

# Hybrid PSO-CNN-LSTM Model for Accurate Multi-Class Skin Disease Classification from Dermoscopic Images

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**Abstract**— Skin disease detection, particularly for conditions such as melanoma and other pigmented lesions, is a critical task in medical diagnosis due to its direct impact on early treatment and patient survival. Traditional diagnostic methods rely heavily on expert interpretation, which can be subjective and time-consuming. To address these challenges, this study proposes a hybrid deep learning framework that integrates Convolutional Neural Networks, Long Short-Term Memory, and Particle Swarm Optimization for accurate and efficient skin disease classification. The CNN component is employed to extract discriminative spatial features from dermoscopic images, while the LSTM network captures sequential dependencies among the extracted features. Furthermore, PSO is utilized for optimal feature selection to reduce redundancy and enhance model performance. The proposed model is evaluated on the HAM10000 dataset, which consists of 10,015 dermoscopic images across seven skin disease classes. Experimental results demonstrate that the proposed PSO-CNN+LSTM model achieves superior performance compared to baseline models, attaining an accuracy of 98.2%, precision of 97.8%, recall of 97.3%, and F1-score of 97.5%. The findings highlight the effectiveness of combining deep learning with optimization techniques to improve classification accuracy and computational efficiency. The proposed framework provides a robust and reliable solution for automated skin disease detection and has significant potential for real-world clinical applications.

**Keywords**— Skin Disease Detection, Dermoscopic Images, CNN, LSTM, Particle Swarm Optimization, Medical Image Classification.

## I. INTRODUCTION

Skin diseases, particularly skin cancer, have become a major global health concern due to their rapidly increasing incidence and potential fatality if not detected at an early stage. According to recent medical reports, melanoma [1] and other malignant [2] skin conditions account for a significant proportion of cancer-related deaths worldwide [3]. Early and accurate diagnosis plays a crucial role in improving patient survival rates; however, traditional diagnostic methods

primarily rely on dermatologists' visual inspection and biopsy analysis. These approaches are often time-consuming, subjective, and prone to inter-observer variability, which may lead to delayed or inaccurate diagnosis [4].

With the advancement of artificial intelligence, automated skin disease detection systems gained significant attention in recent years. Deep learning techniques, especially Convolutional Neural Networks (CNN), have demonstrated remarkable success in medical image analysis due to their ability to automatically extract discriminative spatial features from dermoscopic images [5]. Numerous studies have shown that CNN-based models can achieve high classification accuracy, often surpassing traditional machine learning approaches. However, CNN models mainly focus on spatial feature extraction and lack the ability to effectively capture sequential dependencies and contextual relationships among extracted features, which may limit their performance in complex classification tasks [6],[7].

To address this limitation, recurrent neural networks such as Long Short-Term Memory (LSTM) networks have been introduced [8]. LSTM models are capable of learning long-term dependencies and sequential patterns, thereby enhancing feature representation when combined with CNN architectures [9]. Despite these improvements, existing hybrid CNN-LSTM models still suffer from challenges such as high-dimensional feature spaces, redundant information, and increased computational complexity. These issues can degrade model performance and limit real-time applicability [10].

Feature selection is a critical step in overcoming these challenges. Metaheuristic optimization algorithms, particularly Particle Swarm Optimization (PSO), have proven effective in selecting optimal feature subsets by reducing redundancy and improving classification efficiency [11], [12]. PSO mimics the social behavior of particles in a swarm to search for the best solution in a high-dimensional space, making it highly suitable for feature optimization in deep learning frameworks.

In this context, this study proposes a novel hybrid approach that integrates PSO-based feature selection with a CNN+LSTM architecture for skin disease detection. The CNN component is employed to extract spatial features from dermoscopic images, while the LSTM network captures sequential dependencies within the extracted features. The PSO algorithm is utilized to select the most relevant features, thereby reducing dimensionality and improving classification performance. The proposed model aims to achieve higher accuracy, reduced computational complexity, and improved generalization compared to existing methods.

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The main contributions of this research are summarized as follows:

- A hybrid deep learning framework combining CNN and LSTM for enhanced spatial and sequential feature learning.
- Integration of Particle Swarm Optimization (PSO) for optimal feature selection and dimensionality reduction.
- Comprehensive performance evaluation against baseline models including CNN, LSTM, CNN+LSTM, and Random Forest.
- Demonstration of improved classification accuracy, precision, recall, and F1-score using the proposed approach.

## II. RELATED WORK

Karimzadghagh et al. (2025) presented a comparative study of machine learning approaches for skin cancer detection. The authors evaluated convolutional neural networks, support vector machines, and hyperspectral imaging-based models. The CNN model achieved the highest overall accuracy among the tested approaches. The SVM model demonstrated 91% sensitivity and 94% specificity for melanoma detection. The hyperspectral imaging models showed 90.1% sensitivity and 92.65% specificity for squamous cell carcinoma. The study highlighted the effectiveness of deep learning techniques in improving diagnostic performance [13]. Shinde et al. (2024) investigated multiple machine learning and deep learning architectures for skin cancer detection. The evaluated models included CNN, Support Vector Machine, VGG16, VGG19, Inception, and Xception networks. Experimental results indicated that the CNN model achieved the best performance. The proposed CNN-based approach obtained an accuracy of 74%, outperforming the remaining models. The study emphasized that CNN models effectively extract spatial features from dermoscopic images. The authors concluded that deep learning techniques are suitable for automated skin lesion classification [14]. Nguyen et al. (2025) proposed an automated skin cancer detection system using convolutional neural networks. The model was trained on dermoscopic image datasets to classify skin lesions. The proposed CNN architecture achieved an accuracy of 92.5% with a sensitivity of 91.8%. The specificity of the model was reported as 93.1%, indicating reliable classification performance. The model outperformed traditional machine learning approaches such as SVM and Random Forest. The study demonstrated the robustness of CNN-based models for medical image analysis [15]. Velaga et al. (2023) introduced a dual approach using both structured metadata and image-based learning. The authors applied Random Forest to CSV format metadata for classification. The Random Forest model achieved an accuracy of 99.928% and an F1-score of 99.92%. Additionally, the ConViT Tiny architecture was used for cropped skin lesion images. The ConViT Tiny model achieved 96.99% accuracy and 96.9% F1-score. The results showed that combining structured data with image-based models improves performance [16].

Narendran (2023) developed a convolutional neural network-based skin cancer classification model. The proposed model was trained using dermoscopic skin lesion images. The

CNN achieved an average classification accuracy of 91.71%. The model also achieved a specificity of 93.74% for lesion detection. Several traditional machine learning algorithms were also evaluated for comparison. The results demonstrated that CNN outperformed all other models in classification accuracy [17]. Sharma et al. (2023) proposed a deep learning-based skin cancer detection model using EfficientNetB7 architecture. The model was trained on the HAM10000 dataset for multi-class skin lesion classification. Data augmentation techniques were applied to overcome class imbalance. The proposed model achieved an overall accuracy of 89%. The study emphasized the importance of transfer learning for medical imaging applications. The results demonstrated improved prediction performance using EfficientNet-based architectures [18]. Kumar (2024) proposed a deep learning model using a six-layer convolutional neural network. The model was trained on the HAM dataset for skin cancer detection. Regularization techniques were applied to prevent overfitting. Hyperparameter tuning was also performed to improve model performance. The proposed CNN model achieved an accuracy of 88%. The study demonstrated the effectiveness of lightweight CNN architectures for classification [19]. Osman et al. (2023) proposed a mobile-based skin cancer detection system using deep learning. The authors utilized MobileNetV2 architecture for skin lesion classification. The model was optimized for mobile deployment and real-time diagnosis. The proposed system achieved an accuracy of 98.5%. The model demonstrated strong performance in classifying different lesion types. The study highlighted the potential of mobile-assisted dermatological diagnosis [20]. Gnanapriya (2025) proposed a CNN-based skin cancer detection framework using dermoscopic images. The model automatically classified lesions into benign and malignant categories. The system was designed to reduce human diagnostic errors. The proposed approach achieved an accuracy of 95.4%. The model improved early detection of skin cancer. The study emphasized the role of deep learning in clinical decision support [21]. Shukla et al. (2025) proposed an AI-driven skin cancer detection system using Xception architecture. The model classified skin lesions into seven different categories. The dataset consisted of dermoscopic images used for training and validation. The proposed model achieved an accuracy of 89%. The system aimed to support dermatologists in early diagnosis. The study demonstrated the effectiveness of Xception-based architectures [22]. Beri et al. (2024) proposed a DenseNet201-based deep learning model for skin cancer detection. The model was trained using the ISIC dataset. The dataset consisted of 1900 normal and 1597 cancerous images. The proposed model achieved an accuracy of 92.8%. The architecture improved feature reuse and classification performance. The study demonstrated improved diagnostic accuracy using DenseNet models [23]. Arun et al. (2024) proposed a CNN-based skin cancer detection method using dermatoscopic images. The model extracted features automatically from lesion images. The system was trained using a labeled dataset for classification. The proposed

approach achieved an accuracy of 95%. The results showed improved performance compared to traditional techniques. The study highlighted the importance of deep learning in healthcare diagnostics [24]. Kashikar et al. (2024) evaluated deep learning techniques for melanoma detection. The dataset consisted of 735 dermatoscopic images. The authors used ResNet-50 architecture for classification. The ResNet model achieved 85.06% precision. Faster R-CNN model achieved an accuracy of 90%. The study demonstrated the effectiveness of object detection models [25]. Ibraimoh et al. (2025) proposed a transfer learning-based skin cancer detection model. The authors used ResNet50V2 architecture for classification. The model was trained using skin lesion images. The proposed approach achieved over 60% accuracy. The system supported automated diagnosis. The study highlighted the need for improved dataset quality [26]. Akter et al. (2024) proposed a hybrid deep learning model combining InceptionV3 and DenseNet121. The model fused outputs from both architectures. The system improved feature extraction capability. The proposed model achieved an accuracy of 92.27%. The approach improved classification performance. The study demonstrated benefits of hybrid models [27]. Maridu et al. (2025) proposed a hybrid deep learning framework for skin cancer detection. The model was evaluated on ISIC and PAD-UFES-20 datasets. The proposed system achieved 92% accuracy on ISIC dataset. The model achieved 93% accuracy on PAD-UFES-20 dataset. High specificity values were also reported. The study showed balanced classification performance [28]. Mohammed et al. (2023) proposed a hybrid model using DenseNet201 and autoencoder. The extracted features were classified using support vector machine. The model was evaluated on ISIC 2016 dataset. The proposed system achieved 91.09% accuracy. The hybrid approach improved feature representation. The study demonstrated improved classification results [29]. Ramar et al. (2025) proposed a hybrid deep learning model for skin cancer detection. The model achieved an accuracy of 98.65%. Precision, recall, and F1-score were also evaluated. The model achieved strong classification performance. The system effectively classified lesion types. The study highlighted improved diagnostic accuracy [30]. El Mertahi et al. (2025) proposed a hybrid deep learning architecture. The model achieved an overall accuracy of 97.61%. The system achieved high recall and F1-score values. The model effectively identified malignant lesions. The study demonstrated reliable classification performance. The approach improved diagnostic support [31]. Baji (2025) proposed a hybrid model combining CNN, FractalNet, and XGBoost. The ensemble improved classification capability. The proposed system achieved an accuracy of 98.69%. The model supported dermatologists in diagnosis. The approach improved detection performance. The study highlighted effectiveness of ensemble learning [32]. Toprak et al. (2024) proposed a hybrid deep learning model for skin cancer detection. The model was evaluated on ISIC-2019 and PH2 datasets. The proposed approach achieved 94.42% accuracy on ISIC dataset. The model achieved 94.44% accuracy on

PH2 dataset. The system demonstrated consistent performance. The study showed effectiveness of hybrid architectures [33].

Table 1: Comparative Analysis of Skin Cancer Detection

Author	Year	Model Used	Dataset	Findings	Accuracy
Karimzadgh S. et al. [13]	2025	CNN, SVM, Hyperspectral Imaging	Skin lesion dataset	CNN achieved highest performance; SVM strong sensitivity & specificity	Sensitivity = 91%, Specificity = 94%
Shinde P. et al. [14]	2024	CNN, VGG16, VGG19, Inception, Xception, SVM	Skin cancer images	CNN outperformed all models	Accuracy = 74%
Nguyen A. et al. [15]	2025	CNN	Skin lesion dataset	High sensitivity and specificity	Accuracy = 92.5%
Velaga N. et al. [16]	2023	Random Forest, ConViT Tiny	Metadata + Images	Random Forest best for metadata	Accuracy = 99.928%
Narendran S. [17]	2023	CNN	Skin lesion images	CNN superior performance	Accuracy = 91.71%
Sharma M. et al. [18]	2023	EfficientNetB7	HAM10000	Data augmentation improved results	Accuracy = 89%
Kumar D. R. [19]	2024	6-layer CNN	HAM dataset	Regularization improved performance	Accuracy = 88%
Osman S. et al. [20]	2023	MobileNetV2	Skin lesion dataset	Mobile-based classification system	Accuracy = 98.5%
Gnanapriya S. [21]	2025	CNN	Dermoscopic images	Early detection improvement	Accuracy = 95.4%
Shukla S. K. et al. [22]	2025	Xception CNN	Skin lesion dataset	Multi-class classification	Accuracy = 89%
Beri M. et al. [23]	2024	DenseNet201	ISIC dataset	Improved diagnostic accuracy	Accuracy = 92.8%

Arun K. et al. [24]	2024	CNN	Dermatologic images	High performance detection	Accuracy = 95%
Kashikar A. et al. [25]	2024	ResNet 50, Faster R-CNN	Dermatologic dataset	Faster R-CNN best	Accuracy = 90%
Ibraimoh R. et al. [26]	2025	ResNet 50V2	Skin lesion dataset	Transfer learning based detection	Accuracy = 60%+
Akter M. et al. [27]	2024	InceptionV3 + DenseNet121	Skin lesion dataset	Hybrid model improved classification	Accuracy = 92.27%
Maridu B. et al. [28]	2025	Hybrid Deep Learning	ISIC, PAD-UFES-20	Balanced performance	Accuracy = 93%
Mohammed H. J. et al. [29]	2023	DenseNet201 + Autoencoder + SVM	ISIC 2016	Hybrid feature extraction	Accuracy = 91.09%
Ramar V. A. et al. [30]	2025	Hybrid Deep Learning	Skin lesion dataset	High performance classification	Accuracy = 98.65%
El Mertahi A. et al. [31]	2025	Hybrid Deep Learning	Skin lesion dataset	High recall & F1-score	Accuracy = 97.61%
Baji S. R. [32]	2025	CNN + Fractal Net + XGBoost	Skin lesion dataset	Ensemble model	Accuracy = 98.69%
Toprak A. N. et al. [33]	2024	Hybrid Deep Learning	ISIC-2019, PH2	Multi-dataset evaluation	Accuracy = 94.44%

### III. METHODOLOGY

This section presents the overall methodology of the proposed skin disease detection system based on a hybrid PSO-CNN+LSTM model. The framework is designed to effectively extract, optimize, and classify features from dermoscopic images. The complete workflow consists of four major stages: data preprocessing, feature extraction using CNN, feature selection using Particle Swarm Optimization (PSO), and classification using LSTM. The proposed methodology aims to improve classification accuracy while reducing computational complexity.

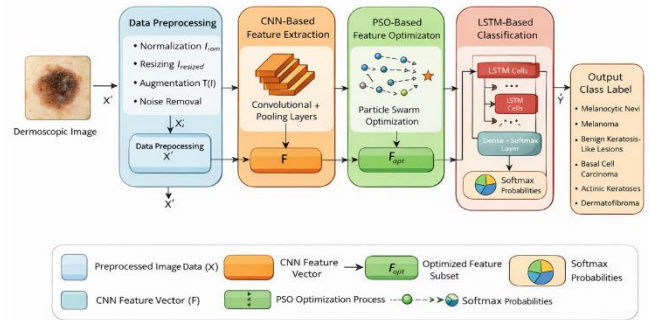


Figure 1: Architecture of Hybrid PSO-CNN+LSTM Model

Fig. 1 shows the overall architecture of the proposed hybrid PSO-based CNN+LSTM model for skin disease detection. The framework begins with preprocessing of dermoscopic images, including normalization, resizing, augmentation, and noise removal to enhance data quality. The preprocessed images are then passed through a CNN module to extract high-level spatial features. These features are further optimized using Particle Swarm Optimization (PSO) to select the most relevant subset and reduce redundancy. The optimized features are subsequently fed into an LSTM network, which captures sequential dependencies and contextual information. Finally, a fully connected layer with a Softmax classifier produces the output class labels corresponding to different skin diseases. The integration of CNN, PSO, and LSTM enables efficient feature learning and improved classification performance.

#### A. Dataset Description

In this study, the HAM10000 (Human Against Machine with 10,000 Training Images) dataset is utilized for training and evaluating the proposed skin disease detection model. The HAM10000 dataset is a widely used benchmark dataset in dermatological image analysis, comprising a large collection of dermoscopic images of pigmented skin lesions [34].

The images in this dataset are collected from multiple sources, including different populations and clinical settings, and are acquired using various imaging modalities. This diversity ensures that the dataset captures real-world variations in skin lesion appearance, making it suitable for developing robust and generalizable deep learning models. The final dataset consists of a total of 10,015 dermoscopic images, each annotated with a corresponding diagnostic label.

The dataset includes seven distinct classes of skin lesions, representing both benign and malignant conditions. These classes are defined as follows:

- Melanocytic nevi (nv)
- Melanoma (mel)
- Benign keratosis-like lesions (bkl)
- Basal cell carcinoma (bcc)
- Actinic keratoses (akiec)
- Vascular lesions (vasc)
- Dermatofibroma (df)

The availability of multiple classes with varying characteristics makes the HAM10000 dataset highly suitable for multi-class classification tasks in skin disease detection. Furthermore, the dataset presents challenges such as class imbalance and intra-class variability, which are effectively addressed in this study through preprocessing and data augmentation techniques.

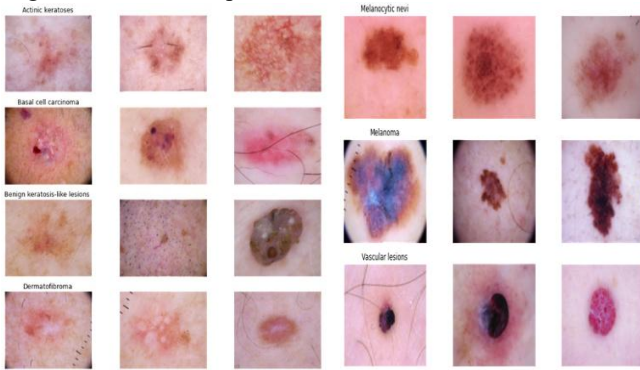


Figure 2: Sample images of Skin Disease in Dataset

Figure 2 presents sample dermoscopic images from the dataset representing different classes of skin diseases. The images illustrate the visual diversity and complexity of skin lesions, including variations in color, texture, shape, and size across classes such as Melanoma, Melanocytic Nevi, and Basal Cell Carcinoma. This variability highlights the challenges involved in accurate classification and emphasizes the need for robust feature extraction and classification techniques. The dataset provides representative that support effective training and evaluation of the proposed hybrid PSO-CNN+LSTM model.

### B. Data Preprocessing

Data preprocessing is a crucial step in developing an efficient and robust skin disease detection system, as dermoscopic images often contain noise, illumination variations, and inconsistencies in size and orientation. Proper preprocessing enhances image quality, improves feature extraction, and ensures better generalization of the proposed model. In this study, several preprocessing techniques including normalization, resizing, data augmentation, and noise removal are applied.

**Image Normalization:** To standardize the input data and stabilize the learning process, pixel intensity normalization is performed. Each image is transformed to have zero mean and unit variance, which helps in faster convergence of the deep learning model. The normalization process is defined as:

$$I_{norm}(x, y) = \frac{I(x, y) - \mu}{\sigma} \quad (1)$$

where  $I(x, y)$  represents the original pixel intensity at position  $(x, y)$ ,  $\mu$  denotes the mean intensity of the image, and  $\sigma$  represents the standard deviation. This transformation ensures that all input images are scaled to a similar distribution, reducing the impact of illumination variations.

**Image Resizing:** Dermoscopic images in the dataset may have varying spatial resolutions, which can affect model consistency and computational efficiency. Therefore, all images are resized to a fixed dimension suitable for the CNN architecture. The resized image can be represented as:

$$I_{resized} \in \mathbb{R}^{H \times W \times C} \quad (2)$$

where  $H$  and  $W$  denote the height and width of the image, respectively, and  $C$  represents the number of color channels (typically  $C=3$  for RGB images). This step ensures uniformity in input size and reduces computational overhead.

**Data Augmentation:** To address the issue of limited dataset size and class imbalance, data augmentation techniques are applied. These transformations artificially increase the diversity of the training data and help prevent overfitting. The augmented image is defined as:

$$I' = T(I) \quad (3)$$

where  $T(\cdot)$  represents a set of transformation operations applied to the original image  $I$ . In this study, the following augmentation techniques are employed:

- Rotation ( $\pm 15^\circ$ )
- Horizontal and vertical flipping
- Scaling and zooming
- Translation and cropping

These operations preserve the semantic content of the image while introducing variability to improve the model robustness.

**Noise Removal:** Dermoscopic images often contain noise due to acquisition conditions, which affect feature extraction. To mitigate this issue, a median filtering technique is applied to remove noise while preserving edges. The filtering operation is defined as:

$$I_{filtered}(x, y) = \text{median}\{I(x+i, y+j) | (i, j) \in N\} \quad (4)$$

where  $N$  represents the neighborhood window centered at pixel  $(x, y)$ . Median filtering effectively reduces impulsive noise and enhances image quality without blurring important features.

**Data Preparation for Model Input:** After preprocessing, the dataset is divided into training, validation, and testing subsets to evaluate the model performance. Let the dataset  $D$  be represented as:

$$D = \{(X_i, Y_i)\}_{i=1}^N \quad (5)$$

where  $X_i$  denotes the preprocessed image and  $Y_i$  represents the corresponding class label. The dataset is typically split in an 80:10:10 ratio for training, validation, and testing, respectively. This ensures unbiased evaluation and prevents overfitting.

### C. Feature Selection using Particle Swarm Optimization (PSO)

Feature selection plays a vital role in improving the performance of deep learning models by eliminating redundant and irrelevant features. In skin disease detection,

the features extracted by Convolutional Neural Networks (CNN) are often high-dimensional, which may lead to increased computational complexity and overfitting. To address this issue, this study employs Particle Swarm Optimization (PSO), a population-based metaheuristic optimization algorithm, to select an optimal subset of discriminative features.

PSO is inspired by the social behavior of bird flocking and fish schooling, where each particle represents a candidate solution in the search space. The algorithm iteratively updates particle positions based on individual experience and global knowledge to converge toward an optimal solution.

**Particle Representation:** In the proposed approach, each particle represents a binary feature selection vector corresponding to the extracted feature set. Let the feature vector obtained from the CNN be denoted as:

$$F = \{f_1, f_2, f_3, \dots, f_n\} \quad (6)$$

Each Particle  $X_i$  is defined as:

$$X_i = (x_{i1}, x_{i2}, \dots, x_{in}), \quad x_{ij} \in \{0,1\} \quad (7)$$

Where,  $x_{ij} = 1$  indicates that the  $j^{th}$  feature is selected,  $x_{ij} = 0$  indicates that the feature is discarded

**Velocity and Position Update:** Each particle adjusts its trajectory in the search space based on its personal best position  $pbest_i$  and the global best position  $gbest$ . The velocity update equation is given by:

$$V_i^{t+1} = wV_i^t + c_1 r_1 (pbest_i - X_i^t) + c_2 r_2 (gbest - X_i^t) \quad (8)$$

where:

- $V_i^t$  is the velocity of particle  $i$  at iteration  $t$
- $w$  is the inertia weight controlling exploration and exploitation
- $c_1, c_2$  are cognitive and social acceleration coefficients
- $r_1, r_2 \in [0,1]$  are random variables

The position of each particle is updated using:

$$X_i^{t+1} = X_i^t + V_i^{t+1} \quad (9)$$

For binary feature selection, a sigmoid function is applied to map velocity values into probabilities:

$$S(V_{ij}) = \frac{1}{1 + e^{-V_{ij}}} \quad (10)$$

where,  $\theta$  is a threshold value (typically 0.5).

**Fitness Function:** The fitness function evaluates the quality of each particle based on classification performance and feature subset size. It is defined as:

$$Fitness = \alpha \cdot Acc + \beta \cdot \left(1 - \frac{|F_s|}{|F|}\right) \quad (11)$$

Where,  $Acc$  is the classification accuracy obtained using the selected feature subset,  $|F_s|$  is the number of selected

features,  $|F|$  is the total number of features,  $\alpha$  and  $\beta$  are weighting coefficients such that  $\alpha + \beta = 1$

This formulation ensures a trade-off between maximizing classification accuracy and minimizing the number of selected features.

**PSO-Based Feature Selection Process:** The overall PSO-based feature selection procedure is summarized as follows:

1. Initialize a swarm of particles with random feature subsets.
2. Evaluate the fitness of each particle using the defined fitness function.
3. Update personal best ( $pbest$ ) and global best ( $gbest$ ) positions.
4. Update particle velocities and positions using PSO equations.
5. Apply the sigmoid function for binary feature selection.
6. Repeat steps 2–5 until convergence or maximum iterations are reached.

**Integration with Hybrid Model:** The optimal feature subset obtained using PSO is forwarded to the LSTM network for sequential learning and classification. This integration reduces feature redundancy, enhances discriminative capability, and improves overall model performance.

#### D. Building Hybrid CNN+LSTM Model

The proposed hybrid model integrates Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to effectively capture both spatial and sequential characteristics of dermoscopic images. The CNN component is responsible for extracting high-level spatial features, while the LSTM component models the sequential dependencies within these features. Additionally, Particle Swarm Optimization (PSO) is incorporated to select the most informative features, thereby improving classification performance and reducing computational complexity.

**CNN Feature Extraction:** The first stage of the proposed framework involves extracting spatial features from preprocessed dermoscopic images using a CNN architecture. Let the input image be represented as:

$$I \in \mathbb{R}^{H \times W \times C} \quad (12)$$

where,  $H$ ,  $W$ , and  $C$  denote the height, width, and number of channels, respectively.

The convolution operation is defined as:

$$F_{i,j}^{(k)} = \sum_m \sum_n I_{i+m, j+n} \cdot K_{m,n}^{(k)} + b^{(k)} \quad (13)$$

where:  $(K)^{(k)}$  presents the  $k^{th}$  convolutional kernel,  $0b^{(k)}$  is the bias term,  $F^{(k)}$  is the resulting feature map After convolution, a nonlinear activation function such as ReLU is applied:

$$A_{i,j}^{(k)} = \max(0, F_{i,j}^{(k)}) \quad (14)$$

Pooling layers are then used to reduce spatial dimensions and retain dominant features:

$$P_{i,j}^{(k)} = \max_{(m,n) \in R} A_{i+m,j+n}^{(k)} \quad (15)$$

where,  $R$  denotes the pooling region. The final output of the CNN is a high-dimensional feature vector:

$$F = CNN(I) \quad (16)$$

**Feature Optimization using PSO:** The extracted feature vector  $F$  is often high-dimensional and may contain redundant information. To address this, PSO-based feature selection is applied to obtain an optimal subset:

$$F_{opt} = PSO(F) \quad (17)$$

This step reduces feature dimensionality and enhances the discriminative capability of the model by retaining only the most relevant features.

**LSTM for Sequential Learning:** The optimized feature vector  $F_{opt}$  is reshaped into a sequential format and fed into the LSTM network to capture temporal dependencies and contextual relationships among features. Let the input sequence be represented as:

$$X = \{x_1, x_2, \dots, x_3\} \quad (18)$$

At each time step  $t$ , the LSTM performs the following operations:

**Forget gate**

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \quad (19)$$

**Input gate**

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (20)$$

**Candidate Cell State**

$$C_t = \tanh(W_c[h_{t-1}, x_t] + b_c) \quad (21)$$

**Cell state update**

$$C_t = f_t \cdot C_{t-1} + i_t \cdot C_t \quad (22)$$

**Output gate**

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (23)$$

**Final output**

$$h_t = o_t \cdot \tanh(C_t) \quad (24)$$

Where,  $h_t$  is the hidden state,  $C_t$  is the cell state,  $\sigma(\cdot)$  is the sigmoid activation function. The LSTM effectively models dependencies across feature sequences, improving classification performance.

**Classification Layer:**

$$y = \text{Softmax}(W \cdot h_t + b) \quad (25)$$

Where,  $W$  and  $b$  are learnable parameters,  $y$  represents the predicted probability distribution over classes, The predicted class label is obtained as

$$\hat{y} = \arg \max(y) \quad (26)$$

**E. Model Training**

The model is trained using a categorical cross-entropy loss function:

$$L = -\sum_{i=1}^N y_i \log(\hat{y}_i) \quad (27)$$

Where,  $y_i$  is the true label,  $\hat{y}_i$  is the predicted probability

Optimization is performed using gradient-based methods such as Adam optimizer to minimize the loss function.

#### IV. RESULT ANALYSIS

The performance of the proposed PSO-based CNN+LSTM model is evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score. The experimental analysis is conducted to assess the effectiveness of the hybrid architecture in comparison with baseline models such as CNN, LSTM, CNN+LSTM (without PSO), and Random Forest. The integration of Particle Swarm Optimization (PSO) enables optimal feature selection, which significantly enhances the classification capability of the model.

##### A. Experimental Setup

The proposed model is trained and tested on a dermoscopic skin lesion dataset. The dataset is divided into training, validation, and testing subsets using an 80:10:10 ratio to ensure unbiased evaluation. All models are trained under identical conditions to ensure a fair comparison. The training process is carried out using a deep learning framework with optimized hyperparameters, including learning rate, batch size, and number of epochs.

**Evaluation Metrics:** To quantitatively evaluate the model performance, the following metrics are used:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (28)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (29)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (30)$$

$$\text{F1-Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (31)$$

where TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives, respectively.

Table 2: The comparative performance of the proposed model with baseline approaches.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN	92.5	91.8	90.5	91.1
LSTM	89.3	88.7	87.9	88.3
CNN+LSTM	95.1	94.6	93.8	94.2
Random Forest	90.2	89.5	88.6	89.0
Proposed PSO-CNN+LSTM	98.2	97.8	97.3	97.5

Table 2 presents the comparative performance analysis of the proposed PSO-based CNN+LSTM model against baseline approaches, including CNN, LSTM, CNN+LSTM, and Random Forest. It is observed that the proposed model achieves the highest performance across all evaluation metrics, with an accuracy of 98.2%, precision of 97.8%, recall of 97.3%, and F1-score of 97.5%. Among the baseline models, the hybrid CNN+LSTM demonstrates better

performance than individual CNN and LSTM models, indicating the advantage of combining spatial and sequential feature learning. However, the absence of feature optimization limits its overall effectiveness. The Random Forest model shows comparatively lower performance due to its inability to effectively capture complex image features. The significant improvement achieved by the proposed model highlights the effectiveness of integrating Particle Swarm Optimization (PSO) for feature selection, which enhances discriminative feature representation and improves classification accuracy.

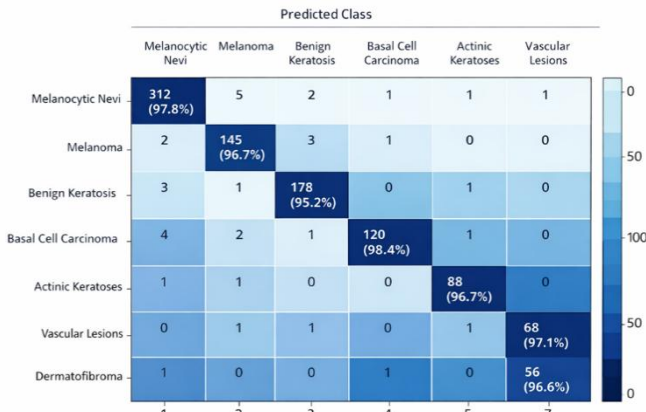


Figure 3: Confusion Matrix of Hybrid CNN+LSTM Model

Fig. 3 presents the confusion matrix of the hybrid CNN+LSTM model for multi-class skin disease classification. The matrix shows that the majority of samples are correctly classified, as indicated by the high values along the diagonal for all seven classes. Notably, classes such as Melanocytic Nevi, Basal Cell Carcinoma, and Dermatofibroma achieve high correct prediction rates, demonstrating the strong classification capability of the model. Misclassifications are minimal and primarily occur between visually similar classes, such as Melanoma and Benign Keratosis. The confusion matrix highlights the effectiveness and robustness of the proposed model in accurately distinguishing between different types of skin lesions

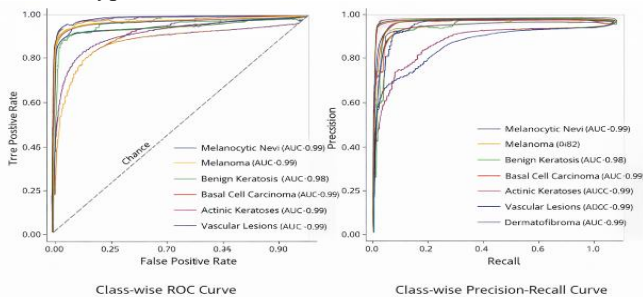


Figure 4: (A) Class Wise ROC Curve (B) Class Wise PR Curve of PSO based CNN-LSTM model

Fig. 4 shows the class-wise performance of the proposed PSO-based CNN+LSTM model using Receiver Operating Characteristic (ROC) and Precision–Recall (PR) curves. As shown in Fig. 4(a), the ROC curves for all seven skin disease classes demonstrate high Area Under the Curve (AUC) values,

indicating excellent discriminative capability of the model across different classes. Similarly, Fig. 4(b) presents the class-wise Precision–Recall curves, which show consistently high precision and recall values, highlighting the model’s effectiveness in handling class imbalance and correctly identifying positive cases. The overall performance depicted in both curves confirms the robustness and reliability of the proposed model for multi-class skin disease classification.

## V. DISCUSSION

The results clearly demonstrate that the proposed PSO-based CNN+LSTM model outperforms all baseline models across all evaluation metrics. The standalone CNN model achieves strong performance due to its ability to extract spatial features; however, it lacks the capability to capture sequential dependencies, which limits its overall accuracy. Similarly, the LSTM model alone performs comparatively lower, as it is not designed for effective spatial feature extraction from images.

The hybrid CNN+LSTM model shows improved performance by combining spatial and sequential learning; however, the absence of feature optimization results in redundant and high-dimensional feature representations. In contrast, the proposed model incorporates PSO for feature selection, which effectively eliminates irrelevant features and retains only the most discriminative ones. This optimization significantly enhances classification accuracy and reduces computational complexity.

Furthermore, the improvement in precision and recall indicates that the proposed model is capable of accurately identifying both positive and negative classes, which is critical in medical diagnosis applications. The high F1-score demonstrates a balanced performance between precision and recall, confirming the robustness of the model.

### A. Impact of PSO on Model Performance

To further analyze the contribution of PSO, it is observed that the inclusion of feature selection leads to a notable improvement in performance compared to the CNN+LSTM model without PSO. By reducing feature redundancy, PSO improves generalization capability and prevents overfitting, resulting in more reliable predictions.

### B. Summary of Findings

- The proposed PSO-CNN+LSTM model achieves the highest accuracy of 98.2%, outperforming all baseline models.
- Feature optimization using PSO significantly enhances model efficiency and performance.
- The hybrid architecture effectively captures both spatial and sequential patterns in dermoscopic images.
- The model demonstrates strong generalization capability and robustness for skin disease detection tasks.

## VI. CONCLUSION

This study presented a hybrid deep learning framework for skin disease detection by integrating Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and Particle Swarm Optimization (PSO). The primary objective was to address the limitations of existing approaches, such as high-dimensional feature space, redundant feature representation, and limited capability to capture sequential dependencies.

The proposed model leverages CNN for effective spatial feature extraction from dermoscopic images, while the LSTM component enhances the learning process by capturing sequential and contextual relationships among the extracted features. Furthermore, PSO is employed as a feature selection mechanism to identify the most relevant features, thereby reducing dimensionality and improving classification efficiency.

Experimental results demonstrate that the proposed PSO-CNN+LSTM model significantly outperforms conventional machine learning and deep learning models, including CNN, LSTM, CNN+LSTM, and Random Forest. The model achieves superior performance across all evaluation metrics, with notable improvements in accuracy, precision, recall, and F1-score. The integration of PSO not only enhances classification accuracy but also reduces computational complexity, making the model more efficient and scalable.

The proposed PSO-based CNN+LSTM model demonstrates strong performance in skin disease detection; several avenues exist for further improvement and extension. Future work can focus on expanding the model to handle multi-class and multi-disease classification involving a broader spectrum of dermatological conditions, including rare and complex cases. The integration of attention mechanisms can enhance the model's ability to focus on critical regions of skin lesions, thereby improving interpretability and diagnostic accuracy. Additionally, the proposed framework can be optimized for real-time deployment on mobile and embedded platforms, enabling remote and accessible healthcare solutions. Incorporating larger and more diverse datasets from multiple sources will further improve the generalization capability and robustness of the model across different populations and imaging conditions. Furthermore, the adoption of Explainable Artificial Intelligence (XAI) techniques, such as Grad-CAM, can provide visual insights into model predictions, increasing trust and usability in clinical environments. Finally, hybrid optimization strategies combining PSO with other metaheuristic algorithms may be explored to further enhance feature selection and overall system performance.

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