



**DAYANANDA SAGAR
UNIVERSITY**



**SCHOOL OF
ENGINEERING**

DAYANANDA SAGAR UNIVERSITY

SCHOOL OF ENGINEERING

Devarakaggalahalli , Harohalli , Kanakpura , Ramanagara Dt.. , Bangalore - 562112

**Bachelor of Technology
in
COMPUTER SCIENCE AND TECHNOLOGY**

REPORT FILE OF PROJECT PHASE - 1

Submitted By

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DEPARTMENT OF COMPUTER SCIENCE & TECHNOLOGY

SCHOOL OF ENGINEERING

DAYANANDA SAGAR UNIVERSITY

(2024-2025)



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CERTIFICATE

This is to certify that the work titled **“ENHANCED CNN AND FEDERATED LEARNING ALGORITHM FOR SECURE AND PRECISE DERMATOLOGICAL DIAGNOSIS”** is carried out by **SOHAN R V [ENG21CT0037] , LIKITH H [ENG21CT0019] , MALLIKARJUNA R [ENG21CT0012] , KAVIYARASU K [ENG22CT1001]** Bonafide students of Bachelor of Technology in Computer Science and Technology at the School of Engineering, Dayananda Sagar University, Bangalore in partial fulfillment for the award of degree in Bachelor of Technology in Computer Science and Technology, during the year 2024-2025.

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DECLARATION

We, **SOHAN R V [ENG21CT0037]** , **LIKITH H [ENG21CT0019]** , **MALLIKARJUNA R [ENG21CT0012]** , **KAVIYARASU K [ENG22CT1001]**, are students of the seventh semester B.Tech in Computer Science and Technology, at School of Engineering, Dayananda Sagar University, hereby declare that the project phase - I titled **“ENHANCED CNN AND FEDERATED LEARNING ALGORITHM FOR SECURE AND PRECISE DERMATOLOGICAL DIAGNOSIS”** has been carried out by us and submitted in partial fulfillment for the award of degree in Bachelor of Technology in Computer Science and Technology during the academic year 2023-2024.

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Place :

Date :

ACKNOWLEDGEMENT

It is a great pleasure for us to acknowledge the assistance and support of many individuals who have been responsible for the successful completion of this CAPSTONE PROJECT PHASE - 1

First, we take this opportunity to express our sincere gratitude to the School of Engineering & Technology, Dayananda Sagar University for providing us with a great opportunity to pursue our bachelor's degree in this institution. We would like to thank **Dr. Udaya Kumar Reddy K R, Dean, School of Engineering & Technology, Dayananda Sagar University** for providing this opportunity. It is immense pleasure to express our sincere thanks to **Dr. M. Shahina Parveen, Chairperson, Department of Computer Science, and Technology, Dayananda Sagar University**, for providing the right academic guidance and motivating us during the course.

We would like to thank our teacher **Prof. Yashaswini B V, Asst. Professor, Department of Computer Science and Technology, Dayananda Sagar University**, for sparing his valuable time to extend help in every step of our course and the CAPSTONE PROJECT PHASE – 1 , which paved the way for smooth progress and the fruitful culmination of the project.

ABSTRACT

The diagnosis of skin diseases, a prevalent global health concern, often begins with visual observation. However, the complex formations, diverse colors, and data security concerns make accurate classification challenging. This project proposes the development of an enhanced Convolutional Neural Network (CNN) model integrated with a Federated Learning approach to ensure secure and precise dermatological diagnosis. A custom image dataset encompassing five skin disease classes was created for this purpose.

The CNN model was compared with various benchmark algorithms, demonstrating significant improvements in precision and recall for diseases such as **acne, eczema, psoriasis, melanoma, and lichen planus**. Federated Learning was employed to address data privacy issues by distributing data across multiple clients while collaboratively updating a central model. The results show that the integration of **CNN-based classification with Federated Learning** not only enhances accuracy but also prioritizes data security, making it a promising approach for advancing skin disease detection.

Keywords : Skin Disease Diagnosis , Convolutional Neural Network (CNN) , Federated Learning , Data Privacy , Medical Image Classification.

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INTRODUCTION

Skin diseases are among the most common medical problems worldwide, affecting millions of people and posing significant challenges for accurate diagnosis and treatment. Traditionally, dermatologists rely on visual examination to diagnose conditions such as acne, dermatitis, psoriasis, melanoma, and lichen planus. However, these diseases often present with complex variations in colour, texture, and shape, making accurate diagnosis difficult. This challenge is further compounded by the need to maintain strict data privacy, as patient information is sensitive and subject to protection regulations.

Given these complexities, there is a need for an automated, privacy-preserving diagnostic system. Recent advancements in artificial intelligence, particularly deep learning, have paved the way for more accurate diagnostic tools. Convolutional Neural Networks (CNNs) have shown remarkable success in image classification, including medical image analysis. CNNs automatically extract key features from images, enabling precise classification of skin disease types. However, CNNs typically require large datasets stored in centralized repositories, raising concerns about data security and privacy breaches.

To address these issues, this project proposes an innovative solution that integrates a CNN model with Federated Learning (FL). Federated Learning is a decentralized approach where multiple devices or institutions collaboratively train a model without sharing raw data. Instead, each device trains a local version of the model and shares only the model updates with a central server, which aggregates these updates to improve the global model. This ensures that sensitive data never leaves the client's device, protecting privacy.

A custom dataset comprising five common skin disease classes was created for this project. The CNN model's performance was compared against existing algorithms, demonstrating significant improvements in accuracy and recall. By using Federated Learning, data privacy was preserved while distributing data across multiple clients and collaboratively updating a central model. This decentralized approach mitigates security concerns and enables the creation of a robust diagnostic tool suitable for various healthcare settings.

This project highlights the potential of combining CNNs with Federated Learning to address both accuracy and privacy challenges in dermatological diagnosis. The proposed solution offers a secure, accurate, and scalable tool that benefits patients and healthcare providers alike.

LITERATURE SURVEY

| SL No. | STUDY | METHODOLOGY | FINDINGS | LINK |
|--------|--|---|--|---|
| 1 | Integrating Attention Mechanism for Cancer Diagnosis-2024 | Single CNN Model enriched with attention mechanism for Skin Cancer Detection Highlighting Critical Lesion Features | Achieved accuracy of 81% using 1,12,707 Datasets | https://ieeexplore.ieee.org/document/10481565 |
| 2 | Improving Skin Lesion Diagnosis: Hybrid Blur Detection for Accurate Dermatological Image Analysis-2021 | Shape analysis algorithms capture intricate shape features of skin lesions, which are then utilized by a deep learning model trained on a diverse dataset of dermatological images. | Achieved accuracy of 80% using 200 Datasets of Skin Lesion Cases | https://ieeexplore.ieee.org/document/10607639 |
| 3 | Utilizing Deep Neural Networks for Enhanced Diagnosis of Dermatological Conditions -2022 | With DNN Model enriched with DenseNet-161 & NasNet | Using two publicly available datasets of Skin Images : DermNet & ISIC Archive with the accuracy of 80% with 23,000 over 1st & 24,000 over 2nd collections | https://ieeexplore.ieee.org/document/10544747 |
| 4 | Enhanced Skin Cancer Classification with AlexNet and Transfer Learning-2023 | With DNN Model enriched with DenseNet-161 & NasNet | Using two publicly available datasets of Skin Images : DermNet & ISIC Archive with the accuracy of 80% with 23,000 over 1st & 24,000 over 2nd collections. | https://ieeexplore.ieee.org/document/10544747 |
| 5 | Performance Improvement of Convolutional Neural Network Architectures for Skin Disease Detection | CNN with AlexNet Combination of ZF Net Hybridization of the networks | AlexNet Algorithm shows the accuracy upto 76.44% Accuracy of 73.75% was obtained on ZF Net Algorithm | https://www.researchgate.net/publication/373191569 |
| 6 | Classification of skin lesions using transfer learning and augmentation with Alex-net | Alex Net with Transfer Learning Combination of the Networks | Accuracy obtained is 71.4 % | https://doi.org/10.1371/journal.pone.0217293 |

PROBLEM STATEMENT

Accurate diagnosis of skin diseases is critical for effective treatment, yet remains challenging due to the visual similarities among different conditions and the complex nature of skin lesions. Traditional diagnostic approaches, primarily reliant on visual inspection by dermatologists, can be subjective and prone to errors, especially when handling diverse and complex cases. Machine learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated potential in automating this diagnosis process. However, training these models typically requires large, centralized datasets, which raises significant data privacy concerns, especially in the medical domain where sensitive patient information is involved. To leverage this, there is a need for an approach that enhances diagnostic accuracy while ensuring data privacy. The current challenge lies in developing a model that can leverage distributed data from multiple sources (e.g., hospitals, clinics) without sharing sensitive patient information. This project aims to integrate Federated Learning with an advanced CNN architecture to achieve secure and precise dermatological diagnosis by collaboratively training a robust model without centralized data storage. The goal is to overcome the limitations of traditional methods and centralized machine learning models by ensuring data security, privacy, and improved diagnostic accuracy in skin disease detection.

PROPOSED FRAMEWORK

The proposed methodology for our project aims to create a comprehensive and secure system for dermatological diagnosis using advanced deep learning techniques and Federated Learning. To achieve this, we are leveraging Convolutional Neural Networks (CNNs) optimized with powerful architectures such as Efficient Net and ResNet-152. These CNN models are chosen for their ability to accurately capture intricate patterns in dermatological images, allowing for the precise classification of skin conditions. Efficient Net is known for its efficiency in balancing accuracy and computational cost, while ResNet-152 offers deep feature extraction capabilities, enabling the model to differentiate between subtle variations in skin disease presentations. In addition to the CNN-based classification, we are integrating Federated Learning (FL) to ensure data privacy and security throughout the model training process. Federated Learning allows multiple healthcare institutions (clients) to collaboratively train a global model on their local data without sharing any raw patient information. Our approach involves using Federated Averaging (Fed Avg) to aggregate the locally trained models from different clients into a central model, which is then updated and distributed back to the clients. Additionally, Federated Proximal (Fed Prox) is employed to handle non-IID (non-independent and identically distributed) data scenarios, ensuring robust training even when data across clients varies significantly. Beyond the software aspect, our methodology also incorporates a hardware component designed to enhance real-time diagnostic capabilities.

This device will allow users to scan a skin lesion, analyze the condition using our trained model, and provide instant feedback about the disease. For instance, if a user scans an acne lesion, the device will offer information about the condition, including potential treatments and whether the lesion shows signs that might indicate a higher risk of progressing to a more serious condition, such as skin cancer. This holistic approach combines state-of-the-art CNN architectures with the privacy-preserving benefits of Federated Learning, alongside a hardware interface for user-friendly, on-the spot diagnosis. By integrating efficient deep learning algorithms, decentralized learning frameworks, and practical diagnostic tools, our system is positioned to advance dermatological care by providing accurate, real time, and privacy-preserving diagnostic support.

SYSTEM SPECIFICATIONS

Software Specifications

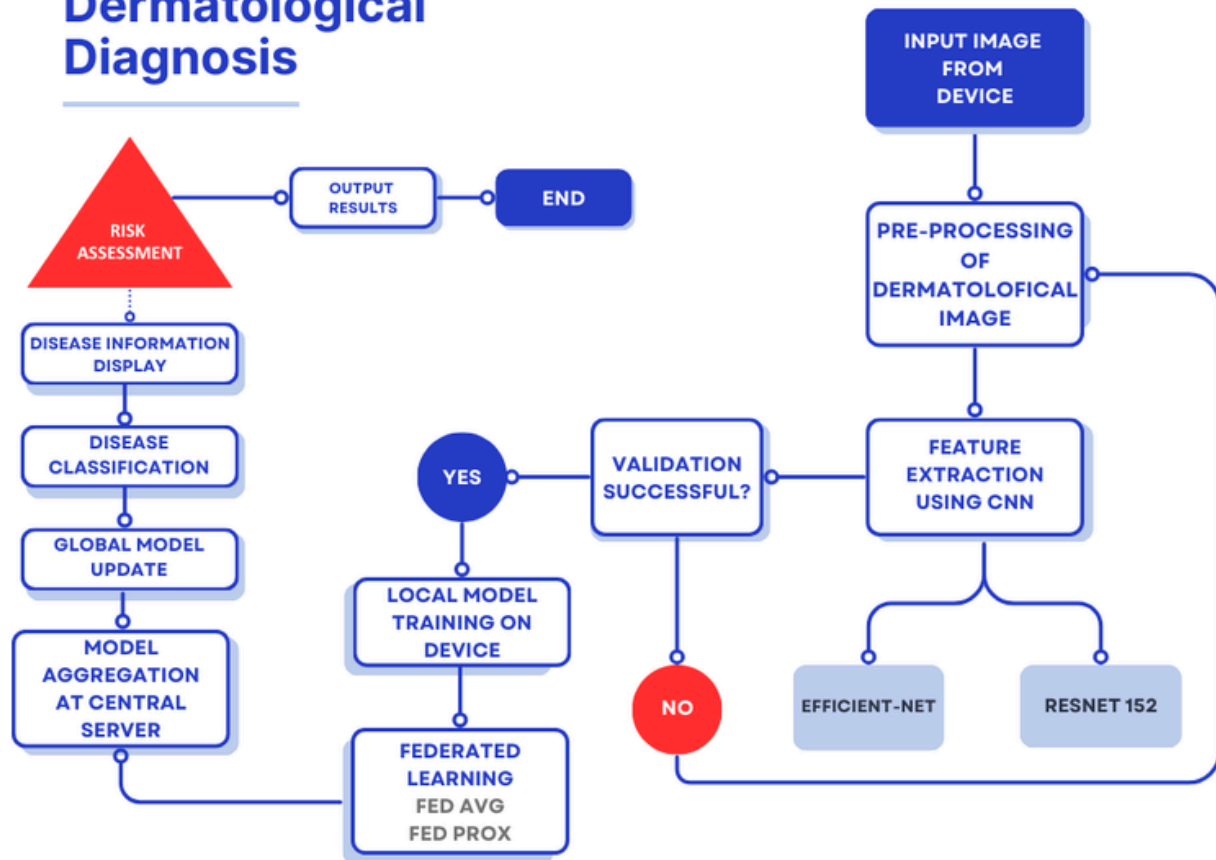
- Operating System: Windows 10/11, macOS, or Linux (Ubuntu 18.04+)
- Frameworks and Libraries: TensorFlow, PyTorch, OpenCV, NumPy, Pandas
- Development Environment: PyCharm, Visual Studio Code, Jupyter Notebook
- Programming Language: Python (v3.7+)
- Federated Learning Tools: Fed Prox , Fed Avg
- Database: Custom skin disease image dataset stored locally or on the cloud

Hardware Design Specifications

- Magnifier-Like Device: Custom-built hardware component for detailed skin disease examination.
- High-Resolution Camera: Integrated for capturing magnified images of the affected area.
- Edge Processing Unit: Embedded system (Raspberry Pi / Jetson Nano) for real-time diagnosis.
- User Interface: Touchscreen or mobile app to display results and interact with the device.

SYSTEM ARCHITECTURE

Dermatological Diagnosis



SYSTEM IMPLEMENTATION

In this project, a Convolutional Neural Network (CNN) was implemented to classify dermatological images into one of five diseases: Acne, Eczema, Lichen Planus, Melanoma, and Psoriasis. The dataset was organized with 12,074 images for training and 3,015 images for validation, each labeled according to the disease. The images were preprocessed by resizing them to 224x224 pixels and normalizing the pixel values to a range between 0 and 1. The CNN model was built using Keras, following a Sequential architecture. The model consisted of several layers: three convolutional layers with increasing filter sizes (32, 64, and 128), each followed by Batch Normalization and MaxPooling layers. These layers were designed to extract and downsample relevant features from the images.

The model also included a Flatten layer to convert the 2D feature maps into a 1D feature vector, which was then passed through a Dense layer with 128 neurons and a Dropout layer for regularization. The output layer consisted of 5 neurons corresponding to the five classes, with a softmax activation function for multi-class classification. The model was compiled using the Adam optimizer, categorical crossentropy as the loss function, and accuracy as the evaluation metric. It was trained for 20 epochs with a batch size of 32. During training, both the accuracy and loss for the training and validation datasets were recorded, and the results were plotted for visual analysis. The model showed good performance, with validation accuracy exceeding 98% after several epochs.

This model will be further evaluated on unseen test data and can be used for predicting the disease in new dermatological images. Future steps include fine-tuning the model's architecture and exploring data augmentation to improve generalization.

OUTPUT

```
(env) PS C:\Users\mohan\OneDrive\Desktop\LIKI> python C:\Users\mohan\OneDrive\Desktop\LIKI\DERMO_PROJECT\scripts\train_cnn_model.py
2024-12-16 23:07:44.351118: I tensorflow/core/util/port.cc:153] oneDNN custom operations are on. You may see slightly different numerical results due to floating-point round-off errors from different computation orders. To turn them off, set the environment variable 'TF_ENABLE_ONEDNN_OPTS=0'.
2024-12-16 23:07:45.774419: I tensorflow/core/util/port.cc:153] oneDNN custom operations are on. You may see slightly different numerical results due to floating-point round-off errors from different computation orders. To turn them off, set the environment variable 'TF_ENABLE_ONEDNN_OPTS=0'.
No GPU found. Training on CPU.
Loading data...
Loading dataset from C:\Users\mohan\OneDrive\Desktop\LIKI\DERMO_PROJECT\data\custom_dataset...
Found 12074 images belonging to 5 classes.
Found 3015 images belonging to 5 classes.
Classes found: {'Acne': 0, 'Eczema': 1, 'LichenPlanus': 2, 'Melanoma': 3, 'Psoriasis': 4}
Training steps per epoch: 377
Validation steps per epoch: 94
Building CNN model...
C:\Users\mohan\OneDrive\Desktop\LIKI\venv\Lib\site-packages\keras\src\layers\convolutional_base_conv.py:107: UserWarning: Do not pass an 'input_shape'/'input_dim' argument to a layer. When using Sequential models, prefer using an 'Input(shape)' object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
2024-12-16 23:07:49.967522: I tensorflow/core/platform/cpu_feature_guard.cc:218] this TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.
To enable the following instructions: AVX2 AVX_VNNI FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.
Model: "sequential"

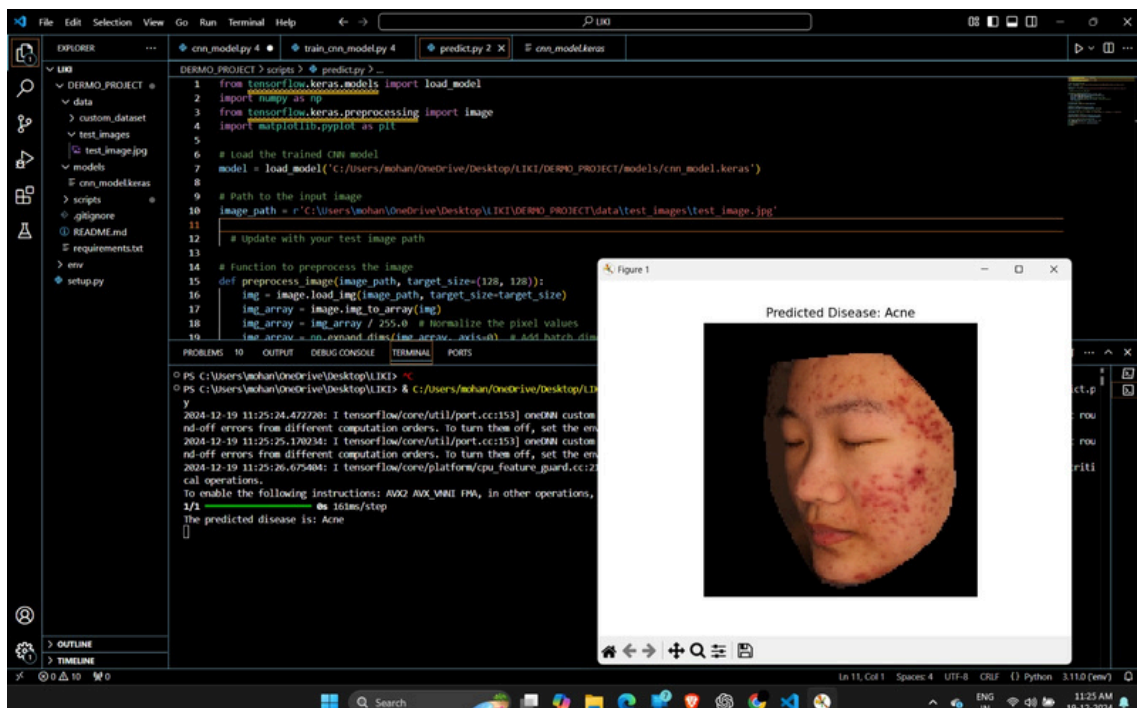
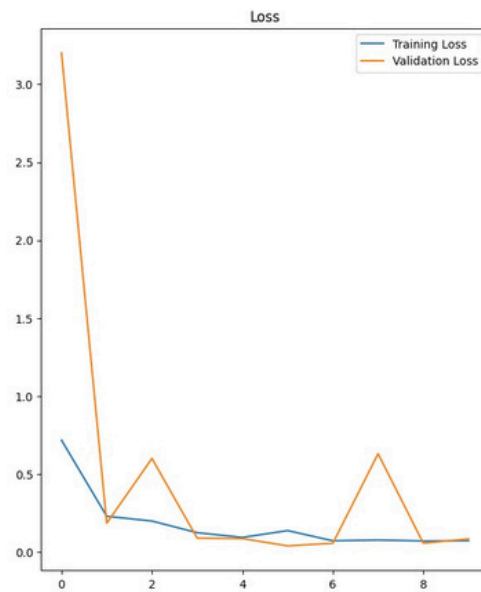
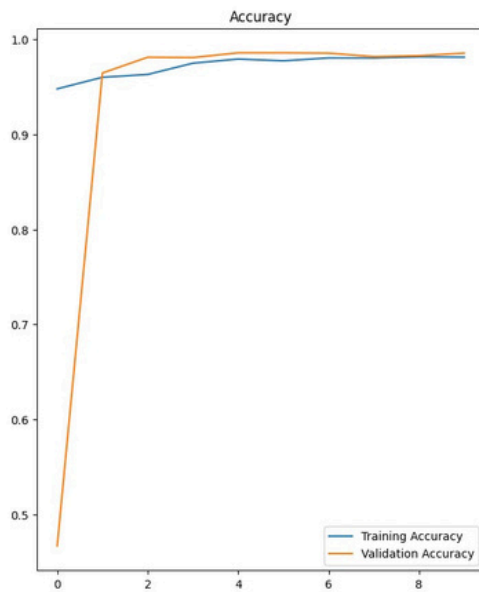
Layer (type)                 Output Shape                 Param #
-----
conv2d (Conv2D)              (None, 128, 128, 32)        896
batch_normalization (BatchNormalization) (None, 128, 128, 32)        128
max_pooling2d (MaxPooling2D) (None, 64, 64, 32)          0
conv2d_1 (Conv2D)            (None, 64, 64, 64)          18,496
batch_normalization_1 (BatchNormalization) (None, 64, 64, 64)          256
max_pooling2d_1 (MaxPooling2D) (None, 32, 32, 64)          0
conv2d_2 (Conv2D)            (None, 28, 28, 128)         71,856
batch_normalization_2 (BatchNormalization) (None, 28, 28, 128)        512
max_pooling2d_2 (MaxPooling2D) (None, 14, 14, 128)         0
flatten (Flatten)            (None, 25088)               0
```

| Layer (type) | Output Shape | Param # |
|--|----------------------|---------|
| conv2d (Conv2D) | (None, 128, 128, 32) | 896 |
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CONCLUSION

In conclusion, the proposed methodology effectively combines advanced Convolutional Neural Networks (EfficientNet and ResNet- 152) with a Federated Learning framework (using FedAvg and FedProx algorithms) to provide secure and precise dermatological disease diagnosis. By leveraging Federated Learning, we ensure that sensitive patient data remains protected, as model training is performed locally on devices, preventing direct data transmission. This approach not only enhances diagnostic accuracy by utilizing robust deep learning architectures but also addresses critical privacy concerns in healthcare. Additionally, the integration of hardware for real-time disease analysis and cancer risk assessment provides users with quick, reliable insights, empowering them with timely health information. The results demonstrate that this system holds significant promise for advancing skin disease diagnosis, offering a secure, efficient, and scalable solution for dermatological healthcare.

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