Journal of Computational Bioengineering and Clinical Medicine

Research Article

Optimization and Mathematical Formulation of a DBNE–AlexNet–BiLSTM Hybrid Network for Dermatological Image Classification

Nitalaksheswara Rao Kolukula [a*], **Jayasree Pinajala** [b], **James Stephen Meka** [c]

[a] Department of Computer Science and Engineering, School of Technology, GITAM University, Visakhapatnam, Andhra Pradesh, India

[b] Department of Computer Science and Engineering, Chaitanya Engineering College, Visakhapatnam, Andhra Pradesh, India

[c] Ambedkar Chair Professor, Andhra University, Visakhapatnam, Andhra Pradesh, India

Article Info

Article history

Received: 29/05/2026

Revised: 18/06/2026

Accepted: 25/06/2026

Keywords:
Bidirectional Long Short-Term Memory (BiLSTM);
Deep Batch-Normalized ELU AlexNet;
Image augmentation;
Skin cancer classification;
Skin lesion segmentation.

ABSTRACT

Skin cancer is one of the deadliest forms of cancer worldwide. Melanoma, the most aggressive type of skin cancer, requires accurate and efficient detection methods for early diagnosis and improved patient outcomes. Biopsies and other traditional diagnostic techniques are disruptive, time-consuming, and often painful. Automated skin cancer classification has been made possible by novel advances in deep learning method. However, processing resolution images, and obtaining high accuracy, and requiring enormous datasets are the challenges for current techniques. In a bid to enhance skin cancer classification, this research proposes a hybrid model that combines Deep Batch-normalized eLU AlexNet (DbneAlexNet) and Bi-directional Long Short-Term Memory (Bi-LSTM). The approach includes pre-processing with Gaussian filters, Region of Interest (RoI) extraction, and skin lesion segmentation using Multi Scale Receptive Field Network (MSRFNet). Geometric and color space transformations are two different image augmentation that enhance dataset diversity. To provide high quality feature representation, feature extraction is performed by applying statistical parameters and Local Vector Pattern (LVP). The proposed hybrid model exceeds current techniques in terms of classification accuracy. Its remarkable 99.6% classification accuracy demonstrates how effective it is at automatically detecting skin cancer. This research addresses the drawback of existing techniques by providing a reliable, non-invasive, and efficient early detection technique.

1. Introduction

Skin cancer, which results from damage to the skin's cells and layers, is broadly classified into melanoma and non-melanoma types. Melanoma, the deadliest, has a survival rate of 20% if spread [1]. Skin cancer can appear as abnormal growths or new moles with irregular shape, colour or size. It can affect various anatomical areas, including the skin, eyes, face and nerve centres [2].

In the diagnostic process, the most commonly used technique is biopsy to identify malignancy, by taking a sample for analysis. However, this approach is laborious, time-consuming, and frequently uncomfortable [3]. Conversely, computer-based technology offers a faster, more practical, and more affordable diagnostic option, particularly for melanoma detection Researchers look into non-invasive ways to detect the symptoms of skin cancer using advance deep learning models. Techniques like Deep Neural Network (DNN), Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and Recurrent Neural Network (RNN) have shown promising results in detecting and classifying cancer cells [4].

AI based algorithms have been developed to detect and classify lesions as benign or skin cancer [5]. Traditional machine learning techniques usually entail first extracting features from disease images and classifying them. The Asymmetry, Border, Colour, Diameter (ABCD) Rule, and the 7-Point Checklist are efficient techniques for identifying different characteristics of skin cancer [6]. Deep learning algorithms have been utilized extensively for skin cancer classification in recent years since they do not require domain expertise or feature extraction [7]. They can examine large-scale datasets more quickly and accurately than typical machine learning techniques, which enables them to successfully extract pertinent properties.

Contributions

- Input skin image from Society for Imaging Informatics in Medicine (SIIM)- International Standard Industrial Classification (ISIC) Melanoma Classification and ISIC Challenge Data Set.
- Pre-processing using Gaussian Filter and (RoI) extraction
- Segment the skin lesion from the surrounding skin using (MSRFNet).
- Apply Image Augmentation using Geometric Transformation and Color Space Transformation to increase the diversity of the training data.
- Extract features from the segmented skin lesion using statistical features and Local Vector Pattern (LVP)
- Classification of skin lesions using the proposed hybrid DBNE-AlexNet-BiLSTM model.

The structure of the paper is as follows: Section 2 presents the literature survey and challenges. Section 3 presents proposed methodology. Section 4 presents results and discussion. Section 5 presents the conclusion and future work.

2. Literature Survey

Atheer bassel et al., [8] suggested a three-fold classifier stacking approach for the classification of benign skin tumors and melanoma combining deep learning, Support Vector Machine

***Corresponding author:** Nitalaksheswara Rao Kolukula
*E-mail address: kolukulanitla@gmail.com
https://10.56158/jcbcm.2026.1.01.2

(SVM), Radio Frequency (RF), Neural Network (NN), K-Nearest Neighbour algorithm (KNN) and logistic regression methods. This approach outperformed the ResNet50 and VGG 16 methods. It requires sizable training dataset, which may be challenging to obtain or resource- intensive to process, potentially limiting its practical applications. P. Jayakanth et al., [9] Implemented an Efficient Skin Disease Classification Framework Using Res-SENet with Hybrid Attention to Analyze Dermatological Images, Chao Xin , Zhifang Liu c et al.,[10] deployed skin trans model using Vision Transformers(ViT) for skin cancer classification. Scalability and robustness was the advantage though it has not been validated in clinical trials and struggles with processing high-resolution images efficiently. A. Magdy et al., [11] created KNN-Public Data Network (PDN) approach using Machine Learning (ML) and Deep Learning (DL) model to maximize accuracy and minimize errors. It may struggle with scalability and efficiency.

2.1. Problem Statement

The drawbacks of the existing methods include the need for large datasets, inadequate accuracy in CNN-SVM models, and challenges in processing high-resolution images and improving accuracy through parameter changes. To address these defaults, we propose a distinct method called "Hybrid DbneAlexNet and Bi-LSTM model for automated skin cancer classification" that uses a Gaussian filter to smooth high resolution images, enhancing feature extraction for greater accuracy[12]. By enhancing texture representation, it uses (LVP) for improve classification performance. Additionally, the proposed approach enhances feature learning with DenseNet-based designs improving gradient flow and efficiency.

3. Proposed Methodology

The proposed methodology for automated skin cancer classification uses the random image, which is extracted from ISIC and SIIM-ISIC datasets. Figure 1 represents the overall proposed methodology which includes the five stages: Retrieval of images from the dataset, pre-processing using Gaussian filter and RoI extraction followed by the skin lesion segmentation using MSRF Net followed by image augmentation. Feature extraction is done by statistical features and LVP and then the image is classified by the proposed method (hybrid DbneAlexNet and Bi-LSTM).

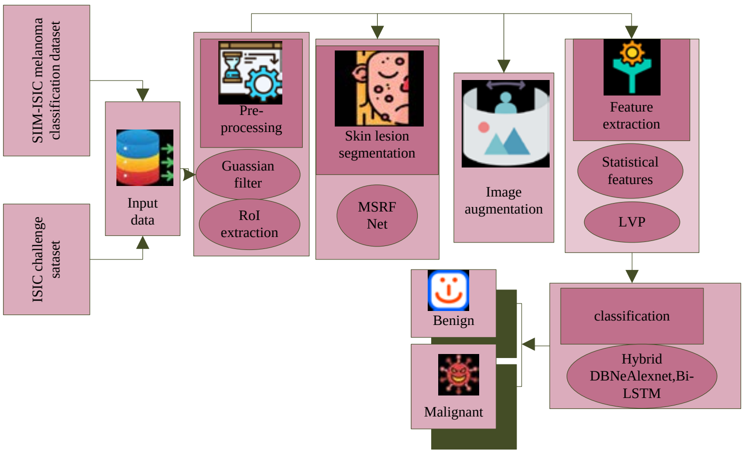


Fig.1. Schematic representation of overall proposed methodology

3.1. Dataset Description

The ISIC Challenge dataset [13] and the SIIM-ISIC [14] melanoma classification dataset are crucial tools for creating and analysing deep learning methods for skin cancer classification. Streams of labelled dermoscopic images of skin cancer compose these datasets which are serve primarily to detect melanoma. It includes distinct group of people to make the dataset diverse, containing images from a range of demographics and skin types.

3.2. Pre-processing using Gaussian Filter and Region of Interest (RoI) extraction

Enhancing the quality of medical images (dermoscopic images) by reducing noise and blurring while retaining significant features like edges and textures is the key to use Gaussian filter for skin cancer detection and classification is the first pre-processing procedure. In the context of skin cancer detection, the mathematical concepts underlying the Gaussian filter required to identify anomalies such as skin lesions or cancer [15].

$$p(u,v) = \quad j(u,v) + q(u,v) \qquad (1)$$

Where j (u, v) is the original image, q(u, v) is the added noise, and p(u, v) is the final image. By using Gaussian filter it reduces noise, smoothen the image, and enhances the visibility of skin lesions.

RoI is the second procedure of pre-processing the image. It focuses on particular region of an image, such as skin lesions, to enhance analysis accuracy[15]. By suppressing unnecessary region, it enhances the algorithm's efficiency and minimizes the computational complexity [16]. It maximizes classification accuracy by eliminating noise from background.

3.3. Skin Lesion Segmentation using MSRFNet

Skin lesion segmentation is the focus of the MSRF-Net, an advanced deep learning technology designed for bio medical image segmentation. The architecture uses a multi scale technique to extract global context and smooth features from images of skin lesions. MSRF-Net efficiently integrates data from many scales through residual fusion, enhancing the ability of technology to detect lesions of various sizes and complexity [17]. The network performs well at handling the challenges associated with skin lesion segmentation, including in lesion size, shape and texture.

3.4. Image Augmentation using Geometric Transformation and Colour Space Transformation

Geometric transformations [18] and colour space transformations are the image augmentation technique used to enhance model generalization by diversifying the dataset. These modifications help the algorithm adapt to different lesion orientations, lighting conditions and noise levels [19]. By enhancing dataset variability, the model becomes more reliable and capable of accurately classifying new skin cancer images.

3.5. Feature Extraction using Statistical Features and LVP

Feature extraction using statistical features is essential for classifying skin cancer as variants in skin lesion colour can provide significant details about possible malignancy. The colour channels are utilized to extract several statistical parameters including mean, variance and standard deviation. These parameters help in differentiating between benign and malignant skin lesions by measuring the texture and intensity shifts inside the lesion [20]. LVP technique can be used to enhance texture analysis in dermoscopy images for skin cancer detection. The vector pool methodology collects local features while retaining the spatial distribution of skin surface points, In contrast to conventional pooling methods that ignore spatial correlations. This makes it possible to record small textural patterns like uneven borders or asymmetry more accurately, which are important markers of malignant cancer. Furthermore, it minimizes the cost of computing by avoiding resource intensive processes like set abstraction. The final outcome is more effective and efficient way to identify skin cancer by evaluating complex skin textures [21].

3.6. Skin Cancer Classification using Proposed Hybrid DbneAlexNet and Bi-LSTM

DbneAlexNet is a deep learning-based feature extractor that uses DenseNet architecture. The following layers contribute the DenseNet architecture for classify skin cancer [22]. Convolution 2D layer is to acquire data from the input image and extracts spatial features using multiple convolutional layers. Maxpooling is applied in the Convolution 2D layer to reduce dimensionality to obtained features and save the most significant data. Dense layer is entirely interconnected layer for learning complex patterns of skin cancer groups.

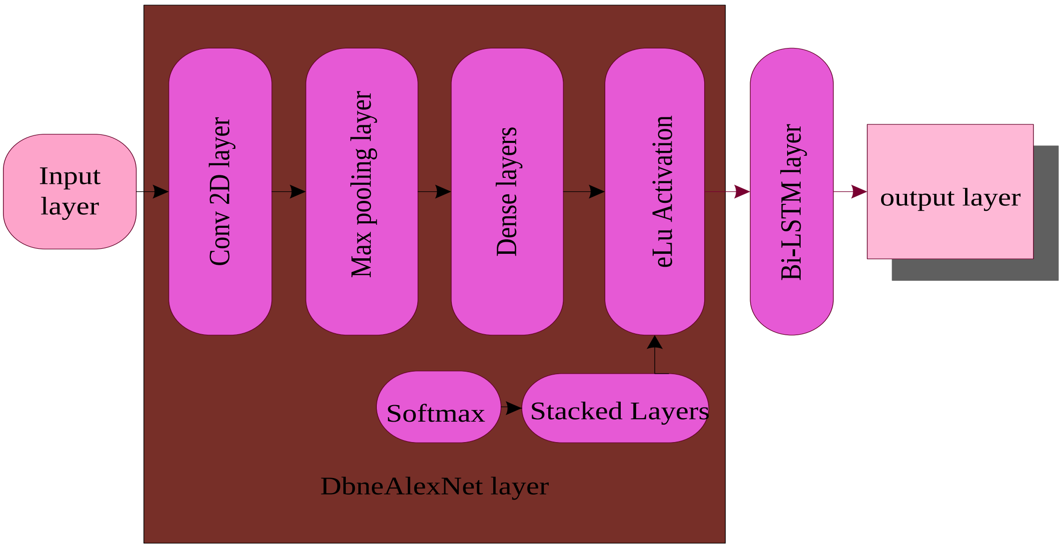


Fig.2. Schematic representation of Hybrid DbneAlexNet and Bi-LSTM

The DBNeAlexNet, a deep learning model, may also be employed to skin cancer classification by leveraging its specialized layer called Exponential Linear Unit (eLU). The eLU activation layer enhances the performance by enabling negative values to push the activations closer to zero and accelerating the training process [23]. Through enhanced feature extraction and classification performance, our method enables more efficient and accurate skin cancer detection.

$$a_z = \sigma(X_o^g uz + U_o^g a_{z-1}^g + d_o^g)\Theta\, tan \rightleftarrows h(G_z^g \Theta C_{z-1}^g + j_z^g \Theta \tilde{C}_z^g \oplus$$
$$\sigma \quad (X_o^d uz + U_o^d a_{z+1}^d + d_o^d)\Theta\, tan \rightleftarrows h(G_z^g \Theta C_{z+1}^d + j_z^d \Theta \tilde{C}_z^d$$
(2)

Here, $a_z$is the final Bi-LSTM , σ is the sigmoid function itself, tan h introduces non linearity, X, U, d are weight metrics and bias term. G_z, j, C_z are forget gate, cell state, input gate respectively and $\oplus$represents concatenation of forward and backward states. The Bi-LSTM [24] technique can be successfully used to sequential data, by utilizing its ability to detect both past and future correlations in the data such as skin cancer classification. Bi-LSTM can enhance classification accuracy in the context of skin cancer by analysing series or sequential images such as changes in lesion. The stacked layer [25] and Softmax of architecture, enable the algorithm to identify complex linkages and patterns in the sequential data, which results it appropriate for identifying minute changes in skin lesions. This method makes optimal use of series or sequential image data to provide reliable, effective, and precise skin cancer detection.

4. Results and Discussion

To evaluate the dominance of the created method, Hybrid DbneAlexNet and Bi-LSTM is analysed using an array of metrics and compared with different existing approaches. The following section covers the techniques and metrics used, as well as the analysis of the Hybrid DbneAlexNet and Bi-LSTM.

4.1. Experimental Design

Table 1 shows the experimental requirements for implementing skin cancer classification. The setup includes python 3.12.7 with visual studio code and jupyter Notebook for coding and execution. NumPy and Pandas handle data manipulation, while Matplotlib and seaborn are used for visualizing results. OpenCV is employed for image processing, and albumentations enhances image augmentation. Tensorflow and keras facilitate deep learning model training, scikit-learn supporting data pre-processing and evaluation. The MSRFNet implementation utilizes pre-trained models or custom architectures for improved performance.

Table 1. Software requirements

Tool/Library	**Version / Notes**
Python	Python 3.12.7.
IDE	Visual Studio Code with Jupyter Notebook kernel.
NumPy, Pandas	for data manipulation.
Matplotlib/Seaborn	For visualization of results
OpenCV	For Image Processing
Tensor-Flow	for model training
Keras	Integrated with Tensor-Flow
scikit-learn	for data pre-processing and evaluation.
Albumentations	For image augmentation
MSRFNet Implementation	Use pre-trained models or custom implementation

4.2. Evaluation Metrics

Accuracy measures the proportion of correctly classified skin lesions. Precision evaluates the proportion of predicted positives are actually positives. Recall measures the proportion of true positives among all actual positive cases. The F1 score is the harmonic mean of precision and recall with a range from 0(worst) to 1(best). The AUC-ROC (Area under the Operating characteristic curve) measure's a model's ability to distinguish between classes, with a higher AUC indicating better performance on the positive class, with 1 being and 0.5 being random guessing.

4.3. Experimental Outcomes Using Data Set 1(ISIC) and Data Set 2(SIIM-ISIC)

Figure 3 displays the experimental outcomes which contains input images in (A) , pre-processed images in (B), ground truth segmented images in (C) with predicted segmented images in (D), augmented images in (E) and output images in (F). the output represents the Benign, malignant and melanoma. The inputs are extracted from the dataset ISIC and SIIM-ISIC.

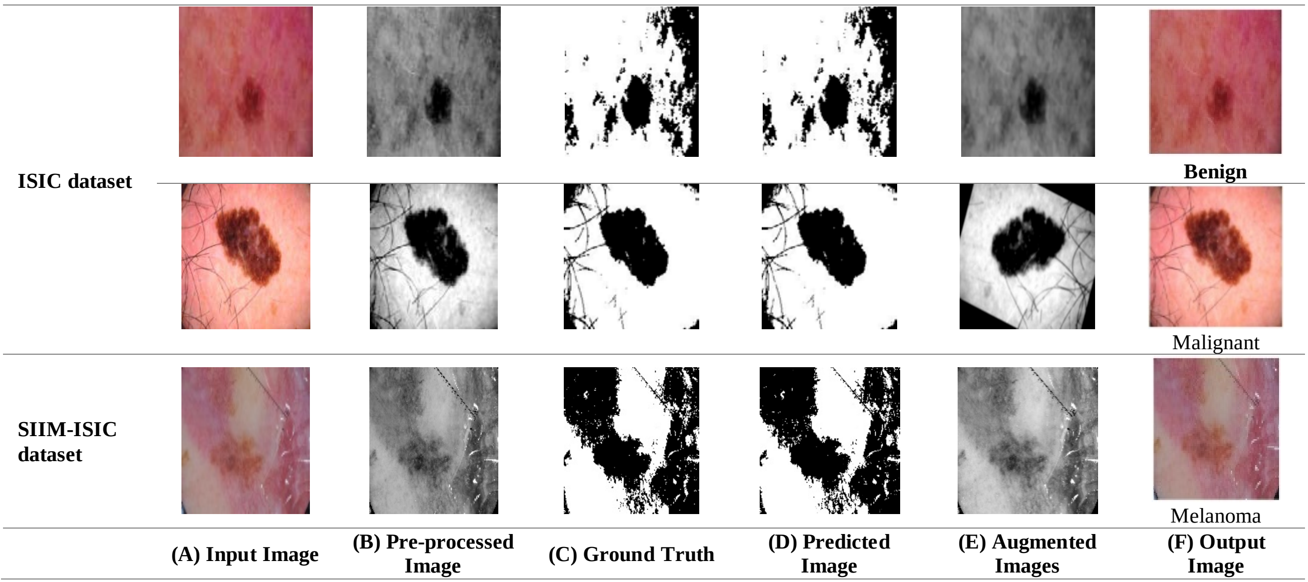


Fig. 3. Experimental outcomes using Dataset 1 and Dataset 2 (ISIC and SIIM-ISIC).

4.4. Graphical representation Using Data Set 1(ISIC) and data Set (SIIM-ISIC)

Figure 4 and 5 displays the testing and validation through accuracy values across epochs in (i). It illustrates how well the model is learning and loss should decrease over time if training is effective in (ii), a 2D matrix where the darker colors indicate higher values, in (iii), a curve closer to the top left corner indicated a better model ROC in (iv).

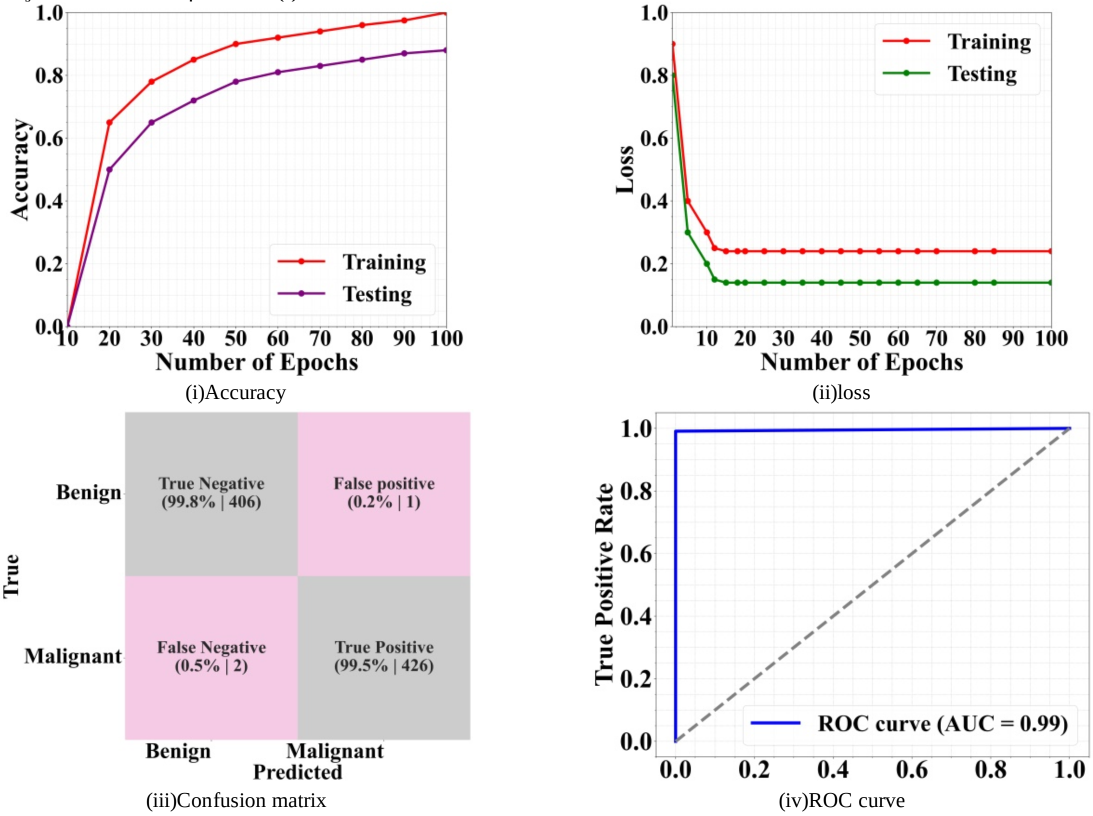
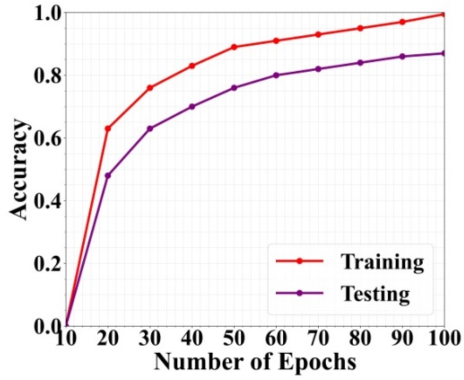
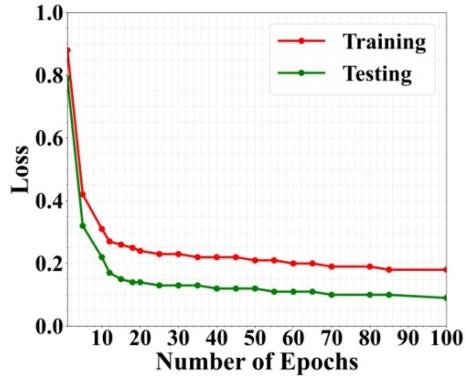


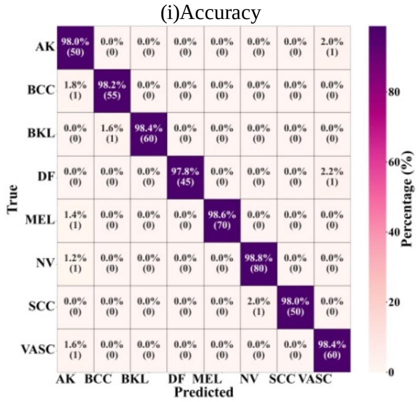
Fig. 4. Graphical representation using dataset 1(ISIC)



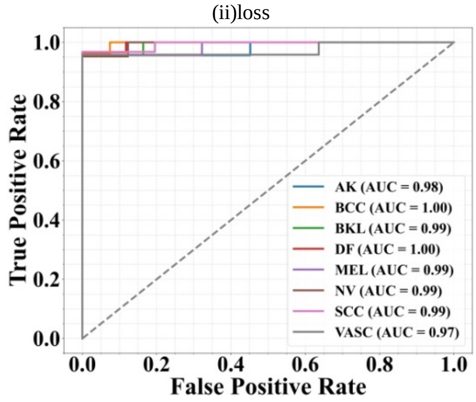
(i)Accuracy



(ii)loss



(iii)Confusion matrix

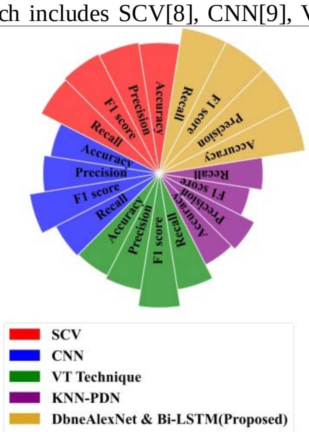


(iv)ROC curve

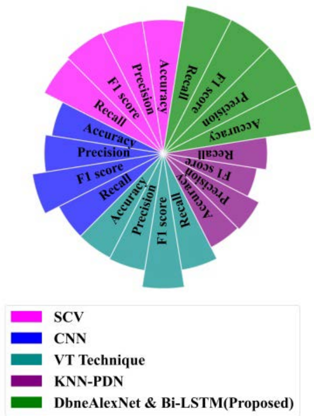
Fig. 5. Graphical representation using dataset 2(SIIM-ISIC)

4.5. Comparative Assessment

Figure 6 displays the comparison chart using the metrics like accuracy, precision, recall, and F1-score with existing methods which includes SCV[8], CNN[9], VT technique[10] and KNN-PDN[11] with the proposed technique hybrid DbneAlexNet and Bi-LSTM using dataset ISIC, SIIM-ISIC. The proposed model DbneAlexNet and Bi-LSTM consistently performs better, as indicated by larger segments in both charts.



6(a) ISIC dataset comparison



6(b)SIIM-ISIC dataset comparison

Fig. 6. Comparison assessment with existing methods

Table 2 displays the comparative analysis of the proposed model that reveals the greatest values across all measures with scores of 99.60, 99.64, 99.66, 99.62 in terms of accuracy, precision, F1 Score and recall respectively for the ISIC dataset. The result proves that the proposed performs significantly better than the other models. Overall, these results are highlights the effectiveness of deep learning in skin cancer detection.

Table 2. Comparative analysis of the proposed and existing methods

Datasets	Metrics	SVM	CNN	VT	KNN-PDN	Proposed DbneAlexNet &Bi-LSTM
ISIC dataset	Accuracy	88.30	74.30	77.20	69	99.60
	Precision	89.50	78.50	79.50	72	99.64
	F1Score	90.50	88.50	90.50	62	99.66
	Recall	89.30	78.30	79.20	70	99.62
SIIM-ISIC dataset	Accuracy	88.9	75	77.9	70.1	99.5
	Precision	89.2	79.2	78.8	71.4	99.7
	F1Score	90.1	88	89.9	63	99.8
	Recall	88.7	77.8	78.5	69.2	99.6

5. Conclusion

The hybrid DbneAlexNet and Bi-LSTM technique offers a robust solution for automated skin cancer classification by leveraging advanced deep learning techniques. The proposed method’s efficiency is boosted by processing only pertinent skin lesion feature by applying Gaussian filtering and RoI extraction.

The accurate feature extraction process by applying statistical features and LVP is further aided by MSRFNet's excellent lesion segmentation. By diversifying the training images, image augmentation approaches improve generalizability and minimize over fitting. The method's exceptional classification accuracy, which combines the advantages of DbneAlexNet and BI-LSTM, makes it easier to detect and diagnose skin cancer early. To enhance the ability of the framework, to manage a variety of skin types, future research could concentrate on multi-dimensional data such as clinical and genetic information. When paired with novel approaches like attention mechanism and transfer learning, real time detection on wearable and mobile devices may further enhance generalization and usability.

Authorship Contributions

Authors contributed equally to this work.

Declaration of conflicting interests

There are no conflicts of interest related to the manuscript.

Funding

The authors received no financial support for the research and/or authorship of this article.

Ethics

There are no ethical issues with the publication of this manuscript.

Data Availability Statement

The datasets used in this study are publicly available from the ISIC Archive and SIIM-ISIC Melanoma Classification dataset repositories.

References

[1] Wu, Y., Chen, B., Zeng, A., Pan, D., Wang, R., & Zhao, S. (2022). Skin cancer classification with deep learning: A systematic review. *Frontiers in Oncology*, 12, 893972. https://doi.org/10.3389/fonc.2022.893972

[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] Adamu, S., Alhussian, H., Aziz, N., Abdulkadir, S. J., Alwadin, A., Abubakar Imam, A., Abdullahi, M., Garba, A., & Saidu, Y. (2024). The future of skin cancer diagnosis: A comprehensive systematic literature review of machine learning and deep learning models. *Cogent Engineering*, 11(1), 2395425. https://doi.org/10.1080/23311916.2024.2395425

[4] Patil, H. (2024). Frontier machine learning techniques for melanoma skin cancer identification and categorization: A thorough review. *Oral Oncology Reports*, 100217. https://doi.org/10.1016/j.oor.2024.100217

[5] Saleh, N., Hassan, M. A., & Salaheldin, A. M. (2024). Skin cancer classification based on an optimized convolutional neural network and multicriteria decision-making. *Scientific Reports*, 14(1), 17323. https://doi.org/10.1038/s41598-024-67424-9

[6] Ali, K., Shaikh, Z. A., Khan, A. A., & Laghari, A. A. (2022). Multiclass skin cancer classification using EfficientNets: A first step towards preventing skin cancer. *Neuroscience Informatics*, 2(4), 100034. https://doi.org/10.1016/j.neuri.2021.100034

[7] Aljohani, K., & Turki, T. (2022). Automatic classification of melanoma skin cancer with deep convolutional neural networks. *AI*, 3(2), 512–525. https://doi.org/10.3390/ai3020029

[8] Salma, W., & Eltrass, A. S. (2022). Automated deep learning approach for classification of malignant melanoma and benign skin lesions. *Multimedia Tools and Applications*, 81(22), 32643–32660. https://doi.org/10.1007/s11042-022-13081-x

[9] Jayakanth, P., & Nesa Kumari, G. R. (2025). Implementation of an efficient skin disease classification framework using Res-SENet with hybrid attention analyzing dermatological images. In *2025 International Conference on Intelligent Innovations in Engineering and Technology (ICIIET)*, Coimbatore, India, 1–6. https://doi.org/10.1109/ICIIET65921.2025.11379188

[10] Xin, C., Liu, Z., Zhao, K., Miao, L., Ma, Y., Zhu, X., Zhou, Q., Wang, S., Li, L., Yang, F., & Xu, S. (2022). An improved transformer network for skin cancer classification. *Computers in Biology and Medicine*, 149, 105939. https://doi.org/10.1016/j.compbiomed.2022.105939

[11] Magdy, A., Hussein, H., Abdel-Kader, R. F., & Abd El Salam, K. (2023). Performance enhancement of skin cancer classification using computer vision. *IEEE Access*, 11, 72120–72133. https://doi.org/10.1109/ACCESS.2023.3294974

[12] Gururaj, H. L., Manju, N., Nagarjun, A., Aradhya, V. M., & Flammini, F. (2023). DeepSkin: A deep learning approach for skin cancer classification. *IEEE Access*, 11, 50205–50214. https://doi.org/10.1109/ACCESS.2023.3274848

[13] Kurtansky, N. R., Primiero, C. A., Betz-Stablein, B., Combalia, M., Guitera, P., Halpern, A., Kentley, J., Kittler, H., Liopyris, K., Malvehy, J., & Rinner, C. (2024). Effect of patient-contextual skin images in human- and artificial intelligence-based diagnosis of melanoma: Results from the 2020 SIIM-ISIC melanoma classification challenge. *Journal of the European Academy of Dermatology and Venereology*. https://doi.org/10.1111/jdv.20479

[14] Gayatri, E., & Aarthy, S. L. (2024). Reduction of overfitting on the highly imbalanced ISIC-2019 skin dataset using deep learning frameworks. *Journal of X-Ray Science and Technology*, 32(1), 53–68. https://doi.org/10.3233/XST-230204

[15] Abuya, T. K., Rimiru, R. M., & Okeyo, G. O. (2023). An image denoising technique using wavelet-anisotropic Gaussian filter-based denoising convolutional neural network for CT images. *Applied Sciences*, 13(21), 12069. https://doi.org/10.3390/app132112069

[16] Javeed, M. A., Ghaffar, M. A., Ashraf, M. A., Zubair, N., Metwally, A. S. M., Tag-Eldin, E. M., Bocchetta, P., Javed, M. S., & Jiang, X. (2023). Lane line detection and object scene segmentation using Otsu thresholding and the fast Hough transform for intelligent vehicles in complex road conditions. *Electronics*, 12(5), 1079. https://doi.org/10.3390/electronics12051079

[17] Srivastava, A., Jha, D., Chanda, S., Pal, U., Johansen, H. D., Johansen, D., Riegler, M. A., Ali, S., & Halvorsen, P. (2021). MSRF-Net: A multi-scale residual fusion network for biomedical image segmentation. *IEEE Journal of Biomedical and Health Informatics*, 26(5), 2252–2263. https://doi.org/10.1109/JBHI.2021.3138024

[18] de la Rosa, F. L., Gómez-Sirvent, J. L., Sánchez-Reolid, R., Morales, R., & Fernández-Caballero, A. (2022). Geometric transformation-based data augmentation on defect classification of segmented images of semiconductor materials using a ResNet50 convolutional neural network. *Expert Systems with Applications*, 206, 117731. https://doi.org/10.1016/j.eswa.2022.117731

[19] Yang, Z., Sinnott, R. O., Bailey, J., & Ke, Q. (2023). A survey of automated data augmentation algorithms for deep learning-based image classification tasks. *Knowledge and Information Systems*, 65(7), 2805–2861. https://doi.org/10.1007/s10115-023-01853-2

[20] Ahammed, M., Mamun, M. A., & Uddin, M. S. (2022). A machine learning approach for skin disease detection and classification using image segmentation. *Healthcare Analytics*, 2, 100122. https://doi.org/10.1016/j.health.2022.100122

[21] Shi, S., Jiang, L., Deng, J., Wang, Z., Guo, C., Shi, J., Wang, X., & Li, H. (2023). PV-RCNN++: Point-voxel feature set abstraction with local vector representation for 3D object detection. *International Journal of Computer Vision*, 131(2), 531–551. https://doi.org/10.1007/s11263-022-01710-9

[22] Girdhar, N., Sinha, A., & Gupta, S. (2023). DenseNet-II: An improved deep convolutional neural network for melanoma cancer detection. *Soft Computing*, 27(18), 13285–13304. https://doi.org/10.1007/s00500-022-07406-z

[23] Rajaretnam, S., & Yesodharan, V. (2024). A novel DbneAlexNet with Gazelle Hunting Optimization Algorithm enabled wild animal detection in WMSN data communication in IoT environment. *International Journal of Communication Systems*, 37(11), e5787. https://doi.org/10.1002/dac.5787

[24] Mughees, N., Jaffery, M. H., Mughees, A., Mughees, A., & Ejsmont, K. (2023). Bi-LSTM-based deep stacked sequence-to-sequence autoencoder for forecasting solar irradiation and wind speed. *Computers, Materials & Continua*, 75(3). https://doi.org/10.32604/cmc.2023.038564

[25] Niyogisubizo, J., Liao, L., Nziyumva, E., Murwanashyaka, E., & Nshimyumukiza, P. C. (2022). Predicting student dropout in university classes using two-layer ensemble machine learning approach: A novel stacked generalization. *Computers and Education: Artificial Intelligence*, 3, 100066. https://doi.org/10.1016/j.caeai.2022.100066