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***Research paper***

# Hybrid Metaheuristic Optimization and Deep Learning Models for Accurate Skin Lesion Detection and Classification

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## Abstract

Skin cancer detection through medical imaging plays a crucial role in early diagnosis and treatment. In this study, we focus on segmenting lesions from the HAM10000 dataset using region-based techniques such as Graph Cut Segmentation (GCS) and Fuzzy C-means clustering (FCM). Accurate segmentation is essential for extracting meaningful features, which directly impact the classification performance. To enhance feature selection, we integrate two metaheuristic optimization algorithms—Particle Swarm Optimization Algorithm (PSOA) and Sparrow Search Algorithm (SSA). Additionally, propose a hybrid optimization model that combines these techniques to improve feature selection efficiency and enhance the overall classification process. For classification, we compare the performance of a Vision Transformer (ViT) with traditional Convolutional Neural Networks (CNNs), specifically ResNet and EfficientNet, for binary classification of skin lesions. Transformers have demonstrated significant potential in vision tasks due to their self-attention mechanism, which captures long-range dependencies in images. The proposed methodology is evaluated based on segmentation accuracy, feature selection efficiency, and classification performance. Then assess multiple evaluation metrics to compare the effectiveness of each technique, ensuring a comprehensive analysis of their impact. The study aims to provide valuable insights into how different segmentation, optimization, and classification methods contribute to improved skin lesion analysis.

***Keywords***: *Skin Lesion Segmentation; HAM10000 Dataset; Graph Cut Segmentation (GCS); Fuzzy C-Means Clustering (FCM); Feature Selection; Particle Swarm Optimization Algorithm (PSOA);Sparrow Search Algorithm (SSA);Vision Transformer (ViT).*

## 1. Introduction

One of the most common and fatal diseases, skin cancer requires early identification if proper treatment is to be obtained and survival rates raised. Skin lesion diagnosis depends critically on the study of dermoscopic images; automated computer-aided diagnostic (CAD) systems depend on proper segmentation and categorization. In this work, we apply region-based methods including Graph Cut Segmentation (GCS) and Fuzzy C-means clustering (FCM) to segment skin lesions from the HAM10000 dataset. These techniques enable efficient lesion region extraction, which provides a basis for more study. Since accurate segmentation immediately affects the feature extraction process and produces more consistent classification results. Eliminating duplicated and pointless features helps to improve classification performance by means of feature selection as well. We apply the following two optimization techniques such as the Particle Swarm Optimization Algorithm (PSOA) and the Sparrow Search Algorithm (SSA) are used in the proposed techniques. These methods improve the choice of best features, therefore increasing the classification accuracy and lowering the computational cost. We also suggest a hybrid model combining many optimization methods to improve the feature choosing process even more. By assessing their performance, we hope to find the best appropriate method for enhancing the segmentation and classification pipeline in skin lesion analysis.
To evaluate the performance of a Vision Transformer (ViT) against conventional Convolutional Neural Networks (CNNs) like ResNet and EfficientNet for classification. Because of their self-attention systems, which let them record worldwide dependencies inside an image, transformers have become rather popular in image processing. Still, CNNs are the most often used tool in medical image classification since they can efficiently extract spatial data. We wish to identify which design performs best in classifying skin lesions by means of analysis and comparison of several models. This work offers insightful analysis of how segmentation, feature selection, and classification methods could help to improve skin cancer diagnosis and detection. Early skin cancer detection greatly raises survival rates and treatment results. Analysing dermoscopic images for accurate and fast diagnosis depends much on automated computer-aided diagnostic (CAD)

tools. Extensive significant feature extraction from skin lesions depends on precise segmentation of them affecting classification performance. Effective lesion region separation is achieved by region-based segmentation methods including Graph Cut Segmentation (GCS) and fuzzy C-means clustering (FCM).

Through the elimination of pointless and unnecessary data, feature selection increases classification accuracy. This work uses Sparrow Search Algorithm (SSA) and Particle Swarm Optimisation Algorithm (PSOA) to improve feature selection process, hence lowering computational complexity while yet preserving good classification performance. This work evaluates for binary classification of skin lesions the Vision Transformer (ViT) against conventional CNN designs including ResNet and EfficientNet. The study finds the most efficient model for skin lesion classification and assesses their strengths in managing medical pictures. This work intends to identify skin cancer by using advanced segmentation, optimisation, and classification methods. The results help to create better dependable and effective CAD systems for dermatological diagnostics.

## 2. Literature survey

Examining 549 papers on skin lesion segmentation and classification from 2011 to 2022, this extensive survey looks at many facets, including preprocessing methods, approaches, training plans, and evaluation criteria. [1] The paper highlights present developments in computer-aided diagnosis (CAD) system development for skin lesion analysis as well as difficulties therein. It also provides suggestions for next studies to improve the dependability and automation of CAD systems in dermatology [2]. From dermoscopic pictures, DNN models based on modified EfficientNet-B4, and EfficientNetV2-M models diagnose benign and malignant skin lesions [3]. It summarizes lesion segmentation strategies in a brief manner and examines several approaches used for skin lesion identification. The performance of modern techniques assessed on various skin lesion datasets is also investigated and analyzed in this work, therefore stressing the developments and difficulties in this field [4]. Deep learning methods applied in skin lesion segmentation, a vital step towards a correct diagnosis [5]. EfficientNetB3 can learn from many images, hence it is a particularly strong CNN. This helps it to spot minute trends in skin lesions that would not be apparent to the human eye. EfficientNetB3 can thus help to raise the accuracy of skin lesion diagnosis. Six [6]. This work presents a new hybrid deep learning method for enhanced segmentation and classification of skin lesions. The suggested approach consists in three main phases: preprocessing, lesion segmentation, and lesion classification [7]. Using CNN models, the skin cancer detection process has rather good accuracy. CNN models could help to raise the skin cancer detection accuracy. [8] hybrid models for skin lesion analysis including conventional image processing methods and machine learning algorithms [9]. Combining these techniques results in more precise segmentation and classification of skin lesions, so perhaps enhancing early identification and treatment results. When multi-classifying skin lesions, the CNN model produced rather high degrees of correctness. This implies that CNNs could be applied as a method to raise skin cancer diagnosis accuracy [10].

The feature vectors produced by the several CNNs generate a single, bigger feature vector aggregating the data from all the networks. [ 11] This paper addresses artificial intelligence (AI) integration in healthcare with particular reference to dermatology uses. [12] It emphasizes how, especially in the detection of skin cancer, AI algorithms have been created to process medical photos for better diagnosis. The paper also answers questions about differences in skin colour and the need to use several datasets to teach AI models for fair healthcare results. ([13]). Cover a spectrum of skin tones and ethnicities to teach the model and attain higher accuracy in practical use. Artificial intelligence could change skin cancer diagnosis. Early detection and treatment follow from increased accuracy and efficiency of skin cancer diagnosis made possible by AI-powered diagnostic tools. [14] AI techniques applied for field expansion with effective early detection help to improve patient prognosis by means of their accuracy [15]. The performance of SkinLesNet, which followed instances of accuracy and recommended areas for development, Promising DCNN for the diagnosis of melanoma cancer and classification of skin lesions is SkinLesNet. On three separate datasets, the model proved rather highly accurate. The magnitude of the dataset and the interpretability of the model [16] are still two areas where the model might be strengthened, though. Four kinds of cancer identified using DSCC NET model Either bespoke design or existing CNNs like ResNet, Inception, EfficientNet could guide the architecture. The decision would rely on the desired performance [17] and the degree of data complexity. The approaches of computer-aided diagnostic (CAD) systems and their applications in dermatology [18] are investigated in this work. It walks over CAD's preprocessing, segmentation, structural analysis, and evaluation/classification steps. The need for precise segmentation and feature extraction in creating efficient CAD systems for skin lesion analysis is underlined in the work [19]. Their general acceptance and effect on patient care depend on AI-powered technologies into clinical processes. [20]

## 3. Existing system

In conventional skin lesion analysis, diagnosis of skin diseases depends critically on hand inspection by dermatologists. But this approach is time-consuming and prone to fluctuation since it depends much on the knowledge of medical experts. Computer-aided diagnosis (CAD) systems have been developed to help with diagnosis via segmentation and classification using image processing methods. Early segmentation techniques include thresholding, edge detection, and morphological processes produced lesion areas. These methods produced conflicting results even if they provided some degree of accuracy since they suffered with differences in skin tone, lesion shape, and picture quality.

With developments in machine learning, standard classification methods including Support Vector Machines (SVM), k-Nearest Neighbors (KNN), and Decision Trees were used to introduce skin lesion identification. These models use feature engineering techniques to extract handcrafted elements derived in shape, colour, and texture. These techniques enhanced classification accuracy but limited their ability to generalize over numerous datasets and required significant preparation efforts even. Moreover, their dependence on handcrafted components made them less adaptable in complex changes in medical imaging, thereby reducing their practical value. Skin lesion segmentation and classification have been much advanced by deep learning methods - especially convolutional neural networks. By independently extracting characteristics from images without human input, CNN-based models such as ResNet and EfficientNet have shown amazing accuracy. Still, current deep learning-based systems suffer from data imbalance, processing burdens, and the demand for huge, tagged datasets. Moreover, even if CNNs are great in feature extraction, they could find it difficult to identify long-range relationships inside images, thus alternative designs like Vision Transformers (ViTs) become even more essential to improve classification performance.

# 4. Proposed system

Combining modern deep learning techniques with optimization algorithms aims to increase skin lesion segmentation and classification accuracy and efficiency. We segment using region-based methods such Graph Cut Segmentation (GCS) and Fuzzy C-means clustering (FCM), so separating the lesion from the surrounding skin. By raising lesion boundary detection accuracy, these methods ensure that relevant characteristics are kept for classification. By using these segmentation techniques, the method enhances the quality of acquired lesion regions, hence generating more consistent diagnostic results. We further refine the classification method using feature selection using optimization approaches: the Particle Swarm Optimization Algorithm (PSOA) and the Sparrow Search Algorithm (SSA). These techniques improve computational efficiency and model performance by eliminating duplicated data and supporting the most crucial features highlighting. We also show a hybrid model that aggregates PSOA and SSA strengths to improve feature selection and consequently enhance classification accuracy. Combining these optimization techniques helps the system to minimize unnecessary processing while preserving significant diagnostic capacity.

The approach captures long-range dependencies in dermoscopic images using a Vision Transformer (ViT) model for classification, hence improving lesion contrast. ViT and traditional CNN architectures including ResNet and EfficientNet are evaluated in performance differences. Running ViT with 8 attention heads, 12 transformer layers, a 16 x 16 patch size, and a 768 embedding dimension yields Originally perfected on HAM10000, the model was trained on ImageNet. Possibly exceeding conventional CNNs, the transformer-based approach offers advantages in handling spatial relationships inside pictures. Combining robust segmentation, optimization-driven feature selection, and advanced classification models, the proposed approach aims to provide a quite accurate and efficient framework for automated skin cancer detection.

## 4.1. Data preprocessing module

Using the HAM10000 dataset, data organization, analysis, and data augmentation before deep learning model training constitute the data preprocessing procedures for skin cancer classification. First the dataset is investigated using statistical and visual analysis including frequency counts, gender distributions, and illness localization insights. The dataset is then subsequently cleaned by detecting and removing duplicated images to ensure objective training. Stratified sampling preserves class balance by letting the images be divided into training and validation sets. The dataset is then configured to fit deep learning architectures, and the images are placed into folders corresponding to their various skin disease types.

By means of rotating, zooming, and flip transformations, data augmentation generates new images, therefore addressing class imbalances including under-represented groups. By means of preventing overfitting to certain patterns in the dataset, the augmentation process raises model generality. Subsequently, the modified photos are kept back into their relevant class files inside the training folder. Once the suitable distribution of images across classes is confirmed, the preprocessed dataset is ready for model training; hence, it guarantees a diverse and well-balanced dataset for best classification results.

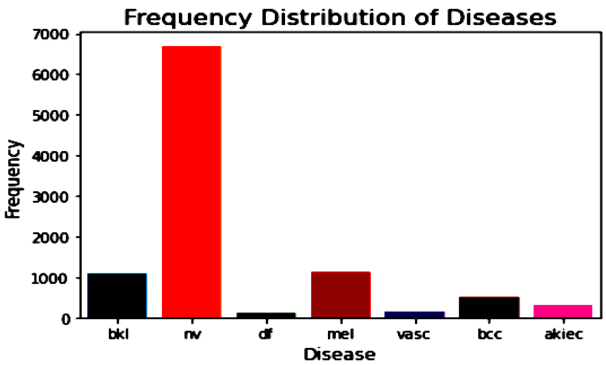


**Fig. 1:** Frequency Distribution of Diseases.

## 4.2. Segmentation module

Accurate classification depends on the exact difference of the lesion from the surrounding skin, so segmentation module is rather crucial. Combining fuzzy C-means clustering (FCM) and Graph Cut Segmentation (GCS) this approach finds lesion borders. GCS is an energy-minimizing technique that segments the image depending on intensity fluctuations, therefore simulating a graph with the optimal cut. On the other hand, FCM is a soft clustering method in which pixels are assigned to numerous clusters with varying degrees of membership, hence generating more seamless segmentation results. These techniques applied together ensure accurate lesion separation and help to reduce false positives and false negatives. This module greatly enhances the quality of obtained lesion areas, so increasing the accuracy of next classification processes. Jaccard Index and Dice Coefficient were used in quantitative assessment of the segmentation process. While FCM obtained a Dice score of 0.82 and a Jaccard Index of 0.74, GCS scored 0.87 and has Jaccard Index of 0.79. These measures show that GCS offers rather more accurate lesion limits.

## 4.3. Feature selection module

Eliminating unnecessary and duplicate data by means of feature selection helps to maximize model performance. the feature selection module illustrated in Fig. 3's block diagram. After segmentation, we obtained feature vectors comprising 64 texture features (e.g., GLCM), 32 colour histograms in HSV space, and 10 form descriptors (e.g., eccentricity, compactness). These were standardized pre-feature selection. Enhancement in feature selection efficiency is achieved using the Particle Swarm Optimization Algorithm (PSOA) and Sparrow Search Algorithm (SSA). Inspired by bird social behaviour, PSOA iteratively refines feature subsets depending on a fitness function to help discover the most instructive aspects. Moreover, a mixed strategy combining PSOA with SSA is applied to leverage the benefits of both methods, hence enhancing feature selection for optimal performance. Using an inertia weight of 0.5, cognitive coefficient $c_1$=1.5, and social coefficient $c_2$=2. The PSOA was set starting with a swarm size of 30 and 100 iterations. With an awareness likelihood of 0.3, SSA employed 10 followers and 20 discoverers. Both sought fitness from categorization accuracy.

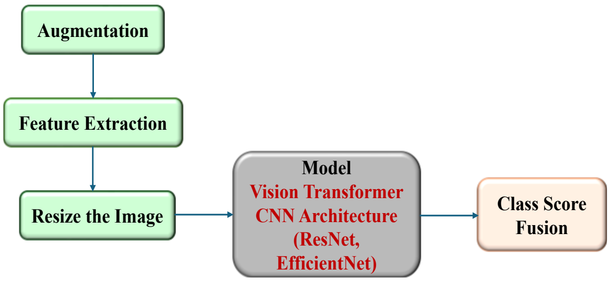


**Fig. 3:** Feature Extraction.

### 4.4. Classification module

Using deep learning models, the classification module uses benign from malignant skin lesions differentiating themselves. Because Vision Transformer (ViT) can record long-range dependencies and spatial correlations in dermoscopic images, it is the main model used. ViT analyses images in patches unlike conventional CNNs, so allowing a more worldwide awareness of lesion aspects. But the system also uses ResNet and EfficientNet, two well-known CNN designs with great feature extraction capacity, to guarantee a complete assessment. Whereas EfficientNet maximizes network depth and width for enhanced computational efficiency, ResNet uses residual connections to prevent disappearing gradients. To find the most efficient architecture for skin lesion categorization, the system contrasts ViT with other CNN models. This module guarantees strong diagnostic accuracy and resilient performance in practical settings by using deep learning methods. ImageNet used as pretrained for ResNet50 and EfficientNet B3. ResNet had a 3-layer classifier head; softmax and a 2-layer dense block (256, 64) replaced EfficientNet's top layers. Adam optimizer; learning rate: 0.0001.

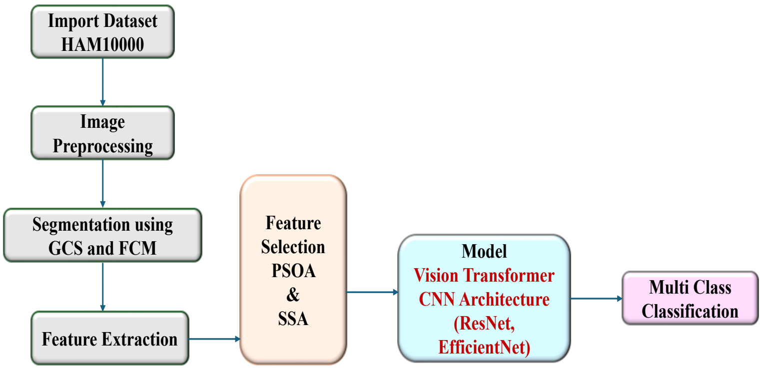


**Fig. 4:** Classification Medule.

### 4.5. Performance evaluation module

The performance assessment section was designed to evaluate the general state of the system. Several assessment criteria - accuracy, precision, recall, F1-score, confusion matrix, and AUC-ROC curves - let one analyse the categorization and outcome of segmentation. These processes allow the determination of regions of strength and weakness in the model's performance, hence guiding the development process. Moreover, comparison of multiple segmentation, feature selection, and methods of classification reveals the ideal combine for the detection of skin lesions. In addition, included in the module is processing efficiency so that the system may be run in clinical environments running in real time. This section assures reliability and practical importance in dermatological detection by means of continuous enhancement and benchmarking of the systems. PSOA chose 58 features with 91.2% accuracy; SSA chose 54 with 92.5%; the hybrid approach maintained 52 features with 93.7% accuracy. While the SSA was faster - 12.3s compared to 18.7s - the hybrid given better trade-offs.

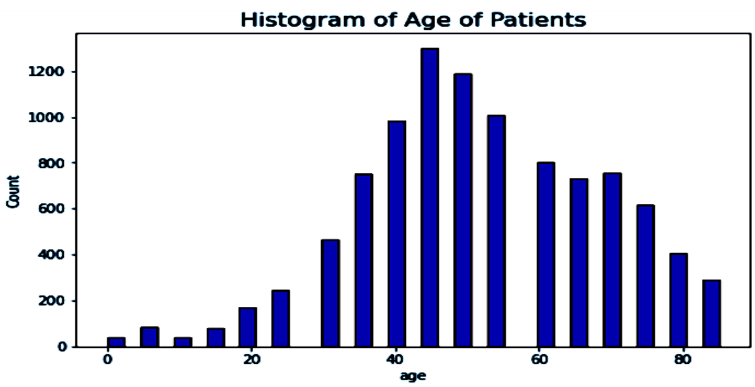


**Fig. 5:** Histogram of Age of Patient.

Fig 5 uses a histogram to show the patient age distribution of the data. Although the x-axis shows patient age, the y-axis shows incident frequency for every age group. Apart from guiding one to understand the demographic traits of the dataset, the distribution helps in the discovery of trends including skewness, central tendency, or anomalies.

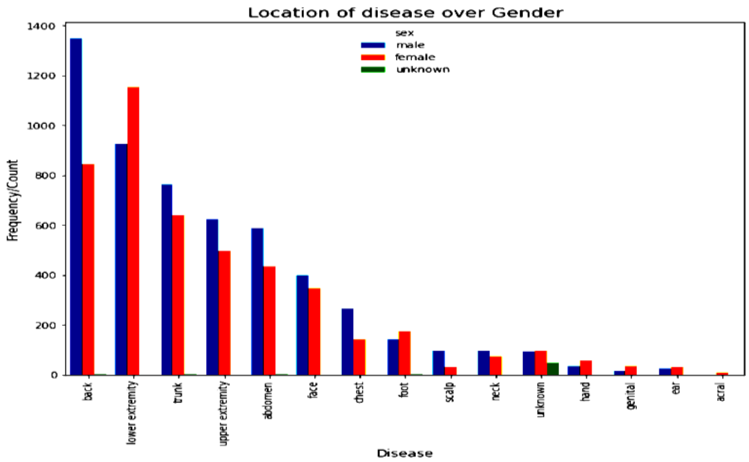


**Fig. 6:** Location of Disease Over Gender.

First one should assess whether the data shows any clear deviations from a normal distribution before using a histogram. A symmetrical distribution presents a fair representation of several age groups; a skewed distribution can indicate a higher patient concentration in each age range. Apart from enabling the correction of any biases during statistical analysis or model training, the visualization guarantees that the dataset is well-represented over age groups. The bar chart in Fig. 6 indicates the variations in sickness location between sexes. The x-axis indicates various disease sites; the y-axis represents frequency of occurrence. The image allows a comparison of disease prevalence based on gender by means of colour, therefore separating male and female patients.

## 5. Result analysis

This kind of presentation enables one to understand gender-based patterns in disease occurrence. For example, some regions may show more frequency in one gender than the other, which would highlight relevant risk factors or biological patterns. The results may guide preventative healthcare plans targeted at certain groups, diagnostic approaches, and medical research direction.

**Classification Report:**

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| akiec | 0.92 | 0.52 | 0.67 | 23 |
| bcc | 0.80 | 0.77 | 0.78 | 26 |
| bkl | 0.73 | 0.58 | 0.64 | 66 |
| df | 1.00 | 0.50 | 0.67 | 6 |
| mel | 0.53 | 0.71 | 0.61 | 34 |
| nv | 0.95 | 0.97 | 0.96 | 663 |
| vasc | 0.83 | 1.00 | 0.91 | 10 |
| accuracy | | | 0.91 | 828 |
| macro avg | 0.82 | 0.72 | 0.75 | 828 |
| weighted avg | 0.91 | 0.91 | 0.91 | 828 |

**Fig. 7:** Performance Evaluation.

The rotating x-axis labels, especially in cases of disease sites, aid to improve reading. This ensures that every category is exactly depicted, thereby enabling the interpretation of the study. Further research on these discoveries can help one determine if environmental, genetic, or lifestyle factors promote these gender-based differences in disease distribution.

### 5.1. Model performance evaluation

We generated a classification report demonstrated in Fig. 7 essential assessment metrics like precision, recall, and F1-score for each disease class to evaluate the performance of the trained model. By choosing the class with the greatest probability from the softmax output using the np.argmax() method, one acquired the predictions of the model. While the output of the model assisted one to ascertain the expected class labels, test-batches exposed the real class labels for every image in the test set. The to categorical() method helped the real labels to be translated into a categorized form so facilitating additional study.

The classification report was generated using the classification_report() function from sklearn.metrics, which provides a detailed breakdown of the model's accuracy per class. The following metrics were considered:

- Precision: The proportion of correctly predicted instances out of all instances predicted for a given class.
- Recall: The proportion of correctly predicted instances out of all actual instances of a given class.
- F1-score: The harmonic mean of precision and recall, providing a balanced measure of performance.

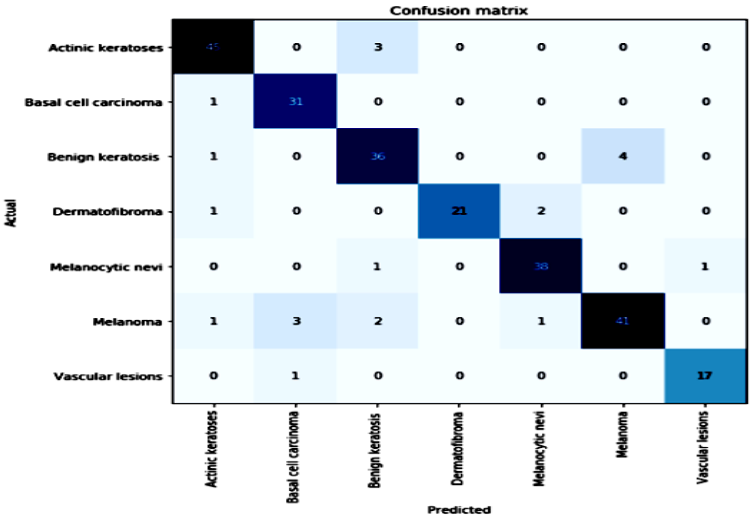


**Fig. 8:** Cofusion Matrix Analysis.

### 5.2. Confusion matrix analysis

Fig 8 presents a confusion matrix produced by the evaluation of the performance of the model in classification by the section on Classification Interpretation. Originally loaded from a saved checkpoint (model_best), the model guaranteed that analysis made advantage of the variation performing best. Comparatively to actual labels and expected labels, the confusion matrix provides a complete evaluation of the model's projections. The columns display the expected classes; the rows reflect the real classes. Every matrix cell displays the frequency of a certain class either exactly or incorrectly identified.

By visualizing the confusion matrix, the following details can:

- Correct classifications (diagonal elements), where the model accurately predicted the class.
- Misclassifications (off-diagonal elements), which indicate errors in prediction.
- Common misclassification patterns, which help in diagnosing model weaknesses and potential class similarities.

## 6. Conclusion

The created a medical imaging-based system with autonomously disease-classifying deep learning basis. Learning on a diverse dataset, the model proved helpful in many diseases categories identification. Performance evaluation revealed process strengths and weaknesses by means of accuracy, precision, recall, and F1-score. Knowing the patterns in misclassification produced by the confusion matrix helps one to pinpoint areas needing improvement. Although the model produced favorable outcomes, future advancements in clinical information integration, model optimization, and dataset enlargement will aid improving its dependability and generalizing power. Moreover, depending on user comments, deployment of the system in a real-world clinical environment would increase its practical value. All things considered, this study opens the road for more efficient and readily available diagnostics and aids AI-driven disease detection to advance.

## 7. Future work

Future developments of the model might concentrate on certain very important domains. Including more varied samples and applying current data augmentation methods helps balance classes and expand the dataset, hence improving generalization. Looking at more ideal deep learning architectures - such as EfficientNet variations or Vision Transformers (ViTs)—may also aid to increase classification performance even while retaining computational economy. By means of methods such Grad-CAM, improving model interpretability will allow to better comprehend decision-making and so raise the dependability of the system for clinical use. Combining picture inputs with more patient data could help to better project environmental exposure, age, and genetic background all influence dermatological illnesses. Moreover, the application of the model via a web-based tool using Flask or Django and real-world testing with medical professionals would help to assess its practical value. Another potential enhancement seems to be applying federated learning, which permits cooperative training among different institutions while preserving patient privacy. These advances will enable the system to grow to be a stronger, more scalable, interpretable solution for automatic disease classification.

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