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DermInsight: A diagnostic System for Human Skin Diseases utilizing Deep Learning

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Abstract Skin diseases present significant challenges in healthcare due to their diverse diagnosis and treatments. They ranked among the top causes of disability because most people ignore their early symptoms due to costly and time-consuming diagnostic methods, which worsen the skin condition with time. This research-based project contributes to the timely and cost-effective identification of seven prevailing skin diseases. We propose a novel deep learning-based system capable of classifying distinct skin diseases, including melanoma, melanocytic nevi, actinic keratoses, benign keratosis, basal cell carcinoma, dermatofibroma, and vascular lesions. By leveraging a comprehensive dataset, HAM10000, our system achieved an impressive accuracy rate of 98.14% in identifying and categorizing these skin diseases. We employ transfer learning and fine-tune three advanced deep learning models, MobileNet, MobileNetV2, and Xception, and evaluate their performance in the classification of seven human skin diseases. Remarkably, MobileNet emerged as the top-performing model, surpassing the capabilities of the other models and existing state-of-the-art methods. In addition, the proposed model is deployed in an Android app named "DermInsight" for the use of dermatologists. The dermatologist uploads the image of the skin lesions of a patient, and the app will predict the disease within 1 to 2 seconds.

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1 Introduction

Skin is the most important organ of the body because it shields our sensitive inner organs from the outer environment. This important organ can be affected due to various environmental factors such as genetic disorders, and an individual's lifestyle [1]. Thus, skin diseases are more widely spread than any other disease and can affect any person, irrespective of their gender, age, and background. According to the World Health Organization (WHO) [2], almost 900 million people are affected by skin diseases. Skin disease may range from mild skin infections to severe, life-threatening skin conditions such as cancer [3].

The human skin consists of cells, and these groups of cells form tissues. The irregular growth of these cells can result in skin diseases. Skin diseases can be classified as benign or malignant. Malignant types are considered skin cancers and are threatening to life, while benign types are not harmful and can be controlled at early stages [4]. Skin cancer is the 17th most common cancer worldwide [5]. Some types of skin diseases, including basal cell carcinoma, squamous cell carcinoma, and melanoma, are considered cancerous diseases [6], whereas melanocytic nevus, actinic keratoses, benign keratosis, dermatofibroma, herpes, and vascular lesions are non-cancerous. However, every type of skin disease can be treated successfully if it is detected earlier [6].

Generally, most people overlook the early symptoms of skin diseases, which worsen with time and not only affect the person's physical health but also have a bad impact on their mental health and social life, as some diseases are chronic and affect the appearance of the person. So, it is beneficial to diagnose skin diseases at the initial stages to control their spread. Moreover, in many developing countries like Pakistan, people usually do not pay much attention to the diagnosis of skin diseases due to the expensive and time-consuming assessments and laboratory tests. Thus, there is a need for a cost-effective and time-efficient system for the identification of human skin diseases.

Some diseases of human skin may reflect common symptoms, and due to the presence of hair on the skin, it is sometimes difficult to accurately diagnose the type of skin disease. With the advancements in technology, Artificial Intelligence (AI) is also used in the dermatology field to make accurate diagnoses of different skin diseases because AI-based tools deeply focus on the small clues that may be ignored by dermatologists in manual assessment. Many researchers have proposed different ways to detect human skin diseases in an automated manner because the automated method is painless and addresses the issues of cost and time [7]. They leverage many image processing, machine learning, and deep learning [8] [9] [10] approaches for an accurate automatic diagnostic system for skin diseases, but still, there is a need for a lot of improvements to make a more user-friendly and efficient system that will be helpful for the patients and also provide ease for the dermatologists to evaluate the effectiveness of their decision-making.

In recent years, Artificial Intelligence has led to substantial improvements in medical fields because of machine learning and deep learning algorithms. Convolutional Neural Networks (CNNs) are pivotal tools for the analysis of dermatological images, with variants like ResNet, DenseNet, AlexNet, and VGG-16 [11] [8] [10]. Despite that, utilizing CNNs poses challenges, such as computational complexity. To address this issue, researchers are using transfer learning techniques and lightweight CNN architectures like MobileNet [1] [12] [13].

In this research, we will focus on developing a method for the diagnosis of skin diseases in humans that will take an image of the diseased part of the skin belonging to seven skin diseases and classify them. We aim to achieve a modular relationship between accuracy and efficiency by utilizing deep learning techniques. Deep learning is the most widely used technology for detecting human skin diseases [14] [15] [12] [16] [17] [18]. We have utilized deep learning models, pre-processing, and transfer learning techniques to extract the complex features from the skin lesion images and to perform the classification task. This study presents a robust mechanism for detecting human skin diseases accurately and efficiently that reduces diagnostic costs and time. The main contributions of our work are:

- Employing the transfer learning capabilities of two pretrained models, MobileNet and Xception, for classifying seven skin diseases.
- Enhanced MobileNet and Xception models by adding layers in sequence, including GlobalMaxPooling2D layer, Batch Normalization layer, Dense layer, Batch Normalization layer, Dropout layer, and Dense layer with softmax activation function.
- Comparative analysis of Enhanced_MobileNet, Enhanced_Xception, and Enhanced_MobileNetV2 based on training accuracy, validation accuracy, testing accuracy, training loss, validation loss, testing loss, precision, recall, f1-score, and computation time.

- Enhanced_MobileNet outperforms Enhanced_Xception and Enhanced_MobileNetV2 models, by achieving a modular balance between accuracy and efficiency with testing accuracy of 98.14%, testing loss of 0.08, and computation time of 5790 sec.
- Developing an Android application named "DermInsight" for accurate and efficient diagnosis of seven skin diseases within 1 to 2 seconds.

The rest of the paper is organized as follows: The available state-of-the-art is mentioned in section 2. After that methodology is explained in section 3. Section 4 describes the evaluation of the proposed method. Functionality of the DermInsight framework is explained in section 5. At the end, section 6 concludes the paper, and section 7 highlights future work and recommendations.

2 Related Work

Several studies have been explored related to the diagnosis of human skin diseases to find out the existing research approaches. This section provides a brief overview of the approaches that are considered for understanding.

Earlier, the researchers have used Artificial Neural Networks (ANNs) for the diagnosis of skin diseases. Arifin, M. S. et al. [19], proposed an automated model that robustly diagnoses six human skin diseases using ANN as a classifier. Similarly, Achakanalli, S. et al. [20], Delia-Maria FILIMON et al. [21], and Hurtado, J. et al. [22] also used ANN for the classification of diseases of human skin. The authors of the study [23], proposed a method to detect nine different diseases of skin with an accuracy of 90% using various algorithms of image processing for feature extraction, and for classification used a feed-forward Artificial Neural Network as well. The Deep Neural Network was also utilized for classification in study [24] and [25], and attained 87.25% and 91% accuracies, respectively. Likewise, a Binary Neural Network was used for classifying skin cancer in research [26]. A study conducted by S. Nandy, S. et al. [27], developed a tool for accurate skin disease diagnosis using techniques such as Machine Learning and Image Processing, with a Neural Network (NN), and achieved a 95% accuracy rate. Further, in research [28], Sheha, M. A. et al. compared the performance of automatic and traditional Multilayer Perceptrons (MLP) dealing with the classification of melanocytic nevi and malignant melanoma.

Moreover, various approaches utilized well-known machine learning algorithms such as Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Decision Tree (DT), Binary Tree (BT), and Multiclass Support Vector Machine (MSVM) for detecting skin diseases. U.B Ansari et al. [29], proposed a model to detect skin cancer with SVM as a classifier. The "m-Skin Doctor" mobile app was developed for detecting melanoma using SVM in [4] and achieved an accuracy of 80%. Victor, A. et al. [30] also proposed a model to detect skin cancer using four different classifiers: SVM, KNN, DT, and BT. The model achieved 93.07% accuracy with the SVM classifier, but other classifiers also performed well. The methodologies proposed in [31] [32], [33] [34] [35] [36] [37] [38], [39] [40] [41] [42] and [7], also extracted features using various techniques and then used SVM for the classification of different skin diseases of humans. Further, Monika, M. et al. [43], created a model that deals with eight types of diseases, and Sahana S. M. et al. [44], proposed an AI framework for classifying benign or malignant skin lesions using MSVM. The model to detect skin-related cancer in the study [45], used different preprocessing techniques, followed by segmentation and feature extraction. After that, three classifiers, Naïve Bayes (NB), DT, and KNN, were utilized for classification, from which the highest accuracy of 82.35% obtained with DT. Besides, an invasive and automated model was created to detect melanoma in the study [46]. After preprocessing and feature extraction, classification was performed using three different classifiers: SVM Linear Kernel, SVM RBF Kernel, and Bayes Net Classifier. Shahi, P. et al. [47], also proposed a model to detect melanoma by using various classifiers, SVM, KNN, DT, and Ensemble Learning (EL). Moreover, Murugan, A. et al. [48], also worked on the detection of melanoma by extracting features using different techniques and performed classification by using three different classifiers: SVM, Random Forest (RF), and KNN. The authors of [49], proposed a model involving image processing techniques followed by classification using DT and Iterative Dichotomiser3 (ID3) classifiers to detect skin disease by using a very small dataset of 40 images. The model scored 87% accuracy using 45 test images, with 6 errors. A user-friendly Android interface in [50], was developed for the diagnosis of five diseases related to using KNN for feature extraction and K-means clustering for the classification task. The approaches proposed in [51] [52] [53] [54] and [55] also used many different machine learning models, including SVM and KNN, for classification. Gaikwad et al. [56], created a model by using supervised Back Propagation Neural Network (BPNN), and unsupervised learning K-means Clustering and SVM techniques to detect skin cancer. In the study [57], Auto-associative Neural Network (AANN) and BPNN were used for the classification of skin cancer, where BPNN achieved a higher accuracy. Furthermore, Mansi Mishra et al. [6], proposed a model to detect skin disease of more than one category using three different classifiers, SVM, KNN, and DT. D. BORDOLOI et al. [58], created an evolutionary model to accurately detect six types of diseases using different preprocessing techniques followed by segmentation using the K-means algorithm. This study used three classifiers, SVM, KNN, and Random Forest, to classify and obtained the highest accuracy using SVM. An early disease detection method was developed in [59], in which NB was used after image pre-processing for the classification of skin diseases, including actinic keratoses, melanoma, psoriasis, and eczema. Furthermore, M. Q Hatem [60], developed a user-friendly GUI that detects the skin lesion as normal or benign by employing the presented model, which performed image processing techniques followed by classification using a KNN classifier.

In recent research, Convolutional Neural Networks (CNNs) are becoming very popular due to their powerful capabilities in image classification. Many researchers made use of CNNs in their proposed methodologies and achieved good results. Nasr-Esfahani, E. et al. [61] focused on deep learning methods to create an automatic melanoma detection system, incorporated K-means clustering for feature extraction, image augmentation, and a Convolutional Neural Network for classification. Rathod, J. et al. [62], Akmalia, N. et al. [63], Samuel et al. [64], Hasan, M. et al. [65], Yunendah et al. [66], R. Roslan et al. [67], T. Afroz et al. [68], V.R. Allugunti [69], K.S. Rao et al. [70], B. Shetty, R. Fernandes et al. [71], D. Santos [15], Srujan S A et al. [9], S. Ahmed et al. [3], Prof. V. Paithankar et al. [72] and A. Jadhav et al. [14] also used Convolutional Neural Networks for the classification of different types of skin conditions.

Some approaches involved the implementation of both Machine Learning and Deep Learning techniques. Karunanayake, R. K. et al. [73], developed an Android app to recognize skin sensitivity, acne type, and acne density using an image. The model used a hybrid approach using both deep learning and machine learning, such as a CNN model with Resnet features, NB, and SVM. Daghrir, J. et al. [74], proposed a model to classify images as melanoma or not and achieved the highest accuracy with the use of CNN as compared to SVM and KNN. However, majority voting achieved the highest accuracy of 88.4% among all. Moreover, in research [75], the researchers created a model by employing a combination of deep learning, machine learning, and image processing techniques. Their study utilized an ensemble model that incorporated both Random Forest and deep Convolutional Neural Networks to detect seven skin diseases.

The use of transfer learning also revolutionized the performance of automated human skin disease diagnostic approaches. Bhavya Sai V et al. [76], presented a methodology for the prediction of cancers of the skin using the pretrained Neural Network Inception V3 and achieved an accuracy of 85%. S.R. Guha et al. [18], developed a model to classify skin lesion images using two techniques: CNN and transfer learning with a VGG16 pretrained model, where VGG16 achieved a higher accuracy. The study [77], also proposed a system to diagnose ten diseases of the skin using image preprocessing and transfer learning techniques. The image preprocessing techniques for this system involved noise removal, removal of unwanted elements, image augmentation, and resizing of images, while transfer learning involved the feature extraction and fine-tuning of the pretrained VGG16 model. Md. F

Rasul, N. et al. [78], created a system utilizing techniques of deep learning, using models like ResNet, InceptionV3, VGG16, and Xception for classification, and SegNet, BCDU-Net, and U-Net for segmentation. In the research [17], a method of early-stage melanoma detection was developed using transfer learning with the EfficientNet-B6 model and with EfficientNet-B4 in [79]. Inception-ResNet-v2 classifier was used in [16], for the detection of skin cancer in lesion images. T. Swapna et al. [10], also proposed a web-based system to detect seven skin diseases using the models of deep learning, like CNN and the three pretrained models, AlexNet, ResNet, and InceptionV3. The results showed that ResNet152V2, in comparison to other models, attained better training and testing accuracies of 88.83% and 64.62%, respectively. Thus, the ResNet architecture was used in a web application for diagnosis. The authors of [80], experimented with different models for the timely identification of melanoma. The results showed that the Inception Resnet model achieved the highest accuracy of 84%, outperforming other models such as CNN, Resnet50, and InceptionV3. Additionally, Kousis, I. et al. [81], created a mobile application that centered on a single deep learning model. In this study, 11 models were trained on the HAM10000 dataset to classify 7 skin diseases, where the DenseNet169 model achieved the highest accuracy of 92.25%. Further, in the research paper [8], by Dr. T. Kameswara Rao et al, the basic CNN model, three pretrained CNN models including VGG16, DenseNet, and InceptionV3, and an ensemble of these pretrained models were used to identify seven skin diseases. The results showed that the basic CNN provides 71%-75% accuracy, VGG16 of 80.3%, DenseNet 82.3%, Inception gave 80.4% accuracy while the ensemble model gave better performance with an accuracy of 85.02%. A system was created using the EfficientNetV2-M model by the authors of [11]. In this, the researchers compared the performance of the modified EfficientNetV2-M model with other deep learning models, specifically with EfficientNet-B4. However, the EfficientNet-V2-M achieved the highest accuracy of 95.49%. In the research paper [82], deep learning techniques were employed, and Google's Inception v4 CNN was utilized as the classifier for the detection of skin diseases, particularly focusing on melanoma.

In addition, the pretrained models such as MobileNet and Xception also provided appreciable results with transfer learning and fine-tuning techniques. MWP Maduranga et al. [12], developed an AI-based android application to identify seven skin disorders using MobileNet with a technique of transfer learning and attained an accuracy of about 85%. The research conducted by Haseeb Younis et al. [13], also presented an efficient approach to classify seven diseases of the skin by fine-tuning the pretrained MobileNet CNN and achieved 97.07% accuracy. Moreover, in the research done by Sadik, R. et al. [1], they proposed a web-based system to detect five skin diseases using two pretrained models, which were Xception and MobileNet. The results showed that Xception and MobileNet, in comparison to other models, had better training and testing accuracies of 97.00% and 96.00%, respectively. Thus, they utilized Xception architecture in a web application for diagnosing diseases of the skin.

From the review of the available literature, we conclude that each approach has its own advantages and limitations that could be improved. Considering the accuracies and efficiencies of the models, the MobileNet and Xception models with fine-tuning appeared to be reasonable models for the diagnosis of human skin disease. However, many improvements are required to upgrade their accuracy and efficiency. Thus, we target these two approaches and propose Enhanced_MobileNet and Enhanced_Xception models, which enhance the results of the existing approaches.

3 METHODOLOGY

This section presents the proposed approach to classify seven human skin diseases using transfer learning by leveraging pretrained deep convolutional neural networks: MobileNet and Xception. Figure 1 outlines the flow of the proposed framework, and then detailed explanations of each step are provided, highlighting the techniques utilized to achieve the desired results.

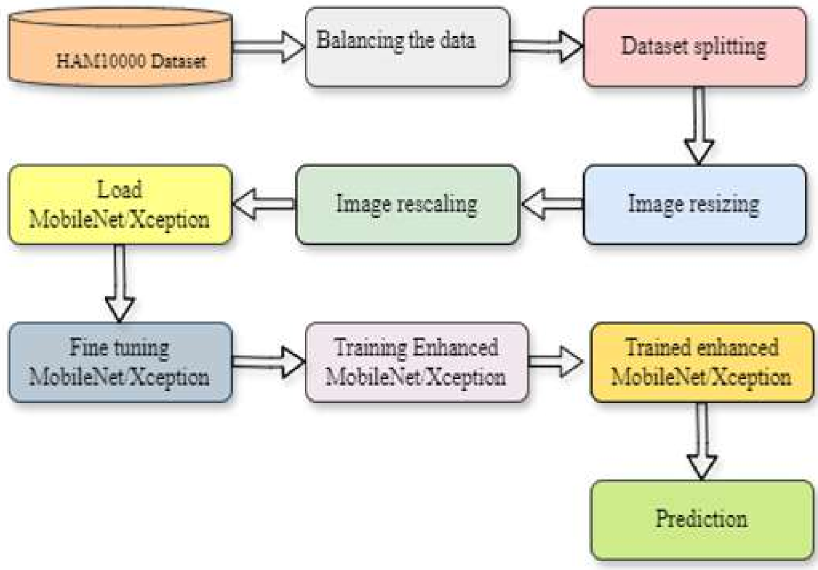

Figure 1. Proposed methodology

3.1 Data Gathering

The dataset that we used for the training, validation and testing of our proposed algorithms was the Skin Cancer MNIST ("Modified National Institute of Standards and Technology Database"): HAM10000 ("Human Against Machine with 10,000 training images") and it was taken from Kaggle [83] [14] [8] [12] [81] [53] [13]. It consists of more than 10,000 images of skin lesions belonging to seven diseases. These seven diseases include melanoma, melanocytic nevi, actinic keratoses, benign keratosis, basal cell carcinoma, dermatofibroma, and vascular lesions. This dataset is easily accessible as it is publicly available. Some of the dataset images are shown in Figure 2.

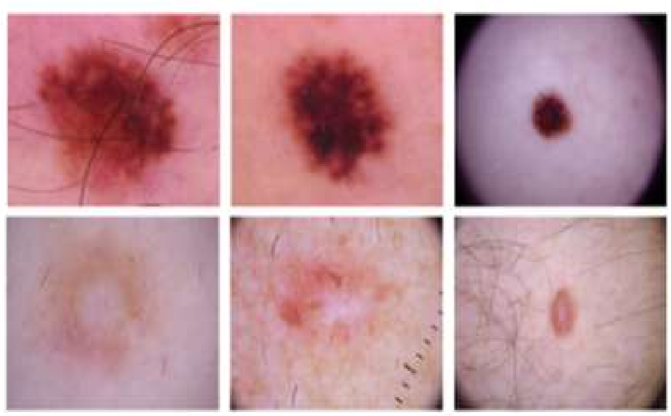

Figure 2. Skin Cancer MNIST: HAM10000 Dataset

3.2 Data Balancing

When the algorithm is trained with an unbalanced dataset, the results are biased as the model identifies the instances of majority classes (classes consisting of more samples) very well, but does not correctly predict the instances of the minority classes (classes consisting of fewer samples). Therefore, it is necessary to balance the dataset before using it. Since the dataset that we selected was not balanced, we balanced it as shown in Figure 3, by using the Random Oversampling technique [6] [53]. In this technique, the additional copies of the instances of the minority classes were created to make a balanced dataset.

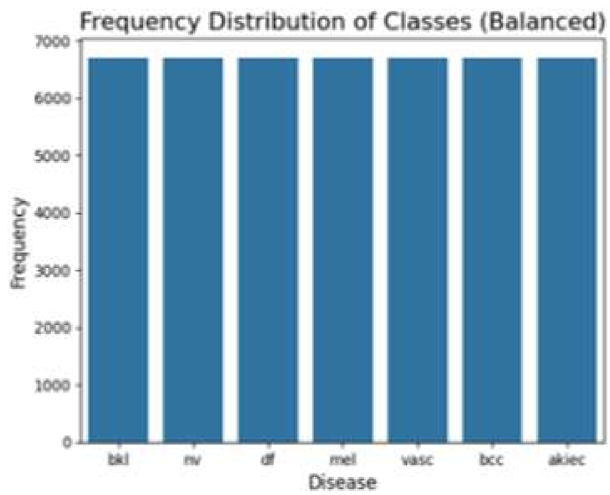

Figure 3. Balanced dataset

3.3 Dataset Splitting

Data splitting is used in building and evaluating machine learning models by ensuring that the model is accurately trained and performs well on new and unseen data. In the proposed methodology, the dataset was split into training, validation, and test sets in a stratified manner, by maintaining a proportional arrangement of 70:15:15 train, validation, and test ratios.

3.4 Image Resizing

Resizing of the skin lesion images was done to make all the images into a unified format. For the Enhanced_MobileNet model, we resized the images 224×224 and for the Enhanced_Xception model, the images were resized to 229×229. Image resizing is also very beneficial to reduce the processing time of the images and to improve the performance of the model.

3.5 Image Rescaling

Image rescaling refers to the adjustment of the size or resolution of the image. The adjustment can be upscaling or downscaling, depending on the purpose for which it is used. In this proposed approach, all pixel values were scaled down to the range between 0 and 1. Image rescaling facilitates uniformity between images to meet the requirements of compatibility with the model structure.

3.6 Load MobileNet / Xception

After preparation and splitting of the dataset, the next step we followed was to load the pretrained model, such as MobileNet and Xception, to leverage their image classification characteristics. MobileNet and Xception models were loaded using the Tensorflow library with their pretrained weights when they were trained on the "ImageNet" dataset. The "include_top" parameter of MobileNet or Xception was set to "False" as we used these pretrained models for feature extraction purposes from the skin lesion images. For this, we included only the convolution base of the MobileNet and Xception models, and omitted the top layers (Fully Connected Layers) of the model. The "classifier.trainable" parameter was set to "False", which means freezing the layers of MobileNet and Xception so that their pretrained weights would not update during training.

3.7 Fine-Tuning MobileNet / Xception

Transfer learning [12] [77] [13] [76] involves taking a pretrained model and using it as the starting point for a new model or task. In our case, we leveraged MobileNet and Xception pretrained models for the detection of seven human skin diseases. Furthermore, to get high performance, fine-tuning [77] was done in which we modified the model as per our requirements. In our fine-tuning approach, we replaced some top layers of MobileNet and Xception models and also added some additional layers for improved results. The layers that we added in sequence were GlobalMaxPooling2D_Layer, BatchNormalization_Layer1, Dense_Layer1, BatchNormalization_Layer2, Dropout to reduce overfitting, and Dense_Layer2 for classification. Figure 4 shows the fine-tuning of the MobileNet and Xception models.

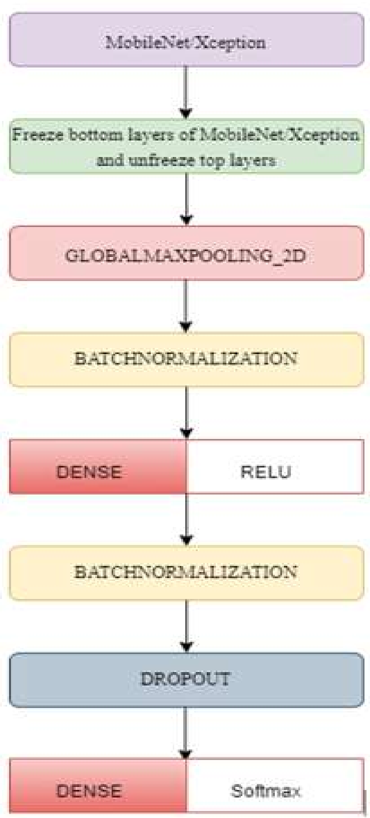

Figure 4. Fine-tuning of MobileNet and Xception model

3.8 Trained Enhanced_MobileNet / Enhanced_Xception

After fine-tuning, the training parameters were set for the Enhanced_MobileNet and Enhanced_Xception models. We set batch size to 64, initial learning rate to 0.001 and used Adam optimizer [3] [9] [71] [16] [70] [79] [68] [13] [25] [66] because of its adaptive learning strength for the optimization of deep neural networks. The categorical cross-entropy loss function [66] [13] was used to measure the difference between predicted and actual class label distributions. We also implemented early stopping to avoid overfitting and to improve the generalization of trained models, and set epochs to 15 for training. After adjusting all the parameters, we started the enhanced models' training.

3.9 Trained Enhanced_MobileNet / Enhanced_Xception

When training was done, we saved our proposed Enhanced_MobileNet and Enhanced_Xception models with a .h5 file so that they can be used later for the diagnosis of seven skin diseases. Then, we used our trained models for the predictions by accessing them from their saved .h5 file using the "load_model" function in the Keras library.

3.10 Prediction

By leveraging our trained Enhanced_MobileNet and Enhanced_Xception, we successfully classified seven skin lesion images, which were passed to them as shown in Figure 5 with good accuracy. Both models classified the skin lesion input images belonging to seven target skin conditions (melanoma, basal cell carcinoma, actinic keratoses, vascular lesions, melanocytic nevi, benign keratosis, and dermatofibroma) correctly.

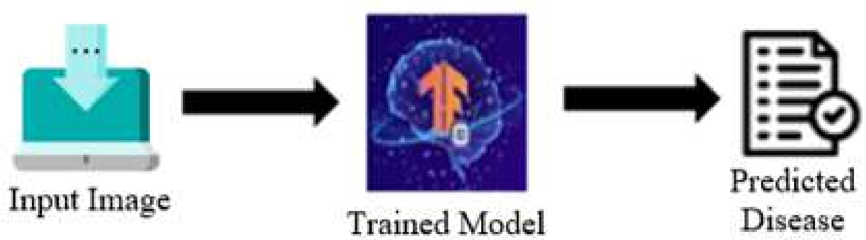

Figure 5. Prediction of Proposed Model

4 RESULTS AND EVALUATION

To evaluate the performance of the proposed models, the evaluation metrics that we used include training, validation, and testing accuracies, which compute the model's capability for correctly detecting skin diseases. The training, testing, and validation losses were used to determine the convergence of the models during the training process. We also tested our proposed methodology using the MobileNetV2 model. Furthermore, we examined the computational time of each model as well. These parameters are summarized in Table 1, providing insights into the results of the proposed models. Moreover, accuracy graphs, loss graphs, confusion matrices, and classification reports were also considered for the proposed models to validate their performance.

The figures 6, 7, and 8 show the training, testing, and validation accuracies and losses of the proposed models.

A confusion matrix was used to evaluate the performance of proposed models by comparing the actual values of the target variable with the values predicted by the model depicted in Figure 9, Figure 10, and Figure 11, respectively.

Table 1. Results of proposed models

Model	Computation Time	Training Accuracy	Validation Accuracy	Testing Accuracy	Training Loss	Validation Loss	Testing Loss
Enhanced_Xception (Transfer Learning)	6284s	97.77%	97.86%	97.34%	0.06	0.07	0.10
Enhanced_MobileNet (Transfer Learning)	5790s	98.82%	98.31%	98.14%	0.03	0.07	0.08
Enhanced_MobileNetV2 (Transfer Learning)	3810s	97.55%	97.65%	97.36%	0.07	0.08	0.09

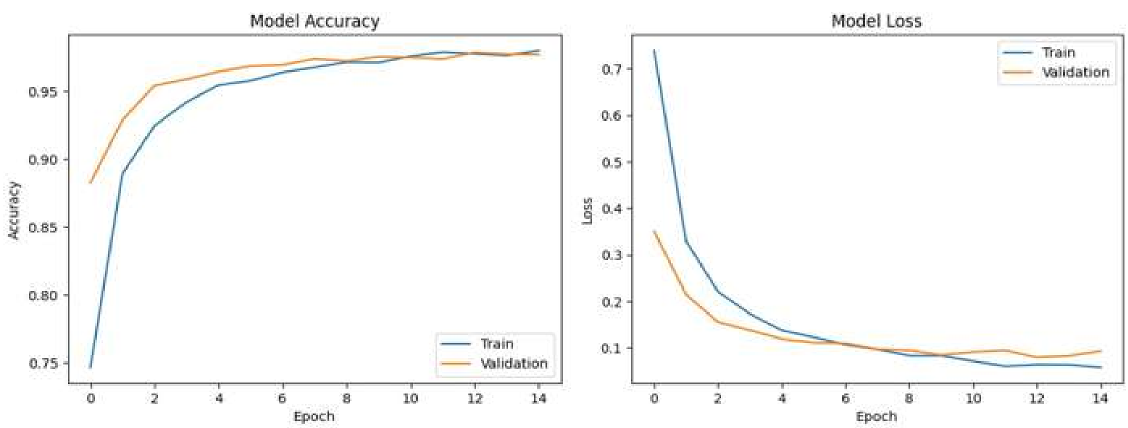

Figure 6. Accuracy and Loss graph of Enhanced_Xception

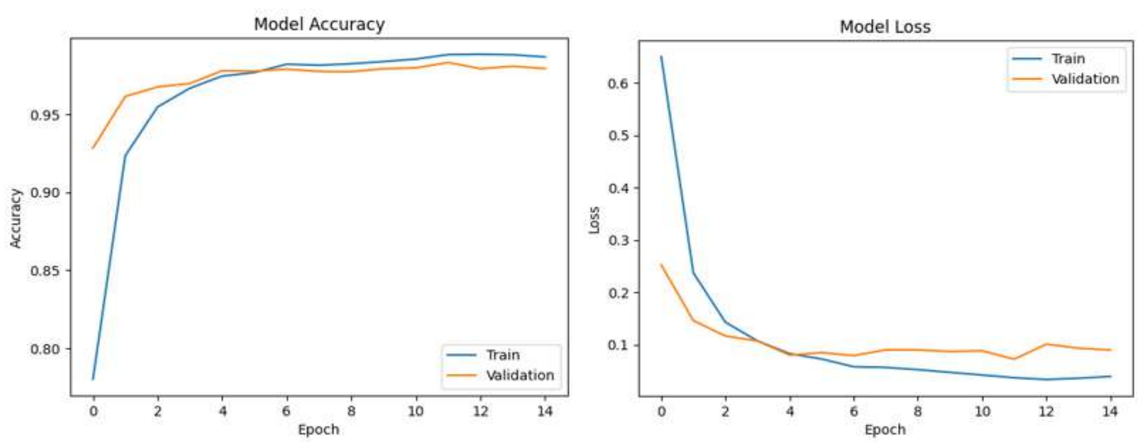

Figure 7. Accuracy and Loss graph of Enhanced_MobileNet

A classification report was used to measure the performance of the proposed model by calculating precision, recall, F1-score, and support of each class. Figure 12, Figure 13, and Figure 14, respectively, illustrates the classification report of proposed Enhanced_Xception, Enhanced_MobileNet, and Enhanced_MobileNetV2 models.

The comparison of the overall precision, recall, and F1-score of the proposed models is shown in Figure 15.

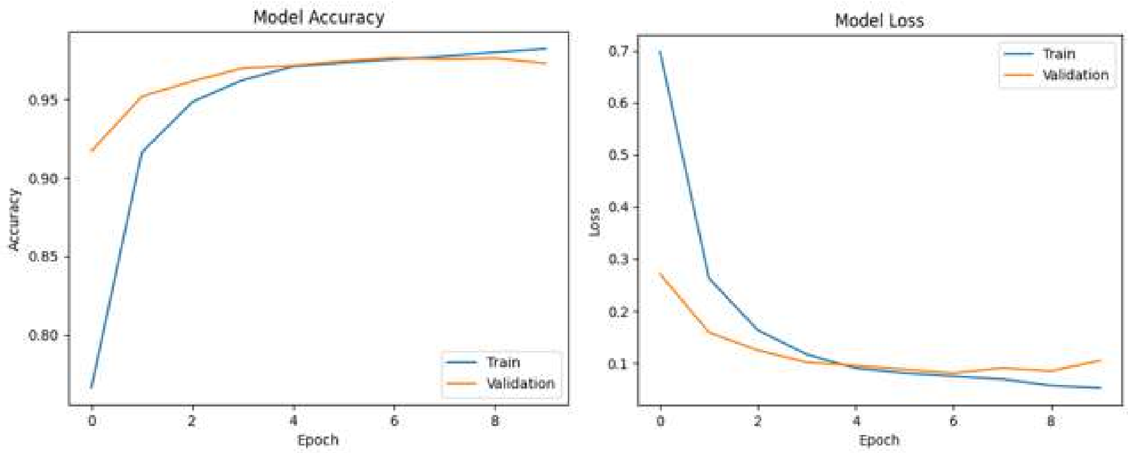

Figure 8. Accuracy and Loss graph of Enhanced_MobileNetV2

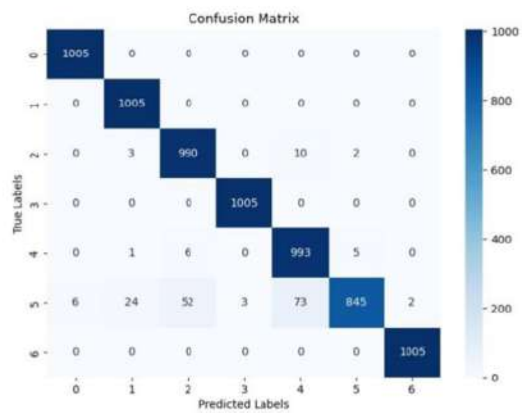

Figure 9. Confusion matrix of Enhanced_Xception

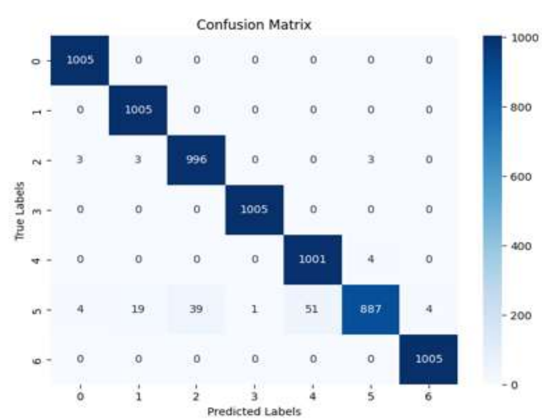

Figure 10. Confusion matrix of Enhanced_MobileNet

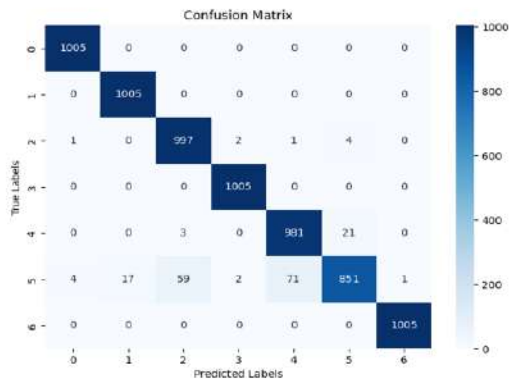

Figure 11. Confusion matrix of Enhanced_MobileNetV2

	precision	recall	f1-score	support
0	0.9941	1.0000	0.9970	1005
1	0.9729	1.0000	0.9863	1005
2	0.9447	0.9851	0.9644	1005
3	0.9970	1.0000	0.9985	1005
4	0.9229	0.9881	0.9543	1005
5	0.9918	0.8408	0.9101	1005
6	0.9980	1.0000	0.9990	1005

Figure 12. Enhanced_Xception with transfer learning

	precision	recall	f1-score	support
0	0.9931	1.0000	0.9965	1005
1	0.9786	1.0000	0.9892	1005
2	0.9623	0.9910	0.9765	1005
3	0.9990	1.0000	0.9995	1005
4	0.9515	0.9960	0.9733	1005
5	0.9922	0.8826	0.9342	1005
6	0.9960	1.0000	0.9980	1005

Figure 13. Enhanced_MobileNet with transfer learning

	precision	recall	f1-score	support
0	0.9950	1.0000	0.9975	1005
1	0.9834	1.0000	0.9916	1005
2	0.9415	0.9920	0.9661	1005
3	0.9960	1.0000	0.9980	1005
4	0.9316	0.9761	0.9534	1005
5	0.9715	0.8468	0.9048	1005
6	0.9990	1.0000	0.9995	1005

Figure 14. Enhanced_MobileNetV2 with transfer learning

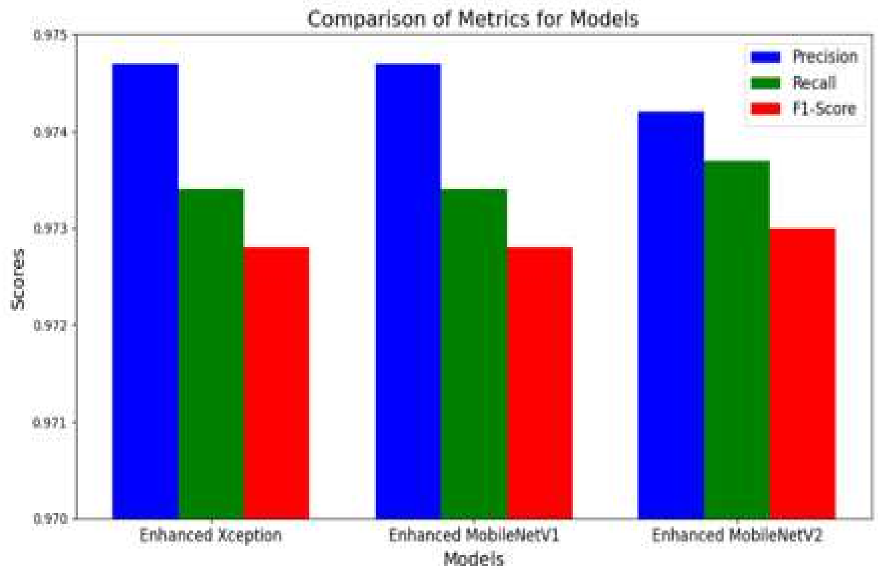

Figure 15. Comparison based on Precision, Recall, and F1-Score

Table 2. Research Synthesis

Reference	Used Architecture	Dataset	Accuracy
[9]	CNN	HAM10000	74% - 75%
[12]	MobileNet with transfer learning	HAM10000	85%
[71]	CNN	HAM10000	95.18%
[81]	DenseNet169	HAM10000	92.25%
[75]	Ensembled Random Forest and DCNN	HAM10000	96.1%
[1]	MobileNet and Xception with transfer learning	Dermnet and HAM10000	MobileNet: 96.00% Xception: 97.00%
Proposed	MobileNet, MobileNetV2, and Xception with transfer learning	HAM10000	MobileNet: 98.14% MobileNetV2: 97.36% Xception: 97.34%

The results showed that the Enhanced_Xception model maintained competitive performance with validation and testing accuracies of 97.86% and 97.34% respectively, with the computation time of 6284 sec. The Enhanced_MobileNet and Enhanced_MobileNetV2 outperformed their existing models in validation and testing accuracies. The Enhanced_MobileNet achieved an impressive testing accuracy of 98.14% with a computation time of 5790 sec, while the Enhanced_MobileNetV2 achieved a testing accuracy of 97.36% with the shortest computation time of 3810 sec among all the models. The Enhanced_MobileNet and Enhanced_Xception models offered superior performance in terms of both accuracy and computational efficiency. Considering the modular balance between accuracy and computational efficiency, the Enhanced_MobileNet model emerged as a promising alternative for rapid and accurate skin disease detection. The performance comparison of the proposed models with findings from the existing relevant literature is showcased in Table 2.

Furthermore, an Android application was preferred for deploying the proposed model due to its potential advantages for accessibility (offline access) and real-world impact. Mobile applications offer the convenience of on-the-go access, allowing users to utilize the model directly from their smartphones. Additionally, mobile deployment aligns with the widespread use of smartphones, providing a broader reach to users. The goal was to enhance accessibility and make the model more user-friendly. For this, we selected the Enhanced_MobileNet model due to its improved accuracy and utilization.

5 DERMINSIGHT: FUNCTIONALITY

The user can use the “DermInsight” app to capture the diseased part of the skin directly from the camera or to upload the skin lesion image. After the image is captured, it is sent to our trained model. The model will detect and classify the type of disease in the image, and display it on the app. Users can also read the necessary information about the seven target diseases from the “diseases” module. Useful tips are also available in the "tips" module to maintain healthy skin. The figures 16 show the basic functionality of the developed app.

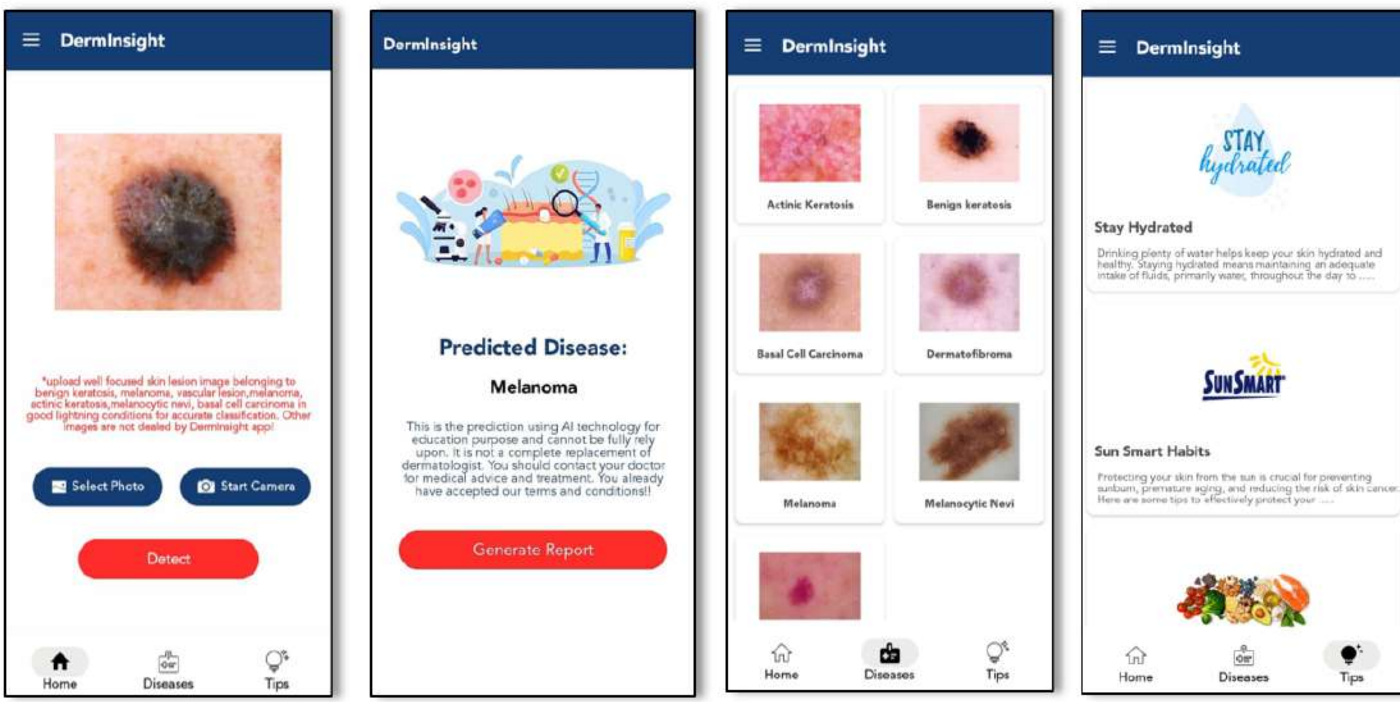

Figure 16. User interface of the DermInsight mobile application showcasing: (a) image input for detection via photo or camera, (b) predicted disease result display, (c) disease category browser, and (d) skincare tips and advice.

6 CONCLUSION

To conclude, the proposed approach for classifying seven human skin diseases utilizing MobileNet, MobileNetV2, and Xception with fine-tuning achieves 98.14% accuracy in 5790 sec, 97.36% in 3810 sec, and 97.34% in 6284 sec, respectively. These results illustrate that the proposed MobileNet has successfully achieved modular results with significantly higher accuracy while simultaneously reducing computational time compared to existing approaches. This advancement underscores the effectiveness of leveraging pretrained models in optimizing performance. Furthermore, we have developed a mobile application, utilizing the proposed Enhanced_MobileNet, to diagnose seven skin diseases. The user can give an image of a skin lesion either by camera or gallery, and also explore the causes, symptoms of skin diseases, and some useful healthy skin tips. However, the results of the diagnosis may vary depending on the quality of the images and lighting conditions.

7 FUTURE WORK AND RECOMMENDATIONS

This research paves various way for future research. Our work focuses on seven skin diseases. In the future, the scope could be expanded to the classification of more skin conditions with more accurate results. Melanoma and melanocytic nevi have appearance similarities; it will be motivated to propose such algorithms that focus on the accurate classification of these two skin diseases. To ensure more generalized results, future work can also involve using more diverse datasets. Moreover, the Enhanced_MobileNet model can be improved to detect skin diseases in any lightning condition to make the DermInsight android application more cooperative.

Author Contributions

Arfa Skandar: Supervision, Conceptualization, Methodology. **Zainab Asim**: Methodology, Data curation, Experiments and implementations, Writing- Reviewing. **Tayyaba Arbab**: Methodology, Investigation, Writing- Original draft preparation, Visualization. **Naila Batool**: Methodology, Experiments and implementations, Writing- Reviewing and Editing.

Compliance with Ethical Standards

It is declared that all authors don't have any conflict of interest. Furthermore, informed consent was obtained from all individual participants included in the study.

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