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MediCynth: An AI-Based Skin Disease Classification System

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Abstract

With the rapid growth of computer technology, accurate and faster results can be obtained, allowing patients to receive timely treatment. Skin diseases are among the most common health problems and may be caused by viruses, bacteria, allergies, fungal infections, and other factors. Early and correct identification of skin diseases is important to prevent severe complications. This paper presents MediCynth, an automated skin disease detection system based on image processing and deep learning techniques. The proposed system analyzes an uploaded image of the affected skin area and predicts the type of skin disease. The model is trained using a combined dataset collected from DermNet, Kaggle, and additional internet sources. It is capable of classifying 27 different skin disease categories, including Acne, Lupus, Psoriasis, Skin Cancer, Vitiligo, Celluli-tis/Impetigo, Hair Loss/Alopecia, Herpes/HPV, Nail Fungus, and Urticaria/Hives. The system uses a Vision Transformer (ViT-B/16) architecture instead of traditional Convolutional Neural Networks (CNN), leveraging transfer learning to improve predic-tion accuracy and reduce diagnosis time. By processing a digital image of the skin, the proposed method identifies the disease and provides a confidence score along with basic guidance. The system is simple, fast, low-cost, and can be accessed from any device with an internet connection. Therefore, image processing and advanced deep learning techniques provide an effective solution for accurate skin disease detection and classification.

Introduction

Artificial Intelligence (AI) enables machines to perform tasks that normally require human intelligence, such as learn-ing, reasoning, and problem solving. Machine Learning (ML), which is a branch of AI, has shown significant success in many medical applications. Among different ML techniques, Deep Learning (DL) has become highly effective for analyzing medical images because it can automatically learn important features from the data.

Deep Learning is a type of Machine Learning that uses multiple layers to process information and make complex decisions. Similar to the human brain, deep learning models combine several simple operations to identify meaningful patterns in images. This makes deep learning very useful in medical image classification and disease detection.

Vision Transformers (ViTs) have recently emerged as a powerful alternative to Convolutional Neural Networks (CNNs) for image processing tasks. Unlike CNNs, which focus on local feature extraction, Vision Transformers cap-ture long-range dependencies and global relationships within

images, leading to improved performance in complex medical image analysis.
A Vision Transformer processes an image by dividing it into fixed-size patches (e.g., 16 × 16), which are then embedded and passed through transformer encoder layers. These layers use self-attention mechanisms to understand relationships be-tween different regions of the image. This allows the model to effectively identify patterns such as texture, color variations, shape, and structural abnormalities in medical images.
Transfer learning further improves the performance of the model by allowing the system to adapt efficiently to new disease categories with reduced training time. Compared to traditional CNN architectures, Vision Transformers provide better scalability and adaptability for diverse datasets.
In recent years, deep learning models have been successfully used in the field of dermatology for skin disease detection. Manual diagnosis of skin diseases may take time and requires experienced dermatologists. In many rural and remote areas, medical experts are not easily available. Therefore, there is a need for an automated system that can identify skin diseases quickly and accurately.
In this work, a Vision Transformer (ViT-B/16)-based skin disease detection system named MediCynth is proposed. The system uses a combined dataset collected from DermNet, Kaggle, and additional internet sources. It can classify 27 different skin disease categories, including common and rare diseases such as Acne, Lupus, Psoriasis, Vitiligo, Skin Cancer, Cellulitis/Impetigo, Hair Loss/Alopecia, Herpes/HPV, Nail Fungus, and Urticaria/Hives. The proposed system provides fast, low-cost, and accessible diagnosis support through a web-based interface.

Literature Review

Skin diseases are among the most common non-fatal health problems in the world. According to recent studies, skin disorders represent one of the major global disease burdens, making early detection and treatment extremely important. Many researchers have proposed computer-aided systems to automatically identify and classify skin diseases using image processing and deep learning techniques.
Several research papers have used Artificial Neural Net-works (ANN) and Convolutional Neural Networks (CNN) for skin disease classification. Traditional ANN-based methods require manual feature extraction from images. Although ANN can identify some important patterns, its overall accuracy is usually lower because the extracted features are limited. Therefore, researchers gradually shifted towards CNN-based methods, which automatically learn image features and pro-vide better performance. More recently, Vision Transformers (ViTs) have emerged as an advanced alternative, offering improved capability in capturing global image relationships.
A widely used dataset in previous studies is the HAM10000 dataset, which contains more than 10,000 dermatoscopic im-ages of different skin lesions. The images were collected by the Department of Dermatology at the Medical University of Vienna and other contributors. HAM10000 is commonly used for training and evaluating machine learning models in dermatology because it contains a large variety of skin lesion images. Many previous studies have used deep learning models such as MobileNet, ResNet, VGG16, and EfficientNet. Among these models, MobileNet is widely preferred because it has a lightweight architecture and fewer trainable parameters. This reduces computational cost and prediction time, making it suitable for web and mobile applications.
One study retrained the MobileNet model for skin disease classification and achieved a training accuracy of 89.9tradi-tional ANN-based classification because CNN automatically extracts important image features. However, the study consid-ered only a small number of disease classes and was limited to a single dataset.
Other research papers have used ResNet50 and EfficientNet for multi-class skin disease detection. These models produced higher accuracy because they can learn deeper image features. However, most existing systems classify only a limited number of diseases such as melanoma, eczema, psoriasis, or acne.
The proposed MediCynth system is different from previous work because it combines images from multiple sources, in-cluding the DermNet dataset, additional datasets from Kaggle, and internet images. Unlike earlier systems, MediCynth can classify 27 different skin disease categories, including Celluli-tis/Impetigo, Hair Loss/Alopecia, Herpes/HPV, Nail Fungus, and Urticaria/Hives. The use of a Vision Transformer (ViT-B/16) and transfer learning improves the overall prediction accuracy and makes the system more suitable for real world diagnosis support.

1. **Deep Learning Approach in MediCynth**

In the proposed MediCynth system, deep learning algo-rithms based on transformer architecture are used to recog-nize complex patterns from skin images. Unlike traditional approaches that require manual feature extraction, the Medi-Cynth model automatically learns important features such as color, texture, shape, and skin lesion patterns from the dataset. Since the project contains 27 different skin disease cate-gories collected from DermNet, Kaggle, and internet sources, advanced deep learning models are more suitable because they can efficiently handle large and complex datasets.

2. Traditional Model Training in MediCynth

Initially, traditional machine learning techniques were stud-ied for skin disease classification. In these methods, the image is first resized to 224 × 224 pixels, and features are extracted manually. These features are then provided to classifiers such as ANN or SVM.

However, these methods were not suitable for the Medi-Cynth dataset because the project contains many disease classes with different visual patterns. Therefore, traditional models provided lower accuracy and were not selected for the final system.

3. Transfer Learning-Based Model Used in MediCynth

To improve the performance of the system, transfer learning was used in MediCynth. The Vision Transformer (ViT-B/16) model was fine-tuned using the custom skin disease dataset.

The image uploaded by the user is first resized to 224 × 224 pixels and then divided into patches before being processed by transformer encoder layers.

The MediCynth system was initially trained on 22 skin disease categories. Later, five additional disease categories—Cellulitis/Impetigo, Hair Loss/Alopecia, Herpes/HPV, Nail Fungus, and Urticaria/Hives—were added, expanding the model to 27 classes.

By fine-tuning the model, the system can classify skin diseases faster and more accurately. Transfer learning also reduces training time and computational cost.

4. Computer-Aided Diagnosis (CAD) in MediCynth

MediCynth works as a Computer-Aided Diagnosis (CAD) system for skin disease detection. The system follows four major stages:

- Image Preprocessing
- Feature Extraction
- Classification
- Prediction and Recommendation

In the preprocessing stage, the uploaded skin image is resized, normalized, and cleaned. In the feature extraction stage, the Vision Transformer extracts global and local features using self-attention mechanisms.

In the classification stage, the system predicts one of the 27 disease categories. Finally, the result is shown to the user along with confidence score and recommendation.

5. Why Vision Transformer Was Selected for MediCynth In-stead of SVM

Support Vector Machine (SVM) was also considered during the study phase. However, SVM works better for small datasets and requires manual feature extraction. Since MediCynth contains more than 10,000 images and 27 skin disease classes, SVM was not effective for this project.

Vision Transformer was selected because it can capture global relationships in images and provide better accuracy compared to traditional methods. It is more suitable for identifying diseases such as Lupus, Vitiligo, Skin Cancer, Cel-lulitis/Impetigo, Nail Fungus, and Herpes/HPV, where subtle visual differences are important.

6. Use of Advanced Deep Learning Models in MediCynth

Advanced deep learning models such as DenseNet, Effi-cientNet, ConvNeXt, and Vision Transformers were studied for the MediCynth project. These models provide better feature extraction and deeper image analysis.

Among them, Vision Transformer (ViT-B/16) was found to be more suitable because:

- It captures long-range dependencies in images
- It provides high classification accuracy
- It adapts well to large and diverse datasets

Therefore, this model was used in the MediCynth skin disease detection system.

7. Ensemble and Multi-Model Possibility in MediCynth

The MediCynth project can also be extended in the future using ensemble learning. In this approach, the predictions from multiple models such as Vision Transformer, ResNet50, and EfficientNet can be combined to improve accuracy.

This will help the system better identify challenging dis-ease categories such as Hair Loss/Alopecia, Herpes/HPV, and Cellulitis/Impetigo.

8. Comparison with Other Machine Learning Techniques

Other algorithms such as Decision Tree, Random Forest, AdaBoost, CART, and KNN were reviewed during the re-search. Although these algorithms are useful for structured data, they do not perform as effectively as deep learning models for image classification tasks.

For example:

- KNN becomes slow when the dataset is large
- Decision Tree and Random Forest

cannot automatically identify image features
- AdaBoost depends strongly on hyperparameter tuning
- CART is suitable only for simple classification problems

Because of these limitations, transformer-based deep learn-ing was chosen as the main approach in MediCynth.

9. Final Observation from Literature Survey

From the literature survey, it was observed that most existing skin disease detection systems classify only a few diseases and use a single dataset.

In contrast, MediCynth combines multiple datasets and can classify 27 different skin diseases, including additional categories such as Cellulitis/Impetigo, Hair Loss/Alopecia, Herpes/HPV, Nail Fungus, and Urticaria/Hives.

Therefore, the proposed system provides a more practical and real-world solution for skin disease detection.

Proposed System

The proposed MediCynth system uses image processing and deep learning techniques to automatically detect and classify skin diseases. In the first stage, image preprocessing is performed on the uploaded skin image. In the second stage, a Vision Transformer (ViT-B/16) based transfer learning model is used to identify the disease category.

Skin diseases are difficult to diagnose because many dis-eases have similar color, texture, and shape. Some diseases also change their appearance at different stages. Therefore, an intelligent system is required that can accurately identify these small visual differences.

The main objective of MediCynth is to predict skin diseases as accurately as possible and provide early diagnosis support. The system reduces the need for manual feature extraction because the transformer-based model automatically learns im-portant image features from the dataset.

MediCynth provides a web-based interface where the user can:

- Upload an image of the affected skin area
- Select visible symptoms or skin concerns
- Click on the “Analyse My Skin” button
- View the predicted disease, confidence score, and recom-mendation

The dataset used in MediCynth is created by combining im-ages from DermNet, Kaggle, and additional internet sources. The final dataset contains more than 10,000 skin images belonging to 27 different disease categories:

- Acne
- Actinic Keratosis
- Benign Tumors
- Bullous
- Candidiasis
- Drug Eruption
- Eczema
- Infestations / Bites
- Lichen
- Lupus
- Moles
- Psoriasis
- Rosacea
- Seborrheic Keratoses
- Skin Cancer
- Sun / Sunlight Damage
- Tinea
- Unknown / Normal
- Vascular Tumors
- Vasculitis
- Vitiligo
- Warts
- Cellulitis / Impetigo
- Hair Loss / Alopecia
- Herpes / HPV
- Nail Fungus
- Urticaria / Hives

The proposed model uses a Vision Transformer (ViT-B/16) architecture instead of traditional Convolutional Neural Net-works (CNNs), as it is highly effective in advanced image classification tasks. The Vision Transformer divides the image into smaller patches (16×16) and processes them using self-attention mechanisms. This allows the model to capture both local and global relationships within the image.

Vision Transformer is suitable for skin disease classification because:

- It captures long-range dependencies across different re-gions of the image
- It automatically learns global and local features without manual feature engineering
- It performs well on complex and diverse datasets
- It can identify subtle and complex visual differences between diseases

The architecture of the proposed MediCynth system con-tains the following stages:

1) **Image Input**

The user uploads a skin image through the web interface.

2) **Image Preprocessing**

- Resize image to 224×224 pixels
- Normalize pixel values
- Remove noise if required
- Apply image augmentation such as

rotation, flip-ping, zooming, and brightness adjustment

3) **Feature Extraction**

The Vision Transformer model extracts important fea-tures by converting the image into patches and applying self-attention mechanisms.

4) **Classification**

The extracted features are passed to classification layers and Softmax activation to classify the image into one of the 27 skin disease categories.

5) **Result Display**

The predicted disease name, confidence score, skin health score, and recommendation are shown to the user.

The MediCynth system was initially developed for 22 skin disease categories. Later, five additional disease categories—Cellulitis / Impetigo, Hair Loss / Alopecia, Herpes / HPV, Nail Fungus, and Urticaria / Hives—were added, expanding the system to 27 classes.

By fine-tuning the model using the extended skin disease dataset, the system achieves better accuracy with reduced training time.

The model can also be extended in the future by integrating hybrid approaches such as combining Vision Transformers with CNN-based models or using ensemble learning.

The proposed MediCynth workflow is shown below:

User Uploads Image → Image Preprocessing → ViT Feature Extraction → 27-Class Disease Classification → Prediction, Confidence Score, and Recommendation

Thus, the proposed system provides a simple, low-cost, and accurate method for skin disease detection that can be accessed from any device with an internet connection.

System Architecture

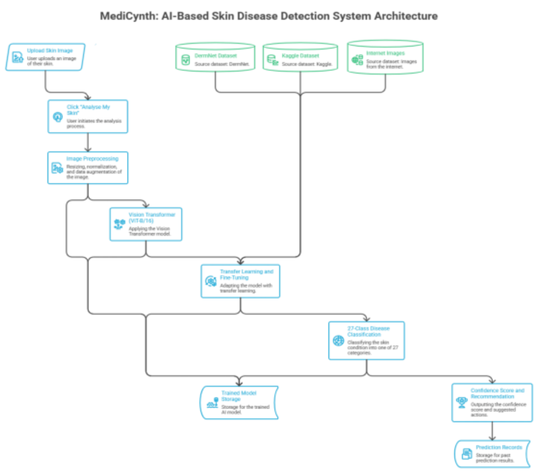

Fig. 1. MediCynth System Architecture

Modeling

1. Module 1: Data Collection and Preprocessing

The data collection and preprocessing module of MediCynth is responsible for collecting skin disease images and preparing them for training and classification. The images used in the project are collected from multiple sources, including the DermNet dataset, additional datasets from Kaggle, and internet sources.

The main dataset contains images for 22 skin disease categories, while five additional disease categories—Cellulitis / Impetigo, Hair Loss / Alopecia, Herpes / HPV, Nail Fungus, and Urticaria / Hives—were added from other datasets and internet images. The final combined dataset contains more than 10,000 images belonging to 27 skin disease classes.

The collected images are stored in digital format and organized according to their disease category. Since the images come from different sources, they may contain variations in size, brightness, background, and quality. Therefore, prepro-cessing is required before training the model.

The preprocessing stage improves image quality and re-moves unnecessary noise and artifacts. The following prepro-cessing techniques are used in MediCynth:

- **Image Resizing**

All images are resized to 224 × 224 pixels so that every image has the same size before being given to the model.

- **Normalization**

Pixel values are normalized to improve training perfor-mance and maintain consistency between images.

- **Noise Removal**

Unwanted noise and image artifacts are reduced to im-prove the clarity of skin lesions.

- **Contrast Enhancement**

The contrast of the image is improved to make the affected skin region more visible.

- **Data Augmentation**

To increase the size of the dataset and avoid overfitting, different augmentation techniques are applied:

  - Rotation
  - Horizontal and Vertical Flipping
  - Zooming
  - Brightness Adjustment
  - Cropping

These preprocessing techniques ensure that the images are clear, consistent, and suitable for training. This improves the overall accuracy of the MediCynth classification model.

After preprocessing, the images are stored in separate folders according to their disease category and are then used for model training and testing. Thus, this module ensures that the input data provided to the Vision Transformer model is reliable and accurate, which is important for correct skin disease classification.

2. Module 2: Training of the Model

The training module of the proposed MediCynth system uses a Vision Transformer (ViT-B/16) based transfer learning model to classify skin disease images after preprocessing. The skin lesion images are first resized and normalized before being passed to the model. Since the model is trained on a large dataset collected from DermNet, Kaggle, and internet sources, it can learn the visual patterns of 27 different skin disease categories.

The MediCynth system was initially developed for 22 skin disease categories. Later, five additional disease categories—Cellulitis / Impetigo, Hair Loss / Alopecia, Herpes / HPV, Nail Fungus, and Urticaria / Hives—were added, expanding the system to 27 classes.

After preprocessing, the Vision Transformer processes the input image by dividing it into fixed-size patches (16 × 16). These patches are then converted into embeddings and passed through transformer encoder layers. The transformer architecture uses a self-attention mechanism to understand the relationships between different parts of the image.

This helps the model detect important features such as skin texture, color variations, lesion boundaries, scaling, redness, pigmentation, and blisters.

Unlike CNNs, which process images locally, the Vision Transformer captures both local and global dependencies, making it more effective for complex medical image analysis.

The training process was carried out in two phases:

- In the first phase, only the classification layer was trained for 5 epochs with a learning rate of 0.001.
- In the second phase, the complete Vision Transformer model was fine-tuned for 7 additional epochs with a learning rate of 0.00001.

Thus, the total training duration of the model was 12 epochs with a batch size of 16.

The output from the transformer encoder is passed to classification layers. These layers use the extracted features to classify the image into one of the 27 skin disease classes. The final layer uses the Softmax function to generate the probability score for each disease category.

The MediCynth model was trained by adjusting different hyperparameters such as:

- Learning Rate
- Batch Size
- Number of Epochs
- Optimizer
- Dropout Rate

Cross-validation and validation datasets were used to im-prove model performance and reduce overfitting. After hyper-parameter tuning, the proposed MediCynth system achieved an overall validation accuracy of 83.79%.

Among the newly added classes, Nail Fungus and Urticaria / Hives achieved the highest accuracies of 93.10% and 92.50%, respectively.

After the training process is completed, the model is saved and later used in the web application for skin disease predic-tion.

3. Module 3: Prediction of the Output

The prediction module of MediCynth uses the trained Vision Transformer model to classify a new skin image uploaded by the user. After preprocessing, the image is entered into the trained model, and the disease category is predicted.

The prediction result is then displayed to the user through the web interface. The interface shows:

- Predicted Disease Name
- Confidence Score
- Analysis Result / Recommendation

For example, if the uploaded image contains symptoms of Nail Fungus, the system may display "Nail Fungus" as the predicted disease with a confidence score of 93.10%. Similarly, if the uploaded image contains symptoms of Lupus, the system may display "Lupus" as the predicted disease with an appropriate confidence score.

During prediction, the uploaded image is first resized and normalized. The processed image is then passed to the Vision Transformer model, which generates probability scores for all 27 disease categories. The class with the highest probability is selected as the final prediction, and the corresponding confidence score is displayed to the user.

During training, the model learns optimal parameters us-ing backpropagation and optimization techniques. The main objective is to minimize the difference between the predicted disease and the actual disease label.

By continuously adjusting the model parameters during training, the system gradually improves its prediction accuracy. Once training is complete, the model can successfully classify new and unseen skin images into the correct disease category.

Results

The trained Vision Transformer (ViT-B/16) model is used in the output prediction module of MediCynth to classify skin disease images. After preprocessing, the skin image is supplied to the trained model, which predicts the disease category based on the extracted features using self-attention mechanisms.

The prediction result is displayed through the MediCynth web interface along with the confidence score and recom-mendation. The system can identify 27 different skin disease categories from the uploaded image.

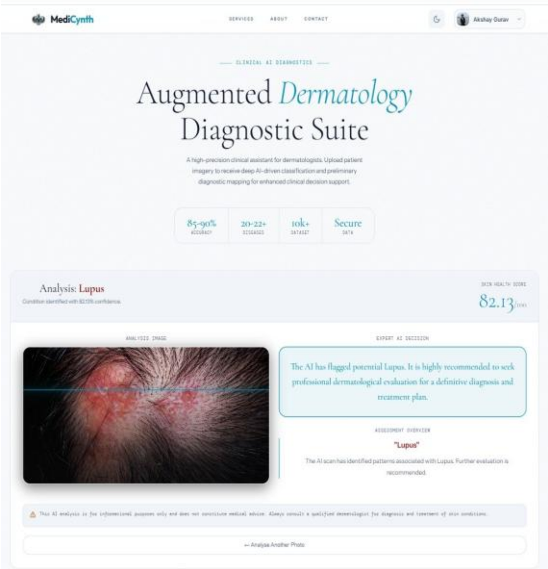

Fig. 2. Prediction Output Interface

Performance Analysis

According to the performance analysis of the proposed MediCynth system, the Vision Transformer (ViT-B/16) model successfully detected and classified skin disease images with good accuracy, precision, and recall. The high accuracy of the model demonstrates its effectiveness in capturing both local and global features, enabling reliable classification of differ-ent types of skin diseases and providing accurate prediction results.

The MediCynth model achieved an overall validation accu-racy of 83.79% on the newly added disease categories. Among these categories, Nail Fungus achieved the highest accuracy of 93.10%, followed by Urticaria / Hives with 92.50%. Cellulitis / Impetigo, Hair Loss / Alopecia, and Herpes / HPV achieved accuracies of 72.6%, 66.7%, and 73.5% respectively.

The confusion matrix and classification report further show that the model performs well in distinguishing between visu-ally similar skin diseases. The results confirm that the Vision Transformer model is effective for multi-class skin disease classification and can support practical diagnosis through the MediCynth web application.

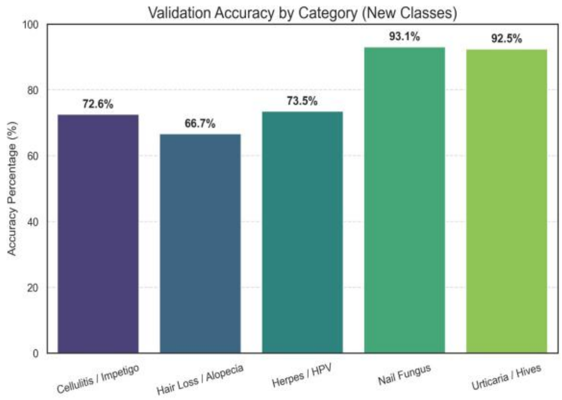

Fig. 3. Validation Accuracy for Newly Added Skin Disease Classes

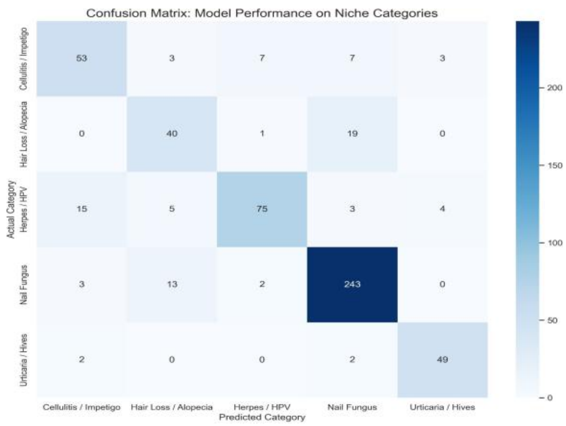

Fig. 4. Confusion Matrix of the Proposed MediCynth Model

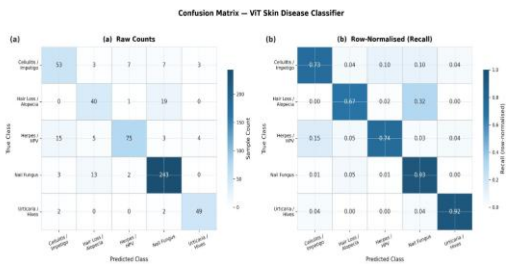

Fig. 5. Detailed Confusion Matrix and Recall Analysis

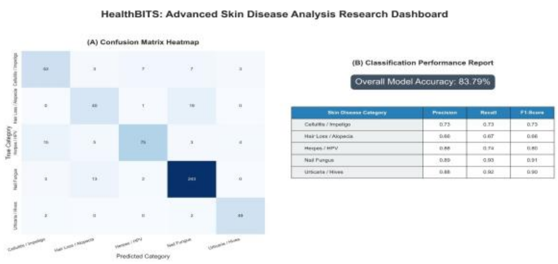

Fig. 6. Precision, Recall and F1-Score of the Model

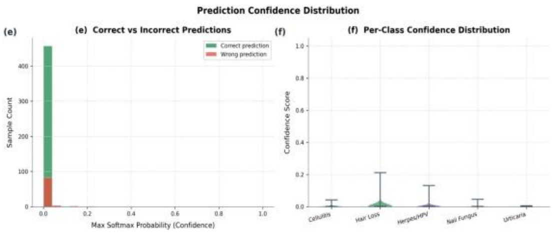

Fig. 7. Prediction Confidence Distribution

Conclusion

MediCynth is an AI-based skin disease classification system that uses a Vision Transformer (ViT- B/16) model to accurately detect and classify skin diseases. The system can identify 27 different skin disease categories using a diverse dataset, providing reliable and fast predictions.

With its web-based interface and use of advanced deep learning techniques, MediCynth offers a cost- effective and accessible solution for early skin disease detection, especially in areas with limited access to dermatologists. Future im-provements can further enhance its accuracy and real-world usability.

References

Akyeramfo-Sam, S., Acheampong, P., Yeboah, D., Nartey, N., and Nti, I. K., “A Web-Based Skin Disease Diagnosis Using Convolutional Neural Networks,” International Journal of Information Technology and Computer Science, vol. 11, no. 11, pp. 54–60, 2019.

Balaji, V. R., Suganthi, S. T., Rajadevi, R., Kumar, V. K., Balaji, B. S., and Pandiyan, S., “Skin Disease Detection and Segmentation Using Dynamic Graph Cut Algorithm and Classification Through Naive Bayes Classifier,” Measurement, vol. 163, 2020, Article 107922.

Patnaik, S. K., Sidhu, M. S., Gehlot, Y., Sharma, B., and Muthu, P., “Au-tomated Skin Disease Identification Using Deep Learning Algorithm.”

Seth, D., Cheldize, K., Brown, D., and Freeman, E., “Global Burden of Skin Disease: Inequities and Innovations,” Current Dermatology Reports, vol. 6, pp. 204–210, 2017.

Soliman, A. A., and Enezi, N., “A Method of Skin Disease Detection Using Image Processing and Machine Learning,” Procedia Computer Science, vol. 163, pp. 85–92, 2019.

Verma, A. K., Pal, S., and Kumar, S., “Comparison of Skin Disease Pre-diction by Feature Selection Using Ensemble Data Mining Techniques,” Informatics in Medicine Unlocked, vol. 16, 2019, Article 100202.

Yu, H. Q., and Reiff-Marganiec, S., “Targeted Ensemble Machine Classi-fication Approach for Supporting IoT Enabled Skin Disease Detection,” IEEE Access, vol. 9, pp. 50244–50252, 2021