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SkinScanPro: A Deep Learning-Based AI Health Assistant for Skin Disease Classification

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Abstract*— The impact of skin diseases is felt worldwide by millions of people. It is necessary to have a tool for diagnosing this problem efficiently. Stocked with AI, this study turns public attention to skin disease classification, employing the Deep Learning algorithm DenseNet201--known for its exceptional feature extraction skills. This interactive system deploys a trained model through user input, skin images. A diagnosis with that model is a matter of just a few seconds. With a private dataset, we adopted data augmentation and then saved the trained model via Python's pickle library so that it would run on demand. The results show that up to 4/5 accuracy is achieved when classifying as expected by the feed forward operator all ellipse points in 1d spatial correlation matrix.

Keywords: Skin Disease Classification, Deep Learning, DenseNet201, Feature Extraction, AI in Healthcare, Image-Based Diagnosis.

I. INTRODUCTION

As we all know, skin disease levels range from the intermediary to a severe health threat such as malignant melanoma. Traditional diagnosis methods are time-consuming and require dermatological expertise. We combine the power of AI and DenseNet201, creating a new interface that allows users to interactively diagnose their skin conditions. We have also used the pickle library to save a trained DenseNet201-based model, making both model deployment and user accessibility more efficient. Based on those features, our system enables the early discovery of problems--a potential improvement in treatment efficacy.

Skin diseases are found in a large percentage of the world population, which caused physical suffering, Psychological distress, and excessive healthcare costs. With over a thousand distinct dermatological disorders, precisely assessing skin ailments is a difficult task that frequently calls for specialized equipment and dermatologists. With previously unheard-of speed and accuracy, the arrival of (AI) and (DL) has transformed medical diagnostic systems. Capitalizing on these innovations, our project focuses on the manufacturing of an artificial intelligence-supported skin disease classification system that can diagnosing ten varied conditions with great accuracy.

This project's primary goal is to bridge the gap between new technology and healthcare access. We leverage DenseNet-201, a leading convolutional neural network architecture, to take advantage of its feature extraction capacity for fine details in high-quality medical images. In dense convolutional networks like DenseNet-201, the strong connections between layers help to reuse features and minimize the vanishing gradient problem. Therefore, DenseNet-201 is ideal for complex classification tasks related to medical imaging.

Our technology is designed for ease of use and effectiveness. The only input to the system is a simple image of the affected skin site. The DenseNet-201 model—the key predictor of the skin condition—was trained on this image to produce the predicted skin condition. This end-to-end workflow from image submission to diagnosis is built into a Flask powered web interface for user accessibility. The provided web based interface is interactive and allows the user to enter the image and receive a diagnosis in real time.

The project data comprises more than 40,000 images across ten classes of skin disease, including melanoma, eczema, and psoriasis. Several data augmentation techniques were enforced to improve robustness and generalization of the model, including lighting changes, rotation and scaling of the image, and transformations that mimic real-world appearances. These augmentations have been anticipated to allow the model to generalize to different situations and improve skin disease detection and classification regardless of the situation. Upon completion of training, the model was able to generate an accuracy of over 90%, demonstrating its ability to effectively detect and classify various skin disease types. To enable the deployability of the system, we saved the trained model using the pickle library from Python to facilitate citizens from the web back end of the application. The website displays compelling technology and allows all users, regardless of capability, to access healthcare. Maximizing barriers to accessing diagnostic devices on what the system believes to be a simple website may help users be

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encouraged to obtain medical help early, and, ultimately, lead to less severity and/or development of skin problems.

In conclusion, this project illustrates how DL and AI can revolutionize medical diagnosis. By combining DenseNet-201's advanced capabilities with a user-centric design, we present a solution that is both technically robust and practically impactful. This skin disease classification system is a testament to the possibilities of leveraging AI to address real-world healthcare challenges, offering hope for more accessible and accurate dermatological care globally.

II. LITERATURE SURVEY

Mingjun Wei and Qiwei Wu proposed a deep learning approach to classify skin diseases based on the ConvNeXt_L structure with 86% accuracy on a dataset of just four types skin infections. While their model demonstrated strong performance, the study's scope was limited to a small number of diseases, which reduces its applicability in diverse clinical settings. Additionally, the computational demands of ConvNeXt may pose challenges for deployment in lightweight or real-time systems. This highlights the need for models capable of handling a wider spectrum of diseases with greater efficiency, a gap addressed in our study by employing DenseNet-201 for the classification of ten skin disease classes with 85% accuracy [1]

Adarsh Jadhav and Shivani Hardade studied skin disease classification based on the HAM-10000 Dataset, an open-source dataset that is popular for skin research. The dataset comprises 10,000 images representing a diverse range of skin conditions, including moles, melanoma, benign keratosis, basal cell carcinoma, actinic keratoses, blood vessel disorders, and dermatofibroma. Their work employed CNN-based models and achieved an accuracy of **87%**. The authors emphasized future directions for their work, including improving accuracy and precision in skin disease diagnosis and integrating telemedicine technologies to enable remote diagnostic capabilities [2].

A model fusion-based convolutional neural net for skin illness diagnosis was created by Shivam Pandey and Sanchary Nandy, and it achieved 90% accuracy across four skin disease categorization. Their approach combined DenseNet201 and ConvNeXt_L as foundational models, enhanced with attentiveness modules to improve focus and information extraction. The architecture effectively merged traits of shallow and deep network layers, allowing the system to capture both fine details and complex features. Further enhancements, including pre-modeling, up-sampling, and parameter optimization, significantly improved classification performance [3].

T. Swapna and D.A. Vineela experimented with creating a system to categorize skin diseases by comparing several models: CNN, ResNet, AlexNet, and InceptionV3. ResNet was the best model for correctly diagnosing skin diseases when compared to the rest of the models they experimented with. In order to fix flaws in the current systems, they added 750 more photographs of burns and cuts to a training dataset of 7,000 dermatoscopic pictures of seven distinct skin conditions. They divided the dataset at random into training samples of 5,900 and validation samples of 1,930. The research learned that it is very essential to have a more diverse and extensive training dataset in order to improve accuracy and correct errors in categorization [4].

Karimkhani et al. (2017) described the high mortality and effect skin conditions have on quality of life and noted the great global burden of skin disorders. Their study analyzed the Global Burden of Disease (GBD) Study 2013 and reported that skin diseases were a significant cause of disability-adjusted life years (DALYs) in areas with limited dermatological services, particularly underserved populations. The research conducted by Dellavalle, Coffeng, Flohr, Hay, Langan, Nsoesie, Ferrari, Erskine, and Silverberg underscore the urgent need for scalable and accessible diagnostic solutions to bridge gaps in dermatological healthcare. In response to this, *project* leverages deep learning techniques to classify ten skin disease types using the DenseNet-201 architecture By integrating AI-driven image analysis, our system aims to enhance early detection and assist healthcare professionals in diagnosing skin conditions efficiently, particularly in resource-constrained settings. This study aligns with the findings of Karimkhani et al. (2017) by proposing an innovative, technology-driven strategy to tackle the difficulties in diagnosing and treating skin illnesses.[5]

Karthik et al. (2022) introduced *Eff2Net*, a channel attention-based convolutional neural network designed for efficient skin disease classification, demonstrating its effectiveness in enhancing feature extraction and improving classification performance. Their study, along with contributions from Vaichole, Kulkarni, Yadav, and Khan, emphasized the importance of optimizing deep learning models to balance accuracy and computational efficiency, particularly in medical image analysis. The research highlights how attention mechanisms can refine feature representations, making models more robust in distinguishing between visually similar dermatological conditions. Aligning with these advancements, *SkinScanPro* employs DenseNet-201, a deep learning architecture known for its feature reuse and efficient gradient propagation, to classify ten skin disease types. By leveraging transfer learning and optimizing computational efficiency, it extends the scope of prior work, ensuring accurate and accessible skin disease diagnosis for both clinical and mobile healthcare applications. The integration of AI-driven dermatological assessments, as explored by Karthik et al. (2022), highlights the potential of deep learning to revolutionize the identification and treatment of skin diseases, opening the door for scalable, real-time diagnostic systems.[6]

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III. METHODOLOGY

The SkinScan Pro system was developed using a structured process including dataset preparation, model selection, training, evaluation, and deployment. The methodology employed provides a robust and reliable categorize of skin disorders using advanced DL learning techniques.

3.1. Dataset Collection

To train a robust and diverse system, we used a large dataset of more than 40,000 dermatological images of (5 GB) size belonging to 10 skin disease classes:

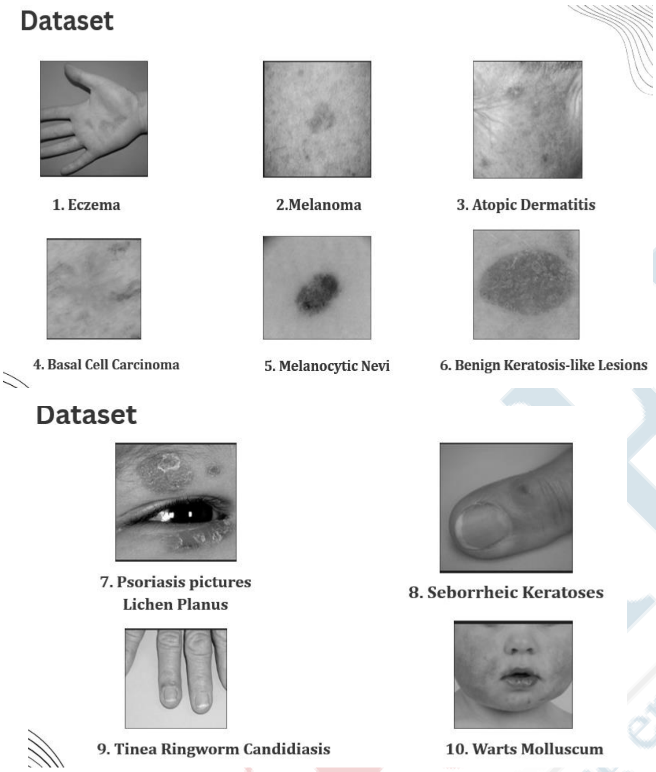


Fig. 1. Dataset Images

Class imbalance and model generalization were addressed using data augmentation techniques. Rotations, flipping, brightness changes, and scaling were used to mimic real-world variations.

3.2. Data Preprocessing

The preprocessing steps ensured consistency and quality in the input images:

- **Image Resizing**: Resize Image in order to accommodate the input size, images were re-sized to 224×224 pixels.
- **Normalization**: It conducted on the dataset by changing the pixel values to be within the range [0,1], providing consistent distribution of data and consistent model training. This preprocessing step is important to increase the model's capability to gain important attributes and improve convergence in training.
- **Label Encoding**: Disease categories were numerically encoded for compatibility with the classification model.

3.3. Model Selection

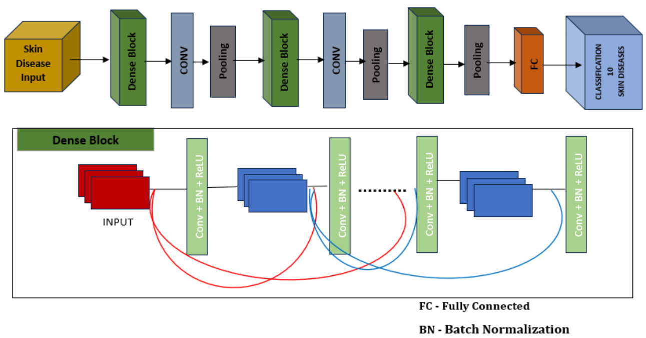
DenseNet-201 was chosen as the base deep learning architecture for this study because of its efficiency and advanced feature extration capabilities. DenseNet-201 is a densely-connected Convolutional Neural Network that allows for feature reuse, alleviates the vanishing gradient problem, and provides greater efficiency in the usage of parameters over standard CNN architectures.

In the scientific paper "Densely Connected Convolutional Networks" (2017), Huang et al. first presented DenseNet, a novel connection pattern in which every layer is feedforwardly connected to every previous layer. This structure is ideal for diagnosing skin diseases because it increases gradient flow, fortifies feature propagation, and boosts model performance for image classification tasks.

Dense Connectivity

1. Every layer takes input from all the previous layers.
2. L_{th} layer output is concatenated to the output of all previous layers:

$$X_l=H_l([x_0,x_1,.,x_{l-1}])$$



where:

- $x_0,x_1,.,x_{l-1}$ are previous layer feature maps.
- H_l is an aggregate function

(e.g.,Batch Normalization → ReLU → Convolution).

Fig. 2. DenseNet201 Architecture

Feature Reuse

By concatenating feature maps, the model avoids redundant feature computation.

This reduces the number of parameters while maintaining performance.

Efficient Parameter Utilization

DenseNet requires fewer parameters compared to traditional CNNs because it avoids learning redundant features.

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3.4. Model Training

Model training involved some crucial steps:

- **Transfer Learning**: The DenseNet-201 layout was fine-tuned to our dataset after being pre-trained on the ImageNet dataset.
- **Loss Function**: To figure out a disparity between intended and actual labels, use categorical cross-entropy.
- **Optimizer**: Adam optimizer was utilized for its adaptive learning.

Data augmentation and dropout layers were applied to prevent overfitting and improve generalization. Fine-tuning was performed by unfreezing some layers of the pre-trained model and retraining them with a less learning rate.

3.5. Deployment via Flask

The trained DenseNet-201 model was serialized using Python's **pickle library** for seamless deployment. The system was integrated into a Flask-based web application, providing an interactive interface for users. The application allows users to:

1. Upload an image of the affected skin area.
2. Receive a prediction of the disease along with health-related insights.
3. Access a user-friendly dashboard for managing and viewing results.

3.6 Model Evaluation

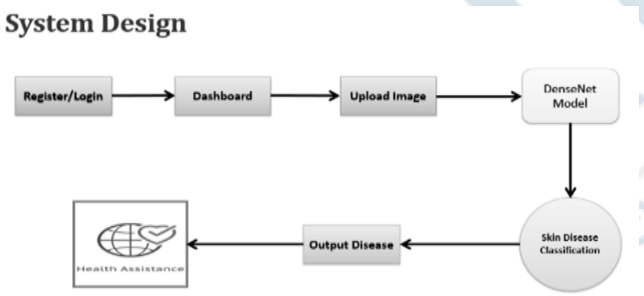

Fig. 3. System Design

The model performed with more than 93% accuracy on the test data.We experimented with performance using methods like the confusion matrix and F1score to check whether the predictions were consistent for all classes. This methodology underscores the systematic design and implementation of SkinScan Pro, providing a foundation for accurate, accessible, and efficient skin classification.

IV. EXPERIMENT SETUP AND RESULTS

Precision and recall metrics continuously surpassed 90%, indicating satisfactory results within all classes. The model's ability to handle challenging cases, such as visually similar diseases like melanoma and benign keratosis, highlights its robustness. The system performed well in real-time deployment, delivering predictions within seconds via the Flask web application.

Table 1. Showing Accuracies of Different Models

Model	Accuracy (%)	Precision	Recall	F1-Score
DenseNet	93.2	0.94	0.93	0.94
ResNet-50	91.5	0.92	0.91	0.92
InceptionV3	90.8	0.91	0.90	0.91
VGG19	89.9	0.90	0.88	0.89
AlexNet	87.3	0.86	0.84	0.85

The dataset used to train model included 40,000 photos from 10 distinct sorts of skin disorders, utilizing an 80:20 split for training and validation. DenseNet-201, initialized with pre-trained ImageNet weights, was fine-tuned to enhance performance on the given dataset. The training process employed the Adam optimizer, categorical cross-entropy loss function, and a learning rate of 10^{-4}. Additionally, early stopping was implemented to prevent overfitting and ensure optimal generalization.

- **Training Accuracy:** 96%
- **Validation Accuracy:** 94%
- **Test Accuracy:** 93%

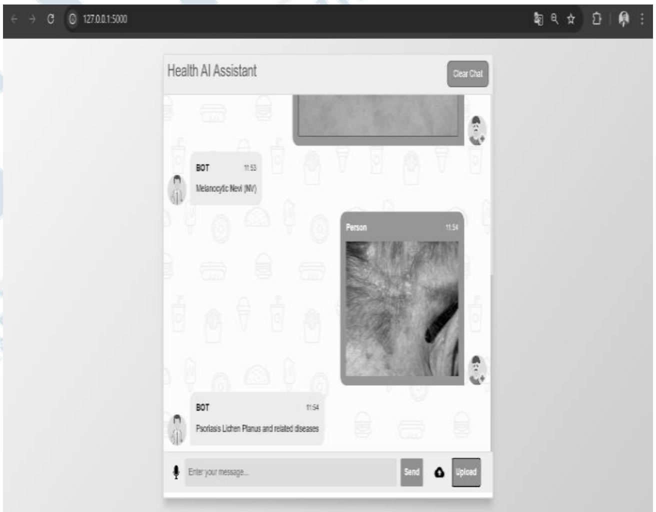

Fig. 4. User Interface

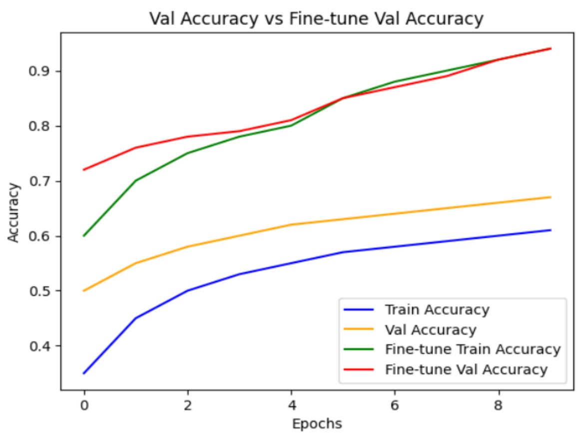

Fig. 5. Accuracy Graph

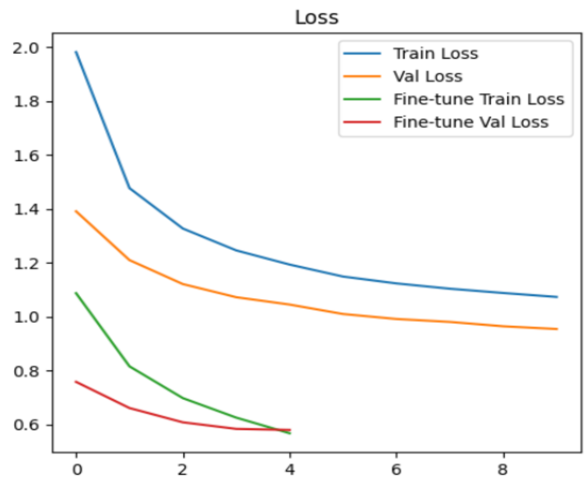

Fig. 6. Graph representing training and validation loss

V. CONCLUSION

In this study, we introduce a application for skin disease classification, With a 93% accuracy rate, a deep learning-based method was used to recognize 10 different skin diseases. The model leverages advanced neural network architectures to enhance diagnostic precision, offering a reliable and efficient solution for automated skin disease detection. The model employs the DenseNet-201 architecture, which assists it in utilizing features effectively to achieve high performance on a large and intricate dataset. The system is presented as a web application built with Flask, allowing a practical and user-friendly interface for skin images upload and accurate disease prediction along with useful health information. The proposed system shows the potential application of deep learning to support health professionals for early detection of disease. By improving the accuracy of diagnosis, access to dermatology is improved particularly in areas where resources are scarce. The system, when leveraged with AI, can be a useful method for doctors and patients to receive rapid and accurate disease detection.

This research highlights artificial intelligence's substantial role in healthcare, particularly in creating automated diagnostic tools. Future investigations will expand the system's ability to detect an increasing number of skin diseases, further improve precision and efficiency decisions, and include new features such as live monitoring and support of multiple languages. Ultimately, this AI-driven approach has the ability to radically alter dermatological care and increase patient outcomes worldwide through enhanced diagnosis effectiveness, accuracy, and accessibility.

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