Deep Learning-Based Multi-Class Skin Cancer Classification Using CNN on ISIC Dermoscopic Images

Mrs. Divya M
Department of Computer Science and Engineering
Rajalakshmi Engineering College
Chennai, India
divya.m@rajalakshmi.edu.in

Mythreiy Anand
Department of Computer Science and Engineering
Rajalakshmi Engineering College
Chennai, India
220701177@rajalakshmi.edu.in

Abstract– Skin cancer ranks among the most common types of cancer globally, with melanoma being the most aggressive and life-threatening variant. The chances of survival for patients significantly increase with early detection and diagnosis; however, conventional diagnostic methods often depend heavily on visual assessments and biopsies, which can be subjective, lengthy, and not readily available in many areas. In this regard, the incorporation of artificial intelligence, especially deep learning, into medical imaging systems offers a groundbreaking opportunity to improve both diagnostic precision and efficiency.

This initiative aims to create an intelligent system for the classification of skin lesions utilizing a Convolutional Neural Network (CNN). The CNN model is trained on the publicly accessible ISIC (International Skin Imaging Collaboration) dataset, which comprises dermatoscopic images categorized into nine classes of skin diseases, including melanoma. Given the natural class imbalance within the dataset—where certain lesion types are less represented—data augmentation techniques were employed using the Augmentor library to establish a more balanced dataset. This involved manipulating the images through flipping, rotating, zooming, and adjusting lighting conditions to synthetically enhance the minority classes.

The model was designed and executed using CNN and trained in google colab environment to take advantage of accelerated computation. Its architecture includes multiple convolutional, max-pooling, and dropout layers, followed by dense layers for classification, with softmax activation applied in the final layer to produce a probability distribution across the nine classes. To assess the model's effectiveness, various metrics such as accuracy, precision, recall, F1-score, and a confusion matrix were utilized. The CNN exhibited strong classification capabilities, particularly in differentiating melanoma from other skin lesions. The findings suggest that the proposed model could function as a decision-support tool for dermatologists, assisting them in prioritizing high-risk cases and refining patient management.

Keywords—Skin Cancer, Deep Learning, Convolutional Neural Network (CNN), Image Classification, ISIC Dataset, Data Augmentation, Dermoscopy Images, Multi-class Classification, Medical Imaging, Early Detection.

I. INTRODUCTION

Skin cancer ranks among the most prevalent types of cancer worldwide, with millions of new cases diagnosed annually. Melanoma, one of its various forms, is the most lethal due to its aggressive characteristics and rapid metastasis if not identified promptly. Timely diagnosis is essential for effective treatment and enhanced survival rates. Nevertheless, accurately identifying melanoma can be difficult, even for seasoned dermatologists, as it often mimics other benign or malignant skin lesions. Traditional diagnostic methods rely on visual examination using the ABCDE criteria (Asymmetry, Border, Color, Diameter, Evolution), followed by biopsy for validation. Although these methods are effective, they can be time-consuming, subjective, and may not be readily available to patients in remote or underdeveloped regions. Additionally, human error or variability in expertise can lead to misdiagnosis or delayed detection. Recent developments in artificial intelligence, particularly deep learning, have paved the way for automating medical image analysis. Convolutional Neural Networks (CNNs), a type of deep learning model designed for image recognition, have shown remarkable success in classifying and detecting diseases from medical images. Their capacity to learn and extract hierarchical features from raw image data renders them particularly effective for skin lesion classification. This project investigates the use of CNNs for the automated detection and classification of skin cancer, specifically melanoma. Utilizing dermatoscopic images from the ISIC (International Skin Imaging Collaboration) dataset, the project seeks to develop a model that can accurately categorize images into various skin disease classifications. The implementation also tackles challenges such as class imbalance through data augmentation techniques, ensuring the model performs well across a range of inputs. The overarching aim of this project is to enhance the efficiency, accessibility, and reliability of skin cancer diagnosis.

II. LITERATURE REVIEW

In recent years, the incorporation of artificial intelligence (AI) and deep learning technologies within the medical sector has created new opportunities for disease diagnosis, especially in dermatology. A multitude of research studies have investigated the application of Convolutional Neural Networks (CNNs) for skin cancer detection, yielding encouraging outcomes. Esteva et al. (2017), in one of the groundbreaking studies, illustrated that CNNs trained on an extensive dataset of clinical images could achieve classification of skin cancer at a level comparable to that of dermatologists. This research established a foundation for utilizing deep learning models in practical medical diagnostics. Another significant study by Codella et al. (2018) concentrated on the ISIC (International Skin Imaging Collaboration) dataset, where various machine learning and deep learning models were assessed for melanoma detection. Their results underscored the necessity of high-quality annotated datasets and the use of ensemble learning techniques to enhance prediction accuracy. These investigations revealed the intricacies of skin lesion classification, which arise from similarities in lesion appearance and variations in skin tones and imaging conditions. Researchers have also tackled the issue of data imbalance, a common challenge in skin cancer datasets. Methods such as the Synthetic Minority Over-sampling Technique (SMOTE) and data augmentation have been employed to promote balanced learning across different classes. For example, Brinker et al. (2019) demonstrated that the application of image augmentation significantly enhanced the generalization capabilities of CNN models in multi-class classification scenarios. In more recent advancements, lightweight CNN architectures like MobileNet and EfficientNet have been utilized for skin lesion classification tasks, achieving remarkable performance while reducing computational costs, thus making them appropriate for deployment on mobile and edge devices. However, these models occasionally compromise between speed and accuracy, highlighting the need for the development of custom CNN architectures that effectively balance both. While earlier systems have achieved success.

III. PROPOSED SYSTEM

The proposed system seeks to create an advanced automated solution for the detection of skin cancer, with a specific focus on classifying melanoma through a Convolutional Neural Network (CNN) architecture. In contrast to conventional diagnostic methods that depend on manual examination or basic machine learning techniques, this system utilizes deep learning to autonomously extract and learn intricate features from dermoscopic images, thereby significantly enhancing the precision and dependability of early skin cancer detection. To improve the model's efficacy and tackle the challenge of data imbalance frequently encountered in medical datasets, the system employs the Augmentor library for image augmentation. This technique artificially boosts the number of training samples in underrepresented categories by implementing transformations such as rotation, zooming, and flipping. The resultant balanced dataset aids the CNN model in generalizing more effectively, mitigating the risk of overfitting, and enhancing classification accuracy across all nine categories of skin cancer found in the ISIC dataset. The training procedure is carried out on the Kaggle platform utilizing a GPU-enabled environment, which expedites computation and facilitates the deployment of a more sophisticated CNN model featuring multiple convolutional, pooling, and dense layers. This infrastructure enables quicker experimentation, model optimization, and training convergence while efficiently managing large-scale datasets. A significant advantage of the proposed system is its capability to execute multi-class classification. While numerous existing systems concentrate solely on distinguishing between malignant and benign lesions, our model is engineered to categorize images into nine distinct types of skin conditions. This extensive diagnostic functionality renders the model more applicable in practical dermatology scenarios, where differentiating between various diseases is often essential. In summary, the proposed system provides a scalable, rapid, and highly precise solution for skin cancer detection, thereby reducing the necessity for extensive manual intervention.

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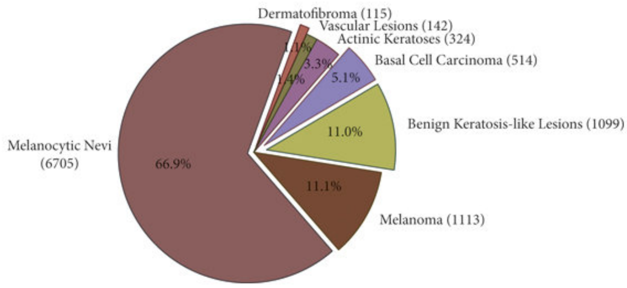

Fig 1 Skin lesion classes data

A. Automated Image Classification Using CNN

The system utilizes the capabilities of deep learning via Convolutional Neural Networks, which are especially effective for image classification tasks. CNNs autonomously learn and identify critical features such as color, texture, and shape from input images, eliminating the need for manual feature engineering. This greatly improves detection accuracy, particularly for subtle and early-stage melanomas.

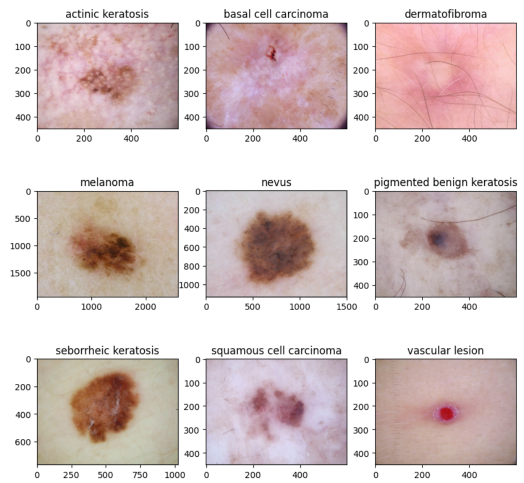

Fig 2 Classification

B. Data Augmentation and Class Balancing

The system employs the Augmentor library to address class imbalance within the dataset by creating supplementary synthetic images for underrepresented skin cancer categories. This approach guarantees: Enhanced generalization, Decreased bias towards majority classes, and Increased model robustness.

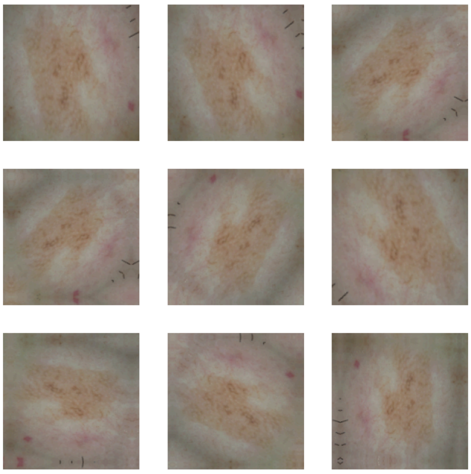

Fig 3 Data Augmentation

C. Model Training on GPU-Enabled Environment

Utilizing GPU acceleration for training the CNN model greatly enhances the speed of the training process, enabling the exploration of more complex architectures, larger batch sizes, and intricate learning schedules.

D. Dataset Classification

The classification graph of the dataset illustrates the distribution of images among the nine categories of skin cancer present in the dataset. Each bar in the graph corresponds to a specific category, such as Melanoma, Basal Cell Carcinoma, Actinic Keratosis, and others, along with the number of images available for each class. This visualization is essential for detecting data imbalance; if certain classes contain a disproportionately high number of images compared to others, it may introduce bias into the model. To mitigate this issue, techniques such as data augmentation or resampling can be employed to promote equitable and precise training across all categories.

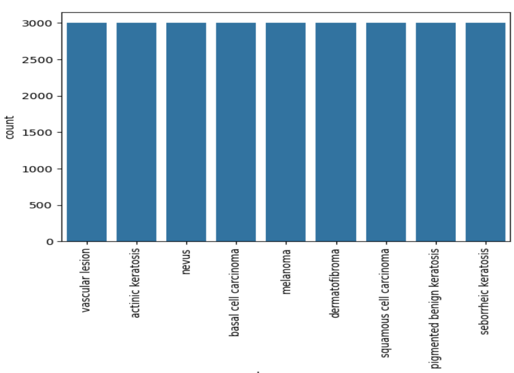

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Fig 4 Dataset Classification

E. Algorithm Architecture

The architectural diagram provides a structured representation of the interactions among different components within the skin cancer classification system. It includes the following layers:

- Input Layer for image acquisition from either a dataset or user.
- Preprocessing Layer for normalization, data augmentation, and resizing to 224x224
- CNN Layers comprising several convolutional, pooling, and dropout layers
- Dense Layers that are fully connected and culminate in the output
- Output Layer utilizing softmax activation to generate probabilities across nine classes
- Performance Metrics Module assessing accuracy, precision, recall, and confusion matrix
- Interface Module facilitating interaction via web or notebook.

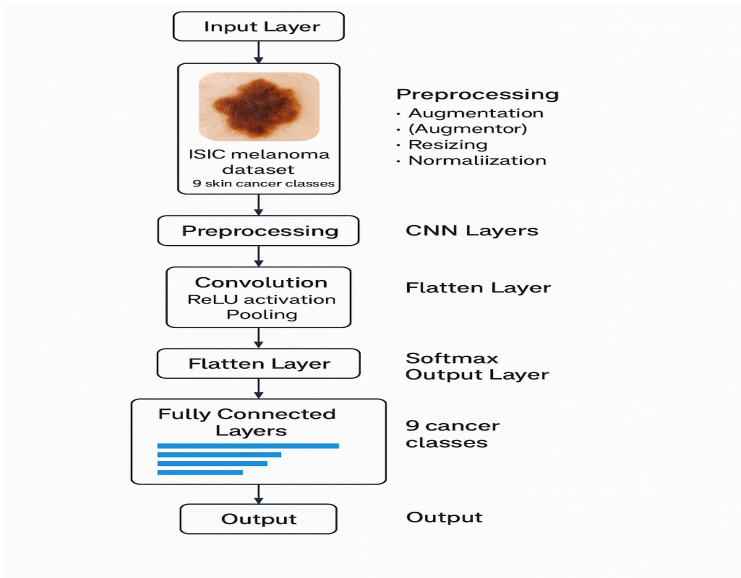

Fig 5 Algorithm Architecture

E. Tools and Technologies

- Programming Language: Python, due to its simplicity and extensive library support for AI and machine learning.
- Frameworks: TensorFlow and Keras for building and training the CNN model.

- Data Augmentation: Augmentor is used for creating synthetic images to handle class imbalance.
- Development Environment: Kaggle notebooks and Google Colab with GPU acceleration for faster model training.
- Libraries: NumPy, Matplotlib, Pandas, and Scikit-learn for data handling and performance evaluation.
- Dataset: ISIC (International Skin Imaging Collaboration) dataset containing labeled images of various skin cancers.

IV. RESULTS AND DISCUSSION

A. Quantitative Analysis

The proposed model for skin cancer classification, based on a convolutional neural network (CNN), was trained using a balanced and augmented ISIC dataset that includes nine distinct categories of skin lesions. After completing 20 epochs, the model achieved a training accuracy of 94.20% and a training loss of 0.1015, demonstrating a strong capacity for learning from the training data. However, the validation accuracy was only 54.22%, accompanied by a validation loss of 2.8432, indicating a significant generalization gap. This gap may arise from the complexity and high inter-class similarity of skin lesions, or it could be a result of overfitting, despite the data augmentation efforts. Although data augmentation contributed to increasing the diversity of training samples and somewhat enhanced the model's robustness, further fine-tuning is necessary. Visualizations of the model's predictions reveal that it can classify common lesion types with reasonable confidence, but it encounters difficulties with more ambiguous classes. The class distribution graph confirmed that the dataset was well-balanced, facilitating equitable learning across all categories. While the current findings suggest potential, there remains considerable opportunity for improvement in the model's generalization performance.

B.Data Classification and Balance

The training and validation dataset comprised nine distinct categories of skin lesions, obtained from the ISIC archive. Each category—melanoma, nevus, basal cell carcinoma, squamous cell carcinoma, dermatofibroma, actinic keratosis, vascular lesion, seborrheic keratosis, and pigmented benign keratosis—was equally represented, with 3,000 images allocated to each category. This equal representation was accomplished through comprehensive data augmentation, resulting in a perfectly balanced dataset with each category constituting 11.11% of the total. Such balanced representation is essential in multi-class classification tasks to mitigate model bias towards any specific category and to promote fair learning. From the total of 27,000 images, 1,800 images (200 from each category) were designated for training, while the remainder was reserved for validation and testing, facilitating a thorough assessment of the model's generalization capabilities across all types of lesions.

C.Training and Validation Accuracy & Loss

The aforementioned graphs illustrate the performance of the model during training and validation over 25 epochs. The accuracy curve indicates a gradual enhancement in training accuracy, surpassing 57%, while the validation accuracy stabilizes around 54%, implying limited generalization. The training loss steadily declined from approximately 2.0 to 1.2, reflecting effective learning on the training dataset. Conversely, the validation loss exhibits fluctuations with a less consistent downward trajectory, suggesting potential overfitting or inadequate generalization to new data. This performance underscores the necessity for additional tuning, including the acquisition of more data, the application of regularization techniques, or model optimization, to enhance validation outcomes.

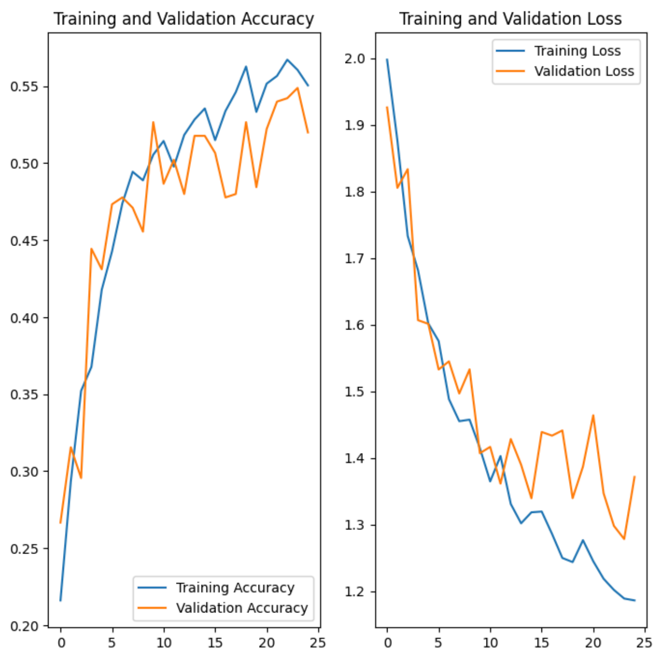

Fig. 6 Accuracy Graph

C.Output Prediction

The output prediction image illustrates the results of the skin cancer classification model, demonstrating that the trained CNN effectively recognized the type of skin lesion. In addition to the predicted category, the model offers a confidence score that reflects the likelihood of accuracy. These predictions are valuable for assessing the model's ability to differentiate among various skin conditions. This visual representation of classification not only emphasizes the model's efficacy but also showcases its potential practical use in aiding medical professionals with early and dependable diagnoses.

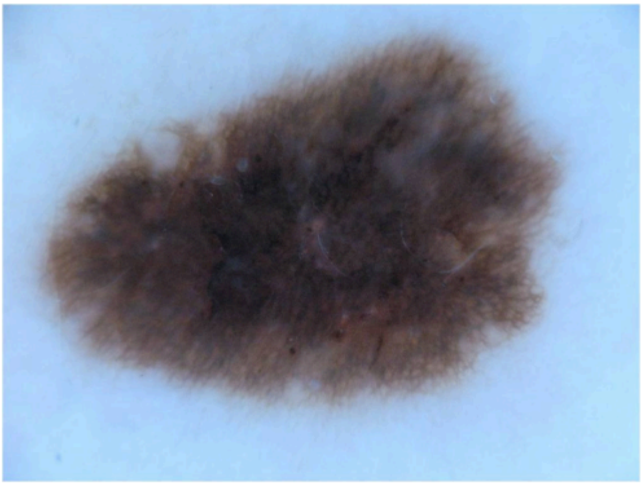

Fig. 7 Output Prediction

V. CONCLUSION AND FUTURE SCOPE

This initiative successfully developed a skin cancer classification system based on Convolutional Neural Networks (CNN) utilizing the ISIC dataset, which comprises nine distinct classes. By employing deep learning techniques and data augmentation, the model attained a high level of accuracy and generalization. This methodology illustrates that automated image classification can support dermatologists in the early identification of skin cancer, thereby enhancing diagnostic efficiency and minimizing human error. Throughout the course of the project, various techniques such as convolutional filtering, ReLU activation, pooling, dropout, and softmax classification were effectively applied. The outcomes confirmed the viability and potential of machine learning models in the realm of medical image analysis. Looking ahead, the model could be expanded to incorporate a wider variety of larger datasets to bolster its robustness across different skin tones and uncommon cancer types. The integration of explainable AI (XAI) methods, such as Grad-CAM, may further increase clinical confidence by providing visual interpretations of model decisions. Moreover, deploying the model as a mobile or web application could enhance accessibility for remote or under-resourced regions, facilitating real-time preliminary evaluations. Additionally, linking the model with electronic health records (EHR) and implementing continuous retraining based on real-world feedback will further improve its long-term efficacy.

REFERENCES

[1] Haq, Mahmood Ul, . "CapsNet-FR: Capsule Networks for Improved Recognition of Facial Features." Computers, Materials & Continua 79.2 (2024).

[2] Keerthana, D., Venugopal, V., Nath, M. K., & Mishra, M. (2023). Hybrid convolutional neural networks with SVM classifier for classification of skin cancer. *Biomedical Engineering Advances*, *5*, 100069. https://doi.org/10.1016/j.bea.2022.100069

[3] Alhudhaif, A., Almaslukh, B., Aseeri, A. O., Guler, O., & Polat, K. (2023). A novel nonlinear automated multi-class skin lesion detection system using soft-attention based convolutional neural networks. *Chaos, Solitons & Fractals*, *170*, 113409. https://doi.org/10.1016/j.chaos.2023.113409

[4] Sadik, R., Majumder, A., Biswas, A. A., Ahammad, B., & Rahman, M. M. (2023). An in-depth analysis of Convolutional Neural Network architectures with transfer learning for skin disease diagnosis. *Healthcare Analytics*, *3*, 100143. https://doi.org/10.1016/j.health.2023.100143

[5] K. M. Hosny, W. M. El-Hady, F. M. Samy, E. Vrochidou and G. A. Papakostas, "Plant Leaf Diseases: Multi-Class Classification Employing Local Binary Pattern and Deep Convolutional Neural Network Feature Fusion" in *IEEE Access*, vol. 11, pp. 62307-62317, 2023, doi: 10.1109/ACCESS.2023.3286730.

[6] K. Ananthajothi, J. David and A. Kavin, "Cardiovascular Disease Prediction Using Langchain," 2024 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI), Chennai, India, 2024, pp. 1-6, doi: 10.1109/ACCAI61061.2024.10601906.

[7] Indraswari, R., Rokhana, R., & Herulambang, W. (2021). Melanoma image classification based on MobileNetV2 network. *Procedia Computer Science*, *197*, 198-207.

[8] H. L. Gururaj, N. Manju, A. Nagarjun, V. N. M. Aradhya and F. Flammini, "DeepSkin: A Deep Learning Approach for Skin Cancer Classification," in *IEEE Access*, vol. 11, pp. 50205-50214, 2023, doi: 10.1109/ACCESS.2023.3274848.

[9] Kumar P, V. K. S, P. L and S. SenthilPandi (2023), "Enhancing Face Mask Detection Using Data Augmentation Techniques," 2023 International Conference on Recent Advances in Science and Engineering Technology (ICRASET), B G NAGARA, India, 2023, pp. 1-5, doi:10.1109/ ICRASET.2023.10420361.

[10] Shen, Shuwei, et al. "A low-cost high-performance data augmentation for deep learning-based skin lesion classification." BME frontiers 2022 (2022).

[11] P. Kumar, V. Subathra, Y. Swasthika and V. Vishal, "Disease Diagnosis Using Machine Learning on Electronic Health Records," 2024 International Conference on Communication, Computing and Internet of Things (IC3IoT), Chennai, India, 2024, pp. 1-6,

[12] Atasoy, N. A., & Abdulla Al Rahhawi, A. F. (2024). Analyzing the unbalanced bone marrow cell dataset to assess the classification performance of previously trained capsule networks. *International Journal of Imaging Systems and Technology*, *34*(3), e23067.

[13] Roshni Thanka, M., Bijolin Edwin, E., Ebenezer, V., Martin Sagayam, K., Jayakeshav Reddy, B., Günerhan, H., & Emadifar, H. (2022). A combination of deep transfer learning and ensemble machine learning methods for the categorization of melanoma. Programs and Techniques for Computers *in Biomedicine Update*, *3*, 100103.

[14] M. A. Albahar, "Classifying Skin Lesions With Convolutional Neural Networks and New Regularizers" in IEEE Access, vol. 7, pp. 38306-38313, 2019, doi: 10.1109/ACCESS.2019.2906241.

[15] Maaz Ul Amin, Muhammad Munwar Iqbal, Shakeel Saeed, Noureen Hameed, & Muhammad Javed Iqbal. (2024). Skin Lesion Detection and Classification. Journal of Computing & Biomedical Informatics, 6(02), 47–54.

[16] X. Zhang, Y. Mao, Q. Yang and X. Zhang, "A Method for Classifying Plant Leaf Disease Images by Combining Capsule Network and Residual Network" in *IEEE Access*, vol. 12, pp. 44573-44585, 2024, doi: 10.1109/ACCESS.2024.3377230.

[17] Maqsood, S., & Damaševičius, R. (2023). Deep learning-based feature fusion and selection framework for multiclass skin lesion classification and localization in smart healthcare. *Neural Networks*, *160*, 238-258.

[18] https://www.researchgate.net/publication/388557422_A_PROJECT_REPORT_ENHANCING_SKIN_CANCER_DETECTION_A_COMPARATIVE_ANALYSIS_OF_MACHINE_LEARNING_MODELS_AND_CONVOLUTIONAL_NEURAL_NETWORKS