Journal of Medical and Health Studies (JMHS)
ISSN: 2710-1452
DOI: 10.32996/jmhs
Journal Homepage: www.al-kindipublisher.com/index.php/jmhs

JMHS
AL-KINDI CENTER FOR RESEARCH AND DEVELOPMENT

| RESEARCH ARTICLE

AI-Driven Early Detection of Skin Cancer in the USA: A Hybrid Image Processing and Neural Network Approach

Md Mehedi Hasan[1], Oishee Ghosh [2], Ahmed Tamim Zabir Prince [3], Dipta Paul[4]✉, Gobinda Goswamee[5], Akash Roy[6], Atunu Saha[7], Shakil Sharker[8]

[1234] Department of Electrical and Electronic Engineering, American International University-Bangladesh (AIUB), Dhaka, Bangladesh.
[567] Department of Computer Science Engineering, American International University-Bangladesh (AIUB), Dhaka, Bangladesh.
[8] Department of Electrical and Electronic Engineering, University of Asia Pacific, Dhaka, Bangladesh.
Corresponding Author: Dipta Paul, **E-mail**: diptapal4@gmail.com

| ABSTRACT

Skin cancer remains the most prevalent form of cancer in the United States, with melanoma posing a serious public health concern due to its potential to become life-threatening if not detected early. However, early-stage skin cancer is highly treatable and timely accurate diagnosis is crucial for improving patient survival rates. In response to the growing demand for accessible and rapid diagnostic tools, this study presents an AI-powered skin cancer detection model tailored for application within the U.S. healthcare landscape. The proposed approach integrates Artificial Neural Networks (ANN) with advanced image processing techniques to facilitate early and non-invasive identification of skin cancer. Dermoscopic images are first collected and pre-processed using noise reduction, contrast enhancement, and normalization to improve diagnostic quality. Segmentation is then performed using thresholding methods to highlight regions with abnormal pigmentation or texture. For feature extraction, a 2D Wavelet Transform is employed to capture critical visual cues at multiple resolutions, reflecting the lesion's structural complexity. These extracted features are input into a Backpropagation Neural Network (BPNN), trained to accurately distinguish between malignant and benign skin lesions. This AI-based diagnostic framework demonstrates high reliability and efficiency, offering valuable clinical support for dermatologists and contributing to timely intervention ultimately supporting the broader objective of improving skin cancer outcomes across the United States.

| KEYWORDS

Cancer Classification, Wavelet Transform. Skin Cancer, Artificial Neural Network, Image Processing, Wavelet Transform, BPNN, Dermoscopic Images.

| ARTICLE INFORMATION

ACCEPTED: 20 July 2025 **PUBLISHED:** 02 August 2025 **DOI:** 10.32996/jmhs.2025.6.3.16

1. Introduction

Cancer continues to be a major global health concern, significantly affecting populations and exhibiting increasing incidence rates in types such as breast cancer, lung cancer, and particularly, skin cancer [1]. Melanoma is especially perilous among skin malignancies, as it constitutes the bulk of skin cancer fatalities despite comprising a lesser proportion of total cases. Melanoma arises from melanocytes, the skin's pigment-producing cells, and first manifests as atypical moles or pigmented lesions. When these lesions ulcerate or hemorrhage, the illness is categorized as malignant melanoma [2], which can metastasis swiftly if not identified promptly.

In the United States, skin cancer is the most commonly diagnosed cancer, with over 5 million cases treated annually, making it a significant public health concern. According to the American Cancer Society, melanoma, the deadliest form of skin cancer, is

expected to cause approximately 8,000 deaths and over 100,000 new cases in 2025 alone. The high prevalence is largely attributed to excessive UV exposure, particularly in states with warmer climates and higher sun exposure, such as California, Florida, and Texas. Despite being largely preventable and highly treatable in its early stages, late detection continues to contribute to poor patient outcomes and high treatment costs. As healthcare systems in the U.S. move toward digital and AI-integrated diagnostics, developing non-invasive, AI-powered screening tools can play a crucial role in improving early detection, reducing diagnostic delays, and ultimately lowering mortality and treatment burden across the country [3], [4] [5].

The prevalence of skin cancer worldwide has been progressively increasing, influenced by variables such as heightened UV exposure, environmental alterations, and aging demographics[6] .

1.1 Melanoma: A Deadly Skin Cancer

Skin cancer broadly includes both benign and malignant tumors that develop in the epidermis. Melanoma, a malignancy originating in melanocytes, is responsible for the majority of deaths connected to skin cancer. Melanoma frequently manifests as atypical moles or pigmented lesions that may ulcerate or hemorrhage, indicating invasive illness. Although constituting about 1% of skin cancer diagnoses, melanoma accounts for the majority of deaths due to its aggressive spreading capability.

Early-stage melanoma has an exceptionally positive prognosis, with five-year survival rates above 95%. However, once metastasis, survival rates decline to below 30%. The disease disseminates swiftly via blood or lymphatic systems, impacting essential organs if not detected promptly. The standard diagnostic procedure entails visual examination utilizing the ABCD criteria—Asymmetry, Border irregularity, Color variation, and Diameter beyond 6 mm—subsequently confirmed through biopsy and histopathological analysis [7]. While precise, biopsies are invasive, uncomfortable, and may unintentionally induce lesion inflammation or the dissemination of tumor cells [8].

1.2 Limitations of Conventional Diagnostic Methods

The prevailing gold-standard diagnostic procedure, notwithstanding its comprehensiveness, encounters numerous constraints:

- Invasiveness: A biopsy necessitates the extraction of tissue samples, potentially resulting in discomfort, infection risk, and emotional anguish for patients [3].
- Histopathological examination necessitates laboratory infrastructure and proficient workers, hence prolonging the diagnostic timeline and escalating healthcare costs.
- Subjectivity: Visual evaluations of ABCD criteria may differ among doctors, resulting in variable accuracy [9].

1.3 Rise of AI-Based Diagnostic Tools

These issues have generated considerable interest in computer-aided diagnostic (CAD) systems designed to enhance early detection in a non-invasive, quick, and cost-effective manner. Recent studies emphasize the capability of powerful AI techniques, such as deep convolutional neural networks (CNNs) and hybrid models that integrate classical statistical characteristics with AI, to achieve or surpass dermatologist-level performance [7] [5]. The SkinSight research is a significant achievement, with over 90% accuracy in lesion classification through the utilization of convolutional neural networks (CNNs) trained on extensive public datasets such as ISIC and HAM10000. Nonetheless, solutions based only on deep learning frequently require substantial datasets and computational power, and they may lack interpretability elements that hinder practical implementation [8] [9] [10].

1.4 Hybrid Approaches with Wavelet Transforms

To achieve equilibrium among performance, interpretability, and resource demands, hybrid models have arisen as formidable instruments. Combining wavelet-based feature extraction with neural networks has demonstrated potential in identifying texture patterns suggestive of malignancy [11]. Using the HAM10000 dataset by integrating discrete wavelet transform (DWT) features with CNN architectures, a paper by Claret reported sensitivity and specificity values of 94% and 91%, respectively. Likewise, Gessert et al.'s hybrid model, which employs Gabor wavelets and small CNN ensembles, attained elevated detection accuracy while preserving model interpretability [12] [13] [14].

1.5 Challenges in AI-Based Skin Cancer Detection

Notwithstanding these achievements, some significant difficulties remain:

- Data paucity and imbalance: Images of malignant lesions are frequently underrepresented relative to benign lesions, resulting in dangers of overfitting and diminished generalization.

- Variability in lesion presentation: Disparities in skin pigmentation, lesion texture, and imaging quality may hinder detection efficacy if preprocessing is insufficient.

- Challenges in healthcare integration include clinical validation, regulatory approval, and the seamless incorporation into medical workflows, necessitating strong performance, interpretability, and minimal false-positive rates [18].

1.6 Proposed Approach and Contributions

In this context, the present study introduces a hybrid AI-driven methodology that combines effective dermoscopic picture preprocessing, 2D wavelet feature extraction, and classification using a streamlined Backpropagation Neural Network (BPNN). Our methodology seeks to equilibrate three fundamental elements:

- Precision: Acquiring distinctive texture attributes while reducing false negatives.

- Efficiency: Maintaining computational and data requirements within feasible limits for practical implementation.

- Explainability: Facilitating physicians' comprehension and confidence in model conclusions by interpretable feature representations [19].

The method employs median filtering and adaptive contrast enhancement to enhance image quality. Thereafter, threshold-based segmentation outlines lesion areas, while 2D wavelet decomposition retrieves multi-resolution statistical information, including mean, standard deviation, and energy metrics (L1/L2 norms) [17]. These features are input into an artificial neural network, trained with NEURAL LAB software to categorize lesions as benign or malignant. The system seeks to achieve superior diagnostic performance with little overhead by utilizing wavelet-based features that capture textural patterns and a semantically transparent classifier. Proposed methodology tackles critical challenges such as limited datasets, model transparency, and resource demands- while providing a feasible route for clinical implementation [18].

2. Literature Review

Skin cancer is the most common type of cancer worldwide, with melanoma as the most severe variant. Timely identification is essential for efficient intervention and enhanced patient results. Recent breakthroughs in artificial intelligence (AI), especially in image processing and neural networks, have markedly improved diagnostic capacities for skin cancer diagnosis. This literature review analyzes the development and present status of AI-driven approaches in skin cancer detection, emphasizing dermoscopic image analysis, feature extraction methods, and classification models.

Dermoscopy is a non-invasive imaging modality that facilitates the observation of subsurface skin structures, assisting in the early identification of skin lesions. Research has shown the efficacy of AI in evaluating dermoscopic pictures for the identification of skin cancer. Esteva et al. created a deep learning model with an extensive dataset of dermoscopic pictures, attaining an accuracy comparable to that of dermatologists in detecting skin cancer. Haenssle et al. utilized a convolutional neural network (CNN) to categorize melanocytic lesions, achieving a sensitivity of 86.6% [22] [23].

Efficient feature extraction is crucial for differentiating malignant from benign tumors. Conventional techniques such as the Gray Level Co-occurrence Matrix (GLCM) have been extensively employed for texture analysis in skin lesions. Recent studies have investigated sophisticated methods to capture more complex aspects. A study presented a deep learning network, FCDS-CNN, which utilizes data augmentation and class weighting to mitigate class imbalance and boost feature extraction, hence improving accuracy in melanoma diagnosis [24] [25].

The categorization of skin lesions as malignant or benign is an essential phase in the diagnostic procedure. Artificial neural networks (ANNs), especially feedforward networks employing backpropagation, have been widely applied for this objective. Takiddin et al. conducted a thorough analysis of 53 research on AI-driven skin cancer detection, emphasizing the prevalence of deep learning methodologies and the utilization of accuracy as the principal evaluation metric. A systematic review by Prabhua et al. underscored the significance of deep neural networks in cancer identification, highlighting its capacity to discern intricate patterns from histological pictures [26] [27].

To improve diagnostic precision, researchers have investigated hybrid models that amalgamate various data sources. Gessert et al. introduced a unified deep learning model that integrates electrical impedance spectroscopy with dermoscopy, exhibiting

enhanced efficacy compared to single-modality models. Mahbod et al. created a hybrid deep neural network that integrates characteristics from various CNN architectures, attaining superior classification performance on skin lesion datasets[28] [29]

Notwithstanding considerable progress, numerous obstacles remain in AI-driven skin cancer diagnosis. Challenges such dataset imbalance, fluctuation in image quality, and the necessity for extensive annotated datasets persistently affect model performance. Moreover, the incorporation of AI tools into clinical practice necessitates rigorous validation and monitoring endorsement. The Washington Post highlights that although AI models have demonstrated superiority over dermatologists in image-based diagnoses, they are incapable of doing physical examinations and patient interviews, emphasizing the necessity of human oversight in clinical decision-making [30]].

The approaches utilized in this research correspond with and enhance prior studies in the discipline. The incorporation of picture preprocessing, segmentation, feature extraction by 2D wavelet transforms, and classification via backpropagation neural networks exemplifies conventional methodologies in AI-driven skin cancer detection. This research enhances the accuracy and reliability of automated skin cancer diagnostic systems by concentrating on dermoscopic images and employing a systematic method for feature extraction and classification.

2. Methodology: Automated Skin Cancer Detection System

This section outlines the comprehensive methodology used for the early diagnosis of skin cancer through dermoscopic images, image processing techniques, and Artificial Neural Networks (ANN).

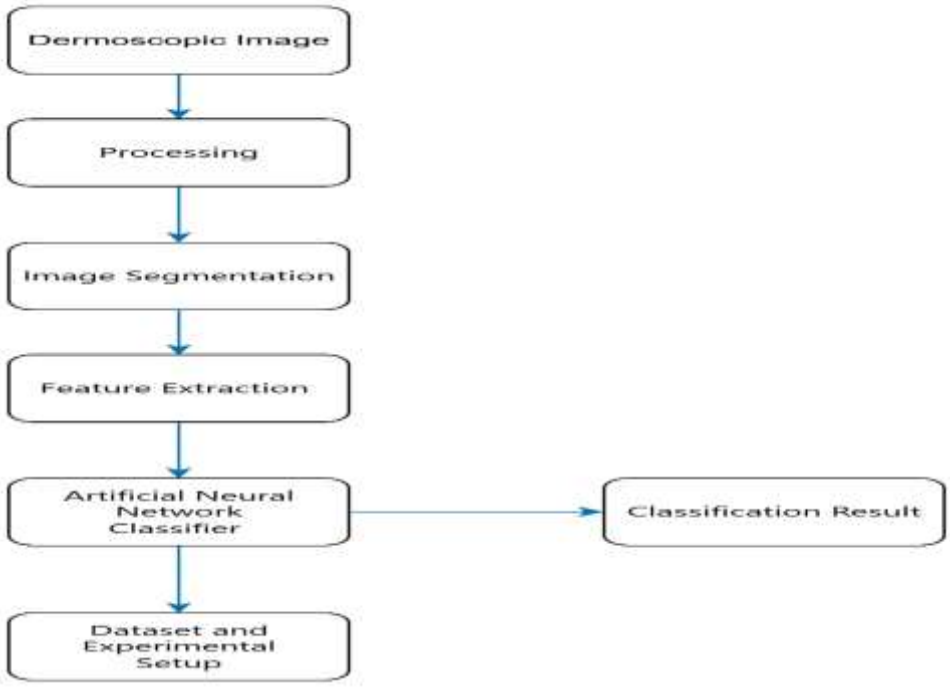


Fig.1. Block Diagram of the research

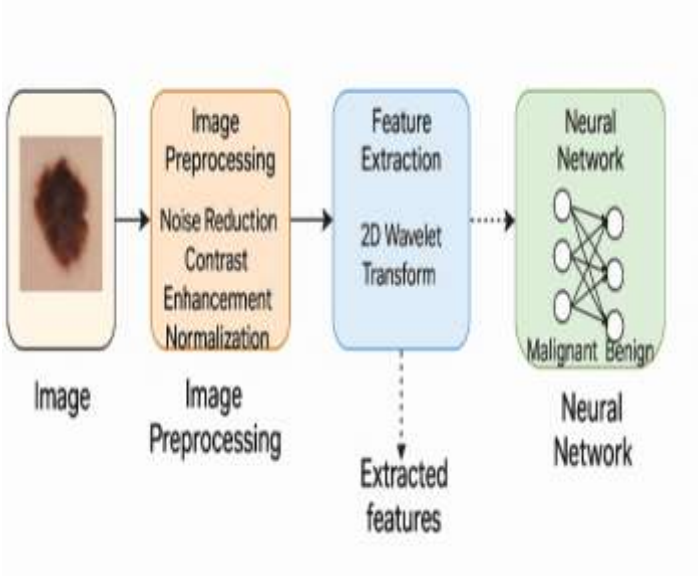
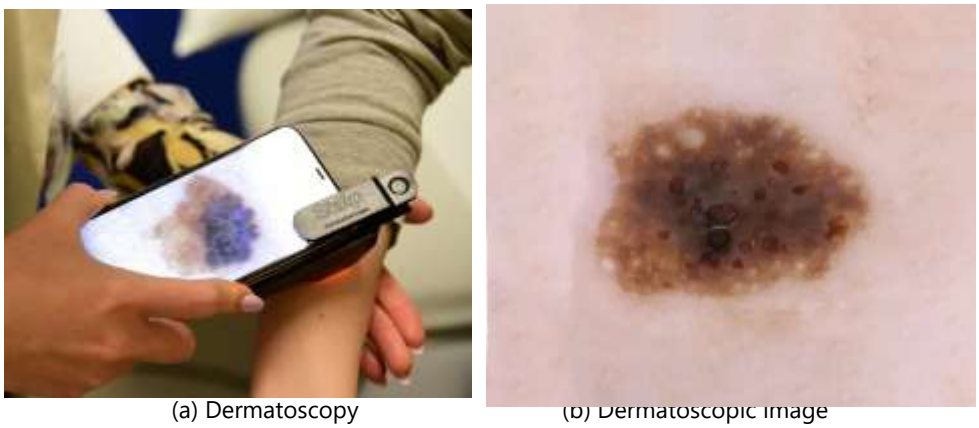


Fig.2. Automated Skin Cancer Detection System

An automatic early identification system is a categorization mechanism that differentiates Malignant Melanoma from other dermatological conditions. This methodology employs Digital Image Processing techniques and Artificial Intelligence for classification purposes. The system receives input in the form of digital Dermoscopic Images. Typically, such photos contain noise, thus it necessitating pre-processing. After that, post-processing is conducted to maintain the edges. Then, the segmentation is performed to distinguish the malignant areas from healthy skin where the malignant pictures include distinctive characteristics. From there, features are extracted with the Two-Dimensional Wavelet Transform in MATLAB program [31]. Finally, these attributes are provided as inputs to the Artificial Neural Networks based on their classifications. It employs the Backpropagation Algorithm for classification and Artificial Neural Networks differentiate Malignant Melanoma from Benign Melanoma, consequently, determining whether the patient has skin cancer or not.

A. Dermoscopy

Dermoscopy, referred to as Dermatoscopy or Epiluminescence Light Microscopy (ELM), is an imaging modality employed to analyze skin lesions via a dermatoscope. The procedure entails the application of an oil immersion between the skin and the optics to diminish light reflection and improve the visibility of subsurface structures [5]. The microscope lens directly exposes the lesion, exposing pigmented structures and nuanced color variations invisible to the unaided eye. Thus, the resultant image (Fig. 4) is referred to as a dermoscopic image.



(a) Dermatoscopy (b) Dermatoscopic image

Fig 3. Dermoscopic method

B. Image Processing

The digital dermoscopic images, generally with a resolution of 360×360 pixels, undergo multiple preprocessing procedures to enhance quality and eliminate artifacts. Common artifacts, like hairs, air bubbles, and variations in skin texture, might impair categorization accuracy. Median filtering is employed to alleviate these effects by diminishing noise while maintaining edge integrity. Morphological operations, including dilation and erosion, are utilized to remove small hairs and bubbles, thereby enhancing the definition of lesion boundaries. Subsequent to noise reduction, contrast enhancement techniques are employed to highlight lesion characteristics, facilitating segmentation. Finally, the photos are transformed into grayscale to facilitate subsequent processing.

C. Segmentation

Segmentation seeks to delineate the region of interest (ROI) - the suspected lesion — from the adjacent healthy skin. This phase is essential for precise feature extraction. This study employs threshold segmentation for its simplicity and efficiency. The grayscale image is binarized using a threshold value, categorizing pixels as either lesion or background. The threshold value is dynamically determined according to image intensity histograms to account for fluctuations in lesion characteristics. Following segmentation, morphological techniques are executed to enhance lesion boundaries and eliminate minor noise abnormalities (Fig. 4).

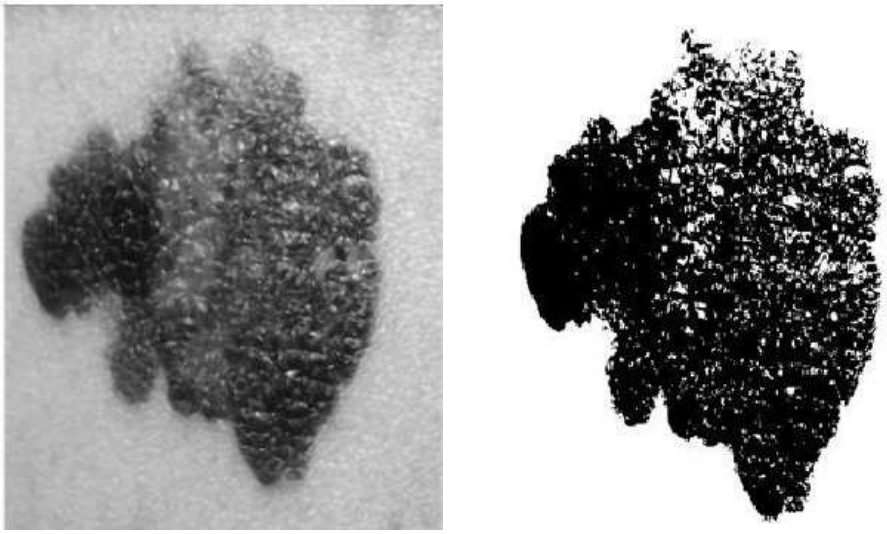


Fig.4. Segmentation

D. Feature Extraction

Precise categorization relies on the extraction of representative features from the segmented lesion. The 2D Wavelet Transform is employed for multi-resolution analysis, decomposing the lesion image into frequency sub-bands that capture texture and structural information. Biorthogonal wavelets (Bior) are utilized at two levels of decomposition, yielding approximation and detail coefficients for vertical, horizontal, and diagonal orientations [32].

Five statistical features are derived from these coefficients to characterize the texture of the lesion.

- ✓ Average
- ✓ Standard Deviation
- ✓ Mean Absolute Deviation
- ✓ L1 Norm
- ✓ L2 Norm

These features are selected for their demonstrated efficacy in differentiating malignant lesions from benign ones in dermatological imaging research[33].

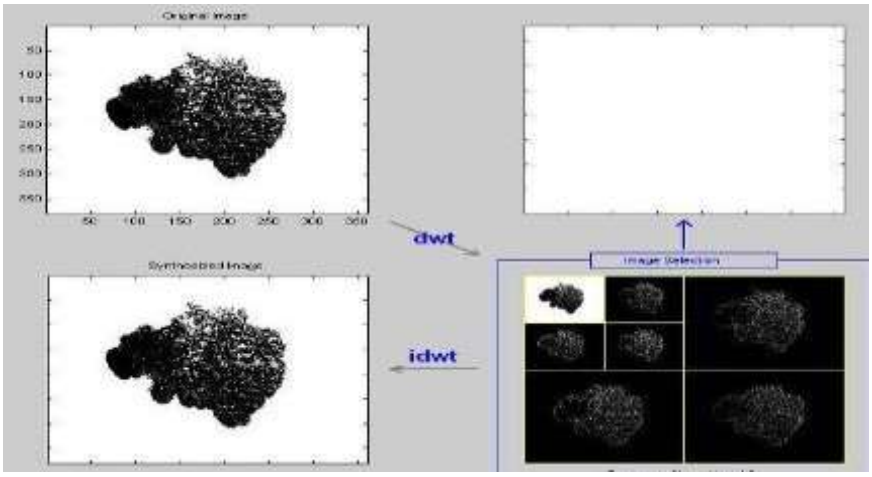


Fig.5. Feature Extraction Utilizing 2D Wavelet Transform

E. Artificial Neural Network Classifier

A feedforward multilayer Artificial Neural Network (ANN) utilizing the Backpropagation (BPN) algorithm serves as the classifier. The network comprises:

- ✓ A five-neuron input layer representing the extracted features.
- ✓ A solitary concealed layer of two neurons.
- ✓ An output layer including a single neuron that generates binary output (0: non-cancerous, 1: malignant).

Weights are initialized randomly and iteratively adjusted to reduce classification error through supervised learning. A linear activation function is utilized in the output layer, yielding discrete binary outputs at convergence of training.

Training is conducted utilizing the NEURAL LAB program, which offers an interactive platform for the building and simulation of artificial neural networks (ANN) [11]. The network undergoes training for 1000 epochs with a learning rate of 0.01, employing Mean Squared Error (MSE) as the loss function. Training persists until the error diminishes beneath a specified threshold[34].

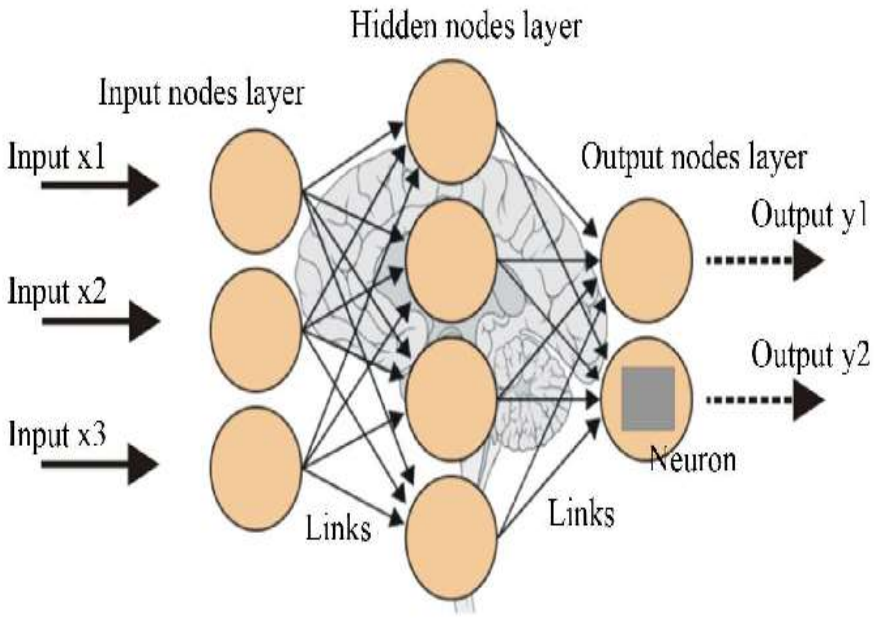


Fig.6. Structure of the Artificial Neural Network

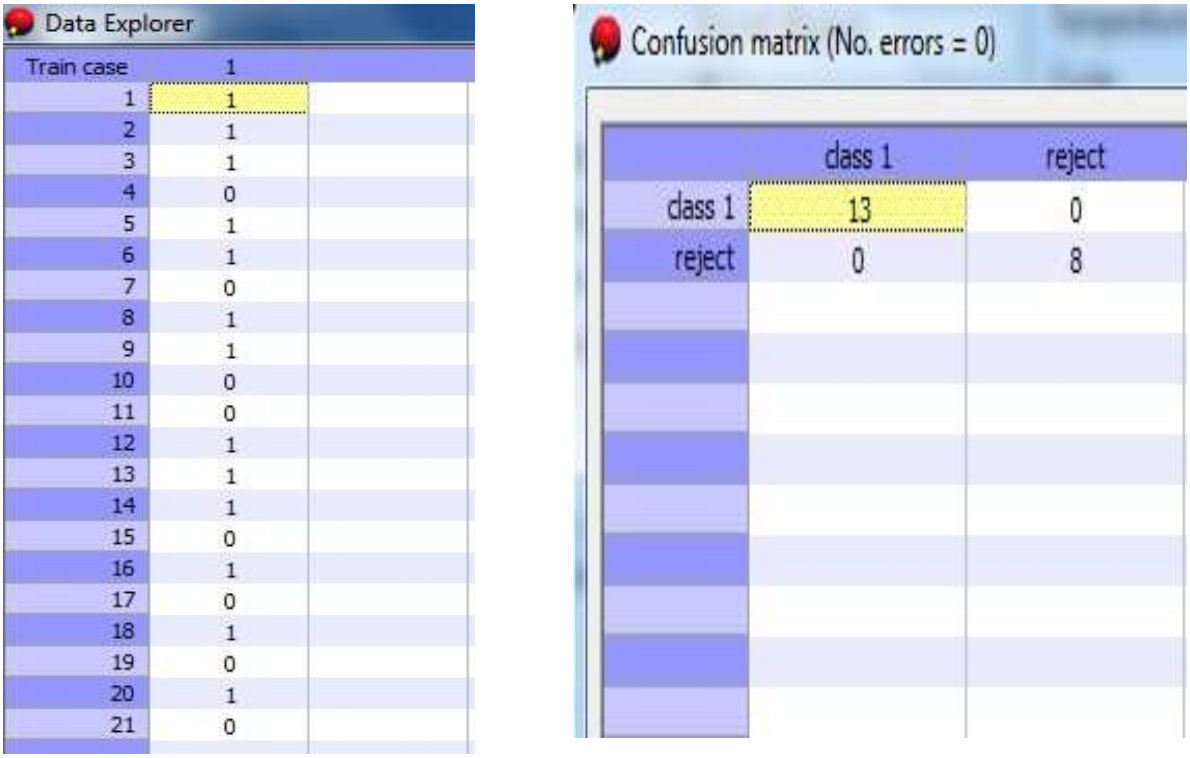
F. Dataset and Experimental Setup

The collection comprises 31 dermoscopic photos obtained from publicly accessible dermatology databases and internet archives, encompassing both malignant and benign cases validated by expert annotation. Every image is adjusted to a uniform resolution of 360×360 pixels. Before categorization, feature values are normalized by min-max scaling to maintain consistency in

input data. The dataset is divided into training and testing sets in a 70:30 proportion. The artificial neural network is trained with the training set, and its performance is assessed using the testing set. The classification results are binary, with '0' denoting benign tumors and '1' signifying malignant melanoma.

In Backpropagation Neural Networks, weights are randomly initialized at the commencement of training. A specific output will be achieved through the training process. Supervised learning is employed in this context. During the forward pass of the signal, the network produces an output based on the initial weights and the employed activation function. The output is compared to the desired output. An error occurs if they are not same. During the reverse pass, the error is back-propagated, and the weights of the hidden output layers are modified. The entire process persists until the error reaches zero. The network is trained using established values. Post-training, the network is capable of executing decision-making processes. In this proposed methodology, five features were provided as input to a multilayer feedforward network [10]. There exists a singular hidden layer of two hidden neurons. Output layer including a single output neuron. The activation function employed is a linear function, producing outputs of either 0 or 1. Zero denotes a non-cancerous or benign condition, while one signifies a cancerous or malignant one. NEURAL LAB is the software utilized for artificial neural network categorization. It is an artificial neural network simulation software that yields favorable outcomes in classification [11]. The network is trained on established characteristics of Malignant and Benign Melanoma. Numerous training epochs are conducted until the Mean Square Error falls below a specified minimum threshold. The classification data is provided as input to the classifier. Twenty-one features of malignant and benign melanoma were provided for classification. The classifier's output is exclusively '0' or '1'. One denotes a malignant condition, while zero signifies a non-cancerous condition [12].

3. Result Analysis



7(a) Confidential output from NEURAL LAB software 7(b) Confusion Matrix of Classified Output

Fig. 7. Output generated using NEURAL LAB software

For the suggested system, 31 dermoscopic images were obtained from the Internet. They underwent Median Filtering. Subsequently, the filtered images underwent segmentation by thresholding. Image feature extraction was performed with the 2D wavelet transform. All of these actions were executed in MATLAB program. Five features were used for classification: Mean, Standard Deviation, Mean Absolute Deviation, L1 Norm, and L2 Norm. The acquired features were sent as inputs to a Feed Forward Neural Network. The activation function employed is a linear function, producing outputs of '0' or '1'. Zero signifies a non-cancerous or benign condition, while one denotes a cancerous or malignant one. The neural network is constructed via NEURAL LAB software. The training is conducted with established values. Post-training, classification data sets were provided to

the network. Twenty-one instances were provided for classification. The network categorizes the provided data as either malignant or noncancerous. Of the 21 instances, 13 were identified as malignant and 8 as non-cancerous. The data is presented in the form of a Confusion Matrix, as illustrated in Fig. 7(b). It possesses a commendable level of precision as well. The proposed approach is demonstrated to be significantly more convenient than the traditional biopsy method. This approach, being Computer-Based Diagnosis, eliminates the necessity for any skin excision for diagnostic purposes. Only the dermoscopic image is required.

TABLE I

Case	Mean	Standard Deviation	Mean Absolute Deviation	L2 Norm	L1 Norm	Output	Diagnosis
1	230	75	45	9.34E+07	1.55E+05	1	Cancerous
2	228	74	46	9.36E+07	1.54E+05	1	Cancerous
3	224	82	54	9.18E+07	1.53E+05	1	Cancerous
4	203	99	80	8.33E+07	1.45E+05	0	Non-Cancerous
5	219	87	61	8.98E+07	1.51E+05	1	Cancerous
6	229	74	45	9.40E+07	1.54E+05	1	Cancerous
7	189	107	93	7.77E+07	1.39E+05	0	Non-Cancerous
8	215	91	66	8.83E+07	1.49E+05	1	Cancerous
9	220.5	59	59	9.05E+07	1.50E+05	1	Cancerous
10	187	111	98	7.67E+07	1.39E+05	0	Non-Cancerous
11	157	118	113	6.43E+07	1.26E+05	0	Non-Cancerous
12	210.2	90.76	69.62	8.68E+07	1.47E+05	1	Cancerous
13	217	88	63	8.90E+07	1.50E+05	1	Cancerous
14	235	66	36.53	9.62E+07	1.56E+05	1	Cancerous
15	178	113.8	104	7.30E+07	1.35E+05	0	Non-Cancerous
16	205	93.48	75	8.43E+07	1.45E+05	1	Cancerous
17	180	111	100	7.38E+07	1.35E+05	0	Non-Cancerous
18	221	84.81	58	9.06E+07	1.52E+05	1	Cancerous
19	200	104	85.5	8.20E+07	1.44E+05	0	Non-Cancerous
20	241	56.53	25.23	1.77E+08	2.12E+05	1	Cancerous
21	250	36	10.42	5.72E+07	1.20E+05	0	Non-Cancerous

4. Conclusion

In this paper, a computer-based approach for the early identification of skin cancer is proposed. It demonstrates superiority as a diagnostic procedure compared to the traditional biopsy technique. Proposed diagnostic methodology employs Digital Image Processing Techniques and Artificial Neural Networks to classify Malignant Melanoma among other skin disorders. Dermoscopic pictures were acquired and subsequently processed using various image processing techniques. The malignant area is delineated from healthy skin by segmentation techniques. The distinctive characteristics of the segmented images were retrieved utilizing the 2-D Wavelet Transform. Finally, the photos were categorized as Cancerous and Non-cancerous based on their attributes. In conclusion, the proposed methodology has achieved a convenient accuracy level and altering these methods can enhance the whole biomedical advancement in the cancer detection system.

Funding: This research received no external funding. This is a self-funded study.
Conflicts of Interest: The authors declare no conflict of interest.
ORCID ID: 0009-0001-2693-8449

References

[1] M. Rahaman, E. Hasan, D. PAUL, M. Al Amin, and M. T. Mia, "Early Detection of Breast Cancer Using Machine Learning: A Tool for Enhanced Clinical Decision Support," *British Journal of Nursing Studies*, vol. 5, no. 1, pp. 55–63, Jun. 2025, doi: 10.32996/BJNS.2025.5.1.6.

[2] F. Ercal, A. Chawla, W. V. Stoecker, H. C. Lee, and R. H. Moss, "Neural Network Diagnosis of Malignant Melanoma From Color Images," *IEEE Trans Biomed Eng*, vol. 41, no. 9, pp. 837–845, 1994, doi: 10.1109/10.312091.

[3] P. Aggarwal, P. Knabel, and A. B. Fleischer, "United States burden of melanoma and non-melanoma skin cancer from 1990 to 2019," *J Am Acad Dermatol*, vol. 85, no. 2, pp. 388–395, Aug. 2021, doi: 10.1016/J.JAAD.2021.03.109,.

[4] "Melanoma Skin Cancer Statistics | American Cancer Society." Accessed: Jul. 16, 2025. [Online]. Available: https://www.cancer.org/cancer/types/melanoma-skin-cancer/about/key-statistics.html?utm_source=chatgpt.com

[5] R. L. Siegel, K. D. Miller, N. S. Wagle, and A. Jemal, "Cancer statistics, 2023," *CA Cancer J Clin*, vol. 73, no. 1, pp. 17–48, Jan. 2023, doi: 10.3322/CAAC.21763;CTYPE:STRING:JOURNAL.

[6] T. Tanaka, R. Yamada, M. Tanaka, K. Shimizu, M. Tanaka, and H. Oka, "A study on the image diagnosis of melanoma," *Annual International Conference of the IEEE Engineering in Medicine and Biology - Proceedings*, vol. 26 III, pp. 1597–1600, 2004, doi: 10.1109/IEMBS.2004.1403485.

[7] PDQ Adult Treatment Editorial Board, "PDQ Melanoma Treatment. Patient Version," *National Cancer Institute*, pp. 1–17, 2019, Accessed: Jul. 03, 2025. [Online]. Available: https://www.cancer.gov/types/skin/patient/melanoma-treatment-pdq

[8] K. Peris *et al.*, "Diagnosis and treatment of basal cell carcinoma: European consensus–based interdisciplinary guidelines," *Eur J Cancer*, vol. 118, pp. 10–34, Sep. 2019, doi: 10.1016/J.EJCA.2019.06.003.

[9] O. K. Pal, D. Paul, E. Hasan, M. Mohammad, M. A. H. Bhuiyan, and F. Ahammed, "Advanced Convolutional Neural Network Model to Identify Melanoma Skin Cancer," *Proceedings of IEEE InC4 2023 - 2023 IEEE International Conference on Contemporary Computing and Communications*, 2023, doi: 10.1109/INC457730.2023.10262990.

[10] M. Dildar *et al.*, "Skin Cancer Detection: A Review Using Deep Learning Techniques," *International Journal of Environmental Research and Public Health 2021, Vol. 18, Page 5479*, vol. 18, no. 10, p. 5479, May 2021, doi: 10.3390/IJERPH18105479.

[11] N. Ashfaq *et al.*, "SkinSight: advancing deep learning for skin cancer diagnosis and classification," *Discover Computing*, vol. 28, no. 1, pp. 1–18, Dec. 2025, doi: 10.1007/S10791-025-09541-1/TABLES/3.

[12] A. Ray, S. Sarkar, F. Schwenker, and R. Sarkar, "Decoding skin cancer classification: perspectives, insights, and advances through researchers' lens," *Scientific Reports 2024 14:1*, vol. 14, no. 1, pp. 1–36, Dec. 2024, doi: 10.1038/s41598-024-81961-3.

[13] R. B. Aswin, J. A. Jaleel, and S. Salim, "Hybrid genetic algorithm - Artificial neural network classifier for skin cancer detection," *2014 International Conference on Control, Instrumentation, Communication and Computational Technologies, ICCICCT 2014*, pp. 1304–1309, Dec. 2014, doi: 10.1109/ICCICCT.2014.6993162.

[14] S. P. A. Claret, J. P. Dharmian, and A. M. Manokar, "Artificial intelligence-driven enhanced skin cancer diagnosis: leveraging convolutional neural networks with discrete wavelet transformation," *Egyptian Journal of Medical Human Genetics*, vol. 25, no. 1, pp. 1–12, Dec. 2024, doi: 10.1186/S43042-024-00522-5/TABLES/5.

[15] O. Attallah, "Skin cancer classification leveraging multi-directional compact convolutional neural network ensembles and gabor wavelets," *Sci Rep*, vol. 14, no. 1, pp. 1–19, Dec. 2024, doi: 10.1038/S41598-024-69954-8;SUBJMETA=117,139,166,639,692,700,705,985;KWRD=BIOMEDICAL+ENGINEERING,COMPUTER+SCIENCE,DIAGNOSIS.

[16] A. H. Alzamili and N. I. R. Ruhaiyem, "A comprehensive review of deep learning and machine learning techniques for early-stage skin cancer detection: Challenges and research gaps," *Journal of Intelligent Systems*, vol. 34, no. 1, Jan. 2025, doi: 10.1515/JISYS-2024-0381/MACHINEREADABLECITATION/RIS.

[17] S. Adamu *et al.*, "The future of skin cancer diagnosis: a comprehensive systematic literature review of machine learning and deep learning models," *Cogent Eng*, vol. 11, no. 1, Dec. 2024, doi: 10.1080/23311916.2024.2395425.

[18] O. Attallah, "Skin cancer classification leveraging multi-directional compact convolutional neural network ensembles and gabor wavelets," *Sci Rep*, vol. 14, no. 1, pp. 1–19, Dec. 2024, doi: 10.1038/S41598-024-69954-8;SUBJMETA=117,139,166,639,692,700,705,985;KWRD=BIOMEDICAL+ENGINEERING,COMPUTER+SCIENCE,DIAGNOSIS.

[19] Y. Andreopoulos *et al.*, "A local wavelet transform implementation versus an optimal row-column algorithm for the 2D multilevel decomposition," *IEEE International Conference on Image Processing*, vol. 3, pp. 330–333, 2001, doi: 10.1109/ICIP.2001.958118.

[20] P. P. Midhun Kumar and J. C. Vigash, "Skin Cancer Detection Using Image Processing," 2023.

[21] "Skin cancer signs are being hunted by AI | WIRED." Accessed: Jul. 03, 2025. [Online]. Available: https://www.wired.com/story/ai-detect-diagnosis-cancer-skin-breast/?utm_source=chatgpt.com

[22] N. Ashfaq *et al.*, "SkinSight: advancing deep learning for skin cancer diagnosis and classification," *Discover Computing*, vol. 28, no. 1, pp. 1–18, Dec. 2025, doi: 10.1007/S10791-025-09541-1/TABLES/3.

[23] G. Singh, A. Kamalja, R. Patil, A. Karwa, A. Tripathi, and P. Chavan, "A comprehensive assessment of artificial intelligence applications for cancer diagnosis," *Artif Intell Rev*, vol. 57, no. 7, pp. 1–52, Jul. 2024, doi: 10.1007/S10462-024-10783-6/FIGURES/8.

[24] K. Nawaz *et al.*, "Skin cancer detection using dermoscopic images with convolutional neural network.," *Sci Rep*, vol. 15, no. 1, p. 7252, Mar. 2025, doi: 10.1038/S41598-025-91446-6,.

[25] A. Takiddin, J. Schneider, Y. Yang, A. Abd-Alrazaq, and M. Househ, "Artificial intelligence for skin cancer detection: Scoping review," *J Med Internet Res*, vol. 23, no. 11, Nov. 2021, doi: 10.2196/22934,.

[26] S. Prabhu, K. Prasad, A. Robels-Kelly, and X. Lu, "AI-based Carcinoma Detection and Classification Using Histopathological Images: A Systematic Review," *Comput Biol Med*, vol. 142, Jan. 2022, doi: 10.1016/j.compbiomed.2022.105209.

[27] A. Mahbod, G. Schaefer, C. Wang, R. Ecker, and I. Ellinge, "Skin Lesion Classification Using Hybrid Deep Neural Networks," *ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings*, vol. 2019-May, pp. 1229–1233, Feb. 2017, doi: 10.1109/ICASSP.2019.8683352.

[28] N. Gessert, M. Bengs, and A. Schlaefer, "Melanoma detection with electrical impedance spectroscopy and dermoscopy using joint deep learning models," p. 37, Nov. 2019, doi: 10.1117/12.2548974.

[29]"AI is coming to skin cancer detection - The Washington Post." Accessed: Jul. 03, 2025. [Online]. Available: https://www.washingtonpost.com/wellness/2025/04/07/ai-is-coming-skin-cancer-detection/?utm_source=chatgpt.com

[30]I. Saif Sulaiman Al Shabibi, "Detection of Skin Diseases Using Matlab".

[31]M. Unser and A. Aldroubi, "A review of wavelets in biomedical applications," *Proceedings of the IEEE*, vol. 84, no. 4, pp. 626–638, 1996, doi: 10.1109/5.488704.

[32]S. Ray and A. Chan, "Automatic feature extraction from wavelet coefficients using genetic algorithms," *Neural Networks for Signal Processing - Proceedings of the IEEE Workshop*, pp. 233–241, 2001, doi: 10.1109/NNSP.2001.943128.

[33]H. T. Lau and A. Al-Jumaily, "Automatically early detection of skin cancer: Study based on nueral netwok classification," *SoCPaR 2009 - Soft Computing and Pattern Recognition*, pp. 375–380, 2009, doi: 10.1109/SOCPAR.2009.80.