# Computer Vision Based Skin Disorder Recognition using EfficientNet: A Transfer Learning Approach

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***Abstract*—Skin disorders have a vital impact on people's health and quality of life, it is essential to develop a reliable and accurate computer vision approach to recognize multiple skin disorders. In this paper, a new rapid recognition approach using EfficientNet has been introduced to diagnose twenty types of skin disorders. Initially, image augmentation techniques have employed, and then eight architectures of EfficientNet between B0 and B7 have trained using the transfer learning approach. To evaluate the performance of models, different experimental studies have employed using a test set of 6300 images of skin disorders dataset that makes the proposed approach more reliable and accurate. EfficientNet-B7 has achieved the highest accuracy 97.10% among all architectures but has taken longer training time. EfficientNet-B0 has taken the lowest training time and has achieved 93.35% accuracy. EfficientNet-B7 has also taken the lowest time in recognizing unseen new images of skin disorders accurately than others.**

***Keywords—Computer Vision, Skin Disorders, Psoriasis, Eczema, Transfer Learning, EfficientNet***

## I. Introduction

The skin is the largest organ of the human body, with a wide range of people from children to elders all over the world are suffering from different types of skin disorders. It is one of the main reasons for the Global Burden of Disease (GBD) [1]. Although there are more than 1000 types of skin or skin related disorders are detected in different countries, but some of these are very impactful on health. These are psoriasis, eczema, acne, rosacea, ringworm, melasma, cold sores, lupus, vitiligo, and hives. It poses a significant threat to patients' mental health, ability to function, well-being, and social participation which is also a reason for non-fatal disability and superstition in poor regions of the world.

About 2-3% of the total population of the world have psoriasis which is an immune-mediated disease, symptoms can start at any age and can appear anywhere on the body [2]. There are five types of psoriasis, these are guttate, pustular, plaque, inverse, and erythrodermic. More than 80% of psoriasis patients are affected with plaque psoriasis which causes red patches on the knees, elbows, and scalp. On the other hand, 25% of psoriasis patients are affected with inverse psoriasis, its signs found on the armpits, under breasts, buttocks, and in the genital area which is deep-red shiny skin. Atopic dermatitis, contact dermatitis, dyshidrotic eczema, hand eczema, neurodermatitis, nummular eczema, stasis dermatitis are the seven types of eczema. Men are less affected by dyshidrotic eczema than women. Nummular eczema causes coin-shaped spots on the skin, and stasis dermatitis causes itchy skin on the lower legs that is more common in people whose age is 50 or more. Acne is another type of skin disease which is usually linked with hormonal fluctuations.

Different medical image processing methods are being studied to reduce the intrinsic work of dermatologists and radiologists. Advanced deep learning approaches make the task easier for recognition, segmentation, etc [3]. Moreover, different imaging techniques like Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Functional Magnetic Resonance Imaging (fMRI), and Positron Emission Tomography (PET), etc. are developed in a radical way [4]. Dermatological image processing techniques have been improving day by day with the development of deep learning algorithms. In recent years, many researches have undergone on numbers of skin diseases using different architectures of Convolutional Neural Network (CNN). Although Psoriasis is taken account into several times, other skin disorders have been classified and recognized [10] [11] [14]. On the other hand, image acquisition, image pre-processing, feature extraction, feature selection, and segmentation based hybrid approaches have been used for skin disease localization. Image Segmentation helps researchers to find out the skin lesion part and different types of statistical and morphological analysis [14]. After the advent of transfer learning, different architectures of CNN like VGG16, Inception-V3, MobileNet, and other networks have been studied with several skin disorders with less computation and high classification accuracy [15]. But their small number of classes for skin disorders do not make the classification robust enough. For this reason, we want to overcome the previously mentioned problems with our research paper.

An innovative and robust computer vision approach for recognizing skin disorders based on EfficientNet is presented in this paper. EfficientNet is one of the state-of-the-art CNN architectures, its family consists of 8 models between B0 and B7. All models of the EfficientNet family have used in this study using the transfer learning approach. According to the experiment results, EfficientNet-B7 has achieved 97.10% accuracy, which is better than other models of EfficientNet.

The key contributions of this research work are:

- To the best of our knowledge, we are the first who works with 20 different types of skin disorders and one healthy skin with better classification accuracy.
- We considered 21 classes and 52500 images for our study where image augmentation is used to increase the size of the dataset for alleviating the overfitting approach.
- To analyse the success of models 6300 images of the testing set of skin disorders dataset have used which makes the experiments results more reliable and accurate.

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The rest of this study is organized as follows. Section 2 introduces and summarizes related work. Section 3 introduces the skin disorders dataset and describes EfficientNet used in this study. Experimental studies are presented in Section 4. The results attained in the study are presented and discussed in Section 5. The study is concluded with Section 6.

## II. Related work

To enhance the quality of life of skin disorders patients, many researchers have made tremendous efforts to recognize skin disorders. Computer vision approaches are now adopted widely to achieve higher accuracy than traditional approaches used in existing studies.

Nurul Akmalia et al. have proposed a method for classifying skin diseases based on shape, color, and texture of skin diseases using local binary pattern (LBP) and convolutional neural network (CNN) that has achieved an average accuracy of 92% [5]. Rola EL SALEH et al. have used VGG16 for identifying eight facial skin diseases and achieved 88% accuracy [6]. Evgin Goceri has used ResNet for classifying skin diseases and achieved 97.01% validation accuracy [7]. Two activation functions such as rectified linear unit (ReLU) and scaled exponential linear unit (SELU) have been used, SELU and without residual block have reached the highest accuracy. Jainesh Rathod et al. have used CNN for diagnosing skin diseases and achieved 70% testing accuracy [8]. T. Shanthi et al. have used AlexNet architecture to diagnosis four different types of skin diseases with a learning rate of 0.01 and achieved an accuracy of 85.7%, 92.3%, 93.3%, and 92.8% for acne, keratosis, eczema herpeticum, and urticaria, respectively [9]. Li-sheng Wei et al. have used support vector machine (SVM) to classify three different types of skin diseases using texture features such as contrast, correlation, entropy, uniformity, and energy, and color features and to segment images, grey-level co-occurrence matrix (GLCM) have used [10]. Anabik Pal et al. used CNN, SVM, and k-nearest neighbour (KNN) for scoring the severity of psoriasis using erythema, scaling, and induration, and CNN based architecture has performed better than others [11]. Nazia Hameed et al. have proposed a method for classifying four skin diseases using AlexNet and error-correcting output codes (ECOC) SVM and achieved 86.21% accuracy, to avoid overfitting 10-fold cross validation technique has used [12]. Shuchi Bhadula et al. have used logistic regression, random forest, kernel SVM, naive bayes, and CNN to detect three skin diseases, CNN has performed better than others and achieved 96% testing accuracy [13]. Tamanna T. K. Munia et al. have used k-means clustering and SVM with the color feature for psoriasis lesion classification, achieved 93.83% accuracy [14]. Md. Aminur Rab Ratul et al. have used VGG16, VGG19, MobileNet, and Inception-V3 to classify seven skin lesions and achieved an accuracy of 87.42%, 85.02%, 88.22%, and 89.81%, respectively [15].

CNNs have obtained satisfactory success in different types of skin disorders recognition according to these studies. For twenty types of skin disorders recognition, an image recognition model that is based on EfficientNet is proposed in this paper.

## III. Materials and Methods

### A. *Dataset*

In this study, the skin disorders dataset has been generated which contains 52500 images of skin disorders and healthy skin. Initially, 6300 images of skin disorders have collected, and then using the image augmentation, the number of images has increased to 52500. Rotation transformations (including 90, 180, and 270 degrees), horizontal and vertical flip, horizontal and vertical shift, random zoom augmentation techniques have been used. Fig. 1 shows 21 different samples of the used dataset. All images have been reshaped into 8 different dimensions by using Pillow which is a library of Python 3 for the purpose of this study.


Fig. 1. Sample from skin disorders dataset: 1) guttate psoriasis 2) pustular psoriasis 3) plaque psoriasis 4) inverse psoriasis 5) erythrodermic psoriasis 6) atopic dermatitis 7) contact dermatitis 8) neurodermatitis 9) dyshidrotic eczema 10) nummular eczema 11) seborrheic dermatitis 12) stasis dermatitis 13) acne 14) rosacea 15) ringworm 16) melasma 17) cold sores 18) lupus 19) vitiligo 20) hives 21) healthy

### B. *EfficientNet*

To discover more reliable and accurate approaches with smaller models is the main aim of computer vision and deep learning, EfficientNet achieves more effective results by uniformly scaling depth, width, and resolution while scaling down the model. It consists of 8 models between B0 and B7, and the number of parameters does not increase as the model number grows, but the accuracy of the model increases surprisingly. EfficientNet-B0 is the base model of the EfficientNet family, the schematic representation of the EfficientNet B0 model is presented below in Fig. 2.

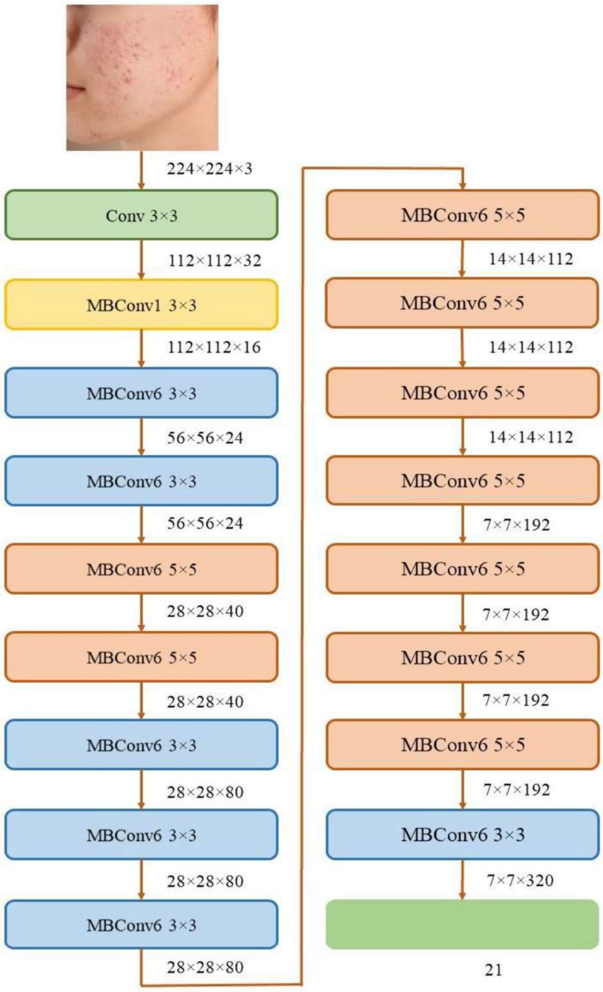


Fig. 2. Schematic representation of EfficientNet B0

While other state-of-the-art CNN models use ReLU as an activation function, EfficientNet uses a new activation function, namely Swish which is a multiplication of linear and sigmoid activation functions. The inverted bottleneck MBConv plays a crucial role in EfficientNet, much fewer channels are connected than expansion layers as direct connections are used between bottlenecks, and blocks of MBConv consists of a layer that compresses the channels after expands. The EfficientNet models achieve both better efficiency and higher accuracy over existing state-of-the-art models CNN models, and EfficientNet-B7 reaches state-of-the-art 84.4% top-1 and 97.1% top-5 accuracy on ImageNet [16]. Compare to traditional layers, the architecture of EfficientNet has in-depth separable convolutions which decrease calculation by almost $k$ factor where the kernel size is $k^2$ that represents the height and weight of the 2D convolution window. To uniformly scale depth, width, and resolution, with the principles presented in (1) the compound coefficient φ is used in compound scaling.

$$depth, d = \alpha^{\varphi}$$

$$width, w = \beta^{\varphi}$$

$$resolution, r = \gamma^{\varphi} \tag{1}$$

$\alpha \geq 1, \beta \geq 1, \gamma \geq 1$

α, β, γ are constants, by using grid search these can be determined, and how many resources are available for model scaling is controlled by φ which is a user-defined coefficient, on the other hand, α, β, γ determine how these extra resources are assigned to the architecture width, depth, and resolution, respectively. The compound scaling method scales baseline EfficientNet-B0 in two steps, at first assuming that there are twice as many resources available, grid search is performed with φ=1, and the best values are found for α, β, γ. And then obtained α, β, γ values are determined as constant, and the baseline network is scaled up to obtain EfficientNet-B1 to B7 with different φ values using (1).

Using the transfer learning approach, eight models of the EfficientNet group have used in this study. In the transfer learning approach, the last few layers of the pre-trained architecture can be dropped and retrained with new layers for the new task. The transfer learning approach saves time and achieves higher accuracy than a model built from scratch.

## IV. Experiments

### A. *Training*

In this study, all deep learning models have been trained with GPU support, and all experimental studies have been conducted in Google Colab. Using Keras 2.4.3 that is an open source deep learning framework in Python 3, all codes have been realized. The skin disorders dataset has been divided into training, validation, and test set inconstantly in this study. All classes of the used dataset contain 2000 training images, 200 validation images, and 300 testing images. To train and fit the models of EfficientNet, 42000 training and 4200 validation images have been used, while 6300 images of the test set of skin disorders dataset have been used to examine the performance of the models.

In this study, all layers of models of EfficientNet have set as trainable true, softmax has used as the activation function of the last layer, and categorical cross entropy has used as a loss function during the training phase of the models. The last fully connected layers of models with 1000 outputs have changed to 21 outputs for the purpose of our study. The early stopping method has used in this study during the training phase with 5 as patience and le-3 minimum change in the loss. Adam optimization method has been used in all models of EfficientNet with a 0.001 learning rate. Eight different input sizes have been used in this study, the mini-batch size has been set to 16, and the validation steps for models have been set to 1.

### B. *Performance Metrics*

The skin disorders dataset contains 21 classes, so multi-class classification has performed in this study using EfficientNet. Equations from 2 to 5 have been calculated by using the values obtained from the confusion matrix after classification using indices such as TP, TN, FP, and FN. Here, TP (True Positive) is the number of accurately predicted skin disorders images in every class, and TN (True Negative) presents the number of accurately predicted images in all classes without the related class. FN (False Negative) is the number of inaccurately classified images from the related class, and FP (False Positive) is the number of inaccurately classified images in other classes without related class [17].

Using sensitivity (Sen), specificity (Spe), accuracy (Acc), and precision (Pre), the performance of all models of EfficientNet have been evaluated in this study. The ratio of accurately classified positives out of all true positives is called sensitivity, while specificity means the ratio of accurately classified negatives out of all true negatives. Accuracy represents the ratio of accurately predicted images out of the total number of images. The ratio of accurately classified positives out of all positive classifications is known as precision.

For a class $v$,

$$Sen(v) = \frac{TP(v)}{TP(v) + FN(v)} \tag{2}$$

$$Spe(v) = \frac{TN(v)}{TN(v) + FP(v)} \tag{3}$$

$$Acc(v) = \frac{TP(v) + TN(v)}{TP(v) + TN(v) + FP(v) + FN(v)} \tag{4}$$

$$Pre(v) = \frac{TP(v)}{TP(v) + FP(v)} \tag{5}$$

## V. Results and Discussions

All models of EfficientNet have been trained by performing transfer learning approach, and to reveal a reliable and accurate computer vision approach for skin disorders recognition is the main motivation of this study. Early stopping techniques have been used during the training phase of all models; the total training time has been evaluated as the period of time until the epoch where the loss values of the models become started to increase. Dividing the total training time with the total number of epochs has been calculated as the time per epoch. Table 1 summarizes the input sizes, the time per epochs (TPE), the number of total parameters, and total misclassification numbers of the models of EfficientNet.

TABLE I. THE TIME PER EPOCHS, AND NUMBER OF TOTAL PARAMETERS FOR EFFICIENTNET MODELS

| Model Name | Input Size | TPE (sec) | Number of Total Parameters | Total Number of Misclassification |
|---|---|---|---|---|
| B0 | 224×224 | 561 | 5,351,592 | 419 |
| B1 | 240×240 | 811 | 7,877,260 | 524 |
| B2 | 260×260 | 842 | 9,198,590 | 366 |
| B3 | 300×300 | 1109 | 12,341,556 | 288 |
| B4 | 380×380 | 1398 | 19,487,844 | 444 |
| B5 | 456×456 | 2114 | 30,583,548 | 352 |
| B6 | 528×528 | 2361 | 43,286,164 | 309 |
| B7 | 600×600 | 3197 | 66,679,708 | 183 |

EfficientNet-B0 has taken the lowest training time comparing to other models, and the number of total parameters has also less than other models. While EfficientNet-B7 has taken 32 hours and 52 minutes for training, 66,679,708 was the total number of parameters, and it has also used the largest input size than others.

Fig. 3 shows the training and test accuracies acquired in the training and test sets of skin disorders dataset for all models of EfficientNet, respectively. Test accuracies have been calculated as the ratio of the total number of accurately predicted samples to the number of total samples. EfficientNet-B7 has achieved the highest training and test accuracy, 97.87% and 97.10%, respectively. While EfficientNet-B1 has achieved 92.79% training accuracy and 91.68% testing accuracy which were the lowest compared to other models. EfficientNet-B0 has achieved 93.35% accuracy on the test set of skin disorders dataset which has taken the lowest time for training. EfficientNet-B3 has achieved the second highest test accuracy, 95.43%.

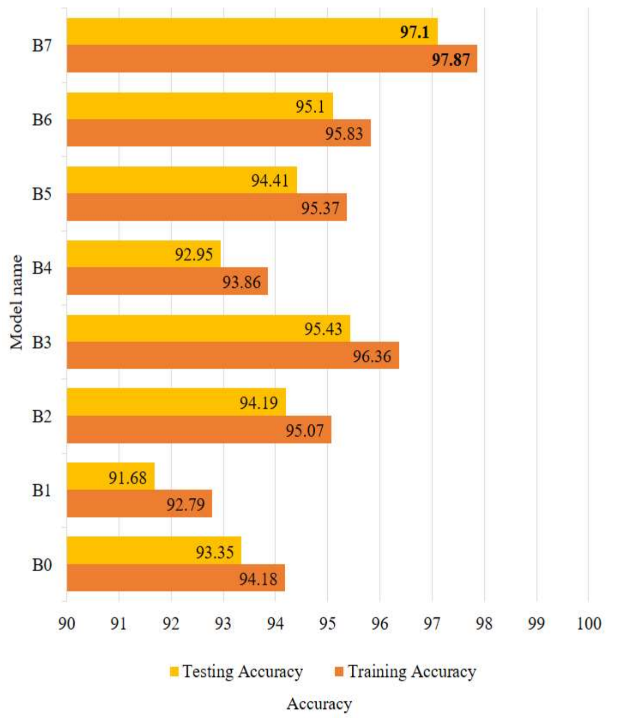


Fig. 3. Training and testing accuracies of all models for skin disorders dataset

EfficientNet-B7 have misclassified 183 images which is the lowest number of false prediction compared to others, on the other hand, EfficientNet-B1 has wrongly predicated 524 images that are the highest number of false prediction. Based on testing accuracy and the total number of false predictions, EfficientNet-B7 has been selected as a final model for recognizing skin disorders which also taken the lowest time in classifying previously unseen new images. To evaluate the recognition time of EfficientNet models, 5 new images have been used, 3 of these were original images, and the rest have generated using image augmentation. EfficientNet-B7 has accurately classified 5 images of different types of skin disorders in only 7.24 seconds, while EfficientNet-B3 has taken 10.52 seconds. EfficientNet-B7 has also shown significant performance and achieved state-of-the-art accuracy on ImageNet [16].

To evaluate the class-wise classification performance of EfficientNet-B7 different types of experimental studies have been introduced on the skin disorders dataset, TP, TN, FP, FN values of the EfficientNet-B7 model have been presented in Table 2. The highest TP value has been obtained by EfficientNet-B7 in dyshidrotic eczema and rosacea class and in the erythrodermic psoriasis class, the highest FP value has been obtained.

TABLE II. CLASSIFICATION RESULT OF EFFICIENTNET-B7

| Class Name | TP | TN | FP | FN |
|---|---|---|---|---|
| Guttate psoriasis | 289 | 5986 | 11 | 14 |
| Pustular psoriasis | 293 | 5988 | 7 | 12 |
| Plaque psoriasis | 291 | 5986 | 9 | 14 |
| Inverse psoriasis | 288 | 5999 | 12 | 1 |
| Erythrodermic psoriasis | 287 | 5985 | 13 | 15 |
| Atopic dermatitis | 290 | 5995 | 10 | 5 |
| Contact dermatitis | 294 | 5991 | 6 | 9 |
| Neurodermatitis | 293 | 5994 | 7 | 6 |
| Dyshidrotic eczema | 295 | 5990 | 5 | 10 |
| Nummular eczema | 291 | 5993 | 9 | 7 |
| Seborrheic dermatitis | 294 | 5984 | 6 | 16 |
| Stasis dermatitis | 288 | 5991 | 12 | 9 |
| Acne | 293 | 5991 | 7 | 9 |
| Rosacea | 295 | 5987 | 5 | 13 |
| Ringworm | 292 | 5988 | 8 | 12 |
| Melasma | 289 | 5995 | 11 | 5 |
| Cold sores | 290 | 5996 | 10 | 4 |
| Lupus | 293 | 5996 | 7 | 4 |
| Vitiligo | 291 | 5992 | 9 | 8 |
| Hives | 288 | 5993 | 12 | 7 |
| Healthy | 293 | 5997 | 7 | 3 |

In the class-wise classification performance of EfficientNet-B7, the inverse psoriasis class has achieved the highest sensitivity, 99.65%, on the other hand, the seborrheic dermatitis class has achieved the lowest sensitivity. EfficientNet-B7 has achieved the highest specificity 99.92% in both the dyshidrotic eczema and rosacea class, while in erythrodermic psoriasis it has achieved the lowest specificity, 99.78%. Like specificity, EfficientNet-B7 has achieved the highest precision value 98.33% in both dyshidrotic eczema and rosacea class. In classifying images of healthy class, EfficientNet-B7 has achieved the highest accuracy, 99.84%. In erythrodermic psoriasis, EfficientNet-B7 has not shown satisfactory performance, the accuracy of this class is less than others. The total number of misclassifications has also been obtained for EfficientNet-B7 and in the erythrodermic psoriasis class, 13 images have wrongly predicated which is the highest misclassifications number. In dyshidrotic eczema, and rosacea class EfficientNet-B7 has shown satisfactory performance, has misclassified only 5 images. Sensitivity, specificity, accuracy, precision, and the number of misclassifications (MC) values of all classes have presented in Table 3.

TABLE III. CLASSIFICATION PERFORMANCE OF EFFICIENTNET-B7 FOR EACH CLASS

| Class Name | Sen (%) | Spe (%) | Pre (%) | Acc (%) | MC |
|---|---|---|---|---|---|
| Guttate psoriasis | 95.38 | 99.82 | 96.33 | 99.60 | 11 |
| Pustular psoriasis | 96.07 | 99.88 | 97.67 | 99.70 | 7 |
| Plaque psoriasis | 95.41 | 99.85 | 97.00 | 99.63 | 9 |
| Inverse psoriasis | **99.65** | 99.80 | 96.00 | 99.79 | 12 |
| Erythrodermic psoriasis | 95.03 | 99.78 | 95.67 | 99.56 | 13 |
| Atopic dermatitis | 98.31 | 99.83 | 96.67 | 99.76 | 10 |
| Contact dermatitis | 97.03 | 99.90 | 98.00 | 99.76 | 6 |
| Neurodermatitis | 97.99 | 99.88 | 97.67 | 99.79 | 7 |
| Dyshidrotic eczema | 96.72 | **99.92** | **98.33** | 99.76 | **5** |
| Nummular eczema | 97.65 | 99.85 | 97.00 | 99.75 | 9 |
| Seborrheic dermatitis | 94.84 | 99.90 | 98.00 | 99.65 | 6 |
| Stasis dermatitis | 96.97 | 99.80 | 96.00 | 99.67 | 12 |
| Acne | 97.02 | 99.88 | 97.67 | 99.75 | 7 |
| Rosacea | 95.78 | **99.92** | **98.33** | 99.71 | **5** |
| Ringworm | 96.05 | 99.87 | 97.33 | 99.68 | 8 |
| Melasma | 98.30 | 99.82 | 96.33 | 99.75 | 11 |
| Cold sores | 98.64 | 99.83 | 96.67 | 99.78 | 10 |
| Lupus | 98.65 | 99.88 | 97.67 | 99.83 | 7 |
| Vitiligo | 97.32 | 99.85 | 97.00 | 99.73 | 9 |
| Hives | 97.63 | 99.80 | 96.00 | 99.70 | 12 |
| Healthy | 98.99 | 99.88 | 97.67 | **99.84** | 7 |

Class-wise classification performance illustrates that the proposed computer vision approach using EfficientNet-B7 realizes end-to-end recognition of skin disorders which provides a remarkable solution. The early stopping technique has used in the training of EfficientNet-B7 determined the 37 epoch as the restoring points for which the validation loss started to increase. The accuracy and loss curve of both training and validation of EfficientNet-B7 with skin disorders dataset is shown below in Fig. 4 and Fig. 5.

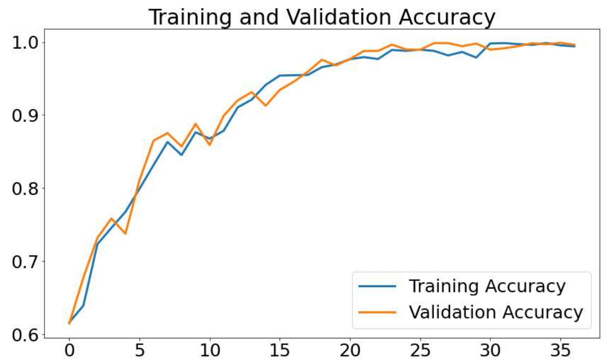


Fig. 4. Training and validation accuracy curve of EfficientNet-B7

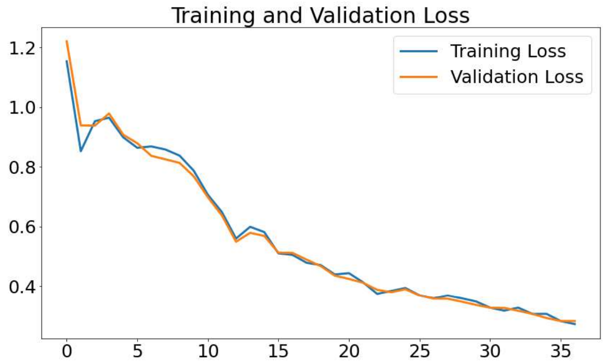


Fig. 5. Training and validation loss curve of EfficientNet-B7

The result of other studies conducted for skin disorders recognition using the computer vision approach has been compared with our study and shown below in Table 4.

TABLE IV. COMPARISON OF COMPUTER VISION APPROACHES FOR SKIN DISORDERS RECOGNITION

| Study | Method | Number of Classes | Accuracy |
|---|---|---|---|
| Nurul Akmalia et al. [5] | LBP, CNN | 6 | 92% |
| Rola EL SALEH et al. [6] | AlexNet | 10 | 88% |
| Evgin Goceri et al. [7] | ResNet | 6 | 97.01% |
| Jainesh Rathod et al. [8] | CNN | 5 | 70% |
| Nazia Hameed et al. [9] | SVM, AlexNet | 5 | 86.21% |
| Shuchi Bhadula et al. [13] | CNN | 3 | 96% |
| Tamanna T. K. Munia et al. [14] | K-means clustering | 3 | 93.83% |
| Md. Aminur Rab Ratul et al. [15] | Inception-V3 | 7 | 89.81% |
| **Our study** | **EfficientNet-B7** | **21** | **97.10%** |

## VI. CONCLUSIONS

In this paper, a real-time, individualized, and extensible computer vision approach using EfficientNet has been employed to recognize 20 different types of skin disorders. Image augmentation techniques have been used to increase the size of the skin disorder dataset and to verify the reliability and validity of the approach, different experimental studies have conducted using a test set of 6300 images. Among 8 models of EfficientNet from B0 to B7, EfficientNet-B7 has achieved the highest accuracy 97.10% on the test set of the dataset which has also accurately predicted 5 unseen images of skin disorders within 7.24 seconds. EfficientNet-B7 has taken the longest training time with 37 epochs, while EfficientNet-B0 has taken the lowest training time but achieved 93.35% test accuracy. All models have trained with the transfer learning approach, and 8 different input sizes have been used for 8 models. Meanwhile, this study explores a rapid and accurate recognition approach for skin disorders that establishes a theoretical foundation for the application of computer vision in the field of medical bioimaging. Therefore, in future works, it will be the focus to recognize different types of skin disorders with their severity scoring, and it is planned to expand the size of the skin disorders dataset and number of classes.

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