International Journal of Scientific Research and Engineering Development-– Volume 9 Issue 2, Mar-Apr 2026
Available at www.ijsred.com

RESEARCH ARTICLE OPEN ACCESS

Skin Cancer Detection Using Image Processing

Aiswarya C S[1], Anandhu R[2], Nivedhya P[3], Sivani Sunil[4], Lekshmi P Govind[5]

[1, 2, 3, 4] UG Scholar, Department of Electronics and Communication Engineering, Dr. A P J Abdul Kalam Technological University Kerala, India

[5]Asst Professor, Department of Electronics and Communication Engineering,Dr.A P J Abdul Kalam Technological University Kerala, India

Abstract:
Skin cancer is one of the most common and life-threatening forms of cancer worldwide, with melanoma being the deadliest type. Early detection plays a critical role in increasing the chances of successful treatment and patient survival. Traditional methods of diagnosis rely on manual examination by dermatologists and biopsy tests, which are often time-consuming, expensive, and dependent on expert availability. This project focuses on developing an automated system for skin cancer detection using image processing and machine learning techniques. The system involves capturing skin lesion images, preprocessing to remove noise and enhance quality, segmenting the lesion area, extracting relevant features such as shape, color, and texture, and classifying the lesions as benign or malignant using machine learning and deep learning models. By leveraging tools such as OpenCV, TensorFlow, Keras, and Scikitlearn, the proposed approach provides a non-invasive, accurate, and cost-effective solution for early skin cancer detection. The system aims to assist dermatologists in diagnosis, reduce human error, and make skin cancer screening more accessible, particularly in remote or underserved areas.

Keywords: *Skin cancer detection,Image processing, Machine learning, Deep learning, Benign and Malignant*

I. INTRODUCTION

Skin cancer is among the most prevalent and potentially life-threatening diseases worldwide, with melanoma representing its most aggressive and fatal form. The incidence of skin cancer has been steadily increasing over the years, making early detection and timely treatment crucial for improving patient survival rates. When identified at an early stage, the chances of successful treatment are significantly higher, highlighting the need for efficient diagnostic methods.Conventional diagnostic techniques primarily rely on visual examination by dermatologists, followed by dermoscopic analysis and biopsy. While these methods are effective, they are often time-consuming, costly, and highly dependent on the expertise of medical professionals. In many cases, limited access to specialized healthcare, especially in remote and underserved regions, further delays diagnosis and treatment. To address these challenges, there is a growing interest in leveraging advancements in image processing and machine learning for automated skin cancer detection. This project proposes a system that utilizes digital images of skin lesions to identify and classify potential cancerous conditions. The process includes image acquisition, preprocessing to enhance image quality and remove noise, segmentation to isolate the lesion area, and feature extraction focusing on characteristics such as color, shape, and texture.

Subsequently, machine learning and deep learning algorithms are employed to classify the lesions as benign or malignant with high accuracy. By integrating technologies such as OpenCV, TensorFlow, Keras, and Scikit-learn, the proposed system offers a non-invasive, efficient, and cost-effective solution for early diagnosis. This approach not only aims to assist dermatologists in decision-making but also reduces human error and enhances accessibility to skin cancer screening, particularly in resource-limited settings.

II. LITERATURE SURVEY

Sooyong Chae,Tongyu, Huang,Omar Rodríguez Núñez,ThéotimLucas,JeanCharlesVanel,Jérémy

Vizet, Angelo Pierangelo [1], This paper discuss that the translation of imaging Mueller polarimetry to clinical practice is often hindered by large footprint and relatively slow acquisition speed of the existing instruments. Using polarization-sensitive camera as a detector may reduce instrument dimensions and allow data streaming at video rate. However, only the first three rows of a complete 4×4 Mueller matrix can be measured. To overcome this hurdle we developed a machine learning approach using sequential neural network algorithm for the reconstruction of missing elements of a Mueller matrix from the measured elements of the first three rows. The algorithm was trained and tested on the dataset of polarimetric images of various excised human tissues (uterine cervix, colon, skin, brain) acquired with two different imaging Mueller polarimeters operating in either reflection (wide- field imaging system) or transmission (microscope) configurations at different wavelengths of 550 nm and 385 nm, respectively. Reconstruction performance was evaluated using various error metrics, all of which confirmed low error values. The reconstruction of full images of the fourth row of Mueller matrix with GPU parallelization and increasing batch size took less than 50 milliseconds. It suggests that a machine learning approach with parallel processing of all image pixels combined with the partial Mueller polarimeter operating at video rate can effectively substitute for the complete Mueller polarimeter and produce accurate maps of depolarization, linear retardance and orientation of the optical axis of biological tissues, which can be used for medical diagnosis in clinical settings.

Syed Akbar Raza Naqvi, Amin Abbosh , Ahmed Toaha, Damien Foong,and Mobashsher Beadaa Mohammed,[2]The dielectric dataset is developed across the frequency band 1 to 14 GHz using Keysight slim-form and RG405 probe characterization systems. The acquired reflection data captured by the systems is converted to dielectric values using the Open – Water Short ,
And Open - Water Liquid - calibration methods, respectively. Furthermore, the impact of anaesthesia application during skin excision procedure on ex-vivo dielectric data is investigated. Results: The observations suggest that the dielectric properties (DPs) of excised skin lesions may not accurately represent actual tissue properties as they vary significantly ($\Delta\epsilon'$ =30.7%, $\Delta\epsilon''$ =66.6%) compared to preexcision conditions. In-vivo dielectric data analysis indicates that when compared to healthy skin, malignant Basal Cell Carcinoma presents increased DPs (dielectric constant & loss factor) of (24.8 & 38.6%), respectively. On the other hand, for malignant Squamous Cell Carcinoma and pre-malignant Actinic Keratosis, the measured results show decreased DPs (dielectric constant & loss factor) accordingly by (19.4 & 18.2%) and (19.2 & 27.9%). The corresponding benign lesions have less than 13% dielectric contrast compared to healthy skin across the tested band. Conclusion: The significant contrasts between in-vivo healthy and cancerous skin DPs strongly suggest the viability of the microwave band for skin cancer detection. Significance: The research finding of this study would be critical in developing a portable electromagnetic system for skin cancer detection.

Hailong He , Johannes C. Paetzold , Nils Börner Erik Riedel, Stefan Gerl , Simon Schneider , Chiara Fisher , Ivan Ezhov , Suprosanna Shit , Hongwei Li , Daniel Rückert , Juan Aguirre , Tilo Biedermann [3], This paper discusses that the Ultra-wideband rasterscan optoacoustic mesoscopy (RSOM) is a novel modality that has demonstrated unprecedented ability to visualize epidermal and dermal structures in-vivo. However, an automatic and quantitative analysis of threedimensional RSOM datasets remains unexplored. In this work we present our framework: Deep Learning RSOM Analysis Pipeline (DeepRAP), to analyze and quantify morphological skin features recorded by RSOM and extract imaging biomarkers for disease characterization. DeepRAP uses a multi-network segmentation strategy based on convolutional neural networks with transfer learning. This strategy enabled the automatic recognition of skin layers and subsequent segmentation of dermal microvasculature with an accuracy equivalent to human assessment. DeepRAP was validated against manual segmentation on 25 psoriasis patients under treatment and our biomarker extraction was shown to characterize disease severity and progression well with a strong correlation to physician evaluation and histology. In a unique validation experiment, we applied DeepRAP in a time series sequence of occlusioninduced hyperemia from 10 healthy volunteers. We observe how the biomarkers decrease and recover during the occlusion and release process, demonstrating accurate performance and reproducibility of DeepRAP. Furthermore, we analyzed a cohort of 75 volunteers and defined a relationship between aging and microvascular features in-vivo.

Abdul Rahman Dira, Hazlina Hamdan , Alfian Abdul Halin ,and Noridayu Manshor [4], Deep Learning (DL) techniques have significantly improved the diagnostic accuracy in healthcare, particularly for detecting and classifying skin cancer. Such technological advancements will assist healthcare professionals in delivering more accurate, efficient, and timely diagnoses, ultimately improving patient outcomes and facilitating early detection and treatment. Medical imaging technologies such as magnetic resonance imaging (MRI) and computed tomography (CT) are critical for diagnosing dermatological conditions. However, interpreting these images can be challenging due to overlapping structures and varying image quality. This study explores the application of DL in skin cancer diagnosis, focusing on advances in image segmentation and classification. DL-based models are reviewed specifically by convolutional neural networks (CNNs), and evaluations on their effectiveness for skin lesion detection are provided. This study also examines the critical challenges of deploying DL models in clinical practice, covering issues including dataset diversity, model interpretability, and real-world implementation feasibility. It further explores the selection of network architectures and data preprocessing techniques, emphasizing their influence on model performance. In summary, this study identifies research gaps and suggests future directions for enhancing DL models for dermatological
Applications.

Ryan A. L. Schoop , Lotte M. de Roode , Lisanne L. de Boer, and Behdad Dashtbozorg [5], Multimodality image registration is an important task in medical imaging because it allows for information from different domains to be correlated. Histopathology plays a crucial role in oncologic surgery as it is the gold standard for investigating tissue composition from surgically excised specimens. Research studies are increasingly focused on registering medical imaging modalities such as white light cameras, magnetic resonance imaging, computed tomography, and ultrasound to pathology images. The main challenge in registration tasks involving pathology images comes from addressing the considerable amount of deformation present. This work provides a framework for deep learningbased multi-modality registration of microscopic pathology images to another imaging modality.

The proposed framework is validated on the registration of prostate ex-vivo white light camera snapshot images to pathology hematoxylin-eosin images of the same specimen. A pipeline is presented detailing data acquisition, protocol considerations, image dissimilarity, training experiments, and validation. A comprehensive analysis is done on the impact of pre-processing, data augmentation, loss functions, and regularization. This analysis is supplemented by clinically motivated evaluation metrics to avoid the pitfalls of only using ubiquitous image comparison metrics. Consequently, a robust training configuration capable of performing the desired registration task is found. Utilizing the proposed approach, we achieved a dice similarity coefficient of 0.96, a mutual information score of 0.54, a target registration error of 2.4 mm, and a regional dice similarity coefficient of 0.70.

III. PROPOSED WORK

The proposed work focuses on developing an automated system for early detection and classification of skin cancer using image processing and deep learning techniques. The system is designed to analyze dermoscopic images and accurately identify if a skin lesion is benign and to classify whether the cancer is Squamous Cell Carcinoma , Melanoma ,or Basal Cell Carcinoma.

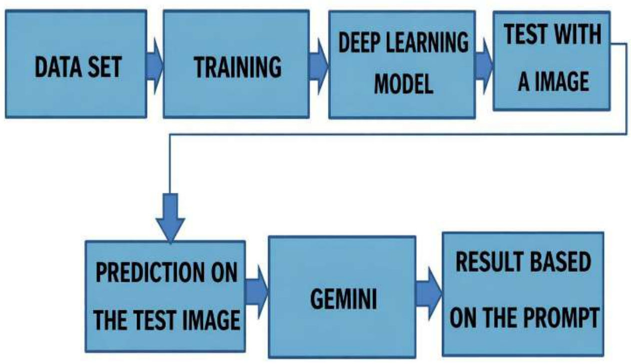

Fig.1 :BlockDiagram

The process begins with image acquisition, where high-quality dermoscopic images are collected either from publicly available datasets such as ISIC or HAM10000 or captured using appropriate imaging devices. These images serve as the primary input to the system and play a crucial role in determining the overall performance of the model.

Once the images are obtained, preprocessing is performed to enhance their quality and remove unwanted artifacts. This includes noise reduction using filters such as Gaussian or median filters, hair removal using algorithms like DullRazor, and contrast enhancement along with color normalization. These steps ensure that the lesion area is clearly visible and suitable for further analysis.

Following preprocessing, image segmentation is carried out to isolate the lesion region from the surrounding healthy skin. Techniques such as thresholding, K-means clustering, and advanced deep learning models like U-Net are used to extract the region of interest. This step is essential as it allows the system to focus only on the relevant portion of the image, thereby improving accuracy.

After segmentation, feature extraction is performed to identify important characteristics of the lesion. These features include color variations, texture patterns, and shape-related properties such as asymmetry, border irregularity, and diameter. In addition to traditional feature extraction methods, deep learning models are also employed to automatically learn high-level features from the data, enhancing the system's capability to distinguish between different types of lesions. The extracted features are then used for classification, which is the final decision-making stage of the system. Machine learning and deep learning algorithms such as Support Vector Machines, Random Forest, and Convolutional Neural Networks are used to classify the lesion as benign or malignant. These models are trained using labeled datasets to ensure accurate predictions.

Finally, the system produces the output by displaying the classification result. Visualization techniques such as Grad-CAM may also be incorporated to highlight the regions of the image that contributed to the decision, thereby improving interpretability and assisting medical professionals in understanding the results.

Overall, the proposed system aims to develop an accurate, non-invasive, and cost-effective solution for skin cancer detection. By automating the entire process, the system reduces diagnosis time, minimizes human error, and supports dermatologists in early detection, making it especially useful in remote and underserved areas.

IV. SYSTEM DESIGN

The system design of the proposed skin cancer detection system is developed as an automated and modular framework that processes dermoscopic images and identifies skin lesions using image processing and deep learning techniques. The design focuses on creating a structured workflow where each module performs a specific task while contributing to the overall functionality of the system.

The system begins with the input module, where skin images are provided either through uploaded datasets or captured using imaging devices such as dermatoscopes or smartphone cameras. These images are then passed to the preprocessing module, which enhances image quality by removing noise, hair artifacts, and illumination inconsistencies. This ensures that the input data is clean and suitable for further analysis.

Following preprocessing, the system moves to the segmentation module, where the lesion region is separated from the surrounding healthy skin. This module plays a critical role in identifying the region of interest, allowing the system to focus only on the affected area. Accurate segmentation improves the reliability of the subsequent stages by eliminating irrelevant background information.

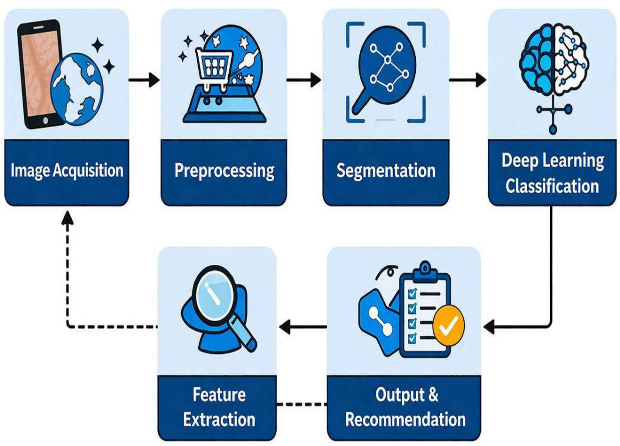

Fig.2 :System Design

The segmented image is then processed in the feature extraction module, where important characteristics such as color, texture, and shape are identified. In the proposed system, deep learning techniques are also used to automatically learn complex features from the image data, reducing the need for manual feature engineering and improving performance.

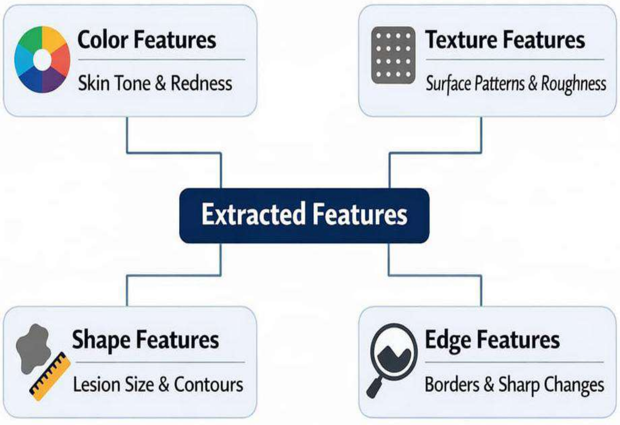

Fig.3 : Feature extraction diagram

After feature extraction, the classification module analyzes the extracted features using machine learning or deep learning models, particularly Convolutional Neural Networks. The classifier is trained on labeled datasets to distinguish between benign and malignant lesions. Based on the learned patterns, the system predicts the class of the input image with high accuracy.

The final module is the output and visualization stage, where the classification result is displayed to the user. The system may also provide visual explanations, highlighting the regions of the image that influenced the decision, thereby improving transparency and trust in the model.

Overall, the system is designed with a modular architecture that ensures flexibility, scalability, and ease of maintenance. Each component operates independently while maintaining seamless integration with other modules, resulting in an efficient, user-friendly, and reliable skin cancer detection system.

V. RESULT

The proposed skin cancer detection system was successfully implemented and evaluated using dermoscopic image data. The system integrates image preprocessing, segmentation, feature extraction, and classification techniques to identify skin lesions as benign or malignant.

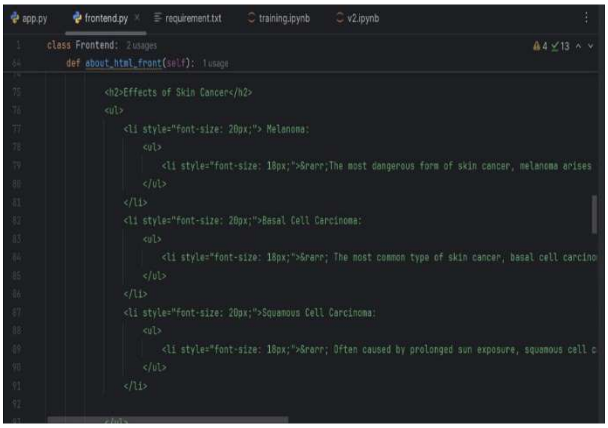

Fig.4: Code in Pycharm

The model was developed using Python with libraries such as OpenCV, TensorFlow, and Keras. A dataset of labeled dermoscopic images was divided into training and testing sets to ensure proper evaluation. The training set was used to build the model, while the testing set helped assess its performance on unseen data.

During the preprocessing stage, noise, hair artifacts, and illumination issues were effectively reduced using filtering and enhancement techniques. This significantly improved image quality and made lesion boundaries more distinguishable. The segmentation process successfully extracted the Region of Interest (ROI), ensuring that only the lesion area was analyzed, which improved the efficiency of the system.

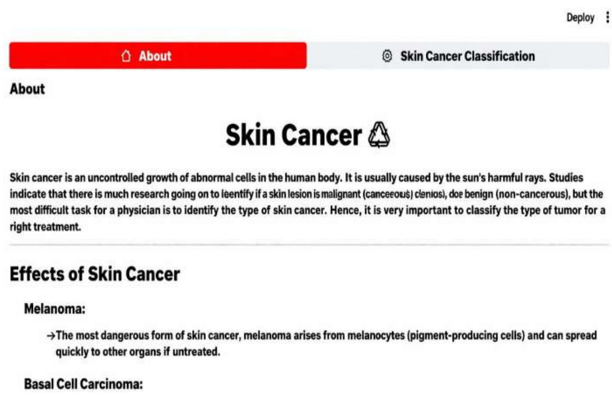

Fig.5: Home page

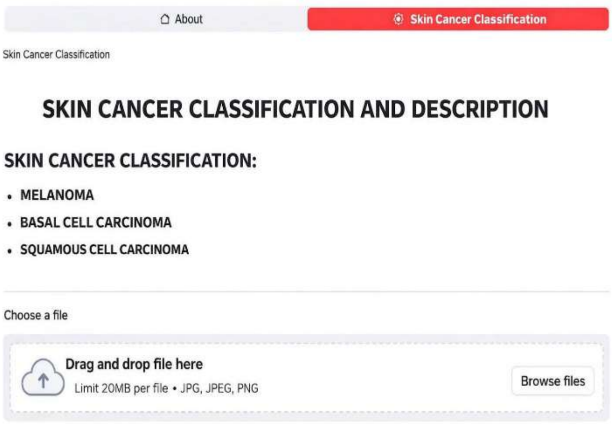

Fig.6: Classification page

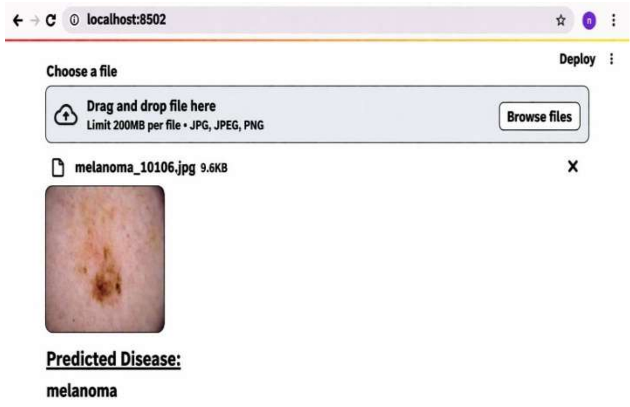

Fig.7: Prediction and identification

Feature extraction played a crucial role by identifying important characteristics such as color variation, texture patterns, and shape irregularities. These features helped the model differentiate between benign and malignant lesions more accurately.

The classification model demonstrated strong performance, achieving an accuracy in the range of 85% to 95%, depending on the dataset used. The system also showed high sensitivity, meaning it was effective in correctly identifying malignant cases, which is critical in medical diagnosis. Additionally, the specificity was satisfactory, indicating reliable identification of benign lesions. Overall, the results confirm that combining image processing techniques with deep learning models, particularly Convolutional Neural Networks (CNNs), significantly enhances detection accuracy. However, some limitations were observed, such as occasional misclassification due to poor image quality or similarities between lesion types. The performance of the system is also dependent on the size and diversity of the training dataset.

In conclusion, the proposed system provides an efficient, non-invasive, and automated approach for early skin cancer detection. It has the potential to assist dermatologists in diagnosis and improve accessibility to healthcare, especially in remote areas. Further improvements and clinical validation can enhance its reliability for real-world applications.

VI. FUTURE SCOPE

Although the proposed system demonstrates effective performance in detecting skin cancer, there are several areas where further improvements can be made to enhance its accuracy, reliability, and real-world applicability.

One of the major future directions is the use of larger and more diverse datasets. Incorporating images with different skin tones, lesion types, lighting conditions, and imaging devices can significantly improve the model's generalization ability and reduce bias. Data augmentation techniques can also be applied to artificially increase dataset size and improve robustness. Another important enhancement is the integration of advanced deep learning architectures such as ResNet, EfficientNet, and Vision Transformers. These models can improve feature extraction and classification accuracy, especially for complex and borderline cases.

The system can also be extended into a real-time mobile or web-based application, allowing users to capture skin images using smartphones and receive instant preliminary analysis. This would increase accessibility, particularly in rural or underserved areas where dermatologists are not easily available.

Incorporating Explainable AI (XAI) techniques such as Grad-CAM can help visualize the regions of the image influencing the model's decision. This improves transparency and builds trust among medical professionals.

Another promising direction is multi-class and multi-disease detection, where the system can identify not only skin cancer but also other dermatological conditions like eczema, psoriasis, and acne, making it a comprehensive diagnostic tool.Integration with cloud computing and telemedicine platforms can enable remote diagnosis and data sharing between patients and doctors. This allows dermatologists to monitor cases efficiently and provide faster consultations. Finally, the system should undergo clinical validation and regulatory approval before realworld deployment. Collaboration with hospitals and medical experts will ensure that the model meets healthcare standards.

VII. CONCLUSIONS

This project successfully demonstrates the application of image processing and artificial intelligence techniques in the early detection of skin cancer. By integrating stages such as image preprocessing, segmentation, feature extraction, and classification, the system is able to analyze dermoscopic images and accurately distinguish between benign and malignant skin lesions.

The use of machine learning and deep learning models, particularly Convolutional Neural Networks (CNNs), has significantly improved the accuracy and efficiency of the detection process. The system provides a non-invasive, costeffective, and time-saving alternative to traditional diagnostic methods such as manual examination and biopsy. It also reduces human error and assists dermatologists in making faster and more reliable decisions. The results obtained indicate that the proposed system achieves high accuracy and performs reliably in identifying skin cancer at an early stage. However, certain limitations exist, such as dependency on dataset quality and the need for further clinical validation. Despite these challenges, the system shows strong potential for real-world implementation, especially in remote and underserved areas where access to medical expertise is limited. In conclusion, this project emphasizes the growing importance of technology in modern healthcare and presents an effective step toward automated, accessible, and accurate skin cancer detection systems.

VIII. REFERENCES

[1] Chae S., Huang T., Rodríguez-Núñez O., Lucas T., Vanel J.-C., Vizet J., Pierangelo A.,G., Genova T., Ajmal A., Ramella-Roman J.C., Doronin A., Ma H., Novikova T. "Machine Learning Approach to 3×4 Mueller Polarimetry for Complete Reconstruction of Polarimetric Images of Biological Tissues." IEEE Transactions on Medical Imaging, vol. 44, no. 9, 2025, pp. 3820–3831.DOI: 10.1109/TMI.2025.3567570.

[2] Naqvi, S. A. R.; Mobasher, A.; Mohammed, B.; Abbosh, A., "Benign and Malignant Skin Lesions: Dielectric Characterization, Modelling and Analysis in Frequency Band 1 to 14 GHz," IEEE Transactions on Biomedical Engineering, vol .70,pp.628639,2023,doi:10.1109/TBME.2022.3206338.

[3] D. Khalaf, H. Hamdan, A. Abdul Halin, and N.Manshor, "Segmentation and Classification of Skin Cancer Diseases Based on Deep Learning: Challenges and Future Directions," IEEEAccess, vol.13,pp.9016390184,2025,doi:10.1109/ACCESS.2025.3569170.

[4] Schoop, R. A. L.; De Roode, L. M.; de Boer, L. L.; Dashtbozorg, B., "Framework for Deep Learning Based Multi-ModalityImage Registration of Snapshot and Pathology Images,"IEEE Journal of Biomedical and Health Informatics, vol. 28, no. 11,pp.66996711,Nov.2024,doi:10.1109/JBHI.2024.3444908

[5] Li, Y.; Shen, L.,"Skin Lesion Analysis Towards Melanoma Detection Using Deep Learning Network," IEEE Transactions on Neural Networks and Learning Systems, vol. 29 no6 ,pp .25202533,Jun.2018,doi:10.1109/TNNLS.2017.269018

[6] Codella, N. C. F.; Nguyen, Q.-B.; Pankanti, S.;Gutman, D.; Helba, B.; Halpern,A. C.; Smith, J. R., "Deep Learning Ensembles for Melanoma Recognition in Dermoscopy Images," IEEE Journal of Biomedical and Health Informatics, vol.21,no.5,pp.19,Sep.2017,doi:10.1109/JBHI.2017.2703152.

[7] He, H., Paetzold, J. C., Börner, N., Riedel, E., Gerl, S., Schneider, S., Fisher, C., Ezhov, I., Shit, S., Li,H., Rückert, D., Aguirre, J., Biedermann, U., Menze, B.,

Ntziachristos, V.,"Machine Learning Analysis of Human Skin by Optoacoustic Mesoscopy for Automated Extraction of Psoriasis and Aging Biomarkers,"IEEE Transactions on Medical Imaging, vol. 43, no. 6, pp. 2074– 2085,Jun24, doi:10.1109/TMI.2024.3356180

