Skin Disease Classification using fine-tuned Xception Deep Learning Technique

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ABSTRACT
Skin diseases rank among the most prevalent health conditions globally, yet their diagnosis remains challenging, primarily due to the intricate interplay of factors such as skin tone, color variations, and hair presence. The diverse manifestations, initial symptom similarities, and uneven distribution of lesion samples further compound the complexity of accurately classifying these disorders. Deep Convolutional Neural Networks (CNNs) have exhibited remarkable potential in improving the precision of skin disease classification. This paper introduces a novel approach to enhance skin disease classification by fine-tuning a pre-trained Xception model. The fine-tuning process entails the incorporation of supplementary layers into the foundational Xception architecture, with selective weight training. The proposed model builds upon an augmented Xception architecture, thoughtfully incorporating depth wise separable convolutions complemented by Batch Normalization and the versatile RELU/SELU activation functions. Comparative analysis against the original Xception model and earlier architectures unequivocally highlights the substantial enhancement in classification accuracy achieved by our network. Empirical results firmly establish the proposed model's efficiency and reliability relative to previous iterations. Notably, the proposed model surpasses contemporary state-of-the-art models, achieving an exceptional accuracy rate of 99% alongside an F1-score of 97%. This research underscores the potential of fine-tuned Xception-based CNNs in significantly advancing the accuracy and reliability of skin disease classification, offering a robust solution to the multifaceted challenges posed by skin disease diagnosis.

General Terms
Image processing, Xception pre-trained model, Relu and Selu activation function, Acne, Hair-loss, Nail fungus, Skin Allergy, state-of-the-art model.

Keywords
Skin Disease Images, Xception Deep learning, OpenCV, Fine-tune, Convolutional neural networks (CNN).

1. INTRODUCTION
The most delicate and important human body organ is skin that protects us against diseases, heat and damage. Unfortunately bacterial and viral infections, fungus, a lack immune system and genetic imbalances can occasionally affect the skin's state. Diseases caused by those variables frequently have gruesome impacts on human existence. Additionally some skin conditions are infectious, putting not only the affected person but also others close to them at danger. Skin diseases are not well known to most people. Occasionally, those diseases don't do too much harm. They may result in serious health problems. Therefore, it is essential to understand their consequences. A number of laboratory pathology tests are used in the diagnosis of skin diseases in order to identify the correct illness. Over the past 10 years, these diseases have been a source of concern due to their rapid appearance and complexity, which also increase the risks associated with living. Due to their high contagiousness, these skin defects must be treated quickly to stop them from spreading. Overall well-being is adversely impacted, which includes mental and physical welfare as well as personal welfare.

Many of these skin abnormalities are quite fatal, especially if left untreated at an early stage. Skin disorders range widely in terms of severity and range of symptoms. They could be either long-term or short-term, painless or excruciating. Certain ones are inherited, while others are influenced by current event. Skin issues can be either non-threatening or potentially fatal. While most skin issues are rather minor, some may indicate a more serious condition. Prejudice affects medical experts' evaluations in a similar way that each human search begins with the terms selected by the user. When a doctor makes an assumption diagnosis, they usually look for evidence to support their theories before ruling out other possible diseases until their theories are proven false.

The order or weight allocated to any of the symptoms would probably bias the findings towards a correct diagnosis, even if another sign is overlooked and not included in the search or taken into immediate consideration. Early control of the illness is essential if it is to be stopped from spreading. Skin conditions can negatively impact a person's mental health as well as their self-esteem in addition to their skin's look. Skin conditions are now a prominent cause of public concern as a result. Early detection and timely treatment of several skin problems are essential to preventing lasting skin damage.

2. REVIEW OF LITERATURE
This research work emphasis on development of robust model for classification of skin disease using fine-tuned Xception deep learning techniques. Various authors have used different machine learning and types of deep learning techniques for classification of skin diseases. Author [1] suggested an efficient solution for skin disease recognition by implementing Convolutional Neural Network (CNN) architectures, MobileNet, and Xception, deep learning techniques were utilized to construct an expert system that could accurately and efficiently recognize different classes of skin diseases and achieved classifications accuracy of 96.00% with MobileNet and 97.00% with Xception model. Author[2] proposed computer-aided techniques in deep learning neural networks such as Convolutional neural networks (CNN) and Residual Neural Networks (ResNet) to predict skin diseases in real-time and they got an accuracy 77% and 68% with CNN and ResNet

respectively. Author [3] developed a model that has an ability to recognize and classify the skin diseases. They demonstrated how the model performance may be enhanced by a reasonable network structure. The authors proposed CNN algorithm with 938 skin images that are Melanoma, nevi, and seborrheic keratosis and achieved 71% of accuracy. They have also tried AlexNet model, which gave better accuracy as 76.1%.

Author[4] suggested deep learning methods CNN and ResNet classification algorithm for an automated computer-aided diagnosis system for multi-class skin (MCS) cancer classification with an exceptionally high accuracy. They performed fine-tuning over seven classes of HAM10000 dataset with five pre-trained convolutional neural networks (CNNs) and four ensemble models, where suggested algorithm given 93.20% of accuracy for single model and 92.83% with an ensemble model. Author[5] developed an automated framework that efficiently performs a reliable automatic lesion classification for dermatology and that follows an ensemble approach by combining ResNet-50 and Inception V3 architectures to classify the seven different skin disease types. The overall accuracy achieved by proposed algorithm is 89.90%.

In paper [6] the authors combined Convolutional Neural Network with three predefined models called Alex Net, ResNet, InceptionV3 classifier. The experiment done with a skin disease dataset consists of 7000 images with seven skin diseases. Author[7] developed a MobileNet model by applying CNN transfer learning methods with 7 skin diseases and created a skin disease classification system on Android application. The author gathered 3,406 skin disease images from online public access dermatology repositories. They used oversampling technique and data augmentation on preprocessing the input data and they got 84.28% accuracy.

Author[8] presented a method for diagnosis of skin cancer from dermoscopy images. The Proposed Xception method was then implemented to MNIST skin cancer dataset .which utilized swish activation function and depthwise separable convolutions. The system showed an improvement in the classification accuracy of the network compared to the original Xception and other architectures. Author[9] used three state-of-the-art deep learning pre-trained models for classification of the skin lesions like ResNet, Xception and DenseNet., They used the HAM10000 dataset for the purpose of training and evaluation of models and obtained balanced accuracy of 78%, 82%, and 82% for ResNet, Xception and DenseNet models respectively. Then they combined the three models using the weighted ensemble technique without any further training and the overall accuracy achieved got 85.8% balanced accuracy.

Authors[10] suggested Deep learning algorithms like Inception_v3, Inception V2 ,and MobileNet for feature extraction and classification. They further combined the Inception V3, MobileNet, Inception V2 and created ensemble models for classification of dermatology. The proposed Inception V3 model achieved better accuracy 88.28% as compared to Inception V2 and MobileNet. Author[11]used Xception as the base model for skin cancer classification and increases its performance by reducing the depth and expanding the breadth of the Xception architecture. They used the HAM10000 dataset, which contains 10,015 images of skin dermatology and classified into seven categories. Authors[12] proposed Xception model that included one pooling layer, two dense layers, and a dropout layer for the purpose of modified architecture of Xception model. This experiment used HAM10000 skin disease dataset with seven classes for skin diseasesThe dataset imbalance was fixed by using data augmentation techniques. The updated model has a classification accuracy of 96.40% for skin disorders.

Author[13] have used Xception, Inception V3, Seresnext101, ResNet50, DenseNet121, GoogleNetand EfficientNet techniques for classification skin diseses. The evaluation results of each model were compared, and then the best results were selected which determines the best model. Author[14] developed CNN model with the help of feature extraction that reduced the need for human labor, such as manual feature extraction and data reconstruction for classification of skin disease. A dataset consists of 10015 skin disease images that include Nevus, Melanoma, and Sebborheic Keratosis and achieved 92% accuracy.In paper[15] the author proposed a fusion model by using convolutional neural network algorithm for skin disease classification with public HAM10000 skin disease dataset . Pre-training, data augmentation, and parameter fine-tuning were conducted to enhance the performance of model. The proposed model created the two baseline models of DenseNet201 and ConvNeXt_L. and fine-tuning of both the model where DenseNet201 and ConvNeXt_L got 95.29% accuracy and 89.99% respectively.Authors[16] have used convolutional neural networks, a technique based on transfer learning, to present a multiclass skin disease classification model. The results of the pre-trained models like VGG16, VGG19, ResNet50, ResNet101, ResNet152, and Xception MobileNet compared in terms of accuracy.

Authors[17] developed a system including VGG16, VGG19, MobileNet, ResNet50, InceptionV3, Inception- ResNetV2, Xception, DenseNet121, DenseNet169, DenseNet201, and NASNet mobile to classify skin diseases with transfer learning approaches. The MobileNet based model achieved best accuracy as 94.1%. Author [18] used CNN-based technique for identifying and classification of skin disease. MobileNet with transfer learning method got a best model for automatic skin disease identification on a Smartphone and achieved accuracy of 85%. In paper [19] the author created a model incorporating convolutional neural networks with long short-term memory (LSTM) classifiers. The author optimizes the problem and achieving a 99% overall accuracy rate by combining Pearson feature selection concepts and the fusing of the correlation between the two loss functions to achieve automatic pneumonia detection in X-ray pictures. In [20] fully connected Convolutional networks like InceptionV3 and XgBoost classifiers are used to predict seven classes based on 74 features and 4,200 images. Authors [21] proposed model by using the ideas of transfer learning and fine-tuning the stacked ensemble method for melanoma classificatio, including Xception, Inceptionv3, InceptionResNet-V2, DenseNet121, and DenseNet201. This methodology performed better than state-of-the-art methods.

Authors [22]investigated a model by adding a group of layers after the Xception model for classification of skin lesions. A seven-class augmentation strategy is used to fine-tune the model over the HAM10,000 dataset in order to reduce the effect of data imbalance. Using a balanced dataset, the proposed model performance achieved 96% accuracy. Authors [23] introduced a Deep learning CNN model for classification of skin disease with HAM10000 dataset. They have also propsed X-R50 model and compared with CNN model and got 97.8% of accuracy. Authors[24] designed computerised model employing MobileNet V2 and Long Short Term Memory (LSTM) was developed for the classification of skin diseases. A grey-level co-occurrence matrix is utilized to evaluate the progression of the disease development and the effectiveness of the system has been evaluated in comparison to other Fine-

Tune models such as the Visual Geometry Group (VGG) Fine-Tuned Neural Networks (FTNN), Convolutional Neural Networks (CNN), and Very Deep Convolutional Networks for Large-Scale Image Recognition. Authors [25] investigated the detection of melanoma using different deep learning technaiues using augmented HAM 10,000 dataset and achieved accuracy 84% by AlexNet model. The other models achieved accuracies 89% and 90% with VGGNet 19 and VGGNet 16 respectively. The highest accuracy achieved 92% with ResNet50 while 90% with Xception model.

3. PROPOSED METHODOLOGY

3.1 Xception Basic Model Architecture

The Xception model framework is composed of 14 groups, with 36 convolutional layers serving as the foundation for feature extraction. Each group incorporates a linear residual connection, except for both the initial and final groups. Figure 1 illustrates the data flow, which consists of three stages: the entry flow, the middle flow (replicated eight times), and the exit flow [25].

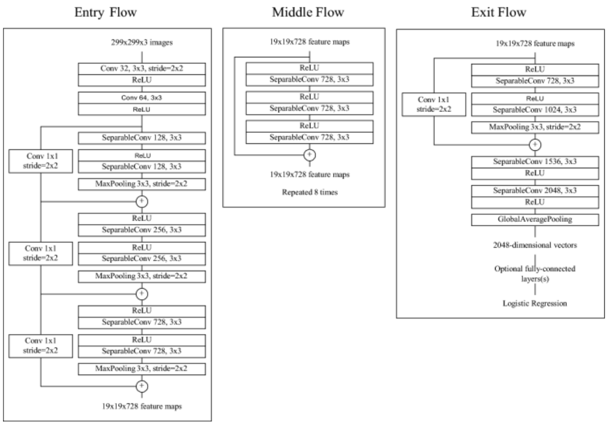

Fig 1. The Xception basic model architecture

3.2. Fine-Tuned Xception Model for Multi-Class Skin Classification

We employed the transfer learning classification technique to identify skin diseases using a pre-trained Xception model. We fine-tuned the model by freezing all layers up to 'group 11,' making them untrainable, while allowing all layers from 'group 11' onwards to be trainable for further training. Additionally, we extended the Xception base model by

```
model_x.summary()
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 sequential_2 (Sequential)   (None, 224, 224, 3)       0

 rescaling_1 (Rescaling)     (None, 224, 224, 3)       0

 xception (Functional)       (None, 7, 7, 2048)        20861480

 global_average_pooling2d_1  (None, 2048)              0
  (GlobalAveragePooling2D)

 dropout_2 (Dropout)         (None, 2048)              0

 flatten_1 (Flatten)         (None, 2048)              0

 dense_2 (Dense)             (None, 512)               1049088

 dropout_3 (Dropout)         (None, 512)               0

 dense_3 (Dense)             (None, 4)                 2052

=================================================================
Total params: 21912620 (83.59 MB)
Trainable params: 11067476 (42.22 MB)
Non-trainable params: 10845144 (41.37 MB)
_________________________________________________________________
```

Fig 2: Fine-tuned Xception model architecture

appending six additional layers at the end, resulting in a total of 138 layers, as illustrated in Figure 2.

In the context of the fine-tuned Xception model's architecture and the process unfolds as follows:

- Firstly, RGB input images are resized to a standardized 224 x 224 pixel resolution. The initial step, `sequential_2`, encompasses image augmentation techniques aimed at enhancing the dataset's diversity. Subsequently, `rescaling_1` takes charge of preprocessing the data by rescaling input images to fall within the range of [-1, 1].
- The heart of the architecture is the `xception` layer, which operates as a feature extractor. It accepts input images sized at 224x224x3 and yields feature maps sized 7x7x2048. The following layer, `global_average_pooling2d_1`, calculates global average pooling over the spatial dimensions of the previous layer's output, producing a fixed-size feature vector with a dimensionality of 2048.
- To mitigate overfitting, `dropout_2` is introduced with a dropout rate set to 0.3. `flatten_1` follows, serving the purpose of converting the 3D feature maps into a 1D vector, a necessary step to prepare the data for fully connected layers.
- The next layer, `dense_2`, is a fully connected layer with 512 units, employing the SELU activation function and 'lecun_normal' kernel initializer. To further guard against overfitting, `dropout_3` is introduced with a dropout rate of 0.1. Finally, the model concludes with a softmax layer that classifies input training images into one of four classes.
- For optimization, the model employs the 'Nadam' adaptive optimizer with a learning rate of 0.00001 and 'SparseCategoricalCrossentropy' as the loss function. To ensure model robustness and prevent overfitting, fine-tuning is conducted over a span of 10 epochs.

In terms of parameterization, the model encompasses a total of 21,912,620 parameters, equivalent to roughly 83.59 MB of memory usage. Of these, 11,067,476 parameters (42.22 MB) are designated as trainable, while the remaining 10,845,144 parameters (41.37 MB) are marked as non-trainable. Non-trainable parameters primarily correspond to the frozen parameters of the pre-trained base model (Xception), which remain unaltered during the fine-tuning process. This comprehensive architecture and parameterization strategy allow the model to effectively classify input images into the specified categories while optimizing for performance and memory efficiency.

4. DATASET DESCRIPTION AND AUGMENTATION

Skin disease image dataset collected from the Kaggle data science website [14], which comprises a total of 5,783 images categorized into four distinct classes: Acne, Nail fungus, Hair loss, and Skin allergy. It is important to note that the entire dataset was utilized for both training and validation purposes, with an 80% allocation for training and the remaining 20% for validation [10]. These images, as found in the Kaggle dataset, are represented in the RGB color space. Although they originally exhibit pixel values within the [0, 255] range, a critical preprocessing step was applied to normalize the RGB values, thereby transforming them into the interval [-1, 1].

Furthermore, the dermoscopic images in the dataset were uniformly resized to dimensions of 224 x 224 x 32 pixels, ensuring consistent input size across all layers of the model. Subsequently, the dataset was partitioned into two subsets: 4,627 images designated for training and 1,156 images reserved for validation purposes. Table 1 shows the description of dataset with training, validation and testing samples with four different classes and Figure 3 shows the sample training dataset of skin disease images.

Table 1. Kaggle Dataset Classes

Classes	No. of Images for Training	No. of Images for validation	No. of Images for test
Acne	1054	207	16
Hair loss	1168	296	36
Nail Fungus	1214	288	22
Skin Allergy	1191	269	22

Fig 3: Sample of training dataset with skin disease images

Data augmentation represents an artificial technique employed to expand the training dataset by generating transformed variants of existing images, obviating the need for additional data collection. The amalgamation of diverse data augmentation techniques has been demonstrated to enhance the generalizability of the training dataset to novel, unexamined data instances, concurrently diminishing the risk of overfitting. The specific data augmentation parameters utilized in this study as shown in Table 2.

Table 2. Dataset Augmentation Parameters

Augmentation parameter	Value	Description
Random Flip	horizontal	Randomly flips the images horizontally with a probability of 0.5
Random Rotation	0.2	Randomly rotates the images by a maximum of 20% of the image width
Random Zoom	0.2	Randomly zooms in or out of the images by a maximum of 20%
Random crop	height and width	Randomly crops the images to the specified height and width (224 x 224)

5. PERFORMANCE EVALUATION AND EXPERIMENTAL RESULTS

This section introduces a detailed analysis of experimental work against latest competitive techniques. This section explores the basic hardware and software requirement for experimental work. We have also explored the experimental results of proposed model.

5.1. Experimental Work Setup

The proposed model was trained and tested on a computing platform equipped with the following specifications: an Apple M1 processor, housing an 8-core CPU composed of 4 performance cores and 4 efficiency cores, complemented by a 7-core GPU and a 16-core Neural Engine, with 8GB of RAM. This platform was meticulously selected to fulfill the demanding computational requirements of training a deep neural network. The implementation was conducted using the Python programming language. For deep learning the Keras framework integrated with TensorFlow was chosen as the development environment. All computations were performed within a Jupyter Notebook environment [12].

5.2 Experimental Results

The fine-tuned Xception model was rigorously assessed using a distinct set of 1156 photographs that were excluded from the original training dataset of 4627 images across four classes. Additionally, a separate set of 96 photos was reserved for comprehensive testing. As illustrated in Figure 4, the fine-tuned Xception model exhibited remarkable performance, achieving a training accuracy of 99.29% and a validation accuracy of 100% and Figure 4 shows training and validation accuracy and loss graph .The training and validation processes were conducted over a span of 10 epochs, where an 'epoch' denotes a complete iteration through the entire training dataset.

An 'EarlyStopping' callback has been incorporated into the model to mitigate overfitting during the training process. This callback is configured to continuously monitor the validation loss during training and will terminate training if the validation loss fails to show improvement for three consecutive epochs, effectively preventing excessive overfitting. Furthermore, to be considered a significant improvement, the validation loss must exhibit a minimum change of 0.01; changes below this threshold are deemed insignificant and do not trigger the early stopping mechanism.

Figure 5 displays the confusion matrix generated by the fine-tuned Xception model, where samples divided into four different classes. The proposed model correctly classified all 16samples into Acne class, all 29 samples correctly classified into hairloss class, all 32 samples correctly classified into Nail Fungus class and 19 samples are correctly classified into skin allergy while 1 sample is incorrectly classified as Acne class. Figure 6 presents the classification report, showing a comprehensive evaluation of the model's classification quality. The evaluation metrics indicate that, for each class, the model exhibits minimum precision and recall values of 94% and 95%, respectively, along with an outstanding average classification accuracy of 99%.

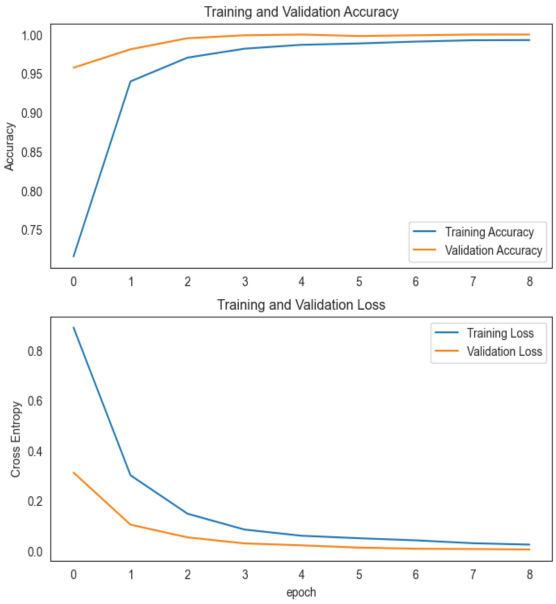

Fig 4: Training and Validation Accuracy and loss of fine-tuned Xception model.

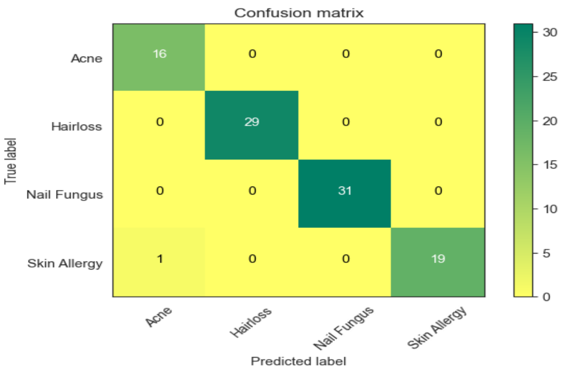

Fig 5: Confusion matrix of fine-tuned Xception model

```
Classification Report:
              precision    recall  f1-score   support

        Acne       0.94      1.00      0.97        16
    Hairloss       1.00      1.00      1.00        29
 Nail Fungus       1.00      1.00      1.00        31
Skin Allergy       1.00      0.95      0.97        20

    accuracy                           0.99        96
   macro avg       0.99      0.99      0.99        96
weighted avg       0.99      0.99      0.99        96
```

Fig 6: Resultant evaluation metrics for fine-tuned Xception model

6. CONCLUSION

A fine-tuned Xception model for the classification of skin diseases is presented in this paper. The base model was pre-trained on the ImageNet dataset, comprising over one million images, to achieve superior accuracy. A comprehensive hyperparameter tuning process was conducted to determine the optimal configuration. Experimental results demonstrate the model's effectiveness in accurately categorizing various skin diseases. The proposed model's performance was rigorously evaluated using a balanced dataset, achieving an impressive accuracy rate of 99%. This performance level positions it competitively among recent state-of-the-art models in the field. In future, we will use different deep learning based models with optimization techniques and preprocessing techniques to enhance the quality of images and improve the performance of model.

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