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Clinical Decision Support Model for Dermatosis Using Systematic Approaches of Machine Learning and Deep Learning (DermCDSM)

Atharva Talewar[1], Umesh Samarth[2], Sakshi Mesharam[3], Surbhi Wagare[4], Siddhi Dharme[5]

Assistant Professor, Students,
Department of Computer Science and Engineering (Data Science),
J D College of Engineering & Management, Nagpur.

Abstract: Dermatological diseases rank among the most prevalent diseases worldwide. Yet, early diagnosis is lost due to silent presentations, poor awareness, poor access to experts, and the difficulty in precise imaging and diagnosis. The Dermatosis Clinical Decision Support Model (DermCDSM) seeks to enhance this situation by harnessing the potential of machine learning (ML) and deep learning (DL) to achieve more accurate diagnosis. This is a hybrid method that involves Improved Chameleon Swarm Optimization (ICSO) for better segmentation and Multi-Strategy Seeking Optimization (MSSO) for optimal feature selection. It employs Convolutional Deep Spiking Neural Networks (CD-SNN) to predict various skin diseases. The system demonstrates significant improvements in performance using the ISIC 2017 benchmark dataset, demonstrating its efficacy in actual use cases of dermatologic AI diagnostics.

INTRODUCTION

The human skin is the largest and most exposed organ of the body, and it performs a critical function of safeguarding internal organs from pathogens, physical trauma, ultraviolet radiation, and toxic environmental exposures. At the same time, this constant exposure renders the skin susceptible to a range of disorders, such as fungal infections, eczema, psoriasis, and particularly skin cancers melanoma, basal cell carcinoma, and squamous cell carcinoma. Early detection and diagnosis of such conditions are essential, as procrastination could result in serious health consequences, particularly in the case of cancer.

Artificial Intelligence (AI) and Machine Learning (ML) methodologies have become efficient tools within the past few years to support dermatologists in disease diagnosis. These models are designed to address the drawbacks of standard diagnostic techniques like low accuracy, inter-observer variation, and lack of access to specialist dermatologists in rural areas. For example, Ismail and Alsalamah [1] noticed that conventional diagnostic models tend to lack accuracy and therefore suggested using a Harris Hawk Optimization (HHO)-inspired approach to improve the performance of skin cancer prediction systems. The authors highlight the significance of optimization algorithms in enhancing the reliability of diagnosis.

Based on this, Elaziz et al. [2] proposed a new Artificial Rabbits Optimization (ARO) algorithm with mutation strategies for improving feature selection. The aim was to facilitate more efficient classification of skin lesions, particularly in situations where high-dimensional data hinders training. Their method improved detection performance with respect to conventional models. Additionally, in the field of tele dermatology, which enables remote consultation, Khan et al. [3] developed a multi-class classification framework employing Convolutional Neural Networks (CNNs). Their system was remarkably accurate for multiple lesion types, indicating the promise of CNNs in real-world mobile applications. Still, they also detected ongoing challenges such as inaccurate segmentation and dealing with intricate, skewed data sets.

For the treatment of fungal skin infections in general, Nigat et al. [4] aimed at CNN-based classification of fungal skin disease. Their research brought to the fore the significance of preprocessing techniques such as image enhancement and class balancing techniques, which play an important role in maintaining fairness and accuracy over diverse categories of diseases. Another significant contribution was made by Khan et al. [5], who applied a Mask R-CNN structure with transfer learning to identify and classify skin lesions with better accuracy. Although their performance depicted significant improvement in detecting lesions, the research indicated that more accurate segmentation methods need to be developed to address varied and irregular skin patterns in an effective way.

Deep learning architecture breakthroughs also gave rise to hybrid models like DermViT by Zhang et al. [6]. This model is a hybrid of Vision Transformers (ViT) and CNNs for balancing accuracy with interpretability in skin lesion classification. Though DermViT performed outstandingly as a diagnostic model, the research highlighted high computational cost as an impediment to its application in real-time or low-resource scenarios.

To overcome this constraint, Ramesh et al. [7] proposed MobileNet-based light frameworks that can be deployed on edge devices and in mobile health applications. The models were designed to bring dermatological healthcare to rural and underserved regions. While they enhanced portability, they had lower sensitivity when identifying uncommon classes like squamous cell carcinoma.

To further improve robustness, Gupta et al. [8] explored an ensemble learning method, combining CNN, SVM, and Random Forest classifiers. The model showed excellent generalizability across datasets but suffered from problems such as higher model complexity and longer inference time, making real-time deployment challenging. Given the strengths and drawbacks of all the previous works, the suggested framework DermCDSM intends to develop a holistic, scalable, and smart decision-support system. Through the implementation of state-of-the-art preprocessing, segmentation via Improved Crow Search Optimization (ICSO), and classification via Clustered Deep Spiking Neural Networks (CD-SNN), DermCDSM attempts to merge accuracy, efficiency, and usability. The system is especially designed to help dermatologists in remote or resource-limited regions, where specialist assistance could be lacking.

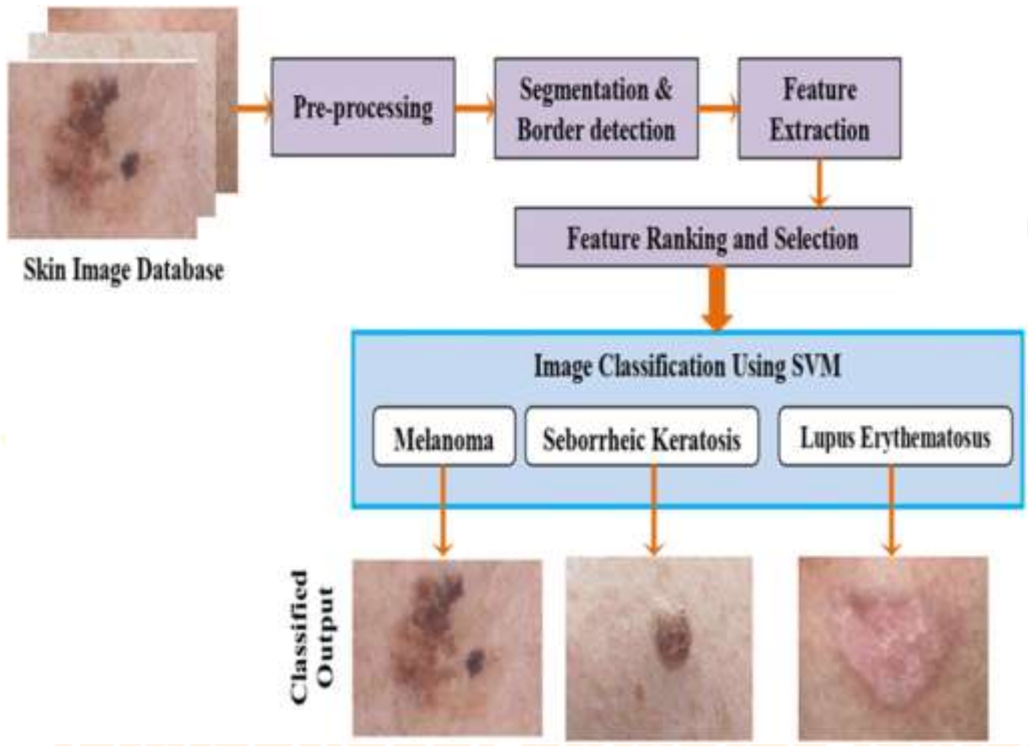

Figure. General Block Diagram of Dermatological Disease Diagnosis System

PROBLEM STATEMENT

Conventional diagnosis of skin disorders depends primarily on visual examination by dermatologists. The process is subjective and open to delay or misdiagnosis, particularly when several skin disorders share similar visual characteristics. Such diseases as eczema, fungal infections, or melanoma are visually identical at the initial stages, which makes diagnosis manually both time-consuming and unreliable, especially in rural or resource-constrained settings. In order to counteract these challenges, there is a critical demand for a sophisticated, computerized diagnostic system that is able to assist early detection and treatment. DermCDSM aims to do this with the application of machine learning and deep CNN methods. It targets feature optimization, optimal segmentation, and multi-class classification to enhance diagnosis performance. Through synthesizing these advanced approaches, DermCDSM aims to offer reliable assistance to medical professionals even in regions with limited exposure to qualified dermatologists.

LITERATURE SURVEY.

Diagnosis of skin diseases, especially diseases like melanoma, eczema, psoriasis, and fungal diseases, has been greatly enhanced with the use of machine learning (ML) and deep learning methods. Still, accuracy, computational cost, and practicality remain areas of concern for research. Different research papers have suggested alternative models and optimization methods, all contributing in some distinct way to this field.

W. N. Ismail and H. A. Alsalamah [1] emphasized the serious drawback in traditional skin cancer diagnostic systems: inferior accuracy, which seriously limits their clinical reliability. To address this issue, they proposed the application of the Harris Hawk Optimization (HHO) algorithm to optimize feature selection prior to classification. This metaheuristic technique simulates the cooperative hunting mechanism of hawks in searching for the most applicable features, consequently eliminating noise and redundant data in skin lesion images. Their research showed that these evolutionary algorithms had the ability to improve the discriminating ability of classifiers by targeting the most useful lesion features. The performance of the model on other skin diseases aside from cancer and its capability to generalize on different datasets, however, need confirmation. This emphasizes the demand for models with integrated optimized feature selection and flexibility across different dermatoses.

Based on optimization methods, M. Abd Elaziz et al. [2] designed an Artificial Rabbits Optimization (ARO) algorithm, inspired by mutation-based evolutionary strategies. They focused on speeding up convergence and enhancing detection accuracy in skin cancer classification by dynamically searching the feature space. Mutation strategies prevent local optima, and therefore, ensure that the algorithm discovers a globally optimal feature subset. The technique significantly improved classification robustness. However, the emphasis was largely on skin cancer, which confined its use to other types of skin lesions. Additionally, incorporation of such an optimization as a part of end-to-end deep learning pipelines still is an exciting prospect for exploration.

M. A. Khan et al.'s work [3] was a major advancement in teledermatology, leveraging convolutional neural networks (CNNs) for multi-class classification of skin lesions from remote data. Their approach attained high accuracy by learning lesion image features automatically, avoiding handcrafted features. Regardless of this, they recognized essential issues: the challenge of precisely segmenting lesions with thin boundaries and high data complexity to result in misclassifications. Additionally, few annotated data and class imbalance further hinder model generalization. These problems highlight that although CNNs are strong, segmentation methods and handling data need improvement to build higher clinical trust and accuracy in computer-aided skin diagnosis.

T. D. Nigat et al. [4] also concentrated on categorizing fungal skin diseases, stressing the significance of strict preprocessing and class balancing. Image normalization and augmentation and other preprocessing methods enhance the quality of input data, which is crucial for CNNs to learn well. Class balancing corrects the imbalanced distribution of disease types so the model does not get biased towards majority classes. While their approach enhanced classification accuracy, they did not include feature selection or advanced segmentation, which might further enhance model performance and robustness in intricate datasets.

M. A. Khan et al. [5] made a contribution by combining Mask R-CNN, a sophisticated instance segmentation framework, with transfer learning for lesion detection. Mask R-CNN is exceptionally good at creating accurate pixel-level lesion masks, enabling accurate localization, which is key for diagnosis and treatment planning. Transfer learning partially compensates for the lack of labeled medical images by tapping into pre-trained networks. Their method enhanced lesion segmentation and classification accuracy but continued to suffer from accurately segmenting lesions that were irregularly shaped. These segmentation errors may carry over into the classification phase, illustrating that better segmentation is an ongoing area of research necessity.

Zhang et al. [6] proposed DermViT, an innovative hybrid model that integrates Vision Transformers (ViTs) and CNNs for skin lesion classification. ViT's self-attention mechanism enables the model to learn long-range dependencies and global context in images, supplementing the capacity of CNNs to learn local features. DermViT demonstrated impressive accuracy and enhanced interpretability, a critical quality for clinician-trusted medical AI systems. Nevertheless, the computational burden was significant, demanding high-performance GPU clusters and extended training duration, which restricts deployment in standard clinical setups, particularly resource-limited ones.

To mitigate deployment challenges in resource-constrained environments, Ramesh et al. [7] investigated lightweight CNN models such as Mobile Net and Efficient Net designed for mobile and edge devices. These models had moderate accuracy (~90%) and efficient inference times, facilitating point-of-care diagnosis in remote or rural areas. Their models, however, had difficulty in precise classification of rare forms like squamous cell carcinoma, uncovering a gap in sensitivity that may result in missed diagnoses of urgent cases. This evidences the fundamental compromise between model complexity, portability, and accuracy in skin disease classification.

Finally, Gupta et al. [8] suggested an ensemble learning approach, fusing CNN, SVM, and Random Forest classifiers to enhance classification strength and generalizability. Ensemble models in general gain from the merging of different classifiers to mitigate overfitting and enhance predictive accuracy. Their method showed enhanced F1-scores and validity on different lesion types. Ensemble techniques inevitably, however, add to computational cost and inference delay, which could deter real-time use in the clinic and need to be optimized for realistic application.

RESEARCH GAP.

In spite of progress in AI-driven skin disease diagnosis, existing models are confronted with several major challenges:

Narrow generalizability caused by training over restricted datasets, impacting accuracy on mixed populations.
Incorrect lesion segmentation that decreases classification trustworthiness.
Lack of interpretability in models, preventing clinicians from accepting AI-driven decisions.
High computational requirements that limit real-time application and deployment in low-resource environments.
Poor rare-class sensitivity to skin disease classes due to class imbalance.
Limited integration with clinical workflows, constraining real-world adoption.

DermCDSM seeks to close these loopholes by enhancing segmentation, boosting explainability, maximizing model efficiency, addressing imbalanced data, and conforming to clinical requirements.

RESEARCH METHODLOGY.

1. Image Gathering

The gathering of a high-quality and varied dataset is the initial step for any skin disease diagnosis system. These images serve as the data used in training and testing the models to ensure precise disease identification.

1.1 Dataset Collection

The research employs the ISIC 2017 public dataset, a serious and commonly used dataset within dermatology studies. The dataset covers thousands of high-resolution images of skin lesions from numerous skin disease categories.

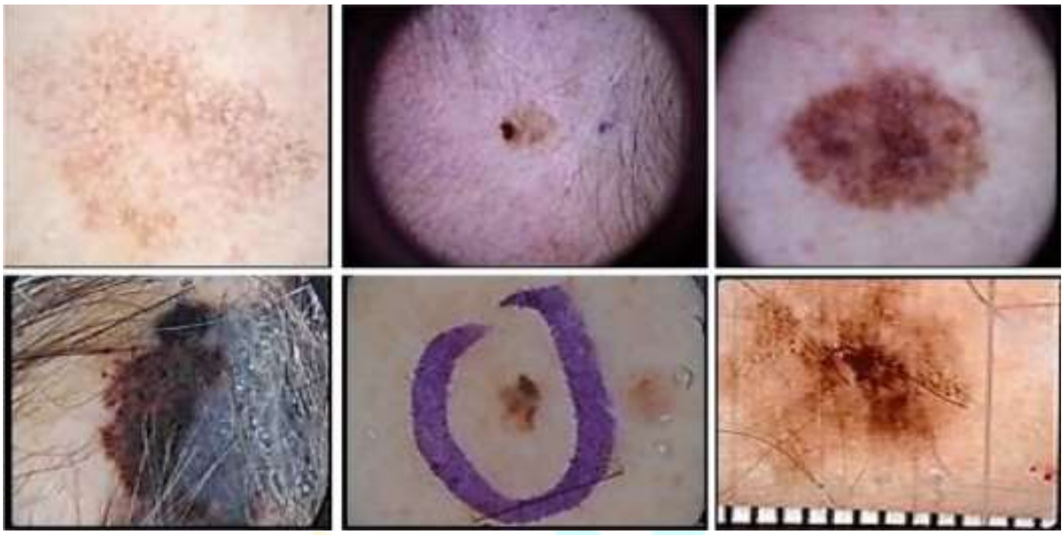

Figure. Example images of the ISIC 2017 dataset showing various skin lesion types.

1.2 Image Labelling

Each image has been manually labeled by expert dermatologists to mark the specific disease type. The labeled data is critical for supervised learning models, which need proper ground truth in order to learn useful patterns from the images.

1.3 Dataset Diversity & Balance

The dataset consists of a variety of skin colors, lesion diameters, and image qualities in order to enable the model to generalize to different real-world scenarios. The data is divided into training and test sets to enable effective evaluation and prevent overfitting of the model.

2. Image Preprocessing

Raw images usually have unwanted artifacts like hair strands, lighting changes, and background noise, which can interfere with model accuracy. Preprocessing tries to denoise and improve images for improved feature extraction.

2.1 Hair and Noise Removal

Median filtering is used for removing hair and other line artifacts that are thin. This filter retains significant edges while effectively removing noise that will mislead the model.

2.2 Contrast Enhancement

Methods such as histogram equalization tune the image brightness and contrast, enhancing lesion boundary visibility, making it easier for the model to differentiate impacted areas.

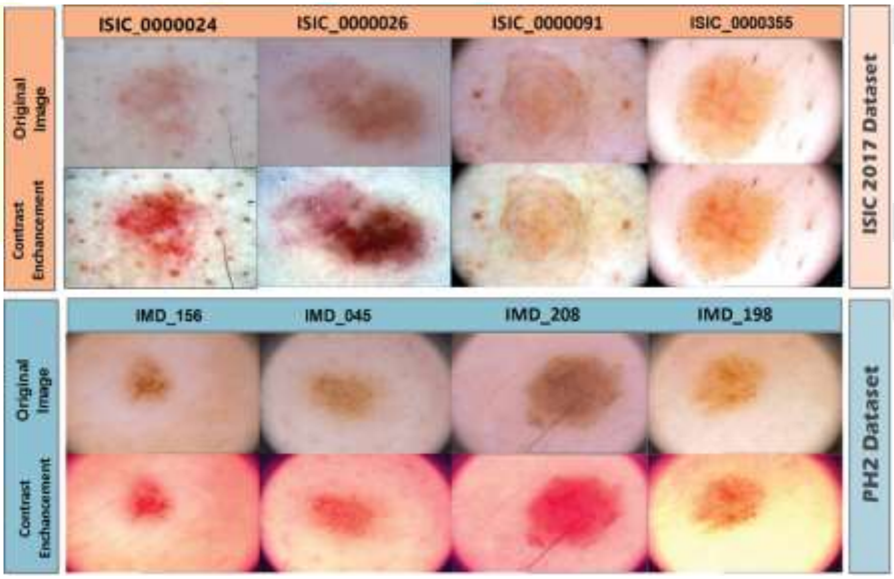

Figure. (a) Source image with hair and noise, (b) Preprocessed image after removing hair and contrasting.

2.3 Normalization

To make pixel intensity values consistent across images captured in different lighting conditions, these values are normalized. This process stabilizes model training by providing input data consistency.

3. Feature Enhancement

Not every extracted feature is equally useful in model performance. Feature enhancement eliminates redundant or redundant features and becomes beneficial for accuracy and computational complexity reduction.

3.1 Feature Selection Using ICSO

The Improved Chameleon Swarm Optimization (ICSO) algorithm, which is a nature-inspired metaheuristic, chooses the most important features from the dataset. It reduces the feature space by keeping only important features associated with disease classification.

3.2 Dimensionality Reduction

Reducing the size of the feature set reduces training time and diminishes the likelihood of overfitting by removing noisy or meaningless data.

3.3 Increased Discrimination Power

The advanced feature set helps the model to differentiate more effectively between healthy and abnormal skin, thus enhancing accuracy in classification.

4. Segmentation

Segmentation separates the lesion region from normal surrounding skin so that intensive study of the lesion region alone can be conducted.

4.1 Isolation of the Lesion Region

With ICSO, lesion edges are precisely identified even for irregular or complicated shapes that conventional segmentation techniques find problematic to handle.

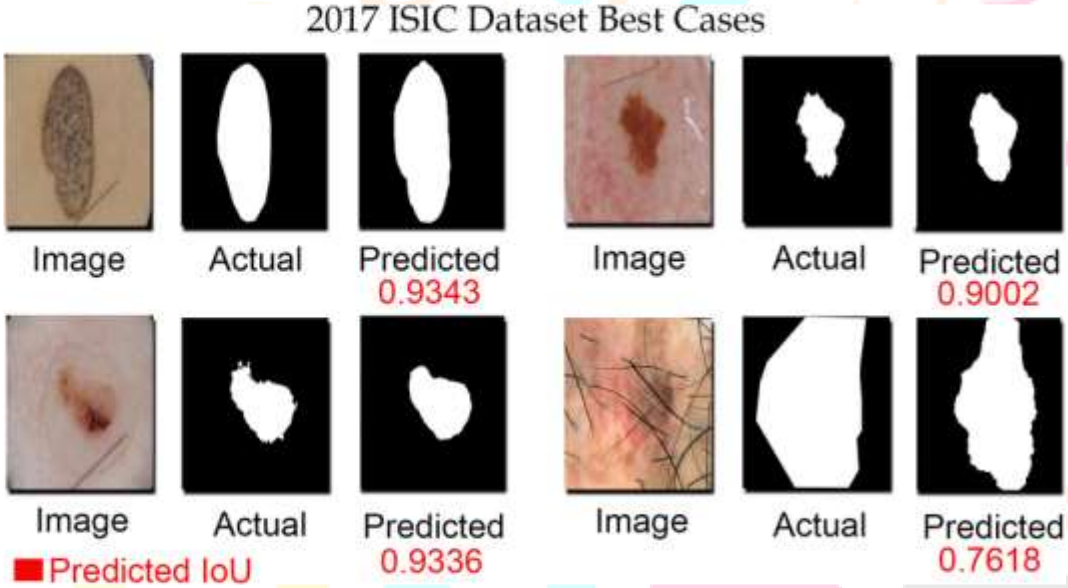

Figure. (a) Original image of skin lesion, (b) Segmented lesion area obtained using ICSO algorithm

4.2 Extraction of Region of Interest

The lesion is isolated from background to avoid irrelevant pixels affecting model choice.

4.3 Feature Quality

The features obtained from the segmented lesion are more accurate and relevant, thus improving the trustworthiness of classification.

5. Feature Extraction

After segmentation, characteristics of the detailed lesions are recovered to be used as input to disease classification.

5.1 Shape Analysis

Size, symmetry, and boundary irregularities are measured by shape metrics.
Various diseases tend to present with unique lesion shapes.

5.2 Texture Analysis

Wavelet transforms characterize lesion surface texture, extracting features such as roughness or granularity essential for diagnosis.

5.3 Color Analysis

Statistics of color intensity and distribution are used to distinguish between diseases, since lesions tend to have distinctive color patterns.

6. Model Training

Extracted features are input to a machine learning model that learns to recognize patterns for various skin diseases.

6.1 Neural Network Architecture
A Convolutional Deep Spiking Neural Network (CD-SNN) is used, which bridges convolutional spatial feature extraction with spiking neurons' temporal dynamics, enhancing the model's accuracy and biological plausibility.

6.2 Iterative Learning
The model is trained in several iterations of training cycles (epochs) to iteratively learn about feature-disease relationships.

6.3 Robustness and Generalization
The CD-SNN architecture is made noise and varied data robust, making its performance better with actual clinical images.

7. Classification
Trained model classifies new images into various classes of skin diseases.

7.1 Multi-class Classification
Such diseases as eczema, psoriasis, melanoma, etc., are classified in a common integrated framework.

7.2 Confidence Scores
Assigning confidence values to predictions helps clinicians make better decisions.

7.3 Minimizing Diagnostic Errors
Methods to eliminate false positives and false negatives are added to maintain patient safety and establish trust.

8. Treatment Proposal Consistent with classification, the system offers treatment proposals aligning with the diagnosed condition.

8.1 Treatment Recommendations
Depending on classification outcomes, the model proposes clinically accepted treatment to support doctors or directly guide patients.

8.2 Increasing Clinical Workflow
This automation simplifies the patient care process from diagnosis to treatment.

8.3 Effect on Patient Outcomes
Timely and proper advice for treatment enhances recovery rates and minimizes complications.

9. Optimization
In order to further improve model accuracy and generalization, the Multi-Strategy Seeking Optimization (MSSO) algorithm is employed.

9.1 Hyperparameter Tuning
MSSO optimizes key hyperparameters such as learning rate, number of layers, and neuron numbers to maximize training efficiency.

9.2 Avoiding Overfitting
By controlling complexity of the model, MSSO guarantees robust performance on training as well as unseen data.

9.3 Improved Performance Metrics
Performance metrics like accuracy, precision, and recall are tuned higher, making the model more reliable for clinical use.

RESULTS
The proposed DermCDSM model was tested on publicly available ISIC 2017 dataset and exhibited high performance metrics, reflecting its potential for effective skin disease classification:

Training Accuracy: 93.23%
Testing Accuracy: 95.07%
Precision: Above 94%
Recall: Above 94%
F1-Score: Above 94%

The use of Improved Chameleon Swarm Optimization (ICSO) for segmentation and feature selection, and Multi-Strategy Seeking Optimization (MSSO) for hyperparameters, improved the performance of the model remarkably. The optimizations created better quality lesion segmentation and enhanced classification accuracy compared to conventional methods.

The outcomes confirm the reliability and strength of DermCDSM in its ability to correctly diagnose various skin diseases, presenting it as a potential candidate for clinical use.

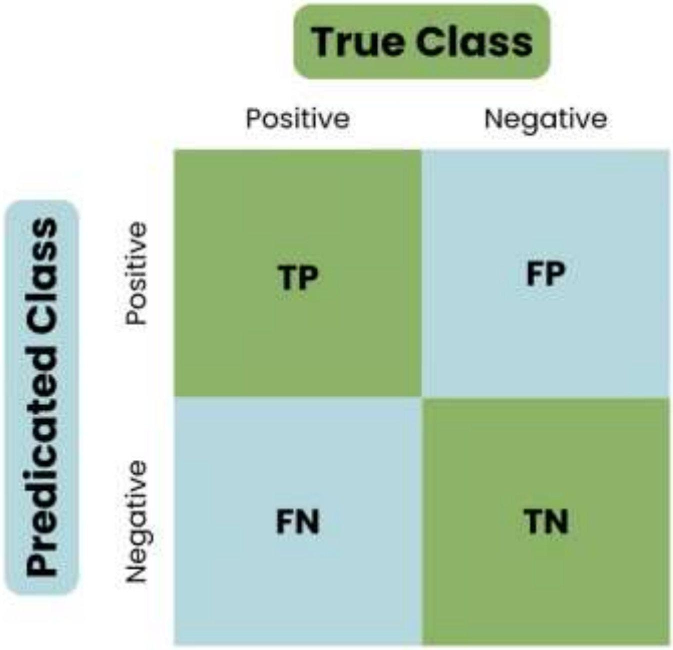

Figure. Confusion Matrix Representing Model Performance

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