International Journal of Current Bio-Medical Engineering (IJCBE)
Volume 3, Issue 1, January – February (2025)

RESEARCH ARTICLE

# AMENET: DEEP LEARNING-BASED AUTOMATED MELANOMA DETECTION USING RESNET50 AND RANDOM FOREST

A. Ashvanth Louison [1,*] and Ben Sujitha[2]

[1]Department of Information Technology, Noorul Islam Centre for higher Education, Thuckalay, Kumaracoil, Tamil Nadu 629180, India.

[2]Assistant Professor, Department of Computer Science of Engineering, Noorul Islam Centre for higher Education, Thuckalay, Kumaracoil, Tamil Nadu 629180, India.

*Corresponding e-mail: ashvanthsamfred@gmail.com*

**Abstract – Melanoma is the most aggressive form of skin cancer responsible for a significant percentage of skin cancer-related fatalities. However, existing deep learning-based melanoma detection methods face several challenges, including dataset imbalance, which affects model generalizability across different skin tones. Additionally, many models require extensive computational resources, lack interpretability, and struggle with variations in image quality and lesion morphology, leading to potential misclassifications. To overcome these challenges, a novel deep learning-based approaches for automated melanoma detection using Random Forest. Initially, the input image is preprocessed using Gaussian filters (GF) to enhance clarity by reducing noise. The deep learning-based ResNet50 is used for extracting features from the Melanoma images. Finally, the extracted features are subsequently fed into Random Forest (RM) classifier that classify Melanoma and Non-Melanoma. The effectiveness of the proposed AMENET was evaluated using F1 score, accuracy, precision, recall, and specificity. The proposed AMENET model achieved a classification accuracy of 98.88%. The proposed AMENET model enhances the total accuracy by 3.85%, 0.86%, 1.03% better than ConvNeXtV2, DSCIMABNet, CNN-ViT respectively.**

***Keywords** – Melanoma disease, skin cancer, Gaussian filters, Random Forest, deep learning, ResNet50.*

## 1. INTRODUCTION

Melanoma is the deadliest form of skin cancer and accounts for about 75% of deaths associated with skin cancer [1]. It develops from melanocytes the pigment-producing cells responsible for skin color. It is one of the most aggressive forms of skin cancer often spreading to other parts of the body if not detected and treated early [2]. Melanoma is primarily caused by excessive exposure to ultraviolet (UV) radiation from the sun or tanning beds, leading to DNA damage in skin cells. Genetic factors and weakened immune systems can also increase the risk [3]. The disease commonly appears as an unusual mole or skin lesion with irregular borders, multiple colors, or rapid growth, making early diagnosis crucial for effective treatment [4]. The severity of melanoma depends on factors such as depth of penetration, lymph node involvement, and metastasis. Treatment options include surgical removal, immunotherapy, targeted therapy, radiation, and chemotherapy depending on the stage of the disease [5]. Early-stage melanoma has a high survival rate but once it spreads to distant organs, prognosis significantly worsens. Preventive measures such as using sunscreen, wearing protective clothing, and avoiding excessive sun exposure, play a vital role in reducing the risk [6].

Deep learning has emerged as a powerful tool in the early detection and classification of melanoma, significantly improving diagnostic accuracy and efficiency [7]. Convolutional Neural Networks (CNN) and advanced architectures like Attention U-Net, ResNet, and EfficientNet have been widely applied to analyze dermoscopic and clinical images for automated melanoma detection [8]. These models extract intricate features from images such as texture, color, and shape, enabling precise differentiation between malignant and benign skin lesions [9]. Integrating attention mechanisms and transformer-based models further enhances feature extraction ensuring more accurate predictions [10]. Additionally, deep learning facilitates real-time diagnosis reducing the dependency on expert dermatologists and improving accessibility to melanoma screening especially in remote areas [11].

However, traditional diagnostic methods relying on visual examination and biopsy are time-consuming, subjective, and highly dependent on expert dermatologists [12]. This leads to delays in diagnosis and potential misclassification of benign and malignant lesions. The increasing incidence of melanoma highlights the need for automated and reliable diagnostic tools [13]. Deep learning-based approaches, particularly convolutional neural networks (CNNs) and attention mechanisms, offer promising solutions for improving accuracy and efficiency in melanoma detection. However, challenges such as dataset imbalance, variations in skin tones, and the need for explainability in AI-driven decisions remain significant barriers. The major research contributions are mentioned below:

- The main goal of this strategy is to develop an AMENET method proposed for the classification of Melanoma Detection using Random, Forest.
- Initially the input images are pre-processed using Gaussian Filter to remove noise from the images.
- In the deep learning-based Resnet model is used for extracting features from the Melanoma images.
- Finally, the extracted features are subsequently fed into Random Forest (RM) classifier that classify Melanoma and Non-Melanoma.
- The effectiveness of the proposed AMENET was evaluated using F1 score, accuracy, precision, recall, and specificity.

The remainder of the work is organized accordingly. Section 2 provides a summary of the literature review; Section 3 discusses about the proposed model and Section 4 focuses at the performance of the proposed approach and compares it to other methods. Section 5 provides a final explanation of the conclusion and future scope.

## 2. LITERATURE SURVEY

Deep learning and machine learning methods have been developed in recent years for the detection and classification of diseases associated with Melanoma. This section discusses some of the relevant studies.

In 2020 Daghrir, J., et al., [14] introduced a hybrid method for melanoma skin cancer detection that can be used to examine any suspicious lesion. A convolutional neural network and two classical machine learning classifiers trained with a set of features describing the borders, texture and the color of a skin lesion. The experiments have shown that using the three methods together, gives the highest accuracy level.

In 2021 Jojoa Acosta, M.F., et al., [15] proposed a deep learning techniques Melanoma diagnosis using on dermatoscopic images. the proposed model achieves an increase in accuracy and balanced accuracy of 3.66% and 9.96%, respectively

In 2025 Sobahi, N., et al., [16] developed a novel AI approach, Extreme Machine Learning (ELM)-Mixer, and apply it to skin cancer detection based on dermoscopy images. The experiments show that the proposed model produced a better overall 94.7% precision, 94.6% recall, 94.6% accuracy, 99.1% specificity, and 94.6% F1-score than the compared state-of-the-art achievements.

In 2022 Alwakid, G., et al., [17] proposed DL as a method for extracting a lesion zone with precision. The image is then analyzed with a convolutional neural network (CNN) and a modified version of Resnet-50 to classify skin lesions. With an accuracy of 0.86, a precision of 0.84, a recall of 0.86, and an F-score of 0.86, the proposed CNN-based Model outperformed the earlier study’s results by a significant margin.

In 2025 Ozdemir, B. and Pacal, I., [18] proposed a deep learning framework for skin cancer detection employing ConvNeXtV2 and focal self-attention mechanisms. The Proposed Model employs ConvNeXtV2 in the first two stages for superior local feature extraction, while focal self-attention in the subsequent stages enhances sensitivity by focusing on diagnostically relevant regions. The Proposed Model achieved robust performance across all classes, with 93.60% accuracy, 91.69% precision, 90.05% recall, and a 90.73% F1-score.

In 2025 Reis, H.C. and Turk, V., [19] introduced deep learning based multi-head attention depthwise separable CNN model for Skin cancer detection. The DSCIMABNet model and modern deep learning models trained on ImageNet are proposed to be combined with the ensemble learning method in the second method. In the experimental results, DSCIMABNet achieved 84.28% accuracy, while the proposed hybrid method achieved 99.40% accuracy.

In 2025 Sajid, M., et al., [20] examined CNNs for Groundbreaking Advances in Early Melanoma Detection and Treatment Strategies. The results indicate the potential of data augmentation techniques in alleviating the issue of insufficient medical images and improving melanoma detection. We attained an overall accuracy of 93.43%, a sensitivity of 99.74%, and a specificity of 88.53% in melanoma detection.

In the literature review, these existing techniques have several drawbacks. However, existing deep learning-based melanoma detection methods face several challenges, including dataset imbalance, which affects model generalizability across different skin tones. Many hybrid models require extensive computational resources, limiting their real-world applicability. Some high-accuracy models lack interpretability, making it difficult for dermatologists to trust AI predictions. Additionally, variations in image quality and lesion morphology impact model robustness, leading to potential misclassifications. To overcome this problem, a novel AMENET model is proposed for automated melanoma detection.

## 3. PROPOSED METHODOLOGY

In this research, a novel AMENET method is proposed for detecting Melanoma disease detection from the dataset. Figure 1 shows the overall process of the proposed AMENET method.

### *3.1. Dataset Description*

The ISIC 2019 Skin Lesion Dataset consists of 25,331 dermoscopic images categorized into eight skin lesion classes: Melanoma (MEL), Nevus (NV), Basal Cell Carcinoma (BCC), Actinic Keratosis (AK), Benign Keratosis (BKL), Dermatofibroma (DF), Vascular Lesions (VASC), and Squamous Cell Carcinoma (SCC). This dataset, provided by the International Skin Imaging Collaboration (ISIC), is widely used for training and evaluating deep learning models for skin cancer classification. The images are high-resolution and come with metadata, enabling researchers to develop computer-aided diagnosis (CAD) systems for early detection of skin cancer.

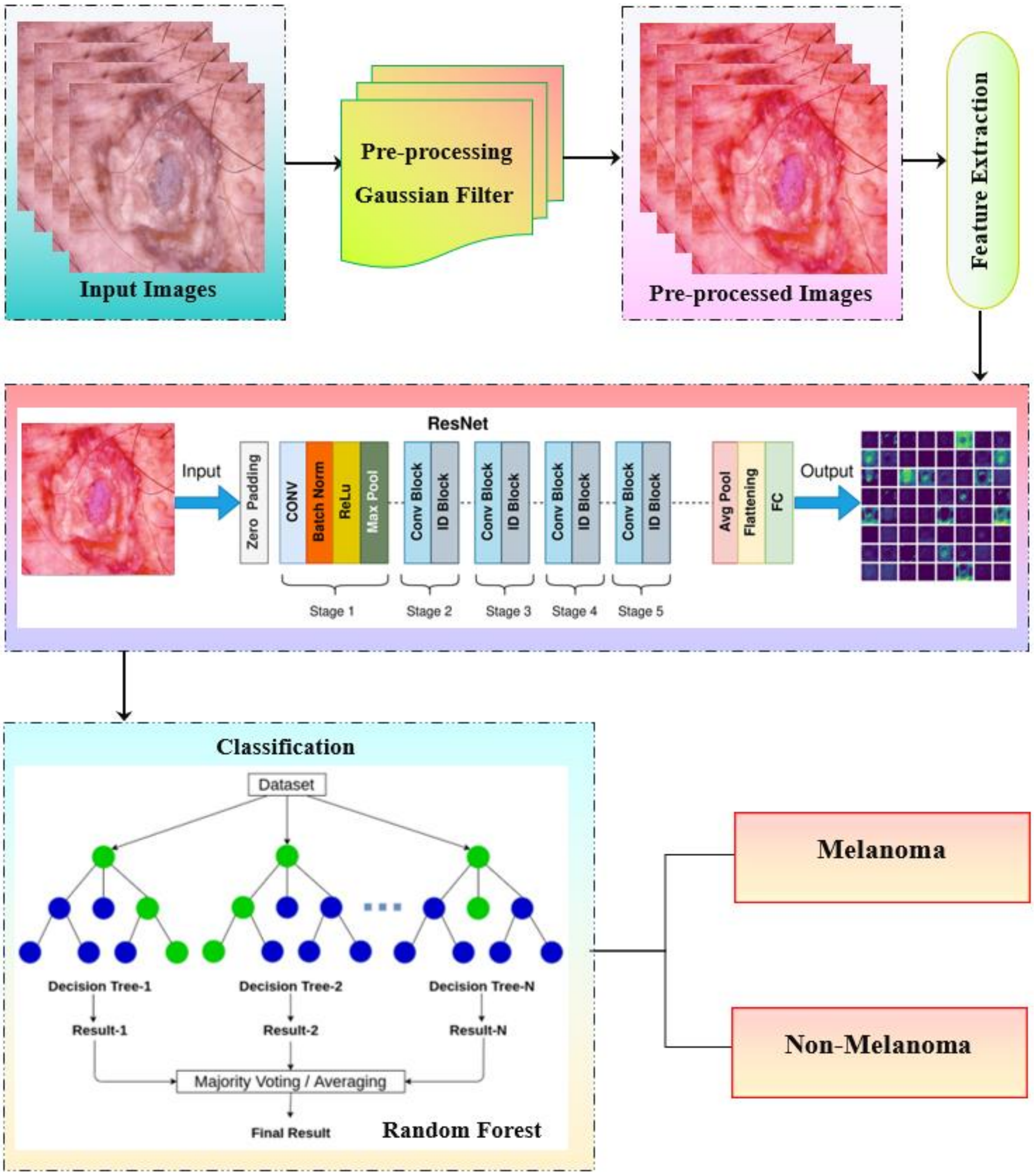


**Figure 1.** The proposed AMENET method

### *3.2. Gaussian Filter (GF)*

Gaussian filter (GF) is used to reduce noise, smooth images, and improve the quality of data from brain imaging, assist in the detection and analysis of Melanoma. GF that uses Finite Impulse Response (FIR) is used to reduce noise in skin image. GF is particularly useful for medical imaging, where noise reduction in improving the detection accuracy of melanoma. The GF is implemented utilizing a 2D matrix of coefficients also referred to as a kernel or utilizing vertical and horizontal 1D convolutions.

The coefficients of the 1D Kernel are calculated using Eq. 1, where $ksize$ is the kernel size, $\sigma$ is the variance, $i$ is an index varying from 0 up to $ksize - 1$, and $\alpha$ is a scale factor that makes $\sum_{i}^{ksize-1} G(i) = 1$. The 2D kernel is an $N \times N$ matrix in which the 1D kernel is multiplied by its transpose ($2D = 1D \times 1D^T$).

$$G(i) = \alpha \times e^{\frac{(i-(ksize-1)/2^2}{2\times\sigma^2}} \quad (1)$$

The 3×3, 5×5, and 7×7 kernels are evaluated in this paper. Using Eq. 1 and a variance of 1.36, the floating-point coefficients for every 1D kernel were determined. The 2D kernel was then obtained by multiplying each 1D kernel size by its transposition. To obtain an initial estimate, the 2D coefficients for every kernel size were rounded to integer values. Compared to floating-point arithmetic, the rounding of coefficients lowers implementation complexity and hardware consumption. The integer coefficients utilized in this work for 3×3, 5×5, and 7×7 kernels are shown in Eq. 2, 3, and 4, respectively.

$$\begin{bmatrix} 15 & 19 & 15 \\ 19 & 24 & 19 \\ 15 & 19 & 15 \end{bmatrix} \tag{2}$$

$$\begin{bmatrix} 2 & 4 & 5 & 4 & 2 \\ 4 & 9 & 12 & 9 & 4 \\ 5 & 12 & 15 & 12 & 5 \\ 4 & 9 & 12 & 9 & 4 \\ 2 & 4 & 5 & 4 & 2 \end{bmatrix} \tag{3}$$

$$\begin{bmatrix} 0 & 1 & 1 & 1 & 1 & 1 & 0 \\ 1 & 2 & 4 & 5 & 4 & 2 & 1 \\ 1 & 4 & 8 & 10 & 8 & 4 & 1 \\ 1 & 5 & 10 & 13 & 10 & 5 & 1 \\ 1 & 4 & 8 & 10 & 8 & 4 & 1 \\ 1 & 2 & 4 & 5 & 4 & 2 & 1 \\ 0 & 1 & 1 & 1 & 1 & 1 & 0 \end{bmatrix} \tag{4}$$

The 3×3, 5×5, and 7×7 kernel functions shown in Eq. 5, 6, and 7 were obtained by multiplying the 2D kernel coefficients by a generic block. The variables $i_\gamma$ are the pixels from the input block, with γ being the pixel's position within the block. Because of the zero-product condition, the terms that used coefficient 0 were removed from Eq. 7.

$$Y_{3\times3} = 15i_0 + 19i_1 + 15i_2 + 19i_3 + 24i_4 + 19i_5 + 15i_6 + 19i_7 + 15i_8 \tag{5}$$

$$Y_{5\times5} = 2i_0 + 4i_1 + 5i_2 + 4i_3 + 2i_4 + 4i_5 + 9i_6 + 12i_7 + 9i_8 + 4i_9 + 5i_{10} + 12i_{11} + 15i_{12} + 12i_{13} + 5i_{14} + 4i_{15} + 9i_{16} + 12i_{17} + 9i_{18} + 4i_{19} + 2i_{20} + 4i_{21} + 5i_{22} + 4i_{23} + 2i_{24} \tag{6}$$

$$Y_{7\times7} = i_1 + i_2 + i_3 + i_4 + i_5 + i_6 + i_7 + 2i_8 + 4i_9 + 5i_{10} + 4i_{11} + 2i_{12} + i_{13} + i_{14} + 4i_{15} + 8i_{16} + 10i_{17} + 8i_{18} + 4i_{19} + i_{20} + i_{21} + 5i_{22} + 10i_{23} + 13i_{24} + 10i_{25} + 5i_{26} + i_{27} + i_{28} + 4i_{29} + 8i_{30} + 10_{31} + 8i_{32} + 4i_{33} + i_{34} + i_{35} + 2i_{36} + 4i_{37} + 5i_{38} + 4i_{39} + 2i_{40} + i_{41} + i_{42} + i_{43} + i_{44} + i_{45} + i_{46} + i_{47} \tag{7}$$

The design space exploration is increased by processing the blocks utilizing equations. Additionally, it offers more space to use approach to decrease the area or increase power efficiency. The Gaussian filter helps in enhancing melanoma skin images by smoothing noise, thereby improving the accuracy of subsequent diagnostic analysis.

### *3.3. Feature Extraction*

ResNet50 is a highly effective tool for feature extraction in melanoma detection. Figure 2 shows that it incorporates residual connections, which enable the network to learn both low- and high-level features. This capability makes ResNet50 particularly suited for identifying subtle abnormalities in melanoma images, such as irregular lesion borders, color variations, and malignant structures.

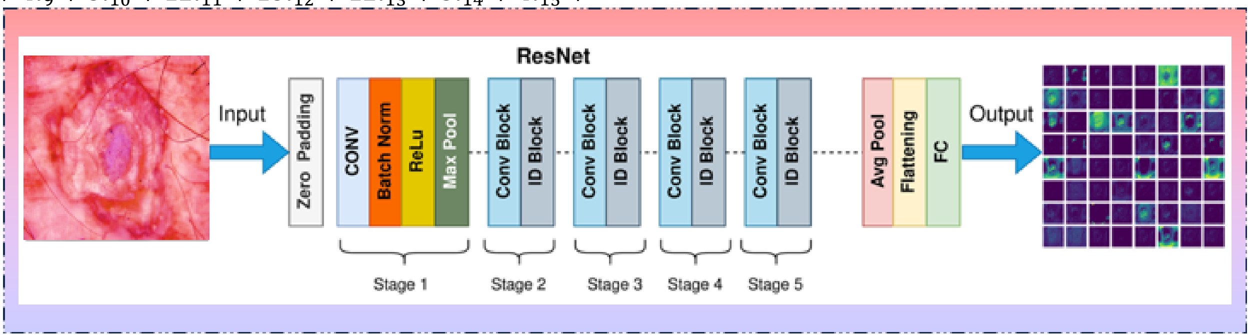


**Figure 2.** The proposed Architecture of ResNet50

The use of ResNet50 for melanoma feature extraction involves employing a pretrained model to leverage its learned weights. Features are typically extracted from intermediate layers, such as the global average pooling layer, which provides a compact and representative feature vector. ResNet50 excels in capturing rich spatial and semantic features, making it highly effective for melanoma detection. Its deep architecture, combined with residual connections, ensures robust learning of both general and specific patterns, which is crucial for identifying malignant skin lesions. Moreover, its scalability allows it to adapt well to various datasets, including dermoscopic and clinical images, making it a versatile choice in medical imaging applications. The mathematical representation of ResNet50 feature extraction is given below:

$$F = GAP(f(X; W, b)) \tag{8}$$

Where GAP is the global average pooling, $f$ represents the ResNet50 transformations, and $W$, $b$ are the model parameters. ResNet50 is a powerful feature extractor for melanoma due to its robust architecture, ability to generalize across domains, and high accuracy in identifying critical patterns. Its integration into deep learning workflows can significantly enhance automated melanoma detection and improve early diagnosis rates.

### 3.4. Random Forest

Random Forests (RF) are nonlinear models used for regression or classification, consisting of an ensemble of decision trees. The forest is constructed using a random sample of the data, with trees being generated independently from one another. It is a popular and effective method for classifying medical images due to its ability to handle high-dimensional data and rank feature importance. The process begins with preprocessing the images to isolate regions of interest, such as skin lesions. Feature extraction follows, where critical attributes like texture, border irregularities, and color properties are derived from the images. The Random Forest model then makes a classification, with the majority vote determining the outcome. RF is particularly advantageous because it reduces overfitting and efficiently manages large, complex datasets. Additionally, it provides a feature priority ranking, helping identify the most relevant attributes for classification while reducing dimensionality. Random Forest is a robust tool for medical image analysis, excelling in tasks like lesion classification, melanoma severity assessment, and differentiation between benign and malignant skin lesions due to its adaptability to noisy data.

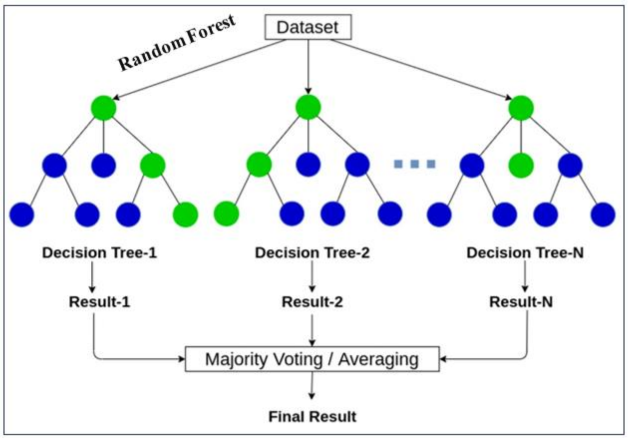


**Figure 3.** The Visual representation of Random Forest

The mathematical representation of Random Forest, the image $I$ is represented as,

$$I \rightarrow X = \{x_1, x_1, \dots, x_n\} \tag{9}$$

Where $X$ is the feature vector consisting of $n$ features. Random Forest is an ensemble of $T$ decision tree $\{h_1(X), h_2(X), \dots., h_T(X)\}$. Mathematically, the decision function of each tree can be represented as:

$$h_t(X) = argmax \sum_{x_i \in X'} (Information\ Gain) \tag{10}$$

Where the information gain is calculated based on the impurity reduction at each split. The Random Forest algorithm offers a powerful and versatile approach for effectively classifying melanoma and other medical imaging tasks by leveraging its robustness against noise and ability to manage complex datasets.

## 4. RESULTS AND DISCUSSIONS

The proposed AMENET technique was evaluated in this section utilizing several metrics like recall, specificity, accuracy, precision, and F1 score, depending on the gathered datasets.

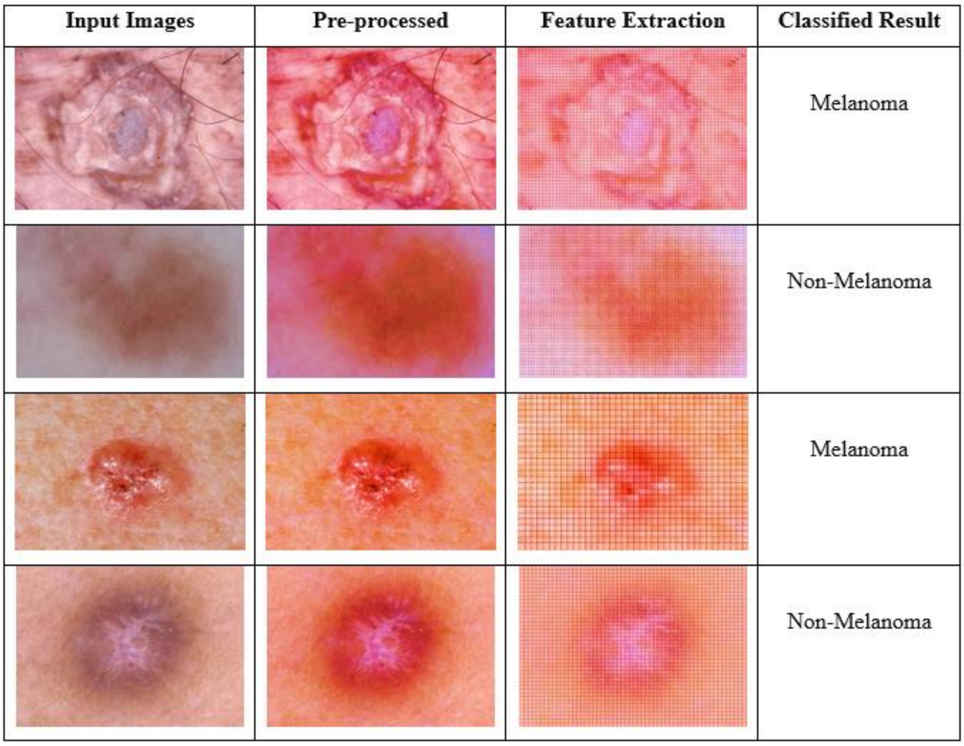


**Figure 4.** The experimental result of the proposed AMENET

The outcomes of the proposed experimental approach AMENET are shown in Figure 4. In column 1, the input melanoma images are displayed. A Gaussian Filter is applied in column 2 to enhance image clarity and remove noise from the melanoma images. Feature extraction using ResNet50 is performed in column 3 to extract critical features from the images. Finally, Random Forest is used in column 4 to classify melanoma and Non-melanoma.

### *4.1. Performance Analysis*

The Common metrics used to evaluate the performance of a classification method include accuracy, precision, recall, specificity, and the F1 score.

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{11}$$

$$Specificity = \frac{TN}{TN+FP} \tag{12}$$

$$Precision = \frac{TP}{TP+FP} \tag{13}$$

$$recall = \frac{TP}{TP+FN} \tag{14}$$

$$f_1 = 2\left(\frac{precision * recall}{precision + recall}\right) \quad (15)$$

where $T_{pos}$ and $T_{neg}$ indicates the actual benefits and drawbacks of the provided images, $F_{pos}$ and $F_{neg}$ shows the sample images false positives and negatives.

**Table 1.** Performance analysis of AMENET model

| Classes | Accuracy | Specificity | precision | Recall | F1score |
|---|---|---|---|---|---|
| Melanoma | 99.31% | 98.23% | 99.54% | 97.48% | 97.22% |
| Non-Melanoma | 98.46% | 98.65% | 98.78% | 96.65% | 98.73% |

Table 1 displays precision, recall, F1 score, accuracy, and specificity proposed technique for various classes. The efficiency metrics of the proposed approch are show in Table 1 for the following classes: Melanoma and Non-melanoma. The suggested method's accuracy is 99.84% for Melanoma and 98.98% for Non-Melanoma.

### 4.2. Comparative Analysis

The proposed model was assessed in comparison to existing approaches to demonstrate its accuracy and efficiency in melanoma detection. When evaluated against traditional methods, it outperforms them in terms of diagnostic accuracy. Performance is measured using F1 score, recall, accuracy, precision, and specificity. In this comparative analysis, the proposed model is benchmarked against three state-of-the-art deep learning methodologies to validate its effectiveness.

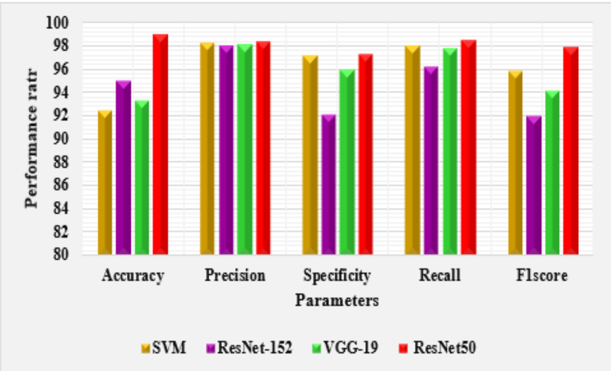


**Figure 5.** Comparison between existing and proposed method

Figure 5 illustrate that traditional network such as SVM, ResNet-152, and VGG-19 approach produced more accurate findings although at a lower level of precision. The proposed method maintains excellent curacy accuracy ranges 98.88%. The proposed method achieves a higher accuracy rate compared to the existing models. Therefore, the proposed AMENET method shows performs better than other techniques.

**Table 2.** Comparison of the existing and proposed model

| Authors | Methods | Accuracy |
|---|---|---|
| Pacal, I., et al., (2025) [3] | CNN-ViT | 97.85% |
| Ozdemir, B. and Pacal, I., (2025) [18] | ConvNeXtV2 | 95.21% |
| Reis, H.C. and Turk, V., (2025) [19] | DSCIMABNet | 98.03% |
| **Proposed** | **AMENET** | **98.88%** |

Table 2 shows a comparison of networks that is not as precise as the proposed AMENET model. The proposed technique maintains excellent accuracy levels of 98.88%. The proposed AMENET model enhances the total accuracy by 3.85%, 0.86%, 1.03% better than ConvNeXtV2, DSCIMABNet, CNN-ViT respectively. The comparison above indicates that in terms of accuracy, the effectiveness of the proposed AMENET model is superior to that of the existing models.

## 5. CONCLUSION

In this research, a novel deep learning-based approaches for automated melanoma detection using Random Forest. Initially, the input image is preprocessed using Gaussian filters (GF) to enhance clarity by reducing noise. The deep learning-based ResNet50 is used for extracting features from the Melanoma images. Finally, the extracted features are subsequently fed into Random Forest (RM) classifier that classify Melanoma and Non-Melanoma. The effectiveness of the proposed AMENET was evaluated using F1 score, accuracy, precision, recall, and specificity. The proposed AMENET model achieved a classification accuracy of 98.88%. The proposed AMENET model enhances the total accuracy by 3.85%, 0.86%, 1.03% better than ConvNeXtV2, DSCIMABNet, CNN-ViT respectively. Future work will focus on enhancing model generalizability across diverse skin tones and addressing dataset imbalances. Additionally, integrating explainable AI techniques will improve trust and interpretability in melanoma diagnosis.

## CONFLICTS OF INTEREST

This paper has no conflict of interest for publishing.

## FUNDING STATEMENT

Not applicable.

## ACKNOWLEDGEMENTS

The author would like to express his heartfelt gratitude to the supervisor for his guidance and unwavering support during this research for his guidance and support.

## REFERENCES

[1] S. Banerjee, S.K. Singh, A. Chakraborty, A. Das, and R. Bag, “Melanoma diagnosis using deep learning and fuzzy logic,” *Diagnostics*, vol. 10, no. 8, pp. 577, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[2] A. Naeem, M.S., Farooq, A. Khelifi, and A. Abid, “Malignant melanoma classification using deep learning: datasets, performance measurements, challenges and opportunities,” *IEEE access*, vol. 8, pp. 110575-110597, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[3] I. Pacal, B. Ozdemir, J. Zeynalov, H. Gasimov, and N. Pacal, "A novel CNN-ViT-based deep learning model for early skin cancer diagnosis," *Biomedical Signal Processing and Control*, vol. 104, pp. 107627, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[4] B. Mazoure, A. Mazoure, J. Bédard, and V. Makarenkov, DUNEScan: a web server for uncertainty estimation in skin cancer detection with deep neural networks. *Scientific Reports*, vol. 12, no. 1, pp. 179, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[5] S. Rajarajeswari, J. Prassanna, M.A. Quadir, J.C. Jackson, S. Sharma, and B. Rajesh, "Skin cancer detection using deep learning," *Research Journal of Pharmacy and Technology*, vol. 15, no. 10, pp. 4519-4525, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[6] X. Lu, and Y.A. Firoozeh Abolhasani Zadeh, "Deep Learning-Based Classification for Melanoma Detection Using XceptionNet," *Journal of Healthcare Engineering*, vol. 2022, no. 1, pp.2196096, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[7] M. Nawaz, Z. Mehmood, T. Nazir, R.A. Naqvi, A. Rehman, M. Iqbal, and T. Saba, "Skin cancer detection from dermoscopic images using deep learning and fuzzy k-means clustering," *Microscopy research and technique*, vol. 85, no. 1, pp. 339-351, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[8] J.V. Tembhurne, N. Hebbar, H.Y. Patil, and T. Diwan, "Skin cancer detection using ensemble of machine learning and deep learning techniques," *Multimedia Tools and Applications*, vol. 82, no. 18, pp. 27501-27524, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[9] R. Ingle, C.K. Selvi, A. Ahilan, N. Muthukumaran, S. Sharma, and M. Kumar, "SERAV Deep-MAD: deep learning-based security–reliability–availability aware multiple D2D environment," *IETE Journal of Research*, pp. 1-14, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[10] H. Bhatt, V. Shah, K. Shah, R. Shah, and M. Shah, "State-of-the-art machine learning techniques for melanoma skin cancer detection and classification: a comprehensive review," *Intelligent Medicine*, vol. 3, no. 03, pp. 180-190, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[11] N.G. Rani, N.H. Priya, A. Ahilan, and N. Muthukumaran, "LV-YOLO: Logistic vehicle speed detection and counting using deep learning based YOLO network," *Signal, Image and Video Processing*, vol. 18, no. 10, pp. 7419-7429, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[12] Ramya Thatikonda, "Walmart Fulfillment Management Services on Supply Chain Performance Optimization using Deep Learning Based Decision Making," International Journal of Computer and Engineering Optimization, vol. 02, no. 01, pp. 07-13, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[13] Aarthi Gopalakrishnan, A. Neelima, and C. Priya, "Deep Learning Model for Tracking Human Behavior in Supermarket Through CCTV Footage," *International Journal of Computer and Engineering Optimization*, vol. 02, no. 01, pp. 01-06, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[14] J. Daghrir, L. Tlig, M. Bouchouicha, and M. Sayadi, "Melanoma skin cancer detection using deep learning and classical machine learning techniques: A hybrid approach," In *2020 5th international conference on advanced technologies for signal and image processing (ATSIP)*, pp. 1-5, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[15] M.F. Jojoa Acosta, L.Y. Caballero Tovar, M.B. Garcia-Zapirain, and W.S. Percybrooks, "Melanoma diagnosis using deep learning techniques on dermatoscopic images," *BMC Medical Imaging*, vol. 21, pp. 1-11, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[16] N. Sobahi, A.M. Alhawsawi, M.M. Damoom, and A. Sengur, "Extreme Learning Machine-Mixer: An Alternative to Multilayer Perceptron-Mixer and Its Application in Skin Cancer Detection Based on Dermoscopy Images," *Arabian Journal for Science and Engineering*, pp. 1-16, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[17] G. Alwakid, W. Gouda, M. Humayun, and N.U. Sama, Melanoma detection using deep learning-based classifications. In *Healthcare*, vol. 10, no. 12, pp. 2481, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[18] B. Ozdemir, and I. Pacal, "An innovative Deep learning framework for skin cancer detection employing ConvNeXtV2 and focal self-attention mechanisms," *Results in Engineering*, vol. 25, pp.103692, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[19] H.C. Reis, and V. Turk, "DSCIMABNet: A novel multi-head attention depthwise separable CNN model for skin cancer detection," *Pattern Recognition*, vol. 159, pp. 111182, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[20] M. Sajid, A.H. Khan, T.S. Malik, A. Bilal, Z. Ahmad, and R. Sarwar, "Enhancing Melanoma Diagnostic: Harnessing the Synergy of AI and CNNs for Groundbreaking Advances in Early Melanoma Detection and Treatment Strategies," *International Journal of Imaging Systems and Technology*, vol. 35, no. 1, pp. e70016, 2025. [CrossRef] [Google Scholar] [Publisher Link]

**AUTHORS**

**Ashvanth Louison A** completed by Bachelor's degree in Computer Science and engineering at Noorul Islam Centre for Higher Education with an CGPA OF 74.25% and i have completed my Masters on Information Technology in SSN college of engineering with the CGPA of 72.58%. And now i have have admitted as a Full Time Research Scholar in dept of Information Technology under the guidence of Dr Ben Sujitha dept of Computer Science and Engineering in noorul islam centre for higher education

**Ben Sujitha** is a Professor at Dept of Computer Science and Engineering in Noorul Islam Centre for Higher Education. She completed her bachelor's degree in information technology in the year 2003 and she has completed M. Tech in information technology and computer science in the year 2007. and she has completed her PH. D in information and communication engineering in the year 2017. She has more than 20 years of teaching experience. She has secured more than 35 publications in national and international journals and attended many international conferences. She has worked in many institutions. At present she is working as Professor in Noorul Islam Centre for Higher Education.

Arrived: 17.01.2025
Accepted: 19.02.2025