iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 **Issue:** IV **Month of publication:** April 2025

DOI: https://doi.org/10.22214/ijraset.2025.69585

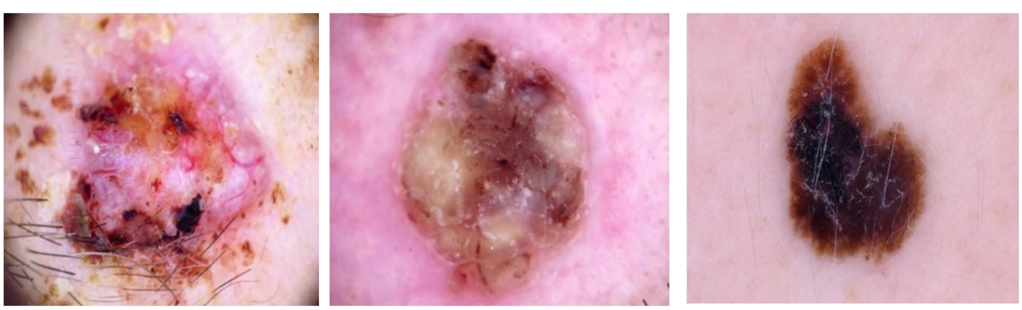
Skin Cancer Detection and Diagnosis Using Deep Learning

Prof. H. R. Khairnar[1], Ankita Chaudhari[2], Omkar Borhade[3], Laxmikant Borse[4], Vaishanavi Kapadi[5]
[1]*Professor, Department of Information Technology, MET's BKC Ioe, Nashik, Maharashtra, India.*
[2, 3, 4, 5]*UG Student, Department of Information Technology, MET's BKC Ioe, Nashik, Maharashtra, India.*

Abstract: Skin cancer, a condition that originates in the skin tissue, can damage surrounding tissues and, in severe cases, lead to disability or even death. Early and accurate diagnosis, coupled with appropriate treatment, plays a crucial role in minimizing its harmful effects. However, diagnosing skin cancer can be challenging for physicians due to the visual similarities between cancerous lesions and benign tumors, often resulting in a time-consuming process. This project focuses on creating an automated system to distinguish between skin cancer and benign tumors using Convolutional Neural Networks (CNNs). The approach introduces a cutting-edge application of deep learning techniques, utilizing CNNs to analyze images of skin lesions uploaded for evaluation. In addition to providing accurate diagnostic support, the system delivers personalized recommendations.
Keywords: Convolutional Neural Network, Deep learning, detection, transfer learning, Skin cancer.

I. INTRODUCTION

Skin cancer is among the most prevalent health issues globally, encompassing various types of cancer that develop in the skin. The incidence of both melanoma and non-melanoma skin cancers has risen significantly in recent years. According to the Skin Cancer Foundation, approximately one in five Americans will be diagnosed with skin cancer during their lifetime.the World Health Organization (WHO) reports that three out of four cancer cases worldwide are related to skin cancer, with increasing prevalence in countries such as the United States, Canada, and Australia. These conditions have a substantial impact on public health worldwide. Individuals with darker skin tones have a 20% to 30% lower likelihood of developing melanoma compared to those with lighter skin; however, they may face varying mortality risks for specific carcinoma types. The three primary types of skin cancer are melanoma, squamous cell carcinoma (SCC), and basal cell carcinoma (BCC).the most significant environmental factor contributing to skin cancer is ultraviolet (UV) radiation from sun exposure. Other contributing factors include aging, fair skin, smoking, HPV infections, genetic predispositions, chronic wounds, and artificial UV radiation. Since untreated skin cancer can be life-threatening, early detection is crucial to improve survival rates.



(a) Basal Cell Carcinoma (BCC) (b) Actinic keratosis (c) Melanoma

Fig.1. Common types of Skin cancer

In recent years, computer vision systems have gained popularity across numerous fields, including medical diagnosis, leather quality inspection, and error detection. These systems, combined with learning algorithms, have significantly advanced disease identification in humans. Convolutional Neural Networks (CNNs) have emerged as a powerful tool in computer vision applications, offering superior predictive capabilities. Fig 1 lists the common forms of skin cancer.

II. LITERATURE SURVEY

This section includes a critical analysis of the relevant literature on academic studies and other resources focused on the identification of skin cancer. The classification in these works basically considers two categories: malignant and benign. Several methods have been proposed with the use of DCNNs and SVMs, which were promising. Very recently, CNNs have gained popularity as tools for the diagnosis of skin cancer. This study uses the Human Against Machine (HAM) 10000 dataset to illustrate the methodology for skin cancer classification. [6]. A dataset consisting of 2,437 training images, 660 test images, and 200 validation images was used for early cancer detection. The deep learning architectures ResNet-101 and Inception-v3 were applied to analyze and classify the images effectively [7]. A dataset consisting of 2,437 training images, 660 test images, and 200 validation images was used for early cancer detection. The deep learning architectures ResNet-101 and Inception-v3 were applied to analyze and classify the images effectively [8]. A GAN was designed for the generation of synthetic images related to skin cancer. This helps to overcome the limitation of training the proposed CNN algorithm with insufficient data. As a result of training the CNN, the best classification accuracy reached around 53%. However, the model had significantly improved and achieved an accuracy of 71% when trained on the original dataset with additional synthetic images included [9]. A GAN was designed for the generation of synthetic images related to skin cancer. This helps to overcome the limitation of training the proposed CNN algorithm with insufficient data. As a result of training the CNN, the best classification accuracy reached around 53%. However, the model had significantly improved and achieved an accuracy of 71% when trained on the original dataset with additional synthetic images included [10]. This paper introduces an automated skin cancer classification system. The system classifies nine different types of skin cancer. In addition, the potential of DCNNs to provide accurate results was also studied. The dataset includes nine clinical categories of skin cancer, which are actinic keratosis, basal cell carcinoma, benign keratosis, dermatofibroma, melanoma, nevus,seborrheic keratosis, squamous cell carcinoma, and vascular lesions [11]. Even though melanoma makes up a relatively small percentage of skin cancer diagnoses in the United States, it is responsible for more than 75% of deaths due to skin cancer. Skin lesion segmentation, driven by machine learning, is one of the most robust techniques for the early detection and effective treatment of skin cancer. In recent years, researchers have been using various architectures of deep networks to perform skin cancer segmentation and diagnosis. [12]. Hybrid detection methods in 2020 were proposed to classify images of skin cancer based on various architectures of deep learning. The used dataset comprised about 3,000 images of patients having some kind of skin disease. Classification of the same into malignant and benign categories was done. The best classification accuracy was found 85.303% with the Exception network out of all the applied models. This approach classifies and can be used to identify the existence or nonexistence of skin cancer in a patient using image processing and deep convolutional neural networks (DCCNs).

III. METHODOLOGY

In this study, we propose a model designed to improve the efficiency of seven types of skin cancer. The framework that takes to take less time compared to the traditional search algorithm that requires a spacious model training. Special types of in -depth architecture, network neural system (CNS), a special in-depth learning architecture, often proceeds for work, such as memorizing images, classification and data processing. Among different types of neurological networks. CNNS is a desired option for memorizing objects and perception, making it perfect for computer-visual applications (CV), such as facial recognition and independent driving systems.

CNN architecture consists of three-digit layer: CONVOLUTION layer, a complete connection and layer. The combined layer plays an important role in separating the most important features of the image while leaving unnecessary information. The types of general integration are the maximum integration, the average group and the total L2 products, with the highest integration as the most commonly used. The highest integration will be divided into small squares and only the maximum maintenance from each region. This technique does not lose too much important information, increasing the calculation efficiency by reducing the number of parameters, reducing the size of the map, features.

Neural networks have three or more layers. And deep learning is a special subset of machine learning. These networks, though, aim to mimic the brain's ability to "learn" from large data sets. But it is still far from the capabilities of the human brain. Single-layer neural networks can infer certain functions. But adding additional hidden layers helps refine predictions and optimize accuracy.

A deep neural network consists of multiple interconnected layers. Each layer improves on the prediction or classification of the previous layer. This process is called forward propagation. It consists of computations that flow through the network. The input layer and output layer contain the visible layers of the deep neural network. The input layer processes the incoming data. while the output layer provides the final classification or prediction. The block diagram of the proposed method is shown in Figure 2.

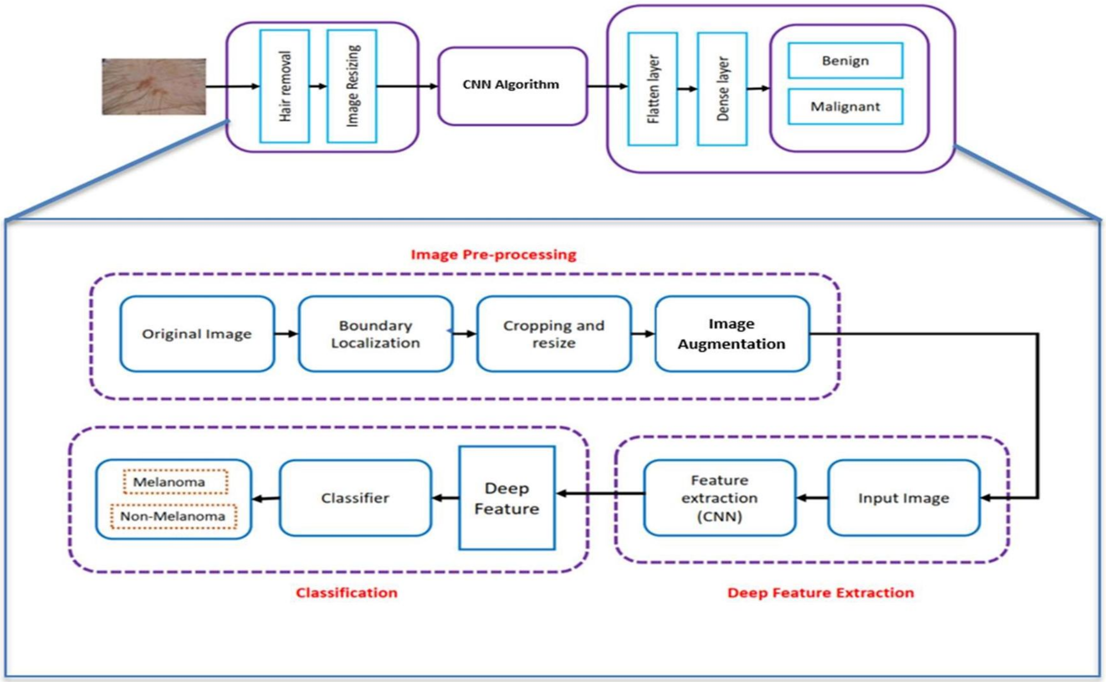


Fig.2 block diagram of the proposed method.

A. Dataset

The International Skin Imaging Collaboration (ISIC) 2018 i.e. (HAM) 10000 has assembled a dataset of 10015 images that include both cancerous and benign conditions. Except for the melanoma mole, which has some prominence in the dataset, all other images are matched according to the classification provided by ISIC in the same number. It is divided into an equal number of images for balanced representation.

The data set contains the following diseases:

- Actinic keratosis
- Basal cell carcinoma
- Dermatofibroma
- Melanoma
- Benign Keratosis-like
- Melanocytic Nevi
- Vascular lesion

B. Pre-Processing

Preprocessing is a significant component that improves the source image quality and the noise levels making the necessary step for this detecting process. The accurate method selection at preprocessing will very much enhance the system's precision. This stage focuses on limiting the backgrounds of an image in order to detect them effectively. The objective is to remove unnecessary and irrelevant background elements to enhance the quality of melanoma images such that the outcome is suitable for further analysis. Techniques like Gaussian smoothing and DullRazor are used to enhance the clarity of the images and eliminate artifacts that might interfere with proper analysis.

C. Gaussian Smoothing for Noise Reduction

The technique applies a Gaussian kernel to the image, which helps suppress high-frequency elements like random noise while preserving the structural details of the lesion.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IV Apr 2025- Available at www.ijraset.com

D. Hair Removal with DullRazor

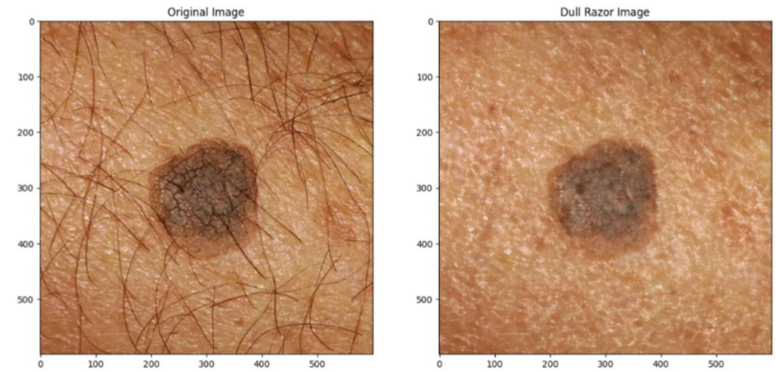


Fig.3. Hair Removal image

Dermoscopic images often contain artifacts like hair and shadows that can mask important information about skin lesions. To overcome this, the DullRazor algorithm is used to remove hair from the images effectively while retaining the relevant features of the lesions, as seen in Fig. 3. Hair regions are detected by edge detection techniques that identify sharp intensity changes. These regions are then replaced by pixel intensities of surrounding pixels using bilinear interpolation to yield a processed image.
The next preprocessing step is data augmentation, which is used to expand the dataset. Data augmentation techniques enhance the dataset by either generating new synthetic data from existing samples or by drastically altering and appending copies of the original data. Fig. 4 depicts some examples of augmented images.

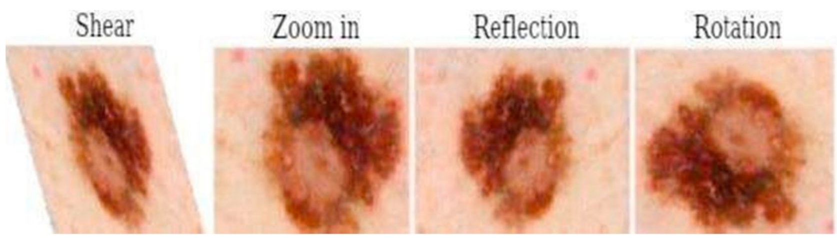


Fig.4. Data Augmentation Representation

E. Deep learning Algorithms

Many AI systems that are designed to perform cognitive and physical tasks without the intervention of human beings rely on deep learning. These systems can be trained with large volumes of diverse datasets, which would improve the accuracy and reliability of the information gathered. According to research in skin cancer diagnosis, employing deep learning would significantly enhance early detection and outcomes in treatment. In this study, one of the most universally recommended deep learning architectures for identification and classification tasks will be employed, the CNNs.

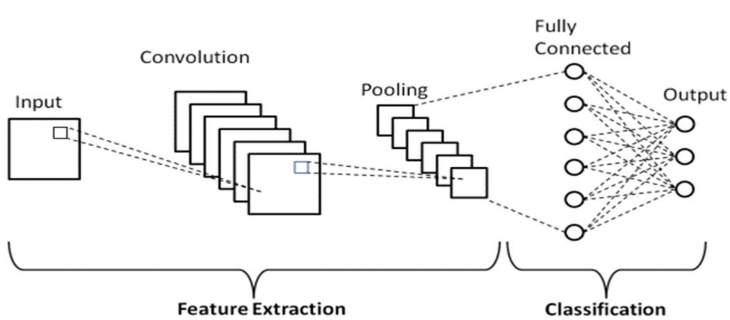


Fig.5. Flowchart of CNN Mechanism

Figure 5 depicts the flow of the CNN mechanism applied for detecting and categorizing skin cancer. A CNN consists of three primary layers: the convolutional layer, the pooling layer, and the fully connected (FC) layer. The convolutional layer is the first stage, responsible for feature extraction, while the FC layer serves as the final stage, providing classification outputs. This increases with the progress from the convolutional layer to the FC layer because it's really complex to provide detailed analysis and predictions.

1) Convolutional Layer*:* The convolutional layer, which is the core component of a CNN, performs most of the computations. There may also be additional convolutional layers following the initial one. In this process, a kernel or filter moves across the image's receptive fields to identify the presence or absence of specific features.
2) Pooling Layer: Like the convolutional layer, the pooling layer applies a kernel or filter to the input image. The pooling layer contains fewer input parameters than the convolutional.
3) Fully Connected Layer: The fully connected (FC) layer in a CNN is responsible for classifying images using the features extracted by the preceding layers. The term "fully connected" means that every node or unit in the previous layer is linked to every node in the next layer.

F. ResNet-101 Architecture

In our proposed methodology, we employ the ResNet-101 (Residual Network) architecture as the backbone of our deep learning model. ResNet-101 is a 101-layer convolutional neural network that introduces residual learning through skip connections, effectively mitigating the vanishing gradient problem often encountered in deep networks. These identity mappings allow the network to learn residual functions with reference to the layer inputs, which accelerates the convergence and improves classification performance.

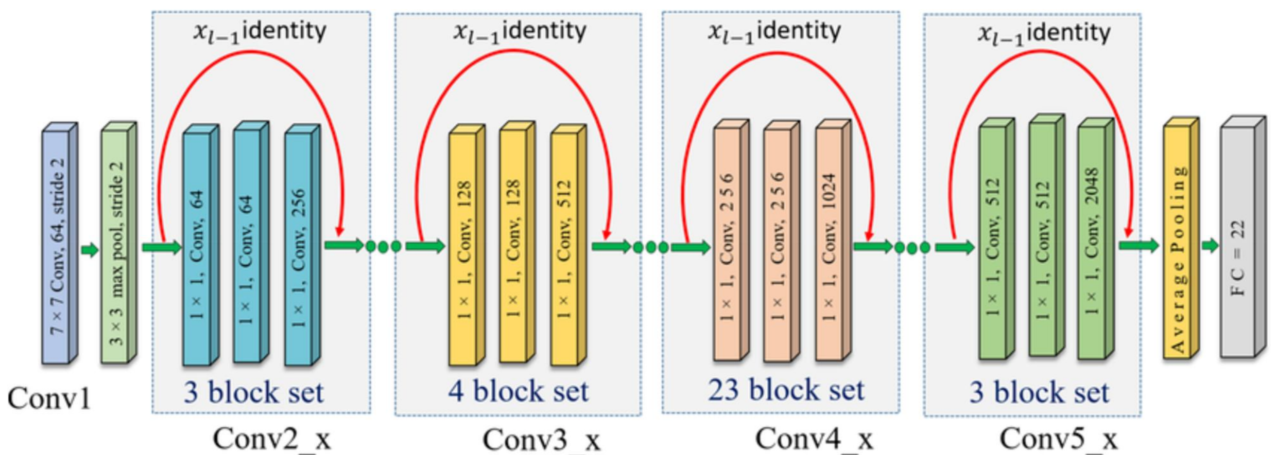


Fig.6.ResNet-101

The ResNet-101 model is pre-trained on the ImageNet dataset, and we apply transfer learning by fine-tuning its weights on our skin cancer dataset. This approach not only reduces training time but also improves performance due to the network's ability to leverage pre-learned low-level and high-level image features. The model processes dermatoscopic images and extracts deep features which are essential for distinguishing between benign and malignant lesions.

G. Integration of Soft Attention Mechanism

To further enhance the model's focus on the most diagnostically relevant areas of the input images, we integrate a Soft Attention mechanism within the architecture. Soft Attention works by assigning continuous-valued weights (attention scores) to different parts of the feature maps extracted by ResNet-101. These weights are learned during training, enabling the network to concentrate more on important regions (such as lesion boundaries, asymmetry, or color variation) while suppressing irrelevant background information.

The Soft Attention module is embedded into the intermediate feature extraction layers. It generates a weighted combination of features by computing a compatibility score between feature vectors and a learnable attention context. This allows the model to adaptively highlight regions that are more informative for classification.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IV Apr 2025- Available at www.ijraset.com

H. Skin Detection Using the YCbCr Color Space Model

A color model that describes skin pixels in images is the YCbCr color space. Since luminance is subtracted from chrominance, it makes it much less sensitive to variation due to illumination compared to the RGB color model.

The method involves converting each pixel from RGB to YCbCr using the following formulas:

$$Y = 0.299 \cdot R + 0.587 \cdot G + 0.114 \cdot B$$

$$Cb = 128 - 0.168736 \cdot R - 0.331264 \cdot G + 0.5 \cdot B$$

$$Cr = 128 + 0.5 \cdot R - 0.418688 \cdot G - 0.081312 \cdot B$$

Once converted, pixels are classified as skin if their values fall within predefined thresholds:

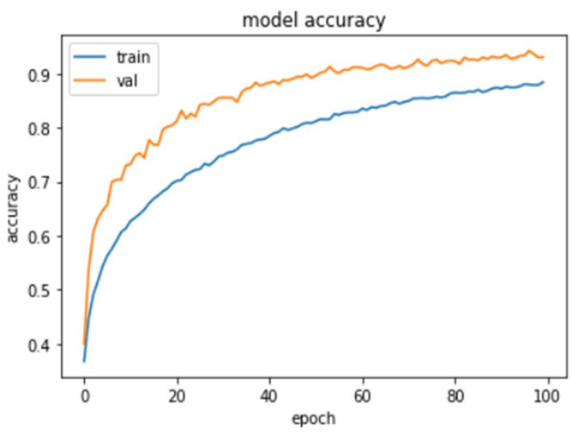
$$Y\ (Luminance): 80 \leq Y \leq 240$$

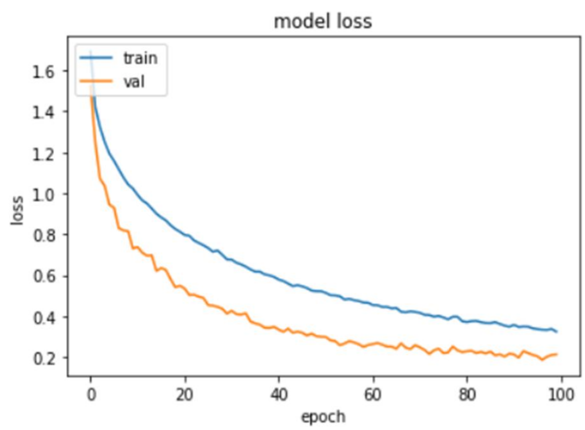
$$Cb\ (Chrominance): 85 \leq Cb \leq 135$$

$$Cr\ (Chrominance): 135 \leq Cr \leq 180$$

These thresholds, derived from empirical research, cover a broad range of skin tones, making the method suitable for diverse populations. This robust initial step ensures that only the relevant skin regions are analyzed, reducing the computational complexity and improving the reliability of downstream processes such as lesion segmentation and classification.

IV. MODELING AND ANALYSIS

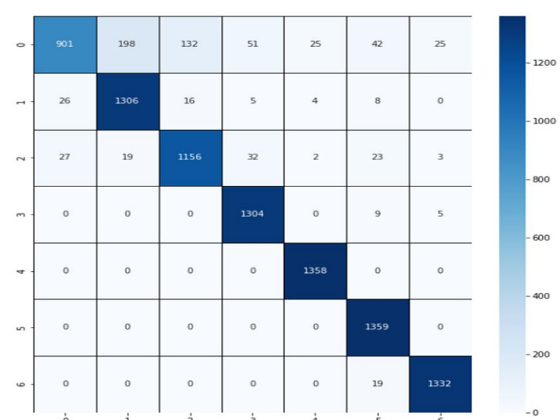




V. RESULTS AND DISCUSSION

Classification Report:

	precision	recall	f1-score	support
0	0.93	1.00	0.96	1359
1	0.94	0.99	0.96	1318
2	0.89	0.92	0.90	1262
3	0.98	0.99	0.98	1351
4	0.94	0.66	0.77	1374
5	0.98	1.00	0.99	1358
6	0.86	0.96	0.90	1365
accuracy			0.93	9387
macro avg	0.93	0.93	0.93	9387
weighted avg	0.93	0.93	0.92	9387

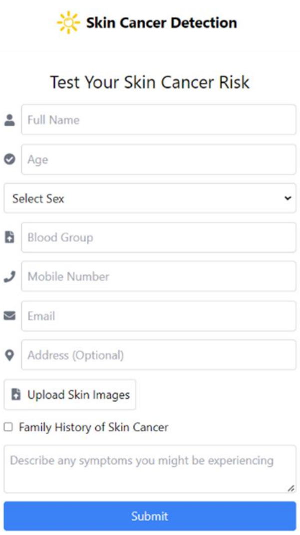


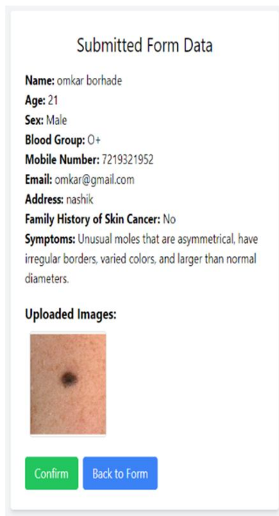
The proposed deep learning model demonstrated robust performance in detecting and classifying various types of skin lesions, achieving an overall **accuracy above 90%**. **Confusion matrix** representing the classification performance of your model across seven classes of skin lesions. The diagonal entries (e.g., 901, 1306, etc.) indicate correctly classified samples for each class, while off-diagonal entries represent misclassifications Precision, recall, and F1-scores were calculated for nine classes, with vascular lesions and dermatofibroma achieving the highest F1-scores of 1.00 and 0.99, respectively. Squamous cell carcinoma and basal cell

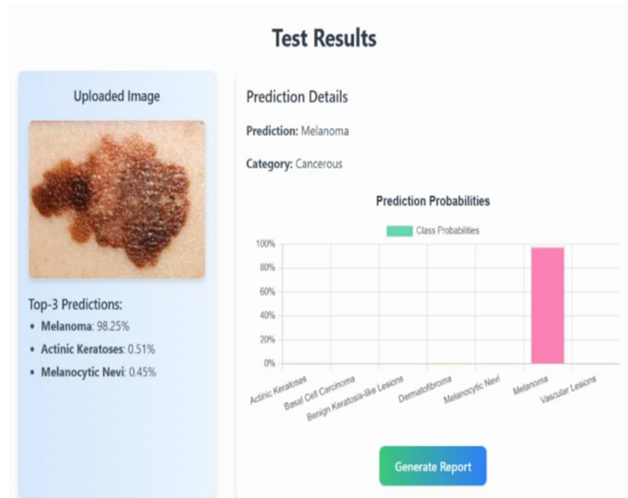
International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IV Apr 2025- Available at www.ijraset.com

carcinoma also showed high precision and recall values above 0.95. However, the model exhibited comparatively lower performance for melanoma, with an F1-score of 0.76, highlighting the need for further improvements in distinguishing this class. The results suggest that the model is effective for skin cancer detection, with potential for clinical application.

VI. USER INTERFACE







VII. LIMITATIONS

While our study has made notable advancements, certain limitations must be acknowledged. Although data augmentation helps increase the diversity of training samples, it may inadvertently cause the model to favor specific augmentation techniques. Another challenge lies in obtaining a well-balanced and diverse dataset, which can affect the model's accuracy in detecting rare or atypical skin lesions. Additionally, the imbalance in the number of images across different classes makes classification more difficult, as the model may struggle to generalize effectively for underrepresented categories. Furthermore, limited access to high-performance GPUs and computational resources presents challenges in efficiently training and fine-tuning deep learning models.

VIII. CONCLUSION

In conclusion, the AI-powered skin cancer detection project represents a groundbreaking advancement in the field of dermatology, offering the potential to revolutionize the way we identify and address this critical healthcare challenge. By harnessing deep learning and image analysis technologies, the system enables early and accurate detection up to accuracy above 90%, reducing diagnostic delays, and improving patient outcomes. Its contribution to enhanced healthcare standards, alongside the generation of data-driven insights for public health, underscores the transformative impact such innovations can have on healthcare. This project not only signifies a pivotal step towards more effective skin cancer diagnosis but also highlights the broader potential of AI in transforming medical practices and improving healthcare delivery

REFERENCES

[1] Priyanka, S., Kavitha, C. and Kumar, M.P.: Deep Learning based Approach for Prediction of Diabetes. In 2023 2nd International Conference for Innovation in Technology (INOCON). IEEE. pp. 1-6. (2023).

[2] Moganam, P.K. and Sathia Seelan, D.A.: Deep learning and machine learning neural network approaches for multi class leather texture defect classification and segmentation. Journal of Leather Science and Engineering, 4(1), p.7. (2022).

[3] Kavitha, C. and Ashok, S.D.: A new approach to spindle radial error evaluation using a machine vision system. Metrology and Measurement Systems, 24(1), 201-219. (2017).

[4] Priyanka, S., Diego Oliva., Kethepalli Mallikarjuna., and M. S. Sudhakar. : l-shaped geometry-based pattern descriptor serving shape retrieval. Expert Systems with Applications, 213. (2023).

[5] Priyanka, S. and Sudhakar. M.S.: Lightweight Spatial Geometric Models Assisting Shape Description and Retrieval. In Computational Intelligence Methods for Super-Resolution in Image Processing Applications. Cham: Springer International Publishing. pp. 209-230. 2021.

[6] Aburaed, N., Panthakkan, A., Al-Saad, M., Amin, S.A. and Mansoor, W., 2020, November. Deep convolutional neural network (DCNN) for skin cancer classification. In 2020 27th IEEE International Conference on Electronics, Circuits and Systems (ICECS) (pp. 1-4). IEEE.
[7] Demir, A., Yilmaz, F. and Kose, O., 2019, October. Early detection of skin cancer using deep learning architectures: resnet-101 and inceptionv3. In 2019 medical technologies congress (TIPTEKNO) (pp. 1-4). IEEE.
[8] Kondaveeti, H.K. and Edupuganti, P., 2020, December. Skin cancer classification using transfer learning. In 2020 IEEE International Conference on Advent Trends in Multidisciplinary Research and Innovation (ICATMRI) (pp. 1-4). IEEE.
[9] Sedigh, P., Sadeghian, R. and Masouleh, M.T., 2019, November. Generating synthetic medical images by using GAN to improve CNN performance in skin cancer classification. In 2019 7th International Conference on Robotics and Mechatronics (ICRoM) (pp. 497-502). IEEE.
[10] Pacheco, A.G. and Krohling, R.A., 2021. An attention-based mechanism to combine images and metadata in deep learning models applied to skin cancer classification. IEEE journal of biomedical and health informatics, 25(9), pp.3554-3563.
[11] Rezaoana, N., Hossain, M.S. and Andersson, K., 2020, December. Detection and classification of skin cancer by using a parallel CNN model.
[12] In 2020 IEEE International Women in Engineering (WIE) Conference on Electrical and Computer Engineering (WIECON-ECE) (pp. 380386). IEEE.
[13] Diame, Z.E., Al-Berry, M.N., Salem, M.A.M. and Roushdy, M., 2021, May. Deep learning architectures for aided melanoma skin disease recognition: a review. In 2021 International Mobile, Intelligent, and Ubiquitous Computing Conference (MIUCC) (pp. 324-329). IEEE.
[14] Hasan, H.A. and Ibrahim, A.A., 2020, October. Hybrid detection techniques for skin cancer images. In 2020 4th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT) (pp. 1-8). IEEE.