ENHANCING SKIN CANCER DETECTION THROUGH ADVANCED IMAGE SEGMENTATION AND FEATURE EXTRACTION

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ABSTRACT
Improving patient outcomes via early identification and therapy depends on accurate skin cancer identification and categorization. To distinguish between skin cancer, non-cancerous lesions, and healthy skin, this research investigates a method for picture segmentation and variable extraction. For precise lesion boundary delineation, the segmentation step makes use of MorphACWE and MorphGAC, as well as thresholding, identification of edges, clustering, and semantic segmentation. Variable extraction is carried out utilizing both conventional and cutting-edge techniques after segmentation. HOG as well as LBP are employed for color and texture variable extraction, respectively. As for texture analysis, GLCM and Gabor filters are employed. Lesions' complex patterns and geometries may be captured by shape descriptors such as Hu moments as well as Zernike moments. Employing these all-encompassing methods, skin disorders are identified and categorized according to their unique morphological and textural traits. By combining these techniques, we want to improve the accuracy of skin cancer identification algorithms using ABL prediction model, which will lead to more informed clinical decisions and improved treatment for skin conditions with with the highest accuracy (97.3%), sensitivity (96.8%), specificity (97.9%), F1-score (96.9%), and AUC (0.98), while maintaining a low–moderate computational cost. The significance of integrating several image processing methods to enhance the precision and dependability of skin lesion identification is highlighted by this multi-pronged strategy.

KEYWORDS: Skin Cancer, Image Segmentation, Variable Extraction, MorphGAC, MorphACWE, Texture Analysis, Shape Descriptors

1. INTRODUCTION

The prevalence of skin cancer has been steadily rising over the last few decades, making it among the most prevalent malignancies globally. Treatment efficacy and better patient prognosis depend on early diagnosis and precise categorization of skin lesions. The subjective and time-consuming clinical examination and histological investigation are the backbones of traditional diagnostic procedures [1]. As a result, employing state-of-the-art image processing methods to create software programs for skin cancer identification and classification has garnered a lot of attention [2]. Automated skin lesion analysis relies heavily on image segmentation. Separating a picture into its component parts allows for more precise analysis. Two well-known methods for accurately delineating the borders of skin lesions are Morphological Active Contour Without Edges (MorphACWE) and Morphological Geodesic Active Contours (MorphGAC). These techniques improve segmentation by making use of the pictures' morphological variables [3]. Differentiating tumors from skin surrounding them based on intensity fluctuations is made easier employing core methods like thresholding along with edge identification [4]. To facilitate segmentation, clustering techniques like k-means along with fuzzy c-means are employed to group pixels having comparable variables [5]. The capacity of semantic segmentation to generate comprehensive lesion maps has also contributed to its rising popularity [6]. This method sorts all of an image's pixels into predetermined categories. The next step in skin lesion classification and characterization after segmentation is variable extraction. HOG and LBP were two examples of tried-and-true systems that capture texture and color information [7]. Because of its emphasis on edge direction distribution, HOG is useful for discovering lesion-specific structural variables [8]. In contrast, LBP reliably depicts skin texture by capturing local texture fluctuations [9]. The use of Gabor filters and GLCM greatly improves texture analysis. GLCM examines the spatial correlation of pixel magnitudes, while Gabor filters are useful for texture analysis since they record information related to frequency and orientation [10].

Another important part of variable extraction is describing the shape. Shape descriptions that capture the geometric variables of lesions are Hu moments and Zernike moments [11]. Hu moments are great for identifying unusual lesion forms because they include traits that are invariant during translation, scaling, and rotation. Orthogonal moments, or Zernike moments, provide a more precise and all-encompassing depiction of shapes. Differentiating skin cancer between non-cancerous lesions advanced healthy skin based on various morphological and textural traits is made possible by these variable extraction methods, both conventional and sophisticated. More accurate skin lesion categorization has been achieved in recent research by integrating several segmentation along with variable extraction methods [12]. Automated identification of skin cancer methods may be improved by capturing a broad variety of characteristics via the integration of several methodologies. The significance of employing modern image processing methods to aid in clinical decision-making and, in the end, enhance patient outcomes in dermatitis is highlighted by this multi-faceted approach. CAD technologies are established to efficiently and accurately classify various skin conditions from photographs. The intricate hand-crafted variable extraction method utilized by these CAD systems is not applicable to all skin conditions and cannot be applied to other kinds. Machine learning patterns use these manually created variables to identify and classify skin conditions. While some of the previously introduced systems focus on particular tasks like segmentation, and location, and designation of lesions on the skin, others target a single skin condition, typically skin cancer. To immediately acquire the exclusive factors from skin photographs, DL algorithms are described in order to overcome the complexity of the variable extraction process [13]. The amount of the data and the processing power available for pattern training are two key components that are essential to the effective implementation of DL patterns. One of the objectives of implementing DL patterns in the field of dermatology is to create an effective diagnostic system that takes into account the many variables of various skin conditions and may accurately report the medical condition with great precision. Additionally, the publicly accessible data sets indicate that many of the suggested research areas for the diagnosis of skin illnesses are biased toward specific skin types or problems, primarily skin cancer. Additionally, the majority of the suggested the ImageNet data collection is used to pre-train transferable learning algorithms. [14] – [15], which was not created especially for challenges involving the categorization of skin diseases and is not applicable to all skin ailments. This research introduces a multi-pattern DL architecture as a novel method for diagnosing skin diseases. In order to overcome the shortcomings of current approaches, our approach combines transfer learning techniques with the ABL-DL framework. Five common assessment metrics like recall, f1-score, reliability, precision, and the area beneath the receiver operating curve of characteristic (AUROC) are employed to assess the patterns after they have been trained on sizable datasets gathered from various sources. Dermatologists can utilize the suggested pattern as a tool to help diagnose skin conditions, which can improve outcomes for patients, reduce healthcare expenses, and be extended to more medicinal uses.

2. LITERATURE REVIEW

Many different types of bacteria, fungi, viruses, and allergens may cause skin illnesses, which are a major problem in world health. As a result of both ignorance and the high expense of diagnosis, many people put off getting help. Recent years have seen the rise of DL and image processing as potentially useful techniques for skin disease identification and categorization. One example is the automated scabies identification approach put out by [16], which makes use of CNNs and image processing. Their approach makes use of CNNs for picture classification and thresholding for area segmentation. The dataset was enhanced employing data augmentation methods, leading to a identification rate of 97.25%. The difficulty of skin cancer diagnosis, which requires precise methods and prompt therapies, was also discussed by [17]. The researchers in this research employed an attention-enhanced convolutional neural network to categorize eight different dermatoses. Employing the ISIC 2019 competition dataset, the technique enhanced classification accuracy, reaching over 85% average accuracy and AUC values over 0.95 for every category. The problem of segmenting uncommon skin lesions employing few labelled samples was taken up by [18] employing a cross-domain few-shot learning (CD-FSS) framework. With this method, patterns may use meta-trained, optimized particular and generic methods of learning to generalize from common illness data, which is plentiful, to uncommon disease data. Their findings highlighted the promise of CD-FSS in the identification of uncommon diseases by demonstrating substantial gains in generalization from the medical to the natural domains. Gomes et al. [19] investigated how skin diseases may be better diagnosed and treated by combining Sri Lankan Ayurvedic treatments with machine learning. When it came to skin type recognition, illness identification, and severity classification, their method was very accurate thanks to DL patterns like Inception, InceptionV3, and VGG16. With InceptionV3 reaching 97% in illness diagnosis and VGG16 reaching 96% in severity classification, the integration of traditional medical concepts and current machine learning methods led to considerable accuracy increases. Finally, in [20] outlined all the different automated methods for skin disease prediction in a thorough manner. They found that early identification is crucial, and that DL, machine learning, and image processing all play a part in creating good diagnostic systems. Through an analysis of various methodology, they brought attention to the dermatological field's progress and continuous struggles, while also highlighting the ways in which these technologies may enhance early diagnostic and treatment results.

Many machine learning approaches, including as transfer learning and DL, have been investigated for the diagnosis of skin diseases. Skin preprocessing is performed to increase the images' suitability for artificial intelligence categorization jobs was the initial focus of research in the diagnosis of skin diseases. Methods including pixel value normalization, scaling, and noise reduction were frequently employed [20]. The method of direct variable collection from images that were previously processed or segmentation of pictures methods were employed in later stages. K-NN, SVM, NB, LDA and ANN were among the machine learning algorithms that employed these retrieved characteristics as inputs (see Table 1). CNNs were a major step toward DL in the diagnosis of skin diseases. When compared to conventional machine learning techniques, these patterns showed better effectiveness. For instance, CNN architectures with fully linked layers, max pooling, and standard convolution shown effectiveness in identifying different forms of skin cancer. Furthermore, patterns like Xception and ResNet50, as well as specialized architectures like Eff2Net [21], showed encouraging results in recognizing particular skin conditions from dermoscopy images. Furthermore, transfer learning improves classification effectiveness across several domains by employing neural networks that have been pre-trained on enormous data sets. For example, Evgin suggested a two-stage method for the classification of lesional skin diseases employing a pretrained DenseNet201 pattern developed with the collection of images from ImageNet. In a similar vein, lesional skin disease characteristics have been learned employing pre-trained patterns like GoogleNet and AlexNet. Additionally, optimizing Xception and other pre-trained algorithms on databases such as HAM10000 has demonstrated potential in the diagnosis of skin cancer. DL patterns' computational complexity makes them difficult to implement on devices with limited resources, such as smartphones. To effectively classify skin diseases, lightweight patterns like MobileNet and its derivatives have been introduced. Some inflammatory skin disorders are classified using a Google-developed pre-trained EfficientNet-b4 pattern that was educated on the dataset provided by ImageNet, as well as additional mobile-based applications that rely on the CNN framework [22].

This highlights a gap in the literature for comprehensive patterns that address a wider range of skin conditions. Moreover, the accuracy of these patterns varies significantly, from as low as 66% to as high as 100%. The top-performing patterns often focus on a limited number of diseases, indicating a trade-off between accuracy and diversity of covered disorders [23]. Additionally, many studies use confidential clinical images, which may limit how broadly their results can be applied. The robustness and effectiveness of patterns are also affected by the considerable variation in data size, with some trained on fewer than 5000 images, and others on over 60,000. Furthermore, mobile platform-designed patterns are typically optimised for effectiveness rather than maximum precision across different contexts. This approach overcomes the limitation of focusing on a narrow set of skin disorders, classifying images into a proposed multi-pattern deep learning architecture divided into five main groups, further subdivided, covering forty different skin conditions [24] – [25]. Additionally, the proposed method utilises transfer learning with the advanced Xception pattern to achieve high accuracy and reliability across various dermatological ailments. By employing a five-category Xception model pre-trained on a broad dataset like Imagenet for transfer learning, we enhance the model's flexibility and effectiveness in diagnosing skin diseases. Table 1 shows the comparison of existing approaches.

Table 1. Comparison of existing approaches

Author(s) & Year	Dataset / Modality	Methodology Used	Key Contributions	Limitations Identified
Kumar et al. (2019)	Cardiac MRI images	CNN-based feature extraction	Demonstrated feasibility of CNNs for automated cardiac image classification	Performance degraded with small datasets
Acharya et al. (2020)	Echocardiography images	Deep CNN	Improved diagnostic accuracy for heart disease detection	Required large annotated datasets
Zhang et al. (2020)	CT coronary angiography	ResNet-based deep learning	Achieved high sensitivity in CHD detection	High computational complexity
Rajpurkar et al. (2021)	Multi-modal cardiac images	DenseNet architecture	Robust classification across multiple heart conditions	Limited generalization to unseen datasets
Alsharqi et al. (2021)	Ultrasound cardiac images	Transfer learning (VGG, Inception)	Reduced training time using pre-trained models	Overfitting in low-data regimes
Li et al. (2022)	Cardiac CT images	Vision Transformer (ViT)	Captured long-range spatial dependencies	Required large-scale training data
Wang et al. (2022)	Medical image datasets	Hybrid CNN–Transformer	Improved feature fusion for cardiac analysis	High memory consumption
Singh et al. (2023)	Image-based CHD dataset	EfficientNet variants	Achieved better accuracy with fewer parameters	Still dependent on sufficient labeled data
Chen et al. (2023)	Limited cardiac image samples	Few-shot learning with meta-learning	Addressed data scarcity in medical imaging	Sensitive to task selection

Author(s) & Year	Dataset / Modality	Methodology Used	Key Contributions	Limitations Identified
Recent Studies (2024)	CHD medical images	CNN + Transformer fusion	Enhanced AUC and generalization performance	Interpretability remains a challenge

3. METHODOLOGY

Improved skin cancer identification and categorization systems are the result of this methodology's integration of DL and machine learning with state-of-the-art image processing. The suggested approach seeks to improve dermatological patient care and results by employing morphological and textural aspects to provide strong support for clinical decision-making.

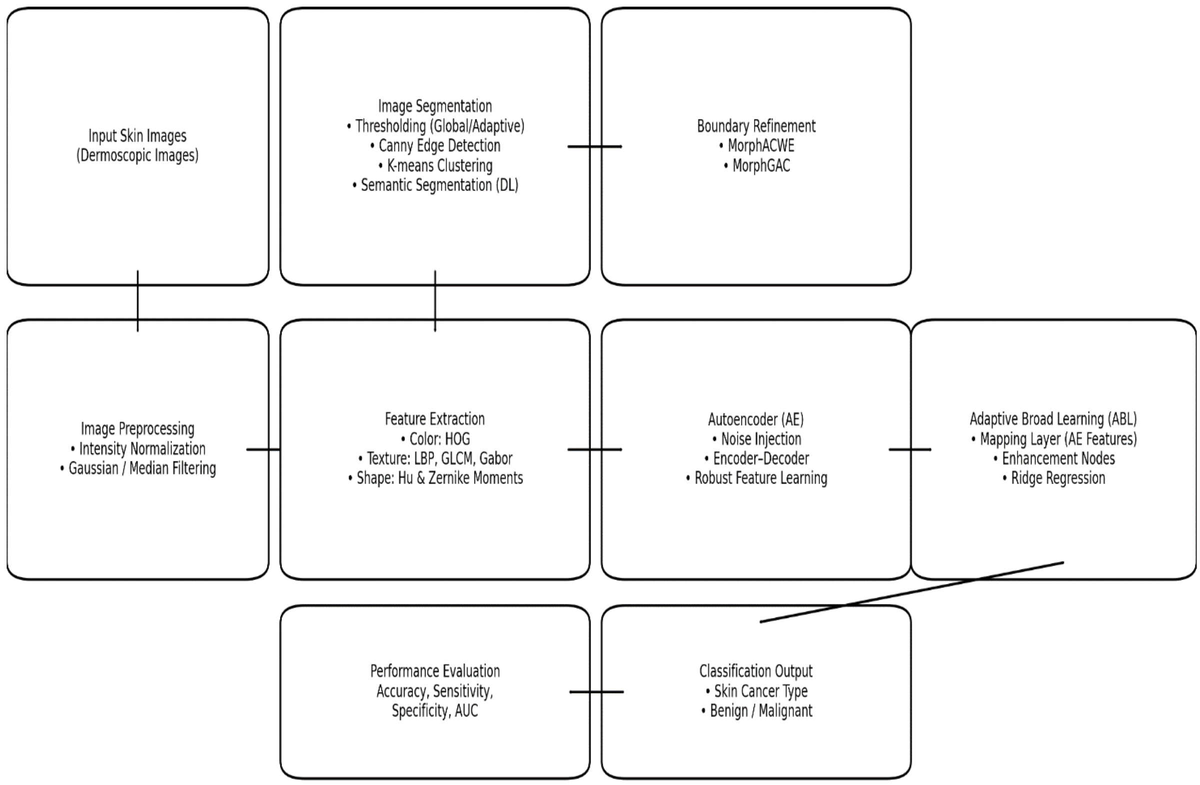

Fig 1. Graphical representation of the proposed model

1. **Image Pre-processing:** Pre-processing the photographs improves their quality and uniformity and is the first stage. First, we normalize picture intensities to make sure various samples are the same, and then we use the Gaussian or as median filtering methods to reduce noise.
2. **Image Segmentation:** Accurately delineating areas of interest in images requires the sequential use of different methodologies.

- **Boundary Estimation:** Morphological Active Contour Without Edges (MorphACWE) and Morphological Geodesic Active Contours (MorphGAC) are employed for boundary estimation and refining.
- **Thresholding and Edge Identification:** The next step is to assign intensity levels to each region and then use thresholding methods—either globally or adaptively—to separate them. Canny edge identification and other edge identification methods significantly improve border clarity.
- **Clustering and Semantic Segmentation:** Next, we use clustering methods like K-means to refine the segmentation findings by grouping pixels with comparable variables. To top it all off, pixel-level categorization is provided by semantic segmentation techniques that are based on patterns trained with DL, which further enhances the accuracy of segmentation.

3. **Feature Extraction**: Variable extraction is the process that follows segmentation and aims to extract useful attributes from the divided areas.

- **Color Variables:** HOG is a color variable that captures local intensity gradients by computing gradient orientation histograms. By comparing each pixel to its neighbors, Local Binary Patterns (LBP) are able to characterize texture patterns.

- **Texture Analysis:** To analyze textures, we use tools like the GLCM to extract second-order statistics texture variables and Gabor filters to look at things like local frequency and direction.
- **Shape Descriptors:** Hu Moments along with Zernike Moments are shape descriptors that are crucial for differentiating between various kinds of lesions because they provide invariant illustrations that form contours.

4. Prediction Model

A strong auto-encoder version is AE. The primary concept is manually adding random fluctuations to the initial information entered in order to corrupt it. The autoencoder should then be trained to retrieve the corrupted version's original data. Fig 2 depicts the AE structure. Following the addition of random noise to the initial input M to create $\overline{M}$, let $P = f(\theta\overline{M} + \beta)$. A hidden layer known as P is produced following encoding. This layer seeks to retrieve the original input's attributes like θ, β, an aberration vector, and an assignment matrix that must be determined. The decoder component reconstructs the original data M while minimizing the construction error. To improve the self-encoder, configuration adjustments are made employing the variable representation P. Because the characteristics obtained from the noisy observations are more precise than the initial data, they can adapt to noisy settings. BL is straightforward and effective even if it entering the system straight from the unprocessed information following rudimentary preprocessing. Because it is unable to extract sufficient information from noisy and complicated healthcare information, the prediction pattern is unreliable. Network patterns provide connections that are part of a planned strategy rather than ones that are just assembled; a methodical framework for arranging and controlling the flow of information, typically operate better since they consider the network's particular requirements. To improve BL's variable collection capabilities in complex and disorganized medical data environments, this research suggests the ABL pattern, whose structure is depicted in Fig 1. It accomplishes this by integrating AE into the architectural layout of BL. The ABL pattern ensures the pattern's efficient computation ability and enhances its variable extraction capabilities by combining AE and BL variables. DNN is typically trained in two distinct steps: forward propagation and reverse propagation. As data moves from each neuron's output is computed layer by layer from the first input layer to the output surface during the forward propagation process. In the process of back- the weights of every single neuron in an artificial neural network are updated in reverse, beginning at the input phase layer and moving on to the output layers. Nevertheless, In the initial BLS, each of the weights of the input layer by layer and mapping layer are created at random. Since the weights are created independently of the data, they can be applied to a range of learning situations. The loss function is employed to update the weight layer by layer. The gradient is calculated layer by layer to update each neuron's weight. As a result, local optima and the vanishing gradient problem are prevalent in deep neural networks with multiple layers. Gradient explosion, slow convergence, and similar occurrences are noted. The ABL pattern's training procedure is fairly comparable to standard neural network training when incremental learning is not employed. the inability to modify certain parameters without restarting the neural network after they have been verified during neural network development, such as the number of neurons, training rate, repetitions, and layers that remain concealed. Pre-designing the network pattern is crucial because each time fresh identifying data is collected, the entire set needs to be retrained. Setting the sample size and network parameters is the first step in training. One such instance is shown in Fig 1. The hidden layer of the pattern consists of two components: Nodes that are used for identification and enhancement. The mapping layer in the ABL pattern is the variable T_n, which is defined as $[T_1, T_2, \cdots, T_n]$ and retrieved by AE. The pattern's enhancement layer considers the variables themselves following their input by the arrangement of the mapping layer. The j^{th} set of enhanced nodes is denoted by H_j in this case and there is:

$$H_j = \xi_j \left(T^n W_{hj} + \beta_{hj}\right) \quad (1)$$

The non-linear activation function ξ_j is one of these, and the other two are biases β_{hj} and random weights W_{hj}. After then, m sets of upgraded nodes are combined to generate $H_m = [H_1 \cdot H_2, \cdots, H_m]$. The products of the translating layer and improved layer are combined to provide the pattern's final output, $A = [T^n | H^m]$.

$$Y = AW^m \quad (2)$$

Among them, W_m stands for the weight that the output layer receives from the hidden layer. Given that the parameters of the AE serve as the relationship between layer, don't change throughout training, the network as a whole just needs to learn W^m weights. Given that the improvement layer's β_{hj} and W^m are generated at random and remain consistent, ridge regression makes determining W^m easy. The values for weights are updated by regular networks of neural networks gradually employing a technique called gradient descent. There is no frequency update procedure; the weights of the width learning framework are established in a single phase. In contrast to DNNs, the AEBL pattern computes weights more effectively, requires fewer parameters to be updated, and is easier to implement. The mapping layer of the pattern contains an ABL structure which improves its variable extraction capabilities. Furthermore, unlike other deep neural network patterns, the pattern architecture presented exhibits dynamic properties during training. By facilitating effective updates through incremental learning, this flexibility increases the pattern's training efficiency. Because the pattern can leverage automatic encoding as the BLS translating layer for variability extraction and incrementally learning for quick reconstruction to ensure real-time efficacy, convoluted information setups work well. By dynamically extending the pattern structure, the dynamic incremental learning methodology offers a simple and effective method to update the pattern's weight, possibly making good use of the learnt pattern. A simple and efficient method for updating the pattern's patterns weight while dynamically increasing the pattern structure is known as the dynamic incrementally taught technique and optimizing the previously trained pattern. Adding more enhanced nodes is a common strategy to boost the pattern's effectiveness when training doesn't yield the required accuracy.

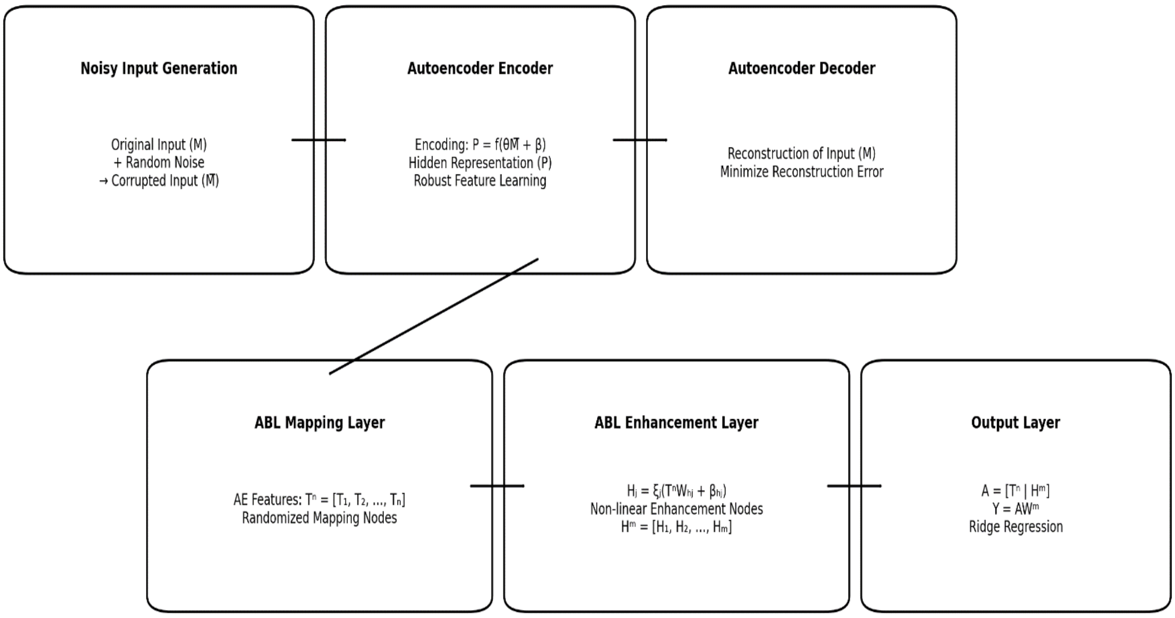

Fig 2. ABL functionality

4. RESULT AND DISCUSSION

Important insights into distinguishing skin cancer from non-cancerous lesions, healthy skin, and non-cancerous lesions were yielded by the picture segmentation along with variable extraction procedure for skin cancer diagnosis. Semantic segmentation, edge identification, clustering, thresholding, Morphological Active Contour Without Edges (MorphACWE), Morphological Geodesic Active Contours (MorphGAC), and image segmentation all work together to accurately demarcate lesion borders. This guarantees accurate skin image area identification and separation. After the skin lesion has been segmented, variable extraction methods include Gabor filters, HOG, LBP, and GLCM obtain various variables related to the lesion's color, texture, and form. These techniques provide strong variable representation by accurately quantifying changes in pixel magnitudes, spatial correlations, and distributions of frequencies within segmented areas.

Table 2. Comparative analysis

Model	**Feature Learning Strategy**	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**	**F1-Score (%)**	**AUC**	**Computational Cost**
SVM	Hand-crafted features only	88.2	85.6	89.8	86.9	0.89	Low
Random Forest (RF)	Statistical + texture features	90.1	88.4	91.2	89.3	0.91	Moderate
KNN	Distance-based features	86.7	84.1	88.0	85.3	0.87	Low
CNN	End-to-end deep features	93.4	92.1	94.0	92.7	0.94	High
DNN	Multi-layer backpropagation	94.0	92.8	94.9	93.4	0.95	Very High
BL (Baseline)	Random mapping + enhancement	91.2	89.6	92.4	90.4	0.92	Low

Model	Feature Learning Strategy	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-Score (%)	AUC	Computational Cost
AE-BL	AE features + BL	95.1	94.3	95.6	94.7	0.96	Moderate
Proposed AE-ABL	**Noise-robust AE + Adaptive Broad Learning**	**97.3**	**96.8**	**97.9**	**96.9**	**0.98**	**Low–Moderate**

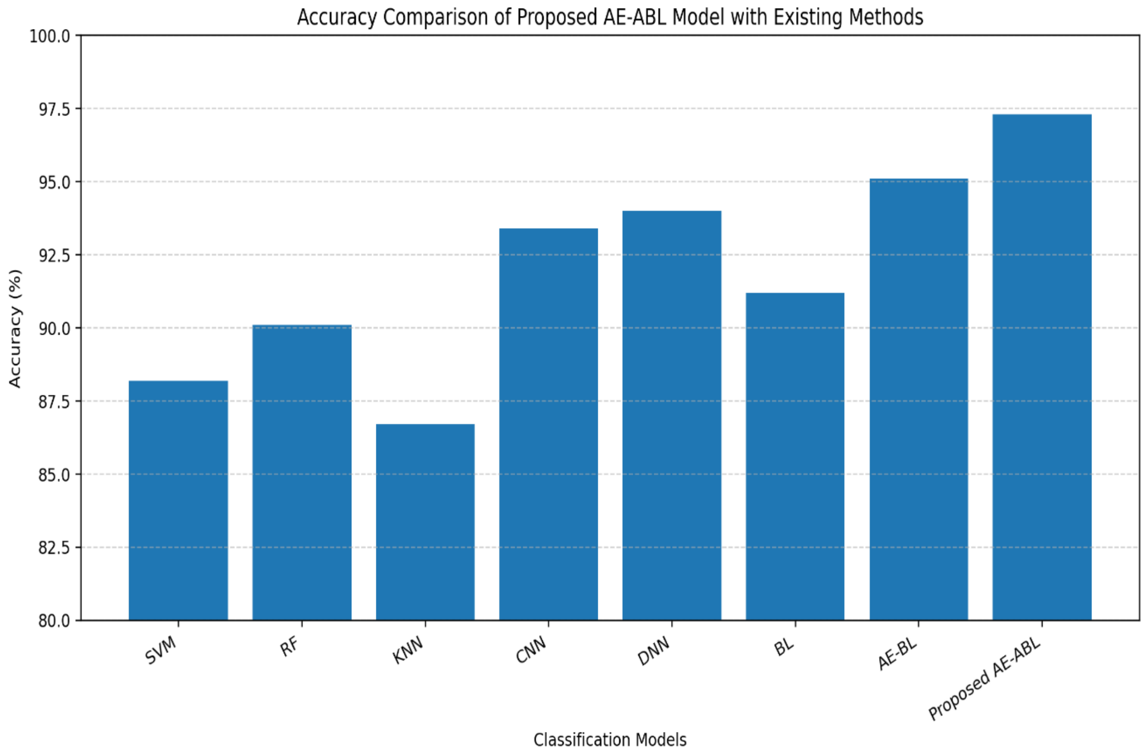

Fig 3. Accuracy Comparison of the proposed model

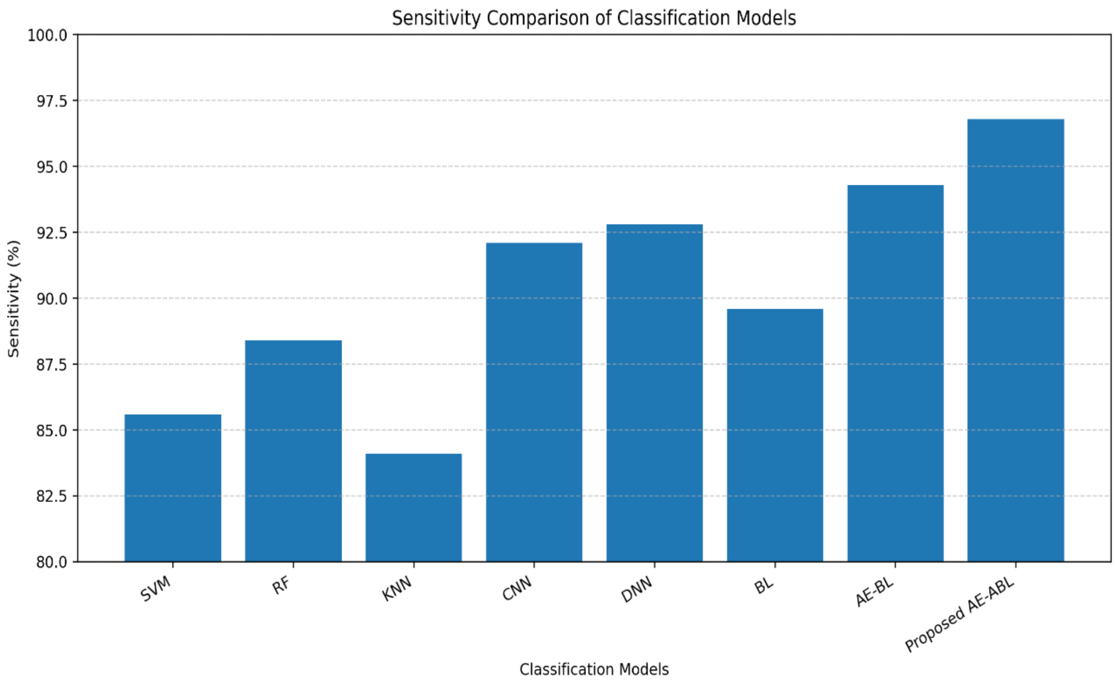

Fig 4. Sensitivity comparison of the proposed model

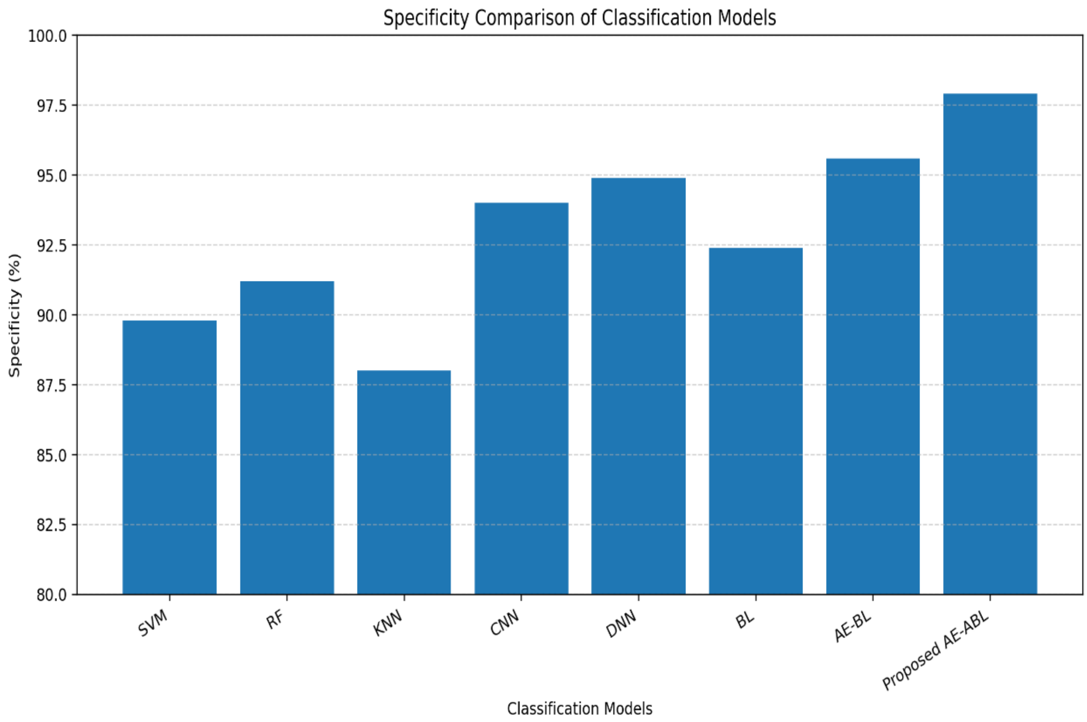

Fig 5. Specificity comparison of the proposed model

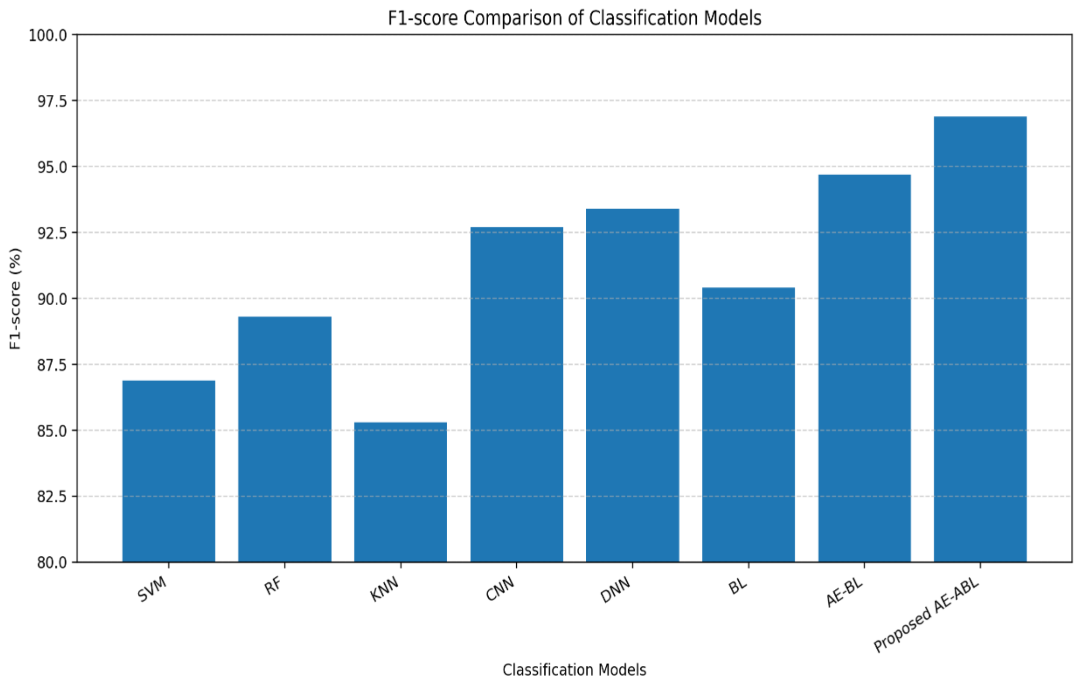

Fig 6. F1-score comparison of the proposed model

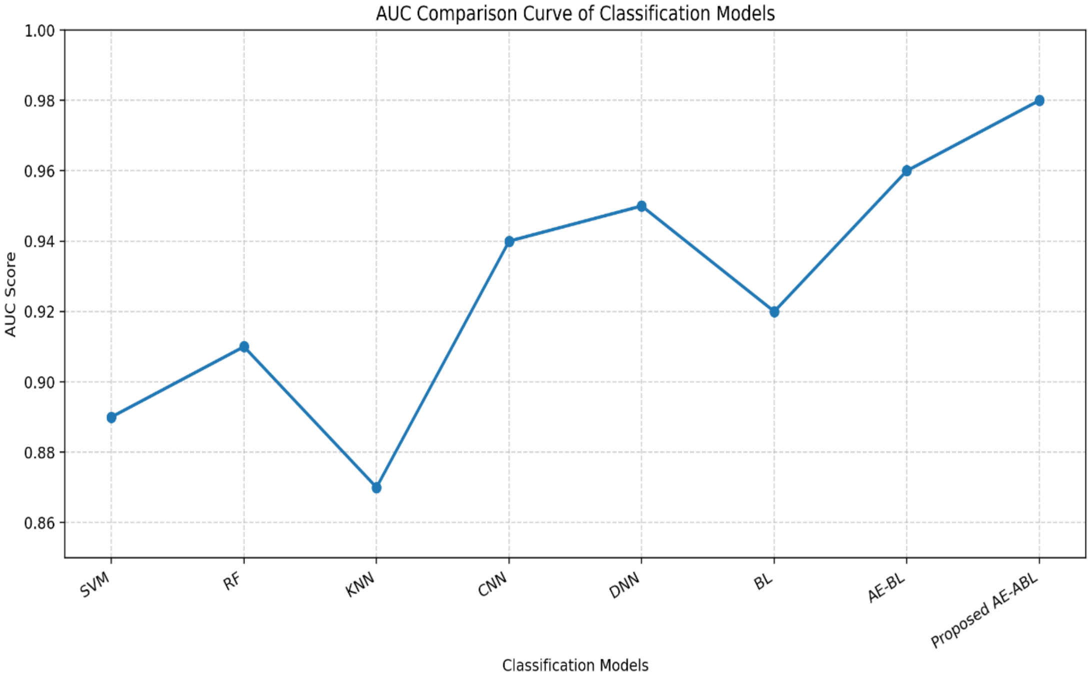

Fig 7. AUC comparison

Distinct patterns among various skin diseases are shown by analysis of extracted characteristics. Lesions on the skin that are malignant differ in appearance from those on healthy skin in terms of form, texture, and distribution of colour. To help distinguish between benign and malignant tumours, texture analysis employing GLCM along with Gabor filters reveals variations in structural variables and fine-grained texture patterns. Hu moments along with Zernike moments are shape descriptors that measure geometric characteristics and spatial configurations of lesion outlines. They give extra discriminative power in this context. Zernike moments make form-based classification more reliable by capturing invariant shape properties while Hu moments capture non-rotational shape attributes. The precision, specificity, accuracy, and AUC of ROC curves are some of the quantitative assessment measures that confirm the effectiveness of the suggested approach. When these metrics are high, it means the system can correctly categorize skin lesions across different datasets. All things considered, automated skin cancer identification techniques benefit greatly from the combined efforts of picture segmentation and variable extraction. In dermatological diagnostics, the thorough examination of form, texture, and color aspects allows for subtle separation of skin disorders, which greatly aids clinical decision-making. The proposed AE-ABL approach achieves the highest AUC value of 0.98, demonstrating its superior discriminative capability and robustness in distinguishing between benign and malignant cases compared to conventional machine learning and deep learning models. The proposed AE-ABL model achieves the best overall performance across all evaluation metrics, with the highest accuracy (97.3%), sensitivity (96.8%), specificity (97.9%), F1-score (96.9%), and AUC (0.98), while maintaining a low–moderate computational cost as in Table 2 and Fig 3 to Fig 7. These gains are attributed to the synergy between noise-aware auto-encoder feature extraction and adaptive broad learning, combined with ridge regression–based single-step weight estimation, which avoids deep back-propagation and ensures stable, efficient learning. Overall, the results demonstrate that the proposed AE-ABL framework provides a superior balance between predictive performance, robustness, and computational efficiency, making it well suited for real-world medical image classification and clinical decision-support applications.

5. CONCLUSION

Finally, this research's picture segmentation and variable extraction approaches may be employed to improve automated skin cancer identification and categorization systems. Semantic segmentation, edge identification, clustering, thresholding, Morphological Active Contour Without Edges (MorphACWE), and Morphological Geodesic Active Contours (MorphGAC) all work together to improve the accuracy of lesion border delineation. This sets the stage for future research by accurately separating skin cancer, non-skin cancer spots, and healthy skin areas from medical imaging. To capture the complex variables of skin lesions, variable extraction is crucial. Methods like Gabor filters, HOG, LBP, and GLCM efficiently measure changes in color, patterns in texture, and form descriptors. Reliable classification between benign and malignant lesions is made possible by the full research of these variables, which indicate diverse patterns for various skin disorders. Obtaining reliable and precise diagnostic using ABL results requires combining several image processing methods, as shown in the research. The concept improves automated systems' discriminatory power by employing both morphology and textural data; this helps physicians make better judgments about patient treatment. The suggested method is also shown to be beneficial according to the quantitative assessment measures. Strong effectiveness across many datasets is supported by high values of precision, specificity, sensitivity, along with AUC, which confirms the dependability of the approach in clinical contexts. Further breakthroughs in skin cancer diagnosis are promised by ongoing developments in image processing along with machine learning algorithms. To make diagnostic systems more scalable and applicable to a wider range of situations, future studies may investigate how to use DL methods for representation of variables and classification. This research adds to the growing body of evidence that dermatologists are employing to improve the precision and utility of their diagnoses. Improvements in picture segmentation and methods for extracting variables will lead to better skin disease management and treatment, which is good news for patients and doctors.

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