Diagnostic Analysis Of Skin Disease Using Deep Learning

Sonam Sirohi
Department of Electronics and Communication Engineering
Galgotia University,
[#]Greater Noida Institute of Technology,
Greater Noida, U.P., India
sonamsirohi.2012@gmail.com

Dipak Kumar Ghosh
Department of Electrical, Electronics and Communications,
Galgotias University,
Greater Noida, U.P., India
dipakkumar05.ghosh@gmail.com

Usha Chauhan
Department of Electrical, Electronics and Communications,
Galgotias University,
Greater Noida, U.P., India
usha.chauhan@galgotiasuniversity.edu.in

Anil Kumar Dubey
Department of Electronics and Communication Engineering
Greater Noida Institute of Technology,
Greater Noida, U.P., India
anilkumardubey10@gmail.com

2025 3rd International Conference on Disruptive Technologies (ICDT) | 979-8-3315-1958-2/25/$31.00 ©2025 IEEE | DOI: 10.1109/ICDT63985.2025.10986683

Abstract- **Skin diseases are common disease mostly ignored but sometimes it becomes dangerous for human being. Ignoring this is not a good sign, but most of the time it's normal to see any skin disease on human body, and its color shows the depth of the seriousness. So it is clear that the image of the skin is the core factor of diagnosis of the disease related with it.Technologies of image processing based on machine learning and ANN provide optimum approaches to find the skin disease which will help in diagnosis of the disease. Over decades of research, edge detection techniques have evolved from simple gradient-based methods to sophisticated deep learning approaches. In this paper edge detection techniques are used to diagnosis of skin disease by finding the color difference of skin from neighboring body cell and comparing it by using machine learning algorithmsand the performances are evaluated on HAM10000 skin cancer dataset. Different machine learning algorithms are used for finding the best image analysis tool for skin disease detection in medical field.**

Keywords - Classifier, CNN-Convolution neural network, Confusion Matrix, DNN-Deep neural network, DL-Deep Learning.

I. INTRODUCTION

As our body outer-cells combines to form the skin, so it is the widest part of human being. Skin color shows the effect of environmental variation and also effect of some internal disease. Proper analysis is required to get exact or approximate idea about the reason. Some of the skin behaviors analysis are-

1) Normal temperature affected red patches due to Sun stroke or too cold temperature;

2) Rashes due to etching fungal infection;

3) Mosquitoes or insect biting;

4) Accidental traces on skin;

5) Cancer cell; etc.

In most cases, it is very easy to ignore, but if it reflects cancer cells, a diagnosis is essential. Different analytical tools are available to achieve the best results from the diagnosis that the effects shown on the skin are normal or cancer cell effects. In the field of image processing, edge detection is a very important fundamental technique, more important than many different applications. At its core, edge recognition serves as a critical step to identify photo boundaries and contours, and is important information for subsequent tasks such as object recognition, image recording, image resolution, image understanding, image segmentation, etc. Provides. By separating areas of sudden changes in intensity, edges cover important visual information, allowing computers to interpret and analyze digital images with human accuracy. The journey of edge recognition technology has been extended for decades, characterized by rich wall carpets from innovation, experimentation and refinement. From the modest beginnings from classical methods to the emergence of highly developed learning approaches, the development of edge recognition reflects the broader trajectory of computer imaging. Understanding this historical advance not only reveals the ingenuity of past pioneers, but also reveals the fundamental principles and challenges that have shaped the image processing landscape. By pursuing a descent from the origins of these technologies to modern methods, we want to disguise the complex innovation threads that have promoted the field. It seeks to convey the differentiated understanding of historical light empts to readers through pioneering contributions, important advancements and paradigm shifts. Conventional edge detection methods , such as the Canny edge detector, Sobel operator, and Prewitt operator relay on mathematical operations and predetermined kernels. The Canny edge detector developed in 1986, became a benchmark for edge recognition using a multi-stage algorithm [1]. In 1963, Roberts introduced one of the earliest edge recognition algorithms, using several folding cores to estimate gradients along diagonal directions [2]. The Sobel operator proposed by Sobel and 1968 proposed that Feldman improve the accuracy of edge recognition by destroying images with the kernel in order to calculate horizontal and vertical gradients [3]. Prewitt operator in 1970, uses convolution, but with particular 3x3 kernels, to compute gradients along both horizontal and vertical axis, much like the Roberts operator does [4]. The image is convolved using a Gaussian kernel as the initial step in the LoG process. By minimizing noise and emphasizing regions with notable variations in intensity, Gaussian smoothning successfully draws attention to possible edges. In 1980, Gaussian smooth Gaussian smooth to recognize Gaussian operator Laplace and edges was explained by the localization of zero-crossing in the second derivation of the image by Marr and Hildreth [5]. Zero cross-edge recognition

Authorized licensed use limited to: UNIVERSITE DE SOUSSE. Downloaded on January 02,2026 at 14:48:47 UTC from IEEE Xplore. Restrictions apply.

provided accurate edge localization by identifying zero crossings in the second derivation of image intensity [6]. Cherry and Freecia operators provided directional sensitivity to edge recognition and improved performance when recognizing edges in several directions [7].

Modern edge recognition techniques use augmented calculation methods and machine learning. The ability to learn hierarchical properties from raw pixel data has made folding networks a highly effective tool for edge identification. CNN-based edge recognition methods such as U-Net and Edgenet achieve excellent performance in edge detection accuracy and robustness [8]. Deep learning-based methods such as capsules and residual networks provide alternative approaches for edge recognition, the use of deep architectures, and learning mechanisms [9]. A powerful and effective solution is generated by optimization algorithms that optimize edge cards or edge recognition parameters such as particle swarms and genetic algorithm optimization [10]. The hybrid approach combines traditional and learning based technologies, balance accuracy, robustness and computational efficiency [11].

II. DIAGNOSIS USING ADVANCE TECHNOLOGIES

Diagnosis of skin diseases is an important field of medical image analysis, and image processing techniques are increasingly being used to improve the accuracy of diagnosis. In these techniques, edge recognition plays a central role in identifying affected areas by distinguishing between disease and healthy skin color. Various edge detection techniques were used to detect irregularities in skin textures. In this study, we proposed a successful segmentation technique combining canny edge detector, two-sided filtering, spline interpolation, polynomial modeling and morphological processes. [12].

Algorithms for machine learning will further improve this process through the classification of skin diseases based on extracted properties. The integration of machine learning and image processing technology has significantly improved the classification of skin diseases. The folding network (CNNS) was examined in detail for its excellent ability to learn hierarchical properties from medical images [13].

Support Vector Machines have also been employed for classification tasks, showing effectiveness in distinguishing between benign and malignant lesions [14]. This section reviews the relevant literature on edge detection methods, machine learning approaches, and their application in skin disease diagnosis.

According to a comparative investigation, deep learning techniques perform better than conventional machine learning classifiers because they can identify intricate patterns in medical images [15]. However, hybrid models combining edge detection with machine learning, such as CNN-SVM models, have been explored to balance computational efficiency and classification accuracy [16].

For detail analysis of skin cancer, it can be broadly categorized in two parts:

1) Melanoma skin cancer
2) Non- Melanoma skin cancer

a) Melanoma: Images of Melanoma are shown in figure 1. Most dangerous type of skin cancer, usually appear on upper layer of skin and then goes to the dipper layer of skin [17].

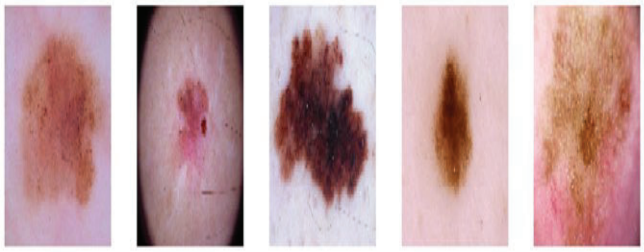

Fig. 1 Melanoma

b) Non-Melanoma - Skin cancer, basal cell carcinoma, squamous cell carcinoma, and the relatively unanticipated malignant melanoma are among the various types of carcinoma. Carcinoma is currently recognized as the most deadly type of cancer in humans [18]. Basal cell carcinoma and squamous cell carcinoma are shown in figure 2.

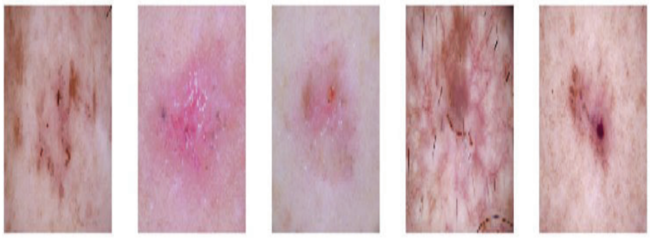

Fig. 2 Non-Melanoma

Diagnostic analysis of cancer cells using modern tools includes several steps of image processing. CAD is a commonly used procedure that provides far higher accuracy than dermatologists' intrusive method. The CAD system provides a mechanism for infection probability estimation and skin disease recognition. The steps used for diagnosis are shown in figure 3.

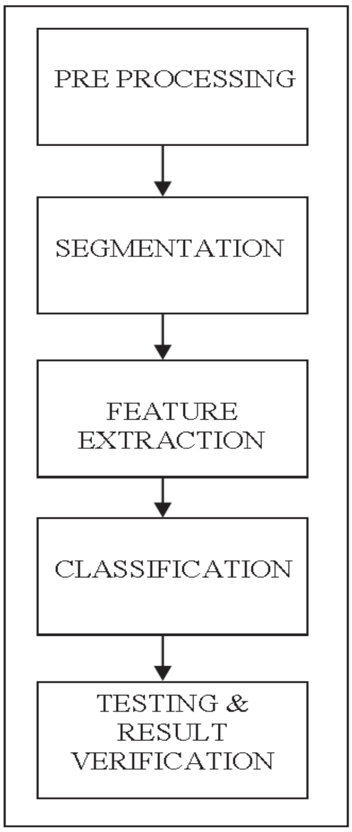

Fig. 3 Steps in Detection using CAD Tools

Authorized licensed use limited to: UNIVERSITE DE SOUSSE. Downloaded on January 02,2026 at 14:48:47 UTC from IEEE Xplore. Restrictions apply.

Deep architectures such as Convolutional Neural Networks are capable of automatically identifying hierarchical aspects that human specialists might miss. However, these algorithms can be difficult to detect skin cancer because they need a lot of labelled data to train [19]. Steps used in detection of skin disease using ANN are shown in figure 4.

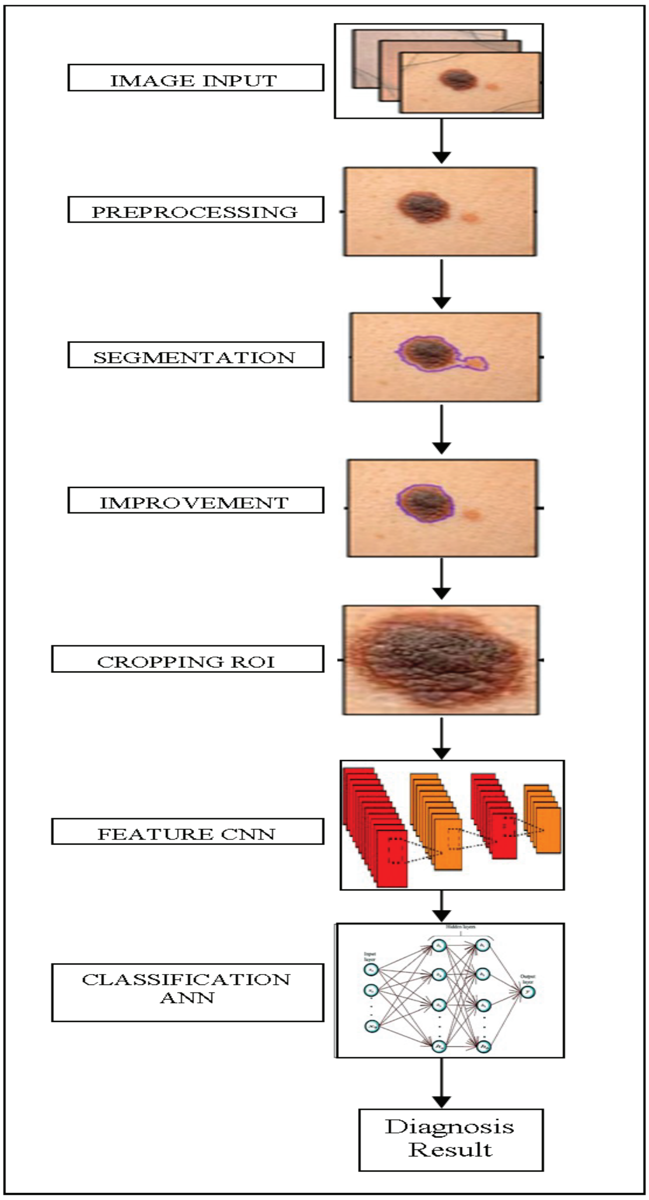

Fig. 4 Skin disease diagnosis using ANN

III. Deep Learning Methods For Skin Disease Detection

Deep learning can manage challenging and complex jobs with a lot of data when conventional machine learning methods don't work. Deep learning methods are shown in figure 5.

Deep convolutional neural network (CNN) have following structure:

1) Input Layer:
The input shape is (150, 150, 3), which corresponds to RGB images of size 150x150.

2) Convolutional Blocks:
Each block includes one or more convolutional layers (Conv2D), followed by batch normalization (BatchNormalization), a non-linear activation function (LeakyReLU), max pooling (MaxPooling2D), and dropout (Dropout).

The padding='same' ensures that the spatial dimensions remain consistent after convolution.

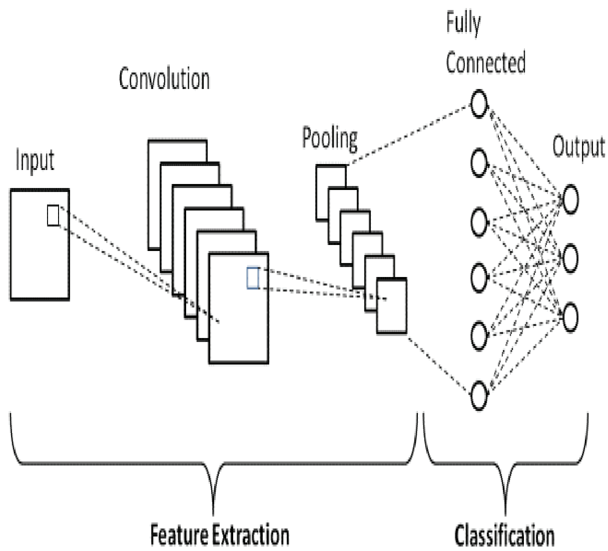

Fig. 5 Deep learning methods for skin disease detection

3) Feature Extraction:
The network progressively increases the number of filters (32, 64, 128, 256) and reduces the spatial dimensions using max pooling.

4) Fully Connected Layers:
After the convolutional layers, the features are flattened using Flatten and passed through two dense layers (512 and 256 units).

Each dense layer is followed by batch normalization, LeakyReLU, and dropout.

5) Output Layer:
The final dense layer uses a softmax activation function to produce probabilities for len(encoder.classes_) classes.

Steps involved in skin disease detection using deep learning methods are:

A. Step 1: Classifier used for detection:

Classifier details involved in the analysis depends on the types of the skin illness. Acne, psoriasis, melanoma, and rosacea are the four kinds of skin illnesses that a Support Vector Machine classifier can identify with 89% accuracy [20].Steps to Build an SVM Classifier are highly influenced by the segmentation of the skin lesion [21].

B. Step 2: Data Collection:

The collection of image samples is the initial step of building the model. At the input images quality is directly related with the trained classification accuracy percentage.Obtain a labeled dataset containing images of the four skin diseases.

Authorized licensed use limited to: UNIVERSITE DE SOUSSE. Downloaded on January 02,2026 at 14:48:47 UTC from IEEE Xplore. Restrictions apply.

C. Step 3: Data Preprocessing:

In medical field the images data model have different steps- The initialworking step is preprocess and the Preprocessing of the images includes resizing, normalization, and possibly augmenting the dataset.

Comparison analysis is performed for utilizing common benchmark datasets to assess the effectiveness of historically nested edge detection methods [22] shown in Table 1. To evaluate each method's accuracy and robustness, evaluation criteria like precision, recall, and F1-score were used.Analysis provides insights into the strengths and limitations of different techniques across various images.

TABLE I. PERFORMANCE COMPARISON OF CLASSICAL AND LEARNING BASED EDGE DETECTION TECHNIQUES

Technique	Precision	Recall	F1-score	Computational Efficiency
Canny Edge Detector	0.85	0.82	0.83	High
Sobel Operator	0.78	0.75	0.76	Moderate
Prewitt Operator	0.77	0.73	0.75	Moderate
CNN-based Methods	0.9	0.88	0.89	Very High
Deep Learning-Based	0.88	0.86	0.87	High

D. Step 4: Feature Extraction:

Extract features from the images. This can be done using techniques like Histogram of Oriented Gradients (HOG), Color Histograms, or deep learning features using a pre-trained CNN [23].

E. Step 5: Dataset Splitting:

After preprocessing, the next step is the model training phase. In this step the pre-processed images are feed into the deep learning models. The model learns to differentiate and categorizes various types of skin lesions based on the features extracted from the images.

F. Step 6: Model Training:

The model is trained using a variety of hyper-parameters in this step, and its performance is tracked using a number of matrices, including accuracy, recall, precision, and F1 score.

G. Step 7: Model Evaluation:

At this step, the trained models' performances are assessed using a different set of photos that weren't part of the training dataset. To determine whether the model can generalize its capacity to correctly categorize fresh, unseen images, this phase is essential.

IV. Result

Model validations of the sampled input data are performed on studies are carried out on publically available skin cancer dataset HAM10000 records [24]. The comparative performances of machine learning and other methods are tabulated in Table 1. Model training and validation loss comparison is shown in figure 6 of the inputs sample data.

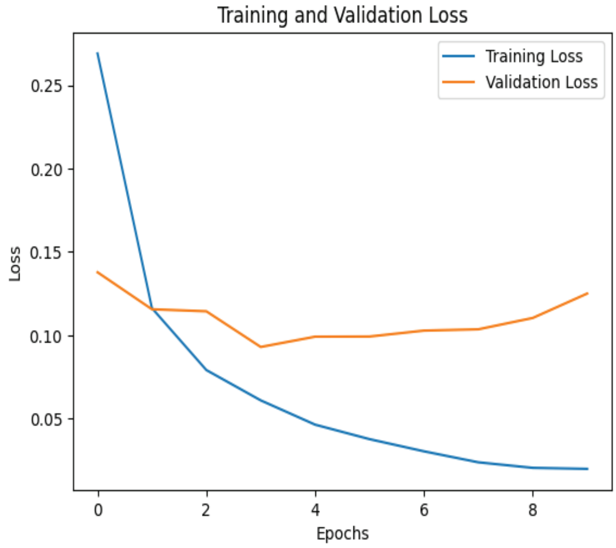

Fig. 6 Loss Comparison graph

Complete analysis of the skin images model are presented in this paper taking especially focus on the skin diseases and are analyzed in detailed way with multiple data. Different Classical and Learning based Edge Detection Techniques are analyzed and it is evaluated that CNN based edge detectors are best and can be used in medical field for proper diagnostic analysis of skin diseases. The confusion matrix is shown in figure 7.

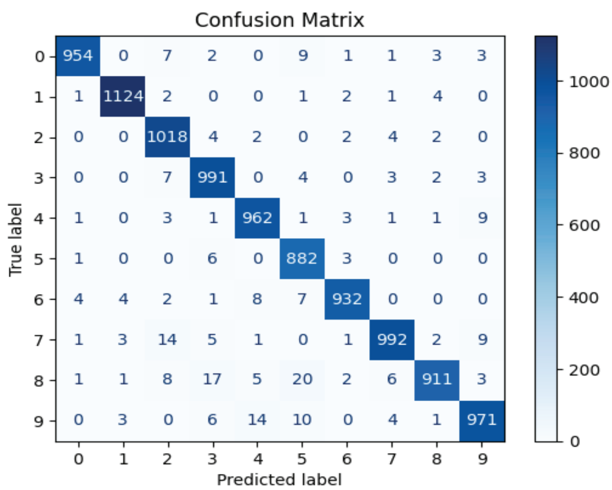

Fig. 7 Confusion Matrix

The complete analysis makes a clear understanding of CNNs and its application in near future medical diagnosis.Despite advancements, challenges remain in ensuring the reliability and generalizing of skin disease detection models. Factors such as variations in lighting conditions, skin tone diversity, and dataset biases impact model performance. Future research should focus on developing robust feature extraction techniques and leveraging multi-modal imaging approaches to improve diagnostic precision. Additionally, the incorporation of explainable AI (XAI) methods could enhance the

Authorized licensed use limited to: UNIVERSITE DE SOUSSE. Downloaded on January 02,2026 at 14:48:47 UTC from IEEE Xplore. Restrictions apply.

interpretability of machine learning models in clinical applications.

V. Conclusion

Recent advances in computer vision technology and the growing need for reliable image processing algorithms have resulted in the prominent development of historical nesting of edge intensity detection. The basis of later development was determined by traditional approaches such as Canny, Sobel, and Robert, leading to progressive techniques for machine learning and deep learning techniques. Through empirical reviews and comparative studies are carried out on publically available skin cancer dataset HAM10000 records, we identified the effectiveness and compatibility of historically nested approaches. Promising results have been observed when edge recognition methods and algorithms for machine learning are applied to the diagnosis of skin diseases. If we are looking for a more effective and more accurate algorithm, edge recognition promises additional improvements and breakthroughs. Diagnosis of skin diseases has been significantly improved by a combination of edge recognition methods and machine learning algorithms. These techniques improve the specific accuracy and effectiveness of disease by comparing the colour of affected skin areas with nearby healthy tissues.

References

[1] J. Canny, “A Computational Approach to Edge Detection”, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. PAMI-8, no. 6, pp. 679-698, Nov. 1986, doi: 10.1109/TPAMI.1986.4767851.

[2] L. Roberts, “Machine perception of three-dimensional solids”, Optical and Electro-optical Information Processing, 1963, pp. 159-194.

[3] I. Sobel andG. Feldman, “A 3x3 isotropic gradient operator for image processing”, Stanford Artificial Intelligence Project Memo AIM-160, 1968.

[4] J. M. S. Prewitt, “Object enhancement and extraction”, Picture Processing and Psychopictorics, B. Lipkin and A. Rosenfeld, Eds., New York: Academic Press, 1970, pp. 75-149.

[5] D. Marr and E. Hildreth, “Theory of edge detection”, Proceedings of the Royal Society of London. Series B. Biological Sciences, 1980, 207(1167), 187-217.

[6] R. Deriche and G. Giraudon, “A computational approach for corner and vertex detection”, International Journal of Computer Vision, 1990, 7(3), pp.111-151.

[7] R. A. Kirsch,“Computer determination of the constituent structure of biological images”, Computers and Biomedical Research, 1971, 4(3), pp.315-328.

[8] O. Ronneberger, P. Fischer and T. Brox, “U-net: Convolutional networks for biomedical image segmentation”, International Conference on Medical Image Computing and Computer-Assisted Intervention, 2015, pp. 234-241.

[9] S. Sabour, N.Frosst, andG. E. Hinton, “Dynamic routing between capsules”, Advances in Neural Information Processing Systems,2017, 30, 3856-3866.

[10] D. E. Goldberg, “Genetic algorithms in search, optimization, and machine learning”,1989, Addison-Wesley.

[11] ChenyangXu and J. L. Prince, “Snakes, shapes, and gradient vector flow”, IEEE Transactions on Image Processing, vol. 7, no. 3, pp. 359-369, March 1998, doi: 10.1109/83.661186.

[12] A. A. A. Al-abayechi and F. S. Abu-Almash, “Skin Lesion Border Detection Based on Best Statistical Model Using Optimal Colour Channel”, Journal of Autonomous Intelligence, 3(1), pp.18-26, 2020, DOI: https://doi.org/10.32629/jai.v3i1.131

[13] A. Esteva, B. Kuprel, R. Novoa et al., “Dermatologist-level classification of skin cancer with deep neural networks”, Nature 542, no. 7639, pp. 115–118, 2017, https://doi.org/10.1038/nature21056

[14] P. Kaur and R. Singh, "Hybrid deep learning model for diagnosing skin cancer", Biomedical Signal Processing and Control, vol. 49, pp. 124–135, 2019.

[15] C. Ou, S. Zhou, R. Yang, W. Jiang, H. He, W. Gan, W. Chen, X. Qin, W. Luo, X. Pi and J. Li, “A deep learning based multimodal fusion model for skin lesion diagnosis using smartphone collected clinical images and metadata”, 2022, Front. Surg. 9:1029991. doi: 10.3389/fsurg.2022.1029991

[16] V. Patel, M. Shah and U. Joshi, “Proposing a Hybrid Technique of Feature Fusion and Convolutional Neural Network for Skin Cancer Detection”, Journal of Healthcare Engineering, 2023, 10630642, doi:10.1155/2023/10630642.

[17] A. Javaid, M. Sadiq and F. Akram, “Skin Cancer Classification Using Image Processing and Machine Learning”, International Bhurban Conference on Applied Sciences and Technologies (IBCAST), Islamabad, Pakistan, 2021, pp. 439-444, doi: 10.1109/IBCAST51254.2021.9393198.

[18] L. G. Rajulu, P. Madan, N. Varshney, D. Yadav, A. K. Set and A. Thakur, “Early Stage Skin Cancer Detection Using Image Processing”,3rd International Conference on Pervasive Computing and Social Networking (ICPCSN), Salem, India, 2023, pp. 744-749, doi: 10.1109/ICPCSN58827.2023.00128.

[19] M. A. Ali, M. Khan and K. I. Sherwani, “Early Skin Cancer Detection Using Deep Learning”, 3rd International Conference on Smart Generation Computing, Communication and Networking (SMART GENCON), Bangalore, India, 2023, pp. 1-6, doi: 10.1109/SMARTGENCON60755.2023.10442168.

[20] R. S. Kumar, A. Singh, S. Srinath, N. K. Thomas and V. Arasu, “Skin Cancer Detection using Deep Learning”, International Conference on Electronics and Renewable Systems (ICEARS), Tuticorin, India, 2022, pp. 1724-1730, doi: 10.1109/ICEARS53579.2022.9751826.

[21] D. Hemalatha, K. N. Latha and P. M. Latha, “Skin Cancer Detection Using Deep Learning Technique”, 2nd International Conference for Innovation in Technology (INOCON), Bangalore, India, 2023, pp. 1-5, doi: 10.1109/INOCON57975.2023.10101344.

[22] T. Le and Y. Duan, “REDN: A Recursive Encoder-Decoder Network for Edge Detection”, IEEE Access, vol. 8, pp. 90153-90164, 2020, doi: 10.1109/ACCESS.2020.2994160.

[23] F. Chollet, “Xception: Deep Learning with Depthwise Separable Convolutions”, IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA, 2017, pp. 1800-1807, doi: 10.1109/CVPR.2017.195.

[24] https://gts.ai/dataset-download/skin-cancer-ham10000/

Authorized licensed use limited to: UNIVERSITE DE SOUSSE. Downloaded on January 02,2026 at 14:48:47 UTC from IEEE Xplore. Restrictions apply.