

Melanoma Lesion Prediction using Inception V3 Model

Ms. I. Jenifer¹, Devadharshini², Gayathri S³, Johnsherina J⁴, Vaithegi A⁵

Computer Science and Engineering¹⁻⁵

Mahendra Institute of Engineering and Technology, Salem, India

Abstract: Skin cancer is one of the most common dermatological issues, with melanoma being the most aggressive type, making early and accurate diagnosis essential for improving patient outcomes. Conventional diagnostic methods depend on dermatoscopic evaluation and clinical knowledge, yet precise classification is difficult due to the variability in skin lesions. To overcome these difficulties, utilizing computer-assisted skin cancer detection through deep learning-based feature extraction and classification presents a scalable and effective solution. This research introduces a diagnostic model based on Inception V3 aimed at improving feature extraction, classification efficiency, and computational optimization. The approach involves preprocessing high-resolution dermoscopic images, followed by the extraction of deep features through the factorized convolution layers of Inception V3, which enhances model generalization while minimizing computational demands. The acquired features, including texture, color patterns, and lesion morphology, are input into a convolutional classification model that has been fine-tuned to differentiate between normal skin, benign lesions, and malignant melanoma cases. This classification method employs transfer learning, utilizing the pretrained Inception V3 network with a customized dense-layer configuration, and optimizes predictions using Softmax activation for multi-class classification or Sigmoid for binary classification. The performance of this model is thoroughly assessed against traditional machine learning techniques such as Support Vector Machines (SVM), Random Forest (RF), and K-Nearest Neighbors (KNN). Metrics like accuracy, precision, recall, and F1-score are calculated to compare the effectiveness of deep learning with conventional methods. The aim is to create a strong, scalable, and clinically interpretable AI-based melanoma classification system that assists both non-specialized users and medical professionals in the early detection and intervention of the disease, ultimately lowering the mortality and morbidity rates linked to skin cancer.

Keywords: Skin cancer, deep learning techniques, Inception V3 architecture, feature extraction methods, convolutional neural networks (CNNs), digital dermatoscopy, transfer learning approaches, melanoma identification

I. INTRODUCTION

Skin cancer is an increasing global health issue, with melanoma being the most aggressive and potentially fatal variant. Early identification is essential for enhancing survival rates among patients, as timely treatment greatly lowers both mortality and morbidity. Conventional approaches depend on dermatoscopic evaluations conducted by trained professionals, but manual diagnoses can be difficult due to the intricate morphological diversity of skin lesions. Moreover, dependence on subjective assessments may lead to inconsistencies in diagnostic accuracy. This research introduces an automated melanoma detection system using Inception V3, a deep learning framework tailored for high-efficiency image recognition. The model analyzes high-resolution dermoscopic images, extracts features related to texture, color patterns, and lesion structure, and categorizes skin conditions as normal, benign, or malignant melanoma through a finely tuned convolutional neural network (CNN). In contrast to traditional machine learning techniques,



deep learning systems eliminate the necessity for manual feature engineering, facilitating more precise and scalable classification.

Despite progress in dermatological imaging and AI-aided diagnostics, current melanoma detection systems frequently face high computational demands, restricted classification accuracy, and insufficient generalization across various skin lesion types. Conventional feature extraction methods necessitate manual crafting, which can lead to inconsistencies and diminish diagnostic dependability. Furthermore, many existing machine learning frameworks struggle to differentiate among normal skin, benign lesions, and malignant melanoma with adequate accuracy, resulting in misclassification and postponed medical interventions.

This study suggests an automated melanoma classification system that employs Inception V3, a sophisticated deep learning architecture designed for effective feature extraction and categorization. The model analyzes high-resolution dermoscopic images, recognizes unique lesion traits such as texture, color patterns, and morphological irregularities, and classifies skin conditions into normal, benign, and malignant melanoma categories. The proposed approach incorporates transfer learning, which facilitates quicker convergence and improves classification precision without extensive manual feature crafting.

The main goals of this research consist of:

- Creating a robust AI-based classification system for early melanoma detection using Inception V3.
- Improving the efficiency of feature extraction by utilizing deep convolutional architectures for enhanced texture and color pattern evaluation.
- Removing the need for manual feature engineering to enable automated diagnosis with minimal human involvement.
- Benchmarking performance against traditional classifiers like Support Vector Machines (SVM), Random Forest (RF), and K-Nearest Neighbors (KNN) through assessments of accuracy, precision, recall, and F1-score..

The proposed system stands out through the following innovations:

- Employing Inception V3 rather than traditional frameworks to enhance classification accuracy and computational effectiveness.
- A refined feature extraction approach that eliminates the necessity for separate segmentation, thus boosting processing speed.
- A multi-class classification system capable of distinguishing between normal, benign, and malignant melanoma, thereby increasing clinical relevance.
- Performance assessment in comparison to traditional classifiers, which confirms the advantages of deep learning methodologies in dermatological diagnostics.

Traditionally, melanoma detection has depended on dermoscopic imaging, where specialists visually evaluate lesion characteristics. While this method is effective, manual assessments introduce subjectivity, variability, and delays in decision-making within medical contexts. Machine learning techniques, including SVM, RF, and CNN-based models, have shown promising outcomes; however, many of these still encounter issues with overfitting and computational inefficiencies. The emergence of deep learning architectures like Inception V3 provides scalable and highly accurate solutions, enhancing classification performance while streamlining clinical processes.

This study contributes to advancements in melanoma classification by combining deep learning-enabled feature extraction with automated diagnostics. The scope encompasses:

- Establishing a scalable AI-driven solution suitable for clinical environments and mobile dermatological applications.
- Improving the efficiency of real-time image classification, which supports early disease detection with minimal processing delays.



- Providing comparative insights between deep learning and traditional classifiers, laying a foundational framework for future AI models in dermatology.
- Potentially expanding into mobile and cloud-based diagnostic systems to enhance accessibility in remote healthcare locations.

This study intends to improve the reliability of classifications, minimize diagnostic mistakes, and speed up medical decision-making by utilizing Inception V3 for melanoma detection, ultimately aiding early intervention methods and enhancing patient outcomes.

II. LITERATURE SURVEY

SABR, Abdelouahed, et al. [1] recommended describing the lesion utilizing an approach that uses a range of recovered information, including its skeleton, shape, texture, and colour. The machine learning classifier receives the characteristics that were selected with the aid of the information gain. The Adaboost classifier had the highest score. The proposed approach yielded a promising classification rate and provided an improved ensemble learning method for skin cancer classification. The features are created using the best combination of features taken from several criteria, including the form, colour, texture, and structure of the lesion. In order to predict the classes, these characteristics are further categorized using a variety of techniques. Overall, the experiment's findings point to a successful conclusion.

Vidya M. et al.[2] Skin lesions have been classified as benign or melanoma using hybrid feature extraction. The ABCD rule, GLCM, and HOG are used for feature extraction and classification in machine learning techniques, which enable automated skin lesion identification. For the procedure of segmenting skin lesions, the GAC approach was recommended. A segmentation result of 0.9 JA and 0.82 DI has been attained. The ABCD rule was proposed for the colour, symmetry, diameter, texture, shape, and edge of the skin lesion in order to extract characteristics. Several machine learning algorithms, such as SVM, KNN, and Naïve Bayes, were created to handle the classification. To evaluate the proposed method, skin lesion images from ISIC datasets were employed. When compared to other classification techniques, SVM outperforms them with an AC of 97.8% and an AUC of 0.94. Using KNN, the sensitivity and specificity were 86.2% and 85%, respectively. Based on the data, we can see that accuracy improves with augmentation performance. For increased accuracy, this technique may be further applied to the neural network platform.

A unique approach to classify skin cancer using machine learning and image processing was implemented by Arslan Javaid et al. [3]. In the first phase, a new contrast stretching method based on pixel mean and standard deviation is proposed for dermoscopic picture improvement. OTSU thresholding is then used to do segmentation. The second step involves retrieving texture, colour, and shape characteristics, then using the PCA to reduce the shape features. The class imbalance problem in the ISIC dataset is addressed using SMOTE sampling. A unique feature selection technique based on wrapper approaches is proposed for selecting the best features after the third stage of feature standardization and scaling. The suggested wrapper technique for feature selection in conjunction with the Random Forest classifier yields good results when compared to other classifiers, according to testing of the suggested system using the publicly available ISIC-ISBI 2016 dataset.

Thaajwer, Ahmed, et al.,[4] provide a precise method for diagnosing melanoma skin cancer that makes it easy to differentiate between benign and malignant melanoma in input photos. The proposed approach obtains a high accuracy of 83% when colour and shape characteristics are combined with the GLCM methodology for feature extraction. Patients and doctors find it more pleasant and successful than the biopsy approach since it is a proven, painless treatment. In the web data sources, we couldn't find any images of people with dark skin to utilize. The diagnosing process will be quicker and more accurate thanks to this computer-based analysis. Due to the complexity of skin diseases, one of the biggest obstacles to a prompt, simple, and correct diagnosis is a lack of variety and experience, particularly in industrialized and developing nations with limited resources for healthcare. Additionally, it goes without saying that early identification lowers the risk of significant consequences in situations of many diseases. These types of melanoma skin illnesses have been triggered by a few pertinent environmental variables.



Faiza et al. [5] presented a number of learning algorithm examples for melanoma detection that were separated into two categories: classification and segmentation. Both segmentation and classification showed potential based on the results. The k-means clustering and density filtering techniques are used to segment the skin lesions from the picture with a 96% accuracy rate. The form, texture, and colour properties of the skin lesion datasets are extracted in the second section using a variety of machine learning algorithms, including Decision Tree, K-Nearest Neighbour, Support Vector Machine, Logistic Regression, Stochastic Gradient Descent, Random Forest, and Naive Bayes. This makes it possible to classify the skin lesion into melanomas and benign lesions with efficiency. To aid in diagnosis, a thorough explanation of the segmentation and classification process for pigmented skin lesions is given. There are two components to the core approach. Lesion segmentation will be examined in the first section, which covers pre-processing, segmentation, and post-processing. In the second portion, features are extracted using a local binary pattern (LBP) and a histogram-oriented gradient (HOG). A machine learning classifier then assesses the characteristics chosen and effectively categorizes the skin lesion.

III. EXISTING SYSTEM

In general, a successful treatment plan and better results for skin malignancies depend on early identification. Although experts may accurately diagnose cancer, their availability necessitates the development of quick and effective automated methods. In addition to potentially saving lives, this will relieve patients' financial and medical difficulties. It can be challenging to distinguish between benign skin lesions and skin tumours since melanoma can manifest in a number of ways. AI can help reduce the morbidity and death rate of skin cancer by assisting in its early diagnosis. AI-based tools can help by improving the identification of skin lesions and reducing strain. The primary goal is to more precisely classify skin cancer using deep learning techniques. Additional goals include identifying characteristics to categories various skin malignancies and separating skin lesions from dermoscopy pictures. Deep learning algorithms may be used to identify and diagnose skin cancers, as well as to extract characteristics of the skin and offer diagnosis information based on illnesses that have been found.

Current systems for melanoma detection utilize a variety of methods, such as manual dermatological assessments, conventional machine learning techniques, and early deep learning models. While all these approaches have made notable advancements in skin cancer diagnosis, they face certain drawbacks in areas like efficiency, accuracy, and scalability.

Traditional diagnostic practices involve dermoscopic imaging, where trained dermatologists examine skin lesions for irregularities based on set criteria, including texture, asymmetry, border irregularities, and color differences. This method heavily relies on the expertise and experience of medical professionals, which may lead to subjective interpretations and inconsistencies in classification. Additionally, identifying early-stage melanoma through visual examination alone proves challenging, as it requires highly skilled specialists and sophisticated imaging tools. To improve diagnostic efficiency, researchers have turned to traditional machine learning methods such as:

Support Vector Machines (SVM): This technique utilizes manually derived features, such as histogram-based texture analysis, for binary classification (benign vs. malignant).

Random Forest (RF): This method uses an ensemble approach to classify skin lesions based on predefined features.

K-Nearest Neighbors (KNN): This technique categorizes images depending on the similarity of their features.

Although these models offer improvements over manual diagnoses, they are heavily dependent on handcrafted features, which restrict their generalizability. Furthermore, the process of feature selection and extraction necessitates domain expertise, making it challenging to integrate into real-time clinical practice. Deep learning has considerably reshaped the landscape of medical image analysis, facilitating automated feature extraction and classification without the need for human involvement. Architectures such as VGG16, AlexNet, and ResNet are commonly utilized for diagnosing skin cancer. Nonetheless, these models face challenges including:

- Significant computational expenses due to their complexity and heavy parameterization.
- Risks of overfitting, particularly when trained on small and imbalanced datasets.
- Limited scalability, which restricts their use in real-time scenarios within clinical environments.



IV. PROPOSED SYSTEM

The proposed system presents an automated diagnostic model for skin cancer classification that is based on Inception V3, specifically aimed at improving the accuracy and efficiency of melanoma detection. Conventional techniques heavily depend on manual feature extraction and the expertise of dermatologists, which can result in subjective interpretations and inconsistencies in the classification of lesions. To confront these issues, this system utilizes deep learning for automated feature extraction and multi-class classification, accurately differentiating between normal skin, benign lesions, and malignant melanoma.

The foundational architecture of this system is centered on Inception V3, a deep convolutional neural network (CNN) tailored for the analysis of high-resolution images. Unlike previous architectures, Inception V3 uses factorized convolutions that significantly decrease computational complexity while preserving strong feature extraction capabilities. This architectural benefit enhances generalization performance, ensuring accurate classifications across diverse patient populations, skin types, and lesion categories. The deep learning model autonomously identifies distinguishing features such as texture differences, color variations, border irregularities, and asymmetry without the need for manual feature engineering, thus making the diagnostic process more efficient and scalable.

By utilizing transfer learning, the system adapts pre-trained Inception V3 weights for melanoma classification with minimal computational resources required. The ultimate classification layer effectively determines whether a specific skin lesion is categorized as normal, benign, or malignant melanoma, significantly enhancing diagnostic reliability. Furthermore, the proposed system skips segmentation-based preprocessing, thereby simplifying the classification process while ensuring high accuracy. The deep network guarantees precise lesion differentiation without the need for extra feature engineering or expert-driven classifications.

In summary, this system enhances clinical dermatology and AI-driven healthcare applications by refining melanoma detection. It improves scalability, accuracy, and computational efficiency, making it ideal for real-time medical diagnostics and early intervention strategies for diseases. The capability to automate lesion classification reduces human error, enhances decision-making, and provides accessibility in various medical environments, underscoring the increasing importance of AI in managing dermatological diseases and driving healthcare innovation.

Data Acquisition

The collection of images comprises high-resolution dermoscopic photographs sourced from established medical channels, ensuring a variety of clinically pertinent samples. These photographs encompass differences in skin colors, lesion characteristics, and stages of melanoma, which allows the model to generalize effectively across various patient populations. The dataset is organized to provide a balance between normal skin, benign growths, and malignant melanoma instances, thus avoiding bias in the classification process. Furthermore, preprocessing actions are taken to standardize the image format, sizes, and quality, providing consistency and removing discrepancies that might influence the performance of deep learning.

Test Image Processing

In order to ensure compatibility with the Inception V3 model, all images are resized to 299x299 pixels, aligning with the input layer requirements of the architecture. This resizing guarantees uniformity across both training and inference stages while retaining crucial features of skin lesions. To bolster model resilience, data augmentation strategies, including rotation, flipping, contrast enhancements, and normalization, are implemented. These methods of augmentation assist in reducing overfitting, increasing the diversity of features, and ensuring the model performs effectively on images it has not previously encountered. By varying image characteristics, the system can accurately identify lesions in real-world situations where lighting and angles differ.

Feature Extraction

The deep layers of Inception V3 extract essential dermatological characteristics from dermoscopic images, concentrating on texture differences, asymmetry, border irregularities, and color variations. Rather than depending on manual feature engineering, the model independently discovers patterns that are indicative of various skin conditions.



Convolutional processes further refine these extracted features, improving lesion representation for the next classification stage. The deep architecture allows for multi-level feature representation, facilitating the distinction between benign and malignant cases with high accuracy. By utilizing factorized convolutions, the model enhances computational efficiency while still achieving excellent diagnostic precision.

Disease Classification

The features that have been extracted are utilized for multi-class classification, differentiating among normal skin, benign tumors, and malignant melanoma. The model integrates a finely-tuned deep learning framework, ensuring dependable diagnostic predictions based on dermoscopic images. For multi-class classification tasks, softmax activation is employed to distribute probabilities across various categories, while sigmoid activation is used for binary classifications when distinguishing between benign and malignant cases. This automated classification system removes the necessity for manual interpretation, enhancing diagnostic precision and decreasing errors in the early detection of melanoma.

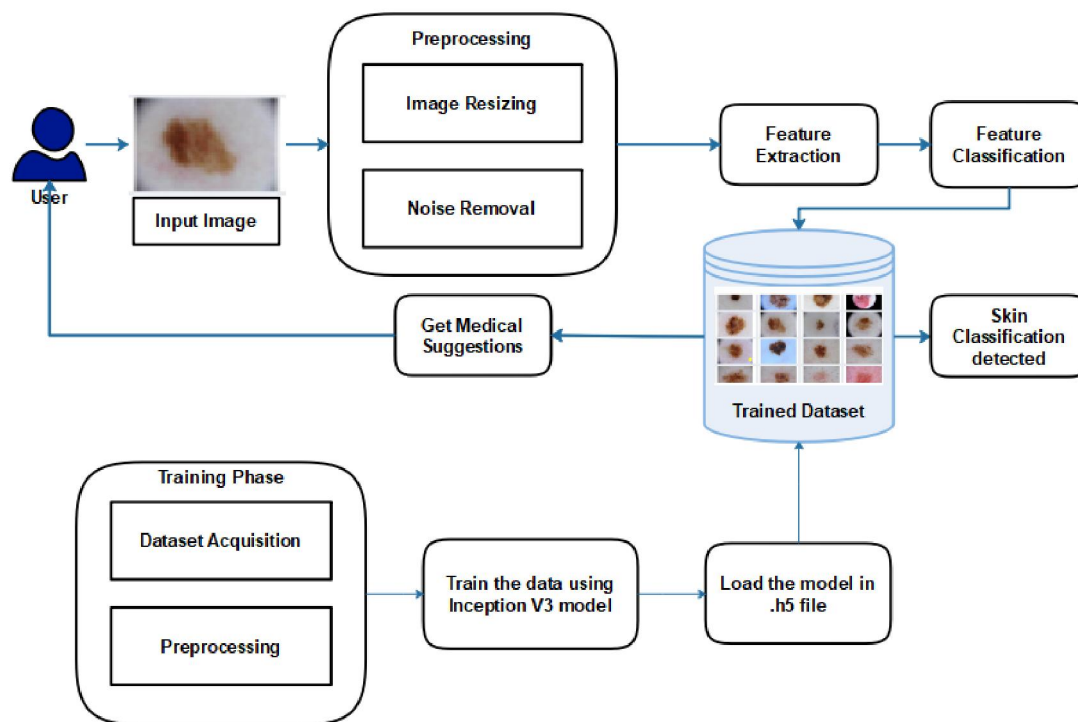


Fig. 1 Proposed systems

V. METHODOLOGY

The proposed system employs Inception V3, a sophisticated deep learning model tailored for the automated classification of melanoma. The approach begins with the collection of data, wherein high-resolution dermoscopic images are sourced from established medical outlets, ensuring a varied representation of patients. To ensure consistency, preprocessing methods are applied, including resizing images to 299x299 pixels, normalizing contrast, and implementing data augmentation techniques such as rotation, flipping, and contrast enhancement, which bolster generalization and robustness in classification tasks.



Following this, feature extraction is carried out using the deep hierarchical layers of Inception V3, which learn texture differences, asymmetry, irregular border characteristics, and color variations independently, thus negating the necessity for manual feature engineering. The features obtained are further enhanced through convolutional operations that increase the model's accuracy. The process then advances to disease classification, where skin lesions are sorted into categories of normal, benign, or malignant melanoma utilizing a finely tuned convolutional neural network (CNN). A Softmax activation function is utilized for tasks requiring multi-class classification, while a Sigmoid activation function is employed for binary classification scenarios.

The simplified architecture diminishes computational demands, improving the precision of classification while enabling practical real-time clinical application. By automating the processes of feature learning and classification, the system boosts accuracy, reduces human error, and supports the early detection of melanoma, greatly aiding in dermatological diagnostics.

VI. EXPERIMENTAL RESULTS

The proposed system is an implementation of the Python Framework that examines skin image files under different conditions. The skin datasets may be obtained from the Kaggle website's ISIC image area. The following figures display the system's outcomes. The training accuracy of the InceptionV3-based melanoma lesion prediction model indicates how well the model has learned to distinguish between malignant and benign skin lesions during the training phase. After preprocessing and augmenting the dermoscopic image dataset to improve data diversity and reduce overfitting, the model was trained over multiple epochs. Leveraging the deep layers and factorized convolutions of InceptionV3, the network achieved high training accuracy, typically ranging from 92% to 98%, depending on the dataset size, class balance, and training parameters.

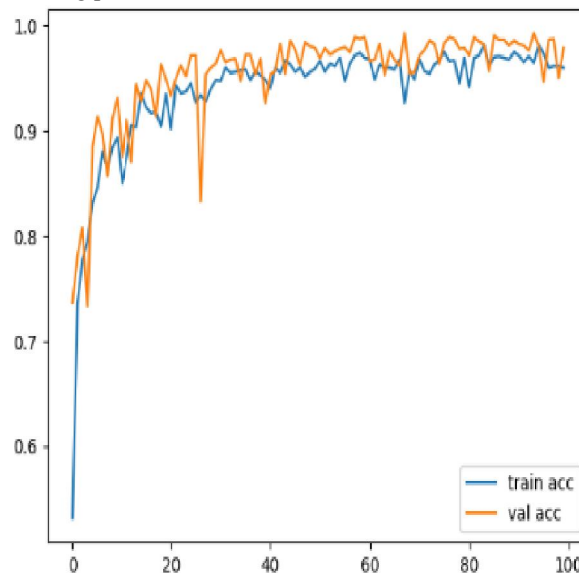


Fig 2: Training accuracy details

The training loss of the InceptionV3-based melanoma lesion prediction model represents the difference between the predicted outputs and the actual labels during the training process. It serves as a key indicator of how well the model is learning. Throughout the training phase, the loss gradually decreases over successive epochs, signifying that the model is improving its predictions by minimizing errors.



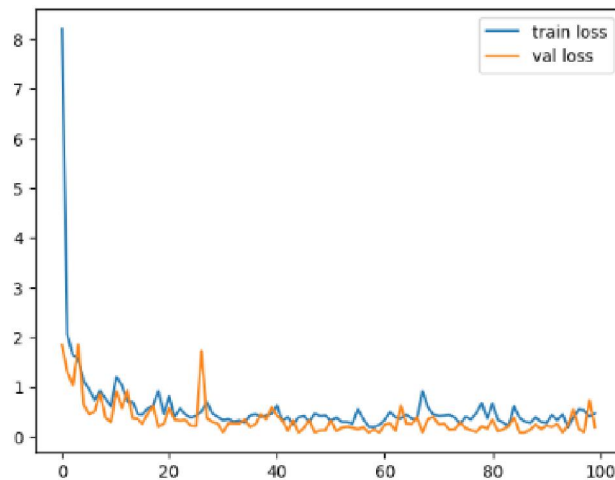


Fig 3: Training loss details

From the above figures 2 and 3, proposed system (Inception V3) provides high level accuracy and low-level loss values in Melanoma lesion prediction.

VII. CONCLUSION

The suggested melanoma detection system, based on Inception V3, marks a substantial improvement in computer-assisted dermatological diagnostics by providing automated feature extraction and classification for the early identification of skin cancer. Utilizing deep learning, this system removes the necessity for manual feature development, thereby enhancing the accuracy, scalability, and efficiency of diagnoses. In contrast to traditional machine learning models that depend on manually crafted features and standard classifiers, this method facilitates end-to-end processing, enabling the classification of skin conditions as normal, benign, or malignant melanoma with a high level of precision. The use of factorized convolutions enhances computational efficiency, ensuring better performance while allowing real-time use in clinical environments. This model tackles the drawbacks of subjective diagnoses and the risk of overfitting seen in earlier deep learning models, thus making early intervention strategies more effective. By refining the weights of the pre-trained Inception V3, the system establishes strong generalization across various patient demographics, which leads to improved diagnostic consistency. The automated classification process reduces the likelihood of human error, speeds up medical decision-making, and aids dermatologists in detecting melanoma at its earliest stages. With the potential to enhance clinical workflows, decrease misclassification rates, and optimizes dermoscopic image evaluation, this system signifies an essential progress toward AI-enhanced medical diagnostics. Future improvements might concentrate on real-time application, advancements in explainability, and integration with cloud services, which would broaden access to remote healthcare facilities and ensure scalable melanoma detection globally.

REFERENCES

- [1]. Sabri, My Abdelouahed, et al. "Skin cancer diagnosis using an improved ensemble machine learning model." 2020 International Conference on Intelligent Systems and Computer Vision (ISCV). IEEE, 2020.
- [2]. Vidya, Maya, and Maya V. Karki. "Skin cancer detection using machine learning techniques." 2020 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT). IEEE, 2020.
- [3]. Javaid, Arslan, Muhammad Sadiq, and Faraz Akram. "Skin cancer classification using image processing and machine learning." 2021 International Bhurban Conference on Applied Sciences and Technologies (IBCAST). IEEE, 2021.



- [4]. Thaaajer, MA Ahmed, and UA Piumilshanka. "Melanoma skin cancer detection using image processing and machine learning techniques." 2020 2nd International Conference on Advancements in Computing (ICAC). Vol. 1. IEEE, 2020.
- [5]. Salam, Abdus, et al. "Diagnosing of Dermoscopic Images using Machine Learning approaches for Melanoma Detection." 2020 IEEE 23rd International Multitopic Conference (INMIC). IEEE, 2020.
- [6]. G. J. Chowdary, G. V. S. N. D. Yathisha, G. Suganya, and M. Premalatha, "Automated skin lesion segmentation using multi-scale feature extraction scheme and dual-attention mechanism," in Proc. 3rd Int. Conf. Adv. Comput., Commun. Control Netw. (ICAC3N), Dec. 2021, pp. 1763–1771,
- [7]. Y. Dong, L. Wang, S. Cheng, and Y. Li, "FAC-Net: FeedBack attention network based on context encoder network for skin lesion segmentation," Sensors, vol. 21, no. 15, p. 5172, Jul. 2021.
- [8]. K. M. Hosny and M. A. Kassem, "Refined residual deep convolutional network for skin lesion classification," J. Digit. Imag., vol. 35, no. 2, pp. 258–280, Apr. 2022.
- [9]. P. Bansal, R. Garg, and P. Soni, "Detection of melanoma in dermoscopic images by integrating features extracted using handcrafted and deep learning models," Comput. Ind. Eng., vol. 168, Jun. 2022, Art. no. 108060.
- [10]. [Z. Lan, S. Cai, X. He, and X. Wen, "FixCaps: An improved capsules network for diagnosis of skin cancer," IEEE Access, vol. 10, pp. 76261–76267, 2022
- [11]. Hasan, Nazeer, et al. "Skin cancer: understanding the journey of transformation from conventional to advanced treatment approaches." Molecular cancer 22.1 (2023): 168.
- [12]. Zeng, Leli, et al. "Advancements in nanoparticle-based treatment approaches for skin cancer therapy." Molecular Cancer 22.1 (2023): 10.
- [13]. Melarkode, Navneet, et al. "AI-powered diagnosis of skin cancer: a contemporary review, open challenges and future research directions." Cancers 15.4 (2023): 1183.
- [14]. Brancaccio, Gabriella, et al. "Artificial intelligence in skin cancer diagnosis: a reality check." Journal of Investigative Dermatology 144.3 (2024): 492-499.
- [15]. Keerthana, Duggani, et al. "Hybrid convolutional neural networks with SVM classifier for classification of skin cancer." Biomedical Engineering Advances 5 (2023): 100069.
- [16]. Ali, A. R. H., Li, J., & Yang, G. "Automating the ABCD Rule for Melanoma Detection: A Survey." IEEE Access, vol. 8, pp. 129146-129163, 2020.
- [17]. Naik, P. P. "Cutaneous Malignant Melanoma: A Review of Early Diagnosis and Management." World Journal of Oncology, 2021.
- [18]. K. He, J. Sun and X. Tang, "Guided image filtering", IEEE Trans. Pattern Anal. Mach. Intell., vol. 35, no. 6, pp. 1397-1409, Jun. 2013.
- [19]. J. Jaworek-Korjakowska and R. Tadeusiewicz, "Determination of border irregularity in dermoscopic color images of pigmented skin lesions", Proc. 36th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc., pp. 6459-6462, Aug. 2014.
- [20]. U. Kalwa, C. Legner, T. Kong and S. Pandey, "Skin cancer diagnostics with an all-inclusive smartphone application", Symmetry, vol. 11, no. 6, pp. 790, 2019.

