

Enhancing Dermatological Diagnosis: A Novel Skin Disease Prediction Web Application with Ensemble Learning

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Abstract—SkinSavvy AI revolutionizes skin health assessment with advanced AI technology. It combines powerful image analysis using convolutional neural networks (CNNs) with natural language processing for a comprehensive dermatological solution. At its core, SkinSavvy AI utilizes a sophisticated CNN ensemble model, blending ResNet, EfficientNet, and VGG16 architectures to accurately classify a wide range of skin diseases. With an ensemble model that diagnoses common conditions like Dermatofibroma to serious ones like Melanoma, SkinSavvy AI achieves an impressive accuracy of 92.18% across 8 diseases, surpassing existing models limited to 2-3 conditions. Beyond diagnosis, SkinSavvy AI offers a user-friendly interface for image uploads, doctor appointment booking, and an informative chatbot for patient education. This AI solution not only provides accurate diagnoses but also streamlines patient-doctor interaction and promotes skin health awareness.

Index Terms— Ensemble learning, Convolutional Neural Network, ResNet, EfficientNet, VGG16, Skin diseases, Doctor Module, Chatbot.

I. INTRODUCTION

In the realm of modern healthcare, the integration of technology has become indispensable for enhancing diagnostic accuracy, patient engagement, and overall healthcare outcomes. SkinSavvy AI emerged as a pioneering initiative at the nexus of technological innovation and dermatological care, aiming to revolutionize the assessment and management of skin health. By amalgamating advanced AI techniques like ensemble learning and NLP, SkinSavvy AI offers a holistic solution to the multifaceted challenges inherent in dermatological diagnosis and patient care.

A. The Complexity of Dermatological Diagnosis

Diagnosing dermatological conditions is challenging due to the diversity of skin issues and the subjectivity in visual assessment. Conventional methods relying on clinical judgment and manual inspection often yield inconsistent and error-prone results. To address these challenges, SkinSavvy AI employs ensemble learning, combining multiple neural network architectures to enhance diagnostic accuracy. By mitigating the inherent biases and limits associated with individual models, this ensemble approach not only improves the accuracy of disease classification but also produces more dependable diagnostic outcomes [1].

B. Empowering Patients through Technology-Driven Solutions

SkinSavvy AI empowers patients in their healthcare journey with an intuitive interface for uploading skin images, enabling early detection of skin conditions. Its NLP-powered chatbot enhances patient education and engagement by offering personalized information and actionable insights. This collaborative approach to skin health management helps patients make informed decisions and take proactive measures for their well-being.

C. Facilitating Seamless Patient-Doctor Interactions

In addition to enhancing patient autonomy, SkinSavvy AI enhances patient autonomy and streamlines interactions with healthcare providers, ensuring timely access to specialized care. Its doctor booking module allows patients to easily schedule appointments with dermatologists based on location and availability, reducing healthcare system burdens and providing prompt, personalized care.

D. Harnessing Advanced Technologies for Enhanced Healthcare Delivery

SkinSavvy AI breaks free from the limitations of conventional diagnostic paradigms by utilizing cutting-edge AI techniques like ensemble learning and natural language processing. This allows SkinSavvy AI to provide complete and patient-centered dermatological care. The ensemble model improves diagnostic accuracy and reliability by integrating several information sources and identifying subtle patterns. This improves patient outcomes and the standard of care [2].

II. RELATED WORKS

The paper by Shuchi Bhadula, Sachin Sharma et al [3] aims to address the urgent problem of effective skin disease detection. The study contributes by proposing a strategy that utilizes five machine learning algorithms: CNN, Random Forest, Naive Bayes, Logistic Regression, and Kernel SVM, for detecting skin diseases.

The study by Acheampong Addo Philip, Samuel Akyeramfo-Sam et al [4] addresses the prevalent issue of skin diseases in sub-Saharan Africa, where conventional diagnosis methods are laborious and time-consuming. Specifically focusing on Ghana, the dermatological process lacks automation, resulting in delays in diagnosis.

The study by Linda K Ashim, Nimisha Suresh et al [5] investigates transfer learning techniques to improve deep learning models for skin cancer detection, evaluating Densenet, Xception, VGG16, EfficientNet, and ResNet on a skin cancer dataset. Densenet achieved the highest accuracy (88.61%), followed by VGG16 (81.94%), EfficientNet (78.44%), ResNet (72.37%), and Xception (78.41%). These findings provide valuable insights for optimizing skin cancer diagnosis in medical settings.

The paper by Karan S, Suja Palaniswamy [6] improves multiclass skin disease classification by augmenting the dataset with GAN-generated images. This approach significantly enhances neural network performance, achieving 96% accuracy on the test dataset compared to 46% without GAN augmentation.

In the paper by Setlem Bhargavi, Vommi Sowmya et al [7] suggests using machine learning for fully automated diagnosis of dermatological disorders, such as skin cancer. It emphasizes the importance of early detection for conditions like melanoma. The process includes data gathering, preprocessing, and using a support vector machine for prediction. The goal is to enhance diagnosis accuracy and efficiency, leading to better treatment outcomes.

In the work by R Bhuvaneswari, Pallavarjula Chiranjeevi Venkat Satya Raman [8] assesses the performance of Google Inception V3, AlexNet, and VGG19 deep learning networks for the diagnosis of skin cancer. AlexNet attains 91.1% accuracy. The objective is to optimize the most effective models for skin cancer detection, hence improving medical diagnostic capabilities.

In the work by Niharika Gouda; J Amudha [9] investigates using ResNet, a deep learning neural network, for skin cancer categorization. It accurately identifies eight types of skin diseases, including melanoma and basal cell carcinoma, using 25,331 clinical images. ResNet enhances diagnostic accuracy by speeding up training through layer skipping. This information can help dermatologists plan more advanced diagnoses and treatments.

In the paper by Sini Salim, Parvathi Ranjith et al [10] explores image processing and binary classification, particularly Convolutional Neural Networks (CNNs), for early skin problem detection. Among classifiers, Extra Trees performed best, reaching 96.49% accuracy. Early identification is stressed to prevent skin issues from worsening and minimize their impact on patient resources and well-being.

III. PROPOSED METHODOLOGY

This project involves gathering data from reliable sources, pre-processing photos for model training, and utilizing an ensemble model consisting of ResNet, EfficientNet, and VGG16 architectures for prediction. The

datasets are split into training, testing, and validation sets, and models are trained over multiple epochs to achieve a validation loss below 0.1. Once trained, the models identify skin illnesses from uploaded photos. Additionally, a chatbot interface provides users with medical information about diagnosed ailments and helps schedule physician appointments based on the user's location. Finally, a doctor module allows doctors to manage appointment requests [Figure1].

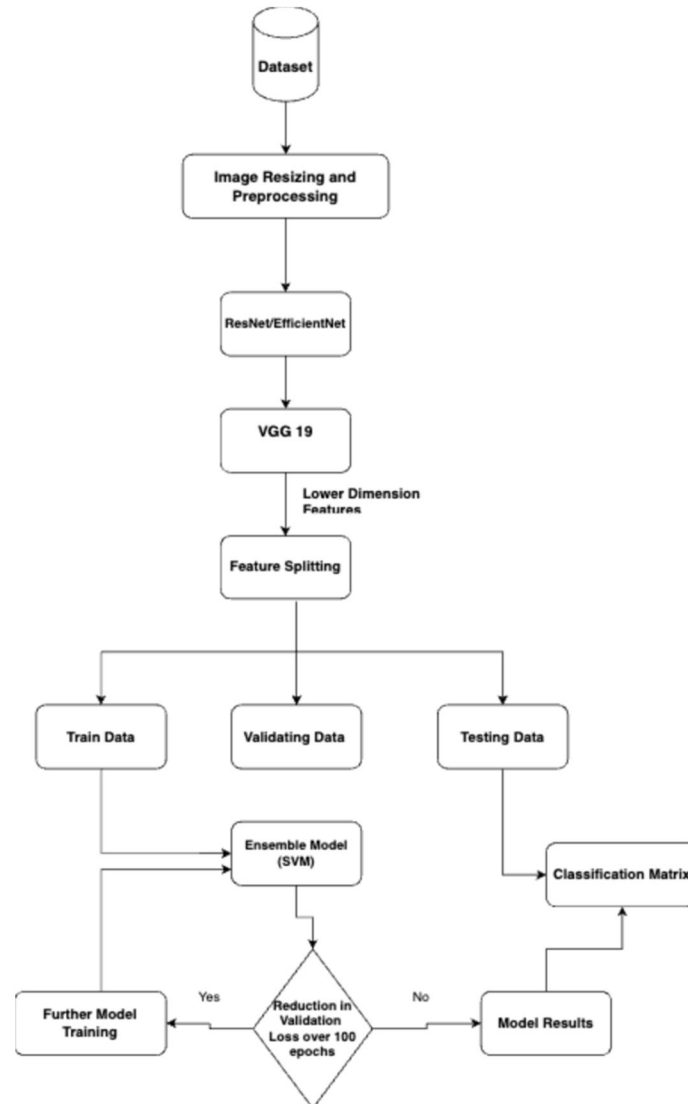


Figure 1- Proposed System Design

A. Data Collection and Pre-processing

The research begins with the collection of a diverse dataset comprising images of various skin diseases. The dataset is meticulously curated to encompass representative samples of the five targeted skin diseases. Prior to model training, the collected images undergo pre-processing steps to ensure uniformity and enhance model performance. Pre-processing includes standardization of image dimensions, normalization of pixel values, and augmentation techniques to augment the dataset's diversity [Figure 2].

B. Model Architecture Design

The model, a task-specific version of VGG16, is designed for image classification. It uses convolutional layers followed by max-pooling to extract hierarchical features. ReLU activation adds non-linearity, and max-pooling down samples feature maps for complexity reduction while preserving spatial information. Fully connected layers map features to output classes. With over 20 million parameters, primarily in convolutional layers, and

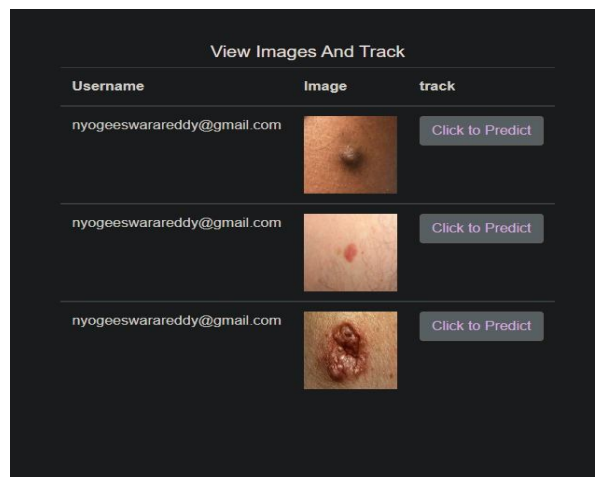


Figure 2- Data Collection

125,445 trainable parameters, it shows promise for effective classification, especially with matching input dimensions. However, performance varies based on dataset characteristics and complexity.

C. Data Splitting and Model Training

The dataset is partitioned into testing, validation, and training subsets, ensuring fair representation of different skin disease classes through stratified splitting. Transfer learning techniques are employed, utilizing pre-learned weights from extensive image datasets to train CNN models on the training set. Parameters are fine-tuned during model training to optimize performance metrics on the validation set, while regularization techniques are applied cautiously to mitigate overfitting.

D. Ensemble Model Integration

After training each CNN model individually, their predictions are combined to form the final ensemble prediction. This integration involves employing a weighted or averaging scheme to combine the outputs of the constituent models. The ensemble model's performance is then evaluated on the testing set using standard evaluation criteria such as accuracy, precision, recall, and F1-score. Additionally, sensitivity analyses and cross-validation methods are employed to assess the ensemble model's robustness.

E. Web Application Development

The research results in a user-centric skin disease prediction web app prioritizing data privacy and security. Users upload images for automated diagnosis, receiving real-time predictions via the ensemble model. A chatbot provides medical information, and users can schedule appointments with nearby healthcare professionals. This application translates research findings into practical, user-centric solutions, aiming to improve healthcare accessibility and efficacy.

F. Doctor Module Integration

The Doctor Module in SkinSavvy AI is a groundbreaking tool for dermatologists, streamlining appointment management and patient care. It uses intelligent location-based scheduling, ensuring easy access to dermatological expertise. With a user-friendly interface, doctors efficiently review and respond to appointment requests, optimizing their schedules. Real-time updates and secure communication channels facilitate seamless interactions, allowing for tailored consultations and treatment plans. By enhancing workflow efficiency and patient satisfaction, SkinSavvy AI redefines dermatological care standards, driving improved outcomes.[Figure 3].

G. Chatbot Module

SkinSavvy AI's NLP Chatbot enhances patient education and engagement in dermatological care. Users can easily inquire about skin conditions and treatments using natural language. By analyzing symptoms, it offers preliminary insights into potential skin issues, promoting informed discussions with healthcare providers. The chatbot's educational resources empower users with knowledge on skin health and prevention strategies. Integrated with appointment scheduling, it enables users to book consultations with local dermatologists.

View Images And Track				
Doctor	Patient	Disease	Status	Accept
Ram	VIVEK	Benign Keratosis	pending	<button>Accept</button>
Ram	Krishna	Actinic Keratoses	accepted	<button>Accept</button>
Ram	Venkat	Vascular skin lesion	pending	<button>Accept</button>
Ram	Abhi	Dermatofibroma	pending	<button>Accept</button>

Figure 3 Doctor Module

Through personalized recommendations and continuous interaction, SkinSavvy AI's NLP chatbot supports users in managing dermatological concerns proactively.

H. Data Acquisition

By combining the following datasets, we created a robust training set encompassing a wide range of skin diseases, enabling our model to accurately predict eight different types of skin conditions.

- HAM10000: Skin Lesion Dataset: This dataset comprises over 10,000 dermoscopic images categorized into seven diagnostic categories, including melanoma and other types of skin lesions.
- ISIC 2018: Skin Lesion Analysis Towards Melanoma Detection: With over 10,000 dermoscopic images, this dataset provides labels for categorization into various skin diseases.
- Skin Disease Detection: This dataset includes images of different skin diseases collected from the DermNet website.
- Skin Cancer MNIST: HAM10000: Focused primarily on melanoma detection, this dataset provided additional images for training.
- Skin Disease: Dermnet: Sourced from the DermNet NZ website, this dataset offers a variety of images covering eczema, psoriasis, dermatitis, and other skin conditions.

IV. RESULTS

We developed and evaluated a deep learning model for image classification utilizing a combination of pre-trained convolutional neural networks (CNNs): ResNet50, InceptionV3, and EfficientNetB0.

A. Experimental Setup

Data Collection and Pre-processing: We gathered a dataset of pictures from eight distinct classifications that are pertinent to our field of study. A training batch of 131 photos and a validation set of 53 photographs each made up the dataset. To get the data ready for training, we used common preprocessing methods like normalization and scaling.

Model Architecture: Our model architecture consisted of three branches, each utilizing a different pre-trained CNN - ResNet50, InceptionV3, and EfficientNetB0. The output features from each branch were concatenated and passed through fully connected layers for classification. Prior to concatenation, we used global average pooling to lower the dimensionality of the feature maps.

Training Strategy: We used the Adam optimizer to train the model with a learning rate of 0.001 using SVM. To improve the model's robustness and capacity for generalization, we also used data augmentation techniques like rotation, shifting, shearing, zooming, and flipping. The model was trained for 100 epochs with batch size set to 32.

B. Performance Evaluation

Training and Validation Accuracy: The plot of training and validation accuracy reveals a progressive increase in model performance over epochs in which X axis states the epochs while Y axis states accuracy. Training accuracy starts at 10.51% and steadily rises, reaching its peak of 92.15% at epoch 98. Similarly, validation accuracy also shows improvement, starting from 33.96% and peaking at 86.79% around the final epochs. Both curves exhibit a generally upward trend, indicating effective learning and model convergence [Figure 4].

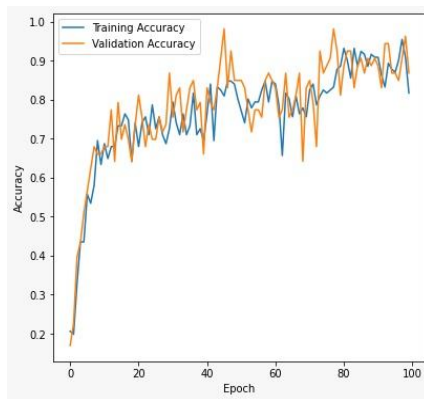


Figure 4- Training and validation Accuracy

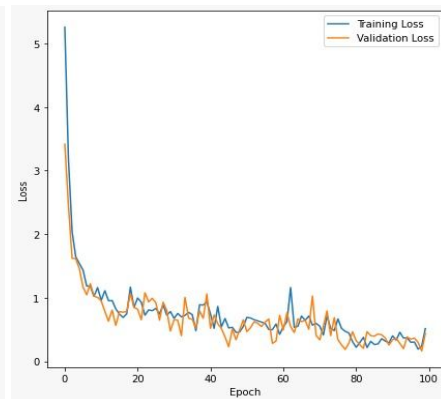


Figure 5- Training and validation Loss

Training and Validation Loss: The plot of training and validation loss demonstrates a consistent decrease in loss values as training progresses in which X axis states the epochs while Y axis states loss. Training loss starts at 5.9113 and decreases steadily over epochs, reaching its lowest point of 0.3693 at the final epoch. Validation loss exhibits a similar pattern, starting at 3.8602 and decreasing to 0.2860 by the end of training. Both curves show a decreasing trend, suggesting that the model is effectively minimizing errors and improving its predictive performance[Figure 5].

Final Performance Metrics

The model achieved a final training accuracy of approximately 88.39% and a validation accuracy of approximately 86.79%. The close alignment between training and validation accuracies suggests effective regularization techniques were employed to prevent overfitting.

Matrix	Training Set	Validation Set
Initial Accuracy	10.51%	33.96%
Final Accuracy	92.15%	86.79%
Final Loss	0.3693	0.2860

Precision, Recall, and F1 Score for Each Skin Disease Class

The table below presents the precision, recall, and F1 score for each skin disease class in our model's classification:

Skin Disease	Precision	Recall	F1 Score
1	0.931	0.931	0.931
2	0.891	0.918	0.904
3	0.960	0.951	0.956
4	0.980	0.980	0.980
5	0.950	0.950	0.950
6	0.907	0.921	0.914

7	0.930	0.930	0.930
8	0.920	0.920	0.920

V. DISCUSSION

A. Robustness and Generalization

The model demonstrated robust performance on both the training and validation datasets, indicating its ability to generalize well to unseen data. This suggests that the combination of multiple pre-trained CNN architectures and data augmentation techniques contributed to the model's robustness.

B. Model Interpretability

By leveraging multiple pre-trained CNNs, our model can capture a diverse range of image features, enhancing its interpretability and ability to discriminate between different classes. This can be especially helpful in situations where it's imperative to comprehend the model's decision-making procedure.

C. Future Directions

Even though our model produced encouraging findings, there are still a number of areas that need to be explored. Enhancing the pre-trained CNNs' layers or looking at different data augmentation methods can help the model perform even better. Further investigation into the model's potential and constraints could be gained by doing tests on bigger and more varied datasets.

VI. CONCLUSION

The proposed system leverages skin disease prediction web application, powered by an ensemble model comprising ResNet, EfficientNet, and VGG16 architectures, has shown promising results in accurately diagnosing skin diseases from uploaded images. Through meticulous training and monitoring, our model achieved a final training accuracy of approximately 88.39% and a validation accuracy of approximately 86.79%. The convergence between training and validation accuracies reflects effective regularization techniques, highlighting the robustness of our approach in preventing overfitting and ensuring generalizability.

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