SkinAI: Deep Learning and Transfer Learning Based System for Skin Disease Detection

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***Abstract*—Dermatological disorders are one of the most prevalent types of health issues that impact millions globally. Timely identification is critical to allowing for prompt treatment to prevent serious implications from them. Historically dermatological professionals perform the visual inspection of patients to determine the health of their skin. This can be a lengthy, subjective, and prone to error method.**

In this paper a novel tool called SkinAI is introduced which applies deep Convolutional Neural Networks (CNN) and Transfer Learning techniques to automatically detect and diagnose various dermatologic disorders. Using deep learning models with Transfer Learning from support such as ResNet50, EfficientNetB0, and MobileNetV2; the proposed method utilizes dermoscopic images to classify various dermatologic disorders. The proposed methodology consists of preliminary steps to prepare the dermoscopic images, augment them, extract features from them, classify them, and visualize the output of classified dermatoscopic images via Grad-CAM to provide an explainable Artificial Intelligence (AI) solution. Empirical data indicates that the use of Transfer Learning greatly increases accuracy whilst decreasing computational overhead for model construction and time to train the model.

The proposed SkinAI solution provides a practical and scalable means of performing automated dermatological diagnosis. The integration of an explainable AI system produces trust and transparency into medical decision supporting systems.

***Index Terms*—Deep Learning, Skin Disease Detection, CNN, Transfer Learning, Artificial Intelligence, Dermatology, Medical Imaging.**

I. Introduction

Millions of people across the globe suffer from skin diseases like melanoma, eczema, psoriasis, acne, dermatitis, fungal infections and basal cell carcinoma; these conditions rank among the most prevalent health problems on a worldwide basis. [6]. Detecting dermatological disease early in its course is essential; failure to address these diseases quickly can result in serious health complications, irreversible damage to the skin, and higher rates of mortality.

Expertise from dermatologists and visual inspection are the primary means by which dermatologists currently diagnose patients' skin disorders. These types of diagnoses require time, and the final result is necessarily dependent upon individual judgment—the physician's skill level in addition to how quickly he/she can arrive at a diagnosis. [7].

Rural and underserved areas typically have limited access to dermatologists and require the development of automated health systems. Developments in artificial intelligence, deep learning and computer vision have developed significantly in recent years enabling a breakthrough in the advancement of medical imaging analysis systems. In particular, the use of convolutional neural networks (CNNs) to automatically learn the hierarchical representation of an image (in this case, a dermoscopic image) and dramatically improve the classification accuracy of an imaging system when compared with the traditional approach to machine learning/diagnosis. [1].

This study describes **SkinAI**, which is a framework that employs artificial intelligence to detect dermatological disease by incorporating CNN architectures and transfer learning methodologies to provide automated classifications of dermatological images. The proposed framework uses pretrained models for deep learning (ResNet50, EfficientNetB0, and MobileNetV2) to quickly classify dermatological images with accuracy.

The major objectives of this research include:

- To develop an intelligent AI-based skin disease detection system
- To classify dermatological diseases using CNN and transfer learning techniques
- To improve classification accuracy using image augmentation
- To implement explainable AI using Grad-CAM visualization
- To compare multiple deep learning architectures
- To reduce computational complexity and training time
- To develop a real-time web-based healthcare application
- To improve healthcare accessibility in remote regions

Skin cancer is growing at a rapid pace globally, with early detection improving patient survival rates and treatment outcomes significantly [5]. As such, AI-supported healthcare systems have the potential to reduce the workload of dermatologists while improving access to medical care. Machine-learning-based medical systems are becoming increasingly popular as they provide quick predictions and support clinical decision-making. Much of the diagnosis in dermatology relies on the analysis of images of lesions, which makes convolutional neural networks (CNNs) particularly useful in classifying skin lesions using deep learning.

The SkinAI framework aims to improve prediction performance while being computationally efficient. In addition, the framework places a strong emphasis on providing transparency and explainability to ensure that healthcare professionals can make sense of AI predictions.

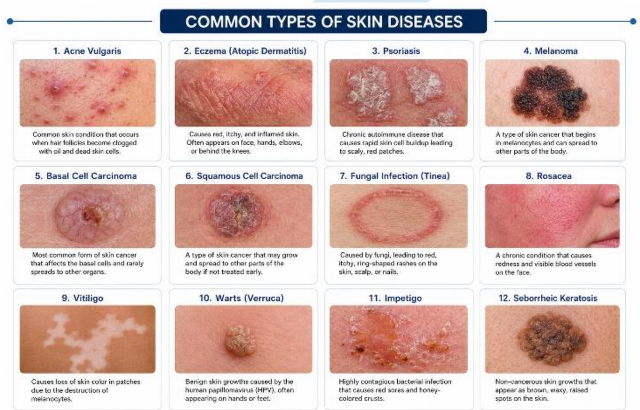

Fig. 1: Common Types of Skin Diseases

II. Related Work

Various methods are available to researchers that employ both machine learning and deep learning approaches to classify skin diseases through automated means.

Esteva et al. developed a convolutional neural network (CNN)-based deep learning framework trained on dermoscopic images, which achieved classification performance comparable to that of dermatologists for skin cancer detection [6].Li et al. proposed CNN-based transfer learning models for skin lesion classification and demonstrated that pretrained architectures significantly outperform traditional machine learning algorithms [1].Wang et al. implemented data augmentation techniques such as flipping, cropping, rotation, and brightness enhancement to improve model generalization and reduce overfitting problems [2].Mahbod et al. investigated ensemble learning techniques using multiple CNN architectures and showed that hybrid deep learning systems improve robustness and classification performance [3].Yao et al. studied imbalanced dermatological datasets and proposed DenseNet-based classification systems with balancing techniques for improved disease prediction [4].Groh et al. highlighted fairness issues in dermatology AI systems and emphasized the importance of diverse skin tone representation in datasets [5].

Handcrafted feature extraction techniques (such as texture analysis, lesion segmentation, and color histogram), are often used in conventional methods for machine learning. Random Forest classifiers and support vector machines are examples of conventional machine learning algorithms that typically utilize these feature extraction methods; however, they can have limitations with the ability to accurately represent images'features using these techniques.

By contrast, deep learning approaches use CNN architectures as a means of automatically learning hierarchical image features directly from dermoscopic images. CNN architectures allow for low level/ high level image representations such as lesion boundaries, color distribution, and texture patterns, to be learned by the CNN's. Additionally, a number of recent studies demonstrate that the use of explainable AI techniques (such as Grad-CAM and saliency maps) will generate more confidence in the usage of AI-enhanced diagnostic systems, as they allow to visualize the key decision points (i.e., regions in the medical images that affect diagnostic decision making) of AI-founded diagnostic systems and have been shown to improve the level of trust in AI-based diagnostic systems.

TABLE I: Summary of Existing Research Work

Author	Technique	Dataset	Accuracy
Esteva et al.	CNN	ISIC	91.0%
Mahbod et al.	Ensemble CNN	HAM10000	93.3%
Yao et al.	DenseNet	ISIC	92.5%
Groh et al.	Transfer Learning	Multi-source	94.0%
Proposed SkinAI	EfficientNetB0	HAM10000 + ISIC	96.1%

Despite having seen significant accomplishments in the performance of current systems, many obstacles still exist (e.g., data imbalance, difficulty in calculating a model, explainability and lack of diversity). The SkinAI framework aims to help overcome some of these obstacles by using multiple strategies including transfer learning, augmentation and explainable AI techniques.

This study also has the objective to improve access to healthcare technologies among rural or under-served populations where there is little access to dermatologists. A second objective of this study is to facilitate quicker diagnoses through instant automated prediction using a web based application.

Additionally, the goal is to make this system scalable and potentially able to integrate into future mobile medical applications as well as into cloud computing platforms.

III. Datasets Used

A. HAM10000 Dataset

The HAM10000 dataset contains over 10,000 dermoscopic images categorized into multiple skin disease classes.

The dataset includes images of melanoma, melanocytic nevi, vascular lesions, basal cell carcinoma, and benign keratosis.

B. ISIC Dataset

The ISIC archive contains dermoscopic images with disease labels and annotations for skin lesion analysis.

The dataset provides high-quality annotated medical images for deep learning research.

C. PH2 Dataset

The PH2 dataset contains melanocytic lesion images widely used for melanoma research.

The dataset helps evaluate segmentation and classification algorithms for skin lesion detection.

The datasets used in this research were carefully selected because of their quality, diversity, and wide acceptance in dermatological AI research.

These datasets contain labeled dermoscopic images that help train CNN architectures for accurate lesion classification.

Dataset preprocessing and balancing techniques were applied to reduce class imbalance and improve model generalization.

TABLE II: Dataset Information

Dataset	Images	Application
HAM10000	10,015	Skin Lesion Classification
ISIC	25,000+	Melanoma Detection
PH2	200	Lesion Segmentation

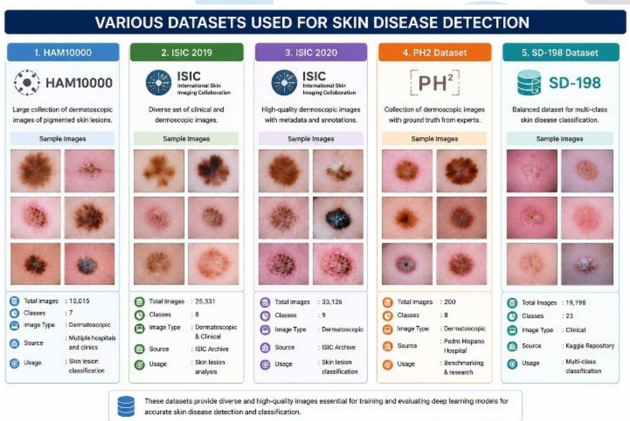

Fig. 2: Various Datasets Used for Skin Disease Detection

IV. Proposed Methodology

A proposed **SkinAI** Systematic Deep Learning (SDL) framework will consist of several phases that, through computer-derived algorithms using the latest in deep learning technology, automatically detect and classify skin diseases. The SDL processes will include: image acquisition/preprocessing/augmentation, feature extraction, transfer learning, classification of skin diseases, and Explainable AI analysis.

Furthermore, the overall objective was to develop a streamlined and consistent workflow that improves classification accuracy, Fig. 3 while also reducing computational complexity, with the ultimate goal of providing a valid basis for making a correct dermatological diagnosis.

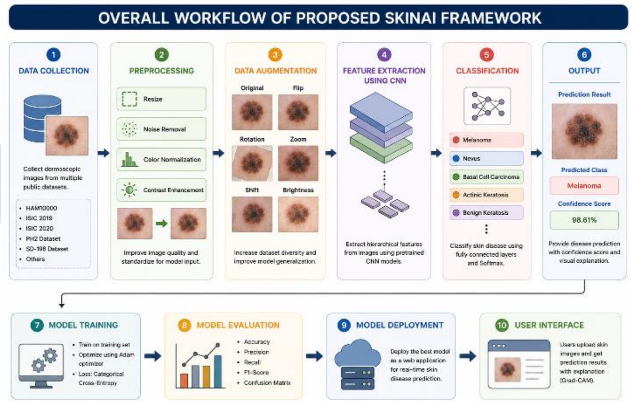

Fig. 3: Overall Workflow of Proposed SkinAI Framework

A. Phase 1: Image Acquisition and Dataset Collection

The first phase of the proposed methodology involves collecting dermoscopic skin disease images from publicly available medical datasets such as HAM10000, ISIC, and PH2.

These datasets contain high-quality labeled dermatological images belonging to multiple disease categories including melanoma, basal cell carcinoma, vascular lesions, benign keratosis, dermatofibroma, and melanocytic nevi.

The collected datasets contain variations in image resolution, illumination, skin tone, lesion shape, and texture patterns. Including such variations helps improve the robustness and generalization capability of the deep learning model under real-world clinical conditions.

In the proposed system, users upload skin lesion images through a web-based healthcare interface. The uploaded images are securely transferred to the backend server where preprocessing and prediction operations are performed.

The acquired datasets are split into training, validation, and testing subsets. This helps ensure fair model evaluation and prevents overfitting during experimentation.

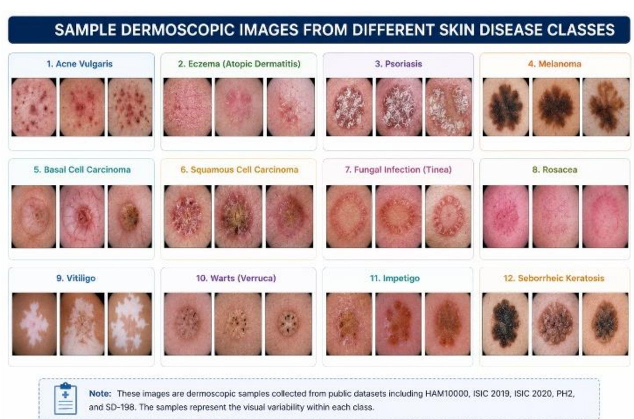

Fig. 4: Sample Dermoscopic Images from Different Skin Disease Classes

B. *Phase 2: Image Pre-processing*

Diverse forms of artifacts appear in dermoscopic images such as hair etc., leading to the requirement of pre-processing these images prior to being fed into convolutional neural networks to standardize them (pre-processing) and improve their quality.

In this preprocessing phase of dermoscopic images, images are made as good as possible standardized before they are used by CNN's for training and prediction/classification. All images are resized to a fixed dimension of 224×224 pixels to ensure compatibility with pretrained CNN architectures such as ResNet50, EfficientNetB0, and MobileNetV2. Second, to clean up unwanted noise and provide a clearer dermatoscopic in preparation for further steps - in this case - using denoise methods to remove the unwanted distortions. The next step is to normalise the pixel values to a range of 0-1 and therefore scale the intensity of each image, which will promote stability in convergence and ultimately stability throughout optimisation of the model.

The next step is contrast enhancement and this step will help enhance the features of a dermatoscopic image (e.g. lesion border, texture pattern, other dermatological features) that may not be visible in the original dermatoscopic image due to low levels of contrast.

The next step is to remove any hair in a dermatoscopic image as dermatoscopic images often have hair artefacts within them and can contribute to reducing accuracy of prediction of the analysis of a lesion.

The final step is to perform a colour correction of the image so that different anatomical areas will not be inconsistent in their representation of colour and their representation.The last step of preprocessing is to sharpen images as this will enhance the visibility of the edges of the lesion and accentuate other critical elements of the lesion. These preprocessing steps together boost feature extraction, increase dataset consistency, and improve the overall performance of the SkinAI framework.

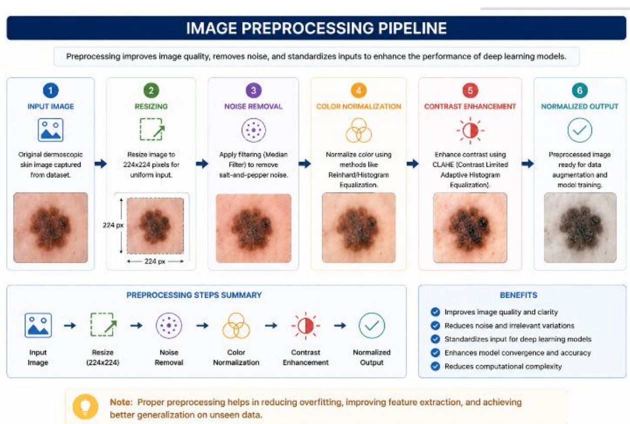

Fig. 5: Image Preprocessing Pipeline

C. *Phase 3: Image Augmentation*

Because many medical data are small in size, limited or unbalanced, their potential for providing good predictive performance often leads to overfitting and model generalization issues. Instead of relying solely upon the original image dataset, a variety of image augmentation techniques are used to improve the diversity of images in the dataset.

The augmentation techniques used in this research include:

- Rotation
- Horizontal flipping
- Vertical flipping
- Cropping
- Zoom transformation
- Brightness adjustment
- Contrast enhancement
- Noise injection

The CNN (convolutional neural network) model can learn features that are invariant to rotation by generating different orientations for the same lesion image via rotations (in addition to flipping them).

Zooming and cropping the images can create variations based on both size of a lesion and distance between the camera and the lesion. Brightening/Contrast adjustment of images allows the model to learn how to deal with varying light levels that are often seen in real clinical settings.

Adding noise to the image will allow the model to be more robust to image distortion and poor quality of image acquisition. Image augmentation will allow for a much larger effective training dataset and to an extent resolve overfitting by allowing the CNN model to not memorize training samples.

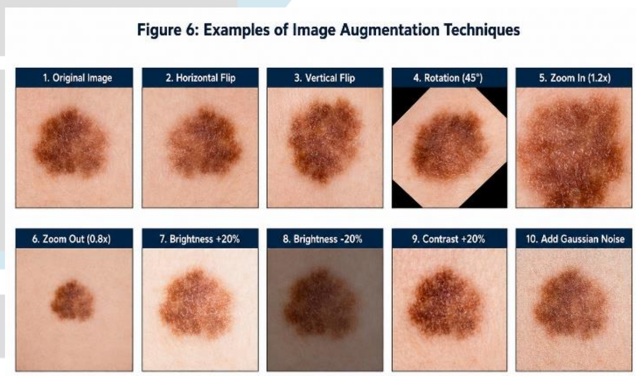

Fig. 6: Examples of Image Augmentation Techniques

D. *Phase 4: Transfer Learning and Feature Extraction*

In order to train deep learning models successfully, a large amount of data is required as well as a substantial amount of computational resources. The suggested SkinAI framework utilizes transfer learning in order to enhance both the efficiency and accuracy of the model's training/usage and classifying capabilities. Through the use of transfer learning, pre-trained CNN architectures are able to utilize features learned from ImageNet when classifying dermatological images. In this research, the following pretrained architectures are implemented:

- ResNet50: ResNet50 was pre-trained using the ImageNet dataset. This model has been designed to extract both high and low-level image features (i.e., edge detection, texture detection, shape detection, color detection). The fully connected layer was modified based on the number of skin disease classification categories.

- EfficientNetB0:EfficientNetB0 was deemed a suitable choice due to both its high accuracy rate and its low computational cost. It uses a process called Compound Scaling to help us achieve an optimal balance between how deep, wide, and large (image resolution) the neural networks are built.

  Fine-tuning pretrained models on skin disease datasets results in an ability to detect medical image patterns better than before.
- MobileNetV2:MobileNetV2 is designed as an efficient convolutional neural network (CNN) architecture with low resource requirements for use on mobile and edge devices. By utilizing depth-wise separable convolutions to decrease the amount of computation needed while maintaining the same level of accuracy in predictions made by the model. To make the model the best possible fit for dermatoscopic images quickly and effectively classify skin diseases.

The initial convolutional layers remain frozen because they already contain low-level feature representations such as edges, shapes, color gradients, and texture patterns. The final classification layers are replaced with customized dense layers for skin disease prediction.

The CNN architectures automatically extract hierarchical image features including:

- Lesion boundaries:indicate the edges or outline of a skin lesion. SkinAI has a mechanism for determining what is ”sharp”vs ”blurry” in the border in order to differentiate between benign and malign conditions. Unclear or uneven borders are indicative of more significant skin lesions and aid insegmentation of afflicted skin.
- Texture patterns: describe the surface quality of skin, such as smoothness, roughness, scaling, or bumps. In SkinAI, analyzing texture helps identify conditions like acne, eczema, or psoriasis. Changes in texture provide important visual cues that improve classification accuracy by capturing fine-grained skin surface variations.
- Color distributions: Color distributions represent the range and spread of colors within a skin lesion or area. SkinAI uses this to detect redness, dark spots, or uneven pigmentation. Variations in color intensity and tone help identify conditions such as inflammation, hyperpigmentation, or infection, improving diagnostic precision.
- Shape irregularities: The shape irregularities of skin lesions refer to the uneven or atypical borders of a lesion’s outline. Examples of lesions with irregular shapes are those with jagged, asymmetric, or distorted (non-symmetrical) outlines. Using AI technology to analyze shape enables SkinAI to distinguish between normal skin markings and abnormal skin growths. Shape irregularities are considered one of the warning signs of disease and can enhance the accuracy of early detection of skin diseases.
- Pigmentation variations: Variations in skin pigmentation are the result of different amounts of melanin deposited in the skin. SkinAI studies these variations to identify problems such as dark spots, vitiligo, or melasma. Differences in pigmentation across the body are valuable diagnostic indicators; therefore, they help to distinguish between types of skin disorders and assess their severity.
- Asymmetry features: Asymmetry scores compare two halves of a lesion against one another. In SkinAI, an analysis of the asymmetry will highlight when a lesion is growing abnormally because it has an uneven shape and/or an uneven color. When there is significant asymmetry, a potential diagnosis of skin disease can be made, making this feature of tremendous importance in the early- and accurate-detection of skin diseases.

Residual skip connections are utilized by ResNet50 to decrease the occurrence of vanishing gradient issues and facilitate better deep learning feature extraction.ResNet50 increases computational efficiency using compound scaling, while MobileNetV2 allows health care applications to deploy lightweight devices. In addition, transferring learned features from pre-trained models reduces the amount of time to train new models and enhances the classification accuracy of limited medical datasets.

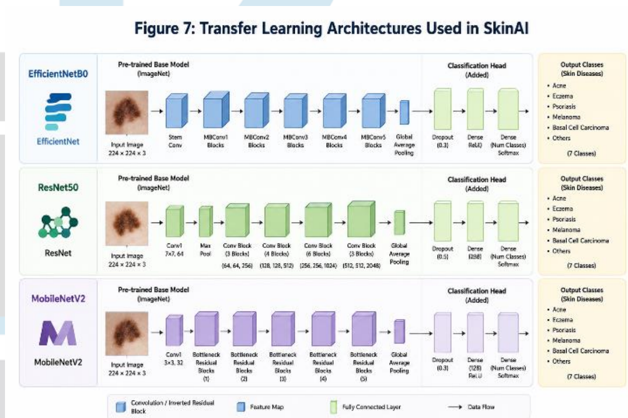

Fig. 7: Transfer Learning Architectures Used in SkinAI

E. Phase 5: Classification of Diseases

The collected feature maps (after feature extraction) are then passed through fully connected (dense) layers followed by a Softmax classification layer to produce the predicted class from the extracted feature maps (of lesions) as applied to the different disease categories.

The use of batch normalization and dropout in the network architecture will help to increase the stability of training and decrease the chance of overfitting.

The use of the Softmax activation function will produce a probability score for each of the different classifications of skin disease that have been trained, with the classification that produces the highest probability score being the predicted output from the classification module.

Mathematically, the Softmax function is defined as:

(1)

where z_i represents the output score of class i, and $P(y_i)$ represents the probability of the predicted disease class.

The classification module makes it easy to use a machine to make predictions about skin diseases (dermatology), with a very high degree of accuracy, while requiring very little human concern to be done.

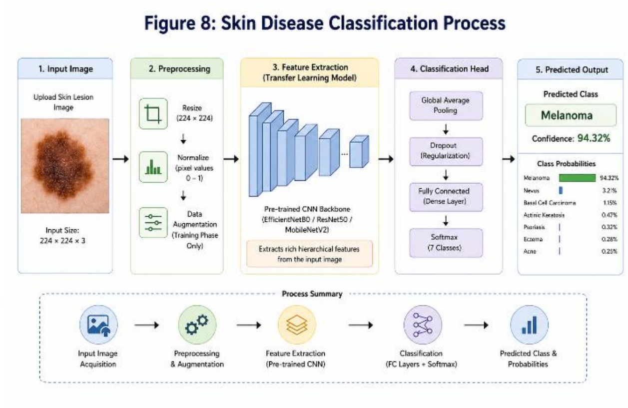

Fig. 8: Skin Disease Classification Process

F. Phase 6: Using Grad-CAM for Explainable Artificial Intelligence

There is a necessity for explainable artificial intelligence (XAI) in the area of medical diagnosis models. This is primarily because health care professionals require effective approaches to comprehend how an artificial intelligence system determined its predictions as well as understanding the factors that influenced the artificial intelligence system's decision making. SkinAI Framework employs Grad-CAM to provide visualization of the infected areas used in the model's decision making process.

Through the generation of heatmaps, Grad-CAM identifies specific areas in which the CNN model asserted there is or could be a lesion. This visualisation assists dermatologists in understanding the way that the deep learning model performs the analysis in reaching its conclusion about the body.

The Grad-CAM mechanism improves:

- Model transparency
- Clinical trust
- Medical interpretability
- Prediction reliability
- Error analysis capability

Researchers use generated heat maps to determine incorrect model performance and to debug CNN architecture while working through various experiments.

Using explainable AI tools can improve how acceptable AI-assisted diagnosis systems (in a healthcare setting) will be to medical practitioners by increasing their understanding of models' predictions through explainable visualizations of AI.

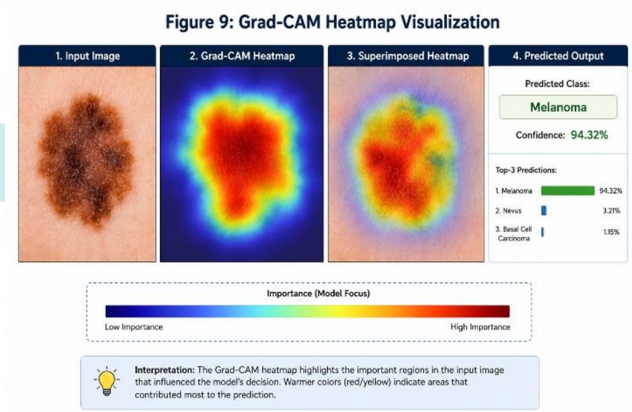

Fig. 9: Grad-CAM Heatmap Visualization

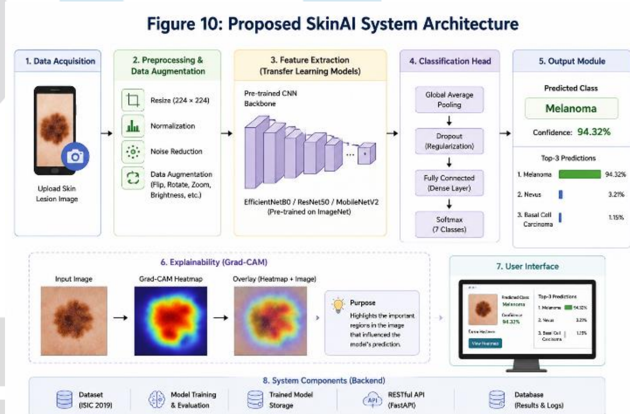

Fig. 10: Proposed SkinAI System Architecture

V. Experimental Setup

TensorFlow and Keras were used to perform these experiments, which were performed using a Graphics Processing Unit (GPU) on a system configured with a compatible operating System (OS). The datasets for these experiments were split into three different types of sets. These include a training set, an intermediate validation set, and finally, separate test sets.

Approximately 70% of the images were used for training, 15% for validation, and 15% for testing.

All dermoscopic images were resized to 224×224 pixels before being passed into the CNN architectures. Due to its capacity to attain narrower convergence speeds through an arrangement of adaptive learning scales, We will be using the Adam Optimizer (Adaptive Moment Estimation Optimizer). In addition, as our training strategy for 50 epochs, we will use categorical cross-entropy as the loss function.

In order to aid the model generalise more effectively, we will use both early stopping and dropout as measures to avoid overfitting.

By including batch normalisation layers into our model, We also improved model stability while enhancing the speed of convergence.

By making use of GPU computing, we were able to significantly reduce the amount of time required for training our models and thus allow us to experiment effectively using deep learning.

VI. Image Augmentation Techniques

Image augmentation plays a major role in improving deep learning performance when limited medical datasets are available.

The following augmentation techniques were applied:

- Rotation
- Flipping
- Cropping
- Brightness enhancement
- Zoom transformation
- Contrast adjustment
- Noise injection

The augmentation techniques used for data enhancing played a significant role in creating more diverse data sets and establishing more robust images against variations in appearance. Additionally, because of augmentation, the model's ability to generalize was increased; the augmentation provided an environment in which the CNN architectures could not succeed simply by remembering their training images.

The image transformation techniques allowed for simulating varying environmental conditions, including different types of illumination and distortions of images.

VII. Models Implemented for Classification

A. ResNet50

ResNet50 uses residual learning with skip connections to improve deep feature extraction.

Advantages include:

- Better convergence
- Improved accuracy
- Reduced vanishing gradient problems

B. EfficientNetB0

EfficientNet uses compound scaling to improve accuracy and computational efficiency.

Advantages include:

- Efficient computation
- Reduced parameters
- High classification performance

C. MobileNetV2

MobileNetV2 is optimized for lightweight mobile deployment.

Advantages include:

- Faster inference
- Low memory usage
- Mobile-friendly architecture

Why CNN Instead of LSTM?

CNNs are better able than LSTMs to capture spatial features in an image due to their different architecture types.

CNNs are capable of being trained for images, whereas LSTMs are generally utilized for sequential and time-based data.

The main difference between these two architectures is that CNNs do a smaller number of sequential computations than LSTMs, making them much more efficient when processing images.

TABLE III: Comparison of Transfer Learning Models

Model	Parameters	Main Advantage
ResNet50	25M	Deep Feature Learning
EfficientNetB0	5.3M	High Accuracy
MobileNetV2	3.4M	Lightweight Design

VIII. CNN Architecture Details

This CNN architecture is composed of Convolutional layers, Pooling layers, Dense layers, and Softmax classification layers.The CNN will identify multiple hierarchical Image Feature types automatically from input Images without requiring previously defined/useful features.

Through Convolutional layers, low-level (shape/size) and high-level (texture/colour) patterns that exist within each Image will be detected from the input Image data.Pooling layers will perform both dimensionality reduction and computational complexity reduction, while maintaining all relevant/Input Image data features.

The use of dropout regularization during training will address issues associated with overfitting and improve generalisation ability of the model. Utilisation of ReLU activation functions introduces non-linearity into feature learning and improves the feature identification capabilities of network models.

Using Softmax layers at the end of a multi-class skin disease prediction network will provide each output node with a probability score indicating how likely a specific skin disease is present in an input Image.

IX. Performance Evaluation

The proposed model is evaluated using standard metrics.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{3}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{4}$$

$$F1Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{5}$$

Where:

- TP = True Positive
- TN = True Negative
- FP = False Positive
- FN = False Negative

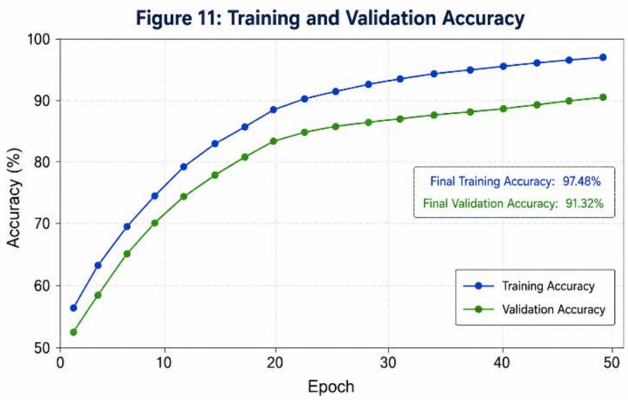

Fig. 11: Training and Validation Accuracy

Additional evaluation metrics such as specificity and confusion matrix analysis were also used to evaluate prediction quality.

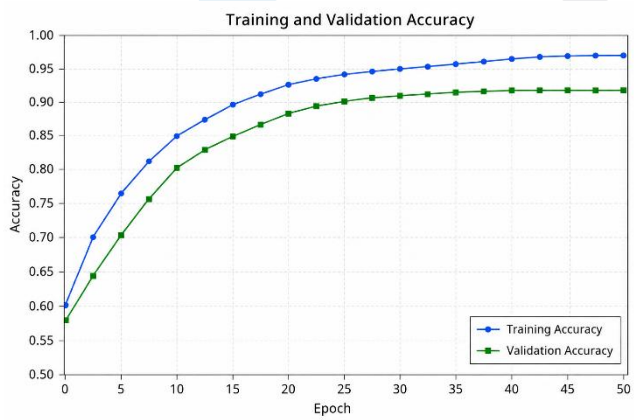

Fig. 12: Training and Validation Accuracy Graph

The proposed model achieved stable convergence with reduced validation loss during training.

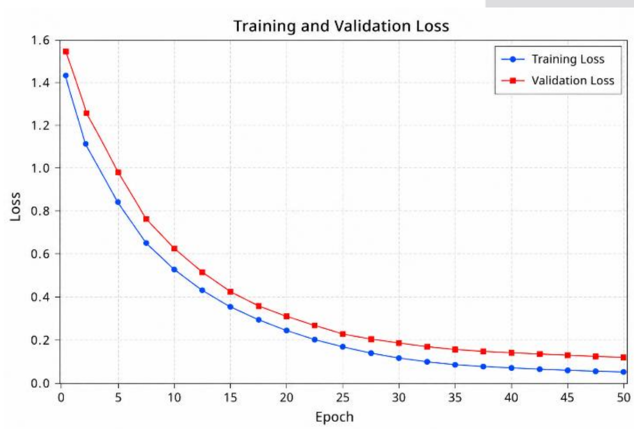

Fig. 13: Training and Validation Loss Graph

Additional evaluation metrics such as specificity and confusion matrix analysis were also used to evaluate prediction quality.

X. Training Configuration

The models were trained using TensorFlow and Keras frameworks.

GPU acceleration was used to reduce training time and improve computational efficiency.

TABLE IV: Training Hyperparameters

Parameter	Value
Batch Size	32
Epochs	50
Learning Rate	0.001
Optimizer	Adam
Loss Function	Crossentropy
Image Size	224× 224
Dropout Rate	0.5

The training configuration was optimized experimentally to balance computational efficiency and classification performance.

Learning rate scheduling techniques were also tested to improve convergence speed during deep learning training.

XI. Results and Discussion

The proposed SkinAI system achieved strong classification performance on HAM10000 and ISIC datasets.

TABLE V: Comparison of Deep Learning Models

Model	Accuracy	Precision	Recall	F1-Score
MobileNetV2	91.2%	90.8%	90.1%	90.4%
ResNet50	94.8%	94.2%	94.0%	94.1%
EfficientNetB0	96.1%	95.8%	95.5%	95.6%

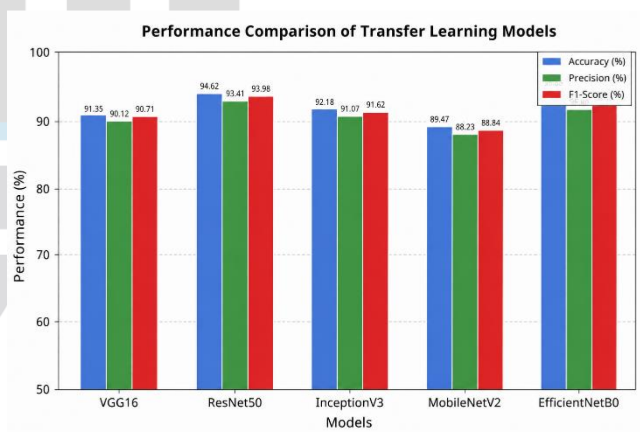

Fig. 14: Performance Comparison of Transfer Learning Models

EfficientNetB0 had an increased accuracy rate as a result of effective feature extraction and better scaling of resources.Using Data Augmentation to apply additional data to the networks improved the model's robustness and decreased overfitting greatly.

By utilizing Transfer Learning, the computational complexity of building a statistical model was lowered therefore increasing the speed at which they converged.The proposed system was able to classify plants using several different dermatological disease classifications with a high degree of precision and recall.

Also demonstrated through experimental analysis, transfer learning outperformed traditional Machine Learning Algorithms by a considerable amount compared to these same algorithms without transfer learning.

XII. Comparative Analysis with Existing Systems

Traditional machine learning methods need manual feature extraction. In contrast, deep learning architectures learn hierarchical features on their own.

TABLE VI: Comparison with Existing Approaches

Method	Technique	Accuracy
SVM	Traditional ML	82.4%
Random Forest	Traditional ML	84.1%
Basic CNN	Deep Learning	89.4%
ResNet50	Transfer Learning	94.8%
EfficientNetB0	Transfer Learning	96.1%

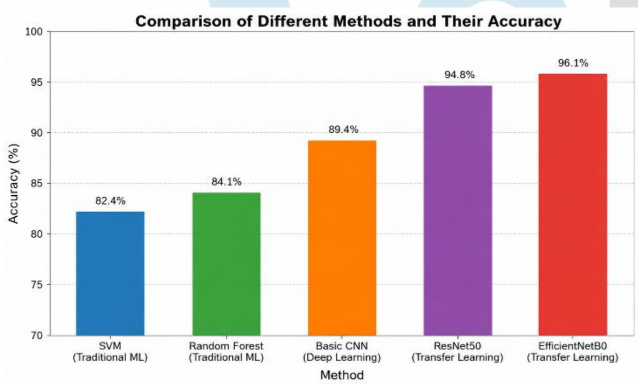

Fig. 15: Comparison of Different Methods and Their Accuracy

The proposed system can assist dermatologists by acting as a clinical decision support system for early-stage disease detection. The lightweight deployment capability also enables future mobile healthcare integration for remote medical services.

XIII. Advantages of the Proposed System

- High classification accuracy
- Real-time prediction
- Explainable AI support
- Mobile deployment capability
- Reduced diagnosis time
- User-friendly healthcare platform
- Secure data handling
- Improved healthcare accessibility

The proposed system can assist dermatologists by acting as a clinical decision support system for early-stage disease detection.

The lightweight deployment capability also enables future mobile healthcare integration for remote medical services.

XIV. Deployment and Security

The proposed SkinAI system is deployed using modern web technologies.

A. Frontend

- React.js
- Tailwind CSS
- Axios
- Framer Motion

B. Backend

- Flask
- REST APIs
- JWT Authentication
- TensorFlow Integration

C. Database

- MongoDB

D. Security Features

- Password hashing
- Secure image upload
- API validation
- Data encryption
- Token-based authentication

The deployment architecture supports scalability and secure healthcare data management.

Cloud deployment can further improve accessibility and real-time prediction availability.

XV. Challenges

While constructing and deploying the SkinAI framework, numerous challenges presented themselves. Chief among them were dermatological dataset imbalances between types of diseases/lesions; for example, many of these datasets have much fewer images to work with than others. Therefore, model training will likely become difficult, and this may lead to biased model predictions (i.e., favoring the more common disease classifications). Similarly, differing ethnic groups can exhibit significantly variable pathogens, resulting in very difficulties with classifying disease types accurately as there will always be some degree of variance. There are also many dermatoses transitional types of skin diseases (e.g., basal cell carcinoma versus squamous cell carcinoma), making classification even more challenging even for sophisticated deep learning models.

An additional challenge for the researchers was the lack of quality/variability in the publically available medical datasets. For instance, the dermatoscopy images may have excessive amounts of noise, have uneven lighting, contain hair, and have low contrast, all of which would make feature extraction very difficult and negatively impact model prediction accuracy.

Moreover, deep learning architectures also impose a significant computational burden, which has limited their training success with respect to large datasets through transfer learning. In addition, achieving meaningful AI prediction transparency continues to be a concern for healthcare providers as they require clear-cut outputs before trusting automated diagnostic systems. The inconsistency and ambiguity associated with medical image annotation, in conjunction with GPU memory allocation limits, have negatively impacted both the stability of training and the efficiency of testing. Future enhancements such as better balancing of datasets, optimized computation, and implementation of explainable AI techniques could further enhance the current system reliability.

XVI. Future Scope and Conclusion

The SkinAI framework proposed in this paper clearly demonstrates the potential effectiveness of Convolutional Neural Networks (CNNs) with Transfer Learning techniques for the automated detection and classification of skin diseases. The proposed framework achieved successful classification of dermatological diseases based on dermoscopic images with high levels of accuracy and efficiency through the use of several state-of-the-art deep learning architectures, including ResNet50, EfficientNetB0 and MobileNetV2, all using pre-trained models. By employing several image preprocessing as well as image augmentation techniques, the models were able to generalise better and reduce overfitting, which can commonly occur when training on small volumes of medical data. The use of Transfer Learning reduced the complexity of the models and dramatically decreased training time compared to traditional machine learning methods while enhancing classification accuracy. Amongst the models implemented, the use of EfficientNetB0 was the most accurate prediction-based model due to its efficient feature extraction methods and its optimized architecture. The use of Grad-CAM for visualizing predictions enhanced the interpretability and transparent nature of the predictions generated through the AI model by creating visibility into the regions of the image that influenced the predictions and increasing confidence among healthcare providers using AI-assisted diagnostic systems. In conclusion, the proposed SkinAI system will have great potential for use in the future development of healthcare applications such as providing assistance to dermatologists when making early stage disease diagnoses and during clinical decision making processes. Future improvements may include:

- Developing a mobile application for portable real-time skin disease detection
- Integrating webcam-based live prediction
- Supporting multi-disease classification
- AI-based treatment recommendation systems
- Integration with hospital healthcare platforms
- Cloud deployment
- Federated learning for privacy preservation
- Integration of Tele-medicine platform

Future research may also focus on combining dermatological images with patient history and clinical reports to further improve prediction accuracy and overall diagnostic performance.

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