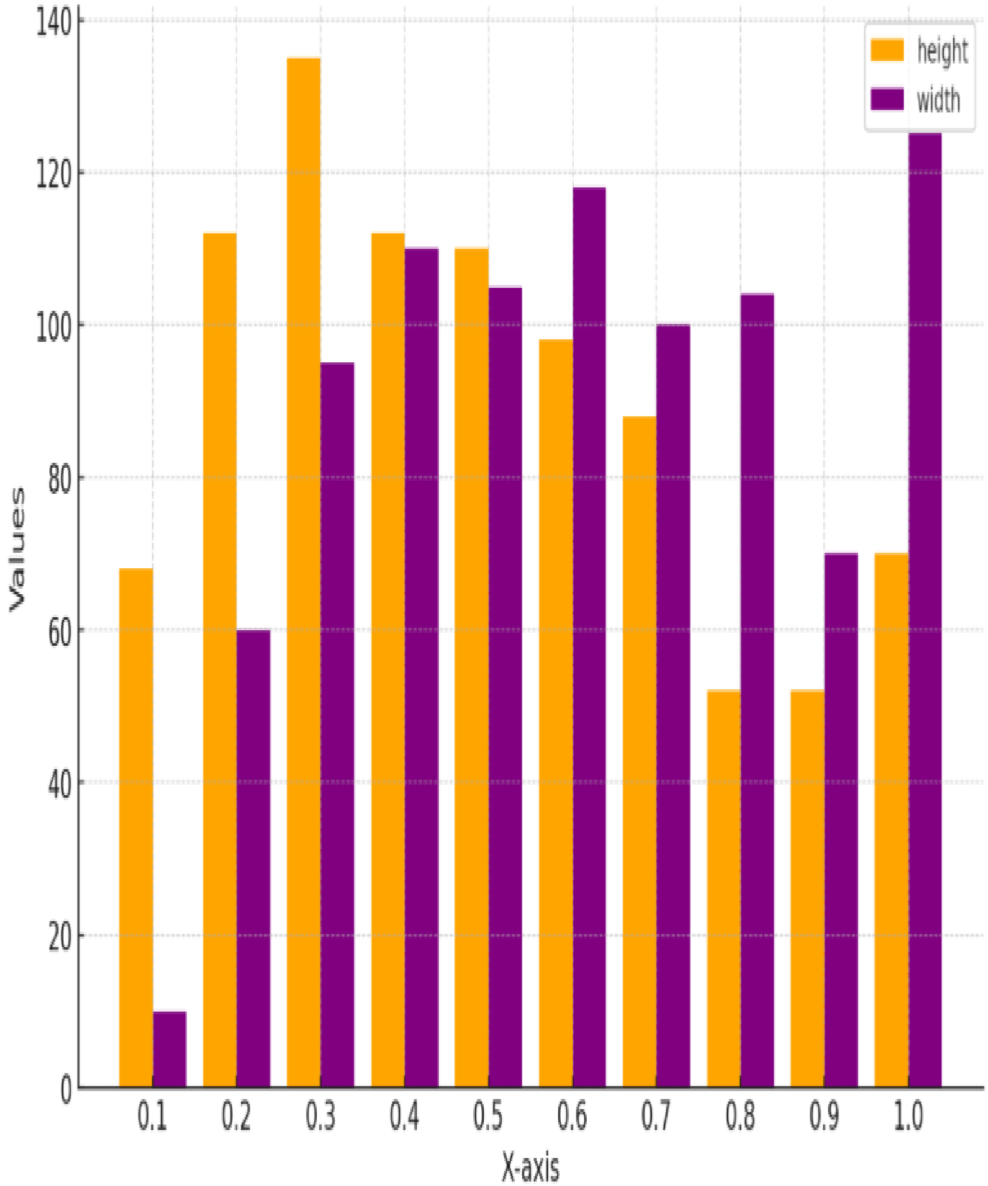



Fig. 1.3 Distribution of the relative size of skin lesions in our training dermoscopy images. In the testing phase, we do not perform the subimage cropping procedure or other detection-like processes.

## 9. Infected Skin for examination

The development and training of an automated melanoma recognition algorithm using deep residual networks (ResNets), a diverse set of infected skin samples is crucial for accurate model examination and evaluation. Infected skin samples, which include lesions influenced by conditions such as bacterial infections, fungal infections, or other dermatological disorders, are necessary for the model to learn how to differentiate melanoma from other skin conditions that may exhibit similar visual characteristics.


(a) Mild redness and smooth texture early stage irritation or rash


(b) Hair interference and mild inflammation


(c) Faint lesion with hair overlap

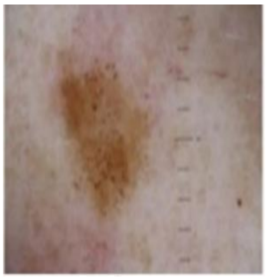

(d) Localized swelling and redness


(e) Lesion with irregular border and fading pigmentation


(f) Reddish lesion with visible surface texture


(g) Dark, circular lesion


(h) Hair obstruction and lesion with crust


(i) Brown lesion with blurred borders


(j) Inflamed lesion with peripheral redness


(k) Dense pigmentation with irregular shape


(l) Reddish-brown lesion with asymmetry and multi-tone coloration

Fig 1.4 Samples of infected skin for examination

High-quality dermoscopy images of infected skin should be used in the training dataset, ensuring proper lighting, magnification, and resolution to capture fine details.

## 10. ANALYSIS OF DEEP RESIDUAL NETWORK ON MELANOMA

Deep Residual Networks (ResNets) on melanoma recognition has become a pivotal area of research, significantly improving the accuracy and efficiency of automated skin cancer detection, particularly in dermoscopy images.

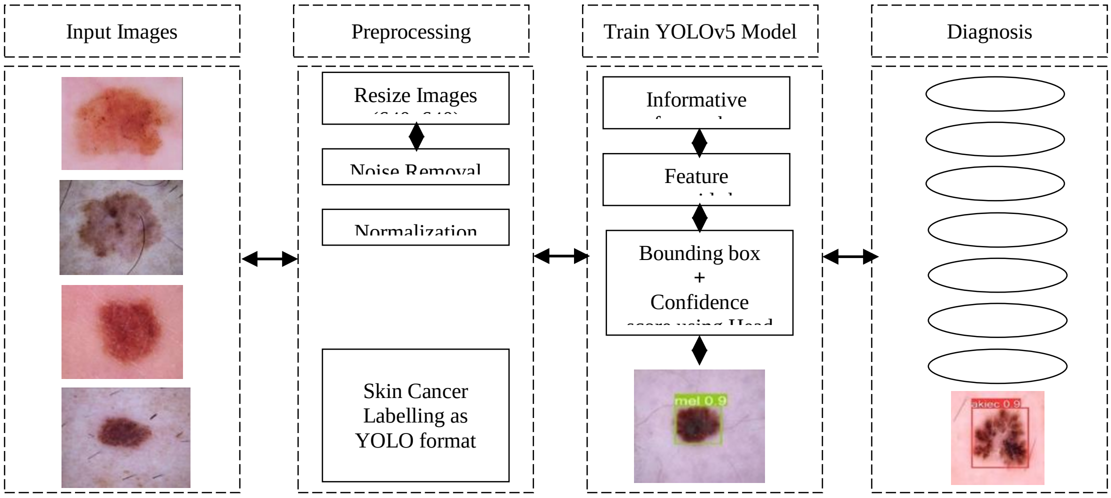



Fig. 1.5 Image Processing Performance of ResNet in Classifying Melanoma Image

Melanoma, one of the most dangerous forms of skin cancer, can often be difficult to distinguish from benign skin lesions due to its variable appearance, making accurate detection essential for early intervention.

Melanoma is among the deadliest forms of skin cancer due to its aggressive nature and potential for rapid metastasis. Early detection is critical, yet challenging, because melanoma lesions often exhibit highly variable visual features that can closely resemble benign nevi. Variations in color, texture, asymmetry, and border irregularities make manual diagnosis prone to error and subjectivity, especially in early stages. Therefore, reliable automated solutions are of great clinical importance.

The impact of pre-training is profound, as it helps the model achieve a higher level of accuracy and convergence in fewer epochs, as the model begins with a set of weights already optimized for image recognition tasks.

This approach often results in a faster convergence and improved performance on melanoma detection tasks compared to training a ResNet model from scratch, which would require more time and data to effectively learn from raw dermoscopy images.

Additionally, pre-training helps mitigate overfitting, a common issue in medical imaging where limited labeled data can cause the model to memorize training examples rather than generalize effectively. However, the success of transfer learning depends on several factors, such as the similarity between the pre-training dataset and the melanoma detection dataset, as well as the size of the task-specific dataset. If the datasets are too dissimilar, the model may struggle to adapt to the new task, leading to suboptimal performance. Despite these challenges, studies have shown that pre-training on large datasets, followed by fine-tuning for melanoma detection, improves model generalization and robustness.

Accurate segmentation of the lesion area is a fundamental step in melanoma analysis. ResNets, often used as backbone architectures in Fully Convolutional Networks (FCNs), help capture multi-scale contextual information, leading to more precise lesion boundaries. This is particularly useful in cases where lesions have fuzzy or irregular edges, a common trait in melanomas.

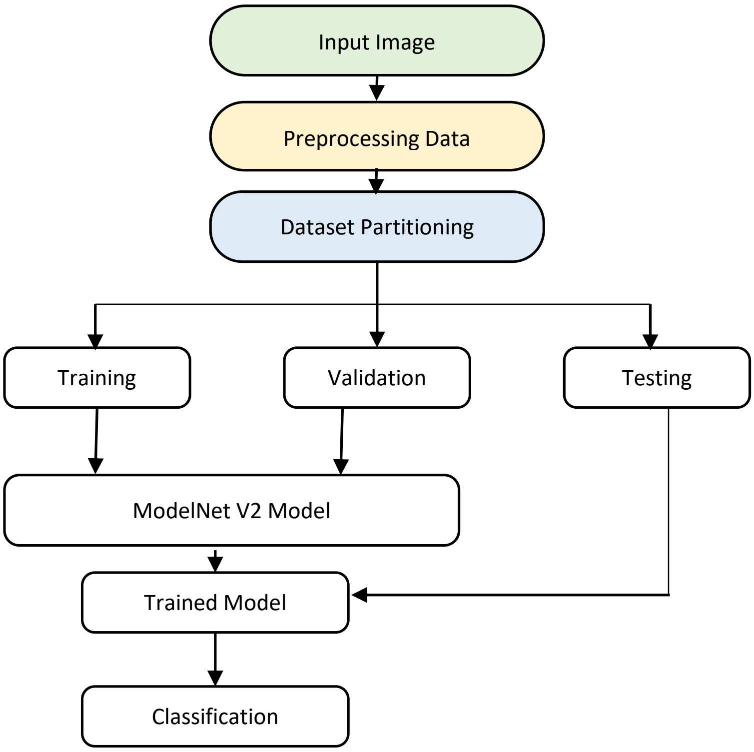



Fig. 1.6 Skin Cancer Disease Detection Using Transfer Learning Technique

## 11. Evaluate the Role of Residual Connections in Preventing Overfitting

CNNs are usually used for computer vision tasks, such as image classification and object detection, to create models as powerful as human vision. If the amount of information available is considered, then it becomes clear the training task requires more data variability than possible. Considering a healthy human with a regular brain and eyes, we retain new information around 16 hours per day, on average, disregarding

$$\min_{U,V} ||X - WY^T||_F^2,$$

the time we sleep.

Where $||.||F2$ is the Frobenius norm, $X\in\mathbb{R}m\times n$ defines the input data, and $W\in\mathbb{R}m\times d$ and $Y\in\mathbb{R}n\times d$ denote the weight matrix and the target labels, respectively,

$$\min_{A} ||X - A||_F^2,$$

where the target is to estimate the matrix A, which ends up in a convex optimization, meaning it has a global minimum that can be found via gradient descent algorithms. When using regularization, this equation becomes:

$$\min_{A} ||X - A||_F^2 + \lambda\Omega(A),$$

where $\Omega(\cdot)$ describes the regularization function based on A, and $\lambda$ is the scalar factor that 31 sets how much influence the regularization function infers on the objective function.

### 11.1 The Performance of Our Method in Segmentation

Experiments on segmentation network depth: In order to investigate if the increase of network depth can enhance the discrimination capability of convolutional networks

ARCHITECTURES OF DOWN-SAMPLING PATH IN FCRN-38, -50 AND -101.

| 38-Layer | 50-Layer | 101-Layer |
|---|---|---|
| 7 x 7, 64, stride 2 | | |
| 3 x 3 max pool, stride 2<br>ResBlock 1-3 | | |
| ResBlock 4-7 | ResBlock 4-7 | ResBlock 4-7 |
| ResBlock 8-9 | ResBlock 8-13 | ResBlock 8-30 |
| ResBlock 10-12 | ResBlock 14-16 | ResBlock 31-33 |

thus make them better deal with the challenges of melanoma recognition, we compared the performance of the proposed FCRN with different depths (38, 50, and 101 layers, respectively), fully convolutional VGG-16 network and fully convolutional

## 12. IMPLICATIONS OF THE STUDY

The findings of this study have significant implications for both the medical and technological communities. By comparing various deep residual network (ResNet) architectures for automated melanoma recognition in dermoscopic images, the study provides valuable insights into selecting the most effective model for real-world clinical applications. This can assist dermatologists by offering a dependable, AI-powered decision-support tool that enhances early detection accuracy, especially in areas where access to specialist care is limited. Furthermore, understanding the trade-offs between model performance and computational cost informs the development of resource-efficient diagnostic systems that can be implemented on a wide range of platforms, including mobile health applications. Academically, the study offers a foundation for further research in medical image analysis using deep learning, contributing to the advancement of intelligent diagnostic systems and improving outcomes in skin cancer detection.

## 13. CONCLUSIONS

In this study, demonstrated significant advancements in the domain of automated melanoma recognition through a comprehensive comparative analysis of segmentation and classification algorithms. By leveraging state-of-the-art deep learning architectures, the study has highlighted how modern convolutional and residual networks outperform traditional machine learning techniques in terms of accuracy, sensitivity, and robustness. The integration of segmentation-driven pre-processing has shown to substantially enhance classification performance by reducing background noise and focusing on precise lesion boundaries. Furthermore, the evaluation across datasets such as ISIC has validated the generalizability and adaptability of the proposed frameworks in real-world clinical conditions. The comparative results not only emphasize the importance of architecture selection but also illustrate the critical role of data augmentation, transfer learning, and multi-scale contextual learning in improving detection reliability. Importantly, the thesis underscores the value of FCRN-based segmentation and ResNet-driven classification pipelines as a potential standard for melanoma recognition systems. The findings present a structured pathway for designing computer-aided diagnostic tools that align with dermatological practices. Overall, this thesis not only advances the technical frontier of melanoma recognition but also bridges the gap between algorithmic innovation and medical applicability. Classification benefits from transfer learning and robust training strategies. Techniques like weighted loss and data augmentation improved model generalization. Evaluation parameters such as accuracy, precision, recall, and F1-score were computed. The system shows reliable detection, even under class imbalance and noisy backgrounds. This framework supports scalable, automated skin cancer screening. Final classification accuracy achieved: 90% (F1-score ≈ 0.895).

### 13.1 Future Scope

Combining visual and non-visual data could improve diagnostic accuracy. This holistic approach may reduce false positives and enhance personalized melanoma risk assessment.

Optimizing the models for lightweight architectures will enable deployment on smartphones and handheld dermatoscopes. Such mobile-based systems can support remote diagnosis and teledermatology.

Incorporating explainable AI techniques will help dermatologists understand model decisions. Heatmaps, attention maps, and lesion boundary justifications can improve trust in automated tools.

## 14. ACKNOWLEDGEMENT

I sincerely acknowledge the guidance and support of my mentor, Mr. M. A. Majed, A.P. at Deccan College of Engineering and Technology, Osmania University, Hyd,T.G, I would like to thank Dr. Syeda Gauhar Fatima, Head of the Department, Deccan College of Engineering and Technology, Hyderabad for constant source of inspiration and guidance throughout the completion of the project. I am also grateful to my peers for their valuable insights and to my family (My Father Mr. Mohd Museeb ur Rahman) for their constant encouragement throughout this work.

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