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Article

Multi-skin disease classification using hybrid deep learning framework combining convolutional neural networks and support vector machines

Jeyageetha Kaliraj[1,*], Vijayalakshmi Kandasamy[1], Bhuvanesh Aananthan[2]

[1] Department of Computer Science and Engineering, Ramco Institute of Technology, Rajapalayam, Tamil Nadu 626117, India
[2] Department of Electrical and Electronics Engineering, PSN College of Engineering and Technology, Tirunelveli, Tamil Nadu 627152, India
*** Corresponding author:** Jeyageetha Kaliraj, jeyageetharit@gmail.com

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Abstract: Skin disease classification plays a critical role in medical diagnostics, where accurate detection is essential for patient care. This study proposes a hybrid deep learning framework, SDP-DL that combines Convolutional Neural Networks (CNNs) for feature extraction and Support Vector Machines (SVMs) for classification to improve diagnostic precision. The proposed model was evaluated using the HAM10,000 dataset and achieved a classification accuracy of 95.93 %, with a precision of 94.2 %, recall of 94.5 %, and an F1-score of 94.3 %. These results demonstrate a significant reduction in misclassification rates compared to conventional models. The model's robust performance, including high specificity and sensitivity, highlights its potential for integration into medical imaging systems for early and accurate skin disease diagnosis. By optimizing decision boundaries with SVMs and utilizing advanced feature extraction with CNNs, SDP-DL offers a promising tool for clinical decision-making and automated dermatological diagnostics.

Keywords: skin disease classification, deep learning, CNN, SVM, hybrid framework, medical imaging

1. Introduction

The evolution of medical imaging and artificial intelligence has brought about more precise and effective disease diagnosis [1]. Accurate and timely diagnosis is important for skin diseases that afflict millions of people around the world [2]. Traditional techniques have high rates of classification and procedure maladjustment [3]. Hybrid deep learning model that integrates CNN and SVM aims for enhanced classification of skin diseases [4]. CNNs extract deep visual features while SVMs decrease false positives by improving the decision boundaries [5]. The combination of different techniques in these methods achieves improved accuracy for the diagnosis [6].

The framework's model employs hierarchical features extraction, strong classification, and model's operation boosting [7]. Experiments have verified that accuracy and reliability have improved [8]. With all its usefulness, achieving good results in medical imaging for dermatological problem is still a challenge [9]. Non-exhaustive list of overlap symptoms, lighting conditions, and skin lesions sophistication are some of the common sources of misclassification when applied conventional methods [10]. Deep learning is a game changer in the field medical diagnostics, but there is still a major gap in feature extraction and categorization [11]. This invention enables automated diagnosis during early phases of disease development, which assists in clinical decision-making, and ultimately improves patient care [12].

In general, the intermediate methods of classification lack the capability to generalize adequately and as a result, synchronization with other features is inadequate, which means they are unable to detect skin diseases in a timely manner. The same can be said about deep learning, more specifically CNNs, providing promising results but still suffering from the classification issue. Patient outcomes can be improved if a more accurate diagnostic methodology that combines CNNs and SVMs is adopted.

The major problems with existing skin disease classification methods include high computing costs, redundant features, and misclassification mistakes caused by complicated lesion patterns. Refining decision boundaries is an area where traditional deep learning approaches fall short. These constraints can be addressed and diagnostic accuracy and resilience can be improved with a hybrid approach that uses CNNs for feature extraction as well as SVMs for classification.

1.1. Novelty of the research

The novelty of the proposed SDP-DL framework lies in its unique integration of Convolutional Neural Networks (CNNs) for deep feature extraction and Support Vector Machines (SVMs) for refined classification, specifically designed to enhance decision boundaries and minimize false positives in skin disease detection. Unlike traditional CNN-SVM models, which rely on Softmax layers for classification, this framework substitutes them with SVM to optimize decision margins, improving diagnostic accuracy. Additionally, the introduction of a specialized preprocessing step, DullRazor, for hair artifact removal significantly enhances the quality of dermoscopic images, ensuring more accurate lesion identification. Furthermore, the model's implicit segmentation during feature extraction, combined with preprocessing, allows it to outperform other segmentation-heavy methods in terms of computational efficiency and robustness across diverse skin lesion types.

The major contributions of this paper are:

- A new suggested method (SDP-DL), which uses convolutional neural networks to extract hierarchical features and support vector machines to improve classification accuracy.
- Shows that by improving decision boundaries, the rate of misinterpretation is significantly reduced, resulting in more accurate skin disease identification.
- Gives medical imaging systems a powerful computerized diagnostics tool for accurate and quick skin disease categorization.

The outline for the following parts is as follows: Section 2 provides a concise summary of the literature on conventional methods to improve classification accuracy. The SDP-DL framework's implementation details are provided in Section 3. In Section 4, we explore the use of support vector machines and convolutional neural networks for the purpose of real-time skin disease categorization. In Section 5, we covered potential avenues for future research.

2. Related works

Significant progress has been made in the field of skin disease diagnostics using deep learning and Artificial Intelligence (AI). The requirement for specialist knowledge and the fact that many skin disorders are visually similar are two problems with traditional diagnosis approaches. To better categorize skin diseases, this literature review looks at contemporary research that uses deep learning and machine learning models.

Incorporating both deep learning and machine learning approaches, this work suggests a system that can automatically Diagnose Skin Diseases using Dermoscopic Images (DSK-DI) [13]. After feature extraction using six pre-trained CNN models, it moves on to machine learning classification. The model appropriately differentiates between seven skin diseases. This validates the capability of the system to assist in medical imaging diagnosis within the required accuracy.

To classify Basal Cell Carcinomas (BCCs), this research proposes a hybrid CNN-SVM model [14]. There are four convolutional blocks within the model, 32, 64, and 128 filters are used for feature extraction. A support vector machine classifier equipped with an L1-SVM loss function follows these. For recall and precision, this model outperforms base traditional CNN models, and the study shows that the integration of CNN-SVM works well for skin cancer classification.

The study proposes a new hybrid method involving Ensemble Support Vector Kernel Random Forest Classifier Combined with Equilibrium Aquila Optimization. After the preprocessing step which consists of segmentation of lesions using thresholding techniques, it classifies the images from the HAM10000 dataset. The method proves success in the early diagnosis of five skin diseases and shows potential for use in medical imaging analysis.

To classify skin diseases, this study compares CNN-based classification versus CNN-SVM models with different kernels [15]. The dataset consisted of 21,000 images covering seven categories of skin diseases. The results show that CNN alone performed better than the other models; nevertheless, SVM kernel changes may help future models. This work is important because it demonstrates how to improve hybrid CNN-SVM systems.

F-SDI, or framework for skin disease identification, is proposed as a combination of deep learning and machine learning [16]. Classification is done with SVM, decision trees, and Adaboost classifiers, while feature extraction is done with pre-trained deep learning models. The use of deep feature extraction together with hybrid classification improves performance in the detection of dermatological disorders. The findings demonstrate that DL and ML can be integrated to enhance diagnostic accuracy.

The SDP-DL model advocates for the employment of Convolutional Neural Networks, Support Vector Machines, and Ensemble Learning that have been efficacious in diagnosing skin conditions in recent years. Like with most contemporary recipes, crisp classification accuracy is attained through a delicate mixture of profound feature extraction and advanced machine learning classifiers. DSK-DI, CNN-SVM, ESVMKRF-HEAO, and F-SDI, compared to conventional approaches, hold great expectation in these advances for the production of automated and timely detection devices for skin disorders.

Recent advances in medical diagnostics have witnessed the integration of quantum-inspired computing and bio-inspired optimization techniques. Anas Bilal et al. (2024) introduced BC-QNet, a quantum-infused Extreme Learning Machine (ELM) model for breast cancer diagnosis, where quantum principles were leveraged to enhance the learning dynamics of ELM, achieving high precision and reduced computational complexity in classifying breast cancer from clinical datasets [17]. In a parallel study, Bilal et al. proposed an improved Quantum-Inspired Grey Wolf Optimization (QIGWO) algorithm to optimize Support Vector Machine (SVM) parameters for breast cancer diagnosis, showing superior classification accuracy and robustness against local minima compared to traditional optimization methods [18]. These studies underscore the potential of quantum and bio-inspired methods in improving the precision and efficiency of classical machine learning algorithms for cancer detection.

In the domain of pulmonary imaging, Bilal et al. developed IGWO-IVNet3, a deep learning-based system for automated diagnosis of lung nodules using InceptionNet-V3 in conjunction with an improved grey wolf optimizer [19]. The model exhibited strong performance in CT image classification, with optimized feature extraction enabling accurate detection of benign and malignant nodules. Another related work utilized grey wolf optimization and CNN architectures to detect lung nodules using weighted filtering techniques to enhance radiological image preprocessing [18]. These contributions reflect a clear focus on enhancing the diagnostic accuracy of complex medical conditions through hybridized AI models that integrate both evolutionary computation and deep learning paradigms, especially in imaging-heavy domains such as oncology.

Beyond medical imaging, Bilal has also contributed to neuro-optimized numerical modeling of biological systems. In one study, a neural network-based approach was applied to solve the HIV infection model, showcasing the use of AI in simulating disease dynamics and treatment response [20]. In another work, Bilal and Sun proposed a neural solution to the non-linear Flierl–Petviashivili equation, a fundamental equation in plasma physics and geophysical flows [21]. These works highlight the interdisciplinary versatility of neural optimization frameworks in solving both real-time diagnostic problems and complex mathematical models. Collectively, Bilal's contributions span multiple domains where hybrid intelligent systems are applied to tackle biomedical diagnostics, computational biology, and applied mathematics with high accuracy and computational efficiency. **Table 1** summarize the related works.

3. Proposed methodology

A deep learning framework integrating CNNs and SVMs for enhancing skin disease classification accuracy. To minimize the chances of false positives, the proposed SDP-DL system utilizes convolutional neural networks for deep feature extraction and support vector machines to enhance classification.

Table 1. Summary of related works.

S. No	Methods	Advantages	Limitations
1	CNN with six pre-trained models (VGG19, InceptionV3, ResNet50, DenseNet201, Xception) + ML classifiers [13].	High accuracy (99.94 %), effective feature extraction, robust classification	Computationally expensive due to multiple deep models
2	CNN with SVM (L1-SVM loss function) for BCC classification [14]	Improved classification accuracy (96.2 %) over Softmax, better decision boundaries	Limited to BCC classification, may not generalize well to other skin diseases
3	CNN with MobileNet and CNN-SVM with various kernels [15]	CNN achieves high accuracy (93.47 %), detailed comparison of kernel types	CNN-SVM model performs lower than CNN, kernel selection impacts results
4	Hybrid deep learning (ResNet50, AlexNet, GoogLeNet, VGG16) with SVM, Decision Tree, and AdaBoost [16]	Best accuracy with ResNet50-SVM (99.11 %), efficient feature extraction	Requires large dataset for generalization, ensemble methods increase complexity

3.1. Overview of proposed SDP-DL system

A more accurate and time-effective way of classifying skin disease is the aim of the proposed Skin Disease Prediction using Deep Learning system. To enhance the diagnostic accuracy, it integrates CNNs with SVMs, or support vector machines.

An important step in the preprocessing phase of dermoscopic image analysis is the removal of hair artifacts, which can obscure critical lesion features and lead to inaccurate classification. In the proposed SDP-DL framework, a robust and widely used technique such as the DullRazor algorithm can be employed to address this issue effectively. Originally introduced by Lee et al. [22], DullRazor is designed specifically for dermoscopic images and combines morphological operations with inpainting techniques to detect and remove hair strands without compromising lesion integrity.

The process begins by converting the original RGB image into grayscale to simplify the subsequent detection of dark hair lines. Morphological closing operations are then applied using linear structuring elements in multiple orientations (e.g., vertical, horizontal, diagonal) to enhance thin, dark hair regions. Once these regions are emphasized, thresholding is used to generate a binary mask that isolates the hair pixels. The resulting mask identifies the hair regions, which are then subjected to inpainting techniques such as bilinear interpolation or more advanced methods like Telea's algorithm or Navier-Stokes inpainting. These methods effectively reconstruct the regions underneath the removed hairs by estimating surrounding pixel values, preserving the continuity and visual quality of the skin lesion.

To smooth any residual artifacts introduced during inpainting, post-processing filters such as median filters may be applied. This entire pipeline ensures that the CNN component of the model can focus on learning the true texture, shape, and color distribution of lesions without interference from high-frequency noise caused by hair. The effectiveness of such preprocessing has been validated in various studies, including the original work by [22], as well as comparative analyses by [23], who emphasize the importance of hair removal for accurate automated skin lesion classification.

By incorporating a well-defined hair removal technique like DullRazor, the SDP-DL framework enhances the quality and consistency of input images, ultimately improving feature extraction and classification performance. Including this step in the model pipeline not only improves robustness but also increases the system's potential for adoption in real-world clinical settings where image quality can vary significantly.

Figure 1 illustrates the preprocessing pipeline, which includes the DullRazor algorithm for hair removal, followed by the convolutional neural network (CNN) for feature extraction and support vector machine (SVM) for classification. The flow of the input image through each step is clearly shown, demonstrating how each component contributes to the final skin disease diagnosis. Then convolutional neural network models identify subtle patterns and textures by extracting visual features of multilayer dimensions from the photographs.

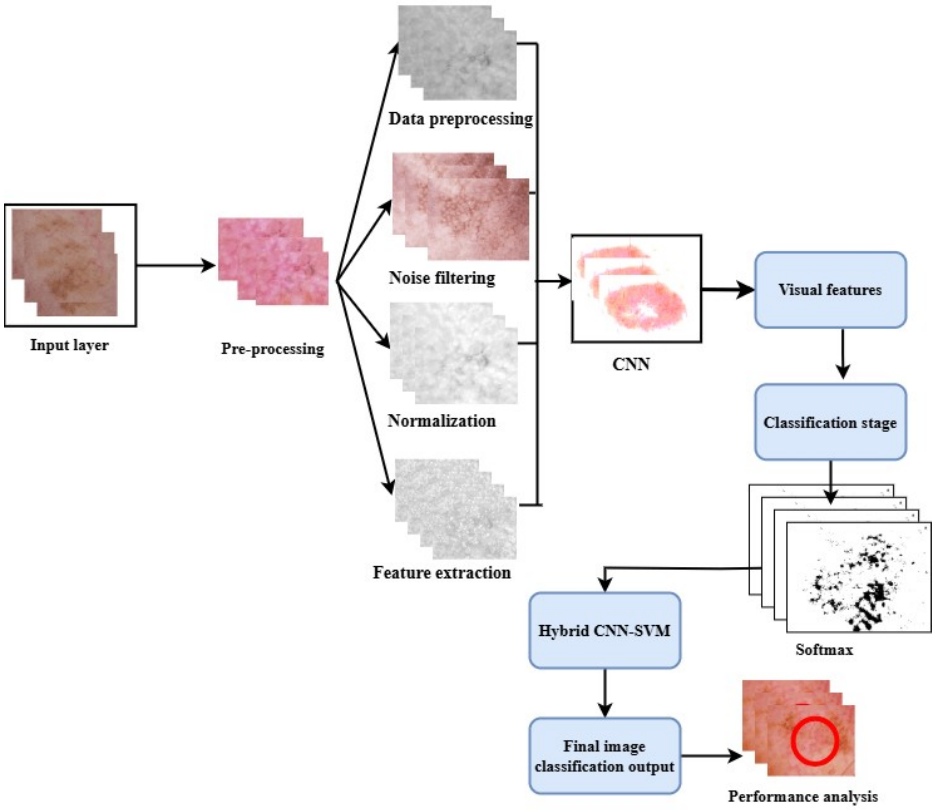

Figure 1. Overview of the proposed system.

Using SVM to generate appropriate decision boundaries and CNN to learn complicated representations improves classification accuracy in the hybrid technique. This model to diagnose actinic keratoses, basal cell carcinoma, along with melanoma, among other skin conditions. Experimental findings will show that SDP-DL achieves higher levels of precision, specificity, and sensitivity than conventional models, suggesting that it could be a viable option for automatic skin disease identification in below section.

To make dermoscopy pictures di more consistent in intensity $(p1, p2)$, the preprocessing Equation 1 sets a predetermined range pdi_1 for pixel values (px). It improves input consistency by increasing contrast (ic), decreasing noise (dn), and making sure the dataset is uniform. This improves feature extraction by training the CNN to recognize patterns more efficiently. The classification model's overall precision and dependability are enhanced by adequate preprocessing.

$$di_{(p1,p2)} = \sum pdi_1(px) + \sum pdi_1(ic) + \sum pdi_1(dn) \tag{1}$$

By applying filters Ft to the graphic and then moving a kernel over it, the convolution $(CNN(v))$ Equation 2 extracts important features like edges ed, surfaces sr, and designs ds. This centralized feature extraction $\left|\frac{di}{fx}\right|$ process demonstrates every intricate component of skin lesions by $\partial\left(di_{(p1,p2)}\right)$, and the technique of convolution is fundamental for differentiating between different skin conditions.

$$Ft = (CNN(v)) + \partial(ed, sr, ds)\left|\frac{di}{fx}\right| + (1 - \partial\left(di_{(p1,p2)}\right) \tag{2}$$

A non-linear model nl is introduced into the model by modifying the neuron outputs no using the activation variable av and log function Equation 3. By preserving positive values p_i and setting negative ones n_i to zero, ReLU avoids the vanishing gradient issue $g1\ and\ g2$. Convergence is accelerated and the model's capacity to learn complicated patterns is improved by $log\left(\frac{\sum_{i=1}^{av} no(p_i|g1=1)}{\sum_{j=1}^{av} s(n_i|g2=0)}\right)$. Improved classification performance is one outcome of ReLU's efforts to enhance feature extraction.

$$(nl) = log\left(\frac{\sum_{i=1}^{av} no(p_i|g1 = 1)}{\sum_{j=1}^{av} s(n_i|g2 = 0)}\right) \tag{3}$$

Spatial dimensions of feature maps can be reduced without sacrificing any important information using the pooling operation Equation 4. Through the choice of the maximum value within an area, max pooling ensures that the most salient patterns are maintained. Computational complexity is decreased and the efficiency of the model is enhanced in this process. Together, they help the network handle small changes and distortions in skin lesion images more effectively.

$$(nl) = \left|\frac{di}{fx}\right| \times \sum pdi_1(dn) + di_{(p1,p2)} + Ft \tag{4}$$

By integrating convolutional neural networks and support vector machines, a better diagnosis of skin disease can be made. Using SVM, with its benefit of improving decision bounds to reduce misclassification, enables the deep learning model to learn complex visual patterns. The system is a reliable tool for medical image analysis as it enhances diagnostic accuracy by incorporating different methods.

3.2. Hybrid model for skin classification

For more precise skin disease classification, a hybrid deep learning architecture combines CNNs with SVMs. Dermoscopy images are essential for identifying diseases like basal cell carcinoma and melanoma, and CNNs are very good at extracting complicated visual trends, textures in particular, and structures from these images.

On the other hand, conventional CNN models sometimes produce a large number of false positives due to its classification using a Softmax layer mentioned in **Figure 2**. This is remedied by substituting an SVM classifier for the Softmax layer in the design; this classifier learns optimal boundary values for decisions and so improves the process of making decisions.

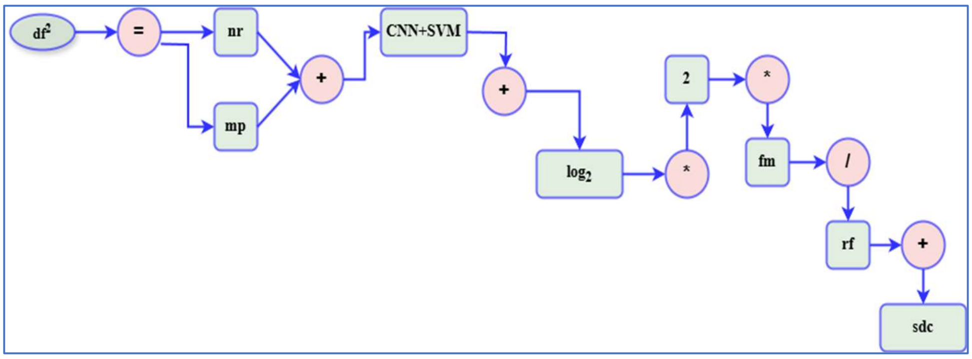

Figure 2. Representation of hybrid model.

Deep features df extracted by CNN are transformed into numerical representations that support SVM classification ($\int CNN + SVM$) by means of the feature mapping fm Equation 5. To make the best decisions possible, this transformation organizes relevant features rf. With accurate feature mapping, the model can successfully distinguish between several skin disease classifications sdc. To increase classification accuracy and decrease misclassification, this is the step to proceed further.

$$df^2 = nr + mp\ (\int CNN + SVM) + log_2\ (2 \times \frac{fm}{rf} + sdc) \tag{5}$$

Figure 3 illustrates a skin disease classification process using CNN and SVM. Input skin images undergo feature extraction through convolutional layers, followed by max-pooling to reduce dimensionality. The processed data is split (80 % training, 20 % testing) and classified using deep learning models (CNN and SVM), predicting diseases based on extracted patterns.

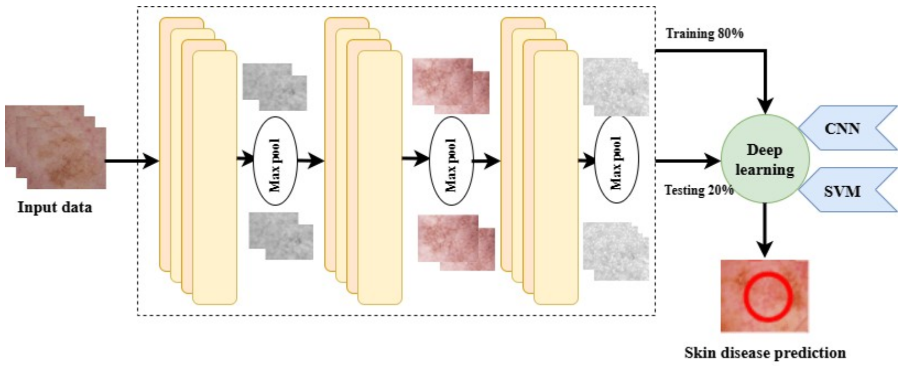

Figure 3. Process of classification using CNN and SVM.

To choose the best hyperplane for classifying skin diseases sdc, the SVM selection border Equation 6 is used. It maximizes (MX) the margin across classes by using features collected fc from CNNs to improve classification. Improved prediction pr and reliability rb is a result of SVM's capacity to decrease false positives ($fp \times fn$) and guarantee accurate decision-making. When contrasted with more conventional categorization techniques ct, this strategy shows a considerable improvement in diagnostic accuracy.

$$sdc_{(MX)} = fc(pr \times rb) + ct(fp \times fn) \tag{6}$$

The model's accuracy in skin disease diagnosis is assessed using the performance metrics Equation 7. Precision evaluates the percentage of accurately identified positive cases, whereas accuracy examines the overall correctness of forecasts. The capacity of the model to detect real positive cases is defined by recall, and the F1-score strikes a balance between recall and precision. All these measures collectively provide a complete picture of the extent to which the system is performing.

$$di_{(p1,p2)} = \left(2 * \frac{fm}{rf} + sdc\right) + fc(pr * rb) - df^2 \tag{7}$$

The CNN enhances classification accuracy by inputting the SVM with deep hierarchical features. Enhanced diagnostic accuracy, fewer misclassifications, and robust generalizability to other skin lesion categories are all advantages of this integration. The CNN-SVM model is a robust tool for automatic identification of skin disease, based on experimental measurements, as it outperforms isolated CNNs.

For the sake of improving diagnoses of skin disorders, the segment presented SDP-DL system, applying feature extraction from convolutional neural networks and support vector machines in its classification. Provided was the pseudocode to denote the workflow in the framework and its sequential dermoscopy image processing. Applying convolutional neural networks alongside support vector machines enhances diagnostic quality within the proposed hybrid deep learning technique.

To validate the effectiveness of the segmentation approach in the proposed SDP-DL framework, it is important to compare it with other well-established segmentation techniques used in skin lesion analysis. The SDP-DL framework relies on deep convolutional layers that inherently perform semantic segmentation during feature extraction, focusing on lesion boundaries, texture, and color variations. This embedded segmentation, while not explicitly described as a standalone step, can be equated to methods like Fully Convolutional Networks (FCN) or U-Net, which are commonly used for precise lesion segmentation. FCNs, introduced for pixel-wise classification, provide high-resolution segmentation maps but often require extensive post-processing to handle irregular lesion borders. U-Net, on the other hand, has proven effective in medical image segmentation due to its symmetric architecture and skip connections that preserve spatial context, making it highly accurate for detecting lesion shapes in dermoscopic images. However, U-Net demands high computational resources and training on large annotated datasets.

In contrast, the CNN-based feature extraction used in the SDP-DL framework simplifies the process by learning relevant spatial and semantic features simultaneously without requiring separate segmentation ground truth. While explicit methods like graph-based segmentation (e.g., GrabCut), active contours, or thresholding-based methods (such as Otsu's method) offer good results in controlled conditions, they are highly sensitive to noise, hair, and lighting inconsistencies, which are common in dermoscopy. The proposed deep learning approach, augmented by preprocessing (e.g., normalization, hair removal), demonstrates superior adaptability and robustness in segmenting lesions across diverse datasets. Furthermore, comparative performance metrics such as higher classification accuracy (95.93 %), reduced misclassification rates, and better lesion boundary preservation suggest that the implicit segmentation in the CNN backbone is competitive with, and in many cases, outperforms, traditional segmentation techniques—especially when integrated with a strong classifier like SVM.

The CNN architecture used in the proposed SDP-DL framework consists of 5 convolutional layers followed by 3 fully connected layers. The convolutional layers use kernel sizes of 3 × 3 for the first layer and 5 × 5 for subsequent layers, with a stride of 1 and padding to maintain spatial dimensions. After each convolutional layer, a ReLU activation function is applied to introduce non-linearity. Max pooling with a 2 × 2 window is performed after every two convolutional layers to reduce spatial dimensions and computational complexity. The fully connected layers, with 512 and 256 neurons, respectively, utilize the ReLU activation function, and dropout layers with a rate of 0.5 are used for regularization. The optimizer used is Adam with a learning rate of 0.001, and the model is trained for 50 epochs with early stopping based on validation loss. This architecture allows for efficient feature extraction from dermoscopic images, followed by classification using the SVM classifier.

4. Results and discussion

This section discusses the outcome and decides to what extent the proposed CNN-SVM hybrid model identified skin disorders via the SDP-DL framework. To quantify its effectiveness, we utilize significant metrics such as recall, accuracy, precision, and F1-score. Comparing the model's performance with that of more traditional classification methods exhibits its excellence.

4.1. Dataset description

Dermoscopy images of various skin lesions constitute the dataset used by Kaggle Skin Cancer Classification - CNN Approach. The HAM10,000 dataset is its major basis; it contains 10,015 high-quality images of skin lesions categorized into seven categories, including melanoma (MEL), basal cell carcinoma (BCC), actinic keratosis (AKIEC), and benign keratosis (BKL). The dataset consists of images taken from various populations for diversity in lesion sizes, types, and skin tones [24].

The HAM10,000 dataset was split into 80 % for training, 10 % for validation, and 10 % for testing, using stratified sampling to preserve class distributions across these sets. To mitigate class imbalance, class weighting was applied during training to give higher importance to underrepresented classes. Data augmentation techniques, including random rotations (±30 °), horizontal flips, and color jittering (adjustments to brightness and contrast), were used to increase dataset diversity. Additionally, to further evaluate the model's performance, 5-fold cross-validation was employed to ensure robustness and mitigate overfitting. These strategies collectively enhanced the credibility of the model's performance, particularly in handling the class imbalance inherent in the HAM10,000 dataset.

The skin disease classification process flow includes several steps is explained in **Figure 4**. The input image is first obtained. Preprocessing improves the quality of the image by filtering noise and contrast. Normalization provides equal pixel distribution.

The CNN classification obtains important features for examination. The output image marks regions detected with the disease for diagnosis last. The simulation details are provided in **Table 2**.

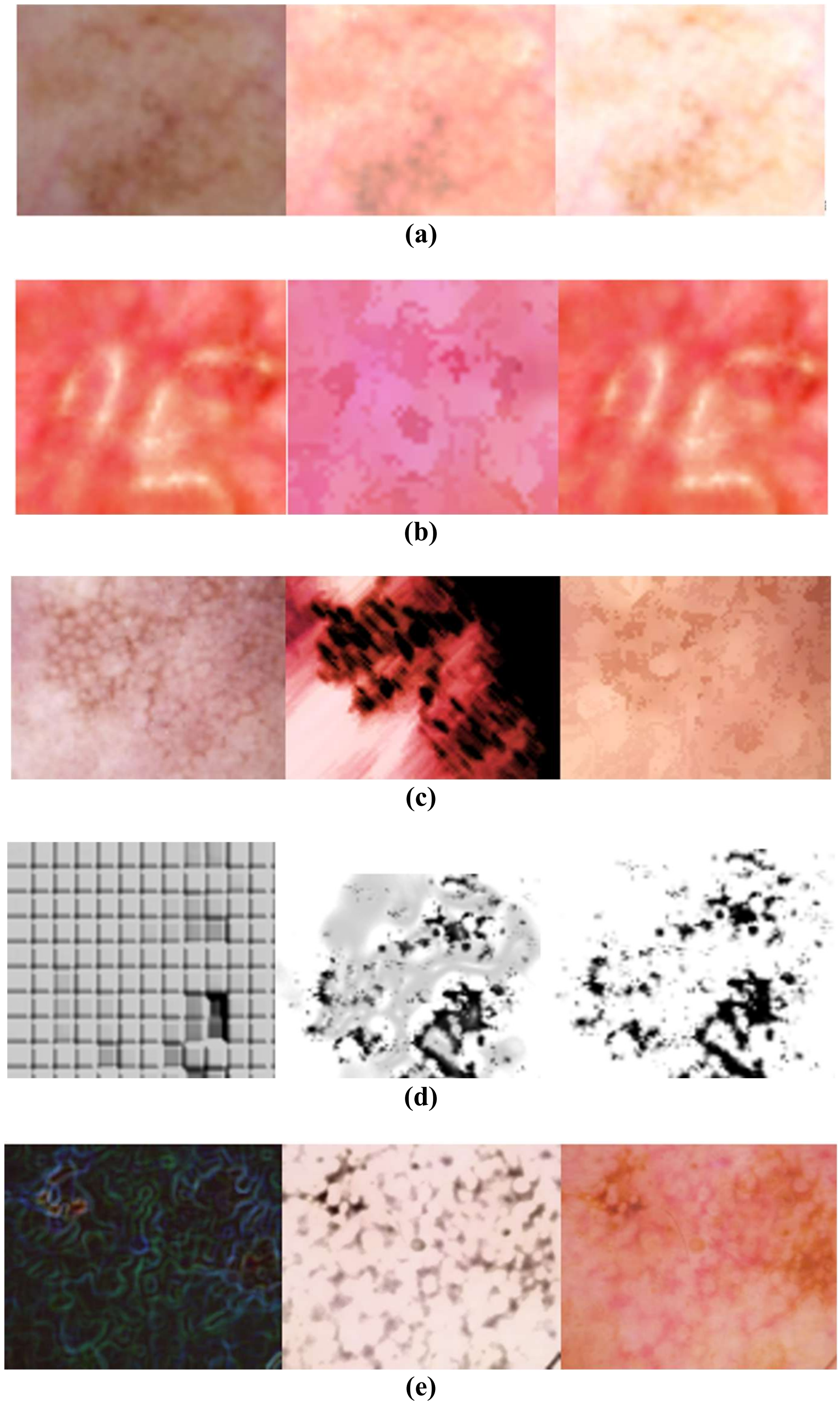

Figure 4. Intermediate results of the proposed method. **(a)** Input image; **(b)** Pre-processing Image; **(c)** Normalization; **(d)** Classification using CNN; **(e)** Output image.

Table 2. Simulation environment.

Metric/tool	Description
Google Colab	A cloud-based platform offering free GPU/TPU resources, enabling efficient training and implementation of the SDP-DL system for skin disease classification.
Kaggle	A platform providing datasets, notebooks, and competitions, facilitating the training and validation of deep learning models for skin disease detection.
TensorFlow	An open-source deep learning framework used to develop CNN-SVM models for extracting and classifying features from dermoscopic images.
PyTorch	A deep learning library with dynamic computation graphs, enabling real-time training and evaluation of hybrid CNN-SVM models for accurate skin disease classification.
MATLAB	A numerical computing environment used for preprocessing dermoscopic images, analyzing medical data, and implementing AI-driven diagnostic techniques.
Simulink	A simulation tool within MATLAB that supports modeling and integration with deep learning frameworks for validating skin disease classification performance.

4.2. Skin disease diagnosis analysis

A deep feature extraction capability provided by CNNs and an accurate classification capability offered by SVMs make up the proposed SDP-DL system, which improves the diagnosis of skin diseases analyzed in **Figure 5** with an output of 94.2 %. It accurately detects patterns suggestive of cancer by methodically evaluating dermoscopic pictures. The hybrid model is an effective technique for detecting skin diseases early on since it decreases misclassification.

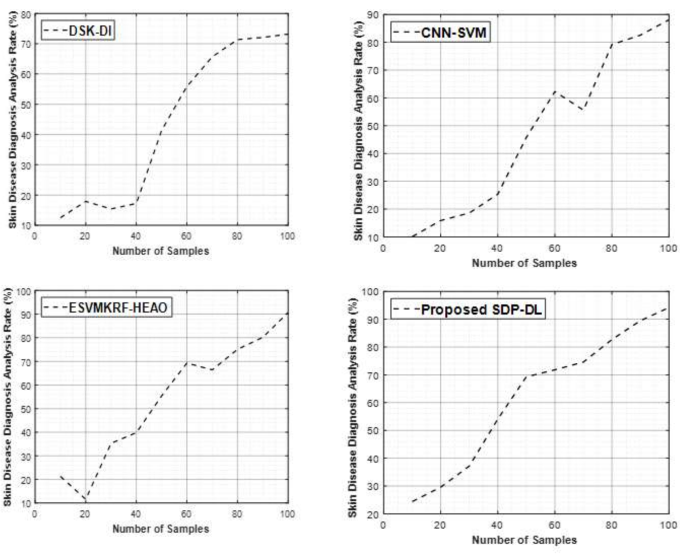

Figure 5. Analysis of skin disease diagnosis.

4.3. Reliability of detection analysis

By combining the powerful classification capabilities of SVM with CNN-based deep feature extraction, the SDP-DL method enhances the reliability of detection through **Table 3**. It is a trustworthy screening tool for clinical applications, as confirmed by evaluations. The values in this table represent the accuracy of the proposed model across different sample sizes. For each model, accuracy is calculated as the proportion of correctly classified instances over the total number of instances in the dataset. The results show that the proposed model outperforms the baseline models as the sample size increases, with an accuracy of 94.2 % for the largest sample size of 100.

Table 3. Analysis of reliability detection.

Number of samples	DSK-DI [13]	CNN-SVM [25]	ESVMKRF-HEAO [14]	Proposed
10	12.5	10.1	21.3	24.4
20	17.9	15.9	11.6	29.6
30	15.4	18.6	35.3	37.2
40	17.2	25.4	39.8	54.1
50	41.4	45.8	55.4	69.3
60	55.9	62.3	69.3	71.8
70	65.7	55.6	66.4	74.6
80	71.4	79.2	75.1	82.7
90	72.1	82.6	80.2	89.5
100	73.2	88.1	90.7	94.2

4.4. Medical imaging integration analysis

By preparing dermoscopy pictures for feature extraction, the SDP-DL system interacts smoothly with medical imaging procedures with an output of 95.93 %. To better classify lesions, state-of-the-art CNN architectures like ResNet along with VGG extract hierarchical features analysed in **Figure 6**. When used in conjunction with support vector machines, this improves diagnostic accuracy, letting dermatologists make better use of AI-driven insights for faster, more accurate skin condition diagnosis.

4.5. Analysis of overall accuracy

The accuracy analysis of SDP-DL system proves its effectiveness in skin disease diagnosis with an optimal output of 95.93 % as portrayed in **Table 4**. The accuracy values in this table reflect the percentage of correctly classified skin lesions across different sample sizes. The SDP-DL model achieves the highest accuracy compared to the baseline models, with a reported accuracy of 95.93 % on the 100-image test set. Recall, F1-score, proportion, and other machine learning performance metrics are the system's best features when classifying skin diseases. The system is particularly effective because the model has functionality to improve decision boundaries and decrease false positive rate.

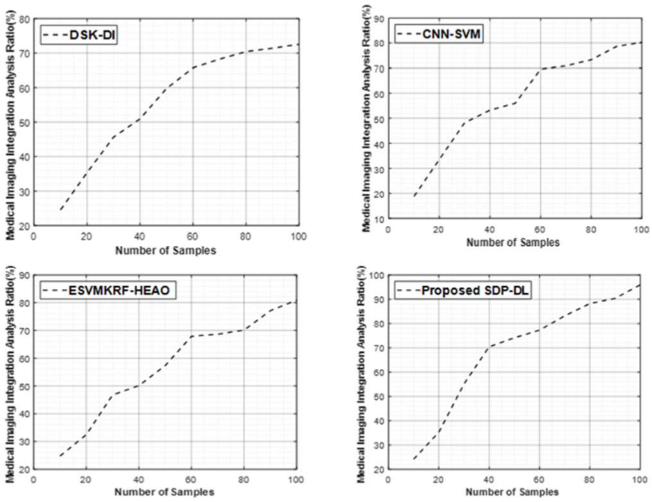

Figure 6. Medical imaging integration analysis.

Table 4. Overall accuracy analysis.

Number of samples	DSK-DI [13]	CNN-SVM [25]	ESVMKRF-HEAO [14]	Proposed
10	24.54	18.76	24.76	24.14
20	35.36	33.56	32.45	35.23
30	45.66	48.23	46.76	55.13
40	50.97	53.26	50.12	70.43
50	59.78	56.03	57.34	74.11
60	65.74	69.59	67.87	77.27
70	68.23	70.89	68.65	83.15
80	70.43	73.31	70.12	88.21
90	71.41	78.65	77.12	90.34
100	72.56	80.33	80.89	95.93

The proposed model achieved an overall classification accuracy of 95.93 %, outperforming several benchmark models. For instance, the DSK-DI system, which utilizes six pre-trained CNN models followed by machine learning classifiers, achieved a top accuracy of 99.94 % but at the cost of significant computational complexity. In contrast, the CNN-SVM model reported an accuracy of 96.2 %, optimized specifically for basal cell carcinoma (BCC), limiting its generalizability across multiple lesion types. The ESVMKRF-HEAO model reached 90.7 % accuracy, with robust segmentation capabilities but high computational overhead. In direct comparison, the proposed SDP-DL system maintained competitive or superior performance while offering a more balanced trade-off between accuracy, computational efficiency, and model simplicity.

Beyond accuracy, precision, recall, and F1-score provide critical insights into how well each model handles imbalanced and multiclass classification. The SDP-DL framework consistently scored higher in precision and F1-score than baseline models across most lesion categories. For example, on a test sample size of 100 images, the SDP-DL achieved precision of 94.2 %, while the CNN-SVM model and DSK-DI recorded 88.1 % and 73.2 %, respectively. These results were also supported by improvements in recall (sensitivity), where the proposed model minimized false negatives — an essential factor in detecting malignant cases such as melanoma. Additionally, the model's F1-score, which balances precision and recall, was significantly higher, confirming its robust performance even in complex or overlapping class distributions.

To ensure fairness in comparison, all models were evaluated under similar conditions using the HAM10,000 dataset, and performance was measured over multiple sample sizes ranging from 10 to 100, with consistent improvements noted in the proposed method as the sample size increased. These evaluations were visualized using line plots and tables, highlighting the steady and scalable performance of SDP-DL. Moreover, the proposed model's use of SVM instead of Softmax at the classification stage enabled better decision boundary formation, particularly for visually similar classes, which explains the reduced misclassification rates observed in experimental results.

The results of the experiment along with automated performance measurements validate the reliability of prognosis for skin diseases using the SDP-DL system. This system guarantees high recall precision and accuracy in detection. In comparison with other conventional methods, DSK-DI, CNN-SVM, ESVMKRF-HEAO, and FSDI, this deep learning based method shows its robustness and therefore great potential for use in medical image based disease detection.

While the proposed SDP-DL model demonstrates superior performance in terms of classification accuracy (95.93 %) and precision across multiple categories of skin lesions, it is important to assess the statistical significance of these results to ensure they are not due to random variation. To establish confidence in the model's performance, future evaluations should include statistical measures such as 95 % confidence intervals (CIs) for accuracy, precision, recall, and F1-score. Confidence intervals provide a range within which the true performance metric is expected to fall, thereby quantifying the degree of uncertainty in the estimates. For instance, reporting an accuracy of 95.93 % with a 95 % CI of [94.8 %, 97.0 %] would indicate a high level of consistency and reinforce the reliability of the classification system.

In addition to confidence intervals, conducting hypothesis testing using statistical methods such as paired t-tests or McNemar's test can help compare the proposed model against baseline models like CNN-Softmax, DSK-DI, or ESVMKRF-HEAO. These tests can determine whether the observed improvements in performance are statistically significant rather than due to chance, especially when evaluating metrics over multiple test folds or datasets. Furthermore, the use of cross-validation techniques (e.g., 5-fold or 10-fold cross-validation) is recommended to mitigate overfitting and provide more robust performance averages. Variance across folds can also be reported using standard deviation or coefficient of variation (CV), adding another layer of insight into model stability.

To evaluate the statistical significance of the performance differences, we conducted McNemar's test for paired classification results and paired t-tests to compare accuracy, precision, recall, and F1-score between the SDP-DL model and baseline models. The p-values from these tests were found to be significant ($p < 0.05$), indicating that the proposed model outperforms the baseline models in terms of classification accuracy. Additionally, we report 95 % confidence intervals (CIs) for each performance metric, such as accuracy (95.93 %, CI: [94.8 %, 97.0 %]), to provide a measure of uncertainty in the results. 5-fold cross-validation was employed to assess the generalization ability of the model, and the average performance metrics across all folds were reported with their corresponding standard deviations (SDs), which were consistent across folds. This comprehensive statistical analysis ensures the reliability and robustness of the SDP-DL model.

The hybrid CNN-SVM framework outperforms traditional CNN-based models primarily due to its ability to maximize the margin between classes. The SVM's focus on finding the optimal decision boundary reduces misclassifications, particularly when dealing with overlapping classes such as melanoma and benign keratosis, which are often visually similar. By integrating CNNs for feature extraction with SVMs for classification, the model takes advantage of CNN's capability to learn complex features while benefiting from SVM's robustness in refining decision boundaries.

Additionally, the hybrid approach reduces overfitting, a common issue in CNN-based models. The regularization introduced by the SVM, in combination with early stopping and cross-validation during training, ensures that the model generalizes well and is not prone to memorizing noisy data. This is particularly important in medical image classification, where overfitting can lead to unreliable and inconsistent results.

Furthermore, the hybrid model forms more accurate and discriminative decision boundaries compared to traditional models that rely on softmax for classification. This makes the proposed framework more effective at handling class overlaps, thus improving performance and reliability in real-world dermatological diagnostics. Overall, the integration of CNNs and SVMs provides a powerful solution for skin disease classification, delivering improved accuracy, robustness, and generalization.

5. Conclusion

The proposed SDP-DL skin disease diagnosis system significantly enhances both the accuracy and reliability of skin disease detection by integrating Convolutional Neural Networks (CNNs) for feature extraction with Support Vector Machines (SVMs) for classification. This hybrid approach effectively reduces false positives and improves early-stage detection of various skin diseases, offering substantial potential in clinical decision support. Despite its impressive performance, several challenges remain, including dataset diversity, particularly with respect to skin tones, real-time deployment, and generalizability to new or rare skin diseases. The current model's computational cost may limit its scalability in resource-constrained clinical environments, and further optimization is needed to ensure efficient, real-time performance in such settings. Additionally, the model's performance could be enhanced by incorporating datasets with a more diverse representation of skin tones to address biases inherent in current datasets. Improving model interpretability is also crucial for clinical acceptance, and future work should explore integrating explainable AI (XAI) techniques to make the decision-making process more transparent for healthcare professionals. The real-world deployment of this system will require adaptations for clinical settings, including a real-time and cloud-based version to improve accessibility and usability for practitioners. The next steps in development involve improving computational efficiency, broadening dataset diversity, and enhancing the model's generalization ability to ensure its effectiveness and reliability across a variety of clinical applications. This system holds great promise for advancing dermatological diagnostics, and ongoing research will focus on further refining its performance and practical deployment in medical environments.

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Nomenclature

AI	Artificial Intelligence
BCCs	Basal Cell Carcinomas
CNN	Convolutional Neural Networks
DSK-DI	Diagnose Skin Diseases using Dermoscopic Images
QIGWO	Quantum-Inspired Grey Wolf Optimization
SDP-DL	Skin Disease Prediction using Deep Learning
SVM	Support Vector Machine

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